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Modelling spatial patterns of forest fire occurrence in the Northwestern region of Vietnam

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ABSTRACT

Forest fires present a significant threat to the tropical forest ecosystem in the northwestern region of Vietnam. Our study aimed to assess the impacts of environmental factors on forest fire occurrence and to map forest fire probability for the whole region. The forest fire occurrence data over the period 2003–2016, environmental factors (climate, fuel condition, topography, and human activity), and the MaxEnt approach were used for this study. The MaxEnt model performed better than the random model (AUC>0.88). Climatic factors (especially climatic seasonality: annual temperature range (bio_07), isothermality (bio_03), and precipitation of warmest quarter (bio_18)) had the highest contribution to the model, followed by population density and elevation. In contrast, fuel condition (Land cover type) had a small contribution to the model. While medium, high, and very high probabilities of forest fire occurred at medium to high elevations (e.g., Dien Bien, Son La, and Lai Chau provinces) throughout southern to northern and western areas, very low and low probability concentrated southeastern areas at lower elevations (mainly in Hoa Binh province). Our results may be helpful references for fire managers and policymakers to establish more effective fire management strategies for the region's forest.

Keywords: Forest fire, machine learning, MaxEnt, remote sensing, Southeast Asia, tropical forest.

1. Introduction

Fires represent one of the main types of disturbance in terrestrial ecosystems globally (Flannigan et al., 2013). While fires have rarely occurred in wet tropical forests (Cochrane 2003; Enright 2011), over the past few decades, increased fire occurrence (a likely ongoing consequence of global environmental change drivers) has caused the degradation of these tropical forest ecosystems. This trend represents a growing threat to the remaining tropical forests in Southeast Asia (SEA) (Langner and Siegert, 2009; Syaufina and Ainuddin, 2011). Fire is projected to increase in SEA as climate changes and the human population continues to grow in the future (Juárez-Orozco et al., 2017; Robinne and Secretariat, 2021). Conservationists are increasingly concerned that the impacts of fire in continental SEA reduce the forest area and biodiversity, alter forest structure and composition, increase soil erosion and greenhouse gas emissions, and

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result in a net loss of species diversity as a consequence of ecosystem simplification (Cochrane, 2003; Syaufina and Ainuddin, 2011; Verma and Jayakumar, 2012). In addition to its devastating effects on tropical forest systems, forest fires result in significant economic losses (Silviana et al., 2019). The cost of damages by the fires in SEA has exceeded $4.5. billion (Cotton, 1999).

Forest fire occurrence results from complex human-environment interactions among forest fuels, climate conditions, ignition agents, topography, and human activities (Goldammer and Seibert, 1990; Herawati and Santoso, 2011). Fire occurrence is strongly affected by weather conditions, both antecedent (conditions conducive to fuel drying) and ambient (conditions conducive to ignition, combustion, and spread) (Bradstock, 2010). Generally, the hotter, drier, and windier weather conditions increase the possibility of wildfires because of reduced fuel moisture and lower energy requirements for pre-heating, especially when these conditions coincide with ignitions (Parisien and Moritz, 2009). Fuel conditions are also a significant factor influencing the occurrence of fire (Bradstock, 2010). Fire occurrence is regulated by fuel's load, moisture content, and flammability (including both live and dead) (Pausas and Keeley, 2009). Topographic variables such as elevation, slope, and aspect strongly impact fire occurrence by influencing the micro weather patterns, moisture, and availability of fuel (Fang et al., 2015). The slope also influences fire spread (Cruz and Alexander, 2017), with slower progression on lower slopes than on upper slopes (Viegas and Pita, 2004). Elevation impacts forest fire via its relationship to temperature, precipitation, and wind, affecting fuel characteristics (Bennett et al., 2010; Camp et al., 1997). Aspect affects forest fire through its effect on fuel moisture (Nyman et al., 2015). Aspects receiving higher solar radiation are warmer; thus, fuels dry faster, support ignition, and spread more readily than on more astonishing aspects (Bennett et al., 2010; Skinner, 2002). Fire occurrence is also affected by human factors such as population density and road distance. High population densities and short distances from roads are related to a high possibility of wildfire occurrence (Knorr et al., 2014; Matin et al., 2017). These previous studies showed that forest fires are complex and non-linear processes influenced by physical and climatic factors. Therefore, modeling and predicting forest fire occurrence remains a challenging task.

In recent years, various approaches have been suggested for spatial pattern modeling of forest fire occurrence globally such as linear and multiple regressions (Oliveira et al., 2012), logistic regression (Guo et al., 2016a), geographically weighted regression (Koutsias et al., 2010), Random forest algorithm (Massada et al., 2012), support vector machines (Thach et al., 2018), kernel logistic regression (Dieu et al., 2016), neural fuzzy (Dieu et al., 2017), convolutional neural network (Zhang et al., 2019), Maximum Entropy (Mishra et al., 2023). These studies showed that machine-learning models have delivered more accurate results than statistical models (Massada et al., 2012).

Among existing modeling approaches, Maximum Entropy (MaxEnt) has been widely used to model the spatial distribution of species in ecological studies (Phillips et al., 2006). The MaxEnt is consistently among the best-performing analytical approaches for this application (Elith et al., 2006) by utilizing the rule of maximum entropy on present data-related environmental variables and habitat suitability (Andrew and Fox, 2020; Phillips et al., 2006). In recent decades, MaxEnt has been used to assess the shape and the importance of the relationships between fire and environmental factors. This is based on the environmental conditions at the fire occurrence points relative to those at a set of background points (Renard et al., 2012). These studies indicated that MaxEnt performed reliable predictions of forest fire distribution and assessments of relationships between forest fire and environmental factors.

The Northwestern (N.W.) region of Vietnam has been ranked the fourth highest in forest coverage within the country (Ministry of Agriculture and Rural Development, 2022a). This region has also experienced the highest number of forest fires (Le et al., 2014; Ministry of Agriculture and Rural Development, 2022b) and is prone to an increasing number of fires, with fire occurrence facilitated by strong Foehn winds (Mau et al., 2018; Nguyen and Reiter, 2014). Most forest fire incidents occur in the dry season, especially between November and April (Le et al., 2014; Trang et al., 2022). Approximately 10,000ha of forest area was burned within the northwestern region in 2005–2020 (Forest Protection Department, 2020). Besides, forest fires caused economic and environmental issues (Le et al., 2014).

