
METHODS AND MEANS OF PROCESSING AND INTERPRETING SPACE INFORMATION

Forest Fire Risk Assessment and Mapping Using Remote Sensing and GIS Techniques: A Case Study in Nghệ An Province, Vietnam

Th. N. Ph. Doan^a, L. H. Trinh^b*, V. R. Zablotskii^c, V. T. Nguyen^a, X. T. Tran^a,
Th. Th. H. Pham^a, Th. Th. H. Le^a, and V. Ph. Le^b

^a *Geomatics in Earth Sciences Research Group, Hanoi University of Mining and Geology, Hanoi, Vietnam*

^b *Le Quy Don Technical University, Hanoi, Vietnam*

^c *Moscow State University of Geodesy and Cartography, Moscow, 105064 Russia*

*e-mail: trinhlehung@lqdtu.edu.vn

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Abstract—This paper presents the results of modeling the risk of forest fires in the west of Nghệ An Province (north-central Vietnam) using remote sensing and GIS data. We built models for the occurrence of forest fires using machine learning methods, including Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Trees (CART). The models took into account nine factors influencing the risk of forest fires, including vegetation cover (the normalized difference vegetation index (NDVI)), surface evapotranspiration, elevation, slope, aspect, wind speed, ground surface temperature, average monthly precipitation, and population density. Various parameters are tested in the RF, SVM, and CART algorithms to select the algorithm with the highest accuracy in forest fire risk prediction. The results show that the RF algorithm with the value of the “numberOfTrees” parameter equal to 100 has the highest accuracy in predicting the risk of forest fires in the study area.

Keywords: forest fire risk, remote sensing, GIS, support vector machine algorithm, Nghệ An province

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INTRODUCTION

Vietnam is a country where a quarter of its territory is mountainous areas with forest cover of more than 42%. Forests are an important ecological resource of the country, necessary for the economic and social development of society. Recently, due to human activity and climate change, the number of forest fires in Vietnam has increased, as well as the damage caused by fires to forest resources.

A forest fire is a catastrophic phenomenon that is difficult to combat. The ignition and spread of forest fires are facilitated by many reasons, including the human factor and topographic and meteorological characteristics of the territory. The development of forest fire hazard forecasting models is an urgent task. Geospatial technologies are effectively used in building forest fire risk forecasting models. Remote sensing and geographic information systems (GIS) allow for the prompt collection of information on forest cover for analysis and management of territories for the purpose of early warning of forest fires (Bondur et al., 2016; Bondur and Gordo, 2018) and their negative consequences, including those associated with emissions of harmful impurities into the atmosphere (Bondur, 2015; Bondur and Ginzburg, 2016).

The study of forest fire danger reveals a close relationship between weather conditions, vegetation moisture, relief factors and the probability of forest fires (Beals, 1914). In addition to meteorological factors such as precipitation, temperature, and air humidity (Williams, 1993), wind speed and population density play an important role in the occurrence of forest fires, which increase the risk of forest fires (Dong, 2005).

Remote sensing and GIS technologies have been used in many studies to build forest fire hazard forecasting models based on a combination of traditional methods and modern spatial data processing methods. One of the first projects in the field of remote sensing and GIS application for forest fire risk forecasting is the European Forest Fire Information System (EFFIS), created by the European Research Cooperation Centre in 2000. The EFFIS system allows for fire hazard forecasting, early detection of forest fires, fire mapping, and forest fire damage assessment. The remote sensing data used in this system are MODIS, VIIRS, and Sentinel 2 MSI satellite images (<https://effis.jrc.ec.europa.eu/apps>).

Yassemi et al. (2008) combined GIS technology, environmental models, and Moore cellular automata (CA) to create a wildfire prediction model in Nordegg Alberta,

Canada. The results show agreement between the model results and fire data in the area under study. The integration of GIS–CA technology enables a realistic modeling of wildfire scenarios (Yassemi et al., 2008). Wimberly et al. (2007) used multitemporal Landsat satellite images to map wildfire intensity in the southern Appalachians, North Carolina, United States. The Normalized Burn Index (NBR) derived from Landsat near-infrared and shortwave infrared images was used to estimate pre- and postfire land cover change. Chowdhury et al. (2013) used MODIS satellite images to determine input parameters such as surface temperature, normalized multiband drought index (NMDI), and temperature wet vegetation index (TVWI) to construct a forest fire risk prediction map (Chowdhury et al., 2013). The results showed that nearly 92% of forest fires occurred in the area categorized as very high fire risk.

Currently, machine learning and deep learning methods (artificial neural network, random forest, support vector machine) are used to improve the accuracy of forest fire prediction models (Vasilakos et al., 2009; Oliveira et al., 2012; Bui et al., 2016, 2017). For example, multiple regression methods (Oliveira et al., 2012), logistic regression (Pourghasemi, 2015), geographically weighted regression (GWR) (Fernandez et al., 2012), and data mining methods (Arpaci et al., 2014) have been studied.

