

Article

Predicting Habitat Suitability and Conserving *Juniperus* spp. Habitat Using SVM and Maximum Entropy Machine Learning Techniques

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Abstract: Support vector machine (SVM) and maximum entropy (MaxEnt) machine learning techniques are well suited to model the habitat suitability of species. In this study, SVM and MaxEnt models were developed to predict the habitat suitability of *Juniperus* spp. in the Southern Zagros Mountains of Iran. In recent decades, drought extension and climate alteration have led to extensive changes in the geographical occurrence of this species and its growth and regeneration are extremely limited in this area. This study evaluated the habitat suitability of *Juniperus* through spatial modeling and predicts appropriate regions for future cultivation and resource conservation. We modeled the natural habitat of *Juniperus* for an area of 700 ha in Sepidan Area in the Fars province using (1) data regarding the presence of the species (295 samples) collected through field surveys and GPS, (2) habitat soil information and indices derived from 60 soil samples collected in the study area, and (3) climatic and topographic datasets collected from various sources. In total, 15 conditioning factors were used for this spatial modeling approach. Receiver operator characteristic (ROC) curves were applied to estimate the accuracy of the habitat suitability models produced by the SVM and MaxEnt techniques. Results indicated logical and similar area under the curve (AUC)-ROC values for the SVM (0.735) and MaxEnt (0.728) models. Both the SVM and MaxEnt methods revealed a significant relationship between the *Juniperus* spp. distribution and conditioning factors. Environmental factors played a vital role in evaluating the presence of *Juniperus* sp. as Max and Min temperatures and annual mean rainfall were the three most important factors for habitat suitability in the study area. Finally, an area with high and very high suitability for the future cultivation of *Juniperus* sp. and for landscape conservation was suggested based on the SVM model.

Keywords: *Juniperus* sp.; habitat suitability mapping; support vector machine; maximum entropy; ecological landscape

1. Introduction

Habitat and biodiversity loss are global concerns related to climate change—especially drought—and serve as an enormous warnings for the future [1–3]. Based on a continuous rate of global warming, a temperature increase of ~4 °C is anticipated in tropical zones and a mean global temperature increase of ~2.5 °C is anticipated by 2100 AD [4,5], which, in turn, changes the habitat

of species. Conservation of natural resources and ecological landscapes is a very important measure to combat the deleterious impact of climate change on ecosystems. Habitat suitability assessment is a valuable modeling approach that can be used to predict the appropriate conditions for cultivating plants to help prevent habitat demolition and biodiversity degradation [6–8]. Furthermore, modeling and habitat mapping are effective and applicable techniques for assessing the relationship between environmental factors and the environment, creating an ecological landscape with high biological diversity, and protecting the natural ecosystem [6,9,10]. Statistical modeling and geographic information systems (GIS) have been widely used in recent years to evaluate the ecological theories in the field of ecosystem and resource conservation and to predict suitable regions for future cultivation in accordance with climate change [8,11,12]. Maximum entropy (MaxEnt) [13] and support vector machines (SVMs) [14,15] are flexible and very powerful techniques. MaxEnt is a machine learning algorithm with a high capability in artificial fitting rules or functional connections (e.g., nonlinear relation) according to appearance information, usage of species' presence, and background data for the prediction of species distribution and habitat suitability [8,16–18]. The MaxEnt algorithm is applied to detect the maximum entropy distribution likelihood and is used to forecast the possible distribution of a target species according to its maximum entropy under different conditions. In addition, MaxEnt can be used with limited distribution data and its classifications are created using only highly accurate presence information [13,16]. SVMs are generally controlled classifiers, which require training samples, and they are not relatively susceptible to training sample size [19,20]. Generally, the self-adaptability, rapid learning speed, and insensitivity to training size make the SVM a reliable method for the intelligent processing of remote sensing data [19–21]. Therefore, the SVM algorithm has the deterministic learning features of nonparametric data, and its high accuracy makes it an important and pleasant tool for habitat suitability mapping with an impressive predictive accuracy [22–26]. MaxEnt and SVMs yielded a good performance with the original data, indicating their sufficient regulation of multicollinearity in spatial distributions studies [25,27]. Their suitability for the assessment of species distribution and habitat suitability models has led them to become popular methods for evaluating habitat requirements in recent years. Both methods are applicable for predicting distribution patterns of plants and assessing their habitat suitability [6,7,15,28,29], biodiversity in the natural landscape [30,31], and the distribution pattern of living creatures [18,32,33]. Genus *Juniperus* is a coniferous plant with a variety of species occurring in the cool and temperate zones of the Northern Hemisphere's mountainous regions. In recent years, drought extension and climate change have impacted the native habitat of juniper in all regions, and many habitats of the *Juniperus* species are threatened around the world [34–39]. Some species of juniper trees are distributed in Iran, with a geographical distribution throughout different regions. In Iran, the north of the Alborz Mountain, the northeast of Kopet Dāg Mountain, the west and southwest of Zagros Mountain, and the south of Jebale-e-Barez Mountains are recognized as natural habitats of *Juniperus* [40–42]. The main objective of the current study was mapping the habitat suitability of *Juniperus* spp. based on presence data of the species in its natural habitat using two machine learning techniques, namely SVM and MaxEnt. The second objective was to compare the performance of two prediction approaches to identify patterns and determine the models' capacity for recognizing and analyzing the habitat suitability of *Juniperus* spp. The graphical outputs of quantitative data depicting the natural habitat of *Juniperus* in Sepidan Area may be used in the decision-making process for landscape planning, i.e., to detect suitable habitats for future cultivation, and for resource conservation through habitat optimization, in particular, considering the importance of environmental factors for species conservation.

