https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

Forest Fire Risk Assessment using Machine Learning and Earth Observation Technique in Himalayan Regions: Insights from Rasuwa District, Nepal

Sudeep Jogi Kanwar[1], Milan Dhakal[1], Ashok Parajuli[2]

[1]Faculty of Forestry, Agriculture and Forestry University, Hetauda, Makawanpur, Nepal

[2]Divison Forests Office, Kathmandu, Bagamati Province, Nepal

Correspondence to: Milan Dhakal (dhklmilan@gmail.com)

Abstract

The complex terrain and increasing forest fire incidents in recent years make high-mountain environments vulnerable to forest fires, posing a threat to ecological and economic well-being. However, research related to forest fire remains limited in the mountain region. The study aimed to assess the forest fire risk by integrating ten predictive layers (biophysical, topographical, climatic, and anthropogenic factors) and a Random Forest (RF) model in Rasuwa, a mountainous district of Nepal. The model was validated using AUC and other statistical metrics. With an AUC of 0.9 and TSS of 0.67, the model shows strong predictive performance and high reliability of the generated fire risk map. The most significant factors in the model's ability to predict the forest fire risk were elevation, temperature, NDVI, and proximity to settlements. The study shows that 29.32% of Rasuwa district's forest is at fire risk, with the highest risk in Kalika Rural Municipality (59.4%). In the study area, approximately 30% of fire incidents occurred at elevations above 3000 meters. This study emphasizes the potential of the RF algorithms and geospatial methods in similar mountainous regions, aiding the concerned stakeholders and authorities in developing effective forest management plans and improving understanding of forest fire risk.

Keywords: Forest Fire Risk Mapping, Random Forest (RF), Geographic Information System (GIS), High Himalayan Region, Remote Sensing

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

Introduction

Forests maintain biodiversity, conserve soil, and safeguard watersheds in mountainous areas (Acharya et al., 2011). However, projected temperature increases in high-altitude ecosystems are greater than those at lower elevations (Wester et al., 2019), raises concerns about wildfires that significantly deteriorate ecosystem services. In the terrestrial environment, fire acts as an ecological tool in the evolution of vegetation if used carefully; otherwise, it acts as a destructive force. (Odum and Barrett, 2004). Fire maintains the sustainability of forest ecosystems through nutrient cycling, controlling the density and growth of new trees, and modifying habitat for species (Noss et al., 2006). On the other hand, it also results in harming people's health, degrading forests, and the functioning of the ecosystem (Reddy et al., 2019), and affecting locals' livelihoods, those who are highly dependent on the forest for their survival (Matin et al., 2017). The challenges posed by forest fires have grown significantly complex, both worldwide and locally, threatening landscapes.

Studies show that the total area burned each year worldwide is estimated to be around 4 million km2, similar in size to India and Pakistan combined (Giglio et al., 2018; Lizundia-Loiola et al., 2020). The growing severity of forest fires in Asia, directly linked to climate change, has led to a 3-4% increase in the burnt area annually (Giglio et al., 2013; Reddy et al., 2019). Annually, forest fires destroy hundreds of hectares of valuable forest resources in Nepal. Forest fires are the primary cause of deforestation and degradation in the High Mountains. Mountain ecosystems are critical in providing numerous services, including approximately half of the world's freshwater supply (Viviroli et al., 2007). Mountainous regions face a growing threat from increasingly frequent and severe forest fires, jeopardizing biodiversity, ecosystem services, and human communities. An analysis of four years of fire incidents revealed that 10–15% of total forest fire events occurred in high-altitude districts of Nepal (Baral et al., 2012). Elevation-driven warming observed worldwide, and specifically in Nepal, is a critical driver of forest fires (Pepin et al., 2022; Thakuri et al., 2019). Warmer temperatures and widespread dryness during fire season (March-May) have diminished the effectiveness of high-elevation flammability barriers, facilitating fire spread in the upslope (Alizadeh et al., 2021). These regions, historically characterized by long fire return intervals and stand-replacing fires, are now experiencing more frequent blazes, threatening forest composition, community dynamics, and population structures (Carter et al., 2018; Paine et al., 1998). In addition to other impacts, climate-driven fires contribute to the spread of invasive grasses into high-elevation habitats, further threatening native vegetation (Lamprecht et al., 2018).

Natural resource managers have been facing a challenge in controlling forest fires to achieve the desired outcomes due to the unpredictable nature of these events in new places and the increasing damage they cause (Artés et al., 2017). The topography, climate, remoteness, and low population at higher elevations make it difficult to control once the fire ignites (Baral et al., 2012). Moreover, due to a lack of resources, labor, and timely control mechanisms, manual fire control systems are unsuccessful in wide areas (Jung et al., 2013). Therefore, it becomes imperative to identify the forest fire risk area before preventing, minimizing, or controlling fire risk and adapting strategies in case a fire breaks out. Modern technology and traditional knowledge applications are crucial in preventing, controlling, and managing forest fires. The combination of geographic information systems (GIS), remote sensing (RS), and modeling is becoming an essential tool in all aspects of wildfire management. In areas with restricted physical access or historical

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

records, remotely sensed data has emerged as one of the critical components of risk mapping, especially in developing countries like Nepal (Dhakal et al., 2024).

Various approaches to forest fire risk modeling exist in the literature, targeting specific aspects of fire behavior and risk with each method. Forest fire research frequently uses logistic regression, multiple linear regression, Multi-Criteria Decision Analysis (MCDA) tools like the Analytical Hierarchical Process (AHP), and fuzzy AHP. More recently, machine learning techniques have risen in popularity because of their ability to predict and model complex fire data patterns, be data-driven, and manage intricate relationships between many factors (Shi and Zhang, 2023). Among them, Random Forest (RF) is a prevalent machine learning method introduced by Breiman (2001), based on ensemble learning. In ecological studies, the RF model has demonstrated impressive accuracy and the capability to model complex interactions among variables (Elith et al., 2008), including in the assessment of fire susceptibility and the creation of risk maps.

The intricate mountainous terrain of Nepal poses a challenge in exploring the relationship between forest fires and potential causative factors. Determining the relative risk, in particular, helps create better plans for managing forest fires by minimizing the risk to people's safety, property, and natural resources (Poudel et al., 2020). Forest fire frequency in Nepal's mountains is escalating, yet localized risk mapping, particularly in Rasuwa district, is lacking. Several researchers investigated the spatial distribution of forest fire risk all over the country and in specific landscapes, which may not account for the unique climatic, topographic, and socioeconomic factors of mountainous terrains, which can influence fire behavior. For instance, Parajuli et al. (2020) developed a spatial forest fire risk map in Nepal's Terai Arc Landscape (TAL) and Chitwan-Annapurna Landscape (ChAL) regions, including Rasuwa District. However, existing landscape-level evaluations lack fine-scale variations required to identify local fire susceptibility. The underutilization of machine learning approaches in forest fire vulnerability forecasting has created a substantial knowledge deficit, especially in South Asia, warranting further studies (Bar et al., 2023; Tariq et al., 2022). Despite the growing use of machine learning in assessing fire risk, its application in mountainous areas like Rasuwa is largely unexplored. A catastrophic wildfire of 2012 nearly devastated the Gatlang forest, burning unchecked for months (Tamang and Udas, 2021). Research has documented an increasing frequency of forest fire incidents in the region (Rayamajhi and Manandhar, 2020). Previous research conducted by Paudel et al. (2020) in the same geographic region, highlighted the importance of long-term monitoring of anthropogenic fire impact on alpine shrublands and urged for sustainable management strategies involving local communities; however, there still remains a crucial gap in the proactive prediction of fire risk

Identifying these research gaps, this study aims to fill the void by developing a comprehensive forest fire risk map, utilizing the Random Forest (RF) model in the Rasuwa district, thus contributing to region-specific fire management. and a data-driven foundation for informed mitigation and planning. The fire patterns and risk zones obtained from the risk map analysis are expected to assist decision-makers in mitigating the effects of forest fires, particularly in mountainous terrain.

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

2. Methodology

2.1 Study Area

Rasuwa District, located within the CHAL between 27°02' and 27°10' North latitude and 85°45' and 85°08' East longitude, is a mountainous area spanning 1,544 square kilometers **(Figure. 1)**, characterized by distinct landscapes and rich cultural heritage. Langtang National Park covers a significant portion of the district, contributing to its rich biodiversity and a unique patchwork of vegetation shaped by diverse topography and geology **(Figure. 1).** The diverse landscape with forests, agricultural land, and snow-covered mountains includes 31.43% forest cover and 16.63 % perpetual snow. While analyzing the elevation characteristics of the study area using DEM, the district's elevation ranges from 614 to 7,227 meters, embracing a wide range of vegetation, including montane tropical forests in the south, subtropical, temperate, subalpine, and alpine forests in the north; in addition, about 68% of the district area is situated above 3,000 meters mean sea level.

