Assessing Forest Fire Susceptibility in the Hindu Kush Himalaya: Implications for Biodiversity and Carbon Stock

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Abstract: The Hindu Kush Himalaya (HKH) is a globally significant biodiversity hotspot, with extensive forests, protected areas (PAs) and substantial carbon reserves. However, increasing frequency and intensity of forest fires threaten its ecological integrity. Despite these concerns, there is a lack of comprehensive spatial assessment of forest fire susceptibility, necessitating a data-driven approach to evaluate environmental risks. This study evaluates forest fire susceptibility and its impact on biodiversity and carbon stocks across the HKH region using remote sensing and machine learning models. The models include Analytic Hierarchy Process, Certainty Factor, Maximum Entropy, and Random Forest (RF), based on thirteen ignition factors, representing environmental, meteorological, edaphic, socio-economic, and topographic factors. Active fire data from MODIS and VIIRS was used for training and testing of models. Model performance, evaluated using Area Under Curve (AUC) of Receiver Operating Characteristic curve, showed that RF (AUC = 0.95) outperformed other models. Results indicate that about 13.54–20.47% of HKH forested region is highly susceptible to forest fires, with higher risk in Himalayan belt, Bangladesh, and Myanmar. Key factors influencing fire risk include wind speed, solar radiation, elevation, and precipitation. Forest fires threaten biodiversity, with around 25,878.66 sq. km of PAs identified as highly vulnerable. Additionally, fire-induced carbon emissions from aboveground biomass, estimated at 32.22 million Mg, jeopardize carbon stocks by depleting stored carbon and increase atmospheric CO_2 levels. Forest fire susceptibility maps and risk assessments provide essential spatial insights for policymakers, supporting proactive fire mitigation, biodiversity conservation efforts, and carbon management.

Keywords: Hindu Kush Himalaya, Forest fire susceptibility, Random forest, Biodiversity, Carbon stock risk, Protected areas

1. Introduction

The Hindu Kush Himalaya (HKH) is a critical biodiversity hotspot encompassing the Himalaya, Indo-Burma, and the mountain ranges of southwest China and Central Asia (Thapa et al. 2021). This region sustains diverse flora and fauna, safeguarded within an extensive network of protected areas (PAs), including national parks, wildlife sanctuaries, and conservation areas, which play a crucial role in preserving global biodiversity and maintaining ecological stability. Along with these, the HKH region also acts as a vital carbon stock, helping to mitigate climate change by storing substantial amounts of carbon (Thapa et al. 2021). However, the rising frequency of forest fires threatens this fragile ecosystem, endangering biodiversity by altering habitats, reducing species richness, and disrupting ecological processes, and accelerating carbon emissions. Despite the region's ecological significance and the rising prevalence of forest fires, comprehensive spatial assessments of forest fire susceptibility, as well as evaluations of risks to biodiversity and carbon stock, remain limited (Dixon et al. 1994).

The fire regimes of the HKH region vary significantly across its diverse landscapes, influenced by both climatic and anthropogenic factors (Singh and Singh, 2025). According to the IPCC AR6 Report and other related studies, these climatic shifts have intensified fire risks across the region, with prolonged droughts and rising temperatures contributing to increased fire occurrences (Allan et al. 2021; Thapa et al. 2021). Additionally, human-induced activities such as shifting cultivation, illegal logging, and forest encroachment further exacerbate fire vulnerability, particularly in fire-prone landscapes (Puri et al. 2011). In the Western Himalaya, frequent forest fires are driven by high fuel loads and low moisture content (Rathore et al. 2019), while in northeast India, shifting cultivation remains a primary factor (Puri et al. 2011). Between 2003 and 2017, India alone recorded 520,861 active forest fires, with the eastern Himalayas being the most affected region (Sannigrahi et al. 2020). Moreover, the transboundary nature of many fires, particularly in Tibet, Sikkim, Bhutan, and northern Nepal, complicates mitigation efforts (Schmidt-Vogt, 1990). These fires not only disrupt ecosystems and biodiversity but also accelerate carbon emissions, threatening the region's role as a critical carbon stock.

With the rapid advancement of geospatial technologies, remote sensing and machine learning techniques have become indispensable tools for monitoring and predicting forest fire occurrences. Satellite-based fire detection systems such as MODIS (Moderate Resolution Imaging Spectroradiometer), VIIRS (Visible Infrared Imaging

Radiometer Suite), and Landsat provide crucial datasets for mapping active fires, assessing post-fire impacts, and modeling fire risk zones. Various studies have employed statistical and machine learning approaches to predict fire susceptibility across different geographical regions. For instance, Frequency Ratio (FR) and Analytic Hierarchy Process (AHP) have been widely used to assess fire vulnerability in Bhutan (Tshering et al. 2020), while Shome et al. (2025) predicted forest fire susceptibility in the Sikkim Himalayan forests using machine learning and deep learning (Rprop + algorithm) frameworks. In the HKH region, studies by Gupta et al. (2020) and Thapa et al. (2021) emphasize the critical role of anthropogenic activities in influencing fire frequency, highlighting the need to integrate socio-economic factors into fire prediction models.

Despite numerous studies on forest fire risk assessment, critical gaps persist in understanding and predicting forest fires in the HKH region. One of the major limitation is lack of comprehensive forest fire susceptibility studies using a consistent methodology for the entire HKH region, resulting in fragmented assessments that fail to capture its heterogeneous landscape and diverse fire dynamics (Bhattarai et al. 2022). Moreover, the reliance on coarse-resolution datasets often fail to capture localized fire dynamics in the region's rugged mountainous terrain. Another significant gap is the limited research regarding the impact of forest fires on biodiversity and carbon stocks in the HKH region, limiting our ability to evaluate threats to biodiversity and ecosystem stability. Moreover, understanding fire-induced carbon loss is essential for assessing its contributions to global carbon cycles. Conserving the HKH's biodiversity and carbon stock requires an integrated approach that combines fire susceptibility analysis with effective fire risk mitigation strategies.

Addressing these gaps requires an interdisciplinary approach that integrates geospatial analysis and machine learning to develop a more holistic understanding of forest fire susceptibility, and risk to PAs and carbon stock in the HKH region. This study models forest fire susceptibility using four statistical and machine learning algorithms, namely, AHP, Certainty Factor (CF), Maximum Entropy (Maxent), and RF with multi-source geospatial data. Additionally, the study assesses the risk to PAs and carbon stock due to forest fire. Given the region's complex topography and diverse climatic conditions, comprehensive spatial assessments are essential to develop effective fire management strategies. The study aims to bridge existing research gaps and provide a scientific basis for improved forest fire management in the HKH region. The findings will offer valuable insights for policymakers, conservationists, and land managers, supporting efforts to mitigate fire risks and preserve the region's biodiversity and ecological integrity.

