Application of earth observation dataset and multi-criteria decision-making technique for forest fire risk assessment in Sikkim, India

*Arnab Laha, Nagarajan Balasubramanian and Rajiv Sinha**

Forest fire is one of the primary and recurring problems in Sikkim, India impacting the ecological heritage of the region. The article presents a fire risk model based on the identification of the major factors that contribute to forest fire, namely, vegetation type, vegetation density, land surface temperature, elevation, slope, aspect, and distance from settlements, rivers and roads, and then integrating them using a multi-criteria decision-making technique in a GIS framework. We document that more than 50% of the area of all the districts except North Sikkim falls into high to moderate risk zones. The model shows that 61% of fire information for resource management system data for the last 16 years coincide with the mapped high-risk zone of the state. Areas with low slope and with moderate vegetation density fall into very high risk, whereas areas with high slope and with high vegetation density correspond to moderate risk zones. Further, aspect and density of human intervention differentiate the very high and high-risk zones of the region. This model has provided a robust geographical representation of fire ignition probability and identification of high-risk areas at different regions for the entire state of Sikkim.

Keywords: Analytic hierarchy process, forest fire risk, multi-criteria decision-making technique, remote sensing, risk map.

FORESTS are the lifeline of human civilization because of the huge resources they provide, and for their far-reaching role in sustaining ecology and biodiversity[1]. However, forests are destroyed annually due to fire, browning, drought legacy, small scale agricultural practices, mining and drilling. Among these, forest fire is the major cause of concern, because it destroys a large area of forest rapidly. Forest fire is known to have several negative impacts on human health[2], natural habitats of animals and biodiversity[3]. Furthermore, it is believed that the increased global warming has escalated the size and frequency of forest fires[4], resulting in frequent migration of wildlife towards human vicinity[5], and loss of rich diversity in terms of flora and fauna. As forest fire is classified as a quasi-natural hazard, it is difficult to prevent it completely, and its short- and long-term negative consequences are experienced by the entire ecosystem. However, its overall impact can be minimized by adopting proper management practices at all levels[6].

Forest fire management is primarily aimed at providing early warning, locations of the vulnerable areas, and facilitating quick response by applying various strategies. It typically involves (a) fire detection[7], (b) forest fire risk assessment[8] and (c) forest fire mitigation[9]. In particular, forest fire risk assessment, the focus of this paper, includes generation of forest fire risk maps that help to design sustainable strategies for forest fire management[8] and plan efficient mitigation measures[10]. However, these maps should be prepared considering the spatial inhomogeneities in terms of vegetation cover, topography and anthropogenic activities so as to achieve region-specific targets for fire risk reduction, fire regime restoration and maintenance.

Further, different techniques and approaches have been employed to assess the burnt areas and to identify the forest fire risk zones in a geographic information system (GIS) environment. Burnt areas can be analysed by 'burn severity' of the area[11] using indices such as normalized burn ratio (NBR)[7], normalized difference vegetation index (NDVI)[12] and normalized multi-band drought index (NMDI)[13]. Satellite imageries[14,15], fire hazard models[16], indicator-based indexing[17–19], fuzzy analytic hierarchy

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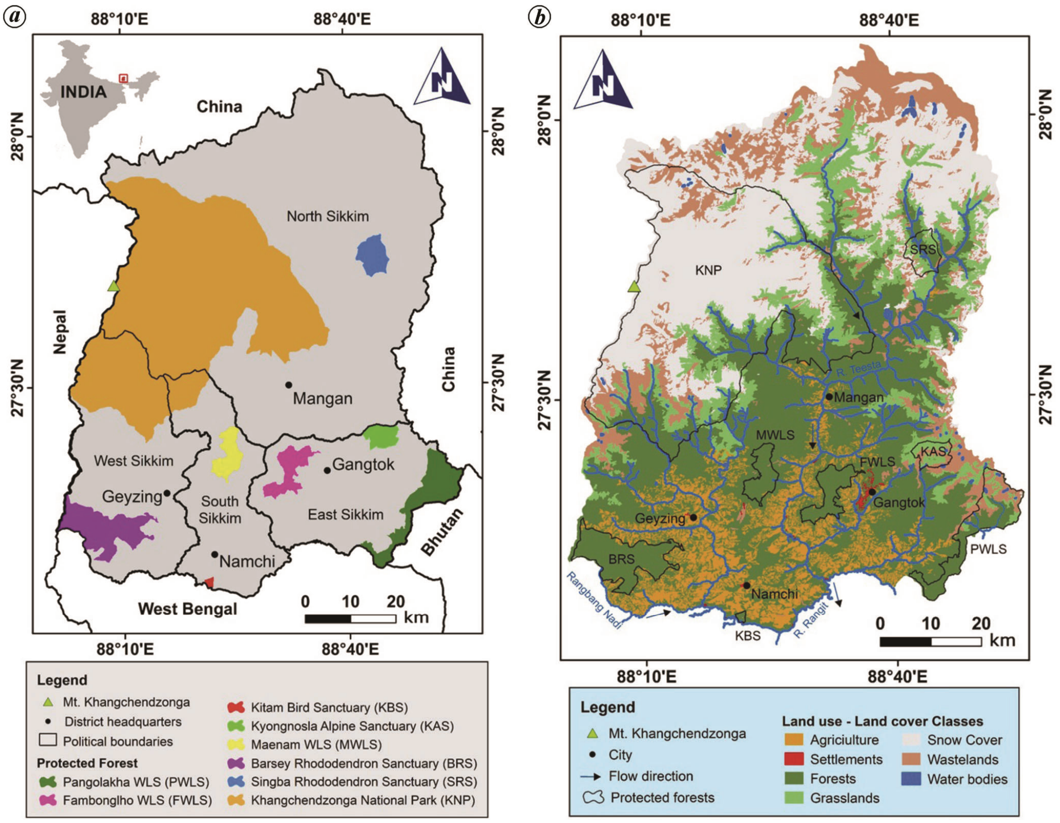

Figure 1. ***a***, Location map of Sikkim with its district and protected forest areas. ***b***, Land use–land cover of Sikkim (2009) at a scale of 1 : 50,000 showing the major LULC classes.

process (fAHP)[20,21] and analytic hierarchy process (AHP)[8] are commonly used to analyse forest fire risk. Among these, AHP has been widely used for forest fire risk assessment in producing spatial distribution of forest fire risk over an area[8]. Generation of forest fire risk map through AHP requires weighing of all the possible factors which could contribute to forest fire, because, as the number of factors increases the accuracy of the result also improves[22]. In this study, we have incorporated all possible variables with reasonable spatial resolution that are freely available to understand the forest fire distribution for the entire Sikkim state.

Forest fire incidences in Sikkim are reported during November to March owing to aridity at the forest floor, and are largely related to anthropogenic factors[21]. According to reports of Forest, Environment and Wildlife Management Department (FEWMD)[23], Sikkim, 113 fire incidences occurred in 2009 which resulted in the burning of ~1600 ha of land. Further, 70 fire incidences with a burnt area of ~170 ha and 64 fire incidences with a burnt area of ~440 ha, were reported in 2010 and 2011 respectively. These incidences were close to roads and habitats, resulting in prompt alert to the local authorities and communities for controlling the fire. However, the forest areas are neither digitally mapped nor classified on the basis of different forest fire risk zones. The present study has considered the terrain and climatic characteristics of different parts of Sikkim in northeast India to design the decision factors that influence the forest fire, and then analyse them in a GIS environment to assess the forest fire risk. Further, a district-wise risk analysis was performed to account for the spatial inhomogeneities in terrain and climatic characteristics.

