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Habitat suitability modeling of Goitered gazelle (*Gazella subgutturosa*): A Maximum Entropy approach from Samelghan plain, Iran

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Abstract
The spatial distribution modeling can simulate the suitability of species habitats on different spatial scales, based on species records and site characteristics to gain insight into ecological, and evolutionary drivers or help predict habitat suitability across large scales. Species distribution models (SDMs) based on presence-absence or presence-only data are widely used in biogeography to indicate the ecological niche and predict the geographical distribution of species habitats. Although presence-absence data is generally of higher quality, it is also less common than presence-only data because it requires more rigorous planning to visit a set of pre-determined sites. Among the algorithms available, the MaxEnt approach is one of the most widely used methods of developing habitat modeling. The MaxEnt uses maximum entropy to generalize specific observations of presence-only data and does not require data where the species is absent within the theoretical framework. This study aims to predict the suitable habitat for Goitered gazelle (*Gazella subgutturosa*) in the Samelghan plain in northeastern Iran. The results showed that the variables of the Mediterranean climate classes, slope 0-5% class, and semi-dense pastures with type Acantholimon-Astragalus are more important than other environmental variables used in modeling. The area under the curve (AUC), Receiver Operating Characteristic (ROC), and the classification threshold illustrate the model performance. Based on the ROC (AUC=0.99) results in this study, it was found that Maxent's performance was very good.
Keywords: Goitered gazelle, MaxEnt, Samelghan plain, SDMs

Introduction

Habitats' study has key importance for the development of wildlife conservation and management (Naqibzadeh et al., 2021a). Ecological studies such as; The habitat suitability models provide plenty of knowledge about the relationships between wildlife and habitats (Kuloba et al., 2015; Naqibzadeh et al., 2021b; Purohit & Rawat, 2021). Species distribution models (SDMs) are increasingly used in environmental management such as habitat studies, endangered species management, and environmental change impacts (Hirzel et al., 2006). The Models predicting the spatial distribution of species (Pearce & Boyce, 2006; Ghanbarian et al., 2019) can simulate the suitability of species habitats on different spatial scales, based on species records and site characteristics (Kuloba et al., 2015; Qin et al., 2017; Mousazade et al., 2019) to gain insight into ecological or evolutionary drivers or to help predict habitat suitability across large scales (Elith & Leathwick, 2009; Kramer-Schadt et al., 2013). Therefore, modeling species distribution has become a key tool in conservation (Kuloba et al., 2015), ecology (Phillips & Dudík, 2008) evolutionary biology (Guisan & Thuiller 2005; Kozak et al., 2008; Dormann et al. 2012; Muscarella et al., 2014), biogeography (Elith et al., 2011), evolution, invasive species control (Phillips et al., 2006) and wildlife management studies (Long et al., 2008; Franklin, 2013; Wan et al., 2016; Zhang et al., 2019a; Li et al., 2020).

In recent years, many techniques for modeling species' niches and distributions have been developed (Guisan & Thuiller, 2005; Kozak et al., 2008; Peterson et al., 2011; Radosavljevic & Anderson, 2014). Computer tools such as a large number of algorithms and software platforms with Geographic Information System (GIS) (Traill & Bigalke, 2007), and statistical modeling techniques to draw up predictive maps (Jiménez-Valverde et al., 2007; Naqibzadeh et al., 2021b) have become more widely used in ecology and conservation biology (Warren et al., 2008; Kamyo & Asanok, 2020). One of the main shortcomings of distribution model predictions is a lack of reliable information on species' absence (Jiménez-Valverde et al., 2007). Species distribution models (SDMs) based on presence-absence or presence-only data are used widely in biogeography to characterize (Naimi et al., 2014). The presence-only data only contains information about species presence, in contrast to presence-absence data which records both where species have been found present and where they have not been found (Warton & Shepherd, 2010; Renner et al., 2015). Although presence-absence data is generally of higher quality, it is also less common than presence-only data because it requires more rigorous planning to visit a set of predetermined sites (Van Strien et al., 2013; Ruete & Leynaud, 2015). The presence-only data allow for easy public and private involvement in biological monitoring and are the dominant source of species occurrence data (Elith et al., 2011; Pédarros et al., 2020).