Iban and Sekertekin (2022) used thermal anomalies from MODIS images and deep learning methods such as support vector machine, discriminant linear analysis, and random forest to predict forest fires in Adana and Mersin, Turkey. The study found that factors such as altitude, slope gradient, and temperature had the greatest impact on the forest fire risk in the observation area (Iban and Sekertekin, 2022).

Ruano et al. (2022) used the normalized difference vegetation index (NDVI), terrain, fire hazard stocks, and transportation infrastructure to build forest fire occurrence models. The experiments explored generalized linear models (GLM) and generalized additive models (GAM) to estimate the probability of forest fires. There are also other works (Jaiswal et al., 2002; Enod et al., 2021; Herrera et al., 2022; Sivrikaya and Kucuk, 2022) that predicted the risk of forest fires based on the combined use of remote sensing data, GIS, and machine and deep learning methods.

Research on forest fire prediction has been conducted in Vietnam since the late 20th century, initially based on the application of the Nesterov cumulative index (Pham, 1988; Vo, 1995; Tran et al., 2010). Later, surface temperature data calculated from thermal infrared satellite images (Landsat and MODIS) began to be used in forest fire prediction, and the prediction results were visualized using GIS (Vuong, 2005; Doan, 2007; Tran et al., 2016). Landsat thermal infrared channel data were used to detect underground fires in coal mines (Trinh, 2014; Trinh and Zablotskii, 2017).

Recently, machine learning methods based on remote sensing data have been used to assess the risk of forest fires in the northern mountainous areas of Vietnam (Nguyen et al., 2018; Dang, 2021; Hoang et al., 2020). It was found that machine learning methods can predict forest fire risks with higher accuracy than traditional methods using hierarchical analysis techniques. Overall, the above papers have demonstrated the effectiveness of remote sensing methods and GIS technology in developing forest fire risk assessment models.

In this paper, three popular machine learning algorithms: random forest (RF), support vector machine (SVM), and classification and regression tree (CART) were used to zone the fire hazard of the forest area. The modeling resulted in a map of forest fire hazard of the western part of Nghệ An Province, Vietnam.

INITIAL DATA AND DATA PROCESSING METHODS

Study Territory and Remote Sensing Data

Area under study. The study area is located in the west of Nghệ An Province, North Central Coast, with geographic coordinates ranging from 18°33' to 20°01' N and from 103°52' to 105°48' E (Fig. 1). The terrain is complex, heavily dissected by hills, mountains, and a system of rivers and streams.

The area of forests and woodlands in Nghệ An Province is more than 58%, (Ministry of Agriculture and Rural Development, Vietnam, 2021). Although the forest cover of the area has tended to increase in recent years, most of the new forest areas in the province are planted forests. The natural forest has shown a noticeable decline in both quality and area.

The province is located in the tropical monsoon climate zone with hot, humid, and rainy summers (May to October) and cold, less rainy winters (November to April). Due to the dry foehn wind blowing from the mountains to the plains and human activities, Nghệ An is an area with complex forest fires and a high level (V, extremely dangerous) of risk of their occurrence.

Remote sensing data. Sentinel 2 MSI multispectral images were used to calculate the vegetation index, and Landsat 8 images were used to calculate the land surface temperature. Remote sensing data was collected and processed directly on the Google Earth Engine (GEE) cloud computing platform.

To create a cloud-free image, 65 Sentinel 2 MSI scenes (Sentinel 2A and Sentinel 2B) collected between November 15, 2021, and January 16, 2022, were selected, and then the NDVI was calculated. Landsat 8 OLI_TIRS multispectral images (track/row: 127/047, 127/046, and 128/046, collected between November 15, 2021, and January 16, 2022) were used to calculate the land surface temperature. Figure 2 shows Landsat 8 and Sentinel 2 MSI images of the western part of Nghệ An province.