Study area

Sikkim is located in the northeastern part of the Himalayan mountain range between 27°5′–28°9′N lat. and 87°9′–88°56′E long.[24]. It is one of the most diverse areas in terms of biodiversity in the world due to its unique physiography[25]. Sikkim is the least populous (0.611 million, as per the census 2011) and the second smallest state of India with an aerial coverage of 7096 sq. km that constitutes 0.67% of the geographical area of the country[24]. This region has an extremely undulating terrain, and the elevation varies from 280 to 8586 m above mean sea level (amsl)[26] including the world's third highest mountain peak, Mt Kanchenjunga (8586 m)[27] close to the border with Nepal (Figure 1 *a*). Sikkim is divided into four districts: East Sikkim, South Sikkim, West Sikkim and North Sikkim with Gangtok, Namchi, Geyzing and Mangan as their respective district headquarters (Figure 1 *a*). We performed the risk analysis of each district separately

Table 1. Terrain and climatic characteristics of each district of Sikkim

District	Area (sq. km)	Temperature (°C)	Rainfall (mm)	Elevation (m)	Settlements	Population (lakh)
North Sikkim	4226	–28 to 30	Maximum: 467 (June) Minimum: 11 (December)	476–8075	>100	0.44
South Sikkim	750	–13 to 28	Maximum: 447 (July) Minimum: 2 (December)	163–5677	>200	1.47
East Sikkim	954	–8 to 24	Maximum: 509 (July) Minimum: 2 (December)	247–4694	>150	2.84
West Sikkim	1166	–19 to 29	Maximum: 324 (August) Minimum: 3 (December)	260–7204	>170	1.36

because of their diverse physiography and demography (Table 1). Sikkim also exhibits a disparate range of flora and fauna and encompasses eight protected areas (Figure 1 *a*) at different altitudes, e.g. Khangchendzonga National Park (KNP) and Kitam Bird Sanctuary (KBS) as the largest and smallest protected forests respectively, in the state. A significant part of the state (~39%) is dominated by important forest types such as the sub-Himalayan wet mixed forest, sub-tropical hill forest, Himalayan subtropical pine forest, wet temperate forest, mixed coniferous forest, eastern oak hemlock forest, oak fir forest, moist alpine scrubs and dry alpine scrubs[28]. Human settlements cover 0.3% of the total area due to dense forest cover and mountainous landscape. The northern part of the state is mostly covered by snow cover and wastelands, whereas the southern part is mostly covered by forests and agriculture (Figure 1 *b*). The Teesta river (309 km long) flows across the length of Sikkim and meets with its largest tributary, the Rangit river, and their combined flow marks the regional boundary between Sikkim and West Bengal[29].

Data and methods

Data

A total of nine parameters namely, vegetation type, vegetation density, land surface temperature (LST), elevation, slope, aspect, and distance from human settlements, roads and river were used to generate a forest fire risk map. We have used satellite datasets (LANDSAT 8, LISS III and ALOS PALSAR DEM) and toposheet (1 : 250,000) to generate the thematic maps of the factors considered in this study. Forest fire also depends on rainfall, wind speed, soil moisture and evapotranspiration; however, these datasets were not used in our study due to their low spatial resolution and unavailability. Figure 2 describes the methodology and the operations to generate the thematic maps.

Generation of thematic layers

Fuel characteristic is the primary factor for the vulnerability of forest fire[30], and so it is important to understand vegetation distribution in a given region. In this study, we have used vegetation type and density map[31], which were prepared from LISS III with 23 m spatial resolution and the available supplementary information[23]. In total, 18 landscape components including 14 broad land cover classes[31] were reclassified into five vegetation type zones, i.e. tropical, temperate, agriculture, alpine and barren area. The former two zones were classified on the basis of presence of forest type at different elevations, whereas the others were classified according to their characteristics. Vegetation density were segregated as per Forest Survey of India (FSI)[32]. Forest with canopy cover of more than 40%, 40–10% and 10–5% was classified as very dense, moderate dense, and open dense forest respectively. Also, the areas that are devoid of trees and have <5% forest cover are classified as scrub; and barren area are completely devoid of trees and shrubs.

LST was obtained from the thermal bands of LANDSAT 8. Digital number (DN) of bands B10 and B11 of LANDSAT 8 OLI/TIRS satellite image was converted to spectral radiance (L_λ) and then to brightness temperature (T_B) using the following equations[33]

$$L_\lambda = \frac{(L_{\max} - L_{\min}) \times Q_{\text{cal}}}{(Q_{\text{cal}\max} - Q_{\text{cal}\min})} + L_{\min} - O_{\text{i}}, \tag{1}$$

$$T_B = \frac{K_2}{\ln(1 + (K_1/L_\lambda))} - 273.15, \tag{2}$$

where $L_{\max}$ and $L_{\min}$ are the maximum and minimum radiances (Wm^{-2} sr^{-1} μm^{-1}) respectively, Q_{cal} the DN value of the pixel, Q_{calmax} and Q_{calmin} the maximum and minimum DN values of pixels, O_{i} the correction value for B10 and B11, K_1 and K_2 the calibration constants obtained from LANDSAT 8 data user's manual, λ is the wavelength of emitted radiance. Finally, LST (°C) was calculated using T_B, ε (land surface emissivity) derived from P_{v} (proportional vegetation) and NDVI. Similar steps were repeated for B10 and B11 separately, and the final LST was calculated by taking the mean of LST obtained from B10 and B11.

The ALOS PALSAR DEM with spatial resolution of 12.5 m was used for topographic mapping. The DEM was also used to generate slope and aspect maps of each district separately. Afterwards, the slope map was classified

