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Maxent modeling for predicting potential distribution of goitered gazelle in central Iran: the effect of extent and grain size on performance of the model

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Abstract: The spatial scale of environmental layers is an important factor to consider in developing an understanding of ecological processes. This study employed Maxent modeling to investigate the geographic distribution of goitered gazelle, *Gazella subgutturosa* (Güldenstädt, 1780), in central Iran using uncorrelated variables at a spatial resolution of 250 m. We used spatial downscaling to downscale WorldClim data to 250-m resolution. We evaluated the sensitivity of the model to different grain and extent sizes from 250 m to 3 km. We compared the performance of the model at different scales using suitability indexes (AUC) and predicted habitat areas. Two models performed with AUC values higher than random (AUC_{un} = 0.957, AUC_{pu} = 0.953). The distribution of potential habitats at 250-m grid size was strongly influenced by bioclimatic data, vegetation type and density, and elevation. There were few spatial divergences between uncorrelated and pruned models. The mean AUC across eight different spatial scales ranged from 0.936 to 0.959. There was a significant negative correlation between grain size and AUC (R^2 = 0.57). An increase in grain size increased the predicted habitat area. The extent size and AUC showed a positive correlation (R^2 = 0.18). Predicted suitability habitat also decreased as extent size increased (R^2 = 0.49). Spatial congruence AUC fluctuated within a small range and the maximum difference occurred between models of 1 × 1 and 2.5 × 2.5 km. These results showed that an increase in extent size is more accurate than an increase in grain size, and the maximum accuracy for predicting distribution of goitered gazelle in Iran was obtained if the grain size and extent size were 750 m.

Key words: Downscaling, extent size, grain size, maxent, goitered gazelle, scale effect, species distribution modeling

1. Introduction

Global biodiversity has diminished in recent decades as a result of habitat degradation and fragmentation, climate change, alien species, pollution, overexploitation, and increasing human population (Primack, 2008; Barnosky et al., 2011). Since habitat degradation is the most important factor in decreasing wildlife populations, most management practices have been focused on managing habitat. Habitat rehabilitation and selection of areas for reintroduction of threatened species require information on species' geographical ranges (Papes and Gaubert, 2007; Polak and Saltz, 2011). In recent years many species distribution models (SDMs) have been used in ecology to address questions related to selecting conservation sites, reintroduction, and developing effective species conservation measures (Guisan et al., 2006; Carnaval and Moritz, 2008; Franklin, 2009).

Grid size (spatial resolution) is an important factor that may affect predictions of species' distributions (Guisan et al., 2007). Due to the scale-based nature of species' responses to ecological patterns and scale dependence of conservation goals, wildlife populations should be considered at various scales to obtain more accurate information. In other words, selecting an appropriate spatial scale is one of the key problems in SDMs (Scott et al., 2002; Graf et al., 2005; Cabeza et al., 2010). The spatial scale of SDMs affects model performance and the ability to obtain accurate information of the details of surface distributions. There are few studies on the effects of losing information when gathering spatial data at coarser scales (Henderson-Sellers et al., 1982; Turner et al., 1989; Guisan et al., 2007). Wiens (1989) noted that choice of spatial scale is critical in analyzing species–environment relations. Guisan and Thuiller (2005) described it as a central problem in bioclimatic modeling.

Grain and extent size are two concepts that have recently been used in SDMs. Based on the definition of Song et al. (2013), grain size or resolution is the unit size of environmental layers used in modeling, and extent size refers to the spatial extent of the analysis (size of domain) used in the calculation of an environmental value for the given grid. Therefore, it is likely that predicting a species'

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distribution based on an appropriate grain and extent size improves the performance of the SDM. Choosing an appropriate grain size for modeling involves addressing such issues as grid cell size of available predictors and characteristics of the species data (Graham et al., 2004; Linke et al., 2005; Huettmann and Diamond, 2006).

Some environmental variables, especially climatic data, are typically available at a coarse spatial scale and may be less effective for fine-scale species distribution modeling (Davis et al., 2010). The recent development of downscaling methods for environmental variables has led to the possibility of using these variables in fine-scale environmental modeling. Downscaling is the process of transferring the climate information from a coarse spatial scale to a fine scale (Flint and Flint, 2012). In the present study, a method developed to include spatial gradients was used to downscale bioclimatic variables to a fine spatial resolution.

Data on species' absence are often unavailable or unreliable (Engler et al., 2004) for threatened species. Therefore, modeling techniques that require presence-only data such as maximum entropy modeling (Maxent) (Phillips et al., 2006) or genetic algorithm for rule set prediction (GARP; Stockwell and Peters, 1999) have been widely used to predict habitat distributions (Hirzel et al., 2002). In this study we chose to use Maxent for several reasons. It only requires species' occurrence points (Elith et al., 2010), it uses continuous and categorical data and the interactions between them, it is not sensitive to collinearity between environmental variables (Philips et al., 2006), the resulting probability distributions are easy to analyze, overfitting can be avoided by using regularization, and it is very robust at detailed scales (Phillips et al., 2006).

The Persian gazelle, also known as goitered gazelle, is distributed in Iran east of the Zagros Mountains (Groves and Grubb, 2011). Until recently they occurred in very large numbers in the arid and semiarid steppes of Iran. Habitat destruction and fragmentation, illegal hunting, and environmental extremes currently confine the species' range to a number of small isolated populations. Distribution modeling can be an effective tool to identify potential areas for introducing goitered gazelle. Since goitered gazelle is one of the main food sources of carnivore species, it plays an important role in the survival of other species in central Iran such as cheetah (*Acinonyx jubatus*) and leopard (*Panthera pardus*) as well.

We studied the application of Maxent distribution modeling for analyzing the habitat distribution of goitered gazelle by changing the grain and extent size to find the best spatial scale for assessing habitat suitability. Our main objectives were to: 1) evaluate the use of our spatial downscaling method to model the habitat distribution of the species at a fine scale, 2) determine the effect of environmental variables on the potential habitat distribution of goitered gazelle at different spatial scales, 3) identify the effect of change in grain and extent size on the performance of the model in order to find the best spatial scale for predicting potential suitable habitats for the species, 4) assess the amount of spatial congruence among different models run by various predictors, and 5) predict suitable habitats of the whole study area (both protected and nonprotected areas).

2. Material and methods

2.1. Study area

Broad-scale habitat suitability modeling was carried out in central Iran (c. 320,000 km^2) covering most of the distribution range of the goitered gazelle. The elevation is highly variable, ranging from 117 to 4429 m. Mean annual temperature and precipitation is 17.6 °C and 117 mm, respectively. Most precipitation occurs during winter. The dominant vegetation is composed of semishrubs and shrubs with sparse grass. Despite the extreme environmental conditions, this part of Iran is rich in biological diversity. There are 6 goitered gazelle populations in this area confined to the protected areas (Figure 1).

