Forest Fire Prediction Modeling in the Terai Arc Landscape of the Lesser Himalayas Using the Maximum Entropy Method

Amit Kumar Verma and **Namitha Nhandadiyil Kaliyathan**, Forest Research Institute, Dehradun, India;

Narendra Singh Bisht, Arunachal Pradesh Forest Department, India;

and **Satinder Dev Sharma** and **Raman Nautiyal**,
Indian Council of Forestry Research & Education, Dehradun, India

Abstract—The Terai Arc Landscape (TAL) is an ecologically important region of the Indian subcontinent, where anthropogenic habitat loss and forest fragmentation are major issues. The most prominent threat is forest fires because of their impacts on the microhabitat and macrohabitat characteristics and the resulting disruption of ecological processes. Moreover, wildfire aggravates conflicts between humans and wildlife in the forest fringe areas. The lack of a proper forest fire monitoring system in the TAL is a major management issue that needs attention for long-term forest viability. Hence, the present study was undertaken using maximum entropy modeling to predict the areas across the TAL at risk of wildfire and to identify key variables associated with fire occurrence. Spatiotemporally independent fire incidence locations along with other environmental variables were used to build the model. The accuracy of the model was assessed using the area under the curve. To evaluate the importance of each variable, a jackknife procedure was adopted. Areas in the projected map were categorized into high fire, marginal fire, and no fire areas. An adaptive forest management strategy can be implemented in the modeled high fire areas to mitigate forest fire and wildlife conflict in the TAL.

Keywords: forest fire, maximum entropy, Terai Arc Landscape, Tiger

INTRODUCTION

A forest fire, whether caused by natural forces or anthropogenic activities, could be an ecological and environmental disaster (Kandya et al. 1998; Saigal 1989). In India, fire affects about 2 to 3 percent of the forested area annually, and on average over 34,000 ha of forests burn each year (Kunwar 2003). Fire hazard is the likelihood of a physical event of a particular magnitude in a given area at a given time, which has the potential to disrupt the functionality of a society, its economy, and its environment (Boonchut 2005). Although fire serves an important function in maintaining the health of certain ecosystems, fires have become a threat to many forests and their biodiversity (Dennis and Meijaard 2001) because of changes in climate and in human use and misuse of fire.

The Terai Arc Landscape (TAL) is an ecologically important region of the Indian subcontinent and is facing the challenges of habitat loss and forest fragmentation due to a variety of threats from natural (catastrophic) and anthropogenic sources. The most prominent threat is human population pressure on natural resources and erratic land development activities in the region, resulting in the decline of forest cover and loss of biodiversity in the TAL (Semwal 2005). Parts of the TAL are reduced to tenuous linkages that connect relatively large

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remaining wildernesses, and in some places these linkages are being lost and need restoration to halt further degradation of these natural habitats. Protect the TAL is imperative as the landscape is a mosaic of two of the most important tiger (*Panthera tigris*) reserves (Rajaji Tiger Reserve [RTR] and Corbett Tiger Reserve [CTR]), and contains the Sonanadi Wildlife Sanctuary. Several segments of forested areas are under different protection categories. The RTR-CTR Tiger Conservation Unit (TCU) is one of the 11 level I TCUs identified on the Indian subcontinent for the long-term conservation of tigers (Dinerstien et al. 1997). This TCU of about 7,500 km^2 stretches from the Yamuna River in the west to the Sharda River in the east. About 30 percent of this TCU is in the protected area (PA) network: 820 km^2 in Rajaji National Park (RNP); and 1,286 km^2 in the CTR, consisting of 521 km^2 in Corbett National Park (CNP), 302 km^2 in Sonanadi Wild Life Sanctuary (WLS), and a 463-km^2 buffer area carved out from the Kalagarh, Ramnagar, and Terai west Forest Divisions (FDs). The remainder makes up 12 Reserved Forests (RFs) from west to east. In contrast with the 521-km^2 core area of the CNP, which is free from human disturbance, the rest of the area is subjected to various types of pressures for fuel wood, fodder collection, and grazing, both from the Gujjar community living inside the forests and from the villages located at the periphery of the PAs (Johnsingh and Negi 2003). The Sonanadi WLS is one of the prime habitats for Asian elephants (*Elephas maximus*) in the landscape and has been designated a tiger nursery. This sensitive area is also not free from human disturbances. Though relocation is being proposed, about 184 Gujjar households were recorded as living inside the sanctuary. There is a dearth of scientific studies on these aspects of the FDs. Ninety percent of the 750 elephants in northwestern India reside in RNP, Sonanadi WLS, CNP, and adjoining areas in this Shivalik-Bhabar physiographic zone (Johnsingh and Joshua 1994). This is one of the five major elephant populations of the country.

Accurate mapping of fire hazard is important to help manage and protect critical tiger and elephant habitat in the TAL. Remote sensing has considerable advantages over a conventional method to map forest fire hazard, because of its continuity of coverage over large areas. Geographic information systems (GIS) are capable of combining different sources of information for modeling or mapping. For the optimal utilization of remote sensing and GIS to model forest fire hazard, however, factors affecting fire spread—fuel type, terrain, and human access—need to be studied. Yet this type of research is generally lacking in the tropical region compared to other regions (Darmawan et al. 2001).

Monitoring techniques based on multispectral satellite-acquired data have demonstrated potential as a means to detect, identify, and map fire danger in vegetation. Fire danger estimation demands frequent monitoring of vegetation stress. Vegetation moisture is a particularly difficult parameter to estimate as it accounts for little spectral variation with respect to other environmental factors (Cohen 1986).