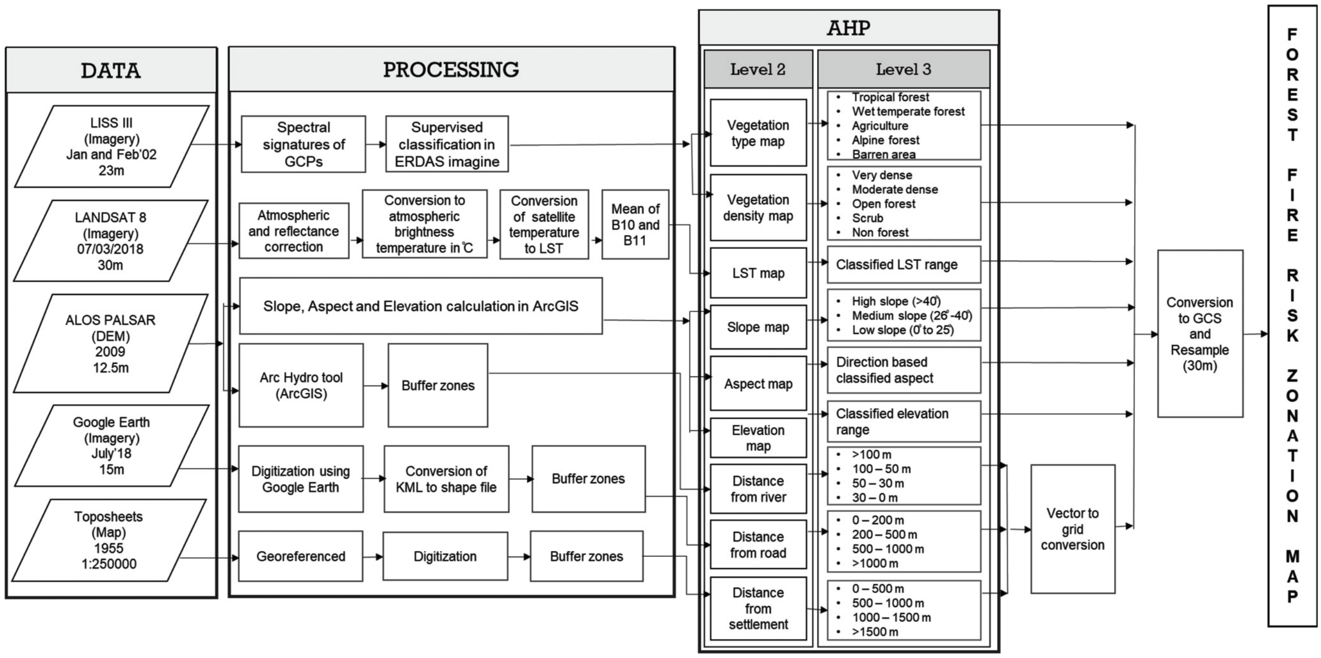

Figure 2. Overall forest fire risk assessment framework to produce forest fire risk zonation map for Sikkim.

into three groups: high slope (>40°), medium slope (40°–26°) and low slope (<25°)[34].

Topographic maps (1 : 250,000) prepared by the US army corps were used to map major settlements (population of more than 5000 capita) for creating buffer zones. During field work, past fire patches were observed within 500–1000 m from the settlements which helped to create multiple ring buffers at 500, 1000, 1500 and above 1500 m around the settlements. Similarly, roads such as national highway (NH), state highway (SH) and major district road (MDR) were digitized onscreen at a scale of 1 : 10,000 and buffer zones of 200, 500, 1000 and >1000 m on either side of the road based on the patches of past forest fire seen in the field. The DEM data was used to extract the major drainage lines using the Arc Hydro tool in ArcGIS 10.5.1 software with a threshold value of 2000. The extracted drainage map was verified by overlaying true colour composite maps created from LANDSAT 8 imagery. Further, rivers were buffered at a distance of 30, 50, 100 m and greater than 100 m based on the observations in the field.

Data integration using AHP

The AHP was used to create a forest fire risk based on a set of nine attributes called decision factors which were further divided into level 3 sub-factors to create a complete hierarchy (Figure 2). These factors and sub-factors were relatively weighted for criteria and preference for alternatives concerning each criterion according to Saaty's 9-point scale[35]. Pair-wise comparisons of various parameters in both levels 2 and 3 were done based on literature review and field experiences. For example, if two factors had similar effect on fire ignition or spreading, then relative value closer to 1 had been given. On the other hand, factors having opposite effect had values close to 9. For both levels estimated eigen element (EEE) and relative importance weightage (RIW) were calculated using eqs (3) and (4) respectively[35]. Further, the forest fire risk index (FFRI) was calculated by integrating RIWs at each level of the hierarchy using eq. (5).

$$\mathrm{EEE} = \sqrt[N]{a_1 * a_2 * a_3 * a_N}, \tag{3}$$

$$\mathrm{RIW} = \frac{\sqrt[N]{a_1 * a_2 * a_3 * a_N}}{\mathrm{EEE}_1 + \mathrm{EEE}_2 + \mathrm{EEE}_3 + \mathrm{EEE}_N}, \tag{4}$$

$$\mathrm{FFRI} = \sum_{i=1}^{N_2} \mathrm{RIW}_i^2 * \mathrm{RIW}_{ij}^3, \tag{5}$$

where a_1, a_2, a_3, a_N are the values of the row elements, N the number of the row elements, FFRI forest fire risk index, N_2 the number of level 2 decision factor, RIW_i^2 the relative importance weight of level 2 decision factor i and RIW_{ij}^3 is the relative importance weight of level 3 sub-factor j of level 2 decision factor i.

In order to check consistency of judgement, consistency index (CI)[36] was used as

$$CI = \frac{\lambda - N}{N - 1}, \tag{6}$$

where maximum eigenvalue ($\lambda_{\max}$) of a matrix is equal to N if and only if the matrix is consistent.

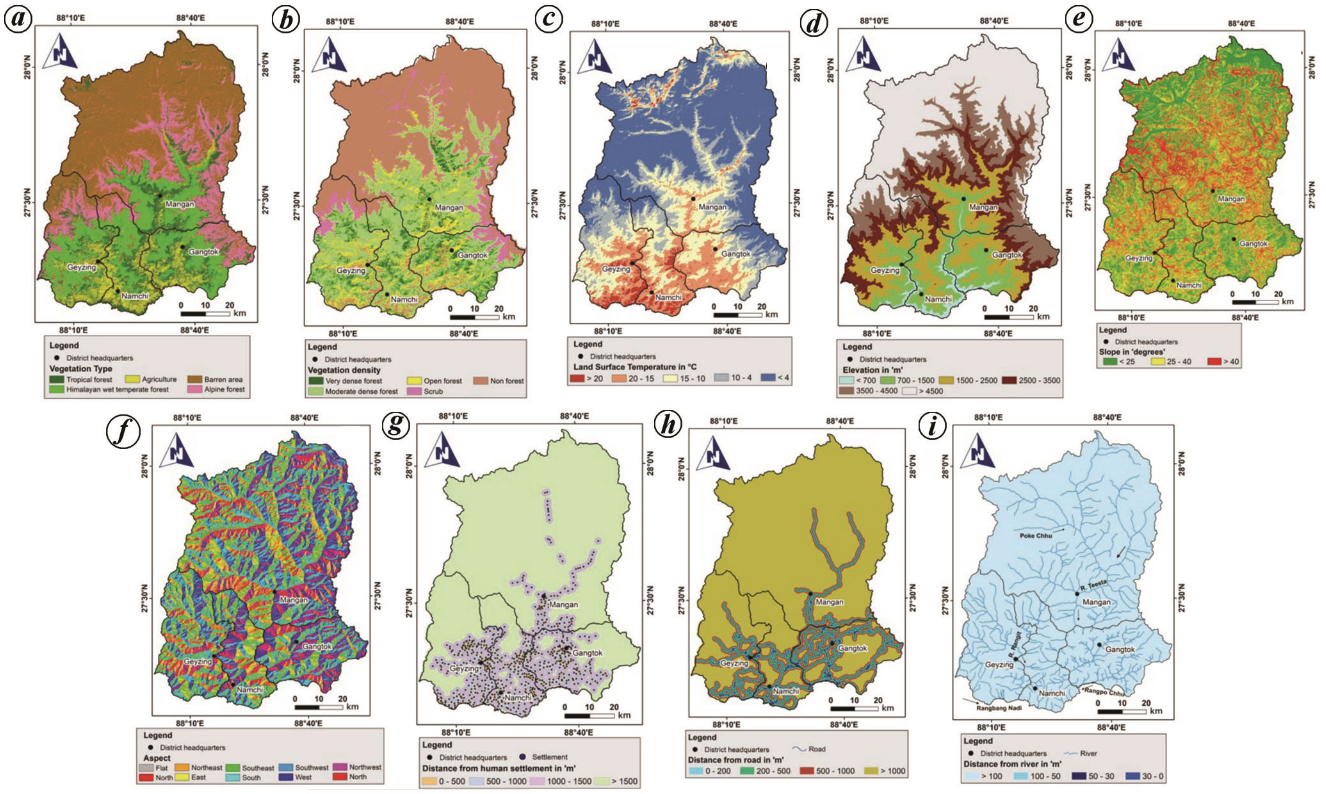

Figure 3. Thematic maps showing the spatial distribution of (***a***) vegetation type, (***b***) vegetation density, (***c***) land surface temperature, (***d***) elevation, (***e***) slope, (***f***) aspect, (***g***) distance from human settlement, (***h***) distance from road and (***i***) distance from river.

