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Habitat Suitability of *Dorema ammoniacum* D. Don. Using Maximum Entropy and Logistic Regression Modeling in Central Region of Iran

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ABSTRACT

Aims: The purpose of this study was to evaluate the competency of logistic regression (LR) and maximum entropy (MaxEnt) models to predict the distribution of *Dorema ammoniacum* D. Don. in rangeland habitats in the central region of Iran, Yazd Province.

Materials & Methods: The potential distribution map of *Dorema ammoniacum* D. Don. was prepared. The homogenous habitats were identified, and vegetation sampling was conducted using a systematic random method. The data, including soil (physical and chemical properties), physiographic (slope, aspect, and altitude), and vegetation data (presence and absence), were used. Soil sampling was performed at two depths of 0-30 and 30-60 cm. The required maps were prepared using the interpolation method. Statistics were taken from 90 plots along nine transects, both in the presence and absence areas. Response curve and Jackknife test (for MaxEnt method) were employed to identify the most important environmental predictive factors. The kappa index was used to determine the agreement between the actual and predicted maps.

Findings: The accuracy of the predicted map was weak in LR Model (AUC= 0.65), but it was considerably high in the MaxEnt model (AUC=0.87). The agreement between the predicted map of the MaxEnt model and ground truths was very good (kappa=0.74), and the agreement between the predicted map generated by LR with the ground-truths was medium (kappa=0.5).

Conclusion: This plant has a limited ecological niche; therefore, the MaxEnt model could take precedence over the LR model because the only data it employs is the presence of the species.

Keywords: Species distribution modeling, Habitat assessment, Response curve, Distribution map.

CITATION LINKS

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Introduction

Determining the habitat suitability of vulnerable species using effective and accurate models can help preserve rangeland ecosystems and valuable habitats. *Dorema ammoniacum* is an endemic in Iran and endangered plant of great importance from the Apiaceae family [1]. This plant is herbaceous and perennial, of about 2 m height with forage, industrial and medicinal values, growing naturally in the arid and desert areas such as central provinces and east and south-east of Iran [1, 2]. Ecological agents, including soil, climate, physiography, and human activity, affect the dissemination of plant species [3, 4]. Therefore, exploring the relationship between species and environment variables is crucial to successful vegetation restoration [5]. The mapping distribution of the geographical and environmental patterns of rare and endangered species is essential to identify destructive human activities threatening biodiversity [6]. There are several methods for predicting habitat suitability maps focusing on the species. Species distribution modeling has grown progressively significant because it deals with resource evaluation, environmental protection, and biodiversity conservation programs [7]. Modeling methods such as generalized linear models, generalized additive models, classification and regression tree analysis, and artificial neural networks need valid information of existence and non-existence statistics to produce statistical functions that are established based on the presence and absence of species and determining the habitat suitability.

On the contrary, specific methods such as Ecological Niche Factor Analysis and MaxEnt require the existing data and can be used when the absence data is insufficient or unavailable [3, 8]. The LR model is a regression method used in the predictive variable constant, and the response variable is binary, and LR is a widely used method among linear models in habitat prediction modeling [9]. The MaxEnt is a machine learning program, which estimates the chance of plant species distribution considering environmental constraints, and its main idea is to estimate the unrecognized possibility of dispersal of a unique plant species [3, 8, 10]. Evaluating the accuracy of the models produced by different methods is an essential issue in predictive models [11]. A quantitative evaluation of model efficiency helps in distinguishing the suitability of the model for specific applications. This might also help to recognize those positions of the model that need improvement [12]. Due to the different capabilities of several plant species distribution modeling methods, selecting a suitable model for plant habitat distribution modeling is of great necessity in order to achieve accurate and appropriate results [13].

In a study, the MaxEnt modeling was employed to predict the possible distribution of the native plant *Rosa arabica* Crép in Egypt. The main environmental factors contain annual temperature, annual precipitation, and elevation identified in the distribution of the mentioned species [14]. In another study, the MaxEnt modeling method was used to predict the distribution of *Cornus Officinalis* in China. The result of this survey showed that the MaxEnt model has high accuracy. Environmental variables determine the distribution patterns for the conservation and recovery of this medicinal species [15]. In another study, the current and future Medusahead and Barbed Goat grass distributions were predicted using the MaxEnt model, and distribution changes were predicted. It was also concluded that climate change might facilitate the attack on Medusahead at higher altitudes [16]. Prediction of jujube potential distribution in Khorasan was made by the MaxEnt method; they predicted suitable habitats in central and eastern Iran because they are partially in line with the ecological conditions of South Khorasan Province, Iran [17].