However, current studies on forest fire drivers and modeling in this region focused on some specific areas (local scale) and years (Thach et al., 2018; Thanh-Van et al., 2020). For example, (Thach et al., 2018) applied machine learning algorithms based on weather conditions, fuel conditions, topography, and distance to the road to analyze the spatial pattern of fire danger in Thuan Chau district, Son La province, in 2016. In recent years, Trang et al. (2022) utilized the MaxEnt approach to assess the importance of some key drivers of forest fire occurrence in Lao Cai, Dien Bien, and Son La provinces and model spatial distribution of forest fire occurrence in these provinces on days with low, medium, and high Modified Nesterov indexes. In general, the results of these studies are not entirely similar. This may be because of differences in topography, climatic and fuel conditions, and other socioeconomic factors. The results of these studies are localized and limited, remaining insufficient to provide adequate information for effective forest fire management on a regional scale. This limitation may pose challenges in generalizing within this region. Therefore, assessing the relationship between forest fire occurrence and environmental factors and modeling the fire distribution for the entire northwestern region is necessary for the forest management authorities and policymakers to develop effective forest fire prevention plans. The study, therefore, was conducted to analyze the effects of environmental and socioeconomic factors on forest fire occurrence and model the potential spatial distribution of forest fire during the 2003–2016 period in N.W. of Vietnam.

2. Materials and methods

2.1. Study area

The northwestern region of Vietnam, including Hoa Binh, Son La, Dien Bien, and Lai Chau provinces, is located at 20°00′–23°23′N and 102°8′–106°00′E, with an area of approximately 37,324 km^2 (General statistics office of Vietnam, 2011; Ministry of Agriculture and Rural Development, 2022a) (Fig. 1). This region bordered by the Northeast and Red-river regions to the east, Laos to the west, Central region to the south, and China to the north. A monsoon tropical climate characterizes the region. Annual average temperature is 20–23°C. Annual precipitation is 1,100–2,400 mm, mainly concentrated in Jun-August. This region has experienced decreased annual rainfall (Ngo-Duc, 2023). The drought period in this region is from November to March. Winter is cold and dry, with mean temperatures from 12 to 17°C, and the minimal temperature may fall to 4°C. Summer is the warm rainy season with temperatures between 25 and 27°C; sometimes, the temperature reaches 42°C. Total hours of sunshine per year are 1,700–2,100. The region experiences 40 days of dry and hot winds from the west (Foehn winds) annually (Van, 2015). Some parts of the region have a montane monsoon tropical climate associated with areas above 1,400 m elevation spread along the Hoang Lien Son, Si Lung, Den Dinh, and Sam Sao ranges with higher rainfall, lower temperature, and cold, cloudy mists (Averyanov et al., 2003; Van, 2015). Vegetation cover is mainly rainforests with four natural sub-forest types, including evergreen broad-leaved forests on alkaline soils; evergreen and semi-deciduous broad-leaved, mixed and coniferous limestone mountain forests; evergreen lowland forests on silicate rocks; evergreen lowland forests on silicate rocks; and evergreen montane and highland forests on silicate rocks (Averyanov et al., 2003). However, decades of disturbances by human activities have created large expanses of degraded land in northern Vietnam (Cochard et al., 2016; Thai et al., 2010). Therefore, most primary forests have been replaced by secondary forests characterized by more open canopy, lower relative humidity, and higher fuel load - thus more susceptible to fire (Phuong et al., 2012).

2.2. Dependent variable: active fire

A total of 18,811 fire occurrence data during the 2003–2016 period, each with a minimum size of 21ha, were downloaded from the Moderate Resolution Imaging Spectroradiometer (MODIS) - Collection 6 MCD64A1 burned area product at 500 m resolution (Andela et al., 2019). We used Vietnam's land use and land cover map from 2003 to 2016 (Phan et al., 2021) to determine whether the fires were forest or non-forest fires. A total of 13,153 forest fires were chosen after removing non-forest fire points and fire points with missing data in one of the environmental predictor variables in the study area. We chose the minimum distance of 2 km between the nearest neighbor fire to limit the potential influence of spatial autocorrelation effects of adjacency of fire points. This distance was thoughtfully selected to align with the resolutions of the MODIS data and environmental variables. Finally, 3,053 points were used in the analysis (Fig. 1).

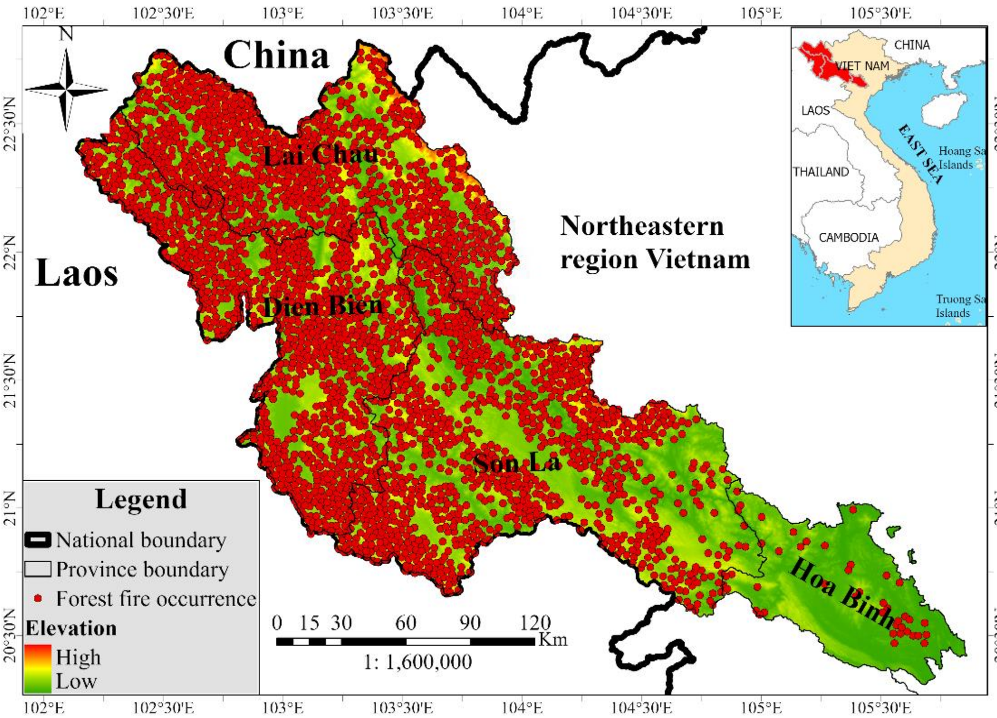

Figure 1. The study area and forest fire occurrence (red dots) over the period 2003–2016 inclusive

