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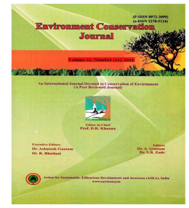

A prediction of suitable habitat mapping of *Pinus roxburghii* sarg. using maxent modeling

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ABSTRACT

Prediction of the potential geographic distribution of species is essential concerning various purposes in protection and conservation. The present study focused on predicting the distribution of *Pinus roxburghii* Sarg. (chir pine) in Uttarakhand Himalayas using the MaxEnt model. The model produced AUC curve with significant value of 0.882 (± 0.023). The study results showed that 426200 ha (5.91%) cover highly potential habitat area for chir pine. Whereas 833900 ha (11.56%), 1019200 ha (14.13%) and 4936000 ha (68.41%) cover good potential, moderately potential and least potential habitat areas, respectively. Based on the jacknife test, it was observed that temperature seasonality (bio4), precipitation of seasonality (bio15) and precipitation of driest month (bio14) are the significant contributors to the occurrence of chir pine in Uttarakhand Himalayas. This study exemplifies the usefulness of the prediction model of species distribution and offers a more effective way to manage chir pine forest by all means, which is beneficial for both the wildlife and human beings for future prospects.

Introduction

Models which predict the potential spatial distribution of species are imperative concerning various applications in conservation biology (Ferrier, 2002; Graham *et al.,* 2004). The maximum entropy (MaxEnt) model (Phillips *et al.,* 2004) is based on species distribution model (SDM) originating from the statistical mechanics. It is the environmental model predicting the potential spatial distribution of species. Species Distribution Modelling (SDM) is a GIS-based method generating maps of where species are suitable to occur. It is also known as habitat modelling, climate envelope modelling and environmental or ecological niche-modelling (ENM). Species distribution models help quantify the correlation between environmental factors and plant and animal species distribution. MaxEnt takes input a list of locations of species presence with a set of environmental predictors. Using such data across the selected study area, MaxEnt extracts a sample of background locations that contrast against the presence locations. Hence, presence is unknown at background locations (Merow *et al.,* 2013). MaxEnt provides spatial distribution maps representing the possibilities of finding the species of concern in a study area. These maps can be produced to represent the probability of locating a particular species in a specific habitat (Baldwin, 2009).

Pinus roxburghii Sarg. (chir pine) is mainly distributed in the subtropical region of western Himalaya, and in this region, chir pine forests occupied a large area. Chir pine has vast ecological values and is a valuable resource for timber and resins. Many studies have reported that chir pine forest has contributed large carbon stock both in tree and soil. Thereby, it plays an immense role in carbon sequestration and mitigation of climate change. Therefore, it is significant to gather information on the suitable habitats of this valuable tree for species conservation and management.

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Material and Methods

The study was conducted in Uttarakhand Himalayas spread over an area of 53,483 km2, located on 28° 44' to 31° 28' N Latitude and 77° 35' to 81° 01' E Longitude, lies on the southern slope of the Himalayan range (Figure 1). Location-specific geo-coordinates (i.e. latitude and longitude) data of chir pine were obtained from the Forest Research Institute, Dehradun. In the present study, 265 geo-coordinates of chir pine were used for predicting the spatial and temporal distribution of chir pine over the study area. For running, the SDM were generated using MaxEnt (Version 3.3.2). The methodology of the chir pine distribution model based on MaxEnt using environmental variables and location coordinates is shown in Figure 2.

In order to model the suitable distribution of chir pine across the study area, nineteen (19) bioclimatic variables were collected i.e., eleven (11) variables for temperature and eight (8) variables for precipitation, and three topographic variables (Table 1). Grid-based bioclimatic layers from the World Clim database (Version 3.4.1, http://www.worldclim.org/bioclim.htm) at 30 arc-seconds spatial resolution were obtained to present the current climatic conditions. Three topographical variables i.e., elevation, slope and elevation, were obtained from the Digital Elevation Model of 30 m spatial resolution (https://earthexplorer.usgs.gov). The required data of the study area were extracted from world data by masking the state boundary in ArcGIS Version 10.3 environment.

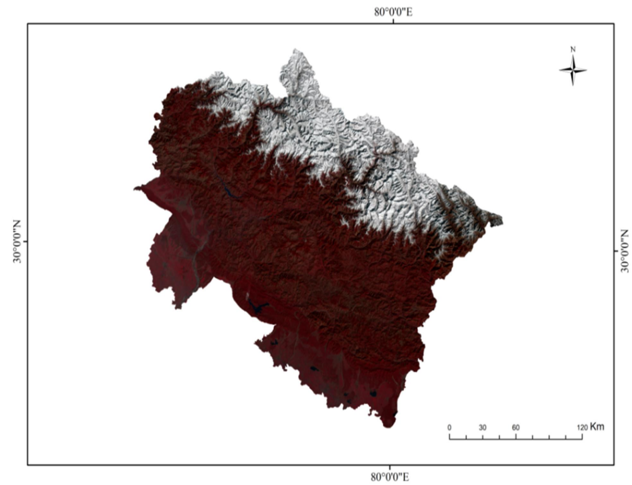

Figure 1: Study area

Table 1: Climatic, topographical variables used for modeling.

