Areas of the Terai Arc landscape in Nepal at risk of forest fire identified by fuzzy analytic hierarchy process

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Ashok Parajuli[1,2], Syed Amir Manzoor[3], Martin Lukac[1,4]*

[1]School of Agriculture, Policy and Development, University of Reading, Reading RG6 6EU, UK

[2]Ministry of Forests and Environment, Bagmati Province, Nepal

[3]Department of Forestry & Range Management, Faculty of Agricultural Sciences & Technology, Bahauddin Zakariya University Multan, Pakistan.

[4]Department of Forest Management, Faculty of Forestry and Wood Sciences, Czech University of Life Sciences, 16521 Prague, Czech Republic

**Corresponding author: Ashok Parajuli: saracaindica07@gmail.com*

Abstract

Forest fire frequency has increased in South Asia in recent decades, with a growing impact on forest ecosystems. Nepal's Terai Arc Landscape (TAL) is one of the most ecologically important landscapes in Asia, hosting a great diversity of endangered flora and fauna. To better predict the threat of fire to forest ecosystems in the TAL, we identified fire-prone areas using fuzzy AHP methods. We produced a fire risk map by applying the weighted linear combination method using topographic (slope, aspect, and elevation), climatic (temperature, precipitation, and wind speed), biophysical (normalised difference vegetation index and landcover classes), and anthropogenic variables (distance to road and proximity to settlements). We then validated the map with records of past fires by applying a confusion matrix. The accuracy of our technique of fire location prediction was above 95%, with a kappa coefficient of 0.93. Locations of medium to very high forest fire risk were found in around 51% of the study area, usually in the vicinity of areas affected by anthropogenic factors. This landscape-level study shows the potential of multicriteria prediction models to inform the preparation of national and regional forest fire management strategies and plans.

Key Words: Forest fire, risk identification, multicriteria decision analysis, fuzzy AHP

Introduction

Forests provide a variety of ecosystem services and are a renewable resource critical to the sustainable development of many countries, including Nepal. Forest ecosystems are increasingly under the pressure of several anthropogenic and natural challenges, such as climate change, land use change, biodiversity loss, biological invasions, and forest fires. Although they are a natural part of the forest renewal cycle, forest fires cause inestimable loss to forest ecosystems due to the reduction of ecosystem service provision (Xiao et al., 2015). In Canada, about 10,000 forest fires are reported each year, affecting nearly 2.5 million hectares of forest (Guo et al., 2015). In North America, more than 130,000 forest fires burned 4.2 million hectares of forests yearly, while in China, an average of 12,000 forest fires between 1950 and 2010 destroyed 670,000 hectares of forests each year (L. Su et al., 2015). Similarly in Europe, forest fires burned around 26,800 hectares per year between 2009 and 2018 (San-Miguel-Ayanz et al., 2019). Forest fires affect plant composition and species richness, increase non-native species presence (Laughlin & Fulé, 2008) and release a substantial amount of carbon into the atmosphere. Fire may trigger land use change with secondary effects on the hydrological cycle and imbalances the water budget (Soulis, 2018), escalates air pollution by generating aerosols (Yin et al., 2019) and declines crop yield (Hinojosa et al., 2021). In addition, forest fire is directly harmful to human health. In the catastrophic forest fire in Australia in 2019/2020, around 437,000 people were exposed to poor to hazardous air quality, with hundreds of deaths (Graham et al., 2021).

The Terai Arc Landscape (TAL), which is located in the Terai and Churia region of Nepal, has six protected areas and is one of the most ecologically important landscapes in the country. Increased fire events in this landscape threaten the destruction of many valuable forest ecosystems (Williamson et al., 2005). Forest fires occur annually in all the physiographic/climatic regions of Nepal, but fire is more severe in Terai and Churia range (Sharma, 1996), aggravated by land-use change (Kunwar & Khaling, 2006). Nepal lacks sufficient statistical data on fire-related forest loss despite its importance for the country's landscape function. In the 2009 fire season alone, uncontrolled forest fires caused 41 fatalities (civilians and firefighters) and destroyed hundreds of thousands of hectares of national forests (Bhujel *et al.*, 2017). Despite the increasing frequency of forest fires frequency and the size of burned areas, the government and stakeholders do not possess sufficient resources or capacity to develop early warning or planning tools (Sibanda *et al.*, 2011). Nepal is one of the countries most vulnerable to climate change due to the large proportion of people primarily dependent on forest and agricultural production (Bhatta & Aggarwal, 2016). In developing countries, forest fire management and information systems are often poorly developed (Dube, 2013), which is also the case in Nepal.

Recently, there has been rapid development and deployment of remote sensing and GIS tools to predict forest fire risk at global to local scales. Remotely sensed data has become one of the fundamental elements in risk mapping, especially in regions with limited physical access or historical records (Meena *et al.*, 2019; Pourghasemi, 2016). Various researchers have used different techniques to identify fire risk, such as logistic regression (Rasyid *et al.*, 2016), multiple linear regression (Liu & Zhang, 2015), frequency ratio method (Tiwari *et al.*, 2021), Analytical Hierarchical Process (Lamat et al., 2021; Krishna Prasad Vadrevu et al., 2010), Fuzzy AHP (Güngöroğlu, 2017; Tiwari *et al.*, 2021), analytical neural networks (Talukdar *et al.*, 2020). The combination of Multi-Criteria Decision Analysis (MCDA) and GIS has been shown to be effective in predicting fire risk and identifying areas at risk. Analytical Hierarchical Process (AHP) has been used in the GIS-MCDA process in different decision-making systems (Akbulak *et al.*, 2018; Vadrevu *et al.*, 2010; Faramarzi *et al.*, 2021). However, this method is criticised for lack of precision as it uses real non-scaled values, also known as crisp numbers (Zhang *et al.*, 2011). Fuzzy Analytical Hierarchical Process (FAHP) can be used to tackle this problem, as the integration of fuzzy values improves the precision and accuracy of the assessment and subsequent decision-making process (Feizizadeh *et al.*, 2014). Furthermore, this method has many advantages over conventional AHP and is a widely used technique in combination with GIS capability (Abedi Gheshlaghi *et al.*, 2021; Burgess, 2011; Feizizadeh *et al.*, 2015). This method has been widely used in environmental and risk modelling, becoming a powerful and important method for predicting risk or hazards (Abedi Gheshlaghi *et al.*, 2021; Mehta *et al.*, 2018; Nyimbili & Erden, 2020; Tiwari *et al.*, 2021).

Understanding fire behaviour, predicting burnt areas, calculating emission scenarios, and preparing short, medium, and long-term management plans is a challenge for policymakers, stakeholders, and forest managers, at the best of times (Sibanda *et al.*, 2011). Although the government of Nepal has identified forest fire as one of the significant drivers of forest degradation and deforestation, it lacks sufficient data to construct a reliable predictive capacity for forest fires (Parajuli *et al.*, 2020). Reflecting the current need to prevent and mitigate forest fires at the landscape level, this study identifies forest fire hotspots in the TAL landscape using the fuzzy AHP method and freely available remote sensing data. In addition to being beneficial to regional and national policymakers, land planners, fire managers, social networks, and other related stakeholders, this study also helps local

REDD+ projects to plan activities to mitigate carbon emissions and reduce ongoing biodiversity loss.

METHODOLOGY

Study Area

The TAL in Nepal covers about 2.4 million ha or 15% of the country's total land area. It stretches along the southern foothills of the Himalayas, with two physiographic zones named Terai (Sanskrit for "lowlands") and the Churia hills (the youngest mountain range in Nepal). Forest covers more than half of the area of the TAL region (1.3 million ha), with an average growth stock of 135 m^3/ha and 115 m^3/ha, respectively, for the Terai and Churia regions (MOFSC, 2015). TAL forests are dominated by broad-leaved Sal (*Shorea robusta*) forest, a commercially valuable tree species used primarily in construction. Agriculture is the main occupation in the area, producing mainly maise, wheat and paddy rice, along with various horticultural crops. Most of the population uses fuelwood for cooking purposes (Pandey *et al*., 2021). Thus, livelihoods and forests are inextricably linked in the TAL (see Figure 1 for a study area map).

