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Mosquito species distribution models: limitations and best practices

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By

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DECLARATION OF CO-AUTHORSHIP / PREVIOUS PUBLICATION

I. Co-Authorship

Chapter 2 incorporates unpublished material co-authored with under the supervision of professor H.J. MacIsaac. In all cases the key ideas, primary contributions, experimental designs, data analysis, interpretation, and writing were performed by myself; H.J. MacIsaac revised and approved the manuscript.

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Chapter 2	Barker JR, MacIsaac HJ (2021) Species distribution models applied to mosquitoes: use, quality assessment, and recommendations for best practice. Ecological Modelling	*In review*

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ABSTRACT

Understanding species distribution is fundamental to ecology and biogeography, with important implications for species management. This is especially true for species of public health concern - such as mosquitoes – which can impart both economic and health impacts. Species distribution models (SDMs) are powerful tools to accomplish this goal. However, obtaining reliable conclusions, those which are accurate and applicable for policy development, from SDMs is not straightforward owing to the many required considerations such as objective with respect to limitations of the available data. The goal of this thesis was to determine recommended methods to address known and unknown mosquito SDM limitations. First, I identified limitations of SDMs across the literature with respect to best-practice standards. I found that mosquito SDMs exhibited a very high proportion of unacceptable practices. Specifically, SDMs require greater attention to temperature and precipitation thresholds within ecologically relevant scales. Secondly, I quantified the ability of SDMs to determine reliable conclusions from imprecise occurrences, occurrences represented as an administrative/geopolitical boundary centroid, of a virtual species designed to reflect mosquitos of public health importance. I found that imprecise occurrences had a strong negative effect on reliability of conclusions. Through careful consideration of SDM model building allowed for appropriate conclusions. General boosted regression models, mean or weighted mean ensembles with balanced training and removal of low contributing predictors, consistently provided reliable conclusions from imprecise occurrences. This thesis provides methodologically recommendations to aid in SDM model development, which should translate into better quality predictions of mosquito and possibly other species distributions and management.

DEDICATION

To all the computers that spent years processing data to make this thesis a reality, and those that paid the utilities bills.

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LIST OF ABBREVIATIONS

Abbreviation	Definition
ANN	Artificial neural network algorithm
BIO1	Annual mean temperature
BIO13	Precipitation of the wettest month
BIO14	Precipitation of the driest month
BIO2	Mean diurnal temperature
BIOCLIM	Bioclimatic envelope algorithm
BS	Brier score
CBI	Continuous Boyce index
CCR	Correct classification rate
CTA	Classification tree analysis algorithm
EMca	Committee average ensemble algorithm
EMmean	Mean ensemble algorithm
EMmedian	Median ensemble algorithm
EMwmean	Weighted mean ensemble algorithm
EV	Elevation
FDA	Flexible discriminant analysis algorithm
GAM	General additive model algorithm
GARP	Genetic algorithm for rule-set production
GBM	General boosting model algorithm
GDD	Growing degree days
J	Jaccard Index
GLM	General linear model algorithm
L_DBF	Deciduous broadleaf forests
L_ENF	Evergreen needle leaf forests
L_MF	Mixed forests
L_UB	Urban settlements
L_WS	Woody savannas
L_WT	Water
MAE	Mean absolute error
MARS	Multiple adaptive regression splines algorithm
MAUP	Modifiable areal unit problem
MaxEnt	Maximum entropy algorithm
MBD	Mosquito borne disease
NDVI	Normalized difference vegetation index
PA	Presence-absence
PB	Presence-background
PD	Human population density
PO	Presence-only
RF	Random forest algorithm
RMSE	Residual mean square error
SC	Snow cover
SDM	Species distribution model

List of abbreviations (continued)

Abbreviation	Definition
SRE	Surface range envelope algorithm
SS	Associated skill score
VIF	Variable inflation factor
X_B	Algorithm X in ensemble SDM R software biomod2
X_O	Algorithm X in original R software
ρ	Spearman’s correlation

CHAPTER 1: GENERAL INTRODUCTION

The earth is undergoing rapid changes in biodiversity owing to anthropogenic pressures including habitat loss, overharvesting, introduction of invasive species, and climate change (Barnosky et al. 2011; Lewis and Maslin 2015). Accordingly, biodiversity conservation, management, and risk assessment efforts increasingly seek accurate forecasts to determine appropriate actions (Guisan et al. 2013). These objectives are often addressed through species distribution models (SDMs), also known as ecological niche models, environmental niche models, habitat suitability models, bioclimatic envelope models, or resource selection functions (Guisan and Zimmerman 2000). SDMs represent numerous different statistical or machine learning algorithms which relate species presence or presumed absence to environmental conditions to determine a species-environment relationship and forecast the corresponding distribution (Elith et al. 2006). SDMs are among the most widely applied biodiversity forecasting method (Zurell et al. 2020) with over 11,000 published studies that have applied or mentioned a form of SDMs, although powerful alternative approaches exist (Buckley 2008; Kearney et al. 2009).

Despite their popularity, SDMs require careful consideration of the response variable (i.e. occurrence records), predictor variables (i.e. environmental data), model building (i.e. addressing model complexity and bias), and model evaluation (i.e. evaluation statistic) to provide realistic and accurate results for management applications (see Araújo et al. 2019). Correspondingly, significant efforts have been undertaken to improve our understanding of how SDMs respond to different situations, including but not limited to, different algorithms, predictors, and quantity and quality of response variables (Wisz et al. 2008; Synes and Osborne 2011; Barbet-Massin et al. 2012; Heikkinen et al. 2012).

Compilation of these efforts has allowed for the creation of SDM standards and recommendations to guide biodiversity assessments. Notably, Araújo et al. (2019) proposed a set of best-practice standards to assess the quality of SDMs applied to biodiversity assessment, outlined by aspects of response variable, predictor variables, model building, and model evaluation. These assessments are taken with respect to different SDM uses of explanation, prediction, and projections. Explanation relates to determining species-environment relationships. Prediction entails mapping of potential distributions or habitat suitability from species-environment relationships within the same time and geographic space, and projection is an extension of predictions to estimate distributions or habitat suitability in new temporal or geographic spaces (Guisan and Zimmermann 2000; Araújo et al. 2019). These standards allow for a framework to assess SDMs against to determine limitations or changes in quality overtime within an application. One limitation experienced across applications is positional error of the response variable (Guisan et al. 2007).

Occurrence databases are increasingly available, but they often contain imprecise occurrences with geographic inaccuracies (Isaac and Pocock 2015; Meyer et al. 2016). Imprecise occurrences inhibit a SDM’s ability to determine the species-environment response, therefore decreasing their utility for management applications (Naimi et al. 2011). Imprecision may be accounted for by aggregation of predictor variables to the known or estimated size of the geographic error (Lechner et al. 2014). In turn, aggregation alters the scale, the level of environmental detail, which will be justifiably used to calibrate SDMs. For SDMs to properly capture a species-environment relationship, the scale must reflect the species' ecology, and is often related to a species' distribution range, body size, or reproduction (Cushman and McGarigal 2004; Jackson and Fahrig 2015). However, the appropriate scale is often unknown (de Knegt et al. 2010). Confidence in SDMs is based on the ability of a model to accurately detect the underlying processes contributing to species distributions (Evans et al. 2013). When SDMs are constructed without consideration of positional error in response data, the corresponding SDM results may hinder utility for management applications (Wu et al. 1997; Nelson 2001). Thus, for management applications it is important to understand the effect imprecise occurrences on SDMs for management applications.

The primary goal of this thesis was to investigate the quality of SDMs to identify limitations and the effect specific response variable conditions. Specifically, I investigated quality related to SDMs applied to mosquitoes. Mosquitoes are of global public health importance, owing to vectored disease causing over one million deaths and suffering for hundreds of millions more people annually (Caraballo and King 2014). These diseases include zika, dengue, yellow fever, Japanese encephalitis, West Nile fever (all *Flavivirus)*, chikungunya (*Alphavirus*), malaria (*Plasmodium*), among others (Moore and Mitchel 1997; Turell et al. 2005). Associated with their increasing global distributions, mosquitoes are considered a growing threat to global security and economic growth (Heymann et al. 2015). The highly invasive mosquitoes *Aedes (Stegomyia) aegypti (L.)* (Diptera: Culicidae) and *A. (Stegomyia) albopictus* (Skuse) are among the fastest spreading mosquito species (Benedict et al. 2007).

The survival, development, and reproduction of these species are believed to be predominantly driven by temperature and precipitation or water availability, depending on the species (Becker et al. 2010; Reinhold et al. 2018). Correspondingly, these factors limit the geographic range of *A. aegpyti* and *A. albopictus*. *A. aegypti* is traditionally observed within tropical areas (Kraemer et al. 2015, 2019). However, *A. albopictus* has a greater ecological and physiological plasticity, therefore allowing for a more extensive geographic range in temperate and tropical temperatures (Kraemer et al. 2015, 2019). The observed differences in distribution are largely driven by *A. albopictus'* ability to diapause, thus allowing for cold- and dry-resistant eggs (Denlinger and Armbruster 2014; Nikookar et al. 2020). Meanwhile, *A. aegypti* has traditionally not been considered to diapause and survival of cold temperature was dependent on indoor refuge (Nikookar et al. 2020). Some populations of *A. aegypti* have observed the ability to diapause, but the trait is not yet widespread (Lima et al. 2016). Both species are container-breeding mosquitoes which have adapted to use human-made containers (i.e. tires, discarded plastics, flower plots) as substitutes of natural breeding locations, tree holes (Barrera et al. 2011). Though, *A. albopictus* is a superior larval competitor and *A. albopictus* thus imposes competitive displacement over *A. aegpyti* (Braks et al. 2004; Lounibos et al. 2016).

A. aegypti and *A. albopictus* occur on every continent owing to human mediated dispersal (i.e. trade of used tires; Ibañez-Justicia 2020). By spreading, these species have extended the ranges of zika, chikungunya, dengue, and yellow fever to over 80, 80, 120, and 40 countries, respectively (Bhatt et al. 2013; Nsoesie et al. 2015; Lessler et al. 2016; Leta et al. 2018). Consequently, there exists growing public health concerns for the contiguous United States as well as Southwestern Ontario as the species spread north (Giordano et al. 2019).

SDMs are commonly applied to determine the distribution of mosquitoes (e.g. Kraemer et al. 2015). However, *A. aegpyti* and *A. albopictus* pose unique issues for SDM applications, particularly in North America. SDMs are widely applied to these species, but only a single comparative study exists (Khatchikian et al. 2011). Further, North American occurrences are predominantly imprecise, only available as geopolitical/administrative centroids (Hahn et al. 2017). Centroids are known inhibitors of SDM performance (Cheng et al. 2021) and alter scale of environmental detail. *A. aegypti* and *A. albopictus* have known flight ranges of ≤1 km (Verdonschot and Besse-Lototskaya 2013) and inhabit micro-niches (Hayden et al. 2010; Lima et al. 2016). These ecological aspects cannot be appropriately captured by use of habitat centroid occurrences, therefore questioning the utility of SDMs for management applications. Understanding the accuracy and reliability of different SDMs to effectively guide mosquito management and policy is essential to limit potential negative health and socio-economic impacts of mosquitoes.

1.1 Thesis objectives

In this thesis, I sought to review and advise mosquito SDM applications. In chapter 2, I reviewed published mosquito SDMs and applied the framework described by Araújo et al. (2019) to determine SDM quality and limitations specific to mosquitoes. From the identified limitations, I provide recommended methods to improve the applicability of SDMs (Chapter 2). In chapter 3, I assessed the effect of imprecise occurrences on SDMs' ability to explain and predict a distribution using a 'virtual species' designed to reflect *A. aegypti* and *A. albopictus*. I compared 30,000 SDMs varying by algorithm, predictor variables, and pseudo-absences across 42 evaluations. From these extensive evaluations, I provided recommended methodologies for different study objectives (Chapter 3). Finally, I briefly summarize the implications of mosquito SDM quality and limitations on management efforts, and novel contributions of this thesis to fields of biogeography and ecological forecasting (Chapter 4).

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CHAPTER 2: SPECIES DISTRIBUTION MODELS APPLIED TO MOSQUTIOES: USE, QUAILTY ASSESSMENT, AND RECOMMENDATIONS FOR BEST PRACTICE

2.1 Introduction

Transmission of diseases by mosquitoes is of global health importance. Mosquito-borne diseases (MBD) can be spread by several mosquito species. For example, dengue, zika, yellow fever and chikungunya are all vectored by *Aedes aegypti* and *Aedes albopictus,* while malaria is vectored by *Anopheles spp.* and Japanese encephalitis and West Nile fever by *Culex spp*. (Calvo et al. 2016; Yang et al. 2018). MBDs cause over one million deaths and suffering for hundreds of millions more people annually (Caraballo and King 2014). MBD are considered a growing threat to global security and economic growth (Heymann et al. 2015). It is estimated that half of the world's population will be at risk of MBD by 2050 (Kraemer et al. 2019). Reducing the public health burden of MBD mainly focuses on understanding and determining areas which are vulnerable to mosquito colonization (Jones et al. 2021). Species distribution models (SDMs) - also known as ecological niche models or environmental niche models - have been widely implemented to anticipate disease introduction and spread (Escobar 2020). SDMs relate the presence, absence, or abundance of a species or disease with environmental conditions to generate hypotheses related a species' potential distribution, thereby improving traditional disease risk maps (Escobar and Craft 2016). Generally, SDM use can be divided into three categories of use: i) explanation, to determine relationships between the species and the environment, therefore providing hypotheses regarding environmental factors that determine a species' distribution; ii) prediction, mapping of potential distributions from the determined species-environment relationship within the same time period or geographic space; and iii) projection, which extends the projections to estimate distributions in new temporal or geographic spaces (Guisan and Zimmermann 2000; Araújo et al. 2019).

Despite their popularity, SDMs have been criticized owing to their assumptions (Sinclair et al. 2010; Araújo and Peterson 2012). Additional concerns focus on response variable selected, predictor variables used, model building, or model evaluation considerations (Jarnevich et al. 2015; Araújo et al. 2019). The response variable is the primary building block of SDMs, defining the location and environmental conditions in which species are known to be present or presumed absent (Guisan and Zimmermann 2000). Predictor variables considered in SDMs dictate the species-environment relationships considered to explain, predict, or project a species' distribution. Model building relates to the fitting of a statistical relationship between response variable and predictor variables. Model evaluation details the applied criteria to assess realism, accuracy, and generality of an SDM.

Recently, there has been increased interest in assessing SDM limitations for specific applications (e.g. Silva et al. 2019), though those pertaining to public health, epidemiology, or MBD have not yet been identified. Given the interest and application of SDMs to mosquitoes, an assessment of limitations and suggested best practices is warranted. General application and limitations of SDMs with respect to epidemiology have been reviewed (Johnson et al. 2019; Escobar 2020). Response data represented by vector occurrence is preferred over disease occurrence to minimize spatial uncertainty (Johnson et al. 2019). However, availability of either vector or disease response data are often aggregated to a coarse administrative/geopolitical boundary that may mislead ecological interpretation (Tjaden et al. 2018; Johnson et al. 2019). Interpretation of ecological characteristics at an aggregated spatial scale (i.e. grain or cell size of raster) may bias results and fail to sufficiently represent the species-environment response, causing inaccurate results (Moudrý et al. 2019; Cheng et al. 2021). Aggregated scales are particularly concerning for mosquitoes. Verdonschot and Besse-Lotoskaya (2014) reviewed mosquito flight literature and found that 91 mosquito species demonstrated average flight ranges of less than 2 km, except for three *Culiseta* species and *Culex annulirostris* which could fly 4.5 and 6.2 km, respectively. These flight ranges are generally well below the scale of a geopolitical region. For example, Johnson et al. (2017) applied contiguous United States county centroids occurrences and regional environmental averages to predict *A. aegypti* and *A. albopictus* distributions, despite these species having flight ranges ≤1 km (Verdonschot and Besse-Lototskaya 2014). Yet, the level at which species respond to different environmental conditions is usually unknown (de Knegt et al. 2010). Although aspects of mosquito response variables have been investigated, consideration of other SDM aspects of predictor variables, model building, and model evaluation are limited. These aspects have not been investigated or reviewed with respect to mosquito SDMs but rather rely on more general SDM reviews.

Recently, Araújo et al. (2019) proposed SDM standards of best practice to guide higher quality SDMs and inferences used in assessments. Best practice standards represent a synthesis of recommendations from current SDM experts to encourage focus on SDM conclusions which are transferable and applicable to policy development. These SDM standards reflect 15 issues across four SDM aspects of response variable, predictor variables, model building, and model evaluation. Each issue and use was scored regarding a level of quality: gold, silver, bronze, or deficient. Araújo et al. (2019) tested these standards against 400 SDM publications between 1995 and 2015 and reported that most aspects of SDMs had improved over time. This conclusion was attained with negligible bias and variation among six assessors for an applicable assessment (Araújo et al. 2019). Arthropods - including mosquitoes - accounted for ~5% of studied cases (Araújo et al. 2019). Assessing published mosquito SDMs against these standards allows for an examination of their adherence to these quality standards.

Here, I provide an in-depth investigation of mosquito SDM quality based on the four SDM aspects identified by Araújo et al. (2019). From my literature review, I sought to: i) determine uses of SDMs applied to mosquitoes by species and regions; ii) assess where MBD are considered of greatest concern based on SDM publications; iii) assess mosquito SDMs against the four aspects outlined by Araújo et al.’s (2019) standards; iv) assess mosquito SDM quality over time; and v) propose recommendations for best practice. It is not my intention to reiterate caveats and guidelines common across SDM literature, but rather to focus on those specific to mosquito applications. I compare my results to Araújo et al. (2019) to identify which issues are particularly problematic to mosquito SDMs.

2.2 Methods

2.2.1 Literature review

I searched the literature to identify SDM publications applied to mosquito species published between 1995 and 2020. Specifically, I queried Web of Science (apps.webofknowledge.com), Scopus (www.elsevier.com/solutions/scopus), Pubmed (www.ncbi.nlm.nih.gov/pubmed/), and Scientific Electronic Library Online (www.scielo.org) with the search terms “species distribut*” OR “habitat distribut*" OR "climat* envelope" OR bioclimat* OR "habitat suitab*" OR niche OR "resource selection" OR SDM OR ENM OR BEM OR BCM OR HSM OR RSF AND model* AND vector OR disease (last accessed May 16, 2021). This search returned 4,441 unique publications. Initial publications were refined to focus on only those that applied or investigated SDMs of mosquitoes and omitting mechanistic models or application of MBD rather than species occurrence, resulting in 127 retained publications.

2.2.2 Assessment of SDM standards

Selected publications were reviewed according to the best-practice standards for models in biodiversity assessments. I provide a summary of the standards below, though full details are found in Araújo et al. (2019). The standards consist of four quality levels: gold, silver, bronze, and deficient. Gold represents aspirational methods that usually require ideal data and next-generation modeling approaches which are seldom available and remain under development, respectively. Silver corresponds to cutting-edge approaches which typically involve imperfect but best available data applied to analysis. Silver methods allow for uncertainty and bias to be reduced, accounted for, or estimated. Bronze standards represent the minimum acceptable practices for SDMs. Finally, deficient standards indicate the use of data and/or SDMs practices that are considered unacceptable to drive policy and practice (Araújo et al. 2019).

Quality levels are defined for each form of SDM use: explanation, prediction, or projection. I reviewed and evaluated publications to determine the use(s) of each SDM. Standards scoring reflects four aspects of SDMs that affect the quality of model outputs:

response variable, predictor variables, model building, and model evaluation. Each aspect was assessed based on three to five sub-issues (Table 2.1).

Response variable quality strongly related to human effort, specifically sampling effort. Sampling effort quality reflects the depth of survey design to encompass all locations and environmental conditions within the range of the taxon, identification of taxon, and quantification of spatial accuracy of resulting records (Araújo et al. 2019). Inaccuracies or bias within any part of sampling effort has the potential to limit SDM ability (Anderson 2012). Though primary field surveys provide more reliable and accurate occurrence records, many rely on records from heterogeneous sources, such as occurrence repositories (i.e. Global Biodiversity Information Facility, www.gbif.org). Therefore, response variable quality also considered the depth that heterogeneous data was cleaned to remove records within justified unreasonable locations, conditions, positional accuracy, and taxonomic identification (Araújo et al. 2019). Spatial accuracy of responses was further characterized if the response assumed or known to represent a precise location (i.e. latitude and longitude from field survey), point within a defined area (i.e. administrative region centroid), or a combination of both.

The quality of predictor variables corresponded to the depth that the predictors are identified, acquired, prepared, and selected related to study objectives and species' biology. This included assessing what evidence or justification was provided regarding the selection and preparation of predictors with respect to biological response, spatial and temporal scale of response variable (Araújo et al. 2019). Ideally, predictors represent conditions that the response variable is dependent on at a relevant spatial and temporal scale with any uncertainty (i.e. measurement error) quantifiable in final SDM. Further, predictors are often investigated to determine which ones demonstrate higher importance to limit a species' distribution (Araújo et al. 2019). If SDMs identified variables of importance - also referred to as high contributing or demonstrated a significant effect - the corresponding variables identified as important were recorded per species. As variable importance estimates vary by algorithm and assessment method (Smith and Santos 2020; Harisena et al. 2021), whether a variable was considered important or not was based on the original authors' interpretation. Given the wide variety of predictors applied, similar and less common predictors were grouped when considering overall importance. For example, temperature may be represented by minimum, maximum, mean, or median air or land surface temperature per month(s). If a specific predictor was applied by less than three publications, it was considered an "other" predictor (i.e. other temperature).

Model building quality represented the degree of SDM techniques considered to address issues of model complexity, bias, noise, collinearity, and uncertainty (Araújo et al. 2019). Proper model building consisted of considering sequences of all choices including algorithm, hyper-parameters, and number of predictors to prevent overfitting and adjust for characteristics of response data. Comparison of all sequences allows for quantification and mapping of uncertainty among model building choices. Additionally, model building includes addressing the effects of a biased survey data and collinearity between predictor variables. Failure to properly account for bias, noise, or collinearity can cause erroneous results (Dormann et al. 2013; Bailey et al. 2014).

Model evaluation related to the quality of methodology used to assess realism, accuracy, and generality of model outputs per model use (Araújo et al. 2019). SDMs are expected to approximate ecological reality and should be evaluated against data that is representative of spatial, temporal, and environmental distributions of the response variable. This includes considering the depth to which theoretical and statistical assumptions of SDMs are addressed, selection of evaluation data, and how meaningful evaluation metrics used were. Ideally, SDMs are evaluated against multiple lines of evidence with no assumptions violated (Araújo et al. 2019). Unreliable or inflated results are possible if SDMs violate assumptions or are evaluated against biased data (Guisan and Zimmermann 2000; Hijmans 2012).

2.2.3 Analysis

I assessed the geographic areas investigated per mosquito genus to determine areas where MBD are seemingly of great concern. To do this, I considered the country or countries in which each publication applied an SDM. Genus was considered at the continent level, excluding global distribution predictions or projections. Total publications per country were mapped in ArcGIS 10.8.1 (Environmental Systems Research Institute 2020).

SDM quality scores were compared relative to the 50% and 90% quantile scores per issue. The 50% and 90% quantiles represent the 50% and 90% levels on an ascending list of quality, respectively. Overall performance per aspect (Table 2.1) was quantified by ‘area inside the line’ measure, a relative metric that reaches 100% if all standard issues reach gold for all studies at or above the given quantile (Araújo et al. 2019). Area inside the line was determined for each quantile line per aspect within a polar coordinate system such that area increased with higher quality scores (Fig. 2.3).

To test the quality of different mosquito SDM studies over time, I fitted an ordinal regression with a Bayesian approach. Regression models were fitted against an interaction of year and aspect. Additionally, a similar model fitted with an interaction of year and issue was determined (Table 2.1). Estimates obtained by this analysis were interpreted approximately as the change in probability that a modeling study will be a higher quality over time. Four chains were run and after a warm-up of 1000 iterations, a further 5000 iterations were sampled with an assumed prior distribution between -1000 and 1000. Bayesian models were fitted with `rstanarm` package in R v4.1.1 (Goodrich et al. 2020; R Core Team 2021). Additionally, temporal trends since the establishment of Araújo et al.'s (2019) standards were determined by comparing quality up to and including 2019 (before, 114 publications) to 2020 onwards (after, 13 publications). I analyzed time trends using G-test of goodness of fit on the frequency of each score per publication published before or after (Table 2.2).

2.3 Results

2.3.1 Literature review

A total of 116 different species from the genera *Aedes, Anopheles, Culex, Ochlerotatus, Culiseta, Haemagogus*, and *Psorophora* were investigated using SDMs. Species of most interest included *A. aegypti, A. albopictus, Culex pipiens, Anopheles gambie,* and *Anopheles aradiensis* which were investigated by 44, 36, 19, 15, and 14 publications, respectively (Appendix A.2: Table A2.1). Prediction and explanation were the most common uses of SDMs (40% of cases), followed by prediction only (27%) (Fig. 2.1a). Seventy-seven percent of studies used presence-only as the response variable, while a further 17% and 6% utilized presence-absence or species abundance data, respectively. Precise locations provided the response variable for 76% of cases, while point within a defined areas or combination were used by 7% and 17%, respectively (Fig. 2.1b). The response variable was represented by primary field collections for 39% of publications, while 61% relied on information from the literature, occurrence repositories, or multiple sources.

Bioclimatic variables (Appendix A.2: Table A2.2) were the most applied predictors (39-63%), followed by elevation (59%) and urban land cover (35%) (Fig. 2.1c). The greatest proportion of importance parameters were slope, elevation, and agricultural land in 53% or more of SDMs, though findings varied by mosquito species and genus (Appendix A.1).

Twenty-three different SDM algorithms were applied to mosquitoes (Fig. 2.1d). Maximum entropy (MaxEnt) was most popular with 68 publications, while general linear models, genetic algorithm for rule-set production, and general boosting methods were next and applied by 18, 15, and 11 studies, respectively. The remaining 19 algorithms were utilized in less than 10 publications each, with 12 algorithms used by a single publication each (Fig. 2.1d). Model complexity was addressed in 40% of studies, particularly when MaxEnt (50% of cases) or ensemble (55%) were considered.

SDMs were evaluated using by a wide variety of metrics, though 10% of publications did not provide any evaluation (Fig. 2.1e). Evaluation was commonly accomplished by area under the receiver operating curve and subsampling of training data. Confusion matrix metrics (i.e. sensitivity, specificity, accuracy) were also common, reported in 34% of SDM studies. Random hold out methods (i.e. random split, cross-validation) were applied across 89% of publications. Model evaluation by independent, re-substitution, and geographically-structured data was used only by 8%, 2%, and 1% of studies, respectively (Fig. 2.1e).

2.3.2 Regions of SDM application

Pan-African distribution studies dominated (20% collectively) the mosquito SDM literature, followed by global (16%), the contiguous United States (12%), Italy (8%), and China (7%). Within Africa, Kenya (12%) and Tanzania (10%) were the most-covered countries (Fig. 2a). The genera investigated varied by continent. *Aedes spp.* were studied extensively in the Americas, Europe, and globally, while *Anopheles spp.* models were confined mainly to African and Asian studies. Oceania had equal representation of *Aedes* and *Anopheles spp.* studies (Fig. 2.2a). SDMs investigating *Aedes spp.* have increased rapidly in recent years, while those addressing *Anopheles* and *Culex spp.* remained relatively constant over time (Fig. 2.2b).

2.3.3 Assessment of SDM standards

All 127 publications observed at least one deficient standard (i.e. unacceptable methods to drive policy and practice) within a single aspect, but no aspect consistently observed deficient standards in all publications. Accordingly, SDMs predominantly demonstrated deficient or bronze practices with 42% and 46% of all assessments, respectively. Silver or gold qualities were demonstrated by 10% and 2% of all assessments, respectively. Higher proportions of silver or gold standards were observed within issues of the response variable, model building, and predictor variables (Table 2.1). Specifically, spatial accuracy of the response variable observed 24% gold quality, while sampling, taxonomic identification, and geographic extent of the response variable considerations were 19%, 13%, and 15% silver quality, respectively. Within model building, considerations of model complexity demonstrated silver quality by 22% of SDMs, and treatment of bias and noise by 20%. Selection of predictor variables improved to silver and gold for 11% and 2% of all SDMs, respectively. Issues related to model evaluation observed silver or gold quality in less than 8% of SDMs. Overall performance - as defined by the area inside the curve (see methods) - revealed that response variables demonstrated the highest quality, with 16% and 45% of possible scores achieved by 50% and 90% quantiles respectively (Fig. 2.3). Both predictor selection and model building were poor overall for 50% quantiles with only 4%. Yet, at the 90% quantile predictor selection and model building increased to 19% and 29%, respectively. Model evaluation remained relatively similar between 50% and 90% quantiles with overall scores of 8% and 12%, respectively (Fig. 2.3).

Across all considered years, the temporal trends of SDM quality were inconsistent (Fig. 2.4). The probability of response variable and model building quality increasing was 7% and 1% over time, respectively. However, quality of predictor variables and model evaluation were more likely to decrease over time by 5% and 1%, respectively. Since the introduction of SDM standards, quality across issues has not changed ($G=1.34$, $df=4$, $p=0.72$) (Table 2.2). Confidence intervals of temporal trends across all years observed positive and negative trends, indicating divergent behavior. Temporal trends were only consistent across years for response variable and predictor variables (Fig. 2.4).

2.4 Discussion

Given the global importance of MBDs, it is essential to develop quality SDMs to aid in mosquito and disease management. The majority of SDMs surveyed here demonstrated unacceptable or minimally acceptable practices, with best available or imperfect practices applied by only 12% of studies. Compared to Araujo et al.'s (2019) assessment of SDMs covering all taxa, I found that mosquito SDMs applied lower quality response variables, lower predictor variables, and lower model evaluation, though they also had better model building considerations (Appendix A.2: Table A2.4). I focus on detailing how mosquito SDMs can enhance their quality in the aforementioned SDM aspects of decreased quality and highlight how mosquito SDMs achieved higher levels of model building quality relative to Araújo et al. (2019).

2.4.1 Response variable

Mosquito response variable quality was inhibited among the 90% quantile relative to that described by Araújo et al. (2019). Notably, only considerations of the environmental extent across which the response variable was sampled indicated lower quality within mosquitoes compared to all taxa (Araújo et al. 2019). For increased applicability of SDMs, the environmental extent must be appropriately represented to determine proper species-environment relationships. Ideally, sampling efforts would be designed to include all regions within the species' environmental tolerances though this is not necessarily feasible owing to accessibility (i.e. private property) and large geographic extents required. I observed that 84% of mosquito SDMs were applied to specific regions, therefore potentially limiting the environmental extent. More often no evidence was provided of species' environmental tolerance but SDMs were fitted with best available mosquito occurrences for the study region (e.g. Dickens et al. 2018). Environmental extent was addressed by a select few SDMs by removal of records in unreasonable environmental conditions (e.g. Gomes et al. 2016) or provided a single line of evidence indicating occurrences occur across all major environments within study area (e.g. Fossog et al. 2015).

Failure to properly account for environmental extent risks truncation of response curves, misidentification of important predictors, and biased predictions/projections leading to unfounded conclusions and management implications (Synes and Osborne 2011; Harisena et al. 2021). Many mosquito species are considered invasive and demonstrate rapid evolution (i.e. *A. albopictus*) (Egizi et al. 2015). Accordingly, considering the native or invaded distribution alone may not represent the entire niche (Medley 2010). Specifically, temperature is a fundamental driver of MBD and mosquito life cycle, followed by precipitation or water availability (depending on species) (Wegbreit and Reisen 2000; Shragai et al. 2017; Mordecai et al. 2019; Franklinos et al. 2019). Therefore, as a minimum, temperature thresholds must be satisfied within the environmental extent and then followed by precipitation. When spatially and temporally explicit records are not available to demonstrate full environmental tolerance as described by physiological studies of a single predictor, it should be avoided, and corresponding effects discussed (Thuiller et al. 2004).

Those wishing to investigate mosquito distributions are encouraged to consider multiple lines of evidence to infer environmental extent, such as historic and current distributions. For example, Metcalf et al. (2014) combined occurrence records from spatial-temporal fossil data, ancient DNA, and palaeoclimatological reconstructions for the American bison, *Bison bison*, to determine the entire environmental extent. Mosquitoes have captured the focus of management efforts since 480 B.C. in Greece and 1812 in the US (Howard and Bishop 1931; Patterson 2004), but occurrence records are not readily available for historical dates. Rather historical management efforts can be considered for potential historical impacts on distribution and environmental extent. Occurrence records are available from literature and museum records as early as 1947 to account for historical environmental extents of some species (Peach and Matthews 2020). Alternatively, SDMs considered over large geographic areas may be able to capture the environmental extent without considering additional records, but evidence should be given related to global, historical ranges, and physiological studies (Kearney et al. 2009; Varela et al. 2009; Barbet-Massin et al. 2010).

2.4.2 Predictor variables

Overall performance of predictor variables applied to mosquito indicated the greatest deficiency compared to all taxa assessments (Araújo et al. 2019). Though selection of predictor variables was consistent with that identified by Araújo et al. (2019), issues of scale and uncertainty of predictor variables demonstrated lower quality within both quantiles. Spatial and temporal scale of predictors must reflect that of the response variable to determine accurate species-environment relationships (Thuiller et al. 2004; Barbet-Massin et al. 2010). Unsurprisingly, predictor scale was dependent on the scales available for selected predictors. For example, I observed a large reliance on pre-calculated bioclimatic variables without justification of the corresponding scale. The gold standard requires the spatial and temporal scale to completely capture the level at which a species interacts with its environment (Araújo et al. 2019). Instead, spatial scale was theoretically justified given response variable sampling design (e.g. Tran et al. 2013) or by known or estimated spatial error in the response variable (e.g. Johnson et al. 2017).

Future applications should estimate an appropriate spatial scale relative to ecological knowledge, if possible. The scale at which a species interacts with any potential predictor is largely unknown and limited by the spatial accuracy of the response variable (de Knegt et al. 2010). Previous authors have suggested the scale can be estimated by dispersal, home, or perceptual range, body size, or reproduction period (Tyre et al. 2001; Mech and Zollner 2002; Jackson and Fahrig 2015). On the other hand, an appropriate scale can be statistically approximated by a sensitivity analysis. Sensitivity analysis involves determining the scale at which one observes high correlation with response variable, therefore approximating the scale at which a species responds to the predictor (e.g. Lechner et al. 2012). Additionally, species interact with the environment at different levels, such that relationships identified at one scale are not necessarily observable at others (Lechner et al. 2012). Therefore, species-environment relationships must be measured at the appropriate scale per predictor, which requires the consideration of multi-scale SDMs (Levin 1992). Previous work has highlighted multi-scales enhance understanding of the species-environmental relationship and provided guidelines (Václavík et al. 2012). Researchers should consider multi-scale SDMs that allow for species-environment responses to be evaluated at an appropriate scale if response variable accuracy is sufficient.

When the response variable contains high positional error or uncertainty, such as with administrative centroids, scale should be aggregated to account for positional error or uncertainty (Moudrý et al. 2019). Nevertheless, aggregation causes loss of fine-scale environmental details, therefore limiting accurate species-environment relationships (Cheng et al. 2021). A potential solution is to integrate additional and more accurate occurrence sets. Pacifici et al. (2019) provided a framework for integrating mis-aligned occurrences sets at varying spatial accuracy. Within the contiguous United States, many counties have widely available mosquito field survey occurrence records, but others are limited to centroids. Therefore, considering all available data, one can create separate SDMs for each response variable and set accuracy with appropriate scale predictors. Then, the researcher can downscale all predictors to a common scale for ensemble, after accounting for individual bias, noise, complexity, and uncertainty (Araújo et al. 2005; Garcia et al. 2012; Merow et al. 2014).

Similarly, temporal scale must reflect the temporal period of the response variable. The reliance on pre-calculated bioclimatic variables limited the temporal scale to 1970-2000 (Fick and Hijmans 2018), though many authors are considering occurrences outside this period (e.g. Hesami et al. 2019). Mismatch between or within response and predictor temporal scales results in mis-specified environmental conditions and biased results (Fernandez et al. 2017). When temporal scale of the response variable is known, predictor temporal scale should reflect it exactly (e.g. Arboleda et al. 2012) or with the next closest temporal period available (e.g. Alaniz et al. 2017). Future studies should calculate temporally-correct predictors from raw values when available. Notably, WorldClim provides raw historical monthly climatic data from 1960 to 2018, such that the corresponding bioclimatic variables can be calculated for the appropriate temporal period by open-source functions (Fick and Hijmans 2018).

After accounting for scale, one must further investigate potential effects of uncertainty within predictors. Uncertainty exists within each predictor associated with aggregation of values within the scale (Barry and Elith 2006; Beale and Lennon 2012).

This uncertainty increases with the spatial and temporal scale considered, thereby increasing bias and potential adverse outcomes on results (Stoklosa et al. 2015). The gold standard requires all sources of uncertainty in the predictors and the effects on SDM result be quantified, mapped, and interpreted (Araújo et al. 2019). Here, I observed that 83% of publications did not address predictor uncertainty. When it was considered, authors tended to address uncertainty by applying different non-collinear predictor sets (e.g. Miller et al. 2012) or simply acknowledged potential uncertainty without mapping or quantifying effects (e.g. Larson et al. 2010). Mapping of effects was only observed when projected onto different climate change scenarios (e.g. Yañez-Arenas et al. 2017) or variation between algorithm interpretation (e.g. Khatchikian et al. 2011). Stoklosa et al. (2015) recommended addressing predictor uncertainty by including the corresponding measure of uncertainty of each predictor. For example, SDM predictors typically reflect an average of values across spatial and temporal scale, therefore uncertainty can be measured by the standard error. This requires authors to retrieve raw environmental values, when possible. If the uncertainty values of a predictor cannot be estimated from raw values, one may estimate certainty relative to model error measurements when applicable (Stoklosa et al. 2015), or consider different aggregates (i.e. min, max, median), though further research is required.

Uncertainty of predictor variables may also be quantified and map relative to uncertainty of algorithm interpretation. Within mosquito SDM literature, only five publications considered the effect of algorithm on predictor interpretation. Instead, MaxEnt was applied by over half of the publications, citing previous performance (Elith et al. (2006). It is important to consider the effect of algorithm on interpretation of predictors to highlight uncertainty. Specifically, variation in response curves, predictor importance, projections/predictions can be quantified and mapped to achieve the gold standard (Elith et al. 2006; Aguirre-Gutiérrez et al. 2013; Kwarteng et al. 2021). Regardless of the amount of uncertainty which can be quantified and mapped, authors must acknowledge and interpret uncertainties within SDMs to improve overall quality.

2.4.3 Model building

Mosquito SDMs demonstrated higher overall performance within model building compared to Araújo et al. (2019), though not consistently across issues. The higher quality observed can be attributed to the 90% quantile in model complexity and treatment of bias and noise in response variable. Possible explanations for this are the inclusion of more recent publications and a smaller sample size therefore allowing for improved model building considerations to be more prevalent within results. Regardless, mosquito SDMs provide modern examples of how to account for complexity and bias. Model complexity related to the number of predictors applied and fine-tuning of hyper-parameters (Merow et al. 2014). The number of predictors applied was considered by assessing collinearity and/or removal of low importance predictors through iterative selection (e.g. Johnson et al. 2017). This process allows for only predictors which evidenced a strong statistical relationship with the response variable to be included, while limiting unstable, biased, or erroneous estimates from the effects of collinearity (Dormann et al. 2013). Likewise, SDM hyper-parameters were often fine-tuned for characteristics of each response variable dataset by manual or automated comparisons within specialized R packages (Muscarella et al. 2014; Cobos et al. 2019) or stepwise Akaike information criteria. For example, the rising popularity of MaxEnt has coincided with increased availability of software to automatically test a range of hyper-parameters, such as included feature classes and regularization multiplier, to determine the best fit against resubstituted or random hold-out of training data. Addressing model complexity in these ways decreases the probability that a model will be overfit, therefore providing more applicable predictions and projections (Araújo and Pearson 2005).

I noted that mosquito SDMs had high dependence on heterogeneous secondary occurrence records from one or more repositories. Mosquito occurrences in repositories were often represented a combination of literature records, citizen science, and organized surveys (Kraemer et al. 2015). Reliance on such heterogeneous sources limits the quality of the response variable and introduces potential bias as each set of records is developed from a different set of objectives (Syfert et al. 2013). The appropriate method to account for bias in the response variable will depend on the bias present, but was often related to sampling, geographic, or environmental bias (Inman et al. 2021). Accordingly, mosquito SDMs demonstrated a wide range of methods to treat bias and noise including Mahalanobis distance (e.g. Ducheyne et al. 2018), spatial thinning (e.g. Drake and Beier 2014), target group sampling (e.g. Wiebe et al. 2017), and bias layers (e.g. Sallam et al. 2016). These methods could be extended further by providing quantitative assessments to indicate the reliability of bias correction methods. Also, though not all publications addressed bias and noise, it was acknowledged and described by over half of the studied publications. Model complexity and treatment of bias can continue to improve by considering multiple lines of independent validation rather than cross-validation or subsampling to demonstrate improved performance and model fit (Araújo et al. 2019).

The one aspect that mosquito SDMs demonstrated was decreased treatment of collinearity at the 90% quantiles related to the previous assessment of Araújo et al. (2019). If not properly addressed, collinearity among predictors in SDMs risks causing unstable parameter estimates, inflated standard error estimates, biased inferences, an inability to separate predictor effects, and erroneous extrapolation (Dormann et al. 2013). Though improving over time, 83% of mosquito SDMs studies failed to acknowledge collinearity issues. Treatment of collinearity gold standard requires authors to demonstrate there is no collinearity among predictors or that the predictors are informed by a full mechanistic understanding of predictor variables to ensure the model is insensitive to collinearity (Araújo et al. 2019). SDMs here demonstrated a large reliance on bioclimatic variables, which are known to be highly collinear (Byers et al. 2013). Rather than relying on bioclimatic predictors, authors should start by selecting predictors which are known to be ecologically relevant, related to known mechanisms, and feasible for data collection (Austin 2002). For example, flood water mosquitoes (i.e. *Aedes macintoshi, Aedes vexans, Ochlerotatus sticticus, Ochlerotatus caspius*) occur within rural areas that experience flooding, high tides or rain to provide abundant larval habitat (Sang et al. 2003; Bogojević et al. 2011; Faraji and Unlu 2016). Accordingly, one could consider land cover, topographic wetness index, tidal zones, distance to coast, and rainfall measures to estimate potential suitable habitat, as opposed to all bioclimatic variables for these species. From here, collinearity can be investigated (Dormann et al. 2013) and highly collinear variables can be excluded or divided into different low collinear predictor sets (e.g. Moua et al. 2017). Alternatively, collineated predictors may be applied if one demonstrates the SDM algorithm is insensitive to collinearity (Araújo et al.

2019). Notably, MaxEnt performance has demonstrated insensitivity to collinearity, but collinearity can hinder interpretation (Kuemmerle et al. 2010; Feng et al. 2019). If collinear predictors are retained, model building should focus on stabilizing estimates by reducing model complexity related to the number of variables (Dormann et al. 2013). This is commonly accomplished by iterative removal of low-contributing or non-significant predictors, to a set of high contributing non-collineated predictors (Zeng et al. 2016; Johnson et al. 2017).

2.4.4 Model evaluation

Model evaluation of mosquito SDMs reflected those described for all taxa by Araújo et al. (2019), except mosquito SDMs indicated a lower 90% quantile of evaluation of model outputs. Mosquito SDMs relied heavily on random hold-out evaluations over independent and re-substitution methods. Splitting the response variable into training and testing provides an improved assessment of a SDM's fit and ability to predict over re-substitution, but limited assessment compared to independent data (Peterson et al. 2007; Bahn and McGill 2013). Re-substitution and random hold-out methods risk biased assessment as using the same data for training and evaluation provides an unrealistic measure of performance (Hijmans 2012; Bahn and McGill 2013). For example, Wenger and Olden (2012) observed SDMs of Brook trout, *Salvelinus fontinalis*, and Brown trout, *Salmo trutta*, had excellent performance when evaluated with random holdout methods but poorly predicted independent data in new locations and climates. Independent data can come from an independent systematic survey in a different space or time from training response variable (Martínez-Meyer et al. 2004; Peterson et al. 2007). Mosquito

SDMs applied independent evaluation from updated field surveys from public health or targeted efforts (e.g. Tran et al. 2013; Ibañez-Justicia and Cianci 2015).

Many researchers describe the lack of independent data for evaluation. When independent evaluation is available, it may be inflated owing to spatial autocorrelation and sampling bias (Hijmans 2012). Specifically, training and testing datasets may fall within close geographic range to one another, thus being non-independent and inflating evaluation (Peterson and Soberón 2012). Rather, mosquito SDMs should focus on geographically independent datasets for an unbiased evaluation. Common practices for geographic structured evaluation data within mosquito SDMs included division by political boundaries (e.g. Levine et al. 2004), latitude, longitude, or quadrants (e.g. Arboleda et al. 2012). Unfortunately, these methods do not directly account for spatial autocorrelation or bias. Instead, training data can be divided into one or more geographically structured datasets with respect to spatial autocorrelation. For example, Capinha et al. (2014) estimated the global range of *A. aegypti* and created training and testing sets by accounting for spatial autocorrelation though alpha shapes. Other methods to account for spatial autocorrelation include removing spatial bias by pairwise distance sampling (Hijmans 2012), automated spatial block cross validation (Valavi et al. 2019) or spatial “leave one out” method (Le Rest et al. 2014). The appropriate method to create geographically-structured training and testing sets will depend on the study objective, extent, and response variable. When response variable sample size is insufficient to create geographically-structured evaluations, repeated sub-sampling in spatial blocks is recommended. Accordingly, re-substitution, random hold-out, and repeated sub-sampling spatial blocks methods only reflects SDM’s ability to estimate training data as opposed to prediction or projection accuracy and should be interpreted and discussed accordingly (Araújo et al. 2019).

2.4.5 Temporal trends

Interest in *Anopheles* and *Culex spp.* remained relatively constant over time, while that of *Aedes spp.* increased. Given the rapid global spread and importance of select *Aedes spp.*, paired with introduction or resurgence of associated MBD, increased interest of *Aedes spp.* distribution is not unexpected (Lessler et al. 2016; Leta et al. 2018). Likewise, while *Anopheles* and *Culex spp.* have a much lower degree of global spread, distribution was assessed within proximity of endemic areas (Gangoso et al. 2020; Liu et al. 2020). As such, interest in *Aedes spp.* is expected to increase in future years in consequence.

Despite mosquito SDM improvements in some issues compared to all taxa by Araújo et al. (2019), overall temporal patterns indicated predominantly divergent behavior across issues. This suggests that most modern mosquito SDMs have not improved on previous models, despite simultaneous SDM research to improve applications over the years. Rather, publications applied the same techniques to new occurrence records or under different conditions. However, since the development of SDM standards, SDM quality has not changed. This suggests not enough time has passed for the standards to be acknowledged and implemented within mosquito distribution forecasting. The same may not be true for all taxonomic groups. Yet these findings must be interpreted with caution as I observed unequal SDM application across years, with no publications in 1999, 2000, and 2003, and only a single year of publications to represent after standard quality.

Response variable and predictor variables were observed to exhibit more consistent increases and decreases in quality across issues over time, respectively. These observed patterns were also detailed by Araújo et al. (2019), but my mosquito-only SDMs demonstrated stronger trends. Generally, response quality has increased owing to increased biodiversity efforts that allow for occurrence repositories with increased detail (Soberón and Peterson 2004). Mosquito reporting and surveys are increasing globally to manage MBD though both standardized active and non-standardized passive surveys (Kampen et al. 2015; Kovach and Smith 2018; Chen et al. 2020). Additionally, there exists increased criticism and technology protocols to better survey efforts (Baldacchino et al. 2015; Parihar et al. 2020; Dormont et al. 2021). Conversely, predictors indicated increasingly haphazard selection limited to bioclimatic variables with little to no justification for selection of predictors, scale, or consideration of uncertainty. High scale environmental data is increasingly available via remote sensing efforts but is rarely applied to SDMs (Pinto-Ledezma and Cavender-Bares 2021). As environmental and other predictors become more accessible, greater consideration of predictor variables is required for mosquito SDMs. Authors and reviewers are encouraged to review best practices in SDMs to focus on enhancing their applicability all SDM aspects and issues.

Finally, it is important to acknowledge that the applied standards reflect a consensus of expert advice, and that scientific standards can be challenged and altered accordingly. As more research on SDMs and mosquito distributions is conducted, strengths and weakness of SDM methods may change (Araújo et al. 2019). I acknowledge accomplishing gold or silver standards may not be possible in all scenarios owing to logistical challenges such as data limitations. The recommendations I outline here provide guidelines for SDM quality improvement. Additionally, variation and biases of standard quality interpretation between observers is natural. Here, SDM quality was assessed by a single individual and therefore uncertainty between assessors could not be quantified or examined. Future standard assessments should apply multiple assessors when possible.

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Table 2.1: Standards for distribution models in biodiversity assessments from Araújo et al. (2019) and percent of observed quality levels per issue and aspect across 127 publications. Total percentages indicate the percent of each quality level for all issues per aspect. Standards levels of deficient, bronze, silver, and gold represent unacceptable, acceptable, cutting-edge, and aspiration quality, respectively.

Aspect	Code	Issue	Deficient	Bronze	Silver	Gold
1. Response variable	1.A	Sampling of response variables	14	64	19	3
	1.B	Identification of taxa	28	57	13	2
	1.C	Spatial accuracy of response variable	14	38	24	24
	1.D	Environmental extent across which response variable is sampled	20	79	2	0
	1.E	Geographic extent across which response variable is sampled (included occurrence data and absence, pseudo-absence, or background data)	53	32	15	1
	Total		26	54	14	6
2. Predictor variables	2.A	Selection of candidate variables	25	62	11	2
	2.B	Spatial and temporal resolution of predictor variables	76	22	2	0
	2.C	Uncertainty in predictor variables (both under current and projected conditions)	83	14	4	0
	Total		61	32	6	1
3. Model building	3.A	Model complexity	58	20	22	0
	3.B	Treatment of bias and noise in response variables	48	32	20	0
	3.C	Treatment of collinearity	53	44	2	1
	3.D	Dealing with modelling and parameter uncertainty	53	46	2	0
	Total		53	36	11	0
4. Model evaluation	4.A	Evaluation of model assumptions	70	29	1	0
	4.B	Evaluation of model outputs	17	74	5	3
	4.C	Measure of model performance	17	76	8	0
	Total		35	60	5	1
All aspects	Total		42	46	10	2

Table 2.2: Change in average count of observed SDM qualities across all issues before and after publication of best-practice standards in 2019. SDM quality was not dependent on time period (G=1.34, df=3, p=0.72). Observed quality percentages per issue before and after is available in Appendix A.2: Table A2.3.

Quality	Before	After
Deficient	7	4
Bronze	7	10
Silver	1	1
Gold	0	0

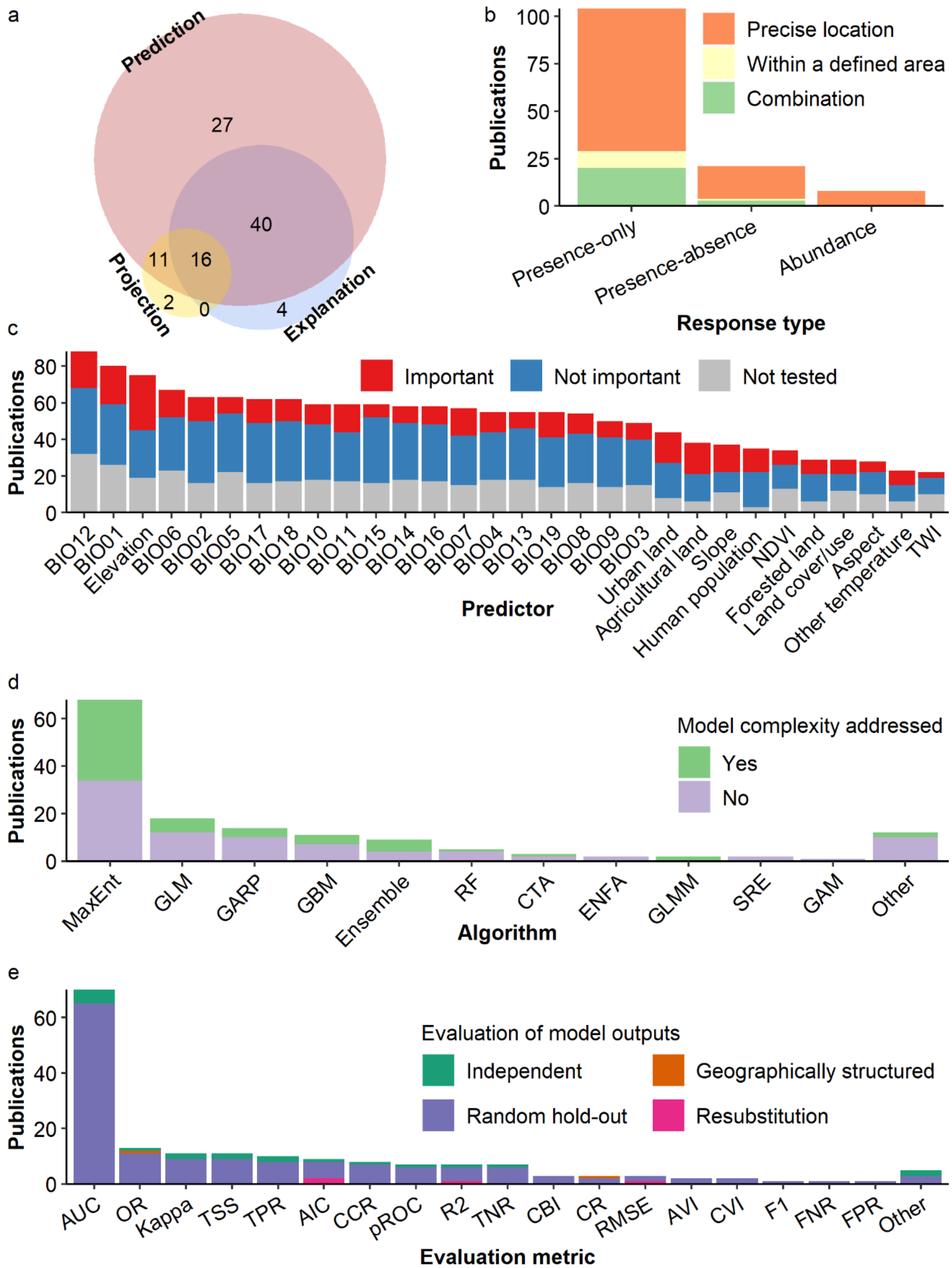

Figure 2.1: Overview of mosquito SDM aspects across the literature. Summary of literature review including purpose of study (a), response data type and reference of

assumed or known precise location (i.e. latitude and longitude from field survey), location within a defined area (i.e. administrative centroid), or combination of both (b), top 30 predictors considered and identified as important (c), algorithm considered with or without consideration of complexity (d), and evaluations considered (e). Numbers in (a) represent percent of publications which considered each single or combined study purpose. Predictor abbreviations: NDVI= normalized difference vegetation index, TWI = topographical wetness index. SDM algorithm abbreviations; MaxEnt = Maximum entropy, GLM = general linear model, GARP = Genetic algorithm for rule-set production, GBM = general boosting method, RF = random forest, CTA = classification tree analysis, ENFA = ecological niche factor analysis, GLMM: general linear mixed model, GLMM = general linear mixed model, SRE = surface range envelope, GAM = general additive model. Other algorithms included Similarity search, alpha-shapes, learning approach for one-class-classification, niche of occurrence, proportional, artificial neural networks, support vector machines, MaxLike, multiple adaptive regression splines, and undefined models. Evaluation metric abbreviations: AUC = area under the receiver operating curve, OR = omission rate, TSS = true skill statistic, TPR = true positive rate (sensitivity), AIC = Akaike information criterion, CCR = correct classification rate, pROC = partial area under the receiver operating curve, R2 = correlation, TNR = true negative rate (specificity), CR = commission error, RMSE = root mean square error, AVI = absolute validation index, CVI = contrast validation index, FNR = false negative rate, FPR = false positive rate. Other evaluation metrics included Bernoulli deviance, error rate, and point biserial correlation.

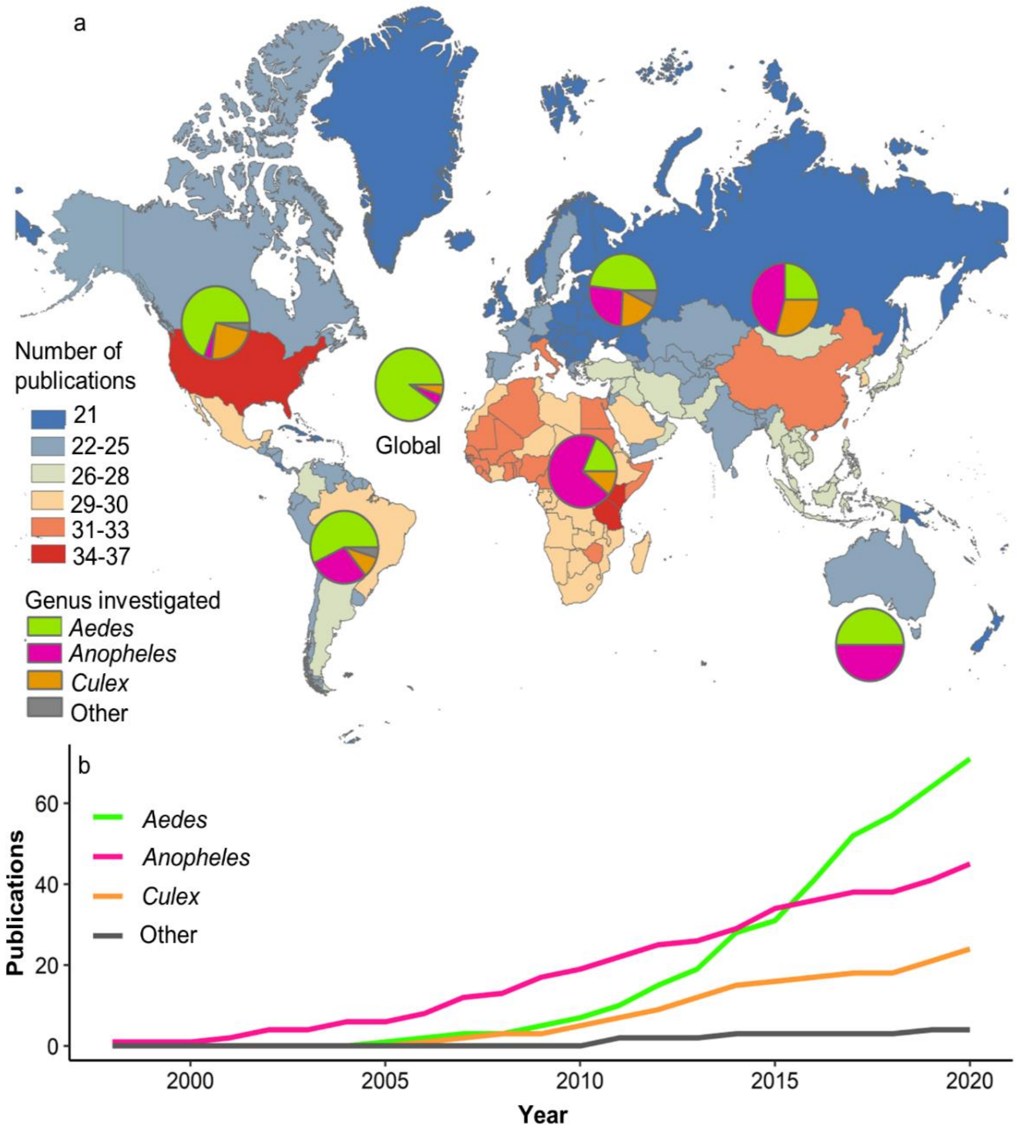

Figure 2: Spatial and temporal publication trends. Number of publications investigating mosquito distribution through SDMs per country and genus representation (proportion) by continent (a), and accumulation of genus investigated per year (b). Publications which considered global distribution are shown by global proportion in the center.

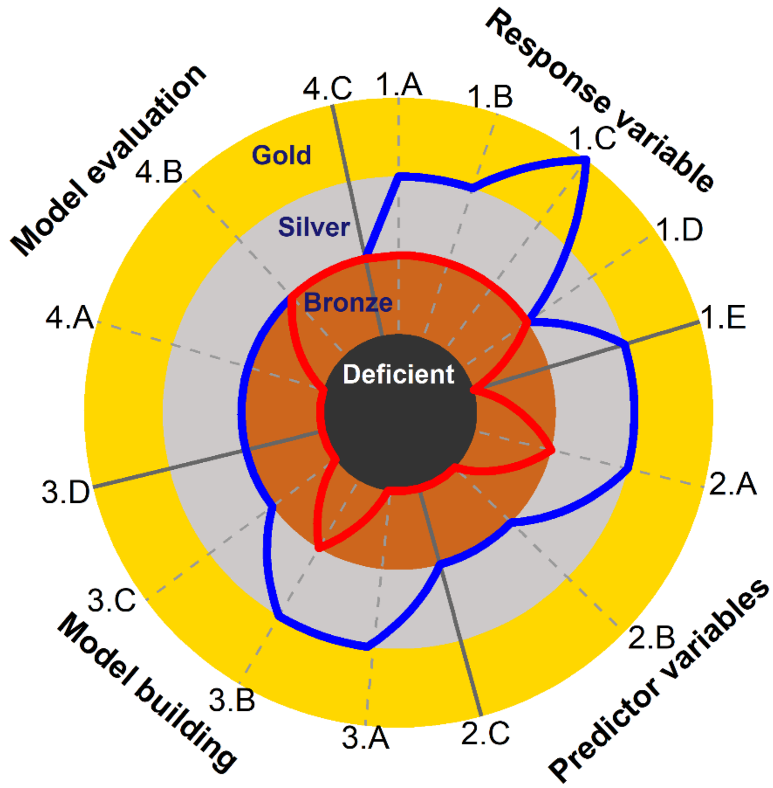

Figure 2.3: Best-practice standards achieved by 127 mosquito SDMs publications (1998-2020). Lines indicate 50% (red) and 90% (blue) quantiles scores for each issue. Coloured rings indicate the level of quality: gold, silver, bronze, and deficient, such that intersection of quantile line at outer-most point of the ring indicates quality per issue. Area inside each respective polygon, defined by either quantile line represents an overall measure of model quality. For definitions of standards, see Araújo et al. (2019). Issue codes are defined in Table 2.1. Raw standard qualities are available in Table 2.1.

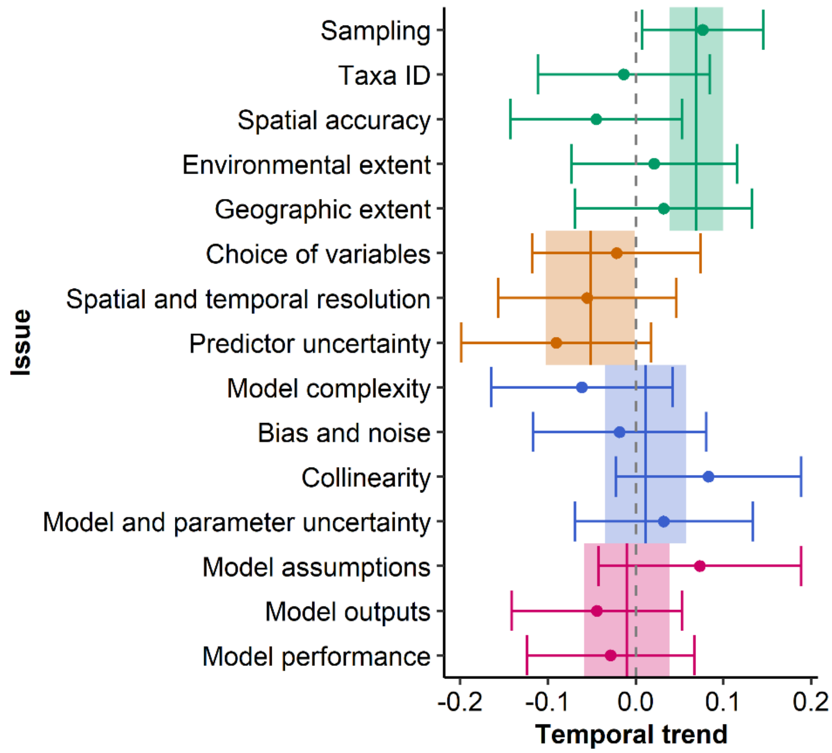

Figure 2.4: Temporal trends in best-practice standards from Bayesian ordinal regression across all years. Temporal trends near zero represent no change in standards over time. Solid vertical bars and shading indicate temporal trend (Bayesian coefficient) and 95% confidence intervals of each aspect, respectively. Standard specific temporal trends and 95% confidence intervals of each issue are shown by points and error bars, respectively. Raw proportions over time are shown in Appendix A.2: Figs. A2.1-4. The four categories considered herein are identified by different colours, within which a total of 15 identified problem areas occur (see Table 2.1 for the former and Araújo et al. (2019) for the latter).

CHAPTER 3: RELIABLE SPECIES DSITRIBUTION MODELS: CONCLUSIONS FROM CENTROID OCCURRENCE REQUIRE CAREFUL DEVELOPMENT

3.1 Introduction

Describing relationships between species occurrence and their environment are fundamental to ecology and biogeography (Huston 2002). Species distribution models (SDMs), also known as ecological niche models, are powerful tools to accomplish this goal. SDMs correlate the occurrence of a species with environmental predictors to explain and/or predict a distribution (Guisan and Zimmerman 2000). Accordingly, SDM objectives related to explanation often include testing hypotheses related to environmental conditions driving the distribution (Bradie and Leung 2017) and estimating response curves (e.g. Ikegami and Jenkins 2018). Meanwhile, prediction objectives entail predicting the probability of occurrence (e.g. Jarnevich and Reynolds 2011) or predicting presence or absence of a species (e.g. Johnson et al. 2017).

The ability of SDMs to explain and/or predict a distribution is dependent on, but not limited to, the algorithm, quantity and quality of response and predictor variables (Wisz et al. 2008; Synes and Osborne 2011; Heikkinen et al. 2012). Previous comparisons have indicated that different algorithms are better suited for different objectives and data (Heikkinen et al. 2012; Aguirre-Gutiérrez et al. 2013). The response variable consists of presences or absences (Wisz et al. 2008). Absence records are rarely available or reliable, with pseudo-absences applied in their place (Barbet-Massin et al. 2012). Pseudo-absences represent a location in which the species has not been observed, whether sampled or not, and is presumed to be absent without a validating absence record (Grimmett et al. 2020). Predictors reflect the abiotic or biotic conditions for which responses are considered (Guisan and Zimmerman 2000). Though generally higher quantities of response variables are recommended (Wisz et al. 2008; but see Boria and Blois 2018), and ideally only predictors with evidenced effects should be considered when possible (Austin 2002). Quality of response and predictor variables greatly impacts SDM performance, as exemplified by the corresponding scale (Lechner et al. 2012). Scale refers to the level of detail and geographic extent of an object or process (Lecours et al. 2015). Depending on the context, scale relates to: the spatial relationship at which a species interacts with the environmental influences (i.e. dispersal range) (Jackson and Fahrig 2015), the spatial characteristics of the occurrence records (i.e. sampling unit, area of observation, positional accuracy) or predictors (i.e. cell size, grain, resolution), and the level of detail applied to the SDM to analyze the distribution (Lecours et al. 2015). For this paper, scale is used to describe the level of spatial detail for each form of data.

If the scale is not explicitly considered, the reliability of SDMs is directly affected (Moudrý et al. 2019). The applied scale must satisfy SDMs' assumptions of: i) the occurrence records contain no error; and ii) the provided environmental predictors are representative of the physiological tolerances or resource requirements of the species' niche (Austin 2002; Osborne and Leitão 2009). However, choice of scale is limited by response variable quality, specifically imprecise records (Cheng et al. 2021). Previous investigations suggested that half or more of repository occurrences are imprecise locations such that they represent centroids of administrative/geopolitical boundaries, hereafter boundaries (Collins et al. 2017; Parks and Davis 2017). Consideration of imprecise responses in SDMs causes changes in variable contribution assessment, interpretation of responses, and an overall decrease in predictive ability (Johnson and Gillingham 2008; Osborne and Leitão 2009; Naimi et al. 2011).

A set of methodological approaches have been suggested but cannot fully correct for imprecision of centroids (e.g. Araújo and New 2007; Pacifici et al. 2019). Park and Davis (2017) illustrated that the effects of centroids may be limited by considering the mean aggregate of each corresponding boundary. However, aggregation causes loss of fine-scale variation which may be an important determinant of species' distributions, therefore is not effective for large boundaries (Collins et al. 2017; Cheng et al. 2021). Additionally, aggregation increases potential artifact effects through the modifiable areal unit problem (MAUP) (Openshaw 1984). MAUP is a source of statistical bias where correlations can vary from positive to negative depending on aggregation scale (i.e. county, state) (Goodchild 2011). For example, Wang and Di (2020) described that disease prevalence was negatively associated with temperature at precise locations but was positive, negative, or not correlated with temperature after aggregation to different regions. Accordingly, the resulting aggregated scale satisfies assumption (i) but potentially violates (ii) through obscuring fine-scale variation and MAUP effects (Pearson and Dawson 2003; Moudrý and Šímová 2012; Manzoor et al. 2018). Further, interpreting responses between scales (i.e. different size and shape boundaries) is considered invalid and potentially renders SDM conclusions meaningless (Nelson 2001; Lecours et al. 2015).

Ecologists are in an awkward position due to the abundance of centroids to produce sophisticated SDMs (Duputié et al. 2014). Reliable SDMs conclusions, those which are accurate and applicable to aid effective management and policy decisions, can only be established if the applied scale captures environmental characteristics driving species' distribution (Vergara et al. 2016). Issues related to centroids remain impossible to solve without more accurate data (Josselin and Louvet 2019). Regardless, application of centroids is common practice in SDMs (e.g. Escobar et al. 2013; Wells and Tonkyn 2014). Notably, occurrence records related to public health are often limited to centroids for privacy protection (Nelson and Brewer 2017). For example, occurrence records of the fast-spreading non-indigenous arbovirus mosquitoes *Aedes aegypti* and *Aedes albopictu*s are predominately available as county centroids within the US (Hahn et al. 2017). *A. aegeypti* and *A. albopictus* have the potential to transmit over 20 pathogens including zika, chikungunya, dengue, and yellow fever viruses (Leta et al. 2018). Aided by human-mediated dispersal and high eco-plasticity, both species have rapidly expanded their range in recent years causing increased introduction and incidence of pathogens within novel regions (Barrera et al. 2011; Weaver 2014; Ibañez-Justicia 2020). Meanwhile, SDM applications of either species are limited as their occurrence records are widely available only as regional occurrences, particularly in North America (Hahn et al. 2017). Johnson et al. (2017) predicted the distribution of *A. aegpyti* and *A. albopictus* within the contiguous US counties from centroids, and indicated unlikely occurrence of both species within Wayne County, MI. However, both species were recorded across the border in the Windsor-Essex region of south-western Ontario, Canada from 2017 to 2019 (Giordano et al. 2019), with *A. albopictus* continuing to be present as of June 2021 (Windsor-Essex County Health Unit 2021). Therefore, raising concern of SDMs trained with imprecise centroids to provide applicable and reliable conclusions to effectively guide management and policy decisions.

There is rising awareness that SDMs must be tested and designed for the desired objective using available data (Aguirre-Gutiérrez et al. 2013). When limited to centroids, choices of algorithm, and quantity of response and predictor variables to best interpret centroids, is unknown. Previous investigations of centroid effects have been limited to probability of occurrence predictions by Maximum Entropy (Collins et al. 2017; Park and Davis 2017; Cheng et al. 2021). It is essential to investigate model building considerations of algorithm, response variable, and predictor variables when centroids are used, and to assess their ability to accomplish each objective. Here, I provide an in-depth analysis of SDMs' ability to achieve common objectives based on centroids of a 'virtual species' (Leroy et al. 2016) in North America. To simulate reality, the virtual species was designed to resemble species with known centroid occurrences, *A. aegypti* and *A. albopictus*. I focus on assessing SDM's ability to explain a species' niche by identifying the correct driving predictors of distribution and estimating appropriate species-environment responses. Additionally, I determine the reliability of SDMs to predict probability of occurrence and binary presence-absence maps from centroids. Lastly, I investigated which SDM methodology is better suited for each objective. This work will guide the use of centroids in SDMs to improve reliability of conclusions.

3.2 Methods

I constructed a realistic species distribution based on similar environmental suitability traits of *A. aegpyti* and *A. albopictus*. Environmental suitability of both species has been primarily related to temperature for development and survival (Brady et al. 2013; Eisen et al. 2014). Additionally, both species are container-breeding species which rely on precipitation for suitable reproduction conditions in natural or human-made containers as substitutes (i.e. tires, flower plots) (Gama and Islamiyah 2013; Dhimal et al. 2015). Though there are differences between the species. Compared to *A. aegypti*, *A.*

albopictus has a greater ecological and physiological plasticity allowing for a more extensive geographic range in temperate and tropical temperatures compared to the traditionally tropical *A. aegypti* (Kraemer et al. 2015). *A. albopictus* has, in turn, successfully established in more northern areas, attributed to its ability to diapause and survive cold winters (Denlinger and Armbruster 2014). *A. aegypti* has only demonstrated diapause in limited populations (Lima et al. 2016). Both species are believed to occur beyond environmentally suitable areas by employing micro-niches as refugia when the macro-climate may not be unsuitable (Hayden et al. 2010; Murdock et al. 2017). Further, the species differ in their relationship with population density. *A. aegypti* is mainly found in urban areas, but *A. albopictus* may be found in urban, peri-urban, rural, or forested habitats (Yang et al. 2021). When species distributions overlap, *A. albopictus* is a superior larval competitor and *A. albopictus* males will cross-mate with *A. aegypti* females causing reproductive losses (Braks et al. 2004; Lounibos et al. 2016).

3.2.1 Predictor variables

All predictors which related to direct or indirect effects, or resource requirements of *A. albopictus a*nd *A. aegypti*, including climate, topography, land cover and use, vegetation indices, and socio-economic predictors were considered (Larson et al. 2010; Mughini-Gras et al. 2014; Alahmed et al. 2015; Moua et al. 2017). I assessed multi-collinearity using Pearson's correlation matrix followed by variance inflation factor (VIF) for all pairs of variables (Naimi et al. 2014; Leroy et al. 2016). Highly correlated variables were excluded ($|r|>0.7$, VIF >10) to prevent analysis errors (Dormann et al. 2013). A single predictor was manually selected from each highly correlated group to reflect environmental predictors important to *A. albopictus a*nd *A. aegypti* distribution based on a literature review (Table 3.1).

Growing degree days (GDD) represented the magnitude of daily mean temperatures above a baseline temperature of 5°C, below which development or survival cannot occur (McMaster and Wilhelm 1997). Normalized difference vegetation index (NDVI) was used to quantify vegetation greenness and provide an understanding of vegetation density (Pettorelli et al. 2005). Human population density (PD) reflected the most recent census data for each administrative boundary (U.S. Census Bureau 2018; Statistics Canada 2018; National Institute of Statistics and Geography 2019). Selected bioclimatic variables (annual mean temperature (BIO1), mean diurnal temperature (BIO2), precipitation of the wettest month (BIO13), and precipitation of the driest month (BIO14)) and GDD were calculated from monthly temperature and precipitation values in `dismo` and `envirem` R packages, respectively (Hijmans et al. 2017; Bemmels 2018). Boundaries in North America were restricted to Canadian health regions, US counties, and Mexican state resulting in a mean scale of 6424 km^2 (Appendix B.2: Table B.1). To represent mean boundary predictor values, I calculated aggregate means of each predictor through Zonal Statistics in ArcGIS 10.6 (Environmental Systems Research Institute 2018). Boundary landcover categories were represented by the mean percent land cover per category within a boundary.

3.2.2 Virtual species design

I designed a virtual species through the `virtualspecies` R package (Leroy et al. 2016). The habitat suitability was designed to reflect common characteristics of *A. aegypti* and *A. albopictus* based on BIO1, BIO13, and elevation at a 1 km^2 scale. This scale was appropriate as both species are known to have mean flight ranges ≤1 km (Verdonschot and Besse-Lototskaya 2014) but could not account for micro-niches. BIO1 directly related to survival and development (Reinhold et al. 2018). BIO13 indicated availability and quality of oviposition sites for reproduction (Becker et al. 2010). Lower elevation related to increased human disturbance, therefore creating more breeding habitat through artificial water-holding containers (i.e. discarded tires, cement tanks, garbage) (Gama and Islamiyah 2013; Dhimal et al. 2015). Accordingly, virtual species' habitat suitability was determined from defined responses of each predictor within North America (Fig. 3.1a). I modeled the virtual species' habitat suitability by a multiplicative suitability index of BIO1, BIO13, and elevation as β-function, logistic, and linear responses, respectively (Fig. 3.1a-c; Appendix B.1). For interpretation and comparison, habitat suitability was interpreted as probability of occurrence. The final probability map was visually examined to ensure similarity to published predictions of *A. aegypti* and *A. albopictus* (Fig. 3.1b).

3.2.3 Modeling building

To train SDMs, I created a geographically-structured response by converting the suitability index into presence-absence records (Fig. 3.1b, c). I randomly generated 3,500 unique, 1 km spatially-thinned, and corrected by suitability presence-only records within the contiguous US and Mexico. These records were then converted into centroids, such that all records within a boundary were represented by one centroid, resulting in 1,414 centroids.

To assess SDM methodology for centroid occurrences, I investigated common model building choices of the: a) algorithm; b) number of pseudo-absences generated;

and c) predictor variable selection (Fig. 3.1d, e). These choices represent how the species-environment relationship is interpreted (a), characterized (b), assessed and predicted against (c) (Elith et al. 2006; Wisz et al. 2008; Aguirre-Gutiérrez et al. 2013).

3.2.3.1 Algorithms

Twelve different distinct algorithms were applied in either their original software, denoted by "_O", or as part of ensemble SDM software, `biomod2` (Thuiller et al. 2020), denoted by "_B" (Table 3.2). Original classification tree analysis, flexible discriminant analysis, generalized additive models, generalized boosting regression methods, generalized linear models, multiple adaptive regression splines, and random forest were constructed using additive formulas. Generalized linear models were also considered with first and second order polynomial variables of all predictors to reflect corresponding `biomod2` formulas. Otherwise, all algorithms were run with default settings for simplicity and comparison. For descriptions of each algorithm, see Elith et al. (2006), Araújo and New (2007), Reiss et al. (2011), and Fitzpatrick et al. (2013).

3.2.3.2 Pseudo-absences

These algorithms represented three broad groups of required response variable: presence-only records (PO), presence-background (PB), or presence-absence (PA) (Table 3.2). To simulate common practice, I considered pseudo-absences instead of known absences for model training. Background points represented all available environmental conditionals and do not assume absence, hereafter pseudo-absence (Phillips et al. 2006). Pseudo-absences must be derived from areas which are accessible to the species (Barve et al. 2011). *A. aegpyti* and *A. albopictus* are primarily distributed by human activity (Gloria-Soria et al. 2016; Eritja et al. 2017), therefore all administrative boundaries were considered accessible. Accordingly, I generated 100,000 pseudo-absences at least 1 km apart within the 1,761 boundaries without a centroid occurrence in the contiguous US and Mexico. Pseudo-absence numbers were considered as equal, double, or triple the number of centroids (1:1, 1:2, 1:3, respectively) (e.g. Tiffin et al. 2019) or a total of 10,000. To ensure consistent training, 100 unique training sets per pseudo-absence level consisting of all centroid occurrences and a random subset without replacement of all pseudo-absences, were determined (Fig. 3.1d).

3.2.3.3 Predictor selection

Under ideal conditions, SDMs should be trained with only predictors for which the species' distribution is well evidenced, hereafter expert (Austin 2002). Yet, these predictors are often unknown. Instead, all predictors with suspected direct, indirect, or resource effects are applied, hereafter *a priori* (e.g. Low et al. 2021). Alternatively, driving predictors are estimated from *a priori* by the percent reduction in model fit when each predictor is randomly permuted, hereafter automated (Harisena et al. 2021). To demonstrate each predictor selection, I first trained SDMs with all predictors to represent *a priori* (Table 3.1). For each *a priori* training set, predictor contribution was calculated per algorithm and pseudo-absence level. Predictor contribution was determined by measure of predictor importance functions in `biomod2` or equivalent functions in `caret` R packages for original algorithms with 1,500 iterations to allow for adequate convergence (Liaw et al. 2019; Kuhn 2020; Thuiller et al. 2020). The corresponding predictor contribution measures were converted to percent contribution such that all values for a single repetition summed to one. Automated predictors represented predictors with greater than 5% percent mean contribution across all training sets per algorithm and pseudo-absence level. Expert predictors were demonstrated by considering only the driving predictors of BIO1, BIO13, and elevation (Fig. 3.1e). Therefore, I generated and compared a total of 30,000 SDMs (25 algorithms x 4 pseudo-absence levels x 3 predictor selections x 100 training sets). SDMs were trained with an 80% random subset of training sets. Algorithms included in ensembles achieved a sensitivity (see 3.2.4.4) of 95% or more of omitted training presence records.

3.2.4 Model evaluation

To reflect common objectives, I evaluated centroid explanation ability through identification of true driving predictors and response curve estimation (Fig. 3.1f, g). Predictive ability was evaluated by accuracy of predicted probability of occurrence and binary discrimination (Fig. 3.1h, i). Each algorithm provided a different range of probabilities for interpretation. Consequently, I normalized all predictions prior to evaluation. Formulas for all evaluations are available in Appendix B.1.

3.2.4.1 Identification of driving predictors

The ability to identify driving predictors was quantified by the Jaccard index (J) (Fig. 3.1f). J is a measure of similarity between two datasets. J ranges from zero to one, such that one and zero indicate identical and no similarities, respectively (Jaccard 1908). I determined J between automated and expert predictors. For each training set and SDM, I determined how many of the three driving predictors were selected during automated selection and divided by the total number of unique automated and expert predictors (e.g. Inman et al. 2021) (Fig. 3.1f).

3.2.4.2 Response curve estimation

Response curves were determined for each driving predictor by extracting the predicted probability and corresponding aggregated predictor values. I smoothed the resulting curves by general additive smoothing to ensure a single probability per environmental value. Expected responses were calculated for each environmental values and compared by root mean square error (RMSE) and Spearman's correlation (ρ) (Fig. 3.1g). RMSE provided a measure of variation between the expected and estimated response values. Greater RMSE values indicated greater error in estimated responses. Meanwhile, ρ indicated if the estimated response curve determined the appropriate pattern relative to the expected one. ρ ranged from -1 to 1, with negative values indicating negative correlation, zero no association, and positive values indicating a positive correlation.

3.2.4.3 Probability of occurrence

Predicted probability of occurrences was evaluated with respect to calibration, bias, skill, accuracy, refinement, and resolution of training and testing regions (Murphy and Winkler 1992). Calibration described the degree to which relative suitability of a presence correlated with predicted probability. Bias indicated the degree to which the predicted probability differed from known probability of occurrence. Skill measured accuracy of the predicted probability relative to an expected binary prediction. Forecast accuracy reflected the overall degree to which binned predicted probability corresponded to the expected binned probability of occurrence. Refinement indicated the mean square difference of binned predicted and expected probability values. Resolution described the ability of SDMs could separate different probabilities relative to expected separation

(Murphy and Winkler 1992). Training evaluations represented comparisons of predicted and expected probability of occurrence within contiguous US and Mexico and testing evaluation was within Canada and Alaska, unless otherwise stated.

Calibration was assessed by the continuous Boyce index (CBI) in the `ecospat` R package (Broennimann et al. 2020). CBI is a measure of the prediction accuracy of occurrence events by determining spearman rank correlation coefficient of predicted-to-expected ratio. CBI values of one, zero, and negative indicated predictions consistent with occurrences, equal to random, and inconsistent with occurrences, respectively (Boyce et al. 2002; Hirzel et al. 2006). Training CBI was determined by 20% of withheld occurrences. I generated 2,000 unique, spatially-thinned by 1 km, and corrected by suitability PA records within Canada and Alaska (Fig. 3.1c). Testing CBI was evaluated against all occurrences within Canada and Alaska.

Unconditional bias and skill were determined by mean absolute error (MAE) and the associated skill score (SS), respectively (Murphy 1988; Roebber 1998). MAE was the mean difference between predicted and expected probability values. A MAE value of zero indicated accurate predictions, greater values indicated higher error in predictions. SS was a measure of mean square error between predicted probabilities and expected binary outcomes. A SS value of one indicated perfect skill, greater than zero indicated better than random, and less than zero indicated worse than random. MAE and SS were determined by extracting corresponding predicted and expected probability values into the appropriate formulas (Appendix B.1).

Forecast accuracy was represented by the Brier score (BS) (Brier 1950; Murphy and Winkler 1992). BS assessed the mean squared error between predicted and expected binned probabilities. A value of zero indicated accurate predictions, 0.25 indicated predictions are equal to random, and greater than 0.25 indicated predictions are inaccurate and worse than random (Brier 1950). Refinement and resolution were quantified as part of BS and examined qualitatively by attribute figures (Murphy 1973; Hsu and Murphy 1986; Wandishin et al. 2005). Higher refinement indicated greater difference in predicted and expected binned probabilities, and zero indicated no difference. Higher values of resolution indicated greater ability to separate different probabilities, with a minimum of zero which indicated no separation (Murphy and Winkler 1992). Attribute diagrams were classified by the ability of each methodology to provide prefect, useful, marginally useful, not useful, or dangerously useless predictions relative (Weisheimer and Palmer 2014). BS, refinement, and resolution values were determined through the `verification` R package (NCAR - Research Applications Laboratory 2015).

3.2.4.4 Presence-absence map

Binary presence-absence predictions were evaluated by discrimination. Discrimination determined the threshold-dependent ability of an SDM to classify presence or absence (Fielding and Bell 1997). Binary maps were created at a minimal presence threshold of omitted training centroids. I defined discrimination by sensitivity, specificity, precision, F1, and correct classification rate (CCR) (Fielding and Bell 1997). Sensitivity and specificity were the probability that the SDM correctly predicted an occurrence. Specificity was the probability that a known absence was predicted correctly. Precision was the probability that a predicted occurrence was an observed occurrence. F1 was the harmonic means of sensitivity and precision. CCR is the conditional probability that presence and absences were correctly classified (Fielding and Bell 1997). All discrimination metrics ranged from zero to one such that one indicated perfect discrimination while those ≤ 0.5 indicated random discrimination. This range of discrimination metrics provided a full perspective of SDMs' ability to classify presence and absences.

Training discrimination was evaluated against the 20% of presence and pseudo-absences withheld. Meanwhile, discrimination was tested against the 2,000 PA within Canada and Alaska described previously (Fig. 3.1c). Accounting for the black-box nature of `biomod2`, SDMs were trained and projected with all a pre-determined 80% presence and pseudo-absence subset. Subsequent thresholds were determined by evaluating prediction against the 80% training data by threshold and evaluation functions in `dismo` R package (Hijmans et al. 2017). Lastly, the fit of each probability and binary evaluation was assessed by minimum difference between training and testing evaluations. Minimal difference is based on the logic that overfit models will predict the training data well, but poorly on test data. Positive values indicate over-fit, while negative values indicate under-fit models (Warren and Seifert 2011).

3.2.5 Analysis

Variation in reliability among model building choices was determined through Type II Wald χ^2 tests fit by linear mixed-effects models in `car` and `lmerTest` R packages (Kuznetsova et al. 2017; Fox and Weisberg 2019). Mixed effects models allowed for the examination of each model building consideration while accounting repeated measures on training sets. A single mixed effect model was determined for each validation and evaluation metric. Mixed-effects models for J included fixed effects of algorithm and pseudo-absences interaction with random effects of training set. Response curve estimation and prediction evaluations mixed-effects models considered all three model building considerations as fixed effects with interactions and random effects of training set. Prior to statistical analysis, all evaluation measures underwent ordered quantile normalization to normalize mixed-effect model residuals (Peterson and Cavanaugh 2020). Minimal difference values were examined according to their absolute value to demonstrate deviation of fit rather than over- vs under-fitted of models.

To determine which methodology was best suited for each objective, I determined the mean relative performances all associated evaluations. First, post-hoc comparisons by estimated marginal means with Dunn–Šidák correction for pairwise comparisons were conduced for each validation and evaluation (Šidák 1967; Length 2020). Post-hoc tests were conducted on pseudo-absences and predictor selection variation per algorithm, and between algorithms, pseudo-absence levels and predictor selections to determine algorithm-specific, and overall performance patterns, respectively. Second, I assigned the resulting marginal means a normalized score from zero to one based on their significance group classification for each post-hoc test, such that SDMs with the same statistical group classification received the same score. A relative performance of one was assigned to the highest or lowest mean if the target value was one (highest) or zero, respectively (Table 3.3). These ranks were interpreted to represent poor, fair, average, good, or excellent relative performance (Fig. 5). Third, relative performance of each model building consideration combination was determined by calculating the relative performance mean across each evaluation per objective. Response curve estimation relative performance was determined by the corresponding normalized mean of RMSE and ρ relative performances for BIO1, BIO13, and elevation. Similarly, prediction relative performance was determined by the normalized mean of against training, testing, and fit performances for all corresponding evaluations per objective. Overall explanation or prediction relative performance was determined by the normalized mean across each respective group of evaluation metrics. Lastly total relative performance was determined by the normalized mean of explanation and prediction scores (Appendix B.2: Table B.5). All SDM computations and analysis were completed in R v.3.6.0 (R Core Team 2019).

3.3 Results

The ability of model building considerations to account for the effects of centroids varied for each evaluation ($p<0.05$; Appendix B.2: Table B2.3). Evaluating the relative performance per objective indicated that at least one SDM successfully limited centroid effects to provide appropriate SDM conclusions (Appendix B.2: Table B.4). However, model building considerations to optimize each evaluation and objective was inconsistent between evaluations, objectives, model type, software, and within algorithms (Appendix B.2: Table B.5; Fig. B2.11). Only two algorithms, multiple adaptive regression splines and surface range envelopes optimized all objectives under a single methodology (Appendix B.2: Fig. 11). These results also highlighted that without careful consideration of model building, SDM conclusions can be rendered useless (Appendix B.2: Table B.4).

3.3.1 Identification of driving predictors

The ability to identify driving predictors from centroids was poor ($J = 0.56\pm0.25$; mean and standard deviation) (Fig. 3.2). Only 15% of SDMs identified the driving predictors. Instead, SDMs typically identified the driving predictors and additional non-driving predictors (57%) or identified two of three driving predictors with (26%) or without (2%) additional predictors (Appendix B.2: Table B.2). GDD, NDVI, and BIO14 were most commonly mis-identified by 62%, 39%, and 32% of SDMs, respectively (Appendix B.2: Fig. B2.1). The effect of pseudo-absences was algorithm-dependent and not consistent within model classes, except envelope methods. Pseudo-absences did not affect predictor identification for 12 of 25 algorithms. I observed that eight algorithms improved identification with equal numbers of pseudo-absences, four for 10,000 pseudo-absences, and one improved at double pseudo-absences (Fig. 3.2). Overall, I observed that the original general additive models with 10,000 pseudo-absences provided the best identification. General linear models from `biomod2` with balanced datasets, and ensemble methods excluding committee average across pseudo-absences, identified all driving predictors, but less consistently. Poor identification was exhibited by envelope and machine learning methods.

3.3.2 Response curve estimation

Estimated response curves determined appropriate positive or negative trends (ρ: 0.71 ± 0.17; mean and standard deviation) but corresponding probabilities were miscalculated (RMSE: 0.42 ± 0.15; Fig. 3.3, Appendix B.2: Fig. B2.2-7). Across driving predictors, only 1% of response trends were poorly estimated ($\rho \leq 0$). On the other hand, only 1% of responses closely approximated the appropriate response (RMSE<0.1) and 28% exhibited high miscalculation (RMSE≥0.5) (Appendix B.2: Table B.4). Altogether, only 0.1% of SDMs resulted in poor trend and response estimation, particularly by artificial neural networks and committee average ensembles.

Estimated response patterns varied between driving predictors (Fig. 3.3). BIO1 response estimates did not capture the expected β-function but indicated a monotonic increase or a negative unimodal response which overpredicted at freezing temperatures by `biomod2` and original algorithms, respectively (Fig. 3.3a-b, Appendix B.2: Fig. B2.2-3). Conversely, BIO13 estimates captured the expected logistic curve but was accurate only at minimal and maximal thresholds. Intermediate precipitation values of BIO13 generally over-estimated corresponding probability (Fig. 3.3c-d, Appendix B.2: Fig. B2.4-5). Responses of BIO1 and BIO13 were further limited by loss of conditions greater than 27°C and 700 mm, respectively, causing truncation (Fig. 3.3a-d). Lastly, elevation exhibited the most consistent estimates of approximately linear monotonic decrease though trends varied. Responses ranged from no response (i.e. `biomod2` classification tree analysis) to approximating the expected monotonic decrease to an asymptote (i.e. original flexible discriminant analysis) (Fig. 3.3e-f, Appendix B.2: Fig. B2.6-7).

Relative performance evaluations indicated that 72% algorithms required training with only the driving predictions and triple or 10,000 pseudo-absences to improve response estimates (Appendix B.2: Fig. B2.11). However, five algorithms achieved the highest response estimation when considered with equal centroids and pseudo-absences and automated predictor selection. These five algorithms included the overall best responses estimated by original general boosting regression methods with balanced training and automated predictor selection. Excellent response estimation was also exhibited by general linear models from `biomod2` with automated and 10,000 pseudo-absences (Appendix B.2: Fig. B2.9b). The most inaccurate responses were estimated by envelope and committee average ensembles models (Appendix B.2: Table B.4, B.5).

3.3.3 Probability of occurrence

Centroids generally reflected expected presence or absences but introduced high amounts of error into occurrence probability predictions owing to an inability to differentiate probabilities (Fig. 3.4). Most predictions exhibited little variation with higher-than-expected proportions of low probable areas, supported by training and testing resolutions of 0.04±0.01 and 0.02±0.01 (mean ±standard deviation), respectively (Fig. 3.4c, e, Appendix B.2: Fig. B2.8). Alternatively, areas of high probability were overpredicted across most of North America, suggesting low probability only within non-coastal areas of western US and Canada (Fig. 3.4g). Low variability of probabilities provided good calibration and skill. Probabilities were consistent (CBI>0) with centroids and testing occurrences for 88% and 82% of SDMs, respectively (Appendix B.2: Table B.4). Further, 58% and 62% of predicted probabilities reflected expected presence or absences in the training and testing region, respectively (SS>0). Lower skill compared to calibration resulted from overprediction of occurrence in expected low probability areas (Fig. 3.4a, g). Observed probability trends resulted in overall bias of 0.19±0.09 and 0.22±0.10 (mean ±standard deviation) in training and testing regions, respectively. This observed error was comparable to that indicated by forecast accuracy and refinement (Appendix B.2: Table B.4). Overall, probability predictions were marginally useful at best (Appendix B.2: Fig. B2.8). Probability predictions were over fit to the training data with minimal differences exhibiting improved calibration, less error, and improved separation of values in the training region. However, the testing region indicated more skill owing to a higher proportion of species absence (Appendix B.2: Table B.4).

Probability of occurrences was best estimated from centroids with equal or double pseudo-absences by 76% of algorithms. Predictor selection required to account for centroids was less consistent, with 40%, 36%, and 24% of algorithms requiring automated, *a priori*, and expert predictors, respectively (Appendix B.2: Fig. B2.11). Across all SDMs, occurrence probability was best estimated by original general regression boosting methods with equal pseudo-absences and automated predictors (Table 3.4). Excellent occurrence probabilities were also generated by ensemble mean and weighted mean with double pseudo-absences and automated predictors. The least reliable probabilities were provided by neural networks and envelope models (Appendix B.2: Fig. B2.10a).

3.3.4 Presence-absence map

Discrimination of presence-absence from centroids exhibited over- and under-prediction of species' presence, depending on region and model building considerations (Fig. 3.4b, d, f, h). For example, boundaries with a high-density of species presence were predominantly correctly classified, but also overpredicted within Mexico and along the U.S.-Mexico border (Precision: 0.5±0.22; F1: 0.62±0.18; mean and standard deviation, Fig. 3.4d, f). Extending classification outside of the training area observed either low detection of species presence or high overprediction (Precision: 0.19±0.13; F1: 0.21±0.1; mean and standard deviation, Fig. 3.4f, h). Boundaries with low density of species presence were under-predicted and mis-classified as absent within both regions (Fig. 3.4d, f), unless presence was vastly over-predicted across Arctic and coastal boundaries

(Fig. 3.4h). As a result, extrapolation of centroid-trained SDMs generally observed improved classification of species absence (Specificity:0.69±0.14; mean and standard deviation) over presence (Sensitivity:0.55±0.12; mean and standard deviation). Overall SDMs could only provide moderately accurate discriminations of presence or absence within both training and testing regions (CCR: 0.68±0.15 and 0.69±0.14, respectively, mean and standard deviation). Further, 86% of SDMs provided better than random discrimination. Accordingly, minimal difference between regions indicated SDMs were overfit to the centroids, with lower discrimination of presences in the testing region compared to absences (Appendix B.2: Table B.4).

Discrimination from centroids improved when considering equal or double pseudo-absences to centroids for 87% of algorithms. Prediction selection considerations were less consistent, with 37%, 34%, and 29% of algorithms requiring automated, *a priori*, and expert predictors, respectively (Appendix B.2: Fig. B2.11). Relative performance indicated the most reliable discrimination was obtained with weighted mean ensembles with equal pseudo-absences to centroids, and automated predictors (Table 3.4). Non-weighted mean ensembles and original general additive models under the same model building considerations also provided excellent discrimination. Poorest discrimination ability was provided by envelope, committee average ensembles, and neural networks models (Appendix B.2: Fig. B2.10b).

3.3.5 Explanation and prediction

The ability of centroids to reliably provide explanations was best achieved by general linear models from `biomod2` with equal pseudo-absences to centroids to identify predictors and then estimate response curves (Table 3.4). Envelope and machine learning methods tended to provide the least reliable explanations (Appendix B.2: Fig. B2.9). While overall predictive ability improved relative to other methodologies when boosting or non-committee average ensemble methods with automated predictors and equal pseudo-absences were considered (Table 3.4). Neural networks and envelope models provided the poorest predictions (Appendix B.2: Fig. B2.10).

Overall, optimization of all SDM objectives from centroids required automated predictor selection regardless of pseudo-absences for 44% of algorithms. Alternatively, application of expert predictors or *a priori* with triple or less pseudo-absences to centroids was required for 38% and 10% of algorithms, respectively (Appendix B.2: Fig. B2.11). Relative performance across all metrics indicated that original general boosting regression methods followed by mean, median, or weighted mean ensembles with equal centroids and pseudo-absences and automated predictor selection provided the most reliable conclusions to explain and predict a distribution (Fig. 3.5). Meanwhile, remaining regression methods provided excellent (original multiple adaptive regression splines, original general additive models, general linear models from `biomod2`) or good (generalized boosting regression method, generalized additive model, flexible discriminant analysis, multiple adaptive regression splines from `biomod2`) relative performance. Machine learning methods exhibited average (Maximum Entropy from `biomod2`, both random forests), fair (original Maximum Entropy, MaxLike, artificial neural network from `biomod2`), or poor (original artificial neural network) relative performance. Finally, poor performance was provided by both envelope methods and committee average ensembles (Table 3.2; Fig. 3.5; Appendix B.2: Table B.5).

3.4 Discussion

SDMs are the most common method for investigating and predicting species distributions and to aid in management action for certain species. Models can be built from different algorithms, predictors, and quantities of response variables, whose conclusions vary in reliability depending on the objective and precision of the response variable. In this study, I evaluated SDMs' ability to provide reliable conclusions regarding identification of driving predictors, estimation of response, prediction of occurrence probability, and presence or absence from centroids of a virtual species. I observed that it is possible to determine appropriate conclusions from centroids if SDMs are constructed with careful consideration of methods used, particularly algorithm. Specifically, general boosting regression methods followed by mean or weighted mean ensembles provided the most accurate conclusions across objectives.

General boosting regression methods provided the most accurate conclusions for half of the considered objectives and overall performance (Table 3.4). General boosting regression methods have previously been highlighted as high-performing (Elith et al. 2006; Wisz et al. 2008; Heikkinen et al. 2012; Rapacciuolo et al. 2012; Mainali et al. 2015) or moderately-performing (Aguirre-Gutiérrez et al. 2013; Breiner et al. 2018) choices. Their strength comes from their use of an iterative mean ensemble of the boosting and regression-tree algorithms to emphasize previously mis-identified training responses (Elith et al. 2008; Shirley et al. 2013). Consequently, general boosting regression methods are known to be adept at interpreting non-linear responses, removal of non-contributing predictors, fit of multiple interactions, accounting of interactions, outliers, and collinearity, and ability to analyze and interpret complex responses (Elith et al. 2008; Yu et al. 2020). Notably related to centroids, the general boosting regression method has a demonstrated ability to interpret occurrence records with positional error (Graham et al. 2008; Naimi et al. 2011; Bombi and D'Amen 2012) and is less affected by coarsening of scale (Aguirre-Gutiérrez et al. 2013). Though general boosting regression methods have been criticized for their tendency to overfit and produce unreasonable probability of occurrences (Becker et al. 2020), I did not observe that here (Appendix B.2: Table B.4).

Similarly, mean or weighted mean ensembles also tended to provide high relative performance across objectives (Fig. 3.5). These methods were able to predict appropriate presence-absence maps while also identifying driving predictors and maintaining excellent probability of occurrence predictions. Ensembles benefit from considering multiple algorithms to highlight areas of agreement. Excellent predictive ability of ensembles stems from presence predictions that are strictly limited to cells for which the majority of SDMs agree (Aguirre-Gutiérrez et al. 2013). Additionally, as all SDMs were able to identify at least two of three driving predictors, ensembles were able to assign lower contributions to non-driving predictors. Ensemble methods have risen in popularity to account for variation among algorithms (Araújo and New 2007; Hao et al. 2019). Hao et al. (2019) compared ensemble to singular methods and found the former were the best or nearly best-performing in most studies. Though ensemble methods can be improved with more careful fine-tuning and consideration of algorithms included as opposed to a sensitivity threshold applied here (Araújo and New 2007).

The recommended use of general boosting regression or ensemble methods contrasts previous SDM mosquito comparisons, which suggested that Maximum Entropy and general linear models provided the highest performance (Khatchikian et al. 2011). However, Khatchikian et al. (2011) evaluated against precise occurrences and did not consider general boosting regression or ensemble models. Though some mosquito distributions have considered general boosting regression methods (Kraemer et al. 2015; Khan et al. 2020), more publications to date rely on Maximum Entropy owing to its perceived flexibility and high performance (Merow et al. 2013). However, I only observed average relative performance of Maximum Entropy overall (Fig. 5). Maximum Entropy is more based in niche theory compared to general boosting regression methods. Maximum Entropy estimates the probability of occurrence by determining the stable equilibrium state of parameters with the highest entropy (Phillips et al. 2006; Phillips and Dudík 2008; Booth et al. 2014). Consideration of centroids reduced environmental heterogeneity thereby incorrectly indicating stable equilibrium from MAUP, potentially leading to the degraded performance of Maximum Entropy (Bombi and D'Amen 2012). As a result, the performance of Maximum Entropy is reduced at coarser scales, while the general boosting regression methods are not. General boosting regression methods have consistently indicated equal or better performance than Maximum Entropy when considered against more coarse scales (Guisan et al. 2007; Graham et al. 2008; Bombi and D'Amen 2012). Bombi and D'Amen (2012) indicated that predictive performance of general boosting regression method was not hindered until a 24-fold change from the suspected true ecological scale. Meanwhile, Guisan et al. (2007) demonstrated Maximum Entropy performance decreased compared to GBM at a minimal 10-fold scale increase. This suggests that despite Maximum Entropy's hold on the SDM literature, its use in applications where coarse scales and MAUP are of concern is ill-advised.

Moreover, other machine learning SDMs are generally considered to provide more accurate results that traditional regression or envelope methods (Elith et al. 2006; Lawler et al. 2006; Prasad et al. 2006). Yet, this was not reflected by my results. For example, random forest is generally detailed as a high performing model (Lawler et al. 2006, Syphard and Franklin 2009; Mi et al. 2017), but only observed below average performance (Fig. 5). Though general boosting regression methods and random forests are both emblems of regression-trees, but random forests do not retrain to highlight mis-identified training responses as done but general boosting regression methods. Rather, random forests improves model fit by controlling the number of predictors, estimating an unbiased error rate, and generating high number of trees (Prasad et al. 2006). The assumption of machine learning superiority may be driven by interpolative evaluation, as opposed to the full diagnostic evaluation conducted here. Further, machine learning methods may require more attention to fine-tuning of hyper-parameterizations to ensure reliable conclusions than was considered here (Araújo et al. 2019). Insufficient effort has been devoted to investigating different machine learning SDM ability to provide reliable conclusions from imprecise or centroid occurrences for further comparison.

Further model building considerations indicated algorithm- and objective-specific effects, with no pattern observed across algorithms, consistent with previous studies (Elith et al. 2006; Synes and Osborne 2011; Barbet-Massin et al. 2012; Heikkinen et al. 2012; Sarquis et al. 2018). These results further support the need to determine SDM methodology for the available data and objective, as opposed to relying on commonly applied algorithms (Aguirre-Gutiérrez et al. 2013; Araújo et al. 2019). It is interesting to note that while only half of algorithms were impacted by pseudo-absences for predictor identification, response curve estimation largely required expert predictors with triple or more pseudo-absences to provide reliable conclusions. Meanwhile, most algorithms produced more reliable predictions when built with equal pseudo-absences and automated selection of predictors.

3.4.1 Identification of driving predictors

General additive models with 10,000 pseudo-absences were required for the most consistent predictor identification. Meanwhile, predictor identification was driven more by algorithm than pseudo-absence level. Predictor identification by SDMs is a common objective (Bradie and Leung 2017), but among the least evaluated. Smith and Santos (2020) evaluated the effects of sample size, scale, and collinearity on general additive models (GAM), GBM, and maximum entropy (MaxEnt) to determine predictor contribution. They concluded that small sample sizes and coarse scales inhibited predictor identification, but algorithm was the greater indicator of identification success. Specifically, GAM and MaxEnt with large sample sizes provided the best identification, but MaxEnt was more affected by coarse scales (Smith and Santos 2020). Therefore, my findings are in partial agreement with Smith and Santos (2020). The smallest sample size considered here was larger than Smith and Santos (2020)'s largest, thus potentially explaining the variation in pseudo-absence number effect. This suggests that though larger sample sizes are better, some algorithms (i.e. original maximum entropy) have upper and lower sample size thresholds for predictor identification. Further, Aguirre-Gutiérrez et al. (2013) indicated only high variability of GAM's variable contribution measures. This is further supported by a decreased predictor selection ability of GAM at lower pseudo-absence levels (Fig. 3.2). Therefore, GAM's predictor identification may not be reflected when less centroids are available (Smith and Santos 2020).

Overall predictor identification was poor. These results corroborate the findings of Inman et al. (2021), who tested the ability of MaxEnt to identify the driving predictors and observed correct identification by only 3% of SDMs when bias was corrected by aggregation. Inhibited predictor identification can be explained by drivers of distribution changing with scale (Hortal et al. 2010; King et al. 2021). Change in scale alters the spatial autocorrelation and heterogeneity within each predictor. Accordingly, SDMs appeared to only select predictors which demonstrated either higher spatial auto correlation or heterogeneity (Appendix B.2: Fig. B2.12). Increased heterogenous predictors and spatial autocorrelation inflates predictor importance, particularly when a distribution is driven by multiple predictors (Connor et al. 2018; Smith and Santos 2020). This suggests driving predictors identified by SDMs trained with centroids can approximate appropriate driving predictors by indicating predictors which demonstrate spatial autocorrelation and heterogeneity at the provided scale. These findings may be limited to the predictor identification method applied. Harisena et al. (2021) detailed the most common variable contribution method by Thuiller et al. (2009), and applied here, is sensitive to spatial autocorrelation, pseudo-replication, and truncated responses. The literature contains countless available methods to identify limiting predictors, and another method or selection threshold may improve predictor identification with centroids (Dormann et al. 2008; Synes and Osborne 2011; Harisena et al. 2021).

3.4.2 Response curve estimation

Aggregation caused truncated species response curves increasing niche width, resulting in only capturing general trends. This finding supports previous observations of species response detection inhibited by mismatched scales (Azaele et al. 2012; Araújo and Rozenfeld 2014; Hamil et al. 2016). Specifically, change in scale is known to alter the shape of responses from linear to asymmetric or skewed curves owing to MAUP (Rydgren et al. 2003; Lechner et al. 2012). As the scale coarsens, heterogeneity is increasingly masked, which makes the expected small-scale ecological patterns less identifiable (Wiens 1989). However, regardless of scale effects on response curve estimation, Guisan and Zimmerman (2000) described that SDMs are not expected to provide realistic species-environment response curves, nor to inform about their underlying mechanisms. Instead, SDMs are correlative models and provide a snapshot of potential niche width (Sinka et al. 2020). Jarnevich et al. (2015) reported that one should consider if the response curve trend is biologically possible and not overly complex. Accordingly, centroids should only be expected to capture the general positive or negative response validated against physiological studies. Here, centroids were able to capture the expected positive or negative trends, thereby indicating appropriate realism for an SDM. However, overestimation of niche breadth suggests that centroids are unsuitable to transfer beyond the training extent (Thuiller et al. 2004; Merow et al. 2014; Manzoor et al. 2018). Future studies may improve niche estimation by considering accounting for uncertainty within predictors, such as standard error or considering additional aggregates (i.e. min, max, median), considering pseudo-absences from a more restrictive range, or only investigating univariate model responses (Thuiller et al. 2004; Winters et al. 2008; Santika and Hutchnison 2009; Stoklosa et al. 2015).

Explanation was best estimated for most algorithms when considering expert predictors and high numbers of pseudo-absences. Requirement of expert predictors for proper explanation re-enforces the requirement of SDMs built with only predictors for which are well evidenced (Guisan and Zimmerman 2000; Araújo et al. 2019). Deviation or additional noise from well-evidenced predictors, such as change of scale or MAUP effects, inhibits the ability of SDMs to determine the expected response (Rydgren et al. 2003; Lechner et al. 2012). Further, high numbers of pseudo-absences allowed for greater training to better fit the appropriate response curves (Wisz et al. 2008). Across SDMs, I identified general linear models (GLMs) with expert or successful automated identification and equal pseudo-absences to centroids provided the best explanation. This SDM successfully identified all driving variables and appropriately estimated responses. This finding is contrary to previous studies which have suggested that GLMs were inferior to other algorithms such as GAM or GBM for response estimation (Santika and Hutchnison 2009). This inconsistency may be due to previous GLMs considering only linear responses, while I considered a higher order approach. Higher order approaches are recommended to provided increased flexibility to fit complex responses (Segurado et al. 2006; Dormann et al. 2007). However, little variation was observed between pseudo-absence levels and explanation ability for GLMs (Appendix B2: Fig. B2.9c). This suggests that despite sample sizes of 2,828 or higher are sufficient to provide response curves at the provided scale.

3.4.3 Probability of occurrence

Predictions of virtual species generally improved when considered with equal pseudo-absences and automated predictor selection. Coarse scales increase the probability of false absences, thus more pseudo-absences bias SDMs to consider more potentially suitable habitat as unsuitable (McPherson et al. 2006). In this study, the 1,414 centroids limited pseudo-absences to a maximum of 1,761 unique environmental conditions. Therefore, consideration of equal pseudo-absences to centroids provided the least bias training relative to other pseudo-absence levels considered, supported by previous studies (Moffett et al. 2007; Phillips and Dudík 2008; Barbet-Massin et al. 2012; Liu et al. 2019; Grimmett et al. 2020). For example, Johnson et al. (2017) indicated discrimination of *A. albopictus* centroids improved when considered with equal background points to centroids. Though fewer pseudo-absences are expected to improve discrimination ability, it only contributed 7% of the final relative performance score and was outweighed by all other evaluation metrics which were not reliant on pseudo-absences.

Automated selection of predictors generally allowed for more accurate spatial conclusions. Accounting for the imprecision of centroids fundamentally alters how the responses and resulting distributions are interpreted (Levin 1992; Barton et al. 2013; Schweiger and Beierkuhnlein 2016). While the effect of one factor may be prominent at a fine scale, its effect may be negligible at another (Schweiger and Beierkuhnlein 2016). For example, Hortal et al. (2010) described how as scale coarsens, the effect of biotic factors on insect distribution decreases and abiotic factors effects increase. Similarly, King et al. (2021) indicated fine scale ($3.14x10^{-4}$ km^2) distributions of seven mammal species were driven by biotic and abiotic factors, but coarse (40 km^2) was driven by abiotic factors. Mouton et al. (2009) suggested data driven SDMs, such as automated predictor selection, outperform expert models as predictors are selected based on the available scale, thus providing a more reliable interpretation. Therefore, automated predictor selection allows for the estimation of driving predictors at the provided scale, to better represent the responses at the observed over expected responses.

Overall probability of occurrence predictions was only moderately accurate with low generality suggesting marginal usefulness in application. Some studies suggest that lower degrees of scale coarsening can preserve environmental characteristics (Guisan et al. 2007; Trivedi et al. 2008; Bombi and D'Amen 2012), but generally scale coarsening decreases SDM predictive performance (Rahbek and Graves 2001; Thompson and McGarigal 2002; Guisan et al. 2007b; Seo et al. 2009; Mertes and Jetz 2018). The degree of scale coarsening observed in this study (Appendix B.2: Table B.1) does not reflect those of the lower degree previously described (≤10 km^2) and therefore supports decreased performance at coarse scales. The observed performance in the current study reflects a greater decrease in predictive ability than previous centroid applications (Collins et al. 2017; Johnson et al. 2017; Cheng et al. 2021). Johnson et al. (2017) applied centroids of *A. aegypti* and *A. albopictus* across the contiguous US counties and observed good AUC scores but without independent validation. Similarly, Collins et al. (2017) compared SDMs trained with precise or centroids to investigate the degree of bias introduced for butterfly, dragonfly, and damselfly species in the contiguous US counties. Niche similarity metrics indicated centroids only somewhat compromised predictions, with the effect more pronounced in larger and environmentally heterogenous counties which could not be accounted for by boundary scale (Collins et al. 2017). Finally, Cheng et al. (2021) applied centroids of a virtual species in France and Germany separately but accounted for positional error by coarsening on a grid rather than boundary aggregate. The resulting predictions reflected the expected distributions according to ρ but decreased in accuracy with larger administrative regions and at coarser scales (Cheng et al. 2021). One possible explanation of decreased degradation in my study is that all previous studies investigated administrative regions within a single country, whereas I applied centroid occurrences across administrative regions of three countries. Consequently, across-country considerations resulted in a larger variation in size and shape of boundaries thereby leading to greater uncertainty and instability of predictors by MAUP (Openshaw 1984). Specifically, larger, and more heterogenous administrative regions introduce greater predictor uncertainty, namely boundaries in the western US or Canada (Collins et al. 2017; Cheng et al. 2021).

3.4.4 Presence-absence map

Prediction of species' presence or absence tended to over-predict presence with some cases of under-prediction, depending on the methodology. Methodology considerations for species presence or absence predictions followed the patterns described in probability of occurrence above. Presence-absence maps require further consideration of the threshold considered. Threshold selection is one of many possible sources of bias in SDMs (Bean et al. 2012; Nenzén and Araújo 2011). In this study, I applied a minimum presence threshold to best approximate expected presence or absence (Fig. 4b). Yet in practice, threshold selection should be considered relative to the desired SDM application and importance of omission and commission errors (Liu et al. 2013).

For example, objectives related to determining where a species is currently to manage the population (i.e. invasive species) require higher thresholds to limit omission error (Norris 2014). Meanwhile if the purpose is early detection, lower thresholds are recommended to ensure all potential areas are highlighted and limit commission error (Jarnevich et al. 2015). Alternatively, thresholds derived from the maximization of sum between sensitivity and specificity or minimization of the difference between sensitivity and specificity are generally seen as superior to others (Jimenez-Valverde and Lobo 2007; Liu et al. 2005), or authors may examine an overlay of different thresholds to determine suitable areas (e.g. Johnson et al. 2017). Admittedly, no previous research has investigated threshold considerations at varying coarse scales or with centroids, therefore future research is required.

3.4.5 Implications

Some inaccuracy in SDM explanations and predictions may seem trivial, but they can pose serious issues when considered to allocate finite resources for species management. Management of mosquito populations often focuses on chemical or biological agents to control the limit reproduction and spread. Yet, these management practices require fine-scale and precise predictions to be effective which are not captured using imprecise occurrences (Fouet and Kamdem 2019; Pascoe et al. 2019). Further, SDMs are often applied to invasive species to determine where successful invasion will occur. The results here, indicated prediction of only administrative regions at highest risk of establishment, given the true high density of species occurrence while misclassifying lower density of true occurrence. This suggests that with very careful consideration of SDM methods, imprecise occurrences can be used to predictor and potentially project areas at highest risk of arthropod vector establishment, if sufficient propagules are introduced in new regions. These corresponding administrative regions would be encouraged to enact public education campaigns and increase vector surveillance accordingly.

However, early detection at lower risk areas were consistently missed by SDMs. This further highlights the loss of environmental detail with the use of centroid occurrences. *A. aegypti* and *A. albopictus*, and other arthropod vectors, often rely on micro-niches or refugia to survive within otherwise unsuitable environments. This detail is lost when considering centroids, therefore the corresponding SDMs are unsuitable for estimating regions with isolated risks. Further investigations on a local scale or with more precise requirements would be required to provide the required to directly reflect management applications. This may be accomplished by additional or alternative methods may be required to provide reliable conclusions from centroids, such as including mixed-effect models (Hamil et al. 2016), Bayesian (Velásquez-Tibatá et al. 2016), integration methods (Collins et al. 2017; Pacifici et al. 2019), or considering movement and biotic factors in addition to abiotic (Soberón and Peterson 2005). Though improved accuracy and quality control of all species occurrence and finer detailed environmental conditions would best allow SDMs to interpret the appropriate response and distribution of mosquitoes and all other species.

Though not directly examined, the combined effect of overestimated niche breadth and misclassification in an adjacent region, suggests that potential projections of occurrence probability into new times or region may be greatly hindered. Specifically, Medley (2010) indicated the niche of *A. albopictus* is not represented by considering the invaded or native niche alone. Range expansion of invasion species have been successfully predicted by SDMs (Peterson et al. 2007; Carlos-Júnior et al. 2015; Mothes et al. 2019). However, the ability to do so has been limited by the sample size, precision, and scale of the response variables (Ensing et al. 2012; Manzoor et al. 2018). When limited to imprecise centroids increased environmental and/or geographic extents may be required for proper niche classification.

Centroid occurrences and resulting ecologically insignificant scales in SDMs are not limited to *A. aegypti* and *A. albopictus.* Approximately half of arthropod vectors and species from all major taxonomic groups' occurrences are limited to centroids in occurrence repositories, particularly within the US (Park and Davis 2017). The results of this study provide guidance to improve centroid application in SDMs, but not conclusive guidelines. SDM methodological evaluations using virtual species are especially useful to address data quality issues (Mendes et al. 2020). Virtual species ensure SDM assumptions are met, including that occurrence records are precise, entire geographic and environmental extent are sampled without bias, species are at equilibrium, and they provide a known truth for evaluation (Guisan and Zimmerman 2000). Conversely, virtual species may introduce bias, though this problem can be reduced by several methods. To ensure ecological realism, virtual species habitat suitability was designed from real ecological and physiological studies of *A. aegypti* and *A. albopictus*. Response curves consisted of different linear and non-linear functions therefore preventing bias towards a particular analysis (Hirzel et al. 2001). Centroid occurrences are observed across many taxonomic groups (Park and Davis 2017). Therefore, one major limitation was the consideration of a single virtual species across SDMs. Additionally, it is important to note that all SDMs in this study were examined under default settings. SDMs may improve when hyper-parameters are adjusted to fit the available data (Merow et al. 2013; Araújo et al. 2019). Future work is required to determine if my results hold true across taxonomic groups.

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Table 3.1: Predictor variables considered. Asterisks indicate predictors which were calculated from source data, see 3.2.1.

Predictor	Abbreviation	Scale	Source
Annual mean temperature*	BIO1	$1\ km^2$	Thornton et al. 1997, 2017
Mean diurnal temperature*	BIO2		
Precipitation of the wettest month*	BIO13		
Precipitation of the driest month*	BIO14		
Growing degree days*	GDD		
Snow cover	SC	$24\ km^2$	Brown and Brasnett 2010
Elevation	EV	30 arc seconds	Earth Resources Observation and Science Center 2017
Deciduous broadleaf forests	L_DBF	0.05°	Friedl et al. 2015
Evergreen needle leaf forests	L_ENF		
Mixed forests	L_MF		
Urban settlements	L_UB		
Water	L_WT		
Woody savannas	L_WS		
Normalized difference vegetation index	NDVI	0.1°	Allen and Sockli 2018
Human population density	PD	Canadian health regions	Statistics Canada 2018
		U.S. counties	U.S. Census Bureau 2018
		Mexican States	National Institute of Statistics and Geography 2019

Table 3.2: SDM algorithms implemented and corresponding R package. Data types indicate presence-absence (PA), presence-background (PB), or presence-only (PO) response variable required.

Algorithm	Abbreviation	Class of model	Data	Software	Reference
Artificial neural network	ANN_O	Machine learning	PA	`nnet`	Venables and Ripley 2002
	ANN_B			`biomod2`	Thuiller et al. 2020
Classification tree analysis	CTA_O	Regression	PA	`rpart`	Therneau and Atkinson 2019
	CTA_B			`biomod2`	Thuiller et al. 2020
Flexible discriminant analysis	FDA_O	Linear and multiple adaptive regression	PA	`mda`	Hastie et al. 2020
	FDA_B			`biomod2`	Thuiller et al. 2020
Generalized additive model	GAM_O	Regression	PA	`gam`	Hastie 2020
	GAM_B			`biomod2`	Thuiller et al. 2020
Generalized boosting regression method	GBM_O	Regression, boosting	PA	`gbm`	Greenwell et al. 2020
	GBM_B			`biomod2`	Thuiller et al. 2020
Generalized linear model	GLM_O	Regression	PA	`Base R`	R Core team 2019
	GLM_B			`biomod2`	Thuiller et al. 2020
Multiple adaptive regression splines	MARS_O	Regression	PA	`earth`	Milborrow et al. 2019
	MARS_B			`biomod2`	Thuiller et al. 2020
Maximum entropy	MaxEnt_O	Machine learning	PB	`dismo`	Hijmans et al. 2017
	MaxEnt_B			`biomod2`	Thuiller et al. 2020
MaxLike	MXL_O	Machine learning	PB	`maxlike`	Royle et al. 2012

Table 3.2 (continued)

Algorithm	Abbreviation	Class of model	Data	Software	Reference
Random forest	RF_O	Machine learning	PA	`randomForest`	Liaw and Wiener 2001
	RF_B			`biomod2`	Thuiller et al. 2020
Surface range envelopes	SRE_O	Envelope	PO	`dismo`	Hijmans et al. 2017
	SRE_B			`biomod2`	Thuiller et al. 2020
Ensemble	EMca_B	Committee average	-	`biomod2`	Thuiller et al. 2020
	EMmean_B	Mean			
	EMmedian_B	Median			
	EMwmean_B	Weighted mean			

Table 3.3: Evaluation metrics applied to assess SDMs ability to achieve each objective. Target values indicate the optimal value of each evaluation to perfectly capture the expected conclusions. Descriptions and formulas for each metric are available in supplementary methods.

Objective	**Evaluation**	**Target value**
Predictor identification	Jaccard index (J)	1
Response curve estimation	Spearman's correlation (ρ)	1
	Root mean square error (RMSE)	0
Probability of occurrence	Continuous Boyce Index (CBI)	1
	Mean absolute error (MAE)	0
	Associated skill score (SS)	1
	Brier Score (BS)	0
	Resolution	Higher
	Refinement	0
	Minimum difference	0
Presence-absence map	Sensitivity	1
	Specificity	1
	Precision	1
	F1	1
	Correct classification rate (CCR)	1
	Minimum difference	0

Table 3.4: Recommended methodology per objective. Overall objectives represent the relative performance for all corresponding objectives. Full relative performances are available in Appendix B2: Table B2.5.

Objective	**Algorithm**	**Pseudo-absences**	**Predictor selection**
Explanation			
Identification of driving predictors	GAM_O	10,000	-
Response curve estimation	GBM_O	1:1	Automated
Overall	GLM_B	1:1	Automated or expert
Prediction			
Probability of occurrence	GBM_O	1:1	Automated
Presence-absence map	EMwmean_B	1:1	Automated
Overall	GBM_O	1:1	Automated
Explanation and prediction			
Overall	GBM_O	1:1	Automated

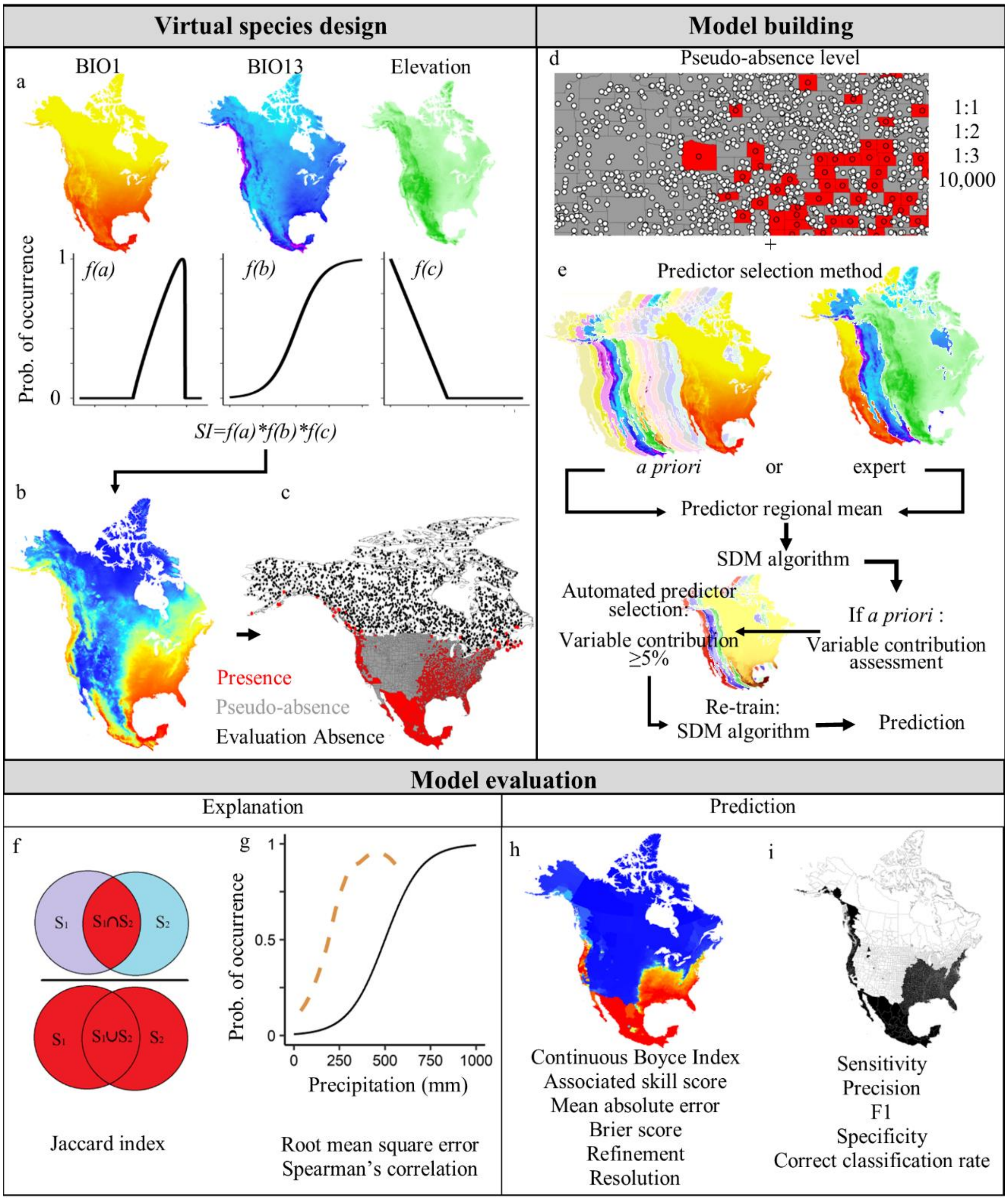

Figure 3.1: Methodology workflow of virtual species design, model building, and evaluation. Virtual species were designed according to response curves from real environmental values of annual mean temperature (BIO1), precipitation of the wettest month (BIO13), and elevation (a), calculation and mapping of virtual species suitability index (b) and converted suitability index to binary training centroid occurrences (red polygon), presumed absences (grey polygon), testing occurrences (red dots) and absences (black dots) (c). Model building consisted of determining random pseudo-absences (white dots) within regions without an occurrence (red dots) at four levels (d), then one of three predictor selection methods, *a priori*, expert, or re-trained with automated predictor

selection derived from *a priori* measure of variable contribution (e). Model evaluation was divided into SDMs' ability to explain or predict a distribution. SDMs' ability to explain was evaluated through their ability to identify the driving predictors by Jaccard index, J, where S_1 is expert predictors, S_2 is the automated predictors, and red areas indicate the values considered to calculate J (f) and estimated response curve (orange-dashed line) accuracy relative to expected species-environment response curve (solid black line) by root mean square error and Spearman's correlation (g). Evaluation of predictions was determined by predicted probability of occurrence predictions (h) compared to true probability (b) and classification of binary presence-absences maps at a minimal training presence threshold (i).