In the present study maximum entropy (Maxent) (Phillips et al. 2006) was used due to its predictability and reliability. The objectives of this study were to generate fire prediction models to 1) predict potential fire occurrence areas using environmental variables in the TAL and 2) identify key environmental variables associated with fire occurrence and areas where fires are likely to occur.

MATERIALS AND METHODS

Study Area

The study was carried out in the Terai Arc Landscape of the Uttarakhand Himalayas (fig. 1) (28°43'29" to 30°30'18" North latitude and 77°34'54" to 80°19' 29" East longitude), located in north India, and covers an area of about 20,223 km^2. The area has an uneven topography, with elevation ranging from 103 m to 3,069 m. The Lansdowne, Ramnagar, Haldwani, Terai west, Terai central, and Terai east Reserved FDs are the important RFs in this portion of the study site.

The TAL has been identified as a priority landscape by the World Wildlife Fund (WWF) Tiger Action Plan 1 and the WWF AREAS programs. The "Terai-Duar Savannas and Grasslands" are also a Global 200 Ecoregion. The total area of the landscape is about 49,500 km^2, of which 30,000 km^2 lies in India. There are 13 PAs on the landscape, from the easternmost Parsa Wildlife Reserve in Nepal to Rajaji National Park to the west in India, which were established to

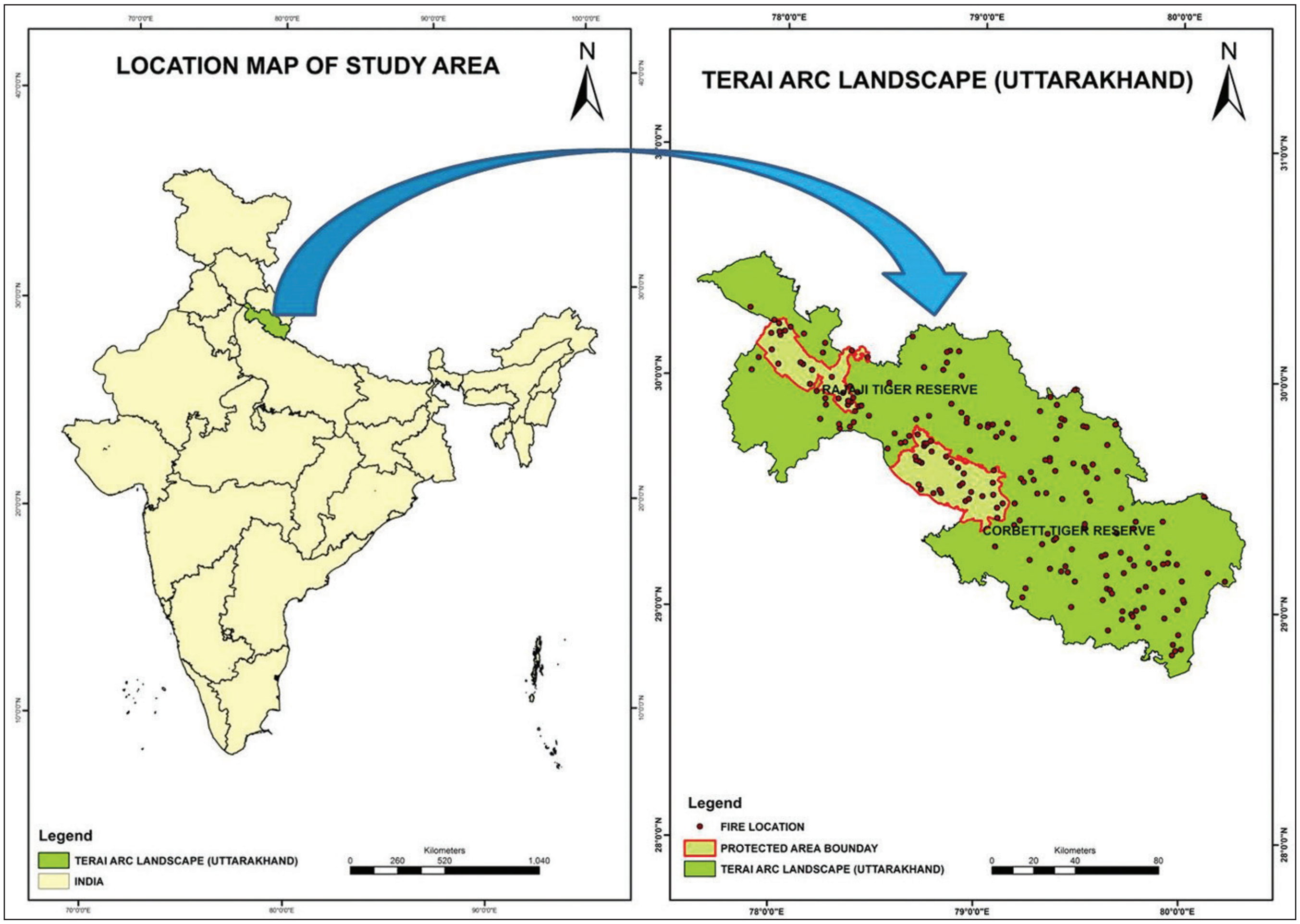

Figure 1—Location map of study area.

protect 3 of the 5 terrestrial flagship species identified by WWF: tiger, Asian elephant, and the greater one-horned rhinoceros (*Rhinoceros unicornis*). The TAL represents one of the densest populations of tigers in the world. The TAL is in the upper Gangetic Plain biogeographic zone 7, and vegetation is mainly of the tropical moist and dry deciduous type. The forests are made up of many economically important species such as *Shorea robusta*, *Dalbergia sissoo*, *Terminalia tomentosa*, and *Acacia catechu*. The Gangetic Plain is also characterized by tall grasses such as *Themeda*, *Saccharum*, *Phragmites*, and *Vetiveria* species. Both these elements (fauna and flora) of the TAL are of global ecological and local economic significance.

