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ANA CRISTINA RODRIGUES FÉLIX

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A UTILIZAÇÃO DE MODELOS ESTATÍSTICOS NA AVALIAÇÃO DE RISCO DE ESPÉCIES EXÓTICAS INVASORAS: UMA REVISÃO SISTEMÁTICA

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Dissertação apresentada à Universidade de Aveiro para cumprimento dos requisitos necessários à obtenção do grau de Mestre em Biologia Aplicada, realizada sob a orientação científica da Doutora Joana Vicente, Investigadora do Centro de Investigação em Biodiversidade e Recursos Genéticos (CIBIO/InBio) da Universidade do Porto, e do Doutor Paulo Silveira, Professor do Departamento de Biologia da Universidade de Aveiro

o júri

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agradecimentos

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palavras-chave

plantas exóticas invasoras, avaliação de risco, modelos estatísticos, modelos de distribuição de espécies, revisão sistemática.

resumo

Quer deliberadamente ou acidentalmente, os seres humanos têm vindo a introduzir espécies exóticas em novos habitats a um ritmo alarmante, sendo que as alterações climáticas que se têm vindo a sentir, por vezes promovem sinergeticamente este fenómeno. A avaliação de risco de espécies exóticas é essencial para apoiar a prevenção de novas introduções no caso de espécies que potencialmente representam algum impacto negativo nos vários componentes dos ecossistemas. Ao longo dos últimos 20 anos, a modelação estatística tem vindo a ser reconhecida como uma ferramenta útil na previsão dos riscos de invasão especificamente no caso de plantas exóticas. Nesta revisão sistemática, analisou-se a aplicação de modelos estatísticos na avaliação do risco de espécies de plantas exóticas, com a finalidade de avaliar como a aplicação destas ferramentas evoluiu ao longo do tempo, bem como identificar as abordagens utilizadas e finalmente as atuais limitações inerentes a estes estudos. Os resultados apoiam que os modelos estáticos e espacialmente explícitos de aprendizagem automática que preveem a distribuição potencial de espécies são as técnicas mais comummente utilizadas, embora algumas limitações pertinentes relacionadas com esses modelos tenham sido também identificadas. Concluiu-se que uma formalização dos protocolos de avaliação de risco deverá incluir de forma estandardizada a utilização de modelos de distribuição de espécies, tanto as técnicas como as abordagens deverão ser cientificamente comprovadas de forma a maximizar a precisão e diminuir os erros dos resultados.

keywords

invasive alien plants, risk assessment, statistical modelling, species distribution models, systematic review.

abstract

Either deliberately or by accident, humans have been introducing exotic species into novel habitats at an alarming rate and the ongoing climate change can synergistically promote this phenomenon, at times. Risk assessment of exotic species is essential to support the prevention of new introductions in the case of species that represent negative impacts on the various components of ecosystems. Over the last 20 years, statistical modelling has been recognized as a useful tool in predicting invasion risks specifically for exotic plants. In this systematic review, the application of statistical models to the risk assessment of alien plant species was analyzed to assess how the application of these tools has evolved over time, as well as to identify the approaches used and finally the current limitations inherent to these studies. The results support that static and spatially explicit machine learning models that predict potential species distribution are the most commonly used techniques, although some pertinent limitations related to these models have also been identified. It has been concluded that a formalization of risk assessment protocols should include the standardized use of species distribution models, and both techniques and approaches should be scientifically proven to maximize accuracy and reduce errors in results.

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Introduction

Biological Invasions

Since the beginnings of invasion ecology, there have always been ambiguities as to what exactly defines and characterizes the phenomenon of a “biological invasion”. Valéry *et al.* (2008) argue that the reason for that is the researchers’ disagreement as to what should be the main criterion applied: either biogeographic barriers or the impacts in the ecosystems and society. In trying to reach a consensus, and after considering various approaches, Valéry *et al.* (2008) proposed a general definition: “A biological invasion consists of a species’ acquiring a competitive advantage following the disappearance of natural obstacles to its proliferation, which allows it to spread rapidly and to conquer novel areas within recipient ecosystems in which it becomes a dominant population”.

The terminologies employed to define alien and invasive species also suffer from these uncertainties; Richardson *et al.* (2000) attribute this phenomenon to two main reasons, the first being the translation of terminology between languages (mainly from European languages to English), and the other being the scale of this thematic having grown so much since terms like “naturalization” were introduced.

Recently, Blackburn *et al.* (2011) proposed a unified framework for biological invasions that acknowledges the need to distinguish species terminology and invasion stage taking into account both the biogeographical barriers to overcome by the species, and the proper management steps to deal with their impacts (Fig. 1). Not all alien species that manage to establish themselves outside their native range become invasive and detrimental to local biodiversity, which is why it’s important to have a clear distinction between “naturalized” and “invasive”, since the latter poses overall greater risks. Nonetheless, this framework doesn’t include the species impacts on the ecosystems, which is fundamental for the definition of “invasive species” in various international organizations, like the Convention on Biological Diversity (CBD) and the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES).

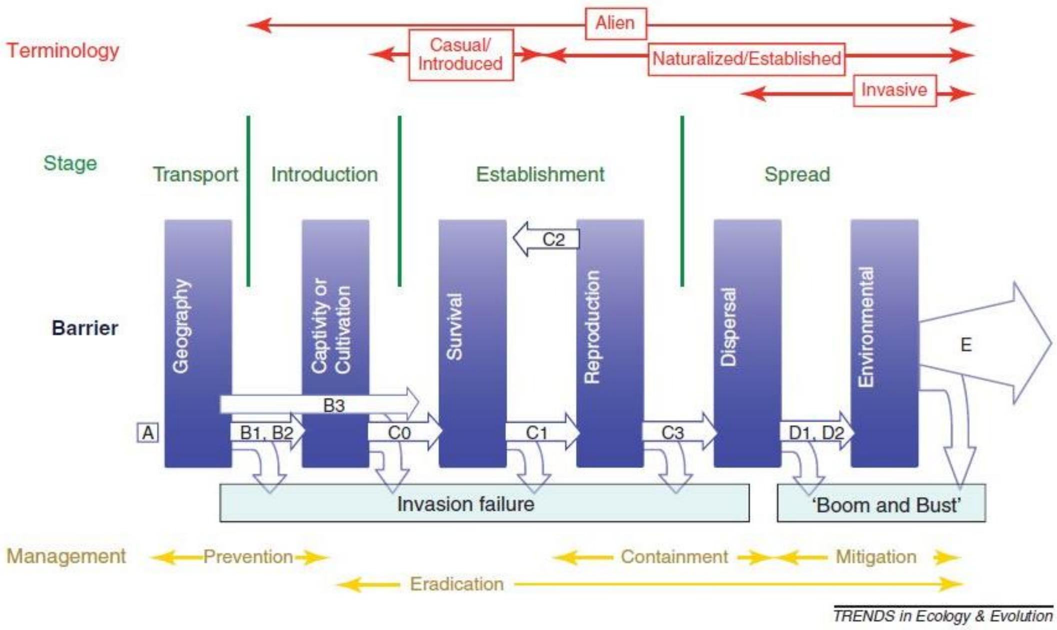

Figure 1 – The proposed unified framework built by Blackburn *et al.* (2011), which emphasizes the distinction between species terminology, stage of invasion, the barriers a species must overcome, and the type of management most appropriate for each stage/species. The unfilled arrows represent the species progress along the process, and the alphanumeric codes represent species and population categories within the invasion stages. Source: Blackburn *et al.* (2011).

The propagule pressure hypothesis is frequently described as the main driver of biological invasions. It's defined by (Lockwood *et al.*, 2005) as "…a composite measure of the number of individuals released into a region to which they are not native.", and the hypothesis states that as the frequency of releases (introduction events) and number of individuals (propagules) increase, the propagule pressure also increases, leading to a higher probability of invasion occurrence. It is well known that globalization plays a major role in the increase of alien species introductions: the advances in technology allow for more, faster international trade routes and travels, which mean more movements of people and goods, which in turn, increase the possibilities of introducing alien species in nonnative ranges (Ehrenfeld, 2005; Meyerson and Mooney, 2007).

Plant Invasions

Either deliberately or by accident, humans have been introducing plant species into new ranges at an alarming rate (Mack *et al.*, 2000). As a result, roughly 3.9% of the existing vascular plant species have established themselves somewhere in the globe, outside their native range (van Kleunen *et al.*, 2015). Ornamental horticulture trade is known to be the main cause of alien plant naturalization and invasion in the world, and coincidentally, some of the species characteristics most desirable in the market (like fast vegetative growth and abundant seedling emergence), are the same ones that promote their invasive behavior (van Kleunen *et al.*, 2018). Specific anthropogenic aspects can be factored in the propagule pressure hypothesis, such as tourism, human population density and vehicle traffic (von der Lippe and Kowarik, 2007; Thuiller *et al.*, 2005; Spear *et al.*, 2013), which match the types of land cover known to be more prone to plant invasions, like agricultural, urban, and industrial land covers (Chytrý *et al.*, 2009).

The human population benefits, directly or indirectly, from the good functioning of the ecosystems; these benefits are more recently known as "Nature Contributions to People (NCP)" (ecosystem services), and they can range from simple concepts like air quality, food production, and water supply, to genetic resources and climate regulation (Diaz *et al.*, 2018). Some impacts of plant invasions in these NCP include local/regional changes in the cycling of soil nutrients, fluctuations in fire regimes, decreased water quality and quantity, and losses in recreation and tourism revenues (Chamier *et al.*, 2012; Ehrenfeld, 2003; Eiswerth *et al.*, 2017; Zavaleta, 2000). But even though these impacts are heterogeneous and dependent on many variables, the loss of native biodiversity in invaded areas is on average, a guaranteed consequence (Vilà *et al.*, 2011).

It is estimated that the environmental transformations that come along with climate change will increase the invasiveness of some alien plant species; elevated CO_2 levels impact the growth of native and alien species alike, but if the alien species possess novel traits, that might give them an advantage to further their spread. Other indirect consequences related with the rise of temperatures and resource availability might cause a ripple effect in nutrient cycling and water availability, aggravating habitat disturbances and affecting the ability of some native species to persist in those habitats (Weltzin *et al.*, 2003). These disturbances, if incorrectly timed (e.g. fluctuating fire regimes) can represent opportunities for invasive species to settle in, due to niche availability (Thuiller *et al.*, 2007).

Risk Assessment and Modelling Tools

In 2014, the European Commission approved Regulation 1143/2014 on the prevention and management of the introduction and spread of invasive alien species, which lists a set of measures to be considered across the European Union, in order to enforce the prevention, detection, eradication, and management of the species of Union concern. Risk assessment is one of the measures expected to be carried out when deciding upon the inclusion of a certain species on the list of invasive alien species of Union concern. In light of this Regulation, Portugal has approved Decree-Law nº 92/2019 which establishes a legal scheme for the control of introduction of alien species, with the creation of a national list of species of which custody, production, or cultivation is forbidden. Prevention measures are the most cost-effective to tackle this threat in long term, so it makes sense to take precautionary action and asses the risks of establishment/invasion, if governments want to avoid wasting huge amounts of money dealing with the spread of an invasive species (Keller *et al.*, 2007). Furthermore, very recently, the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) has launched the first intergovernmental global assessment on invasive alien species, covering every aspect of this problem, from drivers and effects to management options and policy (Stoett *et al.*, 2019), which will be especially important to inform the lawmakers of the way forward.

Kumschick *et al.* (2013) categorized risk assessment (RA) methods in 3 categories: qualitative, semiquantitative, and quantitative, according to the type of approach utilized. They figured that most RAs are semiquantitative, because even though the methods are naturally quantitative, the measurements are still qualitative. The most common approaches relate species geographical occurrences in nature to the characteristics of the environment they currently occupy, using mathematical functions. The species niche is modelled according to the landscape characteristics of its current distribution, and then projected onto a geographical space, allowing researchers to build predictive maps of habitat suitability (Guisan and Zimmermann, 2000). These static models can take a variety of forms, in regression analyses (Haeuser *et al.*, 2018), machine learning models (Szymura *et al.*, 2018), simpler profiling techniques (Natale *et al.*, 2018) and some authors might resort to more than one model in order to compare results (Magarey *et al.*, 2018).

A more uncommon approach to predict the spread of invasive species is the evaluation of population spread and growth over time, which provides a more dynamic overview of what to expect (Muthukrishnan *et al.*, 2015).

Point scoring systems, like the well-known Australian Weed Risk Assessment (AWRA), are usually question based assessments that generate a numerical score to determine if the species can or cannot be imported into the country (Pheloung *et al.*, 1999). However, they require a previous analysis on the species ecology and its undesirable traits. For the AWRA, the species are declared as “accepted”, “rejected”, or “pending further evaluation”, and it’s proven to be an efficient tool (Gordon *et al.*, 2008). Other similar protocols have emerged for other regions in the world; the European and Mediterranean Plant Protection Organization (EPPO) Pest Risk Analysis targets Europe and the Northern African region and it first assesses if the species can be considered as a pest, then proceeding to further evaluate its risk of invasion (Brunel and Petter, 2010); the German-Austrian Black List Information System (GABLIS) was developed as more of a generic tool for not just plant species, however it’s not as prevalent as the other two (Essl *et al.*, 2011). It’s up to the researchers to select the most appropriate approach, according to their goals and data sets available to them.

Aims

Plant invasions show no sign of slowing down; the imminent climate change and ever-growing human activity will only accelerate the rate at which they keep happening. For that reason, it’s important to improve the procedures that allow to prevent, anticipate and early detect new invasions, evaluating the risk of expansion of plant species. To pursuit that main objective, we conducted a systematic review to (1) analyze the extent to which statistical models have been used to assess the risks of alien plant invasions, (2) identify its trends and patterns in that context, (3) evaluate how the scientific studies have evolved over time, (4) identify current limitations, and (5) discuss what might be missing from the field, or what it could benefit from in the future.

Methodology

Overview

The framework used was a standard procedure for literature reviews (Higgins and Green, 2011) with the aim to trace patterns of risk assessment in plant invasion modelling literature. This framework consists in two main steps: literature search and literature review, thoroughly explained in Fig. 2.