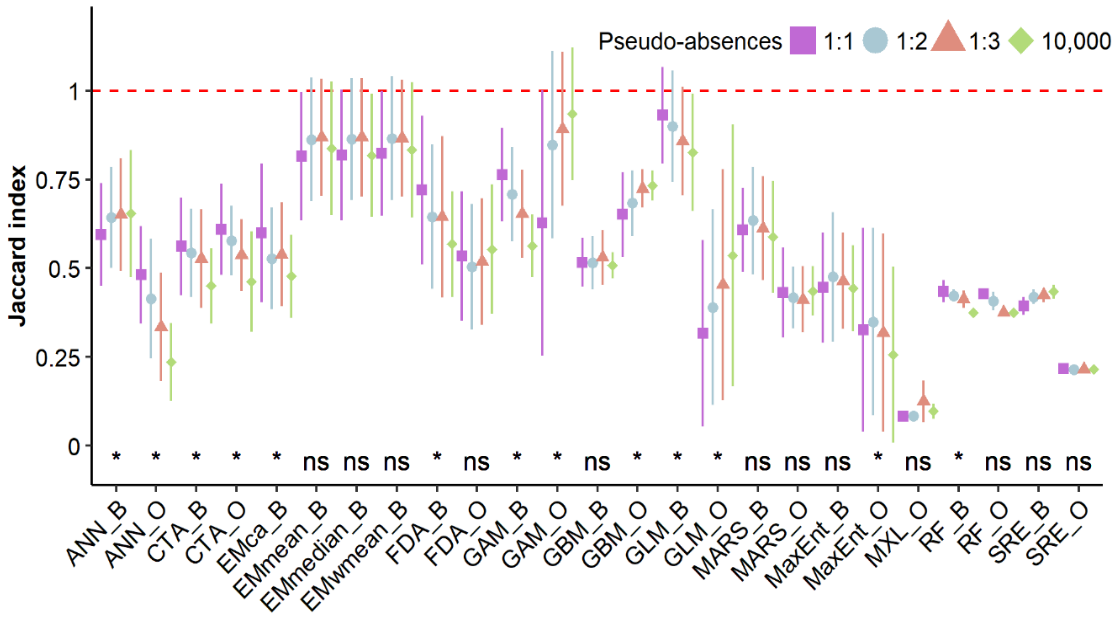

Figure 3.2: Jaccard index per algorithm and pseudo-absences. Algorithm-specific effect of pseudo-absences are shown along x-axis indicating if algorithms observed an effect (*) or not (ns) among pseudo-absences per algorithm.

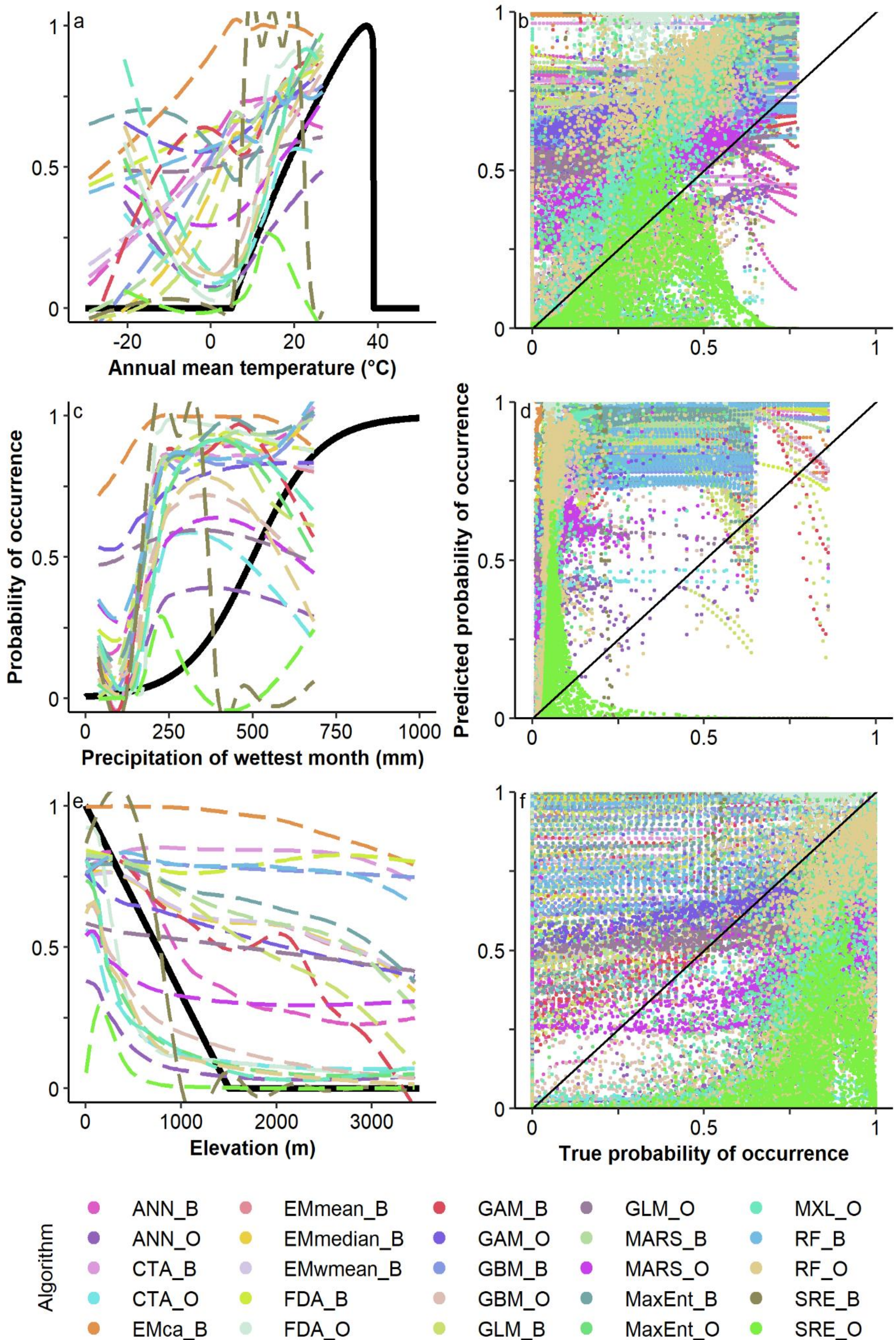
a
b
c
d
e
f
Annual mean temperature (°C)
Precipitation of wettest month (mm)
Elevation (m)
Probability of occurrence
Predicted probability of occurrence
True probability of occurrence
Algorithm
ANN_B
ANN_O
CTA_B
CTA_O
EMca_B
EMmean_B
EMmedian_B
EMwmean_B
FDA_B
FDA_O
GAM_B
GAM_O
GBM_B
GBM_O
GLM_B
GLM_O
MARS_B
MARS_O
MaxEnt_B
MaxEnt_O
MXL_O
RF_B
RF_O
SRE_B
SRE_O

Figure 3.3: Algorithm mean responses of BIO1 (a), BIO13 (c), and elevation (e) with scatterplots of true by predicted probability of occurrence of BIO1 (b), BIO13 (d), and elevation (f). Response curves shown represent general additive smoothing (a, c, e). The expected response is shown by the solid black line (a, c, e), or perfect fit (b, d, f). All responses and corresponding accuracies are available in Appendix B2: Figs B2.2-7 and Table B2.4, respectively.

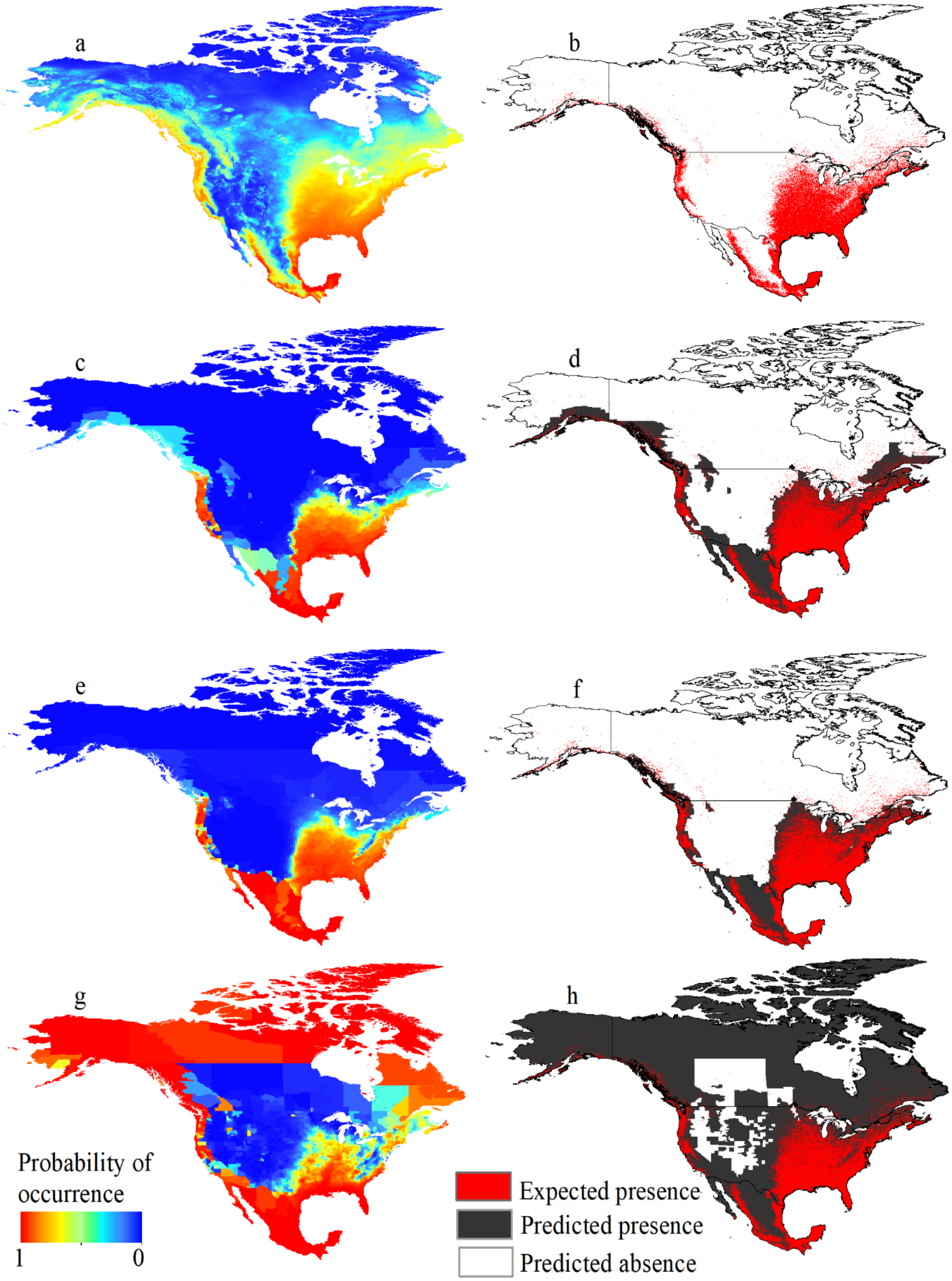

Figure 3.4: Predicted probability of occurrence and binary presence-absence maps compared to expected. Maps correspond to expected probability of occurrence (a), true presence-absence (b). An example of excellent relative performance by GBM_O at 1:1 with automated predictors' predicted probability of occurrence(c) and binary prediction

(d). An example of an average relative performance by GLM_B with 10,000 pseudo-absences and *a priori* predictors' probability of occurrence (e) and binary prediction (f). An example of poor relative performance predictions by ANN_O with 10,000 pseudo-absences and automated predictors' probability of occurrence (g) and binary prediction (h).

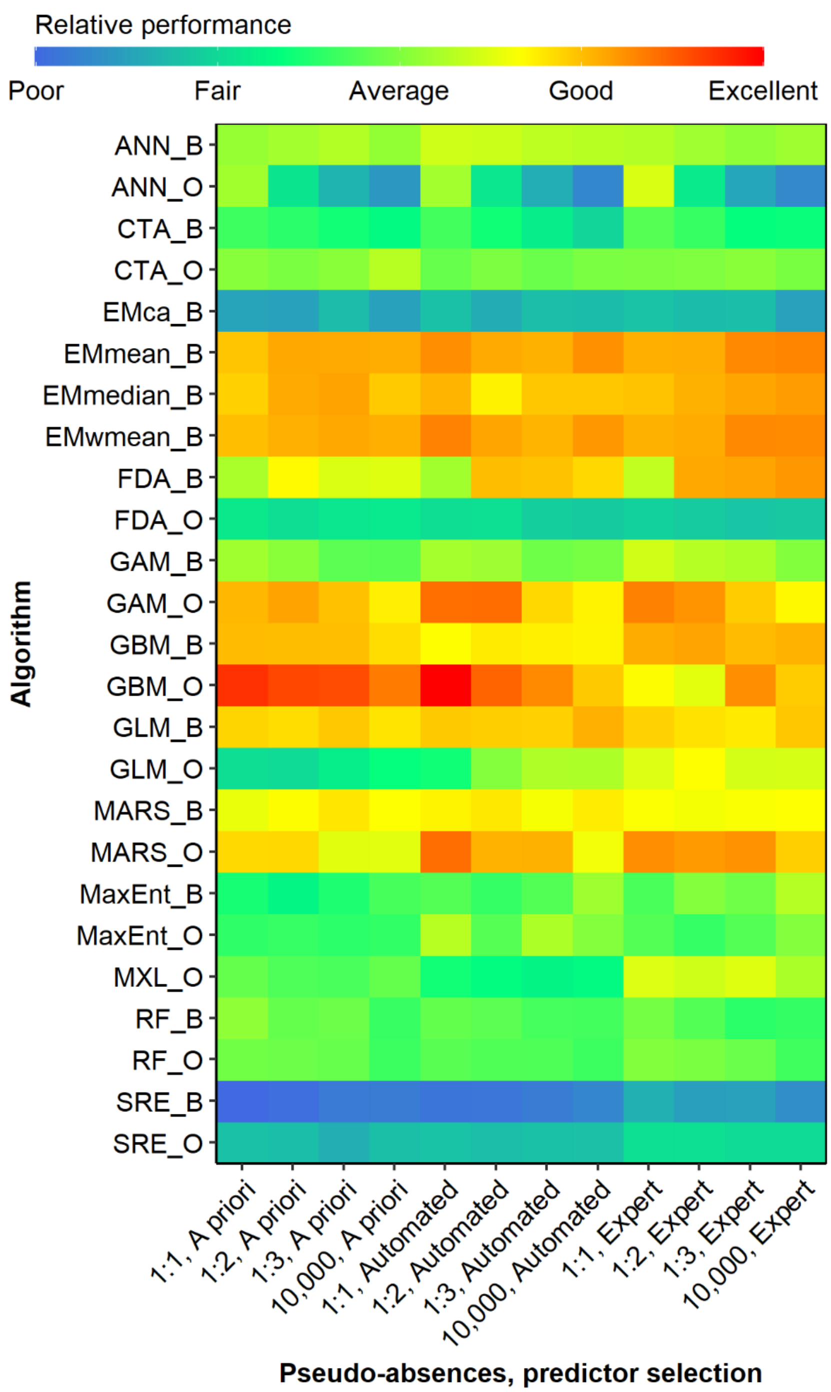

Figure 3.5: Overall relative performance between all considered algorithm, pseudo-absences, and predictor selection considering niche explanation and prediction accuracy. A breakdown of relative performance is available in Appendix B2: Figs. B2.9-11. See Table 2 for SDM abbreviations.

CHAPTER 4: GENERAL DISCUSSION

Changing distribution of mosquitoes and associated disease pose threats to human health and economy (Caraballo and King 2014; Heymann et al. 2015). However, estimating their niche and corresponding distribution by species distribution models (SDMs) is limited by available data for a given objective (Aguirre-Gutiérrez et al. 2013; Araújo et al. 2019). This has given rise to comparative SDM studies related to aspects of response variable, predictor variables, model building, and model evaluation (e.g. Wisz et al. 2008; Heikkinen et al. 2012). Compilation of these efforts has allowed the creation of SDM best-practices and recommendations to guide biodiversity assessments in general (e.g. Araújo et al. 2019; Winship et al. 2020). These general guides can be improved by focusing on application specific recommendations (e.g. Koch 2021). This thesis sought to provide to investigate and determine limitations related mosquito SDMs and provide guidelines for best practice accordingly. Understanding and identification of limitations and corresponding best practices is important to enhance mosquito SDM application for advising management actions.

In this thesis, I identified limitations of SDMs across the literature with respect to best-practice standards (Araújo et al. 2019) and evaluated the impact of centroid occurrence on SDMs' ability to explain and predict the niche of an *Aedes spp.* Despite mosquitos commonly being investigated using SDMs, studies regarding their limitations or recommended methodology are lacking. Khatchikian et al. (2011) compared five algorithms their ability to predict the distribution of *Aedes albopictus* and *Aedes aegypti*, concluding that Maximum Entropy methods (Phillips et al. 2006) and general linear models provided the best accuracy. Expanding the knowledge of SDMs comparisons and limitations related to mosquitos will enhance public health implications to provide improved disease risk maps (Escobar and Craft 2016). Notably, in light of climate change and anthropogenic pressures SDMs will become more important to estimate the risk of all arthropod vectors (Ogden and Lindsay 2016; Ogden and Gachon 2019). Specifically, the high ecological and physiological plasticity paired with human-mediate transport of *A. albopictus* and *A. aegypti* pose the risk of introduction and spread of disease within novel regions (Ibañez-Justicia 2020). *A. albopictus* poses significant threats to public health in northern regions owing to diapausing eggs, while largely non-diapausing *A. aegypti* poses greater risk in tropical regions owing to competitive exclusion and difference in diapause ability (Kraemer et al. 2015, 2019).

In Chapter 2, 42% and 46% of mosquito SDMs across the literature demonstrated unacceptable or minimally acceptable practices for SDM applicability, respectively. Altogether the observed practices suggested potential bias in all aspects of previous mosquito SDMs. First, mosquito response variables were considered across limited environmental extents for predictors at unjustified scales. Consequently, species-environmental relationships risk miscalculation such as truncation of responses curves and corresponding niche width (Thuiller et al. 2004; Synes and Osborne 2011; Harisena et al. 2021). Second, the consideration of collinear predictors risk erroneous predictions from biased parameter estimation (Dormann et al. 2013). Third, relying on random-holdout methods risks inflated evaluations as using the same data for model building and evaluation provides an unrealistic measure of performance (Hijmans 2012; Bahn and McGill 2013). Consequently, mosquito SDMs require more attention to improve their applicability within available data. Though observed standards may have been biased by available literature, expanding taxa considered and inclusion of grey literature would provide a more encompassing sample. Therefore, recommendations to improve mosquito SDMs are validated within this study and continued to be developed and tested by future studies.

A known limitation of SDMs is the imprecise response variable limited to centroid occurrences (Parks and Davis 2017). Specifically, occurrence records of *A. aegypti* and *A. albopictus* are limited to centroids within Canada and the contiguous US (Hahn et al. 2017; Giordano et al. 2019). In Chapter 3, I quantified the ability of SDMs to determine realistic explanations and accurate predictions from centroids at a regional scale of a virtual species designed to reflect common characteristics of *A. albopictus* and *A. aegpyti*. Centroids inhibited the SDM's ability to determine realistic, accurate, and general results which could be effectively applied to advise management strategies and policy. It follows that, regional scales and centroids hold no ecological significance (Huettmann and Diamond 2006). Regional scales do not reflect the scale at which mosquitoes or other species interact with their environment, often described by dispersal range (Jackson and Fahrig 2015). Mosquitos generally only have a dispersal range of <7 km (Verdonschot and Besse-Lototskaya 2014), well below that of any administrative region. Accordingly, centroids result in the inclusion of unsuitable habitat as suitable habitat, resulting in overprediction by misinterpretation of the niche width (Murphy 2021). Overprediction by centroids indicated poor ability to identify potential areas with low density of the species occurrence in the adjacent geographic regions under the best identified methodologies. Correspondingly, this suggests that projecting centroid based SDM results into new spaces or time would be even less reliable to guide policy or management actions. Centroid SDM estimates were only estimated the highest at-risk areas, if propagule pressure introduction was sufficient. Therefore, centroid occurrences limit applicability of SDM for effective invasive species management, particularly mosquitoes and potentially other arthropod vectors. Alternatively, projections into new regions or time would be expected to only suggest areas with environmental conditions which could support a high density of the individual, thus limiting the applicability of effective small bodied invasive species management. As such, it is important to recognize that SDMs should be interpreted as a hypothesis that is only as accurate as the response and predictor variables that were used to train the model (Jarnevich et al. 2015). Meanwhile, in this study I showed that the effects centroids could be reduced through careful consideration of SDM methodology, in support of more recent SDM efforts to fine-tune SDMs for specific applications (Qiao et al. 2015). Overall, the use of imprecise occurrences to train SDMs implies cautious interpretation for management actions. Future work is required to validate the applicability of centroids to management actions across different species, and to identify what methods are best able to negate their effects.

Understanding, predicting, and managing the distribution of mosquitoes is of great intertest globally (Tjaden et al. 2018). Although SDMs are commonly applied to explore mosquito distributions, few studies have addressed their specific limitations and methodologies (but see Khatchikian et al. 2011). To my knowledge, this is the first comprehensive study of mosquito SDMs limitations. Specifically, as SDMs must be designed according to the available data and ecological characteristics of the species, advice for mosquito SDM selection is lacking. Previous efforts have focused on reviews of SDMs across public health applications without providing in-depth analysis or recommendations (Escobar 2020). This thesis addressed both shortcomings. The studies within this thesis help to highlight the limitations faced when working with mosquito occurrence records in SDMs and potential solutions. While mosquito distributions continue to change, there is no certainty that SDM methodology recommendations will be consistent across all applications. Therefore, this thesis provides suggestions to be tested for the available data and objective.

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APPENDICES

Appendix A.1

Percent of publications which identified each predictor variable as important (PI) per mosquito species considered. Publications indicated the number of studies that the predictor's importance was tested. Definitions of bioclimatic predictors are available in Appendix A.2: Table A2.2. General predictors indicate predictors within a common environmental classification that were applied by less than three publications. Abbreviations: EVI=enhanced vegetation index, LAI=leaf area index, MIR=middle-infra-red, NDBI = normalized difference building index, NDVI=normalized difference vegetation index, pop. = population, TCW=tasseled cap wetness, TWI = topographic wetness index.

Genus	Species	Predictor	Publications	PI
Aedes	*aegypti*	BIO06	13	30.8
Aedes	*aegypti*	BIO15	13	15.4
Aedes	*aegypti*	BIO02	12	25
Aedes	*aegypti*	BIO14	12	25
Aedes	*aegypti*	BIO05	12	0
Aedes	*aegypti*	BIO07	11	45.5
Aedes	*aegypti*	BIO13	11	27.3
Aedes	*aegypti*	BIO04	11	18.2
Aedes	*aegypti*	BIO18	11	18.2
Aedes	*aegypti*	Elevation	10	50
Aedes	*aegypti*	Urban land	10	50
Aedes	*aegypti*	BIO19	10	40
Aedes	*aegypti*	BIO01	10	30
Aedes	*aegypti*	BIO12	10	20
Aedes	*aegypti*	BIO17	10	10
Aedes	*aegypti*	Human pop. density	9	55.6
Aedes	*aegypti*	BIO03	9	33.3
Aedes	*aegypti*	BIO11	9	33.3
Aedes	*aegypti*	BIO08	9	22.2
Aedes	*aegypti*	BIO10	9	11.1
Aedes	*aegypti*	BIO16	8	25
Aedes	*aegypti*	BIO09	8	12.5

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Aedes	*aegypti*	Forested land	6	33.3
Aedes	*aegypti*	NDVI	6	33.3
Aedes	*aegypti*	Agricultural land	5	40
Aedes	*aegypti*	Slope	4	50
Aedes	*aegypti*	General landcover/use	4	25
Aedes	*aegypti*	Aspect	3	33.3
Aedes	*aegypti*	General temperature	3	33.3
Aedes	*aegypti*	EVI	3	0
Aedes	*aegypti*	General precipitation	3	0
Aedes	*aegypti*	Shrubland	3	0
Aedes	*aegypti*	Humidity	2	100
Aedes	*aegypti*	BIO010	2	50
Aedes	*aegypti*	Degree days	2	50
Aedes	*aegypti*	Housing	2	50
Aedes	*aegypti*	Barren land	2	0
Aedes	*aegypti*	Animal pop. density	1	100
Aedes	*aegypti*	Artifical lights	1	100
Aedes	*aegypti*	BIO014	1	100
Aedes	*aegypti*	Distance to water	1	100
Aedes	*aegypti*	Land surface temperature	1	100
Aedes	*aegypti*	Max annual temperature	1	100
Aedes	*aegypti*	Min annual temperature	1	100
Aedes	*aegypti*	Photoperiod	1	100
Aedes	*aegypti*	General vegetation	1	0
Aedes	*aegypti*	Grassland	1	0
Aedes	*aegypti*	Monthyl precipitation	1	0
Aedes	*aegypti*	NDBI	1	0
Aedes	*aegypti*	Savannas	1	0
Aedes	*aegypti*	Soil type	1	0
Aedes	*aegypti*	TCW	1	0
Aedes	*aegypti*	TWI	1	0
Aedes	*aegypti*	Waterbodies	1	0
Aedes	*aegypti*	Wetlands	1	0
Aedes	*albopictus*	BIO11	12	50

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Aedes	*albopictus*	BIO10	11	45.5
Aedes	*albopictus*	BIO17	11	45.5
Aedes	*albopictus*	BIO12	11	27.3
Aedes	*albopictus*	BIO18	11	27.3
Aedes	*albopictus*	BIO01	9	44.4
Aedes	*albopictus*	General temperature	9	44.4
Aedes	*albopictus*	BIO07	9	22.2
Aedes	*albopictus*	BIO15	9	22.2
Aedes	*albopictus*	BIO16	8	37.5
Aedes	*albopictus*	Human pop. density	7	42.9
Aedes	*albopictus*	Urban land	7	42.9
Aedes	*albopictus*	BIO02	7	28.6
Aedes	*albopictus*	BIO05	7	28.6
Aedes	*albopictus*	BIO06	7	28.6
Aedes	*albopictus*	Elevation	7	28.6
Aedes	*albopictus*	BIO19	6	33.3
Aedes	*albopictus*	General precipitation	6	33
Aedes	*albopictus*	BIO04	6	16.7
Aedes	*albopictus*	BIO08	6	16.7
Aedes	*albopictus*	BIO13	6	16.7
Aedes	*albopictus*	BIO14	6	0
Aedes	*albopictus*	BIO03	5	0
Aedes	*albopictus*	Agricultural land	4	50
Aedes	*albopictus*	BIO09	4	25
Aedes	*albopictus*	General landcover/use	4	25
Aedes	*albopictus*	Degree days	3	66.7
Aedes	*albopictus*	EVI	3	33.3
Aedes	*albopictus*	Flow accumulation	3	33.3
Aedes	*albopictus*	Forested land	3	33.3
Aedes	*albopictus*	Housing	3	33.3
Aedes	*albopictus*	NDVI	3	33.3
Aedes	*albopictus*	Slope	2	50
Aedes	*albopictus*	Shrubland	2	0
Aedes	*albopictus*	Artifical lights	1	100
Aedes	*albopictus*	BIO014	1	100
Aedes	*albopictus*	Humidity	1	100
Aedes	*albopictus*	Min annual temperature	1	100

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Aedes	*albopictus*	Monthyl precipitation	1	100
Aedes	*albopictus*	Vegetation cover	1	100
Aedes	*albopictus*	Animal pop. density	1	0
Aedes	*albopictus*	Aspect	1	0
Aedes	*albopictus*	Barren land	1	0
Aedes	*albopictus*	Education	1	0
Aedes	*albopictus*	General vegetation	1	0
Aedes	*albopictus*	Income	1	0
Aedes	*albopictus*	Industrial land	1	0
Aedes	*albopictus*	Land surface temperature	1	0
Aedes	*albopictus*	Max annual temperature	1	0
Aedes	*albopictus*	Photoperiod	1	0
Aedes	*albopictus*	Waterbodies	1	0
Aedes	*albopictus*	Wetlands	1	0
Aedes	*cinereus*	Agricultural land	2	50
Aedes	*cinereus*	BIO10	1	100
Aedes	*cinereus*	BIO18	1	100
Aedes	*cinereus*	Elevation	1	100
Aedes	*cinereus*	Animal pop. density	1	0
Aedes	*cinereus*	Barren land	1	0
Aedes	*cinereus*	BIO01	1	0
Aedes	*cinereus*	BIO02	1	0
Aedes	*cinereus*	BIO03	1	0
Aedes	*cinereus*	BIO04	1	0
Aedes	*cinereus*	BIO05	1	0
Aedes	*cinereus*	BIO06	1	0
Aedes	*cinereus*	BIO07	1	0
Aedes	*cinereus*	BIO08	1	0
Aedes	*cinereus*	BIO09	1	0
Aedes	*cinereus*	BIO11	1	0
Aedes	*cinereus*	BIO12	1	0
Aedes	*cinereus*	BIO13	1	0
Aedes	*cinereus*	BIO14	1	0
Aedes	*cinereus*	BIO15	1	0
Aedes	*cinereus*	BIO16	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Aedes	*cinereus*	BIO17	1	0
Aedes	*cinereus*	BIO19	1	0
Aedes	*cinereus*	Forested land	1	0
Aedes	*cinereus*	General landcover/use	1	0
Aedes	*cinereus*	Human pop. density	1	0
Aedes	*cinereus*	Industrial land	1	0
Aedes	*cinereus*	Shrubland	1	0
Aedes	*cinereus*	Urban land	1	0
Aedes	*cinereus*	Waterbodies	1	0
Aedes	*cinereus*	Wetlands	1	0
Aedes	*koreicus*	BIO06	2	50
Aedes	*koreicus*	BIO12	2	50
Aedes	*koreicus*	Degree days	2	50
Aedes	*koreicus*	BIO04	1	100
Aedes	*koreicus*	BIO05	1	100
Aedes	*koreicus*	BIO01	1	0
Aedes	*koreicus*	BIO02	1	0
Aedes	*koreicus*	BIO03	1	0
Aedes	*koreicus*	BIO07	1	0
Aedes	*koreicus*	BIO08	1	0
Aedes	*koreicus*	BIO09	1	0
Aedes	*koreicus*	BIO10	1	0
Aedes	*koreicus*	BIO11	1	0
Aedes	*koreicus*	BIO13	1	0
Aedes	*koreicus*	BIO14	1	0
Aedes	*koreicus*	BIO15	1	0
Aedes	*koreicus*	BIO16	1	0
Aedes	*koreicus*	BIO17	1	0
Aedes	*koreicus*	BIO18	1	0
Aedes	*koreicus*	BIO19	1	0
Aedes	*koreicus*	Min annual temperature	1	0
Aedes	*koreicus*	NDVI	1	0
Aedes	*melanura*	Urban land	1	0
Aedes	*scapularis*	BIO05	1	100
Aedes	*scapularis*	BIO12	1	100
Aedes	*scapularis*	Slope	1	100
Aedes	*scapularis*	Vegetation cover	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Aedes	*serratus*	BIO05	1	100
Aedes	*serratus*	BIO12	1	100
Aedes	*serratus*	Slope	1	100
Aedes	*serratus*	Vegetation cover	1	0
Aedes	*vexans*	Wetlands	4	25
Aedes	*vexans*	Waterbodies	3	33
Aedes	*vexans*	Urban land	3	0
Aedes	*vexans*	BIO01	2	50
Aedes	*vexans*	BIO12	2	50
Aedes	*vexans*	General landcover/use	2	50
Aedes	*vexans*	Forested land	2	0
Aedes	*vexans*	Human pop. density	2	0
Aedes	*vexans*	Aspect	1	100
Aedes	*vexans*	BIO06	1	100
Aedes	*vexans*	BIO07	1	100
Aedes	*vexans*	Degree days	1	100
Aedes	*vexans*	Distance to water	1	100
Aedes	*vexans*	Elevation	1	100
Aedes	*vexans*	General vegetation	1	100
Aedes	*vexans*	Slope	1	100
Aedes	*vexans*	Soil type	1	100
Aedes	*vexans*	TWI	1	100
Aedes	*vexans*	Agricultural land	1	0
Aedes	*vexans*	Animal pop. density	1	0
Aedes	*vexans*	Barren land	1	0
Aedes	*vexans*	BIO02	1	0
Aedes	*vexans*	BIO03	1	0
Aedes	*vexans*	BIO04	1	0
Aedes	*vexans*	BIO05	1	0
Aedes	*vexans*	BIO08	1	0
Aedes	*vexans*	BIO09	1	0
Aedes	*vexans*	BIO10	1	0
Aedes	*vexans*	BIO11	1	0
Aedes	*vexans*	BIO13	1	0
Aedes	*vexans*	BIO14	1	0
Aedes	*vexans*	BIO15	1	0
Aedes	*vexans*	BIO16	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Aedes	*vexans*	BIO17	1	0
Aedes	*vexans*	BIO18	1	0
Aedes	*vexans*	BIO19	1	0
Aedes	*vexans*	Industrial land	1	0
Aedes	*vexans*	MIR	1	0
Aedes	*vexans*	NDVI	1	0
Aedes	*vexans*	Shrubland	1	0
Anopheles	*albimanus*	General precipitation	2	50
Anopheles	*albimanus*	Land surface temperature	2	50
Anopheles	*albimanus*	Elevation	1	100
Anopheles	*albimanus*	BIO19	1	0
Anopheles	*albimanus*	EVI	1	0
Anopheles	*albimanus*	General landcover/use	1	0
Anopheles	*albimanus*	MIR	1	0
Anopheles	*albimanus*	NDVI	1	0
Anopheles	*albitarsis*	BIO04	2	50
Anopheles	*albitarsis*	BIO06	2	50
Anopheles	*albitarsis*	General precipitation	2	50
Anopheles	*albitarsis*	Land surface temperature	2	50
Anopheles	*albitarsis*	NDVI	2	50
Anopheles	*albitarsis*	BIO19	2	0
Anopheles	*albitarsis*	Elevation	2	0
Anopheles	*albitarsis*	Soil type	1	100
Anopheles	*albitarsis*	Aspect	1	0
Anopheles	*albitarsis*	BIO01	1	0
Anopheles	*albitarsis*	BIO02	1	0
Anopheles	*albitarsis*	BIO03	1	0
Anopheles	*albitarsis*	BIO05	1	0
Anopheles	*albitarsis*	BIO07	1	0
Anopheles	*albitarsis*	BIO08	1	0
Anopheles	*albitarsis*	BIO09	1	0
Anopheles	*albitarsis*	BIO10	1	0
Anopheles	*albitarsis*	BIO11	1	0
Anopheles	*albitarsis*	BIO12	1	0
Anopheles	*albitarsis*	BIO13	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*albitarsis*	BIO14	1	0
Anopheles	*albitarsis*	BIO15	1	0
Anopheles	*albitarsis*	BIO16	1	0
Anopheles	*albitarsis*	BIO17	1	0
Anopheles	*albitarsis*	BIO18	1	0
Anopheles	*albitarsis*	EVI	1	0
Anopheles	*albitarsis*	Flow accumulation	1	0
Anopheles	*albitarsis*	Flow direction	1	0
Anopheles	*albitarsis*	General landcover/use	1	0
Anopheles	*albitarsis*	MIR	1	0
Anopheles	*albitarsis*	Slope	1	0
Anopheles	*albitarsis*	TWI	1	0
Anopheles	*albitarsis F*	BIO04	1	100
Anopheles	*albitarsis F*	Soil type	1	100
Anopheles	*albitarsis F*	Aspect	1	0
Anopheles	*albitarsis F*	BIO01	1	0
Anopheles	*albitarsis F*	BIO02	1	0
Anopheles	*albitarsis F*	BIO03	1	0
Anopheles	*albitarsis F*	BIO05	1	0
Anopheles	*albitarsis F*	BIO06	1	0
Anopheles	*albitarsis F*	BIO07	1	0
Anopheles	*albitarsis F*	BIO08	1	0
Anopheles	*albitarsis F*	BIO09	1	0
Anopheles	*albitarsis F*	BIO10	1	0
Anopheles	*albitarsis F*	BIO11	1	0
Anopheles	*albitarsis F*	BIO12	1	0
Anopheles	*albitarsis F*	BIO13	1	0
Anopheles	*albitarsis F*	BIO14	1	0
Anopheles	*albitarsis F*	BIO15	1	0
Anopheles	*albitarsis F*	BIO16	1	0
Anopheles	*albitarsis F*	BIO17	1	0
Anopheles	*albitarsis F*	BIO18	1	0
Anopheles	*albitarsis F*	BIO19	1	0
Anopheles	*albitarsis F*	Elevation	1	0
Anopheles	*albitarsis F*	Flow accumulation	1	0
Anopheles	*albitarsis F*	Flow direction	1	0
Anopheles	*albitarsis F*	Slope	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*albitarsis F*	TWI	1	0
Anopheles	*albitarsis H*	BIO17	1	100
Anopheles	*albitarsis H*	Flow direction	1	100
Anopheles	*albitarsis H*	Soil type	1	100
Anopheles	*albitarsis H*	Aspect	1	0
Anopheles	*albitarsis H*	BIO01	1	0
Anopheles	*albitarsis H*	BIO02	1	0
Anopheles	*albitarsis H*	BIO03	1	0
Anopheles	*albitarsis H*	BIO04	1	0
Anopheles	*albitarsis H*	BIO05	1	0
Anopheles	*albitarsis H*	BIO06	1	0
Anopheles	*albitarsis H*	BIO07	1	0
Anopheles	*albitarsis H*	BIO08	1	0
Anopheles	*albitarsis H*	BIO09	1	0
Anopheles	*albitarsis H*	BIO10	1	0
Anopheles	*albitarsis H*	BIO11	1	0
Anopheles	*albitarsis H*	BIO12	1	0
Anopheles	*albitarsis H*	BIO13	1	0
Anopheles	*albitarsis H*	BIO14	1	0
Anopheles	*albitarsis H*	BIO15	1	0
Anopheles	*albitarsis H*	BIO16	1	0
Anopheles	*albitarsis H*	BIO18	1	0
Anopheles	*albitarsis H*	BIO19	1	0
Anopheles	*albitarsis H*	Elevation	1	0
Anopheles	*albitarsis H*	Flow accumulation	1	0
Anopheles	*albitarsis H*	Slope	1	0
Anopheles	*albitarsis H*	TWI	1	0
Anopheles	*albitarsis I*	BIO08	1	100
Anopheles	*albitarsis I*	BIO11	1	100
Anopheles	*albitarsis I*	Soil type	1	100
Anopheles	*albitarsis I*	Aspect	1	0
Anopheles	*albitarsis I*	BIO01	1	0
Anopheles	*albitarsis I*	BIO02	1	0
Anopheles	*albitarsis I*	BIO03	1	0
Anopheles	*albitarsis I*	BIO04	1	0
Anopheles	*albitarsis I*	BIO05	1	0
Anopheles	*albitarsis I*	BIO06	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*albitarsis I*	BIO07	1	0
Anopheles	*albitarsis I*	BIO09	1	0
Anopheles	*albitarsis I*	BIO10	1	0
Anopheles	*albitarsis I*	BIO12	1	0
Anopheles	*albitarsis I*	BIO13	1	0
Anopheles	*albitarsis I*	BIO14	1	0
Anopheles	*albitarsis I*	BIO15	1	0
Anopheles	*albitarsis I*	BIO16	1	0
Anopheles	*albitarsis I*	BIO17	1	0
Anopheles	*albitarsis I*	BIO18	1	0
Anopheles	*albitarsis I*	BIO19	1	0
Anopheles	*albitarsis I*	Elevation	1	0
Anopheles	*albitarsis I*	Flow accumulation	1	0
Anopheles	*albitarsis I*	Flow direction	1	0
Anopheles	*albitarsis I*	Slope	1	0
Anopheles	*albitarsis I*	TWI	1	0
Anopheles	*aquasalis*	General precipitation	2	50
Anopheles	*aquasalis*	Land surface temperature	2	50
Anopheles	*aquasalis*	Elevation	1	100
Anopheles	*aquasalis*	BIO19	1	0
Anopheles	*aquasalis*	EVI	1	0
Anopheles	*aquasalis*	General landcover/use	1	0
Anopheles	*aquasalis*	MIR	1	0
Anopheles	*aquasalis*	NDVI	1	0
Anopheles	*arabiensis*	Elevation	5	40
Anopheles	*arabiensis*	BIO12	4	50
Anopheles	*arabiensis*	BIO01	4	25
Anopheles	*arabiensis*	BIO02	3	100
Anopheles	*arabiensis*	Agricultural land	3	33.3
Anopheles	*arabiensis*	Forested land	3	33.3
Anopheles	*arabiensis*	General landcover/use	3	0
Anopheles	*arabiensis*	BIO18	2	100
Anopheles	*arabiensis*	BIO07	2	50
Anopheles	*arabiensis*	BIO09	2	50
Anopheles	*arabiensis*	BIO10	2	50
Anopheles	*arabiensis*	BIO13	2	50

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*arabiensis*	BIO14	2	50
Anopheles	*arabiensis*	BIO15	2	50
Anopheles	*arabiensis*	BIO19	2	50
Anopheles	*arabiensis*	EVI	2	50
Anopheles	*arabiensis*	General temperature	2	50
Anopheles	*arabiensis*	Slope	2	50
Anopheles	*arabiensis*	TCW	2	50
Anopheles	*arabiensis*	Aspect	2	0
Anopheles	*arabiensis*	BIO03	2	0
Anopheles	*arabiensis*	BIO04	2	0
Anopheles	*arabiensis*	BIO05	2	0
Anopheles	*arabiensis*	BIO06	2	0
Anopheles	*arabiensis*	BIO08	2	0
Anopheles	*arabiensis*	BIO11	2	0
Anopheles	*arabiensis*	BIO16	2	0
Anopheles	*arabiensis*	BIO17	2	0
Anopheles	*arabiensis*	TWI	2	0
Anopheles	*arabiensis*	Evapotranspiration	1	100
Anopheles	*arabiensis*	Flow accumulation	1	100
Anopheles	*arabiensis*	General precipitation	1	100
Anopheles	*arabiensis*	Human pop. density	1	100
Anopheles	*arabiensis*	Humidity	1	100
Anopheles	*arabiensis*	NDVI	1	100
Anopheles	*arabiensis*	Photoperiod	1	100
Anopheles	*arabiensis*	Savannas	1	100
Anopheles	*arabiensis*	Transportation	1	100
Anopheles	*arabiensis*	Wind	1	100
Anopheles	*arabiensis*	Degree days	1	0
Anopheles	*arabiensis*	Distance to water	1	0
Anopheles	*arabiensis*	Grassland	1	0
Anopheles	*arabiensis*	Max annual temperature	1	0
Anopheles	*arabiensis*	Min annual temperature	1	0
Anopheles	*arabiensis*	Savannas	1	0
Anopheles	*arabiensis*	Shrubland	1	0
Anopheles	*arabiensis*	Soil type	1	0
Anopheles	*arabiensis*	Urban land	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*arabiensis*	Vapor pressure	1	0
Anopheles	*arabiensis*	Vegetation cover	1	0
Anopheles	*arabiensis*	Wetlands	1	0
Anopheles	*atroparvus*	Cloud cover	2	50
Anopheles	*atroparvus*	General temperature	2	50
Anopheles	*atroparvus*	Agricultural land	1	100
Anopheles	*atroparvus*	BIO01	1	100
Anopheles	*atroparvus*	BIO02	1	100
Anopheles	*atroparvus*	BIO12	1	100
Anopheles	*atroparvus*	Forested land	1	100
Anopheles	*atroparvus*	Grassland	1	100
Anopheles	*atroparvus*	Min annual temperature	1	100
Anopheles	*atroparvus*	Shrubland	1	100
Anopheles	*atroparvus*	Degree days	1	0
Anopheles	*atroparvus*	Max annual temperature	1	0
Anopheles	*baimaii*	Degree days	2	50
Anopheles	*baimaii*	Soil type	2	50
Anopheles	*baimaii*	BIO01	1	100
Anopheles	*baimaii*	BIO06	1	100
Anopheles	*baimaii*	BIO09	1	100
Anopheles	*baimaii*	General temperature	1	100
Anopheles	*baimaii*	Monthyl precipitation	1	100
Anopheles	*baimaii*	Wind	1	100
Anopheles	*baimaii*	BIO08	1	0
Anopheles	*baimaii*	BIO15	1	0
Anopheles	*baimaii*	Elevation	1	0
Anopheles	*baimaii*	Humidity	1	0
Anopheles	*bellator*	BIO12	1	100
Anopheles	*bellator*	Vegetation cover	1	100
Anopheles	*bellator*	BIO05	1	0
Anopheles	*bellator*	Slope	1	0
Anopheles	*coluzzii*	EVI	2	50
Anopheles	*coluzzii*	General temperature	2	50
Anopheles	*coluzzii*	TCW	2	50
Anopheles	*coluzzii*	Agricultural land	1	100
Anopheles	*coluzzii*	Elevation	1	100

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*coluzzii*	Human pop. density	1	100
Anopheles	*coluzzii*	Forested land	1	0
Anopheles	*coluzzii*	Grassland	1	0
Anopheles	*coluzzii*	Savannas	1	0
Anopheles	*coluzzii*	Shrubland	1	0
Anopheles	*coluzzii*	Urban land	1	0
Anopheles	*coluzzii*	Wetlands	1	0
Anopheles	*coustani*	BIO04	1	100
Anopheles	*coustani*	BIO07	1	100
Anopheles	*coustani*	BIO16	1	100
Anopheles	*coustani*	BIO19	1	100
Anopheles	*coustani*	Elevation	1	100
Anopheles	*coustani*	BIO01	1	0
Anopheles	*coustani*	BIO02	1	0
Anopheles	*coustani*	BIO03	1	0
Anopheles	*coustani*	BIO05	1	0
Anopheles	*coustani*	BIO06	1	0
Anopheles	*coustani*	BIO08	1	0
Anopheles	*coustani*	BIO09	1	0
Anopheles	*coustani*	BIO10	1	0
Anopheles	*coustani*	BIO11	1	0
Anopheles	*coustani*	BIO12	1	0
Anopheles	*coustani*	BIO13	1	0
Anopheles	*coustani*	BIO14	1	0
Anopheles	*coustani*	BIO15	1	0
Anopheles	*coustani*	BIO17	1	0
Anopheles	*coustani*	BIO18	1	0
Anopheles	*coustani*	General landcover/use	1	0
Anopheles	*crascens*	General temperature	2	50
Anopheles	*crascens*	Soil type	2	50
Anopheles	*crascens*	BIO01	1	100
Anopheles	*crascens*	BIO06	1	100
Anopheles	*crascens*	BIO09	1	100
Anopheles	*crascens*	BIO15	1	100
Anopheles	*crascens*	Elevation	1	100
Anopheles	*crascens*	Humidity	1	100
Anopheles	*crascens*	Monthyl precipitation	1	100

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*crascens*	BIO08	1	0
Anopheles	*crascens*	Degree days	1	0
Anopheles	*crascens*	Wind	1	0
Anopheles	*cruzii*	Slope	1	100
Anopheles	*cruzii*	Vegetation cover	1	100
Anopheles	*cruzii*	BIO05	1	0
Anopheles	*cruzii*	BIO12	1	0
Anopheles	*darlingi*	General landcover/use	3	67
Anopheles	*darlingi*	Elevation	3	33.3
Anopheles	*darlingi*	Human pop. density	3	33.3
Anopheles	*darlingi*	General precipitation	2	50
Anopheles	*darlingi*	Land surface temperature	2	50
Anopheles	*darlingi*	BIO04	1	100
Anopheles	*darlingi*	BIO12	1	100
Anopheles	*darlingi*	Transportation	1	100
Anopheles	*darlingi*	Urban land	1	100
Anopheles	*darlingi*	BIO01	1	0
Anopheles	*darlingi*	BIO02	1	0
Anopheles	*darlingi*	BIO03	1	0
Anopheles	*darlingi*	BIO05	1	0
Anopheles	*darlingi*	BIO06	1	0
Anopheles	*darlingi*	BIO07	1	0
Anopheles	*darlingi*	BIO08	1	0
Anopheles	*darlingi*	BIO09	1	0
Anopheles	*darlingi*	BIO10	1	0
Anopheles	*darlingi*	BIO11	1	0
Anopheles	*darlingi*	BIO13	1	0
Anopheles	*darlingi*	BIO14	1	0
Anopheles	*darlingi*	BIO15	1	0
Anopheles	*darlingi*	BIO16	1	0
Anopheles	*darlingi*	BIO17	1	0
Anopheles	*darlingi*	BIO18	1	0
Anopheles	*darlingi*	BIO19	1	0
Anopheles	*darlingi*	EVI	1	0
Anopheles	*darlingi*	Forested land	1	0
Anopheles	*darlingi*	Geology	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*darlingi*	MIR	1	0
Anopheles	*darlingi*	NDVI	1	0
Anopheles	*darlingi*	TWI	1	0
Anopheles	*deaneorum*	Flow accumulation	1	100
Anopheles	*deaneorum*	Soil type	1	100
Anopheles	*deaneorum*	Aspect	1	0
Anopheles	*deaneorum*	BIO01	1	0
Anopheles	*deaneorum*	BIO02	1	0
Anopheles	*deaneorum*	BIO03	1	0
Anopheles	*deaneorum*	BIO04	1	0
Anopheles	*deaneorum*	BIO05	1	0
Anopheles	*deaneorum*	BIO06	1	0
Anopheles	*deaneorum*	BIO07	1	0
Anopheles	*deaneorum*	BIO08	1	0
Anopheles	*deaneorum*	BIO09	1	0
Anopheles	*deaneorum*	BIO10	1	0
Anopheles	*deaneorum*	BIO11	1	0
Anopheles	*deaneorum*	BIO12	1	0
Anopheles	*deaneorum*	BIO13	1	0
Anopheles	*deaneorum*	BIO14	1	0
Anopheles	*deaneorum*	BIO15	1	0
Anopheles	*deaneorum*	BIO16	1	0
Anopheles	*deaneorum*	BIO17	1	0
Anopheles	*deaneorum*	BIO18	1	0
Anopheles	*deaneorum*	BIO19	1	0
Anopheles	*deaneorum*	Elevation	1	0
Anopheles	*deaneorum*	Flow direction	1	0
Anopheles	*deaneorum*	Slope	1	0
Anopheles	*deaneorum*	TWI	1	0
Anopheles	*dirus complex*	Land surface temperature	2	50
Anopheles	*dirus complex*	MIR	2	50
Anopheles	*dirus complex*	NDVI	2	50
Anopheles	*dirus complex*	Barren land	1	0
Anopheles	*dirus complex*	Elevation	1	0
Anopheles	*dirus complex*	EVI	1	0
Anopheles	*dirus complex*	Forested land	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*dirus complex*	General precipitation	1	0
Anopheles	*dirus complex*	Waterbodies	1	0
Anopheles	*dirus s.l.*	Degree days	2	50
Anopheles	*dirus s.l.*	Soil type	2	50
Anopheles	*dirus s.l.*	BIO01	1	100
Anopheles	*dirus s.l.*	BIO06	1	100
Anopheles	*dirus s.l.*	BIO08	1	100
Anopheles	*dirus s.l.*	BIO09	1	100
Anopheles	*dirus s.l.*	General temperature	1	100
Anopheles	*dirus s.l.*	Monthyl precipitation	1	100
Anopheles	*dirus s.l.*	BIO15	1	0
Anopheles	*dirus s.l.*	Elevation	1	0
Anopheles	*dirus s.l.*	Humidity	1	0
Anopheles	*dirus s.l.*	Wind	1	0
Anopheles	*dirus s.s*	BIO01	1	100
Anopheles	*dirus s.s*	BIO06	1	100
Anopheles	*dirus s.s*	BIO08	1	100
Anopheles	*dirus s.s*	BIO09	1	100
Anopheles	*dirus s.s*	BIO15	1	100
Anopheles	*dirus s.s*	Degree days	1	100
Anopheles	*dirus s.s*	General temperature	1	100
Anopheles	*dirus s.s*	Humidity	1	100
Anopheles	*dirus s.s*	Soil type	1	100
Anopheles	*dirus s.s*	Elevation	1	0
Anopheles	*dirus s.s*	Monthyl precipitation	1	0
Anopheles	*dirus s.s*	Wind	1	0
Anopheles	*farauti*	BIO02	1	100
Anopheles	*farauti*	BIO04	1	100
Anopheles	*farauti*	BIO07	1	100
Anopheles	*farauti*	Elevation	1	100
Anopheles	*farauti*	General precipitation	1	100
Anopheles	*farauti*	General temperature	1	100
Anopheles	*farauti*	Humidity	1	100
Anopheles	*farauti*	Aspect	1	0
Anopheles	*farauti*	BIO01	1	0
Anopheles	*farauti*	BIO03	1	0
Anopheles	*farauti*	BIO08	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*farauti*	BIO09	1	0
Anopheles	*farauti*	BIO10	1	0
Anopheles	*farauti*	BIO11	1	0
Anopheles	*farauti*	BIO12	1	0
Anopheles	*farauti*	BIO13	1	0
Anopheles	*farauti*	BIO14	1	0
Anopheles	*farauti*	BIO15	1	0
Anopheles	*farauti*	BIO16	1	0
Anopheles	*farauti*	BIO17	1	0
Anopheles	*farauti*	BIO18	1	0
Anopheles	*farauti*	BIO19	1	0
Anopheles	*farauti*	Radiation	1	0
Anopheles	*farauti*	Slope	1	0
Anopheles	*freeborni*	General precipitation	2	50
Anopheles	*freeborni*	Land surface temperature	2	50
Anopheles	*freeborni*	BIO19	1	0
Anopheles	*freeborni*	Elevation	1	0
Anopheles	*freeborni*	EVI	1	0
Anopheles	*freeborni*	General landcover/use	1	0
Anopheles	*freeborni*	MIR	1	0
Anopheles	*freeborni*	NDVI	1	0
Anopheles	*funestus*	Forested land	3	33.3
Anopheles	*funestus*	Elevation	3	0
Anopheles	*funestus*	BIO12	2	100
Anopheles	*funestus*	Agricultural land	2	50
Anopheles	*funestus*	BIO01	2	50
Anopheles	*funestus*	General temperature	2	50
Anopheles	*funestus*	TCW	2	50
Anopheles	*funestus*	Aspect	1	100
Anopheles	*funestus*	BIO04	1	100
Anopheles	*funestus*	BIO06	1	100
Anopheles	*funestus*	BIO07	1	100
Anopheles	*funestus*	BIO13	1	100
Anopheles	*funestus*	BIO18	1	100
Anopheles	*funestus*	Evapotranspiration	1	100
Anopheles	*funestus*	Human pop. density	1	100

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*funestus*	Humidity	1	100
Anopheles	*funestus*	Photoperiod	1	100
Anopheles	*funestus*	Savannas	1	100
Anopheles	*funestus*	Savannas	1	100
Anopheles	*funestus*	Slope	1	100
Anopheles	*funestus*	Transportation	1	100
Anopheles	*funestus*	Wind	1	100
Anopheles	*funestus*	BIO02	1	0
Anopheles	*funestus*	BIO03	1	0
Anopheles	*funestus*	BIO05	1	0
Anopheles	*funestus*	BIO08	1	0
Anopheles	*funestus*	BIO09	1	0
Anopheles	*funestus*	BIO10	1	0
Anopheles	*funestus*	BIO11	1	0
Anopheles	*funestus*	BIO14	1	0
Anopheles	*funestus*	BIO15	1	0
Anopheles	*funestus*	BIO16	1	0
Anopheles	*funestus*	BIO17	1	0
Anopheles	*funestus*	BIO19	1	0
Anopheles	*funestus*	EVI	1	0
Anopheles	*funestus*	General landcover/use	1	0
Anopheles	*funestus*	Grassland	1	0
Anopheles	*funestus*	Shrubland	1	0
Anopheles	*funestus*	TWI	1	0
Anopheles	*funestus*	Urban land	1	0
Anopheles	*funestus*	Wetlands	1	0
Anopheles	*gambiae*	Elevation	4	75
Anopheles	*gambiae*	BIO01	3	33.3
Anopheles	*gambiae*	BIO12	3	33.3
Anopheles	*gambiae*	Forested land	3	33.3
Anopheles	*gambiae*	Agricultural land	2	100
Anopheles	*gambiae*	Slope	2	100
Anopheles	*gambiae*	Aspect	2	50
Anopheles	*gambiae*	TCW	2	50
Anopheles	*gambiae*	BIO02	2	0
Anopheles	*gambiae*	TWI	2	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*gambiae*	BIO06	1	100
Anopheles	*gambiae*	BIO11	1	100
Anopheles	*gambiae*	BIO13	1	100
Anopheles	*gambiae*	BIO18	1	100
Anopheles	*gambiae*	Evapotranspiration	1	100
Anopheles	*gambiae*	EVI	1	100
Anopheles	*gambiae*	General temperature	1	100
Anopheles	*gambiae*	Human pop. density	1	100
Anopheles	*gambiae*	Humidity	1	100
Anopheles	*gambiae*	Max annual temperature	1	100
Anopheles	*gambiae*	Photoperiod	1	100
Anopheles	*gambiae*	Savannas	1	100
Anopheles	*gambiae*	Transportation	1	100
Anopheles	*gambiae*	Wind	1	100
Anopheles	*gambiae*	BIO03	1	0
Anopheles	*gambiae*	BIO04	1	0
Anopheles	*gambiae*	BIO05	1	0
Anopheles	*gambiae*	BIO07	1	0
Anopheles	*gambiae*	BIO08	1	0
Anopheles	*gambiae*	BIO09	1	0
Anopheles	*gambiae*	BIO10	1	0
Anopheles	*gambiae*	BIO14	1	0
Anopheles	*gambiae*	BIO15	1	0
Anopheles	*gambiae*	BIO16	1	0
Anopheles	*gambiae*	BIO17	1	0
Anopheles	*gambiae*	BIO19	1	0
Anopheles	*gambiae*	Degree days	1	0
Anopheles	*gambiae*	Flow accumulation	1	0
Anopheles	*gambiae*	General landcover/use	1	0
Anopheles	*gambiae*	Grassland	1	0
Anopheles	*gambiae*	Min annual temperature	1	0
Anopheles	*gambiae*	Savannas	1	0
Anopheles	*gambiae*	Shrubland	1	0
Anopheles	*gambiae*	Urban land	1	0
Anopheles	*gambiae*	Vapor pressure	1	0
Anopheles	*gambiae*	Vegetation cover	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*gambiae*	Wetlands	1	0
Anopheles	*gambiae s.l.*	BIO10	2	100
Anopheles	*gambiae s.l.*	BIO01	2	50
Anopheles	*gambiae s.l.*	BIO05	2	50
Anopheles	*gambiae s.l.*	BIO06	2	50
Anopheles	*gambiae s.l.*	BIO07	2	50
Anopheles	*gambiae s.l.*	BIO08	2	50
Anopheles	*gambiae s.l.*	BIO09	2	50
Anopheles	*gambiae s.l.*	BIO14	2	50
Anopheles	*gambiae s.l.*	BIO17	2	50
Anopheles	*gambiae s.l.*	BIO18	2	50
Anopheles	*gambiae s.l.*	Elevation	2	50
Anopheles	*gambiae s.l.*	BIO02	2	0
Anopheles	*gambiae s.l.*	BIO03	2	0
Anopheles	*gambiae s.l.*	BIO04	2	0
Anopheles	*gambiae s.l.*	BIO11	2	0
Anopheles	*gambiae s.l.*	BIO12	2	0
Anopheles	*gambiae s.l.*	BIO13	2	0
Anopheles	*gambiae s.l.*	BIO15	2	0
Anopheles	*gambiae s.l.*	BIO16	2	0
Anopheles	*gambiae s.l.*	BIO19	2	0
Anopheles	*gambiae s.l.*	Agricultural land	1	100
Anopheles	*gambiae s.l.*	General landcover/use	1	100
Anopheles	*gambiae s.l.*	Slope	1	100
Anopheles	*gambiae s.l.*	Soil type	1	100
Anopheles	*gambiae s.l.*	Urban land	1	100
Anopheles	*gambiae s.l.*	Wetlands	1	100
Anopheles	*gambiae s.l.*	Aspect	1	0
Anopheles	*gambiae s.l.*	Industrial land	1	0
Anopheles	*gambiae s.s.*	BIO02	1	100
Anopheles	*gambiae s.s.*	BIO09	1	100
Anopheles	*gambiae s.s.*	BIO17	1	100
Anopheles	*gambiae s.s.*	BIO18	1	100
Anopheles	*gambiae s.s.*	BIO19	1	100
Anopheles	*gambiae s.s.*	Elevation	1	100
Anopheles	*gambiae s.s.*	General landcover/use	1	100
Anopheles	*gambiae s.s.*	BIO01	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*gambiae s.s.*	BIO03	1	0
Anopheles	*gambiae s.s.*	BIO04	1	0
Anopheles	*gambiae s.s.*	BIO05	1	0
Anopheles	*gambiae s.s.*	BIO06	1	0
Anopheles	*gambiae s.s.*	BIO07	1	0
Anopheles	*gambiae s.s.*	BIO08	1	0
Anopheles	*gambiae s.s.*	BIO10	1	0
Anopheles	*gambiae s.s.*	BIO11	1	0
Anopheles	*gambiae s.s.*	BIO12	1	0
Anopheles	*gambiae s.s.*	BIO13	1	0
Anopheles	*gambiae s.s.*	BIO14	1	0
Anopheles	*gambiae s.s.*	BIO15	1	0
Anopheles	*gambiae s.s.*	BIO16	1	0
Anopheles	*gambie*	General precipitation	2	50
Anopheles	*gambie*	BIO16	1	100
Anopheles	*gambie*	Evapotranspiration	1	100
Anopheles	*gambie*	BIO01	1	0
Anopheles	*gambie*	BIO08	1	0
Anopheles	*gambie*	BIO12	1	0
Anopheles	*gambie*	General temperature	1	0
Anopheles	*gambie*	Max annual temperature	1	0
Anopheles	*gambie*	Min annual temperature	1	0
Anopheles	*janconnae*	BIO19	1	100
Anopheles	*janconnae*	Soil type	1	100
Anopheles	*janconnae*	Aspect	1	0
Anopheles	*janconnae*	BIO01	1	0
Anopheles	*janconnae*	BIO02	1	0
Anopheles	*janconnae*	BIO03	1	0
Anopheles	*janconnae*	BIO04	1	0
Anopheles	*janconnae*	BIO05	1	0
Anopheles	*janconnae*	BIO06	1	0
Anopheles	*janconnae*	BIO07	1	0
Anopheles	*janconnae*	BIO08	1	0
Anopheles	*janconnae*	BIO09	1	0
Anopheles	*janconnae*	BIO10	1	0
Anopheles	*janconnae*	BIO11	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*janconnae*	BIO12	1	0
Anopheles	*janconnae*	BIO13	1	0
Anopheles	*janconnae*	BIO14	1	0
Anopheles	*janconnae*	BIO15	1	0
Anopheles	*janconnae*	BIO16	1	0
Anopheles	*janconnae*	BIO17	1	0
Anopheles	*janconnae*	BIO18	1	0
Anopheles	*janconnae*	Elevation	1	0
Anopheles	*janconnae*	Flow accumulation	1	0
Anopheles	*janconnae*	Flow direction	1	0
Anopheles	*janconnae*	Slope	1	0
Anopheles	*janconnae*	TWI	1	0
Anopheles	*lacbranchiae*	Cloud cover	2	50
Anopheles	*lacbranchiae*	Agricultural land	1	100
Anopheles	*lacbranchiae*	BIO01	1	100
Anopheles	*lacbranchiae*	BIO02	1	100
Anopheles	*lacbranchiae*	Forested land	1	100
Anopheles	*lacbranchiae*	Grassland	1	100
Anopheles	*lacbranchiae*	Max annual temperature	1	100
Anopheles	*lacbranchiae*	Min annual temperature	1	100
Anopheles	*lacbranchiae*	Shrubland	1	100
Anopheles	*lacbranchiae*	BIO12	1	0
Anopheles	*lacbranchiae*	Degree days	1	0
Anopheles	*lacbranchiae*	General temperature	1	0
Anopheles	*maculipennis*	Animal pop. density	2	50
Anopheles	*maculipennis*	BIO01	2	50
Anopheles	*maculipennis*	BIO03	2	50
Anopheles	*maculipennis*	BIO04	2	50
Anopheles	*maculipennis*	BIO06	2	50
Anopheles	*maculipennis*	BIO17	2	50
Anopheles	*maculipennis*	Elevation	2	50
Anopheles	*maculipennis*	BIO02	2	0
Anopheles	*maculipennis*	BIO05	2	0
Anopheles	*maculipennis*	BIO07	2	0
Anopheles	*maculipennis*	BIO08	2	0
Anopheles	*maculipennis*	BIO09	2	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*maculipennis*	BIO10	2	0
Anopheles	*maculipennis*	BIO11	2	0
Anopheles	*maculipennis*	BIO12	2	0
Anopheles	*maculipennis*	BIO13	2	0
Anopheles	*maculipennis*	BIO14	2	0
Anopheles	*maculipennis*	BIO15	2	0
Anopheles	*maculipennis*	BIO16	2	0
Anopheles	*maculipennis*	BIO18	2	0
Anopheles	*maculipennis*	BIO19	2	0
Anopheles	*maculipennis*	NDVI	1	100
Anopheles	*maculipennis*	Agricultural land	1	0
Anopheles	*maculipennis*	Barren land	1	0
Anopheles	*maculipennis*	Forested land	1	0
Anopheles	*maculipennis*	General landcover/use	1	0
Anopheles	*maculipennis*	Human pop. density	1	0
Anopheles	*maculipennis*	Industrial land	1	0
Anopheles	*maculipennis*	Shrubland	1	0
Anopheles	*maculipennis*	Urban land	1	0
Anopheles	*maculipennis*	Waterbodies	1	0
Anopheles	*maculipennis*	Wetlands	1	0
Anopheles	*marajoara*	BIO05	1	100
Anopheles	*marajoara*	Vegetation cover	1	100
Anopheles	*marajoara*	BIO12	1	0
Anopheles	*marajoara*	Slope	1	0
Anopheles	*marajora*	General precipitation	2	50
Anopheles	*marajora*	Land surface temperature	2	50
Anopheles	*marajora*	NDVI	2	50
Anopheles	*marajora*	BIO19	1	0
Anopheles	*marajora*	Elevation	1	0
Anopheles	*marajora*	EVI	1	0
Anopheles	*marajora*	General landcover/use	1	0
Anopheles	*marajora*	MIR	1	0
Anopheles	*marajorara*	BIO16	1	100
Anopheles	*marajorara*	Elevation	1	100
Anopheles	*marajorara*	Aspect	1	0
Anopheles	*marajorara*	BIO01	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*marajorara*	BIO02	1	0
Anopheles	*marajorara*	BIO03	1	0
Anopheles	*marajorara*	BIO04	1	0
Anopheles	*marajorara*	BIO05	1	0
Anopheles	*marajorara*	BIO06	1	0
Anopheles	*marajorara*	BIO07	1	0
Anopheles	*marajorara*	BIO08	1	0
Anopheles	*marajorara*	BIO09	1	0
Anopheles	*marajorara*	BIO10	1	0
Anopheles	*marajorara*	BIO11	1	0
Anopheles	*marajorara*	BIO12	1	0
Anopheles	*marajorara*	BIO13	1	0
Anopheles	*marajorara*	BIO14	1	0
Anopheles	*marajorara*	BIO15	1	0
Anopheles	*marajorara*	BIO17	1	0
Anopheles	*marajorara*	BIO18	1	0
Anopheles	*marajorara*	BIO19	1	0
Anopheles	*marajorara*	Flow accumulation	1	0
Anopheles	*marajorara*	Flow direction	1	0
Anopheles	*marajorara*	Slope	1	0
Anopheles	*marajorara*	Soil type	1	0
Anopheles	*marajorara*	TWI	1	0
Anopheles	*melanoon*	Wetlands	2	50
Anopheles	*melanoon*	Agricultural land	1	100
Anopheles	*melanoon*	Waterbodies	1	100
Anopheles	*melas*	Elevation	2	100
Anopheles	*melas*	General temperature	2	50
Anopheles	*melas*	TCW	2	50
Anopheles	*melas*	BIO13	1	100
Anopheles	*melas*	BIO16	1	100
Anopheles	*melas*	BIO18	1	100
Anopheles	*melas*	BIO19	1	100
Anopheles	*melas*	General landcover/use	1	100
Anopheles	*melas*	Human pop. density	1	100
Anopheles	*melas*	Wetlands	1	100
Anopheles	*melas*	Agricultural land	1	0
Anopheles	*melas*	BIO01	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*melas*	BIO02	1	0
Anopheles	*melas*	BIO03	1	0
Anopheles	*melas*	BIO04	1	0
Anopheles	*melas*	BIO05	1	0
Anopheles	*melas*	BIO06	1	0
Anopheles	*melas*	BIO07	1	0
Anopheles	*melas*	BIO08	1	0
Anopheles	*melas*	BIO09	1	0
Anopheles	*melas*	BIO10	1	0
Anopheles	*melas*	BIO11	1	0
Anopheles	*melas*	BIO12	1	0
Anopheles	*melas*	BIO14	1	0
Anopheles	*melas*	BIO15	1	0
Anopheles	*melas*	BIO17	1	0
Anopheles	*melas*	EVI	1	0
Anopheles	*melas*	Forested land	1	0
Anopheles	*melas*	Grassland	1	0
Anopheles	*melas*	Savannas	1	0
Anopheles	*melas*	Shrubland	1	0
Anopheles	*melas*	Urban land	1	0
Anopheles	*merus*	Elevation	2	100
Anopheles	*merus*	EVI	2	50
Anopheles	*merus*	General temperature	2	50
Anopheles	*merus*	BIO09	1	100
Anopheles	*merus*	BIO14	1	100
Anopheles	*merus*	BIO18	1	100
Anopheles	*merus*	BIO19	1	100
Anopheles	*merus*	Agricultural land	1	0
Anopheles	*merus*	BIO01	1	0
Anopheles	*merus*	BIO02	1	0
Anopheles	*merus*	BIO03	1	0
Anopheles	*merus*	BIO04	1	0
Anopheles	*merus*	BIO05	1	0
Anopheles	*merus*	BIO06	1	0
Anopheles	*merus*	BIO07	1	0
Anopheles	*merus*	BIO08	1	0
Anopheles	*merus*	BIO10	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*merus*	BIO11	1	0
Anopheles	*merus*	BIO12	1	0
Anopheles	*merus*	BIO13	1	0
Anopheles	*merus*	BIO15	1	0
Anopheles	*merus*	BIO16	1	0
Anopheles	*merus*	BIO17	1	0
Anopheles	*merus*	Forested land	1	0
Anopheles	*merus*	General landcover/use	1	0
Anopheles	*merus*	Grassland	1	0
Anopheles	*merus*	Human pop. density	1	0
Anopheles	*merus*	Savannas	1	0
Anopheles	*merus*	Shrubland	1	0
Anopheles	*merus*	TCW	1	0
Anopheles	*merus*	Urban land	1	0
Anopheles	*merus*	Wetlands	1	0
Anopheles	*messeae*	Cloud cover	2	50
Anopheles	*messeae*	Degree days	2	50
Anopheles	*messeae*	General temperature	2	50
Anopheles	*messeae*	Agricultural land	1	100
Anopheles	*messeae*	BIO01	1	100
Anopheles	*messeae*	BIO02	1	100
Anopheles	*messeae*	BIO12	1	100
Anopheles	*messeae*	Forested land	1	100
Anopheles	*messeae*	Grassland	1	100
Anopheles	*messeae*	Min annual temperature	1	100
Anopheles	*messeae*	Shrubland	1	100
Anopheles	*messeae*	Max annual temperature	1	0
Anopheles	*moucheti*	BIO12	2	50
Anopheles	*moucheti*	Elevation	2	50
Anopheles	*moucheti*	Forested land	2	50
Anopheles	*moucheti*	BIO01	2	0
Anopheles	*moucheti*	Agricultural land	1	100
Anopheles	*moucheti*	BIO02	1	100
Anopheles	*moucheti*	BIO03	1	100
Anopheles	*moucheti*	BIO07	1	100
Anopheles	*moucheti*	BIO17	1	100

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*moucheti*	BIO19	1	100
Anopheles	*moucheti*	Evapotranspiration	1	100
Anopheles	*moucheti*	General landcover/use	1	100
Anopheles	*moucheti*	Humidity	1	100
Anopheles	*moucheti*	Photoperiod	1	100
Anopheles	*moucheti*	Slope	1	100
Anopheles	*moucheti*	Transportation	1	100
Anopheles	*moucheti*	Wind	1	100
Anopheles	*moucheti*	Aspect	1	0
Anopheles	*moucheti*	BIO04	1	0
Anopheles	*moucheti*	BIO05	1	0
Anopheles	*moucheti*	BIO06	1	0
Anopheles	*moucheti*	BIO08	1	0
Anopheles	*moucheti*	BIO09	1	0
Anopheles	*moucheti*	BIO10	1	0
Anopheles	*moucheti*	BIO11	1	0
Anopheles	*moucheti*	BIO13	1	0
Anopheles	*moucheti*	BIO14	1	0
Anopheles	*moucheti*	BIO15	1	0
Anopheles	*moucheti*	BIO16	1	0
Anopheles	*moucheti*	BIO18	1	0
Anopheles	*moucheti*	Savannas	1	0
Anopheles	*moucheti*	TWI	1	0
Anopheles	*nemophilous*	Degree days	2	50
Anopheles	*nemophilous*	General temperature	2	50
Anopheles	*nemophilous*	Soil type	2	50
Anopheles	*nemophilous*	BIO01	1	100
Anopheles	*nemophilous*	BIO06	1	100
Anopheles	*nemophilous*	BIO09	1	100
Anopheles	*nemophilous*	Humidity	1	100
Anopheles	*nemophilous*	BIO08	1	0
Anopheles	*nemophilous*	BIO15	1	0
Anopheles	*nemophilous*	Elevation	1	0
Anopheles	*nemophilous*	Monthyl precipitation	1	0
Anopheles	*nemophilous*	Wind	1	0
Anopheles	*nili*	BIO01	2	50
Anopheles	*nili*	BIO12	2	50

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*nili*	Elevation	2	0
Anopheles	*nili*	Agricultural land	1	100
Anopheles	*nili*	BIO02	1	100
Anopheles	*nili*	BIO03	1	100
Anopheles	*nili*	BIO07	1	100
Anopheles	*nili*	BIO17	1	100
Anopheles	*nili*	BIO19	1	100
Anopheles	*nili*	Evapotranspiration	1	100
Anopheles	*nili*	Forested land	1	100
Anopheles	*nili*	Humidity	1	100
Anopheles	*nili*	Photoperiod	1	100
Anopheles	*nili*	Slope	1	100
Anopheles	*nili*	Transportation	1	100
Anopheles	*nili*	Wind	1	100
Anopheles	*nili*	Aspect	1	0
Anopheles	*nili*	BIO04	1	0
Anopheles	*nili*	BIO05	1	0
Anopheles	*nili*	BIO06	1	0
Anopheles	*nili*	BIO08	1	0
Anopheles	*nili*	BIO09	1	0
Anopheles	*nili*	BIO10	1	0
Anopheles	*nili*	BIO11	1	0
Anopheles	*nili*	BIO13	1	0
Anopheles	*nili*	BIO14	1	0
Anopheles	*nili*	BIO15	1	0
Anopheles	*nili*	BIO16	1	0
Anopheles	*nili*	BIO18	1	0
Anopheles	*nili*	General landcover/use	1	0
Anopheles	*nili*	Savannas	1	0
Anopheles	*nili*	TWI	1	0
Anopheles	*nuneztovari*	Elevation	2	50
Anopheles	*nuneztovari*	General precipitation	2	50
Anopheles	*nuneztovari*	Land surface temperature	2	50
Anopheles	*nuneztovari*	BIO12	1	100
Anopheles	*nuneztovari*	Human pop. density	1	100
Anopheles	*nuneztovari*	BIO01	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*nuneztovari*	BIO02	1	0
Anopheles	*nuneztovari*	BIO03	1	0
Anopheles	*nuneztovari*	BIO04	1	0
Anopheles	*nuneztovari*	BIO05	1	0
Anopheles	*nuneztovari*	BIO06	1	0
Anopheles	*nuneztovari*	BIO07	1	0
Anopheles	*nuneztovari*	BIO08	1	0
Anopheles	*nuneztovari*	BIO09	1	0
Anopheles	*nuneztovari*	BIO10	1	0
Anopheles	*nuneztovari*	BIO11	1	0
Anopheles	*nuneztovari*	BIO13	1	0
Anopheles	*nuneztovari*	BIO14	1	0
Anopheles	*nuneztovari*	BIO15	1	0
Anopheles	*nuneztovari*	BIO16	1	0
Anopheles	*nuneztovari*	BIO17	1	0
Anopheles	*nuneztovari*	BIO18	1	0
Anopheles	*nuneztovari*	BIO19	1	0
Anopheles	*nuneztovari*	EVI	1	0
Anopheles	*nuneztovari*	Forested land	1	0
Anopheles	*nuneztovari*	General landcover/use	1	0
Anopheles	*nuneztovari*	General landcover/use	1	0
Anopheles	*nuneztovari*	MIR	1	0
Anopheles	*nuneztovari*	NDVI	1	0
Anopheles	*nuneztovari*	TWI	1	0
Anopheles	*oryzalimnetes*	BIO16	1	100
Anopheles	*oryzalimnetes*	Soil type	1	100
Anopheles	*oryzalimnetes*	Aspect	1	0
Anopheles	*oryzalimnetes*	BIO01	1	0
Anopheles	*oryzalimnetes*	BIO02	1	0
Anopheles	*oryzalimnetes*	BIO03	1	0
Anopheles	*oryzalimnetes*	BIO04	1	0
Anopheles	*oryzalimnetes*	BIO05	1	0
Anopheles	*oryzalimnetes*	BIO06	1	0
Anopheles	*oryzalimnetes*	BIO07	1	0
Anopheles	*oryzalimnetes*	BIO08	1	0
Anopheles	*oryzalimnetes*	BIO09	1	0
Anopheles	*oryzalimnetes*	BIO10	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*oryzalimnetes*	BIO11	1	0
Anopheles	*oryzalimnetes*	BIO12	1	0
Anopheles	*oryzalimnetes*	BIO13	1	0
Anopheles	*oryzalimnetes*	BIO14	1	0
Anopheles	*oryzalimnetes*	BIO15	1	0
Anopheles	*oryzalimnetes*	BIO17	1	0
Anopheles	*oryzalimnetes*	BIO18	1	0
Anopheles	*oryzalimnetes*	BIO19	1	0
Anopheles	*oryzalimnetes*	Elevation	1	0
Anopheles	*oryzalimnetes*	Flow accumulation	1	0
Anopheles	*oryzalimnetes*	Flow direction	1	0
Anopheles	*oryzalimnetes*	Slope	1	0
Anopheles	*oryzalimnetes*	TWI	1	0
Anopheles	*paludis*	BIO02	1	100
Anopheles	*paludis*	BIO03	1	100
Anopheles	*paludis*	BIO07	1	100
Anopheles	*paludis*	BIO17	1	100
Anopheles	*paludis*	BIO19	1	100
Anopheles	*paludis*	BIO01	1	0
Anopheles	*paludis*	BIO04	1	0
Anopheles	*paludis*	BIO05	1	0
Anopheles	*paludis*	BIO06	1	0
Anopheles	*paludis*	BIO08	1	0
Anopheles	*paludis*	BIO09	1	0
Anopheles	*paludis*	BIO10	1	0
Anopheles	*paludis*	BIO11	1	0
Anopheles	*paludis*	BIO12	1	0
Anopheles	*paludis*	BIO13	1	0
Anopheles	*paludis*	BIO14	1	0
Anopheles	*paludis*	BIO15	1	0
Anopheles	*paludis*	BIO16	1	0
Anopheles	*paludis*	BIO18	1	0
Anopheles	*paludis*	Elevation	1	0
Anopheles	*paludis*	General landcover/use	1	0
Anopheles	*plumbeus*	Elevation	2	100
Anopheles	*plumbeus*	Human pop. density	2	0
Anopheles	*plumbeus*	BIO06	1	100

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*plumbeus*	BIO19	1	100
Anopheles	*plumbeus*	Monthyl precipitation	1	100
Anopheles	*plumbeus*	Shrubland	1	100
Anopheles	*plumbeus*	Urban land	1	100
Anopheles	*plumbeus*	Agricultural land	1	0
Anopheles	*plumbeus*	Animal pop. density	1	0
Anopheles	*plumbeus*	Barren land	1	0
Anopheles	*plumbeus*	BIO01	1	0
Anopheles	*plumbeus*	BIO02	1	0
Anopheles	*plumbeus*	BIO03	1	0
Anopheles	*plumbeus*	BIO04	1	0
Anopheles	*plumbeus*	BIO05	1	0
Anopheles	*plumbeus*	BIO07	1	0
Anopheles	*plumbeus*	BIO08	1	0
Anopheles	*plumbeus*	BIO09	1	0
Anopheles	*plumbeus*	BIO10	1	0
Anopheles	*plumbeus*	BIO11	1	0
Anopheles	*plumbeus*	BIO12	1	0
Anopheles	*plumbeus*	BIO13	1	0
Anopheles	*plumbeus*	BIO14	1	0
Anopheles	*plumbeus*	BIO15	1	0
Anopheles	*plumbeus*	BIO16	1	0
Anopheles	*plumbeus*	BIO17	1	0
Anopheles	*plumbeus*	BIO18	1	0
Anopheles	*plumbeus*	Forested land	1	0
Anopheles	*plumbeus*	General landcover/use	1	0
Anopheles	*plumbeus*	General landcover/use	1	0
Anopheles	*plumbeus*	Industrial land	1	0
Anopheles	*plumbeus*	Land surface temperature	1	0
Anopheles	*plumbeus*	MIR	1	0
Anopheles	*plumbeus*	Waterbodies	1	0
Anopheles	*plumbeus*	Wetlands	1	0
Anopheles	*psuedopunctipennis*	General precipitation	2	50
Anopheles	*psuedopunctipennis*	Land surface temperature	2	50
Anopheles	*psuedopunctipennis*	MIR	2	50

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*psuedopunctipennis*	Elevation	1	100
Anopheles	*psuedopunctipennis*	BIO19	1	0
Anopheles	*psuedopunctipennis*	EVI	1	0
Anopheles	*psuedopunctipennis*	General landcover/use	1	0
Anopheles	*psuedopunctipennis*	NDVI	1	0
Anopheles	*quadriannulatus*	BIO01	2	50
Anopheles	*quadriannulatus*	BIO02	2	50
Anopheles	*quadriannulatus*	Degree days	2	50
Anopheles	*quadriannulatus*	BIO12	2	0
Anopheles	*quadriannulatus*	Elevation	2	0
Anopheles	*quadriannulatus*	General landcover/use	2	0
Anopheles	*quadriannulatus*	BIO09	1	100
Anopheles	*quadriannulatus*	BIO11	1	100
Anopheles	*quadriannulatus*	BIO16	1	100
Anopheles	*quadriannulatus*	BIO17	1	100
Anopheles	*quadriannulatus*	BIO18	1	100
Anopheles	*quadriannulatus*	Aspect	1	0
Anopheles	*quadriannulatus*	BIO03	1	0
Anopheles	*quadriannulatus*	BIO04	1	0
Anopheles	*quadriannulatus*	BIO05	1	0
Anopheles	*quadriannulatus*	BIO06	1	0
Anopheles	*quadriannulatus*	BIO07	1	0
Anopheles	*quadriannulatus*	BIO08	1	0
Anopheles	*quadriannulatus*	BIO10	1	0
Anopheles	*quadriannulatus*	BIO13	1	0
Anopheles	*quadriannulatus*	BIO14	1	0
Anopheles	*quadriannulatus*	BIO15	1	0
Anopheles	*quadriannulatus*	BIO19	1	0
Anopheles	*quadriannulatus*	Flow accumulation	1	0
Anopheles	*quadriannulatus*	Max annual temperature	1	0
Anopheles	*quadriannulatus*	Min annual temperature	1	0
Anopheles	*quadriannulatus*	Slope	1	0
Anopheles	*quadriannulatus*	TWI	1	0
Anopheles	*quadriannulatus*	Vapor pressure	1	0
Anopheles	*quadriannulatus*	Vegetation cover	1	0
Anopheles	*quadrimaculatus*	General precipitation	2	50

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*quadrimaculatus*	Land surface temperature	2	50
Anopheles	*quadrimaculatus*	Elevation	1	100
Anopheles	*quadrimaculatus*	BIO19	1	0
Anopheles	*quadrimaculatus*	EVI	1	0
Anopheles	*quadrimaculatus*	MIR	1	0
Anopheles	*quadrimaculatus*	NDVI	1	0
Anopheles	*sacharovi*	Cloud cover	2	50
Anopheles	*sacharovi*	Degree days	2	50
Anopheles	*sacharovi*	General temperature	2	50
Anopheles	*sacharovi*	Agricultural land	1	100
Anopheles	*sacharovi*	BIO02	1	100
Anopheles	*sacharovi*	BIO12	1	100
Anopheles	*sacharovi*	Forested land	1	100
Anopheles	*sacharovi*	Grassland	1	100
Anopheles	*sacharovi*	Min annual temperature	1	100
Anopheles	*sacharovi*	Shrubland	1	100
Anopheles	*sacharovi*	BIO01	1	0
Anopheles	*sacharovi*	Max annual temperature	1	0
Anopheles	*scanloni*	Degree days	2	50
Anopheles	*scanloni*	General temperature	2	50
Anopheles	*scanloni*	Soil type	2	50
Anopheles	*scanloni*	BIO01	1	100
Anopheles	*scanloni*	BIO06	1	100
Anopheles	*scanloni*	BIO09	1	100
Anopheles	*scanloni*	BIO08	1	0
Anopheles	*scanloni*	BIO15	1	0
Anopheles	*scanloni*	Elevation	1	0
Anopheles	*scanloni*	Humidity	1	0
Anopheles	*scanloni*	Monthyl precipitation	1	0
Anopheles	*scanloni*	Wind	1	0
Anopheles	*sergentii*	BIO02	1	100
Anopheles	*sergentii*	BIO03	1	100
Anopheles	*sergentii*	BIO06	1	100
Anopheles	*sergentii*	BIO07	1	100
Anopheles	*sergentii*	BIO09	1	100

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*sergentii*	BIO13	1	100
Anopheles	*sergentii*	BIO14	1	100
Anopheles	*sergentii*	BIO16	1	100
Anopheles	*sergentii*	BIO17	1	100
Anopheles	*sergentii*	BIO19	1	100
Anopheles	*sergentii*	Elevation	1	100
Anopheles	*sergentii*	Soil type	1	100
Anopheles	*sergentii*	Urban land	1	100
Anopheles	*sergentii*	Wetlands	1	100
Anopheles	*sergentii*	Agricultural land	1	0
Anopheles	*sergentii*	Aspect	1	0
Anopheles	*sergentii*	BIO01	1	0
Anopheles	*sergentii*	BIO04	1	0
Anopheles	*sergentii*	BIO05	1	0
Anopheles	*sergentii*	BIO08	1	0
Anopheles	*sergentii*	BIO10	1	0
Anopheles	*sergentii*	BIO11	1	0
Anopheles	*sergentii*	BIO12	1	0
Anopheles	*sergentii*	BIO15	1	0
Anopheles	*sergentii*	BIO18	1	0
Anopheles	*sergentii*	Industrial land	1	0
Anopheles	*sergentii*	Slope	1	0
Anopheles	*stephensi*	BIO01	1	100
Anopheles	*stephensi*	Human pop. density	1	100
Anopheles	*stephensi*	Agricultural land	1	0
Anopheles	*stephensi*	BIO15	1	0
Anopheles	*stephensi*	EVI	1	0
Anopheles	*stephensi*	General landcover/use	1	0
Anopheles	*stephensi*	TCW	1	0
Anopheles	*suprtictus*	Degree days	2	50
Anopheles	*suprtictus*	Agricultural land	1	100
Anopheles	*suprtictus*	BIO01	1	100
Anopheles	*suprtictus*	BIO02	1	100
Anopheles	*suprtictus*	BIO12	1	100
Anopheles	*suprtictus*	Forested land	1	100
Anopheles	*suprtictus*	Grassland	1	100
Anopheles	*suprtictus*	Max annual temp.	1	100

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Anopheles	*suprtictus*	Min annual temperature	1	100
Anopheles	*suprtictus*	Shrubland	1	100
Anopheles	*suprtictus*	Cloud cover	1	0
Anopheles	*suprtictus*	General temperature	1	0
Coquillettidia	*richiardii*	Agricultural land	2	50
Coquillettidia	*richiardii*	Elevation	1	100
Coquillettidia	*richiardii*	Animal pop. density	1	0
Coquillettidia	*richiardii*	Barren land	1	0
Coquillettidia	*richiardii*	BIO01	1	0
Coquillettidia	*richiardii*	BIO02	1	0
Coquillettidia	*richiardii*	BIO03	1	0
Coquillettidia	*richiardii*	BIO04	1	0
Coquillettidia	*richiardii*	BIO05	1	0
Coquillettidia	*richiardii*	BIO06	1	0
Coquillettidia	*richiardii*	BIO07	1	0
Coquillettidia	*richiardii*	BIO08	1	0
Coquillettidia	*richiardii*	BIO09	1	0
Coquillettidia	*richiardii*	BIO10	1	0
Coquillettidia	*richiardii*	BIO11	1	0
Coquillettidia	*richiardii*	BIO12	1	0
Coquillettidia	*richiardii*	BIO13	1	0
Coquillettidia	*richiardii*	BIO14	1	0
Coquillettidia	*richiardii*	BIO15	1	0
Coquillettidia	*richiardii*	BIO16	1	0
Coquillettidia	*richiardii*	BIO17	1	0
Coquillettidia	*richiardii*	BIO18	1	0
Coquillettidia	*richiardii*	BIO19	1	0
Coquillettidia	*richiardii*	Forested land	1	0
Coquillettidia	*richiardii*	General landcover/use	1	0
Coquillettidia	*richiardii*	Human pop. density	1	0
Coquillettidia	*richiardii*	Industrial land	1	0
Coquillettidia	*richiardii*	Shrubland	1	0
Coquillettidia	*richiardii*	Urban land	1	0
Coquillettidia	*richiardii*	Waterbodies	1	0
Coquillettidia	*richiardii*	Wetlands	1	0
Culex	*aegypti*	BIO03	1	100

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Culex	*aegypti*	BIO07	1	100
Culex	*aegypti*	BIO10	1	100
Culex	*aegypti*	BIO11	1	100
Culex	*aegypti*	BIO12	1	100
Culex	*aegypti*	BIO14	1	100
Culex	*aegypti*	BIO19	1	100
Culex	*aegypti*	Slope	1	100
Culex	*aegypti*	BIO01	1	0
Culex	*aegypti*	BIO02	1	0
Culex	*aegypti*	BIO04	1	0
Culex	*aegypti*	BIO05	1	0
Culex	*aegypti*	BIO06	1	0
Culex	*aegypti*	BIO08	1	0
Culex	*aegypti*	BIO09	1	0
Culex	*aegypti*	BIO13	1	0
Culex	*aegypti*	BIO15	1	0
Culex	*aegypti*	BIO16	1	0
Culex	*aegypti*	BIO17	1	0
Culex	*aegypti*	BIO18	1	0
Culex	*melanura*	NDVI	2	50
Culex	*melanura*	Wetlands	1	100
Culex	*melanura*	Agricultural land	1	0
Culex	*melanura*	Distance to water	1	0
Culex	*melanura*	Forested land	1	0
Culex	*melanura*	Human pop. density	1	0
Culex	*melanura*	MIR	1	0
Culex	*melanura*	Urban land	1	0
Culex	*melanura*	Waterbodies	1	0
Culex	*melanura*	Wetlands	1	0
Culex	*modestus*	Agricultural land	3	66.7
Culex	*modestus*	Wetlands	3	33.3
Culex	*modestus*	Waterbodies	2	0
Culex	*modestus*	BIO08	1	100
Culex	*modestus*	BIO09	1	100
Culex	*modestus*	BIO19	1	100
Culex	*modestus*	Elevation	1	100
Culex	*modestus*	Animal pop. density	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Culex	*modestus*	Barren land	1	0
Culex	*modestus*	BIO01	1	0
Culex	*modestus*	BIO02	1	0
Culex	*modestus*	BIO03	1	0
Culex	*modestus*	BIO04	1	0
Culex	*modestus*	BIO05	1	0
Culex	*modestus*	BIO06	1	0
Culex	*modestus*	BIO07	1	0
Culex	*modestus*	BIO10	1	0
Culex	*modestus*	BIO11	1	0
Culex	*modestus*	BIO12	1	0
Culex	*modestus*	BIO13	1	0
Culex	*modestus*	BIO14	1	0
Culex	*modestus*	BIO15	1	0
Culex	*modestus*	BIO16	1	0
Culex	*modestus*	BIO17	1	0
Culex	*modestus*	BIO18	1	0
Culex	*modestus*	Forested land	1	0
Culex	*modestus*	General landcover/use	1	0
Culex	*modestus*	Human pop. density	1	0
Culex	*modestus*	Industrial land	1	0
Culex	*modestus*	Shrubland	1	0
Culex	*modestus*	Urban land	1	0
Culex	*nigripalpus*	Elevation	2	50
Culex	*nigripalpus*	BIO03	1	100
Culex	*nigripalpus*	BIO04	1	100
Culex	*nigripalpus*	BIO11	1	100
Culex	*nigripalpus*	BIO12	1	100
Culex	*nigripalpus*	BIO13	1	100
Culex	*nigripalpus*	BIO14	1	100
Culex	*nigripalpus*	Urban land	1	100
Culex	*nigripalpus*	Aspect	1	0
Culex	*nigripalpus*	BIO01	1	0
Culex	*nigripalpus*	BIO02	1	0
Culex	*nigripalpus*	BIO05	1	0
Culex	*nigripalpus*	BIO06	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Culex	*nigripalpus*	BIO07	1	0
Culex	*nigripalpus*	BIO08	1	0
Culex	*nigripalpus*	BIO09	1	0
Culex	*nigripalpus*	BIO10	1	0
Culex	*nigripalpus*	BIO15	1	0
Culex	*nigripalpus*	BIO16	1	0
Culex	*nigripalpus*	BIO17	1	0
Culex	*nigripalpus*	BIO18	1	0
Culex	*nigripalpus*	BIO19	1	0
Culex	*nigripalpus*	General topography	1	0
Culex	*nigripalpus*	LAI	1	0
Culex	*nigripalpus*	Slope	1	0
Culex	*nigripalpus*	Waterbodies	1	0
Culex	*pipiens*	Agricultural land	7	28.6
Culex	*pipiens*	Urban land	6	66.7
Culex	*pipiens*	BIO01	5	40
Culex	*pipiens*	Human pop. density	5	20
Culex	*pipiens*	BIO02	4	25
Culex	*pipiens*	BIO12	4	25
Culex	*pipiens*	BIO06	4	0
Culex	*pipiens*	BIO16	4	0
Culex	*pipiens*	Waterbodies	4	0
Culex	*pipiens*	Wetlands	4	0
Culex	*pipiens*	BIO04	3	33.3
Culex	*pipiens*	BIO08	3	33.3
Culex	*pipiens*	BIO09	3	33.3
Culex	*pipiens*	BIO17	3	33.3
Culex	*pipiens*	BIO18	3	33.3
Culex	*pipiens*	BIO03	3	0
Culex	*pipiens*	BIO05	3	0
Culex	*pipiens*	BIO07	3	0
Culex	*pipiens*	BIO10	3	0
Culex	*pipiens*	BIO11	3	0
Culex	*pipiens*	BIO13	3	0
Culex	*pipiens*	BIO14	3	0
Culex	*pipiens*	BIO15	3	0
Culex	*pipiens*	BIO19	3	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Culex	*pipiens*	Elevation	2	100
Culex	*pipiens*	EVI	2	50
Culex	*pipiens*	Forested land	2	50
Culex	*pipiens*	General landcover/use	2	50
Culex	*pipiens*	Distance to water	2	0
Culex	*pipiens*	TWI	2	0
Culex	*pipiens*	Aspect	1	100
Culex	*pipiens*	Degree days	1	100
Culex	*pipiens*	Photoperiod	1	100
Culex	*pipiens*	Slope	1	100
Culex	*pipiens*	Animal pop. density	1	0
Culex	*pipiens*	Barren land	1	0
Culex	*pipiens*	General vegetation	1	0
Culex	*pipiens*	Grassland	1	0
Culex	*pipiens*	Industrial land	1	0
Culex	*pipiens*	MIR	1	0
Culex	*pipiens*	NDVI	1	0
Culex	*pipiens*	Shrubland	1	0
Culex	*pipiens*	Soil type	1	0
Culex	*pipiens*	Vegetation cover	1	0
Culex	*quinquefasciatus*	BIO02	2	50
Culex	*quinquefasciatus*	BIO11	2	50
Culex	*quinquefasciatus*	BIO14	2	0
Culex	*quinquefasciatus*	BIO15	2	0
Culex	*quinquefasciatus*	BIO18	2	0
Culex	*quinquefasciatus*	Urban land	2	0
Culex	*quinquefasciatus*	LAI	1	100
Culex	*quinquefasciatus*	Agricultural land	1	0
Culex	*quinquefasciatus*	Aspect	1	0
Culex	*quinquefasciatus*	BIO01	1	0
Culex	*quinquefasciatus*	BIO03	1	0
Culex	*quinquefasciatus*	BIO04	1	0
Culex	*quinquefasciatus*	BIO05	1	0
Culex	*quinquefasciatus*	BIO06	1	0
Culex	*quinquefasciatus*	BIO07	1	0
Culex	*quinquefasciatus*	BIO08	1	0
Culex	*quinquefasciatus*	BIO09	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Culex	*quinquefasciatus*	BIO10	1	0
Culex	*quinquefasciatus*	BIO12	1	0
Culex	*quinquefasciatus*	BIO13	1	0
Culex	*quinquefasciatus*	BIO16	1	0
Culex	*quinquefasciatus*	BIO17	1	0
Culex	*quinquefasciatus*	BIO19	1	0
Culex	*quinquefasciatus*	Elevation	1	0
Culex	*quinquefasciatus*	Forested land	1	0
Culex	*quinquefasciatus*	General topography	1	0
Culex	*quinquefasciatus*	Shrubland	1	0
Culex	*quinquefasciatus*	Slope	1	0
Culex	*quinquefasciatus*	Waterbodies	1	0
Culex	*quiquefasciatus*	BIO03	1	100
Culex	*quiquefasciatus*	BIO11	1	100
Culex	*quiquefasciatus*	BIO13	1	100
Culex	*quiquefasciatus*	BIO18	1	100
Culex	*quiquefasciatus*	BIO01	1	0
Culex	*quiquefasciatus*	BIO02	1	0
Culex	*quiquefasciatus*	BIO04	1	0
Culex	*quiquefasciatus*	BIO05	1	0
Culex	*quiquefasciatus*	BIO06	1	0
Culex	*quiquefasciatus*	BIO07	1	0
Culex	*quiquefasciatus*	BIO08	1	0
Culex	*quiquefasciatus*	BIO09	1	0
Culex	*quiquefasciatus*	BIO10	1	0
Culex	*quiquefasciatus*	BIO12	1	0
Culex	*quiquefasciatus*	BIO14	1	0
Culex	*quiquefasciatus*	BIO15	1	0
Culex	*quiquefasciatus*	BIO16	1	0
Culex	*quiquefasciatus*	BIO17	1	0
Culex	*quiquefasciatus*	BIO19	1	0
Culex	*quiquefasciatus*	Elevation	1	0
Culex	*salinarius*	Waterbodies	2	50
Culex	*salinarius*	Distance to water	1	100
Culex	*salinarius*	Agricultural land	1	0
Culex	*salinarius*	Forested land	1	0
Culex	*salinarius*	Human pop. density	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Culex	*salinarius*	MIR	1	0
Culex	*salinarius*	NDVI	1	0
Culex	*salinarius*	Urban land	1	0
Culex	*salinarius*	Wetlands	1	0
Culex	*salinarius*	Wetlands	1	0
Culex	*tarsalis*	Degree days	2	100
Culex	*tarsalis*	Agricultural land	1	100
Culex	*tarsalis*	Aspect	1	100
Culex	*tarsalis*	BIO01	1	100
Culex	*tarsalis*	BIO12	1	100
Culex	*tarsalis*	General landcover/use	1	100
Culex	*tarsalis*	General temperature	1	100
Culex	*tarsalis*	General vegetation	1	100
Culex	*tarsalis*	Humidity	1	100
Culex	*tarsalis*	Slope	1	100
Culex	*tarsalis*	General precipitation	1	100
Culex	*tarsalis*	Soil type	1	100
Culex	*tarsalis*	TWI	1	100
Culex	*tarsalis*	Distance to water	1	0
Culex	*tarsalis*	Urban land	1	0
Culex	*theileri*	Agricultural land	2	50
Culex	*theileri*	BIO01	2	50
Culex	*theileri*	BIO04	2	50
Culex	*theileri*	BIO05	2	50
Culex	*theileri*	BIO07	2	50
Culex	*theileri*	BIO08	2	50
Culex	*theileri*	Elevation	2	50
Culex	*theileri*	BIO02	2	0
Culex	*theileri*	BIO03	2	0
Culex	*theileri*	BIO06	2	0
Culex	*theileri*	BIO09	2	0
Culex	*theileri*	BIO10	2	0
Culex	*theileri*	BIO11	2	0
Culex	*theileri*	BIO12	2	0
Culex	*theileri*	BIO13	2	0
Culex	*theileri*	BIO14	2	0
Culex	*theileri*	BIO15	2	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Culex	*theileri*	BIO16	2	0
Culex	*theileri*	BIO17	2	0
Culex	*theileri*	BIO18	2	0
Culex	*theileri*	BIO19	2	0
Culex	*theileri*	Forested land	1	100
Culex	*theileri*	Animal pop. density	1	0
Culex	*theileri*	Barren land	1	0
Culex	*theileri*	General landcover/use	1	0
Culex	*theileri*	Human pop. density	1	0
Culex	*theileri*	Industrial land	1	0
Culex	*theileri*	NDVI	1	0
Culex	*theileri*	Shrubland	1	0
Culex	*theileri*	Urban land	1	0
Culex	*theileri*	Waterbodies	1	0
Culex	*theileri*	Wetlands	1	0
Culex	*tritaeniorhynchus*	BIO08	2	100
Culex	*tritaeniorhynchus*	BIO12	2	50
Culex	*tritaeniorhynchus*	BIO13	2	50
Culex	*tritaeniorhynchus*	BIO18	2	50
Culex	*tritaeniorhynchus*	Elevation	2	50
Culex	*tritaeniorhynchus*	BIO01	2	0
Culex	*tritaeniorhynchus*	BIO02	2	0
Culex	*tritaeniorhynchus*	BIO03	2	0
Culex	*tritaeniorhynchus*	BIO04	2	0
Culex	*tritaeniorhynchus*	BIO05	2	0
Culex	*tritaeniorhynchus*	BIO06	2	0
Culex	*tritaeniorhynchus*	BIO07	2	0
Culex	*tritaeniorhynchus*	BIO09	2	0
Culex	*tritaeniorhynchus*	BIO10	2	0
Culex	*tritaeniorhynchus*	BIO11	2	0
Culex	*tritaeniorhynchus*	BIO14	2	0
Culex	*tritaeniorhynchus*	BIO15	2	0
Culex	*tritaeniorhynchus*	BIO16	2	0
Culex	*tritaeniorhynchus*	BIO17	2	0
Culex	*tritaeniorhynchus*	BIO19	2	0
Culex	*tritaeniorhynchus*	Aspect	1	0
Culex	*tritaeniorhynchus*	Slope	1	0

Appendix A.1 (continued)

Genus	**Species**	**Predictor**	**Publications**	**PI**
Culex	*vexans*	Agricultural land	1	100
Culex	*vexans*	Distance to water	1	0
Culiseta	*longiareolata*	Wetlands	2	50
Culiseta	*longiareolata*	BIO05	1	100
Culiseta	*longiareolata*	BIO06	1	100
Culiseta	*longiareolata*	BIO09	1	100
Culiseta	*longiareolata*	BIO15	1	100
Culiseta	*longiareolata*	BIO18	1	100
Culiseta	*longiareolata*	Agricultural land	1	0
Culiseta	*longiareolata*	Animal pop. density	1	0
Culiseta	*longiareolata*	Barren land	1	0
Culiseta	*longiareolata*	BIO01	1	0
Culiseta	*longiareolata*	BIO02	1	0
Culiseta	*longiareolata*	BIO03	1	0
Culiseta	*longiareolata*	BIO04	1	0
Culiseta	*longiareolata*	BIO07	1	0
Culiseta	*longiareolata*	BIO08	1	0
Culiseta	*longiareolata*	BIO10	1	0
Culiseta	*longiareolata*	BIO11	1	0
Culiseta	*longiareolata*	BIO12	1	0
Culiseta	*longiareolata*	BIO13	1	0
Culiseta	*longiareolata*	BIO14	1	0
Culiseta	*longiareolata*	BIO16	1	0
Culiseta	*longiareolata*	BIO17	1	0
Culiseta	*longiareolata*	BIO19	1	0
Culiseta	*longiareolata*	Elevation	1	0
Culiseta	*longiareolata*	Forested land	1	0
Culiseta	*longiareolata*	General landcover/use	1	0
Culiseta	*longiareolata*	Human pop. density	1	0
Culiseta	*longiareolata*	Industrial land	1	0
Culiseta	*longiareolata*	Shrubland	1	0
Culiseta	*longiareolata*	Urban land	1	0
Culiseta	*longiareolata*	Waterbodies	1	0
Culiseta	*melanura*	TCW	2	50
Culiseta	*melanura*	Agricultural land	1	100
Culiseta	*melanura*	General landcover/use	1	0
Culiseta	*melanura*	General precipitation	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Culiseta	*melanura*	Industrial land	1	0
Culiseta	*melanura*	Soil type	1	0
Culiseta	*melanura*	Waterbodies	1	0
Haemagogus	*leucocelaenus*	Humidity	2	50
Haemagogus	*leucocelaenus*	BIO09	1	100
Haemagogus	*leucocelaenus*	BIO16	1	100
Haemagogus	*leucocelaenus*	Elevation	1	0
Haemagogus	*leucocelaenus*	General vegetation	1	0
Haemagogus	*leucocelaenus*	Industrial land	1	0
Haemagogus	*leucocelaenus*	TWI	1	0
Haemagogus	*leucocelaenus*	Wind	1	0
Ochlerotatus	*caspius*	Animal pop. density	2	50
Ochlerotatus	*caspius*	BIO01	1	100
Ochlerotatus	*caspius*	BIO07	1	100
Ochlerotatus	*caspius*	BIO11	1	100
Ochlerotatus	*caspius*	Elevation	1	100
Ochlerotatus	*caspius*	Agricultural land	1	0
Ochlerotatus	*caspius*	Barren land	1	0
Ochlerotatus	*caspius*	BIO02	1	0
Ochlerotatus	*caspius*	BIO03	1	0
Ochlerotatus	*caspius*	BIO04	1	0
Ochlerotatus	*caspius*	BIO05	1	0
Ochlerotatus	*caspius*	BIO06	1	0
Ochlerotatus	*caspius*	BIO08	1	0
Ochlerotatus	*caspius*	BIO09	1	0
Ochlerotatus	*caspius*	BIO10	1	0
Ochlerotatus	*caspius*	BIO12	1	0
Ochlerotatus	*caspius*	BIO13	1	0
Ochlerotatus	*caspius*	BIO14	1	0
Ochlerotatus	*caspius*	BIO15	1	0
Ochlerotatus	*caspius*	BIO16	1	0
Ochlerotatus	*caspius*	BIO17	1	0
Ochlerotatus	*caspius*	BIO18	1	0
Ochlerotatus	*caspius*	BIO19	1	0
Ochlerotatus	*caspius*	Forested land	1	0
Ochlerotatus	*caspius*	General landcover/use	1	0
Ochlerotatus	*caspius*	Human pop. density	1	0

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Ochlerotatus	*caspius*	Industrial land	1	0
Ochlerotatus	*caspius*	Shrubland	1	0
Ochlerotatus	*caspius*	Urban land	1	0
Ochlerotatus	*caspius*	Waterbodies	1	0
Ochlerotatus	*caspius*	Wetlands	1	0
Ochlerotatus	*dorsalis*	Agricultural land	2	50
Ochlerotatus	*dorsalis*	Wetlands	2	50
Ochlerotatus	*dorsalis*	BIO02	1	100
Ochlerotatus	*dorsalis*	BIO14	1	100
Ochlerotatus	*dorsalis*	BIO15	1	100
Ochlerotatus	*dorsalis*	BIO17	1	100
Ochlerotatus	*dorsalis*	Animal pop. density	1	0
Ochlerotatus	*dorsalis*	Barren land	1	0
Ochlerotatus	*dorsalis*	BIO01	1	0
Ochlerotatus	*dorsalis*	BIO03	1	0
Ochlerotatus	*dorsalis*	BIO04	1	0
Ochlerotatus	*dorsalis*	BIO05	1	0
Ochlerotatus	*dorsalis*	BIO06	1	0
Ochlerotatus	*dorsalis*	BIO07	1	0
Ochlerotatus	*dorsalis*	BIO08	1	0
Ochlerotatus	*dorsalis*	BIO09	1	0
Ochlerotatus	*dorsalis*	BIO10	1	0
Ochlerotatus	*dorsalis*	BIO11	1	0
Ochlerotatus	*dorsalis*	BIO12	1	0
Ochlerotatus	*dorsalis*	BIO13	1	0
Ochlerotatus	*dorsalis*	BIO16	1	0
Ochlerotatus	*dorsalis*	BIO18	1	0
Ochlerotatus	*dorsalis*	BIO19	1	0
Ochlerotatus	*dorsalis*	Elevation	1	0
Ochlerotatus	*dorsalis*	Forested land	1	0
Ochlerotatus	*dorsalis*	General landcover/use	1	0
Ochlerotatus	*dorsalis*	Human pop. density	1	0
Ochlerotatus	*dorsalis*	Industrial land	1	0
Ochlerotatus	*dorsalis*	Shrubland	1	0
Ochlerotatus	*dorsalis*	Urban land	1	0
Ochlerotatus	*dorsalis*	Waterbodies	1	0
Ochlerotatus	*geniculatus*	BIO18	1	100

Appendix A.1 (continued)

Genus	Species	Predictor	Publications	PI
Ochlerotatus	*geniculatus*	BIO19	1	100
Ochlerotatus	*geniculatus*	Elevation	1	100
Ochlerotatus	*geniculatus*	Forested land	1	100
Ochlerotatus	*geniculatus*	Shrubland	1	100
Ochlerotatus	*geniculatus*	Agricultural land	1	0
Ochlerotatus	*geniculatus*	Animal pop. density	1	0
Ochlerotatus	*geniculatus*	Barren land	1	0
Ochlerotatus	*geniculatus*	BIO01	1	0
Ochlerotatus	*geniculatus*	BIO02	1	0
Ochlerotatus	*geniculatus*	BIO03	1	0
Ochlerotatus	*geniculatus*	BIO04	1	0
Ochlerotatus	*geniculatus*	BIO05	1	0
Ochlerotatus	*geniculatus*	BIO06	1	0
Ochlerotatus	*geniculatus*	BIO07	1	0
Ochlerotatus	*geniculatus*	BIO08	1	0
Ochlerotatus	*geniculatus*	BIO09	1	0
Ochlerotatus	*geniculatus*	BIO10	1	0
Ochlerotatus	*geniculatus*	BIO11	1	0
Ochlerotatus	*geniculatus*	BIO12	1	0
Ochlerotatus	*geniculatus*	BIO13	1	0
Ochlerotatus	*geniculatus*	BIO14	1	0
Ochlerotatus	*geniculatus*	BIO15	1	0
Ochlerotatus	*geniculatus*	BIO16	1	0
Ochlerotatus	*geniculatus*	BIO17	1	0
Ochlerotatus	*geniculatus*	General landcover/use	1	0
Ochlerotatus	*geniculatus*	Human pop. density	1	0
Ochlerotatus	*geniculatus*	Industrial land	1	0
Ochlerotatus	*geniculatus*	Urban land	1	0
Ochlerotatus	*geniculatus*	Waterbodies	1	0
Ochlerotatus	*geniculatus*	Wetlands	1	0
Psorophora	*ferox*	BIO05	1	100
Psorophora	*ferox*	BIO12	1	100
Psorophora	*ferox*	Slope	1	100
Psorophora	*ferox*	Vegetation cover	1	0

Appendix A.2

Table A2.1: Number of publications which applied species distribution models per mosquito species.

Species		Species	
Aedes aegypti	44	*Culiseta longiareolata*	3
Aedes albopictus	36	*Aedes cinereus*	2
Culex pipiens	19	*Aedes cozumelensis*	2
Anopheles gambiae	15	*Anopheles albimanus*	2
Anopheles arabiensis	14	*Anopheles atroparvus*	2
Culex quinquefasciatus	8	*Anopheles belenrae*	2
Anopheles albitarsis	6	*Anopheles braziliensis*	2
Anopheles darlingi	6	*Anopheles kleini*	2
Anopheles funestus	6	*Anopheles koliensis*	2
Culex modestus	6	*Anopheles koreicus*	2
Aedes vexans	5	*Anopheles lindesayi*	2
Anopheles lesteri	4	*Anopheles marajoara*	2
Anopheles merus	4	*Anopheles melanoon*	2
Anopheles nuneztovari	4	*Anopheles moucheti*	2
Anopheles sinensis	4	*Anopheles nili*	2
Culex theileri	4	*Anopheles oswaldoi*	2
Culex tritaeniorhynchus	4	*Anopheles pullus*	2
Culiseta melanura	4	*Anopheles quadriannulatus*	2
Ochlerotatus caspius	4	*Anopheles quadrimaculatus*	2
Aedes japonicus	3	*Anopheles sacharovi*	2
Aedes vecans	3	*Anopheles sinerorides*	2
Anopheles dirus	3	*Anopheles stephensi*	2
Anopheles farauti	3	*Anopheles richiardii*	2
Anopheles maculipennis	3	*Culex coronator*	2
Anopheles melas	3	*Culex tarsalis*	2
Anopheles minimus	3	*Culex thriambus*	2
Anopheles plumbeus	3	*Ochlerotatus dorsalis*	2
Culex restuans	3	*Ochlerotatus geniculatus*	2
Culex salinarius	3	*Aedes africanus*	1

Table A2.1 (continued)

Species		Species	
Aedes caspius	1	*Anopheles janconnae*	1
Aedes geniculatus	1	*Anopheles lacbranchiae*	1
Aedes koreicus	1	*Anopheles latens*	1
Aedes scapularis	1	*Anopheles leucosphyrus*	1
Aedes serratus	1	*Anopheles maculatus*	1
Aedes sticticus	1	*Anopheles marakoara*	1
Aedes togoi	1	*Anopheles marteri*	1
Anopheles aconitus	1	*Anopheles maverlius*	1
Anopheles annularis	1	*Anopheles messeae*	1
Anopheles aquasalis	1	*Anopheles nemophilous*	1
Anopheles baimaii	1	*Anopheles nunextovari*	1
Anopheles balabacensis	1	*Anopheles oryzalimnetes*	1
Anopheles barbirostris	1	*Anopheles peryassui*	1
Anopheles bellator	1	*Anopheles pseudopunctipennis*	1
Anopheles bwambae	1	*Anopheles punctualtus*	1
Anopheles coluzzii	1	*Anopheles scaloni*	1
Anopheles coustani	1	*Anopheles sergentii*	1
Anopheles crascens	1	*Anopheles smaragdinus*	1
Anopheles cruzii	1	*Anopheles subpictus*	1
Anopheles culicifacies	1	*Anopheles sundaicus*	1
Anopheles daciae	1	*Anopheles superpictus*	1
Anopheles deaneorum	1	*Anopheles suprtictus*	1
Anopheles diluvialis	1	*Anopheles takasagoensis*	1
Anopheles elegans	1	*Anopheles triannualtatus*	1
Anopheles flavirostris	1	*Anopheles triannulatus*	1
Anopheles fluviatilis	1	*Culex hortensis*	1
Anopheles freeborni	1	*Culex nigripalpus*	1
Anopheles harrisoni	1	*Haemagogus leucocelaenus*	1
Anopheles inundatus	1	*Psorophora ferox*	1

Table A2.2: Descriptions of bioclimatic variables.

Abbreviation	Description
BIO01	Annual mean temperature (°C)
BIO02	Mean diurnal range (°C)
BIO03	Isothermality (100*(BIO2/BIO7))
BIO04	Temperature seasonality (100*standard deviation)
BIO05	Maximum temperature of the coldest month (°C)
BIO06	Minimum temperature of the coldest month (°C)
BIO07	Temperature annual range (°C) (BIO05-BIO06)
BIO08	Mean temperature of wettest quarter (°C)
BIO09	Mean temperature of driest quarter (°C)
BIO10	Mean temperature of warmest quarter (°C)
BIO11	Mean temperature of coldest quarter (°C)
BIO12	Annual precipitation (mm)
BIO13	Precipitation of wettest month (mm)
BIO14	Precipitation of driest month (mm)
BIO15	Precipitation seasonality (coefficient of variation)
BIO16	Precipitation of wettest quarter (mm)
BIO17	Precipitation of driest quarter (mm)
BIO18	Precipitation of warmest quarter (mm)
BIO19	Precipitation of coldest quarter (mm)

Table A2.3: Percent of observed quality levels per issue and aspect for publications published up to the release of SDM standards in 2019 (before) or 2020 onwards (after). Definition of issues are provided in Table 2.1. Standards levels of deficient, bronze, silver, and gold represent unacceptable, acceptable, cutting-edge, and aspiration quality, respectively. Standards levels of deficient, bronze, silver, and gold represent unacceptable, acceptable, cutting-edge, and aspiration quality, respectively.

Aspect	**Issue**	**Deficient**		**Bronze**		**Silver**		**Gold**	
		Before	After	Before	After	Before	After	Before	After
Response variable	1.A	15.8	0	61.7	84.6	20	7.7	2.5	7.7
	1.B	29.2	15.4	55	76.9	13.3	7.7	2.5	0
	1.C	15	0	34.2	76.9	25.8	7.7	25	15.4
	1.D	21.7	0	76.7	100	1.7	0	0	0
	1.E	57.5	7.7	25.8	84.6	16.7	0	0	7.7
	Total	27.8	4.6	50.7	84.6	15.5	4.6	6	6.2
Predictor variable	2.A	26.7	7.7	60.8	69.2	10	23.1	2.5	0
	2.B	76.7	69.2	20.8	30.8	2.5	0	0	0
	2.C	82.5	84.6	13.3	15.4	4.2	0	0	0
	Total	61.9	53.9	31.7	38.5	5.6	7.7	0.8	0
Model building	3.A	59.2	46.2	20	23.1	20.8	30.8	0	0
	3.B	51.7	15.4	29.2	53.9	19.2	30.8	0	0
	3.C	57.5	15.4	40.8	76.9	0.8	7.7	0.8	0
	3.D	55	30.8	44.2	61.5	0.8	7.7	0	0
	Total	55.8	26.9	33.5	53.9	10.4	19.2	0.2	0
Model evaluation	4.A	71.7	53.9	27.5	46.2	0.8	0	0	0
	4.B	17.5	15.4	73.3	84.6	5.8	0	3.3	0
	4.C	16.7	15.4	75.8	76.9	7.5	7.7	0	0
	Total	35.3	28.2	58.9	69.2	4.7	2.6	1.1	0
All aspects	Total	43.6	25.1	43.9	64.1	10	8.7	2.4	2.1

Table A2.4: Relative area inside the line achieved across SDM aspects for mosquito SDMs compared to a sample of all taxa SDMs by Araújo et al. (2019). All taxa measures were recalculated from reported values on a polar coordinate system rather than radar coordinate system for comparison. The 50% and 90% quantiles represented the 50% and 90% of the way up an ascending list of sorted quality, respectively.

SDM aspect	**50% quantile**			**90% quantile**		
	Mosquitoes	All taxa	Difference	Mosquitoes	All taxa	Difference
Response variable	16%	16%	0%	45%	52%	-7%
Predictor variables	4%	12%	-8%	19%	25%	-6%
Model building	4%	4%	0%	29%	23%	6%
Model evaluation	8%	8%	0%	12%	19%	-7%

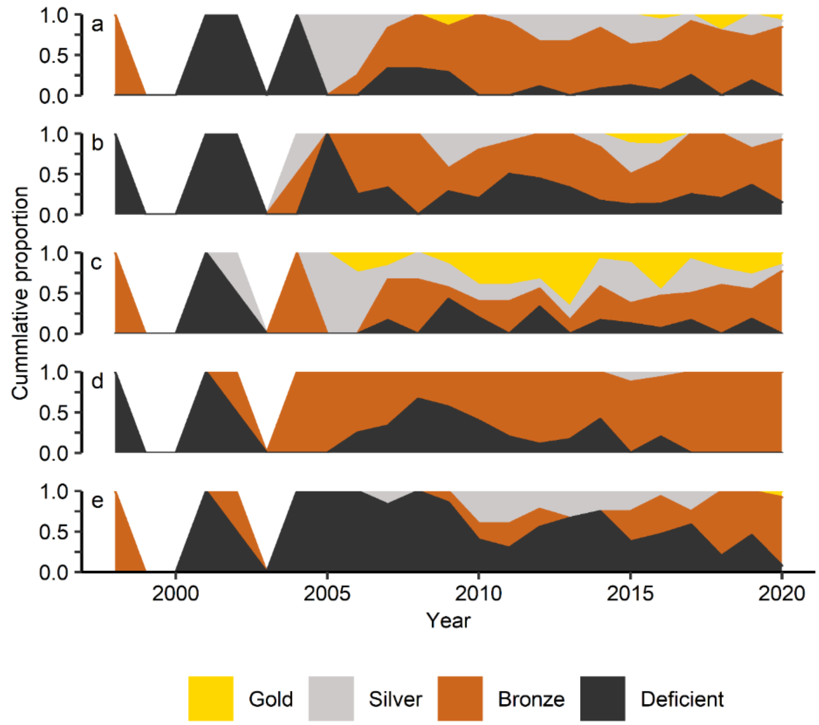


Figure A2.1: Yearly proportion of response variable standards scores with respect to sampling (a), taxa identification (b), spatial accuracy (c), environmental extent (d), and geographic extent (e). Standards were developed in Araújo et al. (2019).

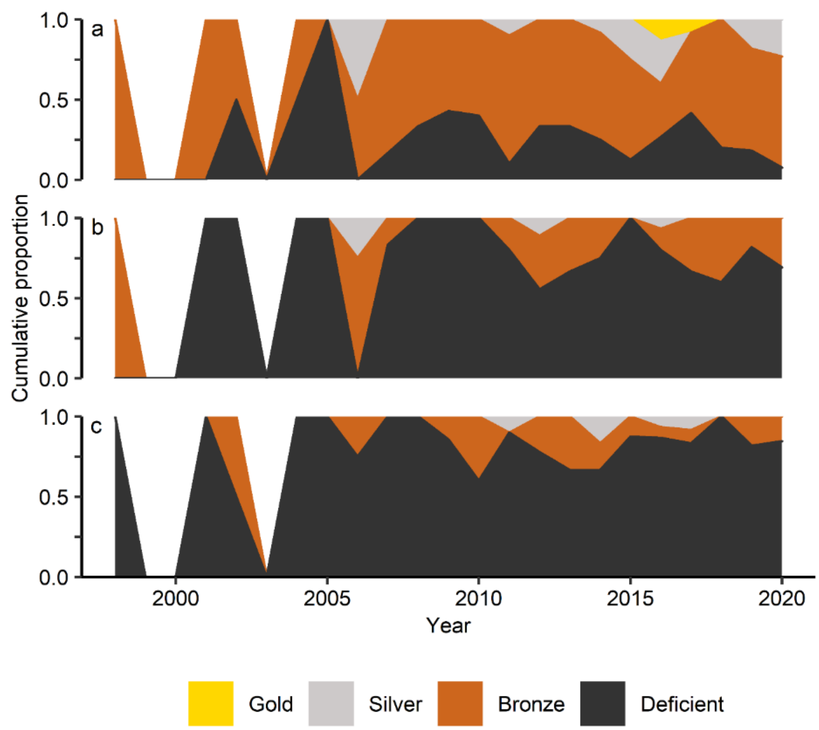


Figure A2.2: Yearly proportion of predictor variables standards scores with respect to choice of predictors (a), spatial and temporal resolution (b), and uncertainty (c). Standards were developed in Araújo et al. (2019).

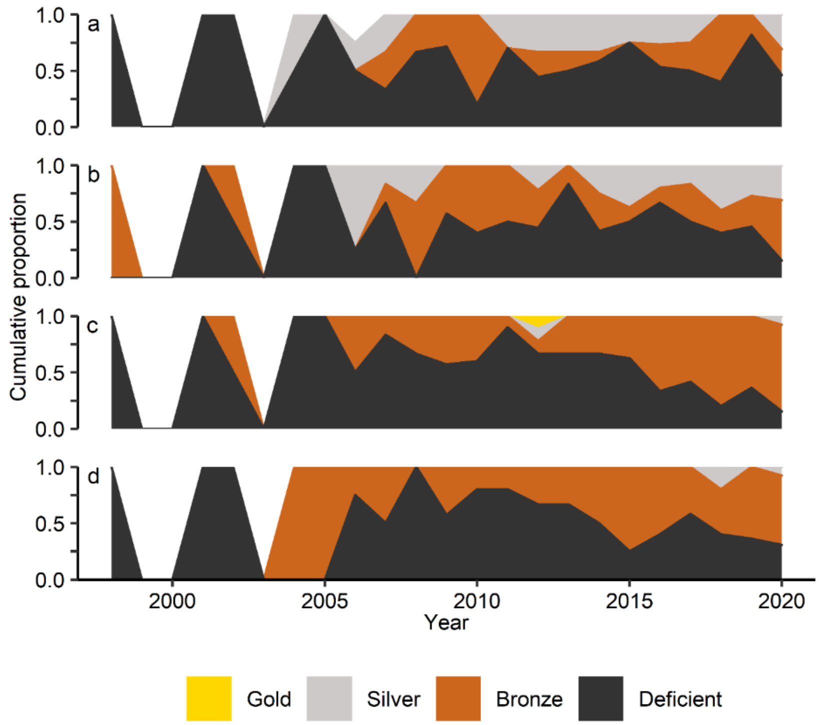


Figure A2.3: Yearly proportion of model building standards scores with respect to model complexity (a), bias and noise (b), collinearity (c), and model and parameter uncertainty (d). Standards were developed in Araújo et al. (2019).

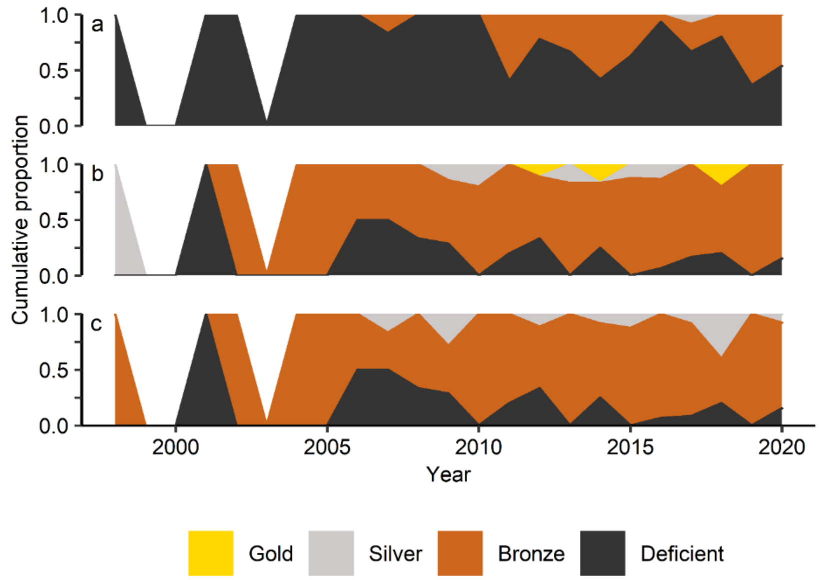


Figure A2.4: Yearly proportion of model evaluation standards scores with respect to model assumptions (a), outputs (b), and performance (c). Standards were developed in Araújo et al. (2019).

Appendix B.1

Virtual species design

Virtual species' habitat suitability was from defined response curves of each predictor within North America (Fig. 1a). I modeled BIO1 response as a β-function pattern to allow for specific upper and lower thresholds with different slopes, eq. (1), representing temperature thresholds for survival and development (Cunze et al. 2016; Koch et al. 2016).

$$f(a) = (a-5)^{0.9}(39-a)^{0.05} \qquad \text{eq. (1)}$$

BIO13 was modeled as a logistic function, eq. (2), representing a gradual increase in suitability success and maximum asymptote to represent the availability of oviposition sites as precipitation increased (Alaniz et al. 2017).

$$f(b) = \frac{1}{1+e^{\frac{-(b-125)}{25}}} \qquad \text{eq. (2)}$$

Elevation response was expressed as a piecewise linear decrease to represent lower host population and pooling water availability at higher elevations, eq. (3) (Alaniz et al. 2017; Santos and Menese 2017).

$$f(c) = \begin{cases} \frac{-1}{1500}c + 1, if\ c \leq 1500 \\ 0, if\ c > 1500 \end{cases} \qquad \text{eq. (3)}$$

I determined the overall habitat suitability as a multiplicative relationship of predictors, eq. (4),

$$SI = f(a) * f(b) * f(c) \qquad \text{eq. (4)}$$

where *f(a)*, *f(b)*, and *f(c)* represent species-environment responses for BIO1, BIO13, and elevation, respectfully (eq. 1-3).

