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Species Distribution Modelling under Climate Change Scenarios for Maritime Pine (*Pinus pinaster* Aiton) in Portugal

Cristina Alegria [1,2,*], Alice M. Almeida [1], Natália Roque [1,2,3], Paulo Fernandez [1,4] and Maria Margarida Ribeiro [1,2,5]

1 Instituto Politécnico de Castelo Branco, 6000-084 Castelo Branco, Portugal
2 CERNAS-IPCB—Pólo de Castelo Branco do Centro de Estudos de Recursos Naturais, Ambiente e Sociedade, Instituto Politécnico de Castelo Branco, Unidade de Investigação e Desenvolvimento, 6000-084 Castelo Branco, Portugal
3 QRural—Qualidade de Vida no Mundo Rural, Instituto Politécnico de Castelo, Unidade de Investigação e Desenvolvimento, 6000-084 Castelo Branco, Portugal
4 MED&CHANGE—Mediterranean Institute for Agriculture, Environment and Development & CHANGE–Global Change and Sustainability Institute, Universidade de Évora, 7006-554 Évora, Portugal
5 CEF—Forest Research Centre, School of Agriculture, University of Lisbon, 1349-017 Lisbon, Portugal
* Correspondence: crisalegria@ipcb.pt

Abstract: To date, a variety of species potential distribution mapping approaches have been used, and the agreement in maps produced with different methodological approaches should be assessed. The aims of this study were: (1) to model Maritime pine potential distributions for the present and for the future under two climate change scenarios using the machine learning Maximum Entropy algorithm (MaxEnt); (2) to update the species ecological envelope maps using the same environmental data set and climate change scenarios; and (3) to perform an agreement analysis for the species distribution maps produced with both methodological approaches. The species distribution maps produced by each of the methodological approaches under study were reclassified into presence–absence binary maps of species to perform the agreement analysis. The results showed that the MaxEnt-predicted map for the present matched well the species' current distribution, but the species ecological envelope map, also for the present, was closer to the species' empiric potential distribution. Climate change impacts on the species' future distributions maps using the MaxEnt were moderate, but areas were relocated. The 47.3% suitability area (regular-medium-high), in the present, increased in future climate change scenarios to 48.7%–48.3%. Conversely, the impacts in species ecological envelopes maps were higher and with greater future losses than the latter. The 76.5% suitability area (regular-favourable-optimum), in the present, decreased in future climate change scenarios to 58.2%–51.6%. The two approaches combination resulted in a 44% concordance for the species occupancy in the present, decreasing around 30%–35% in the future under the climate change scenarios. Both methodologies proved to be complementary to set species' best suitability areas, which are key as support decision tools for planning afforestation and forest management to attain fire-resilient landscapes, enhanced forest ecosystems biodiversity, functionality and productivity.

Keywords: species distribution modelling; species ecological envelope; MaxEnt software; RCP 4.5 to RCP 8.5 climate change scenarios; concordance

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1. Introduction

Forest species geographic distribution maps have been widely produced as they are a key tool for conservation, afforestation planning and forest management [1]. More recently, concerns about the impact of climate change on species distributions have also urged predicting species' geographic distributions for the future [2–8]. Over time, several approaches have been used to produce species geographic distribution maps, from ecological and bioclimatic empiric-based to the use of spatial statistical modelling techniques (e.g., Species Distribution Models–SDMs) [1,9,10].

Before the mid-1980s, the SDMs were constrained by the lack of reliable interpolated climatic data on large spatial scales (e.g., species occurrence sites were often distant from meteorological stations) [1]. In the late 1990s and early 2000s, the release of global climatic surfaces, such as the WorldClim database [11], provided the environmental data most used in SDMs to predict present species' geographic distributions. To forecast the impact of climate change on species' geographic distributions, the future Global Climate Model (GCM) environmental data outputs have been used. Future projections are generally based on a specific emission scenario, which represents a hypothetical image of the possible trend in greenhouse gas emissions [1]. Alternative pathways for environmental, socio-economic, technological, and demographic development are also included. Currently, the most used projections have been generated by the IPCC 5th Assessment Report (AR5). Emission scenarios are represented by "Representative Concentration Pathways" (RCPs) with four possibilities trajectories of increasing severity (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5) [1].

The SDMs simulate species suitability distribution by relating occurrences data with environmental variables and generating maps that predict past, present or future species distributions [1,3,12–14]. Several modelling statistical techniques have been used in SDMs to date, firstly including species presence-only data and later handling a higher amount of information and including both species presence and absence data [1]. The SDMs are usually obtained by testing a set of candidate models using various statistical techniques (e.g., classical regression (CR), generalised linear models (GLM), and machine learning (ML) algorithms) to select the best-performing model [3,6].

The SDMs based on ML algorithms are complex models, data-driven, typically using a large number of environmental variables in the modelling process. They are based on the assumption that the environmental conditions where the species exist indicate that they are suitable for the species. For instance, the ML Maximum Entropy (MaxEnt) algorithm has been extensively used to produce SDMs [5,7,13–15]. The MaxEnt algorithm uses species' presence data and additional information about the external environment where the species is located (i.e., the background) that is automatically obtained during computation through a spatial random sampling procedure. The MaxEnt algorithm estimates the maximum probability of the species distribution and compares it with the maximum entropy probability of the entire study area [1]. However, the SDMs have limitations on predicting species distribution outside the range of the data used in the modelling process [5,15].

An advantage of the SDMs, for they are based on spatial statistical modelling techniques, is the selection of explanatory variables and algorithms by using the goodness of "fit" indicator to evaluate the simulated species distribution maps with the best performances [1,6]. Commonly, a consensus model is produced by using the balanced projections obtained with the best algorithms [6]. To obtain the different modelling algorithms' relative accuracy, some indicators were consistently applied: Area Under Curve (AUC) or Receiver Operating Characteristic (ROC), Kappa or Cohen's Kappa coefficient, and the True Skill Statistic (TSS). The first is generated using the AUC curve analysis, and the others are derived from a confusion matrix classification system [1,6].

Currently, the access to big spatial data on environmental variables together with powerful spatial modelling techniques supported by Artificial Intelligence, such as ML algorithms of Classification and Regression Trees (CART), Random Forest (RD), and Maximum Entropy (MaxEnt), and coupled with Geographic Information Systems (GIS), have allowed obtaining SDMs with high performances [1,3,12,13]. Nevertheless, the SDMs predictions are intimately dependent on the species distribution, climate, soil, and land cover datasets, model explanatory variables selection, the choice of the GCM, and the climate scenario used in the modelling process [1,4]. Moreover, most SDMs make use of 'realised niches', often deriving these from the current spatial distributions of forest species. This has limitations, as SDMs are not able to consider the relationships between species and other biotic components, e.g., pests and diseases. Additionally, most SDMs forest studies under climate change ignore those issues, thus determining a species' climatic requirements only from their natural distributions and applying climate change scenarios [1,10]. Indeed, one should note that the fundamental niche represents the entire habitat suitable for a considered species where it can grow and reproduce in the absence of competitors. The realised niche is defined as the smaller part of the expressed fundamental niche as a result of the inter and intra-specific competition for available resources in a specific environment, i.e., the geographic zone [1,10].

Several species' geographic distribution maps are available for forest species in mainland Portugal, obtained by ecological and bioclimatic empiric-based approaches [12,16–26] or modelling techniques (e.g., SDMs) [12–14]. As a result, for the same species, various distribution maps are possible.

Thus, considering the variety of methodological approaches used, assessing their agreement is of utmost importance. Regarding the methodological approach to use, a relevant issue is the comparison between those that require the species' presence data to simulate a species' spatial distribution [12–14], such as the ML MaxEnt algorithm, to other methodologies that are ecologically and empirically-based, such as the species ecological envelope [2,17], that can produce species suitability maps without the need of species presence data.

The ecological envelopes are based on expert knowledge and/or biological information about the species by observational data. They have the advantage of producing species suitability maps by using a limited set of environmental variables without needing species presence data. As a result, they are often simple, more conservative, and may be better at identifying suitable areas for the species [10].

Maritime pine ecological envelopes were produced for mainland Portugal, for the present and future under climate change scenarios, in a previous study [2]. Afterwards, modelling Maritime pine spatial distribution using the ML MaxEnt algorithm approach for comparison purposes became relevant. To our best knowledge, this investigation has not yet been performed.

This study was focused on the species Maritime pine, which forests an area representing 22% of Portuguese forests (713,100 ha) [27]. It provides a significant amount of timber harvested in Portugal as raw material for the wood-based industry [27]. However, there is a concerning issue regarding its sustainability, as over the last 50 years (1965–2015), these specific areas have been decreasing mainly due to the impact of wildfires [27–30]. Currently, future climate change scenarios anticipate an increase in the frequency and severity of wildfires [31] and a broad loss of the species' productive potential [2,12,25,26,32]. So, producing reliable species suitability maps for the present and for the future under climate change scenarios is key for adequate species afforestation planning. Indeed, knowing the best species suitability areas for the present and future under climate change scenarios is paramount for designing fire-resilient landscapes and enhancing forest ecosystems' biodiversity, functionality, and productivity [21].

