Stochastic Environmental Research and Risk Assessment (2020) 34:2259–2275
https://doi.org/10.1007/s00477-020-01872-3

ORIGINAL PAPER

Predictive modeling of forest fire using geospatial tools and strategic allocation of resources: eForestFire

Abdul Qayum[1] · Firoz Ahmad[2] · Rakesh Arya[3] · Rajesh Kumar Singh[4]

Accepted: 31 August 2020 / Published online: 14 September 2020
© Springer-Verlag GmbH Germany, part of Springer Nature 2020

Abstract
Fire is among major threats to the world's forests, leading to tremendous biodiversity losses. Forest fire in India has greatly increased in the last few decades; the state of Arunachal Pradesh, a recognized Himalayan biodiversity hotspot, is extremely prone to this disaster. The objective of this study was to develop GIS integrated mapping of direct and indirect factors, leading to a predictive model to identify settlements/villages for the strategic allocation of resources towards damage mitigation and control. Initial hotspots were generated by integrating factors of socio-economy, geography and climate, using differential weightage. The intersection of these with fire data, led to identification of final hotspots within the predictive model. The model was improved by linking it to a mobile App and the WebGIS portal. Of the 5258 settlements/villages, a total of 560 were found to be at high fire risk. Percentage correlation increased from 63 to 74, after data revision through the App. A focused intervention on predicted villages was undertaken, resulting in a decrease of 31% of fire incidence in comparison of last five years (2015–20) data. Such advanced information about fire disaster with optimal use of limited resources was greatly helpful, and helped protect the rich Himalayan biodiversity.

Keywords Forest fire · Biodiversity · GIS mapping · eForestFire · e-governance · Predictive model · Arunachal pradesh

1 Introduction

There have been increased global forest fire linked threats in the recent past (Pandey 2018), which have the potential to bring systematic changes in the functions of many ecosystems (Bond and Keeley 2005; Donald et al. 2004). The Australian fire (Shukman 2020) and Amazon fire (Yadvinder et al. 2009) were largely climate linked disasters, but also occurred in part due to improper local forest management practices, leading to the tremendous loss of biodiversity. Climatic conditions are important in determining vegetation distribution and the local ecology of forests (Kirschbaum et al. 1996). Climate interacts significantly with vegetation (Sharma and Rikhari 1997), and its severity plays a crucial role in forest fires (Harrison et al. 2010). The temperature during the summer enhances evapo-transpiration and makes the forest floors very dry (Vicente-Serrano et al. 2010). Factors such as a prolonged summer, absence of precipitation for long periods, and reduction in the number of rainy days, aggravate the situation and increase the probability of forest fire. The dynamics of fire in forests are largely dependent on accumulated fuel composed of dried leaves, twigs or stems (Finney 2001), weather severity (Koutsias et al. 2012), presence of ignition source and forest dependent human population (Bradstock 2010).

Fire incidences adversely impact the ecology of the forest (Roy 2003), wildlife habitat (Engstrom 2010), microclimate, biodiversity (Tropical 2001), air quality (Riebauand Fox 2001), causes damage to the other environmental, recreational values (Davidenko and Eritsov 2003) and negatively affects the socio-economic conditions and livelihood of the forest-dependent communities (Aggarwal

✉ Abdul Qayum
agmu247@ifs.nic.in

[1] Department of Forest and Wildlife, UT Administration, Chandigarh, India

[2] Vindhyan Ecology and Natural History Foundation, Mirzapur, Uttar Pradesh, India

[3] Center for the Study of Regional Development, School of Social Sciences JNU, New Delhi, India

[4] Department of Environment and Forests, Govt of Arunachal Pradesh, Itanagar, India

et al. 2009). Socio-economic factors are critically linked to forest fires (Kim et al. 2019) and fire incidences are largely due to the activity of forest-fringe human populations (Flannigan et al. 2005).

The cause of forest fires in India is anthropogenic in nature and typically linked to an accident or due to the negligence. In tropical dry deciduous forests, fire occurs due to the faulty traditionally old collection procedure of *Madhuca indica* flowers and to enhance better flush of *Diospyros melanoxylon* leaves during summer (Dwyer et al. 1999; Ahmad et al. 2018). Shifting cultivation which involves slash and burnforests is prevalent in almost every part of north-eastern India (Raman et al. 1998), and the state of Arunachal Pradesh is no exception. It is one of the most widely followed traditional practices in the tribal-dominated Asian regions (Heinemann et al. 2017), largely exercised in India by the forest dominated communities, and is a major reason of forest fires. Ahmad et al. (2018) has characterized factors affecting Himalayan forest fire for the state of Arunachal Pradesh, India. Local communities living under poor socio-economic conditions at the forest fringes, continue to burn forests in order to meet their livelihood needs (Saha 2002).There are studies on forest fires at regional as well as national level, highlighting the interweaving relationship of fire driving factors in India (Ahmad and Goparaju 2018, Ahmad et al. 2017).

Predictive modeling is a basic tool used, in this case, for planning and protecting the forest from degradation, and it significantly supports environmental sustainability (Eugenio et al. 2016; Mercer and Prestemon 2005). It is the process of forecasting the outcomes by the integration of various dependent aspects, through specialized software after cross-validating using statistical methods (Rouse 2018). It can be potentially applied to geographical information system (GIS) especially in forest fire modeling (Zhijun et al. 2009; Leblon et al. 2002; Chandra 2005).

Geospatial systems such as remote sensing and GIS are powerful tools to evaluate forest fire risks and trends (Yang et al. 2007; Ahmad and Goparaju 2017; Chavan et al. 2012). A study by Giriraj et al. (2010) using Advanced Along Track Scanning Radiometer (A) ATSR night-time satellite data revealed that the Central Highlands, Eastern Highlands, Central Plateau and Deccan peninsula were the most affected high fire prone zones and accounted for approximately 36% of the total fire incidences in India during 1997–2005.

This study was intended to predict forest fire points by utilizing decadal forest fire data from the Forest Survey of India (FSI), and mapping it on the GIS platform with the objective to analyze forest fire events and their distribution, and generate fire hotspots at the lowest administrative unit (village level). The work integrates various direct and indirect factors of socio-economy, as well as geographic and climatic factors, to find the initial hotspot and its correlation with actual data obtained from FSI. It aimed to obtain a predictive model by integrating actual and remote sensing data of fire inducing factors to obtain hotspots, for the strategic allocation of limited government resources, which ultimately leads to an early warning system (Sharma and Pant 2017). The spatial analysis of forest fires in Arunachal Pradesh was carried out based upon the decadal (2008–2016) forest fire count datasets, and analyzed for spatial variability in diverse geographical and socio-economic gradients (Ahmad et al. 2018).Forest fire frequency, occurrence and its extent of spread worldwide can be characterized by weather and climatic condition, landscape fuel characteristics, ignition agents, and anthropogenic factors (Leone et al. 2003).

The study aimed to bring in the citizen science approach in forest fire management, by developing a Mobile App to gather data that would help in the prediction of fires and allocation of resources specifically in the context of Himalayan geography. The predictive model would integrate forest fire affecting factors such as poverty (Ahmad et al. 2018), population density (Survey of India topo sheet), forest cover (Hansen et al. 2013), forest type (Roy et al. 2003), long term (1970–2000) annual temperature and rainfall (Fick and Hijmans 2017), slope and elevation (ASTER DEM). The prime aim was to devise a method to take 'Right Method', at 'Right Time' and at 'Right Place' i.e. how, when and where to intervene to mitigate fire-linked disasters. There has been a research gap in the area of fire predictive modeling (Finney et al 2011), which requires significant support in the form of government resources in this tribal-dominated Himalayan state of Arunachal Pradesh, which is noted for its diverse forest types/cover, topography, climate condition, and complex socio-economics.

2 Material and methods

2.1 Study area

The state Arunachal Pradesh is known for Himalayan biodiversity, with a forest cover of 79.6% of the geographic area (FSI 2019), extending from 26°37′23′′N to 29°27′30′′N latitude and 91°32′36′′E–97°24′42′′E longitude, with an area of 83,743 km^2 and a human population of 1.38 million, of which 68.8% are tribal. Arunachal Pradesh is bounded by the international borders of Bhutan, Tibet, China and Myanmar (Fig. 1). The state has a vast topographic variation, with altitude varying from 60 to 7000 m MSL and receiving an annual rainfall of 2000–5000 mm. Shifting cultivation is the major agricultural practice, where land is cleared for growing crops by

