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Predicting distribution of plant species in arid rangelands of central Iran using probabilistic methods

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Abstract
The quantification of complex relationships between environmental variables and plant habitat distribution is difficult and crucial. The present study employed Logistic Regression (LR), Maximum Entropy (MaxEnt) and Artificial Neural Network (ANN) methods to model plant habitat distribution and identifies the most appropriate modeling approach. The study was conducted in Poshtkouh rangelands, Yazd Province, central Iran. Vegetation was sampled using randomize-systematic sampling method. Soil samples were taken from 0-30 and 30-80 cm depths. The highest values of Kappa index (0.57) belonged to the ANN. Average Kappa values for the MaxEnt and LR were 0.56 and 0.48, respectively. The performance of LR model was higher for species with high marginality and low tolerance, e.g. *Cornulaca monacantha*, and lower for species with low marginality and high tolerance, e.g. *Artemisia sieberi*. The ANN and MaxEnt provided better models for species with complex distribution patterns such as widespread species. In fact, differences in the optimal ecological range of plant species, could affect the accuracy of predictive distribution models.

Keywords: Artificial neural network, Habitat distribution, Logistic regression, Maximum entropy, Rangelands

Introduction
Quantification of plant-environment interactions and habitats' abiotic and biotic characteristics are key issues in identification of spatial distribution of range plant species. It is also very important in selection of most appropriate habitat in conservation plan of rangelands ecosystem (Splechtna, 2001). Species distribution modeling (SDM), as a powerful tool, has been applied in many studies to locate the places where could provide the ecological requirements of plant species (Anderson and Martinez-Meyer, 2004; Khalasi Ahvazi et al., 2012; Piri Sahragard *et al*., 2018). Most applications of SDM are based on statistical assessments of relationships between species presence and habitat potential drivers (Guisan and Zimmermann, 2000). The geographic distribution of a species is then predicted by mapping the area where these environmental requirements are met (Elith *et al*., 2006). In other words, results obtained from SDM can be used to generate habitat-suitability maps, which can indicate the potential distribution of a given species.

Many ecological data have typical nonlinear relationship and some explanatory variables demonstrate a strong collinear relationship (Guisan *et al*., 2002). In other words, asymmetric and other complex (non-Gaussian) response curves are more frequently observed in the data (Thuiller *et al*., 2003; Zare Chahouki *et al*., 2010). Numerous studies have reported that different modeling methods are enable to generate basically different predictions (Segurado and Araújo, 2004; Elith *et al*., 2006; Xu *et al*., 2012; Piri Sahragard and Zare Chahouki, 2015). Piri Sahragard and Zare Chahouki (2015) evaluated the performance of plant habitat prediction models in Hoze Soltan rangelands of Qom Province and found that the model performance is strongly influenced by the type of plant species that is being modeled. Although some models performed generally better, no one was the best in all circumstances.

Logistic Regression (LR) as a Generalized Linear Models (GLM) is an appropriate model to analyze binary response variables (Guisan *et al*., 1999). MaxEnt is a general-purpose method for making predictions or inferences from incomplete information (Pearson *et al*., 2007). MaxEnt needs species-presence data and does not need species absence or pseudo-absence data, but distinguishes between species presences and random points from a background area using a probability distribution (Ardestani *et al*., 2015; Zare Chahouki and Piri Sahragard, 2016). ANN as machine learning techniques usually treated as a 'black-box', with which the weights are uninterpretable due to the presence of hidden layers and the non-linearity of the activation function (Aertsen *et al*., 2010).

Due to different capability of LR, MaxEnt and ANN models and budget limits, it is important to find out which model (presence/absence data based models or only presence data based models) is desirable in different environmental conditions. On the other hand, determination of potential habitats and understanding the changes in distribution of plant species can provide valuable knowledge for rangeland managers. In this study, three different types of validated statistical models that commonly used in the estimation of plant habitat distribution were employed along with layers of environmental variables across the study area. The objectives of this study were 1): to predict the habitat distribution of plant species by LR, MaxEnt and ANN models, 2) to compare the prediction accuracy of those methods in estimating of the range plant species, and 3) to generate the binary maps of plant habitat distribution.

