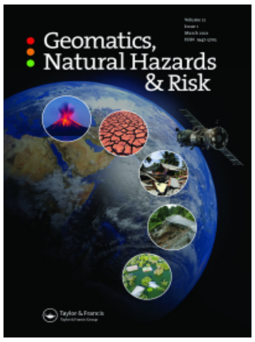

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Forest fire risk mapping using GIS and remote sensing in two major landscapes of Nepal

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ABSTRACT

Forest fires have increased at an alarming rate in recent years, with multiple consequences in Nepal's forest ecosystem and landscapes. The research used remote sensing and GIS technology as well as statistical tools for developing forest fires risk models in two major landscapes of Nepal, i.e., Terai Arc Landscape (TAL) and Chitwan Annapurna Landscape (CHAL). A multi-parametric weighted index model was adopted to derive and demarcate the forest fire-risk map with risk variables such as vegetation, topographic factors, land surface temperature, and proximity to the road and settlements. To enhance the use of a fire risk map, collinearity between variables was checked (VIF <2) and validated with the Moderate Resolution Imaging Spectroradiometer (MODIS) hotspots and Kernel Density Estimation (KDE) method. The MODIS hotspot data from 2001 to 2018 was also evaluated which indicates that the number of fire counts has a strong relation (R^2 =0.82) with the burn area. Broadleaved forest in the pre-monsoon season is highly vulnerable to forest fire. More than half of the total forested area (65%) is in high fire risk, particularly in the TAL region. The study results could assist the decision-makers to implement preventive measures by minimizing the risk and impacts of forest fires.

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KEYWORDS
Fire management; fire risk index model; MODIS; landscape

1. Introduction

Forest fire frequency is increasing globally with the significant incidents occurring in Asia (Giglio et al. 2006). Wildfires have major environmental and ecological issues (Zhang et al. 2016), threaten human lives (Bowman et al. 2009), causing massive losses of lives and properties (Russell-Smith et al. 2007). Satellite data can help detect forest fires in different

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land use (Kaufman et al. 1998; Justice et al. 2006) and the Geographical Information System (GIS) and remote sensing techniques have been used widely to assess and predict the fire frequency (Roy et al. 2002; Giglio et al. 2006; Abedi Gheshlaghi et al. 2020). Assessment of the integrated spatial-temporal pattern of hazardous natural events is essential in disaster risk management, however, this aspect is often neglected (Loboda and Csiszar 2007; Middendorp et al. 2013), and majority of the studies consider these two dimensions separately. The MODIS satellite exploits middle infrared and thermal infrared bands to identify thermal anomalies and generate fire locations and has relatively better accuracy (Roy et al. 2002; Pereira et al. 2017). Fire-risk maps are widely developed in many countries at coarse resolution using wildland fuel models or vegetation maps (Chuvieco et al. 2004; Hessburg et al. 2007) as an early warning precaution. Fire risk zone is an area where fires are likely to occur that might impact other places as well (Jaiswal et al. 2002 ; Erten et al. 2004). An accurate risk zone mapping is essential to abate the possible effects of fires in the forest (Jaiswal et al. 2002).

TAL and CHAL are two significant landscapes in Nepal and are considered to be Asia's important biodiversity ecoregion. Forest fires are one of the major ecological threats that affect different regions of these landscapes annually, mainly in the pre-monsoon season (WWF Nepal 2017). The main objective of this study was to identify where and when are the fire most likely to occur. This is crucial to understand the factors associated with forest fires and for planning strategies to reduce forest fires, to control and manage the sources of ignition, and to identify areas at risk (Leone et al. 2003; Koutsias et al. 2016; Parajuli and Haynes 2015). Developing an integrated forest fire risk zone can therefore be helpful in deciding the problems taking into account of the human and biophysical factors.

2. Study area

TAL was declared as a transboundary conservation landscape representing Asia's most crucial biodiversity ecoregion of the TeraiDuar Savanna and Grassland (Wikramanayake et al. 2001) CHAL, which includes four WWF Global 200 ecoregions, was identified in 1999 to maintain north-south ecological connectivity (Figure 1). Both landscapes cover nine protected areas and three Ramsar sites from the elevation range from about 100 m in the Terai to over 8,000 m in the Himalaya (WWF Nepal 2017). More than 75% of the forests of the lowland Terai and Churia fall within the TAL boundary, while CHAL covers 38% of the landscape under forest cover (Figure 2). It is the habitat of many endangered and rare flora and fauna. However, most forests are highly fragmented (WWF Nepal 2017). People in these areas are still heavily dependent upon forests and ecosystem services for their livelihoods and wellbeing (GoN/Ministry of Forests and Soil Conservation 2016).

3. Materials and methods

3.1. Independent variables

In this study, variables directly related to fire occurrences have been taken as independent variables. Aspect, slope, elevation, vegetation, temperature, road, settlement are independent parameters to the forest fire (Figure 3) (Sass and Sarcletti 2017).

