Research Article:

ASSESSING FOREST FIRE SUSCEPTIBILITY IN BHOJPUR DISTRICT, NEPAL: A GIS-AHP INTEGRATED APPROACH

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ABSTRACT

Forest fires have been a major threat to forest ecosystems, as well as human populations, depending on forest. Bhojpur district, which has rich biodiversity and extensive forest cover, faces similar recurrent fires threats during dry season causing ecological and socio-economic losses. However, no detailed fire risk zonation map exists, limiting proactive management. Therefore, this study was required to identify and map areas of varying fire susceptibility to support risk mitigation. A Geographic Information Systems and the Analytic Hierarchy Process was employed to model potential fire risk map through the integration of eleven geospatial variables: Land Use Land Cover, Normalised Difference Vegetation Index, Land Surface Temperature, Slope, Aspect, Elevation, Precipitation, Wind Speed, Topographic Wetness Index, Distance to Roads, and Distance to Population. The consistency ratio was 0.08, and the Area Under the Curve was 0.826, indicating valid and acceptable structural model. 20.72% of the land was classified as high risk, 78.93% as moderate risk, and a tiny portion was classified as extreme or low risk. This map is considered an essential tool for authorities in assessing, analyzing, and formulating risk mitigation, as well as forest ecosystem resilience management strategies.

Keywords: Land use land cover, land surface temperature, pre-monsoon season

INTRODUCTION

The ecological, environmental, and socio-economic impacts of forest fires are manifold, indicating a major concern regarding these fires in forest ecosystems across the globe. Deforestation has been cited as one of the major effects of forest fires, but forest fires also change the physical properties of soils (Giri & Shrestha, 2000). Additionally, forest fires are sources of numerous gases such as carbon dioxide (CO_2), nitrous oxide (N_2O), carbon monoxide (CO), nitrogen oxides (NOx), ammonia (NH_3), sulfur dioxide (SO_2), and non-methane organic compounds (NMOCs), leading to air pollution and hence negatively affecting the lives of humans and animals (Urbanski, 2014). The impacts of forest fires include loss of biodiversity, disruption of the carbon cycle, global warming, and changes in vegetation ecosystems (Alkhatib, 2014; Harper et al., 2018). Hence, there is a dire need to recognize the forest fire phenomenon in order to ensure the health and well-being of flora and fauna as well as to ensure the conservation of our natural environment.

In Nepal, there is uneven occurrence of forest fires, mainly during the dry season, from November to June (Bhujel et al., 2017). Such occurrences happen due to an intricate combination of various environmental factors. Under weather conditions such as low humidity, high winds, conducive terrain, and wind directions, forest fires develop with incredible speed, provided there is fuel availability (Wen et al., 2018; Teodoro et al., 2013). Therefore, in the context of Nepal, there is an alarming rate of forest fires, as more than 200,000 hectares of forest land is destroyed by fires every year (Pandey et al., 2022; Ghimire et al., 2024). It is reported that nearly 89% of forest fires, which take place during the dry season, have human involvement (Matin et al., 2017), which happens mainly during March, April, and May. On an average, the Koshi Province, which comprises districts such as Bhojpur, records 220 cases of forest fires, destroying 8,672 hectares of forest land (Bhujel et al., 2022). According to the National Disaster Risk Reduction and Management Authority, from 2013 to 2023, 769 persons have lost their lives, while 2,568 persons were injured in 18,791 forest fires, resulting in financial losses worth more than Rs. 22 billion (Prasad & Khanal, 2023). Koshi Province, with districts such as Bhojpur, experiences 220 forest fires on a yearly basis, covering a total area of 8,672 hectares (Bhujel et al., 2022).

The spatial identification of the distribution of forest fire susceptibility has become a major component in modern approaches to disaster management. A reliable prediction of potential forest fire hazard areas can be accomplished with the aid of field activities, remote sensing (RS), geographic information systems (GIS), as well as statistical analysis. Timely, accurate spatial, as well as temporal data can be acquired with the usage of geospatial technology, thus offering adequate information for complex fire modeling (Ganteaume et al., 2013; Modugno et al., 2016; Vallejo-Villalta et al., 2019). The integration of multi-criteria decision-making (MCDM) methods into spatial analysis provides an innovative way of analyzing fire risk zones (Rasooli et al., 2018; Novo et al., 2020). The most frequently used MCDM methods in identifying potential fire risk zones is known as the analytic hierarchy process (AHP), which has been successfully used with GIS in identifying high-risk areas across the globe (Rahmati et al., 2015; Pourghasemi et al., 2016; Van Hoang et al., 2020; Nuthammachot et al., 2021).

AHP is a mathematical approach to solving complex problems related to decision-making. This approach, which considers the results of combining pairs of complex decisions, helps decision-makers establish the order of preference for their individual goals to make a superior decision (Saaty, 1980; El Jazouli et al., 2019). Researchers used this method to assess the geographical vulnerability of a region to different aspects of natural calamities, such as forest fires, with convincing results (Kayet et al., 2020; Busico et al., 2019; Akbulak et al., 2018; Bhusal et al., 2024). When it comes to predicting forest fire zones, the weights of the individual elements of the thematic maps, i.e., assessing their individual weights, have to be of major concern, which results in applying AHP, given its sensitivity to results (Vadrevu et al., 2010; Sharma et al., 2014).