Consequently, this research's working hypothesis was that the species distribution modelling (SDM by ML MaxEnt algorithm) and the ecological envelope approaches are complementary methodologies. The aims of this study were the following: (1) to model Maritime pine potential distributions for the present and for the future in 2070 under two climate change scenarios (e.g., RCP 4.5 and RCP 8.5) using the MaxEnt; (2) to update the species ecological envelope maps with the same environmental data set and climate change scenarios; and (3) to perform an agreement analysis for the species distribution maps produced with the MaxEnt and the ecological envelopes.

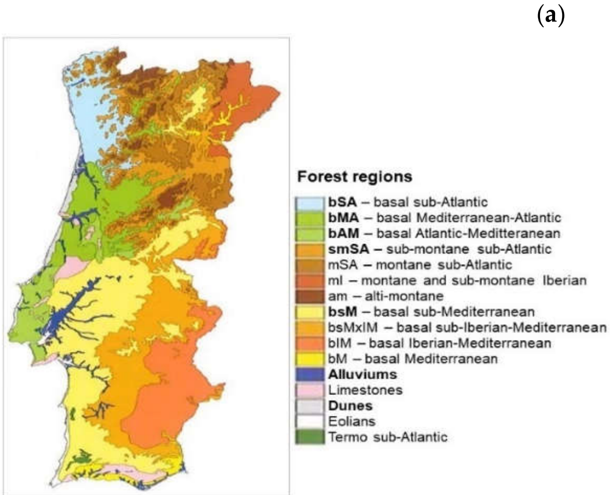
To that end, the species distribution in the present was modelled using as input data the species occurrences data extracted from the land use and land cover (LULC) official map for mainland Portugal in 1995, the bioclimatic variables (1960 and 1990), the elevation data, and the soil data. Afterwards, the species distribution was projected to 2070 under the two climate change scenarios mentioned above. Finally, the species suitability maps obtained by the MaxEnt and by the ecological envelope were compared by performing an agreement analysis.

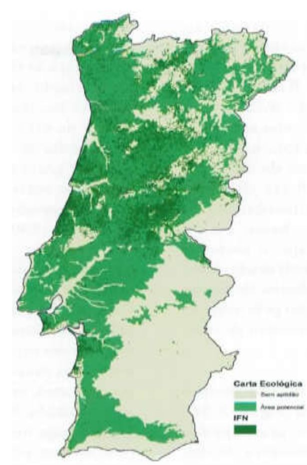
2. Materials and Methods

2.1. Study Area

The study area is mainland Portugal (36.9636° N 9.4944° W and 42.1543° N 6.1892° W), located in the Iberian Peninsula (Figure 1a). The annual temperature ranges from about 7 °C in the northern and central inland highlands to about 18 °C on the south coast. The average annual precipitation has the highest values in the north and northwest regions and the lowest values in the south and inland. The study area includes two climate classifications: (i) Hot-summer Mediterranean in the south and central inland and lower elevations (below 800 m); and (ii) Temperate Mediterranean in the north and northwest region of the country and higher elevations (above 800 m) [33].

(**a**)





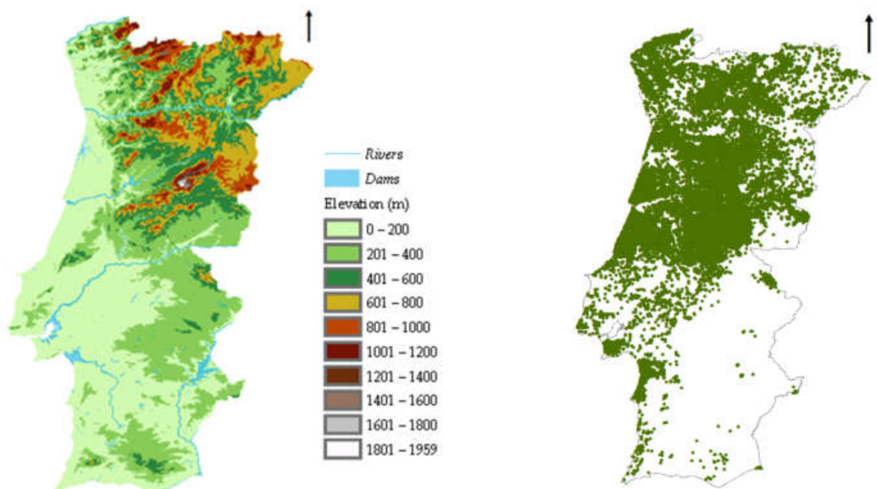
(**b**) (**c**)

Figure 1. Study area: (**a**) Geographic location, (**b**) Forest regions for mainland Portugal [19], and (**c**) Maritime pine potential empirical distribution [25]. Legend: Forest regions of Maritime pine occurrence (in bold)—**bMA**—basal (0–400 m) Mediterranean–Atlantic; **bAM**—basal (0–400 m) Atlantic–Mediterranean; **bsM**—basal (0–400 m) sub-Mediterranean; **bSA**—basa l (0–400 m) Sub-Atlantic; and **smSA**—sub-montane (400–700 m) sub-Atlantic.

The most emblematic species potential distribution map in Portugal is the ecological zoning map published in 1959 [16], wherein species potential geographic distributions were defined according to the following change vectors: (1) one related to the Maritime influence (coastal to inland) versus the Mediterranean influence (north to south); and (2) the other related to elevation (bottom land to mountain areas). In 1982, a map based on a synthetic expression of the ecological zoning map differentiating 11 forest regions in Portugal was published [16,19] (Figure 1b).

Regarding the forest regions map for mainland Portugal [19], it is possible to extract the Maritime pine's empirical potential geographic distribution [25]. This species' climatic optimum is in the following ecological zones: bMA—basal (0–400 m) Mediterranean–Atlantic; bAM—basal (0–400 m) Atlantic–Mediterranean; bsM—basal (0–400 m) sub-Mediterranean; bSA—basal (0–400 m) Sub-Atlantic; and smSA—sub-montane (400–700 m) sub-Atlantic (Figure 1b).

Indeed, current Maritime pine distribution in Portugal corresponds to a coastal strip penetrating in the north and centre inland up to elevations of 700–900 m, preferably in the southwest to north-facing slopes where the Atlantic influence is still felt (Figure 2a,b). The climatic optimum corresponds broadly to an average temperature between 13 and 15 °C, an average temperature of the coldest month between 8 and 10 °C, and an average annual precipitation between 500 mm and 1200–1400 mm. Regarding elevation, basal regions (0–400 m) are the most favourable. The species has severe limitations to growth above 800 m due to wind and snow and has increased susceptibility to pests and diseases [19]. The species does not grow well in intense and prolonged colds and snow. As a pioneer species, it grows well in poor soil with light textures, preferably siliceous [34,35].



(**a**) (**b**)

Figure 2. Study area: (**a**) Elevation; and (**b**) Maritime pine occurrences (green dots) extracted from COS1995.

2.2. Data

2.2.1. Species Occurrence Data

The LULC in 1995, named COS1995 [36], was used to extract the Maritime pine's occurrences (Figure 2b). The COS1995 was available through Web Feature Services (WFS) [37]. The COS1995 map at 1:25000 scale, corresponding to a minimum cartographic unit of one ha, and a five-level hierarchical classification with 89 classes segmentation in the most detailed level allowed the extraction of the species occurrences data. The Maritime pine occurrences data was extracted from the COS1995 class "pure maritime pine stands". One occurrence was extracted per grid cell of ≈1 km^2, consistent with the environment variables spatial resolution, resulting in a final set of 19,272 records (Figure 2b) represented as latitude/longitude coordinates in the WGS84 coordinate reference system (EPSG:4326), the coordinate system used throughout this work.

2.2.2. Environmental Data

The Maritime pine potential distributions for the present and future climate change scenarios were predicted using three types of environmental variables: bioclimatic variables (temperature and precipitation-related variables), topographic-related variables (elevation) (Table 1), and soil data (Figure 3 and Table 2).

The bioclimatic variables and the elevation data were downloaded from WorldClim v1.4 with a resolution of 30 arc seconds (≈1 km) [11]. For the present, 19 bioclimatic variables generated with data collected during the period between 1960 and 1990 were downloaded. The projected bioclimatic variables were also downloaded considering Phase 5 of the Coupled Model Intercomparison Project (CMIP5) General Circulation Model CCSM4 for the year 2070 (average from 2060 to 2080) and the Representation Concentration Pathways 4.5 (RCP 4.5) and 8.5 (RCP 8.5), moderate and high emissions scenarios [38], respectively as they cover a wide range of anthropogenic driving [11] (Table 1). The soil data was derived from the ESDBv2 Raster Library in grid cell ≈1 km^2 [39–41].

