Spatial Assessment of Forest Fire Risk Across Forest Types in Palpa District, Western Nepal: A Remote Sensing and GIS Approach

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ABSTRACT

Forest fire is one of the challenging issues of forest management in Nepal. Climate change has triggered forest fire occurrences in Nepal's hilly regions, increasing fire incidences and severity. This makes these regions more vulnerable to forest fires. The management of forest fires requires planning and effort from people to reduce its hazards effectively. This study aims to identify the forest fire risk zones across different forest types in Palpa district of western Nepal. We used different spatial variables related to land use and terrain to model the forest fire risk zones. Seven potential influential factors: land use land cover, slope, aspect, elevation, land surface temperature, distance to roads, and proximity to settlements were analyzed using a multi-parametric weighted index model to create a forest fire risk index and predict the overall forest fire risk map. The resulted fire risk map was classified into five risk zones: very low, low, medium, high, and very high, covering 3.11%, 12.55%, 12.88%, 45.07%, and 26.39% of the study area respectively. The prepared map was evaluated using field-level fire occurrence points and Visible Infrared Imaging Radiometer Suite (VIIRS) fire points. The fire occurrence points were overlaid on forest-type maps to assess fire occurrence across different forest types. The accuracy assessment result shows that the model effectively identified the forest fire risk zones as most of the fire locations fell within these predicted regions. By forest type, Pine Forest was found to be the most vulnerable to fire followed by Sal Forest. The findings of this study enhance the understanding of forest fire risk zones, which is helpful to community members, planners, policymakers, and government agencies in preparing effective forest fire management strategies for this vulnerable district of Nepal.

Keywords : *Fire behavior, fire hazard, fire management, fire vulnerability, MODIS*

INTRODUCTION

Forests are important terrestrial ecosystems of the earth that provide the basis of living, such as clean air, water, food, and shelter for billions of organisms. It plays an important role in reducing soil erosion, climate change mitigation and balancing ecosystems. On the other hand, the global status of forests has decreased annually due to anthropogenic factors such as population growth, deforestation, encroachment, urbanization, and forest fire (Kumar *et al.*, 2022). In recent years, forest fires have become one of the leading causes of forest destruction. Fire is used as a traditional tool across South Asia to support activities such as agricultural land and pasture management, which often becomes uncontrolled, and escapes mainly during the dry season (Sharma *et al.*, 2012). Forest fires can also cause disturbances in nature that can harm large areas of forests, reducing the benefits provided by ecosystems and the economic value of natural resources (Cochrane, 2003).

In Nepal, forest covers about 45.31% of land surface (FRTC, 2022). The frequency and intensity of forest fires have been increased with an increase in forest cover posing major challenges for forest management in the country (Bhattarai *et al.*, 2022). The forest fire report of 2021 showed Nepal's unprecedented forest fire crisis, which led to fatalities and extensive devastation of fauna, flora, agricultural produces and domestic livestock across 22 distinct administrative regions, encompassing a minimum of 60 conflagrations (Thapa *et al.*, 2021). Nepal experiences a peak in forest fires during dry season, especially from March to May, with a significant portion of hilly districts considered highly vulnerable to forest fires (Matin *et al.*, 2017). Nepal's pre-monsoon season experiences the most frequent forest fires, with over half of the Terai Arc Landscape,which extends along the lower region of the country, being especially susceptible to forest fire (Bhujel *et al.*, 2022; Parajuli *et al.*, 2020). The increasing frequency and intensity of forest fires can be manifested to the weakening cooperation and support within the community forest user groups (CFUGs) mainly due to the shift in forest-based livelihoods of people (Matin *et al.*, 2017; Tiwari *et al.*, 2022).

Forest fire assessment in Nepal was performed by both direct field observation and indirect methods through remote sensing (RS) techniques (Matin *et al.*, 2017). The direct method of forest fire observation was tedious due to greater time consumption, difficult geography, and high-risk factors. Therefore, we used remote sensing techniques and a geographical information system (GIS) for forest fire risk assessment in this study. RS techniques and GIS have been widely used for assessing land use changes, soil moisture, groundwater exploration, and forest fire occurences in different regions of Nepal (Talchabhadel *et al.*, 2019; Devkota *et al.*, 2023; Mishra *et al.*, 2023; Dhakal *et al.*, 2024).

Palpa district has been identified as a forest fire-prone area. In mid-April 2024, a forest fire destroyed about 3,586 hectares of forest in Palpa district (Kathmandu Post, 2024). The wildfires reached settlement areas, devastating homes and causing casualties among livestock. The rate of forest fire in Palpa district has been increasing over the years, which is attributed to burning of crop residue in field, chasing of wild animals, prolonged drought, and other human activities that make the fire uncontrollable(Palpa DFO, 2022). The study from forest research and training center has classified the district forests into six major forest types (FRTC, 2021). Each forest type has different susceptibility to forest fire. However, there are no documented studies to identify the vulnerable forest types in the district. Therefore, this study was designed to assess the forest fire risk of different types of forests and the underlying biophysical factors to trigger fire sensitivity of forests in Palpa district of western Nepal. The findings of study help formulate appropriate forest management planning according to forest types and biophysical conditions of the region.