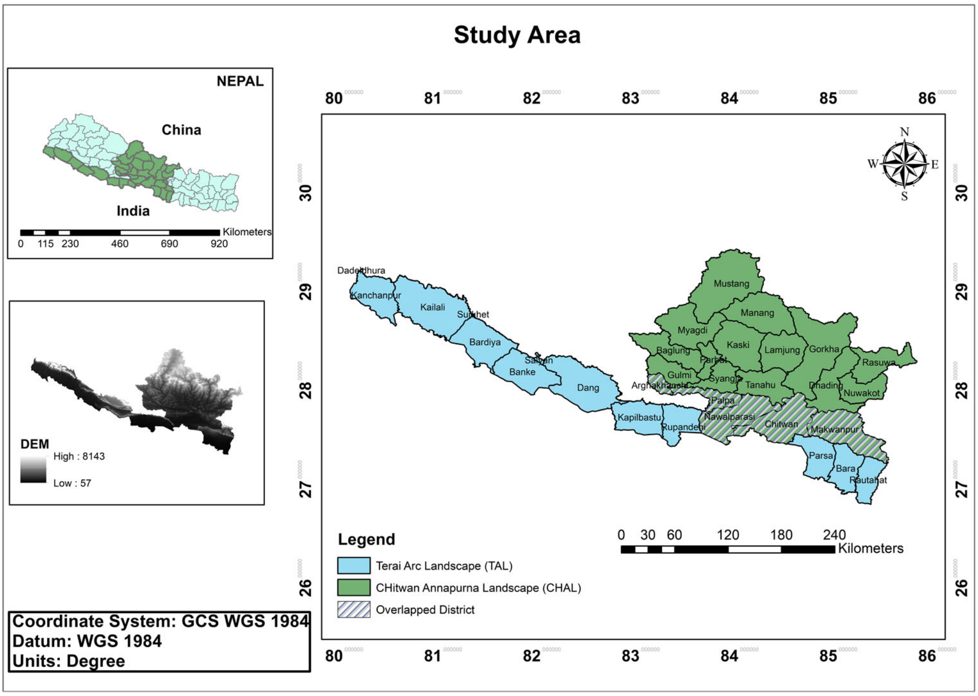

Figure 1. Study area.

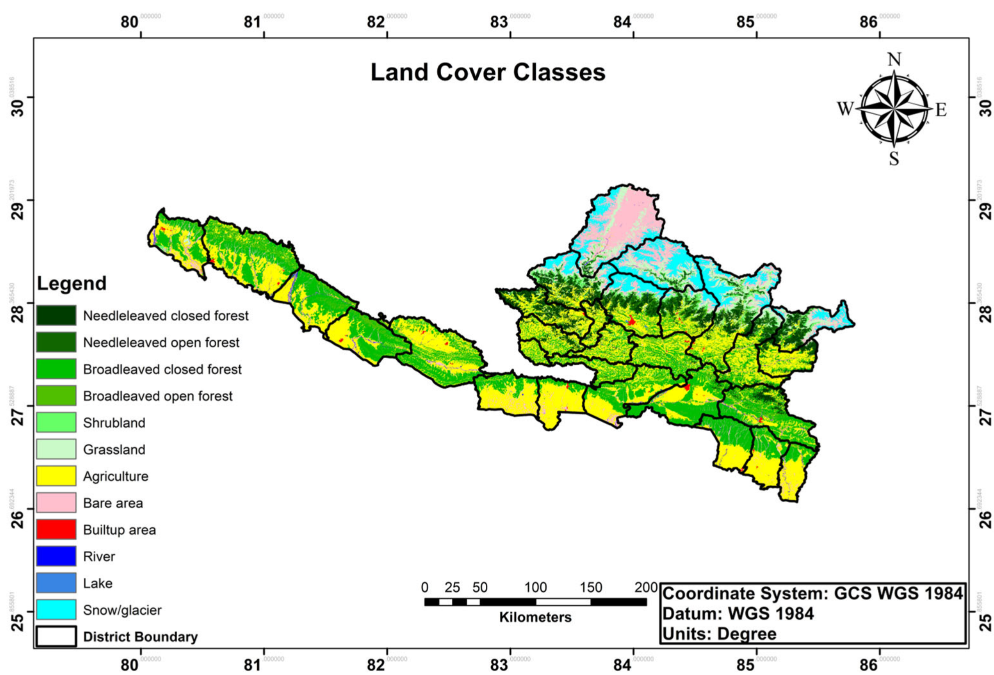

Figure 2. Land cover class of the study area.

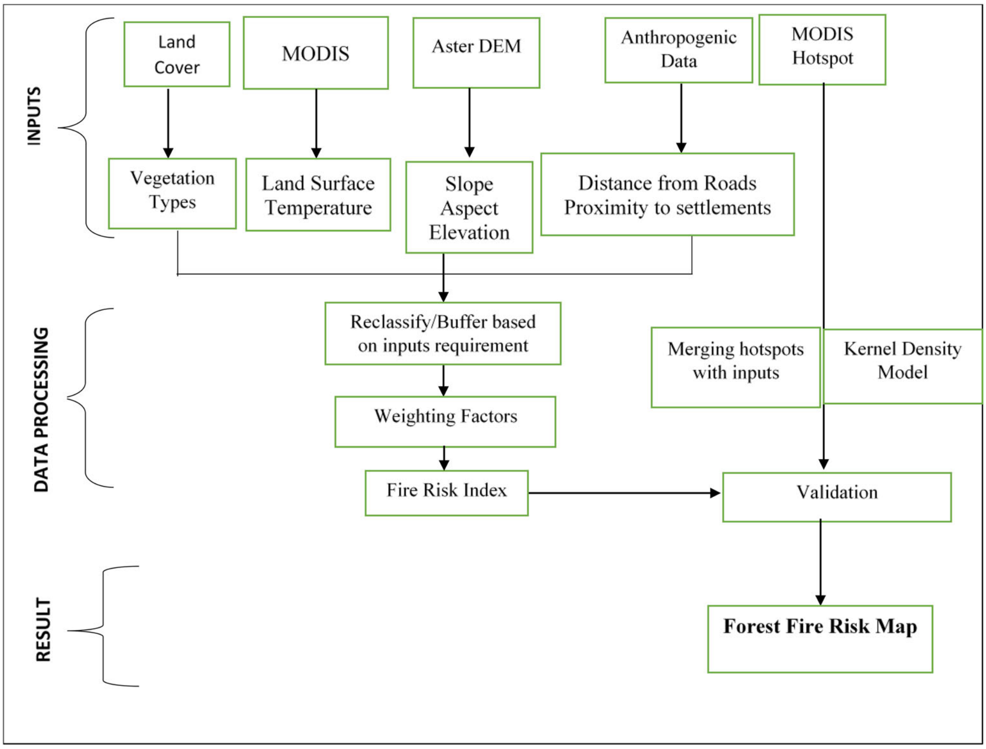

Figure 3. Methodological framework.