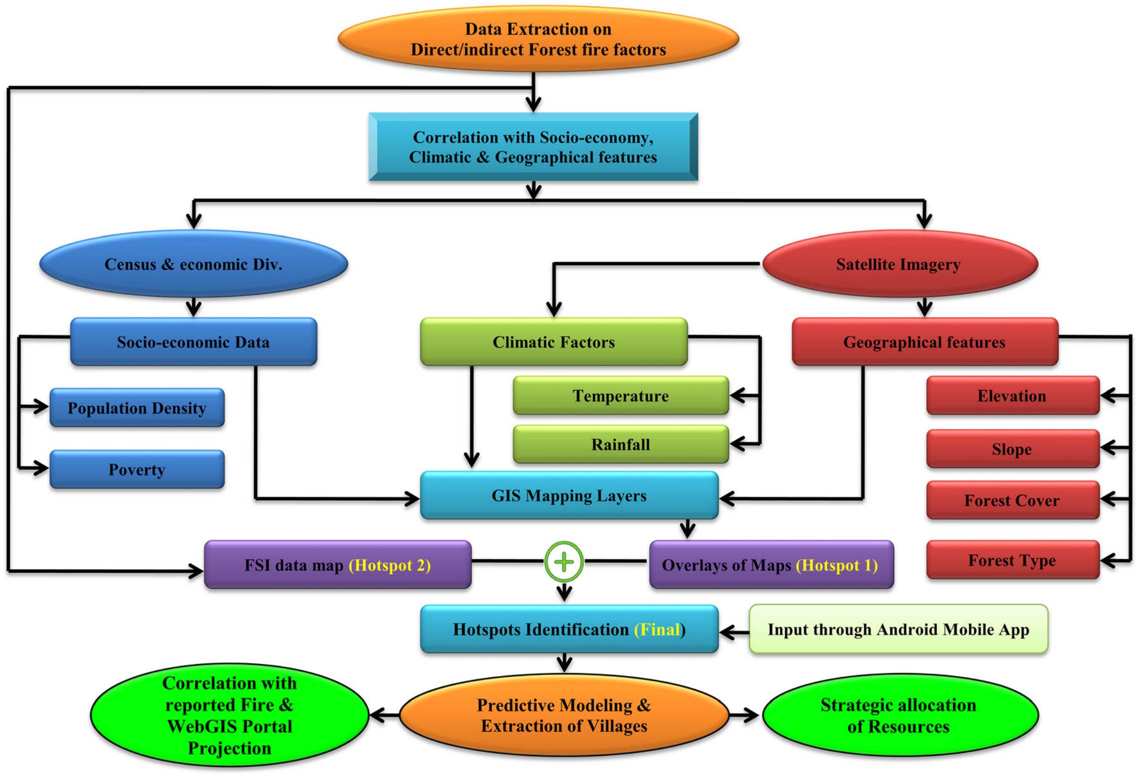


Fig. 1 Schematic flowchart for the Predictive modeling

first removing vegetation and then burning it (Ramakrishnan 1993). This area was selected as it has alarming forest fire incidences (Ramya 2012). Research on fire with predictive modeling will greatly help in mitigating forest fire devastations, by making available an early warning system, which will significantly help in safeguarding the fragile Himalayan ecology of this area.

2.2 Schematic flowchart and data attributes

Eight direct and indirect factors affecting forest fires were taken based upon extensive literature survey and stake holder's consultation (Ahmad et al. 2018), apart from the distribution of fire across different vegetation types (Vadrevu et al. 2013) and evaluation of spatio-temporal dimension (Pew and Larsen 2001). From this, individual maps were produced and it was the initial hotspot (Hotspot 1). The FSI (nine year) data was also mapped to analyze the forest fire incidence reported from the state (Hotspot 2). These hotspots corresponding to nine factors were integrated using weighted mean to get final hotspots or priority settlements/villages, in order to derive the predictive model (Fig. 2).

Data used, attributes and rationale of using the data are given in Table 1.

2.3 Forest fire factors, pre-processing and statistical analysis

Forest fire factors were extracted for the modeling purposes, while the fire real-time data for the period 1-1-2018–31-12-2018 of NASA Fire Information for Resource Management System was used for cross-validation of the model outcome. Initially, grids of 5 × 5 km shapefiles were created and projection (UTM Zone-46) was assigned, which generated a total of 3,582 grids. All raster data were evaluated over the generated grids on ArcGIS 10.1 through 'Spatial analyst tool'. Mean raster values of each parameter was systematically joined and stored in the attribute column of grid shape files.

Before the true model, each parameter was analyzed and its relationship with forest fire points was evaluated (Table 1) using Cramer's V coefficient (CVC) statistical method (Liebetrau 1983). The CVC values were calculated as per Eq. (1),

$$V = \sqrt{\frac{\varphi^2}{\min(k-1, r-1)}} = \sqrt{\frac{\chi^2/n}{\min(k-1, r-1)}} \tag{1}$$

where φ is the coefficient of contingency, χ is derived from Pearson's chi-squared test, n is the grand total of observations, k represents the number of columns and r represents number of rows in the month-wise forest fire

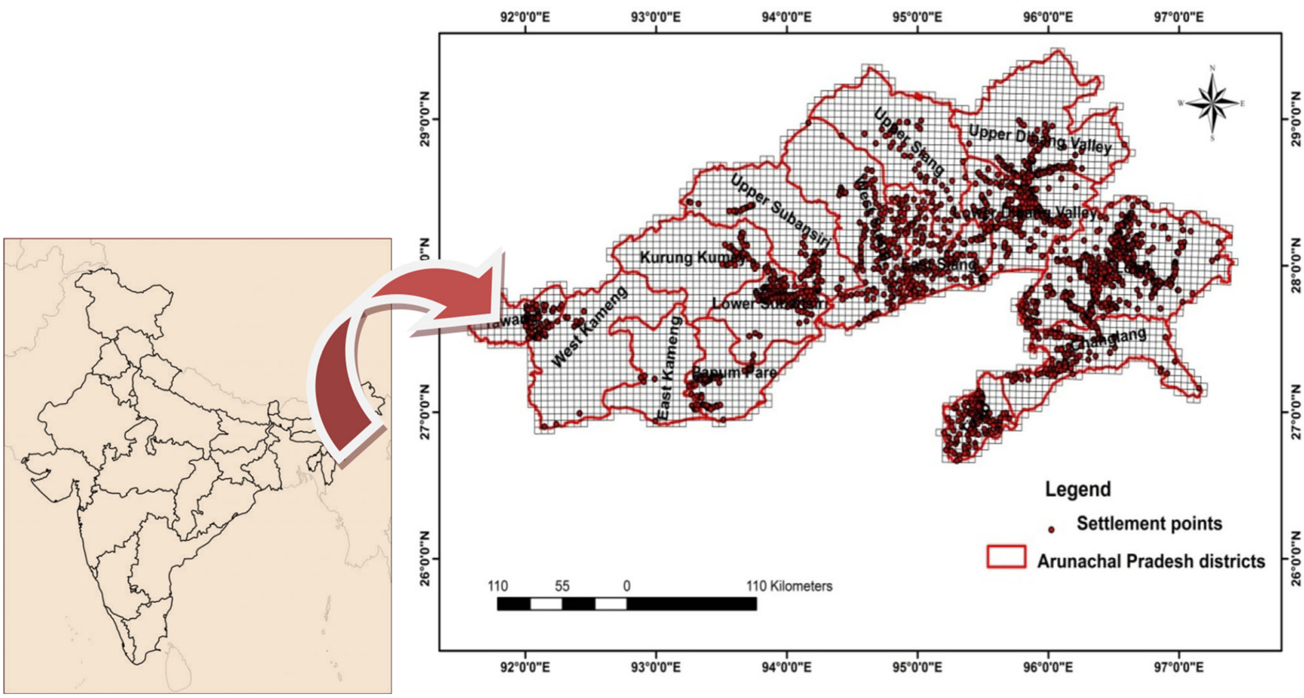


Fig. 2 Study area: settlements of Arunachal Pradesh, India

Table 1 Data attributes and rationale

S.No	Data used	Attributes	Rationale
1	MODIS	Forest fire detection	36 spectral bands
2	ASTER- DEM	Topography (Elevation and slope)	30 m spatial resolution with 20 m and 30 m accuracy for vertical and horizontal data with 95% CI
3	SPOT4	Vegetation	1 km resolution
4	National Centers for Environmental Prediction (NCEP)- Climate Forecast System Reanalysis	Meteorology	Datasets such temperature, precipitation, wind velocity, relative humidity and solar radiation are available on daily basis

frequency. CVC was preferred over simple Pearson correlation coefficient to examine the relationship because, under heavy noise conditions, extracting correlation coefficient between two sets of stochastic variables is non-trivial and analysis may lead to a degraded correlation.

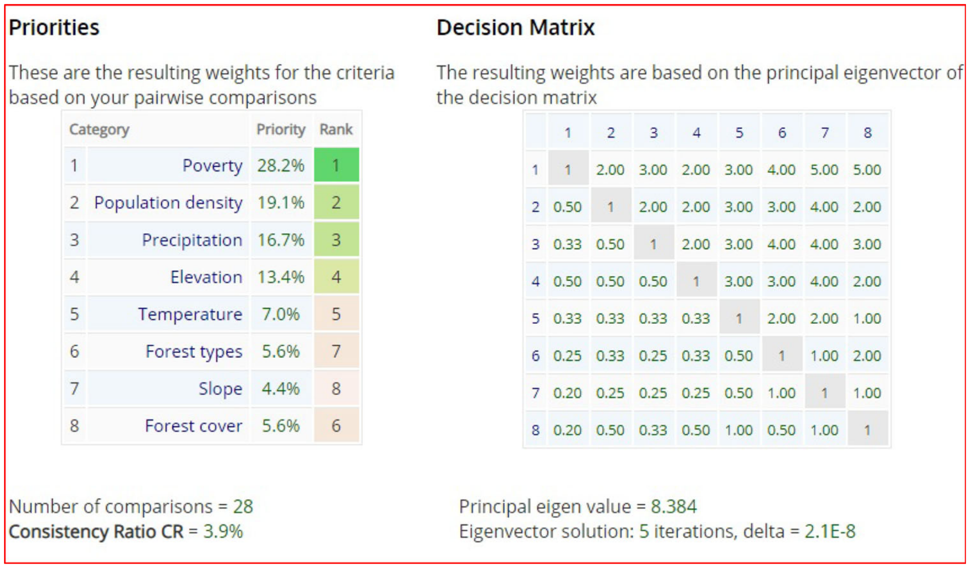
The individual maps (Figs. 5, 6 and 7) were assigned mean weight based on inputs observed in statistical findings of CVC (Table 2) and in conjugation with in situ experience by the process of Analytic Hierarchy Process (AHP) calculated (Fig. 3) using pair wise comparison (Hamid et al. 2016; Saaty 1980). The weight of each parameter obtained through AHP was corrected based upon the field findings and experts' opinion (Table 2, Column 4), which was used subsequently for developing the initial hotspot (Hotspot 1) by integrating all eight risk driving factors (Fig. 8A).