The effects of climate changes on the distribution of endemic *Ferula xylorhachis* in Iran were assessed using the MaxEnt modeling tools. The results indicated that the most suitable areas for the presence of the studied species would have variability over time [18]. The probable dispersal of three species, *Artemisia aucheri* and *Bromus tomentellus*-*Festuca ovina*, were served in Iran using the MaxEnt model. They concluded that the actual map correspondence with the prediction map, which was performed at an acceptable level [8]. The prediction efficiency of LR to MaxEnt for distribution modeling of rangeland plants in western Taftan Mountain, southeastern Iran, were evaluated and observed that LR and MaxEnt modeling methods had similar performance with a narrow ecological niche [19]. Many studies used MaxEnt and LR modeling methods to predict the spatial pattern of many plant species habitats in Iran's rangelands. They concluded that the MaxEnt modeling methods were suitable for predicting the distribution of the plants with limited ecological distribution, e.g., *Rheum ribes*, *A. sieberi-A. Aucheri, Ephedra strobilaceae, Agropyron intermedium,* and *Stipa barbata* [20, 21, 22, 23, 24, 25].

The first phase of this study was performed using LR [26]. To compare the accuracy and advantages of the models obtained from these two methods, it was decided to model results using MaxEnt. Considering the limited spatial distribution range, along with the lack of available information on *D. ammoniacum*, we focused on ecological distribution modeling using environmental factors to estimate the most suitable areas in Yazd Province, Iran, and introduce this species for rangeland restoration and species conservation. Evaluation of the prediction performance of LR in comparison with the MaxEnt methods in distribution modeling of this species is another objective of the current study in the rangelands of Bafgh county- Yazd Province, Iran.

Materials and Methods

Study area

Area of this study with 64515 ha, located in the western part of Yazd Province, 50 km far from the city of Bafgh (55° 42′ 00″-56° 02′ 00″ E and 31° 26′ 30″-31° 47′ 00″N - Figure 1). The elevation of the selected habitat varies from 1800 to 2600 meters above sea level. Climatic variables, including average annual temperature and annual rainfall of sampling points, were also extracted using information from the nearest meteorological stations (1996 to 2018). Annual precipitation ranges from 130 to 170 mm in the study area. The amount of mean annual rainfall in the study year (2018) was about 150 mm. Snowfall and cold climate are common in the winter season over the study area, and the average yearly temperature is 15.5°C. The amount of rainfall during the rainy season (spring) is about 50 to 60 mm. Plant species such as *Aellenia subaphylla*, *Artemisia sieberi, Astragalus spp., Cousinia deserti*, *Eurotia certatoides*, *Gymnocarpus decander, Hammada slicinica*, *Launea acanthoides, Petropyron aucheri*, *Salsola tomentosa*, *Zygophyllum atriplicoides,* and *Z. euryterum* are co-habitat at the study area [27].

Data collection

In the selected habitat of the presence of *D. ammoniacum,* the sampling process was conducted during May 2018, when most species were at the peak growing stage. In the habitat, the sites with *D. ammoniacum* distribution were chosen as the existence of this species; near each of the selected sites, with the same edaphic and ecological conditions, the second sites, as the absence of *D. ammoniacum* distribution, were selected as the absence sites. Afterward, eighteen transect lines (9 for the presence and 9 for the absence of *D. ammoniacum*) in the length of 300-350m were established on a random-systematic method on the sites with the presence and absence of *D. ammoniacum* (Figure 1).

