

# Maximum entropy-based forest fire likelihood mapping: analysing the trends, distribution, and drivers of forest fires in Sikkim Himalaya.

Polash Banerjee (✉ [banerjee.polash@gmail.com](mailto:banerjee.polash@gmail.com))  
Sikkim Manipal University

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## Research Article

**Keywords:** GIS, Likelihood map, Machine learning, MaxEnt, Wildfire

**Posted Date:** April 15th, 2021

**DOI:** <https://doi.org/10.21203/rs.3.rs-22646/v3>

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**Version of Record:** A version of this preprint was published on April 30th, 2021. See the published version at <https://doi.org/10.1080/02827581.2021.1918239>.

# Abstract

The recent episodes of forest fires in Brazil and Australia of 2019 are tragic reminders of the hazards of forest fire. Globally incidents of forest fire events are on the rise due to human encroachment into the wilderness and climate change. Sikkim with a forest cover of more than 47%, suffers seasonal instances of frequent forest fire during the dry winter months. To address this issue, a GIS-aided and MaxEnt machine learning-based forest fire prediction map has been prepared using a forest fire inventory database and maps of environmental features. The study indicates that amongst the environmental features, climatic conditions and proximity to roads are the major determinants of forest fires. Model validation criteria like ROC curve, correlation coefficient, and Cohen's Kappa show a good predictive ability (AUC = 0.95, COR = 0.81,  $\kappa$  = 0.78). The outcomes of this study in the form of a forest fire prediction map can aid the stakeholders of the forest in taking informed mitigation measures.

## 1. Introduction

The incidents of forest fire in Sikkim Himalaya take a peak during the dry period of the year from November to March due to the accumulation of dry biomass over the forest floor. These incidents may occur by natural causes like lightning as Sikkim falls under the northeast region of India, which is considered a high lightning zone. Furthermore, the winter drought-like conditions prevailing in Sikkim Himalaya is also accountable for forest fires (Kusre & Lalringliana, 2014). Anthropogenic causes of forest fires in Sikkim include intentional and accidental factors. Bonfires by the cattle herders, burning of the forest floor to deter wild animals from entering the agrarian land, and logging induced decrease in forest canopy cover are the intentional causes of forest fires in Sikkim. While, sparks from uphill moving vehicles, electric transformers located in forested areas, the use of a traditional torch called Rankoo, throwing away of live bidi, and cigarette butts are the accidental causes (Joshi et al., 2018; S. Sharma et al., 2014). Recent studies indicate that Sikkim forests are under intense threat due to climate change, anthropogenic pressure and natural hazards (A. Banerjee et al., 2019).

Forest fires can be considered as mixed blessing. Low-intensity forest fires open the canopy cover and removes dead wood, providing a space for new plants to grow. Also, the burning of the forest releases the nutrients bound with the biomass to the soil, rejuvenating forest growth. Forest fires also offer new ecological niches for wildlife to proliferate. In contrast, high-intensity forest fires lead to loss of soil biota, volatilization of soil nutrients, increase in soil erosion, and a decline in biodiversity and forest biomass (Chandra & Bhardwaj, 2015; Parashar & Biswas, 2003).

A wide range of features have been considered for the prediction of forest fires. According to the review of forest fire in the Indian context done by Joseph et al. (2009), topographical features like altitude, aspect, slope, Topographic Wetness Index (TWI) have been used in forest fire prediction (Arpaci et al., 2014; Estes et al., 2017; Flannigan & Harrington, 1988; Guo et al., 2016; Jaafari et al., 2018; T. Kim et al., 2015; Ljubomir et al., 2019; Sachdeva et al., 2018; Sharma et al., 2014; Tien Bui et al., 2019; Yathish et al., 2019). These features are partly accountable for the type and distribution of vegetation. In addition, topographic features influence the direction and speed of a forest fire (Guo et al., 2016; Maingi & Henry, 2007; Minnich & Bahre, 1995). Meteorological features like average precipitation, temperature, humidity, and wind speed have been used to understand forest fire characteristics. In other studies, lightning has been focused to predict forest fires (Chen et al., 2015). These meteorological features can act as triggering and conditioning factors for the start and spread of forest fires (Guo et al., 2016; Turco et al., 2013). For instance, limited precipitation, low humidity, and high temperature create dry forest biomass that acts as fuel for forest fires. While wind speed influences the rapidity and extent of the spread of forest fires (Tošić et al., 2019). Vegetational features like vegetation type, Normalized Vegetation Difference Index (NDVI), tree cover fraction; human-induced features like proximity to the road network, human habitation, or Wildland-Urban Interface (WUI); and in-situ factors like soil moisture, soil texture and fuel density have also been used for forest fire prediction (Gheshlaghi et al., 2020; Jaafari et al., 2018; Mhawej et al., 2015; Satir et al., 2016)

A forest fire or wildfire prediction map has become a valuable tool for disaster management and ecological restoration. Multicriteria decision analysis such as Analytic Hierarchy Process (AHP) (Ljubomir et al., 2019), Analytical Network Process (ANP) (Gheshlaghi et al., 2020; Regodic et al., 2018; Yathish et al., 2019) and other forms of expert opinion based methods (Goleiji et al., 2017) have been applied in forest fire prediction mapping. In these methods, the model criteria and alternatives are considered as a hierarchical structure. This is followed by the ranking of the model criteria and alternatives based on a certain scale. Based on the ranking, the importance or weights of the model criteria and alternatives are estimated and then used in the GIS-aided prediction mapping (P. Banerjee et al., 2018). However, expert opinion-based prediction mapping may suffer subjective bias. Moreover, these methods are deterministic. As a result, they may not be suitable for a phenomenon that involves uncertainty, such as a forest fire (Ishizaka & Labib, 2009; Mendoza & Martins, 2006). Machine learning methods such as kernel logistic regression, support vector machine, random forest, fuzzy logic (Nami et al. 2018; Tien Bui, Hoang, and Samui, 2019), MaxEnt (Martín et al., 2019), multilayer perceptron (Tien Bui, Le, and Hoang, 2018), deep learning and convolutionary neural networks (Zhang, Wang, and Liu 2019) have been extensively used in forest fire prediction mapping (Ghorbanzadeh, Kamran, and Blaschke, 2019; Tehrani et al., 2019). Contrary to expert opinion-based methods, machine learning methods do not suffer from subjective bias. Moreover, these methods encompass the uncertainty associated with the modelling of a phenomenon. However, machine learning may suffer issues like model overfitting. These methods heavily rely on the training dataset and take time to learn. Furthermore, these methods require a large dataset of events of interest for proper training of the model (Chollet & Allaire, 2018; Géron, 2017). Another important limitation of the machine learning method, to be specific methods involving artificial neural networking, is that they achieve efficiency and accuracy at the cost of interpretability of the model (Chollet & Allaire, 2018).