2. Study Area

The study area includes the HKH region located in Southern Asia, encompassing parts of Afghanistan, Pakistan, India, Bhutan, China, Nepal, Myanmar, and Bangladesh (Figure: 1). This geo-ecological area, spanning approximately 4.3 million km² between 16º to 40º N latitudes and 61º to 105º E longitudes, is highly vulnerable to climate change and global warming, which has increased forest fire risks (You et al. 2017). The region encompasses diverse climatic zones, ranging from arid and semi-arid conditions in the west to monsoon-dominated regions in the east, with extreme temperature variations influenced by altitude and seasonal shifts. The HKH is a global biodiversity hotspot, supporting a rich diversity of flora and fauna, including numerous endemic and endangered species such as the snow leopard, red panda, and Himalayan musk deer, thriving across its diverse ecosystems. Its forests, ranging from subtropical and temperate woodlands to alpine ecosystems, serve as crucial habitats for biodiversity and function as key carbon stocks.

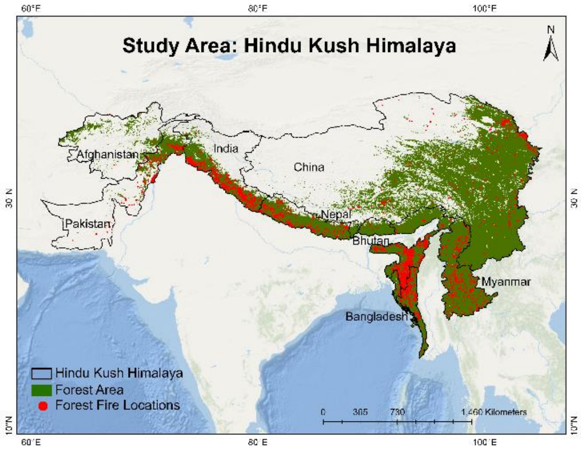

Figure 1: Study Area Map with the Distribution of Forest Fire Locations (Feb-June, 2024)

3. Material and Methods

3.1 Dataset Used

The fire locations are acquired from the MODIS (Moderate-Resolution Imaging Spectro Radiometer) and VIIRS (Visible Infrared Imaging Radiometer Suite) data, retrieved from NASA Earthdata – Fire Information for Resource Management System (FIRMS). The thirteen ignition factors, representing environmental, meteorological, edaphic, socio-economic, and topographic factors influencing forest fires, are sourced from various datasets, as detailed in Table 1. The PAs data was retrieved from World Database on Protected Areas (WDPA) (IUCN, UNEP, WCMC 2005). The above-ground biomass density (AGBD) data from Global Ecosystem Dynamics Investigation (GEDI) has been retrieved from Google Earth Engine (GEE) catalogue (Dubayah et al. 2022).

3.2 Methodology

3.2.1 Forest Fire Location

Forest fire occurrences and their locations are necessary for developing a predictive model to map forest fire susceptibility. Therefore, a forest fire inventory was prepared using MODIS and VIIRS data from NASA Earth Data-FIRMS for the 2024 fire season (February to June) (Mamgain et al. 2023). Data from Terra, Aqua, and Suomi NPP satellites were used, with fire locations filtered for high confidence (>90) and spatially thinned to 1 km in R Studio. Out of 3,491 fire locations, 2,443 (≈70%) were

Table 1: Details of the Various Data Used in the Study

S. No.	Variables	Unit	Source	Spatial resolution (m)	Time Period
1.	Fire Locations	-	MODIS/ VIIRS	1000/375	2024
2.	Aspect	Degree	SRTM DEM	30	-
3.	Elevation	m	SRTM DEM	30	-
4.	Slope	Degree	SRTM DEM	30	-
5.	Topographic Wetness Index	-	SRTM DEM	30	-
6.	Precipitation	mm	TerraClimate	4638	2024
7.	Solar radiation	W/m^2	TerraClimate	4638	2024
8.	Wind Speed	m/s	TerraClimate	4638	2024
9.	Soil Moisture	mm	TerraClimate	4638	2024
10.	Forest Density	-	MODIS	500	2024
11.	Land Surface Temperature	K	MODIS	1000	2024
12.	Distance to Road	m	OSM	–	-
13.	Land Use Land Cover	-	MODIS	500	2024
14.	Population density	Person/10,000 m^2	GHSL	100	2020
15.	Above Ground Biomass Density	Mg/ha	GEDI	1000	2019-2021
16.	Protected Areas	-	WDPA	-	-

used for modeling, and 1048 (≈30%) were used for validation. The methodological flowchart is shown in Figure: 2.

3.2.2 Forest Fire Ignition Factors

Forest fires are influenced by a range of environmental, meteorological, edaphic, socio-economic, and topographic factors. This study analyses thirteen ignition factors selected based on well-established global fire science literature, evidence from region-specific studies relevant to the study area, and practical considerations of dataset availability and consistency (Bhattarai et al, 2022; Gillett et al. 2004; Gupta et al. 2020; Jain et al. 1996; Kumari and Pandey, 2020; Mamgain et al. 2023). Widely used factors in global fire risk assessments include aspect, elevation, slope, precipitation, solar radiation, wind speed, soil moisture, forest density, and land surface temperature (LST). Regionally tailored factors, reflecting local fire regimes and anthropogenic influence, include land use land cover (LULC), population density, and proximity to roads. The complete set of factors used in this study is presented in Figure: 3.

Topographic factors play a crucial role in forest fire susceptibility by affecting fuel moisture, fire spread, and intensity (Mamgain et al. 2023). Aspect influences sunlight exposure, accelerating vegetation drying and increasing ignition risk, while elevation impacts temperature and oxygen levels, shaping fire behavior. Steeper slopes facilitate rapid fire movement, whereas the TWI quantifies topographic influence on hydrological processes, indicating moisture retention and its impact on fuel availability and flammability. These variables are derived from the Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) at 30m resolution.

The TWI, formulated by Moore et al. (1991) is computed using equation 1.

$$TWI = ln\frac{\alpha}{Tan\,\beta} \quad (1)$$

where α is the cumulative upslope area draining through a point per unit contour length, and β represents the slope at that point.

Meteorological factors significantly impact fire dynamics by influencing fuel dryness, ignition probability, and fire spread (Reddy et al. 2019). Precipitation maintains soil and vegetation moisture, reducing fire susceptibility, whereas solar radiation accelerates evaporation, increasing fuel dryness. Wind speed facilitates fire propagation by supplying oxygen and dispersing embers, while soil moisture availability determines fuel combustibility, with drier conditions exacerbating fire severity. These meteorological factors are sourced from TerraClimate (Gillett et al. 2004). Vegetation characteristics influence fire risk, with dense, moisture-rich forests being less susceptible, while fragmented or degraded forests increase fire likelihood due to greater fuel availability (Mamgain et al. 2023). The forest density layer was prepared using the Normalized Difference Vegetation Index (NDVI). LST, derived from MODIS data using GEE, serves as an indicator of surface heating, contributing to vegetation drying and increasing ignition potential. Anthropogenic factors, including LULC, road networks, and population density, also impact fire risk. Deforestation and urbanization create fragmented landscapes that enhance fire spread (Sharma, 2019). LULC, classified into six categories, such as agriculture, built-up, forest, grassland, waterbody, and wasteland, using MODIS data, determines fire susceptibility based on land type. Road networks, obtained from OpenStreetMap (OSM) were converted into