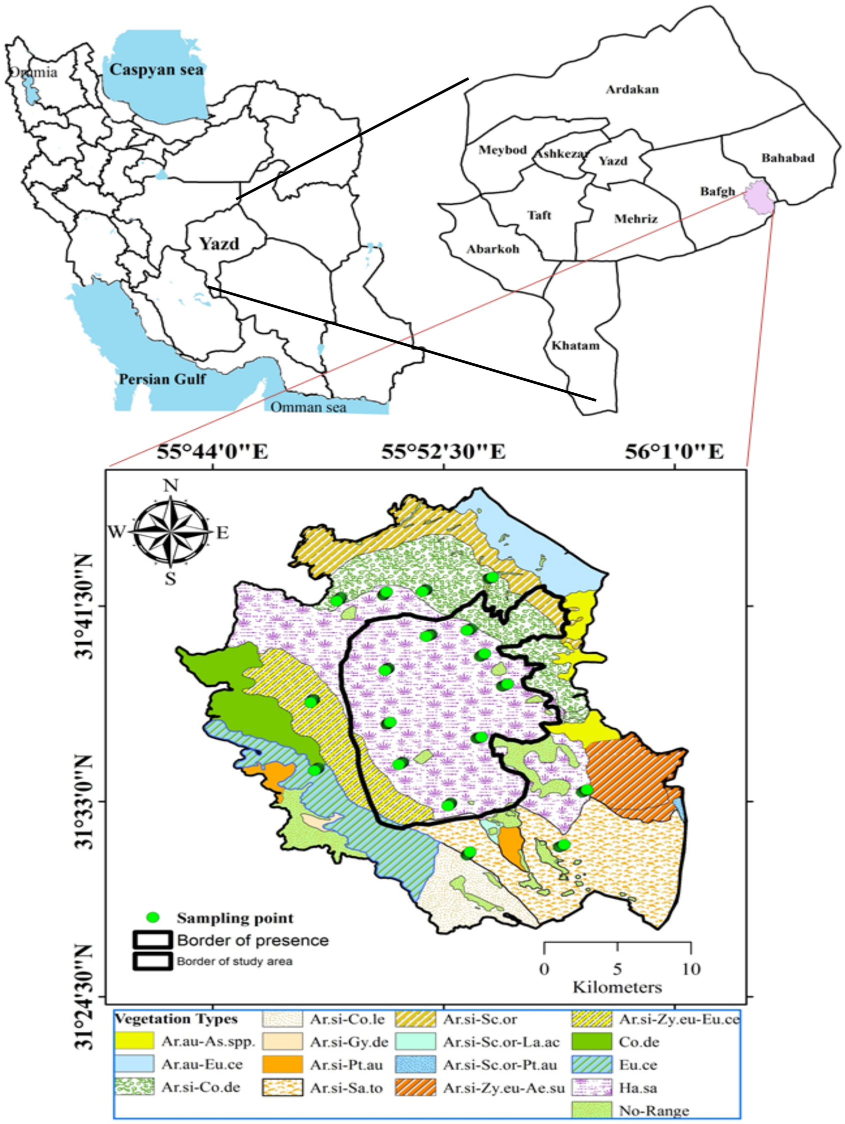

Figure 1) General location, vegetation type, and the sampling data area of the study region, in the west of Yazd Province, Iran.

The size of sampling plots was determined between 4 to 16 m^2 according to the type of plant species, their cover density using the minimum area method [27]. In general, data were collected from 180 sampling plots. Within each quadrat, the existence and non-existence of the *D. ammoniacum* were recorded. The soil sampling was performed from the beginning and end of each transect (eighteen soil samples along each transect line, from 0–30 cm and 30-50 cm depth). Accordingly, 0-30 cm and 30-60 cm depths were selected as the first and second depths of the soil, respectively. Afterward, the physical and chemical properties of the soil samples were measured at the lab according to the routine procedure based on standard laboratory methods. Soil factors include texture (Bouyoucos hydrometer method), saturation moisture (SP), salinity (EC/Saturated extraction method), acidity (pH/Potentiometric method), lime (TNV), organic carbon (OC), organic matter (OM/Walky and Block method), soluble solutes include: Na, Ca (Flame photometer method), Mg, K, Cl^-, $Co3^{2-}$, Hco_3^- (Litration method) and $So4^{2-}$ (Spectrophotometer method) were measured [28, 29]. The physical characteristics and vegetation information of the study area are listed in Table 1.

Table 1) Physical characteristics and vegetation information of the study area.

Transect	Latitude/ Longitude	Elevation (m)	Slope (%)	Aspect	Precipitation (mm)	Temperature (°c)	Texture soil	Dominant and accompanying species	Soil Type	Cover (%)	Bare soil (%)	Stone (%)	Litter (%)	Condition Rangeland	Trend
1	55°53’31”/31°40’31”	2242	7.2	SE	169	39	Sa.Si	*Hammada salicornia- Artemisia sieberi- Calligonum poligonoides*	C.R	9	48	35	9	Poor	_
2	55°52’2.1”/31°40’16”	2140	7.4	SE	158	38.9	Sa.Si	“””	C.R	8	49	34	10	Poor	_
3	55°55’24”/31°36’21”	2098	7.4	S	154	38.7	Sa.Si	“””	C.R	7.5	50	34.5	10	Poor	_
4	55°50’27”/31°38’47”	2019	14	S	146	38.3	Sa.Si	“””	C.R	7	50	35	13	Poor	_
5	55°52’45”/31°32’55”	2119	5	S	146	38.8	Sa.Si	“””	C.R	8	49	35	11	Poor	_
6	55°50’59”/31°34’42”	2082	3	S	152	38.6	Sa.Si	“””	C.R	7.5	49	34	9.5	Poor	_
7	55°53’50”/31°39’18”	2072	5.3	SW	151.7	38.6	Sa.Si	“””	C.R	9	48	32	10	Poor	_
8	55°54’39”/31°38’00”	1996	3.9	S	144	38.2	Sa.Si	“””	C.R	8	50	32	10	Poor	_
9	55°47’42”/31°35’44”	2041	5.6	SW	148.6	38.4	Sa.Si	“””	C.R	9.5	47	38	5.5	Poor	_
10	55°47’42”/31°37’25”	1976	7.6	NW	141.8	38	Sa.Si	*Artemisia sieberi- Zygophyllum europterum- Eurotia ceratoides*	C.R	9	48	35	8	Poor	_
11	55°47’52”/31°34’27”	1943	3.5	SE	138	38	Sa.Si	*Eurotia ceratoides*	C.R	8	45	33	14	Poor	_
12	55°53’21”/31°30’39”	1955	2.4	S	139	37.8	Sa.Si	*Artemisia sieberi- Salsola tomentosa- Aellenia subaphylla*	L.L-C.G	9	33	47	11	Poor	_
13	55°57’35”/31°33’24”	1914	2	S	135	37	Si.Sa	“””	L.L-C.G	9	45	34	10	Poor	0
14	55°56’45”/31°31’01”	2066	24	SE	151	38	Si.Sa.C	“””	L.L-C.G	8	48	35	8	Poor	0
15	55°51’52”/31°42’2.7”	1943	4	SW	138	37.7	Si.Sa.C	*Artemisia sieberi- Cousinia deserti*	C.R	7.4	44	44	4.6	Poor	0
16	55°50’16”/31°41’58”	1901	3.4	NE	134	37.6	Si.Sa	“”	C.R	6	49	32	12	Poor	0
17	55°48’42”/31°41’52”	1855	10	SW	129	37	Si.Sa	“”	C.R	7.8	39	42	11.2	Poor	0
18	55°54’9.3”/31°42’41”	1950	6.8	SE	139	37	Si.Sa	“”	C.R	7	41	37	15	Poor	0