The bioclimatic variables followed the original WorldClim symbology, wherein the first variables from *BIO1* to *BIO11* are temperature-related variables and variables from *BIO12* to *BIO19* are precipitation-related variables (Table 1). The topographic-related variable used was elevation (*E*) (Table 1). The soil-related variable used the soil codes (*WRBFU*) according to the international classification system (Figure 3 and Table 2).

Table 1. Summary statistics for bioclimatic and elevation variables for the study area and species occurrences.

		Study Area				**Species Occurrences**			
Symbol	**Variable**	**Min**	**Max**	**Mean**	**Std**	**Min**	**Max**	**Mean**	**Std**
BIO1	Annual mean temperature (°C)	5.9	17.6	15.0	1.8	8.6	17.6	14.3	1.5
BIO2	Mean diurnal range (°C)	5.2	11.7	9.5	1.0	5.6	11.3	9.2	0.9
BIO3	Isothermality (%)	31.0	50.0	39.8	2.7	31.0	50.0	39.8	2.7
BIO4	Temperature seasonality (%)	2596.0	6118.0	4860.8	721.2	2788.0	6116.0	4778.2	747.2
BIO5	Max. temperature of the warmest month (°C)	19.4	34.0	28.6	2.5	21.5	32.5	27.5	2.1
BIO6	Min. temperature of the coldest month (°C)	−2.9	9.2	5.0	2.3	−1.5	8.8	4.5	2.0
BIO7	Temperature annual range (°C)	12.2	29.3	23.5	2.9	13.4	28.8	23.0	2.9
BIO8	Mean temperature of the wettest quarter (°C)	0.1	13.8	9.5	2.5	2.6	13.4	8.7	2.2
BIO9	Mean temperature of the driest quarter (°C)	13.3	24.9	21.2	1.7	15.8	24.2	20.5	1.3
BIO10	Mean temperature of the warmest quarter (°C)	13.3	25.0	21.4	1.8	15.9	24.3	20.6	1.4
BIO11	Mean temperature of the coldest quarter (°C)	1.0	131.0	89.9	22.8	2.6	12.7	8.4	2.0
BIO12	Annual precipitation (mm)	459.0	1798.0	844.8	270.4	475.0	1730.0	1022.2	209.4
BIO13	Precipitation of the wettest month (mm)	64.0	272.0	122.1	38.5	65.0	270.0	148.4	31.0
BIO14	Precipitation of the driest month (mm)	0.0	37.0	8.1	5.8	0.0	32.0	10.7	4.4
BIO15	Precipitation seasonality (%)	39.0	72.0	56.3	5.4	39.0	71.0	54.7	3.4
BIO16	Precipitation of the wettest quarter (mm)	180.0	719.0	346.9	102.8	180.0	711.0	415.3	80.8
BIO17	Precipitation of the driest quarter (mm)	13.0	157.0	52.1	25.5	13.0	141.0	66.2	18.8
BIO18	Precipitation of the warmest quarter (mm)	15.0	161.0	55.2	27.7	16.0	147.0	70.2	21.2
BIO19	Precipitation of the coldest quarter (mm)	168.0	719.0	342.5	104.5	168.0	711.0	412.6	82.1
E	Elevation (m)	0.0	1959.0	322.7	263.7	2.0	1446.0	380.2	262.3

Legend: Min—minimum; Max—maximum; Std—standard deviation.

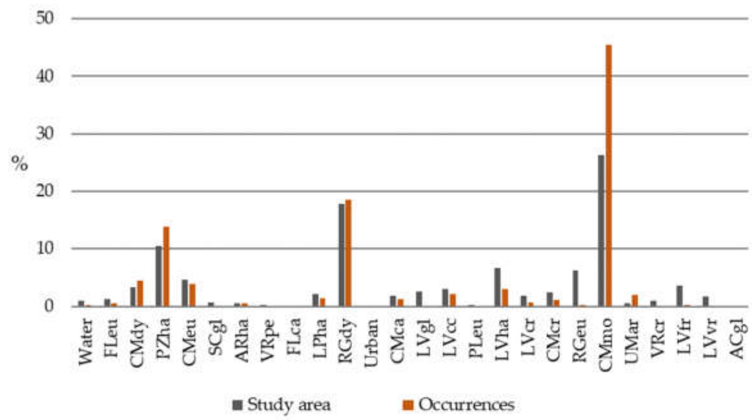


Figure 3. Soil codes (*WRBFU*) in the study area and in Maritime pine occurrences.

Table 2. Soil codes (WRBFU) according to the international classification system.

Code	WRFBU	Group	Qualifier	Study Area (%)	Occurrences (%)
2	Water	-	-	0.9	0.3
27	FLeu	Fluvisol	Eutric	1.2	0.6
29	CMdy	Cambisol	Dystric	3.3	4.6
30	PZha	Podzol	Haplic	10.5	13.8
35	CMeu	Cambisol	Eutric	4.6	4.0
54	SCgl	Solonchak	Gleyic	0.6	0.1
59	ARha	Arenosol	Haplic	0.6	0.5
65	VRpe	Vertisol	Pellic	0.2	0.0
67	FLca	Fluvisol	Calcaric	0.0	0.0
72	LPha	Leptosol	Haplic	2.1	1.4
74	RGdy	Regosol	Dystric	17.8	18.5
76	Urban	-	-	0.1	0.0
87	CMca	Cambisol	Calcaric	1.8	1.2
89	LVgl	Luvisol	Gleyic	2.6	0.0
90	LVcc	Luvisol	Calcic	3.1	2.1
91	PLeu	Planosol	Eutric	0.2	0.0
92	LVha	Luvisol	Haplic	6.6	3.1
107	LVcr	Luvisol	Chromic	1.8	0.7
108	CMcr	Cambisol	Chromic	2.4	1.1
109	RGeu	Regosol	Eutric	6.2	0.2
119	CMmo	Cambisol	Mollic	26.3	45.5
124	UMar	Umbrisol	Arenic	0.5	2.0
125	VRcr	Vertisol	Chromic	1.0	0.1
127	LVfr	Luvisol	Ferric	3.7	0.2
129	LVvr	Luvisol	Fluvic	1.6	0.0
130	ACgl	Acrisol	Gleyic	0.0	0.0

2.3. Methods

2.3.1. MaxEnt Modelling Approach

In this study, the MaxEnt software, based on the ML algorithm of Maximum Entropy, was used to simulate Maritime pine potential distributions for the present and for the future (2070) under two climate change scenarios (RCP 4.5 and RCP 8.5) [5,42].

The MaxEnt software allows modelling species potential distribution using presence-only data and a set of environmental variables. To select the best-performing set of variables, three procedures were considered as follows: (1) using the MaxEnt software selection module; (2) using the *virtualspecies* R package [43]; and (3) using the same set of variables that defined the species ecological envelope.

Regarding the first procedure, the MaxEnt model was first fitted using the 21 environmental variables (*BIO1* to *BIO19*, *E*, and *WRBFU*). Secondly, the MaxEnt allowed computing for each variable the respective per cent contribution, the permutation importance, and the Jackknife test results. The best eight variables (*BIO4, BIO10, BIO12, BIO13, BIO16, BIO18, E,* and *WRBFU*) were selected and used to run the MaxEnt model. Lastly, the best seven variables (*BIO4, BIO10, BIO12, BIO13, BIO18, E,* and *WRBFU*) were selected to run the final MaxEnt model.

Moving to the second procedure, from the original set of 21 environmental variables, an exploratory data analysis was performed aiming to discard the most correlated variables, using the function *removeCollinearity* from the R package *virtualspecies*. The collinearity among the 21 environmental variables was verified by using Pearson's correlation coefficient, and the multicollinearity cut-off = 0.6 was used to select the subset of non-collinear variables. The final set included the best six uncorrelated variables (*BIO3, BIO4, BIO5, BIO8, BIO15,* and *WRBFU*).

Finally, the third procedure considered the ecological envelope variables (*BIO5, BIO6, BIO7, BIO12, E,* and *WRBFU*) [12] to run the MaxEnt model.

Afterwards, the species' potential distribution was modelled using Maritime pine occurrences data and the correspondent set of selected explanatory variables obtained by the three above-referenced procedures. The MaxEnt parameter's settings included removing duplicate presence records, writing plot data, using a regularisation multiplier of 1, a maximum number of iterations of 1500, and 50,000 background points. The considered output was the Cloglog, which expresses the suitability of each grid cell [0–1], with the higher values corresponding to a suitable location for the Maritime pine. The remaining parameters were set to default values. The AUC of the ROC was used to assess the model's accuracy. The AUC values range from 0 to 1, with higher values corresponding to a better model's prediction [15,44].

Future models were developed projecting the best species potential distribution for the present to the future (2070) under the two climate change scenarios (RCP 4.5 and RCP 8.5). Present and future species' potential distribution ranges were assessed by analysing the suitability classes and using the correspondent presence–absence maps. Firstly, the potential distribution maps for all scenarios were reclassified into five suitability classes using an equal interval percentage approach: (1) non-suitable area [0–0.2[, (2) low-suitability area [0.2–0.4[, (3) regular-suitability area [0.4–0.6[, (4) medium-suitability area [0.6–0.8[, and (5) high-suitability area [0.8–1.0]. Secondly, to define the species' suitable and unsuitable Maritime pine habitats, the potential distribution maps were reclassified into binary presence–absence maps using the 10th percentile training presence "Cloglog" threshold. This threshold sets the value that excludes 10% of the areas with the lowest predicted values and constitutes a stricter criterion leading to a smaller geographical prediction [45] than other ones. The values under the threshold were set to 0, representing absences (unsuitable areas) and the values over the threshold were set to 1, representing presences (suitable areas).