In the last 15 years, only one study has been conducted in this area to identify the cause of forest fires. A study by Kunwar & Khaling (2006) reported that 58.06% of forest fires are started deliberately, followed by negligence (22%) and accidents (20%). The research also mentioned that the dry season shedding of leaves in these deciduous forests leads to the accumulation of a considerable amount of dry leaves and litter acting as fuel for the forest fire. In recent years, forest fires in the study area are increasing as major fire incidents were recorded in the years 2009, 2012, 2016, 2019 and 2021, especially in the month of March to May (Bhujel *et al.,* 2017; Matin *et al.*, 2017; Parajuli *et al.,* 2020; Qadir *et al.*, 2021). Qadir *et al*., (2021) predicted that the areas have the highest risk of forest fire incidents in the coming year.

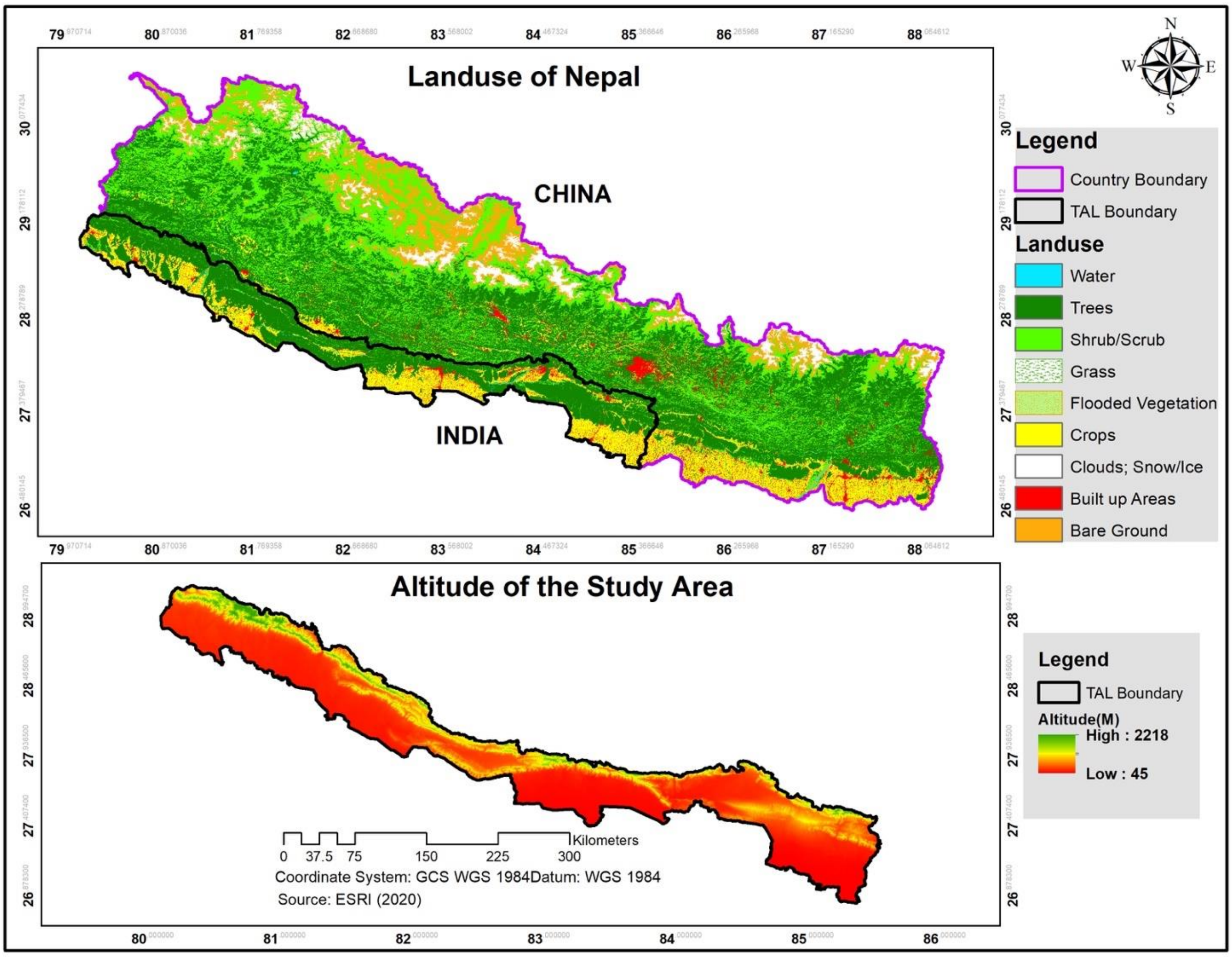

Figure 1 Study Area

Data Acquisition

Visible Infrared Imaging Radiometer Suite (VIIRS) with 375m spatial resolution thermal anomalies was used to extract the fire points (Schroeder, 2017). All fire incidents observed between 2012 and 2021 were downloaded from http://earthdata.nasa.gov/data/nrt-data/firms. The detection confidence of VIIRS data varies; confidence above 30% is considered sufficient, while higher confidence is recommended to reduce false alarm incidents (Giglio et al., 2020). In this study, forest fire incidents with a confidence level below 30% were discarded, alongside all fires detected outside forested areas, such as grassland or shrublands. Based on the literature review (see Appendix A), ten variables that affect forest fires were considered when creating the forest fire risk map (Table 1).

Table 1 General information on predictor variables used in this study

Classes	Variables	Spatial Resolution	Data Period	Data Type	Source
	Elevation	30 m	2000-2013	Raster	Aster DEM
Topographical	Aspect	30m	2000-2013	Raster	Aster DEM
	Slope	30m	2000-2013	Raster	Aster DEM
Biophysical	Land Cover	30m	2010	Raster	ICIMOD
	NDVI	30m	2021	Raster	Sentinel 2
Climatic	Temperature	4.5km	2000-2018	Raster	Worldclim
	Precipitation	4.5km	2000-2018	Raster	Worldclim
	Wind	250 m	2020	Raster	Global wind Atlas
Anthropogenic	Distance from Road	1:25000	2015	Vector (Polyline)	Department of Survey
	Proximity to settlement	1:25000	2015	Vector (Points)	Department of Survey
Past Forest fire points		375m	2012-2021	Vector (Polygon)	VIIRS

Data Processing

Aster global DEM (30m spatial resolution) was downloaded from the USGS website (https://earthexplorer.usgs.gov/) to describe the topography. For further classification of DEM, slope and aspect were derived using the Spatial Analyst tool in ArcGIS 10.5. Temperature and precipitation data were downloaded from Worldclim for 2000-2018 (Fick & Hijmans, 2017), the mean monthly temperature and precipitation of the pre-monsoon season (March-May) of each year was averaged, and a separate layer was generated. Wind speed was downloaded from the Global Wind Atlas (https://globalwindatlas.info/). The Sentinel- 2A NDVI data were downloaded from the Copernicus Open Access Website in Level 1c format for the period from 2021/01/01 to 2021/02/06. Data describing land use type were provided by ICIMOD Nepal (https://rds.icimod.org/Home/DataDetail?metadataId=9224) with a spatial resolution of 30m. The road and settlement location were acquired from the Department of Survey https://opendatanepal.com/dataset?q=settlement&sort=score+desc%2C+metadata_modified+desc; the vector polyline and points shapefile were rasterised using the Euclidean distance method in the

ArcGIS spatial analyst tool. The variables were converted into raster images of 30×30 m resolution (**Error! Reference source not found.**). See Appendix B for the images of each variable used.

