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Research Article

Nepal's carbon stock and biodiversity are under threat from climate exacerbated forest fires

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ABSTRACT

Forest fires pose a growing threat worldwide, causing damage to ecosystems and releasing significant amounts of carbon. We analyze a national-scale forest fire susceptibility over the past two decades at a sub-decadal level in Nepal. We utilized earth observations and the Random Forest machine learning algorithm within the Google Earth Engine framework to analyze forest fire susceptibility on both spatial and temporal scales. A range of terrain- and climate-related variables were used to train and validate the random forest machine-learning model. Our results show that ongoing and projected changes in weather, land-use and human interventions will likely impact the severity and extent of forest fires in the nation. We estimate that forest fires could potentially release more than 170 million tons of soil organic carbon and 325 million tons of above-ground wood carbon with parallel biodiversity loss in Nepal alone, thus requiring forest management and fire mitigation efforts in the region.

1. Introduction

Forests are critical to preserving biodiversity, native plants and animals, culture, ecological sustainability, and climate regulation (Brockerhoff et al., 2017). However, a tiny spark in the forest or the sun's heat can trigger a catastrophic fire. Once ignited, a forest fire can spread quickly, leaving nothing in its wake (Martell, 2001; Pyne, 2013). Uncontrolled and deleterious forest fires are becoming more frequent (Rogers et al., 2020), posing a widespread threat to human health and life, ecosystems, and infrastructure (Richardson et al., 2022). According to the United Nations, from 2000 to 2019, these disasters affected a staggering 4.2 billion people and resulted in an estimated global economic loss of approximately 2.97 trillion US dollars (UNDRR, 2020). Furthermore, these forest fires release a substantial amount of carbon into the atmosphere (Bedia et al., 2015; Park et al., 2023). For example, boreal fires in 2021 released a record-high 0.48 billion metric tons of carbon (Zheng et al., 2023).

The occurrence and severity of forest fires depend mainly upon three factors - fuel (i.e., combustible forest biomass), heat, and oxygen, and are modulated by a combination of factors. They range from atmospheric and geographical conditions, fuel availability, and ignition patterns (Matin et al., 2017; Moayedi and Khasmakhi, 2023; Hong et al., 2018; Bustillo Sánchez et al., 2021). The high occurrences of forest fires are largely attributed to hot and dry climates in combination with higher proximity to human settlements (Richardson et al., 2022). Forest fires can be caused by natural as well as anthropogenic factors. Anthropogenic factors include activities by grazers, poachers, or collectors of non-timber forest products, as well as instances of neglect and accidents in Nepal (Kunwar and Khaling, 2006). In anthropogenic causes, socioeconomic factors play a significant role in increasing the risk and impact of forest fires. For

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instance, in the Brazilian Amazon, exposure to fire risk could increase smallholders' reliance on fire-intensive land uses, thus contributing to a cycle of risk and dependence (Cammelli et al., 2020).

Among many factors, natural weather and climate variability substantially influence vegetation dynamics and fuel aridity (Abatzoglou et al., 2018). For example, precipitation deficits induce moisture stress, increasing the flammability of fuel. High temperatures, low humidity, and strong winds are other climatic conditions that can intensify forest fires (Hoffmann, 2003). Notably, the atmospheric conditions might be a crucial factor in determining the likelihood of ignition and the spread and intensity of forest fires (Abatzoglou et al., 2018). While existing literature acknowledges the importance of forests and the increasing occurrences of forest fires (Akay et al., 2022; Chen et al., 2023; Dos Reis et al., 2021), there is a notable research gap in the understanding of the causative factors and the spatial and temporal patterns of forest fires, particularly in developing countries like Nepal.

In South Asian countries, including Nepal, limited rainfall during winter and early pre-monsoon periods increases the vulnerability of dry vegetation to forest fires (Hamal et al., 2022; Harris et al., 2008). Hot and windy conditions from March to May provide an optimal forest fire environment (Matin et al., 2017). They can spread quickly, especially those in difficult-to-reach areas. In Nepal, an average of 400,000 ha of land are burned annually by forest fires (Bajracharya, 2002). Still, limited studies (Matin et al., 2017; Parajuli et al., 2015) have explored potential causative parameters for forest fires in Nepal. This lack of region-specific understanding hinders the development and implementation of effective forest fire management practices tailored to Nepal's unique environmental and socio-economic conditions. Further, despite the increasing severity of the situation, a significant research gap exists regarding the potential impact of these forest fires on carbon emissions and the consequences for local biodiversity in Nepal.

This study aims to address the above-highlighted research gaps on forest fires in Nepal. Our main objective is to explore various factors and discuss the spatiotemporal dynamics of nationwide forest fires. Dynamic fire susceptibility maps that provide valuable insights into the varying levels of fire susceptibility across the country were developed using machine learning models that utilize earth observations. We have also estimated the potential carbon loss and assessed the impacts on biodiversity. These estimates can be used to develop recommendations for effective forest fire management. A sound understanding of spatiotemporal behaviors and the causes and consequences of forest fires is crucial for designing, developing, and implementing effective fire management strategies. Besides protecting forests, such strategies would contribute to achieving various sustainable development goals (SDGs), which need to be rescued from failing (Pradhan, 2023).

2. Study area, data, and methods

2.1. Study area

Nepal is located in the middle portion of the Hindu Kush Himalayan Region. It spreads over an area of 147,516 sq. km and extends between latitudes 26° and 31°N and longitudes 80° and 89°E. The country spans over 885 km east to west, and the width varies from 145 to 248 km north-south. Administratively, there are 77 districts in Nepal, and geographically, it is divided into three regions: Terai, Hills, and Mountains, accounting for 68 % (21 districts), 17 % (40 districts), and 15 % (16 districts), respectively. Climatologically, Nepal has four seasons: winter (December–February), pre-monsoon (March–May), monsoon (June–September), and post-monsoon (October–November) (Talchabhadel et al., 2019). Nepal is home to 35 forest types, 75 vegetation types, and 118 ecosystems, along with four global biodiversity hotspots (Chettri et al., 2008; Matin et al., 2017). Climatic zones vary from tropical to Polar, corresponding to altitudes ranging from 60 m to 8848.86 m (Karki et al., 2016).

Nepal is among the most vulnerable countries, ranked 4th, 11th, and 30th in climate change, earthquake, and flood risk, respectively (Shrestha, 2019). Additionally, forest fires occur annually in all major physiographic/climatic regions of Nepal. Bajracharya (2002) and S. Khanal (2015) reported that 375,000 ha of forests were burnt from 2001 to 2015. These wildfires have resulted in significant loss of life and economic damage, with 1491 reported deaths and substantial financial losses of around 30 million Nepali rupees between 1971 and 2016 cited in (Shrestha, 2019). Likewise, increasing incidences of forest fires are affecting natural vegetation and causing major destruction of human settlements (Parajuli et al., 2015) (Fig. S1).

