Application of GIS and AHP Method in Forest Fire Risk Zone Mapping: a Study of the Parambikulam Tiger Reserve, Kerala, India

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Abstract

Forest fires are one of the most common natural hazards that occur in the Western Ghats region. There are many protected areas in this part of the Western Ghats; therefore, fire can pose a serious threat to habitats and wildlife. In the past, fires have also affected the Parambikulam Tiger Reserve. The objectives of this study are to demarcate the fire risk zones using GIS techniques and to evaluate the influence of each factor on fire initiation. The following factors are selected for the analysis: land cover types, slope angle, aspect, topographic wetness index, distance from the settlement, distance from the road, distance from the tourist spot, and distance from the anti-poaching camp shed. The analytical hierarchy process method is used to determine the weights, and the ArcGIS and ERDAS Imagine software tools are used to create the fire risk zone map. The area of the prepared map is divided into the following five risk zones: very low, low, moderate, high, and very high. The risk zone map has been validated using fire incidence data for the period from 2002 to 2020 collected from the forest fire portal of the Forest Survey of India. It was found that 71% of fire incidences fall in high-risk and very high–risk zones of the prepared map. The validation using the receiver operating characteristic curve analysis, with an area under ROC curve value of 0.795, confirms the prediction accuracy of the risk zone map. The prepared fire risk zone map will help the planners, officials of the forest, and the disaster management departments to take appropriate mitigation measures in order to prevent future fires and thereby protect the valuable forest resources.

Keywords Analytical hierarchy process · Forest fire · GIS · Parambikulam Tiger Reserve · Western Ghats

Introduction

Forest ecosystems are important constituents of terrestrial bio-diversity, and hence the effective management of this natural resource is essential (Soman and Anitha 2020). Fires are one of the most common hazards that occur in forests worldwide. Fires occur due to natural processes, such as lightning, and due to anthropogenic activities (Abdi et al. 2018; Busico et al. 2019; Manna and Bandyopadhyay 2019). The anthropogenic or human-induced fires occur due to accidents, negligence, or arson (Novo et al. 2020). In addition to deaths, forest fires can pose many direct or indirect damages. Fires can significantly affect regional climate, land surface hydrology, biogeochemical processes, wildlife habitats, and the livelihoods of communities (Ambadan et al. 2020). Forest fires can destruct habitats and the biota (Pastro et al. 2011), resulting in post-fire soil erosion (Chen 2006), land degradation (Nadporozhskaya et al. 2018) or desertification (Santín and Doerr 2016), removal of organic matter and deterioration of soil structure and porosity (Certini 2005), emission of greenhouse gases (Sannigrahi et al. 2020), and release of particulate matter, which cause respiratory, cardiovascular, ophthalmic, and psychiatric problems (Finlay et al. 2012); contaminate air by the fire plumes; and contaminate soil and water due to the deposition of particulate and other materials and due to the fire suppression runoff that contains toxic or hazardous materials (Martin

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et al. 2016). The protected areas in the Western Ghats region of Kerala, a biodiversity hotspot, were frequently affected by fires (Ajin et al. 2014, 2016a, 2016b, 2017a, 2017b; Vinod et al. 2016). The Western Ghats is one of the 25 biodiversity hotspots of the world and is home to endemic flora and fauna (Nameer et al. 2001). Hence, it is critically important to demarcate the fire risk zones so that proper mitigation measures can be adopted in order to prevent or minimize the impacts of fire.

Several studies used GIS techniques in order to delineate forest fire risk zones (Ajin et al. 2016c, 2018; Dong et al. 2005; Veena et al. 2017; Yin et al. 2004). Researchers effectively used methods such as fuzzy logic (Gheshlaghi et al. 2020; Soto 2012), frequency ratio (Pradhan et al. 2007), artificial neural network (Dimuccio et al. 2011; Satir et al. 2016), analytical network process (Gheshlaghi 2019; Gheshlaghi et al. 2020), weights of evidence (Ye et al. 2017), logistic regression (Deng et al. 2013; Mohammadi et al. 2014; Pan et al. 2016), support vector machine (Gigović et al. 2019; Hong et al. 2018), random forest (Arpaci et al. 2014; Gigović et al. 2019; Leuenberger et al. 2018; Pourtaghi et al. 2016), and neuro-fuzzy system (Bui et al. 2017; Kaur and Sood 2019) for delineating the fire risk/susceptible zones. Many researchers (Arca et al. 2020; Busico et al. 2019; Eskandari 2017; Eskandari and Miesel 2017; Güngöroğlu 2017; Kayet et al. 2020; Nuthammachot and Stratoulias 2019; Novo et al. 2020; Tiwari et al. 2020) effectively used analytical hierarchy process (AHP) or/and fuzzy-AHP methods for delineating the forest fire susceptible/risk zones.

The Parambikulam Tiger Reserve located in the southern Western Ghats region of India is selected as the study area. The objectives of the study are to delineate the forest fire risk zones in the study area using the AHP method and GIS techniques, to assess the influence of each factor on fire initiation, and to find the reasons for fire occurrence in the study area. Factors such as land cover types, slope angle, aspect, topographic wetness index (TWI), distance from the settlement, distance from the road, distance from the tourist spot, and distance from the anti-poaching camp shed are selected for the forest fire risk zonation.

Study Area

The Parambikulam Tiger Reserve (PKMTR) is situated between 76° 30′ 0″ and 76° 55′ 0″ E longitudes and 10° 15′ 0″ and 10° 35′ 0″ N latitudes (Fig. 1). This tiger reserve with a total area of 643.66 km^2 comprises the core area of 390.89 km^2 and the buffer area of 252.77 km^2 (Sreehari and Nameer 2016). The major vegetation types of PKMTR are west coast tropical evergreen forests, west coast tropical semi evergreen forests, southern moist mixed deciduous forests, southern dry mixed deciduous forests, and teak plantation. The major peaks in PKMTR are Karimalagopuram (1438 m), Pandaravarai

(1290 m), Vengoli (1120 m), and Puliyarapadam (1010 m) (Sreehari and Nameer 2016). It has three man-made reservoirs, namely Parambikulam, Thunacadavu, and Peruvaripallam, with a cumulative water spread area of 20.66 km^2 (Jobin and Nameer 2012). The sociocultural relevance of the area is signified by the existence of four indigenous communities, namely Kadar, Muthuvar, Malasar, and Malamalasar, which are distributed in the following six tribal colonies: Sungam, Kadas, Kuriarkutty, Pooppara, Fifth colony, and Earth Dam colony (Soman and Anitha 2020). Apart from tiger, PKMTR hosts a wide range of vertebrate and invertebrate wildlife, such as elephant (*Elephas maximus*), gaur (*Bos gaurus*), leopard (*Panthera pardus*), sloth bear (*Melursus ursinus*), spotted deer (*Axis axis*), and sambar deer (*Rusa unicolor*), which are some of the major mammalian fauna.

