Assessing forest fire risks using geo-spatial techniques in western Nepal

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Abstract

Forest fires are a significant threat to Nepal's ecological and socio-economic stability, particularly in vulnerable regions. Despite increasing fire frequency and intensity, research on spatially explicit risk assessment in Nepal remains limited; therefore, this study maps forest fire risks, identifies key contributing factors, and proposes actionable management strategies for Lumbini Province. Fire incidents and burned areas (2012–2024) were derived from MODIS and VIIRS datasets, while topographic, climatic, biophysical, and anthropogenic data were sourced from open-access repositories. Primary data from key informant interviews revealed causes, impacts, challenges, and preventive measures. Spatial layers were processed using GIS/RS techniques and integrated using a Weighted Linear Combination (WLC) model to create a forest fire risk map, categorising the region into five risk levels. The WLC model identified land cover (20%), road proximity (15%), settlement proximity (15%), NDVI (15%), and temperature (10%) as the dominant drivers, revealing that 57.42 per cent of forests are in very-high to high-risk zones**.** The findings revealed fires peak in the pre-monsoon season (March-May), with April accounting for 76.85 per cent of occurrences. High-risk areas feature broad-leaved closed forests, temperatures >40°C, gentle slopes <15%, south-facing aspects, and proximity to humans. The risk model correctly predicted 78.22 per cent of historical fire incidents within the identified high-to-very-high risk zones, supported by a confusion matrix (Kappa: 0.94) and ROC curve analysis (AUC: 0.803). Furthermore, perception analysis of forest managers emphasised the urgent need for proactive measures, including increased funding, specialised training, and the development of early warning systems to support sustainable forest management.

Keywords: Forest fire risk, Geospatial techniques, Weighted linear combination, Lumbini Province, Fire management

INTRODUCTION

Forest fires are increasing across the globe due to climate change, human activity, and rising temperatures, leading to increased fires and deforestation (You, 2023). The fires are major contributors to greenhouse gas emissions, biodiversity loss, and land degradation, impacting ecosystems and human communities worldwide (Keeley *et al.*, 2016). Around 0.4 per cent of the global land surface is reportedly burned annually, covering 30 - 46 million km^2 (Randerson *et al.*, 2012).

Forest fires are a persistent issue in Nepal, especially during the dry season, leading to significant ecological and socio-economic impacts. According to Khanal (2015), between 2001 and 2015, approximately 375,000 hectares of forests were burned, impacting 18 districts throughout the country. Past studies have shown that climatic variables such as rising temperatures and decreasing rainfall are the major drivers of increased forest fire frequency in South Asia and the Hindu Kush Himalayan region (Matin *et al.*, 2017; Sharma, 2006). In Nepal, the frequency of forest fires rose sharply in between 2000 and 2017, coinciding with altered precipitation patterns and extended drought periods (Bhujel *et al.*, 2017).

Geographic Information Systems (GIS) and remote sensing (RS) technologies are crucial in identifying, categorising, and mapping areas susceptible to forest fires (Zhang, 2024). Satellite technology has revolutionised the tracking and analysis of critical environmental parameters, including vegetation, topography, historical fire patterns, burned areas, and climatic factors (Chuvieco and Congalton, 1989). Integrating Earth observation data with GIS technology enables accurate assessment and mapping of forest fire dynamics. This approach has proven effective for estimating emissions (Cruz-López *et al.*, 2019) and identifying areas prone to forest fire hazards (Adaktylou *et al.*, 2020). Fischer *et al.* (2016) highlight the critical role of evidence-based analysis in assisting policymakers, planners, and authorities in disaster prevention.

Fire risk mapping in Nepal was initiated, integrating MODIS data with the help of RS and GIS technologies. Among these, a notable work was contributed by (Bhujel *et al.*, 2022; Matin *et al.*, 2017; Parajuli *et al.*, 2015; Qadir *et al.*, 2021) proposed a spatially distributed fire risk index using historic fire data, land cover, temperature, and topography. Likewise, Parajuli *et al.*(2020) further analysed fire risk in the Terai Arc Landscape (TAL) and Chitwan Annapurna Landscape (CHAL) regions using variables such as aspect, slope, elevation, vegetation, and proximity to roads and settlements.

The growing frequency and severity of forest fires in Nepal have become a critical environmental and socio-economic issue, severely threatening forest ecosystems, biodiversity, and local communities (Pandey *et al.*, 2022). Lumbini Province, with 48.8 per cent forest cover (Province Planning Commission, 2076), is highly vulnerable, with fires impacting livelihoods, biodiversity, air quality, and climate due to its extensive forest cover, representative ecological conditions, high vulnerability in national NDRRMA/MODIS datasets, and research gap amid prior focus on TAL/Chure/Sudurpashchim regions (Bhujel *et al.*, 2022; Matin *et al.*, 2017; NDRRMA, 2024); however, comprehensive studies on spatial-temporal fire patterns remain lacking in this critical region.

This study fills this critical knowledge gap by mapping forest fire risks in Lumbini Province (2012–October 2024) using GIS, RS, and the Weighted Linear Combination (WLC) method. The WLC approach was prioritised over complex machine learning algorithms because it facilitates a knowledge-driven framework that integrates expert-defined weightings with biophysical variables (Ersoy *et al.*, 2025). The method also provides greater transparency in representing fuel availability (land cover/NDVI), ignition sources (road and settlement proximity), and fire propagation drivers (topography and climate), making it particularly suitable for Nepal's data-scarce context (Nikolić *et al.*, 2023).The research aims to assess forest fire hazards and create a fire risk map to inform policymakers, planners, and stakeholders, contributing to improved fire management and future planning in Nepal.

METHODOLOGY

Study area

The research was conducted in the Lumbini Province of Nepal, which lies in the western part of the country, covering an area of 22,288 km2. The Province area equals 15.1 per cent of the country's total land (Province Planning Commission, 2024). It shares borders with Karnali Province to the north, while Sudurpashchim Province lies to the west. Gandaki forms its eastern and northern parts, while Uttar Pradesh of India shares the southern border with the province. Geologically, it ranges between 27°20' N to 29°00′ N latitude and 81°21′ E to 84°02′ E longitude (Figure 1).

The Province administratively comprises 12 districts and 109 local administrative units: four sub-metropolitan cities, 32 municipalities, and 73 rural municipalities, divided into 983 wards (Constitution of Nepal, 2015).

Topographically, it is divided into five regions: High Himalayas (3.1%), High Mountains (9.1%), Middle Mountains (32.2%), Siwalik (27.9%), and Terai (27.6%), with elevation ranging from below 500 meters to above 5,000 meters (National Statistics Office, 2024). Climatically, Lumbini Province experiences mild winters, hot summers, and varied monsoon rainfall, with some areas experiencing droughts and others above-normal precipitation (Department of Hydrology and Meteorology, 2024).