Maximum entropy or MaxEnt is a popular machine learning method widely being used in species distribution and earth hazard modelling (Feng & Hong, 2009; Harte, 2011; Pourghasemi & Rossi, 2018). Unlike most machine learning methods such as logistic regression, support vector machine, random forest, k-nearest neighbour, and artificial neural network, that use presence-absence instance dataset for training, the MaxEnt uses presence-background instance dataset for training. MaxEnt is based on the principle, that the probability distribution that maximizes entropy for the current state of knowledge subject to the constraints of the features is the best fit model for the phenomenon under consideration (De Martino & De Martino, 2018). It is popular primarily because it considers 'minimum assumption' while selecting a probability distribution (Warton, 2013). Moreover, this method considers a more realistic presence-background dataset, in the sense that in nature hardly any absence data is available. On the other hand, MaxEnt needs a large presence-dataset to perform reliable

predictions (Elith et al., 2011; Steven J. Phillips & Dudík, 2008). Also, a study has suggested that MaxEnt is equivalent to Generalized Linear Model (GLM) when it comes to Point Process Models (PPMs) such as forest fire events (Fithian & Hastie, 2013). MaxEnt has been used in several forest fire prediction mappings. Studies indicate that MaxEnt performed equally well in comparison to other machine learning methods in predicting forest fires. (Arpaci et al., 2014; Fernández-Manso & Quintano, 2020; Fonseca et al., 2016; Kim et al., 2015; Lim et al., 2017; Massada et al., 2013; Peters et al., 2013)

In this study, MaxEnt has been applied to prepare a forest fire prediction map of Sikkim Himalaya using MODIS and Ground data-based forest fire inventory. The major objectives of this study are to:

- Prepare a historical forest fire inventory dataset and environmental feature maps encompassing meteorological, topographical, ecological, in-situ, and anthropogenic factors that induce forest fires in Sikkim Himalaya.
- Analyse the temporal trend of the forest fires.
- Analyse the prediction model to identify the role of environmental features in forest fires.
- Validate the model based on robust criteria and geovisualize the forest fire predictions to identify areas prone to forest fires.

The study has indicated that MaxEnt is a reliable machine learning method in predicting areas prone to forest fires in Sikkim Himalaya.

## 2. Materials And Methods

### 2.1 Study area

Sikkim is a small eastern Himalayan state of India neighbored by Tibet in the North, Nepal in the west, Bhutan in the east and the state of West Bengal in the south. It extends from 27° 00' 46" N to 28° 07' 48" N latitude and 88° 00' 58" E to 88° 55' 25" E longitude. The elevation of Sikkim varies from 280 meters in the South to 8586 meters in the North, crowned by the world's third highest mountain peak, Mt. Khangchendzonga (Shukla et al., 2018). Sikkim, apart from having four seasons of winter, summer, spring, and autumn, has a monsoon season lasting from June to September. It has a subtropical climate in the south and a tundra climate in the north. The two main rivers of Sikkim include the Teesta River and its tributary, the Rangeet (ENVIS Sikkim, 2019) (**Figure 1**).

Sikkim is endowed with various vegetation ecotypes based on the elevation and climatic conditions. For example, Himalayan subtropical broadleaf forests are found in the lower elevations, Eastern Himalayan broadleaf forests in the temperate zone above the elevation of 1500 metres, Eastern Himalayan subalpine conifer forests from 3500 to 5000 metres and Eastern Himalayan alpine shrub and meadows in the higher elevations (O'Neill, 2019; O'Neill et al., 2020). The dry winter season from December to March in Sikkim is characterised by windy weather and dry forest biomass, which create the right conditions for forest fires. It is more common in the deciduous Sal forest ecosystem, followed by the temperate oak and subalpine conifer forests. Erratic rainfall, climate change, and conversion of forest land into other land uses have increased the vulnerability of the forests in Sikkim, leading to a growing trend of forest fire incidents (P. Banerjee et al., 2020; R. Sharma et al., 2012).

### 2.2 Data sources

The active fire data from the years 2000-2019 of Moderate Resolution Imaging Spectroradiometer (MODIS) was accessed from the data archive at the Fire Information for Resource Management System (FIRMS) site (<https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms/active-fire-data>). However, it is to be noted that the MODIS-FIRMS provided fire events data only from November 2000 onwards. The MODIS-FIRMS dataset was combined with the forest fire inventory prepared from the GPS-tagged dataset of the Forest and Environment Department, Government of Sikkim. In many instances, the government dataset lacked the Latitude-Longitude data. In such cases, the forest fire events were dropped from the final dataset. Unlike the dataset accessed from the government source, the MODIS-FIRMS dataset includes fire events that had a spectral signature not less than 1 km resolution. The fire events dataset thus prepared was intersected with the historical maximum forest fraction raster data (**SupplementFigure S1**) (Shimada et al., 2014) to exclude fire incidents beyond the forest cover of the study area. This data pruning process generated a fire dataset of 754 events.

The environmental feature raster maps or simply the features used in this study included precipitation (*avgPrep*), ambient air temperature (*avgTemp*) and wind speed (*avgWind*) averaged over the dry period of Sikkim, prepared from the monthly data accessed from Worldclim 2 (<http://www.worldclim.com/version2>) (Fick & Hijmans, 2017). For this study, amongst several data resolutions, the 30 seconds resolution average monthly climate data of 1970-2000 was taken from Worldclim 2. Also, features like aspect, plan curvature (*PlanCurv*), profile curvature (*profileCurv*), slope, and TWI were derived from the Digital Elevation Model (DEM) (Jarvis, A., H.I. Reuter, A., Nelson, E. Guevara. 2008). The DEM used in this study was the product of Shuttle Radar Topography Mission (SRTM) of 90m resolution derived from CGIAR/SRTM90\_V4 image with a data collection timeframe from 2000-02-11 to 2000-02-22 (<https://srtm.csi.cgiar.org/>). The NDVI of the study area was prepared from the Advanced Spaceborne Thermal Emission and Reflection Radiometer data (ASTER Mount Gariwang image, 2018). The NDVI data of 250m resolution was prepared from MODIS/006/MOD13Q1 image, computed from the atmospherically corrected bi-directional surface reflectance that has been masked from water, clouds, heavy aerosols, and cloud shadows (<https://doi.org/10.5067/MODIS/MOD13Q1.006>). The timeframe of NDVI data collection was from 2000-02-18 to 2020-07-02. Features like per cent tree cover (Sexton et al., 2013) and population density (CIESIN 2018) were also used in the modelling. The per cent tree cover was the product of a 30 meters resolution image of GLCF/GLS\_TCC of Global Landsat Tree Cover Continuous Fields, prepared from three-year epochs of 2000, 2005 and 2010 assessing the woody vegetation greater than 5 meters in height (<https://lpdaac.usgs.gov/products/mod44bv006/>). In-situ features, namely, soil surface carbon content (*soilCarbon*) (<https://zenodo.org/record/2525553>) (Tomislav Hengl & Ichsani Wheeler, 2018) and soil surface water content (*soilWater*) (<https://zenodo.org/record/2784001>) (Tomislav Hengl & Surya Gupta, 2019) were accessed from OpenLandMap. The population density data was availed from the Gridded Population of the World, Version 4.11 (GPWv4) (<https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11>)

released in December 2018 prepared by the Center for International Earth Science Information Network (CIESIN), Columbia University (CIESIN, 2018). Features like vector datasets of the road network, water bodies and human habitations were accessed from © OpenStreetMap contributors and used to prepare proximity raster maps such as *proxRoads*, *proxWater* and *proxPlace* of the respective features (<https://www.openstreetmap.org/>). The features selected for this study were based on prevailing literature specific to forest fire studies of Northeast Himalaya (Joseph et al., 2009), explorative analysis using a wide variety of features and their impact on the model performance (Table 1). Environmental feature maps used in this study can be found in the supplement (Figure S2 a-o).