Materials and Methods

PKMTR falls in the Survey of India (SoI) topographic maps numbered 58 B/10, 58 B/11, 58 B/14, and 58 B/15 at the 1:50,000 scale. The data used in this study include Landsat 8 Operational Land Imager (OLI) satellite images, Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM), SoI topographic maps, Google Earth Pro data, and secondary data collected from the Kerala Forests & Wildlife Department. The thematic layers of factors such as land cover types, slope angle, aspect, TWI, distance from the settlement, distance from the road, distance from the tourist spots, and distance from the anti-poaching camp shed were prepared using ArcGIS 10.6 and ERDAS Imagine 8.4 software tools. The thematic layers of factors such as slope angle, aspect, TWI, distance from the settlement, distance from the road, distance from the tourist spot, and distance from the anti-poaching camp shed were classified using the natural breaks (Jenks) classification method. All the spatial data were projected to Universal Transverse Mercator (WGS 84; 43N). The thematic layers were then resampled with a spatial resolution of 30 m and combined using the Raster calculator tool in the ArcGIS software after assigning the weights determined by the AHP method to generate the forest fire risk zone map. The Microsoft Excel was used to derive the AHP weights. The prepared fire risk zone map was then validated using the fire incidence points for the period from 1 November 2002 to 7 November 2020 collected from the forest fire portal of the Forest Survey of India (FSI). The RStudio software was used for the ROC curve analysis and the area under a receiver operating characteristic curve (AUC) value estimation. The major analysis involved in the mapping process is shown in the flowchart (Fig. 2).
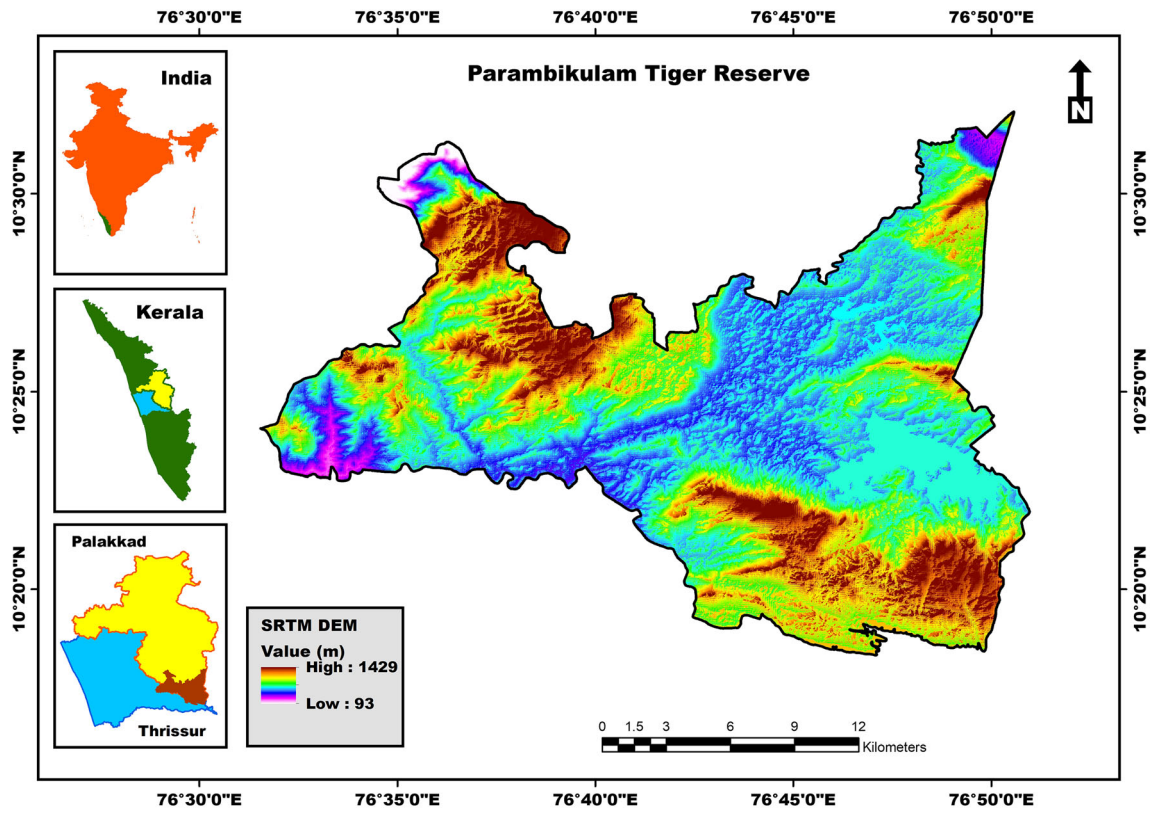
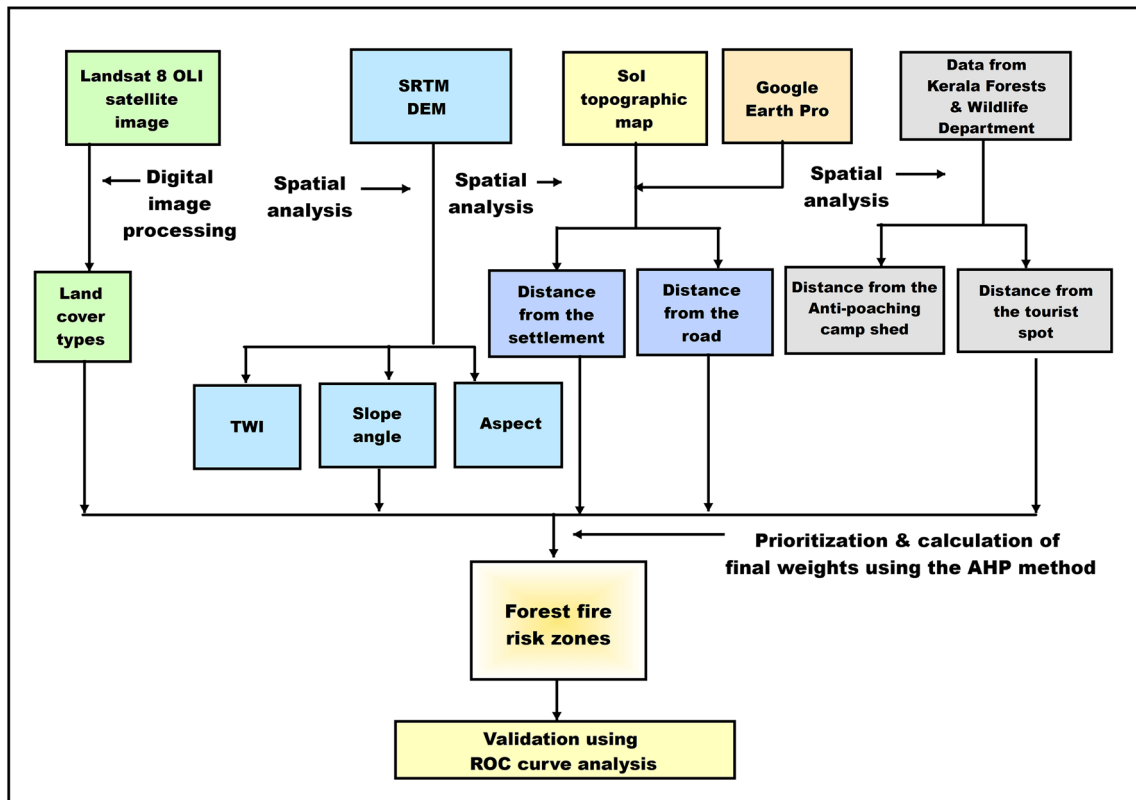Fig. 1 Study area: Parambikulam Tiger Reserve

Fig. 2 Flowchart of the method

Causative Factors

Land Cover Types

The vegetation is fuel for the fire, and the fire spread depends on the type of vegetation cover, the fuel spacing, etc. Forest fire is more prevalent in areas where the vegetation is dry and thick (Veena et al. 2017) because flames spread quickly if fuels are closer. The Landsat 8 OLI satellite image with a spatial resolution of 30 m was used to derive the land cover types in the study area. For the supervised classification of the satellite image, the ERDAS Imagine software was used. For classifying different land cover types present in this area, the maximum likelihood (ML) classification method was used. The seven land cover types present in this area are agricultural land, barren land, built-up area, evergreen forest, scrubland, deciduous forest, and water body (Fig. 3).