The meteorological station of Dhunche, the district headquarters, records the mean annual precipitation and temperature of 1605 mm and 15.6 °C, respectively, with the lowest temperature of 8.7 °C in January and the highest temperature of 20.6 °C in July (Shrestha et al., 2017). Rayamajhi & Manandhar (2020) found that from 1989 to 2018, the study area experienced an annual rise in the maximum and average temperatures by 0.0532°C and 0.0202°C, respectively. Furthermore, the increase in monsoon precipitation by 2.1 mm and the decrease in winter precipitation by 0.5 mm in the region highlight the consequences of climate change. The district is at high risk of forest fire considering the diversity of vegetation, an evident rise in temperature, and a drop in winter precipitation. The selection of the study area as the Rasuwa district of Nepal allows for an in-depth exploration of forest fire risk in the Himalayas. The district's unique blend of vulnerable biodiversity, difficult terrain, and socio-economic complexity makes it an ideal research area for the study of forest fires.

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

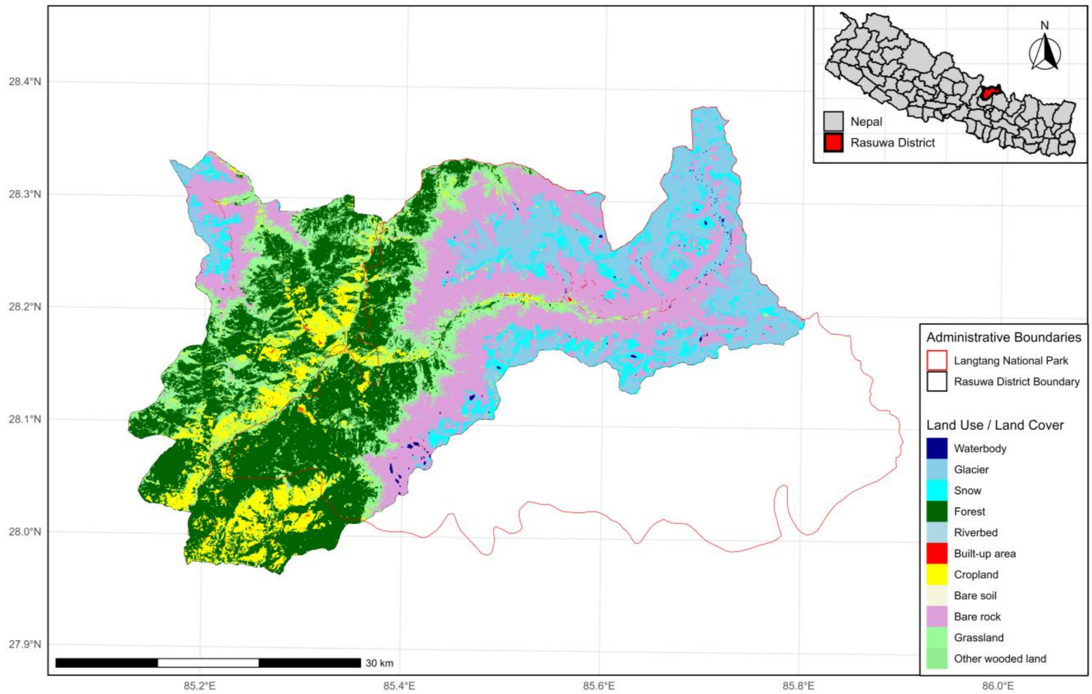

Figure 1: The location map of the study area shows different land covers and Langtang National Park.

2.2 Datasets Used

2.2.1 Forest Fire Incidents

In this study, forest fire incident data between 2012 and 2024, from the Suomi National Polar-orbiting Partnership - Visible Infrared Imaging Radiometer Suite (SNPP-VIIRS) sensor with a spatial resolution of 375 m, recorded specifically on the vegetated areas (forest areas, grassland, and other wooded land) were considered. To enhance the reliability and robustness of the data, data with nominal and high confidence levels above 30% were selected for the study (Giglio et al., 2016).

To enhance the predictive capacity of the model, the spatial distribution of forest fire incidents must be calibrated or evenly distributed (Boria et al., 2014). Therefore, the fire incidents were spatially filtered with minimum distance threshold of 100 meters between fire incidents. In the end, 757 incidents of forest fire remained after spatial thinning.

2.2.2 Forest Fire Conditioning Factors

Initially, the most influential variables related to forest fire were selected from the literature (Dhakal et al., 2024; Matin et al., 2017; Mishra et al., 2023; Parajuli et al., 2023; Tiwari et al., 2021). It is worth noting that, vegetation (NDVI and landcover), topography (elevation, slope, aspect, and TWI), anthropogenic factors (distances from the settlement

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

and proximity to road), and the meteorologic factors (precipitation, temperature, and wind speed) were the main factors of forest fires in the high mountains (Xie et al., 2022). Malczewski. (2000) suggests that model uncertainty can be mitigated by rescaling factors with different spatial resolutions; thus, predictor layers were resampled to 30 meters.

Table 1: Remote Sensing and GIS Datasets

Category	Predictors	Sources	Data Format	Resolution
Biophysical	Land Cover	(FRTC, 2024)	Raster	30 m
	NDVI	Landsat 8	Raster	30 m
Topographical	Slope Elevation Aspect TWI	SRTM DEM	Raster	30 m
Anthropogenic	Distance from Settlement	(Settlements in Nepal | Humanitarian Dataset | HDX, 2024)	Vector	1:50,000 30m (raster)
	Distance from Road	(Nepal Roads (OpenStreetMap Export)., 2024)		
Climatic	Precipitation	(Hijmans et al., 2005)	Raster	1000m
	LST	MOD11C3 V6.1	Raster	1000m
	Wind Speed	https://globalwindatlas.info/en	Raster	250 m
Fire Incidents	VIIRS hotspot	(NASA | LANCE | FIRMS)	Vector	375 m

Biophysical factors

Vegetation affects forest fires and fire behavior (Erten et al., 2004). In addition, dry and dense vegetation in closer proximity to human access is more prone to forest fires and spreads swiftly (Dhakal et al., 2024). This study utilized the National Land Cover Map of Nepal for 2022, developed by the Forest Research and Training Centre (FRTC) as a part of the NLCMS project (FRTC, 2024). The map provides land cover classified into 11 specific categories (**Figure** 1) and illustrates its variation across the country with a spatial resolution of 30 m. However, it has not differentiated the forest into different types, restricting the classifications necessary for effective forest fire risk mapping. Assessment of NDVI indicates vegetation density, health, and the soil and plants' moisture content (Jiang et al., 2006), which impacts the susceptibility to forest fire risk.

Topographic

Elevation plays a significant role in forest fire risk by regulating topographic, climatic, and hydrologic factors (Falkowski et al., 2005; Tiwari et al., 2021). At higher elevations, high rainfall, low temperatures, and high humidity result in fewer fire occurrences, unlike at lower elevations (Chuvieco and Congalton, 1989). On steeper slopes, fuel preheats and fires spread upward quickly (Jaiswal et al., 2002). A steeper slope influences the local wind speed and fosters an accelerating fire upslope (Ajin et al., 2016). Aspects significantly influence the microclimate of the slope: the amount of solar radiation received, temperature, moisture content, wind flow, and ultimately, vegetation growth

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

(Jaafari et al., 2018). TWI indicates the amount of soil moisture and surface saturation distributed spatially (Yong et al., 2012), influencing the initiation of forest fires (Adab et al., 2013). The SRTM DEM, acquired from USGS Earth Explorer, was used to analyze elevation, slope, aspect, and TWI.

Anthropogenic factors

Proximity to settlements, a critical indicator, evaluates the pressure on the forest ecosystem through forest fires, deforestation, and overexploitation of forest resources imposed by anthropogenic activities (Jaafari et al., 2018; Jaiswal et al., 2002). The spatial distribution of settlements in Rasuwa district was assessed with the "Settlements in Nepal" dataset from the UN OCHA, with a scale of 1:50,000. The dataset was rasterized using the Euclidean distance function, a spatial analyst tool in ArcGIS. People close to the forest may start fires deliberately or unintentionally (Erten et al., 2004). Pedestrians and vehicles moving along the road may initiate the fires purposefully or accidentally. Dhakal et al. (2024) point out that the road is an influential factor in the prevalence of anthropogenic fires. The Nepal Roads (OpenStreetMap Export) dataset of 2023, which is detailed and regularly updated, is utilized in this study. The dataset lacks a single specified scale; however, the vector layer was rasterized using the Euclidean distance function and resampled to 30m resolution.

Climatic Factors

Precipitation influences the variation of fuel and surface moisture (Kayet et al., 2020). Decreasing precipitation reduces fuel moisture and elevates the probability of forest fires, and vice versa. This study utilized the Bio-12 (annual precipitation) layer to model forest fire risk, a comprehensive set of bioclimatic variables. In ecological and environmental studies, the BioClim dataset is widely used because of its high resolution and accuracy (Hijmans et al., 2005). Besides precipitation, rising temperatures significantly increase the evapotranspiration rate, drying out fuels and creating suitable conditions for forest fire risk. Temperature increases may also indirectly affect mountain ecology, such as forest fire lines moving uphill (Alizadeh et al., 2021). The MODIS Land Surface Temperature (LST), specifically, the MOD11C3 V6.1 product, which provides 8-day composite land surface temperature at a spatial resolution of 1 km, was processed using GEE. The LST dataset was refined to cover the observations spanning from 2000 to 2024, a total of 24 years; furthermore, Daytime LST values were extracted from the 'LST_Day_1km' band within the collection. A long-term average daytime LST was produced by aggregating the resulting images with a median reducer. While LST highlights the thermal conditions of the landscape, the wind depletes soil and fuel moisture, fans the flame with fresh oxygen, and exacerbates the risk of rapid ignition and vicious burning (Kanga et al., 2017; Wang et al., 2021).

