Forestry: Journal of Institute of Forestry, Nepal 20 (2023) 61-78

DOI: https://doi.org/10.3126/forestry.v20i1.64283

Forestry: Journal of Institute of Forestry, Nepal

Journal homepage: www.nepjol.info/index.php/forestry

Forest Fire Dynamics in Nepal's Mid-hills: Insights from Spatial Analysis and Risk Mapping of Doti District

Khagendra Prasad Joshi[1*], Ashok Parajuli[2], Keshav Ayer[1], Rashmi Bhatt[1] and Ambika Prasad Gautam[1]

[1] Kathmandu Forestry College, Kathmandu, Nepal
[2] Ministry of Forests and Environment, Bagmati Province, Nepal

KEYWORDS

Fire risk mapping
Forest fire
Mid-hills
Spatial analysis
VIIRS

ABSTRACT

Forest fires have significantly contributed to forest degradation and pollution all over Nepal. Despite their high severity, limited studies have been conducted on the spatial-temporal analysis and risk mapping of these fires especially in the Mid-hill region. This study aims to fill this gap by analyzing Visible Infrared Imaging Radiometer Suite (VIIRS) data from 2012 to 2022, along with satellite imagery, using remote sensing and geographic information systems (GIS) technology. Nine variables, including land class, distance to roads, proximity to settlements, temperature, wind speed, precipitation, slope, aspect, and elevation, were utilized to identify forest fire patterns and create a fire risk map. A multi-parametric hierarchical weighted index model was employed, with multicollinearity checked (VIF<2) to ensure model accuracy and validated by Area Under Curve (AUC=0.787). The study revealed an increasing trend of forest fires, particularly during March to May, in broad-leaved forests near human interference. Out of the total forested area of 1447.58 km^2, 42.9%, 46.03%, and 11.07% were classified under high, moderate, and low-risk zones, respectively. The study emphasizes the recurring forest fire problem in often-neglected Mid-hill districts and underscores the need to prioritize them in future strategies.

INTRODUCTION

Forest fires represent a critical threat to global forest ecosystems, posing catastrophic consequences for ecology, the environment, populations, and property (Kala, 2023; Sastry, 2002). With approximately 4.06 billion hectares of the Earth's surface covered by forests, an estimated 82.09 million hectares of forest experience annual burning making forest fires a significant concern for forest degradation (Zhang et al., 2020). These fires, primarily influenced by a complex interplay of natural and human-induced factors, including fuel composition, weather conditions, and ignition sources, constitute a multifaceted phenomenon responsible for an increasing number of incidents on a global scale (Jain et al., 2020; Tariq et al., 2021).

**corresponding author*
*Email: * joshikp01@gmail.com*
Received: 08 September 2023 Accepted: 06 February 2024

Recent advancements in Remote Sensing (RS) and Geographic Information Systems (GIS) have revolutionized forest fire susceptibility mapping by harnessing various techniques to assess factors like vegetation, climate, human activities, and topography (Calkin et al., 2014; Castelli et al., 2015; Khalid et al., 2015). These technologies, in conjunction with historical fire records, facilitate the development of precise predictive models on a global scale, utilizing spatial relationships between influencing variables (Bowman & Murphy, 2010; Calkin et al., 2014; Matin et al., 2017; Nelson & Chomitz, 2011; Samanta et al., 2011; Viegas et al., 1999). The integration of diverse data sources has significantly enhanced forest fire risk assessments, providing critical insights into the complexities of fire occurrences across different spatial scales. Various mapping techniques such as predictive modeling (Qadir et al., 2021), deep learning (Mishra et al., 2023), regression analysis (Mohammadi et al., 2014), Analytical Hierarchical Process (Goleiji et al., 2017), and systematic fire rating (Chuvieco & Congalton, 1989; Matin et al., 2017; Parajuli et al., 2020) have been employed to construct fire risk maps. These methodologies offer diverse approaches to assess and predict forest fire risks, contributing to a more comprehensive understanding of fire dynamics.

In context of Nepal, forest fires pose a significant and escalating threat to its natural landscape (Kunwar & Khaling, 2006). Each year, the country witnesses a surge in active fire incidents and burning days, leading to a disturbing trend of more frequent forest fires (Parajuli et al., 2015). The threat of forest degradation in Nepal stems significantly from various factors, with fires accounting for 27.75% of the damage, ranking second only to grazing, cutting, and lopping, as reported by the Department of Forest Research and Survey (DFRS, 2015). Particularly vulnerable to fire outbreaks is the western part of the country, where seasonal dynamics of short and late monsoons contribute to heightened fire incidents (Kansakar et al., 2004; Parajuli et al., 2015). Specifically, the Far-western province stands out as highly susceptible, detecting 19% of Nepal's total fires despite covering only 16.94% of the forest area (Thapa et al., 2021; DFRS, 2015). Contrary to the perception that hilly regions like the Mid-hills are less prone to fires compared to lower elevated regions, research shows that the western hilly districts, such as Doti, remain at a high risk due to the aforementioned seasonal characteristics (Matin et al., 2017). Despite Mid-hills' vulnerability to disasters like forest fires, they are underrepresented in Nepal's policy and research, as previous researches have predominantly focused on the Terai or Chure regions (Badal & Mandal, 2021; Bhusal & Mandal, 2020; Kunwar, 2006; Parajuli et al., 2023), creating a research gap in understanding fire dynamics and risks in these areas.

Addressing these gaps, this research centers its focus on Doti, situated in the Mid-hill region, characterized by unique vulnerabilities such as challenging geography, harsh climate, economic constraints, and disintegrating forest-people relationships (Karki et al., 2022; Tiwari et al., 2022). This study aims to fill the void by conducting a spatial-temporal analysis of forest fires in Doti, offering insights into the district's fire risk extent and developing a replicable risk index applicable to similar Mid-hill regions. By focusing on Doti district, this research seeks to contribute essential insights into fire dynamics, enhance fire prevention and response measures, addressing the critical research gaps in understanding forest fires within Nepal's vulnerable Mid-hill areas.

MATERIALS AND METHODS

Study area

The research was conducted across the entire area of Doti District, encompassing two municipalities, seven rural municipalities, and a section of Khaptad National Park. The district's geographical coordinates range from latitudes 28˚54' to 29˚28'N and longitudes 80˚30' to 81˚14'E, with elevations varying between 292 and 3,287 meters above mean sea level. The Doti district was selected for this study for two main reasons. Firstly, Doti primarily consists of forested land, accounting for 71.3% of the total area. Secondly, Doti possesses frequent forest fire occurrence and has been identified as one of high risk districts at national level forest fire risk mapping of Nepal (Matin et al., 2017). Additionally, the district includes a very small portion of the highly sensitive Chure region and the ecologically diverse Khaptad National Park. Given these factors, developing a robust fire management plan is imperative to mitigate the risks posed by wildfires to both natural ecosystems and human-inhabited areas.