Slope Angle

The slope is a crucial factor that influences the strength of fire. The steeper slope leads to more fuel preheating (Estes et al. 2017). The spread of fire is faster in uphill areas but slower in downhill areas (Jaiswal et al. 2002). The slope was derived from the SRTM DEM with a spatial resolution of 30 m using the ArcGIS Spatial Analyst (surface analysis) tool. The slope

of the study area is grouped into five classes (0–7.09°, 7.09–14.49°, 14.49–22.50°, 22.50–32.68°, and 32.68–78.62°) as shown in Fig. 4.

Aspect

The aspect of an area influences the fire behavior directly by the amount of solar radiation and moisture availability and indirectly by changes in the vegetation composition and density (Estes et al. 2017). The southern aspects are subjected to greater solar radiation, and the western aspects receive a higher rate of heating (Setiawan et al. 2004). Hence, the southern and western aspects are more prone to fires. The aspect was derived from the SRTM DEM using the ArcGIS Spatial Analyst (surface analysis) tool. The aspect (Fig. 5) is grouped into the following nine classes: Flat, North, Northeast, East, Southeast, South, Southwest, West, and Northwest.

Topographic Wetness Index

TWI refers to the spatial distribution of soil moisture and surface saturation (Yong et al. 2012). Large forest fires exclusively occur under low soil moisture conditions (Krueger et al. 2015). The topographic wetness index was derived from the SRTM DEM with a spatial
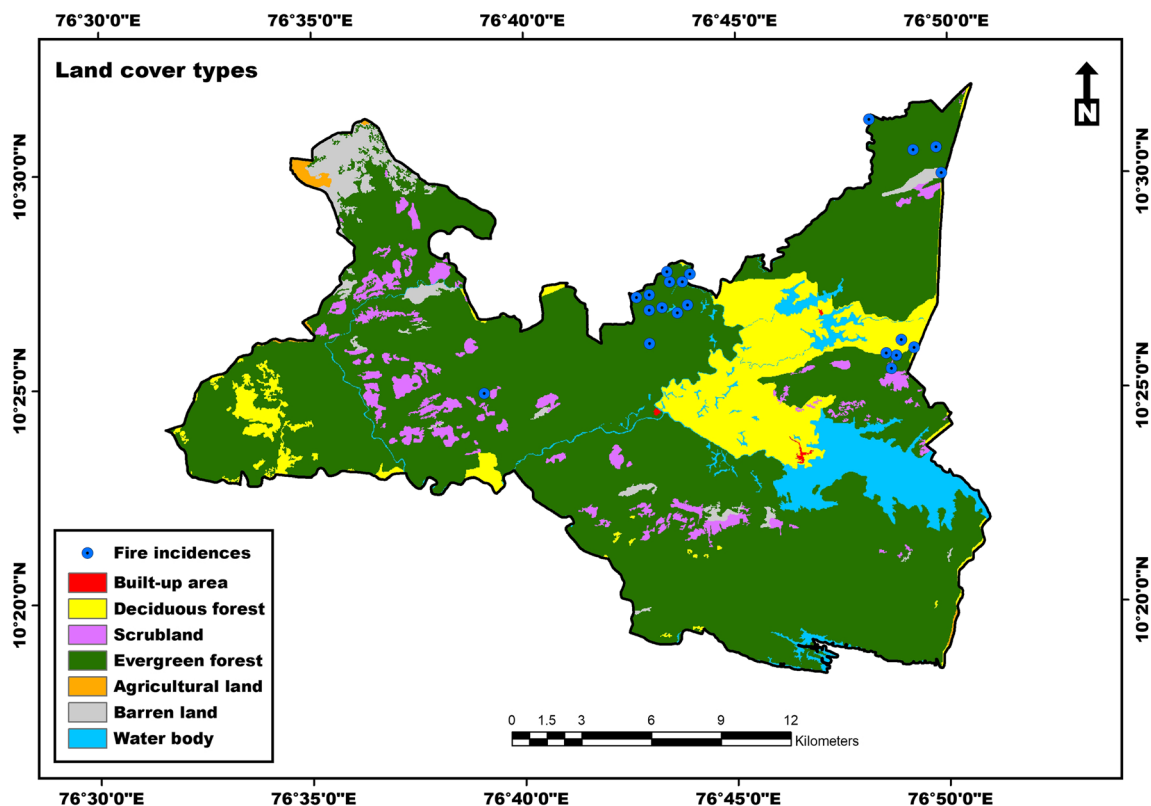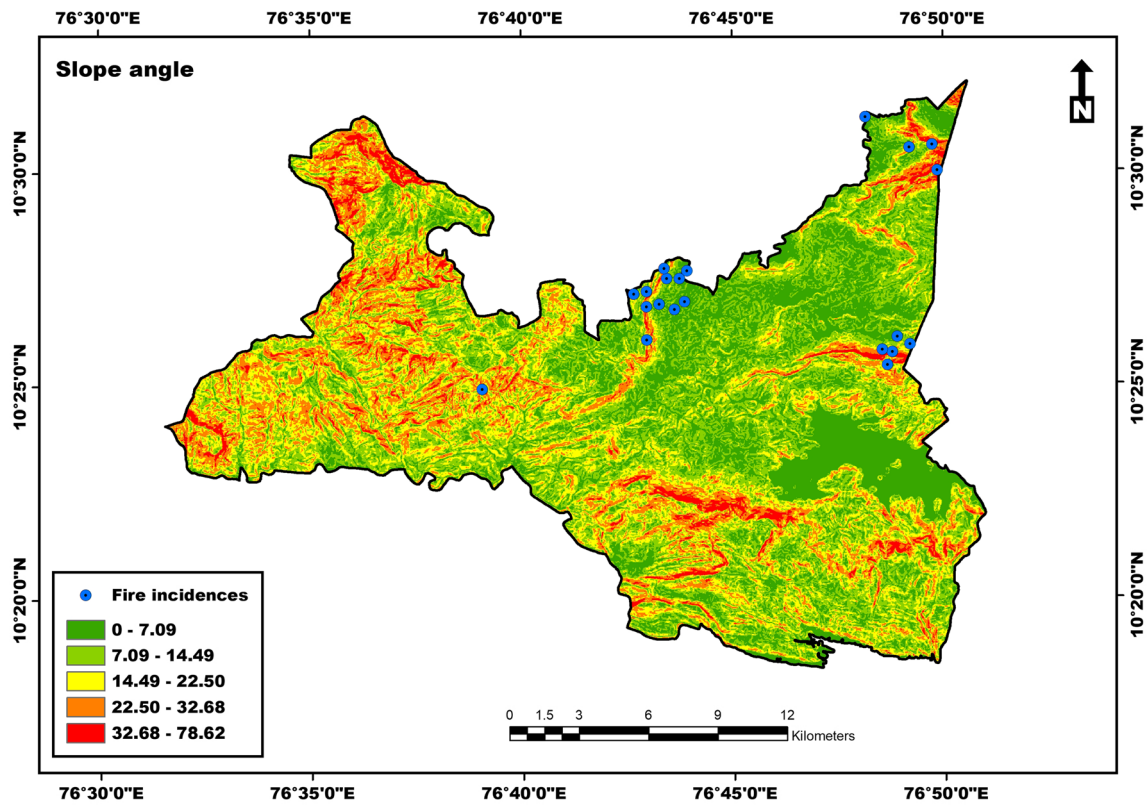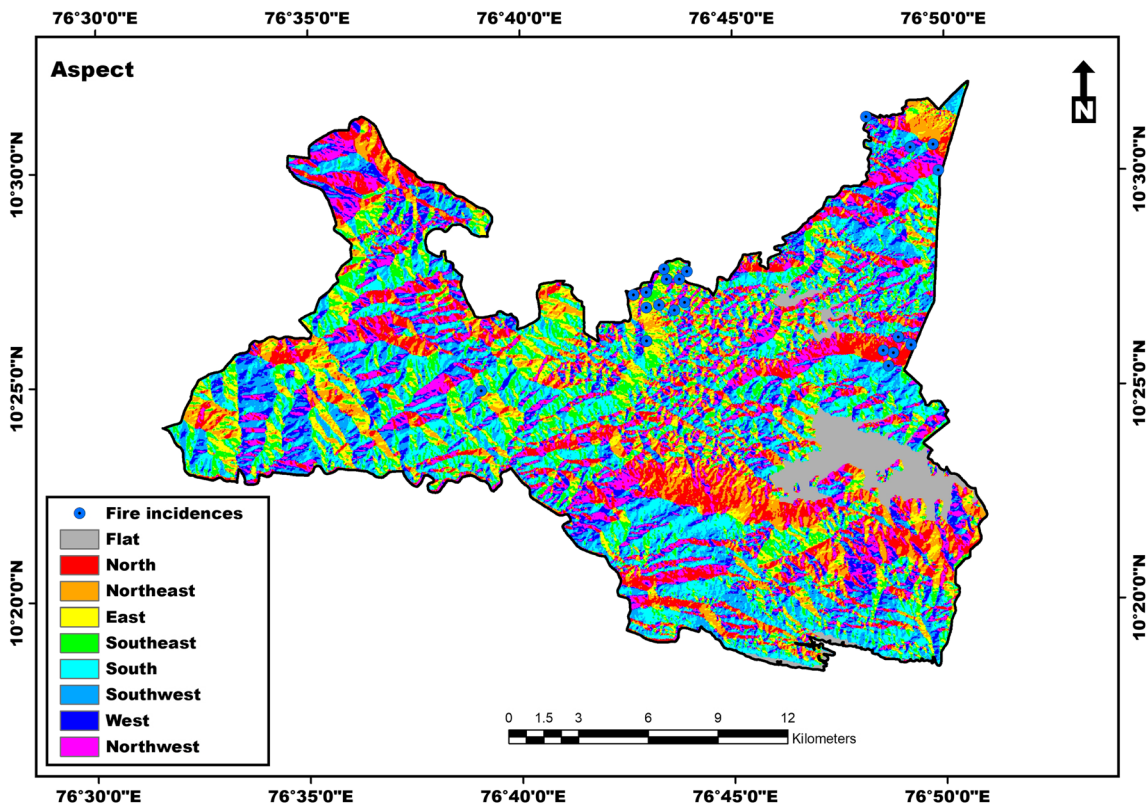