Nepal has recently been plagued by an alarming rise in forest fires (Fig. 1). These fires have caused significant environmental damage and impacted the air quality and well-being of the population, particularly in the capital city, Kathmandu (Rives, 2022). Most fire burn areas occur from March to May, with a peak of more than 91% in the lowlands of western and central Nepal (Hamal et al., 2022). In 2016, Nepal's forest area burned about 0.22 million hectares, or 3.4%, a 33 percent increase over the previous 15 years (Bhujel et al., 2018). The spring of 2021 witnessed an unprecedented wildfire season, with active fires detected at a rate ten times higher than in 2001–2020, contributing to hazardous air pollution levels (Pokharel et al., 2021).

2.2. Data

2.2.1. Forest fire inventory

To analyze forest fire occurrences, trends, and susceptibility in Nepal, we utilized the dataset provided by the Fire Information for Resource Management System (FIRMS) from NASA (Davies et al., 2009). This dataset includes a comprehensive inventory of forest fires detected through the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery. The MODIS satellite system offers valuable data for monitoring forest fires, with its ability to capture images near-real-time information.

2.2.2. Environmental variables

The relentless forces of nature can exert a significant influence on forest fires, both in terms of their initiation and the extent to which they escalate. We have utilized three sets of variables to estimate the fire risks: rainfall-based, temperature-based, and terrain-based factors. By examining the relationships between these variables and forest fires, we aim to provide a more accurate assessment of the likelihood and severity of such events. The selection of these variables is based on past literature (Moayedi and Khasmakhi, 2023; Bustillo Sánchez et al., 2021), empirical evidence, and expert judgment, ensuring that the approach remains robust and relevant.

Rainfall-based variables play a significant role in determining the risk of forest fires. Factors such as the number of consecutive dry days (CDD) and consecutive wet days (CWD) directly impact the moisture levels in vegetation, which in turn affect its flammability (O, Hou, and Orth, 2020). Additionally, extreme precipitation events like heavy and very heavy precipitation days (R20, R50, and R100) can either mitigate or intensify the risk of forest fires (F. Chen, Niu, et al., 2014; F. Chen, Fan, et al., 2014). Generally, a higher frequency of wet days (R1) and total annual precipitation (PRCPTOT) can lower the risk of fires, while extended periods of dryness can increase it. We used IMERG precipitation data to calculate 21 rainfall-based variables (Table S1). Detailed descriptions of these rainfall-based variables can be found in (Talchabhadel et al., 2022).

Temperature-based variables also contribute to the likelihood of forest fires. Elevated temperatures can accelerate the evaporation process, leading to faster drying of vegetation and creating a more favorable environment for fires to ignite and spread (Turco et al., 2017). Variables such as the number of warm days (WD) and warm nights (WN), the mean daily max and min temperatures (TXm and TNm), and the diurnal temperature range (DTR) are all relevant in this context. Additionally, extreme temperature events, such as frost days (FD) and ice days (ID), can impact vegetation health and influence fire susceptibility. These

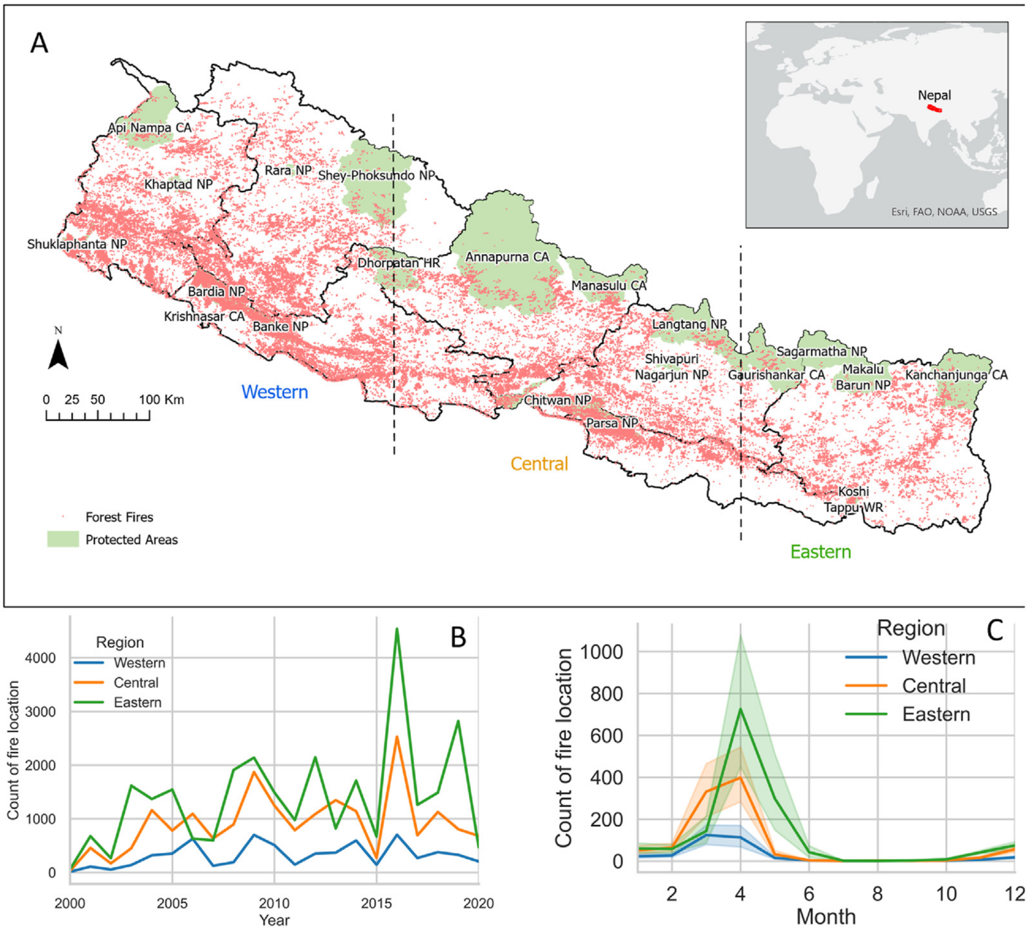


Fig. 1. (A) Spatial distribution of forest fires demarcated by Fire Information for Resource Management System from NASA overlaid over the map of Nepal and protected areas. The location of the country is indicated in the inset located at the top right. (B) Inter-annual variation in the count of forest fires in western, central, and eastern regions of the country. (C) Monthly variation in the count of forest fires in the same three regions, where the spread in the graph represents the inter-annual variation at confidence intervals set at 95%.

temperature-based indices are adapted from the joint CCl/WCRP/JCOMM Expert TeamExpert Team on Climate Change Detection and Indices (ETCCDI) (https://www.wcrp-climate.org/etccdi-members) and CCI Expert Team on Sector-Specific Climate Indices (ET-SCI) (https://climpact-sci.org/about/project/).

Terrain-based variables provide insights into the topographical features that can affect the spread and intensity of forest fires. Factors such as elevation, slope, and aspect influence the distribution of vegetation and the microclimatic conditions within a landscape (Cadd et al., 2019; Dearborn and Danby, 2017; Merschel et al., 2018), thereby impacting the likelihood of fires. For example, steeper slopes may lead to faster fire spread, while certain aspects may expose the vegetation to more sunlight and wind, leading to faster drying. Furthermore, terrain attributes such as hillshade, horizontal and vertical curvature, and shape index play a role in shaping the propagation of fires through a landscape, influencing their intensity and spatial extent (Alqadhi et al., 2022; Cortes et al., 2023; Moayedi and Khasmakhi, 2023).

