Ecological Processes

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Landscape structure and suitable habitat analysis for effective restoration planning in semi-arid mountain forests

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Abstract

Background: Suitable habitat and landscape structure play a pivotal role in the success of forest restoration projects. This study aimed to model the habitat suitability of wild almond (*Amygdalus scoparia* Spach) using three individual species distribution models (SDMs), i.e., backpropagation artificial neural network (BP-ANN), maximum entropy (MaxEnt), generalized linear model (GLM), as well as the ensemble technique along with measuring the landscape metrics and analyzing the relationship between the distribution of the suitable habitat of the species in different landform classes in Fars Province, southern Iran.

Results: There was no clear difference in the prediction performance of the models. The BP-ANN had the highest accuracy (AUC = 0.935 and k= 0.757) in modeling habitat suitability of *A. scoparia*, followed by the ensemble technique, GLM, and MaxEnt models with the AUC values of 0.890, 0.887, and 0.777, respectively. The highest discrimination capacity was associated to the BP-ANN model, and the highest reliability was related to the ensemble technique. Moreover, evaluation of variable importance showed that the occurrence of *A. scoparia* was strongly dependent on climatic variables, particularly isothermality (Bio 3), temperature seasonality (Bio 4), and precipitation of driest quarter (Bio 17). Analysis of the distribution of species habitat in different landform classes revealed that the canyon, mountain top, upland drainage, and hills in valley classes had the highest suitability for the species establishment.

Conclusions: Considering the importance of landform in the establishment of plant habitats, the combination of the outputs of the SDMs, landform, and the use of landscape metrics could provide both a clear view of habitat conditions and the possibility of analyzing habitat patches and their relationships that can be very useful in managing the remaining forests in semi-arid regions. The canyon, mountain top, and upland drainage classes were found to be the most important landforms to provide the highest suitable environmental conditions for the establishment of *A. scoparia*. Therefore, such landforms should be given priority in restoration projects of forest in the study area.

Keywords: *Amygdalus scoparia*, DOMAIN presence-only model, Ensemble technique, Individual distribution models, Landscape metrics, Pseudo-absence points

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Introduction

Predicting the distribution of plant species in a specific region has become an increasingly important issue in ecology, phytogeography, and conservation biology (Mi et al. 2017). One of the ecological theories supporting species distribution modeling is the niche theory. The potential distribution of a species or realized niche is a subset of the species' fundamental niche in which biotic and abiotic conditions are suitable for species occurrence (Stiels and Schidelko 2018; Pecchi et al. 2019). Plant response to variation of environmental factors is recognized as one of the important aspects of species ecological niche. It is also important to determine the ecological range of a species or its response model to environmental variables. Thus, plant response could play a significant role in management and restoration of a species in natural habitats (Coudun and Gégout 2006).

Species distribution models (SDMs) are quantitative and empirical ecological models specifying the relationships between species and the environment. These models are constructed using species location data and environmental variables (Elith and Franklin 2017). They can generate prediction maps of species distribution, which are usually used as both inputs to other analysis and a tool to identify the ecological conditions required for species (Guisan and Thuiller 2005; Peterson et al. 2011). On the other hand, the relationship between environmental variables and plant distribution has been described by a variety of modeling methods, such as the generalized linear model (GLM), generalized cumulative model (GAM), and machine-learning (ML) algorithms, including artificial neural networks (ANN), TreeNet (boosting), random forest (bagging), Classification and Regression Tree (CART), and maximum entropy (MaxEnt) (Williams et al. 2009; Miller 2010; Lei et al. 2011; Wang et al. 2015; Zare Chahouki and Piri Sahragard 2016; Mi et al. 2017; Piri Sahragard et al. 2019).

Additionally, given the significant effects of climate variables on plant distribution (Zarenistanak et al. 2014) and the necessity to study the species distribution changes at different scales, the use of climatic models are essential for understanding the potential distribution, ecological needs, sustainable exploitation, and restoration of plant habitats. On a global and continental scale, climate is the main factor controlling the distribution of plants, while at the regional level climate and topography are major contributing factors to species distribution (Pearson and Dawson 2003).

Moreover, quantifying the spatial distribution of plants and their relationship with landscape metrics and understanding the spatial and temporal variations of landscape composition are necessary for biological resource conservation, environmental impact assessment, and identification of the most influential factors in landscape composition (Chefaoui 2014; Zare Chahouki et al. 2016). In addition, landscape metrics are used in habitat suitability mapping to identify the best management practices for the restoration of degraded habitats (Pflüger and Balkenhol 2014; Auffret et al. 2015). The landscape metrics are categorized into three levels of patch, class, and landscape (Uuemaa et al. 2011).