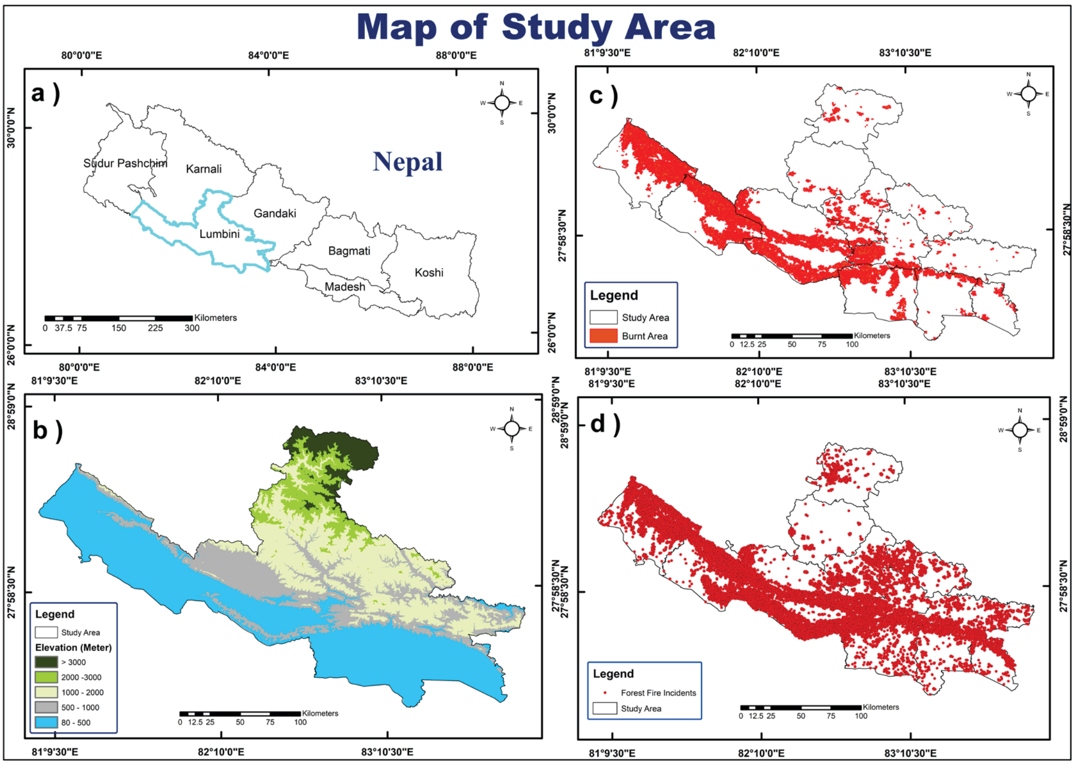

Figure 1: a) Map of Nepal b) Elevation of study area c) Brunt area of study area (2012-2024) d) Fire incidents in study area (2012-2024).

Data and collection methods

The research used both primary and secondary data. Primary data required to understand the causes, impacts, and management strategies for forest fires were collected through interviews with selected key informants, including Divisional Forest Office (DFO) staff such as forest officers and rangers. A purposive sampling method was used to select the key informant based on their role in managing and mitigating forest fire risk in their respective district. Five informants per district were selected to ensure proper representation to maintain the feasibility across all 12 districts, yielding a target sample of 60 respondents Out of these, 41 responses were received, yielding a response rate of 68.3 per cent. The perception data were collected using a structured questionnaire with a five-point Likert scale (1 = strongly disagree/ very poor to 5 = strongly agree/very good). Respondents rated statements across five preparedness dimensions: (i) availability of firefighting equipment and resources; (ii) adequacy of staff training and institutional capacity; (iii) effectiveness of early warning and communication systems; (iv) inter-agency coordination; and (v) community participation in fire management. Each participant's response was grouped into a category and averaged to form a readiness value for each section. Then the scores were interpreted using ranges, such as values from 1.00-1.80 were considered very poor, while 1.81- 2.60 were considered poor. Between 2.61 and 3.40 reflected moderate performance. Anything from 3.41 through 4.20 showed good standing, whereas 4.21 to 5.00 indicated very good outcomes. Data were collected using Google Forms and subsequently processed and analysed in Microsoft Excel.

Forest fire incidents data for the period 2012-2024, which are based on the Visible Infrared Imaging Radiometer Suite (VIIRS) on board the three satellites: VIIRS S-NPP, NOAA-20, and NOAA-21, were acquired from NASA's Earth data FIRMS. Detection confidence, a measure ranging from 0 per cent to 100 per cent, is used to estimate the reliability of fire detection. Confidence levels above 30 per cent are considered more accurate (Giglio *et al.*, 2013). In this study, data with confidence levels exceeding 30 per cent have been utilised to enhance the accuracy of results. Burnt area data were derived from the MODIS MCD64A1 product, which has a spatial resolution of 500 meters and covers the period from 2012 to 2024 under Window 18 (South Asia). The dataset was downloaded from the University of Maryland server (ftp://ba1.geog.umd.edu/). The shape files were subsequently projected and clipped to the study area, and the burnt area was calculated using ArcGIS 10.8.

Variable used in the forest fire risk mapping

Based on the literature review, ten key variables influencing forest fires were identified and used to develop the forest fire risk map. For this study, satellite imagery, along with various vector and raster data products, was utilised. Table 1 presents the data models and sources for the different criteria maps. The variables were selected to prioritise the most accurate data available. These variables are categorised into four groups: topographical factors (elevation, slope, and aspect), climatic factors (temperature, precipitation, and wind speed), anthropogenic factors (proximity to settlements and distance from roads), and biophysical factors (land cover classes and NDVI).

Table 1: Variables and data used to assess forest fire risks

S.N.	Variables	Spatial Resolution	Data Period	Data Type	Source
1	Elevation	30 m	2000-2013	Raster	Aster DEM
2	Aspect	30 m	2000-2013	Raster	Aster DEM
3	Slope	30 m	2000-2013	Raster	Aster DEM
4	LULC	30 m	2010	Raster	ICIMOD
5	Temperature	1 km	2012-2024	Rater	MODIS
6	Precipitation	5.5 Km	2012-2024	Raster	Climate Hazards Group at UCSB (CHIRPS)
7	Distance From Road	1:25000	2024	vector	Humanitarian Data Exchange
8	Wind Speed	250m	2023	Raster	Global wind Atlas
9	NDVI	10 m	2023	Raster	Sentinel 2
10	Proximity to Settlement	1:25000	2015	Vector	OCHA Nepal
11	Forest Fire Points	375m	2012-2024	Vector	FIRMS
12.	Burnt Area	500m	2012-2024	Vector	NASA MODIS
13.	Perception Data			Likert Scale	Primary data

Data processing and analysis

Forest fire risk analysis

This study collected data and fire points from several sources to identify fire risk locations. Using ArcGIS software, the study processed data for extraction, projection, and clipping to the area of interest. To ensure uniformity, all raster datasets were resampled to a pixel size of 30 x 30 meters.

The WLC method integrated all variables to produce the final fire risk map. The study validated the risk map using three approaches: overlaying historical fire data, generating a confusion matrix, and performing AUC-ROC analysis (Figure 2).

Processing and analysis of spatial data

Topographic information, Aster Global DEM downloaded from USGS (https://earthexplorer.usgs.gov/) was mosaicked, projected, and clipped into the area of interest. Slope and aspect layers were then derived in the ArcGIS spatial analyst tool- ArcGIS 10.8.