2.3.2. Ecological Envelope Approach

In a previous study, the Maritime pine ecological envelope [2] was based on the methodology published in the Portuguese Regional Forest Management Plans in 2005 [17]. The Maritime pine ecological envelope [2] was defined by five variables: minimum temperature in January (°C), maximum temperature in August (°C), annual precipitation (mm), elevation (m) and lithology, and the thresholds published in Regional Forest Management Plans in 2005 [17].

In a subsequent study, Maritime pine distribution for the present was modelled using the ML Random Forest algorithm [12] with similar variables to the ecological envelope and with a set of variables selected by its relative importance. Still, the model using ecological envelope similar variables as regressor variables resulted in a better fitting efficiency proving how robust these variables are in explaining current species distribution. Although, the variables *BIO6* and *BIO5* performed better than the previous variables' minimum temperature in January (°C) and maximum temperature in August (°C). In that study, Maritime pine ecological envelope thresholds were also validated using a ML CART algorithm. The new thresholds were quite close to the ones published in Portuguese Regional Forest Management Plans in 2005 [17]. Regarding the lithology constrain (difference of limestone), soils different to Luvisols calcic, Cambisols calcarean, and Fluvisols calcic were considered [12]

As a result, the selected raster input layers used to define the species' ecological envelope were the following variables (Table 3): *BIO5*—maximum temperature of the hottest month (°C), *BIO6*—minimum temperature of the coldest month (°C), *BIO7*—temperature annual range (°C), *BIO12*—annual precipitation (mm), *E*—elevation (m), and *WRBFU*—soil codes.

Table 3. Maritime pine ecological envelopes variables and thresholds [12].

Temperature Limits (°C)	Temperature Range (°C)	Precipitation (mm)	Elevation (m)	Soil
BIO5 < 29.8 *BIO6* > 2.6	*BIO7* ≤ 25.1	*BIO12* > 821	*E* < 731	Soils different of Limestone (LVcc, CMca, and FLca)

In this study, the Maritime pine ecological envelopes were updated using the variables and the thresholds in Table 2 [12]. Firstly, these variables, in the present and projected to the future (2070) under the two climate change scenarios (RCP 4.5 and RCP 8.5), were reclassified by the Boolean method using the thresholds in Table 2 to obtain the correspondent binary maps (0—not suitable, 1—suitable). Secondly, the species ecological envelope for the present and for the future was obtained by map algebra as follows: (*BIO5* × *BIO6*) + *BIO7* + *BIO12* + *E* + *WRBFU.* As a result, a map of five suitability classes was obtained as follows: (1) unsuitable, (2) marginal, (3) regular, (4) favourable, and (5) optimum.

Finally, the species binary presence–absence maps were obtained by reclassifying these five suitability classes as follows: 0—not suitable by the aggregation of unsuitable and marginal suitability classes; and 1—suitable by the aggregation of regular, favourable, and optimum suitability classes.

2.3.3. Methodological Approaches Agreement Analysis

For an effective comparison of the Maritime pine potential distribution maps obtained by the two methodological approaches, for the present and for the future (2070) under the two climate change scenarios (RCP 4.5 and RCP 8.5), the correspondent derived species binary presence–absence distribution maps were used.

The differences between species potential distribution maps obtained by the two methodological approaches were compared to determine the agreement area using the following procedures: (1) Cohen's Kappa coefficient derived from a confusion matrix classification system; and (2) the ArcGIS Combine tool (Spatial Analyst).

Cohen's Kappa coefficient [46] is an agreement measure for qualitative classes and minimises the impact of chance on classifications. Cohen's Kappa coefficient (Kappa) approach is widely used and was integrated into the ArcGIS software package.

To evaluate the Kappa coefficient, a random sampling of 1000 points was used to produce an error matrix. This matrix was obtained by comparing the species distribution maps by the MaxEnt and the ecological envelope methodological approaches [47]. The Kappa values and interpretation used are expressed in Table 4 [46].

Table 4. Kappa values and interpretation [46].

Kappa Value	Interpretation
Below 0.00	Poor
0.00–0.20	Slight
0.21–0.40	Fair
0.41–0.60	Moderate
0.61–0.80	Substantial
0.81–1.00	Almost perfect

The GIS workflow for the methodological procedures used in this study is presented in Figure 4.

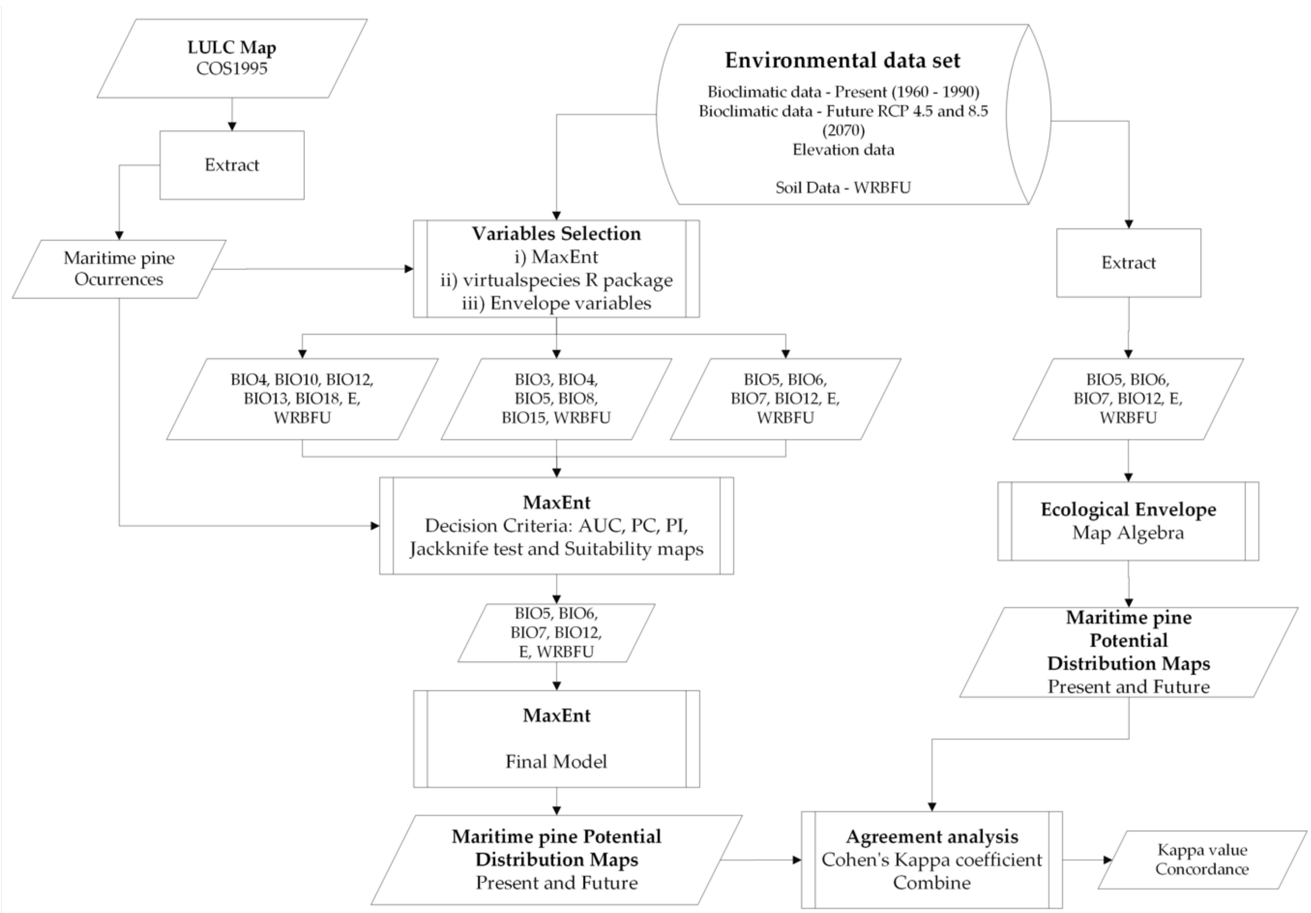


Figure 4. GIS workflow for the species distribution maps production by the two methodological approaches (MaxEnt and ecological envelope) and agreement analysis between them.

3. Results

3.1. MaxEnt Modelling Approach

3.1.1. Explanatory Variables Selection

The best-performing set of variables obtained by each of the three procedures considered are synthesised in Table 5, and the corresponding species potential distribution maps are in Figure 5. Each procedure generated a different set of variables, yet they performed similarly considering the AUC value and the derived maps.