2.2. Species and biogeographical data

Species occurrence consisted of point data collected through field surveys and from records kept by the Iranian Department of Environment. Finding presence point data of goitered gazelle is difficult because of the declining populations. We used available presence records (n = 180) from the entire range of goitered gazelle across the study area during 2011–2014 for model development. The coordinates of all the occurrence points were recorded using a hand-held multichannel Global Positioning System (GPS) receiver with positional accuracy of ±5 m.

We applied Maxent modeling using presence-only data to predict suitable habitats for the goitered gazelle in central Iran at a fine resolution (250 m). We selected 12 uncorrelated environmental variables in four classes (climatic, topographic, vegetation, and anthropogenic) presumed to determine the distribution of goitered gazelle at the studied scale (Hu and Jiang, 2010; Moreno et al., 2011; Ahmadzadeh et al., 2013; Hosseini et al., 2013; Mondal et al., 2013). Projections, grid cell size, and spatial extent were manipulated to ensure consistency across all layers using Arc GIS 9.3. All maps were projected to Lambert conformal conic (WGS84 datum) with a grid cell size of 250 m. The categorical data were resampled to 250-km spatial resolution using the majority resampling function. Continuous variables such as bioclimatic data were downscaled to this target resolution using the downscaling method described below. The following paragraphs describe each environmental dataset in more detail.

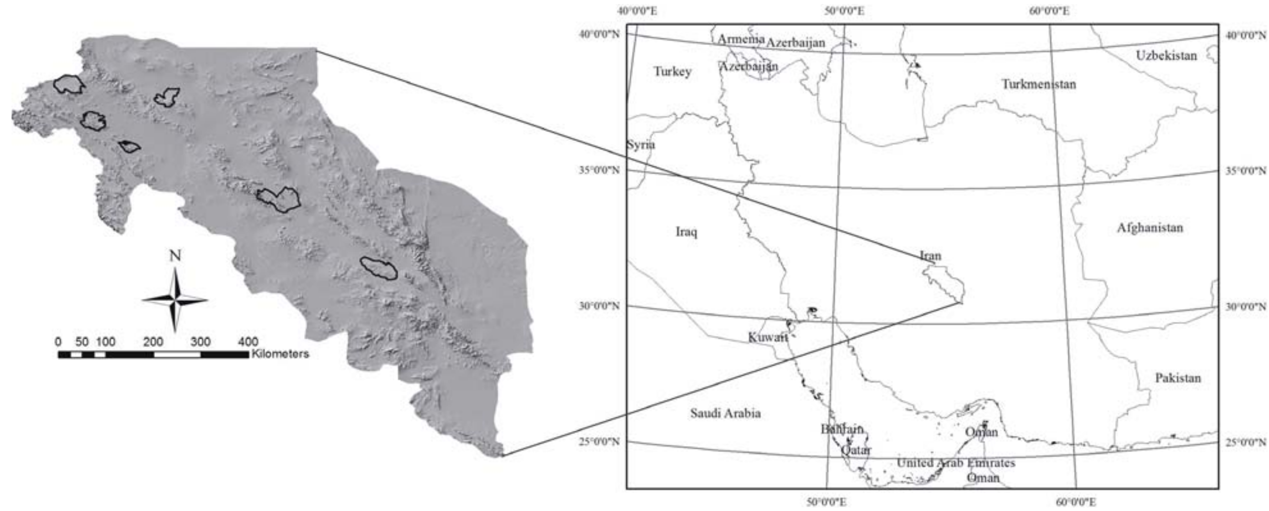

Figure 1. The location of the study area on a map of western Asia (right). Inset shows DEM of study area with polygons indicating the protected areas where populations of goitered gazelle occur.

2.2.1. Preprocessing of climate variables

We obtained information on climatic conditions within the study area from the WorldClim database (http://www.worldclim.org; developed by Hijmans et al., 2005). We used a spatial downscaling method to transfer the original 1-km resolution of WorldClim data to the target resolution of 250 m (Flint and Flint, 2012). This model combines a spatial gradient and inverse-distance-squared (GIDS) weighting to WorldClim data with multiple regression. The location and elevation of the new fine-resolution grid cell relative to a coarse-resolution grid cell is used to weight the parameters based on the following equation:

$$Z = \left[\sum_{i=1}^{N} \frac{Z_i + (X - X_i) * C_x + (Y - Y_i) * C_y + (E - E_i) * C_e}{d_i^2} \right] \Big/ \left[\sum_{i=1}^{N} \frac{1}{d_i^2} \right]$$

where Z is the estimated climatic variable at the specific location defined by easting (X) and northing (Y) coordinates and elevation (E); Z_i is the climatic variable from the 1-km grid cell i; X_i, Y_i, and E_i are easting and northing coordinates and elevation of the 1-km grid cell i, respectively; N is the number of 1-km grid cells in a specified search radius; C_x, C_y, and C_e are regression coefficients for easting, northing, and elevation, respectively; and d_i is the distance from the 250-m site to 1-km grid cell i (Flint and Flint, 2012). We used a 30-km search radius to calculate bioclimatic data at the 250-m resolution.

Inclusion of all 19 bioclimatic variables in SDMs may cause 'overfitting' of the model and uncertainties due to the high degree of correlation among variables (Heikkinen et al., 2006; Peterson and Nazakawa, 2008; Ahmadzadeh et al., 2013; Boria et al., 2014). Therefore, after downscaling climatic variables to the 250-m grid size, we conducted a principal component analysis (PCA) based on all 19 bioclimatic variables for all species' presence points. Principal components (PCs) with eigenvalues greater than one were then used in SDM analyses instead of the original bioclimatic variables (Ahmadzadeh et al., 2013; Porfirio et al., 2014).

2.2.2. Preprocessing of topographic variables

We extracted elevation, roughness, and slope position variables from a DEM with 250-m resolution. Following Weiss (2001), the study area was classified into six discrete slope position classes. A topographic position index (TPI) threshold value ± 1 standard deviation (SD) in a 3000-m search radius was used to classify the landscape. Standard deviation was calculated based on all elevation values in the study area using a 90-m DEM. In addition, a 5-degree slope was used to distinguish between areas with middle and flat slopes (Tagil and Jennes, 2008). Surface roughness was calculated at the 250-m cell size using the method specified by Hobson (1972). Average surface roughness was calculated as the average value of surface roughness in each 250-m grid cell.

2.2.3. Preprocessing of vegetation variables

Vegetation variables used were vegetation type, normalized difference vegetation index (NDVI), density of vegetation type 1 and 2 (dense and semidense rangeland with more than 25% canopy cover), and density of range type 3 (scarce rangeland with 5% to 25% canopy cover). NDVI values were calculated for 12 months in 2012 separately using MODIS (Moderate Resolution Imaging Spectroradiometer) images obtained at 250-m resolution. We used PCA to reduce the correlative NDVI variables into a smaller number of uncorrelated linear combinations of the original variables (PCs) due to significant correlations among 12 NDVI layers. Vegetation type layer was extracted from a vegetation map of Iran and reclassified into 41 classes based on dominant species.