MATERIALS AND METHODS

Study area

The study area covers a geographic area of Palpa district (Figure 1), which was chosen due to its high susceptibility to forest fire. Palpa district is situated between latitude 27°34'N and 27°57'N and longitude 83°15'E and 84°22'E, with an altitude ranging from 152 m to 1936 m. It spans two physiographic zones, primarily the middle-mountain region, and the Churia region, encompassing a total area of 136,595 hectares. Palpa district stretches approximately 70 km from east to west and 20 km from north to south. The dominant forest species in this district include Sal (Shorea robusta) and Asna (Terminalia tomentosa), which is also characterized by Chilaune (Schima wallichhii), Katus (Castanopsis spp.), and Chir-pine (Pinus roxburghii). In and around the Kaligandaki corridor, prominent riverine species include Khair (Acacia catechu) and Simal *(Bombax ceiba)*.

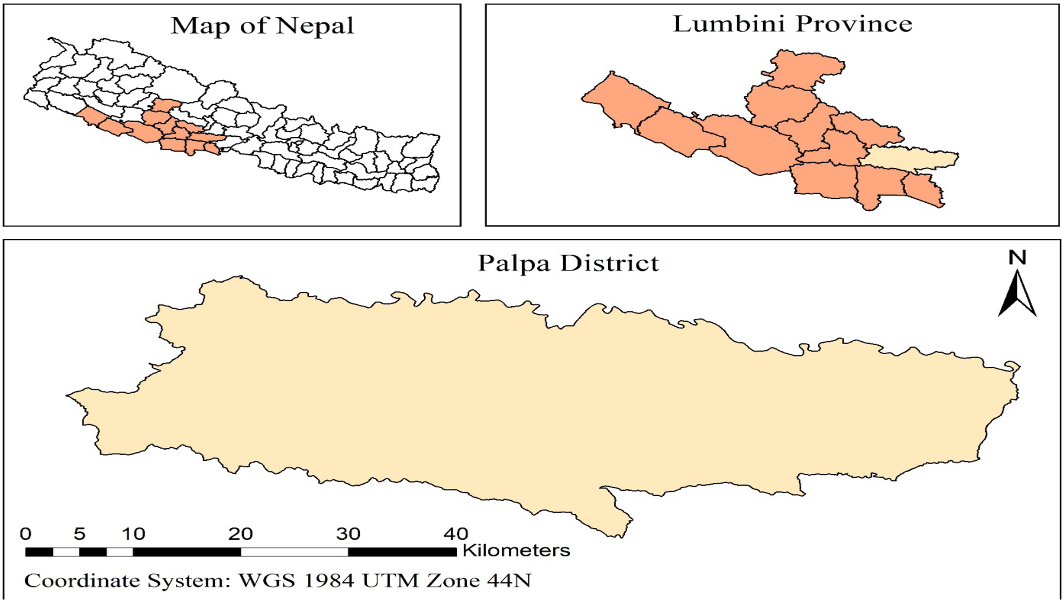


Figure 1: *Map of the study area*

Data collection and preparation of thematic maps

For preparation of a forest fire risk map, seven factors – land use land cover, land surface temperature, distance to road, proximity to the settlement, aspect, slope, and elevation were chosen and thematic maps were prepared (Figure 2).

Land use land cover (LULC) map

The Sentinel-2 mission, part of the European Space Agency's (ESA) Copernicus program, provides crucial data for monitoring land use and land cover (LULC). The Sentinel-2 satellites deliver high-resolution optical imagery, making it invaluable data for LULC analysis (Dhakal *et al.*, 2022) which refers to the physical and biological cover on the surface of the land. Land use changes and impacts on land cover are key measures of environmental change caused by human activities, especially in rapidly developing areas. Information on such land use change patterns is required for sustainable development planning. Commencement of the Sentinel-2 satellite in mid-2015 and Landsat-9 satellite in late 2021 is opening new possibilities in Earth observation and monitoring through higher spatial, spectral, and temporal resolutions. Many researchers have been curious to compare improvements in these two satellites. This research tests the real difference in the quality of the results delivered by Sentinel-2 and Landsat-9 imagery when basic classification methods are applied. This study aims to assess the precision of the LULC classifications derived from Sentinel-2 and Landsat-9 data and to reveal which dataset presents greater accuracy. The Google Earth Engine (GEE. For this study, the LULC data of imagery of the year 2024, with a spatial resolution of 10 m, was obtained from the Environmental Systems Research Institute (ESRI) website (Land Cover Explorer). The downloaded Sentinel-2 satellite images consisted of two tiles covering the study area, which were mosaicked to form a single LULC raster. This raster was resampled to a spatial resolution of 30m and masked using the boundary shapefile of the study area. The LULC raster of the study area was reclassified into six land use classes: forest, water bodies, cropland, built-up areas, bare areas, and rangeland. Forest areas cover about 60.39% of the total study area, followed by rangeland (33.54%). Other land-use classes constitute around 6% of the total area. The LULC raster was then reclassified into five classes, with values assigned from 1 to 5 according to their potential to create forest fire hazards.