The current research aims to study the fire incidents in the Bhojpur district of Nepal. The geographical region covered by the Bhojpur district is 1507 square km, and the district is located at an altitude varying from 110 to 4200 meters above mean sea level. In addition, it covers 73037 hectares of forest areas and possesses rich biodiversity, including *Pinus roxburghii, Pinus wallichiana, Taxus baccata, Larix himalaica*, and other wild herbs. Like all districts in Koshi Province, fire incidents also take place in the Bhojpur district every year (Bhujel et al., 2022). For efficient fire prevention and suppression, appropriate fire logistics and infrastructure, adequate investment in finance, and exact knowledge about fire zones are needed (Sharma et al., 2015). Western countries have already adopted the strategy of fire danger maps to ensure better preparedness against fire incidents. Similarly, Nepal can also benefit from the development and popularization of maps of wildfire risk zones to ensure better preparedness (Sharma, 2006; Sharma et al., 2015; McCaffrey, 2015).

This study seeks to assess forest fire risk in the Bhojpur District using Geographic Information Systems (GIS) and the Analytical Hierarchy Process (AHP) modelling technique, and to devise fire risk zone maps. The spatial and temporal distribution of forest fires was analysed, relevant geospatial databases were created, and forest fire risk zones were mapped using GIS and AHP, which was cross validated against MODIS historical data and the ROC AUC curve. By using a combination of Land Use Land Cover (LULC), Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), slope, aspect, elevation, precipitation, wind speed, Topographic Wetness Index (TWI), and distances from roads and settlements, this study provides local actors (including local government, forest managers, and local communities) with a much-needed tool to assist in the prioritization of fire management activities and to reduce fire related threats and improve the resilience of the forests of Bhojpur District.

RESEARCH METHODS

Study area

The study was conducted in Bhojpur District of Nepal (Fig. 1). The district encompasses 1,507 square kilometres. It is situated between approximately 110 and 4200 meters above sea level, within the geographical coordinates of 26°53' to 27°46' north latitude and 86°53' to 87°17' east longitude. Forests also cover a major portion of the land by approximately 73,037 hectares. According to the results of the 2021 A.D. census, it was stated that the district has covered a total of 157,923 people with varying ethnic backgrounds: Rai (34.1%), Kshetri (17.7%), Tamang (10.8%), and many more. Such geographical complexity has created a diversified patchwork of vegetation. Major species found in the area include *Pinus roxburghii, Pinus wallichiana, Taxus baccata, Larix himalaica, Elaeocarpus ganitrus*, and *Rhododendron arboretum*, alongside various medicinal plants such as *Bergenia ligulate* and *Asparagus racemosus* (Tiwari, 2024).