Temperature data for 2012 to 2024, which was obtained from MODIS, were processed in Google Earth Engine to develop a Layer representing the mean monthly temperature for the pre-monsoon season, i.e., from March to May. Similarly, the wind speed data for the year 2023 at a resolution of 250 m were downloaded from the Global Wind Atlas https://globalwindatlas.info/en. The

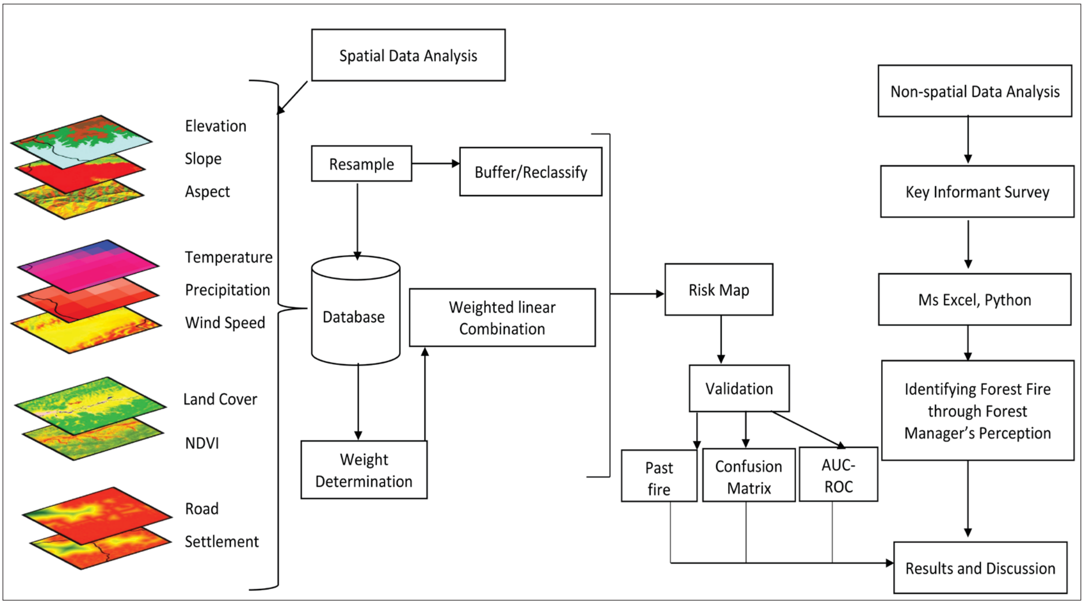

Figure 2: Framework for identifying forest fire risk zone in Lumbini Province

precipitation data for 2012-2024 were sourced from CHIRPS, available at a spatial resolution of 5.5 km.

Land cover classification data for the years 2010 and 2019, with a spatial resolution of 30 meters, were obtained from ICIMOD. Data on roads and settlements was obtained from the HOTOSM Nepal Roads dataset via the Humanitarian Data Exchange and OCHA Nepal. These vector point shape files were converted into a raster format using the Euclidean distance tool in the ArcGIS spatial analyst tool.

Also, the NDVI data from 2023 was extracted in 10 m resolution using Sentinel-2 imagery. The forest fire point data for 2012-2024 were derived from NASA FIRMS at a resolution of 375 m.

Development of forest fire risk model

Finally, the study reclassified and weighted ten critical parameters-land cover, NDVI, temperature, slope, distance to roads, proximity to settlement areas, elevation, aspect, wind speed, and precipitation-to analyse forest fire risk. Since many factors exhibit highly variant fire frequency patterns dependent on intensity and severity, weights were assigned through an extensive literature review, rating each variable by established fire potential (Adab *et al.*, 2011; Chuvieco *et al.*, 2010; Mohajane *et al.*, 2021; Parajuli *et al.*, 2020). Land cover received the highest weight (0.20) as the primary fuel source (Ajin *et al.*, 2016), followed by distance to roads, proximity to settlements, and NDVI (0.15 each) due to anthropogenic ignition dominance and fuel continuity (Chuvieco *et al.*, 2010; Sivrikaya *et al.*, 2014), temperature as desiccation driver (0.10) (Matin *et al.*, 2017), and topographic/climatic factors at 0.05 each. Each variable was scored 1-5 (5=highest risk), combined through WLC for the final risk map.

The WLC method was employed to calculate the Forest Fire Risk Map (FFRM). The equation used was:

FFRM = LC * 0.20 + DR * 0.15 + PS * 0.15 +ND*0.15+ T * 0.10 + A * 0.05 + E * 0.05 + S * 0.05 + P * 0.05 + WS * 0.05........................ equation 1

where, FFRM is the forest fire risk map, LC is the Landover, DR stands for the distance from the road, PS is the proximity to the settlement, ND means normalised difference vegetation index, T is the temperature, A is the aspect, E is the elevation, S means slope, P stands for precipitation and WS is the wind speed. Each variable's contribution to fire risk was calculated based on its percentage influence. The weighted linear combination method is used because it is flexible and can merge different kinds of data. It offers a structured, transparent, and easy-to-apply risk assessment process.

Model validation

This study used three validation methods. The first method overlaid the 2024 forest fire points on the Forest Fire Risk Map, assuming that many forest fires would likely occur in medium- to extremely high-risk zones. This year was selected as a temporal benchmark due to its highest fire incidents and burnt area in the study period.

The second validation method calculated the various metrics of the user's accuracy, producer's accuracy, kappa coefficient, and overall accuracy using a confusion matrix developed with a support vector machine. This was done similarly to Jensen (1996) (cited in Jung *et al.*, 2013). A total of 100 random points were generated in ArcGIS and validated against a ground-based map available in Google Earth Pro. Each point was categorised into one of five risk levels (from 1 to 5), ranging from extremely low to very high risk. Additionally, these points were analysed with respect to surrounding features, such as forest density, towns, and roads, to verify their risk categorisation. Correct and incorrect classifications were recorded in the confusion matrix, and the following metrics have been computed by the corresponding equations:

1. Producer's Accuracy = $\frac{Caa}{C.a} * 100\%$ equation 2

   where, *Caa* is the value at the intersection of a column, and *C.a* is the row total.

2. Overall Accuracy = $\frac{\sum_{a=1}^{u} Caa}{Q} * 100\%$ equation 3

   where U is the total number of classes and Q is the total number of pixels

3. Kappa Coefficient = $\frac{\frac{\sum_{a=1}^{u} Caa}{Q} \quad \frac{\sum_{a=1}^{u} CaC.a}{Q^2}}{1 - \frac{\sum_{a=1}^{u} CaC.a}{Q^2}}$ equation 4

   where $Ca.$ is the row total.

Finally, the cross-validation of the forest fire risk model was performed using the ROC curve approach. This method evaluates the performance by showing the area under the curve, representing the true positive rate, or sensitivity, versus the false positive rate, or 1-specificity. In constructing the ROC-AUC, the final risk map, forest fire points, and non-fire points were used. The non-fire points were generated in ArcGIS using spatially balanced sampling, and historical fire incidences of 2024 were used as validation points. The ROC tool from the ArcSDM toolset in ArcGIS was used to develop the ROC-AUC curve based on the methodology by (Das *et al.*, 2023; Mabdeh *et al.*, 2024). ArcSDM was very efficient in categorical map analysis.

RESULTS

Distribution of forest fires

Table 2 illustrates notable variation in forest fire incidents and burnt areas among 12 districts in the study area from 2012 to October 2024. Dang reported the highest number of incidents (27,164 or 24.74%), followed by Bardiya (22,953 or 20.90%) and Banke (21,281 or 19.38%), collectively accounting for over two-thirds of the total incidents. The mentioned districts also reported considerable areas affected by burning, with Dang representing the highest of 2,254.78 km^2, followed by Bardiya and Banke, thus clearly representing the strong association between the frequency of fire incidents and the extend of area affected. The overall fire density of Lumbini Province was 11.68 incidents per km^2 of forest area during 2012-2024.