Arid forests are sparsely vegetated land with xerophytic trees and shrubs, which are mostly distributed in mountainous regions of deserts in central, western, and southern Iran. Xerophytic plant species, such as *Amygdalus scoparia* (Rosaceae), *Pistacia mutica* (Anacardiaceae), and *Ephedra* sp. (Ephedraceae) species, are salient woody species in dry lands that have evolved over time to survive in dry regions. Wild almond (*Amygdalus scoparia*) has tremendous importance for livelihood and survival of local communities and arid mountain forest health and production. Stands of *Amygdalus scoparia* are largely distributed over dry and hot mountains of Iran, Turkey, Afghanistan, Turkmenistan, and western Pakistan. This plant is highly drought-tolerant and plays a valuable role in soil conservation and slope stabilization in arid and semi-arid mountains (Haidarian Aghakhani et al. 2017). *Amygdalus scoparia* is a pioneer species capable of colonizing sites lacking developed soil and providing favorable conditions for establishment of other species by creating microclimate and coping with unfavorable conditions in rock debris and slopes (Morshedi and Koravand 2016). Wild almond, furthermore, plays a critical role in the livelihood of local communities in arid mountainous regions of Iran (Browicz and Zohary 1996). Despite the tremendous importance of this species for the livelihood and survival of local communities and arid mountain forest health and production, overutilization during last decades, canopy cover reduction, and increased soil erosion (Nejabat et al. 2017) were serious threats to survival and regeneration of *A. scoparia.* These factors have also imposed intolerable pressure on habitats (Haidarian Aghakhani et al. 2017). Therefore, it is essential to study various aspects of the species restoration and management to conserve and improve its economic, social, and ecological values. A study on the ecological needs of *A. scoparia* in Markazi Province, central Iran, revealed that its distribution and its quantitative and qualitative characteristics are mostly influenced by physiographic factors (i.e., landform, altitude, slope direction, and aspect) and some soil properties, particularly sand content (Goodarzi et al. 2012). Further, geographic orientation has been introduced as an important factor in distribution of *A. scoparia* in semi-arid forests of Zagros Mountain Range, western Iran (Salarian et al. 2008). In general, a set of physiographic characteristics, such as altitude, slope, aspect, soil properties, and geological formation, has been reported as the most significant factors influencing the distribution of *A. scoparia* in semi-arid mountain forests of Iran (Tavakol Neko et al. 2012; Piri Sahragard et al. 2017).

Despite several studies carried out to describe the ecological needs of *A. scoparia* in Iran, lack of studies on the potential habitat distribution and landscape composition analyses has imposed serious restrictions on proper management and restoration of *A. scoparia* habitats. In this study, therefore, the distribution of *A. scoparia* was investigated mainly based upon topography, geology, and climatic variables (Lou et al. 2018). This study aimed to (1) assess the capability of the SDMs algorithms, i.e., BP-ANN, MaxEnt, and GLM as well as the ensemble technique in predicting habitat suitability of *A. scoparia*; (2) identify the most suitable habitats for *A. scoparia* and its ecological needs for restoration purposes; and (3) evaluate the suitable habitat distribution of *A. scoparia* in different landform classes based on landscape metrics analysis.

Materials and methods

Study area

This study was carried out in the southern part of the Zagros Mountains and the Iran-Turanian floristic zone of Fars Province, southern Iran. Fars Province lies within 27° 2′ to 31° 42′ N latitude and 52° 42′ to 55° 36′ E longitude (Fig. 1). This area with semi-arid climate experiences average annual temperature and precipitation of 18 °C and 307 mm, respectively (Arvin and Shojaeezadeh 2014).

Data collection and preprocessing

Presence data

For field studies, pure habitats (habitats in which canopy cover of *A. scoparia* was greater than 75%) (Gholizadeh et al. 2017) of *A. scoparia* were delineated. Also, field sampling was carried out by a combination of systematic-randomized method in 2018. After the establishment of transects, species presence points were recorded along the transects using the GPS. Since most SDMs are sensitive to the bias in samples, a maximum distance of 1 km was observed for recording presence points. In addition, after collection of dataset, the autocorrelation of re-presence points within a radius of 1 km was investigated using the SDM toolbox functions.

Environmental variables

Environmental factors affecting species distribution are different depending on the grain (resolution or size of an observation) and extant (study area consideration) (Franklin 2010). By scrutinizing available literature related to habitat characteristics of *A. scoparia*, climate variables (i.e., average monthly temperature and precipitation for 1970–2000 from the Global Climate Database (http://www.worldclim.org)) were used for distribution modeling of the species in the study area. In addition, a digital elevation model (DEM) with an accuracy of 32 m prepared from USGS data (https://earthexplorer.usgs.gov/) was used to analyze the effect of topographic factors. Aspect and slope variables were also extracted from DEM by using Spatial Analyst Tools in ArcGIS 10.4.1. Further, compound topographic index (CTI) and heat