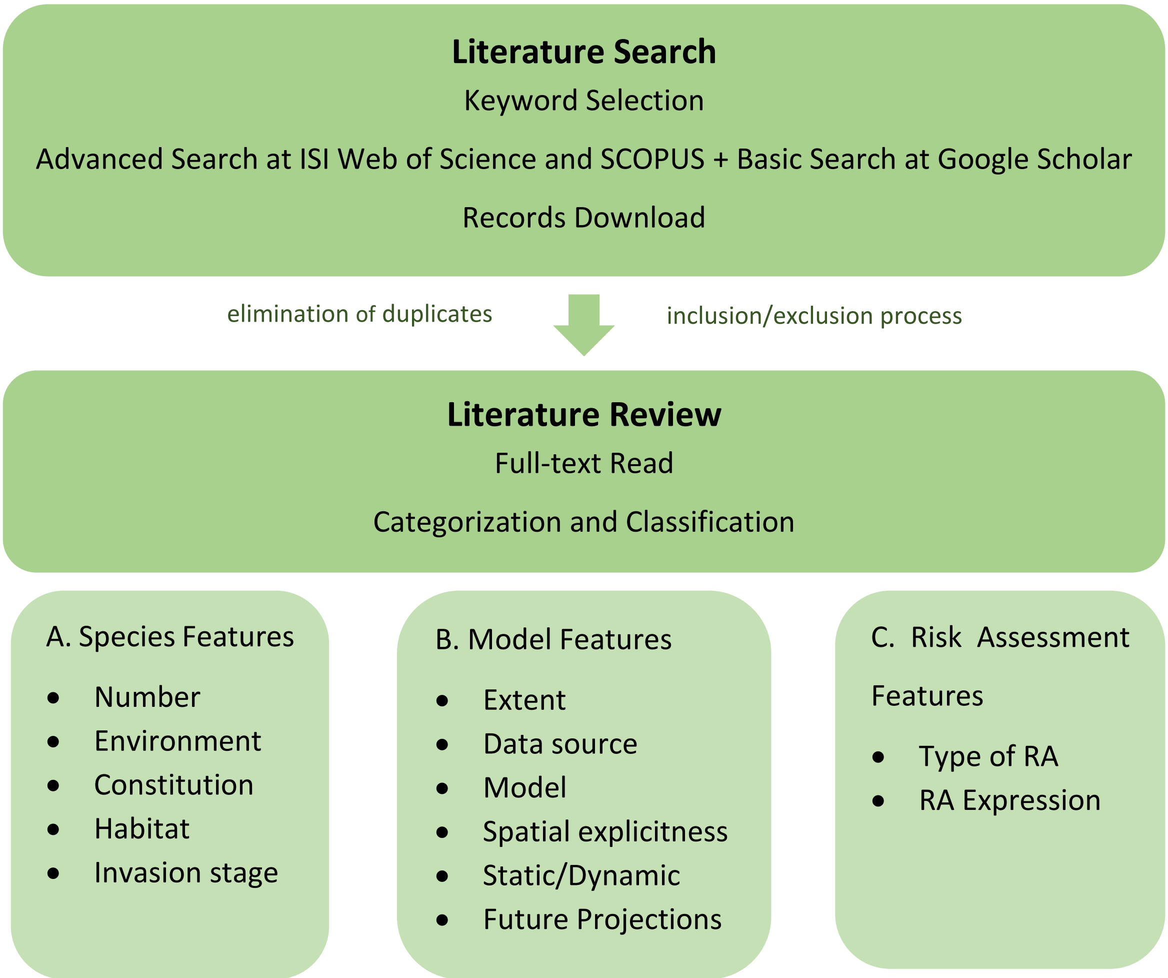

Figure 2 – Analytical framework built for reviewing the use of statistical modelling tools in the risk assessment of alien plant invasions. First, a literature search was conducted in ISI Web of Science and SCOPUS, with carefully selected keywords. A third search in Google Scholar was conducted for reliability evaluation of the previous searches. After eliminating duplicates and submitting the records to an inclusion/exclusion process based on their titles, abstracts and keywords, a final list of records was carried to the actual review. Finally, the records were classified according to 3 categories regarding their studied species, used model, and risk assessment features.

Literature Search

The literature search begins with selecting the keywords to be utilized in the search engines. For this review, the selection process followed the Population-Intervention-Comparison-Outcome (PICO) strategy, in order to build the broadest set of keywords possible. Thus, the specification for this review is Population as “invasive plant”, Intervention as “modelling”, and the Outcome as “risk assessment”.

For the Population aspect of this strategy, the set of keywords applied was one previously built by a team of researchers with a different goal in the field of plant invasions (Vaz *et al.*, 2018), and then kindly provided to us for this research, as a total of 74 words or expressions related to “invasive plant”. Next, for the Intervention as “modelling”, only 3 keywords were selected using Buchadas *et al.* (2017) as source. For the Outcome “risk assessment” 10 expressions were compiled based on Kumschick *et al.* (2013), as well as on the EU Regulation 1143/2014 on Invasive Alien Species. Hence, a list of the most common and unambiguous words or expressions was gathered, with the idea of broadening the search as much as possible. That list can be found below in Table 1, exactly as it was used onto each search engine’s search boxes.

Table 1 – List of keywords selected for the search engines, divided in the 3 categories representing the key aspects of this review, as well as their sources.

Keyword List	Source(s)
"plant invader*" OR "introduced plant*" OR "non-native plant*" OR "nonnative plant*" OR "invasive plant*" OR "exotic plant*" OR "alien plant*" OR "plant invasion*" OR "nonindigenous plant*" OR "non-indigenous plant*" OR "allochthonous plant*" OR "tree invader*" OR "introduced tree*" OR "non-native tree*" OR "nonnative tree*" OR "invasive tree*" OR "exotic tree*" OR "alien tree*" OR "tree invasion*" OR "nonindigenous tree*" OR "non-indigenous tree*" OR "allochthonous tree*" OR "forest invader*" OR "introduced forest*" OR "non-native forest*" OR "nonnative forest*" "invasive forest*" OR "exotic forest*" OR "alien forest*" OR "forest invasion*" OR "Nonindigenous forest*" OR "non-indigenous forest*" OR "allochthonous forest*" OR "introduced vegetation*" OR "non-native vegetation*" OR "nonnative vegetation*" OR "invasive vegetation*" OR "exotic vegetation*" OR "alien vegetation*" OR "nonindigenous vegetation*" OR "non-indigenous vegetation*" OR "allochthonous vegetation*" OR "shrub invader*" OR "introduced shrub*" OR "non-native shrub*" OR "nonnative shrub*" OR "invasive shrub*" OR "exotic shrub*" OR "alien shrub*" OR "shrub invasion*" OR "nonindigenous shrub*" OR "non-indigenous shrub*" OR "allochthonous shrub*" OR "herb invader*" OR "introduced herb*" OR "Non-native herb*" OR "nonnative herb*" OR "invasive herb*" OR "exotic herb*" OR "alien herb*" OR "herb invasion*" OR "nonindigenous herb*" OR "non-indigenous herb*" OR "allochthonous herb*" OR "introduced landscape" OR "non-native landscape" OR "nonnative landscape" OR "invasive landscape" OR "exotic landscape" OR "alien landscape" OR "nonindigenous landscape" OR "non-indigenous landscape" OR "allochthonous landscape" OR "novel ecosystem*"	Vaz *et al.* (2018)
"risk assessment" OR "invasion risk" OR "risk analys?s" OR "risk evaluation" OR "risk of invasion" OR "risk of introduction" OR "introduction risk" OR "invasion potential" OR "establishment risk" OR "risk of establishment"	Kumschick *et al.* (2013), EU Regulation 1143/2019
"model*" OR "simulat*" OR "predict*"	Buchadas *et al.* (2017)

The symbols between keywords are search engine operators, which allow for a more advanced and specific search, and work like mathematical expressions. A list of every operator used and its effects can be found below, in Table 2.

Table 2 – List of operators used in the list of keywords, designed to allow for a more advanced search in the selected search engines, as well as their respective effects within the engine, and some examples.

Search engine operator	Effect	Example
“” (quotation marks)	searches records containing the exact words	“nonnative landscape”
OR	searches for records containing each word or both	“nonnative landscape” OR “invasive landscape”
* (asterisk)	the search engine fills in after the words, meaning it could be anything after that specific word	“introduced herb*” – will also search for “introduced herbs”
? (question mark)	searches for words where the question mark can be replaced by any character	“risk analys?s” – will search for both “analysis” and “analyses”

The time span for the search was from 1900 to 2018, and it was conducted during November 2018 at ISI Web of Science (http://webofknowledge.com) and SCOPUS (http://scopus.com), where the advanced search feature allows for a multi-topic search, and where each group of keywords corresponded to one topic. Utilizing the features available in each website, a list of every result in ISI Web of Science and SCOPUS was downloaded onto an excel sheet, where duplicates (results that appeared on both engines) were eliminated.

A third search was conducted on Google Scholar to judge the reliability of the previous search, using the three main keywords (“invasive plant”, “risk assessment”, and “modelling”), but only retrieving the first 50 results, ordered by popularity, to check for any article that was missed by the first two engines, which were then added to the list of records.

Before the literature review, this list of results was subjected to an inclusion/exclusion process, where only the title, keywords and abstract of every record was examined in order to evaluate which ones should be included in the second step of this review. The intent was to include only records that focus in the usage of statistical modelling tools to assess the risk of invasion by alien plant species. This way, unsuitable records that include some listed keywords but aren't exactly about the specific field being reviewed are also discarded. The full text of the final list of records was downloaded and each record was numbered to facilitate the next process.

Literature Review

To begin the literature review, the next step involved reading the full text of every record in the final database and follow a previously built categorization and classification protocol. This protocol was divided in 3 groups of features regarding: A – species features, B – model features and C – risk assessment features, as detailed below in Table 3:

Table 3 – List of categories and classes used in the sorting of each record, divided by their features. Group A envelopes the categories regarding the species features. Group B envelopes the categories concerning the model features. Group C envelopes de categories relating to the risk assessment accomplished for each record.

	Category	Classes
Group A	Nº of species	Individual or Multispecies
Group A	Environment	Aquatic, Terrestrial, or NA
Group A	Constitution	Herbaceous, Shrub, Tree, or Several
Group A	Continent	Europe, Asia, South America, North America, Africa, Oceania, Antarctica, Global, or NA
Group A	Invaded Habitat	Freshwater, Riparian, Urban, others, Several, or NA
Group A	Invasion Stage	Introduced, Naturalized, or Invasive
Group B	Extent	Local, Regional, National, Multinational, Continental, or Global
Group B	Data Source	Existing Database, Field Data, Expert Data, Literature, or Remote Sensing
Group B	Model	Regression Analysis, Profile Techniques, Machine Learning, Decision Trees, Bayesian Approach, Ensemble Modelling, Population Dynamics, or Mechanistical Model
Group B	Spatial Output	Spatially Explicit or Not Spatially Explicit
Group B	Temporal Output	Static or Dynamic
Group C	RA Output	Potential Distribution, Invasion Risk, Predicted Species Richness, Population Dynamics, Point Scoring System, or None
Group C	RA Method	Qualitative, Semiquantitative, or Quantitative
Group C	Impacts	Environmental, Socio-economic, others
Group C	Affected services	Biodiversity, Health, Security, others

The number of species is classified as “Individual” when only one species is in focus in the study. However, when two or three species are individually modelled in the same article, instead of classifying it as “Multispecies”, that record was divided in two or three entries, which are then classified as “Individual” and further treated as two or three different entries for the rest of the process. This way it’s possible to more thoroughly explore relevant records, since it becomes possible to classify different studies within the same record.

The species environment was almost always classified as either aquatic or terrestrial, although for the semi-aquatic species they were included in the terrestrial class. The NA (Not Applicable) class in this category usually applied to records where whole taxa were modelled but it wasn’t possible to determine the environment of every species.

The species constitution was divided into the 3 usual terminologies: herbs, shrubs, and trees. The “Several” option, like in every other class where it applies, is used for instances where it’s not possible to distinguish the classes, either because it’s a larger number of species to specify, or because a whole taxon is considered. When encountering species of cacti, the size of the species determined if it was considered as a shrub or a tree, but never as an herb. When encountering a species of algae, they were considered as herbaceous.

The “Several” option was more needed than generally for the invaded habitat category, since frequently the modelled area was larger enough to encompass more than one type of habitat.

For the species invasion stage, in some articles, the only terminology used to describe the species in question was “nonnative” or “alien”, and in those cases, they were simply classified as “Introduced”, since there was no indication of it being already in a later stage of invasion.

The model range is divided by tiers of geographical scales, from “Local” to “Global”, since many authors didn’t specify the area extension in distance units.

The data source for each of the studies was divided according to the authors' own words on where it came from. "Expert Data" relates to information the authors claimed to have obtained from experts in their respective fields, regardless of that same data being available through other sources or not. "Existing Database" relates to any kind of database on any scale (regional, national, global, etc) where usually one can find occurrences for the species in question.

The modelling technique classifications were grouped partly based on the works of Elith *et al.* (2006). For this review a couple more classifications were added since the variety of modelling tools available nowadays is much wider. "Profile Techniques" include systems such as BIOCLIM, DOMAIN, CLIMEX and the Mahalanobis Distance. "Regression Analysis" mostly comprise diverse forms of linear models like Generalized Linear Model, Generalized Linear Mixed Model and Additive Linear Model. "Machine Learning" models include Random Forest and Boosted Regression Trees, as well as the more common MaxEnt model. "Population Dynamics" was the selected terminology to embody models focused on the species populations dynamics, like the use of Integrodifference Equations, a FATE-HD model or Recruitment Curves. "Bayesian Approach" includes processes in which a Bayesian model or inference was used. Finally, "Ensemble Modelling" consists of instances where two or more related types of modelling tools were combined to achieve one final, more accurate model.

After identifying which models are used, they were also classified according to their spatial and temporal outputs. Hybrid models, which include both static and dynamic components, were included in the "Dynamic" class.

The Risk Assessment Output classification was split according to the diverse ways in which the results were presented in the records. "Potential Distribution" is the broader class, which includes potential distribution maps, habitat suitability maps and probabilities of occurrence. "Invasion Risk" includes mainly invasion risk maps and tables. "Population Dynamics" applies to "Population Dynamics" models where the results frequently show population growth and spread. "Predicted Species Richness" is a very specific class that mainly included predicted species richness maps and tables. “Point Scoring System” concerns risk assessment processes, like the Australian Weed Risk Assessment System for example, as well as other similar methods.

The RA Method characterization is inspired on the classification of the methods, described by Kumschick *et al.* (2013). “Semiquantitative” risk assessment applies when even though the methods used are quantitative, the measures and scales used for the assessment are qualitative, and therefore can’t be fully defined as quantitative or qualitative.

The Impacts and Services Affected categories are dependent on the authors own concern with detailing those aspects in their works, but the idea was to divide them in the basic classes of impacts and their consequences for the environment and the society.

Data Analyses

Cohen’s Kappa testing

After classifying each record in the possible categories, and before proceeding to the principal component analysis, the data organized in text was converted into binary code. A new excel sheet was created, where instead of corresponding categories and classes to each numbered record, there’s only the corresponding classes and Yes (1) or No (0) answers for each of the records. For instance, record nº 1 would have a correspondence of 1 (Yes) to “Individual” and 0 (No) to “Multispecies”, and so on through the rest of the classes. This way the data can be further and thoroughly analyzed in the appropriate software.