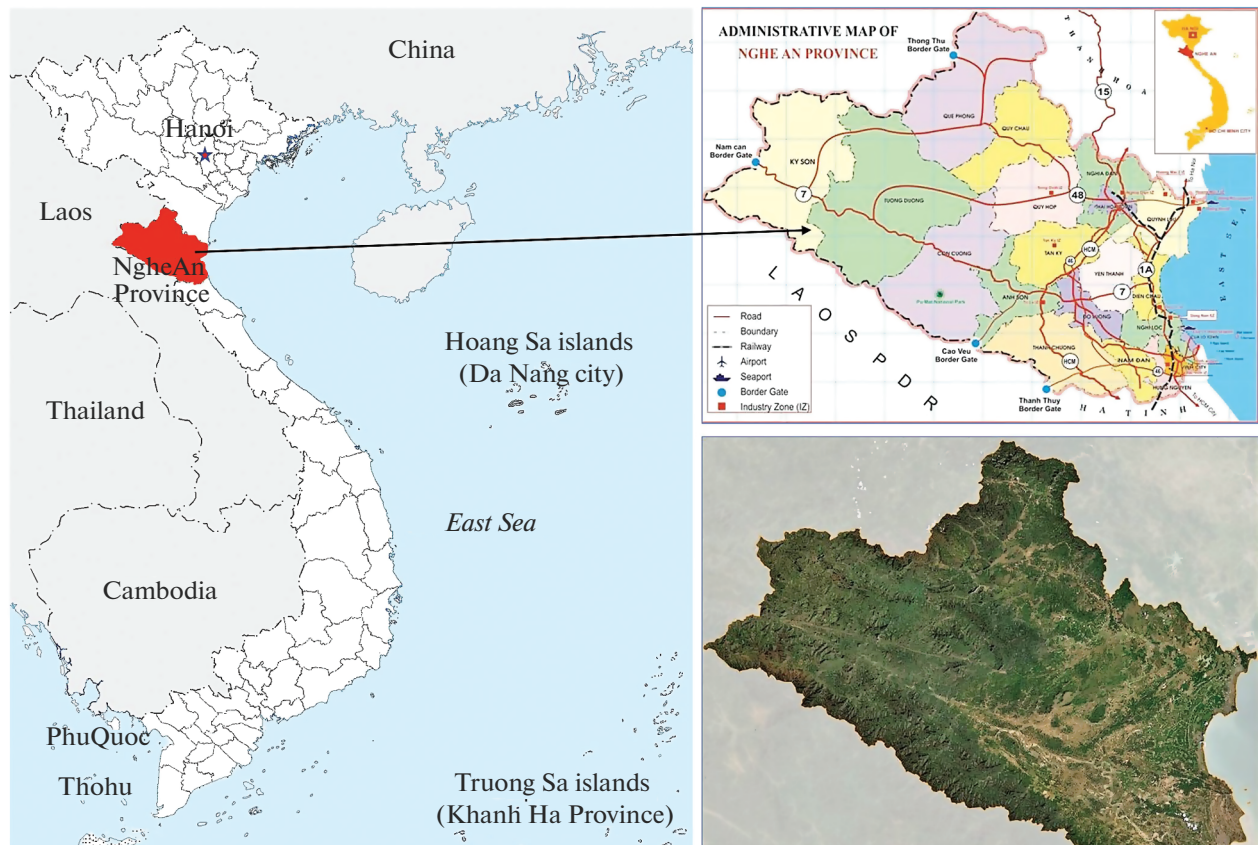


Fig. 1. Location of the study area. Administrative map is shown in the top right; Landsat image of Nghệ An province is on the bottom.

Data Processing Methodology

The following parameters were used in the forest fire risk prediction models for the study area:

1. NDVI.
2. Surface evapotranspiration (according to MODIS data).
3. Terrain altitude above sea level (DEM SRTM).
4. Slope gradient.
5. Slope aspect.
6. Wind speed.
7. Land surface temperature.
8. Average monthly precipitation.
9. Population density.

The NDVI (Rouse et al., 1973) characterized the amount of plant biomass in forest fire prediction models and was calculated from the spectral reflectance values in the red and near infrared channels of Sentinel 2 MSI.

Surface evapotranspiration was calculated from the MODIS satellite imagery dataset on the GEE platform with a spatial resolution of 1000 m. Surface temperature was calculated from the thermal infrared channel of the Landsat 8 satellite based on the NASA

model (<https://www.usgs.gov/landsat-missions/landsat-8-data-usershandbook>):

$$T_B = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)}, \quad (1)$$

where T_B is the surface brightness temperature (K); K_1 and K_2 are the first and second calibration constants recorded in the Landsat image metadata file.

The surface temperature was calculated using the NDVI, taking into account the surface emissivity, according to the method proposed by Valor and Caselles (1996):

$$\varepsilon = \varepsilon_v P_v + \varepsilon_s (1 - P_v), \quad (2)$$

where ε is the emissivity of a nonuniform surface; ε_v is the emissivity of pure vegetation; ε_s is the emissivity of open soil; and P_v is the ratio of the area of vegetation and soil in a pixel, calculated using the formula

$$P_v = \left(\frac{\text{NDVI} - \text{NDVI}_{\min}}{\text{NDVI}_{\max} - \text{NDVI}_{\min}} \right)^2. \quad (3)$$

