

## Predicting the distribution of plant species using logistic regression (Case study: Garizat rangelands of Yazd province)

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### Abstract

The aim of this research was to study the relationships between presence of plant species and environmental factors in Garizat rangelands of Yazd province and providing their predictive habitat models. After delimitation of the study area, sampling was performed using randomized-systematic method. Accordingly, vegetation data including presence and cover percentage were determined in each quadrat. The topographic conditions were recorded in plot locations. Soil samples were taken at depths of 0-30 and 30-80 cm in each plot. The measured soil variables included texture, lime, saturation moisture, gypsum, acidity (pH), E<sub>c</sub> and soluble ions (Na<sup>+</sup>, K<sup>+</sup>, Mg<sup>2+</sup>, Cl<sup>-</sup>, CO<sub>3</sub><sup>2-</sup>, HCO<sub>3</sub><sup>-</sup> and SO<sub>4</sub><sup>2-</sup>). Logistic regression technique was used to analyze the collected data. The results showed that the vegetation distribution is mainly related to soil characteristics such as texture, gravel, EC, gypsum, lime and OM. The presence of *Artemisia sieberi*-*Zygophyllum eurypterum* has relation with gravel, lime, available water and pH. *Ephedra strobilaceae*-*Zygophyllum eurypterum* has positive relation with gypsum. *Rheum ribes*-*Artemisia sieberi* has relation with clay and OM. *Cornulaca monacantha* has also relation with elevation above sea, gravel and gypsum. The presence of *Seidlitzia rosmarinus* has relation with lime. Electrical conductivity is the most factors effect on presence of *Tamarix ramosissima*.

**Keywords:** Logistic regression; Environmental factors; *Artemisia sieberi*; *Tamarix ramosissima*; *Ephedra strobilaceae*; *Zygophyllum eurypterum*; *Rheum ribes*

### 1. Introduction

Predictive modeling of plant species' distributions based on their relationship with environmental variables is important for a range of management activities. Examples include management of threatened species and communities, risk assessment of non-native species in new environments, and the estimation of the magnitude of biological responses to environmental changes (Ferrier, 2002; Barry and Elith, 2006).

The analysis of species-environment relationship has always been a central issue in ecology. The importance of climate to explain plant distribution was reported earlier on

(Humboldt and Bonpland, 1807; de Candolle, 1855). Climate in combination with other environmental factors has been much used to explain the main vegetation patterns around the world (e.g. Salisbury, 1926; Cain, 1944; Good, 1953; McArthur, 1972; Box, 1981; Stott, 1981; Walter, 1985; Woodward, 1987; Ellenberg, 1988). The quantification of such species-environment relationships represents the core of predictive geographical modeling in ecology. These models are generally based on various hypotheses as to how environmental factors control the distribution of species and communities (Austin, 2002).

Numerous methods have been developed for building predictive species habitat models. Guisan and Zimmermann (2000) presented a comprehensive review and classified the methods into two categories: (1) regression-

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based methods; and (2) environmental envelope methods. Regression methods relate species response to single or multiple environmental predictors. These methods include frequently used approaches such as logistic regression (LR; Hosmer and Lemeshow, 1989), generalized additive modeling (GAM; Hastie and Tibshirani, 1990), and classification and regression tree (CART; Breiman et al., 1984).

Logistic regression is a frequently used regression method for modelling species distributions (Guisan and Zimmermann, 2000; Rushton et al., 2004). This is a particular case of Generalised Linear Models (GLM, McCullagh and Nelder, 1983). GLM has been recognized in ecology for some time as having great advantages for dealing with data with different error structures particularly presence/absence data that is the common type of data available for spatial modelling of species distributions (Nicholls, 1989, 1991; Rushton et al., 2004). In the other hands, logistic regression is one of the methods that can predict the probability of occurrence of each plant species related to site condition factors.

Ecologists believe that the relationships between plant species and environmental factors is non-linear (McCune, 2004). Function of logistic regression is a sigmoid curve. This method has been used by Wu and Huffer (1998), Bio et al., 2002; Austin et al., 1990; Carter et al., 2006; Lassueur et al., 2006 for predictive species modeling. In this paper, we examined the relationship between occurrence of plant species with environmental factors in Garizat rangelands of Yazd province. Then, provided prediction maps for species using LR models.

