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PREDICTING HABITAT SUITABILITY OF *Pistacia atlantica* DESF WITH MAXENT AND GIS IN THE NORTHWESTERN REGIONS OF ALGERIA

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ABSTRACT

Pistacia atlantica is a tree species, in Algeria that are included in the list of protected species and considered endangered. Prediction of the potential geographic distribution of this species and mapping of the most habitat suitability to promote their introduction are important from the point of view of their conservation and restoration. 23 environmental variables, as well as a total of 296 points of presence were used to predict the potential distribution of *Pistacia atlantica* in an area of 62 203 km^2 using Maxent modelling. The Maxent model was evaluated using the area under the receiver operating characteristic curve (AUC) and the True Skill Statistics (TSS). The model generated was rated excellent (AUC> 0.94, TSS = 0.78). The results of this study present the most appropriate areas of this species and provide a useful reference for the implementation of conservation and management strategies for this species in the study area.

Keywords: *Pistacia atlantica* Desf; conservation; habitat suitability; Maxent; northwestern regions of Algeria.

INTRODUCTION

In the world, the genus Pistacia (family: Anacardiaceae) comprises eleven species, its range is discontinuous and has four phytogeography regions: Mediterranean, Irano-Touranian, Sino-Japanese, and Mexican [1], of which Pistacia atlantica is one of the species with medicinal and commercial value [2].

Pistacia atlantica is a tree species, that are included in the list of protected species and considered endangered in Algeria [3,4]. The population size of this species in Algeria is declining year after year in response to anthropogenic and climatic threats of medium to high impact [2].

Understanding the distribution patterns of threatened species and their habitat suitability is crucial for many aspects of their conservation and environmental management, such as the reintroduction of the species into its natural habitat or into new areas adapted to the distribution model [5].

Ecological modelling techniques, in particular, species distribution models (SDM), have developed substantially in recent decades [6,7], and have become a valuable tool for assessing habitat adequacy and resource conservation to protect threatened plant species [8,9].

Various SDM, such as Generalized linear model (GLM), Support vector machine (SVM) General Rule Set Production (GARP), and Maximum Entropy (Maxent) were used to assess ecological requirements, ecological responses, and distribution areas [6,10].

Maxent is widely used in studies on areas suitable for threatened species, the suitability of the climatic environment for specific species and priority assessments for species conservation [11,12], as its performance is better than other SDM [13,14].

The objective of this study is to predict the potential distribution of *Pistacia atlantica* in the northwestern regions of Algeria. The results provide a useful reference in planning, conservation strategies for this threatened tree species.

MATERIALS AND METHODS

Study Area

The study area located in the northwestern Algeria, between 33. 90º at 36.33 ° North latitude and -2.21° at 2.66° longitudes, covers a total area of 62 203 km^2. The climate in our study area is Mediterranean.

Species Occurrence Data

The geographic coordinates of the sites containing *P. atlantica* were identified during a field survey with forestry services. We recorded natural populations of *P. atlantica* with an accuracy level of ≤10 am using a geographic positioning system (Garmin). A total of 296 occurrences of *P. atlantica* was recorded in the study area.

Environmental Variable Data Sets

The 19 bioclimatic variables with a 1 km spatial resolution were downloaded from the Worldclim version 2.0 database [15]. The topographic variables embedded in the model are variables derived from the digital elevation model (DEM) using algorithms available in SAGA GIS6.1 (http: // www.saga-gis.org) (Table 1). All variables were clipped according to the study area and then resampled at 1 km spatial resolution in the Arc GIS 10.3 software.

To reduce the multicollinearity among the 23 tested environmental variables for Maxent modelling [16], all variables were initially subjected to a correlation analysis using the “corrplot” package in R [17], then variables with a cross-correlation coefficient value 80%, only one was selected [18] (Table 1).

Modeling Procedure

Maxent software (ver. 3.4.1) [19] was used in this study. To build the Maxent model, we selected 75% of the data for model training and 25% were used to test the predictive ability of the model [10]. The following parameters were chosen: maximum number of background points = 10,000, convergence threshold = 0.00001, regularization multiplier = 1 and maximum number of iterations = 5,000. This allowed a model enough time for the model [20].

