GIS Based Forest Fire Susceptibility Modelling Using Frequency Ratio: A Case Study in Palpa District

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Abstract

Forest fires in today's world have become a serious problem affecting the environment, economy, humans, and the global ecosystem. The integration of GIS-based methods and remote sensing imagery is widely used to assess forest fire-prone areas. This study applied the Frequency Ratio (FR) method to evaluate spatial fire susceptibility by analyzing the relationship between historical fire hotspots and contributing factors in Palpa District, Nepal. A total of 330 fire hotspots from 2014 to 2024 were spatially digitized to create an inventory map of historical forest fire events. These hotspots were divided into two groups: 65% (217 points) for training and 35% (113 points) for validation. Forest fire causative factors were categorized into biological (land cover types, NDVI), meteorological (temperature, wind speed), topographic (slope, elevation, aspect), and human-driven (distance from roads, distance from settlements), and were used as parameters to assess the forest fire susceptibility map.The study area was classified into five fire susceptibility zones: very high, high, moderate, low, and very low. The results indicate that high- and moderate-risk zones cover the largest proportion of the area (350.23 km² and 386.21 km², respectively) and together account for more than 60% of recorded fire hotspots. Very high-risk areas, although spatially limited (201.90 km²), also show a significant concentration of past fire incidents. In contrast, low- and very low-risk zones exhibit comparatively fewer hotspots, confirming lower fire susceptibility. The strong correspondence between FR-derived risk classes and historical fire occurrences demonstrates the reliability of the FR method for fire susceptibility mapping. These findings provide valuable support for prioritizing fire prevention, monitoring, and resource allocation in Palpa District.

Keywords: Frequency Ratio (FR), Forest Susceptibility, Topographic Factors, Fire hotspots.

1. Introduction

1.1 Background

Forest fire, also called wildfire, is prescribed as an unplanned and unmanaged fire that ignites and spreads through natural vegetation—such as forests, grasslands, shrublands, or tundra-using available fuels and driven by environmental factors like wind, temperature, terrain. Wildfires have major environmental and ecological issues, threaten human lives, causing massive losses of lives and properties (Parajuli et al., 2020). Climate and human actions, such as temperature, precipitation, and sacrifice, are significant elements that can trigger forest fires. Even though fires pose a serious threat to many forests and biodiversity, remarkably little research has been done on how they affect forest ecosystems and biodiversity. Every year, a forest fire in Nepal consumes 400,000 hectares of land (Bajracharya, 2002). Forest fires are most common in Nepal during the dry season, which runs from November to June, with the maximum concentration happening between March and May. The worst years were 2009 and 2016, when numerous catastrophic forest fires were reported; in 2016, forest fires burned over 12,000 community woods across 50 districts, killing 15 people (CIFOR 2017; SERVIR Global 2018). NASA designated Nepal as a nation "most vulnerable to wildfires" in April 2009 after

358 flames were reported in a single day (The Kathmandu Post).

Forest fires generally occur naturally or artificially. Forest fires that occur naturally may be linked to dry weather conditions, volcanic eruptions, or lightning caused by crashing rock debris and climate change too. Trekkers' unextinguished campfires, unextinguished bidis, matchsticks, and cigarette butts, railway engine sparks, and burning of fields close to forests etc., are some of the reasons why unintentional fires are started by irresponsible people (Gupta & Kaushik, 2012). As per the Nepal Disaster Risk Reduction Authority, 64% of fire in 2021 are set by people intentionally. Since forest fires are a recurrent issue worldwide, it is essential to conduct spatial analysis of forest fires and identify susceptibility zones to enhance prevention and prediction techniques (Tian et al. 2013), and within the last ten years, this requirement has grown significantly (Miller and Ager, 2013). Researchers are now interested in modeling forest fire areas due to the advancements in RS and GIS (Mangeon et al., 2015). This study was started as a step in that direction, with the primary goal being to create a map of the fire risk assessment of the Palpa area in Nepal using using expert opinion and a frequency ratio (FR) model, a form of GIS based multi-criteria decision making (MCDM) tool. A crucial part of fire analysis and management, forest-fire risk mapping is dependent on several variables, including temperature, population, NDVI, topography, vegetation type, land cover, and distance from roads and settlements. Forest-fire risk maps can assist in identifying and locating hazardous zones, as well as formulating a pre-management plan to help mitigate hazards.

The FR method is a bivariate statistical technique that quantifies the correlation between past fire incidence and conditioning criteria such as terrain, vegetation types, climatic condition, and proximity to human activities. This technique determines the ratio of the likelihood that a fire will occur in a particular factor class to the likelihood that that class will occur throughout the full research area. A greater correlation between the conditioning factor and the occurrence of fire is shown by a higher frequency ratio value. The fire risk models provide a suitable concept to understand characterization of fire risk (Adab et al., 2013). Since it is a data-driven and objective method based on the statistical link between past fire occurrences and conditioning factors, the Frequency Ratio (FR) model offers significant advantages over other MCDA techniques like AHP and FAHP.