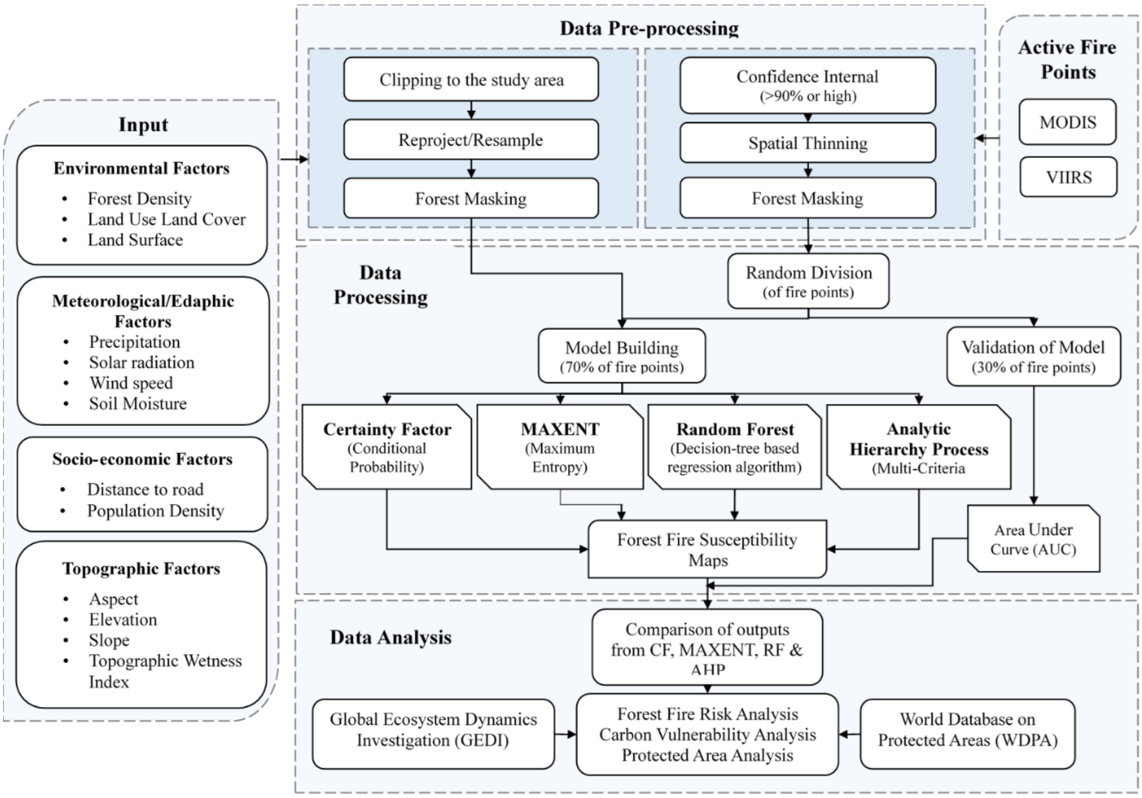

Figure 2: Methodology Flowchart for the Study

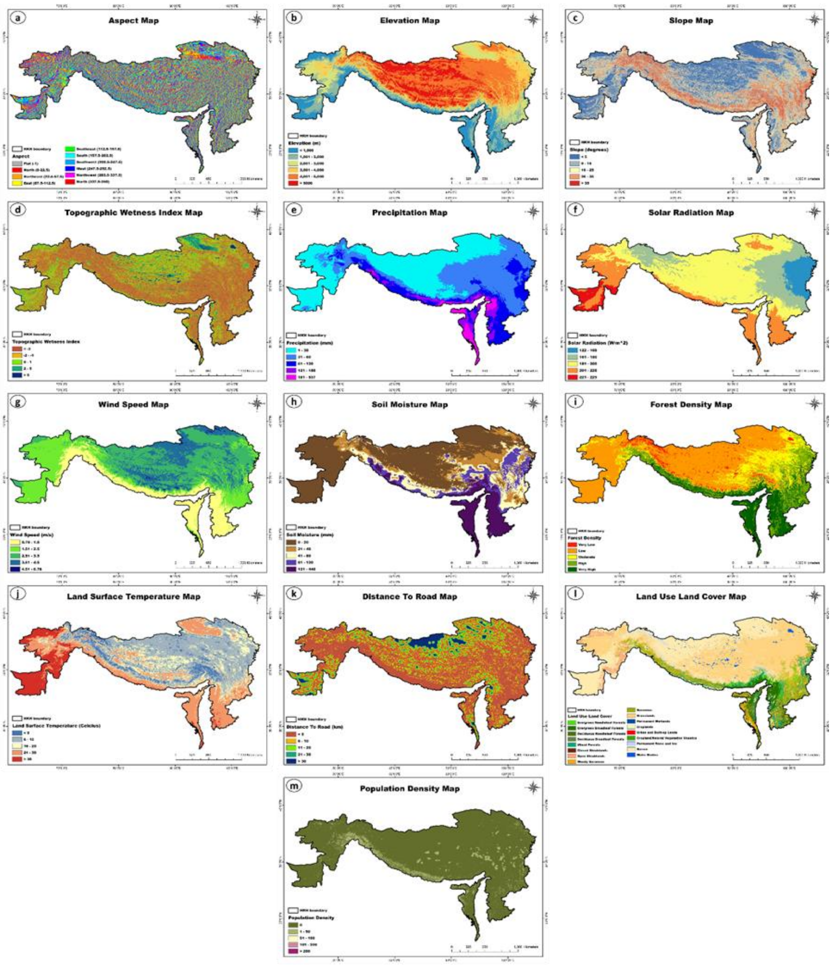

Figure 3: Ignition factor layers: (a) Aspect; (b) Elevation; (c) Slope; (d) Topographic Wetness Index – TWI; (e) Precipitation; (f) Solar Radiation; (g) Wind Speed; (h) Soil Moisture, (i) Forest Density; (j) Land Surface Temperature – LST; (k) Road Distance; (l) Land Use Land Cover; (m) Population Density

Euclidean distance in ArcGIS 10.2, with proximity to roads indicating higher ignition risks, while population density, sourced from the Global Human Settlement Layer (GHSL), indicates human-induced fire threats. All ignition layers were projected and resampled to 1 km resolution in R Studio for further analysis.

3.2.3 Model Building

In this study, four statistical and machine learning algorithms, namely, AHP, CF, Maxent, and RF were employed to map forest fire susceptibility in the HKH region. AHP decomposes a problem into a hierarchy of criteria, sub-criteria, and alternatives, enabling systematic pairwise comparisons using expert judgment (Saaty, 2008). It is particularly effective in multi-criteria decision analysis (MCDA), providing a robust framework for integrating qualitative and quantitative data (Kumari and Pandey, 2020; Lamat et al. 2021). In this study, the CF model determine the relationship between the fire ignition variables and the locations of forest fire occurrences. The CF weights are determined for the thirteen forest fire factors by overlaying the MODIS and VIIRS fire locations and calculating the final weights according to equation S1 (Shortliffe and Buchanan, 1975; Heckerman, 1986). Maxent is a machine learning technique based on maximum entropy principle (Kim et al. 2019). In this study, the model is trained in Maxent 3.1, using 70% of fire locations as training points for generating a fire probability map (0–1), where higher values indicate greater fire susceptibility (Phillips et al. 2005, 2006). RF is an ensemble learning technique, enhances decision tree accuracy by generating bootstrapped datasets for multiple tree constructions (Breiman, 2001; Catani et al. 2013; Stojanova et al. 2006). In this study, RF model is trained in R studio, with fire locations as the dependent variable and thirteen ignition factors as independent variables. This study utilizes 30% of the fire locations as testing points for model validation, that were not used for model training. The receiver operator characteristic (ROC) curve was used to plot the true-positive rate against the false-positive rate and the area under the curve (AUC) serves as a quantitative indicator of the model's efficacy and its performance. AUC values range from 0.0 to 1.0, where values closer to 1.0 indicate higher model performance (Kim et al. 2019).