Table 5. Explanatory variables selection by procedure: (1) MaxEnt software selection module; (2) Virtualspecies R package; and (3) Ecological envelope variables.

Procedure	Variables	AUC	10th Percentile *
MaxEnt (7 var)	*BIO4, BIO10, BIO12, BIO13, BIO18, E, WRBFU*	0.74	0.39
Virtualspecies (VS 6 var)	*BIO3, BIO4, BIO5, BIO8, BIO15, WRBFU*	0.73	0.39
Envelope variables (6 var)	*BIO5, BIO6, BIO7, BIO12, E, WRBFU*	0.74	0.40

Legend: * Suitable/Not suitable.

The variable per cent contribution (PC), the permutation importance (PI), and the Jackknife test results for each procedure are shown in Table 6. The variables that contributed most to the Maritime pine distribution were: *BIO12*, *BIO13*, and *WRBFU* (85.5%) for MaxEnt (7 var); *BIO5*, *BIO15*, and *WRBFU* (87.6%) for VS 6 var; *BIO12*, and *WRBFU* (88.1%) for Envelope 6 var.

The Jackknife test results showed that the variable that most decreased the gain when it is omitted (TGw) was: *WRBFU* for both MaxEnt (7 var) and VS 6 var, and *BIO12* for Envelope 6 var. Thus, indicating that these variables contained valid information for the model that other variables did not. The variables that contributed most to the gain (TGo) were: *BIO13* and *BIO12* for MaxEnt (7 var), *WRBFU* for VS 6 var, and *BIO12* for Envelope 6 var showing that these variables by themselves had more useful information to the models. The Jackknife results also showed that the gain of using one variable by itself did not exceed the gain of using all variables, meaning that each variable contributed to improving the model's prediction accuracy. However, some variables had minimal impacts on the models.

Based on the results presented above, and the ecological knowledge and requirements of the species, the Envelope 6 var set was selected as the best model to simulate the Maritime pine's present and future potential distributions.

Table 6. Variables contribution for each variable set selected.

MaxEnt 7 var					VS 6 var					Envelope 6 var				
Var	PC	PI	TGw	TGo	Var	PC	PI	TGw	TGo	Var	PC	PI	TGw	TGo
BIO12	52.49	2.53	0.37	0.27	*BIO5*	34.80	15.57	0.32	0.13	*BIO12*	72.91	59.93	0.32	0.27
BIO13	18.54	29.21	0.37	0.27	*BIO15*	31.30	18.38	0.33	0.13	*WRBFU*	15.22	8.73	0.34	0.21
WRBFU	14.50	12.43	0.34	0.21	*WRBFU*	21.48	13.47	0.31	0.21	*BIO5*	4.35	8.34	0.36	0.12
BIO10	5.35	13.86	0.36	0.15	*BIO4*	6.63	28.29	0.33	0.04	*BIO6*	3.21	12.17	0.36	0.07
BIO18	4.59	20.63	0.36	0.22	*BIO8*	3.90	16.87	0.34	0.09	*BIO7*	2.58	4.77	0.36	0.06
BIO4	3.18	14.98	0.36	0.04	*BIO3*	1.89	7.42	0.34	0.02	*E*	1.73	6.06	0.36	0.06
E	1.35	6.36	0.37	0.06										

Legend: Var—variable; PC—per cent contribution; PI—permutation importance; TGw—regularised training gain without this variable; TGo—regularised training gain with only this variable.

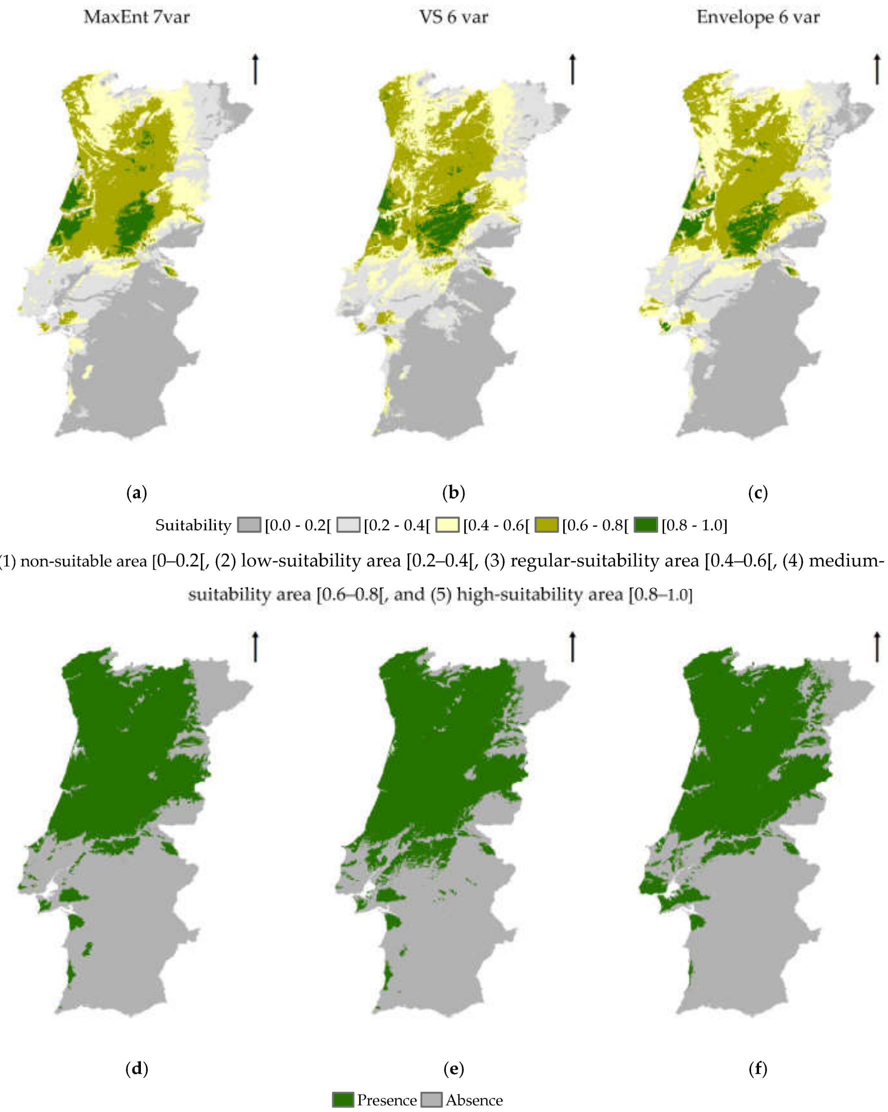
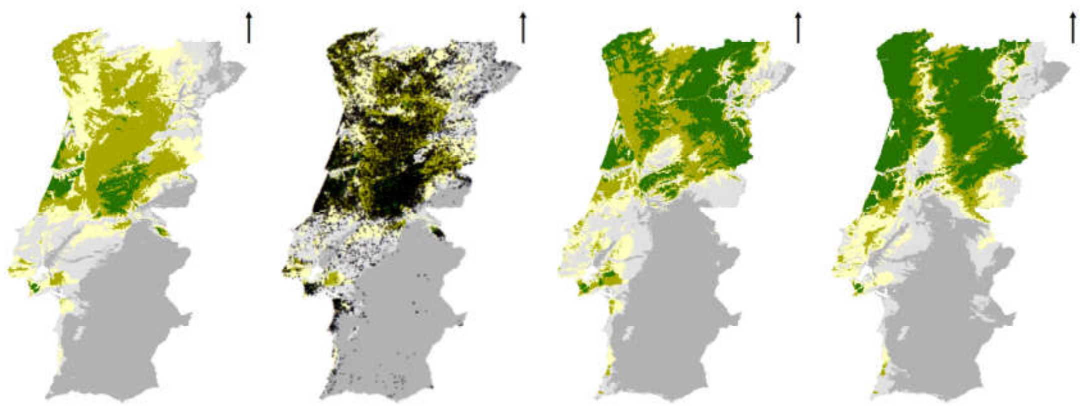


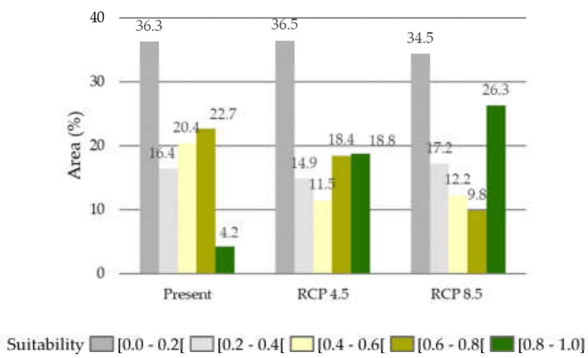
Figure 5. MaxEnt simulation procedures—Maritime pine potential distributions for the present (suitability classes and presence–absence maps): (**a**) MaxEnt software selection module (MaxEnt 7 var); (**b**) Virtualspecies R package (VS 6 var); (**c**) ecological envelope variables (Envelope 6 var); (**d**) presence–absence map (MaxEnt 7 var); (**e**) presence–absence map (VS 6 var); and (**f**) presence–absence map (Envelope 6 var).