2. Materials and Methods

2.1. Study Area

The study area is located in the Sepidan Area of the Fars province. This area contains approximately 700 ha of the natural habitat of juniper and is located in Southern Iran (Figure 1). As part of the Zagros mountain range, the studied area has a moderate climate, distinctive seasons, and abundant rainfall (<http://www.irimo.ir>). Long-term annual average temperature and rainfall are 12–13 °C and 500–550 mm, respectively. Topographically, the elevation of Sepidan Area ranges from 2183 to 2830 m a.s.l. according to the digital elevation model (DEM) of the study area, while slope degrees range from 0 to 73°.

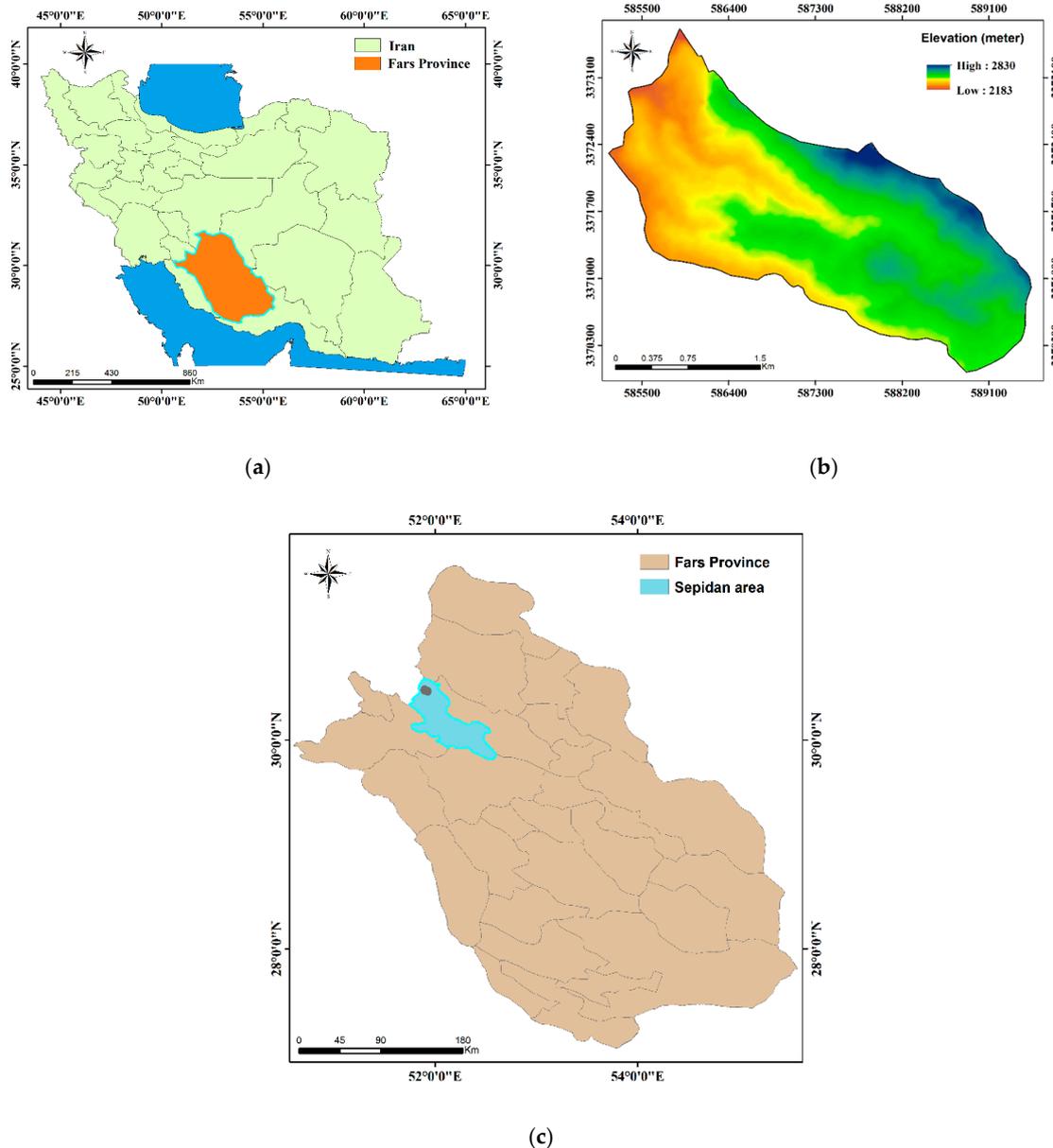


Figure 1. Location map of the study area. Fars province in Iran (a), Sepidan Area in Fars province (b), habitat basin and DEM (c).

2.2. Ecology of *Juniperus* Habitat in Southern Iran

Juniperus species is an evergreen tree with habitats distributed in dry and semi-dry, cold climates with moderate summer temperatures and an annual rainfall of about 400 mm in the high-mountain environments of the Irano—Turanian region [43,44]. Drought extension, climate change, human activity (fuelwood), and overgrazing in the past decades have led to a recession of *Juniperus* habitats. Today, the remaining habitats of *juniperus*—an endangered species—are in scattered spots [44].

2.3. Methodology

To generate habitat suitability maps, the current study was conducted in five main phases, (i) creating a species distribution inventory map of *Juniperus* spp. in their natural habitats, (ii) dataset preparation, (iii) multicollinearity analysis of different independent variables, (iv) habitat suitability modeling using MaxEnt and SVM models, and (v) validation and selection of the best model.