To assess the quality of the model fit we tested two methods: The area under the receiver operating characteristic curve (AUC) [21], the value of the AUC varies between 0 and 1, this value is interpreted as proposed by Hoffman and al. [22]: AUC > 0,90: the model is excellent, 0,8≤ AUC ≤ 0,90: the model is good, 0,7≤ AUC ≤ 0,8: the model is Acceptable, 0,6≤ AUC ≤ 0,70 (Bad). AUC ≤0,60 (Invalid).

The true skill statistic (TSS) was chosen as the associated measure to predict the accuracy of the assessment which is not affected by the size of the validation set [23]. The TSS had a range of values from -1 to +1. TSS = +1 means perfect agreement and values of zero or less mean no better than random performance [24]. Jackknife analyses were performed to assess the importance of variables [25].

Table 1. Tested environmental variables for maxent modelling

Type	Variable	Description	Source
Bioclimatic variables	**BIO1**	Annual Mean Temperature	WorldClim
	BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp))	WorldClim
	BIO3	Isothermality (BIO2/BIO7) (* 100)	WorldClim
	BIO4	Temperature Seasonality (standard deviation *100)	WorldClim
	BIO5	Max Temperature of Warmest Month	WorldClim
	BIO6	Min Temperature of Coldest Month	WorldClim
	BIO7	Temperature Annual Range (BIO5-BIO6)	WorldClim
	BIO8	Mean Temperature of Wettest Quarter	WorldClim
	BIO9	Mean Temperature of Driest Quarter	WorldClim
	BIO10	Mean Temperature of Warmest Quarter	WorldClim
	BIO11	Mean Temperature of Coldest Quarter	WorldClim
	BIO12	Annual Precipitation	WorldClim
	BIO13	Precipitation of Wettest Month	WorldClim
	BIO14	Precipitation of Driest Month	WorldClim
	BIO15	Precipitation Seasonality (Coefficient of Variation)	WorldClim
	BIO16	Precipitation of Wettest Quarter	WorldClim
	BIO17	Precipitation of Driest Quarter	WorldClim
	BIO18	Precipitation of Warmest Quarter	WorldClim
	BIO19	Precipitation of Coldest Quarter	WorldClim
Topographic variables	ALT	Altitude	SRTM
	FA	Flow Accumulation	SAGA GIS6.1
	TWI	Topographic wetness index	SAGA GIS6.1
	TRI	Topographic Ruggedness Index	SAGA GIS6.1

** The variables in bold, selected by a multi-collinearity test, were used in the modelling*

RESULTS AND DISCUSSION

Maxent is an established ecological model, uses presence data only to predict the distribution of a species based on the theory of maximum entropy [19,26], and it can generate reliable models with only five locations [27,28]. In the case of this study a total of 296 points of presence was used for training and testing data well distributed in space to increase the reliability of this prediction, these points of presence are considered a robust dataset, as Baldwin [29] found that with more than 30 points, the prediction of the potential distribution stabilizes.

After the correlation matrix analysis, 13 highly correlated variables (|R|> 0.80) were removed (Fig. 1), so we use the remaining 10 variables in the final analysis.

In Fig. 2, the lines of omission from the training and test data were close to predicted omission rates, in addition the AUCs values for the training data and the test data were close to 1 ($AUC_{training}$ = 0,944, AUC_{test} = 0,946) (Fig. 03), indicating the excellent performance of the Maxent model, thus validating the accuracy of the model [8,30]. And the evaluation of the Maxent model using the True Skill Statistic (TSS = 0.784) indicates that the performance is very good [23].