Land surface temperature (LST) map

Annual mean land surface temperature data (2012-2023) was obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard the Terra satellite. The MOD11C3 product, part of NASA's Land Processes Distributed Active Archive Center

(LP DAAC), was accessed through the Level-1 and Atmosphere Archive and Distribution System Distributed Active Archive Center (LAADS DAAC) (MOD11C3 Product). The MODIS LST data was resampled to a spatial resolution of 30m using cubic resampling techniques and masked using the boundary shapefile of the study area. The LST layer was reclassified into five temperature categories, from 1 to 5, with 1 representing the lowest and 5 the highest temperature classes. The prepared LST map shows that the 20-23°C class covers about 35.47% of the study area, followed by 24-25°C (20.57%), 23-24°C (17.93%), <20°C (16.1%), and >25°C (9.93%).

Digital elevation model (DEM) and derived maps

The Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) with a spatial resolution of 30m was downloaded from the ESRI website (SRTM Data) to generate an aspect, slope, and elevation map. This dataset is widely used for understanding and analyzing the Earth's topography (Thomas *et al.*, 2015) deriving conventionally from contour data of topographic maps, provides sufficient information regarding the continuously varying topographic surface of the Earth. Though space-borne DEMs are increasingly being used in earth-environmental applications, suitability of various freely available spaceborne DEMs (e.g., advanced spaceborne thermal emission and reflection) ASTER. The thematic layers used in the study are shown in Figure 2.

i. Aspect map

The SRTM DEM was initially filled to eliminate small imperfections. The DEM was then masked using the "extract by mask" tool, extracting the DEM of the study area. The aspect map was divided into nine classes, and values were assigned from 1 to 5 based on the potential of different aspects that escalate forest fire hazards. The aspect map of the study area shows that the northern aspect covers the district's highest area (17.5%), followed by the southern aspect (14.5%). The northern aspect has the lowest forest fire risk, while the south and southwest aspects have a higher forest fire risk (Subedi *et al.*, 2022).

ii. Slope and elevation maps

The DEM of the study area was used to prepare the slope and elevation map layers. Both maps were reclassified into five classes, with values assigned from 1 to 5 based on their potential to create fire hazards. The slope map shows that about half of the study area (50.9%) has a slope of 20-35 degrees. About 23.31% of the area falls under a 10-20-degree slope, followed by 35-45 degrees (13.35%), <10 degrees (10.6%), and >45 degrees (1.84%). The elevation map indicates that elevations less than 400m cover 3.05% of the area, followed by 400-800m (26.04%), 800-1200m (44.78%), 1200-1600m (24.26%), and >1600m (1.87%).

Road network and settlement maps

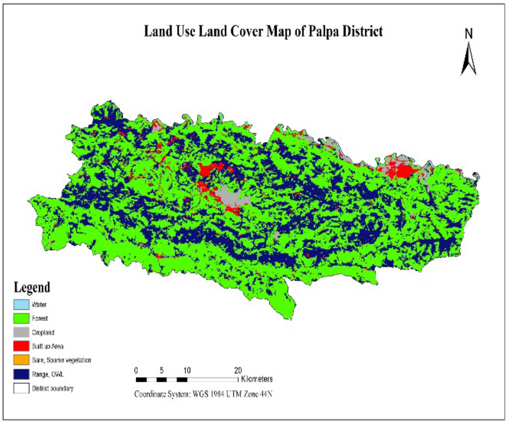
Road network and settlement data for the study area were obtained from the ICIMOD website. The data was used for generating classified distance maps from settlement and roads as follows:

i. Proximity to settlement map

The settlement data was clipped using the boundary shapefile of the study area. The polygons were subjected to a multi-ring buffer into five classes of distance to settlement: <1000m, 1000-1500m, 1500-2000m, 2000-2500m, and >2500m. The resulting vector file was converted to a raster format, and a proximity to the settlement map was created. Values ranging from 1 to 5 were assigned based on their potential to cause forest fires due to human activities. The proximity to settlement map shows that about 46.19% of the area falls within 1000m, followed by 18.90% within 1000-1500m, 14.42% within 1500-2000m, 9.38% within 2000-2500m, and 11.11% beyond 2500m.

ii. Road network map

The road network data was clipped using the boundary shapefile of the study area and subjected to a multi-ring buffer in five classes. The assumption is that forests closer to roads are susceptible to fires, as supported by previous studies (Narayanaraj *et al.*, 2012). The vector file was then converted to a raster format, and a road network map was prepared. The road network map reveals that 25.43% of the area falls within 500m of a road, 12.84% within 500-1000 m, 17.60% within 1000-1500m, 20.83% within 1500-2000m, and 23.30% beyond 2000 m from the main road (highways).