Annual trends of forest fire

Fire incidents in Lumbini Province, Nepal, based on VIIRS data (2012–2024), shows significant variation over the years. In 2024, fire incidents peaked at 26,146, followed by 19,679 incidents in 2021 and 12,310 in 2023. In contrast, 2015 recorded the lowest number of incidents at 1,241, while 2020 had only 801 incidents. Fire incidents were relatively higher in 2016 and 2022, with counts reaching 11,154 and 7,734, respectively (Figure 3). On average, Lumbini Province experienced approximately 8,446 fire incidents per year over the past 13 years, with notable peaks occurring in 2024, 2021, and 2023. Most fire incidents were recorded in the pre-monsoon season, i.e. March - May taking a considerable share of 98.0 per cent. The respective shares for April and May are 76.85 per cent and 13.45 per cent of the fire outbreaks, with another 7.74 per cent happening during March.

Table 2: Fire incidents and burnt area in different districts of Lumbini Province during 2012-2024

S.N.	District Name	No. of fire Incidents	% of fire incidents	Burnt Area(sq. km)	District Area(sq. km)
1.	Arghakhanchi	8563	7.80	969.66	1239.66
2.	Banke	21281	19.38	1407.38	1879.78
3.	Bardiya	22953	20.90	1468.06	1999.68
4.	Dang	27164	24.74	2254.78	3001.97
5.	Gulmi	3040	2.77	324.57	1108.64
6.	Kapilbastu	7591	6.91	1057.64	1651.72
7.	Nawalparasi_west	2747	2.50	352.57	727.15
8.	Palpa	5332	4.86	686.46	1463.73
9.	Pyuthan	5444	4.96	1128.70	1321.12
10.	Rolpa	846	0.77	383.76	1885.13
11.	Rukum_east	739	0.67	1272.52	1682.37
12.	Rupandehi	4099	3.73	467.85	1305.68
Grand Total		109,799	100	11773.95	19266.63

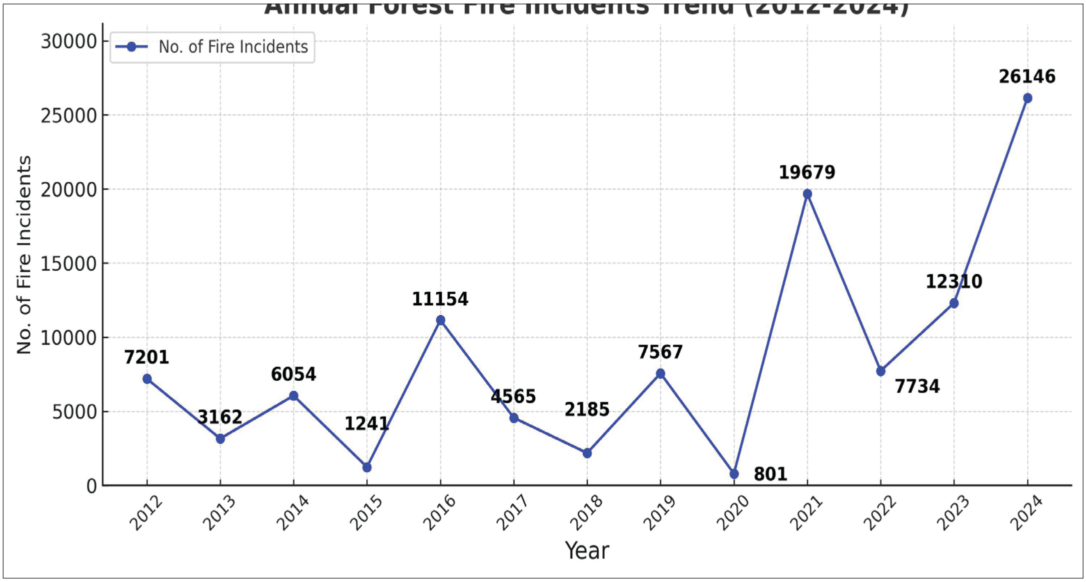

Figure 3: Annual forest fire incidents

Fire incidents in protected area within Lumbini Province

The study investigated the distribution patterns of forest fire incidents in protected areas on a yearly basis from 2012 to 2024. Over the past 13 years, Bardiya National Park recorded the highest number of incidents at 20,507, followed by Banke National Park with 15,543 incidents. In contrast, Dhorpatan Hunting Reserve recorded very few fire incidents, with a total of 35, while Krishnasaar Conservation Area had no recorded fire incidents (Figure 4).

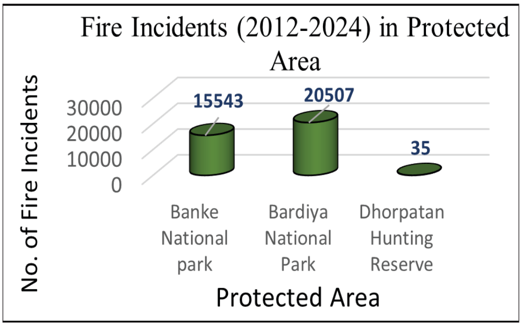

Figure 4: Fire incidents records in protected area

Local unit with the highest fire incidents

Out of the 109 local government units in the Province, Rapti Sonari rural municipality in Banke (17,435), Rajpur in Dang (8,631), and Gadhawa in Dang (4,436) experienced the most fire incidents during 2012 to 2024. Of the municipalities, Sitganga in Arghakhanchi had the most incidents (6,970), followed by Lamahi in Dang (3,122) and Shivaraj in Kapilbastu (2,620). The number of incidents is lower in sub-metropolitan cities, such as Butwal (1,073), Tulsipur (382), and Nepalgunj (1), while Ghorahi in Dang reported 2,876 fire incidents (Table 3).

Magnitude of burnt area

The burnt area record indicated that the years 2016, 2024, and 2023 had the highest burnt area: precisely, the year 2016 recorded the highest burnt area of 2718.79 km^2, followed by the year 2024 with a burn of 2385.70 km^2, and the year 2023 with a 1526.72 km^2. It is reported that the lowest burnt areas in 2015 and 2020 were 65.27 km^2 and 28.64 km^2, respectively (Figure 5). The average burnt area per year from 2012 to 2024 of Lumbini province is approximately 1052.51 km^2.

Table 3: Local unit with highest fire incidents in the study area

Administrative Zone	Local Unit Name	District Name	No. of Fire Incidents
	Rapti Sonari	Banke	17435
	Rajpur	Dang	8631
Rural Municipality	Gadhawa	Dang	4436
	Babai	Banke	2955
	Banglachuli	Dang	2134
	Sitganga	Arghakanchi	6970
	Lamahi	Dang	3122
Municipality	Shivaraj	Kapilbastu	2620
	Buddhabhumi	Kapilbastu	2469
	Kohalpur	Banke	2145
Sub Metropolitan city	Ghorahi	Dang	2876
	Butwal	Rupandehi	1073
Tulsipur		Dang	382
	Nepalgunj	Banke	1