2.2.4. Preprocessing of anthropogenic variables

We calculated farmland and settlement density in the study area using a land cover map. Search radius is a key factor in calculating density maps. We considered the home range size of goitered gazelle as the search radius to calculate farmland and settlement density. A few studies that have been conducted to estimate the home range of goitered gazelle show that sedentary populations of this species have a home range ranging from 2 to 8 km^2 (Baharav, 1982; Habibi, 1993; Mendelssohn et al., 1995; Martin, 2000; Durmuş, 2010). We considered a circular home range with a radius of 1300-m (a home range of approximately 5 km^2). Therefore, a 1300-m search radius was used to calculate farmland and settlement density for each grid cell.

2.3. Modeling procedure

To avoid pseudoreplication we removed duplicate presence points using only one location record per 250-m grid cell (Trethowan et al., 2010; Fourcade et al., 2014; Giles et al., 2014). The Maxent distribution is calculated for the set of grid cells that contains data on all 12 environmental variables in 250-m resolution. First, we used all 12 uncorrelated variables to build the uncorrelated model in 250-m resolution. Then we built the pruned model based on results of a jackknifing analysis using the 5 most important predictors selected on the basis of the uncorrelated model. Environmental variables were applied to run the Maxent program using 10 replicates and the cross-validate run type (Khaki Sahneh et al., 2014; Kailihiwa, 2015; Beatty and Provan, 2015). The jackknifing procedure was used to assess variable importance and the receiver operating characteristic (ROC) curve was used to test model performance. An area under the curve (AUC) value greater than 0.7 is considered to be potentially significant, while scores of 0.5 imply a predictive discrimination that is no better than random (Elith et al., 2006). Continuous outputs were transformed into presence/absence maps by maximum training sensitivity plus specificity thresholds (Hu and Jiang, 2010). We calculated spatial overlap between uncorrelated and pruned models by Schoener's D index (Schoener, 1968):

$$\mathrm{DIVERG} = (|a-b|)$$

where || is the absolute value of the difference between uncorrelated and pruned models, and a and b represent the uncorrelated and pruned models (Parolo et al., 2008).

2.4. Model validation and sensitivity of goitered gazelle distribution model to spatial scale

The initial resolution of uncorrelated environmental predictors (250 m) was coarsened in eight different scales (250 × 250, 500 × 500, 750 × 750, 1000 × 1000, 1500 × 1500, 2000 × 2000, 2500 × 2500, and 3000 × 3000 m) to test the effect of changing grain and extent size on model performance. First, we used a fixed grain size at 250-m resolution and used the surrounding environmental information in the seven other scales as input to calculate a value for that cell using focal statistics in ArcMap (Song et al., 2013). Next, the initial resolution of each environmental layer (250 m) was coarsened seven times (250 m to 3000 m) using a resampling method. In both methods, the majority and mean methods were used to calculate a value for a given cell for categorical and continuous data, respectively. In any one coarse cell, there may have been more than one occurrence point, so we reduced these to one record per cell. We used the ROC analyses as reliability measurements to evaluate the predictive performance of the different models (Philips et al., 2006). We calculated a Pearson correlation between grain and extent size and AUC for each method to assess the effect of change in grain and extent size on performance of the model (Song et al., 2013). We evaluated model accuracy with the tenfold cross-validation method on the training set.

3. Results

3.1. Explanatory predictors

We used 12 uncorrelated environmental predictors to run the Maxent model (Table 1). The first and second axes of the PCA analysis on bioclimatic variables accounted for 66% and 25% of the total variance, respectively (Table 2). In addition, the results of a PCA analysis on 12 NDVI indices showed that the first two axes of the PCA analysis accounted for 87% of the total variance. PC1 was mainly correlated with the NDVI of autumn and winter months and PC2 was correlated with the NDVI index of spring months ($r > 0.8$). We used the two first PCs in the Maxent model.

3.2. Habitat distribution modeling at the 250-m grid size

Using Maxent, the model calibration test for goitered gazelle yielded satisfactory results. The ROC analyses revealed that the performance of the uncorrelated model based on 12 biogeographic predictors was better than random ($AUC_{un} = 0.957$). Among the input environmental variables based on the jackknifing analysis results, bioPCA1, vegetation type, elevation, bioPCA2, and density of vegetation type 3 were the five most effective predictors when used individually (Figure 2). Additionally, bioPCA1, vegetation type, elevation, bioPCA2, and density of vegetation type 1_2 decreased the regularized training gain the most when omitted. Finally, based on the jackknifing analysis, percent of contribution, and permutation importance, the five environmental variables that most strongly influenced the suitability of a habitat for goitered gazelle in 250-m resolution were bioPCA1, vegetation type, elevation, bioPCA2, and density of vegetation 1_2. Therefore, in the second model, which was a pruned model, we ran the Maxent model using these variables. The performance of the pruned model was also significantly better than

Table 1. Environmental predictor variables used to model the habitat distribution of goitered gazelle in central Iran.

Code	Variable	Model
Bio-PCA1	The first PCs of PCA analysis of 19 bioclimatic variables	Uncorrelated and pruned
Bio-PCA2	The second PCs of PCA analysis of 19 bioclimatic variables	Uncorrelated and pruned
NDVI-PCA1	The first PCs of PCA analysis of 12 NDVI layers	Uncorrelated
NDVI-PCA2	The first PCs of PCA analysis of 12 NDVI layers	Uncorrelated
Elevation	Elevation	Uncorrelated and pruned
Roughness	Roughness	Uncorrelated
SP	Slope position	Uncorrelated and pruned
RT	Vegetation type	Uncorrelated and pruned
Rng1_2	Density of vegetation types 1 and 2	Uncorrelated
Rng3	Density of vegetation type 3	Uncorrelated
SD	Settlement density	Uncorrelated
FD	Farmland density	Uncorrelated

Table 2. Summary of the principal components analysis of the 19 bioclimatic variables extracted from the occurrence points of goitered gazelle in central Iran.