It has been suggested that the consistency ratio (CR) of 0.1 or less than 0.1 may be considered as an acceptable upper limit[35]. CR is the rescaled version of CI, which is procured by dividing CI by real number that depends on sample size[37]. Risk maps generated using FFRI were classified into four classes using mean (μ) and standard deviation (σ) of the histogram distribution as very high risk (FRRI $> (\mu + \sigma)$), high risk ($(\mu + \sigma) \geq$ FRRI $> \mu$), moderate risk ($\mu \geq$ FRRI $> (\mu - \sigma)$) and low risk ($(\mu - \sigma) \geq$ FRRI). Each district will have different values of mean and standard deviation, but we have classified the risk zones based on the average values of mean and standard deviation, so that FRRI is distributed similarly in all districts. The classified risk maps were further validated with the help of fire information for resource management system (FIRMS) data and field visit.

Results and discussion

Figure 3 *a–h* shows the thematic maps of all nine factors considered for this study. The vegetation type (VT) and vegetation density (VD) maps (Figure 3 *a* and *b*) show the dominance of tropical and alpine forest regions with moderate density at middle elevations. The non-forested area in vegetation density map (Figure 3 *b*) is higher than the barren area in vegetation type map (Figure 3 *a*), because agricultural lands are also incorporated in the non-forested areas. The LST map (Figure 3 *c*) shows a large variability (–28°C to 30°C) in temperature with a prominent high-temperature area in the southern part of the state at lower altitudes. Elevation, slope and aspect maps (Figure 3 *d–f*) summarize the terrain characteristics of Sikkim and clearly differentiate the high-altitude, high-slope North Sikkim from low-altitude with large patches of flatter areas in South Sikkim districts. Three other important factors that were used in forest fire risk assessment were the distance from human settlements (Figure 3 *g*), roads (Figure 3 *h*) and rivers (Figure 3 *i*), which primarily characterize the level of human disturbance in different parts of the state.

All nine factors discussed above were integrated using their relative weightage factors computed from AHP (Table 2) to produce the forest fire risk map for Sikkim in a GIS environment (Figure 4 *a*). Barring the northern snow covered part, a large part of the state (36%) lies in very high and high-risk zones and 21% lies in a moderate risk zone (Figure 4 *c*). Very high risk zones of the state are mainly governed by the tropical forest, agricultural areas and moderate dense forest. However, other factors like aspect, LST, distance from human settlement and roads influence high and moderate risk zones within the state. We noted a significant spatial variability in fire risk across the different districts of Sikkim due to different combinations of these factors (Figure 5 *a–d*).

Table 2. Pair-wise comparison matrix of level 2 decision factors

Decision factors	Vegetation type	Vegetation density	LST	Slope	Elevation	Distance from settlement	Aspect	Distance from road	Distance from river	EEE	RIW
Vegetation type	1	2	3	5	3	5	6	5	8	3.625	0.287
Vegetation density	1/2	1	3	4	3	4	5	4	7	2.785	0.220
LST	1/3	1/3	1	4	2	5	4	5	4	1.921	0.152
Slope	1/5	1/4	1/4	1	3	4	3	4	5	1.277	0.101
Elevation	1/3	1/3	1/2	1/3	1	3	5	3	6	1.196	0.095
Distance settlement from	1/5	1/4	1/5	1/4	1/3	1	3	2	4	0.647	0.051
Aspect	1/6	1/5	1/4	1/3	1/5	1/3	1	4	5	0.537	0.042
Distance road from	1/5	1/4	1/5	1/4	1/3	1/2	1/4	1	6	0.441	0.035
Distance river from	1/8	1/7	1/4	1/5	1/6	1/4	1/5	1/6	1	0.221	0.017
						Consistency index: 0.099					

EEE, Estimated Eigen element and RIW, Relative importance weight.

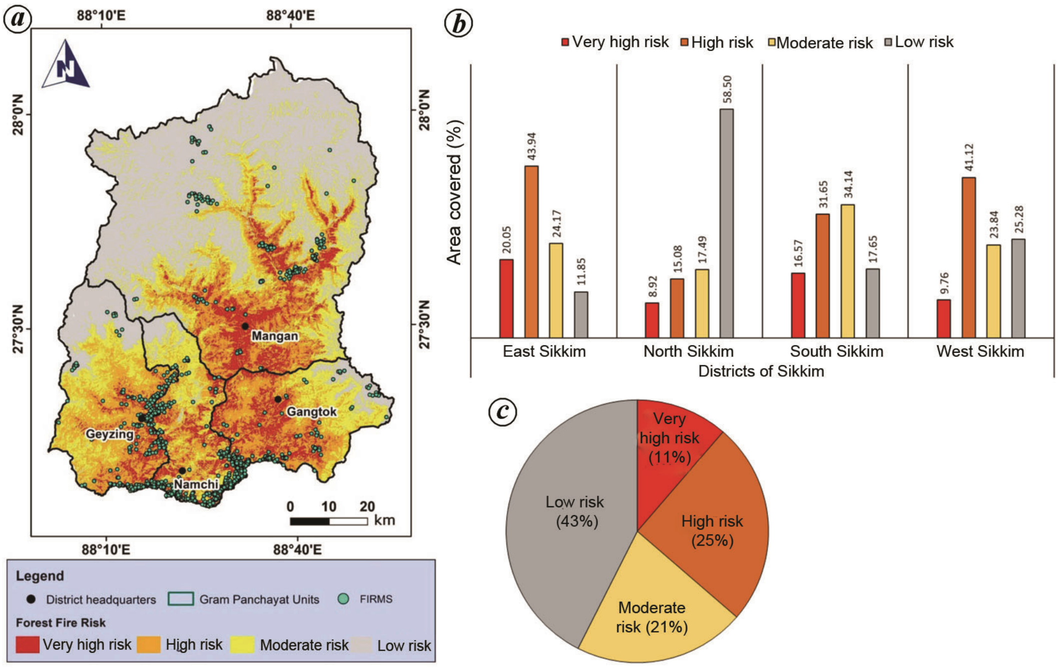

Figure 4. ***a***, Spatial distribution of forest fire risk in different districts and protected areas of Sikkim; very high risk (FRRI > 3.35); high risk (3.35 ≥ FRRI > 2.55); moderate risk (2.55 ≥ FRRI > 1.75); low risk (FRRI ≤ 1.75). ***b***, Area covered in percentage by each district in different risk zones. ***c***, Distribution of different risk zones all over Sikkim.