### 2.3 Maximum entropy – the MaxEnt Model

The MaxEnt algorithm does prediction by minimizing the relative entropy between the probability density of the presence-only instances of the target variable from that of the instances of background landscape data (Elith et al., 2011). For instance, for a landscape,  $L$  the algorithm uses forest fire occurrences ( $y = 1$ ) over a vector of environmental features,  $\mathbf{z}$ . The MaxEnt algorithm attempts to minimize the distance of the probability densities of features in case of forest fire occurrences,  $f_1(\mathbf{z})$  from the probability densities of features of the background or the null model,  $f_0(\mathbf{z})$  over the landscape  $L$ . The minimization of the distance function is achieved by maximizing a penalized likelihood model, subject to the model constraints given by the probability densities of features of the landscape (Steven J. Phillips & Dudík, 2008).

Unlike conventional machine learning methods like logistic regression or random forest which use the presence-absence data, MaxEnt uses presence-background data for the prediction of the forest fires. The absence data capture the environmental conditions of landscape that do not have forest fires, while the background data attempts to understand the characteristics of the overall landscape environment. In this sense, background data demands fewer assumptions in comparison to absence data and they are in a continuum with the presence data (S. Phillips & Elith, 2011; Steven J. Phillips et al., 2009; Ward et al., 2009). Unfortunately, this may make MaxEnt prone to sample selection bias, a condition where some areas of the landscape may be oversampled than the other areas. Furthermore, MaxEnt is prone to overfitting the predictive model to presence-only data (Devisscher et al., 2016). However, recent MaxEnt software uses transformation algorithms like linear, quadratic, product, categorical, threshold, and hinge for the standardization of the prediction features and regularization of the model to prevent model overfitting (Elith et al., 2011).

Forest fires, like most natural phenomena, rarely have data in their absence. This makes MaxEnt more appropriate for forest fire studies as it requires presence-only data for their predictions (Arnold et al., 2014; Steven J. Phillips & Elith, 2013).

### 2.4 Data processing and preparation of forest fire prediction map

Initially, all feature maps were projected from the geographic projection system of GCS-WGS-1984 to the plane projection system of WGS-1984-UTM-Zone-45N, which is suitable for the study area. Next, Euclidean distance raster maps were prepared from the polyline vector maps of the road network, water bodies network and point vector map of human habitations. These raster maps were prepared to measure the proximity of fire events to roads, water bodies and human habitations. Topographic feature maps of aspect, slope, curvatures and TWI were prepared from DEM. Raster maps of averaged NDVI and averaged tree cover (*treeCov*) were used in this study to train the algorithm. Thereafter, all feature maps were resampled to have the same spatial extent and cell size of 30.7 meters, as that of the *proxRoad* raster. After this, the feature maps were normalized, such that the pixel values of the maps were in the range from zero to one (Chang, 2017). This is a standard procedure in machine learning to reduce the computation time. All these geoprocessing methods were performed in the ArcGIS framework. The normalized maps were exported in GeoTiff format as they are readily readable by R-programming language. Furthermore, the presence-only dataset of forest fire events was stored as a Comma-Separated Values (CSV) file.

The forest fire prediction map was prepared in the RStudio environment using R packages named 'raster' (Hijmans, 2020), 'rgdal' (Bivand et al., 2019) and 'dismo' (Hijmans et al., 2017). The first two packages were mainly used for raster images related spatial operations, while *dismo* was used for bridging between R and MaxEnt software. The MaxEnt software used in this study is a java program-based package (S.J. Phillips et al., n.d.). During the preparation of the prediction map, all the feature maps were stacked with matching extents and feature attributes were extracted from the feature stack using the fire event coordinates present in the presence-only dataset. The dataset was analysed using SPSS statistical package to identify the multicollinearity of the features. Features with high multicollinearity were dropped from the raster stack and the presence-only dataset was repopulated with feature values devoid of multicollinear features. In this way, the presence-only dataset was data pruned to generate a more reliable dataset. The dataset was divided into 25% testing data and the rest was used for training of MaxEnt. Furthermore, the training dataset was divided into five-folds for crossvalidation. This was followed by the preparation of a background dataset by selecting 1000 random points from the extent of the study area. The number of background points has a direct impact on the model efficiency and efficacy. Usually, 1000 or more background points provide satisfactory performance for MaxEnt depending on the spatial extent and spatial heterogeneity of the study area (Steven J. Phillips & Dudík, 2008). Similar to the preparation of the presence-only dataset, the background dataset was populated with the feature attributes and divided into train-test datasets and the train set was further divided into five-fold datasets for crossvalidation. During crossvalidation process, repetitively any one out of the five sub-datasets was used for testing while the rest were used for training the MaxEnt algorithm. An average of the errors generated from the repeated testing helps in the tuning of the model parameters for better performance of MaxEnt.

The MaxEnt-based prediction was applied to the entire extent of the study area, considering every cell as an instant. The model output was exported as a GeoTiff raster and classified into five qualitative categories applying the natural breaks method in the ArcGIS framework (P. Banerjee et al., 2020; Jenks, 1967; McMaster, 1997). Jenks natural breaks is a reliable and popular map data classification method amongst the cartographers. It divides the data range into natural categories that minimizes the variance within categories while maximizes the variance between the categories (Jenks, 1967). This results in an increase in the goodness of fit of the classification.

All Model validation criteria like Receiver Operating Characteristic (ROC) curve (Peres & Cancelliere, 2014), correlation coefficient, and Cohen's kappa (Vakhshoori & Zare, 2018) were used to evaluate the model performance.

- ROC curve is a popular diagnostic and visualization tool that plots the true positive rate of the model against the false positive rate. Here, the true positive rate is the probability of classifying the presence-only instances correctly by the algorithm. In contrast, the false positive rate is the probability of misclassifying the background instances as presence-only instances. The performance of the algorithm is assessed by estimating the Area Under the Curve (AUC) of the ROC curve. AUC close to 1 indicates good performance of the algorithm (Géron, 2017).
- The correlation coefficient compares how well the predicted values of forest fire estimated by MaxEnt match with the observed values (Caniani et al., 2016). A value close to 0.9 indicates a strong correlation between the model predictions and the observed.
- Cohen's Kappa statistic measures the agreement between two categorical scales, such as binary outcomes of predicted and observed events of forest fire. The kappa is the ratio of the deviation of the observed value, from the predicted, to one less predicted value equation (1) (Sim & Wright, 2005):

$$\kappa = \frac{p_o - p_e}{1 - p_e} \quad (1)$$

Kappa value close to one is satisfactory for model validation.

The methodology of the study is illustrated below (Figure 2).

### 3. Results

Plotting of the yearly forest fire events indicated a highly fluctuating but increasing pattern of forest fire occurrences over the years. The Holt's forecast model showed a growing trend of forest fires in Sikkim Himalaya suggesting a rise of 83 forest fire events in 2019 to 97 by 2022, with a margin of error of  $\pm 62$  events (Figure 3).

Correlation analysis indicated that the feature like popDen was strongly correlated with avgPrep and avgTemp, primarily because most of the human population was in the subtropical southern parts of Sikkim. Additionally, avgTemp had a strong correlation with avgPrep, as the subtropical Sikkim gets the bulk of rainfall (Table 1). Multicollinearity analysis indicated that the Variance Inflation Factor (VIF) of the independent feature variables of avgTemp was within acceptable limits (VIF < 5), except for popDen. Hence, multicollinear variable like population density was dropped from the model (Table 2).