Among the algorithms available, one of the most widely used methods of developing SDMs is the Maximum entropy (MaxEnt) method (Phillips et al., 2017; Tourne et al., 2019). MaxEnt uses entropy to generalize specific observations of presence-only data and does not require or even incorporate points where the species is absent within the theoretical framework (Kamyo & Asanok, 2020). Maxent model is a useful technique to predict the potentially suitable habitat (Evcin et al., 2019; Qin et al., 2020), geographical species distribution (Phillips et al., 2006; Jiménez-Valverde, 2012; Merow et al., 2014; Mi et al., 2016; Fronczak et al., 2017; Wan et al., 2019; Wang et al., 2019; Kamyo & Asanok, 2020) based on the most significant environmental conditions (Phillips et al., 2006; Moreno et al., 2011; Tourne et al., 2019). MaxEnt model for simulating the suitable geographical distribution of species, has more advantages than other models, including a good performance with incomplete datasets, short model running time, easy operation, small sample size requirements, and high simulation precision (Hernandez et al., 2006; Phillips et al., 2006; Pearson et al., 2007; Li et al., 2020).

Many habitats outside the area under the management of the Department of Environment are of particular importance, especially in providing shelter and food for wildlife, which can provide a good place for fauna and flora. The purpose of this study is to model the habitat of the Goitered gazelle in these areas with the MaxEnt method. It should be noted that many of these habitats are important in wildlife conservation and management, and should be considered in conservation discussions of fauna and flora. The importance of this region is also due to the existence of the archaeological site in the basin that may bring an understanding of the past wildlife through the study of ancient faunal remains. Undergoing zooarchaeological analyses at Tappeh Rivi will give the opportunity to reconstruct past environments and also human pressure on the wildlife and in particular gazelles that were a commonly hunted species on the Iranian Plateau (Mashkour, 1999 and 2001) and in particular in the northeast of Iran and southern central Asia (Mashkour 2013a and b).

Material and methods

Modeling can be made by using many variables in wildlife studies. MaxEnt model can use environmental variables and presence-only data (Evcin et al., 2019) to calculate the constraints and explores the possible distribution of maximum entropy under this condition, and then predicts the habitat suitability of the species in the study area (Phillips et al., 2006; Merow et al., 2013; Zhang et al., 2019bHabitat modeling based on species' absence and presence data is complicated because of the lack of data about the absence of species in the area (Naqibzadeh et al., 2021a). Therefore, the modeling technique used for the Goitered gazelle in the area was based on presence-only data.

Goitered Gazelle is listed as Vulnerable under criterion A2 because of ongoing declines due to poaching, habitat degradation from overgrazing, competition with livestock, and industrial and commercial development. The decline is estimated to have exceeded 30% in the last 14 years

(IUCN Redlist, 2017). The Samelghan plain (10 km south of Atrak Valley) extends from latitudes 37º 21´ to 37º 40´ N and longitudes 56º 26´ to 57º 06´ E in Northern Khorasan province, North-East of Iran. The Samelghan plain's total area is 111660 hectares extending from 575 to 2676 m above the mean sea leve (Fig. 1).