Very high risk zones in all districts were comparatively lower than the high and moderate risk zones. We observed that the very high risk zones accounted for 20%, 16%, 9% and 8% of the area in East Sikkim, South Sikkim, West Sikkim and North Sikkim respectively. Several areas in all the four districts such as areas near central part of East Sikkim, i.e. Gangtok, Namnag and Pakyong (Figure 5 *a*); Jorthang, Kitam, Chumthang and Melli in South Sikkim (Figure 5 *b*); Dentam, Gyalshing, Kaluk, Kamling and Naya Bazar in West Sikkim (Figure 5 *c*) and Mangan, Lingdem, Sangtok and Namok in North Sikkim (Figure 5 *d*) lie in very high risk zone due to alder, oak and agriculture. The oak and alder trees are highly vulnerable to fire because they contain less moisture and have high calorific value[15,38–40]. Field photographs (Figure 6 *b*) also confirm that oak trees are more prone to fire. Also, due to agricultural land, these areas are more vulnerable to forest fire in all the districts except North Sikkim, as slash and burn type agricultural practices have been followed all over the state[24] and are in close proximity to human settlements[41]. Forest in these areas, especially in North Sikkim, is within a range of 500 m from road and 1000 m from human settlements. Several incidences of accidental fire due to bonfire in the trekking trails (Figure 6 *e*), and half burnt cigarette buds disposed by the driver and people have also been reported[42,43]. Overall, the moderately dense and open type of forests are found in these areas except in South Sikkim (Figure 3 *b*), which cause the fire to spread at higher rate[44] than in very dense forest due to more passage of air in between them[34].

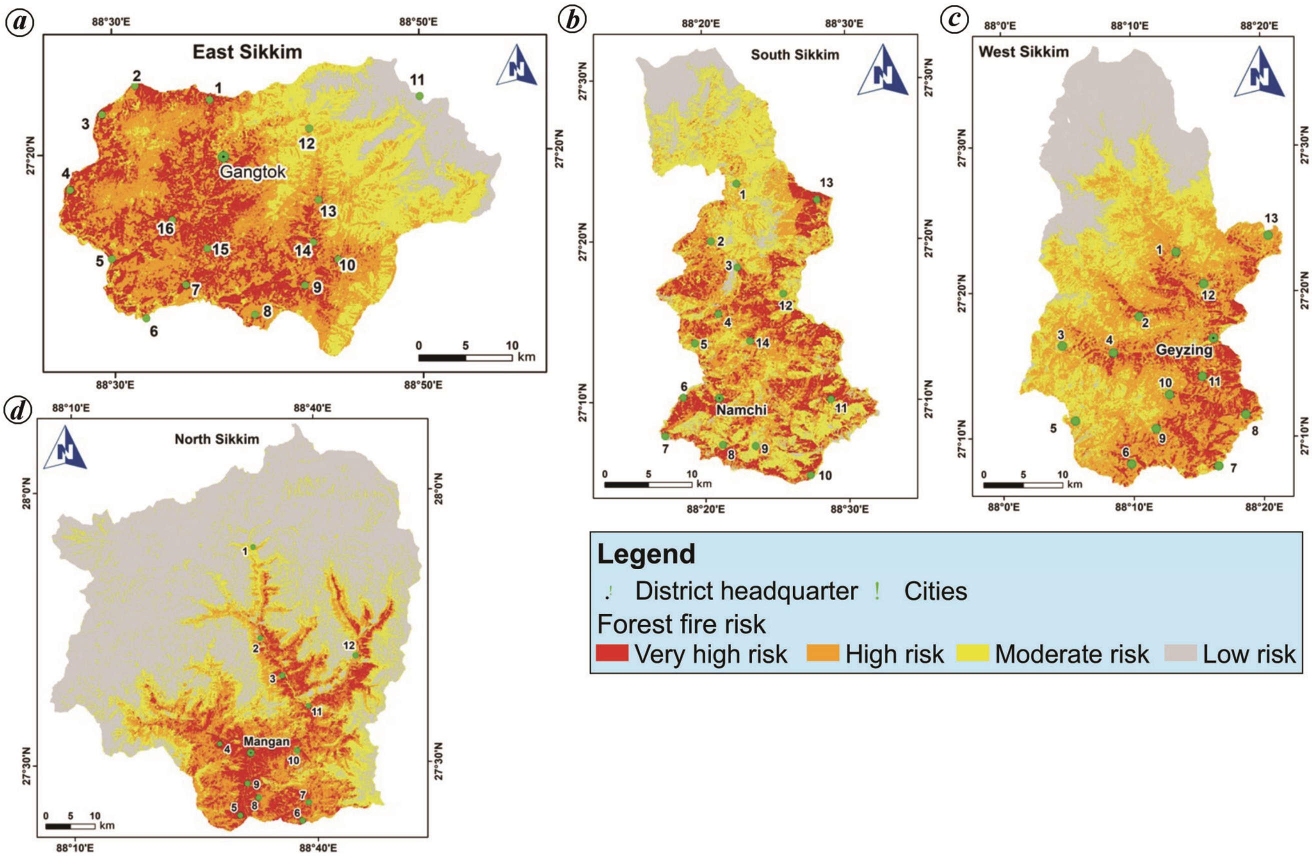

Figure 5. District-wise forest fire risk maps for Sikkim; the numbers 1, 2, 3, … correspond to the location of sites mentioned in the text. ***a***, East Sikkim (1, Navey; 2, Dikchu; 3, Kumbul; 4, Singbe; 5, Singtam; 6, Rangpo; 7, Padamche; 8, Rhenok; 9, Rongli; 10, Lingtam; 11, Nathula; 12, Legyap; 13, Sirichen; 14, Chentang; 15, Pakyong; 16, Namnang). ***b***, South Sikkim (1, Phamtam; 2, Lingdam; 3, Ravangla; 4, Rayong; 5, Subuk; 6, Chautare; 7, Jorthang; 8, Kitam; 9, Mangranm; 10, Melli; 11, Namthang; 12, Chumthang; 13, Lingi; 14, Damthan). ***c***, West Sikkim (1, Yuksam; 2, Darap; 3, Singkhop; 4, Dentam; 5, Ahale; 6, Daramdin; 7, Naya Bazar; 8, Kamling; 9, Soreng; 10, Siribadam; 11, Kaluk; 12, Gerethang, 13, Karchi). ***d***, North Sikkim (1, Thangu; 2, Lachen; 3, Denga; 4, Lingdem; 5, Sangtok; 6, Tingdo; 7, Sirdong; 8, Namok; 9, Rotak; 10, Naga Namgor, 11, Chungthang; 12, Lachun).

Aspect and slope do not have a great influence on fire in these areas; however, LST and elevation of these areas are more than 15°C and less than 1500 m respectively, which significantly influence forest fires[15].