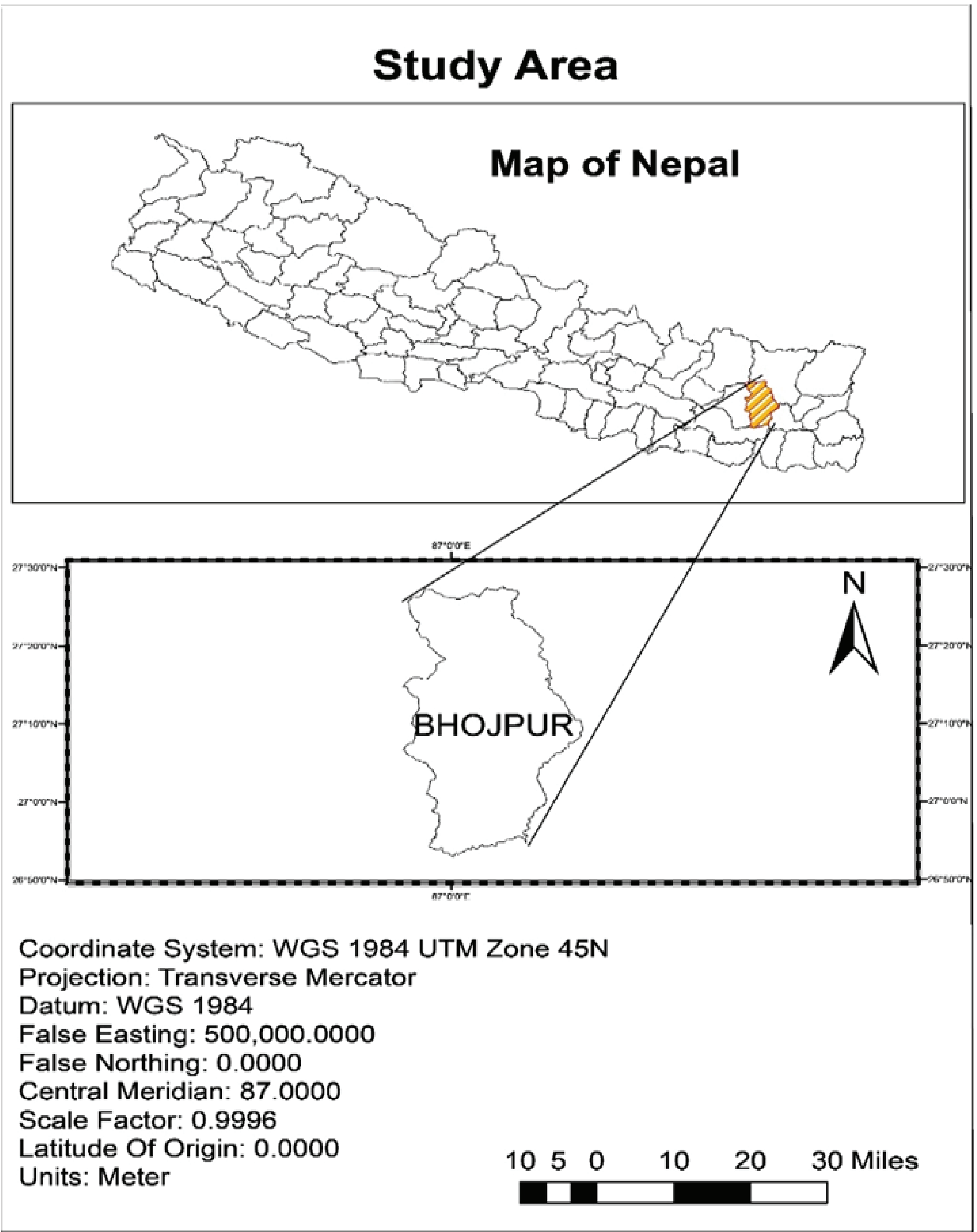

Fig. 1. Map of the study area

Methods of data collection

Data Collection for the study involved collecting various types of spatial data from 11 sources (described in detail in Table 1) to create thematic layers required for the forest fire risk model. The spatial datasets include: ICIMOD (Land Cover); USGS Earth Explorer (SRTM DEM for Slope, Aspect, Elevation, and TWI); USGS (Landsat 8 OLI-TIRS for NDVI); UN OCHA (roads and settlements data); CHIRPS (precipitation); MODIS (LST); Global Wind Atlas (wind speed); NASA FIRMS (fire hotspot data). To determine the relative percentage weight of each factor contributing to forest fires, the literature was analysed, and expert opinion was sought. The percent weightage assigned to each factor contributing to forest fires is as follows: LST (16%), Elevation (14%), LULC (13%), Distance to Settlement (13%), Slope (10%), Precipitation (9%), Aspect (7%), Distance to Road (7%), NDVI (5%), TWI (3%), and Wind Speed (3%). As the government of Nepal does not have data on the location and number of forest fires, data were obtained from the NASA FIRMS database, which is related to ICIMOD, for the years 2003 to 2024, using MODIS hotspot data at a 30% confidence level.

The distinctive dataset, their sources, and their resolution are indicated in Table 1. The 2010 land cover data was obtained from ICIMOD for developing LULC classes. SRTM 1 Arc-Second Global data from the USGS Earth Explorer was utilized to generate slope, aspect, and elevation maps, as well as to calculate the Topographic Wetness Index (TWI). The road network and settlement clusters were gathered from the UN OCHA. Land Surface Temperature (LST) maps were created using MODIS MOD11C3 V6.1 data. Precipitation data were sourced from the CHIRPS Pentad dataset, and wind speed data were obtained from the Global Wind Atlas. Furthermore, various literature related to the study's subject were investigated to enhance understanding and inform the assignment of relative weightings to the forest fire-impacting elements via pairwise comparison (Tiwari, 2024).

Table 1. Remote sensing and GIS datasets

Factors	Sources	Data Format	Resolution	Data Period
Land Cover	ICIMOD - International Centre for Integrated Mountain Development	Raster	30 m	2010
NDVI	Landsat 8 OLI-TIRS (https://earthexplorer.usgs.gov/)	Raster	30 m	2023
Slope Elevation Aspect TWI	SRTM DEM (https://earthexplorer.usgs.gov/)	Raster	30 m	2014
Distance from Settlement Distance from Road	UN OCHA (OCHA (unocha.org))	Vector	1:25000	2015
Precipitation	CHIRPS Pentad: Climate Hazards Group InfraRed Precipitation with Station Data	Raster	4.8 km	2000-2024
LST	MODIS MOD11C3 V6.1(LP DAAC - Data (usgs.gov))	Raster	5.6 km	2000-2024
Wind Speed	Global Wind Atlas (Global Wind Atlas)	Raster	250 m	2020
MODIS hotspot	Fire Information for Resource Management System (NASA | LANCE | FIRMS)	Vector	1 Km	2003-2024

While it is true that the LULC datasets used in this research date to 2010, which is before some of the fire incidents occurred in 2003-2024, it is the most recent high-resolution (30 m) LULC map available from ICIMOD for this region. In addition, based on the field investigation and expert opinion, no major land transformation has occurred in the study area since 2010. No significant change has been observed in the prevalence of forest types or the extent of cropland. Hence, the use of the LULC dataset of 2010 may be regarded as valid for the purposes of this research.

Data analysis

Software and tools

The data analysis was performed using a suite of software tools. ArcGIS 10.8 was the primary platform for geospatial analysis, including the generation of thematic layers (LULC, NDVI, elevation, aspect, slope, distance from road, distance from settlement, Wind Speed, TWI, Precipitation), reclassification, and overlay analysis. Particularly, Google Earth Engine was utilized to analyze satellite images to produce maps of LST. For LST, MODIS MOD11C3 V6.1 satellite images (5.6 km resolution) were analyzed using Google Earth Engine to produce LST maps. NDVI was derived from Landsat 8 OLI-TIRS imagery (30 m resolution). For statistical analysis and representation of data using tables and charts, MS Excel 2019 was used.

Generation of thematic layers

The criteria established to judge the risk of a forest fire were then applied to develop various thematic layers. Here, the land cover map downloaded from ICIMOD was classified into different land use land cover (LULC) scenarios using ArcGIS spatial analyst. It is important to note that the Normalised Difference Vegetation Index (NDVI) was derived from the Landsat 8 OLI-TIRS satellite images. On the same note, layers such as slope, aspect, and elevation, as well as the topographic wetness index (TWI), were derived from the SRTM DEM map and processed using ArcGIS spatial analyst. TWI was computed using the formula: $TWI = \ln(\alpha/\tan\beta)$; in this case, α represents the local catchment area, and β represents the local slope (Yong et al., 2012). Additionally, the Euclidean distance tool was employed to develop layers such as distance from settlement and distance from road using ArcGIS.