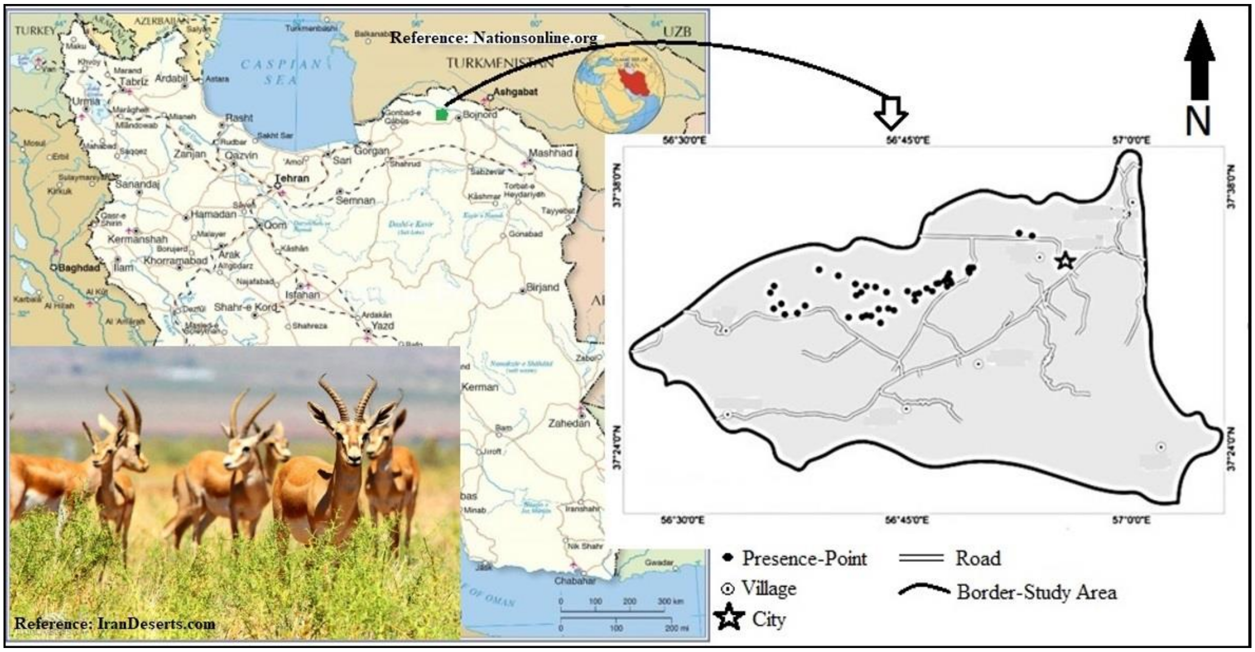


Figure 1. The location of the study area in Iran

The environmental variables used for modeling include topography and geomorphology, climatology, land use, vegetation, water resources, and human development variables such as villages and roads. Also, class maps of slope percentages and the main aspects were prepared by using DEM. All variables were converted to raster maps after digitization with 30×30 m cell size. To collect occurrence records, the distance sampling method (Waltert et al., 2008; Thomas et al., 2010), direct observations, footprints, repose imprints, feces, and tracks were used. One of the advantages of MaxEnt as a modeling method is that it can work even with a very small sample size (Pearson et al., 2006; Phillips et al., 2006; Phillips & Dudík, 2008; Saupe et al., 2015; Zhang et al., 2019b; Karami et al., 2020). In this research, the geographical coordinates of the point were recorded using the Global Positioning System (GPS) as the present point, and a total of 43 points were obtained for the species of Goitered gazelle in the Samelghan plain.

Results

MaxEnt model produces this data: Prediction Maps (Prediction Maps); response curve (Response Curves) with an AUC (Area Under Curve); and Jackknife's results of analysis help researchers interpret and understand the outcomes of the MaxEnt model. MaxEnt model output is logistic, which assigned each grid cell of the study area values ranging from 0 (completely unsuitable) to 1 (fully suitable) (Signorini et al., 2014; Alcala-Canto et al., 2018). therefore, if this value reaches 1, the habitat has higher desirability for the species, and, conversely, reaches zero, the habitat desirability is reduced (Gormley et al., 2011) (Fig. 2).

