Ecography

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Supplemental material

(1) Ecological niche modeling using MaxEnt

We ran a second niche model, using MaxEnt, which strongly reduces extrapolation of species potential distribution, compared with other methods (Elith et al. 2006). We observed some reduction in the potential distribution of bobcats south of the Isthmus of Tehuantepec, particularly in the State of Campeche (Fig. 3A), but still enough area (in Chiapas and Yucatán, depicted in black and grey), to allow potential resident bobcat population in this region (Fig. S1). The Maxent software package (ver. 2.2; Phillips et al. 2006) was used to construct an ecological niche model projected as a potential distribution. Among several niche modeling software packages currently available, Maxent has been shown to be robust for modeling presence-only occurrence data (Elith et al. 2006), using a maximum entropy method. Given a set of point localities and environmental layers over geographical space, Maxent estimates the predicted distribution by finding the distribution of maximum entropy (the distribution closest to uniform) subject to the constraint that the expected value (expectation) of each feature (derived from the environmental layers) under this estimated distribution matches its empirical average over sample locations (Phillips et al. 2006). The resulting distribution model is a relative probability distribution over all grid cells in the chosen geographical space, and expresses the relative probability of the occurrence of a species in a grid cell as a function of the values of the environmental variables in that grid cell. A high value of the function in a particular grid cell indicates that it is predicted to have suitable conditions for that species. The sum of relative probabilities adds up to 1 across the landscape.

For environmental variables, 23 layers (L), each at a resolution of ca 1 km or 30′′ (0.008333° × 0.008333°), were obtained from the WorldClim database (interpolated from global climate datasets; Hijmans et al. 2005). The variables included: L1 = annual mean temperature, L2 = mean diurnal range (monthly mean [maximum temperature – minimum temperature]), L3 = isothermality (L2/L7), L4 = temperature seasonality (standard deviation), L5 = maximum temperature of the warmest month, L6 = minimum temperature of the coldest month, L7 = annual temperature range (L5–L6), L8 = mean temperature of the wettest quarter, L9 = mean temperature of the driest quarter, L10 = mean temperature of the warmest quarter, L11 = mean temperature of the coldest quarter, L12 = annual precipitation, L13 = precipitation of the wettest month, L14 = precipitation of the driest month, L15 = precipitation seasonality (coefficient of variation), L16 = precipitation of the wettest quarter, L17 = precipitation of the driest quarter, L18 = precipitation of the warmest quarter, L19 = precipitation of the coldest quarter, L21 = elevation, L22 = slope, and L23 = aspect. The first 21 layers were taken from the U.S. Geological Survey's Hydro-1K data set <www.usgs.gov> and slope and aspect were derived from the elevation data using the Surface Analysis Tool from the Spatial Analyst extension of ArcMap 9.0. All climate and spatial layers were clipped to a rectangular box containing the study region (Fig. 2), and were resampled to a 0.02° × 0.02° resolution in ArcGIS.

Following published recommendations, Maxent was run for 500 iterations without the threshold feature and without duplicates so that there was at most one sample per pixel. Linear, quadratic and product features were used (Phillips et al. 2004, 2006; Pawar et al. 2007). The convergence threshold was set to 1.0×10^{-5}, which is a conservative value based upon North American breeding bird survey data and small mammal data from Latin America (Phillips et al. 2006). The accuracy of the ecological niche model was evaluated by constructing the model using only 75% of the available records, with the remaining 25% used for testing purposes as the validation dataset. Model accuracy was determined using a receiver operating characteristic (ROC) analysis (Phillips et al. 2006). By calculating the sensitivity and specificity of a model at all possible thresholds, a ROC curve was produced with sensitivity plotted on the y-axis and (1 – specificity) plotted on the x-axis. The area under the curve (AUC) of the resulting plot provides a measure of model performance. An optimal model, one that predicted each occurrence of a species and for which each prediction was accurate, would have an AUC of 1.0 while a model that predicted species occurrences at random would have an AUC of 0.5 (Phillips et al. 2006). Following the recommendations of Pawar et al. (2007), niche models possessing an AUC > 0.75 and a p-value of < 0.05 (for the sensitivity and specificity test) were retained for this analysis. Finally, the relative probabilities predicted by Maxent were converted into probabilities of presence for bobcats by dividing all relative probabilities across the landscape by the highest relative probability achieved for this species (black to white color gradient; Fig. 2). This normalization assumes that the species is at least present in the cell with the highest predicted relative probability of its occurrence.