Component	PCA1	PCA2
Eigenvalue	11.92	4.44
Percent	66.22	24.66
Cumulative percent	66.22	90.87
Contribution of the variables		
BIO1, Annual mean temperature	0.95	0.25
BIO2, Mean diurnal range	–0.32	0.82
BIO3, Isothermality	–0.19	0.97
BIO4, Temperature seasonality	0.61	–0.77
BIO5, Max temperature of warmest month	0.97	0.00
BIO6, Min temperature of coldest month	0.91	0.34
BIO7, Temperature annual range	0.15	–0.89
BIO8, Mean temperature of wettest quarter	0.85	0.48
BIO9, Mean temperature of driest quarter	0.98	–0.06
BIO10, Mean temperature of warmest quarter	0.97	0.11
BIO11, Mean temperature of coldest quarter	0.87	0.44
BIO12, Annual precipitation	–0.98	–0.09
BIO13, Precipitation of wettest month	–0.95	0.05
BIO14, Precipitation of driest month	0.00	0.00
BIO15, Precipitation seasonality	0.13	0.86
BIO16, Precipitation of wettest quarter	–0.95	0.15
BIO17, Precipitation of driest quarter	0.88	–0.20
BIO18, Precipitation of warmest quarter	–0.89	0.11
BIO19, Precipitation of coldest quarter	–0.97	0.06

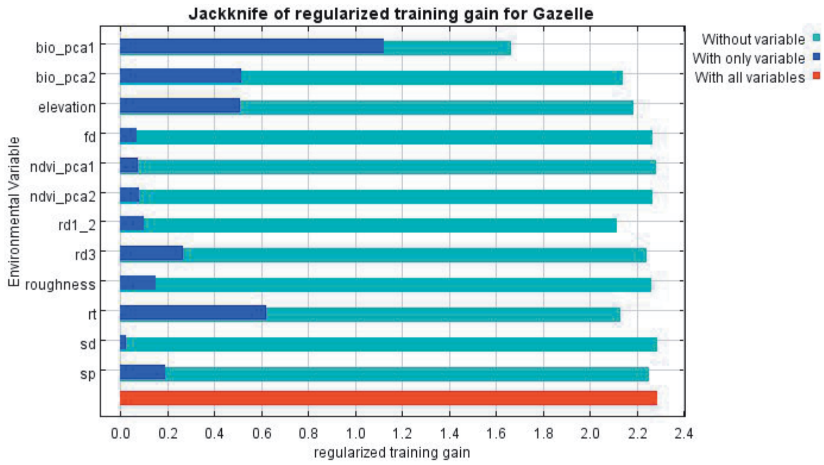

Figure 2. Jackknifing test of variable importance in the development of the uncorrelated model at 250-m resolution. Blue bars indicate the gain achieved when including that predictor only. Green gray bars show how much the total gain is diminished without the given predictor. Red bar indicate the gain achieved when including all predictors.

random (AUC_{pu} = 0.953). The species' distribution maps of the goitered gazelle based on uncorrelated and pruned model results showed similar spatial patterns (Figure 3). Areas with high habitat suitability when applying the maximum training sensitivity plus specificity threshold accounted for only 6.7% of the study area. Potential habitats with high suitability for goitered gazelle were identified in the northwestern and central part of the study area.

The results of a spatial congruence test using the method of Parolo et al. (2008) showed few divergences among the uncorrelated and pruned models (Figure 4). A spatial overlap between models using Schoener's D index (Schoener, 1968) also revealed approximately 75% convergence. In other words, the uncorrelated and the pruned model showed the same suitable and unsuitable habitat extent.

According to the result of the jackknifing test, bioclimatic variables were the most important predictors in gazelle distribution, so we ran Maxent with just the 19 bioclimatic variables. Temperature seasonality (Bioclim 4), mean temperature of coldest quarter (Bioclim 11), and precipitation of coldest quarter (Bioclim 19) were

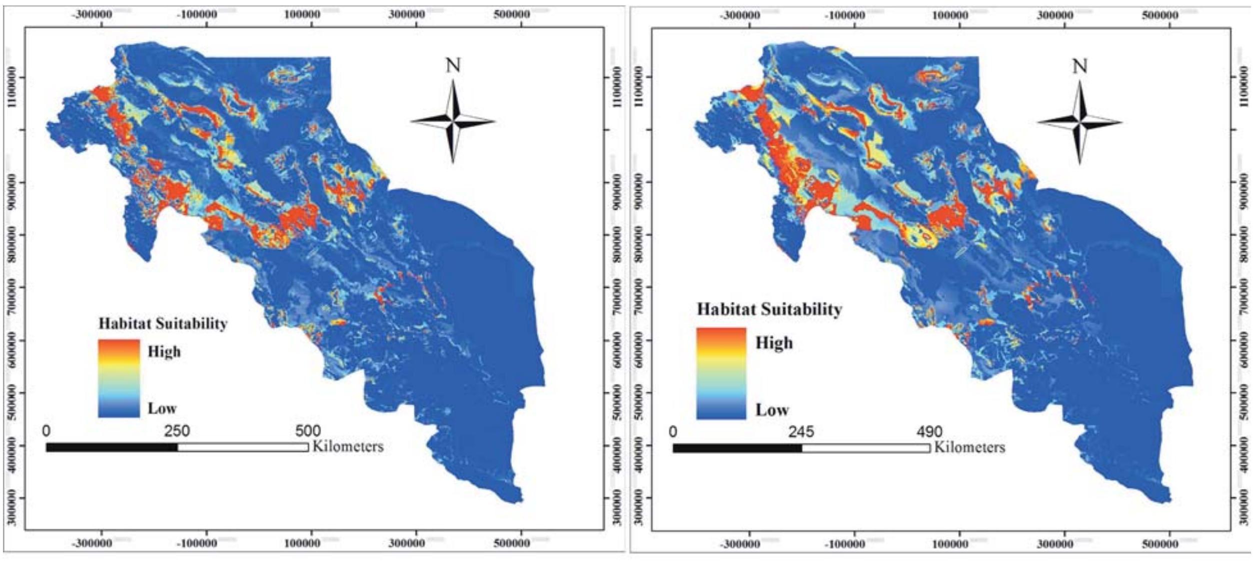

Figure 3. Goitered gazelle distribution maps based on the uncorrelated model (left) and the pruned model (right) for the 250-m grid size.