1.2 Literature Review

Forest fire risk assessment aims to identify areas that are vulnerable to fire occurrence by analyzing the interactions of environmental, climatic, and human factors. Topographic factors (elevation, slope, aspect), Features of the forest's structure (kind of vegetation), land use/cover, climatic factors (temperature, wind speed), and human activities (agricultural activities, settlements, road network) can be used to summarize these factors. The combination of fieldwork, RS data, GIS techniques, and statistical methods can build reliable spatial prediction of the potential forest fire hazard area for different regions (Abdo et al., 2022). In recent years, GIS-based MultiCriteria Decision-Making (MCDM) techniques have gained popularity for evaluating the risk of natural hazards like fire. A Frequency Ratio (FR) is a GIS-based statistical method for spatial prediction, particularly in mining and natural hazard assessment (such as landslides, fires) that analyses relationship between past incidents and influencing factors.FR method's basic idea is to calculate the likelihood that current risk occurrences will recur in the future in proportion to the current geographic features that serve as the primary causes of forest fires (Abdo et al., 2022). As in forest fire selected in our study, it calculates the ratio of fire occurrence to non-occurrence for different classes of each conditioning element. Various research indicates FR as simple and effective when enough historical data are available. Since FR models do not take expert knowledge into account and presume factor independence, their usefulness in complicated contexts with interacting variables may be limited.

Numerous researchers have successfully identified forest fire risk zones using RS data and GIS techniques (Adab et al. 2013, Dong et al. 2005, Dong et al. 2006, Eugenio et al. 2016, Gheshlaghi et al.

2019, Goldarag et al. 2016, Jaiswal et al. 2002, Mirdeilami et al. 2015, Pradhan et al. 2007, Sivrikaya et al. 2014, Soto 2012, Teodoro and Duarte 2013). Using vegetation, land use, moisture, slope, aspect, elevation, distance from roads, and proximity to settlements as fire-causing factors, Bhandari and Lamichhane (2023) developed the fire hazard assessment in Suryabinayak Municipality using the FR approach. They concluded that most previous fire hotspots were in high and very high-risk zones (Tiwari et al., 2021) developed Forest fire risk maps using RF, AHP and fuzzy AHP modelling techniques and compared their performance. Aspect, slope, elevation, curvature, NDVI, NDMI, TWI, soil, rainfall, temperature, wind speed, road, settlement, distance to drainage and historical fire data were used as parameters. Two groups of historical fire data were created for training and validation. These parameters after classification and buffering were rated based on their potential and weight was assigned based on literature review. The ROC and AUC were implemented for the validation and comparison evaluation between three forest fire susceptibility maps. According to the results, at 83.47%, FAHP had the best prediction accuracy, followed by AHP and FR at 81.75% and 77.21%, respectively. Such forest fire risk made using different components helps in the prediction of when and where forest fires are likely to most occurs and can be used in warning and monitoring system in future.