3.2.4 Forest Fire Risk Analysis

a. Protected Areas

This study assesses the risks to biodiversity in the HKH region by evaluating the exposure of PAs to forest fire susceptibility. The WDPA, jointly developed by United Nations Environment Programme - World Conservation Monitoring Centre (UNEP-WCMC) and the International Union for Conservation of Nature (IUCN) World Commission (IUCN, UNEP, WCMC 2005), was used to obtain spatial information on designated conservation areas. These PAs were overlaid onto forest fire susceptibility map to identify regions with high to very high fire susceptibility.

b. Carbon Stock

The vulnerability of the HKH region's carbon stock to forest fires was assessed using mean AGBD data from the GEDI. The GEDI L4B product provides AGBD estimates at a 1 km spatial resolution, based on observations recorded between April 18, 2019, and August 4, 2021 (Dubayah et al. 2022). By overlaying the forest fire susceptibility map with AGBD data, the total carbon stock at risk of being released into the atmosphere due to forest fires was estimated, emphasizing the region's vulnerability and potential carbon emissions.

4. Results

4.1 Forest Fire Susceptibility Assessment

This study evaluates forest fire susceptibility across the HKH region using the RF model. The pixel values were classified into five classes: 0.05 indicated very low, 0.05 – 0.1 indicated low, 0.1 – 0.3 indicated moderate, 0.3 – 0.6 indicated high, and > 0.6 indicated very high forest fire susceptibility. The RF model-based forest fire susceptibility map indicates that 48.86% of the HKH region falls under very low risk, 9.64% under low risk, 8.42% under moderate risk, 12.71% under high risk, and 20.29% under very high risk (Figure: 5). Forest Fire Susceptibility analysis reveals that the mid-altitude forests of Himachal Pradesh, Uttarakhand, Nepal, and parts of north-eastern India as the most fire-prone areas. Bhutan, Bangladesh, and Myanmar also exhibit high susceptibility, while Afghanistan and Pakistan face moderate risk. In contrast, eastern China shows very low susceptibility across all models, reinforcing regional variations in fire risk.

Among the thirteen forest fire ignition factors, wind speed emerges as the most influential factor (0.098), followed by solar radiation (0.075), elevation (0.063), and precipitation (0.055). The importance of other factors decreases in the order of soil moisture, LST, distance to road, forest density, LULC, and slope degree, with TWI, aspect, and population density being the least important. This prioritization can guide feature selection by focusing on key factors. In terms of accuracy, the RF model outperformed AHP, CF, and Maxent models, with an overall accuracy of 95.20% (Figure: 4).

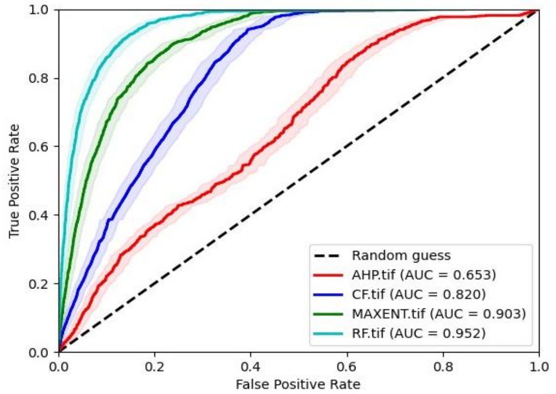

Figure 4: ROC curves for forest fire susceptibility map in the HKH region from Analytic Hierarchy Process (AHP), Certainty Factor (CF), Maximum Entropy (Maxent), and Random Forest (RF)

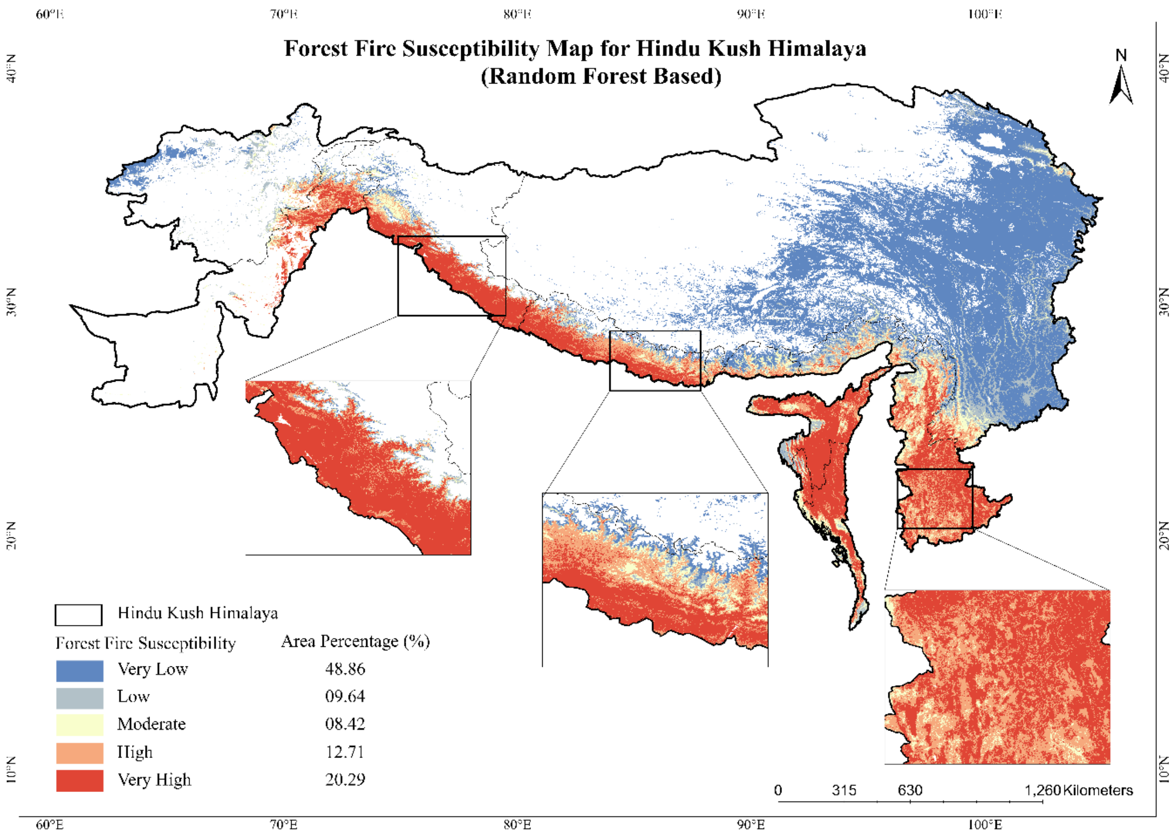

Figure 5: Forest Fire Susceptibility Map of Hindu Kush Himalaya Based on Random Forest

4.2 Risk to Protected Areas

The analysis of forest fire susceptibility within the PAs of the HKH region reveals that approximately 14,574.96 sq. km is categorized as very highly susceptible to forest fires, while an additional 11,303.70 sq. km falls under high susceptibility (Figure: 6). Among these PAs, the Hukaung Valley Wildlife Sanctuary in India emerges as the most vulnerable, with around 1,869 sq. km identified as very highly to highly susceptible. This is followed by Bumpha Bum Wildlife Sanctuary in Myanmar, where 1,299.32 sq. km is classified under high susceptibility. Other significantly affected areas include the Natmataung National Park in Myanmar and Chitwan National Park in Nepal.