2.3 Methodological Framework

The overall methodological framework of the study was divided into three parts: data acquisition and preprocessing; preparation and preprocessing of forest fire and non-fire incidents before model configuration and training; and deployment of the model and validation of the final tuned model using the ROC curve and several statistical metrics.

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

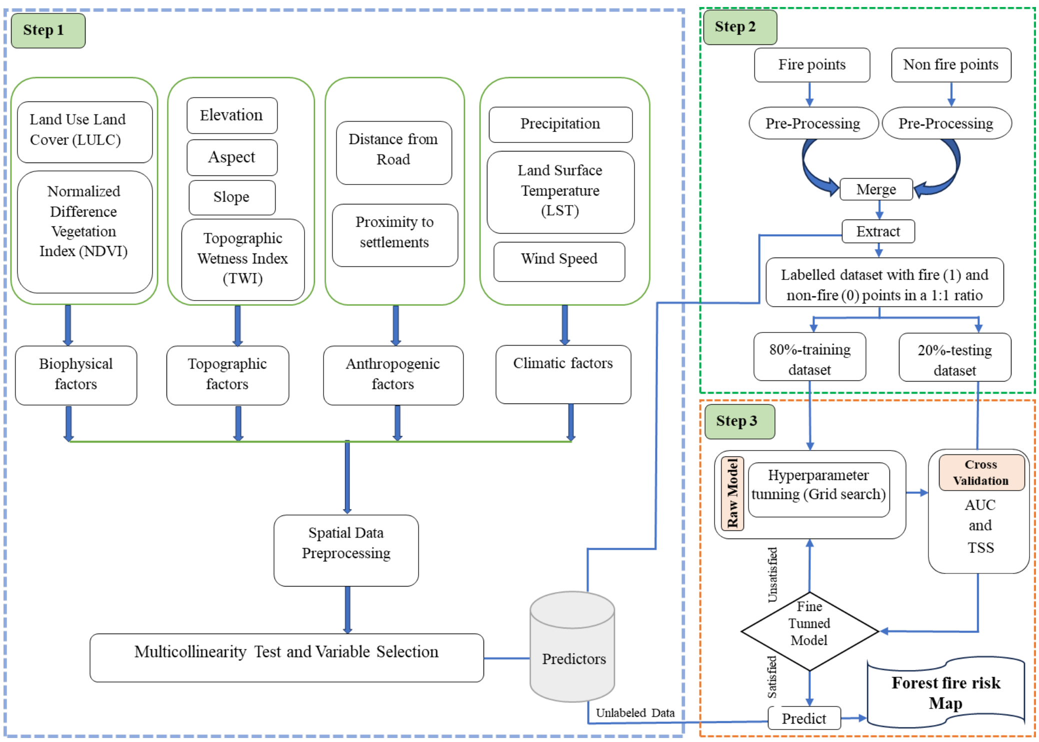

Figure 2: Overall methodological framework of the study

2.4 Multicollinearity test

When two or more predictor variables are strongly correlated, rather than independent, this is known as multicollinearity. This might result in a less accurate assessment of the impact of an independent variable on the dependent variable (Dormann et al., 2013). Therefore, a multicollinearity test was performed to examine the correlation among the predictors. This study applied the most frequently used metrics: variance inflation factor (VIF) to assess the extent of multicollinearity. A VIF above 10 suggests high multicollinearity, resulting in poorly estimated regression coefficients, and requires attention (Akinwande et al., 2015). Hence, only variables having a VIF ≤ 10 were taken into account for additional analysis.

2.5 Dataset configuration

The forest fire incidents, dependent variables, are divided into two classes: the occurrence (fire points) and non-occurrence (non-fire points). After spatial thinning, 757 forest fire incidents remain for model building. For accurate binary classification and to enhance the performance of machine learning, a supplementary dataset, i.e., non-fire points, was required (Tien Bui et al., 2017). In this study, non-fire incidents were generated randomly and intersected with fire incidents in a way that they do not overlap with fire incidents. Furthermore, the ratio of labelled fire (1) and non-fire (0) incidents was adjusted to 1:1. Ultimately, 1514 incidents were used for model building and configuration. These datasets were randomly grouped, where 80% was used as a training set for model training, while 20% was used

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

as a test set for model validation to avoid potential overfitting and for validating the predictive performance of the model with unseen data.

2.6 Model training and configuration

In the realm of predictive modeling, this study employed the Random Forest (RF) model using the 'random forest' package (Liaw and Wiener, 2002) in R (R Core Team, 2015). The Random Forest model, which leverages multiple decision trees for accurate prediction, robustness to noise and outliers, and reduces overfitting (Breiman, 2001).

In this study, key hyperparameters were tuned using a comprehensive grid search to enhance the predictive performance of the model: the number of decision trees (ntree), the minimum size of terminal nodes (node size), the number of variables randomly selected per split (mtry), and randomization. For each combination of search space, the RF model was trained and validated. This study aimed to identify the optimal parameter measured by AUC on the test dataset, a standard metric for evaluating the performance of binary classifiers (Fawcett, 2006), which was validated after each iteration. The best predictive performance of the model was identified by comparing AUC scores on each iteration. The model with the highest AUC, resulting from a specific hyperparameter combination, was chosen for further study.

2.7 Variable importance and partial dependency plots

Since numerous factors usually impact hazards. The RF model has assessed two important measures to examine the impact of different variables on the predictive performance of the model: the mean decrease in accuracy (MDA) and the mean decrease in Gini (MDG). This study assesses the variable importance using MDG, which calculates the aggregate decrease in Gini impurity, which is supplied by each variable across all the trees within the ensemble. Although MDG is computationally efficient and widely used, it might show a bias with variables with numerous categories or continuous data (Strobl et al., 2007). Despite this, it offers a useful summary of variable importance for the study's spatial classification system.

In addition to calculating variable importance, partial dependence plots (PDPs) were also calculated to complement the findings. This approach highlights the connection between individual features and outcomes, explicitly visualizing their effects on prediction results. A PDP illustrates the marginal impacts of one or more predictor variables on projected outcomes and is generated using the 'pdp' package in R (Greenwell, 2017).

2.8 Validation of the map

After generating a model, assessing its training and predictive effectiveness is crucial. To determine the prediction efficacy of these selected approaches, validation is imperative in assessing forest fire vulnerability (Jaafari et al., 2018). The model created for forest fire probability mapping was evaluated and compared employing receiver operating characteristics (ROC) and True skill Statistics (TSS). The ROC curve can be used as a numerical measure through the calculation of the area under the curve (AUC). The value of AUC is between 0.5 and 1.0, and a value closer to 1 indicates a model with a better predictive capability (Yesilnacar and Topal, 2005). Moreover, TSS is a widely used metric in ecological and spatial modeling because it compensates for the limitations of kappa while keeping all of its advantages, and it evaluates predictive reliability by considering positive and negative prediction rates, and a TSS value close to 1 indicates perfect agreement.(Allouche et al., 2006). After generating a reliable forest

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

fire risk model and following the risk assessment, the risk map was masked out with only the forest cover of the district for further analysis of risk area assessment and zonation. This step ensured that the risk analysis focused solely on areas that are susceptible to forest fires and hold ecological relevance.

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

3. Results

3.1 Multicollinearity Assessment

The initial step was to examine the relationship between the 11 predictive variables that influence fire ignition and spread before generating a reliable fire risk model. This study assessed variance inflation factors (VIF) for multicollinearity issues between predictors. However, one factor (i.e., precipitation) was found to have multicollinearity issues; thus, the factor was eliminated in the final modeling. Since the estimated values of VIF indicate no significant linear association among the remaining factors, the remaining 10 factors were included for model development.

3.2 Descriptive Analysis of Fire Incidents

The temporal analysis of fire incidences over the last 13 years reveals that approximately 91.86 % of cases occurred from January to April, indicating these as the highly fire-prone months (Figure. 3). April recorded 283 counts, the highest number of fire incidents, while the months from July to October recorded no fire instances in the past 13 years. Similarly, the annual fire statistics from 2012 to 2024 reveal a substantial decline in 2015 before increasing to more than 100 incidents in 2016. The escalated occurrences of 223 in 2023 from 24 in 2022 demonstrate the increasing trend of fires, especially in recent years. Overall, across 13 years, the Rasuwa District had a total of 835 fire incidents. Spatial analysis of fire incidents showed that forest fires occurred at of 4,525 m elevation. In addition to this, analysis indicated that nearly 30% of incidents occurred at elevations exceeding 3000 meters, demonstrating their occurrence even at high altitudes.

