



Ground squirrels (*Spermophilus fulvus*) habitat suitability using MaxEnt and ENFA modeling approaches

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Abstract

During this study, the habitat suitability of Ground squirrels has been investigated based on species data and various habitat data such as topographic variables, distal variables, and bioclimatic factors. Two model evaluation indices, including Boyce and Idrisi tests, indicated the models' performances. Based on findings, mean annual precipitation and landuse as well as slope direction showed to be the most important factors influencing the species' habitat use.

Keywords: Ground Squirrels, Ecological Niche Factor Analysis, Maximum Entropy

Introduction

Yellow ground squirrel, (*Spermophilus fulvus* Lichtenstein, 1823) can be found in semi-arid, semidesert, and desert habitats of southern Russia, Central Asia, Caucasia, Northern Iran, Afghanistan, and Northe-west of China (IUCN, 2019). These organisms can be regarded as ecosystem engineers, and key species in most of Eurasia, America, and Africa's landscapes (Thorington et al. 2012). In Iran, this species can be found in two distinct geographic regions, located at the northeast and northwest, such as Khorasan Razavi, Khorasan Shoamli, Zanjan, Kurdistan, Hamadan, Qazvin, and Alrborz municipal area (Kryštufek and Vohralik, 2012, Karami et al. 2016). These groups of rodents are very sensitive to landscape change, and habitat fragmentation in most of their global distribution (Ziaei, 2010). As one of the major aspects of wildlife management and conservation, habitat management, and habitat conservation play a major role in species' long-term sustainability (McComb 2015, Morrison and Mathewson 2015, Lopez et al. 2017). For habitat management, the existence of robust data on the habitat features is necessary, and these data also should show the temporal changes of the habitats as well. It means that time serious data on the habitat peculiarities, is vital for effective habitat management (Somveille et al. 2015).

During this research, we modeled habitat features of the target species in their presence points, using Ecological Niche Factor Analysis (ENFA) and Maximum Entropy modeling (MaxEnt) approach. For this modeling activity, we provided topographic maps, climatic maps, and distance to features maps such as distance to the water resources, then both models has been compared together. Some previous studies indicated that small mammals such as rodents, are affected mostly by local habitat features and less impacted by large-scale habitat features such as landscape scale, or macro habitat features (Simonetti 1989). However, this research showed that some macro habitat variables can affect the target species.

Material and methods

In this research, we used different topographic maps extracted from the digital elevation model (DEM), as well as bioclimatic variables from the worldclim database for the current time (Hijmans et al.,2005). Other land features and resources such as rivers are also extracted from the land-use map.

Results and discussion

Prepared base maps, which used as an input data for both modeling approaches, ENFA and MaxEnt have been shown in the following pictures (Fig. 1)





Figure 1. Digital model map of the study area

Figure 2. Slope (degree) map of the study area



Figure 3. Directional map of the study area



Figure 4. Average annual rainfall map of the study area



Figure 5. Land use map of the study area



Figure 6. Map of the distance from the river of the study area



The area under curve (AUC=0.94) indicates the MaxEnt model high performance (Fig. 7).

Figure 7. The area under the curve (AUC) shows the MaxEnt model performance

Response curves for each variable can be seen in the following figures (Fig. 8). We found that the most suitable habitat for the ground squirrels can be found above the 2000 m from sea level and in areas where the slope is less than five degrees. The species is also can be found in areas where the mean annual precipitation is higher than 400 mm and are close to the farms. The species tends to select habitats closer to the water resources.

Jackknife output indicating the parameters' importance in the species' habitat use has been shown in the following figure (Fig. 9). This analysis showed that mean annual precipitation and landuse pattern has mostly affected the species' habitat usage. In the next order, the variables such as slope, azimuth, and distance to the water resources can be classified as influencing factors.



Figure 8. The AUC curves for the used variables



Figure 9. importance output Jackknife variables

The habitat suitability map gained from the MaxEnt modeling methodology can be seen in the following figure (Fig. 10). This map shows two categories of suitable and unsuitable habitats based on a threshold of 0.46 obtained from TSS values.



Figure 10. categorizing suitable and unsuitable habitats for the target species based on the MaxEnt modeling approach.