2.3. Independent variables

Environmental variables used in this study are shown in Table 1. Nineteen bioclimatic variables were obtained from the Worldclim dataset (version 2.1; http://www.worldclim.org) at approximately 1 km spatial resolution (Fick and Hijmans, 2017). The elevation layer was extracted from the Global Digital Elevation Map (GDEM) generated from the Consultative Group on International Agricultural Research - Consortium for Spatial Information (CGIAR-CSI) with a resolution of approx.90m (Jarvis et al., 2008). Slope and aspect were generated from the elevation layer by using the Surface Analysis toolbox in ArcGIS Pro (ESRI, 2019). The MODIS 500-m Land Cover Type Product (MCD12Q1) in 2016 was downloaded from the Land Processes Distributed Active Archive Center (LPDAAC) of the United States Geological Survey (USGS) and the National Aeronautics and Space Administration (NASA) (https://lpdaac.usgs.gov/products/mcd12q1v006/). This product was used as a source of fuel condition, which was identified into 12 classes by Sulla-Menashe and Friedl (2018). Population density data at 30 arc-second resolution (approximately 1km) during the period 2000–2020 was obtained from the Socioeconomic Data and Applications Center (SEDAC) (https://sedac.ciesin.columbia.edu) (Center for International Earth Science Information Network Columbia University, 2018). Finally, all variables were resampled to the preferred resolution (90 × 90 m) using the nearest neighbor method by the Resample tool in ArcGIS Pro (ESRI, 2019).

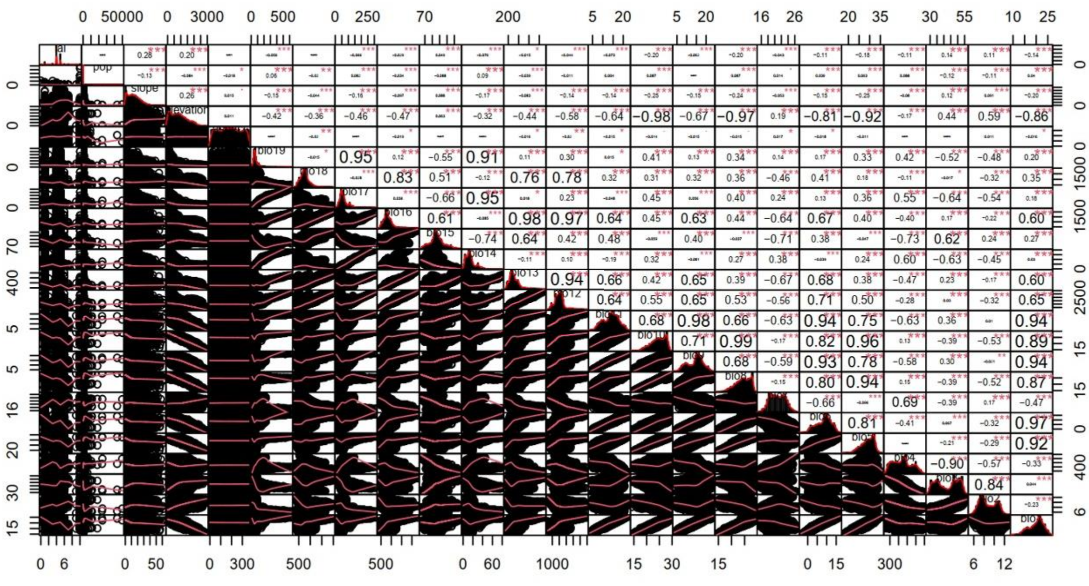

Figure A.1. Correlation matrix of variables. r values and *, **, and *** indicate p < 0.05, p < 0.01, and p <0.001, respectively, in cells. The full names for variables are provided in Table 1

To avoid autocorrelation between environmental variable pairs, we randomly created 17,000 points with a minimum distance of 2 km between these points in the region, which found a balance between the resolution of environmental variables. Then, each point was assigned environmental variable values. The Pearson correlation coefficient was used to calculate the correlation between pairs of variables. We did not include variables with a high correlation coefficient of greater than 0.8 in the same model (Fig. A.1). As a result, 12 variables were eventually selected for this study (Table 1).

Table 1. Environmental predictors used for forest fire occurrence modelling

Variable	Unit	Code	Source/Reference
Annual mean temperature	°C	bio_01	Worldclim (http://www.worldclim.org)
Annual mean diurnal range (Mean of monthly =max temp - min temp)	°C	bio_02	
Isothermality (BIO2/BIO7) (* 100)	***-***	***bio_03***	
Temperature seasonality (standard deviation *100)	C of V	bio_04	
Max temperature of warmest month	°C	bio_05	
Min temperature of coldest month	°C	bio_06	
Annual temperature range (BIO5-BIO6)	***°C***	***bio_07***	
Mean temperature of wettest quarter	°C	bio_08	
Mean temperature of driest quarter	°C	bio_09	
Mean temperature of warmest quarter	°C	bio_10	
Mean temperature of coldest quarter	***°C***	***bio_11***	
Annual precipitation	***mm***	***bio_12***	
Precipitation of wettest month	mm	bio_13	
Precipitation of driest month	mm	bio_14	
Precipitation seasonality (Coefficient of variation)	***mm***	***bio_15***	
Precipitation of wettest quarter	mm	bio_16	
Precipitation of driest quarter	***mm***	***bio_17***	
Precipitation of warmest quarter	***mm***	***bio_18***	
Precipitation of coldest quarter	mm	bio_19	
Topography			
Elevation	***m***	***elevation***	***The CGIAR Consortium for Spatial Information (CGIAR-CSI) (Jarvis et al., 2008); https://srtm.csi.cgiar.org***
Slope	***degree***	***slope***	***Calculated from digital elevation model***
Aspect	***degree***	***aspect***	***Calculated from digital elevation model***
Fuel variables			
Land cover type	***type***	***lai***	***Land Cover Type Product (Sulla-Menashe and Friedl, 2018) (https://lpdaac.usgs.gov/products/mcd12q1v006/).***
Human activity			
Population density	***persons/km^2***	***pop***	***Socioeconomic Data and Applications Center (SEDAC) (Center for International Earth Science Information Network, 2018) (https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11)***

Note: The highlighted variables (in bold and italic), selected through multi-collinearity test, were used in modelling

2.4. MaxEnt modelling

The MaxEnt software version 3.4.4 (downloaded from https://biodiversityinformatics.amnh.org/open_source/maxent/) (Phillips et al., 2022) was used for this study. The dataset of forest fire occurrence was described in section 2.2. 75% of the data were selected for training and the remaining (25%) for testing. The dataset was in Excel files in CSV format to run MaxEnt in "samples with data" mode. The regularization multiplier value was set at 4 to limit model complexity. The selection was selected to compare model performance across training and test datasets. A reduction in AUC from training to test indicates that the model may be too complex and overfit the training data. Maximum iterations were 5,000. The maximum number of background (pseudo-absence) points was 10,000. Thirty replicates were kept for model building. The other values in the model were kept as default (Phillips, 2005).