## **2. Material and methods**

### *2.1. Study area*

This research was conducted in Garizat rangelands. The study area was 94130 ha. Garizat rangelands are located in the southern of Garizat region of the Yazd province in center of Iran (31° 04' 53''N, 53° 40' 04''E to 31° 21' 26''N, 54° 14' 58''E) (Fig. 1). The maximum elevation of 2100 m and the minimum elevation is 1400 m. Average annual precipitation ranges from 200 mm to 45 mm (Zare Chahouki, 2006).

### *2.2. Data collection*

Sampling was done in homogeneous units resulted from overlaying of hypsometric, aspect,

slope and geologic maps. Within each unit 3-5 parallel transects with 300-500 m length, each containing 30-50 quadrates (according to vegetation variations) were established and the sampling procedure was randomized-systematic. The quadrate size was determined for each vegetation type using the minimal area method; hence suitable quadrate size for different species ranged from 1\*2m to 10\*10m (2-100 m<sup>2</sup>). Floristic list, density and canopy cover percentage were determined in each quadrate. Soil samples were taken from 0-30 and 30-80 cm in starting and ending points of each transect.

These samples were air-dried, thoroughly mixed, and passed through a 2mm sieve to get rid of gravel and boulders. The weight of gravel in each sample plot was determined and expressed as a percentage of the total weight of the soil sample. The portion finer than 2mm was kept for physical and chemical analysis according to Jackson (1967) and Allen and Stainer (1974). Soil texture was determined by the hydrometer analysis (Bouyoucos, 1962), saturation moisture (weighting method), organic carbon (determined using Walkely and Black rapid titration, Black, 1979), pH in saturation extract (determined by pH meter), electrical conductivity (ECe) (determined by conductivity meter), lime (determined using 1N HCl, Jackson, 1967), soluble calcium and magnesium (determined by titration with solution EDTA method), soluble chlorine (determined by titration with AgNO<sub>3</sub>), soluble carbonate and bicarbonate (determined by titration with H<sub>2</sub>SO<sub>4</sub> using methylorange and phenolphthalein, respectively) and soluble sodium and potassium (determined by flame photometry method).

### *2.3. Data Analysis*

Logistic regression (LR) is a kind of generalized linear model (GLM) suitable for analysis when response data are binary. It uses a logit link to describe the relationship between the response and the linear sum of the predictor variables (Miller and Franklin, 2002). This is accomplished by applying the following regression equation, in which presence/absence of an object is transformed into a continuous probability  $y$  ranging from 0 to 1. Values close to 1 represent high probability of presence, whereas values close to 0 represent high probability of absence. In order to discrete  $y$  into presence and absence, a posterior threshold is assigned.

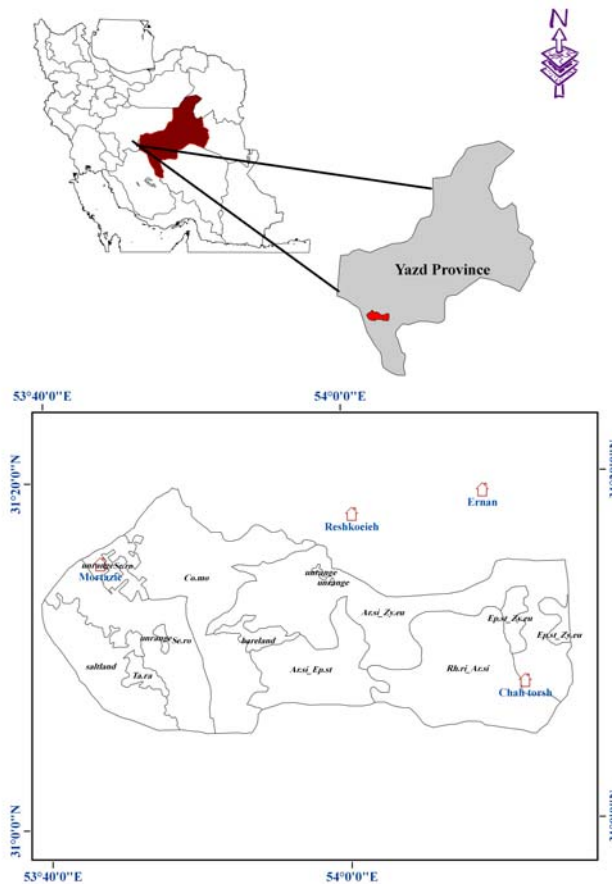


Fig. 1. Location of the study area

Occurrence probability of each plant species is calculated with respect to the combined effect of site conditions with the following equation:

$$Y = \frac{\exp(LP)}{(1 + \exp(LP))} = \frac{\exp(b_0 + b_1x_1 + b_2x_2 + \dots + b_nx_n)}{1 + \exp(b_0 + b_1x_1 + b_2x_2 + \dots + b_nx_n)} \quad (1)$$

or

$$Y = \frac{1}{1 + e^{-(b_0 + b_1x_1 + b_2x_2 + \dots + b_nx_n)}} \quad (2)$$

Where  $y$  is the probability;  $x_n$  is explanatory variable;  $b_0$  is the constant; and  $\exp$  is an exponential function.

To assess possible collinearity problems, model coefficients and their errors are checked for irregularities and approximate variance inflation factors (VIF) are calculated for the final regression models (De Veaux and Ungar, 1994; Dallal 2001).  $VIF = 1/(1 - R^2)$ , with a coefficient of determination ( $R^2$ ) obtained from the regression of each explanatory variable (the way it appears in the model; i.e. in its linear or quadratic form) against all other explanatory variables present in the model (also using linear or quadratic terms as modeled). A VIF greater than 10 is often considered to point at possible

collinearity problems (Dallal, 2001). Notice that the computed variance inflation factors are approximate. We used exclusively linear models (with first and second-order model terms) for VIF calculation, as  $R^2$  is not readily available for GLM.

Models are calculated with individual selected variables and their combination (SPSS, 13.0). The best model is selected based on two criteria; i.e. approximate variance explained (Nagelkerka R square) and goodness of fit (Hosmer and Lemeshow test statistic; for details refer to SPSS 13.0).

#### 2.4. Mapping prediction models

To plants predictive mapping, it is necessary to prepare the maps of all affective factors of models. Topographic data (elevation, slope, and aspect) were derived from DEM with accuracy 10m.

To mapping soil characteristics, geostatistical method including variogram analysis and Kriging interpolation were used by GS<sup>+</sup> Ver. 5.1.1.

Based on obtained predictive models for each species (through LR method) related predictive maps were prepared in GIS (Fig. 3).

### 2.5. Model evaluation

The best measure of agreement between observed (actual vegetation types) and predicted presence/absence is Kappa (Cohen 1960; Monserud and Leemans, 1992; Bell and Fiedling, 1997; Zimmermann and Guisan, 2000; Moisen and Frescino, 2002; Robertson et al. 2003; Liu et al. 2005). Its calculation is based on marginal probability of a contingency table. Kappa is used as the main measure, in the study, to evaluate the models. Monserud and Leemans (1992) suggested the following ranges of agreement for the  $\kappa$  statistic: no agreement, <0.05; very poor, 0.05–0.20; poor, 0.20–0.40; fair, 0.40–0.55; good, 0.55–0.70; very good, 0.70–0.85; excellent, 0.85–0.99; and perfect, 0.99–1.00. Negative values indicate extremely poor agreement (Monserud and Leemans, 1992). We used these ranges to describe the levels of agreement reported here using two tests.

$$P(Rh.ri - Ar.si) = \frac{1}{1 + e^{-(-4.041clay_1 + 12.577OM_1 + 27.653)}} \quad (Eq.1)$$

$$P(Ar.si - Zy.eu) = \frac{1}{1 + e^{-(-0.781gravel_1 + 0.592gravel_2 - 0.734lim_2 + 0.483AW_1 + 5.452pH_2 - 40.798)}} \quad (Eq.2)$$

$$P(Ep.st - Zy.eu) = \frac{1}{1 + e^{-(1.880gy_2 - 47.277)}} \quad (Eq.3)$$

$$P(Co.mo) = \frac{1}{1 + e^{-(-0.115abs + 6.548gravel_1 - 6.229gy_1 + 94.378)}} \quad (Eq.4)$$

$$P(Se.ro) = \frac{1}{1 + e^{-(2.362lime_1 - 70.517)}} \quad (Eq.5)$$

$$P(Ta.ra) = \frac{1}{1 + e^{-(1.218EC_1 - 24.408)}} \quad (Eq.6)$$

### 3.2. Mapping prediction models

For soil characteristics mapping, at the first, spatial structure of data was evaluated in GS<sup>+</sup> for windows and component of variogram was