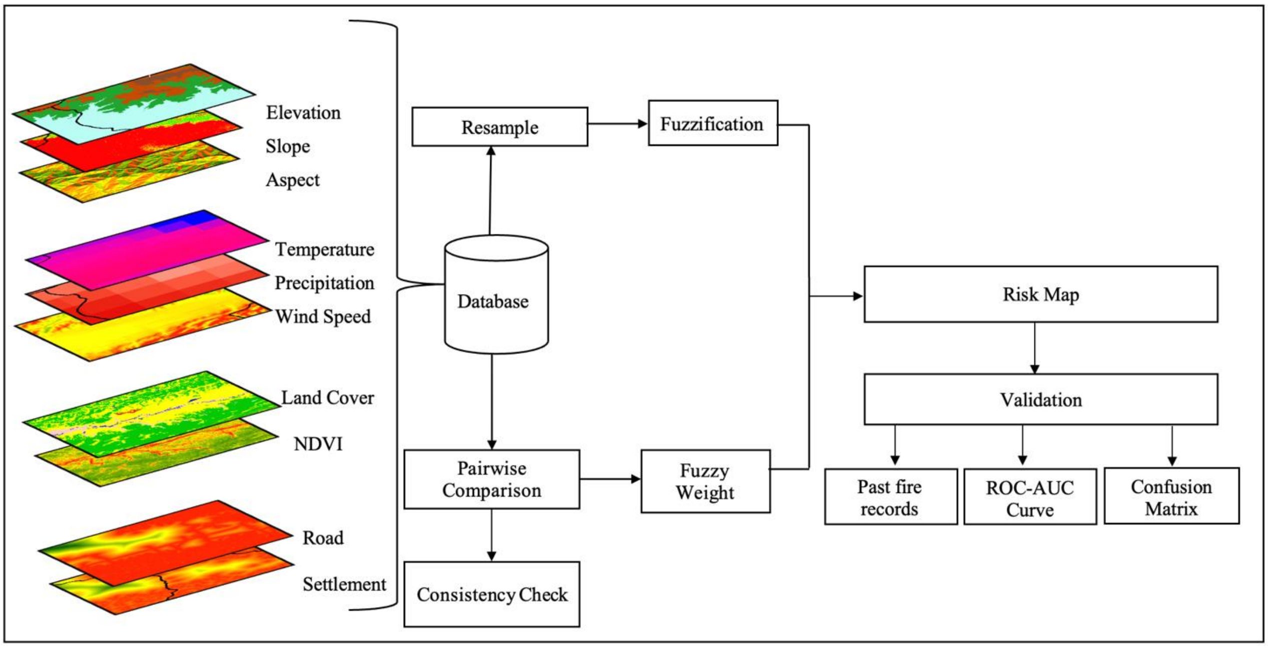

Figure 2 Methodological framework for the identification of fire risk zones

Multi-Criteria Decision Analysis

Buckley (1985) fuzzy extend method analysis was applied, using triangular fuzzy numbers to obtain the fuzzy pairwise comparison matrix proposed by Saaty (1980), see Appendix C. This method has been extensively used by (Chen et al., 2011; Tiwari et al., 2021) to assess the forest fire risk map and offers an appropriate solution to the reciprocal comparison matrix (Demirel et al., 2018). In this study, the consistency ratio was less than 0.04 (Ymax 10.65, CI 0.07 and RI 1.49), suggesting that the assigned weights are consistent. Verbal variables were applied with the triangular membership function, and crisp numbers were converted to three real numbers (l, m, u) (Tiwari et al., 2021), where l stands for min (lower possible bound), m for medium, and u for max (upper possible bound), see Appendix D. Later, defuzzification was also applied to change the weights into the crisp value proposed by (Chou & Chang, 2008).

To perform the fuzzy membership function in ArcGIS, the value of each input raster was transformed and a scale between 0 to 1 (see Appendix E). Values near 1 represent a higher chance of forest fire risk, and values near 0 indicate a very low risk (see Appendix F for images). The aspect and land cover layer had to be reclassified from 1 to 5 as it does not possess the desired minimum or maximum value. This constraint was also applied to the land cover classes layer for agriculture, water bodies, built-up areas, and barren lands, as suggested by (Malczewski, 2000). After obtaining the value between 0 and 1, the priority weight derived from fuzzy AHP logic was multiplied with each of the ten variables using $FFRM = \sum_{t=1}^{m}\sum_{f=1}^{n}(NFW_t * FC_f)$……………..Equation *1* (Tiwari *et al.*, 2021).

$$FFRM = \sum_{t=1}^{m}\sum_{f=1}^{n}(NFW_t * FC_f) \text{……………..Equation 1}$$

where FFRM is the Forest Fire Risk Map, NFW_t means the normalised fuzzy weight, FC_f stands for the normalised score of every class, m is the number of criteria, while n represents the number of classes. For the weighted linear combination method, different weight values of each variable based on their risk potential were used (*Equation 2*).

$$\text{FFRM} = LC * 0.20 + DR * 0.15 + PS * 0.13 + NDVI * 0.11 + T * 0.10 + A * 0.08 + E * 0.06 + S * 0.06 + P * 0.06 + WS * 0.05 \text{..............................}\textit{Equation 2}$$

where FFRM is forest fire risk map, LC is the landcover, DR stands for the distance from the road, PS is the proximity to the settlement, NDVI means normalised difference vegetation index, T is the temperature, A is an aspect, E is the elevation, S means slope, R stands for precipitation and WS is the wind speed.

Validation

Three validation methods were used in this study. The first method overlaid forest fire points of 2021 on the FFRM. The second method calculated the confusion matrix using a support vector machine to identify the user's accuracy, producer's accuracy, kappa coefficient, and overall accuracy (Jensen, 1996). At first, 100 random points were generated automatically by the ArcGIS tool representing all classifications from very low to very high-risk categories. Each of the 100 random points was overlaid on the ground base map in ArcGIS, and the points were then manually verified to ascertain if the autogenerated points fell on the five classifications of the predicted risk map. For each point, we manually verified the density of the forest, distance to settlement, and road nearby to ascertain that the point represents the same category as the prediction. Later, a confusion table was created, incorporating correct and incorrect points/classifications. Finally, producer accuracy, overall accuracy, and Kappa coefficient were calculated using equations $Producer\ Accuracy =$

$\frac{C_{aa}}{C_{.a}} * 100\%$ .... Equation 3, Overall accuracy = $\frac{\sum_{a=1}^{u} C_{aa}}{Q} * 100\%$ .... Equation 4 and Kappa coefficient = $\frac{\sum_{a=1}^{u} \frac{C_{aa}}{Q} - \sum_{a=1}^{u} \frac{C_{a.}C_{.a}}{Q^2}}{1 - \sum_{a=1}^{u} \frac{C_{a.}C_{.a}}{Q^2}}$........Equation 5, respectively (Bahari et al., 2014):

1. $Producer\ Accuracy = \frac{C_{aa}}{C_{.a}} * 100\%$ .... Equation 3

   where, C_{aa} is an element at the position of the row and column

   C_{aa} is the sum of the column

2. Overall accuracy = $\frac{\sum_{a=1}^{u} C_{aa}}{Q} * 100\%$ .... Equation 4

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

3. Kappa coefficient = $\frac{\sum_{a=1}^{u} \frac{C_{aa}}{Q} - \sum_{a=1}^{u} \frac{C_{a.}C_{.a}}{Q^2}}{1 - \sum_{a=1}^{u} \frac{C_{a.}C_{.a}}{Q^2}}$........Equation 5

where $C_{a.}$ is the sum of the row

As for the third method of cross-validation, the receiver operating characteristic (ROC) curve method was applied to predict the forest fire risk model. This was based on true-positive rate (sensitivity) and false-positive rate (1-specificity) corresponding to the area under the curve (AUC). The ROC-AUC was established using ArcSDM in the ArcGIS software, the step required forest fire points, non-fire points and the final layer of risk (Mabdeh et al., 2022; Mitra & Das, 2022; Z. Su et al., 2018). ArcSDM is an effective tool for categorical map analysis (George et al., 2022), in here 267 past fire points were randomly selected using the sub-set feature in ArcGIS and a corresponding 267 non-fire points were created using spatially balanced points under ArcGIS. Finally, under the ArcSDM tool, the ROC-AUC tool was used to generate the ROC-AUC curve.

Results

Fire Incident Record

Together, 1,07,443 fire points in the TAL were identified in TAL between 2012 and 2021. Most fire incidents were recorded in the pre-monsoon season, i.e., March-May (83.55%). From January to May, a slightly extended period accounts for almost 99% of fire incidents and represents the fire season in this area. On average, 10,742 forest fires have occurred annually (**Error! Reference source not found.**), with the highest number of forest fires recorded in 2016 (21,166), followed by 2021 (18,544) and 2019 (13,825). Approximately 65% of all recorded forest fires occurred between 2016 and 2021, suggesting an increasing trend of forest fires.