Executing of ENFA modeling approaches yielded various data matrices such as the global correlation matrix, The species covariance matrix, the global mean vector, the species mean vector, the eigenvalues, and their explained variance, and the scores matrix (eigenvector matrix). The output Eigenvalues (EGVs) have important data and there are separate EGVs for each map. If the target species have a random distribution, all of the EGVs will be equal with one, and the closer to zero indicates that the species is more specialist (Table 1).

aspect-box	bio-box	dem-box	land use- box	river-box	slop- box
3.921	9.639	9.757	9.606	9.605	0.751
9.639	26.532	26.484	26.442	26.441	1.98
9.757	26.848	27.169	26.756	26.755	2.009
9.606	26.442	26.756	26.352	26.351	1.972
9.605	26.441	26.755	26.351	26.350	1.972
0.751	1.98	2.009	1.972	1.972	0.207

Table 1. Variance-Covariance matrix of environmental variables

The score matrix also give valuable information on the variables importance. If the variable's value is close to zero, it indicates that, the specific variable doesn't show any useful data to characterize the species habitat usage. Therefore, we can remove that variable from the modeling process. The Marginality shows how much the species tend to select the marginal values of the corresponding environment variable. Table 2 shows the score matrix obtained from ENFA analysis.

Table 2. Score matrix obtained from ENFA modeling approach.

Score matrix	1	2	3	4	5	9
aspect-box	-0.963	0.04	0.267	0	0	0
bio-box	-0.994	0.093	-0.059	0.003	-0.002	0
dem-box	-0.994	0.088	-0.059	-0.006	0	0
land use-box	-0.994	0.093	-0.059	0.002	0.001	0
river-box	-0.994	0.093	-0.059	0.002	0.001	0
slop-box	-0.892	-0.452	-0.024	0	0	0

Global marginality can be estimated to show the species' habitat use pattern and how much is a generalist or specialist species. To calculate these parameters we can use the following relation where m_s and m_G indicate mean species distribution and mean global distribution:

$$M = |mS - mG| / 1.96 SG$$

Global tolerance shows the species tolerance of the species with regard to the environmental factors and it is also inverse of speciality factor. Global specialization, is opposite of Global tolerance as T=1/S. The amount of justified variance for the first eigen vector in principle component analysis (PCA) can be taken as the species specialization factor.

To prepare the ENFA habitat suitability map, first, we need to obtain the Factor map which then will be used as an input for habitat suitability modeling. During this modeling approach, the user can define the number of needed variables, but also there is a criterion entitled Broken Steak Criterion in Biomapper which can be used to determine the number of necessary variables. We used three maps for habita suitability modeling which covered 92 percent of the necessary information for executing the model. The following table shows each map's share in the modeling process (Table 3).

Percent information	Amount of the information	Map
71.8	1.43	ENFA-01_ST
12.87	0.25	ENFA-02_ST
7.26	0.14	ENFA-03_ST
92	1.8	Total

Table 3. Each map's percent contribution to the modeling process

For habitat suitability modeling (HSM) using Biomapper, there is the possibility to benefit from various algorithms such as Median, Distance Geometric Mean, Distance Harmonic Mean, and Minimum Distance. In the Biomapper 4 script, there is another index entitled Boyce. The higher Boyce index and lower standard deviation will indicate the most suitable algorithm for the

modeling process (Hirzel et al, 2006). Based on Boyce and SD values we used the Harmonic mean algorithm in our modeling approach (Table 4).

	Algoritm	Boyce Index ± SD
1	Median	516/0±4768
2	Harmonic	2207/0±781/0
3	Geometric	2911/0±684/0
4	Minimal Distance	188/0±774/0

Table 4. Different values of the Boyce and SD in determining the best algorithm.

Determining the habitat suitability categories using the Boyce index

From the linear graph obtained from the Boyce index, the vertical axis (Fi) shows the ratio of predicted values for each class to expected values (Fi = Oi / Ei). Therefore, the more Fi, the better the obtained model (Boyce et al.,2002). Values higher than 1 (Fi>1) indicate habitats with higher suitabilities (Strubbe & Matthysen, 2008; Boyce et al., 2002). Using the Boyce index, three classes have been determined for habitat suitability and each category's area has been calculated by Idrisi software. This analysis indicated that most areas belong to unsuitable habitats which the class number one (Fig. 11).