Assigning weightage to the AHP model

The relative weights of each factor were determined using the Analytic Hierarchy Process (AHP) method, which is a mathematical method used to solve problems involving complex decisions. AHP is known to support decisions with a coherent structure of tasks. A structured way of making decisions is provided by AHP, especially with simple tasks (Saaty, 1980). Additionally, to determine the weights of two factors, the 1-9 scale was employed. Finally, the ranking of these factors was based on the relevance of the parameters based on research, opinions from seven experts (two from Division Forest Office, two from academia, and one each from local government, the Nepal Police, and the Armed Police Force), and self-determined decisions (Pradeep et al., 2022; Nikhil et al., 2021; Lamat et al., 2021).

Important steps in determining weightage to the AHP model involved defining the pairwise comparison matrix, determining the eigenvector and weighting value, and determining the consistency ratio (Saaty, 1980). First and foremost, the eigenvector (V_p) was determined. Then the weighting value (C_p), which was obtained from the computed eigenvector, ensured that the summation of every weighting value was equal to 1. The consistency index (CI) was computed as follows: $CI = (\lambda_{max} - n)/(n - 1)$. Then the consistency ratio was computed as follows: (CR = CI/RI, where RI is the random inconsistency). According to Saaty (1980), when the consistency ratio computed is less than 0.1, the computed result is acceptable. Furthermore, in this research study, consistency ratio of 0.08 was computed as the result for the valid pairwise comparison matrix (Tiwari, 2024).

Preparation of forest fire risk map

After calculating the final weights for each factor through the AHP method, the Forest Fire Risk Index (FFRI) was computed using the following equation (Tiwari, 2024):

$$FFRI = 0.13 * LULC + 0.05 * NDVI + 0.10 * S + 0.07 * A + 0.14 * E + 0.03 * TWI + 0.13 * DS + 0.07 * DR + 0.16 * LST + 0.09 * P + 0.03 * WS \quad (1)$$

Where: LULC = Land Use Land Cover, NDVI = Normalised Difference Vegetation Index, S = Slope, A = Aspect, E = Elevation, TWI = Topographic Wetness Index, DS = Distance from Settlement, DR = Distance from Road, LST = Land Surface Temperature, P = Precipitation, and WS = Wind Speed.
Using the Weighted Overlay tool in ArcGIS, this weighted equation was applied to produce the final forest fire risk zonation map.

Accuracy assessment

One of the important measures towards ensuring modelling research is effective is checking the accuracy of the outputs from a prediction. The assessment of accuracy was based on the hotspot data from MODIS satellites between 2000 and 2024, using a confidence level of 30% or higher. As the weightings of the AHP model were based entirely on expert knowledge and the literature (rather than obtained via statistical fitting to the fire data), the same MODIS dataset may be employed for testing without introducing circular fitting. Nevertheless, since the fire pattern description (for instance, the percentage of fires occurring within each land-use/land-cover category) was derived from the same MODIS dataset, there is some lack of independence. Thus, the results of testing should be considered a means of evaluating model consistency, not its actual predictive ability on completely independent data. The inherent assumption was that a high number of historical incidents of forest fires should fall within the high-risk class, followed by the medium and low classes on the generated map.

Validation of the result

The forest fire risk map was validated using the Receiver Operating Characteristic (ROC) curve and the Area Under Curve (AUC) value. The same MODIS hotspot dataset (2003-2024) was also used for model validation, although it should be noted that the AHP model was not calibrated on these data. In other words, the AUC value is a measure of how well the expert-based map correlates with actual fire occurrences. ROC analysis examines the relationship between a binary classifier's sensitivity (true positive rate) and specificity (actual negative rate) (Flach, 2016). The AUC is a scalar measure of a binary classifier's overall performance (Hanley & McNeil, 1982). An AUC of 0.5 indicates random chance, while an AUC of 1.0 represents perfect accuracy (Zou et al., 2007). According to Lüdemann et al. (2006), an AUC value above 0.9 is considered excellent, above 0.8 is good, above 0.7 is acceptable, above 0.6 is poor, and below 0.5 is a failure. The MODIS hotspot data with a confidence level >= 30% were used as actual positive values for this validation.

RESULTS

Analytic hierarchy process (AHP) model and parameter weighting

The development of a robust FFRI model using the Analytic Hierarchy Process was the first critical step in the present study. Based on the opinions of experts and a literature review (Van Hoang et al., 2020), a pairwise comparison matrix for the selected eleven geospatial factors was prepared. From Table 2, it can be seen that LST comes out as the most influential factor with a weight of 0.16, followed by Elevation (0.14). LULC and Distance from Settlement were given equal weights at 0.13. Slope (0.10) and Precipitation (0.09) were other major contributors. Moderate influence factors included Aspect and Distance from Road (both 0.07), while NDVI (0.05), TWI (0.03), and Wind Speed (0.03) were assigned the lowest weights.

Table 2. Normalised pairwise comparison matrix and computed factor weights for the AHP model

Factors	LULC	NDVI	Sl	As	El	TWI	DS	DR	Ppt	LST	WS
LULC	1	2	2	3	1/3	4	2	2	2	1/3	4
NDVI	1/2	1	1/2	1/3	1/3	3	1/2	1/2	1/2	1/2	2
Sl	1/2	2	1	3	2	2	1/2	2	1/2	1/2	3
As	1/3	3	1/3	1	1/2	5	1/2	1/2	1/2	1/2	3
El	3	3	0.5	2	1	4	1/3	2	2	2	3
TWI	1/4	1/3	0.5	1/5	1/4	1	1/3	1/3	1/3	1/4	1/2
DS	1/2	2	2	2	3	3	1	2	3	1/2	2
DR	1/2	2	1/2	2	1/2	3	1/2	1	1/2	1/3	2
Ppt	1/2	2	2	2	1/2	3	1/3	2	1	1/3	3
LST	3	2	2	2	1/2	4	2	3	3	1	4
WS	1/4	1/2	1/3	1/3	1/3	2	1/2	1/2	1/3	1/4	1