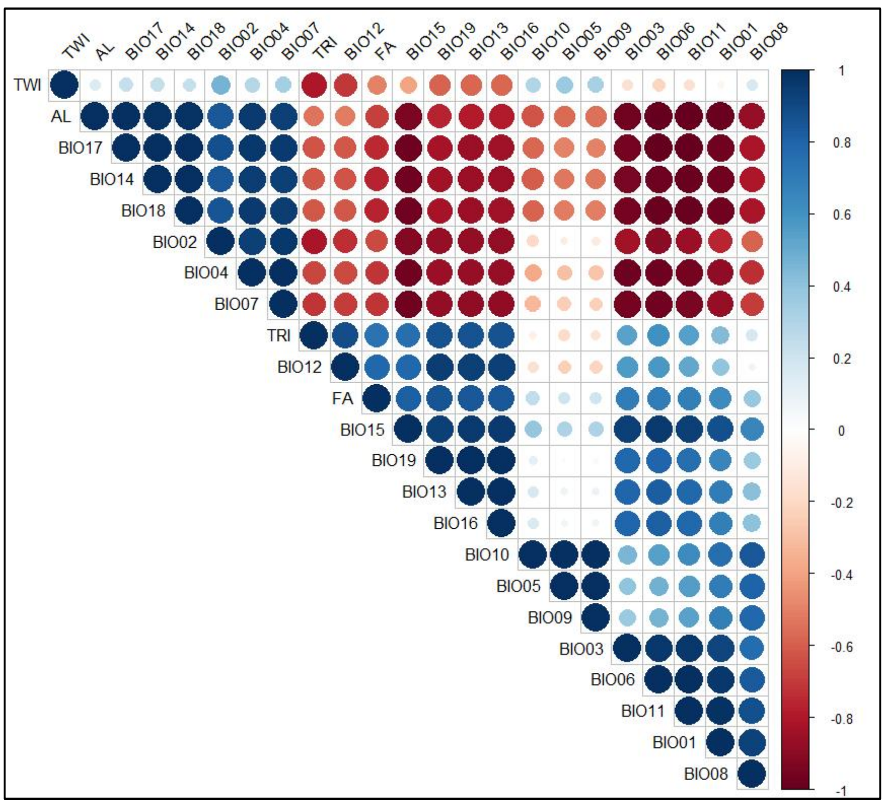

Fig. 1. Correlations between quantitative input variables

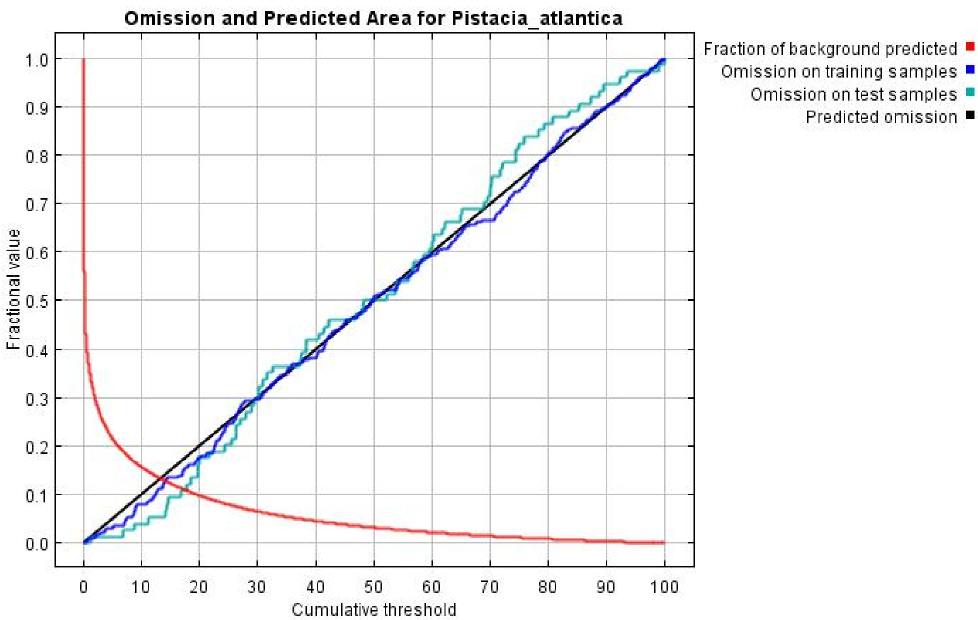

Fig. 2. Omission rates versus predicted area for *Pïstacia atlantica*

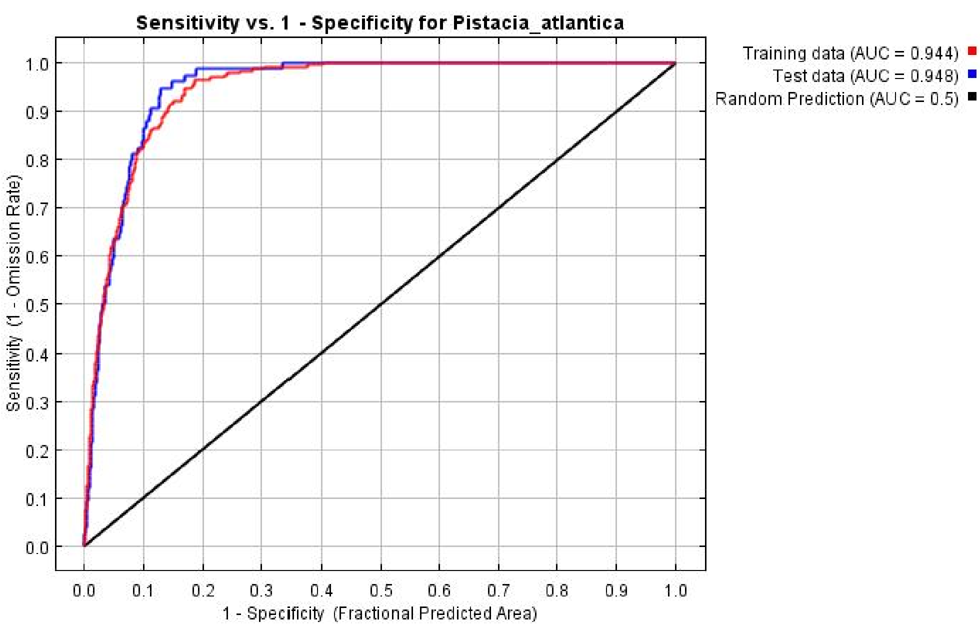

Fig. 3. Receiver operating characteristic curve with area under curve (AUC)

Jackknife analysis results of training gain, test gain indicated that the potential distribution of *P. Atlantica* were more influenced by the variable flow Accumulation (FA) followed by annual precipitation (Bio12) and by precipitation seasonality (BIO15) (Fig. 4).

The variable Flow Accumulation (FA) is the most contributor to the model with a percentage of 87% (Table 2) and provides very high gains (1.7) when used in isolation and areas that were predicted as highly suitable were mainly associated with high flow accumulation (Fig. 5), this corresponds well to the fact that the *P. Atlantica* usually only grows on the edges of wadi beds and large temporarily humid depressions [31,32]. At the wadi beds, Ifticene-Habani et al. [31] found that the length of the lateral roots of the *P. Atlantica* can reach more than 20 m, which allows the tree to take advantage of the water placed at its disposal in various forms (rain, fog, dew).

Maxent generates a probability raster of potential distribution of the species with a range of values ranging from 0 to 1, representing habitat suitability. In this study, a logistic threshold of 10 percent presence of training was applied, which allows the selection of the value above which 90% of the learning samples are correctly classified. To set the minimum threshold of 10%, the first Maxent results CSV file in the results section has been scanned. The column titled "10 percentile training presence logistic threshold" was opened, the value of the last row of this column, was used to reclassify the model results in Arcgis10.3[30] (Fig. 6).

According to the map of the potential distribution of this species generated in this study (Fig. 6), 54927.26 km^2 (88.30%) of the study area have a very low potential, 3601.15 km^2 (5.7%) have a low potential, 1623.91 (2.6%) km^2 have moderate potential, 1058.20 (1.7%) km^2 have good potential and 992.52 (1.6%) km^2 have high potential.