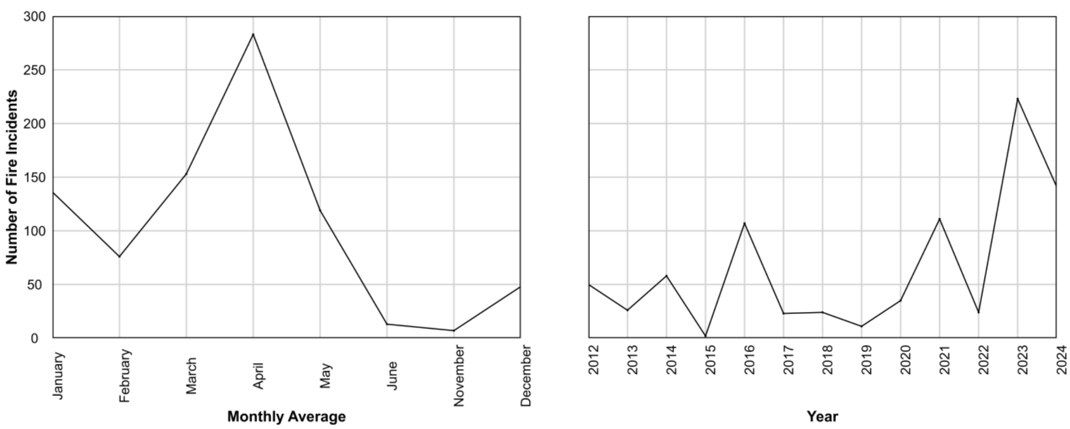

Figure 3: Fire incidents analysis for the year and the month in the Rasuwa district

3.3 Model Validation

The ROC curve implemented as a validation method in this study attains an AUC value of 0.90, indicating the reliability of the generated risk model in identifying vulnerable areas. The model achieved a True Skill Statistic (TSS) value of 0.67, which signifies its strong predictive performance with balanced capability in identifying both fire and non-fire areas.

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

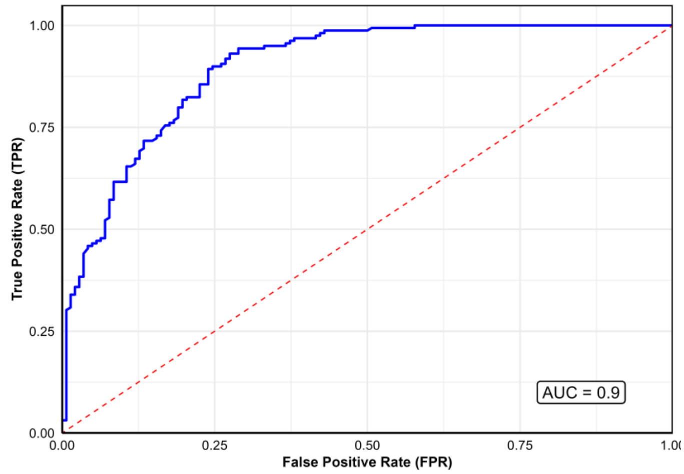

Figure 4: Receiver Operating Characteristic (ROC) and Area Under the Curve (AUC) values for the predictive models

3.4 Variable Importance Analysis

Elevation is the most significant factor in forest fire risk mapping, followed by land surface temperature and NDVI, and TWI is the least significant factor.

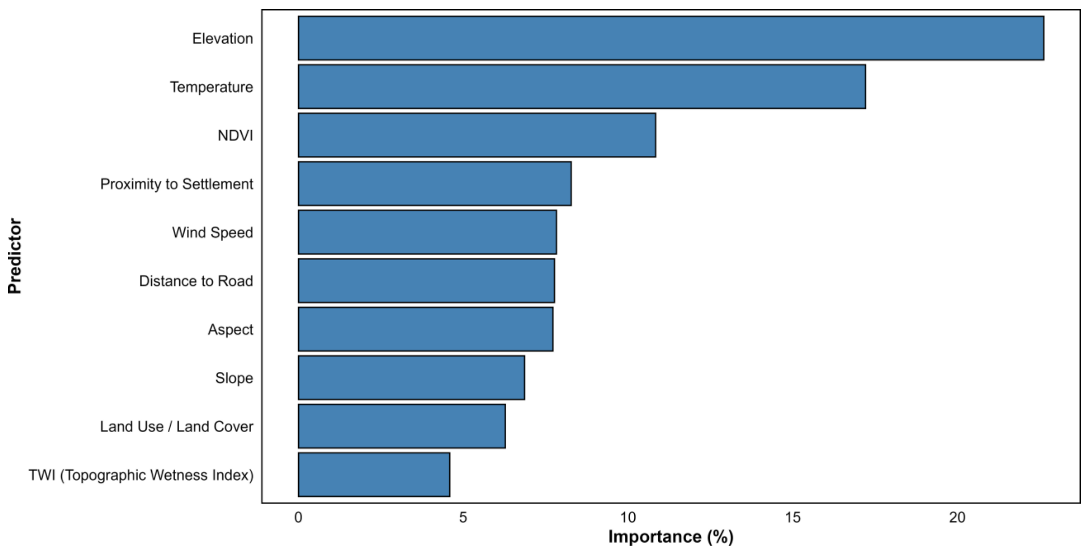

Figure 5: Variable importance generated by RF modeling

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

3.5 Partial Dependence Plots (PDPs)

Partial dependency plots (PDPs) illustrate the marginal effect of each predictor variable influencing the likelihood of forest fires on the expected probability of fires, while holding other variables constant.

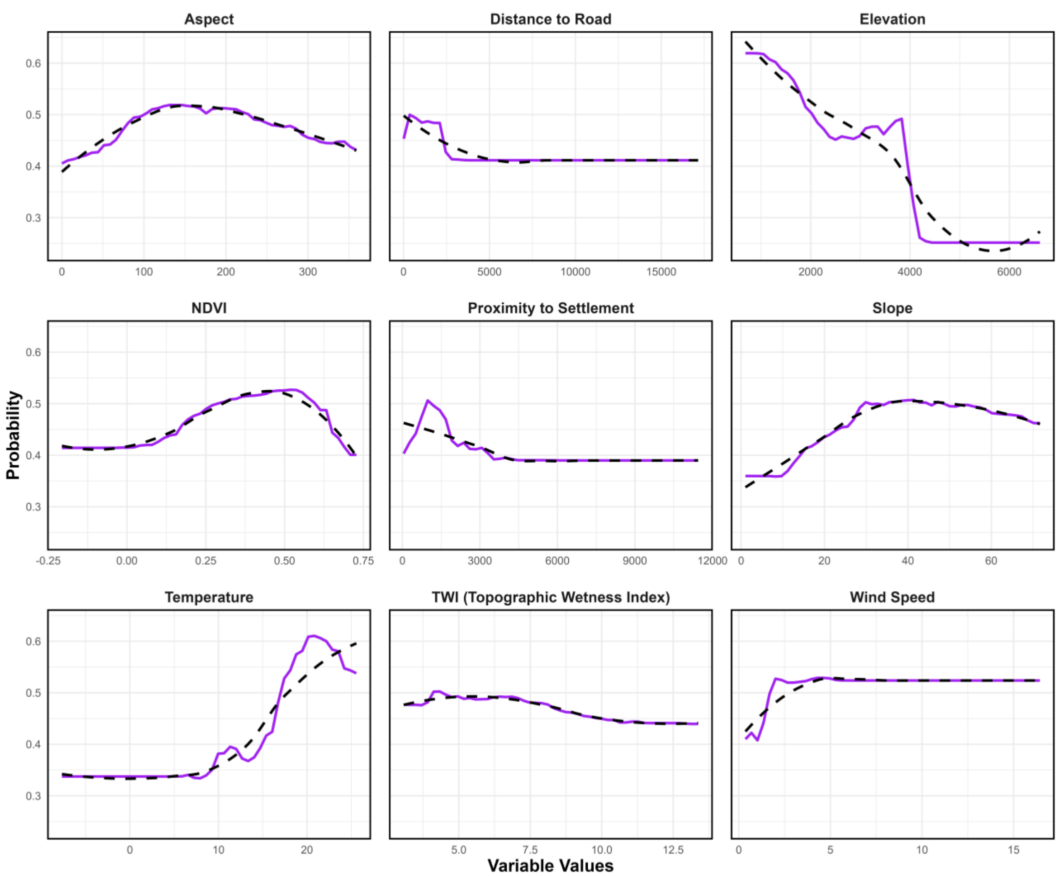

Figure 6: PDPs of forest fire conditioning factors

The risk of fire peaks between 100 (East-Southeast) and 200 degrees (South-Southwest) of aspect. Likewise, within 3000 meters of both settlements and roads, the fire risk is significant and stabilizes beyond that range. The risk of forest fire is most likely at lower elevations (from 1,000 to approximately 2,500 m), gradually diminishing as altitude increases. Conversely, the PDP largely shows a horizontal trend between 2,500 and 4,000 m elevation, with noticeable fluctuations. Moreover, the risk of fire is stabilizing around 4,200 meters. Similarly, NDVI values between 0.4 and 0.6 showed a high possibility of fire risk. The presence of flammable grass and shrubs, and conifer species that can be prone to catching fire at this range, indicates an environment where fires are a risk, especially during dry periods or in areas affected by human activities, such as farming or grazing. The risk of fire is minimal on lower slopes, while it is

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

highest on slopes ranging from 30 to 60 degrees; after that, it begins to decline slightly. Similarly, as the temperature rises, the likelihood of fire risk also increases, demonstrating a positive relationship between fire risk and temperature. At lower TWI levels, the likelihood of fire occurrences is higher and decreases as TWI increases, indicating the negative relationship between fire occurrences and TWI. Below 5 m/s, the probability of fire is at its peak; beyond this threshold, it stabilizes, showing the unusual association between fire and wind speed.

