Using models and connectivity analysis to predict the current and future patterns of invasion by Silver-wattle (*Acacia dealbata* Link) in Northwest Iberian Peninsula

Alice Lucas Roxo

Mestrado em Ecologia, Ambiente e Território
Departamento de Biologia
2013

Orientador
Professor Doutor João Honrado
Professor Auxiliar na Faculdade de Ciências da Universidade do Porto e Investigador no Centro de Investigação em Biodiversidade e Recursos Genéticos CIBIO -UP
Faculdade de Ciências da Universidade do Porto

Coorientador
Doutora Joana Vicente
Investigadora no Centro de Investigação em Biodiversidade e Recursos Genéticos CIBIO –UP
Faculdade de Ciências da Universidade do Porto

Todas as correções determinadas pelo júri, e só essas, foram efetuadas.

O Presidente do Júri,

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Abstract

Biological invasions are one of the major promoters of biodiversity loss worldwide. Invasions by alien species are thought enhanced by changes in climate and disturbance regimes, as well as by other environmental shifts. Preserving native biodiversity and ecosystems from invasion by alien species requires comprehensive studies and measures to anticipate impacts, and to protect species and habitats of high conservation value. This can be achieved using species distribution models (SDM) to predict the distribution of invasive alien species (IAS) in a region of interest, both for current conditions and under scenarios of future environmental changes.

In this research, we modeled the distribution of *Acacia dealbata* Link (an aggressive IAS) in the cross-border context of Galicia and North of Portugal, in order to predict and explain the current distribution of *Acacia dealbata* and to forecast possible impacts of future climate change scenarios on that distribution. We applied a combined predictive modeling (CPM) approach, where we fitted species distribution models using subsets of predictors previously classified as acting at regional or local scales, that were spatially combined to obtain the final projections. These combined models predict a wider variety of potential species responses, providing more informative projections of species distributions and dynamics than traditional models. This approach was complemented by connectivity analyses of the distribution of the invader, to evaluate current and future conflicts between this IAS and high conservation value areas.

Model projections suggest that the distribution of *Acacia dealbata* in the study area will increase in the future, if climate changes scenarios are confirmed, and that these changes in environment will increase the connectivity of the species distribution in the area. Therefore, using CMPs and connectivity analysis it is possible to support resource prioritization for anticipation and monitoring of IAS impacts. CMPs can support measures to prevent invasions in this region as well as cross-border management in which both borders will work together and focus their efforts to protect and conserve specific important habitats.

Key words: *Acacia*; Climate change; Protected areas; Combined predictive modelling; Species distribution models.

Resumo

As invasões biológicas são um dos principais promotores da perda de biodiversidade a nível global. Considera-se que a invasão por parte de espécies exóticas pode ser estimulada por alterações climáticas e dos regimes de perturbação, bem como por outras mudanças ambientais. Preservar a biodiversidade nativa e os ecossistemas das invasões por espécies exóticas requer estudos exaustivos e medidas para antecipar os impactos das mesmas e proteger as espécies e habitats de elevado valor de conservação. A utilização de modelos de distribuição de espécies (SDMs) permite prever a distribuição de espécies exóticas invasoras (EEI) numa certa região, tanto para as condições atuais como para cenários futuros de mudanças ambientais.

Neste trabalho, modelámos a distribuição de *Acacia dealbata* Link (uma invasora agressiva) num contexto transfronteiriço (Galiza e Norte de Portugal), de forma a explicar a atual distribuição da *Acacia dealbata* e a antecipar os possíveis efeitos das alterações climáticas nesta região. Desenvolvemos um modelo preditivo combinado (MPC), em que os modelos de distribuição foram ajustados usando subconjuntos de variáveis anteriormente classificadas como importantes à escala regional ou à escala local, tendo os dois submodelos sido espacialmente combinados de forma a obter as projeções finais. Estes modelos combinados fornecem uma maior variedade de potenciais respostas das espécies, proporcionando projeções da distribuição e dinâmica de espécies mais informativas que os modelos. Esta abordagem foi complementada com análises de conectividade da distribuições da espécie invasora, para avaliar os conflitos atuais e futuros entre a sua distribuição e áreas de elevado valor de conservação.

Os resultados mostram que a distribuição de *Acacia dealbata* na área de estudo irá aumentar no futuro, se as previsões de alterações climáticas se confirmarem, e que estas alterações no ambiente irão aumentar a conectividade da distribuição da espécie na área. Desta forma, através da utilização de MPCs e análises de conectividade identificámos as áreas com maior probabilidade de serem afetadas por esta invasora, com particular destaque para a rede regional de áreas protegidas, e é possível apoiar a priorização de recursos para antecipação e monitorização dos impactos das EEIs. Esta abordagem pode apoiar medidas de prevenção de invasões nesta região e pode também auxiliar a gestão transfronteiriça das invasões biológicas e de outras ameaças atuais e futuras à integridade ecológica dos habitats e à conservação da sua biodiversidade.

Palavras – chave: Acacia; Alterações climáticas; Áreas protegidas; Modelos preditivos combinados; Modelos de distribuição de espécies.

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List of Abbreviations:

ANN - Artificial Neutral Networks

AP - Annual Precipitation

AUC – Area Under the Curve

CPM – Combine Predictive Models

CTA - Classification Tree Analysis

DensRiv – Density of local hydrographic network

DensRoad - Density of local road network

DistRiv - Distance to main river

DistRoad – Distance to roads

EEI – Espécies Exóticas Invasoras

FDA - Flexible discriminant Analysis

GAM - Generalised Additive Models (GAM),

GBM - Generalised Boosting Models (GBM)

GLM - Generalised Linear Models (GLM)

GPP - Mean gross annual primary productivity

IAS – Invasive Alien Species

ICNB – Instituto for Conservação da Natureza e Biodiversidade

IPPC – Intergovernmental Panel on Climate Change

IUCN – International Union for Conservation of Nature

K – Cohen´s K

MARS - Multivariate Adaptive Regression Splines

MPAR – Mean perimeter-area ratio

MPC – Modelo Preditivo Combinado

MSI – Mean shape index

MTCM - Minimum Temperature of Coldest Mont

pArL - Percentage cover of arable land

pArS - Percentage cover of artificial stands

pBiFo - Percentage cover of broad-leaf forest

pCamb – Percentage of cambissoils

pCoFo - Percentage cover of conifer forest

pMixFo - Percentage cover of mix forest

PS- Precipitation Seasonality

RF - Random Forest

ROC – Receiver Operating Characteristic

SDM – Species Distribution Models

SRE - Surface Range Envelop

TAR – Temperature Annual Range

TSS – True Skill Statistics

1. Introduction

1.1. Climatic change and threats to biodiversity

The Earth's biosphere is facing an increasing degradation and loss of diversity due to human activities and other anthropogenic pressure on the global environment (Vitousek et al., 1977). To understand these changes it's important to be aware of the concept of biodiversity. Biodiversity is the variability among living organisms from all sources and the ecological complexes of which they are part, which includes diversity within species, between species as well as of ecosystems (Millenium Ecosystem Assessment, 2005). Biodiversity is fundamental to ecosystem structure and functioning, and it supports the broad spectrum of goods and services that humans derive from natural systems (Staudinger et al., 2012).

Human alteration of the global environment has induced the sixth extinction event in history of life (Dirzo and Raven, 2003; Chapin et al., 2000) promoting changes in the global distribution of organisms (Chapin et al., 2000). Modifications in species distribution can change both ecosystem processes, and the resilience of ecosystems to environmental changes (Staudinger et al., 2012, Chapin et al., 2000), with thoughtful consequences in ecosystem services (Chapin et al., 2000). The major causes of biodiversity decline are: land use changes, invasive species, pollution, climate change and overexploitation resulting from economic, sociopolitical, cultural, demographic, technological, and other indirect drivers (Millennium Ecosystem Assessment, 2005).

1.2. Biological invasions as a driver of biodiversity change

Biological invasions can be defined as the introduction and spread of exotic organisms into regions outside of their native range (Méndez et al., 2011), and they are among the most important human-driven agents of change in natural environments worldwide (Narščius et al., 2012). The rate of biological invasions is quickly increasing last years (Essl et al., 2011) and invasive species are causing negative effects on both biodiversity and human well-being (Essl et al., 2011). Impacts of invader species include: modifications in composition, structure and functioning of the ecosystems (Terereai et al., 2013), habitat changes by elimination and/or reduction of native species (Narščius et al., 2012), biotic homogenization, loss of biodiversity and loss of ecosystem services in many parts of the world (Castro-Díez et al., 2011).

Plants invasions have become recognized as a major threat to both natural and human-exploited ecosystems worldwide (Hobbs and Humphries, 1995), as they affect ecosystem structure and function (Lake and Leishman, 2004). Human activities helped (intentionally and accidentally) that many plant species grow outside their native ranges, some of these non-native plants overcome several barriers, becoming invasive (Bradley et al. 2010). To a successful invasion many different mechanisms are involved (Gulezian and Nyberg, 2010) and many different stages/ecological processes need to be overcome at different spatial scales (Brown et al., 2008; Richardson et al., 2000). The first barrier corresponds to a major geographical barrier that the plant overcomes through human help (Figure 1, Barrier A); after, the species is called casual. The second barrier corresponds to an environmental filter, involving biotic and abiotic factors (Figure 1; Barrier B). Then, the species needs to overcome the reproduction barrier (Figure 1; Barrier C). After overcoming these three first barriers, a taxon is considered successfully naturalized. A species or population can be called invasive if overcomes the local/regional dispersal barriers (Figure 1; Barrier D), the environmental barrier(s) in human modified or alien-dominated vegetation (Figure 1; Barrier E), and the environmental barriers in natural or semi-natural vegetations (Figure 1; Barrier E; Richardson et al., 2000). Moreover, the extent of invasion by alien species is a function of ecosystem-level properties (invasibility), propagule pressure, characteristics of the invasive species (invasiveness), and the properties of the individual native species in the ecosystem (Westphal et al., 2008).