C.R: Calcaric- Regosols; L.L: Lithic Leptosols; C. G: Calcaric Gypsic; C. R: Calcaric Regosols; +: Positive trend; -: Negative Trend 0: Stable Trend; Sa. Si: Sandy silty; Si. Sa: Silty sandy; Si. Sa. C: Silty Sandy Clay

Data analysis

Preparation of maps of all influential variables is essential for producing a prediction map. Initially, the digital elevation model map of the study area was produced. Environmental variables were quantified using extracted DEM from 1:25,000 scale topographic map and geology maps (1:100,000). In order to map the soil and slope properties used, first, the presence or absence of spatial structure between the data using the components of the variogram model in GS+ v.5.1.1 software was assessed. Among the different Gaussian, spherical, exponential, and linear models, the best model was evaluated based on root mean squared error (RMSE). After drawing the variogram model and selecting the best model based on the variogram components, the data's spatial structure was surveyed. In order to select the best interpolation method, the indices of mean absolute error (MAE), mean bias error (MBE), and root mean square error (RMSE) were used. The distribution of *D. ammoniacum* in this area was modeled using LR and MaxEnt. Multivariate linearity was explored using variance inflation factor (VIF), less than 5 for all independent variables. For the LR method, $SPSS_{ver}18$ software was used. Input layers of factors prepared using spatial statistics and geographic information systems (GIS) facilities. For the MaxEnt method, maps of environmental factors were built into the ASCII template, and $MaxEnt_{ver}3.3$ software was applied for modeling the species distribution [25]. In this software, 25% of recorded data were reserved for model testing, and the remaining data were used in the training stage. The Jackknife test was employed to distinguish the most influential environmental factors on the distribution pattern of the species under study [19].

Evaluating the accuracy of the predicted models

Accuracy assessment of the predicted map of the species distribution has been done using the comparison of the actual and predicted maps. For this purpose, a cut-off point must be specified to convert continuous probabilities into binary probabilities (presence and absence). The approaches to determinate the falling threshold are divided into subjective and objective categories. An optimal occurrence threshold was determined using the sensitivity specificity equality approach and kappa maximization approach. The maps, classified according to the optimal threshold, were then chosen as the existence or non-existence of this plant species. Afterward, the suitability generated by the models and actual maps was assessed by using the kappa coefficient [5].

Moreover, the models were also evaluated by accurate skill statistics (TSS). The statistical value of AUC varies from 0.5 (cases uninformative the model such as correct existence and non-existence) to 1 (cases perfect discrimination). The AUC statistic presented the model's superiority in recognition among existence and non-existence areas [5, 30]. The statistical value near unity showed a better consistency of the prediction model with the recorded sampling data and reality. The kappa index was calculated to evaluate the agreement between the predicted and actual maps using TerrSet 18.31 software. The highest and lowest values of the Kappa index were relevant to the agreement among forecasted and documented maps [31].

Findings

The results of the spatial study of soil and slope parameters are presented in Table 2. The results indicate that the selected variables are in the strong and medium range of spatial dependence. Table 3 presents the results related to evaluating error rate and deviation of interpolation methods using the cross-validation method and MAE, MBE, and RMSE parameters.

Table 2) Components of variogram an example of soil and physiographic characteristics of Bafgh habitat.

Variables	Variogram Model	Piece Effect (C0)	Threshold (C0+c)	Explanation Coefficient (R2)	Ratio C/C0+C	Spatial Dependence
Slope	Gaussian	0.1	59	0.66	0.998	Strong
Lime2*	Gaussian	8.6	218	0.83	0.96	Strong
Clay2	Spherical	0.33	1	0.3	0.7	Medium
Cl-1	Spherical	0.03	1.32	0.4	0.997	Strong
Na2	Spherical	0.01	5.3	0.68	0.998	Strong
Mg1	Gaussian	0.04	4.4	0.73	0.99	Strong

*Code1 indicates the first depth (0-30 cm), and Code 2 indicates the second depth (30-60 cm) of the soil

Table 3) Evaluation of error rate and deviation of methods used for interpolation of soil and climate characteristics and physiography of Bafgh habitat.

