



International Journal of Environment and Geoinformatics (IJECEO) is an international, multidisciplinary, peer reviewed, open access journal.

Modelling Distribution of Asia Minor Spiny Mouse (*Acomys Cilicicus*) Using Maximum Entropy

**Banu Kaya ÖZDEMİREL., Ortaç ÇETİNTAŞ., Mustafa SÖZEN.,
Muhsin ÇOĞAL, Ferhat MATUR**

Chief in Editor

Prof. Dr. Cem Gazioğlu

Co-Editors Prof. Dr. Dursun Zafer Şeker, Prof. Dr. Şinasi Kaya,

Prof. Dr. Ayşegül Tanık and Assist. Prof. Dr. Volkan Demir

Editorial Committee (September 2022)

Assoc. Prof. Dr. Abdullah Aksu (TR), Assoc. Prof. Dr. Uğur Algancı (TR),
Prof. Dr. Levent Bat (TR), Prof. Dr. Paul Bates (UK), İrşad Bayırhan (TR), Prof. Dr. Bülent
Bayram (TR), Prof. Dr. Luis M. Botana (ES), Prof. Dr. Nuray Çağlar (TR), Prof. Dr. Sukanta Dash (IN), Dr. Soofia T.
Elias (UK), Prof. Dr. A. Evren Erginal (TR), Assoc. Prof. Dr. Cüneyt Erenoğlu (TR), Dr. Dieter Fritsch (DE), Prof. Dr.
Manik Kalubarme (IN), Dr. Hakan Kaya (TR), Assist. Prof. Dr. Serkan Kükreçer (TR), Assoc. Prof. Dr. Maged
Marghany (MY), Prof. Dr. Micheal Meadows (ZA), Prof. Dr. Masafumi Nakagawa (JP), Prof. Dr. Burcu Özsoy,
Prof. Dr. Hasan Özdemir (TR), Prof. Dr. Chyssy Potsiou (GR), Prof. Dr. Erol Sarı (TR), Prof. Dr. Maria Paradiso (IT),
Prof. Dr. Petros Patias (GR), Prof. Dr. Barış Salihoğlu (TR), Assist. Prof. Dr. Başak Savun-Hekimoğlu (TR), Prof. Dr.
Elif Sertel, (TR), Prof. Dr. Füsün Balık Şanlı (TR), Dr. Duygu Ülker (TR), Prof. Dr. Seyfettin Taş (TR), Assoc. Prof.
Dr. Ömer Suat Taşkın (TR), Assist. Prof. Dr. Tuba Ünsal (TR), Assist. Prof. Dr. Sibel Zeki (TR)

Abstracting and Indexing: TR DIZIN, DOAJ, Index Copernicus, OAJI, Scientific Indexing Services, International Scientific Indexing, Journal Factor, Google Scholar, Ulrich's Periodicals Directory, WorldCat, DRJI, ResearchBib, SOBIAD

Research Article

Modelling Distribution of Asia Minor Spiny Mouse (*Acomys Cilicicus*) Using Maximum Entropy

Banu Kaya Özdemirel^{1,*} , Ortaç Çetintaş² , Mustafa Sözen² , Muhsin Çoğal² ,
Ferhat Matur³ 

¹ Middle East Technical University, Department of Biological Sciences, Ankara, Turkey

² Bülent Ecevit University, Arts and Science Faculty, Department of Biology, Zonguldak, Turkey

³ Department of Biology, Faculty of Science, Dokuz Eylül University, İzmir, Turkey

* Corresponding author: B.K. Özdemirel

E-mail: banukaya00@gmail.com

Received 13.08.2021

Accepted 26.01.2022

How to cite: Özdemirel et al. (2022). Modelling Distribution Of Asia Minor Spiny Mouse (*Acomys Cilicicus*) Using Maximum Entropy, *International Journal of Environment and Geoinformatics (IJECEO)*, 9(3): 118-000, doi. 10.30897/ijegeo.979699

Abstract

Acomys cilicicus is a narrow range, endemic spiny mouse species of Turkey. Some issues have been uncertain about its distribution and status. Therefore, in the study, we aimed to identify species' spatial distribution and understand the impact of environmental factors on species. We used maximum entropy modeling to fulfill these purposes. The results showed that the distribution of the species is restricted in the coastal part of the study area, the human population is one of the severe threats for the species distribution, and the fluctuations of climatic conditions may adversely affect the species distribution. We hope that these outputs can be valuable for the species' conservation efforts and guide the conservation of *Acomys cilicicus* and other narrowly distributed species.