Table 2 Crammer's V coefficients of fire risk driving factors

Socio-economical features	Population density	0.51	20%
	Poverty	0.72	30%
Geographical features	Forest cover	0.32	5%
	Forest type	0.37	5%
	Slope	0.34	4%
	Elevation	0.42	13%
Climatic features	Temperature	0.39	7%
	Precipitation	0.44	15%

2.4 Data extraction and sources

Different data sets with attributes and rationale were used in the study (Table 1). Spatial Analyst tool was employed



Priorities

These are the resulting weights for the criteria based on your pairwise comparisons

	Category	Priority	Rank
1	Poverty	28.2%	1
2	Population density	19.1%	2
3	Precipitation	16.7%	3
4	Elevation	13.4%	4
5	Temperature	7.0%	5
6	Forest types	5.6%	7
7	Slope	4.4%	8
8	Forest cover	5.6%	6

Number of comparisons = 28
Consistency Ratio CR = 3.9%

Decision Matrix

The resulting weights are based on the principal eigenvector of the decision matrix

	1	2	3	4	5	6	7	8
1	1	2.00	3.00	2.00	3.00	4.00	5.00	5.00
2	0.50	1	2.00	2.00	3.00	3.00	4.00	2.00
3	0.33	0.50	1	2.00	3.00	4.00	4.00	3.00
4	0.50	0.50	0.50	1	3.00	3.00	4.00	2.00
5	0.33	0.33	0.33	0.33	1	2.00	2.00	1.00
6	0.25	0.33	0.25	0.33	0.50	1	1.00	2.00
7	0.20	0.25	0.25	0.25	0.50	1.00	1	1.00
8	0.20	0.50	0.33	0.50	1.00	0.50	1.00	1

Principal eigen value = 8.384
Eigenvector solution: 5 iterations, delta = 2.1E-8

Fig. 3 Weight matrix (initial)—Using pair wise comparison (AHP)

to generate thematic layer and digital elevation model (DEM) for elevation and slope extraction. For socio-economy, methodology from Nair et al. (2013) was used for generating a poverty and population density map; subsequently it was brought into the GIS domain, of which 'Vegetation Instrument' was used to extract vegetation cover. The fire events in each vegetation class were analyzed. Meteorological datasets (1979–2004) of NCEP were extracted and exported onto the ArcGIS platform for further analysis.

2.5 GIS integrated mapping: hotspot identification

Individual maps were prepared for all eights factors and were integrated to identify an initial hotspot, which was also correlated with the ninth factor (FSI Forest Fire 2019); later all these nine factors were integrated to find a final hotspot and was called predictive model. Subsequently, villages/human settlements were extracted to analyze spatio-temporal trend during the years 2008 to 2016. Fire data was downloaded from FSI, which was developed with the use of MODIS (Terra/Aqua). The administrative boundary of Arunachal Pradesh state and districts were obtained from DIVA-GIS. Subsequently, forest fire hotspots were detected as follows:-

1. GIS layers for 8 factors were created individually based on natural breaks classes
2. Individual layers were integrated, using differential weights (Table 2, Column 4) and mathematical Eq. (3)
3. Final Fire Hotspot (FHS)

$$\mathbf{FHS} = \mathbf{HS_1} \cap \mathbf{HS_2} \tag{2}$$

where $\mathbf{HS_1}$ is integrated mapping of Socio-economy, Climate and Geographical factors (hotspot 1), $\mathbf{HS_2}$ is hotspot 2 corresponding to cumulated fire data of 2008–2016, while the final hotspot (Qayum et al. 2015) is defined as -

$$HS = \prod_{1}^{n} n = (factor\ 1)(factor\ 2)\ldots(factor\ n) \tag{3}$$

4. Multiplicative (not additive) function was used to optimize the respective ranks of forest fire factors/GIS layers.
5. Citizen centric input was obtained through the linked Android App (eForestFire), which was used to refine the predictive model at step 3.
6. A webGIS portal (www.webgis.co.in) was also linked through JSON file to obtain live fire point maps, apart from revised hotspot or predicted villages on a real time basis.
7. The list of priority villages was extracted as the outcome of the predictive model.

3 Results

A total of 560 villages/settlements were found to be at high risk of fire, out of the total of 5,258 extracted (***Additional file, attached***). The initial percentage correlation of forest fire factors with satellite data was 63%, which increased to 74% after revision of the model by adding the input from citizens through the Android mobile App, reporting actual fire cases on ground. As per the reports obtained from the NASA, a decrease of 31% in fire incidence was reported in year 2019 in comparison to the last five years, due to focused and strategic intervention on the predicted high fire risk villages, and some other initiatives taken in the state (Fig. 4). The CVC values of various factors affecting forest fire were found to be more than 0.3 (Table 2). Wang et al. (2016) explains that CVC values greater than 0.3 show strong relationships with the driving factors.

3.1 Individual layer mapping for fire factors

Socio-economic factors (Figs. 5A and B), climatic factors (Figs. 6A and B) and geographical factors (Figs. 7A-D), were mapped individually first and later integrated using differential weighted mean (Table 2) and Hotspot 1 (Fig. 8A) was obtained separately from Hotspot 2 using fire data points (Fig. 8B). Subsequently, the final hotspot (Fig. 8C) was obtained from both hotspots, as an outcome of the predictive model.

3.2 Socio-economy maps

Of the forest fire points, 42.3% were found in high poverty index area, while 73% of forest fire occurred in areas where population density was 6–50. Altobellis (1983) and Mercer and Prestemon (2005) found that occurrence of forest fire and its intensity is positively correlated with rural population density and poverty.

3.3 Climatic factors maps

The meteorological station (ID-283947) recorded the data for all parameters from 01-01-1979 to 31-12-2014 on a daily basis, and this was analyzed to establish if there was a relationship with fire incidence. The temperature during the hot weather enhances the rate of evapo-transpiration, making the forest drier and prone to fire, whereas precipitation significantly influences the fuel moisture (Swetnam and Betancourt 1998; Littell et al. 2009). The rainfall map showed the mean annual precipitation in the range of 369

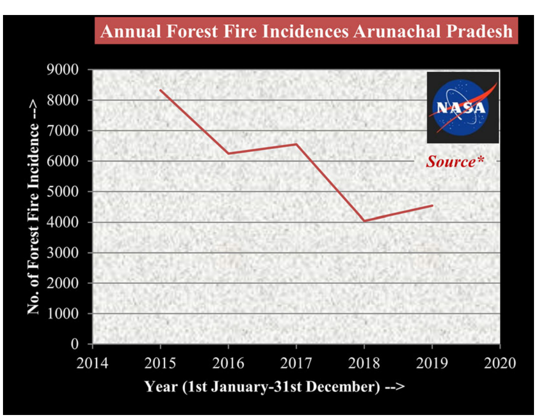


Fig. 4 Forest fire incidences (NASA FIRMS, Data—MODIS C6 and VIIRS) *

to 3206 mm (Fig. 6A). The southern parts of Arunachal Pradesh have significantly higher precipitation. Bhagawati et al. (2017) also found a similar precipitation profile in the state. The mean annual temperature varies from the Himalayan mountaintops to the foothills. On the northern side, the mean temperature was found to be much lower than in the southern plains and along the foothills, where it varies from 23 to 26.4 °C (Fig. 6B).

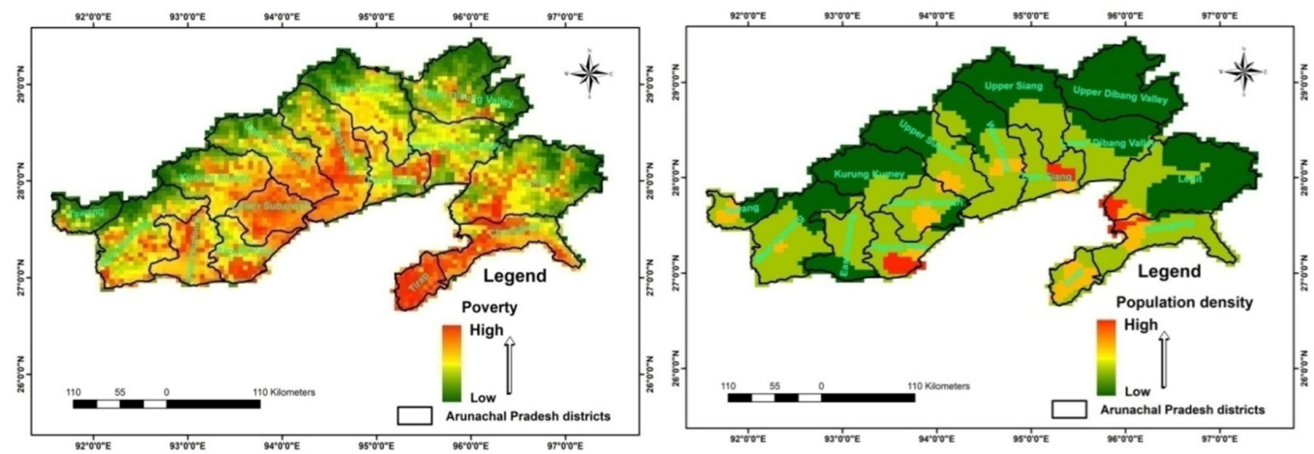
3.4 Geographical features analysis

The maximum fire incidences were found in the lower elevation regions with altitude less than 1500 m (Fig. 7A). The altitude is relatively high in the northern part of the state, the Himalayan region, and very low in the southern plains. Elevation affects velocity of the wind and temperature, and it is an important geographic parameter which affects the fire vulnerability (Rothermel 1991). The average slope varies significantly along the elevation gradients, and is high in the districts of Lohit, Lower and Upper Dibang Valley (Fig. 7B). The rate of fire spread is higher uphill than downhill, thus there will be faster movement of fire in high gradient areas (Kushla and Ripple 1997).