Table 1. Dataset used in the study.

Dataset	File Type	Data Type	Details	Spatial Resolution	Source
MODIS Fire Data	SHP	Point/Polygon	Longitude, latitude, burn date, burnt area confidence	1 Km	NASA/MODIS/FIRMS/ESDOS
ASTER DEM	Tiff	Raster	Elevation, Slope, Aspect	30 m	Vertex/Alaska Satellite Facility
Land Cover 2010	Tiff	Raster	Land Cover Classes of Nepal	30 m	ICIMOD
Land Surface Temperature	HDF	Raster	Monthly temperatures of day and night time	1Km	NASA/MODIS/MOD11C3
Study Area Boundary	SHP	Polygon	Outlines of all study district		ICIMOD
Road	SHP	Lines	Highway and associated Roads	1:250000	ICIMOD
Settlements	SHP	Points	Cluster of settlements	1:25,000	OCHA Nepal

3.1.1. Topography

There is an effect of terrain attributes on the forest survival following wildfire (Kushla and Ripplee1997). Hence, under topographic variation, slope, aspect, and elevation were extracted using Aster DEM (30 m) as mentioned in Table 1. For slope (Figure 4a) and elevation (Figure 4b), the points were extracted using ArcGIS, whereas, for aspect (Figure 4c) which was in non-numerical form, calculation of proportionate values was done into nine classes (Guo et al. 2016).

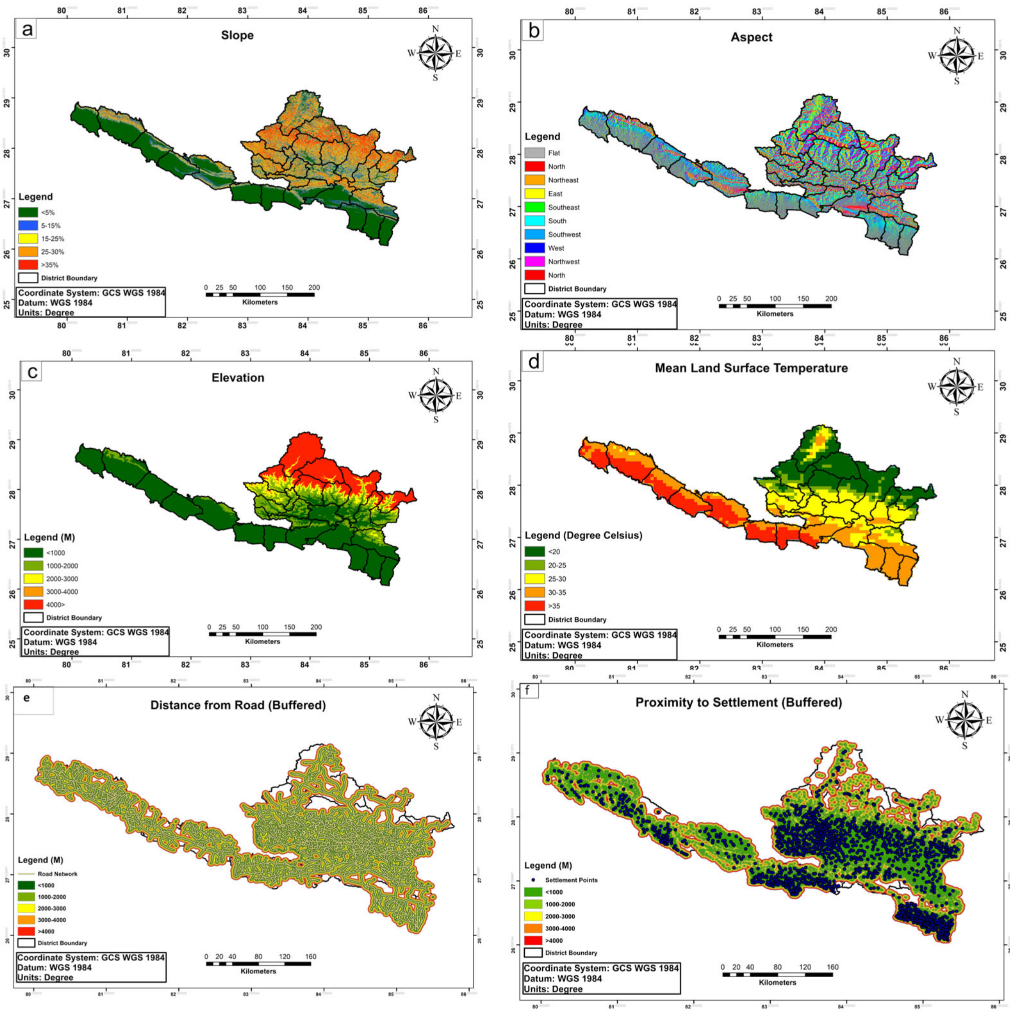

Figure 4. Variables (a) Slope (b) Aspect (c) Elevation (d) Mean land surface temperature (e) Distance from road and (f) Proximity to settlement.

3.1.2. Land cover

Land cover is considered to be the critical factor for spreading fire and has high weightage for influencing the risk (Chuvieco and Congalton 1989). Hence, vegetation analysis was carried out by grouping into seven different classifications through the data provided by ICIMOD with the spatial resolution of 30 m. Vegetation extraction was done using ArcGIS by estimating proportionate vegetation types in the study area (Figure 2).

3.1.3. Land Surface temperature (LST)

High temperature is directly related to the relative humidity and moisture content of the fuels (Hussin et al. 2008). The LST algorithm uses brightness temperatures in the MODIS bands 31 and 32 to produce day and night LST products at 1 km spatial resolutions in swath format. It uses the MODIS Level-1B 1-km and creates LST HDF files. In this study, monthly mean land surface temperature from 2001 to 2018 was extracted from NASA/MODIS. The pre-monsoon period (March-May) is considered to be high-temperature tenure in Nepal that results in drought and forest fires (Matin et al. 2017). To generate an effective model for the fire risk area, monthly temperature of the pre-monsoon season (March-May) for each year (2001-2018) was averaged and then generated a layer (Figure 4d). 5 to 20 °C fall in temperature was observed during this period under CHAL, and the fall in temperature above 35 °C under TAL areas.