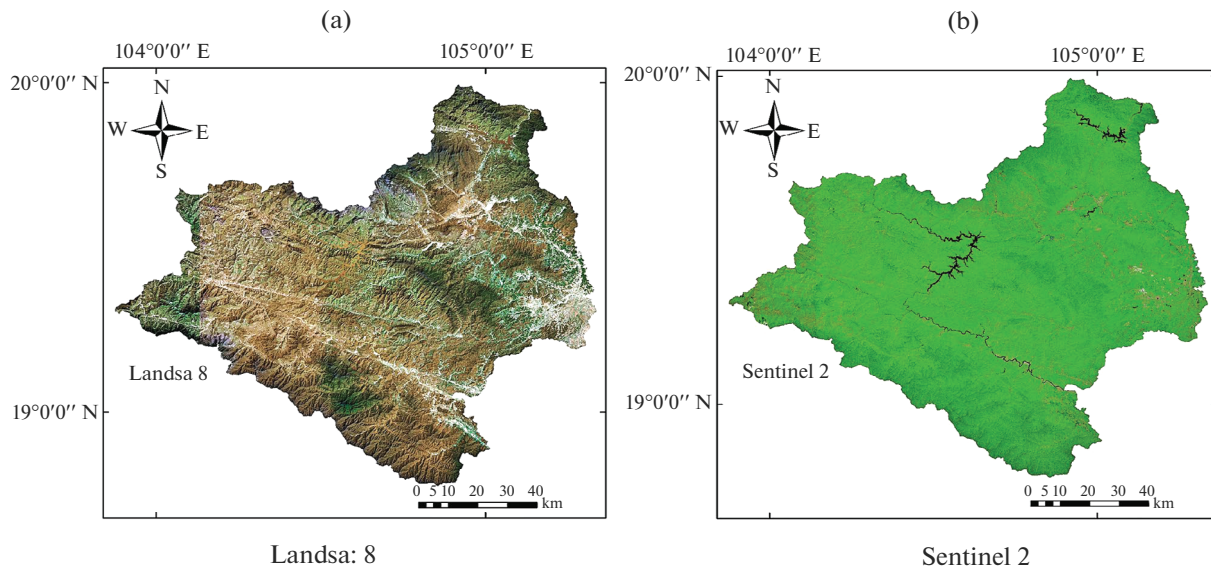


Fig. 2. Landsat 8 and Sentinel 2 images of the study area.

In the final part of the data processing algorithm, the land surface temperature (LST) was calculated using the formula

$$LST = \frac{T_B}{1 + \frac{\lambda T_B}{\rho} \ln \epsilon}, \quad (4)$$

where λ is the wavelength; ρ is a constant (1.438×10^{-2} m K).

A digital elevation model based on the Shuttle Radar Topography Mission (DEM SRTM) with a spatial resolution of 30 m was used to create GIS layers of topographic data. The data were saved and edited using ArcGIS10 software.

Data on population density in the study area were obtained from the WorldPop database (<https://data.worldpop.org/>). Data on wind speed, average monthly precipitation, and surface evapotranspiration were obtained from the WorldClim database (<https://data.worldclim.org/>). The resolution of the images taken from the WorldPop and WorldClim databases was 1000 m.

All nine GIS layers of the forest fire prediction model data were interpolated to a spatial resolution of 10 m to ensure resolution consistency with the Sentinel 2 MSI images. The data were normalized to the same spatial resolution using the nearest neighbor interpolation algorithm.

The fire dataset included 120 points collected from 2019 to 2023 based on fire records from the Department of Forestry, the Ministry of Agriculture and Rural Development of Vietnam, and FIRMS (NASA) fire data, as well as 204 points where no forest fires were observed during this period. Of the entire forest fire dataset, 70% of the points were used to train the

model, and the remaining 30% were used to test the accuracy of the model.

The model input data was processed on the Google Earth Engine (GEE) platform, designed for remote sensing data analysis. The results obtained in GEE are compatible with GIS such as QGIS, ArcGIS, and Foris. JavaScript programming language and Code Editor were used for processing to transfer Landsat 8/9 and Sentinel 2 MSI image data to the platform and perform the processing, analysis, display and output stages. All nine data layers were created and processed on the GEE platform and then used in the model.

The block diagram of the forest fire risk mapping methodology using remote sensing and GIS data is shown in Fig. 3.

In the computational experiment, computer models were trained that corresponded to three selected machine learning algorithms (RF, SVM, and CART). Each of the presented algorithms minimized the loss function by training on a test set of points. When assessing the risk of forest fires based on nine GIS layers, each pixel of the images was assigned a fire probability with a value from 0 to 1, which corresponds to a low to high fire risk. The accuracy of training was assessed on a control set of points in two ways: visually and based on the ROC-AUC metric. By varying the model parameters, the best trained model (RF 100) was selected, with the help of which the study area was zoned for fire hazard. The probability of forest fire danger for each pixel was divided into five levels: “very low” (0.1–0.4), “low” (0.4–0.65), “medium” (0.65–0.8), “high” (0.8–0.9), and “very high” (0.9–1.0), with the threshold values chosen according to the study (Nguyen et al., 2018). The result of the zoning of the territory is presented on a color map.