Starting with the meteorological features, the fire events were more common in moderate to warmer areas (11 – 24°C). Like avgTemp, the fire events were more common in areas with moderate to higher avgPrep (35 - 55mm). In contrast, fire events were common in areas with low avgWind (1.4 - 1.7 ms<sup>-1</sup>). Moving onto topographic features, the bulk of the fire events were observed in the flatter slopes (5 - 7 degree), lower TWI (4 – 6 value) and moderate aspect (81 - 217 degree). The PlanCurv and profileCurv had nominal influence in the prediction of forest fires. In the case of PlanCurv, the convex curvature of 0.765 had some influence on forest fire occurrences. The concave curvature of 0.488 of the profileCurv had some influence in predicting forest fires. Looking at the ecological features, fire events were common to areas with moderate to high NDVI values (0.5 - 0.7) having moderate treeCov (31- 55% of the area). In-site features indicated that areas with moderate soilCarbon and low soilWater were more prone to forest fires. Furthermore, fire events were skewed towards areas close to the water bodies (0 – 800m), human habitations (0 – 3000m), and roadways (0 – 800m) (Figure 4).

In terms of the contribution of the features towards prediction of forest fires, proxRoads explained 43% of the events, followed by avgTemp that explained almost 17% of fire events. Environmental features, namely, proxRoads, avgTemp, treeCov, avgPrep, proxPlace and avgWind together explained 85% of the forest fire events. TWI had no contribution in the prediction value. Hence, TWI was dropped from the MaxEnt model (Figure 5).

The MaxEnt method-based forest fire prediction map of 30.7m resolution showed a probability range from 0 to 1, indicating no chance of forest fire occurrences to very high chances of forest fire occurrences (Figure 6). The prediction map was further categorized into very low, low, medium, high, and very high chances of forest fire incidents for the sake of convenience (Figure 7). Out of the total study area, 351 km<sup>2</sup> was under the very high probability of forest fires, while 451 km<sup>2</sup> was under the high probability of forest fire occurrences. Thereby, these two categories together constituted 11% of the total study area (Figure 8).

Model validation criteria like the ROC curve showed an Area Under the Curve (AUC) of 0.957 (Figure 9a). The correlation coefficient was estimated to be 0.809 and Cohen's Kappa was estimated to be 0.78 (Figure 9b).

### 4. Discussion

In this study, the Holt's forecast modelling indicated an alarming rise in forest fires in Sikkim Himalaya. Hence an attempt has been made to prepare the forest fire prediction map of Sikkim Himalaya using the MaxEnt machine learning method. The study indicated that the estimation of the probability of forest fires by MaxEnt was satisfactory as per the model validation criteria.

It was observed that out of the 15 predictor features, six of them, namely proxRoad, avgTemp, treeCov, avgPrep, proxPlace, avgWind, were able to explain 85% of forest fire events. Due to the difficult terrain, many of the human activities in Sikkim are confined around the roadways. This also includes human habitations. The limited contribution of topographic and ecological features in explaining forest fires further reinforce the disproportionate influence of human activities and meteorological factors in of forest fire occurrences. Together, these two feature sets explain 47.5% of forest fires. This indicates with a fair amount of confidence, that forest fires in Sikkim Himalaya primarily occur due to human activities and are facilitated by climatic conditions. This observation was similar to a previous study done in the Amazonian forest of Bolivia (Devijscher et al., 2016). In addition, studies conducted in the Huron–Manistee National Forest, Michigan, USA, suggested that development activities such as road networks were the major determinants of forest fire occurrences (Massada et al., 2013). Other studies on forest fire prediction modelling also suggest that proximity to roads and human settlements are the major

determinants of forest fires (Arpaci et al., 2014; Jaafari et al., 2018; Maingi & Henry, 2007). Areas with low to moderate tree cover were more susceptible to forest fires. Furthermore, areas with moderate temperature and precipitation with very low wind speed were more prone to forest fire incidents. Again, these areas are prevalent in the valleys of southern Sikkim Himalaya which are dominated by agrarian land, human habitations, and road networks. This observation further indicates that the ecological and meteorological conditions are the conditioning factors of forest fires in Sikkim.

In contrast to the mainland India where forest fires are common during the hot dry summer (Joseph et al., 2009), majority of forest fires in Sikkim Himalaya occurs during the cold dry period from November to March. As observed in this study, the bulk of the forest fires were in the southern part of Sikkim. This is mainly due to the logging activities there. Moreover, higher vehicular traffic explained by the greater road network in southern Sikkim makes the dry vegetation vulnerable to fire due to engine sparks and cigarette or bidi butts. The limited number of forest fires in the high altitude of Sikkim is primarily due to lightning. Moreover, the high contrast of the warmer climate in southern Sikkim compared to the very cold climatic conditions of northern Sikkim makes the former more vulnerable to forest fires (R. Sharma et al., 2012). This study also indicated that forested areas close to human habitations are at a higher risk of forest fire occurrences. An aspect from East to South-West direction had more contribution towards forest fires. Aspect influences soil moisture, solar radiation, vegetation composition and density (Estes et al., 2017). Furthermore, forest patches of valley areas that receive moderate rainfall having moderate temperature and low wind speed were prone to forest fire. The higher values of model validation criteria suggested that the model prediction was satisfactory.

Being fundamentally distinct from other machine learning methods, MaxEnt uses a presence-only dataset to train itself (Elith et al., 2011). However, like many studies have shown earlier, the present study also indicated that this distinction of MaxEnt does not limit its capability in generating reliable hazard prediction maps (Arpaci et al., 2014; Fernández-Manso & Quintano, 2020; Fonseca et al., 2016; Kim et al., 2015; Lim et al., 2017; Massada et al., 2013; Peters et al., 2013). In this study, a limited set of features have been considered for forest fire prediction. This was primarily due to the availability of reliable data. However, other features like lightning activity in North Sikkim, dry fuel biomass, and vegetation type could be considered to improve the model.

The forest fire prediction map of Sikkim Himalaya can be considered as a decision support tool for stakeholders of forest resources. Forest managers such as forest rangers and forest-dependent communities can mitigate forest fires by allocating their fire control resources to areas more prone to forest fire incidents. The population of forest fire-prone areas can be educated about the impacts of their activities on the occurrence of forest fire. Targeted law enforcement against irresponsible activities like illegal logging, negligent smoking and bonfire, slash and burn farming, and traffic management can be achieved from the forest fire prediction map.

## 5. Conclusion

Applications of remote sensing imageries, machine learning and geospatial analysis can mitigate forest fires by identifying areas that were relatively more prone to forest fire occurrences. MaxEnt-based forest fire prediction map of Sikkim Himalaya indicated that anthropogenic features, mainly road network, tree cover fraction and meteorological features were mainly accountable for forest fire incidents. Although, a forest fire can be considered as an opportunity for the forest to rejuvenate, an increase in the frequency and extent of forest fires can lead to damage of the forest health. The prediction map can be used as a decision support tool by the stakeholders to mitigate the occurrences of forest fires. The applications of MaxEnt can be extended to other forms of earth hazards like landslides, flood, and drought prediction. The MaxEnt model can be further improved by expanding the feature set, followed by factor analysis to identify the most relevant explanatory features of forest fires. A comparative analysis of the MaxEnt along with other machine learning methods can be performed to assess the efficiency and efficacy of the MaxEnt. The outcomes of this study can be internalized into forest management policies by applying geographically targeted resource allocation and law enforcement towards forest fire mitigation.