Further, East Sikkim and West Sikkim have 40% and 20% of the areas falling under high-risk and moderate risk zone respectively (Figure 4 *b*). Moderately dense and open forest of conifer trees, sal, thickets and middle hill are found in both the zones. Conifer and sal trees secrete resins, which have low ignition temperature, but their needles have more calorific value (4800 kcal/kg) than all other tree species (2895–3511 kcal/kg)[39], resulting in quick ignition of fire[15]. Needles of chir pine trees found in the southern boundary of West and South Sikkim are also vulnerable to fire[15], which result in high-risk zone (Figure 7 *c*). While vegetation type and density are quite similar in high and moderate risk zones, we have noted differences in terrain and climatic characteristics which define the spreading of fire in a particular zone[40,45,46]. Some of the notable areas that fall into high risk zones include Chungthang, Lachung and Lachen in North Sikkim, the Kitam Bird Sanctuary in South Sikkim, the Fambhonglho Wildlife Sanctuary, and the area between Singtam and Pakyong in East Sikkim, and the Yuksam, Soreng, Daramdin and eastern part of Barsey Rhododendron Sanctuary in West Sikkim (Figure 5 *a*–*d*). These areas have an altitude up to 2000 m and experience high temperature of 30°–15°C from February to May[24], which increases the chance of ignition of forest fire. However, areas like Legyap (East Sikkim), Phamtam (South Sikkim), northeast of Yuksam and Singkhop (West Sikkim) lie in moderate risk zones with altitude above 2000 m and temperature less than 15°C. It is also observed that high slope areas (above 40°) such as Yuksam, Lingdem (North Sikkim), Lachen and Phamtam fall into moderate risk zone. This is because, the fire incidences are more common in the low slope areas (0° to 20°)[42] and in the ridge areas[47,48], but the spreading rate of fire almost doubles upslope[49]. However, it was noticed that south and east-facing terrain showed high risk patches of fire since southern and eastern aspect receive more sunlight, robust winds and more biomass in northern hemisphere[50,51]. Thus, high dense forest in South Sikkim shows very high risk patches, which is an exception because, these high dense

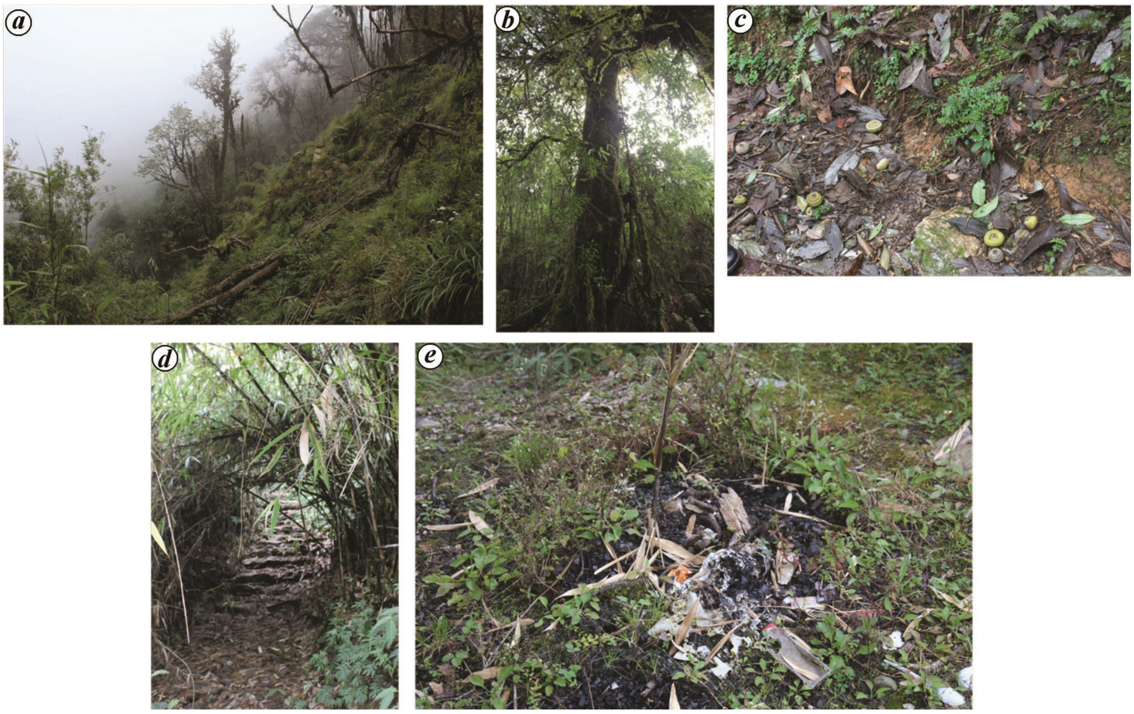

Figure 6. Field photos of Fambhanglho Wildlife Sanctuary in East Sikkim. ***a***, Area affected by fire in 2016. ***b***, 200-year-old oak tree. ***c***, Oak fruits lying down which are prone to fire. ***d***, Bamboo trees at the side of trekking trail. ***e***, Anthropogenic activities in protected area near dense forested areas.

forests are in the eastern terrain. In contrast, north facing slopes in West Sikkim near Gyalshing show patches of very high risk in comparison to the south facing slopes that show high-risk patches, because of agricultural field and moderately dense forest (Figure 3 *a*). Along with these parameters, distances from human settlements (>1000 m) and roads (>500 m) make several districts such as Legyap, Mangranm and south of Namthang (South Sikkim); Yuksam, Lachung and Lingdem to fall under moderate risk zone.

Generally, the areas at higher altitude (>4000 m) fall into low risk zones. These areas such as, Kyongnosla Alpine Sanctuary (East Sikkim), northern part of West Sikkim, and 60% of the area in North Sikkim are covered with snow and are devoid of human settlements and roads[24]. Vegetation like alpine and scrubs are found in these regions, which makes them least vulnerable to fire.

FIRMS data for the last 16 years and field photographs taken on October 2018 were used to validate the forest fire risk map (Figure 4). Previous work[24] and forest officials of Fambhanglho Wildlife and Kitam Bird Sanctuary suggested that these sanctuaries experienced a large number of fire incidences compared to other protected areas of the state. The primary reason of fire in these regions is attributed to accidental and unintentional fires caused by (Figure 6 *e*) by local people and tourists, as both the sanctuaries are close to national highway (Figure 7 *f*) and are popular tourist places. The rhododendron, bamboo and oak species are found in Fambhanglho Wildlife Sanctuary (Figure 6 *b* and *c*), whereas chir pine, sal wild date palm are found in Kitam Bird Sanctuary (Figure 7 *a* and *c*). As explained earlier, these trees are highly vulnerable to fire. We also documented that the areas under high-risk showed maximum number of forest fire incidences and low risk areas showed few incidences in each district. Our analysis shows that overall, 61% of FIRMS data and 82% of the past forest fire incidences lie in very high and high-risk zones over the state. In South and West Sikkim, most of the FIRMS data of forest fires lie in high-risk zone. On the other hand, in North and East Sikkim, about 60% of the FIRMS data lies in very high risk zones. However, only 18% of the FIRMS data in the state lies in low risk zone. We therefore argue that our forest fire risk analysis is fairly robust at this scale, and can serve as a guide to take up detailed investigations in the major hotspots of forest fire risk.