Cohen’s Kappa tests were ran for every pair of variables, previously titled classes, in IBM SPSS Statistics 24, using the Crosstabs function. These Cohen’s Kappa tests help in eliminating redundant information, by identifying which variables are significantly associated with each other. So the goal was to determine which of those classes were the most relevant for this review, and therefore select which ones to carry onto the principal component analysis.

A total of 1,032 pairs were evaluated (every class paired with each other), and according to the established criteria, a relevant pair of variables would have a Kappa value of at least 10%, either positively or negatively correlated (0,1 or -0,1), and a Significance (p value) less or equal to 0,05.

Principal Component Analysis

A Principal Component Analysis (PCA) is a statistical method that allows the user to highlight variations and patterns in a dataset comprised of observations whose variables might be correlated with each other. It digs out information from the classification matrix of the dataset, converting the correlations it finds between variables (or lack of correlations) into a two-dimensional space, usually a graph. Variables that are highly correlated tend to gather together, forming clusters in the resulting graph.

For this review, a Cohen's Kappa test was conducted on the variables available to reduce the amount of data in order to produce more accurate results.

Results

Literature Search

The first literature search, conducted using the ISI Web of Science search engine and using the keywords listed in the previous section, produced the results presented below (Fig. 3). With only the keywords related to "Plant Invasions" there were a total of 16,496 records. With the keywords related to "Plant Invasions" and "Risk Assessment", there were a total of 538 records. Finally, with all three groups of keywords, "Plant Invasions", "Risk Assessment" and "Model", the number of records was 419, although only the first 389 were considered since the review was conducted in November of 2018, while these results are updated to July 1st 2019.

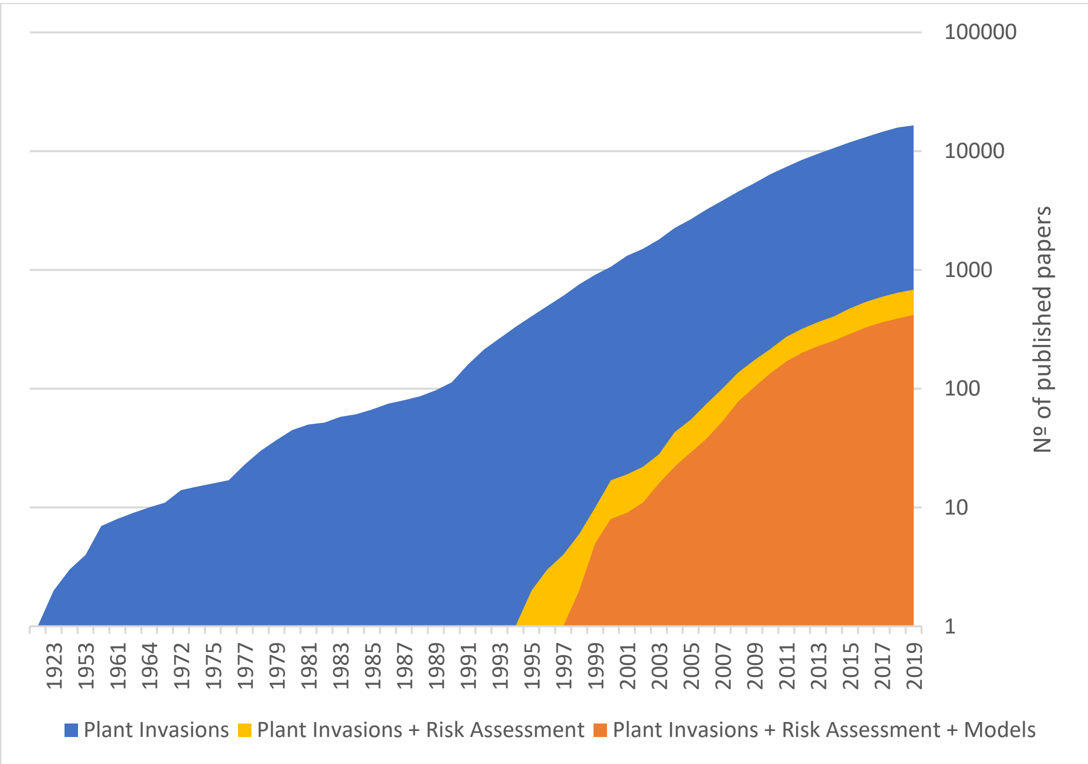

Figure 3 – The cumulative number of papers retrieved during the search, per year, from the ISI Web Of Science search engine (updated July 1st 2019), on plant invasions, risk assessment within plant invasions, and modelling within risk assessment of plant invasions.

The second search, using the SCOPUS search engine resulted in 1,223 records. The third search, for evaluation purposes at Google Scholar (where only the first 50 records were selected) resulted in the addition of 4 records that were not selected in the previous search at ISI Web of Science or SCOPUS.

After the inclusion/exclusion process that involved examining the title, keywords, and abstract of every record (for more details on this process refer to the previous section), and after removing duplicates (records that were selected on more than one search engine), 206 records were held for the next step, as summarized in Table 4:

Table 4 – Number of records retrieved per search engine and their total. Number of records carried onto the literature review, after the inclusion/exclusion process.

Search Engine	Nº of records (3 keywords)
ISI Web of Science	389
SCOPUS	1,223
Google Scholar (in the first 50 results)	4 (“new”)
Total	1,616
After inclusion/exclusion process and duplicates removal	206

Literature Review

After reading through the full-text of those 206 records, 59 were excluded as they didn’t meet all the inclusion requirements previously established. As a result of the categorization and classification process, and how one unique record might translate into various entries in the excel sheet where the data was organized, 147 records amounted to 189 unique entries (or individual studies). A list of those records is provided in Appendix A.

Group A – Species features

Regarding the species features (category group A – refer to the previous section for more details on categories), the number of species in focus per entry was almost even between an “Individual” species and “Multispecies” (Fig. 4).

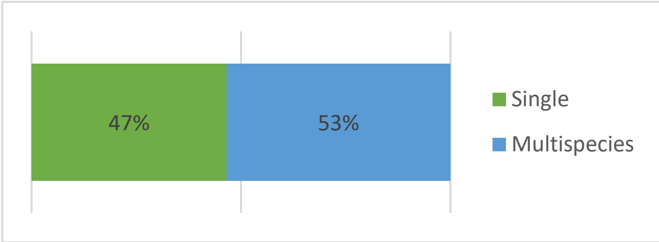

Figure 4 – Percentage of entries per Nº of Species class.

Concerning the species environment, most of the invasive species studied were terrestrial species (Fig. 5).

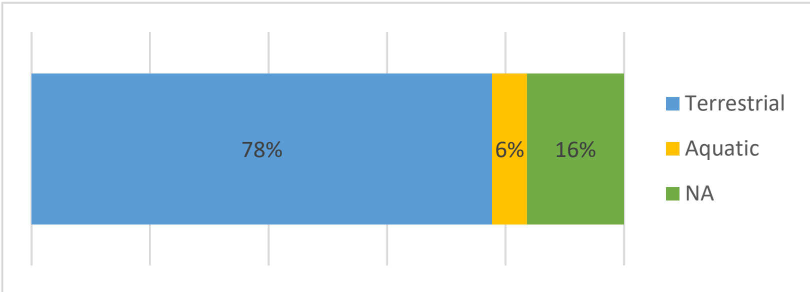

Figure 5 – Percentage of entries per Environment class.

For most entries, the species in focus had multiple constitutions, which could not be distinguished into only one type. For the entries in which they could, herbaceous species and shrubs were more frequent than trees (Fig.6).

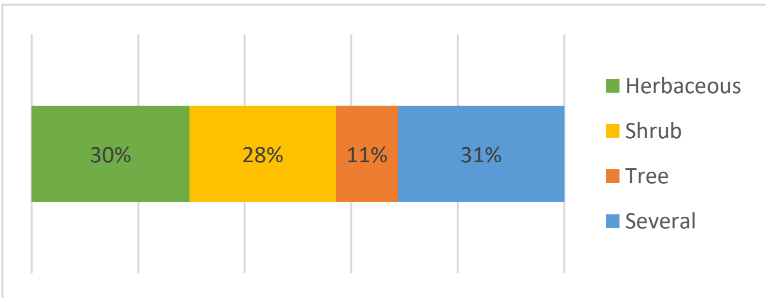

Figure 6 – Percentage of entries per Constitution class.

When it comes to study region, North America and Europe have the most entries of studies completed by region. Out of 189 entries, 21 of them represent global studies and 3 of them represent studies where location was not applicable (Fig. 7).

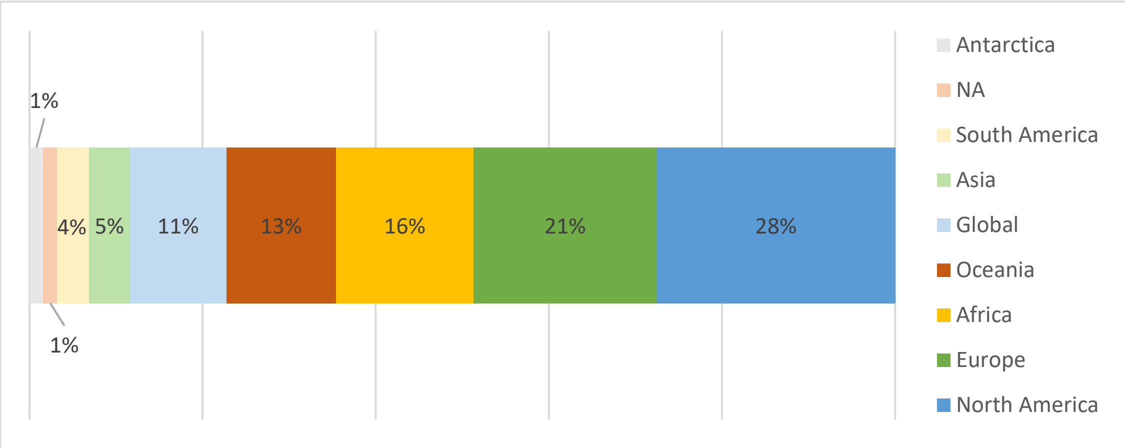

Figure 7 – Percentage of entries per Region class.

Concerning the invasion stage of the species in focus, most of them are classified as "Invasive" (Fig. 8).

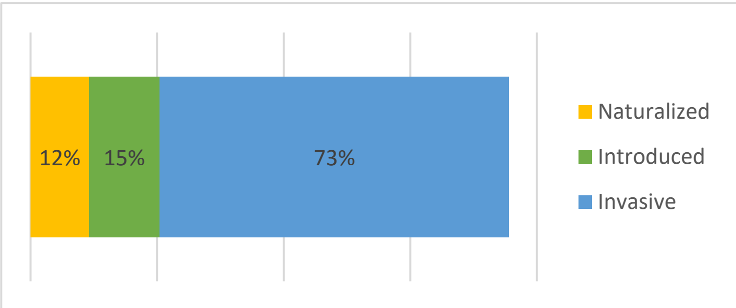

Figure 8 – Percentage of entries per Invasion Stage class.

There was a great number of possibilities regarding the type of habitat invaded in each of the entries, but most of the studies included more than one, therefore "Several" was the most common classification (Fig. 9).

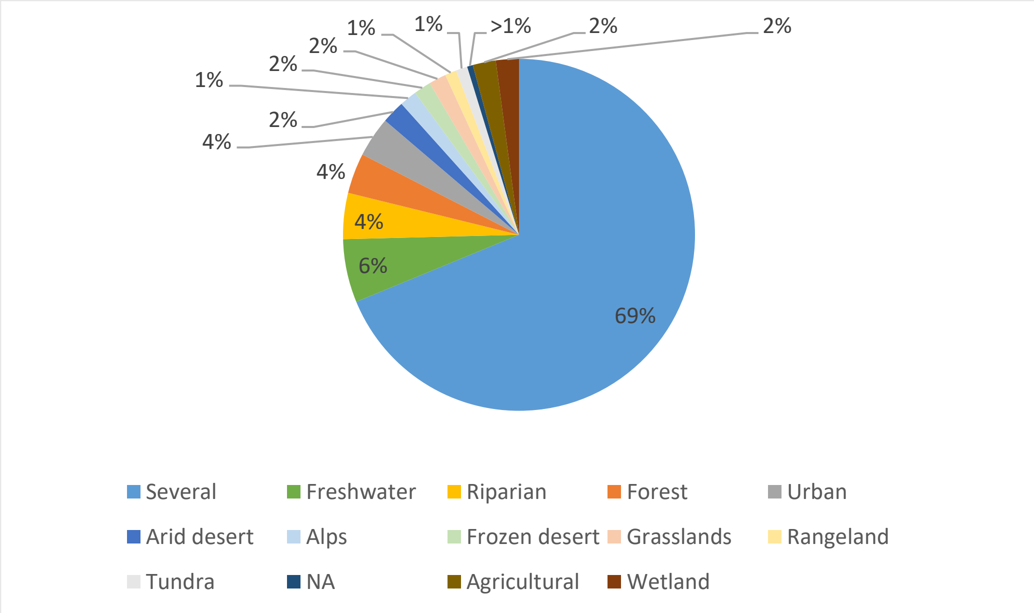

Figure 9 – Percentage of entries per Invaded Habitat class.

Group B – Model features

Regarding the model features (category group B – refer to the previous section for more details on categories), the most common data source was "Database", used in more than half of the entries (Fig. 10).

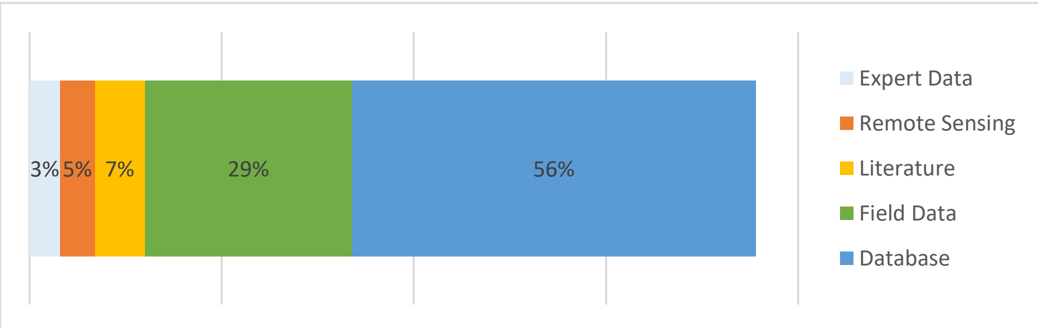

Figure 10 – Percentage of entries per Data Source class.

Concerning the extent of the models used in each entry, “National” and “Regional” ranges amount to the majority of it, followed by “Local” models (Fig. 11).