Variables		Code	Source	Type
Climate	Bio1=Annual Mean Temperature	bio1	Worldclim	Continuous
	Bio2=Mean Diurnal Range (Mean of monthly (max temp-min temp))	bio2		
	Bio3=Isothermality (P2/P7)*(100)	bio3		
	Bio4=Temperature Seasonality (standard deviation*100)	bio4		
	Bio5=Max Temperature of Warmest Month	bio5		
	Bio6=Min Temperature of Coldest Month	bio6		
	Bio7=Temperature Annual Range (P5-P6)	bio7		
	Bio8=Mean Temperature of Wettest Quartet	bio8		
	Bio9= Mean Temperature of Driest Quartet	bio9		
	Bio10= Mean Temperature of Warmest Quartet	bio10		
	Bio11= Mean Temperature of Coldest Quartet	bio11		
	Bio12=Annual Precipitation	bio12		
	Bio13=Precipitation of Wettest Month	bio13		
	Bio14= Precipitation of Driest Month	bio14		
	Bio15=Precipitation of Seasonality (Coefficient of Variation)	bio15		
	Bio16= Precipitation of Wettest Quartet	bio16		
	Bio17= Precipitation of Driest Quartet	bio17		
	Bio18= Precipitation of Warmest Quartet	bio18		
	Bio19= Precipitation of Coldest Quartet	bio19		
Elevation		Elevation	Calculated from DEM	Contin uous
Slope(^{0})		Slope		
Aspect(^{0})		Aspect		

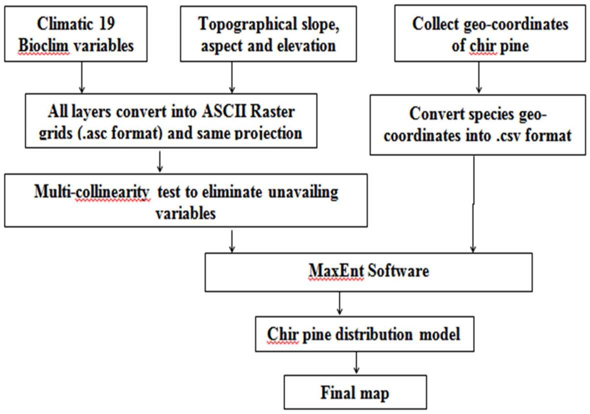

Figure 2: The methodology of chir pine distribution model base on MaxEnt modeling.

Multi-collinearity test was performed by using cross correlations (Pearson correlation coefficients, r) among those environmental variables using R software of version 4.0.2 (Figure 3). Pairwise comparisons were made for all 19 bioclimatic variables and highly correlated variables were removed using Pearson's correlation statistic. When two variables had a value of Pearson's coefficient |r| ≥ 0.85, only the one with higher relative importance and higher predictive power expressed in terms of per cent contribution was selected for model development. So, the variables i.e., Bio 2, Bio 4, Bio 12, Bio13, Bio 14, Bio 15 and aspect were selected through the multi-collinearity test and further used in modeling. The details of those bioclimatic variables are given in Hijmans *et al.,* 2005. The features such as linear, quadratic and hinge were used with the maximum number of background points of 10000 (Phillips and Dudík, 2008). For model framing many replicates were run and the occurrence locations were partitioned into two subsamples randomly, employing 80% of the locations as the training dataset and 20% for testing the resulting (partitioned) models. Model with iterations of 500 was tried. The accuracy of the model was found out by employing AUC (area under the curve) of a receiver operating characteristic (ROC) plot which value ranges from 0.5 = random to 1 = perfect discrimination and to evaluate the variables' importance jackknife procedure (Yang *et al.,* 2013) was adopted.