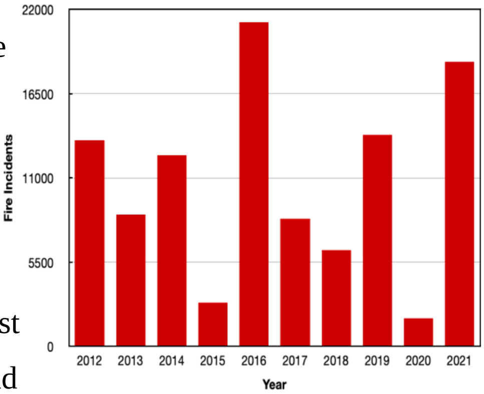

Figure 2 Forest fire incidents recorded from 2012 to 2021

Fire incidence and predictor variables

We categorised the values of each of the 10 variables into five sub-categories based on indicative fire risk potential: from very low (1) to very high (5). For example, a high fire risk potential score was given to high NDVI values (>0.5), while NDVI values less than 0.1 were considered low fire risk due to low fuel load. Fire incidents were overlaid on each of the variables in ArcGIS, most fire points were found in the very high risk rating category (see Appendix G), apart from settlement proximity. This predictor variable was slightly different, as the relationship with fire occurrence was not directly proportional. We found that the number of fires near settlements or roads (>1000m) was smaller (26182) than in the following distance category 1000-2000 m (32630).

Fire risk map

The final map was produced after applying all fuzzy weights based on their risk of influence (Figure 3). Around 24% of the study area was found to be at very high risk of fire, followed by 18.56% under high risk. About 47% of the TAL region is covered by agriculture, and these areas typically fall under the very low risk.

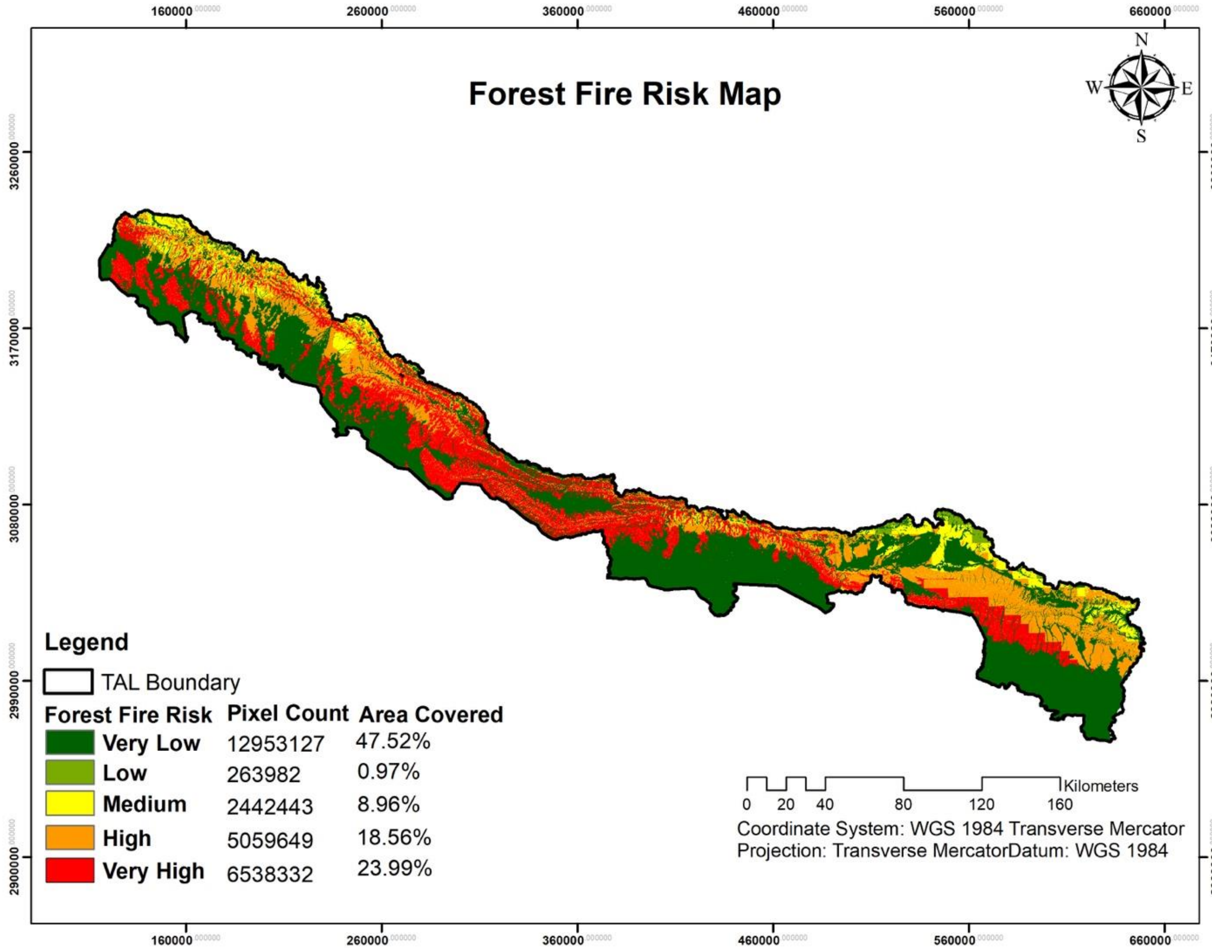

Figure 3 Forest fire risk map of TAL including the percentage of risk areas

Validation of the risk map

We tested the accuracy of our prediction map by applying two methods. First, the 2021 fire incidents were overlaid over the fire risk map (Kanga & Singh, 2017; R S *et al.*, 2016). In this validation step, 98.15% of fire incidents in 2021 occurred at medium to very high risk areas (Figure 4).

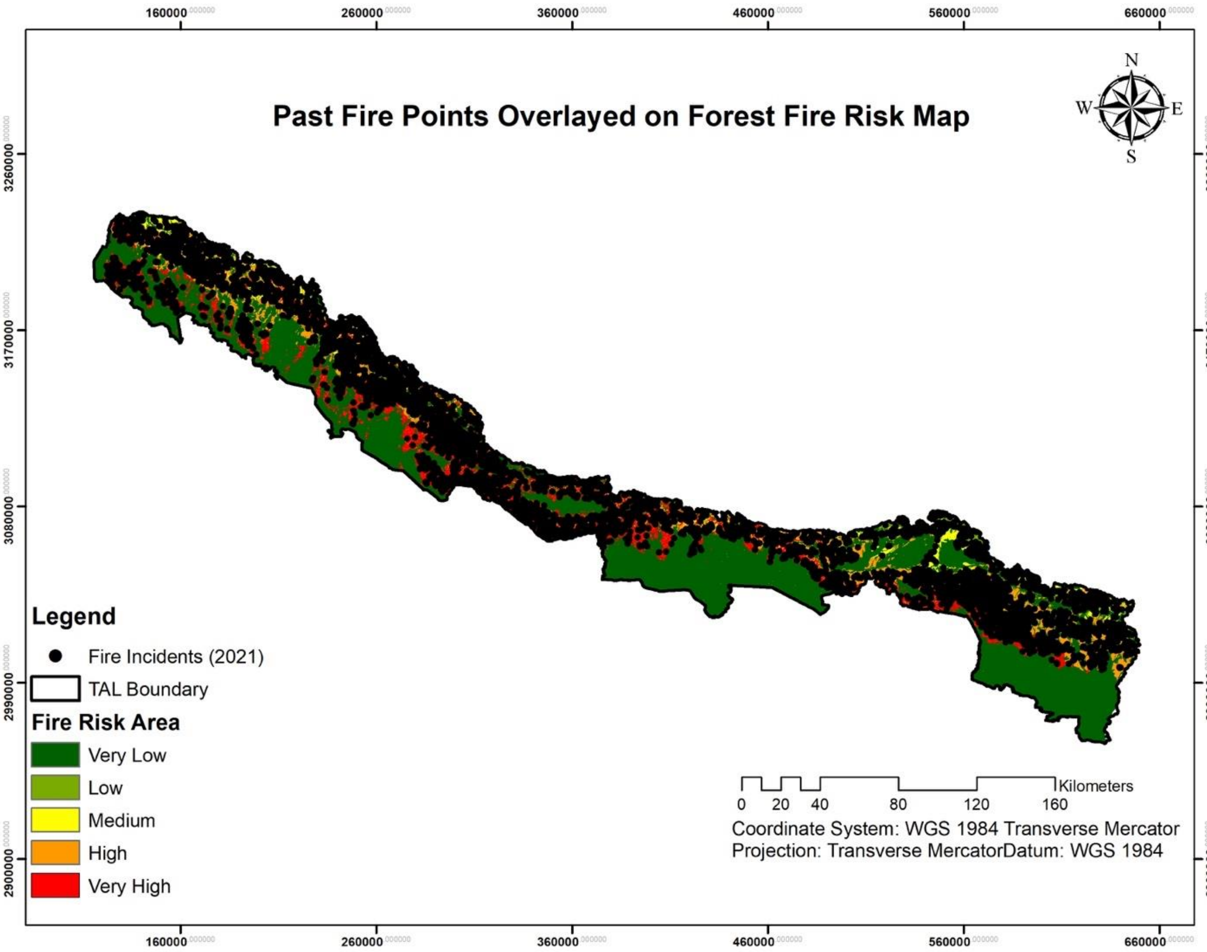

Figure 4 Fire incidents of 2021 overlaid on the produced map

The confusion matrix was applied by using a support vector machine in ArcGIS Pro (Avinash *et al.*, 2019). Table 2 shows that very low-risk area identification has 100% user accuracy, while very high-risk areas are identified with 96% accuracy. The minimum accuracy was 0.84% in the high-risk zone. In this study, the kappa coefficient was 0.93.