The area under the curve (AUC) was used to determine the accuracy of the model (ranging from 0 to 1) (Fielding and Bell, 1997; Phillips et al., 2006). The AUC values above 0.7 are considered reasonable performance (Elith, 2000; Phillips et al., 2006). The jackknife procedure was used to assess the importance of variables.

Finally, the result of the MaxEnt models was a map layer representing forest fire probability values (with values ranging from 0 (no fire probability) to 1 (high fire probability)). Then, ArcGIS 10.1 was used to transform this map layer into a raster (.tif) file. We used the "10th percentile training presence logistic threshold" to determine the cut-off value. Five classes were classified based on the suggestion of Nhongo et al. (2019): Very low (< 0.25), Low (0.25–0.36), Moderate (0.36–0.47), High (0.47–0.58), and Very High (> 0.58).

3. Results

The results of the MaxEnt model showed that the mean training AUC was 0.8859± 0.003, and the mean testing AUC was 0.8856 ±0.003, indicating good model performance. That means that forest fire occurrence data and environmental variable data used in the modeling can effectively predict the potential distribution of forest fires in this region (Fig. 2).

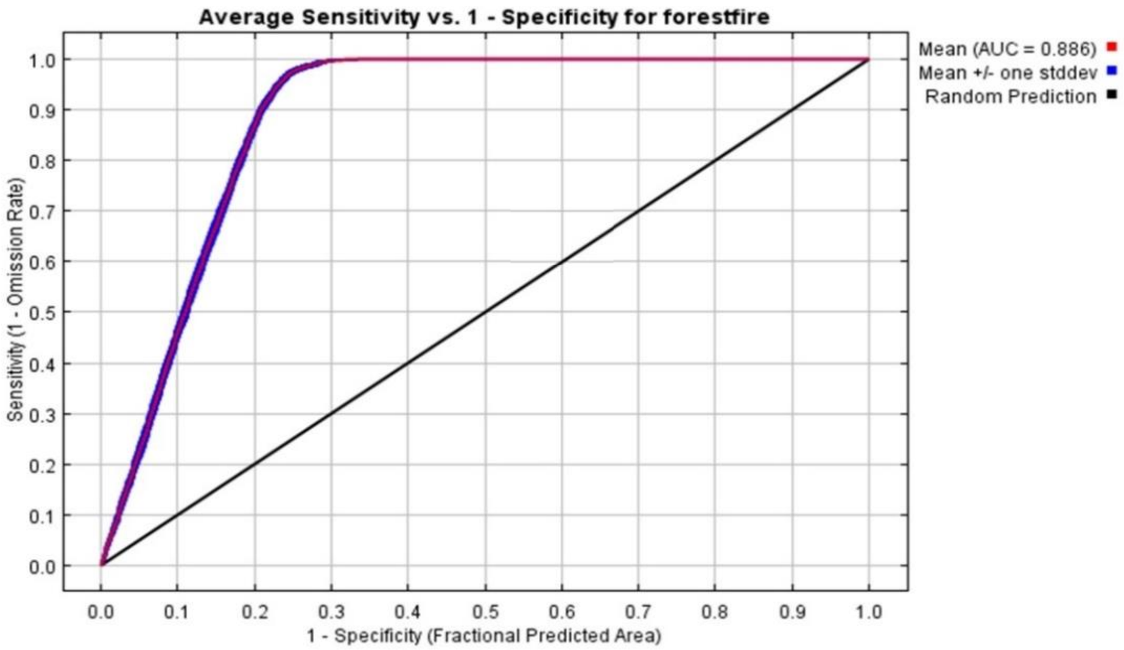

Figure 2. The AUC curves (created for the MaxEnt model) in the developing forest fire probability model

The contribution of the 12 variables to the model is shown in Table 2. Among these variables, the top five variables, including annual temperature range (bio_07), population density (pop), precipitation of warmest quarter (bio_18), isothermally (bio_03), and elevation, had the most contribution to the model with 95.1% of cumulative contribution (Table 2). Thus, these variables had the most significant effect on forest fire occurrence in the northwestern region. The remaining environmental variables had a small or negligible effect on forest fire distribution.

Table 2. Percentage contribution and permutation importance of each variable in the final MaxEnt model. The full names for variables are provided in Table 1

Variable	Percent contribution	Permutation importance
bio_07	50.1	66.1
pop	15.7	13.7
bio_18	11	6.3
bio_03	9.6	8.9
elevation	8.7	0.3
bio_11	2.8	1.9
slope	1.3	1
bio_15	0.5	1.1
bio_12	0.1	0.4
lai	0.1	0.1
bio_17	0	0.2
aspect	0	0

The result of the jackknife test of variable importance showed that the annual temperature range (bio_07) had the most valuable and unique information of all the variables and was thus identified as the main factor affecting the spatial distribution of forest fires in this region, followed by population density (pop), precipitation of warmest quarter (bio_18), precipitation seasonality (bio_15), isothermality (bio_03) (Fig. 3).

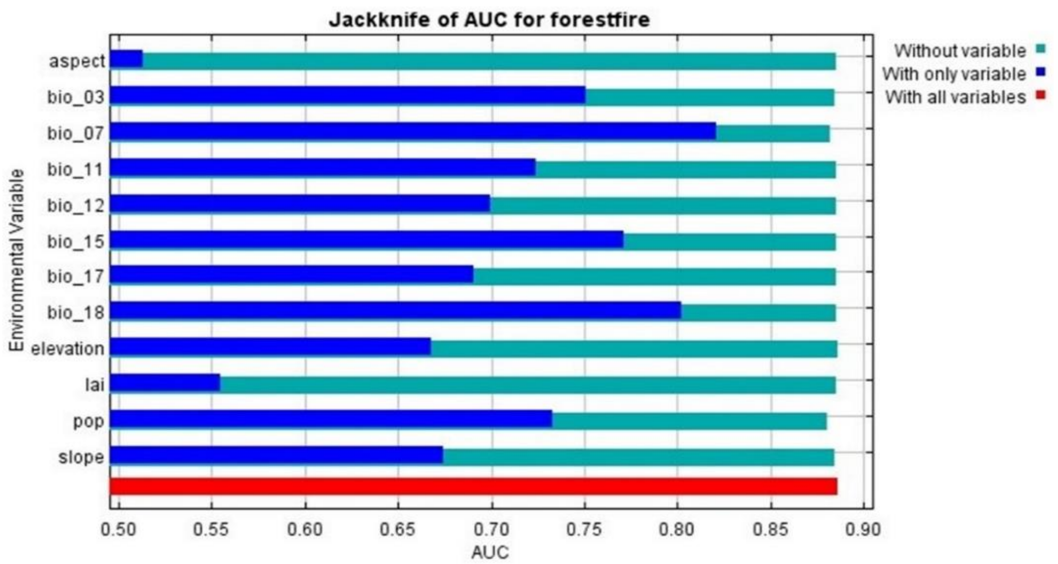

Figure 3. Jackknife test of variable importance for modelling of the spatial distribution of forest fire occurrence within the northwestern region of Vietnam. The full names for variables are provided in Table 1

Response curves results of five variables with more than 8% contribution to the model were shown in Fig. 4. Forest fire probability seemed to prefer some conditions as follows: elevation was 800–1200 m, population density was lower than 300 persons/km^2, bio_07 ranged 18–19°, bio_03 ranged 45 to 50, and bio_18 ranged 900–1,200 mm. The forest fire was likely to happen in low population density areas at medium to high elevations with dry climates and high extreme temperatures.