Parameters	Error (%)	Methods		
		Kriging	IDW	NDW
Slope	MAE	2.85	2.35	5.09
	MBE	-0.12	0.07	-1.01
	RSME	4.27	3.68	8.3
Lime2	MAE	33.45	0.14	6.8
	MBE	0.3	-0.02	-1.32
	RSME	76.54	0.17	8.3
Clay2	MAE	0.15	0.12	5.63
	MBE	0.015	0.02	-0.8
	RSME	0.2	0.14	6.6
Cl-1	MAE	0.008	0.014	0.6
	MBE	-0.001	-0.005	-0.11
	RSME	0.01	0.02	0.83
Na2	MAE	0.025	0.027	1.59
	MBE	-0.02	-0.02	-1.03
	RSME	0.19	0.035	2.26
Mg1	MAE	0.07	0.03	0.07
	MBE	0.002	0.0003	-0.23
	RSME	0.08	0.038	1.73

The dash mark in the table indicates the appropriate method for generating the map.

The accuracy assessment of the predictive models in the *D. ammoniacum* habitat in the rangelands of Bafgh, Yazd, is presented in Table 4.

Table 4) Statistics of accuracy assessment of the models and the accuracy level of predictive models in the *D. ammoniacum* habitat in the rangelands of Bafgh, Yazd.

LR		MaxEnt	
AUC	Accuracy level	AUC	Accuracy level [5, 29]
0.65	Week	0.79	Acceptable

Inverse distance weighting and kriging methods were selected as the appropriate method for interpolation. Figure 2 presents the most appropriate predicted and actual map of *D. ammoniacum* habitats resulting from the LR and MaxEnt methods, respectively (predicted habitats are shown in green) in the rangelands of Bafgh-Yazd.

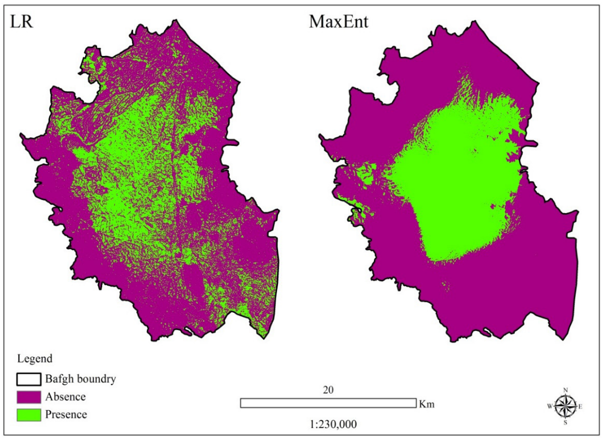

Figure 2) Habitat-suitability maps for *D. ammoniacum* in the rangelands of Bafgh, Yazd, as computed by the two models: Left) LR, Right) MaxEnt.

The input variables of prediction models provided by LR and the coefficient values are shown in Table 5.

Table 5) Input variables of predictive models generated by LR, along with their coefficients in *D. ammoniacum* habitat in the rangelands of Bafgh-Yazd.

Intercept	Predictive variable	Coefficient
285.07	Slope	-29.77
	Lime (30-60 cm depth)	-3.36
	Clay (30-60 cm depth)	-5.14

To determine the efficiency of predicted models by the LR method, the accuracy level of the model for *D. ammoniacum* habitats was weak (AUC=0.65). To determine the efficiency of the predicted model by the MaxEnt, the model was run with arrangements of variables in the MaxEnt method. The accuracy of the MaxEnt model was acceptable (AUC=0.87) for this species (Table 1).
The agreement between the prediction of presence or absence of *D. ammoniacum* and reality was measured using the kappa index. The agreement level of the kappa coefficient regarding the predicted map produced by LR and the actual map was medium (K=0.5) in *D. ammoniacum* habitat, while the level of agreement of the kappa coefficient between the predicted map produced by MaxEnt and the actual map in this habitat was very good (K=0.74). The actual and predicted maps obtained from the LR and MaxEnt are presented in Figure 2. The percentage of slope and lime at 30-60 cm soil and the percentage of clay soils at a depth of 30-60 cm was the most influential variable in distributing *D. ammoniacum* species (Table 5). In other words, the existence of this species was directly relevant to the slope factor, lime amount (at 30-60 cm depth) and, clay amount of soil in (in 30-60 cm depth).
The Jackknife test was used for determining the relative significance of variables. The results showed that introducing a new factor into predictive models in the case of the MaxEnt method does not improve the model accuracy. The output of the Jackknife test for *D. ammoniacum* is represented in Figure 3.
The efficient variables on the distribution of *D. ammoniacum* species were Cl- related to the first soil depth (0-30 cm), Na related to