Precipitation data were sourced from the IMERG dataset (Huffman et al., 2015) at a 0.1-degree resolution (~11,132 m), while temperature data were obtained from the ERA5 Land dataset (Muñoz Sabater, 2019), also at a 0.1-degree resolution. For terrain features, we processed the data at a much finer 30 m resolution to capture detailed topographical variations. To ensure compatibility with MODIS fire susceptibility data, all datasets were resampled to a common spatial resolution of 30 m using bilinear interpolation, which preserved the detail of higher-resolution terrain data while aligning it with broader-scale climate data. This methodology is widely used for landscape analysis at different scales (Gnyawali et al., 2023). The terrain analysis was conducted on Google Earth Engine (GEE) for efficient high-resolution processing over large geographic extents (Safanelli et al., 2020). We also ignored data gaps in applied water mask in elevation processing (Safanelli et al., 2020). By incorporating these wide ranges of variables, we aimed to attain a comprehensive set of factors influencing forest fire susceptibility.

3. Methods

As the frequency and severity of forest fires continue to escalate and change, it is crucial to understand the underlying factors that influence their occurrence and spread. Changing climate has amplified extreme events, rendering them more frequent, simultaneous, and persistent (Pradhan et al., 2022). Thus, by employing sub-decadal analysis (2001–2005, 2006–2010, 2011–2015, and 2016–2020), our study aimed to uncover subtle changes and trends that might otherwise be obscured in broader timeframes.

We analyzed the susceptibility of forest fires in Nepal by utilizing a machine learning approach and employing the powerful and freely available Google Earth Engine (GEE) for geospatial analysis and simulation. The overall methodological framework is represented in Fig. 2.

Firstly, the forest fire location datasets from FIRMS NASA (Fig. 1) and other environmental covariates (Tables S1, S2, and S3) were collected. The environmental covariates were further selected by using Recursive Feature Elimination method (Fig. S9). Then, model training was carried out for the periods of 2001–2005, 2006–2010, 2011–2015, and 2016–2020 separately to understand how forest fire susceptibility has evolved over the past two decades. In machine learning terms, the environmental covariates were used as 'features' and past forest fire and randomly generated non-forest fire locations were used as 'target'. The out-of-the-bag error estimate was used for model tuning and to prevent overfitting. We assessed the performance of the trained machine learning model by comparing its predictions with the test dataset for specific

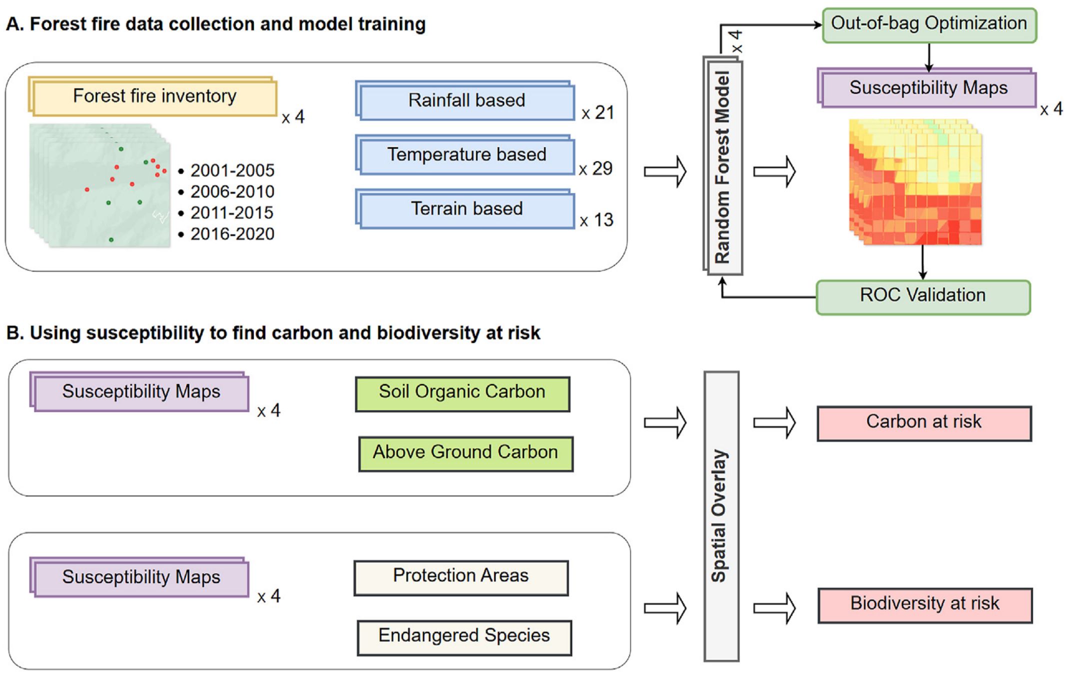


Fig. 2. Workflow for assessing forest fire susceptibility and its impact on carbon and biodiversity. (A) Forest fire data collection and model training: A forest fire inventory is created for different time periods (2001–2005, 2006–2010, 2011–2015, 2016–2020), and developed environmental variables based on rainfall (21 variables), temperature (29 variables), and terrain (13 variables). These datasets are processed with a Random Forest Model, optimized using out-of-bag methods, and validated with ROC analysis to produce susceptibility maps for forest fire. (B) Using susceptibility to find carbon and biodiversity at risk: The susceptibility maps are overlaid with soil organic carbon and above-ground carbon data to estimate carbon at risk, and with protection area and endangered species data to identify biodiversity at risk.

periods, employing the area under the curve method (AUC) to gauge the model's efficiency.

Subsequently, a susceptibility analysis was performed using the trained machine learning model over Nepal. This process generated spatial maps of forest fire susceptibility, which helped identify areas with a higher likelihood of experiencing forest fire events in the future, given the prevailing environmental conditions. The susceptibility values, calculated on a scale of 0–100, indicate a greater susceptibility to forest fires at higher values.

We then identified the controlling factors of forest fire susceptibility. By examining the feature importance within the machine learning model, we aimed to ascertain the most significant factors influencing forest fire susceptibility in Nepal. Then, we estimate below-ground/above-ground carbon stock at susceptible forest fires (carbon at risk) and biodiversity at risk (Fig. 2).

3.1. Random forest in Google Earth Engine

We employed the Random Forest model (Breiman, 2001) in GEE to develop forest fire susceptibility maps. The Random Forest model is an ensemble learning method that combines multiple decision trees, improving predictive accuracy and reducing overfitting. Also, the random forest machine learning utilizes decision trees to make predictions. Unlike linear regression models, which are susceptible to multicollinearity (Hushchyna et al., 2023), random forest is generally robust to multicollinearity (Breiman, 2001). To configure and calibrate the model, we used hyperparameters - the number of trees, variables per split, minimum leaf population, bag fraction, maximum nodes, and randomization seed. If we denote the dataset as D, with N total observations ($\frac{N}{2}$ for each class), and the set of covariates as $X = \{x_1, x_2, x_3, \ldots x_n\}$. Following steps were performed for training the model:

1. Partition the dataset D into training and testing sets, D_{train} and D_{test} by 70% for training and 30% for testing.
2. Train the Random Forest model on D_{train} using the covariates X as features.
3. For each observation in D_{test}, probability of the location being 1 (forest fire) or 0 (non-forest fire) using the trained Random Forest model (Breiman, 2001).