The consistency of pairwise comparison was verified by using the Consistency Ratio (CR), which was found to be 0.08. According to Saaty (1980), for AHP to be considered acceptable, the value of CR should be below 0.1. Thus, it is concluded that the created model of AHP has validity. The final FFRI model was derived as follows:

$$FFRI = 0.13 * LULC + 0.05 * NDVI + 0.10 * S + 0.07 * A + 0.14 * E + 0.03 * TWI + 0.13 * DS + 0.07 * DR + 0.16 * LST + 0.09 * P + 0.03 * WS \quad (2)$$

(Where: LULC=Land Use Land Cover, NDVI=Normalized Difference Vegetation Index, S=Slope, A=Aspect, E=Elevation, TWI=Topographic Wetness Index, DS=Distance from Settlement, DR=Distance from Road, LST=Land Surface Temperature, P=Precipitation, WS=Wind Speed)

Each of these factors was classified and ratings from 1 (Very Low) to 5 (Very High) are allocated depending on the capacity they possess to affect fire risk using peer-reviewed research and field verification (Subedi et al., 2022; Nikhil et al., 2021; Vadrevu et al., 2006). For example, within the LULC class, Forest and Cropland are classified as "Very High" risk (5), while Water Body and Bare Rock classes are classified as "Very Low" risk (1). Furthermore, within the Slope class, the 30-45 degrees class is allocated the highest risk within the factor, and within the Aspect class hazard, south-facing classes are considered the hazard.

Historical fire regime and climatic context

The MODIS fire hotspot data analysis from 2003-2024 showed variability in terms of temporal aspects of forest fire occurrences in Bhojpur District (Fig. 2). The highest number of forest fires, as depicted by MODIS analysis, accounted for 53, which occurred in 2021. This was followed by 2014 and 2023, with 42 fire occurrences. On the contrary, there were few fire occurrences in 2017 and 2020. It was clear that there was a specific seasonality, with most of the forest fires occurring during the pre-monsoon season. The highest fire occurrences were in March, with 183 fire incidents. It followed a slight decline in April, with 158 fire incidents. Of interest to note is that there were no fire incidents during July, August, and September, which is during the monsoon season.

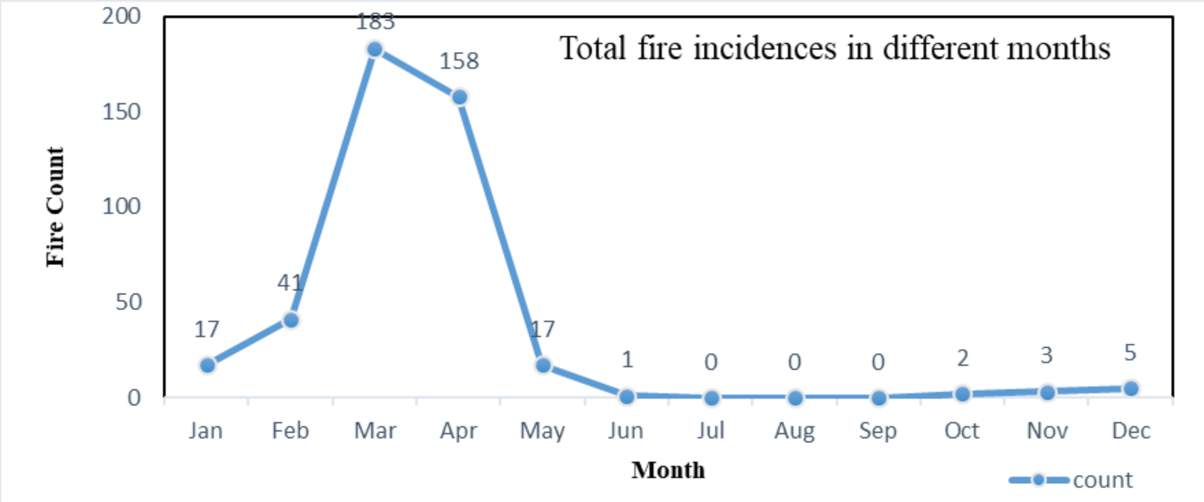

Fig. 2. Total number of fire incidents in different months (MODIS fire hotspot, 2003-2024).

Climatic factors were also considered in these patterns of fire. An assessment of rainfall patterns revealed that the highest rainfall amount of 1484.58 mm occurred in 2007, while the lowest rainfall of 1083.07 occurred in 2023. At the same time, analysis of Land Surface Temperature (LST) patterns revealed that the highest average monthly LST of 19.5°C occurred in 2024. In addition, the patterns of fire distribution are quite uneven and varied over local bodies of the district. For instance, Hatuwagadi Rural Municipality had the highest number of fires, 100, whereas Pauwadungma and Ramprasad Rai had comparatively lower numbers, such as 85 and 63, respectively.

Relationship between predictive variables and fire incidents

To understand what drives fire events, historical MODIS fire data was superimposed onto each of the classified thematic layers. Strong relations were found between fire events and specific classes of each driver, as identified by the predictive variables.

Land Use Land Cover (LULC) was identified as a major contributor. The findings showed that 48.71% of the entire fire incidents were in the Cropland category, followed by Forests with 36.07% (Fig. 3). This concurs with the theoretical argument that both land cover types have sufficient fuel load for fire occurrences, especially with crop residue burning.