Fig. 3 Land cover types

Fig. 4 Slope angle

Fig. 5 Aspect

resolution of 30 m. TWI was calculated using Eq. 1 (Beven and Kirkby 1979) and ArcGIS Spatial Analyst tools.

$$TWI = \ln(\alpha/\tan\beta) \tag{1}$$

where α is the specific catchment area ($A = A/L$, catchment area (A) divided by the contour length (L)) and β is the local slope.

The present study has classified the study area into five classes (1.85–5.41, 5.41–6.81, 6.81–8.83, 8.83–11.70, and 11.70–19.66) based on the topographic wetness index as shown in Fig. 6.

Distance from the Settlement

The expansion of the wildland–urban interface (WUI) can increase the damages, and more people can be at risk (Tedim et al. 2014). Human-induced fires can be intentional or unintentional. The tribes may set fire to scare wild animals away, to make charcoal, and to collect non-timber forest products. When the fire is not fully extinguished, it may escalate to a disastrous forest fire. Unextinguished cigarette butts thrown by people and campfires set by people can also result in the accidental forest fire. Firewood is used by the tribes residing in the surrounding areas for cooking and other purposes. Sparks produced by such burning can eventually lead to a fire in the nearby forest. Controlled burning is carried out by the forest department in order to avoid large forest fires by burning all the fuel content in the forest before the dry season. Sometimes this fire spreads due to carelessness and leads to large fires. The deliberate forest fires mainly result from the fire set by tribes as a part of tribal traditions, and to clear off the path from dry litter. In some cases, some miscreants also burn forests to settle scores with the forest department and to encroach the forest land. The settlements were digitized from the SoI topographic maps and updated using Google Earth Pro data, and the distance from the settlement layer was generated using the ArcGIS Spatial Analyst (Euclidean distance) tool. PKMTR is divided into five zones (0–2.42 km, 2.42–4.77 km, 4.77–8.05 km, 8.05–11.78 km, and 11.78–16.69 km) based on the distance from the settlements as shown in Fig. 7.