## 3. Results

### 3.1. LR models

In the study area, 6 communities; *Rheum ribes-Artemisia sieberi*, *A. sieberi-Zygophyllum. Eurypterum*, *Ephedra strobilaceae-Z. eurypterum*, *Cornulaca monocrnatha*, *Seidlitzia rosmarinus* and *Tamarix ramosissima* from north to south of study area, respectively, were distinguished.

Predictive models of abovementioned communities are represented in equation 1-6. Regarding equation 1, occurrence of *R. ribes-A. sieberi* community has inverse relation with clay and positive relation with OM. *A. sieberi-Zygophyllum. E.* community is significantly affected by the presence of gravel, lime, available water and pH (Eq. 2). Equation 3 shows that occurrence of *E. strobilaceae-Z. eurypterum* community is dependent to second layer gypsum.

Factors affecting the distribution of *C. monocrnatha* is elevation, gravel and gypsum of first layer.

Occurrence of *S. rosmarinus* community has positive relation with lime of second layer.

*T. ramosissima* community is significantly affected by the presence of EC of first layer.

determined (Table 1 and Fig. 2). In next stage, point map of soil characteristics were prepared in Arc GIS 9.2. Finally, using component variogram and kriging interpolation, soil map characteristics in 1:50000 scale were provided.

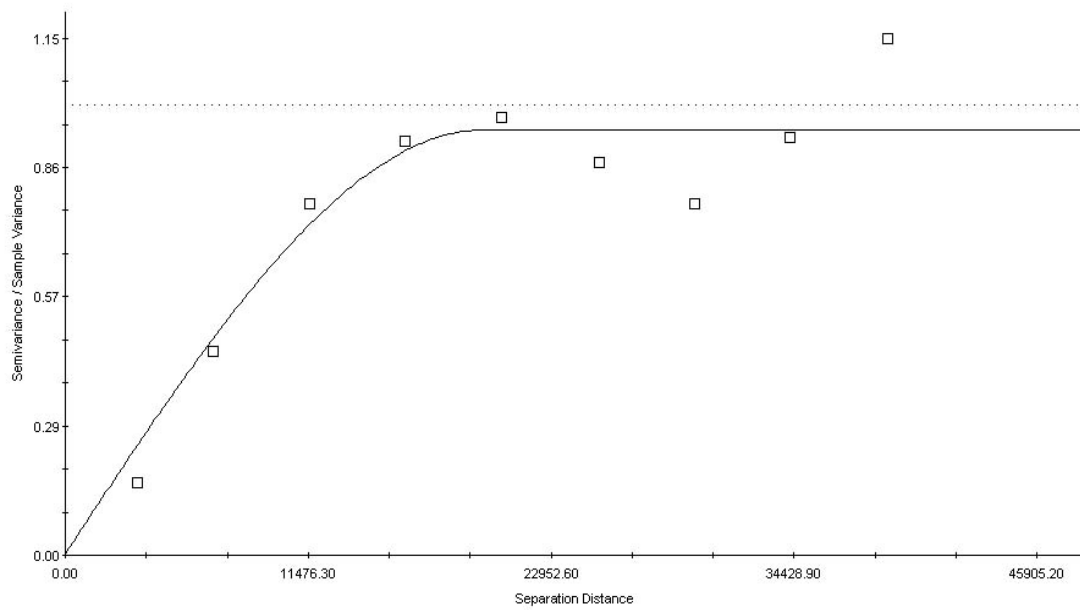


Fig. 2. Variogram model for gravel content of the first depth of soils in Garizat rangelands

Table 1. Components of variogram analysis for selected soil characteristics. For vegetation types and variables abbreviations, see Appendix A.