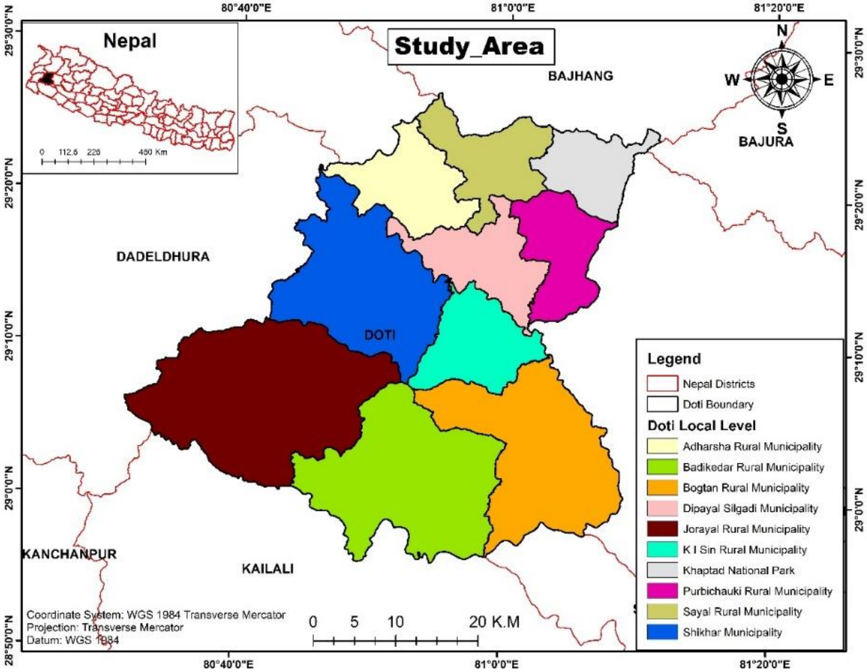


Figure 1: Location of Doti District in western Nepal along with its administrative division.

Data collection

The analysis of fire archives was conducted using real-time fire-detected fire points. The data were obtained from the Fire Information for Resource Management System (FIRMS), which provides valuable and accurate information for geospatial analysis. FIRMS utilizes data from both the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Visible Infrared Imaging Radiometer Suite (VIIRS) to identify active fires. While both VIIRS and MODIS show agreement with each other, the higher resolution and improved nighttime performance of VIIRS, a whiskbroom scanner radiometer, make it a superior tool for fire management and mapping, especially in smaller areas (Schroeder et al., 2014). For this study, VIIRS fire archive data were used to conduct spatial analysis on nine variables related to four locality factors: vegetation (land class), anthropogenic (distance to road and proximity to settlement), topographic (slope, aspect, and elevation), and climatic (land surface temperature, precipitation, and wind speed). The data utilized for the analysis were sourced from different verified sources, as detailed in Table 1.

Table 1: Dataset used in the study

SN	Data	Format	Data period	Resolution	Sources
1.	Fire occurrence data	SHP	2012-2022	375m	NASA/FIRMS /VIIRS
2.	ASTER DEM	TIFF	2019	30m	NASA/LAADSDAAC/USGS
3.	Land surface temperature	HDF	2012-2022	1000m	LAADSDAAC/MOD11C3
4.	Precipitation	TIFF	2012-2018	2.5min(≈4500m)	Worldclim
5.	Administrative and district boundary	SHP	2022	1:25000	Department of Survey
6.	Settlement	SHP	2015	1:25000	OCHA
7.	Road network	SHP	2010	1:250000	ICIMOD
8.	Land cover	SHP	2010	30m	ICIMOD
9.	Wind speed (10m)	TIFF	2022	300m	Wind atlas
10.	Slope/Aspect/Elevation	TIFF	2019	30m	Prepared From DEM

Data analysis

Arc GIS 10.5 was employed for geospatial processing of the satellite images. Layers for each variable were created according to the specifications outlined in Table 3, following the methodology depicted in Figure 2.

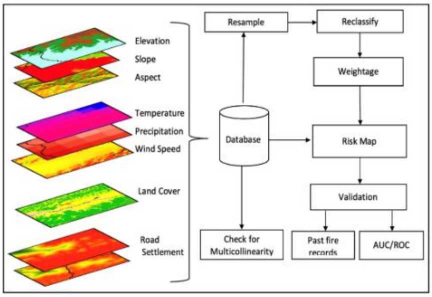


Figure 2: Methodological Framework

The archive fire points obtained from the Earth Observing System Data and Information System (EOSDIS) archive data tool, specifically VIIRS data, were extracted. These fire points were used to analyze trends and patterns in the layers representing various locality factors. Additionally, they served as a validation tool for the final risk map generated in the study.

The study extensively examined influential factors in forest fires, encompassing vegetation, anthropogenic elements, topography, and climatic conditions. Vegetation type was crucial in providing fuel content for fires, as it represents the organic matter available for ignition and combustion (Salas & Chuvieco, 1994). The land cover mapping utilized ICIMOD's land class shapefile from 2010, resulting in nine distinct classes (Figure 3).

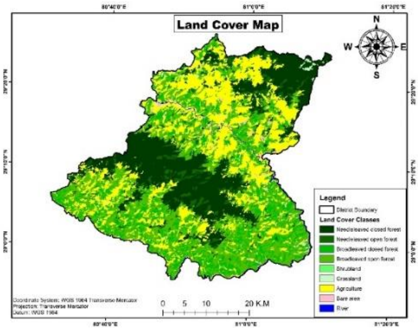


Figure 3: Land cover of Doti District

Anthropogenic factors, particularly road and settlement proximity, are found to significantly influence forest fires (Kolanek et al., 2021), and their impact was assessed using proximity analysis, generating layers for distance to the road (Figure 4a) and proximity to settlements (Figure 4b). Similarly, Topography plays a pivotal role in determining forest fire hazards, with elevation, slope, and aspect having notable impacts on fire behavior (Artsybashev, 1984; Brown & Davis, 1973). Slope, aspect and elevation were derived from the Digital Elevation Model (DEM) using ARC-GIS (Figure 4c, 4d and 4e). Climatic variables, including temperature, precipitation, and wind speed, were significant in influencing forest fire dynamics. Temperature data (Figure 4f) from MODIS's MOD11C3 product provided monthly averages at a 1 km resolution (Parajuli et al., 2020). Precipitation data from Worldclim covered the years 2010-2018 (Figure 4g) (Fick & Hijmans, 2017), while wind speed data (Figure 4h) from the Global Wind Atlas offered wind speeds at a height of 10 meters (Global Wind Atlas, version 3.0). Combining these variables allowed for a comprehensive assessment of fire risk within the study area.