Let $P(y = 1|X)$ be the probability of a location being classified as 1 (forest fire) given the covariates X. The Random Forest model is an ensemble of decision trees. Suppose there are T decision trees in the Random Forest model, and let $t_i(i = 1, 2, \ldots, T)$ represent the individual decision trees.

For each observation x in D_{test}, the probability of being classified as 1 (forest fire) is calculated as:

$$P(y = 1|X = x) = \frac{1}{T}\sum_{i=1}^{T} I(t_i(x) = 1) \tag{1}$$

Where $I(.)$ is the indicator function, and $t_i(x)$ is the class label predicted by the $i - th$ decision tree for the observation x. The susceptibility for each location in D can then be calculated as the probability $P(y = 1|X = x)$.

3.2. Model training and validation

On training the model, we calculated the Out of Bag (OOB) error estimate. The OOB error estimate is a performance metric specific to random forest models, which measures the prediction error based on the instances not used in building each tree (the "out-of-bag" samples). For each data point i in the dataset, we identified the set of trees T(i) in the forest that did not use i in their bootstrap samples.

For each data point i, we utilized the trees in $T(i)$ to predict the class label and determine the majority vote. Then, we computed the OOB error as the proportion of incorrectly classified data points: OOB Error = (Number of incorrectly classified data points)/(Total number of data points).

On validating our random forest model, we employed the Area Under the Receiver Operating Characteristic (AUC-ROC) curve technique. The AUC-ROC curve is a graphical representation of the model's ability to distinguish between positive and negative classes in a binary classification problem. The curve is generated by plotting the true positive rate (TPR) against the false positive rate (FPR) at varying threshold levels. The AUC is the area under the ROC curve and serves as a single numeric summary of the model's performance. We computed the TPR and FPR using the following formulas:

$$\text{True Positive Rate (Sensitivity)} : TPR = TP \,/\, (TP + FN) \tag{2}$$

$$\text{False Positive Rate } (1 - \text{Specificity}) : FPR = FP \,/\, (FP + TN) \tag{3}$$

To obtain the AUC-ROC curve, we ranked the predicted probabilities for each instance, calculated the TPR and FPR for each threshold from 0 to 1, plotted the TPR against the FPR, and finally computed the area under the curve using a numerical integration method.

3.3. Estimation of carbon at risk

We intersected sub-decadal susceptibility and soil organic carbon and above-ground woody carbon. Then, we categorized the carbon stocks susceptible to various severity (medium to high) areas over time. We finally quantified the carbon at risk, considering the areas that are very highly susceptible. We quantify the carbon at risk as the complete removal of SOC and woody carbon after the forest fire (Sirin et al., 2021; Seydewitz et al., 2023; Schuur et al., 2003; Auclair and Carter, 1993).

3.3.1. Soil organic carbon

We used soil organic carbon (SOC) predicted by Shiva Khanal et al. (2023) at 30 m spatial resolution in metric tons per hectare (Fig. S5.b). They estimated SOC of the topsoil (0–30 cm) using a Quantile Regression Forest model leveraging gridded predictors at a 30 m spatial resolution year 2010–2014 utilizing a combination of remote sensing data and field measurements. The SOC dataset was harmonized to the susceptibility raster at the same spatial grid using the nearest neighbor method (Zhu, 2017). The unit was then converted to million tons per pixel to calculate the total SOC sum. The SOC was then estimated at different susceptibility classes: 1–40, 41–60, 61–80, and 81–100. We ignored forest with zero (0) susceptibility to avoid possible confusion with background pixels. We define forest fire susceptibility higher than 40 as high susceptible zone to calculate SOC at risk.

3.3.2. Above-ground wood carbon

We used the dataset containing above-ground woody biomass density at a 30 m spatial resolution by Global Forest Watch based on the methodology provided by (Baccini et al., 2012). To convert biomass density into carbon density, each pixel value in the above-ground biomass (AGB) map was multiplied by 0.5, a conversion factor suggested by (Seydewitz et al., 2023) (Fig. S5.a). Similar to SOC, we harmonized the image to suceptibility raster at the sane spatial grid using the nearest neighbor method. Subsequently, the carbon contained in the woody biomass was estimated for the same susceptibility units and classes as for soil organic carbon, specifically 1–40, 41–60, 61–80, and 81–100. We define forest fire susceptibility higher than 40 as high susceptible zone to calculate wood carbon at risk.

3.4. Estimation of biodiversity at risk

Estimating the risk of forest fires to biodiversity is complex. There are many factors to consider, such as animals, plants, trees, insects, and even microorganisms that makeup ecosystems. Plus, many forests provide important resources like medicinal plants. To address this, we initiated our study by estimating the susceptibility of various protected areas in Nepal to forest fires (Fig. 1). Based on this data, we calculated a forest fire susceptibility score for each protected area. Following this, we ranked the protected areas based on these susceptibility to identify the areas at risk. We then reviewed secondary data from protected authorities (Government of Nepal, Department of National Parks and Wildlife Conservation, 2022, 2023) to determine the specific species in danger within each high-risk protected area and aimed to provide a more nuanced understanding of the threat forest fires pose to biodiversity.

4. Results

4.1. Forest fire susceptibility

We observe variation in forest fire susceptibility across Nepal sub-nationally in the last two decades (see Fig. 3 and Table 1). Mainly, the provinces of Lumbini, Madhesh, and Sudurpashchim exhibited an overall increase in forest fire susceptibility over the years, while Koshi Province showed a general decrease. The other provinces exhibit a mixed trend with