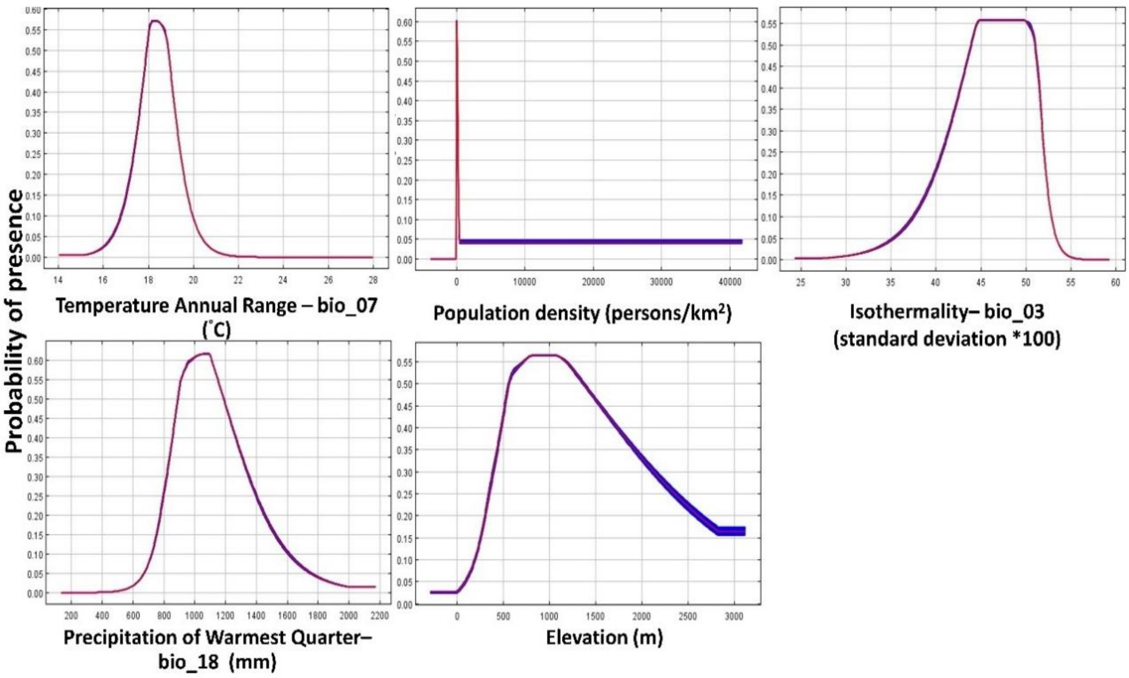

Figure 4. Relationship between significant environmental variables - showing above-average percent contribution > 8% in MaxEnt models - and fire occurrence in northwestern region of Vietnam

The forest fire probability map is shown in Fig. 5. Overall, there is a very low probability of forest fire concentrated in the southeastern areas of the region (Hoa Binh province and southeastern portions of Son La province). In contrast, a very high probability of forest fire was widespread throughout the southwest and northwest (Dien Bien and Lai Chau provinces and the remaining areas of Son La province). Areas with a moderate probability of forest fire contracted to the east and southeast and were more restricted topographically. The results showed that the total forest fire area with high and very high probabilities in this region was 15,374 km^2 (~65%), followed by the forest fire area with medium probability (3,034 km^2; ~13%), and the total forest fire area with low and very low probabilities (5,209 km^2; ~22%) (Table A.1).

Table A.1. The areas, and mean and standard deviation (S.D.) of elevation of each category of forest fire probability in the northwestern region of Vietnam

Category	Areas (km^2)	Elevation (m)
Very low	3,821	376 (± 248)
Low	1,388	720 (± 272)
Medium	3,034	1,002 (± 624)
High	11,433	1,005 (± 409)
Very high	3,941	972 (± 209)