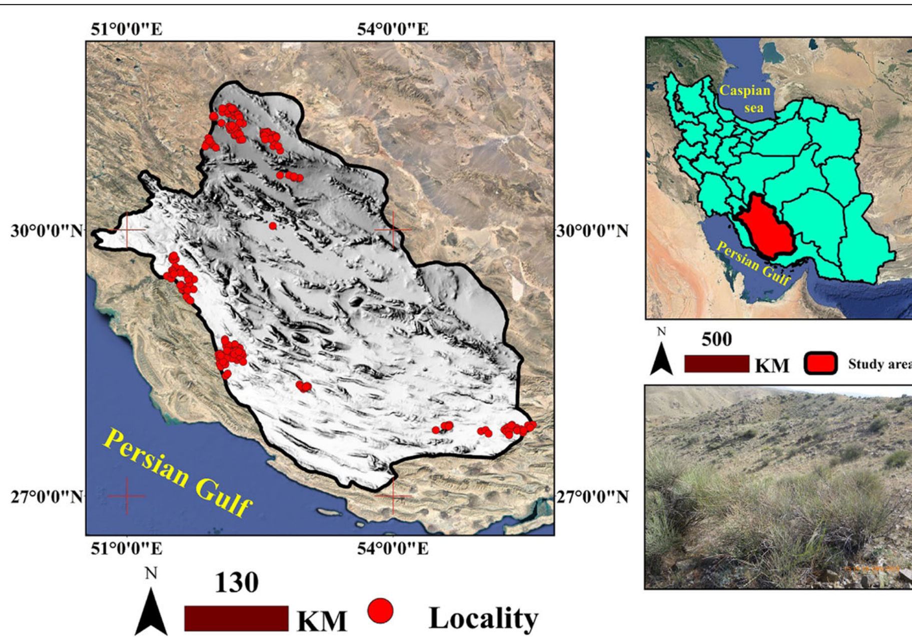

Fig. 1 Location of the study area and current habitats of *Amygdalus scoparia* (red points) in Fars Province, southern Iran

load index (HLI) were derived from DEM by using Geomorphometry and Gradient Metrics toolbox (Evans et al. 2014) in ArcGIS 10.4.1.

The heat load received by geographical direction was calculated using Eq. 1.

$$\mathrm{HI} = [1 - \cos(\theta - 45)]_{/2} \tag{1}$$

where θ is the value of azimuth in degrees and HI is the value of the heat load index between 0 and 1. The northeast-facing slopes have a value of 0 (coolest aspect), and the southwest-facing slopes have a value of 1 (warmest aspect) (McCune and Keon 2002). In addition, geological map at the scale of 1:250,000 was included in the modeling. In addition, vegetation density index was extracted from Aqua Vegetation Indices 16-Day Global 500 m (MYD13A1 V6 product) in Google Earth Engine (Gorelick et al. 2017). All cell sizes were also fixed with the finest resolution of WorldClim dataset (approximately 1 × 1 km precision). Table 1 shows the environmental variables used in the modeling along with the variation range of each variable. Prior to modeling, the correlation coefficients between the variables was investigated using ArcGIS 10.4.1 functions and variables with correlation higher than 0.85 were removed from the modeling process (Duan et al. 2014).

Generating the pseudo-absence data

Due to the necessity of access to the absence points for habitat suitability modeling using group discrimination methods, pseudo-absence points are required. The choice of pseudo-absence points was made using a two-step modeling approach and intermediate models (Wisz and Guisan 2009). Based on this approach, the potential habitat suitability was modeled using the DOMAIN method. The output of this method is a 0 and 1 map, wherein suitable areas for the distribution of a species have a value of 1, while the unsuitable areas have a value of 0. To achieve proper pseudo-absence points, which increase the efficiency of the model used, 10 series of pseudo-absence points were constructed, and the model accuracy best series of points were used in the modeling process. Thus, 200 absence points, which were equal to the number of presence points in the areas identified as unsuitable for the establishment and growth of *A. scopari*, were randomly generated *a* (Barbet-Massin et al. 2012; Liu et al. 2019). In the next step, the presence and pseudo-absence points (200 presence and 200 pseudo-absence points) were randomly divided into two parts of training (75%) and testing (25%) data.

Running the models, prediction performance, and optimal threshold limit

Since the selection of a single modeling algorithm cannot guarantee the highest prediction accuracy, it is necessary to employ a multiple ensemble approach to achieve a greater accuracy (Thuiller et al. 2009). The ensemble approach is more reliable than individual models in this study (Poulos et al. 2012; Latif et al. 2013). Thus, the SDMs used in this study included BP-ANN, GLM, MaxEnt, and the ensemble technique, which have been employed in numerous studies (Ardestani et al. 2015; Yi et al. 2016). The ModEco software package (v 1.0) was also used to run the models (Guo and Liu 2010).

The prediction performance of the models was evaluated by the AUC (area under the curve) statistic as a threshold independent criterion. For such statistic, values above 0.7 indicate good performance, and values

Table 1 Details of environmental variables used in habitat suitability modeling of *Amygdalus scoparia* in Fars Province, southern Iran

S/n	Variable	Variation range	Unit
1	Bio 3 (isothermality)	32–43	Dimensionless
2	Bio 4 (temperature seasonality)	5784–9017	°C
3	Bio 13 (precipitation of wettest month)	27–86	mm
4	Bio 14 (precipitation of driest month)	0–2	mm
5	Bio 15 (precipitation seasonality)	79–126	Fraction
6	Bio 17 (precipitation of driest quarter)	0–17	mm
7	Bio 19 (precipitation of coldest quarter)	66–201	mm
8	Altitude	117–3735	m
9	Slope	0–59.18	%
10	Aspect	1–9	-
11	Soil type	1–13	-
12	CTI (compound topographic index)	3.92–19.15	-
13	HLI (heat load index)	0.53–1.14	-
14	NDVI (normalized difference vegetation index)	−0.08–1	-

below 0.5 represent random output of the model (Marmion et al. 2009; Liu et al. 2011). Further, the weighted averaging was used based on the AUC to combine the results of other models. Moreover, since the performance of the models is evaluated by dependent and independent threshold-based measures (Liu et al. 2011), we measured the model prediction performance by those criteria to approve that the models showed a higher performance. Therefore, the use of accuracy, as weight to intersect the maps of each model, was done based on non-threshold-dependent values (AUC) or threshold-dependent values (Kappa index, *k*). These models have been run with selecting default parameters in the ModEco 1.0 software package (Guo and Liu 2010).