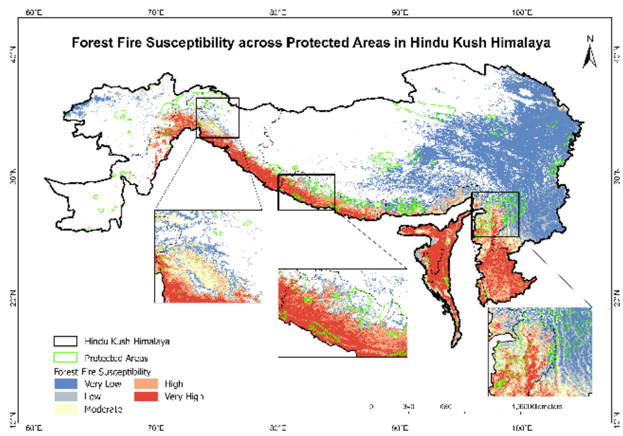

Figure 6: Forest Fire Susceptibility Across Protected Areas in the Hindu Kush Himalaya

The Figure: 7 illustrates the distribution of forest fire susceptible area and the number of PAs across eight countries within the HKH region. India emerges as the nation with the largest expanse of forest fire susceptible area in PAs, encompassing approximately 10,476 sq. km. Myanmar follows closely with 8,123.26 sq. km. Nepal and China contribute 4,257.23 sq. km and 1,818.25 sq. km respectively, while the remaining countries have relatively smaller proportions. In terms of count of PAs, India leads with 25, likely attributed to its vast size and diverse ecosystems. Myanmar and Nepal have 23 and 17 PAs, respectively. The remaining countries have fewer PAs, with Afghanistan having only one. This emphasizes the significant variation in forest fire susceptible area within the PAs across the HKH region.

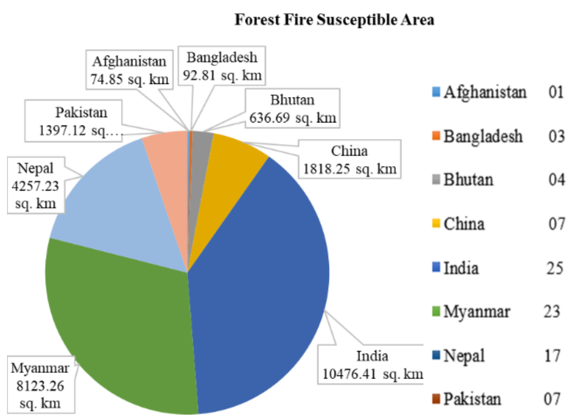

Figure 7: Forest Fire Susceptibility Across Protected Areas Country-Wise

4.3 Risk to Carbon Stock

The AGBD stored in forests within the HKH region is shown in Figure: 8. The spatial distribution of AGBD highlights significant carbon stocks concentrated in the forested landscapes of India, Nepal, Bhutan, Bangladesh, Myanmar, and southeastern China. The exclusion of non-forested areas such as grasslands and croplands through forest masking ensures a more accurate representation of AGBD specific to forest ecosystems. This refined mapping provides valuable insights into biomass distribution, which is crucial for understanding carbon stock vulnerability under varying fire susceptibility conditions.

The relationship between forest fire susceptibility and carbon storage is illustrated in Figure: 9, revealing a clear trend of increasing carbon vulnerability with higher fire susceptibility.

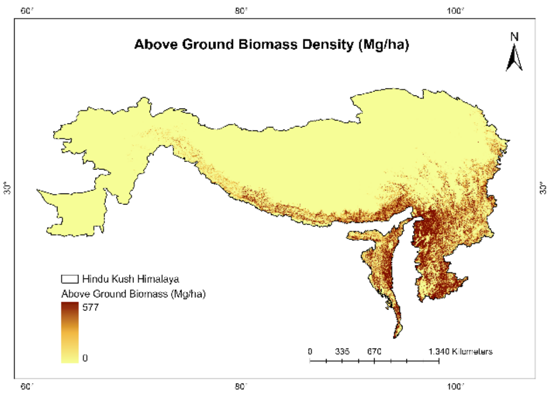

Figure 8: Mean Above Ground Biomass Density in the Hindu Kush Himalaya Region

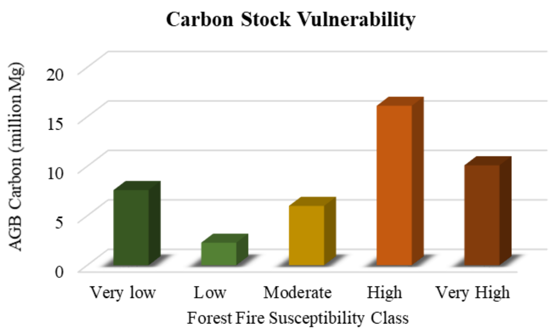

Figure 9: Carbon Stock Vulnerability in the Hindu Kush Himalaya Region

The AGB carbon is lowest in the low and moderate forest fire susceptibility classes, amounting to 2.28 million Mg and 6 million Mg, respectively. The very low susceptibility class holds approximately 7.60 million Mg of AGB carbon, whereas forests classified as highly susceptible contain the highest carbon stock, reaching 16.12 million Mg. The very high susceptibility class also holds a substantial carbon stock of 10.10 million Mg, indicating that a significant portion of above-ground biomass is at risk due to forest fires. This trend underscores the importance of integrating fire susceptibility assessments into carbon stock management strategies to mitigate potential losses and enhance forest resilience in the HKH region.

5. Discussion

The HKH region harbors diverse ecosystems, encompassing a vast network of PAs that protect a rich array of endemic and threatened species across its forests, grasslands, and alpine habitats. However, these regions have been experiencing several forest fire incidents, which are expected to become more prevalent and severe in the future due to land use changes and climate change (Rusk et al. 2022). These fires pose a significant threat to biodiversity and carbon stocks, endangering critical ecosystems and accelerating carbon release into the atmosphere. Effective disaster risk reduction (DRR) for forest fires requires a comprehensive assessment of fire susceptibility, aiding in the development of targeted conservation and mitigation strategies. This study identifies key drivers of forest fire occurrences and evaluates an appropriate methodological framework for modeling forest fire susceptibility across the HKH region. The findings provide insights into fire-prone PAs and quantify the vulnerability of carbon stocks, aiding in conservation planning and climate change mitigation.

