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Assessing the Influence of Environmental Parameters on Amur Tiger Distribution in the Russian Far East Using a MaxEnt Modeling Approach

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A R T I C L E I N F O

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A B S T R A C T

A better understanding of which biological and anthropogenic parameters are strong predictors of suitable habitats for tigers will help address conservation planning in those areas, which is crucial for maintaining connectivity and preventing further population fragmentation. The aim of this study was to develop a spatial model based on a number of environmental and anthropogenic variables as well as tiger presence data from a 2005 large-scale winter survey to predict Amur tiger distribution within its range in the RFE. Modeling the geographic distribution of Amur tigers required an application of the MaxEnt algorithm using a dataset of 1027 tiger track records and a set of environmental variables, such as distance to rivers, elevation and habitat type, and anthropogenic variables, such as distance to forest and main roads, distance to settlements and vegetation cover change. The models were divided into two groups based on elevation and habitat type. Elevation (AUC = 0.821) appeared to be a better predictor of habitat suitability for tigers than habitat type (AUC = 0.784).

Introduction

Currently, predictive spatial modeling based on the analysis of environmental parameters is widely used in the fields of environmental protection, ecology, epidemiology, planning of protected areas and other areas (Thomas et al., 2004; Thuiller et al., 2005;

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Graham et al., 2006). When creating models of geographical distributions of species, if there are available data on the presence and absence of animals, general statistical approaches are typically applied. However, most data on the absence of species are scarce. Therefore, spatial modeling methods requiring only information on presence are needed (Graham et al., 2004; Phillips et al., 2006). One of these methods for analysis of the relationship between the locations of species and the environmental characteristics that determine the overall suitability for a given species is MaxEnt (Maximum Entropy). The purpose of this study is to demonstrate the possibility of using this method to assess the impact of environment parameters on the distribution of the Amur tiger in the Russian Far East.

Once, a vast range of Amur tiger subspecies covered the southern part of the Russian Far East, North-East China and the Korean Peninsula (Pikunov et al., 2010). Intensive economic development of the region in the late XIX — early XX century resulted in catastrophic destruction and fragmentation of tiger habitats. Legal and illegal hunting of the Amur tiger in that period also led to a significant reduction in the population and habitats of this predator. Currently, the only viable population of this subspecies is preserved in the south of the Russian Far East (Pikunov et al., 2010; Miquelle et al., 1999, 2010).

Natural reserves play an important role in maintaining the core population of the Amur tiger in the Far East. Due to enhanced protection in protected areas, there are a higher number of ungulates, less human disturbance, and therefore a higher number of adults and stable social structure of groups of Amur tigers leading to higher reproduction rates. However, the small area of nature reserves (3–4% of range of the Amur tiger in Russia) does not prevent further extermination of the predator (Carroll and Miquelle, 2006). Therefore, an understanding of what biological and anthropogenic parameters affect the spread of the tiger outside of the reserve is essential in order to support the establishment of new protected areas, ecological corridors between disjunct groups, as well as to form recommendations on land use management in tiger habitats.

Materials and Methods

Modeling required data on tiger presence locations (geographic coordinates of tracks) collected during a 2004–2005 winter snowtrack survey (Miquelle et al., 2007). The data were collected during the entire snow season. Of the total dataset of 3949 points, 25% of the records were randomly selected. The final set of 1027 records was checked for the degree of spatial autocorrelation using Moran's I test.

To build the model, the following environmental and anthropogenic parameters were also chosen: distance to the river, distance to the nearest settlement, distance to the forest road and main road, habitat type, altitude, and degree of vegetation change. The last parameter is the percentage of change in land coverage between 2000 and 2005. The degree of vegetation change is calculated using analysis of MODIS satellite images (MODerate-resolution Imaging Spectroradiometer, NASA Terra satellite, USA). All variables were converted into the format of raster images with a cell size of 100 m^2. The original habitat classification was simplified by combining 52 categories in 10 types based on the dominant vegetation characteristics: broad-leaved forests, small-leaved forests, coniferous-deciduous forests, larch dominated forests, fir and spruce-dominated forests, wetlands, open woodlands, farmlands, young woods and riverine forests. The preparation and analysis of spatial data were performed using ArcGIS 10.0 (Environmental Systems Research Institute, USA).

Inclusion in the MaxEnt model of strongly correlated variables can introduce a bias in the analysis and lead to misinterpretation. For the assessment of the degree of correlation between continuous variables, the Pearson test was applied. The variables with a correlation coefficient higher than 0.5 were not included in a single model. In addition, for the assessment of the relationship between categorical and continuous variables, a general linear model was applied. Variables were grouped to reduce the degree of correlation and maximize the contribution of each variable to the model.

While building MaxEnt models, 25% of sample records were used as a training dataset and 75% as a testing one. A jackknife test was used to assess the relative contribution of each of the variables to the model (Phillips et al., 2006). The area under the receiver operating characteristic curve (AUC) was used to evaluate model fitness and performance (Phillips and Dudik, 2008).

Results

A strong positive correlation was found in five pairs of variables (Table. 1).

The highest correlation coefficient was found between the distance to the nearest settlement and the distance to the main road. Accordingly, two separate MaxEnt models were developed, and each contained an entire set of continuous variables and only one variable of the pair.

Nine of the ten habitat types had a statistically significant relationship with mean elevation (Table 2), which also imposes restrictions on the inclusion of these two parameters in the same model.

Based on these results, the following four models were developed, comprising a set of least statistically related variables (Table. 3):

A elevation, distance to rivers, distance to the forest road, distance to the nearest settlement, and degree of vegetation change;
B elevation, distance to rivers, distance to the main road, and degree of vegetation change;
C habitat type, distance to rivers, distance to the forest road, distance to the nearest settlement, and degree of vegetation change;
D habitat type, distance to rivers, distance to the main road of main use, and degree of vegetation change.

The highest AUC values in two pairs of models were observed for models A and C. Despite the strong statistically significant relationship between the types of habitats and altitudes, their relative contribution to the model is different. For models A and C, the distance to the river is the second variable in the percentage of contribution, followed by the degree of vegetation change and distance to