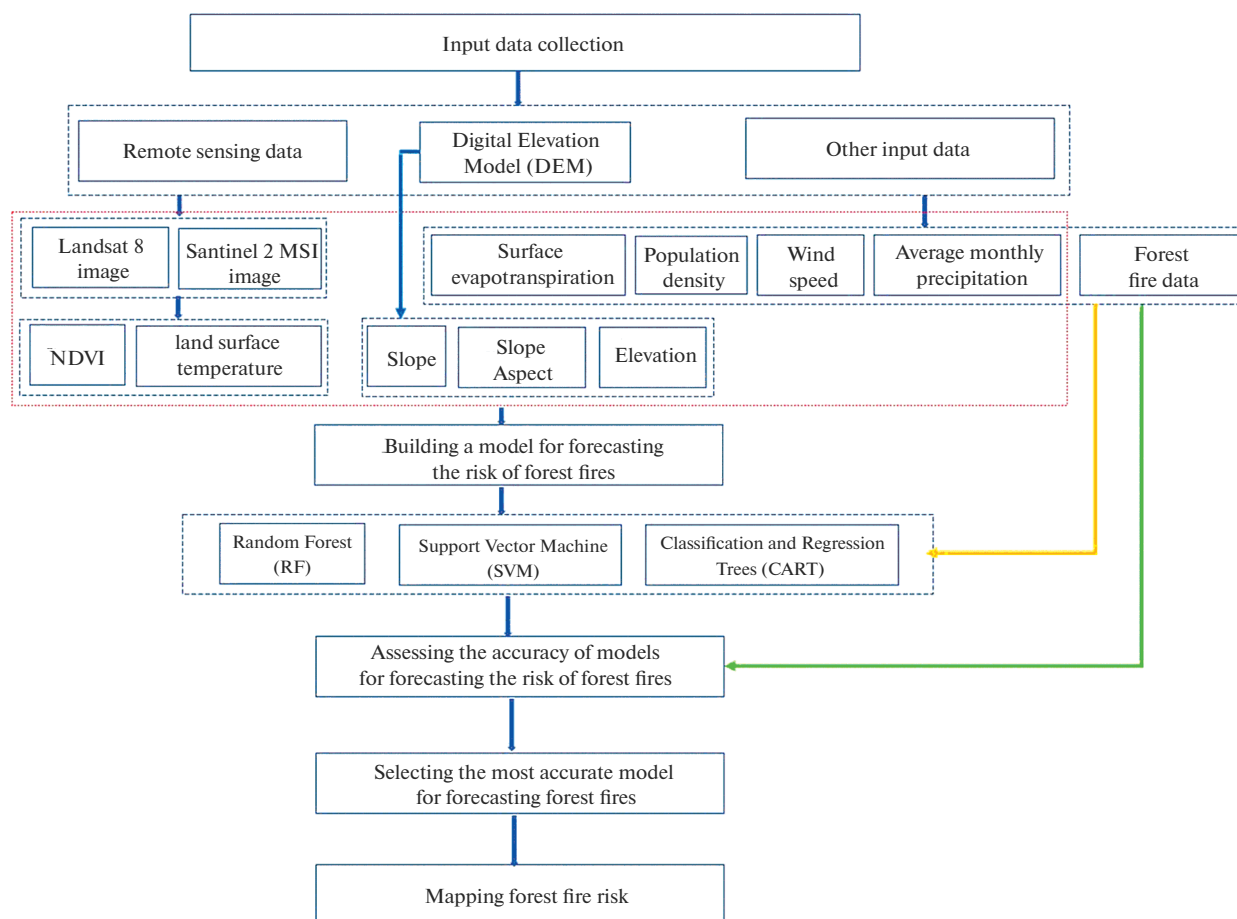


Fig. 3. Flow chart of a methodology for mapping forest fire risk using remote sensing and GIS data.

RESULTS AND DISCUSSION

Figure 4 shows the SRTM digital elevation model of the study area with a spatial resolution of 30 m. The results of constructing the information layers of terrain altitude, slope, and slope aspect are shown in Figs. 5a, 5b, and 5c. Fig. 5d shows the information layer of surface evapotranspiration. The vegetation layer (NDVI) and the layer of data on the earth's surface temperature are presented in Figs. 5d and 5e. From Fig. 5d it follows that the NDVI value of the study area varies in the range from -0.74 to 0.85 , while the vegetation has positive NDVI values greater than 0.2 . The open surface is characterized by NDVI values from 0 to 0.2 ; the water surface has negative NDVI values.

From Fig. 5e it follows that in the study area the surface temperature fluctuates in the range from 15.1°C to 35.5°C . Low temperature areas are concentrated in mountainous areas with dense vegetation; high temperature areas are typical for populated areas and open surfaces. The entire range of earth surface temperatures is divided into nine ranges. The wind speed information layer is shown in Fig. 5g. It follows from the figure that the wind speed varies in the range

from 1.5 to 2.9 m/s. In most of the study area, the wind speed did not exceed 1.9 m/s. Areas with a wind speed of more than 2 m/s are concentrated in the southern part of the study area.

The average monthly precipitation information layer is shown in Fig. 5h. The precipitation amount varies from 113 mm/month to 164 mm/month. It follows from the figure that in the study area the precipitation amount is mostly below 130 mm/month. Areas with an average monthly precipitation of more than 130 mm/month are concentrated in the south of the study area.

The population density information layer is shown in Fig. 5i. As follows from this figure, the population density varies from 3 people/ km^2 to 627 people/ km^2 . Most of the study area with low population density (less than 25 people/ km^2) is concentrated in high-mountain forested areas. Areas with a population density above 100 people/ km^2 are located mainly in the east and south of the study area.