The maximum Kappa (MaxKappa) method was also used to determine the optimal threshold limit. In this method, after applying different values of the threshold level to the continuous map, the threshold leading to the maximum value of Kappa index was selected as the optimal threshold limit. This method is widely used to measure model accuracy when only presence data are available using some indices, such as Kappa, TSS, and ROC (Liu et al. 2005; Zhang et al. 2019).

Importance of variables

In this research, random forest regression method was used to determine the effect of each variable on the suitability of the predicted areas in habitat modeling. Values of the predicted suitability for presence points were considered dependent variables, and effective environmental variables were regarded as independent variables. Also, out of 100% of presence points, 70% and 30% of them were considered as training and testing data, respectively. The model was eventually run in the R.3.5.2 software (R Development Core Team 2014). The MAE, MSE, and RMSE functions were used to evaluate the results of the regression model fit.

Analysis of suitable habitat distribution using landscape metrics

Landform classes were determined using the digital elevation model (DEM) and topography tools toolbox. Landforms were divided into 10 classes (Dilts 2015). The binary map of the suitable habitat obtained from the ensemble approach and landscape metrics was further used to quantitatively analyze the distribution of species habitat in each class of landforms (Auffret et al. 2015). In the present study, in the FRAGSTATS 2.2 software, metrics available were used at the levels of class and landscape (Table 2).

Results

Prediction performance of the models

Prediction performance of the DOMAIN model showed that this model was highly capable of identifying suitable and unsuitable areas (AUC=0.94). Subsequently, only small areas of Fars Province in the southwest and north parts were found to be suitable for the species establishment. Figure 2 shows the result of DOMAIN model and pseudo-absence points in unsuitable habitat.

In general, the relative success of three individual modeling methods in predicting species occurrence showed that the AUC values of models were higher than their Kappa values. Therefore, the AUC was used to construct the ensemble map. Compared to other models, the BP-ANN had the highest AUC value (0.935), followed by the ensemble technique, GLM, and MaxEnt with the AUC values of 0.890, 0.887, and 0.777, respectively. Subsequently, the maximum and minimum threshold values of 0.23 and 0.45 were applied to the BP-ANN and the ensemble approach models, respectively (Table 3). After applying the threshold, the accuracy of classification was presented on the basis of the Kappa index. In the end, the highest value of Kappa index was related to BP-ANN (0.757), while its lowest value was associated to MaxEnt (0.438).

Table 2 Metrics used at the class and landscape levels to analyze the distribution of the suitable habitat of *Amygdalus scoparia* in different classes of landform (McGarigal 2012)

Metrics	Abbreviation	Units	Range
Number of patch	NP	None	NP> 0
Total edges	TE	Meters	TE≥ 0
Edge density	ED	Meters per hectares	ED≥ 0
Mean patch size	MPS	Hectares	MPS> 0
Mean shape index	MSI	None	MSI≥ 1
Large patch index	LPI	%	0 < LPI < 100
Contagion index	CONTAG	%	CONTAG> 0
Shannon's diversity index	SHDI	None	SHDI > 0
Euclidean mean nearest neighbor	MNN	M	MNN > 0
Landscape shape index	LSI	None	LSI ≥ 1

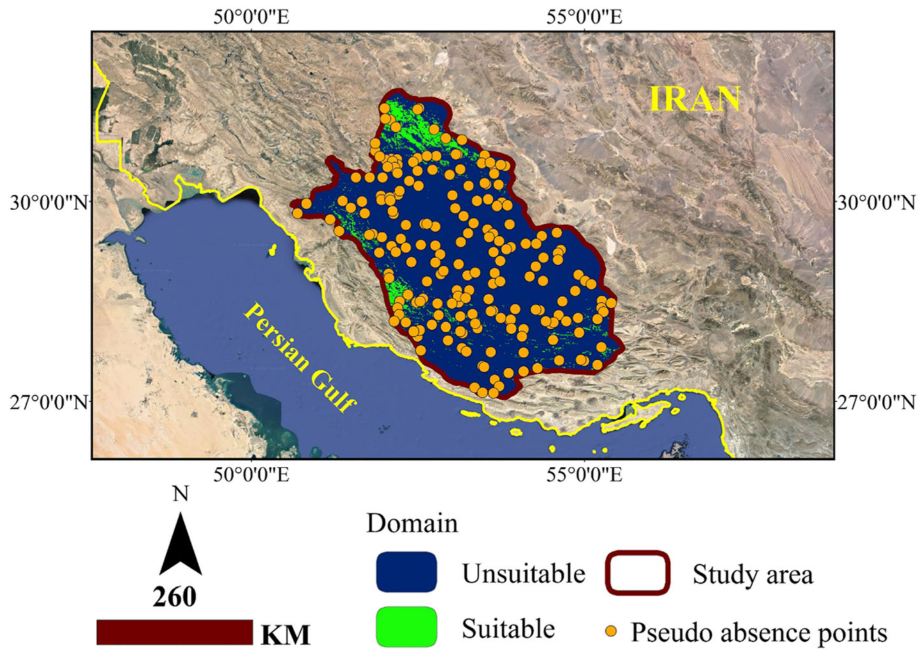

Fig. 2 Result of DOMAIN present only model and location of pseudo-absence points

Potential distribution map of *A. scoparia*

The continuous spatial suitability map of *A. scoparia* derived from the BP-ANN model showed that in addition to the narrow strip of west and north of the province, small areas in the southern and southwestern border of the province also have potential for species establishment. Moreover, distribution map derived from the GLM indicated that in most parts of Fars Province, including southeast, south, southwest, west, and north, the species is likely to occur. Contrarily, central parts were shown to be non-susceptible for *A. scoparia* establishment. On the other hand, based on the MaxEnt model, the probability of the species presence throughout the province has increased, and the species can potentially be distributed in the southeastern, eastern, and partially in northeastern parts of the province. Furthermore, intersected map obtained from the ensemble application of the models showed an overview of the conditions of the implemented models, indicating susceptible habitat conditions for the establishment of species in east, south, west, and north parts of the province (Fig. 3).