Figure 1. Ecological niche modeling of bobcats *Lynx rufus* projected as potential distribution using the Maxent software package (ver. 2.2; Phillips et al. 2006). Note some reduction in the potential distribution of bobcats south of the Isthmus of Tehuantepec (Fig. 3A), but still enough area (in Chiapas and Yucatán, depicted in black and grey), to allow potential resident bobcat population in this region.

References

Elith, J. et al. 2006. Novel methods improve prediction of species' distributions from occurrence data. – Ecography 29: 129–151.

Hijmans, R. J. et al. 2005. Very high resolution interpolated climate surfaces for global land areas. – Int. J. Climatol. 25: 1965–1978.

Pawar, S. et al. 2007. Conservation assessment and prioritization of areas in northeast India: priorities for amphibians and reptiles. – Biol. Conserv. 136: 346–361.

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(2) Principal component analysis

A principal component analysis (PCA) was conducted to test if the environmental space (conditions) south of the Isthmus of Tehuantepec (IT) really fell within those where the bobcat is known to occur. First, we extracted all environmental data of point data used for building the bobcat distribution model (Fig. S2, grey dots). Then we extracted 500 random points of the environmental data from the predicted bobcat distribution south of the IT (Table S1; Fig. S2, black dots, below). The PCA showed that Prin Comp1 explained 35% of the variation, Prin Comp2 explained 32% of the variation, and Prin Comp3 explained 16% of the variation. The three components altogether explained 83% of data variation. Further, the PCA showed a fair amount of overlap in the environmental conditions of the random points from the predicted distribution south of the IT, with the point data where bobcats occur (Fig. S2). These results show that similar environmental condition exist south of the IT to allow establishment of bobcat populations if abiotic factors solely determined bobcat distribution.

Table S1. Principal component analysis (PCA) testing if the environmental conditions, including the 22 environmental variables of the WorldClim database (Hijmans et al. 2005, see above), from the predicted distribution of bobcats south of the Isthmus of Tehuantepec are similar within those where bobcats occur. The three components altogether (Prin Comp1, Prin Comp2, and Prin Comp3) explained 83% of data variation. See text of the supplemental material for nomenclature of environmental variables.

	Prin Comp1	Prin Comp2	Prin Comp 3
Eigenvalue	7.7075	7.1137	3.4437
Percent	35.0341	32.3349	15.6533
Cum Percent	35.0341	67.369	83.0223
	Eigenvectors		
BIO_1	0.27396	0.22	0.13709
BIO_2	–0.28768	0.04976	0.16107
BIO_3	0.15379	–0.26401	0.19844
BIO_4	–0.24351	0.22009	–0.13421
BIO_5	0.06375	0.3416	0.12738
BIO_6	0.33856	0.0862	0.08951
BIO_7	–0.29557	0.16349	0.00296
BIO_8	0.15604	0.29714	0.0981
BIO_9	0.27945	0.20214	0.08594
BIO_10	0.13763	0.33259	0.07688
BIO_11	0.32323	0.09778	0.16812
BIO_12	0.23346	–0.24882	0.04727
BIO_13	0.19836	–0.25701	0.14889
BIO_14	0.20476	–0.04386	–0.41688
BIO_15	–0.11177	–0.07542	0.46403
BIO_16	0.1785	–0.26432	0.17455
BIO_17	0.1947	–0.04764	–0.42953
BIO_18	0.17109	–0.21582	0.12026
BIO_19	0.18123	–0.00303	–0.40875
DEM	–0.21514	–0.27682	–0.02436
SLOPE	–0.0242	–0.25008	0.02598
TOPOIND	0.01711	0.19322	0.10557