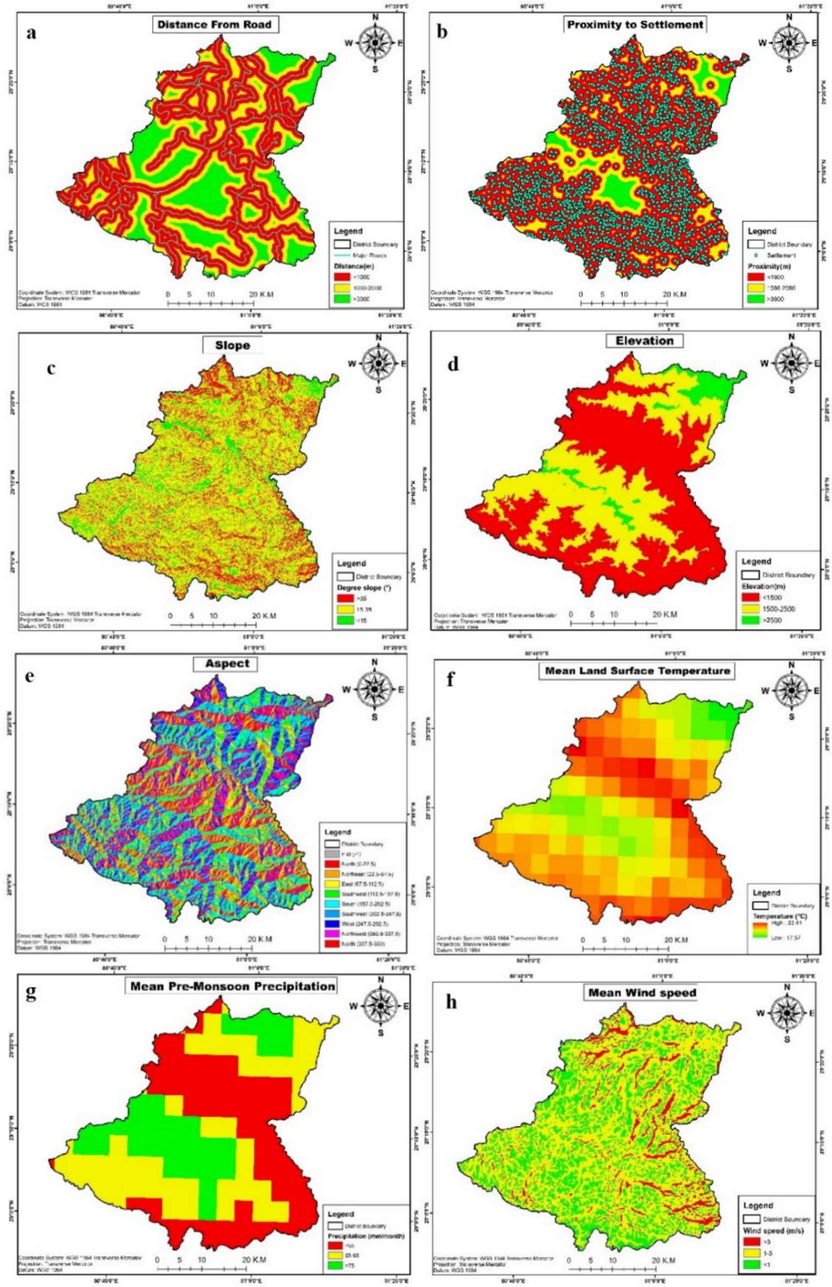


Figure 4: Layers (a) Distance from the road, (b) Proximity to settlement, (c) Slope, (d) Elevation, (e) Aspect, (f) Temperature, (g) Precipitation and (h) Wind speed

Test for multi-collinearity

This study employed statistical methods to validate the fire risk index and examine multi-collinearity (Parajuli et al., 2020). Multi-collinearity refers to a strong correlation among explanatory variables in regression models. Tolerance and VIF are diagnostic tools used to assess multi-collinearity. In this research, land class, land surface temperature, slope, distance from road, proximity to settlement, precipitation, wind speed, aspect, and elevation were the independent variables, while VIIRS fire archive data served as the dependent variable. The results showed no issues with multi-collinearity as all nine variables had high tolerance values (above 0.6) and low VIF values (below 1.5) (Davis et al., 2017; Parajuli et al., 2020).

Table 2: Tolerance and VIF test

Variables	Unstandardized Coefficients		Standardized Coefficients	Collinearity Statistics	
	B	Std. Error	Beta	Tolerance	VIF
(Constant)	4392.51	146.799			
Land class	70.317	20.017	.047	.689	1.452
Settlement	-.135	.051	-.033	.783	1.278
Road	.136	.021	.077	.851	1.176
Temperature	.044	.012	.043	.916	1.091
Slope	4.923	.838	.067	.966	1.035
Wind speed	105.049	21.872	.054	.966	1.035
Precipitation	-.110	.008	-.152	.903	1.107
Aspect	-.036	.242	-.002	.985	1.016
Elevation	-1.453	.057	-.349	.670	1.493

Dependent Variable: Fire archive points

Fire risk index

In the field of forest fire mapping, researchers have not reached a consensus on which specific variables are essential for creating accurate fire risk maps. Instead, numerous studies have proposed integrating various factors, such as climate data (including rainfall, temperature, humidity, and wind), topography data (encompassing elevation, slope, and aspect), and land use data, into comprehensive fire models (Chuvieco & Congalton, 1989; Hernandez-Leal et al., 2006; Jaiswal et al., 2002; Matin et al., 2017; Bhusal & Mandal et al., 2020; Singh et al., 2020; Parajuli et al., 2020; Mohajane et al., 2021; Parajuli et al., 2023). The integration of multiple variables aims to capture the complexity of fire behavior and the underlying environmental conditions that influence fire occurrence and spread. However, the specific combination of variables and their respective weights in the fire risk model may vary across studies, leading to a lack of universal agreement on the most optimal approach.

For this study, a total of nine variables were carefully selected, following a hierarchical fire rating scheme for each variable and its components, which aligns with the methodology suggested by Chuvieco & Congalton (1989). To determine the appropriate weights for these variables, insights from existing fire risk mapping research were employed. Notably, geographic relevance played a key role in selecting the literature sources used in the study. Among the 16 sources referenced, seven focused on Nepal (Bhusal & Mandal, 2020; Faisal et al., 2023; Matin et al., 2017; Parajuli et al., 2020, 2023; Qadir et al., 2021;

Singh et al., 2020), while the remaining nine originated from neighboring countries, such as India (Jaiswal et al., 2002; Tiwari et al., 2021), China (Zhao et al., 2021), and other Asian nations (Abedi Gheshlaghi et al., 2020; Eskandari, 2017; Ozenen Kavlak et al., 2021; Sari, 2021; Sivrikaya et al., 2014). By incorporating insights from diverse sources, this study developed a comprehensive and contextually relevant fire risk map for the study area. The overall mean result showed that land cover was given the highest weightage followed by temperature, distance from road, and proximity to settlement and all other variables were given very similar weightage.

Furthermore, the variables were reclassified into three classes and the classes of each dataset were ranked on a scale of 1-3, (1- High, 2- Moderate and 3-low) according to their influence on fire through fire frequency analysis as shown in Figure 8. Table 3 shows the assigned weights and ratings for all layers. Once all layers were reclassified and each assigned a rank, a model was developed to overlay this data according to defined weights to produce a fire risk map using the Spatial analyst (weighted overlay) tool in ArcGIS model builder where the input layers were given weights that all add up to 100%. The model can be summed up as

FRI = 35% LC +15% LST + 10%DR + 10% PS + 10%S +5%P+ 5%W+ 5% A + 5% E

Where, LC is land class, DR represents the distance from the road, PS means proximity to the settlement, LST is the land surface temperature, S is the slope, P is the precipitation, W is wind speed, A is the aspect and E is the elevation.

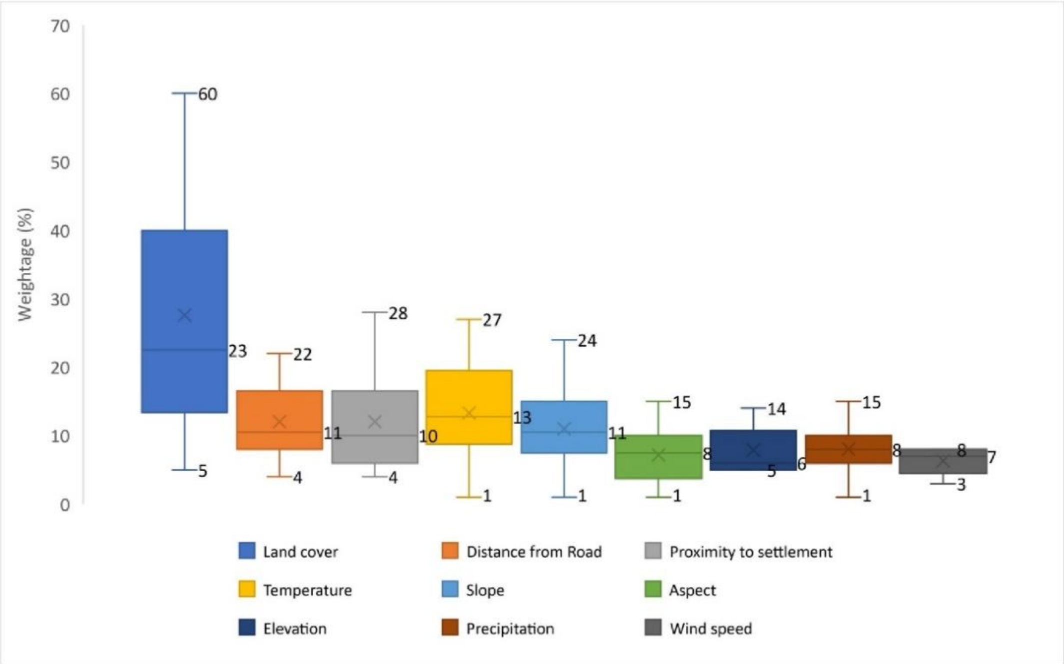


Figure 5: Boxplots of the weightage given in the literature to the various variables converted to percentage