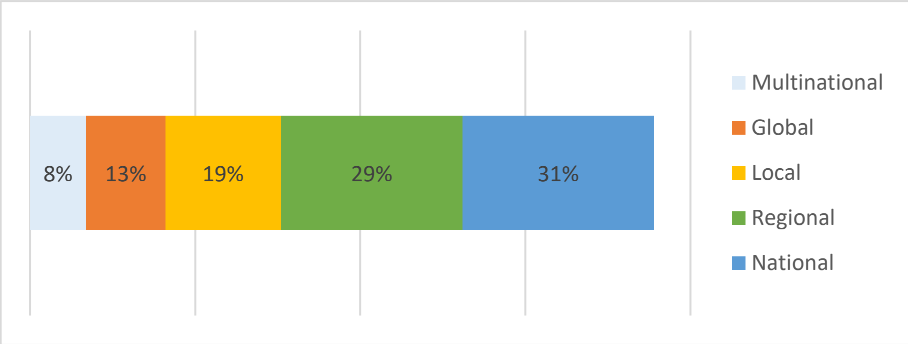

Figure 11 – Percentage of entries per Model Range class.

In relation to the actual modelling tools used in the studies, “Machine Learning” models are the most popular, followed by “Ensemble Modelling” (Fig. 12).

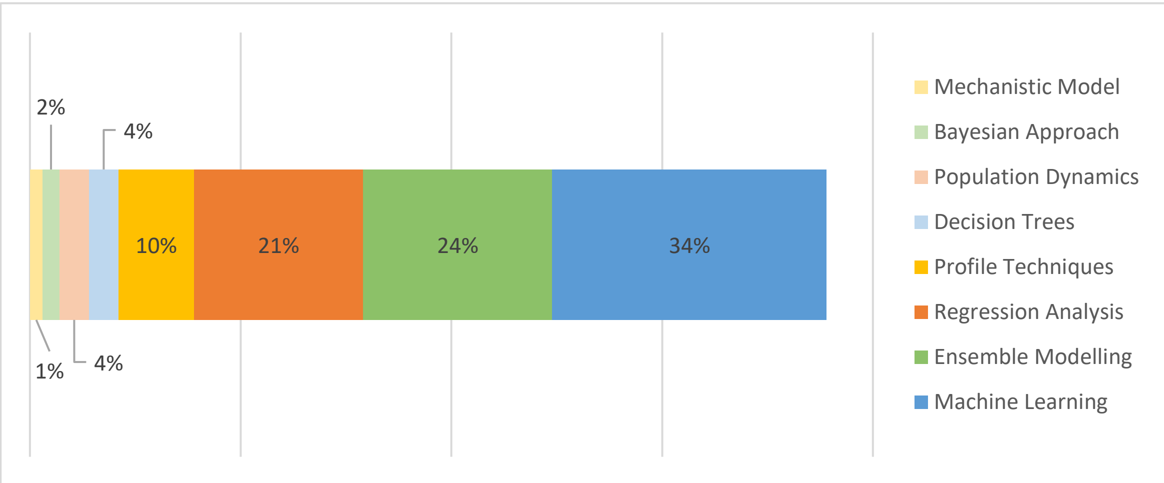

Figure 12 – Percentage of entries per Model class.

Regarding to the spatial explicitness of the models, there's a clear prevalence of "Spatially Explicit" models (Fig. 13).

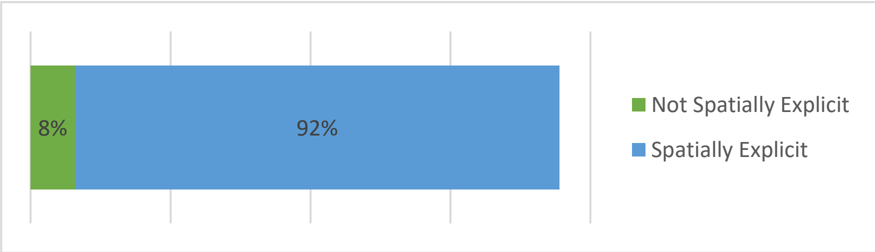

Figure 13 – Percentage of entries per Spatial Output class.

The same overwhelming difference appears in favor of "Static" models (Fig. 14).

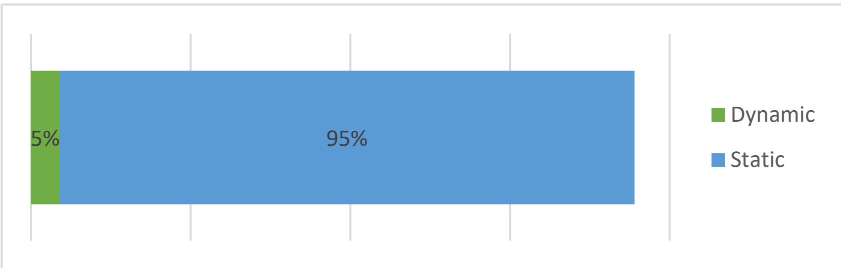

Figure 14 – Percentage of entries per Temporal Output class.

Group C – Risk Assessment output and data

Concerning the risk assessment output and data (category group C – refer to the previous section for more details on categories), "Potential Distribution" was the most common type of RA, followed by "Invasion Risk" (Fig. 15).

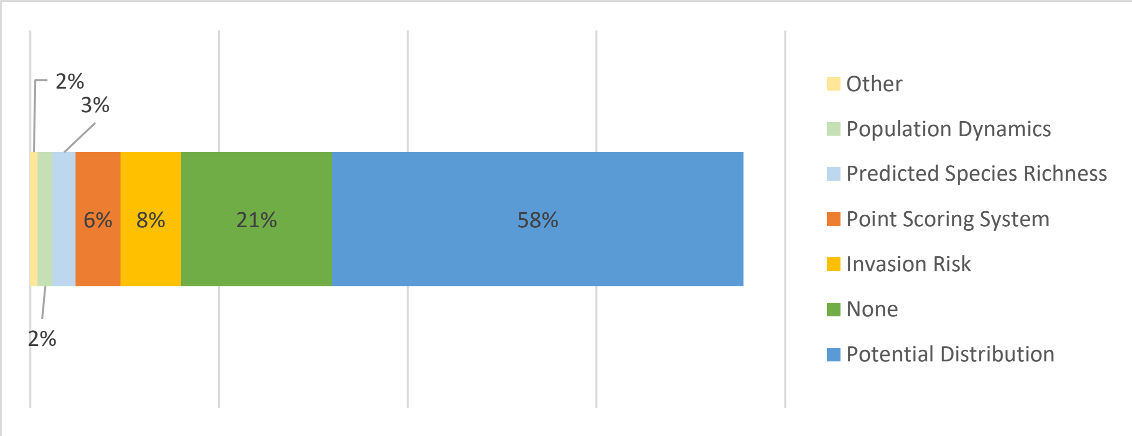

Figure 15 – Percentage of records per Risk Assessment Output class.

Finally, regarding the classification of the method used, "Qualitative" methods were more popular (Fig. 16).

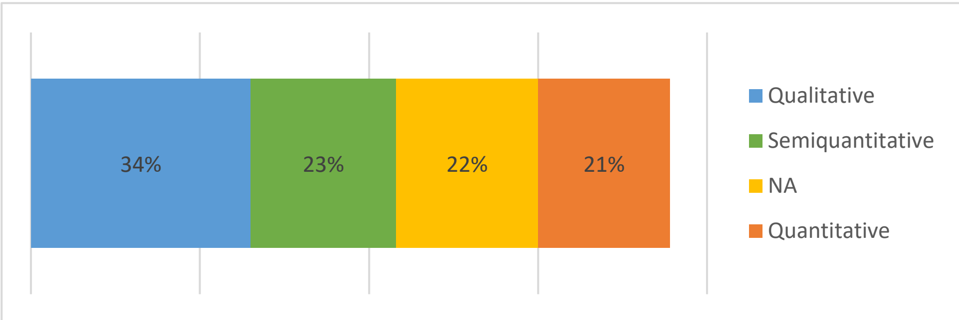

Figure 16 – Percentage of entries per Risk Assessment Method class.

Cohen's Kappa Testing Results

According to the established criteria for "relevant" variables (Kappa value of at least 10% either positively or negatively correlated and significance less or equal to 0,05), and after analyzing which ones appeared more frequently, the selected variables are listed below in Table 5. For a complete list of variable combinations and their Kappa and significance values, see Appendix A.

Table 5 – Variables (classes) selected after running a Cohen's Kappa test to determine which ones are relevant for PCA analysis.

Categories	Variables (Classes)
Model	Regression Analysis, Profile Techniques, Machine Learning, Decision Trees, Bayesian Approach, Ensemble Modelling, Population Dynamics, and Mechanistic Model
Spatially Explicit	Spatially Explicit and Not Spatially Explicit
Static/Dynamic	Static and Dynamic
RA Output	Potential Distribution, Invasion Risk, Predicted Species Richness, Population Dynamics, Point Scoring System, and None
RA Method	Qualitative, Semiquantitative, and Quantitative

Principal Component Analysis Results

The PCA was carried out on software Canoco 5 (Šmilauer and Lepš, 2014) with a total of 22 variables of 189 entries. The first two components account for 65% of the total variation (Table 6), and they are represented in the scatterplot illustrated in Fig. 17, where 4 clusters of variables can be distinguished:

- Cluster Set 1 – “Machine Learning” + “Spatially Explicit” + “Static”
- Cluster Set 2 – “Ensemble Modelling” + “Potential Distribution” + “Qualitative” + "Semiquantitative
- Cluster Set 3 – “Regression Analysis” + “Not Spatially Explicit” + “No RA "
- Cluster Set 4 – Every remaining variable

Table 6 – Summary of results of PCA with 22 variables for 189 samples (entries). Eigenvalues and cumulative percentage of total variance along 4 components.

Component	Eigenvalues	Cumulative % variance
1	0,570	57,0%
2	0,080	65,0%
3	0,068	71,8%
4	0,062	78,0%

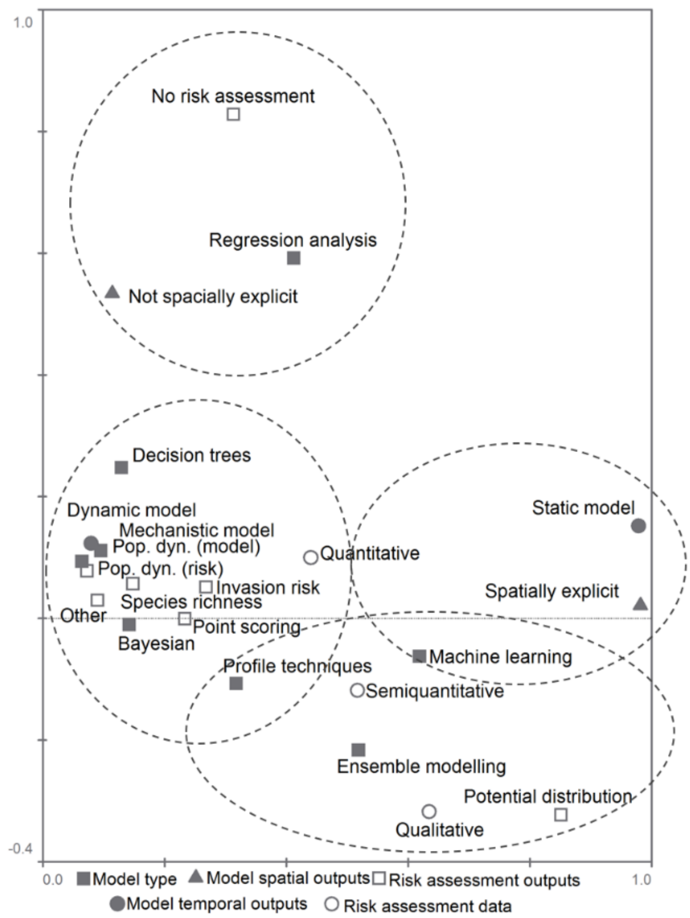

Figure 17 – PCA scatterplot of the 189 entries classified in relation to 5 cluster sets of 22 classes (variables), performed on Canoco 5®. "Risk Assessment data" refers to "Risk Assessment Method".

Discussion

Literature Search

The number of search results in the SCOPUS search engine (n=1,223) was abnormally larger than the number of results in the ISI Web of Science search engine (n=389), even though the same set of keywords was used, in the same order. This is probably due to the search engine's "KEYWORDS+" feature, which automatically attributed keywords to every uploaded record, by relating it with other records about the same topics. These keywords were usually broader concepts, such as "biologic invasions", so consequently, a huge part of the records that came up in the search results contained our selected keywords but related to other similar fields (mostly insect invasions, pest control and management, etc, but also management of plant invasions). However, these results were easily discarded in the inclusion/exclusion process, since the titles were usually enough to realize that those records did not meet the requirements. Another explanation is the number of active journals covered by both search engines, which is higher for SCOPUS than for ISI Web of Knowledge (Mongeon and Paul-Hus, 2016).

Literature Review

During the inclusion/exclusion process it was possible to notice instances where some titles and/or abstracts did not directly reflect the content of the records. They were mostly records whose titles were of a more informal nature, instead of the standard, more precise and direct titles (Gallardo and Aldridge, 2015; Simberloff, 2008).

After applying the inclusion/exclusion process to the records, there were still some of them (n=59) that were discarded while being reviewed. One of the reasons was simple human error and some misinterpretations in the inclusion/exclusion process of records. In addition, the idea was to be as inclusive as possible during that process, since it was preferable to include records to be discarded later than to exclude records that should be included. Another reason is the structuring of the title and/or abstract of records, which as previously mentioned above, didn't always reflect the aims and the methodologies used.

This translated into some records not meeting the requirements, for example, not using statistical modelling tools.

Three of the Classes in the review framework (refer to the Methodology section), “Habitat”, “Impacts”, and “Ecosystem Services Affected” were not considered as variables for the Cohen’s Kappa Tests and the PCA. The classification of the habitat in each record varied a lot, which meant many different habitats to be considered, when even most of the records were classified with “Several” (most of the modelling was done at bigger scales). Furthermore, it’s possible that the terminology used for the habitats might have been redundant with the same habitats having different names in different records. In relation to the “Impacts” and the “Ecosystem Services Affected”, only a portion of the most recent records (mostly 2016 and up) mentioned those topics (Natale *et al.*, 2018). Most articles focused on the general aspects of plant invasions without providing more in-depth assessment of its threats and impacts in that specific context (Faleiro *et al.*, 2015; Thomas and Moloney, 2014).

An issue noticed to be more prevalent in older records was the interchangeable usage of the terms “invasive”, “naturalized”, and “established” when referring to the species in focus. This is a topic previously discussed by Richardson *et al.* (2000), where they assessed the different contexts in which the term “naturalized” was used in the field, and called for a standardization of invasion ecology terminology. In more recent records though, it’s possible to verify that those calls have been answered, since authors seem to make clearer and less open usage of those terms, improving the coherency of the studies (Lalla *et al.*, 2018).