3.1.2. MaxEnt Model

Maritime pine potential distributions were modelled by MaxEnt using the six environmental variables of the ecological envelope as explanatory variables. The species distributions simulated by MaxEnt for the present and for the future (2070) under the RCP 4.5 and RCP 8.5 climate change scenarios (Figure 6) showed that: (1) medium-high suitability areas [0.6–0.8[and [0.8–1.0] represented respectively 26.9%, 37.2%, and 45.9%, were mostly located at the north of the country having a good correspondence to the current species distribution; (2) high suitable areas [0.8–1.0[increased from the present to the future (2070), particularly in the RCP 8.5 scenario (respectively, 4.2%, 18.8%, and 26.3%); and (3) regular-medium suitability areas [0.4–0.6[and [0.6–0.8] decreased from the present to the future (2070) (respectively, 43.1%, 29.9%, and 22.0%).



(**a**) (**b**) (**c**) (**d**)



(1) non-suitable area [0–0.2[, (2) low-suitability area [0.2–0.4[, (3) regular-suitability area [0.4–0.6[,

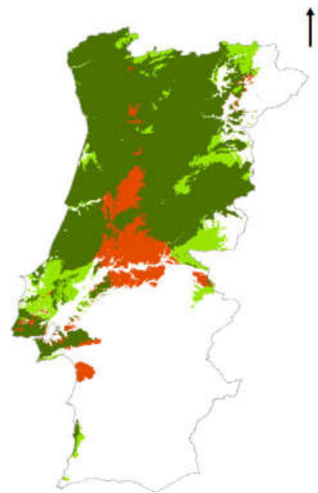
(4) medium-suitability area [0.6–0.8[, and (5) high-suitability area [0.8–1.0]

(**e**)

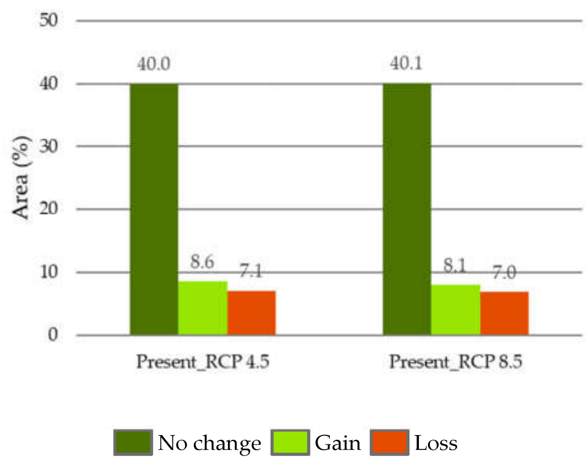
Figure 6. MaxEnt—Maritime pine potential distributions for the present and for the future under climate change scenarios: (**a**) Present; (**b**) Present with the species' occurrences (black dots); (**c**) Future 2070—RCP 4.5; (**d**) Future 2070—RCP 8.5; and (**e**) Suitability areas (%) in the present and for the future (2070) under the RCP 8.5 and RCP 8.5 climate change scenarios.

The changes in the Maritime pine distribution area between the present and future (2070), under the RCP 4.5 and RCP 8.5 climate change scenarios, were similar, with gains of 8.6%–8.1% and losses of 7.1%–7.0%, respectively (Figure 7). However, a change in the species distribution pattern between the present and the future was observed, caused by the appearance of newly suitable areas, which compensated for the losses.

(**a**)



(**b**)

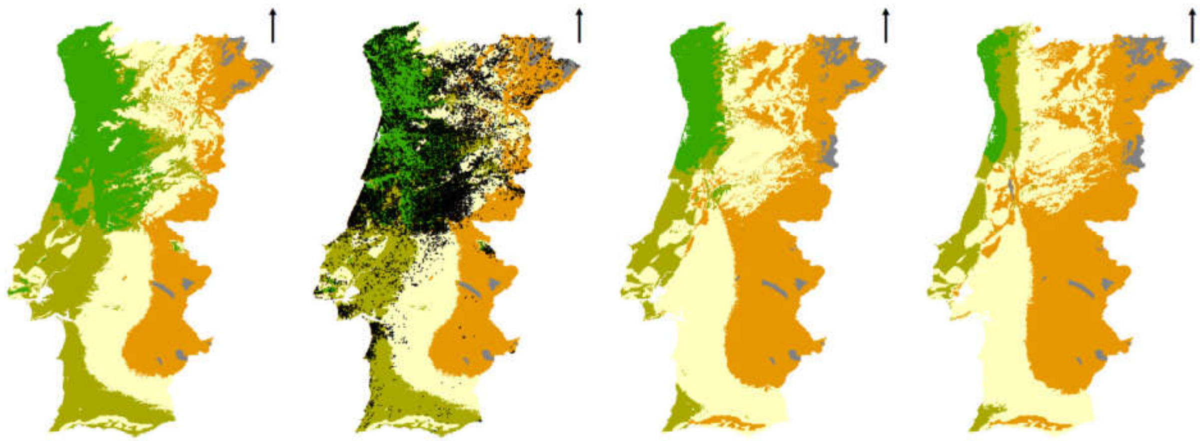


(**c**)

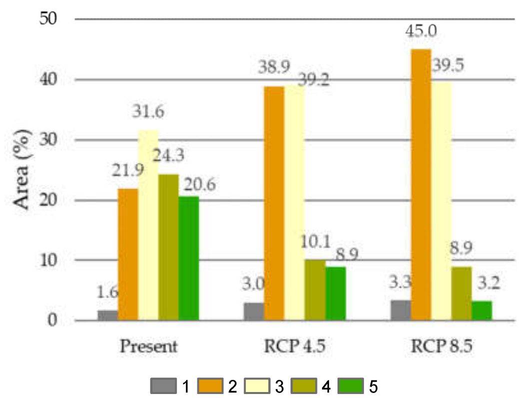
Figure 7. MaxEnt—Maritime pine distribution area changes under the climate change scenarios: (**a**) Present to future 2070 under RCP 4.5 climate change scenario; (**b**) Present to future 2070 under RCP 8.5 climate change scenario; and (**c**) No change, gains, and losses areas (%) between present and future.

3.2. Ecological Envelope Approach

The ecological envelope maps analysis for the present (Figure 8a) showed that: (1) the areas with the greatest suitability (favourable–optimum) were found in a strip along the coast, but a larger area in the north of the country matches with the species' greatest occurrence area (Figure 8b); (2) a decrease from the present to the future 2070, regarding the areas with the highest suitability (favourable–optimum), were observed, with the greatest reduction in the RCP 8.5 climate change scenario (Figure 8e), respectively 44.9%, 19.0% and, 3.2%; and (3) a slight increase regarding the areas with regular suitability were observed, respectively 31.6%, 39.2% and, 39.5% (Figure 8e).



(**a**) (**b**) (**c**) (**d**)



(1) unsuitable, (2) marginal, (3) regular, (4) favourable, and (5) optimum

(**e**)

Figure 8. Ecological envelope—Maritime pine potential distributions for the present and for the future under climate change scenarios: (**a**) Present; (**b**) Present with the species' occurrences (black dots); (**c**) Future 2070—RCP 4.5; (**d**) Future 2070—RCP 8.5; and (**e**) Suitability areas (%) in the present and for the future (2070) under the RCP 8.5 and RCP 8.5 climate change scenarios.

The changes in the Maritime pine distribution area between the present and future (2070), under the RCP 4.5 and RCP 8.5 climate change scenarios, showed only great losses in species suitability area with 18.4% and 24.8%, respectively (Figure 9).