Based on the binary maps, suitable potential habitats for the studied species covered 24.07, 30.74, 43.05, and 23.55% of Fars Province in BP-ANN, GLM, MaxEnt, and ensemble approach, respectively (Fig. 4). Thus, we can state that the maximum and minimum areas of suitable habitats corresponded to the maps obtained from the MaxEnt model and the ensemble approach, respectively. Table 4 demonstrates the area and percent of suitable/unsuitable habitat for each model in Fars Province.

Analysis of variable importance by accuracy reduction method

Table 3 shows the importance of the variables employed in the modeling process. The results of random forest regression analysis in the BP-ANN model showed that Bio 3 (isothermality) and Bio 17 (precipitation of driest quarter) variables with 37% justification of species distribution variations had the most influence on the presence of *A. scoparia* in the study area. On the contrary, slope degree and aspect had the least effects on species distribution in the study area. In other words, Bio 3 and Bio

Table 3 Threshold, TPR (true positives rate), and highest kappa value

Model/technique	Area under curve (AUC)	Threshold limit	TPR	Kappa index
ANN	0.935	0.23	0.927	0.757
MaxEnt	0.777	0.40	0.808	0.438
GLM	0.887	0.34	0.922	0.616
Ensemble	0.890	0.45	0.876	0.706

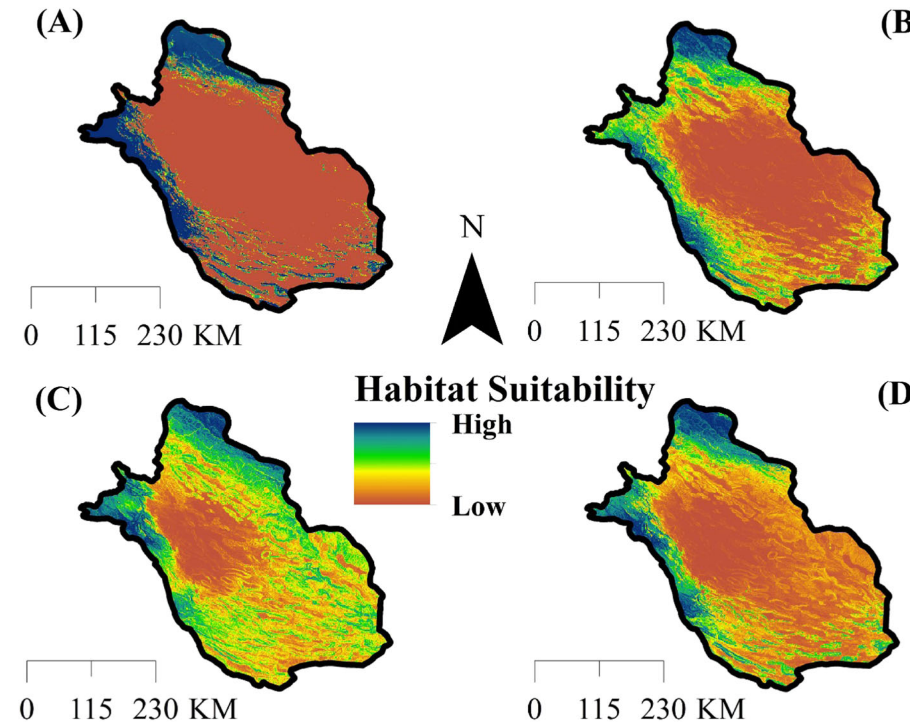

Fig. 3 Continuous map of habitat suitability for *Amygdalus scoparia* in Fars Province, southern Iran. **a** BP-ANN model, **b** GLM model, **c** MaxEnt model, and **d** ensemble technique