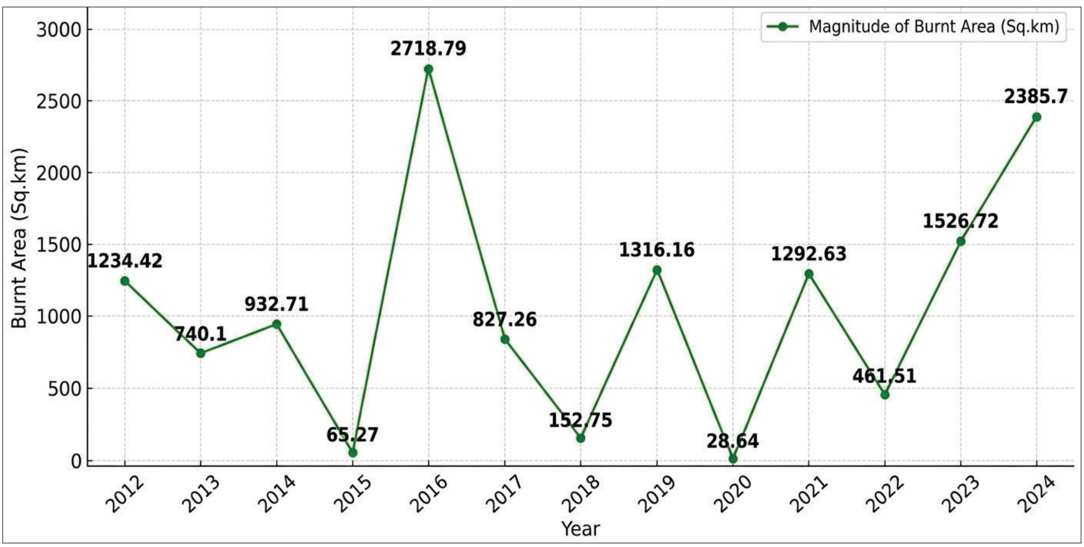

Figure 5: Annual trend of burnt area

Fire incidents comparison with the variables

Table 4 shows a good association between various environmental and geographical factors and fire hazard levels. By land cover, fire risk tends to be relatively high, especially within "Broad-leaved Closed Forest," accounting for as much as 74.3 per cent of fires. Accordingly, its range on a vegetative density scale referred to as the Normalised Difference Vegetation Index (NDVI)-NDVI provides evidence for higher amounts of fire events with particularly intensive vegetative mass, although confined to "0.4-0.5."

Also, fire risk is related to the proximity to roads and settlements, showing higher risk near roads (<1000m) at 34.2 per cent and settlements (<1000m) at 34.94 per cent. Temperature was one of the critical variables, incidents above 90.9 per cent for temperatures >40°C. Low elevations, like 80 to 500 meters, contributed 48 per cent towards incidents. Aspect analysis shows that slopes oriented towards the south aspect had the highest incidents with a share of 31.42 per cent. Gentle slopes (<15%) and areas with moderate precipitation (100-150mm) yielded the highest values of fire risk, contributing 29.36 per cent and 57.89 per cent, respectively. Lastly, wind speed analysis showed that the highest fire incidents were associated with moderate winds at 2-3 m/s, contributing 47.34 per cent.

Table 4 Fire incidents comparison with the variables used in the study.

Variables	Weight (%)	Classes	Fire Rating Classes	Value	% of Fire Incidents	No. of Fire Incidents	% of Pixel Count
Land Cover	20	Bare area, Building /river/lake	Very Low Risk	0	0.25	270	5.32
		Agriculture	Very Low Risk	1	0.00	0	42.95
		Shrub land/Grass-land	Low Risk	2	0.68	744	1.98
		Needle leaved Open Forest	Medium Risk	3	0.77	843	4.59
		Needle leaved closed Forest/ Broad leaved Open Forest	High Risk	4	24.01	26362	17.42
		Broad leaved Closed Forest	Very High Risk	5	74.30	81580	27.74
NDVI	15	<0.2	Very Low Risk	1	0.30	332	11.49
		0.2-0.3	Low Risk	2	3.65	4004	24.15
		0.3-0.4	Medium Risk	3	36.79	40398	30.87
		0.4-0.5	High Risk	4	56.99	62579	28.21
		>0.5	Very High Risk	5	2.26	2486	5.28

Distance to Road (Meter)	15	>4000	Very Low Risk	1	17351	15.80	7.64
		3000-4000	Low Risk	2	12147	11.06	6.07
		2000-3000	Medium Risk	3	20133	18.34	13.99
		1000-2000	High Risk	4	22613	20.59	20.81
		<1000	Very High Risk	5	37555	34.20	51.49
Prox-imity to Settlement (Meter)	15	>4000	Very Low Risk	1	13.55	14876	5.34
		3000-4000	Low Risk	2	8.93	9802	3.06
		2000-3000	Medium Risk	3	19.97	21929	7.05
		1000-2000	High Risk	4	22.61	24827	10.92
		<1000	Very High Risk	5	34.94	38365	73.63
Tempera-ture (De-gree C)	10	<25	Very Low Risk	1	0.13	141	0.31
		25-30	Low Risk	2	0.24	268	2.96
		30-35	Medium Risk	3	0.36	399	5.68
		35-40	High Risk	4	8.36	9180	13.39
		>40	Very High Risk	5	90.90	99811	77.65
Elevation (Meter)	5	>3000	Very Low Risk	1	0.12	132	4.95
		2000-3000	Low Risk	2	0.60	663	7.37
		1000-2000	Medium Risk	3	12.15	13341	24.24
		500-1000	High Risk	4	39.13	42959	20.50
		80-500	Very High Risk	5	48.00	52704	42.94
Aspect	5	Flat	Very Low Risk	1	8.41	9232	8.94
		North	Low Risk	2	9.52	10450	15.25
		East	Medium Risk	3	19.39	21288	22.65
		West	High Risk	4	31.26	34327	25.49
		South	Very High Risk	5	31.42	34502	27.67
Slope (%)	5	>45	Very Low Risk	1	26.14	28697	30.81
		35-45	Low Risk	2	15.37	16873	10.33
		25-35	Medium Risk	3	15.97	17537	9.39
		15-25	High Risk	4	13.17	14460	7.45
		<15	Very High Risk	5	29.36	32232	42.03
Precipita-tion (mm)	5	>250	Very Low Risk	1	1.68	1844	3.33
		200-250	Low Risk	2	3.41	3745	13.39
		150-200	Medium Risk	3	31.96	35089	34.42
		100-150	High Risk	4	57.89	63558	38.31
		<100	Very High Risk	5	5.07	5563	10.55
Wind Speed (m/s)	5	<1	Very Low Risk	1	0.75	822	2.51
		1-2	Low Risk	2	23.90	26240	22.04
		2-3	Medium Risk	3	47.34	51976	45.76
		3-4	High Risk	4	20.01	21969	23.21
		>4	Very High Risk	5	8.01	8792	6.49

Forest fire risk index model of Lumbini Province

The final map was created using derived weights based on fire risk effects. The Figure 6 below shows that the regions at risk of fire include 2.85 per cent of the study area with very high risk, 54.57 per cent with a high risk, and 36.11 per cent at medium risk. Approximately 5.18 per cent of the area is classified as very low risk. For the study area, this distribution reflects that more than two-thirds of the area is at risk of forest fires, as 57.42 per cent of the forest area falls within the high to very high-risk classification, making this Province highly susceptible to forest fire.

District with forest fire risk zone

Table 5 illustrates the distribution of forest fire zones among the districts in the study area. Dang has the highest proportion of its area (58.03%) categorised under medium to very high-risk zones. This is followed by Bardiya (44.45%) and Banke (35.79%), which also exhibit considerable fire risk. In contrast, districts such as Nawalparasi West (9.37%) and Gulmi (13.61%) have the lowest proportions of areas under fire risk zones.