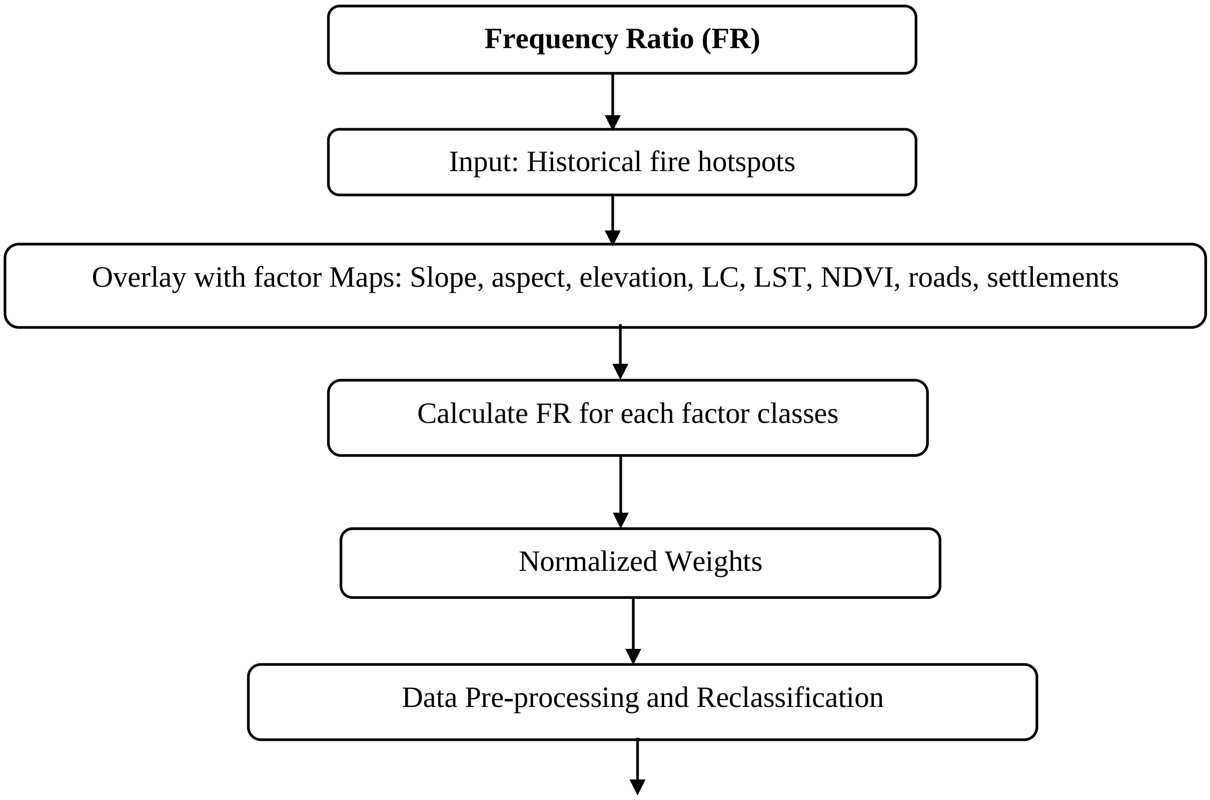
1.3 Objectives

The main goal of this study is to evaluate and map the susceptibility of forest fires using the Frequency Ratio (FR) model by examining the spatial correlation between specific anthropogenic, topographic, climatic elements and past fire incidents. The specific objectives are:

- To identify and select key forest fire influencing factors (e.g. topographic, climatic, anthropogenic factors)
- To create a zonation map of forest fire danger (susceptibility) and categorize it into risk levels ranging from extremely low to extremely high.

2. Methodology

The methodology shown in Fig. 1 is undertaken in this Study.



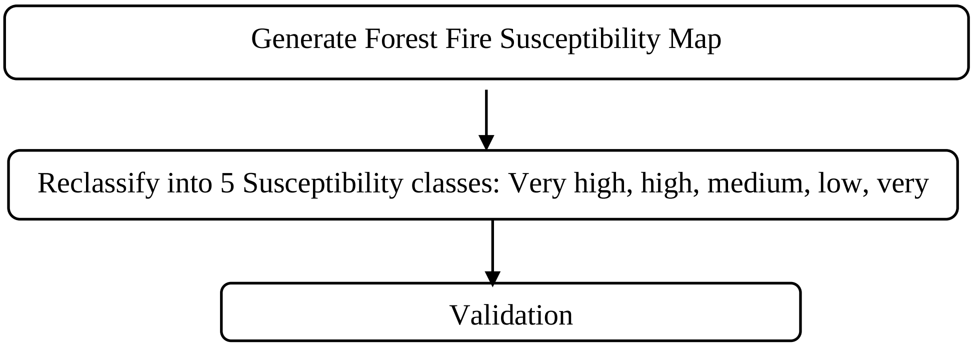


Fig. 1: Flowchart showing Methodology

2.1 Study Area

One of the seventy-seven districts of Nepal, a landlocked nation in South Asia, Palpa district is part of the Lumbini Zone. It is situated between 27º34" and 27º54" N and 83º15" and 84º22" E, with an elevation range of 152 to 1936 meters above sea level. The district, with Tansen as its headquarters, covers an area of 1,373 km^2 and it is flanked to the west by the districts of Gulmi and Arghakhanchi; to the north by Gulmi, Syangja, and Tanhun; to the east by Nawalparasi and Tanhun; and to the south by Rupandehi and Nawalparasi. Geographically, the Chure hill region (18%) and the mid-mountain hill region (82%) make up the Palpa district. The Palpa district has 67607 hectares of total forest, 44,332 hectares of agricultural land, 23,736 hectares of shrubland, 538 hectares of water bodies, and 70 hectares of bare land. According to ICIMOD's Forest Detection and Monitoring System in Nepal, Tinahu Rural Municipality has recorded the highest number of fire events over the past 11 years at all local levels.