The forest fire susceptibility analysis for the HKH region highlights that the Himalayan belt, including the Indian states of Himachal and Uttarakhand, as well as the entire range of hills in Nepal and Bhutan, stretching to Bangladesh and Myanmar, is highly susceptible to forest fire. Long-term trend analysis of the wildfire in the Himalayan vegetation over the last two decades shows that the western Himalaya is drier than the eastern part with the abundance of coniferous and dry deciduous forests that makes the region more susceptible to fire (Mamgain et al. 2023). Since 2020, Nepal's National DRR and Management Authority identified 2,700 forest fires that might be attributed to a 0.2°C increase in temperature and dry conditions (Bhattarai et al. 2022). Bhutan's high sensitivity to forest fires is associated with coniferous forests, low elevations and steep slopes, and regions adjacent to settlements and roads (Tshering et al. 2020). Slash and burn agriculture is the main cause of forest fire incidences in Bangladesh and Myanmar, suggesting that most forest fires are caused by anthropogenic activity (Reddy et al. 2019). The northeast region of Pakistan falls into the very high to high susceptibility category, which can be attributed to changes in weather, fuel quality, and land use caused by anthropogenic activity (Tariq et al. 2021). Afghanistan is susceptible to forest fires on a low to moderate scale, while East China is susceptible on a very low scale. This could be related to the Chinese government's recent efforts to strengthen its capacity for forest fire prevention and management (Zhong et al. 2003).

Meteorological factors are the primary drivers of forest fire occurrences, as they directly influence ignition, spread, and intensity. Among these, wind speed is the most critical factor, as it accelerates fire spread by supplying oxygen and carrying embers over long distances, potentially igniting new fires. High wind speeds can turn small, controlled fires into uncontrollable wildfires, making suppression efforts more challenging. This is followed by solar radiation and precipitation, where intense solar exposure, and extended dry spells increases the susceptibility to forest fires. These findings are supported by previous studies (Mohajane et al. 2021; Tariq et al. 2021) which emphasize the significance of climate variables in influencing forest fire susceptibility. Given that the HKH region is very sensitive and is highly vulnerable to climate change, seasonal droughts have become increasingly prevalent, leading to significant moisture deficits and altering precipitation patterns, which in turn enhance fire risk (Sharma, 2019). The complex terrain of the HKH region influences both the East Asian monsoon and global atmospheric circulation (Yanai and Li, 1994), influencing precipitation patterns that peak at approximately 80 mm before gradually declining. Anthropogenic disturbances also play a crucial role in increasing forest fire susceptibility. Fires are primarily concentrated in areas where forests and agricultural lands intersect, as agricultural expansion and settlement growth amplify human interaction with forests. This escalates fire risks through slash-and-burn practices, accidental ignitions, and unmanaged land clearing (Puri et al. 2011). Moreover, forests near roads face a higher incidence of fires due to human negligence. These patterns highlight the influence of land use in shaping fire occurrences, particularly in the Himalayan region. Adhikari et al. (2024) analyzed how LULC changes lead to rising disasters in the HKH region. The combined impact of anthropogenic activities and climatic factors further exacerbates forest fire vulnerability.

The PAs of the HKH region serve as critical conservation zones, safeguarding rich biodiversity and endemic species (Chettri et al. 2008). However, the increasing forest fires in these regions have profound ecological consequences, disrupting biodiversity, altering ecosystem dynamics, and threatening conservation efforts. The spatial analysis reveals that India, with 25 PAs, has the largest area vulnerable to fires (10,476.41 sq. km), followed by Myanmar (8,123.26 sq. km) and Nepal (4,257.23 sq. km). These PAs are home to diverse ecosystems, ranging from tropical forests to alpine meadows, which provide habitat for numerous rare and endangered species. The destruction of vegetation leads to habitat loss, affecting both flora and fauna, particularly fire-sensitive and endemic species. Many species struggle to recover due to habitat fragmentation and competition from invasive plants that thrive in post-fire landscapes (Pereira et al, 2012). Fires also impact keystone and endangered species, causing cascading ecological imbalances (Mistry and Bizerril, 2011). Moreover, this also disrupt wildlife corridors, forcing species to migrate, increasing human-wildlife conflicts, and threatening conservation efforts (Pereira et al, 2012). High fire susceptibility in key PAs like Chitwan National Park (Nepal), Natmataung National Park (Myanmar), and Hukaung Valley Wildlife Sanctuary (India) underscores the urgent need for proactive management strategies.

Previous studies confirm that climate change, coupled with anthropogenic activities such as deforestation, agricultural burning, and encroachment, has exacerbated fire risks in these protected landscapes (Chaudhary et al. 2022; Giri, 2022). While PAs are designed to shield biodiversity from external threats, their growing exposure to wildfires raises concerns about their long-term effectiveness. The analysis focused on determining the extent of fire-prone zones within PAs and assessing their vulnerability, highlighting the most at-risk conservation areas. Understanding these risks is crucial for developing integrated fire management and mitigation strategies to enhance the resilience of these critical conservation zones.

The HKH region acts as a crucial carbon stock due to its extensive forests, grasslands, and peatlands that store vast amounts of carbon (Guo et al. 2021). The increasing frequency of forest fire have a profound impact on the carbon stock by releasing large amounts of stored carbon into the atmosphere, reducing the capacity of ecosystems to sequester carbon. A study conducted in Pakistan revealed that forest fires result in an average annual emission of 7280 ± 5369 Gg of CO_2 (Mannan et al. 2017). Meanwhile, the highest emission, approximately 22799 Gg of CO_2 occurred in 2009 due to the burning of 145.6 ha of forest (Mannan et al. 2017). These fires not only lead to carbon emissions but also disrupt the natural carbon sequestration processes. This study observed that regions with higher forest fire susceptibility exhibit elevated AGBD. The high amount of AGB carbon in the high forest fire susceptible areas can be attributed to the presence of dense mixed forest, i.e., coniferous and broad leaf. Coniferous forests are very flammable in nature, thus making the region highly susceptible to forest fires (Gupta et al. 2018). A similar observation was made in a study conducted by Sannigrahi et al. (2020) in Indian forests where a high net primary productivity has observed in regions with higher forest fire events. The intricate relationship between high carbon stocks and very high forest fire susceptibility highlights the need for comprehensive strategies to protect these critical carbon reservoirs.

MODIS (1 km) and VIIRS (375 m) active fire products, though widely recognized for fire monitoring, have spatial and temporal constraints that may limit the detection of very small or short-lived events. The absence of ground-based measurements may also influence the accuracy of forest fire susceptibility mapping and carbon stock risk estimations, as remote sensing datasets inherently involve uncertainties. However, the maps have been validated using literature from individual studies conducted in various regions. Moreover, this study assesses the impact of fires on PAs and carbon stock, and it does not account for long-term ecological recovery dynamics, which may differ across ecosystems within the HKH region. Additionally, the study primarily analyzes large-scale patterns, which may not fully capture localized variations in fire behavior and microclimatic influences, underscoring the need for finer-scale analyses to enhance targeted conservation efforts.