Distance from the Road

The presence of the road is an important factor in the occurrence of human-induced fires (Ricotta et al. 2018). Fires may occur deliberately or accidentally by moving travelers and vehicles on the road (Veena et al. 2017). Wildfire can occur from sparks by cooking near forest roads, campfires set by visitors near forest roads, and coal tar heating for road construction (Satendra and Kaushik 2014) or from refurbishing and repairing existing roads. The roads were digitized from the SoI topographic maps and updated using Google Earth Pro data, and the distance from the
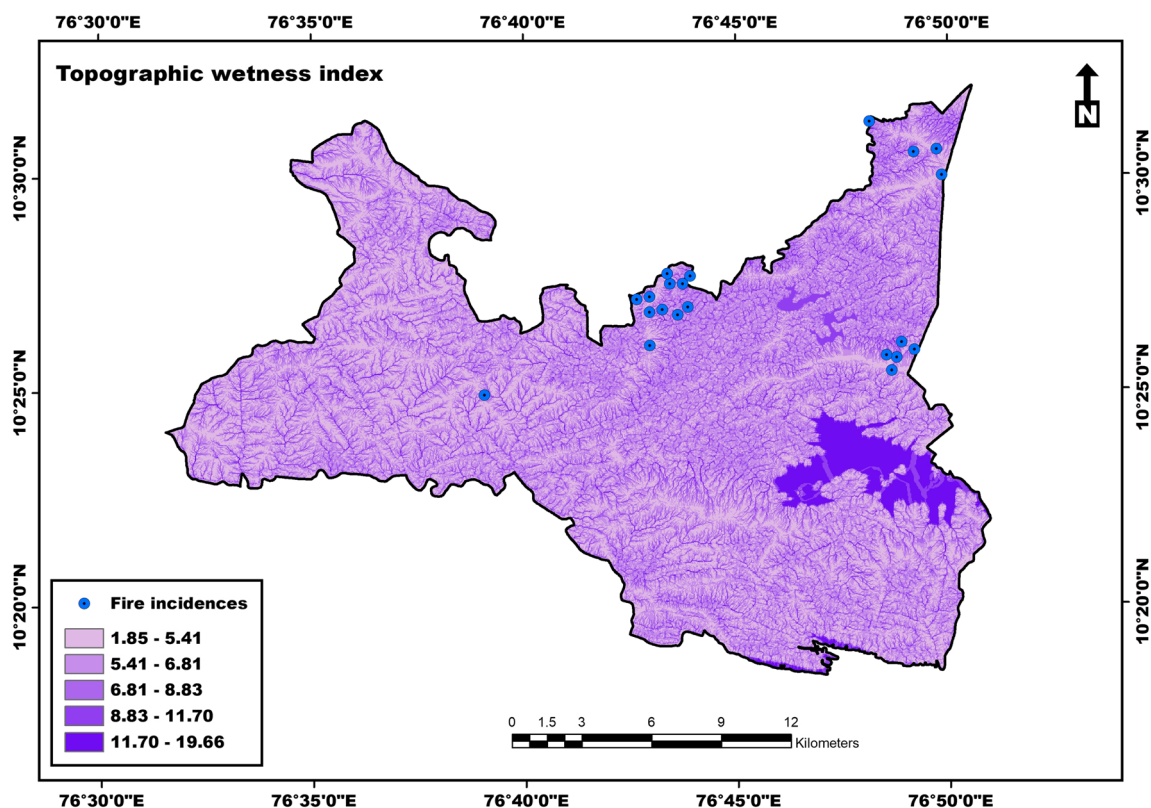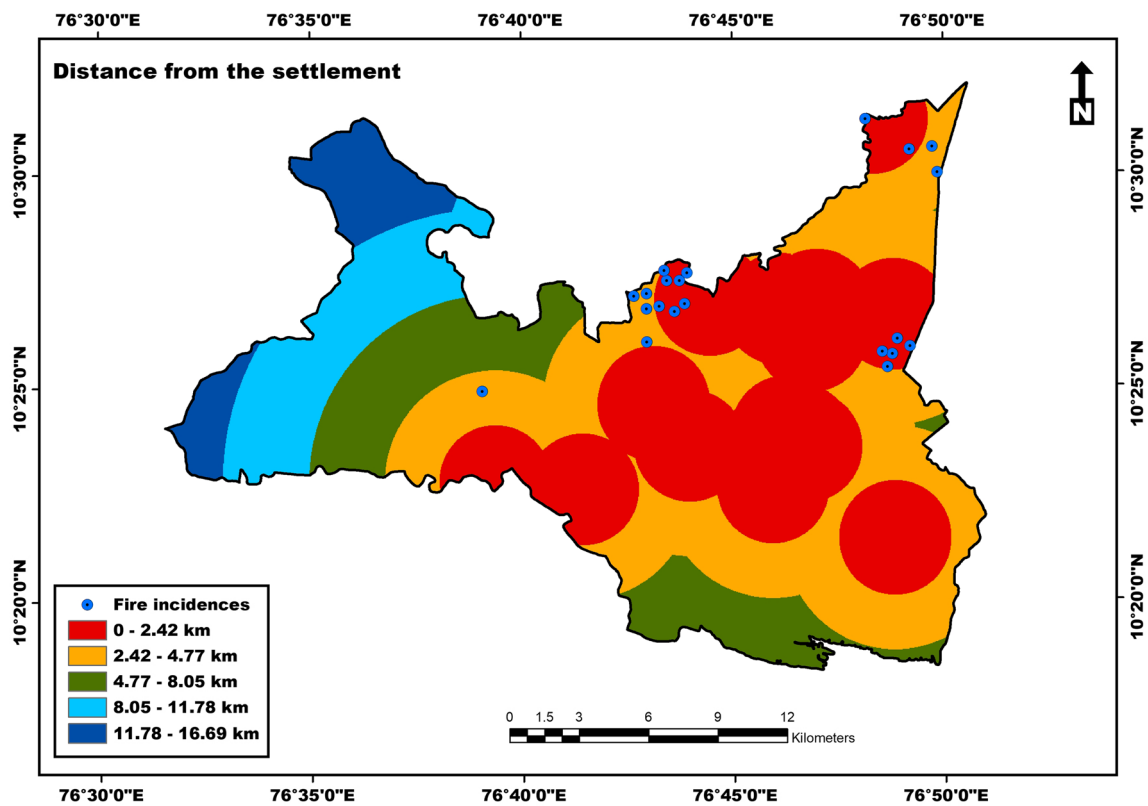

Fig. 6 Topographic wetness index
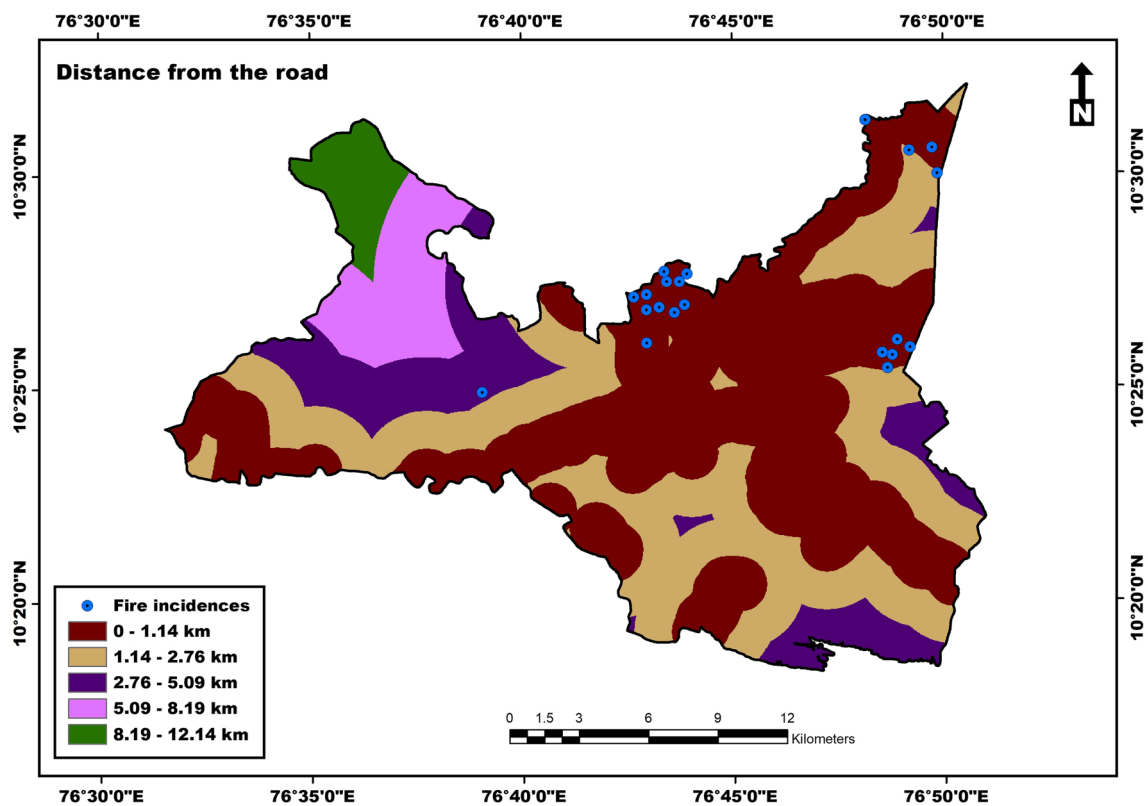
Fig. 7 Distance from the settlement