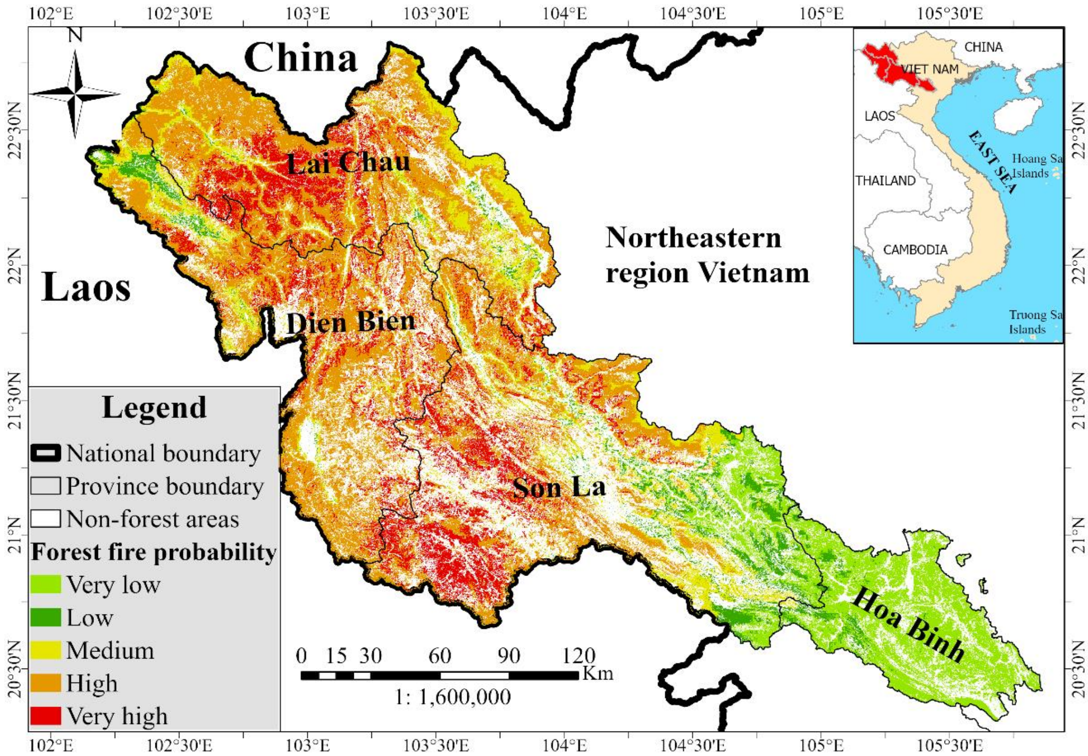

Figure 5. Forest fire probability for the northwestern region of Vietnam

4. Discussions

4.1. Environmental determinants of forest fire in the N.W. region of Vietnam

Our study has shown that reasonable predictions about the spatial distribution of forest fire occurrence in N.W. of Vietnam were created by considering a combination of variables representing the fire environment triangle (i.e., climate, topography, fuel condition, and human activities). However, it is not straightforward to understand the relationships between these factors and forest fire occurrence because the fire-environment relationships are complex and multicollinear (Renard et al., 2012). The importance of each factor in explaining forest fire occurrence varies significantly across regions, such as in the Xishuangbanna and Leizhou Peninsula regions in China (Su et al., 2021), Western Ghats of India (Renard et al., 2012), and California, the United States (Parisien and Moritz, 2009).

Unsurprisingly, climatic factors are the most potent predictor of forest fire probability in the N.W. Vietnam (~74% of contribution and ~85% of permutation importance to model variation), whereas the remaining factors (topography, human activities, and vegetation) are less important (Table 2). Temperature and precipitation are essential factors influencing the occurrence of forest fires. Low rainfall and high temperatures can impact fuel conditions by causing tree mortality and reducing fuel moisture, rapidly promoting fire ignition and spread (Chang et al., 2013; Holsinger et al., 2016).

The MaxEnt results showed that regional temperature and precipitation patterns significantly influenced forest fire probability in the N.W. region, in particular, the annual temperature range (bio_07), isothermality (bio_03), and precipitation of the warmest quarter (bio_18). Temperature and precipitation affect the distribution and growth of plants by maintaining plant physiological and biochemical activities and ecological processes (Barker et al., 2006; Walther et al., 2005), thereby influencing fuel conditions. Our results are consistent with previous studies that found climatic factors were more important than other factors in modeling forest fire on a regional scale (Guo et al., 2016b; Mishra et al., 2023; Renard et al., 2012; Su et al., 2021). For instance, forest fires were more likely to occur in areas associated with annual temperature range (bio_07) from 18 to 19°C and isothermality (bio_03) from 45 to 50, indicating an increased forest fire probability in areas with a moderate and high annual temperature range and an increasing isothermality (Fig. 4 & A.3), which agrees with previous studies in other regions (Hoyos et al., 2017; Verma et al., 2018). In terms of precipitation, forest fire seemed to prefer to occur in areas with low to moderate precipitation in the warmest quarter, low precipitation in driest quarter and precipitation seasonality (Fig. 4, A.2 & A.3). Accordingly, forest fire occurrence was higher in seasonally dry areas, which is consistent with previous studies that showed increasing fire probability with increase in precipitation seasonality (Chuvieco et al., 2008; van der Werf et al., 2006). The influence of temperature and precipitation on forest fires is a hint of the effect of climate change on forest fires in the future.

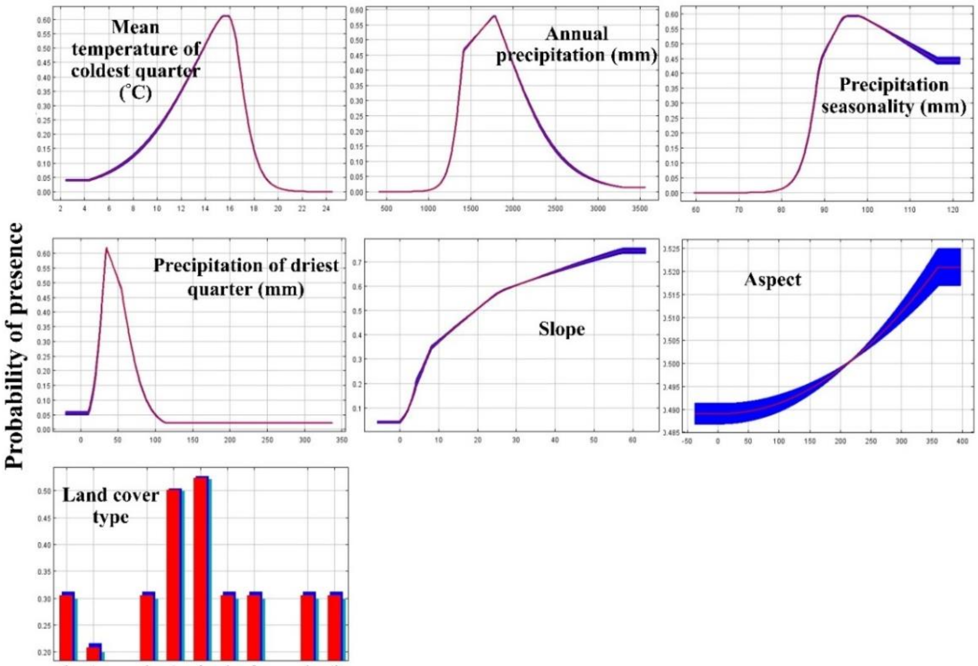

Figure A.2. Relationship between environmental variables with average percent contribution < 8% in MaxEnt models and fire occurrence in northwestern region of Vietnam. Land cover type: 0: Water bodies; 1: Grassland; 3: Broadleaf croplands; 4: Savannas; 5: Evergreen broadleaf forests; 6: Deciduous broadleaf forests; 7: Evergreen needleleaf forests; 9: Non-Vegetated lands; 10: Urban and build-up lands