Model evaluation

SDMs were evaluated for their ability to explain and predict based on predicted suitability across North America. Each algorithm provided a different range of predicted values for interpretation. As such, predicted relative suitability values were normalized following eq. (5) for comparison and to reflect the known virtual species' habitat suitability,

$$z_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \qquad \text{eq. (5)}$$

where x_i, is the original raster value of cell *i*, x_{min} and x_{max} are original the minimum and maximum of all *i* respectively, and z_i is the normalized value of x_i.

Identification of driving predictors

Jaccard index (J) (Jaccard 1908) was calculated to provide a measure of each SDM's ability to identify limiting predictors (BIO1, BIO13, elevation). J is a measure of similarity between two data sets, eq. (6),

$$J = \frac{S_1 \cap S_2}{S_1 \cup S_2} \qquad \text{eq. (6)}$$

where S_1 is expert predictors, and S_2 is the automated predictors. For each training set and SDM, I determined how many of the three driving predictors were selected during automated selection and divided by the total number of unique automated and expert predictors (e.g. Inman et al. 2021) (Fig. 1f). J ranges from zero to one, such that one and zero indicated all and no driving predictors were selected by automated predictor selection, respectively.

Response curve estimation

Response curves were estimated by generalized additive model smoothing of all predicted probabilities per driving predictor to allow for parametric and nonparametric smoothing. Aggregated environmental values of each estimated response curve were applied to calculate corresponding true suitability values of BIO1, BIO13, and elevation following eq. (1-3). Predicted and true response curves were compared by root mean square error (RMSE), eq. (7), and Spearman's correlation (ρ), eq. (8).

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(a_j - b_j\right)^2} \qquad \text{eq. (7)}$$

Where, n is the number of environmental values, a_j is the predicted relative suitability at environmental value j, and b_j is the true habitat suitability at environmental value j (Fig. 1g).

$$\rho = \frac{6\sum d_i^2}{n(n^2-1)} \qquad \text{eq. (8)}$$

Where ρ is the Spearman's rank correlation coefficient, d_i is the difference between the two ranks of observations, and n is the number of observations.

Probability of occurrence

Calibration was assessed by the continuous Boyce index (CBI). CBI is a measure of the prediction accuracy of occurrence events by determining spearman rank correlation coefficient of predicted-to-expected ratio, eq (11), by partitioning habitat suitability predictions into classes and by calculating frequency. CBI calculated two frequencies P_i and E_i:

$$P_i = \frac{p_i}{\sum_{j=1}^{b} p_j} \qquad \text{eq. (9)}$$

P_i is the predicted frequency of evaluation points. Such that, p_i is the number of evaluation points predicted by the model to fall in the habitat suitability class i, b is the number of habitat suitability bins, and $\sum p_j$ is the total number of evaluation points.

$$E_i = \frac{a_i}{\sum_{j=1}^{b} a_j} \qquad \text{eq. (10)}$$

E_i is the expected frequency of evaluation points, the frequency expected from a random distribution across the study area. Where a_i is the number of grid cells belonging to habitat suitability class i, or area covered by the class i, and $\sum a_i$ is the overall number of cells in the whole study area. For each class i, the predicted-to-expected ratio F_i is:

$$F_i = \frac{P_i}{E_i} \qquad \text{eq. (11)}$$

The CBI is then calculated by the plot of P/E against the men habitat suitability of each class. Specifically, CBI measure the monotonic increase by the Spearman rank coefficient between F_i and i (Boyce et al. 2002; Hirzel et al. 2006).

Unconditional bias of predictions was determined by mean absolute error (MAE), eq. (12),

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i| \qquad \text{eq. (12)}$$

where, n is the number of predicted 1 km^2 raster cells, x_i is the predicted probability in cell i, and y_i is the true probability value in cell i (Fig. 1b).

Skill was assessed by the associated skill score (SS) (Murphy 1988; Roebber 1998), eq. (13).

$$SS = 1 - \frac{\left[\frac{1}{n}\sum_{i=1}^{n}\left(x_i - x_{ref_0}\right)^2\right]}{\left[\frac{1}{n}\sum_{i=1}^{n}\left(x_{ref_i} - x_{ref_0}\right)^2\right]} \qquad \text{eq. (13)}$$

Where the numerator of eq. (13) represents the mean square error of x_i, the predicted probability in cell i, to the known presence or absence of the virtual species, x_{ref_0}. The denominator of eq. (13) is mean square error of x_{ref_i}, the true probability in cell i, to true binary presence or absence, x_{ref_0}, in cell *i* (Murphy 1988; Roebber 1998).

Forecast accuracy was represented by the Brier score (BS) (Brier 1950), eq. (14).

$$BS = \frac{1}{N}\sum_{k=1}^{K} n_k(f_k - \bar{o}_k)^2 - \frac{1}{N}\sum_{k=1}^{K} n_k(\bar{o}_k - \bar{o})^2 + \bar{o}(1 - \bar{o}) \qquad \text{eq. (14)}$$

where N is the number of predictions issued, K is the number of raster cells, $\bar{o}$ is the observed predicted probability base rate for presence to occur such that $\bar{o} = \sum_{t=1}^{N} o_t/N$, n_k is the number of cells with the same predicted probability, and $\bar{o}_k$ is the observed frequency given prediction of probability f_k (Murphy 1973). Refinement and resolution were quantified as part of BS (Murphy 1973; Wandishin et al. 2005). BS can be deconstructed into three components to isolate refinement and resolution values eq. (15).

$$BS = Refinment - Resoltion + Uncertainty \qquad \text{eq. (15)}$$

Probability of occurrence was further assessed by attribute diagrams and minimal difference. Attribute diagrams, also known as reliability diagrams, qualitatively examine the quality of each prediction relative to refinement and resolution with respect to the known habitat suitability (Hsu and Murphy 1986). Attribute diagrams were classified by the ability of each methodology to provide prefect, useful, marginally useful, not useful, or dangerously useless predictions relative to the known suitability as defined by Weisheimer and Palmer (2014).

Presence-absence predictions

All discrimination metrics were derived from a confusion matrix (Table S7).

Table S7: Confusion matrix (classification table) for SDMs.

		Predicted	
		Present	Absent
Observed	Present	True positive (TP)	False negative (FN)
	Absent	False positive (FP)	True negative (TN)

Sensitivity is the probability that the SDM correctly predicted an observation, eq. (16).

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \qquad \text{eq. (16)}$$

Specificity is the probability that a known absence is predicted correctly, eq. (17).

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \qquad \text{eq. (17)}$$

Precision is the probability that a predicted occurrence is an observed occurrence, eq. (18).

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \qquad \text{eq. (18)}$$

F1 is the harmonic means of sensitivity and precision. F1 provides an overall measure of model’s ability to classify presence records, eq. (19).

$$\text{F1} = \frac{2*\text{TP}}{2*\text{TP+FP+FN}} = \frac{2*(Precision*Sensitivity)}{(Precision+Sensitivity)} \qquad \text{eq. (19)}$$

Finally, CCR is the conditional probability that presence and absence records are correctly classified, eq. (20).

$$\mathrm{CCR} = \frac{\mathrm{TP+TN}}{\mathrm{TP+FP+FN+TN}} \qquad \text{eq. (20)}$$

The fit each probability of occurrence and binary prediction evaluation was assessed by minimum difference between training and testing evaluations (x_{Diff}). Difference between the training and testing value for any single metric, indicated if a model is over- or under- parameterized. This metric is based on the logic that overfit models will predict the training data well, but poorly on test data. Positive values indicate over-parameterized models, while negative models under-parameterized model (Warren and Seifert 2011). The difference of each prediction evaluation metric was determined. Such that x_{Diff} represents,

$$x_{Diff} = x_{Train} - x_{Test} \qquad \text{eq. (20)}$$

where x_{Train} and x_{Test} are the training and testing metrics, such that x is replaced by any one of the prediction evaluation metrics.

Appendix B.2

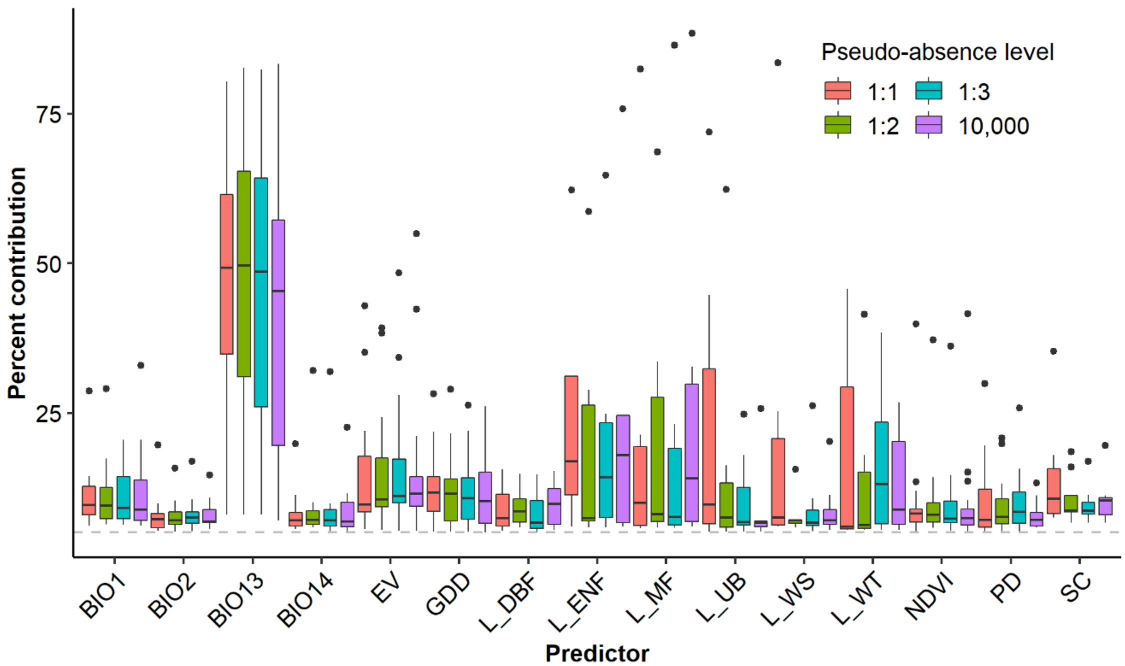


Figure B2.1: Boxplot of SDMs per pseudo-absence level which selected each predictor during automated selection. Full variable selection results are available in Table S2. Within a boxplot, the boundary of the box closest to zero indicates the 25th percentile, and boundary closest to one represents the 75th percentile. The black line within the box indicates the median. Whiskers above and below the box indicate the 10th and 90th percentiles. Black dots above or below whiskers represent outliers. Grey dashed line indicated selection threshold of 5%. Predictor abbreviations: BIO1: annual mean temperature, BIO2: mean diurnal temperature, BIO13: precipitation of the wettest month, BIO14: precipitation of the driest month, GDD: growing degree days, SC: snow cover, EV: elevation, L_BDF: deciduous broadleaf forests, L_ENF: evergreen needle leaf forests, L_MF: mixed forests, L_UB: urban settlements, L_WT: water, L_WS: woody savannas, NDVI: normalized difference vegetation index, PD: human population density.

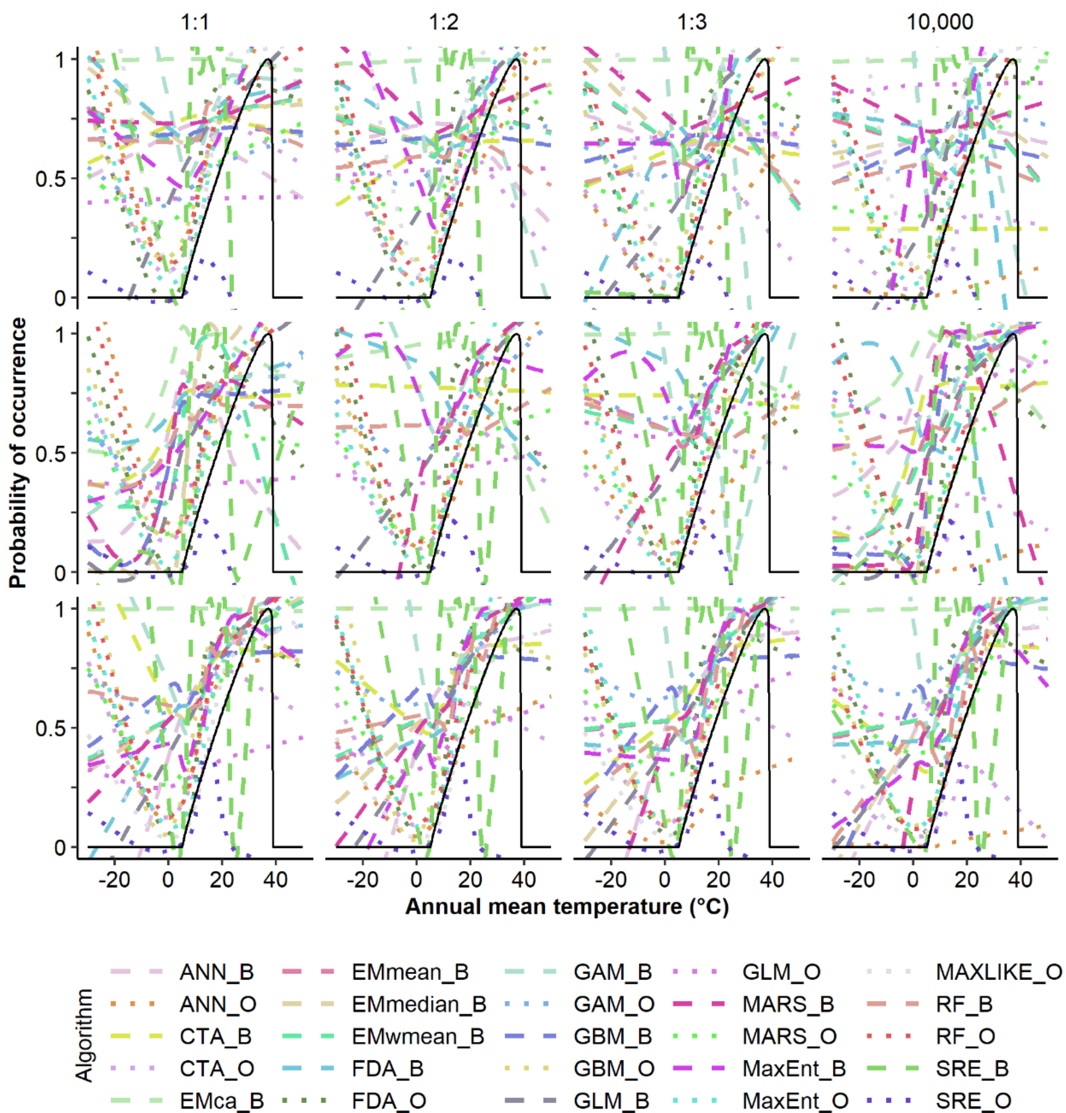


Figure B2.2: Response curves of mean annual temperature, BIO1, for all considered SDM methodology. Algorithm is shown by line-type and colour, predictor selection by rows and pseudo-absence level by columns. The expected probability of occurrence curve is shown by the solid black line. Missing automated values indicate the predictor was not selected.

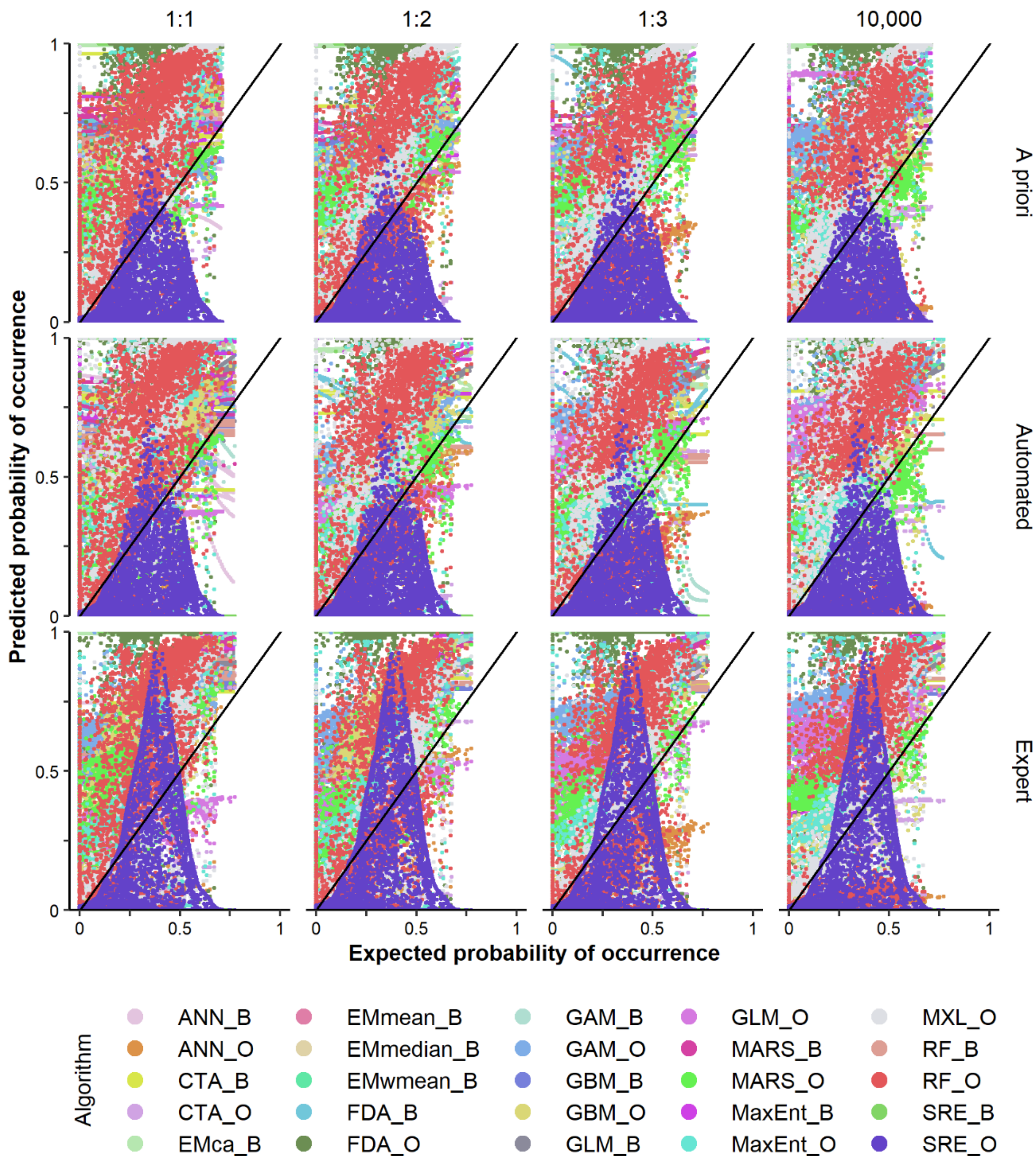


Figure B2.3: Scatterplot of expected by estimated response of mean annual temperature, BIO1, under all considered algorithms, pseudo-absences, and predictor selection methods. Points which fall on the diagonal line indicate accurate estimation. Algorithm is shown by colour, pseudo-absence level by columns and predictor selection method by rows.

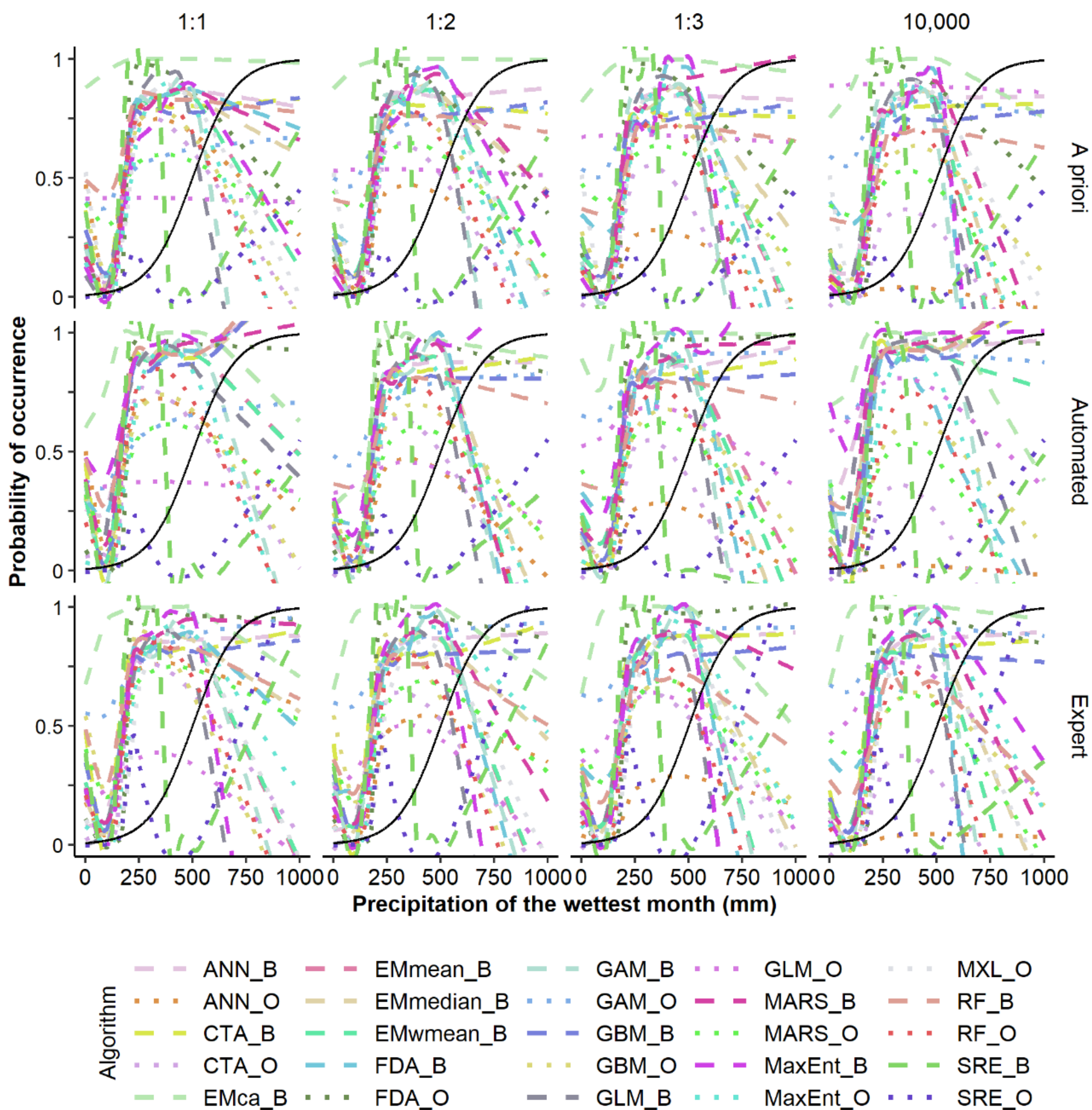


Figure B2.4: Response curves of precipitation of the wettest month, BIO13, for all considered SDM methodology. Algorithm is shown by line-type and colour, predictor selection by rows and pseudo-absence level by columns. The expected probability of occurrence curve is shown by the solid black line. Missing automated values indicate the predictor was not selected.

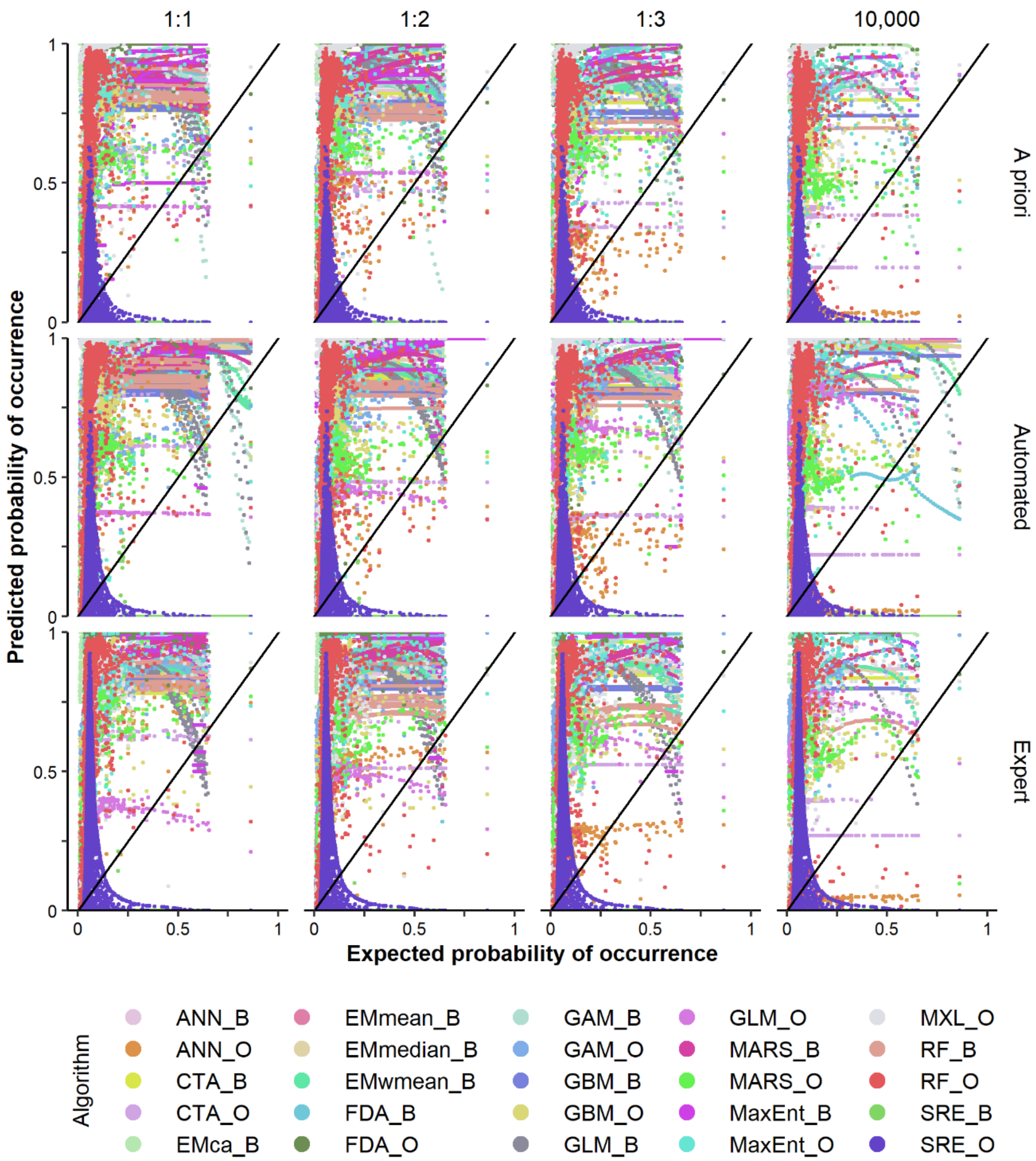


Figure B2.5: Scatterplot of expected by estimated response of precipitation of the wettest month, BIO13, under all considered algorithms, pseudo-absences, and predictor selection methods. Points which fall on the diagonal line indicate accurate estimated. Algorithm is shown by colour, pseudo-absence level by columns and predictor selection method by rows.

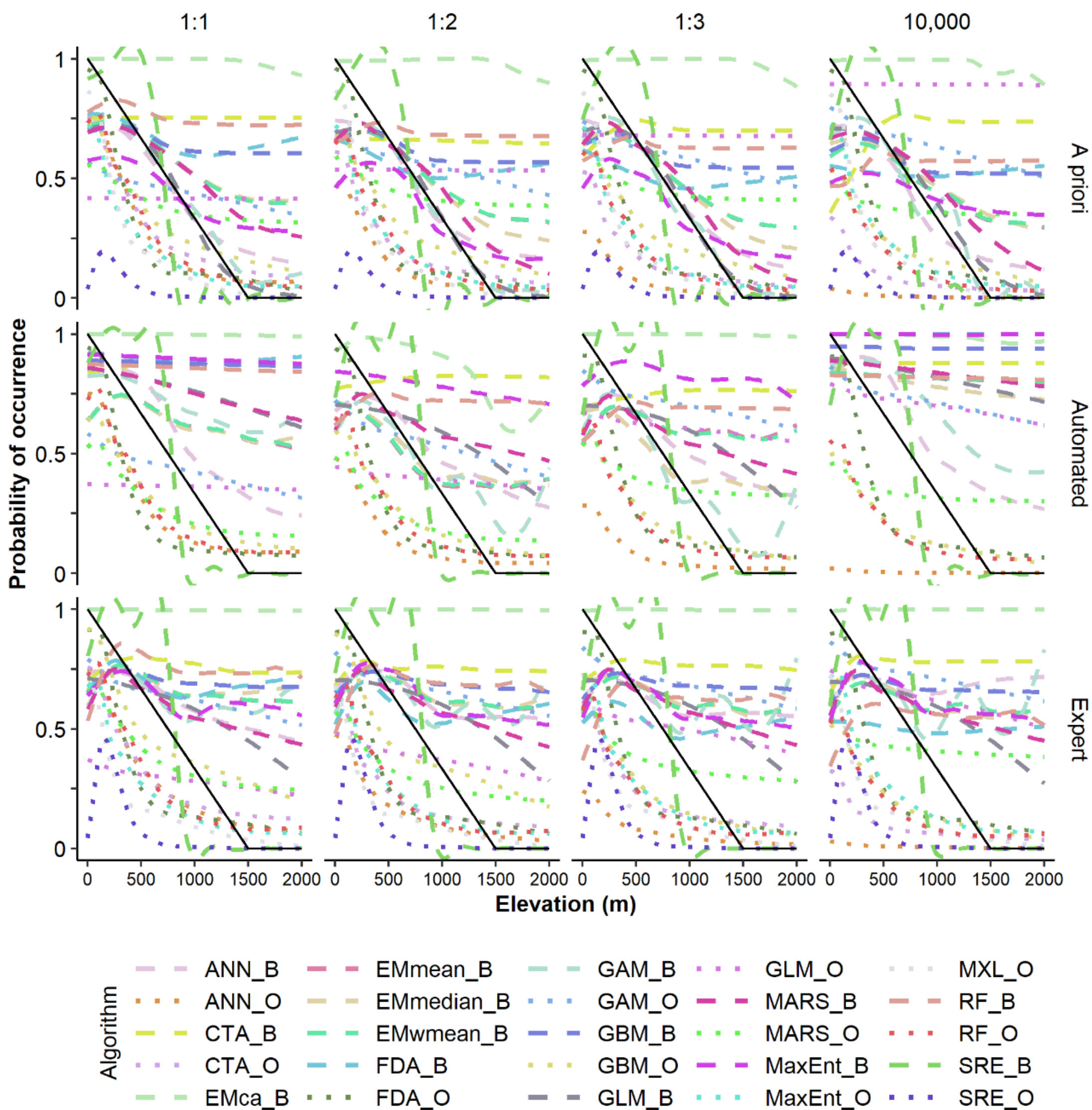


Figure B2.6: Response curves of elevation for all considered SDM methodology. Algorithm is shown by line-type and colour, predictor selection by rows and pseudo-absence level by columns. The expected probability of occurrence curve is shown by the solid black line. Missing automated values indicate the predictor was not selected.

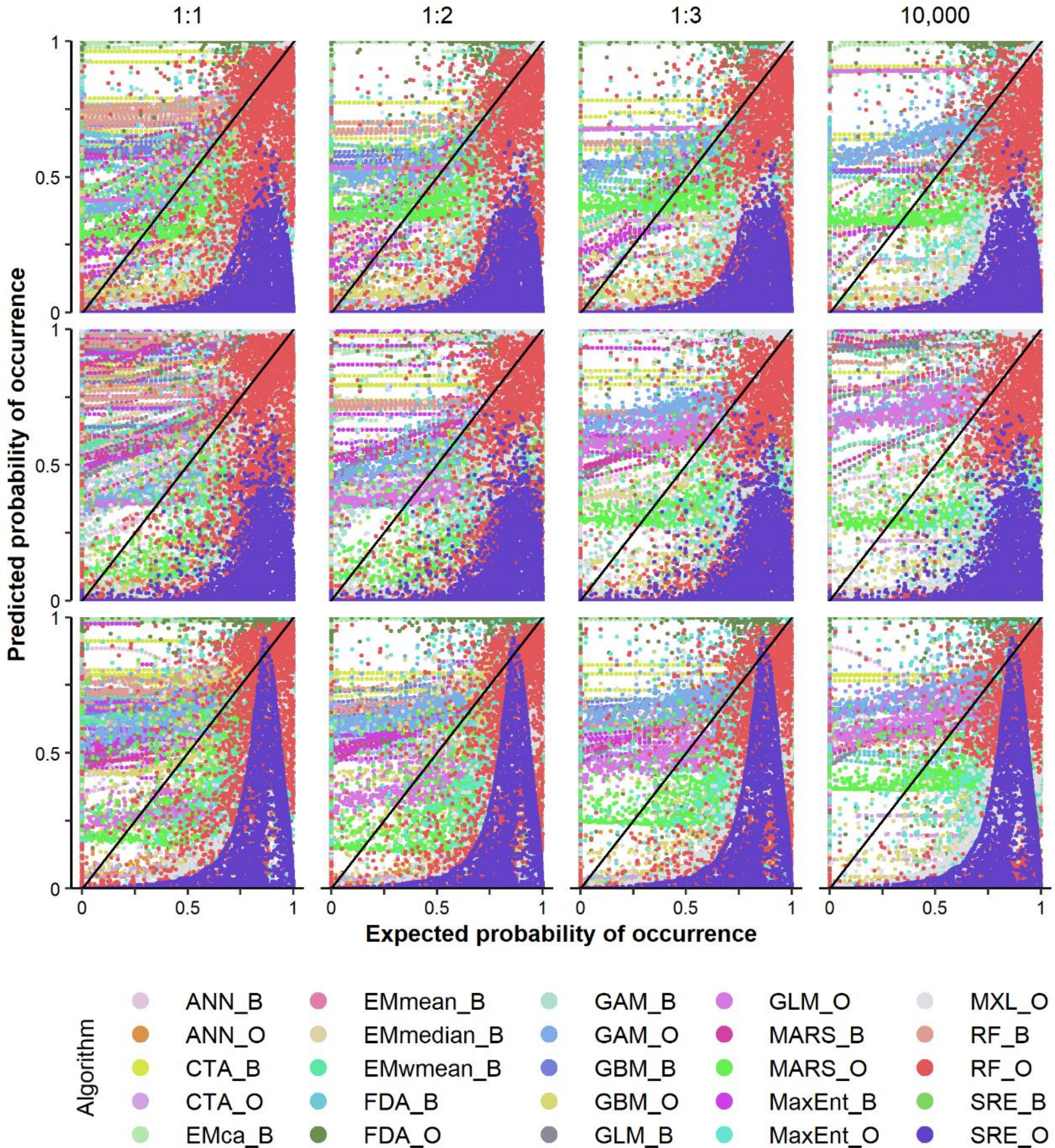


Figure B2.7: Scatterplot of expected by estimated response of elevation under all considered algorithms, pseudo-absences, and predictor selection methods. Points which fall on the diagonal line indicate accurate estimation. Algorithm is shown by colour, pseudo-absence level by columns and predictor selection method by rows.

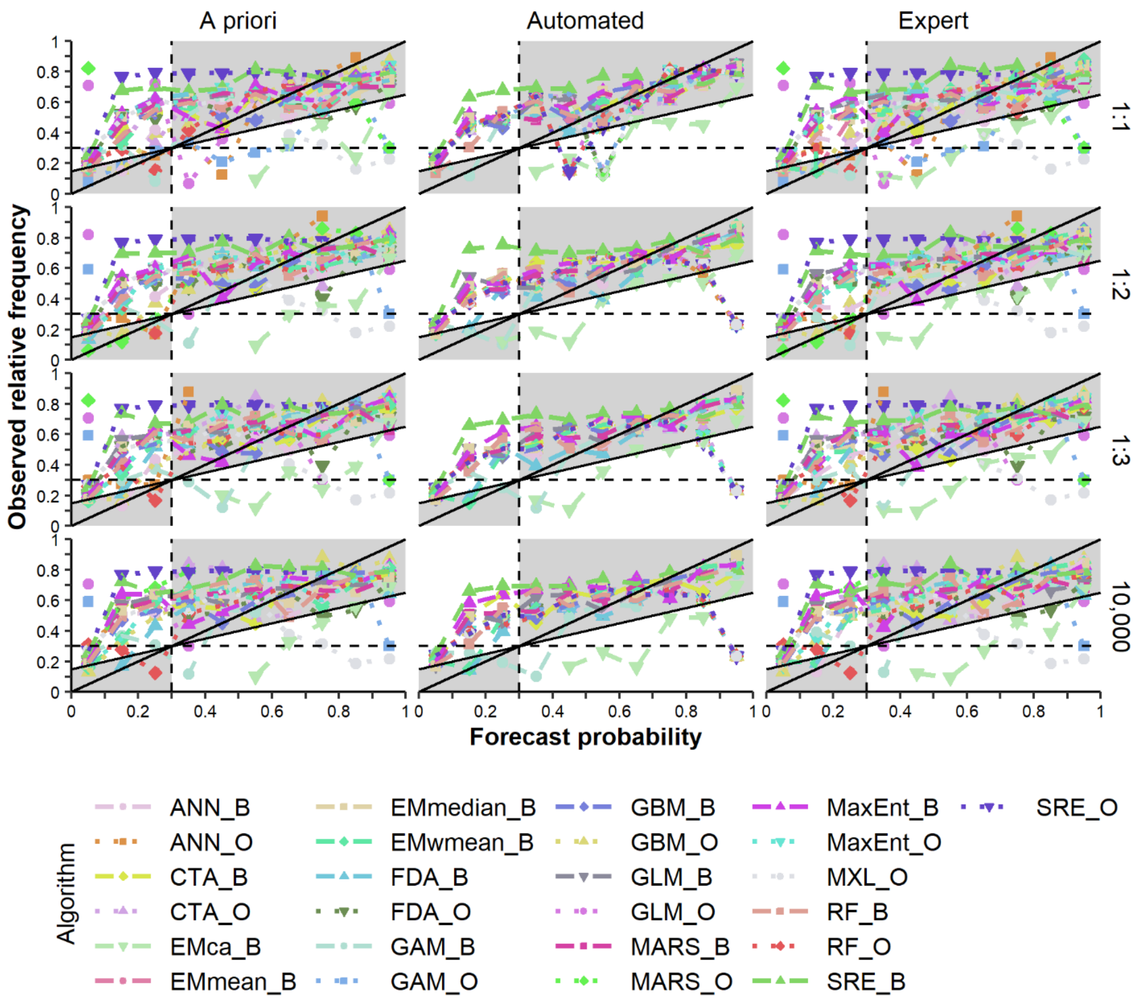
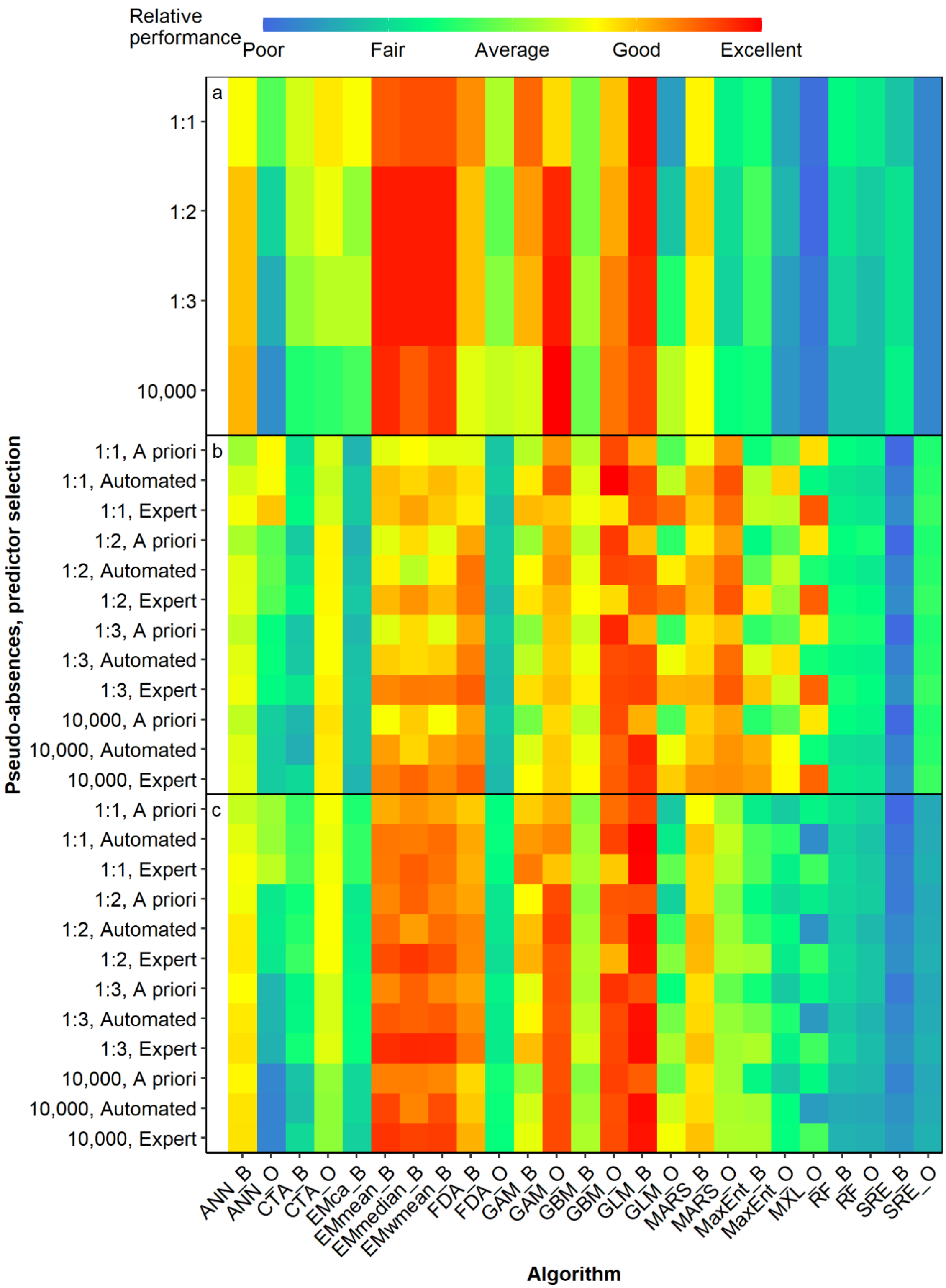


Figure B2.8: Attribute diagrams each SDM algorithm, pseudo-absence level, and predictor-selection method of virtual species distribution across training and testing regions. The solid 45° line indicates prefect prediction relative to the known habitat suitability. Observed values above the 45° line indicate under prediction, while under the 45° line indicate over prediction. The horizontal dashed line indicates no resolution, and vertical dashed line indicates no refinement. The remaining solid diagonal line located halfway between perfect prediction and no resolution line indicates no skill. Shaded areas identify points which contribute to positive Brier scores.



Relative performance
Poor
Fair
Average
Good
Excellent
a
b
c
Pseudo-absences, predictor selection
1:1
1:2
1:3
10,000
1:1, A priori
1:1, Automated
1:1, Expert
1:2, A priori
1:2, Automated
1:2, Expert
1:3, A priori
1:3, Automated
1:3, Expert
10,000, A priori
10,000, Automated
10,000, Expert
ANN_B
ANN_O
CTA_B
CTA_O
EMca_B
EMmean_B
EMmedian_B
EMwmean_B
FDA_B
FDA_O
GAM_B
GAM_O
GBM_B
GBM_O
GLM_B
GLM_O
MARS_B
MARS_O
MaxEnt_B
MaxEnt_O
MXL_O
RF_B
RF_O
SRE_B
SRE_O
Algorithm

Figure B2.9: Relative performance of explanation evaluations; identification of driving predictors (a), response curve estimations (b), and overall explanation ability (c). Colour of each cell represents the relative performance of each algorithm, pseudo-absences, and predictor selection interaction. Overall explanation ability (c) represents the normalized mean of each corresponding value in (a) and (b). Identification of driving predictors (a) was only considered under *a priori* predictor selection, but values were attributed to all corresponding algorithm and pseudo-absence pairs for overall explanation ability estimation. Raw relative performance values are available in Table S5.

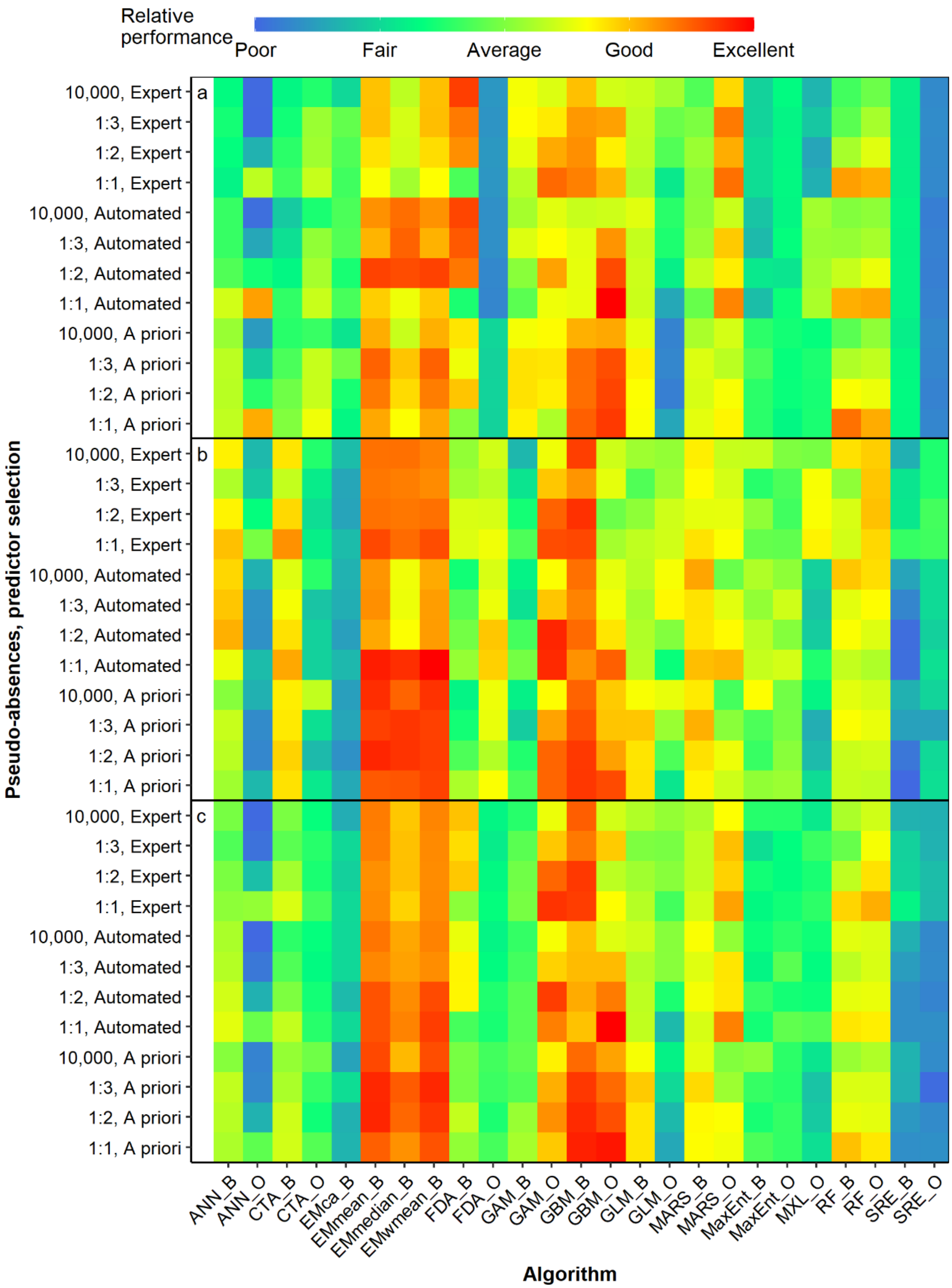

Relative performance
Poor
Fair
Average
Good
Excellent
Pseudo-absences, predictor selection
a
b
c
10,000, Expert
1:3, Expert
1:2, Expert
1:1, Expert
10,000, Automated
1:3, Automated
1:2, Automated
1:1, Automated
10,000, A priori
1:3, A priori
1:2, A priori
1:1, A priori
ANN_B
ANN_O
CTA_B
CTA_O
EMca_B
EMmean_B
EMmedian_B
EMwmean_B
FDA_B
FDA_O
GAM_B
GAM_O
GBM_B
GBM_O
GLM_B
GLM_O
MARS_B
MARS_O
MaxEnt_B
MaxEnt_O
MXL_O
RF_B
RF_O
SRE_B
SRE_O
Algorithm

Figure B2.10: Relative performance of prediction evaluations; probability of occurrence (a), binary presence-absence prediction (b), and overall prediction ability (c). Colour of each cell represents the relative performance of each algorithm, pseudo-absences, and predictor selection interaction. Overall prediction ability (c) represents the normalized mean of each corresponding value in (a) and (b). Raw relative performance values are available in Table S5.

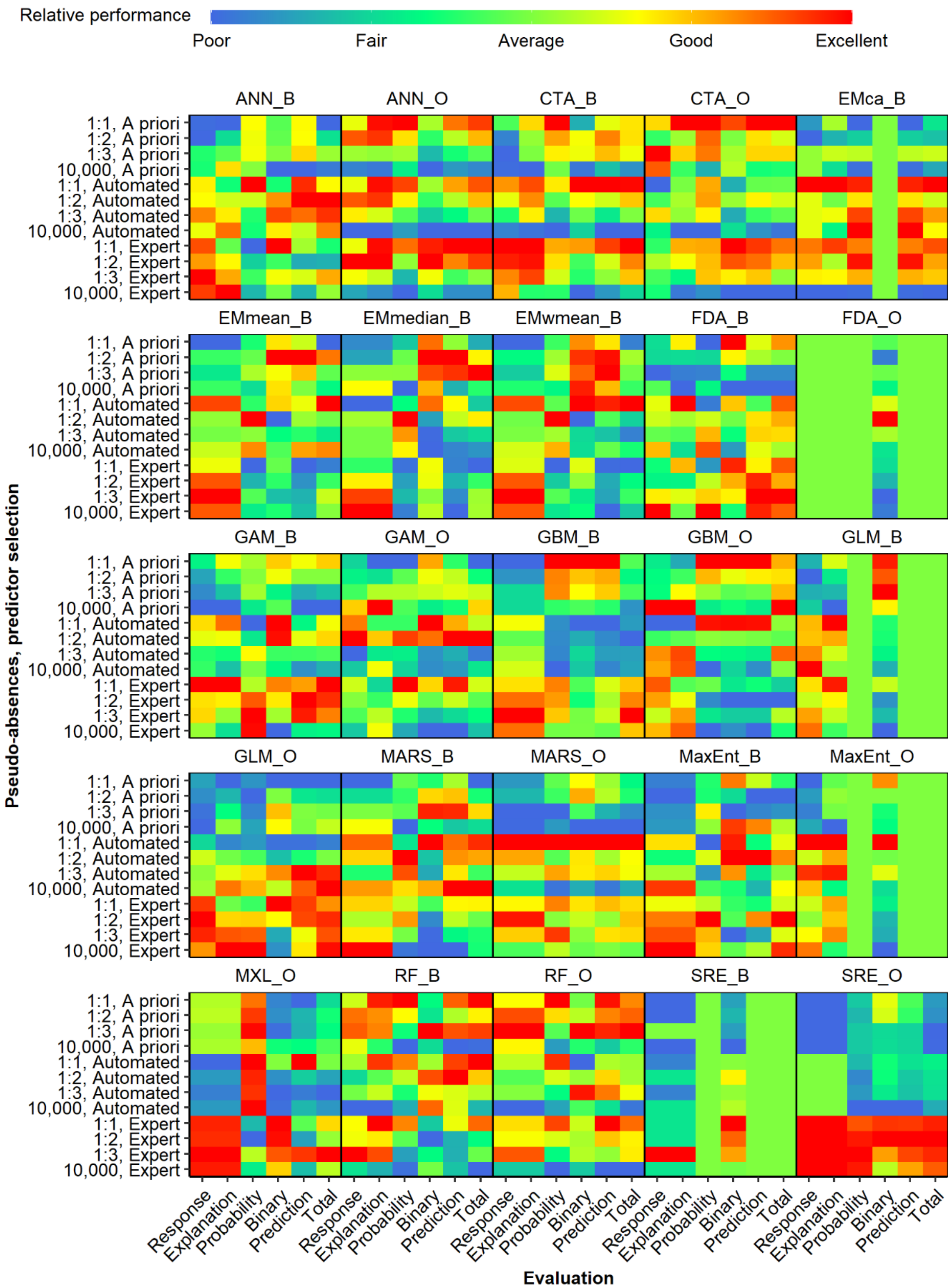

Relative performance
Poor
Fair
Average
Good
Excellent
ANN_B
ANN_O
CTA_B
CTA_O
EMca_B
EMmean_B
EMmedian_B
EMwmean_B
FDA_B
FDA_O
GAM_B
GAM_O
GBM_B
GBM_O
GLM_B
GLM_O
MARS_B
MARS_O
MaxEnt_B
MaxEnt_O
MXL_O
RF_B
RF_O
SRE_B
SRE_O
1:1, A priori
1:2, A priori
1:3, A priori
10,000, A priori
1:1, Automated
1:2, Automated
1:3, Automated
10,000, Automated
1:1, Expert
1:2, Expert
1:3, Expert
10,000, Expert
Pseudo-absences, predictor selection
Response
Explanation
Probability
Binary
Prediction
Total
Evaluation

Figure B2.11: Relative performance of considered pseudo-absences and predictor selection methods per algorithm and objective. Relative performances are per algorithm panel. Raw relative performance values are available in Appendix B2: Table B2.5.

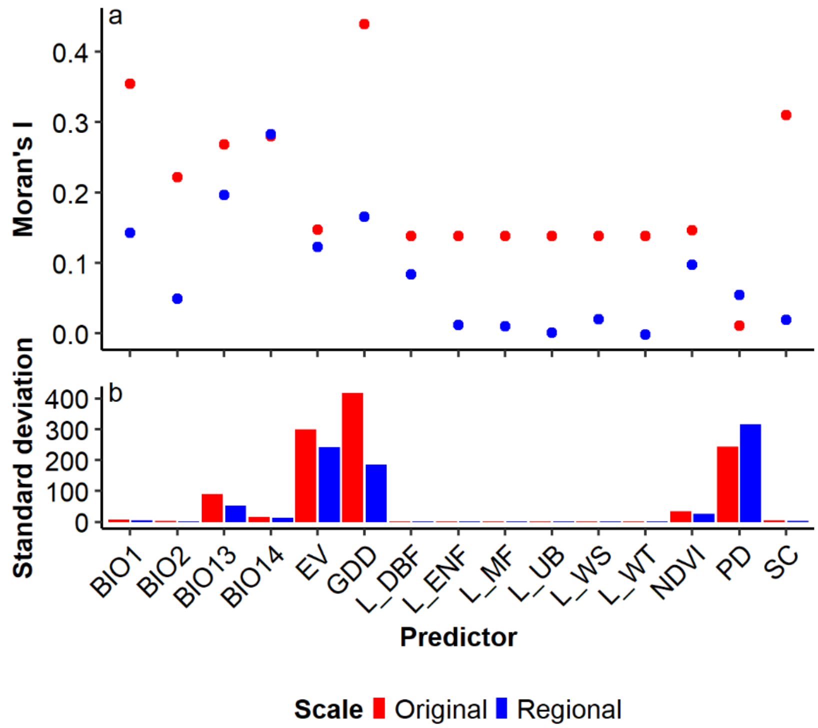


Figure B2.12: Moran's I (a) and standard deviation of predictor values (b) observed at the original, 1 km^2, or regional scales. Moran's I indicates how related species occurrences are based on their location and corresponding observed environmental, and is a measure of spatial autocorrelation. A positive Moran's I value indicate that near observations are more similar than far observations and zero values indicate random distribution. Standard deviation indicates predictor heterogeneity. Moran I and predictor standard deviation were calculated through raster R package for occurrences at original 1 km^2 and aggregated regional scale. Population density at 1 km^2 were retrieved from Oak Ridge Laboratory LandScan global population density.

Table B2.1: Summary statistics of regional scale (km^2) considered in SDMs per country, calculated under North America Albers Equal Area Conic projection.

Region	n	Mean	SD	Minimum	Q1	Median	Q3	Maximum
Canadian health regions	126	89619.77	253516.13	134.03	4197.17	16430.82	47292.95	2094275.86
United States counties	3006	2974.05	9552.97	4.95	1138.11	1639.62	2448.15	383017.81
Mexican states	32	61129.89	53729.01	1338.77	23408.92	58478.46	73843.59	247537.50
All	3164	6423.97	50043.74	4.95	1150.87	1682.16	2597.44	2094275.86

Table B2.2: Mean percent predictor contribution of all *a priori* variables per algorithm and pseudo-absence level applied to the virtual species. Standard deviations are given in parentheses. Bolded values indicated selected predictors. Abbreviations: BIO1: annual mean temperature, BIO2: mean diurnal temperature range, BIO5: maximum temperature of the warmest month, BIO6: minimum temperature of the coldest month, BIO13: precipitation of the wettest month, BIO14: precipitation of the driest month, EV: elevation, GDD: growing degree days: L_DBF: deciduous broadleaf forests landcover, L_ENF: evergreen needle leaf forests percent land cover, L_MF: mixed forest percent land cover, L_UB: percent urban landcover, L_WS: woody savannas percent land cover L_WT: water percent land cover, NDVI: normalized difference vegetation index, PD: human population density, SC: snow cover.

Algorithm	Pseudo-absence level	BIO01	BIO02	BIO13	BIO14	EV	GDD
ANN_B	1:1	**0.12 (0.08)**	0.02 (0.01)	**0.58 (0.15)**	0.05 (0.02)	**0.14 (0.1)**	**0.24 (0.13)**
ANN_B	1:2	**0.13 (0.08)**	0.02 (0.01)	**0.66 (0.11)**	0.04 (0.02)	**0.13 (0.09)**	**0.15 (0.06)**
ANN_B	1:3	**0.13 (0.07)**	0.02 (0.01)	**0.66 (0.11)**	0.04 (0.02)	**0.14 (0.1)**	**0.14 (0.06)**
ANN_B	10,000	**0.13 (0.07)**	0.02 (0.01)	**0.66 (0.11)**	0.04 (0.02)	**0.14 (0.09)**	**0.13 (0.06)**
ANN_O	1:1	**0.13 (0.13)**	0 (0)	**0.16 (0.08)**	0.02 (0.03)	**0.33 (0.25)**	**0.17 (0.12)**
ANN_O	1:2	**0.13 (0.12)**	0.02 (0.03)	**0.16 (0.08)**	0.04 (0.03)	**0.31 (0.25)**	**0.14 (0.1)**
ANN_O	1:3	**0.12 (0.09)**	0.03 (0.03)	**0.15 (0.06)**	0.05 (0.03)	**0.27 (0.23)**	**0.14 (0.1)**
ANN_O	10,000	**0.1 (0.05)**	**0.06 (0.02)**	**0.1 (0.05)**	**0.06 (0.02)**	**0.12 (0.11)**	**0.07 (0.01)**
CTA_B	1:1	**0.18 (0.09)**	0.03 (0.02)	**0.55 (0.1)**	0.04 (0.03)	**0.13 (0.05)**	**0.2 (0.06)**
CTA_B	1:2	**0.17 (0.09)**	0.04 (0.02)	**0.55 (0.09)**	**0.07 (0.04)**	**0.12 (0.04)**	**0.16 (0.04)**
CTA_B	1:3	**0.16 (0.09)**	0.05 (0.02)	**0.51 (0.1)**	**0.08 (0.04)**	**0.14 (0.05)**	**0.16 (0.04)**
CTA_B	10,000	**0.16 (0.1)**	**0.07 (0.03)**	**0.47 (0.11)**	**0.09 (0.04)**	**0.15 (0.05)**	**0.15 (0.02)**
CTA_O	1:1	**0.1 (0.08)**	0 (0.01)	**0.61 (0.22)**	0 (0.01)	0.01 (0.02)	**0.17 (0.07)**
CTA_O	1:2	**0.1 (0.09)**	0 (0)	**0.61 (0.23)**	0 (0.01)	0 (0.01)	**0.18 (0.05)**
CTA_O	1:3	**0.11 (0.09)**	0 (0)	**0.58 (0.2)**	0.01 (0.03)	0 (0)	**0.21 (0.07)**
CTA_O	10,000	**0.13 (0.1)**	0 (0.01)	**0.56 (0.21)**	0.03 (0.06)	0 (0)	**0.25 (0.1)**
EMca_B	1:1	**0.1 (0.08)**	0.04 (0.02)	**0.42 (0.27)**	0.05 (0.03)	**0.16 (0.12)**	0.05 (0.05)
EMca_B	1:2	**0.1 (0.08)**	**0.05 (0.02)**	**0.39 (0.26)**	0.03 (0.03)	**0.17 (0.12)**	0.04 (0.04)

Table B2.2 (continued)

Algorithm	Pseudo-absence level	BIO01	BIO02	BIO13	BIO14	EV	GDD
EMca_B	1:3	**0.11 (0.08)**	0.05 (0.02)	**0.37 (0.24)**	0.04 (0.02)	**0.19 (0.13)**	0.04 (0.04)
EMca_B	10,000	**0.12 (0.09)**	0.03 (0.03)	**0.34 (0.22)**	0.03 (0.03)	**0.19 (0.12)**	0.04 (0.03)
EMmean_B	1:1	**0.16 (0.09)**	0.01 (0)	**0.56 (0.3)**	0.02 (0.01)	**0.05 (0.03)**	0.04 (0.03)
EMmean_B	1:2	**0.15 (0.08)**	0.01 (0)	**0.57 (0.3)**	0.03 (0.01)	**0.05 (0.03)**	0.04 (0.02)
EMmean_B	1:3	**0.11 (0.08)**	0.01 (0)	**0.57 (0.3)**	0.03 (0.01)	**0.05 (0.04)**	0.04 (0.02)
EMmean_B	10,000	**0.1 (0.07)**	0.01 (0)	**0.57 (0.3)**	0.04 (0.01)	**0.05 (0.04)**	0.03 (0.02)
EMmedian_B	1:1	**0.15 (0.09)**	0 (0)	**0.58 (0.31)**	0.02 (0.01)	0.04 (0.03)	0.03 (0.03)
EMmedian_B	1:2	**0.14 (0.08)**	0 (0)	**0.59 (0.31)**	0.03 (0.01)	0.05 (0.04)	0.04 (0.02)
EMmedian_B	1:3	**0.13 (0.07)**	0 (0)	**0.58 (0.31)**	0.03 (0.01)	**0.05 (0.04)**	0.04 (0.02)
EMmedian_B	10,000	**0.12 (0.06)**	0.01 (0)	**0.59 (0.31)**	0.03 (0.01)	**0.05 (0.04)**	0.03 (0.02)
EMwmean_B	1:1	**0.16 (0.09)**	0.01 (0)	**0.56 (0.3)**	0.02 (0.01)	**0.05 (0.03)**	0.04 (0.03)
EMwmean_B	1:2	**0.15 (0.08)**	0.01 (0)	**0.57 (0.3)**	0.03 (0.01)	**0.05 (0.03)**	0.04 (0.02)
EMwmean_B	1:3	**0.11 (0.08)**	0.01 (0)	**0.57 (0.3)**	0.03 (0.01)	**0.05 (0.04)**	0.04 (0.02)
EMwmean_B	10,000	**0.1 (0.07)**	0.01 (0)	**0.57 (0.3)**	0.04 (0.01)	**0.05 (0.04)**	0.03 (0.02)
FDA_B	1:1	**0.15 (0.11)**	0.01 (0.01)	**0.74 (0.08)**	0.02 (0.02)	0.03 (0.02)	**0.13 (0.12)**
FDA_B	1:2	**0.2 (0.13)**	0.01 (0.01)	**0.66 (0.08)**	0.03 (0.02)	0.02 (0.01)	**0.2 (0.16)**
FDA_B	1:3	**0.22 (0.13)**	0.02 (0.01)	**0.64 (0.09)**	0.03 (0.02)	0.02 (0.01)	**0.2 (0.18)**
FDA_B	10,000	**0.18 (0.1)**	0.01 (0.01)	**0.66 (0.12)**	0.03 (0.02)	0.01 (0.01)	**0.21 (0.15)**
EMmean_B	1:1	**0.14 (0.11)**	0 (0.01)	**0.54 (0.25)**	0.04 (0.06)	0.02 (0.04)	**0.2 (0.12)**
EMmean_B	1:2	**0.14 (0.11)**	0.01 (0.02)	**0.54 (0.25)**	0.05 (0.05)	0.02 (0.04)	**0.2 (0.13)**
EMmean_B	1:3	**0.11 (0.11)**	0.01 (0.02)	**0.51 (0.23)**	0.04 (0.05)	0.03 (0.05)	**0.21 (0.14)**
EMmean_B	10,000	**0.11 (0.11)**	0.01 (0.02)	**0.52 (0.23)**	0.05 (0.06)	0.03 (0.05)	**0.19 (0.13)**
FDA_O	1:1	**0.18 (0.09)**	0.01 (0.01)	**0.68 (0.08)**	**0.06 (0.02)**	**0.08 (0.03)**	0.04 (0.04)
FDA_O	1:2	**0.16 (0.06)**	0.01 (0.02)	**0.69 (0.1)**	**0.06 (0.01)**	**0.09 (0.03)**	0.05 (0.02)

Table B2.2 (continued)

Algorithm	Pseudo-absence level	BIO01	BIO02	BIO13	BIO14	EV	GDD
FDA_O	1:3	**0.15 (0.06)**	0.02 (0.02)	**0.65 (0.11)**	**0.06 (0.01)**	**0.1 (0.03)**	**0.09 (0.05)**
FDA_O	10,000	**0.16 (0.09)**	0.01 (0)	**0.56 (0.3)**	0.02 (0.01)	**0.05 (0.03)**	0.04 (0.03)
GAM_B	1:1	**0.15 (0.08)**	0.01 (0)	**0.57 (0.3)**	0.03 (0.01)	**0.05 (0.03)**	0.04 (0.02)
GAM_B	1:2	**0.11 (0.08)**	0.01 (0)	**0.57 (0.3)**	0.03 (0.01)	**0.05 (0.04)**	0.04 (0.02)
GAM_B	1:3	**0.1 (0.07)**	0.01 (0)	**0.57 (0.3)**	0.04 (0.01)	**0.05 (0.04)**	0.03 (0.02)
GAM_B	10,000	**0.13 (0.04)**	0.04 (0.03)	**0.68 (0.12)**	**0.07 (0.01)**	**0.1 (0.03)**	0.04 (0.01)
GAM_O	1:1	**0.14 (0.1)**	0 (0.01)	**0.29 (0.19)**	0.01 (0.01)	**0.21 (0.16)**	0.02 (0.01)
GAM_O	1:2	**0.27 (0.04)**	0 (0.01)	**0.15 (0.06)**	0.02 (0.01)	**0.1 (0.07)**	0.02 (0.01)
GAM_O	1:3	**0.19 (0.07)**	0 (0)	**0.28 (0.16)**	0.02 (0.01)	**0.3 (0.17)**	0.02 (0.01)
GAM_O	10,000	**0.2 (0.05)**	0 (0)	**0.23 (0.14)**	0.02 (0.01)	**0.36 (0.17)**	0.02 (0.01)
GBM_B	1:1	**0.14 (0.09)**	0 (0)	**0.77 (0.04)**	0.01 (0.01)	0.05 (0.02)	**0.15 (0.06)**
GBM_B	1:2	**0.12 (0.07)**	0 (0)	**0.81 (0.03)**	0.01 (0)	0.04 (0.01)	**0.12 (0.04)**
GBM_B	1:3	**0.11 (0.07)**	0 (0)	**0.81 (0.03)**	0.01 (0)	0.05 (0.01)	**0.12 (0.04)**
GBM_B	10,000	**0.1 (0.06)**	0 (0)	**0.82 (0.02)**	0.01 (0)	0.05 (0.01)	**0.11 (0.04)**
GBM_O	1:1	**0.16 (0.07)**	0.01 (0)	**0.66 (0.06)**	0.02 (0.01)	**0.08 (0.03)**	**0.12 (0.03)**
GBM_O	1:2	**0.16 (0.08)**	0 (0)	**0.66 (0.05)**	0.01 (0.01)	**0.09 (0.02)**	**0.14 (0.02)**
GBM_O	1:3	**0.18 (0.08)**	0 (0)	**0.64 (0.05)**	0.01 (0)	**0.09 (0.02)**	**0.14 (0.03)**
GBM_O	10,000	**0.18 (0.08)**	0 (0)	**0.63 (0.05)**	0.01 (0)	**0.1 (0.02)**	**0.15 (0.02)**
GLM_B	1:1	**0.12 (0.05)**	0.01 (0.02)	**0.75 (0.1)**	0.03 (0.02)	**0.1 (0.05)**	0.01 (0.02)
GLM_B	1:2	**0.12 (0.05)**	0.02 (0.02)	**0.75 (0.13)**	0.04 (0.02)	**0.1 (0.05)**	0.02 (0.02)
GLM_B	1:3	**0.12 (0.05)**	0.02 (0.02)	**0.74 (0.14)**	0.04 (0.01)	**0.11 (0.04)**	0.02 (0.02)
GLM_B	10,000	**0.12 (0.05)**	0.03 (0.01)	**0.73 (0.16)**	0.05 (0.01)	**0.11 (0.04)**	0.02 (0.01)
GLM_O	1:1	**0.13 (0.13)**	0.01 (0.01)	**0.15 (0.1)**	0.01 (0.02)	**0.13 (0.17)**	0.02 (0.04)
GLM_O	1:2	**0.13 (0.13)**	0.01 (0.01)	**0.23 (0.21)**	0.01 (0.02)	**0.1 (0.12)**	0.02 (0.03)

Table B2.2 (continued)

Algorithm	Pseudo-absence level	BIO01	BIO02	BIO13	BIO14	EV	GDD
GLM_O	1:3	**0.14 (0.13)**	0.01 (0.02)	**0.21 (0.2)**	0.01 (0.01)	**0.13 (0.16)**	0.02 (0.03)
GLM_O	10,000	**0.14 (0.12)**	0.02 (0.02)	**0.25 (0.26)**	0.02 (0.01)	**0.18 (0.18)**	0.01 (0.01)
MARS_B	1:1	0.05 (0.06)	0 (0.01)	**0.66 (0.08)**	0.03 (0.02)	**0.09 (0.05)**	**0.17 (0.08)**
MARS_B	1:2	0.03 (0.04)	0 (0.01)	**0.69 (0.06)**	0.03 (0.02)	**0.11 (0.04)**	**0.14 (0.06)**
MARS_B	1:3	0.02 (0.03)	0 (0.01)	**0.68 (0.07)**	0.03 (0.02)	**0.1 (0.05)**	**0.13 (0.07)**
MARS_B	10,000	0.01 (0.02)	0 (0)	**0.69 (0.06)**	0.04 (0.02)	**0.1 (0.04)**	**0.11 (0.06)**
MARS_O	1:1	0.13 (0.1)	0 (0.01)	**0.44 (0.16)**	**0.06 (0.04)**	**0.07 (0.03)**	**0.19 (0.06)**
MARS_O	1:2	0.13 (0.1)	0 (0.01)	**0.4 (0.13)**	**0.08 (0.03)**	**0.09 (0.03)**	**0.21 (0.04)**
MARS_O	1:3	0.12 (0.1)	0.01 (0.03)	**0.36 (0.11)**	**0.08 (0.04)**	**0.09 (0.03)**	**0.16 (0.09)**
MARS_O	10,000	0.15 (0.08)	0.01 (0.02)	**0.33 (0.09)**	**0.11 (0.03)**	**0.08 (0.03)**	**0.13 (0.08)**
MaxEnt_B	1:1	0.22 (0.17)	0.03 (0.03)	**0.57 (0.15)**	0.05 (0.05)	**0.06 (0.04)**	**0.15 (0.08)**
MaxEnt_B	1:2	0.18 (0.13)	0.03 (0.03)	**0.59 (0.16)**	0.04 (0.04)	**0.05 (0.04)**	**0.15 (0.08)**
MaxEnt_B	1:3	0.17 (0.13)	0.04 (0.03)	**0.63 (0.12)**	0.04 (0.03)	**0.05 (0.04)**	**0.15 (0.06)**
MaxEnt_B	10,000	0.14 (0.09)	0.04 (0.02)	**0.69 (0.11)**	0.03 (0.02)	0.04 (0.02)	**0.13 (0.05)**
MaxEnt_O	1:1	0.15 (0.26)	0.05 (0.1)	**0.47 (0.36)**	0.03 (0.08)	**0.06 (0.17)**	**0.15 (0.19)**
MaxEnt_O	1:2	0.15 (0.25)	0.03 (0.08)	**0.42 (0.33)**	0.03 (0.11)	**0.07 (0.19)**	**0.14 (0.18)**
MaxEnt_O	1:3	0.17 (0.28)	0.05 (0.09)	**0.48 (0.34)**	0.03 (0.1)	0.05 (0.15)	**0.16 (0.19)**
MaxEnt_O	10,000	0.17 (0.27)	0.04 (0.07)	**0.42 (0.34)**	0.04 (0.1)	**0.07 (0.21)**	**0.11 (0.16)**
MXL_O	1:1	0.11 (0.07)	**0.04 (0)**	**0.53 (0.34)**	**0.04 (0)**	0.03 (0.02)	**0.03 (0)**
MXL_O	1:2	0.1 (0.08)	**0.09 (0.02)**	**0.3 (0.31)**	**0.09 (0.02)**	**0.06 (0.07)**	**0.05 (0.01)**
MXL_O	1:3	0.1 (0.09)	**0.09 (0.02)**	**0.3 (0.31)**	**0.09 (0.02)**	**0.06 (0.07)**	**0.05 (0.01)**
MXL_O	10,000	0.07 (0.06)	**0.09 (0.02)**	**0.15 (0.19)**	**0.09 (0.02)**	0.05 (0.05)	**0.05 (0.01)**
RF_B	1:1	0.21 (0.1)	**0.07 (0.01)**	**0.43 (0.07)**	**0.07 (0.01)**	**0.15 (0.05)**	**0.13 (0.01)**
RF_B	1:2	0.22 (0.09)	**0.08 (0.01)**	**0.4 (0.08)**	**0.08 (0.01)**	**0.16 (0.06)**	**0.14 (0.01)**

Table B2.2 (continued)

Algorithm	Pseudo-absence level	BIO01	BIO02	BIO13	BIO14	EV	GDD
RF_B	1:3	0.23 (0.09)	**0.08 (0.01)**	**0.36 (0.08)**	**0.09 (0.01)**	**0.17 (0.06)**	**0.15 (0.01)**
RF_B	10,000	0.24 (0.09)	**0.09 (0.01)**	**0.3 (0.1)**	**0.11 (0.01)**	**0.2 (0.08)**	**0.15 (0.01)**
RF_O	1:1	0.19 (0.07)	**0.09 (0.01)**	**0.33 (0.11)**	**0.08 (0.01)**	**0.14 (0.06)**	**0.15 (0.01)**
RF_O	1:2	0.2 (0.09)	**0.1 (0.01)**	**0.29 (0.1)**	**0.1 (0.01)**	**0.16 (0.07)**	**0.14 (0.01)**
RF_O	1:3	0.2 (0.1)	**0.1 (0.01)**	**0.26 (0.09)**	**0.11 (0.01)**	**0.17 (0.07)**	**0.14 (0.01)**
RF_O	10,000	0.21 (0.1)	**0.11 (0.01)**	**0.22 (0.08)**	**0.12 (0.01)**	**0.18 (0.09)**	**0.14 (0.01)**
SRE_B	1:1	0.18 (0.08)	**0.1 (0.01)**	**0.32 (0.14)**	**0.07 (0.01)**	**0.21 (0.08)**	**0.06 (0.01)**
SRE_B	1:2	0.18 (0.07)	**0.11 (0.01)**	**0.34 (0.14)**	**0.07 (0.01)**	**0.21 (0.07)**	0.05 (0)
SRE_B	1:3	0.18 (0.06)	**0.11 (0.01)**	**0.35 (0.14)**	**0.06 (0.01)**	**0.2 (0.07)**	0.05 (0)
SRE_B	10,000	0.17 (0.06)	**0.11 (0)**	**0.36 (0.15)**	**0.06 (0.01)**	**0.2 (0.06)**	0.04 (0)
SRE_O	1:1	0.11 (0.05)	**0.12 (0.02)**	**0.17 (0.12)**	**0.11 (0.02)**	**0.25 (0.23)**	0.03 (0)
SRE_O	1:2	0.11 (0.05)	**0.12 (0.02)**	**0.17 (0.12)**	**0.11 (0.02)**	**0.25 (0.23)**	0.03 (0)
SRE_O	1:3	0.11 (0.05)	**0.12 (0.02)**	**0.17 (0.12)**	**0.11 (0.02)**	**0.25 (0.23)**	0.03 (0)
SRE_O	10,000	0.11 (0.05)	**0.12 (0.02)**	**0.17 (0.12)**	**0.11 (0.02)**	**0.25 (0.23)**	0.03 (0)
Algorithm	**Pseudo-absence level**	**L_DBF**	**L_ENF**	**L_MF**	**L_UB**	**L_WS**	**L_WT**
ANN_B	1:1	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
ANN_B	1:2	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
ANN_B	1:3	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
ANN_B	10,000	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
ANN_O	1:1	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
ANN_O	1:2	0.02 (0.03)	0.02 (0.03)	0.02 (0.03)	0.02 (0.03)	0.02 (0.03)	0.02 (0.03)
ANN_O	1:3	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)
ANN_O	10,000	**0.06 (0.02)**	**0.06 (0.02)**	**0.06 (0.02)**	**0.06 (0.02)**	**0.06 (0.02)**	**0.06 (0.02)**

Table B2.2 (continued)

Algorithm	Pseudo-absence level	L_DBF	L_ENF	L_MF	L_UB	L_WS	L_WT
CTA_B	1:1	0.01 (0.01)	0 (0)	0 (0.01)	0 (0.01)	0.02 (0.01)	0 (0.01)
CTA_B	1:2	0.01 (0.01)	0 (0)	0 (0)	0.01 (0.01)	0.02 (0.01)	0 (0)
CTA_B	1:3	0.01 (0.01)	0 (0)	0 (0.01)	0.01 (0.01)	0.02 (0.01)	0 (0)
CTA_B	10,000	0.01 (0.01)	0 (0)	0 (0)	0.01 (0.01)	0.02 (0.01)	0 (0)
CTA_O	1:1	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
CTA_O	1:2	0 (0)	0 (0.01)	0 (0)	0 (0)	0 (0)	0 (0)
CTA_O	1:3	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
CTA_O	10,000	0 (0)	0 (0)	0 (0.01)	0 (0)	0 (0)	0 (0)
EMca_B	1:1	0.02 (0.01)	0 (0)	0.01 (0.01)	0.01 (0)	0.02 (0.01)	0.01 (0)
EMca_B	1:2	0.03 (0.01)	0 (0)	0.01 (0.01)	0.01 (0)	0.02 (0.01)	0.01 (0)
EMca_B	1:3	0.02 (0.01)	0 (0)	0.01 (0)	0.01 (0)	0.02 (0.01)	0.01 (0)
EMca_B	10,000	0.03 (0.01)	0.01 (0)	0.01 (0)	0.01 (0)	0.03 (0.01)	0.01 (0)
EMmean_B	1:1	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
EMmean_B	1:2	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
EMmean_B	1:3	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
EMmean_B	10,000	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
EMmedian_B	1:1	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
EMmedian_B	1:2	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
EMmedian_B	1:3	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
EMmedian_B	10,000	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
EMwmean_B	1:1	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
EMwmean_B	1:2	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
EMwmean_B	1:3	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
EMwmean_B	10,000	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)

Table B2.2 (continued)

Algorithm	Pseudo-absence level	L_DBF	L_ENF	L_MF	L_UB	L_WS	L_WT
FDA_B	1:1	0.01 (0.01)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
FDA_B	1:2	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
FDA_B	1:3	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
FDA_B	10,000	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
EMmean_B	1:1	0.02 (0.05)	0 (0)	0 (0.01)	0 (0.02)	0 (0.01)	0 (0)
EMmean_B	1:2	0.01 (0.03)	0 (0.01)	0 (0.01)	0 (0.02)	0 (0.01)	0 (0)
EMmean_B	1:3	0.02 (0.05)	0 (0.01)	0 (0.01)	0 (0.01)	0 (0.01)	0 (0.01)
EMmean_B	10,000	0.01 (0.03)	0 (0)	0 (0.01)	0 (0.02)	0 (0.01)	0 (0)
FDA_O	1:1	0 (0)	0 (0)	0.01 (0.01)	0.01 (0)	0.01 (0)	0.01 (0)
FDA_O	1:2	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0.01 (0)
FDA_O	1:3	0 (0)	0 (0)	0 (0)	0.01 (0)	0.01 (0)	0.01 (0)
FDA_O	10,000	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
GAM_B	1:1	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
GAM_B	1:2	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
GAM_B	1:3	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
GAM_B	10,000	0 (0)	0.01 (0)	0 (0)	0.01 (0)	0.01 (0)	0.01 (0)
GAM_O	1:1	0 (0)	0 (0)	0 (0)	0.02 (0.13)	0.01 (0.08)	0.05 (0.2)
GAM_O	1:2	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
GAM_O	1:3	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	**0.06 (0.18)**
GAM_O	10,000	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0.05 (0.17)
GBM_B	1:1	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
GBM_B	1:2	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
GBM_B	1:3	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
GBM_B	10,000	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)

Table B2.2 (continued)

Algorithm	Pseudo-absence level	L_DBF	L_ENF	L_MF	L_UB	L_WS	L_WT
GBM_O	1:1	0.01 (0)	0 (0)	0.01 (0.01)	0.01 (0.01)	0.02 (0.01)	0.01 (0.01)
GBM_O	1:2	0.01 (0)	0 (0)	0.02 (0.01)	0.01 (0)	0.02 (0.01)	0.01 (0.01)
GBM_O	1:3	0 (0)	0 (0)	0.02 (0.01)	0.01 (0)	0.02 (0.01)	0.01 (0.01)
GBM_O	10,000	0 (0)	0 (0)	0.03 (0.01)	0.01 (0)	0.02 (0)	0.01 (0)
GLM_B	1:1	0 (0.01)	0 (0)	0 (0.01)	0 (0)	0 (0)	0 (0)
GLM_B	1:2	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
GLM_B	1:3	0 (0.01)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
GLM_B	10,000	0 (0.01)	0 (0)	0 (0)	0 (0)	0 (0)	0.01 (0)
GLM_O	1:1	0.01 (0.02)	0.02 (0.11)	**0.15 (0.34)**	0.03 (0.14)	0.1 (0.11)	0.23 (0.26)
GLM_O	1:2	0 (0.01)	0.02 (0.11)	**0.1 (0.28)**	0.02 (0.12)	0.09 (0.09)	0.3 (0.29)
GLM_O	1:3	0 (0.01)	0.01 (0.09)	**0.23 (0.41)**	0 (0.01)	0.06 (0.06)	0.19 (0.24)
GLM_O	10,000	0 (0)	0.04 (0.17)	**0.22 (0.4)**	0 (0.01)	0.03 (0.04)	0.09 (0.21)
MARS_B	1:1	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
MARS_B	1:2	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
MARS_B	1:3	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
MARS_B	10,000	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
MARS_O	1:1	0.01 (0.03)	0 (0)	0 (0.01)	0.01 (0.02)	0.01 (0.02)	0 (0.01)
MARS_O	1:2	0.01 (0.03)	0 (0)	0 (0.01)	0 (0.01)	0.01 (0.02)	0 (0)
MARS_O	1:3	0.01 (0.02)	0 (0)	0 (0.01)	0 (0.01)	0.02 (0.03)	0 (0)
MARS_O	10,000	0 (0)	0 (0)	0 (0)	0 (0)	0.02 (0.03)	0 (0)
MaxEnt_B	1:1	0.02 (0.05)	0.04 (0.07)	0.04 (0.08)	0.01 (0.02)	0.01 (0.01)	0.02 (0.02)
MaxEnt_B	1:2	0.01 (0.04)	0.05 (0.09)	0.05 (0.08)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
MaxEnt_B	1:3	0 (0.01)	0.02 (0.04)	0.03 (0.04)	0.01 (0.02)	0.01 (0.01)	0.02 (0.02)
MaxEnt_B	10,000	0 (0.02)	0.02 (0.05)	0.03 (0.04)	0.01 (0)	0.01 (0.02)	0.01 (0.01)

Table B2.2 (continued)

Algorithm	Pseudo-absence level	L_DBF	L_ENF	L_MF	L_UB	L_WS	L_WT
MaxEnt_O	1:1	0.01 (0.03)	0.04 (0.09)	0.05 (0.1)	0.01 (0.06)	0 (0.03)	0.04 (0.09)
MaxEnt_O	1:2	0.01 (0.04)	**0.07 (0.12)**	**0.08 (0.2)**	0.01 (0.05)	0 (0)	0.04 (0.08)
MaxEnt_O	1:3	0.01 (0.03)	**0.05 (0.11)**	0.05 (0.1)	0.02 (0.05)	0 (0.03)	0.05 (0.09)
MaxEnt_O	10,000	0.01 (0.03)	**0.05 (0.1)**	**0.07 (0.19)**	0.04 (0.11)	0.01 (0.03)	0.03 (0.07)
MXL_O	1:1	**0.03 (0)**	**0.03 (0)**	**0.03 (0)**	**0.03 (0)**	**0.03 (0)**	**0.03 (0)**
MXL_O	1:2	**0.05 (0.01)**	**0.05 (0.01)**	**0.05 (0.01)**	**0.05 (0.01)**	**0.05 (0.01)**	**0.05 (0.01)**
MXL_O	1:3	**0.05 (0.01)**	**0.05 (0.01)**	**0.05 (0.01)**	**0.05 (0.01)**	**0.05 (0.01)**	**0.05 (0.01)**
MXL_O	10,000	**0.05 (0.01)**	**0.05 (0.01)**	**0.05 (0.01)**	**0.05 (0.01)**	**0.05 (0.01)**	**0.05 (0.01)**
RF_B	1:1	0.03 (0)	0 (0)	0.01 (0)	0.01 (0)	0.03 (0)	0.01 (0)
RF_B	1:2	0.03 (0)	0 (0)	0.01 (0)	0.01 (0)	0.03 (0)	0.01 (0)
RF_B	1:3	0.03 (0)	0 (0)	0.01 (0)	0.01 (0)	0.03 (0)	0.01 (0)
RF_B	10,000	0.02 (0)	0 (0)	0.01 (0)	0.01 (0)	0.02 (0)	0.01 (0)
RF_O	1:1	0.03 (0)	0 (0)	0.01 (0)	0.01 (0)	0.03 (0)	0.01 (0)
RF_O	1:3	0.03 (0)	0 (0)	0.01 (0)	0.01 (0)	0.03 (0)	0.01 (0)
RF_O	10,000	0.03 (0)	0 (0)	0.01 (0)	0.01 (0)	0.03 (0)	0.01 (0)
SRE_B	1:1	0.03 (0)	0 (0)	0.01 (0)	0.01 (0)	0.02 (0)	0.01 (0)
SRE_B	1:2	0 (0)	0.02 (0)	0.03 (0)	0.02 (0)	0.03 (0)	0.02 (0)
SRE_B	1:3	0 (0)	0.02 (0)	0.02 (0)	0.02 (0)	0.02 (0)	0.01 (0)
SRE_B	10,000	0 (0)	0.02 (0)	0.02 (0)	0.01 (0)	0.02 (0)	0.01 (0)
SRE_O	1:1	0 (0)	0.02 (0)	0.02 (0)	0.01 (0)	0.02 (0)	0.01 (0)
SRE_O	1:2	0.04 (0)	0.04 (0)	0.04 (0)	0.05 (0)	**0.05 (0.01)**	0.04 (0.02)
SRE_O	1:3	0.04 (0)	0.04 (0)	0.05 (0)	0.05 (0)	**0.05 (0.01)**	0.04 (0.02)
SRE_O	10,000	0.04 (0)	0.04 (0)	0.05 (0)	0.05 (0)	**0.05 (0.01)**	0.04 (0.02)

Table B2.2 (continued)

Algorithm	**Pseudo-absence level**	**NDVI**	**PD**	**SC**
ANN_B	1:1	0.05 (0.02)	0.03 (0.01)	0.01 (0)
ANN_B	1:2	0.04 (0.02)	0.02 (0.01)	0 (0)
ANN_B	1:3	0.04 (0.02)	0.02 (0.01)	0 (0)
ANN_B	10,000	0.04 (0.02)	0.02 (0.01)	0 (0)
ANN_O	1:1	**0.06 (0.04)**	**0.14 (0.19)**	0 (0)
ANN_O	1:2	**0.07 (0.06)**	**0.12 (0.14)**	0.02 (0.03)
ANN_O	1:3	**0.09 (0.06)**	**0.12 (0.12)**	0.03 (0.03)
ANN_O	10,000	**0.07 (0.01)**	**0.08 (0.05)**	**0.06 (0.02)**
CTA_B	1:1	0.04 (0.03)	0.03 (0.02)	0 (0)
CTA_B	1:2	0.05 (0.02)	0.03 (0.02)	0 (0)
CTA_B	1:3	**0.07 (0.04)**	0.04 (0.02)	0 (0)
CTA_B	10,000	**0.09 (0.03)**	0.04 (0.02)	0 (0)
CTA_O	1:1	0 (0.02)	0 (0)	0 (0)
CTA_O	1:2	0 (0.01)	0 (0)	0 (0)
CTA_O	1:3	0.01 (0.02)	0 (0)	0 (0)
EMca_B	1:1	0.02 (0.03)	0 (0)	0 (0)
EMca_B	1:2	0.04 (0.04)	0.04 (0.02)	0 (0)
EMca_B	1:3	**0.05 (0.05)**	0.04 (0.02)	0 (0)
EMca_B	10,000	**0.06 (0.06)**	0.03 (0.02)	0 (0)
EMmean_B	1:1	**0.07 (0.07)**	0.04 (0.01)	0 (0)
EMmean_B	1:2	0.01 (0.01)	0 (0)	0.01 (0)
EMmean_B	1:3	0.02 (0.02)	0 (0)	0.01 (0)
EMmean_B	10,000	0.04 (0.02)	0 (0)	0.01 (0)
EMmedian_B	1:1	0.01 (0.01)	0 (0)	0.01 (0)

Table B2.2 (continued)

Algorithm	**Pseudo-absence level**	**NDVI**	**PD**	**SC**
EMmedian_B	1:2	0.02 (0.02)	0 (0)	0.01 (0)
EMmedian_B	1:3	0.03 (0.02)	0 (0)	0.01 (0)
EMmedian_B	10,000	0.04 (0.03)	0 (0)	0.01 (0)
EMwmean_B	1:1	0.01 (0.01)	0 (0)	0.01 (0)
EMwmean_B	1:2	0.02 (0.02)	0 (0)	0.01 (0)
EMwmean_B	1:3	0.02 (0.02)	0 (0)	0.01 (0)
EMwmean_B	10,000	0.04 (0.02)	0 (0)	0.01 (0)
FDA_B	1:1	0.02 (0.02)	0 (0)	0.01 (0)
FDA_B	1:2	0.04 (0.02)	0 (0)	0.01 (0)
FDA_B	1:3	0.04 (0.02)	0 (0)	0.01 (0)
FDA_B	10,000	**0.05 (0.02)**	0 (0)	0.02 (0)
FDA_O	1:1	0.03 (0.04)	0 (0.01)	0.02 (0.03)
FDA_O	1:2	0.03 (0.04)	0 (0.01)	0.03 (0.04)
FDA_O	1:3	0.03 (0.05)	0 (0.01)	0.02 (0.04)
FDA_O	10,000	0.02 (0.04)	0 (0.01)	0.02 (0.03)
GAM_B	1:1	0.02 (0.02)	0.01 (0.01)	0.02 (0)
GAM_B	1:2	0.03 (0.02)	0 (0)	0.01 (0)
GAM_B	1:3	0.03 (0.03)	0 (0)	0.01 (0)
GAM_B	10,000	0.04 (0.03)	0.01 (0)	0.01 (0)
GAM_O	1:1	0.01 (0.01)	0 (0)	**0.23 (0.34)**
GAM_O	1:2	0.01 (0)	0 (0)	**0.06 (0.05)**
GBM_B	1:1	0.01 (0.01)	0 (0)	0.03 (0.04)
GBM_B	1:2	0.02 (0.01)	0 (0)	0.01 (0)
GBM_B	1:3	0.02 (0.01)	0 (0)	0 (0)

Table B2.2 (continued)

Algorithm	**Pseudo-absence level**	**NDVI**	**PD**	**SC**
GBM_B	10,000	0.02 (0.01)	0 (0)	0 (0)
GBM_O	1:1	0.03 (0.01)	0.04 (0.02)	0.01 (0)
GBM_O	1:2	0.03 (0.01)	0.02 (0.01)	0.01 (0)
GBM_O	1:3	0.03 (0.01)	0.02 (0.01)	0.01 (0)
GBM_O	10,000	0.04 (0.01)	0.01 (0)	0.02 (0.01)
GLM_B	1:1	0.01 (0.02)	0 (0)	0.02 (0)
GLM_B	1:2	0.02 (0.03)	0 (0)	0.02 (0)
GLM_B	1:3	0.04 (0.03)	0 (0)	0.01 (0)
GLM_B	10,000	0.05 (0.03)	0 (0)	0.01 (0)
GLM_O	1:1	0.01 (0.02)	0.01 (0.05)	**0.08 (0.14)**
GLM_O	1:2	0.01 (0.02)	0 (0.01)	0.03 (0.03)
GLM_O	1:3	0.02 (0.02)	0 (0)	0.02 (0.02)
GLM_O	10,000	0.01 (0.01)	0 (0)	0.01 (0.01)
MARS_B	1:1	0.04 (0.04)	0 (0)	0.02 (0.01)
MARS_B	1:2	0.05 (0.05)	0 (0)	0.01 (0)
MARS_B	1:3	0.05 (0.05)	0 (0)	0.01 (0)
MARS_B	10,000	**0.05 (0.04)**	0 (0)	0.01 (0)
MARS_O	1:1	0.04 (0.04)	0 (0.01)	0.05 (0.03)
MARS_O	1:2	0.05 (0.04)	0 (0.01)	**0.06 (0.03)**
MARS_O	1:3	**0.05 (0.04)**	0 (0)	**0.08 (0.03)**
MARS_O	10,000	**0.05 (0.04)**	0 (0)	**0.1 (0.03)**
MaxEnt_B	1:1	0.05 (0.03)	0.01 (0.02)	0.01 (0.01)
MaxEnt_B	1:2	0.04 (0.03)	0.01 (0.02)	0.01 (0.03)
MaxEnt_B	1:3	**0.05 (0.03)**	0.01 (0.02)	0.01 (0)

Table B2.2 (continued)

Algorithm	**Pseudo-absence level**	**NDVI**	**PD**	**SC**
MaxEnt_B	10,000	**0.06 (0.03)**	0.01 (0.01)	0.01 (0.01)
MaxEnt_O	1:1	**0.19 (0.33)**	0 (0.02)	0.02 (0.06)
MaxEnt_O	1:2	**0.14 (0.28)**	0.01 (0.03)	0.03 (0.07)
MaxEnt_O	1:3	**0.19 (0.31)**	0.01 (0.06)	0.02 (0.06)
MaxEnt_O	10,000	**0.21 (0.34)**	0 (0)	0.05 (0.09)
MXL_O	1:1	**0.04 (0)**	**0.04 (0)**	**0.04 (0)**
MXL_O	1:2	**0.09 (0.02)**	**0.09 (0.02)**	**0.09 (0.02)**
MXL_O	1:3	**0.09 (0.02)**	**0.09 (0.02)**	**0.09 (0.02)**
MXL_O	10,000	**0.09 (0.02)**	**0.09 (0.02)**	**0.09 (0.02)**
RF_B	1:1	**0.1 (0.02)**	0.04 (0.01)	0 (0)
RF_B	1:2	**0.09 (0.01)**	0.04 (0)	0 (0)
RF_B	1:3	**0.09 (0.01)**	0.05 (0)	0 (0)
RF_B	10,000	**0.08 (0.01)**	**0.06 (0.01)**	0 (0)
RF_O	1:1	**0.13 (0.01)**	0.04 (0)	0 (0)
RF_O	1:2	**0.12 (0.01)**	0.05 (0)	0 (0)
RF_O	1:3	**0.11 (0.01)**	**0.06 (0.01)**	0 (0)
RF_O	10,000	**0.11 (0.01)**	**0.07 (0.01)**	0 (0)
SRE_B	1:1	**0.15 (0.01)**	**0.14 (0.01)**	0.01 (0)
SRE_B	1:2	**0.16 (0.01)**	**0.14 (0.01)**	0.01 (0)
SRE_B	1:3	**0.16 (0.01)**	**0.14 (0.01)**	0 (0)
SRE_B	10,000	**0.16 (0.01)**	**0.14 (0.01)**	0 (0)
SRE_O	1:1	**0.13 (0.03)**	**0.14 (0.03)**	**0.15 (0.03)**
SRE_O	1:2	**0.13 (0.03)**	**0.14 (0.03)**	**0.14 (0.03)**
SRE_O	1:3	**0.13 (0.03)**	**0.14 (0.03)**	**0.15 (0.03)**

Table B2.2 (continued)

Algorithm	**Pseudo-absence level**	**NDVI**	**PD**	**SC**
SRE_O	10,000	**0.13 (0.03)**	**0.14 (0.03)**	**0.14 (0.03)**

Table B2.3: Results of Type II Wald $\chi 2$ tests. Metric abbreviations available in Table 3.3.

Metric	Validation	Model building consideration	DF	$\chi 2$	p-value
J	-	Pseudo-absence level	3	27.59	<0.01
J	-	Algorithm	24	13210.08	<0.01
J	-	Pseudo-absence level:Algorithm	72	796.55	<0.01
RMSE	All driving predictors	Algorithm	24	33462.72	<0.01
RMSE	All driving predictors	Pseudo-absence level	3	165.54	<0.01
RMSE	All driving predictors	Predictor selection	2	64.05	<0.01
RMSE	All driving predictors	Algorithm:Pseudo-absence level	72	2298.25	<0.01
RMSE	All driving predictors	Algorithm:Predictor selection	48	1944.43	<0.01
RMSE	All driving predictors	Pseudo-absence level:Predictor selection	6	21.94	<0.01
RMSE	All driving predictors	Algorithm:Pseudo-absence level:Predictor selection	143	387.39	<0.01
RMSE	BIO1	Algorithm	24	103348.9	<0.01
RMSE	BIO1	Pseudo-absence level	3	1404.26	<0.01
RMSE	BIO1	Predictor selection	2	421.39	<0.01
RMSE	BIO1	Algorithm:Pseudo-absence level	72	14080.33	<0.01
RMSE	BIO1	Algorithm:Predictor selection	48	8921.69	<0.01
RMSE	BIO1	Pseudo-absence level:Predictor selection	6	148.28	<0.01
RMSE	BIO1	Algorithm:Pseudo-absence level:Predictor selection	143	2715.59	<0.01
RMSE	BIO13	Algorithm	24	90221.18	<0.01
RMSE	BIO13	Pseudo-absence level	3	1625.06	<0.01
RMSE	BIO13	Predictor selection	2	609.35	<0.01

Table B2.3 (continued)

Metric	Validation	Model building consideration	DF	χ2	p-value
RMSE	BIO13	Algorithm:Pseudo-absence level	72	15453.45	<0.01
RMSE	BIO13	Algorithm:Predictor selection	48	6729.63	<0.01
RMSE	BIO13	Pseudo-absence level:Predictor selection	6	147.95	<0.01
RMSE	BIO13	Algorithm:Pseudo-absence level:Predictor selection	143	1632.28	<0.01
RMSE	Elevation	Algorithm	24	111553.1	<0.01
RMSE	Elevation	Pseudo-absence level	3	2888.47	<0.01
RMSE	Elevation	Predictor selection	2	305.09	<0.01
RMSE	Elevation	Algorithm:Pseudo-absence level	72	22971.96	<0.01
RMSE	Elevation	Algorithm:Predictor selection	48	7739.82	<0.01
RMSE	Elevation	Pseudo-absence level:Predictor selection	6	55.92	<0.01
RMSE	Elevation	Algorithm:Pseudo-absence level:Predictor selection	143	2666	<0.01
ρ	All driving predictors	Algorithm	24	239118.13	<0.01
ρ	All driving predictors	Pseudo-absence level	3	747.97	<0.01
ρ	All driving predictors	Predictor selection	2	6143.5	<0.01
ρ	All driving predictors	Algorithm:Pseudo-absence level	72	16390.76	<0.01
ρ	All driving predictors	Algorithm:Predictor selection	48	7510.89	<0.01
ρ	All driving predictors	Pseudo-absence level:Predictor selection	6	28.38	<0.01
ρ	All driving predictors	Algorithm:Pseudo-absence level:Predictor selection	143	904.56	<0.01
ρ	BIO1	Algorithm	24	108254	<0.01

Table B2.3 (continued)

Metric	Validation	Model building consideration	DF	χ2	p-value
ρ	BIO1	Pseudo-absence level	3	47	<0.01
ρ	BIO1	Predictor selection	2	1142.47	<0.01
ρ	BIO1	Algorithm:Pseudo-absence level	72	7639.72	<0.01
ρ	BIO1	Algorithm:Predictor selection	48	12664.49	<0.01
ρ	BIO1	Pseudo-absence level:Predictor selection	6	274.99	<0.01
ρ	BIO1	Algorithm:Pseudo-absence level:Predictor selection	143	2787.82	<0.01
ρ	BIO13	Algorithm	24	187471.45	<0.01
ρ	BIO13	Pseudo-absence level	3	109.47	<0.01
ρ	BIO13	Predictor selection	2	27974.04	<0.01
ρ	BIO13	Algorithm:Pseudo-absence level	72	11674.69	<0.01
ρ	BIO13	Algorithm:Predictor selection	48	22602.87	<0.01
ρ	BIO13	Pseudo-absence level:Predictor selection	6	344.34	<0.01
ρ	BIO13	Algorithm:Pseudo-absence level:Predictor selection	143	6315.27	<0.01
ρ	Elevation	Algorithm	24	114759.47	<0.01
ρ	Elevation	Pseudo-absence level	3	353.02	<0.01
ρ	Elevation	Predictor selection	2	1951.5	<0.01
ρ	Elevation	Algorithm:Pseudo-absence level	72	12925.11	<0.01
ρ	Elevation	Algorithm:Predictor selection	48	18011.47	<0.01
ρ	Elevation	Pseudo-absence level:Predictor selection	6	60.56	<0.01

Table B2.3 (continued)

Metric	Validation	Model building consideration	DF	χ2	p-value
ρ	Elevation	Algorithm:Pseudo-absence level:Predictor selection	143	1451.69	<0.01
CBI	Training region	Pseudo-absence level	3	91.56	<0.01
CBI	Training region	Predictor selection	2	2606.67	<0.01
CBI	Training region	Algorithm:Pseudo-absence level	72	3545.56	<0.01
CBI	Training region	Algorithm:Predictor selection	48	3263.37	<0.01
CBI	Training region	Pseudo-absence level:Predictor selection	6	184.67	<0.01
CBI	Training region	Algorithm:Pseudo-absence level:Predictor selection	144	1559.92	<0.01
CBI	Testing region	Algorithm	24	34946.64	<0.01
CBI	Testing region	Pseudo-absence level	3	68.79	<0.01
CBI	Testing region	Predictor selection	2	2931.1	<0.01
CBI	Testing region	Algorithm:Pseudo-absence level	72	3365.36	<0.01
CBI	Testing region	Algorithm:Predictor selection	48	5678.22	<0.01
CBI	Testing region	Pseudo-absence level:Predictor selection	6	46.34	<0.01
CBI	Testing region	Algorithm:Pseudo-absence level:Predictor selection	144	2075.88	<0.01
CBI	Training region	Algorithm	24	49435.82	<0.01
CBI	Minimal difference	Algorithm	24	26750.55	<0.01
CBI	Minimal difference	Pseudo-absence level	3	248.2	<0.01
CBI	Minimal difference	Predictor selection	2	1975.53	<0.01
CBI	Minimal difference	Algorithm:Pseudo-absence level	72	4186.85	<0.01

Table B2.3 (continued)

Metric	Validation	Model building consideration	DF	$\chi 2$	p-value
CBI	Minimal difference	Algorithm:Predictor selection	48	5011.64	<0.01
CBI	Minimal difference	Pseudo-absence level:Predictor selection	6	155.74	<0.01
CBI	Minimal difference	Algorithm:Pseudo-absence level:Predictor selection	144	1803.86	<0.01
MAE	Training region	Algorithm	24	177039.64	<0.01
MAE	Training region	Pseudo-absence level	3	2556.82	<0.01
MAE	Training region	Predictor selection	2	5226.57	<0.01
MAE	Training region	Algorithm:Pseudo-absence level	72	12541.09	<0.01
MAE	Training region	Algorithm:Predictor selection	48	6382.53	<0.01
MAE	Training region	Pseudo-absence level:Predictor selection	6	12.99	0.04
MAE	Training region	Algorithm:Pseudo-absence level:Predictor selection	144	1113.85	<0.01
MAE	Testing region	Algorithm	24	227831.08	<0.01
MAE	Testing region	Pseudo-absence level	3	650.54	<0.01
MAE	Testing region	Predictor selection	2	250.95	<0.01
MAE	Testing region	Algorithm:Pseudo-absence level	72	7925	<0.01
MAE	Testing region	Algorithm:Predictor selection	48	6281.81	<0.01
MAE	Testing region	Pseudo-absence level:Predictor selection	6	29.73	<0.01
MAE	Testing region	Algorithm:Pseudo-absence level:Predictor selection	144	1561.88	<0.01
MAE	Minimal difference	Algorithm	24	58917.54	<0.01
MAE	Minimal difference	Pseudo-absence level	3	277.3	<0.01

Table B2.3 (continued)

Metric	Validation	Model building consideration	DF	χ2	p-value
MAE	Minimal difference	Predictor selection	2	5890.35	<0.01
MAE	Minimal difference	Algorithm:Pseudo-absence level	72	12563.53	<0.01
MAE	Minimal difference	Algorithm:Predictor selection	48	14446.66	<0.01
MAE	Minimal difference	Pseudo-absence level:Predictor selection	6	139.4	<0.01
MAE	Minimal difference	Algorithm:Pseudo-absence level:Predictor selection	144	3162.36	<0.01
SS	Training region	Algorithm	24	552261.37	<0.01
SS	Training region	Pseudo-absence level	3	1025.6	<0.01
SS	Training region	Predictor selection	2	1844.7	<0.01
SS	Training region	Algorithm:Pseudo-absence level	72	14427.7	<0.01
SS	Training region	Algorithm:Predictor selection	48	51506.18	<0.01
SS	Training region	Pseudo-absence level:Predictor selection	6	198.3	<0.01
SS	Training region	Algorithm:Pseudo-absence level:Predictor selection	144	6346.06	<0.01
SS	Testing region	Algorithm	24	633419.76	<0.01
SS	Testing region	Pseudo-absence level	3	153.29	<0.01
SS	Testing region	Predictor selection	2	6165.82	<0.01
SS	Testing region	Algorithm:Pseudo-absence level	72	33827.79	<0.01
SS	Testing region	Algorithm:Predictor selection	48	30102.95	<0.01
SS	Testing region	Pseudo-absence level:Predictor selection	6	322.05	<0.01
SS	Testing region	Algorithm:Pseudo-absence level:Predictor selection	144	7637.99	<0.01

Table B2.3 (continued)

Metric	Validation	Model building consideration	DF	χ2	p-value
SS	Minimal difference	Algorithm	24	131295.45	<0.01
SS	Minimal difference	Pseudo-absence level	3	608.97	<0.01
SS	Minimal difference	Predictor selection	2	7845.53	<0.01
SS	Minimal difference	Algorithm:Pseudo-absence level	72	7044.39	<0.01
SS	Minimal difference	Algorithm:Predictor selection	48	19537.61	<0.01
SS	Minimal difference	Pseudo-absence level:Predictor selection	6	125.23	<0.01
SS	Minimal difference	Algorithm:Pseudo-absence level:Predictor selection	144	4450.19	<0.01
BS	Training region	Algorithm	24	110092.2	<0.01
BS	Training region	Pseudo-absence level	3	2316.84	<0.01
BS	Training region	Predictor selection	2	8273.29	<0.01
BS	Training region	Algorithm:Pseudo-absence level	72	15277.54	<0.01
BS	Training region	Algorithm:Predictor selection	48	10806.05	<0.01
BS	Training region	Pseudo-absence level:Predictor selection	6	20.05	<0.01
BS	Training region	Algorithm:Pseudo-absence level:Predictor selection	144	2005.81	<0.01
BS	Testing region	Algorithm	24	64088.45	<0.01
BS	Testing region	Pseudo-absence level	3	823.29	<0.01
BS	Testing region	Predictor selection	2	123.76	<0.01
BS	Testing region	Algorithm:Pseudo-absence level	72	11595	<0.01
BS	Testing region	Algorithm:Predictor selection	48	5607.54	<0.01
BS	Testing region	Pseudo-absence level:Predictor selection	6	36.51	<0.01

Table B2.3 (continued)

Metric	Validation	Model building consideration	DF	χ2	p-value
BS	Testing region	Algorithm:Pseudo-absence level:Predictor selection	144	1738.73	<0.01
BS	Minimal difference	Algorithm	24	39513.9	<0.01
BS	Minimal difference	Pseudo-absence level	3	329.58	<0.01
BS	Minimal difference	Predictor selection	2	9341.7	<0.01
BS	Minimal difference	Algorithm:Pseudo-absence level	72	7422.98	<0.01
BS	Minimal difference	Algorithm:Predictor selection	48	22224.74	<0.01
BS	Minimal difference	Pseudo-absence level:Predictor selection	6	276.69	<0.01
BS	Minimal difference	Algorithm:Pseudo-absence level:Predictor selection	144	3674.41	<0.01
Refinement	Training region	Algorithm	24	94812.98	<0.01
Refinement	Training region	Pseudo-absence level	3	2443.2	<0.01
Refinement	Training region	Predictor selection	2	4617.41	<0.01
Refinement	Training region	Algorithm:Pseudo-absence level	72	14974.06	<0.01
Refinement	Training region	Algorithm:Predictor selection	48	7041.51	<0.01
Refinement	Training region	Pseudo-absence level:Predictor selection	6	20.47	<0.01
Refinement	Training region	Algorithm:Pseudo-absence level:Predictor selection	144	2146.22	<0.01
Refinement	Testing region	Algorithm	24	63649.18	<0.01
Refinement	Testing region	Pseudo-absence level	3	814.58	<0.01
Refinement	Testing region	Predictor selection	2	363.65	<0.01
Refinement	Testing region	Algorithm:Pseudo-absence level	72	11820.48	<0.01

Table B2.3 (continued)

Metric	Validation	Model building consideration	DF	χ2	p-value
Refinement	Testing region	Algorithm:Predictor selection	48	5380.2	<0.01
Refinement	Testing region	Pseudo-absence level:Predictor selection	6	39.97	<0.01
Refinement	Testing region	Algorithm:Pseudo-absence level:Predictor selection	144	1831.78	<0.01
Refinement	Minimal difference	Algorithm	24	29321.07	<0.01
Refinement	Minimal difference	Pseudo-absence level	3	298.19	<0.01
Refinement	Minimal difference	Predictor selection	2	8277.07	<0.01
Refinement	Minimal difference	Algorithm:Pseudo-absence level	72	5484.14	<0.01
Refinement	Minimal difference	Algorithm:Predictor selection	48	16107.06	<0.01
Refinement	Minimal difference	Pseudo-absence level:Predictor selection	6	176.2	<0.01
Refinement	Minimal difference	Algorithm:Pseudo-absence level:Predictor selection	144	2342.61	<0.01
Resolution	Training region	Algorithm	24	99624.6	<0.01
Resolution	Training region	Pseudo-absence level	3	754.46	<0.01
Resolution	Training region	Predictor selection	2	20521.65	<0.01
Resolution	Training region	Algorithm:Pseudo-absence level	72	9884.04	<0.01
Resolution	Training region	Algorithm:Predictor selection	48	13945.3	<0.01
Resolution	Training region	Pseudo-absence level:Predictor selection	6	110.93	<0.01
Resolution	Training region	Algorithm:Pseudo-absence level:Predictor selection	144	2373.02	<0.01
Resolution	Testing region	Algorithm	24	99030.77	<0.01
Resolution	Testing region	Pseudo-absence level	3	1528.71	<0.01

Table B2.3 (continued)

Metric	**Validation**	**Model building consideration**	**DF**	**χ2**	**p-value**
Resolution	Testing region	Predictor selection	2	5406.13	<0.01
Resolution	Testing region	Algorithm:Pseudo-absence level	72	8933.51	<0.01
Resolution	Testing region	Algorithm:Predictor selection	48	17581.58	<0.01
Resolution	Testing region	Pseudo-absence level:Predictor selection	6	718.37	<0.01
Resolution	Testing region	Algorithm:Pseudo-absence level:Predictor selection	144	2615.46	<0.01
Resolution	Minimal difference	Algorithm	24	38707.1	<0.01
Resolution	Minimal difference	Pseudo-absence level	3	40	<0.01
Resolution	Minimal difference	Predictor selection	2	36300.94	<0.01
Resolution	Minimal difference	Algorithm:Pseudo-absence level	72	6273.14	<0.01
Resolution	Minimal difference	Algorithm:Predictor selection	48	16355.97	<0.01
Resolution	Minimal difference	Pseudo-absence level:Predictor selection	6	363.88	<0.01
Resolution	Minimal difference	Algorithm:Pseudo-absence level:Predictor selection	144	2090.9	<0.01
Sensitivity	Testing region	Algorithm	24	35048	<0.01
Sensitivity	Testing region	Pseudo-absence level	3	60.62	<0.01
Sensitivity	Testing region	Predictor selection	2	2701.67	<0.01
Sensitivity	Testing region	Algorithm:Pseudo-absence level	72	3896.72	<0.01
Sensitivity	Testing region	Algorithm:Predictor selection	48	15229.92	<0.01
Sensitivity	Testing region	Pseudo-absence level:Predictor selection	6	225.18	<0.01
Sensitivity	Testing region	Algorithm:Pseudo-absence level:Predictor selection	144	2419.35	<0.01

Table B2.3 (continued)

Metric	Validation	Model building consideration	DF	χ2	p-value
Sensitivity	Minimal difference	Algorithm	24	35048	<0.01
Sensitivity	Minimal difference	Pseudo-absence level	3	60.62	<0.01
Sensitivity	Minimal difference	Predictor selection	2	2701.67	<0.01
Sensitivity	Minimal difference	Algorithm:Pseudo-absence level	72	3896.72	<0.01
Sensitivity	Minimal difference	Algorithm:Predictor selection	48	15229.92	<0.01
Sensitivity	Minimal difference	Pseudo-absence level:Predictor selection	6	225.18	<0.01
Sensitivity	Minimal difference	Algorithm:Pseudo-absence level:Predictor selection	144	2419.35	<0.01
Specificity	Training region	Algorithm	24	113798.36	<0.01
Specificity	Training region	Pseudo-absence level	3	9.21	<0.01
Specificity	Training region	Predictor selection	2	57.97	<0.01
Specificity	Training region	Algorithm:Pseudo-absence level	72	3146.22	<0.01
Specificity	Training region	Algorithm:Predictor selection	48	2160.28	<0.01
Specificity	Training region	Pseudo-absence level:Predictor selection	6	16.1	0.01
Specificity	Training region	Algorithm:Pseudo-absence level:Predictor selection	144	650.68	<0.01
Specificity	Testing region	Algorithm	24	23754.87	<0.01
Specificity	Testing region	Pseudo-absence level	3	60.74	<0.01
Specificity	Testing region	Predictor selection	2	690.79	<0.01
Specificity	Testing region	Algorithm:Pseudo-absence level	72	1350.59	<0.01
Specificity	Testing region	Algorithm:Predictor selection	48	4625.78	<0.01
Specificity	Testing region	Pseudo-absence level:Predictor selection	6	102.31	<0.01

Table B2.3 (continued)

Metric	Validation	Model building consideration	DF	χ2	p-value
Specificity	Testing region	Algorithm:Pseudo-absence level:Predictor selection	144	607.84	<0.01
Specificity	Minimal difference	Algorithm	24	34450	<0.01
Specificity	Minimal difference	Pseudo-absence level	3	61.84	<0.01
Specificity	Minimal difference	Predictor selection	2	23.88	<0.01
Specificity	Minimal difference	Algorithm:Pseudo-absence level	72	1430.87	<0.01
Specificity	Minimal difference	Algorithm:Predictor selection	48	1952.73	<0.01
Specificity	Minimal difference	Pseudo-absence level:Predictor selection	6	22.35	<0.01
Specificity	Minimal difference	Algorithm:Pseudo-absence level:Predictor selection	144	481.18	<0.01
Precision	Training region	Algorithm	24	242615.4	<0.01
Precision	Training region	Pseudo-absence level	3	139982.96	<0.01
Precision	Training region	Predictor selection	2	18.51	<0.01
Precision	Training region	Algorithm:Pseudo-absence level	72	32825.11	<0.01
Precision	Training region	Algorithm:Predictor selection	48	2269.22	<0.01
Precision	Training region	Pseudo-absence level:Predictor selection	6	35.65	<0.01
Precision	Training region	Algorithm:Pseudo-absence level:Predictor selection	144	924.11	<0.01
Precision	Testing region	Algorithm	24	34662.13	<0.01
Precision	Testing region	Pseudo-absence level	3	96	<0.01
Precision	Testing region	Predictor selection	2	695.11	<0.01
Precision	Testing region	Algorithm:Pseudo-absence level	72	3030.96	<0.01

Table B2.3 (continued)

Metric	Validation	Model building consideration	DF	χ2	p-value
Precision	Testing region	Algorithm:Predictor selection	48	17609.79	<0.01
Precision	Testing region	Pseudo-absence level:Predictor selection	6	217.83	<0.01
Precision	Testing region	Algorithm:Pseudo-absence level:Predictor selection	144	1988.67	<0.01
Precision	Minimal difference	Algorithm	24	58172.87	<0.01
Precision	Minimal difference	Pseudo-absence level	3	28872.99	<0.01
Precision	Minimal difference	Predictor selection	2	334.39	<0.01
Precision	Minimal difference	Algorithm:Pseudo-absence level	72	18370.28	<0.01
Precision	Minimal difference	Algorithm:Predictor selection	48	5466.48	<0.01
Precision	Minimal difference	Pseudo-absence level:Predictor selection	6	263.51	<0.01
Precision	Minimal difference	Algorithm:Pseudo-absence level:Predictor selection	144	8147.63	<0.01
F1	Training region	Algorithm	24	258347.8	<0.01
F1	Training region	Pseudo-absence level	3	144182.85	<0.01
F1	Training region	Predictor selection	2	14	<0.01
F1	Training region	Algorithm:Pseudo-absence level	72	36327.15	<0.01
F1	Training region	Algorithm:Predictor selection	48	2131.61	<0.01
F1	Training region	Pseudo-absence level:Predictor selection	6	42.78	<0.01
F1	Training region	Algorithm:Pseudo-absence level:Predictor selection	144	1020.75	<0.01
F1	Testing region	Algorithm	24	37396.04	<0.01
F1	Testing region	Pseudo-absence level	3	42.77	<0.01

Table B2.3 (continued)

Metric	Validation	Model building consideration	DF	χ2	p-value
F1	Testing region	Predictor selection	2	268.66	<0.01
F1	Testing region	Algorithm:Pseudo-absence level	72	2837.45	<0.01
F1	Testing region	Algorithm:Predictor selection	48	5932.84	<0.01
F1	Testing region	Pseudo-absence level:Predictor selection	6	127.14	<0.01
F1	Testing region	Algorithm:Pseudo-absence level:Predictor selection	144	1457.13	<0.01
F1	Minimal difference	Algorithm	24	77346.37	<0.01
F1	Minimal difference	Pseudo-absence level	3	53553.42	<0.01
F1	Minimal difference	Predictor selection	2	255.49	<0.01
F1	Minimal difference	Algorithm:Pseudo-absence level	72	8463.68	<0.01
F1	Minimal difference	Algorithm:Predictor selection	48	6656.69	<0.01
F1	Minimal difference	Pseudo-absence level:Predictor selection	6	204.04	<0.01
F1	Minimal difference	Algorithm:Pseudo-absence level:Predictor selection	144	1936.96	<0.01
CCR	Training region	Algorithm	24	149147.96	<0.01
CCR	Training region	Pseudo-absence level	3	14194.6	<0.01
CCR	Training region	Predictor selection	2	61.75	<0.01
CCR	Training region	Algorithm:Pseudo-absence level	72	18039.57	<0.01
CCR	Training region	Algorithm:Predictor selection	48	2875.34	<0.01
CCR	Training region	Pseudo-absence level:Predictor selection	6	55.07	<0.01
CCR	Training region	Algorithm:Pseudo-absence level:Predictor selection	144	1025.95	<0.01

Table B2.3 (continued)

Metric	Validation	Model building consideration	DF	$\chi 2$	p-value
CCR	Testing region	Algorithm	24	23402.85	<0.01
CCR	Testing region	Pseudo-absence level	3	42.43	<0.01
CCR	Testing region	Predictor selection	2	563.53	<0.01
CCR	Testing region	Algorithm:Pseudo-absence level	72	1481.8	<0.01
CCR	Testing region	Algorithm:Predictor selection	48	5216.92	<0.01
CCR	Testing region	Pseudo-absence level:Predictor selection	6	112.64	<0.01
CCR	Testing region	Algorithm:Pseudo-absence level:Predictor selection	144	688.65	<0.01
CCR	Minimal difference	Algorithm	24	20517.41	<0.01
CCR	Minimal difference	Pseudo-absence level	3	5245.5	<0.01
CCR	Minimal difference	Predictor selection	2	200.65	<0.01
CCR	Minimal difference	Algorithm:Pseudo-absence level	72	6539.1	<0.01
CCR	Minimal difference	Algorithm:Predictor selection	48	1238.2	<0.01
CCR	Minimal difference	Pseudo-absence level:Predictor selection	6	128.72	<0.01
CCR	Minimal difference	Algorithm:Pseudo-absence level:Predictor selection	144	1864.1	<0.01

Table B2.4: Mean (standard deviation) of all explanation and prediction evaluations. Missing residual mean square error and Spearman's correlation values indicate the predictor was not selected.