Table 3: Variables used with their weightage, value and ratings assigned to them

Variable	Weight (%)	Class	Value assigned	Fire rating class
Land Class	35	Broad-leaved closed/ open forest	1	High
		Shrubland/Grassland	2	Moderate
		Needle leaved closed/open forest	3	Low
Land surface temperature (˚C)	15	>29	1	High
		23-29	2	Moderate
		<23	3	Low
Distance to road (m)	10	<1000	1	High
		1000-2000	2	Moderate
		2000-3000	3	Low
Proximity to settlement (m)	10	<1000	1	High
		1000-2000	2	Moderate
		2000-3000	3	Low
Slope (˚)	10	0-15	1	High
		15-35	2	Moderate
		>35	3	Low
Aspect	5	South/South-west/South-east	1	High
		West/East	2	Moderate
		North/ North-west/North-east	3	Low
Elevation (m)	5	<1500	1	High
		1500-2500	2	Moderate
		>2500	3	Low
Precipitation (mm/month)	5	44-55	1	High
		55-65	2	Moderate
		65-75	3	Low
Wind speed (m/s)	5	>3	1	High
		1-3	2	Moderate
		<1	3	Low

Model validation

The accuracy of the model was evaluated through two methods. Firstly, the model's performance was assessed by overlaying the archived fire counts from VIIRS to compare the predicted fire risk with the actual fire occurrences. Secondly, the receiver operating characteristic (ROC) curve and area under the curve (AUC) method were employed to quantitatively measure the efficiency of the prepared risk map. The ROC curve depicts the relationship between sensitivity (true positive rate) and specificity (true negative rate) (Flach, 2010). On the other hand, the AUC provides a single scalar value that indicates the performance of the classified image. A higher AUC value, ranging from 0.9 to a maximum of 1, indicates outstanding performance, while values between 0.8 and 0.9 represent excellent performance, and values between 0.7 and 0.8 indicate acceptable results (Hosmer Jr et al., 2013). The ROC-AUC curve was calculated using the ArcSDM tool in ArcGIS, utilizing the fire points from the year 2022 for this analysis. The decision to use only the 2022 fire points was due to the high number of fire points detected by VIIRS during the study period, which resulted in frequent errors and crashes while calculating the ROC curve with the ArcSDM tool.

RESULTS

Trends of forest fire in Doti district

Out of the total study period spanning from 2012 to 2022, the VIIRS satellite recorded a substantial number of 9365 fire incidents in the district. Among these, 671 fire hotspots were detected at a low confidence level and were subsequently excluded from the analysis. Additionally, fires identified in agricultural areas were also removed from the dataset. After careful filtering, a total of 6810 forest fire incidents were observed in the region.

The analysis of annual fire occurrence revealed a noticeable upward trend in forest fires within the district, as indicated by the positive values of the Mann-Kendall trend test (tau = 0.127, Sens slope = 14.85). This positive trend signifies an increase in the frequency of forest fires over time. However, the statistical significance of the trend was deemed insignificant ($p < 0.05$) due to the presence of exceptionally high fire counts in the years 2016 and 2021, followed by relatively lower fire incidents in the subsequent years. Notably, the year 2021 recorded the highest incidence of forest fires, followed closely by 2016, together accounting for a substantial 51.9% of the total forest fires detected during the entire study period.

Temporal analysis of the VIIRS fire Research showed that most fire was seen during the pre-monsoon period of March-May. During these three months total of 6295 fire counts were detected which is 92.43% of the total fire detected by VIIRS (Figure 7).

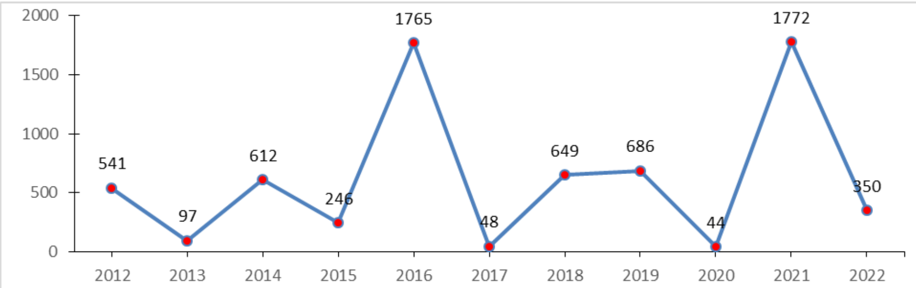


Figure 6: Annual fire counts in Doti district.

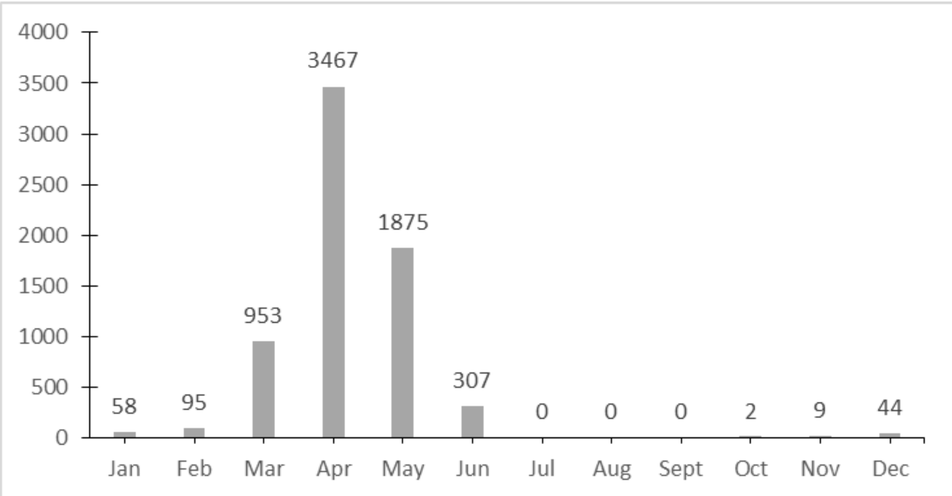
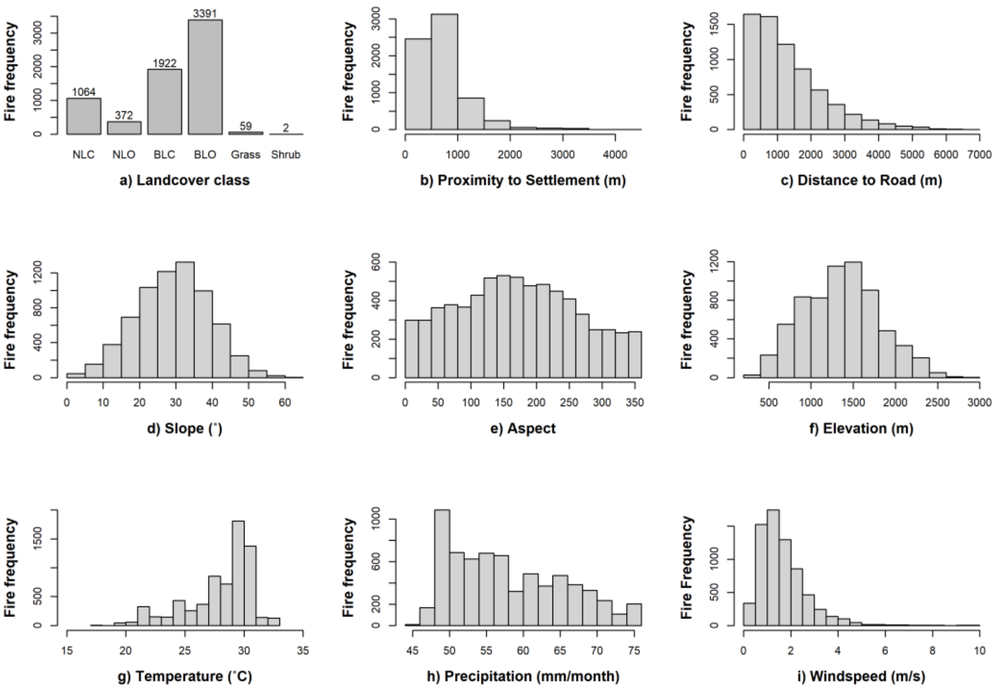