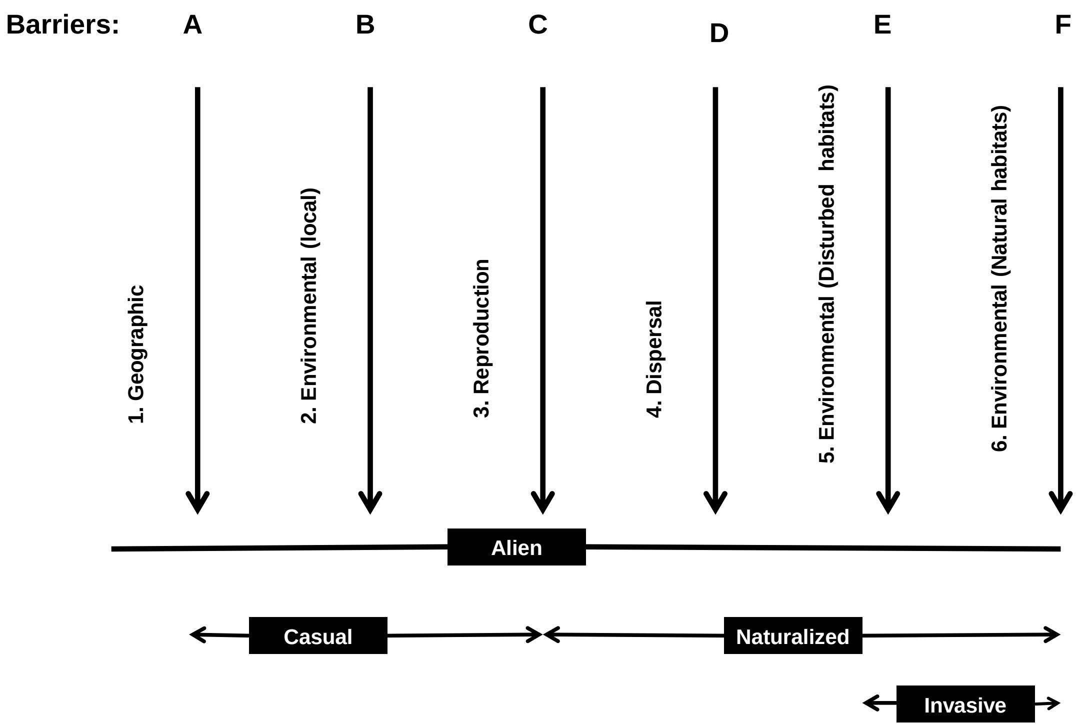

Figure 1 - Stages of invasion process and their representative barriers (from Richardson et al., 2000).

Alien invaders are often "passengers" privileged (Gaertner and Richardson, 2011) by other environmental changes (Gaertner and Richardson, 2011), such as rising temperature, increased atmospheric carbon dioxide (CO_2), extreme events in precipitation, nitrogen (N) deposition, and disturbances associated with changes in land use or land cover (Bradley et al., 2009). For example, changes in climatic conditions might directly influence the likelihood of alien species in a territory, and also affect the naturalization success (Walther et al., 2009). Synergic effects between alien invaders and global changes difficult the individualization between both the effects of alien species on the native ecosystems, and the effects of the disturbance that lead to the initial plant invasion (Gaertner and Richardson, 2011).

1.3. The specific case of invasive acacias

The invasive alien plants belonging to genus *Acacia* are among the most common invaders in many parts of the world (González-Muñoz et al., 2012), affecting ecosystems structure and functioning worldwide (Lorenzo et al., 2010), and are already present in sensitive habitats in Europe (coastal dunes, river courses, natural parks and biosphere reserves; Lorenzo et al., 2010). Therefore invasions by Acacia genus (wattles) represents a threat to natural habitats through competition and replacement of native species, homogenization of the community, and loss of native biodiversity (Fuentes-Ramírez et al., 2011). Some characteristics of this genus promote the threat to native ecosystems and species, particularly the high colonization capacity, e.g. in places disturbed by fire, harvesting and other types of human disturbance (Fuentes-Ramírez et al., 2011). Some key traits are present in this genus promoting the dominance in competitive interactions with native species as: rapid growth rates and ability to out-compete native plants; capacity to accumulate high volumes of biomass; large, persistent seed banks, and the capacity to fix nitrogen (Le Maitre et al., 2011). There are at least eight wattle species naturalized and potential invasive plants in the south of Europe (Lorenzo et al., 2010): *A. dealbata, A. melanoxylon, A. retinodes, A. saligna, A. karroo, A. pycnantha, A. mearnsii,* and *A. longif*olia. Three of the *Acacia* species: A*. dealbata; A. melanoxylon,* and *A. longif*olia are the most problematic invaders in France, Portugal, Spain and Italy, particularly in conservation areas, being *A. dealbata* the most widespread species (Lorenzo et al., 2010).

1.4. Protected areas

According to International Union Conservation of Nature (IUCN, 2008), a protected area is “a clearly defined geographical space, recognized, and managed, through legal or other effective means, to achieve the long term conservation of nature with associated ecosystem services and cultural values” (http://www.iucn.org/). Protected areas comprises more than 12.7% of the planet’s land surface (Geldmann et al., 2013) being an important tool and strategy to maintain habitat integrity and species diversity, ensuring the maintenance of natural processes across landscapes and ecosystems (http://www.cbd.int/protected/overview/). The designation and maintenance of protected areas is the most important and efficient conservation strategy worldwide (Kleinbauer et al., 2010), nonetheless the importance of nature reserves varies depending the regions of the world, related to the degree of anthropic transformation of the territory (Pysek et al., 2002). Although protected areas remain a crucial key to global diversity conservation strategies, they remain susceptible to anthropogenic changes and consequences (Spear et al., 2013), especially to alien plant invasion. Alien invader species are very problematic for conservation value areas due to the potentially threat to the persistence of native species (Uddin et al., 2013). The degree of a reserve invasion can be related in some cases with the total number of visitors

(Pysek et al., 2002). Recently Pysek et al. (2002) shown that nature reserves all over the world are invaded about half as often as sites outsides reserves.

1.5. Using models to achieve and anticipate patterns of invasion

Species distribution models (SDM) are empirical models that relate field observations to environmental predictors variables centered on the statistical or theoretical derived response surfaces (Guisan and Thuiller, 2005). The use of SDMs has grown in the last two decades due to the recognized application value in applied scientific fields as ecosystem management and biodiversity conservation (Rodríguez-Reya et al., 2013). SDMs can also be applied in fundamental ecological questions as, such as the ecological impacts of climate and land-use changes in biological invasions (Vicente et al., 2011; Guisan and Thuiller, 2005). Many scientific studies in invasions applied SDMs as a tool, for example: to assess species invasion and proliferation, to model species assemblages (biodiversity, composition), to quantify the environmental niche of the species, to support appropriate management plans for species recovery (mapping suitable sites for species reintroduction), to support conservation planning and reserve selection (suggesting surveyed sites of high potential of occurrence for rare species; Guisan and Thuiller, 2005). Despite many recent applied purposes of SDMs related to climate change and conservation planning, the use of these tools in theoretical ecology and evolution is re-emerging (Guisan and Thuiller, 2005).

According to Nentwig et al. 2008, the main research fields of biological invasions can be classified as: pathways of biological invasions, traits of a good invader, patterns of invasion and invasibility, ecological impacts of biological invasions, economy and socio-economy of biological invasions, and finally, prevention and management of biological invasions. One of the major goals in biological invasion studies is to understand which and how biotic and abiotic factors constrain the spread of invasive species, determining current and future potential distributions (Wang and Jackson, 2011; Farashi et al., 2013). Research efforts must be directed to find ways to anticipate invasions in order to protect global biodiversity from the effects of alien species (Vicente et al., 2011; Jones, 2012). This goal can be partially achieved determining the potential geographic extent of invasions, requiring predictive tools to assess the geographic distribution of invasive species under current and future environmental conditions (Vicente et al., 2011; Farashi et al., 2013). These predictions can simplify the early detection of invasive species and maximize monitoring efficiency (Jones, 2012).

Ongoing climate and land-use changes are forecasted to boost the invasion of alien species in several habitats (Vicente et al., 2011) being important to have a multi-scale approaches due to most of the pathways of species introductions result from human activities at several spatial and temporal scales (Vicente et al., 2011; Razgour et al., 2011). Although most of the studies using SDMs considered environmental predictors at a single grain size and fixed spatial extent, factors driving the distribution and abundance of organisms can act at different scales (Vicente et al., 2011; Guisan and Thuiller, 2005). For example: topography, geomorphology, human land-use or biotic interactions are usually considered to operate at regional and local scales while climate operate at the global scale (Vicente et al., 2011; Elith and LeathwicK, 2009).

There are several available modelling tools (Thuiller et al*.,* 2009), being *Biomod2* one of the newest and accurate statistical package. *Biomod2* is implemented in the R statistical software (Georges and Thuiller, 2013), allowing the calibration of ensemble forecasting species distributions, overcoming a range of uncertainties and assumptions in the methodological models. This package allows the calibration of a model applying 10 different modelling techniques, and to forecast the potential species distribution under different environmental conditions (climate and land use change scenarios; Thuiller et al. 2009). Due to the complex nature of species range dynamics and the related factors acting at multiple spatial scales, modelling species distribution is a challenging procedure (Vicente et al., 2011; Guisan and Thuiller, 2005).

1.6. Objectives

In this work we applied a combined predictive modelling (CPM) framework to: (1) identify the areas that are today potentially invaded by Silver-wattle (*Acacia dealbata* Link) in Northwest Iberian Peninsula (Galicia and North of Portugal); and (2) forecast the effects of climate changes on the distribution of this species by projecting the models for future conditions. Our rationale was that the application of CMPs to predict the current and future patterns of invasion can support measures to prevent invasions in the study region and support cross-border management to protect important habitats from invasion.

2. Methods

2.1. Study area

The study area is located in the Northwest Iberian Peninsula (Fig. 2), covering the North Portugal and Galicia. This area presents a high plant biodiversity, with more than 3000 species and subspecies, many of them endemic of this region (http://www.biodiversidade.eu/pt/info/proxecto/). This region is experiencing a strong environmental disturbance promoted by many factors, like invasive species, creating a serious threat to conservation of biodiversity (http://www.biodiversidade.eu/pt/info/proxecto/).

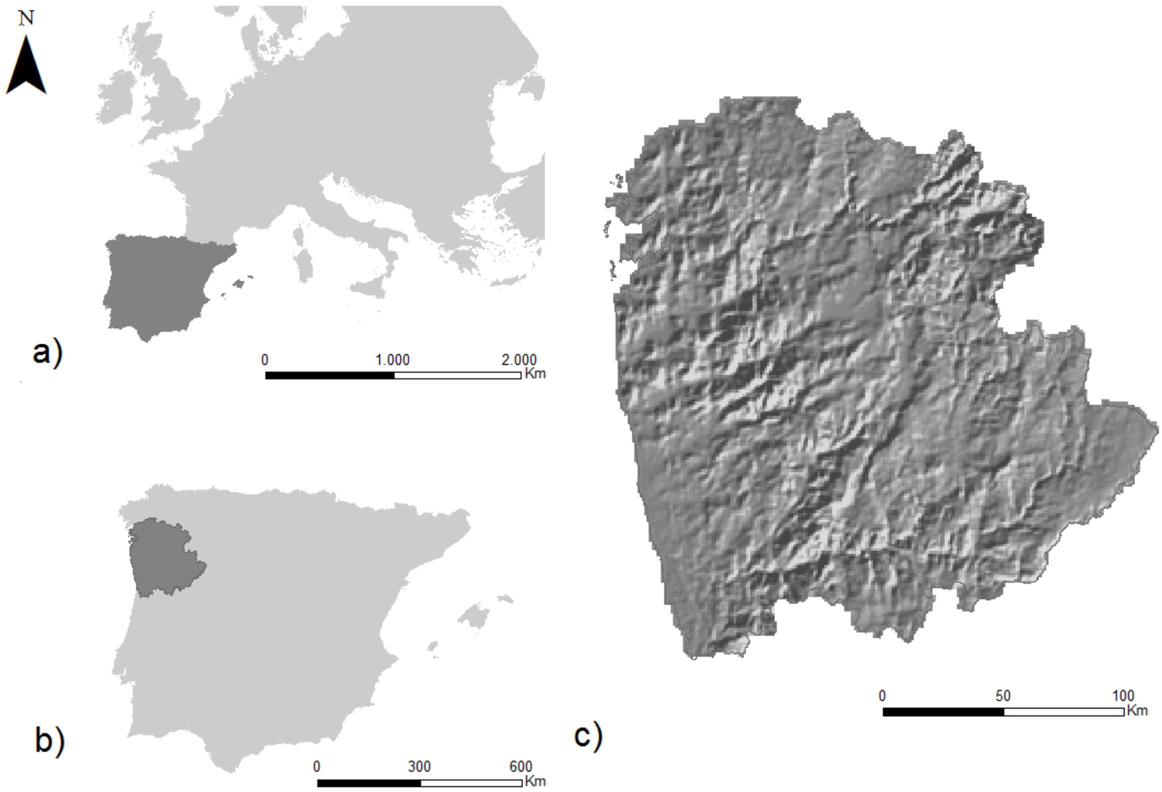

Figure 2 – Location of the study area in Europe (a) and Iberian Peninsula (b) with digital elevation model detail (c).