2.3.1. Creating a Species Distribution Inventory Map of *Juniperus* spp. in its Natural Habitats

To create a species distribution inventory map, we first identified the natural habitats of the *Juniperus* spp. in the Sepidan Area. Next, we registered the location of 295 samples of this species in 700 ha of the studied site using extensive field surveys and a Handy GPS app Android (version 32.6, <https://www.binaryearth.net/HandyGPS/index.php>). We then selected 70% (206 trees) of the identified samples for modeling and used the remaining 30% (89 trees) to validate two machine learning models using a random selection method [45]. This selection was conducted using geospatial modeling environment (GME) tools in ArcGIS 10.6.1 (ESRI, Redlands, CA, USA).

2.3.2. Multicollinearity Analysis among Independent Variables

Next, we conducted a collinearity test among 15 conditioning factors, including topographical, climatic, and soil data, using two indices. These indices were VIF (variance inflation factor) and tolerance (T). According to O'Brian [46], when VIF is greater than or equal to five and T is lower than 0.1, then collinearity exists among independent variables. This status can decrease the accuracy of models.

2.3.3. Dataset Preparation

Our literature review revealed that different topographical, climatic, and soil data are required to evaluate a species habitat model [12,47–51]. Therefore, we selected fifteen factors that affect habitat suitability to model the juniper species habitat, including elevation, slope degree, aspect, profile and plan curvatures, topographic wetness index (TWI), annual mean rainfall, distance to streams, distance to urban areas, annual mean Min/Max temperatures, and soil indices such as pH, electrical conductivity (EC), presence of clay, and organic matter (OM). We extracted topographical features, such as slope, aspect, plan and profile curvatures, elevation, and TWI, from ALOS-DEM with 12.5 m × 12.5 m resolution (Figure 2A–F). This DEM was downloaded from the ALOS PALSAR (The Phased Array type L-band Synthetic Aperture Radar) satellite website (<https://vertex.daac.asf.alaska.edu/>). Furthermore, we obtained climate data, including annual mean rainfall and Min and Max annual mean temperatures (Figure 2G–I), from Fars Meteorological Bureau (<http://www.farsmet.ir>). In terms of soil data, we collected 60 soil samples from the study area in a depth of 0–30 cm to prepare the soil feature maps. These samples were then sent to the Shiraz University Laboratory, where the values of pH, EC, organic matter, and percentage of clay were measured for each sample. We then applied the inverse distance weight (IDW) interpolation method to create soil feature maps (Figure 2J–M). In addition, distance to streams and distance to urban areas were constructed from the topographical map at a scale of 1:25,000 (Figure 2N–O). A description of these habitat suitability conditioning factors is shown in Table 1.

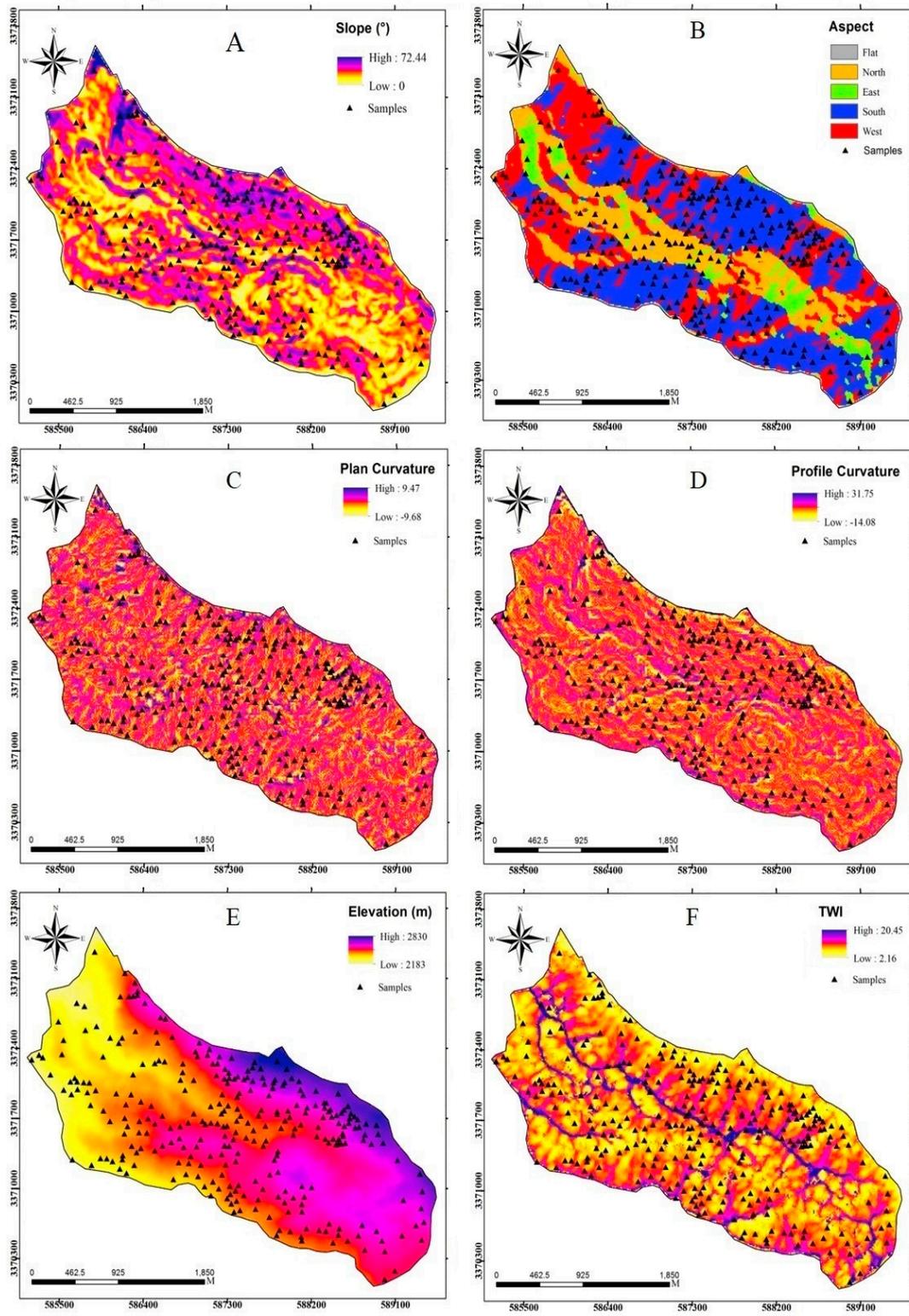


Figure 2. Cont.