Datasets

The data used were Landsat 8 for November 21, 2013 (30-m spatial resolution), the Survey of India toposheet on a 1:50,000 scale with 20-m contour intervals, Cartosat digital elevation model (30-m resolution), and WorldClim bioclimatic data, ver. 1.4 (environmental variables; http://www.worldclim.org/bioclim.htm) (Hijmans et al. 2005). TRIMBLE® (Sunnyvale, California) JUNO® global positioning system was used for field purposes. Fire data for 2000 through 2014 were collected from the State forest department in the form of a point shape file. The digital boundary of the TAL was collected from IT Cell, Uttarakhand Forest Department, PA management plans, and work plans of divisions in the TAL.

Software Used

Erdas Imagine 2013 (DataONE, Albuquerque, NM) was used for digital image processing work and ArcGIS 10.1 (Esri®, Redlands, California) was used for map composition. For data analysis, we used Maxent and DIVA-GIS software, ver. 2 (Hijmans et al. 2002) for reducing spatial autocorrelation and ENMTools (Warren et al. 2010) for checking multicollinearity between predictor variables.

Environmental Fire Predictors

For inputting spatial data into GIS, we created resource maps using remote sensing, coupled with limited ground checks. The forest-type layer was generated by using a supervised classification approach in which 30 training sets were taken from Google Earth as ground control points. The forest cover map was generated using an unsupervised classification approach used for vegetation density mapping using Erdas Imagine 2013 software. The study area was classified into 50 spectral classes using an unsupervised image classification approach. Eventually the vegetation of the study area was stratified into four major types on the basis of density (table 1) as per the fundamental criteria of the Forest Survey of India (FSI 2013). Slope, aspect, and elevation maps were generated from the Cartosat 30-m digital elevation model using a boundary vector layer in ArcMap 10.1.

Table 1—Predictor variables tested for prediction modeling of fire in the Terai Arc Landscape.

Climate variable	Code	Source	Type
Bio 1 = Annual Mean Temperature	*Bio1*	Worldclim	continuous
Bio 2 = Mean Diurnal Range (Mean of monthly [maximum temperature – minimum temperature])	*Bio2*		
Bio 3 = Isothermality (P2/P7) × 100	*Bio3*		
Bio 4 = Temperature Seasonality (standard deviation × 100)	*Bio4*		
Bio 5 = Max Temperature of Warmest Month	*Bio5*		
Bio 6 = Min Temperature of Coldest Month	*Bio6*		
Bio 7 = Temperature Annual Range (P5–P6)	*Bio7*		
Bio 8 = Mean Temperature of Wettest Quarter	*Bio8*		
Bio 9 = Mean Temperature of Driest Quarter	*Bio9*		
Bio 10 = Mean Temperature of Warmest Quarter	*Bio10*		
Bio 11 = Mean Temperature of Coldest Quarter	*Bio11*		
Bio 12 = Annual Precipitation	*Bio12*		
Bio 13 = Precipitation of Wettest Month	*Bio13*		
Bio 14 = Precipitation of Driest Month	*Bio14*		
Bio 15 = Precipitation of Seasonality (Coefficient of Variation)	*Bio15*		
Bio 16 =Precipitation of Wettest Quarter	*Bio16*		
Bio 17 =Precipitation of Driest Quarter	*Bio17*		
Bio 18 =Precipitation of Warmest Quarter	*Bio18*		
Bio 19 =Precipitation of Coldest Quarter	*Bio19*		
Elevation (m)	*elevation*	Cartosat digital elevation model (DEM)	continuous
Slope (°) Aspect (°)	*Slope* *Aspect*	Calculated from Cartosat DEM	continuous
Distance to the nearest village/ tribal settlement (m)	*D2v*	Field data GPS location	continuous
Distance to the nearest water source (m)	*D2d*	Survey of India (SOI) toposheet	continuous
Distance to the nearest watch station (m)	*D2wt*	Field data GPS location	continuous
Distance to the nearest road (m)	*D2r*	SOI-toposheet	continuous
Actual evapotranspiration	*AET*	CGIR	continuous

(continued on next page)

Table 1 (continued)—Predictor variables tested for prediction modeling of fire in the Terai Arc Landscape.

Climate variable	Code	Source	Type
Aridity index	*AI Index*	CGIR	continuous
Population density	*Population density*	Diva GIS	continuous
Forest cover type 1 = Very Dense Forest 2 = Moderately Dense Forest 3 = Open Forest 4 = Scrub 5 = Water 6 = Nonforest	*fcm*	Satellite data	categorical
Forest type 1=Tropical Moist Deciduous 2=Dry Deciduous 3=Northern Subtropical Broadleaved 4=Himalayan Temperate Forest	*ftm*	Satellite data	categorical

Road network and drainage network layers were digitized from the Survey of India toposheet at 1:50,000 scale using ArcMap 10.1. The GPS location of the habitation and forest watch station was collected from field visits. Initially 19 bioclimatic variables from the WorldClim database were considered. A subset of Bioclim 30-m resolution of study area was clipped using the boundary vector layer in ArcMap 10.1.