Materials and Methods

***Study area*:** This study was carried out in the Poshtkouh rangelands, the south-facing slopes of the Shirkouh Mountains, Yazd Province, Central Iran. The study site with an area of 170,000 ha lies within 31º 04´ 27´´ to 31º 33´ 11´´ N latitudes and 54º 15´ 19´´ to 53º 40´ 06´´ E longitudes (Fig 1). The terrain condition is very diverse ranges from mountainous to flat areas. The climate is cold steppic to semi-desert. Annual average precipitation ranges from 250 mm, in Shirkouh Mountain, to 80 mm in the margin of Kavir-e Abarkouh. Maximum elevation is 3970 m in Shirkouh Mountain and drops to the minimum elevation of 1450 m in the margin of Kavir-e Abarkouh. Minimum temperature is 8°C recorded in December, whereas the highest temperature touches +45°C in June (Zare Chahouki *et al*., 2010).

Data collection: Data were taken in summer, 2014. To maximize spatial variation in the dataset, 3-5 parallel transects with 300-500 m length were established in each homogeneous unit. The sample size (30-50 quadrats) was determined using statistical method with respect to vegetation variations. The quadrat size was determined with minimal area method, ranged from 1 m × 2 m to10 m × 10 m or 2-100 m^2. Eight profiles were dug at each habitat to sample soils from 0-30 and 31-80 cm depths. Soil variables including texture, available moisture content, organic matter, pH in the saturation extract, EC, and lime content were measured in the laboratory. All other predictor variables were then modeled on the basis of the DEM. Slope degree and aspect were calculated in the ArcGIS 9.3 using inbuilt functions (Table 1).

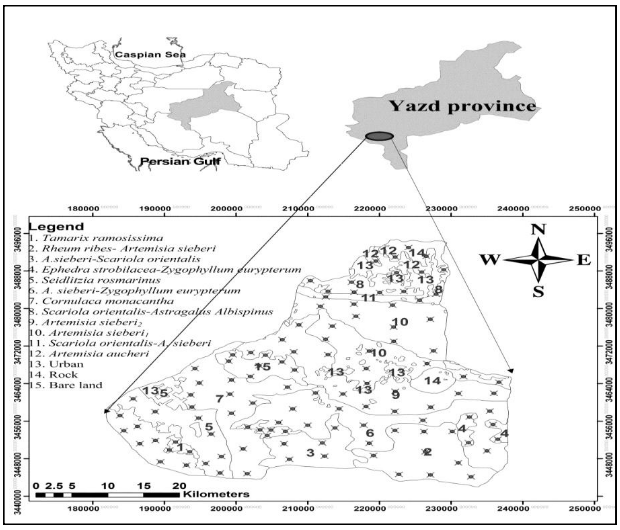

Fig 1. General location along with vegetation map and location of the sampling point in the Poshtkouh rangelands, central Iran. Numbers and symbols show the number of vegetation types and location of sampling points, respectively

Predictive modeling: The logistic regression describes the relationship between the response and the linear sum of the predictor variables, is described by using a logit link in the LR (Miller and Franklin, 2002). A maximum likelihood estimation algorithm is then applied to estimate the probabilities (Lorena *et al*., 2011). Relationships were extracted using SPSS ver 18. The MaxEnt estimates the probability of species presence, ranging from 0 to 1. Only presence data of plant species is used in MaxEnt model as response variable (Baldwin, 2009; Hosseini *et al*., 2013; Zare Chahouki and Piri Sahragard, 2016). Because of the continuous output of MaxEnt, it is necessary to determine an optimal threshold for determining the presence or absence of the target species (Phillips *et al*., 2006).

In ANN modeling, initially, the environmental variables were standardized to get zero mean and unit standard deviation. Then the ANN model was built and trained using tangent sigmoid transfer function and Levenberg-Marquardt learning rule in the MATLAB software. An optimal network of each habitat was selected based on statistical index such as Mean Square Error (MSE) and R^2. These criteria assess the model accuracy and correlation of the estimated and observed values,

Table 1. Vegetation types modeled and the number of presence observations in training and test dataset