The area extent is 35017 km², covering the transition between the Mediterranean and Atlantic biogeographic regions (Rívas-Martínez et al., 2004). The study area is very heterogeneous, with elevation ranging from the sea level (west) to 2059 m in the eastern mountains, with the major rivers, as Douro, Tua, and Cenza, running from east to west. The geology of the mountains is overwhelmed by acid igneous and metamorphic rocks that form acid soils (Roucoux et al., 2005). The study area presents a very complex land cover (more than 11 classes of land cover, according to the European Environment Agency) and a large network of protected sites: Parque Nacional Peneda-Geres, Parque Natural de Montesinho and Parque Natural de Alvão in Portugal and Serra Candán and Pena Trevinca in Spain. Currently this region has a temperate climate (Roucoux et al., 2005) and carries the full force of the westerly winds bringing cyclones from the Atlantic (Roucoux et al., 2005). The precipitation levels in the area are the highest in the whole peninsula (Roucoux et al., 2005) (up to 3000mm per year in the eastern mountain summits). The annual mean temperatures ranges from ca. 5°C to ca. 17°C, where the summers are cool (18-22ºC (Roucoux et al., 2005) and winters are mild and frost-free (10-13ºC around the coast) (Roucoux et al., 2005).

2.2. Test species and occurrence data

The test species is an alien invader plant from the *Leguminosae* family, *Acacia dealbata* Link (Fig. 3). This wattle species is original from the southeast of Australia and found in a wide range of different habitats, from coastal to subalpine regions, and from high rainfall to arid inland areas, growing in tropical, subtropical and warm temperate regions (Lorenzo et al., 2009).

Figure 3 – *Acacia dealbata* Link.

This species can be found in areas with over 500 mm rainfall, typically at altitudes from 350-1000m above the sea level (Lorenzo et al., 2009). Introduced in Europe in the 1820s (Carballeira and Reigosa, 1999), and planted as an ornamental plant in southern Europe, which offered favorable climates for this development, with sufficient sun exposure an little frosts, becoming widely naturalized in this area (Lorenzo et al., 2009). In the Southwest Europe this species occurs in riparian zones, water courses and sunny edges of pinewoods, or on the south and west facing slopes, where it forms dense stands that choke in the natural vegetation and it often invades area under intensive agriculture uses and further away from the sea than other *Acacia* species present in these regions (Lorenzo *et al*, 2009). *Acacia dealbata* was introduced in the Iberian Peninsula in the second half of the 19th century (Sanz Elorza et al., 2004) and became a problematic species in Portugal and Spain, where it is threatening the native flora and becoming a serious environmental problem. In addition to its great colonizing capacity it leads to a very low covering of undergrowth species caused by its alellopathic ability (Vicente *et al*, 2011).

The occurrence dataset for Portugal was collected from previous scientific works (Vicente et al., 2013) and Spain data were and provided by Direccion Xeral de Conservacion da Natureza da Xunta da Galicia. Sampling sites were selected using a random-stratified strategy (Vicente et al., 2013), employing climate (mean annual temperature) and bedrock as stratifying layer. Sampling units were cells of 1km^2 in which presents where collected between March and April 2011.

2.3. Selection and classification of environmental predictors

We selected 53 predictors that, by expert knowledge and according to previous reporting in scientific literature, operate as determinants of ecology and distribution of the target species (see annex 1). To avoid correlation, we applied the Spearman rank correlation coefficient (non-parametric test), to select the predictors with lowest correlation between each other. We use the software STATISTICA to select the predictors and only those with correlation lower than 0.5 were considered (Vicente et al., 2011). Therefore we select 17 environmental predictors to calibrate the models (Table 1 describes the predictors chosen). Climate predictors were obtained using information from the WorlClim database in raster format with a spatial resolution of 1km^2 while the remaining environmental predictors were obtained from detailed environmental maps.

The environmental predictors were classified a priori as “regional” or “local” based on ecological theory and their spatial scale of variation using a statistical predictor classification based on spatial autocorrelation (Vicente et al., 2011).Using point pattern statistic (PPSA—spdep R package; available at http://cran.r-project.org/web/packages/spdep) we calculated Geary’s c autocorrelation measure for all predictor variables for increasing neighbourhood distances. At least, we performed a hierarchical clustering based on a Euclidean distance matrix of all Geary's values and the two groups in the final classification tree were very well separated corresponding to predictors with local versus regional influence (Vicente et al., 2011).

Table 1 – Environmental predictors used in the combined models, with reference to the variable type, description of the predictors, information format, data source and references in literature.

Predictors	Description	Information format	Data source	References
MTCM	Min Temperature of Coldest Month			Férnandez et al., 2012; Gaikwad et al., 2011; Liu et. al, 2013Thuiller et al. 2005; Vicente et al., 2010; Vicente et al., 2011; Vicente et al., 2013a; Vicente et al., 2013b; Vicente et al., 2013d;
TAR	Temperature Annual Range	Raster	www.worldclim.org	Castro-Díez et al., 2011;Férnandez et al., 2012; Gallien et al., 2012; Castro-Díez et al., 2011;Vicente et al., 2013°
AP	Annual Precipitation			Barrows and Murphy- Maiscal, 2012; Castro-Díez et al., 2011; Crossman and Cooke, 2011; Férnandez et al., 2012; Gaikwad et al., 2011; Vicente et al., 2013c
PS	Precipitation Seasonality			Castro-Díez et al., 2011;Férnandez et al., 2012; Gaikwad et al., 2011; Vicente et al., 2013a; Vicente et al., 2013c;
DensRiv	Density of local hydrographic network			Vicente et al., 2011 Vicente et al., 2013a; Vicente et al., 2013c
DensRoad	Density of local road network	Vectorial	www.vdstech.com	Vicente et al., 2013a; Vicente et al., 2013b
Distrv	Distance to main rivers			Catford et al. 2011; Vicente et al., 2010; Vicente et al., 2011; Vicente et al., 2013b; Vicente et al., 2013d
Distroad	Distance to roads			Catford et al., 2011; Vicente et al., 2013b
pCamb	Percentage of cambisoils	Vectorial	www.eea.europa.eu	Vicente et al., 2013a; Vicente et al., 2013c
pBiFo	Percentage cover of broad-leaf forest			Vicente et al., 2013a; Vicente et al., 2013c; http://www.europe-aliens.org/pdf/Acacia_dealbata.pdf
pCoFo	Percentage cover of conifer forest			Vicente et al., 2013c; http://www.europe-aliens.org/pdf/Acacia_dealbata.pdf
pMixFo	Percentage	Vectorial	www.eea.europa.eu	Vicente et al., 2013a; Vicente et al., 2013c

	cover of mix forest			
pArS	Percentage cover of artificial stands			Vicente et al., 2013ª
pArL	Percentage cover of arable land			Vicente et al. 2013a; Vicente et al., 2013c; http://www.europe-aliens.org/pdf/Acacia_dealbata.pdf
MPAR	Mean perimeter-area ratio	Vectorial	Patch Analyst (Rempel et al., 2012)	Vicente et al., 2013ª
MSI	Mean shape index			Lomba et al., 2010; Vicente et al., 2013a; Vicente et al., 2013d; Vicente et al., 2010; Vicente et al., 2013b;
GPP	Mean gross annual primary productivity	Raster	http://www.ntsg.umt.edu/project/mod17#data-product	Vicente et al., 2010; Vicente et al., 2013b; Vicente et al., 2013c; Vicente et al., 2013d

This classification is due to the fact that processes drive the distribution of species are linked to several levels of ecological complexity and is expressed at different spatial scales (Vicente et al., 2011).

2.4. Conceptual combined modelling framework

We applied a modeling framework developed in a previous study (Vicente et al., 2011) with combined forecasting models for current and future distribution of *Acacia dealbata* using BIOMOD 2 in the R statistical software (R Development Core Team 2012). In the combined approach, distinct models are fitted using either “regional” or “local” predictors, and with the spatially combination of the two partial models we obtained a final model. All the models were produced for the same spatial extent and using the same grain size (1km²) (Vicente et al., 2011).

We followed an analytical design divided into four steps, as illustrated in Fig. 4:

- First, we classified the predictor variables as regional or local, based on the Geary’s C autocorrelation measure (see Environmental predictor and predictor classification) (Fig. 4a);
- Second, we fitted the two partial models: the regional partial model and the local partial model, using the subset of regional predictors and the subset of local predictors, respectively (Fig. 4b);
- Third, we mapped the partial model outputs (regional and par local) in the software ArcGis (ESRI 2010) (Fig. 4c);
- Fourth, we produced the combined model by overlapping the spatial predictions of the regional and the local partial models, obtaining the four possible combinations of them (See table in Fig. 4d).

The predictions obtained from these models were contained to procure a final prediction map that includes both local and regional constraints (Vicente et al., 2011). This final map included four combinations of predictions that do not formally represent classes of probability of occurrence, however we assume that the probability of occurrence is maximum in type A and reaches a minimum value in type D (Vicente et al., 2011).