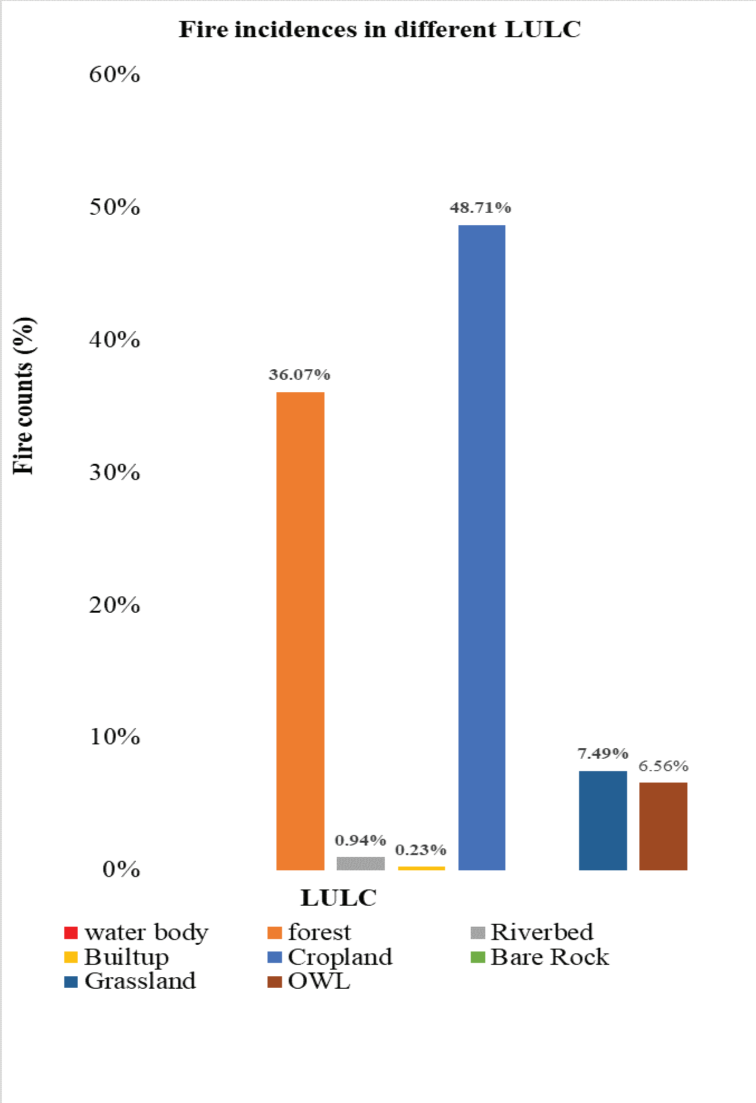

Fig. 3. LULC versus fire incidents (percentage of total fires per LULC class).

The Land Surface Temperature (LST) showed significant association with fires. The highest frequency of fire incidence was 53.62% within the Land Surface Temperature range of 20-25°C, followed by 21.54% occurring within the 25-33°C temperature range. Only 1.4% of total fires occurred within areas with temperature lower than 10°C, further emphasizing that fire occurrence depends on higher Land Surface Temperatures and dry conditions.

Similarly, topographical factors played an important role in controlling the fires. Elevation maintained strong control over the occurrence of fires, with 68.61% of the fires being reported in the range of 117-1000 m. Fire occurrences were minimal in the range of elevations between 2000 and 3000 m, i.e., only 3.04%. This was probably due to increased altitude, cool air, high moisture, and increased fuel availability. Additionally, the slope component also confirmed the fire confinement principle, as 54.33% of the fires occurred in the range of 30-45 degrees. Fire occurrences were particularly high in the south-facing slope, accounting for 23.42% of the fire occurrences, whereas the south-east-facing slope reported only 19.20% of the fire occurrences. This was probably due to increased solar gain on the slope, hence increased dryness.

Similarly, human cause showed a strong relation with the fire ignition points. The road distance analysis showed perhaps the strongest relation where 67.21% of the fires were within 500 meters from the road. Another strong relation that was seen was where 44.26% of the fires were within 1500 meters and 3000 meters from the settlement. This shows that human proximity has to be taken into account when determining the cause of forest fires in Bhojpur.

Forest fire risk zonation map

The integration of all the weighted factors using the Weighted Overlay tool of the ArcGIS resulted in the final Forest Fire Risk Zonation map for the Bhojpur District. The final map produced is categorically classified under four different risk rates, as shown in Fig. 4 below: Very High, High, Moderate, and Low.