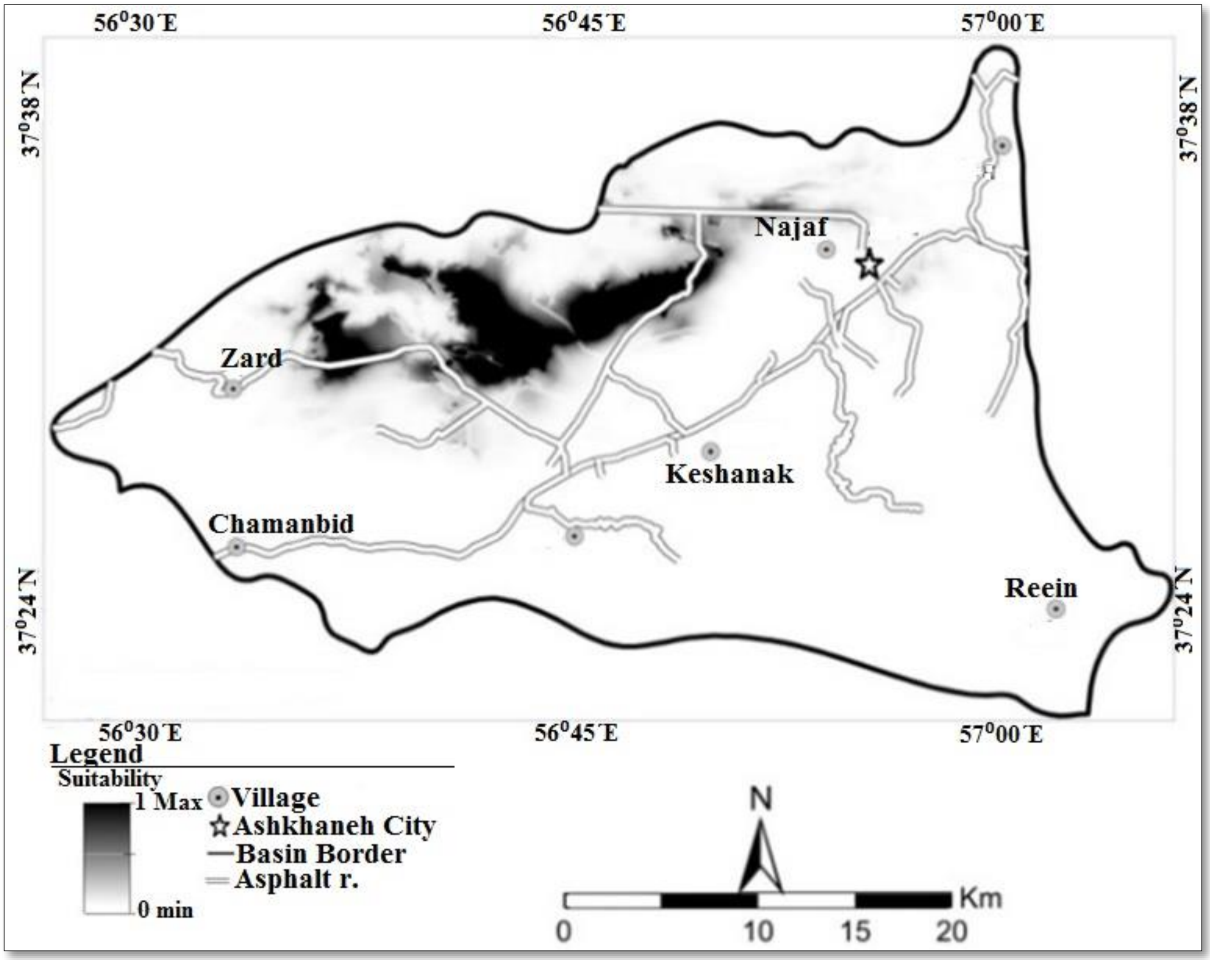


Figure 2. The Habitat continuous map

Jackknife plot and response curves

MaxEnt can also estimate occupancy (referred to as 'logistic output') if the above assumptions are met, and users have additional knowledge of the occurrence probability of a species under 'average' conditions (Phillips & Dudík, 2008; Yackulic et al., 2013). To evaluate the accuracy of each model, we used the threshold-in-dependent Area Under the Curve ("AUC") calculated from the "Receiver Operating Curve" (ROC) (Fielding & Bell, 1997; Pearce & Ferrier, 2000). The ROC curve plots sensitivity against 1-specificity for all possible values of the threshold habitat suitability above which the habitat is assumed to be suitable (Fielding & Bell, 1997). The AUC can be interpreted as the probability that a randomly chosen presence site will be more highly ranked than a randomly chosen absence one (Pearce & Ferrier, 2000; Merow et al., 2013; Alatawi et al., 2020). An area under the receiver operating characteristic curve was examined for additional precision analyses (Evcin et al., 2019). The area under the curve (AUC) of the receiver operating characteristics (ROC) is a recommended index for model validation (Fielding & Bell, 1997; Moreno et al., 2011; Merow et al., 2013; Fand et al., 2014; Ghanbarian et al., 2019) as well as is a common way to assess the performance of a species distribution model with the binary response (Pédarros et al., 2020).

Briefly, The ROC plot ranges from 0.5 to 1.0. Values close to 1 mean better performance (Phillips et al. 2006; Yuan et al., 2015; Ghanbarian et al., 2019; Wan et al., 2019; Kamyo & Asanok, 2020). Values of ROC are described as an excellent model between 0.9 and 1, good between 0.8 and 0.9, fair between 0.7 and 0.8, and poor below 0.7 (Alcala-Canto et al. 2018; Evcin et al., 2019; Ito et al., 2020). In this model, the area below the curve for the Goitered gazelle species was 0.990, with a standard deviation of 0.001, which indicates the ability to detect very good performance. (Fig. 3).