Vegetation types	Abbreviation	Number of presence (Training subset)	Number of presence (Test subset)	Habitat
Artemisia aucheri	Ar. au	45	5	Upper elevations, high slope, sandy soils
Scariola orientalis- A. sieberi	Sc. or-Ar. si	35	25	Upper elevations, pebble soils , cool and mountain area
Scariola orientalis- Astragalus Albispinus	Sc. or-As. al	40	10	Upper elevations, pebble soils , cool and mountain area
Artemisia sieberi$_1$	Ar. si_1	38	12	Widespread, arid and semiarid rangelands
Artemisia sieberi$_2$	Ar. si_2	33	17	Widespread, arid and semiarid rangelands
A. sieberi- Scariola.orientalis	Ar.si- Sc .or	39	11	Widespread, arid and semiarid rangelands
A.sieberi-Zygophyllm euryp-terum	Ar. si- Zy. eu	31	19	Gypsi soils of the lowland
Rheum ribes- Artemisia sieberi	Rh. ri-Ar. si	42	8	Fine texture soils
Ephedra strobilacea- Zygo-phyllm eurypterum	Ep. St- Zy. eu	30	20	Gypsi soils of the lowland
Cornulaca monacantha	Co. mo	40	10	Narrow zone, The salinized areas
Seidlitzia rosmarinus	Se. ro	20	30	Narrow zone, The salinized areas
Tamarix ramosissima	Ta. ra	25	15	Narrow zone, The salinized areas

*Code 1 and 2 in *A. sieberi* habitat indicates that these two vegetation types are different from each other in terms of plant composition.

respectively. MSE varies between zero (as the best performance) and 1 (as the lowest performance). In addition, higher values of R^2 demonstrate the better performance of the model. Consequently, the most accurate models were used in order to predict the probability of the presence or absence of each species in unsampled areas (Piri Sahragard and Zare Chahouki, 2015). Overall, 600 spatial points were used in modeling process. The available data were divided randomly into three sets *i.e.* 60% (360 spatial point), 20% (120 spatial point) and 20% subset for model training, testing and validation in the each dataset.

The area under curve (AUC) was used for evaluation of the models performance (Fielding and Bell, 1997; Ardestani *et al*., 2015). Moreover, overall assessment of predictive models accuracy was done by using the prediction errors (sensitivity and specificity). The number of presence points of all plant species was also considered (Table 1). Finally, the Kappa index was applied to evaluate the agreement between observed and predicted maps. Furthermore, by setting a threshold optimum, model output was converted into binary predictions (Miller and Franklin, 2002; Freeman and Moisen, 2008; Piri Sahragard *et al*., 2015).

Results and Discussion

Model accuracy assessment: According to the obtained AUC values (Swets, 1988), the MaxEnt and ANN models led to better results in all habitats (Table 2). The results of LR models were better for *A. aucheri*, *R. ribes*, *A. sieberi*, *C. monacantha*, *S. rosmarinus* and *T. ramosissima.* Differences were small for the other plant species except for the *A. sieberi$_2$* which obtained a low AUC (< 0.8). Moreover, the MaxEnt model performed much better than the LR model, except in *A. sieberi$_2$* habitat. Evaluation of MaxEnt models accuracy by AUC indicated good and acceptable accuracies for all plant habitats, except in *A. sieberi* which had wide ecological range. These results demonstrate a good predictive accuracy for *A. aucheri*, *A. sieberi$_1$*, *R. ribes*, *A. sieberi*, *E. strobilacea- Z. eurypterum*, *S. rosmarinus* and *T. ramosissima*, an acceptable predictive model accuracy for *S. orientalis-A. sieberi*, *S. orientalis-A. Albispinus*, *A. sieberi- S. orientalis*, *A. sieberi-Z. eurypterum*, *C. monacantha* and weak predictive model accuracy for *A.*

sieberi. MaxEnt, as a generative method, can be used for protecting susceptible habitats to invasion and impacts of climate change through providing key information regarding the environmental tolerance of plant species (Elith *et al*., 2006). This finding was in agreement with the findings of Zare Chahouki and Piri Sahragard (2016) who reported earlier that the MaxEnt model is substantially excellent model to predict geographical distributions of plant species with narrow ecological niches. On the other hand, the MaxEnt is a preferred option, when user friendliness is an important issue.

Table 2. AUC values from ROC plots displaying accuracy of predictive models of studied habitats in Poshtkouh rangelands

Vegetation types	Models					
	LR	Classification accuracy	MaxEnt	Classification accuracy	ANN	Classification accuracy
Ar. au	0.95	Good	0.97	Good	0.93	Good
Sc. or-Ar. si	0.75	Acceptable	0.75	Acceptable	0.86	Acceptable
Sc. or-As. al	0.80	Acceptable	0.80	Acceptable	0.95	Good
Ar. si1	0.77	Acceptable	0.97	Good	0.97	Good
Ar. si2	0.63	Poor	0.63	Poor	0.94	Good
Ar.si- Sc .or	0.71	Acceptable	0.71	Acceptable	0.97	Good
Ar. si- Zy. eu	0.83	Acceptable	0.83	Acceptable	0.95	Good
Rh. ri-Ar. si	0.94	Good	0.94	Good	0.96	Good
Ep. St- Zy. eu	0.86	Acceptable	0.97	Good	0.97	Good
Co. mo	0.95	Good	0.78	Acceptable	0.98	Good
Se. ro	0.95	Good	0.98	Good	0.98	Good
Ta. ra	0.95	Good	0.99	Good	0.99	Good

AUC is a ranking-based measure of classification performance and indicates diagnostic power of the model between the presence and absence. AUC value closer to 1 indicates a better fit with reality.