Geographical features and its distribution pattern have a significant relationship with fire (Vadrevu et al. 2008; Matin et al. 2017). These attributes affect the wind pattern and determine the rate and direction of the fire spread, and finally determine area damaged by fire. The forest fires vary across different forest types (Ahmad et al. 2019). Some forest types are ideal habitats for good faunal and floral diversity, apart from valuable timber species with high tree density. The study area is also known as one of the mega biodiversity zones of the world (Myers et al. 2000). The state has very diverse forests, such as tropical and sub-tropical mountain forests, broadleaved, and evergreen at elevations of more than 1000 m (Fig. 7C).The forest cover map revealed that dense forest regions are primarily found in the southern parts, and are more prone to fire (Fig. 7D).

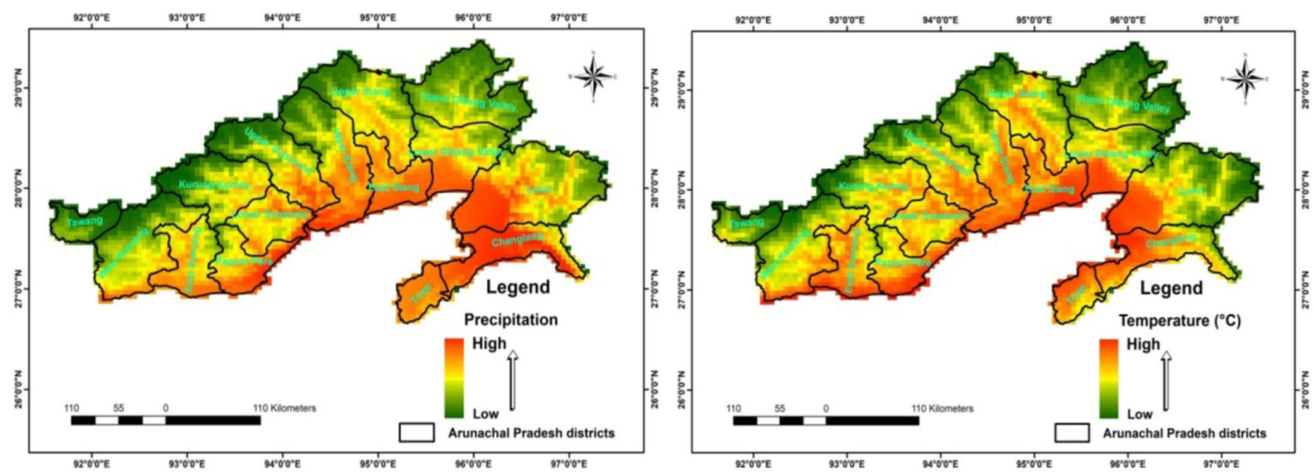
4 Integrated mapping: Forest fire hotspot

The predictive model was derived from the final hotspot obtained from hotspots 1 and 2 (Fig. 8 A and B). The list of villages/settlements extracted is the outcome of model (Fig. 8C). The list is periodically modified if there is substantial change observed on the fire affected ground, or if there are many new inputs through the mobile App about actual occurrence of forest fire. The study highlights the significant relationship of forest fire with bio-physical or physio-geographical and socio-economic dimensions. The evaluation of the map significantly revealed the high



(a) Poverty **(b)** Population density

Fig. 5 **a** Poverty **b** Population density



(a) Rainfall map **(b)** Temperature map

Fig. 6 **a** Rainfall map **b** Temperature map

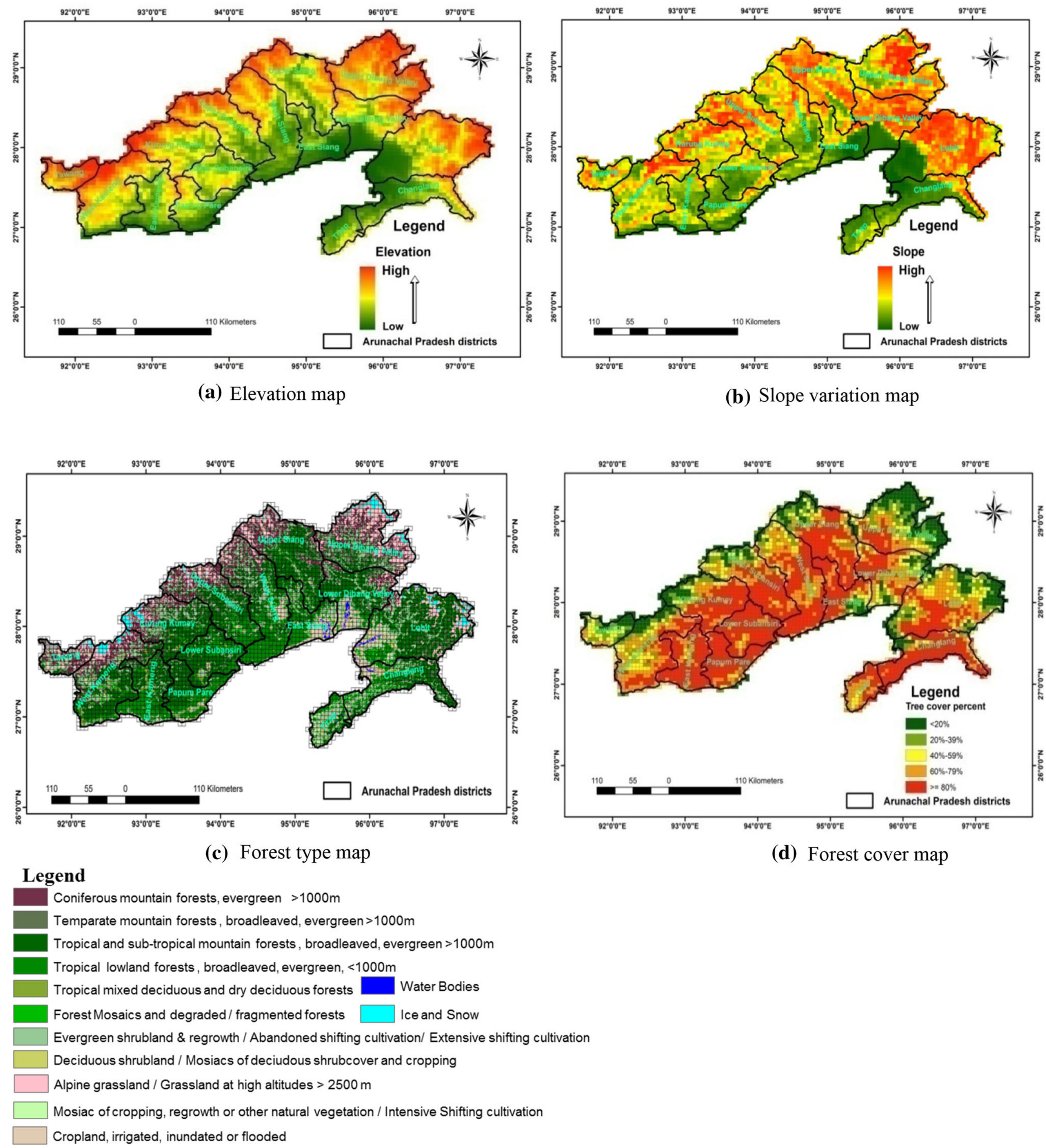
intensity of fires in the districts of Tirap and Lower Subansiri.

In southern Arunachal Pradesh, the areas affected most by forest fires were east and west Kameng districts. The increasing availability of detailed and accurate spatial datasets of forest fire enable in identifying forest fire hotspots and their extent, thereby aiding in the management and prevention of forest fire (Stocks et al. 2002).

5 Correlation matrix: Initial fire hotspot analysis and validation

A correlation was drawn against various direct and indirect factors to find inter-weaving behavior among factors affecting fire (Table 3). A correlation of 63% was found with the factors of the hotspot mapping (Hotspot 1) with FSI data on ground (Hotspot 2).

A cross-validation was done by generating 100 random points with point vector file, and two columns were created. The first column represented all the grid values of fire factors (Hotspot 1) and the second column was the value of fire hotspots generated from satellite data for the period 2008–2016. The CVC was found to be 0.51, while correlation coefficient (significant at 0.01 levels, 2-tailed) was found to be 0.612. The investigation using statistical methods and in situ validation, highlight that fire vulnerability is significantly related to geo-economic vulnerability.



(a) Elevation map **(b)** Slope variation map

(c) Forest type map **(d)** Forest cover map

Fig. 7 **a** Elevation map **b** Slope variation map **c** Forest type map **d** Forest cover map

6 Fire reporting system (eForestFire)

Fire Reporting System is the quick process of bringing fire-related information meaningfully up to the village level, and the efficient interaction of local people with Government officials. The WebGIS portal was developed with manifold functional details (Table 4). The data obtained through Android Mobile App ‘eForestFire’ ensured the functionality in terms of efficiency and better services, which bridges the predictive model with the portal. The App can be freely accessed from the Google Play Store (Android App, 2019). These services were extremely useful in terms of interactions, raising awareness and visibility