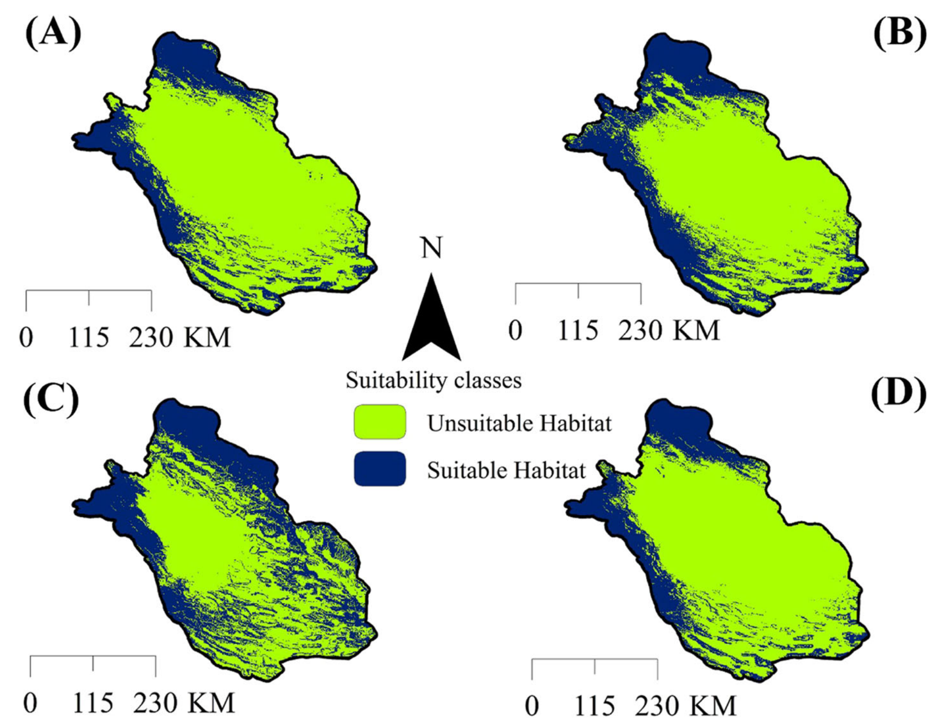

Fig. 4 Discrete habitat suitability map of *Amygdalus scoparia* after applying optimal threshold limits in Fars Province. **a** BP-ANN, **b** GLM; **c** MaxEnt, and **d** ensemble technique

Table 4 Importance of environmental variables (%) used in predictive models by the random forest regression analysis

Variable	ANN model	MaxEnt model	GLM model	Ensemble technique
Bio 3	22.09	31.35	31.73	30.74
Bio 17	14.89	14.55	18.59	18.03
Bio 13	14.07	17.70	19.03	16.87
Ndvi	14.03	15.17	11.56	17.35
Dem	12.34	17.43	13.63	11.45
Bio 19	12.19	23.23	15.72	15.63
Bio 15	10.63	12.33	14.55	12.40
Bio 4	9.57	30.73	22.38	23.32
Soil	9.20	20.15	12.85	14.14
Bio 14	4.26	3.77	9.40	4.77
HLI	3.99	8.30	0.66	2.99
CTI	2.99	5.23	4.88	4.24
Slope	2.40	8.38	6.53	2.23
Aspect	1.50	1.30	0.03	1.84

HLI heat load index, *CTI* compound topographic index

17 variables were better predictors of habitat distribution than the others. In the MaxEnt model, both Bio 3 and Bio 4 (temperature seasonality), with justification of about 46% of the variations, had the most impact on the model implementation and distribution of the study species. In this model, the least influence was related to the slope aspect. Moreover, the results of sensitivity analysis of the GLM and the ensemble approach verified that the Bio 3 and Bio 4 variables had the highest (50 and 48%, respectively) impacts on habitat suitability and subsequently on the spatial distribution of *A. scoparia* (Table 5). Hence, it is safe to say that the random forest regression model performed well in modeling (Table 6).

Analysis of spatial distribution of suitable habitat using landscape metrics

The results of landscape metrics in different classes of landform and the relationship between species habitat distribution and different landforms are presented in Table 6. The highest (1,474,162.19 ha) and lowest (53.28 ha) habitat covers of the species were observed in canyons and open slope landforms, respectively, followed by mountain tops, upland drainages, and hills in valleys (Table 7). Furthermore, according to the NUMP metric, the highest and lowest numbers of patches were in upland drainages and open slopes (1255 and 1 patches, respectively). The high value of NUMP in the upland drainage class indicated the fragmentation and scattered distribution of the suitable habitat of the species. The mean shape size (MSI) also showed that in most distributed habitat patches, landform classes had near-squared shapes, indicating pixel distribution. In open slopes, the MSI index value was 1, suggesting that there was only square-shape pixel in this class. However, the highest amount of complexity in the metric shape was calculated in the mountain top and canyon classes. Additionally, based on the results of the total edge (TE) metrics, the highest and lowest edges belonged to the canyons and open slopes (2,3875,595.2 and 3528.8, respectively). Considering the calculated metrics related to the open slope class and the low number and size of patches in this class, it seemed that the open slopes of landform did not play much role in suitable habitat of the species. Based on the edge density (ED) metric, the lowest and highest edges were assigned to the plains and shallow valleys, respectively, indicating the discrete distribution of the suitable habitat in the shallow valleys. The largest patch index (LPI) was also calculated 19.17, suggesting that the distribution of the suitable habitat of the species in different landform classes is small patches but not dominant; because this metric shows the percentage of the largest patch to total area. The high value of LPI, on the other side, represented the dominance of a particular class in the landscape. This value (19.17) covering the

Table 5 Evaluation functions of the random forest regression performance in analyzing the importance of variables

Parameter	BP-ANN model	MaxEnt model	GLM model	Ensemble technique
MAE	0.07	0.08	0.1	0.06
MSE	0.02	0.01	0.01	0.00
RMSE	0.14	0.11	0.12	0.09

Table 6 Area (km^2) and percent of different classes of habitat suitability for *Amygdalus scoparia* in Fars Province, southern Iran