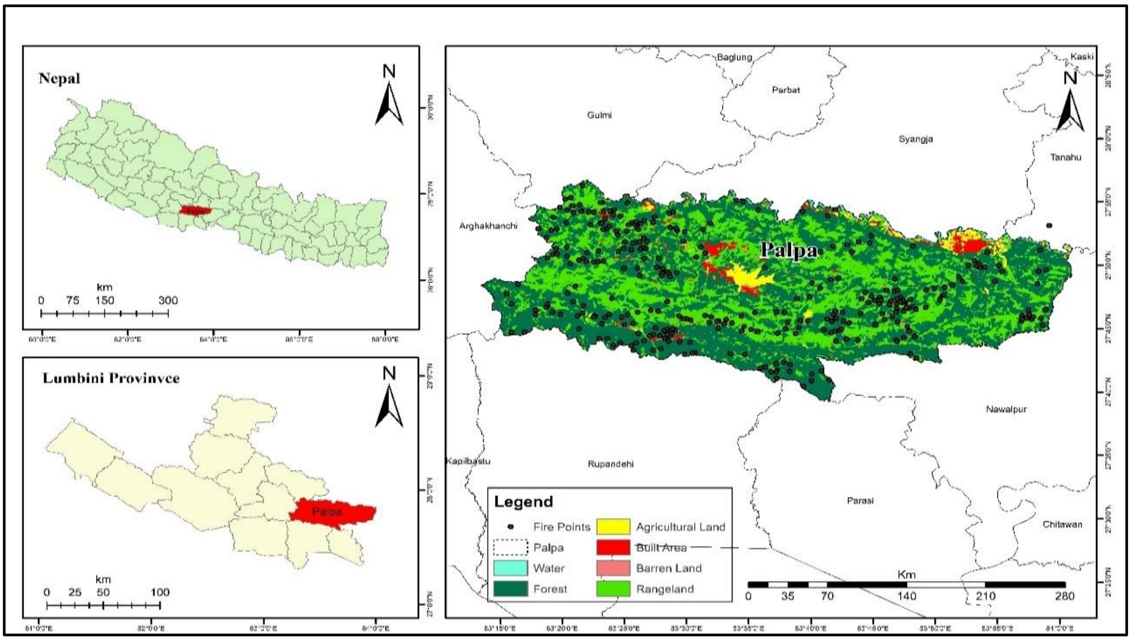


Fig. 2: Study Area: Palpa District

2.2 Datasets

Table 1: Datasets used in this Study

Data	Data type	Resolution	Source	Inputs
DEM	Raster	12.5m	ALOS PALSAR	Slope, elevation, aspect

Land Cover	Raster	10m	ESRI	Vegetation types (forest, grassland, shrubs, water bodies)
Road	lines		Survey Department	Proximity to road
Settlements	Points		Survey Department	Distance from settlements
Wind	Raster		Global wind atlas	Wind speed
NDVI			Sentinel 2(Google Earth Engine)	NDVI
Land Surface Temperature			Landsat 8(USGS)	Land Surface Temperature
MODIS	Point	1km	ICIMOD FIRMS	Fire points
Study area boundary	polygon		Survey Department	Outline of study area

A variety of parameters must be considered throughout the process of conducting a forest fire risk assessment analysis. ALOS PALSAR DEM was imported into ArcGIS 10.5, projected into UTZ Zone 44 and WGS1984 and trimmed to research area extent. Topographic factors: Elevation, slope, aspect were calculated using DEM. Slope and aspect map were developed using Slope function and aspect function in ArcGIS. Land cover classes were extracted from ESRI Sentinel-2. Distance to roads and settlements data were used as provided by survey department of Nepal and buffered into classes and mapped by Euclidean distance function in ArcGIS. Global wind atlas provided the mean wind speed. Since the vegetation cover has strong impact on fire occurrence, NDVI was generated using Sentinel 2 image in google earth engine (code from earth engine data catalog) that uses the Equation (1):

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

Where, *NIR* is spectral reflectance of near-infrared bands. Denser green vegetation is indicated by higher NDVI values, which range from -1 to 1, while less dense vegetation is indicated by lower values. Land Surface Temperature (LST) from Landsat 8 was obtained that involves converting thermal band (Band 10) Digital Numbers (DNs) to Top-of-Atmosphere (TOA) Radiance, then to Brightness Temperature (BT), and finally correcting for emissivity and atmospheric effects using vegetation indices (NDVI) to derive LST in Celsius. The study area outline was obtained from administrative map as provided by Survey Department of Nepal. Historical MODIS fire data were collected from FIRMS and divided into two parts: training data and validation purposes. Total 330 forest fires were recorded from 2014 to 2024. 65% (i.e. 217) of the 330 fire locations were chosen at random and utilized as training data in the FR method. Remaining 35% (113) was used as a validation.

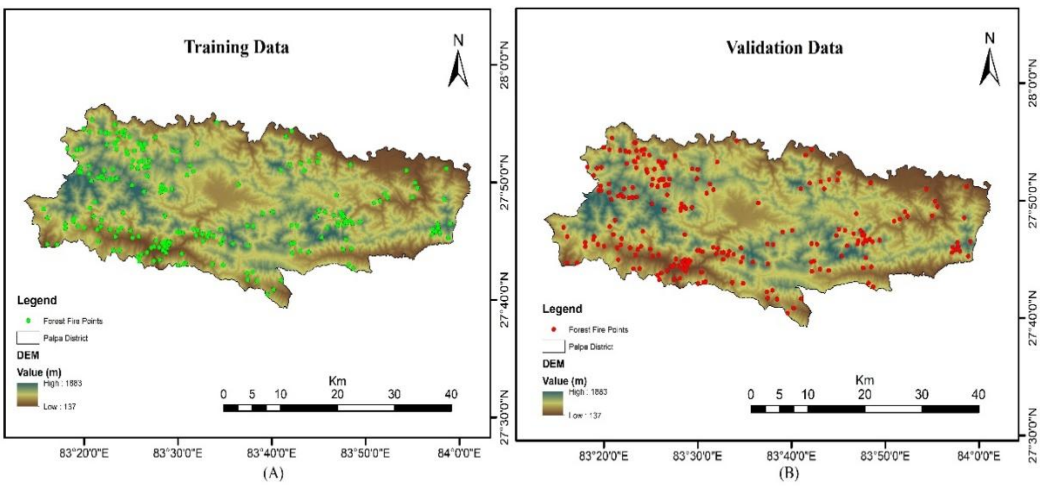


Fig. 3: Forest fire locations (A) Training Point (B) Validation point data

2.3 Frequency Ratio

The favorability function is the foundation of the frequency ratio approach. Higher FR weights show a strong correlation between that class and the frequency of forest fires. The quantitative association between forest fire occurrence locations and all forest fire conditioning factors was extracted using a FR to simulate forest fire-prone areas. The FR is calculated by using Equation (2) (Abdo et al., 2022).