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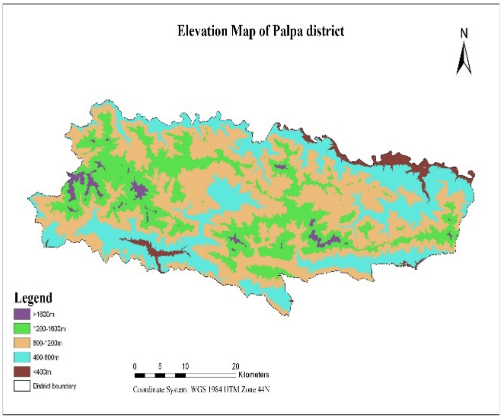

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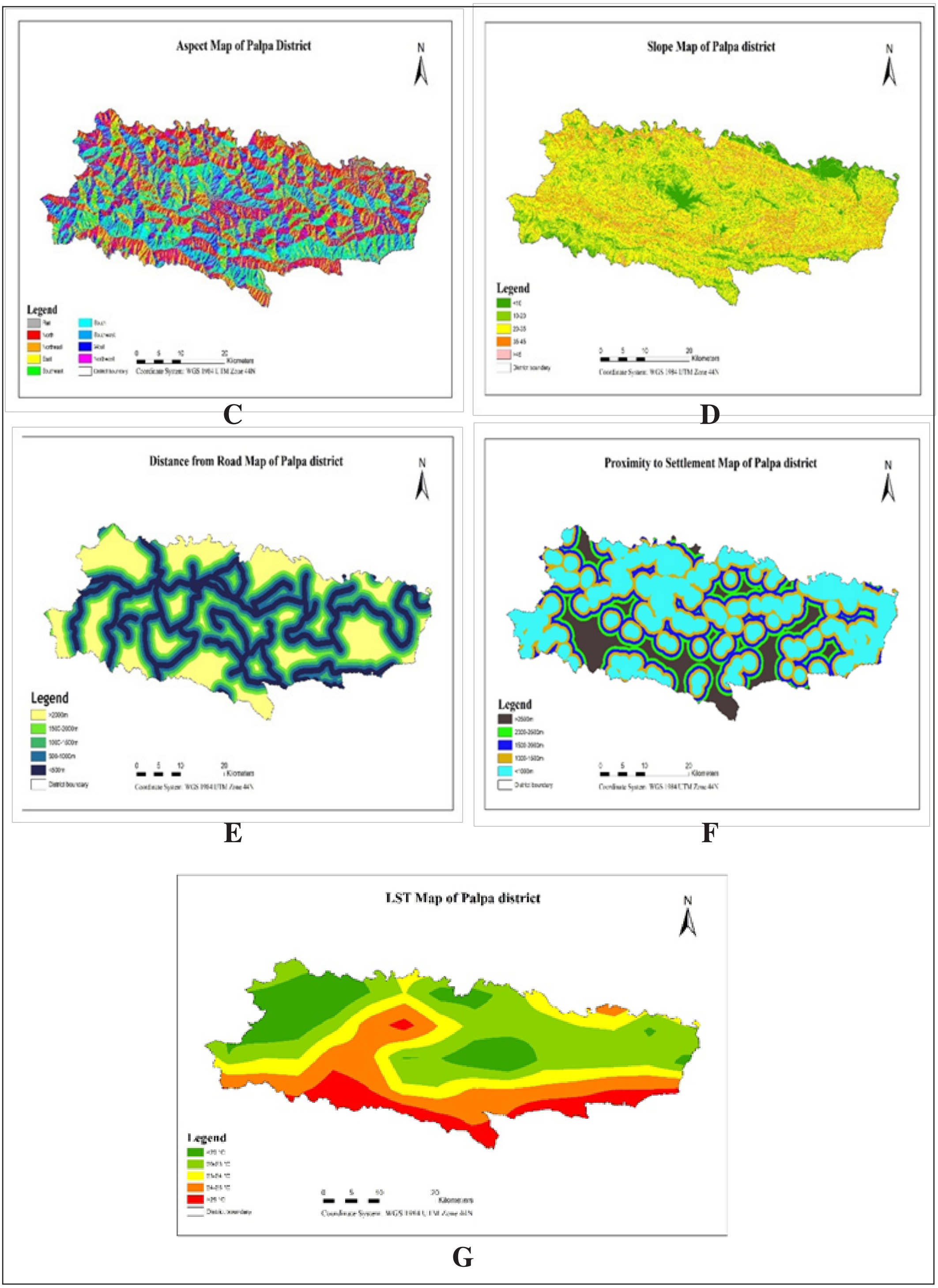

Figure 2: *Seven thematic layers for forest fire risk map (A) LULC map, (B) Elevation map, (C) Aspect map, (D) Slope map, (E) Distance from road map, (F) Proximity to the settlement map, and (G) Land surface temperature map*

Forest fire risk mapping

The overall methodology for the preparation of the forest fire risk zone map is shown in Figure 3. Seven factors were used for the generation of forest fire risk map. These factors were weightage and overlayed using the forest fire risk index (FFRI) model. The overall process was analyzed using Arc GIS 10.8. The final map was validated using field-level fire points and VIIRS data sets. Further, the fire points were overlayed upon the forest type map to analyze which forest types were more susceptible to forest fire.