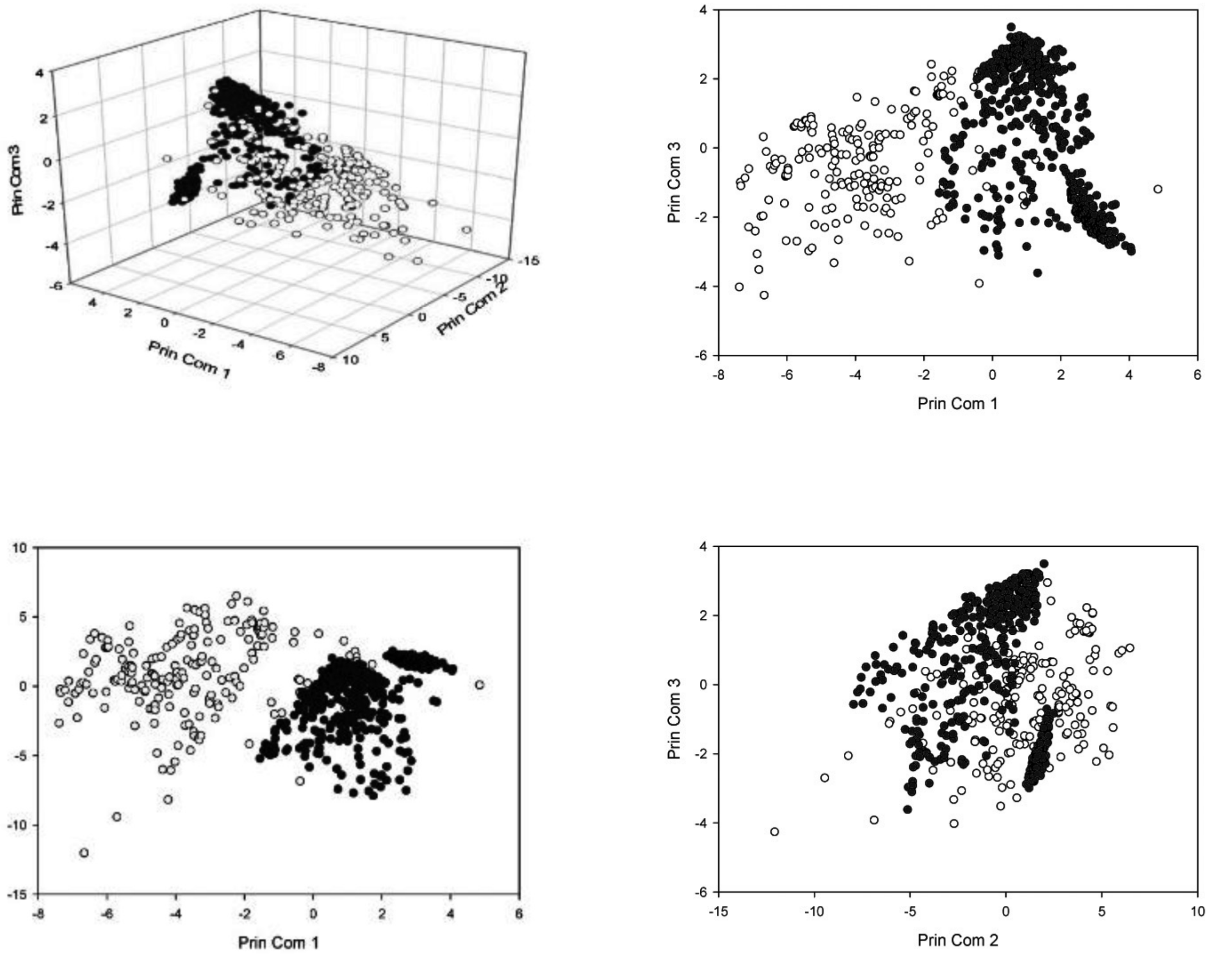

Figure 2. PCA showing the overlap of the environmental data of point data used for building the bobcat distribution model (grey dots), and the extracted 500 random points of the environmental data from the predicted bobcat distribution south of the IT (black dots), for Prin Comp1, Prin Comp2, and Prin Comp3, altogether; Prin Comp 1 and Prin Comp2; Prin Comp1 and Prin Comp3; and Prin Comp2 and Prin Comp3, respectively. Note the amount of overlap in the environmental conditions of the random points from the predicted distribution south of the IT, with the point data where bobcats occur.