Algorithm	Pseudo-absences	Predictor selection	Jaccard index	Residual mean square error		
				BIO1	BIO13	Elevation
ANN_B	1:1	*A priori*	0.59 (0.15)	0.34 (0.02)	0.56 (0.03)	0.37 (0.01)
ANN_B	1:2	*A priori*	0.64 (0.14)	0.34 (0.02)	0.56 (0.03)	0.37 (0.01)
ANN_B	1:3	*A priori*	0.65 (0.16)	0.34 (0.03)	0.56 (0.03)	0.37 (0.01)
ANN_B	10000	*A priori*	0.65 (0.18)	0.34 (0.03)	0.56 (0.03)	0.37 (0.01)
ANN_B	1:1	Automated		0.33 (0.03)	0.55 (0.03)	0.37 (0.01)
ANN_B	1:2	Automated		0.33 (0.02)	0.55 (0.02)	0.37 (0.01)
ANN_B	1:3	Automated		0.33 (0.02)	0.55 (0.02)	0.37 (0.01)
ANN_B	10000	Automated		0.33 (0.03)	0.55 (0.03)	0.38 (0.01)
ANN_B	1:1	Expert		0.34 (0.03)	0.56 (0.03)	0.36 (0.01)
ANN_B	1:2	Expert		0.34 (0.04)	0.56 (0.04)	0.37 (0.02)
ANN_B	1:3	Expert		0.32 (0.03)	0.55 (0.03)	0.37 (0.01)
ANN_B	10000	Expert		0.32 (0.03)	0.54 (0.03)	0.38 (0.01)
ANN_O	1:1	*A priori*	0.48 (0.14)	0.29 (0.01)	0.51 (0.01)	0.33 (0.01)
ANN_O	1:2	*A priori*	0.41 (0.17)	0.22 (0.07)	0.31 (0.13)	0.51 (0.15)
ANN_O	1:3	*A priori*	0.33 (0.15)	0.24 (0.09)	0.2 (0.11)	0.63 (0.15)
ANN_O	10000	*A priori*	0.24 (0.11)	0.32 (0.05)	0.09 (0.03)	0.76 (0.06)
ANN_O	1:1	Automated		-	0.5 (0.01)	0.33 (0.02)
ANN_O	1:2	Automated		-	0.31 (0.12)	0.51 (0.15)
ANN_O	1:3	Automated		-	0.2 (0.11)	0.62 (0.14)
ANN_O	10000	Automated		0.33 (0.04)	0.08 (0.02)	0.77 (0.04)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Jaccard index	Residual mean square error BIO1	BIO13	Elevation
ANN_O	1:1	Expert		0.28 (0.01)	0.49 (0.01)	0.34 (0.03)
ANN_O	1:2	Expert		0.21 (0.07)	0.3 (0.12)	0.52 (0.14)
ANN_O	1:3	Expert		0.25 (0.1)	0.18 (0.11)	0.65 (0.14)
ANN_O	10000	Expert		0.33 (0.05)	0.09 (0.02)	0.77 (0.05)
CTA_B	1:1	*A priori*	0.56 (0.14)	0.36 (0.03)	0.56 (0.04)	0.39 (0.02)
CTA_B	1:2	*A priori*	0.54 (0.12)	0.36 (0.03)	0.55 (0.03)	0.41 (0.03)
CTA_B	1:3	*A priori*	0.53 (0.14)	0.35 (0.02)	0.55 (0.02)	0.42 (0.03)
CTA_B	10000	*A priori*	0.45 (0.11)	0.35 (0.02)	0.54 (0.02)	0.43 (0.03)
CTA_B	1:1	Automated		0.35 (0.03)	0.55 (0.03)	0.4 (0.02)
CTA_B	1:2	Automated		0.35 (0.03)	0.55 (0.03)	0.41 (0.02)
CTA_B	1:3	Automated		0.35 (0.02)	0.54 (0.02)	0.42 (0.02)
CTA_B	10000	Automated		0.35 (0.02)	0.54 (0.01)	0.45 (0.02)
CTA_B	1:1	Expert		0.35 (0.03)	0.55 (0.04)	0.39 (0.02)
CTA_B	1:2	Expert		0.34 (0.03)	0.54 (0.03)	0.4 (0.02)
CTA_B	1:3	Expert		0.34 (0.02)	0.54 (0.02)	0.41 (0.02)
CTA_B	10000	Expert		0.33 (0.02)	0.53 (0.01)	0.42 (0.02)
CTA_O	1:1	*A priori*	0.61 (0.13)	0.28 (0.01)	0.5 (0.01)	0.37 (0.01)
CTA_O	1:2	*A priori*	0.58 (0.1)	0.19 (0.01)	0.38 (0.01)	0.45 (0)
CTA_O	1:3	*A priori*	0.54 (0.1)	0.16 (0.01)	0.31 (0.01)	0.5 (0)
CTA_O	10000	*A priori*	0.46 (0.14)	0.18 (0.01)	0.18 (0.01)	0.61 (0)
CTA_O	1:1	Automated		0.28 (0.01)	0.5 (0)	-

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Jaccard index	Residual mean square error		
				BIO1	**BIO13**	**Elevation**
CTA_O	1:2	Automated		0.19 (0.01)	0.38 (0.01)	-
CTA_O	1:3	Automated		0.15 (0.01)	0.31 (0.01)	-
CTA_O	10000	Automated		-	0.17 (0.01)	-
CTA_O	1:1	Expert		0.28 (0.01)	0.5 (0.01)	0.37 (0.01)
CTA_O	1:2	Expert		0.19 (0.01)	0.38 (0.01)	0.45 (0)
CTA_O	1:3	Expert		0.19 (0.01)	0.38 (0.01)	0.45 (0)
CTA_O	10000	Expert		0.18 (0.01)	0.16 (0.01)	0.62 (0)
EMca_B	1:1	*A priori*	0.6 (0.2)	0.65 (0.03)	0.88 (0.03)	0.33 (0.05)
EMca_B	1:2	*A priori*	0.53 (0.14)	0.65 (0.03)	0.88 (0.03)	0.32 (0.05)
EMca_B	1:3	*A priori*	0.54 (0.15)	0.65 (0.02)	0.87 (0.03)	0.31 (0.04)
EMca_B	10000	*A priori*	0.48 (0.12)	0.63 (0.03)	0.85 (0.03)	0.29 (0.04)
EMca_B	1:1	Automated		0.62 (0.09)	0.84 (0.1)	0.31 (0.03)
EMca_B	1:2	Automated		0.65 (0.02)	0.87 (0.02)	0.31 (0.03)
EMca_B	1:3	Automated		0.64 (0.02)	0.87 (0.02)	0.3 (0.03)
EMca_B	10000	Automated		0.63 (0.04)	0.84 (0.04)	0.31 (0.04)
EMca_B	1:1	Expert		0.65 (0.02)	0.87 (0.02)	0.3 (0.02)
EMca_B	1:2	Expert		0.65 (0.01)	0.87 (0.01)	0.3 (0.02)
EMca_B	1:3	Expert		0.65 (0.01)	0.88 (0.01)	0.31 (0.02)
EMca_B	10000	Expert		0.65 (0.02)	0.88 (0.02)	0.32 (0.04)
EMmean_B	1:1	*A priori*	0.82 (0.18)	0.32 (0.01)	0.57 (0.01)	0.34 (0.01)
EMmean_B	1:2	*A priori*	0.86 (0.17)	0.3 (0.01)	0.54 (0.01)	0.35 (0.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Jaccard index	Residual mean square error BIO1	BIO13	Elevation
EMmean_B	1:3	*A priori*	0.87 (0.17)	0.29 (0.01)	0.53 (0.01)	0.36 (0.01)
EMmean_B	10000	*A priori*	0.84 (0.19)	0.27 (0.01)	0.52 (0.01)	0.37 (0.01)
EMmean_B	1:1	Automated		0.31 (0.01)	0.53 (0.01)	0.35 (0.01)
EMmean_B	1:2	Automated		0.32 (0.01)	0.52 (0.01)	0.36 (0.01)
EMmean_B	1:3	Automated		0.27 (0.01)	0.49 (0.02)	0.38 (0.01)
EMmean_B	10000	Automated		0.25 (0.01)	0.47 (0.01)	0.4 (0.01)
EMmean_B	1:1	Expert		0.31 (0.01)	0.54 (0.01)	0.36 (0.01)
EMmean_B	1:2	Expert		0.28 (0.01)	0.51 (0.01)	0.38 (0.01)
EMmean_B	1:3	Expert		0.27 (0.01)	0.49 (0.01)	0.38 (0.01)
EMmean_B	10000	Expert		0.26 (0.01)	0.48 (0.01)	0.39 (0.01)
EMmedian_B	1:1	*A priori*	0.82 (0.18)	0.31 (0.01)	0.55 (0.02)	0.34 (0.01)
EMmedian_B	1:2	*A priori*	0.86 (0.17)	0.29 (0.01)	0.52 (0.01)	0.35 (0.01)
EMmedian_B	1:3	*A priori*	0.87 (0.17)	0.28 (0.01)	0.52 (0.01)	0.35 (0.01)
EMmedian_B	10000	*A priori*	0.82 (0.17)	0.27 (0.01)	0.51 (0.01)	0.35 (0.01)
EMmedian_B	1:1	Automated		0.3 (0.02)	0.53 (0.02)	0.36 (0.01)
EMmedian_B	1:2	Automated		0.3 (0.02)	0.53 (0.02)	0.36 (0.01)
EMmedian_B	1:3	Automated		0.33 (0.01)	0.53 (0.01)	0.34 (0.01)
EMmedian_B	10000	Automated		0.32 (0.01)	0.53 (0.01)	0.34 (0.01)
EMmedian_B	1:1	Expert		0.3 (0.01)	0.53 (0.01)	0.36 (0.01)
EMmedian_B	1:2	Expert		0.28 (0.01)	0.51 (0.01)	0.37 (0)
EMmedian_B	1:3	Expert		0.27 (0.01)	0.5 (0.01)	0.37 (0)

Table B2.4 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Jaccard index**	**Residual mean square error**		
				BIO1	**BIO13**	**Elevation**
EMmedian_B	10000	Expert		0.27 (0.01)	0.49 (0.01)	0.37 (0)
EMwmean_B	1:1	*A priori*	0.82 (0.18)	0.32 (0.01)	0.57 (0.01)	0.34 (0.01)
EMwmean_B	1:2	*A priori*	0.87 (0.17)	0.3 (0.01)	0.54 (0.01)	0.35 (0.01)
EMwmean_B	1:3	*A priori*	0.87 (0.16)	0.29 (0.01)	0.53 (0.01)	0.36 (0.01)
EMwmean_B	10000	*A priori*	0.83 (0.19)	0.27 (0.01)	0.52 (0.01)	0.37 (0.01)
EMwmean_B	1:1	Automated		0.31 (0.01)	0.53 (0.01)	0.35 (0.01)
EMwmean_B	1:2	Automated		0.32 (0.01)	0.52 (0.01)	0.36 (0.01)
EMwmean_B	1:3	Automated		0.27 (0.01)	0.49 (0.02)	0.38 (0.01)
EMwmean_B	10000	Automated		0.25 (0.01)	0.47 (0.02)	0.39 (0.01)
EMwmean_B	1:1	Expert		0.31 (0.01)	0.54 (0.01)	0.36 (0.01)
EMwmean_B	1:2	Expert		0.28 (0.01)	0.51 (0.01)	0.38 (0.01)
EMwmean_B	1:3	Expert		0.27 (0.01)	0.49 (0.01)	0.38 (0.01)
EMwmean_B	10000	Expert		0.26 (0.01)	0.48 (0.01)	0.39 (0.01)
FDA_B	1:1	*A priori*	0.72 (0.21)	0.32 (0.01)	0.54 (0.01)	0.38 (0.01)
FDA_B	1:2	*A priori*	0.65 (0.2)	0.23 (0.01)	0.43 (0.01)	0.47 (0.01)
FDA_B	1:3	*A priori*	0.64 (0.23)	0.21 (0.01)	0.39 (0.01)	0.5 (0.01)
FDA_B	10000	*A priori*	0.57 (0.15)	0.19 (0.01)	0.38 (0.01)	0.48 (0.01)
FDA_B	1:1	Automated		0.31 (0.01)	0.53 (0.01)	0.39 (0)
FDA_B	1:2	Automated		0.22 (0.01)	0.42 (0.01)	0.47 (0.01)
FDA_B	1:3	Automated		0.2 (0.01)	0.38 (0.01)	0.5 (0.01)
FDA_B	10000	Automated		0.18 (0.01)	0.37 (0.01)	0.48 (0.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Jaccard index	Residual mean square error BIO1	BIO13	Elevation
FDA_B	1:1	Expert		0.31 (0.01)	0.54 (0.01)	0.39 (0.01)
FDA_B	1:2	Expert		0.22 (0.01)	0.42 (0.01)	0.47 (0.01)
FDA_B	1:3	Expert		0.2 (0.01)	0.39 (0.01)	0.5 (0.01)
FDA_B	10000	Expert		0.18 (0.01)	0.36 (0.02)	0.49 (0.02)
FDA_O	1:1	*A priori*	0.53 (0.18)	0.48 (0.01)	0.68 (0.01)	0.47 (0.01)
FDA_O	1:2	*A priori*	0.5 (0.18)	0.48 (0.01)	0.68 (0.01)	0.47 (0.01)
FDA_O	1:3	*A priori*	0.52 (0.18)	0.48 (0.01)	0.68 (0.01)	0.47 (0.01)
FDA_O	10000	*A priori*	0.55 (0.18)	0.48 (0.01)	0.68 (0.01)	0.47 (0.01)
FDA_O	1:1	Automated		-	0.68 (0.01)	0.47 (0.01)
FDA_O	1:2	Automated		-	0.68 (0.01)	0.47 (0.01)
FDA_O	1:3	Automated		0.48 (0.01)	0.68 (0.01)	0.48 (0.01)
FDA_O	10000	Automated		0.48 (0.01)	0.68 (0.01)	0.48 (0.01)
FDA_O	1:1	Expert		0.48 (0.01)	0.68 (0.01)	0.48 (0.01)
FDA_O	1:2	Expert		0.48 (0.01)	0.68 (0.01)	0.48 (0.01)
FDA_O	1:3	Expert		0.48 (0.01)	0.68 (0.01)	0.48 (0.01)
FDA_O	10000	Expert		0.48 (0.01)	0.68 (0.01)	0.48 (0.01)
GAM_B	1:1	*A priori*	0.76 (0.13)	0.3 (0.02)	0.54 (0.02)	0.34 (0.01)
GAM_B	1:2	*A priori*	0.71 (0.13)	0.31 (0.01)	0.55 (0.01)	0.34 (0.01)
GAM_B	1:3	*A priori*	0.65 (0.12)	0.31 (0.01)	0.55 (0.01)	0.34 (0.01)
GAM_B	10000	*A priori*	0.56 (0.09)	0.31 (0.01)	0.55 (0.01)	0.35 (0.01)
GAM_B	1:1	Automated		0.28 (0.01)	0.5 (0.01)	0.37 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Jaccard index	Residual mean square error		
				BIO1	**BIO13**	**Elevation**
GAM_B	1:2	Automated		0.28 (0.01)	0.5 (0)	0.37 (0)
GAM_B	1:3	Automated		0.29 (0.01)	0.51 (0.01)	0.36 (0)
GAM_B	10000	Automated		0.28 (0.01)	0.5 (0)	0.37 (0)
GAM_B	1:1	Expert		0.28 (0.01)	0.5 (0)	0.36 (0)
GAM_B	1:2	Expert		0.28 (0.01)	0.5 (0)	0.36 (0)
GAM_B	1:3	Expert		0.28 (0.01)	0.5 (0)	0.36 (0)
GAM_B	10000	Expert		0.28 (0)	0.5 (0)	0.36 (0)
GAM_O	1:1	*A priori*	0.63 (0.37)	0.33 (0.11)	0.46 (0.23)	0.4 (0.17)
GAM_O	1:2	*A priori*	0.85 (0.26)	0.37 (0.13)	0.57 (0.17)	0.33 (0.09)
GAM_O	1:3	*A priori*	0.89 (0.22)	0.39 (0.12)	0.6 (0.13)	0.31 (0.05)
GAM_O	10000	*A priori*	0.94 (0.19)	0.43 (0.09)	0.66 (0.09)	0.29 (0.03)
GAM_O	1:1	Automated		0.31 (0.06)	0.45 (0.18)	0.37 (0.16)
GAM_O	1:2	Automated		0.35 (0.06)	0.56 (0.08)	0.29 (0.06)
GAM_O	1:3	Automated		0.48 (0.05)	0.71 (0.05)	0.3 (0.03)
GAM_O	10000	Automated		0.49 (0.01)	0.72 (0.01)	0.3 (0.01)
GAM_O	1:1	Expert		0.41 (0.05)	0.64 (0.05)	0.29 (0.01)
GAM_O	1:2	Expert		0.44 (0.03)	0.67 (0.03)	0.29 (0.01)
GAM_O	1:3	Expert		0.47 (0.02)	0.69 (0.02)	0.29 (0.01)
GAM_O	10000	Expert		0.49 (0.01)	0.72 (0.01)	0.3 (0.01)
GBM_B	1:1	*A priori*	0.52 (0.07)	0.35 (0.01)	0.6 (0.01)	0.32 (0.01)
GBM_B	1:2	*A priori*	0.52 (0.08)	0.35 (0.01)	0.6 (0.01)	0.32 (0.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Jaccard index	Residual mean square error		
				BIO1	BIO13	Elevation
GBM_B	1:3	*A priori*	0.53 (0.08)	0.35 (0.01)	0.6 (0.01)	0.32 (0.01)
GBM_B	10000	*A priori*	0.51 (0.04)	0.35 (0.01)	0.6 (0.01)	0.32 (0)
GBM_B	1:1	Automated		0.33 (0.01)	0.56 (0.01)	0.36 (0)
GBM_B	1:2	Automated		0.34 (0.01)	0.57 (0.01)	0.36 (0)
GBM_B	1:3	Automated		0.34 (0.01)	0.57 (0.01)	0.36 (0)
GBM_B	10000	Automated		0.34 (0.01)	0.57 (0.01)	0.36 (0)
GBM_B	1:1	Expert		0.33 (0.01)	0.56 (0.01)	0.35 (0)
GBM_B	1:2	Expert		0.33 (0.01)	0.56 (0.01)	0.35 (0)
GBM_B	1:3	*A priori*	0.53 (0.08)	0.35 (0.01)	0.6 (0.01)	0.32 (0.01)
GBM_B	10000	*A priori*	0.51 (0.04)	0.35 (0.01)	0.6 (0.01)	0.32 (0)
GBM_B	1:1	Automated		0.33 (0.01)	0.56 (0.01)	0.36 (0)
GBM_B	1:2	Automated		0.34 (0.01)	0.57 (0.01)	0.36 (0)
GBM_B	1:3	Automated		0.34 (0.01)	0.57 (0.01)	0.36 (0)
GBM_B	10000	Automated		0.34 (0.01)	0.57 (0.01)	0.36 (0)
GBM_B	1:1	Expert		0.33 (0.01)	0.56 (0.01)	0.35 (0)
GBM_B	1:2	Expert		0.33 (0.01)	0.56 (0.01)	0.35 (0)
GBM_B	1:3	Expert		0.34 (0.01)	0.56 (0.01)	0.35 (0)
GBM_B	10000	Expert		0.33 (0)	0.56 (0)	0.35 (0)
GBM_O	1:1	*A priori*	0.65 (0.12)	0.27 (0.02)	0.5 (0.02)	0.31 (0.02)
GBM_O	1:2	*A priori*	0.68 (0.09)	0.23 (0.02)	0.46 (0.02)	0.34 (0.02)
GBM_O	1:3	*A priori*	0.72 (0.05)	0.21 (0.02)	0.43 (0.02)	0.37 (0.02)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Jaccard index	Residual mean square error BIO1	BIO13	Elevation
GBM_O	10000	*A priori*	0.73 (0.04)	0.14 (0.01)	0.33 (0.02)	0.44 (0.02)
GBM_O	1:1	Automated		0.23 (0.02)	0.45 (0.02)	0.35 (0.02)
GBM_O	1:2	Automated		0.19 (0.02)	0.4 (0.02)	0.39 (0.02)
GBM_O	1:3	Automated		0.17 (0.01)	0.38 (0.01)	0.41 (0.01)
GBM_O	10000	Automated		0.14 (0)	0.32 (0.01)	0.46 (0.01)
GBM_O	1:1	Expert		0.38 (0.02)	0.64 (0.02)	0.26 (0.01)
GBM_O	1:2	Expert		0.36 (0.02)	0.61 (0.02)	0.28 (0.01)
GBM_O	1:3	Expert		0.18 (0.01)	0.38 (0.02)	0.41 (0.01)
GBM_O	10000	Expert		0.15 (0.01)	0.33 (0.02)	0.46 (0.01)
GLM_B	1:1	*A priori*	0.93 (0.14)	0.28 (0.04)	0.52 (0.04)	0.35 (0.03)
GLM_B	1:2	*A priori*	0.9 (0.16)	0.28 (0.03)	0.51 (0.03)	0.35 (0.03)
GLM_B	1:3	*A priori*	0.86 (0.15)	0.28 (0.03)	0.52 (0.03)	0.34 (0.02)
GLM_B	10000	*A priori*	0.83 (0.17)	0.28 (0.03)	0.52 (0.03)	0.35 (0.03)
GLM_B	1:1	Automated		0.28 (0.01)	0.51 (0.01)	0.34 (0.01)
GLM_B	1:2	Automated		0.28 (0.01)	0.51 (0.01)	0.35 (0.01)
GLM_B	1:3	Automated		0.28 (0.01)	0.51 (0.01)	0.34 (0)
GLM_B	10000	Automated		0.27 (0.01)	0.5 (0.01)	0.35 (0)
GLM_B	1:1	Expert		0.28 (0.01)	0.51 (0.01)	0.34 (0.01)
GLM_B	1:2	Expert		0.28 (0.01)	0.51 (0.01)	0.34 (0)
GLM_B	1:3	Expert		0.28 (0.01)	0.51 (0.01)	0.34 (0.01)
GLM_B	10000	Expert		0.27 (0.01)	0.5 (0.01)	0.35 (0.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Jaccard index	Residual mean square error		
				BIO1	BIO13	Elevation
GLM_O	1:1	*A priori*	0.32 (0.26)	0.43 (0.19)	0.41 (0.39)	0.59 (0.17)
GLM_O	1:2	*A priori*	0.39 (0.28)	0.5 (0.2)	0.52 (0.41)	0.57 (0.16)
GLM_O	1:3	*A priori*	0.45 (0.33)	0.56 (0.2)	0.64 (0.39)	0.52 (0.14)
GLM_O	10000	*A priori*	0.54 (0.37)	0.67 (0.13)	0.84 (0.26)	0.46 (0.09)
GLM_O	1:1	Automated		0.41 (0.19)	0.37 (0.37)	0.61 (0.17)
GLM_O	1:2	Automated		0.39 (0.18)	0.4 (0.34)	0.54 (0.19)
GLM_O	1:3	Automated		0.45 (0.22)	0.59 (0.33)	0.45 (0.13)
GLM_O	10000	Automated		0.52 (0.21)	0.69 (0.29)	0.41 (0.11)
GLM_O	1:1	Expert		0.32 (0.17)	0.29 (0.32)	0.57 (0.15)
GLM_O	1:2	Expert		0.33 (0.18)	0.38 (0.32)	0.5 (0.16)
GLM_O	1:3	Expert		0.4 (0.19)	0.5 (0.34)	0.45 (0.16)
GLM_O	10000	Expert		0.44 (0.2)	0.62 (0.28)	0.39 (0.11)
MARS_B	1:1	*A priori*	0.61 (0.12)	0.29 (0.01)	0.51 (0.01)	0.36 (0.01)
MARS_B	1:2	*A priori*	0.63 (0.15)	0.28 (0.02)	0.51 (0.02)	0.36 (0.01)
MARS_B	1:3	*A priori*	0.61 (0.15)	0.28 (0.02)	0.51 (0.02)	0.36 (0.01)
MARS_B	10000	*A priori*	0.59 (0.16)	0.27 (0)	0.5 (0.01)	0.36 (0.01)
MARS_B	1:1	Automated		0.28 (0.01)	0.51 (0.01)	0.36 (0.01)
MARS_B	1:2	Automated		0.28 (0)	0.5 (0)	0.36 (0)
MARS_B	1:3	Automated		0.28 (0)	0.5 (0)	0.37 (0.01)
MARS_B	10000	Automated		0.27 (0)	0.5 (0)	0.37 (0)
MARS_B	1:1	Expert		0.28 (0.01)	0.51 (0.01)	0.36 (0.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Jaccard index	Residual mean square error		
				BIO1	**BIO13**	**Elevation**
MARS_B	1:2	Expert		0.28 (0)	0.51 (0)	0.36 (0.01)
MARS_B	1:3	Expert		0.28 (0)	0.51 (0)	0.36 (0)
MARS_B	10000	Expert		0.28 (0)	0.5 (0)	0.36 (0)
MARS_O	1:1	*A priori*	0.43 (0.13)	0.27 (0.15)	0.43 (0.21)	0.42 (0.12)
MARS_O	1:2	*A priori*	0.42 (0.09)	0.29 (0.16)	0.47 (0.21)	0.4 (0.11)
MARS_O	1:3	*A priori*	0.41 (0.09)	0.3 (0.17)	0.47 (0.22)	0.42 (0.12)
MARS_O	10000	*A priori*	0.44 (0.07)	0.23 (0.11)	0.37 (0.17)	0.45 (0.12)
MARS_O	1:1	Automated		-	0.38 (0.11)	0.41 (0.08)
MARS_O	1:2	Automated		-	0.33 (0.05)	0.45 (0.04)
MARS_O	1:3	Automated		0.22 (0.1)	0.41 (0.13)	0.41 (0.08)
MARS_O	10000	Automated		0.21 (0.08)	0.34 (0.16)	0.46 (0.11)
MARS_O	1:1	Expert		0.28 (0.12)	0.49 (0.14)	0.36 (0.06)
MARS_O	1:2	Expert		0.2 (0.09)	0.39 (0.12)	0.42 (0.08)
MARS_O	1:3	Expert		0.22 (0.09)	0.41 (0.13)	0.4 (0.08)
MARS_O	10000	Expert		0.26 (0.08)	0.42 (0.17)	0.42 (0.11)
MaxEnt_B	1:1	*A priori*	0.45 (0.16)	0.31 (0.02)	0.51 (0.08)	0.44 (0.09)
MaxEnt_B	1:2	*A priori*	0.48 (0.18)	0.3 (0.02)	0.48 (0.11)	0.47 (0.11)
MaxEnt_B	1:3	*A priori*	0.46 (0.14)	0.3 (0.02)	0.51 (0.07)	0.44 (0.07)
MaxEnt_B	10000	*A priori*	0.44 (0.12)	0.29 (0.01)	0.5 (0.07)	0.44 (0.07)
MaxEnt_B	1:1	Automated		0.27 (0.02)	0.46 (0.08)	0.44 (0.08)
MaxEnt_B	1:2	Automated		0.29 (0.02)	0.48 (0.07)	0.45 (0.08)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Jaccard index	Residual mean square error		
				BIO1	BIO13	Elevation
MaxEnt_B	1:3	Automated		0.27 (0.01)	0.46 (0.04)	0.44 (0.04)
MaxEnt_B	10000	Automated		0.26 (0.01)	0.47 (0.01)	0.42 (0.01)
MaxEnt_B	1:1	Expert		0.27 (0.02)	0.47 (0.07)	0.43 (0.07)
MaxEnt_B	1:2	Expert		0.27 (0.01)	0.47 (0.04)	0.42 (0.04)
MaxEnt_B	1:3	Expert		0.27 (0.01)	0.47 (0.04)	0.42 (0.05)
MaxEnt_B	10000	Expert		0.26 (0)	0.48 (0)	0.41 (0.01)
MaxEnt_O	1:1	*A priori*	0.33 (0.29)	0.29 (0.03)	0.46 (0.1)	0.46 (0.1)
MaxEnt_O	1:2	*A priori*	0.35 (0.26)	0.29 (0.02)	0.45 (0.11)	0.46 (0.1)
MaxEnt_O	1:3	*A priori*	0.32 (0.28)	0.29 (0.02)	0.45 (0.11)	0.46 (0.1)
MaxEnt_O	10000	*A priori*	0.26 (0.25)	0.29 (0.03)	0.46 (0.11)	0.45 (0.1)
MaxEnt_O	1:1	Automated		0.27 (0.01)	0.48 (0.02)	-
MaxEnt_O	1:2	Automated		0.27 (0.02)	0.45 (0.09)	-
MaxEnt_O	1:3	Automated		-	0.48 (0.02)	-
MaxEnt_O	10000	Automated		0.27 (0.01)	0.47 (0.05)	-
MaxEnt_O	1:1	Expert		0.27 (0.02)	0.46 (0.08)	0.44 (0.07)
MaxEnt_O	1:2	Expert		0.28 (0.03)	0.46 (0.08)	0.44 (0.08)
MaxEnt_O	1:3	Expert		0.27 (0.02)	0.46 (0.07)	0.44 (0.07)
MaxEnt_O	10000	Expert		0.27 (0.02)	0.48 (0.04)	0.42 (0.05)
MXL_O	1:1	*A priori*	0.08 (0)	0.27 (0.03)	0.48 (0.04)	0.42 (0.03)
MXL_O	1:2	*A priori*	0.08 (0)	0.27 (0.03)	0.48 (0.04)	0.41 (0.03)
MXL_O	1:3	*A priori*	0.13 (0.06)	0.27 (0.03)	0.48 (0.05)	0.42 (0.04)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Jaccard index	Residual mean square error		
				BIO1	BIO13	Elevation
MXL_O	10000	*A priori*	0.1 (0.02)	0.27 (0.03)	0.47 (0.05)	0.42 (0.03)
MXL_O	1:1	Automated		0.37 (0.07)	0.58 (0.08)	-
MXL_O	1:2	Automated		0.37 (0.07)	0.57 (0.09)	-
MXL_O	1:3	Automated		0.37 (0.07)	0.57 (0.08)	-
MXL_O	10000	Automated		0.38 (0.07)	0.58 (0.08)	-
MXL_O	1:1	Expert		0.24 (0.06)	0.38 (0.12)	0.5 (0.1)
MXL_O	1:2	Expert		0.24 (0.05)	0.35 (0.14)	0.52 (0.12)
MXL_O	1:3	Expert		0.25 (0.06)	0.38 (0.13)	0.49 (0.12)
MXL_O	10000	Expert		0.24 (0.05)	0.37 (0.13)	0.5 (0.11)
RF_B	1:1	*A priori*	0.44 (0.03)	0.34 (0.01)	0.57 (0)	0.35 (0)
RF_B	1:2	*A priori*	0.42 (0.02)	0.29 (0)	0.5 (0)	0.42 (0)
RF_B	1:3	*A priori*	0.41 (0.02)	0.28 (0)	0.47 (0)	0.46 (0)
RF_B	10000	*A priori*	0.38 (0)	0.27 (0)	0.42 (0)	0.53 (0)
RF_B	1:1	Automated		0.35 (0)	0.55 (0.01)	0.39 (0)
RF_B	1:2	Automated		0.32 (0)	0.49 (0)	0.46 (0)
RF_B	1:3	Automated		0.31 (0)	0.46 (0)	0.49 (0)
RF_B	10000	Automated		0.32 (0)	0.44 (0)	0.54 (0)
RF_B	1:1	Expert		0.35 (0)	0.55 (0.01)	0.39 (0)
RF_B	1:2	Expert		0.31 (0)	0.49 (0)	0.46 (0)
RF_B	1:3	Expert		0.3 (0)	0.45 (0.01)	0.49 (0)
RF_B	10000	Expert		0.31 (0)	0.43 (0)	0.55 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Jaccard index	Residual mean square error		
				BIO1	**BIO13**	**Elevation**
RF_O	1:1	*A priori*	0.43 (0.01)	0.35 (0)	0.55 (0)	0.37 (0)
RF_O	1:2	*A priori*	0.41 (0.03)	0.31 (0)	0.49 (0)	0.44 (0)
RF_O	1:3	*A priori*	0.38 (0)	0.3 (0)	0.46 (0)	0.48 (0)
RF_O	10000	*A priori*	0.38 (0)	0.31 (0)	0.43 (0)	0.54 (0)
RF_O	1:1	Automated		0.36 (0)	0.56 (0)	0.39 (0)
RF_O	1:2	Automated		0.32 (0)	0.5 (0)	0.46 (0)
RF_O	1:3	Automated		0.31 (0)	0.47 (0)	0.49 (0)
RF_O	10000	Automated		0.33 (0)	0.45 (0)	0.54 (0)
RF_O	1:1	Expert		0.35 (0)	0.56 (0)	0.39 (0)
RF_O	1:2	Expert		0.32 (0)	0.49 (0)	0.46 (0)
RF_O	1:3	Expert		0.31 (0)	0.47 (0)	0.49 (0)
RF_O	10000	Expert		0.32 (0)	0.44 (0)	0.55 (0)
SRE_B	1:1	*A priori*	0.39 (0.03)	0.53 (0)	0.68 (0)	0.51 (0)
SRE_B	1:2	*A priori*	0.42 (0.02)	0.53 (0)	0.68 (0)	0.51 (0)
SRE_B	1:3	*A priori*	0.42 (0.02)	0.53 (0)	0.68 (0)	0.51 (0)
SRE_B	10000	*A priori*	0.43 (0.02)	0.53 (0)	0.68 (0)	0.51 (0)
SRE_B	1:1	Automated		0.53 (0)	0.72 (0)	0.45 (0)
SRE_B	1:2	Automated		0.53 (0)	0.72 (0)	0.45 (0)
SRE_B	1:3	Automated		0.53 (0)	0.72 (0)	0.45 (0)
SRE_B	10000	Automated		0.53 (0)	0.72 (0)	0.45 (0)
SRE_B	1:1	Expert		0.56 (0)	0.76 (0)	0.41 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Jaccard index	Residual mean square error		
				BIO1	BIO13	Elevation
SRE_B	1:2	Expert		0.56 (0)	0.76 (0)	0.41 (0)
SRE_B	1:3	Expert		0.56 (0)	0.76 (0)	0.41 (0)
SRE_B	10000	Expert		0.56 (0)	0.76 (0)	0.41 (0)
SRE_O	1:1	*A priori*	0.22 (0.01)	0.26 (0)	0.13 (0)	0.68 (0)
SRE_O	1:2	*A priori*	0.21 (0.01)	0.26 (0)	0.13 (0)	0.68 (0)
SRE_O	1:3	*A priori*	0.21 (0.01)	0.26 (0)	0.13 (0)	0.68 (0)
SRE_O	10000	*A priori*	0.22 (0.01)	0.26 (0)	0.13 (0)	0.68 (0)
SRE_O	1:1	Automated		0.25 (0)	0.15 (0)	-
SRE_O	1:2	Automated		0.25 (0)	0.15 (0)	-
SRE_O	1:3	Automated		0.25 (0)	0.15 (0)	-
SRE_O	10000	Automated		0.25 (0)	0.15 (0)	-
SRE_O	1:1	Expert		0.24 (0)	0.28 (0)	0.58 (0)
SRE_O	1:2	Expert		0.24 (0)	0.28 (0)	0.58 (0)
SRE_O	1:3	Expert		0.24 (0)	0.28 (0)	0.58 (0)
SRE_O	10000	Expert		0.24 (0)	0.28 (0)	0.58 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Spearman's correlation			Continuous Boyce index (Calibration)		
			BIO1	BIO13	Elevation	Train	Test	Fit
ANN_B	1:1	*A priori*	0.72 (0.04)	0.87 (0.04)	0.72 (0.04)	0.75 (0.09)	0.28 (0.16)	0.47 (0.18)
ANN_B	1:2	*A priori*	0.72 (0.03)	0.88 (0.04)	0.72 (0.04)	0.76 (0.08)	0.23 (0.13)	0.53 (0.14)
ANN_B	1:3	*A priori*	0.72 (0.03)	0.88 (0.03)	0.73 (0.03)	0.77 (0.11)	0.28 (0.17)	0.49 (0.2)
ANN_B	10000	*A priori*	0.72 (0.03)	0.88 (0.05)	0.74 (0.04)	0.72 (0.09)	0.29 (0.15)	0.43 (0.17)
ANN_B	1:1	Automated	0.73 (0.04)	0.9 (0.04)	0.73 (0.03)	0.88 (0.08)	0.56 (0.17)	0.32 (0.17)
ANN_B	1:2	Automated	0.73 (0.03)	0.91 (0.03)	0.72 (0.04)	0.9 (0.04)	0.48 (0.16)	0.42 (0.17)
ANN_B	1:3	Automated	0.74 (0.03)	0.91 (0.03)	0.72 (0.03)	0.89 (0.03)	0.46 (0.12)	0.44 (0.12)
ANN_B	10000	Automated	0.74 (0.05)	0.91 (0.04)	0.71 (0.03)	0.87 (0.09)	0.46 (0.11)	0.41 (0.16)
ANN_B	1:1	Expert	0.74 (0.05)	0.92 (0.04)	0.71 (0.04)	0.92 (0.06)	0.35 (0.18)	0.57 (0.19)
ANN_B	1:2	Expert	0.73 (0.06)	0.93 (0.05)	0.7 (0.04)	0.89 (0.13)	0.39 (0.18)	0.5 (0.2)
ANN_B	1:3	Expert	0.74 (0.05)	0.92 (0.05)	0.7 (0.03)	0.92 (0.05)	0.41 (0.18)	0.5 (0.19)
ANN_B	10000	Expert	0.74 (0.05)	0.92 (0.04)	0.69 (0.02)	0.91 (0.08)	0.38 (0.22)	0.54 (0.23)
ANN_O	1:1	*A priori*	0.67 (0.06)	0.77 (0.05)	0.81 (0.05)	0.66 (0.18)	0.34 (0.31)	0.32 (0.32)
ANN_O	1:2	*A priori*	0.53 (0.29)	0.6 (0.33)	0.61 (0.34)	0.48 (0.34)	0.23 (0.35)	0.25 (0.35)
ANN_O	1:3	*A priori*	0.36 (0.34)	0.41 (0.38)	0.43 (0.4)	0.33 (0.34)	0.14 (0.27)	0.19 (0.3)
ANN_O	10000	*A priori*	0.08 (0.22)	0.08 (0.24)	0.09 (0.25)	0.07 (0.2)	0.03 (0.15)	0.04 (0.13)
ANN_O	1:1	Automated	-	0.74 (0.09)	0.8 (0.1)	0.62 (0.21)	0.32 (0.3)	0.3 (0.27)
ANN_O	1:2	Automated	-	0.59 (0.31)	0.63 (0.34)	0.46 (0.33)	0.3 (0.29)	0.16 (0.27)
ANN_O	1:3	Automated	-	0.41 (0.37)	0.44 (0.4)	0.33 (0.34)	0.18 (0.27)	0.16 (0.23)
ANN_O	10000	Automated	0.04 (0.17)	0.05 (0.19)	0.05 (0.18)	0.03 (0.13)	0.01 (0.09)	0.02 (0.11)
ANN_O	1:1	Expert	0.67 (0.14)	0.85 (0.17)	0.76 (0.15)	0.85 (0.23)	0.52 (0.25)	0.32 (0.3)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Spearman's correlation			Continuous Boyce index (Calibration)		
			BIO1	BIO13	Elevation	Train	Test	Fit
ANN_O	1:2	Expert	0.55 (0.33)	0.68 (0.39)	0.57 (0.33)	0.65 (0.39)	0.31 (0.28)	0.35 (0.34)
ANN_O	1:3	Expert	0.33 (0.37)	0.39 (0.45)	0.33 (0.38)	0.34 (0.4)	0.11 (0.23)	0.23 (0.34)
ANN_O	10000	Expert	0.07 (0.23)	0.08 (0.26)	0.06 (0.2)	0.05 (0.17)	0.02 (0.08)	0.04 (0.16)
CTA_B	1:1	*A priori*	0.62 (0.08)	0.75 (0.06)	0.6 (0.06)	0.64 (0.1)	0.28 (0.21)	0.36 (0.23)
CTA_B	1:2	*A priori*	0.59 (0.08)	0.72 (0.07)	0.57 (0.07)	0.63 (0.07)	0.27 (0.13)	0.37 (0.14)
CTA_B	1:3	*A priori*	0.58 (0.07)	0.7 (0.07)	0.56 (0.07)	0.63 (0.08)	0.14 (0.19)	0.48 (0.21)
CTA_B	10000	*A priori*	0.55 (0.08)	0.67 (0.08)	0.53 (0.08)	0.63 (0.06)	0.13 (0.13)	0.5 (0.15)
CTA_B	1:1	Automated	0.63 (0.07)	0.77 (0.04)	0.61 (0.05)	0.65 (0.11)	0.4 (0.22)	0.25 (0.26)
CTA_B	1:2	Automated	0.64 (0.07)	0.75 (0.05)	0.59 (0.05)	0.69 (0.1)	0.22 (0.2)	0.48 (0.25)
CTA_B	1:3	Automated	0.6 (0.06)	0.72 (0.06)	0.56 (0.06)	0.71 (0.07)	0.12 (0.19)	0.59 (0.21)
CTA_B	10000	Automated	0.56 (0.05)	0.66 (0.05)	0.51 (0.05)	0.73 (0.08)	-0.12 (0.19)	0.85 (0.2)
CTA_B	1:1	Expert	0.64 (0.07)	0.79 (0.05)	0.61 (0.05)	0.69 (0.1)	0.42 (0.2)	0.26 (0.23)
CTA_B	1:2	Expert	0.63 (0.06)	0.78 (0.05)	0.61 (0.05)	0.68 (0.11)	0.29 (0.23)	0.39 (0.26)
CTA_B	1:3	Expert	0.61 (0.05)	0.75 (0.05)	0.58 (0.05)	0.71 (0.08)	0.29 (0.21)	0.42 (0.23)
CTA_B	10000	Expert	0.59 (0.05)	0.73 (0.05)	0.57 (0.05)	0.66 (0.1)	0.19 (0.21)	0.47 (0.24)
CTA_O	1:1	*A priori*	0.73 (0.03)	0.84 (0.03)	0.69 (0.03)	0.84 (0.18)	0.79 (0.23)	0.04 (0.3)
CTA_O	1:2	*A priori*	0.71 (0.02)	0.86 (0.03)	0.67 (0.02)	0.88 (0.18)	0.92 (0.15)	-0.04 (0.23)
CTA_O	1:3	*A priori*	0.7 (0.02)	0.86 (0.02)	0.67 (0.01)	0.94 (0.13)	0.98 (0.09)	-0.04 (0.14)
CTA_O	10000	*A priori*	0.68 (0.02)	0.9 (0.02)	0.68 (0.02)	0.92 (0.13)	0.87 (0.25)	0.05 (0.26)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Spearman's correlation			Continuous Boyce index (Calibration)		
			BIO1	BIO13	Elevation	Train	Test	Fit
CTA_O	1:1	Automated	0.74 (0.03)	0.85 (0.03)	-	0.78 (0.24)	0.77 (0.22)	0 (0.32)
CTA_O	1:2	Automated	0.71 (0.02)	0.87 (0.02)	-	0.91 (0.17)	0.92 (0.14)	-0.01 (0.22)
CTA_O	1:3	Automated	0.7 (0.02)	0.87 (0.02)	-	0.96 (0.11)	0.98 (0.09)	-0.02 (0.13)
CTA_O	10000	Automated	-	0.91 (0.03)	-	0.96 (0.1)	1 (0.02)	-0.04 (0.09)
CTA_O	1:1	Expert	0.74 (0.03)	0.86 (0.03)	0.67 (0.03)	0.86 (0.16)	0.8 (0.2)	0.06 (0.26)
CTA_O	1:2	Expert	0.71 (0.03)	0.87 (0.03)	0.65 (0.02)	0.94 (0.1)	0.89 (0.14)	0.05 (0.17)
CTA_O	1:3	Expert	0.71 (0.03)	0.87 (0.03)	0.65 (0.02)	0.93 (0.13)	0.92 (0.14)	0 (0.2)
CTA_O	10000	Expert	0.66 (0.04)	0.92 (0.03)	0.65 (0.03)	0.96 (0.08)	1 (0)	-0.04 (0.08)
EMca_B	1:1	*A priori*	0.36 (0.12)	0.56 (0.18)	0.51 (0.14)	0.56 (0.49)	0.37 (0.57)	0.19 (0.78)
EMca_B	1:2	*A priori*	0.33 (0.12)	0.52 (0.2)	0.48 (0.17)	0.47 (0.4)	0.58 (0.37)	-0.11 (0.55)
EMca_B	1:3	*A priori*	0.34 (0.08)	0.55 (0.16)	0.52 (0.14)	0.8 (0.28)	0.76 (0.29)	0.04 (0.38)
EMca_B	10000	*A priori*	0.35 (0.07)	0.57 (0.12)	0.53 (0.1)	0.36 (0.62)	0.37 (0.65)	0 (0.95)
EMca_B	1:1	Automated	0.39 (0.09)	0.63 (0.09)	0.57 (0.06)	0.56 (0.41)	0.5 (0.5)	0.06 (0.62)
EMca_B	1:2	Automated	0.35 (0.07)	0.59 (0.11)	0.54 (0.1)	0.57 (0.35)	0.26 (0.31)	0.3 (0.41)
EMca_B	1:3	Automated	0.36 (0.06)	0.59 (0.1)	0.55 (0.08)	0.54 (0.5)	0.44 (0.49)	0.1 (0.61)
EMca_B	10000	Automated	0.37 (0.06)	0.6 (0.08)	0.55 (0.07)	0.58 (0.48)	0.5 (0.49)	0.07 (0.69)
EMca_B	1:1	Expert	0.4 (0.05)	0.64 (0.06)	0.56 (0.03)	0.54 (0.5)	0.45 (0.32)	0.09 (0.61)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Spearman's correlation			Continuous Boyce index (Calibration)		
			BIO1	BIO13	Elevation	Train	Test	Fit
EMca_B	1:2	Expert	0.39 (0.03)	0.63 (0.06)	0.56 (0.03)	0.53 (0.5)	0.51 (0.32)	0.02 (0.59)
EMca_B	1:3	Expert	0.39 (0.04)	0.61 (0.06)	0.55 (0.05)	0.7 (0.33)	0.79 (0.24)	-0.08 (0.41)
EMca_B	10000	Expert	0.37 (0.07)	0.54 (0.12)	0.5 (0.1)	0.54 (0.49)	0.07 (0.65)	0.47 (0.82)
EMmean_B	1:1	*A priori*	0.77 (0.02)	0.87 (0.01)	0.67 (0.02)	0.95 (0.02)	0.41 (0.12)	0.54 (0.12)
EMmean_B	1:2	*A priori*	0.77 (0.01)	0.86 (0.01)	0.65 (0.02)	0.93 (0.02)	0.45 (0.16)	0.48 (0.16)
EMmean_B	1:3	*A priori*	0.77 (0.01)	0.86 (0.01)	0.65 (0.01)	0.92 (0.02)	0.47 (0.15)	0.45 (0.15)
EMmean_B	10000	*A priori*	0.77 (0.01)	0.85 (0.01)	0.64 (0.01)	0.91 (0.02)	0.47 (0.09)	0.43 (0.1)
EMmean_B	1:1	Automated	0.75 (0.01)	0.92 (0.01)	0.72 (0.02)	0.97 (0.01)	0.67 (0.06)	0.3 (0.07)
EMmean_B	1:2	Automated	0.63 (0.01)	0.96 (0.01)	0.73 (0.01)	0.92 (0.02)	0.85 (0.04)	0.07 (0.04)
EMmean_B	1:3	Automated	0.73 (0.02)	0.89 (0.02)	0.7 (0.02)	0.96 (0.01)	0.61 (0.07)	0.35 (0.07)
EMmean_B	10000	Automated	0.73 (0.02)	0.9 (0.02)	0.7 (0.01)	0.96 (0.02)	0.65 (0.07)	0.31 (0.07)
EMmean_B	1:1	Expert	0.76 (0.01)	0.92 (0.01)	0.72 (0.02)	0.97 (0.02)	0.67 (0.12)	0.3 (0.12)
EMmean_B	1:2	Expert	0.75 (0.01)	0.92 (0.01)	0.71 (0.01)	0.97 (0.02)	0.67 (0.11)	0.29 (0.11)
EMmean_B	1:3	Expert	0.75 (0.01)	0.92 (0.01)	0.71 (0.01)	0.97 (0.01)	0.71 (0.08)	0.27 (0.08)
EMmean_B	10000	Expert	0.75 (0.01)	0.92 (0.01)	0.71 (0.01)	0.96 (0.01)	0.69 (0.08)	0.28 (0.08)
EMmedian_B	1:1	*A priori*	0.76 (0.02)	0.87 (0.01)	0.69 (0.03)	0.93 (0.02)	0.26 (0.12)	0.67 (0.12)
EMmedian_B	1:2	*A priori*	0.76 (0.02)	0.87 (0.01)	0.68 (0.02)	0.9 (0.03)	0.26 (0.15)	0.64 (0.16)
EMmedian_B	1:3	*A priori*	0.76 (0.01)	0.87 (0.01)	0.68 (0.02)	0.91 (0.02)	0.34 (0.14)	0.57 (0.15)
EMmedian_B	10000	*A priori*	0.77 (0.01)	0.86 (0.01)	0.68 (0.01)	0.88 (0.02)	0.29 (0.1)	0.59 (0.1)
EMmedian_B	1:1	Automated	0.74 (0.05)	0.91 (0.05)	0.71 (0.04)	0.97 (0.01)	0.65 (0.08)	0.32 (0.08)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Spearman's correlation			Continuous Boyce index (Calibration)		
			BIO1	BIO13	Elevation	Train	Test	Fit
EMmedian_B	1:2	Automated	0.74 (0.05)	0.91 (0.05)	0.71 (0.04)	0.94 (0.02)	0.85 (0.03)	0.09 (0.03)
EMmedian_B	1:3	Automated	0.64 (0)	0.97 (0.01)	0.75 (0.01)	0.94 (0.02)	0.86 (0.02)	0.08 (0.03)
EMmedian_B	10000	Automated	0.64 (0)	0.97 (0)	0.75 (0.01)	0.94 (0.02)	0.87 (0.02)	0.07 (0.03)
EMmedian_B	1:1	Expert	0.76 (0.01)	0.93 (0.01)	0.72 (0.02)	0.96 (0.02)	0.57 (0.15)	0.4 (0.15)
EMmedian_B	1:2	Expert	0.76 (0.01)	0.93 (0.01)	0.71 (0.01)	0.97 (0.02)	0.61 (0.1)	0.36 (0.1)
EMmedian_B	1:3	Expert	0.76 (0.01)	0.93 (0.01)	0.72 (0.01)	0.97 (0.01)	0.59 (0.11)	0.38 (0.11)
EMmedian_B	10000	Expert	0.75 (0.01)	0.93 (0)	0.71 (0.01)	0.97 (0.02)	0.6 (0.1)	0.37 (0.1)
EMwmean_B	1:1	*A priori*	0.77 (0.02)	0.87 (0.01)	0.67 (0.02)	0.95 (0.02)	0.4 (0.1)	0.55 (0.1)
EMwmean_B	1:2	*A priori*	0.77 (0.01)	0.86 (0.01)	0.65 (0.02)	0.93 (0.03)	0.43 (0.17)	0.5 (0.17)
EMwmean_B	1:3	*A priori*	0.77 (0.01)	0.86 (0.01)	0.65 (0.01)	0.92 (0.02)	0.47 (0.15)	0.45 (0.15)
EMwmean_B	10000	*A priori*	0.77 (0.01)	0.85 (0.01)	0.64 (0.01)	0.91 (0.02)	0.47 (0.11)	0.44 (0.11)
EMwmean_B	1:1	Automated	0.75 (0.02)	0.92 (0.01)	0.72 (0.02)	0.97 (0.01)	0.67 (0.07)	0.3 (0.07)
EMwmean_B	1:2	Automated	0.63 (0.01)	0.96 (0.01)	0.73 (0.01)	0.92 (0.02)	0.85 (0.04)	0.07 (0.04)
EMwmean_B	1:3	Automated	0.73 (0.02)	0.89 (0.02)	0.7 (0.02)	0.96 (0.01)	0.62 (0.07)	0.34 (0.08)
EMwmean_B	10000	Automated	0.73 (0.01)	0.9 (0.01)	0.7 (0.01)	0.96 (0.01)	0.61 (0.09)	0.35 (0.09)
EMwmean_B	1:1	Expert	0.76 (0.02)	0.92 (0.01)	0.72 (0.02)	0.97 (0.02)	0.66 (0.12)	0.3 (0.12)
EMwmean_B	1:2	Expert	0.75 (0.01)	0.92 (0.01)	0.71 (0.01)	0.97 (0.02)	0.67 (0.11)	0.3 (0.11)
EMwmean_B	1:3	Expert	0.75 (0.01)	0.92 (0.01)	0.71 (0.01)	0.97 (0.01)	0.71 (0.09)	0.26 (0.09)
EMwmean_B	10000	Expert	0.75 (0.01)	0.92 (0.01)	0.71 (0.01)	0.96 (0.01)	0.69 (0.09)	0.27 (0.09)
FDA_B	1:1	*A priori*	0.75 (0.02)	0.89 (0.02)	0.7 (0.03)	0.87 (0.06)	-0.09 (0.19)	0.96 (0.2)
FDA_B	1:2	*A priori*	0.76 (0.02)	0.89 (0.01)	0.69 (0.02)	0.74 (0.06)	-0.03 (0.11)	0.77 (0.12)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Spearman's correlation			Continuous Boyce index (Calibration)		
			BIO1	BIO13	Elevation	Train	Test	Fit
FDA_B	1:3	*A priori*	0.76 (0.02)	0.89 (0.01)	0.69 (0.02)	0.71 (0.09)	0.2 (0.17)	0.51 (0.19)
FDA_B	10000	*A priori*	0.76 (0.01)	0.88 (0.01)	0.69 (0.02)	0.73 (0.08)	0.56 (0.09)	0.17 (0.13)
FDA_B	1:1	Automated	0.77 (0.02)	0.94 (0.01)	0.7 (0.01)	0.89 (0.04)	0.26 (0.15)	0.63 (0.16)
FDA_B	1:2	Automated	0.77 (0.01)	0.94 (0.01)	0.69 (0.01)	0.73 (0.08)	0.32 (0.13)	0.41 (0.16)
FDA_B	1:3	Automated	0.77 (0.01)	0.94 (0.01)	0.69 (0.01)	0.59 (0.07)	0.46 (0.16)	0.13 (0.18)
FDA_B	10000	Automated	0.77 (0.01)	0.9 (0.01)	0.69 (0.01)	0.75 (0.09)	0.67 (0.09)	0.08 (0.13)
FDA_B	1:1	Expert	0.76 (0.02)	0.93 (0.01)	0.7 (0.02)	0.91 (0.04)	0.36 (0.19)	0.56 (0.2)
FDA_B	1:2	Expert	0.76 (0.01)	0.94 (0.01)	0.69 (0.02)	0.81 (0.08)	0.3 (0.12)	0.5 (0.14)
FDA_B	1:3	Expert	0.77 (0.01)	0.93 (0.01)	0.7 (0.02)	0.7 (0.1)	0.36 (0.13)	0.35 (0.13)
FDA_B	10000	Expert	0.77 (0.01)	0.94 (0.01)	0.69 (0.02)	0.55 (0.14)	0.55 (0.09)	0 (0.18)
FDA_O	1:1	*A priori*	0.64 (0.02)	0.79 (0.02)	0.63 (0.02)	0 (0)	0 (0)	0 (0)
FDA_O	1:2	*A priori*	0.64 (0.02)	0.8 (0.02)	0.63 (0.02)	0 (0)	0 (0)	0 (0)
FDA_O	1:3	*A priori*	0.64 (0.02)	0.79 (0.01)	0.63 (0.02)	0 (0)	0 (0)	0 (0)
FDA_O	10000	*A priori*	0.64 (0.02)	0.8 (0.02)	0.63 (0.03)	0 (0)	0 (0)	0 (0)
FDA_O	1:1	Automated	-	0.8 (0.01)	0.62 (0.02)	0 (0)	0 (0)	0 (0)
FDA_O	1:2	Automated	-	0.81 (0.02)	0.62 (0.02)	0 (0)	0 (0)	0 (0)
FDA_O	1:3	Automated	0.64 (0.03)	0.81 (0.02)	0.6 (0.03)	0 (0)	0 (0)	0 (0)
FDA_O	10000	Automated	0.64 (0.03)	0.81 (0.02)	0.6 (0.03)	0 (0)	0 (0)	0 (0)
FDA_O	1:1	Expert	0.64 (0.03)	0.82 (0.02)	0.59 (0.03)	0 (0)	0 (0)	0 (0)
FDA_O	1:2	Expert	0.63 (0.03)	0.82 (0.02)	0.59 (0.03)	0 (0)	0 (0)	0 (0)
FDA_O	1:3	Expert	0.64 (0.04)	0.81 (0.02)	0.59 (0.03)	0 (0)	0 (0)	0 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Spearman's correlation			Continuous Boyce index (Calibration)		
			BIO1	BIO13	Elevation	Train	Test	Fit
FDA_O	10000	Expert	0.63 (0.03)	0.82 (0.02)	0.59 (0.04)	0 (0)	0 (0)	0 (0)
GAM_B	1:1	*A priori*	0.74 (0.04)	0.84 (0.02)	0.65 (0.03)	0.88 (0.06)	0.22 (0.17)	0.66 (0.2)
GAM_B	1:2	*A priori*	0.73 (0.03)	0.83 (0.02)	0.63 (0.02)	0.83 (0.04)	0.26 (0.15)	0.57 (0.15)
GAM_B	1:3	*A priori*	0.72 (0.03)	0.82 (0.02)	0.63 (0.02)	0.84 (0.05)	0.24 (0.18)	0.6 (0.18)
GAM_B	10000	*A priori*	0.71 (0.02)	0.81 (0.01)	0.62 (0.01)	0.81 (0.05)	0.16 (0.12)	0.65 (0.13)
GAM_B	1:1	Automated	0.74 (0.02)	0.89 (0.01)	0.68 (0.02)	0.9 (0.07)	0.27 (0.16)	0.63 (0.18)
GAM_B	1:2	Automated	0.73 (0.02)	0.89 (0.01)	0.68 (0.01)	0.88 (0.06)	0.34 (0.11)	0.53 (0.12)
GAM_B	1:3	Automated	0.7 (0.02)	0.87 (0.02)	0.67 (0.01)	0.79 (0.06)	0.47 (0.1)	0.32 (0.1)
GAM_B	10000	Automated	0.71 (0.02)	0.88 (0.01)	0.67 (0.01)	0.81 (0.05)	0.27 (0.11)	0.54 (0.13)
GAM_B	1:1	Expert	0.75 (0.02)	0.9 (0.01)	0.69 (0.02)	0.87 (0.08)	0.37 (0.13)	0.49 (0.15)
GAM_B	1:2	Expert	0.73 (0.02)	0.9 (0.01)	0.68 (0.01)	0.82 (0.07)	0.4 (0.12)	0.42 (0.14)
GAM_B	1:3	Expert	0.73 (0.02)	0.89 (0.01)	0.68 (0.01)	0.8 (0.04)	0.42 (0.09)	0.38 (0.09)
GAM_B	10000	Expert	0.72 (0.01)	0.89 (0.01)	0.68 (0.01)	0.77 (0.04)	0.36 (0.1)	0.41 (0.11)
GAM_O	1:1	*A priori*	0.75 (0.02)	0.91 (0.02)	0.79 (0.01)	0.26 (0.37)	0.59 (0.29)	-0.33 (0.53)
GAM_O	1:2	*A priori*	0.76 (0.01)	0.9 (0.01)	0.79 (0.02)	0.44 (0.28)	0.47 (0.24)	-0.03 (0.41)
GAM_O	1:3	*A priori*	0.77 (0.01)	0.89 (0.01)	0.79 (0.01)	0.48 (0.26)	0.46 (0.23)	0.02 (0.4)
GAM_O	10000	*A priori*	0.78 (0.01)	0.88 (0.01)	0.8 (0.01)	0.56 (0.18)	0.38 (0.17)	0.18 (0.25)
GAM_O	1:1	Automated	0.75 (0.01)	0.92 (0.01)	0.8 (0.01)	0.14 (0.29)	0.57 (0.23)	-0.43 (0.41)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Spearman's correlation			Continuous Boyce index (Calibration)		
			BIO1	BIO13	Elevation	Train	Test	Fit
GAM_O	1:2	Automated	0.76 (0.01)	0.92 (0.01)	0.81 (0.01)	0.32 (0.2)	0.52 (0.18)	-0.21 (0.3)
GAM_O	1:3	Automated	0.78 (0.01)	0.92 (0.01)	0.78 (0.01)	0.9 (0.13)	0.53 (0.12)	0.37 (0.11)
GAM_O	10000	Automated	0.8 (0.01)	0.91 (0.01)	0.79 (0.01)	0.95 (0.05)	0.46 (0.06)	0.49 (0.1)
GAM_O	1:1	Expert	0.77 (0.02)	0.93 (0.01)	0.78 (0.01)	0.83 (0.08)	0.66 (0.11)	0.17 (0.19)
GAM_O	1:2	Expert	0.78 (0.01)	0.93 (0.01)	0.78 (0.01)	0.87 (0.05)	0.62 (0.09)	0.25 (0.14)
GAM_O	1:3	Expert	0.78 (0.01)	0.92 (0.01)	0.78 (0.01)	0.91 (0.05)	0.56 (0.09)	0.35 (0.13)
GAM_O	10000	Expert	0.79 (0.01)	0.91 (0.01)	0.79 (0.01)	0.96 (0.02)	0.46 (0.06)	0.5 (0.08)
GBM_B	1:1	*A priori*	0.77 (0.02)	0.85 (0.02)	0.67 (0.02)	0.96 (0.01)	0.29 (0.13)	0.67 (0.13)
GBM_B	1:2	*A priori*	0.78 (0.01)	0.85 (0.01)	0.67 (0.02)	0.96 (0.01)	0.21 (0.08)	0.75 (0.08)
GBM_B	1:3	*A priori*	0.78 (0.01)	0.84 (0.01)	0.67 (0.01)	0.96 (0.01)	0.2 (0.1)	0.76 (0.1)
GBM_B	10000	*A priori*	0.79 (0.01)	0.84 (0.01)	0.68 (0.01)	0.96 (0.01)	0.17 (0.07)	0.79 (0.07)
GBM_B	1:1	Automated	0.77 (0.01)	0.91 (0.01)	0.69 (0.01)	0.94 (0.02)	0.54 (0.16)	0.39 (0.16)
GBM_B	1:2	Automated	0.77 (0.01)	0.91 (0.01)	0.69 (0.01)	0.94 (0.03)	0.57 (0.14)	0.37 (0.14)
GBM_B	1:3	Automated	0.77 (0.01)	0.91 (0.01)	0.7 (0.01)	0.95 (0.01)	0.57 (0.1)	0.38 (0.1)
GBM_B	10000	Automated	0.78 (0.01)	0.91 (0.01)	0.7 (0)	0.95 (0.01)	0.59 (0.09)	0.36 (0.09)
GBM_B	1:1	Expert	0.75 (0.01)	0.9 (0.01)	0.71 (0.02)	0.96 (0.02)	0.58 (0.11)	0.37 (0.12)
GBM_B	1:2	Expert	0.75 (0.01)	0.9 (0.01)	0.72 (0.01)	0.97 (0.01)	0.56 (0.12)	0.41 (0.13)
GBM_B	1:3	Expert	0.75 (0.01)	0.9 (0.01)	0.72 (0.01)	0.96 (0.01)	0.52 (0.12)	0.44 (0.11)
GBM_B	10000	Expert	0.75 (0.01)	0.9 (0.01)	0.72 (0.01)	0.96 (0.01)	0.51 (0.14)	0.45 (0.14)
GBM_O	1:1	*A priori*	0.75 (0.01)	0.91 (0.01)	0.75 (0.02)	0.92 (0.05)	0.42 (0.13)	0.5 (0.13)
GBM_O	1:2	*A priori*	0.75 (0.01)	0.92 (0.01)	0.74 (0.01)	0.91 (0.04)	0.49 (0.08)	0.42 (0.07)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Spearman's correlation			Continuous Boyce index (Calibration)		
			BIO1	BIO13	Elevation	Train	Test	Fit
GBM_O	1:3	*A priori*	0.74 (0.01)	0.92 (0.01)	0.74 (0.01)	0.9 (0.04)	0.55 (0.1)	0.35 (0.1)
GBM_O	10000	*A priori*	0.74 (0.01)	0.93 (0)	0.73 (0.01)	0.83 (0.05)	0.59 (0.1)	0.24 (0.09)
GBM_O	1:1	Automated	0.77 (0.01)	0.91 (0.01)	0.71 (0.02)	0.95 (0.02)	0.73 (0.06)	0.22 (0.06)
GBM_O	1:2	Automated	0.76 (0.01)	0.92 (0.01)	0.7 (0.02)	0.94 (0.02)	0.76 (0.06)	0.18 (0.06)
GBM_O	1:3	Automated	0.76 (0.01)	0.92 (0.01)	0.7 (0.01)	0.93 (0.02)	0.75 (0.05)	0.18 (0.05)
GBM_O	10000	Automated	0.75 (0.01)	0.94 (0.01)	0.7 (0.01)	0.91 (0.03)	0.79 (0.05)	0.12 (0.06)
GBM_O	1:1	Expert	0.85 (0.01)	0.86 (0.01)	0.79 (0.02)	0.99 (0)	0.27 (0.1)	0.73 (0.09)
GBM_O	1:2	Expert	0.86 (0.01)	0.87 (0.01)	0.78 (0.02)	0.99 (0)	0.27 (0.08)	0.73 (0.08)
GBM_O	1:3	Expert	0.75 (0.01)	0.93 (0.01)	0.71 (0.01)	0.95 (0.02)	0.76 (0.05)	0.19 (0.05)
GBM_O	10000	Expert	0.74 (0.01)	0.94 (0)	0.71 (0.01)	0.95 (0.02)	0.78 (0.06)	0.17 (0.06)
GLM_B	1:1	*A priori*	0.74 (0.05)	0.9 (0.05)	0.7 (0.04)	0.92 (0.08)	0.09 (0.13)	0.83 (0.15)
GLM_B	1:2	*A priori*	0.75 (0.04)	0.9 (0.04)	0.69 (0.04)	0.92 (0.05)	0.13 (0.1)	0.79 (0.11)
GLM_B	1:3	*A priori*	0.76 (0.06)	0.9 (0.04)	0.69 (0.04)	0.92 (0.07)	0.16 (0.13)	0.76 (0.14)
GLM_B	10000	*A priori*	0.77 (0.05)	0.89 (0.05)	0.68 (0.04)	0.9 (0.07)	0.13 (0.12)	0.77 (0.13)
GLM_B	1:1	Automated	0.76 (0.01)	0.95 (0.01)	0.75 (0.02)	0.98 (0.01)	0.5 (0.09)	0.47 (0.09)
GLM_B	1:2	Automated	0.76 (0.01)	0.95 (0.01)	0.74 (0.01)	0.97 (0.01)	0.56 (0.07)	0.42 (0.07)
GLM_B	1:3	Automated	0.76 (0.01)	0.95 (0)	0.75 (0.01)	0.97 (0.01)	0.52 (0.06)	0.46 (0.06)
GLM_B	10000	Automated	0.76 (0.01)	0.95 (0)	0.74 (0.01)	0.97 (0.01)	0.55 (0.07)	0.42 (0.07)
GLM_B	1:1	Expert	0.77 (0.01)	0.95 (0.01)	0.75 (0.01)	0.98 (0.01)	0.46 (0.1)	0.51 (0.09)
GLM_B	1:2	Expert	0.76 (0.01)	0.95 (0)	0.74 (0.01)	0.98 (0.01)	0.52 (0.08)	0.46 (0.08)
GLM_B	1:3	Expert	0.76 (0.01)	0.95 (0)	0.75 (0.01)	0.98 (0)	0.48 (0.06)	0.5 (0.06)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Spearman's correlation			Continuous Boyce index (Calibration)		
			BIO1	BIO13	Elevation	Train	Test	Fit
GLM_B	10000	Expert	0.76 (0.01)	0.95 (0)	0.75 (0)	0.98 (0.01)	0.54 (0.1)	0.44 (0.1)
GLM_O	1:1	*A priori*	0.7 (0.11)	0.85 (0.09)	0.69 (0.07)	0.61 (0.51)	0.42 (0.43)	0.19 (0.57)
GLM_O	1:2	*A priori*	0.71 (0.08)	0.86 (0.07)	0.69 (0.07)	0.48 (0.58)	0.29 (0.48)	0.19 (0.78)
GLM_O	1:3	*A priori*	0.73 (0.04)	0.87 (0.05)	0.7 (0.04)	0.63 (0.46)	0.31 (0.41)	0.32 (0.58)
GLM_O	10000	*A priori*	0.75 (0.01)	0.88 (0.01)	0.71 (0.01)	0.67 (0.48)	0.26 (0.26)	0.41 (0.49)
GLM_O	1:1	Automated	0.72 (0.08)	0.9 (0.06)	0.72 (0.05)	0.49 (0.46)	0.46 (0.43)	0.03 (0.41)
GLM_O	1:2	Automated	0.75 (0.05)	0.93 (0.03)	0.72 (0.03)	0.66 (0.48)	0.57 (0.4)	0.08 (0.2)
GLM_O	1:3	Automated	0.76 (0.02)	0.93 (0.01)	0.72 (0.01)	0.77 (0.42)	0.69 (0.33)	0.08 (0.31)
GLM_O	10000	Automated	0.77 (0.01)	0.94 (0.01)	0.73 (0.01)	0.85 (0.34)	0.68 (0.34)	0.17 (0.24)
GLM_O	1:1	Expert	0.76 (0.01)	0.95 (0.01)	0.75 (0.02)	0.99 (0.02)	0.73 (0.14)	0.26 (0.14)
GLM_O	1:2	Expert	0.76 (0.01)	0.95 (0.01)	0.74 (0.01)	0.99 (0.01)	0.72 (0.13)	0.27 (0.14)
GLM_O	1:3	Expert	0.77 (0.01)	0.95 (0.01)	0.73 (0.01)	0.99 (0.01)	0.68 (0.19)	0.31 (0.2)
GLM_O	10000	Expert	0.78 (0.01)	0.94 (0.01)	0.73 (0.01)	0.99 (0.01)	0.62 (0.19)	0.38 (0.19)
MARS_B	1:1	*A priori*	0.72 (0.02)	0.87 (0.02)	0.7 (0.03)	0.93 (0.04)	0.25 (0.18)	0.68 (0.19)
MARS_B	1:2	*A priori*	0.73 (0.05)	0.87 (0.04)	0.7 (0.03)	0.88 (0.07)	0.17 (0.14)	0.71 (0.16)
MARS_B	1:3	*A priori*	0.74 (0.03)	0.87 (0.02)	0.7 (0.02)	0.9 (0.04)	0.15 (0.18)	0.75 (0.19)
MARS_B	10000	*A priori*	0.74 (0.02)	0.87 (0.01)	0.7 (0.02)	0.89 (0.04)	0.16 (0.13)	0.73 (0.13)
MARS_B	1:1	Automated	0.75 (0.02)	0.91 (0.02)	0.71 (0.03)	0.97 (0.01)	0.38 (0.16)	0.58 (0.16)
MARS_B	1:2	Automated	0.75 (0.01)	0.9 (0.01)	0.7 (0.02)	0.96 (0.02)	0.57 (0.15)	0.39 (0.15)
MARS_B	1:3	Automated	0.74 (0.01)	0.89 (0.01)	0.7 (0.01)	0.96 (0.03)	0.45 (0.15)	0.51 (0.16)
MARS_B	10000	Automated	0.74 (0.01)	0.89 (0.01)	0.7 (0.01)	0.96 (0.03)	0.33 (0.13)	0.63 (0.14)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Spearman's correlation			Continuous Boyce index (Calibration)		
			BIO1	BIO13	Elevation	Train	Test	Fit
MARS_B	1:1	Expert	0.75 (0.02)	0.91 (0.02)	0.7 (0.02)	0.95 (0.04)	0.44 (0.17)	0.51 (0.18)
MARS_B	1:2	Expert	0.75 (0.02)	0.91 (0.01)	0.71 (0.02)	0.96 (0.03)	0.49 (0.16)	0.47 (0.16)
MARS_B	1:3	Expert	0.75 (0.01)	0.91 (0.01)	0.71 (0.01)	0.97 (0.02)	0.46 (0.14)	0.51 (0.14)
MARS_B	10000	Expert	0.76 (0.01)	0.9 (0.01)	0.71 (0.01)	0.95 (0.06)	0.41 (0.14)	0.54 (0.16)
MARS_O	1:1	*A priori*	0.75 (0.02)	0.89 (0.02)	0.72 (0.02)	0.59 (0.35)	0.48 (0.29)	0.11 (0.27)
MARS_O	1:2	*A priori*	0.75 (0.01)	0.9 (0.01)	0.7 (0.02)	0.59 (0.24)	0.54 (0.2)	0.05 (0.26)
MARS_O	1:3	*A priori*	0.76 (0.01)	0.89 (0.01)	0.7 (0.01)	0.52 (0.37)	0.45 (0.23)	0.06 (0.42)
MARS_O	10000	*A priori*	0.75 (0.01)	0.88 (0.01)	0.68 (0.01)	0.49 (0.26)	0.52 (0.24)	-0.03 (0.32)
MARS_O	1:1	Automated	-	0.91 (0.01)	0.71 (0.02)	0.65 (0.15)	0.56 (0.15)	0.09 (0.2)
MARS_O	1:3	Automated	0.76 (0.01)	0.9 (0.01)	0.69 (0.02)	0.48 (0.19)	0.5 (0.23)	-0.02 (0.23)
MARS_O	10000	Automated	0.76 (0.01)	0.89 (0.01)	0.67 (0.02)	0.39 (0.21)	0.56 (0.21)	-0.17 (0.26)
MARS_O	1:1	Expert	0.76 (0.02)	0.92 (0.01)	0.7 (0.02)	0.95 (0.03)	0.6 (0.17)	0.35 (0.18)
MARS_O	1:2	Expert	0.76 (0.02)	0.93 (0.01)	0.69 (0.02)	0.9 (0.06)	0.68 (0.13)	0.21 (0.15)
MARS_O	1:3	Expert	0.76 (0.02)	0.93 (0.01)	0.69 (0.02)	0.91 (0.06)	0.7 (0.11)	0.22 (0.12)
MARS_O	10000	Expert	0.76 (0.01)	0.93 (0.01)	0.67 (0.02)	0.83 (0.08)	0.8 (0.15)	0.03 (0.16)
MaxEnt_B	1:1	*A priori*	0.66 (0.16)	0.76 (0.15)	0.6 (0.14)	0.82 (0.11)	0.33 (0.2)	0.49 (0.23)
MaxEnt_B	1:2	*A priori*	0.64 (0.19)	0.74 (0.19)	0.57 (0.17)	0.78 (0.18)	0.34 (0.23)	0.43 (0.3)
MaxEnt_B	1:3	*A priori*	0.69 (0.11)	0.78 (0.11)	0.6 (0.09)	0.81 (0.12)	0.31 (0.23)	0.5 (0.26)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Spearman's correlation			Continuous Boyce index (Calibration)		
			BIO1	**BIO13**	**Elevation**	**Train**	**Test**	**Fit**
MaxEnt_B	10000	*A priori*	0.7 (0.14)	0.78 (0.12)	0.59 (0.11)	0.82 (0.09)	0.22 (0.16)	0.6 (0.17)
MaxEnt_B	1:1	Automated	0.71 (0.17)	0.84 (0.16)	0.63 (0.15)	0.8 (0.11)	0.21 (0.22)	0.59 (0.26)
MaxEnt_B	1:2	Automated	0.69 (0.17)	0.82 (0.16)	0.62 (0.13)	0.82 (0.09)	0.35 (0.21)	0.47 (0.21)
MaxEnt_B	1:3	Automated	0.72 (0.08)	0.86 (0.09)	0.64 (0.07)	0.83 (0.08)	0.06 (0.22)	0.77 (0.24)
MaxEnt_B	10000	Automated	0.75 (0.03)	0.89 (0.02)	0.7 (0.01)	0.88 (0.04)	-0.06 (0.13)	0.94 (0.14)
MaxEnt_B	1:1	Expert	0.71 (0.14)	0.86 (0.15)	0.64 (0.12)	0.78 (0.14)	0.32 (0.19)	0.47 (0.24)
MaxEnt_B	1:2	Expert	0.73 (0.07)	0.9 (0.09)	0.66 (0.07)	0.85 (0.12)	0.29 (0.15)	0.56 (0.19)
MaxEnt_B	1:3	Expert	0.74 (0.07)	0.9 (0.08)	0.67 (0.06)	0.86 (0.07)	0.23 (0.15)	0.63 (0.17)
MaxEnt_B	10000	Expert	0.75 (0.01)	0.92 (0.01)	0.68 (0.01)	0.89 (0.04)	0.23 (0.17)	0.66 (0.18)
MaxEnt_O	1:1	*A priori*	0.65 (0.21)	0.78 (0.19)	0.63 (0.17)	0.75 (0.26)	0.19 (0.39)	0.56 (0.47)
MaxEnt_O	1:2	*A priori*	0.65 (0.19)	0.79 (0.21)	0.63 (0.19)	0.79 (0.22)	0.22 (0.35)	0.57 (0.41)
MaxEnt_O	1:3	*A priori*	0.65 (0.18)	0.79 (0.18)	0.63 (0.17)	0.75 (0.24)	0.24 (0.38)	0.51 (0.43)
MaxEnt_O	10000	*A priori*	0.66 (0.19)	0.79 (0.18)	0.63 (0.16)	0.78 (0.22)	0.27 (0.4)	0.51 (0.44)
MaxEnt_O	1:1	Automated	0.75 (0.02)	0.89 (0.03)	-	0.85 (0.08)	0.36 (0.34)	0.49 (0.34)
MaxEnt_O	1:2	Automated	0.7 (0.15)	0.84 (0.16)	-	0.79 (0.23)	0.23 (0.35)	0.56 (0.37)
MaxEnt_O	1:3	Automated	-	0.88 (0.03)	-	0.85 (0.07)	0.34 (0.28)	0.51 (0.28)
MaxEnt_O	10000	Automated	0.73 (0.09)	0.87 (0.09)	-	0.83 (0.16)	0.27 (0.36)	0.56 (0.36)
MaxEnt_O	1:1	Expert	0.69 (0.17)	0.86 (0.15)	0.63 (0.14)	0.81 (0.14)	0.29 (0.3)	0.51 (0.28)
MaxEnt_O	1:2	Expert	0.67 (0.19)	0.85 (0.18)	0.61 (0.16)	0.79 (0.18)	0.32 (0.26)	0.47 (0.29)
MaxEnt_O	1:3	Expert	0.7 (0.17)	0.87 (0.15)	0.64 (0.14)	0.8 (0.17)	0.3 (0.29)	0.5 (0.33)
MaxEnt_O	10000	Expert	0.73 (0.11)	0.89 (0.11)	0.66 (0.09)	0.82 (0.15)	0.3 (0.29)	0.52 (0.32)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Spearman's correlation			Continuous Boyce index (Calibration)		
			BIO1	BIO13	Elevation	Train	Test	Fit
MXL_O	1:1	*A priori*	0.75 (0.05)	0.8 (0.04)	0.83 (0.04)	0.59 (0.17)	0.19 (0.22)	0.39 (0.22)
MXL_O	1:2	*A priori*	0.74 (0.05)	0.8 (0.04)	0.83 (0.04)	0.6 (0.15)	0.24 (0.19)	0.36 (0.21)
MXL_O	1:3	*A priori*	0.74 (0.05)	0.8 (0.04)	0.83 (0.04)	0.61 (0.16)	0.19 (0.21)	0.42 (0.22)
MXL_O	10000	*A priori*	0.74 (0.05)	0.8 (0.04)	0.82 (0.04)	0.58 (0.17)	0.15 (0.21)	0.44 (0.23)
MXL_O	1:1	Automated	0.62 (0.04)	0.8 (0.02)	-	0.74 (0.11)	0.55 (0.28)	0.19 (0.27)
MXL_O	1:2	Automated	0.65 (0.05)	0.83 (0.03)	-	0.71 (0.17)	0.49 (0.26)	0.22 (0.24)
MXL_O	1:3	Automated	0.65 (0.05)	0.83 (0.03)	-	0.73 (0.16)	0.51 (0.28)	0.23 (0.27)
MXL_O	10000	Automated	0.65 (0.05)	0.83 (0.03)	-	0.74 (0.13)	0.48 (0.24)	0.26 (0.24)
MXL_O	1:1	Expert	0.77 (0.04)	0.92 (0.06)	0.77 (0.07)	0.63 (0.25)	0.26 (0.25)	0.37 (0.37)
MXL_O	1:2	Expert	0.77 (0.03)	0.92 (0.06)	0.77 (0.07)	0.59 (0.26)	0.3 (0.23)	0.29 (0.38)
MXL_O	1:3	Expert	0.76 (0.04)	0.91 (0.07)	0.78 (0.08)	0.63 (0.27)	0.33 (0.24)	0.3 (0.37)
MXL_O	10000	Expert	0.77 (0.04)	0.91 (0.07)	0.78 (0.08)	0.64 (0.18)	0.31 (0.19)	0.33 (0.27)
RF_B	1:1	*A priori*	0.65 (0.02)	0.74 (0.01)	0.6 (0.02)	0.95 (0.02)	0.16 (0.11)	0.79 (0.11)
RF_B	1:2	*A priori*	0.61 (0.01)	0.71 (0.01)	0.56 (0.01)	0.92 (0.02)	0.21 (0.08)	0.71 (0.08)
RF_B	1:3	*A priori*	0.59 (0.01)	0.69 (0.01)	0.53 (0.01)	0.91 (0.02)	0.24 (0.09)	0.67 (0.1)
RF_B	10000	*A priori*	0.53 (0.01)	0.63 (0.01)	0.47 (0.01)	0.89 (0.03)	0.31 (0.07)	0.58 (0.07)
RF_B	1:1	Automated	0.61 (0.01)	0.76 (0.01)	0.62 (0.01)	0.92 (0.03)	0.4 (0.11)	0.52 (0.11)
RF_B	1:2	Automated	0.58 (0.01)	0.74 (0.01)	0.59 (0.01)	0.91 (0.03)	0.43 (0.11)	0.48 (0.12)
RF_B	1:3	Automated	0.56 (0.01)	0.73 (0.01)	0.58 (0.01)	0.89 (0.03)	0.46 (0.09)	0.42 (0.1)
RF_B	10000	Automated	0.52 (0.01)	0.68 (0.01)	0.55 (0.01)	0.9 (0.03)	0.49 (0.08)	0.41 (0.08)
RF_B	1:1	Expert	0.62 (0.01)	0.77 (0.01)	0.62 (0.01)	0.9 (0.04)	0.61 (0.11)	0.3 (0.12)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Spearman's correlation			Continuous Boyce index (Calibration)		
			BIO1	BIO13	Elevation	Train	Test	Fit
RF_B	1:2	Expert	0.59 (0.01)	0.76 (0.01)	0.6 (0.01)	0.9 (0.04)	0.55 (0.12)	0.35 (0.13)
RF_B	1:3	Expert	0.57 (0.01)	0.74 (0.01)	0.59 (0.01)	0.93 (0.03)	0.51 (0.11)	0.42 (0.12)
RF_B	10000	Expert	0.53 (0.01)	0.7 (0)	0.56 (0)	0.95 (0.02)	0.44 (0.15)	0.51 (0.15)
RF_O	1:1	*A priori*	0.61 (0.01)	0.76 (0.01)	0.64 (0.01)	0.9 (0.04)	0.36 (0.19)	0.54 (0.2)
RF_O	1:2	*A priori*	0.58 (0.01)	0.75 (0.01)	0.62 (0.01)	0.88 (0.04)	0.39 (0.17)	0.49 (0.18)
RF_O	1:3	*A priori*	0.56 (0.01)	0.73 (0.01)	0.61 (0.01)	0.87 (0.04)	0.42 (0.15)	0.45 (0.17)
RF_O	10000	*A priori*	0.53 (0.01)	0.7 (0.01)	0.59 (0.01)	0.86 (0.04)	0.5 (0.12)	0.37 (0.12)
RF_O	1:1	Automated	0.6 (0.01)	0.76 (0.01)	0.61 (0.01)	0.88 (0.05)	0.39 (0.14)	0.5 (0.16)
RF_O	1:2	Automated	0.57 (0.01)	0.74 (0.01)	0.59 (0.01)	0.86 (0.05)	0.41 (0.15)	0.46 (0.18)
RF_O	1:3	Automated	0.56 (0.01)	0.72 (0.01)	0.58 (0.01)	0.87 (0.06)	0.38 (0.15)	0.49 (0.17)
RF_O	10000	Automated	0.52 (0.01)	0.69 (0.01)	0.55 (0.01)	0.88 (0.04)	0.51 (0.1)	0.36 (0.12)
RF_O	1:1	Expert	0.61 (0.01)	0.77 (0.01)	0.62 (0.01)	0.93 (0.05)	0.54 (0.13)	0.39 (0.15)
RF_O	1:2	Expert	0.58 (0.01)	0.75 (0.01)	0.6 (0.01)	0.93 (0.03)	0.59 (0.15)	0.34 (0.15)
RF_O	1:3	Expert	0.57 (0.01)	0.74 (0.01)	0.59 (0.01)	0.92 (0.04)	0.56 (0.14)	0.36 (0.15)
RF_O	10000	Expert	0.53 (0.01)	0.7 (0.01)	0.56 (0.01)	0.93 (0.03)	0.46 (0.16)	0.46 (0.16)
SRE_B	1:1	*A priori*	0.25 (0.01)	0.38 (0.01)	0.36 (0.01)	0 (0)	0 (0)	0 (0)
SRE_B	1:2	*A priori*	0.25 (0.01)	0.39 (0.01)	0.36 (0.01)	0 (0)	0 (0)	0 (0)
SRE_B	1:3	*A priori*	0.25 (0.01)	0.39 (0.01)	0.36 (0.01)	0 (0)	0 (0)	0 (0)
SRE_B	10000	*A priori*	0.25 (0.01)	0.39 (0.01)	0.36 (0.01)	0 (0)	0 (0)	0 (0)
SRE_B	1:1	Automated	0.42 (0.01)	0.52 (0)	0.52 (0.01)	0 (0)	0 (0)	0 (0)
SRE_B	1:2	Automated	0.42 (0.01)	0.52 (0.01)	0.52 (0.01)	0 (0)	0 (0)	0 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Spearman's correlation BIO1	BIO13	Elevation	Continuous Boyce index (Calibration) Train	Test	Fit
SRE_B	1:3	Automated	0.42 (0.01)	0.52 (0)	0.52 (0.01)	0 (0)	0 (0)	0 (0)
SRE_B	10000	Automated	0.42 (0.01)	0.52 (0.01)	0.52 (0.01)	0 (0)	0 (0)	0 (0)
SRE_B	1:1	Expert	0.43 (0)	0.55 (0)	0.52 (0)	0 (0)	0 (0)	0 (0)
SRE_B	1:2	Expert	0.43 (0)	0.55 (0.01)	0.52 (0)	0 (0)	0 (0)	0 (0)
SRE_B	1:3	Expert	0.44 (0.01)	0.56 (0.01)	0.53 (0.01)	0 (0)	0 (0)	0 (0)
SRE_B	10000	Expert	0.43 (0.01)	0.56 (0.01)	0.52 (0.01)	0 (0)	0 (0)	0 (0)
SRE_O	1:1	*A priori*	0.4 (0.01)	0.57 (0.01)	0.56 (0.01)	0.25 (0.1)	0.14 (0.34)	0.11 (0.35)
SRE_O	1:2	*A priori*	0.4 (0.01)	0.57 (0.01)	0.56 (0.01)	0.27 (0.12)	0.12 (0.36)	0.15 (0.39)
SRE_O	1:3	*A priori*	0.4 (0.01)	0.57 (0.01)	0.56 (0.01)	0.26 (0.11)	0.14 (0.34)	0.12 (0.35)
SRE_O	10000	*A priori*	0.4 (0.01)	0.57 (0.01)	0.56 (0.01)	0.26 (0.1)	0.15 (0.32)	0.1 (0.33)
SRE_O	1:1	Automated	0.42 (0.01)	0.59 (0.01)	-	0.21 (0.05)	-0.09 (0.36)	0.3 (0.37)
SRE_O	1:2	Automated	0.42 (0.01)	0.6 (0.01)	-	0.21 (0.05)	-0.13 (0.35)	0.35 (0.35)
SRE_O	1:3	Automated	0.42 (0.01)	0.59 (0.01)	-	0.21 (0.05)	-0.1 (0.37)	0.31 (0.37)
SRE_O	10000	Automated	0.42 (0.01)	0.59 (0.01)	-	0.21 (0.05)	-0.15 (0.33)	0.36 (0.34)
SRE_O	1:1	Expert	0.47 (0.01)	0.61 (0.01)	0.57 (0.01)	0.42 (0.04)	-0.14 (0.12)	0.57 (0.13)
SRE_O	1:2	Expert	0.47 (0.01)	0.61 (0.01)	0.57 (0.01)	0.43 (0.04)	-0.12 (0.11)	0.55 (0.12)
SRE_O	1:3	Expert	0.47 (0.01)	0.61 (0.01)	0.57 (0.01)	0.42 (0.04)	-0.11 (0.12)	0.53 (0.13)
SRE_O	10000	Expert	0.47 (0.01)	0.61 (0.01)	0.58 (0.01)	0.42 (0.05)	-0.13 (0.12)	0.54 (0.13)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Mean absolute error (Bias)			Associated skill score (Skill)		
			Train	Test	Fit	Train	Test	Fit
ANN_B	1:1	*A priori*	0.21 (0.01)	0.26 (0.02)	-0.05 (0.01)	0.92 (0.01)	0.91 (0.01)	0.01 (0.01)
ANN_B	1:2	*A priori*	0.21 (0.01)	0.26 (0.01)	-0.05 (0.01)	0.92 (0)	0.91 (0.01)	0.01 (0.01)
ANN_B	1:3	*A priori*	0.21 (0.01)	0.26 (0.01)	-0.05 (0.01)	0.92 (0.01)	0.91 (0.01)	0.02 (0.01)
ANN_B	10000	*A priori*	0.21 (0.01)	0.26 (0.02)	-0.05 (0.01)	0.93 (0.01)	0.91 (0.01)	0.02 (0.01)
ANN_B	1:1	Automated	0.2 (0.01)	0.26 (0.02)	-0.06 (0.02)	0.94 (0.01)	0.91 (0.01)	0.02 (0.01)
ANN_B	1:2	Automated	0.2 (0.01)	0.27 (0.02)	-0.07 (0.02)	0.94 (0)	0.9 (0.01)	0.03 (0.01)
ANN_B	1:3	Automated	0.2 (0.01)	0.27 (0.02)	-0.07 (0.01)	0.93 (0)	0.9 (0.01)	0.03 (0.01)
ANN_B	10000	Automated	0.2 (0.01)	0.27 (0.02)	-0.07 (0.02)	0.93 (0)	0.9 (0.01)	0.03 (0.01)
ANN_B	1:1	Expert	0.19 (0)	0.29 (0.03)	-0.09 (0.02)	0.94 (0)	0.89 (0.01)	0.04 (0.01)
ANN_B	1:2	Expert	0.19 (0.01)	0.28 (0.03)	-0.09 (0.02)	0.94 (0)	0.9 (0.02)	0.04 (0.01)
ANN_B	1:3	Expert	0.19 (0.01)	0.28 (0.03)	-0.09 (0.03)	0.94 (0)	0.9 (0.02)	0.04 (0.01)
ANN_B	10000	Expert	0.19 (0.01)	0.28 (0.03)	-0.09 (0.02)	0.94 (0)	0.9 (0.01)	0.04 (0.01)
ANN_O	1:1	*A priori*	0.06 (0.01)	0.07 (0.02)	0 (0.01)	-0.19 (0.11)	-0.1 (0.18)	-0.09 (0.1)
ANN_O	1:2	*A priori*	0.14 (0.09)	0.13 (0.05)	0.01 (0.05)	-0.22 (0.52)	-0.12 (0.53)	-0.1 (0.09)
ANN_O	1:3	*A priori*	0.21 (0.09)	0.16 (0.04)	0.04 (0.05)	-0.1 (0.76)	0.05 (0.7)	-0.15 (0.13)
ANN_O	10000	*A priori*	0.29 (0.04)	0.21 (0.02)	0.08 (0.03)	0.5 (0.56)	0.62 (0.5)	-0.11 (0.07)
ANN_O	1:1	Automated	0.06 (0.01)	0.06 (0.01)	0 (0.01)	-0.59 (0.1)	-0.44 (0.21)	-0.14 (0.14)
ANN_O	1:2	Automated	0.14 (0.1)	0.12 (0.05)	0.02 (0.05)	-1.67 (1.01)	-1.13 (0.44)	-0.54 (0.61)
ANN_O	1:3	Automated	0.21 (0.1)	0.16 (0.05)	0.05 (0.06)	-2.43 (1.04)	-1.5 (0.38)	-0.93 (0.67)
ANN_O	10000	Automated	0.3 (0.03)	0.21 (0.01)	0.09 (0.02)	-3.33 (0.29)	-1.88 (0.08)	-1.45 (0.22)
ANN_O	1:1	Expert	0.06 (0.01)	0.08 (0.03)	-0.03 (0.03)	-0.66 (0.08)	-0.73 (0.41)	0.07 (0.37)

Table B2.4 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Mean absolute error (Bias)**			**Associated skill score (Skill)**		
			Train	**Test**	**Fit**	**Train**	**Test**	**Fit**
ANN_O	1:2	Expert	0.14 (0.1)	0.14 (0.04)	0 (0.07)	-1.71 (0.99)	-1.33 (0.4)	-0.38 (0.74)
ANN_O	1:3	Expert	0.33 (0)	0.21 (0)	0.11 (0)	-2.62 (1.03)	-1.64 (0.34)	-0.98 (0.77)
ANN_O	10000	Expert	0.31 (0.04)	0.21 (0.01)	0.1 (0.03)	-3.44 (0.41)	-1.88 (0.07)	-1.55 (0.33)
CTA_B	1:1	*A priori*	0.23 (0.01)	0.28 (0.01)	-0.06 (0.01)	0.91 (0.01)	0.89 (0.01)	0.02 (0.01)
CTA_B	1:2	*A priori*	0.23 (0.01)	0.29 (0.01)	-0.06 (0.01)	0.91 (0.01)	0.89 (0.01)	0.02 (0.01)
CTA_B	1:3	*A priori*	0.24 (0.01)	0.3 (0.01)	-0.06 (0.01)	0.9 (0.01)	0.89 (0.01)	0.02 (0)
CTA_B	10000	*A priori*	0.25 (0.01)	0.3 (0.01)	-0.06 (0.01)	0.9 (0.01)	0.88 (0.01)	0.02 (0.01)
CTA_B	1:1	Automated	0.22 (0.02)	0.29 (0.01)	-0.06 (0.01)	0.92 (0.01)	0.89 (0.01)	0.02 (0.01)
CTA_B	1:2	Automated	0.22 (0.01)	0.29 (0.01)	-0.07 (0.01)	0.91 (0.01)	0.89 (0.01)	0.02 (0.01)
CTA_B	1:3	Automated	0.23 (0.01)	0.3 (0.01)	-0.07 (0.01)	0.91 (0.01)	0.88 (0.01)	0.02 (0.01)
CTA_B	10000	Automated	0.25 (0.01)	0.31 (0.01)	-0.06 (0.01)	0.9 (0.01)	0.88 (0.01)	0.02 (0.01)
CTA_B	1:1	Expert	0.21 (0.01)	0.28 (0.01)	-0.07 (0.01)	0.92 (0.01)	0.9 (0.01)	0.02 (0.01)
CTA_B	1:2	Expert	0.22 (0.01)	0.28 (0.01)	-0.06 (0.01)	0.92 (0.01)	0.9 (0.01)	0.02 (0.01)
CTA_B	1:3	Expert	0.22 (0.01)	0.29 (0.01)	-0.07 (0.01)	0.92 (0.01)	0.89 (0.01)	0.02 (0.01)
CTA_B	10000	Expert	0.23 (0.01)	0.29 (0.01)	-0.07 (0.01)	0.91 (0.01)	0.89 (0.01)	0.02 (0)
CTA_O	1:1	*A priori*	0.07 (0)	0.09 (0.01)	-0.02 (0.01)	-0.22 (0.07)	-0.29 (0.07)	0.07 (0.04)
CTA_O	1:2	*A priori*	0.09 (0)	0.11 (0)	-0.02 (0)	-0.45 (0.1)	-0.45 (0.08)	0.01 (0.05)
CTA_O	1:3	*A priori*	0.12 (0)	0.13 (0)	-0.01 (0)	-0.62 (0.14)	-0.57 (0.08)	-0.05 (0.07)
CTA_O	10000	*A priori*	0.18 (0)	0.17 (0)	0.02 (0)	-1.21 (0.26)	-0.86 (0.11)	-0.35 (0.16)
CTA_O	1:1	Automated	0.07 (0)	0.09 (0.01)	-0.02 (0.01)	-0.68 (0.03)	-0.82 (0.06)	0.14 (0.05)
CTA_O	1:2	Automated	0.09 (0)	0.11 (0)	-0.02 (0)	-1.14 (0.03)	-1.1 (0.04)	-0.04 (0.04)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Mean absolute error (Bias)			Associated skill score (Skill)		
			Train	Test	Fit	Train	Test	Fit
CTA_O	1:3	Automated	0.12 (0)	0.13 (0)	-0.02 (0)	-1.47 (0.02)	-1.27 (0.03)	-0.2 (0.04)
CTA_O	10000	Automated	0.18 (0)	0.17 (0)	0.02 (0)	-2.21 (0.04)	-1.56 (0.02)	-0.65 (0.04)
CTA_O	1:1	Expert	0.06 (0)	0.09 (0.01)	-0.03 (0.01)	-0.68 (0.03)	-0.83 (0.07)	0.15 (0.06)
CTA_O	1:2	Expert	0.09 (0)	0.11 (0)	-0.02 (0)	-1.14 (0.03)	-1.1 (0.04)	-0.04 (0.05)
CTA_O	1:3	Expert	0.09 (0)	0.11 (0)	-0.02 (0)	-1.14 (0.03)	-1.1 (0.04)	-0.04 (0.05)
CTA_O	10000	Expert	0.18 (0)	0.16 (0)	0.02 (0)	-2.21 (0.04)	-1.54 (0.03)	-0.67 (0.04)
EMca_B	1:1	*A priori*	0.45 (0.05)	0.49 (0.07)	-0.04 (0.02)	0.75 (0.06)	0.73 (0.07)	0.02 (0.02)
EMca_B	1:2	*A priori*	0.44 (0.06)	0.49 (0.08)	-0.05 (0.02)	0.75 (0.06)	0.74 (0.08)	0.02 (0.02)
EMca_B	1:3	*A priori*	0.43 (0.05)	0.48 (0.07)	-0.04 (0.02)	0.77 (0.06)	0.75 (0.07)	0.02 (0.02)
EMca_B	10000	*A priori*	0.42 (0.05)	0.46 (0.06)	-0.04 (0.01)	0.78 (0.05)	0.76 (0.06)	0.02 (0.01)
EMca_B	1:1	Automated	0.36 (0.06)	0.4 (0.08)	-0.03 (0.02)	0.82 (0.05)	0.81 (0.06)	0.01 (0.02)
EMca_B	1:2	Automated	0.37 (0.06)	0.41 (0.08)	-0.04 (0.02)	0.81 (0.05)	0.8 (0.07)	0.01 (0.02)
EMca_B	1:3	Automated	0.37 (0.05)	0.4 (0.06)	-0.03 (0.02)	0.82 (0.04)	0.81 (0.05)	0.01 (0.02)
EMca_B	10000	Automated	0.36 (0.06)	0.39 (0.08)	-0.03 (0.02)	0.82 (0.05)	0.82 (0.06)	0.01 (0.01)
EMca_B	1:1	Expert	0.38 (0.04)	0.41 (0.06)	-0.04 (0.02)	0.82 (0.03)	0.81 (0.04)	0.01 (0.01)
EMca_B	1:2	Expert	0.38 (0.04)	0.41 (0.06)	-0.03 (0.02)	0.81 (0.04)	0.81 (0.05)	0.01 (0.01)
EMca_B	1:3	Expert	0.4 (0.04)	0.44 (0.05)	-0.04 (0.02)	0.8 (0.03)	0.79 (0.04)	0.01 (0.01)
EMca_B	10000	Expert	0.42 (0.04)	0.47 (0.06)	-0.05 (0.02)	0.78 (0.04)	0.76 (0.06)	0.02 (0.02)
EMmean_B	1:1	*A priori*	0.2 (0.01)	0.25 (0.01)	-0.04 (0.01)	0.93 (0.01)	0.92 (0.01)	0.01 (0.01)
EMmean_B	1:2	*A priori*	0.21 (0.01)	0.24 (0.01)	-0.03 (0.01)	0.93 (0)	0.92 (0.01)	0 (0.01)
EMmean_B	1:3	*A priori*	0.21 (0.01)	0.24 (0.01)	-0.03 (0.01)	0.93 (0)	0.93 (0.01)	0 (0.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Mean absolute error (Bias)			Associated skill score (Skill)		
			Train	Test	Fit	Train	Test	Fit
EMmean_B	10000	*A priori*	0.21 (0.01)	0.24 (0.01)	-0.03 (0.01)	0.93 (0)	0.93 (0.01)	0 (0.01)
EMmean_B	1:1	Automated	0.18 (0)	0.25 (0.01)	-0.07 (0)	0.95 (0)	0.92 (0)	0.03 (0)
EMmean_B	1:2	Automated	0.18 (0)	0.22 (0)	-0.04 (0)	0.95 (0)	0.94 (0)	0.01 (0)
EMmean_B	1:3	Automated	0.18 (0.01)	0.24 (0.01)	-0.06 (0.01)	0.95 (0)	0.92 (0.01)	0.02 (0)
EMmean_B	10000	Automated	0.18 (0.01)	0.24 (0.01)	-0.05 (0.01)	0.95 (0)	0.93 (0.01)	0.02 (0)
EMmean_B	1:1	Expert	0.18 (0)	0.26 (0.01)	-0.08 (0.01)	0.95 (0)	0.92 (0)	0.03 (0)
EMmean_B	1:2	Expert	0.18 (0)	0.25 (0.01)	-0.07 (0.01)	0.95 (0)	0.92 (0)	0.03 (0)
EMmean_B	1:3	Expert	0.18 (0)	0.25 (0.01)	-0.06 (0)	0.95 (0)	0.92 (0)	0.03 (0)
EMmean_B	10000	Expert	0.18 (0)	0.25 (0.01)	-0.06 (0)	0.95 (0)	0.92 (0)	0.03 (0)
EMmedian_B	1:1	*A priori*	0.21 (0.01)	0.26 (0.01)	-0.04 (0.01)	0.92 (0.01)	0.92 (0.01)	0.01 (0.01)
EMmedian_B	1:2	*A priori*	0.22 (0.01)	0.26 (0.01)	-0.04 (0.01)	0.92 (0.01)	0.92 (0.01)	0 (0.01)
EMmedian_B	1:3	*A priori*	0.23 (0.01)	0.26 (0.01)	-0.03 (0.01)	0.92 (0.01)	0.92 (0.01)	0 (0.01)
EMmedian_B	10000	*A priori*	0.23 (0.01)	0.27 (0.01)	-0.03 (0.01)	0.91 (0)	0.91 (0.01)	0 (0.01)
EMmedian_B	1:1	Automated	0.19 (0)	0.26 (0.01)	-0.07 (0.01)	0.95 (0)	0.92 (0)	0.03 (0)
EMmedian_B	1:2	Automated	0.19 (0)	0.23 (0)	-0.04 (0)	0.95 (0)	0.93 (0)	0.01 (0)
EMmedian_B	1:3	Automated	0.19 (0)	0.23 (0)	-0.04 (0)	0.95 (0)	0.93 (0)	0.01 (0)
EMmedian_B	10000	Automated	0.19 (0)	0.23 (0)	-0.04 (0)	0.94 (0)	0.93 (0)	0.01 (0)
EMmedian_B	1:1	Expert	0.19 (0)	0.27 (0.01)	-0.08 (0.01)	0.95 (0)	0.91 (0)	0.03 (0)
EMmedian_B	1:2	Expert	0.19 (0)	0.26 (0.01)	-0.08 (0)	0.95 (0)	0.91 (0)	0.03 (0)
EMmedian_B	1:3	Expert	0.19 (0)	0.26 (0.01)	-0.07 (0)	0.95 (0)	0.92 (0)	0.03 (0)
EMmedian_B	10000	Expert	0.19 (0)	0.27 (0.01)	-0.07 (0)	0.94 (0)	0.91 (0)	0.03 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Mean absolute error (Bias)			Associated skill score (Skill)		
			Train	Test	Fit	Train	Test	Fit
EMwmean_B	1:1	*A priori*	0.2 (0.01)	0.24 (0.01)	-0.04 (0.01)	0.93 (0.01)	0.92 (0.01)	0.01 (0.01)
EMwmean_B	1:2	*A priori*	0.21 (0.01)	0.24 (0.01)	-0.03 (0.01)	0.93 (0)	0.92 (0.01)	0 (0.01)
EMwmean_B	1:3	*A priori*	0.21 (0.01)	0.24 (0.01)	-0.03 (0.01)	0.93 (0)	0.93 (0.01)	0 (0.01)
EMwmean_B	10000	*A priori*	0.21 (0.01)	0.24 (0.01)	-0.03 (0.01)	0.93 (0)	0.93 (0.01)	0 (0.01)
EMwmean_B	1:1	Automated	0.18 (0)	0.25 (0.01)	-0.07 (0.01)	0.95 (0)	0.92 (0)	0.03 (0)
EMwmean_B	1:2	Automated	0.18 (0)	0.22 (0)	-0.04 (0)	0.95 (0)	0.94 (0)	0.01 (0)
EMwmean_B	1:3	Automated	0.18 (0.01)	0.24 (0.01)	-0.06 (0.01)	0.95 (0)	0.92 (0.01)	0.02 (0)
EMwmean_B	10000	Automated	0.18 (0.01)	0.24 (0.01)	-0.05 (0.01)	0.95 (0)	0.93 (0.01)	0.02 (0)
EMwmean_B	1:1	Expert	0.18 (0)	0.26 (0.01)	-0.08 (0.01)	0.95 (0)	0.92 (0)	0.03 (0)
EMwmean_B	1:2	Expert	0.18 (0)	0.25 (0.01)	-0.07 (0.01)	0.95 (0)	0.92 (0)	0.03 (0)
EMwmean_B	1:3	Expert	0.18 (0)	0.25 (0.01)	-0.06 (0)	0.95 (0)	0.92 (0)	0.03 (0)
EMwmean_B	10000	Expert	0.18 (0)	0.25 (0.01)	-0.06 (0)	0.95 (0)	0.92 (0)	0.02 (0)
FDA_B	1:1	*A priori*	0.21 (0.01)	0.27 (0.01)	-0.06 (0.01)	0.93 (0)	0.91 (0.01)	0.02 (0)
FDA_B	1:2	*A priori*	0.22 (0)	0.22 (0.01)	0 (0.01)	0.92 (0)	0.94 (0)	-0.02 (0)
FDA_B	1:3	*A priori*	0.23 (0)	0.2 (0)	0.03 (0.01)	0.92 (0)	0.95 (0)	-0.03 (0)
FDA_B	10000	*A priori*	0.23 (0)	0.19 (0)	0.05 (0)	0.92 (0)	0.96 (0)	-0.04 (0)
FDA_B	1:1	Automated	0.19 (0)	0.27 (0.01)	-0.08 (0.01)	0.94 (0)	0.91 (0.01)	0.04 (0)
FDA_B	1:2	Automated	0.18 (0)	0.21 (0.01)	-0.02 (0)	0.95 (0)	0.94 (0)	0.01 (0)
FDA_B	1:3	Automated	0.19 (0)	0.19 (0)	0 (0)	0.95 (0)	0.95 (0)	0 (0)
FDA_B	10000	Automated	0.19 (0)	0.18 (0)	0.01 (0.01)	0.95 (0)	0.96 (0)	-0.01 (0)
FDA_B	1:1	Expert	0.19 (0)	0.26 (0.01)	-0.08 (0.01)	0.94 (0)	0.91 (0.01)	0.03 (0.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Mean absolute error (Bias)			Associated skill score (Skill)		
			Train	Test	Fit	Train	Test	Fit
FDA_B	1:2	Expert	0.18 (0)	0.21 (0.01)	-0.03 (0)	0.95 (0)	0.94 (0)	0.01 (0)
FDA_B	1:3	Expert	0.19 (0)	0.19 (0)	-0.01 (0)	0.95 (0)	0.95 (0)	0 (0)
FDA_B	10000	Expert	0.19 (0)	0.18 (0)	0.01 (0.01)	0.95 (0)	0.96 (0)	-0.01 (0)
FDA_O	1:1	*A priori*	0.16 (0.01)	0.19 (0)	-0.03 (0.01)	-0.85 (0.04)	-0.98 (0.06)	0.13 (0.05)
FDA_O	1:2	*A priori*	0.16 (0.01)	0.19 (0)	-0.03 (0.01)	-0.84 (0.05)	-0.98 (0.06)	0.13 (0.04)
FDA_O	1:3	*A priori*	0.16 (0.01)	0.19 (0)	-0.03 (0.01)	-0.84 (0.04)	-0.98 (0.05)	0.14 (0.04)
FDA_O	10000	*A priori*	0.16 (0.01)	0.19 (0)	-0.03 (0.01)	-0.84 (0.05)	-0.98 (0.06)	0.13 (0.04)
FDA_O	1:1	Automated	0.14 (0)	0.19 (0)	-0.06 (0)	-1.29 (0.04)	-1.71 (0.04)	0.42 (0.05)
FDA_O	1:2	Automated	0.14 (0)	0.19 (0)	-0.05 (0)	-1.28 (0.05)	-1.7 (0.04)	0.42 (0.05)
FDA_O	1:3	Automated	0.14 (0)	0.19 (0.01)	-0.05 (0)	-1.25 (0.07)	-1.64 (0.1)	0.39 (0.06)
FDA_O	10000	Automated	0.14 (0)	0.19 (0.01)	-0.05 (0)	-1.26 (0.06)	-1.65 (0.08)	0.39 (0.06)
FDA_O	1:1	Expert	0.14 (0)	0.19 (0.01)	-0.05 (0.01)	-1.24 (0.06)	-1.61 (0.1)	0.36 (0.07)
FDA_O	1:2	Expert	0.14 (0)	0.19 (0.01)	-0.05 (0.01)	-1.24 (0.07)	-1.6 (0.11)	0.35 (0.08)
FDA_O	1:3	Expert	0.14 (0)	0.19 (0.01)	-0.05 (0.01)	-1.24 (0.08)	-1.61 (0.12)	0.37 (0.07)
FDA_O	10000	Expert	0.14 (0)	0.19 (0.01)	-0.05 (0.01)	-1.25 (0.07)	-1.61 (0.11)	0.36 (0.07)
GAM_B	1:1	*A priori*	0.23 (0.01)	0.26 (0.01)	-0.04 (0.01)	0.92 (0.01)	0.91 (0.01)	0 (0.01)
GAM_B	1:2	*A priori*	0.23 (0)	0.26 (0.01)	-0.02 (0.01)	0.91 (0)	0.91 (0)	0 (0)
GAM_B	1:3	*A priori*	0.23 (0)	0.26 (0.01)	-0.02 (0.01)	0.91 (0)	0.91 (0)	0 (0)
GAM_B	10000	*A priori*	0.24 (0)	0.26 (0.01)	-0.02 (0)	0.91 (0)	0.91 (0)	0 (0)
GAM_B	1:1	Automated	0.2 (0.01)	0.27 (0.02)	-0.07 (0.01)	0.94 (0)	0.91 (0.01)	0.03 (0.01)
GAM_B	1:2	Automated	0.2 (0)	0.26 (0.01)	-0.07 (0.01)	0.94 (0)	0.91 (0.01)	0.03 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Mean absolute error (Bias)			Associated skill score (Skill)		
			Train	Test	Fit	Train	Test	Fit
GAM_B	1:3	Automated	0.2 (0)	0.26 (0.01)	-0.06 (0.01)	0.94 (0)	0.92 (0.01)	0.02 (0)
GAM_B	10000	Automated	0.2 (0)	0.26 (0.01)	-0.05 (0.01)	0.94 (0)	0.91 (0)	0.02 (0)
GAM_B	1:1	Expert	0.19 (0)	0.26 (0.01)	-0.07 (0.01)	0.95 (0)	0.92 (0.01)	0.03 (0.01)
GAM_B	1:2	Expert	0.19 (0)	0.25 (0.01)	-0.06 (0.01)	0.95 (0)	0.92 (0)	0.02 (0)
GAM_B	1:3	Expert	0.19 (0)	0.25 (0.01)	-0.06 (0)	0.95 (0)	0.92 (0)	0.02 (0)
GAM_B	10000	Expert	0.19 (0)	0.25 (0.01)	-0.06 (0)	0.95 (0)	0.92 (0)	0.02 (0)
GAM_O	1:1	*A priori*	0.12 (0.09)	0.08 (0.08)	0.04 (0.03)	-0.5 (0.78)	-0.04 (0.51)	-0.46 (0.28)
GAM_O	1:2	*A priori*	0.1 (0.07)	0.07 (0.08)	0.02 (0.02)	-0.18 (0.41)	0.16 (0.28)	-0.34 (0.14)
GAM_O	1:3	*A priori*	0.09 (0.06)	0.07 (0.07)	0.02 (0.01)	-0.1 (0.24)	0.22 (0.16)	-0.32 (0.08)
GAM_O	10000	*A priori*	0.1 (0.05)	0.08 (0.06)	0.02 (0.01)	-0.05 (0.19)	0.26 (0.13)	-0.31 (0.06)
GAM_O	1:1	Automated	0.09 (0.08)	0.05 (0.05)	0.04 (0.03)	-0.59 (0.85)	-0.12 (0.55)	-0.48 (0.3)
GAM_O	1:2	Automated	0.07 (0.03)	0.04 (0.02)	0.03 (0.01)	-0.01 (0.24)	0.28 (0.16)	-0.3 (0.09)
GAM_O	1:3	Automated	0.1 (0.05)	0.11 (0.05)	0 (0.01)	-0.01 (0.17)	0.24 (0.13)	-0.25 (0.05)
GAM_O	10000	Automated	0.11 (0.01)	0.11 (0.01)	0 (0)	0 (0.03)	0.25 (0.02)	-0.25 (0.01)
GAM_O	1:1	Expert	0.07 (0.02)	0.07 (0.02)	0 (0)	-0.21 (0.04)	0.08 (0.02)	-0.29 (0.02)
GAM_O	1:2	Expert	0.08 (0.01)	0.08 (0.02)	0 (0)	-0.22 (0.04)	0.08 (0.02)	-0.3 (0.02)
GAM_O	1:3	Expert	0.09 (0.01)	0.09 (0.01)	0 (0)	-0.25 (0.04)	0.06 (0.02)	-0.31 (0.02)
GAM_O	10000	Expert	0.11 (0.01)	0.11 (0.01)	0 (0)	-0.29 (0.03)	0.04 (0.02)	-0.33 (0.01)
GBM_B	1:1	*A priori*	0.17 (0)	0.22 (0.01)	-0.04 (0)	0.95 (0)	0.94 (0)	0.02 (0)
GBM_B	1:2	*A priori*	0.18 (0)	0.22 (0)	-0.04 (0)	0.95 (0)	0.93 (0)	0.02 (0)
GBM_B	1:3	*A priori*	0.18 (0)	0.22 (0)	-0.05 (0)	0.95 (0)	0.93 (0)	0.02 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Mean absolute error (Bias)			Associated skill score (Skill)		
			Train	Test	Fit	Train	Test	Fit
GBM_B	10000	*A priori*	0.18 (0)	0.23 (0)	-0.05 (0)	0.95 (0)	0.93 (0)	0.02 (0)
GBM_B	1:1	Automated	0.18 (0)	0.24 (0.01)	-0.06 (0)	0.95 (0)	0.92 (0)	0.03 (0)
GBM_B	1:2	Automated	0.18 (0)	0.24 (0)	-0.06 (0)	0.95 (0)	0.92 (0)	0.03 (0)
GBM_B	1:3	Automated	0.18 (0)	0.24 (0)	-0.06 (0)	0.95 (0)	0.92 (0)	0.03 (0)
GBM_B	10000	Automated	0.19 (0)	0.25 (0)	-0.06 (0)	0.95 (0)	0.92 (0)	0.03 (0)
GBM_B	1:1	Expert	0.17 (0)	0.22 (0)	-0.05 (0)	0.95 (0)	0.93 (0)	0.02 (0)
GBM_B	1:2	Expert	0.17 (0)	0.22 (0)	-0.05 (0)	0.95 (0)	0.93 (0)	0.02 (0)
GBM_B	1:3	Expert	0.17 (0)	0.23 (0)	-0.05 (0)	0.95 (0)	0.93 (0)	0.02 (0)
GBM_B	10000	Expert	0.18 (0)	0.23 (0)	-0.05 (0)	0.95 (0)	0.93 (0)	0.02 (0)
GBM_O	1:1	*A priori*	0.03 (0)	0.04 (0.01)	-0.01 (0)	-0.02 (0.06)	0.01 (0.06)	-0.03 (0.02)
GBM_O	1:2	*A priori*	0.04 (0.01)	0.05 (0.01)	-0.01 (0)	-0.15 (0.06)	-0.09 (0.06)	-0.05 (0.02)
GBM_O	1:3	*A priori*	0.05 (0.01)	0.06 (0.01)	-0.01 (0)	-0.23 (0.07)	-0.16 (0.06)	-0.07 (0.02)
GBM_O	10000	*A priori*	0.08 (0.01)	0.08 (0.01)	-0.01 (0)	-0.52 (0.07)	-0.37 (0.05)	-0.16 (0.03)
GBM_O	1:1	Automated	0.04 (0.01)	0.05 (0.01)	-0.01 (0)	-0.1 (0.07)	-0.11 (0.06)	0.01 (0.03)
GBM_O	1:2	Automated	0.06 (0.01)	0.07 (0.01)	-0.02 (0)	-0.28 (0.06)	-0.28 (0.05)	0 (0.02)
GBM_O	1:3	Automated	0.06 (0)	0.08 (0)	-0.02 (0)	-0.37 (0.04)	-0.36 (0.03)	-0.01 (0.02)
GBM_O	10000	Automated	0.09 (0)	0.1 (0)	-0.02 (0)	-0.59 (0.04)	-0.51 (0.03)	-0.08 (0.02)
GBM_O	1:1	Expert	0.04 (0)	0.05 (0.01)	-0.01 (0.01)	-0.25 (0.05)	-0.47 (0.08)	0.23 (0.03)
GBM_O	1:2	Expert	0.04 (0)	0.06 (0.01)	-0.02 (0.01)	-0.34 (0.05)	-0.61 (0.07)	0.27 (0.03)
GBM_O	1:3	Expert	0.06 (0)	0.08 (0)	-0.02 (0)	-0.79 (0.06)	-0.77 (0.04)	-0.02 (0.03)
GBM_O	10000	Expert	0.08 (0.01)	0.1 (0)	-0.02 (0)	-1.07 (0.07)	-0.96 (0.04)	-0.1 (0.04)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Mean absolute error (Bias)			Associated skill score (Skill)		
			Train	Test	Fit	Train	Test	Fit
GLM_B	1:1	*A priori*	0.24 (0.01)	0.27 (0.01)	-0.04 (0.01)	0.91 (0.01)	0.91 (0.01)	0 (0.01)
GLM_B	1:2	*A priori*	0.24 (0.01)	0.27 (0.01)	-0.04 (0.01)	0.91 (0.01)	0.91 (0.01)	0 (0.01)
GLM_B	1:3	*A priori*	0.24 (0.01)	0.27 (0.01)	-0.04 (0.01)	0.91 (0.01)	0.91 (0.01)	0 (0.01)
GLM_B	10000	*A priori*	0.24 (0.01)	0.27 (0.01)	-0.04 (0.01)	0.91 (0.01)	0.91 (0.01)	0 (0)
GLM_B	1:1	Automated	0.19 (0)	0.26 (0.01)	-0.08 (0.01)	0.95 (0)	0.92 (0.01)	0.03 (0)
GLM_B	1:2	Automated	0.19 (0)	0.27 (0.01)	-0.08 (0.01)	0.95 (0)	0.92 (0.01)	0.03 (0)
GLM_B	1:3	Automated	0.19 (0)	0.26 (0.01)	-0.08 (0.01)	0.95 (0)	0.92 (0.01)	0.03 (0)
GLM_B	10000	Automated	0.19 (0)	0.26 (0.01)	-0.07 (0.01)	0.95 (0)	0.92 (0.01)	0.03 (0)
GLM_B	1:1	Expert	0.19 (0)	0.26 (0.01)	-0.08 (0.01)	0.95 (0)	0.92 (0.01)	0.03 (0)
GLM_B	1:2	Expert	0.19 (0)	0.27 (0.01)	-0.08 (0.01)	0.95 (0)	0.92 (0)	0.03 (0)
GLM_B	1:3	Expert	0.19 (0)	0.26 (0.01)	-0.08 (0.01)	0.95 (0)	0.92 (0.01)	0.03 (0)
GLM_B	10000	Expert	0.19 (0)	0.26 (0.01)	-0.08 (0)	0.95 (0)	0.92 (0)	0.03 (0)
GLM_O	1:1	*A priori*	0.26 (0.08)	0.22 (0.1)	0.04 (0.05)	-1.48 (0.74)	-0.66 (0.46)	-0.81 (0.28)
GLM_O	1:2	*A priori*	0.29 (0.07)	0.26 (0.1)	0.03 (0.06)	-1.42 (0.7)	-0.64 (0.42)	-0.78 (0.28)
GLM_O	1:3	*A priori*	0.29 (0.06)	0.29 (0.1)	0.01 (0.05)	-1.22 (0.56)	-0.52 (0.33)	-0.7 (0.23)
GLM_O	10000	*A priori*	0.32 (0.03)	0.35 (0.06)	-0.02 (0.04)	-1.05 (0.3)	-0.44 (0.17)	-0.61 (0.13)
GLM_O	1:1	Automated	0.26 (0.09)	0.21 (0.11)	0.05 (0.05)	-1.52 (0.77)	-0.69 (0.49)	-0.82 (0.29)
GLM_O	1:2	Automated	0.21 (0.11)	0.17 (0.11)	0.04 (0.06)	-1.17 (0.99)	-0.47 (0.58)	-0.7 (0.42)
GLM_O	1:3	Automated	0.19 (0.1)	0.18 (0.13)	0.01 (0.05)	-0.68 (0.59)	-0.2 (0.36)	-0.48 (0.24)
GLM_O	10000	Automated	0.2 (0.1)	0.2 (0.13)	-0.01 (0.04)	-0.55 (0.55)	-0.14 (0.35)	-0.41 (0.21)
GLM_O	1:1	Expert	0.2 (0.07)	0.15 (0.07)	0.05 (0.05)	-1.92 (1)	-0.99 (0.58)	-0.93 (0.42)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Mean absolute error (Bias)			Associated skill score (Skill)		
			Train	Test	Fit	Train	Test	Fit
GLM_O	1:2	Expert	0.16 (0.08)	0.12 (0.07)	0.04 (0.04)	-1.45 (1.03)	-0.7 (0.61)	-0.74 (0.42)
GLM_O	1:3	Expert	0.16 (0.08)	0.14 (0.09)	0.02 (0.04)	-1.14 (0.99)	-0.51 (0.59)	-0.63 (0.4)
GLM_O	10000	Expert	0.14 (0.08)	0.14 (0.1)	0 (0.03)	-0.76 (0.65)	-0.29 (0.4)	-0.47 (0.25)
MARS_B	1:1	*A priori*	0.23 (0.01)	0.27 (0.01)	-0.04 (0.01)	0.91 (0.01)	0.91 (0.01)	0 (0.01)
MARS_B	1:2	*A priori*	0.23 (0.01)	0.27 (0.01)	-0.04 (0.01)	0.91 (0.01)	0.91 (0.01)	0 (0.01)
MARS_B	1:3	*A priori*	0.23 (0.01)	0.27 (0.02)	-0.04 (0.01)	0.91 (0.01)	0.91 (0.01)	0 (0.01)
MARS_B	10000	*A priori*	0.23 (0.01)	0.28 (0.01)	-0.04 (0.01)	0.91 (0)	0.91 (0.01)	0.01 (0.01)
MARS_B	1:1	Automated	0.19 (0)	0.27 (0.01)	-0.08 (0.01)	0.94 (0)	0.91 (0.01)	0.03 (0.01)
MARS_B	1:2	Automated	0.19 (0)	0.26 (0.01)	-0.07 (0.01)	0.94 (0)	0.91 (0.01)	0.03 (0)
MARS_B	1:3	Automated	0.19 (0)	0.26 (0.01)	-0.07 (0.01)	0.94 (0)	0.91 (0.01)	0.03 (0)
MARS_B	10000	Automated	0.2 (0)	0.27 (0.01)	-0.07 (0.01)	0.94 (0)	0.91 (0)	0.03 (0)
MARS_B	1:1	Expert	0.19 (0)	0.27 (0.02)	-0.08 (0.01)	0.94 (0)	0.91 (0.01)	0.03 (0.01)
MARS_B	1:2	Expert	0.19 (0)	0.26 (0.01)	-0.07 (0.01)	0.94 (0)	0.91 (0.01)	0.03 (0.01)
MARS_B	1:3	Expert	0.19 (0)	0.27 (0.01)	-0.08 (0.01)	0.94 (0)	0.91 (0.01)	0.03 (0.01)
MARS_B	10000	Expert	0.19 (0)	0.27 (0.01)	-0.08 (0.01)	0.94 (0)	0.91 (0.01)	0.04 (0.01)
MARS_O	1:1	*A priori*	0.1 (0.07)	0.09 (0.07)	0.02 (0.02)	-0.49 (0.57)	-0.16 (0.39)	-0.33 (0.24)
MARS_O	1:2	*A priori*	0.11 (0.06)	0.09 (0.06)	0.02 (0.02)	-0.44 (0.46)	-0.11 (0.36)	-0.33 (0.18)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Mean absolute error (Bias)			Associated skill score (Skill)		
			Train	Test	Fit	Train	Test	Fit
MARS_O	1:3	*A priori*	0.12 (0.07)	0.1 (0.07)	0.02 (0.02)	-0.53 (0.56)	-0.14 (0.4)	-0.39 (0.22)
MARS_O	10000	*A priori*	0.1 (0.06)	0.07 (0.05)	0.03 (0.02)	-0.59 (0.53)	-0.16 (0.39)	-0.43 (0.17)
MARS_O	1:1	Automated	0.07 (0.03)	0.07 (0.03)	0 (0.01)	-0.42 (0.34)	-0.26 (0.23)	-0.16 (0.15)
MARS_O	1:2	Automated	0.08 (0.01)	0.08 (0.02)	0 (0.01)	-0.57 (0.16)	-0.41 (0.16)	-0.17 (0.05)
MARS_O	1:3	Automated	0.08 (0.02)	0.06 (0.03)	0.02 (0.01)	-0.39 (0.32)	-0.1 (0.34)	-0.29 (0.08)
MARS_O	10000	Automated	0.1 (0.04)	0.08 (0.05)	0.03 (0.01)	-0.63 (0.47)	-0.24 (0.41)	-0.39 (0.09)
MARS_O	1:1	Expert	0.06 (0.04)	0.07 (0.03)	-0.01 (0.02)	-0.55 (0.38)	-0.44 (0.36)	-0.1 (0.21)
MARS_O	1:2	Expert	0.07 (0.03)	0.08 (0.03)	0 (0.02)	-0.81 (0.46)	-0.64 (0.44)	-0.17 (0.16)
MARS_O	1:3	Expert	0.07 (0.03)	0.06 (0.04)	0.01 (0.01)	-0.72 (0.46)	-0.48 (0.48)	-0.25 (0.07)
MARS_O	10000	Expert	0.09 (0.05)	0.07 (0.05)	0.02 (0.01)	-0.85 (0.68)	-0.41 (0.57)	-0.44 (0.12)
MaxEnt_B	1:1	*A priori*	0.3 (0.05)	0.33 (0.03)	-0.03 (0.03)	0.87 (0.05)	0.87 (0.02)	0 (0.03)
MaxEnt_B	1:2	*A priori*	0.31 (0.06)	0.33 (0.03)	-0.02 (0.03)	0.86 (0.06)	0.87 (0.03)	-0.01 (0.03)
MaxEnt_B	1:3	*A priori*	0.29 (0.04)	0.32 (0.02)	-0.02 (0.02)	0.87 (0.03)	0.87 (0.02)	0 (0.02)
MaxEnt_B	10000	*A priori*	0.29 (0.04)	0.32 (0.02)	-0.02 (0.02)	0.87 (0.04)	0.88 (0.02)	0 (0.02)
MaxEnt_B	1:1	Automated	0.26 (0.06)	0.32 (0.03)	-0.07 (0.04)	0.9 (0.05)	0.87 (0.02)	0.03 (0.03)
MaxEnt_B	1:2	Automated	0.26 (0.05)	0.32 (0.03)	-0.06 (0.03)	0.9 (0.05)	0.88 (0.02)	0.02 (0.03)
MaxEnt_B	1:3	Automated	0.25 (0.03)	0.32 (0.02)	-0.07 (0.02)	0.91 (0.03)	0.88 (0.01)	0.03 (0.02)
MaxEnt_B	10000	Automated	0.24 (0.01)	0.31 (0.01)	-0.07 (0.01)	0.92 (0)	0.88 (0.01)	0.03 (0.01)
MaxEnt_B	1:1	Expert	0.25 (0.05)	0.31 (0.03)	-0.07 (0.03)	0.91 (0.04)	0.88 (0.02)	0.03 (0.03)
MaxEnt_B	1:2	Expert	0.24 (0.03)	0.31 (0.02)	-0.07 (0.02)	0.92 (0.02)	0.88 (0.01)	0.03 (0.01)
MaxEnt_B	1:3	Expert	0.24 (0.03)	0.31 (0.02)	-0.07 (0.02)	0.92 (0.03)	0.88 (0.01)	0.03 (0.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Mean absolute error (Bias)			Associated skill score (Skill)		
			Train	Test	Fit	Train	Test	Fit
MaxEnt_B	10000	Expert	0.23 (0.01)	0.31 (0.01)	-0.08 (0.01)	0.92 (0)	0.88 (0.01)	0.04 (0)
MaxEnt_O	1:1	*A priori*	0.13 (0.05)	0.14 (0.02)	-0.01 (0.03)	-0.76 (0.43)	-0.66 (0.18)	-0.1 (0.35)
MaxEnt_O	1:2	*A priori*	0.13 (0.05)	0.14 (0.03)	-0.01 (0.03)	-0.76 (0.49)	-0.67 (0.21)	-0.1 (0.32)
MaxEnt_O	1:3	*A priori*	0.13 (0.06)	0.14 (0.03)	-0.01 (0.03)	-0.78 (0.5)	-0.67 (0.22)	-0.11 (0.32)
MaxEnt_O	10000	*A priori*	0.13 (0.05)	0.13 (0.03)	-0.01 (0.03)	-0.72 (0.45)	-0.64 (0.19)	-0.09 (0.33)
MaxEnt_O	1:1	Automated	0.08 (0.01)	0.12 (0.02)	-0.04 (0.01)	-0.88 (0.15)	-1.09 (0.17)	0.21 (0.05)
MaxEnt_O	1:2	Automated	0.1 (0.05)	0.13 (0.03)	-0.03 (0.03)	-1.06 (0.56)	-1.11 (0.24)	0.05 (0.39)
MaxEnt_O	1:3	Automated	0.09 (0.01)	0.12 (0.02)	-0.04 (0.01)	-0.89 (0.14)	-1.1 (0.16)	0.2 (0.06)
MaxEnt_O	10000	Automated	0.09 (0.03)	0.12 (0.02)	-0.03 (0.02)	-0.94 (0.31)	-1.08 (0.22)	0.14 (0.2)
MaxEnt_O	1:1	Expert	0.09 (0.04)	0.12 (0.02)	-0.03 (0.02)	-1 (0.46)	-1.09 (0.19)	0.09 (0.31)
MaxEnt_O	1:2	Expert	0.1 (0.05)	0.12 (0.02)	-0.03 (0.03)	-1.04 (0.52)	-1.1 (0.22)	0.06 (0.37)
MaxEnt_O	1:3	Expert	0.09 (0.04)	0.12 (0.02)	-0.03 (0.03)	-0.99 (0.46)	-1.1 (0.2)	0.1 (0.35)
MaxEnt_O	10000	Expert	0.08 (0.03)	0.12 (0.02)	-0.03 (0.02)	-0.92 (0.3)	-1.08 (0.14)	0.16 (0.24)
MXL_O	1:1	*A priori*	0.12 (0.01)	0.13 (0.01)	-0.01 (0.01)	-0.77 (0.11)	-0.7 (0.11)	-0.08 (0.07)
MXL_O	1:2	*A priori*	0.12 (0.01)	0.13 (0.01)	-0.01 (0.01)	-0.76 (0.11)	-0.7 (0.09)	-0.07 (0.06)
MXL_O	1:3	*A priori*	0.12 (0.01)	0.13 (0.02)	-0.01 (0.01)	-0.77 (0.12)	-0.69 (0.12)	-0.08 (0.07)
MXL_O	10000	*A priori*	0.12 (0.01)	0.13 (0.01)	-0.01 (0.01)	-0.79 (0.12)	-0.71 (0.1)	-0.08 (0.08)
MXL_O	1:1	Automated	0.12 (0.01)	0.09 (0.01)	0.03 (0.01)	-0.89 (0.24)	-0.59 (0.23)	-0.3 (0.11)
MXL_O	1:2	Automated	0.12 (0.01)	0.1 (0.02)	0.02 (0.01)	-0.94 (0.32)	-0.71 (0.31)	-0.23 (0.1)
MXL_O	1:3	Automated	0.12 (0.01)	0.1 (0.01)	0.02 (0.01)	-0.97 (0.3)	-0.73 (0.28)	-0.23 (0.1)
MXL_O	10000	Automated	0.12 (0.01)	0.1 (0.02)	0.02 (0.01)	-0.92 (0.29)	-0.69 (0.3)	-0.23 (0.1)