Characteristic	Model	Nugget effect (%)	Sill (%)	Effective range (m)	Lag distance (m)	Correlation Coefficient
gr1	Spherical	0.00287	0.94532	19740	4590.52	0.89
gr2	Spherical	0.0444	0.95820	15640	4590.52	0.81
clay1	Spherical	0.00276	1.03634	23680	4590.52	0.95
clay2	Spherical	0.10491	0.97463	16880	4590.52	0.84
A.W.1	Exponential	0.32999	10.42999	18990	4590.52	0.78
A.W.2	Spherical	0.17000	8.72000	15720	4590.52	0.79
O.M1	Spherical	0.00850	3.79235	91710	4590.52	0.96
O.M2	Spherical	0.00215	3.919989	91710	4590.52	0.97
lime1	Spherical	0.26279	2.16991	101100	4590.52	0.73
lime2	Spherical	0.34209	1.94708	101100	4590.52	0.69
gy1	Spherical	0.003754	2.12352	852900	4590.52	0.90
gy2	Spherical	0.24988	2.23559	81740	4590.52	0.78
pH1	Spherical	0.13731	2.60071	101100	4590.52	0.97
pH2	Spherical	0.66694	1.49709	92480	4590.52	0.93
EC1	Spherical	0.32951	1.64325	93530	4590.52	0.82
EC2	Spherical	0.36977	1.71377	97030	4590.52	0.88

3.3. Model evaluation

The accuracy of the predicted maps were tested with actual vegetation maps. In this study, the adequacy of vegetation type mapping was evaluated using kappa statistics. The values of Kappa coefficient based on LR of predicted and

actual maps of vegetation cover indicates the accordance of predicted map for *C. monocantha* habitat is excellent and for *E. strobilicea-Z. eurypterum*, *S. rosmarinus* and *T. ramosissima* habitat is good. While for *R. ribes-A. sieberi* and *A. sieberi-Z. eurypterum* habitat is Fair (Table 2).

Table 2. Kappa coefficient and accordance classes for predicted vegetation types. For vegetation types abbreviations

Vegetation type	Kappa Coefficient	Accordance class
<i>R. ribes-A. sieberi</i>	0.51	Fair
<i>A. sieberi-Z. eurypterum</i>	0.42	Fair
<i>E. strobilicea-Z. eurypterum</i>	0.58	good
<i>C. monocantha</i>	0.90	Excellent
<i>S. rosmarinus</i>	0.60	good
<i>T. ramosissima</i>	0.56	good