Figure 7: Fire occurrence per month

Fire patterns across various variables



Note: The abbreviation in the Figure 8a are Needle leaved closed forest (NLC), Needle leaved open forest (NLO), Broad leaved closed forest (BLC), Broad leaved open forest (BLO).

Figure 8: Forest fire incidence in (a) land-cover (b) settlement, (c) roads, (d) slope, (e) aspect, (f) elevation, (g) temperature, (h) precipitation and (i) wind speed

The spatial analysis of the fire archive data revealed that the major contributors to forest fires in the district were Broadleaved closed forest and Broadleaved open forest, accounting for approximately 78% of the total fire incidences. The needle-leaved forest also experienced a significant number of fires. The analysis of fire points showed that fire counts increased substantially near anthropogenic factors, with about 82% of fires detected within 1000m of human settlements and 47% within 1000m of roads. Additionally, 77% of fires occurred within a 2000m radius of the major road network.

The frequency of fires was concentrated in areas with slopes between 15-40 degrees, with higher slopes contributing to the majority (91%) of detected fires, particularly those above 15 degree slope. South-facing areas exhibited the highest fire incidence, followed by east, west, and then north-facing areas. In terms of elevation, the majority of fires were detected in the 500 to 2000 meters above sea level range, showing a negative relationship between fire occurrences and increasing elevation. Higher temperatures were associated with a higher frequency of fires, with about 61% of fires occurring in temperatures above 29˚C. Moreover, areas with lower precipitation rates (below 65 mm/month) had a higher concentration (79.6%) of total fires. Finally, the majority of fires (63.9%) were detected in areas with wind speeds ranging from 1-3 m/s.

Forest fire risk map

The risk map was created with High, Moderate and Low risk area category, each occupying 42.9%, 46.03% and 11.07% of forest area (Figure 9). Furthermore, using the risk map risk ranking was also done for each local administration of the district by calculating percentage of high risk zone in each local unit and further verified through VIIRS fire archive data (Table 4). Badikedar was the highest ranked forest fire susceptible local administration with 23.04% of risk zone while Khaptad ranked lowest with absence of high risk area. The high risk Municipality Badikedar, Bogtan and Jorayal covered 65.89% of high risk area and recorded 77.5% (5049) of total forest fire. The higher risk wards from each municipality were ranked on the basis of high risk zones concentration in them.

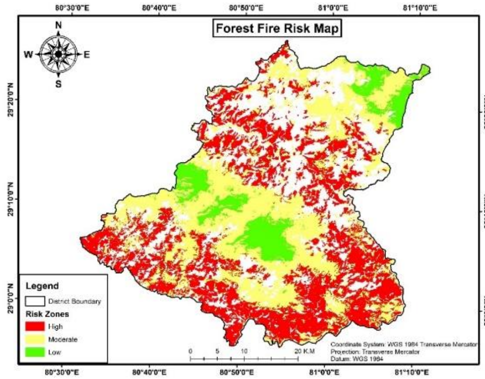


Figure 9: Forest fire risk map of Doti

Table 4: Risk ranking of local units

Rank	Municipality Name	Type	High-Risk zone (%)	Fire Count (VIIRS)	High-Risk Ward (No.)	Remarks
1.	Badikedar	Rural municipality	23.04	1216	1,2,3	High Risk
2.	Bogtan	Rural municipality	22.44	1572	1,2,3,7	
3.	Jorayal	Rural Municipality	20.41	2472	2,3,4,6	
4.	Sikhar	Municipality	11.68	658	4,5,11	Moderate Risk
5.	Dipayal silgadhi	Municipality	7.57	283	1,7,8	
6.	K I Sin	Rural municipality	4.78	161	3,4,5	
7.	Adarsha	Rural municipality	4.77	154	5,2	
8.	Purbichauki	Rural municipality	3.48	114	1,7	Low Risk
9.	Sayal	Rural municipality	1.89	113	1,2	
10	Khaptad	National Park	0	67	-	
		TOTAL	100%	6810		

Model validation

Validation of the output fire map is necessary for a complete and accurate depiction of the fire hazard. We overplayed the VIIRS fire archive data in the fire risk map and found that the high-risk areas were found to be the most fire-prone as they recorded the highest incidence of fire points and highest density count per Km^2 (5.9) followed by moderate (3.7) and low-risk areas (1.3) (Table 5).

Table 5: Merging VIIRS Fire archive data with fire risk map

SN	Risk zone	Area (Km^2)	Fire counts (no)	Fire counts (%)	Density (per km^2)
1	High	632.7369	3712	56.98	5.9
2	Moderate	678.7134	2586	39.69	3.7
3	Low	163.137	216	3.33	1.3

The validation was further done through the AUC and ROC curve. The ROC curve calculated is shown in Figure 10. The calculated area under the curve value was found to be 0.787, which shows that the prepared risk map is accurate in terms of prediction capability.

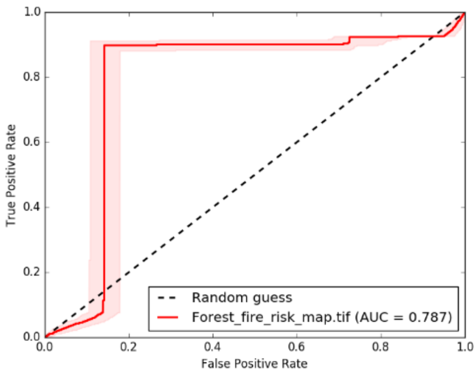


Figure 10: ROC curve for the created fire risk map

DISCUSSION

In this study, we conducted an analysis of fire trends and patterns in one of the high-risk-prone districts of Nepal, utilizing satellite imageries and VIIRS data from 2012 to 2022. Additionally, we developed a fire index based on spatial analysis for risk mapping in the Doti district. The discussion of our findings is presented in the following subtopics.

Temporal distribution of fire

Our study revealed an increasing trend of fire in the district, with a notable concentration of fire incidents in 2016 and 2022. This rising trend is consistent with reports from other studies conducted throughout Nepal, such as Bhujel et al. (2017) and NASA (2021) which also recorded high fire incidence during those years. The major fire months in the district were identified to be from March to May, coinciding with the prolonged summer season and limited rainfall, as previously reported in studies conducted in the country (Bajracharya, 2002; Parajuli et al., 2015, 2020; Singh et al., 2020). Furthermore, the pre-monsoon months in Nepal, which coincide with shedding season for many tree species (Bajracharya, 2002; Bhujel et al., 2017), contribute to an increase in fire incidents during this period. The escalating number of forest fire cases indicates that current management strategies in the area are insufficient to prevent fires, warranting significant reform.