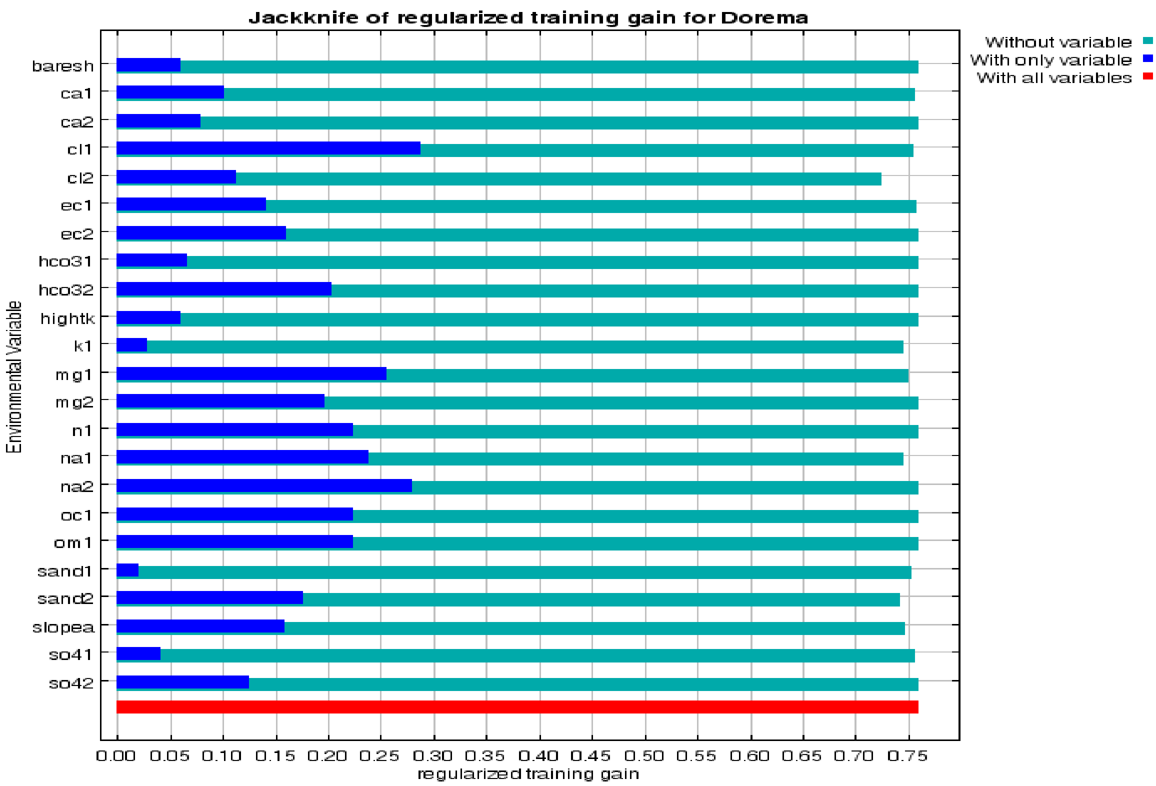

Figure 3) The output of the Jackknife test for determination of environmental variables importance value in *D. ammoniacum* habitat in the rangelands of Bafgh-Yazd.

the second soil depth (30-60 cm), and Mg related to the first soil depth (0-30 cm). These variables are the most influential parameters in obtaining the most accurate model. According to the jackknife test assessment results and the response curve, the relation between the probabilities of plant species presenting with environmental variables can be specified. According to the obtained AUC values and AUC classification for the MaxEnt modeling method, the prediction accuracy of the *D. ammoniacum* habitat model was evaluated to be at an acceptable level (AUC=0.87, Figure 4).

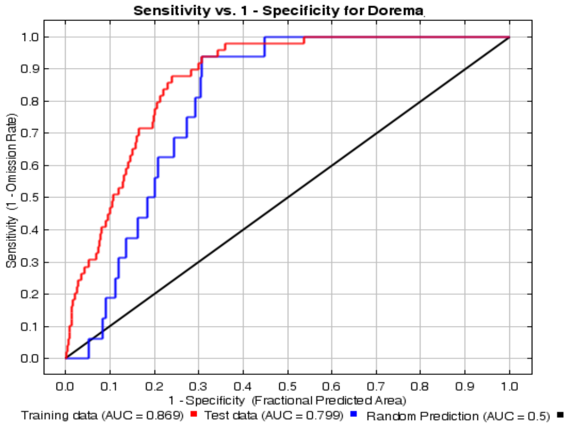

Figure 4) ROC curves of sensitivity vs. specificity (Training data: 75%, Test data: 25%).