Fire Occurrence Data

Fire incidence data from 2000 through 2014 were compiled by assessing the distribution of fire in the TAL as recorded by the forest department in Uttarakhand. Over the 15-year period, a total of 7,833 fires were reported in the TAL, of which 2,184 fires occurred in PAs (RNP and CTR). For the present study only 200 spatiotemporally independent fire locations were used for model building. The spatiotemporally autocorrelated fire locations were removed after testing using DIVA-GIS, ver. 2 (Hijmans et al. 2002). Only one location per 1-km grid cell was used if more than one observation was clustered in a grid (i.e., to avoid autocorrelation with a low sample size) (Pearson et al. 2007; Phillips et al. 2006).

Environmental Variables

A series of bioclimatic environmental variables obtained from the WorldClim database, ver. 1.4 (http://www.worldclim.org/bioclim.htm) (Hijmans et al. 2005) were selected. These metrics are derived from monthly temperature and rainfall data and represent biologically meaningful variables for characterizing a species' range. Thirty-one environmental variables were used. These included 11 variables for temperature and 8 for precipitation, expressing spatial variations in annual means, seasonality, extreme or limiting climatic factors, and elevation-interpolated climate surfaces at a resolution of 1 arc-second, or approximately 30 m × 30 m (derived from monthly temperature and rainfall records worldwide) (Hijmans and Graham 2006; Hijmans et al. 2005). Elevation data were used to generate the slope and aspect data layers. The forest density cover and forest type layer were generated from satellite data. All the spatial data layers were created at 30-m spatial resolution using the nearest neighbor resampling technique using Erdas 2013 and ArcGIS 10.1 software. ENMTools ver. 1.3 (Warren et al. 2010) was used to test multicollinearity between predictor variables. The ENMTools output matrix of Pearson Correlation Coefficients (r) was used, and variables with r greater than 0.7 were removed from the model building.

Fire Modeling

The Maxent software package, ver. 3.3.3.e (http://www.cs.princeton.edu/~schapire/maxent/) (Phillips et al. 2004) was used for fire prediction modeling. Maxent implements a maximum entropy algorithm, which generates a probability distribution map of similar conditions across the landscape considering the characteristics of the GPS-defined occurrence locations (Elith et al. 2011; Phillips et al. 2006). Maxent is a machine learning algorithm used to predict robust ecological niches of a species, based on presence records, even when only a few are available (Elith et al. 2006; Kumar and Stohlgren 2009; Papeş and Gaubert 2007; Phillips et al. 2006). This model has an advantage where presence and absence data are limited (Elith et al. 2006; Phillips and Dudík 2008).

Model Parameter Settings

The maximum number of background points was 5,000 and linear, quadratic, and hinge features were used (Phillips and Dudík 2008). One hundred replicates were run for model building (Flory et al. 2012) and the occurrence locations were partitioned randomly into two subsamples, using 75 percent of the locations as the training dataset and the remaining 25 percent for testing the resulting (partitioned) models. The accuracy of the model was evaluated using the area under the curve (AUC) of a receiver operating characteristic (ROC) plot (ranging from 0.5 = random to 1 = perfect discrimination). A jackknife procedure was adopted to assess the variables' importance (Yang et al. 2013). The average of 100 model predictions was used to produce a probability map of fire occurrence. The other settings for the default model parameters and values were used.

RESULTS

The Maxent model predicted hazard maps of fire based on available datasets with a mean training AUC value of 0.926 ± 0.016 and mean testing AUC value of 0.888 $\pm$ 0.013, indicating the model's high discrimination capacity. The model performed well, with a low omission rate at a 10-percent threshold ($p < 0.0002$). A fire probability map was generated from the model output where the values of fire probability range from 0 to 1 (fig. 2). The classified predicted occurrence map (fig. 3) shows good discrimination between high fire, marginal fire, and no fire areas. High and marginal fire areas covered 7.32 percent and 60.40 percent, respectively, of the total study area. Based on a 10-percent training presence logistic threshold, values below 0.2 were categorized as no fire areas. All values above 0.6 were categorized as high fire and those between 0.2 and 0.6 as marginal fire areas.

The classified predicted occurrence map showed that 23.06 percent of the CTR area was in the high fire category and 65.55 percent of the area was in the marginal fire category. Similarly, for RNP, 18.04 percent of the total area was in the high fire category and 79.0 percent of the area was in the marginal fire category.

Response curves showed how each environmental variable responded to predicted areas, both for each variable and its correlation with other variables. The results demonstrated that fires occur in dry deciduous forests (forest type 2) more than other forest types.

The Maxent program estimates the relative contribution of environmental variables in model development. Forest type, forest cover, precipitation in the wettest month, and distance to the closest village contributed the most, with 22.6 percent, 20.5 percent, 12.6 percent, and 8.2 percent, respectively. In terms of permutation importance, however, mean temperature of the coldest quarter, distance to settlement, precipitation in the wettest month, elevation, and precipitation in the driest quarter had the highest values: 14.4 percent, 11.1 percent, 8.7 percent, 8.3 percent, and 8.3 percent, respectively (fig. 4). The environmental variable with the highest gain when used in isolation is distance to settlement, which therefore appears to have the most useful information by itself (fig. 5). The environmental variable that has the largest effect when omitted is forest type, which therefore appears to have the most information that is not present in the other variables.