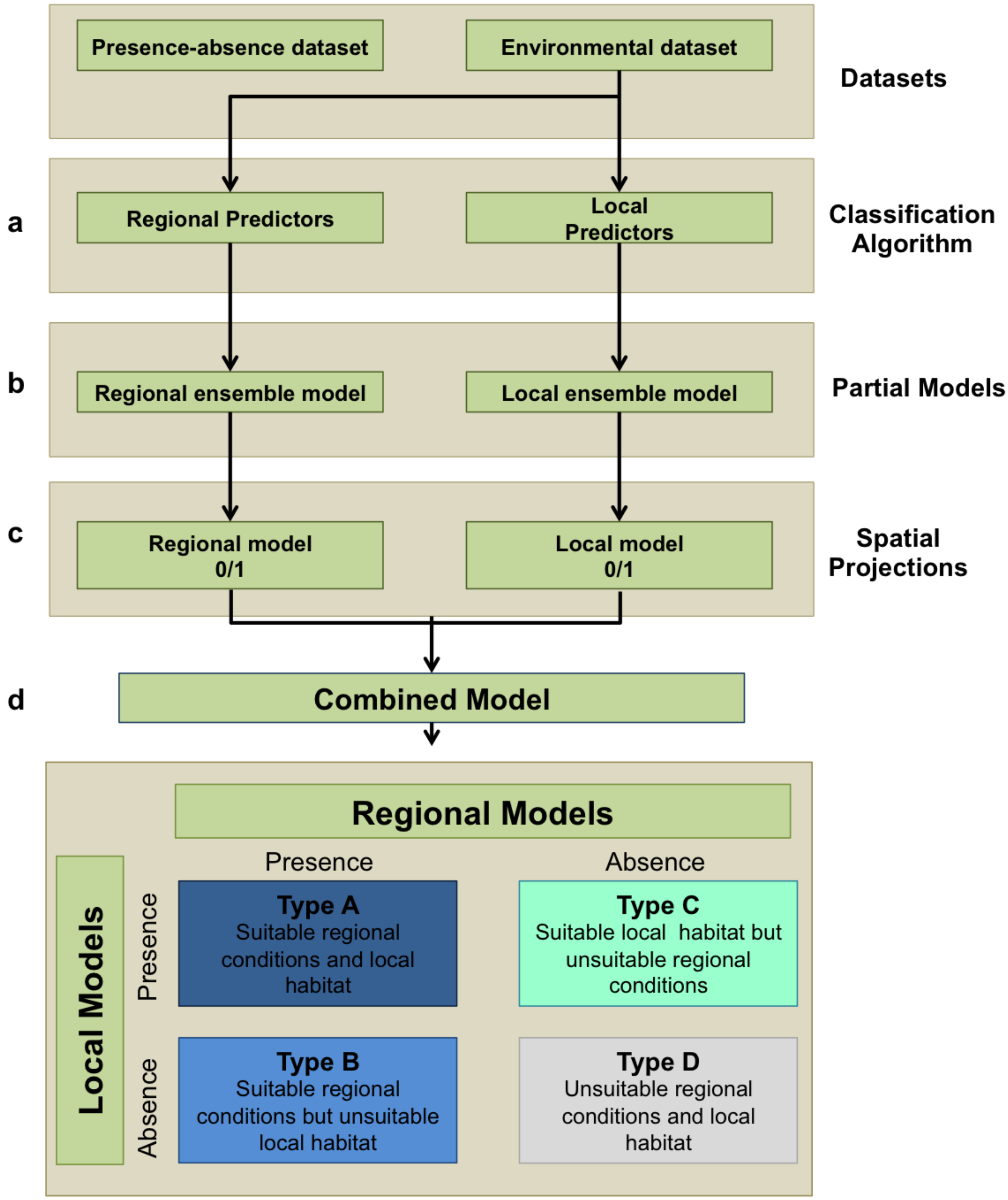

Figure 4 - Analytical design for developing combined predictive models (CPMs), with all the possible combinations (Type A – regional and local suitability, Type B – only regional suitability, Type C – only local suitability and Type D – no suitability) obtained in a final prediction maps (Vicente et al., 2011).

2.5. Model fitting and evaluation

Model fitting can be defined as “the estimation and adjustment of the model parameters and constants to improve the agreement between model output and a data set”(Guisan and Zimmermann, 2000). In this study, Biomod 2 was used to fit models using the ten available techniques: (1) Generalised Linear Models (GLM), (2) Generalised Boosting Models (GBM), (3) Generalised Additive Models (GAM), (4) Classification Tree Analysis (CTA), (5) Multivariate Adaptive Regression Splines (MARS), (6) Random Forest (RF), (7) MAXENT, (8) Artificial Neutral Networks (ANN), (9) Flexible discriminant Analysis (FDA) and, (10) Surface Range Envelop (SRE or usually called BIOCLIM (Thuiller *et al*, 2013)).

Evaluation of a model is related to the measure of adequacy that depends on the specific purpose of the project and the domain in which the model is supposed to be applicable (Guisan and Zimmermann, 2000). In Biomod, the evaluation of models includes two types of analysis: assessments of the goodness-of-a fit (explanatory power) and a model accuracy (predictive power) (Thuiller et al., 2009).The former uses standard approaches associated with each technique (for example, ANOVA decomposition) and the latter can be performed with three procedures: Cohen's K (K), the area under the relative operating characteristic curve (AUC) and the true skill statistics (TSS; Thuiller et al., 2009). This evaluation can be used to investigate the variability of predictions across modeling techniques. In Biomod, a table displaying the AUC/K/TSS values in produced for each model and for each species, and can be used for selecting the "best" model (the model that provides greater accuracy on the test data for each species) Thuiller et al., 2009)). We used the area under the curve (AUC) of a receiver operating characteristic (ROC) plot (Fielding and Bell 1987). The AUC was obtained as an output for each model. BIOMOD uses a repeated split-sample procedure, keeping 20% of the initial data out of the calibration for subsequent validation of the predictions. The number of repetitions was set to 50 (Vicente et al., 2011). Model predictions were stacked into a single ensemble model using a weighted approach, available for generating ensemble models in BIOMOD. This approach ranks models by their AUC evaluation, and only models with AUC >0.7 were used (Vicente et al., 2011). We converted the probabilistic predictions of the ensemble models into binary following the ROC – thresholding approach used in Elith et al. (2006) and discussed in Liu et al. (2005). Finally, we estimated the number of sampled presences and absence predicted in each class of the models.

2.6. Spatial projections under current and future climate conditions

Spatially combined scenarios projections were mapped over the full geographical extent of the study using the software ArcGIS (ESRI 2010). Outcomes from climate change scenarios for *Acacia dealbata* were derived by re-projecting models for 2020 and 2050. We use scenarios available in WorlClime.org, with a resolution of 1km² (30 arc-second resolution grid) (Vicente et al., 2011). With the spatial combination of current and future species distributions, future species dynamics can be predicted. CPMs provide five different prediction types: “no change”, “colonization”, “extinction”, deterioration of the conditions” and “improvement of the conditions” (Fig. 5), providing more informative and dynamic predictions. We chose two scenarios from the Intergovernmental Panel on Climate Change – IPCC (Vicente et al., 2013), driven by a global circulation model (HadCM3): A1 (very rapid growth with increasing globalization, and high increases in temperatures), and B2 (describes a world in which the emphasis is on local solutions to economic, social and environmental suitability, yielding moderate increases to temperature). Future scenarios only include changes in regional climatic processes.

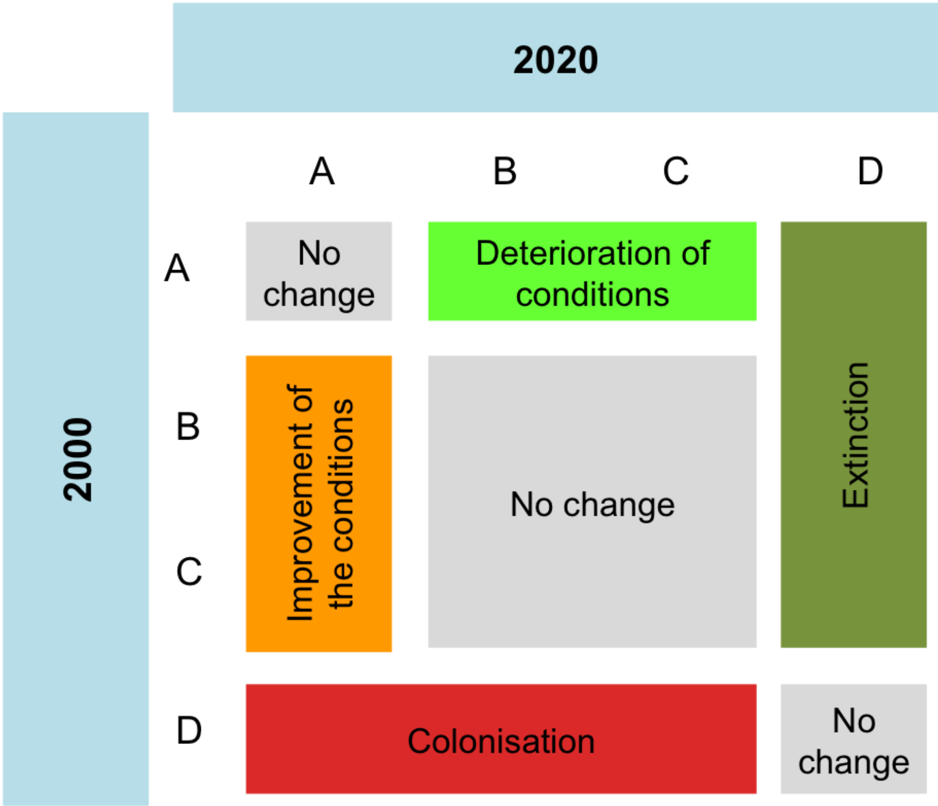

Figure 5 – Possible combinations for species distributions dynamics using combined models (Vicente et al., 2011). The letters A, B, C and D refers to the different possible combinations (A- regional and local suitability, B- only regional suitability. C- only local suitability and D- no suitability).

2.7. Current and future conflicts with protected areas

The models of the species were used to forecast the current and future species distributions and their conflict with the protected areas present in the study area, by spatially overlapping the potential distribution maps with a map of the protected area, corresponding to Natura 2000 networks. With this projection it's possible to determine the potential threats to the protected areas in the near future, as well as the possible impacts that may arise from them. By overlapping the models of the species with a map of protected areas (corresponding to Nature Network 2000 – ICNF for Portugal and to Espacios Naturales Protegidos en España for Spain) the distribution maps of combined models allow a detection of present and future invasion areas.

2.8. Connectivity of the distribution of the invasive species

First, we calculated the temporal changes in spatial connectivity of predicted suitable areas for the test species across the test area, using the connectivity index developed by Randy et al., 2009 (Vicente et al., 2013). We considered value of species presence: probability of 1 for the response type A, probability of 0.5 for response type B and C, and probability of 0 for response type D. The connectivity index attains a maximum value of 1 when all the cells surrounding a focal suitable cell are also suitable (Vicente et al., 2013). We quantified the changes in the spatial relationship between protected areas and the connectivity of predicted areas using the raster calculator in ArcGIS 9.3 (ESRI, 2010). Then, we analysed the trend of connectivity for the specie in space (full area and inside protected areas) and time (2020 and 2050). At last, a Spearman rank correlation test was used to identify significant relations between connectivity and protection value.