On the complete opposite side, however, some older records didn’t specify the stage of invasion in which the alien species being studied was. In these instances, the species were only described as “nonnative”, “alien”, or “exotic” (Zalba *et al.*, 2000). In terms of invasion stage, for this review they were classified as “Introduced”, since there was no indication that they might have been in later stages of the invasion process.

Search Results

It's noticeable the overwhelming bias towards the studying of terrestrial species, which reflects the more challenging nature of predicting de distribution of invasive species in aquatic ecosystems (Havel *et al.*, 2015).

Although many records couldn't be distinguished individually for the species constitution, most of the ones which did were either herbs or shrubs (Fig.6). Common traits of invasive species include vegetative growth and better dispersal mechanisms, which are also common traits amongst herbs and shrubs, which can become invasive more easily (Gao *et al.*, 2018).

It's a fact that citizen science can help expand datasets and contribute to predicting distributions (Delaney *et al.*, 2008), so in studies conducted at smaller scales, many times surveys and resident inquiries were incorporated in the studies. For this review, this type of data was included in the "Field Data" classification, and it comes as no surprise that most of the entries where field data was used, the scales of the models where mostly "Local" or "Regional".

The "Point Scoring System" classification includes risk assessment procedures that might not include statistical modelling per se, due to the fact that the keywords selected ("simulat*" and "predict*") don't always imply their use.

Integrative Results

Four clusters of variables could be distinguished along the axis of the first two principal components (see Fig 17 – Results section). The first one comprises "Machine Learning" model types with "Static" and "Spatially Explicit", which are two prevalent characteristics of species distribution models (SDMs), one of the most popular approaches when predicting species risk of invasion (Fan *et al.*, 2018; Obiakara and Fourcade, 2018; Rodríguez-Merino *et al.*, 2018). Within these approaches, are machine learning algorithms which, the results show, is the most used modelling tool for risk assessment, confirming its relation to static and spatially explicit models. During the reviewing process it was possible to notice a growing interest over the years in the utilization of machine learning algorithms, like MaxEnt (Manzoor *et al.*, 2018; Obiakara and Fourcade, 2018; Wan and Wang, 2018).

The second cluster of variables relates the "Ensemble Modelling" approach with "Potential Distribution", "Qualitative", and "Semiquantitative" risk assessment outputs and data. Ensemble modelling consists in the combination of results from different (but related) modelling techniques. Usually, these modelling techniques are SDMs that would also work individually, but the assemblage of various approaches is intended to increase the accuracy of the predicted distribution (Capinha and Anastácio, 2011; Valavi *et al.*, 2019). Potential distribution (or habitat/climatic suitability) maps are the most common risk assessment output for species distribution models. Since it combines multiple approaches, the method is commonly classified as qualitative (provides average qualitative measurements) or semiquantitative (Lalla *et al.*, 2018; Luizza *et al.*, 2016), hence their association with ensemble modelling.

The third cluster of variables relates "Regression Analysis" approaches with "Not Spatially Explicit" and "No Risk Assessment". Very little entries combined "Not Spatially Explicit" models with any type of risk assessment, since most of the outputs for risk assessment resulted of spatially explicit approaches (Fig. 13). However, some studies relied on regression analyses focused on features that might affect the potential distribution of some species (like seed dispersal and the variability of other traits) and how these intrinsic characteristics should be considered when performing risk assessment, posteriorly (Klonner *et al.*, 2016).

The fourth cluster of variables envelopes every remaining variable and its closeness to the origin point of the scatterplot reflects their lower impact on the variance. However it's possible to observe certain variables closer to each other that correspond to a more specific type of risk assessment, namely the "Population Dynamics" model and risk assessment output, and "Dynamic" modelling, which very often showed up together during the review (Muthukrishnan *et al.*, 2015; Pittman *et al.*, 2015). These are usually dynamic analyses since they evaluate the spread of a population over time.

Risk assessment over time

Landis (2019) evaluated the progress of ecological risk assessment as a topic in the journal *Risk Analysis*, which started in the 1980s with the problematic of chemicals and contaminated sites. The theme then spread into a variety of other subjects, and the author attributes the establishment of the journal as a “venue for the risk assessment of nonindigenous or invasive species” to Mark. C. Anderson (New Mexico State University) in 2004, thanks to an assortment of articles by that author being published in that year, even though this subject was already seen as a valuable research topic before. According to Landis, these articles were very relevant in setting up a framework for general invasive species risk assessment (Andersen *et al.*, 2004b; Andersen *et al.*, 2004a). Since then, risk assessment of alien species has become a very defined individual subject, with the establishment of requirements and new and adapted frameworks being developed (Colnar and Landis, 2007; Roy *et al.*, 2018; Ziller *et al.*, 2019).

According to the search results (Fig. 3), plant invasions have been brought to attention early in the 20th century, but only ramped up by the 1980/90s. Following that, the application of the risk assessment concept to alien plant invasions dates back to 1986 (maximum of 1 paper per year until 1998, therefore not visible in the graphic) but the use of statistical models for this subject didn’t start till 1994. The development of better technology, that lead to more and different tools available (Magarey *et al.*, 2018), and the awakening to the imminence of climate change and its impacts on the success of invasive species (Weltzin *et al.*, 2003), should be partly responsible for the growing interest in this topic since the mid 2000s.

Limitations

One of the most common limitations to the application of statistical models to predict invasive species distribution relies on the assumption that those species preserve their niche in novel habitats (niche stability). It has been shown that niche shifts can happen during the naturalization of alien species (Early and Sax, 2014), and consequentially, the predicted risk of invasion from these approaches might turn out inaccurate. Still, in some cases researchers should be able to predict these niche dynamics by accounting species traits (like dispersal functions) into the utilized models, therefore improving the accuracy of their projections (Atwater *et al.*, 2018).

Insufficiency of data is another commonly found limitation when using statistical models for risk assessment purposes. Studies aiming to determine the naturalization success of introduced species rely on time since introduction (residence time) to increase the explanatory power of the models and accurately predict the future of those species (Wilson *et al.*, 2007), but sometimes that information is simply unavailable or unknown. Occurrence data in global/regional databases, especially larger databases and ranges, sometimes lacks field investigation to validate its legitimacy and if it's up-to-date; however, there are validation methods to decrease those inaccuracies in some models (Merow *et al.*, 2013). Even taxonomic identification difficulties might lead to an underrepresentation of the species in occurrence data; when possible, choosing databases that are carefully managed by legitimate institutions/organizations should help eliminate those problems. In addition, geographical locations with more people might mean more occurrence data than in lesser populated regions.

Conclusion

Over time, with the development of computer technology and new approaches, the integration of statistical models into the risk assessment of alien plant invasions has grown in a very fast rate. Static and spatially explicit models that predict the potential distribution (or climatic/habitat suitability) are the most widely used, with outputs presented in a geographical space allowing a better visualization the risk of invasion/potential, current, and future distribution of a given alien species. Ensemble modelling as a method to improve the accuracy of these studies has grown to be on par with the use of single models. However, the limitations surrounding these approaches and precision of the results are commonly associated with the validity of the data and niche conservatism. Researchers should take these limitations into account and overcome them as possible, since technology is in constant evolution and there are ways to reduce the impact of limitations.

The standardization of the terminology around biological invasions is a process that took some years to fully lodge itself in this field, but which improved the coherency between different studies and the community. The same could be said for the methodologies followed when conducting risk assessment, considering that establishing certain general requirements for this process (instead of researchers going about it each in their own way) should increase the coherency of this field of study, even though some space for adaptation can be left open.

Investing in statistical modelling tools for the risk assessment of invasive alien species is the way to go about the problematic at hand. Despite current limitations, there is no simpler or more precise way of knowing where and when to act to prevent and manage the spread of invasive alien species, in order to minimize their impacts on the ecosystems, which is ultimately in the best interest of governments and societies.

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Appendices

Appendix A

List of records considered for this review

Ahrens, C., Chung, J., Meyer, T. & Auer, C. (2017). Bentgrass Distribution Surveys and Habitat Suitability Maps Support Ecological Risk Assessment in Cultural Landscapes. *Weed Science* 59(2): 145-154.

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Appendix B

List of variable combinations and their respective Kappa and significance values

Variable Combinations	Kappa Value	≅ Significance
Individual * Aquatic	-0,001	0,968
Individual * Terrestrial	0,291	0,000
Individual * Herbaceous	0,158	0,021
Individual * Several	-0,571	0,000
Individual * Shrub	0,374	0,000
Individual * Tree	0,042	0,394
Individual * Introduced	-0,087	0,110
Individual * Invasive	0,051	0,416
Individual * Naturalized	0,032	0,528
Individual * Continental	0,016	0,525
Individual * Global	-0,069	0,182
Individual * Local	0,064	0,278
Individual * Multinational	-0,012	0,754
Individual * National	-0,003	0,960
Individual * Regional	0,003	0,963
Individual * Database	-0,070	0,328
Individual * Expert Data	-0,016	0,621
Individual * Field Data	0,091	0,181
Individual * Literature	-0,068	0,085
Individual * Remote Sensing	0,065	0,050
Individual * Bayesian Approach	0,004	0,872
Individual * Decision Trees	-0,051	0,086
Individual * Ensemble Modelling	-0,016	0,807
Individual * Machine Learning	0,045	0,523
Individual * Mechanistic Model	-0,009	0,656
Individual * Population Dynamics	0,086	0,004
Individual * Profile Techniques	0,016	0,723
Individual * Regression Analysis	-0,076	0,223
Individual * Not Spatially Explicit	-0,054	0,215
Individual * Spatially Explicit	0,047	0,215
Individual * Dynamic	0,111	0,001
Individual * Static	-0,096	0,001
Individual * Both	-0,019	0,394
Individual * CC	0,002	0,964
Individual * LULC	0,025	0,124
Individual * No	-0,007	0,894
Individual * Invasion Risk	-0,008	0,848
Individual * No RA	-0,187	0,003
Individual * Other	0,002	0,910
Individual * Point Scoring Sys	0,079	0,037
Individual * Population Dynamics	0,004	0,872
Individual * Potential Distribution	0,143	0,044
Individual * Predicted Species Richness	-0,040	0,142
Individual * Qualitative	0,175	0,013
Individual * Quantitative	0,001	0,986
Individual * Semiquantitative	0,005	0,943
Multispecies * Aquatic	0,001	0,968

Multispecies * Terrestrial	-0,317	0,000
Multispecies * Herbaceous	-0,148	0,021
Multispecies * Several	0,538	0,000
Multispecies * Shrub	-0,349	0,000
Multispecies * Tree	-0,037	0,394
Multispecies * Introduced	0,078	0,110
Multispecies * Invasive	-0,054	0,416
Multispecies * Naturalized	-0,028	0,528
Multispecies * Continental	-0,014	0,525
Multispecies * Global	0,061	0,182
Multispecies * Local	-0,058	0,278
Multispecies * Multinational	0,010	0,754
Multispecies * National	0,003	0,960
Multispecies * Regional	-0,003	0,963
Multispecies * Database	0,071	0,328
Multispecies * Expert Data	0,013	0,621
Multispecies * Field Data	-0,085	0,181
Multispecies * Literature	0,059	0,085
Multispecies * Remote Sensing	-0,056	0,050
Multispecies * Bayesian Approach	-0,003	0,872
Multispecies * Decision Trees	0,044	0,086
Multispecies * Ensemble Modelling	0,015	0,807
Multispecies * Machine Learning	-0,043	0,523
Multispecies * Mechanistic Model	0,007	0,656
Multispecies * Population Dynamics	-0,074	0,004
Multispecies * Profile Techniques	-0,014	0,723
Multispecies * Regression Analysis	0,069	0,223
Multispecies * Not Spatially Explicit	0,047	0,215
Multispecies * Spatially Explicit	-0,054	0,215
Multispecies * Dynamic	-0,096	0,001
Multispecies * Static	0,111	3,329
Multispecies * Both	0,017	0,394
Multispecies * CC	-0,002	0,964
Multispecies * LULC	-0,021	0,124
Multispecies * No	0,008	0,894
Multispecies * Invasion Risk	0,007	0,848
Multispecies * No RA	0,170	0,003
Multispecies * Other	-0,002	0,910
Multispecies * Point Scoring Sys	-0,069	0,037
Multispecies * Population Dynamics	-0,003	0,872
Multispecies * Potential Distribution	-0,146	0,044
Multispecies * Predicted Species Richness	0,035	0,142
Multispecies * Qualitative	-0,167	0,013
Multispecies * Quantitative	-0,001	0,986
Multispecies * Semiquantitative	-0,004	0,943
Aquatic * Herbaceous	0,124	0,011
Aquatic * Several	0,018	0,704
Aquatic * Shrub	-0,106	0,035
Aquatic * Tree	-0,084	0,215
Aquatic * Introduced	0,077	0,231
Aquatic * Invasive	-0,016	0,470

Aquatic * Naturalized	-0,022	0,748
Aquatic * Continental	0,222	0,001
Aquatic * Global	-0,087	0,192
Aquatic * Local	-0,097	0,103
Aquatic * Multinational	0,028	0,701
Aquatic * National	0,050	0,294
Aquatic * Regional	-0,005	0,922
Aquatic * Database	0,036	0,238
Aquatic * Expert Data	-0,052	0,472
Aquatic * Field Data	-0,005	0,922
Aquatic * Literature	-0,067	0,353
Aquatic * Remote Sensing	-0,055	0,445
Aquatic * Bayesian Approach	-0,032	0,615
Aquatic * Decision Trees	0,069	0,330
Aquatic * Ensemble Modelling	-0,064	0,238
Aquatic * Machine Learning	0,036	0,426
Aquatic * Mechanistic Model	-0,026	0,664
Aquatic * Population Dynamics	-0,047	0,503
Aquatic * Profile Techniques	-0,004	0,960
Aquatic * Regression Analysis	0,029	0,609
Aquatic * Not Spatially Explicit	0,005	0,939
Aquatic * Spatially Explicit	-0,001	0,939
Aquatic * Dynamic	0,050	0,487
Aquatic * Static	-0,006	0,487
Aquatic * Both	0,106	0,098
Aquatic * CC	0,077	0,231
Aquatic * LULC	-0,018	0,724
Aquatic * No	-0,027	0,102
Aquatic * Invasion Risk	0,085	0,233
Aquatic * No RA	-0,014	0,803
Aquatic * Other	-0,018	0,724
Aquatic * Point Scoring Sys	0,028	0,701
Aquatic * Population Dynamics	-0,032	0,615
Aquatic * Potential Distribution	-0,025	0,398
Aquatic * Predicted Species Richness	0,080	0,249
Aquatic * Qualitative	0,036	0,426
Aquatic * Quantitative	-0,012	0,836
Aquatic * Semiquantitative	-0,021	0,710
Terrestrial * Herbaceous	0,059	0,187
Terrestrial * Several	-0,331	0,000
Terrestrial * Shrub	0,179	0,000
Terrestrial * Tree	0,073	0,008
Terrestrial * Introduced	-0,027	0,381
Terrestrial * Invasive	0,047	0,511
Terrestrial * Naturalized	0,002	0,953
Terrestrial * Continental	-0,026	0,039
Terrestrial * Global	0,050	0,080
Terrestrial * Local	0,059	0,089
Terrestrial * Multinational	-0,033	0,094
Terrestrial * National	-0,033	0,476
Terrestrial * Regional	-0,017	0,699