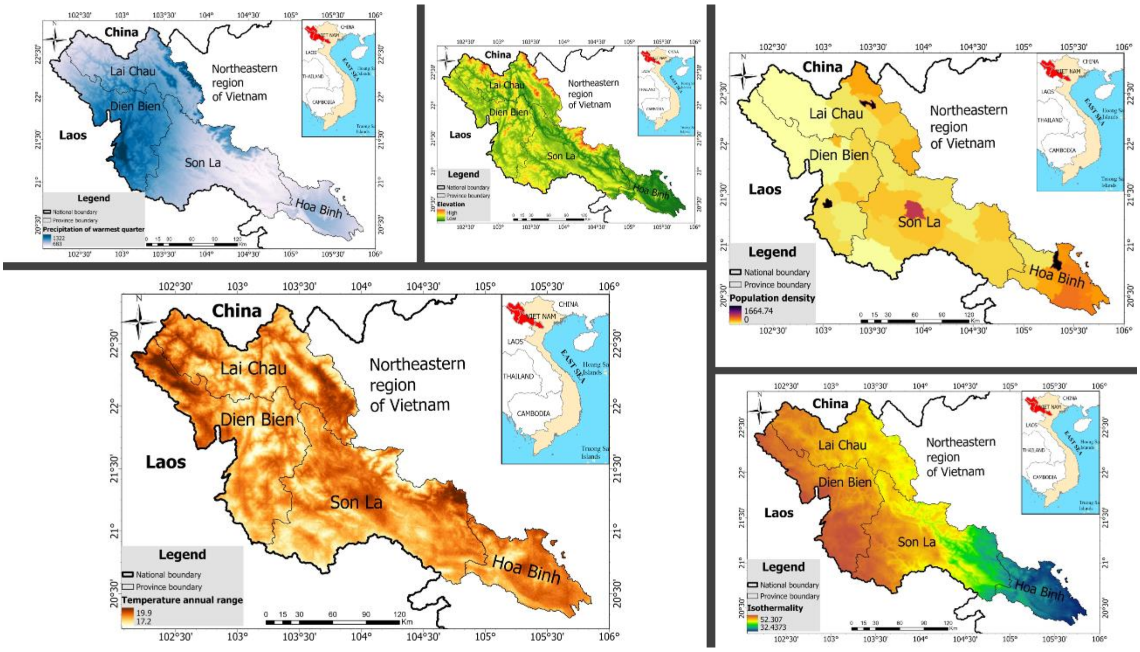

Figure A.3. Spatial distribution of the most influential environmental variables in the model within the northwestern region of Vietnam

Regarding anthropogenic variables, population density was also strongly correlated to forest fire occurrence (Table 2). Population density has a significant negative relationship with forest fire occurrence (Fig. 4). This is inconsistent with previous studies that found that higher population density offers a higher potential for fire occurrence (Matin et al., 2017). The result may be because most human activities causing forest fires in Vietnam were caused by human activities (e.g., slash and burn farming and harvesting bee's honey) (Hoang, 2007). These activities were often conducted adjacent to and within natural forests away from towns and villages. Our findings, indicating a higher fire frequency in forested areas at higher elevations and farther from villages, suggest that ignitions are most likely related to the range of human activities mentioned earlier, plus natural ignitions (lightning). Additionally, fire suppression at low populated areas is less likely after an ignition occurs (Fig. 5 & A.3).

In the group of topographic variables, elevation was a more significant contributor than aspect and slope in explaining fire occurrence (Table 2). The result of this study's elevation-fire occurrence relation follows previous studies (Xuan et al., 2023; Zhang and Lim, 2019; Zhang et al., 2016). Elevation affects forest fires by influencing all drivers of forest fires, such as vegetation composition and fuel moisture (Castro and Chuvieco, 1998). Previous studies reported that the probability of forest fire was higher at higher elevations because high elevations have good drainage and an increased level of solar exposure, leading to surface fuels typically drying quickly (Fang et al., 2015; Holden et al., 2009; Su et al., 2021). The MaxEnt results reported that most forest fires occurred between 500 and 1,500m elevation in the study area (Fig. 4 & A.3). This may be because most natural forests with high species diversity and greater continuous extent are located at these elevation ranges (Averyanov et al., 2003; Phuong et al., 2012). However, the forest fire probability decreased at higher elevations due to lower temperatures, higher rainfall, and less frequent drying fuels (Yakubu et al., 2015).

Although aspect and slope had low contributions to the model in explaining forest fire occurrence in the N.W. region, forest fires tended to occur in areas related to the southwest and northwest aspects (Fig. A.2 & A.4). Higher Solar radiation loading on the south and west aspects led to more open canopies and more rapid fuel drying. Additionally, the Western slopes of this region are more directly affected by Foehn winds, leading to hotter and drier conditions (Nguyen and Reiter, 2014). The result of the MaxEnt model also found a positive relationship between slope and forest fire occurrence, which is consistent with previous studies (Yakubu et al., 2015). In the study region, most fires occurred in areas with slope values from 20° to 30° (Fig. A.2 & A.4), indicating the high potential for fire occurrence due to the steep terrain. This explains that fuel may be drier, and fires spread faster due to heat transfer to unburned fuel by flame radiation in steep slopes (Yakubu et al., 2015).