$$FR = \frac{S/M}{Q/R} \tag{2}$$

Where, S determines the number of forest fire events for each class of each motivating parameter, M determines the total number of forest fire events, Q defines the number of pixels for each class of the criterion, and R determines the total number of pixels. The proportionate relationship to the occurrence of forest fires is indicated by FR values. Higher FR indicates higher chance of forest fire and vice versa. Calculated FR of each factor is summed to develop the fire risk map as:

$$\text{Forest Risk Map} = \Sigma_{\{i=1\}}^{\{n\}} \mathrm{FR_i} \text{ n=number of factors} \tag{3}$$

3. Results and Discussion

3.1 Preparation of Thematic map

Nine thematic layers: Land cover, Elevation, Aspect, LST, Slope, Proximity to road, distance to settlement, NDVI, and wind speed, were looked at to identify the fire in the study area which are explained below:

Land cover defines physical features of earth surface. It shows how people use land for various social and economic activities. Compared to sparse and moist vegetation, dry and thick vegetation LC is more susceptible to fire (Vadrevu et al., 2010). Water, trees, crops, developed areas, barren terrain, and rangeland are among the land cover types identified here.

Elevation is an important physiographic feature that affects fire behavior, exposure to the dominating wind, and the amount and duration of rainfall (Gaither et al., 2011). The study region was separated into five classes based on its elevation, which ranged from 137 to 1883 meters): 0-500m, 500-700m, 700-900m, 900-1100m, and <1100m.

Aspect indicates the way a slope faces. The amount of sunlight that a location receives is related to its aspect. Because southern exposure areas have greater burning points than northern exposure areas, forest fires typically occur more frequently in southern aspect areas than in northern aspect areas (Chuvieco & Congalton, 1989). The aspect map for the study area was divided into nine classes, namely Flat (-1-0°), North (0°-22.5° and 337.5°-360°), North-East (22.5°-67.5°), East (67.5°-112.5°), South-East (112.5°-157.5°), South (157.5° 202.5°), South-West (202.5°-247.5°), West (247.5°-292.5°), and North-West (292.5°-337.5°).

A forest fire is significantly influenced by the temperature of the land surface. Due to the seasonal drying of fuel, such as needles, leaves, twigs, and dead trees, high temperatures contributed to the increasing rate of evapotranspiration, creating unfavorable conditions that were conducive to a fire explosion. (Bonora et al., 2013). LST for the year 2021 was calculated which varied from 20 to 35 degrees and is divided into 5 classes: less than 25, 25-27, 27-29, 29-31 and more than 35.

Slope is a measure of how steep a terrain is (Rather et al., 2018). Fires are more prone on steep slopes. In this study, the slope factor is grouped into five classes: 0-15, 15-30, 30-45, 45-60 and >60 degrees.

Forest areas close to road networks are more at fire risk since they are influenced by various human activities such as carelessly tossing burning cigarette butts or matchsticks, increases the risk of fire in regions close to highways (Gupta & Kaushik, 2012). Depending upon the distance, our area has been buffered into 5 classes. 0-200m, 400m 800m, 1000m.

Settlements simply mean society or community where people live. The planning of evacuations, the distribution of firefighting resources, and the creation of fire protection techniques in regions where human habitation and fire-prone environments coexist are all influenced by settlement statistics (Mahmud et al., 2009). Based on that, settlement is classified and buffered into 5 classes: 0-600m, 600-1200m, 1200-1800m, 1800-2400m, 2400-3000m.

NDVI shows the density, health, and moisture content of vegetation—all of which are important aspects of the behavior and vulnerability of forest fires. NDVI ranges from -1.0 to +1.0. Dense, healthy vegetation is indicated by higher positive values; sparse or damaged vegetation is indicated by values near zero; and non-vegetated environments, such as water, are indicated by negative values. NDVI ranges from -1.0 to +1.0. The NDVI was classified into 5 classes: <0, 0-0.15, 0.15-0.30, 0.30-0.45 and >0.45.

Wind speed is one of the most important climatic variables affecting the initiation, spread, intensity, and direction of forest fires. Higher wind speeds hasten the spread of fire by pushing flames toward unburned fuel because fire spreads in the direction of the dominant wind. Here the mean wind speed varied from 0.67 to 4.5m/s and divided into 5 classes.