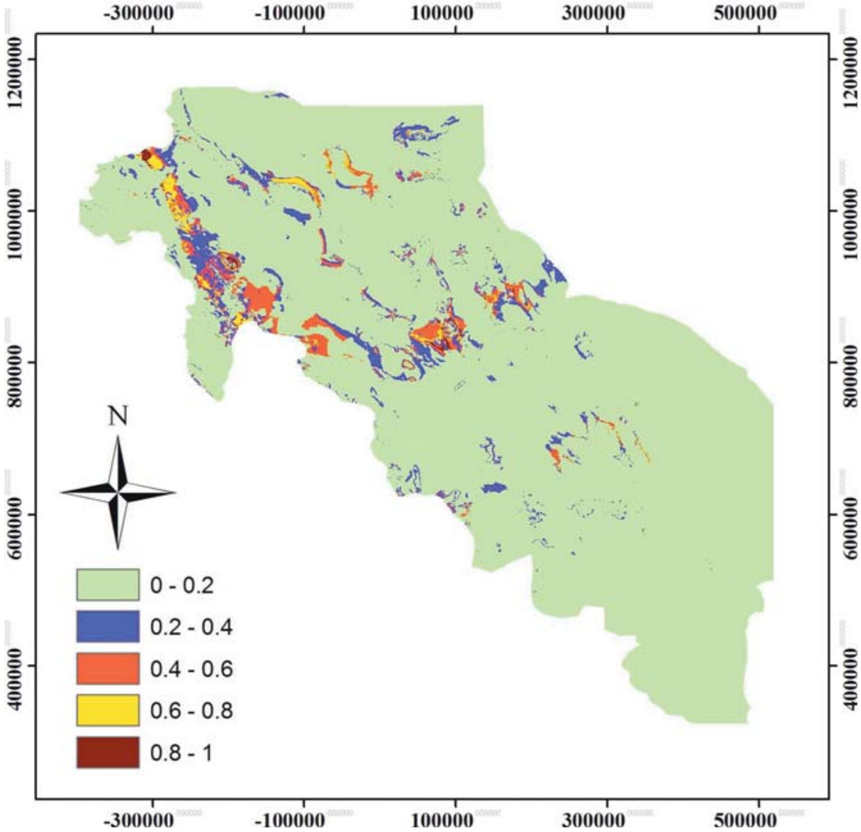

Figure 4. Divergence between the uncorrelated and pruned models estimated through Parolo divergence index at 250-m resolution. As is shown, there was little divergence (0–0.2) between models in most of the study area.

respectively the first three most important predictors of goitered gazelle distribution. Temperature seasonality is the amount of temperature variation over a given period, with larger seasonality indicating greater variability. The temperature seasonality of the whole study area and the gazelle presence points were 8286 and 8764, respectively. The response curve for 'temperature seasonality' showed that the highest probability of goitered gazelle presence was related to areas having the highest values of temperature seasonality. The mean temperature of the coldest quarter of the study area and the gazelle presence points was 6.9 °C and 4.1 °C, respectively. The mean temperature of the coldest quarter in the predicted suitable range based on the maximum training sensitivity plus specificity threshold was 3.7 °C. The precipitation of the coldest quarter of the study area and gazelle presence points was 59.8 mm and 55.5 mm per year, respectively. The precipitation of the coldest quarter in the predicted suitable range, based on maximum training sensitivity plus specificity threshold, was 57.3 mm. The response curves for precipitation of the coldest quarter showed that the highest predicted suitability occurs in areas of medium precipitation (40–90 mm per year).

3.3. Model validation and sensitivity of the goitered gazelle distribution model to spatial scale

3.3.1. Grain size

In the species distribution model with a 250-m grain size and extent size, the habitat area of the goitered gazelle represented 6.7% of the study area. The value of the AUC was 0.957. The mean AUC across eight different scales ranged from 0.929 to 0.959. AUC decreased slightly as the expansion of the grain size increased (Figure 5). There was an increase in AUC as the grain size increased from 250 m to 750 m and after that the AUC decreased to 0.929. Differences in AUC between fine- and coarse-grain models revealed a significant negative correlation between grain size and the AUC ($R^2 = 0.57$). An increase of the grain size increased the predicted habitat area (Figure 5). As the grain size increased, spatial congruence AUC fluctuated within a small range. The maximal difference was only 0.019 and occurred between models of the 1 × 1 and 2.5 × 2.5 km probability surface (Figure 6).

3.3.2. Extent size

The expansion of the extent size caused the AUC to increase slightly. Likewise, with regard to grain size, there

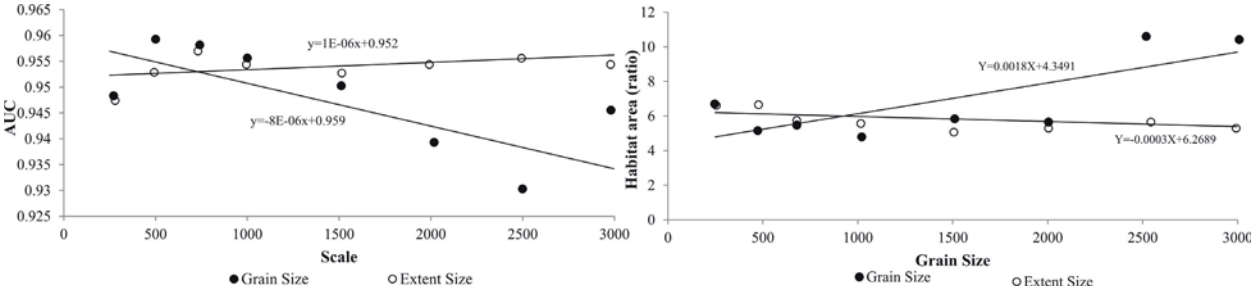

Figure 5. The change in performance index (AUC, left) and habitat suitability area (right) of the output model with increasing extent size (open circles) and grain size (filled circles) from 250 to 3000 m.

was an increase in AUC from 250 to 750 m, but beyond that the AUC decreased to 0.948. The extent size and the AUC showed an insignificant correlation (R^2 = 0.18) and the result of linear regression confirmed such correlation (Figure 5). Predicted habitat suitability decreased as extent size increased, but this change was not significant (R^2 = 0.24; Figure 5). The maximum accuracy was obtained when the grain size and extent size were adjusted to 750 m.

4. Discussion

The present study examined the application of species distribution modeling for predicting habitat suitability of goitered gazelle at coarse and fine spatial scales using appropriate environmental predictors.

We assessed the habitat distribution of goitered gazelle at 250-m resolution using two uncorrelated and pruned models. Comparing suitable habitat distribution maps, insignificant difference was detected between the two models. Pruned models also showed high AUC and performed better than random.

Bioclimatic variables and vegetation type were the most effective indicators for estimating the suitability of habitat for the species. Climate plays an important role in determining the species' distribution and evaluating the relationships between environmental factors and biological entities (Bailey, 1985; Morelle and Lejeune, 2015).

Suitability of the central parts of the study area is limited for goitered gazelle due to warm and dry climatic conditions. High temperature and low precipitation (and as a consequence fewer food and water sources) limit the species' distribution. Climatic variables determine the species' distribution at regional (Lomba et al., 2010) or larger scales (Gaston, 1994). Temperature seasonality and temperature and precipitation of the coldest quarter were recognized as the most important climatic variables limiting the distribution of goitered gazelle in central Iran. These climatic variables are likely strong determinants of goitered gazelle survival in winter. Precipitation of the coldest quarter may also affect reproductive success. Elevation may indirectly affect the distribution of goitered gazelle as it has a direct effect on the climatic conditions of a given site. If global climate change results in more extreme climatic conditions in the future, it may have a significant impact on the size and distribution of goitered gazelle.