3.1.4. Proximity to roads and settlements

Distance to a road and settlements can be a useful tool to identify the risk areas where maximum human activities occur (Chuvieco and Congalton 1989). A study by Hussin et al. (2008) also indicates that the fire scars were high in the area closer to roads and rivers due to increased movements which contributed to the fires. Hence, proximity to road network (Figure 4e) and settlements (Figure 4f) with the resolution of 1:250000 was used and grouped into following categories: 0-1000 m, 1000-2000 m, 2000-3000 m, 3000-4000 m, and above 4000 m. Multiple ring buffers with 1000 m intervals were then carried out using ArcGIS.

3.2. Dependent Variables: fire incidents and burned area

When all the aforementioned independent variables have a favorable environment for the ignition, forest fire incidents and their burn area or size is the only result of the driven force. Hence, burnt incidents and its size has been taken as a dependent variable in this study. Archive fire points were extracted from The Earth Observing System Data and Information System (EOSDIS) Archive Data Tool, and a polygon was made covering the study area from 2001 to 2018 as shown in Figure 3. For the burn area detections, Fire Information for Resource Management System (FIRMS) makes available information on active fires using the MODIS instrument (1 km resolution) onboard NASA's Aqua and Terra satellites (NASA/University of Maryland 2002). Detection confidence is estimated and ranges from 0% to 100%, where above 30% has better accuracy (Giglio et al. 2003). Therefore, in this study, more than 30% of confidence data have been used. Altogether, 21272 forest fire counts (80% of total counts) were detected, altering 20,550 Km^2 of the forested area. Year 2016 had the highest counts of forest fire followed by 2009 (Figure 5). Similarly, above two-thirds (86%) of the forest fires were seen during the pre-monsoon season (March-May). According to the Annual Report of GoN/DHM (2014), pre-monsoon period's annual temperature was recorded higher than the average temperature in TAL areas. Accumulation of dry fuel gets higher in this period making the fuel more flammable (Sharma1996). R^2 coefficient, 0.82, (Figure 6) shows a strong relationship between an increase in forest fire counts with the area burnt (Giglio et al. 2006; Tansey et al. 2008).

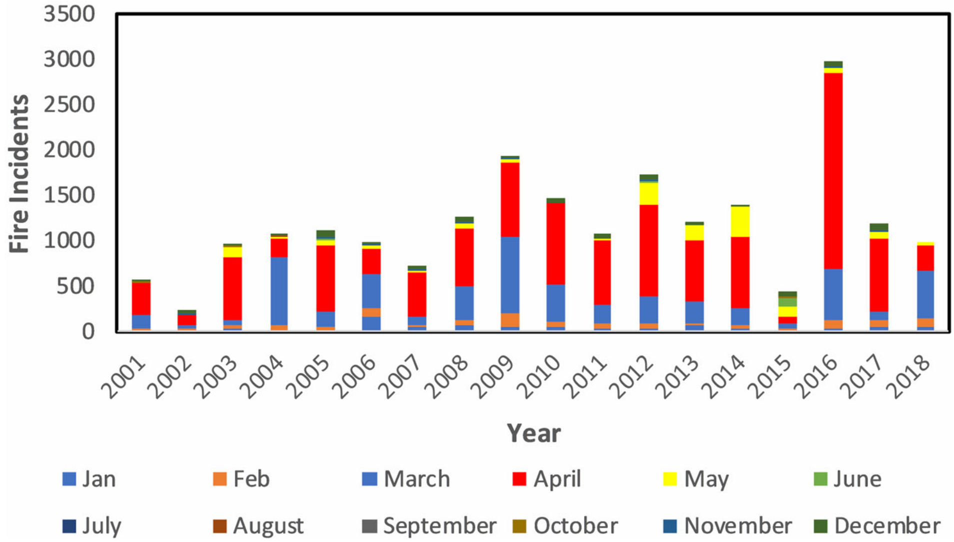

Figure 5. Forest Fire trends from 2001 to 2018(x-axis-year and y-axis-number of fires).

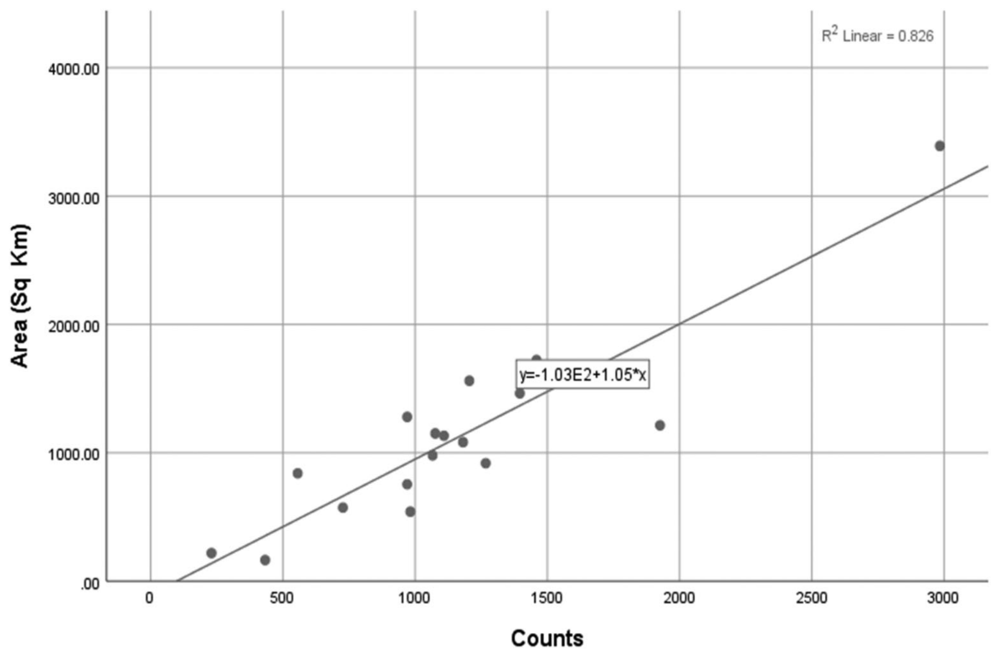

Figure 6. Relation between fire counts on the x axis and burnt area on the y axis.