3.6 Forest Fire Risk Map (FFRM)

The forest fire risk map generated using the Random Forest model was categorized into five risk classes through the Natural Breaks classification method. The classification is based on the dispersal of the data, determining optimal natural gaps between the data by detecting an intrinsic pattern embedded within the data (Jenks, 1967). Based on fire risk assessment, 29.32% of the area is at High and Very High risk of forest fire. Moderate-risk areas, making up 23.62% of the region, are where fire is likely to occur occasionally. Meanwhile, regions with low or very low fire risk, consisting of 47.04% of the area, experience minimal fire susceptibility.

Table 2: Risk classes with their corresponding percentage contribution and area (in hectares) for the study region.

Risk Class	Percentage Covered (%)	Area (ha)
Very Low Risk	18.25	12,015.60
Low Risk	28.79	18,954.71
Medium	23.62	15,551.35
High	17.53	11,540.50
Very High	11.79	7,760.66

The risk map illustrates that the west side of Langtang National Park in Rasuwa district falls under the Very High and High-risk classes. The regions of the west side have low elevation, high LST, and difficult terrain that hinders controlling the fire, which are the probable reasons for falling into highly risky areas.

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

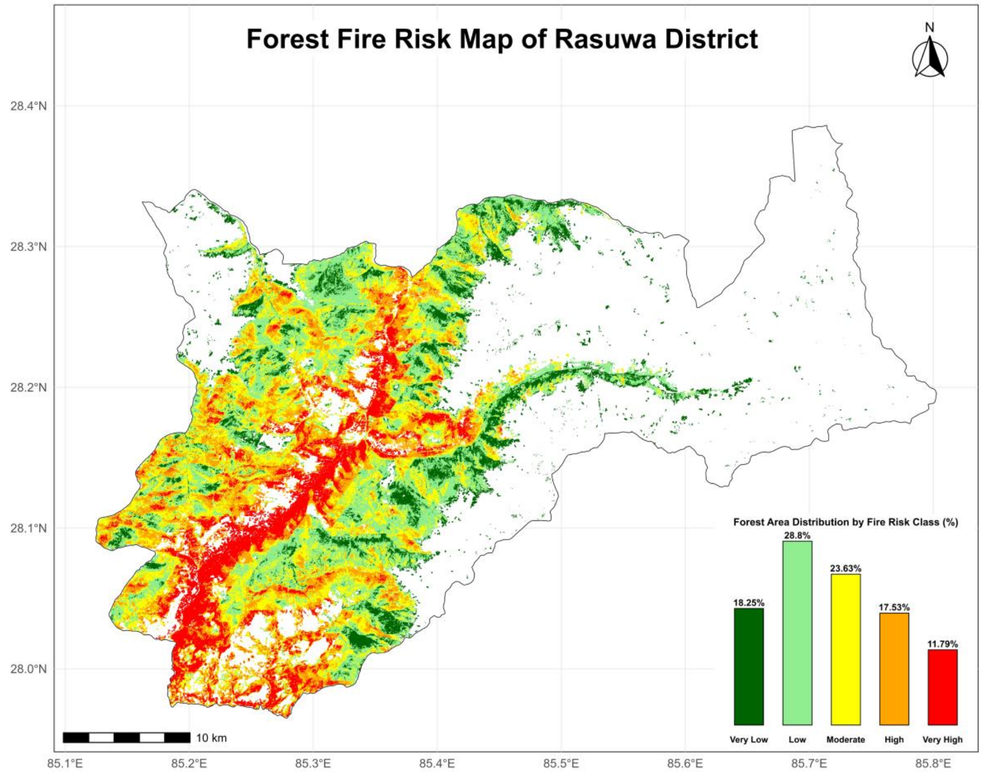

Figure 7: Forest fire risk map of Rasuwa district

3.7 Forest Fire Risk Zonation

The forest fire risk zonation revealed differences in risk areas among various local bodies. With a proportion of 59.4%, Kalika Rural Municipality had the highest proportion of high-risk areas, compared to Gosaikunda, which had the least at 20.2%. However, the highest risk areas were located in Gosainkunda Rural Municipality with 31,919 hectares, then Aamachhodingmo with 13,572 hectares, and Uttargaya with 9,483 hectares.

Table 3: Risk area distribution across local bodies

Local bodies	Total forest area (ha)	High and very high-risk Coverage (ha)	High Risk (Proportion %)
Uttargaya Rural Municipality	9,483	4,025	42.4
Aamachhodingmo Rural Municipality	13,572	4,443	32.7
Naukunda Rural Municipality	7,822	2,568	32.8
Kalika Rural Municipality	3,134	1,861	59.4
Gosaikunda Rural Municipality	31,919	6,435	20.2

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

4. DISCUSSION

This study integrated remote sensing, geospatial data, and the Random Forest (RF) algorithm to assess the vulnerability of forest fires, including 10 causative factors in the Rasuwa district of Nepal. Forest fires in high mountain regions cause deforestation and degradation, exacerbated by inaccessible mountainous terrain and a narrow time window of occurrence, thwarting suppression efforts (Baral et al., 2012; Sharples, 2009). Precise mapping of the risk of forest fires becomes critical for efficient forest management and conservation.

This study utilized VIIRS I-Band 375 m active fire data from NASA for a spatiotemporal analysis of forest fire incidents over 13 years, which provides a great response. The Moderate Resolution Imaging Spectroradiometer (MODIS) overlooks fires that the VIIRS can detect. The trend of fire incidents in the Rasuwa district is increasing, with significant spikes in 2016, 2021, and 2023, similar to the highest forest fire counts in the country. This study observed that forest fires occur most frequently between March and May, when Nepal experienced a prolonged drought with nearly six months of no precipitation and heavy fuel accumulation on the forest floor. This observation aligns with prior research, including (Dhakal et al., 2024; Matin et al., 2017; Parajuli et al., 2020). Furthermore, a higher number of fire incidents was also observed in January, which aligns with the findings of Mishra et al. (2023), who argued that a large portion of burnt areas at high elevations occurred from November to January. These winter fire incidents can be attributed to warm and dry winter conditions that reduce moisture levels in both the atmosphere and fuels (Negi and Kumar, 2016), along with human activities such as land clearing, agricultural and pasture land burning (Kunwar and Khaling, 2006) and tourism-related campfires at higher elevations.

The degree of influence of forest fire-causing factors may differ by the area and circumstances (Eskandari and Miesel, 2017). In this study, the RF model assigned the greatest importance to elevation, which aligns with the findings of Bar et al. (2022), conducted in the Western Himalayas, India. The PDP curve for elevation reveals a distinct nonlinear relationship with the fire risk probability. Initially, the fire risk showed a steady decline with an increase in elevation from lower altitudes to 2,500 meters. In this region, elevation governed fire risk through fuel availability (resinous litter of conifer species), temperature gradient, and anthropogenic activities, which set fire either deliberately or accidentally (Pragya et al., 2023). Conversely, the curve becomes comparatively stable and slightly fluctuates between 2,500m and 4000m, which indicates a moderate but consistent level of fire risk. Kumari et al. (2025) argued that this elevation range consists of subalpine forests, subalpine shrubland, or grasslands; in dry conditions, the vegetation can still facilitate the fire spread. Traditionally, the herders used seasonal vegetation burning and cattle rotation to maintain the pastoral landscape (Karki and McVeigh, 2000), which might be the sources of ignition. Notably, around 30% of fire incidents in the study area occurred above 3000m, highlighting that even high-altitude regions, traditionally considered as low-risk, can be susceptible. This highlights the necessity of including alpine and subalpine zones in fire risk assessments, where topographic and land-use complexities can create localized fire-prone environments. Following elevation, temperature received the highest importance score, indicating its significant impact. The observation agrees with the studies that conclude temperature and humidity have a greater impact on forest fires in higher-altitude areas (Hernández-Leal et al., 2008), where they accelerate fuel drying and fire ignition. Particularly, the temperature above 15°C had a strong positive impact, suggesting a higher risk of fire in warmer regions. NDVI is

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

a widely used metric for quantifying vegetation health and signifies fuel load (Jiang et al., 2006) and has received great importance after the elevation and LST. Areas with 0.4–0.6 NDVI values were identified as critical fire-prone zones, characterized by shrubs and semi-dense vegetation that offer adequate fuel loads and airflow conducive to ignition. This study found that needle-leaved open forests are the most prone to fire. With their high resin, low moisture content, and structural traits, coniferous trees make them highly flammable and cause rapid fire spread (Demir and Akay, 2024). Alongside vegetation and topographic factors, anthropogenic activities increase the prevalence of forest fires. The road network and settlements near the forest influence the forest fire risk, as more incidents were recorded near these areas. The findings of this study revealed a progressive decline in risk as the distance from roads and settlements increased, with the highest fire likelihood within 3,000 meters, suggesting a strong anthropogenic influence (Dhakal et al., 2024; Jaafari et al., 2018). The 30-60-degree slope showed the highest fire risks, and the above-60-degree slope exhibited the lowest. This pattern may be attributable to fuel availability and human accessibility; the steeper the slope becomes, the vegetation density decreases (Li et al., 2015); in addition, anthropogenic activities also decrease, reducing both ignition probability and fuel continuity. This finding of minimal fire probabilities in the highest slope class aligns with Kayet et al. (2020). Baltaci & Yildirim (2020) argued that, contrary to the generally accepted opinion, fire risk decreased with an increasing slope in certain locations. While slope affects the fire spread rates, vegetation on the southern aspect witnessed higher fire incidents in this study due to faster humidity loss and increased flammability from sunlight exposure in the northern hemisphere, corroborating the findings of Tomar et al. (2021). Wind speed directly affects the rate of spread until other limiting factors like fuel and terrain take over (Pimont et al., 2012). In this study, as wind speed increases beyond 4m/s, limiting factors such as fuel discontinuity, variation in moisture content, and other topographic influences may hinder the additional spread, which leads to an observed plateau in risk. Moreover, strong wind speed in high-elevation regions may not necessarily lead to more fire incidents if vegetation is sparse. The observation of the study highlights that the moderate wind speed in fuel-rich, human-influenced high elevation belts may show the most concerning combination of fire risk.