Forest fire risk model

The forest fire risk model was developed by incorporating field observations and findings from secondary literature focusing on physiographical and geographical regions identical to our study area was adapted for our study. This model performed well in hilly terrain which was used and tested by other researchers (Abedi Gheshlaghi, 2019; Alkhatib, 2014; Jaiswal *et al.*, 2002; Parajuli *et al.*, 2020; Subedi *et al.*, 2022)with multiple consequences in Nepal's forest ecosystem and landscapes. The research used remote

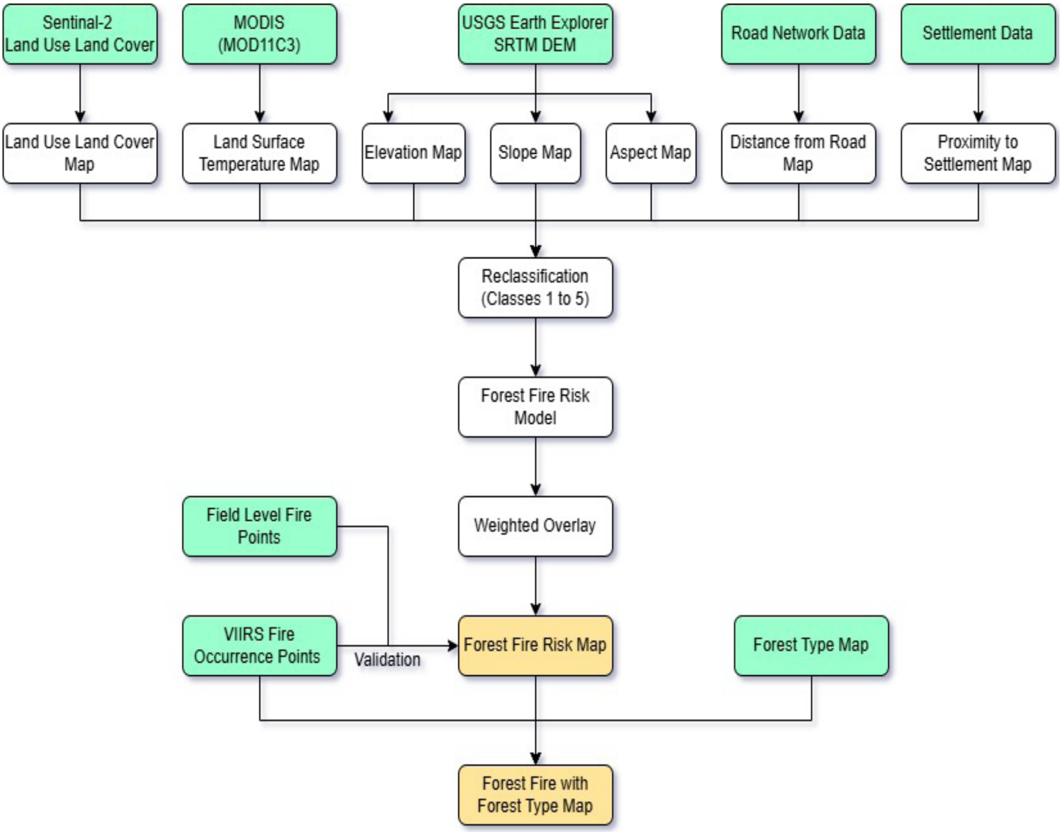

Figure 3: *Methodological chart of forest fire risk zonation*

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). The model uses seven factors that assign weightage according to equation 1 to develop a Forest Fire Risk Index (FRI) map.

FRI = 40 LULC + 20 LST + 10 S + 10 DR + 10 PS + 5 A + 5 .... Eq 1

Here, FRI is the Fire risk index, LULC is land use land cover, LST is land surface temperature, S is slope, DR is distance from the road, PS is proximity to the settlement, A is aspect, and E is elevation map.

Assignation of weightage to parameters and fire risk zonation

The thematic layers were subjected to weighted overlay analysis according to the assigned weightage on the fire risk index to prepare the forest fire risk zone map of the study area. The assigned weightage for each factor is shown in Table 1.

Table 1: Weightage assigned to thematic map layers

Factors	Weight (%)	Class	Value Assigned	Rating
Land use land cover	40	Water	1	Very low
		Forest Trees	5	Very High
		Cropland	3	Medium
		Built up	1	Very low
		Bare area	2	Low
		Rangeland	4	High
Land Surface Temperature (degree Celsius)	20	<20	1	Very low
		20-23	2	Low
		23-24	3	Medium
		24-25	4	High
		>25	5	Very High
Slope (degree)	10	<10	1	Very low
		10-20	2	Low
		20-35	3	Medium
		35-45	4	High
		>45	5	Very High

Distance from Road (m)	10	<500	5	Very High
		500-1000	4	High
		1000-1500	3	Medium
		1500-2000	2	Low
		>2000	1	Very low
Proximity to settlement (m)	10	<1000	5	Very High
		1000-1500	4	High
		1500-2000	3	Medium
		2000-2500	2	Low
		>2500	1	Very low
Aspect	5	Flat	1	Very low
		North	1	Very low
		Northeast	2	Low
		East	3	Medium
		Southeast	4	High
		South	5	Very High
		Southwest	5	Very High
		West	3	Medium
		Northwest	2	Low
Elevation (m)	5	<400	5	Very High
		400-800	4	High
		800-1200	3	Medium
		1200-1600	2	Low
		>1600	1	Very low

Source: *(Alkhatib 2014; Jaiswal et al., 2002; Parajuli et al., 2020; Subedi et al., 2022)*

Verification of forest fire risk zone map

To verify the forest fire risk zone map for the study area, both field data and satellite-based (VIIRS) fire archive data were used. Visible Infrared Imaging Radiometer Suite is an advanced instrument on the Suomi NPP and NOAA-20 satellites, that offers high-resolution 375m fire detection through its multi-spectral capabilities across visible, near-infrared, and thermal infrared bands. This enables effective identification of thermal anomalies related to fires, even under challenging conditions like cloud cover. VIIRS archive fire data from 2012 to 2023 were analyzed, with fire incidents filtered to include only those with a confidence level greater than 30% to ensure accuracy.