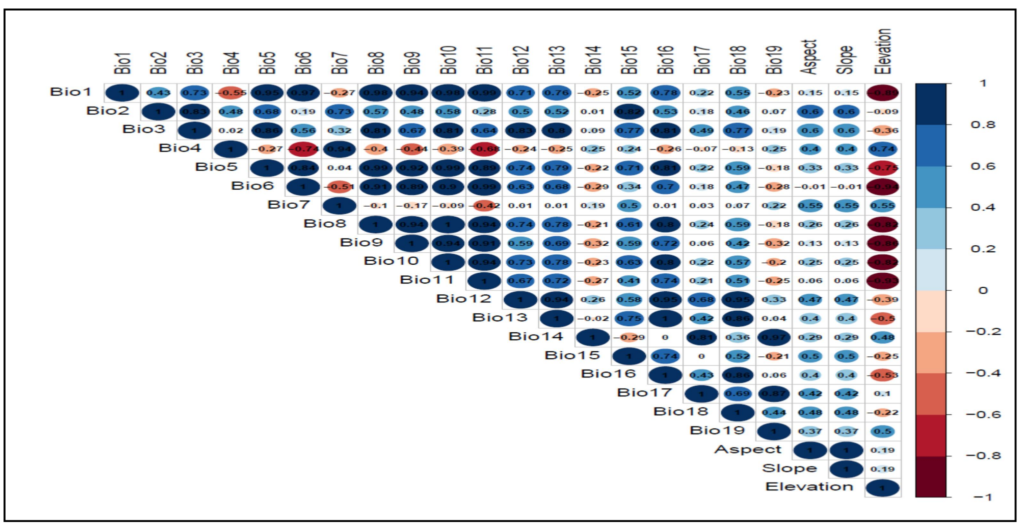

Figure 3: Multi collinearity test among the environmental variables by using cross correlations (Pearson correlation coefficients, r).

Results and Discussion

Based on the results, it was observed that the mean AUC value obtained was 0.882±0.023. This value was obtained when model parameters were set to 500 iterations and 15 replicates. The AUC value of 0.882 shows moderate to excellent predictive ability of the model and as well as high discrimination capacity of the model (Fig.4). The potential habitats probability was classified into four classes based on MaxEnt model prediction output range as >0.6 (high potential), 0.4-0.6 (good potential), 0.2-0.4 (moderate potential) and <0.2 (least potential). The habitat suitability area map (Fig.5) of chir pine showed that 426200 ha (5.91%) covered highly potential, 833900 ha (11.56%) covered good potential, 1019200 ha (14.13%) covered moderately potential while 4936000 ha (68.41%) area covered the least potential. The blue bars of jacknife graph (Fig.6) indicate the gain achieved when considering only individual environmental predictors while green grey bars indicate the diminishing total gain without the environmental predictors. The red bar indicates the gain obtained when considering all the environmental predictors. Based on the results through jacknife test, it was observed that temperature seasonality (bio 4), precipitation of seasonality (bio 15) and precipitation of driest month (bio 14) are the significant contributors to the occurrence of chir pine in Uttarakhand Himalayas. Temperature seasonality is a vital bioclimatic variable, which plays a significant role in determining the suitable distribution of chir pine, as it engulfed temperature change all through the course of the year. As chir pine prefers to grow in warmer aspects; temperature seasonality rightly contributes to the distribution of this species which is also reported by (Chakraborty *et al.,* 2016). Also, precipitation of seasonality and precipitation of driest month displayed a major contribution which is correctly illustrated by the model as this species require low-temperature and less rainfall for its growth.

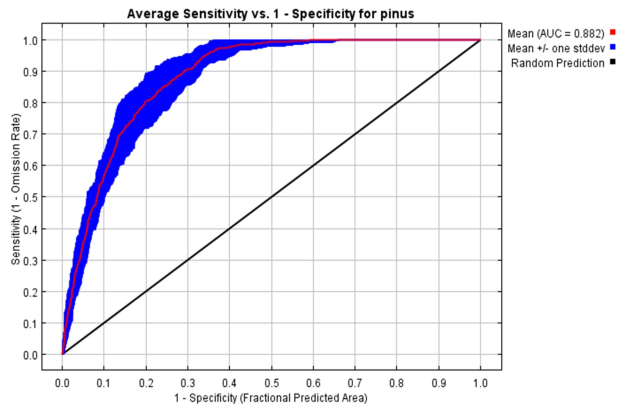

Figure 4: The ROC curve showed performances of the model, and the mean AUC is 0.882