Frequent fires at higher altitudes are having a wider impact on mountain ecosystems. Forest fires are a major concern in the western part of Langtang National Park in Rasuwa District. Various studies and reports show the region's vulnerability, including a news report on a 25-hectare wildfire in the park (Margadarsannews, 2021). Notably, this study revealed that the areas up to 4,000 meters in altitude are prone to fire risk, further reinforcing that forest fires are becoming more common at higher elevations. The study conducted by Dhungana et al. (2024) highlighted fire occurrences in the high-elevation mixed conifer forest of Rasuwa, emphasizing their significant impact on the soil physicochemical properties and the need for understanding fire dynamics in vulnerable mountain ecosystems. A forest fire had severely affected the ecosystem in the Gatlang areas, and restoration efforts are currently underway. Additionally, the rising risk of wildfires in high-altitude areas could severely affect hydrological significance. For instance, the light-absorbing carbonaceous aerosols in wildfire smoke reduce snow's reflectivity (albedo) when deposited, leading to faster snowmelt (Bond et al., 2013). These findings underline the urgent need for action on climate change and wildfire management in vulnerable mountain ecosystems.

Our result highlights the imminent risk of forest fire in Rasuwa, with 29.32% of the area in high and very high risk. While the forest fire risk map generated by Parajuli et al. (2020) identifies Rasuwa district as part of a wider fire risk hotspot, particularly the southwest part. Our high-resolution map reveals a more complex pattern. Although the district is considered a hotspot, fire risk is highly inconsistent, with some areas showing low risk. Validation is imperative for communicating forest fire risk maps; users must feel confident in the information to act on it (Feizizadeh and Blaschke, 2014). The model demonstrated the strong predictive performance, as indicated by an AUC value of 0.90 and a TSS value of 0.67.

This study has some limitations. The Random Forest, although a powerful algorithm, operates as a black-box model since it does not assess regression coefficients or confidence intervals, limiting the clear understanding of its decision-making mechanisms (Cutler et al., 2007; Prasad et al., 2006). Thus, future research should use explainable AI techniques, such as SHapley Additive exPlanations (SHAP) values, to clarify individual variable importance and address interpretability challenges inherent in this algorithm (Talukdar et al., 2024). Additionally, the study's reliance on multiple, coarse-resolution datasets and the absence of ground-verified fire incident data may have compromised the spatial precision of the result. Future studies should integrate high-resolution data and ground truthing through field surveys or community-based participatory mapping for improved model accuracy and robust validation.

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

Conclusion

This study employed the combination of GIS and the RF using environmental, topographical, biophysical, and anthropogenic variables to comprehensively analyze forest fire risk in the Rasuwa district of Nepal. According to the study, 19301.16 hectares of Rasuwa district's forest are at risk of fire, with Kalika and Uttargaya Rural Municipality being a key vulnerable area. Given the strong performance of the model, the produced fire risk map offers reliability and an advantageous instrument for decision-making that could assist local government agencies, forest managers, and community stakeholders in enhancing ecosystem resilience and forest fire management. Our study demonstrated the efficacy of GIS and machine learning algorithms in forest fire risk assessment; however, the study had certain limitations. Further research could strengthen the methodology by incorporating fire causation factors, other explainable algorithms, and ensemble learning techniques to improve accuracy. Additionally, utilizing multi-source, high-resolution remote sensing data, including detailed socio-economic and vegetation-specific variables, and ground-truth validation would bolster the credibility and robustness of the findings at finer scales.

Code availability

All source code is shared on GitHub: https://github.com/dhklmilan/Forest_Fire_Risk_Modeling.git

Data availability statement

The data supporting the findings of this study are available upon reasonable request to the corresponding author, D. Milan.

Author contribution

SJK designed the study, conducted the investigation, curated and analyzed the data, prepared the original draft of the manuscript, and developed the visualizations. MD contributed to methodology development, software implementation, and project administration, and was responsible for rewriting, editing, and preparing the final version of the manuscript. AP supervised the research work, validated the findings, and contributed to reviewing and editing the manuscript.

Funding

No funding has been received by any of the authors for this work.

Competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. This research utilized publicly available datasets and climate models. The authors declare no competing interests.

Acknowledgments

The authors are thankful to the reviewer and all experts involved in the research. Special thanks to Milan Sapkota for the overview of forest fire incidents inside Langtang National Park, and we are very grateful to Sushank Pokhrel for reviewing the manuscript.

References:

Acharya, K. P., Dangi, R. B., and Acharya, M.: Understanding forest degradation in Nepal, Unasylva, 62, 238, 2011.

Adab, H., Kanniah, K. D., and Solaimani, K.: Modeling forest fire risk in the northeast of Iran using remote sensing and GIS techniques, Natural Hazards, 65, 1723–1743, https://doi.org/10.1007/s11069-012-0450-8, 2013.

Ajin, R., Loghin, A.-M., Vinod, P., and Jacob, M.: Forest Fire Risk Zone Mapping Using RS and GIS Techniques: A Study in Achankovil Forest Division, Kerala, India, Journal of Earth, Environment and Health Sciences, 2, 109, https://doi.org/10.4103/2423-7752.199288, 2016.

Akinwande, M. O., Dikko, H. G., and Samson, A.: Variance Inflation Factor: As a Condition for the Inclusion of Suppressor Variable(s) in Regression Analysis, Open J Stat, 05, 754–767, https://doi.org/10.4236/OJS.2015.57075, 2015.

Alizadeh, M. R., Abatzoglou, J. T., Luce, C. H., Adamowski, J. F., Farid, A., and Sadegh, M.: Warming enabled upslope advance in western US forest fires, ATMOSPHERIC, AND PLANETARY SCIENCES, 118, https://doi.org/10.1073/pnas.2009717118/-/DCSupplemental, 2021.

Allouche, O., Tsoar, A., and Kadmon, R.: Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS), Journal of Applied Ecology, 43, 1223–1232, https://doi.org/10.1111/J.1365-2664.2006.01214.X, 2006.

Artés, T., Cencerrado, A., Cortés, A., and Margalef, T.: Time aware genetic algorithm for forest fire propagation prediction: exploiting multi-core platforms, Concurr Comput, 29, https://doi.org/10.1002/CPE.3837, 2017.

Baltaci, U. and Yildirim, F.: Effect of Slope on the Analysis of Forest Fire Risk, Hacettepe Journal of Biology and Chemistry, 48, 373–379, https://doi.org/10.15671/hjbc.753080, 2020.

Bar, S., Ranjan Parida, B., Pandey, A. C., Uma Shankar, B., Kumar, P., Panda, S. K., and Behera, M. D.: Title Page Modeling and prediction of fire occurrences along an elevational gradient in Western Himalayas, 2022.

Bar, S., Parida, B. R., Pandey, A. C., Shankar, B. U., Kumar, P., Panda, S. K., and Behera, M. D.: Modeling and prediction of fire occurrences along an elevational gradient in Western Himalayas, Applied Geography, 151, 102867, https://doi.org/10.1016/J.APGEOG.2022.102867, 2023.

Baral, N. R., Acharya, D. P., and Rana, C. J.: Study on drivers of deforestation and degradation of forests in high mountain regions of Nepal, REDD Cell, Ministry of Forest and Soil Conservation, Nepal, 2012.

Bond, T. C., Doherty, S. J., Fahey, D. W., Forster, P. M., Berntsen, T., Deangelo, B. J., Flanner, M. G., Ghan, S., Kärcher, B., Koch, D., Kinne, S., Kondo, Y., Quinn, P. K., Sarofim, M. C., Schultz, M. G., Schulz, M., Venkataraman, C., Zhang, H., Zhang, S., Bellouin, N., Guttikunda, S. K., Hopke, P. K., Jacobson, M. Z., Kaiser, J. W., Klimont, Z., Lohmann, U., Schwarz, J. P., Shindell, D., Storelvmo, T., Warren, S. G., and Zender, C. S.: Bounding the role of black

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

carbon in the climate system: A scientific assessment, Journal of Geophysical Research: Atmospheres, 118, 5380–5552, https://doi.org/10.1002/JGRD.50171, 2013.

Boria, R. A., Olson, L. E., Goodman, S. M., and Anderson, R. P.: Spatial filtering to reduce sampling bias can improve the performance of ecological niche models, Ecol Modell, 275, 73–77, https://doi.org/10.1016/J.ECOLMODEL.2013.12.012, 2014.

Breiman, L.: Random forests, Mach Learn, 45, 5–32, 2001.