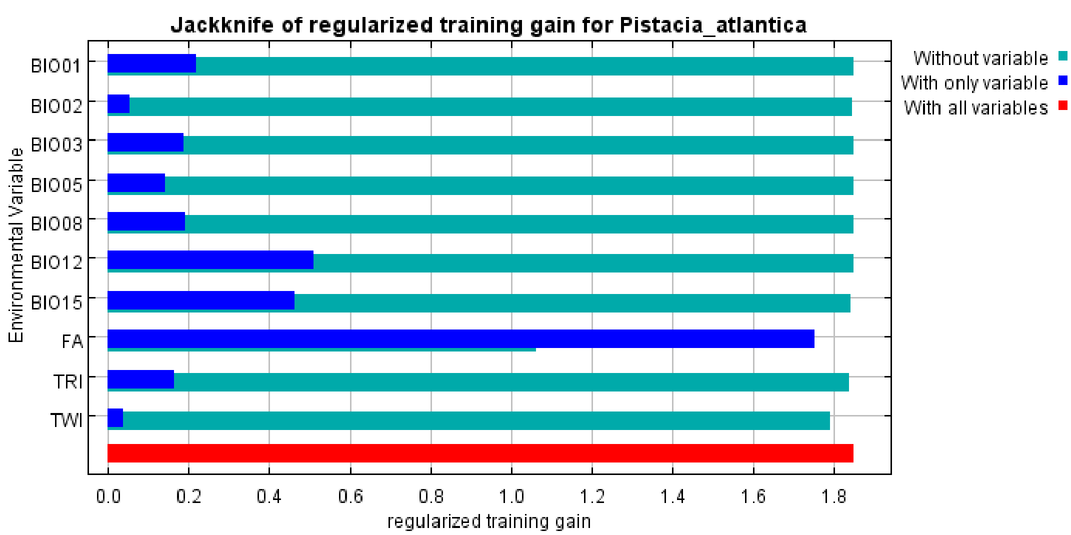

Fig. 4. Jackknife plot of training gain for *P. Atlantica*

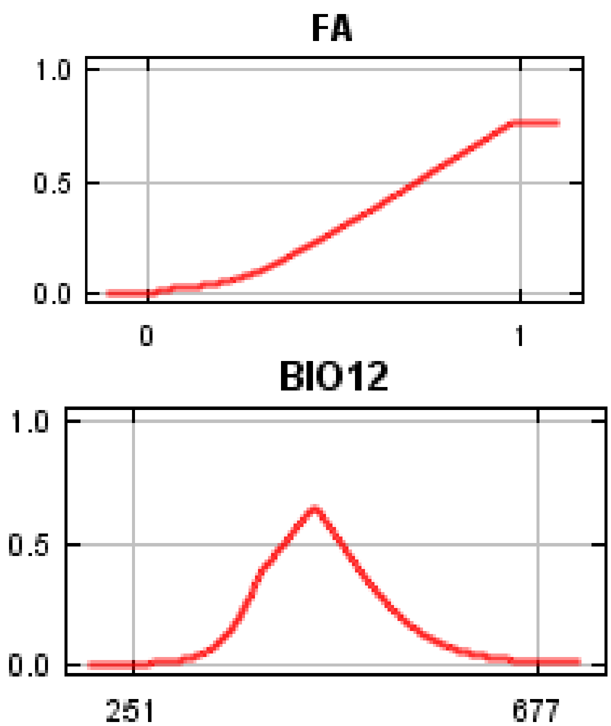

Fig. 5. Response curves of the most influential predictors variables in *P. Atlantica* habitat distribution model

Table 2. Relative contributions (%) and permutation importance (%) of the variables to the Maxent model for *P. atlantica*

Variable	Percent contribution	Permutation importance
FA	87	93.3
BIO03	5.6	0
TWI	2.8	1.8
BIO02	2.5	0.2
BIO01	0.7	0.2
BIO15	0.6	3.7
TRI	0.4	0.4
BIO05	0.3	0
BIO12	0.1	0.2
BIO08	0	0.2