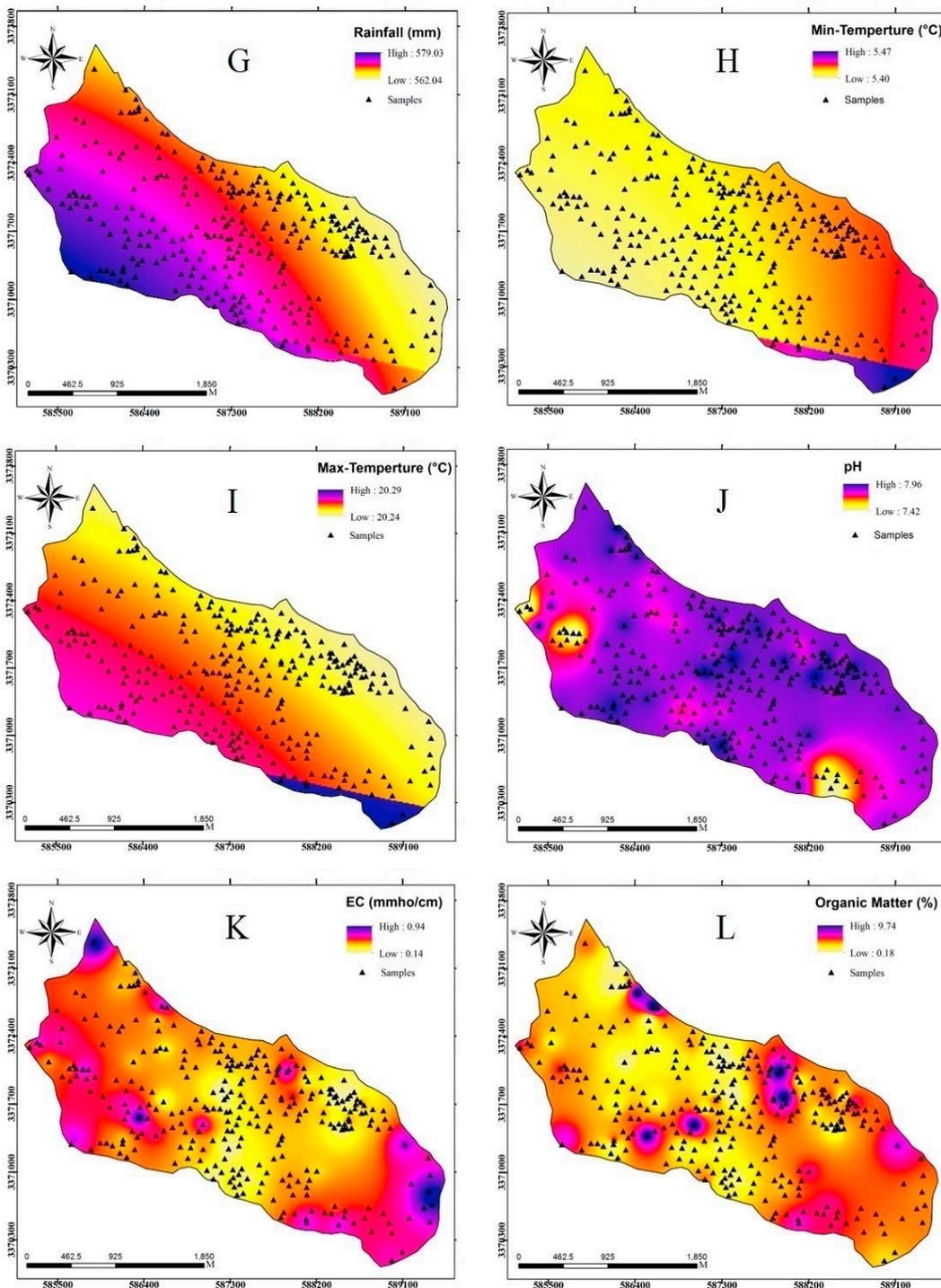


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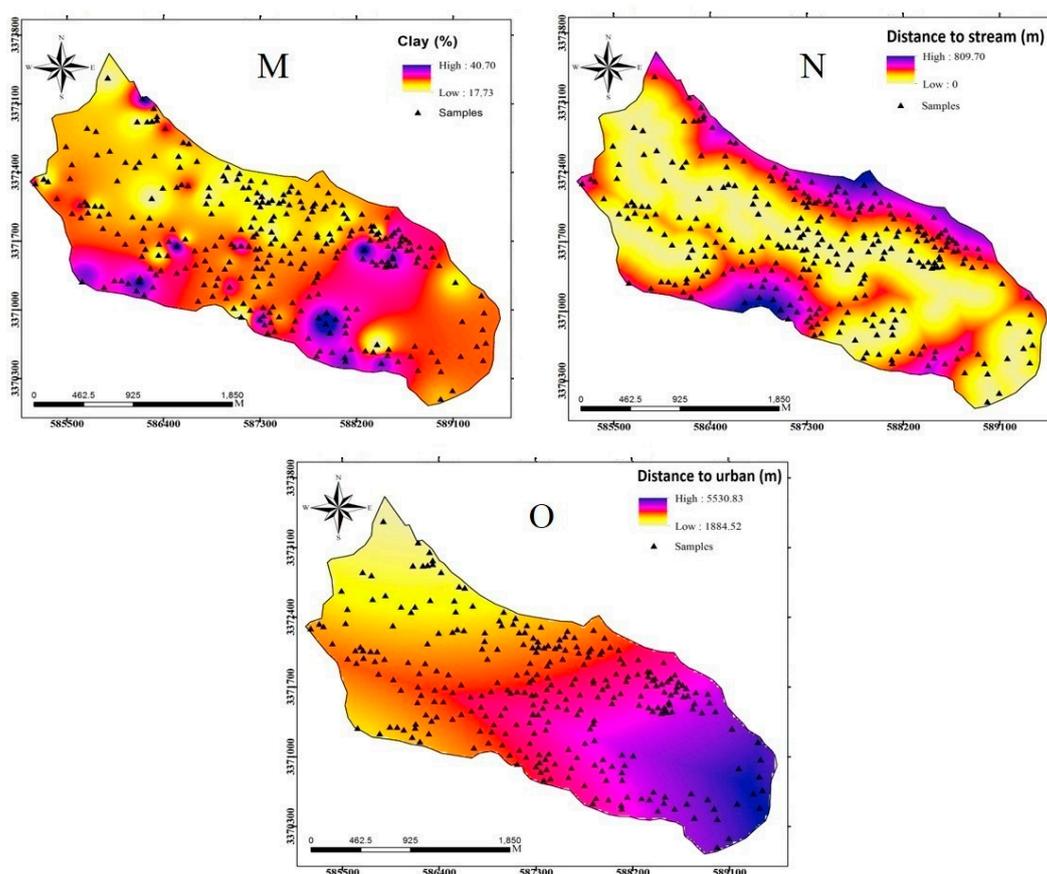


Figure 2. Conditioning factor maps of the study area: slope (A), aspect (B), plan curvature (C), profile curvatures (D), elevation (E), topographic wetness index (TWI) (F), rainfall (G), Min temperature (H), Max temperature (I), pH (J), electrical conductivity (EC) (K), organic matter (L), percentage of clay (M), distance to stream (N), and distance to urban (O).

Table 1. Habitat suitability conditioning factors in the present study.

Category	Conditioning Factors	Data Scale
Topographic factors	Slope degree	Continuous
	Aspect	Categorical (5 classes)
	Plan curvature	Continuous
	Profile curvature	Continuous
	Elevation	Continuous
	TWI	Continuous
Climatic factors	Rainfall	Continuous
	Min temperature	Continuous
	Max temperature	Continuous
Soil factors	pH	Continuous
	EC	Continuous
	Clay	Continuous
	Organic matter	Continuous
Environmental factors	Distance to stream	Continuous
	Distance to urban	Continuous

2.4. Habitat Suitability Spatial Modeling

2.4.1. Maximum Entropy (MaxEnt) Model

To model the species habitat using the MaxEnt model, we first downloaded MaxEnt software version 3.4.0 from a portal (https://biodiversityinformatics.amnh.org/open_source/maxent/), and used it to predict the *Juniperus* habitat suitability. The MaxEnt model has been used to estimate the likelihood of species livability based on presence data and randomly generated background points to detect the maximum entropy distribution [7,8,11,12]. Entropy is the property that is well-known as a link between data and information. The maximum entropy model led to greater utilization of data entropy, allowing us to explore and extract information and develop unexpected outcomes [45,50]. The MaxEnt model is an advantageous approach to simulating habitat suitability because it can be used for presence-only data with a small sample size and works very well for inadequate or incomplete data [48,52]. Moreover, environmental layers in both categorical and continuous format can be used by MaxEnt, and its likelihood is correct, constant, and reliable even if the sample size is small. Also, its capability of creating a habitat suitability map with simple commentary and high explicit result is useful for future species cultivation and conservation programs [49,52,53]. We assessed the relative importance of conditioning factors using the Jackknife test [12,13].