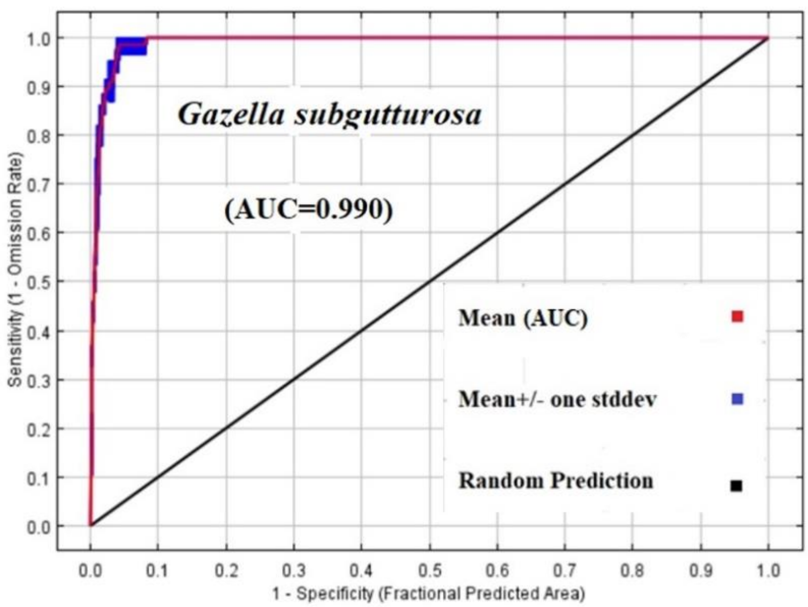


Figure 3. The ROC curve and AUC value of the model for Goitered gazelle

The jackknife plot validation model was used for the validation of the model (Pearson et al., 2007) The jackknife plot was used to assess the relative importance of the variables (Phillips et al., 2006; Zhang et al., 2018; Evcin et al., 2019). The assessment capacity of the species distribution model by AUC is criticized because of its relativity (Lobo et al., 2008). The AUC may be a good statistical measure of discrimination ability but it often fails to quantify the ecological likelihood of modeled distribution especially when estimated from presence-only data (Lobo et al., 2008;

Pédarros et al., 2020). The Jackknife plot shows the importance of variables in three different colors; The blue color indicates how much of the species information is justified when running the model with only one variable, the light green indicates the implementation of the model without the desired variable, and the red color indicates the implementation of the model with all variables (Phillips et al., 2004). The Jackknife plot generally shows how environmentally friendly variables are effective in species distribution, based on The Jackknife plot, which can be used to determine which variable alone is most influential in modeling. Thus, the distance from the Mediterranean climate is the most effective variable in the development of Goitered gazelle species modeling (Fig. 4) which can be removed by the greatest decrease occurs in the amount of AUC.