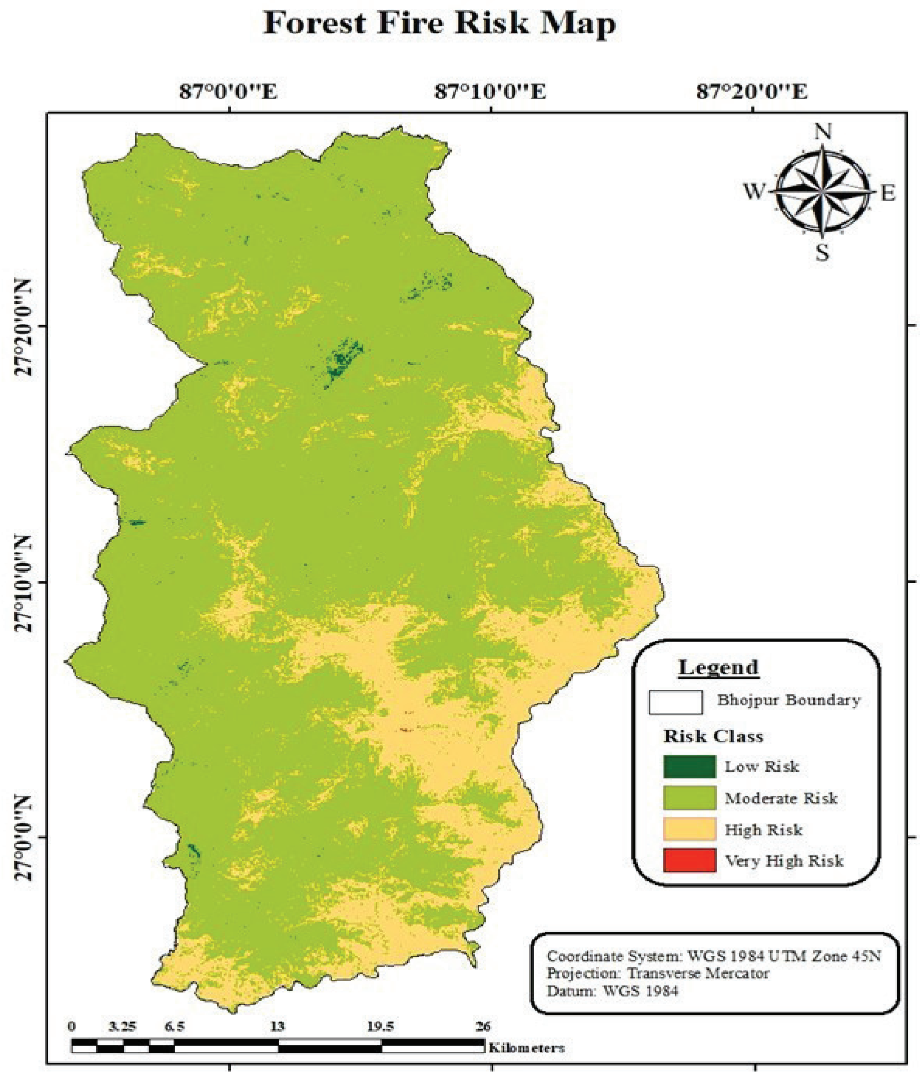

Fig. 4. Forest fire risk zonation map of Bhojpur district, Nepal

The aerial distribution of these risk classes is presented in Table 3. It can be observed that most of the district falls under the Moderate risk category, which covers 1190.373 sq. km (78.93% of the total area). A significant area under study falls under the High-risk zone, covering 312.5475 sq. km (20.72%). The Low and Very High-risk zones are pretty negligible, being 5.0445 sq. km (0.33%) and 0.1431 sq. km (0.009%), respectively. The previous distribution allows seeing that extreme risk could be localized, and on the other hand, a big portion of the district may reach fire under the propitious conditions, being over 99% classified between Moderate or Higher classes.

Table 3. Area covered by different forest fire risk classes.

Risk Class	Risk Area (sq.km)	Risk Area %	Fire counts
Very High risk	0.1431	0.009489	5
High risk	312.5475	20.72447	268
Moderate risk	1190.373	78.93155	153
Low risk	5.0445	0.334492	1

Accuracy assessment and model validation

The practical utility of the risk zonation map was evaluated using the historical overlay of the MODIS fire hotspots. It was found that there was a strong relation between the predicted risk zones and the actual fires. Of the total 427 historical fire incidents used for validation, 268 (62.76%) were found within the high-risk zone, while 153 (35.83%) incidents were found within the moderate-risk zone. Only one incident fell within the low-risk zone, while five incidents fell within the Very high-risk zone. In summary, 98.59% of the total historical incidents were found within the moderate or high-risk zones (Fig. 5).

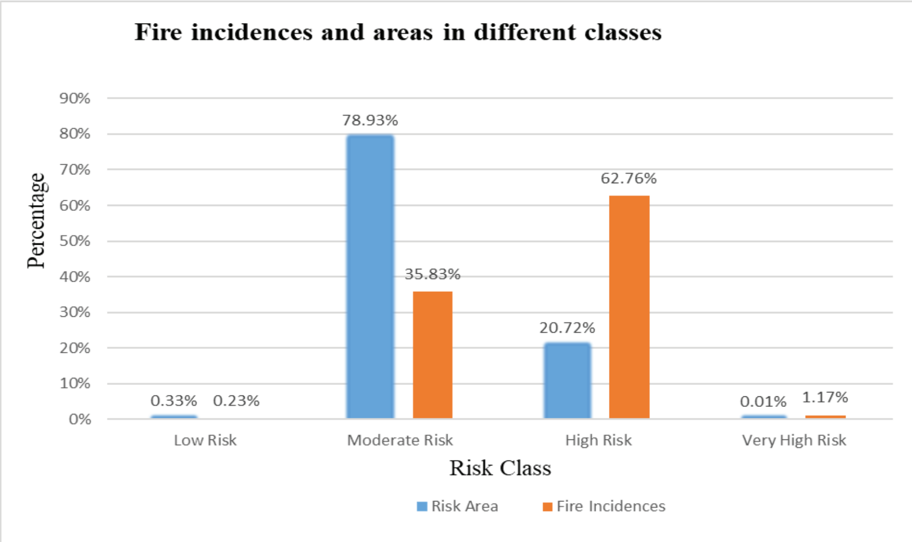

Fig. 5. Total fire incidents and total area by risk class.

To statistically validate the results for the purpose of arriving at concrete conclusions, the Receiver Operating Characteristic (ROC) curve has been used. During the process of using the ROC curve for validating the results obtained from the various models, the Area Under Curve (AUC) value is calculated as 0.826. It can thus be concluded, as per the classification done by Lüdemann et al. (2006), that results above 0.8 are categorized as "good".

DISCUSSION

AHP results ranked the factors as follows: Land Surface Temperature (LST, 16%), Elevation (14%), LULC (13%), and Distance to Settlement (13%). Such a ranking is corroborated by studies on fire hazards conducted in South Asia. For example, Adab et al. (2013) found LST and elevation to be the dominant factors in northeastern Iran, whereas Nuthammachot & Stratoulias (2021) came to the same conclusion when examining fire risks in Thailand. The presence of these two factors among the most significant ones stems from the fact that higher temperatures reduce fuel moisture content, thereby increasing their flammability. Elevation affects the fire hazard in the area by influencing temperature, humidity, and the types of vegetation present. At elevations below 1000 m in Bhojpur, temperatures are warmer, and precipitation is lower. This observation is explained by Rothermel (1983), who noted that fire occurrences decline with increasing elevation due to colder, wetter conditions.