Keywords: *Acomys cilicicus*, Maxent Modeling, Spatial Distribution, Impact of Environmental Predictors, Turkey

Introduction

The target species of the study, *Acomys cilicicus*, is one of Turkey's endemic spiny mouse species. *Acomys cilicicus* was previously known as the narrow range endemic species and hence, was listed as critically endangered (CR) in the IUCN red list of threatened species (Amori et al., 2008). However, it was described as data deficient (DD) in 2008 because of the lack of knowledge about its distribution. It has also been reported to be most likely conspecific with the widespread species *Acomys cahirinus* (Amori et al., 2008). On the other hand, insufficient knowledge about its distribution and uncertain assessment of its status has led to the conservation targets of this endemic species not being determined adequately until now. It is known that the identification of species spatial distribution is one of the main issues in biodiversity conservation. It is especially essential for endemic, threatened, and rare species since species distribution determines how conservation action plans are formed. However, a simple description of species distribution is insufficient for effective biodiversity conservation and management. Instead, using more sophisticated approaches to identify species distribution and figure out complicated ecological relationships should be a priority and adopted as an integral part of conservation studies. Conservation efforts considering these points can meet requirements that ensure species' long-term survival. Therefore, in the study, we aimed to model the spatial distribution of *Acomys cilicicus* and investigate the effects of environmental factors on species distribution. Maximum entropy (Maxent) modeling was used for this purpose

(Phillips and Dudík, 2008; Phillips et al., 2006). It is based on the maximum entropy prediction and predicts the potential distribution of species from a set of environmental predictors and presence-only data (Young et al., 2009; Phillips et al., 2004). The software is highly effective in solving complex relations between predictors and response variables (Elith et al., 2011; Elith et al., 2006) and thus, produces good predictions of species distribution. This and its sensitivity to small sample sizes and clumped data have made the software the most widely used distribution modeling algorithm (Wisz et al., 2008). The model outputs indicate priority distribution areas of the species and reveal the effects of environmental factors on species distribution. Therefore, this study may provide the required information for the future conservation of this narrow range species and serve as outputs to plan future species research.

Materials and Methods

Study area

The study area is in the middle south of Turkey (Figure 1A) and lies between latitude 36.31 to 36.75 and longitude 33.88 to 34.31. It occupies approximately a 1500 km² area (Figure 1B). The area is about 38 km away from Mersin province and covers the Erdemli district. It extends between the Mediterranean coastal plain and the western part of the high Taurus Mountains and has an altitude range of roughly 0 to 1600 m (Figure 1B). The coastline mainly contains broad agricultural areas, while meadows and forests dominate the high sections. The region is quite rural and maintains its green

image throughout the year. It hosts many animal species and demonstrates high plant diversity.

Modeled species and occurrence data

Acomys cilicicus is known as the Asia Minor, or Turkish spiny mouse since the back of both males and females are covered with coarse, inflexible spine-like hairs. The species is only known from Turkey's south coast, the type locality (Çetintaş et al., 2017; Amori et al., 2008). The taxon is a species of rodent in the family Muridae (Musser and Carleton, 2005). It is a small, terrestrial, and social rodent. *Acomys cilicicus* is a nocturnal species like most species of the spiny mice, but it may be active in the morning and late afternoon. Species is omnivorous, thus fed to grass, seeds, and insects (Aulagnier et al., 2010). In the study, the sample survey

area had to be limited to the region on the southern coast of the study area based on the knowledge that it is a local narrowly distributed endemic species (Figure 1B, C).

Moreover, inadequate information about its habitat preferences did not allow our field experts to expand the sample survey area. Therefore, occurrence records of the species were collected from its type locality and immediate environment. Records were obtained using 100 traps for each locality, placing them on a line with 10 m intervals. The same trapping and record procedure were followed for all localities. As a result, 27 occurrence records of *Acomys cilicicus* were gathered for analysis (Figure 1B, C). Distance between these records ranges from 0.250 km to 15.8 km (Figure 1C).