After learning the RF, SVM, and CART models using the test set of forest fires, the risk of forest fires was predicted. To assess the accuracy of the forecast-

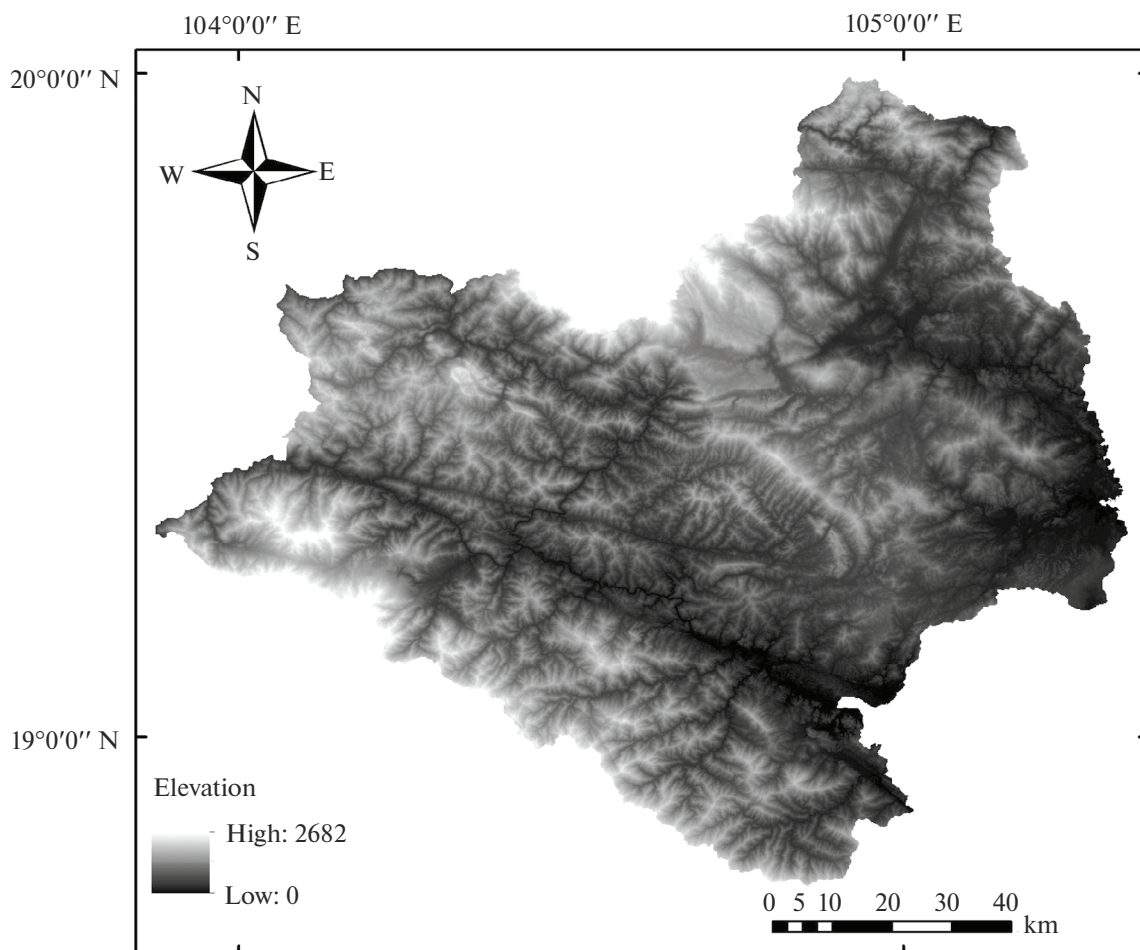


Fig. 4. Digital elevation model SRTM of the study area.

Table 1. Forecasting the risk of forest fire using RF, SVM, and CART methods with different parameters

Method	Territory	Level of forest fire risk				
		very low	low	average	high	very high
RF3	Fire hazardous	0	3	6	8	19
	Nonfire hazardous	11	18	21	9	2
RF100	Fire hazardous	0	2	3	8	23
	Nonfire hazardous	14	25	15	5	2
RF200	Fire hazardous	2	2	9	20	3
	Nonfire hazardous	8	17	17	12	7
CART5	Fire hazardous	0	2	1	4	29
	Nonfire hazardous	8	11	10	2	30
CART30	Fire hazardous	0	2	2	8	24
	Nonfire hazardous	10	19	2	1	29
SVM30	Fire hazardous	0	3	2	25	6
	Nonfire hazardous	0	5	3	38	15
SVM25	Fire hazardous	1	3	11	18	3
	Nonfire hazardous	3	17	8	28	5