Table 3. The best architecture of a neural network model along overview of the predictor variables entering the different ANN models in Poshtkouh rangelands

Vegetation types	Architecture	Variable(s) entered into the models	Number of hidden layers	Transfer function	Learning rule	MSE	R^2
A. aucheri	1;8;2	Gravel1*	1	tansig	LM	0.03	0.60
S. orientalis-A. sieberi	3;15;2	Elevation, gravel1 and Om1	1	tansig	LM	0.53	0.75
S. orientalis-A. Albispinus	2;10;2	Elevation and Clay1	1	tansig	LM	0.40	0.69
*A. sieberi**$_1$	4;15;2	Elevation, Gravel2, Clay2 and Om2	1	tansig	LM	0.64	0.88
A. sieberi$_2$	2;7;2	Ec1 and Lime1	1	tansig	LM	0.01	0.96
A.sieberi- S.orientalis	2;15;2	Clay2 and AW1	1	tansig	LM	0.11	0.98
A. sieberi-Z. eurypterum	5;18;2	Gravel1, Gravel2, Lime2, Ph2 and AW1	1	tansig	LM	0.04	0.97
R. ribes-A. sieberi	2;13;2	Clay1 and Om1	1	tansig	LM	0.07	0.93
E. strobilacea- Z.eurypterum	1;11;2	Gyps 2	1	tansig	LM	0.02	0.94
C. monacantha	3;9;2	Elevation, Gravel1 and Gyps1	1	tansig	LM	0.01	0.99
S. rosmarinus	1;7;2	Lime1	1	tansig	LM	0.08.	0.96
T. ramosissima	1;3;2	Ec1	1	tansig	LM	0.06	0.98

**Code 1 and 2 in soil properties is related to the soil characteristics, were measured in the first (0–30 cm) and second (30–80 cm) layers, respectively.*

Based on the results, the ANN models obtained the highest AUC values in all habitats. In fact, the ANN showed better performance in all habitats. Consequently, its AUC was good in 11 out of 12 habitats. The low AUC values indicate that the LR models were not proper in different vegetation types. The validation results of predictive models also confirmed these findings (Table 3).This was in agreement with the findings of Lorena *et al*. (2011) who reported that the ANN compared with the LR models was able to estimate the plant habitat distribution more accurately. In fact, the ANN had remarkable ability in modeling of complex nonlinear relationships between variables and phenomena and could be a more valid alternative for spatial statistical methods (Piccinini, 2011). Our results were in consistent with other studies that found the ANN models had high discriminative ability in prediction of plant species presence or absence. In fact, the ANN models are more applicable for vegetation distribution modeling than the regression models (Mi *et al*., 2010; Lorena *et al*., 2011; Zare Chahouki *et al*., 2012; Piri Sahragard and Zare Chahouki, 2015).

Overall accuracy assessment of predictive models showed that in the LR models, the highest and lowest sensitivity was related to *A. sieberi* and *C. monacantha* habitats. The sensitivity values obtained for each models in the LR model indicated that the model related to *C. monacantha* was the poorest model because none of the probability of presence values exceeded 0.2 (the lowest sensitivity).The most accurate model was found for *A. sieberi* habitat to classify the presence or absence of species in this habitat (sensitivity=0.85). The poorest MaxEnt model was in *C. monacantha* habitat because optimal threshold model ability (0.2) did not exceed 0.42 in diagnosis the presence or absence of plant species. Moreover, the poorest and most powerful models of the ANN with 0.4 and 0.82 diagnostic ability were in *T. ramosissima* and *A. sieberi*$_1$ habitats, respectively (Table 4). This coincided with observations made by Araujo and Williams (2000) and Manel *et al*. (2001) who explored that sensitivity index value (proportion of false negatives) was higher for species of widespread and lower for species of restricted distribution. The study also reported that the specificity (proportion of false positives) was lower for species of widespread niche and higher for species of restricted niche. In contrast, Ardestani *et al*. (2015) reported that AUC values tend to be lower for species that had wide distribution. Furthermore, Elith and Burgman (2002) did not find clear associations between modelling success and species characteristics such as rarity.