Future research should focus on long-term ecological recovery dynamics in fire-affected ecosystems of the HKH, including vegetation regeneration, species composition shifts, and soil carbon recovery. Multi-temporal remote sensing combined with field assessments can enhance understanding of recovery trajectories across diverse forest types. Investigating the influence of climate variability, land-use changes, and human interventions will aid in developing adaptive fire management strategies. Further studies on prescribed burning and traditional fire management practices are needed to assess their role in ecosystem resilience. Establishing long-term monitoring frameworks with ecological indicators, carbon flux assessments, and biodiversity metrics will support sustainable conservation and fire mitigation efforts.

Assessing forest fire susceptibility and identifying key influencing factors can help mitigate future fire incidents and promote sustainable forest management (Kim et al. 2019; Pourghasemi et al. 2020; Pourtaghi et al. 2016). Susceptibility maps serve as essential tools for implementing preventive and precautionary measures, such as such as remote sensing-based fire monitoring, early warning systems, habitat restoration, community-driven conservation efforts, and cross-border collaboration to mitigate fire risks (Jain et al. 1996). Additionally, forest fires within PAs pose a significant threat to biodiversity conservation, as these regions harbor diverse and often endemic species. Forest fires not only lead to habitat loss but also contribute to carbon emissions, exacerbating climate change. Effective forest fire management strategies within PAs are crucial to preserving ecological integrity, maintaining carbon sequestration potential, and ensuring the long-term sustainability of forest ecosystems in the HKH region.

6. Conclusion

Being a global biodiversity hotspot, HKH is home to numerous endemic and endangered species, yet it faces escalating threats from forest fires. These fires disrupt ecological balance, fragment habitats, and endanger wildlife, particularly in PAs, where conservation efforts are crucial for sustaining biodiversity. This study integrates remote sensing, GIS, and advanced modeling techniques to assess fire susceptibility by analyzing environmental, meteorological, socio-economic, and topographic factors. The findings reveal that the Himalayan belt, Bangladesh, and Myanmar are the most fire-prone areas, whereas Afghanistan and East China exhibit lower susceptibility. Approximately 13.55–20.47% of the HKH region is highly vulnerable, with meteorological conditions and elevation playing a dominant role in fire occurrence. The increasing intensity and frequency of forest fires threaten not only biodiversity but also ecosystem stability in the HKH region. Fires accelerate habitat degradation, reducing the resilience of forests and making them more susceptible to invasive species. Additionally, they contribute to a substantial release of 32.22 million Mg of carbon from above-ground biomass, exacerbating climate change and further stressing ecosystems. Given these challenges, integrating geospatial analysis with advanced fire prediction models is crucial for effective conservation planning. Targeted fire management strategies are essential to mitigate biodiversity loss, enhance habitat connectivity, and support long-term ecological sustainability in this ecologically significant region.

Statements and Declarations

All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors.

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Availability of data and materials

All datasets utilized in this study are publicly available and can be accessed through open sources. Data generated during the study can be made available by the corresponding author upon reasonable request.

Competing interests

The authors declare that they have no competing interests.

Authors' contributions

BG: Conceptualization, data curation, methodology, investigation, formal analysis, validation, visualization, writing – original draft, and editing. SM: Conceptualization, data curation, methodology, investigation, formal analysis, validation, visualization, writing – original draft, and editing. AR: Conceptualization, methodology, project administration, supervision, and review and editing. All authors read and approved the final manuscript.

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References

Adhikari, B. R., S. Gautam, T. P. P. Sharma, and S. Devkota. 2024. "Land cover, land use change and its implication to disasters in the Hindu Kush Himalayan region." Pp. 7–27 in *Surface Environments and Human Interactions: Reflections from Asia*. Singapore: Springer Nature Singapore.

Allan, R. P., E. Hawkins, N. Bellouin, and B. Collins. 2021. *IPCC 2021: Summary for policymakers*.

Bhattarai, N., S. Dahal, S. Thapa, S. Pradhananga, B. S. Karky, R. S. Rawat, K. Windhorst, T. Watanabe, R. B. Thapa, and R. Avatar. 2022. "Forest fire in the Hindu Kush Himalayas: A major challenge for climate action." *Journal of Forest and Livelihood* 21(1).

Breiman, Leo. 2001. "Random forests." *Machine Learning* 45:5–32. https://doi.org/10.1023/A:1010933404324.

Catani, F., D. Lagomarsino, S. Segoni, and V. Tofani. 2013. "Landslide susceptibility estimation by random forests technique: Sensitivity and scaling issues." *Natural Hazards and Earth System Sciences* 13(11):2815–2831. https://doi.org/10.5194/nhess-13-2815-2013.

Chaudhary, S., K. Uddin, N. Chettri, R. Thapa, and E. Sharma. 2022. "Protected areas in the Hindu Kush Himalaya: A regional assessment of the status, distribution, and gaps." *Conservation Science and Practice* 4(10):e12793.

Chettri, N., B. Shakya, R. Thapa, and E. Sharma. 2008. "Status of a protected area system in the Hindu Kush-Himalayas: An analysis of PA coverage." *International Journal of Biodiversity Science and Management* 4(3):164–178.

Dixon, R. K., A. M. Solomon, S. Brown, R. A. Houghton, M. C. Trexler, and J. Wisniewski. 1994. "Carbon pools and flux of global forest ecosystems." *Science* 263(5144):185–190. https://doi.org/10.1126/science.263.5144.185.

Dubayah, R. O., J. Armston, S. P. Healey, Z. Yang, P. L. Patterson, S. Saarela, G. Stahl, L. Duncanson, and J. R. Kellner. 2022. *GEDI L4B gridded aboveground biomass density, version 2*. Oak Ridge, TN: ORNL DAAC. https://doi.org/10.3334/ORNLDAAC/2017.

Gillett, N. P., A. J. Weaver, F. W. Zwiers, and M. D. Flannigan. 2004. "Detecting the effect of climate change on Canadian forest fires." *Geophysical Research Letters* 31(18). https://doi.org/10.1029/2004GL020876.

Giri, S. 2022. *Assessing the wildfire of Chitwan National Park, Nepal*. Master's thesis, Høgskolen i Innlandet.

Guo, D., X. Song, R. Hu, X. Zhu, Y. Jiang, S. Cai, et al. 2021. "Large-scale analysis of the spatiotemporal changes of net ecosystem production in Hindu Kush Himalayan region." *Remote Sensing* 13(6):1180.

Gupta, A., C. M. Bhatt, A. Roy, and P. Chauhan. 2020. "COVID-19 lockdown: A window of opportunity to understand the role of human activity on forest fire incidences in the Western Himalaya, India." *Current Science* 119(2):390–398. https://doi.org/10.18520/cs/v119/i2/390-398.

Gupta, S., A. Roy, D. Bhavsar, R. Kala, S. Singh, and A. S. Kumar. 2018. "Forest fire burnt area assessment in biodiversity-rich regions using geospatial technology: Uttarakhand forest fire event 2016." *Journal of the Indian Society of Remote Sensing* 46:945–955. https://doi.org/10.1007/s12524-018-0757-3.