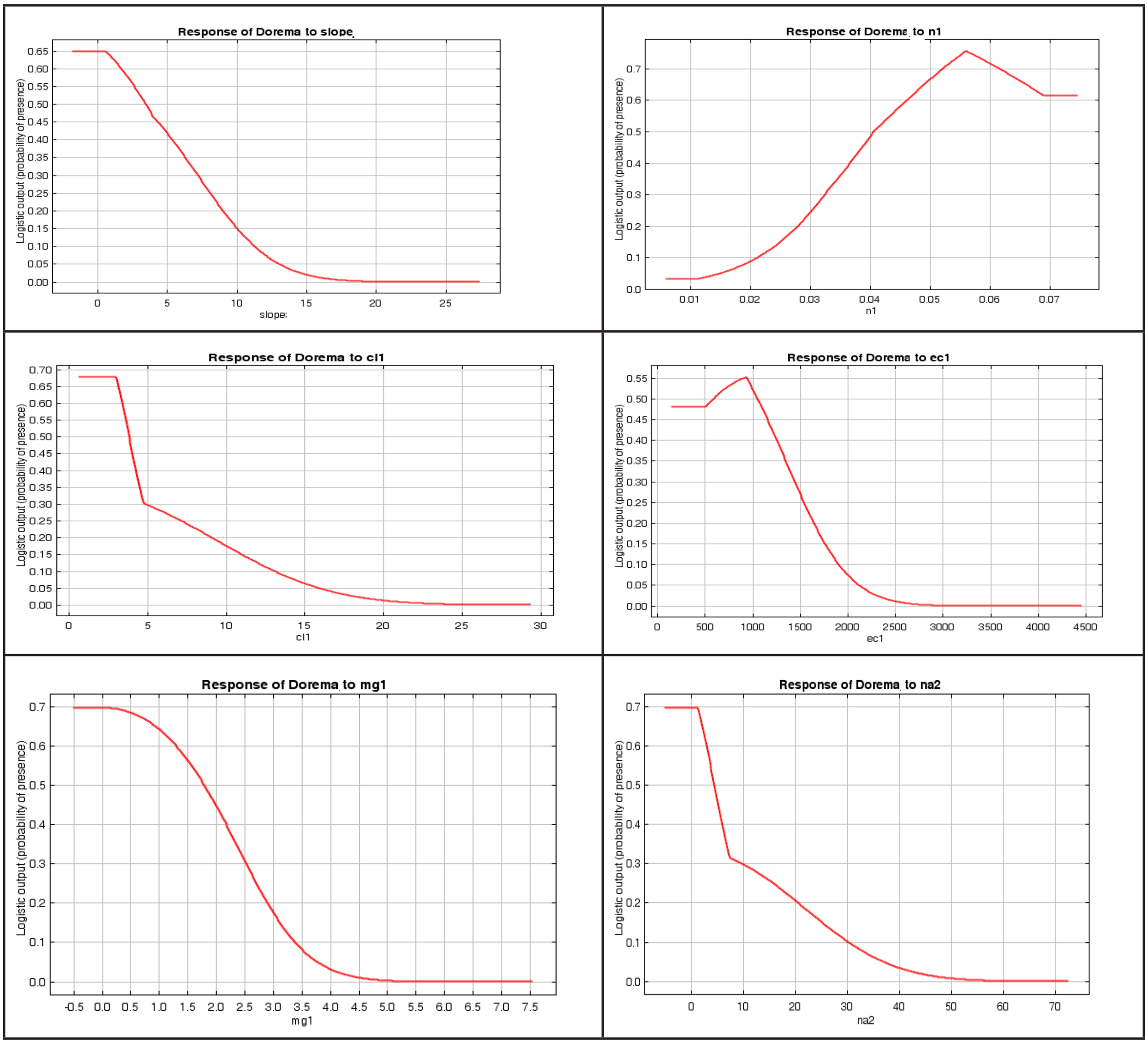

Figure 5) Response curves of the most influential predictors for *D. ammoniacum* habitat.

These curves can represent practical environmental situations for *D. ammoniacum*. Analysis of response curves for environmental factors indicated that the highest probability of this species could have occurred in the slope gradient of about 0-10%. Additionally, the probability of occurrence of this species increases and remains constant with the nitrate values 0.01 to 0.06% at the first depth of soil (0-30 cm) and organic carbon of 0-30 cm soil depth, which varies from 0.15 to 0.65%.

The response curves of the most influential predictors in determining the suitable habitats of *D. ammoniacum* have been presented in Figure 5.

Discussion

One of the important approaches of modeling by LR is predicting habitat fit based on presence and absence data. The produced spatial pattern of a plant species is calibrated; thus, such models can be used for introducing adaptive species in the restoration of rangelands. In this regard, environmental variables play an essential role in the foundation of vegetation [32]. MaxEnt only requires data of a plant species to map the distribution of its habitat; it could be widely employed compared with other standard methods. One model that predicts potential distribution may be based on essential and some factors [33]. Insignificant variables might be able to improve a model's prediction accuracy.

This study showed that models produced based on LR and MaxEnt have different functions in predicting the distribution of *D. ammoniacum* species in Bafgh rangelands of Yazd. In the LR model, the value of accuracy in the model is weak (AUC=0.65). However, the accuracy of the MaxEnt model is acceptable according to the area under the curve criterion (AUC=0.87). The statistical value of AUC as a statistical indicator of the accuracy of a model in predicting plant species is affected by ecological niche. So the MaxEnt method can predict the spatial distribution of species with limited ecological niches more perfectly than LR modeling methods. Because the selected species has a limited ecological distribution, so the accuracy of the model obtained from the MaxEnt is higher than the LR method, which is consistent with the studies conducted by other studies [19, 30].

It has been introduced that species response curves are influenced by the extent of the species ecological niche and affect the efficiency of the modeling results [7, 30].

In the MaxEnt, the absence of species is not considered, and the probability of occurrence of any species is predicted based on the relationship between specific species distribution and environmental variables [19]. It is also possible to study the influence of each variable on the model efficiency separately using AUC. Therefore, to increase the agreement of the model, less effective variables can be removed from the model [30].