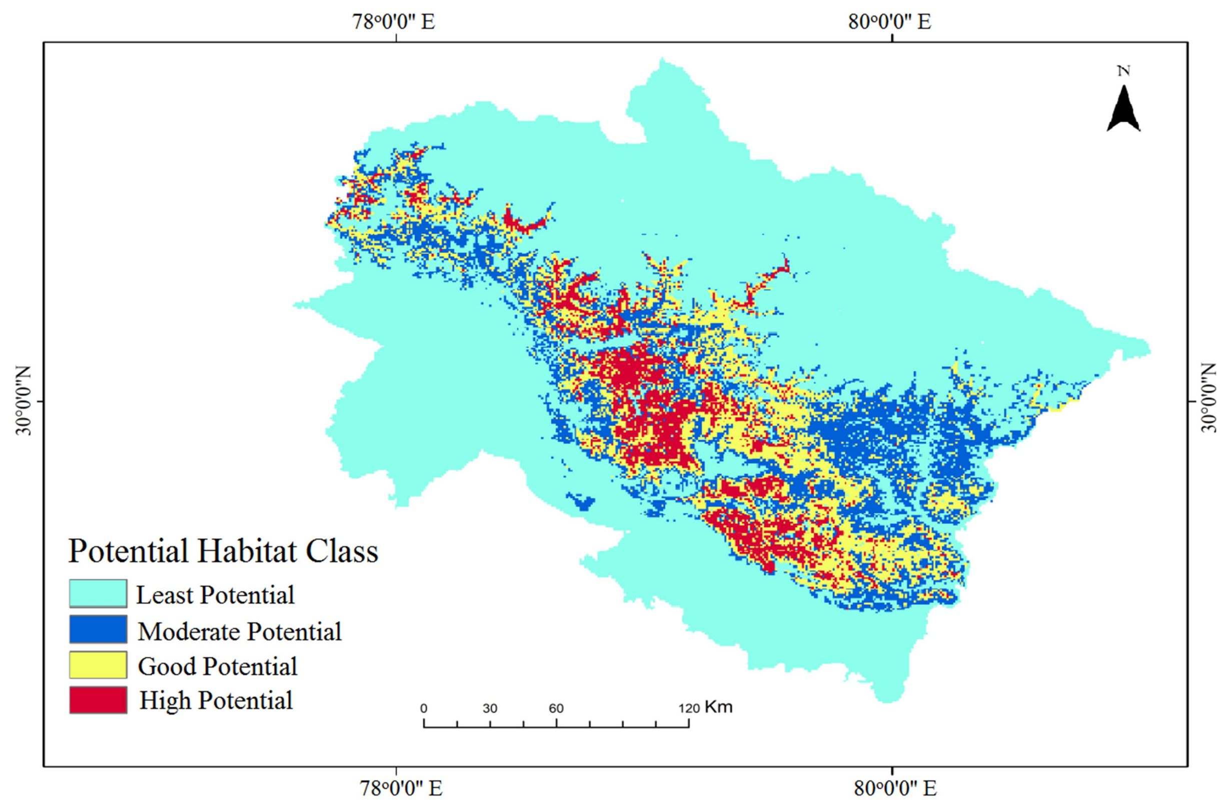

Figure 5: Habitat suitability map of chir pine based on MaxEnt modeling

Jackknife of AUC for Chir pine

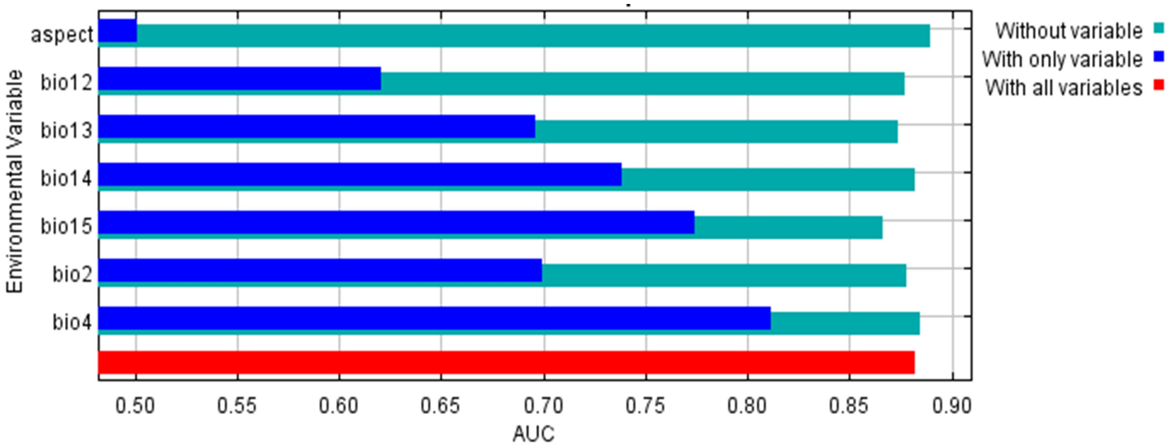

Figure 6: Evaluation of the relative importance of environmental variables for chir pine through jackknife test

Conclusion

The map resulting in the present modeling will be of great help in conservation plans and work as an ideal for collecting presence and absence data on chir pine distribution. Temperature seasonality, precipitation of seasonality and precipitation of driest month plays an essential role in predicting the distribution of pine. The least and moderate potential habitats predicted in the study should be used for carrying out adaptive forest policies and management for conservation strategies. This study exemplifies the usefulness of the prediction model of species distribution and offers a more effective way to manage pine forest by all means, which is beneficial for both the wildlife and human beings for future prospects.

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