3.3. Test for multicollinearity

Multicollinearity test was carried out before running a validation. High discrepancy between the data was checked to precisely validate the data and to get accurate results. High correlation between variables (multicollinearity) is a common problem

Table 2. Multiple regression of data used.

Parameters	Unstandardized Coefficients: Coefficient	Unstandardized Coefficients: Std. Error	Standardized Coefficients: Beta	Collinearity Statistics: Tolerance	Collinearity Statistics: VIF
(Constant)	−145611.886				
Burnt Size	3361.917	1275.917	0.024	0.982	1.018
Aspect	−123.956	155.474	−0.007	0.979	1.022
Slope	−4683.377	1695.085	−0.032	0.600	1.666
Elevation	34.478	30.802	0.013	0.621	1.611
Land Cover	9132.250	12951.623	0.006	0.998	1.002
Temperature	10043.057	4473.097	0.021	0.977	1.024
Road	19.861	12.056	0.015	0.973	1.028
Settlement	20.664	14.416	0.013	0.991	1.009

when estimating models, distorting the model estimation, or interfering with accurate estimation (Chang et al. 2013; Kutner et al. 2004).To check the relationships between the variables in the range of the data used (O'brien 2007), multiple linear regression method can be used because it is reasonably flexible and accepts a mixture of continuous and categorical variables as well as non- normally distributed variables (Catry et al. 2009). Variance Inflation Factors (VIF) are used to detect multicollinearity among predictors in a multiple linear regression model (Belsley et al. 1980). According to the thumb rule, if any of the VIF values exceed 5 or 10, it implies that the associated regression coefficients are poorly estimated because of the multicollinearity (Kennedy 1992; Chang et al. 2013).

The result F-test (<0.0011) allows a statistically significant relationship between the two variables at a 95% confidence level (Table 2). VIF for all the eight model variables ranged below 1.7, suggesting a low correlation between all the variables (Davis et al. 2017). Hence, there is a sufficient evidence to conclude low discrepancy of data between burn area, aspect, slope, elevation, temperature, land cover, proximity to the settlement, and the road network. The adjusted model confirms that the explanatory variables are closely related to the dependent, i.e., burnt size.

3.4. Determining the fire risk index model

To get a practical conclusion and avoid error to the model, weight was given based on a review of literature, and each variable was rated on the basis of their fire potential (Chuvieco and Congalton 1989; Jaiswal et al. 2002; Andrews et al. 2005; Hernandez-Leal and Arbelo 2006). Each independent variable with different classes was categorized distinctly based on their forest fire influences as 1 (Very High) to 5 (Very Low). These factors were then weighted in the percentage of their influence, as shown in Table 3. After determining each weightage, all the layers were overlaid in ArcGIS. Hence, the risk model was developed with the equation given below.

$$\mathbf{FRI} = \mathbf{40\%LC} + \mathbf{20\%LST} + \mathbf{10\%S} + \mathbf{10\%DR} + \mathbf{10\%PS} + \mathbf{5\%A} + \mathbf{5\%E} \quad (1)$$

where FRI is the fire risk index, LC is the land cover, LST stands for land surface temperature, S is the slope, DR means the distance from the road, PS is the proximity

Table 3. Weight, value and rating assigned to different variable.

Variable	Weight (%)	Class	Value Assigned	Rating
Land Cover	40	Broad leaved Closed Forest	1	Very High
		Broadleaved Open Forest	2	High
		Grassland	3	Medium
		Shrubland	4	Low
		Needle leaved Open Forest	4	Low
		Needle leaved Closed Forest	4	Low
		Barren Land	5	Very Low
Temp (C)	20	>35	1	Very High
		30-35	2	High
		25-30	3	Medium
		20-25	4	Low
		5-20	5	Very Low
Slope (%)	10	<5	1	Very High
		5-15	2	High
		15-25	3	Medium
		25-35	4	Low
		>35	5	Very Low
Distance to Road (M)	10	<1000	1	Very High
		1000-2000	2	High
		2000-3000	3	Medium
		3000-4000	4	Low
		4000-5000	5	Very Low
Proximity to Settlement (M)	10	<1000	1	Very High
		1000-2000	2	High
		2000-3000	3	Medium
		3000-4000	4	Low
		>4000	5	Very Low
Elevation(M)	5	57-1000	1	Very High
		1000-2000	2	High
		2000-3000	3	Medium
		3000-4000	4	Low
		>4000m	5	Very Low
Aspect	5	South	1	Very High
		South West	1	Very High
		South East	2	High
		West	3	Medium
		East	3	Medium
		North West	4	Low
		North East	4	Low
		North	5	Very Low

to the settlement, A is the aspect and E is the elevation. Finally, a fire risk zone map was produced based on these analyses.

3.5. Model validation

Validating the model will increase the predictive power or accuracy after merging with a real-world dataset (Beguería 2006). As the model was derived from seven different independent variables, separate forest fire incidents data have been used to validate the map. Firstly, archive fire counts were overlaid in each fire risk zone assuming that higher fire counts fall under the higher risk rating in the assigned category. Secondly, KDE was used to compare the result of the fire risk model. KDE's objective is to produce a smooth density surface of point events over the space by computing event intensity as density estimation (Serra-Sogas et al. 2008). For both methods, the MODIS hotspots have been used as an input.