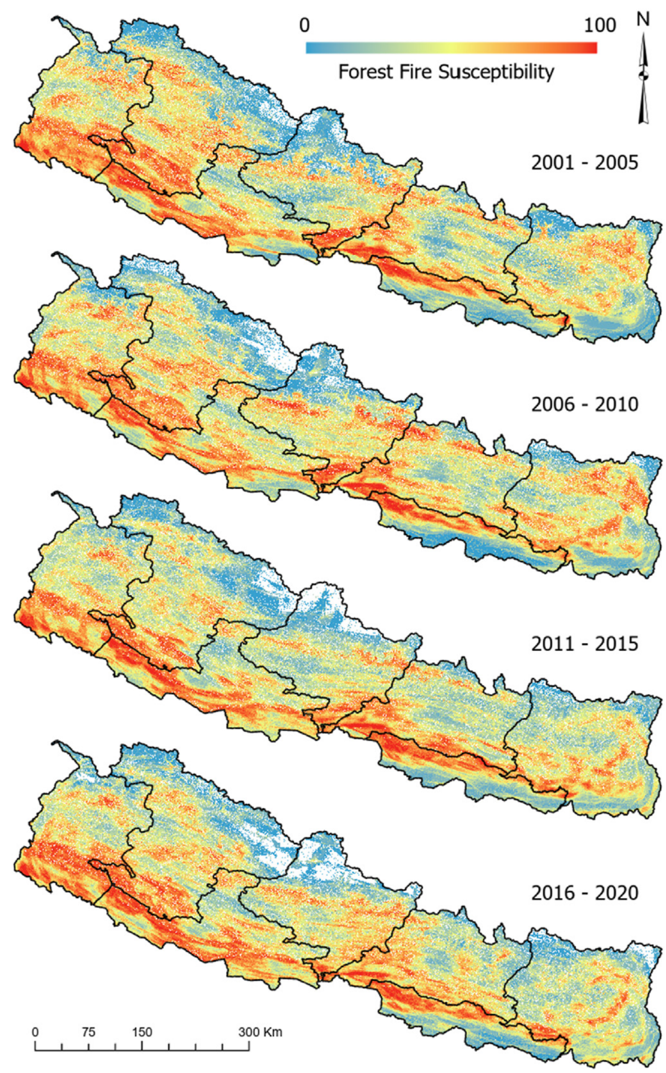
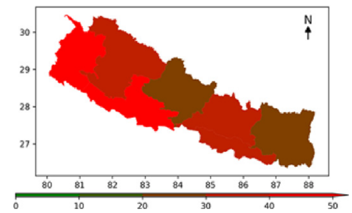
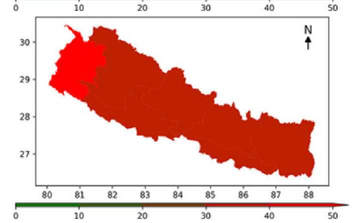
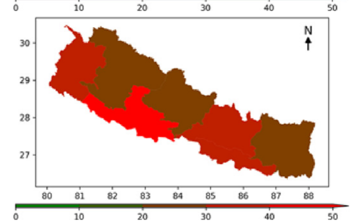
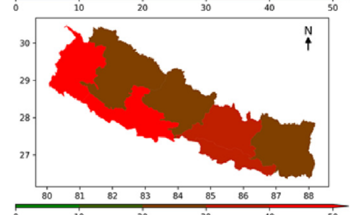


Fig. 3. National scale fire susceptibility maps in four sub-decades: 2001–2005, 2006–2010, 2011–2015, and 2016–2020. In these maps, the blue areas represent lower susceptibility to forest fires, while the red areas indicate higher susceptibility. By comparing the maps across different periods, we can observe the changes in forest fire susceptibility and identify potential trends or patterns. The forest fire susceptibility was predicted on a scale of 0–100, with higher values indicating a greater susceptibility to forest fires. The hotspots and coldspots presented in Fig. S7, shows that the susceptibility has an increasing trend in the southern part of Nepal.

Table 1
Province-wise statistics on forest fire susceptibility. Mean represents the spatial average value of forest fire susceptibility, and STD represents the spatial standard deviation of forest fire susceptibility over the provinces. The spatial map shows the susceptibility averaged to each province for each period. The standard deviation is also in the range of the mean due to the huge spatial variation within a province.

Province	Mean ± STD	Period	Spatial map
Gandaki	22.86 ± 23.87	2001–2005	
Lumbini	37.8 ± 27.07		
Bagmati	30.36 ± 23.51		
Sudurpashchim	38.93 ± 25.73		
Madhesh	32.11 ± 28.92		
Koshi	22.55 ± 20.08		
Karnali	28.15 ± 26.61		
Gandaki	27.15 ± 25.73	2006–2010	
Lumbini	37.59 ± 25.08		
Bagmati	32.77 ± 24.68		
Sudurpashchim	36.72 ± 25.9		
Madhesh	31.89 ± 30.02		
Koshi	28.07 ± 23.11		
Karnali	24.51 ± 25.14		
Gandaki	19.81 ± 21.95	2011–2015	
Lumbini	39.85 ± 26.81		
Bagmati	30.37 ± 25.82		
Sudurpashchim	33.59 ± 25.37		
Madhesh	36.63 ± 30.49		
Koshi	24.75 ± 21.19		
Karnali	22.8 ± 23.66		
Gandaki	23.55 ± 23.38	2016–2020	
Lumbini	43.17 ± 27.08		
Bagmati	31.34 ± 23.96		
Sudurpashchim	37.49 ± 28.27		
Madhesh	34.78 ± 29.91		
Koshi	21.64 ± 19.99		
Karnali	24.54 ± 25.49		

no clear overall increase or decrease. These findings on the spatial dynamics of forest fire susceptibility in Nepal are hoped to help decision-makers and stakeholders develop targeted strategies for forest fire prevention and management in each province. The efficacy of community forest user groups and Divisional Forest Offices in controlling and managing forest fires can be one of the contributing factors behind these observations.

In the Bagmati province, Chitwan consistently had the highest susceptibility throughout the years, with a peak in 2011–2015 (60.69) (Fig. S8). Makawanpur and Dhading had increasing susceptibility trends, while Kavrepalanchok had an increase in susceptibility from 17.12 in 2001–2005 to 31.56 in 2016–2020. The changes in susceptibility could be attributed to several dynamic factors, including climatic variables accompanied by anthropogenic disturbances (Bhujel et al., 2018; Parajuli et al., 2020). For example, the increased road proximity in these areas has introduced more human activity and ignition sources into the forested regions. At the same time, the rise in population fuels urban development and rural-urban migration, resulting in fallow land and increased forest cover and fuel. These activities contribute to more fuels that heighten forest fire susceptibility.

In the Gandaki province, Nawalparasi East had the highest susceptibility in 2001–2005 and 2006–2010 but experienced a considerable decrease in the following years. Lamjung, on the other hand, displayed an increase in susceptibility, reaching 40.82 in 2016–2020.

The Karnali province exhibited an overall increase in forest fire susceptibility, with Surkhet having the highest susceptibility throughout the years, peaking at 62.06 in 2016–2020. Other districts such as Salyan, Dailekh, and Jajarkot also showed increasing trends.

In the Koshi province, Udayapur and Terhathum had the highest susceptibility values in the 2011–2015 and 2016–2020 periods. In contrast, other districts like Dhankuta and Panchthar experienced a decrease in susceptibility over time.

The Lumbini province demonstrated increasing susceptibility, with Bardiya having the highest values across all periods. Banke and Kapilvastu also showed increasing trends, while Arghakhanchi experienced a steady increase throughout the years, reaching 44.39 in 2016–2020. This increased forest fire susceptibility could put medicinal herbs worth millions and wildlife at risk (A. G. Singh and Ghimire, 2022).

In the Madhesh province, Parsa consistently had the highest susceptibility, peaking at 62.42 in 2011–2015. Bara and Sarlahi displayed increasing trends, while Rautahat and Mahottari experienced fluctuations in susceptibility over the years. The largest forest cover area in Parsa, delayed rainfall, long dry periods, more litter fall, natural fires, and cigarette smoke all play a role in the highest forest fire susceptibility in this area (Badal, Mandal, and Others, 2021).