Carter, V. A., Power, M. J., Lundeen, Z. J., Morris, J. L., Petersen, K. L., Brunelle, A., Anderson, R. S., Shinker, J. J., Turney, L., Koll, R., and Bartlein, P. J.: A 1,500-year synthesis of wildfire activity stratified by elevation from the U.S. Rocky Mountains, Quaternary International, 488, 107–119, https://doi.org/10.1016/J.QUAINT.2017.06.051, 2018.

Chuvieco, E. and Congalton, R. G.: Application of Remote Sensing and Geographic Information Systems to Forest Fire Hazard Mapping, 147–159 pp., 1989.

Cutler, D. R., Edwards, T. C., Beard, K. H., Cutler, A., Hess, K. T., Gibson, J., and Lawler, J. J.: Random forests for classification in ecology, Wiley Online LibraryDR Cutler, TC Edwards Jr, KH Beard, A Cutler, KT Hess, J Gibson, JJ LawlerEcology, 2007•Wiley Online Library, 88, 2783–2792, https://doi.org/10.1890/07-0539.1, 2007.

Demir, A. and Akay, A. E.: Forest Fire Risk Mapping Using GIS Based Analytical Hierarchy Process Approach, European Journal of Forest Engineering, 10, 15–28, https://doi.org/10.33904/EJFE.1400233, 2024.

Dhakal, M., Bhatta, B., Lamichhane, P., and Parajuli, A.: Synergistic approaches in forest fire risk mapping using fuzzy AHP and machine learning models in the Chure Tarai Madhesh Landscape (CTML) of Nepal, Geomatics, Natural Hazards and Risk, 15, https://doi.org/10.1080/19475705.2024.2436540, 2024.

Dhungana, B. P., Chhetri, V. T., Baniya, C. B., Sharma, S. P., Ghimire, P., and Vista, S. P.: Post-fire Effects on Soil Properties in High altitude Mixed-conifer Forest of Nepal, Trees, Forests and People, 17, 100633, https://doi.org/10.1016/J.TFP.2024.100633, 2024.

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J. R. G., Gruber, B., Lafourcade, B., Leitão, P. J., Münkemüller, T., Mcclean, C., Osborne, P. E., Reineking, B., Schröder, B., Skidmore, A. K., Zurell, D., and Lautenbach, S.: Collinearity: a review of methods to deal with it and a simulation study evaluating their performance, Ecography, 36, 27–46, https://doi.org/10.1111/J.1600-0587.2012.07348.X, 2013.

Elith, J., Leathwick, J. R., and Hastie, T.: A working guide to boosted regression trees, Journal of animal ecology, 77, 802–813, 2008.

Erten, E., Kurgun, V., and Musaoglu, N.: Forest fire risk zone mapping from satellite imagery and GIS: a case study, in: XXth Congress of the International Society for Photogrammetry and Remote Sensing, Istanbul, Turkey, 222–230, 2004.

Eskandari, S. and Miesel, J. R.: Comparison of the fuzzy AHP method, the spatial correlation method, and the Dong model to predict the fire high-risk areas in Hyrcanian forests of Iran, Geomatics, Natural Hazards and Risk, 8, 933–949, https://doi.org/10.1080/19475705.2017.1289249, 2017.

Falkowski, M. J., Gessler, P. E., Morgan, P., Hudak, A. T., and Smith, A. M. S.: Characterizing and mapping forest fire fuels using ASTER imagery and gradient modeling, For Ecol Manage, 217, 129–146, https://doi.org/10.1016/j.foreco.2005.06.013, 2005.

Fawcett, T.: An introduction to ROC analysis, Pattern Recognit Lett, 27, 861–874, https://doi.org/10.1016/J.PATREC.2005.10.010, 2006.

Feizizadeh, B. and Blaschke, T.: An uncertainty and sensitivity analysis approach for GIS-based multicriteria landslide susceptibility mapping, International Journal of Geographical Information Science, 28, 610–638, https://doi.org/10.1080/13658816.2013.869821, 2014.

FRTC: National Land Cover Monitoring System of Nepal., 2024.

Giglio, L., Randerson, J. T., and Van Der Werf, G. R.: Analysis of daily, monthly, and annual burned area using the fourth-generation global fire emissions database (GFED4), J Geophys Res Biogeosci, 118, 317–328, https://doi.org/10.1002/JGRG.20042, 2013.

Giglio, L., Schroeder, W., and Justice, C. O.: The collection 6 MODIS active fire detection algorithm and fire products, Remote Sens Environ, 178, 31–41, https://doi.org/10.1016/J.RSE.2016.02.054, 2016.

Giglio, L., Boschetti, L., Roy, D. P., Humber, M. L., and Justice, C. O.: The Collection 6 MODIS burned area mapping algorithm and product, Remote Sens Environ, 217, 72–85, https://doi.org/10.1016/J.RSE.2018.08.005, 2018.

Greenwell, B. M.: pdp: An R package for constructing partial dependence plots, 2017.

Hernández-Leal, P. A., González-Calvo, A., Arbelo, M., Barreto, A., and Alonso-Benito, A.: Synergy of GIS and remote sensing data in forest fire danger modeling, IEEE J Sel Top Appl Earth Obs Remote Sens, 1, 240–247, https://doi.org/10.1109/JSTARS.2008.2009043, 2008.

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., and Jarvis, A.: Very high resolution interpolated climate surfaces for global land areas, International Journal of Climatology, 25, 1965–1978, https://doi.org/10.1002/JOC.1276, 2005.

Jaafari, A., Zenner, E. K., and Pham, B. T.: Wildfire spatial pattern analysis in the Zagros Mountains, Iran: A comparative study of decision tree based classifiers, Ecol Inform, 43, 200–211, https://doi.org/10.1016/j.ecoinf.2017.12.006, 2018.

Jaiswal, R., Mukherjee, S., Raju, K. D., and Saxena, R.: Forest fire risk zone mapping from satellite imagery and GIS, International Journal of Applied Earth Observation and Geoinformation, 4, 1–10, 2002.

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

Jenks, G. F.: The data model concept in statistical mapping, International yearbook of cartography, 7, 186–190, 1967.

Jiang, Z., Huete, A. R., Chen, J., Chen, Y., Li, J., Yan, G., and Zhang, X.: Analysis of NDVI and scaled difference vegetation index retrievals of vegetation fraction, Remote Sens Environ, 101, 366–378, https://doi.org/10.1016/J.RSE.2006.01.003, 2006.

Jung, J., Kim, C., Jayakumar, S., Kim, S., Han, S., Kim, D. H., and Heo, J.: Forest fire risk mapping of Kolli Hills, India, considering subjectivity and inconsistency issues, Natural Hazards, 65, 2129–2146, https://doi.org/10.1007/s11069-012-0465-1, 2013.

Kanga, S., Tripathi, G., and Singh, S. K.: Forest fire hazards vulnerability and risk assessment in Bhajji forest range of Himachal Pradesh (India): a geospatial approach, Journal of Remote Sensing & GIS, 8, 1–16, 2017.

Karki, J. and McVeigh, C.: Status Paper of Langtang National Park, Grassland Ecology and Management in Protected Areas of Nepal. Technical and Status Papers on Grasslands for Mountain Protected Areas, 3, 121–132, 2000.

Kayet, N., Chakrabarty, A., Pathak, K., Sahoo, S., Dutta, T., and Hatai, B. K.: Comparative analysis of multi-criteria probabilistic FR and AHP models for forest fire risk (FFR) mapping in Melghat Tiger Reserve (MTR) forest, J For Res (Harbin), 31, 565–579, https://doi.org/10.1007/s11676-018-0826-z, 2020.

Kumari, S., Mamgain, S., Roy, A., and Prince, H. C.: Characterising spatial clusters of forest fire activity in the Western Himalayan region of India: implications for conservation and management, Int J Wildland Fire, 34, 1–13, https://doi.org/10.1071/WF23163, 2025.

Kunwar and Khaling: Forest fire in the Terai, Nepal: causes and community management interventions, International Forest Fire News, 34, 46–54, 2006.

Lamprecht, A., Semenchuk, P. R., Steinbauer, K., Winkler, M., and Pauli, H.: Climate change leads to accelerated transformation of high-elevation vegetation in the central Alps, New Phytologist, 220, 447–459, https://doi.org/10.1111/NPH.15290, 2018.

Li, J., Liu, Y., Cao, M., and Xue, B.: Space-Time Characteristics of Vegetation Cover and Distribution: Case of the Henan Province in China, Sustainability 2015, Vol. 7, Pages 11967-11979, 7, 11967–11979, https://doi.org/10.3390/SU70911967, 2015.

Liaw, A. and Wiener, M.: Classification and Regression by randomForest, 2, 2002.

Lizundia-Loiola, J., Otón, G., Ramo, R., and Chuvieco, E.: A spatio-temporal active-fire clustering approach for global burned area mapping at 250 m from MODIS data, Remote Sens Environ, 236, 111493, https://doi.org/10.1016/J.RSE.2019.111493, 2020.

Malczewski, J.: On the Use of Weighted Linear Combination Method in GIS: Common and Best Practice Approaches, Transactions in GIS, 4, 5–22, https://doi.org/10.1111/1467-9671.00035, 2000.

https://doi.org/10.5194/egusphere-2025-2492
Preprint. Discussion started: 5 June 2025

Margadarsannews: 25 hectares forest affected by fire in Langtang National park., , 16th April, 2021.