2.4.2. Support Vector Machine (SVM) Model

The support vector machine (SVM) model is a controlled machine learning system, which is used to predict habitat suitability with remote sensing information, and is applicable for handling small data samples [19]. The SVM model, as a binary classifier, is used to optimize algorithms to determine the optimal hyperplane of two separate classes [54]. Generalization of limited training samples is a general restriction in remote sensing, and SVMs are a well-suited model for generalizing the limited samples in remote sensing applications [15,19,24]. The SVM was used to enhance the accuracy of predictions while avoiding the drawbacks of overfitting associated with learning algorithms based on statistical and optimization theories [15,19,55]. The SVM is a desirable model due to its superior experimental function in comparison to artificial neural network functions. The training process of the SVM is easy and avoids overfitting bugs, and the model can be applied as a proper algorithmic approach for big data and to detect the preminent trade-off between overfitting and over generalization [19].

2.5. Validation of Habitat Suitability Maps (HSMs)

We used the receiver operator characteristic (ROC) curve to validate the HSMs that were created using two machine learning methods, as mentioned before. In the ROC method, the cumulative percentage of the suitability classes is located on the X-axis, versus the cumulative percentage of the training set within those classes on the Y-axis [45,56]. ROC curve analyses have been extensively used in modeling studies to assess binary classifications and evaluate the diagnostic accuracy of an event occurrence [57,58]. Moreover, the ROC method has a graphical display with a high discrimination capability that depicts sensitivity estimates (probability of a true positive) versus one minus specificity (probability of a false positive) of an occurrence for all possible threshold values, and it is an effective method for modeling the anticipated distribution of a plant species [58,59].