Model	Suitable	% of total area	Unsuitable	% of total area
BP-ANN	29,969.68	24.07	94,500.51	75.93
GLM	38,268.79	30.74	86,194.58	69.26
MaxEnt	53,580.76	43.05	70,876.22	56.95
Ensemble	29,316.46	23.55	95,151.42	76.45

desired habitat in the landform classes was related to the valleys. Further, based on the value of CONTAG metric (55.17), it can be declared that the suitable habitat of the species is contiguous in different landform classes, and there are patches between different classes of landform. This value (55.17) also indicated that the suitable habitat of the species is contiguous in different landform classes, and there are common patches between landform classes. The SHDI was opposite to the CONTAG metric. Since the value of SHDI was not zero, it had a small share in the distribution of the desired habitat in different classes of landform. The habitat of the species had little diversity in terms of covering different landform classes. Also, the value of MNN metric (3659.93 m) showed that the suitable habitat of the species in different classes of landform was on average 3659 m apart. Besides, considering the value of LSI metric, we can assert that there was considerable perturbation in various classes of landform creating a complex feature for the species suitable habitat.

Discussion

Due to the unknown extent of suitable habitats for the establishment of *A. scoparia* and its mountainous and rocky habitats, it is necessary to use different modeling methods to identify potential suitable areas for the expansion of current habitats. Moreover, given the limited distribution of the species, it is difficult to define geographical boundary for its habitat. This brings about the modeling level to be chosen subjectively (Williams et al. 2009). On the other hand, study of the interaction between the species and its surrounding environment, as one of the functions of the SDMs, is an important aspect of ecological studies (Thakur et al. 2017). Therefore, knowledge obtained from the SDMs can be used to protect and restore plant habitats.

Suitable habitat analysis

The used models were clearly different in prediction performance and identification of the potential distribution areas of the species. The BP-ANN and the ensemble approach were the best and most accurate models in predicting suitable habitat of *A. scoparia*. Although the discrimination capacity of all models was at a favorable level, the BP-ANN had the highest ability to discriminate between presence and absence points (AUC = 0.935). It has been reported that the model's discrimination capacity and output reliability indices are highly important in measuring the prediction accuracy of the SDMs (Liu et al. 2011; Piri Sahragard and Zare Chahuki 2015). The relative importance of these indices (i.e., capacity discrimination and output reliability) is influenced by the type of use and the user proficiency (Pearce and Ferrier 2000). In the present study, the BP-ANN was a more efficient model than others in predicting the distribution of *A. scoparia* potential habitats because of its higher discrimination capacity in distinction of presence and

Table 7 Evaluation of the distribution of suitable habitat of *Amygdalus scoparia* in landform classes based on the landscape metrics analysis

Landscape metrics (class level)						
Landform	**Habitat coverage (ha)**	**TE**	**ED**	**MPS**	**NP**	**MSI**
Canyons	1,474,162.19	23,875,595.2	3.62	1709.65	863	1.4
Shallow valleys	8086.38	520,492.2	12.36	85.1	139	1.02
Upland drainages	177,652.24	7,962,648.6	10.08	185.11	1255	1.16
U-shaped valleys	47,321.34	2,401,321.7	4.29	133.65	474	1.1
Plains	1278.82	84,690.3	1.35	81.21	23	1.02
Open slopes	53.28	3528.8	7.56	77.83	1	1
Upper slopes	11,258.62	728,689.1	11.16	84.65	194	1.02
Hills in valleys	134,928.50	625,6492.8	8.19	168.4	1062	1.14
Mid slope ridges	7871.33	495,790.9	8.68	91.41	126	1.03
Mountain tops	855,816.76	18,668,908.7	5.67	820.6	1090	1.42
		Landscape metrics (landscape level)				
		LPI	CONTAG	SHDI	MNN	LSI
All type of landforms		19.17	55.17	1.15	3659.93	46.37

absence points. However, the largest and smallest predicted suitable areas (43.05% and 23.55% of total area of Fars Province, respectively) for *A. scoparia* were related to the MaxEnt model and the ensemble approach. The prediction performance of models can vary on the basis of used mathematical functions (Haidarian Aghakhani et al. 2017; Piri Sahragard et al. 2017).

Analysis of the true positive rate (TPR) and a criterion for assessment of model's prediction accuracy, moreover, indicated that the BP-ANN with the sensitivity of 0.927 and the MaxEnt model with the sensitivity of 0.808 had the highest and lowest ability to distinguish between presence and absence points. In other words, the model obtained from the MaxEnt was the weakest model in discriminating presence points from absence ones because the ability of the model to detect presence and absence points did not exceed 0.808 with regard to the optimal threshold of 0.4. In consistent with these findings, Norris (2014) reported that the model must be highly sensitive due to the unique environmental conditions, the limited habitat size, and the need to identify highly suitable areas to protect and manage rare plants habitats. Additionally, because of the ability of the BP-ANN to model nonlinear relationships between variables, it can be a valid alternative to regression methods and other widely used SDMs. The superiority of the BP-ANN over other models has been also reported in several studies (Rasztovits et al. 2012; Abbasi and Zare Chahuki 2014; Rasztovits et al. 2014; Kafaei et al. 2020). Consequently, this study recommends the use of BP-ANN model for studies of *A. scoparia* habitats.