Table B2.4 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Mean absolute error (Bias)**			**Associated skill score (Skill)**		
			Train	**Test**	**Fit**	**Train**	**Test**	**Fit**
MXL_O	1:1	Expert	0.13 (0.04)	0.16 (0.03)	-0.03 (0.03)	-1.56 (0.52)	-1.47 (0.3)	-0.1 (0.39)
MXL_O	1:2	Expert	0.15 (0.06)	0.17 (0.03)	-0.02 (0.05)	-1.73 (0.68)	-1.52 (0.31)	-0.21 (0.51)
MXL_O	1:3	Expert	0.13 (0.05)	0.15 (0.04)	-0.02 (0.04)	-1.54 (0.62)	-1.4 (0.42)	-0.15 (0.42)
MXL_O	10000	Expert	0.13 (0.05)	0.16 (0.04)	-0.02 (0.04)	-2.81 (0.84)	-2.56 (0.51)	-0.25 (0.6)
RF_B	1:1	*A priori*	0.21 (0)	0.22 (0.01)	-0.02 (0.01)	0.93 (0)	0.93 (0)	0 (0)
RF_B	1:2	*A priori*	0.24 (0)	0.26 (0.01)	-0.02 (0.01)	0.91 (0)	0.91 (0)	0 (0)
RF_B	1:3	*A priori*	0.25 (0)	0.27 (0.01)	-0.02 (0.01)	0.9 (0)	0.9 (0)	0 (0)
RF_B	10000	*A priori*	0.28 (0)	0.3 (0.01)	-0.01 (0.01)	0.87 (0)	0.88 (0)	-0.01 (0)
RF_B	1:1	Automated	0.21 (0.01)	0.23 (0.01)	-0.02 (0.01)	0.93 (0)	0.93 (0)	0.01 (0)
RF_B	1:2	Automated	0.23 (0)	0.26 (0.01)	-0.03 (0.01)	0.91 (0)	0.91 (0)	0.01 (0)
RF_B	1:3	Automated	0.24 (0)	0.27 (0.01)	-0.03 (0.01)	0.9 (0)	0.9 (0)	0.01 (0)
RF_B	10000	Automated	0.26 (0)	0.29 (0.01)	-0.02 (0)	0.88 (0)	0.88 (0)	0 (0)
RF_B	1:1	Expert	0.21 (0)	0.23 (0.01)	-0.03 (0.01)	0.93 (0)	0.92 (0)	0.01 (0)
RF_B	1:2	Expert	0.23 (0)	0.27 (0.01)	-0.04 (0.01)	0.91 (0)	0.9 (0)	0.01 (0)
RF_B	1:3	Expert	0.25 (0)	0.29 (0.01)	-0.04 (0.01)	0.9 (0)	0.89 (0)	0.01 (0)
RF_B	10000	Expert	0.27 (0)	0.31 (0)	-0.04 (0)	0.88 (0)	0.87 (0)	0.01 (0)
RF_O	1:1	*A priori*	0.07 (0)	0.07 (0)	0 (0)	-0.17 (0.04)	-0.1 (0.05)	-0.07 (0.03)
RF_O	1:2	*A priori*	0.09 (0)	0.09 (0)	0 (0)	-0.41 (0.03)	-0.28 (0.05)	-0.12 (0.03)
RF_O	1:3	*A priori*	0.11 (0)	0.1 (0)	0.01 (0.01)	-0.53 (0.03)	-0.36 (0.04)	-0.17 (0.03)
RF_O	10000	*A priori*	0.13 (0)	0.11 (0)	0.01 (0)	-0.74 (0.02)	-0.48 (0.04)	-0.26 (0.02)
RF_O	1:1	Automated	0.07 (0)	0.07 (0)	0 (0)	-0.44 (0.04)	-0.46 (0.07)	0.02 (0.04)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Mean absolute error (Bias)			Associated skill score (Skill)		
			Train	Test	Fit	Train	Test	Fit
RF_O	1:2	Automated	0.09 (0)	0.09 (0)	0 (0)	-0.74 (0.03)	-0.7 (0.06)	-0.04 (0.03)
RF_O	1:3	Automated	0.1 (0)	0.1 (0)	0 (0)	-0.89 (0.03)	-0.79 (0.05)	-0.1 (0.03)
RF_O	10000	Automated	0.12 (0)	0.12 (0)	0.01 (0)	-1.13 (0.03)	-0.92 (0.05)	-0.21 (0.03)
RF_O	1:1	Expert	0.07 (0)	0.08 (0)	-0.01 (0)	-0.48 (0.05)	-0.56 (0.08)	0.07 (0.04)
RF_O	1:2	Expert	0.09 (0)	0.1 (0)	-0.01 (0)	-0.79 (0.04)	-0.8 (0.07)	0.01 (0.04)
RF_O	1:3	Expert	0.1 (0)	0.11 (0)	-0.01 (0)	-0.96 (0.03)	-0.93 (0.07)	-0.03 (0.04)
RF_O	10000	Expert	0.12 (0)	0.13 (0)	0 (0)	-1.21 (0.02)	-1.06 (0.04)	-0.14 (0.02)
SRE_B	1:1	*A priori*	0.34 (0)	0.38 (0)	-0.04 (0)	0.83 (0)	0.82 (0)	0.01 (0)
SRE_B	1:2	*A priori*	0.34 (0)	0.39 (0)	-0.04 (0)	0.83 (0)	0.82 (0)	0.01 (0)
SRE_B	1:3	*A priori*	0.34 (0)	0.39 (0)	-0.04 (0)	0.83 (0)	0.82 (0)	0.01 (0)
SRE_B	10000	*A priori*	0.34 (0)	0.39 (0)	-0.04 (0)	0.83 (0)	0.82 (0)	0.01 (0)
SRE_B	1:1	Automated	0.36 (0)	0.39 (0)	-0.03 (0)	0.81 (0)	0.82 (0)	0 (0)
SRE_B	1:2	Automated	0.36 (0)	0.39 (0)	-0.03 (0)	0.81 (0)	0.82 (0)	0 (0)
SRE_B	1:3	Automated	0.36 (0)	0.39 (0)	-0.03 (0)	0.81 (0)	0.82 (0)	0 (0)
SRE_B	10000	Automated	0.36 (0)	0.39 (0)	-0.03 (0)	0.81 (0)	0.82 (0)	0 (0)
SRE_B	1:1	Expert	0.34 (0)	0.38 (0)	-0.04 (0)	0.83 (0)	0.82 (0)	0.01 (0)
SRE_B	1:2	Expert	0.34 (0)	0.38 (0)	-0.04 (0)	0.83 (0)	0.82 (0)	0.01 (0)
SRE_B	1:3	Expert	0.34 (0)	0.38 (0)	-0.04 (0)	0.83 (0)	0.82 (0)	0.01 (0)
SRE_B	10000	Expert	0.34 (0)	0.38 (0)	-0.04 (0)	0.83 (0)	0.82 (0)	0.01 (0)
SRE_O	1:1	*A priori*	0.24 (0)	0.2 (0)	0.05 (0)	-1.79 (0.01)	-1.11 (0)	-0.68 (0.01)
SRE_O	1:2	*A priori*	0.24 (0)	0.2 (0)	0.05 (0)	-1.79 (0.01)	-1.11 (0.01)	-0.68 (0.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Mean absolute error (Bias)			Associated skill score (Skill)		
			Train	Test	Fit	Train	Test	Fit
SRE_O	1:3	*A priori*	0.24 (0)	0.2 (0)	0.05 (0)	-1.79 (0.01)	-1.11 (0.01)	-0.68 (0.01)
SRE_O	10000	*A priori*	0.24 (0)	0.2 (0)	0.05 (0)	-1.79 (0.01)	-1.11 (0.01)	-0.68 (0.01)
SRE_O	1:1	Automated	0.23 (0)	0.19 (0)	0.04 (0)	-2.71 (0.01)	-1.78 (0.01)	-0.94 (0.01)
SRE_O	1:2	Automated	0.23 (0)	0.19 (0)	0.04 (0)	-2.72 (0.01)	-1.78 (0)	-0.94 (0.01)
SRE_O	1:3	Automated	0.23 (0)	0.19 (0)	0.04 (0)	-2.72 (0.03)	-1.78 (0.02)	-0.94 (0.01)
SRE_O	10000	Automated	0.23 (0)	0.19 (0)	0.04 (0)	-2.72 (0.01)	-1.78 (0)	-0.94 (0.01)
SRE_O	1:1	Expert	0.22 (0)	0.19 (0)	0.03 (0)	-2.55 (0.01)	-1.76 (0.01)	-0.78 (0.01)
SRE_O	1:2	Expert	0.22 (0)	0.19 (0)	0.03 (0)	-2.54 (0.01)	-1.76 (0.01)	-0.78 (0.01)
SRE_O	1:3	Expert	0.22 (0)	0.19 (0)	0.03 (0)	-2.55 (0.03)	-1.76 (0.02)	-0.78 (0.01)
SRE_O	10000	Expert	0.22 (0)	0.19 (0)	0.03 (0)	-2.55 (0.01)	-1.76 (0.01)	-0.78 (0.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy)			Refinement		
			Train	Test	Fit	Train	Test	Fit
ANN_B	1:1	*A priori*	0.08 (0.01)	0.09 (0.01)	-0.01 (0.01)	0.05 (0.01)	0.07 (0.01)	-0.02 (0)
ANN_B	1:2	*A priori*	0.08 (0.01)	0.09 (0.01)	-0.01 (0)	0.05 (0)	0.07 (0.01)	-0.02 (0)
ANN_B	1:3	*A priori*	0.08 (0.01)	0.09 (0.01)	-0.01 (0)	0.04 (0.01)	0.07 (0.01)	-0.02 (0)
ANN_B	10000	*A priori*	0.08 (0.01)	0.09 (0.01)	-0.02 (0.01)	0.04 (0.01)	0.07 (0.01)	-0.02 (0.01)
ANN_B	1:1	Automated	0.07 (0.01)	0.09 (0.01)	-0.02 (0.01)	0.04 (0)	0.07 (0.01)	-0.03 (0.01)
ANN_B	1:2	Automated	0.07 (0)	0.1 (0.01)	-0.03 (0.01)	0.04 (0)	0.08 (0.01)	-0.04 (0.01)
ANN_B	1:3	Automated	0.07 (0)	0.1 (0.01)	-0.03 (0.01)	0.04 (0)	0.08 (0.01)	-0.04 (0.01)
ANN_B	10000	Automated	0.07 (0)	0.1 (0.01)	-0.03 (0.01)	0.04 (0)	0.08 (0.01)	-0.04 (0.01)
ANN_B	1:1	Expert	0.06 (0)	0.11 (0.01)	-0.05 (0.01)	0.04 (0)	0.09 (0.01)	-0.05 (0.01)
ANN_B	1:2	Expert	0.06 (0)	0.11 (0.02)	-0.04 (0.01)	0.04 (0)	0.09 (0.01)	-0.05 (0.01)
ANN_B	1:3	Expert	0.06 (0)	0.1 (0.02)	-0.04 (0.01)	0.04 (0)	0.08 (0.02)	-0.05 (0.01)
ANN_B	10000	Expert	0.06 (0)	0.11 (0.01)	-0.04 (0.01)	0.04 (0)	0.09 (0.01)	-0.05 (0.01)
ANN_O	1:1	*A priori*	0.06 (0.01)	0.06 (0.02)	0 (0.01)	0.03 (0.01)	0.05 (0.01)	-0.02 (0.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy) Train	Test	Fit	Refinement Train	Test	Fit
ANN_O	1:2	*A priori*	0.13 (0.07)	0.12 (0.03)	0.01 (0.04)	0.08 (0.05)	0.09 (0.03)	-0.01 (0.03)
ANN_O	1:3	*A priori*	0.18 (0.07)	0.14 (0.03)	0.04 (0.05)	0.13 (0.05)	0.11 (0.02)	0.02 (0.04)
ANN_O	10000	*A priori*	0.25 (0.03)	0.17 (0.01)	0.08 (0.02)	0.18 (0.02)	0.13 (0)	0.05 (0.01)
ANN_O	1:1	Automated	0.06 (0.01)	0.06 (0.01)	0 (0.01)	0.03 (0.01)	0.04 (0.01)	-0.01 (0.01)
ANN_O	1:2	Automated	0.13 (0.08)	0.11 (0.04)	0.02 (0.05)	0.09 (0.06)	0.09 (0.03)	0 (0.04)
ANN_O	1:3	Automated	0.19 (0.08)	0.14 (0.03)	0.05 (0.06)	0.13 (0.06)	0.11 (0.02)	0.02 (0.04)
ANN_O	10000	Automated	0.25 (0.02)	0.17 (0)	0.08 (0.02)	0.18 (0.01)	0.13 (0)	0.05 (0.01)
ANN_O	1:1	Expert	0.06 (0.01)	0.08 (0.03)	-0.02 (0.03)	0.03 (0.01)	0.06 (0.03)	-0.03 (0.03)
ANN_O	1:2	Expert	0.13 (0.08)	0.13 (0.03)	0 (0.06)	0.09 (0.06)	0.1 (0.03)	-0.01 (0.05)
ANN_O	1:3	Expert	0.2 (0.08)	0.15 (0.02)	0.05 (0.07)	0.15 (0.06)	0.12 (0.02)	0.03 (0.05)
ANN_O	10000	Expert	0.27 (0.03)	0.17 (0)	0.1 (0.03)	0.19 (0.02)	0.13 (0)	0.06 (0.02)
CTA_B	1:1	*A priori*	0.09 (0.01)	0.1 (0.01)	-0.01 (0.01)	0.05 (0.01)	0.07 (0.01)	-0.02 (0)
CTA_B	1:2	*A priori*	0.09 (0.01)	0.1 (0.01)	-0.01 (0)	0.06 (0.01)	0.07 (0)	-0.02 (0)
CTA_B	1:3	*A priori*	0.09 (0.01)	0.1 (0.01)	-0.01 (0)	0.06 (0.01)	0.08 (0.01)	-0.02 (0)
CTA_B	10000	*A priori*	0.1 (0.01)	0.11 (0.01)	-0.01 (0.01)	0.06 (0.01)	0.08 (0.01)	-0.02 (0.01)
CTA_B	1:1	Automated	0.08 (0.01)	0.1 (0.01)	-0.02 (0.01)	0.05 (0.01)	0.08 (0.01)	-0.03 (0.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy)			Refinement		
			Train	Test	Fit	Train	Test	Fit
CTA_B	1:2	Automated	0.08 (0.01)	0.1 (0.01)	-0.02 (0.01)	0.05 (0.01)	0.08 (0.01)	-0.03 (0.01)
CTA_B	1:3	Automated	0.09 (0.01)	0.11 (0.01)	-0.02 (0.01)	0.05 (0.01)	0.09 (0.01)	-0.03 (0.01)
CTA_B	10000	Automated	0.1 (0.01)	0.12 (0.01)	-0.02 (0.01)	0.06 (0.01)	0.09 (0.01)	-0.03 (0.01)
CTA_B	1:1	Expert	0.08 (0.01)	0.1 (0.01)	-0.02 (0.01)	0.05 (0.01)	0.08 (0.01)	-0.03 (0.01)
CTA_B	1:2	Expert	0.08 (0.01)	0.1 (0.01)	-0.02 (0.01)	0.05 (0.01)	0.08 (0.01)	-0.03 (0.01)
CTA_B	1:3	Expert	0.08 (0.01)	0.1 (0.01)	-0.02 (0.01)	0.05 (0.01)	0.08 (0.01)	-0.03 (0)
CTA_B	10000	Expert	0.08 (0.01)	0.1 (0)	-0.02 (0)	0.05 (0.01)	0.08 (0)	-0.03 (0)
CTA_O	1:1	*A priori*	0.07 (0.01)	0.09 (0.01)	-0.02 (0.01)	0.04 (0.01)	0.07 (0.01)	-0.03 (0.01)
CTA_O	1:2	*A priori*	0.09 (0.01)	0.11 (0.01)	-0.02 (0)	0.06 (0.01)	0.08 (0)	-0.02 (0)
CTA_O	1:3	*A priori*	0.11 (0.01)	0.12 (0.01)	-0.01 (0)	0.09 (0.01)	0.1 (0.01)	-0.01 (0)
CTA_O	10000	*A priori*	0.17 (0.01)	0.15 (0.01)	0.02 (0.01)	0.14 (0.01)	0.12 (0)	0.02 (0.01)
CTA_O	1:1	Automated	0.07 (0.01)	0.09 (0.01)	-0.02 (0.01)	0.04 (0)	0.07 (0)	-0.03 (0.01)
CTA_O	1:2	Automated	0.09 (0.01)	0.11 (0.01)	-0.02 (0)	0.06 (0)	0.08 (0)	-0.02 (0)
CTA_O	1:3	Automated	0.11 (0.01)	0.12 (0.01)	-0.01 (0)	0.08 (0.01)	0.1 (0)	-0.01 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy) Train	Test	Fit	Refinement Train	Test	Fit
CTA_O	10000	Automated	0.18 (0)	0.15 (0)	0.03 (0)	0.15 (0)	0.12 (0)	0.03 (0)
CTA_O	1:1	Expert	0.07 (0)	0.09 (0.01)	-0.03 (0.01)	0.04 (0)	0.07 (0.01)	-0.03 (0.01)
CTA_O	1:2	Expert	0.09 (0.01)	0.11 (0.01)	-0.02 (0)	0.06 (0)	0.08 (0)	-0.02 (0)
CTA_O	1:3	Expert	0.09 (0)	0.11 (0.01)	-0.02 (0)	0.06 (0)	0.08 (0)	-0.02 (0)
CTA_O	10000	Expert	0.17 (0.01)	0.15 (0.01)	0.02 (0.01)	0.14 (0.01)	0.12 (0.01)	0.02 (0.01)
EMca_B	1:1	*A priori*	0.22 (0.05)	0.23 (0.06)	-0.01 (0.01)	0.18 (0.04)	0.21 (0.05)	-0.03 (0.01)
EMca_B	1:2	*A priori*	0.21 (0.06)	0.22 (0.06)	-0.01 (0.01)	0.17 (0.05)	0.2 (0.05)	-0.03 (0.01)
EMca_B	1:3	*A priori*	0.2 (0.05)	0.21 (0.06)	-0.01 (0.01)	0.17 (0.04)	0.19 (0.05)	-0.02 (0.01)
EMca_B	10000	*A priori*	0.19 (0.04)	0.21 (0.05)	-0.01 (0.01)	0.16 (0.04)	0.19 (0.05)	-0.03 (0.01)
EMca_B	1:1	Automated	0.15 (0.04)	0.16 (0.06)	-0.01 (0.02)	0.11 (0.04)	0.14 (0.06)	-0.03 (0.02)
EMca_B	1:2	Automated	0.16 (0.05)	0.17 (0.06)	-0.01 (0.02)	0.12 (0.04)	0.15 (0.06)	-0.03 (0.02)
EMca_B	1:3	Automated	0.15 (0.04)	0.16 (0.05)	0 (0.01)	0.11 (0.03)	0.14 (0.05)	-0.03 (0.01)
EMca_B	10000	Automated	0.15 (0.04)	0.15 (0.06)	0 (0.01)	0.11 (0.04)	0.14 (0.05)	-0.03 (0.01)
EMca_B	1:1	Expert	0.16 (0.03)	0.16 (0.04)	-0.01 (0.01)	0.13 (0.03)	0.15 (0.04)	-0.03 (.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy) Train	Test	Fit	Refinement Train	Test	Fit
EMca_B	1:2	Expert	0.16 (0.03)	0.17 (0.04)	0 (0.01)	0.13 (0.03)	0.16 (0.04)	-0.03 (0.01)
EMca_B	1:3	Expert	0.18 (0.03)	0.18 (0.04)	-0.01 (0.01)	0.14 (0.03)	0.17 (0.04)	-0.03 (0.01)
EMca_B	10000	Expert	0.2 (0.04)	0.21 (0.05)	-0.02 (0.02)	0.16 (0.03)	0.2 (0.05)	-0.04 (0.02)
EMmean_B	1:1	*A priori*	0.07 (0.01)	0.08 (0.01)	-0.01 (0)	0.04 (0)	0.06 (0.01)	-0.02 (0.01)
EMmean_B	1:2	*A priori*	0.07 (0)	0.07 (0)	0 (0)	0.04 (0)	0.06 (0)	-0.01 (0)
EMmean_B	1:3	*A priori*	0.07 (0)	0.07 (0)	0 (0)	0.04 (0)	0.06 (0)	-0.01 (0)
EMmean_B	10000	*A priori*	0.07 (0)	0.08 (0.01)	0 (0.01)	0.04 (0)	0.06 (0)	-0.02 (0.01)
EMmean_B	1:1	Automated	0.05 (0)	0.08 (0)	-0.03 (0)	0.03 (0)	0.06 (0)	-0.04 (0)
EMmean_B	1:2	Automated	0.05 (0)	0.07 (0)	-0.01 (0)	0.03 (0)	0.05 (0)	-0.02 (0)
EMmean_B	1:3	Automated	0.05 (0)	0.08 (0.01)	-0.02 (0)	0.03 (0)	0.06 (0)	-0.03 (0)
EMmean_B	10000	Automated	0.05 (0)	0.07 (0.01)	-0.02 (0)	0.03 (0)	0.06 (0)	-0.03 (0)
EMmean_B	1:1	Expert	0.05 (0)	0.08 (0.01)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.04 (0)
EMmean_B	1:2	Expert	0.05 (0)	0.08 (0)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.03 (0)
EMmean_B	1:3	Expert	0.05 (0)	0.08 (0)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.03 (0)
EMmean_B	10000	Expert	0.05 (0)	0.08 (0)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.03 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy) Train	Test	Fit	Refinement Train	Test	Fit
EMmedian_B	1:1	*A priori*	0.08 (0.01)	0.08 (0.01)	-0.01 (0)	0.04 (0.01)	0.06 (0.01)	-0.02 (0.01)
EMmedian_B	1:2	*A priori*	0.08 (0.01)	0.08 (0)	0 (0)	0.05 (0.01)	0.06 (0)	-0.01 (0.01)
EMmedian_B	1:3	*A priori*	0.08 (0)	0.08 (0)	0 (0)	0.05 (0.01)	0.06 (0)	-0.01 (0.01)
EMmedian_B	10000	*A priori*	0.08 (0)	0.08 (0.01)	0 (0.01)	0.05 (0.01)	0.07 (0)	-0.01 (0.01)
EMmedian_B	1:1	Automated	0.05 (0)	0.08 (0)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.04 (0)
EMmedian_B	1:2	Automated	0.05 (0)	0.07 (0)	-0.01 (0)	0.04 (0)	0.05 (0)	-0.02 (0)
EMmedian_B	1:3	Automated	0.05 (0)	0.07 (0)	-0.01 (0)	0.04 (0)	0.06 (0)	-0.02 (0)
EMmedian_B	10000	Automated	0.06 (0)	0.07 (0)	-0.01 (0)	0.04 (0)	0.06 (0)	-0.02 (0)
EMmedian_B	1:1	Expert	0.06 (0)	0.09 (0.01)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.04 (0)
EMmedian_B	1:2	Expert	0.05 (0)	0.09 (0)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.04 (0)
EMmedian_B	1:3	Expert	0.05 (0)	0.08 (0)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.03 (0)
EMmedian_B	10000	Expert	0.06 (0)	0.09 (0)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.04 (0)
EMwmean_B	1:1	*A priori*	0.07 (0.01)	0.07 (0.01)	-0.01 (0)	0.04 (0)	0.06 (0.01)	-0.02 (0.01)
EMwmean_B	1:2	*A priori*	0.07 (0)	0.07 (0)	0 (0)	0.04 (0)	0.06 (0)	-0.01 (0)
EMwmean_B	1:3	*A priori*	0.07 (0)	0.07 (0)	0 (0)	0.04 (0)	0.05 (0)	-0.01 (0)
EMwmean_B	10000	*A priori*	0.07 (0)	0.08 (0.01)	0 (0.01)	0.04 (0)	0.06 (0)	-0.02 (0.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy) Train	Test	Fit	Refinement Train	Test	Fit
EMwmean_B	1:1	Automated	0.05 (0)	0.08 (0)	-0.03 (0)	0.03 (0)	0.06 (0)	-0.04 (0)
EMwmean_B	1:2	Automated	0.05 (0)	0.07 (0)	-0.01 (0)	0.03 (0)	0.05 (0)	-0.02 (0)
EMwmean_B	1:3	Automated	0.05 (0)	0.08 (0.01)	-0.02 (0)	0.03 (0)	0.06 (0)	-0.03 (0)
EMwmean_B	10000	Automated	0.05 (0)	0.07 (0.01)	-0.02 (0)	0.03 (0)	0.06 (0)	-0.03 (0)
EMwmean_B	1:1	Expert	0.05 (0)	0.08 (0.01)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.04 (0)
EMwmean_B	1:2	Expert	0.05 (0)	0.08 (0)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.03 (0)
EMwmean_B	1:3	Expert	0.05 (0)	0.08 (0)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.03 (0)
EMwmean_B	10000	Expert	0.05 (0)	0.08 (0)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.03 (0)
FDA_B	1:1	*A priori*	0.08 (0)	0.09 (0.01)	-0.01 (0)	0.04 (0)	0.07 (0)	-0.02 (0)
FDA_B	1:2	*A priori*	0.08 (0)	0.07 (0)	0.01 (0)	0.04 (0)	0.04 (0)	0 (0)
FDA_B	1:3	*A priori*	0.08 (0)	0.06 (0)	0.02 (0)	0.04 (0)	0.03 (0)	0.01 (0)
FDA_B	10000	*A priori*	0.08 (0)	0.05 (0)	0.03 (0)	0.04 (0)	0.02 (0)	0.02 (0)
FDA_B	1:1	Automated	0.06 (0)	0.1 (0.01)	-0.04 (0)	0.03 (0)	0.08 (0)	-0.05 (0)
FDA_B	1:2	Automated	0.05 (0)	0.06 (0)	-0.01 (0)	0.02 (0)	0.04 (0)	-0.02 (0)
FDA_B	1:3	Automated	0.05 (0)	0.05 (0)	0 (0)	0.01 (0)	0.02 (0)	-0.01 (0)
FDA_B	10000	Automated	0.05 (0)	0.04 (0)	0.01 (0)	0.01 (0)	0.02 (0)	-0.01 (0)
FDA_B	1:1	Expert	0.06 (0)	0.1 (0.01)	-0.04 (0.01)	0.04 (0)	0.08 (0.01)	-0.04 (0.01)
FDA_B	1:2	Expert	0.05 (0)	0.06 (0)	-0.01 (0)	0.02 (0)	0.04 (0)	-0.02 (0)
FDA_B	1:3	Expert	0.05 (0)	0.05 (0)	0 (0)	0.01 (0)	0.02 (0)	-0.01 (0)
FDA_B	10000	Expert	0.05 (0)	0.04 (0)	0.01 (0)	0.01 (0)	0.02 (0)	-0.01 (0)

Table B2.4 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Brier Score (Forecast Accuracy)**			**Refinement**		
			Train	**Test**	**Fit**	**Train**	**Test**	**Fit**
FDA_O	1:1	*A priori*	0.13 (0)	0.15 (0)	-0.02 (0.01)	0.08 (0)	0.12 (0)	-0.03 (0)
FDA_O	1:2	*A priori*	0.13 (0.01)	0.15 (0)	-0.02 (0.01)	0.08 (0)	0.12 (0)	-0.03 (0)
FDA_O	1:3	*A priori*	0.13 (0)	0.15 (0)	-0.02 (0.01)	0.08 (0)	0.12 (0)	-0.03 (0)
FDA_O	10000	*A priori*	0.13 (0)	0.15 (0)	-0.02 (0)	0.08 (0)	0.12 (0)	-0.03 (0)
FDA_O	1:1	Automated	0.11 (0)	0.16 (0)	-0.05 (0)	0.07 (0)	0.12 (0)	-0.05 (0)
FDA_O	1:2	Automated	0.11 (0)	0.16 (0)	-0.05 (0)	0.07 (0)	0.12 (0)	-0.05 (0)
FDA_O	1:3	Automated	0.11 (0)	0.15 (0.01)	-0.04 (0)	0.07 (0)	0.12 (0)	-0.05 (0)
FDA_O	10000	Automated	0.11 (0)	0.15 (0)	-0.04 (0)	0.07 (0)	0.12 (0)	-0.05 (0)
FDA_O	1:1	Expert	0.11 (0)	0.15 (0.01)	-0.04 (0)	0.07 (0)	0.12 (0)	-0.05 (0)
FDA_O	1:2	Expert	0.11 (0)	0.15 (0.01)	-0.04 (0.01)	0.07 (0)	0.12 (0)	-0.05 (0)
FDA_O	1:3	Expert	0.11 (0)	0.15 (0.01)	-0.04 (0)	0.07 (0)	0.12 (0)	-0.05 (0)
FDA_O	10000	Expert	0.11 (0)	0.15 (0.01)	-0.04 (0)	0.07 (0)	0.12 (0)	-0.05 (0)
GAM_B	1:1	*A priori*	0.08 (0.01)	0.08 (0.01)	0 (0.01)	0.05 (0.01)	0.06 (0)	-0.01 (0.01)
GAM_B	1:2	*A priori*	0.08 (0)	0.08 (0)	0 (0)	0.05 (0)	0.06 (0)	0 (0)
GAM_B	1:3	*A priori*	0.08 (0)	0.08 (0)	0 (0)	0.05 (0)	0.06 (0)	0 (0)
GAM_B	10000	*A priori*	0.08 (0)	0.08 (0)	0 (0)	0.05 (0)	0.06 (0)	0 (0)
GAM_B	1:1	Automated	0.06 (0)	0.09 (0.01)	-0.03 (0.01)	0.03 (0)	0.07 (0.01)	-0.03 (0)
GAM_B	1:2	Automated	0.06 (0)	0.08 (0.01)	-0.03 (0)	0.03 (0)	0.06 (0.01)	-0.03 (0)
GAM_B	1:3	Automated	0.06 (0)	0.08 (0)	-0.02 (0)	0.03 (0)	0.06 (0)	-0.03 (0)
GAM_B	10000	Automated	0.06 (0)	0.08 (0)	-0.02 (0)	0.03 (0)	0.06 (0)	-0.03 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy) Train	Test	Fit	Refinement Train	Test	Fit
GAM_B	1:1	Expert	0.05 (0)	0.08 (0.01)	-0.03 (0.01)	0.03 (0)	0.06 (0.01)	-0.03 (0)
GAM_B	1:2	Expert	0.05 (0)	0.08 (0)	-0.02 (0)	0.03 (0)	0.06 (0)	-0.03 (0)
GAM_B	1:3	Expert	0.05 (0)	0.07 (0)	-0.02 (0)	0.03 (0)	0.06 (0)	-0.03 (0)
GAM_B	10000	Expert	0.05 (0)	0.07 (0)	-0.02 (0)	0.03 (0)	0.06 (0)	-0.03 (0)
GAM_O	1:1	*A priori*	0.12 (0.08)	0.08 (0.07)	0.04 (0.03)	0.08 (0.07)	0.06 (0.06)	0.02 (0.03)
GAM_O	1:2	*A priori*	0.09 (0.06)	0.07 (0.07)	0.02 (0.02)	0.06 (0.05)	0.05 (0.06)	0.01 (0.02)
GAM_O	1:3	*A priori*	0.09 (0.05)	0.07 (0.06)	0.02 (0.01)	0.06 (0.04)	0.05 (0.06)	0.01 (0.02)
GAM_O	10000	*A priori*	0.1 (0.05)	0.08 (0.06)	0.02 (0.01)	0.06 (0.04)	0.06 (0.05)	0 (0.01)
GAM_O	1:1	Automated	0.09 (0.08)	0.05 (0.05)	0.04 (0.03)	0.06 (0.06)	0.04 (0.04)	0.03 (0.02)
GAM_O	1:2	Automated	0.07 (0.02)	0.04 (0.02)	0.03 (0.01)	0.04 (0.02)	0.03 (0.02)	0.01 (0.01)
GAM_O	1:3	Automated	0.1 (0.04)	0.11 (0.05)	0 (0.01)	0.08 (0.03)	0.09 (0.04)	-0.01 (0.01)
GAM_O	10000	Automated	0.11 (0.01)	0.11 (0.01)	0 (0)	0.08 (0.01)	0.09 (0.01)	-0.01 (0)
GAM_O	1:1	Expert	0.07 (0.02)	0.07 (0.02)	0 (0)	0.05 (0.02)	0.05 (0.02)	0 (0)
GAM_O	1:2	Expert	0.08 (0.01)	0.08 (0.02)	0 (0)	0.06 (0.01)	0.06 (0.01)	0 (0)
GAM_O	1:3	Expert	0.09 (0.01)	0.09 (0.01)	0 (0)	0.07 (0.01)	0.07 (0.01)	-0.01 (0)
GAM_O	10000	Expert	0.11 (0.01)	0.11 (0.01)	0 (0)	0.08 (0.01)	0.09 (0.01)	-0.01 (0)
GBM_B	1:1	*A priori*	0.05 (0)	0.06 (0)	-0.01 (0)	0.02 (0)	0.05 (0)	-0.02 (0)
GBM_B	1:2	*A priori*	0.05 (0)	0.06 (0)	-0.01 (0)	0.03 (0)	0.05 (0)	-0.02 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy) Train	Test	Fit	Refinement Train	Test	Fit
GBM_B	1:3	*A priori*	0.05 (0)	0.06 (0)	-0.01 (0)	0.03 (0)	0.05 (0)	-0.02 (0)
GBM_B	10000	*A priori*	0.05 (0)	0.07 (0)	-0.02 (0)	0.03 (0)	0.05 (0)	-0.03 (0)
GBM_B	1:1	Automated	0.05 (0)	0.08 (0)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.04 (0)
GBM_B	1:2	Automated	0.05 (0)	0.08 (0)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.04 (0)
GBM_B	1:3	Automated	0.05 (0)	0.08 (0)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.04 (0)
GBM_B	10000	Automated	0.06 (0)	0.09 (0)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.04 (0)
GBM_B	1:1	Expert	0.05 (0)	0.07 (0)	-0.02 (0)	0.03 (0)	0.06 (0)	-0.03 (0)
GBM_B	1:2	Expert	0.05 (0)	0.07 (0)	-0.02 (0)	0.03 (0)	0.06 (0)	-0.03 (0)
GBM_B	1:3	Expert	0.05 (0)	0.07 (0)	-0.02 (0)	0.03 (0)	0.06 (0)	-0.03 (0)
GBM_B	10000	Expert	0.05 (0)	0.08 (0)	-0.02 (0)	0.03 (0)	0.06 (0)	-0.03 (0)
GBM_O	1:1	*A priori*	0.04 (0)	0.04 (0.01)	-0.01 (0)	0.01 (0)	0.03 (0.01)	-0.02 (0)
GBM_O	1:2	*A priori*	0.04 (0.01)	0.05 (0.01)	-0.01 (0)	0.02 (0)	0.04 (0.01)	-0.02 (0)
GBM_O	1:3	*A priori*	0.05 (0.01)	0.06 (0.01)	-0.01 (0)	0.02 (0.01)	0.05 (0.01)	-0.02 (0)
GBM_O	10000	*A priori*	0.08 (0.01)	0.08 (0.01)	0 (0)	0.04 (0.01)	0.07 (0.01)	-0.02 (0)
GBM_O	1:1	Automated	0.04 (0.01)	0.05 (0.01)	-0.01 (0)	0.02 (0)	0.04 (0.01)	-0.02 (0)
GBM_O	1:2	Automated	0.05 (0.01)	0.07 (0.01)	-0.02 (0)	0.03 (0)	0.06 (0)	-0.03 (0)
GBM_O	1:3	Automated	0.06 (0)	0.08 (0.01)	-0.02 (0)	0.04 (0)	0.06 (0)	-0.03 (0)
GBM_O	10000	Automated	0.08 (0)	0.1 (0)	-0.02 (0)	0.06 (0)	0.08 (0)	-0.03 (0)
GBM_O	1:1	Expert	0.04 (0)	0.05 (0.01)	-0.01 (0.01)	0.01 (0)	0.03 (0.01)	-0.02 (0.01)
GBM_O	1:2	Expert	0.04 (0)	0.06 (0.01)	-0.02 (0)	0.01 (0)	0.04 (0.01)	-0.03 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy)			Refinement		
			Train	Test	Fit	Train	Test	Fit
GBM_O	1:3	Expert	0.06 (0)	0.08 (0.01)	-0.02 (0)	0.04 (0)	0.06 (0)	-0.03 (0)
GBM_O	10000	Expert	0.08 (0.01)	0.1 (0)	-0.02 (0)	0.05 (0.01)	0.08 (0)	-0.03 (0)
GLM_B	1:1	*A priori*	0.08 (0.01)	0.08 (0.01)	0 (0)	0.06 (0.01)	0.07 (0.01)	-0.01 (0)
GLM_B	1:2	*A priori*	0.08 (0.01)	0.08 (0.01)	0 (0)	0.06 (0.01)	0.07 (0.01)	-0.01 (0)
GLM_B	1:3	*A priori*	0.08 (0.01)	0.08 (0.01)	0 (0)	0.06 (0.01)	0.07 (0)	-0.01 (0)
GLM_B	10000	*A priori*	0.08 (0.01)	0.08 (0.01)	0 (0.01)	0.06 (0.01)	0.07 (0)	-0.01 (0)
GLM_B	1:1	Automated	0.05 (0)	0.08 (0.01)	-0.03 (0)	0.04 (0)	0.07 (0.01)	-0.04 (0)
GLM_B	1:2	Automated	0.05 (0)	0.08 (0.01)	-0.03 (0)	0.04 (0)	0.07 (0)	-0.04 (0)
GLM_B	1:3	Automated	0.05 (0)	0.08 (0.01)	-0.03 (0)	0.04 (0)	0.07 (0.01)	-0.04 (0)
GLM_B	10000	Automated	0.05 (0)	0.08 (0.01)	-0.03 (0)	0.04 (0)	0.07 (0)	-0.03 (0)
GLM_B	1:1	Expert	0.05 (0)	0.08 (0.01)	-0.03 (0)	0.04 (0)	0.07 (0)	-0.04 (0)
GLM_B	1:2	Expert	0.05 (0)	0.08 (0.01)	-0.03 (0)	0.04 (0)	0.07 (0)	-0.04 (0)
GLM_B	1:3	Expert	0.05 (0)	0.08 (0.01)	-0.03 (0)	0.04 (0)	0.07 (0)	-0.04 (0)
GLM_B	10000	Expert	0.05 (0)	0.08 (0.01)	-0.03 (0)	0.04 (0)	0.07 (0)	-0.03 (0)
GLM_O	1:1	*A priori*	0.25 (0.06)	0.21 (0.09)	0.04 (0.05)	0.17 (0.06)	0.17 (0.09)	0 (0.05)
GLM_O	1:2	*A priori*	0.26 (0.06)	0.24 (0.09)	0.03 (0.06)	0.19 (0.06)	0.2 (0.09)	-0.01 (0.06)
GLM_O	1:3	*A priori*	0.27 (0.05)	0.26 (0.09)	0.01 (0.05)	0.2 (0.05)	0.22 (0.09)	-0.03 (0.05)
GLM_O	10000	*A priori*	0.29 (0.02)	0.31 (0.05)	-0.02 (0.03)	0.22 (0.02)	0.27 (0.05)	-0.05 (0.03)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy)			Refinement		
			Train	Test	Fit	Train	Test	Fit
GLM_O	1:1	Automated	0.23 (0.07)	0.19 (0.09)	0.04 (0.05)	0.16 (0.06)	0.15 (0.09)	0.01 (0.05)
GLM_O	1:2	Automated	0.2 (0.09)	0.15 (0.09)	0.04 (0.06)	0.14 (0.07)	0.12 (0.09)	0.02 (0.05)
GLM_O	1:3	Automated	0.18 (0.09)	0.17 (0.12)	0.01 (0.05)	0.13 (0.07)	0.14 (0.11)	-0.01 (0.05)
GLM_O	10000	Automated	0.19 (0.09)	0.19 (0.11)	-0.01 (0.04)	0.15 (0.07)	0.17 (0.1)	-0.02 (0.05)
GLM_O	1:1	Expert	0.2 (0.07)	0.15 (0.07)	0.05 (0.05)	0.16 (0.06)	0.12 (0.06)	0.04 (0.04)
GLM_O	1:2	Expert	0.16 (0.08)	0.13 (0.07)	0.04 (0.04)	0.13 (0.06)	0.11 (0.07)	0.03 (0.04)
GLM_O	1:3	Expert	0.16 (0.08)	0.14 (0.09)	0.02 (0.05)	0.13 (0.07)	0.12 (0.08)	0.01 (0.05)
GLM_O	10000	Expert	0.14 (0.08)	0.14 (0.1)	0 (0.04)	0.12 (0.07)	0.12 (0.1)	-0.01 (0.04)
MARS_B	1:1	*A priori*	0.08 (0.01)	0.09 (0.01)	0 (0)	0.06 (0.01)	0.07 (0.01)	-0.01 (0.01)
MARS_B	1:2	*A priori*	0.08 (0.01)	0.09 (0.01)	0 (0.01)	0.06 (0.01)	0.07 (0.01)	-0.01 (0.01)
MARS_B	1:3	*A priori*	0.08 (0.01)	0.09 (0.01)	0 (0.01)	0.06 (0.01)	0.06 (0.01)	-0.01 (0.01)
MARS_B	10000	*A priori*	0.08 (0)	0.09 (0)	-0.01 (0)	0.05 (0)	0.07 (0)	-0.01 (0)
MARS_B	1:1	Automated	0.06 (0)	0.09 (0.01)	-0.03 (0.01)	0.03 (0)	0.07 (0.01)	-0.04 (0.01)
MARS_B	1:2	Automated	0.06 (0)	0.09 (0.01)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.04 (0)
MARS_B	1:3	Automated	0.06 (0)	0.09 (0.01)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.03 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy) Train	Test	Fit	Refinement Train	Test	Fit
MARS_B	10000	Automated	0.06 (0)	0.09 (0)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.03 (0)
MARS_B	1:1	Expert	0.06 (0)	0.09 (0.01)	-0.03 (0.01)	0.03 (0)	0.07 (0.01)	-0.04 (0.01)
MARS_B	1:2	Expert	0.06 (0)	0.09 (0.01)	-0.03 (0)	0.03 (0)	0.07 (0.01)	-0.04 (0)
MARS_B	1:3	Expert	0.06 (0)	0.09 (0.01)	-0.03 (0)	0.03 (0)	0.07 (0.01)	-0.04 (0)
MARS_B	10000	Expert	0.06 (0)	0.09 (0.01)	-0.03 (0)	0.03 (0)	0.07 (0)	-0.04 (0)
MARS_O	1:1	*A priori*	0.1 (0.07)	0.09 (0.06)	0.02 (0.02)	0.06 (0.06)	0.06 (0.06)	0 (0.02)
MARS_O	1:2	*A priori*	0.11 (0.06)	0.09 (0.06)	0.02 (0.02)	0.06 (0.05)	0.07 (0.05)	0 (0.02)
MARS_O	1:3	*A priori*	0.12 (0.06)	0.1 (0.07)	0.02 (0.02)	0.07 (0.06)	0.07 (0.06)	0 (0.02)
MARS_O	10000	*A priori*	0.1 (0.05)	0.07 (0.05)	0.03 (0.02)	0.05 (0.05)	0.04 (0.05)	0.01 (0.01)
MARS_O	1:1	Automated	0.07 (0.03)	0.07 (0.03)	0 (0.01)	0.04 (0.03)	0.05 (0.03)	-0.01 (0.01)
MARS_O	1:2	Automated	0.08 (0.01)	0.09 (0.02)	0 (0.01)	0.05 (0.02)	0.07 (0.02)	-0.02 (0.01)
MARS_O	1:3	Automated	0.08 (0.03)	0.06 (0.03)	0.02 (0.01)	0.04 (0.03)	0.04 (0.04)	0 (0.02)
MARS_O	10000	Automated	0.1 (0.04)	0.08 (0.05)	0.03 (0.01)	0.06 (0.04)	0.05 (0.05)	0.01 (0.01)
MARS_O	1:1	Expert	0.06 (0.04)	0.07 (0.03)	-0.01 (0.02)	0.04 (0.03)	0.05 (0.02)	-0.02 (0.02)
MARS_O	1:2	Expert	0.07 (0.03)	0.07 (0.03)	0 (0.02)	0.04 (0.03)	0.06 (0.03)	-0.02 (0.02)
MARS_O	1:3	Expert	0.07 (0.03)	0.06 (0.04)	0.01 (0.01)	0.04 (0.03)	0.04 (0.04)	-0.01 (0.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy) Train	Test	Fit	Refinement Train	Test	Fit
MARS_O	10000	Expert	0.09 (0.04)	0.07 (0.04)	0.02 (0.01)	0.05 (0.05)	0.04 (0.04)	0 (0.01)
MaxEnt_B	1:1	*A priori*	0.12 (0.04)	0.12 (0.02)	0 (0.03)	0.08 (0.03)	0.09 (0.02)	-0.01 (0.02)
MaxEnt_B	1:2	*A priori*	0.13 (0.05)	0.12 (0.03)	0.01 (0.03)	0.09 (0.03)	0.09 (0.02)	-0.01 (0.02)
MaxEnt_B	1:3	*A priori*	0.12 (0.03)	0.11 (0.02)	0 (0.02)	0.08 (0.02)	0.08 (0.01)	-0.01 (0.01)
MaxEnt_B	10000	*A priori*	0.11 (0.02)	0.11 (0.01)	0 (0.01)	0.08 (0.02)	0.08 (0.01)	-0.01 (0.01)
MaxEnt_B	1:1	Automated	0.09 (0.04)	0.12 (0.02)	-0.02 (0.03)	0.06 (0.03)	0.09 (0.01)	-0.03 (0.02)
MaxEnt_B	1:2	Automated	0.09 (0.04)	0.11 (0.02)	-0.02 (0.03)	0.06 (0.03)	0.09 (0.01)	-0.03 (0.02)
MaxEnt_B	1:3	Automated	0.08 (0.02)	0.11 (0.01)	-0.03 (0.01)	0.06 (0.02)	0.09 (0.01)	-0.03 (0.01)
MaxEnt_B	10000	Automated	0.08 (0)	0.11 (0.01)	-0.03 (0.01)	0.05 (0)	0.09 (0.01)	-0.03 (0)
MaxEnt_B	1:1	Expert	0.08 (0.03)	0.11 (0.02)	-0.03 (0.02)	0.05 (0.03)	0.09 (0.01)	-0.03 (0.02)
MaxEnt_B	1:2	Expert	0.08 (0.02)	0.11 (0.01)	-0.03 (0.01)	0.05 (0.02)	0.09 (0.01)	-0.03 (0.01)
MaxEnt_B	1:3	Expert	0.08 (0.02)	0.11 (0.01)	-0.03 (0.01)	0.05 (0.02)	0.09 (0.01)	-0.04 (0.01)
MaxEnt_B	10000	Expert	0.07 (0)	0.11 (0.01)	-0.03 (0)	0.05 (0)	0.09 (0.01)	-0.04 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy) Train	Test	Fit	Refinement Train	Test	Fit
MaxEnt_O	1:1	*A priori*	0.11 (0.04)	0.12 (0.02)	-0.01 (0.03)	0.08 (0.03)	0.09 (0.01)	-0.02 (0.02)
MaxEnt_O	1:2	*A priori*	0.11 (0.04)	0.12 (0.02)	0 (0.03)	0.08 (0.03)	0.09 (0.02)	-0.02 (0.02)
MaxEnt_O	1:3	*A priori*	0.12 (0.05)	0.12 (0.02)	0 (0.03)	0.08 (0.03)	0.09 (0.02)	-0.02 (0.02)
MaxEnt_O	10000	*A priori*	0.11 (0.04)	0.12 (0.02)	-0.01 (0.03)	0.07 (0.03)	0.09 (0.01)	-0.02 (0.02)
MaxEnt_O	1:1	Automated	0.08 (0.01)	0.11 (0.01)	-0.03 (0.01)	0.05 (0.01)	0.09 (0.01)	-0.04 (0.01)
MaxEnt_O	1:2	Automated	0.09 (0.04)	0.11 (0.02)	-0.02 (0.03)	0.06 (0.03)	0.09 (0.01)	-0.03 (0.02)
MaxEnt_O	1:3	Automated	0.08 (0.01)	0.11 (0.01)	-0.03 (0.01)	0.05 (0.01)	0.09 (0.01)	-0.04 (0.01)
MaxEnt_O	10000	Automated	0.08 (0.02)	0.11 (0.02)	-0.03 (0.02)	0.05 (0.02)	0.09 (0.01)	-0.03 (0.01)
MaxEnt_O	1:1	Expert	0.08 (0.03)	0.11 (0.02)	-0.03 (0.02)	0.06 (0.03)	0.09 (0.01)	-0.03 (0.02)
MaxEnt_O	1:2	Expert	0.09 (0.04)	0.11 (0.02)	-0.02 (0.03)	0.06 (0.03)	0.09 (0.01)	-0.03 (0.02)
MaxEnt_O	1:3	Expert	0.08 (0.04)	0.11 (0.02)	-0.03 (0.02)	0.06 (0.03)	0.09 (0.01)	-0.03 (0.02)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy) Train	Test	Fit	Refinement Train	Test	Fit
MaxEnt_O	10000	Expert	0.08 (0.02)	0.11 (0.01)	-0.03 (0.02)	0.05 (0.02)	0.09 (0.01)	-0.04 (0.01)
MXL_O	1:1	*A priori*	0.11 (0.01)	0.12 (0.01)	-0.01 (0.01)	0.07 (0.01)	0.1 (0.01)	-0.03 (0.01)
MXL_O	1:2	*A priori*	0.11 (0.01)	0.12 (0.01)	-0.02 (0.01)	0.07 (0.01)	0.1 (0.01)	-0.03 (0.01)
MXL_O	1:3	*A priori*	0.11 (0.01)	0.12 (0.01)	-0.01 (0.01)	0.07 (0.01)	0.1 (0.01)	-0.03 (0.01)
MXL_O	10000	*A priori*	0.11 (0.01)	0.13 (0.01)	-0.01 (0.01)	0.07 (0.01)	0.1 (0.01)	-0.03 (0.01)
MXL_O	1:1	Automated	0.11 (0.01)	0.09 (0.01)	0.02 (0.01)	0.07 (0.01)	0.07 (0.01)	0 (0.01)
MXL_O	1:2	Automated	0.11 (0.01)	0.1 (0.02)	0.02 (0.01)	0.07 (0.01)	0.07 (0.01)	0 (0.01)
MXL_O	1:3	Automated	0.11 (0.01)	0.1 (0.01)	0.02 (0.01)	0.07 (0.01)	0.07 (0.01)	0 (0.01)
MXL_O	10000	Automated	0.11 (0.01)	0.09 (0.01)	0.02 (0.01)	0.07 (0.01)	0.07 (0.01)	0 (0.01)
MXL_O	1:1	Expert	0.12 (0.04)	0.15 (0.03)	-0.02 (0.03)	0.09 (0.03)	0.11 (0.02)	-0.03 (0.03)
MXL_O	1:2	Expert	0.13 (0.05)	0.15 (0.03)	-0.02 (0.04)	0.1 (0.04)	0.12 (0.02)	-0.02 (0.03)
MXL_O	1:3	Expert	0.12 (0.05)	0.14 (0.04)	-0.02 (0.04)	0.09 (0.04)	0.11 (0.03)	-0.02 (0.03)
MXL_O	10000	Expert	0.12 (0.05)	0.14 (0.03)	-0.02 (0.04)	0.09 (0.04)	0.11 (0.03)	-0.02 (0.03)
RF_B	1:1	*A priori*	0.07 (0)	0.07 (0)	0 (0)	0.03 (0)	0.04 (0)	-0.01 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy) Train	Test	Fit	Refinement Train	Test	Fit
RF_B	1:2	*A priori*	0.09 (0)	0.08 (0)	0 (0)	0.05 (0)	0.06 (0)	-0.01 (0)
MXL_O	1:3	Expert	0.12 (0.05)	0.14 (0.04)	-0.02 (0.04)	0.09 (0.04)	0.11 (0.03)	-0.02 (0.03)
MXL_O	10000	Expert	0.12 (0.05)	0.14 (0.03)	-0.02 (0.04)	0.09 (0.04)	0.11 (0.03)	-0.02 (0.03)
RF_B	1:1	*A priori*	0.07 (0)	0.07 (0)	0 (0)	0.03 (0)	0.04 (0)	-0.01 (0)
RF_B	1:2	*A priori*	0.09 (0)	0.08 (0)	0 (0)	0.05 (0)	0.06 (0)	-0.01 (0)
RF_B	1:3	*A priori*	0.1 (0)	0.09 (0)	0 (0)	0.05 (0)	0.06 (0)	-0.01 (0)
RF_B	10000	*A priori*	0.12 (0)	0.11 (0)	0.01 (0)	0.07 (0)	0.07 (0)	-0.01 (0)
RF_B	1:1	Automated	0.06 (0)	0.07 (0)	0 (0)	0.03 (0)	0.05 (0)	-0.02 (0)
RF_B	1:2	Automated	0.08 (0)	0.08 (0)	0 (0)	0.04 (0)	0.06 (0)	-0.02 (0)
RF_B	1:3	Automated	0.09 (0)	0.09 (0)	0 (0)	0.05 (0)	0.07 (0)	-0.02 (0)
RF_B	10000	Automated	0.11 (0)	0.1 (0)	0.01 (0)	0.06 (0)	0.07 (0)	-0.01 (0)
RF_B	1:1	Expert	0.07 (0)	0.07 (0)	-0.01 (0)	0.03 (0)	0.05 (0)	-0.02 (0)
RF_B	1:2	Expert	0.08 (0)	0.09 (0)	-0.01 (0)	0.04 (0)	0.07 (0)	-0.02 (0)
RF_B	1:3	Expert	0.09 (0)	0.1 (0)	-0.01 (0)	0.05 (0)	0.07 (0)	-0.02 (0)
RF_B	10000	Expert	0.11 (0)	0.11 (0)	0 (0)	0.06 (0)	0.08 (0)	-0.02 (0)
RF_O	1:1	*A priori*	0.07 (0)	0.06 (0)	0.01 (0)	0.04 (0)	0.05 (0)	-0.01 (0)
RF_O	1:2	*A priori*	0.09 (0)	0.08 (0)	0.01 (0)	0.05 (0)	0.06 (0)	-0.01 (0)
RF_O	1:3	*A priori*	0.1 (0)	0.09 (0)	0.01 (0.01)	0.06 (0)	0.06 (0)	-0.01 (0)
RF_O	10000	*A priori*	0.12 (0)	0.1 (0)	0.02 (0)	0.07 (0)	0.07 (0)	-0.01 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Brier Score (Forecast Accuracy)			Refinement		
			Train	Test	Fit	Train	Test	Fit
RF_O	1:1	Automated	0.07 (0)	0.07 (0)	0 (0)	0.03 (0)	0.05 (0)	-0.01 (0)
RF_O	1:2	Automated	0.08 (0)	0.08 (0)	0 (0)	0.05 (0)	0.06 (0)	-0.02 (0)
RF_O	1:3	Automated	0.09 (0)	0.09 (0)	0 (0)	0.05 (0)	0.06 (0)	-0.01 (0)
RF_O	10000	Automated	0.11 (0)	0.1 (0)	0.01 (0)	0.06 (0)	0.07 (0)	-0.01 (0)
RF_O	1:1	Expert	0.07 (0)	0.07 (0)	-0.01 (0)	0.03 (0)	0.05 (0)	-0.02 (0)
RF_O	1:2	Expert	0.08 (0)	0.09 (0)	-0.01 (0)	0.05 (0)	0.07 (0)	-0.02 (0)
RF_O	1:3	Expert	0.1 (0)	0.1 (0)	-0.01 (0)	0.05 (0)	0.07 (0)	-0.02 (0)
RF_O	10000	Expert	0.11 (0)	0.11 (0)	0 (0)	0.06 (0)	0.08 (0)	-0.02 (0)
SRE_B	1:1	*A priori*	0.14 (0)	0.14 (0)	-0.01 (0)	0.09 (0)	0.11 (0)	-0.02 (0)
SRE_B	1:2	*A priori*	0.14 (0)	0.14 (0)	-0.01 (0)	0.09 (0)	0.1 (0)	-0.02 (0)
SRE_B	1:3	*A priori*	0.14 (0)	0.14 (0)	-0.01 (0)	0.09 (0)	0.11 (0)	-0.02 (0)
SRE_B	10000	*A priori*	0.14 (0)	0.15 (0)	-0.01 (0)	0.09 (0)	0.11 (0)	-0.02 (0)
SRE_B	1:1	Automated	0.15 (0)	0.15 (0)	0.01 (0)	0.1 (0)	0.11 (0)	-0.01 (0)
SRE_B	1:2	Automated	0.15 (0)	0.15 (0)	0 (0)	0.1 (0)	0.11 (0)	-0.01 (0)
SRE_B	1:3	Automated	0.15 (0)	0.15 (0)	0 (0)	0.1 (0)	0.11 (0)	-0.01 (0)
SRE_B	10000	Automated	0.15 (0)	0.15 (0)	0.01 (0)	0.1 (0)	0.11 (0)	-0.01 (0)
SRE_B	1:1	Expert	0.14 (0)	0.14 (0)	0 (0)	0.09 (0)	0.11 (0)	-0.02 (0)
SRE_B	1:2	Expert	0.14 (0)	0.14 (0)	0 (0)	0.09 (0)	0.11 (0)	-0.02 (0)
SRE_B	1:3	Expert	0.14 (0)	0.14 (0)	0 (0)	0.09 (0)	0.11 (0)	-0.02 (0)
SRE_B	10000	Expert	0.14 (0)	0.14 (0)	0 (0)	0.09 (0)	0.11 (0)	-0.02 (0)
SRE_O	1:1	*A priori*	0.22 (0)	0.17 (0)	0.05 (0)	0.16 (0)	0.13 (0)	0.03 (0)