Terrestrial * Database	-0,060	0,348
Terrestrial * Expert Data	0,011	0,499
Terrestrial * Field Data	0,103	0,020
Terrestrial * Literature	-0,073	0,000
Terrestrial * Remote Sensing	0,014	0,411
Terrestrial * Bayesian Approach	-0,002	0,893
Terrestrial * Decision Trees	-0,034	0,024
Terrestrial * Ensemble Modelling	0,066	0,100
Terrestrial * Machine Learning	-0,100	0,041
Terrestrial * Mechanistic Model	0,009	0,351
Terrestrial * Population Dynamics	0,022	0,150
Terrestrial * Profile Techniques	0,029	0,233
Terrestrial * Regression Analysis	-0,002	0,962
Terrestrial * Not Spatially Explicit	-0,050	0,030
Terrestrial * Spatially Explicit	0,135	0,030
Terrestrial * Dynamic	0,014	0,411
Terrestrial * Static	-0,043	0,411
Terrestrial * Both	-0,002	0,893
Terrestrial * CC	-0,027	0,381
Terrestrial * LULC	0,006	0,447
Terrestrial * No	0,047	0,511
Terrestrial * Invasion Risk	-0,006	0,780
Terrestrial * No RA	-0,082	0,029
Terrestrial * Other	-0,008	0,342
Terrestrial * Point Scoring Sys	0,010	0,632
Terrestrial * Population Dynamics	-0,002	0,893
Terrestrial * Potential Distribution	0,167	0,011
Terrestrial * Predicted Species Richness	-0,023	0,096
Terrestrial * Qualitative	0,062	0,205
Terrestrial * Quantitative	-0,021	0,564
Terrestrial * Semiquantitative	0,058	0,138
Herbaceous * Introduced	0,021	0,752
Herbaceous * Invasive	0,002	0,968
Herbaceous * Naturalized	-0,025	0,691
Herbaceous * Continental	0,018	0,607
Herbaceous * Global	0,027	0,671
Herbaceous * Local	-0,096	0,167
Herbaceous * Multinational	0,080	0,110
Herbaceous * National	-0,012	0,869
Herbaceous * Regional	0,000	1,000
Herbaceous * Database	0,018	0,776
Herbaceous * Expert Data	0,021	0,618
Herbaceous * Field Data	-0,077	0,290
Herbaceous * Literature	-0,028	0,592
Herbaceous * Remote Sensing	0,078	0,081
Herbaceous * Bayesian Approach	-0,006	0,838
Herbaceous * Decision Trees	0,031	0,435
Herbaceous * Ensemble Modelling	-0,170	0,018
Herbaceous * Machine Learning	0,018	0,804
Herbaceous * Mechanistic Model	0,004	0,887
Herbaceous * Population Dynamics	0,065	0,104

Herbaceous * Profile Techniques	0,104	0,000
Herbaceous * Regression Analysis	-0,107	0,133
Herbaceous * Not Spatially Explicit	0,008	0,882
Herbaceous * Spatially Explicit	-0,004	0,882
Herbaceous * Dynamic	0,078	0,081
Herbaceous * Static	-0,036	0,081
Herbaceous * Both	-0,041	0,190
Herbaceous * CC	0,021	0,752
Herbaceous * LULC	-0,021	0,356
Herbaceous * No	0,018	0,656
Herbaceous * Invasion Risk	-0,024	0,672
Herbaceous * No RA	-0,162	0,022
Herbaceous * Other	-0,021	0,356
Herbaceous * Point Scoring Sys	-0,018	0,717
Herbaceous * Population Dynamics	0,028	0,367
Herbaceous * Potential Distribution	0,173	0,005
Herbaceous * Predicted Species Richness	-0,061	0,106
Herbaceous * Qualitative	0,115	0,112
Herbaceous * Quantitative	0,068	0,336
Herbaceous * Semiquantitative	-0,020	0,778
Several * Introduced	0,094	0,150
Several * Invasive	-0,038	0,462
Several * Naturalized	-0,035	0,571
Several * Continental	0,014	0,668
Several * Global	0,044	0,477
Several * Local	-0,137	0,047
Several * Multinational	0,039	0,420
Several * National	-0,060	0,413
Several * Regional	0,105	0,150
Several * Database	0,045	0,483
Several * Expert Data	0,081	0,051
Several * Field Data	-0,198	0,006
Several * Literature	0,123	0,014
Several * Remote Sensing	-0,026	0,551
Several * Bayesian Approach	-0,008	0,786
Several * Decision Trees	-0,006	0,878
Several * Ensemble Modelling	0,025	0,726
Several * Machine Learning	0,065	0,371
Several * Mechanistic Model	-0,031	0,240
Several * Population Dynamics	-0,038	0,325
Several * Profile Techniques	-0,140	0,014
Several * Regression Analysis	0,095	0,177
Several * Not Spatially Explicit	0,092	0,090
Several * Spatially Explicit	-0,048	0,090
Several * Dynamic	-0,058	0,182
Several * Static	0,029	0,182
Several * Both	-0,008	0,786
Several * CC	0,065	0,318
Several * LULC	-0,021	0,338
Several * No	-0,024	0,571
Several * Invasion Risk	0,062	0,258

Several * No RA	0,176	0,012
Several * Other	0,013	0,564
Several * Point Scoring Sys	-0,023	0,631
Several * Population Dynamics	0,025	0,413
Several * Potential Distribution	-0,241	0,000
Several * Predicted Species Richness	0,102	0,005
Several * Qualitative	-0,079	0,277
Several * Quantitative	0,022	0,749
Several * Semiquantitative	-0,118	0,098
Shrub * Introduced	-0,084	0,215
Shrub * Invasive	0,001	0,991
Shrub * Naturalized	0,086	0,183
Shrub * Continental	-0,014	0,703
Shrub * Global	-0,115	0,078
Shrub * Local	0,277	0,000
Shrub * Multinational	-0,115	0,027
Shrub * National	-0,031	0,665
Shrub * Regional	-0,022	0,757
Shrub * Database	-0,078	0,202
Shrub * Expert Data	-0,079	0,075
Shrub * Field Data	0,213	0,003
Shrub * Literature	-0,055	0,310
Shrub * Remote Sensing	-0,017	0,716
Shrub * Bayesian Approach	0,033	0,309
Shrub * Decision Trees	0,003	0,949
Shrub * Ensemble Modelling	0,017	0,813
Shrub * Machine Learning	0,027	0,702
Shrub * Mechanistic Model	0,007	0,820
Shrub * Population Dynamics	0,003	0,949
Shrub * Profile Techniques	-0,065	0,279
Shrub * Regression Analysis	-0,029	0,689
Shrub * Not Spatially Explicit	-0,047	0,412
Shrub * Spatially Explicit	0,022	0,412
Shrub * Dynamic	0,019	0,689
Shrub * Static	-0,008	0,689
Shrub * Both	0,071	0,032
Shrub * CC	-0,115	0,089
Shrub * LULC	0,055	0,021
Shrub * No	0,006	0,881
Shrub * Invasion Risk	-0,014	0,814
Shrub * No RA	-0,029	0,689
Shrub * Other	-0,021	0,381
Shrub * Point Scoring Sys	0,094	0,071
Shrub * Population Dynamics	-0,041	0,213
Shrub * Potential Distribution	0,020	0,739
Shrub * Predicted Species Richness	-0,024	0,545
Shrub * Qualitative	-0,046	0,518
Shrub * Quantitative	-0,107	0,133
Shrub * Semiquantitative	0,173	0,017
Tree * Introduced	-0,058	0,421

Tree * Invasive	0,030	0,322
Tree * Naturalized	-0,034	0,638
Tree * Continental	-0,034	0,638
Tree * Global	0,060	0,411
Tree * Local	-0,044	0,531
Tree * Multinational	-0,025	0,712
Tree * National	0,123	0,043
Tree * Regional	-0,104	0,099
Tree * Database	0,015	0,723
Tree * Expert Data	-0,066	0,294
Tree * Field Data	0,086	0,173
Tree * Literature	-0,095	0,175
Tree * Remote Sensing	-0,072	0,265
Tree * Bayesian Approach	-0,037	0,463
Tree * Decision Trees	-0,060	0,328
Tree * Ensemble Modelling	0,168	0,011
Tree * Machine Learning	-0,127	0,029
Tree * Mechanistic Model	0,054	0,238
Tree * Population Dynamics	-0,060	0,328
Tree * Profile Techniques	-0,005	0,941
Tree * Regression Analysis	0,051	0,456
Tree * Not Spatially Explicit	-0,109	0,129
Tree * Spatially Explicit	0,024	0,129
Tree * Dynamic	-0,072	0,265
Tree * Static	0,013	0,265
Tree * Both	-0,037	0,463
Tree * CC	0,034	0,636
Tree * LULC	-0,020	0,606
Tree * No	-0,001	0,980
Tree * Invasion Risk	-0,050	0,482
Tree * No RA	0,013	0,849
Tree * Other	0,065	0,089
Tree * Point Scoring Sys	-0,090	0,194
Tree * Population Dynamics	-0,037	0,463
Tree * Potential Distribution	0,044	0,289
Tree * Predicted Species Richness	-0,053	0,366
Tree * Qualitative	0,012	0,836
Tree * Quantitative	0,018	0,796
Tree * Semiquantitative	-0,037	0,587
Introduced * Continental	0,016	0,741
Introduced * Global	0,064	0,374
Introduced * Local	-0,045	0,532
Introduced * Multinational	0,067	0,305
Introduced * National	-0,136	0,036
Introduced * Regional	0,091	0,174
Introduced * Database	0,087	0,067
Introduced * Expert Data	-0,011	0,851
Introduced * Field Data	-0,121	0,070
Introduced * Literature	-0,050	0,454
Introduced * Remote Sensing	0,039	0,522
Introduced * Bayesian Approach	-0,038	0,399

Introduced * Decision Trees	-0,002	0,968
Introduced * Ensemble Modelling	-0,022	0,749
Introduced * Machine Learning	0,037	0,555
Introduced * Mechanistic Model	0,037	0,363
Introduced * Population Dynamics	-0,002	0,968
Introduced * Profile Techniques	0,115	0,104
Introduced * Regression Analysis	-0,104	0,142
Introduced * Not Spatially Explicit	-0,019	0,785
Introduced * Spatially Explicit	0,005	0,785
Introduced * Dynamic	-0,019	0,749
Introduced * Static	0,004	0,749
Introduced * Both	-0,038	0,399
Introduced * CC	0,036	0,623
Introduced * LULC	-0,020	0,553
Introduced * No	0,001	0,984
Introduced * Invasion Risk	0,083	0,231
Introduced * No RA	0,003	0,970
Introduced * Other	-0,020	0,553
Introduced * Point Scoring Sys	0,067	0,305
Introduced * Population Dynamics	0,091	0,045
Introduced * Potential Distribution	-0,060	0,192
Introduced * Predicted Species Richness	-0,055	0,299
Introduced * Qualitative	-0,017	0,786
Introduced * Quantitative	0,008	0,910
Introduced * Semiquantitative	-0,013	0,856
Invasive * Continental	-0,010	0,506
Invasive * Global	-0,024	0,453
Invasive * Local	0,007	0,851
Invasive * Multinational	0,004	0,873
Invasive * National	0,125	0,014
Invasive * Regional	-0,096	0,049
Invasive * Database	-0,059	0,379
Invasive * Expert Data	-0,013	0,494
Invasive * Field Data	0,028	0,569
Invasive * Literature	0,023	0,329
Invasive * Remote Sensing	0,006	0,742
Invasive * Bayesian Approach	0,016	0,219
Invasive * Decision Trees	0,013	0,441
Invasive * Ensemble Modelling	-0,032	0,475
Invasive * Machine Learning	-0,027	0,614
Invasive * Mechanistic Model	-0,017	0,119
Invasive * Population Dynamics	-0,016	0,335
Invasive * Profile Techniques	-0,002	0,936
Invasive * Regression Analysis	0,063	0,128
Invasive * Not Spatially Explicit	0,005	0,852
Invasive * Spatially Explicit	-0,011	0,852
Invasive * Dynamic	-0,009	0,660
Invasive * Static	0,021	0,660
Invasive * Both	0,016	0,219
Invasive * CC	-0,039	0,259
Invasive * LULC	0,008	0,387

Invasive * No	0,025	0,725
Invasive * Invasion Risk	-0,026	0,322
Invasive * No RA	0,013	0,750
Invasive * Other	-0,007	0,461
Invasive * Point Scoring Sys	-0,027	0,236
Invasive * Population Dynamics	-0,014	0,295
Invasive * Potential Distribution	0,078	0,258
Invasive * Predicted Species Richness	0,009	0,563
Invasive * Qualitative	0,047	0,381
Invasive * Quantitative	-0,058	0,159
Invasive * Semiquantitative	0,027	0,531
Naturalized * Continental	0,029	0,587
Naturalized * Global	0,004	0,958
Naturalized * Local	0,030	0,671
Naturalized * Multinational	-0,091	0,183
Naturalized * National	-0,064	0,295
Naturalized * Regional	0,076	0,232
Naturalized * Database	-0,035	0,426
Naturalized * Expert Data	0,071	0,257
Naturalized * Field Data	0,076	0,232
Naturalized * Literature	-0,035	0,609
Naturalized * Remote Sensing	-0,073	0,253
Naturalized * Bayesian Approach	-0,037	0,452
Naturalized * Decision Trees	-0,060	0,316
Naturalized * Ensemble Modelling	0,088	0,187
Naturalized * Machine Learning	0,002	0,966
Naturalized * Mechanistic Model	0,050	0,258
Naturalized * Population Dynamics	0,081	0,176
Naturalized * Profile Techniques	-0,120	0,097
Naturalized * Regression Analysis	-0,033	0,636
Naturalized * Not Spatially Explicit	0,003	0,966
Naturalized * Spatially Explicit	-0,001	0,966
Naturalized * Dynamic	0,061	0,345
Naturalized * Static	-0,011	0,345
Naturalized * Both	-0,037	0,452
Naturalized * CC	0,072	0,319
Naturalized * LULC	-0,020	0,597
Naturalized * No	-0,012	0,617
Naturalized * Invasion Risk	0,003	0,966
Naturalized * No RA	-0,033	0,636
Naturalized * Other	0,062	0,100
Naturalized * Point Scoring Sys	0,034	0,622
Naturalized * Population Dynamics	-0,037	0,452
Naturalized * Potential Distribution	-0,005	0,905
Naturalized * Predicted Species Richness	0,020	0,732
Naturalized * Qualitative	-0,053	0,371
Naturalized * Quantitative	0,124	0,074
Naturalized * Semiquantitative	-0,044	0,513
Continental * Database	0,043	0,043
Continental * Expert Data	-0,034	0,634