3. Results

3.1. Predictions and determinants of current distributions

The potential distribution of the species *Acacia dealbata* under current conditions is illustrated in Figure 6. The combined predictive model was calibrated using 17 environmental variables "a priori" classified as "regional" and "local" (see Table 2).

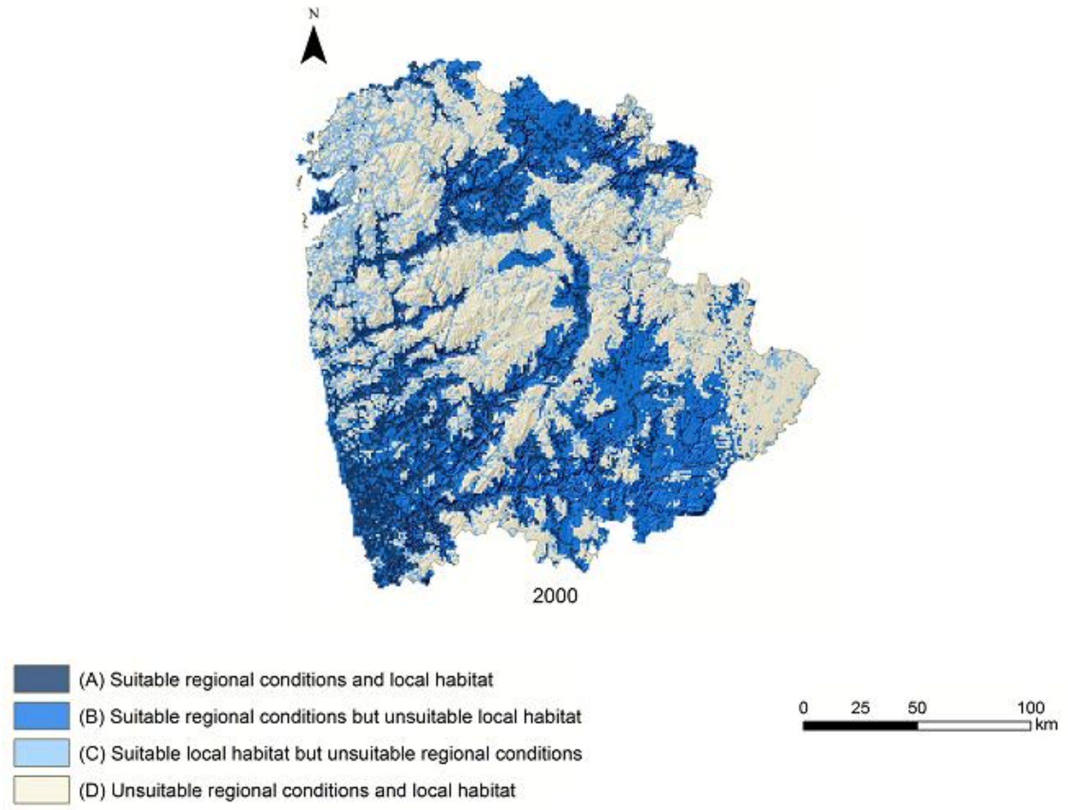

Figure 6 - Spatial projection *of Acacia dealbata* potential distribution using combined models, under current conditions (2000).

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Table 2 – Environmental predictors selected to calibrate the combined models.

Predictors	Description	Scale of variation
AP	Annual Precipitation	Regional
DistRiv	Distante to main river	Regional
GPP	Mean gross annual primary productivityMM	Regional
MTCM	Min Temperature of Coldest Mont	Regional
pCamb	% of cambissoils (*per* 1km^2)	Regional
PS	Precipitation Seasonality	Regional
TAR	Temperature Annual Range	Regional
DensRiv	Density of local hydrographic network	Local
DensRoad	Density of local road network	Local
Distroad	Distance to roads	Local
MPAR	Mean perimeter-area ratio	Local
MSI	Mean shape index	Local
PArL	% cover of arable land (*per* 1km^2)	Local
PArS	% cover of artificial stands (*per* 1km^2)	Local
pBiFo	% cover of broad-leaf forest (*per* 1km^2)	Local
pCoFo	% cover of conifer forest (*per* 1km^2)	Local
pMixFo	% cover of mix forest (*per* 1km^2)	Loca

The partial regional model was calibrated with 7 environmental variables, and an AUC value of 0.849 was obtained, while the partial local model was calibrated with 10 environmental variables with a final AUC value of 0.887. From the 7 regional environmental predictors, the most important for partial regional model calibration were Minimum Temperature of Coldest Month (MTCM, with a value of 0.394), Annual Precipitation (AP, with a value of 0.282) and Temperature Annual Range (TAR, with a value of 0.238). Considering the partial local model, between the total of 10 local predictors, the most important were Density of local road network (DensRoad, with a value of 0.392), percentage of arable land (pArL, with a value of 0.173)and percentage cover of mixed forest (pMixFo, with a value of 0.197).

Under current climate conditions (2000), the potential percentage of predicted area for *Acacia dealbata* in areas with regional and local suitability, type A, was 18.3%. For areas with only-regional suitability, type B, the percentage of predicted area 27% while in the areas with only local suitability, type C, the percentage of predicted area was

14%. Finally, for areas predicted to be unsuitable for the species (unsuitable local and regional conditions), type D, the percentage of predicted area was 40.7% (Table 3).

Table 3 – Predicted percentage of the study area occupied by each “occupancy type” in the combined models, for the test species, under current conditions (2000).

Occupancy types	Percentage of predicted área
Type A - regional and local suitability	**18.3%**
Type B - only regional suitability	27.0%
Type C - only local suitability	14.0%
Type D - no suitability	40.7%

3.2. Forecast of future distributions

The spatial distribution of the test species under future climate conditions for the year 2020 is illustrated in Figure 7. The combined models for the A1 scenario (Fig. 7-b) and for the B2 scenario (Fig. 7-d) were obtained by overlapping the spatial projections of the local and the regional partial models.

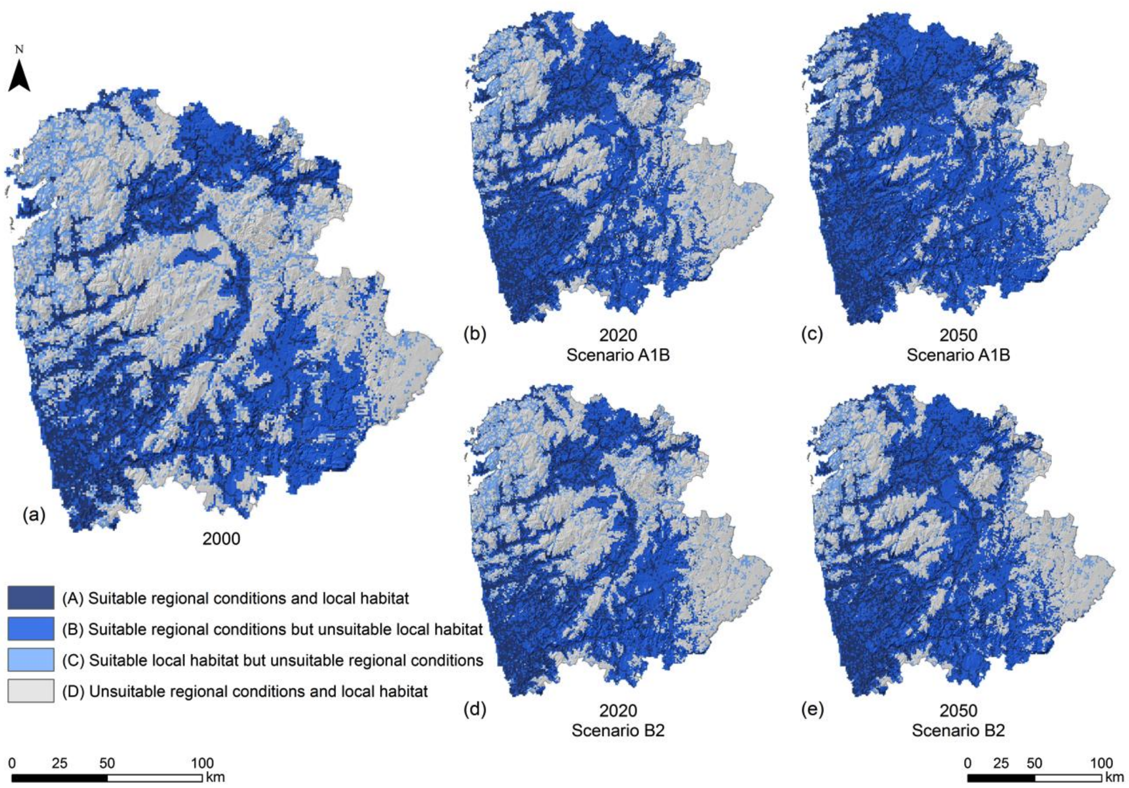

Figure 7- Spatial projections under current conditions (2000 - a) and future conditions - 2020 A1 scenario (b) and Bb2 scenario (d) and 2050 A1 scenario (c) and B2 scenario (e).

Under future conditions (2020) considering A1 climatic scenario, predicted area with local and regional suitability, type A, was 22.3%.The percentage for areas with only regional suitability, type B, was 33.3%, and for areas with only local suitability, type C was 10%. Finally, unsuitable regional and local areas, type D, were predicted as 34.4%. For B2 climatic scenario, type A (both regional and local suitability) predicted area was 20%, type B (regional suitability) was 28.9%, for type C (local suitability) was 12.3% and for type D (both regional and local unsuitability) was 38.8% (Table 4).

Table 4 - Predicted percentage of the study area occupied by each "occupancy type" in the combined models, for the test species, under future conditions (2020), for the a1 and b2 scenarios.

	Percentage of predicted area	
Occupancy types	A1	B1
Type A - regional and local suitability	**22.3%**	**20.0%**
Type B - only regional suitability	33.3%	28.9%
Type C - only local suitability	10.0%	12.3%
Type D - no suitability	34.4%	38.8%

A spatial distribution for the species *Acacia dealbata*, under future climate conditions for the year 2050 is presented in the figure 7, where the combined model for the A1 scenario (fig. 7- c) and for the B2 scenario(fig 7- e).

In table 5 is presented the estimated percentage of the study area occupied by each "occupancy types". Areas predicted with both regional and local suitability (Type A) was 26,5% in A1 scenario and 22.8% in B2 scenario. The percentage of area predicted to be type B (only regional suitability) was 46% in the a1 scenario and 36.4% in the b2 scenario, and the percentage of areas predicted as type C (only local suitability) was 5.8% in the a1 scenario and 9,4% in b2. Areas predicted as unsuitable local and regional conditions (Type D) was 21.7% and 31.4% in the a1 and b2 scenarios, respectively.

Table 5 - Predicted percentage of the study area occupied by each "occupancy type" in the combined models, for the test species, under future conditions (2050), for the a1 and b2 scenarios.