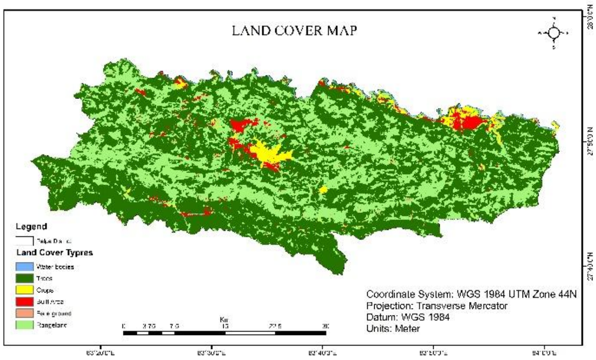


Fig. 4: LC Map

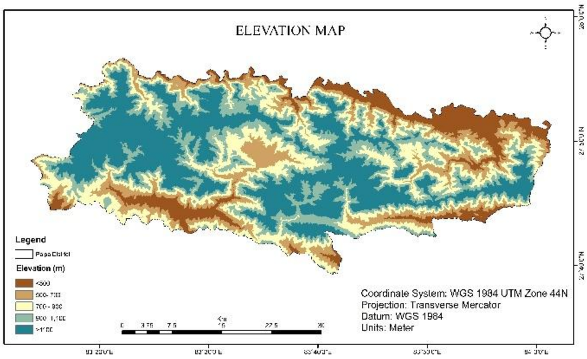


Fig. 5: Elevation Map

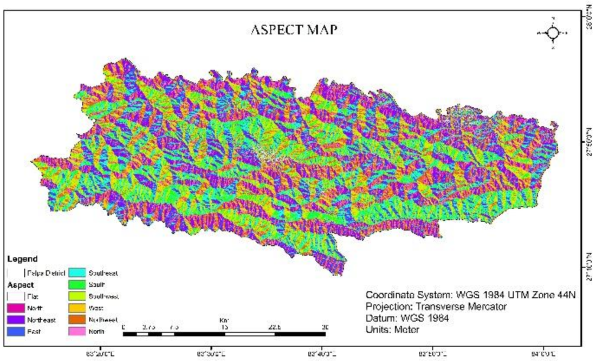


Fig. 6: Aspect Map

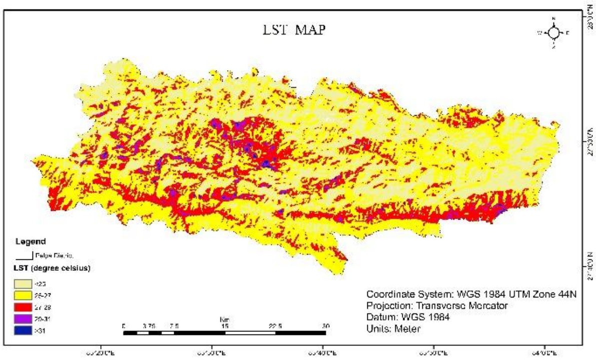


Fig. 7: LST Map

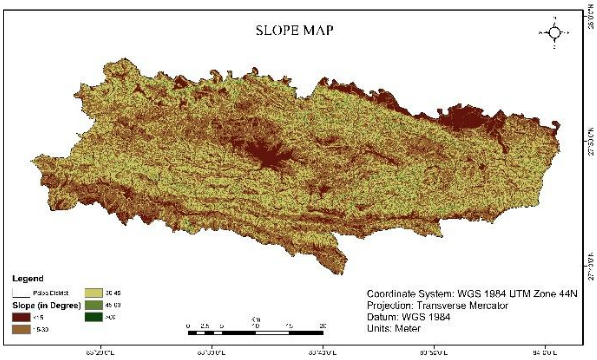


Fig. 8: Slope Map

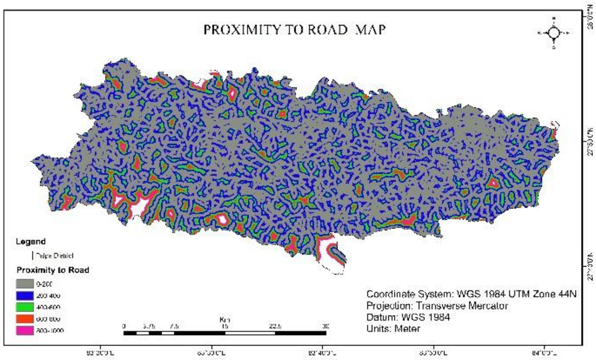


Fig. 9: Proximity to Road Map

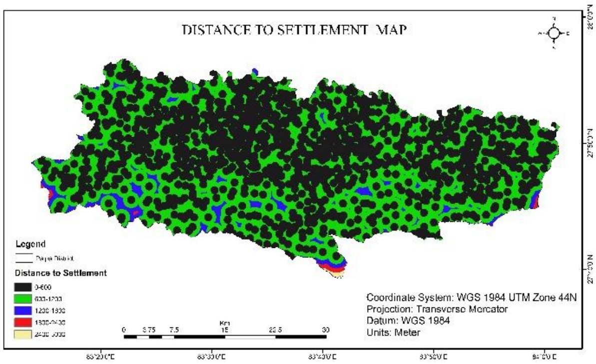


Fig. 10: Proximity to Settlement Map

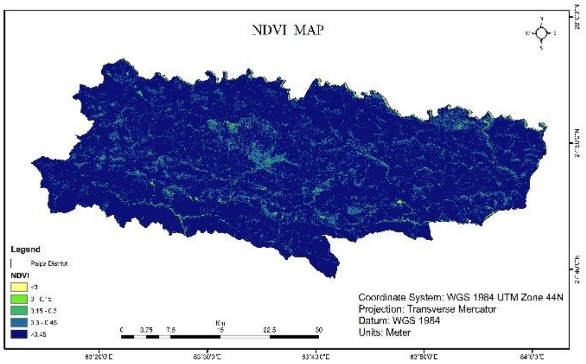


Fig. 11: NDVI Map

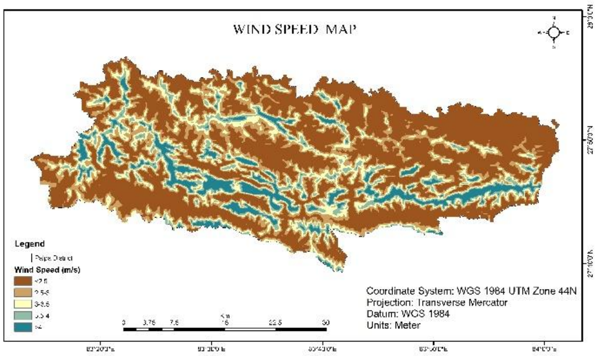


Fig. 12: Wind Speed Map

3.2 Forest Fire Susceptibility Map

217 forest fire points were used as a training dataset to show the spatial relationship between past fire incidents and selected factors. *Table 3* shows the frequency ratio of each class. These all-calculated frequency ratios of each respective factors were summed to prepare final fire risk map using Equation *3*. The map was then classified into 5 classes as Very high, High, Medium, Low, very low. (Fig. 13).

Table 3: Spatial relation of criteria and forest fire

Factors	Class	Total no. of pixel in each classified class	Total pixel in %(A)	Total number of forest fire pixel	% of forest fire(B)	Frequency Ratio (B/A)
Elevation	1	1329499	14.19	31	14.29	1.01
	2	2172117	23.19	43	19.82	0.85
	3	2497518	26.66	61	28.11	1.05
	4	2212797	23.62	53	24.42	1.03
	5	1155963	12.34	29	13.36	1.08