The Kappa index in the model obtained by the LR method is 0.5; therefore, the agreement level compared to the MaxEnt method is low, but MexEnt with the kappa value of 0.74 has a very good agreement level. As a remarkable result, the maximum kappa and AUC values obtained for the MaxEnt model and the LR model had lower accuracy values in comparison. Hence, the MaxEnt model is more suitable than the LR method for *D. ammoniacum* in the study area.

Moreover, the performance of the models used in this study also shows that the accuracy of the resulting models in modeling the presence and absence of the selected species is different. This may reason by a significant difference in the performance of the methods was used. In addition to the ecological niche of the species, the quality of the data, which can be used, also affects the performance of the model, so that the incorrect prediction of the species distribution, different scale, and spatial resolution cause other performance of the models [30, 34].

According to the results of MaxEnt and LR, a large number of edaphic variables (EC, N, Cl, Mg, Na, OC, OM, and lime) and physiographic variables (slope and elevation) in the distribution of species *D. ammoniacum* in the Bafgh habitats, Yazd Province of Iran are participating. Moreover, the physical and chemical properties of the soil and the physiographic characteristics of the selected area contain valuable information for the distribution of the selected species. Some soil properties such as Co_3^{2-}, Hco_3^- and So_4^- have a smaller share in the habitat distribution of the studied species. Numerous studies have emphasized the importance of soil properties on the habitat distribution of plant species [3, 5, 8, 13, 14, 17, 19, 23, 30, 34]. In addition, in some habitat settings, physiographic-related factors such as slope, aspect, and elevation are played an essential role in the distribution of plant species. They are essential to consider in modeling a given species such as *D. ammoniacum* [8, 15, 21, 24, 30]. Considering the obtained information, the relationship between ecological variables and the distribution of the selected species shows that in the evaluated habitats due to habitats situation (almost plain and flat lands), the role of soil variables in comparison with the topographic and climatic variables in the presence of *D. ammoniacum* is more effective. In this regard, the results of Ghorbani et al. (2020) identified the importance of topographic, climatic, and soil factors on ANPP variations in rangelands of the QezelOzan-Kosar gradient in Ardabil Province [40]. The results conveyed that variables including TNV and clay related to the second soil depth (30-60 cm) and slope were the input variables of the LR model for *D. ammoniacum*. In the MaxEnt modeling approach, based on the response curve of *D. ammoniacum*, some variables, such as slope, Cl, Mg, and EC, are related to the first soil depth (0-30 cm), which has a negative relationship with the presence of *D. ammoniacum*, so that with the decrease of the slope percentage, the presence of the selected species has increased. However, the presence of *D. ammoniacum* is positively related to the N and OC, and with the increase of N and OC of the first soil depth, the presence of the selected has been confirmed (Figure 5).

Response curves, the most effective predictors in the presence of species *D. ammoniacum,* have indicated that the selected species has the highest presence in the slope range of 0-8%. The ecological range of the variable N related to the first soil depth (0-30cm) is 0.02-0.07%. Of course, the most present probability of the selected species is in the range of 0.03-0.07%. The ecological range of the Cl variable related to the first soil depth (0-30cm) is 0-25%, but the most probability of the presence of the selected species is in the range of 0-5%. Moreover, the ecological range of the EC related to the first depth of the soil is 500-2500 $ds.m^{-1}$. However, the most probability of the presence of the selected species is in the range of 500-1500 $ds.m^{-1}$. The ecological range of the Mg variable related to the first soil depth (0-30cm) is 0-4%, but the most probability of the presence of the selected species is in the range of 0-3%. It should be noted that the ecological range of the variable Na is related to the second soil depth (30-60cm), which is 0-30%, but the most probability of the presence of the selected species is in the range of 0-30%. Overall, *D. ammoniacum* prefers low-slope, low EC, and higher fertility conditions. Considering the linear relation between species existence and environmental variables, the LR model can be a good option approved in different studies [13, 19]. While the MaxEnt describes the relationships between the species presence probability and the environmental variables nonlinearly using the response curve. Thus, if there are non-linear relationships between environmental variables and the probability of species presence, MaxEnt can produce a more accurate habitat prediction map. Moreover, MaxEnt requires fewer variables to produce a model in comparison with LR. The present study showed that the MaxEnt modeling method is a generative procedure. The results of this modeling approach can provide critical information on the range of plant resistance and can be used to protect endangered plants. Moreover, the predicted distribution can be used in locating suitable areas to restore potential habitats of the species-area under study.

Conclusion

The suitability map of vulnerable species *D. ammoniacum* was mapped using MaxEnt and LR modeling in the central region of Bafgh-Yazd, Iran. Accuracy assessment of the models showed different results in predicting maps of the *D. ammoniacum*. The result of MaxEnt is more accurate than the LR model. Therefore, the distribution pattern of *D. ammoniacum* can be mapped using a low number of presence data with environmental variables. In the Bafgh habitat, according to the MaxEnt map, the areas located in the north and west of the habitat are prone to the restoration of *D. ammoniacum*. In this region, soil and physiographic parameters had the highest impact on species distribution.

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