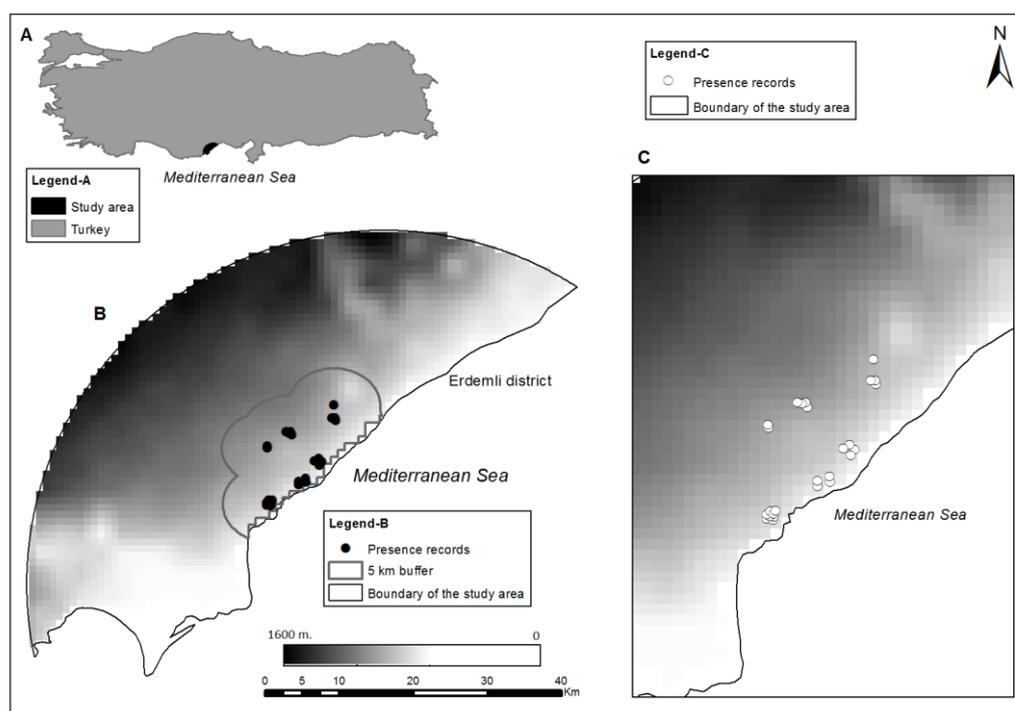


Fig. 1. (A) location of the study area, (B) altitude and 5 km buffer zone (C) distribution of the presence record

Environmental predictors

Environmental predictors considering their biological relevance for species distribution were gathered in modeling analysis (Fourcade et al., 2014; Nazeri et al., 2012). Accordingly, 17 climate predictors were obtained from the WorldClim database (URL 1). Altitude, aspect, and slope were determined as topographic predictors of the species and used in modeling. The global land cover map provided by European Spatial Agency was also added in modeling analysis. Before including the model, the map was reclassified according to the species' habitat requirements, and the resulting 9 class land cover map was included in the analysis. On the other hand, target species are subject to human disturbances due to the rural human population and their activities in the area. The influence of these disturbances should be reflected in the model. Our field experts determined roads (especially secondary roads), rural settlement (total rural population of the area $\geq 45,000$), and agricultural areas

as the human disturbances for species and digital layers of the disturbances were produced as distance to roads, distance to settlements, and distance to agricultural areas applying fuzzy membership functions. In addition, an accessibility layer was generated and added in the modeling analysis to avoid bias from sampling. The layer was produced as a linear combination of fuzzy road and ruggedness and showed the measure of accessibility for each pixel. All environmental predictors were afterward resampled to 1 km spatial resolution interpolating cell values based on the values of nearest neighbor cells and tested for multicollinearity, applying a preliminary correlation analysis ($-0.70 < r < 0.70$, correlation threshold). The accessibility and land cover maps were excluded from this analysis since the accessibility layer was used for bias correction and the land cover map is a categorical map. Consequently, 20 environmental predictors were included in the modeling analysis (Table 1).

Table 1. Environmental predictors included in Maxent modelling analysis

Environmental Predictor	Type	Source
<i>Climate Predictors</i>		
Temperature annual range		
Min Temperature of Coldest Month		
Max Temperature of Warmest Month		
Precipitation of Coldest Quarter		
Precipitation of Driest Quarter		
Precipitation of Warmest Quarter		
Precipitation of Wettest Quarter		
Precipitation Seasonality	Continuous	WorldClim database
Temperature Seasonality		
Annual Precipitation		
Mean Diurnal Range		
Isothermality		
Annual Mean Temperature		
Mean Temperature of Coldest Quarter		
Mean Temperature of Driest Quarter		
Mean Temperature of Warmest Quarter		
Mean Temperature of Wettest Quarter		
<i>Topographic Predictors</i>		
Altitude		USGS
Slope	Continuous	Derived from DEM
Northern and Eastern Aspect		
<i>Human Disturbance Predictors</i>		
Distance to roads		
Distance to settlement	Continuous	Derived with fuzzy function
Distance to agricultural areas		Extracted from Land Cover
<i>Land Cover Predictor</i>	Categorical	European Spatial Agency
<i>Accessibility layer</i>	Continuous	Derived from road and ruggedness

* Environmental predictors written in bold excluded from the modelling analysis due to the high correlation coefficient values.

Maximum entropy modeling

In the study, the MaxEnt model was performed with tuned model parameters to obtain a species-specific, optimum model prediction. Accordingly, the starting point should be to determine an appropriate background sample. Background sample directly affects the relative probability of presence (Elith et al., 2011; Vanderwal et al., 2009). Therefore, it should meet the environmental conditions of the ecological problem we are working on. As previously stated, the target species, *Acomys cilicicus*, is a narrowly distributed local endemic species. It means that habitat requirements are too specific and are restricting factors to the distribution of the species. At that point, the correct application is to build a model with the known spatial extent of the species (e.g., Rhoden et al., 2017; Peterman et al., 2013). Accordingly, the distribution model was fitted, generating 2500 random background points within a 5 km buffer that surrounds the presence records of the species and then projected to the defined study area (Figure 1). Model complexity was afterward adjusted by feature classes and regularization coefficient (β). Feature classes are mathematical functions to transform predictor variables, and they define species' responses to environmental conditions (Morales et al., 2017; Syfert et al., 2013). The study used linear, quadratic, and hinge feature classes. Thus, a simpler model suitable for few occurrence

records was built instead of modeling complex environmental responses, balancing the model complexity.