Table B2.4 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Brier Score (Forecast Accuracy)**			**Refinement**		
			Train	**Test**	**Fit**	**Train**	**Test**	**Fit**
SRE_O	1:2	*A priori*	0.22 (0)	0.17 (0)	0.05 (0)	0.16 (0)	0.13 (0)	0.03 (0)
SRE_O	1:3	*A priori*	0.22 (0)	0.17 (0)	0.05 (0)	0.16 (0)	0.13 (0)	0.03 (0)
SRE_O	10000	*A priori*	0.22 (0)	0.17 (0)	0.05 (0)	0.16 (0)	0.13 (0)	0.03 (0)
SRE_O	1:1	Automated	0.21 (0)	0.17 (0)	0.04 (0)	0.16 (0)	0.13 (0)	0.03 (0)
SRE_O	1:2	Automated	0.21 (0)	0.17 (0)	0.04 (0)	0.16 (0)	0.13 (0)	0.03 (0)
SRE_O	1:3	Automated	0.21 (0)	0.17 (0)	0.04 (0)	0.16 (0)	0.13 (0)	0.03 (0)
SRE_O	10000	Automated	0.21 (0)	0.17 (0)	0.04 (0)	0.16 (0)	0.13 (0)	0.03 (0)
SRE_O	1:1	Expert	0.2 (0)	0.17 (0)	0.03 (0)	0.15 (0)	0.13 (0)	0.02 (0)
SRE_O	1:2	Expert	0.2 (0)	0.17 (0)	0.03 (0)	0.15 (0)	0.13 (0)	0.02 (0)
SRE_O	1:3	Expert	0.2 (0)	0.17 (0)	0.03 (0)	0.15 (0)	0.13 (0)	0.02 (0)
SRE_O	10000	Expert	0.2 (0)	0.17 (0)	0.03 (0)	0.15 (0)	0.13 (0)	0.02 (0)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Resolution**			**Sensitivity**		
			Train	**Test**	**Fit**	**Train**	**Test**	**Fit**
ANN_B	1:1	*A priori*	0.04 (0)	0.03 (0)	0.02 (0)	1 (0)	0.57 (0.06)	0.33 (0.06)
ANN_B	1:2	*A priori*	0.04 (0)	0.03 (0)	0.02 (0)	1 (0)	0.59 (0.06)	0.31 (0.06)
ANN_B	1:3	*A priori*	0.04 (0)	0.03 (0)	0.02 (0)	1 (0)	0.57 (0.08)	0.33 (0.08)
ANN_B	10000	*A priori*	0.04 (0)	0.03 (0)	0.02 (0)	1 (0)	0.57 (0.07)	0.33 (0.07)
ANN_B	1:1	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.66 (0.06)	0.24 (0.06)
ANN_B	1:2	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.64 (0.05)	0.26 (0.05)
ANN_B	1:3	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.64 (0.05)	0.26 (0.05)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Resolution			Sensitivity		
			Train	Test	Fit	Train	Test	Fit
ANN_B	10000	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.64 (0.05)	0.26 (0.05)
ANN_B	1:1	Expert	0.06 (0)	0.02 (0)	0.04 (0)	1 (0)	0.57 (0.07)	0.33 (0.07)
ANN_B	1:2	Expert	0.06 (0)	0.02 (0)	0.04 (0)	1 (0)	0.59 (0.06)	0.31 (0.06)
ANN_B	1:3	Expert	0.05 (0)	0.02 (0)	0.04 (0)	1 (0)	0.6 (0)	0.3 (0)
ANN_B	10000	Expert	0.05 (0)	0.02 (0)	0.04 (0)	1 (0)	0.59 (0.08)	0.31 (0.08)
ANN_O	1:1	*A priori*	0.05 (0.01)	0.02 (0.01)	0.02 (0)	1 (0)	0.5 (0.12)	0.4 (0.12)
ANN_O	1:2	*A priori*	0.03 (0.02)	0.01 (0.01)	0.02 (0.01)	1 (0)	0.56 (0.11)	0.34 (0.11)
ANN_O	1:3	*A priori*	0.02 (0.02)	0.01 (0.01)	0.01 (0.01)	1 (0)	0.59 (0.1)	0.31 (0.1)
ANN_O	10000	*A priori*	0 (0.01)	0 (0)	0 (0.01)	1 (0)	0.65 (0.05)	0.25 (0.05)
ANN_O	1:1	Automated	0.05 (0.01)	0.02 (0.01)	0.03 (0)	1 (0)	0.55 (0.11)	0.35 (0.11)
ANN_O	1:2	Automated	0.04 (0.02)	0.02 (0.01)	0.02 (0.01)	1 (0)	0.58 (0.09)	0.32 (0.09)
ANN_O	1:3	Automated	0.02 (0.02)	0.01 (0.01)	0.02 (0.01)	1 (0)	0.61 (0.08)	0.29 (0.08)
ANN_O	10000	Automated	0 (0.01)	0 (0)	0 (0.01)	1 (0)	0.66 (0.03)	0.24 (0.03)
ANN_O	1:1	Expert	0.05 (0.01)	0.02 (0.01)	0.03 (0.01)	1 (0)	0.56 (0.07)	0.34 (0.07)
ANN_O	1:2	Expert	0.04 (0.02)	0.01 (0.01)	0.03 (0.02)	1 (0)	0.57 (0.08)	0.33 (0.08)
ANN_O	1:3	Expert	0.02 (0.02)	0.01 (0.01)	0.02 (0.02)	1 (0)	0.6 (0.08)	0.3 (0.08)
ANN_O	10000	Expert	0 (0.01)	0 (0)	0 (0.01)	1 (0)	0.65 (0.06)	0.25 (0.06)
CTA_B	1:1	*A priori*	0.04 (0)	0.03 (0)	0.02 (0)	1 (0)	0.53 (0.09)	0.37 (0.09)
CTA_B	1:2	*A priori*	0.04 (0)	0.03 (0)	0.02 (0)	1 (0)	0.48 (0.08)	0.42 (0.08)
CTA_B	1:3	*A priori*	0.04 (0)	0.03 (0)	0.02 (0)	1 (0)	0.44 (0.11)	0.46 (0.11)
CTA_B	10000	*A priori*	0.04 (0)	0.02 (0)	0.02 (0)	1 (0)	0.41 (0.07)	0.49 (0.07)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Resolution			Sensitivity		
			Train	Test	Fit	Train	Test	Fit
CTA_B	1:1	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.54 (0.12)	0.36 (0.12)
CTA_B	1:2	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.49 (0.13)	0.41 (0.13)
CTA_B	1:3	Automated	0.04 (0)	0.02 (0)	0.03 (0)	1 (0)	0.47 (0.09)	0.43 (0.09)
CTA_B	10000	Automated	0.04 (0)	0.02 (0)	0.03 (0)	1 (0)	0.38 (0.09)	0.52 (0.09)
CTA_B	1:1	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.57 (0.1)	0.33 (0.1)
CTA_B	1:2	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.51 (0.12)	0.39 (0.12)
CTA_B	1:3	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.49 (0)	0.41 (0)
CTA_B	10000	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.46 (0.09)	0.44 (0.09)
CTA_O	1:1	*A priori*	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.59 (0.1)	0.31 (0.1)
CTA_O	1:2	*A priori*	0.05 (0)	0.01 (0)	0.03 (0)	1 (0)	0.55 (0.11)	0.35 (0.11)
CTA_O	1:3	*A priori*	0.05 (0)	0.01 (0)	0.03 (0)	1 (0)	0.58 (0.11)	0.32 (0.11)
CTA_O	10000	*A priori*	0.04 (0)	0.01 (0)	0.03 (0)	1 (0)	0.61 (0.02)	0.29 (0.02)
CTA_O	1:1	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.61 (0.08)	0.29 (0.08)
CTA_O	1:2	Automated	0.05 (0)	0.01 (0)	0.03 (0)	1 (0)	0.61 (0.07)	0.29 (0.07)
CTA_O	1:3	Automated	0.05 (0)	0.01 (0)	0.04 (0)	1 (0)	0.63 (0.06)	0.27 (0.06)
CTA_O	10000	Automated	0.05 (0)	0.01 (0)	0.04 (0)	1 (0)	0.62 (0.01)	0.28 (0.01)
CTA_O	1:1	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.59 (0.07)	0.31 (0.07)
CTA_O	1:2	Expert	0.05 (0)	0.01 (0)	0.03 (0)	1 (0)	0.6 (0.07)	0.3 (0.07)
CTA_O	1:3	Expert	0.05 (0)	0.01 (0)	0.03 (0)	1 (0)	0.6 (0.07)	0.3 (0.07)
CTA_O	10000	Expert	0.05 (0)	0.01 (0)	0.04 (0)	1 (0)	0.62 (0.01)	0.28 (0.01)
EMca_B	1:1	*A priori*	0.04 (0.01)	0.02 (0.01)	0.01 (0.01)	1 (0)	0.67 (0.01)	0.23 (0.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Resolution Train	Resolution Test	Resolution Fit	Sensitivity Train	Sensitivity Test	Sensitivity Fit
EMca_B	1:2	*A priori*	0.03 (0.01)	0.03 (0.01)	0.01 (0)	1 (0)	0.67 (0)	0.23 (0)
EMca_B	1:3	*A priori*	0.04 (0.01)	0.03 (0.01)	0.01 (0)	1 (0)	0.67 (0)	0.23 (0)
EMca_B	10000	*A priori*	0.04 (0.01)	0.03 (0.01)	0.02 (0)	1 (0)	0.67 (0)	0.23 (0)
EMca_B	1:1	Automated	0.04 (0.01)	0.03 (0)	0.01 (0)	1 (0)	0.65 (0.05)	0.25 (0.05)
EMca_B	1:2	Automated	0.04 (0.01)	0.03 (0.01)	0.01 (0)	1 (0)	0.67 (0)	0.23 (0)
EMca_B	1:3	Automated	0.04 (0.01)	0.03 (0)	0.01 (0)	1 (0)	0.67 (0)	0.23 (0)
EMca_B	10000	Automated	0.04 (0.01)	0.03 (0.01)	0.01 (0)	1 (0)	0.67 (0)	0.23 (0)
EMca_B	1:1	Expert	0.05 (0.01)	0.03 (0)	0.02 (0)	1 (0)	0.67 (0)	0.23 (0)
EMca_B	1:2	Expert	0.04 (0.01)	0.03 (0)	0.02 (0)	1 (0)	0.67 (0)	0.23 (0)
EMca_B	1:3	Expert	0.04 (0.01)	0.03 (0)	0.01 (0)	1 (0)	0.67 (0)	0.23 (0)
EMca_B	10000	Expert	0.04 (0.01)	0.03 (0.01)	0.01 (0)	1 (0)	0.67 (0)	0.23 (0)
EMmean_B	1:1	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.55 (0.09)	0.35 (0.09)
EMmean_B	1:2	*A priori*	0.05 (0)	0.03 (0)	0.01 (0)	1 (0)	0.55 (0.1)	0.35 (0.1)
EMmean_B	1:3	*A priori*	0.05 (0)	0.03 (0)	0.01 (0)	1 (0)	0.55 (0.11)	0.35 (0.11)
EMmean_B	10000	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.53 (0.1)	0.37 (0.1)
EMmean_B	1:1	Automated	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.61 (0.04)	0.29 (0.04)
EMmean_B	1:2	Automated	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.69 (0.03)	0.21 (0.03)
EMmean_B	1:3	Automated	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.62 (0.07)	0.28 (0.07)
EMmean_B	10000	Automated	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.66 (0.05)	0.24 (0.05)
EMmean_B	1:1	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.61 (0.05)	0.29 (0.05)
EMmean_B	1:2	Expert	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.63 (0.03)	0.27 (0.03)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Resolution			Sensitivity		
			Train	Test	Fit	Train	Test	Fit
EMmean_B	1:3	Expert	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.63 (0.03)	0.27 (0.03)
EMmean_B	10000	Expert	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.64 (0.03)	0.26 (0.03)
EMmedian_B	1:1	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.55 (0.08)	0.35 (0.08)
EMmedian_B	1:2	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.54 (0.08)	0.36 (0.08)
EMmedian_B	1:3	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.52 (0.1)	0.38 (0.1)
EMmedian_B	10000	*A priori*	0.05 (0)	0.02 (0)	0.02 (0)	1 (0)	0.49 (0.09)	0.41 (0.09)
EMmedian_B	1:1	Automated	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.62 (0.03)	0.28 (0.03)
EMmedian_B	1:2	Automated	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.68 (0.02)	0.22 (0.02)
EMmedian_B	1:3	Automated	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.68 (0.02)	0.22 (0.02)
EMmedian_B	10000	Automated	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.68 (0.02)	0.22 (0.02)
EMmedian_B	1:1	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.62 (0.05)	0.28 (0.05)
EMmedian_B	1:2	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.63 (0.03)	0.27 (0.03)
EMmedian_B	1:3	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.63 (0.04)	0.27 (0.04)
EMmedian_B	10000	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.63 (0.03)	0.27 (0.03)
EMwmean_B	1:1	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.55 (0.09)	0.35 (0.09)
EMwmean_B	1:2	*A priori*	0.05 (0)	0.03 (0)	0.01 (0)	1 (0)	0.55 (0.1)	0.35 (0.1)
EMwmean_B	1:3	*A priori*	0.05 (0)	0.03 (0)	0.01 (0)	1 (0)	0.55 (0.1)	0.35 (0.1)
EMwmean_B	10000	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.53 (0.1)	0.37 (0.1)
EMwmean_B	1:1	Automated	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.62 (0.04)	0.28 (0.04)
EMwmean_B	1:2	Automated	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.68 (0.03)	0.22 (0.03)
EMwmean_B	1:3	Automated	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.62 (0.07)	0.28 (0.07)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Resolution			Sensitivity		
			Train	Test	Fit	Train	Test	Fit
EMwmean_B	10000	Automated	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.66 (0.06)	0.24 (0.06)
EMwmean_B	1:1	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.61 (0.06)	0.29 (0.06)
EMwmean_B	1:2	Expert	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.63 (0.04)	0.27 (0.04)
EMwmean_B	1:3	Expert	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.63 (0.04)	0.27 (0.04)
EMwmean_B	10000	Expert	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.64 (0.04)	0.26 (0.04)
FDA_B	1:1	*A priori*	0.04 (0)	0.03 (0)	0.02 (0)	1 (0)	0.5 (0.09)	0.4 (0.09)
FDA_B	1:2	*A priori*	0.04 (0)	0.03 (0)	0.01 (0)	1 (0)	0.47 (0.07)	0.43 (0.07)
FDA_B	1:3	*A priori*	0.03 (0)	0.02 (0)	0.02 (0)	1 (0)	0.46 (0.08)	0.44 (0.08)
FDA_B	10000	*A priori*	0.04 (0)	0.02 (0)	0.02 (0)	1 (0)	0.45 (0.06)	0.45 (0.06)
FDA_B	1:1	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.61 (0.05)	0.29 (0.05)
FDA_B	1:2	Automated	0.05 (0)	0.03 (0)	0.03 (0)	1 (0)	0.63 (0.04)	0.27 (0.04)
FDA_B	1:3	Automated	0.04 (0)	0.01 (0)	0.03 (0)	1 (0)	0.63 (0.04)	0.27 (0.04)
FDA_B	10000	Automated	0.04 (0)	0.02 (0)	0.03 (0)	1 (0)	0.55 (0.04)	0.35 (0.04)
FDA_B	1:1	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.6 (0.06)	0.3 (0.06)
FDA_B	1:2	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.63 (0.03)	0.27 (0.03)
FDA_B	1:3	Expert	0.04 (0)	0.01 (0)	0.03 (0)	1 (0)	0.62 (0)	0.28 (0)
FDA_B	10000	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.63 (0.03)	0.27 (0.03)
FDA_O	1:1	*A priori*	0.03 (0)	0 (0)	0.02 (0)	1 (0)	0.42 (0.09)	0.48 (0.09)
FDA_O	1:2	*A priori*	0.03 (0)	0 (0)	0.02 (0)	1 (0)	0.42 (0.1)	0.48 (0.1)
FDA_O	1:3	*A priori*	0.03 (0)	0 (0)	0.02 (0)	1 (0)	0.41 (0.09)	0.49 (0.09)
FDA_O	10000	*A priori*	0.03 (0)	0 (0)	0.02 (0)	1 (0)	0.42 (0.11)	0.48 (0.11)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Resolution			Sensitivity		
			Train	Test	Fit	Train	Test	Fit
FDA_O	1:1	Automated	0.04 (0)	0 (0)	0.04 (0)	1 (0)	0.45 (0.05)	0.45 (0.05)
FDA_O	1:2	Automated	0.04 (0)	0 (0)	0.04 (0)	1 (0)	0.46 (0.05)	0.44 (0.05)
FDA_O	1:3	Automated	0.04 (0)	0 (0)	0.04 (0)	1 (0)	0.5 (0.07)	0.4 (0.07)
FDA_O	10000	Automated	0.04 (0)	0 (0)	0.04 (0)	1 (0)	0.5 (0.05)	0.4 (0.05)
FDA_O	1:1	Expert	0.04 (0)	0 (0)	0.03 (0)	1 (0)	0.56 (0.08)	0.34 (0.08)
FDA_O	1:2	Expert	0.04 (0)	0 (0)	0.03 (0)	1 (0)	0.55 (0.08)	0.35 (0.08)
FDA_O	1:3	Expert	0.04 (0)	0 (0)	0.04 (0)	1 (0)	0.54 (0.08)	0.36 (0.08)
FDA_O	10000	Expert	0.04 (0)	0 (0)	0.03 (0)	1 (0)	0.54 (0.08)	0.36 (0.08)
GAM_B	1:1	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.6 (0.09)	0.3 (0.09)
GAM_B	1:2	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.65 (0.06)	0.25 (0.06)
GAM_B	1:3	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.65 (0.06)	0.25 (0.06)
GAM_B	10000	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.66 (0.05)	0.24 (0.05)
GAM_B	1:1	Automated	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.58 (0.08)	0.32 (0.08)
GAM_B	1:2	Automated	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.63 (0.07)	0.27 (0.07)
GAM_B	1:3	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.69 (0.05)	0.21 (0.05)
GAM_B	10000	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.63 (0.05)	0.27 (0.05)
GAM_B	1:1	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.58 (0.09)	0.32 (0.09)
GAM_B	1:2	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.64 (0.06)	0.26 (0.06)
GAM_B	1:3	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.64 (0)	0.26 (0)
GAM_B	10000	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.63 (0.02)	0.27 (0.02)
GAM_O	1:1	*A priori*	0.04 (0.02)	0.02 (0.01)	0.02 (0.01)	1 (0)	0.55 (0.04)	0.35 (0.04)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Resolution			Sensitivity		
			Train	Test	Fit	Train	Test	Fit
GAM_O	1:2	*A priori*	0.04 (0.01)	0.02 (0.01)	0.02 (0.01)	1 (0)	0.53 (0.04)	0.37 (0.04)
GAM_O	1:3	*A priori*	0.04 (0.01)	0.02 (0.01)	0.02 (0.01)	1 (0)	0.49 (0.05)	0.41 (0.05)
GAM_O	10000	*A priori*	0.04 (0.01)	0.02 (0)	0.02 (0.01)	1 (0)	0.44 (0.05)	0.46 (0.05)
GAM_O	1:1	Automated	0.04 (0.02)	0.02 (0.01)	0.02 (0.01)	1 (0)	0.57 (0.02)	0.33 (0.02)
GAM_O	1:2	Automated	0.05 (0.01)	0.03 (0)	0.02 (0.01)	1 (0)	0.57 (0.02)	0.33 (0.02)
GAM_O	1:3	Automated	0.05 (0.01)	0.02 (0)	0.03 (0.01)	1 (0)	0.55 (0.03)	0.35 (0.03)
GAM_O	10000	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.51 (0.02)	0.39 (0.02)
GAM_O	1:1	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.57 (0.03)	0.33 (0.03)
GAM_O	1:2	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.56 (0.03)	0.34 (0.03)
GAM_O	1:3	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.54 (0.03)	0.36 (0.03)
GAM_O	10000	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.51 (0.01)	0.39 (0.01)
GBM_B	1:1	*A priori*	0.05 (0)	0.04 (0)	0.02 (0)	1 (0)	0.54 (0.07)	0.36 (0.07)
GBM_B	1:2	*A priori*	0.05 (0)	0.04 (0)	0.02 (0)	1 (0)	0.51 (0.07)	0.39 (0.07)
GBM_B	1:3	*A priori*	0.05 (0)	0.04 (0)	0.02 (0)	1 (0)	0.47 (0.05)	0.43 (0.05)
GBM_B	10000	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.47 (0.05)	0.43 (0.05)
GBM_B	1:1	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.57 (0.09)	0.33 (0.09)
GBM_B	1:2	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.55 (0.09)	0.35 (0.09)
GBM_B	1:3	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.5 (0.08)	0.4 (0.08)
GBM_B	10000	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.51 (0.07)	0.39 (0.07)
GBM_B	1:1	Expert	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.64 (0.06)	0.26 (0.06)
GBM_B	1:2	Expert	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.61 (0.07)	0.29 (0.07)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Resolution			Sensitivity		
			Train	Test	Fit	Train	Test	Fit
GBM_B	1:3	Expert	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.59 (0)	0.31 (0)
GBM_B	10000	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.55 (0.04)	0.35 (0.04)
GBM_O	1:1	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.55 (0.08)	0.35 (0.08)
GBM_O	1:2	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.62 (0.04)	0.28 (0.04)
GBM_O	1:3	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.63 (0.03)	0.27 (0.03)
GBM_O	10000	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.65 (0.02)	0.25 (0.02)
GBM_O	1:1	Automated	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.62 (0.05)	0.28 (0.05)
GBM_O	1:2	Automated	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.63 (0.02)	0.27 (0.02)
GBM_O	1:3	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.64 (0.02)	0.26 (0.02)
GBM_O	10000	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.64 (0.02)	0.26 (0.02)
GBM_O	1:1	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.29 (0.03)	0.61 (0.03)
GBM_O	1:2	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.29 (0.02)	0.61 (0.02)
GBM_O	1:3	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.64 (0.02)	0.26 (0.02)
GBM_O	10000	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.64 (0.02)	0.26 (0.02)
GLM_B	1:1	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.48 (0.07)	0.42 (0.07)
GLM_B	1:2	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.49 (0.07)	0.41 (0.07)
GLM_B	1:3	*A priori*	0.05 (0)	0.04 (0)	0.02 (0)	1 (0)	0.48 (0.05)	0.42 (0.05)
GLM_B	10000	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.48 (0.05)	0.42 (0.05)
GLM_B	1:1	Automated	0.06 (0)	0.03 (0)	0.04 (0)	1 (0)	0.56 (0.05)	0.34 (0.05)
GLM_B	1:2	Automated	0.06 (0)	0.03 (0)	0.04 (0)	1 (0)	0.57 (0.04)	0.33 (0.04)
GLM_B	1:3	Automated	0.06 (0)	0.03 (0)	0.04 (0)	1 (0)	0.56 (0.04)	0.34 (0.04)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Resolution			Sensitivity		
			Train	Test	Fit	Train	Test	Fit
GLM_B	10000	Automated	0.06 (0)	0.03 (0)	0.03 (0)	1 (0)	0.59 (0.04)	0.31 (0.04)
GLM_B	1:1	Expert	0.06 (0)	0.03 (0)	0.04 (0)	1 (0)	0.54 (0.04)	0.36 (0.04)
GLM_B	1:2	Expert	0.06 (0)	0.03 (0)	0.04 (0)	1 (0)	0.55 (0.03)	0.35 (0.03)
GLM_B	1:3	Expert	0.06 (0)	0.03 (0)	0.04 (0)	1 (0)	0.56 (0)	0.34 (0)
GLM_B	10000	Expert	0.06 (0)	0.03 (0)	0.04 (0)	1 (0)	0.57 (0.04)	0.33 (0.04)
GLM_O	1:1	*A priori*	0 (0)	0 (0)	0 (0)	1 (0)	0.51 (0.14)	0.39 (0.14)
GLM_O	1:2	*A priori*	0 (0)	0 (0)	0 (0)	1 (0)	0.49 (0.13)	0.41 (0.13)
GLM_O	1:3	*A priori*	0 (0)	0 (0)	0 (0)	1 (0)	0.46 (0.1)	0.44 (0.1)
GLM_O	10000	*A priori*	0 (0)	0 (0)	0 (0)	1 (0)	0.41 (0.07)	0.49 (0.07)
GLM_O	1:1	Automated	0.01 (0.01)	0 (0.01)	0 (0.01)	1 (0)	0.48 (0.14)	0.42 (0.14)
GLM_O	1:2	Automated	0.02 (0.03)	0.01 (0.01)	0.01 (0.02)	1 (0)	0.57 (0.1)	0.33 (0.1)
GLM_O	1:3	Automated	0.03 (0.03)	0.01 (0.01)	0.02 (0.02)	1 (0)	0.57 (0.06)	0.33 (0.06)
GLM_O	10000	Automated	0.04 (0.03)	0.02 (0.01)	0.02 (0.02)	1 (0)	0.56 (0.04)	0.34 (0.04)
GLM_O	1:1	Expert	0.04 (0.02)	0.01 (0.01)	0.02 (0.01)	1 (0)	0.59 (0.04)	0.31 (0.04)
GLM_O	1:2	Expert	0.05 (0.02)	0.02 (0.01)	0.03 (0.01)	1 (0)	0.58 (0.04)	0.32 (0.04)
GLM_O	1:3	Expert	0.05 (0.02)	0.02 (0.01)	0.03 (0.01)	1 (0)	0.56 (0.04)	0.34 (0.04)
GLM_O	10000	Expert	0.05 (0.02)	0.02 (0.01)	0.03 (0.01)	1 (0)	0.53 (0.05)	0.37 (0.05)
MARS_B	1:1	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.55 (0.07)	0.35 (0.07)
MARS_B	1:2	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.53 (0.08)	0.37 (0.08)
MARS_B	1:3	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.52 (0.08)	0.38 (0.08)
MARS_B	10000	*A priori*	0.05 (0)	0.03 (0)	0.02 (0)	1 (0)	0.51 (0.07)	0.39 (0.07)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Resolution			Sensitivity		
			Train	**Test**	**Fit**	**Train**	**Test**	**Fit**
MARS_B	1:1	Automated	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.58 (0.08)	0.32 (0.08)
MARS_B	1:2	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.63 (0.04)	0.27 (0.04)
MARS_B	1:3	Automated	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.6 (0.06)	0.3 (0.06)
MARS_B	10000	Automated	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.56 (0.08)	0.34 (0.08)
MARS_B	1:1	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.6 (0.07)	0.3 (0.07)
MARS_B	1:2	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.63 (0.06)	0.27 (0.06)
MARS_B	1:3	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.61 (0.06)	0.29 (0.06)
MARS_B	10000	Expert	0.06 (0)	0.02 (0)	0.03 (0)	1 (0)	0.61 (0.07)	0.29 (0.07)
MARS_O	1:1	*A priori*	0.04 (0.01)	0.02 (0.01)	0.02 (0.01)	1 (0)	0.55 (0.09)	0.35 (0.09)
MARS_O	1:2	*A priori*	0.03 (0.01)	0.02 (0.01)	0.02 (0.01)	1 (0)	0.55 (0.07)	0.35 (0.07)
MARS_O	1:3	*A priori*	0.03 (0.01)	0.01 (0.01)	0.02 (0.01)	1 (0)	0.54 (0.07)	0.36 (0.07)
MARS_O	10000	*A priori*	0.03 (0.01)	0.01 (0.01)	0.02 (0.01)	1 (0)	0.54 (0.06)	0.36 (0.06)
MARS_O	1:1	Automated	0.04 (0)	0.02 (0)	0.02 (0)	1 (0)	0.56 (0.08)	0.34 (0.08)
MARS_O	1:2	Automated	0.04 (0)	0.02 (0)	0.02 (0)	1 (0)	0.6 (0.04)	0.3 (0.04)
MARS_O	1:3	Automated	0.04 (0.01)	0.02 (0.01)	0.02 (0.01)	1 (0)	0.56 (0.05)	0.34 (0.05)
MARS_O	10000	Automated	0.03 (0.01)	0.01 (0.01)	0.02 (0.01)	1 (0)	0.55 (0.06)	0.35 (0.06)
MARS_O	1:1	Expert	0.05 (0)	0.03 (0)	0.03 (0)	1 (0)	0.62 (0.06)	0.28 (0.06)
MARS_O	1:2	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.64 (0.03)	0.26 (0.03)
MARS_O	1:3	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.64 (0.03)	0.26 (0.03)
MARS_O	10000	Expert	0.04 (0.01)	0.01 (0.01)	0.03 (0.01)	1 (0)	0.64 (0.02)	0.26 (0.02)
MaxEnt_B	1:1	*A priori*	0.04 (0.01)	0.02 (0.01)	0.02 (0.01)	1 (0)	0.52 (0.12)	0.38 (0.12)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Resolution			Sensitivity		
			Train	Test	Fit	Train	Test	Fit
MaxEnt_B	1:2	*A priori*	0.04 (0.01)	0.02 (0.01)	0.02 (0.01)	1 (0)	0.51 (0.11)	0.39 (0.11)
MaxEnt_B	1:3	*A priori*	0.04 (0.01)	0.02 (0.01)	0.02 (0)	1 (0)	0.51 (0)	0.39 (0)
MaxEnt_B	10000	*A priori*	0.04 (0.01)	0.02 (0)	0.02 (0)	1 (0)	0.53 (0.08)	0.37 (0.08)
MaxEnt_B	1:1	Automated	0.05 (0.01)	0.02 (0)	0.03 (0.01)	1 (0)	0.49 (0.1)	0.41 (0.1)
MaxEnt_B	1:2	Automated	0.05 (0.01)	0.02 (0)	0.03 (0.01)	1 (0)	0.51 (0.09)	0.39 (0.09)
MaxEnt_B	1:3	Automated	0.05 (0.01)	0.02 (0)	0.03 (0)	1 (0)	0.47 (0.08)	0.43 (0.08)
MaxEnt_B	10000	Automated	0.05 (0)	0.02 (0)	0.04 (0)	1 (0)	0.44 (0.05)	0.46 (0.05)
MaxEnt_B	1:1	Expert	0.05 (0.01)	0.02 (0)	0.03 (0.01)	1 (0)	0.55 (0.09)	0.35 (0.09)
MaxEnt_B	1:2	Expert	0.05 (0.01)	0.02 (0)	0.04 (0)	1 (0)	0.57 (0.07)	0.33 (0.07)
MaxEnt_B	1:3	Expert	0.05 (0.01)	0.02 (0)	0.04 (0)	1 (0)	0.57 (0)	0.33 (0)
MaxEnt_B	10000	Expert	0.06 (0)	0.02 (0)	0.04 (0)	1 (0)	0.58 (0.05)	0.32 (0.05)
MaxEnt_O	1:1	*A priori*	0.04 (0.01)	0.01 (0)	0.02 (0.01)	1 (0)	0.5 (0.11)	0.4 (0.11)
MaxEnt_O	1:2	*A priori*	0.04 (0.01)	0.01 (0.01)	0.02 (0.01)	1 (0)	0.5 (0.11)	0.4 (0.11)
MaxEnt_O	1:3	*A priori*	0.04 (0.01)	0.01 (0.01)	0.02 (0.01)	1 (0)	0.48 (0.12)	0.42 (0.12)
MaxEnt_O	10000	*A priori*	0.04 (0.01)	0.01 (0)	0.02 (0.01)	1 (0)	0.51 (0.12)	0.39 (0.12)
MaxEnt_O	1:1	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.47 (0.07)	0.43 (0.07)
MaxEnt_O	1:2	Automated	0.05 (0.01)	0.02 (0)	0.03 (0.01)	1 (0)	0.48 (0.11)	0.42 (0.11)
MaxEnt_O	1:3	Automated	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.47 (0.09)	0.43 (0.09)
MaxEnt_O	10000	Automated	0.05 (0.01)	0.02 (0)	0.03 (0)	1 (0)	0.49 (0.11)	0.41 (0.11)
MaxEnt_O	1:1	Expert	0.05 (0.01)	0.02 (0)	0.03 (0.01)	1 (0)	0.59 (0.08)	0.31 (0.08)
MaxEnt_O	1:2	Expert	0.05 (0.01)	0.02 (0)	0.03 (0.01)	1 (0)	0.59 (0.09)	0.31 (0.09)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Resolution			Sensitivity		
			Train	Test	Fit	Train	Test	Fit
MaxEnt_O	1:3	Expert	0.05 (0.01)	0.02 (0)	0.03 (0.01)	1 (0)	0.58 (0.08)	0.32 (0.08)
MaxEnt_O	10000	Expert	0.05 (0.01)	0.02 (0)	0.03 (0)	1 (0)	0.57 (0.07)	0.33 (0.07)
MXL_O	1:1	*A priori*	0.04 (0)	0.02 (0)	0.02 (0)	1 (0)	0.61 (0.08)	0.29 (0.08)
MXL_O	1:2	*A priori*	0.04 (0)	0.01 (0)	0.02 (0)	1 (0)	0.61 (0.08)	0.29 (0.08)
MXL_O	1:3	*A priori*	0.04 (0)	0.02 (0)	0.02 (0)	1 (0)	0.61 (0.09)	0.29 (0.09)
MXL_O	10000	*A priori*	0.04 (0)	0.01 (0)	0.02 (0)	1 (0)	0.59 (0.05)	0.31 (0.05)
MXL_O	1:1	Automated	0.03 (0)	0.02 (0)	0.01 (0)	1 (0)	0.65 (0.04)	0.25 (0.04)
MXL_O	1:2	Automated	0.03 (0)	0.02 (0)	0.01 (0)	1 (0)	0.73 (0.05)	0.17 (0.05)
MXL_O	1:3	Automated	0.03 (0)	0.02 (0)	0.01 (0)	1 (0)	0.73 (0.03)	0.17 (0.03)
MXL_O	10000	Automated	0.03 (0)	0.02 (0)	0.01 (0)	1 (0)	0.72 (0.04)	0.18 (0.04)
MXL_O	1:1	Expert	0.04 (0.01)	0.01 (0.01)	0.04 (0.01)	1 (0)	0.55 (0.08)	0.35 (0.08)
MXL_O	1:2	Expert	0.04 (0.01)	0.01 (0.01)	0.04 (0.01)	1 (0)	0.56 (0.06)	0.34 (0.06)
MXL_O	1:3	Expert	0.04 (0.01)	0.01 (0.01)	0.04 (0.01)	1 (0)	0.56 (0.06)	0.34 (0.06)
MXL_O	10000	Expert	0.04 (0.01)	0.01 (0.01)	0.04 (0.01)	1 (0)	0.56 (0.08)	0.34 (0.08)
RF_B	1:1	*A priori*	0.04 (0)	0.03 (0)	0.01 (0)	1 (0)	0.29 (0.04)	0.61 (0.04)
RF_B	1:2	*A priori*	0.04 (0)	0.02 (0)	0.01 (0)	1 (0)	0.33 (0.04)	0.57 (0.04)
RF_B	1:3	*A priori*	0.03 (0)	0.02 (0)	0.01 (0)	1 (0)	0.36 (0.05)	0.54 (0.05)
RF_B	10000	*A priori*	0.03 (0)	0.02 (0)	0.01 (0)	1 (0)	0.43 (0.05)	0.47 (0.05)
RF_B	1:1	Automated	0.05 (0)	0.02 (0)	0.02 (0)	1 (0)	0.33 (0.06)	0.57 (0.06)
RF_B	1:2	Automated	0.04 (0)	0.02 (0)	0.02 (0)	1 (0)	0.41 (0.06)	0.49 (0.06)
RF_B	1:3	Automated	0.04 (0)	0.01 (0)	0.02 (0)	1 (0)	0.46 (0.07)	0.44 (0.07)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Resolution Train	Resolution Test	Resolution Fit	Sensitivity Train	Sensitivity Test	Sensitivity Fit
RF_B	10000	Automated	0.03 (0)	0.01 (0)	0.02 (0)	1 (0)	0.51 (0.04)	0.39 (0.04)
RF_B	1:1	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.47 (0.06)	0.43 (0.06)
RF_B	1:2	Expert	0.04 (0)	0.02 (0)	0.03 (0)	1 (0)	0.49 (0.04)	0.41 (0.04)
RF_B	1:3	Expert	0.04 (0)	0.01 (0)	0.02 (0)	1 (0)	0.49 (0)	0.41 (0)
RF_B	10000	Expert	0.03 (0)	0.01 (0)	0.02 (0)	1 (0)	0.51 (0.02)	0.39 (0.02)
RF_O	1:1	*A priori*	0.04 (0)	0.02 (0)	0.02 (0)	1 (0)	0.29 (0.08)	0.61 (0.08)
RF_O	1:2	*A priori*	0.04 (0)	0.02 (0)	0.02 (0)	1 (0)	0.32 (0.05)	0.58 (0.05)
RF_O	1:3	*A priori*	0.03 (0)	0.02 (0)	0.02 (0)	1 (0)	0.34 (0.06)	0.56 (0.06)
RF_O	10000	*A priori*	0.02 (0)	0.01 (0)	0.01 (0)	1 (0)	0.46 (0.06)	0.44 (0.06)
RF_O	1:1	Automated	0.05 (0)	0.02 (0)	0.02 (0)	1 (0)	0.31 (0.05)	0.59 (0.05)
RF_O	1:2	Automated	0.04 (0)	0.02 (0)	0.02 (0)	1 (0)	0.36 (0.06)	0.54 (0.06)
RF_O	1:3	Automated	0.04 (0)	0.01 (0)	0.02 (0)	1 (0)	0.37 (0.06)	0.53 (0.06)
RF_O	10000	Automated	0.03 (0)	0.01 (0)	0.02 (0)	1 (0)	0.5 (0.05)	0.4 (0.05)
RF_O	1:1	Expert	0.05 (0)	0.02 (0)	0.03 (0)	1 (0)	0.46 (0.07)	0.44 (0.07)
RF_O	1:2	Expert	0.04 (0)	0.02 (0)	0.03 (0)	1 (0)	0.49 (0.04)	0.41 (0.04)
RF_O	1:3	Expert	0.04 (0)	0.01 (0)	0.02 (0)	1 (0)	0.5 (0.04)	0.4 (0.04)
RF_O	10000	Expert	0.03 (0)	0.01 (0)	0.02 (0)	1 (0)	0.53 (0.03)	0.37 (0.03)
SRE_B	1:1	*A priori*	0.03 (0)	0.01 (0)	0.02 (0)	1 (0)	0.67 (0)	0.23 (0)
SRE_B	1:2	*A priori*	0.03 (0)	0.01 (0)	0.01 (0)	1 (0)	0.67 (0)	0.23 (0)
SRE_B	1:3	*A priori*	0.03 (0)	0.01 (0)	0.01 (0)	1 (0)	0.67 (0)	0.23 (0)
SRE_B	10000	*A priori*	0.03 (0)	0.01 (0)	0.02 (0)	1 (0)	0.67 (0)	0.23 (0)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Resolution			Sensitivity		
			Train	Test	Fit	Train	Test	Fit
SRE_B	1:1	Automated	0.03 (0)	0.01 (0)	0.02 (0)	1 (0)	0.67 (0)	0.23 (0)
SRE_B	1:2	Automated	0.03 (0)	0.01 (0)	0.02 (0)	1 (0)	0.67 (0)	0.23 (0)
SRE_B	1:3	Automated	0.03 (0)	0.01 (0)	0.02 (0)	1 (0)	0.67 (0)	0.23 (0)
SRE_B	10000	Automated	0.03 (0)	0.01 (0)	0.02 (0)	1 (0)	0.67 (0)	0.23 (0)
SRE_B	1:1	Expert	0.03 (0)	0.01 (0)	0.02 (0)	1 (0)	0.26 (0)	0.64 (0)
SRE_B	1:2	Expert	0.03 (0)	0.01 (0)	0.02 (0)	1 (0)	0.26 (0)	0.64 (0)
SRE_B	1:3	Expert	0.03 (0)	0.01 (0)	0.02 (0)	1 (0)	0.28 (0)	0.62 (0)
SRE_B	10000	Expert	0.03 (0)	0.01 (0)	0.02 (0)	1 (0)	0.27 (0.06)	0.63 (0.06)
SRE_O	1:1	*A priori*	0.02 (0)	0 (0)	0.02 (0)	1 (0)	0.34 (0.03)	0.56 (0.03)
SRE_O	1:2	*A priori*	0.02 (0)	0 (0)	0.02 (0)	1 (0)	0.34 (0.02)	0.56 (0.02)
SRE_O	1:3	*A priori*	0.02 (0)	0 (0)	0.02 (0)	1 (0)	0.33 (0)	0.57 (0)
SRE_O	10000	*A priori*	0.02 (0)	0 (0)	0.02 (0)	1 (0)	0.34 (0.03)	0.56 (0.03)
SRE_O	1:1	Automated	0.02 (0)	0 (0)	0.02 (0)	1 (0)	0.28 (0.06)	0.62 (0.06)
SRE_O	1:2	Automated	0.02 (0)	0 (0)	0.02 (0)	1 (0)	0.29 (0.05)	0.61 (0.05)
SRE_O	1:3	Automated	0.02 (0)	0 (0)	0.02 (0)	1 (0)	0.29 (0.05)	0.61 (0.05)
SRE_O	10000	Automated	0.02 (0)	0 (0)	0.02 (0)	1 (0)	0.29 (0.06)	0.61 (0.06)
SRE_O	1:1	Expert	0.02 (0)	0 (0)	0.02 (0)	1 (0)	0.32 (0.04)	0.58 (0.04)
SRE_O	1:2	Expert	0.02 (0)	0 (0)	0.02 (0)	1 (0)	0.32 (0.04)	0.58 (0.04)
SRE_O	1:3	Expert	0.02 (0)	0 (0)	0.02 (0)	1 (0)	0.32 (0.04)	0.58 (0.04)
SRE_O	10000	Expert	0.02 (0)	0 (0)	0.02 (0)	1 (0)	0.32 (0.04)	0.58 (0.04)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Specificity			Precision		
			Train	Test	Fit	Train	Test	Fit
ANN_B	1:1	*A priori*	0.6 (0.03)	0.72 (0.06)	-0.11 (0.07)	0.69 (0.02)	0.15 (0.06)	0.55 (0.06)
ANN_B	1:2	*A priori*	0.6 (0.02)	0.72 (0.06)	-0.12 (0.06)	0.53 (0.02)	0.15 (0.05)	0.38 (0.05)
ANN_B	1:3	*A priori*	0.6 (0.04)	0.73 (0.07)	-0.14 (0.07)	0.43 (0.02)	0.15 (0.08)	0.27 (0.08)
ANN_B	10000	*A priori*	0.59 (0.03)	0.72 (0.06)	-0.13 (0.06)	0.24 (0.01)	0.15 (0.06)	0.09 (0.06)
ANN_B	1:1	Automated	0.6 (0.04)	0.72 (0.04)	-0.12 (0.07)	0.69 (0.02)	0.13 (0.05)	0.56 (0.05)
ANN_B	1:2	Automated	0.6 (0.03)	0.74 (0.03)	-0.14 (0.04)	0.53 (0.02)	0.18 (0.06)	0.35 (0.06)
ANN_B	1:3	Automated	0.6 (0.03)	0.74 (0.03)	-0.14 (0.05)	0.43 (0.02)	0.17 (0.05)	0.26 (0.06)
ANN_B	10000	Automated	0.6 (0.03)	0.73 (0.05)	-0.14 (0.04)	0.24 (0.01)	0.17 (0.06)	0.07 (0.06)
ANN_B	1:1	Expert	0.59 (0.04)	0.75 (0.05)	-0.16 (0.05)	0.69 (0.02)	0.2 (0.07)	0.48 (0.07)
ANN_B	1:2	Expert	0.59 (0.04)	0.74 (0.05)	-0.15 (0.05)	0.53 (0.02)	0.18 (0.07)	0.35 (0.07)
ANN_B	1:3	Expert	0.58 (0)	0.75 (0)	-0.17 (0)	0.42 (0)	0.18 (0)	0.23 (0)
ANN_B	10000	Expert	0.59 (0.03)	0.74 (0.05)	-0.15 (0.05)	0.24 (0.01)	0.2 (0.09)	0.04 (0.09)
ANN_O	1:1	*A priori*	0.52 (0.1)	0.66 (0.1)	-0.14 (0.15)	0.66 (0.04)	0.09 (0.09)	0.57 (0.1)
ANN_O	1:2	*A priori*	0.41 (0.23)	0.57 (0.16)	-0.16 (0.15)	0.46 (0.07)	0.06 (0.07)	0.4 (0.08)
ANN_O	1:3	*A priori*	0.27 (0.27)	0.49 (0.17)	-0.22 (0.17)	0.33 (0.08)	0.04 (0.06)	0.28 (0.08)
ANN_O	10000	*A priori*	0.06 (0.17)	0.37 (0.11)	-0.31 (0.08)	0.13 (0.03)	0.03 (0.04)	0.1 (0.04)
ANN_O	1:1	Automated	0.51 (0.1)	0.6 (0.13)	-0.09 (0.18)	0.65 (0.04)	0.06 (0.06)	0.59 (0.08)
ANN_O	1:2	Automated	0.39 (0.22)	0.54 (0.15)	-0.16 (0.16)	0.45 (0.07)	0.05 (0.05)	0.39 (0.08)
ANN_O	1:3	Automated	0.28 (0.27)	0.49 (0.17)	-0.21 (0.17)	0.32 (0.07)	0.04 (0.04)	0.28 (0.07)
ANN_O	10000	Automated	0.03 (0.13)	0.35 (0.08)	-0.32 (0.07)	0.13 (0.03)	0.02 (0.03)	0.1 (0.02)
ANN_O	1:1	Expert	0.52 (0.14)	0.74 (0.06)	-0.22 (0.14)	0.66 (0.05)	0.17 (0.07)	0.5 (0.08)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Specificity Train	Specificity Test	Specificity Fit	Precision Train	Precision Test	Precision Fit
ANN_O	1:2	Expert	0.43 (0.25)	0.65 (0.18)	-0.23 (0.1)	0.47 (0.08)	0.16 (0.1)	0.31 (0.06)
ANN_O	1:3	Expert	0.25 (0.28)	0.52 (0.22)	-0.28 (0.08)	0.32 (0.08)	0.11 (0.11)	0.21 (0.05)
ANN_O	10000	Expert	0.05 (0.16)	0.37 (0.13)	-0.32 (0.04)	0.13 (0.03)	0.04 (0.07)	0.09 (0.04)
CTA_B	1:1	*A priori*	0.67 (0.05)	0.76 (0.02)	-0.09 (0.06)	0.74 (0.03)	0.18 (0.06)	0.55 (0.07)
CTA_B	1:2	*A priori*	0.71 (0.05)	0.76 (0.02)	-0.06 (0.06)	0.61 (0.04)	0.21 (0.07)	0.4 (0.09)
CTA_B	1:3	*A priori*	0.73 (0.06)	0.77 (0.03)	-0.04 (0.06)	0.53 (0.06)	0.2 (0.09)	0.33 (0.11)
CTA_B	10000	*A priori*	0.73 (0.05)	0.77 (0.02)	-0.04 (0.05)	0.33 (0.04)	0.21 (0.07)	0.12 (0.08)
CTA_B	1:1	Automated	0.69 (0.06)	0.76 (0.03)	-0.07 (0.06)	0.75 (0.03)	0.21 (0.09)	0.54 (0.1)
CTA_B	1:2	Automated	0.7 (0.05)	0.76 (0.03)	-0.06 (0.06)	0.61 (0.04)	0.19 (0.09)	0.41 (0.1)
CTA_B	1:3	Automated	0.73 (0.06)	0.75 (0.03)	-0.03 (0.06)	0.53 (0.05)	0.18 (0.09)	0.35 (0.1)
CTA_B	10000	Automated	0.76 (0.05)	0.76 (0.03)	0 (0.06)	0.35 (0.05)	0.2 (0.14)	0.15 (0.15)
CTA_B	1:1	Expert	0.67 (0.05)	0.75 (0.03)	-0.08 (0.06)	0.74 (0.03)	0.2 (0.08)	0.53 (0.09)
CTA_B	1:2	Expert	0.68 (0.06)	0.75 (0.03)	-0.07 (0.06)	0.59 (0.04)	0.2 (0.07)	0.39 (0.08)
CTA_B	1:3	Expert	0.68 (0)	0.76 (0)	-0.08 (0)	0.49 (0)	0.22 (0)	0.27 (0)
CTA_B	10000	Expert	0.72 (0.05)	0.76 (0.03)	-0.04 (0.06)	0.31 (0.04)	0.2 (0.08)	0.11 (0.09)
CTA_O	1:1	*A priori*	0.54 (0.06)	0.62 (0.2)	-0.08 (0.2)	0.67 (0.02)	0.13 (0.12)	0.54 (0.12)
CTA_O	1:2	*A priori*	0.53 (0.04)	0.66 (0.18)	-0.12 (0.19)	0.5 (0.02)	0.16 (0.16)	0.34 (0.16)
CTA_O	1:3	*A priori*	0.53 (0.06)	0.66 (0.18)	-0.14 (0.2)	0.4 (0.03)	0.16 (0.16)	0.24 (0.16)
CTA_O	10000	*A priori*	0.49 (0.02)	0.77 (0)	-0.28 (0.02)	0.21 (0.01)	0.15 (0)	0.06 (0.01)
CTA_O	1:1	Automated	0.52 (0.06)	0.56 (0.2)	-0.04 (0.2)	0.66 (0.02)	0.1 (0.1)	0.57 (0.1)
CTA_O	1:2	Automated	0.52 (0.05)	0.63 (0.18)	-0.11 (0.19)	0.49 (0.02)	0.11 (0.08)	0.38 (0.08)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Specificity Train	Specificity Test	Specificity Fit	Precision Train	Precision Test	Precision Fit
CTA_O	1:3	Automated	0.52 (0.07)	0.59 (0.2)	-0.06 (0.22)	0.4 (0.03)	0.1 (0.06)	0.3 (0.07)
CTA_O	10000	Automated	0.5 (0.04)	0.72 (0.02)	-0.23 (0.05)	0.21 (0.01)	0.14 (0)	0.07 (0.01)
CTA_O	1:1	Expert	0.52 (0.04)	0.65 (0.17)	-0.13 (0.17)	0.66 (0.02)	0.13 (0.08)	0.53 (0.08)
CTA_O	1:2	Expert	0.53 (0.04)	0.63 (0.18)	-0.1 (0.18)	0.5 (0.02)	0.11 (0.06)	0.39 (0.07)
CTA_O	1:3	Expert	0.53 (0.04)	0.67 (0.16)	-0.14 (0.17)	0.4 (0.01)	0.12 (0.06)	0.27 (0.06)
CTA_O	10000	Expert	0.5 (0.03)	0.72 (0.01)	-0.22 (0.03)	0.21 (0.01)	0.14 (0)	0.07 (0.01)
EMca_B	1:1	*A priori*	0.27 (0.15)	0.34 (0.03)	-0.07 (0.15)	0.58 (0.05)	0.02 (0)	0.56 (0.05)
EMca_B	1:2	*A priori*	0.26 (0.15)	0.33 (0)	-0.07 (0.15)	0.41 (0.05)	0.02 (0)	0.39 (0.05)
EMca_B	1:3	*A priori*	0.29 (0.13)	0.33 (0)	-0.04 (0.13)	0.32 (0.04)	0.02 (0)	0.31 (0.04)
EMca_B	10000	*A priori*	0.4 (0.2)	0.33 (0)	0.07 (0.2)	0.2 (0.05)	0.02 (0)	0.19 (0.05)
EMca_B	1:1	Automated	0.27 (0.11)	0.36 (0.09)	-0.1 (0.08)	0.58 (0.05)	0.03 (0.04)	0.55 (0.03)
EMca_B	1:2	Automated	0.24 (0.1)	0.33 (0)	-0.1 (0.1)	0.4 (0.03)	0.02 (0)	0.38 (0.03)
EMca_B	1:3	Automated	0.25 (0.09)	0.33 (0)	-0.08 (0.09)	0.31 (0.03)	0.02 (0)	0.29 (0.03)
EMca_B	10000	Automated	0.31 (0.17)	0.33 (0)	-0.03 (0.17)	0.19 (0.06)	0.02 (0)	0.17 (0.06)
EMca_B	1:1	Expert	0.3 (0.12)	0.34 (0.04)	-0.04 (0.13)	0.59 (0.04)	0.02 (0)	0.57 (0.04)
EMca_B	1:2	Expert	0.3 (0.1)	0.33 (0)	-0.03 (0.1)	0.42 (0.03)	0.02 (0)	0.4 (0.03)
EMca_B	1:3	Expert	0.25 (0.11)	0.33 (0)	-0.08 (0.11)	0.31 (0.04)	0.02 (0)	0.29 (0.04)
EMca_B	10000	Expert	0.25 (0.14)	0.33 (0)	-0.08 (0.14)	0.16 (0.04)	0.02 (0)	0.14 (0.04)
EMmean_B	1:1	*A priori*	0.69 (0.04)	0.76 (0.03)	-0.07 (0.05)	0.75 (0.02)	0.24 (0.08)	0.51 (0.08)
EMmean_B	1:2	*A priori*	0.7 (0.04)	0.77 (0.03)	-0.07 (0.04)	0.6 (0.03)	0.25 (0.09)	0.36 (0.09)
EMmean_B	1:3	*A priori*	0.7 (0.04)	0.76 (0.03)	-0.06 (0.04)	0.5 (0.03)	0.25 (0.1)	0.25 (0.1)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Specificity			Precision		
			Train	Test	Fit	Train	Test	Fit
EMmean_B	10000	*A priori*	0.71 (0.03)	0.77 (0.03)	-0.06 (0.04)	0.3 (0.03)	0.27 (0.09)	0.03 (0.09)
EMmean_B	1:1	Automated	0.71 (0.06)	0.75 (0.02)	-0.04 (0.06)	0.76 (0.05)	0.23 (0.06)	0.53 (0.07)
EMmean_B	1:2	Automated	0.65 (0.04)	0.73 (0.02)	-0.08 (0.04)	0.57 (0.03)	0.14 (0.01)	0.43 (0.03)
EMmean_B	1:3	Automated	0.76 (0.05)	0.74 (0.04)	0.02 (0.06)	0.56 (0.05)	0.16 (0.06)	0.4 (0.07)
EMmean_B	10000	Automated	0.76 (0.05)	0.73 (0.03)	0.03 (0.05)	0.35 (0.07)	0.15 (0.05)	0.21 (0.06)
EMmean_B	1:1	Expert	0.69 (0.04)	0.75 (0.03)	-0.06 (0.04)	0.74 (0.03)	0.2 (0.06)	0.54 (0.06)
EMmean_B	1:2	Expert	0.7 (0.04)	0.75 (0.03)	-0.05 (0.04)	0.6 (0.03)	0.17 (0.05)	0.43 (0.05)
EMmean_B	1:3	Expert	0.7 (0.03)	0.74 (0.03)	-0.04 (0.04)	0.5 (0.03)	0.16 (0.04)	0.34 (0.04)
EMmean_B	10000	Expert	0.72 (0.03)	0.75 (0.02)	-0.02 (0.04)	0.31 (0.02)	0.15 (0.03)	0.16 (0.03)
EMmedian_B	1:1	*A priori*	0.64 (0.04)	0.77 (0.03)	-0.12 (0.05)	0.72 (0.02)	0.24 (0.07)	0.48 (0.06)
EMmedian_B	1:2	*A priori*	0.65 (0.03)	0.77 (0.02)	-0.12 (0.04)	0.56 (0.02)	0.27 (0.07)	0.3 (0.07)
EMmedian_B	1:3	*A priori*	0.65 (0.03)	0.77 (0.03)	-0.12 (0.04)	0.46 (0.02)	0.29 (0.09)	0.18 (0.08)
EMmedian_B	10000	*A priori*	0.65 (0.03)	0.77 (0.02)	-0.12 (0.03)	0.26 (0.01)	0.32 (0.07)	-0.06 (0.07)
EMmedian_B	1:1	Automated	0.65 (0.06)	0.75 (0.03)	-0.11 (0.06)	0.72 (0.04)	0.22 (0.06)	0.5 (0.07)
EMmedian_B	1:2	Automated	0.59 (0.03)	0.73 (0.02)	-0.14 (0.03)	0.52 (0.02)	0.14 (0.01)	0.38 (0.02)
EMmedian_B	1:3	Automated	0.59 (0.03)	0.73 (0.02)	-0.14 (0.03)	0.42 (0.02)	0.14 (0.01)	0.28 (0.02)
EMmedian_B	10000	Automated	0.58 (0.03)	0.73 (0.02)	-0.15 (0.03)	0.23 (0.01)	0.15 (0.01)	0.09 (0.01)
EMmedian_B	1:1	Expert	0.63 (0.03)	0.75 (0.03)	-0.12 (0.04)	0.71 (0.02)	0.2 (0.06)	0.51 (0.06)
EMmedian_B	1:2	Expert	0.65 (0.03)	0.75 (0.02)	-0.1 (0.04)	0.56 (0.02)	0.17 (0.04)	0.39 (0.05)
EMmedian_B	1:3	Expert	0.64 (0.03)	0.75 (0.02)	-0.12 (0.04)	0.45 (0.02)	0.17 (0.04)	0.28 (0.05)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Specificity Train	Specificity Test	Specificity Fit	Precision Train	Precision Test	Precision Fit
EMmedian_B	10000	Expert	0.64 (0.02)	0.75 (0.03)	-0.11 (0.03)	0.26 (0.01)	0.18 (0.05)	0.08 (0.04)
EMwmean_B	1:1	*A priori*	0.7 (0.04)	0.76 (0.03)	-0.06 (0.05)	0.75 (0.02)	0.24 (0.08)	0.51 (0.08)
EMwmean_B	1:2	*A priori*	0.71 (0.04)	0.76 (0.03)	-0.06 (0.05)	0.61 (0.03)	0.24 (0.09)	0.36 (0.09)
EMwmean_B	1:3	*A priori*	0.71 (0.04)	0.76 (0.03)	-0.05 (0.05)	0.51 (0.03)	0.25 (0.1)	0.25 (0.1)
EMwmean_B	10000	*A priori*	0.72 (0.04)	0.77 (0.03)	-0.05 (0.04)	0.31 (0.03)	0.28 (0.09)	0.03 (0.09)
EMwmean_B	1:1	Automated	0.7 (0.04)	0.76 (0.03)	-0.06 (0.05)	0.75 (0.03)	0.23 (0.06)	0.52 (0.06)
EMwmean_B	1:2	Automated	0.66 (0.04)	0.73 (0.02)	-0.08 (0.04)	0.57 (0.03)	0.14 (0.01)	0.43 (0.03)
EMwmean_B	1:3	Automated	0.76 (0.05)	0.73 (0.04)	0.03 (0.06)	0.56 (0.05)	0.16 (0.06)	0.4 (0.07)
EMwmean_B	10000	Automated	0.76 (0.05)	0.73 (0.03)	0.03 (0.05)	0.35 (0.05)	0.14 (0.05)	0.21 (0.06)
EMwmean_B	1:1	Expert	0.69 (0.04)	0.75 (0.03)	-0.06 (0.04)	0.75 (0.02)	0.2 (0.07)	0.55 (0.07)
EMwmean_B	1:2	Expert	0.7 (0.03)	0.74 (0.03)	-0.04 (0.04)	0.6 (0.03)	0.17 (0.05)	0.43 (0.05)
EMwmean_B	1:3	Expert	0.7 (0.03)	0.74 (0.02)	-0.04 (0.04)	0.5 (0.03)	0.16 (0.04)	0.35 (0.04)
EMwmean_B	10000	Expert	0.72 (0.03)	0.74 (0.02)	-0.02 (0.04)	0.31 (0.02)	0.15 (0.03)	0.16 (0.03)
FDA_B	1:1	*A priori*	0.59 (0.03)	0.75 (0.05)	-0.16 (0.05)	0.69 (0.01)	0.2 (0.08)	0.49 (0.08)
FDA_B	1:2	*A priori*	0.58 (0.03)	0.75 (0.04)	-0.17 (0.04)	0.52 (0.02)	0.18 (0.1)	0.34 (0.1)
FDA_B	1:3	*A priori*	0.58 (0.03)	0.76 (0.02)	-0.18 (0.04)	0.42 (0.02)	0.14 (0.07)	0.27 (0.07)
FDA_B	10000	*A priori*	0.57 (0.02)	0.76 (0.02)	-0.19 (0.03)	0.22 (0.01)	0.14 (0.05)	0.09 (0.05)
FDA_B	1:1	Automated	0.58 (0.04)	0.73 (0.05)	-0.15 (0.07)	0.68 (0.02)	0.14 (0.05)	0.54 (0.06)
FDA_B	1:2	Automated	0.59 (0.02)	0.7 (0.07)	-0.11 (0.07)	0.52 (0.01)	0.1 (0.04)	0.42 (0.04)
FDA_B	1:3	Automated	0.58 (0.03)	0.69 (0.07)	-0.1 (0.08)	0.42 (0.02)	0.1 (0.04)	0.32 (0.05)
FDA_B	10000	Automated	0.57 (0.02)	0.72 (0.04)	-0.15 (0.04)	0.23 (0.01)	0.11 (0.04)	0.12 (0.04)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Specificity Train	Specificity Test	Specificity Fit	Precision Train	Precision Test	Precision Fit
FDA_B	1:1	Expert	0.58 (0.04)	0.74 (0.02)	-0.16 (0.04)	0.68 (0.02)	0.17 (0.06)	0.52 (0.06)
FDA_B	1:2	Expert	0.59 (0.03)	0.74 (0.02)	-0.16 (0.04)	0.52 (0.02)	0.14 (0.01)	0.38 (0.02)
FDA_B	1:3	Expert	0.57 (0)	0.75 (0)	-0.18 (0)	0.41 (0)	0.14 (0)	0.27 (0)
FDA_B	10000	Expert	0.57 (0.02)	0.74 (0.02)	-0.17 (0.03)	0.23 (0.01)	0.14 (0.01)	0.09 (0.01)
FDA_O	1:1	*A priori*	0.58 (0.23)	0.77 (0.03)	-0.19 (0.23)	0.69 (0.07)	0.24 (0.12)	0.45 (0.14)
FDA_O	1:2	*A priori*	0.56 (0.24)	0.75 (0.07)	-0.19 (0.24)	0.52 (0.08)	0.22 (0.11)	0.3 (0.13)
FDA_O	1:3	*A priori*	0.58 (0.22)	0.77 (0.03)	-0.19 (0.22)	0.43 (0.07)	0.22 (0.1)	0.2 (0.12)
FDA_O	10000	*A priori*	0.59 (0.2)	0.77 (0.03)	-0.18 (0.2)	0.24 (0.04)	0.24 (0.11)	0 (0.12)
FDA_O	1:1	Automated	0.5 (0.28)	0.77 (0.02)	-0.27 (0.29)	0.66 (0.09)	0.27 (0.04)	0.39 (0.1)
FDA_O	1:2	Automated	0.57 (0.23)	0.76 (0.05)	-0.19 (0.24)	0.52 (0.08)	0.26 (0.06)	0.26 (0.1)
FDA_O	1:3	Automated	0.54 (0.25)	0.75 (0.05)	-0.21 (0.26)	0.41 (0.08)	0.21 (0.09)	0.2 (0.12)
FDA_O	10000	Automated	0.54 (0.25)	0.75 (0.05)	-0.2 (0.26)	0.23 (0.05)	0.21 (0.09)	0.02 (0.1)
FDA_O	1:1	Expert	0.52 (0.27)	0.75 (0.04)	-0.23 (0.28)	0.66 (0.09)	0.18 (0.07)	0.48 (0.12)
FDA_O	1:2	Expert	0.51 (0.27)	0.75 (0.04)	-0.23 (0.28)	0.5 (0.09)	0.18 (0.07)	0.32 (0.11)
FDA_O	1:3	Expert	0.53 (0.21)	0.75 (0.03)	-0.22 (0.21)	0.41 (0.06)	0.19 (0.08)	0.22 (0.1)
FDA_O	10000	Expert	0.55 (0.17)	0.75 (0.03)	-0.2 (0.16)	0.23 (0.03)	0.2 (0.07)	0.03 (0.08)
GAM_B	1:1	*A priori*	0.61 (0.03)	0.61 (0.12)	0 (0.12)	0.7 (0.02)	0.1 (0.08)	0.6 (0.08)
GAM_B	1:2	*A priori*	0.61 (0.02)	0.53 (0.13)	0.08 (0.13)	0.54 (0.01)	0.05 (0.04)	0.48 (0.05)
GAM_B	1:3	*A priori*	0.62 (0.03)	0.46 (0.15)	0.16 (0.15)	0.44 (0.02)	0.04 (0.04)	0.41 (0.05)
GAM_B	10000	*A priori*	0.62 (0.02)	0.48 (0.11)	0.14 (0.11)	0.25 (0.01)	0.03 (0.02)	0.21 (0.02)
GAM_B	1:1	Automated	0.6 (0.04)	0.68 (0.12)	-0.08 (0.13)	0.69 (0.02)	0.14 (0.09)	0.56 (0.1)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Specificity Train	Specificity Test	Specificity Fit	Precision Train	Precision Test	Precision Fit
GAM_B	1:2	Automated	0.6 (0.03)	0.62 (0.13)	-0.02 (0.13)	0.53 (0.02)	0.08 (0.07)	0.44 (0.07)
GAM_B	1:3	Automated	0.61 (0.02)	0.46 (0.13)	0.15 (0.14)	0.43 (0.02)	0.04 (0.04)	0.39 (0.04)
GAM_B	10000	Automated	0.6 (0.02)	0.5 (0.11)	0.1 (0.11)	0.24 (0.01)	0.03 (0.02)	0.21 (0.02)
GAM_B	1:1	Expert	0.6 (0.04)	0.64 (0.14)	-0.04 (0.14)	0.69 (0.02)	0.13 (0.11)	0.57 (0.11)
GAM_B	1:2	Expert	0.59 (0.02)	0.55 (0.14)	0.05 (0.14)	0.53 (0.01)	0.05 (0.06)	0.47 (0.06)
GAM_B	1:3	Expert	0.58 (0)	0.5 (0)	0.08 (0)	0.42 (0)	0.03 (0)	0.38 (0)
GAM_B	10000	Expert	0.59 (0.02)	0.42 (0.08)	0.17 (0.09)	0.24 (0.01)	0.02 (0.01)	0.21 (0.01)
GAM_O	1:1	*A priori*	0.59 (0.04)	0.77 (0.02)	-0.18 (0.04)	0.69 (0.02)	0.29 (0.03)	0.4 (0.04)
GAM_O	1:2	*A priori*	0.59 (0.02)	0.78 (0.02)	-0.18 (0.03)	0.52 (0.02)	0.29 (0.02)	0.23 (0.03)
GAM_O	1:3	*A priori*	0.59 (0.03)	0.77 (0.02)	-0.18 (0.04)	0.42 (0.02)	0.31 (0.04)	0.11 (0.04)
GAM_O	10000	*A priori*	0.59 (0.02)	0.77 (0.02)	-0.18 (0.04)	0.23 (0.01)	0.34 (0.04)	-0.11 (0.05)
GAM_O	1:1	Automated	0.6 (0.03)	0.77 (0.02)	-0.17 (0.04)	0.69 (0.02)	0.28 (0.03)	0.41 (0.03)
GAM_O	1:2	Automated	0.59 (0.03)	0.78 (0.02)	-0.19 (0.03)	0.52 (0.02)	0.29 (0.01)	0.23 (0.02)
GAM_O	1:3	Automated	0.59 (0.02)	0.76 (0.02)	-0.17 (0.04)	0.42 (0.01)	0.26 (0.02)	0.16 (0.02)
GAM_O	10000	Automated	0.59 (0.02)	0.75 (0.02)	-0.16 (0.03)	0.23 (0.01)	0.28 (0.02)	-0.04 (0.02)
GAM_O	1:1	Expert	0.59 (0.03)	0.78 (0.02)	-0.18 (0.04)	0.69 (0.02)	0.27 (0.03)	0.42 (0.03)
GAM_O	1:2	Expert	0.59 (0.02)	0.78 (0.02)	-0.19 (0.03)	0.52 (0.01)	0.27 (0.01)	0.25 (0.02)
GAM_O	1:3	Expert	0.59 (0.02)	0.76 (0.02)	-0.18 (0.03)	0.42 (0.01)	0.27 (0.01)	0.15 (0.02)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Specificity Train	Specificity Test	Specificity Fit	Precision Train	Precision Test	Precision Fit
GAM_O	10000	Expert	0.59 (0.02)	0.75 (0.02)	-0.16 (0.02)	0.23 (0.01)	0.28 (0.02)	-0.04 (0.02)
GBM_B	1:1	*A priori*	0.67 (0.03)	0.77 (0.02)	-0.1 (0.04)	0.73 (0.02)	0.26 (0.05)	0.48 (0.05)
GBM_B	1:2	*A priori*	0.66 (0.03)	0.77 (0.02)	-0.11 (0.03)	0.57 (0.02)	0.27 (0.05)	0.3 (0.05)
GBM_B	1:3	*A priori*	0.66 (0.03)	0.78 (0.02)	-0.11 (0.03)	0.47 (0.02)	0.3 (0.06)	0.17 (0.05)
GBM_B	10000	*A priori*	0.65 (0.02)	0.77 (0.02)	-0.12 (0.03)	0.27 (0.01)	0.29 (0.05)	-0.03 (0.05)
GBM_B	1:1	Automated	0.64 (0.04)	0.75 (0.03)	-0.11 (0.05)	0.71 (0.02)	0.22 (0.09)	0.5 (0.09)
GBM_B	1:2	Automated	0.63 (0.03)	0.76 (0.03)	-0.13 (0.04)	0.55 (0.02)	0.24 (0.08)	0.31 (0.08)
GBM_B	1:3	Automated	0.63 (0.03)	0.76 (0.03)	-0.13 (0.03)	0.45 (0.02)	0.28 (0.07)	0.17 (0.06)
GBM_B	10000	Automated	0.63 (0.02)	0.77 (0.02)	-0.14 (0.03)	0.25 (0.01)	0.29 (0.05)	-0.04 (0.05)
GBM_B	1:1	Expert	0.66 (0.03)	0.75 (0.03)	-0.09 (0.04)	0.72 (0.02)	0.19 (0.06)	0.53 (0.06)
GBM_B	1:2	Expert	0.65 (0.03)	0.76 (0.03)	-0.11 (0.04)	0.56 (0.02)	0.22 (0.06)	0.34 (0.06)
GBM_B	1:3	Expert	0.62 (0)	0.76 (0)	-0.14 (0)	0.44 (0)	0.24 (0)	0.2 (0)
GBM_B	10000	Expert	0.64 (0.02)	0.77 (0.02)	-0.13 (0.03)	0.26 (0.01)	0.26 (0.03)	0 (0.03)
GBM_O	1:1	*A priori*	0.62 (0.04)	0.77 (0.02)	-0.15 (0.04)	0.7 (0.02)	0.25 (0.07)	0.46 (0.06)
GBM_O	1:2	*A priori*	0.61 (0.03)	0.75 (0.02)	-0.14 (0.03)	0.54 (0.02)	0.17 (0.04)	0.37 (0.04)
GBM_O	1:3	*A priori*	0.61 (0.03)	0.75 (0.02)	-0.14 (0.03)	0.43 (0.02)	0.15 (0.02)	0.28 (0.02)
GBM_O	10000	*A priori*	0.6 (0.02)	0.75 (0.02)	-0.16 (0.03)	0.24 (0.01)	0.15 (0.01)	0.09 (0.01)
GBM_O	1:1	Automated	0.62 (0.04)	0.75 (0.03)	-0.14 (0.05)	0.7 (0.02)	0.2 (0.07)	0.5 (0.07)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Specificity Train	Specificity Test	Specificity Fit	Precision Train	Precision Test	Precision Fit
GBM_O	1:2	Automated	0.61 (0.03)	0.73 (0.02)	-0.13 (0.04)	0.53 (0.02)	0.15 (0.02)	0.39 (0.03)
GBM_O	1:3	Automated	0.61 (0.03)	0.73 (0.02)	-0.12 (0.03)	0.43 (0.02)	0.14 (0.01)	0.29 (0.02)
GBM_O	10000	Automated	0.6 (0.02)	0.73 (0.02)	-0.13 (0.03)	0.24 (0.01)	0.14 (0.01)	0.1 (0.01)
GBM_O	1:1	Expert	0.58 (0.03)	0.75 (0.01)	-0.17 (0.03)	0.68 (0.02)	0.61 (0.08)	0.07 (0.08)
GBM_O	1:2	Expert	0.58 (0.03)	0.75 (0.01)	-0.17 (0.03)	0.52 (0.02)	0.63 (0.06)	-0.11 (0.06)
GBM_O	1:3	Expert	0.6 (0.02)	0.73 (0.02)	-0.13 (0.03)	0.43 (0.02)	0.14 (0.01)	0.29 (0.02)
GBM_O	10000	Expert	0.59 (0.02)	0.73 (0.02)	-0.13 (0.03)	0.24 (0.01)	0.14 (0.01)	0.1 (0.01)
GLM_B	1:1	*A priori*	0.59 (0.04)	0.76 (0.04)	-0.17 (0.05)	0.69 (0.02)	0.28 (0.07)	0.4 (0.07)
GLM_B	1:2	*A priori*	0.58 (0.03)	0.77 (0.03)	-0.18 (0.03)	0.52 (0.02)	0.28 (0.08)	0.24 (0.08)
GLM_B	1:3	*A priori*	0.59 (0.03)	0.77 (0.02)	-0.18 (0.04)	0.42 (0.02)	0.3 (0.05)	0.12 (0.05)
GLM_B	10000	*A priori*	0.58 (0.02)	0.77 (0.03)	-0.19 (0.03)	0.23 (0.01)	0.31 (0.05)	-0.08 (0.05)
GLM_B	1:1	Automated	0.59 (0.03)	0.74 (0.02)	-0.16 (0.04)	0.69 (0.02)	0.16 (0.04)	0.52 (0.04)
GLM_B	1:2	Automated	0.59 (0.02)	0.74 (0.02)	-0.15 (0.03)	0.53 (0.02)	0.15 (0.02)	0.38 (0.02)
GLM_B	1:3	Automated	0.59 (0.03)	0.74 (0.02)	-0.15 (0.03)	0.42 (0.02)	0.15 (0.02)	0.27 (0.02)
GLM_B	10000	Automated	0.59 (0.02)	0.74 (0.02)	-0.15 (0.03)	0.23 (0.01)	0.15 (0.02)	0.08 (0.02)
GLM_B	1:1	Expert	0.6 (0.04)	0.75 (0.02)	-0.15 (0.04)	0.69 (0.02)	0.17 (0.04)	0.52 (0.04)
GLM_B	1:2	Expert	0.59 (0.03)	0.75 (0.02)	-0.16 (0.04)	0.52 (0.02)	0.15 (0.02)	0.37 (0.03)
GLM_B	1:3	Expert	0.57 (0)	0.76 (0)	-0.18 (0)	0.41 (0)	0.15 (0)	0.26 (0)
GLM_B	10000	Expert	0.59 (0.02)	0.75 (0.02)	-0.16 (0.03)	0.23 (0.01)	0.15 (0.01)	0.09 (0.01)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Specificity			Precision		
			Train	Test	Fit	Train	Test	Fit
GLM_O	1:1	*A priori*	0.4 (0.24)	0.64 (0.2)	-0.24 (0.15)	0.62 (0.08)	0.23 (0.18)	0.39 (0.15)
GLM_O	1:2	*A priori*	0.48 (0.2)	0.67 (0.19)	-0.19 (0.17)	0.48 (0.07)	0.28 (0.17)	0.21 (0.15)
GLM_O	1:3	*A priori*	0.54 (0.12)	0.72 (0.15)	-0.17 (0.11)	0.4 (0.04)	0.33 (0.16)	0.08 (0.13)
GLM_O	10000	*A priori*	0.58 (0.04)	0.78 (0.05)	-0.2 (0.04)	0.23 (0.01)	0.41 (0.09)	-0.18 (0.09)
GLM_O	1:1	Automated	0.43 (0.24)	0.71 (0.14)	-0.27 (0.22)	0.64 (0.08)	0.2 (0.13)	0.44 (0.11)
GLM_O	1:2	Automated	0.54 (0.16)	0.74 (0.1)	-0.2 (0.16)	0.51 (0.05)	0.15 (0.07)	0.36 (0.05)
GLM_O	1:3	Automated	0.58 (0.07)	0.76 (0.03)	-0.18 (0.07)	0.42 (0.02)	0.18 (0.06)	0.24 (0.06)
GLM_O	10000	Automated	0.58 (0.02)	0.77 (0.02)	-0.18 (0.02)	0.23 (0.01)	0.19 (0.06)	0.04 (0.06)
GLM_O	1:1	Expert	0.59 (0.02)	0.74 (0.02)	-0.16 (0.03)	0.69 (0.01)	0.15 (0.03)	0.53 (0.03)
GLM_O	1:2	Expert	0.59 (0.02)	0.74 (0.02)	-0.15 (0.03)	0.52 (0.01)	0.16 (0.03)	0.37 (0.03)
GLM_O	1:3	Expert	0.58 (0.02)	0.74 (0.02)	-0.16 (0.03)	0.42 (0.01)	0.17 (0.04)	0.25 (0.05)
GLM_O	10000	Expert	0.59 (0.02)	0.74 (0.02)	-0.16 (0.02)	0.23 (0.01)	0.18 (0.05)	0.05 (0.05)
MARS_B	1:1	*A priori*	0.6 (0.03)	0.75 (0.05)	-0.15 (0.05)	0.69 (0.01)	0.2 (0.07)	0.49 (0.07)
MARS_B	1:2	*A priori*	0.6 (0.03)	0.74 (0.06)	-0.14 (0.07)	0.53 (0.01)	0.23 (0.09)	0.3 (0.09)
MARS_B	1:3	*A priori*	0.6 (0.03)	0.76 (0.05)	-0.16 (0.06)	0.43 (0.02)	0.26 (0.09)	0.17 (0.09)
MARS_B	10000	*A priori*	0.6 (0.02)	0.75 (0.05)	-0.15 (0.05)	0.24 (0.01)	0.26 (0.07)	-0.03 (0.07)
MARS_B	1:1	Automated	0.59 (0.03)	0.75 (0.03)	-0.16 (0.04)	0.69 (0.02)	0.22 (0.07)	0.47 (0.07)
MARS_B	1:2	Automated	0.59 (0.02)	0.73 (0.05)	-0.15 (0.05)	0.52 (0.02)	0.17 (0.05)	0.35 (0.05)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Specificity Train	Specificity Test	Specificity Fit	Precision Train	Precision Test	Precision Fit
MARS_B	1:3	Automated	0.59 (0.02)	0.74 (0.04)	-0.15 (0.04)	0.42 (0.01)	0.19 (0.06)	0.23 (0.06)
MARS_B	10000	Automated	0.59 (0.02)	0.76 (0.04)	-0.17 (0.04)	0.24 (0.01)	0.25 (0.08)	-0.01 (0.07)
MARS_B	1:1	Expert	0.6 (0.03)	0.74 (0.06)	-0.14 (0.07)	0.69 (0.02)	0.18 (0.06)	0.51 (0.07)
MARS_B	1:2	Expert	0.59 (0.03)	0.72 (0.1)	-0.13 (0.1)	0.52 (0.02)	0.17 (0.07)	0.35 (0.07)
MARS_B	1:3	Expert	0.59 (0.02)	0.74 (0.06)	-0.15 (0.07)	0.42 (0.01)	0.19 (0.07)	0.23 (0.07)
MARS_B	10000	Expert	0.59 (0.02)	0.73 (0.08)	-0.15 (0.08)	0.23 (0.01)	0.2 (0.07)	0.04 (0.07)
MARS_O	1:1	*A priori*	0.6 (0.07)	0.73 (0.12)	-0.13 (0.12)	0.69 (0.03)	0.2 (0.09)	0.5 (0.09)
MARS_O	1:2	*A priori*	0.59 (0.03)	0.75 (0.05)	-0.16 (0.06)	0.52 (0.02)	0.19 (0.09)	0.34 (0.09)
MARS_O	1:3	*A priori*	0.58 (0.07)	0.74 (0.07)	-0.16 (0.06)	0.42 (0.02)	0.16 (0.07)	0.26 (0.07)
MARS_O	10000	*A priori*	0.57 (0.03)	0.75 (0.04)	-0.18 (0.05)	0.22 (0.01)	0.14 (0.05)	0.08 (0.05)
MARS_O	1:1	Automated	0.59 (0.03)	0.76 (0.03)	-0.17 (0.04)	0.69 (0.02)	0.22 (0.07)	0.47 (0.07)
MARS_O	1:2	Automated	0.58 (0.03)	0.75 (0.02)	-0.17 (0.04)	0.52 (0.02)	0.17 (0.03)	0.35 (0.03)
MARS_O	1:3	Automated	0.58 (0.03)	0.76 (0.03)	-0.18 (0.04)	0.41 (0.02)	0.18 (0.07)	0.24 (0.07)
MARS_O	10000	Automated	0.57 (0.03)	0.75 (0.04)	-0.18 (0.05)	0.22 (0.01)	0.15 (0.04)	0.07 (0.04)
MARS_O	1:1	Expert	0.59 (0.03)	0.74 (0.04)	-0.15 (0.05)	0.69 (0.02)	0.17 (0.06)	0.52 (0.06)
MARS_O	1:2	Expert	0.59 (0.02)	0.74 (0.03)	-0.15 (0.04)	0.52 (0.01)	0.14 (0.02)	0.38 (0.02)
MARS_O	1:3	Expert	0.59 (0.02)	0.74 (0.02)	-0.15 (0.03)	0.42 (0.01)	0.14 (0.01)	0.28 (0.01)
MARS_O	10000	Expert	0.58 (0.02)	0.75 (0.02)	-0.17 (0.02)	0.23 (0.01)	0.14 (0.01)	0.09 (0.01)
MaxEnt_B	1:1	*A priori*	0.56 (0.16)	0.73 (0.09)	-0.17 (0.19)	0.68 (0.05)	0.18 (0.1)	0.5 (0.11)
MaxEnt_B	1:2	*A priori*	0.53 (0.2)	0.72 (0.09)	-0.19 (0.22)	0.51 (0.07)	0.16 (0.1)	0.35 (0.1)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Specificity			Precision		
			Train	Test	Fit	Train	Test	Fit
MaxEnt_B	1:3	*A priori*	0.59 (0)	0.72 (0)	-0.14 (0)	0.42 (0)	0.16 (0)	0.26 (0)
MaxEnt_B	10000	*A priori*	0.59 (0.12)	0.75 (0.07)	-0.16 (0.09)	0.24 (0.03)	0.2 (0.06)	0.04 (0.06)
MaxEnt_B	1:1	Automated	0.56 (0.14)	0.76 (0.05)	-0.2 (0.13)	0.68 (0.05)	0.22 (0.09)	0.45 (0.09)
MaxEnt_B	1:2	Automated	0.56 (0.15)	0.74 (0.07)	-0.18 (0.12)	0.52 (0.05)	0.2 (0.07)	0.33 (0.07)
MaxEnt_B	1:3	Automated	0.58 (0.09)	0.76 (0.06)	-0.17 (0.05)	0.42 (0.03)	0.19 (0.07)	0.23 (0.07)
MaxEnt_B	10000	Automated	0.59 (0.02)	0.77 (0.03)	-0.18 (0.03)	0.23 (0.01)	0.21 (0.06)	0.02 (0.06)
MaxEnt_B	1:1	Expert	0.56 (0.13)	0.73 (0.07)	-0.17 (0.11)	0.68 (0.04)	0.15 (0.07)	0.53 (0.08)
MaxEnt_B	1:2	Expert	0.58 (0.07)	0.74 (0.05)	-0.15 (0.05)	0.52 (0.03)	0.14 (0.06)	0.38 (0.07)
MaxEnt_B	1:3	Expert	0.58 (0)	0.73 (0)	-0.16 (0)	0.42 (0)	0.13 (0)	0.28 (0)
MaxEnt_B	10000	Expert	0.6 (0.02)	0.74 (0.03)	-0.15 (0.03)	0.24 (0.01)	0.15 (0.05)	0.09 (0.05)
MaxEnt_O	1:1	*A priori*	0.55 (0.17)	0.74 (0.06)	-0.19 (0.15)	0.68 (0.06)	0.19 (0.09)	0.49 (0.09)
MaxEnt_O	1:2	*A priori*	0.54 (0.17)	0.75 (0.07)	-0.21 (0.17)	0.51 (0.06)	0.2 (0.08)	0.31 (0.09)
MaxEnt_O	1:3	*A priori*	0.53 (0.18)	0.75 (0.08)	-0.21 (0.19)	0.41 (0.06)	0.22 (0.12)	0.19 (0.13)
MaxEnt_O	10000	*A priori*	0.55 (0.16)	0.74 (0.08)	-0.19 (0.14)	0.23 (0.03)	0.19 (0.09)	0.04 (0.09)
MaxEnt_O	1:1	Automated	0.58 (0.07)	0.76 (0.03)	-0.18 (0.06)	0.69 (0.03)	0.24 (0.08)	0.44 (0.08)
MaxEnt_O	1:2	Automated	0.55 (0.15)	0.76 (0.05)	-0.21 (0.14)	0.51 (0.05)	0.21 (0.1)	0.3 (0.1)
MaxEnt_O	1:3	Automated	0.59 (0.02)	0.76 (0.02)	-0.17 (0.03)	0.42 (0.01)	0.25 (0.1)	0.18 (0.1)
MaxEnt_O	10000	Automated	0.58 (0.09)	0.75 (0.06)	-0.18 (0.05)	0.23 (0.02)	0.21 (0.11)	0.03 (0.1)
MaxEnt_O	1:1	Expert	0.55 (0.16)	0.72 (0.07)	-0.17 (0.12)	0.67 (0.06)	0.14 (0.07)	0.54 (0.07)
MaxEnt_O	1:2	Expert	0.52 (0.18)	0.71 (0.1)	-0.19 (0.14)	0.5 (0.06)	0.14 (0.06)	0.37 (0.07)
MaxEnt_O	1:3	Expert	0.55 (0.13)	0.72 (0.09)	-0.17 (0.08)	0.41 (0.04)	0.14 (0.07)	0.27 (0.06)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Specificity			Precision		
			Train	Test	Fit	Train	Test	Fit
MaxEnt_O	10000	Expert	0.58 (0.09)	0.74 (0.03)	-0.16 (0.08)	0.23 (0.02)	0.14 (0.05)	0.09 (0.05)
MXL_O	1:1	*A priori*	0.55 (0.05)	0.49 (0.04)	0.06 (0.07)	0.66 (0.02)	0.02 (0.01)	0.64 (0.02)
MXL_O	1:2	*A priori*	0.53 (0.04)	0.49 (0.04)	0.04 (0.06)	0.49 (0.02)	0.02 (0)	0.47 (0.02)
MXL_O	1:3	*A priori*	0.53 (0.04)	0.49 (0.04)	0.05 (0.07)	0.39 (0.02)	0.02 (0)	0.37 (0.02)
MXL_O	10000	*A priori*	0.54 (0.08)	0.62 (0.04)	-0.08 (0.06)	0.22 (0.02)	0.11 (0.04)	0.11 (0.04)
MXL_O	1:1	Automated	0.53 (0.08)	0.57 (0.04)	-0.04 (0.07)	0.66 (0.03)	0.08 (0.02)	0.58 (0.03)
MXL_O	1:2	Automated	0.52 (0.03)	0.43 (0.04)	0.09 (0.04)	0.48 (0.02)	0.03 (0.01)	0.46 (0.02)
MXL_O	1:3	Automated	0.52 (0.03)	0.43 (0.05)	0.09 (0.05)	0.38 (0.01)	0.03 (0.01)	0.36 (0.02)
MXL_O	10000	Automated	0.52 (0.03)	0.42 (0.03)	0.1 (0.03)	0.21 (0.01)	0.02 (0)	0.18 (0.01)
MXL_O	1:1	Expert	0.57 (0.09)	0.76 (0.03)	-0.19 (0.09)	0.68 (0.03)	0.2 (0.07)	0.48 (0.07)
MXL_O	1:2	Expert	0.56 (0.1)	0.76 (0.05)	-0.2 (0.09)	0.51 (0.04)	0.2 (0.07)	0.31 (0.07)
MXL_O	1:3	Expert	0.57 (0.07)	0.76 (0.05)	-0.18 (0.05)	0.42 (0.03)	0.2 (0.07)	0.22 (0.06)
MXL_O	10000	Expert	0.56 (0.05)	0.75 (0.03)	-0.19 (0.05)	0.22 (0.02)	0.16 (0.06)	0.06 (0.06)
RF_B	1:1	*A priori*	0.97 (0.01)	0.78 (0.02)	0.19 (0.03)	0.97 (0.01)	0.4 (0.11)	0.56 (0.11)
RF_B	1:2	*A priori*	0.98 (0.01)	0.78 (0.02)	0.2 (0.02)	0.96 (0.01)	0.34 (0.06)	0.62 (0.06)
RF_B	1:3	*A priori*	0.99 (0.01)	0.78 (0.02)	0.21 (0.02)	0.96 (0.02)	0.33 (0.06)	0.63 (0.06)
RF_B	10000	*A priori*	0.99 (0)	0.77 (0.02)	0.22 (0.02)	0.96 (0.01)	0.27 (0.05)	0.69 (0.05)
RF_B	1:1	Automated	0.97 (0.01)	0.77 (0.02)	0.2 (0.03)	0.97 (0.01)	0.39 (0.17)	0.57 (0.17)
RF_B	1:2	Automated	0.98 (0.01)	0.77 (0.02)	0.21 (0.03)	0.97 (0.01)	0.33 (0.11)	0.63 (0.11)
RF_B	1:3	Automated	0.99 (0)	0.76 (0.03)	0.23 (0.03)	0.97 (0.02)	0.27 (0.09)	0.69 (0.09)
RF_B	10000	Automated	0.99 (0)	0.77 (0.02)	0.22 (0.02)	0.96 (0.01)	0.28 (0.07)	0.68 (0.07)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Specificity			Precision		
			Train	Test	Fit	Train	Test	Fit
RF_B	1:1	Expert	0.97 (0.01)	0.76 (0.03)	0.21 (0.03)	0.97 (0.01)	0.23 (0.07)	0.73 (0.07)
RF_B	1:2	Expert	0.98 (0.01)	0.76 (0.02)	0.22 (0.03)	0.96 (0.02)	0.23 (0.05)	0.72 (0.05)
RF_B	1:3	Expert	0.96 (0)	0.77 (0)	0.19 (0)	0.87 (0)	0.25 (0)	0.63 (0)
RF_B	10000	Expert	0.99 (0)	0.77 (0.02)	0.23 (0.02)	0.96 (0.01)	0.26 (0.03)	0.69 (0.03)
RF_O	1:1	*A priori*	0.97 (0.01)	0.76 (0.08)	0.21 (0.08)	0.97 (0.01)	0.45 (0.17)	0.53 (0.17)
RF_O	1:2	*A priori*	0.99 (0.01)	0.77 (0.02)	0.22 (0.03)	0.97 (0.01)	0.4 (0.14)	0.57 (0.13)
RF_O	1:3	*A priori*	0.99 (0)	0.78 (0.02)	0.21 (0.02)	0.98 (0.01)	0.36 (0.1)	0.62 (0.09)
RF_O	10000	*A priori*	1 (0)	0.77 (0.03)	0.23 (0.03)	0.97 (0.02)	0.24 (0.07)	0.73 (0.07)
RF_O	1:1	Automated	0.97 (0.01)	0.76 (0.02)	0.21 (0.02)	0.97 (0.01)	0.44 (0.18)	0.53 (0.18)
RF_O	1:2	Automated	0.99 (0.01)	0.77 (0.02)	0.22 (0.02)	0.97 (0.01)	0.39 (0.13)	0.58 (0.13)
RF_O	1:3	Automated	0.99 (0)	0.77 (0.02)	0.22 (0.03)	0.97 (0.01)	0.37 (0.11)	0.61 (0.1)
RF_O	10000	Automated	1 (0)	0.77 (0.03)	0.23 (0.03)	0.96 (0.01)	0.29 (0.08)	0.67 (0.07)
RF_O	1:1	Expert	0.97 (0.01)	0.77 (0.02)	0.2 (0.03)	0.97 (0.01)	0.31 (0.08)	0.66 (0.08)
RF_O	1:2	Expert	0.99 (0.01)	0.77 (0.03)	0.22 (0.03)	0.97 (0.01)	0.31 (0.06)	0.66 (0.06)
RF_O	1:3	Expert	0.99 (0.01)	0.77 (0.03)	0.22 (0.02)	0.97 (0.02)	0.29 (0.07)	0.68 (0.06)
RF_O	10000	Expert	0.99 (0)	0.76 (0.02)	0.23 (0.02)	0.96 (0.01)	0.26 (0.06)	0.7 (0.05)
SRE_B	1:1	*A priori*	0 (0)	0.33 (0)	-0.33 (0)	0.5 (0)	0.02 (0)	0.48 (0)
SRE_B	1:2	*A priori*	0 (0)	0.33 (0)	-0.33 (0)	0.33 (0)	0.02 (0)	0.31 (0)
SRE_B	1:3	*A priori*	0 (0)	0.33 (0)	-0.33 (0)	0.25 (0)	0.02 (0)	0.23 (0)
SRE_B	10000	*A priori*	0 (0)	0.33 (0)	-0.33 (0)	0.12 (0)	0.02 (0)	0.1 (0)
SRE_B	1:1	Automated	0.16 (0.25)	0.33 (0)	-0.18 (0.25)	0.54 (0.06)	0.02 (0)	0.52 (0.06)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Specificity			Precision		
			Train	Test	Fit	Train	Test	Fit
SRE_B	1:2	Automated	0.15 (0.25)	0.33 (0)	-0.18 (0.25)	0.37 (0.07)	0.02 (0)	0.35 (0.07)
SRE_B	1:3	Automated	0.15 (0.25)	0.33 (0)	-0.18 (0.25)	0.28 (0.06)	0.02 (0)	0.26 (0.06)
SRE_B	10000	Automated	0.16 (0.25)	0.33 (0)	-0.17 (0.25)	0.14 (0.04)	0.02 (0)	0.12 (0.04)
SRE_B	1:1	Expert	0.5 (0.03)	0.75 (0)	-0.25 (0.03)	0.63 (0.01)	0.67 (0)	-0.04 (0.01)
SRE_B	1:2	Expert	0.5 (0.02)	0.75 (0)	-0.25 (0.02)	0.46 (0.01)	0.67 (0)	-0.21 (0.01)
SRE_B	1:3	Expert	0.49 (0)	0.74 (0)	-0.25 (0)	0.36 (0)	0.66 (0)	-0.29 (0)
SRE_B	10000	Expert	0.49 (0.01)	0.74 (0.06)	-0.25 (0.06)	0.19 (0.01)	0.66 (0.09)	-0.47 (0.09)
SRE_O	1:1	*A priori*	0.41 (0.04)	0.76 (0.02)	-0.35 (0.04)	0.61 (0.02)	0.15 (0.03)	0.46 (0.03)
SRE_O	1:2	*A priori*	0.41 (0.03)	0.76 (0.02)	-0.35 (0.03)	0.43 (0.01)	0.15 (0.02)	0.28 (0.02)
SRE_O	1:3	*A priori*	0.41 (0)	0.77 (0)	-0.36 (0)	0.34 (0)	0.14 (0)	0.19 (0)
SRE_O	10000	*A priori*	0.41 (0.03)	0.76 (0.02)	-0.35 (0.04)	0.17 (0.01)	0.14 (0.03)	0.03 (0.02)
SRE_O	1:1	Automated	0.43 (0.04)	0.78 (0.03)	-0.34 (0.04)	0.61 (0.02)	0.12 (0.06)	0.49 (0.07)
SRE_O	1:2	Automated	0.43 (0.03)	0.77 (0.03)	-0.34 (0.03)	0.44 (0.01)	0.13 (0.06)	0.31 (0.07)
SRE_O	1:3	Automated	0.43 (0.03)	0.77 (0.03)	-0.35 (0.03)	0.34 (0.01)	0.14 (0.05)	0.21 (0.06)
SRE_O	10000	Automated	0.43 (0.03)	0.77 (0.03)	-0.34 (0.03)	0.18 (0.01)	0.13 (0.06)	0.05 (0.07)
SRE_O	1:1	Expert	0.44 (0.04)	0.77 (0.02)	-0.33 (0.04)	0.62 (0.01)	0.26 (0.09)	0.35 (0.09)
SRE_O	1:2	Expert	0.44 (0.03)	0.77 (0.02)	-0.33 (0.03)	0.45 (0.01)	0.26 (0.08)	0.19 (0.08)
SRE_O	1:3	Expert	0.44 (0.03)	0.76 (0.02)	-0.32 (0.03)	0.35 (0.01)	0.25 (0.08)	0.1 (0.08)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	Specificity Train	Specificity Test	Specificity Fit	Precision Train	Precision Test	Precision Fit
SRE_O	10000	Expert	0.44 (0.03)	0.77 (0.02)	-0.32 (0.04)	0.18 (0.01)	0.27 (0.1)	-0.09 (0.1)
Algorithm	**Pseudo-absences**	**Predictor selection**	**F1 Train**	**F1 Test**	**F1 Fit**	**Correct classification rate Train**	**Correct classification rate Test**	**Correct classification rate Fit**
ANN_B	1:1	*A priori*	0.78 (0.01)	0.21 (0.07)	0.58 (0.07)	0.75 (0.01)	0.71 (0.06)	0.04 (0.06)
ANN_B	1:2	*A priori*	0.67 (0.01)	0.21 (0.06)	0.46 (0.06)	0.7 (0.02)	0.72 (0.06)	-0.01 (0.05)
ANN_B	1:3	*A priori*	0.58 (0.02)	0.22 (0.09)	0.36 (0.09)	0.67 (0.03)	0.73 (0.07)	-0.06 (0.06)
ANN_B	10000	*A priori*	0.37 (0.01)	0.21 (0.07)	0.17 (0.07)	0.63 (0.03)	0.72 (0.06)	-0.09 (0.06)
ANN_B	1:1	Automated	0.78 (0.01)	0.21 (0.06)	0.57 (0.06)	0.75 (0.02)	0.72 (0.04)	0.03 (0.05)
ANN_B	1:2	Automated	0.67 (0.01)	0.26 (0.06)	0.41 (0.06)	0.7 (0.02)	0.74 (0.03)	-0.04 (0.03)
ANN_B	1:3	Automated	0.58 (0.02)	0.25 (0.05)	0.33 (0.05)	0.67 (0.02)	0.74 (0.03)	-0.06 (0.04)
ANN_B	10000	Automated	0.38 (0.02)	0.25 (0.06)	0.12 (0.06)	0.63 (0.03)	0.73 (0.05)	-0.1 (0.04)
ANN_B	1:1	Expert	0.78 (0.01)	0.27 (0.05)	0.51 (0.05)	0.75 (0.02)	0.75 (0.05)	0 (0.05)
ANN_B	1:2	Expert	0.66 (0.02)	0.25 (0.06)	0.41 (0.06)	0.7 (0.03)	0.74 (0.05)	-0.04 (0.05)
ANN_B	1:3	Expert	0.57 (0)	0.25 (0)	0.31 (0)	0.66 (0)	0.75 (0)	-0.09 (0)
ANN_B	10000	Expert	0.37 (0.01)	0.26 (0.06)	0.11 (0.06)	0.63 (0.02)	0.74 (0.05)	-0.11 (0.05)
ANN_O	1:1	*A priori*	0.77 (0.02)	0.12 (0.1)	0.64 (0.1)	0.72 (0.04)	0.66 (0.1)	0.06 (0.11)
ANN_O	1:2	*A priori*	0.61 (0.06)	0.09 (0.08)	0.51 (0.08)	0.58 (0.14)	0.57 (0.16)	0.01 (0.1)
ANN_O	1:3	*A priori*	0.48 (0.08)	0.07 (0.07)	0.41 (0.08)	0.44 (0.19)	0.49 (0.16)	-0.05 (0.11)
ANN_O	10000	*A priori*	0.23 (0.04)	0.05 (0.04)	0.18 (0.04)	0.17 (0.15)	0.37 (0.11)	-0.2 (0.07)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	F1 Train	F1 Test	F1 Fit	Correct classification rate Train	Correct classification rate Test	Correct classification rate Fit
ANN_O	1:1	Automated	0.76 (0.02)	0.1 (0.07)	0.66 (0.07)	0.71 (0.04)	0.6 (0.12)	0.11 (0.13)
ANN_O	1:2	Automated	0.6 (0.06)	0.08 (0.07)	0.51 (0.07)	0.57 (0.13)	0.54 (0.15)	0.02 (0.11)
ANN_O	1:3	Automated	0.48 (0.07)	0.07 (0.06)	0.4 (0.07)	0.45 (0.19)	0.49 (0.16)	-0.05 (0.11)
ANN_O	10000	Automated	0.23 (0.03)	0.04 (0.03)	0.18 (0.02)	0.15 (0.12)	0.36 (0.08)	-0.21 (0.05)
ANN_O	1:1	Expert	0.76 (0.03)	0.23 (0.06)	0.54 (0.05)	0.72 (0.06)	0.74 (0.06)	-0.02 (0.07)
ANN_O	1:2	Expert	0.61 (0.07)	0.21 (0.11)	0.4 (0.06)	0.59 (0.15)	0.65 (0.18)	-0.06 (0.06)
ANN_O	1:3	Expert	0.47 (0.08)	0.15 (0.13)	0.32 (0.05)	0.42 (0.2)	0.53 (0.21)	-0.1 (0.03)
ANN_O	10000	Expert	0.23 (0.04)	0.06 (0.07)	0.17 (0.03)	0.17 (0.14)	0.38 (0.12)	-0.21 (0.02)
CTA_B	1:1	*A priori*	0.81 (0.02)	0.23 (0.05)	0.58 (0.05)	0.79 (0.02)	0.76 (0.02)	0.03 (0.03)
CTA_B	1:2	*A priori*	0.73 (0.03)	0.23 (0.05)	0.5 (0.06)	0.77 (0.03)	0.76 (0.02)	0.01 (0.04)
CTA_B	1:3	*A priori*	0.67 (0.04)	0.21 (0.07)	0.46 (0.09)	0.77 (0.05)	0.76 (0.02)	0.01 (0.05)
CTA_B	10000	*A priori*	0.48 (0.05)	0.2 (0.05)	0.28 (0.07)	0.75 (0.04)	0.76 (0.02)	-0.01 (0.05)
CTA_B	1:1	Automated	0.82 (0.02)	0.25 (0.08)	0.56 (0.08)	0.8 (0.03)	0.75 (0.03)	0.04 (0.04)
CTA_B	1:2	Automated	0.72 (0.03)	0.23 (0.08)	0.5 (0.09)	0.77 (0.04)	0.75 (0.02)	0.02 (0.04)
CTA_B	1:3	Automated	0.67 (0.04)	0.22 (0.07)	0.45 (0.09)	0.77 (0.04)	0.75 (0.03)	0.02 (0.05)
CTA_B	10000	Automated	0.5 (0.05)	0.17 (0.07)	0.33 (0.09)	0.78 (0.05)	0.75 (0.03)	0.02 (0.05)
CTA_B	1:1	Expert	0.81 (0.02)	0.26 (0.07)	0.55 (0.07)	0.79 (0.02)	0.75 (0.03)	0.04 (0.03)
CTA_B	1:2	Expert	0.71 (0.03)	0.24 (0.07)	0.47 (0.07)	0.75 (0.04)	0.75 (0.02)	0.01 (0.05)
CTA_B	1:3	Expert	0.63 (0)	0.24 (0)	0.39 (0)	0.74 (0)	0.75 (0)	-0.02 (0)
CTA_B	10000	Expert	0.46 (0.04)	0.23 (0.07)	0.23 (0.08)	0.74 (0.04)	0.75 (0.02)	-0.01 (0.05)
CTA_O	1:1	*A priori*	0.78 (0.01)	0.17 (0.1)	0.61 (0.1)	0.74 (0.02)	0.62 (0.2)	0.12 (0.2)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	F1			Correct classification rate		
			Train	Test	Fit	Train	Test	Fit
CTA_O	1:2	*A priori*	0.65 (0.01)	0.16 (0.09)	0.49 (0.09)	0.67 (0.02)	0.65 (0.17)	0.01 (0.18)
CTA_O	1:3	*A priori*	0.55 (0.02)	0.17 (0.09)	0.38 (0.09)	0.63 (0.04)	0.66 (0.18)	-0.04 (0.19)
CTA_O	10000	*A priori*	0.34 (0.01)	0.24 (0)	0.1 (0.01)	0.55 (0.02)	0.76 (0)	-0.22 (0.02)
CTA_O	1:1	Automated	0.78 (0.01)	0.13 (0.09)	0.65 (0.09)	0.73 (0.02)	0.56 (0.19)	0.18 (0.19)
CTA_O	1:2	Automated	0.65 (0.02)	0.17 (0.08)	0.48 (0.09)	0.66 (0.03)	0.63 (0.18)	0.03 (0.18)
CTA_O	1:3	Automated	0.56 (0.02)	0.15 (0.09)	0.4 (0.1)	0.63 (0.04)	0.59 (0.19)	0.04 (0.2)
CTA_O	10000	Automated	0.34 (0.02)	0.22 (0.01)	0.12 (0.02)	0.55 (0.04)	0.72 (0.02)	-0.17 (0.04)
CTA_O	1:1	Expert	0.78 (0.01)	0.19 (0.08)	0.59 (0.08)	0.73 (0.01)	0.65 (0.16)	0.09 (0.17)
CTA_O	1:2	Expert	0.65 (0.01)	0.17 (0.08)	0.48 (0.08)	0.67 (0.02)	0.63 (0.17)	0.03 (0.17)
CTA_O	1:3	Expert	0.56 (0.01)	0.19 (0.07)	0.37 (0.08)	0.63 (0.02)	0.67 (0.16)	-0.03 (0.16)
CTA_O	10000	Expert	0.34 (0.01)	0.22 (0)	0.12 (0.01)	0.55 (0.03)	0.72 (0.01)	-0.17 (0.03)
EMca_B	1:1	*A priori*	0.73 (0.03)	0.04 (0.01)	0.69 (0.04)	0.63 (0.07)	0.34 (0.03)	0.29 (0.08)
EMca_B	1:2	*A priori*	0.58 (0.05)	0.04 (0)	0.54 (0.05)	0.51 (0.1)	0.34 (0)	0.17 (0.1)
EMca_B	1:3	*A priori*	0.49 (0.04)	0.04 (0)	0.45 (0.04)	0.47 (0.1)	0.34 (0)	0.13 (0.1)
EMca_B	10000	*A priori*	0.33 (0.07)	0.04 (0)	0.3 (0.07)	0.47 (0.17)	0.34 (0)	0.13 (0.17)
EMca_B	1:1	Automated	0.73 (0.03)	0.05 (0.04)	0.68 (0.03)	0.63 (0.05)	0.37 (0.08)	0.26 (0.06)
EMca_B	1:2	Automated	0.57 (0.03)	0.04 (0)	0.53 (0.03)	0.49 (0.06)	0.34 (0)	0.15 (0.06)
EMca_B	1:3	Automated	0.48 (0.03)	0.04 (0)	0.44 (0.03)	0.44 (0.07)	0.34 (0)	0.1 (0.07)
EMca_B	10000	Automated	0.31 (0.07)	0.04 (0)	0.27 (0.07)	0.39 (0.15)	0.34 (0)	0.05 (0.15)
EMca_B	1:1	Expert	0.74 (0.03)	0.04 (0.01)	0.7 (0.03)	0.65 (0.05)	0.34 (0.03)	0.3 (0.07)
EMca_B	1:2	Expert	0.59 (0.03)	0.04 (0)	0.55 (0.03)	0.53 (0.07)	0.34 (0)	0.19 (0.07)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	F1			Correct classification rate		
			Train	Test	Fit	Train	Test	Fit
EMca_B	1:3	Expert	0.47 (0.04)	0.04 (0)	0.44 (0.04)	0.44 (0.08)	0.34 (0)	0.1 (0.08)
EMca_B	10000	Expert	0.28 (0.05)	0.04 (0)	0.24 (0.05)	0.34 (0.12)	0.34 (0)	0 (0.12)
EMmean_B	1:1	*A priori*	0.82 (0.01)	0.28 (0.06)	0.53 (0.06)	0.8 (0.02)	0.76 (0.03)	0.04 (0.04)
EMmean_B	1:2	*A priori*	0.72 (0.02)	0.29 (0.06)	0.43 (0.06)	0.77 (0.02)	0.76 (0.03)	0 (0.03)
EMmean_B	1:3	*A priori*	0.65 (0.03)	0.28 (0.06)	0.36 (0.06)	0.75 (0.03)	0.76 (0.03)	-0.01 (0.04)
EMmean_B	10000	*A priori*	0.45 (0.03)	0.3 (0.06)	0.15 (0.07)	0.73 (0.03)	0.76 (0.03)	-0.03 (0.04)
EMmean_B	1:1	Automated	0.82 (0.02)	0.31 (0.05)	0.51 (0.05)	0.81 (0.03)	0.75 (0.02)	0.05 (0.04)
EMmean_B	1:2	Automated	0.69 (0.02)	0.23 (0.02)	0.46 (0.02)	0.74 (0.03)	0.73 (0.02)	0 (0.03)
EMmean_B	1:3	Automated	0.69 (0.04)	0.24 (0.06)	0.45 (0.07)	0.8 (0.04)	0.74 (0.04)	0.06 (0.05)
EMmean_B	10000	Automated	0.51 (0.06)	0.23 (0.05)	0.27 (0.06)	0.78 (0.04)	0.73 (0.03)	0.05 (0.05)
EMmean_B	1:1	Expert	0.81 (0.02)	0.28 (0.06)	0.53 (0.06)	0.79 (0.02)	0.75 (0.03)	0.05 (0.03)
EMmean_B	1:2	Expert	0.72 (0.02)	0.25 (0.05)	0.46 (0.05)	0.76 (0.02)	0.74 (0.03)	0.02 (0.03)
EMmean_B	1:3	Expert	0.64 (0.02)	0.25 (0.04)	0.39 (0.04)	0.75 (0.02)	0.74 (0.02)	0.01 (0.03)
EMmean_B	10000	Expert	0.46 (0.03)	0.24 (0.03)	0.22 (0.04)	0.74 (0.03)	0.74 (0.02)	0 (0.04)
EMmedian_B	1:1	*A priori*	0.8 (0.01)	0.3 (0.05)	0.5 (0.05)	0.77 (0.02)	0.76 (0.03)	0.01 (0.03)
EMmedian_B	1:2	*A priori*	0.69 (0.02)	0.31 (0.05)	0.38 (0.05)	0.73 (0.02)	0.76 (0.02)	-0.03 (0.03)
EMmedian_B	1:3	*A priori*	0.61 (0.02)	0.31 (0.05)	0.3 (0.05)	0.71 (0.02)	0.76 (0.02)	-0.05 (0.03)
EMmedian_B	10000	*A priori*	0.41 (0.02)	0.31 (0.05)	0.09 (0.05)	0.68 (0.02)	0.76 (0.02)	-0.08 (0.03)
EMmedian_B	1:1	Automated	0.8 (0.02)	0.31 (0.06)	0.49 (0.06)	0.77 (0.03)	0.75 (0.03)	0.02 (0.04)
EMmedian_B	1:2	Automated	0.66 (0.02)	0.23 (0.02)	0.43 (0.02)	0.69 (0.02)	0.73 (0.02)	-0.04 (0.03)
EMmedian_B	1:3	Automated	0.57 (0.02)	0.23 (0.01)	0.34 (0.02)	0.67 (0.02)	0.73 (0.02)	-0.06 (0.03)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	F1			Correct classification rate		
			Train	Test	Fit	Train	Test	Fit
EMmedian_B	10000	Automated	0.37 (0.01)	0.24 (0.01)	0.13 (0.02)	0.62 (0.02)	0.73 (0.02)	-0.11 (0.03)
EMmedian_B	1:1	Expert	0.79 (0.01)	0.28 (0.06)	0.51 (0.06)	0.76 (0.01)	0.75 (0.03)	0.01 (0.03)
EMmedian_B	1:2	Expert	0.69 (0.02)	0.26 (0.04)	0.43 (0.04)	0.73 (0.02)	0.75 (0.02)	-0.01 (0.03)
EMmedian_B	1:3	Expert	0.6 (0.02)	0.26 (0.04)	0.34 (0.04)	0.7 (0.02)	0.75 (0.02)	-0.05 (0.03)
EMmedian_B	10000	Expert	0.4 (0.02)	0.27 (0.04)	0.13 (0.04)	0.67 (0.02)	0.75 (0.02)	-0.08 (0.03)
EMwmean_B	1:1	*A priori*	0.82 (0.01)	0.29 (0.06)	0.53 (0.06)	0.8 (0.02)	0.76 (0.03)	0.04 (0.04)
EMwmean_B	1:2	*A priori*	0.72 (0.02)	0.29 (0.06)	0.44 (0.07)	0.77 (0.02)	0.76 (0.03)	0.01 (0.04)
EMwmean_B	1:3	*A priori*	0.65 (0.03)	0.29 (0.06)	0.36 (0.06)	0.76 (0.03)	0.76 (0.03)	0 (0.04)
EMwmean_B	10000	*A priori*	0.46 (0.03)	0.3 (0.07)	0.16 (0.08)	0.74 (0.03)	0.76 (0.03)	-0.02 (0.04)
EMwmean_B	1:1	Automated	0.82 (0.02)	0.32 (0.06)	0.5 (0.06)	0.8 (0.02)	0.76 (0.03)	0.04 (0.03)
EMwmean_B	1:2	Automated	0.7 (0.02)	0.23 (0.02)	0.46 (0.02)	0.74 (0.02)	0.73 (0.02)	0.01 (0.03)
EMwmean_B	1:3	Automated	0.69 (0.04)	0.24 (0.06)	0.45 (0.07)	0.8 (0.04)	0.73 (0.04)	0.07 (0.05)
EMwmean_B	10000	Automated	0.5 (0.05)	0.23 (0.05)	0.28 (0.07)	0.78 (0.04)	0.73 (0.03)	0.05 (0.05)
EMwmean_B	1:1	Expert	0.82 (0.01)	0.28 (0.06)	0.54 (0.06)	0.8 (0.02)	0.75 (0.03)	0.05 (0.03)
EMwmean_B	1:2	Expert	0.72 (0.02)	0.26 (0.05)	0.46 (0.05)	0.77 (0.02)	0.74 (0.02)	0.03 (0.03)
EMwmean_B	1:3	Expert	0.65 (0.02)	0.24 (0.03)	0.4 (0.04)	0.75 (0.02)	0.74 (0.02)	0.01 (0.03)
EMwmean_B	10000	Expert	0.47 (0.03)	0.24 (0.03)	0.22 (0.03)	0.75 (0.03)	0.74 (0.02)	0.01 (0.03)
FDA_B	1:1	*A priori*	0.78 (0.01)	0.23 (0.07)	0.55 (0.07)	0.74 (0.01)	0.74 (0.05)	0 (0.05)
FDA_B	1:2	*A priori*	0.66 (0.01)	0.2 (0.06)	0.46 (0.06)	0.69 (0.02)	0.74 (0.03)	-0.05 (0.04)
FDA_B	1:3	*A priori*	0.57 (0.02)	0.19 (0.05)	0.38 (0.05)	0.66 (0.02)	0.75 (0.02)	-0.09 (0.04)
FDA_B	10000	*A priori*	0.36 (0.01)	0.18 (0.03)	0.18 (0.03)	0.61 (0.02)	0.75 (0.02)	-0.15 (0.03)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	F1 Train	F1 Test	F1 Fit	Correct classification rate Train	Correct classification rate Test	Correct classification rate Fit
FDA_B	1:1	Automated	0.78 (0.01)	0.21 (0.06)	0.56 (0.06)	0.74 (0.02)	0.73 (0.05)	0.01 (0.06)
FDA_B	1:2	Automated	0.66 (0.01)	0.17 (0.06)	0.49 (0.06)	0.69 (0.02)	0.7 (0.07)	-0.01 (0.07)
FDA_B	1:3	Automated	0.57 (0.02)	0.16 (0.06)	0.41 (0.07)	0.66 (0.02)	0.69 (0.07)	-0.02 (0.08)
FDA_B	10000	Automated	0.36 (0.01)	0.17 (0.05)	0.19 (0.05)	0.61 (0.02)	0.72 (0.03)	-0.11 (0.04)
FDA_B	1:1	Expert	0.78 (0.01)	0.24 (0.04)	0.53 (0.04)	0.74 (0.02)	0.74 (0.02)	0 (0.03)
FDA_B	1:2	Expert	0.66 (0.01)	0.23 (0.01)	0.43 (0.02)	0.69 (0.02)	0.74 (0.02)	-0.05 (0.03)
FDA_B	1:3	Expert	0.56 (0)	0.23 (0)	0.34 (0)	0.65 (0)	0.74 (0)	-0.09 (0)
FDA_B	10000	Expert	0.36 (0.01)	0.22 (0.01)	0.14 (0.02)	0.61 (0.02)	0.74 (0.02)	-0.12 (0.03)
FDA_O	1:1	*A priori*	0.76 (0.04)	0.22 (0.08)	0.54 (0.08)	0.72 (0.09)	0.76 (0.03)	-0.04 (0.09)
FDA_O	1:2	*A priori*	0.64 (0.06)	0.2 (0.08)	0.44 (0.1)	0.66 (0.14)	0.75 (0.07)	-0.09 (0.15)
FDA_O	1:3	*A priori*	0.56 (0.06)	0.21 (0.07)	0.35 (0.1)	0.65 (0.15)	0.76 (0.03)	-0.11 (0.15)
FDA_O	10000	*A priori*	0.37 (0.05)	0.21 (0.07)	0.16 (0.09)	0.62 (0.17)	0.76 (0.03)	-0.14 (0.17)
FDA_O	1:1	Automated	0.74 (0.04)	0.29 (0.05)	0.46 (0.06)	0.69 (0.11)	0.76 (0.02)	-0.08 (0.11)
FDA_O	1:2	Automated	0.64 (0.06)	0.28 (0.05)	0.36 (0.08)	0.66 (0.13)	0.75 (0.05)	-0.09 (0.15)
FDA_O	1:3	Automated	0.55 (0.07)	0.25 (0.07)	0.3 (0.11)	0.62 (0.17)	0.75 (0.05)	-0.13 (0.19)
FDA_O	10000	Automated	0.36 (0.06)	0.25 (0.07)	0.11 (0.1)	0.58 (0.21)	0.74 (0.05)	-0.16 (0.22)
FDA_O	1:1	Expert	0.74 (0.04)	0.24 (0.05)	0.5 (0.07)	0.69 (0.1)	0.74 (0.04)	-0.05 (0.11)
FDA_O	1:2	Expert	0.63 (0.07)	0.24 (0.05)	0.39 (0.08)	0.63 (0.16)	0.74 (0.04)	-0.11 (0.17)
FDA_O	1:3	Expert	0.55 (0.06)	0.25 (0.05)	0.3 (0.08)	0.61 (0.14)	0.75 (0.03)	-0.14 (0.15)
FDA_O	10000	Expert	0.36 (0.04)	0.25 (0.05)	0.1 (0.06)	0.59 (0.14)	0.75 (0.03)	-0.16 (0.14)
GAM_B	1:1	*A priori*	0.79 (0.01)	0.14 (0.08)	0.65 (0.08)	0.76 (0.01)	0.61 (0.12)	0.15 (0.12)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	F1			Correct classification rate		
			Train	Test	Fit	Train	Test	Fit
GAM_B	1:2	*A priori*	0.67 (0.01)	0.09 (0.05)	0.58 (0.05)	0.71 (0.01)	0.53 (0.13)	0.17 (0.13)
GAM_B	1:3	*A priori*	0.59 (0.02)	0.07 (0.06)	0.53 (0.06)	0.69 (0.02)	0.46 (0.15)	0.23 (0.15)
GAM_B	10000	*A priori*	0.39 (0.01)	0.06 (0.03)	0.33 (0.03)	0.65 (0.02)	0.48 (0.1)	0.17 (0.11)
GAM_B	1:1	Automated	0.78 (0.01)	0.19 (0.11)	0.59 (0.11)	0.75 (0.02)	0.68 (0.12)	0.07 (0.12)
GAM_B	1:2	Automated	0.67 (0.02)	0.13 (0.08)	0.53 (0.09)	0.7 (0.02)	0.62 (0.12)	0.08 (0.12)
GAM_B	1:3	Automated	0.59 (0.01)	0.07 (0.05)	0.51 (0.06)	0.68 (0.02)	0.47 (0.13)	0.22 (0.13)
GAM_B	10000	Automated	0.38 (0.01)	0.06 (0.04)	0.31 (0.04)	0.64 (0.02)	0.5 (0.11)	0.13 (0.11)
GAM_B	1:1	Expert	0.78 (0.01)	0.16 (0.11)	0.62 (0.11)	0.75 (0.02)	0.64 (0.14)	0.11 (0.14)
GAM_B	1:2	Expert	0.66 (0.01)	0.09 (0.07)	0.57 (0.07)	0.7 (0.02)	0.55 (0.13)	0.15 (0.13)
GAM_B	1:3	Expert	0.57 (0)	0.06 (0)	0.51 (0)	0.66 (0)	0.5 (0)	0.16 (0)
GAM_B	10000	Expert	0.37 (0.01)	0.05 (0.02)	0.33 (0.02)	0.63 (0.02)	0.43 (0.08)	0.21 (0.09)
GAM_O	1:1	*A priori*	0.78 (0.01)	0.35 (0.02)	0.43 (0.02)	0.75 (0.02)	0.77 (0.02)	-0.02 (0.03)
GAM_O	1:2	*A priori*	0.66 (0.01)	0.34 (0.02)	0.32 (0.02)	0.7 (0.02)	0.77 (0.02)	-0.08 (0.02)
GAM_O	1:3	*A priori*	0.58 (0.01)	0.33 (0.03)	0.25 (0.03)	0.67 (0.02)	0.77 (0.02)	-0.1 (0.03)
GAM_O	10000	*A priori*	0.37 (0.01)	0.31 (0.03)	0.06 (0.04)	0.62 (0.02)	0.76 (0.02)	-0.14 (0.03)
GAM_O	1:1	Automated	0.78 (0.01)	0.36 (0.03)	0.43 (0.03)	0.75 (0.02)	0.77 (0.02)	-0.02 (0.03)
GAM_O	1:2	Automated	0.66 (0.01)	0.36 (0.02)	0.29 (0.03)	0.69 (0.02)	0.78 (0.02)	-0.08 (0.03)
GAM_O	1:3	Automated	0.58 (0.01)	0.33 (0.02)	0.25 (0.02)	0.67 (0.02)	0.75 (0.02)	-0.09 (0.03)
GAM_O	10000	Automated	0.37 (0.01)	0.32 (0.02)	0.05 (0.02)	0.63 (0.02)	0.75 (0.02)	-0.12 (0.03)
GAM_O	1:1	Expert	0.78 (0.01)	0.34 (0.03)	0.44 (0.03)	0.75 (0.02)	0.77 (0.02)	-0.03 (0.02)
GAM_O	1:2	Expert	0.66 (0.01)	0.34 (0.02)	0.32 (0.02)	0.69 (0.01)	0.77 (0.02)	-0.08 (0.02)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	F1			Correct classification rate		
			Train	Test	Fit	Train	Test	Fit
GAM_O	1:3	Expert	0.57 (0.01)	0.33 (0.02)	0.24 (0.02)	0.66 (0.02)	0.76 (0.02)	-0.09 (0.02)
GAM_O	10000	Expert	0.37 (0.01)	0.32 (0.01)	0.05 (0.02)	0.62 (0.02)	0.74 (0.01)	-0.12 (0.02)
GBM_B	1:1	*A priori*	0.81 (0.01)	0.31 (0.04)	0.5 (0.04)	0.79 (0.02)	0.76 (0.02)	0.02 (0.03)
GBM_B	1:2	*A priori*	0.7 (0.01)	0.31 (0.03)	0.39 (0.03)	0.74 (0.02)	0.77 (0.02)	-0.03 (0.03)
GBM_B	1:3	*A priori*	0.62 (0.02)	0.31 (0.03)	0.31 (0.03)	0.72 (0.02)	0.77 (0.02)	-0.05 (0.03)
GBM_B	10000	*A priori*	0.41 (0.01)	0.3 (0.02)	0.11 (0.03)	0.68 (0.02)	0.77 (0.02)	-0.08 (0.02)
GBM_B	1:1	Automated	0.8 (0.01)	0.26 (0.06)	0.53 (0.06)	0.77 (0.02)	0.74 (0.03)	0.02 (0.03)
GBM_B	1:2	Automated	0.68 (0.01)	0.29 (0.06)	0.39 (0.06)	0.72 (0.02)	0.75 (0.03)	-0.03 (0.03)
GBM_B	1:3	Automated	0.6 (0.02)	0.3 (0.05)	0.3 (0.05)	0.7 (0.02)	0.76 (0.03)	-0.06 (0.03)
GBM_B	10000	Automated	0.39 (0.01)	0.32 (0.05)	0.08 (0.05)	0.66 (0.02)	0.76 (0.02)	-0.1 (0.03)
GBM_B	1:1	Expert	0.8 (0.01)	0.28 (0.06)	0.52 (0.06)	0.78 (0.02)	0.75 (0.03)	0.03 (0.03)
GBM_B	1:2	Expert	0.69 (0.02)	0.3 (0.05)	0.4 (0.05)	0.73 (0.02)	0.76 (0.02)	-0.03 (0.03)
GBM_B	1:3	Expert	0.59 (0)	0.32 (0)	0.27 (0)	0.69 (0)	0.76 (0)	-0.07 (0)
GBM_B	10000	Expert	0.4 (0.01)	0.33 (0.02)	0.07 (0.03)	0.67 (0.02)	0.76 (0.02)	-0.09 (0.03)
GBM_O	1:1	*A priori*	0.79 (0.01)	0.3 (0.05)	0.49 (0.05)	0.76 (0.02)	0.77 (0.02)	0 (0.03)
GBM_O	1:2	*A priori*	0.67 (0.02)	0.25 (0.03)	0.42 (0.03)	0.71 (0.02)	0.75 (0.02)	-0.04 (0.03)
GBM_O	1:3	*A priori*	0.59 (0.02)	0.24 (0.02)	0.35 (0.02)	0.68 (0.02)	0.75 (0.02)	-0.07 (0.03)
GBM_O	10000	*A priori*	0.38 (0.01)	0.24 (0.01)	0.14 (0.02)	0.64 (0.02)	0.75 (0.02)	-0.12 (0.03)
GBM_O	1:1	Automated	0.79 (0.01)	0.29 (0.06)	0.5 (0.06)	0.76 (0.02)	0.75 (0.03)	0.01 (0.03)
GBM_O	1:2	Automated	0.67 (0.01)	0.23 (0.03)	0.44 (0.03)	0.7 (0.02)	0.73 (0.02)	-0.03 (0.03)
GBM_O	1:3	Automated	0.58 (0.01)	0.23 (0.01)	0.36 (0.02)	0.68 (0.02)	0.73 (0.02)	-0.05 (0.03)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	F1 Train	F1 Test	F1 Fit	Correct classification rate Train	Correct classification rate Test	Correct classification rate Fit
GBM_O	10000	Automated	0.38 (0.01)	0.23 (0.01)	0.15 (0.02)	0.64 (0.02)	0.73 (0.02)	-0.09 (0.03)
GBM_O	1:1	Expert	0.78 (0.01)	0.12 (0.06)	0.66 (0.06)	0.74 (0.02)	0.74 (0.01)	0 (0.02)
GBM_O	1:2	Expert	0.66 (0.01)	0.11 (0.05)	0.55 (0.05)	0.69 (0.02)	0.74 (0.01)	-0.05 (0.02)
GBM_O	1:3	Expert	0.58 (0.01)	0.23 (0.01)	0.35 (0.02)	0.68 (0.02)	0.73 (0.02)	-0.05 (0.02)
GBM_O	10000	Expert	0.37 (0.01)	0.23 (0.01)	0.15 (0.01)	0.63 (0.02)	0.72 (0.02)	-0.09 (0.03)
GLM_B	1:1	*A priori*	0.78 (0.01)	0.29 (0.05)	0.49 (0.05)	0.74 (0.02)	0.76 (0.04)	-0.01 (0.04)
GLM_B	1:2	*A priori*	0.66 (0.01)	0.29 (0.04)	0.37 (0.04)	0.69 (0.02)	0.76 (0.03)	-0.07 (0.03)
GLM_B	1:3	*A priori*	0.57 (0.01)	0.31 (0.04)	0.26 (0.05)	0.67 (0.02)	0.76 (0.02)	-0.1 (0.03)
GLM_B	10000	*A priori*	0.37 (0.01)	0.31 (0.03)	0.05 (0.03)	0.62 (0.02)	0.76 (0.03)	-0.14 (0.03)
GLM_B	1:1	Automated	0.78 (0.01)	0.24 (0.03)	0.54 (0.03)	0.74 (0.02)	0.74 (0.02)	0 (0.03)
GLM_B	1:2	Automated	0.66 (0.01)	0.23 (0.02)	0.44 (0.02)	0.7 (0.02)	0.74 (0.02)	-0.04 (0.03)
GLM_B	1:3	Automated	0.58 (0.01)	0.23 (0.02)	0.35 (0.02)	0.67 (0.02)	0.74 (0.02)	-0.07 (0.03)
GLM_B	10000	Automated	0.37 (0.01)	0.23 (0.02)	0.14 (0.02)	0.63 (0.02)	0.74 (0.02)	-0.11 (0.03)
GLM_B	1:1	Expert	0.78 (0.01)	0.24 (0.03)	0.55 (0.03)	0.75 (0.02)	0.74 (0.02)	0 (0.03)
GLM_B	1:2	Expert	0.66 (0.01)	0.22 (0.02)	0.44 (0.02)	0.69 (0.02)	0.74 (0.02)	-0.05 (0.03)
GLM_B	1:3	Expert	0.57 (0)	0.23 (0)	0.34 (0)	0.65 (0)	0.75 (0)	-0.1 (0)
GLM_B	10000	Expert	0.37 (0.01)	0.23 (0.01)	0.14 (0.02)	0.62 (0.02)	0.74 (0.02)	-0.12 (0.03)
GLM_O	1:1	*A priori*	0.74 (0.05)	0.19 (0.14)	0.55 (0.1)	0.66 (0.1)	0.63 (0.19)	0.03 (0.13)
GLM_O	1:2	*A priori*	0.63 (0.06)	0.23 (0.13)	0.4 (0.1)	0.63 (0.12)	0.67 (0.18)	-0.04 (0.14)
GLM_O	1:3	*A priori*	0.56 (0.04)	0.26 (0.11)	0.29 (0.1)	0.63 (0.09)	0.71 (0.14)	-0.08 (0.1)
GLM_O	10000	*A priori*	0.37 (0.02)	0.3 (0.06)	0.07 (0.06)	0.62 (0.03)	0.77 (0.05)	-0.15 (0.04)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	F1			Correct classification rate		
			Train	Test	Fit	Train	Test	Fit
GLM_O	1:1	Automated	0.75 (0.05)	0.21 (0.12)	0.53 (0.09)	0.68 (0.1)	0.7 (0.14)	-0.02 (0.13)
GLM_O	1:2	Automated	0.65 (0.05)	0.22 (0.07)	0.43 (0.04)	0.66 (0.1)	0.74 (0.09)	-0.07 (0.11)
GLM_O	1:3	Automated	0.57 (0.02)	0.25 (0.05)	0.32 (0.04)	0.66 (0.05)	0.76 (0.03)	-0.1 (0.05)
GLM_O	10000	Automated	0.37 (0.01)	0.26 (0.04)	0.11 (0.04)	0.62 (0.02)	0.76 (0.02)	-0.14 (0.02)
GLM_O	1:1	Expert	0.78 (0.01)	0.23 (0.02)	0.55 (0.03)	0.74 (0.01)	0.74 (0.02)	0 (0.02)
GLM_O	1:2	Expert	0.66 (0.01)	0.23 (0.02)	0.43 (0.02)	0.69 (0.01)	0.74 (0.02)	-0.05 (0.02)
GLM_O	1:3	Expert	0.57 (0.01)	0.24 (0.03)	0.33 (0.04)	0.66 (0.02)	0.74 (0.02)	-0.08 (0.03)
GLM_O	10000	Expert	0.37 (0.01)	0.24 (0.03)	0.13 (0.03)	0.62 (0.01)	0.74 (0.02)	-0.11 (0.02)
MARS_B	1:1	*A priori*	0.78 (0.01)	0.26 (0.06)	0.53 (0.06)	0.75 (0.01)	0.74 (0.05)	0.01 (0.05)
MARS_B	1:2	*A priori*	0.67 (0.01)	0.26 (0.08)	0.4 (0.08)	0.7 (0.02)	0.74 (0.06)	-0.04 (0.06)
MARS_B	1:3	*A priori*	0.58 (0.02)	0.29 (0.08)	0.29 (0.08)	0.68 (0.02)	0.75 (0.05)	-0.08 (0.05)
MARS_B	10000	*A priori*	0.37 (0.01)	0.28 (0.06)	0.09 (0.06)	0.63 (0.02)	0.74 (0.05)	-0.11 (0.05)
MARS_B	1:1	Automated	0.78 (0.01)	0.28 (0.05)	0.5 (0.05)	0.75 (0.02)	0.75 (0.03)	0 (0.03)
MARS_B	1:2	Automated	0.66 (0.01)	0.25 (0.05)	0.41 (0.05)	0.69 (0.02)	0.73 (0.04)	-0.04 (0.05)
MARS_B	1:3	Automated	0.58 (0.01)	0.26 (0.05)	0.32 (0.05)	0.67 (0.01)	0.74 (0.04)	-0.07 (0.04)
MARS_B	10000	Automated	0.37 (0.01)	0.3 (0.07)	0.07 (0.07)	0.63 (0.02)	0.76 (0.04)	-0.13 (0.04)
MARS_B	1:1	Expert	0.78 (0.01)	0.26 (0.06)	0.52 (0.06)	0.75 (0.01)	0.74 (0.05)	0.01 (0.06)
MARS_B	1:2	Expert	0.66 (0.01)	0.25 (0.08)	0.41 (0.08)	0.69 (0.02)	0.72 (0.09)	-0.03 (0.1)
MARS_B	1:3	Expert	0.57 (0.01)	0.27 (0.07)	0.3 (0.07)	0.66 (0.02)	0.73 (0.06)	-0.07 (0.06)
MARS_B	10000	Expert	0.37 (0.01)	0.27 (0.07)	0.1 (0.07)	0.62 (0.02)	0.73 (0.08)	-0.11 (0.08)
MARS_O	1:1	*A priori*	0.78 (0.02)	0.25 (0.09)	0.53 (0.09)	0.75 (0.03)	0.73 (0.12)	0.02 (0.11)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	F1			Correct classification rate		
			Train	Test	Fit	Train	Test	Fit
MARS_O	1:2	*A priori*	0.66 (0.02)	0.24 (0.07)	0.42 (0.07)	0.69 (0.02)	0.75 (0.05)	-0.05 (0.05)
MARS_O	1:3	*A priori*	0.57 (0.02)	0.22 (0.07)	0.36 (0.07)	0.66 (0.05)	0.74 (0.06)	-0.07 (0.06)
MARS_O	10000	*A priori*	0.36 (0.01)	0.21 (0.06)	0.15 (0.06)	0.61 (0.02)	0.74 (0.04)	-0.13 (0.05)
MARS_O	1:1	Automated	0.78 (0.01)	0.28 (0.07)	0.5 (0.07)	0.75 (0.02)	0.75 (0.03)	-0.01 (0.03)
MARS_O	1:2	Automated	0.66 (0.01)	0.25 (0.03)	0.41 (0.03)	0.69 (0.02)	0.75 (0.02)	-0.06 (0.03)
MARS_O	1:3	Automated	0.57 (0.02)	0.25 (0.06)	0.32 (0.06)	0.66 (0.02)	0.75 (0.03)	-0.09 (0.03)
MARS_O	10000	Automated	0.36 (0.01)	0.22 (0.05)	0.14 (0.06)	0.61 (0.02)	0.74 (0.04)	-0.13 (0.04)
MARS_O	1:1	Expert	0.78 (0.01)	0.24 (0.05)	0.54 (0.05)	0.74 (0.01)	0.74 (0.04)	0.01 (0.04)
MARS_O	1:2	Expert	0.66 (0.01)	0.23 (0.03)	0.43 (0.03)	0.69 (0.02)	0.74 (0.03)	-0.05 (0.03)
MARS_O	1:3	Expert	0.57 (0.01)	0.23 (0.01)	0.35 (0.01)	0.67 (0.02)	0.74 (0.02)	-0.07 (0.02)
MARS_O	10000	Expert	0.37 (0.01)	0.23 (0.01)	0.14 (0.01)	0.62 (0.02)	0.74 (0.02)	-0.12 (0.02)
MaxEnt_B	1:1	*A priori*	0.77 (0.03)	0.22 (0.1)	0.56 (0.1)	0.73 (0.07)	0.72 (0.09)	0.01 (0.11)
MaxEnt_B	1:2	*A priori*	0.65 (0.06)	0.2 (0.11)	0.44 (0.1)	0.66 (0.12)	0.72 (0.09)	-0.06 (0.15)
MaxEnt_B	1:3	*A priori*	0.58 (0)	0.21 (0)	0.37 (0)	0.67 (0)	0.72 (0)	-0.05 (0)
MaxEnt_B	10000	*A priori*	0.38 (0.04)	0.26 (0.06)	0.12 (0.05)	0.63 (0.11)	0.74 (0.07)	-0.12 (0.07)
MaxEnt_B	1:1	Automated	0.77 (0.03)	0.25 (0.07)	0.52 (0.07)	0.73 (0.06)	0.75 (0.05)	-0.02 (0.06)
MaxEnt_B	1:2	Automated	0.66 (0.05)	0.24 (0.07)	0.42 (0.06)	0.68 (0.09)	0.74 (0.07)	-0.06 (0.07)
MaxEnt_B	1:3	Automated	0.57 (0.03)	0.23 (0.06)	0.34 (0.06)	0.66 (0.06)	0.75 (0.06)	-0.09 (0.04)
MaxEnt_B	10000	Automated	0.37 (0.01)	0.24 (0.05)	0.13 (0.05)	0.63 (0.02)	0.76 (0.03)	-0.13 (0.03)
MaxEnt_B	1:1	Expert	0.77 (0.03)	0.2 (0.07)	0.57 (0.06)	0.73 (0.06)	0.73 (0.06)	0.01 (0.05)
MaxEnt_B	1:2	Expert	0.66 (0.02)	0.21 (0.06)	0.45 (0.06)	0.69 (0.04)	0.73 (0.05)	-0.04 (0.04)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	F1 Train	F1 Test	F1 Fit	Correct classification rate Train	Correct classification rate Test	Correct classification rate Fit
MaxEnt_B	1:3	Expert	0.57 (0)	0.2 (0)	0.37 (0)	0.66 (0)	0.73 (0)	-0.07 (0)
MaxEnt_B	10000	Expert	0.38 (0.01)	0.22 (0.05)	0.15 (0.05)	0.63 (0.02)	0.74 (0.03)	-0.11 (0.03)
MaxEnt_O	1:1	*A priori*	0.77 (0.04)	0.23 (0.09)	0.55 (0.07)	0.73 (0.07)	0.74 (0.06)	-0.01 (0.07)
MaxEnt_O	1:2	*A priori*	0.65 (0.05)	0.23 (0.08)	0.42 (0.07)	0.66 (0.11)	0.74 (0.07)	-0.08 (0.11)
MaxEnt_O	1:3	*A priori*	0.56 (0.06)	0.22 (0.09)	0.34 (0.09)	0.63 (0.13)	0.74 (0.07)	-0.11 (0.14)
MaxEnt_O	10000	*A priori*	0.36 (0.04)	0.22 (0.08)	0.14 (0.08)	0.59 (0.14)	0.73 (0.08)	-0.14 (0.12)
MaxEnt_O	1:1	Automated	0.78 (0.02)	0.25 (0.05)	0.53 (0.05)	0.74 (0.03)	0.76 (0.03)	-0.02 (0.03)
MaxEnt_O	1:2	Automated	0.65 (0.04)	0.23 (0.08)	0.42 (0.07)	0.67 (0.09)	0.75 (0.05)	-0.08 (0.08)
MaxEnt_O	1:3	Automated	0.58 (0.01)	0.25 (0.06)	0.33 (0.06)	0.67 (0.02)	0.76 (0.02)	-0.09 (0.03)
MaxEnt_O	10000	Automated	0.37 (0.02)	0.23 (0.07)	0.14 (0.07)	0.62 (0.07)	0.75 (0.06)	-0.13 (0.04)
MaxEnt_O	1:1	Expert	0.77 (0.04)	0.2 (0.07)	0.57 (0.06)	0.73 (0.07)	0.71 (0.07)	0.01 (0.05)
MaxEnt_O	1:2	Expert	0.64 (0.06)	0.2 (0.07)	0.44 (0.06)	0.65 (0.11)	0.71 (0.1)	-0.06 (0.09)
MaxEnt_O	1:3	Expert	0.56 (0.04)	0.21 (0.07)	0.36 (0.06)	0.64 (0.09)	0.72 (0.08)	-0.08 (0.05)
MaxEnt_O	10000	Expert	0.37 (0.02)	0.21 (0.05)	0.15 (0.05)	0.62 (0.07)	0.74 (0.03)	-0.12 (0.07)
MXL_O	1:1	*A priori*	0.76 (0.02)	0.05 (0.01)	0.72 (0.02)	0.72 (0.02)	0.49 (0.04)	0.23 (0.05)
MXL_O	1:2	*A priori*	0.64 (0.02)	0.05 (0)	0.59 (0.02)	0.66 (0.03)	0.49 (0.04)	0.16 (0.05)
MXL_O	1:3	*A priori*	0.55 (0.02)	0.05 (0.01)	0.5 (0.02)	0.62 (0.03)	0.49 (0.04)	0.14 (0.06)
MXL_O	10000	*A priori*	0.35 (0.02)	0.16 (0.04)	0.19 (0.04)	0.58 (0.07)	0.62 (0.04)	-0.04 (0.05)
MXL_O	1:1	Automated	0.76 (0.02)	0.13 (0.02)	0.63 (0.02)	0.72 (0.03)	0.57 (0.04)	0.15 (0.03)
MXL_O	1:2	Automated	0.63 (0.01)	0.05 (0.01)	0.58 (0.02)	0.65 (0.02)	0.43 (0.04)	0.21 (0.04)
MXL_O	1:3	Automated	0.54 (0.01)	0.05 (0.02)	0.49 (0.02)	0.61 (0.02)	0.44 (0.05)	0.18 (0.05)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	F1			Correct classification rate		
			Train	Test	Fit	Train	Test	Fit
MXL_O	10000	Automated	0.34 (0.01)	0.05 (0)	0.29 (0.01)	0.57 (0.02)	0.43 (0.02)	0.14 (0.03)
MXL_O	1:1	Expert	0.77 (0.02)	0.27 (0.07)	0.51 (0.06)	0.74 (0.04)	0.76 (0.03)	-0.02 (0.05)
MXL_O	1:2	Expert	0.65 (0.03)	0.27 (0.07)	0.38 (0.05)	0.67 (0.06)	0.75 (0.05)	-0.08 (0.06)
MXL_O	1:3	Expert	0.57 (0.03)	0.27 (0.07)	0.3 (0.06)	0.65 (0.05)	0.75 (0.05)	-0.1 (0.04)
MXL_O	10000	Expert	0.36 (0.02)	0.23 (0.07)	0.13 (0.06)	0.6 (0.04)	0.74 (0.03)	-0.14 (0.05)
RF_B	1:1	*A priori*	0.93 (0)	0.14 (0.06)	0.79 (0.06)	0.94 (0)	0.77 (0.02)	0.17 (0.02)
RF_B	1:2	*A priori*	0.93 (0.01)	0.2 (0.05)	0.73 (0.05)	0.95 (0)	0.77 (0.02)	0.19 (0.02)
RF_B	1:3	*A priori*	0.93 (0.01)	0.24 (0.06)	0.69 (0.06)	0.97 (0)	0.77 (0.02)	0.19 (0.02)
RF_B	10000	*A priori*	0.93 (0.01)	0.26 (0.04)	0.67 (0.04)	0.98 (0)	0.77 (0.02)	0.22 (0.02)
RF_B	1:1	Automated	0.93 (0)	0.18 (0.08)	0.75 (0.08)	0.93 (0)	0.76 (0.02)	0.18 (0.02)
RF_B	1:2	Automated	0.93 (0.01)	0.26 (0.06)	0.67 (0.06)	0.96 (0)	0.76 (0.02)	0.19 (0.02)
RF_B	1:3	Automated	0.93 (0.01)	0.27 (0.05)	0.66 (0.05)	0.97 (0)	0.76 (0.03)	0.21 (0.02)
RF_B	10000	Automated	0.93 (0.01)	0.31 (0.05)	0.62 (0.05)	0.98 (0)	0.76 (0.02)	0.22 (0.02)
RF_B	1:1	Expert	0.93 (0.01)	0.27 (0.05)	0.67 (0.06)	0.93 (0.01)	0.76 (0.03)	0.18 (0.03)
RF_B	1:2	Expert	0.93 (0.01)	0.28 (0.04)	0.65 (0.04)	0.95 (0.01)	0.76 (0.02)	0.19 (0.02)
RF_B	1:3	Expert	0.89 (0)	0.29 (0)	0.6 (0)	0.94 (0)	0.76 (0)	0.18 (0)
RF_B	10000	Expert	0.93 (0.01)	0.31 (0.02)	0.62 (0.02)	0.98 (0)	0.76 (0.02)	0.22 (0.02)
RF_O	1:1	*A priori*	0.94 (0)	0.12 (0.07)	0.81 (0.07)	0.94 (0)	0.75 (0.08)	0.18 (0.08)
RF_O	1:2	*A priori*	0.94 (0.01)	0.18 (0.07)	0.76 (0.07)	0.96 (0)	0.76 (0.02)	0.2 (0.02)
RF_O	1:3	*A priori*	0.94 (0.01)	0.2 (0.07)	0.73 (0.07)	0.97 (0)	0.77 (0.02)	0.2 (0.02)
RF_O	10000	*A priori*	0.93 (0.01)	0.26 (0.05)	0.68 (0.05)	0.98 (0)	0.76 (0.03)	0.22 (0.03)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	F1 Train	F1 Test	F1 Fit	Correct classification rate Train	Correct classification rate Test	Correct classification rate Fit
RF_O	1:1	Automated	0.93 (0)	0.15 (0.08)	0.78 (0.08)	0.94 (0.01)	0.75 (0.02)	0.18 (0.02)
RF_O	1:2	Automated	0.93 (0.01)	0.22 (0.07)	0.72 (0.07)	0.96 (0)	0.76 (0.02)	0.2 (0.02)
RF_O	1:3	Automated	0.94 (0.01)	0.24 (0.06)	0.69 (0.06)	0.97 (0)	0.76 (0.02)	0.2 (0.02)
RF_O	10000	Automated	0.93 (0.01)	0.31 (0.05)	0.62 (0.05)	0.98 (0)	0.76 (0.03)	0.22 (0.02)
RF_O	1:1	Expert	0.93 (0)	0.3 (0.05)	0.63 (0.05)	0.94 (0.01)	0.76 (0.02)	0.17 (0.03)
RF_O	1:2	Expert	0.93 (0.01)	0.33 (0.04)	0.61 (0.04)	0.96 (0)	0.76 (0.02)	0.19 (0.02)
RF_O	1:3	Expert	0.93 (0.01)	0.32 (0.04)	0.61 (0.04)	0.97 (0)	0.76 (0.03)	0.21 (0.02)
RF_O	10000	Expert	0.93 (0.01)	0.32 (0.04)	0.61 (0.04)	0.98 (0)	0.76 (0.02)	0.22 (0.02)
SRE_B	1:1	*A priori*	0.67 (0)	0.04 (0)	0.63 (0)	0.5 (0)	0.34 (0)	0.16 (0)
SRE_B	1:2	*A priori*	0.5 (0)	0.04 (0)	0.46 (0)	0.33 (0)	0.34 (0)	-0.01 (0)
SRE_B	1:3	*A priori*	0.4 (0)	0.04 (0)	0.36 (0)	0.25 (0)	0.34 (0)	-0.09 (0)
SRE_B	10000	*A priori*	0.22 (0)	0.04 (0)	0.18 (0)	0.12 (0)	0.34 (0)	-0.22 (0)
SRE_B	1:1	Automated	0.68 (0.02)	0.04 (0)	0.64 (0.02)	0.55 (0.08)	0.34 (0)	0.21 (0.08)
SRE_B	1:2	Automated	0.53 (0.05)	0.04 (0)	0.49 (0.05)	0.42 (0.14)	0.34 (0)	0.08 (0.14)
SRE_B	1:3	Automated	0.43 (0.05)	0.04 (0)	0.39 (0.05)	0.35 (0.16)	0.34 (0)	0.01 (0.16)
SRE_B	10000	Automated	0.25 (0.05)	0.04 (0)	0.21 (0.05)	0.25 (0.21)	0.34 (0)	-0.09 (0.21)
SRE_B	1:1	Expert	0.73 (0.01)	0.05 (0)	0.68 (0.01)	0.68 (0.02)	0.74 (0)	-0.06 (0.02)
SRE_B	1:2	Expert	0.6 (0.01)	0.05 (0)	0.55 (0.01)	0.62 (0.01)	0.74 (0)	-0.12 (0.01)
SRE_B	1:3	Expert	0.51 (0)	0.05 (0)	0.46 (0)	0.58 (0)	0.73 (0)	-0.14 (0)
SRE_B	10000	Expert	0.31 (0.01)	0.05 (0)	0.27 (0.01)	0.54 (0.01)	0.73 (0.06)	-0.19 (0.06)
SRE_O	1:1	*A priori*	0.72 (0.01)	0.15 (0.02)	0.58 (0.03)	0.66 (0.02)	0.75 (0.02)	-0.1 (0.03)

Table B2.4 (continued)

Algorithm	Pseudo-absences	Predictor selection	F1			Correct classification rate		
			Train	**Test**	**Fit**	**Train**	**Test**	**Fit**
SRE_O	1:2	*A priori*	0.58 (0.01)	0.15 (0.02)	0.43 (0.02)	0.57 (0.02)	0.76 (0.02)	-0.18 (0.03)
SRE_O	1:3	*A priori*	0.49 (0)	0.15 (0)	0.34 (0)	0.53 (0)	0.76 (0)	-0.23 (0)
SRE_O	10000	*A priori*	0.29 (0.01)	0.15 (0.02)	0.15 (0.02)	0.47 (0.03)	0.76 (0.02)	-0.29 (0.04)
SRE_O	1:1	Automated	0.73 (0.01)	0.11 (0.05)	0.62 (0.05)	0.67 (0.02)	0.77 (0.02)	-0.1 (0.03)
SRE_O	1:2	Automated	0.59 (0.01)	0.11 (0.05)	0.48 (0.05)	0.59 (0.02)	0.76 (0.02)	-0.17 (0.03)
SRE_O	1:3	Automated	0.5 (0.01)	0.11 (0.04)	0.39 (0.05)	0.54 (0.02)	0.76 (0.02)	-0.22 (0.03)
SRE_O	10000	Automated	0.3 (0.01)	0.11 (0.05)	0.19 (0.06)	0.49 (0.02)	0.76 (0.02)	-0.28 (0.03)
SRE_O	1:1	Expert	0.73 (0.01)	0.16 (0.05)	0.57 (0.05)	0.67 (0.02)	0.76 (0.02)	-0.09 (0.03)
SRE_O	1:2	Expert	0.6 (0.01)	0.17 (0.05)	0.43 (0.05)	0.6 (0.02)	0.76 (0.02)	-0.17 (0.03)
SRE_O	1:3	Expert	0.5 (0.01)	0.16 (0.05)	0.34 (0.05)	0.56 (0.02)	0.75 (0.02)	-0.2 (0.03)
SRE_O	10000	Expert	0.31 (0.01)	0.16 (0.05)	0.14 (0.06)	0.5 (0.03)	0.76 (0.02)	-0.26 (0.04)

Table B2.5: Relative performance scores of all evaluations. Shaded regions indicate the evaluations to determine the total relative performance per evaluation as shown in bold per shaded section. Bolded bright blue cells indicate relative performance per objective, calculated by the normalized mean of all total relative performances prior to last objective total. Bolded bright yellow cells represent the relative performance per model use, as determined by the normalized mean of corresponding objective relative performances. A value of one indicates highest performance relative to all other SDMs per evaluation.

Algorithm	Pseudo-absences	Predictor selection	Predictor identification	Response curve estimation Residual mean square error			
			Jaccard index	**BIO1**	**BIO13**	**Elevation**	**Total**
ANN_B	1:1	*A priori*	**0.661**	0.209	0.179	0.581	**0.389**
ANN_B	1:1	Automated	**0.661**	0.254	0.209	0.606	**0.429**
ANN_B	1:1	Expert	**0.661**	0.244	0.189	0.645	**0.432**
ANN_B	1:2	*A priori*	**0.746**	0.194	0.163	0.596	**0.382**
ANN_B	1:2	Automated	**0.746**	0.259	0.209	0.567	**0.415**
ANN_B	1:2	Expert	**0.746**	0.244	0.194	0.626	**0.426**
ANN_B	1:3	*A priori*	**0.746**	0.219	0.184	0.616	**0.408**
ANN_B	1:3	Automated	**0.746**	0.254	0.209	0.571	**0.415**
ANN_B	1:3	Expert	**0.746**	0.313	0.245	0.576	**0.455**
ANN_B	10000	*A priori*	**0.763**	0.214	0.184	0.621	**0.408**
ANN_B	10000	Automated	**0.763**	0.284	0.23	0.547	**0.425**
ANN_B	10000	Expert	**0.763**	0.343	0.27	0.527	**0.457**
ANN_O	1:1	*A priori*	**0.441**	0.498	0.464	0.901	**0.747**
ANN_O	1:1	Automated	**0.441**	0.527	0.52	0.906	**0.784**
ANN_O	1:1	Expert	**0.441**	0.622	0.577	0.828	**0.812**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Predictor identification	Response curve estimation Residual mean square error			
			Jaccard index	BIO1	BIO13	Elevation	Total
ANN_O	1:2	*A priori*	**0.237**	0.876	0.918	0.143	**0.777**
ANN_O	1:2	Automated	**0.237**	0.881	0.908	0.177	**0.788**
ANN_O	1:2	Expert	**0.237**	0.91	0.913	0.148	**0.791**
ANN_O	1:3	*A priori*	**0.153**	0.791	0.974	0.025	**0.718**
ANN_O	1:3	Automated	**0.153**	0.796	0.954	0.049	**0.722**
ANN_O	1:3	Expert	**0.153**	0.756	0.969	0.03	**0.704**
ANN_O	10000	*A priori*	**0.085**	0.308	0.995	0.01	**0.527**
ANN_O	10000	Automated	**0.085**	0.249	1	0.005	**0.503**
ANN_O	10000	Expert	**0.085**	0.269	0.99	0.015	**0.511**
CTA_B	1:1	*A priori*	**0.61**	0.149	0.199	0.463	**0.325**
CTA_B	1:1	Automated	**0.61**	0.199	0.219	0.448	**0.348**
CTA_B	1:1	Expert	**0.61**	0.199	0.219	0.488	**0.363**
CTA_B	1:2	*A priori*	**0.576**	0.139	0.204	0.419	**0.306**
CTA_B	1:2	Automated	**0.576**	0.174	0.219	0.414	**0.324**
CTA_B	1:2	Expert	**0.576**	0.224	0.255	0.429	**0.364**
CTA_B	1:3	*A priori*	**0.525**	0.149	0.224	0.379	**0.302**
CTA_B	1:3	Automated	**0.525**	0.169	0.235	0.34	**0.298**
CTA_B	1:3	Expert	**0.525**	0.224	0.265	0.409	**0.36**
CTA_B	10000	*A priori*	**0.373**	0.164	0.26	0.31	**0.295**
CTA_B	10000	Automated	**0.373**	0.144	0.281	0.246	**0.269**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Predictor identification	Response curve estimation Residual mean square error			
			Jaccard index	BIO1	BIO13	Elevation	Total
CTA_B	10000	Expert	**0.373**	0.244	0.321	0.34	**0.363**
CTA_O	1:1	*A priori*	**0.695**	0.527	0.469	0.611	**0.645**
CTA_O	1:1	Automated	**0.695**	0.557	0.49	0.537	**0.635**
CTA_O	1:1	Expert	**0.695**	0.557	0.49	0.547	**0.639**
CTA_O	1:2	*A priori*	**0.644**	0.95	0.867	0.251	**0.83**
CTA_O	1:2	Automated	**0.644**	0.955	0.867	0.232	**0.824**
CTA_O	1:2	Expert	**0.644**	0.955	0.867	0.236	**0.826**
CTA_O	1:3	*A priori*	**0.576**	0.98	0.908	0.108	**0.801**
CTA_O	1:3	Automated	**0.576**	0.985	0.908	0.099	**0.799**
CTA_O	1:3	Expert	**0.576**	0.95	0.867	0.236	**0.824**
CTA_O	10000	*A priori*	**0.39**	0.96	0.939	0.044	**0.779**
CTA_O	10000	Automated	**0.39**	0.965	0.944	0.044	**0.783**
CTA_O	10000	Expert	**0.39**	0.96	0.949	0.039	**0.781**
EMca_B	1:1	*A priori*	**0.661**	0.01	0.005	0.911	**0.372**
EMca_B	1:1	Automated	**0.661**	0.02	0.01	0.946	**0.391**
EMca_B	1:1	Expert	**0.661**	0.01	0.005	0.961	**0.391**
EMca_B	1:2	*A priori*	**0.525**	0.01	0.005	0.916	**0.373**
EMca_B	1:2	Automated	**0.525**	0.01	0.005	0.956	**0.389**
EMca_B	1:2	Expert	**0.525**	0.01	0.005	0.956	**0.389**
EMca_B	1:3	*A priori*	**0.576**	0.01	0.005	0.956	**0.389**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Predictor identification	Response curve estimation Residual mean square error			
			Jaccard index	BIO1	BIO13	Elevation	Total
EMca_B	1:3	Automated	**0.576**	0.015	0.01	0.966	**0.397**
EMca_B	1:3	Expert	**0.576**	0.01	0.005	0.951	**0.387**
EMca_B	10000	*A priori*	**0.424**	0.02	0.01	0.99	**0.409**
EMca_B	10000	Automated	**0.424**	0.02	0.01	0.951	**0.393**
EMca_B	10000	Expert	**0.424**	0.01	0.005	0.916	**0.373**
EMmean_B	1:1	*A priori*	**0.881**	0.294	0.133	0.877	**0.523**
EMmean_B	1:1	Automated	**0.881**	0.393	0.306	0.783	**0.594**
EMmean_B	1:1	Expert	**0.881**	0.373	0.276	0.724	**0.551**
EMmean_B	1:2	*A priori*	**0.966**	0.448	0.24	0.749	**0.576**
EMmean_B	1:2	Automated	**0.966**	0.328	0.337	0.739	**0.563**
EMmean_B	1:2	Expert	**0.966**	0.547	0.423	0.542	**0.607**
EMmean_B	1:3	*A priori*	**0.966**	0.493	0.296	0.69	**0.593**
EMmean_B	1:3	Automated	**0.966**	0.677	0.582	0.522	**0.714**
EMmean_B	1:3	Expert	**0.966**	0.731	0.597	0.517	**0.74**
EMmean_B	10000	*A priori*	**0.949**	0.716	0.372	0.586	**0.672**
EMmean_B	10000	Automated	**0.949**	0.856	0.735	0.433	**0.812**
EMmean_B	10000	Expert	**0.949**	0.836	0.699	0.438	**0.791**
EMmedian_B	1:1	*A priori*	**0.898**	0.358	0.23	0.882	**0.589**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Predictor identification	Response curve estimation Residual mean square error			
			Jaccard index	**BIO1**	**BIO13**	**Elevation**	**Total**
EMmedian_B	1:1	Automated	**0.898**	0.433	0.327	0.744	**0.603**
EMmedian_B	1:1	Expert	**0.898**	0.418	0.311	0.734	**0.587**
EMmedian_B	1:2	*A priori*	**0.966**	0.512	0.347	0.808	**0.669**
EMmedian_B	1:2	Automated	**0.966**	0	0	0	**0**
EMmedian_B	1:2	Expert	**0.966**	0.587	0.439	0.616	**0.658**
EMmedian_B	1:3	*A priori*	**0.966**	0.612	0.362	0.808	**0.715**
EMmedian_B	1:3	Automated	**0.966**	0.279	0.301	0.897	**0.592**
EMmedian_B	1:3	Expert	**0.966**	0.662	0.515	0.626	**0.723**
EMmedian_B	10000	*A priori*	**0.881**	0.746	0.398	0.759	**0.763**
EMmedian_B	10000	Automated	**0.881**	0.299	0.316	0.892	**0.604**
EMmedian_B	10000	Expert	**0.881**	0.776	0.607	0.557	**0.778**
EMwmean_B	1:1	*A priori*	**0.898**	0.289	0.133	0.887	**0.525**
EMwmean_B	1:1	Automated	**0.898**	0.403	0.311	0.773	**0.597**
EMwmean_B	1:1	Expert	**0.898**	0.368	0.276	0.724	**0.549**
EMwmean_B	1:2	*A priori*	**0.966**	0.443	0.24	0.754	**0.576**
EMwmean_B	1:2	Automated	**0.966**	0.328	0.337	0.739	**0.563**
EMwmean_B	1:2	Expert	**0.966**	0.547	0.423	0.542	**0.607**
EMwmean_B	1:3	*A priori*	**0.966**	0.488	0.286	0.7	**0.591**
EMwmean_B	1:3	Automated	**0.966**	0.677	0.582	0.522	**0.714**
EMwmean_B	1:3	Expert	**0.966**	0.741	0.602	0.517	**0.746**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Predictor identification	Response curve estimation Residual mean square error			
			Jaccard index	**BIO1**	**BIO13**	**Elevation**	**Total**
EMwmean_B	10000	*A priori*	**0.932**	0.716	0.372	0.596	**0.676**
EMwmean_B	10000	Automated	**0.932**	0.851	0.73	0.443	**0.812**
EMwmean_B	10000	Expert	**0.932**	0.831	0.699	0.438	**0.789**
FDA_B	1:1	*A priori*	**0.814**	0.333	0.25	0.512	**0.439**
FDA_B	1:1	Automated	**0.814**	0.358	0.291	0.458	**0.444**
FDA_B	1:1	Expert	**0.814**	0.353	0.265	0.498	**0.448**
FDA_B	1:2	*A priori*	**0.746**	0.905	0.796	0.182	**0.755**
FDA_B	1:2	Automated	**0.746**	0.915	0.821	0.172	**0.766**
FDA_B	1:2	Expert	**0.746**	0.915	0.811	0.167	**0.76**
FDA_B	1:3	*A priori*	**0.746**	0.925	0.847	0.113	**0.756**
FDA_B	1:3	Automated	**0.746**	0.935	0.867	0.103	**0.764**
FDA_B	1:3	Expert	**0.746**	0.945	0.857	0.123	**0.772**
FDA_B	10000	*A priori*	**0.627**	0.965	0.878	0.153	**0.8**
FDA_B	10000	Automated	**0.627**	0.965	0.883	0.167	**0.808**
FDA_B	10000	Expert	**0.627**	0.965	0.888	0.138	**0.798**
FDA_O	1:1	*A priori*	**0.559**	0.065	0.041	0.192	**0.119**
FDA_O	1:1	Automated	**0.559**	0.07	0.046	0.167	**0.114**
FDA_O	1:1	Expert	**0.559**	0.06	0.041	0.158	**0.104**
FDA_O	1:2	*A priori*	**0.458**	0.065	0.056	0.197	**0.127**
FDA_O	1:2	Automated	**0.458**	0.07	0.046	0.167	**0.114**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Predictor identification	Response curve estimation Residual mean square error			
			Jaccard index	BIO1	BIO13	Elevation	Total
FDA_O	1:2	Expert	**0.458**	0.06	0.046	0.158	**0.106**
FDA_O	1:3	*A priori*	**0.508**	0.06	0.051	0.207	**0.127**
FDA_O	1:3	Automated	**0.508**	0.065	0.046	0.163	**0.11**
FDA_O	1:3	Expert	**0.508**	0.06	0.041	0.163	**0.106**
FDA_O	10000	*A priori*	**0.593**	0.06	0.051	0.202	**0.125**
FDA_O	10000	Automated	**0.593**	0.065	0.046	0.163	**0.11**
FDA_O	10000	Expert	**0.593**	0.065	0.046	0.158	**0.108**
GAM_B	1:1	*A priori*	**0.864**	0.423	0.24	0.842	**0.604**
GAM_B	1:1	Automated	**0.864**	0.567	0.48	0.635	**0.675**
GAM_B	1:1	Expert	**0.864**	0.597	0.474	0.714	**0.716**
GAM_B	1:2	*A priori*	**0.797**	0.398	0.214	0.862	**0.591**
GAM_B	1:2	Automated	**0.797**	0.537	0.48	0.635	**0.663**
GAM_B	1:2	Expert	**0.797**	0.557	0.48	0.695	**0.694**
GAM_B	1:3	*A priori*	**0.763**	0.383	0.204	0.857	**0.579**
GAM_B	1:3	Automated	**0.763**	0.473	0.408	0.64	**0.61**
GAM_B	1:3	Expert	**0.763**	0.552	0.485	0.709	**0.7**
GAM_B	10000	*A priori*	**0.61**	0.398	0.224	0.813	**0.576**
GAM_B	10000	Automated	**0.61**	0.517	0.515	0.601	**0.655**
GAM_B	10000	Expert	**0.61**	0.542	0.531	0.665	**0.697**
GAM_O	1:1	*A priori*	**0.712**	0.413	0.474	0.744	**0.654**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Predictor identification	Response curve estimation Residual mean square error			
			Jaccard index	**BIO1**	**BIO13**	**Elevation**	**Total**
GAM_O	1:1	Automated	**0.712**	0.458	0.556	0.872	**0.756**
GAM_O	1:1	Expert	**0.712**	0.085	0.077	0.98	**0.458**
GAM_O	1:2	*A priori*	**0.949**	0.303	0.23	0.921	**0.583**
GAM_O	1:2	Automated	**0.949**	0.259	0.219	0.985	**0.587**
GAM_O	1:2	Expert	**0.949**	0.08	0.066	0.98	**0.452**
GAM_O	1:3	*A priori*	**0.966**	0.204	0.138	0.961	**0.522**
GAM_O	1:3	Automated	**0.966**	0.055	0.031	0.97	**0.423**
GAM_O	1:3	Expert	**0.966**	0.075	0.036	0.975	**0.435**
GAM_O	10000	*A priori*	**1**	0.085	0.071	0.995	**0.462**
GAM_O	10000	Automated	**1**	0.055	0.02	0.966	**0.417**
GAM_O	10000	Expert	**1**	0.055	0.026	0.97	**0.421**
GBM_B	1:1	*A priori*	**0.492**	0.114	0.107	0.926	**0.46**
GBM_B	1:1	Automated	**0.492**	0.234	0.153	0.64	**0.412**
GBM_B	1:1	Expert	**0.492**	0.229	0.158	0.764	**0.461**
GBM_B	1:2	*A priori*	**0.492**	0.109	0.092	0.936	**0.456**
GBM_B	1:2	Automated	**0.492**	0.199	0.122	0.685	**0.404**
GBM_B	1:2	Expert	**0.492**	0.224	0.153	0.778	**0.463**
GBM_B	1:3	*A priori*	**0.542**	0.124	0.102	0.941	**0.468**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Predictor identification Jaccard index	Response curve estimation Residual mean square error			
GBM_B	1:3	Automated	**0.542**	0.174	0.117	0.714	**0.403**
GBM_B	1:3	Expert	**0.542**	0.239	0.148	0.798	**0.475**
GBM_B	10000	*A priori*	**0.475**	0.119	0.097	0.931	**0.46**
GBM_B	10000	Automated	**0.475**	0.179	0.117	0.675	**0.39**
GBM_B	10000	Expert	**0.475**	0.234	0.153	0.759	**0.459**
GBM_O	1:1	*A priori*	**0.746**	0.692	0.505	0.946	**0.859**
GBM_O	1:1	Automated	**0.746**	0.9	0.77	0.823	**1**
GBM_O	1:1	Expert	**0.746**	0.09	0.082	1	**0.47**
GBM_O	1:2	*A priori*	**0.78**	0.896	0.765	0.793	**0.984**
GBM_O	1:2	Automated	**0.78**	0.955	0.842	0.478	**0.912**
GBM_O	1:2	Expert	**0.78**	0.129	0.087	0.995	**0.486**
GBM_O	1:3	*A priori*	**0.831**	0.93	0.801	0.645	**0.953**
GBM_O	1:3	Automated	**0.831**	0.975	0.872	0.374	**0.891**
GBM_O	1:3	Expert	**0.831**	0.97	0.862	0.394	**0.893**
GBM_O	10000	*A priori*	**0.847**	0.995	0.893	0.281	**0.87**
GBM_O	10000	Automated	**0.847**	0.995	0.903	0.212	**0.846**
GBM_O	10000	Expert	**0.847**	0.99	0.898	0.232	**0.85**
GLM_B	1:1	*A priori*	**0.983**	0.607	0.393	0.813	**0.727**
GLM_B	1:1	Automated	**0.983**	0.647	0.408	0.828	**0.755**
GLM_B	1:1	Expert	**0.983**	0.612	0.388	0.867	**0.749**
GLM_B	1:2	*A priori*	**0.966**	0.602	0.393	0.818	**0.727**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Predictor identification	Response curve estimation Residual mean square error			
			Jaccard index	BIO1	BIO13	Elevation	Total
GLM_B	1:2	Automated	**0.966**	0.637	0.408	0.823	**0.749**
GLM_B	1:2	Expert	**0.966**	0.577	0.383	0.852	**0.727**
GLM_B	1:3	*A priori*	**0.949**	0.592	0.352	0.842	**0.716**
GLM_B	1:3	Automated	**0.949**	0.647	0.418	0.833	**0.761**
GLM_B	1:3	Expert	**0.949**	0.632	0.403	0.847	**0.755**
GLM_B	10000	*A priori*	**0.915**	0.617	0.342	0.837	**0.72**
GLM_B	10000	Automated	**0.915**	0.781	0.561	0.788	**0.854**
GLM_B	10000	Expert	**0.915**	0.736	0.52	0.803	**0.826**
GLM_O	1:1	*A priori*	**0.119**	0.095	0.658	0.084	**0.335**
GLM_O	1:1	Automated	**0.119**	0.154	0.765	0.079	**0.4**
GLM_O	1:1	Expert	**0.119**	0.627	0.918	0.118	**0.667**
GLM_O	1:2	*A priori*	**0.203**	0.05	0.332	0.103	**0.194**
GLM_O	1:2	Automated	**0.203**	0.259	0.638	0.232	**0.452**
GLM_O	1:2	Expert	**0.203**	0.572	0.755	0.325	**0.663**
GLM_O	1:3	*A priori*	**0.373**	0.03	0.112	0.167	**0.124**
GLM_O	1:3	Automated	**0.373**	0.174	0.199	0.424	**0.32**
GLM_O	1:3	Expert	**0.373**	0.338	0.367	0.552	**0.504**
GLM_O	10000	*A priori*	**0.576**	0.005	0.005	0.246	**0.103**
GLM_O	10000	Automated	**0.576**	0.07	0.066	0.562	**0.28**
GLM_O	10000	Expert	**0.576**	0.224	0.143	0.709	**0.432**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Predictor identification	Response curve estimation Residual mean square error			
			Jaccard index	BIO1	BIO13	Elevation	Total
MARS_B	1:1	*A priori*	**0.678**	0.502	0.434	0.655	**0.638**
MARS_B	1:1	Automated	**0.678**	0.577	0.459	0.66	**0.68**
MARS_B	1:1	Expert	**0.678**	0.542	0.444	0.65	**0.656**
MARS_B	1:2	*A priori*	**0.729**	0.562	0.449	0.704	**0.688**
MARS_B	1:2	Automated	**0.729**	0.622	0.51	0.64	**0.711**
MARS_B	1:2	Expert	**0.729**	0.532	0.434	0.67	**0.656**
MARS_B	1:3	*A priori*	**0.695**	0.582	0.413	0.729	**0.692**
MARS_B	1:3	Automated	**0.695**	0.612	0.5	0.631	**0.699**
MARS_B	1:3	Expert	**0.695**	0.547	0.429	0.68	**0.664**
MARS_B	10000	*A priori*	**0.661**	0.667	0.526	0.67	**0.747**
MARS_B	10000	Automated	**0.661**	0.672	0.571	0.606	**0.742**
MARS_B	10000	Expert	**0.661**	0.632	0.495	0.645	**0.711**
MARS_O	1:1	*A priori*	**0.305**	0.791	0.643	0.537	**0.79**
MARS_O	1:1	Automated	**0.305**	0.965	0.837	0.468	**0.91**
MARS_O	1:1	Expert	**0.305**	0.761	0.566	0.719	**0.821**
MARS_O	1:2	*A priori*	**0.254**	0.771	0.541	0.591	**0.763**
MARS_O	1:2	Automated	**0.254**	1	0.893	0.251	**0.86**
MARS_O	1:2	Expert	**0.254**	0.95	0.786	0.478	**0.888**
MARS_O	1:3	*A priori*	**0.237**	0.687	0.52	0.527	**0.695**
MARS_O	1:3	Automated	**0.237**	0.94	0.714	0.532	**0.877**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Predictor identification	Response curve estimation Residual mean square error			
			Jaccard index	BIO1	BIO13	Elevation	Total
MARS_O	1:3	Expert	**0.237**	0.92	0.73	0.547	**0.881**
MARS_O	10000	*A priori*	**0.339**	0.886	0.801	0.36	**0.821**
MARS_O	10000	Automated	**0.339**	0.94	0.832	0.32	**0.839**
MARS_O	10000	Expert	**0.339**	0.711	0.648	0.532	**0.759**
MaxEnt_B	1:1	*A priori*	**0.356**	0.388	0.357	0.32	**0.427**
MaxEnt_B	1:1	Automated	**0.356**	0.751	0.724	0.296	**0.71**
MaxEnt_B	1:1	Expert	**0.356**	0.682	0.658	0.325	**0.668**
MaxEnt_B	1:2	*A priori*	**0.424**	0.438	0.454	0.256	**0.46**
MaxEnt_B	1:2	Automated	**0.424**	0.478	0.551	0.291	**0.529**
MaxEnt_B	1:2	Expert	**0.424**	0.766	0.679	0.35	**0.72**
MaxEnt_B	1:3	*A priori*	**0.407**	0.468	0.378	0.315	**0.465**
MaxEnt_B	1:3	Automated	**0.407**	0.786	0.74	0.291	**0.728**
MaxEnt_B	1:3	Expert	**0.407**	0.801	0.704	0.365	**0.75**
MaxEnt_B	10000	*A priori*	**0.356**	0.483	0.388	0.305	**0.472**
MaxEnt_B	10000	Automated	**0.356**	0.821	0.719	0.345	**0.756**
MaxEnt_B	10000	Expert	**0.356**	0.806	0.684	0.374	**0.748**
MaxEnt_O	1:1	*A priori*	**0.136**	0.507	0.653	0.266	**0.572**
MaxEnt_O	1:1	Automated	**0.136**	0.751	0.633	0.374	**0.705**
MaxEnt_O	1:1	Expert	**0.136**	0.721	0.709	0.32	**0.702**
MaxEnt_O	1:2	*A priori*	**0.169**	0.522	0.668	0.276	**0.588**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Predictor identification Jaccard index	Response curve estimation Residual mean square error BIO1	BIO13	Elevation	Total
MaxEnt_O	1:2	Automated	**0.169**	0.697	0.73	0.291	**0.688**
MaxEnt_O	1:2	Expert	**0.169**	0.657	0.714	0.3	**0.67**
MaxEnt_O	1:3	*A priori*	**0.119**	0.498	0.673	0.271	**0.578**
MaxEnt_O	1:3	Automated	**0.119**	0.726	0.628	0.369	**0.691**
MaxEnt_O	1:3	Expert	**0.119**	0.706	0.689	0.32	**0.688**
MaxEnt_O	10000	*A priori*	**0.102**	0.512	0.638	0.286	**0.576**
MaxEnt_O	10000	Automated	**0.102**	0.756	0.694	0.325	**0.712**
MaxEnt_O	10000	Expert	**0.102**	0.736	0.663	0.355	**0.704**
MXL_O	1:1	*A priori*	**0.017**	0.662	0.587	0.384	**0.655**
MXL_O	1:1	Automated	**0.017**	0.154	0.194	0.493	**0.337**
MXL_O	1:1	Expert	**0.017**	0.846	0.827	0.187	**0.746**
MXL_O	1:2	*A priori*	**0**	0.652	0.571	0.399	**0.651**
MXL_O	1:2	Automated	**0**	0.199	0.209	0.502	**0.365**
MXL_O	1:2	Expert	**0**	0.826	0.867	0.133	**0.732**
MXL_O	1:3	*A priori*	**0.034**	0.687	0.612	0.374	**0.671**
MXL_O	1:3	Automated	**0.034**	0.189	0.209	0.453	**0.341**
MXL_O	1:3	Expert	**0.034**	0.811	0.806	0.241	**0.745**
MXL_O	10000	*A priori*	**0.051**	0.687	0.612	0.335	**0.655**
MXL_O	10000	Automated	**0.051**	0.159	0.168	0.507	**0.335**
MXL_O	10000	Expert	**0.051**	0.841	0.852	0.207	**0.762**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Predictor identification	Response curve estimation Residual mean square error			
			Jaccard index	BIO1	BIO13	Elevation	Total
RF_B	1:1	*A priori*	**0.322**	0.184	0.128	0.768	**0.433**
RF_B	1:1	Automated	**0.322**	0.134	0.173	0.458	**0.307**
RF_B	1:1	Expert	**0.322**	0.149	0.189	0.473	**0.325**
RF_B	1:2	*A priori*	**0.271**	0.463	0.546	0.33	**0.537**
RF_B	1:2	Automated	**0.271**	0.328	0.592	0.232	**0.462**
RF_B	1:2	Expert	**0.271**	0.358	0.622	0.222	**0.482**
RF_B	1:3	*A priori*	**0.237**	0.642	0.75	0.217	**0.645**
RF_B	1:3	Automated	**0.237**	0.378	0.76	0.128	**0.508**
RF_B	1:3	Expert	**0.237**	0.453	0.776	0.128	**0.544**
RF_B	10000	*A priori*	**0.186**	0.701	0.816	0.074	**0.638**
RF_B	10000	Automated	**0.186**	0.323	0.791	0.064	**0.473**
RF_B	10000	Expert	**0.186**	0.393	0.801	0.059	**0.503**
RF_O	1:1	*A priori*	**0.288**	0.149	0.173	0.547	**0.349**
RF_O	1:1	Automated	**0.288**	0.1	0.153	0.468	**0.289**
RF_O	1:1	Expert	**0.288**	0.104	0.158	0.483	**0.299**
RF_O	1:2	*A priori*	**0.22**	0.363	0.617	0.286	**0.508**
RF_O	1:2	Automated	**0.22**	0.274	0.536	0.232	**0.417**
RF_O	1:2	Expert	**0.22**	0.318	0.587	0.227	**0.454**
RF_O	1:3	*A priori*	**0.186**	0.428	0.77	0.158	**0.544**
RF_O	1:3	Automated	**0.186**	0.348	0.724	0.133	**0.484**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Predictor identification	Response curve estimation Residual mean square error			
			Jaccard index	BIO1	BIO13	Elevation	Total
RF_O	1:3	Expert	**0.186**	0.378	0.745	0.128	**0.502**
RF_O	10000	*A priori*	**0.186**	0.408	0.801	0.069	**0.512**
RF_O	10000	Automated	**0.186**	0.264	0.781	0.064	**0.444**
RF_O	10000	Expert	**0.186**	0.303	0.786	0.064	**0.462**
SRE_B	1:1	*A priori*	**0.203**	0.045	0.051	0.089	**0.074**
SRE_B	1:1	Automated	**0.203**	0.04	0.026	0.261	**0.131**
SRE_B	1:1	Expert	**0.203**	0.025	0.015	0.389	**0.172**
SRE_B	1:2	*A priori*	**0.271**	0.045	0.056	0.089	**0.076**
SRE_B	1:2	Automated	**0.271**	0.04	0.026	0.271	**0.135**
SRE_B	1:2	Expert	**0.271**	0.025	0.015	0.389	**0.172**
SRE_B	1:3	*A priori*	**0.271**	0.045	0.061	0.094	**0.08**
SRE_B	1:3	Automated	**0.271**	0.04	0.026	0.271	**0.135**
SRE_B	1:3	Expert	**0.271**	0.035	0.015	0.404	**0.182**
SRE_B	10000	*A priori*	**0.305**	0.045	0.061	0.089	**0.078**
SRE_B	10000	Automated	**0.305**	0.04	0.026	0.271	**0.135**
SRE_B	10000	Expert	**0.305**	0.025	0.015	0.394	**0.174**
SRE_O	1:1	*A priori*	**0.068**	0.816	0.98	0.025	**0.73**
SRE_O	1:1	Automated	**0.068**	0.871	0.959	0.034	**0.748**
SRE_O	1:1	Expert	**0.068**	0.886	0.929	0.054	**0.749**
SRE_O	1:2	*A priori*	**0.068**	0.816	0.985	0.025	**0.732**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Predictor identification	Response curve estimation Residual mean square error			
			Jaccard index	**BIO1**	**BIO13**	**Elevation**	**Total**
SRE_O	1:2	Automated	**0.068**	0.866	0.964	0.03	**0.746**
SRE_O	1:2	Expert	**0.068**	0.886	0.929	0.054	**0.749**
SRE_O	1:3	*A priori*	**0.068**	0.816	0.985	0.02	**0.73**
SRE_O	1:3	Automated	**0.068**	0.866	0.964	0.03	**0.746**
SRE_O	1:3	Expert	**0.068**	0.891	0.923	0.054	**0.749**
SRE_O	10000	*A priori*	**0.068**	0.816	0.985	0.02	**0.73**
SRE_O	10000	Automated	**0.068**	0.861	0.964	0.03	**0.744**
SRE_O	10000	Expert	**0.068**	0.891	0.934	0.054	**0.753**

Algorithm	Pseudo-absences	Predictor selection	Response curve estimation Spearman's correlation				Response curve estimation	Explanation
			BIO1	**BIO13**	**Elevation**	**Total**		
ANN_B	1:1	*A priori*	0.51	0.544	0.807	**0.62**	**0.541**	**0.591**
ANN_B	1:1	Automated	0.565	0.698	0.839	**0.7**	**0.61**	**0.632**
ANN_B	1:1	Expert	0.653	0.879	0.766	**0.766**	**0.653**	**0.658**
ANN_B	1:2	*A priori*	0.531	0.615	0.818	**0.655**	**0.558**	**0.652**
ANN_B	1:2	Automated	0.619	0.791	0.797	**0.736**	**0.625**	**0.691**
ANN_B	1:2	Expert	0.612	0.896	0.682	**0.73**	**0.628**	**0.693**
ANN_B	1:3	*A priori*	0.571	0.61	0.844	**0.675**	**0.584**	**0.667**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Response curve estimation Spearman's correlation				Response curve estimation	Explanation
			BIO1	BIO13	Elevation	Total		
ANN_B	1:3	Automated	0.639	0.797	0.786	**0.741**	**0.628**	**0.693**
ANN_B	1:3	Expert	0.653	0.819	0.734	**0.735**	**0.646**	**0.704**
ANN_B	10000	*A priori*	0.551	0.593	0.87	**0.671**	**0.582**	**0.676**
ANN_B	10000	Automated	0.639	0.764	0.776	**0.726**	**0.625**	**0.701**
ANN_B	10000	Expert	0.653	0.846	0.615	**0.705**	**0.628**	**0.703**
ANN_O	1:1	*A priori*	0.374	0.253	0.979	**0.535**	**0.672**	**0.538**
ANN_O	1:1	Automated	0.299	0.181	0.974	**0.485**	**0.66**	**0.531**
ANN_O	1:1	Expert	0.381	0.467	0.927	**0.592**	**0.74**	**0.579**
ANN_O	1:2	*A priori*	0.116	0.049	0.276	**0.147**	**0.448**	**0.285**
ANN_O	1:2	Automated	0.102	0.044	0.323	**0.156**	**0.459**	**0.292**
ANN_O	1:2	Expert	0.15	0.104	0.135	**0.13**	**0.444**	**0.283**
ANN_O	1:3	*A priori*	0.034	0.005	0.01	**0.017**	**0.337**	**0.169**
ANN_O	1:3	Automated	0.034	0.005	0.016	**0.018**	**0.34**	**0.171**
ANN_O	1:3	Expert	0.014	0.005	0.005	**0.008**	**0.324**	**0.162**
ANN_O	10000	*A priori*	0	0	0	**0**	**0.229**	**0.065**
ANN_O	10000	Automated	0	0	0	**0**	**0.216**	**0.058**
ANN_O	10000	Expert	0	0	0	**0**	**0.22**	**0.06**
CTA_B	1:1	*A priori*	0.259	0.22	0.24	**0.239**	**0.273**	**0.403**
CTA_B	1:1	Automated	0.286	0.253	0.266	**0.268**	**0.302**	**0.42**
CTA_B	1:1	Expert	0.293	0.28	0.286	**0.286**	**0.322**	**0.431**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Response curve estimation Spearman's correlation				Response curve estimation	Explanation
			BIO1	**BIO13**	**Elevation**	**Total**		
CTA_B	1:2	*A priori*	0.197	0.165	0.146	**0.169**	**0.22**	**0.351**
CTA_B	1:2	Automated	0.293	0.209	0.182	**0.228**	**0.265**	**0.378**
CTA_B	1:2	Expert	0.279	0.258	0.271	**0.269**	**0.311**	**0.405**
CTA_B	1:3	*A priori*	0.184	0.143	0.125	**0.151**	**0.206**	**0.313**
CTA_B	1:3	Automated	0.218	0.154	0.12	**0.164**	**0.212**	**0.317**
CTA_B	1:3	Expert	0.238	0.231	0.193	**0.221**	**0.279**	**0.356**
CTA_B	10000	*A priori*	0.143	0.099	0.062	**0.101**	**0.172**	**0.202**
CTA_B	10000	Automated	0.15	0.093	0.042	**0.095**	**0.155**	**0.192**
CTA_B	10000	Expert	0.204	0.176	0.135	**0.172**	**0.251**	**0.249**
CTA_O	1:1	*A priori*	0.619	0.407	0.573	**0.533**	**0.618**	**0.657**
CTA_O	1:1	Automated	0.639	0.429	0.448	**0.505**	**0.596**	**0.644**
CTA_O	1:1	Expert	0.639	0.473	0.474	**0.529**	**0.612**	**0.654**
CTA_O	1:2	*A priori*	0.463	0.484	0.49	**0.479**	**0.679**	**0.663**
CTA_O	1:2	Automated	0.483	0.549	0.411	**0.481**	**0.678**	**0.662**
CTA_O	1:2	Expert	0.469	0.522	0.432	**0.475**	**0.675**	**0.661**
CTA_O	1:3	*A priori*	0.422	0.5	0.51	**0.477**	**0.664**	**0.614**
CTA_O	1:3	Automated	0.442	0.538	0.453	**0.478**	**0.663**	**0.613**
CTA_O	1:3	Expert	0.476	0.56	0.438	**0.491**	**0.684**	**0.626**
CTA_O	10000	*A priori*	0.395	0.747	0.542	**0.561**	**0.704**	**0.528**
CTA_O	10000	Automated	0.388	0.758	0.458	**0.535**	**0.69**	**0.519**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Response curve estimation Spearman's correlation				Response curve estimation	Explanation
			BIO1	**BIO13**	**Elevation**	**Total**		
CTA_O	10000	Expert	0.34	0.808	0.443	**0.53**	**0.686**	**0.517**
EMca_B	1:1	*A priori*	0.034	0.027	0.036	**0.033**	**0.169**	**0.371**
EMca_B	1:1	Automated	0.048	0.071	0.141	**0.087**	**0.213**	**0.397**
EMca_B	1:1	Expert	0.061	0.088	0.12	**0.09**	**0.214**	**0.398**
EMca_B	1:2	*A priori*	0.02	0.016	0.026	**0.021**	**0.163**	**0.287**
EMca_B	1:2	Automated	0.027	0.044	0.078	**0.05**	**0.189**	**0.303**
EMca_B	1:2	Expert	0.054	0.082	0.115	**0.084**	**0.21**	**0.315**
EMca_B	1:3	*A priori*	0.02	0.027	0.047	**0.032**	**0.178**	**0.326**
EMca_B	1:3	Automated	0.034	0.049	0.089	**0.057**	**0.198**	**0.338**
EMca_B	1:3	Expert	0.054	0.066	0.094	**0.071**	**0.201**	**0.34**
EMca_B	10000	*A priori*	0.027	0.038	0.057	**0.041**	**0.194**	**0.245**
EMca_B	10000	Automated	0.034	0.049	0.089	**0.057**	**0.196**	**0.246**
EMca_B	10000	Expert	0.041	0.022	0.031	**0.031**	**0.169**	**0.231**
EMmean_B	1:1	*A priori*	0.932	0.533	0.5	**0.655**	**0.631**	**0.775**
EMmean_B	1:1	Automated	0.728	0.819	0.812	**0.786**	**0.749**	**0.845**
EMmean_B	1:1	Expert	0.816	0.824	0.792	**0.811**	**0.741**	**0.84**
EMmean_B	1:2	*A priori*	0.912	0.489	0.422	**0.607**	**0.629**	**0.824**
EMmean_B	1:2	Automated	0.279	0.984	0.854	**0.706**	**0.683**	**0.856**
EMmean_B	1:2	Expert	0.762	0.863	0.74	**0.788**	**0.756**	**0.899**
EMmean_B	1:3	*A priori*	0.898	0.462	0.406	**0.589**	**0.626**	**0.822**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Response curve estimation Spearman's correlation				Response curve estimation	Explanation
			BIO1	**BIO13**	**Elevation**	**Total**		
EMmean_B	1:3	Automated	0.633	0.687	0.651	**0.657**	**0.73**	**0.884**
EMmean_B	1:3	Expert	0.748	0.863	0.75	**0.787**	**0.824**	**0.939**
EMmean_B	10000	*A priori*	0.912	0.445	0.385	**0.581**	**0.661**	**0.833**
EMmean_B	10000	Automated	0.605	0.742	0.688	**0.678**	**0.793**	**0.911**
EMmean_B	10000	Expert	0.701	0.841	0.724	**0.755**	**0.83**	**0.933**
EMmedian_B	1:1	*A priori*	0.871	0.505	0.589	**0.655**	**0.665**	**0.805**
EMmedian_B	1:1	Automated	0.646	0.775	0.776	**0.732**	**0.72**	**0.838**
EMmedian_B	1:1	Expert	0.864	0.896	0.802	**0.854**	**0.786**	**0.877**
EMmedian_B	1:2	*A priori*	0.844	0.582	0.562	**0.663**	**0.71**	**0.872**
EMmedian_B	1:2	Automated	1	1	1	**1**	**0.576**	**0.792**
EMmedian_B	1:2	Expert	0.796	0.907	0.776	**0.826**	**0.806**	**0.929**
EMmedian_B	1:3	*A priori*	0.816	0.505	0.557	**0.626**	**0.712**	**0.873**
EMmedian_B	1:3	Automated	0.293	0.995	0.906	**0.731**	**0.713**	**0.874**
EMmedian_B	1:3	Expert	0.803	0.896	0.786	**0.828**	**0.84**	**0.949**
EMmedian_B	10000	*A priori*	0.85	0.484	0.526	**0.62**	**0.732**	**0.835**
EMmedian_B	10000	Automated	0.293	0.995	0.906	**0.731**	**0.719**	**0.828**
EMmedian_B	10000	Expert	0.796	0.901	0.776	**0.824**	**0.866**	**0.914**
EMwmean_B	1:1	*A priori*	0.925	0.527	0.505	**0.653**	**0.63**	**0.785**
EMwmean_B	1:1	Automated	0.741	0.819	0.823	**0.794**	**0.755**	**0.858**
EMwmean_B	1:1	Expert	0.816	0.813	0.781	**0.804**	**0.736**	**0.847**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Response curve estimation Spearman's correlation				Response curve estimation	Explanation
			BIO1	BIO13	Elevation	Total		
EMwmean_B	1:2	*A priori*	0.912	0.489	0.427	**0.609**	**0.63**	**0.825**
EMwmean_B	1:2	Automated	0.279	0.989	0.854	**0.707**	**0.684**	**0.857**
EMwmean_B	1:2	Expert	0.755	0.863	0.74	**0.786**	**0.754**	**0.898**
EMwmean_B	1:3	*A priori*	0.912	0.462	0.406	**0.593**	**0.627**	**0.823**
EMwmean_B	1:3	Automated	0.633	0.687	0.651	**0.657**	**0.73**	**0.884**
EMwmean_B	1:3	Expert	0.776	0.863	0.771	**0.803**	**0.837**	**0.947**
EMwmean_B	10000	*A priori*	0.905	0.44	0.385	**0.577**	**0.661**	**0.823**
EMwmean_B	10000	Automated	0.592	0.742	0.688	**0.674**	**0.79**	**0.9**
EMwmean_B	10000	Expert	0.701	0.83	0.724	**0.751**	**0.827**	**0.921**
FDA_B	1:1	*A priori*	0.789	0.67	0.698	**0.719**	**0.628**	**0.733**
FDA_B	1:1	Automated	0.918	0.923	0.688	**0.843**	**0.706**	**0.78**
FDA_B	1:1	Expert	0.857	0.885	0.688	**0.81**	**0.688**	**0.769**
FDA_B	1:2	*A priori*	0.85	0.67	0.609	**0.71**	**0.784**	**0.785**
FDA_B	1:2	Automated	0.85	0.945	0.625	**0.807**	**0.849**	**0.824**
FDA_B	1:2	Expert	0.871	0.929	0.604	**0.801**	**0.842**	**0.82**
FDA_B	1:3	*A priori*	0.884	0.654	0.599	**0.712**	**0.786**	**0.787**
FDA_B	1:3	Automated	0.85	0.934	0.573	**0.786**	**0.835**	**0.816**
FDA_B	1:3	Expert	0.918	0.918	0.703	**0.846**	**0.877**	**0.84**
FDA_B	10000	*A priori*	0.85	0.621	0.568	**0.68**	**0.788**	**0.718**
FDA_B	10000	Automated	0.85	0.736	0.583	**0.723**	**0.819**	**0.736**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Response curve estimation Spearman's correlation				Response curve estimation	Explanation
			BIO1	BIO13	Elevation	Total		
FDA_B	10000	Expert	0.918	0.923	0.615	**0.819**	**0.873**	**0.768**
FDA_O	1:1	*A priori*	0.293	0.286	0.339	**0.306**	**0.208**	**0.334**
FDA_O	1:1	Automated	0.361	0.324	0.312	**0.332**	**0.222**	**0.342**
FDA_O	1:1	Expert	0.293	0.363	0.219	**0.291**	**0.191**	**0.324**
FDA_O	1:2	*A priori*	0.293	0.291	0.333	**0.306**	**0.212**	**0.276**
FDA_O	1:2	Automated	0.347	0.33	0.292	**0.323**	**0.216**	**0.278**
FDA_O	1:2	Expert	0.286	0.363	0.188	**0.279**	**0.185**	**0.26**
FDA_O	1:3	*A priori*	0.293	0.286	0.339	**0.306**	**0.212**	**0.306**
FDA_O	1:3	Automated	0.299	0.335	0.224	**0.286**	**0.191**	**0.294**
FDA_O	1:3	Expert	0.293	0.352	0.203	**0.282**	**0.187**	**0.291**
FDA_O	10000	*A priori*	0.293	0.297	0.323	**0.304**	**0.21**	**0.355**
FDA_O	10000	Automated	0.299	0.341	0.224	**0.288**	**0.192**	**0.345**
FDA_O	10000	Expert	0.286	0.357	0.177	**0.273**	**0.182**	**0.339**
GAM_B	1:1	*A priori*	0.66	0.396	0.417	**0.491**	**0.571**	**0.729**
GAM_B	1:1	Automated	0.639	0.665	0.562	**0.622**	**0.688**	**0.799**
GAM_B	1:1	Expert	0.741	0.731	0.62	**0.697**	**0.756**	**0.839**
GAM_B	1:2	*A priori*	0.585	0.39	0.349	**0.441**	**0.534**	**0.668**
GAM_B	1:2	Automated	0.599	0.659	0.552	**0.603**	**0.671**	**0.748**
GAM_B	1:2	Expert	0.599	0.725	0.547	**0.624**	**0.699**	**0.765**
GAM_B	1:3	*A priori*	0.544	0.374	0.328	**0.415**	**0.512**	**0.634**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Response curve estimation Spearman's correlation				Response curve estimation	Explanation
			BIO1	**BIO13**	**Elevation**	**Total**		
GAM_B	1:3	Automated	0.442	0.577	0.479	**0.499**	**0.58**	**0.674**
GAM_B	1:3	Expert	0.612	0.692	0.594	**0.633**	**0.708**	**0.751**
GAM_B	10000	*A priori*	0.49	0.346	0.297	**0.378**	**0.487**	**0.529**
GAM_B	10000	Automated	0.497	0.588	0.51	**0.532**	**0.623**	**0.61**
GAM_B	10000	Expert	0.524	0.643	0.536	**0.568**	**0.666**	**0.635**
GAM_O	1:1	*A priori*	0.741	0.764	0.969	**0.825**	**0.803**	**0.777**
GAM_O	1:1	Automated	0.769	0.879	0.979	**0.876**	**0.887**	**0.826**
GAM_O	1:1	Expert	0.816	0.907	0.943	**0.889**	**0.742**	**0.74**
GAM_O	1:2	*A priori*	0.844	0.742	0.964	**0.85**	**0.782**	**0.905**
GAM_O	1:2	Automated	0.83	0.852	0.979	**0.887**	**0.807**	**0.919**
GAM_O	1:2	Expert	0.939	0.89	0.943	**0.924**	**0.76**	**0.892**
GAM_O	1:3	*A priori*	0.884	0.676	0.969	**0.843**	**0.746**	**0.894**
GAM_O	1:3	Automated	0.952	0.819	0.943	**0.905**	**0.734**	**0.886**
GAM_O	1:3	Expert	0.959	0.857	0.948	**0.921**	**0.75**	**0.896**
GAM_O	10000	*A priori*	0.959	0.604	0.969	**0.844**	**0.716**	**0.896**
GAM_O	10000	Automated	0.986	0.786	0.953	**0.908**	**0.733**	**0.906**
GAM_O	10000	Expert	0.98	0.775	0.958	**0.904**	**0.733**	**0.906**
GBM_B	1:1	*A priori*	0.912	0.434	0.484	**0.61**	**0.571**	**0.509**
GBM_B	1:1	Automated	0.85	0.758	0.573	**0.727**	**0.618**	**0.537**
GBM_B	1:1	Expert	0.728	0.709	0.766	**0.734**	**0.648**	**0.554**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Response curve estimation Spearman's correlation				Response curve estimation	Explanation
			BIO1	**BIO13**	**Elevation**	**Total**		
GBM_B	1:2	*A priori*	0.946	0.451	0.495	**0.63**	**0.581**	**0.515**
GBM_B	1:2	Automated	0.85	0.797	0.625	**0.757**	**0.633**	**0.545**
GBM_B	1:2	Expert	0.741	0.747	0.776	**0.755**	**0.662**	**0.563**
GBM_B	1:3	*A priori*	0.973	0.434	0.531	**0.646**	**0.597**	**0.554**
GBM_B	1:3	Automated	0.918	0.764	0.635	**0.773**	**0.642**	**0.581**
GBM_B	1:3	Expert	0.782	0.747	0.828	**0.786**	**0.687**	**0.608**
GBM_B	10000	*A priori*	0.966	0.418	0.521	**0.635**	**0.586**	**0.508**
GBM_B	10000	Automated	0.905	0.775	0.661	**0.78**	**0.64**	**0.539**
GBM_B	10000	Expert	0.769	0.747	0.812	**0.776**	**0.673**	**0.559**
GBM_O	1:1	*A priori*	0.782	0.758	0.922	**0.821**	**0.906**	**0.857**
GBM_O	1:1	Automated	0.816	0.874	0.88	**0.857**	**1**	**0.913**
GBM_O	1:1	Expert	0.993	0.484	0.958	**0.812**	**0.7**	**0.736**
GBM_O	1:2	*A priori*	0.728	0.758	0.76	**0.749**	**0.925**	**0.889**
GBM_O	1:2	Automated	0.837	0.835	0.677	**0.783**	**0.91**	**0.88**
GBM_O	1:2	Expert	0.993	0.516	0.943	**0.817**	**0.712**	**0.763**
GBM_O	1:3	*A priori*	0.694	0.879	0.865	**0.813**	**0.949**	**0.933**
GBM_O	1:3	Automated	0.81	0.879	0.667	**0.785**	**0.9**	**0.904**
GBM_O	1:3	Expert	0.769	0.896	0.719	**0.794**	**0.907**	**0.908**
GBM_O	10000	*A priori*	0.653	0.912	0.849	**0.805**	**0.901**	**0.915**
GBM_O	10000	Automated	0.728	0.923	0.677	**0.776**	**0.871**	**0.897**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Response curve estimation Spearman's correlation				Response curve estimation	Explanation
			BIO1	BIO13	Elevation	Total		
GBM_O	10000	Expert	0.694	0.94	0.719	**0.784**	**0.878**	**0.901**
GLM_B	1:1	*A priori*	0.687	0.72	0.708	**0.705**	**0.766**	**0.916**
GLM_B	1:1	Automated	0.871	0.967	0.901	**0.913**	**0.909**	**1**
GLM_B	1:1	Expert	0.85	0.956	0.911	**0.906**	**0.901**	**0.996**
GLM_B	1:2	*A priori*	0.701	0.703	0.609	**0.671**	**0.745**	**0.893**
GLM_B	1:2	Automated	0.864	0.973	0.875	**0.904**	**0.9**	**0.985**
GLM_B	1:2	Expert	0.878	0.962	0.88	**0.906**	**0.89**	**0.979**
GLM_B	1:3	*A priori*	0.823	0.703	0.599	**0.708**	**0.763**	**0.894**
GLM_B	1:3	Automated	0.871	0.962	0.891	**0.908**	**0.909**	**0.98**
GLM_B	1:3	Expert	0.891	0.962	0.917	**0.923**	**0.915**	**0.984**
GLM_B	10000	*A priori*	0.898	0.681	0.568	**0.716**	**0.77**	**0.877**
GLM_B	10000	Automated	0.844	0.978	0.88	**0.901**	**0.952**	**0.986**
GLM_B	10000	Expert	0.844	0.962	0.885	**0.897**	**0.936**	**0.976**
GLM_O	1:1	*A priori*	0.435	0.456	0.62	**0.504**	**0.441**	**0.211**
GLM_O	1:1	Automated	0.537	0.714	0.776	**0.676**	**0.581**	**0.294**
GLM_O	1:1	Expert	0.844	0.962	0.896	**0.9**	**0.856**	**0.457**
GLM_O	1:2	*A priori*	0.503	0.495	0.62	**0.539**	**0.391**	**0.231**
GLM_O	1:2	Automated	0.707	0.901	0.802	**0.804**	**0.686**	**0.406**
GLM_O	1:2	Expert	0.878	0.962	0.859	**0.899**	**0.853**	**0.505**
GLM_O	1:3	*A priori*	0.619	0.566	0.672	**0.619**	**0.404**	**0.34**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Response curve estimation Spearman's correlation				Response curve estimation	Explanation
			BIO1	**BIO13**	**Elevation**	**Total**		
GLM_O	1:3	Automated	0.844	0.901	0.812	**0.852**	**0.648**	**0.484**
GLM_O	1:3	Expert	0.85	0.951	0.849	**0.883**	**0.762**	**0.552**
GLM_O	10000	*A priori*	0.707	0.599	0.719	**0.675**	**0.428**	**0.474**
GLM_O	10000	Automated	0.884	0.934	0.839	**0.886**	**0.648**	**0.605**
GLM_O	10000	Expert	0.898	0.945	0.833	**0.892**	**0.73**	**0.653**
MARS_B	1:1	*A priori*	0.558	0.511	0.656	**0.575**	**0.641**	**0.66**
MARS_B	1:1	Automated	0.796	0.764	0.714	**0.758**	**0.775**	**0.74**
MARS_B	1:1	Expert	0.728	0.78	0.677	**0.728**	**0.745**	**0.722**
MARS_B	1:2	*A priori*	0.626	0.571	0.656	**0.618**	**0.693**	**0.721**
MARS_B	1:2	Automated	0.707	0.742	0.693	**0.714**	**0.764**	**0.763**
MARS_B	1:2	Expert	0.735	0.769	0.729	**0.744**	**0.754**	**0.758**
MARS_B	1:3	*A priori*	0.701	0.544	0.656	**0.634**	**0.704**	**0.708**
MARS_B	1:3	Automated	0.653	0.648	0.646	**0.649**	**0.717**	**0.716**
MARS_B	1:3	Expert	0.776	0.753	0.755	**0.761**	**0.769**	**0.746**
MARS_B	10000	*A priori*	0.667	0.571	0.656	**0.631**	**0.731**	**0.704**
MARS_B	10000	Automated	0.673	0.637	0.677	**0.663**	**0.748**	**0.714**
MARS_B	10000	Expert	0.83	0.747	0.76	**0.779**	**0.804**	**0.747**
MARS_O	1:1	*A priori*	0.721	0.659	0.776	**0.719**	**0.807**	**0.538**
MARS_O	1:1	Automated	0.769	0.758	0.745	**0.757**	**0.893**	**0.589**
MARS_O	1:1	Expert	0.81	0.868	0.641	**0.773**	**0.856**	**0.567**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Response curve estimation Spearman's correlation				Response curve estimation	Explanation
			BIO1	**BIO13**	**Elevation**	**Total**		
MARS_O	1:2	*A priori*	0.769	0.709	0.677	**0.718**	**0.793**	**0.5**
MARS_O	1:2	Automated	0.782	0.802	0.625	**0.737**	**0.854**	**0.536**
MARS_O	1:2	Expert	0.83	0.901	0.578	**0.77**	**0.889**	**0.556**
MARS_O	1:3	*A priori*	0.796	0.676	0.63	**0.701**	**0.747**	**0.463**
MARS_O	1:3	Automated	0.83	0.747	0.604	**0.727**	**0.857**	**0.528**
MARS_O	1:3	Expert	0.837	0.879	0.573	**0.763**	**0.881**	**0.542**
MARS_O	10000	*A priori*	0.796	0.626	0.542	**0.655**	**0.783**	**0.544**
MARS_O	10000	Automated	0.83	0.687	0.51	**0.676**	**0.806**	**0.557**
MARS_O	10000	Expert	0.871	0.879	0.51	**0.753**	**0.812**	**0.561**
MaxEnt_B	1:1	*A priori*	0.354	0.236	0.229	**0.273**	**0.346**	**0.295**
MaxEnt_B	1:1	Automated	0.483	0.412	0.339	**0.411**	**0.577**	**0.432**
MaxEnt_B	1:1	Expert	0.497	0.484	0.401	**0.46**	**0.585**	**0.437**
MaxEnt_B	1:2	*A priori*	0.293	0.187	0.151	**0.21**	**0.324**	**0.322**
MaxEnt_B	1:2	Automated	0.401	0.368	0.302	**0.357**	**0.45**	**0.397**
MaxEnt_B	1:2	Expert	0.619	0.714	0.469	**0.601**	**0.698**	**0.544**
MaxEnt_B	1:3	*A priori*	0.429	0.264	0.26	**0.318**	**0.393**	**0.353**
MaxEnt_B	1:3	Automated	0.517	0.478	0.391	**0.462**	**0.617**	**0.486**
MaxEnt_B	1:3	Expert	0.68	0.747	0.516	**0.648**	**0.743**	**0.56**
MaxEnt_B	10000	*A priori*	0.415	0.264	0.208	**0.296**	**0.383**	**0.317**
MaxEnt_B	10000	Automated	0.728	0.665	0.677	**0.69**	**0.772**	**0.547**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Response curve estimation Spearman's correlation				Response curve estimation	Explanation
			BIO1	BIO13	Elevation	Total		
MaxEnt_B	10000	Expert	0.782	0.874	0.547	**0.734**	**0.795**	**0.561**
MaxEnt_O	1:1	*A priori*	0.306	0.269	0.344	**0.306**	**0.441**	**0.221**
MaxEnt_O	1:1	Automated	0.728	0.632	0.604	**0.655**	**0.724**	**0.389**
MaxEnt_O	1:1	Expert	0.408	0.495	0.354	**0.419**	**0.577**	**0.302**
MaxEnt_O	1:2	*A priori*	0.327	0.28	0.339	**0.315**	**0.455**	**0.249**
MaxEnt_O	1:2	Automated	0.456	0.401	0.464	**0.44**	**0.583**	**0.325**
MaxEnt_O	1:2	Expert	0.367	0.423	0.292	**0.361**	**0.525**	**0.291**
MaxEnt_O	1:3	*A priori*	0.32	0.275	0.339	**0.311**	**0.447**	**0.214**
MaxEnt_O	1:3	Automated	0.694	0.626	0.604	**0.641**	**0.709**	**0.37**
MaxEnt_O	1:3	Expert	0.449	0.555	0.396	**0.467**	**0.599**	**0.305**
MaxEnt_O	10000	*A priori*	0.333	0.286	0.359	**0.326**	**0.455**	**0.209**
MaxEnt_O	10000	Automated	0.578	0.505	0.573	**0.552**	**0.664**	**0.333**
MaxEnt_O	10000	Expert	0.592	0.665	0.464	**0.573**	**0.673**	**0.338**
MXL_O	1:1	*A priori*	0.714	0.313	0.99	**0.672**	**0.709**	**0.31**
MXL_O	1:1	Automated	0.272	0.319	0.333	**0.308**	**0.321**	**0.08**
MXL_O	1:1	Expert	0.891	0.819	0.938	**0.882**	**0.885**	**0.414**
MXL_O	1:2	*A priori*	0.673	0.308	0.995	**0.659**	**0.699**	**0.293**
MXL_O	1:2	Automated	0.306	0.379	0.38	**0.355**	**0.365**	**0.096**
MXL_O	1:2	Expert	0.816	0.879	0.932	**0.876**	**0.875**	**0.397**
MXL_O	1:3	*A priori*	0.639	0.302	0.995	**0.645**	**0.701**	**0.315**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Response curve estimation Spearman's correlation				Response curve estimation	Explanation
			BIO1	BIO13	Elevation	Total		
MXL_O	1:3	Automated	0.306	0.385	0.375	**0.355**	**0.353**	**0.109**
MXL_O	1:3	Expert	0.837	0.802	0.943	**0.861**	**0.872**	**0.416**
MXL_O	10000	*A priori*	0.653	0.313	0.984	**0.65**	**0.696**	**0.322**
MXL_O	10000	Automated	0.299	0.385	0.365	**0.35**	**0.346**	**0.114**
MXL_O	10000	Expert	0.816	0.764	0.943	**0.841**	**0.868**	**0.424**
RF_B	1:1	*A priori*	0.313	0.192	0.245	**0.25**	**0.335**	**0.269**
RF_B	1:1	Automated	0.231	0.242	0.302	**0.258**	**0.275**	**0.233**
RF_B	1:1	Expert	0.265	0.253	0.318	**0.279**	**0.297**	**0.246**
RF_B	1:2	*A priori*	0.245	0.148	0.109	**0.168**	**0.337**	**0.24**
RF_B	1:2	Automated	0.17	0.198	0.219	**0.196**	**0.316**	**0.227**
RF_B	1:2	Expert	0.204	0.225	0.255	**0.228**	**0.347**	**0.245**
RF_B	1:3	*A priori*	0.211	0.121	0.073	**0.135**	**0.373**	**0.241**
RF_B	1:3	Automated	0.15	0.17	0.167	**0.162**	**0.319**	**0.209**
RF_B	1:3	Expert	0.17	0.198	0.234	**0.201**	**0.361**	**0.234**
RF_B	10000	*A priori*	0.116	0.077	0.021	**0.071**	**0.33**	**0.185**
RF_B	10000	Automated	0.109	0.11	0.083	**0.101**	**0.263**	**0.146**
RF_B	10000	Expert	0.136	0.126	0.104	**0.122**	**0.292**	**0.163**
RF_O	1:1	*A priori*	0.231	0.242	0.37	**0.281**	**0.311**	**0.234**
RF_O	1:1	Automated	0.224	0.225	0.281	**0.244**	**0.257**	**0.202**
RF_O	1:1	Expert	0.252	0.247	0.307	**0.269**	**0.278**	**0.215**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Response curve estimation Spearman's correlation BIO1	BIO13	Elevation	Total	Response curve estimation	Explanation
RF_O	1:2	*A priori*	0.177	0.203	0.302	**0.227**	**0.359**	**0.223**
RF_O	1:2	Automated	0.163	0.181	0.198	**0.181**	**0.284**	**0.178**
RF_O	1:2	Expert	0.19	0.214	0.25	**0.218**	**0.326**	**0.203**
RF_O	1:3	*A priori*	0.156	0.176	0.266	**0.199**	**0.36**	**0.203**
RF_O	1:3	Automated	0.15	0.159	0.167	**0.159**	**0.304**	**0.17**
RF_O	1:3	Expert	0.163	0.181	0.214	**0.186**	**0.331**	**0.186**
RF_O	10000	*A priori*	0.122	0.137	0.172	**0.144**	**0.31**	**0.174**
RF_O	10000	Automated	0.116	0.115	0.094	**0.108**	**0.253**	**0.14**
RF_O	10000	Expert	0.129	0.132	0.13	**0.13**	**0.276**	**0.153**
SRE_B	1:1	*A priori*	0.007	0.005	0.005	**0.006**	**0**	**0**
SRE_B	1:1	Automated	0.068	0.011	0.047	**0.042**	**0.051**	**0.03**
SRE_B	1:1	Expert	0.075	0.027	0.047	**0.05**	**0.077**	**0.046**
SRE_B	1:2	*A priori*	0.007	0.005	0.005	**0.006**	**0.001**	**0.041**
SRE_B	1:2	Automated	0.068	0.016	0.052	**0.046**	**0.056**	**0.073**
SRE_B	1:2	Expert	0.075	0.027	0.052	**0.051**	**0.079**	**0.087**
SRE_B	1:3	*A priori*	0.007	0.005	0.005	**0.006**	**0.003**	**0.042**
SRE_B	1:3	Automated	0.068	0.016	0.052	**0.046**	**0.056**	**0.073**
SRE_B	1:3	Expert	0.082	0.033	0.068	**0.061**	**0.089**	**0.093**
SRE_B	10000	*A priori*	0.007	0.005	0.005	**0.006**	**0.002**	**0.061**
SRE_B	10000	Automated	0.068	0.016	0.052	**0.046**	**0.056**	**0.093**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Response curve estimation Spearman's correlation				Response curve estimation	Explanation
			BIO1	BIO13	Elevation	Total		
SRE_B	10000	Expert	0.075	0.027	0.052	**0.051**	**0.08**	**0.107**
SRE_O	1:1	*A priori*	0.054	0.038	0.099	**0.064**	**0.372**	**0.14**
SRE_O	1:1	Automated	0.068	0.049	0.094	**0.07**	**0.385**	**0.148**
SRE_O	1:1	Expert	0.095	0.055	0.156	**0.102**	**0.406**	**0.16**
SRE_O	1:2	*A priori*	0.054	0.038	0.099	**0.064**	**0.373**	**0.141**
SRE_O	1:2	Automated	0.068	0.049	0.099	**0.072**	**0.385**	**0.148**
SRE_O	1:2	Expert	0.088	0.055	0.151	**0.098**	**0.403**	**0.159**
SRE_O	1:3	*A priori*	0.054	0.038	0.104	**0.066**	**0.373**	**0.141**
SRE_O	1:3	Automated	0.068	0.049	0.099	**0.072**	**0.385**	**0.148**
SRE_O	1:3	Expert	0.095	0.06	0.156	**0.104**	**0.407**	**0.161**
SRE_O	10000	*A priori*	0.054	0.038	0.104	**0.066**	**0.373**	**0.141**
SRE_O	10000	Automated	0.068	0.049	0.094	**0.07**	**0.383**	**0.147**
SRE_O	10000	Expert	0.095	0.06	0.161	**0.106**	**0.41**	**0.163**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Continuous Boyce index				Mean absolute error			
			Train	Test	Fit	Calibration	Train	Test	Fit	Bias
ANN_B	1:1	*A priori*	0.243	0.261	0.364	**0.239**	0.305	0.327	0.351	**0.25**
ANN_B	1:1	Automated	0.463	0.728	0.663	**0.595**	0.385	0.353	0.253	**0.253**
ANN_B	1:1	Expert	0.667	0.383	0.158	**0.361**	0.412	0.167	0.011	**0.099**
ANN_B	1:2	*A priori*	0.243	0.189	0.239	**0.167**	0.299	0.314	0.351	**0.243**
ANN_B	1:2	Automated	0.525	0.617	0.478	**0.511**	0.374	0.231	0.086	**0.138**
ANN_B	1:2	Expert	0.582	0.444	0.277	**0.396**	0.444	0.179	0.017	**0.119**
ANN_B	1:3	*A priori*	0.249	0.272	0.332	**0.233**	0.305	0.301	0.31	**0.224**
ANN_B	1:3	Automated	0.48	0.55	0.435	**0.455**	0.358	0.218	0.069	**0.121**
ANN_B	1:3	Expert	0.616	0.478	0.283	**0.422**	0.439	0.205	0.023	**0.129**
ANN_B	10000	*A priori*	0.198	0.267	0.435	**0.25**	0.31	0.288	0.305	**0.219**
ANN_B	10000	Automated	0.458	0.55	0.457	**0.454**	0.353	0.218	0.092	**0.127**
ANN_B	10000	Expert	0.627	0.417	0.212	**0.379**	0.401	0.186	0.017	**0.105**
ANN_O	1:1	*A priori*	0.186	0.372	0.592	**0.341**	0.963	0.936	0.914	**0.95**
ANN_O	1:1	Automated	0.158	0.344	0.658	**0.344**	0.968	0.962	0.92	**0.964**
ANN_O	1:1	Expert	0.621	0.683	0.582	**0.607**	0.968	0.865	0.471	**0.756**
ANN_O	1:2	*A priori*	0.085	0.183	0.745	**0.291**	0.668	0.756	0.626	**0.659**
ANN_O	1:2	Automated	0.079	0.3	0.848	**0.368**	0.674	0.769	0.621	**0.664**
ANN_O	1:2	Expert	0.282	0.328	0.625	**0.371**	0.668	0.699	0.213	**0.478**
ANN_O	1:3	*A priori*	0.045	0.1	0.891	**0.299**	0.364	0.66	0.362	**0.404**
ANN_O	1:3	Automated	0.04	0.133	0.902	**0.313**	0.364	0.66	0.345	**0.398**