Fire activity across various variables

The intensity and spread of fires are influenced by numerous factors, and our study focused on various variables, including land class, distance to roads, proximity to settlements, land surface temperature, precipitation, wind speed, slope, aspect, and elevation. The spatial analysis for fire frequency was conducted separately for each factor. Our results indicated that the majority of fires occurred in broad-leaved forests, consistent with findings from other researchers in the country (Matin et al., 2017; Parajuli et al., 2020). This high fire incidence in broad-leaved forests can be attributed to the presence of species like *Shorea robusta*, which accumulates substantial dry biomass during dry seasons (Verma et al., 2013; Nhongo et al., 2020). We also observed a higher fire incidence in areas closer to settlements and roads, contrary to various previous fire mapping studies (Kolanek et al., 2021; Thapa et al., 2021; Parajuli et al., 2020; Matin et al., 2017). Human activities, such as cigarette disposal, poaching, agricultural burning, and accidental causes, are major contributors to fires in forest areas near roads and settlements (Kunwar & Khaling, 2006).

In our analysis, we found that fire incidents were significantly higher in areas with a slope of 15-35 degrees, consistent with findings by Bhusal & Mandal (2020). This can be attributed to the preheating effect of flames uphill, which increases the rate of fire spread with an increase in slope (Pyne et al., 1996). The south, southwest, and southeast regions showed the highest fire incidence, influenced by higher solar radiation, resulting in reduced humidity, increased fuel and soil temperature, and exposure to flowing winds (Lin and Rinaldi 2009). Additionally, most fire incidents were observed at elevations below 1500m, in line with studies by Parajuli et al. (2020) and Matin et al. (2017), which reported high fire incidence at lower elevations, while Lutz et al. (2011) observed a negative relationship between elevation and fire frequency and burn severity.

Furthermore, higher temperatures were associated with drier vegetation, increasing the risk of fire, with more than half (51%) of fire cases reported at temperatures above 29˚C, consistent with findings in other studies (Khanal et al., 2015; Thapa et al., 2021; Parajuli et al., 2020; Matin et al., 2017). Our analysis also revealed that areas with precipitation below 55 mm/month recorded the most fire counts, highlighting the increased fire hazard in dry regions (Flannigan et al., 2016). Wind speed is another critical factor that affects fire magnitude, with fire spread being 50% or more fast during wind speeds of 2-6m/s (Beer, 1991). However, in our study, almost two-thirds (67.59%) of fire incidents were reported in the 1-3 m/s wind speed range. This could be attributed to relatively few areas in our study region with high wind speeds.

Fire risk index and validation

Based on the spatial analysis, we developed a fire risk index (FRI) to create an accurate and replicable methodology for fire risk mapping. To justify the use of variables and reduce data redundancy, we checked VIF>2. The risk map derived from the FRI indicated that the majority of forest areas fell under the high (42.9%) and moderate (46.03%) risk zones, indicating that Doti is an overall high-risk area, which aligns with previous reports (Matin et al., 2017). The produced risk map shows it is essential not to overlook mid-hill regions while planning fire strategies, as our study observed an increasing trend of fire incidence, with around 42% of mid-hill forests found to be at high risk for fires, in line with the findings of Tiwari et al. (2022).

To validate the produced risk map, we employed two methods: overlaying VIIRS fire archive points and utilizing ROC and AUC analysis (Chhetri & Kayastha, 2015; Chuvieco & Congalton, 1989). The high-risk areas on the map demonstrated higher fire density compared to moderate and low-risk regions, validating the accuracy of the map using real-time fire points, consistent with other studies conducted in Nepal (Parajuli et al., 2020; Bhusal & Mandal, 2020; Mishra et al., 2023). The AUC value obtained for our risk map was 0.78, suggesting its accuracy. This value is comparable to those reported in other studies, such as Parajuli et al. (2023) in the Terai arc landscape of Nepal (AUC=0.83) and Nikhil et al. (2021) in Parambikulam tiger reserve, India (AUC=0.79). Thus, our hierarchical scheme of fire rating, utilizing literature and fire archive analysis, can produce acceptable and accurate results similar to those obtained from AHP and Fuzzy AHP methodologies used in other studies. However, some studies have reported higher AUC values, like Goleiji et al. (2017), who reported an AUC value of 0.92 for forest fire risk mapping using an integrated approach of AHP and analytical network process. The disparity could be attributed to the removal of agricultural, river, and urban areas from our risk map, as they fall outside the scope of our study. To further improve the risk map, the incorporation of socio-economic data along with higher resolution satellite or drone images could be considered, which, in Nepal, has been limited thus far.

CONCLUSION

This study analyzes increasing fire activity in one of the high risk mid-hill district of Nepal. The findings emphasize the vulnerability of broadleaved forests near human activities, highlighting the significant human influence on fire incidents. Furthermore, south sided forests in lower elevated areas with slope above 15 degrees, having temperature above 29 ˚C, precipitation range below 65 mm/month and wind speed in the range of 1-3m/s were found to be at high risk of forest fire. We found increasing trend of fire incidence in the district and about 42% of the areas in high risk underscores the urgency of addressing fire management strategies and including mid-hill regions in fire risk policies. Neglecting these areas may lead to further damage from recurring forest fires, posing severe threats to ecosystems and communities. The risk map and ward-level information provided here offer valuable insights for policymakers to plan effective fire risk policies, prioritize essential fire infrastructures, and safeguard regions with limited financial capabilities and infrastructure resources. Future research should consider incorporating socio-economic data and high-resolution imagery to improve the accuracy and effectiveness of fire risk mapping. By addressing these aspects, more robust strategies can be developed to prevent and control forest fires, safeguarding Nepal's natural resources and communities from their devastating impacts. With the knowledge gained from this study, we anticipate proactive measures will be taken to mitigate fire risks and ensure the long-term sustainability of Doti District's diverse ecosystems and landscapes.

ACKNOWLEDGEMENT

The study was financially supported by the Ministry of Industry, Tourism, Forest and Environment (MOITFE), Sudurpaschim province. We would like to express our gratitude to Mr. Sachchidananda Joshi and the whole team of Samaj Sewa Doti (SSD) for their coordination and active support. Furthermore, we would like to thank and acknowledge NASA, ICIMOD, Department of survey, OCHA, Worldclim and Wind atlas for providing us respective data. The views and interpretation in this paper are those of authors and not of above mentioned organizations.

REFERENCES

Abedi Gheshlaghi, H., Feizizadeh, B., & Blaschke, T. (2020). GIS-based forest fire risk mapping using the analytical network process and fuzzy logic. *Journal of Environmental Planning and Management*, *63*(3), 481–499. https://doi.org/10.1080/09640568.2019.1594726

Artsybashev, E. S. (1984). FOREST FIRES AND THEIR CONTROL. In *For Fires and Their Control*. Oxonian.

Badal, D., & Mandal, R. A. (2021). Spatial Assesment of Forest Fire Distribution, Occurrence and Dynamics in Province-2, Nepal. *Biomedical Journal of Scientific & Technical Research*, *35*(2), 27441-27459.

Bajracharya, K. M. (2002). Forest fire situation in Nepal. *International Forest Fire News* , *26*, 84–86.

Beer, T. (1991). The interaction of wind and fire. *Boundary-Layer Meteorology*, *54*(3), 287–308. https://doi.org/10.1007/BF00183958

Bhujel, K. B., Maskey-Byanju, R., & Gautam, A. P. (2017). Wildfire Dynamics in Nepal from 2000-2016. *Nepal Journal of Environmental Science*, *5*, 1–8.

https://doi.org/10.3126/NJES.V5I0.22709

Bhusal, S., & Mandal, R. A. (2020). Forest fire occurrence, distribution and future risks in Arghakhanchi district, Nepal. *International Journal of Geography*, *2*(1), 10–20.