Forest type map

The forest-type map was obtained from the Forest Research and Training Center published in 2021 (FRTC, 2021). The forest type maps were classified into six major forest classes based on species types. These species types were, *Acacia catechu* & *Dalbergia sissoo* forest, lower mixed hardwood forest, *Pinus roxburghii* forest, Quercus Forest, Sal Forest, and tropical mixed hardwood forest. The field-level fire points and VIIRS fire occurrence data were overlayed over the forest-type map to assess which forest type was more susceptible to the forest fire.

RESULTS

Forest fire risk zone

The forest fire risk zone map is shown in Figure 4. The degree of fire risk, the percentage, and the area of each zone are shown in Table 2.

The forest fire risk index map shows that 26.39% of the district area falls under "very high", 45.07% under "high", 12.88% under "medium" and 15.66% under "low" and "very low" fire risk zones. Overall, the district was found to be vulnerable to forest fire because 71.46% of the area was under high or very high forest fire-prone region.

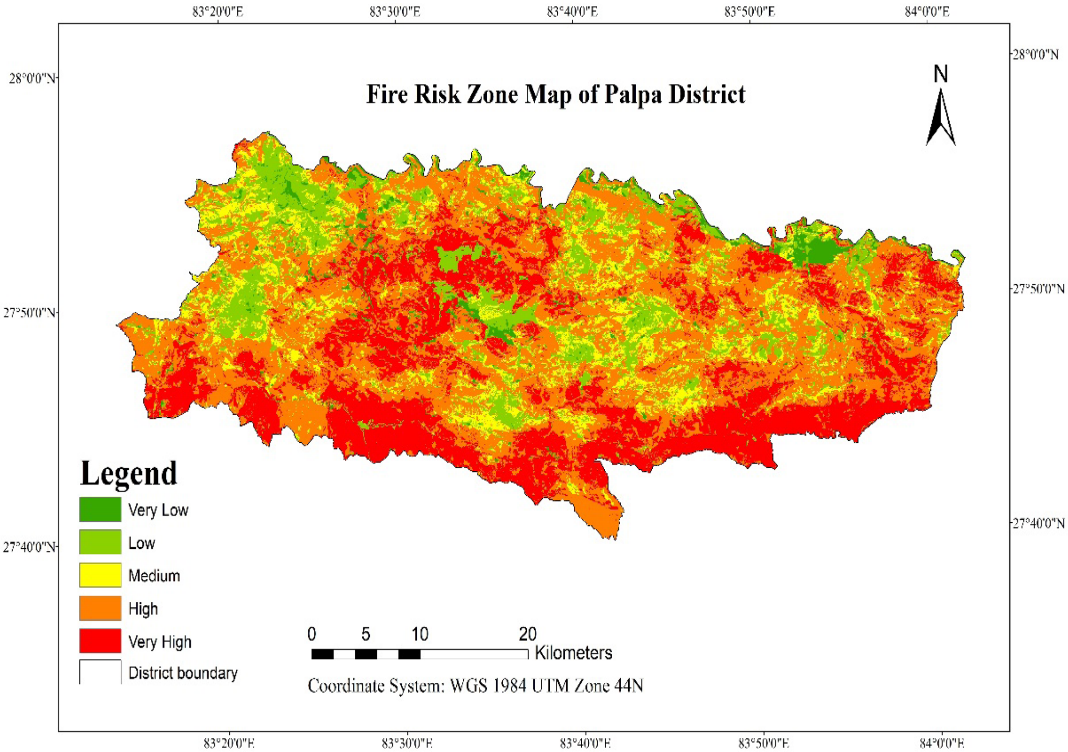

Figure 4: *Forest fire risk map of study area*

Table 2: Area coverage of forest fire risk zones

Forest fire risk zones	Area (Sq.km)	% of Area
Very Low	45.426902	3.11
Low	182.796399	12.55
Medium	187.667811	12.88
High	656.529803	45.07
Very High	384.070521	26.39

Figure 5 shows a clear association between fire incident density and fire risk classification. Areas that are classified under high and very high-risk zones not only cover substantial portions of the district but also account for the majority of fire incidents, highlighting higher vulnerability to forest fire. Conversely, the areas with very low and low-risk zones cover smaller areas of the district with significantly fewer fire incidents and lower fire densities.

Table 3 shows that 82.57% of incidences were recorded in the high and very high-risk zones, which showed the reliability of the parameters used for analysis. This agrees well with the present observation that most of the fire incidence points fall spatially over the forest areas closer to roads and settlements with lower elevations and high slopes.