The BP-ANN model indicated that out of the total area of Fars province, about 29,969 km^2 (24.07%) had a high suitability for establishment of *A. scoparia*. But in 94,500.51 km^2 (75.93%) of the province, the prevailing environmental conditions did not meet the ecological requirements of the species. Distribution pattern of the potential habitats also showed that the west and north of the province were potentially more suitable for expansion of the current habitats provided that other environmental conditions are met. Further, given the unsuitable areas for species establishment, it can be declared that climatic constraints can limit the expansion of current habitats to areas with special environmental conditions. Piri Sahragard et al. (2019) reported that *A. scoparia* was only found in areas with shallow soil and abundant gravels where these conditions are more frequent in certain elevation ranges (ca. 1500–2150 m above sea level). This point should be also considered in conservation and afforestation plans (Tavakol Neko et al. 2012).

Landscape structure analysis

Analysis of habitat distribution in landform classes indicated that *A. scoparia* was mainly distributed in the canyon, mountain top, and upland drainage classes. For example, according to the LPI metric, 19.17% of the total suitable habitat of the species was located in the canyon class. Habitat suitability was higher in the canyons and mountain tops than in other classes. For instance, the highest complexity and the lowest edge density (ED) were in the canyons and mountain tops. The highest number of patch (NP) was in the upland drainage class, indicating that the species' habitat was fragmented in this class of landform. The low value of MSI metric and low number and small size of patches in open slope class illustrate that this class of landform did not have considerable contribution in suitable habitat distribution. It has been reported that some metrics, such as NP, ED, and MSI, are the most important metrics in assessing the landscape and separating plant habitats (Sfougaris et al. 2014; Piri Sahragard et al. 2015; Zare Chahouki et al. 2016). In this research, the relationship between the calculated metrics and the spatial distribution of the species in different landform classes showed that the most suitable habitats of the species were located in the mountain tops and upland drainages with shallow soil and abundant pebbles. In fact, these classes have created the possibility of the emergence of continuous habitats with high complexity and low edge for *A. scoparia*. We further noticed that the suitability of landform for the species was decreased by descending to lower altitude and flat landform. In other words, the highest presence of the species occurred in landforms with medium to light soil texture and abundant pebbles, which are coincident with ecological needs of the species (Tavakol Neko et al. 2012). It has been reported that the probability of *A. scoparia* occurrence could be limited by altitude in different parts of Iran so that the highest occurrence of *A. scoparia* habitat has been observed in elevation of 1500–2150 m above sea level (Tavakol Neko et al. 2012; Piri Sahragard et al. 2018).

In addition, the relationship between species presence probability and dominant environmental variables revealed that the Isothermal and Precipitation of Driest Quarter justified about 36% of the variation habitat distribution. These variables contribute significantly (22.09% and 14.89%, respectively) in habitat suitability determination. Slope had the least effect on variation of habitat distribution, indicating that model implementation with this variable alone could not be useful for habitat prediction of *A. scoparia*. Thus, it can be concluded that the isothermal, annual temperature, and rainfall in the driest season with considerable justification of the species distribution variations have the greatest contribution in determining habitat suitability of *A. scoparia*. Consistently, Haidarian Aghakhani et al. (2017) reported that the annual temperature and rainfall are important variables affecting the occurrence of *A. scoparia* so that this species could mostly appear in areas with mean annual temperature of 24–26 °C and annual rainfall of 400 to 600 mm.

Conclusion

This study aimed to analyze the suitable habitat of *A. scoparia* in different landform classes by integrating landscape metrics and the SDMs in Fars Province, southern Iran. The BP-ANN was found to be the most accurate model for predicting the distribution of *A. scoparia* habitats in the study area. The most suitable habitats for the potential distribution of the species, with an area of 29,969 km^2, were located in the northern and western regions of the province. Moreover, analysis of landscape metrics showed that the canyons, mountain tops, and upland drainages were the most important landforms for *A. scoparia* establishment since they can provide the most favorable environmental conditions. As a result, these landforms should be given priority in the restoration of *A. scoparia* habitats at the northern and western regions of the province. Consequently, integration of landscape composition related to landforms and accurate SDM for predicting the distribution of plant habitats can provide valuable knowledge for the restoration of degraded habitats. However, due to the limitations of the SDMs, caution should be taken in interpreting the results of such approaches.

Climatic variables, including Bio 3 (isothermality) and Bio 17 (precipitation of driest quarter), were the most important drivers of *A. scoparia* occurrence in the study area. These factors could significantly impact the potential distribution or realized niche of the species. However, by considering the biophysical factors, such as inter-species interaction, geomorphological characteristics, and soil type, we can achieve more reliable results in habitat distribution modelling generates.

Finally, it should be pointed out that for future studies, finding out the effectiveness of integrated landscape composition and the SDMs approach in predicting the potential habitat of plant species with different distribution ranges can be an attractive research field. Such research not only develops the use of new frameworks in spatial distribution modeling of plant habitats but also helps forest managers and other authorities with the effective restoration of degraded habitats by generating accurate information and maps.

Abbreviations

BP-ANN: Backpropagation artificial neural network; MaxEnt: Maximum entropy; GLM: Generalized linear model; SDMs: Species distribution models; CTI: Compound topographic index; HLI: Heat load index; DEM: Digital elevation model; AUC: Area under the curve

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Authors' contributions

Authors have equally contributed in conception and design of the study, data collection, modelling and mapping, drafting the manuscript, and approval of the article.

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Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Ethics approval and consent to participate

Not applicable.

Consent for publication

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Competing interests

The authors declare no competing interests.

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