	Percentage of predicted area	
Occupancy types	A1	B2
Type A - regional and local suitability	**26.5%**	**22.8%**
Type B - only regional suitability	46.0%	36.4%
Type C - only local suitability	5.8%	9.4%
Type D - no suitability	21.7%	31.4%

3.3. Range dynamics between years 2000 and 2050

Based on the potential distribution of the species predicted for the years of 2000, 2020 and 2050, we analysed the potential range dynamics for the species *Acacia dealbata* between the time periods: 2000-2020; 2000-2050; and 2020-2050. Predicted changes in range dynamics for the species *Acacia dealbata* between 2000-2020, 2000-2050 and 2020-2050 (under climate change scenarios) are shown in Figure 8.

For the three time periods, predominate dynamic obtained was the response type "no change" (see Table 6). In both scenarios, for the responses type "Improvement of the conditions" and "Colonization", from the periods 2000-2020 to 2000-2050 an increase of the response was observed, and for the period of 2020-2050 a decrease was observed compared to the time period 2000-2050. For the response type "Deterioration of the conditions", for both scenarios, a decrease trend was observed from the period of 2000-2020 to the period of 2000-2050. From time period 2000-2050 to 2020-2050 the obtained values were the same. Finally, for the response type "extinction", a decreasing of the values was observed from the time period 2000-2020 to 2000-2050 and also from the time period of 2000-2050 to 2020-2050.

Table 6 – Dynamic of environmental suitability for the test species from combined modes, under climate change scenarios, for the periods 2000-2020, 2000-2050 and 2020-2050.

Scenarios	Dynamics	No change	Improvement	Deterioration	Extinction	Colonization
A1B	2000-2020	77.9%	5.1%	1.0%	4.9%	**11.1%**
	2000-2050	68.1%	8.6%	0.3%	2.0%	**2.1%**
	2020-2050	80.0%	4.5%	0.3%	1.3%	**13.9%**
B2	2000-2020	89.9%	2.7%	0.9%	4.3%	**6.2%**
	2000-2050	79.1%	5.2%	0.6%	2.9%	**12.2%**
	2020-2050	84.2%	3.4%	0.6%	2.2%	**9.6%**

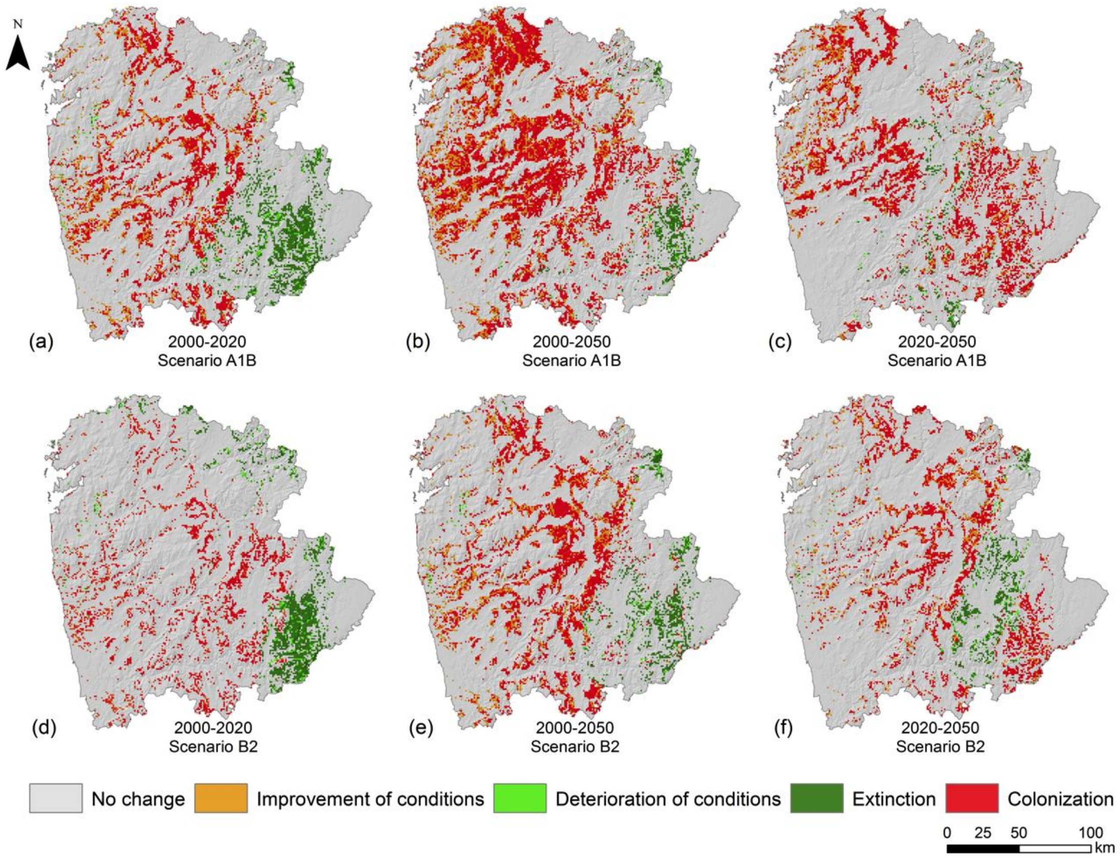

Figure 8 – Changes in the potential and dynamic of the test species between 2000-2020 (for the A1 scenario – a- and the B2 scenario - d), 2000-2050 (for the A1 scenario – b- and the B2 scenario - e) and 2020-2050 (for the A1 scenario – c - and the B2 scenario - f).

3.4. Current and future conflicts with protected areas

In Table 7 we present the percentage of area of Natura 2000 sites occupied by the different response types for the test species *Acacia dealbata,* for current (2000) and future (2020 and 2050) environmental conditions (Figure 9).For the climatic scenario A1, the percentage of predicted area with the response types A (regional and local suitability for the species) within Natura 2000 sites increases in the year 2020 and 2050. Considering predicted type B (regional suitability) and D (both unsuitable regional and local) inside the Natura 2000 sites, it's predicted no changes for the year 2020 followed by an increase of predicted percentage of type B (regional suitability), and a decrease in the type D (both regional and local unsuitability), for 2050. The percentage of occupancy of the type C (local suitability) inside the Natura 2000 sites decreases both years.

For the climatic scenario B2, a decrease of the percentage of occupancy of the species inside Natura 2000 sites can be observed for the year of 2020 for response types A (regional and local suitability) and B (regional suitability), followed by an increase in the year 2050. An increase of the percentage is observed for response types C (local suitability) and D (both regional and local unsuitability) for the year 2020, while in 2050 the percentage decreases.

Table 7– Percentage of occupancy in Natura 2000 for each occurrence type (regional and local suitability (type A), only regional suitability (type B), only local suitability (type C), and no suitability (type D), for the test species, for current (2000) and future (2000, 2050) conditions.

	Percentage of predicted area				
Occupancy type	2000	2020 a1	2020b2	2050a1	2050b2
Type A - regional and local suitability	**9.0%**	**10.6%**	**8.6%**	**13.9%**	**11.0%**
Type B - only regional suitability	18.9%	18.9%	15.4%	34.5%	22.2%
Type C - only local suitability	11.8%	10.2%	12.2%	6.9%	9.8%
Type D - no suitability	60.3%	60.3%	63.8%	44.7%	57.0%

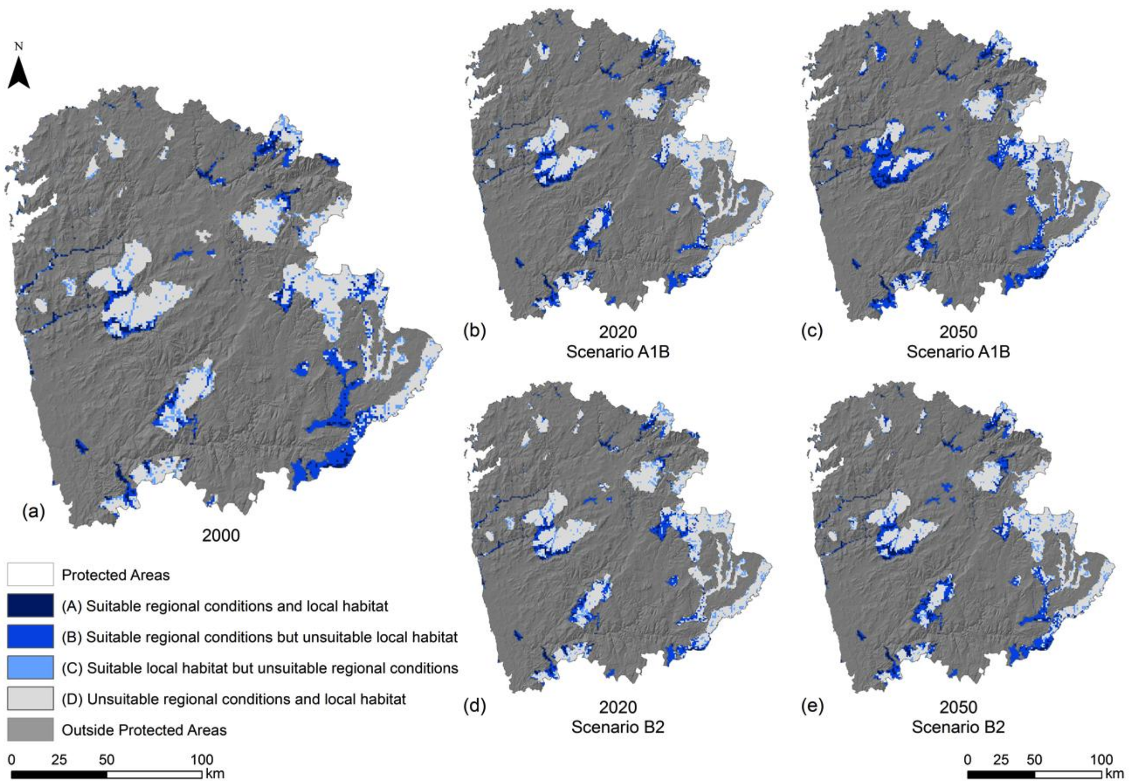

Figure 9- Spatial projections of invasion within Natura 2000 sites (protected areas for combined models, under current (2000) and future conditions (2020 and 2050).

Predominate dynamic type predicted by the combined models in each time period within Natura 2000, was “No change” (see Fig 10 and Table 8). For both climatic scenarios, responses types “deterioration of the conditions” and “extinction” decreased from the time period 2000-2020 to 2000-2050 and from the time period 2000-2050 to 2020-2050. Considering the A1 climatic scenario, the response types “Improvement of the conditions” and “Colonization”, from the time period 2000-2020 to 2000-2050, was increasing and then, from the time period 2000-2050 to 2020-2050, was decreased. Considering the B2 climatic scenario, from the time period 2000-2020 to 2000-2050 and 2000-2050 to 2020-2050, an increasing was observed.

Table 8 – Percentage of occupancy in Natura 2000 of each dynamic type (no change, improvement of the conditions, deterioration of the conditions, extinction and colonization), for the test species, for the periods 2000-2020, 2000-2050 and 2020-2050.