Conclusion

Our study was motivated by the reports of increasing incidences of forest fire in Sikkim and was aimed at delineating the different zones at risk to forest fire. The results derived from the risk modelling showed that the vegetation type, aspect, slope were the important factors in the spreading of forest fire, whereas the anthropogenic factors were the primary reasons for the ignition of forest fire in Sikkim. In consequence, moderate dense forest on

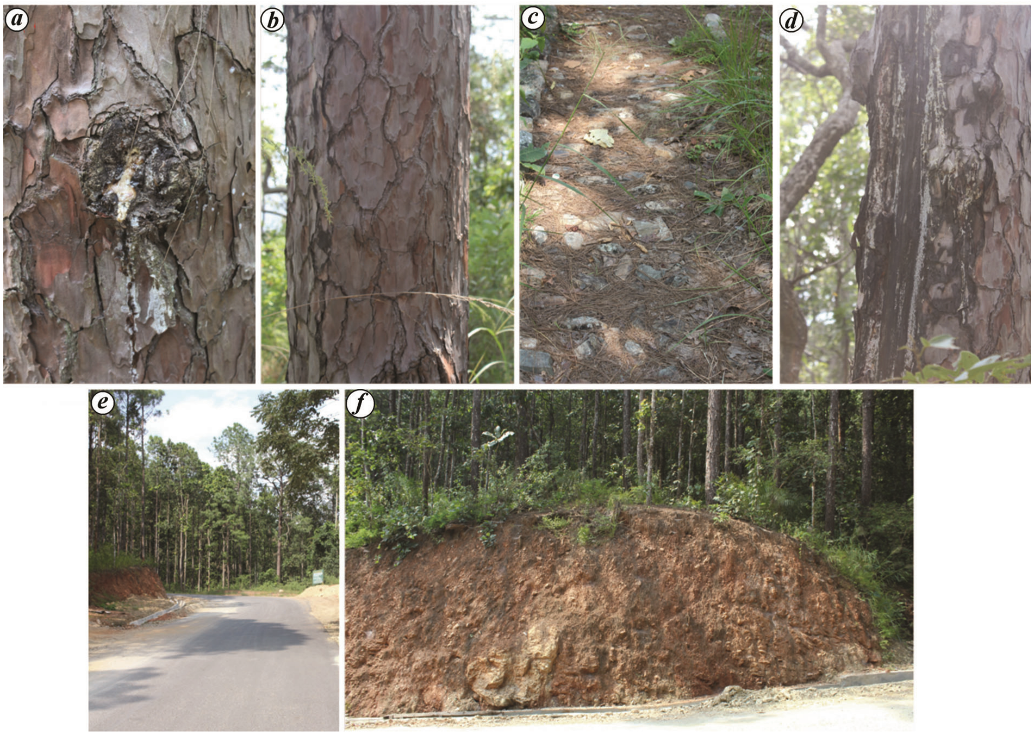

Figure 7. Field photos of Kitam Bird Sanctuary in South Sikkim. ***a***, Resin of chir pine tree having high calorific value. ***b***, Bark of chir pine trees which are prone to fire. ***c***, Accumulated Chir pine needles which are prone to surface fire. ***d***, 2017 forest fire patch. ***e***, Trees planted at the side of national highway. ***f***, Very dense forested areas in terrain having slope greater than 30°.

medium slope, forest area adjacent to the road and human settlement, and forest on the southern and eastern part of the hill would be more affected by the fire. Our study reveals that about 36% of Sikkim lies in very high and high-risk zones and 21% in the moderate risk zone. This means that more than half of the state is under a serious threat of forest fire. Typically, tropical forest, agricultural lands, moderately dense forest, dense human settlements mark the areas in a very high-risk zone. More importantly, three major sanctuaries, namely Kitam Bird Sanctuary, Fambhaglho Wildlife Sanctuary, and Barsey National Park and several important areas such as Gangtok Pakyong, Melli, Jorthang, Kaluk, Naya Bazar, Gyalshing and Mangan fall under very high to high-risk zone. This study should help to plan detailed high resolution work in these hotspots and to plan mitigation measures.

1. Kramer, P. J., Carbon dioxide concentration, photosynthesis, and dry matter production. *Bioscience*, 1981, **31**, 29–33.
2. Cochrane, M. A. and Ryan, K. C., Fire and fire ecology: concepts and Principles. In *Tropical Fire Ecology* (ed. Cochrane, M. A.), Springer, Switzerland AG, 2009, pp. 25–62.
3. Laurance, W. F. and Williamson, G. B., Positive feedbacks among forest fragmentation, drought, and climate change in the Amazon. *Conserve. Biol.*, 2001, **15**, 1529–1535.
4. Cochrane, M. A., Fire science for rainforests. *Nature*, 2003, **421**, 913–919.
5. Thirgood, S., Woodroffe, R. and Rabinowitz, A., The impact of human-wildlife conflict on human lives and livelihoods. *Conserv. Biol. Series*, 2005, **9**, 13.
6. Collins, R. D., de Neufville, R., Claro, J., Oliveira, T. and Pacheco, A. P., Forest fire management to avoid unintended consequences: a case study of portugal using system dynamics. *J. Environ. Manage.*, 2013, **130**, 1–9.
7. Lentile, L. B. *et al.*, Remote sensing techniques to assess active fire characteristics and post-fire effects. *Int. J. Wildland Fire*, 2006, **15**, 319–345.
8. Eugenio, F. C. *et al.*, Applying gis to develop a model for forest fire risk: a case study in espírito santo, brazil. *J. Environ. Manage.*, 2016, **173**, 65–71.
9. Koetz, B., Morsdorf, F., Van der Linden, S., Curt, T. and Allgöwer, B., Multi-source land cover classification for forest fire management based on imaging spectrometry and lidar data. *Forest Ecol. Manage.*, 2008, **256**, 263–271.
10. You, W., Lin, L., Wu, L., Ji, Z., Zhu, J., Fan, Y. and He, D., Geographical information system-based forest fire risk assessment integrating national forest inventory data and analysis of its spatio-temporal variability. *Ecol. Indic.*, 2017, **77**, 176–184.
11. Cocke, A. E., Fulé, P. Z. and Crouse, J. E., Comparison of burn severity assessments using differenced normalized burn ratio and ground data. *Int. J. Wildland Fire*, 2005, **14**, 189–198.
12. Escuin, S., Navarro, R. and Fernandez, P., Fire severity assessment by using NBR (normalized burn ratio) and NDVI (normalized difference vegetation index) derived from landsat TM/ETM images. *Int. J. Remote Sensing*, 2008, **29**, 1053–1073.
13. Wang, L., Qu, J. J. and Hao, X., Forest fire detection using the normalized multi- band drought index (NMDI) with satellite measurements. *Agric. Forest Meteorol.*, 2008, **148**, 1767–1776.
14. Guangmeng, G. and Mei, Z., Using modis land surface temperature to evaluate forest fire risk of northeast china. *IEEE Geosci. Remote Sensing Lett.*, 2004, **1**, 98–100.
15. Sharma, S. and Pant, H., Vulnerability of Indian Central Himalayan forests to fire in a warming climate and a participatory preparedness approach based on modern tools. *Curr. Sci.*, 2017, **112**, 2100–2105.
16. Cosentino, M. J., Woodcock, C. E. and Franklin, J., Scene analysis for wildland fire-fuel characteristics in a mediterranean climate. In

Proceedings of the International Symposium on Remote Sensing of Environment, Environmental Research Institute of Michigan, University of Michigan, USA, 11–15 May 1981, pp. 635–646.

