Goitered Gazelle's (*Gazella Subgutturosa*) Habitat Desirability Modeling by Using Maximum Entropy (Maxent) Method

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Abstract

The models predicting the spatial distribution of species can simulate the suitability of species habitats on different spatial scales, based on species records and site characteristics to gain insight into ecological or evolutionary drivers or to help predict habitat suitability across large scales. Species distribution models (SDMs) based on presence-absence or presence-only data use widely in biogeography to characterize the ecological niche of species and to predict the geographical distribution of their habitat. 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, one of the most widely used methods of developing SDMs is the Maximum Entropy (MaxEnt) method. The 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. The purpose of this study is 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 curve (AUC), Receiver Operating Characteristic (ROC), and the classification threshold shows model performance. Based on the ROC (AUC=0.99) results in this study, it was found that Maxent's performance was very good. Desirability habitat was classified based on the threshold value (0.0277) and the ROC, which approx 11% of the area, predicted suitable habitat for Goitered gazelle.

Keywords: SDMs; MaxEnt; Goitered gazelle; Samelghan plain; Iran.

Introduction

Habitats' study has key importance for the development of wildlife conservation policies, evaluation, and conservation (Suleman *et al*., 2020). Ecological studies such as; Habitat Suitability models provide plenty of knowledge about the relationships of wildlife with habitats (Allouche *et al*., 2008; Kuloba *et al*., 2015). Species distribution models (SDMs) are increasingly being used in environmental management, such as habitat suitability studies (Luo *et al*., 2020), managing endangered species, and environmental change impacts (Hirzel *et al*., 2006). The Models predicting the spatial distribution of species (Guisan & Zimmermann, 2000; Pearce and 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 (Allouche *et al*., 2008; 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 & Zimmermann, 2000; 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 (Guilbault *et al*., 2019) 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,. 2021) have been become more widely used in ecology and conservation biology (Guisan & Zimmermann 2000; 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 (Guilbault *et al*., 2019) are used widely in biogeography to characterize the ecological niche of species and to predict the geographical distribution of their habitat (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;

Guilbault *et al*., 2019). 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; Xu *et al*., 2015; Mi *et al*., 2016; Fronczak *et al*., 2017; Wan *et al*., 2019; Wang *et al*., 2019; Kamyo & Asanok, 2020) on the basis of the most significant environmental conditions (Phillips *et al.,* 2006; Moreno *et al*., 2011; Tourne *et al*., 2019). MaxEnt model on 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; Ortega-Huerta and Peterson, 2008; 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 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 due to the existence of the Rivi archaeological site in the basin because based on the samples obtained from zooarcheological studies, the historical distribution of species can be understood. Also, with zooarchaeology and analysis of animal remains, it is possible to reconstruct past habitats (Mashkour *et al.,* 1999, Mashkour, 2001; Mashkour, 2013; Neer, 2017). Indeed, this study may serve as a pilot project and will give a basic outline for future investigations along with the Tappe Rivi Project that will estimate wildlife versus animal management through ancient times and in comparison to modern fauna.

Matrial 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 at the study area (Phillips *et al*., 2006; Merow *et al*., 2013; Zhang *et al*., 2019b).

The Samelghan plain (10 km south of Atrak valley) is located in Northern Khorasan province, North East of Iran, and exhibit an ancient settlement area of more than 100 ha with four major Tappe ruins. The archaeological remains date back from the Late Bronze and Iron Age throughout the early historic periods of the Achaemenid and sasanid empire (approx. 1500 BC until 500 AD), plus a succeeding village-like occupation during Early Islamic times (Jafari & Thomalsky 2016; Thomalsky, 2016). The study area covers an area of 111660 hectares (Figure 1), which is located in the geographical position of $37^0\ 21´$ to $37^0\ 40´$ north latitude and $56^0\ 26´$ to $57^0\ 06´$ east longitude.

Fig1. the location of the study area in Iran

The environmental (classified) 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. In order 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 the MaxEnt as a modeling method is that it is able to 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 presence point, and a total of 43 points were obtained for the species of Goitered gazelle in the Samelghan plain. After closing the border of the region based on the watershed, all variables were prepared according to the border.

Results and Discussion

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 to 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; Huercha *et al*., 2020). therefore, that 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) (Figure 2).

Fig2: 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; Huercha et al., 2020) as well as is a common way to assess the performance of a species distribution model with binary response (Pédarros *et al*., 2020).

Briefly, The ROC plot ranges from 0.5 to 1.0. Values close to 1 means better performance (Phillips et al. 2006; Yuan *et al*., 2015; Ghanbarian *et* al., 2019; Wan *et al*., 2019; Huercha *et al*., 2020; 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; Preau *et al*., 2018; Evcin *et al*., 2019; Huercha *et al*., 2020; 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. (Figure 3).

Fig3: the ROC curve and AUC value

The jackknife plot validation model was used for the validation of 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 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 modelled 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 (Figure 4) which can be removed by The greatest decrease occurs in the amount of AUC.

Fig4: the jackknife test in determining the importance of variables

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 have an effect on 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 of Goitered gazelle 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, show 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 , was 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 (Figure 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 including: 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 also 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, 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 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 increasing or decreasing the distance from the variable, what 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 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 gazella 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 Goitered gazella in the Ashkhneh basin are not necessarily variables that reduce the likelihood of presence. because, if we examine some of the obtained variables based on the response curves, by 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 have an effect on 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, the percent contribution values table, provide Maxent a threshold for habitat classification that shows the final suitability map for Goitered gazella in the Ashkhaneh area. The suitability classification map shows that Goitered gazelle's habitat covers the northern parts of the basin, which has all the suitable conditions for 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 as the area as a "No-hunting area".

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