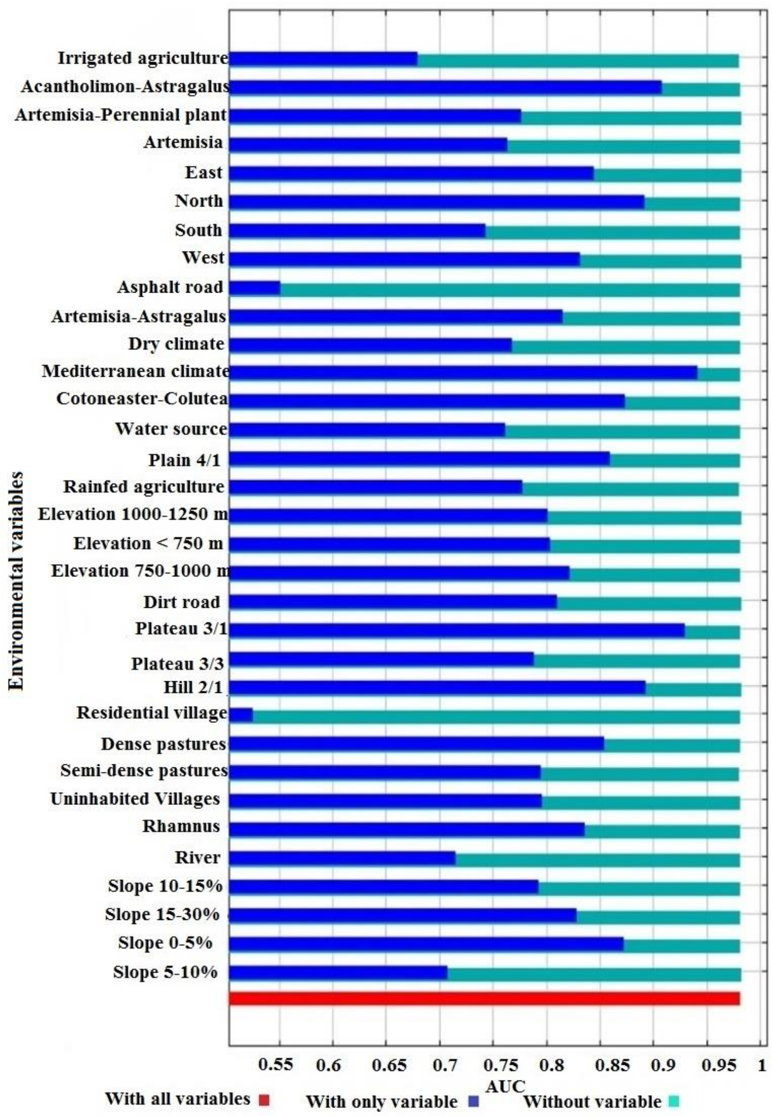
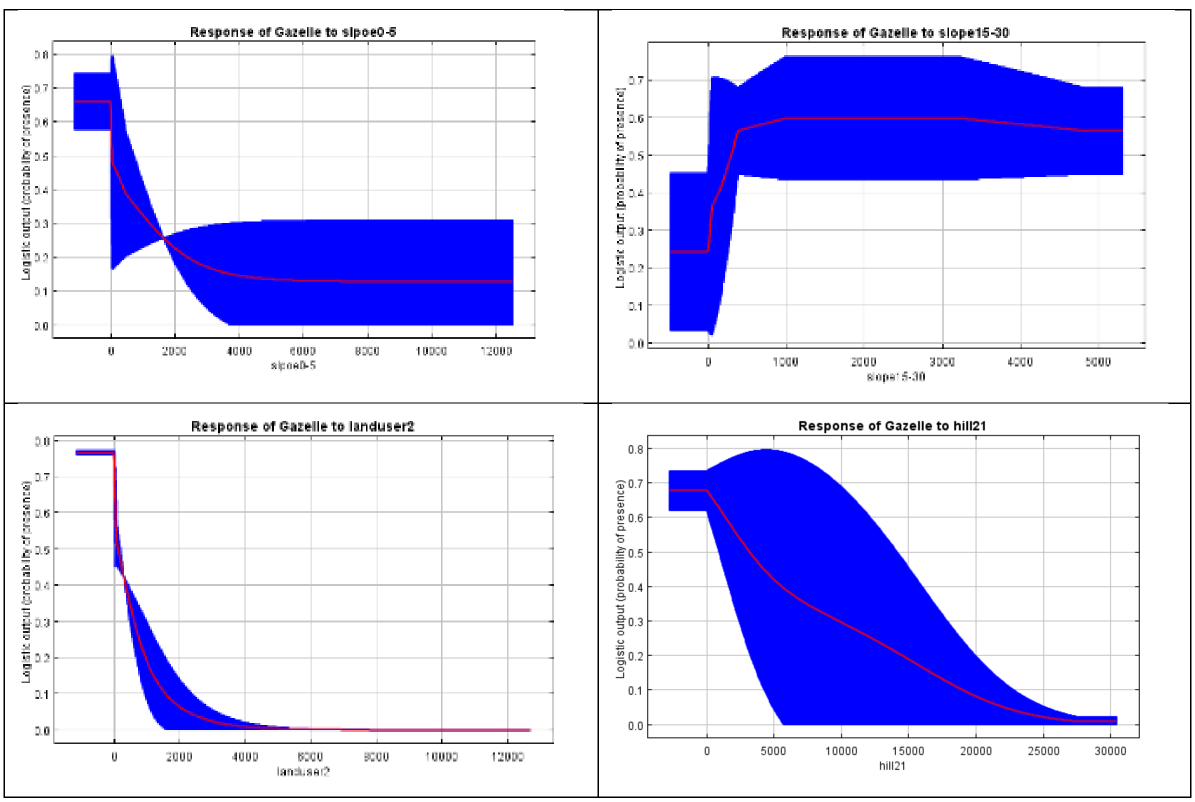


Figure 4. The jackknife test in determining the importance of variables in study area

If all variables are in their mean values, the response curve to each variable will be in the form of graphs in which the red color indicates the average value of each variable in the two repetitions and the blue color indicates the standard deviation. In the graphs related to the environmental variables, the X-axis indicates the distance from the desired variable and the Y-axis indicates the probability of species presence, which ultimately determines the habitat suitability for the species being studied. Figure 5, shows the Goitered gazelle response curve to environmental variables. According to Figure 5, environmental variables have different effects on the distribution and presence of the species and ultimately the suitability of the Goitered gazelle habitat. According to the response curves, the distance from the conditions of the Mediterranean climate variable increases the probability of the presence of Goitered gazelle and then has a linear effect on the probability of presence. The response curve to the distance from the slope of 5-0%, so that the more the distance from the environmental conditions with this feature (slope of 5-0%) is reduced, the probability of the presence of the species is reduced and as a result, the desirability of the habitat will be reduced. The Goitered gazelle's response to the semi-dense rangeland variable is similar to the 5-0% slope variable. However, as inferred from Figure 5, a slope of 15-30% is one of the factors that will increase the likelihood of the presence of the species by increasing the distance from it. Other variables also affect the probability of species presence, which can be interpreted by responding to the positive or negative effects of habitat suitability.