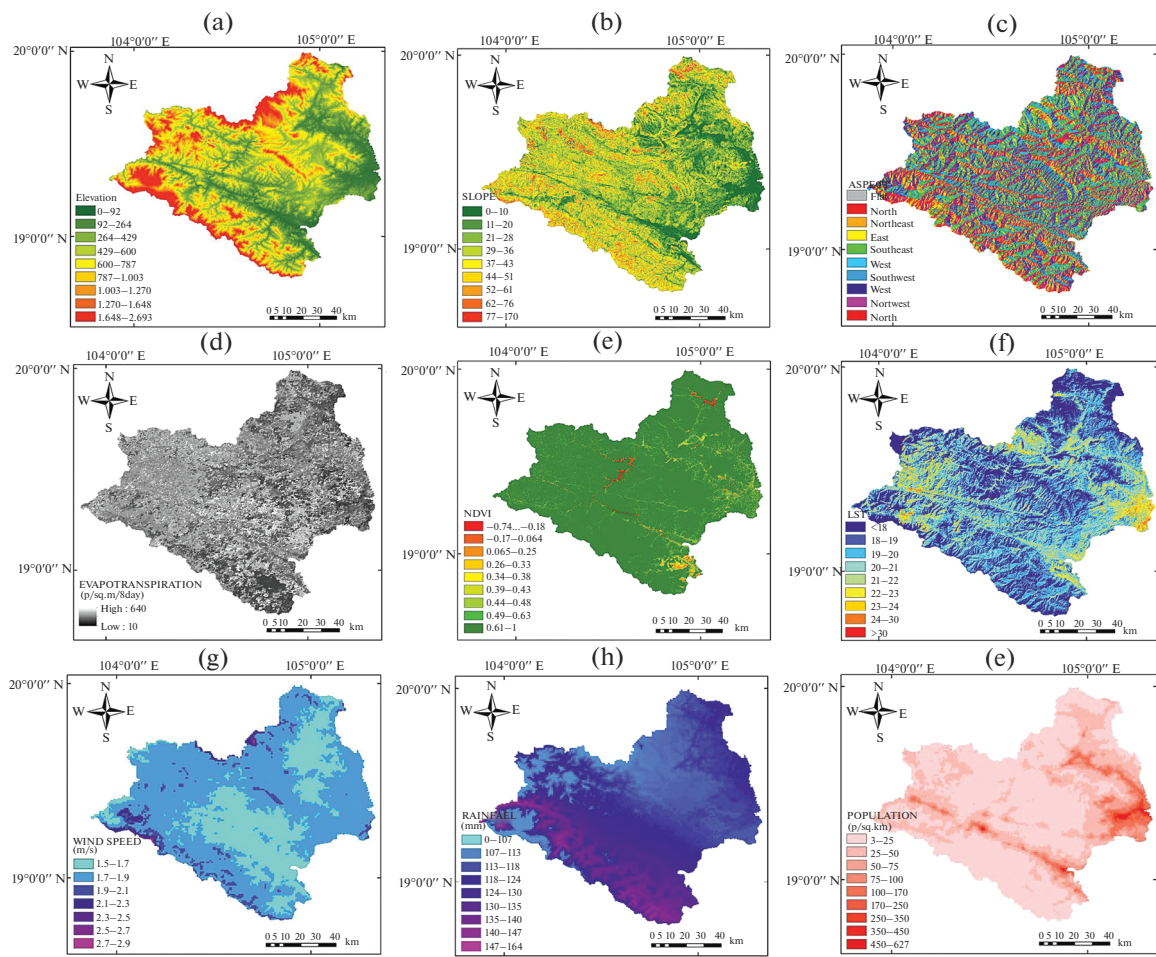


Fig. 5. Information layers—input data for forest fire hazard forecasting models: terrain elevation (a), slope inclination (b), slope aspect (c), surface evapotranspiration (g), NDVI (d), surface temperature (e), wind speed (g), average monthly precipitation (h), and population density (i).

ing models, a control dataset (the Forest Protection Department database) consisting of 36 fire-hazardous and 61 non-fire-hazardous areas was used. A comparison of the forest fire forecasting results obtained by different algorithms is presented in Table 1. An analysis of the obtained results shows that the use of the random forest method with the “number of decision trees” parameter value equal to 100 (RF100) yields the most accurate results of forest fire risk zoning. Of the 36 points of past forest fires, 31 points fell into the area with a high and very high degree of forest fire danger (which corresponds to 86.11%), and 23 points fell into the area with a very high degree of fire danger.

Only points with past forest fires were in the area of low fire hazard and 3 points in the medium fire

hazard area. No points with past forest fires were found in the very low fire hazard area. Most of the non-fire-hazardous areas were in the very low (14/61 points), low (25/61 points), and medium (15/61 points) fire hazard areas. Only 5 points were in the high fire hazard area and 2 points were in the very high fire hazard area. The area under the curve (AUC) of the receiver operating characteristic (ROC) is a commonly used metric to measure the accuracy of a model. The AUC value ranges from 0 to 1, with the higher the AUC value, the better the data classification model. Table 2 shows the result of a forest fire hazard assessment based on logistic regression in data classification, which confirms that the RF100 method has the highest AUC value of 0.951. The random forest method