In the Sudur Pashchim province, Kanchanpur had the highest susceptibility throughout the years, followed by Kailali. Dadeldhura and Doti displayed increasing trends, while Achham had a slight decrease and then increased again in 2016–2020. These temporal forest fire susceptibility models were validated using AUC-ROC scores, and all models achieved acceptable scores (AUC-ROC >0.7) (Fig. S4).

4.2. *Environmental impacts*

4.2.1. *Carbon at risk*

We analyzed the SOC stock stored in forests and above-ground woody carbon (Fig. S5) with different levels of susceptibility to average forest fires susceptibility across all periods to find carbon at risk. With forest fire susceptibility, a significant dynamic of carbon storage is observed. A trend of decreasing mean SOC with increasing susceptibility to forest fires is observed (Fig. 4a). For the susceptibility ranges of 1–40, 41–60, 61–80, and 81–100, the average SOC was calculated as 87.9, 71.7, 56.6, and 44.9 metric tons/ha, respectively. This trend implies that regions with higher susceptibility to forest fires generally hold less carbon in the soil. In effect, this trend underlines a critical aspect of the soil carbon stock affected by forest fires (Page et al., 2002).

The total SOC at risk (Fig. 4b) in the same susceptibility ranges is 232.2, 95.9, 61.21, and 25.28 million tons, respectively. A combined total of 173.2 (~170) million tons of SOC is stored in high-risk forest fire zones (susceptibility >40). Also, the decreasing trend of SOC at risk suggests that as susceptibility to fires increases, less SOC remains, primarily due to its release to the atmosphere during previous forest fire events.

In examining the mean above-ground woody carbon levels (Fig. 4c), there is a noticeable increase across the susceptibility ranges of 1–40, 41–60, 61–80, and 81–100, with average values of approximately 68.2, 108.1, 134, and 171.1 metric tons/ha, respectively. The total wood carbon at risk in the same susceptibility ranges is 324.6, 145.5, 116.6, and 63.3 million tons, respectively (Fig. 4d). A combined total of 325.4 (~325) million tons of wood carbon is stored in high-risk forest fire zones (susceptibility >40). Like the trend observed in SOC, the average woody carbon does not decrease with increased susceptibility to forest fires. Instead, there is an upward trend. This suggests that areas with higher susceptibility may contain more mature or denser forests, possibly due to a history of selective adaptation or resilience to fires, leading to higher above-ground carbon content.

These results, however, shows the significance of forest fires as a factor influencing the carbon dynamics of a landscape. It is plausible that deforestation could play a role (Seydewitz et al., 2023), particularly in regions where forest cover is decreasing. However, given the patterns observed, forest fires appear to be a driver of carbon stock changes in these areas, also supported by Fig. S6. The observed dynamic of increasing/shifting forest fire susceptibility, particularly in southern Nepal (Fig. S7), underscores the need for forest fire management strategies. The increased risk threatens existing carbon stocks and future carbon sequestration potential, which may be critical for climate change mitigation efforts.

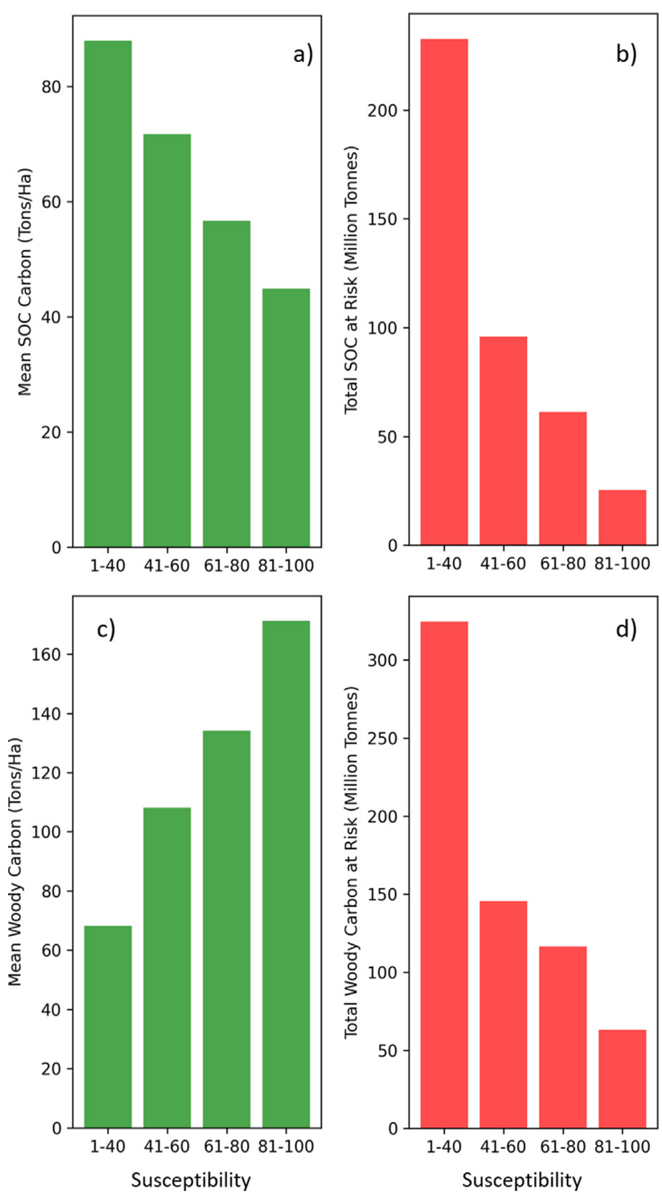


Fig. 4. Carbon stock at risk in relation to forest fire susceptibility. (a) Mean soil organic carbon (SOC) with susceptibility ranges; (b) Total SOC at risk for each susceptibility range; (c) Average woody carbon for each susceptibility range; (d) Total woody carbon at risk for each susceptibility range.

4.2.2. *Biodiversity at risk*

Forest fires can lead to significant biodiversity loss, particularly in areas with high fire susceptibility. Throughout the years, the Koshi Tappu Wildlife Reserve, Chitwan, Banke, Bardia, Shuklaphanta and Parsa National Parks have consistently shown high susceptibility to forest fires (Fig. 5), with higher spatially averaged susceptibility values. This indicates that these protected areas are more prone to forest fires, which could lead to severe environmental and ecological impacts if not managed effectively and if effective fire preparedness measures are not taken by concerned stakeholders. These protected areas are home to numerous endemic and endangered species of plants and animals. Koshi Tappu Wildlife Reserve is a home to endangered Wild Water Buffalos, Hog deer, Wild boar and Spotted deers among others. At Bardia National Park, some notable species include the Royal Bengal Tiger, Wild elephants, and translocated One-horned rhino. Chitwan National Park, which is also a natural World Heritage Site, hosts species such as the One-horned rhinoceros, Sloth bear, Golden monitor lizard, and Gaur. Parsa