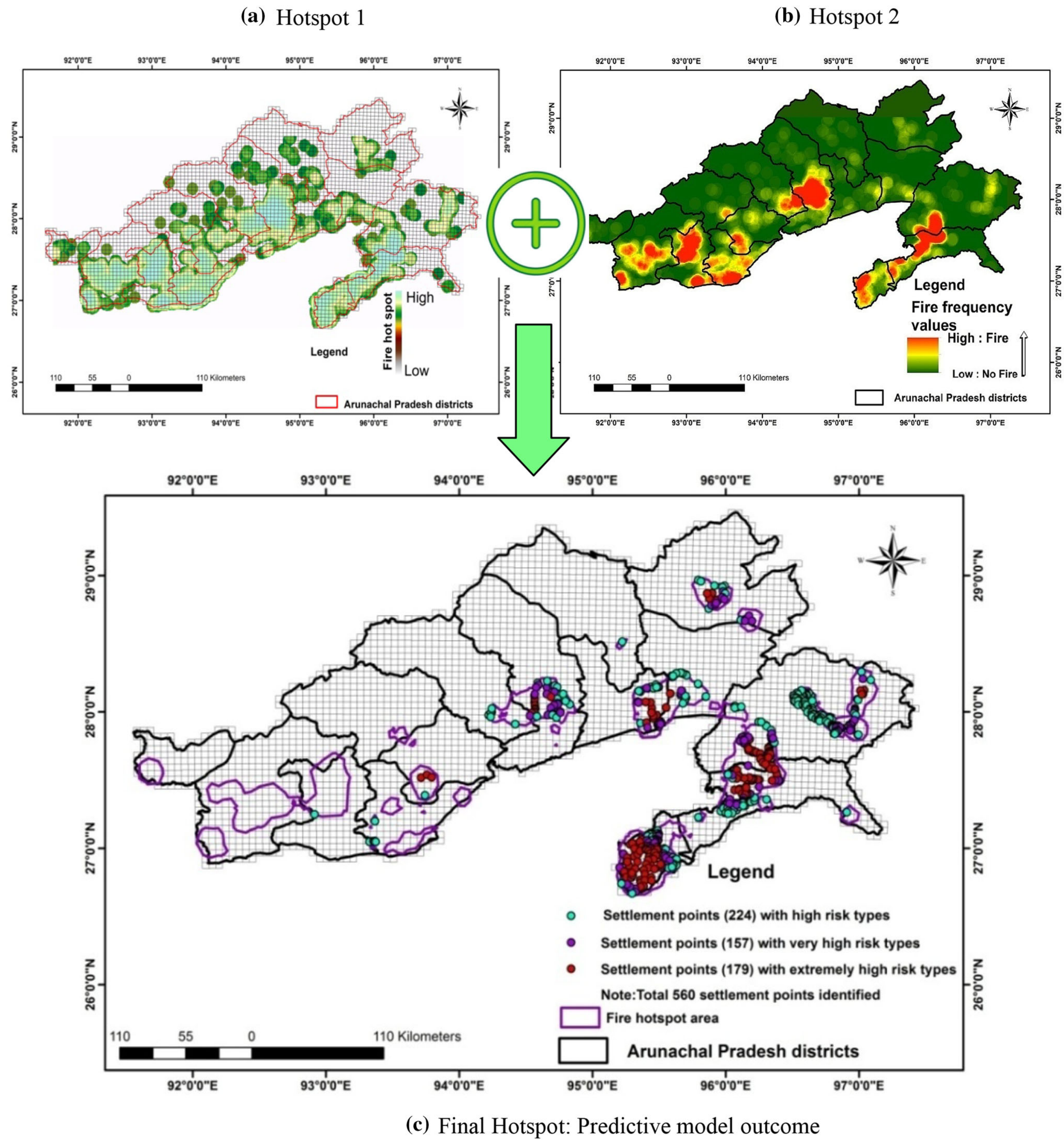


Fig. 8 **a** Hotspot 1 **b** Hotspot 2 **C** Final Hotspot: Predictive model outcome

to all the stake holders, as it not only helps in identifying forest fire hotspots with significant accuracy, but also improves the prediction model with each submission of field data after occurrence of fire. This intervention led to an improvement in the correlation to 74%.

7 Discussion

7.1 Major segments of this study

There were four major segments (Fig. 9):

1. Mapping of eight factors linked to forest fire incidences was done. In light of these factors, eight maps were

Table 3 Correlation Matrix

Pearson Correlation	Poverty	Population Density	Elevation	Slope	Temp-erature	Rain-fall	Geo-Economic Vulnerability	Fire Incidences	Fire Vulnerability
Poverty	1								
Population density	−0.080*	1							
Elevation	−0.212*	−0.329*	1						
Slope	−0.053*	−0.402*	0.585*	1					
Temperature	0.220*	0.309*	−0.983*	−0.527**	1				
Rainfall	0.230*	0.321*	−0.93*	−0.593*	0.896*	1			
Geo-economic vulnerability	−0.014	0.001	−0.027	−0.050*	0.026	0.023	1		
Fire incidences	0.087*	0.123*	−0.331*	−0.324*	0.314*	0.334*	−0.007	1	
Fire vulnerability	−0.014	0.001	−0.027	−0.050*	0.026	0.023	0.63*	−0.007	1

*Correlation is significant at the 0.01 level (2-tailed)

Table 4 WebGIS functional details

Function	Platforms	Function	Platforms
Web server	IIS	Development environment-application	Leaflet OS-JS
Application server	Windows-2012-r2	Development environment-web	Leaflet OS-JS
Operational system	Window Server	Spatial data editor	QGIS 3.10.1 ’A Coruña’
Browser	Chrome, Firefox, Safari 5 + , Opera 12 + , IE 7–11, Edge	Spatial data manager	QGIS 3.10.1 ’A Coruña’
DBMS	Cloud SQL (window)	Web visualization for spatial data	Leaflet OS Library
Creation and updating of queries	Open source java script (OS-JS) Libraries and Brackets. Release.1.14.1		

Fig. 9 Project outline

generated initially, and these maps were then integrated.
2. The FSI data and the factors-based map were compared, i.e. points where the study predicted forest fires and actual points where fire was reported were compared to find a percentage correlation and to validate that the study has considered the correct set of parameters.
3. In the third part, these two hotspots were merged, to improve the model and obtain the final hotspot.
4. Subsequently, the Android-based app was developed, which has facilitated citizen-centric inputs from the public, and it was linked to the portal to have a bird's eye-view on the fire incidences of the whole state.

The work aimed to improve some of the limitations of the FSI's fire reporting system, such as lack of public participation, distinction between fire in forest areas (wildfire) and fire in revenue areas, reporting of false data points as it lacked human interface and usually there is a time lag of 4 h in the reporting. And, more importantly, it lacked predictive modeling, which this study achieved, eventually leading to the development of an early warning system.

The human activity of the local population in the forest-fringes significantly impacts the incidence of fire. The poverty and weak socio-economic condition of the inhabitants of the forest compel them to do some activity for their livelihood including burning of certain patches for growing vegetables etc. It is also reported that forest fire are set intensely by people for the collection of Mahua (*Madhuca latifolia*) flower, Sal seed and Tendu (*Diospyros melanoxylon*) leaves (Chandra and Bhardwaj 2015). The study area has a significant tribal population living in remote areas inside the forests under weak socio-economic conditions. The ancient practice of shifting cultivation is largely responsible for the fire incidences. This study found that poverty was significantly high in the districts of Tirap and Lower Subansiri, where there were also relatively higher fire incidences.

7.2 The overall outcome of the study

The state has been able to save tremendous loss to the flora-fauna, human life and public property through the initiative of 'eForestFire'. This has not only raised awareness among citizens, but also enabled Government officials to create fire lines, watch towers etc. at the right places, at the right time, thereby being able to check the fires at the early stage. It has helped the concerned agencies in taking important policy-related decisions during fire-linked disaster management, and in tackling cases of forest fire, thereby, minimizing the damage. The project has brought people closer to the government functionaries, by ensuring a meaningful people participation mechanism, also for other environment, forests and wildlife-related issues.

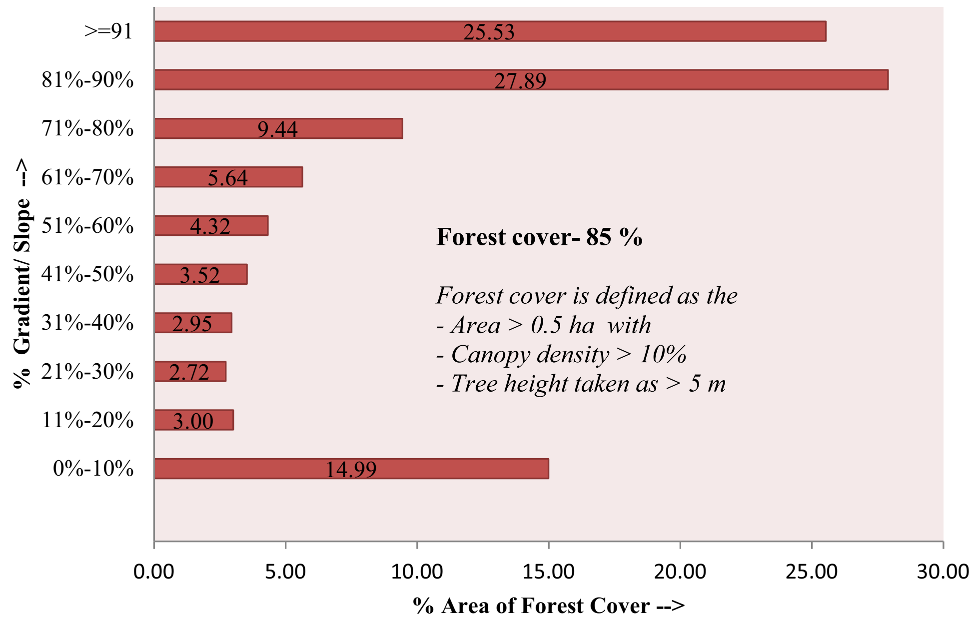
Approximately 11% of villages were found vulnerable, and they required priority attention towards fire mitigation. This study has mobilized the limited resources for strategic allocation towards the construction of watchtowers, and strengthening the village community meaningfully by creating fire awareness among youths. It has greatly reduced the damage to human property and wildlife. Due to this timely intervention and efficient information dissemination, the forest fire incidences reported in 2019 were around 31% less than before the start of the project. In the year 2017, a total of 6551 cases of forest fire were reported, while in 2019incidences were limited to 4535 cases as reported from the NASA FIRMS (Source- MODIS C6 and VIIRS).

There are sizeable threats to the forests of Arunachal Pradesh, and forest fire is certainly one major threat apart from deforestation and habitat shrinkage. To validate the argument, the forest cover of the state was evaluated using the methodology adopted by Goparaju and Ahmad (2019), and it was found that in the year 2000, canopy density was 85%, which is $\sim$ 3.5% and $\sim$ 5% more than that of 2001 and 2019, as per FSI reports, respectively (Fig. 10).