Table 2. AUC values of different methods for forecasting forest fire risk

Method	RF3	RF100	RF200	CART5	CART30	SVM25	SVM30
AUC	0.947	0.951	0.938	0.905	0.916	0.756	0.743

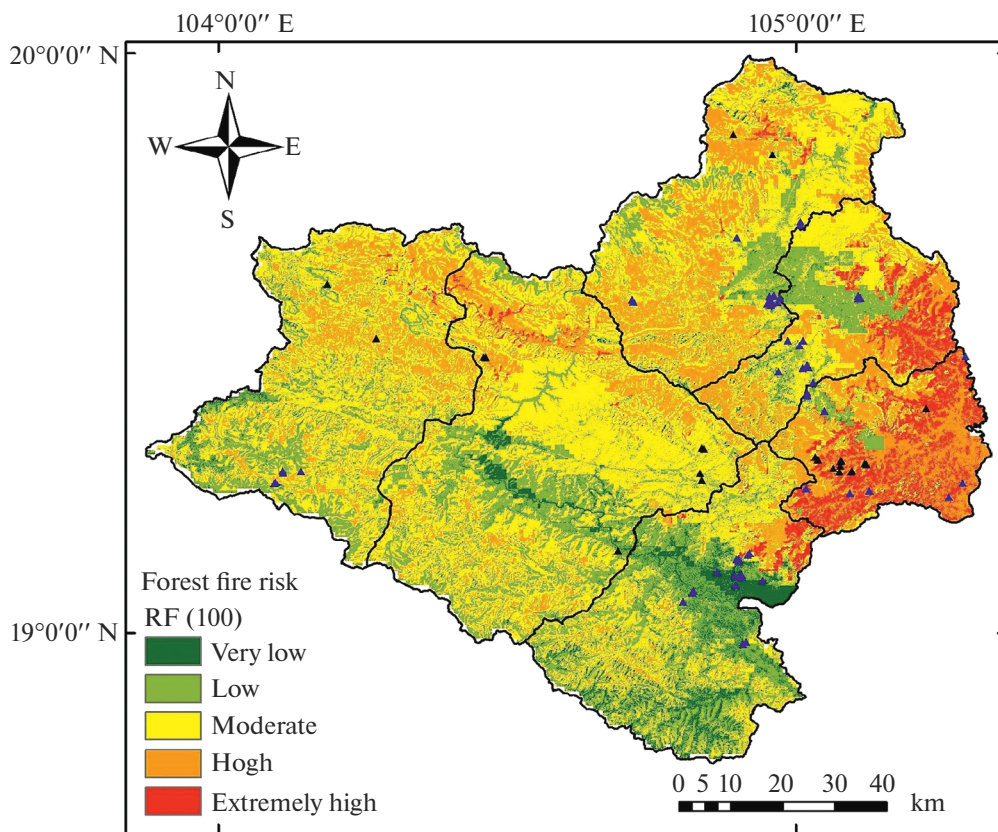


Fig. 6. Map of forest fire hazard (western Nghệ An province). Black triangles are locations of former fires; blue triangles are fires that did not develop into forest fires due to timely warning.

with the “number of decision trees” parameter equal to 100 was used to construct a map of the forest fire hazard of the western part of Nghệ An Province (Fig. 6). The results of zoning the fire hazard of the study area are presented in Table 3. The analysis of the results shows that almost half of the territory has an average level of forest fire hazard, highlighted in yellow in Fig. 6. The territory of very low and low fire hazard accounts for 5.75% and 30% of the total area, located mainly in the southeast of the study area. The territory of high fire hazard accounts for 16.68% of the total area and is located in the western part of Nghệ An Province. At the same time, the territory of very high fire hazard

accounts for 4.63% of the total area and is highlighted in red in Fig. 6. Such areas are characterized by high population density, secondary forests, and forest plantations.

CONCLUSIONS

In this work, random forest, support vector machine, classification tree, and regression tree methods were used to assess the risk of forest fire using machine learning. The following factors were taken into account to train the forecasting models: vegetation cover presence and condition, surface evapotranspiration, terrain elevation, slope and aspect, wind speed, land surface temperature, average monthly precipitation, and population density of the territory.

Sentinel 2 MSI and Landsat 8 satellite images were used to create NDVI and surface temperature data layers. Input topographic data layers, such as slope and aspect and terrain elevation, were extracted from the SRTM digital elevation model with a spatial resolution of 30 m. Population density, average monthly precipitation, wind speed, and surface evapotranspiration were obtained from the WorldPop and WorldClim global databases. The databases of the Forest Protection Department of the Ministry of Agriculture and

Table 3. Results of zoning the risk of forest fire in the study area

No.	Level of forest fire risk	Area, ha	Area, %
1	Very low	636.65	5.75
2	Low	3271.13	29.56
3	Average	4800.45	43.38
4	High	1845.96	16.68
5	Very high	511.35	4.63

Rural Development of Vietnam provided data on forest fires that occurred in the study area. A visual comparison of the locations of predicted and past forest fires, as well as the location of fire-safe areas and calculation of the AUC values of the ROC curve, shows that the random forest method with the “number of decision trees” parameter equal to 100 has the highest predictive accuracy.

The machine learning–based method for zoning forest fire risk using remote sensing and GIS data can be used for monitoring and early warning of the population about forest fire danger in order to reduce damage from forest fires.

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CONFLICT OF INTEREST

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