On the other hand, the Regularization coefficient was applied to prevent model prediction from overfitting or underfitting (Merow et al., 2013; Elith et al., 2010). It is a type of penalty and adjusts model by identifying the number and type of functional forms of predictors (Merow et al., 2013; Syfert et al., 2013); thus, it enables the model to vary from simple to complex. We tested three different levels of complexity in the study by setting the regularization coefficient at 1, 1.3, and 1.5. Cross-validation with 5-fold was used to evaluate the prediction accuracy of the model. The advantage of this, it uses all data for both training and testing and provides efficient use of a small sample size. Finally, the model was performed with 5000 iterations, and a logistic distribution map ranging from 0 to 1 was produced. Model performance was assessed with the AUC (Area Under the Curve) metric of ROC (Receiver Operator Characteristic) curve (Almalki et al., 2015; Morovati et al., 2015). It is plotted sensitivity (true positive) against 1- specificity (false positive) and measure separability of the model. Values closer to 1.0 indicate better model performance (Villordon et al., 2006). We also evaluated the spatial pattern of predicted probability with threshold-dependent binomial test and applied a 10%

training presence logistic threshold (0.443) to distinguish predicted presences (suitable habitats) and absences (unsuitable habitats) for the species. This test enables us to figure out the model's prediction performance as well. Additionally, the importance of predictor variables was measured with the leave one out jackknife approach, and environmental predictors making the greatest contribution to the model were determined. Lastly, response curves of the environmental predictors indicating the highest permutation importance on the model prediction were examined, and the impact of environmental predictors on the species distribution was evaluated. The response curves were by the spatial resolution of environmental predictors with 1*1 km².

Results

The spatial distribution of *Acomys cilicicus* was modeled associating climatic, topographic, biologic, and disturbance predictors with the presence only data of the species. The model was built at three different levels of complexity, applying β coefficients as 1, 1.3, and 1.5. Results indicated that the model built at β , equal to 1.3, predicted the distribution of the target species with a high success rate. The performance of the related model was evaluated using both ROC analysis and threshold-dependent binomial test. According to the ROC analysis, the mean AUC value was 0.92 and 0.89 for training and testing with a standard deviation of 0.035. This result indicated that the model generated much better predictions than random. The threshold-dependent binomial test was applied with a 10% training presence logistic threshold. It is a one-tailed binomial test, and its null hypothesis states that test points are predicted no

better than a random prediction with the same fractional predicted area. This test investigates model performance based on the extrinsic omission rate. According to the result, the model performed well with a low omission rate at 10% training presence logistic threshold ($p=0.00093$, $p<0.001$, one-tailed). That is, the null hypothesis was rejected. Thus, it has been confirmed that the model performed better distribution prediction than the random one. Consequently, both the ROC analysis and the binomial test showed high discrimination capacity and robust predictive accuracy of the model. The spatial pattern of species distribution was evaluated by the logistic predicted map of the model, and it was seen that suitable habitats for *Acomys cilicicus* are primarily concentrated in the coastline where the species are recorded (Figure 2A). In addition, fragmented small habitat patches are observed in different parts of the study area (Figure 2A). However, a remarkable result observed on the logistic map is another region in the northeast of the study area, indicating high habitat suitability for distribution of the target species (Figure 2A). Although our field expert has not yet examined the region, satellite images also confirm the habitat suitability of the region for the distribution of the target species. Lastly, the logistic predicted map was classified applying 10 % training presence logistic thresholds. The classified map of the species distribution has a good discrimination capacity between unsuitable and suitable habitats (Figure 2B). According to the map, the suitable habitat of the target species occupied 28.4 % of the study area (Figure 2B). This result signifies that overall predicted suitable habitats cover a tiny portion of the study area.