4. Results and discussion

4.1. Fire risk index model

Each factor that influences the forest fire have been discussed and analysed separately. It is important to note that the overlapped districts of both regions have been counted under the TAL areas as TAL has occupied most of the area. This was done to make the comparison easy and fruitful. According to the land cover class-map, total study area was 5220423.12 ha, and 58.9% of the study area was forested. Broadleaved forest was found to be the major type of forest followed by needle leaved forest. Figure 7a shows that the broadleaved closed forests have 67% of the total forest fire followed by broadleaved open forest (12%) representing the highest counts in TAL areas. Sharma (1996) states that in the forest of plain areas, the continuous fuel consists of 1 to 4 layers of species with 95% volume where Sal (*Shorea robusta*) leaves accounted for 90%. Forest fire is highest in April among all the months during 2016, followed by March in 2009 in broadleaved closed forest; Matin et al. (2017) and Parajuli et al. (2015) have reported similar results as well. Ajin et al. (2016) found the highest forest fire occurrence in a deciduous forest in India, where dry vegetation was more susceptible to fire in the central and southwest parts. Jaiswal et al. (2002) and Ariapour and Shariff (2015) state that 40% of the fire incidences were recorded within 1 km of a road with 65% of the fires in the areas below the elevation of 1000 m. Matin et al. (2017) recorded the occurrences of 60% of the total forest fire as it has heavy leaf fall during summer (i.e., March–June), contributing to the accumulation of leaf litter. Similarly, Matin et al. (2017) recorded 72% of the fire when the temperature was above 30 °C with a slope of less than 5% in plain lands where the results showed that 41% of the fires in Nepal are recorded within 1 km of a settlement and the areas closer to the human settlements were more prone to forest fires Parajuli. Ajin et al. (2016); Ariapour and Shariff (2015); Jaiswal et al. (2002) state that the proximity to the roads plays a vital role in the incidence of fire corresponding to the physical activity from tourists on roads, throwing unextinguished cigarette butts onto the dry litter, and heating bitumen/asphalt for road surfacing. In this study, 73.33% (11 out of 15) of the forest fires occurred close to the roads. Mean temperature of March and May was above 30 °C in TAL, which occupies 74% of the fire as shown in Figure 7b. It has been suggested that the higher the temperature, higher is the risk of forest fire (Hussin et al. 2008; Khanal 2015; Matin et al. 2017). Mean temperature of CHAL at the time was only 5 °C to 20 °C.

Two-thirds (71%) of the forest fires occurred in areas where the slope was below 25% (Figure 7c), mainly found in the southern aspect of TAL, followed by 60.19% of the fires occurring in the western and eastern aspects with 23% slope (Figure 7d). Sharma (1996) also claimed that most of the Terai part lies in the southernmost east to Nepal's west belt. However, according to Matin et al. (2017), that there was no exact pattern of forest fires in different aspects over the whole country's study. The southern aspect receives more sunlight resulting in higher temperatures, which makes fuel drier than in the north (Prasad et al. 2008). Almost 86% of the fires are concentrated in the elevation range of 1000 m as shown in Figure 7e. Forest fires were found to be decreased with the increase in distance from the settlement in the CHAL region