Furthermore, models accuracy comparison showed that the ANN had the highest Kappa index (average kappa = 0.57). Average Kappa index values for MaxEnt and LR models were 0.55 and 0.48, respectively (Table 5). According to the Kappa index the agreement between observed and predictive maps generated by the LR models for *C. monocantha* was excellent (Fig 2). Zare Chahouki *et al*. (2012) reported that low tolerance species might be better modeled by individual GLMs that better fit the ecological preference of each plant species. In other words, the vastness of the species ecological niche can negatively affect the accuracy of models which generated by the LR (Guisan and Zimmermann, 2000; Zare Chahouki *et al*., 2010; Piri Sahragard and Zare Chahouki, 2016). Moreover, the agreement between predicted maps generated by MaxEnt with documented maps were very

Table 4. Optimum probability threshold and sensitivity-specificity for all models based on test data for models obtained from ANN than other models

Models	LR			MaxEnt			ANN		
Vegetation types	Optimum probability	Sensi -tivity	Speci -ficity	Optimum probability	Sensi -tivity	Speci -ficity	Optimum probability	Sensitivity	Specificity
Ar. au	0.3	0.45	0.83	0.5	0.50	0.91	0.7	0.65	0.97
Sc. or-Ar. si	0.4	0.50	0.90	0.3	0.53	0.96	0.8	0.58	0.96
Sc. or-As. al	0.3	0.43	0.87	0.2	0.57	0.95	0.5	0.46	0.97
Ar. si$_1$	0.3	0.85	0.76	0.4	0.68	0.80	0.3	0.82	0.80
Ar. si$_2$	0.3	0.46	0.75	0.6	0.58	0.86	0.4	0.72	0.75
Ar.si- Sc .or	0.3	0.55	0.91	0.2	0.56	0.97	0.7	0.74	0.85
Ar. si- Zy. eu	0.5	0.79	0.77	0.2	0.57	0.90	0.4	0.75	0.79
Rh. ri-Ar. si	0.6	0.68	0.83	0.4	0.64	0.97	0.6	0.45	0.88
Ep. St- Zy. eu	0.7	0.50	0.84	0.4	0.55	0.97	0.4	0.50	0.90
Co. mo	0.2	0.30	0.89	0.2	0.42	0.96	0.5	0.48	0.95
Se. ro	0.5	0.33	0.81	0.7	0.43	0.99	0.5	0.64	0.99
Ta. ra	0.6	0.55	0.86	0.3	0.45	0.98	0.5	0.40	0.94

good for *R. ribes-A. sieberi* (Kappa value = 0.93) and weak for *T. ramosissima* habitats (Kappa value = 0.31). According to the results of ANN, agreement level of predicted and observed maps of plant habitat distribution was different and the most accurate predictive map of habitat belonged to *S. rosmarinus* habitat (Fig 2).

Therefore, two groups were created on the basis of species spatial distribution and they were all significantly different from each other. The first group included species with low tolerance and narrow extent of occurrence such as *C. monacantha*, and the second group consisted of species with widespread distribution or high environmental tolerance such as *A. sieberi*. Furthermore, some factors such as type of environmental variables, data quality and spatial scale or resolution can affect model accuracy. Since these factors could be source of variation or uncertainty in model performance (Segurado and Araujo, 2004; Piri Sahragard and Zare Chahouki, 2015).

Table 5. Kappa index values and the category of agreement between predicted and observed maps in the studied plant habitats of Poshtkouh rangelands by the methods used