Table 5 Distribution of forest fire risk zone by districts

Districts	Medium to very high risk zone (%)	Districts	Medium to very high risk zone (%)
Dang	58.03	Pyuthan	17.23
Bardiya	44.45	Palpa	17.00
Banke	35.79	Arghakhan-chi	16.96
Kapilbastu	32.46	Rukum_ east	14.82
Rolpa	22.99	Gulmi	13.61
Rupandehi	17.33	Nawalpara-si_west	9.37

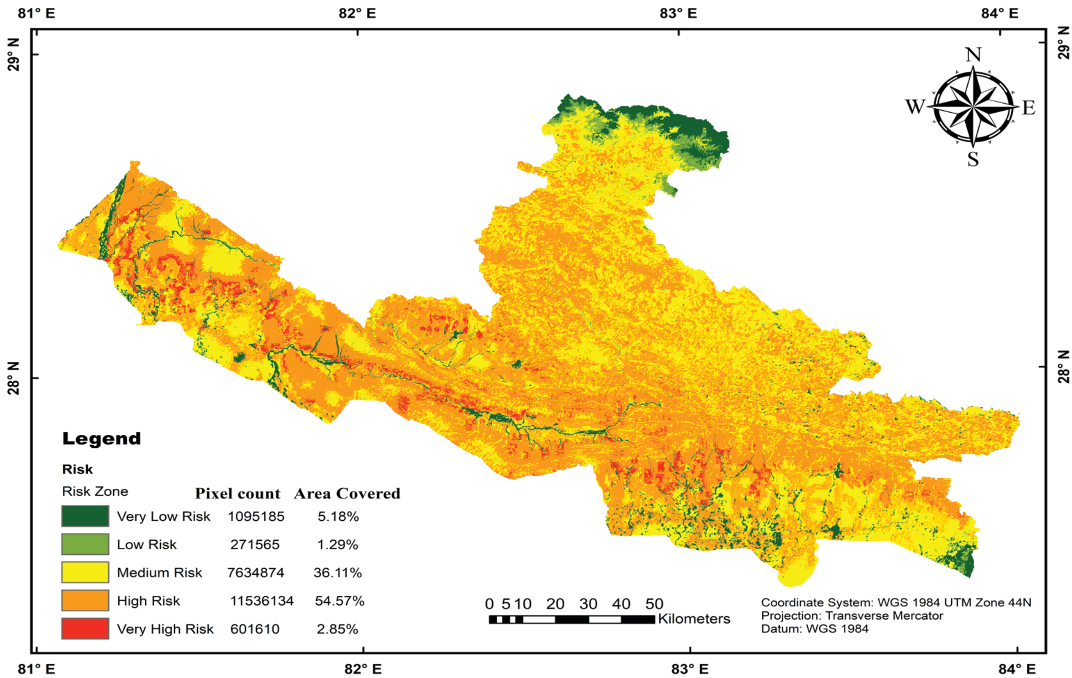

Figure 6: Forest fire risk map of Lumbini Province including the percentage of risk areas

Table 6 Risk area covered in each zone and past forest fire (2024) overlaid in each zone

Fire Risk	% Area of Fire risk zone	No. of Fire Incidents (2024)	% of Fire incidents
Very Low	5.18%	84	0.32 %
Low	1.29%	21	0.08 %
Medium	36.11%	5,590	21.38 %
High	54.57%	19,498	74.57 %
Very High	2.85%	953	3.65 %
Total		26,146	

Validity of the findings

This study validated fire risk maps using three approaches: overlaying 2024 fire points for consistency, generating a confusion matrix to assess reliability via user accuracy and kappa coefficient, and evaluating performance through an ROC curve using the ARC SDM toolbox.

First, the 2024 fire incidents were overlaid over the fire risk map (Kanga and Singh, 2017; R S *et al.*, 2016). In this validation step, 99.6 per cent of fire incidents in 2024 occurred at medium to very high-risk areas (Figure 8). A confusion matrix, which helps validate the generated risk map when there are more than two classes (Shinga *et al.*, 2024). Classes such as true positives, true negatives, false positives, and false negatives display classification outcomes. Random points were generated across the study area to estimate this. Table 7 shows that user accuracy reached 100 per cent in the very low, low, and very high classes. In contrast, the medium class showed the lowest accuracy, at 89 per cent, highlighting areas that may require model improvement. The kappa coefficient reached 0.94, indicating a very high agreement between predicted and observed classifications.

This study evaluated the fire risk map's performance using the AUC, which measures the map's efficiency in distinguishing between high- and low-risk zones. The ROC-curve for the forest fire risk map is shown in Figure 7. The overall AUC-value of 0.803, indicates a very good predictive accuracy.

Table 7 Result obtained from the confusion matrix

Class Value	Very Low	Low	Medium	High	Very High	Total	User Accuracy	Kappa
Very Low	10.00	0.00	0.00	0.00	0.00	10.00	1.00	
Low	0.00	10.00	0.00	0.00	0.00	10.00	1.00	
Medium	0.00	3.00	32.00	1.00	0.00	36.00	0.89	
High	0.00	0.00	1.00	54.00	0.00	55.00	0.98	
Very High	0.00	0.00	0.00	0.00	10.00	10.00	1.00	
Total	10.00	13.00	33.00	55.00	10.00	121.00		
Producer Accuracy	1.00	0.77	0.97	0.98	1.00	0.00	0.96	
Kappa								0.94

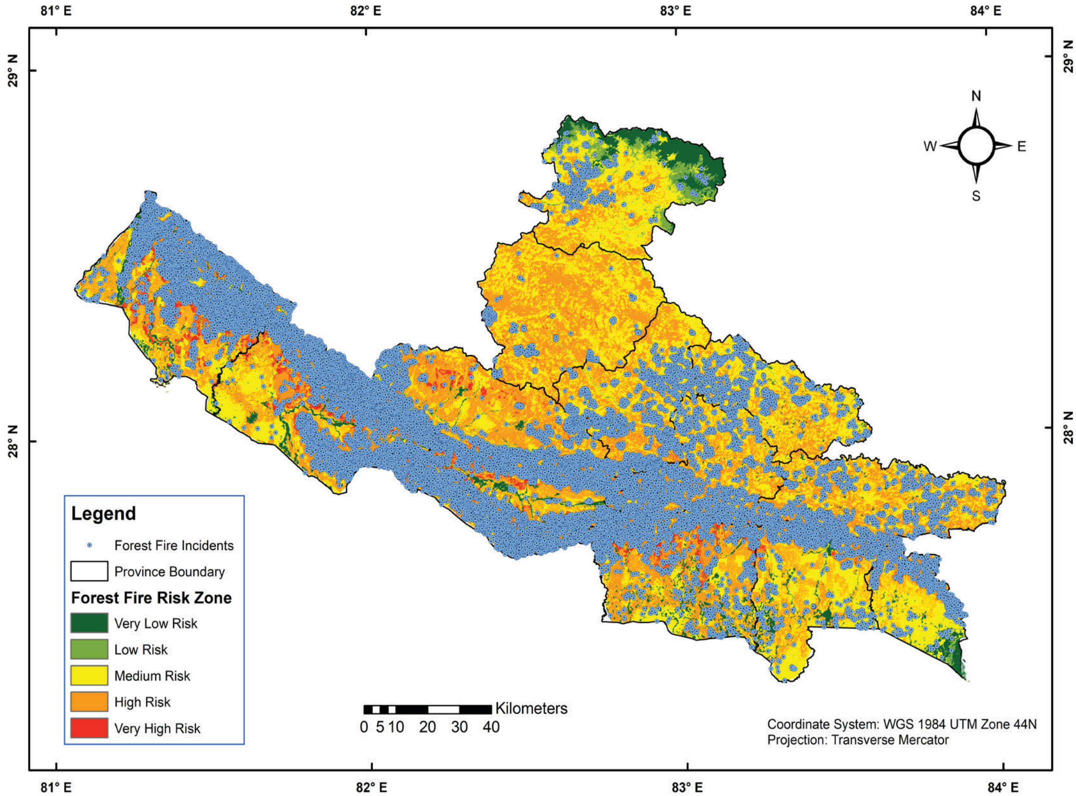

Figure 8: Forest fire incidents on forest fire risk map

Perception of key informants about forest fire in Lumbini Province

The increasing recurrence of forest fires in Nepal points to a need for more available management strategies and technologies in tackling the problem effectively (Parajuli *et al.*, 2022). Human intervention and support have conventionally been used to mitigate risks in fire-prone areas. (Doerr and Santín, 2016).