In addition to bioclimatic variables, though less important, the influence of vegetation type and density in determining the distribution of goitered gazelle was

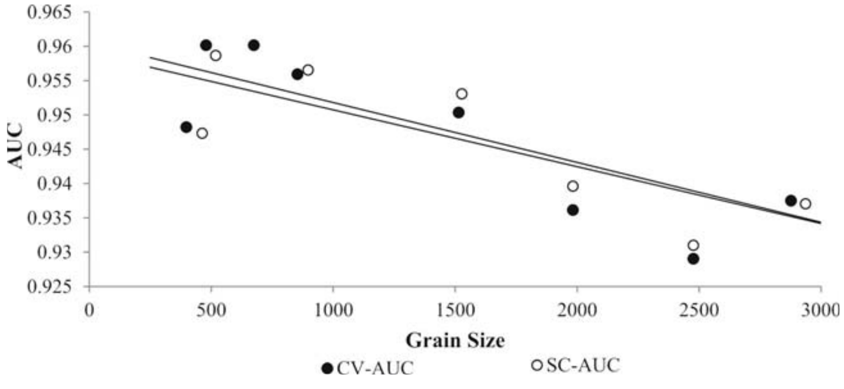

Figure 6. Total cross-validation AUC (CV-AUC) and spatial congruence AUC (SC-AUC) for a range of grain sizes.

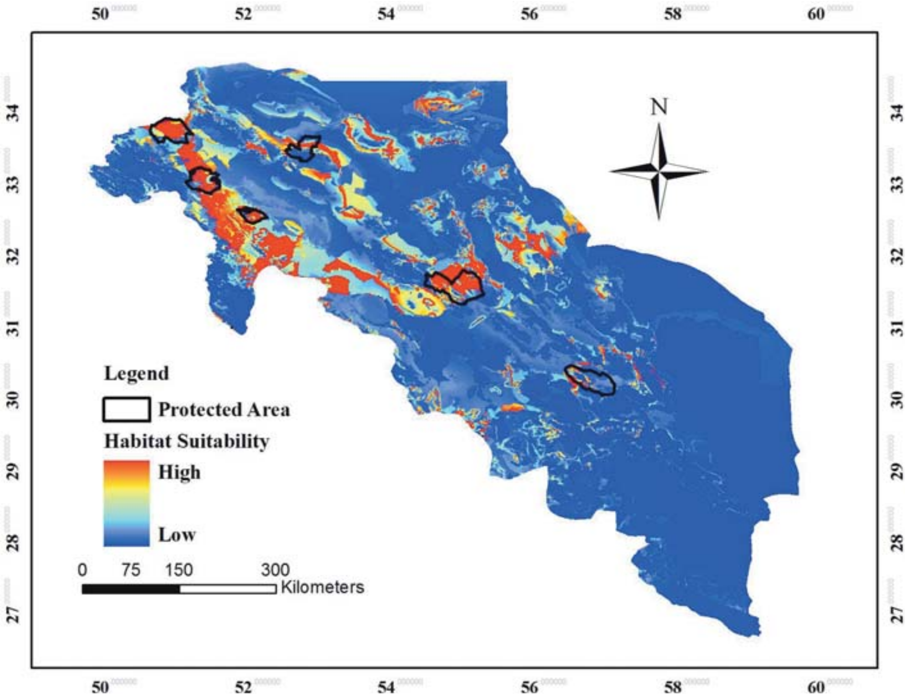

Figure 7. Location of the protected area containing goitered gazelle in central Iran.

considerable. Vegetation type, vegetation density, and plant species diversity have previously been recognized as important determinants of herbivores' habitat suitability (Hu and Jiang, 2010). Vegetation provides food for goitered gazelles, but may also offer shade at times of day when they are resting.

Gazelles are known to eat a variety of grasses, forbs, and shrubs during different seasons (Olson et al., 2010; Xu et al., 2012). Overlapping the produced suitability map with the vegetation type map revealed that *Artemisia* spp. are dominant in most of the locations determined to be suitable for goitered gazelle. Gazelles consume *Artemisia* spp. particularly in autumn and winter (Mowlavi, 1978; Jiang et al., 2002; Yoshihara et al., 2008; Olson et al., 2010; Xu et al., 2012). Similarly, *Artemisia frigida*, a dwarf shrub with high protein content, is the most common species in the habitat of Mongolian gazelle *Procapra gutturosa* in eastern Mongolia (Olson et al., 2010).

During autumn and winter the nutritional quality and quantity of the plant species decreased and were below the gazelle's nutritional need (Bagherirad et al., 2014). The percentage of protein in grasses decreased more than in shrubs, and thus bushes sustained more nutrition than grasses (Beck and Peek, 2005; Bagherirad et al., 2014). To obtain the required critical minerals, particularly during mating, pregnancy, and lactation, when more food with high levels of protein and energy are needed, gazelles have to selectively forage on nutritious plants; hence, areas dominated with forbs and shrubs such as *Artemisia* attracts gazelles (Olson et al., 2010). In the Khosh-Yeylagh Wildlife Refuge, central Iran, these shrubs constituted 86% of the diet of the goitered gazelle (Mowlavi, 1978).

The *Artemisia* vegetation type has been shown to be the most suitable vegetation type for goitered gazelle. Hosseini et al. (2013) studied potential suitable habitats for *Artemisia sieberi* and *Artemisia aucheri* in central Iran and noted that habitat suitability for both of these species was high in areas with elevation between 2300 and 2500 m. The preferred elevation by goitered gazelle, as determined on the basis of this study, was 1500 to 2500 m and may support the dependence of the species on the *Artemisia* vegetation type.

Increasing the extent size in the habitat distribution model improved the performance of the output model. The results of this study showed that assessment of environmental information surrounding a grid cell to calculate an environmental value for the grid cell improves the possibility of obtaining the appropriate information concerning environmental variables reflected by that grid cell. The results of this study suggest that the maximum extent size should be approximately 750 m. If the extent size is greater than 750 m, the performance of the habitat suitability index decreases and the predicted habitat suitability increases dramatically (Figure 5). We increased grid size from an initial resolution of 250 × 250 m to 3 × 3 km. Contrary to expanding extent size, the results of increasing grain size showed that model accuracy declined if grid size increased beyond 750 m. With the scale increased from 250 m to 3 km, AUC decreased slightly and the spatial congruence of the AUC fluctuated slightly. Based on our results, the best spatial scale for both grain and extent size to model habitat distribution of goitered gazelle in central Iran is 750 m.

The present research showed that a habitat distribution model that not only reflects habitat information at a given grid size but also information about the surrounding environment can be highly accurate. Thus, it seems from our results that changes in extent size improved the model and changes in grain size degraded performance. This result was also confirmed by other studies (Seo et al., 2009; Guisan et al., 2007; Gottschalk et al., 2011; Song et al., 2013). Namely, Seo et al. (2009) examined the effect of increase in grid size on performance of species' distribution and found that model accuracy and spatial output agreement decrease when the scale increases 64-fold. Guisan et al. (2007) suggested that change in grain size does not have a substantial effect on species distribution models. Song et al. (2013) showed that grain size greater than 1.5 km decreases the accuracy of the habitat suitability index and increases predicted habitat suitability.