Continental * Field Data	-0,051	0,152
Continental * Literature	-0,040	0,538
Continental * Remote Sensing	-0,035	0,612
Continental * Bayesian Approach	-0,024	0,739
Continental * Decision Trees	-0,032	0,657
Continental * Ensemble Modelling	-0,050	0,205
Continental * Machine Learning	0,038	0,222
Continental * Mechanistic Model	-0,020	0,773
Continental * Population Dynamics	0,14	0,051
Continental * Profile Techniques	-0,043	0,462
Continental * Regression Analysis	-0,003	0,949
Continental * Not Spatially Explicit	-0,042	0,491
Continental * Spatially Explicit	0,005	0,491
Continental * Dynamic	0,113	0,105
Continental * Static	-0,009	0,105
Continental * Both	-0,024	0,739
Continental * CC	0,080	0,108
Continental * LULC	-0,015	0,815
Continental * No	-0,014	0,194
Continental * Invasion Risk	0,057	0,348
Continental * No RA	-0,049	0,240
Continental * Other	-0,015	0,815
Continental * Point Scoring Sys	-0,039	0,555
Continental * Population Dynamics	-0,024	0,739
Continental * Potential Distribution	0,021	0,306
Continental * Predicted Species Richness	-0,030	0,682
Continental * Qualitative	-0,052	0,101
Continental * Quantitative	0,046	0,278
Continental * Semiquantitative	0,081	0,044
Global * Database	0,111	0,013
Global * Expert Data	0,066	0,286
Global * Field Data	-0,151	0,019
Global * Literature	-0,039	0,574
Global * Remote Sensing	-0,074	0,241
Global * Bayesian Approach	0,036	0,455
Global * Decision Trees	-0,061	0,304
Global * Ensemble Modelling	-0,060	0,379
Global * Machine Learning	0,021	0,732
Global * Mechanistic Model	0,047	0,279
Global * Population Dynamics	-0,061	0,304
Global * Profile Techniques	0,092	0,202
Global * Regression Analysis	-0,003	0,966
Global * Not Spatially Explicit	-0,002	0,980
Global * Spatially Explicit	0,000	0,980
Global * Dynamic	-0,074	0,241
Global * Static	0,014	0,241
Global * Both	-0,038	0,441
Global * CC	0,064	0,374
Global * LULC	-0,020	0,588
Global * No	-0,010	0,698
Global * Invasion Risk	0,054	0,447

Global * No RA	0,034	0,622
Global * Other	0,059	0,111
Global * Point Scoring Sys	-0,032	0,639
Global * Population Dynamics	0,036	0,455
Global * Potential Distribution	-0,035	0,416
Global * Predicted Species Richness	-0,054	0,342
Global * Qualitative	-0,090	0,135
Global * Quantitative	0,002	0,979
Global * Semiquantitative	0,055	0,422
Local * Database	-0,226	0,000
Local * Expert Data	-0,024	0,654
Local * Field Data	0,319	0,000
Local * Literature	0,027	0,661
Local * Remote Sensing	0,016	0,769
Local * Bayesian Approach	-0,039	0,335
Local * Decision Trees	-0,015	0,769
Local * Ensemble Modelling	0,021	0,769
Local * Machine Learning	-0,106	0,112
Local * Mechanistic Model	0,024	0,505
Local * Population Dynamics	0,188	0,000
Local * Profile Techniques	-0,058	0,395
Local * Regression Analysis	0,053	0,465
Local * Not Spatially Explicit	0,046	0,485
Local * Spatially Explicit	-0,014	0,485
Local * Dynamic	0,164	0,003
Local * Static	-0,045	0,003
Local * Both	0,067	0,101
Local * CC	-0,159	0,027
Local * LULC	0,035	0,249
Local * No	0,035	0,263
Local * Invasion Risk	-0,087	0,187
Local * No RA	0,186	0,010
Local * Other	0,035	0,249
Local * Point Scoring Sys	-0,010	0,864
Local * Population Dynamics	0,067	0,101
Local * Potential Distribution	-0,081	0,113
Local * Predicted Species Richness	-0,057	0,235
Local * Qualitative	-0,212	0,002
Local * Quantitative	0,026	0,719
Local * Semiquantitative	0,066	0,363
Multinational * Database	0,064	0,045
Multinational * Expert Data	-0,054	0,452
Multinational * Field Data	-0,116	0,024
Multinational * Literature	0,015	0,837
Multinational * Remote Sensing	0,043	0,548
Multinational * Bayesian Approach	0,096	0,122
Multinational * Decision Trees	-0,049	0,483
Multinational * Ensemble Modelling	-0,033	0,548
Multinational * Machine Learning	0,113	0,015
Multinational * Mechanistic Model	-0,026	0,649

Multinational * Population Dynamics	-0,049	0,483
Multinational * Profile Techniques	-0,010	0,885
Multinational * Regression Analysis	-0,108	0,064
Multinational * Not Spatially Explicit	-0,078	0,276
Multinational * Spatially Explicit	0,012	0,276
Multinational * Dynamic	-0,058	0,423
Multinational * Static	0,007	0,423
Multinational * Both	-0,033	0,599
Multinational * CC	-0,043	0,514
Multinational * LULC	-0,018	0,711
Multinational * No	0,016	0,368
Multinational * Invasion Risk	-0,078	0,276
Multinational * No RA	-0,066	0,261
Multinational * Other	-0,018	0,711
Multinational * Point Scoring Sys	0,110	0,13
Multinational * Population Dynamics	-0,033	0,599
Multinational * Potential Distribution	0,001	0,962
Multinational * Predicted Species Richness	0,188	0,006
Multinational * Qualitative	0,054	0,240
Multinational * Quantitative	-0,021	0,726
Multinational * Semiquantitative	0,011	0,848
National * Database	0,167	0,009
National * Expert Data	-0,081	0,052
National * Field Data	-0,072	0,321
National * Literature	-0,002	0,971
National * Remote Sensing	-0,090	0,038
National * Bayesian Approach	-0,041	0,173
National * Decision Trees	0,026	0,498
National * Ensemble Modelling	0,025	0,726
National * Machine Learning	-0,031	0,670
National * Mechanistic Model	0,002	0,936
National * Population Dynamics	-0,071	0,069
National * Profile Techniques	-0,019	0,741
National * Regression Analysis	0,095	0,177
National * Not Spatially Explicit	0,092	0,090
National * Spatially Explicit	-0,048	0,090
National * Dynamic	-0,058	0,182
National * Static	0,029	0,182
National * Both	-0,008	0,786
National * CC	-0,050	0,442
National * LULC	-0,021	0,338
National * No	0,045	0,285
National * Invasion Risk	-0,092	0,091
National * No RA	0,041	0,561
National * Other	-0,021	0,338
National * Point Scoring Sys	0,039	0,420
National * Population Dynamics	-0,008	0,786
National * Potential Distribution	0,019	0,757
National * Predicted Species Richness	0,004	0,909
National * Qualitative	0,113	0,120
National * Quantitative	-0,059	0,399

National * Semiquantitative	-0,118	0,098
Regional * Database	-0,162	0,010
Regional * Expert Data	0,095	0,030
Regional * Field Data	0,041	0,575
Regional * Literature	0,010	0,856
Regional * Remote Sensing	0,119	0,010
Regional * Bayesian Approach	0,031	0,338
Regional * Decision Trees	0,035	0,394
Regional * Ensemble Modelling	0,058	0,418
Regional * Machine Learning	-0,014	0,846
Regional * Mechanistic Model	-0,031	0,269
Regional * Population Dynamics	-0,035	0,394
Regional * Profile Techniques	0,028	0,638
Regional * Regression Analysis	-0,068	0,338
Regional * Not Spatially Explicit	-0,085	0,137
Regional * Spatially Explicit	0,040	0,137
Regional * Dynamic	-0,020	0,666
Regional * Static	0,009	0,666
Regional * Both	-0,005	0,873
Regional * CC	0,121	0,070
Regional * LULC	0,016	0,500
Regional * No	-0,071	0,072
Regional * Invasion Risk	0,146	0,010
Regional * No RA	-0,153	0,032
Regional * Other	-0,021	0,369
Regional * Point Scoring Sys	-0,048	0,346
Regional * Population Dynamics	-0,041	0,201
Regional * Potential Distribution	0,077	0,209
Regional * Predicted Species Richness	0,010	0,793
Regional * Qualitative	0,157	0,029
Regional * Quantitative	0,024	0,733
Regional * Semiquantitative	-0,036	0,621
Database * Bayesian Approach	-0,004	0,821
Database * Decision Trees	0,002	0,931
Database * Ensemble Modelling	-0,060	0,303
Database * Machine Learning	0,080	0,231
Database * Mechanistic Model	0,006	0,696
Database * Population Dynamics	-0,017	0,491
Database * Profile Techniques	0,019	0,618
Database * Regression Analysis	-0,024	0,661
Database * Not Spatially Explicit	0,002	0,953
Database * Spatially Explicit	-0,003	0,953
Database * Dynamic	-0,038	0,169
Database * Static	0,047	0,169
Database * Both	-0,004	0,821
Database * CC	0,107	0,025
Database * LULC	-0,002	0,874
Database * No	-0,116	0,051
Database * Invasion Risk	0,002	0,953
Database * No RA	-0,004	0,937

Database * Other	-0,002	0,874
Database * Point Scoring Sys	0,045	0,161
Database * Population Dynamics	-0,004	0,821
Database * Potential Distribution	-0,055	0,449
Database * Predicted Species Richness	0,013	0,578
Database * Qualitative	0,059	0,373
Database * Quantitative	-0,093	0,091
Database * Semiquantitative	0,042	0,461
Expert Data * Bayesian Approach	-0,029	0,671
Expert Data * Decision Trees	-0,041	0,571
Expert Data * Ensemble Modelling	0,045	0,353
Expert Data * Machine Learning	-0,022	0,568
Expert Data * Mechanistic Model	-0,024	0,714
Expert Data * Population Dynamics	-0,041	0,571
Expert Data * Profile Techniques	0,019	0,769
Expert Data * Regression Analysis	0,014	0,786
Expert Data * Not Spatially Explicit	0,029	0,675
Expert Data * Spatially Explicit	-0,004	0,675
Expert Data * Dynamic	-0,047	0,518
Expert Data * Static	0,004	0,518
Expert Data * Both	-0,029	0,671
Expert Data * CC	0,048	0,407
Expert Data * LULC	-0,017	0,765
Expert Data * No	-0,007	0,598
Expert Data * Invasion Risk	-0,060	0,379
Expert Data * No RA	-0,031	0,540
Expert Data * Other	-0,017	0,765
Expert Data * Point Scoring Sys	-0,054	0,452
Expert Data * Population Dynamics	-0,029	0,671
Expert Data * Potential Distribution	0,044	0,081
Expert Data * Predicted Species Richness	-0,038	0,601
Expert Data * Qualitative	-0,022	0,568
Expert Data * Quantitative	0,108	0,036
Expert Data * Semiquantitative	-0,035	0,480
Field Data * Bayesian Approach	0,031	0,338
Field Data * Decision Trees	-0,035	0,394
Field Data * Ensemble Modelling	0,086	0,235
Field Data * Machine Learning	-0,063	0,383
Field Data * Mechanistic Model	0,005	0,854
Field Data * Population Dynamics	0,035	0,394
Field Data * Profile Techniques	-0,134	0,023
Field Data * Regression Analysis	0,072	0,311
Field Data * Not Spatially Explicit	-0,019	0,741
Field Data * Spatially Explicit	0,009	0,741
Field Data * Dynamic	0,049	0,280
Field Data * Static	-0,022	0,280
Field Data * Both	0,031	0,338
Field Data * CC	-0,152	0,023
Field Data * LULC	-0,021	0,369
Field Data * No	0,078	0,048

Field Data * Invasion Risk	-0,052	0,363
Field Data * No RA	0,044	0,536
Field Data * Other	-0,021	0,369
Field Data * Point Scoring Sys	-0,014	0,777
Field Data * Population Dynamics	-0,005	0,873
Field Data * Potential Distribution	0,037	0,545
Field Data * Predicted Species Richness	-0,025	0,512
Field Data * Qualitative	-0,063	0,383
Field Data * Quantitative	-0,004	0,955
Field Data * Semiquantitative	0,047	0,510
Literature * Bayesian Approach	-0,033	0,583
Literature * Decision Trees	0,054	0,430
Literature * Ensemble Modelling	-0,004	0,949
Literature * Machine Learning	-0,014	0,776
Literature * Mechanistic Model	-0,026	0,635
Literature * Population Dynamics	-0,051	0,464
Literature * Profile Techniques	0,124	0,085
Literature * Regression Analysis	-0,032	0,597
Literature * Not Spatially Explicit	-0,008	0,917
Literature * Spatially Explicit	0,001	0,917
Literature * Dynamic	-0,060	0,403
Literature * Static	0,007	0,403
Literature * Both	-0,033	0,583
Literature * CC	-0,104	0,119
Literature * LULC	-0,019	0,699
Literature * No	0,032	0,080
Literature * Invasion Risk	0,067	0,353
Literature * No RA	0,053	0,380
Literature * Other	0,117	0,015
Literature * Point Scoring Sys	-0,071	0,331
Literature * Population Dynamics	-0,033	0,583
Literature * Potential Distribution	-0,028	0,384
Literature * Predicted Species Richness	-0,045	0,499
Literature * Qualitative	-0,043	0,373
Literature * Quantitative	0,057	0,349
Literature * Semiquantitative	-0,078	0,180
Remote Sensing * Bayesian Approach	-0,030	0,651
Remote Sensing * Decision Trees	0,087	0,228
Remote Sensing * Ensemble Modelling	-0,046	0,359
Remote Sensing * Machine Learning	-0,003	0,945
Remote Sensing * Mechanistic Model	-0,024	0,696
Remote Sensing * Population Dynamics	0,087	0,228
Remote Sensing * Profile Techniques	0,090	0,184
Remote Sensing * Regression Analysis	-0,040	0,449
Remote Sensing * Not Spatially Explicit	0,020	0,770
Remote Sensing * Spatially Explicit	-0,003	0,770
Remote Sensing * Dynamic	0,183	0,012
Remote Sensing * Static	-0,018	0,012
Remote Sensing * Both	-0,030	0,651
Remote Sensing * CC	0,039	0,522