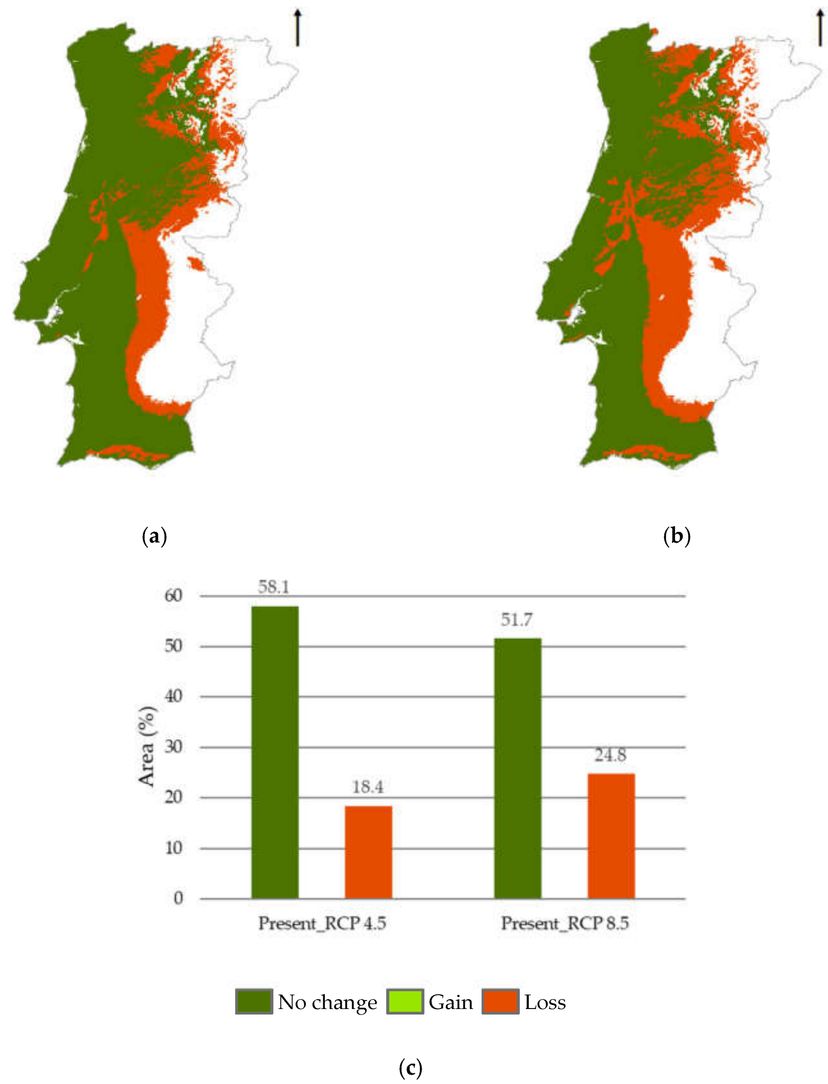


Figure 9. Ecological envelope—Maritime pine distribution area changes under the climate change scenarios: (**a**) Present to future 2070 under RCP 4.5 climate change scenario; (**b**) Present to future 2070 under RCP 8.5 climate change scenario; and (**c**) No change, gains, and losses areas (%) between present and future.

3.3. Methodological Approaches Agreement Analysis

The analysis of the binary presence–absence maps (Figure 10) showed that, in the present, the species presence simulated by MaxEnt was 47.1%, while species presence obtained by the ecological envelope was 76.5%, with a 44.2% concordance (Figure 11). For the future (2070), under the RCP 4.5 and RCP 8.5 climate change scenarios, the presence area by MaxEnt slightly increased conversely to a decrease in the ecological envelope (Figure 10). Thus, the agreement between the two methodological approaches decreased to 34.6% and 31.2% for RCPs 4.5 and 8.5, respectively (Figure 11).

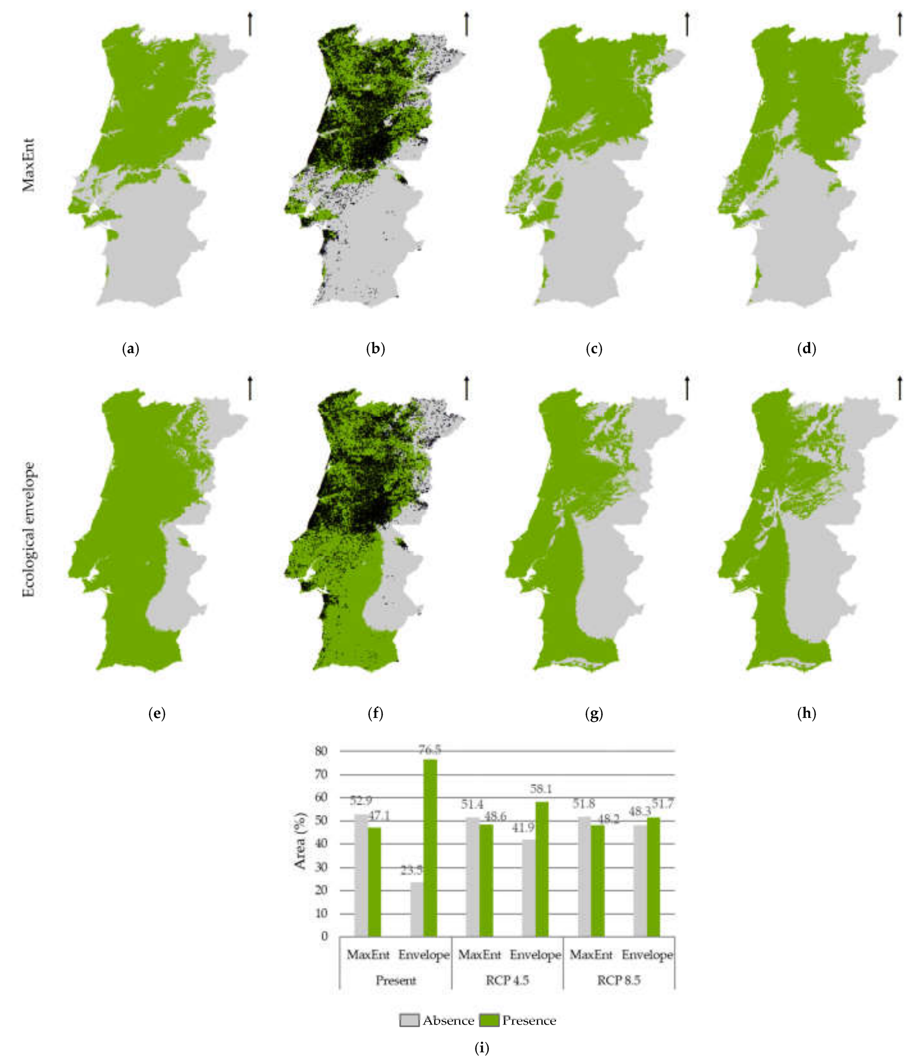
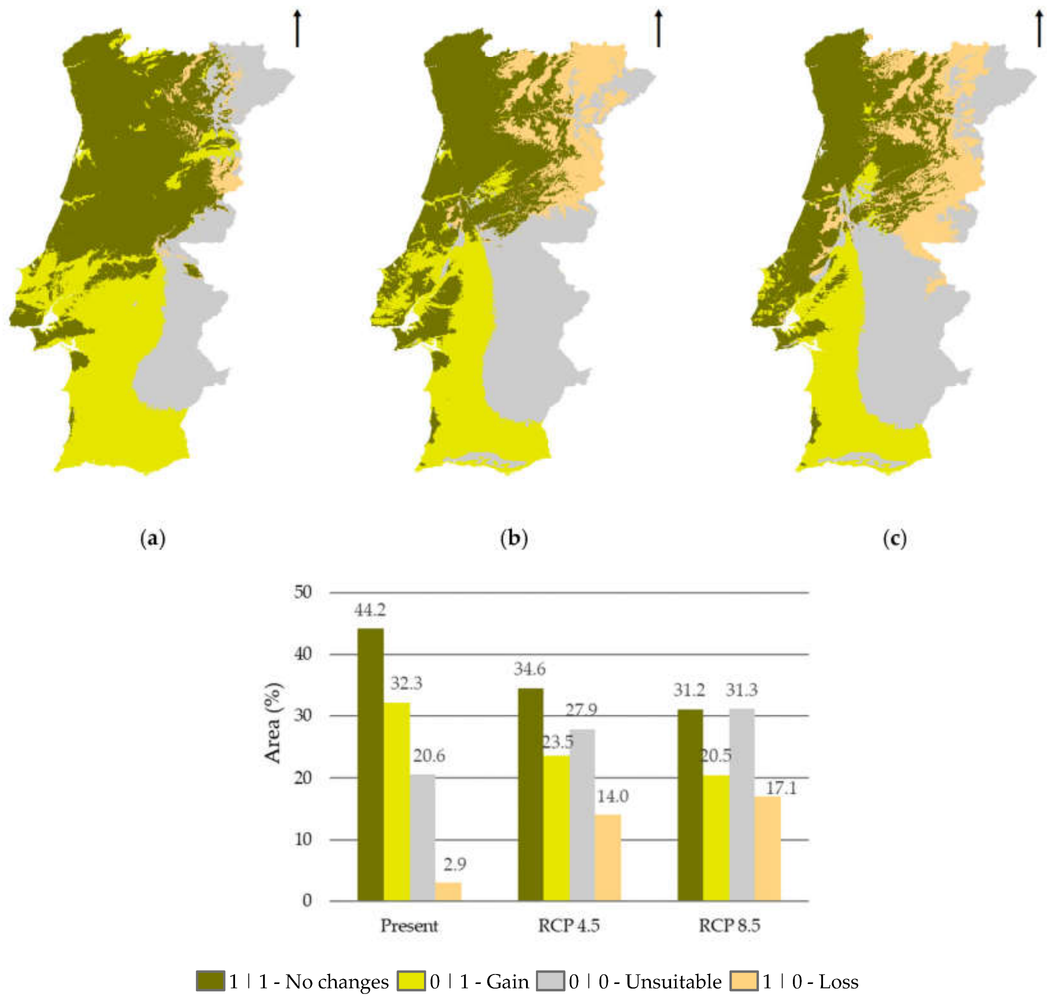


Figure 10. MaxEnt vs. ecological envelope—Maritime pine presence–absence distribution maps (**a**) MaxEnt—Present; (**b**) MaxEnt—Present with the species' occurrences (black dots); (**c**) MaxEnt–Future (2070)—RCP 4.5; (**d**) MaxEnt—Future (2070)—RCP 8.5; (**e**) Ecological envelope—Present; (**f**) Ecological envelope—Present with the species' occurrences (black dots); (**g**) Ecological envelope—Future (2070)—RCP 4.5; (**h**) Ecological envelope—Future (2070)–RCP 8.5; and (**i**) Comparison areas (%) under climate change scenarios.