Table 2 Results obtained from the confusion matrix

	Number of autogenerated points obtained under fire risk category							
Class Value	**Very Low**	**Low**	**Medium**	**High**	**Very High**	**Total**	**User Accuracy**	**Kappa cofficient**
Very Low	48.00	0.00	0.00	0.00	0.00	48.00	1.00	0.00
Low	0.00	9.00	1.00	0.00	0.00	10.00	0.90	0.00
Medium	0.00	1.00	9.00	0.00	0.00	10.00	0.90	0.00

High	0.00	0.00	3.00	16.00	0.00	19.00	0.84	0.00
Very High	0.00	0.00	0.00	1.00	23.00	24.00	0.96	0.00
Total	48.00	10.00	13.00	17.00	23.00	111.00	0.00	0.00
P_Accuracy	1.00	0.90	0.69	0.94	1.00	0.00	0.95	0.00
Kappa	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.93

Lastly, the ROC curve for the forest fire risk map was calculated and is shown In Figure 6. The overall ROC value of the fire risk map was 0.81, indicating very high accuracy.

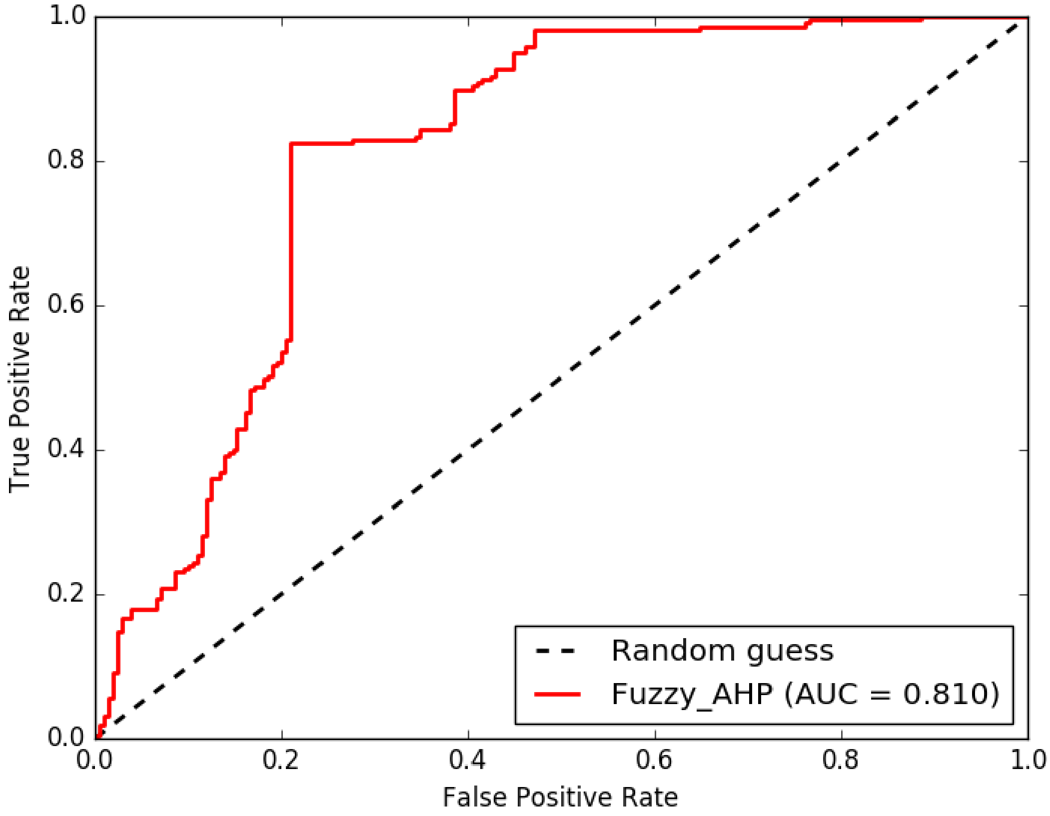

Figure 5: ROC curve for fuzzy-AHP model, where x axis represents false positive rate and y axis represents true positive rate.

Discussion

In this research, we integrate fuzzy logic and a hierarchical analytical process to examine the forest fire risk of the TAL, one of Nepal's most important landscapes. We constructed a spatially explicit analysis, considering several parameters likely to influence fire frequency and severity. The forest fire in TAL seems to be increasing over the years, suggesting that current management practices and methods are inadequate to address forest fire risk. Matin *et al.*, (2017) and Parajuli *et al.*, (2020) concluded that increasing forest fire occurrence is due to anthropogenic activities; however, various variables may be at play. Whatever the reason, forest fires will profoundly impact the TAL ecosystem unless there is a change in the management approach. Analysing forest fire risk can play an important role in designing and implementing effective early detection systems, ideally in collaboration with local stakeholders. Fire avoidance and management in the fire-prone landscape can free resources for other development priorities (Doerr & Santín, 2016) and, unlike other natural hazards, fire risk can be reduced by effective planning (Donovan & Brown, 2007). The goal is to preserve the functioning of existing socio-ecological systems in the TAL by enhancing management's adaptive capacity (Robinne et al., 2018).

We used VIIRS-derived fire incidents to validate our risk map, offering a verification mode completely independent of the set of predictor variables used in its construction. However, the annual variation in fire frequency and location can present a challenge to this methodology. Here, the highest fire counts were recorded in 2016, a finding confirmed by several other studies (Bhujel *et al.,* 2017; Matin *et al.*, 2017; Parajuli *et al.,* 2020). The oft-cited reason for this peak is the precipitation deficit recorded in that year (Hamal *et al.,* 2022) and Bhattarai *et al*., (2022) also documented the worrying trend of increasing fire frequency. In South Asia, forest fires usually occur in the period from February to May (Reddy *et al.,* 2019; Sahu *et al.*, 2015; Upadhyay *et al.*, 2022); we found that 83.55% of forest fires in the TAL were recorded in the pre-monsoon season (March to May). Resource-limited assessment and prediction of forest fires in this region should focus on the fire season only and achieve reasonable accuracy. However, the assessment methodology may be sensitive to the variation between fire seasons; the number of forest fire incidents in 2021 increased by 250% in the pre-monsoon season compared to 2010 (Bhattarai *et al.,* 2022).

Amongst the variables potentially explaining fire risk tested in this study, land cover classes and anthropogenic factors represented approximately 48% of the fuzzy weight. Other studies also show that land cover and anthropogenic factors drive forest fire occurrence (Bhujel *et al.,* 2017; Jaiswal *et al.,* 2002; Matin *et al.*, 2017; Parajuli *et al.,* 2020; Qadir *et al.*, 2021; Sari, 2021). Unsurprisingly, land cover class was the main factor describing forest fire in our study as it determines several variables critical to the probability and severity of a fire (Carmenta *et al.,* 2011; Sam *et al.,* 2022; Vadrevu *et al.,* 2006). Specifically, broadleaved forest was identified as the land cover class most prone to fire, its heavy annual leaf fall results in a substantial accumulation of fuel load on the forest floor (Qadir *et al.*, 2021; Sharma, 1996). Sharma (1996) observed in 1995 that about 90 % of the

Terai forests experienced between one and three fires each year in the pre-monsoon season. As fuel load plays a vital role in sustaining and spreading fire, the spatial distribution of broadleaved forests and fuel within them is critical for predicting areas at risk (Krishna P Vadrevu et al., 2006).