In the MODIS hotspot analysis, the maximum number of fires was observed in March (183 fires) and April (158 fires) whereas, no fire incidents were recorded in the monsoon season (July–September). This is an inherent pattern in fire occurrence in the Nepalese pre-monsoon dry season characterized by the availability of combustible material, i.e., leaf litter from deciduous forest and agricultural stubble along with lower humidity and higher temperature. According to Bhujel et al. (2017) and Ghimire et al. (2024), such fire incidences occurred in March-May in Nepal with March–May fires being over 80% of the annual fires. The annual variation (maxima of fires in 2021, i.e., 53 fires; followed by 2014 and 2023) is due to climatic variations such as dry spells or La Niña effect.

Individual factor analysis of historical fires produced results with a logical fit to fire science frameworks. The predominance on south- and southeast-facing slopes, for example, is a classic case because solar insolation driven by fire results in increased warmth, reduced humidity, and drier fuels compared to north-facing slopes (Setiawan et al., 2004; Bhusal & Mandal, 2020). Regarding mid-slopes between 30° and 45° being dominant for fire incidences, it fits the theory of fire spread uphill (Rothermel, 1983). Fire incidence decreases on very steep slopes-i.e., > 60°-due to the nonexistence of continuous fuel loads on steep coarse terrains, a point noted by Sibanda et al. (2011). The very few fire incidents in areas with high Topographic Wetness Index (TWI) and high NDVI are expected, as both indicate higher soil and vegetation moisture content, thereby creating a barrier to fire ignition and spread (Adab et al., 2013; Al-Fugara et al., 2021).

The fire season in Nepal occurs during the dry pre-monsoon season, particularly in March and April. There is a marked absence of fire during the monsoon months of July to September (Bhujel et al., 2017; Parajuli et al., 2015). This is the time of year when dry leaf litter accumulated from deciduous forests and agricultural land is available and receptive to burning, providing fuel and coupling with the dry atmosphere and high heat. There is interannual variability, as noted from the 2014 and 2021fire outbreaks and dry spells, which could be explained by the climatic conditions (Bhujel et al., 2022).

The final rank map combines and visualises these diverse threats. A significant outcome is the area-wide classification, where more than 99% of the district was classified as moderate or higher risk. Additionally, the identification of the ‘Very High’ risk area, despite its size (0.009%), will be helpful for more efficient and 'justifiable' allocation of organisational attention. On the other hand, the large ‘High’ risk area (20.72%) and 62.76% of all historical burns are the main area that needs more attention when management actions are being decided. The map is validated because it uses independent MODIS data and is indeed useful, as 98.59% of the historical burns occurred in the High and Moderate risk zones. Hence the model is very accurate. This is as good as other works in the vicinity (Matin et al. 2017); 80% of burns in Nepal occurred in high- to very-high-risk zones. The AHP-GIS of fire warning systems in Vietnam was successfully used by Van Hoang et al. (2020).

With reference to Lüdemann et al. (2006), the ROC-AUC of 0.826 indicates strong statistical robustness and is consistent with the results of other fire risk studies using AHP, including Pradeep et al. (2022) and Nikhil et al. (2021). The results indicate that the variables and their corresponding weights successfully represent the spatial characteristics of fire risk in Bhojpur.

There are several limitations in this study. The first one is the temporal inconsistency between the LULC dataset (2010) and the entire set of fire incident records (2003–2024). Although the claim that there have been very few changes in land cover types in Bhojpur District since 2003 is plausible, using a static LULC map may introduce systematic bias, especially for the most recent fire years. It is recommended that further work use the newly developed LULC maps to achieve higher accuracy. Another limitation is the rather low resolution (1 km) of the MODIS hotspot data. This may be a source of inaccuracy as fire events may be poorly represented in heterogeneous landscapes. VIIRS hotspot data (375 m resolution) is suggested as an alternative.

CONCLUSION

The occurrence of forest fires in Bhojpur district is not accidental and follows a pattern based on certain topographic, climatic, and anthropogenic factors. This research proves that a map developed through expert opinion analysis can efficiently segregate areas susceptible to forest fires from low-risk regions, despite the lack of reliable field information. This zonation of forest fire risk will help the concerned stakeholders in planning and executing appropriate measures for effective disaster mitigation. Based on the information about probable fire-prone sites, the administration may strategically position their firefighting equipment, prepare fire breaks, conduct controlled burns before the onset of dry season, and educate the populace residing in high-risk locations, especially along roadside regions. Such a proactive strategy will minimize ecological as well as financial impacts in the mid-hill districts of Nepal.

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AUTHOR CONTRIBUTIONS

ST: Conceptualization, Methodology, Data Curation, Formal Analysis, Visualization, Writing – original draft, Writing – review & editing; **PC:** Formal Analysis, Visualization, Writing – review & editing; **PA:** Visualization, Writing – review & editing; **JG:** Supervision, Validation, Writing – review & editing.

CONFLICT OF INTEREST

The authors have no conflicts of interest regarding the published material. All authors reviewed the document prior to submission to the Journal of Agriculture and Forestry University.

ETHICAL APPROVAL AND PERMITS

No human or animal experiments were involved during the study, and prior approvals were obtained where applicable. Expert opinions used in the AHP weighting process were obtained solely for academic and technical evaluation purposes.

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