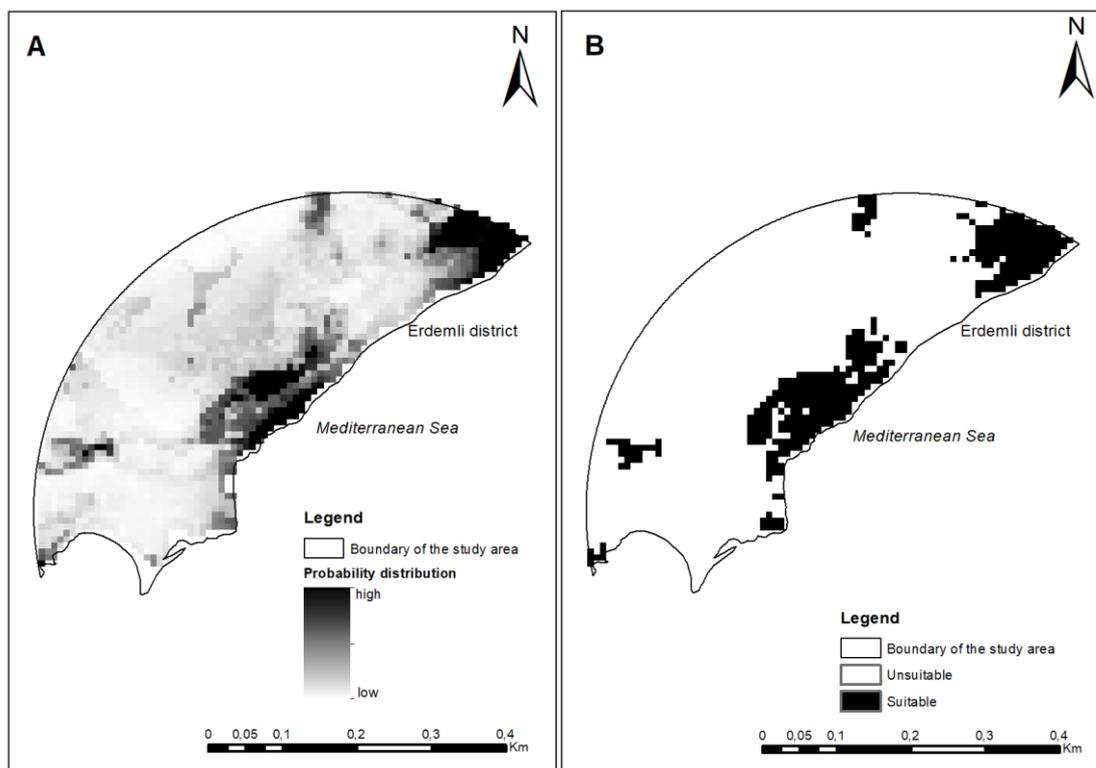


Fig.2. (A) model's predicted probability map (B) classified probability map showing suitable and unsuitable habitats

Table 2. The relative contribution of environmental predictors to the Maxent model

Environmental Predictor	Permutation Importance
Distance to settlement	26.3
Northern aspect	26
Distance to agricultural area	10.3
Mean temperature of driest quarter	8.3
Annual precipitation	7.3
Temperature seasonality	6.7
Land cover	3.1
Distance to roads	2.8
Diurnal range	2.3
Precipitation of driest quarter	1.9
Eastern aspect	1.4
Isothermality, min temperature of coldest month, annual mean temperature, accessibility, max temperature of warmest month, slope, precipitation of warmest quarter, precipitation seasonality, temperature annual range	0-0.9