Heckerman, D. 1986. "Probabilistic interpretations for MYCIN's certainty factors." Pp. 167–196 in *Machine Intelligence and Pattern Recognition*, Vol. 4. https://doi.org/10.1016/B978-0-444-70058-2.50017-6.

Jain, A., S. A. Ravan, R. K. Singh, K. K. Das, and P. S. Roy. 1996. "Forest fire risk modelling using remote sensing and geographic information system." *Current Science*:928–933.

Kim, S. J., C.-H. Lim, G. S. Kim, J. Lee, T. Geiger, O. Rahmati, Y. Son, and W. K. Lee. 2019. "Multi-temporal analysis of forest fire probability using socio-economic and environmental variables." *Remote Sensing* 11(1):86. https://doi.org/10.3390/rs11010086.

Kumari, B., and A. C. Pandey. 2020. "Geo-informatics-based multi-criteria decision analysis (MCDA) through analytic hierarchy process (AHP) for forest fire risk mapping." *Journal of Earth System Science* 129:1–16.

Lamat, R., M. Kumar, A. Kundu, and D. Lal. 2021. "Forest fire risk mapping using analytic hierarchy process and earth observation datasets." *SN Applied Sciences* 3(4):425.

Mamgain, S., A. Roy, H. C. Karnatak, and P. Chauhan. 2023. "Satellite-based long-term spatiotemporal trends of wildfire in Himalayan vegetation." *Natural Hazards* 116(3):3779–3796. https://doi.org/10.1007/s11069-023-05835-z.

Mannan, A., Z. Feng, A. Ahmad, M. Beckline, S. Saeed, J. Liu, et al. 2017. "CO2 emission trends and risk zone mapping of forest fires in Pakistan." *Applied Ecology and Environmental Research* 17(2):2983–3002.

Mistry, J., and M. Bizerril. 2011. "Why it is important to understand the relationship between people, fire and protected areas." *Biodiversidade Brasileira* 1(2):40–49.

Mohajane, M., R. Costache, F. Karimi, Q. B. Pham, A. Essahlaoui, H. Nguyen, G. Laneve, and F. Oudija. 2021. "Remote sensing and machine learning for forest fire mapping." *Ecological Indicators* 129:107869.

Moore, I. D., R. B. Grayson, and A. R. Ladson. 1991. "Digital terrain modelling: A review." *Hydrological Processes* 5(1):3–30.

Pereira, P., P. Mierauskas, X. Úbeda, J. Mataix-Solera, and A. Cerda. 2012. "Fire in protected areas: Effects and management." *Environmental Research, Engineering and Management* 59(1):52–62.

Phillips, S. J. 2005. "A brief tutorial on Maxent." *AT&T Research* 190(4):231–259.

Phillips, S. J., R. P. Anderson, and R. E. Schapire. 2006. "Maximum entropy modeling of species geographic distributions." *Ecological Modelling* 190(3–4):231–259.

Pourghasemi, H. R., A. Gayen, R. Lasaponara, and J. P. Tiefenbacher. 2020. "Machine learning techniques for forest fire modelling." *Environmental Research* 184:109321.

Pourtaghi, Z. S., H. R. Pourghasemi, R. Aretano, and T. Semeraro. 2016. "Forest fire susceptibility modelling using data mining techniques." *Ecological Indicators* 64:72–84.

Puri, K., G. Areendran, K. Raj, S. Mazumdar, and P. K. Joshi. 2011. "Forest fire risk assessment using geospatial tools." *Journal of Forestry Research* 22:641–647.

Rathore, P., A. Roy, and H. Karnatak. 2019. "Vulnerability of oak forest ecosystems under climate change." *Biodiversity and Conservation* 28(8–9):2275–2294.

Reddy, C. S., N. G. Bird, S. Sreelakshmi, T. M. Manikandan, M. Asra, P. H. Krishna, et al. 2019. "Spatio-temporal hotspots of forest fires in South Asia." *Environmental Monitoring and Assessment* 191:1–17.

Rusk, J., A. Maharjan, P. Tiwari, T. H. K. Chen, S. Shneiderman, M. Turin, and K. C. Seto. 2022. "Multi-hazard susceptibility in the Hindu Kush Himalaya." *Science of the Total Environment* 804:150039.

Saaty, T. L. 2008. “Decision making with the analytic hierarchy process.” *International Journal of Services Sciences* 1(1):83–98.

Sannigrahi, S., F. Pilla, B. Basu, A. S. Basu, K. Sarkar, S. Chakraborti, et al. 2020. “Effects of forest fire on carbon emission in India.” *Science of the Total Environment* 725:138331.

Schmidt-Vogt, D. 1990. “Fire in high altitude forests of the Nepal Himalaya.” Pp. 191–199 in *Fire in Ecosystem Dynamics*. The Hague.

Sharma, S. P., and K. Tshering. 2019. “Wildfires in the Hindu Kush-Himalayan region.” *Fire Management Today* 77(1):23–28.

Shome, P., A. J. Prakash, D. Mudi, S. Das, S. Behera, et al. 2025. “Machine learning and deep learning for forest fire susceptibility.” *Journal of the Indian Society of Remote Sensing*:1–16.

Shortliffe, E. H., and B. G. Buchanan. 1975. “A model of inexact reasoning in medicine.” *Mathematical Biosciences* 23(3–4):351–379.

Singh, S. P., and V. Singh. 2025. “Forest fire regime in Himalaya likely to change.” *International Journal of Ecology and Environmental Sciences* 51(1):3–5.

Stojanova, D., P. Panov, A. Kobler, S. Džeroski, and K. Taškova. 2006. “Predicting forest fires using data mining.” Pp. 255–258 in *Proceedings of SiKDD 2006*, Ljubljana, Slovenia.

Tariq, A., H. Shu, S. Siddiqui, B. G. Mousa, I. Munir, A. Nasri, et al. 2021. “Forest fire monitoring using geospatial analysis.” *Geomatics, Natural Hazards and Risk* 12(1):1212–1233.

Thapa, S., V. S. Chitale, S. Pradhan, B. Shakya, S. Sharma, S. Regmi, et al. 2021. “Forest fire detection and monitoring.” Pp. 147–167 in *Earth Observation Science and Applications for Risk Reduction*.

Tshering, K., P. Thinley, M. S. Tehrany, U. Thinley, and F. Shabani. 2020. “A comparison of AHP and frequency ratio techniques in forest fire prediction.” *Forecasting* 2(2):36–58.

UNEP-WCMC and IUCN. 2025. *Protected Planet: The World Database on Protected Areas (WDPA)*. Cambridge, UK.

Yanai, M., and C. Li. 1994. “Mechanism of heating and boundary layer over the Tibetan Plateau.” *Monthly Weather Review* 122(2):305–323.

You, Q. L., G. Y. Ren, Y. Q. Zhang, Y.-Y. Ren, X.-B. Sun, Y. J. Zhan, A. B. Shrestha, and R. Krishnan. 2017. “Observed climate change in the Hindu Kush Himalayan region.” *Advances in Climate Change Research* 8(3):141–147.

Zhong, M., W. Fan, T. Liu, and P. Li. 2003. “Statistical analysis of forest fire safety in China.” *Fire Safety Journal* 38(3):257–269.