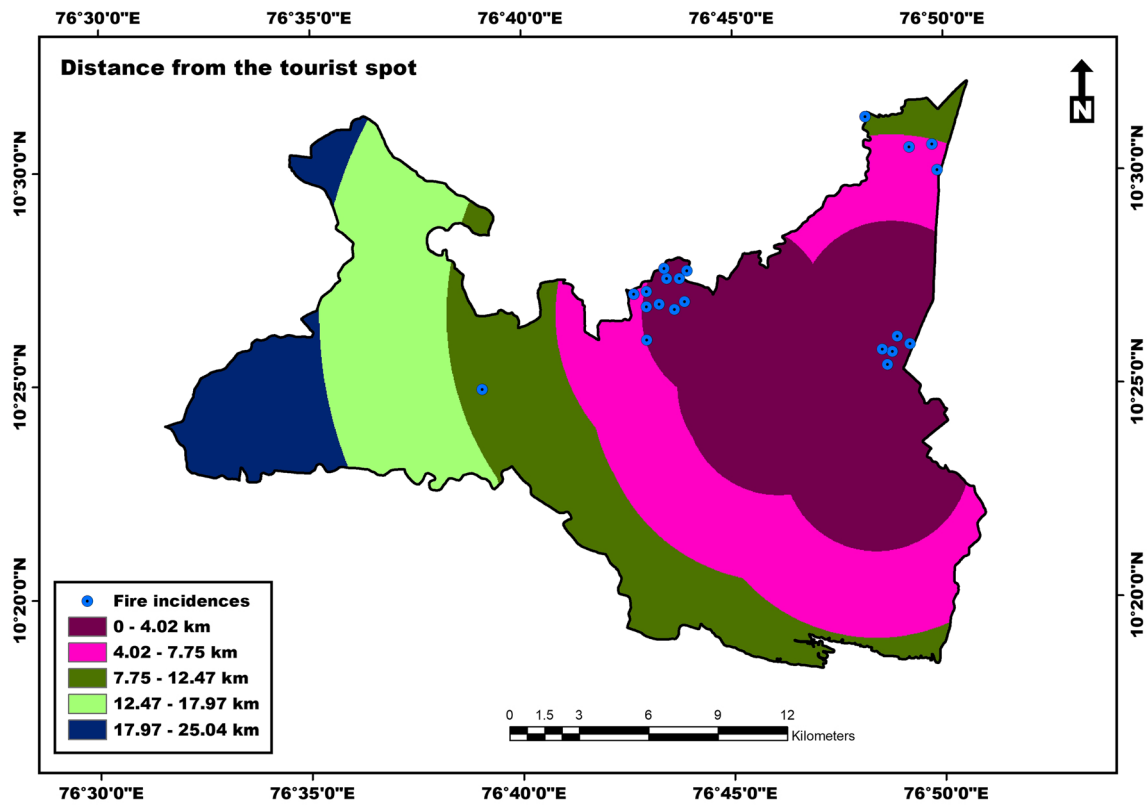**Fig. 8** Distance from the road

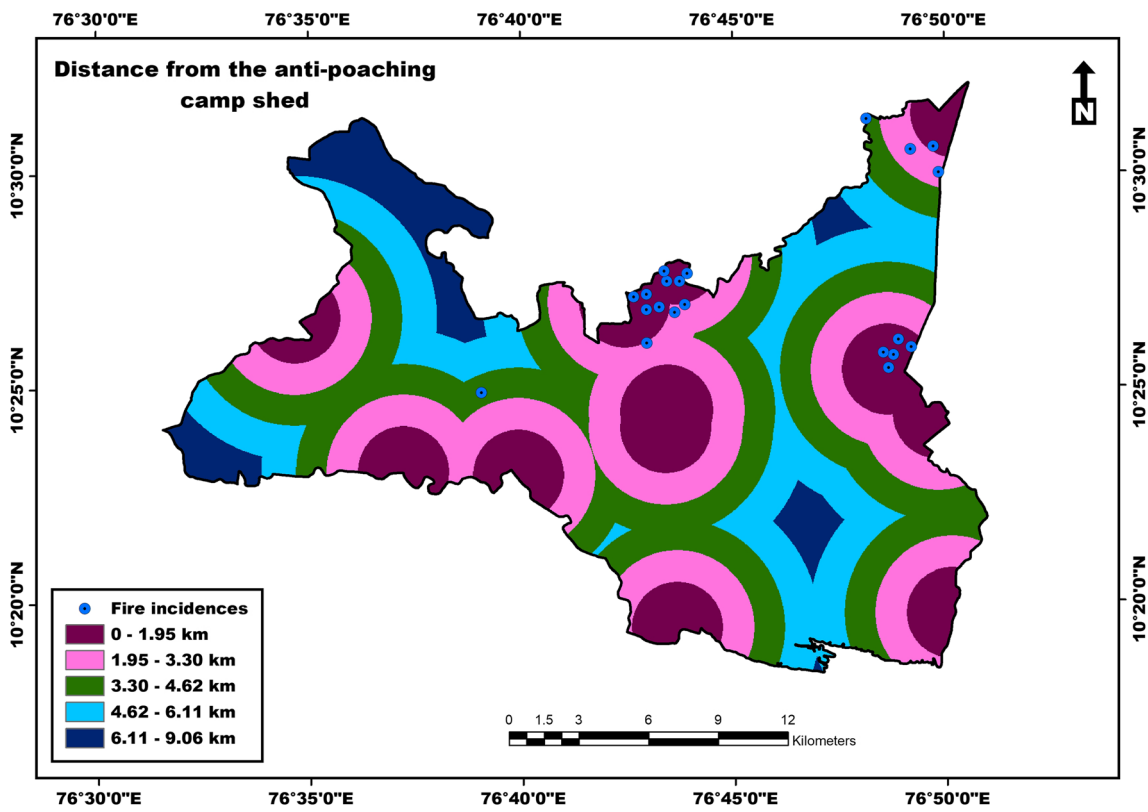**Fig. 9**   Distance from the tourist spot

Fig. 10   Distance from the anti-poaching camp shed

Table 1 The Saaty rating scale (Saaty 1980)

Intensity of scale	Definition	Explanation
1	Equal importance	2 factors contribute equally to the objective
3	Somewhat more important	Experience and judgment slightly favor 1 over the other
5	Much more important	Experience and judgment strongly favor 1 over the other
7	Very much more important	Experience and judgment very strongly favor 1 over the other
9	Absolutely more important	The evidence favoring 1 over the other is of the highest possible validity
2, 4, 6, 8	Intermediate values	When compromise is needed

road layer was derived using the spatial analyst (Euclidean distance) tool in the ArcGIS software. Based on the distance from the settlements, PKMTR is classified into five zones (0–1.14 km, 1.14–2.76 km, 2.76–5.09 km, 5.09–8.19 km, and 8.19–12.14 km) as shown in Fig. 8.