We overlaid the protected areas in central Iran on our predicted habitat suitability map. The results showed that a majority of the protected areas except Bidooeyeh (south of the study area, Kerman Province) were in the suitable range (Figure 7). Habitat distribution models can help to suggest new areas in which to introduce populations of goitered gazelle on the basis of high suitability of presence. These areas have ideal habitat conditions for persistence of the species and should facilitate the prioritization of new areas. Potential habitats with high suitability were distributed in the northwestern and central parts of the study area (Figure 3). Figure 7 shows that the areas with high habitat suitability for the goitered gazelle are continuous patches in the northwestern parts of the study area. These areas could be used for in situ conservation and reintroduction of the species in the wild. Our results could therefore be useful for management of goitered gazelle and in the conservation of biological diversity in the region.

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References

Ahmadzadeh F, Flecks M, Carretero MA, Bohme W, Ilgaz C, Engler GO, Harris DJ, Uzum N, Rodder D (2013). Rapid lizard radiation lacking niche conservatism: ecological diversification within a complex landscape. J Biogeogr 40: 1807-1818.

Bagherirad E, Ahmad N, Amirkhani M, Abdullah M, Mesdaghi, M, Kabudi A (2014). Seasonal habitat use of Persian Gazelles (*Gazella subgutturosa subgutturosa*) based on vegetation parameters at Golestan National Park, Iran. Arid Land Res Manag 28: 464-484.

Baharav D (1982). Desert habitat partitioning by the *dorcas gazelle*. J Arid Environ 5: 323-335.

Bailey RG (1985). Ecological regionalization in Canada and the United States. Geoforum 16: 265-275.

Barnosky AD, Matzke N, Tomiya S, Wogan GOU, Swartz B, Quental TB, Marshall C, McGuire JL, Lindsey EL, Maguire KC et al. (2011). Has the earth's sixth mass extinction already arrived? Nature 471: 51-57.

Beatty GE, Provan J (2014). Phylogeographical analysis of two cold-tolerant plants with disjunct Lusitanian distributions does not support in situ survival during the last glaciation. J Biogeogr 41: 2185-2193.

Beck JL, Peek LM (2005). Great Basin summer range forage quality: do plants nutrients meet elk requirements? West N Am Naturalist 65: 516-527.

Boria RA, Olson LE, Goodman SM, Anderson, RP (2014). Spatial filtering to reduce sampling bias can improve the performance of ecological niche models. Ecol Model 275: 73-77.

Cabeza M, Arponen A, Jäättelä L, Kujala H, Van Teeffelen A, Hanski I (2010). Conservation planning with insects at three different spatial scales. Ecography 33: 54-63.

Carnaval AC, Moritz C (2008). Historical climate modeling predicts patterns of current biodiversity in the Brazilian Atlantic forest. J Biogeogr 35: 1187-1201.

Davis FW, Borchert M, Meentemeyer RL, Flint AL, Rizzo DM (2010). Pre-impact forest composition and ongoing tree mortality associated with sudden oak death in the Big Sur region, California. Forest Ecol Manag 259: 2342-2354.

Durmuş M (2010). Determination of home range size and habitat selection of gazelles (*Gazella subgutturosa*) by GPS telemetry in Şanlıurfa. MSc, Middle East Technical University, Ankara, Turkey.

Elith J, Graham CH, Anderson RP (2006). Novel methods improve prediction of species' distributions from occurrence data. Ecography 29: 129-151.

Elith J, Phillips S, Hastie T, Dudík M, Chee Y, Yates C (2010). A statistical explanation of MaxEnt for ecologists. Diver Dist 17: 43-57.

Engler R, Guisan A, Rechsteiner L (2004). An improved approach for predicting the distribution of rare and endangered species from occurrence and pseudo-absence data. J Appl Ecol 41: 263-274.

Flint LE, Flint AL (2012). Downscaling future climate scenarios to fine scales for hydrologic and ecological modeling and analysis. Ecological Processes 1: 2.

Fourcade Y, Engler JO, Rodder D, Secondi J (2014). Mapping species distributions with MAXENT using a geographically biased sample of presence data: A performance assessment of methods for correcting sampling bias. PLoS One 9: e97122.

Franklin J (2009). Mapping Species Distributions: Spatial Inference and Prediction. Cambridge, UK: Cambridge University Press.

Gaston KJ (1994). Rarity. Population and Community Biology Series 13. London, UK: Chapman and Hall.

Giles JR, Peterson AT, Busch JD, Olafson PU, Scoles GA, Bavey R, Pound JM, Kammlah DM, Lohmeyer KH, Wagner DM (2014) Invasive potential of cattle fever ticks in the southern United States. Parasite Vector 7: 189.

Gottschalk TK, Aue B, Hotes S, Ekschmitt K (2011). Influence of grain size on species–habitat models. Ecol Model 222: 3403-3412.

Graf RF, Bollmann K, Suter W, Bugmann H (2005). The importance of spatial scale in habitat models: capercaillie in the Swiss Alps. Landscape Ecol 20: 703-717.

Graham CH, Ferrier S, Huettmann F, Moritz C, Peterson AT (2004). New developments in museum-based informatics and applications in biodiversity analysis. Trends Ecol Evol 19: 497-503.

Groves CP, Grubb P (2011). Ungulate Taxonomy. Baltimore, MD, USA: John Hopkins University Press.

Guisan A, Broennimann O, Engler R, Vust M, Yoccoz NG, Lehmann A, Zimmermann NE (2006). Using niche-based models to improve the sampling of rare species. Conserv Biol 20: 501-511.

Guisan A, Graham CH, Elith J, Huettmann F (2007). Sensitivity of predictive species distribution models to change in grain size. Divers Distrib 13: 332-340.

Guisan A, Thuiller W (2005). Predicting species distribution: offering more than simple habitat models. Ecol Lett 8: 993-1009.

Habibi K (2001). Pakistan. In: Mallon DP, Kingswood SC, editors. Antelopes. Part 4: North Africa, the Middle East and Asia. Global Survey and Regional Action Plans. Gland, Switzerland: IUCN/SSC Antelope Specialist Group, IUCN, pp. 122-128.

Heikkinen RK, Luoto M, Araujo MB, Virkkala R, Thuiller W, Sykes MT (2006). Methods and uncertainties in bioclimatic envelope modelling under climate change. Prog Phys Geogr 30: 751-777.

Henderson-Sellers A, Wilson MF, Thomas G (1982). The effect of spatial resolution on archives of land cover type. Clim Chang 7: 391-402.

Hijmans RJ, Cameron SE, Parra JL, Jones PG, Jarvis A (2005). Very high resolution interpolated climate surfaces for global land areas. Int J Climatol 25: 1965-1978.

Hirzel AH, Hausser J, Chessel D, Perrin N (2002). Ecological-niche factor analysis: how to compute habitat-suitability maps without absence data? Ecology 83: 2027-2036.