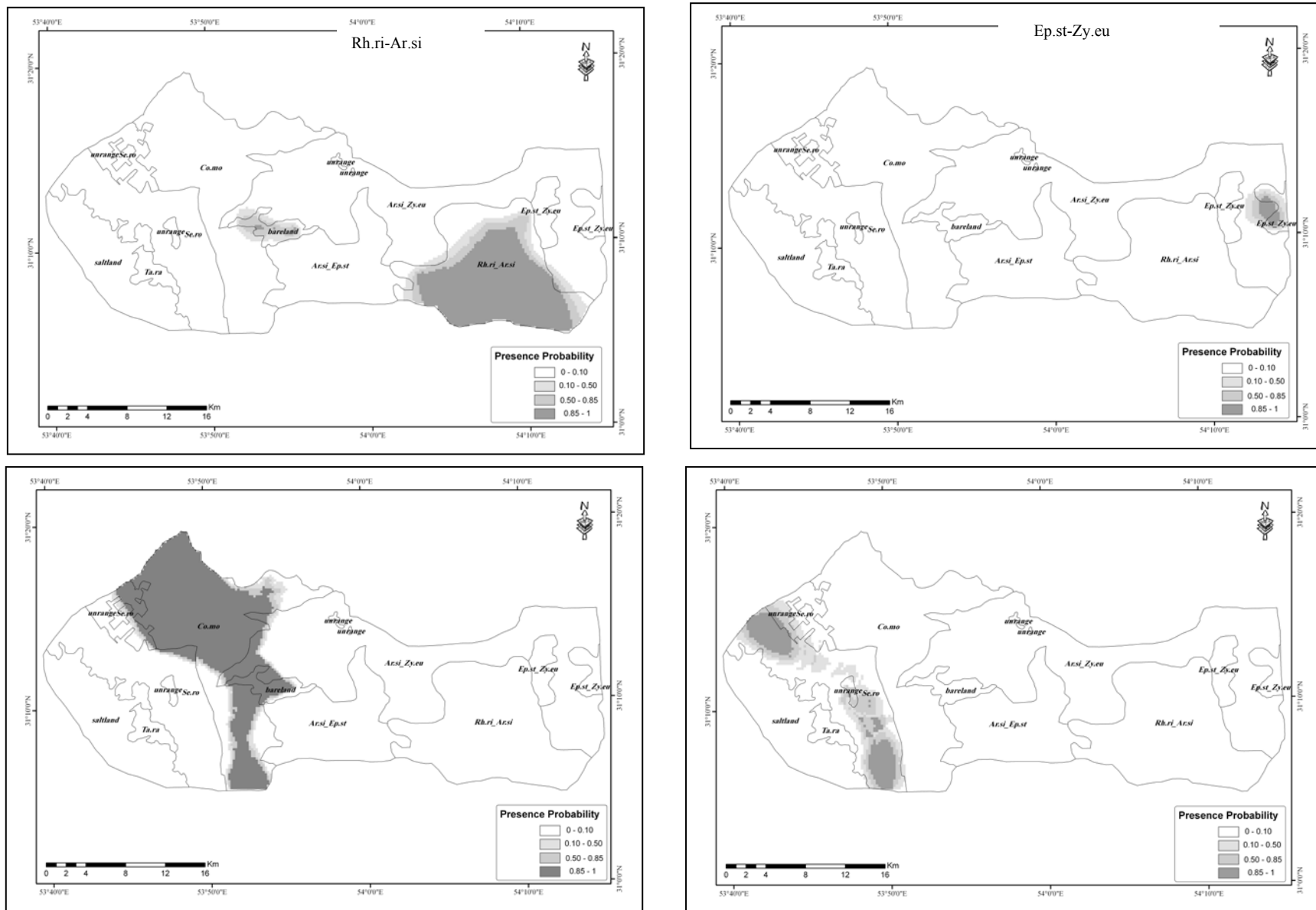


Fig. 3. Predicted map of vegetation types provided by logistic regression

#### 4. Discussion and conclusion

The results showed that the presence of vegetation types was related to edaphic and topographic factors. In general, the most important ecological factors affecting on vegetation of Garizat rangelands are elevation, gravel, texture, lime, EC, pH, gypsum, available water and organic matter. Soil physical properties are affecting on water availability (Enright et al, 2005). Similar to our findings, Tavili et al (2009) and Enright et al (2005) showed that those environmental factors that affect on water availability were the most effective on distribution of vegetation in arid rangelands.

Predictive maps of *E. strobilacea*-*Z. eurypterum*, *C. monachantha*, *S. rosmarinus* and *T. ramosissima*, which have narrow amplitude, high accordance with actual vegetation map prepared for the study area. Among species of study area, predictive model of *R. ribes*-*A. sieberi* and *A. sieberi*-*Z. eurypterum*, due to its ability to grow in different habitat conditions, is not possible.

In conclusion, our work has shown that evaluating a habitat suitability model based only on presences is possible. The result of this research confirmed that both GIS expert system and logistic regression model are capable of predicting the spatial distribution of plant species (Yang, 2004).

Logistic regression is a suitable method in prediction of different plant species occurrence. In this study, predictive models of vegetation types were provided based on absence-presence of species, using logistic regression. Comparing results of prediction with real vegetation map of the study area shows that in logistic regression method absence-presence of species, as a dependent variable, is an effective factor for predictive species modeling. In this method, it is not necessary to use quantification attributes like density, frequency, biomass and canopy cover. These properties are severely affected by sampling method, shape, size and number of quadrat, as well as precipitation, while absence-presence is not dependent to above-mentioned factors.

Based on the prediction models, it is possible to estimate the probability of presence/absence of plant species in response to environmental factors (He et al, 2007). In case of calibration of the resulted models for each species, it is possible to apply such models in introduction of plant species for rangeland rehabilitation activities considering the environmental factors affecting establishment of vegetation cover.

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