## Declarations

**Funding:** None

**Conflicts of interest/Competing interests:** None

**Availability of data and material:**

<https://doi.org/10.6084/m9.figshare.12894149.v1>

**Code availability:**

<https://doi.org/10.6084/m9.figshare.12894149.v1>

**Authors' contributions:** Planning, data gathering, data processing, modelling and interpretation.

**Acknowledgements:**

I acknowledge the use of data and imagery from LANCE FIRMS operated by NASA's Earth Science Data and Information System (ESDIS) with funding provided by NASA Headquarters.

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## Tables

Table 1: cross-correlation analysis of the environmental feature.

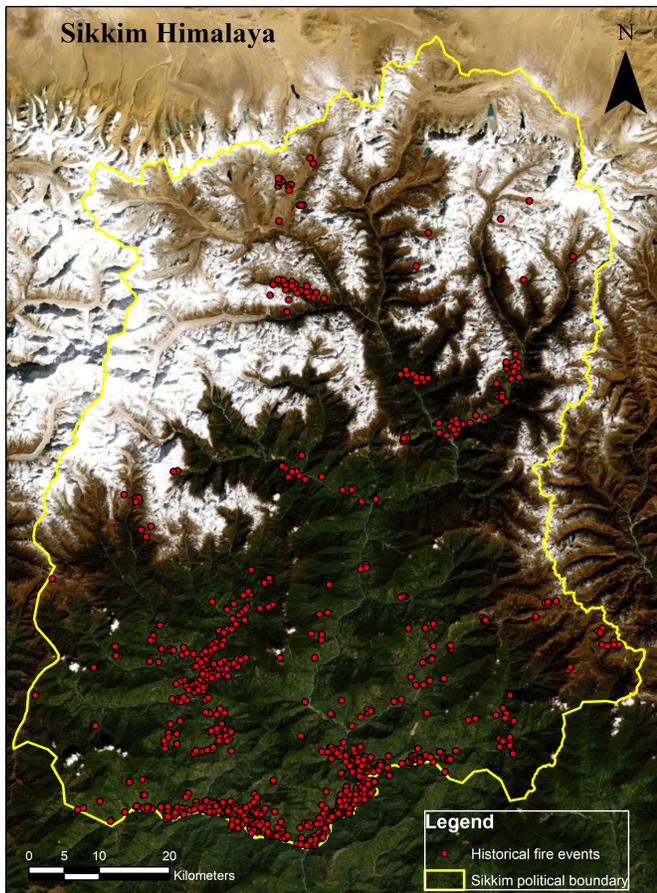
aspect	1.000													
avgPrep	-0.006	1.000												
avgTemp	-0.010	0.960	1.000											
avgWind	-0.016	-0.512	-0.510	1.000										
NDVI	0.075	0.343	0.336	-0.633	1.000									
PlanCurv	0.008	-0.006	0.003	0.012	-0.017	1.000								
popDen	0.045	0.709	0.718	-0.674	0.415	0.002	1.000							
profileCurv	0.003	-0.015	-0.009	-0.020	-0.024	-0.362	0.008	1.000						
proxPlace	0.013	-0.362	-0.354	0.491	-0.290	-0.032	-0.507	0.009	1.000					
proxRoads	-0.056	-0.362	-0.346	0.514	-0.393	-0.061	-0.539	0.051	0.613	1.000				
proxWater	0.008	-0.257	-0.272	0.225	-0.028	0.006	-0.307	-0.060	0.407	0.326	1.000			
slope	-0.097	-0.172	-0.155	0.032	0.055	0.013	-0.170	-0.063	0.031	0.139	0.059	1.000		
soilCarbon	-0.041	-0.532	-0.533	0.419	-0.162	-0.007	-0.760	0.003	0.387	0.357	0.214	0.098	1.000	
soilWater	-0.042	0.040	0.042	-0.052	0.110	-0.062	0.119	-0.056	0.095	0.001	0.102	-0.095	-0.028	1.000
treeCov	0.144	0.127	0.120	-0.278	0.604	-0.038	0.085	-0.032	0.053	-0.012	0.064	-0.019	0.126	
TWI	0.042	0.015	0.003	0.033	-0.068	-0.511	-0.018	0.217	0.033	0.015	-0.060	-0.391	0.041	
	<i>aspect</i>	<i>avgPrep</i>	<i>avgTemp</i>	<i>avgWind</i>	<i>NDVI</i>	<i>PlanCurv</i>	<i>popDen</i>	<i>profileCurv</i>	<i>proxPlace</i>	<i>proxRoads</i>	<i>proxWater</i>	<i>slope</i>	<i>soilCarbon</i>	<i>soilWater</i>

Table 2: Multicollinearity analysis of environmental features.

Features	VIF*
aspect	1.054
avgPrep	1.742
avgWind	2.416
NDVI	2.815
PlanCurv	1.612
profileCurv	1.181
proxPlace	1.904
proxRoads	1.943
proxWater	1.249
slope	1.388
soilCarbon	1.651
soilWater	1.071
treeCov	1.926
TWI	1.731