Slope	1	1671902	17.85	25	11.52	0.65
	2	4228963	45.14	90	41.47	0.92
	3	3105095	33.15	91	41.94	1.27
	4	343954	3.67	10	4.61	1.26
	5	17980	0.19	1	0.46	2.40
Aspect	1	104741	1.12	3	1.38	1.24
	2	700936	7.48	10	4.61	0.62
	3	1258669	13.44	25	11.52	0.86
	4	995184	10.62	21	9.68	0.91
	5	1115513	11.91	22	10.14	0.85
	6	1217040	12.99	43	19.82	1.53
	7	1214076	12.96	33	15.21	1.17
	8	930341	9.93	23	10.60	1.07
	9	1135941	12.13	23	10.60	0.87
	10	695453	7.42	14	6.45	0.87
Proximity to Roads	1	5593559	59.71	109	50.23	0.84
	2	2445528	26.11	74	34.10	1.31
	3	883221	9.43	21	9.68	1.03
	4	317457	3.39	9	4.15	1.22
	5	128129	1.37	4	1.84	1.35
Proximity to Settlements	1	5864166	60.84	128	58.99	0.97
	2	3168771	32.88	78	35.94	1.09
	3	296383	3.08	11	5.07	1.65
	4	299115	3.10	0	0.00	0.00
	5	9459	0.10	0	0.00	0.00
Wind speed	1	4843169	51.70	101	46.54	0.90
	2	1878878	20.06	43	19.82	0.99
	3	1292381	13.80	42	19.35	1.40
	4	759662	8.11	14	6.45	0.80
	5	593804	6.34	17	7.83	1.24

NDVI	1	4839837	51.66	0	0.00	0.00
	2	1879711	20.07	1	0.46	0.02
	3	1293215	13.80	4	1.84	0.13
	4	760495	8.12	19	8.76	1.08
	5	594636	6.35	193	88.94	14.01
LST	1	2757493	29.44	65	29.95	1.02
	2	4400101	46.97	107	49.31	1.05
	3	1952477	20.84	41	18.89	0.91
	4	225576	2.41	4	1.84	0.77
	5	32247	0.34	0	0.00	0.00
LC	1	91282	0.97	0	0.00	0.00
	2	5180598	55.30	158	72.81	1.32
	3	325286	3.47	1	0.46	0.13
	4	349660	3.73	2	0.92	0.25
	5	18707	0.20	0	0.00	0.00
	6	3402361	36.32	56	25.81	0.71