Hobson RD (1972). Surface roughness in topography: quantitative approach. In: Chorley RJ, editor. Spatial Analysis in Geomorphology. London, UK: Metheur, pp. 225-245.

Hosseini SZ, Kappas M, Zare Chahouki MA, Gerold G, Erasmi S, Rafiei Emam A (2013). Modelling potential habitats for *Artemisia sieberi* and *Artemisia aucheri* in Poshtkouh area, central Iran using the maximum entropy model and geostatistics. Ecol Inform 18: 61-68.

Hu J, Jiang Z (2010). Predicting the potential distribution of the endangered Przewalski's gazelle. J Zool 282: 54-63.

Huettmann F, Diamond AW (2006). Large-scale effects on the spatial distribution of seabird in the Northwest Atlantic. Land Ecol 21: 1089-1108.

Jiang ZW, Takatsuki S, Li J, Wang W, Gao Z, Ma J (2002). Seasonal variations in foods and digestion of Mongolian gazelles in China. J Wildl Manage 66: 40-47.

Kailihiwa SH (2015) Using maxent to model the distribution of prehistoric agricultural features in a portion of the Hōkūliʻa subdivision in Kona, Hawaii. MSc thesis, University of Southern California, Los Angeles, CA, USA.

Khaki Sahneh S, Nouri Z, Alizadeh Shabani A, Ahmadi M, Dehdar Dargahie M (2014). Bioclimatic niche model to predict Afghan Pika (*Ochotona rufescens*) distribution range in Iran. Biological Forum – An International Journal 6: 98-109.

Linke J, Franklin SE, Huettmann F, Stenhouse GB (2005). Seismic cutlines, changing landscape metrics and grizzly bear landscape use in Alberta. Landcape Ecol 20: 811-826.

Lomba A, Pellissier L, Randin C, Vicente J, Moreira F, Honrado J, Guisan A (2010). Overcoming the rare species modelling paradox: a novel hierarchical framework applied to an Iberian endemic plant. Biol Conserv 143: 2647-2657.

Martin L (2000). Gazelle (*Gazella* spp.) behavioral ecology: predicting animal behaviour for prehistoric environments in south-west Asia. J Zool 250: 13-30.

Mendelssohn H, Yom-Tov Y, Groves CP (1995). *Gazella gazella*. Mamm Species 490: 1-7.

Mondal K, Sankar K, Qureshi Q (2013). Factors influencing the distribution of leopard in a semiarid landscape of Western India Acta Theriol 58: 179-187.

Morelle K, Lejeune P (2015). Seasonal variations of wild boar *Sus scrofa* distribution in agricultural landscapes: a species distribution modeling approach. Eur J Wildl Res 61: 45-56.

Moreno R, Zamora R, Molina JR, Vasquez A, Herrera MA (2011). Predictive modeling of microhabitats for endemic birds in South Chilean temperate forests using maximum entropy (Maxent). Ecol Inform 6: 364-370.

Mowlavi M (1978). Ecological studies of the goitered gazelle (*Gazella Subgutturosa*) in Khosh Yeilagh Wildlife Refuge, Iran. MSc thesis, Michigan State University, East Lansing, MI, USA.

Olson KA, Murray MG, Fulle TK (2010). Vegetation composition and nutritional quality of forage for gazelles in Eastern Mongolia. Rangeland Ecol Manage 63: 593-598.

Papes M, Gaubert P (2007). Modelling ecological niches from low numbers of occurrences: assessment of the conservation status of poorly known viverrids (Mammalia, Carnivora) across two continents. Diversity Distrib 13: 890-902.

Parolo G, Rossi G, Ferrarini A (2008). Toward improved species niche modelling: *Arnica montana* in the Alps as a case study. J Appl Ecol 45: 1410-1418.

Peterson AT, Nazakawa Y (2008). Environmental data sets matter in ecological niche modelling: an example with *Solenopsis invicta* and Solenopsis richteri. Glob Ecol Biogeogr 17: 135-144.

Phillips SJ, Anderson RP, Schapire RE (2006). Maximum entropy modeling of species geographic distributions. Ecol Model 190: 231-259.

Polak T, Saltz D (2011). Reintroduction as an ecosystem restoration technique. Conserv Biol 25: 424-427.

Porfirio LL, Harris RMB, Lefroy EC, Hugh S, Gould SF, Lee G, Bindoff NL, Mackey B (2014). Improving the use of species distribution models in conservation planning and management under climate change. PLoS One 9: e113749.

Primack R (2008). A Primer of Conservation Biology. 4th ed. Sunderland, MA, USA: Sinauer Associates.

Schaller GB (1998). Wildlife of the Tibetan Steppe. Chicago, IL, USA: University of Chicago Press.

Schoener TW (1968). Anolis lizards of Bimini: resource partitioning in a complex fauna. Ecology 49: 704-726.

Scott JM, Heglund PJ, Morrison ML (2002). The influence of spatial scales on landscape description and wildlife habitat assessment. In: Covelo CA, editor. Predicting Species Occurrences: Issues of Accuracy and Scale. Washington, DC, USA: Island Press.

Seo C, Thorne JH, Hannah L, Thuiller W (2009). Scale effects in species distribution models: implications for conservation planning under climate change. Biol Lett 5: 39-43.

Song W, Kim E, Lee D, Lee M, Jeon SW (2013). The sensitivity of species distribution modeling to scale differences. Ecol Model 248: 113-118.

Stockwell DRB, Peters DP (1999). The GARP modelling system: Problems and solutions to automated spatial prediction. Internat J Geogr Infor Syst 13: 143-158.

Tagil S, Jenness J (2008). GIS-based automated landform classification and topographic, landcover and geologic attributes of landform around the Yazoren Polje, Turkey. J Appl Sci 8: 910-921.

Trethowan PD, Robertson MP, McConnachie AJ (2010). Ecological niche modelling of an invasive alien plant and its potential biological control agents. S Afr J Bot 77: 137-146.

Turner MG, Dale VH, Gardner RH (1989). Predicting across scales: theory development and testing. Landscape Ecol 3: 245-252.

Weiss A (2001). Topographic position and landform analysis. Poster presentation. In: Environmental Sciences Research Institute User Conference; 2005; San Diego, CA, USA.

Wiens JA (1989). Spatial scaling in ecology. Funct Ecol 3: 385-397.

Xu W, Xia C, Lin J, Yang W, Blank DA, Qiao J, Liu W (2012). Diet of *Gazella subgutturosa* (Guldenstaedt, 1780) and food overlap with domestic sheep in Xinjiang, China. Folia Zool 61: 54-60.

Yoshihara Y, Ito TY, Lhagvasuren B, Takatsuki S (2008). A comparison of food resources used by Mongolian gazelles and sympatric livestock in three areas in Mongolia. J Arid Environ 72: 48-55.