Table B2.5 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Probability of occurrence**							
			Continuous Boyce index				**Mean absolute error**			
			Train	**Test**	**Fit**	**Calibration**	**Train**	**Test**	**Fit**	**Bias**
ANN_O	1:3	Expert	0.051	0.061	0.87	**0.28**	0.064	0.545	0	**0.107**
ANN_O	10000	*A priori*	0.011	0.039	0.989	**0.301**	0.118	0.571	0.029	**0.148**
ANN_O	10000	Automated	0	0.028	0.995	**0.294**	0.096	0.564	0.017	**0.133**
ANN_O	10000	Expert	0.006	0.033	0.989	**0.296**	0.091	0.558	0.006	**0.124**
CTA_B	1:1	*A priori*	0.141	0.256	0.549	**0.267**	0.257	0.192	0.282	**0.153**
CTA_B	1:1	Automated	0.147	0.467	0.707	**0.402**	0.273	0.173	0.19	**0.117**
CTA_B	1:1	Expert	0.175	0.494	0.734	**0.432**	0.294	0.199	0.178	**0.131**
CTA_B	1:2	*A priori*	0.136	0.233	0.582	**0.268**	0.225	0.147	0.27	**0.119**
CTA_B	1:2	Automated	0.181	0.178	0.337	**0.176**	0.262	0.154	0.184	**0.103**
CTA_B	1:2	Expert	0.169	0.283	0.505	**0.271**	0.289	0.186	0.195	**0.13**
CTA_B	1:3	*A priori*	0.124	0.072	0.332	**0.116**	0.182	0.135	0.282	**0.103**
CTA_B	1:3	Automated	0.186	0.061	0.136	**0.063**	0.219	0.122	0.167	**0.068**
CTA_B	1:3	Expert	0.186	0.283	0.457	**0.26**	0.273	0.167	0.161	**0.103**
CTA_B	10000	*A priori*	0.13	0.083	0.288	**0.106**	0.16	0.115	0.282	**0.087**
CTA_B	10000	Automated	0.203	0	0.005	**0**	0.16	0.096	0.201	**0.049**
CTA_B	10000	Expert	0.158	0.139	0.342	**0.156**	0.246	0.141	0.172	**0.088**
CTA_O	1:1	*A priori*	0.655	0.933	0.815	**0.794**	0.92	0.84	0.747	**0.833**
CTA_O	1:1	Automated	0.616	0.917	0.815	**0.774**	0.925	0.846	0.724	**0.829**
CTA_O	1:1	Expert	0.723	0.944	0.859	**0.839**	0.947	0.84	0.69	**0.822**
CTA_O	1:2	*A priori*	0.831	0.978	0.918	**0.911**	0.807	0.769	0.787	**0.779**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Continuous Boyce index				Mean absolute error			
			Train	Test	Fit	Calibration	Train	Test	Fit	Bias
CTA_O	1:2	Automated	0.938	0.989	0.957	**0.968**	0.824	0.769	0.736	**0.765**
CTA_O	1:2	Expert	0.921	0.972	0.929	**0.946**	0.824	0.763	0.73	**0.76**
CTA_O	1:3	*A priori*	0.955	0.994	0.967	**0.98**	0.749	0.705	0.885	**0.769**
CTA_O	1:3	Automated	1	0.994	0.973	**0.998**	0.765	0.705	0.851	**0.762**
CTA_O	1:3	Expert	0.927	0.983	0.962	**0.964**	0.824	0.763	0.73	**0.76**
CTA_O	10000	*A priori*	0.904	0.967	0.94	**0.942**	0.578	0.667	0.845	**0.673**
CTA_O	10000	Automated	0.989	1	0.984	**1**	0.572	0.667	0.839	**0.669**
CTA_O	10000	Expert	0.96	1	0.978	**0.988**	0.561	0.673	0.799	**0.652**
EMca_B	1:1	*A priori*	0.616	0.489	0.168	**0.385**	0	0	0.408	**0.03**
EMca_B	1:1	Automated	0.452	0.683	0.473	**0.506**	0.043	0.038	0.569	**0.123**
EMca_B	1:1	Expert	0.582	0.578	0.261	**0.438**	0.027	0.019	0.54	**0.098**
EMca_B	1:2	*A priori*	0.266	0.772	0.462	**0.467**	0.005	0	0.391	**0.025**
EMca_B	1:2	Automated	0.39	0.239	0.685	**0.4**	0.032	0.019	0.494	**0.082**
EMca_B	1:2	Expert	0.565	0.667	0.37	**0.504**	0.027	0.019	0.534	**0.096**
EMca_B	1:3	*A priori*	0.853	0.911	0.842	**0.868**	0.005	0	0.402	**0.03**
EMca_B	1:3	Automated	0.582	0.606	0.674	**0.598**	0.037	0.019	0.575	**0.115**
EMca_B	1:3	Expert	0.684	0.939	0.701	**0.765**	0.021	0.013	0.477	**0.069**
EMca_B	10000	*A priori*	0.192	0.511	0.065	**0.202**	0.011	0.006	0.408	**0.036**
EMca_B	10000	Automated	0.627	0.683	0.44	**0.558**	0.043	0.045	0.592	**0.134**
EMca_B	10000	Expert	0.588	0.078	0.087	**0.197**	0.016	0	0.351	**0.014**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Continuous Boyce index				Mean absolute error			
			Train	Test	Fit	Calibration	Train	Test	Fit	Bias
EMmean_B	1:1	*A priori*	0.734	0.461	0.212	**0.434**	0.342	0.417	0.425	**0.327**
EMmean_B	1:1	Automated	0.881	0.833	0.717	**0.804**	0.615	0.385	0.132	**0.307**
EMmean_B	1:1	Expert	0.864	0.833	0.717	**0.798**	0.599	0.359	0.063	**0.265**
EMmean_B	1:2	*A priori*	0.644	0.539	0.348	**0.478**	0.316	0.442	0.563	**0.379**
EMmean_B	1:2	Automated	0.588	0.95	0.94	**0.821**	0.61	0.526	0.414	**0.467**
EMmean_B	1:2	Expert	0.859	0.844	0.728	**0.804**	0.583	0.385	0.149	**0.301**
EMmean_B	1:3	*A priori*	0.576	0.594	0.418	**0.499**	0.305	0.462	0.649	**0.416**
EMmean_B	1:3	Automated	0.847	0.806	0.63	**0.751**	0.561	0.442	0.259	**0.357**
EMmean_B	1:3	Expert	0.887	0.878	0.772	**0.842**	0.572	0.417	0.19	**0.325**
EMmean_B	10000	*A priori*	0.514	0.589	0.451	**0.487**	0.294	0.455	0.69	**0.425**
EMmean_B	10000	Automated	0.802	0.822	0.696	**0.764**	0.551	0.462	0.328	**0.387**
EMmean_B	10000	Expert	0.847	0.867	0.755	**0.818**	0.54	0.429	0.236	**0.335**
EMmedian_B	1:1	*A priori*	0.633	0.211	0.054	**0.249**	0.294	0.34	0.391	**0.266**
EMmedian_B	1:1	Automated	0.859	0.822	0.69	**0.782**	0.519	0.34	0.098	**0.24**
EMmedian_B	1:1	Expert	0.853	0.733	0.522	**0.687**	0.513	0.276	0.034	**0.189**
EMmedian_B	1:2	*A priori*	0.52	0.228	0.092	**0.228**	0.267	0.321	0.5	**0.29**
EMmedian_B	1:2	Automated	0.706	0.956	0.924	**0.86**	0.524	0.494	0.414	**0.422**
EMmedian_B	1:2	Expert	0.876	0.8	0.609	**0.751**	0.476	0.295	0.08	**0.2**
EMmedian_B	1:3	*A priori*	0.525	0.367	0.158	**0.304**	0.241	0.321	0.575	**0.309**
EMmedian_B	1:3	Automated	0.712	0.961	0.935	**0.868**	0.481	0.487	0.414	**0.403**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Continuous Boyce index				Mean absolute error			
			Train	**Test**	**Fit**	**Calibration**	**Train**	**Test**	**Fit**	**Bias**
EMmedian_B	1:3	Expert	0.898	0.761	0.543	**0.722**	0.46	0.301	0.109	**0.207**
EMmedian_B	10000	*A priori*	0.429	0.283	0.125	**0.228**	0.219	0.263	0.54	**0.265**
EMmedian_B	10000	Automated	0.712	0.967	0.951	**0.876**	0.433	0.468	0.414	**0.377**
EMmedian_B	10000	Expert	0.87	0.783	0.587	**0.735**	0.428	0.288	0.103	**0.187**
EMwmean_B	1:1	*A priori*	0.734	0.439	0.179	**0.414**	0.348	0.423	0.431	**0.334**
EMwmean_B	1:1	Automated	0.881	0.839	0.723	**0.808**	0.62	0.385	0.132	**0.309**
EMwmean_B	1:1	Expert	0.864	0.828	0.712	**0.794**	0.604	0.365	0.063	**0.269**
EMwmean_B	1:2	*A priori*	0.655	0.506	0.299	**0.453**	0.316	0.442	0.557	**0.377**
EMwmean_B	1:2	Automated	0.593	0.95	0.94	**0.823**	0.61	0.526	0.414	**0.467**
EMwmean_B	1:2	Expert	0.864	0.833	0.717	**0.798**	0.588	0.391	0.155	**0.308**
EMwmean_B	1:3	*A priori*	0.571	0.589	0.408	**0.491**	0.316	0.462	0.638	**0.415**
EMwmean_B	1:3	Automated	0.825	0.817	0.652	**0.754**	0.561	0.442	0.259	**0.357**
EMwmean_B	1:3	Expert	0.87	0.883	0.777	**0.84**	0.572	0.417	0.195	**0.327**
EMwmean_B	10000	*A priori*	0.52	0.567	0.429	**0.473**	0.294	0.449	0.678	**0.418**
EMwmean_B	10000	Automated	0.825	0.8	0.62	**0.737**	0.545	0.462	0.322	**0.382**
EMwmean_B	10000	Expert	0.847	0.872	0.761	**0.822**	0.535	0.429	0.241	**0.335**
FDA_B	1:1	*A priori*	0.446	0.006	0	**0.088**	0.321	0.288	0.27	**0.21**
FDA_B	1:1	Automated	0.486	0.217	0.098	**0.214**	0.508	0.282	0.04	**0.192**
FDA_B	1:1	Expert	0.582	0.4	0.174	**0.343**	0.508	0.288	0.057	**0.201**
FDA_B	1:2	*A priori*	0.209	0.017	0.022	**0.014**	0.289	0.538	0.96	**0.558**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Continuous Boyce index				Mean absolute error			
			Train	Test	Fit	Calibration	Train	Test	Fit	Bias
FDA_B	1:2	Automated	0.215	0.35	0.489	**0.306**	0.556	0.564	0.713	**0.575**
FDA_B	1:2	Expert	0.288	0.306	0.288	**0.243**	0.572	0.551	0.655	**0.555**
FDA_B	1:3	*A priori*	0.186	0.161	0.272	**0.149**	0.267	0.583	0.621	**0.437**
FDA_B	1:3	Automated	0.107	0.561	0.87	**0.481**	0.481	0.641	0.989	**0.682**
FDA_B	1:3	Expert	0.186	0.394	0.62	**0.359**	0.513	0.609	0.937	**0.662**
FDA_B	10000	*A priori*	0.215	0.728	0.875	**0.582**	0.225	0.654	0.362	**0.349**
FDA_B	10000	Automated	0.237	0.839	0.908	**0.642**	0.385	0.66	0.862	**0.604**
FDA_B	10000	Expert	0.102	0.706	0.897	**0.541**	0.439	0.66	0.902	**0.64**
FDA_O	1:1	*A priori*	0	0.022	1	**0.294**	0.663	0.635	0.684	**0.632**
FDA_O	1:1	Automated	0	0.022	1	**0.294**	0.679	0.59	0.287	**0.469**
FDA_O	1:1	Expert	0	0.022	1	**0.294**	0.69	0.622	0.333	**0.503**
FDA_O	1:2	*A priori*	0	0.022	1	**0.294**	0.663	0.641	0.672	**0.63**
FDA_O	1:2	Automated	0	0.022	1	**0.294**	0.679	0.596	0.293	**0.474**
FDA_O	1:2	Expert	0	0.022	1	**0.294**	0.684	0.628	0.339	**0.506**
FDA_O	1:3	*A priori*	0	0.022	1	**0.294**	0.663	0.641	0.678	**0.633**
FDA_O	1:3	Automated	0	0.022	1	**0.294**	0.684	0.615	0.316	**0.492**
FDA_O	1:3	Expert	0	0.022	1	**0.294**	0.69	0.622	0.328	**0.501**
FDA_O	10000	*A priori*	0	0.022	1	**0.294**	0.663	0.647	0.69	**0.639**
FDA_O	10000	Automated	0	0.022	1	**0.294**	0.684	0.615	0.316	**0.492**
FDA_O	10000	Expert	0	0.022	1	**0.294**	0.684	0.628	0.339	**0.506**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Continuous Boyce index				Mean absolute error			
			Train	Test	Fit	Calibration	Train	Test	Fit	Bias
GAM_B	1:1	*A priori*	0.486	0.178	0.076	**0.192**	0.251	0.288	0.471	**0.261**
GAM_B	1:1	Automated	0.605	0.244	0.103	**0.269**	0.358	0.256	0.121	**0.155**
GAM_B	1:1	Expert	0.452	0.411	0.315	**0.351**	0.471	0.327	0.126	**0.227**
GAM_B	1:2	*A priori*	0.311	0.217	0.158	**0.172**	0.203	0.34	0.701	**0.35**
GAM_B	1:2	Automated	0.486	0.367	0.217	**0.312**	0.369	0.295	0.172	**0.194**
GAM_B	1:2	Expert	0.328	0.444	0.462	**0.371**	0.487	0.378	0.207	**0.284**
GAM_B	1:3	*A priori*	0.345	0.183	0.12	**0.159**	0.209	0.34	0.701	**0.352**
GAM_B	1:3	Automated	0.254	0.578	0.679	**0.471**	0.358	0.372	0.276	**0.259**
GAM_B	1:3	Expert	0.26	0.461	0.549	**0.384**	0.476	0.397	0.241	**0.3**
GAM_B	10000	*A priori*	0.271	0.117	0.082	**0.094**	0.193	0.34	0.713	**0.35**
GAM_B	10000	Automated	0.277	0.239	0.201	**0.184**	0.337	0.353	0.287	**0.248**
GAM_B	10000	Expert	0.243	0.389	0.495	**0.332**	0.465	0.404	0.259	**0.305**
GAM_O	1:1	*A priori*	0.017	0.778	0.446	**0.373**	0.781	0.955	0.46	**0.714**
GAM_O	1:1	Automated	0	0.739	0.44	**0.351**	0.888	1	0.46	**0.772**
GAM_O	1:1	Expert	0.384	0.828	0.842	**0.668**	0.925	0.949	0.96	**0.959**
GAM_O	1:2	*A priori*	0.073	0.6	0.668	**0.41**	0.866	0.974	0.713	**0.851**
GAM_O	1:2	Automated	0.028	0.672	0.745	**0.447**	0.936	1	0.695	**0.881**
GAM_O	1:2	Expert	0.435	0.811	0.788	**0.661**	0.882	0.878	0.977	**0.922**
GAM_O	1:3	*A priori*	0.102	0.578	0.647	**0.404**	0.877	0.968	0.741	**0.864**
GAM_O	1:3	Automated	0.65	0.683	0.582	**0.617**	0.797	0.795	0.983	**0.859**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Continuous Boyce index				Mean absolute error			
			Train	Test	Fit	Calibration	Train	Test	Fit	Bias
GAM_O	1:3	Expert	0.571	0.711	0.62	**0.612**	0.829	0.833	0.994	**0.891**
GAM_O	10000	*A priori*	0.113	0.422	0.793	**0.405**	0.85	0.91	0.81	**0.858**
GAM_O	10000	Automated	0.819	0.55	0.326	**0.538**	0.77	0.776	0.994	**0.846**
GAM_O	10000	Expert	0.808	0.533	0.304	**0.52**	0.775	0.782	1	**0.853**
GBM_B	1:1	*A priori*	0.808	0.283	0.054	**0.339**	0.647	0.538	0.397	**0.479**
GBM_B	1:1	Automated	0.689	0.694	0.527	**0.616**	0.594	0.462	0.236	**0.368**
GBM_B	1:1	Expert	0.774	0.75	0.571	**0.682**	0.652	0.526	0.322	**0.448**
GBM_B	1:2	*A priori*	0.763	0.178	0.033	**0.277**	0.636	0.526	0.385	**0.466**
GBM_B	1:2	Automated	0.718	0.733	0.565	**0.654**	0.588	0.449	0.23	**0.359**
GBM_B	1:2	Expert	0.864	0.717	0.505	**0.679**	0.652	0.513	0.328	**0.445**
GBM_B	1:3	*A priori*	0.825	0.172	0.027	**0.295**	0.626	0.519	0.379	**0.457**
GBM_B	1:3	Automated	0.729	0.733	0.554	**0.654**	0.578	0.436	0.23	**0.35**
GBM_B	1:3	Expert	0.842	0.661	0.424	**0.622**	0.642	0.5	0.316	**0.432**
GBM_B	10000	*A priori*	0.78	0.144	0.011	**0.263**	0.567	0.487	0.356	**0.414**
GBM_B	10000	Automated	0.74	0.756	0.603	**0.684**	0.529	0.41	0.207	**0.313**
GBM_B	10000	Expert	0.814	0.656	0.402	**0.602**	0.631	0.481	0.299	**0.414**
GBM_O	1:1	*A priori*	0.661	0.472	0.283	**0.437**	1	0.994	0.948	**1**
GBM_O	1:1	Automated	0.746	0.9	0.837	**0.823**	0.995	0.981	0.891	**0.971**
GBM_O	1:1	Expert	0.972	0.233	0.038	**0.374**	0.995	0.987	0.902	**0.978**
GBM_O	1:2	*A priori*	0.576	0.622	0.484	**0.533**	0.989	0.987	0.925	**0.985**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Continuous Boyce index				Mean absolute error			
			Train	Test	Fit	Calibration	Train	Test	Fit	Bias
GBM_O	1:2	Automated	0.701	0.906	0.87	**0.82**	0.979	0.897	0.822	**0.907**
GBM_O	1:2	Expert	0.983	0.228	0.038	**0.376**	0.989	0.955	0.764	**0.911**
GBM_O	1:3	*A priori*	0.508	0.694	0.636	**0.59**	0.984	0.968	0.914	**0.971**
GBM_O	1:3	Automated	0.65	0.906	0.875	**0.804**	0.952	0.859	0.799	**0.873**
GBM_O	1:3	Expert	0.734	0.906	0.864	**0.831**	0.957	0.859	0.787	**0.87**
GBM_O	10000	*A priori*	0.305	0.761	0.804	**0.601**	0.909	0.872	0.943	**0.916**
GBM_O	10000	Automated	0.559	0.928	0.908	**0.791**	0.856	0.795	0.816	**0.818**
GBM_O	10000	Expert	0.751	0.917	0.88	**0.847**	0.866	0.808	0.805	**0.823**
GLM_B	1:1	*A priori*	0.695	0.05	0.005	**0.196**	0.193	0.231	0.5	**0.227**
GLM_B	1:1	Automated	0.944	0.65	0.359	**0.631**	0.508	0.288	0.057	**0.201**
GLM_B	1:1	Expert	0.91	0.544	0.255	**0.543**	0.519	0.288	0.04	**0.198**
GLM_B	1:2	*A priori*	0.61	0.106	0.011	**0.187**	0.198	0.231	0.5	**0.229**
GLM_B	1:2	Automated	0.898	0.711	0.489	**0.684**	0.492	0.288	0.057	**0.194**
GLM_B	1:2	Expert	0.932	0.661	0.391	**0.643**	0.508	0.288	0.046	**0.196**
GLM_B	1:3	*A priori*	0.644	0.117	0.033	**0.212**	0.209	0.237	0.489	**0.231**
GLM_B	1:3	Automated	0.898	0.656	0.402	**0.632**	0.497	0.288	0.057	**0.196**
GLM_B	1:3	Expert	0.949	0.589	0.293	**0.587**	0.503	0.288	0.057	**0.199**
GLM_B	10000	*A priori*	0.531	0.089	0.022	**0.157**	0.198	0.218	0.46	**0.209**
GLM_B	10000	Automated	0.898	0.7	0.467	**0.672**	0.471	0.301	0.092	**0.204**
GLM_B	10000	Expert	0.915	0.683	0.435	**0.66**	0.471	0.288	0.075	**0.193**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Continuous Boyce index				Mean absolute error			
			Train	Test	Fit	Calibration	Train	Test	Fit	Bias
GLM_O	1:1	*A priori*	0.638	0.517	0.69	**0.592**	0.171	0.474	0.224	**0.207**
GLM_O	1:1	Automated	0.294	0.611	0.87	**0.567**	0.209	0.532	0.195	**0.232**
GLM_O	1:1	Expert	0.966	0.894	0.766	**0.875**	0.406	0.724	0.224	**0.392**
GLM_O	1:2	*A priori*	0.429	0.339	0.359	**0.332**	0.123	0.346	0.264	**0.154**
GLM_O	1:2	Automated	0.655	0.761	0.946	**0.779**	0.422	0.686	0.247	**0.393**
GLM_O	1:2	Expert	0.977	0.889	0.755	**0.873**	0.636	0.795	0.391	**0.571**
GLM_O	1:3	*A priori*	0.599	0.356	0.337	**0.392**	0.107	0.231	0.368	**0.144**
GLM_O	1:3	Automated	0.768	0.867	0.886	**0.837**	0.508	0.647	0.483	**0.501**
GLM_O	1:3	Expert	0.989	0.85	0.685	**0.838**	0.658	0.769	0.523	**0.62**
GLM_O	10000	*A priori*	0.746	0.206	0.228	**0.351**	0.07	0.096	0.46	**0.113**
GLM_O	10000	Automated	0.898	0.861	0.891	**0.884**	0.503	0.577	0.58	**0.509**
GLM_O	10000	Expert	0.994	0.806	0.56	**0.778**	0.711	0.769	0.718	**0.716**
MARS_B	1:1	*A priori*	0.672	0.194	0.049	**0.256**	0.219	0.256	0.471	**0.236**
MARS_B	1:1	Automated	0.859	0.422	0.147	**0.441**	0.396	0.25	0.052	**0.141**
MARS_B	1:1	Expert	0.785	0.522	0.261	**0.492**	0.455	0.282	0.063	**0.18**
MARS_B	1:2	*A priori*	0.492	0.122	0.043	**0.162**	0.225	0.244	0.454	**0.227**
MARS_B	1:2	Automated	0.842	0.744	0.533	**0.691**	0.417	0.308	0.144	**0.206**
MARS_B	1:2	Expert	0.791	0.628	0.375	**0.574**	0.471	0.295	0.092	**0.202**
MARS_B	1:3	*A priori*	0.525	0.089	0.033	**0.159**	0.23	0.256	0.46	**0.236**
MARS_B	1:3	Automated	0.825	0.528	0.261	**0.508**	0.39	0.288	0.138	**0.186**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Continuous Boyce index				Mean absolute error			
			Train	Test	Fit	Calibration	Train	Test	Fit	Bias
MARS_B	1:3	Expert	0.893	0.572	0.277	**0.555**	0.449	0.269	0.063	**0.173**
MARS_B	10000	*A priori*	0.475	0.111	0.038	**0.15**	0.209	0.212	0.42	**0.195**
MARS_B	10000	Automated	0.836	0.361	0.109	**0.397**	0.38	0.288	0.144	**0.184**
MARS_B	10000	Expert	0.831	0.45	0.196	**0.459**	0.406	0.231	0.04	**0.133**
MARS_O	1:1	*A priori*	0.164	0.622	0.81	**0.502**	0.845	0.891	0.839	**0.86**
MARS_O	1:1	Automated	0.186	0.733	0.88	**0.576**	0.941	0.942	0.931	**0.951**
MARS_O	1:1	Expert	0.797	0.789	0.614	**0.72**	0.973	0.936	0.851	**0.93**
MARS_O	1:2	*A priori*	0.198	0.689	0.842	**0.55**	0.829	0.885	0.868	**0.862**
MARS_O	1:2	Automated	0.09	0.678	0.88	**0.521**	0.872	0.853	0.96	**0.901**
MARS_O	1:2	Expert	0.554	0.856	0.821	**0.731**	0.93	0.923	0.862	**0.913**
MARS_O	1:3	*A priori*	0.119	0.556	0.696	**0.42**	0.77	0.853	0.782	**0.794**
MARS_O	1:3	Automated	0.096	0.65	0.853	**0.503**	0.898	0.968	0.828	**0.905**
MARS_O	1:3	Expert	0.616	0.872	0.826	**0.762**	0.957	0.981	0.885	**0.955**
MARS_O	10000	*A priori*	0.09	0.672	0.799	**0.489**	0.818	0.929	0.592	**0.769**
MARS_O	10000	Automated	0.056	0.722	0.777	**0.487**	0.818	0.917	0.701	**0.806**
MARS_O	10000	Expert	0.362	0.922	0.913	**0.719**	0.893	0.955	0.833	**0.9**
MaxEnt_B	1:1	*A priori*	0.345	0.361	0.332	**0.3**	0.08	0.083	0.46	**0.112**
MaxEnt_B	1:1	Automated	0.282	0.167	0.13	**0.134**	0.15	0.077	0.103	**0**
MaxEnt_B	1:1	Expert	0.282	0.344	0.337	**0.273**	0.182	0.096	0.115	**0.024**
MaxEnt_B	1:2	*A priori*	0.282	0.372	0.37	**0.295**	0.075	0.071	0.552	**0.141**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Continuous Boyce index				Mean absolute error			
			Train	Test	Fit	Calibration	Train	Test	Fit	Bias
MaxEnt_B	1:2	Automated	0.333	0.4	0.364	**0.322**	0.139	0.096	0.218	**0.047**
MaxEnt_B	1:2	Expert	0.412	0.278	0.163	**0.233**	0.214	0.103	0.092	**0.03**
MaxEnt_B	1:3	*A priori*	0.316	0.317	0.266	**0.25**	0.086	0.09	0.632	**0.183**
MaxEnt_B	1:3	Automated	0.339	0.044	0.027	**0.073**	0.144	0.09	0.132	**0.014**
MaxEnt_B	1:3	Expert	0.418	0.183	0.098	**0.177**	0.209	0.096	0.075	**0.019**
MaxEnt_B	10000	*A priori*	0.322	0.183	0.114	**0.149**	0.091	0.096	0.667	**0.2**
MaxEnt_B	10000	Automated	0.446	0.017	0	**0.092**	0.176	0.096	0.121	**0.024**
MaxEnt_B	10000	Expert	0.469	0.183	0.071	**0.186**	0.225	0.096	0.04	**0.012**
MaxEnt_O	1:1	*A priori*	0.288	0.156	0.141	**0.136**	0.701	0.699	0.73	**0.689**
MaxEnt_O	1:1	Automated	0.407	0.406	0.31	**0.33**	0.866	0.756	0.5	**0.686**
MaxEnt_O	1:1	Expert	0.339	0.289	0.261	**0.246**	0.845	0.75	0.517	**0.682**
MaxEnt_O	1:2	*A priori*	0.367	0.178	0.152	**0.177**	0.711	0.705	0.764	**0.709**
MaxEnt_O	1:2	Automated	0.299	0.183	0.163	**0.158**	0.802	0.718	0.5	**0.647**
MaxEnt_O	1:2	Expert	0.328	0.333	0.359	**0.293**	0.824	0.744	0.489	**0.661**
MaxEnt_O	1:3	*A priori*	0.282	0.189	0.217	**0.174**	0.695	0.699	0.776	**0.704**
MaxEnt_O	1:3	Automated	0.395	0.378	0.283	**0.307**	0.856	0.75	0.529	**0.691**
MaxEnt_O	1:3	Expert	0.35	0.294	0.245	**0.246**	0.845	0.737	0.506	**0.673**
MaxEnt_O	10000	*A priori*	0.356	0.222	0.223	**0.214**	0.722	0.712	0.753	**0.711**
MaxEnt_O	10000	Automated	0.379	0.25	0.179	**0.217**	0.834	0.731	0.546	**0.682**
MaxEnt_O	10000	Expert	0.373	0.294	0.234	**0.25**	0.861	0.75	0.489	**0.677**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Continuous Boyce index				Mean absolute error			
			Train	Test	Fit	Calibration	Train	Test	Fit	Bias
MXL_O	1:1	*A priori*	0.119	0.15	0.516	**0.208**	0.754	0.712	0.885	**0.774**
MXL_O	1:1	Automated	0.226	0.711	0.832	**0.564**	0.743	0.827	0.661	**0.728**
MXL_O	1:1	Expert	0.203	0.211	0.397	**0.218**	0.722	0.679	0.443	**0.58**
MXL_O	1:2	*A priori*	0.124	0.194	0.576	**0.248**	0.765	0.712	0.862	**0.769**
MXL_O	1:2	Automated	0.22	0.644	0.783	**0.521**	0.743	0.808	0.764	**0.76**
MXL_O	1:2	Expert	0.147	0.317	0.489	**0.269**	0.663	0.673	0.408	**0.541**
MXL_O	1:3	*A priori*	0.136	0.139	0.457	**0.189**	0.759	0.718	0.879	**0.776**
MXL_O	1:3	Automated	0.243	0.656	0.788	**0.535**	0.738	0.788	0.759	**0.749**
MXL_O	1:3	Expert	0.232	0.361	0.489	**0.316**	0.727	0.705	0.46	**0.598**
MXL_O	10000	*A priori*	0.119	0.094	0.413	**0.151**	0.749	0.705	0.874	**0.765**
MXL_O	10000	Automated	0.243	0.633	0.75	**0.513**	0.743	0.801	0.77	**0.76**
MXL_O	10000	Expert	0.153	0.322	0.549	**0.295**	0.706	0.692	0.448	**0.581**
RF_B	1:1	*A priori*	0.734	0.128	0.016	**0.242**	0.316	0.506	0.856	**0.516**
RF_B	1:1	Automated	0.588	0.444	0.25	**0.388**	0.332	0.487	0.73	**0.467**
RF_B	1:1	Expert	0.542	0.794	0.717	**0.668**	0.326	0.468	0.644	**0.424**
RF_B	1:2	*A priori*	0.571	0.178	0.043	**0.211**	0.187	0.353	0.77	**0.375**
RF_B	1:2	Automated	0.548	0.5	0.353	**0.431**	0.241	0.333	0.586	**0.318**
RF_B	1:2	Expert	0.537	0.694	0.614	**0.592**	0.235	0.276	0.511	**0.265**
RF_B	1:3	*A priori*	0.548	0.2	0.06	**0.217**	0.128	0.218	0.793	**0.31**
RF_B	1:3	Automated	0.452	0.556	0.467	**0.458**	0.155	0.224	0.609	**0.252**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Continuous Boyce index				Mean absolute error			
			Train	Test	Fit	Calibration	Train	Test	Fit	Bias
RF_B	1:3	Expert	0.667	0.65	0.462	**0.568**	0.134	0.167	0.437	**0.156**
RF_B	10000	*A priori*	0.463	0.311	0.136	**0.254**	0.102	0.128	0.885	**0.3**
RF_B	10000	Automated	0.497	0.611	0.5	**0.506**	0.123	0.16	0.707	**0.253**
RF_B	10000	Expert	0.757	0.522	0.261	**0.482**	0.112	0.109	0.5	**0.15**
RF_O	1:1	*A priori*	0.503	0.4	0.207	**0.326**	0.904	0.917	0.954	**0.936**
RF_O	1:1	Automated	0.463	0.428	0.31	**0.359**	0.914	0.904	0.971	**0.942**
RF_O	1:1	Expert	0.678	0.689	0.538	**0.614**	0.914	0.878	0.914	**0.91**
RF_O	1:2	*A priori*	0.446	0.433	0.321	**0.359**	0.813	0.84	0.954	**0.872**
RF_O	1:2	Automated	0.418	0.456	0.386	**0.38**	0.845	0.827	0.966	**0.883**
RF_O	1:2	Expert	0.655	0.767	0.641	**0.671**	0.84	0.814	0.897	**0.85**
RF_O	1:3	*A priori*	0.424	0.483	0.402	**0.398**	0.775	0.821	0.931	**0.841**
RF_O	1:3	Automated	0.441	0.422	0.332	**0.357**	0.791	0.801	0.989	**0.862**
RF_O	1:3	Expert	0.616	0.733	0.609	**0.633**	0.786	0.769	0.908	**0.817**
RF_O	10000	*A priori*	0.401	0.639	0.582	**0.511**	0.717	0.756	0.862	**0.768**
RF_O	10000	Automated	0.429	0.656	0.598	**0.533**	0.743	0.75	0.943	**0.806**
RF_O	10000	Expert	0.644	0.583	0.38	**0.506**	0.733	0.712	0.96	**0.794**
SRE_B	1:1	*A priori*	0	0.022	1	**0.294**	0.053	0.045	0.42	**0.072**
SRE_B	1:1	Automated	0	0.022	1	**0.294**	0.037	0.032	0.615	**0.136**
SRE_B	1:1	Expert	0	0.022	1	**0.294**	0.048	0.064	0.477	**0.099**
SRE_B	1:2	*A priori*	0	0.022	1	**0.294**	0.053	0.045	0.414	**0.07**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Continuous Boyce index				Mean absolute error			
			Train	Test	Fit	Calibration	Train	Test	Fit	Bias
SRE_B	1:2	Automated	0	0.022	1	**0.294**	0.037	0.032	0.592	**0.127**
SRE_B	1:2	Expert	0	0.022	1	**0.294**	0.053	0.058	0.466	**0.094**
SRE_B	1:3	*A priori*	0	0.022	1	**0.294**	0.048	0.045	0.414	**0.068**
SRE_B	1:3	Automated	0	0.022	1	**0.294**	0.037	0.026	0.598	**0.127**
SRE_B	1:3	Expert	0	0.022	1	**0.294**	0.059	0.051	0.46	**0.092**
SRE_B	10000	*A priori*	0	0.022	1	**0.294**	0.048	0.045	0.414	**0.068**
SRE_B	10000	Automated	0	0.022	1	**0.294**	0.037	0.038	0.603	**0.134**
SRE_B	10000	Expert	0	0.022	1	**0.294**	0.059	0.051	0.46	**0.092**
SRE_O	1:1	*A priori*	0.034	0.067	0.723	**0.222**	0.166	0.583	0.374	**0.303**
SRE_O	1:1	Automated	0.023	0.017	0.527	**0.129**	0.235	0.603	0.477	**0.377**
SRE_O	1:1	Expert	0.062	0	0.158	**0.004**	0.278	0.622	0.603	**0.449**
SRE_O	1:2	*A priori*	0.04	0.056	0.652	**0.195**	0.166	0.583	0.374	**0.303**
SRE_O	1:2	Automated	0.023	0.006	0.489	**0.112**	0.235	0.596	0.471	**0.372**
SRE_O	1:2	Expert	0.068	0	0.185	**0.016**	0.283	0.622	0.592	**0.447**
SRE_O	1:3	*A priori*	0.04	0.067	0.739	**0.23**	0.166	0.583	0.374	**0.303**
SRE_O	1:3	Automated	0.023	0.011	0.511	**0.121**	0.235	0.603	0.471	**0.375**
SRE_O	1:3	Expert	0.062	0	0.234	**0.031**	0.283	0.622	0.603	**0.451**
SRE_O	10000	*A priori*	0.04	0.1	0.761	**0.25**	0.166	0.583	0.374	**0.303**
SRE_O	10000	Automated	0.023	0	0.446	**0.094**	0.235	0.603	0.471	**0.375**
SRE_O	10000	Expert	0.062	0	0.19	**0.016**	0.283	0.622	0.603	**0.451**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Associated skill score				Brier Score			
			Train	Test	Fit	Skill	Train	Test	Fit	Forecast Accuracy
ANN_B	1:1	*A priori*	0.67	0.69	0.781	**0.721**	0.521	0.521	0.639	**0.557**
ANN_B	1:1	Automated	0.742	0.807	0.683	**0.752**	0.574	0.574	0.417	**0.517**
ANN_B	1:1	Expert	0.758	0.608	0.361	**0.581**	0.32	0.32	0.028	**0.209**
ANN_B	1:2	*A priori*	0.67	0.684	0.781	**0.719**	0.521	0.521	0.661	**0.564**
ANN_B	1:2	Automated	0.737	0.655	0.481	**0.631**	0.432	0.432	0.106	**0.313**
ANN_B	1:2	Expert	0.768	0.626	0.372	**0.594**	0.355	0.355	0.033	**0.235**
ANN_B	1:3	*A priori*	0.68	0.684	0.743	**0.71**	0.521	0.521	0.594	**0.541**
ANN_B	1:3	Automated	0.727	0.632	0.454	**0.61**	0.414	0.414	0.1	**0.298**
ANN_B	1:3	Expert	0.768	0.632	0.399	**0.605**	0.379	0.379	0.061	**0.261**
ANN_B	10000	*A priori*	0.686	0.684	0.716	**0.702**	0.491	0.491	0.556	**0.508**
ANN_B	10000	Automated	0.722	0.637	0.486	**0.621**	0.414	0.414	0.106	**0.3**
ANN_B	10000	Expert	0.747	0.62	0.393	**0.593**	0.355	0.355	0.056	**0.243**
ANN_O	1:1	*A priori*	0.387	0.404	0.322	**0.374**	0.893	0.893	0.722	**0.841**
ANN_O	1:1	Automated	0.289	0.327	0.295	**0.306**	0.959	0.959	0.761	**0.899**
ANN_O	1:1	Expert	0.268	0.205	0.109	**0.195**	0.686	0.686	0.078	**0.478**
ANN_O	1:2	*A priori*	0.345	0.363	0.311	**0.342**	0.314	0.314	0.383	**0.327**
ANN_O	1:2	Automated	0.041	0.099	0.098	**0.079**	0.349	0.349	0.383	**0.351**
ANN_O	1:2	Expert	0.026	0.076	0.087	**0.062**	0.195	0.195	0.028	**0.123**
ANN_O	1:3	*A priori*	0.33	0.386	0.279	**0.334**	0.101	0.101	0.161	**0.104**
ANN_O	1:3	Automated	0.015	0.041	0.027	**0.026**	0.101	0.101	0.122	**0.091**

Table B2.5 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Probability of occurrence**							
			Associated skill score				**Brier Score**			
			Train	**Test**	**Fit**	**Skill**	**Train**	**Test**	**Fit**	**Forecast Accuracy**
ANN_O	1:3	Expert	0.01	0.023	0.033	**0.02**	0.077	0.077	0.006	**0.034**
ANN_O	10000	*A priori*	0.407	0.462	0.29	**0.389**	0.041	0.041	0.011	**0.012**
ANN_O	10000	Automated	0.005	0.012	0.005	**0.006**	0.036	0.036	0.006	**0.006**
ANN_O	10000	Expert	0	0.006	0	**0**	0.03	0.03	0	**0**
CTA_B	1:1	*A priori*	0.588	0.579	0.738	**0.641**	0.438	0.438	0.628	**0.496**
CTA_B	1:1	Automated	0.634	0.573	0.623	**0.616**	0.396	0.396	0.361	**0.376**
CTA_B	1:1	Expert	0.665	0.596	0.601	**0.627**	0.408	0.408	0.306	**0.365**
CTA_B	1:2	*A priori*	0.541	0.561	0.71	**0.61**	0.414	0.414	0.644	**0.485**
CTA_B	1:2	Automated	0.598	0.567	0.623	**0.602**	0.373	0.373	0.344	**0.354**
CTA_B	1:2	Expert	0.649	0.591	0.634	**0.631**	0.414	0.414	0.35	**0.384**
CTA_B	1:3	*A priori*	0.521	0.55	0.743	**0.61**	0.385	0.385	0.7	**0.484**
CTA_B	1:3	Automated	0.552	0.544	0.617	**0.576**	0.337	0.337	0.406	**0.351**
CTA_B	1:3	Expert	0.624	0.573	0.596	**0.603**	0.391	0.391	0.339	**0.364**
CTA_B	10000	*A priori*	0.515	0.526	0.743	**0.601**	0.349	0.349	0.717	**0.466**
CTA_B	10000	Automated	0.51	0.52	0.667	**0.571**	0.272	0.272	0.45	**0.321**
CTA_B	10000	Expert	0.577	0.556	0.628	**0.593**	0.361	0.361	0.383	**0.359**
CTA_O	1:1	*A priori*	0.376	0.351	0.328	**0.354**	0.527	0.527	0.383	**0.473**
CTA_O	1:1	Automated	0.253	0.187	0.262	**0.235**	0.515	0.515	0.328	**0.446**
CTA_O	1:1	Expert	0.258	0.181	0.257	**0.233**	0.497	0.497	0.25	**0.407**
CTA_O	1:2	*A priori*	0.32	0.322	0.607	**0.419**	0.314	0.314	0.489	**0.363**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence: Associated skill score: Train	Test	Fit	Skill	Brier Score: Train	Test	Fit	Forecast Accuracy
CTA_O	1:2	Automated	0.108	0.105	0.508	**0.242**	0.314	0.314	0.439	**0.346**
CTA_O	1:2	Expert	0.113	0.105	0.448	**0.223**	0.32	0.32	0.428	**0.346**
CTA_O	1:3	*A priori*	0.278	0.275	0.557	**0.373**	0.201	0.201	0.728	**0.368**
CTA_O	1:3	Automated	0.046	0.094	0.23	**0.123**	0.201	0.201	0.656	**0.343**
CTA_O	1:3	Expert	0.108	0.105	0.432	**0.216**	0.308	0.308	0.422	**0.336**
CTA_O	10000	*A priori*	0.103	0.175	0.12	**0.133**	0.136	0.136	0.328	**0.186**
CTA_O	10000	Automated	0.021	0.076	0.049	**0.047**	0.148	0.148	0.156	**0.135**
CTA_O	10000	Expert	0.021	0.076	0.038	**0.044**	0.154	0.154	0.289	**0.185**
EMca_B	1:1	*A priori*	0.433	0.468	0.705	**0.54**	0.012	0.012	0.628	**0.203**
EMca_B	1:1	Automated	0.464	0.503	0.814	**0.599**	0.112	0.112	0.667	**0.286**
EMca_B	1:1	Expert	0.464	0.497	0.825	**0.601**	0.077	0.077	0.678	**0.265**
EMca_B	1:2	*A priori*	0.443	0.468	0.727	**0.551**	0.024	0.024	0.694	**0.234**
EMca_B	1:2	Automated	0.464	0.497	0.836	**0.605**	0.083	0.083	0.7	**0.277**
EMca_B	1:2	Expert	0.464	0.497	0.874	**0.618**	0.077	0.077	0.744	**0.288**
EMca_B	1:3	*A priori*	0.448	0.468	0.738	**0.557**	0.03	0.03	0.7	**0.24**
EMca_B	1:3	Automated	0.464	0.497	0.852	**0.61**	0.095	0.095	0.711	**0.289**
EMca_B	1:3	Expert	0.459	0.474	0.842	**0.597**	0.047	0.047	0.683	**0.247**
EMca_B	10000	*A priori*	0.448	0.468	0.803	**0.579**	0.03	0.03	0.611	**0.21**
EMca_B	10000	Automated	0.464	0.503	0.863	**0.616**	0.124	0.124	0.728	**0.315**
EMca_B	10000	Expert	0.438	0.468	0.76	**0.56**	0.018	0.018	0.533	**0.175**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Associated skill score				Brier Score			
			Train	Test	Fit	Skill	Train	Test	Fit	Forecast Accuracy
EMmean_B	1:1	*A priori*	0.716	0.883	0.869	**0.832**	0.769	0.769	0.811	**0.786**
EMmean_B	1:1	Automated	0.948	0.86	0.536	**0.789**	0.716	0.716	0.233	**0.551**
EMmean_B	1:1	Expert	0.918	0.83	0.464	**0.745**	0.633	0.633	0.139	**0.462**
EMmean_B	1:2	*A priori*	0.701	0.895	0.945	**0.856**	0.787	0.787	0.917	**0.835**
EMmean_B	1:2	Automated	0.948	0.953	0.77	**0.9**	0.911	0.911	0.567	**0.8**
EMmean_B	1:2	Expert	0.907	0.854	0.536	**0.774**	0.675	0.675	0.222	**0.519**
EMmean_B	1:3	*A priori*	0.701	0.918	0.951	**0.866**	0.822	0.822	0.956	**0.873**
EMmean_B	1:3	Automated	0.933	0.889	0.628	**0.826**	0.746	0.746	0.311	**0.599**
EMmean_B	1:3	Expert	0.912	0.877	0.568	**0.794**	0.698	0.698	0.256	**0.547**
EMmean_B	10000	*A priori*	0.691	0.901	0.934	**0.851**	0.757	0.757	0.85	**0.792**
EMmean_B	10000	Automated	0.943	0.912	0.661	**0.848**	0.781	0.781	0.394	**0.652**
EMmean_B	10000	Expert	0.866	0.877	0.585	**0.784**	0.698	0.698	0.272	**0.553**
EMmedian_B	1:1	*A priori*	0.675	0.784	0.869	**0.784**	0.651	0.651	0.806	**0.703**
EMmedian_B	1:1	Automated	0.84	0.813	0.503	**0.726**	0.609	0.609	0.172	**0.457**
EMmedian_B	1:1	Expert	0.82	0.713	0.421	**0.658**	0.521	0.521	0.094	**0.37**
EMmedian_B	1:2	*A priori*	0.629	0.801	0.934	**0.797**	0.669	0.669	0.928	**0.757**
EMmedian_B	1:2	Automated	0.845	0.947	0.803	**0.875**	0.893	0.893	0.583	**0.794**
EMmedian_B	1:2	Expert	0.82	0.778	0.486	**0.702**	0.58	0.58	0.161	**0.433**
EMmedian_B	1:3	*A priori*	0.603	0.813	0.918	**0.786**	0.68	0.68	0.933	**0.767**
EMmedian_B	1:3	Automated	0.83	0.942	0.776	**0.858**	0.882	0.882	0.567	**0.78**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Associated skill score				Brier Score			
			Train	Test	Fit	Skill	Train	Test	Fit	Forecast Accuracy
EMmedian_B	1:3	Expert	0.825	0.784	0.497	**0.709**	0.604	0.604	0.189	**0.459**
EMmedian_B	10000	*A priori*	0.593	0.76	0.94	**0.772**	0.621	0.621	0.856	**0.7**
EMmedian_B	10000	Automated	0.814	0.93	0.77	**0.847**	0.864	0.864	0.561	**0.766**
EMmedian_B	10000	Expert	0.814	0.766	0.486	**0.696**	0.556	0.556	0.161	**0.417**
EMwmean_B	1:1	*A priori*	0.716	0.883	0.874	**0.833**	0.775	0.775	0.817	**0.792**
EMwmean_B	1:1	Automated	0.954	0.86	0.536	**0.791**	0.728	0.728	0.233	**0.56**
EMwmean_B	1:1	Expert	0.923	0.836	0.47	**0.751**	0.639	0.639	0.144	**0.468**
EMwmean_B	1:2	*A priori*	0.701	0.895	0.945	**0.856**	0.793	0.793	0.928	**0.843**
EMwmean_B	1:2	Automated	0.948	0.953	0.77	**0.9**	0.911	0.911	0.567	**0.8**
EMwmean_B	1:2	Expert	0.912	0.86	0.541	**0.779**	0.686	0.686	0.228	**0.529**
EMwmean_B	1:3	*A priori*	0.701	0.918	0.956	**0.868**	0.828	0.828	0.961	**0.879**
EMwmean_B	1:3	Automated	0.938	0.889	0.628	**0.827**	0.746	0.746	0.317	**0.6**
EMwmean_B	1:3	Expert	0.912	0.877	0.574	**0.796**	0.704	0.704	0.261	**0.553**
EMwmean_B	10000	*A priori*	0.696	0.901	0.929	**0.851**	0.757	0.757	0.844	**0.79**
EMwmean_B	10000	Automated	0.948	0.912	0.656	**0.848**	0.799	0.799	0.4	**0.666**
EMwmean_B	10000	Expert	0.866	0.877	0.59	**0.786**	0.698	0.698	0.278	**0.555**
FDA_B	1:1	*A priori*	0.686	0.667	0.699	**0.691**	0.479	0.479	0.55	**0.498**
FDA_B	1:1	Automated	0.778	0.661	0.41	**0.622**	0.426	0.426	0.067	**0.295**
FDA_B	1:1	Expert	0.794	0.684	0.432	**0.643**	0.456	0.456	0.089	**0.323**
FDA_B	1:2	*A priori*	0.66	0.959	0.765	**0.803**	0.876	0.876	0.717	**0.827**

Table B2.5 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Probability of occurrence**							
			Associated skill score				**Brier Score**			
			Train	**Test**	**Fit**	**Skill**	**Train**	**Test**	**Fit**	**Forecast Accuracy**
FDA_B	1:2	Automated	0.964	0.971	0.863	**0.943**	0.97	0.97	0.706	**0.888**
FDA_B	1:2	Expert	0.969	0.965	0.842	**0.935**	0.964	0.964	0.661	**0.869**
FDA_B	1:3	*A priori*	0.639	0.977	0.492	**0.71**	0.953	0.953	0.483	**0.8**
FDA_B	1:3	Automated	0.979	0.988	0.973	**0.991**	0.994	0.994	0.983	**1**
FDA_B	1:3	Expert	0.985	0.982	1	**1**	0.988	0.988	0.972	**0.992**
FDA_B	10000	*A priori*	0.613	0.994	0.366	**0.665**	0.982	0.982	0.244	**0.738**
FDA_B	10000	Automated	0.948	1	0.82	**0.933**	1	1	0.711	**0.911**
FDA_B	10000	Expert	0.985	1	0.874	**0.963**	1	1	0.783	**0.935**
FDA_O	1:1	*A priori*	0.191	0.14	0.273	**0.202**	0.112	0.112	0.417	**0.2**
FDA_O	1:1	Automated	0.062	0.047	0.077	**0.061**	0.083	0.083	0.028	**0.046**
FDA_O	1:1	Expert	0.093	0.07	0.098	**0.086**	0.101	0.101	0.05	**0.066**
FDA_O	1:2	*A priori*	0.191	0.152	0.273	**0.206**	0.118	0.118	0.411	**0.202**
FDA_O	1:2	Automated	0.067	0.053	0.077	**0.064**	0.083	0.083	0.028	**0.046**
FDA_O	1:2	Expert	0.093	0.07	0.109	**0.09**	0.107	0.107	0.061	**0.074**
FDA_O	1:3	*A priori*	0.191	0.146	0.262	**0.2**	0.112	0.112	0.417	**0.2**
FDA_O	1:3	Automated	0.082	0.058	0.093	**0.077**	0.089	0.089	0.039	**0.054**
FDA_O	1:3	Expert	0.093	0.064	0.098	**0.084**	0.101	0.101	0.044	**0.064**
FDA_O	10000	*A priori*	0.191	0.152	0.284	**0.21**	0.118	0.118	0.428	**0.208**
FDA_O	10000	Automated	0.077	0.058	0.093	**0.075**	0.089	0.089	0.039	**0.054**
FDA_O	10000	Expert	0.088	0.07	0.104	**0.086**	0.101	0.101	0.061	**0.07**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Associated skill score				Brier Score			
			Train	Test	Fit	Skill	Train	Test	Fit	Forecast Accuracy
GAM_B	1:1	*A priori*	0.613	0.702	0.863	**0.734**	0.716	0.716	0.833	**0.758**
GAM_B	1:1	Automated	0.758	0.684	0.492	**0.651**	0.592	0.592	0.211	**0.459**
GAM_B	1:1	Expert	0.83	0.83	0.536	**0.74**	0.704	0.704	0.239	**0.545**
GAM_B	1:2	*A priori*	0.536	0.754	0.913	**0.742**	0.692	0.692	0.928	**0.774**
GAM_B	1:2	Automated	0.763	0.731	0.546	**0.687**	0.657	0.657	0.267	**0.522**
GAM_B	1:2	Expert	0.835	0.86	0.601	**0.773**	0.769	0.769	0.328	**0.62**
GAM_B	1:3	*A priori*	0.531	0.743	0.918	**0.738**	0.692	0.692	0.967	**0.787**
GAM_B	1:3	Automated	0.753	0.789	0.645	**0.737**	0.74	0.74	0.389	**0.621**
GAM_B	1:3	Expert	0.83	0.871	0.639	**0.788**	0.811	0.811	0.372	**0.664**
GAM_B	10000	*A priori*	0.526	0.708	0.929	**0.728**	0.698	0.698	0.944	**0.783**
GAM_B	10000	Automated	0.732	0.772	0.672	**0.733**	0.71	0.71	0.444	**0.62**
GAM_B	10000	Expert	0.82	0.865	0.645	**0.785**	0.805	0.805	0.383	**0.664**
GAM_O	1:1	*A priori*	0.299	0.392	0.082	**0.259**	0.84	0.84	0.128	**0.601**
GAM_O	1:1	Automated	0.284	0.357	0.066	**0.236**	0.988	0.988	0.1	**0.693**
GAM_O	1:1	Expert	0.381	0.427	0.158	**0.325**	0.888	0.888	0.861	**0.885**
GAM_O	1:2	*A priori*	0.371	0.433	0.126	**0.312**	0.911	0.911	0.322	**0.716**
GAM_O	1:2	Automated	0.418	0.456	0.153	**0.345**	1	1	0.283	**0.764**
GAM_O	1:2	Expert	0.376	0.421	0.148	**0.317**	0.704	0.704	0.972	**0.797**
GAM_O	1:3	*A priori*	0.397	0.439	0.137	**0.326**	0.905	0.905	0.378	**0.731**
GAM_O	1:3	Automated	0.418	0.444	0.186	**0.352**	0.444	0.444	0.95	**0.611**

Table B2.5 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Probability of occurrence**							
			Associated skill score				**Brier Score**			
			Train	**Test**	**Fit**	**Skill**	**Train**	**Test**	**Fit**	**Forecast Accuracy**
GAM_O	1:3	Expert	0.366	0.415	0.131	**0.306**	0.509	0.509	1	**0.673**
GAM_O	10000	*A priori*	0.412	0.45	0.142	**0.337**	0.769	0.769	0.478	**0.672**
GAM_O	10000	Automated	0.428	0.444	0.175	**0.352**	0.325	0.325	0.989	**0.543**
GAM_O	10000	Expert	0.356	0.409	0.115	**0.295**	0.349	0.349	0.994	**0.561**
GBM_B	1:1	*A priori*	0.985	0.953	0.732	**0.9**	0.947	0.947	0.6	**0.836**
GBM_B	1:1	Automated	0.928	0.865	0.552	**0.79**	0.598	0.598	0.183	**0.453**
GBM_B	1:1	Expert	1	0.942	0.678	**0.883**	0.858	0.858	0.367	**0.695**
GBM_B	1:2	*A priori*	0.964	0.942	0.71	**0.881**	0.941	0.941	0.617	**0.838**
GBM_B	1:2	Automated	0.923	0.854	0.536	**0.779**	0.592	0.592	0.161	**0.441**
GBM_B	1:2	Expert	0.995	0.936	0.661	**0.873**	0.84	0.84	0.344	**0.675**
GBM_B	1:3	*A priori*	0.959	0.942	0.721	**0.883**	0.935	0.935	0.622	**0.835**
GBM_B	1:3	Automated	0.902	0.848	0.536	**0.77**	0.592	0.592	0.161	**0.441**
GBM_B	1:3	Expert	0.99	0.936	0.656	**0.87**	0.84	0.84	0.356	**0.679**
GBM_B	10000	*A priori*	0.887	0.924	0.689	**0.842**	0.864	0.864	0.517	**0.75**
GBM_B	10000	Automated	0.856	0.83	0.497	**0.735**	0.527	0.527	0.111	**0.379**
GBM_B	10000	Expert	0.974	0.924	0.65	**0.859**	0.763	0.763	0.3	**0.607**
GBM_O	1:1	*A priori*	0.423	0.409	0.579	**0.475**	1	1	0.828	**0.951**
GBM_O	1:1	Automated	0.402	0.404	0.694	**0.504**	0.982	0.982	0.633	**0.872**
GBM_O	1:1	Expert	0.366	0.31	0.197	**0.293**	0.988	0.988	0.65	**0.881**
GBM_O	1:2	*A priori*	0.392	0.404	0.393	**0.399**	0.988	0.988	0.756	**0.918**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Associated skill score				Brier Score			
			Train	Test	Fit	Skill	Train	Test	Fit	Forecast Accuracy
GBM_O	1:2	Automated	0.361	0.363	0.754	**0.497**	0.858	0.858	0.528	**0.75**
GBM_O	1:2	Expert	0.351	0.257	0.164	**0.259**	0.941	0.941	0.433	**0.775**
GBM_O	1:3	*A priori*	0.371	0.398	0.317	**0.365**	0.976	0.976	0.739	**0.904**
GBM_O	1:3	Automated	0.345	0.345	0.749	**0.484**	0.692	0.692	0.506	**0.629**
GBM_O	1:3	Expert	0.206	0.211	0.563	**0.329**	0.734	0.734	0.5	**0.655**
GBM_O	10000	*A priori*	0.304	0.345	0.251	**0.302**	0.722	0.722	0.9	**0.784**
GBM_O	10000	Automated	0.289	0.287	0.311	**0.297**	0.396	0.396	0.478	**0.416**
GBM_O	10000	Expert	0.129	0.158	0.306	**0.198**	0.426	0.426	0.467	**0.432**
GLM_B	1:1	*A priori*	0.552	0.725	0.896	**0.732**	0.609	0.609	0.95	**0.724**
GLM_B	1:1	Automated	0.892	0.825	0.47	**0.736**	0.633	0.633	0.122	**0.456**
GLM_B	1:1	Expert	0.897	0.795	0.437	**0.717**	0.609	0.609	0.106	**0.434**
GLM_B	1:2	*A priori*	0.557	0.731	0.923	**0.745**	0.615	0.615	0.928	**0.721**
GLM_B	1:2	Automated	0.871	0.807	0.464	**0.722**	0.615	0.615	0.122	**0.444**
GLM_B	1:2	Expert	0.881	0.789	0.443	**0.712**	0.604	0.604	0.111	**0.432**
GLM_B	1:3	*A priori*	0.567	0.749	0.94	**0.76**	0.633	0.633	0.956	**0.743**
GLM_B	1:3	Automated	0.871	0.819	0.475	**0.729**	0.615	0.615	0.122	**0.444**
GLM_B	1:3	Expert	0.876	0.819	0.481	**0.733**	0.627	0.627	0.133	**0.456**
GLM_B	10000	*A priori*	0.577	0.696	0.962	**0.753**	0.615	0.615	0.917	**0.717**
GLM_B	10000	Automated	0.861	0.842	0.508	**0.745**	0.663	0.663	0.178	**0.496**
GLM_B	10000	Expert	0.851	0.807	0.486	**0.722**	0.621	0.621	0.144	**0.456**

Table B2.5 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Probability of occurrence**							
			Associated skill score				**Brier Score**			
			Train	**Test**	**Fit**	**Skill**	**Train**	**Test**	**Fit**	**Forecast Accuracy**
GLM_O	1:1	*A priori*	0.093	0.211	0.027	**0.11**	0.041	0.041	0.033	**0.02**
GLM_O	1:1	Automated	0.072	0.193	0.022	**0.095**	0.077	0.077	0.028	**0.042**
GLM_O	1:1	Expert	0.026	0.135	0.016	**0.058**	0.183	0.183	0.028	**0.115**
GLM_O	1:2	*A priori*	0.098	0.222	0.027	**0.115**	0.012	0.012	0.061	**0.009**
GLM_O	1:2	Automated	0.139	0.263	0.044	**0.149**	0.225	0.225	0.061	**0.155**
GLM_O	1:2	Expert	0.093	0.193	0.033	**0.106**	0.391	0.391	0.072	**0.273**
GLM_O	1:3	*A priori*	0.124	0.281	0.033	**0.146**	0.006	0.006	0.078	**0.01**
GLM_O	1:3	Automated	0.232	0.363	0.071	**0.223**	0.26	0.26	0.1	**0.193**
GLM_O	1:3	Expert	0.139	0.251	0.06	**0.15**	0.367	0.367	0.133	**0.277**
GLM_O	10000	*A priori*	0.134	0.327	0.055	**0.172**	0	0	0.139	**0.027**
GLM_O	10000	Automated	0.263	0.386	0.098	**0.25**	0.166	0.166	0.172	**0.153**
GLM_O	10000	Expert	0.216	0.339	0.077	**0.212**	0.42	0.42	0.294	**0.369**
MARS_B	1:1	*A priori*	0.562	0.678	0.907	**0.723**	0.538	0.538	0.883	**0.653**
MARS_B	1:1	Automated	0.784	0.684	0.432	**0.639**	0.521	0.521	0.111	**0.375**
MARS_B	1:1	Expert	0.804	0.719	0.459	**0.668**	0.55	0.55	0.139	**0.405**
MARS_B	1:2	*A priori*	0.567	0.678	0.885	**0.718**	0.544	0.544	0.867	**0.651**
MARS_B	1:2	Automated	0.799	0.766	0.525	**0.704**	0.592	0.592	0.2	**0.455**
MARS_B	1:2	Expert	0.809	0.731	0.464	**0.675**	0.568	0.568	0.161	**0.425**
MARS_B	1:3	*A priori*	0.562	0.684	0.896	**0.721**	0.562	0.562	0.85	**0.658**
MARS_B	1:3	Automated	0.784	0.737	0.519	**0.687**	0.586	0.586	0.206	**0.453**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Associated skill score				Brier Score			
			Train	Test	Fit	Skill	Train	Test	Fit	Forecast Accuracy
MARS_B	1:3	Expert	0.804	0.69	0.426	**0.647**	0.533	0.533	0.117	**0.385**
MARS_B	10000	*A priori*	0.562	0.643	0.902	**0.709**	0.521	0.521	0.783	**0.606**
MARS_B	10000	Automated	0.773	0.737	0.53	**0.687**	0.586	0.586	0.222	**0.458**
MARS_B	10000	Expert	0.789	0.673	0.415	**0.632**	0.503	0.503	0.094	**0.358**
MARS_O	1:1	*A priori*	0.304	0.38	0.153	**0.281**	0.751	0.751	0.55	**0.685**
MARS_O	1:1	Automated	0.314	0.351	0.257	**0.309**	0.87	0.87	0.789	**0.848**
MARS_O	1:1	Expert	0.294	0.298	0.388	**0.329**	0.888	0.888	0.544	**0.776**
MARS_O	1:2	*A priori*	0.309	0.392	0.137	**0.281**	0.692	0.692	0.578	**0.654**
MARS_O	1:2	Automated	0.289	0.333	0.246	**0.291**	0.604	0.604	0.839	**0.682**
MARS_O	1:2	Expert	0.196	0.228	0.279	**0.235**	0.769	0.769	0.561	**0.701**
MARS_O	1:3	*A priori*	0.294	0.374	0.098	**0.257**	0.645	0.645	0.45	**0.577**
MARS_O	1:3	Automated	0.335	0.398	0.158	**0.299**	0.911	0.911	0.472	**0.768**
MARS_O	1:3	Expert	0.222	0.281	0.18	**0.229**	0.923	0.923	0.606	**0.822**
MARS_O	10000	*A priori*	0.273	0.368	0.077	**0.241**	0.852	0.852	0.194	**0.632**
MARS_O	10000	Automated	0.247	0.345	0.093	**0.229**	0.817	0.817	0.267	**0.632**
MARS_O	10000	Expert	0.201	0.292	0.077	**0.19**	0.876	0.876	0.483	**0.747**
MaxEnt_B	1:1	*A priori*	0.49	0.52	0.847	**0.625**	0.278	0.278	0.717	**0.417**
MaxEnt_B	1:1	Automated	0.577	0.52	0.443	**0.518**	0.272	0.272	0.111	**0.205**
MaxEnt_B	1:1	Expert	0.619	0.532	0.432	**0.532**	0.325	0.325	0.117	**0.243**
MaxEnt_B	1:2	*A priori*	0.474	0.515	0.874	**0.627**	0.249	0.249	0.728	**0.4**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Associated skill score				Brier Score			
			Train	Test	Fit	Skill	Train	Test	Fit	Forecast Accuracy
MaxEnt_B	1:2	Automated	0.572	0.532	0.492	**0.537**	0.32	0.32	0.217	**0.274**
MaxEnt_B	1:2	Expert	0.644	0.538	0.421	**0.539**	0.349	0.349	0.111	**0.258**
MaxEnt_B	1:3	*A priori*	0.479	0.52	0.913	**0.644**	0.296	0.296	0.828	**0.467**
MaxEnt_B	1:3	Automated	0.567	0.52	0.421	**0.507**	0.284	0.284	0.15	**0.226**
MaxEnt_B	1:3	Expert	0.644	0.532	0.404	**0.532**	0.343	0.343	0.094	**0.248**
MaxEnt_B	10000	*A priori*	0.479	0.52	0.94	**0.653**	0.331	0.331	0.878	**0.509**
MaxEnt_B	10000	Automated	0.608	0.532	0.421	**0.525**	0.314	0.314	0.122	**0.237**
MaxEnt_B	10000	Expert	0.655	0.532	0.377	**0.526**	0.337	0.337	0.089	**0.242**
MaxEnt_O	1:1	*A priori*	0.237	0.24	0.333	**0.272**	0.243	0.243	0.461	**0.305**
MaxEnt_O	1:1	Automated	0.186	0.117	0.219	**0.174**	0.349	0.349	0.117	**0.259**
MaxEnt_O	1:1	Expert	0.155	0.105	0.23	**0.163**	0.325	0.325	0.106	**0.239**
MaxEnt_O	1:2	*A priori*	0.242	0.234	0.355	**0.279**	0.254	0.254	0.522	**0.334**
MaxEnt_O	1:2	Automated	0.139	0.105	0.257	**0.167**	0.302	0.302	0.15	**0.238**
MaxEnt_O	1:2	Expert	0.144	0.105	0.208	**0.152**	0.32	0.32	0.1	**0.233**
MaxEnt_O	1:3	*A priori*	0.232	0.234	0.344	**0.272**	0.237	0.237	0.528	**0.323**
MaxEnt_O	1:3	Automated	0.18	0.111	0.224	**0.172**	0.337	0.337	0.122	**0.253**
MaxEnt_O	1:3	Expert	0.16	0.105	0.191	**0.152**	0.32	0.32	0.1	**0.233**
MaxEnt_O	10000	*A priori*	0.247	0.246	0.339	**0.279**	0.266	0.266	0.511	**0.338**
MaxEnt_O	10000	Automated	0.17	0.123	0.257	**0.184**	0.325	0.325	0.167	**0.26**
MaxEnt_O	10000	Expert	0.18	0.123	0.235	**0.18**	0.337	0.337	0.094	**0.244**

Table B2.5 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Probability of occurrence**							
			Associated skill score				**Brier Score**			
			Train	**Test**	**Fit**	**Skill**	**Train**	**Test**	**Fit**	**Forecast Accuracy**
MXL_O	1:1	*A priori*	0.216	0.234	0.41	**0.289**	0.219	0.219	0.583	**0.33**
MXL_O	1:1	Automated	0.18	0.269	0.158	**0.203**	0.527	0.527	0.333	**0.456**
MXL_O	1:1	Expert	0.052	0.082	0.24	**0.124**	0.16	0.16	0.1	**0.124**
MXL_O	1:2	*A priori*	0.227	0.234	0.377	**0.281**	0.213	0.213	0.539	**0.311**
MXL_O	1:2	Automated	0.165	0.222	0.208	**0.199**	0.467	0.467	0.494	**0.47**
MXL_O	1:2	Expert	0.036	0.076	0.191	**0.1**	0.13	0.13	0.083	**0.098**
MXL_O	1:3	*A priori*	0.227	0.234	0.383	**0.283**	0.231	0.231	0.589	**0.34**
MXL_O	1:3	Automated	0.16	0.216	0.191	**0.19**	0.45	0.45	0.478	**0.453**
MXL_O	1:3	Expert	0.057	0.088	0.268	**0.137**	0.189	0.189	0.117	**0.15**
MXL_O	10000	*A priori*	0.206	0.228	0.388	**0.276**	0.207	0.207	0.572	**0.318**
MXL_O	10000	Automated	0.175	0.222	0.202	**0.201**	0.467	0.467	0.506	**0.474**
MXL_O	10000	Expert	0.01	0	0.153	**0.053**	0.172	0.172	0.117	**0.138**
RF_B	1:1	*A priori*	0.706	0.93	0.984	**0.883**	0.917	0.917	0.928	**0.928**
RF_B	1:1	Automated	0.711	0.906	0.918	**0.854**	0.888	0.888	0.9	**0.898**
RF_B	1:1	Expert	0.711	0.871	0.858	**0.822**	0.846	0.846	0.789	**0.832**
RF_B	1:2	*A priori*	0.546	0.684	0.989	**0.748**	0.621	0.621	0.939	**0.729**
RF_B	1:2	Automated	0.582	0.649	0.885	**0.713**	0.592	0.592	0.889	**0.691**
RF_B	1:2	Expert	0.567	0.614	0.809	**0.67**	0.497	0.497	0.717	**0.567**
RF_B	1:3	*A priori*	0.5	0.602	0.967	**0.697**	0.462	0.462	0.872	**0.596**
RF_B	1:3	Automated	0.51	0.585	0.913	**0.676**	0.473	0.473	0.972	**0.639**

Table B2.5 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Probability of occurrence**							
			Associated skill score				**Brier Score**			
			Train	**Test**	**Fit**	**Skill**	**Train**	**Test**	**Fit**	**Forecast Accuracy**
RF_B	1:3	Expert	0.505	0.55	0.798	**0.624**	0.396	0.396	0.733	**0.504**
RF_B	10000	*A priori*	0.479	0.526	0.831	**0.618**	0.349	0.349	0.644	**0.441**
RF_B	10000	Automated	0.495	0.532	0.989	**0.679**	0.414	0.414	0.761	**0.525**
RF_B	10000	Expert	0.485	0.509	0.869	**0.627**	0.284	0.284	0.978	**0.51**
RF_O	1:1	*A priori*	0.392	0.404	0.35	**0.385**	0.929	0.929	0.789	**0.889**
RF_O	1:1	Automated	0.325	0.316	0.612	**0.421**	0.899	0.899	0.917	**0.912**
RF_O	1:1	Expert	0.309	0.281	0.366	**0.321**	0.834	0.834	0.822	**0.835**
RF_O	1:2	*A priori*	0.34	0.363	0.284	**0.331**	0.68	0.68	0.778	**0.714**
RF_O	1:2	Automated	0.242	0.234	0.514	**0.332**	0.627	0.627	0.95	**0.737**
RF_O	1:2	Expert	0.211	0.199	0.574	**0.33**	0.485	0.485	0.75	**0.57**
RF_O	1:3	*A priori*	0.304	0.345	0.24	**0.298**	0.521	0.521	0.689	**0.574**
RF_O	1:3	Automated	0.18	0.211	0.301	**0.232**	0.497	0.497	0.928	**0.64**
RF_O	1:3	Expert	0.149	0.164	0.536	**0.285**	0.402	0.402	0.8	**0.531**
RF_O	10000	*A priori*	0.237	0.304	0.169	**0.238**	0.414	0.414	0.456	**0.421**
RF_O	10000	Automated	0.119	0.17	0.213	**0.167**	0.426	0.426	0.672	**0.503**
RF_O	10000	Expert	0.103	0.129	0.257	**0.163**	0.29	0.29	0.956	**0.507**
SRE_B	1:1	*A priori*	0.469	0.497	0.803	**0.596**	0.166	0.166	0.761	**0.355**
SRE_B	1:1	Automated	0.454	0.485	0.978	**0.645**	0.142	0.142	0.794	**0.35**
SRE_B	1:1	Expert	0.464	0.503	0.891	**0.625**	0.178	0.178	0.922	**0.418**
SRE_B	1:2	*A priori*	0.469	0.491	0.792	**0.59**	0.166	0.166	0.772	**0.359**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Associated skill score				Brier Score			
			Train	Test	Fit	Skill	Train	Test	Fit	Forecast Accuracy
SRE_B	1:2	Automated	0.459	0.485	0.989	**0.651**	0.142	0.142	0.817	**0.358**
SRE_B	1:2	Expert	0.464	0.503	0.88	**0.622**	0.172	0.172	0.911	**0.41**
SRE_B	1:3	*A priori*	0.469	0.485	0.787	**0.586**	0.166	0.166	0.767	**0.357**
SRE_B	1:3	Automated	0.459	0.48	0.995	**0.651**	0.142	0.142	0.822	**0.36**
SRE_B	1:3	Expert	0.464	0.503	0.874	**0.62**	0.172	0.172	0.894	**0.405**
SRE_B	10000	*A priori*	0.469	0.485	0.781	**0.584**	0.16	0.16	0.728	**0.339**
SRE_B	10000	Automated	0.459	0.485	0.989	**0.651**	0.142	0.142	0.806	**0.354**
SRE_B	10000	Expert	0.464	0.503	0.874	**0.62**	0.172	0.172	0.906	**0.408**
SRE_O	1:1	*A priori*	0.031	0.105	0.044	**0.059**	0.053	0.053	0.022	**0.024**
SRE_O	1:1	Automated	0.01	0.018	0.011	**0.011**	0.065	0.065	0.033	**0.036**
SRE_O	1:1	Expert	0.015	0.035	0.027	**0.024**	0.071	0.071	0.083	**0.057**
SRE_O	1:2	*A priori*	0.031	0.105	0.044	**0.059**	0.053	0.053	0.022	**0.024**
SRE_O	1:2	Automated	0.01	0.018	0.011	**0.011**	0.059	0.059	0.033	**0.032**
SRE_O	1:2	Expert	0.015	0.035	0.027	**0.024**	0.071	0.071	0.083	**0.057**
SRE_O	1:3	*A priori*	0.031	0.105	0.038	**0.057**	0.053	0.053	0.017	**0.022**
SRE_O	1:3	Automated	0.01	0.018	0.011	**0.011**	0.065	0.065	0.033	**0.036**
SRE_O	1:3	Expert	0.015	0.029	0.027	**0.022**	0.071	0.071	0.083	**0.057**
SRE_O	10000	*A priori*	0.031	0.105	0.038	**0.057**	0.053	0.053	0.017	**0.022**
SRE_O	10000	Automated	0.01	0.018	0.011	**0.011**	0.065	0.065	0.033	**0.036**
SRE_O	10000	Expert	0.015	0.035	0.027	**0.024**	0.071	0.071	0.083	**0.057**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Refinement				Resolution			
			Train	**Test**	**Fit**	**Refinement**	**Train**	**Test**	**Fit**	**Resolution**
ANN_B	1:1	*A priori*	0.578	0.596	0.631	**0.611**	0.398	0.845	0.851	**0.789**
ANN_B	1:1	Automated	0.734	0.478	0.23	**0.488**	0.63	0.68	0.495	**0.659**
ANN_B	1:1	Expert	0.646	0.267	0.037	**0.321**	0.878	0.418	0.011	**0.435**
ANN_B	1:2	*A priori*	0.562	0.596	0.652	**0.613**	0.414	0.887	0.867	**0.822**
ANN_B	1:2	Automated	0.693	0.366	0.096	**0.39**	0.652	0.546	0.415	**0.573**
ANN_B	1:2	Expert	0.661	0.323	0.048	**0.349**	0.867	0.423	0.016	**0.435**
ANN_B	1:3	*A priori*	0.599	0.602	0.62	**0.616**	0.42	0.881	0.856	**0.818**
ANN_B	1:3	Automated	0.688	0.348	0.086	**0.379**	0.624	0.51	0.426	**0.549**
ANN_B	1:3	Expert	0.677	0.342	0.07	**0.367**	0.84	0.428	0.043	**0.437**
ANN_B	10000	*A priori*	0.62	0.516	0.551	**0.57**	0.425	0.732	0.739	**0.701**
ANN_B	10000	Automated	0.672	0.348	0.086	**0.373**	0.602	0.495	0.431	**0.535**
ANN_B	10000	Expert	0.656	0.323	0.064	**0.352**	0.818	0.392	0.048	**0.413**
ANN_O	1:1	*A priori*	0.901	0.894	0.77	**0.869**	0.53	0.603	0.516	**0.589**
ANN_O	1:1	Automated	0.927	0.932	0.818	**0.907**	0.597	0.619	0.479	**0.609**
ANN_O	1:1	Expert	0.849	0.634	0.31	**0.607**	0.851	0.505	0.112	**0.508**
ANN_O	1:2	*A priori*	0.297	0.292	0.428	**0.343**	0.232	0.237	0.707	**0.377**
ANN_O	1:2	Automated	0.25	0.304	0.439	**0.335**	0.309	0.309	0.67	**0.427**
ANN_O	1:2	Expert	0.224	0.205	0.075	**0.169**	0.409	0.129	0.255	**0.205**
ANN_O	1:3	*A priori*	0.104	0.112	0.337	**0.186**	0.077	0.088	0.872	**0.314**
ANN_O	1:3	Automated	0.083	0.112	0.241	**0.146**	0.083	0.108	0.872	**0.326**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Refinement				Resolution			
			Train	Test	Fit	Refinement	Train	Test	Fit	Resolution
ANN_O	1:3	Expert	0.052	0.087	0.027	**0.054**	0.044	0.026	0.766	**0.224**
ANN_O	10000	*A priori*	0.031	0.043	0.07	**0.047**	0.017	0.01	0.979	**0.3**
ANN_O	10000	Automated	0.026	0.037	0.064	**0.041**	0.006	0.005	0.995	**0.3**
ANN_O	10000	Expert	0.01	0.031	0	**0.012**	0	0	1	**0.298**
CTA_B	1:1	*A priori*	0.474	0.453	0.69	**0.547**	0.431	0.763	0.75	**0.722**
CTA_B	1:1	Automated	0.531	0.354	0.31	**0.404**	0.541	0.423	0.404	**0.463**
CTA_B	1:1	Expert	0.542	0.373	0.31	**0.414**	0.663	0.438	0.335	**0.494**
CTA_B	1:2	*A priori*	0.422	0.422	0.69	**0.519**	0.381	0.768	0.803	**0.726**
CTA_B	1:2	Automated	0.521	0.329	0.262	**0.376**	0.497	0.381	0.431	**0.437**
CTA_B	1:2	Expert	0.526	0.373	0.364	**0.427**	0.669	0.454	0.34	**0.506**
CTA_B	1:3	*A priori*	0.391	0.398	0.706	**0.505**	0.326	0.716	0.862	**0.704**
CTA_B	1:3	Automated	0.479	0.286	0.273	**0.35**	0.436	0.361	0.468	**0.417**
CTA_B	1:3	Expert	0.516	0.348	0.337	**0.406**	0.613	0.418	0.351	**0.469**
CTA_B	10000	*A priori*	0.359	0.36	0.642	**0.46**	0.293	0.593	0.819	**0.614**
CTA_B	10000	Automated	0.375	0.248	0.326	**0.32**	0.354	0.309	0.489	**0.366**
CTA_B	10000	Expert	0.49	0.323	0.342	**0.39**	0.558	0.397	0.399	**0.457**
CTA_O	1:1	*A priori*	0.667	0.59	0.455	**0.579**	0.569	0.34	0.314	**0.398**
CTA_O	1:1	Automated	0.734	0.571	0.396	**0.576**	0.608	0.309	0.218	**0.358**
CTA_O	1:1	Expert	0.74	0.553	0.353	**0.557**	0.652	0.309	0.149	**0.347**
CTA_O	1:2	*A priori*	0.344	0.323	0.604	**0.43**	0.519	0.242	0.25	**0.303**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Refinement				Resolution			
			Train	**Test**	**Fit**	**Refinement**	**Train**	**Test**	**Fit**	**Resolution**
CTA_O	1:2	Automated	0.354	0.323	0.561	**0.419**	0.619	0.247	0.112	**0.288**
CTA_O	1:2	Expert	0.359	0.323	0.556	**0.418**	0.646	0.253	0.096	**0.295**
CTA_O	1:3	*A priori*	0.193	0.217	0.861	**0.43**	0.536	0.227	0.213	**0.287**
CTA_O	1:3	Automated	0.198	0.217	0.791	**0.408**	0.657	0.247	0.053	**0.279**
CTA_O	1:3	Expert	0.354	0.323	0.54	**0.411**	0.619	0.232	0.096	**0.274**
CTA_O	10000	*A priori*	0.099	0.112	0.636	**0.286**	0.425	0.16	0.191	**0.197**
CTA_O	10000	Automated	0.073	0.106	0.471	**0.218**	0.552	0.175	0.021	**0.185**
CTA_O	10000	Expert	0.094	0.143	0.61	**0.285**	0.475	0.149	0.043	**0.148**
EMca_B	1:1	*A priori*	0.021	0.012	0.444	**0.16**	0.232	0.773	0.947	**0.725**
EMca_B	1:1	Automated	0.125	0.081	0.39	**0.2**	0.331	0.851	0.915	**0.791**
EMca_B	1:1	Expert	0.109	0.043	0.412	**0.19**	0.459	0.938	0.883	**0.873**
EMca_B	1:2	*A priori*	0.026	0.019	0.535	**0.195**	0.227	0.835	0.963	**0.758**
EMca_B	1:2	Automated	0.115	0.056	0.278	**0.15**	0.249	0.768	0.941	**0.728**
EMca_B	1:2	Expert	0.104	0.043	0.417	**0.19**	0.448	0.912	0.883	**0.856**
EMca_B	1:3	*A priori*	0.036	0.019	0.572	**0.211**	0.298	0.923	0.957	**0.827**
EMca_B	1:3	Automated	0.12	0.075	0.401	**0.2**	0.271	0.809	0.936	**0.754**
EMca_B	1:3	Expert	0.078	0.025	0.332	**0.146**	0.37	0.897	0.915	**0.829**
EMca_B	10000	*A priori*	0.042	0.019	0.289	**0.117**	0.365	0.753	0.846	**0.73**
EMca_B	10000	Automated	0.151	0.087	0.38	**0.208**	0.238	0.727	0.931	**0.7**
EMca_B	10000	Expert	0.047	0.012	0.107	**0.055**	0.243	0.814	0.952	**0.751**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Refinement				Resolution			
			Train	Test	Fit	Refinement	Train	Test	Fit	Resolution
EMmean_B	1:1	*A priori*	0.708	0.795	0.674	**0.737**	0.459	0.943	0.872	**0.87**
EMmean_B	1:1	Automated	0.938	0.621	0.171	**0.585**	0.884	0.737	0.362	**0.739**
EMmean_B	1:1	Expert	0.906	0.559	0.155	**0.548**	0.934	0.665	0.234	**0.672**
EMmean_B	1:2	*A priori*	0.635	0.826	0.813	**0.77**	0.481	0.985	0.92	**0.92**
EMmean_B	1:2	Automated	0.755	0.851	0.626	**0.756**	0.983	0.907	0.234	**0.803**
EMmean_B	1:2	Expert	0.865	0.578	0.209	**0.558**	0.95	0.706	0.261	**0.71**
EMmean_B	1:3	*A priori*	0.625	0.839	0.834	**0.778**	0.514	0.99	0.926	**0.94**
EMmean_B	1:3	Automated	0.911	0.677	0.321	**0.646**	0.906	0.742	0.346	**0.744**
EMmean_B	1:3	Expert	0.844	0.596	0.283	**0.583**	0.967	0.778	0.293	**0.764**
EMmean_B	10000	*A priori*	0.594	0.658	0.69	**0.657**	0.519	0.804	0.686	**0.751**
EMmean_B	10000	Automated	0.859	0.689	0.385	**0.654**	0.945	0.825	0.362	**0.806**
EMmean_B	10000	Expert	0.818	0.584	0.299	**0.575**	0.967	0.789	0.319	**0.781**
EMmedian_B	1:1	*A priori*	0.599	0.671	0.711	**0.67**	0.47	0.897	0.814	**0.828**
EMmedian_B	1:1	Automated	0.885	0.516	0.144	**0.523**	0.89	0.68	0.309	**0.692**
EMmedian_B	1:1	Expert	0.797	0.429	0.139	**0.461**	0.956	0.634	0.176	**0.642**
EMmedian_B	1:2	*A priori*	0.495	0.696	0.882	**0.702**	0.564	0.979	0.872	**0.934**
EMmedian_B	1:2	Automated	0.703	0.851	0.684	**0.758**	0.989	0.887	0.202	**0.782**
EMmedian_B	1:2	Expert	0.786	0.491	0.203	**0.501**	0.972	0.665	0.186	**0.668**
EMmedian_B	1:3	*A priori*	0.453	0.683	0.936	**0.701**	0.641	0.985	0.84	**0.956**
EMmedian_B	1:3	Automated	0.682	0.826	0.679	**0.741**	0.983	0.809	0.144	**0.718**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Refinement				Resolution			
			Train	**Test**	**Fit**	**Refinement**	**Train**	**Test**	**Fit**	**Resolution**
EMmedian_B	1:3	Expert	0.792	0.509	0.214	**0.512**	0.972	0.675	0.186	**0.672**
EMmedian_B	10000	*A priori*	0.469	0.54	0.797	**0.611**	0.591	0.665	0.495	**0.635**
EMmedian_B	10000	Automated	0.651	0.807	0.668	**0.72**	0.983	0.799	0.154	**0.719**
EMmedian_B	10000	Expert	0.76	0.484	0.209	**0.491**	0.967	0.624	0.122	**0.618**
EMwmean_B	1:1	*A priori*	0.708	0.801	0.679	**0.741**	0.464	0.948	0.872	**0.875**
EMwmean_B	1:1	Automated	0.943	0.627	0.171	**0.589**	0.901	0.747	0.362	**0.751**
EMwmean_B	1:1	Expert	0.917	0.559	0.16	**0.553**	0.934	0.67	0.245	**0.679**
EMwmean_B	1:2	*A priori*	0.635	0.832	0.807	**0.77**	0.481	0.985	0.92	**0.92**
EMwmean_B	1:2	Automated	0.755	0.851	0.626	**0.756**	0.983	0.907	0.234	**0.803**
EMwmean_B	1:2	Expert	0.865	0.59	0.209	**0.563**	0.95	0.711	0.277	**0.719**
EMwmean_B	1:3	*A priori*	0.63	0.845	0.834	**0.782**	0.508	0.99	0.926	**0.937**
EMwmean_B	1:3	Automated	0.911	0.677	0.321	**0.646**	0.906	0.742	0.346	**0.744**
EMwmean_B	1:3	Expert	0.844	0.596	0.289	**0.585**	0.967	0.773	0.298	**0.764**
EMwmean_B	10000	*A priori*	0.604	0.658	0.679	**0.657**	0.519	0.804	0.691	**0.754**
EMwmean_B	10000	Automated	0.865	0.708	0.396	**0.666**	0.956	0.83	0.351	**0.808**
EMwmean_B	10000	Expert	0.818	0.59	0.305	**0.579**	0.967	0.784	0.319	**0.778**
FDA_B	1:1	*A priori*	0.609	0.522	0.545	**0.567**	0.381	0.856	0.872	**0.796**
FDA_B	1:1	Automated	0.75	0.366	0.07	**0.401**	0.768	0.485	0.282	**0.538**
FDA_B	1:1	Expert	0.745	0.385	0.091	**0.412**	0.812	0.562	0.303	**0.602**
FDA_B	1:2	*A priori*	0.641	0.932	1	**0.871**	0.287	0.804	0.92	**0.752**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Refinement				Resolution			
			Train	Test	Fit	Refinement	Train	Test	Fit	Resolution
FDA_B	1:2	Automated	0.974	0.938	0.599	**0.85**	0.702	0.711	0.457	**0.689**
FDA_B	1:2	Expert	0.974	0.932	0.594	**0.846**	0.707	0.686	0.447	**0.675**
FDA_B	1:3	*A priori*	0.74	0.975	0.882	**0.88**	0.16	0.335	0.846	**0.451**
FDA_B	1:3	Automated	0.99	1	0.914	**0.984**	0.409	0.211	0.351	**0.285**
FDA_B	1:3	Expert	0.99	0.994	0.904	**0.978**	0.425	0.191	0.266	**0.245**
FDA_B	10000	*A priori*	0.661	0.988	0.759	**0.815**	0.177	0.443	0.83	**0.5**
FDA_B	10000	Automated	0.99	1	0.963	**1**	0.403	0.412	0.495	**0.437**
FDA_B	10000	Expert	0.99	1	0.936	**0.991**	0.475	0.485	0.479	**0.495**
FDA_O	1:1	*A priori*	0.203	0.137	0.23	**0.192**	0.077	0.077	0.59	**0.183**
FDA_O	1:1	Automated	0.255	0.099	0.021	**0.126**	0.249	0.052	0.037	**0**
FDA_O	1:1	Expert	0.276	0.118	0.053	**0.15**	0.254	0.072	0.101	**0.04**
FDA_O	1:2	*A priori*	0.214	0.143	0.225	**0.195**	0.077	0.082	0.585	**0.183**
FDA_O	1:2	Automated	0.26	0.112	0.032	**0.135**	0.254	0.052	0.043	**0.005**
FDA_O	1:2	Expert	0.276	0.13	0.064	**0.158**	0.254	0.072	0.112	**0.045**
FDA_O	1:3	*A priori*	0.208	0.143	0.23	**0.195**	0.077	0.077	0.585	**0.181**
FDA_O	1:3	Automated	0.276	0.112	0.043	**0.144**	0.254	0.062	0.074	**0.024**
FDA_O	1:3	Expert	0.281	0.118	0.048	**0.15**	0.26	0.067	0.085	**0.033**
FDA_O	10000	*A priori*	0.203	0.143	0.246	**0.199**	0.077	0.077	0.601	**0.188**
FDA_O	10000	Automated	0.266	0.112	0.048	**0.143**	0.254	0.062	0.08	**0.026**
FDA_O	10000	Expert	0.271	0.124	0.064	**0.154**	0.254	0.072	0.112	**0.045**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Refinement				Resolution			
			Train	Test	Fit	Refinement	Train	Test	Fit	Resolution
GAM_B	1:1	*A priori*	0.521	0.776	0.909	**0.747**	0.657	0.964	0.713	**0.897**
GAM_B	1:1	Automated	0.812	0.584	0.294	**0.572**	0.851	0.474	0.138	**0.506**
GAM_B	1:1	Expert	0.854	0.658	0.364	**0.635**	0.978	0.644	0.112	**0.627**
GAM_B	1:2	*A priori*	0.458	0.764	0.984	**0.747**	0.569	0.959	0.782	**0.886**
GAM_B	1:2	Automated	0.833	0.646	0.374	**0.627**	0.845	0.479	0.181	**0.525**
GAM_B	1:2	Expert	0.891	0.758	0.433	**0.705**	0.967	0.639	0.133	**0.63**
GAM_B	1:3	*A priori*	0.458	0.77	0.979	**0.747**	0.575	0.964	0.771	**0.886**
GAM_B	1:3	Automated	0.875	0.745	0.422	**0.691**	0.785	0.49	0.287	**0.55**
GAM_B	1:3	Expert	0.896	0.789	0.476	**0.731**	0.967	0.655	0.165	**0.651**
GAM_B	10000	*A priori*	0.448	0.752	0.973	**0.736**	0.586	0.84	0.617	**0.766**
GAM_B	10000	Automated	0.802	0.727	0.487	**0.682**	0.751	0.5	0.324	**0.556**
GAM_B	10000	Expert	0.885	0.795	0.481	**0.732**	0.961	0.629	0.17	**0.639**
GAM_O	1:1	*A priori*	0.406	0.795	0.519	**0.582**	0.503	0.433	0.601	**0.539**
GAM_O	1:1	Automated	0.609	0.957	0.578	**0.726**	0.635	0.582	0.569	**0.651**
GAM_O	1:1	Expert	0.62	0.857	0.995	**0.837**	0.928	0.66	0.223	**0.662**
GAM_O	1:2	*A priori*	0.547	0.876	0.781	**0.746**	0.508	0.521	0.553	**0.559**
GAM_O	1:2	Automated	0.729	0.981	0.877	**0.876**	0.641	0.722	0.548	**0.707**
GAM_O	1:2	Expert	0.401	0.689	0.989	**0.704**	0.851	0.562	0.207	**0.576**
GAM_O	1:3	*A priori*	0.573	0.876	0.829	**0.771**	0.475	0.521	0.564	**0.549**
GAM_O	1:3	Automated	0.255	0.391	0.92	**0.53**	0.779	0.515	0.255	**0.545**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Refinement				Resolution			
			Train	Test	Fit	Refinement	Train	Test	Fit	Resolution
GAM_O	1:3	Expert	0.318	0.466	0.952	**0.587**	0.801	0.531	0.223	**0.547**
GAM_O	10000	*A priori*	0.49	0.752	0.925	**0.733**	0.409	0.485	0.606	**0.522**
GAM_O	10000	Automated	0.208	0.255	0.872	**0.451**	0.762	0.598	0.362	**0.622**
GAM_O	10000	Expert	0.219	0.255	0.872	**0.455**	0.768	0.613	0.372	**0.636**
GBM_B	1:1	*A priori*	0.964	0.919	0.599	**0.84**	0.685	1	0.862	**0.993**
GBM_B	1:1	Automated	0.948	0.565	0.128	**0.555**	0.713	0.577	0.394	**0.605**
GBM_B	1:1	Expert	0.964	0.795	0.348	**0.713**	0.906	0.794	0.388	**0.787**
GBM_B	1:2	*A priori*	0.953	0.913	0.626	**0.844**	0.696	1	0.867	**1**
GBM_B	1:2	Automated	0.948	0.559	0.123	**0.551**	0.729	0.567	0.367	**0.596**
GBM_B	1:2	Expert	0.958	0.789	0.364	**0.714**	0.912	0.722	0.346	**0.738**
GBM_B	1:3	*A priori*	0.953	0.907	0.626	**0.842**	0.691	1	0.862	**0.995**
GBM_B	1:3	Automated	0.948	0.553	0.118	**0.547**	0.729	0.577	0.367	**0.6**
GBM_B	1:3	Expert	0.953	0.783	0.369	**0.712**	0.923	0.758	0.34	**0.756**
GBM_B	10000	*A priori*	0.922	0.857	0.508	**0.774**	0.669	0.964	0.702	**0.897**
GBM_B	10000	Automated	0.927	0.484	0.102	**0.512**	0.707	0.557	0.378	**0.586**
GBM_B	10000	Expert	0.932	0.72	0.316	**0.666**	0.895	0.691	0.33	**0.709**
GBM_O	1:1	*A priori*	1	0.969	0.663	**0.891**	0.707	0.918	0.59	**0.844**
GBM_O	1:1	Automated	0.979	0.95	0.583	**0.851**	0.939	0.933	0.441	**0.888**
GBM_O	1:1	Expert	1	0.969	0.652	**0.888**	0.646	0.448	0.362	**0.503**
GBM_O	1:2	*A priori*	0.984	0.963	0.588	**0.859**	0.669	0.918	0.622	**0.841**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Refinement				Resolution			
			Train	**Test**	**Fit**	**Refinement**	**Train**	**Test**	**Fit**	**Resolution**
GBM_O	1:2	Automated	0.88	0.795	0.492	**0.734**	0.845	0.82	0.436	**0.792**
GBM_O	1:2	Expert	0.995	0.957	0.428	**0.806**	0.608	0.402	0.356	**0.462**
GBM_O	1:3	*A priori*	0.969	0.907	0.567	**0.827**	0.602	0.902	0.676	**0.828**
GBM_O	1:3	Automated	0.698	0.609	0.476	**0.603**	0.79	0.701	0.41	**0.702**
GBM_O	1:3	Expert	0.719	0.646	0.497	**0.63**	0.829	0.701	0.383	**0.708**
GBM_O	10000	*A priori*	0.615	0.571	0.578	**0.597**	0.453	0.851	0.782	**0.785**
GBM_O	10000	Automated	0.411	0.335	0.513	**0.426**	0.669	0.443	0.33	**0.496**
GBM_O	10000	Expert	0.464	0.379	0.524	**0.462**	0.707	0.448	0.303	**0.504**
GLM_B	1:1	*A priori*	0.37	0.547	0.925	**0.623**	0.746	0.995	0.787	**0.984**
GLM_B	1:1	Automated	0.724	0.453	0.209	**0.469**	1	0.876	0.09	**0.732**
GLM_B	1:1	Expert	0.734	0.435	0.176	**0.455**	1	0.871	0.08	**0.725**
GLM_B	1:2	*A priori*	0.38	0.571	0.925	**0.635**	0.713	1	0.83	**0.991**
GLM_B	1:2	Automated	0.719	0.441	0.203	**0.461**	1	0.876	0.09	**0.732**
GLM_B	1:2	Expert	0.724	0.435	0.182	**0.453**	0.994	0.861	0.064	**0.711**
GLM_B	1:3	*A priori*	0.385	0.59	0.92	**0.641**	0.724	1	0.835	**0.998**
GLM_B	1:3	Automated	0.714	0.447	0.209	**0.463**	1	0.876	0.08	**0.727**
GLM_B	1:3	Expert	0.719	0.453	0.209	**0.467**	1	0.876	0.069	**0.722**
GLM_B	10000	*A priori*	0.396	0.54	0.856	**0.606**	0.674	0.974	0.761	**0.931**
GLM_B	10000	Automated	0.703	0.472	0.262	**0.486**	1	0.892	0.106	**0.746**
GLM_B	10000	Expert	0.693	0.441	0.219	**0.457**	1	0.876	0.074	**0.725**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Refinement				Resolution			
			Train	Test	Fit	Refinement	Train	Test	Fit	Resolution
GLM_O	1:1	*A priori*	0.042	0.068	0.048	**0.052**	0.022	0.021	0.979	**0.307**
GLM_O	1:1	Automated	0.047	0.093	0.059	**0.066**	0.028	0.026	0.973	**0.31**
GLM_O	1:1	Expert	0.068	0.174	0.048	**0.097**	0.459	0.237	0.479	**0.376**
GLM_O	1:2	*A priori*	0.016	0.019	0.016	**0.015**	0.017	0.015	0.984	**0.305**
GLM_O	1:2	Automated	0.141	0.23	0.08	**0.151**	0.166	0.108	0.824	**0.342**
GLM_O	1:2	Expert	0.146	0.323	0.166	**0.214**	0.746	0.459	0.309	**0.528**
GLM_O	1:3	*A priori*	0.005	0.006	0.011	**0.006**	0.017	0.01	0.989	**0.305**
GLM_O	1:3	Automated	0.13	0.248	0.112	**0.165**	0.392	0.18	0.559	**0.357**
GLM_O	1:3	Expert	0.182	0.286	0.267	**0.248**	0.773	0.485	0.33	**0.562**
GLM_O	10000	*A priori*	0	0	0.005	**0**	0.011	0.01	0.989	**0.303**
GLM_O	10000	Automated	0.104	0.143	0.123	**0.124**	0.547	0.237	0.484	**0.418**
GLM_O	10000	Expert	0.219	0.348	0.39	**0.323**	0.807	0.567	0.324	**0.611**
MARS_B	1:1	*A priori*	0.443	0.596	0.877	**0.648**	0.564	0.928	0.745	**0.853**
MARS_B	1:1	Automated	0.823	0.453	0.134	**0.477**	0.845	0.593	0.239	**0.602**
MARS_B	1:1	Expert	0.823	0.503	0.171	**0.506**	0.901	0.572	0.197	**0.599**
MARS_B	1:2	*A priori*	0.438	0.596	0.882	**0.648**	0.586	0.954	0.766	**0.884**
MARS_B	1:2	Automated	0.849	0.553	0.203	**0.543**	0.829	0.562	0.271	**0.595**
MARS_B	1:2	Expert	0.839	0.528	0.198	**0.529**	0.878	0.536	0.16	**0.556**
MARS_B	1:3	*A priori*	0.438	0.609	0.893	**0.656**	0.586	0.969	0.771	**0.893**
MARS_B	1:3	Automated	0.828	0.547	0.219	**0.539**	0.856	0.562	0.229	**0.588**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Refinement				Resolution			
			Train	Test	Fit	Refinement	Train	Test	Fit	Resolution
MARS_B	1:3	Expert	0.833	0.497	0.171	**0.508**	0.873	0.515	0.128	**0.53**
MARS_B	10000	*A priori*	0.443	0.516	0.807	**0.597**	0.58	0.866	0.654	**0.792**
MARS_B	10000	Automated	0.766	0.534	0.278	**0.534**	0.917	0.593	0.191	**0.613**
MARS_B	10000	Expert	0.807	0.46	0.15	**0.479**	0.878	0.469	0.09	**0.494**
MARS_O	1:1	*A priori*	0.641	0.739	0.807	**0.74**	0.243	0.423	0.771	**0.494**
MARS_O	1:1	Automated	0.844	0.814	0.749	**0.815**	0.42	0.696	0.734	**0.68**
MARS_O	1:1	Expert	0.865	0.82	0.684	**0.802**	0.796	0.758	0.42	**0.735**
MARS_O	1:2	*A priori*	0.635	0.702	0.797	**0.722**	0.16	0.309	0.787	**0.413**
MARS_O	1:2	Automated	0.583	0.54	0.647	**0.599**	0.315	0.588	0.771	**0.6**
MARS_O	1:2	Expert	0.74	0.714	0.743	**0.744**	0.652	0.649	0.452	**0.636**
MARS_O	1:3	*A priori*	0.552	0.652	0.824	**0.686**	0.127	0.273	0.835	**0.403**
MARS_O	1:3	Automated	0.776	0.913	0.845	**0.858**	0.188	0.407	0.777	**0.465**
MARS_O	1:3	Expert	0.87	0.882	0.941	**0.912**	0.525	0.567	0.495	**0.561**
MARS_O	10000	*A priori*	0.729	0.932	0.807	**0.836**	0.088	0.144	0.798	**0.311**
MARS_O	10000	Automated	0.635	0.888	0.829	**0.797**	0.144	0.17	0.628	**0.271**
MARS_O	10000	Expert	0.854	0.95	0.947	**0.932**	0.171	0.165	0.511	**0.229**
MaxEnt_B	1:1	*A priori*	0.245	0.28	0.695	**0.412**	0.293	0.526	0.574	**0.474**
MaxEnt_B	1:1	Automated	0.427	0.248	0.176	**0.287**	0.669	0.314	0.186	**0.374**
MaxEnt_B	1:1	Expert	0.49	0.286	0.193	**0.327**	0.751	0.356	0.122	**0.401**
MaxEnt_B	1:2	*A priori*	0.219	0.261	0.727	**0.408**	0.249	0.541	0.606	**0.476**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Refinement				Resolution			
			Train	Test	Fit	Refinement	Train	Test	Fit	Resolution
MaxEnt_B	1:2	Automated	0.432	0.298	0.358	**0.368**	0.657	0.304	0.186	**0.364**
MaxEnt_B	1:2	Expert	0.505	0.311	0.203	**0.344**	0.823	0.366	0.043	**0.402**
MaxEnt_B	1:3	*A priori*	0.229	0.317	0.84	**0.468**	0.304	0.608	0.548	**0.504**
MaxEnt_B	1:3	Automated	0.443	0.255	0.219	**0.309**	0.707	0.314	0.101	**0.353**
MaxEnt_B	1:3	Expert	0.505	0.292	0.187	**0.332**	0.834	0.376	0.027	**0.404**
MaxEnt_B	10000	*A priori*	0.234	0.311	0.866	**0.477**	0.32	0.299	0.532	**0.366**
MaxEnt_B	10000	Automated	0.484	0.286	0.23	**0.338**	0.785	0.33	0.032	**0.363**
MaxEnt_B	10000	Expert	0.51	0.286	0.171	**0.326**	0.862	0.387	0.005	**0.412**
MaxEnt_O	1:1	*A priori*	0.292	0.236	0.465	**0.335**	0.265	0.222	0.537	**0.309**
MaxEnt_O	1:1	Automated	0.505	0.323	0.182	**0.341**	0.735	0.345	0.117	**0.386**
MaxEnt_O	1:1	Expert	0.484	0.286	0.241	**0.341**	0.74	0.345	0.112	**0.386**
MaxEnt_O	1:2	*A priori*	0.286	0.248	0.508	**0.352**	0.287	0.227	0.521	**0.314**
MaxEnt_O	1:2	Automated	0.422	0.267	0.251	**0.317**	0.646	0.294	0.186	**0.354**
MaxEnt_O	1:2	Expert	0.464	0.286	0.235	**0.332**	0.718	0.34	0.122	**0.379**
MaxEnt_O	1:3	*A priori*	0.276	0.242	0.529	**0.354**	0.282	0.216	0.543	**0.316**
MaxEnt_O	1:3	Automated	0.495	0.304	0.203	**0.338**	0.724	0.335	0.112	**0.374**
MaxEnt_O	1:3	Expert	0.484	0.273	0.187	**0.319**	0.757	0.351	0.112	**0.396**
MaxEnt_O	10000	*A priori*	0.307	0.255	0.503	**0.359**	0.276	0.237	0.527	**0.316**
MaxEnt_O	10000	Automated	0.474	0.304	0.257	**0.349**	0.68	0.309	0.122	**0.348**
MaxEnt_O	10000	Expert	0.5	0.286	0.171	**0.323**	0.812	0.371	0.059	**0.406**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Refinement				Resolution			
			Train	Test	Fit	Refinement	Train	Test	Fit	Resolution
MXL_O	1:1	*A priori*	0.281	0.211	0.46	**0.321**	0.204	0.263	0.612	**0.333**
MXL_O	1:1	Automated	0.333	0.596	0.963	**0.64**	0.11	0.335	0.92	**0.462**
MXL_O	1:1	Expert	0.219	0.168	0.321	**0.238**	0.453	0.119	0	**0.105**
MXL_O	1:2	*A priori*	0.292	0.205	0.406	**0.305**	0.227	0.242	0.585	**0.322**
MXL_O	1:2	Automated	0.318	0.484	0.963	**0.597**	0.138	0.32	0.904	**0.46**
MXL_O	1:2	Expert	0.188	0.143	0.294	**0.21**	0.387	0.093	0.005	**0.066**
MXL_O	1:3	*A priori*	0.292	0.224	0.46	**0.329**	0.232	0.278	0.601	**0.348**
MXL_O	1:3	Automated	0.302	0.435	0.968	**0.577**	0.138	0.309	0.899	**0.453**
MXL_O	1:3	Expert	0.24	0.186	0.39	**0.275**	0.475	0.139	0.005	**0.127**
MXL_O	10000	*A priori*	0.26	0.199	0.449	**0.306**	0.193	0.242	0.606	**0.317**
MXL_O	10000	Automated	0.323	0.491	0.957	**0.599**	0.138	0.32	0.904	**0.46**
MXL_O	10000	Expert	0.219	0.174	0.38	**0.26**	0.442	0.124	0.005	**0.105**
RF_B	1:1	*A priori*	0.781	0.944	0.898	**0.889**	0.376	0.902	0.91	**0.831**
RF_B	1:1	Automated	0.844	0.894	0.717	**0.831**	0.486	0.495	0.495	**0.511**
RF_B	1:1	Expert	0.812	0.87	0.658	**0.792**	0.519	0.464	0.463	**0.498**
RF_B	1:2	*A priori*	0.536	0.826	0.888	**0.762**	0.221	0.691	0.926	**0.674**
RF_B	1:2	Automated	0.609	0.689	0.69	**0.673**	0.348	0.325	0.511	**0.38**
RF_B	1:2	Expert	0.589	0.571	0.594	**0.593**	0.343	0.289	0.473	**0.345**
RF_B	1:3	*A priori*	0.438	0.665	0.909	**0.681**	0.155	0.521	0.952	**0.58**
RF_B	1:3	Automated	0.5	0.565	0.722	**0.605**	0.215	0.237	0.569	**0.307**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Refinement				Resolution			
			Train	Test	Fit	Refinement	Train	Test	Fit	Resolution
RF_B	1:3	Expert	0.484	0.404	0.583	**0.497**	0.21	0.201	0.505	**0.26**
RF_B	10000	*A priori*	0.328	0.416	0.93	**0.567**	0.061	0.258	0.968	**0.426**
RF_B	10000	Automated	0.365	0.435	0.807	**0.543**	0.138	0.186	0.734	**0.324**
RF_B	10000	Expert	0.349	0.342	0.626	**0.445**	0.133	0.139	0.649	**0.262**
RF_O	1:1	*A priori*	0.729	0.925	0.882	**0.859**	0.359	0.552	0.697	**0.571**
RF_O	1:1	Automated	0.771	0.901	0.802	**0.838**	0.492	0.515	0.5	**0.526**
RF_O	1:1	Expert	0.755	0.863	0.679	**0.778**	0.514	0.459	0.463	**0.493**
RF_O	1:2	*A priori*	0.521	0.752	0.877	**0.728**	0.182	0.351	0.729	**0.415**
RF_O	1:2	Automated	0.568	0.733	0.775	**0.703**	0.331	0.33	0.516	**0.377**
RF_O	1:2	Expert	0.557	0.559	0.61	**0.584**	0.337	0.284	0.473	**0.34**
RF_O	1:3	*A priori*	0.417	0.64	0.914	**0.667**	0.149	0.268	0.793	**0.392**
RF_O	1:3	Automated	0.495	0.615	0.786	**0.642**	0.199	0.237	0.58	**0.305**
RF_O	1:3	Expert	0.458	0.41	0.615	**0.502**	0.199	0.206	0.516	**0.262**
RF_O	10000	*A priori*	0.312	0.435	0.979	**0.584**	0.055	0.191	0.941	**0.382**
RF_O	10000	Automated	0.354	0.46	0.85	**0.563**	0.116	0.186	0.755	**0.323**
RF_O	10000	Expert	0.339	0.348	0.706	**0.471**	0.122	0.134	0.681	**0.269**
SRE_B	1:1	*A priori*	0.177	0.186	0.754	**0.377**	0.088	0.191	0.878	**0.368**
SRE_B	1:1	Automated	0.135	0.155	0.802	**0.369**	0.066	0.103	0.67	**0.226**
SRE_B	1:1	Expert	0.156	0.174	0.652	**0.332**	0.094	0.119	0.601	**0.214**
SRE_B	1:2	*A priori*	0.177	0.193	0.77	**0.385**	0.088	0.201	0.894	**0.38**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence							
			Refinement				Resolution			
			Train	Test	Fit	Refinement	Train	Test	Fit	Resolution
SRE_B	1:2	Automated	0.135	0.155	0.791	**0.365**	0.072	0.103	0.66	**0.223**
SRE_B	1:2	Expert	0.161	0.174	0.652	**0.333**	0.099	0.119	0.596	**0.214**
SRE_B	1:3	*A priori*	0.172	0.186	0.765	**0.379**	0.088	0.196	0.888	**0.375**
SRE_B	1:3	Automated	0.135	0.149	0.791	**0.363**	0.072	0.098	0.66	**0.221**
SRE_B	1:3	Expert	0.167	0.174	0.642	**0.332**	0.105	0.113	0.585	**0.209**
SRE_B	10000	*A priori*	0.177	0.18	0.701	**0.357**	0.088	0.155	0.803	**0.318**
SRE_B	10000	Automated	0.135	0.161	0.797	**0.369**	0.072	0.103	0.665	**0.226**
SRE_B	10000	Expert	0.167	0.174	0.647	**0.333**	0.105	0.113	0.59	**0.212**
SRE_O	1:1	*A priori*	0.047	0.05	0.326	**0.142**	0.033	0.036	0.809	**0.243**
SRE_O	1:1	Automated	0.062	0.062	0.465	**0.198**	0.039	0.046	0.713	**0.207**
SRE_O	1:1	Expert	0.089	0.087	0.733	**0.306**	0.05	0.052	0.638	**0.181**
SRE_O	1:2	*A priori*	0.047	0.05	0.326	**0.142**	0.033	0.031	0.803	**0.238**
SRE_O	1:2	Automated	0.057	0.062	0.46	**0.195**	0.039	0.041	0.713	**0.205**
SRE_O	1:2	Expert	0.089	0.087	0.733	**0.306**	0.05	0.057	0.644	**0.185**
SRE_O	1:3	*A priori*	0.047	0.05	0.326	**0.142**	0.033	0.031	0.814	**0.243**
SRE_O	1:3	Automated	0.057	0.068	0.46	**0.197**	0.039	0.046	0.718	**0.209**
SRE_O	1:3	Expert	0.089	0.087	0.738	**0.308**	0.05	0.052	0.638	**0.181**
SRE_O	10000	*A priori*	0.047	0.05	0.326	**0.142**	0.033	0.031	0.814	**0.243**
SRE_O	10000	Automated	0.057	0.068	0.455	**0.195**	0.039	0.046	0.723	**0.212**
SRE_O	10000	Expert	0.089	0.087	0.733	**0.306**	0.05	0.052	0.633	**0.178**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence	Presence-absence map Sensitivity Train	Test	Fit	Sensitivity
ANN_B	1:1	*A priori*	**0.584**	0.5	0.597	0.597	**0.597**
ANN_B	1:1	Automated	**0.607**	0.5	0.934	0.934	**0.934**
ANN_B	1:1	Expert	**0.307**	0.5	0.602	0.602	**0.602**
ANN_B	1:2	*A priori*	**0.575**	0.5	0.658	0.658	**0.658**
ANN_B	1:2	Automated	**0.438**	0.5	0.878	0.888	**0.883**
ANN_B	1:2	Expert	**0.336**	0.5	0.684	0.679	**0.681**
ANN_B	1:3	*A priori*	**0.578**	0.5	0.577	0.577	**0.577**
ANN_B	1:3	Automated	**0.404**	0.5	0.893	0.898	**0.895**
ANN_B	1:3	Expert	**0.359**	0.5	0.673	0.684	**0.679**
ANN_B	10000	*A priori*	**0.532**	0.5	0.577	0.577	**0.577**
ANN_B	10000	Automated	**0.404**	0.5	0.893	0.898	**0.895**
ANN_B	10000	Expert	**0.326**	0.5	0.663	0.663	**0.663**
ANN_O	1:1	*A priori*	**0.775**	0.5	0.286	0.281	**0.283**
ANN_O	1:1	Automated	**0.79**	0.5	0.495	0.49	**0.492**
ANN_O	1:1	Expert	**0.58**	0.5	0.526	0.52	**0.523**
ANN_O	1:2	*A priori*	**0.387**	0.5	0.515	0.51	**0.513**
ANN_O	1:2	Automated	**0.359**	0.5	0.643	0.643	**0.643**
ANN_O	1:2	Expert	**0.165**	0.5	0.612	0.612	**0.612**
ANN_O	1:3	*A priori*	**0.22**	0.5	0.694	0.694	**0.694**
ANN_O	1:3	Automated	**0.139**	0.5	0.74	0.74	**0.74**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence	Presence-absence map Sensitivity			
				Train	Test	Fit	Sensitivity
ANN_O	1:3	Expert	**0**	0.5	0.719	0.719	**0.719**
ANN_O	10000	*A priori*	**0.114**	0.5	0.923	0.923	**0.923**
ANN_O	10000	Automated	**0.015**	0.5	0.939	0.939	**0.939**
ANN_O	10000	Expert	**0.003**	0.5	0.908	0.908	**0.908**
CTA_B	1:1	*A priori*	**0.503**	0.5	0.372	0.367	**0.37**
CTA_B	1:1	Automated	**0.396**	0.5	0.408	0.403	**0.406**
CTA_B	1:1	Expert	**0.416**	0.5	0.582	0.582	**0.582**
CTA_B	1:2	*A priori*	**0.479**	0.5	0.199	0.199	**0.199**
CTA_B	1:2	Automated	**0.317**	0.5	0.23	0.224	**0.227**
CTA_B	1:2	Expert	**0.389**	0.5	0.332	0.327	**0.329**
CTA_B	1:3	*A priori*	**0.43**	0.5	0.122	0.122	**0.122**
CTA_B	1:3	Automated	**0.264**	0.5	0.184	0.189	**0.186**
CTA_B	1:3	Expert	**0.355**	0.5	0.204	0.561	**0.383**
CTA_B	10000	*A priori*	**0.385**	0.5	0.102	0.102	**0.102**
CTA_B	10000	Automated	**0.217**	0.5	0.087	0.087	**0.087**
CTA_B	10000	Expert	**0.316**	0.5	0.153	0.153	**0.153**
CTA_O	1:1	*A priori*	**0.647**	0.5	0.648	0.648	**0.648**
CTA_O	1:1	Automated	**0.596**	0.5	0.755	0.755	**0.755**
CTA_O	1:1	Expert	**0.593**	0.5	0.689	0.689	**0.689**
CTA_O	1:2	*A priori*	**0.593**	0.5	0.434	0.429	**0.431**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence	Presence-absence map Sensitivity			
				Train	Test	Fit	Sensitivity
CTA_O	1:2	Automated	**0.551**	0.5	0.735	0.735	**0.735**
CTA_O	1:2	Expert	**0.542**	0.5	0.709	0.709	**0.709**
CTA_O	1:3	*A priori*	**0.594**	0.5	0.638	0.638	**0.638**
CTA_O	1:3	Automated	**0.523**	0.5	0.827	0.827	**0.827**
CTA_O	1:3	Expert	**0.535**	0.5	0.699	0.699	**0.699**
CTA_O	10000	*A priori*	**0.405**	0.5	0.735	0.735	**0.735**
CTA_O	10000	Automated	**0.366**	0.5	0.77	0.776	**0.773**
CTA_O	10000	Expert	**0.378**	0.5	0.796	0.796	**0.796**
EMca_B	1:1	*A priori*	**0.316**	0.5	0.949	0.954	**0.952**
EMca_B	1:1	Automated	**0.426**	0.5	0.913	0.913	**0.913**
EMca_B	1:1	Expert	**0.417**	0.5	0.949	0.954	**0.952**
EMca_B	1:2	*A priori*	**0.361**	0.5	0.949	0.954	**0.952**
EMca_B	1:2	Automated	**0.364**	0.5	0.949	0.954	**0.952**
EMca_B	1:2	Expert	**0.437**	0.5	0.949	0.954	**0.952**
EMca_B	1:3	*A priori*	**0.48**	0.5	0.954	0.949	**0.952**
EMca_B	1:3	Automated	**0.441**	0.5	0.954	0.949	**0.952**
EMca_B	1:3	Expert	**0.461**	0.5	0.954	0.949	**0.952**
EMca_B	10000	*A priori*	**0.276**	0.5	0.949	0.954	**0.952**
EMca_B	10000	Automated	**0.432**	0.5	0.949	0.954	**0.952**
EMca_B	10000	Expert	**0.246**	0.5	0.949	0.954	**0.952**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence	Presence-absence map Sensitivity			
				Train	Test	Fit	Sensitivity
EMmean_B	1:1	*A priori*	**0.78**	0.5	0.444	0.439	**0.441**
EMmean_B	1:1	Automated	**0.73**	0.5	0.75	0.75	**0.75**
EMmean_B	1:1	Expert	**0.661**	0.5	0.75	0.75	**0.75**
EMmean_B	1:2	*A priori*	**0.84**	0.5	0.49	0.48	**0.485**
EMmean_B	1:2	Automated	**0.914**	0.5	0.98	0.98	**0.98**
EMmean_B	1:2	Expert	**0.703**	0.5	0.837	0.852	**0.844**
EMmean_B	1:3	*A priori*	**0.872**	0.5	0.48	0.485	**0.482**
EMmean_B	1:3	Automated	**0.764**	0.5	0.811	0.811	**0.811**
EMmean_B	1:3	Expert	**0.749**	0.5	0.857	0.857	**0.857**
EMmean_B	10000	*A priori*	**0.774**	0.5	0.378	0.372	**0.375**
EMmean_B	10000	Automated	**0.809**	0.5	0.949	0.954	**0.952**
EMmean_B	10000	Expert	**0.746**	0.5	0.888	0.883	**0.885**
EMmedian_B	1:1	*A priori*	**0.664**	0.5	0.495	0.49	**0.492**
EMmedian_B	1:1	Automated	**0.645**	0.5	0.791	0.791	**0.791**
EMmedian_B	1:1	Expert	**0.546**	0.5	0.786	0.786	**0.786**
EMmedian_B	1:2	*A priori*	**0.713**	0.5	0.403	0.398	**0.401**
EMmedian_B	1:2	Automated	**0.9**	0.5	0.959	0.959	**0.959**
EMmedian_B	1:2	Expert	**0.605**	0.5	0.827	0.827	**0.827**
EMmedian_B	1:3	*A priori*	**0.741**	0.5	0.357	0.352	**0.355**
EMmedian_B	1:3	Automated	**0.871**	0.5	0.969	0.969	**0.969**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence	Presence-absence map			
				Sensitivity			
				Train	Test	Fit	Sensitivity
EMmedian_B	1:3	Expert	**0.611**	0.5	0.821	0.816	**0.819**
EMmedian_B	10000	*A priori*	**0.595**	0.5	0.23	0.224	**0.227**
EMmedian_B	10000	Automated	**0.856**	0.5	0.964	0.964	**0.964**
EMmedian_B	10000	Expert	**0.579**	0.5	0.821	0.816	**0.819**
EMwmean_B	1:1	*A priori*	**0.781**	0.5	0.485	0.474	**0.48**
EMwmean_B	1:1	Automated	**0.737**	0.5	0.77	0.776	**0.773**
EMwmean_B	1:1	Expert	**0.667**	0.5	0.745	0.745	**0.745**
EMwmean_B	1:2	*A priori*	**0.835**	0.5	0.505	0.5	**0.503**
EMwmean_B	1:2	Automated	**0.914**	0.5	0.974	0.974	**0.974**
EMwmean_B	1:2	Expert	**0.711**	0.5	0.827	0.827	**0.827**
EMwmean_B	1:3	*A priori*	**0.872**	0.5	0.439	0.434	**0.436**
EMwmean_B	1:3	Automated	**0.766**	0.5	0.801	0.801	**0.801**
EMwmean_B	1:3	Expert	**0.751**	0.5	0.857	0.857	**0.857**
EMwmean_B	10000	*A priori*	**0.769**	0.5	0.362	0.357	**0.36**
EMwmean_B	10000	Automated	**0.809**	0.5	0.944	0.944	**0.944**
EMwmean_B	10000	Expert	**0.749**	0.5	0.862	0.862	**0.862**
FDA_B	1:1	*A priori*	**0.509**	0.5	0.291	0.286	**0.288**
FDA_B	1:1	Automated	**0.368**	0.5	0.745	0.745	**0.745**
FDA_B	1:1	Expert	**0.431**	0.5	0.724	0.724	**0.724**
FDA_B	1:2	*A priori*	**0.741**	0.5	0.173	0.173	**0.173**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence	Presence-absence map Sensitivity			
				Train	Test	Fit	Sensitivity
FDA_B	1:2	Automated	**0.843**	0.5	0.837	0.852	**0.844**
FDA_B	1:2	Expert	**0.813**	0.5	0.837	0.852	**0.844**
FDA_B	1:3	*A priori*	**0.646**	0.5	0.143	0.143	**0.143**
FDA_B	1:3	Automated	**0.884**	0.5	0.852	0.847	**0.849**
FDA_B	1:3	Expert	**0.839**	0.5	0.776	0.77	**0.773**
FDA_B	10000	*A priori*	**0.699**	0.5	0.138	0.138	**0.138**
FDA_B	10000	Automated	**0.909**	0.5	0.505	0.5	**0.503**
FDA_B	10000	Expert	**0.918**	0.5	0.821	0.816	**0.819**
FDA_O	1:1	*A priori*	**0.235**	0.5	0.107	0.107	**0.107**
FDA_O	1:1	Automated	**0.066**	0.5	0.133	0.133	**0.133**
FDA_O	1:1	Expert	**0.1**	0.5	0.531	0.526	**0.528**
FDA_O	1:2	*A priori*	**0.237**	0.5	0.107	0.107	**0.107**
FDA_O	1:2	Automated	**0.071**	0.5	0.158	0.158	**0.158**
FDA_O	1:2	Expert	**0.107**	0.5	0.48	0.485	**0.482**
FDA_O	1:3	*A priori*	**0.235**	0.5	0.102	0.102	**0.102**
FDA_O	1:3	Automated	**0.087**	0.5	0.26	0.255	**0.258**
FDA_O	1:3	Expert	**0.097**	0.5	0.429	0.423	**0.426**
FDA_O	10000	*A priori*	**0.243**	0.5	0.112	0.112	**0.112**
FDA_O	10000	Automated	**0.087**	0.5	0.265	0.26	**0.263**
FDA_O	10000	Expert	**0.104**	0.5	0.429	0.423	**0.426**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence	Presence-absence map Sensitivity			
				Train	Test	Fit	Sensitivity
GAM_B	1:1	*A priori*	**0.685**	0.5	0.699	0.699	**0.699**
GAM_B	1:1	Automated	**0.452**	0.5	0.648	0.648	**0.648**
GAM_B	1:1	Expert	**0.574**	0.5	0.622	0.622	**0.622**
GAM_B	1:2	*A priori*	**0.705**	0.5	0.913	0.913	**0.913**
GAM_B	1:2	Automated	**0.513**	0.5	0.827	0.827	**0.827**
GAM_B	1:2	Expert	**0.636**	0.5	0.898	0.893	**0.895**
GAM_B	1:3	*A priori*	**0.704**	0.5	0.918	0.918	**0.918**
GAM_B	1:3	Automated	**0.623**	0.5	0.985	0.985	**0.985**
GAM_B	1:3	Expert	**0.668**	0.5	0.847	0.842	**0.844**
GAM_B	10000	*A priori*	**0.654**	0.5	0.929	0.929	**0.929**
GAM_B	10000	Automated	**0.55**	0.5	0.857	0.857	**0.857**
GAM_B	10000	Expert	**0.654**	0.5	0.842	0.837	**0.839**
GAM_O	1:1	*A priori*	**0.561**	0.5	0.459	0.459	**0.459**
GAM_O	1:1	Automated	**0.647**	0.5	0.587	0.587	**0.587**
GAM_O	1:1	Expert	**0.863**	0.5	0.566	0.571	**0.569**
GAM_O	1:2	*A priori*	**0.686**	0.5	0.383	0.378	**0.38**
GAM_O	1:2	Automated	**0.788**	0.5	0.612	0.612	**0.612**
GAM_O	1:2	Expert	**0.778**	0.5	0.546	0.541	**0.543**
GAM_O	1:3	*A priori*	**0.699**	0.5	0.25	0.245	**0.247**
GAM_O	1:3	Automated	**0.667**	0.5	0.449	0.444	**0.446**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence	Presence-absence map Sensitivity			
				Train	Test	Fit	Sensitivity
GAM_O	1:3	Expert	**0.691**	0.5	0.423	0.418	**0.421**
GAM_O	10000	*A priori*	**0.67**	0.5	0.128	0.128	**0.128**
GAM_O	10000	Automated	**0.628**	0.5	0.337	0.332	**0.334**
GAM_O	10000	Expert	**0.621**	0.5	0.342	0.337	**0.339**
GBM_B	1:1	*A priori*	**0.875**	0.5	0.418	0.413	**0.416**
GBM_B	1:1	Automated	**0.637**	0.5	0.566	0.571	**0.569**
GBM_B	1:1	Expert	**0.833**	0.5	0.883	0.878	**0.88**
GBM_B	1:2	*A priori*	**0.856**	0.5	0.311	0.306	**0.309**
GBM_B	1:2	Automated	**0.635**	0.5	0.5	0.495	**0.497**
GBM_B	1:2	Expert	**0.813**	0.5	0.745	0.745	**0.745**
GBM_B	1:3	*A priori*	**0.857**	0.5	0.189	0.184	**0.186**
GBM_B	1:3	Automated	**0.631**	0.5	0.27	0.265	**0.268**
GBM_B	1:3	Expert	**0.8**	0.5	0.673	0.684	**0.679**
GBM_B	10000	*A priori*	**0.769**	0.5	0.179	0.179	**0.179**
GBM_B	10000	Automated	**0.594**	0.5	0.301	0.296	**0.298**
GBM_B	10000	Expert	**0.749**	0.5	0.474	0.469	**0.472**
GBM_O	1:1	*A priori*	**0.926**	0.5	0.495	0.49	**0.492**
GBM_O	1:1	Automated	**1**	0.5	0.816	0.821	**0.819**
GBM_O	1:1	Expert	**0.763**	0.5	0.031	0.031	**0.031**
GBM_O	1:2	*A priori*	**0.911**	0.5	0.806	0.806	**0.806**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence	Presence-absence map Sensitivity			
				Train	Test	Fit	Sensitivity
GBM_O	1:2	Automated	**0.902**	0.5	0.857	0.857	**0.857**
GBM_O	1:2	Expert	**0.685**	0.5	0.02	0.026	**0.023**
GBM_O	1:3	*A priori*	**0.899**	0.5	0.832	0.832	**0.832**
GBM_O	1:3	Automated	**0.806**	0.5	0.867	0.867	**0.867**
GBM_O	1:3	Expert	**0.789**	0.5	0.872	0.872	**0.872**
GBM_O	10000	*A priori*	**0.78**	0.5	0.903	0.903	**0.903**
GBM_O	10000	Automated	**0.603**	0.5	0.893	0.898	**0.895**
GBM_O	10000	Expert	**0.608**	0.5	0.878	0.888	**0.883**
GLM_B	1:1	*A priori*	**0.661**	0.5	0.219	0.214	**0.217**
GLM_B	1:1	Automated	**0.598**	0.5	0.531	0.526	**0.528**
GLM_B	1:1	Expert	**0.562**	0.5	0.429	0.423	**0.426**
GLM_B	1:2	*A priori*	**0.666**	0.5	0.235	0.23	**0.232**
GLM_B	1:2	Automated	**0.601**	0.5	0.561	0.556	**0.559**
GLM_B	1:2	Expert	**0.579**	0.5	0.449	0.444	**0.446**
GLM_B	1:3	*A priori*	**0.684**	0.5	0.209	0.209	**0.209**
GLM_B	1:3	Automated	**0.59**	0.5	0.561	0.556	**0.559**
GLM_B	1:3	Expert	**0.583**	0.5	0.204	0.561	**0.383**
GLM_B	10000	*A priori*	**0.633**	0.5	0.209	0.209	**0.209**
GLM_B	10000	Automated	**0.628**	0.5	0.653	0.653	**0.653**
GLM_B	10000	Expert	**0.595**	0.5	0.592	0.592	**0.592**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence	Presence-absence map Sensitivity			
				Train	**Test**	**Fit**	**Sensitivity**
GLM_O	1:1	*A priori*	**0.135**	0.5	0.321	0.316	**0.319**
GLM_O	1:1	Automated	**0.141**	0.5	0.214	0.204	**0.209**
GLM_O	1:1	Expert	**0.285**	0.5	0.679	0.673	**0.676**
GLM_O	1:2	*A priori*	**0.05**	0.5	0.23	0.224	**0.227**
GLM_O	1:2	Automated	**0.298**	0.5	0.561	0.556	**0.559**
GLM_O	1:2	Expert	**0.44**	0.5	0.622	0.622	**0.622**
GLM_O	1:3	*A priori*	**0.067**	0.5	0.163	0.163	**0.163**
GLM_O	1:3	Automated	**0.371**	0.5	0.577	0.577	**0.577**
GLM_O	1:3	Expert	**0.472**	0.5	0.531	0.526	**0.528**
GLM_O	10000	*A priori*	**0.059**	0.5	0.097	0.097	**0.097**
GLM_O	10000	Automated	**0.386**	0.5	0.51	0.505	**0.508**
GLM_O	10000	Expert	**0.546**	0.5	0.393	0.388	**0.39**
MARS_B	1:1	*A priori*	**0.633**	0.5	0.459	0.459	**0.459**
MARS_B	1:1	Automated	**0.467**	0.5	0.633	0.633	**0.633**
MARS_B	1:1	Expert	**0.508**	0.5	0.719	0.719	**0.719**
MARS_B	1:2	*A priori*	**0.614**	0.5	0.388	0.383	**0.385**
MARS_B	1:2	Automated	**0.591**	0.5	0.837	0.852	**0.844**
MARS_B	1:2	Expert	**0.535**	0.5	0.816	0.821	**0.819**
MARS_B	1:3	*A priori*	**0.622**	0.5	0.347	0.342	**0.344**
MARS_B	1:3	Automated	**0.535**	0.5	0.704	0.704	**0.704**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence	Presence-absence map Sensitivity			
				Train	Test	Fit	Sensitivity
MARS_B	1:3	Expert	**0.496**	0.5	0.76	0.76	**0.76**
MARS_B	10000	*A priori*	**0.556**	0.5	0.327	0.321	**0.324**
MARS_B	10000	Automated	**0.514**	0.5	0.556	0.551	**0.554**
MARS_B	10000	Expert	**0.438**	0.5	0.73	0.73	**0.73**
MARS_O	1:1	*A priori*	**0.678**	0.5	0.454	0.449	**0.452**
MARS_O	1:1	Automated	**0.826**	0.5	0.556	0.551	**0.554**
MARS_O	1:1	Expert	**0.853**	0.5	0.781	0.781	**0.781**
MARS_O	1:2	*A priori*	**0.659**	0.5	0.48	0.485	**0.482**
MARS_O	1:2	Automated	**0.686**	0.5	0.714	0.714	**0.714**
MARS_O	1:2	Expert	**0.774**	0.5	0.872	0.872	**0.872**
MARS_O	1:3	*A priori*	**0.577**	0.5	0.423	0.418	**0.421**
MARS_O	1:3	Automated	**0.735**	0.5	0.551	0.546	**0.548**
MARS_O	1:3	Expert	**0.84**	0.5	0.872	0.872	**0.872**
MARS_O	10000	*A priori*	**0.611**	0.5	0.413	0.408	**0.411**
MARS_O	10000	Automated	**0.598**	0.5	0.464	0.454	**0.459**
MARS_O	10000	Expert	**0.716**	0.5	0.893	0.898	**0.895**
MaxEnt_B	1:1	*A priori*	**0.387**	0.5	0.352	0.347	**0.349**
MaxEnt_B	1:1	Automated	**0.191**	0.5	0.224	0.219	**0.222**
MaxEnt_B	1:1	Expert	**0.258**	0.5	0.495	0.49	**0.492**
MaxEnt_B	1:2	*A priori*	**0.388**	0.5	0.316	0.311	**0.314**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence	Presence-absence map Sensitivity			
				Train	Test	Fit	Sensitivity
MaxEnt_B	1:2	Automated	**0.284**	0.5	0.306	0.301	**0.304**
MaxEnt_B	1:2	Expert	**0.259**	0.5	0.607	0.607	**0.607**
MaxEnt_B	1:3	*A priori*	**0.429**	0.5	0.204	0.561	**0.383**
MaxEnt_B	1:3	Automated	**0.182**	0.5	0.184	0.189	**0.186**
MaxEnt_B	1:3	Expert	**0.237**	0.5	0.204	0.561	**0.383**
MaxEnt_B	10000	*A priori*	**0.39**	0.5	0.367	0.362	**0.365**
MaxEnt_B	10000	Automated	**0.205**	0.5	0.122	0.122	**0.122**
MaxEnt_B	10000	Expert	**0.235**	0.5	0.628	0.628	**0.628**
MaxEnt_O	1:1	*A priori*	**0.316**	0.5	0.265	0.26	**0.263**
MaxEnt_O	1:1	Automated	**0.348**	0.5	0.194	0.194	**0.194**
MaxEnt_O	1:1	Expert	**0.32**	0.5	0.689	0.689	**0.689**
MaxEnt_O	1:2	*A priori*	**0.345**	0.5	0.281	0.276	**0.278**
MaxEnt_O	1:2	Automated	**0.278**	0.5	0.199	0.199	**0.199**
MaxEnt_O	1:2	Expert	**0.318**	0.5	0.684	0.679	**0.681**
MaxEnt_O	1:3	*A priori*	**0.34**	0.5	0.199	0.199	**0.199**
MaxEnt_O	1:3	Automated	**0.338**	0.5	0.184	0.189	**0.186**
MaxEnt_O	1:3	Expert	**0.31**	0.5	0.617	0.617	**0.617**
MaxEnt_O	10000	*A priori*	**0.357**	0.5	0.301	0.296	**0.298**
MaxEnt_O	10000	Automated	**0.315**	0.5	0.245	0.24	**0.242**
MaxEnt_O	10000	Expert	**0.325**	0.5	0.571	0.566	**0.569**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence	Presence-absence map Sensitivity			
				Train	Test	Fit	Sensitivity
MXL_O	1:1	*A priori*	**0.367**	0.5	0.765	0.765	**0.765**
MXL_O	1:1	Automated	**0.557**	0.5	0.913	0.913	**0.913**
MXL_O	1:1	Expert	**0.16**	0.5	0.469	0.464	**0.467**
MXL_O	1:2	*A priori*	**0.362**	0.5	0.76	0.76	**0.76**
MXL_O	1:2	Automated	**0.546**	0.5	0.995	0.995	**0.995**
MXL_O	1:2	Expert	**0.135**	0.5	0.536	0.531	**0.533**
MXL_O	1:3	*A priori*	**0.369**	0.5	0.76	0.76	**0.76**
MXL_O	1:3	Automated	**0.534**	0.5	1	1	**1**
MXL_O	1:3	Expert	**0.211**	0.5	0.541	0.536	**0.538**
MXL_O	10000	*A priori*	**0.337**	0.5	0.668	0.668	**0.668**
MXL_O	10000	Automated	**0.546**	0.5	0.99	0.99	**0.99**
MXL_O	10000	Expert	**0.17**	0.5	0.52	0.515	**0.518**
RF_B	1:1	*A priori*	**0.852**	0.5	0.031	0.031	**0.031**
RF_B	1:1	Automated	**0.771**	0.5	0.051	0.051	**0.051**
RF_B	1:1	Expert	**0.792**	0.5	0.184	0.189	**0.186**
RF_B	1:2	*A priori*	**0.663**	0.5	0.056	0.056	**0.056**
RF_B	1:2	Automated	**0.594**	0.5	0.092	0.092	**0.092**
RF_B	1:2	Expert	**0.552**	0.5	0.23	0.224	**0.227**
RF_B	1:3	*A priori*	**0.563**	0.5	0.077	0.077	**0.077**
RF_B	1:3	Automated	**0.529**	0.5	0.148	0.148	**0.148**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence	Presence-absence map Sensitivity			
				Train	Test	Fit	Sensitivity
RF_B	1:3	Expert	**0.451**	0.5	0.204	0.561	**0.383**
RF_B	10000	*A priori*	**0.45**	0.5	0.117	0.117	**0.117**
RF_B	10000	Automated	**0.504**	0.5	0.321	0.316	**0.319**
RF_B	10000	Expert	**0.419**	0.5	0.296	0.291	**0.293**
RF_O	1:1	*A priori*	**0.775**	0.5	0.031	0.031	**0.031**
RF_O	1:1	Automated	**0.782**	0.5	0.036	0.036	**0.036**
RF_O	1:1	Expert	**0.771**	0.5	0.158	0.158	**0.158**
RF_O	1:2	*A priori*	**0.644**	0.5	0.046	0.046	**0.046**
RF_O	1:2	Automated	**0.643**	0.5	0.066	0.071	**0.069**
RF_O	1:2	Expert	**0.627**	0.5	0.24	0.235	**0.237**
RF_O	1:3	*A priori*	**0.585**	0.5	0.061	0.061	**0.061**
RF_O	1:3	Automated	**0.553**	0.5	0.082	0.082	**0.082**
RF_O	1:3	Expert	**0.551**	0.5	0.276	0.27	**0.273**
RF_O	10000	*A priori*	**0.521**	0.5	0.168	0.168	**0.168**
RF_O	10000	Automated	**0.52**	0.5	0.255	0.25	**0.253**
RF_O	10000	Expert	**0.475**	0.5	0.398	0.393	**0.395**
SRE_B	1:1	*A priori*	**0.32**	0.5	0.949	0.954	**0.952**
SRE_B	1:1	Automated	**0.31**	0.5	0.949	0.954	**0.952**
SRE_B	1:1	Expert	**0.301**	0.5	0	0	**0**
SRE_B	1:2	*A priori*	**0.324**	0.5	0.949	0.954	**0.952**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Probability of occurrence	Presence-absence map Sensitivity			
				Train	Test	Fit	Sensitivity
SRE_B	1:2	Automated	**0.31**	0.5	0.949	0.954	**0.952**
SRE_B	1:2	Expert	**0.298**	0.5	0	0	**0**
SRE_B	1:3	*A priori*	**0.32**	0.5	0.954	0.949	**0.952**
SRE_B	1:3	Automated	**0.309**	0.5	0.954	0.949	**0.952**
SRE_B	1:3	Expert	**0.294**	0.5	0.01	0.01	**0.01**
SRE_B	10000	*A priori*	**0.296**	0.5	0.949	0.954	**0.952**
SRE_B	10000	Automated	**0.312**	0.5	0.949	0.954	**0.952**
SRE_B	10000	Expert	**0.296**	0.5	0.005	0.005	**0.005**
SRE_O	1:1	*A priori*	**0.065**	0.5	0.066	0.071	**0.069**
SRE_O	1:1	Automated	**0.057**	0.5	0.015	0.015	**0.015**
SRE_O	1:1	Expert	**0.072**	0.5	0.041	0.041	**0.041**
SRE_O	1:2	*A priori*	**0.058**	0.5	0.066	0.071	**0.069**
SRE_O	1:2	Automated	**0.049**	0.5	0.02	0.026	**0.023**
SRE_O	1:2	Expert	**0.075**	0.5	0.046	0.046	**0.046**
SRE_O	1:3	*A priori*	**0.066**	0.5	0.071	0.066	**0.069**
SRE_O	1:3	Automated	**0.055**	0.5	0.026	0.02	**0.023**
SRE_O	1:3	Expert	**0.079**	0.5	0.046	0.046	**0.046**
SRE_O	10000	*A priori*	**0.071**	0.5	0.061	0.061	**0.061**
SRE_O	10000	Automated	**0.048**	0.5	0.02	0.026	**0.023**
SRE_O	10000	Expert	**0.075**	0.5	0.041	0.041	**0.041**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			Specificity				Precision			
			Train	Test	Fit	Specificity	Train	Test	Fit	Precision
ANN_B	1:1	*A priori*	0.529	0.273	0.766	**0.582**	0.843	0.316	0.126	**0.278**
ANN_B	1:1	Automated	0.51	0.23	0.707	**0.536**	0.843	0.209	0.107	**0.216**
ANN_B	1:1	Expert	0.439	0.602	0.44	**0.549**	0.83	0.653	0.257	**0.501**
ANN_B	1:2	*A priori*	0.529	0.267	0.777	**0.584**	0.604	0.321	0.408	**0.302**
ANN_B	1:2	Automated	0.503	0.335	0.62	**0.54**	0.597	0.444	0.456	**0.382**
ANN_B	1:2	Expert	0.452	0.398	0.571	**0.526**	0.591	0.469	0.471	**0.399**
ANN_B	1:3	*A priori*	0.477	0.46	0.647	**0.588**	0.384	0.357	0.597	**0.304**
ANN_B	1:3	Automated	0.51	0.292	0.652	**0.538**	0.39	0.418	0.626	**0.351**
ANN_B	1:3	Expert	0.329	0.075	0.913	**0.487**	0.34	0.27	0.66	**0.271**
ANN_B	10000	*A priori*	0.432	0.292	0.685	**0.522**	0.132	0.337	0.879	**0.309**
ANN_B	10000	Automated	0.49	0.261	0.652	**0.519**	0.145	0.408	0.888	**0.355**
ANN_B	10000	Expert	0.445	0.404	0.554	**0.519**	0.138	0.546	0.922	**0.436**
ANN_O	1:1	*A priori*	0.194	0.18	0.543	**0.336**	0.774	0.087	0.087	**0.113**
ANN_O	1:1	Automated	0.155	0.124	0.598	**0.321**	0.748	0.071	0.068	**0.084**
ANN_O	1:1	Expert	0.206	0.429	0.217	**0.311**	0.78	0.398	0.233	**0.34**
ANN_O	1:2	*A priori*	0.123	0.106	0.37	**0.215**	0.447	0.046	0.383	**0.078**
ANN_O	1:2	Automated	0.084	0.093	0.408	**0.21**	0.428	0.061	0.383	**0.076**
ANN_O	1:2	Expert	0.148	0.28	0.168	**0.215**	0.459	0.357	0.529	**0.308**
ANN_O	1:3	*A priori*	0.058	0.062	0.201	**0.111**	0.233	0.026	0.573	**0.056**
ANN_O	1:3	Automated	0.045	0.043	0.207	**0.101**	0.233	0.046	0.578	**0.068**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			Specificity				Precision			
			Train	Test	Fit	Specificity	Train	Test	Fit	Precision
ANN_O	1:3	Expert	0.045	0.13	0.065	**0.081**	0.233	0.143	0.738	**0.194**
ANN_O	10000	*A priori*	0.006	0.019	0.038	**0.014**	0	0.01	0.83	**0.06**
ANN_O	10000	Automated	0.006	0.006	0.038	**0.009**	0	0.005	0.83	**0.058**
ANN_O	10000	Expert	0.006	0.025	0.038	**0.016**	0.006	0.041	0.854	**0.09**
CTA_B	1:1	*A priori*	0.774	0.634	0.886	**0.855**	0.899	0.48	0.112	**0.379**
CTA_B	1:1	Automated	0.806	0.602	0.918	**0.868**	0.906	0.587	0.131	**0.444**
CTA_B	1:1	Expert	0.787	0.472	0.902	**0.805**	0.899	0.556	0.155	**0.438**
CTA_B	1:2	*A priori*	0.826	0.696	0.973	**0.931**	0.704	0.648	0.364	**0.49**
CTA_B	1:2	Automated	0.819	0.652	0.967	**0.91**	0.698	0.526	0.354	**0.422**
CTA_B	1:2	Expert	0.794	0.516	0.908	**0.826**	0.679	0.577	0.403	**0.461**
CTA_B	1:3	*A priori*	0.858	0.814	0.973	**0.988**	0.579	0.561	0.495	**0.45**
CTA_B	1:3	Automated	0.858	0.584	0.984	**0.905**	0.572	0.459	0.466	**0.382**
CTA_B	1:3	Expert	0.852	0.075	0.913	**0.684**	0.491	0.27	0.612	**0.321**
CTA_B	10000	*A priori*	0.865	0.758	0.984	**0.973**	0.233	0.628	0.84	**0.482**
CTA_B	10000	Automated	0.871	0.727	0.989	**0.966**	0.258	0.5	0.801	**0.412**
CTA_B	10000	Expert	0.845	0.627	0.973	**0.913**	0.22	0.566	0.874	**0.462**
CTA_O	1:1	*A priori*	0.168	0.236	0.228	**0.228**	0.78	0.153	0.15	**0.179**
CTA_O	1:1	Automated	0.142	0.099	0.266	**0.181**	0.761	0.082	0.097	**0.109**
CTA_O	1:1	Expert	0.135	0.149	0.201	**0.173**	0.755	0.184	0.17	**0.192**
CTA_O	1:2	*A priori*	0.148	0.255	0.147	**0.197**	0.497	0.179	0.437	**0.194**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			Specificity				Precision			
			Train	**Test**	**Fit**	**Specificity**	**Train**	**Test**	**Fit**	**Precision**
CTA_O	1:2	Automated	0.142	0.149	0.168	**0.163**	0.484	0.128	0.408	**0.148**
CTA_O	1:2	Expert	0.155	0.168	0.245	**0.204**	0.503	0.133	0.403	**0.157**
CTA_O	1:3	*A priori*	0.155	0.329	0.13	**0.222**	0.289	0.219	0.583	**0.183**
CTA_O	1:3	Automated	0.161	0.118	0.174	**0.161**	0.296	0.097	0.544	**0.107**
CTA_O	1:3	Expert	0.148	0.242	0.196	**0.211**	0.289	0.168	0.592	**0.163**
CTA_O	10000	*A priori*	0.09	0.727	0.06	**0.321**	0.044	0.413	0.947	**0.336**
CTA_O	10000	Automated	0.116	0.143	0.109	**0.129**	0.05	0.173	0.917	**0.208**
CTA_O	10000	Expert	0.11	0.137	0.114	**0.126**	0.057	0.163	0.908	**0.201**
EMca_B	1:1	*A priori*	0.026	0	0.712	**0.268**	0.667	0	0.107	**0.027**
EMca_B	1:1	Automated	0.026	0.006	0.848	**0.322**	0.679	0.031	0.121	**0.056**
EMca_B	1:1	Expert	0.026	0	0.859	**0.324**	0.679	0.02	0.097	**0.039**
EMca_B	1:2	*A priori*	0.026	0	0.674	**0.254**	0.314	0	0.403	**0**
EMca_B	1:2	Automated	0.019	0	0.81	**0.303**	0.302	0.02	0.413	**0.009**
EMca_B	1:2	Expert	0.026	0	0.891	**0.336**	0.352	0.02	0.379	**0.017**
EMca_B	1:3	*A priori*	0.026	0	0.837	**0.315**	0.233	0	0.539	**0.027**
EMca_B	1:3	Automated	0.026	0	0.842	**0.317**	0.226	0.02	0.558	**0.043**
EMca_B	1:3	Expert	0.026	0	0.723	**0.272**	0.226	0.02	0.558	**0.043**
EMca_B	10000	*A priori*	0.135	0	0.473	**0.219**	0.063	0	0.757	**0.05**
EMca_B	10000	Automated	0.065	0	0.696	**0.277**	0.038	0.02	0.772	**0.055**
EMca_B	10000	Expert	0.039	0	0.734	**0.281**	0.013	0.02	0.811	**0.062**