Types and causes of forest fire

Based on the information gathered from the key informants, the three leading causes of forest fires within the study area are given in (Figure 9). Deliberate causes were cited by 55 per cent as the primary cause, Accidental causes by 36 per cent, and fire from agriculture activities like slash and burn by 9 per cent. In Nepal, human activities are also identified as the primary origin of forest fires. The

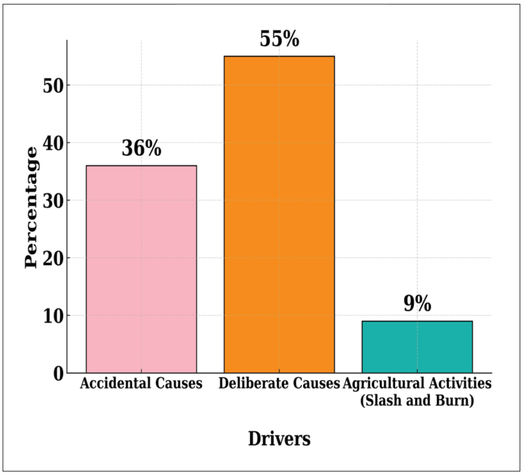

Figure 9: Drivers of forest fire

same respondents, however, clarified that in the studied area, most fires occur either on the ground (31%) or on the surface (61%), crown fires are minimal, just 8 per cent. The respondents reported March (8.3%) and April (83.4%) as forest fire-prone months.

Impact of forest fires on forest types and management systems

The analysis showed that forest fire affect community forest the most, with 83.3 per cent of respondents identifying them as highly affected, compared to 16.7 per cent for government-managed forests. A majority, 84 per cent of respondents reported an increase in forest fire occurrences over time, while 16 per cent reported no increase, and none observed a decrease. Sub-tropical broad-pine forests were identified as the most affected forest type (41.7%), with tropical forests and sub-tropical broad-leaved forests (25% each) and lower temperate broad-leaved forests (8.3%) being the least affected.

Perceived challenges, preparedness, and preventive measures in forest fire management

The results show the challenges of forest fires, district-level preparedness, and prevention measures. Lack of funding and resources (25%) is the single most obstructive component, followed by insufficient training and equipment (20%) and lack of early warning systems (15%) (Figure 10). According to the district-wise preparedness score, Nawalparasi West, Rukum East, and Rupandehi have comparatively better preparedness, with a score of 4.0. At the same time, Banke and Dang are the least prepared, with scores of 2.0 and 2.5, respectively (Figure 11). In terms of preventive measures applied in the districts, firebreaks/fire lines (33.3%) and community education and awareness (30%) were the strategies identified as being most effective, followed by controlled burning (20%) (Figure 12).

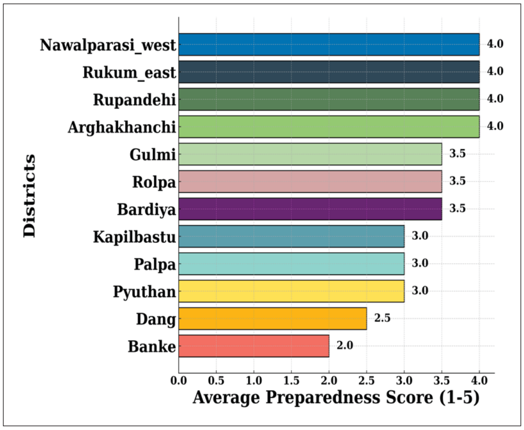

Figure 11: District wise preparedness score

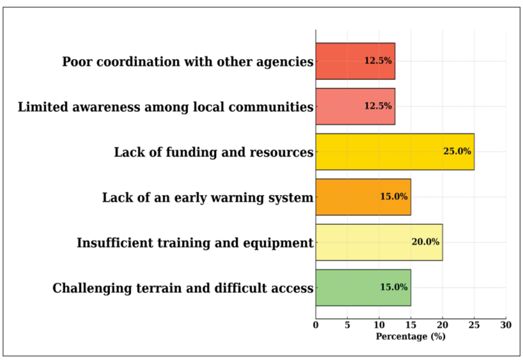

Figure 10: Key challenges in forest fire management

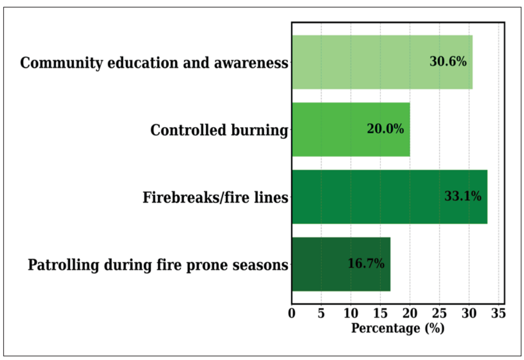

Figure 12: Effective preventive measures in the study area

DISCUSSION

Assessing the status and trends of forest fire

This study highlights how environmental and human factors interact to shape forest fire patterns. In this case, land cover appeared to be one of the decisive elements influencing the fire risk. Considering the rest of the categories, the class of broadleaved closed forests reported 74.30 per cent of the fire incidents Sal-dominated broadleaved forests exhibit extreme pre-monsoon fire proneness due to March-April leaf shedding creating continuous litter layers (8-12% moisture) and live fuel moisture declining to 60-80 per cent, forming highly flammable surface fuel beds under 35-42°C conditions (Timilsina *et al.*, 2007). The same findings were recorded by Ajin *et al.* (2016) in the deciduous forests of India. Likewise, temperature increased the probability of fire incident occurrences, with 90.90 per cent occurring at temperatures above 40°C. This finding is supported by recent studies such as Ma *et al.* (2024) and Matin *et al.* (2017), which stated that high temperatures and drought conditions raise the probability of forest fires by increasing the drying of fuels. Aspect also plays an essential role; southern aspects witnessed 31.42 per cent of the fire incidents. It has been consistent with Adab *et al.* (2011), who concluded that the Southern aspects have higher temperatures and robust winds, lower humidity and reduced fuel moisture, which results in a high vulnerability to fire incidents.

Elevation also influences fire patterns, with lowland areas (80-500 meters) experiencing 48 per cent of incidents, reflecting increased human activities and drier conditions (Matin *et al.*, 2017). Proximity to roads and settlements is another critical factor, with 34.20 per cent of fires occurring within 1 km of roads and 34.94 per cent within 1 km of settlements. This result is also supported by the work of Sivrikaya *et al.* (2014) and Parajuli *et al.* (2020), who also documented more fire occurrences near anthropogenic activities due to accidental ignition.

Interestingly, areas with high NDVI values (>0.5) recorded fewer fire incidents despite being classified as high-risk zones. Dense vegetation with higher moisture content inhibits ignition (Chuvieco *et al.*, 2008). and these areas are often remote with limited human interference, reducing fire occurrences (Archibald *et al.*, 2013).