7.3 Information dissemination system: the mobile app

The 'eForestFire' app is a Fire Reporting System, an effort to ease governance by involving people, and to promote e-Governance. The App is an integral part of the study. With the help of this user-friendly App, citizens can report fire incidents in their nearby forest areas, and can also be in direct touch with the concerned authorities (Divisional Forest Officers). It is crucial not only in improving the Predictive Model, but also greatly helps the agencies (Forest Dept.) in tackling cases of forest fires due to its inherent and easy information dissemination system, thereby minimizing the damage of life and property to a great extent. It is specifically designed to work in offline setup, considering the internet connectivity issues of the Himalayan State. It does not require any expertise and has the capability to deliver a report with just a click (Fig. 11). Input is taken to get the exact location of a forest fire. After hitting the submit button, citizens can contact officials through email, WhatsApp or SMS, through a predesigned standardized message or through telephone or mobile call. Each input generates a data point that can be projected on the web portal to have a 'Bird's eye view' of the state's forest fires, and to revise the model with greater accuracy.

Fig. 10 Estimated forest cover percentage the state (Year 2000)



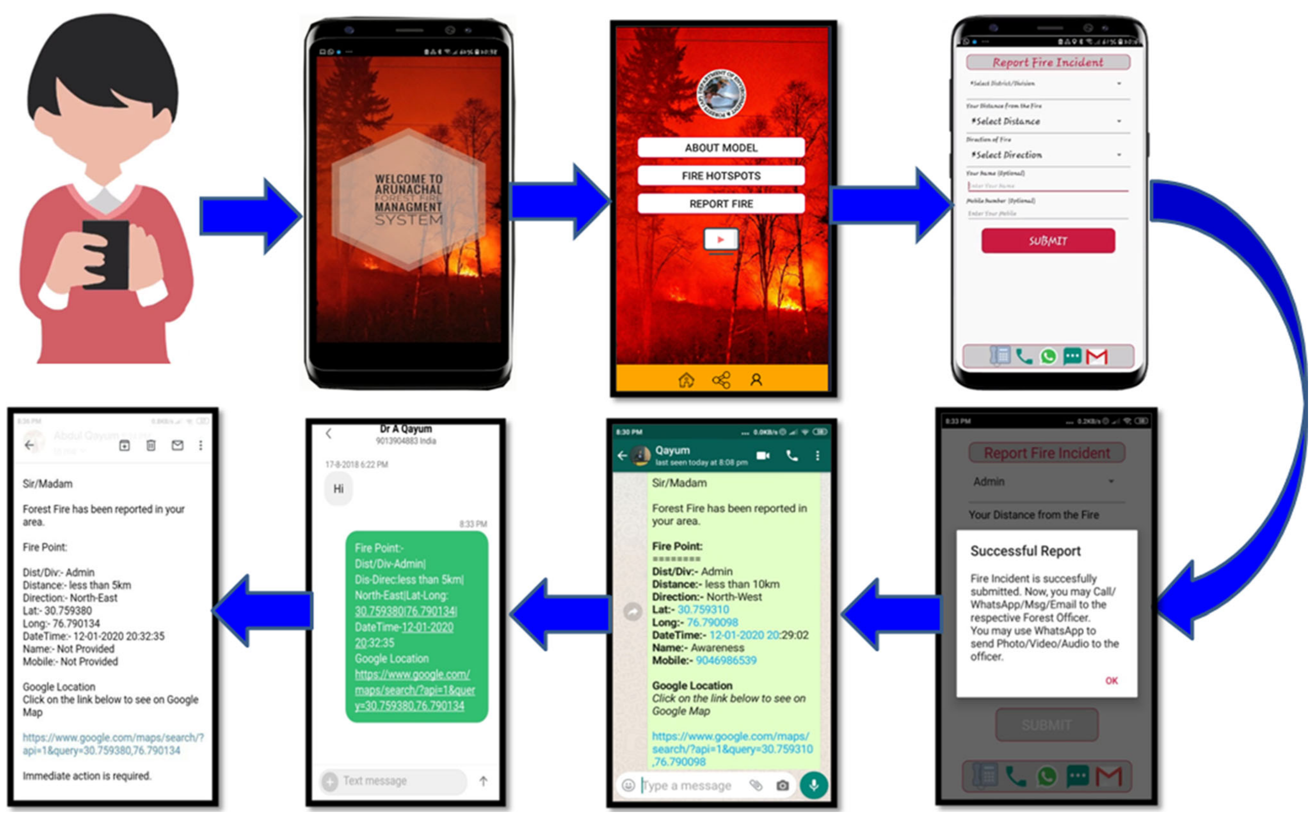


Fig. 11 Data reporting pathway

7.4 Improvement in efficiency and reduction in waiting time: real time updation

Remote-sensing information is experiencing technical improvement with the rapid development of sensors which improve the spatial resolution. This will help with attaining significantly high accuracy in future fire mappings.

However, the innovation in GIS technology haspaved the way for new emerging tools, and has strengthened the productivity in various applications including fire modeling. Addition of WebGIS and the mobile App in fire monitoring has significantly helped in real-time monitoring, investigation and updation of fire events through live maps, and has greatly reduced the response time (Fig. 12). Fire points used had limitation of data resolution because of satellite sensor capability, which compromised the project's strength, but the efficiency has been improved with the mobile input of on-ground reports of fire incidences.

7.5 Situation before the initiative

The forest-dwelling communities of Arunachal Pradeshare at regular risk of wildfires. With so many lives and biodiversity at stake, there was no option but to predict and prevent the fires. The non-availability of data and lack of fine satellite data with greater resolution were the main bottlenecks, apart from the lack of information on forest fire history (Chuvieco et al. 2008). Had there been datasets with high resolution, results would have been of greater accuracy. Further, the lack of any such study affected policy making, and became a limiting factor in the current study. No scientific method existed for allocation of Government resources towards fire fighting, especially in terms of cutting fire lines, creation of watchtowers and for allocation of sites for watch and ward duties, etc. There was a kind of policy paralysis, especially when it came to the issue of forest fire disaster management.

7.6 Strategy adopted

Advanced technological tools such as Remote Sensing and GIS were adopted to identify hotspots and other thematic layers, which were precisely mapped with appropriate spatial and temporal information. The methodology is cost-effective, easy to compute, and can be managed with minimal manpower. Additionally, other parameters such as socio-economy and physio-geographic data were used. All were investigated for their intricate correlations with forest fire incidences.

7.7 Innovations

A strong correlation was established between metrological parameters (relative humidity, precipitation, solar radiation and maximum temperature)and forest fires, while minimum temperature and wind velocity were found to be quite

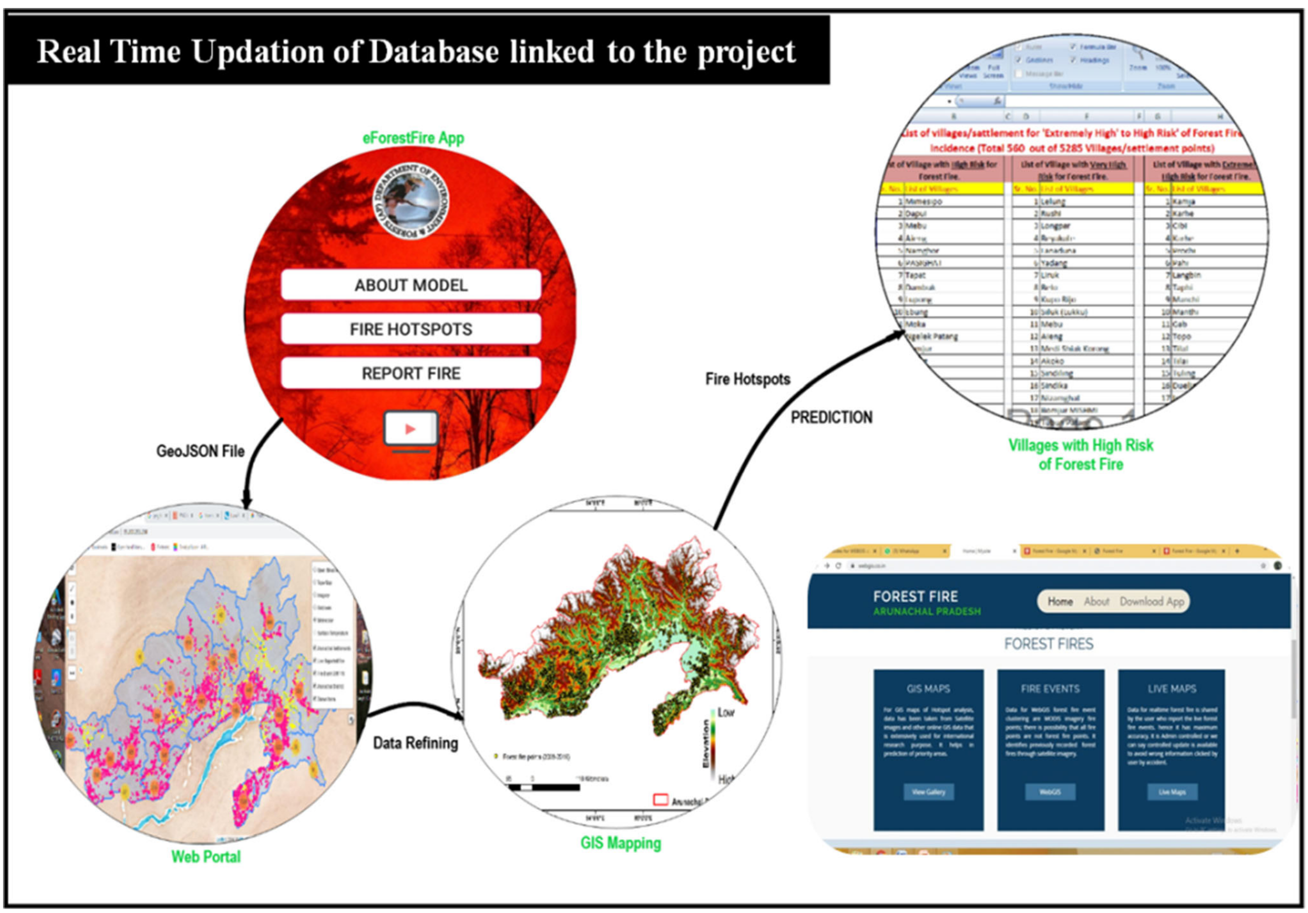


Fig. 12 Real time data updation mechanism

unrelated. Though the fire points used had low data resolution, the efficiency was improved with citizen centric inputs though the mobile App. Government bodies, NGOs and the local administration should involve citizens in various forest conservation activities through empowered village forest management committees, which in turn will enhance the livelihood opportunities and will reduce dependency on forest resources to a great extent.