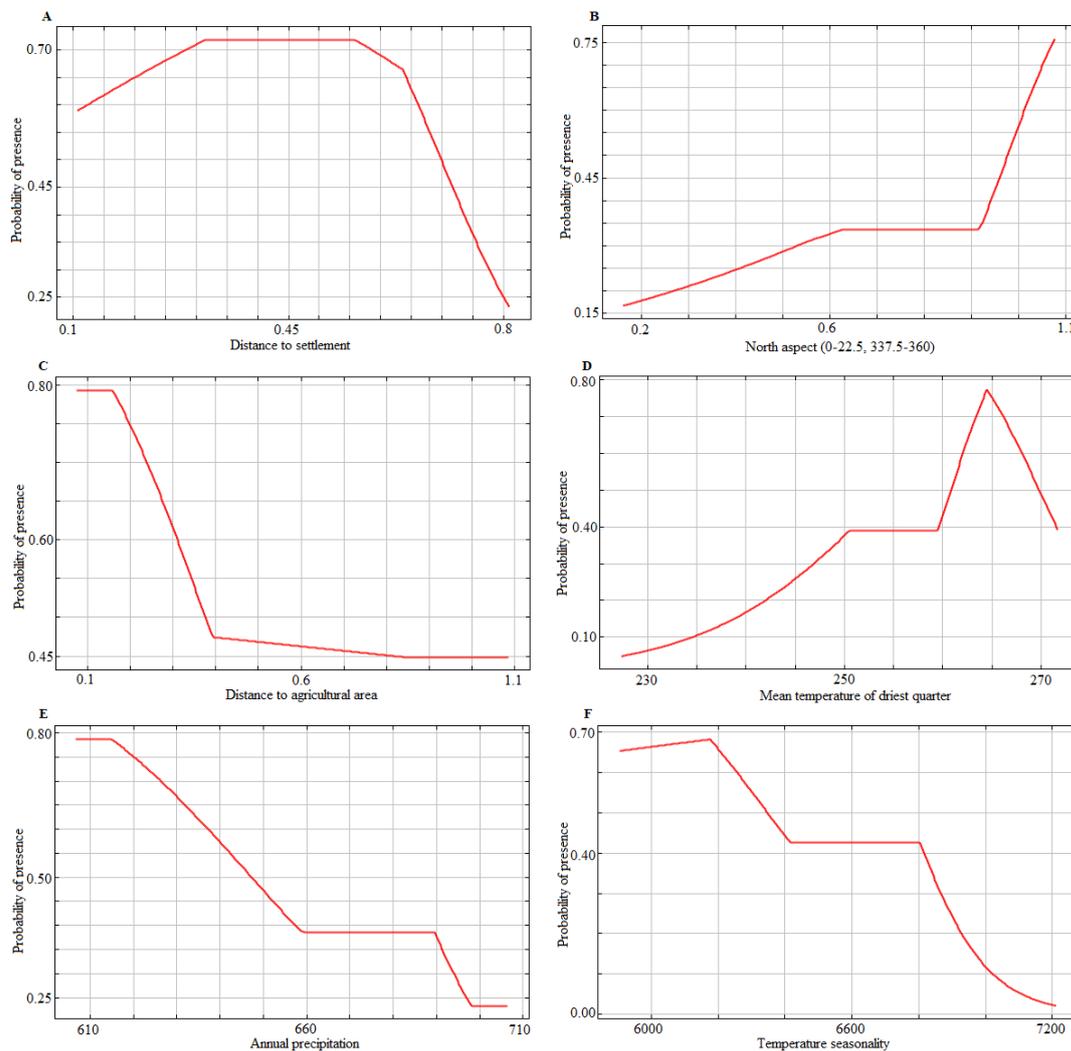


Fig. 3. Response curves of the predictors indicating the highest contribution on the predicted distribution model.

Maxent estimates the relative contribution of environmental predictors for the predicted model, and the higher permutation importance indicates the more impact the environmental predictors have on predicting the potential distribution of the species. In the present study, distance to settlement, north aspect, and distance to agricultural area predictors significantly contributed to the model with 26.3, 26, and 10.3 %, respectively (Table

2). On the other hand, precipitation of warmest quarter, precipitation seasonality, temperature annual range did not contribute to the model prediction (permutation importance 0, Table 2). In this case, the Maxent model can be re-run without these environmental predictors. It may also be considered to drop some of the other relatively unimportant environmental predictors from the model, such as isothermality, min temperature of the

coldest month, annual mean temperature, accessibility, the max temperature of the warmest month, and slope (permutation importance are 0.9, 0.9, 0.6, 0.6, 0.4 and 0.2 respectively, Table 2).

Response curves demonstrated how each environmental predictor responded to the predicted distribution model. In the study, we only evaluated the response of 6 environmental predictors that have permutation importance greater than 5% on the predicted model (Table 2). Accordingly, it is understood that the species do not like being close to the people; thus, habitat suitability increases with increasing distance from settlements (Figure 3A). Another response curve revealed the relationship between species distribution and aspect preference (Figure 3B). Accordingly, Although *Acomys cilicicus* lives on the southern coast of Turkey, it mostly prefers areas of the northern aspect, and its probability of presence decrease as the aspect returns northeast direction (Figure 3B). Unlike distance to settlement predictor, habitat suitability decreases with increasing distance from agricultural areas. It indicates that the species need agricultural areas to feed (Figure 3C).

On the other hand, the probability of presence increases from 0.05 to 0.80 as the mean temperature of the driest quarter increases to around 26.3 ° (Figure 3D). However, the probability of presence decreases when the mean temperature of the driest quarter rises above 26.5° (Figure 3D). The results indicated that *Acomys cilicicus* does not prefer cold and hot temperatures. It means that the mean temperature of the driest quarter, around 26.3 °-

26.4 ° is appropriate for species distribution. It is also seen that presence of *Acomys cilicicus* decrease where annual precipitation is above 615 mm. (Figure 3E).

Nevertheless, the probability of presence is about 0.80 when the annual precipitation is less than 615 mm (Figure 3E). This result shows that target species avoid areas with high annual precipitation. Lastly, the response curve of temperature seasonality was evaluated, and probability distribution decreased from approximately 0.7 to 0.1 at a temperature seasonality of 720 (it is the temperature coefficient of variation, Figure 3F). Temperature seasonality is the amount of temperature variation over a given period (O'Donnell and Ignizio, 2012). Our result showed that *Acomys cilicicus* is sensitive to high-temperature variation and does not prefer high-temperature seasonality areas.

The Maxent internal Jackknife test indicated the importance of predictors for the model. Accordingly, annual precipitation, mean temperature of driest quarter, annual mean temperature, minimum temperature of the coldest month are the four most critical environmental predictors for habitat distribution of *Acomys cilicicus* (Figure 4). The results mean that these predictors have high gain when used in isolation and thus, contain the most useful information for the model (Almalki et al., 2015; Phillips et al., 2006). The environmental predictor that decreases the gain the most when excluded from the model is the distance to settlements (Figure 4). This result showed that it has the most useful information that is not present in other environmental predictors.