Figure 11. Habitat suitabilityapproach categories obtained from the ENFA modeling

The habitat suitability models obtained from the ENFA modeling approaches have been shown in the following figures (Fig. 12 and 13)



Figure 12. Habitat suitability map obtained from ENFA modeling approach



Figure 13. Classified habitat suitability map in three classes of the unsuitable, medium, and suitable habitats in the ENFA model

The evaluation of the models ability to predict the species' presence using the Crossvalidation approach

Using the cross-validation approach, it is possible to verify the prediction ability of the models. To this, the species observation points should be divided into random K divisions, or parts, and use only K-1 parts in the modeling approach. The rest of the observation points will be then used for model accuracy evaluation. This process will be repeated K times. In this study, we assigned 10 for the number of K and then the map was divided into two divisions. Each division (i) covers A_i of the total area and compromises some part of the observations (N_i). This finally can be used to model's verification since we can calculate the frequency of allocated points and areas for each division ($F_i = N_i/A_i$). The values of the resulting F_i can be used for model evaluation (Hirzel, 2000). In this research, we put the Random seed equal to 1. The R_s value or R^2 obtained equally with 0.8 which indicates the reasonability of the produced model.

The Boyce index ranges from -1 to +1 and the positive values indicate a model that benefits from the observation points, the values closer to zero, show a random model, and negative values indicate habitats with lower qualities (Hirzel et al, 2006). Using Logistic regression analysis and six independent environmental variables, we found that the R sq values tend to be 0.2 and ROC to 1 which indicates the model accuracy (Pontius & Schneider 2001). The resulting values from the logistic regression have been presented in the following table (Table 5).

Independent	Pseudo R-Square	Roc
environmental		
variable		
Azimuth	0.21	0.92
Landuse	0.22	0.92
Annual mean	0.22	0.93
percipitation		
Slope	0.20	0.92
DEM	0.22	0.93
Distance from water	0.22	0.93
resources		

 Table 5. Logistic regression results in model verification

This study shows that both models, ENFA and MaxEnt have high overlaps in the produced habitat suitability. In the ENFA model, the most important variable in the species' habitat suitability is the distance to the water resources. So, we can conclude that the water resources either from running waters, springs, and mean annual precipitation are very critical for the target species, and therefore, climate change and extended drought can affect the species' long-term viability and sustainability.

References

- Karami, M., Feizollahi, K., Ghadirian, T. 2016. Encyclopedia of Iran Mammals. Jahad Publication House, Alborz Province, 292 P.
- Ziaei, H. 2009. A field guide for the Iran mammals, Sepehr publication institute.
- IUCN. 2019. The IUCN Red List of threatened species. Version 2019-2. http://www.iucnredlist.org. Accessed 08 August 2019.

- Thorington, R.W.J.; Koprowski, J.L.; Steele, M.A. and Whatton, J.F., 2012. Squirrels of the world. JHU Press.
- Kryštufek, B. and Vohralík, V., 2012. Taxonomic revision of the Palaearctic rodents (Rodentia): Sciuridae: Xerinae 1 (Eutamias and Spermophilus). Lynx, n. s. (Praha). Vol. 43, No. 1-2, pp: 17-111.
- McComb, B. C. 2015. Wildlife habitat management: concepts and applications in forestry. CRC Press, New York, New York, USA.
- Morrison, M. L., and H. A. Mathewson. 2015. Wildlife habitat conservation: concepts, challenges, and solutions. Johns Hopkins University Press, Baltimore, Maryland, USA.
- Lopez, R. R., M. L. Morrison, and I. D. Parker. 2017. Applied wildlife habitat management. Texas A&M University Press, College Station, USA.
- Somveille M, Rodrigues A. S. L, and, Manica A. 2015. Why do birds migrate? A macroecological perspective. Global Ecology and Biogeography. DOI: 10.1111/geb.12298
- Hijmans, R.J., Cameron, S. E., Parra, J. L., Jones, P. G. and Jarvis, A. 2005. Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology, 25: 1965–1978.
- Boyce, M., Vernier, P., Nielsen, S. & Schmiegelow, F. 2002. Evaluating resource selection functions. – Ecological Modelling, 157: 281–300.
- Strubbe, D. & Matthysen, E. 2009. Predicting the potential distribution of invasive ring-necked parakeets Psittacula krameri in northern Belgium using an ecological niche modelling approach. – Biological Invasions, 11: 497–513.