Table B2.5 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Presence-absence map**							
			Specificity				**Precision**			
			Train	**Test**	**Fit**	**Specificity**	**Train**	**Test**	**Fit**	**Precision**
EMmean_B	1:1	*A priori*	0.819	0.72	0.929	**0.922**	0.906	0.724	0.209	**0.55**
EMmean_B	1:1	Automated	0.832	0.528	0.962	**0.866**	0.906	0.699	0.16	**0.513**
EMmean_B	1:1	Expert	0.813	0.46	0.935	**0.823**	0.906	0.622	0.146	**0.469**
EMmean_B	1:2	*A priori*	0.832	0.814	0.929	**0.962**	0.686	0.76	0.447	**0.576**
EMmean_B	1:2	Automated	0.748	0.205	0.902	**0.69**	0.66	0.291	0.34	**0.281**
EMmean_B	1:2	Expert	0.819	0.379	0.973	**0.809**	0.686	0.439	0.33	**0.361**
EMmean_B	1:3	*A priori*	0.832	0.727	0.951	**0.937**	0.516	0.75	0.65	**0.587**
EMmean_B	1:3	Automated	0.877	0.323	0.978	**0.812**	0.629	0.383	0.383	**0.332**
EMmean_B	1:3	Expert	0.832	0.36	0.984	**0.811**	0.509	0.429	0.49	**0.348**
EMmean_B	10000	*A priori*	0.845	0.87	0.962	**1**	0.214	0.842	0.927	**0.62**
EMmean_B	10000	Automated	0.884	0.242	0.995	**0.79**	0.258	0.286	0.728	**0.272**
EMmean_B	10000	Expert	0.865	0.385	0.995	**0.837**	0.22	0.398	0.801	**0.344**
EMmedian_B	1:1	*A priori*	0.716	0.758	0.755	**0.831**	0.887	0.735	0.267	**0.574**
EMmedian_B	1:1	Automated	0.703	0.528	0.821	**0.764**	0.881	0.679	0.223	**0.522**
EMmedian_B	1:1	Expert	0.652	0.484	0.75	**0.702**	0.874	0.571	0.204	**0.457**
EMmedian_B	1:2	*A priori*	0.742	0.826	0.777	**0.875**	0.654	0.821	0.549	**0.64**
EMmedian_B	1:2	Automated	0.4	0.186	0.636	**0.451**	0.572	0.296	0.413	**0.276**
EMmedian_B	1:2	Expert	0.729	0.41	0.848	**0.74**	0.642	0.49	0.403	**0.4**
EMmedian_B	1:3	*A priori*	0.748	0.857	0.788	**0.893**	0.447	0.857	0.801	**0.68**
EMmedian_B	1:3	Automated	0.387	0.18	0.625	**0.44**	0.333	0.301	0.587	**0.247**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			Specificity				Precision			
			Train	Test	Fit	Specificity	Train	Test	Fit	Precision
EMmedian_B	1:3	Expert	0.697	0.46	0.793	**0.726**	0.434	0.485	0.573	**0.379**
EMmedian_B	10000	*A priori*	0.742	0.832	0.783	**0.879**	0.195	0.929	0.942	**0.66**
EMmedian_B	10000	Automated	0.335	0.199	0.56	**0.403**	0.119	0.342	0.864	**0.298**
EMmedian_B	10000	Expert	0.716	0.422	0.826	**0.731**	0.182	0.531	0.913	**0.445**
EMwmean_B	1:1	*A priori*	0.826	0.752	0.935	**0.938**	0.906	0.74	0.204	**0.555**
EMwmean_B	1:1	Automated	0.819	0.602	0.94	**0.881**	0.906	0.719	0.194	**0.54**
EMwmean_B	1:1	Expert	0.819	0.484	0.957	**0.843**	0.906	0.612	0.126	**0.454**
EMwmean_B	1:2	*A priori*	0.832	0.739	0.946	**0.94**	0.692	0.745	0.437	**0.567**
EMwmean_B	1:2	Automated	0.761	0.224	0.908	**0.704**	0.667	0.311	0.335	**0.292**
EMwmean_B	1:2	Expert	0.832	0.36	0.984	**0.811**	0.686	0.449	0.33	**0.366**
EMwmean_B	1:3	*A priori*	0.839	0.733	0.973	**0.95**	0.528	0.77	0.646	**0.601**
EMwmean_B	1:3	Automated	0.884	0.273	0.978	**0.796**	0.635	0.383	0.374	**0.33**
EMwmean_B	1:3	Expert	0.832	0.311	0.989	**0.794**	0.516	0.403	0.481	**0.334**
EMwmean_B	10000	*A priori*	0.858	0.832	0.978	**0.997**	0.22	0.847	0.922	**0.623**
EMwmean_B	10000	Automated	0.884	0.217	0.984	**0.777**	0.258	0.224	0.728	**0.242**
EMwmean_B	10000	Expert	0.865	0.329	1	**0.818**	0.226	0.393	0.791	**0.34**
FDA_B	1:1	*A priori*	0.406	0.578	0.505	**0.552**	0.811	0.577	0.243	**0.447**
FDA_B	1:1	Automated	0.323	0.304	0.527	**0.425**	0.792	0.214	0.136	**0.208**
FDA_B	1:1	Expert	0.342	0.317	0.495	**0.425**	0.799	0.403	0.199	**0.335**
FDA_B	1:2	*A priori*	0.342	0.553	0.424	**0.487**	0.56	0.423	0.485	**0.368**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			Specificity				Precision			
			Train	Test	Fit	Specificity	Train	Test	Fit	Precision
FDA_B	1:2	Automated	0.387	0.174	0.745	**0.483**	0.566	0.112	0.35	**0.152**
FDA_B	1:2	Expert	0.361	0.298	0.516	**0.433**	0.56	0.276	0.417	**0.262**
FDA_B	1:3	*A priori*	0.303	0.646	0.315	**0.467**	0.314	0.214	0.602	**0.203**
FDA_B	1:3	Automated	0.381	0.161	0.799	**0.496**	0.333	0.102	0.5	**0.107**
FDA_B	1:3	Expert	0.252	0.075	0.913	**0.457**	0.321	0.27	0.612	**0.238**
FDA_B	10000	*A priori*	0.213	0.627	0.239	**0.397**	0.082	0.189	0.864	**0.204**
FDA_B	10000	Automated	0.245	0.199	0.582	**0.377**	0.094	0.138	0.825	**0.167**
FDA_B	10000	Expert	0.265	0.298	0.418	**0.36**	0.094	0.204	0.859	**0.216**
FDA_O	1:1	*A priori*	0.658	0.857	0.658	**0.81**	0.849	0.699	0.311	**0.559**
FDA_O	1:1	Automated	0.535	0.876	0.37	**0.662**	0.792	0.847	0.393	**0.644**
FDA_O	1:1	Expert	0.555	0.46	0.543	**0.578**	0.792	0.464	0.252	**0.388**
FDA_O	1:2	*A priori*	0.626	0.776	0.576	**0.736**	0.591	0.658	0.553	**0.532**
FDA_O	1:2	Automated	0.645	0.727	0.625	**0.743**	0.597	0.816	0.655	**0.662**
FDA_O	1:2	Expert	0.542	0.453	0.549	**0.573**	0.541	0.459	0.505	**0.386**
FDA_O	1:3	*A priori*	0.658	0.882	0.641	**0.813**	0.409	0.668	0.748	**0.543**
FDA_O	1:3	Automated	0.606	0.658	0.554	**0.676**	0.39	0.617	0.752	**0.511**
FDA_O	1:3	Expert	0.426	0.547	0.364	**0.494**	0.333	0.515	0.699	**0.407**
FDA_O	10000	*A priori*	0.677	0.913	0.63	**0.828**	0.164	0.704	0.893	**0.511**
FDA_O	10000	Automated	0.613	0.565	0.609	**0.664**	0.138	0.602	0.922	**0.463**
FDA_O	10000	Expert	0.458	0.584	0.408	**0.537**	0.132	0.556	0.927	**0.44**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			Specificity				Precision			
			Train	Test	Fit	Specificity	Train	Test	Fit	Precision
GAM_B	1:1	*A priori*	0.594	0.112	0.848	**0.576**	0.855	0.122	0.058	**0.156**
GAM_B	1:1	Automated	0.51	0.242	0.668	**0.526**	0.843	0.23	0.102	**0.224**
GAM_B	1:1	Expert	0.51	0.193	0.717	**0.526**	0.843	0.199	0.087	**0.202**
GAM_B	1:2	*A priori*	0.6	0.068	0.739	**0.521**	0.623	0.056	0.262	**0.11**
GAM_B	1:2	Automated	0.484	0.124	0.821	**0.529**	0.597	0.092	0.32	**0.143**
GAM_B	1:2	Expert	0.452	0.087	0.766	**0.482**	0.591	0.061	0.282	**0.106**
GAM_B	1:3	*A priori*	0.639	0.012	0.299	**0.348**	0.415	0.015	0.359	**0.035**
GAM_B	1:3	Automated	0.561	0.031	0.38	**0.357**	0.403	0.056	0.388	**0.064**
GAM_B	1:3	Expert	0.329	0.075	0.913	**0.487**	0.346	0.066	0.398	**0.046**
GAM_B	10000	*A priori*	0.639	0.031	0.603	**0.47**	0.17	0.041	0.714	**0.101**
GAM_B	10000	Automated	0.523	0.062	0.696	**0.473**	0.164	0.051	0.738	**0.115**
GAM_B	10000	Expert	0.452	0.031	0.353	**0.305**	0.138	0.031	0.728	**0.088**
GAM_O	1:1	*A priori*	0.419	0.839	0.321	**0.586**	0.824	0.878	0.374	**0.665**
GAM_O	1:1	Automated	0.51	0.845	0.37	**0.64**	0.836	0.878	0.359	**0.664**
GAM_O	1:1	Expert	0.445	0.863	0.283	**0.59**	0.83	0.832	0.345	**0.632**
GAM_O	1:2	*A priori*	0.439	0.894	0.288	**0.602**	0.572	0.893	0.684	**0.702**
GAM_O	1:2	Automated	0.413	0.925	0.25	**0.589**	0.56	0.903	0.694	**0.705**
GAM_O	1:2	Expert	0.348	0.839	0.25	**0.532**	0.56	0.847	0.655	**0.659**
GAM_O	1:3	*A priori*	0.426	0.888	0.31	**0.603**	0.358	0.923	0.835	**0.686**
GAM_O	1:3	Automated	0.387	0.571	0.402	**0.503**	0.352	0.806	0.786	**0.601**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			Specificity				Precision			
			Train	Test	Fit	Specificity	Train	Test	Fit	Precision
GAM_O	1:3	Expert	0.342	0.64	0.342	**0.489**	0.333	0.842	0.806	**0.619**
GAM_O	10000	*A priori*	0.387	0.882	0.304	**0.584**	0.126	0.959	0.85	**0.596**
GAM_O	10000	Automated	0.387	0.46	0.446	**0.478**	0.132	0.847	0.981	**0.609**
GAM_O	10000	Expert	0.342	0.435	0.44	**0.449**	0.126	0.847	0.976	**0.603**
GBM_B	1:1	*A priori*	0.8	0.764	0.875	**0.91**	0.899	0.796	0.272	**0.612**
GBM_B	1:1	Automated	0.69	0.453	0.832	**0.735**	0.881	0.673	0.228	**0.522**
GBM_B	1:1	Expert	0.755	0.416	0.88	**0.764**	0.893	0.531	0.175	**0.432**
GBM_B	1:2	*A priori*	0.768	0.857	0.826	**0.915**	0.673	0.837	0.544	**0.655**
GBM_B	1:2	Automated	0.684	0.64	0.723	**0.762**	0.635	0.776	0.519	**0.594**
GBM_B	1:2	Expert	0.735	0.609	0.815	**0.805**	0.648	0.663	0.476	**0.524**
GBM_B	1:3	*A priori*	0.781	0.95	0.804	**0.947**	0.453	0.898	0.782	**0.693**
GBM_B	1:3	Automated	0.671	0.727	0.679	**0.774**	0.421	0.872	0.796	**0.673**
GBM_B	1:3	Expert	0.71	0.075	0.913	**0.63**	0.44	0.27	0.709	**0.344**
GBM_B	10000	*A priori*	0.761	0.901	0.772	**0.908**	0.201	0.888	0.99	**0.667**
GBM_B	10000	Automated	0.665	0.82	0.647	**0.794**	0.176	0.903	0.966	**0.651**
GBM_B	10000	Expert	0.723	0.745	0.701	**0.808**	0.189	0.811	1	**0.628**
GBM_O	1:1	*A priori*	0.632	0.82	0.587	**0.759**	0.868	0.781	0.306	**0.606**
GBM_O	1:1	Automated	0.619	0.522	0.663	**0.671**	0.862	0.607	0.223	**0.478**
GBM_O	1:1	Expert	0.323	0.584	0.391	**0.48**	0.792	0.995	0.971	**1**
GBM_O	1:2	*A priori*	0.587	0.534	0.614	**0.645**	0.616	0.444	0.427	**0.377**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			Specificity				Precision			
			Train	Test	Fit	Specificity	Train	Test	Fit	Precision
GBM_O	1:2	Automated	0.574	0.211	0.728	**0.561**	0.61	0.327	0.408	**0.307**
GBM_O	1:2	Expert	0.335	0.584	0.391	**0.484**	0.56	0.995	0.854	**0.829**
GBM_O	1:3	*A priori*	0.581	0.46	0.636	**0.622**	0.409	0.372	0.573	**0.312**
GBM_O	1:3	Automated	0.568	0.18	0.761	**0.559**	0.403	0.255	0.558	**0.244**
GBM_O	1:3	Expert	0.51	0.174	0.717	**0.519**	0.39	0.245	0.563	**0.235**
GBM_O	10000	*A priori*	0.497	0.528	0.516	**0.571**	0.145	0.347	0.859	**0.31**
GBM_O	10000	Automated	0.51	0.174	0.707	**0.514**	0.157	0.24	0.85	**0.259**
GBM_O	10000	Expert	0.452	0.155	0.69	**0.479**	0.138	0.235	0.854	**0.25**
GLM_B	1:1	*A priori*	0.419	0.758	0.375	**0.576**	0.824	0.867	0.369	**0.658**
GLM_B	1:1	Automated	0.4	0.373	0.516	**0.476**	0.811	0.413	0.184	**0.339**
GLM_B	1:1	Expert	0.477	0.453	0.543	**0.546**	0.836	0.434	0.18	**0.359**
GLM_B	1:2	*A priori*	0.323	0.783	0.272	**0.509**	0.56	0.862	0.67	**0.674**
GLM_B	1:2	Automated	0.439	0.335	0.565	**0.495**	0.585	0.347	0.422	**0.312**
GLM_B	1:2	Expert	0.374	0.441	0.462	**0.472**	0.566	0.352	0.427	**0.308**
GLM_B	1:3	*A priori*	0.4	0.851	0.321	**0.583**	0.333	0.908	0.82	**0.659**
GLM_B	1:3	Automated	0.406	0.366	0.527	**0.48**	0.352	0.367	0.607	**0.298**
GLM_B	1:3	Expert	0.297	0.075	0.913	**0.474**	0.321	0.27	0.621	**0.243**
GLM_B	10000	*A priori*	0.316	0.795	0.266	**0.51**	0.113	0.934	0.898	**0.601**
GLM_B	10000	Automated	0.4	0.36	0.522	**0.474**	0.132	0.347	0.864	**0.307**
GLM_B	10000	Expert	0.374	0.416	0.467	**0.464**	0.132	0.337	0.864	**0.302**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			Specificity				Precision			
			Train	Test	Fit	Specificity	Train	Test	Fit	Precision
GLM_O	1:1	*A priori*	0.135	0.422	0.12	**0.245**	0.717	0.582	0.403	**0.482**
GLM_O	1:1	Automated	0.181	0.621	0.13	**0.342**	0.736	0.413	0.325	**0.371**
GLM_O	1:1	Expert	0.4	0.385	0.516	**0.481**	0.811	0.362	0.165	**0.304**
GLM_O	1:2	*A priori*	0.187	0.708	0.223	**0.412**	0.472	0.755	0.718	**0.602**
GLM_O	1:2	Automated	0.323	0.596	0.304	**0.451**	0.547	0.24	0.442	**0.251**
GLM_O	1:2	Expert	0.406	0.354	0.538	**0.48**	0.572	0.403	0.437	**0.34**
GLM_O	1:3	*A priori*	0.239	0.807	0.245	**0.477**	0.308	0.883	0.859	**0.653**
GLM_O	1:3	Automated	0.4	0.714	0.348	**0.542**	0.371	0.505	0.665	**0.404**
GLM_O	1:3	Expert	0.335	0.335	0.505	**0.434**	0.333	0.429	0.641	**0.336**
GLM_O	10000	*A priori*	0.31	1	0.223	**0.568**	0.101	0.985	0.767	**0.556**
GLM_O	10000	Automated	0.335	0.745	0.277	**0.502**	0.126	0.566	0.932	**0.444**
GLM_O	10000	Expert	0.342	0.348	0.505	**0.441**	0.126	0.495	0.942	**0.414**
MARS_B	1:1	*A priori*	0.497	0.54	0.554	**0.59**	0.836	0.607	0.248	**0.477**
MARS_B	1:1	Automated	0.419	0.484	0.478	**0.511**	0.83	0.658	0.286	**0.518**
MARS_B	1:1	Expert	0.465	0.398	0.543	**0.52**	0.836	0.474	0.214	**0.396**
MARS_B	1:2	*A priori*	0.516	0.584	0.592	**0.628**	0.597	0.709	0.539	**0.553**
MARS_B	1:2	Automated	0.387	0.317	0.56	**0.467**	0.566	0.454	0.466	**0.377**
MARS_B	1:2	Expert	0.387	0.286	0.495	**0.43**	0.566	0.418	0.461	**0.357**
MARS_B	1:3	*A priori*	0.51	0.758	0.489	**0.653**	0.39	0.811	0.796	**0.627**
MARS_B	1:3	Automated	0.432	0.391	0.592	**0.524**	0.377	0.531	0.675	**0.424**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			Specificity				Precision			
			Train	Test	Fit	Specificity	Train	Test	Fit	Precision
MARS_B	1:3	Expert	0.342	0.354	0.457	**0.425**	0.333	0.52	0.68	**0.4**
MARS_B	10000	*A priori*	0.477	0.627	0.527	**0.606**	0.138	0.827	0.956	**0.59**
MARS_B	10000	Automated	0.452	0.708	0.408	**0.581**	0.138	0.781	0.937	**0.558**
MARS_B	10000	Expert	0.374	0.429	0.413	**0.449**	0.132	0.566	0.951	**0.457**
MARS_O	1:1	*A priori*	0.51	0.559	0.408	**0.547**	0.836	0.49	0.228	**0.41**
MARS_O	1:1	Automated	0.432	0.621	0.435	**0.551**	0.811	0.694	0.296	**0.531**
MARS_O	1:1	Expert	0.406	0.348	0.527	**0.473**	0.811	0.403	0.194	**0.339**
MARS_O	1:2	*A priori*	0.394	0.609	0.44	**0.534**	0.566	0.536	0.49	**0.429**
MARS_O	1:2	Automated	0.335	0.453	0.44	**0.454**	0.553	0.51	0.466	**0.398**
MARS_O	1:2	Expert	0.387	0.304	0.538	**0.454**	0.566	0.281	0.413	**0.266**
MARS_O	1:3	*A priori*	0.387	0.528	0.484	**0.518**	0.333	0.383	0.636	**0.311**
MARS_O	1:3	Automated	0.316	0.59	0.353	**0.465**	0.314	0.531	0.689	**0.4**
MARS_O	1:3	Expert	0.387	0.292	0.533	**0.447**	0.333	0.276	0.583	**0.232**
MARS_O	10000	*A priori*	0.219	0.478	0.321	**0.374**	0.082	0.332	0.869	**0.277**
MARS_O	10000	Automated	0.226	0.472	0.337	**0.38**	0.075	0.388	0.903	**0.318**
MARS_O	10000	Expert	0.284	0.348	0.429	**0.39**	0.107	0.265	0.859	**0.252**
MaxEnt_B	1:1	*A priori*	0.445	0.59	0.44	**0.547**	0.818	0.454	0.218	**0.379**
MaxEnt_B	1:1	Automated	0.355	0.714	0.31	**0.51**	0.799	0.689	0.316	**0.532**
MaxEnt_B	1:1	Expert	0.374	0.323	0.516	**0.448**	0.799	0.281	0.16	**0.256**
MaxEnt_B	1:2	*A priori*	0.368	0.509	0.386	**0.466**	0.541	0.327	0.471	**0.304**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			Specificity				Precision			
			Train	Test	Fit	Specificity	Train	Test	Fit	Precision
MaxEnt_B	1:2	Automated	0.477	0.503	0.467	**0.536**	0.591	0.551	0.5	**0.453**
MaxEnt_B	1:2	Expert	0.387	0.335	0.538	**0.466**	0.566	0.25	0.413	**0.251**
MaxEnt_B	1:3	*A priori*	0.471	0.075	0.913	**0.54**	0.396	0.27	0.612	**0.275**
MaxEnt_B	1:3	Automated	0.445	0.677	0.386	**0.559**	0.377	0.541	0.675	**0.429**
MaxEnt_B	1:3	Expert	0.329	0.075	0.913	**0.487**	0.365	0.158	0.612	**0.204**
MaxEnt_B	10000	*A priori*	0.548	0.634	0.511	**0.629**	0.164	0.643	0.961	**0.515**
MaxEnt_B	10000	Automated	0.406	0.77	0.332	**0.559**	0.132	0.684	0.961	**0.519**
MaxEnt_B	10000	Expert	0.477	0.379	0.598	**0.539**	0.151	0.306	0.859	**0.293**
MaxEnt_O	1:1	*A priori*	0.406	0.596	0.397	**0.518**	0.805	0.531	0.252	**0.427**
MaxEnt_O	1:1	Automated	0.394	0.677	0.326	**0.517**	0.824	0.765	0.325	**0.587**
MaxEnt_O	1:1	Expert	0.335	0.248	0.5	**0.399**	0.786	0.214	0.15	**0.212**
MaxEnt_O	1:2	*A priori*	0.323	0.64	0.304	**0.468**	0.535	0.536	0.519	**0.427**
MaxEnt_O	1:2	Automated	0.277	0.671	0.255	**0.444**	0.541	0.597	0.539	**0.47**
MaxEnt_O	1:2	Expert	0.258	0.273	0.418	**0.348**	0.522	0.214	0.432	**0.221**
MaxEnt_O	1:3	*A priori*	0.29	0.702	0.261	**0.463**	0.314	0.638	0.743	**0.479**
MaxEnt_O	1:3	Automated	0.4	0.72	0.353	**0.546**	0.377	0.745	0.777	**0.579**
MaxEnt_O	1:3	Expert	0.284	0.311	0.451	**0.384**	0.314	0.24	0.617	**0.222**
MaxEnt_O	10000	*A priori*	0.323	0.615	0.342	**0.473**	0.101	0.485	0.922	**0.387**
MaxEnt_O	10000	Automated	0.368	0.665	0.359	**0.515**	0.132	0.561	0.932	**0.445**
MaxEnt_O	10000	Expert	0.387	0.342	0.516	**0.46**	0.132	0.26	0.859	**0.262**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			Specificity				Precision			
			Train	Test	Fit	Specificity	Train	Test	Fit	Precision
MXL_O	1:1	*A priori*	0.2	0.056	0.924	**0.435**	0.767	0.036	0.029	**0.056**
MXL_O	1:1	Automated	0.155	0.081	0.989	**0.452**	0.742	0.077	0.083	**0.09**
MXL_O	1:1	Expert	0.342	0.683	0.315	**0.496**	0.805	0.633	0.272	**0.486**
MXL_O	1:2	*A priori*	0.155	0.05	0.946	**0.424**	0.478	0.036	0.291	**0.043**
MXL_O	1:2	Automated	0.135	0.037	0.87	**0.383**	0.465	0.046	0.301	**0.047**
MXL_O	1:2	Expert	0.271	0.646	0.266	**0.436**	0.535	0.587	0.524	**0.455**
MXL_O	1:3	*A priori*	0.155	0.05	0.929	**0.418**	0.277	0.031	0.437	**0.013**
MXL_O	1:3	Automated	0.135	0.037	0.853	**0.377**	0.264	0.046	0.456	**0.024**
MXL_O	1:3	Expert	0.323	0.652	0.31	**0.475**	0.327	0.592	0.704	**0.444**
MXL_O	10000	*A priori*	0.174	0.087	0.897	**0.427**	0.069	0.143	0.85	**0.169**
MXL_O	10000	Automated	0.135	0.037	0.864	**0.381**	0.05	0.046	0.762	**0.069**
MXL_O	10000	Expert	0.232	0.447	0.293	**0.357**	0.088	0.378	0.883	**0.31**
RF_B	1:1	*A priori*	0.89	0.975	0.234	**0.782**	0.956	0.98	0.092	**0.642**
RF_B	1:1	Automated	0.897	0.957	0.212	**0.769**	0.962	0.959	0.063	**0.621**
RF_B	1:1	Expert	0.89	0.714	0.19	**0.667**	0.956	0.73	0	**0.474**
RF_B	1:2	*A priori*	0.929	0.969	0.185	**0.776**	0.925	0.949	0.049	**0.59**
RF_B	1:2	Automated	0.935	0.925	0.163	**0.754**	0.95	0.939	0.029	**0.588**
RF_B	1:2	Expert	0.929	0.689	0.147	**0.656**	0.918	0.745	0.005	**0.466**
RF_B	1:3	*A priori*	0.948	0.994	0.179	**0.79**	0.937	0.944	0.034	**0.587**
RF_B	1:3	Automated	0.961	0.789	0.103	**0.689**	0.969	0.847	0.01	**0.543**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			Specificity				Precision			
			Train	Test	Fit	Specificity	Train	Test	Fit	Precision
RF_B	1:3	Expert	0.923	0.075	0.913	**0.711**	0.912	0.27	0.039	**0.247**
RF_B	10000	*A priori*	0.987	0.876	0.114	**0.736**	0.931	0.847	0.01	**0.524**
RF_B	10000	Automated	0.987	0.851	0.109	**0.724**	0.931	0.852	0.01	**0.527**
RF_B	10000	Expert	0.981	0.789	0.103	**0.697**	0.918	0.811	0.01	**0.501**
RF_O	1:1	*A priori*	0.91	1	0.201	**0.786**	0.981	0.974	0.141	**0.676**
RF_O	1:1	Automated	0.916	0.839	0.158	**0.711**	0.987	0.98	0.117	**0.669**
RF_O	1:1	Expert	0.903	0.894	0.212	**0.748**	0.975	0.913	0.019	**0.583**
RF_O	1:2	*A priori*	0.942	0.975	0.141	**0.767**	0.987	0.969	0.078	**0.645**
RF_O	1:2	Automated	0.955	0.925	0.125	**0.747**	0.994	0.969	0.073	**0.646**
RF_O	1:2	Expert	0.935	0.839	0.136	**0.711**	0.975	0.918	0.024	**0.588**
RF_O	1:3	*A priori*	0.974	1	0.152	**0.792**	1	0.954	0.044	**0.627**
RF_O	1:3	Automated	0.974	0.981	0.13	**0.777**	1	0.964	0.053	**0.637**
RF_O	1:3	Expert	0.968	0.789	0.114	**0.696**	0.987	0.893	0.015	**0.577**
RF_O	10000	*A priori*	1	0.789	0.092	**0.7**	0.975	0.714	0	**0.476**
RF_O	10000	Automated	0.994	0.801	0.098	**0.704**	0.943	0.878	0.015	**0.548**
RF_O	10000	Expert	0.994	0.696	0.087	**0.66**	0.937	0.837	0.01	**0.522**
SRE_B	1:1	*A priori*	0	0	0.027	**0**	0.484	0	0.267	**0.017**
SRE_B	1:1	Automated	0.013	0	0.054	**0.015**	0.572	0.02	0.189	**0.032**
SRE_B	1:1	Expert	0.103	0.497	0.082	**0.247**	0.73	1	0.981	**0.976**
SRE_B	1:2	*A priori*	0	0	0.027	**0**	0.233	0	0.51	**0.012**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			Specificity				Precision			
			Train	Test	Fit	Specificity	Train	Test	Fit	Precision
SRE_B	1:2	Automated	0.013	0	0.043	**0.011**	0.283	0.02	0.451	**0.018**
SRE_B	1:2	Expert	0.097	0.491	0.076	**0.24**	0.447	1	0.723	**0.712**
SRE_B	1:3	*A priori*	0	0	0.027	**0**	0.176	0	0.689	**0.073**
SRE_B	1:3	Automated	0.013	0	0.049	**0.013**	0.208	0.02	0.631	**0.069**
SRE_B	1:3	Expert	0.129	0.075	0.913	**0.411**	0.27	0.99	0.534	**0.528**
SRE_B	10000	*A priori*	0	0	0.027	**0**	0	0	0.83	**0.055**
SRE_B	10000	Automated	0.013	0	0.049	**0.013**	0.006	0.02	0.816	**0.061**
SRE_B	10000	Expert	0.097	0.466	0.071	**0.229**	0.031	1	0.277	**0.289**
SRE_O	1:1	*A priori*	0.058	0.702	0.016	**0.283**	0.692	0.316	0.301	**0.29**
SRE_O	1:1	Automated	0.071	0.988	0.016	**0.395**	0.711	0.107	0.238	**0.166**
SRE_O	1:1	Expert	0.071	0.907	0.022	**0.367**	0.723	0.801	0.451	**0.617**
SRE_O	1:2	*A priori*	0.052	0.696	0.005	**0.274**	0.403	0.342	0.568	**0.292**
SRE_O	1:2	Automated	0.071	0.932	0.016	**0.374**	0.415	0.148	0.515	**0.177**
SRE_O	1:2	Expert	0.077	0.938	0.027	**0.383**	0.428	0.791	0.762	**0.619**
SRE_O	1:3	*A priori*	0.032	0.075	0	**0.03**	0.239	0.27	0.733	**0.257**
SRE_O	1:3	Automated	0.065	0.944	0.016	**0.377**	0.245	0.194	0.728	**0.22**
SRE_O	1:3	Expert	0.071	0.857	0.033	**0.352**	0.252	0.786	0.845	**0.571**
SRE_O	10000	*A priori*	0.052	0.696	0.011	**0.276**	0.019	0.281	0.995	**0.283**
SRE_O	10000	Automated	0.071	0.963	0.016	**0.386**	0.025	0.117	0.985	**0.201**
SRE_O	10000	Expert	0.077	0.919	0.027	**0.376**	0.025	0.811	0.947	**0.522**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			F1				Correct classification rate			
			Train	Test	Fit	F1	Train	Test	Fit	CCR
ANN_B	1:1	*A priori*	0.827	0.362	0.167	**0.432**	0.844	0.467	0.271	**0.663**
ANN_B	1:1	Automated	0.82	0.397	0.192	**0.463**	0.844	0.6	0.292	**0.734**
ANN_B	1:1	Expert	0.807	0.747	0.323	**0.741**	0.828	0.76	0.401	**0.852**
ANN_B	1:2	*A priori*	0.593	0.356	0.419	**0.44**	0.672	0.493	0.443	**0.675**
ANN_B	1:2	Automated	0.587	0.69	0.52	**0.693**	0.661	0.72	0.526	**0.814**
ANN_B	1:2	Expert	0.573	0.586	0.51	**0.618**	0.639	0.707	0.531	**0.8**
ANN_B	1:3	*A priori*	0.38	0.471	0.611	**0.495**	0.517	0.653	0.609	**0.755**
ANN_B	1:3	Automated	0.387	0.615	0.692	**0.632**	0.533	0.707	0.63	**0.797**
ANN_B	1:3	Expert	0.347	0.132	0.717	**0.337**	0.489	0.747	0.734	**0.843**
ANN_B	10000	*A priori*	0.113	0.379	0.859	**0.429**	0.3	0.493	0.719	**0.631**
ANN_B	10000	Automated	0.133	0.621	0.939	**0.632**	0.322	0.68	0.776	**0.754**
ANN_B	10000	Expert	0.12	0.655	0.955	**0.654**	0.306	0.707	0.802	**0.771**
ANN_O	1:1	*A priori*	0.76	0.144	0.076	**0.209**	0.717	0.333	0.214	**0.515**
ANN_O	1:1	Automated	0.74	0.126	0.051	**0.172**	0.689	0.213	0.167	**0.425**
ANN_O	1:1	Expert	0.767	0.466	0.263	**0.514**	0.706	0.707	0.448	**0.792**
ANN_O	1:2	*A priori*	0.44	0.08	0.303	**0.117**	0.139	0.187	0.333	**0.235**
ANN_O	1:2	Automated	0.42	0.109	0.303	**0.122**	0.122	0.133	0.302	**0.188**
ANN_O	1:2	Expert	0.453	0.454	0.53	**0.481**	0.161	0.307	0.62	**0.434**
ANN_O	1:3	*A priori*	0.24	0.04	0.515	**0.1**	0.044	0.067	0.589	**0.254**
ANN_O	1:3	Automated	0.24	0.08	0.525	**0.13**	0.05	0.067	0.557	**0.242**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			F1				Correct classification rate			
			Train	Test	Fit	F1	Train	Test	Fit	CCR
ANN_O	1:3	Expert	0.24	0.236	0.692	**0.321**	0.039	0.107	0.786	**0.362**
ANN_O	10000	*A priori*	0	0.017	0.833	**0.133**	0.011	0	0.969	**0.384**
ANN_O	10000	Automated	0	0.011	0.823	**0.123**	0.006	0	0.974	**0.384**
ANN_O	10000	Expert	0.007	0.052	0.854	**0.169**	0.011	0	0.979	**0.389**
CTA_B	1:1	*A priori*	0.88	0.466	0.157	**0.519**	0.922	0.787	0.281	**0.852**
CTA_B	1:1	Automated	0.893	0.678	0.202	**0.68**	0.933	0.773	0.25	**0.837**
CTA_B	1:1	Expert	0.887	0.695	0.222	**0.698**	0.922	0.76	0.26	**0.83**
CTA_B	1:2	*A priori*	0.687	0.471	0.343	**0.518**	0.889	0.813	0.323	**0.868**
CTA_B	1:2	Automated	0.687	0.534	0.343	**0.556**	0.889	0.773	0.312	**0.845**
CTA_B	1:2	Expert	0.673	0.563	0.394	**0.595**	0.856	0.72	0.349	**0.822**
CTA_B	1:3	*A priori*	0.567	0.385	0.419	**0.441**	0.894	0.827	0.328	**0.88**
CTA_B	1:3	Automated	0.56	0.454	0.439	**0.49**	0.889	0.76	0.307	**0.836**
CTA_B	1:3	Expert	0.48	0.132	0.561	**0.324**	0.833	0.747	0.552	**0.918**
CTA_B	10000	*A priori*	0.233	0.31	0.758	**0.4**	0.85	0.827	0.417	**0.9**
CTA_B	10000	Automated	0.26	0.264	0.662	**0.331**	0.906	0.787	0.307	**0.857**
CTA_B	10000	Expert	0.227	0.529	0.813	**0.558**	0.806	0.76	0.432	**0.856**
CTA_O	1:1	*A priori*	0.827	0.207	0.106	**0.304**	0.8	0.24	0.161	**0.487**
CTA_O	1:1	Automated	0.82	0.149	0.071	**0.245**	0.767	0.16	0.094	**0.403**
CTA_O	1:1	Expert	0.8	0.282	0.141	**0.353**	0.761	0.307	0.188	**0.512**
CTA_O	1:2	*A priori*	0.5	0.201	0.369	**0.263**	0.461	0.32	0.328	**0.444**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			F1				Correct classification rate			
			Train	Test	Fit	F1	Train	Test	Fit	CCR
CTA_O	1:2	Automated	0.487	0.241	0.384	**0.288**	0.4	0.267	0.292	**0.374**
CTA_O	1:2	Expert	0.507	0.253	0.379	**0.303**	0.467	0.28	0.276	**0.404**
CTA_O	1:3	*A priori*	0.3	0.247	0.576	**0.294**	0.283	0.347	0.505	**0.456**
CTA_O	1:3	Automated	0.313	0.195	0.54	**0.25**	0.283	0.2	0.271	**0.279**
CTA_O	1:3	Expert	0.307	0.287	0.606	**0.34**	0.311	0.36	0.5	**0.473**
CTA_O	10000	*A priori*	0.033	0.534	0.96	**0.534**	0.106	0.893	0.984	**0.849**
CTA_O	10000	Automated	0.04	0.328	0.934	**0.4**	0.111	0.587	0.948	**0.693**
CTA_O	10000	Expert	0.04	0.316	0.924	**0.387**	0.111	0.533	0.943	**0.665**
EMca_B	1:1	*A priori*	0.707	0.006	0.035	**0.072**	0.294	0	0.005	**0.069**
EMca_B	1:1	Automated	0.713	0.052	0.04	**0.106**	0.311	0	0.01	**0.079**
EMca_B	1:1	Expert	0.72	0.034	0.03	**0.094**	0.356	0	0	**0.095**
EMca_B	1:2	*A priori*	0.373	0.006	0.247	**0**	0.078	0	0.104	**0.014**
EMca_B	1:2	Automated	0.34	0.029	0.288	**0.018**	0.067	0	0.125	**0.019**
EMca_B	1:2	Expert	0.4	0.029	0.232	**0.02**	0.089	0	0.062	**0**
EMca_B	1:3	*A priori*	0.24	0	0.429	**0.025**	0.056	0	0.156	**0.028**
EMca_B	1:3	Automated	0.233	0.029	0.475	**0.065**	0.044	0	0.177	**0.033**
EMca_B	1:3	Expert	0.233	0.029	0.475	**0.065**	0.044	0	0.182	**0.035**
EMca_B	10000	*A priori*	0.047	0	0.737	**0.093**	0.056	0	0.151	**0.026**
EMca_B	10000	Automated	0.027	0.029	0.773	**0.119**	0.033	0	0.229	**0.051**
EMca_B	10000	Expert	0.013	0.029	0.793	**0.124**	0.022	0	0.37	**0.112**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			F1				Correct classification rate			
			Train	Test	Fit	F1	Train	Test	Fit	CCR
EMmean_B	1:1	*A priori*	0.893	0.782	0.273	**0.783**	0.933	0.813	0.266	**0.862**
EMmean_B	1:1	Automated	0.893	0.92	0.303	**0.882**	0.956	0.773	0.224	**0.835**
EMmean_B	1:1	Expert	0.893	0.799	0.283	**0.799**	0.928	0.76	0.245	**0.826**
EMmean_B	1:2	*A priori*	0.68	0.833	0.48	**0.81**	0.889	0.893	0.365	**0.925**
EMmean_B	1:2	Automated	0.653	0.489	0.399	**0.542**	0.783	0.693	0.37	**0.786**
EMmean_B	1:2	Expert	0.68	0.632	0.409	**0.649**	0.883	0.72	0.307	**0.815**
EMmean_B	1:3	*A priori*	0.5	0.782	0.616	**0.753**	0.85	0.8	0.411	**0.885**
EMmean_B	1:3	Automated	0.627	0.569	0.444	**0.601**	0.933	0.707	0.219	**0.791**
EMmean_B	1:3	Expert	0.487	0.609	0.571	**0.616**	0.844	0.72	0.344	**0.814**
EMmean_B	10000	*A priori*	0.207	0.868	0.894	**0.795**	0.75	0.893	0.495	**0.921**
EMmean_B	10000	Automated	0.267	0.489	0.773	**0.534**	0.911	0.68	0.234	**0.776**
EMmean_B	10000	Expert	0.227	0.557	0.808	**0.572**	0.817	0.72	0.385	**0.821**
EMmedian_B	1:1	*A priori*	0.867	0.816	0.333	**0.823**	0.894	0.84	0.328	**0.886**
EMmedian_B	1:1	Automated	0.86	0.902	0.348	**0.879**	0.9	0.773	0.307	**0.848**
EMmedian_B	1:1	Expert	0.853	0.77	0.308	**0.773**	0.883	0.76	0.318	**0.839**
EMmedian_B	1:2	*A priori*	0.653	0.897	0.586	**0.894**	0.772	0.893	0.49	**0.929**
EMmedian_B	1:2	Automated	0.547	0.5	0.485	**0.536**	0.622	0.667	0.516	**0.766**
EMmedian_B	1:2	Expert	0.64	0.69	0.48	**0.701**	0.75	0.72	0.443	**0.816**
EMmedian_B	1:3	*A priori*	0.44	0.897	0.737	**0.858**	0.694	0.893	0.583	**0.936**
EMmedian_B	1:3	Automated	0.353	0.517	0.672	**0.543**	0.45	0.653	0.635	**0.736**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			F1				Correct classification rate			
			Train	Test	Fit	F1	Train	Test	Fit	CCR
EMmedian_B	1:3	Expert	0.427	0.684	0.652	**0.673**	0.672	0.76	0.568	**0.857**
EMmedian_B	10000	*A priori*	0.187	0.92	0.965	**0.856**	0.561	0.853	0.693	**0.906**
EMmedian_B	10000	Automated	0.1	0.546	0.914	**0.553**	0.233	0.707	0.807	**0.74**
EMmedian_B	10000	Expert	0.173	0.736	0.914	**0.709**	0.506	0.72	0.677	**0.812**
EMwmean_B	1:1	*A priori*	0.893	0.793	0.283	**0.796**	0.95	0.84	0.26	**0.88**
EMwmean_B	1:1	Automated	0.893	0.943	0.338	**0.917**	0.944	0.787	0.255	**0.85**
EMwmean_B	1:1	Expert	0.893	0.782	0.258	**0.774**	0.933	0.76	0.24	**0.826**
EMwmean_B	1:2	*A priori*	0.68	0.787	0.465	**0.774**	0.889	0.827	0.328	**0.877**
EMwmean_B	1:2	Automated	0.66	0.511	0.399	**0.559**	0.806	0.707	0.354	**0.795**
EMwmean_B	1:2	Expert	0.68	0.672	0.404	**0.669**	0.889	0.72	0.297	**0.813**
EMwmean_B	1:3	*A priori*	0.513	0.793	0.621	**0.771**	0.861	0.813	0.391	**0.887**
EMwmean_B	1:3	Automated	0.633	0.557	0.424	**0.586**	0.939	0.693	0.208	**0.783**
EMwmean_B	1:3	Expert	0.493	0.557	0.551	**0.578**	0.85	0.707	0.328	**0.803**
EMwmean_B	10000	*A priori*	0.22	0.874	0.884	**0.8**	0.794	0.853	0.469	**0.911**
EMwmean_B	10000	Automated	0.26	0.448	0.768	**0.503**	0.911	0.68	0.229	**0.773**
EMwmean_B	10000	Expert	0.227	0.552	0.803	**0.566**	0.822	0.72	0.359	**0.811**
FDA_B	1:1	*A priori*	0.793	0.471	0.212	**0.504**	0.817	0.72	0.375	**0.816**
FDA_B	1:1	Automated	0.773	0.345	0.207	**0.414**	0.811	0.653	0.328	**0.761**
FDA_B	1:1	Expert	0.773	0.54	0.278	**0.572**	0.811	0.707	0.38	**0.809**
FDA_B	1:2	*A priori*	0.547	0.299	0.414	**0.375**	0.589	0.72	0.604	**0.816**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			F1				Correct classification rate			
			Train	Test	Fit	F1	Train	Test	Fit	CCR
FDA_B	1:2	Automated	0.547	0.259	0.369	**0.324**	0.6	0.413	0.411	**0.59**
FDA_B	1:2	Expert	0.547	0.443	0.48	**0.499**	0.594	0.707	0.578	**0.801**
FDA_B	1:3	*A priori*	0.34	0.27	0.586	**0.337**	0.406	0.773	0.76	**0.829**
FDA_B	1:3	Automated	0.353	0.23	0.51	**0.277**	0.433	0.4	0.474	**0.536**
FDA_B	1:3	Expert	0.333	0.132	0.657	**0.294**	0.417	0.747	0.734	**0.809**
FDA_B	10000	*A priori*	0.053	0.247	0.848	**0.31**	0.183	0.773	0.922	**0.8**
FDA_B	10000	Automated	0.067	0.247	0.838	**0.311**	0.194	0.573	0.792	**0.653**
FDA_B	10000	Expert	0.073	0.379	0.889	**0.424**	0.2	0.707	0.854	**0.746**
FDA_O	1:1	*A priori*	0.74	0.454	0.253	**0.486**	0.711	0.813	0.531	**0.883**
FDA_O	1:1	Automated	0.727	0.782	0.419	**0.771**	0.583	0.893	0.677	**0.928**
FDA_O	1:1	Expert	0.727	0.552	0.338	**0.587**	0.617	0.72	0.589	**0.822**
FDA_O	1:2	*A priori*	0.507	0.333	0.455	**0.396**	0.411	0.72	0.724	**0.79**
FDA_O	1:2	Automated	0.52	0.77	0.616	**0.758**	0.444	0.773	0.729	**0.832**
FDA_O	1:2	Expert	0.473	0.54	0.571	**0.567**	0.311	0.72	0.807	**0.782**
FDA_O	1:3	*A priori*	0.36	0.374	0.626	**0.434**	0.361	0.853	0.812	**0.869**
FDA_O	1:3	Automated	0.34	0.609	0.742	**0.631**	0.222	0.76	0.865	**0.786**
FDA_O	1:3	Expert	0.32	0.575	0.737	**0.596**	0.189	0.76	0.885	**0.78**
FDA_O	10000	*A priori*	0.12	0.408	0.909	**0.48**	0.228	0.867	0.901	**0.855**
FDA_O	10000	Automated	0.107	0.638	0.944	**0.63**	0.139	0.72	0.932	**0.76**
FDA_O	10000	Expert	0.08	0.586	0.96	**0.592**	0.156	0.76	0.932	**0.786**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			F1				Correct classification rate			
			Train	Test	Fit	F1	Train	Test	Fit	CCR
GAM_B	1:1	*A priori*	0.833	0.155	0.066	**0.253**	0.867	0.227	0.135	**0.499**
GAM_B	1:1	Automated	0.82	0.351	0.136	**0.403**	0.844	0.387	0.203	**0.595**
GAM_B	1:1	Expert	0.82	0.282	0.096	**0.338**	0.844	0.293	0.172	**0.537**
GAM_B	1:2	*A priori*	0.613	0.098	0.152	**0.14**	0.683	0.12	0.094	**0.346**
GAM_B	1:2	Automated	0.58	0.184	0.268	**0.24**	0.656	0.253	0.198	**0.443**
GAM_B	1:2	Expert	0.573	0.121	0.172	**0.142**	0.644	0.147	0.13	**0.357**
GAM_B	1:3	*A priori*	0.407	0.023	0.293	**0.057**	0.606	0.027	0.021	**0.233**
GAM_B	1:3	Automated	0.4	0.103	0.313	**0.113**	0.567	0.027	0.042	**0.224**
GAM_B	1:3	Expert	0.347	0.132	0.318	**0.101**	0.489	0.08	0.109	**0.244**
GAM_B	10000	*A priori*	0.16	0.057	0.692	**0.168**	0.372	0.04	0.099	**0.167**
GAM_B	10000	Automated	0.153	0.092	0.722	**0.202**	0.344	0.093	0.146	**0.2**
GAM_B	10000	Expert	0.12	0.052	0.697	**0.143**	0.317	0.013	0.052	**0.107**
GAM_O	1:1	*A priori*	0.793	0.989	0.475	**0.966**	0.822	0.933	0.464	**0.958**
GAM_O	1:1	Automated	0.82	0.994	0.5	**1**	0.844	0.96	0.458	**0.979**
GAM_O	1:1	Expert	0.807	0.971	0.46	**0.955**	0.828	0.973	0.479	**0.987**
GAM_O	1:2	*A priori*	0.56	0.977	0.707	**0.958**	0.633	0.96	0.677	**0.982**
GAM_O	1:2	Automated	0.547	1	0.747	**0.988**	0.611	1	0.698	**1**
GAM_O	1:2	Expert	0.547	0.983	0.722	**0.963**	0.589	0.96	0.688	**0.966**
GAM_O	1:3	*A priori*	0.36	0.96	0.793	**0.881**	0.494	0.92	0.776	**0.945**
GAM_O	1:3	Automated	0.36	0.931	0.788	**0.861**	0.472	0.773	0.719	**0.84**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			F1				Correct classification rate			
			Train	Test	Fit	F1	Train	Test	Fit	CCR
GAM_O	1:3	Expert	0.34	0.954	0.798	**0.868**	0.439	0.8	0.755	**0.854**
GAM_O	10000	*A priori*	0.107	0.891	0.99	**0.806**	0.267	0.867	0.896	**0.87**
GAM_O	10000	Automated	0.107	0.908	0.995	**0.82**	0.272	0.72	0.839	**0.778**
GAM_O	10000	Expert	0.107	0.902	0.995	**0.816**	0.244	0.72	0.844	**0.768**
GBM_B	1:1	*A priori*	0.88	0.874	0.338	**0.868**	0.917	0.88	0.307	**0.905**
GBM_B	1:1	Automated	0.86	0.724	0.283	**0.735**	0.889	0.72	0.302	**0.816**
GBM_B	1:1	Expert	0.873	0.764	0.298	**0.776**	0.911	0.76	0.281	**0.835**
GBM_B	1:2	*A priori*	0.667	0.851	0.571	**0.866**	0.811	0.92	0.479	**0.954**
GBM_B	1:2	Automated	0.633	0.833	0.566	**0.833**	0.722	0.787	0.495	**0.858**
GBM_B	1:2	Expert	0.647	0.828	0.556	**0.831**	0.756	0.787	0.479	**0.867**
GBM_B	1:3	*A priori*	0.447	0.862	0.732	**0.838**	0.733	0.84	0.573	**0.925**
GBM_B	1:3	Automated	0.413	0.868	0.742	**0.828**	0.65	0.8	0.625	**0.892**
GBM_B	1:3	Expert	0.433	0.925	0.763	**0.886**	0.667	0.747	0.641	**0.882**
GBM_B	10000	*A priori*	0.193	0.822	0.949	**0.793**	0.578	0.947	0.703	**0.962**
GBM_B	10000	Automated	0.167	0.937	0.98	**0.863**	0.422	0.893	0.786	**0.904**
GBM_B	10000	Expert	0.173	0.948	0.975	**0.871**	0.522	0.893	0.74	**0.929**
GBM_O	1:1	*A priori*	0.847	0.885	0.369	**0.873**	0.878	0.907	0.406	**0.945**
GBM_O	1:1	Automated	0.84	0.81	0.338	**0.807**	0.872	0.76	0.344	**0.846**
GBM_O	1:1	Expert	0.773	0.155	0.061	**0.215**	0.811	0.72	0.391	**0.821**
GBM_O	1:2	*A priori*	0.607	0.598	0.505	**0.642**	0.683	0.773	0.547	**0.858**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			F1				Correct classification rate			
			Train	Test	Fit	F1	Train	Test	Fit	CCR
GBM_O	1:2	Automated	0.6	0.5	0.47	**0.559**	0.678	0.68	0.479	**0.781**
GBM_O	1:2	Expert	0.54	0.144	0.217	**0.163**	0.583	0.72	0.599	**0.811**
GBM_O	1:3	*A priori*	0.4	0.534	0.641	**0.563**	0.572	0.76	0.646	**0.847**
GBM_O	1:3	Automated	0.4	0.431	0.631	**0.495**	0.567	0.64	0.562	**0.75**
GBM_O	1:3	Expert	0.387	0.431	0.636	**0.49**	0.539	0.64	0.589	**0.749**
GBM_O	10000	*A priori*	0.133	0.534	0.894	**0.554**	0.339	0.773	0.828	**0.829**
GBM_O	10000	Automated	0.147	0.42	0.859	**0.473**	0.339	0.64	0.74	**0.726**
GBM_O	10000	Expert	0.127	0.408	0.864	**0.457**	0.322	0.613	0.745	**0.709**
GLM_B	1:1	*A priori*	0.793	0.782	0.354	**0.771**	0.817	0.787	0.438	**0.876**
GLM_B	1:1	Automated	0.787	0.483	0.247	**0.528**	0.817	0.72	0.37	**0.813**
GLM_B	1:1	Expert	0.82	0.483	0.242	**0.544**	0.839	0.72	0.37	**0.824**
GLM_B	1:2	*A priori*	0.54	0.805	0.616	**0.791**	0.583	0.84	0.667	**0.898**
GLM_B	1:2	Automated	0.56	0.408	0.465	**0.478**	0.633	0.707	0.536	**0.8**
GLM_B	1:2	Expert	0.547	0.391	0.475	**0.466**	0.6	0.72	0.594	**0.817**
GLM_B	1:3	*A priori*	0.36	0.92	0.783	**0.851**	0.483	0.88	0.766	**0.917**
GLM_B	1:3	Automated	0.36	0.425	0.641	**0.474**	0.483	0.707	0.667	**0.79**
GLM_B	1:3	Expert	0.333	0.132	0.667	**0.3**	0.456	0.747	0.734	**0.827**
GLM_B	10000	*A priori*	0.093	0.897	1	**0.808**	0.222	0.867	0.911	**0.857**
GLM_B	10000	Automated	0.107	0.448	0.889	**0.484**	0.283	0.72	0.818	**0.774**
GLM_B	10000	Expert	0.107	0.402	0.884	**0.454**	0.25	0.72	0.839	**0.768**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			F1				Correct classification rate			
			Train	Test	Fit	F1	Train	Test	Fit	CCR
GLM_O	1:1	*A priori*	0.727	0.339	0.222	**0.392**	0.439	0.293	0.286	**0.402**
GLM_O	1:1	Automated	0.747	0.437	0.253	**0.48**	0.567	0.427	0.469	**0.607**
GLM_O	1:1	Expert	0.787	0.466	0.237	**0.511**	0.817	0.72	0.375	**0.816**
GLM_O	1:2	*A priori*	0.467	0.569	0.551	**0.569**	0.278	0.373	0.536	**0.48**
GLM_O	1:2	Automated	0.54	0.351	0.475	**0.438**	0.439	0.707	0.661	**0.767**
GLM_O	1:2	Expert	0.553	0.477	0.49	**0.53**	0.628	0.707	0.568	**0.811**
GLM_O	1:3	*A priori*	0.32	0.741	0.737	**0.695**	0.339	0.453	0.677	**0.611**
GLM_O	1:3	Automated	0.36	0.603	0.702	**0.616**	0.422	0.813	0.766	**0.857**
GLM_O	1:3	Expert	0.34	0.506	0.677	**0.531**	0.422	0.707	0.677	**0.767**
GLM_O	10000	*A priori*	0.087	0.845	0.985	**0.764**	0.211	0.96	0.927	**0.902**
GLM_O	10000	Automated	0.107	0.638	0.949	**0.633**	0.239	0.88	0.901	**0.866**
GLM_O	10000	Expert	0.107	0.54	0.919	**0.557**	0.256	0.707	0.823	**0.757**
MARS_B	1:1	*A priori*	0.82	0.644	0.293	**0.67**	0.844	0.72	0.344	**0.814**
MARS_B	1:1	Automated	0.793	0.776	0.343	**0.762**	0.822	0.76	0.396	**0.847**
MARS_B	1:1	Expert	0.813	0.649	0.298	**0.672**	0.839	0.707	0.328	**0.798**
MARS_B	1:2	*A priori*	0.587	0.707	0.535	**0.712**	0.661	0.707	0.521	**0.805**
MARS_B	1:2	Automated	0.547	0.615	0.53	**0.631**	0.611	0.707	0.526	**0.784**
MARS_B	1:2	Expert	0.547	0.615	0.515	**0.622**	0.606	0.547	0.484	**0.688**
MARS_B	1:3	*A priori*	0.387	0.839	0.742	**0.795**	0.544	0.787	0.682	**0.863**
MARS_B	1:3	Automated	0.367	0.667	0.707	**0.66**	0.5	0.707	0.651	**0.791**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			F1				Correct classification rate			
			Train	Test	Fit	F1	Train	Test	Fit	CCR
MARS_B	1:3	Expert	0.34	0.73	0.727	**0.694**	0.433	0.707	0.656	**0.762**
MARS_B	10000	*A priori*	0.127	0.782	0.97	**0.741**	0.328	0.72	0.812	**0.792**
MARS_B	10000	Automated	0.12	0.92	0.99	**0.831**	0.317	0.787	0.859	**0.839**
MARS_B	10000	Expert	0.107	0.753	0.965	**0.71**	0.261	0.693	0.802	**0.744**
MARS_O	1:1	*A priori*	0.82	0.58	0.258	**0.611**	0.839	0.627	0.307	**0.751**
MARS_O	1:1	Automated	0.793	0.81	0.348	**0.785**	0.822	0.787	0.422	**0.871**
MARS_O	1:1	Expert	0.793	0.557	0.273	**0.591**	0.817	0.707	0.354	**0.8**
MARS_O	1:2	*A priori*	0.547	0.615	0.505	**0.616**	0.611	0.76	0.604	**0.845**
MARS_O	1:2	Automated	0.54	0.621	0.545	**0.64**	0.583	0.72	0.615	**0.819**
MARS_O	1:2	Expert	0.547	0.448	0.475	**0.5**	0.6	0.707	0.562	**0.796**
MARS_O	1:3	*A priori*	0.353	0.42	0.631	**0.461**	0.422	0.707	0.672	**0.764**
MARS_O	1:3	Automated	0.327	0.684	0.712	**0.649**	0.411	0.76	0.75	**0.82**
MARS_O	1:3	Expert	0.353	0.448	0.652	**0.49**	0.444	0.707	0.672	**0.775**
MARS_O	10000	*A priori*	0.053	0.379	0.889	**0.412**	0.183	0.72	0.88	**0.756**
MARS_O	10000	Automated	0.053	0.46	0.914	**0.474**	0.183	0.72	0.875	**0.754**
MARS_O	10000	Expert	0.087	0.448	0.899	**0.478**	0.222	0.72	0.854	**0.762**
MaxEnt_B	1:1	*A priori*	0.807	0.489	0.202	**0.516**	0.761	0.613	0.339	**0.724**
MaxEnt_B	1:1	Automated	0.78	0.638	0.298	**0.645**	0.744	0.76	0.453	**0.837**
MaxEnt_B	1:1	Expert	0.787	0.322	0.177	**0.39**	0.778	0.653	0.344	**0.752**
MaxEnt_B	1:2	*A priori*	0.54	0.368	0.449	**0.433**	0.383	0.52	0.63	**0.641**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			F1				Correct classification rate			
			Train	Test	Fit	F1	Train	Test	Fit	CCR
MaxEnt_B	1:2	Automated	0.573	0.557	0.505	**0.598**	0.556	0.707	0.62	**0.802**
MaxEnt_B	1:2	Expert	0.547	0.351	0.434	**0.418**	0.583	0.693	0.542	**0.773**
MaxEnt_B	1:3	*A priori*	0.393	0.132	0.601	**0.296**	0.55	0.56	0.552	**0.7**
MaxEnt_B	1:3	Automated	0.367	0.483	0.641	**0.512**	0.428	0.76	0.724	**0.816**
MaxEnt_B	1:3	Expert	0.347	0.132	0.596	**0.266**	0.489	0.56	0.641	**0.713**
MaxEnt_B	10000	*A priori*	0.153	0.661	0.939	**0.668**	0.278	0.72	0.839	**0.781**
MaxEnt_B	10000	Automated	0.107	0.557	0.919	**0.567**	0.289	0.84	0.875	**0.859**
MaxEnt_B	10000	Expert	0.14	0.414	0.869	**0.472**	0.333	0.72	0.797	**0.787**
MaxEnt_O	1:1	*A priori*	0.793	0.534	0.232	**0.553**	0.744	0.707	0.427	**0.8**
MaxEnt_O	1:1	Automated	0.793	0.592	0.293	**0.623**	0.806	0.787	0.443	**0.873**
MaxEnt_O	1:1	Expert	0.773	0.333	0.197	**0.401**	0.739	0.48	0.328	**0.647**
MaxEnt_O	1:2	*A priori*	0.527	0.523	0.505	**0.55**	0.422	0.72	0.688	**0.778**
MaxEnt_O	1:2	Automated	0.533	0.5	0.495	**0.534**	0.472	0.773	0.708	**0.835**
MaxEnt_O	1:2	Expert	0.513	0.333	0.455	**0.4**	0.367	0.44	0.609	**0.586**
MaxEnt_O	1:3	*A priori*	0.34	0.489	0.652	**0.506**	0.283	0.72	0.823	**0.776**
MaxEnt_O	1:3	Automated	0.36	0.575	0.682	**0.587**	0.478	0.8	0.74	**0.865**
MaxEnt_O	1:3	Expert	0.34	0.333	0.631	**0.402**	0.35	0.507	0.677	**0.641**
MaxEnt_O	10000	*A priori*	0.087	0.448	0.914	**0.487**	0.15	0.707	0.917	**0.752**
MaxEnt_O	10000	Automated	0.107	0.483	0.914	**0.52**	0.211	0.76	0.87	**0.783**
MaxEnt_O	10000	Expert	0.107	0.333	0.879	**0.41**	0.217	0.707	0.833	**0.744**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			F1				Correct classification rate			
			Train	Test	Fit	F1	Train	Test	Fit	CCR
MXL_O	1:1	*A priori*	0.753	0.052	0.025	**0.121**	0.728	0.067	0.016	**0.305**
MXL_O	1:1	Automated	0.733	0.149	0.081	**0.2**	0.7	0.173	0.135	**0.397**
MXL_O	1:1	Expert	0.78	0.736	0.328	**0.721**	0.789	0.8	0.458	**0.879**
MXL_O	1:2	*A priori*	0.467	0.052	0.146	**0.023**	0.389	0.067	0.115	**0.194**
MXL_O	1:2	Automated	0.46	0.08	0.162	**0.045**	0.356	0.013	0.042	**0.12**
MXL_O	1:2	Expert	0.527	0.741	0.591	**0.73**	0.528	0.773	0.682	**0.849**
MXL_O	1:3	*A priori*	0.287	0.046	0.338	**0.026**	0.261	0.053	0.141	**0.141**
MXL_O	1:3	Automated	0.273	0.092	0.359	**0.058**	0.206	0.013	0.089	**0.072**
MXL_O	1:3	Expert	0.34	0.741	0.737	**0.706**	0.378	0.773	0.771	**0.821**
MXL_O	10000	*A priori*	0.047	0.19	0.823	**0.257**	0.133	0.253	0.51	**0.346**
MXL_O	10000	Automated	0.033	0.075	0.753	**0.139**	0.117	0.013	0.141	**0.055**
MXL_O	10000	Expert	0.06	0.494	0.929	**0.508**	0.178	0.733	0.906	**0.772**
RF_B	1:1	*A priori*	0.953	0.184	0.005	**0.306**	0.961	0.92	0.099	**0.848**
RF_B	1:1	Automated	0.947	0.293	0.01	**0.369**	0.961	0.827	0.094	**0.802**
RF_B	1:1	Expert	0.94	0.713	0.051	**0.638**	0.961	0.8	0.094	**0.79**
RF_B	1:2	*A priori*	0.913	0.305	0.02	**0.362**	0.978	0.933	0.073	**0.849**
RF_B	1:2	Automated	0.94	0.701	0.045	**0.628**	0.978	0.893	0.062	**0.826**
RF_B	1:2	Expert	0.907	0.759	0.076	**0.66**	0.967	0.8	0.062	**0.778**
RF_B	1:3	*A priori*	0.933	0.557	0.035	**0.533**	0.989	0.987	0.062	**0.874**
RF_B	1:3	Automated	0.96	0.718	0.056	**0.656**	0.989	0.8	0.052	**0.783**

Table B2.5 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Presence-absence map**							
			F1				**Correct classification rate**			
			Train	**Test**	**Fit**	**F1**	**Train**	**Test**	**Fit**	**CCR**
RF_B	1:3	Expert	0.9	0.132	0.131	**0.318**	0.972	0.747	0.068	**0.758**
RF_B	10000	*A priori*	0.92	0.626	0.045	**0.572**	1	0.92	0.036	**0.837**
RF_B	10000	Automated	0.913	0.914	0.111	**0.777**	1	0.893	0.036	**0.824**
RF_B	10000	Expert	0.907	0.879	0.111	**0.753**	1	0.893	0.036	**0.824**
RF_O	1:1	*A priori*	0.987	0.167	0	**0.312**	0.961	0.787	0.083	**0.779**
RF_O	1:1	Automated	0.98	0.247	0.005	**0.359**	0.961	0.773	0.078	**0.77**
RF_O	1:1	Expert	0.967	0.856	0.086	**0.76**	0.961	0.893	0.099	**0.835**
RF_O	1:2	*A priori*	0.993	0.276	0.01	**0.387**	0.983	0.88	0.062	**0.822**
RF_O	1:2	Automated	0.987	0.448	0.025	**0.494**	0.983	0.813	0.057	**0.789**
RF_O	1:2	Expert	0.967	0.966	0.126	**0.848**	0.983	0.88	0.062	**0.822**
RF_O	1:3	*A priori*	1	0.333	0.015	**0.428**	0.994	0.96	0.057	**0.862**
RF_O	1:3	Automated	0.993	0.557	0.035	**0.569**	0.994	0.893	0.052	**0.829**
RF_O	1:3	Expert	0.973	0.943	0.116	**0.833**	0.989	0.853	0.052	**0.808**
RF_O	10000	*A priori*	0.987	0.626	0.04	**0.608**	1	0.84	0.026	**0.795**
RF_O	10000	Automated	0.933	0.908	0.101	**0.78**	1	0.84	0.031	**0.797**
RF_O	10000	Expert	0.927	0.937	0.121	**0.805**	1	0.813	0.026	**0.782**
SRE_B	1:1	*A priori*	0.587	0	0.091	**0.03**	0.072	0	0.12	**0.019**
SRE_B	1:1	Automated	0.62	0.029	0.081	**0.061**	0.111	0	0.047	**0.003**
SRE_B	1:1	Expert	0.693	0.069	0.04	**0.104**	0.561	0.72	0.63	**0.816**
SRE_B	1:2	*A priori*	0.247	0	0.399	**0.011**	0.022	0	0.411	**0.131**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map							
			F1				Correct classification rate			
			Train	Test	Fit	F1	Train	Test	Fit	CCR
SRE_B	1:2	Automated	0.293	0.029	0.364	**0.035**	0.039	0	0.193	**0.037**
SRE_B	1:2	Expert	0.427	0.069	0.227	**0.057**	0.211	0.72	0.849	**0.755**
SRE_B	1:3	*A priori*	0.18	0	0.616	**0.1**	0.017	0	0.74	**0.28**
SRE_B	1:3	Automated	0.2	0.029	0.566	**0.099**	0.028	0	0.328	**0.095**
SRE_B	1:3	Expert	0.28	0.086	0.389	**0.076**	0.167	0.56	0.891	**0.679**
SRE_B	10000	*A priori*	0	0	0.828	**0.12**	0	0	0.984	**0.386**
SRE_B	10000	Automated	0.007	0.029	0.818	**0.135**	0.017	0	0.714	**0.268**
SRE_B	10000	Expert	0.02	0.063	0.778	**0.139**	0.094	0.693	0.964	**0.742**
SRE_O	1:1	*A priori*	0.68	0.172	0.182	**0.242**	0.394	0.787	0.776	**0.837**
SRE_O	1:1	Automated	0.693	0.115	0.101	**0.168**	0.461	0.92	0.781	**0.932**
SRE_O	1:1	Expert	0.7	0.213	0.187	**0.28**	0.511	0.8	0.724	**0.873**
SRE_O	1:2	*A priori*	0.4	0.178	0.475	**0.253**	0.128	0.787	0.958	**0.798**
SRE_O	1:2	Automated	0.407	0.126	0.374	**0.166**	0.144	0.867	0.953	**0.84**
SRE_O	1:2	Expert	0.42	0.247	0.475	**0.305**	0.172	0.853	0.938	**0.84**
SRE_O	1:3	*A priori*	0.213	0.132	0.687	**0.24**	0.083	0.747	0.99	**0.773**
SRE_O	1:3	Automated	0.247	0.138	0.581	**0.201**	0.1	0.867	0.984	**0.834**
SRE_O	1:3	Expert	0.253	0.218	0.646	**0.291**	0.117	0.787	0.969	**0.797**
SRE_O	10000	*A priori*	0.013	0.161	0.874	**0.25**	0.056	0.787	1	**0.784**
SRE_O	10000	Automated	0.013	0.115	0.843	**0.205**	0.061	0.893	1	**0.836**
SRE_O	10000	Expert	0.02	0.224	0.904	**0.309**	0.072	0.813	0.995	**0.801**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map	Prediction	Overall
ANN_B	1:1	*A priori*	**0.542**	**0.559**	**0.589**
ANN_B	1:1	Automated	**0.642**	**0.631**	**0.65**
ANN_B	1:1	Expert	**0.748**	**0.517**	**0.602**
ANN_B	1:2	*A priori*	**0.576**	**0.574**	**0.629**
ANN_B	1:2	Automated	**0.769**	**0.607**	**0.668**
ANN_B	1:2	Expert	**0.68**	**0.494**	**0.609**
ANN_B	1:3	*A priori*	**0.594**	**0.586**	**0.644**
ANN_B	1:3	Automated	**0.74**	**0.57**	**0.649**
ANN_B	1:3	Expert	**0.562**	**0.438**	**0.584**
ANN_B	10000	*A priori*	**0.508**	**0.509**	**0.607**
ANN_B	10000	Automated	**0.719**	**0.557**	**0.647**
ANN_B	10000	Expert	**0.683**	**0.49**	**0.612**
ANN_O	1:1	*A priori*	**0.177**	**0.456**	**0.505**
ANN_O	1:1	Automated	**0.187**	**0.471**	**0.509**
ANN_O	1:1	Expert	**0.491**	**0.527**	**0.565**
ANN_O	1:2	*A priori*	**0.068**	**0.164**	**0.211**
ANN_O	1:2	Automated	**0.092**	**0.162**	**0.213**
ANN_O	1:2	Expert	**0.338**	**0.192**	**0.225**
ANN_O	1:3	*A priori*	**0.076**	**0.071**	**0.098**

Table B2.5 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Presence-absence map**	**Prediction**	**Overall**
ANN_O	1:3	Automated	**0.095**	**0.033**	**0.079**
ANN_O	1:3	Expert	**0.212**	**0.021**	**0.067**
ANN_O	10000	*A priori*	**0.163**	**0.059**	**0.036**
ANN_O	10000	Automated	**0.162**	**0**	**0**
ANN_O	10000	Expert	**0.18**	**0.003**	**0.003**
CTA_B	1:1	*A priori*	**0.705**	**0.607**	**0.513**
CTA_B	1:1	Automated	**0.78**	**0.588**	**0.512**
CTA_B	1:1	Expert	**0.81**	**0.618**	**0.534**
CTA_B	1:2	*A priori*	**0.723**	**0.604**	**0.484**
CTA_B	1:2	Automated	**0.704**	**0.497**	**0.44**
CTA_B	1:2	Expert	**0.716**	**0.546**	**0.482**
CTA_B	1:3	*A priori*	**0.693**	**0.557**	**0.438**
CTA_B	1:3	Automated	**0.656**	**0.437**	**0.375**
CTA_B	1:3	Expert	**0.589**	**0.451**	**0.404**
CTA_B	10000	*A priori*	**0.687**	**0.527**	**0.362**
CTA_B	10000	Automated	**0.624**	**0.391**	**0.283**
CTA_B	10000	Expert	**0.699**	**0.493**	**0.369**
CTA_O	1:1	*A priori*	**0.284**	**0.445**	**0.562**
CTA_O	1:1	Automated	**0.232**	**0.383**	**0.523**
CTA_O	1:1	Expert	**0.3**	**0.422**	**0.548**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map	Prediction	Overall
CTA_O	1:2	Automated	**0.232**	**0.357**	**0.518**
CTA_O	1:2	Expert	**0.258**	**0.367**	**0.522**
CTA_O	1:3	*A priori*	**0.266**	**0.402**	**0.516**
CTA_O	1:3	Automated	**0.204**	**0.324**	**0.474**
CTA_O	1:3	Expert	**0.293**	**0.383**	**0.513**
CTA_O	10000	*A priori*	**0.585**	**0.479**	**0.511**
CTA_B	1:3	*A priori*	**0.693**	**0.557**	**0.438**
CTA_B	1:3	Automated	**0.656**	**0.437**	**0.375**
CTA_B	1:3	Expert	**0.589**	**0.451**	**0.404**
CTA_B	10000	*A priori*	**0.687**	**0.527**	**0.362**
CTA_B	10000	Automated	**0.624**	**0.391**	**0.283**
CTA_B	10000	Expert	**0.699**	**0.493**	**0.369**
CTA_O	1:1	*A priori*	**0.284**	**0.445**	**0.562**
CTA_O	1:1	Automated	**0.232**	**0.383**	**0.523**
CTA_O	1:1	Expert	**0.3**	**0.422**	**0.548**
CTA_O	1:2	*A priori*	**0.182**	**0.352**	**0.516**
CTA_O	1:2	Automated	**0.232**	**0.357**	**0.518**
CTA_O	1:2	Expert	**0.258**	**0.367**	**0.522**
CTA_O	1:3	*A priori*	**0.266**	**0.402**	**0.516**
CTA_O	1:3	Automated	**0.204**	**0.324**	**0.474**
CTA_O	1:3	Expert	**0.293**	**0.383**	**0.513**

Table B2.5 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Presence-absence map**	**Prediction**	**Overall**
CTA_O	10000	*A priori*	**0.585**	**0.479**	**0.511**
CTA_O	10000	Automated	**0.387**	**0.339**	**0.432**
CTA_O	10000	Expert	**0.378**	**0.341**	**0.431**
EMca_B	1:1	*A priori*	**0.144**	**0.167**	**0.259**
EMca_B	1:1	Automated	**0.176**	**0.25**	**0.318**
EMca_B	1:1	Expert	**0.185**	**0.25**	**0.318**
EMca_B	1:2	*A priori*	**0.091**	**0.162**	**0.211**
EMca_B	1:2	Automated	**0.121**	**0.181**	**0.229**
EMca_B	1:2	Expert	**0.131**	**0.231**	**0.263**
EMca_B	1:3	*A priori*	**0.137**	**0.259**	**0.284**
EMca_B	1:3	Automated	**0.155**	**0.247**	**0.284**
EMca_B	1:3	Expert	**0.137**	**0.248**	**0.286**
EMca_B	10000	*A priori*	**0.122**	**0.13**	**0.171**
EMca_B	10000	Automated	**0.163**	**0.246**	**0.234**
EMca_B	10000	Expert	**0.189**	**0.152**	**0.175**
EMmean_B	1:1	*A priori*	**0.884**	**0.875**	**0.858**
EMmean_B	1:1	Automated	**0.963**	**0.893**	**0.905**
EMmean_B	1:1	Expert	**0.905**	**0.818**	**0.863**
EMmean_B	1:2	*A priori*	**0.951**	**0.95**	**0.925**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map	Prediction	Overall
EMmean_B	1:2	Automated	**0.78**	**0.893**	**0.911**
EMmean_B	1:2	Expert	**0.851**	**0.811**	**0.891**
EMmean_B	1:3	*A priori*	**0.915**	**0.948**	**0.923**
EMmean_B	1:3	Automated	**0.812**	**0.824**	**0.889**
EMmean_B	1:3	Expert	**0.843**	**0.833**	**0.924**
EMmean_B	10000	*A priori*	**0.941**	**0.906**	**0.906**
EMmean_B	10000	Automated	**0.804**	**0.846**	**0.916**
EMmean_B	10000	Expert	**0.852**	**0.837**	**0.923**
EMmedian_B	1:1	*A priori*	**0.888**	**0.81**	**0.839**
EMmedian_B	1:1	Automated	**0.94**	**0.829**	**0.867**
EMmedian_B	1:1	Expert	**0.86**	**0.724**	**0.831**
EMmedian_B	1:2	*A priori*	**0.933**	**0.865**	**0.905**
EMmedian_B	1:2	Automated	**0.664**	**0.817**	**0.836**
EMmedian_B	1:2	Expert	**0.844**	**0.749**	**0.873**
EMmedian_B	1:3	*A priori*	**0.931**	**0.88**	**0.914**
EMmedian_B	1:3	Automated	**0.644**	**0.788**	**0.865**
EMmedian_B	1:3	Expert	**0.835**	**0.747**	**0.883**
EMmedian_B	10000	*A priori*	**0.868**	**0.757**	**0.827**
EMmedian_B	10000	Automated	**0.648**	**0.781**	**0.836**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map	Prediction	Overall
EMmedian_B	10000	Expert	**0.853**	**0.739**	**0.86**
EMwmean_B	1:1	*A priori*	**0.914**	**0.893**	**0.873**
EMwmean_B	1:1	Automated	**1**	**0.919**	**0.927**
EMwmean_B	1:1	Expert	**0.901**	**0.819**	**0.867**
EMwmean_B	1:2	*A priori*	**0.919**	**0.928**	**0.914**
EMwmean_B	1:2	Automated	**0.795**	**0.902**	**0.917**
EMwmean_B	1:2	Expert	**0.853**	**0.816**	**0.893**
EMwmean_B	1:3	*A priori*	**0.916**	**0.948**	**0.924**
EMwmean_B	1:3	Automated	**0.794**	**0.815**	**0.884**
EMwmean_B	1:3	Expert	**0.818**	**0.819**	**0.921**
EMwmean_B	10000	*A priori*	**0.934**	**0.899**	**0.897**
EMwmean_B	10000	Automated	**0.778**	**0.83**	**0.901**
EMwmean_B	10000	Expert	**0.83**	**0.825**	**0.91**
FDA_B	1:1	*A priori*	**0.558**	**0.524**	**0.646**
FDA_B	1:1	Automated	**0.529**	**0.424**	**0.618**
FDA_B	1:1	Expert	**0.622**	**0.516**	**0.661**
FDA_B	1:2	*A priori*	**0.435**	**0.588**	**0.709**
FDA_B	1:2	Automated	**0.484**	**0.678**	**0.778**
FDA_B	1:2	Expert	**0.618**	**0.738**	**0.809**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map	Prediction	Overall
FDA_B	1:3	*A priori*	**0.357**	**0.487**	**0.655**
FDA_B	1:3	Automated	**0.446**	**0.679**	**0.774**
FDA_B	1:3	Expert	**0.545**	**0.711**	**0.805**
FDA_B	10000	*A priori*	**0.31**	**0.49**	**0.62**
FDA_B	10000	Automated	**0.355**	**0.64**	**0.71**
FDA_B	10000	Expert	**0.525**	**0.746**	**0.785**
FDA_O	1:1	*A priori*	**0.662**	**0.424**	**0.377**
FDA_O	1:1	Automated	**0.727**	**0.363**	**0.349**
FDA_O	1:1	Expert	**0.649**	**0.337**	**0.325**
FDA_O	1:2	*A priori*	**0.567**	**0.369**	**0.317**
FDA_O	1:2	Automated	**0.739**	**0.373**	**0.32**
FDA_O	1:2	Expert	**0.613**	**0.32**	**0.281**
FDA_O	1:3	*A priori*	**0.638**	**0.41**	**0.355**
FDA_O	1:3	Automated	**0.644**	**0.327**	**0.303**
FDA_O	1:3	Expert	**0.576**	**0.293**	**0.283**
FDA_O	10000	*A priori*	**0.645**	**0.419**	**0.386**
FDA_O	10000	Automated	**0.616**	**0.31**	**0.322**
FDA_O	10000	Expert	**0.606**	**0.314**	**0.321**
GAM_B	1:1	*A priori*	**0.429**	**0.552**	**0.659**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map	Prediction	Overall
GAM_B	1:1	Automated	**0.486**	**0.448**	**0.641**
GAM_B	1:1	Expert	**0.434**	**0.49**	**0.685**
GAM_B	1:2	*A priori*	**0.376**	**0.532**	**0.615**
GAM_B	1:2	Automated	**0.423**	**0.447**	**0.613**
GAM_B	1:2	Expert	**0.358**	**0.481**	**0.64**
GAM_B	1:3	*A priori*	**0.221**	**0.441**	**0.548**
GAM_B	1:3	Automated	**0.267**	**0.42**	**0.558**
GAM_B	1:3	Expert	**0.275**	**0.451**	**0.616**
GAM_B	10000	*A priori*	**0.304**	**0.46**	**0.502**
GAM_B	10000	Automated	**0.307**	**0.401**	**0.513**
GAM_B	10000	Expert	**0.175**	**0.384**	**0.518**
GAM_O	1:1	*A priori*	**0.867**	**0.737**	**0.784**
GAM_O	1:1	Automated	**0.946**	**0.834**	**0.863**
GAM_O	1:1	Expert	**0.9**	**0.934**	**0.871**
GAM_O	1:2	*A priori*	**0.867**	**0.81**	**0.893**
GAM_O	1:2	Automated	**0.95**	**0.919**	**0.96**
GAM_O	1:2	Expert	**0.872**	**0.867**	**0.917**
GAM_O	1:3	*A priori*	**0.787**	**0.771**	**0.866**
GAM_O	1:3	Automated	**0.74**	**0.724**	**0.837**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map	Prediction	Overall
GAM_O	1:3	Expert	**0.739**	**0.738**	**0.849**
GAM_O	10000	*A priori*	**0.667**	**0.683**	**0.82**
GAM_O	10000	Automated	**0.664**	**0.657**	**0.811**
GAM_O	10000	Expert	**0.648**	**0.643**	**0.803**
GBM_B	1:1	*A priori*	**0.928**	**0.958**	**0.759**
GBM_B	1:1	Automated	**0.808**	**0.747**	**0.661**
GBM_B	1:1	Expert	**0.907**	**0.92**	**0.763**
GBM_B	1:2	*A priori*	**0.926**	**0.945**	**0.756**
GBM_B	1:2	Automated	**0.861**	**0.777**	**0.681**
GBM_B	1:2	Expert	**0.937**	**0.926**	**0.771**
GBM_B	1:3	*A priori*	**0.896**	**0.928**	**0.767**
GBM_B	1:3	Automated	**0.829**	**0.755**	**0.689**
GBM_B	1:3	Expert	**0.805**	**0.84**	**0.749**
GBM_B	10000	*A priori*	**0.87**	**0.861**	**0.706**
GBM_B	10000	Automated	**0.853**	**0.748**	**0.663**
GBM_B	10000	Expert	**0.917**	**0.877**	**0.743**
GBM_O	1:1	*A priori*	**0.902**	**0.972**	**0.955**
GBM_O	1:1	Automated	**0.875**	**1**	**1**
GBM_O	1:1	Expert	**0.549**	**0.668**	**0.726**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map	Prediction	Overall
GBM_O	1:2	*A priori*	**0.789**	**0.896**	**0.931**
GBM_O	1:2	Automated	**0.699**	**0.839**	**0.895**
GBM_O	1:2	Expert	**0.476**	**0.579**	**0.692**
GBM_O	1:3	*A priori*	**0.741**	**0.861**	**0.936**
GBM_O	1:3	Automated	**0.653**	**0.755**	**0.863**
GBM_O	1:3	Expert	**0.633**	**0.733**	**0.853**
GBM_O	10000	*A priori*	**0.734**	**0.787**	**0.886**
GBM_O	10000	Automated	**0.634**	**0.624**	**0.789**
GBM_O	10000	Expert	**0.602**	**0.608**	**0.783**
GLM_B	1:1	*A priori*	**0.705**	**0.7**	**0.839**
GLM_B	1:1	Automated	**0.572**	**0.585**	**0.823**
GLM_B	1:1	Expert	**0.584**	**0.57**	**0.813**
GLM_B	1:2	*A priori*	**0.7**	**0.7**	**0.827**
GLM_B	1:2	Automated	**0.563**	**0.581**	**0.813**
GLM_B	1:2	Expert	**0.519**	**0.543**	**0.789**
GLM_B	1:3	*A priori*	**0.74**	**0.734**	**0.846**
GLM_B	1:3	Automated	**0.549**	**0.566**	**0.802**
GLM_B	1:3	Expert	**0.439**	**0.498**	**0.767**
GLM_B	10000	*A priori*	**0.66**	**0.657**	**0.796**

Table B2.5 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Presence-absence map**	**Prediction**	**Overall**
GLM_B	10000	Automated	**0.575**	**0.604**	**0.826**
GLM_B	10000	Expert	**0.54**	**0.565**	**0.799**
GLM_O	1:1	*A priori*	**0.28**	**0.14**	**0.158**
GLM_O	1:1	Automated	**0.343**	**0.181**	**0.225**
GLM_O	1:1	Expert	**0.606**	**0.421**	**0.442**
GLM_O	1:2	*A priori*	**0.432**	**0.18**	**0.191**
GLM_O	1:2	Automated	**0.503**	**0.368**	**0.386**
GLM_O	1:2	Expert	**0.604**	**0.511**	**0.516**
GLM_O	1:3	*A priori*	**0.534**	**0.25**	**0.287**
GLM_O	1:3	Automated	**0.674**	**0.511**	**0.505**
GLM_O	1:3	Expert	**0.539**	**0.491**	**0.531**
GLM_O	10000	*A priori*	**0.638**	**0.306**	**0.389**
GLM_O	10000	Automated	**0.657**	**0.51**	**0.57**
GLM_O	10000	Expert	**0.527**	**0.528**	**0.605**
MARS_B	1:1	*A priori*	**0.681**	**0.669**	**0.685**
MARS_B	1:1	Automated	**0.751**	**0.613**	**0.698**
MARS_B	1:1	Expert	**0.703**	**0.609**	**0.686**
MARS_B	1:2	*A priori*	**0.706**	**0.673**	**0.72**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map	Prediction	Overall
MARS_B	1:2	Automated	**0.698**	**0.655**	**0.733**
MARS_B	1:2	Expert	**0.633**	**0.584**	**0.692**
MARS_B	1:3	*A priori*	**0.769**	**0.715**	**0.736**
MARS_B	1:3	Automated	**0.703**	**0.625**	**0.691**
MARS_B	1:3	Expert	**0.67**	**0.583**	**0.685**
MARS_B	10000	*A priori*	**0.693**	**0.631**	**0.688**
MARS_B	10000	Automated	**0.785**	**0.66**	**0.709**
MARS_B	10000	Expert	**0.687**	**0.558**	**0.672**
MARS_O	1:1	*A priori*	**0.602**	**0.65**	**0.609**
MARS_O	1:1	Automated	**0.762**	**0.831**	**0.734**
MARS_O	1:1	Expert	**0.663**	**0.788**	**0.699**
MARS_O	1:2	*A priori*	**0.645**	**0.664**	**0.596**
MARS_O	1:2	Automated	**0.672**	**0.696**	**0.633**
MARS_O	1:2	Expert	**0.635**	**0.725**	**0.659**
MARS_O	1:3	*A priori*	**0.512**	**0.537**	**0.508**
MARS_O	1:3	Automated	**0.629**	**0.699**	**0.63**
MARS_O	1:3	Expert	**0.611**	**0.75**	**0.665**
MARS_O	10000	*A priori*	**0.422**	**0.504**	**0.534**
MARS_O	10000	Automated	**0.469**	**0.524**	**0.552**
MARS_O	10000	Expert	**0.594**	**0.667**	**0.631**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map	Prediction	Overall
MaxEnt_B	1:1	*A priori*	**0.525**	**0.433**	**0.361**
MaxEnt_B	1:1	Automated	**0.592**	**0.356**	**0.394**
MaxEnt_B	1:1	Expert	**0.465**	**0.322**	**0.378**
MaxEnt_B	1:2	*A priori*	**0.405**	**0.363**	**0.338**
MaxEnt_B	1:2	Automated	**0.578**	**0.404**	**0.4**
MaxEnt_B	1:2	Expert	**0.521**	**0.355**	**0.454**
MaxEnt_B	1:3	*A priori*	**0.432**	**0.403**	**0.376**
MaxEnt_B	1:3	Automated	**0.525**	**0.312**	**0.399**
MaxEnt_B	1:3	Expert	**0.383**	**0.261**	**0.412**
MaxEnt_B	10000	*A priori*	**0.667**	**0.518**	**0.419**
MaxEnt_B	10000	Automated	**0.563**	**0.348**	**0.451**
MaxEnt_B	10000	Expert	**0.591**	**0.382**	**0.477**
MaxEnt_O	1:1	*A priori*	**0.537**	**0.398**	**0.302**
MaxEnt_O	1:1	Automated	**0.609**	**0.46**	**0.426**
MaxEnt_O	1:1	Expert	**0.46**	**0.355**	**0.323**
MaxEnt_O	1:2	*A priori*	**0.512**	**0.4**	**0.319**
MaxEnt_O	1:2	Automated	**0.506**	**0.358**	**0.337**
MaxEnt_O	1:2	Expert	**0.418**	**0.329**	**0.303**
MaxEnt_O	1:3	*A priori*	**0.489**	**0.384**	**0.291**

Table B2.5 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Presence-absence map**	**Prediction**	**Overall**
MaxEnt_O	1:3	Automated	**0.604**	**0.451**	**0.411**
MaxEnt_O	1:3	Expert	**0.432**	**0.333**	**0.313**
MaxEnt_O	10000	*A priori*	**0.482**	**0.39**	**0.292**
MaxEnt_O	10000	Automated	**0.52**	**0.388**	**0.357**
MaxEnt_O	10000	Expert	**0.498**	**0.381**	**0.356**
MXL_O	1:1	*A priori*	**0.258**	**0.263**	**0.278**
MXL_O	1:1	Automated	**0.375**	**0.445**	**0.251**
MXL_O	1:1	Expert	**0.682**	**0.392**	**0.403**
MXL_O	1:2	*A priori*	**0.183**	**0.217**	**0.244**
MXL_O	1:2	Automated	**0.222**	**0.348**	**0.208**
MXL_O	1:2	Expert	**0.661**	**0.364**	**0.379**
MXL_O	1:3	*A priori*	**0.154**	**0.204**	**0.248**
MXL_O	1:3	Automated	**0.201**	**0.328**	**0.204**
MXL_O	1:3	Expert	**0.659**	**0.408**	**0.413**
MXL_O	10000	*A priori*	**0.31**	**0.277**	**0.291**
MXL_O	10000	Automated	**0.23**	**0.353**	**0.221**
MXL_O	10000	Expert	**0.49**	**0.285**	**0.351**
RF_B	1:1	*A priori*	**0.593**	**0.747**	**0.516**
RF_B	1:1	Automated	**0.589**	**0.697**	**0.47**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map	Prediction	Overall
RF_B	1:1	Expert	**0.609**	**0.721**	**0.49**
RF_B	1:2	*A priori*	**0.598**	**0.638**	**0.442**
RF_B	1:2	Automated	**0.662**	**0.635**	**0.434**
RF_B	1:2	Expert	**0.616**	**0.584**	**0.416**
RF_B	1:3	*A priori*	**0.663**	**0.618**	**0.432**
RF_B	1:3	Automated	**0.631**	**0.579**	**0.394**
RF_B	1:3	Expert	**0.52**	**0.468**	**0.347**
RF_B	10000	*A priori*	**0.631**	**0.532**	**0.356**
RF_B	10000	Automated	**0.741**	**0.629**	**0.386**
RF_B	10000	Expert	**0.706**	**0.558**	**0.357**
RF_O	1:1	*A priori*	**0.584**	**0.696**	**0.47**
RF_O	1:1	Automated	**0.562**	**0.687**	**0.448**
RF_O	1:1	Expert	**0.717**	**0.772**	**0.501**
RF_O	1:2	*A priori*	**0.606**	**0.632**	**0.429**
RF_O	1:2	Automated	**0.622**	**0.641**	**0.41**
RF_O	1:2	Expert	**0.747**	**0.705**	**0.458**
RF_O	1:3	*A priori*	**0.64**	**0.617**	**0.411**
RF_O	1:3	Automated	**0.669**	**0.616**	**0.392**
RF_O	1:3	Expert	**0.74**	**0.656**	**0.422**

Table B2.5 (continued)

Algorithm	Pseudo-absences	Predictor selection	Presence-absence map	Prediction	Overall
RF_O	10000	*A priori*	**0.612**	**0.563**	**0.366**
RF_O	10000	Automated	**0.709**	**0.62**	**0.378**
RF_O	10000	Expert	**0.73**	**0.605**	**0.378**
SRE_B	1:1	*A priori*	**0**	**0.085**	**0.014**
SRE_B	1:1	Automated	**0.014**	**0.087**	**0.032**
SRE_B	1:1	Expert	**0.403**	**0.311**	**0.161**
SRE_B	1:2	*A priori*	**0.032**	**0.106**	**0.048**
SRE_B	1:2	Automated	**0.013**	**0.086**	**0.055**
SRE_B	1:2	Expert	**0.282**	**0.237**	**0.143**
SRE_B	1:3	*A priori*	**0.126**	**0.158**	**0.077**
SRE_B	1:3	Automated	**0.067**	**0.117**	**0.072**
SRE_B	1:3	Expert	**0.277**	**0.232**	**0.144**
SRE_B	10000	*A priori*	**0.161**	**0.165**	**0.091**
SRE_B	10000	Automated	**0.133**	**0.158**	**0.104**
SRE_B	10000	Expert	**0.16**	**0.164**	**0.115**
SRE_O	1:1	*A priori*	**0.263**	**0.089**	**0.092**
SRE_O	1:1	Automated	**0.265**	**0.086**	**0.095**
SRE_O	1:1	Expert	**0.417**	**0.184**	**0.154**
SRE_O	1:2	*A priori*	**0.249**	**0.076**	**0.086**

Table B2.5 (continued)

Algorithm	**Pseudo-absences**	**Predictor selection**	**Presence-absence map**	**Prediction**	**Overall**
SRE_O	1:2	Automated	**0.231**	**0.061**	**0.081**
SRE_O	1:2	Expert	**0.421**	**0.188**	**0.156**
SRE_O	1:3	*A priori*	**0.124**	**0.008**	**0.049**
SRE_O	1:3	Automated	**0.253**	**0.077**	**0.09**
SRE_O	1:3	Expert	**0.375**	**0.163**	**0.143**
SRE_O	10000	*A priori*	**0.239**	**0.079**	**0.087**
SRE_O	10000	Automated	**0.252**	**0.073**	**0.087**
SRE_O	10000	Expert	**0.373**	**0.16**	**0.143**

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