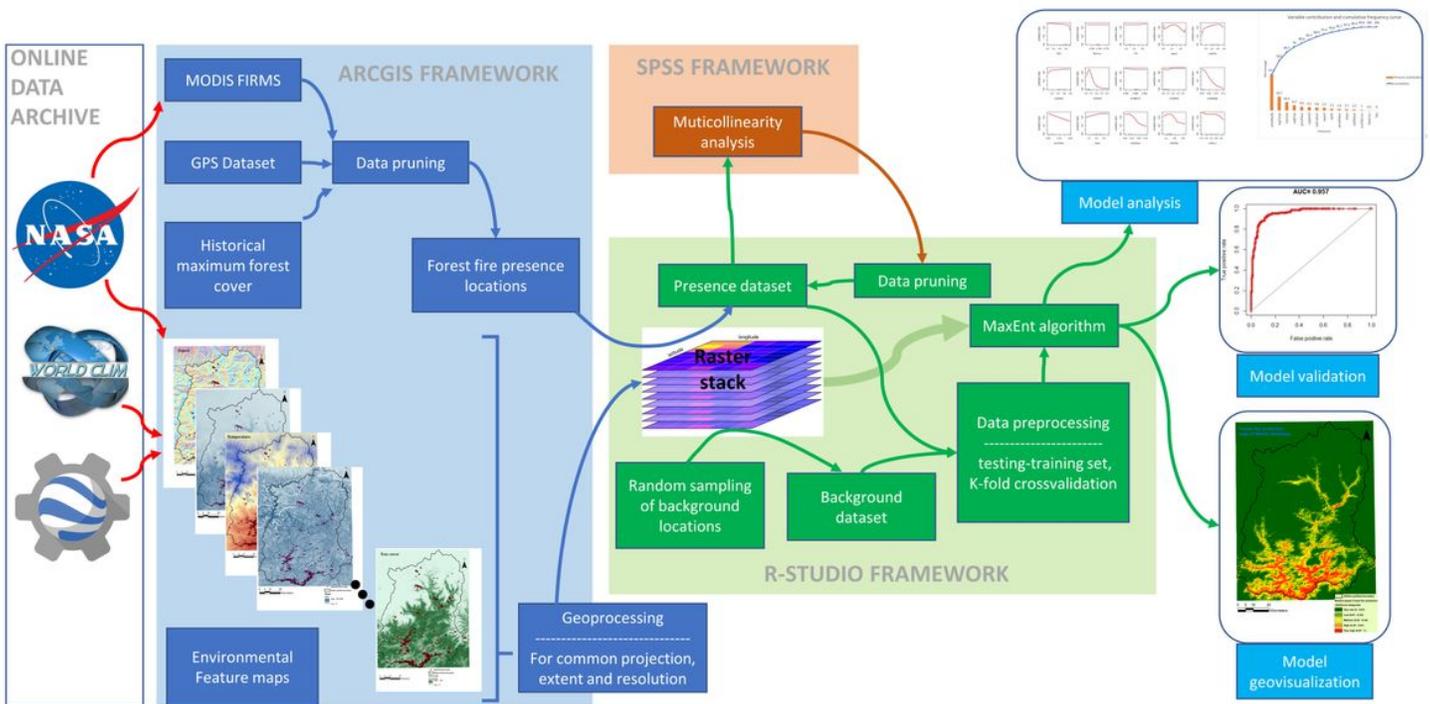
\*Independent variable is avgTemp

## Figures



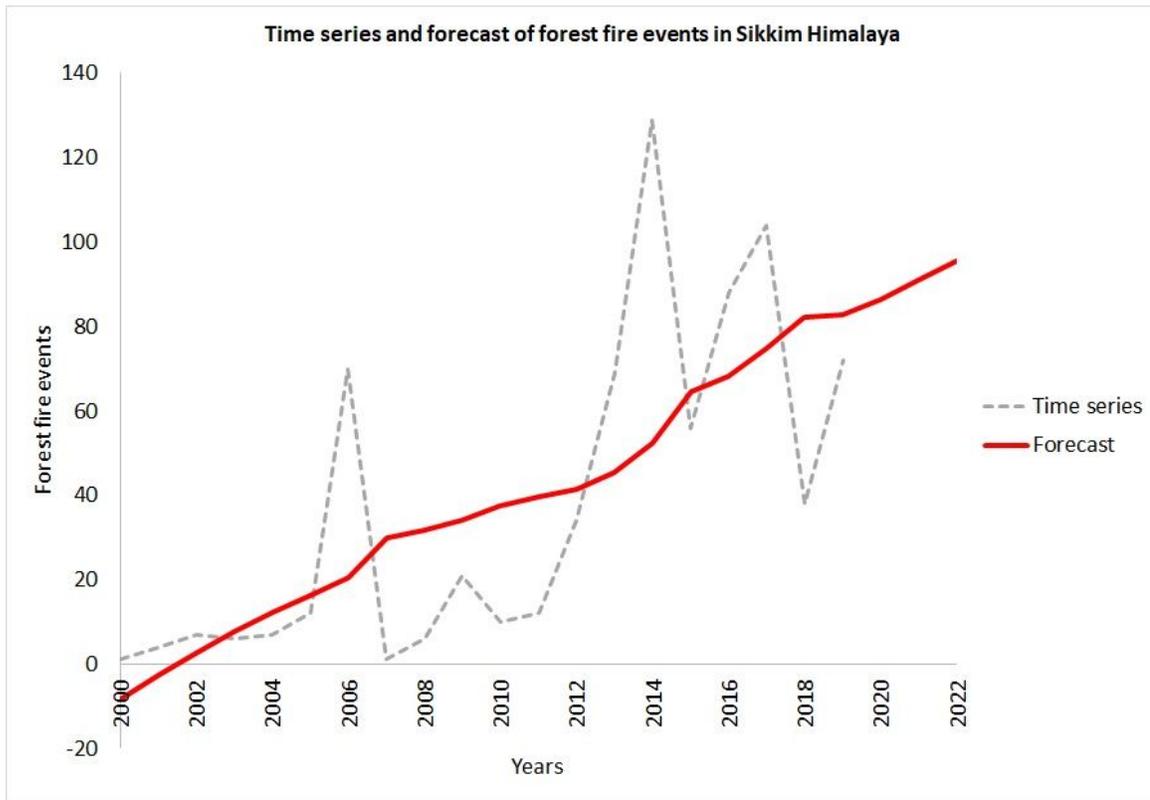
**Figure 1**

Study area. (a) Sikkim Himalaya is crowned in the north by snow-covered mountains including Mt. Khangchendzonga. The southern part of Sikkim has a wide variety of vegetation including several endemic flora and fauna, and water bodies in the form of streams and rivers. The human presence is reflected in the form of agrarian land, human habitations, dams, and a dense network of roadways. The forest fire events take certain patterns clustered along the roadways and valley areas. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.



**Figure 2**

Methodology of the model. Feature maps accessed from online archives like NASA, WorldClim and Google Earth Engine were geoprocessed as rasters with common data format, extent, resolution, and projection in the ArcGIS framework. The forest fire inventory was prepared from the GPS dataset and MODIS FIRMS. The feature maps were stacked and the forest fire dataset, as well as the background dataset, were populated with feature values in the RStudio framework. Feature multicollinearity was analysed in the SPSS framework. Data pruning was done wherever appropriate. The forest fire prediction map was prepared using the MaxEnt algorithm. The model was further evaluated using model validation and analysis criteria. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.



**Figure 3**  
 Forest fire trend analysis. Holt's forecast model was used to forecast the likelihood of forest fire events up to the year 2022. The forecast has an average boundary of  $\pm 62.343$  forest fire events from 2020 onwards.