Bowman, D. M., & Murphy, B. P. (2010). Fire and biodiversity. In *Conservation biology for all* (pp. 163–180). Oxford University Press Oxford, UK.

Brown, A. A., & Davis, K. P. (1973). *Forest fire: control and use*.

Calkin, D. E., Cohen, J. D., Finney, M. A., & Thompson, M. P. (2014). How risk management can prevent future wildfire disasters in the wildland-urban interface. *Proceedings of the National Academy of Sciences*, *111*(2), 746–751. https://doi.org/10.1073/pnas.1315088111

Castelli, M., Vanneschi, L., & Popovič, A. (2015). Predicting Burned Areas of Forest Fires: An Artificial Intelligence Approach. *Fire Ecology*, *11*(1). https://doi.org/10.4996/fireecology.1101106

Chhetri, S. K., & Kayastha, P. (2015). Manifestation of an Analytic Hierarchy Process (AHP) Model on Fire Potential Zonation Mapping in Kathmandu Metropolitan City, Nepal. *ISPRS Int. J. Geo Inf.*, *4*(1), 400–417. https://doi.org/10.3390/IJGI4010400

Chuvieco, E., & Congalton, R. G. (1989). Application of remote sensing and geographic information systems to forest fire hazard mapping. *Remote Sensing of Environment*, *29*(2), 147–159. https://doi.org/10.1016/0034-4257(89)90023-0

Davis, R., Yang, Z., Yost, A., Belongie, C., & Cohen, W. (2017). The normal fire environment—Modeling environmental suitability for large forest wildfires using past, present, and future climate normals. *Forest Ecology and Management*, *390*, 173–186. https://doi.org/10.1016/J.FORECO.2017.01.027

DFRS. (2015). *State of Nepal's Forests*. Department of forest research and survey. Kathmandu, Nepal.

Eskandari, S. (2017). A new approach for forest fire risk modeling using fuzzy AHP and GIS in Hyrcanian forests of Iran. *Arabian Journal of Geosciences*, 10(8), 190. https://doi.org/10.1007/s12517-017-2976-2

Faisal, A. A., Kafy, A.-A., Afroz, F., & Rahaman, Z. A. (2023). Exploring and forecasting spatial and temporal patterns of fire hazard risk in Nepal's tiger conservation zones. *Ecological Modelling*, *476*, 110244. https://doi.org/10.1016/j.ecolmodel.2022.110244

Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. *International Journal of Climatology*, *37*(12), 4302–4315. https://doi.org/10.1002/JOC.5086

Flach, P. A. (2010). ROC Analysis. In C. Sammut & G. I. Webb (Eds.), Encyclopedia of Machine Learning (pp. 869–875). Springer US. https://doi.org/10.1007/978-0-387-30164-8_733

Flannigan, M. D., Wotton, B. M., Marshall, G. A., de Groot, W. J., Johnston, J., Jurko, N., & Cantin, A. S. (2016). Fuel moisture sensitivity to temperature and precipitation: Climate change implications. *Climatic Change*, *134*(1), 59–71. https://doi.org/10.1007/s10584-015-1521-0

Goleiji, E., Hosseini, S. M., Khorasani, N., & Monavari, S. M. (2017). Forest fire risk assessment-an integrated approach based on multicriteria evaluation. *Environmental Monitoring and Assessment*, *189*(12), 612. https://doi.org/10.1007/s10661-017-6225-7

Hernandez-Leal, P. A., Arbelo, M., & Gonzalez-Calvo, A. (2006). Fire risk assessment using satellite data. *Advances in Space Research*, *37*(4), 741–746.

https://doi.org/10.1016/J.ASR.2004.12.053

Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Applied logistic regression (Vol. 398). John Wiley & Sons.

Jain, P., Coogan, S. C. P., Subramanian, S. G., Crowley, M., Taylor, S., & Flannigan, M. D. (2020). A review of machine learning applications in wildfire science and management. *Environmental Reviews*, *28*(4), 478–505. https://doi.org/10.1139/er-2020-0019

Jaiswal, R. K., Mukherjee, S., Raju, K. D., Saxena, R., Jaiswal, R. K., Mukherjee, S., Raju, K. D., & Saxena, R. (2002). Forest fire risk zone mapping from satellite imagery and GIS. *IJAEO*, *4*(1), 1–10. https://doi.org/10.1016/S0303-2434(02)00006-5

Kala, C. P. (2023). Environmental and socioeconomic impacts of forest fires: A call for multilateral cooperation and management interventions. *Natural Hazards Research*, *3*(2), 286–294. https://doi.org/10.1016/j.nhres.2023.04.003

Kansakar, S. R., Hannah, D. M., Gerrard, J., & Rees, G. (2004). Spatial pattern in the precipitation regime of Nepal. *International Journal of Climatology*, *24*(13), 1645–1659. https://doi.org/10.1002/JOC.1098

Karki, G., Kunwar, R., Bhatta, B., & Devkota, N. R. (2022). Climate change effects, adaptation and community-based forest management in the mid-hills of Tanahu and Kaski districts, Nepal. *International Forestry Review*, *24*(4), 573–593. https://doi.org/10.1505/146554822836282509

Khalid, N., Ahmad, S., Erum, S., & Butt, A. (2015). Monitoring forest cover change of Margalla Hills over a period of two decades (1992-2011): A spatiotemporal perspective. *Journal of Ecosystem and Ecography*, *6*, 174–181.

Khanal, S., Buddhi, L., & Sri M.K. (2015). Wildfire trends in Nepal based on MODIS burnt-area data. *Banko Janakari*, *25*(1), 76–79. https://doi.org/10.3126/BANKO.V25I1.13477

Kolanek, A., Szymanowski, M., & Raczyk, A. (2021). Human activity affects forest fires: The impact of anthropogenic factors on the density of forest fires in Poland. *Forests*, *12*(6). https://doi.org/10.3390/F12060728

Kunwar, R. M., & Khaling, S. (2006). Forest fire in the Terai, Nepal Causes and Community Management Interventions, *International Forest fire news 34*: 46-54.

Lin, J., & Rinaldi, S. (2009). A derivation of the statistical characteristics of forest fires. *Ecological Modelling*, *220*(7), 898–903. https://doi.org/10.1016/J.ECOLMODEL.2009.01.011

Lutz, J. A., Key, C. H., Kolden, C. A., Kane, J. T., & van Wagtendonk, J. W. (2011). Fire Frequency, Area Burned, and Severity: A Quantitative Approach to Defining a Normal Fire Year. *Fire Ecology*, *7*(2), 51–65. https://doi.org/10.4996/FIREECOLOGY.0702051

Matin, M. A., Chitale, V. S., Murthy, M. S. R., Uddin, K., Bajracharya, B., & Pradhan, S. (2017). Understanding forest fire patterns and risk in Nepal using remote sensing, geographic information system and historical fire data. *International Journal of Wildland Fire*, *26*(4), 276–286. https://doi.org/10.1071/WF16056

Mishra, B., Panthi, S., Poudel, S., & Ghimire, B. R. (2023). Forest fire pattern and vulnerability mapping using deep learning in Nepal. *Fire Ecology*, *19*(1), 1–15. https://doi.org/10.1186/S42408-022-00162-3/TABLES/6