3. Results

3.1. Collinearity of Conditioning Factors

Results of the multicollinearity test of independent variables are shown in Table 2. These results indicate that the lowest T and highest VIF for elevation are 0.172 and 5.803, respectively. Therefore, in this research, there is no multicollinearity among the effective independent factors.

Table 2. Multicollinearity of the effective factors in the study area.

Model	Unstandardized Coefficients		Standardized Coefficients	t-statistics	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance (T)	VIF
(Constant)	−149.246	69.238		−2.156	0.032		
Distance to urban	6.382×10^{-5}	0.000	0.092	0.988	0.324	0.235	4.253
TWI	0.029	0.016	0.119	1.799	0.073	0.469	2.133
Slope degree	0.007	0.003	0.110	1.892	0.059	0.612	1.634
Rainfall	0.039	0.018	0.119	2.174	0.030	0.685	1.460
Distance to Stream	0.000	0.000	0.084	1.401	0.162	0.574	1.743
Profile curvature	−0.029	0.034	−0.046	−0.869	0.385	0.728	1.374
Plan curvature	−0.006	0.041	−0.009	−0.148	0.882	0.623	1.604
pH	−0.453	0.379	−0.069	−1.194	0.233	0.626	1.598
Organic matter	0.039	0.027	0.089	1.451	0.148	0.543	1.842
Min temperature	−11.712	3.311	−0.252	−3.537	0.000	0.407	2.459
Max temperature	10.670	3.435	0.205	3.107	0.002	0.473	2.115
EC	−0.170	0.273	−0.038	−0.623	0.533	0.541	1.848
Elevation	0.000	0.001	−0.063	−0.580	0.562	0.172	5.803
Clay	0.013	0.009	0.082	1.444	0.150	0.646	1.549
Aspect	0.009	0.023	0.019	0.389	0.697	0.862	1.160

3.2. Implementation of MaxEnt and SVM Models

Subsequent to the models' implementation, we prepared the HSMs using two machine learning methods and categorized them into five suitability classes, namely, very low, low, moderate, high, and very high according to the natural breaks (jenks) classification technique [45,60–62]. According to the created habitat suitability maps, the examined models showed different patterns in regard to habitat suitability area (Figure 3). The SVM model achieved the highest areal percentage of the very high suitability class (36%), whereas the MaxEnt model achieved the highest areal percentage of the very low suitability class (25%) (Figure 4). The predicted percentage and area for each habitat suitability class within each model are presented in Figure 4a,b. Therefore, the results of the MaxEnt and SVM comparison showed a significant difference between the models regarding the anticipated suitability classes and the percentage of predicted area in two very low and very high classes (Figure 4a). The area of each suitability class was determined, and the results indicate that the very high class of the SVM model covers the largest area; furthermore, the predicted area for the very low and very high classes significantly differs among the models (Figure 4b). However, there is no significant variation between the models regarding the percentage and area in the low, moderate, and high suitability classes (Figure 4a,b).

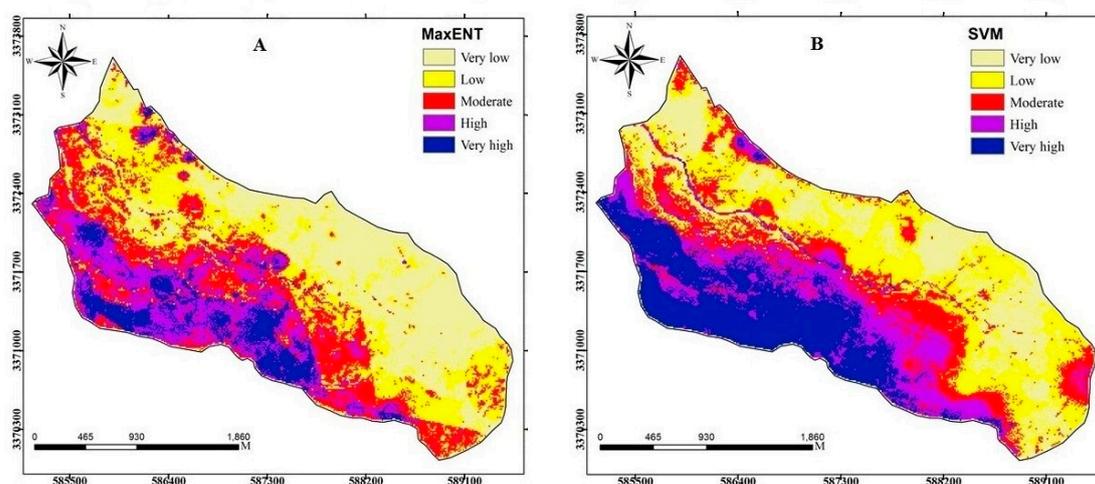


Figure 3. Habitat suitability maps using: (A) maximum Entropy (MaxEnt), and (B) support vector machines (SVM) models.

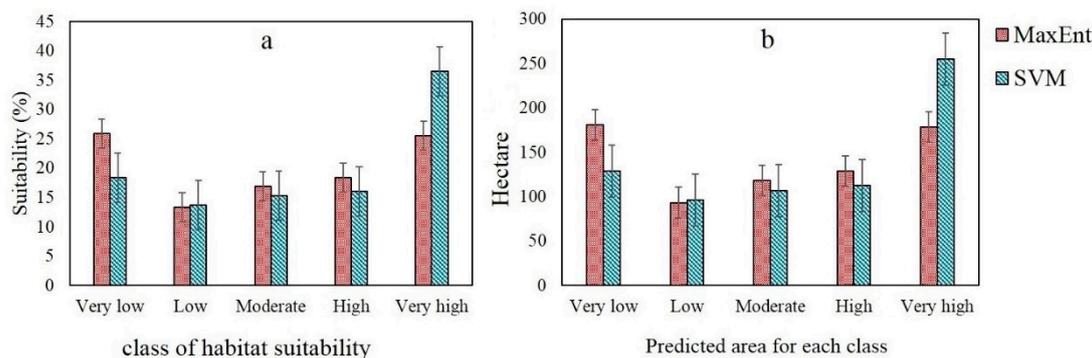


Figure 4. Percentages of different habitat suitability classes (a), and (b) predicted area for each class of habitat suitability.