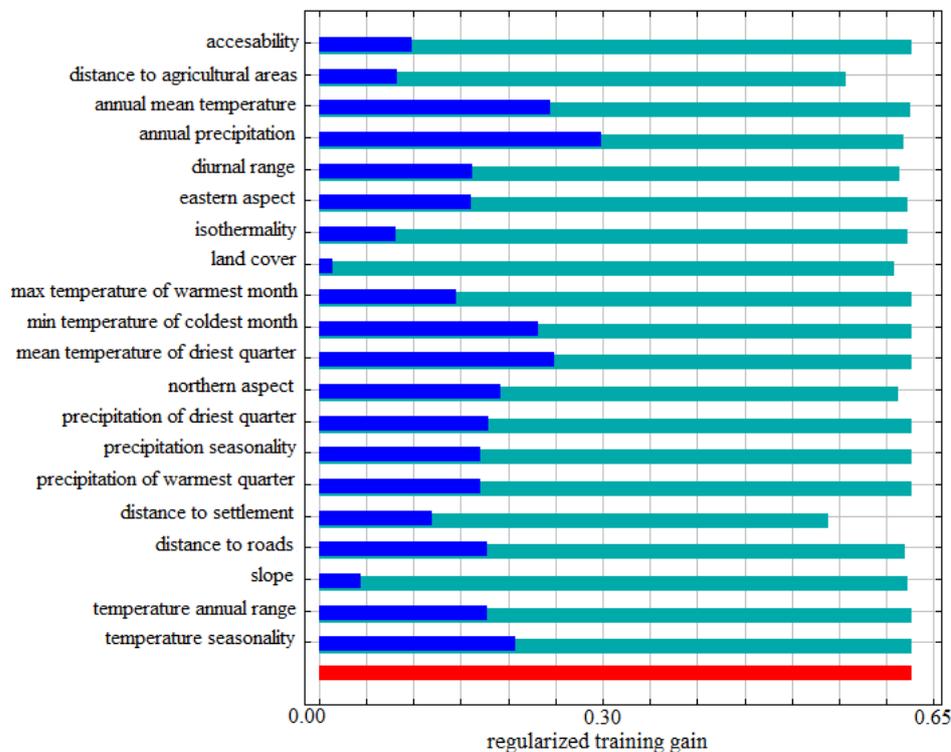


Fig. 4. Jackknife test indicating the importance of predictors in the regularized training gain for the distribution model

Discussion and Conclusion

The model presented in the study was built on a few species occurrence records applying species-specific model parameters. Results indicated the high discrimination capacity of the model and thus supported that the model is an appropriate method for estimating species distribution. One of the main outputs of the model was the species distribution map and displayed that *Acomys cilicicus* is distributed in small remnant habitats (28.4 % of the total study area) (Fig. 2B). The distribution map of the species indicated potential current suitable habitat and pointed high priority survey areas for the species. Therefore, the output may be a valuable guide to serve conservation efforts and plan future studies of the target species. One of the crucial findings of the study is that *Acomys cilicicus* avoids settlements. Ecologically speaking, this signifies that human existence is a threat to the distribution of target species. This finding points out the importance of conservation efforts for this narrow range of endemic species' remaining population. At this point, the species distribution map is a crucial resource showing where conservation efforts should be concentrated. Some study results are also a warning against the adverse effects of climate change on the species. Accordingly, mean temperature of the driest quarter, annual precipitation, and temperature seasonality had the highest contribution in model prediction (Table 2), and their response curves indicated that temperature and precipitation fluctuations negatively affect the probability of presence (Fig. 4). It is clear that these predictors are an essential determinant of species distribution, and therefore, species distribution is sensitive to their changes. Shortly, the results support the adverse effects of climate change on the species distribution and show that this vulnerable species needs conservation measures for its long-term survival. However, it should be noted that if environmental predictors were on a finer scale, then the species' response to environmental conditions could be evaluated in more detail with smoother curves. In addition, the most challenging part of this study was the few occurrence records and limited spatial extent of the study due to the narrow distribution of the target species. Therefore, providing new species records and expanding the study area can make model inputs more compatible and improve model outputs. This approach will contribute to improving the conservation strategies of the species in the long term.

Acknowledgements

This study was financially supported by the scientific and technological research council of Turkey (TUBITAK TOVAG-113R029), and Bulent Ecevit University (Project no: 2012-10-06-10).

References

Almalki, M., Alrashidi, M., O'Connell, M.J., Shobrak, M., Szekeley, T. (2015). Modelling the distribution of wetland birds on the red seacoast in the kingdom of