The second and third most important variables determining forest fire were distance from the road (0.15) and proximity to settlement (0.13). Together, these two variables represent the anthropogenic factor, previously shown as a key determinant of fire frequency (Bhujel *et al.*, 2022; Kunwar & Khaling, 2006; Matin *et al.*, 2017; Parajuli *et al.*, 2020; Sibanda *et al.*, 2011). Proximity to road had higher fuzzy weight than proximity to settlement, probably reflecting the kind of human activity undertaken in either setting. Romero-Calcerrada *et al.* (2008) found that among all the anthropogenic factors, the highest fire risk was associated with proximity to roads. Tiwari *et al.* (2021) argued that distance to road and settlement might have a lower impact on risk in specific locations, an effect largely driven by human behaviour and habits. Parajuli *et al.*, (2022) state that most forest fires in the Terai region are due to human negligence and lack of awareness, indicating that human population density during critical periods may be the underlying driver. In this light, selecting the variables influencing forest fire and considering them in the right context is critically important when conducting multicriteria analysis. For example, studies typically consider steep slopes as a factor contributing to fire risk, but most forests in the TAL are on gentler slopes; a relatively modest slope of 15% is considered a very high-risk zone in this study. Burgess (2011) and Matin *et al.*, (2017) arrived at similar conclusion while analysing the fire risk zone in one of the districts in this study area; slopes considered at low risk elsewhere were elevated to the highest risk category. Qadir *et al.*, (2021) found significantly higher fire incidence (55%) on the lower steep slope (<15%) in Nepal and UğurBaltacı (2020) found that the risk of fire decreases as the slope increases in some specific locations. We think this atypical finding is due to strong confounding with settlement proximity, humans typically settle the flat or shallow slope terrain first. Our study shows that proximity to roads and settlements is a strong fire predictor, potentially confounding slope steepness.

Validation of fire risk maps is one of the most important aspects of their communication, users must be confident in the presented data in order to act on it (Feizizadeh *et al.*, 2014; Pourghasemi *et al.*, 2016). We overlaid 2021 fire points over the final risk map, Figure 4 shows that around 82% of recorded incidents occurred within the very high and high-risk zones as identified by our map. Matin *et al.* (2017) carried out a similar exercise for forest fire counts derived from MODIS hotspots in Nepal and found that 80% of forest fires were in very high to high-risk zones. To date, most of the research identifying forest fire risk areas in Nepal found that the TAL region is the very high-risk zone in the country (Parajuli *et al.*, 2015; Qadir *et al.,* 2021; Ranabhat *et al.*, 2022). A recent study carried out by Bhujel *et al.,* (2022) also found that the country's central and western regions have high fire-prone areas, similar to the risk identified in this study. Conversely, and supporting the methodology applied to fire risk map creation in this study, there were only limited fire counts in the very low and low regions (1.58%). Eskandari (2017) obtained a similar result (3% under low and very low and 80% for high and very high) when calculating the accuracy assessment of the fire risk using fuzzy AHP method. We also assessed our map's accuracy by computing the confusion matrix's kappa coefficient describing the overall accuracy among the classified fire risk map from very low risk to very-high risk. In our study, the overall accuracy was 95%, the kappa coefficient was 0.93 and the AUC value was 0.81, suggesting the map is accurate and fit for purpose. The AUC value above 0.80 is considered highly accurate and well-accepted (Jafarzadeh et al., 2017). Tiwari et al., (2021) report similar results from India when comparing the AUC values under fuzzy-AHP, AHP and frequency methods of forest fire risk map where the highest AUC value was under fuzzy-AHP method (0.83).

Many scholars use expert opinion to identify fuzzy weights of different variables (Fu et al., 2020; Krishna Prasad Vadrevu et al., 2010). Nguyen *et al*. (2009) argue that fuzzy methods may be successful without the use of any expert knowledge. In this study, fuzzy weights were assigned based on information found in the literature (shown in Appendix A). There are many examples in which expert opinions were not considered when applying fuzzy theory logic, but still leading to a realistic and reliable outcome (Langarizadeh & Orooji, 2018; Liyi *et al.,* 2010; Zhang *et al.*, 2020). However, the methodology is not foolproof; uncertainty might propagate through the model if spatially explicit variables with different resolutions are present in the predictor dataset (Malczewski, 2006), necessitating rescaling where possible (Feizizadeh & Blaschke, 2014). New technology and satellite products arriving in near future may alleviate this issue to some extent; using high-resolution imagery supported by drone-based short-distance surveys may significantly improve the accuracy of the result (Afghah et al., 2019).

Conclusion

The study identifies fire hotspot areas in one of Nepal's ecologically most important landscapes. Most forest fires occur in the pre-monsoon season (83.55%), as the heavy leaf fall in broadleve woodlands leads to a substantial fuel load on the forest floor. The fuzzy AHP method applied here shows that land cover classes and anthropogenic factors accounted for 48% of fuzzy weight, indicating that areas with high forest and human population density are at the highest fire risk. The resulting high-resolution risk map may serve as a useful tool for preventing, managing, and controlling forest fires in the TAL. It can also be used to set up early warning processes or emergency response plans at the landscape level. Further research incorporating different MCDA-based expert opinion or additional variables could potentially increase the accuracy of this methodology.

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Author contributions

Ashok Parajuli: Conceptualisation, formal analysis, software, investigation writing-orginal draft. **Syed Amir Manzoor**: Writing-review & editing. ***Martin Lukac:*** Supervision, Validation, Writing-review & editing

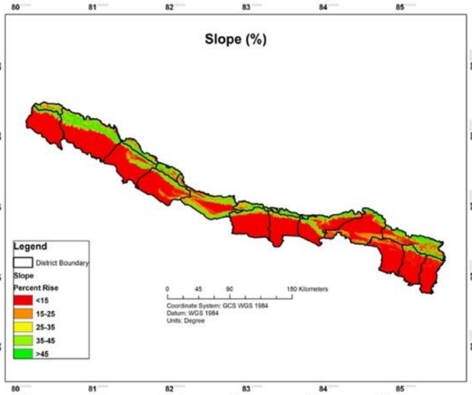
Supplementary

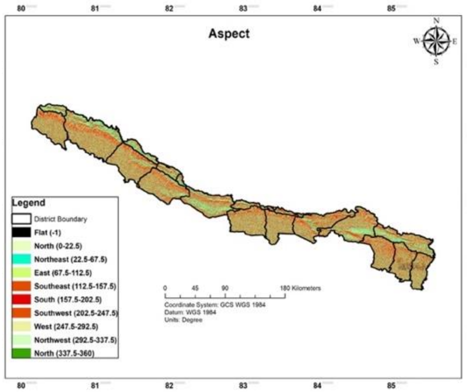
Appendix A: Variables used in different literatures

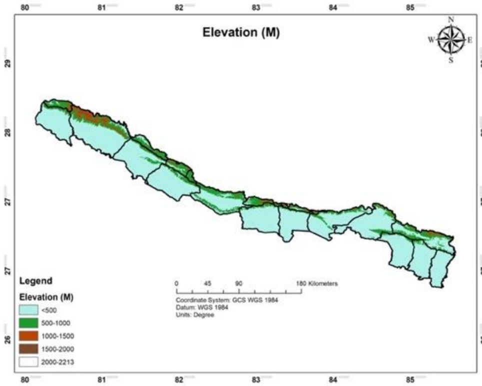
Sources	Slope	Aspect	Elev	Temp	Precip	Wind Speed	Land Cover	NDVI	Dinstance from Road	Proximity to the settlement
Jaiswal *et al.*, (2002)	*								*	*
Vadrevu *et al.*, (2010)	*	*	*	*	*		*			
Jung *et al.*, (2013)	*	*					*		*	*
Sivrikaya *et al.*, (2014)	*								*	*
Pourghasemi *et al.*, (2016)	*	*	*	*	*	*	*	*	*	*
Eugenio *et al.*, (2016)	*	*	*	*	*				*	
You *et al.*, (2017)	*	*	*	*	*				*	*
Matin *et al.*, (2017)	*	*	*	*			*		*	*
Eskandari, (2017)	*	*	*	*	*	*	*		*	*
Jafarzadeh *et al.*, (2017)	*	*	*	*	*		*		*	*
Akbulak *et al.*, (2018)	*	*	*					*	*	*
Ghorbanzadeh *et al.*, (2020)	*	*	*	*	*	*	*	*	*	*
Zeleke (2020)	*	*	*	*	*	*	*		*	*