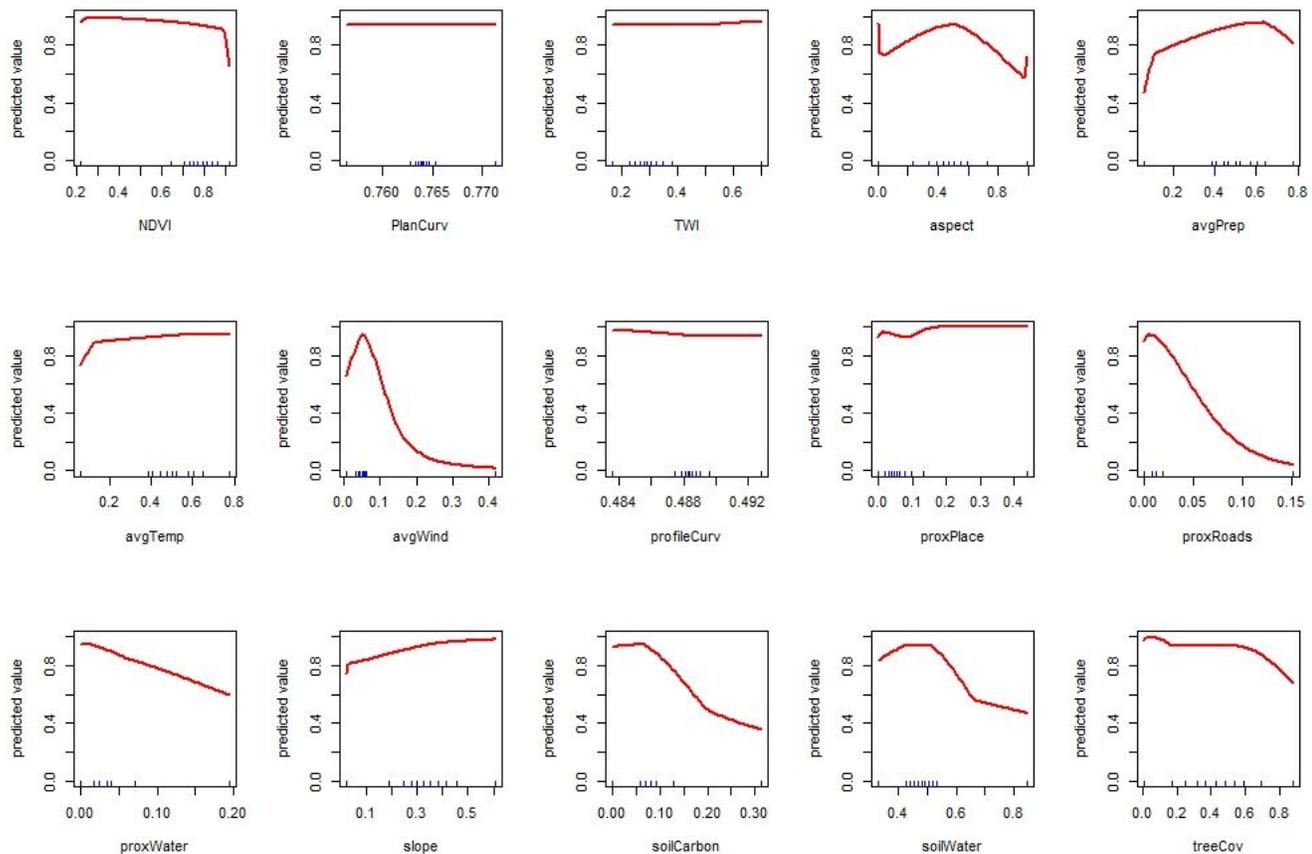


Figure 4

Response of the MaxEnt prediction to the feature values.

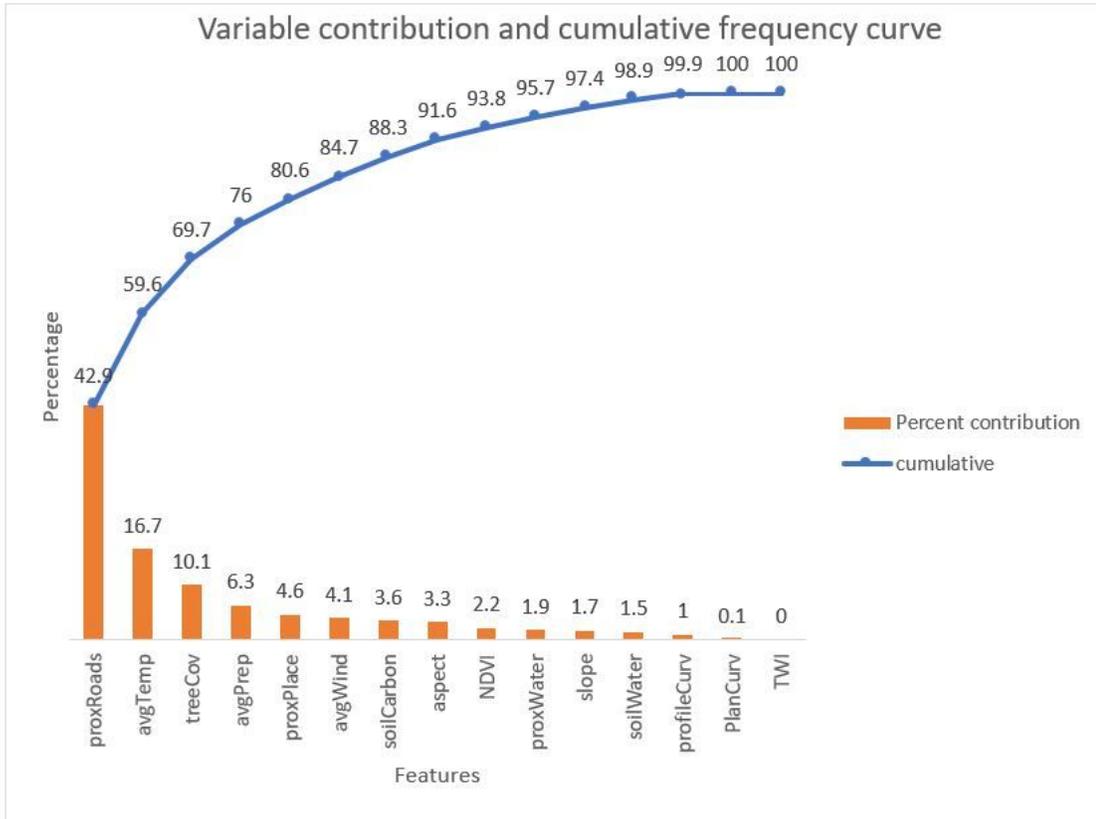
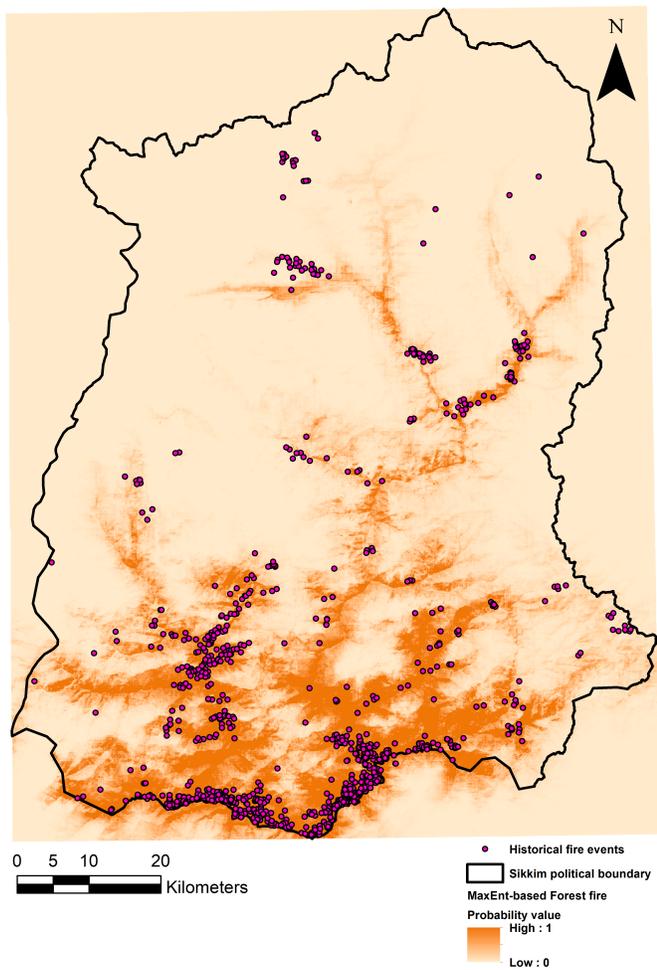


Figure 5

Importance of feature variables.