Vegetation types	Model	Kappa (*k*)	Levels of agreement
	LR	0.47	Fair
A. aucheri	MaxEnt	0.41	Fair
	ANN	0.60	**Good**
	LR	0.30	Weak
S. orientalis-A. sieberi	MaxEnt	0.35	Weak
	ANN	0.40	**Fair**
	LR	0.50	Good
S. orientalis-As. Albispinus	MaxEnt	0.42	Fair
	ANN	0.57	**Fair**
	LR	0.33	Weak
A. sieberi$_1$	**MaxEnt**	0.74	**Very good**
	ANN	0.50	Fair
	LR	0.43	Fair
A. sieberi$_2$	MaxEnt	0.51	Fair
	ANN	0.60	**Good**
	LR	0.25	Weak
A.sieberi- S.orientalis	**MaxEnt**	0.58	**Good**
	ANN	0.38	Poor
	LR	0.42	Fair
A. sieberi-Z. eurypterum	**MaxEnt**	0.47	**Fair**
	ANN	0.30	Poor
	LR	0.51	Fair
R. ribes-A. sieberi	**MaxEnt**	**0.93**	**Excellent**
	ANN	0.80	Very good
	LR	0.58	Good
E. strobilacea- Z.eurypterum	MaxEnt	0.64	Good
	ANN	0.68	Good
	LR	**0.90**	**Excellent**
C. monacantha	MaxEnt	0.61	Good
	ANN	0.75	Very good
	LR	0.60	Good
S. rosmarinus	MaxEnt	0.76	Very good
	ANN	**0.86**	**Excellent**
	LR	0.56	**Good**
T. ramosissima	MaxEnt	0.31	Weak
	ANN	0.46	Fair

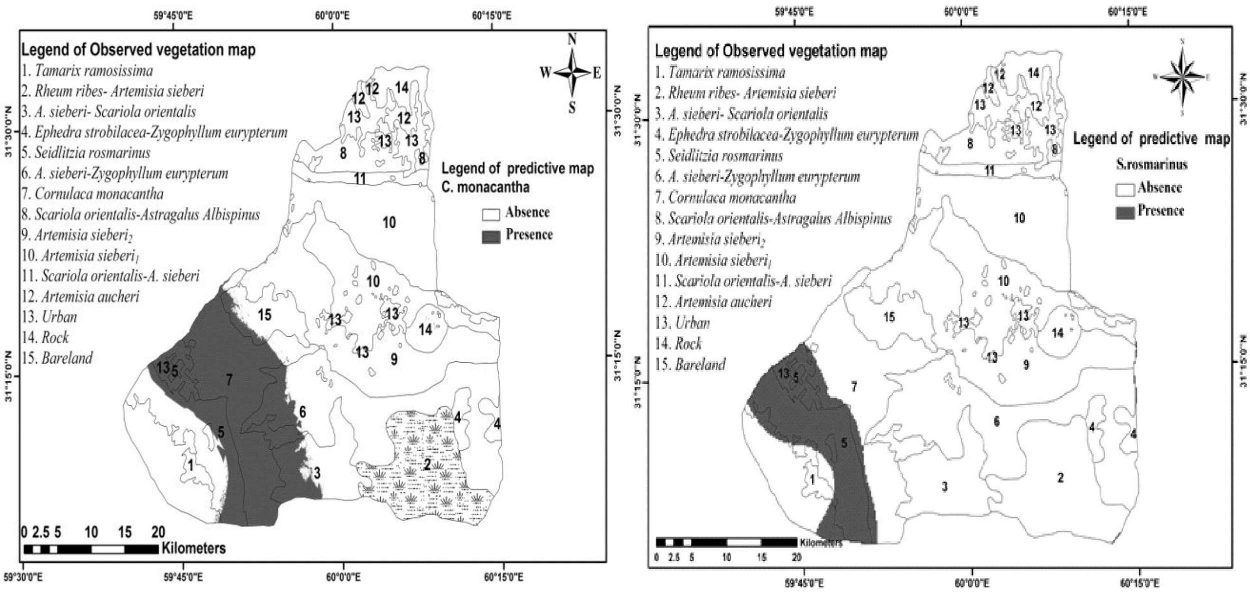

Fig 2. The most accurate prediction and observed maps of *C. monocantha* and *S. rosmarinus* habitats resulting from the LR and ANN methods, respectively (predictive map is shown in black color).

Conclusion

From the present study several conclusions can be drawn. First, due to the differences in the predictive accuracy of models, the application of models will be less effective if their accuracy of its predictions is not assessed. Second, the predictive performance of used models could be affected by the ecological niche extent of different plant species. So the LR model is a good alternative for species with high marginality and low tolerance. But the machine learning approaches such as ANN and MaxEnt generated more accurate models for species with complex distribution patterns such as widespread species. Third, it is unlike that a single best modeling procedure will ever be identified. In general, different methods have their own strengths and weaknesses and the choice of the appropriate method depends on the ecological niche of plant species, type of data available, assumptions and goals of the modeling. Therefore, in addition to statistical considerations, ecological niche extent of plant species must be considered to choose an appropriate approach of habitat distribution modeling.

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