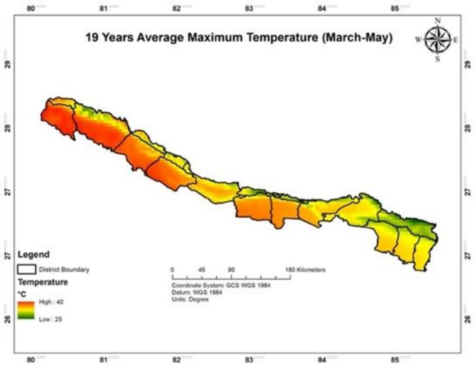
Abedi *et al.*, (2021)	*	*	*	*	*	*	*	*	*	*
Faramarzi *et al.*, (2021)	*	*	*	*	*	*	*	*	*	*
Sari (2021)	*	*	*	*	*	*	*	*	*	*
Tiwari *et al.*, (2021)	*	*	*	*	*	*	*	*	*	*

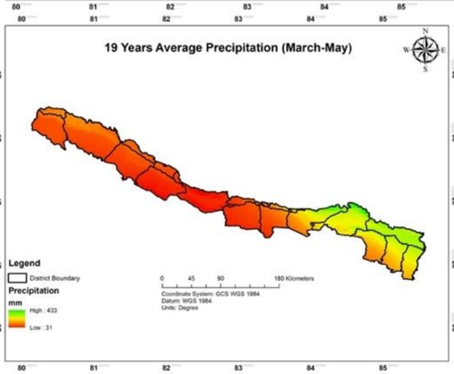
Appendix B: Map of different variables used

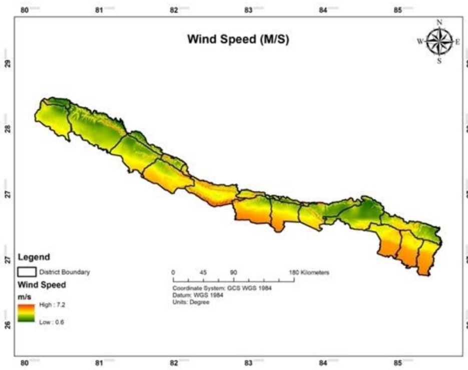


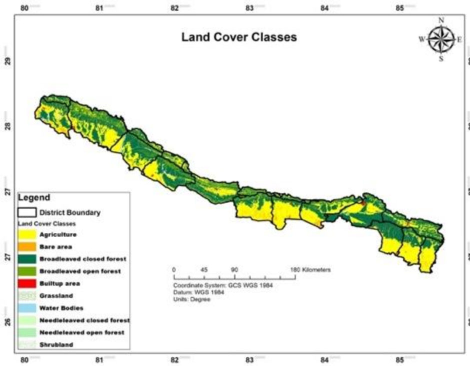


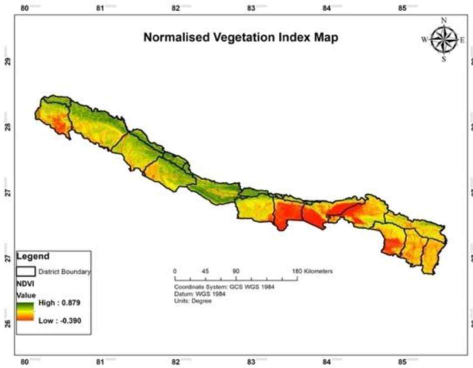


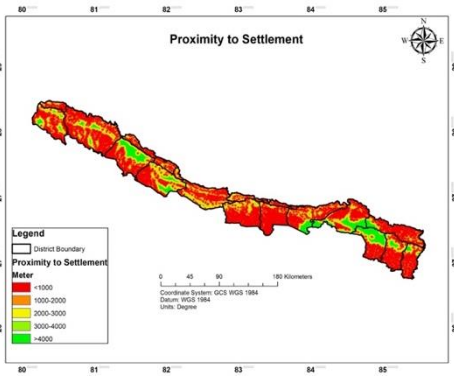


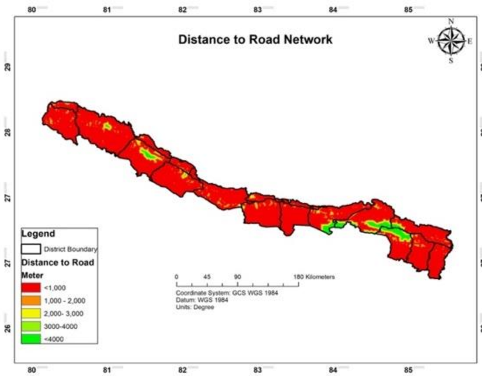












Appendix C : Fuzzy AHP Pairwise ComparisionMatrix

Variables	**Landuse**			**Distance from Road**			**Distance from Settlement**			**NDVI**			**Aspect**			**Elevation**			**Slope**			**Temperature**			**Rainfall**			**Wind**		
Landuse	1.0	1.0	1.0	1.0	2.0	3.0	1.0	2.0	3.0	1.0	2.0	3.0	2.0	3.0	4.0	3.0	4.0	5.0	3.0	4.0	5.0	1.0	2.0	3.0	2.0	3.0	4.0	2.0	3.0	4.0
Distance from Road				1.0	1.0	1.0	1.0	2.0	3.0	1.0	2.0	3.0	1.0	2.0	3.0	2.0	3.0	4.0	2.0	3.0	4.0	1.0	2.0	3.0	1.0	2.0	3.0	1.0	2.0	3.0
Distance from Settlement							1.0	1.0	1.0	1.0	2.0	3.0	1.0	2.0	3.0	2.0	3.0	4.0	2.0	3.0	4.0	1.0	2.0	3.0	1.0	2.0	3.0	1.0	2.0	3.0
NDVI										1.0	1.0	1.0	1.0	2.0	3.0	1.0	2.0	3.0	1.0	2.0	3.0	1.0	2.0	3.0	1.0	2.0	3.0	1.0	2.0	3.0
Aspect													1.0	1.0	1.0	1.0	2.0	3.0	1.0	2.0	3.0	0.3	0.5	1.0	1.0	2.0	3.0	1.0	2.0	3.0
Elevation																1.0	1.0	1.0	1.0	2.0	3.0	0.3	0.5	1.0	1.0	2.0	3.0	1.0	2.0	3.0
Slope																			1.0	1.0	1.0	0.3	0.5	1.0	1.0	2.0	3.0	1.0	2.0	3.0
Temperature																						1.0	1.0	1.0	1.0	2.0	3.0	1.0	2.0	3.0
Rainfall																									1.0	1.0	1.0	1.0	2.0	3.0
Wind																												1.0	1.0	1.0