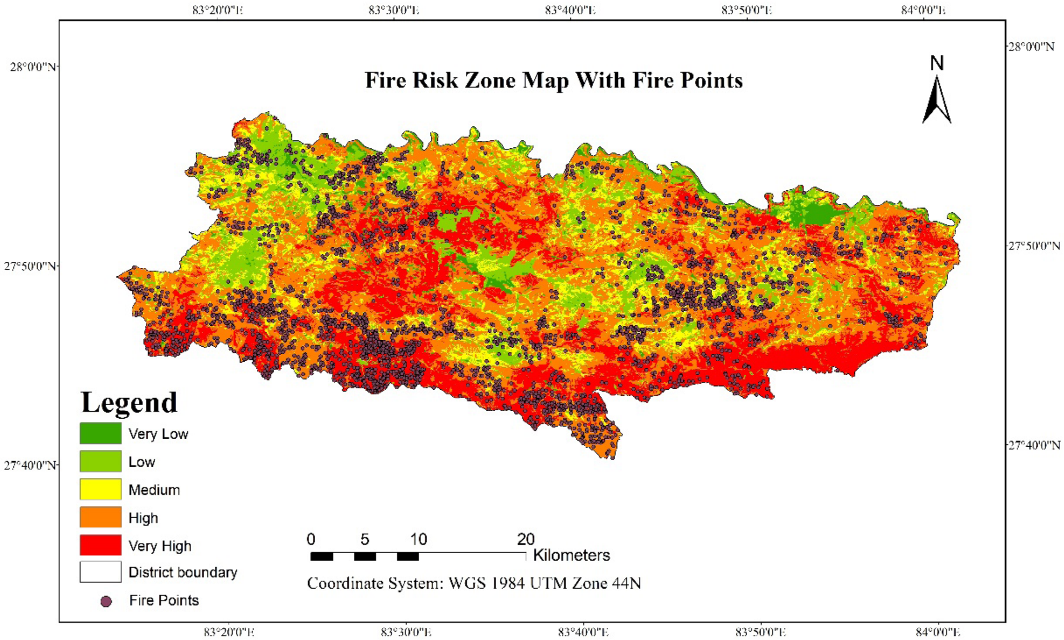

***Figure 5:** Forest fire risk map with fire points*

Table 3: *Fire points with different forest fire risk zones*

Forest fire risk zones	Number of fire counts	Percentage fire Counts	Fire density per km^2
Very Low	20	0.68	0.44
Low	230	7.91	1.26
Medium	257	8.84	1.37
High	1243	42.75	1.89
Very High	1157	39.82	3.01

Forest fire vulnerability on different forest types of Study area

The analysis of forest fire vulnerability across various forest types in the study area, as illustrated in Figure 6, reveals notable differences in fire incidence rates. The analysis of fire occurrence points with forest types from February to May shows that *Pinus roxburghii* forest exhibits the highest rate of fire incidence, recorded at 3.98 occurrences per square kilometer. In contrast, the *Acacia catechu* and *Dalbergia sissoo* forests demonstrate the lowest fire incidence rate, with 1.69 occurrences per km^2. The Sal Forest is observed to have a fire incidence rate of 3.72 per km^2, while the tropical mixed hardwood forest shows a rate of 3.20 per km2. The lower mixed hardwood forest, which covers the largest area among all forest types, has a fire incidence rate of 2.34 per km^2. Lastly, the Quercus

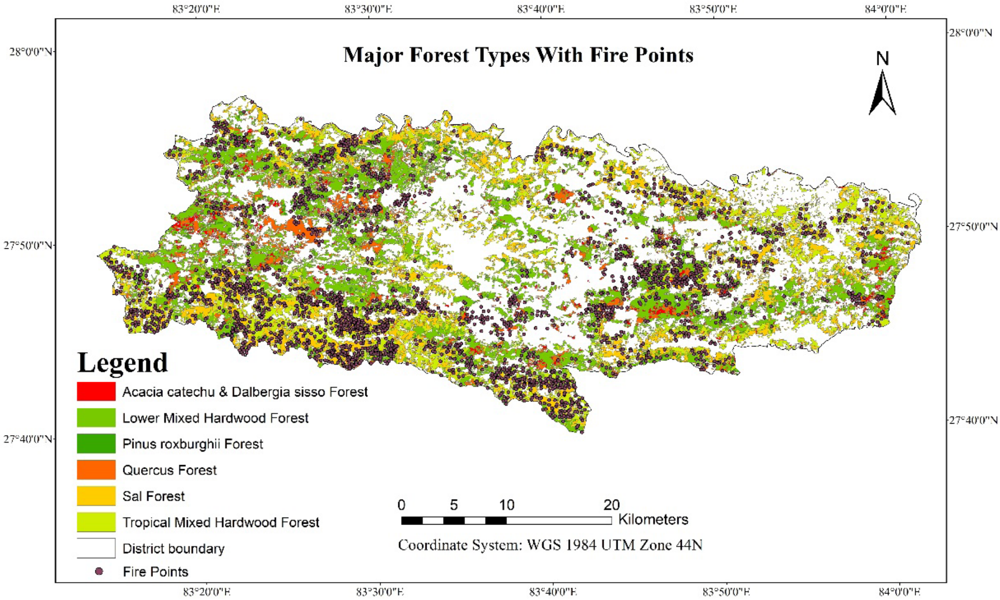

Figure 6: Fire points with forest types

Table 4: Distribution of fire points with forest type

Forest type	Area in km²	Fire Counts	Counts per km²
Acacia catechu and *Dalbergia sissoo* Forest	32.57	55	1.69
Lower Mixed Hardwood Forest	294.46	690	2.34
Pinus roxburghii Forest	13.81	55	3.98
Quercus Forest	61.62	119	1.93
Sal Forest	160.74	598	3.72
Tropical Mixed Hardwood Forest	211.05	675	3.20