Scenarios	**Dynamics**	**No change**	**Improvement**	**Deterioration**	**Extinction**	**Colonization**
A1B	2000-2020	82.2%	2.8%	1.2%	6.9%	**6.9%**
	2000-2050	70.4%	5.5%	0.6%	3.9%	**19.6%**
	2020-2050	79.3%	3.5%	0.1%	0.7%	**16.4%**
B2	2000-2020	84.4%	1.3%	1.6%	8.1%	**4.6%**
	2000-2050	84.3%	2.8%	0.8%	4.4%	**7.7%**
	2020-2050	85.9%	2.9%	0.5%	2.0%	**8.7%**

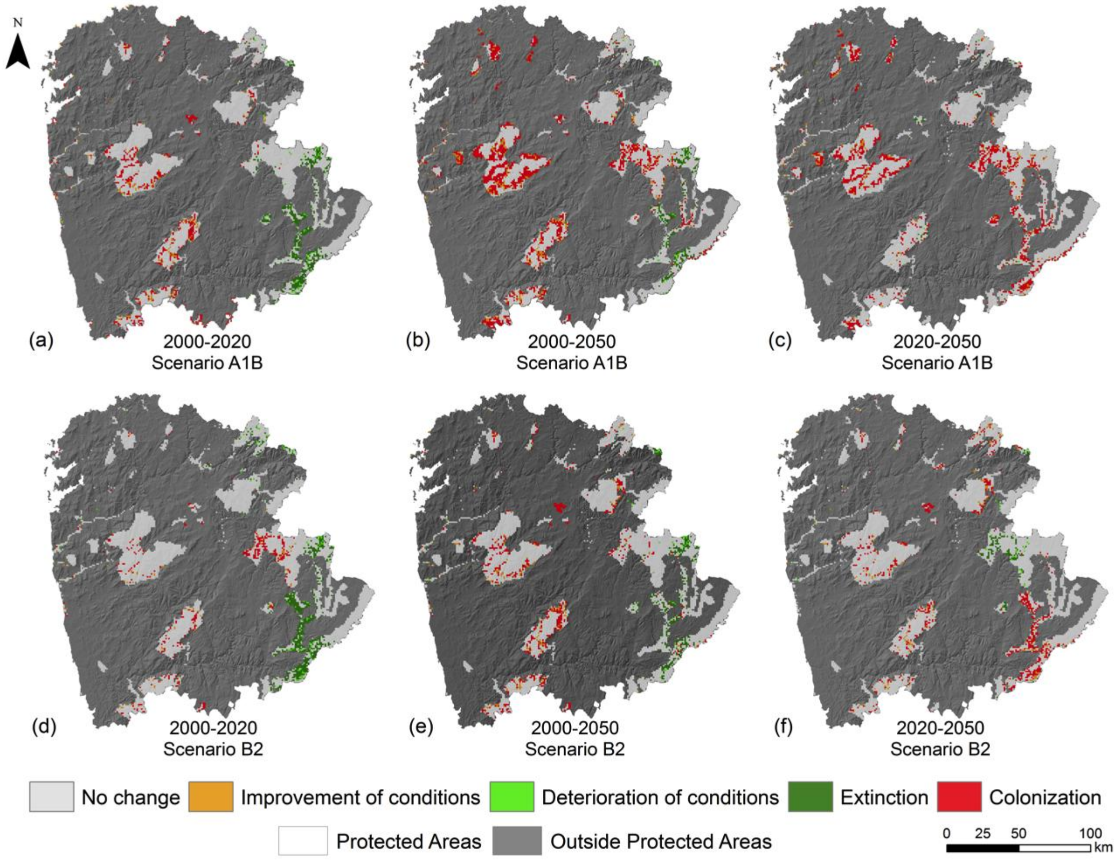

Figure 10- Changes in the potential distribution and dynamics of the test species from combined models between 2000-2020, 2000-2050 and 2020-2050 within Natura 2000 sites.

3.5. Current and future connectivity of invasive species distribution

The connectivity of the invasive *species Acacia dealbata* in the study area is illustrated in the Fig. 11, under current (2000) and future (2020 and 2050) environmental conditions.

An increase of the high connectivity values of the species in this area was observed, for the years of 2020 and 2050, under both climatic scenarios (Table 9).

Table 9 – Percentage of occupancy of each type of connectivity of the invasive species on the test study, under current (2000) and future conditions (2020 and 2050).

		A1		**B2**	
	2000	2020	2050	2020	2050
High	**14.0%**	**22.3%**	**26.5%**	**20.0%**	**22.8%**
Medium	18.2%	10.0%	5.8%	12.3%	9.4%
Low	27.1%	33.3%	46.0%	28.9%	36.4%
Very Low	40.7%	34.4%	21.7%	38.8%	31.4%

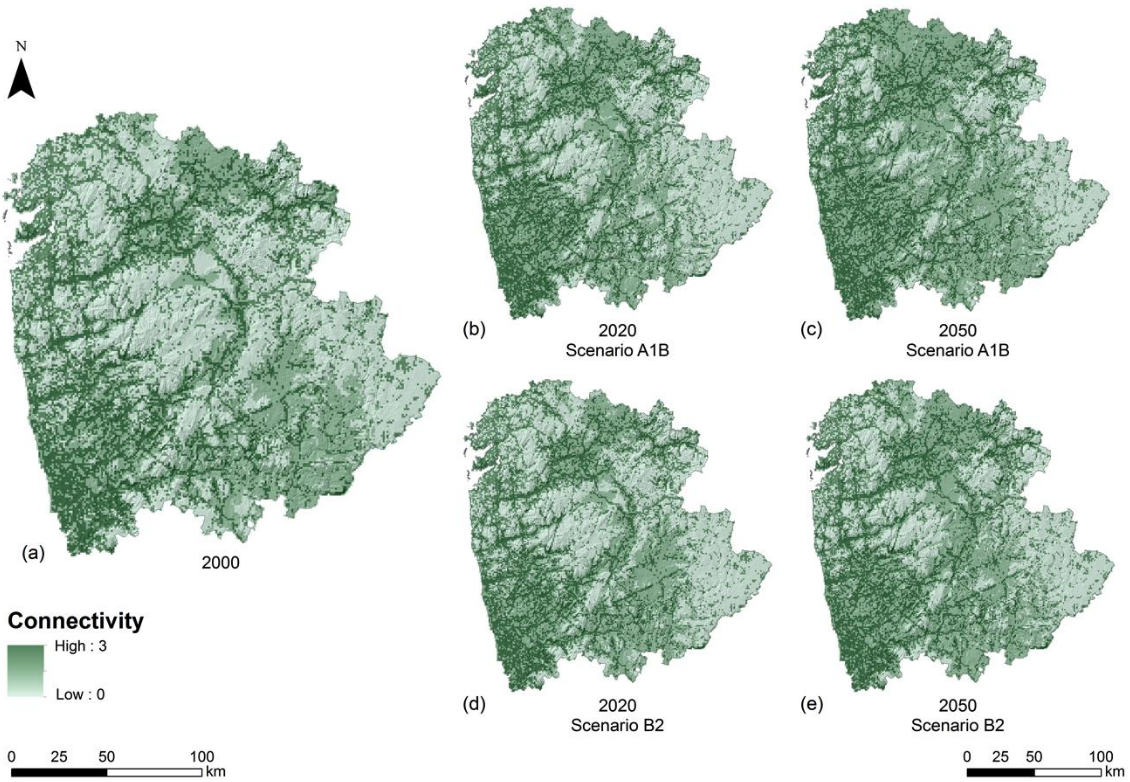

Figure 11 – Spatial projections of the connectivity of the alien species in the study area, under current (2000) and future (1010 and 2050) conditions.

4. Discussion

4.1. Using models to predict biological invasions

Species distribution models plays an important role in the field of biological invasions since invasions represent a growing threat to biodiversity and once introduced species are establish, they become difficult to eradicate, so, preventing future invasions is the most cost-effective form of management (Broennimann and Guisan, 2008).

Species distribution models (SDMs) have been widely used to predict potential distribution of alien invasive species (Jones et al., 2012), and can be directly applied to the development of management strategies, to determine containment boundaries, and to identify priority areas for early detection and rapid responses (Robinson et al., 2010). Protected areas all over the world are important refuges, particularly for species with high conservation values (Beaumont et al. 2009). Currently, invasive species are present in all nature reserves worldwide (Pysek et al., 2002) and species distribution models have been widely used to predict the expansion of alien species into protected areas and their potential impacts on biodiversity and ecosystem services (Kleinbauer et al. 2010). The predictions obtained using SDMs stress that the threat of alien invader species in nature reserves will potentially increase in the future, unless effective control measures are adopted (Pysek et al., 2002). Under changing climate conditions, invasive species are more likely to adopt to the new conditions and this will intensify the joint trait poses by climate warming and invasive species on native populations (Gallardo and Aldridge, 2013).

Less attention has been paid to the related problem that climate change may not only drive endangered species out of reserves but might also foster the invasion of alien species into reserve networks (Kleinbauer et al., 2010). The increasing risk of invasion under climate change scenarios stressed the importance of pro-active management strategies in particular, integrated management plans of nature conservation areas (Kleinbauer et al., 2010).

In this study, a robust and efficient framework was applied, to predict current and future potential distribution of an aggressive alien invader plant species in the study area, as well as to identify areas of possible conflict between the species and protected areas under current and future environmental conditions. We predicted current patterns of conflict for *Acacia dealbata* in the Northwest of the Iberian Peninsula and their future dynamics under alternative climate change scenarios.

4.2. Current and future conflicts with protected areas in the test region

Acacia dealbata has been document in several parts of the world such as Portugal and Spain (Fuentes-Ramírez et al., 2011; González-Muñoz et al., 2012). According to González-Muñoz et al., 2012, Acacia dealbata spreads in the Northwest of the Iberian Peninsula throughout abandoned agriculture lands, cleared areas after fires and road limits.