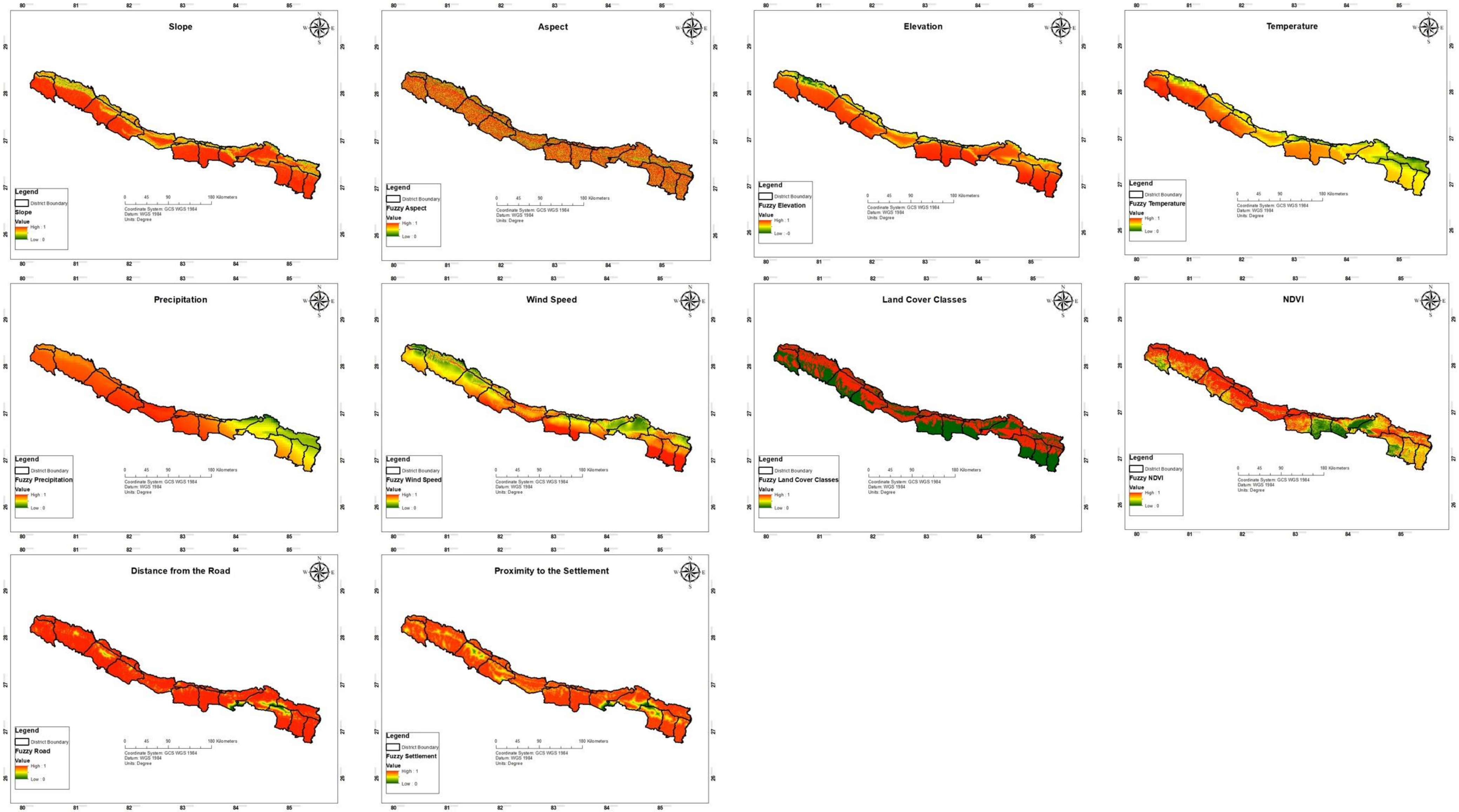
Appendix D: Linguistic variables and their respective numbers

Linguistic Variables	Triangular fuzzy numbers	Reciprocal Triangular Fuzzy Numbers
Extremely strong	(9,9,9)	(1/9, 1/9, 1/9)
Very strong	(6,7,8)	(1/8, 1/7, 1/6)
Strong	(4,5,6)	(1/6, 1/5, 1/4)
Moderately strong	(2,3,4)	(1/4, 1/3, 1/2)
Equally strong	(1,1,1)	(1,1,1)
Intermediate	(7,8,9) (5,6,7) (3,4,5), (1,2,3)	(1/9, 1/8, 1/7), (1/7, 1/6,1/5), (1/5, 1/4, 1/3), (1/3, 1/2,1)

Appendix E : Assigning maximum and minimum value in the membership function

Factor	Criteria	Risk Rating	Rating	Linear Thresholds Min	Linear Thresholds Max
Aspect	Southern, east and western Aspect more vulnerable	South/Southwest	5	1	5
		Southeast	4		
		East/West	3		
		Northeast/Northwest	2		
		Flat/North	1		
Slope	Slope in TAL areas less than <15% is at higher risk	high value to higher risk		45	0
Elevation	Increase in elevation also increases the higher precipitation	high value to higher risk		2200	0
Temperature	Higher temperatures increase the fire risk	high value to higher risk		25	40
Precipitation	Less precipitation higher risk of fire	high value to higher risk		433	33
Wind Speed	High wind speed increases the rate of spread	high value to higher risk		0.6	7.2
Landcover	Broadleaved forest has higher risk of fire than other types	Broadleaved closed forest	5	0	5
		Needle leaved closed forest/Broadleaved open forest	4		
		Needle leaved open forest	3		
		Shrubland/Grassland	2		
		Agriculture	0		
		Bare area/Built-up area/River/Lake	0		
NDVI	Higher NDVI, higher chance to fire risk	high value to higher risk		0	0.8
Distance from Road	Frequent movement near roads has higher chance of fire ignition	high value to higher risk		10000	0
Distance from Settlement	Settlement near to the forest has greater chance for fire ignition	high value to higher risk		10000	0

Appendix F: Fuzzification of each layer between 0 and 1.Values near 1 is high risk areas



Appendix G : Rating of variables and their relation with the fire counts

Variables	Rating	Pixel Counts	% of pixel counts	No of Fire Incidents	% of fire incidents	Fuzzy Weight
Slope (%)						
>15	5	17860928	65.38%	31442	29.26%	
15-25	4	2334543	8.55%	13911	12.95%	
25-335	3	2351230	8.61%	16505	15.36%	0.06
35-4545	2	1958751	7.17%	16910	15.74%	
>45	1	2811343	10.29%	28674	26.69%	
Elevation (m)						
57-500	5	20939725	76.50%	61123	56.89%	
500-1000	4	5184445	18.94%	39369	36.64%	
1000-1500	3	1147990	4.19%	6416	5.97%	0.06
1500-2000	2	99178	0.36%	519	0.48%	
>2000	1	1204	0.00%	15	0.01%	
Aspect						
South/South West	5	9024541	33.04%	37552	34.95%	
South East	4	4198746	15.37%	15640	14.56%	
East/West	3	7054757	25.83%	26952	25.09%	0.08
North East/North West	2	5642563	20.66%	21566	20.07%	
Flat/North	1	1396188	5.11%	5732	5.33%	
Precipiation (mm)						
<100	5	15414759	55.62%	59449	55.33%	
100-200	4	5551398	20.05%	19483	18.13%	
200-300	3	6023239	9.90%	24843	23.12%	0.06
300-400	2	788458	13.91%	3430	3.19%	
>400	1	142002	0.52%	237	0.22%	
Temperature (Celcuis)						
>39	5	3759237	14.61%	5928	5.52%	
36-39	4	8512136	32.38%	30245	28.15%	
33-36	3	11408146	41.11%	57185	53.22%	0.10
30-33	2	2723943	10.83%	13616	12.67%	
<30	1	193179	1.06%	468	0.44%	
Wind Speed (m/s)						
>4	5	3886342	14.20%	9613	8.95%	
3-4	4	10836903	39.59%	41759	38.87%	
2-3	3	10145045	37.06%	46307	43.10%	0.05
1-2	2	2490673	9.10%	9755	9.08%	
0.6-1	1	13966	0.05%	8	0.01%	
NDVI						
>0.5	5	2072700	35.24%	65317	60.80%	
0.4-0.5	4	7609566	16.53%	17531	41.62%	

0.3-0.4	3	8903516	15.88%	13110	11.82%	
0.2-0.3	2	5324415	12.00%	6508	5.52%	
<0.2	1	3563442	20.35%	4971	4.46%	0.11
Land cover classes						
Broadleaved closed forest	5	11813853	43.27%	86339	80.36%	
Needleleaved closed forest/Broadleaved open forest	4	2329217	8.53%	20007	18.62%	
Needleleaved open forest	3	22288	0.08%	116	0.11%	
Shrubland/Grassland	2	164720	0.60%	980	0.91%	0.20
Agriculture	1	11116014	40.72%	0	0.00%	
Bare area/Builtup area/River/Lake	0	1854736	6.79%	0	0.00%	
Distance from the road (m)						
<1000	5	23722608	86.66%	77549	72.18%	
1000-2000	4	1701440	6.22%	14020	13.05%	
2000-3000	3	630493	2.30%	5371	5.00%	0.15
3000-4000	2	390840	1.43%	3368	3.13%	
>4000	1	927548	3.39%	7134	6.64%	
Proximity to the settlement (m)						
<1000	5	15753551	57.55%	26182	24.37%	
1000-2000	4	5762782	21.05%	32630	30.37%	
2000-3000	3	2487175	9.09%	19059	17.74%	0.13
3000-4000	2	1253403	4.58%	10727	9.98%	
>4000	1	2115815	7.73%	18844	17.54%	

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