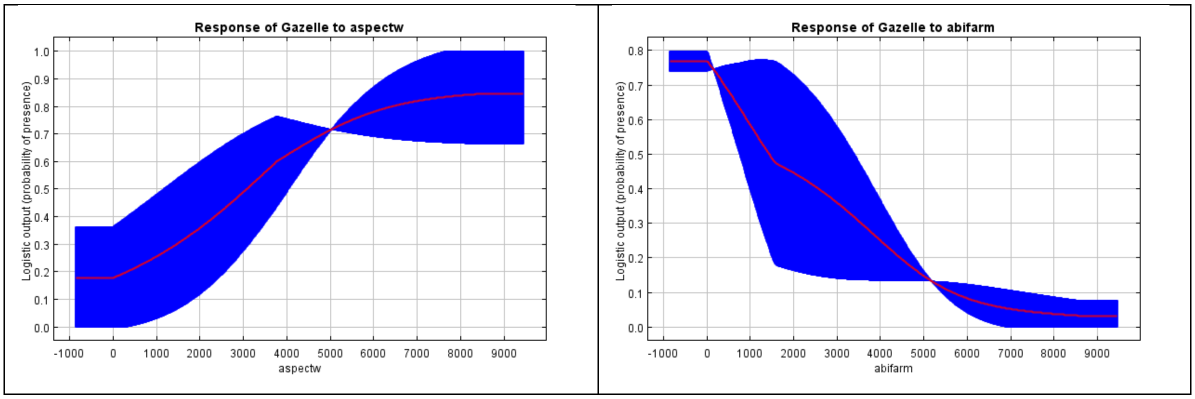


Figure 5. The response curves illustrating the relationship of predicted probability of Goitered gazelle occurrence to environmental variables

To determine the importance of each of the available variables from the statistics calculated by the software based on the share of each variable in the model (Phillips et al., 2012), the response curves of the variables for the single-variable model and the Jacqueline test for Evaluating AUC changes was used when deleting any variable (Yost et al., 2008). Table 1, shows the relative share of each of the environmental variables in the distribution of Goitered gazelle at the surface of the Ashkhaneh watershed. As it is known, the distance from the slope of 5-0% and the distance from the semi-dense rangeland have the highest participation in Goitered gazelle distribution.

Table 1. Percent contribution values of variables used in modeling

Variable	Percent contribution	Variable	Percent contribution
The Slope 0-5%	34.3	The slope 5-10%	0.4
Semi-dense pastures	25	Artemisia-Perennial plant	0.3
Dirt road	6.1	Southern Aspects	0.3
Western Aspects	4.7	Plateau 3/3	0.2
Hill 2/1	4.6	Western Aspects	0.2
The slope 15-30%	4.4	Eastern Aspects	0.2
Mediterranean climate	3.7	Asphalt road	0.2
Rainfed agriculture	3.7	Residential village	0.1
Plain 4/1	2.5	The slope 10-15%	0.1
Northern Aspects	2.5	Uninhabited Villages	0.1
Irrigated agriculture	2.2	Dense pastures	0.1
Artemisia	1.9	Plateau 3/1	0.1
Elevation <750 m	1	Elevation 1000-1250 m	0.1
River	0.6	-	-

Maps for Goitered gazelle were entered into the ArcGIS10.3 software by the Maxent software in ASC format and converted to a raster format so that according to the threshold value obtained from the model 0.0277 for Goitered gazelle to be classified into two desirable and undesirable classes (Fig. 6). High threshold values indicate optimal habitat and lower values than threshold indicate adverse habitat for both species.