3.3. Importance of Effective Factors

We assessed the relative importance of the effective factors with the Jackknife variance estimation method for the area under the curve (AUC), and the analysis results are shown in Figure 5. According to the results of the relative importance test, the Max and Min temperature factors are deemed most important for HSM, followed by annual mean rainfall, distance from urban area, TWI, distance to streams, slope degree, clay percentage, organic matter, elevation, profile curvature, EC, aspect, plan curvature, and pH (Figure 5).

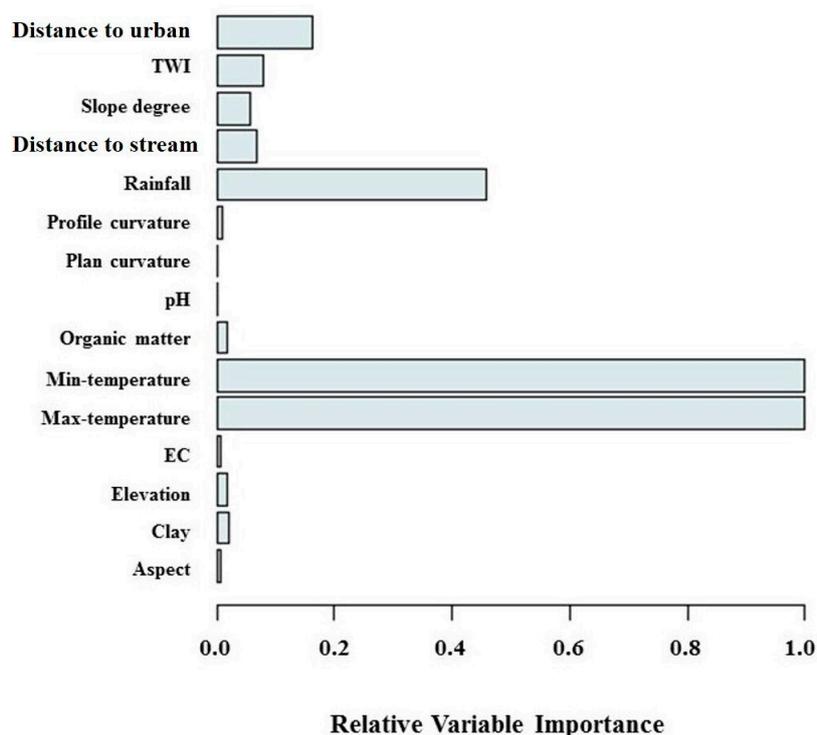


Figure 5. Analysis of the relative importance of effective factors.

3.4. Validation of MaxEnt and SVM Models

We validated the *Juniperus* habitat suitability maps using the ROC curve for both the SVM and MaxEnt models. Figure 6 depicts the validation results of both models. The area under the curve (AUC) value was used to assess the SVM and MaxEnt models separately and in comparison. According to the AUC values of SVM (0.735) and MaxEnt (0.728), both models suggested a logical and satisfactory

output for the prediction of *Juniperus* habitat suitability (Figure 6). Furthermore, there are no significant differences between the two approaches for evaluating the species' habitat suitability.

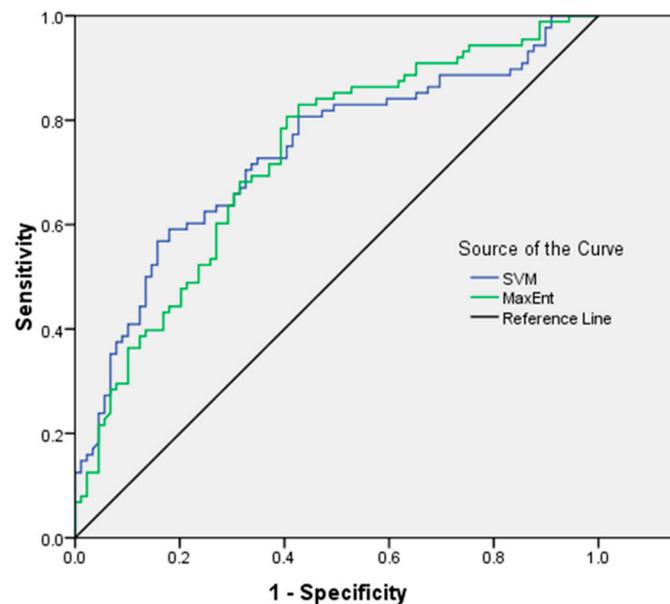


Figure 6. Receiver operator characteristic (ROC) curve of sensitivity vs specificity of *Juniperus* habitat for SVM and MaxEnt models.

4. Discussion

Habitat fragmentation has negative effects on biodiversity. Therefore, the conservation and restoration of the habitat system is the main objective in future conservation scheduling [63]. Assessing the effective factors of natural habitat and habitat mapping are crucial for enforcing useful acts. Generally, in the evaluation of habitat suitability, multicollinearity of effective factors as a negative parameter increases the extra noise in all the models [8,64,65]. In this study, however, no multicollinearity was detected among any of the climatic, environmental, and soil condition variables used as conditioning factors for the *Juniperus* habitat suitability model.