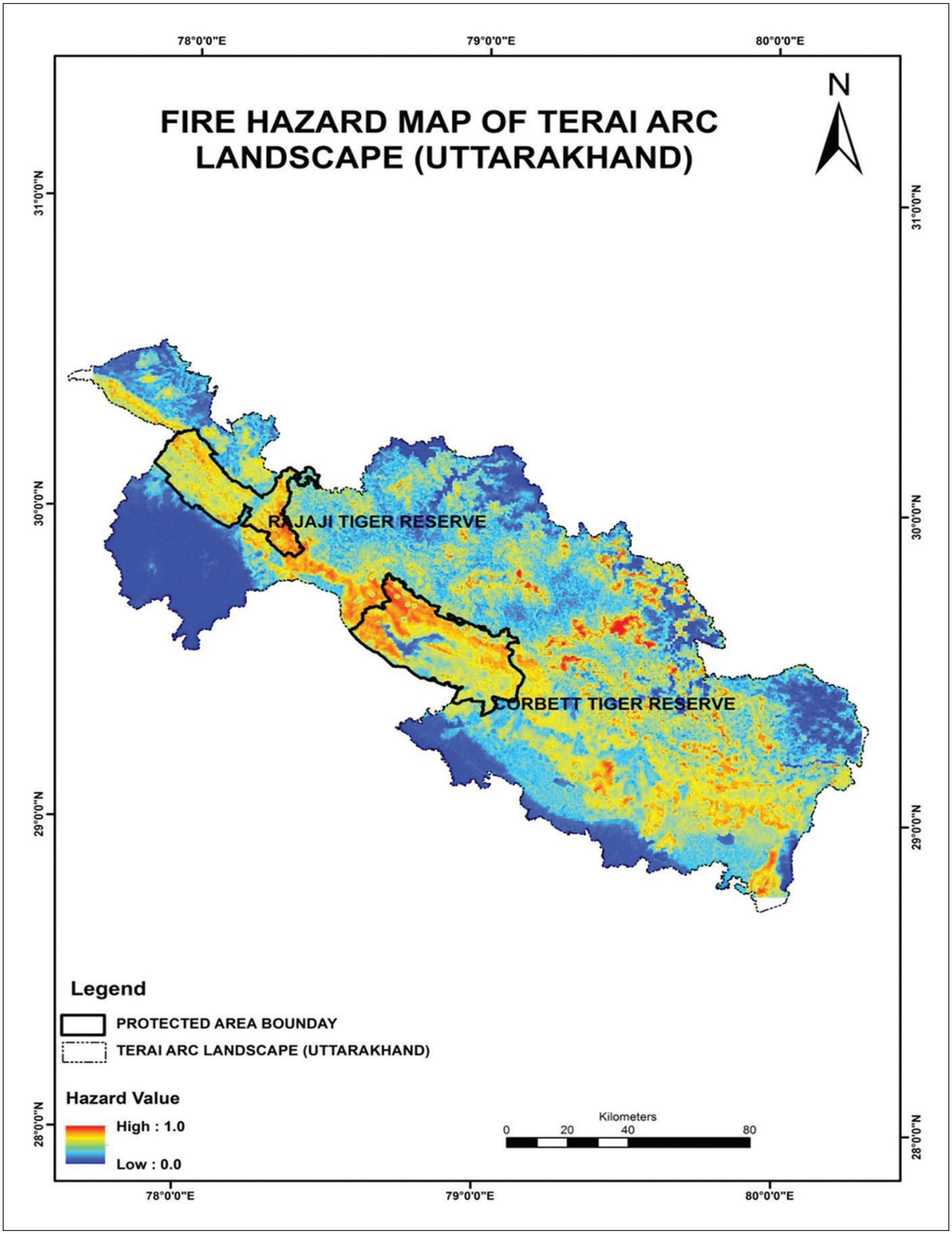

Figure 2—Predicted fire hazard map from low to high probability value.