Distance from the Tourist Spot

Wildlife sanctuaries, national parks, and tiger reserves provide an ideal environment for recreational activities. The tourists visiting these protected areas can trigger accidental forest fires. The campfires set by tourists, thrown unextinguished cigarettes, and the sparks while they cook near forests may spread fire sometimes and lead to large fires. The location of tourist spots was collected from the Kerala Forest and Wildlife Department. In areas close to tourist spots, the possibility of forest fires is considered high. The spatial analyst (Euclidean distance) tool was used to generate the distance from the tourist spot layer. Based on the distance from the tourist spot, the study area is divided into five zones (0–4.02 km, 4.02–7.75 km, 7.75–12.47 km, 12.47–17.97 km, and 17.97–25.04 km) as shown in Fig. 9.

Distance from the Anti-poaching Camp Shed

Anti-poaching camp sheds are established across the protected areas in order to effectively manage the largely inaccessible areas. These buildings serve as base camps from which forest managers can perambulate the area that helps monitor the poaching and other illegal activities within the forest. Smugglers and poachers initiate forest fires for concealing the stumps of illegal felling. Anti-poaching camp sheds also act as fire-monitoring stations throughout the fire season. A well-equipped camp shed can respond quickly during an emergency, as time is the limiting factor in certain areas that are difficult to reach. The anti-poaching camp sheds may also impact the forest area if the staff handle fire sources irresponsibly. The areas close to camp sheds are usually less likely affected because they are strictly supervised. The location of anti-poaching camp sheds was collected from the Kerala Forest and Wildlife Department. The spatial analyst (Euclidean distance) tool in the ArcGIS software was used to prepare the distance from the anti-poaching camp shed layer. Based on the distance from the anti-poaching camp shed, the study area is divided into five zones (0–1.95 km, 1.95–3.30 km, 3.30–4.62 km, 4.62–6.11 km, and 6.11–9.06 km) as shown in Fig. 10.

Table 2 Pairwise comparison matrix

	LCT	Slp.	Asp.	TWI	DS	DR	DTS	DAPCS
LCT	1	2	3	4	5	6	7	8
Slp.	1/2	1	2	3	4	5	6	7
Asp.	1/3	1/2	1	2	3	4	5	6
TWI	1/4	1/3	1/2	1	2	3	4	5
DS	1/5	1/4	1/3	1/2	1	2	3	4
DR	1/6	1/5	1/4	1/3	1/2	1	2	3
DTS	1/7	1/6	1/5	1/4	1/3	1/2	1	2
DAPCS	1/8	1/7	1/6	1/5	1/4	1/3	1/2	1
$\sum$	2.72	4.59	7.45	11.28	16.08	21.83	28.50	36.00

LCT land cover types, *Slp.* slope angle, *Asp.* aspect, *TWI* topographic wetness index, *DS* distance from the settlement, *DR* distance from the road, *DTS* distance from the tourist spot, *DAPCS* distance from the anti-poaching camp shed

Table 3 Eigenvector and weighting coefficient

	Vp	Cp
LCT	3.76	0.33
Slp.	2.66	0.23
Asp.	1.82	0.16
TWI	1.22	0.11
DS	0.82	0.07
DR	0.55	0.05
DTS	0.38	0.03
DAPCS	0.27	0.02
$\sum$	11.48	1.00

Table 4   Normalized matrix

	LCT	Slp.	Asp.	TWI	DS	DR	DTS	DAPCS	∑ of rank	[C]	[D] = [A] × [C]	[E] = [D]/[C]	λ_{max}	CI	CR
LCT	0.37	0.44	0.40	0.35	0.31	0.27	0.25	0.22	2.61	0.33	2.78	8.51	8.29	0.04	0.03
Slp.	0.18	0.22	0.27	0.27	0.25	0.23	0.21	0.19	1.82	0.23	1.94	8.55			
Asp.	0.12	0.11	0.13	0.18	0.19	0.18	0.18	0.17	1.25	0.16	1.33	8.47			
TWI	0.09	0.07	0.07	0.09	0.12	0.14	0.14	0.14	0.86	0.11	0.90	8.33			
DS	0.07	0.05	0.04	0.04	0.06	0.09	0.11	0.11	0.59	0.07	0.60	8.17			
DR	0.06	0.04	0.03	0.03	0.03	0.05	0.07	0.08	0.40	0.05	0.40	8.07			
DTS	0.05	0.04	0.03	0.02	0.02	0.02	0.04	0.06	0.27	0.03	0.27	8.07			
DAPCS	0.05	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.19	0.02	0.20	8.16			
∑	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	8.00	1.00		66.33			

Prioritization and Calculation of Final Weights Using the AHP Method

The AHP method (Saaty 1980) can be used to efficiently evaluate complex decisions. By testing the accuracy of evaluations, the AHP method reduces bias in the decision-making process. For the construction of the judgment matrix, a 1–9 scale (Table 1) is used in the AHP modeling. The major steps involved in the AHP method are constructing a matrix for pair-wise comparisons (Table 2), eigenvector and weighting coefficient calculation (Table 3), and consistency ratio calculation (Table 4).

The eigenvector (Vp) is calculated using Eq. 2 as follows:

$$Vp = \sqrt[k]{W1x\ldots Wk} \tag{2}$$

where k is the number of factors, and W is the ratings of the factors.

The weighting coefficient (Cp) is calculated using Eq. 3 as follows:

$$Cp = \frac{Vp}{Vp1 + \ldots Vpk} \tag{3}$$

The sum of Cp of all parameters of a matrix must be equal to 1.

The matrix is normalized by dividing each element by the sum of the column. By averaging each row, the priority vector, [C], is calculated. The overall priority, [D], is calculated by multiplying each column of the matrix by the corresponding priority vector. The rational priority, [E], is determined by dividing each overall priority by the priority vector.

Table 5   Random index (Saaty 1980)

	Number of criteria									
	2	3	4	5	6	7	8	9	10	11
RI	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51

The eigenvalue (λ_{max}) is determined using Eq. 4 as follows:

$$\lambda max = \frac{[E]}{k} \tag{4}$$

The consistency index (CI) is calculated using Eq. 5 as follows:

$$CI = (\lambda_{max} - k)/(k-1) \tag{5}$$

The consistency ratio (CR) is determined using Eq. 6 as follows:

$$CR = \frac{CI}{RI} \tag{6}$$

where RI is the random index. RI is the average CI depending on the order k of the matrix (Kil et al. 2016) and utilizes the value given by Saaty (1980) as in Table 5.

The CR should be less than 0.1; otherwise, the judgments are not credible, and the exercises should be repeated (Saaty 1980). In this analysis, CR is 0.030 (less than 0.1), so the judgments are reliable.