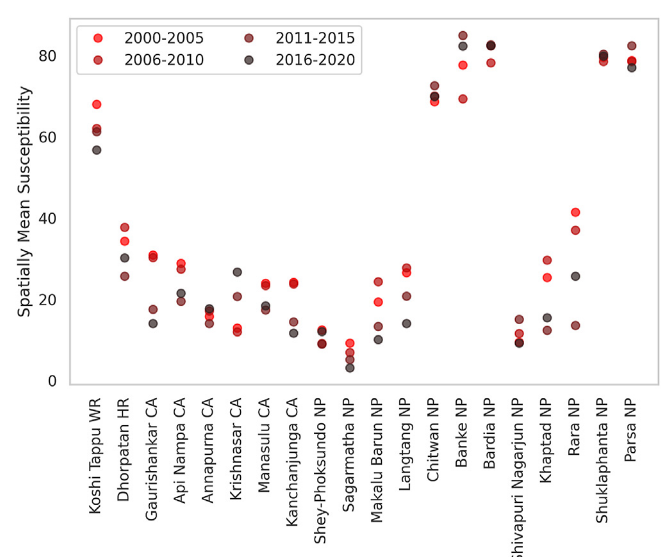


Fig. 5. Variation in Forest Fire Susceptibility across protected Areas in Nepal (2001–2020). Dots shows the changes in forest fire susceptibility, measured by spatial mean susceptibility values, for different protected areas in Nepal over four sub decades (2001–2005, 2006–2010, 2011–2015, and 2016–2020). CA is a Conservation Area, NP is a National Park, WR is a Wildlife Reserve and HR is a Hunting Reserve.

National Park is home to wildlife like the Wild Asian elephant, Striped hyena, and Langur. The Shuklaphanta National Park is known for its Swamp deer population. Additionally, various bird species can be found across these regions. The increasing frequency and intensity of forest fires in these regions pose a significant threat to these species and their habitats, disrupting ecological processes and food chains (Ergazaki and Andriotou, 2010).

On the other hand, several protected areas, such as Shey-Phoksundo National Park, Rara National Park, and Langtang National Park, have shown a decline in susceptibility to forest fires over time. The Sagarmatha National Park and the Kanchanjunga protected area have experienced the most significant reductions in forest fire susceptibility, with their mean values in the 2016–2020 period falling well below 10. These areas mostly lie in mountain regions, and the improvements could result from effective forest management practices, a lower risk of fire ignition, or changes in environmental factors that reduce fire propagation.

The Annapurna, Manaslu, Makalu Barun and other conservation protected areas have maintained relatively stable forest fire susceptibility levels over the years. However, it is still important to monitor these areas closely to ensure that they remain less susceptible to forest fires in the future.

Comparing the situation in Nepal to the devastating wildfires that occurred in Australia during 2019–2020, we can draw parallels in terms of the severe impact on biodiversity. The Australian wildfires resulted in the death or displacement of an estimated three billion animals, including mammals, birds, and reptiles (Legge et al., 2022). This event led to long-term consequences for the affected ecosystems, with some species pushed closer to extinction.

In summary, we identified the wild water buffalos, Hog deer, Wild boar and Spotted deers in Koshi Tappu Wildlife Reserve; royal bengal tiger, wild elephants, and translocated one-horned rhinoceros in Bardia National Park; the one-horned rhinoceros, sloth bear, golden monitor lizard, and gaur in Chitwan National Park; Wild Asian elephant, Striped hyena, and Langur in Parsa Wildlife Reserve; and the swamp deer in Shuklaphanta Wildlife Reserve as species at significant risk due to forest fires.

5. Discussion

Our research explores forest fire susceptibility over the past two decades on a sub-decadal scale, focusing on Nepal with findings relevant to the global context. We identified forest fire hotspots nationally with spatiotemporal analysis. In particular, the southwestern region, the central Chure area, and hilly western regions of Nepal are more susceptible, where fires tend to be more intense in forest areas with dense tree cover, low elevations, and lower slopes dominated by species such as Pines and Sals (Qadir et al., 2021). Over recent decades, the increase in population and activities in these previously uninhabited regions have contributed to these dynamics, along with high surface temperatures, low rainfall, and fuel accumulation. Our analysis suggests that forest fires could release more than 495 million tons of carbon into the atmosphere. Our study advances the understanding of forest fire susceptibility in four notable ways.

First, we introduced a dynamic assessment of susceptibility, and highlighted a marked shift towards increased risk in the southern part of the country. Second, we incorporated climate variables, identifying a link between climate change indicators and forest fire occurrences. Third, we estimate the potential release of approximately 170 million tons of soil organic carbon and 325 million tons of wood carbon at risk due to forest fires. Although forests can regrow after fires, it often takes nearly a decade to recover to their previous levels (Pandey et al., 2022). Lastly, we expanded the geographical scope to a national level in Nepal, whereas previous studies primarily focused on the southern belt (Parajuli et al., 2023). These findings are hoped to offer valuable insights for forest fire management in Nepal.

The analysis of forest fire susceptibility in protected areas across Nepal has important policy implications. By prioritizing resources and budget allocation to areas with the highest risk, we can potentially meet SDG 13 (Climate Action) and SDG 15 (Life on Land) by reducing the impact of forest fires on air quality, ecosystems, and soil health. By understanding the unique challenges and dynamics of each area, tailored strategies can be designed to address the specific risks and environmental factors that contribute to forest fire susceptibility. There is a pressing need for flexible, risk-based fire management strategies (Clarke et al., 2023). These strategies include public awareness campaigns, capacity building of local communities in fire management, fire preparedness plans at local levels, implementing early warning systems, and promoting sustainable land-use practices to reduce the likelihood of fire ignition. Addressing forest fire risk requires climate actions and mitigation measures that promotes sustainable development goals holistically (Pradhan et al., 2025).

Forest fires have a significant direct impact on air quality by releasing substantial amounts of smoke, particulate matter, and other pollutants into the atmosphere. It can result in respiratory issues, especially for individuals with pre-existing health conditions like asthma or heart disease. Furthermore, forest fires can cause harm to ecosystems and contribute to climate change by emitting greenhouse gasses like CO_2 into the air. The increase in air pollution levels caused by forest fires can also have an adverse effect on numerous domestic flights. Additionally, the rise in air pollution could result in a surge in the number of patients suffering from respiratory diseases, lung cancer, heart disease, hypertension, and stroke. Specifically, the smoke generated from forest fires typically flows into and settles in the bowl-shaped valley (i.e., Kathmandu), a densely populated capital city, causing a haze over the region (Rives, 2022). Also, forest fires can indirectly impact food-supply, tourism, and local economies.

Environmental stressors, such as erosion or degradation, negatively impact the amount of SOC stock (González-Pérez et al., 2004). Forest fires are a prominent factor that can disrupt the natural carbon cycle. They alter the carbon sequestration function of vegetation, meaning that the vegetation can no longer be able to absorb as much carbon dioxide from the atmosphere. Instead, the burned vegetation releases carbon dioxide into the air, making the fire site a significant carbon source rather than a carbon sink (Page et al., 2002). Carbon release is a significant concern under SDG 13 (Climate Action). Furthermore, these burned areas are also prone to soil erosion. It can be particularly problematic because the topsoil typically contains a high concentration of organic matter (Aksoy et al., 2016). It can have a negative impact on soil health and the overall ecosystem, as these organic contents are key nutrients for many living organisms (Parashar and Biswas, 2003).