17. Jain, A., Ravan, S. A., Singh, R., Das, K. and Roy, P., Forest fire risk modelling using remote sensing and geographic information system. *Curr. Sci.*, 1996, **70**, 928–933.
18. Jaiswal, R. K., Mukherjee, S., Raju, K. D. and Saxena, R., Forest fire risk zone mapping from satellite imagery and gis. *Int. J. Appl. Earth Observ. Geoinf.*, 2002, **4**, 1–10.
19. Malik, T., Rabbani, G. and Farooq, M., Forest fire risk zonation using remote sensing and GIS technology in Kansrao forest range of Rajaji National Park, Uttarakhand, India. *Int. J. Adv. Remote Sensing GIS*, 2013, **2**, 86–95.
20. Vadrevu, K. P., Eaturu, A. and Badarinath, K., Fire risk evaluation using multicriteria analysis – a case study. *Environ. Monit. Assess.*, 2010, **166**, 223–239.
21. Sharma, R., Sharma, N., Shrestha, D., Luitel, K. K., Arrawatia, M. and Pradhan, S., Study of forest fires in Sikkim Himalayas, India using remote sensing and gis-techniques. Climate Change in Sikkim: Patterns, Impacts and Initiatives, Government of Sikkim, Gangtok, India, 2012, pp. 233–244.
22. Koczkodaj, W. W. *et al.*, Important facts and observations about pairwise comparisons (the special issue edition). *Fund. Inform.*, 2016, **144**, 291–307.
23. FEWMD, Environmental Initiatives of the State Government (1994–2016), pp. 1–124.
24. Sharma, S., Joshi, V. and Chhetri, R. K., Forest fire as a potential environmental threat in recent years in Sikkim, Eastern Himalayas, India. *Climate Change Environ. Sustain.*, 2014, **2**, 55–61.
25. Panda, A. K. and Misra, S., Health traditions of Sikkim Himalaya. *J. Ayurveda Integr. Med.*, 2010, **1**, 183.
26. Kumar, P. and Ghose, M., Estimation of pyrogenic carbon emissions from forests of Sikkim Himalaya, India: a geoinformatics approach. *Curr. Sci.*, 2017, **113**, 1864–1872.
27. Rai, S. C. and Sundriyal, R. C., Tourism and biodiversity conservation: the Sikkim Himalaya. *Ambio*, 1997, **26**, 235–242.
28. Champion, H. G., A preliminary survey of forest types of India and Burma. *Indian Forestry Record (NS) Silviculture*, Government of India Press, New Delhi, 1936, vol. 1, p. 286.
29. Khawas, V. and Tamang, R. K., Conservation and management of water resource in Sikkim Himalaya: some suggestions. *Spatio-Econ. Develop. Rec.*, 2005, **12**, 27–31.
30. Adab, H., Kanniah, K. D. and Solaimani, K., Modeling forest fire risk in the northeast of Iran using remote sensing and gis techniques. *Nat. Hazards*, 2013, **65**, 1723–1743.
31. Tambe, S., Arrawatia, M. and Sharma, N., Assessing the priorities for sustainable forest management in the Sikkim Himalaya, India: a remote sensing based approach. *J. Indian Soc. Remote Sensing*, 2011, **39**, 555–564.
32. FSI, The state of forest report 2005, Forest Survey of India, Dehradun.
33. Barsi, J. A., Schott, J. R., Hook, S. J., Raqueno, N. G., Markham, B. L. and Radocinski, R. G., Landsat-8 thermal infrared sensor (tirs) vicarious radiometric calibration. *Remote Sensing*, 2014, **6**, 11607–11626.
34. Chuvieco, E. and Congalton, R. G., Application of remote sensing and geographic information systems to forest fire hazard mapping. *Remote Sensing Environ.*, 1989, **29**, 147–159.
35. Saaty, T., *The Analytic Hierarchy Process*, Agric. Econ. Rev., McGraw Hill, New York, 1980, p. 70.
36. Saaty, T. L., A scaling method for priorities in hierarchical structures. *J. Math. Psychol.*, 1977, **15**, 234–281.
37. Alonso, J. A. and Lamata, M. T., Consistency in the analytic hierarchy process: a new approach. *Int. J. Uncertain., Fuzz. Knowl. Syst.*, 2006, **14**, 445–459.
38. Song, H.-S. and Lee, S.-H., Effects of wind and tree density on forest fire patterns in a mixed-tree species forest. *Forest Sci. Technol.*, 2017, **13**, 9–16.
39. Chandran, M., Sinha, A. and Rawat, R., Replacing controlled burning practice by alternate methods of reducing fuel load in the Himalayan long leaf pine (*Pinus roxburghii* sarg.) forests. In Fifth International Wildland Fire Conference, Sun City, South Africa, 2011, pp. 9–13.
40. Somashekar, R., Nagaraja, B. and Urs, K., Monitoring of forest fires in Bhadra wildlife sanctuary. *J. Indian Soc. Remote Sensing*, 2008, **36**, 99–104.
41. Xu, D., Shao, G., Dai, L., Hao, Z., Tang, L. and Wang, H., Mapping forest fire risk zones with spatial data and principal component analysis. *Sci. China Ser. E: Technol. Sci.*, 2006, **49**, 140–149.
42. Mhawej, M., Faour, G. and Adjizian-Gerard, J., A novel method to identify likely causes of wildfire. *Climate Risk Manage.*, 2017, **16**, 120–132.
43. Somashekar, R., Ravikumar, P., Kumar, C. M., Prakash, K. and Nagaraja, B., Burnt area mapping of Bandipur National Park, India using irs 1c/1d liss iii data. *J. Indian Soc. Remote Sensing*, 2009, **37**, 37–50.
44. Gheshlaghi, H. A., Using gis to develop a model for forest fire risk mapping. *J. Indian Soc. Remote Sensing*, 2019, **47**, 1173–1185.
45. Chavan, M., Das, K. and Suryawanshi, R., Forest fire risk zonation using remote sensing and gis in Huynial watershed, Tehri Garhwal district, UA. *Int. J. Basic Appl. Res.*, 2012, **2**, 6–12.
46. Anitha, S., Soujanya, S. and Rajkumar, G., An approach for identifying the forest fire using land surface imagery by locating the abnormal temperature distribution. *IOSR J. Comput. Eng.*, 2013, **14**, 06–12.
47. Fang, L., Yang, J., Zu, J., Li, G. and Zhang, J., Quantifying influences and relative importance of fire weather, topography, and vegetation on fire size and fire severity in a Chinese boreal forest landscape. *For. Ecol. Manage.*, 2015, **356**, 2–12.
48. Wood, S. W., Murphy, B. P. and Bowman, D. M., Firescape ecology: how topography determines the contrasting distribution of fire and rain forest in the south west of the Tasmanian wilderness world heritage area. *J. Biogeogr.*, 2011, **38**, 1807–1820.
49. Weise, D. R. and Biging, G. S., Effects of wind velocity and slope on fire behavior. In Fire Safety Science – Proceedings of the Fourth International Symposium (ed. Kashiwagi, T.), International Association for Fire Safety Science, Boston, USA, 1994, pp. 1041–1051.
50. Singh, R. P. and Ajay, K., Fire risk zone assessment in Chitrakoot area, Satna MP, India. *Res. J. Agric. For. Sci.*, 2013, 1–4.
51. Setiawan, I., Mahmud, A., Mansor, S., Shariff, A. M. and Nuruddin, A., GIS-grid-based and multi-criteria analysis for identifying and mapping peat swamp forest fire hazard in Pahang, Malaysia. *Disaster Prev. Manag.*, 2004, **13**(5), 379–386.

ACKNOWLEDGEMENTS. The authors thank the Indian Institute of Technology Kanpur for providing scholarship to AL from the Ministry of Human Resource and Development, Govt of India for pursuing his Master's programme. We acknowledge the funding for this work from the Swiss Agency for Development and Cooperation (SDC), India through the Helvetas Swiss Intercorporation and UNDP India. We are also grateful to the officials of the Forest Department of the Sikkim government for providing us data on vegetation type, density and protected forest boundaries of the Sikkim state.

Received 4 April 2021; revised accepted 14 August 2021

doi: 10.18520/cs/v121/i8/1022-1031