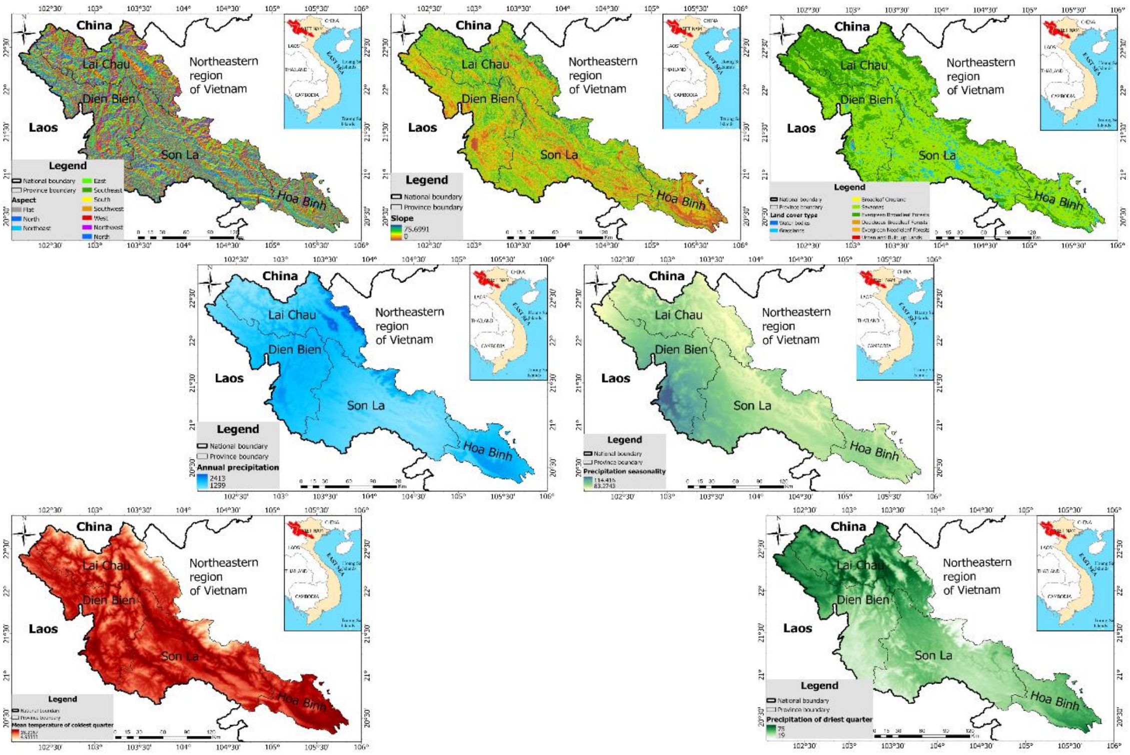

Figure A.4. Spatial distribution of less influential environmental variables in the model within the northwestern region of Vietnam. Aspect: Flat (-1°), North (0°–22.5°), Northeast (22.5°–67.5°), East (67.5°–112.5°), Southeast (112°–157.5°), South (157.5°–202.5°), Southwest (202.5°–247.5°), West (247.5°–292.5°), Northwest (292.5°–337.5°), North (337.5°–360°)

On the contrary, the fuel condition (Land cover type) showed a minimal contribution to the model, indicating a significant overlap with other variables. This may be because the information within the vegetation layer is already encompassed by more influential variables (e.g., climatic variables and topography), especially on large spatial scales (e.g., regional scale) (Pfeifer et al., 2018; Xu et al., 2020). The result may be because of the coarse spatial resolution and the relatively simple spatial composition of N.W. forests, leading to a failure to provide sufficient or correct information on fuel conditions. The results agree with Renard et al. (2012) in the Western Ghats of India and Guo et al. (2016b) in Fujian, China. These studies found that vegetation variables were less important in explaining forest fire occurrence as they depended on climate, and it was simple in forest type classification. Although vegetation-related variables within the model were not negligible, the results of MaxEnt indicated that forest fire seemed to occur in Savannas areas with 10–60% tree cover and Evergreen broadleaf forests with 60% or higher tree cover (Fig. A.2 & A.4).

4.2. Spatial modeling of probability of occurrence

The forest fire probability map in the N.W. region of Vietnam was generated from the final MaxEnt model by considering a combination of four main influencing factors, including climatic, fuel conditions, topography, and human activities. The high probability of forest fire mainly occurred throughout the southwestern and northwestern areas and constituted a total area of 15,374 $km^{2,}$ representing 65%. These areas were average above 900 m of elevation (Fig. 5, Table A.1), where most natural forests with high species diversity were located (Averyanov et al., 2003; Phuong et al., 2012). The forested areas were likely to experience an increased risk of fire because these vegetation types were more open, which led to a reduction of understory humidity and an increase in the load and dryness of dead fuels (Cochrane, 2003; Cochrane and Schulze, 1999; Enright, 2011). Additionally, these areas were characterized by lower annual precipitation and were more directly affected by Foehn winds, resulting in hotter and drier compared to other areas (Nguyen and Reiter, 2014; Van, 2015). Thus, forest fire probability may be higher in these areas. The results are coherent with previous studies (Le et al., 2014; Trang et al., 2022) and agree with the MODIS observed fires (MODIS dataset) (Fig. 1).

Nevertheless, most areas with a very low probability of forest fires were concentrated in southeastern areas. In the areas, most forests (including natural, bamboo, and plantation forests) were located at low elevations (<800m) (Table A.1) and close to villagers (Food and Agricultural Organization of The United Nations, 2009; Cochard et al., 2016). These forested areas were often actively protected against fire by villagers through weeding twice annually and collecting fuelwood (Trang and Hoi, 2009; Nambiar et al., 2015), resulting in fuel load reduction and a low probability of forest fire. Also, the southeastern areas may be partly affected by a tropical cyclone from the East Sea (Schmidt-Thomé et al., 2014), bringing heavy rains (Pham and Vu, 2020), resulting in high fuel moisture content, and then leading to low probability of forest fire.

5. Limitation and further research

The high level of impact from climate factors (especially climatic seasonality) within the model is a hint for future impacts of climate change on forest fire probability. Thus, more in-depth studies on the future impacts of climate change on forest fire occurrence should be paid attention. Although we used a limited set of factors influencing forest fire occurrence at coarse resolution because of the availability of these reliable data, the MaxEnt model provided an acceptable accuracy in modeling forest fire probability within this region. However, further studies should consider other factors related to fuel condition (i.e., Normal difference water index (NDWI), Enhanced vegetation index 2 (EVI2), Normalized difference vegetation index (NDVI), Gross primary productivity (GPP)), and other human activities (i.e., distance to road, human footprint), or satisfactory resolution of variables using for model. Previous studies showed that these variables were strongly correlated to forest fire occurrence (Burapapol and Nagasawa, 2016; Chuvieco, 2003; Mansuy et al., 2019; Nurdiana and Risdiyanto, 2015; Parisien et al., 2012; Sumarga, 2017; Xuan et al., 2023). Also, Bekar et al. (2020) demonstrated that spatial resolution was an important factor affecting model performance and the importance of predictors.

The forest fire probability map provides valuable information to forest management activities on areas' likelihood of forest fire occurrence. Fire management efforts should be prioritized in middle and high mountainous forests along with steep slopes in southwest and northwest aspects. Additionally, the population living in forest fire-prone areas may be educated about the influences of their activities on forest fire occurrence (e.g., illegal logging, slash and burn farming).

6. Conclusions

In this study, we used the MaxEnt approach combined with climatic, fuel condition, topography, and human activities to understand better-influencing factors and probability areas of forest fire within northwestern Vietnam from 2003–2016.

The results from the Maxent model showed that annual temperature range, population density, precipitation of the warmest quarter, isothermality, and elevation had the highest contributions to model forest fire in the northwestern region of Vietnam. Forest fires were likely to occur in forested areas at elevation of 800–1,200 m a.s.l., with an annual temperature range of 18–19°C, precipitation of warmest quarter ranging from 900–1,200 mm, isothermality between 45 and 50, and low population density (less than 300 persons/km^2). High and very high probabilities of forest fires were concentrated in the southwest and northwest of the N.W. region (Dien Bien and Lai Chau province, and most areas of Son La province), while very low and low probability of forest fire occurred in the southeastern areas of the region (Hoa Binh province and southeastern portions of Son La province). The areas of high and very high forest fire probabilities were approximately 15,374 km^2 (~65%), followed by areas with medium probability (3,034 km^2; ~13%) and areas with low and very low probability (5,209km^2; ~22%). The study's findings may provide valuable references for forest fire management in this region.

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