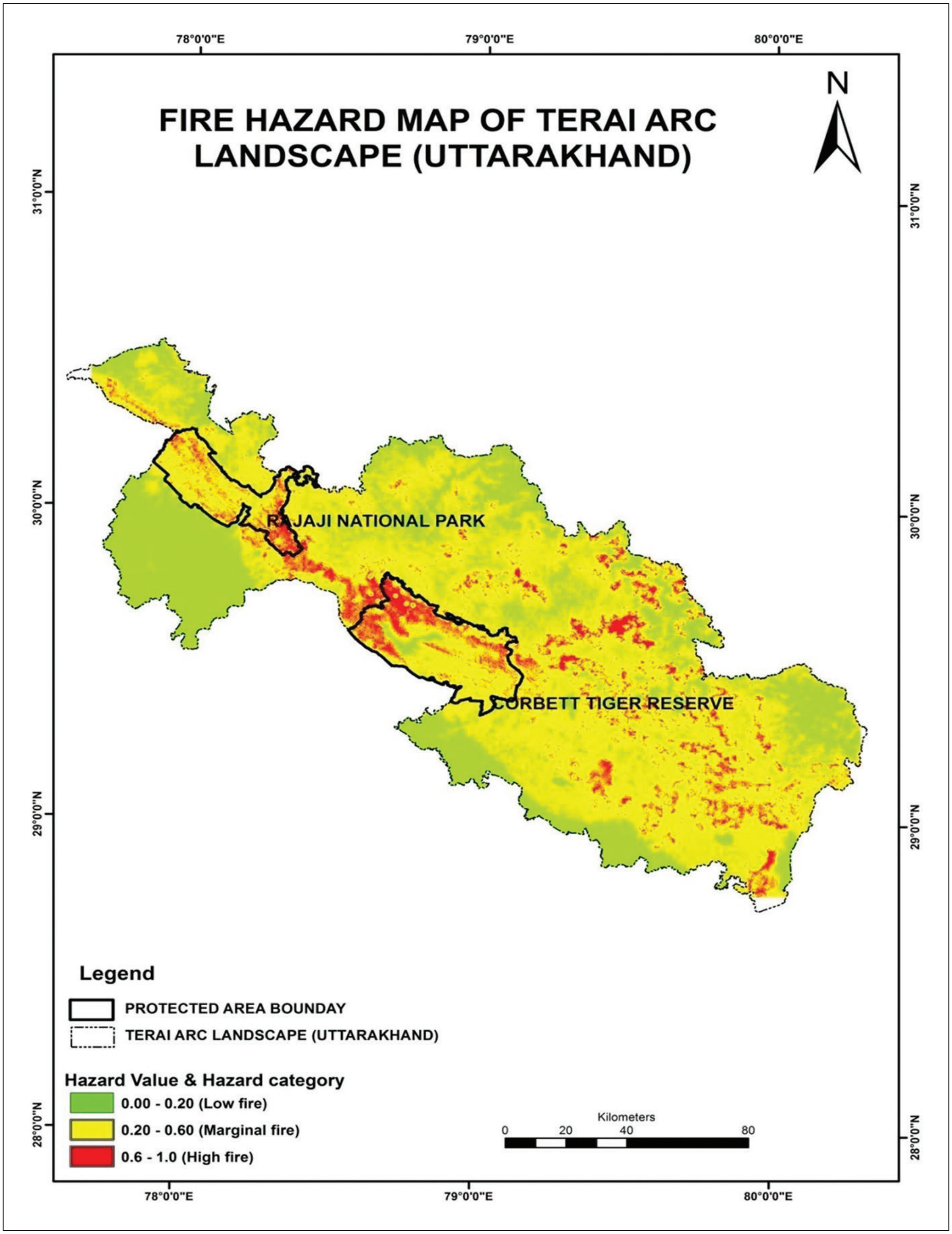

Figure 3—Classified predicted fire hazard map.

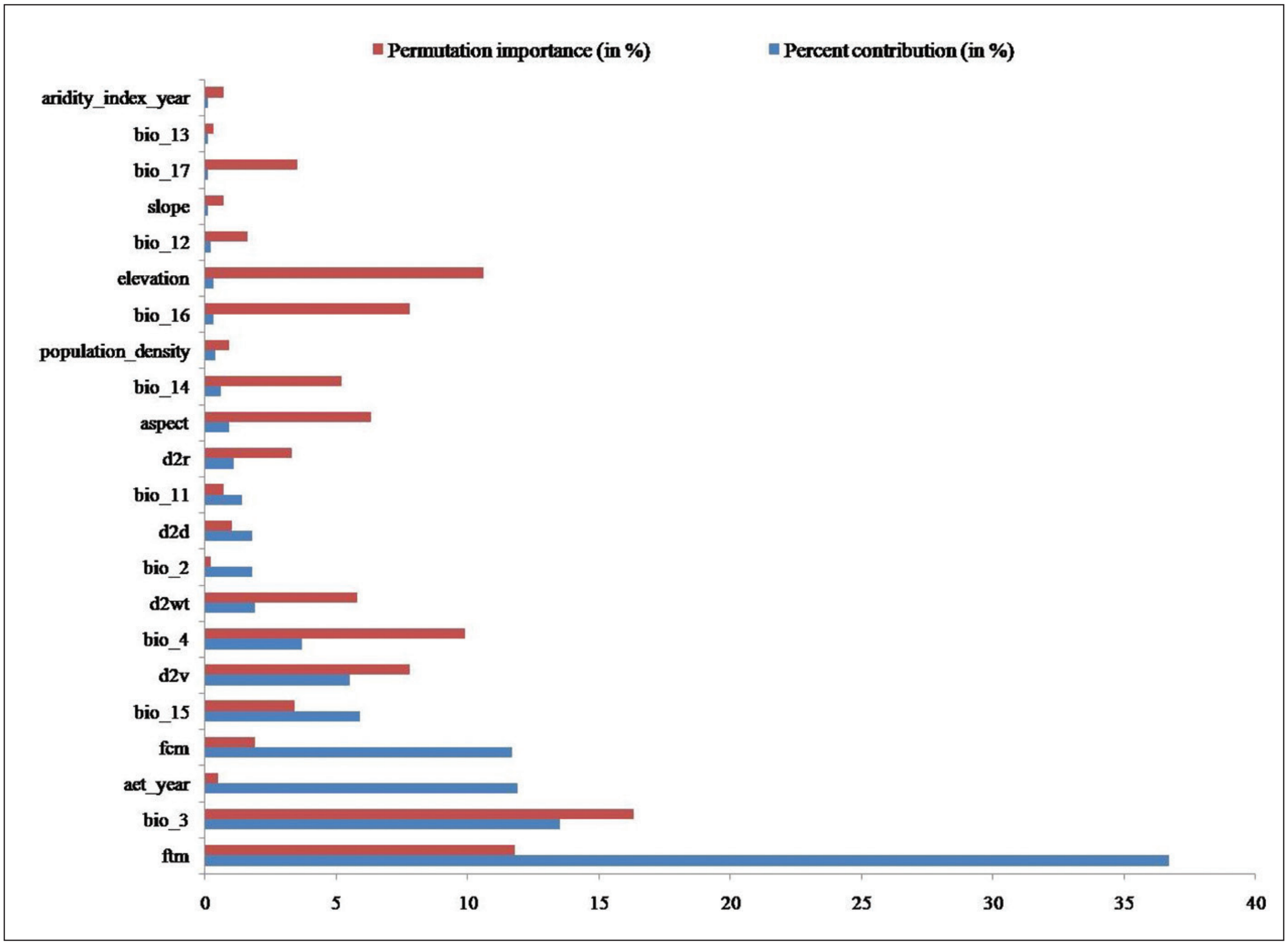

Figure 4—Percent contribution and permutation importance of predictor variables. See table 1 for explanations of codes for variables.