7.8 Business process engineering

The satellite image processing and GIS Software was used to create a spatial distribution pattern through various thematic maps. The data were integrated scientifically to identify the forest fire hotspots and to develop the predictive model, which was used to identify by rank the most fire-affected villages.The study utilizes an advanced GIS modelling engineering process, which generates not only fire hotspots, but also gives an early warning system to take adequate preventive measures.

7.9 Simplification of procedure

There was no procedure of fire reporting except one thermal sensor set up by the Forest Survey of India (Forest Fire Alert, 2020), where a message is sent to the registered officials, but it lagged time and accuracy in the reporting. Also, it could not distinguish between forest fire and crop residue burning.

This study helped achieve the following-

1. Scientifically highlighting actual cause of forest fire, thus helping in its effective control.
2. Forest fire hotspot identification with very high accuracy (74%).
3. Simplification of procedure for generating hotspots, by using the Point Density sub-module of the Spatial Analyst tool of ArcGIS.

7.10 Adaptability and sustainability

The work is based on programming and algorithms, which can be suitably modified to cater to future requirements. Any feature such as the ‘proximity to the forest areas’ etc. can be added easily in order to improve the model. ArcGIS tool offers wider application for adaptability, which has been proved in many instances. The findings of the work will have a long-term impact, and will greatly help in potential allocation of limited resource. The system and protocol developed will serve for all future changes also.

7.11 Future works (replicability and scalability)

The entire world has witnessed the recent catastrophe of the Australian wildfires. This model can be suitably used for predicting vulnerable pockets there, just by altering a few local parameters. Having information on these high-risk pockets could have surely reduced the extent of damage and losses (Zhang et al. 2015). With better resolution data sets, it can be applied to any part of the globe. There were certain limitations in the model such as real-time monitoring, which is now taken care of by the App, where input along with the geo-tagged photographs can be uploaded by any user in future.

The concept can be extended to the whole country, and it is in the process of being replicated in another state (say Madhya Pradesh) in India to check inter-operability, replicability and scalability of the project. It can be replicated easily by changing datasets for any other geographical location.

8 Conclusion

The spatial technology has tremendous potential in environmental monitoring and assessment of forest fire incidences, and can be potentially used towards strategic resource allocation. This study proved to be useful to the people residing in forest-fringe areas as an early warning system, to take preventive measures during the event of fire break. The beneficiaries will understand the cause of fire scientifically, and things can be planned in accordance to minimize forest fire linked disaster. It will potentially benefit all stakeholders, especially the forest department and local inhabitants. It educates them in realising the ill-practices of shifting cultivation. Approximately 11% of villages were found vulnerable, and these needed priority attention towards fire mitigation. The government institutions need to implement these outcomes through various forest conservation activities, which in turn will enhance the livelihood opportunities of the forest-dependent community and will reduce dependency on forests to a great extent.

The state has been able to save tremendous loss to the biodiversity, flora-fauna, human life and public property by the initiative of ‘eForestFire’, which has not only raised awareness among citizens but enabled authorities to create fire lines, watch towers etc. at the right place and at right time, and fire could be checked before its actual occurrence. It has helped agencies in taking important policy related decisions during fire linked disaster management and in tackling cases of forest fires. The App involves people in fire mitigation on multidimensional approach, which greatly enhances the existing machinery of the Forests Department as maximum governance with limited resources.

8.1 Additional files

1. List of predicted villages (priority hotspots)
2. Short film on detailed study: https://www.youtube.com/watch?v=jR43OVswRKAandt=2s
3. Tutorial on using the linked android mobile app

Acknowledgements The authors are grateful to the Department of Administrative Reforms and Public Grievances, Govt. of India for bestowing the work a 'National Award for e-Governance' for year 2019-20 for linked project of 'eForestFire'. We are greatful to the Department of Environment and Forests, Govt of Arunachal Pradesh Itanagar for the opportunity of research involving applications of technology in mitigating forest fires and for the ground support in order to have field verification, Sh Pradeep Mishra, IFS DFO Seoni, Govt of Madhya Pradesh for writing codes against the details provided and designing the linked Android mobile App and Sh Sasyesh Chaturvedi for his continuous feedbacks of the work. We are also greatful to the Dept of Forest and Wildlife, UT Administration Chandigarh and especially to Sh. Debendra Dalai, Chief Conservator of Forests for the supports at many occasions and also to Dr Laxmi Goparaju for her technical supports.

Author contributions AQ conceptualized the idea of predictive modeling and designed the overall layout of the work, fixed various dimensions and linked it to the e-Governance initiative and wider application of technology in forest fire mitigation. The idea of forest fire mapping was initiated by FA, he prepared all the GIS maps and made critical evaluation of the work. FA assisted in writing initial draft while RA designed webGIS portal and did correlation matrix work. RKS ensured implementation and ground support for the field verification also. All authors read and approved the final manuscript.

Funding This is to declare that no fund was received from any source.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

Aggarwal A, Paul V, Das S (2009) Forest resources: degradation, livelihoods, and climate change. In: Datt D, Nischal S (eds) Looking back to change track. TERI, New Delhi

Ahmad F, Goparaju L (2017) Geospatial Assessment of Forest Fires in Jharkhand. Indian J Sci Technol. https://doi.org/10.17485/ijst/2017/v10i21/113215

Ahmad F, Goparaju L (2018) Climate change and its impact on forest fire in the state of Himachal Pradesh and Uttarakhand states of India: remote sensing and GIS analysis. Contemp Trends Geosci 7(2):229–246. https://doi.org/10.2478/ctg-2018-0016

Ahmad F, Goparaju L, Qayum A (2018) Himalayan forest fire characterization in relation to topography, socio-economy and meteorology parameters in Arunachal Pradesh. India Spat Inf Res 26:305. https://doi.org/10.1007/s41324-018-0175-1

Ahmad F, Goparaju L, Qayum A (2019) Geo-spatial perspective of vegetation health evaluation and climate change scenario in India. Spat Inf Res. https://doi.org/10.1007/s41324-018-00231-3

Altobellis AT (1983) A survey of rural population density and forest fire occurrence in the south, 1956–1970. USDA forest service, southern forest experiment station. research note SO-294, New Orleans, 4 p. https://doi.org/10.2737/SO-RN-294

Android App (2019) eForestFire, from google play store at https://play.google.com/store/apps/details?id=mac.shubh2.com.final_screen. Accessed 10 Dec 2019

Bhagawati R, Bhagawati K, Jini D et al (2017) Review on climate change and its impact on agriculture of Arunachal Pradesh in the Northeastern Himalayan region of India. Nat Environ Pollut Technol 16(2):535–539

Bond WJ, Keeley JE (2005) Fire as a global "herbivore": the ecology and evolution of flammable ecosystems. Trends Ecol Evol 20:387–394

Bradstock RA (2010) Abiogeographical model of fire regimes in Australia: current and future implications. Glob Ecol Biogeogr 19:145–158

Chandra KK, Bhardwaj AK (2015) Incidence of forest fire in India and its effect on terrestrial ecosystem dynamics, nutrient and microbial status of soil. Int J Agric For 5(2):69–78. https://doi.org/10.5923/j.ijaf.20150502.01

Chandra S (2005) Application of Remote Sensing and GIS Technology in Forest Fire Risk Modeling and Management of Forest Fires: A Case Study in the Garhwal Himalayan Region. In: van Oosterom P, Zlatanova S, Fendel EM (eds) Geo-information for Disaster Management. Springer, Heidelberg

Chavan ME, Das KK, Suryawanshi RS (2012) Forest fire risk zonation using remote sensing and GIS in huynial watershed, Tehri Garhwal district, UA. Int J Basic Appl 02:6–12

Chuvieco E, Englefield P, Trishchenko AP, Luo Y (2008) Generation of long time series of burn area maps of the boreal forest from NOAA–AVHRR composite data. Remote Sens Environ 112:2381–2396

Davidenko EP, Eritsov A (2003) The fire season in 2002 in Russia. report of the aerial forest fire service. Avialesookhrana Int For Fire News 28:15–17

Donald M, Gedalof Z, David L, Peterson PM (2004) Climatic change, wildfire, and conservation. Conserv Biol 18(4):890–902

Dwyer EJ, Pereira JMC, Gŕegoire JM, DaCamera CC (1999) Characterization of the spatio-temporal patterns of global fire activity using satellite imagery for the period April 1992 to March 1993. J Biogeo 1:57–69

Engstrom RT (2010) First-order fire effects on animals: review and recommendations. J Assoc Fire Ecol 6:115–130. https://doi.org/10.4996/FIREECOLOGY.0601115

Eugenio FC, DosSantos AR, Fiedler NC, Ribeiro GA, DaSilva AG, Santos D, Schettino VR (2016) Applying GIS to develop a model for forest fire risk: a case study in EspíritoSanto, Brazil. J Environ Manag 173:65–71. https://doi.org/10.1016/j.jenvman.2016.02.021

Fick SE, Hijmans RJ (2017) Worldclim 2: new 1-km spatial resolution climate surfaces for global land areas. Int J Climtol. https://doi.org/10.1002/joc.5086

Flannigan MD, Logan KA, Amiro BD, Skinner WR, Stocks BJ (2005) Future area burned in Canada. Clim Chang 72:1–16