Predictions of current conflicts between *Acacia dealbata* and the protected areas stressed that the species is already potentially spread over most of the study area, which is in accordance with Lorenzo et al. (2010). *Acacia dealbata* has attained invasive and high distribution proportions in some habitats and protected sites.
Considering future predictions, the models forecasted that areas with climate and habitat/landscape suitable conditions for *Acacia dealbata* will increase. In year 2020, for the climatic scenario A1, trends of species distribution inside and outside of the protected areas, was similar for the response types A (both suitable conditions) and C (local suitability), but different for the response types B (regional suitability) and D (both unsuitable conditions). In the same year, for the B2 climatic scenario, predictions of occupancy were different inside and outside the protected areas. For the year 2050, in both scenarios, the trends of occupancy of this species were similar within and outside of protected areas. The results for the total study area were consistent with previous studies, confirming that that the percentage of suitable places for the species *Acacia dealbata* will potentially increase in the years 2020 and 2050, in both climatic scenarios (Vicente et al., 2013). For the year 2020, the trends of species distribution were different within and outside protected areas in both climatic scenarios, probably due to the fact that protected areas geographically overlaps with areas of high elevation and lack f of dispersal corridors (Vicente et al., 2013). For the year 2050, the trends observed were the same inside and outside protected areas probably likely because the environmental changes predicted for the future will increase the distribution of the species inside the protected areas. The species dynamics for the time periods 2000-2050 and 2020-2050, in the climatic scenario A1, are similar within and outside protected areas for all response types, except for the response "colonization". Considering B2 climatic scenario, predicted species dynamics for the time period 2000-2050 are similar inside and outside the protected areas. For the time period 2020-2050, the predicted species dynamics were similar considering the response types "no

change" and "deteorization of the conditions" and different for the responses "improvement of the conditions", "extinction" and "colonization". This way, we realize that the "colonization" dynamic will prevail although we also ascertain the "deteorization of conditions" and "extinction" dynamics, mostly in eastern and northern areas (especially in the protected areas located in the Superior Douro).

Conflicts with protected areas currently mostly take place in the western part of the studied region due to the areas of introduction being located along the coastline, and the spatial configuration of the dispersal corridors in the region (Vicente et al., 2013). This is consistent with scientific literature that recognizes the importance of dispersal corridors for the unintentional transport of alien invasive species, specially the roads (Saumel and Kowarik, 2010, González-Muñoz et al., 2012). This way, *Acacia dealbata* can probably be even more problematic species in the future, promoted by longer residence time and its ability to colonise different habitat types (Vicente et al., 2013).

4.3. Effectiveness of CPMs for predicting conflicts between plant invaders and protected areas

The use of species distribution modelling has grown in the last two decades (Rodríguez-Rey et al., 2013) and has been used in a wide range of applications orientated to evaluation and planning conservation of valuable elements of biodiversity and ecosystems, as well as to forecast biodiversity responses to environmental changes (Vicente et al., 2011). SDM's can be uses in various applications like advice to various levels of government and associated agencies on the likelihood of the presence of habitat, predicting habitat outside the known range of a species for threatened species survey, land-use planning, translocations and scenario planning, designing corridors for biodiversity conservation and modelling invasive species and species that are not at equilibrium (Liu et al., 2013).

CPM's can be particularly important in the study of biological invasions, predicting when and where invasions will occur (Vicente et al., 2013). The combined models allowed the prediction of a wider variety of potential species responses, providing more informative projections of species distributions and dynamics than traditional, non-combined models. This models forecast intermediate dynamics between colonization and extinction, recognizing the areas where environmental changes can occur but the occurrence status of the species may not the affected (Vicente et al., 2011). Combined predictive models can discriminate local and regional environmental variables effects and importance on species potential distributions, which can be important in many conservation and management issues (Vicente et al., 2013).

In this study, it was possible to address that climate played a determinate role in constrain of the *Acacia dealbata* potential distribution in the study area. This could be verified due to the spatial distribution patterns of the partial regional model (climatic predictors) were similar to the spatial pattern of distribution obtained in the final combined model. These results are consistent with the theory that the invasive potential of the species is being enhanced by global climate change, which increases the areas susceptible to colonization (Lorenzo et al., 2010). It is also possible to observe the influence of local and regional variables on the maps of spatial predictions of the species, where the areas of environmental suitability correspond mostly with low altitude, where the temperatures are higher. This is consistent with the theory that a decrease of invasive plants is observe with increasing altitude (Pysek et al*.,* 2012), although Becker et al*.,* 2005 suggests that many species, particularly those previously restricted to low or intermediate altitudes, have advanced their altitudinal limits over the past few decades. Ecological and biogeographical theories predicted that species distributions are determined by processes acting at multiple spatial and temporal scales (Vicente et al., 2011), in which climate determine species distribution at border spatial scales and land use and soil properties at local scale (Vicente et al., 2011). Discriminating local from regional effects of environmental factors on species distribution is important in many conservation and management issues (Vicente et al., 2013). For example, it is possible to locally influence environmental conditions through planning and management (e. g. land uses policies) and constrain invasive species expansion towards areas of high protection value but it is not possible to control regional effects (e.g. climate Vicente et al., 2013).

Combined predictive models can forecast the potential distribution of a species (e.g. invasive) under future environmental conditions, allowing the anticipation of measures for management and conservation of protected areas. Combined predictive models can also allow the identification of areas where the invader species will be more problematic or spatially where more suitable conditions for the species will coincide with protected areas (Vicente et al., 2013).

Finally, these models can support the development of optimization monitoring networks, aimed at preventing new biological invasions.

4.4. CPMs, connectivity of invader distributions, and protected areas

Connectivity analysis is useful in ecology research (Vicente et al., 2013), and it elucidates patterns, thereby providing important insights into the processes that drive plant invasions in habitats (Minor et al., 2009). Surfaces with high connectivity represent potential dispersal corridors and areas with high connectivity will be the ones where management may be less effective, as local control measures may be counteracted by immigration and propagule pressure from neighbouring invaded areas (Vicente et al., 2013).

In this study, we used a connectivity index based on the nearest neighbours that is considered a crude connectivity metric, although simpler to obtain. However, combined predictive models projections allowed to weight the potential suitable areas for the *Acacia dealbata* species by evaluating and quantification of the availability of both regional conditions and suitable local habitat.

Areas with high connectivity of the species will be the ones with less effective management, as local control measures may be counteracted and propagule pressure from neighboring invaded areas (Vicente *el al.,* 2013). For the test species, connectivity was predicted to increase in the future. Although connectivity of suitable areas for the species inside protected areas is lower than across the full areas (because protected areas coincide with areas of high elevation) the changes in environmental conditions predicted for the future may change the connectivity of the species (Vicente et al., 2013). In conclusion, the connectivity analysis showed that protected areas will potentially suffer a high pressure from *Acacia dealbata* under future environmental conditions.

5. Conclusions

Using a combined predictive modeling approach to forecast the current and future distribution of *Acacia dealbata* in Northwest Iberian Peninsula, as well as assessing its current and future conflicts with protected areas, we conclude that:

- Models predict that the area with suitable conditions of climate (regional) and habitat/landscape (local) will increase in the future, if the climate change scenarios are confirmed;
- The species currently invades nature reserves in the study area, and models predict that the percentage of occupancy will increase in the future; and
- Connectivity analysis showed that changes in future environment may increase the connectivity of *Acacia dealbata* distribution in the test area.

From an applied perspective, our results suggest that:

- Spatial predictions of the models provide an important basis for the efficient control of this invasive species in invaded areas and for the early detection of new areas of invasion;
- CMP projections can support measures to prevent invasions in this region and promote cross-border management of invasions; and
- Connectivity analyses are important in invasion ecology, as they can contribute to prioritize management actions considering regional dispersal corridors and the probability of recolonization after local control measures have been undertaken.

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Annex

Annex 1: Environmental predictors select to apply the Spearman rank correlation coefficient.

Variable type	Predictors	Description	References
Climate	ANT	Annual Mean Temperature	Broennimann and Guisan, 2008
	AP	Annual Precipitation	Barrows and Murphy- Maiscal, 2012
	I	Isothermality	Castro-Díez et al., 2011
	MDR	Mean Diurnal Range	Crossman and Cooke, 2011
	MTCM	Min Temperature of Coldest Month	Evangelista et al., 2011
	MTCQ	Min Temperature of Coldest Qaurter	Férnandez et al., 2012 ; Fischer et al.,
	MTDQ	Mean Temperature of Driest Quarter	Fischer et al., 2011
	MTWM	Max Temperature of Warmest Month	Gaikwad et al., 2011; Gallien et al., 2012
	MTWaQ	Mean Temperature of Warmest Quarter	Godoy et al., 2008
	MTWeQ	Mean Temperature of Wettest Quarter	Ohlemuller et al., 2006; Pino et al., 2005
	PCQ	Precipitation of Coldest Quarter	Trethowan et al., 2011; Thuiller et al. 2005
	PDM	Precipitation of Driest Month	Vicente et al., 2010; Vicente et al., 2011
	PDQ	Precipitation of Driest Quarter	Vicente et al., 2013a; Vicente et al., 2013b
	PS	Precipitation Seasonality	Vicente et al., 2013c; Vicente et al., 2013d
	PWM	Precipitation of Wettest Month	Vicente et al., 2013ª
	PWaQ	Precipitation of Warmest Quarter	
	PWeQ	Precipitation of Wettest Quarter	
	TAR	Temperature Annual Range	
	TS	Temperature Seasonality	
Land cover (Landscape composition)	pArL	% cover of arable land (per 1 km²)	
	pArS	% cover of artificial stands (per 1 km²)	Chytry et al., 2008
	pBiFo	% cover of broad-leaf forest (per 1 km²)	http://www.europe-aliens.org
	pCoFo	% cover of conifer forest (per 1 km²)	g/pdf/Acacia_dealbata.pdf
	pHAa	% cover of heterogeneous agricultural areas (per 1 km²)	Ohlemuller et al., 2006
	pMiFo	% cover of mix forest (per 1 km²)	Pino et al., 2005
	pOs	% cover of open spacie with small or no vegetation (per 1 km²)	Vicente et al., 2013a
	pPas	% cover of pastures land (per 1 km²)	Vicente et al., 2013d
	pPeCr	% cover of permanent crops (per 1 km²)	
	pSHv	% cover of scrub and/or herbaceous vegetation associations (per 1 km²)	
	Pwa	% cover of water (per 1 km²)	
Transport and hydrographic network	DensRail	Density of local rail network	Catford et al. 2011
	DensRiv	Density of local hydrographic network	Vicente et al., 2010; Vicente et al., 2011
	DensRoad	Density of local road network	Vicente et al., 2013a; Vicente et al., 2013b
	DistRail	Distance to rails	Vicente et al., 2013c; Vicente et al., 2013d
	DistRiv	Distance to rivers	
	DistRoad	Distance to roads	
Soil	pCamb	% of cambissoils (per 1 km²)	

	pFluvi	% of fluvissoils (per 1 km²)	
	pHist	% of histossoils (per 1 km²)	
	pLit	% of lithossoils (per 1 km²)	
	pLuvi	% of luvissoils (per 1 km²)	Vicente et al., 2013a
	pPodz	% of podzossoils (per 1 km²)	Vicente et al., 2013b
	pRank	% of rankerssoils (per 1 km²)	
	pRego	% of regossoils (per 1 km²)	
Lanscape Structure	Ed	Edge Density	
	GPP	Mean gross annual primary productivity	Lomba et al., 2010
	MPAR	Mean perimeter-area ratio	Vicente et al., 2010
	MPFD	Mean patch fractal dimensions	Vicente et al., 2013a; Vicente et al., 2013b
	MPS	Mean patch size	Vicente et al., 2013c; Vicente et al., 2013d
	MSI	Mean shape index	Vicente et al., 2013ª
	NumP	Number of patches	
	PSSD	Patch size standart deviation	
	TE	Total Edge	