Remote Sensing * LULC	0,167	0,003
Remote Sensing * No	-0,019	0,219
Remote Sensing * Invasion Risk	0,105	0,129
Remote Sensing * No RA	-0,084	0,111
Remote Sensing * Other	-0,018	0,751
Remote Sensing * Point Scoring Sys	-0,058	0,423
Remote Sensing * Population Dynamics	0,128	0,055
Remote Sensing * Potential Distribution	-0,004	0,895
Remote Sensing * Predicted Species Richness	0,099	0,164
Remote Sensing * Qualitative	0,056	0,171
Remote Sensing * Quantitative	0,052	0,335
Remote Sensing * Semiquantitative	-0,044	0,393
Bayesian Approach * Not Spatially Explicit	-0,035	0,539
Bayesian Approach * Spatially Explicit	0,004	0,539
Bayesian Approach * Dynamic	-0,030	0,651
Bayesian Approach * Static	0,002	0,651
Bayesian Approach * Both	0,234	0,001
Bayesian Approach * CC	0,026	0,562
Bayesian Approach * LULC	-0,014	0,834
Bayesian Approach * No	-0,017	0,092
Bayesian Approach * Invasion Risk	-0,035	0,539
Bayesian Approach * No RA	-0,040	0,295
Bayesian Approach * Other	-0,014	0,834
Bayesian Approach * Point Scoring Sys	-0,033	0,599
Bayesian Approach * Population Dynamics	-0,022	0,766
Bayesian Approach * Potential Distribution	0,013	0,478
Bayesian Approach * Predicted Species Richness	0,179	0,012
Bayesian Approach * Qualitative	-0,011	0,689
Bayesian Approach * Quantitative	0,105	0,007
Bayesian Approach * Semiquantitative	-0,040	0,273
Decision Trees * Not Spatially Explicit	0,221	0,001
Decision Trees * Spatially Explicit	-0,029	0,001
Decision Trees * Dynamic	-0,043	0,547
Decision Trees * Static	0,004	0,547
Decision Trees * Both	-0,028	0,692
Decision Trees * CC	-0,063	0,261
Decision Trees * LULC	-0,017	0,780
Decision Trees * No	0,017	0,207
Decision Trees * Invasion Risk	0,037	0,573
Decision Trees * No RA	0,160	0,001
Decision Trees * Other	-0,017	0,780
Decision Trees * Point Scoring Sys	-0,049	0,483
Decision Trees * Population Dynamics	-0,028	0,692
Decision Trees * Potential Distribution	-0,056	0,018
Decision Trees * Predicted Species Richness	-0,056	0,018
Decision Trees * Qualitative	-0,042	0,254
Decision Trees * Quantitative	-0,021	0,672
Decision Trees * Semiquantitative	-0,068	0,143
Ensemble Modelling * Not Spatially Explicit	-0,143	0,019

Ensemble Modelling * Spatially Explicit	0,056	0,019
Ensemble Modelling * Dynamic	-0,086	0,086
Ensemble Modelling * Static	0,031	0,086
Ensemble Modelling * Both	-0,040	0,258
Ensemble Modelling * CC	0,045	0,522
Ensemble Modelling * LULC	-0,021	0,427
Ensemble Modelling * No	0,002	0,966
Ensemble Modelling * Invasion Risk	0,045	0,465
Ensemble Modelling * No RA	-0,168	0,021
Ensemble Modelling * Other	0,066	0,011
Ensemble Modelling * Point Scoring Sys	-0,033	0,548
Ensemble Modelling * Population Dynamics	0,002	0,955
Ensemble Modelling * Potential Distribution	0,099	0,081
Ensemble Modelling * Predicted Species Richness	-0,059	0,164
Ensemble Modelling * Qualitative	0,165	0,019
Ensemble Modelling * Quantitative	-0,100	0,166
Ensemble Modelling * Semiquantitative	0,052	0,473
Machine Learning * Not Spatially Explicit	-0,043	0,408
Machine Learning * Spatially Explicit	0,025	0,408
Machine Learning * Dynamic	-0,062	0,132
Machine Learning * Static	0,035	0,132
Machine Learning * Both	-0,011	0,689
Machine Learning * CC	0,091	0,146
Machine Learning * LULC	0,040	0,050
Machine Learning * No	-0,076	0,086
Machine Learning * Invasion Risk	-0,043	0,408
Machine Learning * No RA	-0,123	0,075
Machine Learning * Other	-0,021	0,303
Machine Learning * Point Scoring Sys	0,084	0,071
Machine Learning * Population Dynamics	-0,011	0,689
Machine Learning * Potential Distribution	0,071	0,276
Machine Learning * Predicted Species Richness	0,028	0,413
Machine Learning * Qualitative	0,062	0,394
Machine Learning * Quantitative	-0,037	0,593
Machine Learning * Semiquantitative	0,082	0,241
Mechanistic Model * Not Spatially Explicit	0,081	0,119
Mechanistic Model * Spatially Explicit	-0,009	0,119
Mechanistic Model * Dynamic	-0,024	0,696
Mechanistic Model * Static	0,002	0,696
Mechanistic Model * Both	-0,018	0,797
Mechanistic Model * CC	-0,030	0,467
Mechanistic Model * LULC	-0,013	0,857
Mechanistic Model * No	0,007	0,414
Mechanistic Model * Invasion Risk	-0,027	0,595
Mechanistic Model * No RA	0,065	0,052
Mechanistic Model * Other	-0,013	0,857
Mechanistic Model * Point Scoring Sys	-0,026	0,649
Mechanistic Model * Population Dynamics	-0,026	0,649
Mechanistic Model * Potential Distribution	-0,013	0,390
Mechanistic Model * Predicted Species Richness	-0,022	0,752

Mechanistic Model * Qualitative	-0,001	0,969
Mechanistic Model * Quantitative	-0,030	0,373
Mechanistic Model * Semiquantitative	-0,031	0,343
Population Dynamics * Not Spatially Explicit	0,221	0,001
Population Dynamics * Spatially Explicit	-0,029	0,001
Population Dynamics * Dynamic	0,870	0,000
Population Dynamics * Static	-0,077	0,000
Population Dynamics * Both	-0,028	0,692
Population Dynamics * CC	-0,002	0,968
Population Dynamics * LULC	-0,017	0,780
Population Dynamics * No	0,003	0,795
Population Dynamics * Invasion Risk	-0,054	0,412
Population Dynamics * No RA	0,024	0,625
Population Dynamics * Other	-0,017	0,780
Population Dynamics * Point Scoring Sys	0,061	0,380
Population Dynamics * Population Dynamics	0,346	0,000
Population Dynamics * Potential Distribution	-0,056	0,018
Population Dynamics * Predicted Species Richness	0,124	0,088
Population Dynamics * Qualitative	-0,042	0,254
Population Dynamics * Quantitative	0,072	0,139
Population Dynamics * Semiquantitative	-0,025	0,586
Profile Techniques * Not Spatially Explicit	-0,098	0,175
Profile Techniques * Spatially Explicit	0,019	0,175
Profile Techniques * Dynamic	-0,068	0,319
Profile Techniques * Static	0,010	0,319
Profile Techniques * Both	-0,036	0,512
Profile Techniques * CC	0,066	0,352
Profile Techniques * LULC	-0,019	0,645
Profile Techniques * No	-0,011	0,623
Profile Techniques * Invasion Risk	0,095	0,189
Profile Techniques * No RA	-0,112	0,088
Profile Techniques * Other	-0,019	0,645
Profile Techniques * Point Scoring Sys	-0,082	0,245
Profile Techniques * Population Dynamics	-0,036	0,512
Profile Techniques * Potential Distribution	0,068	0,070
Profile Techniques * Predicted Species Richness	-0,050	0,419
Profile Techniques * Qualitative	0,080	0,143
Profile Techniques * Quantitative	-0,029	0,662
Profile Techniques * Semiquantitative	0,034	0,593
Regression Analysis * Not Spatially Explicit	0,066	0,302
Regression Analysis * Spatially Explicit	-0,023	0,302
Regression Analysis * Dynamic	-0,040	0,449
Regression Analysis * Static	0,013	0,449
Regression Analysis * Both	0,055	0,154
Regression Analysis * CC	-0,175	0,014
Regression Analysis * LULC	-0,021	0,461
Regression Analysis * No	0,065	0,052
Regression Analysis * Invasion Risk	-0,016	0,805
Regression Analysis * No RA	0,271	0,000

Regression Analysis * Other	-0,021	0,461
Regression Analysis * Point Scoring Sys	-0,023	0,693
Regression Analysis * Population Dynamics	-0,040	0,295
Regression Analysis * Potential Distribution	-0,118	0,029
Regression Analysis * Predicted Species Richness	-0,012	0,784
Regression Analysis * Qualitative	-0,226	0,001
Regression Analysis * Quantitative	0,088	0,227
Regression Analysis * Semiquantitative	-0,065	0,372
Not Spatially Explicit * Dynamic	0,276	0,000
Not Spatially Explicit * Static	-0,039	0,000
Not Spatially Explicit * Both	-0,035	0,539
Not Spatially Explicit * CC	-0,121	0,081
Not Spatially Explicit * LULC	-0,019	0,665
Not Spatially Explicit * No	0,040	0,050
Not Spatially Explicit * Invasion Risk	-0,092	0,204
Not Spatially Explicit * No RA	0,431	0,000
Not Spatially Explicit * Other	-0,019	0,665
Not Spatially Explicit * Point Scoring Sys	-0,078	0,276
Not Spatially Explicit * Population Dynamics	0,172	0,003
Not Spatially Explicit * Potential Distribution	-0,173	0,000
Not Spatially Explicit * Predicted Species Richness	-0,048	0,449
Not Spatially Explicit * Qualitative	-0,157	0,002
Not Spatially Explicit * Quantitative	-0,054	0,401
Not Spatially Explicit * Semiquantitative	-0,141	0,023
Spatially Explicit * Dynamic	-0,039	0,000
Spatially Explicit * Static	0,276	0,000
Spatially Explicit * Both	0,004	0,539
Spatially Explicit * CC	0,032	0,081
Spatially Explicit * LULC	0,002	0,665
Spatially Explicit * No	-0,130	0,050
Spatially Explicit * Invasion Risk	0,017	0,204
Spatially Explicit * No RA	-0,152	0,000
Spatially Explicit * Other	0,002	0,002
Spatially Explicit * Point Scoring Sys	0,012	0,276
Spatially Explicit * Population Dynamics	-0,020	0,003
Spatially Explicit * Potential Distribution	0,224	0,000
Spatially Explicit * Predicted Species Richness	0,006	0,449
Spatially Explicit * Qualitative	0,092	0,002
Spatially Explicit * Quantitative	0,019	0,401
Spatially Explicit * Semiquantitative	0,053	0,023
Dynamic * Both	-0,03	0,651
Dynamic * CC	-0,019	0,749
Dynamic * LULC	0,167	0,003
Dynamic * No	-0,005	0,735
Dynamic * Invasion Risk	-0,065	0,350
Dynamic * No RA	0,048	0,360
Dynamic * Other	-0,018	0,751
Dynamic * Point Scoring Sys	0,043	0,548
Dynamic * Population Dynamics	0,287	0,000
Dynamic * Potential Distribution	-0,059	0,027

Dynamic * Predicted Species Richness	0,099	0,164
Dynamic * Qualitative	-0,062	0,132
Dynamic * Quantitative	0,097	0,071
Dynamic * Semiquantitative	-0,044	0,393
Static * Both	0,002	0,651
Static * CC	0,004	0,749
Static * LULC	-0,010	0,003
Static * No	0,019	0,735
Static * Invasion Risk	0,009	0,350
Static * No RA	-0,015	0,360
Static * Other	0,001	0,751
Static * Point Scoring Sys	-0,005	0,548
Static * Population Dynamics	-0,021	0,000
Static * Potential Distribution	0,078	0,027
Static * Predicted Species Richness	-0,008	0,164
Static * Qualitative	0,035	0,132
Static * Quantitative	-0,030	0,071
Static * Semiquantitative	0,015	0,393
Both * Invasion Risk	-0,035	0,539
Both * No RA	0,007	0,849
Both * Other	-0,014	0,834
Both * Point Scoring Sys	-0,033	0,599
Both * Population Dynamics	-0,022	0,766
Both * Potential Distribution	-0,024	0,181
Both * Predicted Species Richness	0,384	0,000
Both * Qualitative	-0,042	0,143
Both * Quantitative	0,057	0,142
Both * Semiquantitative	0,004	0,914
CC * Invasion Risk	-0,070	0,313
CC * No RA	-0,175	0,014
CC * Other	0,048	0,159
CC * Point Scoring Sys	0,012	0,852
CC * Population Dynamics	-0,038	0,399
CC * Potential Distribution	0,093	0,044
CC * Predicted Species Richness	0,069	0,194
CC * Qualitative	0,064	0,307
CC * Quantitative	-0,028	0,694
CC * Semiquantitative	0,125	0,076
LULC * Invasion Risk	-0,019	0,665
LULC * No RA	-0,021	0,461
LULC * Other	-0,011	0,883
LULC * Point Scoring Sys	-0,018	0,711
LULC * Population Dynamics	-0,014	0,834
LULC * Potential Distribution	0,016	0,223
LULC * Predicted Species Richness	-0,016	0,797
LULC * Qualitative	-0,021	0,303
LULC * Quantitative	0,029	0,302
LULC * Semiquantitative	0,025	0,302

No * Invasion Risk	0,026	0,201
No * No RA	0,080	0,016
No * Other	-0,008	0,236
No * Point Scoring Sys	0,002	0,902
No * Population Dynamics	0,009	0,344
No * Potential Distribution	-0,103	0,092
No * Predicted Species Richness	-0,039	0,002
No * Qualitative	-0,005	0,903
No * Quantitative	-0,015	0,645
No * Semiquantitative	-0,067	0,054
Invasion Risk * Qualitative	0,129	0,013
Invasion Risk * Quantitative	-0,054	0,401
Invasion Risk * Semiquantitative	-0,025	0,69
No RA * Qualitative	-0,355	0,000
No RA * Quantitative	-0,264	0,000
No RA * Semiquantitative	-0,250	0,001
Other * Qualitative	-0,021	0,303
Other * Quantitative	0,079	0,005
Other * Semiquantitative	-0,021	0,440
Point Scoring Sys * Qualitative	0,200	0,000
Point Scoring Sys * Quantitative	-0,064	0,277
Point Scoring Sys * Semiquantitative	-0,110	0,052
Population Dynamics * Qualitative	-0,042	0,143
Population Dynamics * Quantitative	0,154	0,000
Population Dynamics * Semiquantitative	-0,040	0,273
Potential Distribution * Qualitative	0,091	0,162
Potential Distribution * Quantitative	0,107	0,045
Potential Distribution * Semiquantitative	0,238	0,000
Predicted Species Richness * Qualitative	-0,002	0,956
Predicted Species Richness * Quantitative	0,036	0,435
Predicted Species Richness * Semiquantitative	0,027	0,530