Forest is found to have fire incidence rate of 1.93 per km². The distribution of fire points across different forest types is further detailed in Table 4.

This result shows the varying degrees of fire vulnerability among different forest types in the study area, with the *Pinus roxburghii* Forest and Sal Forest being highly vulnerable to forest fire, *Acacia catechu* and *Dalbergia sissoo* forest being the least vulnerable to forest fires.

DISCUSSION

This study used remote sensing techniques, GIS, and a forest fire risk model to classify the forest fire risk map of the study area. Remote sensing data has the potential to enhance forest fire management (Barmpoutis *et al.*, 2020). However, challenges remain in integrating various sensors minimizing uncertainty, and improving statistical validation methods (Chuvieco *et al.*, 2020). The seven factors were assigned to calculate the forest fire risk map of the study area. The derived forest fire map has been classified into five forest fire risk zones in which the maximum region of 45.07% and 26.39% area was found under high and very high forest fire vulnerability. The analysis shows that the majority of the area was susceptible to forest fires. The study by Matin *et al*. (2017), shows that hilly districts of Nepal were more vulnerable to forest fires. Similarly, the analysis of forest fires with different land cover classes shows that higher fire density was found in the forest class followed by the rangeland class. It may be due to forests having a high accumulation of flammable biomass due to which they are more prone to fire hazards. The findings of our study aligned with the findings of other studies where extensive forest cover correlates with higher forest fire risks (Bond *et al.*, 2005; Matin *et al.*, 2017). Similarly, the study in Chitwan-Annapurna Landscape has indicated that forested areas dominated by Sal Forest have a high forest fire incidence due to the presence of dense vegetation and dry nature (Chitale *et al.*, 2018). Further, the forest fire-prone area was found high in the area having a high land surface temperature. Higher temperatures can increase the risk of forest fires by reducing moisture content in vegetation which increases the likelihood of fire ignition (Bowman *et al*., 2009; Vilardell *et al*., 2023). A recent study on forest fire about climatic factors also highlights higher temperatures and prolonged dryness significantly increase fire vulnerability in the Hill regions (Kalwar, 2022). Similarly, the steeper slopes geography of the study area might also be the reason for forest fire risk since fire spreads by accelerating the movement of flames uphill (Sharples, 2009). Moreover, areas closer to roads (23.30% within 500 m) and settlements (46.19% within 1000 m) are often more accessible to people and thus experience higher human activity, which can increase the likelihood of fire incidents due to accidental ignitions (Syphard *et al*., 2007). For instance, similar findings in California have demonstrated the need for careful management near human settlements to prevent accidental fires (Syphard *et al*., 2007). In Nepal, human activities such as farming and road construction have also been identified as significant contributors to fire incidences (Aryal *et al*., 2014).

The analysis of fire incidence across different forest types shows diverse variations in forest fire incidence with forest type. The Pinus roxburghii forests have been found to have the highest fire incidence rate (3.98 counts/km^2), followed by Sal forests (3.72 counts/km^2). These forests are highly vulnerable due to their resinous and dry nature, which makes them more flammable (Fernandes *et al*., 2004). Similarly, the Acacia catechu and Dalbergia sissoo forests have the lowest rate of fire incidence (1.69 counts/km^2), which may be due to their less flammable vegetation structure and higher moisture content (Gordon *et al*., 2017). This result aligns with global patterns of fire occurrence where pine and resinous forests tend to have higher fire risks (Chuvieco *et al*., 2008). Further, studies on Pinus roxburghii forests show that these forests were more vulnerable to forest fire due to their dry needles and high resin content (Bargali *et al*., 2020). Therefore, forest fire vulnerability assessment and appropriate management plan should be formulated to mitigate fire risk hazards of this climatically vulnerable district.

CONCLUSION

The majority of the study area falls under very high and high forest fire risk zones that reveal the district is vulnerable to forest fire. The result of the accuracy assessment shows that majority of fire points lie under high and very high forest fire risk zones, which concludes the classified forest fire map using the forest fire risk model has acceptable accuracy. Similarly, the assessment of forest type map with forest fire occurrence zone shows that more fire points density was found under

Pine Forest (*Pinus roxburghii*) forest followed by Sal Forest (*Shorea robusta*) forest. The findings of this paper will be helpful for planners, policymakers, and government bodies to develop appropriate forest fire management strategies for Palpa district. Similarly, formulation of appropriate forest fire management strategies specifically based on forest types is recommended.

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