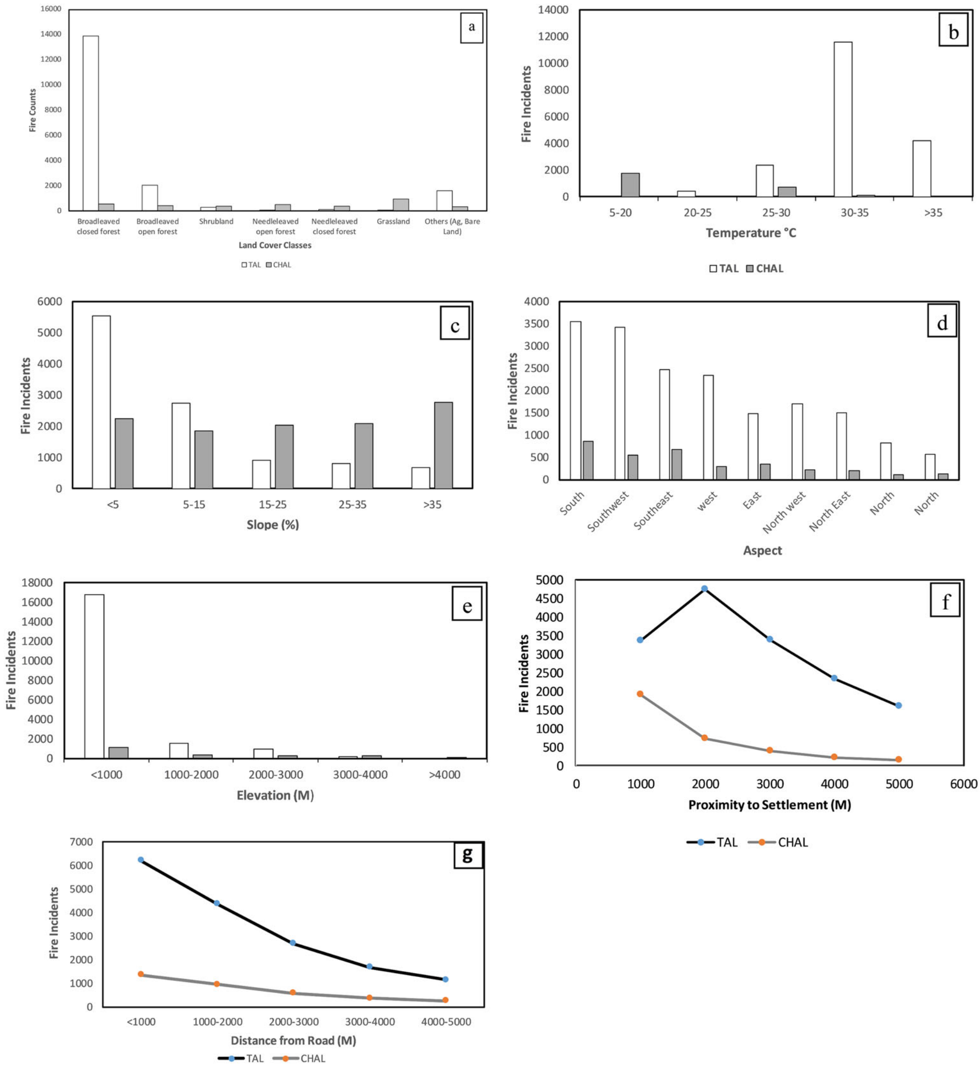

Figure 7. Forest fire incidents in different (a) Land cover classes, (b) Temperature, (c) Slope, (d) Aspect, (e) Elevation, (f) Settlement and (g) Road.

similar to the result of Matin et al. (2017). Interestingly, fire counts were higher within 2000 m (25%) than within 1000 m (17%) of settlements in the TAL area. However, fire counts were decreasing with the distance after 2000 m away from a settlement (Figure 7f). While making the fire risk zone, the risk was predicted to be at a distance near to habitat of 1000 m. A study by Hussin et al. (2008) indicates that people often go far from their settlement to set fire, possibly explaining why the fire zones occur after 1000 m away. Meanwhile, the road nearby from the forest can be riskier, as 38% of fires occurred in the forest with a distance of 1000 m followed by 1000-2000 m (28%) as in Figure 7g. Anthropogenic ignitions frequently occurred

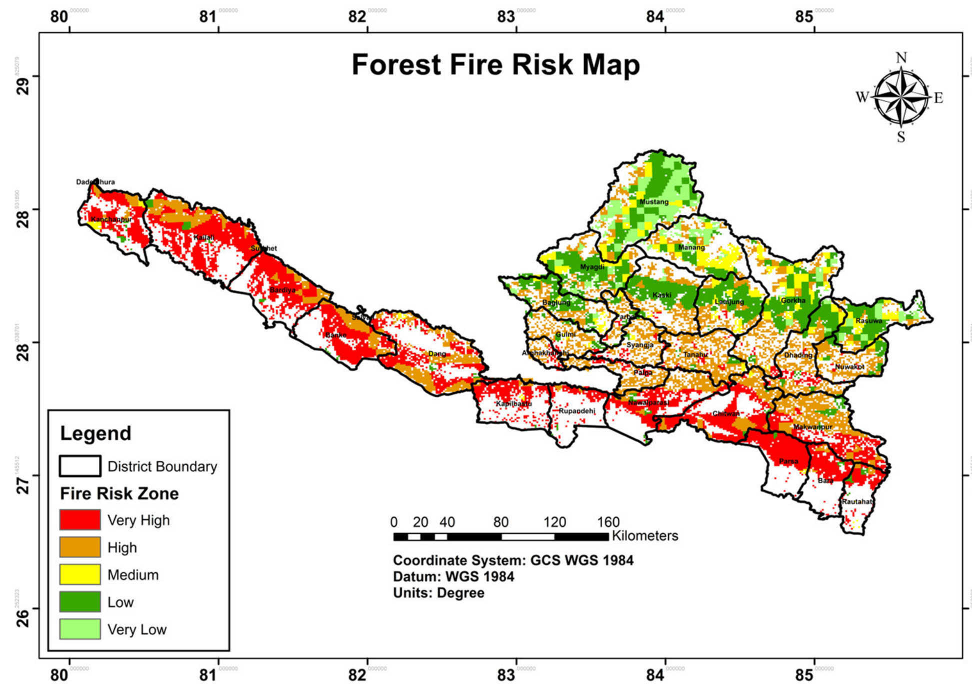

Figure 8. Developed forest fire risk index map combining all influencing variables.

Table 4. Comparison of forest fire risk areas in TAL and CHAL.

Risk Zone	% of Total Risk	Risk Area TAL (%)	Risk Area CHAL (%)
Very High	33.1	30.85	2.22
High	32.3	12.99	19.32
Medium	7.1	0.47	6.65
Low	21.1	1.33	19.72
Very Low	6.4	0.00	6.44
Total	100.00	45.64	54.36

Table 5. District with high risk zone.

Study District	% of High-Risk Area	Study District	% of High-Risk Area
Chitwan	63	Tanahu	54
Kailali	63	Kanchanpur	50
Makwanpur	62	Nawalparasi	49
Banke	61	Syangja	43
Bardiya	58	Arghakhanchi	43
Palpa	58	Bara	40
Parsa	56	Kapilbastu	40
Dang	55	Dhading	40

along the road corridors and other areas, where human activity was high (Keeley and Fotheringham 2003).

Based on the weightage given to each parameter according to their influence on forest fire, the values were overlaid using GIS techniques, and the forest fire risk map was delineated (Figure 8). It shows that very high-risk areas cover 33.1%, followed by