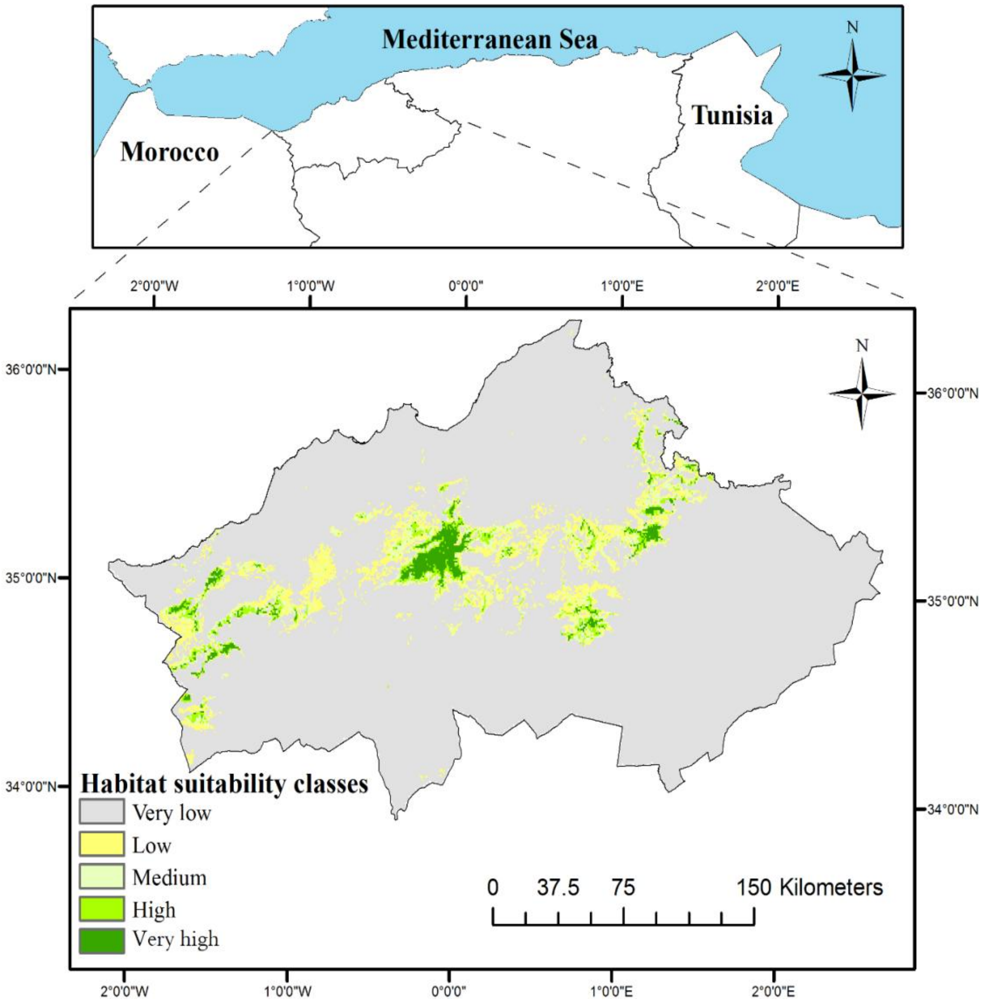

Fig. 6. Habitat suitability classes for *P. Atlantica*

This map can help to identify new subpopulations, plan the restoration and implementation of natural habitat conservation strategies [33,34], and further assist in analysing habitat needs and disturbance risks [8,35,36].

This map may also facilitate the selection of the most suitable areas to promote reforestation of this species and the creation of protected areas [34,37]

CONCLUSION

Spatial distribution model and mapping of appropriate areas for *P. Atlantica* were successfully analysed by Maxent and GIS using occurrence data and environmental variables. The model predicted that an area of 992.52 km^2 in the study area was ideally suited to P. atlantica. The results can facilitate and assist in the discovery of new populations, planning conservation strategies. These results can also be used to protect the high-potential habitats of this threatened tree from perturbation risks such as deforestation and overgrazing. In this study, the mapping of suitable areas for *P. Atlantica* was analysed focusing solely on current climate data, while ignoring the effect of climate change, which could also lead to a change in suitable habitats for *P. Atlantica* in northwest Algeria. In this regard, additional studies are desirable to assess the effect of climate change on the spatial distribution of this species.

AUTHORS' CONTRIBUTIONS

This work was carried out in collaboration between all authors. Author MD designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors FZY and MT managed the analyses of the study and the literature searches. All authors read and approved the final manuscript.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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