MaxEnt and SVM have been widely used for modeling the habitat suitability of species [8,10,15,48,66]. Therefore, recent and future occurrences of species can be quickly and easily evaluated using MaxEnt [67]. Moreover, Mollalo et al. [21] suggested that the SVM classifier—when joined with GIS and remote sensing data—is a beneficial and inexpensive method for identifying the habitat suitability of species. Previous studies indicated a higher accuracy of the SVM [21,68] model compared to the MaxEnt [69] model for evaluating Papatasi habitat suitability. The findings of our study suggest the habitat suitability map generated by the SVM model has the largest suitable area for future cultivation of *Juniperus*. SVM is an efficient classifier with a strong capability of recognizing and detecting the habitat suitability of *Juniperus*. In this regard, previous studies comparing the SVM and random forests (RF) methods determined the highest overall accuracy of the SVM classifier for modeling coastal habitats, with a minor misclassification occurring in the SVM model [22]. Also, SVM and MaxEnt were comparatively used to spatially model landslide occurrence, and the results show that the highest areal percentage was allocated to the high susceptibility class by the SVM model, whereas the MaxEnt model allocated the lowest areal percentage to the high susceptibility class [45]. Therefore, this result highlights the superior performance of SVM in detecting the habitat suitability of *Zataria multiflora* Boiss [25]. Hence, the SVM is a useful tool for future planning regarding the conservation and management of plant species habitats.

Moreover, SVM optimization will be carried out in the shortest time and the SVM method requires a training sample, hence it needs to segregate the optimization of training patterns for each proximity,

density, and inhomogeneity variable. Preparing the training data can lead to improving the results of the SVMs [15,68]. In presence and absence classification models (MaxEnt and SVM), the AUC-ROC is an important threshold for related indices to assess a model's capability of distinguishing presence from absence [21,48,70]. Hence, the AUC statistically prepares a single differentiation measure for all ranges of thresholds that is equal to the nonparametric Wilcoxon test [71]. Models with $AUC < 0.5$ showed the worst performance (which rarely occurred in reality), while models with $AUC > 0.5$ performed better than random [8]. Our results showed a nonsignificant difference between the AUC value of the SVM (0.735) and MaxEnt (0.728) models, and both models had logical and acceptable AUC values. Previous studies confirmed a slight difference in outcomes of AUC for the SVM, Logistic regression (LR), and RF classifiers [21], but other studies suggested a better performance of the MaxEnt model when dealing with a small sample, and it tends to create restricted predictions [72].

Environmental factors have important effects on the distribution of species within their habitat [73,74]. Previous studies indicated the strong dependence between the ecogeographical variables (EGV) and the size of the training dataset on habitat suitability predictions using MaxEnt and SVM models [8,10,74,75]. In general, temperature and precipitation factors were found to have a more damaging impact on environmental factors related to species distribution [76]. The distribution pattern of *Juniperus* species in natural habitats depends on climatic and ecological conditioning factors [77,78]. Miller et al. [79] reported that temperature changes in the long-term, rainfall amount and distribution, and the expanse and duration of fire events are the main effective factors determining abundance and distribution of forests of *Juniperus occidentalis* Hook. Furthermore, temperature, rainfall, and altitude are the most effective factors determining the distribution of *J. drupacea* Labill. [76,78]. Moreover, the distribution patterns of *J. excelsa* Bieb. in Lebanon were affected by humidity and slope degrees [77]. The results of our importance analysis of efficient factors indicated that Max and Min temperatures are the most important variables in habitat suitability modeling of *Juniperus*. In this regard, Wei et al. [8] used the MaxEnt model to predict suitable regions for current and future cultivation of safflower (*Carthamus tinctorius* L.), and their results showed that Max temperature and rainfall played an important role in forecasting the possible distribution of safflower. Also, effects of environmental variables on modeling the distribution pattern of native (*Morella Faya* L.) and invasive (*Pittosporum undulatum* Vent., and *Acacia melanoxylon* R. Br.) woody species in the Azorean forests showed that annual mean temperature (TM) and annual mean relative humidity (RHM) played the most important role in the distribution pattern of species in the final model [74].

Furthermore, other conditioning factors, including the amount of rainfall, distance to urban areas, TWI, distance to streams, and slope degree, were recognized as important variables influencing juniper habitat suitability. This result is in line with the previous results of studies assessing the importance of various environmental factors on distribution patterns and habitat suitability modeling [76–78]. Consequently, although the models correctly analyzed the effects of different possible conditioning factors on habitat suitability, the areas predicted by the models are not definite. On the other hand, regarding species conservation and future cultivation, landscape planners should make correct and farsighted decisions about target species and their relationships with the conditioning factors, suitability of the cultivation area, and climate change.

5. Conclusions

In this study, two different machine learning models, namely, SVM and MaxEnt, were used to assess the habitat suitability of *Juniperus* sp. using 295 occurrence records and 15 effective habitat factors. Results suggested that the abilities of SVM and MaxEnt are similar for assessing the habitat suitability of this species based on its presence data and the effective factors used in this study. The SVM is a sensible model for assessing habitat ecosystems, even with a comparatively limited dataset. The results indicated that the most important input factors for modeling the habitat suitability of *Juniperus* sp. are climatic variables. The study area of *Juniperus* sp. in this research ranged in elevation between 2180–2830 m a.s.l. Therefore, in these conditions, results indicated that Max and

Min temperatures and rainfall are the three most important climatic factors, and TWI and slope degree are the two most important topographical factors, as they had the strongest effect on habitat suitability. Accordingly, landscape and conservation managers should pay more attention to Max and Min air temperature and rainfall. Otherwise, these habitats will become unmanageable within a relatively short period of time. Moreover, future cultivations should pay particular attention to the parameters TWI index, slope degree, and distance to streams.

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