Mohajane, M., Costache, R., Karimi, F., Bao Pham, Q., Essahlaoui, A., Nguyen, H., Laneve, G., & Oudija, F. (2021). Application of remote sensing and machine learning algorithms for forest fire mapping in a Mediterranean area. *Ecological Indicators*, *129*. https://doi.org/10.1016/J.ECOLIND.2021.107869

Mohammadi, F., Bavaghar, M. P., & Shabanian, N. (2014). Forest Fire Risk Zone Modeling Using Logistic Regression and GIS: An Iranian Case Study. *Small-Scale Forestry*, *13*(1), 117–125. https://doi.org/10.1007/s11842-013-9244-4

NASA. (2021). *A Fierce Fire Season in Nepal*. https://earthobservatory.nasa.gov/images/148185/a-fierce-fire-season-in-nepal

Nelson, A., & Chomitz, K. M. (2011). Effectiveness of Strict vs. Multiple Use Protected Areas in Reducing Tropical Forest Fires: A Global Analysis Using Matching Methods. *PLOS ONE*, *6*(8), e22722. https://doi.org/10.1371/journal.pone.0022722

Nhongo, E. J. S., D. Fontana, and L. Guasselli. (2020). Spatio-temporal patterns of wildfires in the Niassa Reserve–Mozambique, using remote sensing data. *bioRxiv*. https://www.biorxiv.org/content/10.1101/2020.01.16.908780v1.full.

Nikhil, S., Danumah, J. H., Saha, S., Prasad, M. K., Rajaneesh, A., Mammen, P. C., Ajin, R. S., & Kuriakose, S. L. (2021). Application of GIS and AHP Method in Forest Fire Risk Zone Mapping: A Study of the Parambikulam Tiger Reserve, Kerala, India. *Journal of Geovisualization and Spatial Analysis*, *5*(1), 14. https://doi.org/10.1007/s41651-021-00082-x

Ozenen Kavlak, M., Cabuk, S. N., & Cetin, M. (2021). Development of forest fire risk map using geographical information systems and remote sensing capabilities: Ören case. *Environmental Science and Pollution Research*, *28*(25), 33265–33291. https://doi.org/10.1007/s11356-021-13080-9

Parajuli, A., Chand, D., Rayamajhi, B. K., Khanal, R., Baral, S., Malla, Y., & Poudel, S. (2015). Spatial and temporal distribution of forest fires in Nepal. *XIV World Forestry Congress*, 7–11.

Parajuli, A., Gautam, A. P., Sharma, S. P., Bhujel, K. B., Sharma, G., Thapa, P. B., Bist, B. S., & Poudel, S. (2020). Forest fire risk mapping using GIS and remote sensing in two major landscapes of Nepal. *Geomatics, Natural Hazards and Risk*, *11*(1), 2569–2586. https://doi.org/10.1080/19475705.2020.1853251

Parajuli, A., Manzoor, S. A., & Lukac, M. (2023). Areas of the Terai Arc landscape in Nepal at risk of forest fire identified by fuzzy analytic hierarchy process. *Environmental Development, 45*. https://doi.org/10.1016/j.envdev.2023.100810

Pyne, J. S., Andrews. L. Patricia, & Laven, D. R. (1996). *Introduction to wildland Fire* (2nd ed.). wiley-interscience prublication. https://books.google.com/books/about/Introduction_to_Wildland_Fire.html?id=yT6bzpUyFIwC

Qadir, A., Talukdar, N. R., Uddin, M. M., Ahmad, F., & Goparaju, L. (2021). Predicting forest fire using multispectral satellite measurements in Nepal. Remote Sensing Applications: Society and Environment, 23, 100539. https://doi.org/10.1016/j.rsase.2021.100539

Salas, J., & Chuvieco, E. (1994). Geographic information systems for wildland fire risk mapping. *Wildfire*, *3*(2), 7-13.

Samanta, S., Pal, D. K., Lohar, D., & Pal, B. (2011). Modelling of Temperature and Rainfall of West Bengal through Remote Sensing and GIS Techniques. *International Journal of Geoinformatics*, *7*(2), 31.

Sari, F. (2021). Forest fire susceptibility mapping via multi-criteria decision analysis techniques for Mugla, Turkey: A comparative analysis of VIKOR and

TOPSIS. *Forest Ecology and Management*, *480*. https://doi.org/10.1016/j.foreco.2020.118644

Sastry, N. (2002). Forest fires, air pollution, and mortality in Southeast Asia. *Demography*, *39*(1), 1–23. https://doi.org/10.1353/dem.2002.0009

Schroeder, W., Oliva, P., Giglio, L., & Csiszar, I. A. (2014). The New VIIRS 375m active fire detection data product: Algorithm description and initial assessment. *Remote Sensing of Environment*, *143*, 85–96. https://doi.org/10.1016/J.RSE.2013.12.008

Singh, B., Maharjan, M., & Thapa, M. S. (2020). Wildfire Risk Zonation of Sudurpaschim Province, Nepal. *Forestry: Journal of Institute of Forestry, Nepal*, *17*, 155–173. https://doi.org/10.3126/forestry.v17i0.33633

Sivrikaya, F., Sağlam, B., Akay, A., & Bozali, N. (2014). Evaluation of Forest Fire Risk with GIS. *Polish Journal of Environmental Studies*.

Tariq, A., Shu, H., Siddiqui, S., Mousa, B. G., Munir, I., Nasri, A., Waqas, H., Lu, L., & Baqa, M. F. (2021). Forest fire monitoring using spatial-statistical and Geo-spatial analysis of factors determining forest fire in Margalla Hills, Islamabad, Pakistan. *Geomatics, Natural Hazards and Risk*, *12*(1), 1212–1233. https://doi.org/10.1080/19475705.2021.1920477

Thapa, S., Chitale, V. S., Pradhan, S., Shakya, B., Sharma, S., Regmi, S., Bajracharya, S., Adhikari, S., & Dangol, G. S. (2021). Forest Fire Detection and Monitoring. *Earth Observation Science and Applications for Risk Reduction and Enhanced Resilience in Hindu Kush Himalaya Region*, 147–167. https://doi.org/10.1007/978-3-030-73569-2_8

Tiwari, A., Shoab, M., & Dixit, A. (2021). GIS-based forest fire susceptibility modeling in Pauri Garhwal, India: A comparative assessment of frequency ratio, analytic hierarchy process and fuzzy modeling techniques. *Natural Hazards*, *105*(2), 1189–1230. https://doi.org/10.1007/s11069-020-04351-8

Tiwari, S., Paudel, N. S., Sze, J., & Karki, R. (2022). Unravelling the Local Dynamics of Increasing Fires in Community Forests of Mid-hills of Nepal. Journal of Forest and Livelihood. *Journal of Forest and Livelihood*, *21*(1).

Verma, A. M., Singh. D., Dev Sharma. S., & Kamlesh K. (2013). Forest fire risk zonation in Raipur Range, Mussoorie Forest Division using: GIS and remote sensing technology. *International Journal of Advanced Scientific and Technical Research*. 6, 141-150.

Viegas, D. X., Bovio, G., Ferreira, A., Nosenzo, A., & Sol, B. (1999). Comparative study of various methods of fire danger evaluation in southern Europe. *International Journal of Wildland Fire*, *9*(4), 235–246. https://doi.org/10.1071/wf00015

Zhang, Z., Long, T., He, G., Wei, M., Tang, C., Wang, W.. & Zhang, X. (2020). Study on global burned forest areas based on Landsat data. *Photogrammetric Engineering & Remote Sensing*, *86*(8), 503-508.

Zhao, P., Zhang, F., Lin, H., & Xu, S. (2021). GIS-Based Forest Fire Risk Model: A Case Study in Laoshan National Forest Park, Nanjing. *Remote Sensing*, *13*(18). https://doi.org/10.3390/rs13183704