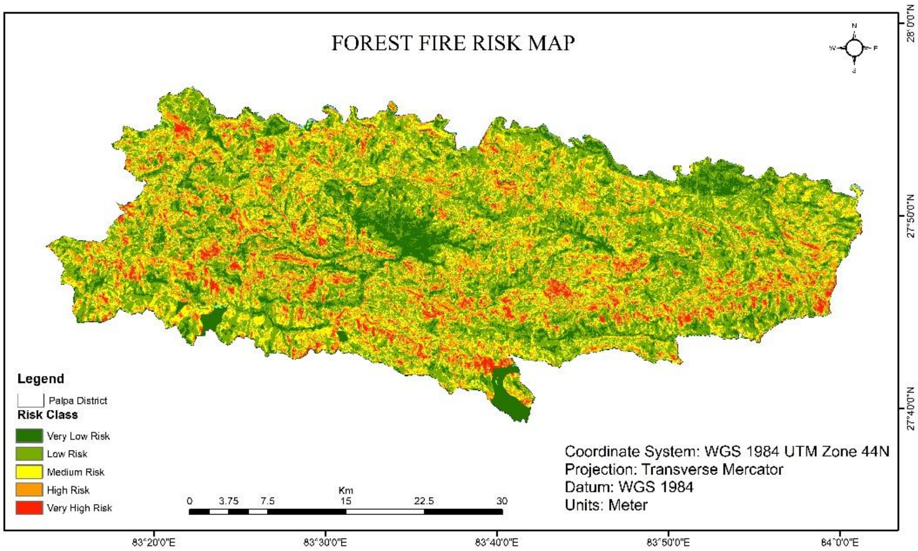


Fig. 13: Forest fire Susceptibility Map

3.3 Validation

As mentioned above, 35% of the total historical fire hotspots (i.e., 113 points) were used for validation. Table 4 shows that 30 points fall within very high susceptibility zones, 33 within high, 25 within moderate, 16 within low, and 9 within very low susceptibility zones when these points are overlaid on the forest fire susceptibility map. Fig. 14 illustrates the spatial distribution of these validation points across the susceptibility classes. The overlay of independent validation points on the susceptibility map provides a basis for assessing model performance by examining how well observed fire occurrences correspond to predicted susceptibility zones. A reliable model is expected to have a higher concentration of validation points within high and very high susceptibility classes, and fewer points in low and very low classes. In this study, most validation points (63 out of 113) are in high and very high susceptibility zones, demonstrating a strong agreement between predicted susceptibility and actual fire occurrences. This distribution indicates that the Frequency Ratio (FR) model has good predictive capability. Overall, the study effectively utilizes the relationship between historical fire occurrences and contributing topographic, meteorological, biological, and human-driven factors to generate a scientifically supported forest fire susceptibility assessment using the FR approach.

Table 4: Classification of fire risk zonation

Risk Index	FR	Past hotspots	
	Area (km^2)	Number	%
Very high	201.90	30	16.81
High	350.23	33	33.63
Moderate	386.21	25	27.43
Low	361.50	16	14.16
Very low	163.90	9	7.96

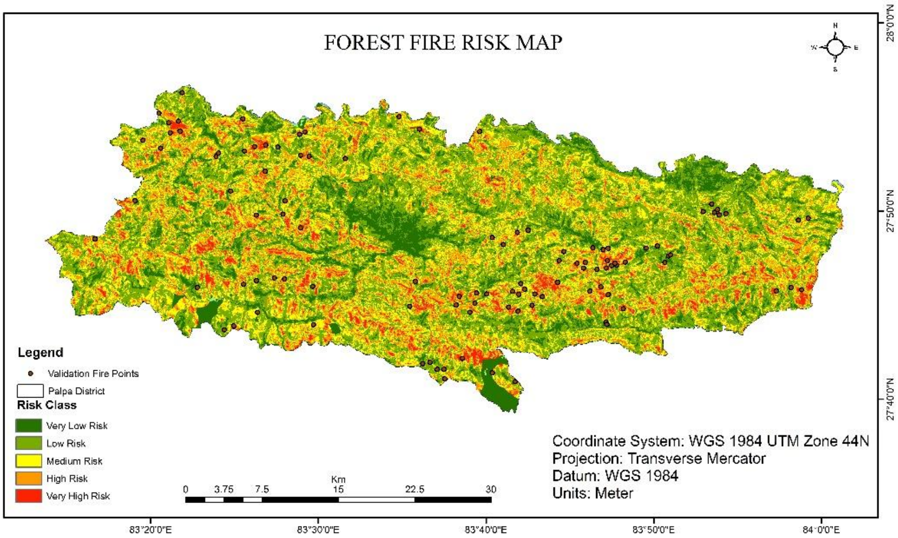


Fig. 14: Spatial Distribution of Forest Fire Points

4.Conclusion and Recommendation

The main elements impacting forest fire in Palpa District are successfully identified by the Fire Risk Susceptibility Map created using the Frequency Ratio (FR) approach. The susceptibility zone was classified into five zones: Very high, High, Medium, Low and Very low. The result demonstrates that fire occurrences are disproportionately clustered in higher-risk areas. Strong concordance between the FR model and historical fire occurrence is demonstrated by the fact that very high- and high-risk classes account for a significant fraction of historical fire hotspots, although covering a smaller portion of the overall area than moderate and low classes. While low and very low risk zones record relatively fewer occurrences, moderate risk areas also exhibit significant fire incidence.

Overall, the findings support the FR method's efficacy in identifying fire-prone regions and emphasize the necessity of giving fire prevention and control initiatives top priority in Palpa District's very high- and high-risk zones. Risk maps must be updated frequently to account for land use change, human activities, vegetation dynamics, and climate variability—all of which are crucial in the context of Nepal's many biological zones. Finally, incorporating susceptibility map into national fire management policies and district-level forest management plans will enhance decision-making, lessen socioeconomic and environmental losses, and promote sustainable forest management in Nepal.

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