The Random Forest methodology has demonstrated robustness and reliability in predicting forest fire susceptibility (Bustillo Sánchez et al., 2021; Hong et al., 2018; Mohajane et al., 2021; Pourghasemi et al., 2020). Nonetheless, advanced machine learning techniques (state-of-the-art) could still be explored in future research to enhance the model's accuracy and predictive power. Moreover, incorporating more variables, particularly in-situ measurements, could result in more accurate and reliable outcomes. We have developed a comprehensive dataset for predicting forest fire susceptibility, which is valuable in the context of the expanding field of machine learning. This approach allowed us to train models using many parameters, offering a significant advantage over other studies that rely on a limited set of terrain and climatic variables. Additionally, we developed a national-scale model, which is a more comprehensive approach than focusing on specific areas. For example, some previous studies (Parajuli et al., 2020; Parajuli et al., 2023) only focused on the Terai region.

Another aspect to consider is the influence of forest fires on the water cycle and hydrological processes. Forest fires can lead to changes in landslide occurrence and susceptibility, often increasing the likelihood of debris flows due to reduced moisture conditions. It, in turn, makes the area more susceptible to plant water stress, resulting in a shorter life span for affected plants. These complex relationships highlight the need for additional research to understand better and manage these effects. Forest fires also have the potential to alter groundwater recharge. After a fire, water can infiltrate the ground more directly with removed vegetation cover, possibly increasing recharge rates, or dried soil can become water repellent and promote debris flows. Such debris flows can even trigger massive compound hazards in the Himalayas (Talchabhadel et al., 2023). However, while forest fire smoke is generally associated with negative health and environmental consequences, it is important to consider some potential benefits as well. These advantages include nutrient recycling, pest control, climate regulation, smoke-induced germination, and ecosystem rejuvenation. The potential changes in groundwater recharge rates following a forest fire are closely linked to SDG 6 (Clean Water and Sanitation). Forest fires can impact the quality and availability of freshwater resources, affecting the ability to achieve SDG 6.4, which aims to substantially increase water-use efficiency and ensure sustainable withdrawals and supply of freshwater.

While our study offers several advancements, it's essential to acknowledge its limitations. First, the FIRMS data may not accurately capture all actual forest fires. They might include domestic fires, potentially leading to an over- or underestimation of certain features' impact on forest fire susceptibility as FIRMS relies primarily on satellite data, specifically the detection of thermal anomalies using sensors such as the Moderate Resolution Imaging Spectroradiometer (MODIS - 1 km resolution) or the Visible Infrared Imaging Radiometer Suite (VIIRS - 375 m resolution). The large differences in spatial resolution in input variables and data gaps in terrain derivatives could have introduced some uncertainties in bilinear interpolation. Also, we used nearest neighbhor to harmonize the carbon stock rasters (both SOC and wood carbon) to susceptibility raster which might have lead to over/underestimation of the original carbon stock data. We acknowledge and enourage that much better estimation can be made in the future with better carbon stock data and models. Second, our choice of the Random Forest model could be outperformed by more advanced deep learning models or better locally validated forest fire database, suggesting another avenue for future investigation. Lastly, we have treated forest fire events as point events; however, considering their spread could provide a more nuanced understanding of their growth and impact rather than only considering triggering environment. Incorporating spread areas and wind factors into future models could refine the predictive performance and facilitate additional analyses. Also, using advanced explainable machine learning methods like SHAP (Dahal et al., 2023) or LIME (Thi et al., 2024) may provide nuanced insights rather than using variable importance from random forest models.

As forest fires are a global concern, the lessons from this study in Nepal can be relevant to other parts of the world facing similar challenges. In particular, regions in South Asia, such as Northeast India, Bhutan, and northern parts of Myanmar and Bangladesh share similarities with Nepal regarding forest types, topography, and climate (P. Singh and Dey, 2021). Thus, the methodology we used to analyze and predict forest fire susceptibility and mitigation strategies has implications for regions globally experiencing rapid population growth and urbanization, especially where these factors coincide with susceptible forest areas.

6. Conclusion

Forest fires are a universal concern, impacting countries across the globe. Our findings in Nepal reflect a broader, worldwide trend. The risks associated with forest fires, such as the potential release of substantial amounts of SOC and woody carbon, are not limited to Nepal alone. Globally, billions of tons of SOC and woody carbon and biodiversity are under threat due to forest fires, contributing to the exacerbation of climate change. Additionally, our study highlights that six out of 20 protected areas in Nepal are at high risk from forest fires. This trend is mirrored globally as protected areas and biodiversity hotspots worldwide face significant threats from escalating forest fire incidences. Our national scale dynamic susceptibility analysis also reflects a pattern of increased forest fire risks due to climatic and anthropogenic factors.

Future research in forest fire dynamics has the potential to incorporate advanced climate models like CMIP6, which are available on the GEE platform. Integrating climate-forcing data from such models could enhance the understanding of projected impact on forest fire occurrence and severity, creating more comprehensive predictive models. Considering a wider range of climatic variables and their interactions, these models could provide improved projections of future forest fire risks. The findings from these models could inform management strategies and policy-making, supporting the sustainable development of more resilient and sustainable forest ecosystems in the face of increasing threats from forest fires.

Simultaneously, there is an opportunity to explore the role of socioeconomic and cultural factors in the occurrence and management of forest fires. A deeper investigation into the influence of local communities, traditional knowledge, and land-use practices on forest fire dynamics can unearth valuable insights for creating contextually relevant fire management strategies. For instance, understanding the perception and preparedness of local communities regarding forest fires can be vital for effective risk communication and for implementing community-based fire management interventions.

Future research also presents an opportunity to integrate these socioeconomic, cultural, and ecological factors with sophisticated, data-driven approaches. This could yield a more holistic understanding of forest fires, transcending the natural-physical dimensions to encompass human and societal interactions. The amalgamation of these varied yet interconnected perspectives can ultimately contribute to a comprehensive strategy that mitigates the negative impacts of forest fires on both human and natural systems. Thus, future advancements in this field have the potential to offer multifaceted solutions that address the complex and global challenge of forest fires.

Data and code availability

The code and required datasets for forest fire susceptibility modeling will be available upon request. The updated forest fire inventory can be downloaded from NASA's Fire Information for Resource Management System at https://firms.modaps.eosdis.nasa.gov/.

CRediT author statement

Conceptualization: K.D., R.T., P.P.; Methodology: K.D., R.T., P.P., S.P., D.S.; Software: K.D., R.T.; Writing – Original Draft Preparation: K.D., R.T.; Writing – Review & Editing: K.D., R.T., P.P., S.P., D.S., R.C., A.P.G., R.T., S.G., S.K.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, we used ChatGPT to improve the language and readability of the manuscript. The tool was not used in the original draft. After using this tool, we reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.infgeo.2025.100003.

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