**Figure 6**

Spatial probability distribution map of forest fires over the study area based on the estimation of the MaxEnt model. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

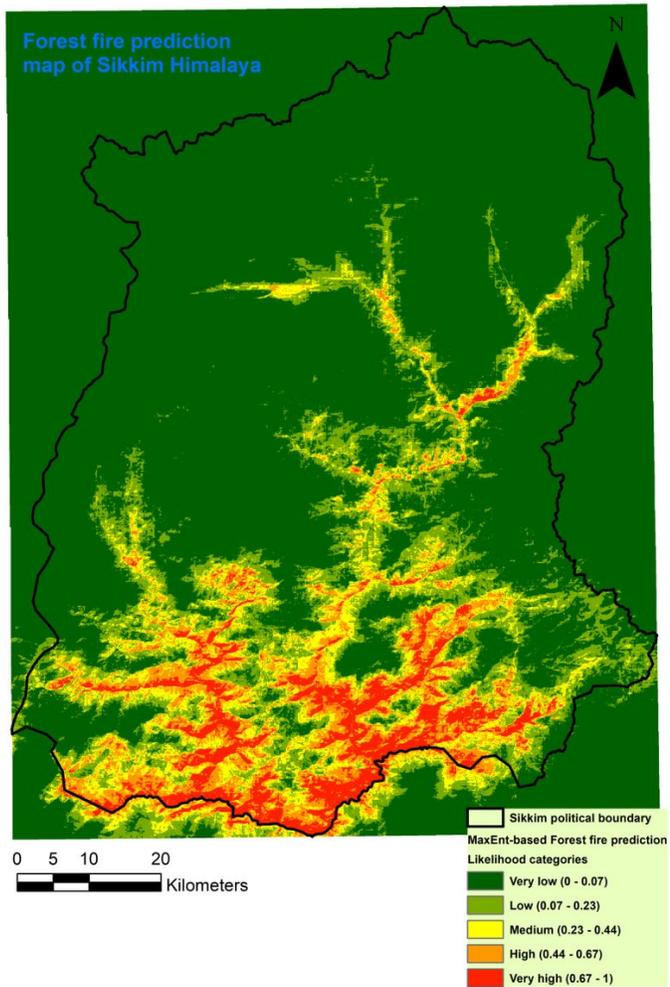


Figure 7

MaxEnt-based categorised forest fire prediction map of Sikkim Himalaya. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

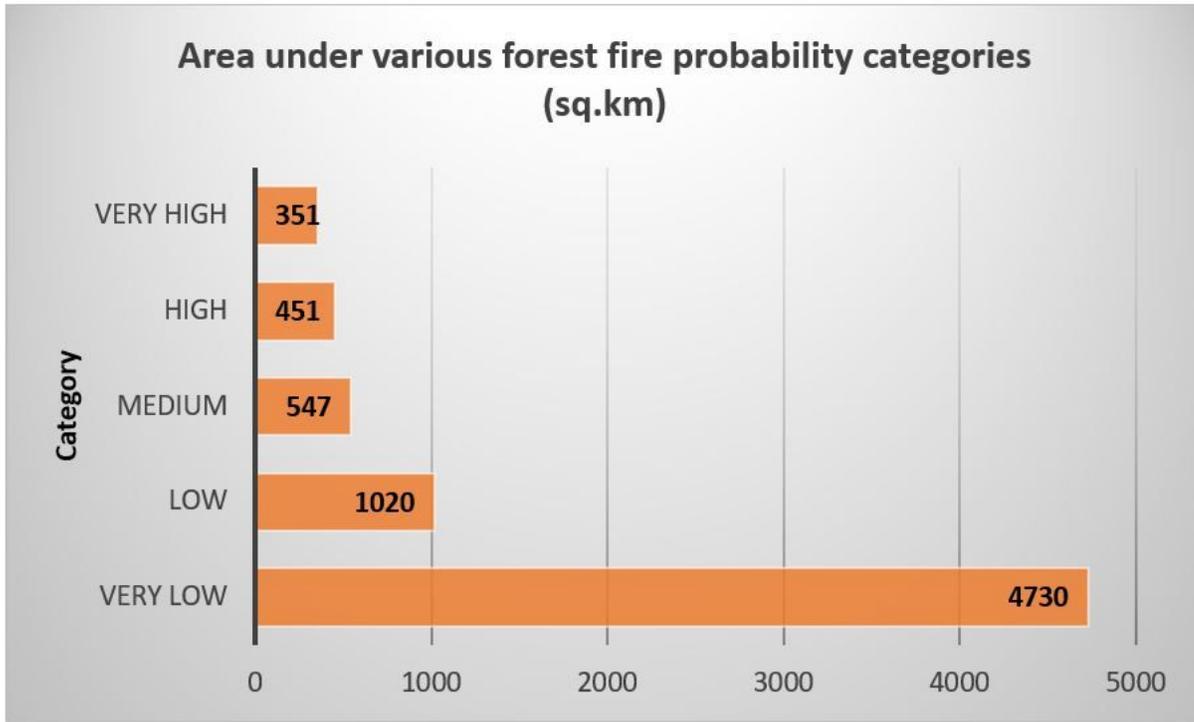


Figure 8

Forest fire likelihood category-wise distribution of the study area.

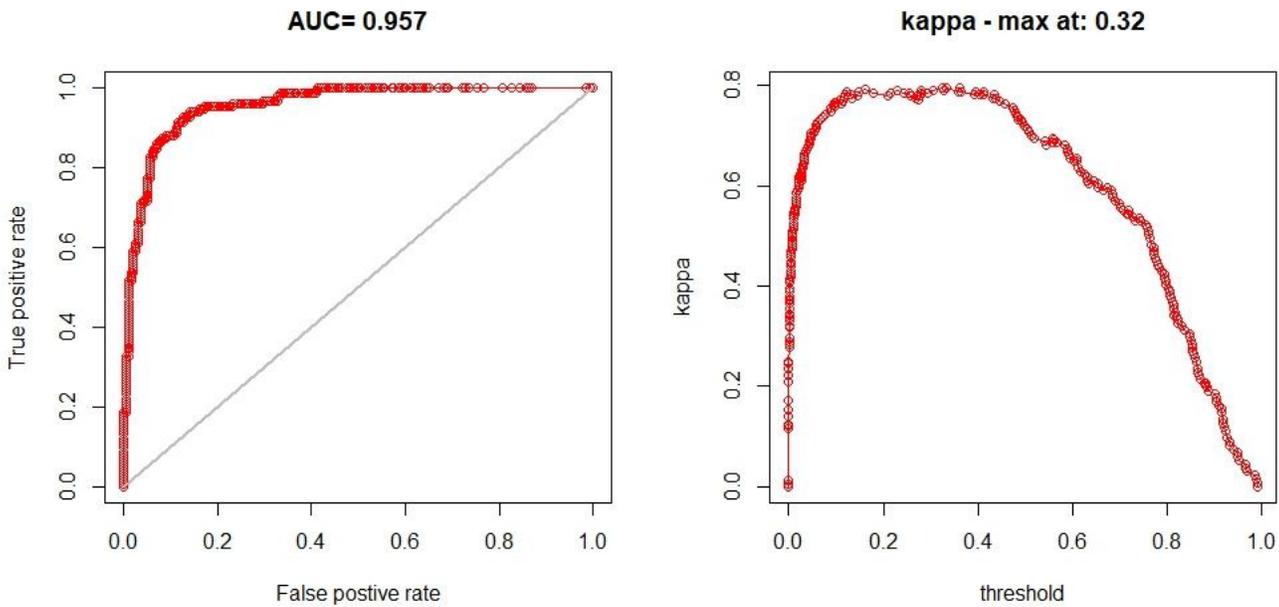


Figure 9

Model validation. (a: left:) ROC curve and AUC value. (b: right:) Cohen's Kappa curve.

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [3MaxEntLISTOFFIGURESonlyfeaturemapsassupplements.docx](#)