Developing a forest fire risk map of Lumbini Province

The WLC method successfully combined ten key variables to create a forest fire risk map, categorizing 57.42 per cent of forests are in very-high to high-risk zones. Variables such as land cover, proximity to roads, and NDVI received the highest weights, emphasising their importance in fire risk (Akay and Erdoan, 2017; Chuvieco *et al.*, 2010). Susceptibility mapping for forest fires uses a dependent variable such as a forest fire inventory along with several independent variables, usually topographic factors-elevation, slope, and aspect-climatic factors including rainfall, temperature, humidity, and wind, anthropogenic factors concerning proximity to settlements and roads, and land use characteristics, as suggested by (Carmel *et al.*, 2009; Jaiswal *et al.*, 2002; Mohajane *et al.*, 2021).

Accuracy assessment

Validation is one of the important parts of preparing the risk map (Feizizadeh & Blaschke, 2014; Pourghasemi *et al.*, 2016). Overlaying

2024 fire incidents revealed a strong correlation, with high-risk zones (54.57% of the area) accounting for 74.57 per cent of fire incidents and very high-risk zones (2.85% of the area) capturing 3.65 per cent, consistent with the role of historical data highlighted by (Ajin *et al.*, 2016; Kanga and Singh, 2017; Vadrevu *et al.*, 2010).

In this study, the user accuracy was 96 per cent, and the kappa coefficient was approximately 0.94, indicating that the map was accurately produced. Kappa coefficients in this range represent substantial and reliable agreement (Rwanga *et al.*, 2017). Similarly, Parajuli *et al.* (2023) reported comparable results, with 95 per cent overall accuracy and a kappa coefficient of 0.93, further supporting the reliability of such validation methods.

The ROC-AUC analysis, with an AUC value of 0.803, confirmed a predictive accuracy of 80.3 per cent, aligning with another similar research. As Carter *et al.* (2016) suggests that an AUC value exceeding 0.7 reflects good predictive performance, further validating the model. Similarly, research conducted in the Halgurd-Sakran Core Zone achieved an AUC score of 0.76, indicating a reliable predictive capability in assessing forest fire risk (Khan *et al.*, 2024).

Perception analysis

The study found that 55 per cent of forest fires were caused deliberately, aligning with Kunwar *et al.* (2006), who reported that 58 per cent of anthropogenic forest fires were due to deliberate burning by grazers, poachers, hunters, and non-timber forest product harvesters. These activities reflect significant unsustainable human pressure on forest ecosystems.

Additionally, 36 per cent of the fires in this study were accidental, while 9 per cent were linked to agricultural activities such as slash-and-burn. Likewise, numerous authors claim that whether intentional or not, human activity is the main reason behind the majority of fires worldwide (Ryan and Hamin, 2008; Shindler *et al.*, 2009)

Likewise, the study found that the most vulnerable month to fire is March to May, i.e., the pre-monsoon season. To support this, many scholars have also concluded that the majority of forest fires in Nepal take place in the hotter, drier pre-monsoon season (March-May) (Bhujel *et al.*, 2017; Khanal, 2015; Matin *et al.*, 2017; Parajuli *et al.*, 2015).

Limitations of the study

This study has some limitations that might have affected the findings and their interpretations. The reliance on VIIRS data (2012 onward) limited the use of longer-term MODIS trends (since 2001). The MODIS burnt area product (MCD64A1) resolution (500 meters) likely missed smaller fires and finer details. Though helpful, validation using historical fire points and confusion matrices did not fully capture dynamic fire behaviour or spatial inconsistencies, and ROC curves were confined to risk zone comparisons.

The WLC method assumes variable independence, potentially ignoring interactions such as wind direction and slope effects, which may influence fire behaviour. Critical variables like fuel moisture and community fire practices were excluded due to data gaps, reducing model comprehensiveness. This study utilised the 2010 land cover dataset from ICIMOD due to the absence of a reclassified forest category in the more recent land cover datasets of Nepal.

CONCLUSION AND RECOMMENDATION

Conclusion

This study provides a comprehensive geospatial evaluation of forest fire risks in Lumbini Province, Nepal, utilising the WLC approach. The findings highlight significant temporal and spatial patterns of forest fires, alongside key drivers that exacerbate these risks. Among the districts, Dang, Bardiya, and Banke stand out as critical hotspots, collectively accounting for over 65per cent of fire incidents and more than 43 per cent of the total burnt area.

Temporal analysis shows that forest fires are heavily concentrated during the pre-monsoon season, with 98.04 per cent of incidents occurring in March, April, and May. April emerges as the peak month for fire activity. Anthropogenic factors, such as proximity to settlements and roads, along with biophysical characteristics like land cover type (e.g., broad-leaved closed forests), low elevation, and southern aspects, predominantly influence fire frequency and spread.

The fire risk model developed in this study demonstrated good predictive accuracy, classifying 57.4 per cent of Province Forest into high to very high-risk zones, as validated by historical fire data and an AUC value of 80.3 per cent. Validation using a confusion matrix confirmed the model's reliability, with an overall accuracy of 96 per cent and a kappa coefficient of 0.94, indicating a strong agreement between the predicted and observed classifications.

The study identifies key challenges in forest fire management, with funding (25%), training (20%), and early warning systems (15%) highlighted as primary obstacles. Districts like Nawalparasi West and Rukum East appear more prepared (score: 4.0), whereas Banke and Dang exhibit lower levels of preparedness (scores: 2.0 and 2.5, respectively). Effective prevention strategies include firebreaks (33.3%) and community education (30%). The study highlights an important need for management of fires in the pre-monsoon months, specifically in high fire occurrence regions like Dang, Bardiya, and Banke. Such findings highlight the need for early warning systems, community participation, and resource allocation strategies to reduce fire risks, thus providing tangible insights to policymakers, planners, and forest managers.

Recommendation

Policy and planning should focus on high-risk districts, including Dang, Bardiya, and Banke, emphasising integrating forest fire risk maps into regional disaster management plans for optimising resource allocation and preparedness. The rural municipalities require special attention, specifically, those labelled high-risk, such as Rapti Sonari of Banke and Rajpur of Dang, with advanced early warning mechanisms, training, and resource allocations at all levels.

Protected areas, notably Bardiya National Park and Banke National Park, are under very high forest fire risk zones, necessitating the adoption of preventative measures such as controlled burning operations. Proactive fire management should be done during the pre-monsoon season, from March to May, with particular emphasis on April, which is usually the peak month for fires due to the accumulated dry fuel. It is recommended that future researchers focus on investigating the occurrence of fire incidents in protected areas, where, despite low anthropogenic activities, significant fire events are reported, to understand the underlying natural and ecological factors driving these occurrences.

Interventions should, therefore, focus on zones of high to very high risks, representing 57.4 per cent of the forest area, while introducing sustainable land-use management practices in the low-risk areas for long-term resilience. Provincial and landscape-level analyses using refined climatic data, scrutinized field data on fire scars, species-specific fuel, and burnt areas should be the focus of future works. While the existing work on fire occurrence and risk is great, the implementation of high-resolution satellite data (like Sentinel-2, WorldView-3) will provide the granularity needed to understand the main drivers of the fire risk by detecting the finer details of vegetation.

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Data availability statement: The data will be made available with a reasonable request to the corresponding author.

Declaration of generative AI in writing: During the preparation of this work, the author(s) used ChatGPT and Gemini in the writing process for improving clarity, conciseness and readability of the manuscript. After using AI-assisted content, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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