DISCUSSION

The study predicted the potential areas of fire occurrence in the TAL of the lesser Himalayas, India based on available presence records. The output of this model can be used to assist conservation planning and serve as a benchmark for future collection of presence and absence data on fire. Maxent models only identify regions with similar environmental conditions to occurrence localities across the species distribution range (Pearson et al. 2007). Forest type plays an important role in predicting the occurrence of fire, and the model output and previous field surveys revealed that the occurrence of fire in dry deciduous forest having canopy density between 40 and 70 percent and located near a village or other settlement is high compared to other areas. The variation of fire with elevation showed that the probability of fire was high up to an elevation of 2,000 m. Sizable anthropogenic disturbances in the study area were observed during the field visit, and the model also predicted high probability of fire in the forest areas near settlement locations.

The model predicted three categories of fire occurrence areas under high (1,481 km^2), marginal (12,218 km^2), and no fire (6,524 km^2) in the TAL. The model predicted that 10 percent of the total area with predicted potential fire was inside the protected area network.

The Maxent software is user-friendly and has a good ability to predict forest fires. The high fire areas predicted in our study should be used as a base map for management of fire. This study exemplifies the usefulness of prediction modeling of forest fire

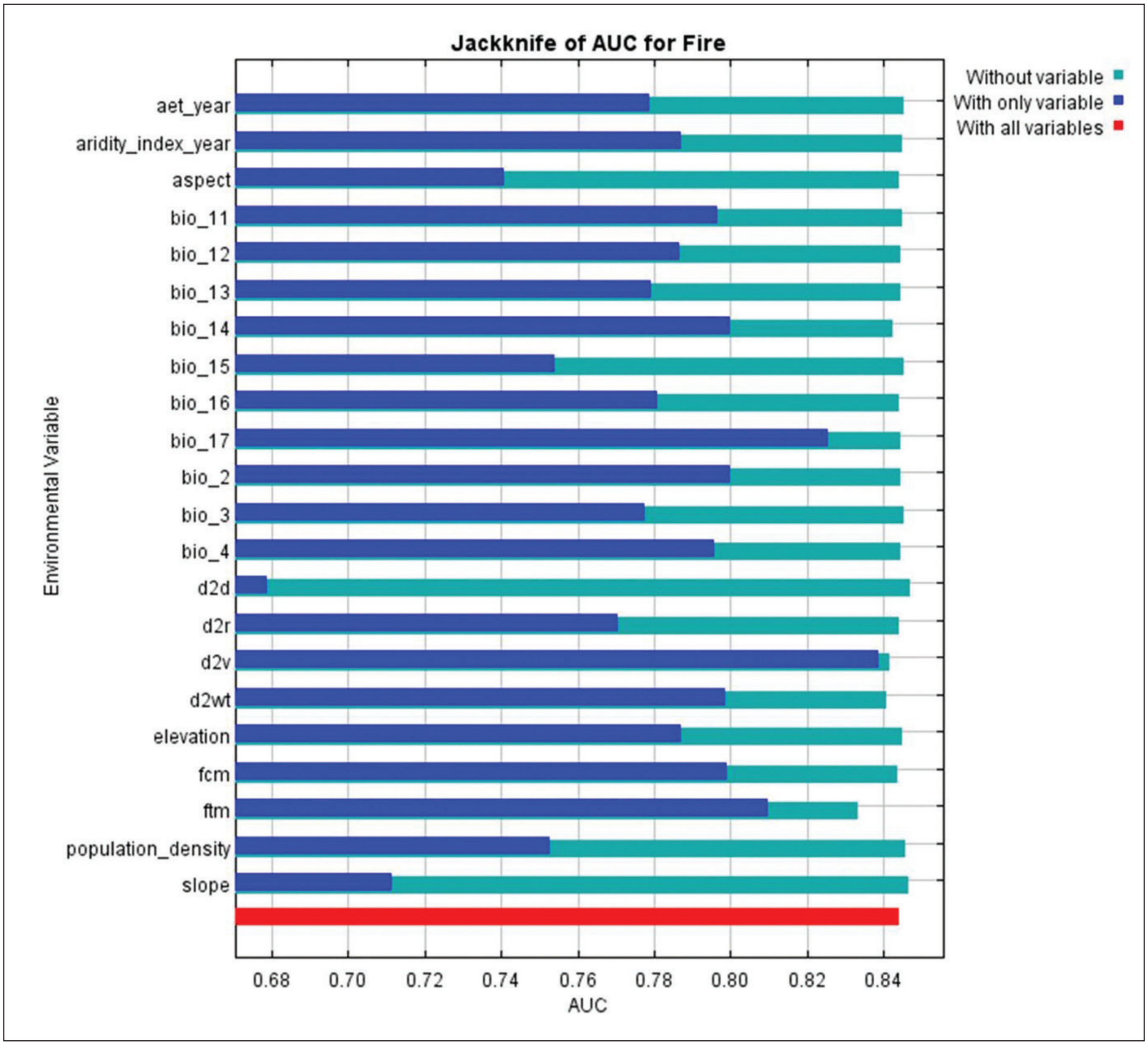

Figure 5—Jackknife of area under the curve (AUC) for fire. See table 1 for explanations of codes for variables.

and offers a more effective way for management of forest fire. The results of this study can be used for preparatory planning for mitigation and management of forest fires in the TAL. Overall, this study depicts a model for conservation of biodiversity, which is beneficial for both wildlife and human beings.

REFERENCES

Boonchut, Prat. 2005. Decision support for hazardous material routing. Enschede, the Netherlands: International Institute for GeoInformation Science and Earth Observation. Master of Science thesis. 121 p. https://systems.enpress-publisher.com/index.php/JGC/article/view/618.