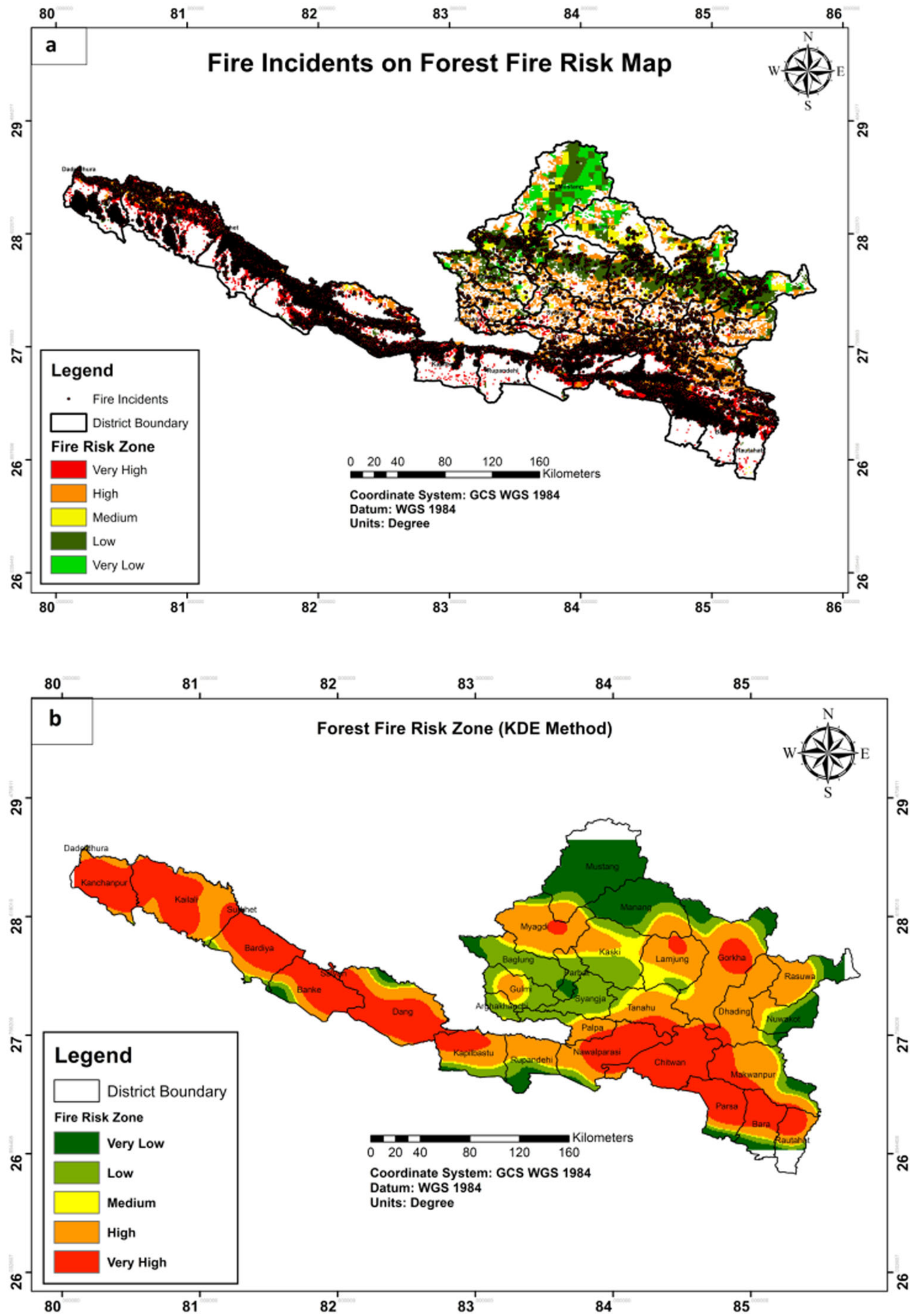

Figure 9. (a) MODIS fire hotspots merged with FRI Map, (b) Fire risk map produced by KDE Method from MODIS fire hotspots.

Table 6. Comparison of risk area with FRI and KDE.

Risk Zone	% of Risk Area from FRI	% of Risk Area from KDE
Very High	33.1	32.8
High	32.3	32.5
Medium	7.1	6.0
Low	21.1	15.7
Very Low	6.4	13

high risk areas with 32.3% (Table 4). Figure 8 clearly shows that the most of the part of TAL is in a red alert zone allocating very high risk and higher-risk areas. 16 out of 33 districts, especially under Terai and Siwalik, fall under the risk above 40% (Table 5), making the region vulnerable to forest fire. This also suggests that the TAL area is much more vulnerable than the CHAL area.

4.2. Model validation

Merging the fire risk map with fire events not only delivers a consistent and complete final risk digital map (Preisler et al. 2004) but also allows the map to be integrated into a cohesive risk assessment process (Fairbrother and Turnley 2005). Most fire incidents fall under very high and high-risk variables, with 87.1% of fire counts (Figure 9a). According to Zhang et al. (2017), KDE works as an appropriate development of a decision support system, as this method has been used as a tool for validation technique for forest fire risk map. Figure 9b shows the map generated using the KDE method. The comparison of risk areas identified by validation of fire points and KDE in Table 6 illustrates that high and very high-risk areas are almost similar to the area generated by the fire risk index map. In contrast, the low-risk zone is decreased, and very low risk has been increased in KDE. It could be because of the less concentrated fire points in low and very low risk zones.

5. Conclusion

Analysis of the MODIS hotspot and all the influencing variables from the time period 2001 to 2018 indicates that the TAL area is highly sensitive to forest fire in comparison to CHAL area. High surface temperature, low rainfall, and the amount of accumulated fuels in the forest contributes to the forest fire. In particular, following factors are responsible for the high risk of forest fire in these two landscapes: broad-leaved closed forest; average temperature of 30°-35°C; slope<5°; south and south-western aspect; elevational range of <1000m in close proximity of settlement in TAL within 2000m, and, CHAL at 1000m; and the distance of < 1000m from the road respectively.

65.4% of the total area of the TAL is under a high fire risk zone; however, only 21.54% in CHAL is likely to be in the high-risk zone. Forests are most prone to high fire risk during the month of April in Nepal. Therefore, realizing TAL's vulnerability, reliable and effective fire mitigating measures should be adopted, and fire preparedness training to the local stakeholders and managers should be encouraged. Nepal faces tremendous forest fires during the dry season for which efficient forest fire risk assessment, warning, and monitoring system need to be improved (Matin et al. 2017). These variables should be taken into care, and areas under these features should be carefully monitored throughout the year by community-based firefighting groups.

Data availability statement

The data that support the findings of this study are available from the corresponding author A. Parajuli upon reasonable request.

Disclosure statement

No potential conflict of interest was reported by the authors.

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