The final weights obtained using the AHP method is shown in Eq. 7:

$$FRZ = (0.33 \times LCT) + (0.23 \times Slp.) + (0.16 \times Asp.)$$
$$+ (0.11 \times TWI) + (0.07 \times DS) + (0.05 \times DR)$$
$$+ (0.03 \times DTS) + (0.02 \times DAPCS) \tag{7}$$

Validation of the Result

The prepared fire risk zone map was validated using the ROC curve analysis. The ROC analysis investigates the relationship between the sensitivity (true positive rate) and specificity (true negative rate) of a binary classifier (Flach 2011). The ROC curve is the plot of the sensitivity versus 1 − the specificity (Franzen 2011). The AUC is a single scalar value that

Table 6 Area and percentage of risk zones and fire incidence details

Forest fire risk zones	Area (km^2)	Percentage of the area of the fire risk zones	No. of fire incidences	Percentage of fire incidences
Very low	30.57	4.75	0	0.00
Low	39.26	6.10	0	0.00
Moderate	175.27	27.23	6	28.57
High	249.80	38.81	9	42.86
Very high	148.76	23.11	6	28.57
Total	643.66	100	21	100

measures the overall performance of a binary classifier (Hanley and McNeil 1982). The AUC value ranges between 0.5 and 1, where the minimum value represents the performance of a random classifier, and the maximum value indicates a perfect classifier (Melo 2013). The AUC result was outstanding for values above 0.9, excellent for values between 0.8 and 0.9, and acceptable for values between 0.7 and 0.8 (Hosmer and Lemeshow 2000).

Results and Discussion

Forest fire risk zones in PKMTR were demarcated using the AHP method and geospatial tools (Fig. 11). The area of the forest fire risk map was divided into the following five risk zones: very low, low, moderate, high, and very high (Table 6). A total of 21 fire incidents were recorded in PKMTR during the period from November 2002 to November 2020. By overlaying the incidence points over the risk zone map, it was found that 15 (71%) fire incidences spatially fall over the high-risk and very high–risk zones. In this area, the angle of slope and the land cover types do not show a significant influence on fire occurrence. Most of the fires occurred in areas that are covered with evergreen forest than the deciduous forest, and only five fires were recorded on higher slopes. The surface moisture plays an important role in fire occurrence. The majority of the fires occurred in areas with lesser moisture content. It was found that most of the fire incidences occurred in the vicinity of settlements (14 fire incidences) and roads (18 fire incidences). This confirms the anthropogenic origin of
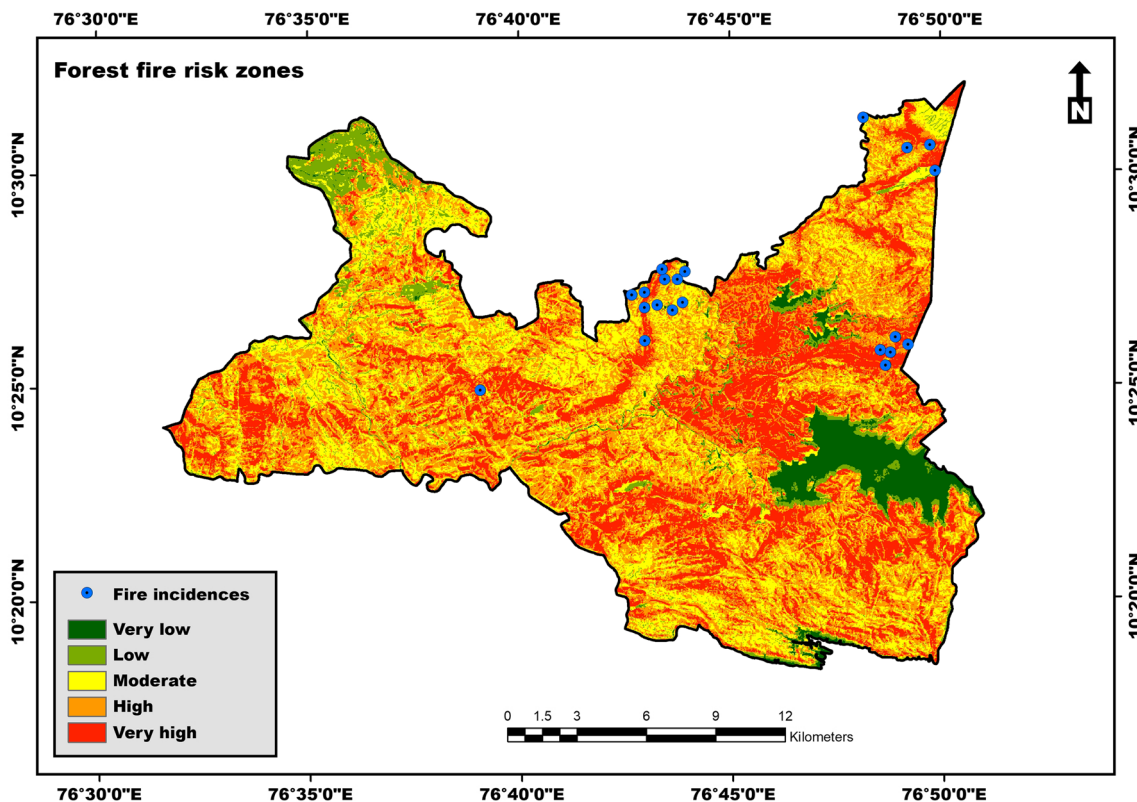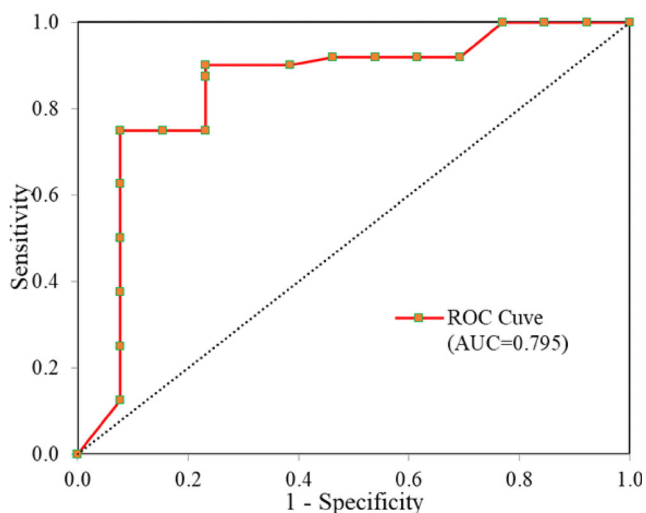

Fig. 11 Forest fire risk zones

Fig. 12 ROC curve

fires. In close proximity to the camp sheds, a large number of fire incidences (14) occurred. This reaffirms the requirement of fire watchtowers and efficient monitoring in this area. In this study, the ROC curve with an AUC value of 0.795 shows that the prepared risk zone map is acceptable (Fig. 12).

Conclusions

The present study demarcated the forest fire risk zones in PKMTR using geospatial tools and assessed the influence of various factors on fire initiation. This study classified PKMTR into the following five risk zones: very low, low, moderate, high, and very high. The high-risk and very high–risk zones together constitute 61.92% of the study area. It was found that the factors such as topographic wetness index, roads, and settlements demonstrate a strong correlation with forest fire occurrences. This confirms the anthropogenic origin of fires. From the study, it was observed that 71% of fire incidences spatially fall over the high-risk and very high–risk zones. The ROC curve analysis with an AUC value of 0.795 proves the acceptability of the result. This study suggests the requirement of fire watchtowers and effective fire monitoring in areas with more fire events. The risk zone map will help land use planners and decision-makers to establish fire protection strategies for identifying appropriate locations for fire watchtowers, fire lines, sensors installation, etc., in order to minimize potential impacts of fire.

Declarations

Ethics Approval and Consent to Participate   This article does not contain any studies with human participants or animals performed by any of the authors. Informed consent is not applicable.

Conflict of Interest   The authors declare no competing interests.

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