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

Mishra, B., Panthi, S., Poudel, S., and Ghimire, B. R.: Forest fire pattern and vulnerability mapping using deep learning in Nepal, Fire Ecology, 19, https://doi.org/10.1186/s42408-022-00162-3, 2023.

Negi, M. S. and Kumar, A.: Assessment of increasing threat of forest fires in Uttarakhand, using remote sensing and GIS techniques, Global Journal of Advanced Research, 3, 457–468, 2016.

Noss, R. F., Franklin, J. F., Baker, W. L., Schoennagel, T., and Moyle, P. B.: Managing fire-prone forests in the western United States, Front Ecol Environ, 4, 481–487, 2006.

Settlements in Nepal | Humanitarian Dataset | HDX: https://data.humdata.org/dataset/settlements-in-nepal, last access: 20 September 2024.

Odum, E. P. and Barrett, G. W.: Fundamentals of Ecology. 5th Edition, 2004.

Nepal Roads (OpenStreetMap Export).: https://data.humdata.org/dataset/hotosm_npl_roads, last access: 18 September 2024.

Paine, R. T., Tegner, M. J., and Johnson, E. A.: Compounded perturbations yield ecological surprises, Ecosystems, 1, 535–545, https://doi.org/10.1007/S100219900049/METRICS, 1998.

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

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

Paudel, A., Markwith, S. H., Konchar, K., Shrestha, M., and Ghimire, S. K.: Anthropogenic fire, vegetation structure and ethnobotanical uses in an alpine shrubland of Nepal's Himalaya, Int J Wildland Fire, 29, 201–214, https://doi.org/10.1071/WF19098, 2020.

Pepin, N. C., Arnone, E., Gobiet, A., Haslinger, K., Kotlarski, S., Notarnicola, C., Palazzi, E., Seibert, P., Serafin, S., Schöner, W., Terzago, S., Thornton, J. M., Vuille, M., and Adler, C.: Climate Changes and Their Elevational Patterns in the Mountains of the World, Reviews of Geophysics, 60, https://doi.org/10.1029/2020RG000730, 2022.

Pimont, F., Dupuy, J. L., and Linn, R. R.: Coupled slope and wind effects on fire spread with influences of fire size: a numerical study using FIRETEC, Int J Wildland Fire, 21, 828–842, https://doi.org/10.1071/WF11122, 2012.

Poudel, S., Funakawa, S., Shinjo, H., and Mishra, B.: Understanding households' livelihood vulnerability to climate change in the Lamjung district of Nepal, Environ Dev Sustain, 22, 8159–8182, https://doi.org/10.1007/S10668-019-00566-3/METRICS, 2020.

Pragya, Kumar, M., Tiwari, A., Majid, S. I., Bhadwal, S., Sahu, N., Verma, N. K., Tripathi, D. K., and Avtar, R.: Integrated Spatial Analysis of Forest Fire Susceptibility in the Indian Western Himalayas (IWH) Using Remote Sensing and GIS-Based Fuzzy AHP Approach, Remote Sensing 2023, Vol. 15, Page 4701, 15, 4701, https://doi.org/10.3390/RS15194701, 2023.

Prasad, A., Iverson, L., Ecosystems, A. L.-, and 2006, undefined: Newer classification and regression tree techniques: bagging and random forests for ecological prediction, SpringerAM Prasad, LR Iverson, A LiawEcosystems, 2006•Springer, 9, 181–199, https://doi.org/10.1007/s10021-005-0054-1, 2006.

R Core Team: RStudio: Integrated Development for R. RStudio, Inc., Boston, MA, 2015.

Rayamajhi, N. and Manandhar, B.: Impact of Climate Change and Adaptation Measures on Transhumance Herding System in Gatlang, Rasuwa, Air, Soil and Water Research, 13, https://doi.org/10.1177/1178622120951173, 2020.

Reddy, C. S., Bird, N. G., Sreelakshmi, S., Manikandan, T. M., Asra, M., Krishna, P. H., Jha, C. S., Rao, P. V. N., and Diwakar, P. G.: Identification and characterization of spatio-temporal hotspots of forest fires in South Asia, Environ Monit Assess, 191, 1–17, https://doi.org/10.1007/S10661-019-7695-6/METRICS, 2019.

Sharples, J. J.: An overview of mountain meteorological effects relevant to fire behaviour and bushfire risk, Int J Wildland Fire, 18, 737–754, https://doi.org/10.1071/WF08041, 2009.

Shi, C. and Zhang, F.: A Forest Fire Susceptibility Modeling Approach Based on Integration Machine Learning Algorithm, Forests, 14, https://doi.org/10.3390/f14071506, 2023.

Shrestha, K. B., Chhetri, P. K., and Bista, R.: Growth responses of Abies spectabilis to climate variations along an elevational gradient in Langtang National Park in the central Himalaya, Nepal, Journal of Forest Research, 22, 274–281, https://doi.org/10.1080/13416979.2017.1351508, 2017.

Strobl, C., Boulesteix, A. L., Zeileis, A., and Hothorn, T.: Bias in random forest variable importance measures: Illustrations, sources and a solution, BMC Bioinformatics, 8, 1–21, https://doi.org/10.1186/1471-2105-8-25/FIGURES/11, 2007.

Talukdar, S., Shahfahad, Bera, S., Naikoo, M. W., Ramana, G. V., Mallik, S., Kumar, P. A., and Rahman, A.: Optimisation and interpretation of machine and deep learning models for improved water quality management in Lake Loktak, J Environ Manage, 351, 119866, https://doi.org/10.1016/J.JENVMAN.2023.119866, 2024.

Tamang, D. D. and Udas, P. B.: Climate change, gendered vulnerabilities and resilience in high mountain communities: The case of Upper Rasuwa in Gandaki River Basin, Hindu Kush Himalayas, in: Engendering Climate Change, Routledge India, 106–124, 2021.

Tariq, A., Shu, H., Siddiqui, S., Munir, I., Sharifi, A., Li, Q., and Lu, L.: Spatio-temporal analysis of forest fire events in the Margalla Hills, Islamabad, Pakistan using socio-economic and environmental variable data with machine learning methods, J For Res (Harbin), 33, 183–194, https://doi.org/10.1007/S11676-021-01354-4/METRICS, 2022.

Thakuri, S., Dahal, S., Shrestha, D., Guyennon, N., Romano, E., Colombo, N., and Salerno, F.: Elevation-dependent warming of maximum air temperature in Nepal during 1976–2015, Atmos Res, 228, 261–269, https://doi.org/10.1016/j.atmosres.2019.06.006, 2019.

Tien Bui, D., Bui, Q. T., Nguyen, Q. P., Pradhan, B., Nampak, H., and Trinh, P. T.: A hybrid artificial intelligence approach using GIS-based neural-fuzzy inference system and particle swarm optimization for forest fire susceptibility modeling at a tropical area, Agric For Meteorol, 233, 32–44, https://doi.org/10.1016/J.AGRFORMET.2016.11.002, 2017.

Tiwari, A., Shoab, M., and Dixit, A.: 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, 1189–1230, https://doi.org/10.1007/s11069-020-04351-8, 2021.

Tomar, J. S., Kranjčić, N., Đurin, B., Kanga, S., and Singh, S. K.: Forest fire hazards vulnerability and risk assessment in Sirmaur district forest of Himachal Pradesh (India): A geospatial approach, ISPRS Int J Geoinf, 10, 447, 2021.

Viviroli, D., Dürr, H. H., Messerli, B., Meybeck, M., and Weingartner, R.: Mountains of the world, water towers for humanity: Typology, mapping, and global significance, Water Resour Res, 43, https://doi.org/10.1029/2006WR005653, 2007.

Wang, X., Zhang, Y., Luo, M., Xiao, K., Wang, Q., Tian, Y., Qiu, W., Xiong, Y., Zheng, C., and Li, H.: Radium and nitrogen isotopes tracing fluxes and sources of submarine groundwater discharge driven nitrate in an urbanized coastal area, Science of the Total Environment, 763, 144616, 2021.

Wester, P., Mishra, A., Mukherji, A., and Shrestha, A. B.: The Hindu Kush Himalaya assessment: mountains, climate change, sustainability and people, Springer Nature, 2019.

Xie, L., Zhang, R., Zhan, J., Li, S., Shama, A., Zhan, R., Wang, T., Lv, J., Bao, X., and Wu, R.: Wildfire Risk Assessment in Liangshan Prefecture, China Based on An Integration Machine Learning Algorithm, Remote Sens (Basel), 14, https://doi.org/10.3390/rs14184592, 2022.

Yesilnacar, E. and Topal, T.: Landslide susceptibility mapping: A comparison of logistic regression and neural networks methods in a medium scale study, Hendek region (Turkey), Eng Geol, 79, 251–266, https://doi.org/10.1016/J.ENGGEO.2005.02.002, 2005.

Yong, B., Ren, L.-L., Hong, Y., Gourley, J. J., Chen, X., Zhang, Y.-J., Yang, X.-L., Zhang, Z.-X., and Wang, W.-G.: A novel multiple flow direction algorithm for computing the topographic wetness index, Hydrology research, 43, 135–145, 2012.