- Saudi Arabia. *Applied Ecology and Environmental Research*, 13(1), 67-84.
- Amori, G., Hutterer, R., Kryštufek, B., Yigit, N. (2008). The IUCN Red List of Threatened Species. 2008: e.T264A13050432.
- Aulagnier, S., Haffner, P., Mitchell-Jones, T.J., Moutou, F., Zima, J. (2010). Guide des mammifères d'Europe, d'Afrique du Nord et du Moyen-Orient. Delachaux & Niestlé SA, Paris.
- Çetintaş, O., Matur, F., Sözen, M. (2017). Distribution and conservation of *Acomys cilicicus* (Mammalia: Rodentia) in Turkey. *Turkish Journal of Zoology*, 41(6), 1059–1068.
- Elith J, Kearney M, Phillips S. (2010) The art of modelling range-shifting species Methods. *Ecology and Evolution*, 1(4), 330-342.
- Elith, J., Graham, C.H., Anderson, R.P., Dudi'k, M., Ferrier, S. (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography*, 29, 129–151.
- Elith, J., Phillips, S.J., Hastie, T., Dudi'k, M., Chee, Y.E. (2011). A statistical explanation of MaxEnt for ecologists. *Diversity and Distribution*, 17, 43–47.
- Fourcade, Y., Engler, J.O., Rödder, D., Secondi, J. (2014). Mapping Species Distribution with MAXENT Using a Geographically Biased Sample of Presence Data: A Performance Assessment of Methods for Correcting Sampling Bias. *PLoS ONE*, 9(5), e97122.
- Elith J, Kearney M, Phillips S. (2010) The art of modelling range-shifting species Methods. *Ecology and Evolution*, 1(4), 330-342.
- Merow, C., Smith, M.J., Silander, J.A.Jr. (2013). A practical guide to Maxent for modelling species' distributions: what it does, and why inputs and settings matter. *Ecography*, 36(10), 1058–1069.
- Morales, N.S., Fernandez, I.C., Baca-Gonzalez, V. (2017). MaxEnt's parameter configuration and small samples: are we paying attention to recommendations? A systematic review. *PeerJ*, 5: e3093.
- Morovati, M., Panahandeh, M., Rousta, Z., Shorakaei, M.J. (2015). Habitat desirability modelling of cheetah (*Acinonyx jubatus venaticus*) using maximum entropy model in central Iran (A case study: Yazd province-Dareh Anjir wildlife refuge). *Applied Ecology and Environmental Research*, 13(3), 725-739.
- Musser, G.G., Carleton, M.D. (2005). Superfamily Muroidea. In Wilson, D. E., Reeder, D. M., *Mammal Species of the World: A Taxonomic and Geographic Reference* (3rd ed.), Johns Hopkins University Press, ISBN 978-0-8018-8221-0. OCLC 62265494, pp. 894–1531.
- Nazeri, M., Jusoff, K., Madani, N., Mahmud, A.R., Bahman, A.R., Kumar, L. (2012). Predictive Modelling and Mapping of Malayan Sun Bear (*Helarctos malayanus*) Distribution Using Maximum Entropy. *PLoS ONE*, 7(10), e48104.
- O'Donnell, M.S., Ignizio, D.A. (2012). Bioclimatic predictors for supporting ecological applications in the conterminous United States. U.S. Geological Survey Data Series, 691, 10.

- Peterman, W.E., Crawford, J.A., Kuhns, A.R. (2013). Using species distribution and occupancy modelling to guide survey efforts and assess species status. *Journal for Nature Conservation*, 21(2), 114-121.
- Phillips, S.J., Dudík, M. (2008). Modelling of species distributions with Maxent: new extensions and a comprehensive evaluation. *Ecography*, 31, 161-175.
- Phillips, S.J., Anderson, R.P., Schapire, R.E. (2006). Maximum entropy modelling of species geographic distributions. *Ecological Modelling*, 190, 231-259.
- Phillips, S.J., Dudík, M., Schapire, R.E. (2004). A maximum entropy approach to species distribution modelling. Proceedings of the twenty-first international conference on Machine learning, Banff, Canada, pp. 655-662.
- Rhoden, C.M., Peterman, W.E., Taylor, C.A. (2017). Maxent-directed field surveys identify new populations of narrowly endemic habitat specialists. *PerrJ*, 5: e3632.
- Syfert, M.M., Smith, M.J., Coomes, D.A. (2013). The Effects of Sampling Bias and Model Complexity on the Predictive Performance of Maxent Species Distribution Models. *PLoS ONE*, 8(2), e55158.
- URL 1 .www.worldclim.org/
- VanDerWal, J., Shoo, L.P., Graham, C., Williams, S.E. (2009). Selecting pseudo-absence data for presence-only distribution modelling: how far should you stray from what you know? *Ecological Modelling*, 220(4), 589-594.
- Villordon, A., Njuguna, W., Gichuki, S., Ndolo, P., Kulembeka, H., Jeremiah, S.C., Labonte, D., Yada, B., Tukamuhabwa, P., Mwanga, R.O.M. (2006). Using GIS-based tools and distribution modelling to determine sweetpotato germplasm exploration and documentation priorities in sub-Saharan Africa. *HortScience*, 41(6), 1377-1381.
- Wisz, M.S., Hijmans, R.J., Li, J., Peterson, A.T., Graham C.H. (2008). Effects of sample size on the performance of species distribution models. *Diversity and Distribution*, 14(5), 763-773.
- Young, B.E., Franke, I., Hernandez, P.A., Herzog, S.K., Paniagua, L., Tovar, C., Valqui, T. (2009). Using spatial models to predict areas of endemism and gaps in the protection of Andean slope birds. *The Auk*, 126(3), 554-565.