(**d**)

Figure 11. MaxEnt vs. ecological envelope—Maritime pine's presence–absence maps combined: (**a**) Present; (**b**) Future (2070)—RCP 4.5; (**c**) Future (2070)—RCP 8.5; and (**d**) No changes, gain, unsuitable and loss areas (%).

The results showed that Kappa values (Table 7) decreased with the severity of the climate change scenario, indicating that the agreement between MaxEnt and ecological envelope approaches decreased, as expected, corroborating the results obtained by the previous procedure.

Table 7. Comparison of the MaxEnt and species ecological envelopes methodologies using Kappa index.

Scenario	Kappa Index	Interpretation
Present	0.32	Fair
Future 2070–RCP 4.5	0.26	Fair
Future 2070–RCP 8.5	0.24	Fair

4. Discussion

This study explored two different methodological approaches for species geographic distribution: (1) the MaxEnt modelling that required the species presence data; and (2) the species ecological envelope that was produced without the need for species presence data. Both methodological approaches were essayed for the species Maritime pine in mainland Portugal.

Regarding this study's first aim, to model Maritime pine potential distributions for the present and for the future in 2070 under two climate change scenarios (e.g., RCP 4.5 and RCP 8.5) using the MaxEnt, the results revealed that during the process of selecting the best-performing set of variables for the MaxEnt modelling approach, the species distribution was mainly determined by the variables annual precipitation (*BIO12*) and the soil (*WRBFU*), respectively with 72.9% and 15.2% contributions, summing up to 88.1%. The temperature-related variables (*BIO5*, *BIO6* and *BIO7*) had a 10.2% contribution. The elevation was the variable with the smallest contribution, 1.7%. The species occurs in a wide range of soil types, but mainly in the Cambisols molic (45%), Regosols dystric (18%) and Podzols haplic (14%).

These findings are in accordance with a previous study, wherein a Bayesian ML approach was performed using species presence/absence data extracted from the LULC–COS 1995 to highlight the most influential environmental variables on current species distribution [2]. Indeed, it was found that the distribution of Maritime pine was mainly determined by precipitation-related variables, but the elevation and temperature-related variables were very important in differentiating species productivity [2].

Regarding the MaxEnt best-performing SDM used in this study, an overall accuracy of 74% was achieved. This accuracy is similar to a SDM for the species in Spain (AUC = 73%) obtained by ML using the Random Forest algorithm [3].

For the present, MaxEnt predicted a 47.3% suitability area (e.g., regular-medium-high). For the future (2070) climate change scenarios (RCP 4.5 and RCP 8.5) essayed, the projected temperature-related variables (*BIO5, BIO6*, and *BIO7*) tended to increase, and the precipitation-related variable (*BIO12*) was likely to decrease. As a result, the species potential distribution predicted by MaxEnt for the present and for future climate change scenarios showed no differences in the distribution areas (48.7%–48.3%) since, in the future, the losses are compensated by newly suitable areas' appearance. However, a change in species' potential distribution pattern between the present and the future was predicted.

Moving to the second aim, to update the species' ecological envelope maps with the same environmental data set and climate change scenarios, the results revealed that Maritime pine is adapted to a large range of climatic conditions species, but its vegetative vigour depends on a range of environmental variables. Indeed, comparing the species occurrence environmental variables limits and range with the ecological envelope variables thresholds, it was observed that more than 76% of the occurrences are within the observed limits, but only 49.2% of the occurrences satisfied the thresholds. It must be emphasised that the variables used to define the species' ecological envelope were the same best-performing set of variables selected for MaxEnt modelling, proving how robust these variables are.

For the present, the ecological envelope predicted a 76.5% suitability area (e.g., regular-favourable-optimum). For the future (2070) under the climate change scenarios (RCP 4.5 and RCP 8.5) used, the ecological envelope projections revealed a considerable negative impact over the species distribution areas (58.2%–51.6%), though higher in the RCP 8.5 scenario.

Overall, the species' potential distribution forecasted by the MaxEnt for the present was very similar to the one available by the EPIC WebGIS Portugal, with a spatial resolution of 25 m, an interactive spatial data infrastructure with data visualisation tools that makes available maps at a national scale [24]. Those authors used three types of predictive models to evaluate forest species potential distribution, namely: (i) species distribution models (e.g., ML CART algorithm); (ii) geobotanical models of potential natural vegetation; and iii) typological models of riparian geo-series. Forest species suitability maps were also validated with LULC–COS 2007 data if available for the species [24]. Conversely, the species' potential distribution for the present, obtained by the ecological envelope approach in this study, was very similar to the one obtained by other authors [25], using a process-based model GOTILWA+ and the climate regional model HadRM2-3 dataset.

Regarding the impacts of climate change on Maritime pine's potential distribution obtained in this study, results were consistent with previous studies for mainland Portugal [25,26]. Indeed, a general trend indicating a decrease in the species suitability for the main Portuguese forest species (e.g., Eucalypts, Maritime pine, and Cork oak) in the south and in the inland of the country, was predicted by using the process-based model GOTILWA+ and the regional climate model HadRM2-3 for 2070–2100 [25]. Once again, but using a bioclimatic approach, the predictions for the future (2040–2060) under two climate change scenarios (RCP 4.5 and RCP 8.5) unfolded that Maritime pine will be moderately reduced and relocated [26].

For the third aim, to perform an agreement analysis for the species distribution maps produced by the MaxEnt and the ecological envelope approaches, when comparing the species potential distributions for the present, the species presence simulated by MaxEnt was 47.1% and by the ecological envelope was 76.5%, with a 44.2% concordance. For the future (2070), under the RCP 4.5 and RCP 8.5 climate change scenarios, the presence area by MaxEnt slightly increased conversely to a decrease in the ecological envelope, and so the agreement between them decreased to 34.6% and 31.2% for RCPs 4.5 and 8.5, respectively. Moreover, the MaxEnt prediction map showed a higher agreement with the species' current distribution when compared to the one obtained by the ecological envelope. By contrast, the ecological envelope produced a broad species potential distribution that was closer to the species' empirical distribution map extracted from the forest regions map for mainland Portugal [19]. Indeed, the SDMs predictions are intimately dependent on the species distribution, climate, soil, and land cover datasets, model explanatory variables selection, and the choice of the GCM and climate scenario that is used in the modelling process [1,4]. Moreover, a study pointed out also that the SDMs for Maritime pine in the Western Mediterranean Basin and European Atlantic coast, the fundamental niche of the species, have better characterised when they included molecular information [48]. Hitherto, neither of the two methodologies essayed considered species adaptability and the risk of diseases and wildfires when projecting species' distributions for the future.

5. Conclusions

The two methodological approaches used in this study to map Maritime pine potential distributions for the present and for the future (2070) under two climate change scenarios (RCP 4.5 and RCP 8.5) were revealed to be mutually complementary. The MaxEnt modelling approach predicted maps were more likely to express the species' current distributions due to the dependence on species occurrences. A 47.3% suitability area (e.g., regular-medium-high) was predicted for the present, which increased in future climate change scenarios to 48.7%–48.3%. Conversely, the species distribution maps produced by the ecological envelope approach were closer to the species' potential empirical distribution. A 76.5% suitability area (e.g., regular-favourable-optimum) was obtained for the present, which decreased in future climate change scenarios to 58.2%–51.6%. The ensembled maps by the combination of the two approaches resulted in 44% species presence concordance area in the present, which decreased in the future (2070) to 35% and 30%, respectively, for RCP 4.5 and RCP 8.5 climate change scenarios. Indeed, these maps highlighted the best species suitability areas for the present and future under climate change scenarios and so are key as support decision tools for future afforestation and forest management planning, namely on designing fire-resilient landscapes and enhancing forest ecosystems biodiversity, functionality, and productivity.

In that sense, it is important to study the impact of climate change as well on fire-resistant Mediterranean species distributions that can be used in alternative future afforestation in mainland Portugal. Thus, further investigation is being made to improve these species distribution maps by validating/selecting the best environmental variables and thresholds and using more recent climate change data sets. Species adaptability and the risk of diseases and wildfires when projecting species' distributions for the future will also be studied.

Finally, regarding this study's findings, it is recommended that in future studies, for other species and regions, when producing species geographic distributions, both methodological approaches should be essayed, keeping in mind that the SDMs (e.g., MaxEnt) are more complex and data-driven while the ecological envelope approach is simpler and more conservative on identifying suitable areas for the species.

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