Finney MA (2001) Design of regular landscape fuel treatment patterns for modifying fire growth and behavior. For Sci 47:219–229

Finney MA, McHugh CW, Grenfell IC et al (2011) A simulation of probabilistic wildfire risk components for the continental United States. Stoch Environ Res Risk Assess 25:973–1000. https://doi.org/10.1007/s00477-011-0462-z

Forest Fire Alert (2020) Forest survey of India, forest fire alert system 3.0. http://117.239.115.41/smsalerts/index.php. Accessed 5 Apr 2020

FSI (2019) http://fsi.nic.in/isfr19/vol2/isfr-2019-vol-ii-arunachal-pradesh.pdf. Accessed 20 Apr 2020

FSI Forest Fire (2019) http://fsi.nic.in/forest-fire-activities. Accessed 2 Ap 2020

Giriraj A, Babar S, Jentsch A, Sudhakar S, Murthy MSR (2010) Tracking fires in India using advanced along track scanning radiometer (a) atsr data. Remote Sens. https://doi.org/10.3390/rs2020591

Pourghasemi HR, Beheshtirad M, Pradhan B (2016) A comparative assessment of prediction capabilities of modified analytical hierarchy process (M-AHP) and Mamdani fuzzy logic models using Netcad-GIS for forest fire susceptibility mapping. Geomat Nat Hazards Risk 7(2):861–885

Hansen MC, Potapov PV, Moore R, Hancher M, Turubanova SA, Tyukavina A, Thau D, Stehman SV, Goetz SJ, Loveland TR, Kommareddy A, Egorov A, Chini L, Justice CO, Townshend JRG (2013) High-resolution global maps of 21st-century forest cover change. Science 342(6160):850–853

Harrison S, Marlon J, Bartlein P (2010) Fire in the Earth System. In: Dodson J (ed) Changing climates earth systems and society. International year of planet earth. Springer, Dordrecht

Heinimann et al (2017) A global view of shifting cultivation: recent, current, and future extent. PLoS ONE. https://doi.org/10.1371/journal.pone.0184479

Kim SJ, Lim C, Kim H, Lee GS, Geiger J, Rahmati T, Son O, Lee YWK (2019) Multi-temporal analysis of forest fire probability using socio-economic and environmental variables. Remote Sens 11:86. https://doi.org/10.3390/rs11010086

Kirschbaum MUF, Cannell MGR, Cruz RVO, Galinski W, Cramer WP (1996) Climate change impacts on forests. In: Watson RT, Zinyowera MC, Moss RH, Dokken DJ (eds) Climate change 1995. Impacts, adaptation and mitigation of climate change: scietific-technical analyses. Cambridge University Press, Cambridge

Koutsias N, Xanthopoulos G, Founda D, Xystrakis F, Nioti F, Pleniou M, Mallinis G, Arianoutsou M (2012) On the relationships between forest fires and weather conditions in Greece from long-term national observations (1894–2010). Int J Wildl Fire 22:493–507

Kushla JD, Ripple WJ (1997) The role of terrain in a fire mosaic of a temperate coniferous forest. For Ecol Manag 95:97–107

Leblon B, Kasischke E, Alexander M, Doyle M, Abbott M (2002) Fire danger monitoring using ERS-1 SAR images in the case of Northern Boreal forests. Nat Hazards 27:231–255

Leone V, Koutsias N, Martinez J, Vega-Garcia C, Allgower B (2003) The human factor in fire danger assessment. In: Chuvieco E (ed) Wildland fire danger estimation and mapping. The role of remote sensing data. World Scientific, New Jersey, pp 143–196

AM Liebetrau 1983 Measures of Association; Quantitative applications in the social sciences series, Sage Publications: Newbury Park, CA, USA 32 15–16

Littell JS, McKenzie D, Peterson DL, Westerling AL (2009) Climate and wildfire area burned in western U.S. ecoprovinces, 1916–2003. Ecol Appl 19(4):1003–1021

Matin MA et al (2017) Understanding forest fire patterns and risk in Nepal using remote sensing, geographic information system and historical fire data. Int J Wildland Fire 26:276–286

Mercer DE, Prestemon JP (2005) Comparing production function models for wildfire risk analysis in the wildland–urban interface. For Policy Econ 7:782–795

Myers N, Mittermeier RA, Mittermeier CG, Fonseca GAB, Kent J (2000) Biodiversity hotspots for conservation priorities. Nature 403:853–858

Nair M, Ravindranath NH, Sharma N et al (2013) Poverty index as a tool for adaptation intervention to climate change in northeast India. Clim Dev 5(1):14–32. https://doi.org/10.1080/17565529.2012.751337

Pandey K (2018) Forest fires in India increased by 125 per cent in last two years. https://www.downtoearth.org.in/news/environment/forest-fires-in-india-increased-by-125-per-cent-in-last-two-years-60349

Pew KL, Larsen CPS (2001) GIS analysis of spatial and temporal patterns of human-caused wildfires in the temperate rain forest of Vancouver Island, Canada. For Ecol Manag 140:1–18

Qayum A, Arya R, Kumar P, Lynn AM (2015) Socio-economic, epidemiological and geographic features based on GIS-integrated mapping to identify malarial hotspots. Malar J. https://doi.org/10.1186/s12936-015-0685-4

Ramakrishnan PS (1993) Shifting agriculture and sustainable development: an interdisciplinary study from Northeastern India. Unesco and Oxford University Press, New Delhi

Raman TRS, Rawat GS, Johnsingh AJT (1998) Recovery of tropical rainforest avifauna in relation to vegetation succession following shifting cultivation in Mizoram. North-East India J Appl Ecol 35:214–231

Ramya T (2012) Causes and effects of rampant forest fire in highlands Arunachal: a study from Kurung Kumey district. Radix Int J Res Soc Sci 1(7):1–10. https://doi.org/10.2139/ssrn.2556216

Riebau AR, Fox D (2001) The new smoke management. Int J Wildland Fire 10:415–427

Rothermel RC 1991 Predicting behavior and size of crown fires in the Northern Rocky mountains. Res. Pap. INT-438. Ogden, UT: U.S. Dept. of Agriculture, Forest Service, Intermountain Research Station 46

Rouse M (2018) Predictive modeling. https://searchenterpriseai.techtarget.com/definition/predictive-modeling

Roy PS (2003) Forest fire and degradation assessment using satellite remote sensing and geographic information system fire and degradation assessment using satellite remote sensing and geographic information system. Satell Remote Sens GIS Appl Agric Meteorol 30(361):400

Saaty TL (1980) The analytic hierarchy process. McGraw-Hill International, New York

Saha S (2002) Anthropogenic fire regime in a deciduous forest of central India. Curr Sci 82:1144–1147

Sharma S, Rikhari HC (1997) Forest fire in the central Himalaya: climate and recovery of trees. Int J Biometeorol 40:63–70. https://doi.org/10.1007/s004840050020

Sharma S, Pant H (2017) Vulnerability of Indian Central Himalayan forests to fire in a warming climate and a participatory preparedness approach based on modern tools. Curr Sci 112(10):2100–2105

Shukman D (2020) Sir David Attenborough warns of climate crisis moment. BBC. https://www.bbc.com/news/science-environment-51123638. Accessed 21 Apr 2020

Stocks BJ, Mason JA, Todd JB, Bosch EM, Wotton BM, Amiro BD, Flannigan MD, Hirsch KG, Logan KA, Martell DL, Skinner WR (2002) Large forest fires in Canada, 1959–1997. J Geophy Res-Atmos 108:5.1–5.12

Swetnam TW, Betancourt JL (1998) Mesoscale disturbance and ecological response to decadal climatic variability in the American Southwest. J Clim 11(12):3128–3147

Tropical T (2001). Secretariat of the convention on biological diversity. Impacts of human-caused fires on biodiversity and ecosystem functioning, and their causes in tropical, temperate and boreal forest biomes, Montreal. SCBD (CBD Technical Series no. 5). 42

Vadrevu KP, Badarinath KV, Anuradha E (2008) Spatial patterns in vegetation fires in the Indian region. Environ Monit Assess 147(1–3):1–13. https://doi.org/10.1007/s10661-007-0092-6

Vadrevu KP, Csiszar I, Ellicott E, Giglio L, Badarinath KVS, Vermote Justice C (2013) Hotspot analysis of vegetation fires and intensity in the Indian region. IEEE J Sel Top Appl Earth Obs Remote Sens. https://doi.org/10.1109/JSTARS.2012.2210699

Vicente-Serrano SMS, Beguería S, López-Moreno JI (2010) A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. J Clim 23:1696–1718

Wang W, Zhang C, Allen JM, Li W, Boyer MA, Segerson K, Silander-Jr JA (2016) Analysis and prediction of land use changes related to invasive species and major driving forces in the state of connecticut. Land 5:25. https://doi.org/10.3390/land5030025

Malhi Y, Luiz EOCA, Galbraith D, Huntingford C, Fisher R, Zelazowski P, Sitch S, McSweeney C, Meir P (2009) Exploring the likelihood and mechanism of a climate-change-induced dieback of the Amazon rainforest. Proc Natl Acad Sci USA 106(49):20610–20615. https://doi.org/10.1073/pnas.0804619106

Yang J, He HS, Shifley SR, Gustafson EJ (2007) Spatial patterns of modern period human-caused fire occurrence in the Missouri Ozark Highlands. For Sci 53:1–15

Zhang Q, Cui L, Zhang J et al (2015) Grid based dynamic risk assessment for grassland fire disaster in Hulunbuir. Stoch Environ Res Risk Assess 29:589–598. https://doi.org/10.1007/s00477-014-0909-0

Zhijun T, Jiquan Z, Xingpeng L (2009) GIS-based risk assessment of grassland fire disaster in western Jilin province, China. Stoch Environ Res Risk Assess 23:463–471. https://doi.org/10.1007/s00477-008-0233-7

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.