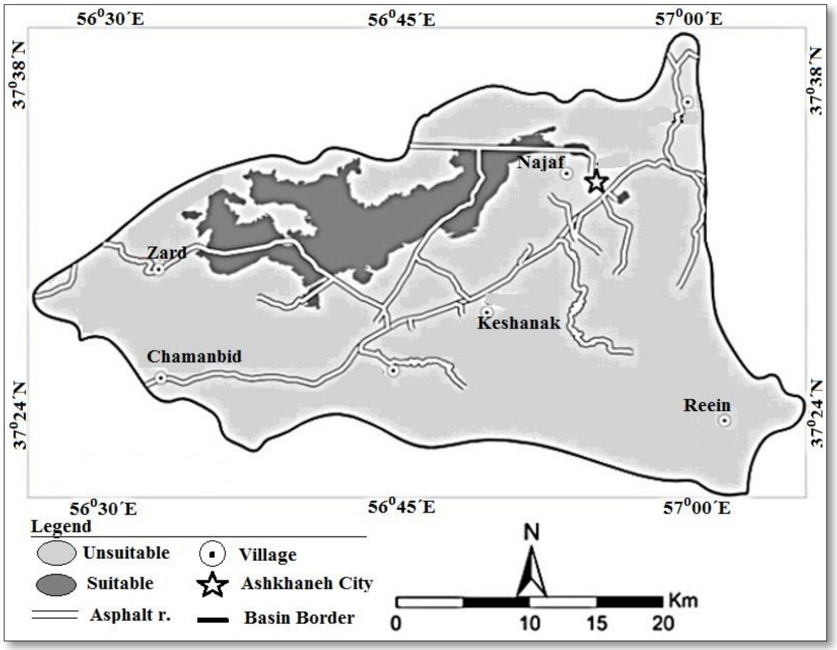


Figure 6. The Habitat classification map

Discussion

The models provide a quantitative assessment of species extinction risk, identify potential threats to all animal species, and provide maps of the world's mammal distribution points. Habitat evaluation and suitability provide strategic priorities for the protection of global mammals (Crooks et al., 2017). Modeling methods can be used for different purposes, including; Determining the suitability of species habitats (Toor et al., 2011) Predicting the trend of species expansion at the level of a region (Giovanelli et al., 2010) as well as predicting high-risk areas of conflict between wildlife and human species (Leung et al., 2002).

To determine the importance of environmental variables in the habitat suitability modeling of Goitered gazelle in the Samelghan plain, the Maxent uses three factors: the Jackknife plot, the percent contribution values of variables, and species response curves to these variables.

According to the Jackknife plot, the variables that were most important in the habitat modeling include Mediterranean climate class, plateau 3.1 (plateaus with characteristics; medium and low altitudes, medium to high erosion on limestone and sand), and plant type *Acantholimon-Astragalus*. Also, other environmental variables were effective in modeling, but the impact of these variables was more noticeable than them. The effect of these variables is such that by removing each of these, there will be significant changes in habitat modeling. According to the Jackknife plot, variables such as residential villages were the variables that had the least effect on the modeling. That is, removing this variable does not make much difference in modeling. The second factor is the percent contribution values table of variables in the habitat modeling. This table shows the participation percentage of each variable in determining the suitable habitat for the studied species at the basin. As shown in the table, variables such as 0-5% slope class, and semi-dense pasture class were among the variables that had the most participation in modeling. Based on this table, it can be determined how much each variable has contributed to creating the final habitat suitability map for the Goitered gazelle. After determining the important variables in habitat modeling, based on response curves (third factor) can determine the impact of each variable on the probability of species presence. Based on these curves, it can be determined that by increasing or decreasing the distance from the variable, changes occur in the probability of species presence and habitat suitability.

the results showed that the species showed different responses to different environmental variables. the slope 0-5% variable; this variable is one of the variables that have the most participation in modeling, based on the species response curve, the probability of species presence decreases with increasing distance from this variable. So, it can be seen that the Goitered gazelle prefers areas with a slope of 0-5% compared to other slope classes. Climatic conditions, in turn, are effective in habitat modeling, according to the Jackknife plot, the Mediterranean climate class is a variable that is more important than other variables. However, based on the response curve of this variable, the probability of the presence of the species changes less, ie with increasing distance from this variable, the probability of presence increases and after a certain distance, there is no change in the probability of presence.

Another important variable in Goitered gazelle modeling is the distance from the semi-dense pasture variable. pastures are very important in the food supply, the Maxent's results showed that Goitered gazelle prefers semi-dense pastures with type *Acantholimon-Astragalus* vegetation over other variables, as shown in the species response curve to these variables with increasing distance from this variable, the probability of presence much reduced. The variables obtained from the results of the Jackknife plot and the percent contribution values table for the Goitered gazelle in the Samelghan plain are not necessarily variables that reduce the likelihood of presence. because, if we examine some of the obtained variables based on the response curves, increasing the distance from it, increases or causes fluctuations in the probability of presence, which can be influenced by other variables or other factors in the habitats such as the existence of competing species, predators and human activities. Variables such as classes of slope 15-30% are among the variables that the probability of species presence will increase with increasing distance from it so that Goitered gazelle avoids these areas and prefers other slope classes to this variable.

Other variables also affect the probability of species presence, which can be explained by interpreting the response curves to their positive or negative effects on habitat desirability.

The results of the Jackknife plot, and the percent contribution values table, provide Maxent with a threshold for habitat classification that shows the final suitability map for Goitered gazelle in the Ashkhaneh area. The suitability classification map shows that the Goitered gazelle's habitat covers the northern parts of the basin, which has all the suitable conditions for the species.

The study showed that approx. 11% of the Samelghan plain is a suitable habitat for Goitered gazelle. Based on the research, it is suggested that since the area is not under the protection of the Environment Organization; other species should be identified and examined, if possible, to define the area as a "No-hunting area".

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