Cohen, Jack D. 1986. Estimating fire behavior with FIRECAST: User's manual. Gen. Tech. Rep. PSW-GTR-90. Berkeley, CA: U.S. Department of Agriculture, Forest Service, Pacific Southwest Research Station. 11 p.

Darmawan, Mulyanto; Aniya, Masamu; Tsuyuki, Satoshi. 2001. Forest fire hazard model using remote sensing and geographic information systems: Toward understanding of land and forest degradation in lowland areas of East Kalimantan, Indonesia. Paper presented at the 22nd Asian Conference on Remote Sensing; 2001 November 5–9; Singapore. 2001 Centre for Remote Imaging, Sensing and Processing (CRISP), National University of Singapore; Singapore Institute of Surveyors and Valuers (SISV); Asian Association of Remote Sensing (AARS). https://crisp.nus.edu.sg/~acrs2001/pdf/234darmawan.pdf. [Accessed 2019 June 14].

Dennis, Rona; Meijaard, Erik. 2001. Impact of human-caused fires on biodiversity & ecosystem functioning, and their causes in tropical, temperate & boreal forest biomes. CBD Technical Series No.5. Montreal, QC: Convention on Biological Diversity. 21 p.

Dinerstien, Eric; Wikramanayake, Eric D.; Robinson, John; [et al.]. 1997. A framework for identifying high priority areas and actions for the conservation of tigers in the wild. Washington, DC: World Wildlife Fund/Wildlife Conservation Society. 72 p.

Elith, Jane; Phillips, Steven J.; Hastie, Trevor; [et al.]. 2011. A statistical explanation of MaxEnt for ecologists. Diversity and Distributions. 17: 43–57.

Elith, Jane; Graham, Catherine H.; Anderson, Robert P.; [et al.]. 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography. 29: 129–151.

Flory, Abigail R.; Kumar, Sunil; Stohlgren, Thomas J.; Cryan, Paul M. 2012. Environmental conditions associated with bat white nose syndrome mortality in the north-eastern United States. Journal of Applied Ecology. 49: 680–689.

Forest Survey of India [FOI]. 2013. India state of forest report. Ministry of Environment & Forests, Government of India.

Hijmans, Robert J.; Cameron, Susan E.; Parra, Juan L.; [et al.]. 2005. Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology. 25: 1965–1978.

Hijmans, R.J, Graham, Catherine H. 2006. The ability of climate envelope models to predict the effect of climate change on species distributions. Global Change Biology. 12: 2272–2281.

Hijmans, Robert J.; Guarino, Luigi; Bussink, Coen; Rojas, Edwin. 2002 DIVA-GIS Ver. 2. A geographic information system for the analysis of biodiversity data. Manual. Lima, Peru: International Potato Center.

Johnsingh, A.J.T.; Joshua, Justus. 1994. Conserving Rajaji and Corbett National Parks—The elephant as a flagship species. Oryx. 28: 135–140.

Johnsingh, A.J.T.; Negi, A.S. 2003. Status of tiger and leopard in Rajaji-Corbett Conservation Unit, northern India. Biological Conservation. 11: 385–393.

Kandya, A.K.; Kimothi, M.M.; Jadhav, R.N.; Agarwal, J.P. 1998. Application of GIS in identification of fire prone areas—A feasibility study in parts of Junagarh (Gujrat, India). Indian Forester. 7: 531–535.

Kumar, Sunil; Stohlgren, Thomas J. 2009. Maxent modeling for predicting suitable habitat for threatened and endangered tree *Canacomyrica monticola* in New Caledonia. Journal of Ecology and Natural Environment. 1: 94–98.

Kunwar, P.; Kachhawaha, T.S. 2003. Spatial distribution of area affected by forest fire in Uttaranchal using remote sensing and GIS techniques. Journal of the Indian Society of Remote Sensing. 31: 145–148.

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 and Distributions. 13: 890–902.

Pearson, Richard G.; Raxworthy, Christopher J.; Nakamura, Miguel; Peterson, A. Townsend. 2007. Predicting species distributions from small numbers of occurrence records: A test case using cryptic geckos in Madagascar. Journal of Biogeography. 34: 102–117.

Phillips, Steven J.; Anderson, Robert P.; Schapire, Robert E. 2006. Maximum entropy modeling of species geographic distributions. Ecological Modelling. 190: 231–259.

Phillips, Steven J.; Dudík, Miroslav. 2008. Modeling of species distributions with Maxent: New extensions and a comprehensive evaluation. Ecography. 31: 161–175.

Phillips, Steven J.; Dudík, Miroslav; Schapire, Robert E. 2004. Maxent software for modeling species niches and distributions. Available at http://rob.schapire.net. [Accessed 2019 June 14].

Saigal, P.M. 1989. A suggested classification of forest fires in India by types and causes. In: Proceedings of the National Seminar on Forest Fire Fighting; 1989 November 2–3; Kulamaru, Kerala, India.

Semwal, Rajeev L. 2005. The Terai Arc Landscape in India: Securing protected areas in the face of global change. New Delhi, India: World Wildlife Fund-India, New Delhi. 47 p.

Warren, Dan L.; Glor, Richard E.; Turelli, Michael. 2010. ENMTools: A toolbox for comparative studies of environmental niche models. Ecography. 33: 607–611.

Yang, Xue-Qing; Kushwaha, S.P.S.; Saran, S.; [et al.]. 2013. MaxEnt modeling for predicting the potential distribution of medicinal plant, *Justicia adhatoda* L. in Lesser Himalayan foothills. Ecological Engineering. 51: 83–87.