Received: July 20, 2026 | Received in revised form: September 21, 2026 | Accepted: October 6, 2026 | Available: November 2, 2026

JOURNAL OF APPLIED RESEARCH ON SCIENCE AND TECHNOLOGY
JARST
INSTITUTE OF RESEARCH AND DEVELOPMENT
RAJAMANGALA UNIVERSITY OF TECHNOLOGY THANYABURI
ISSN ONLINE: 2773-9473
https://ph01.tci-thaijo.org/index.php/rmutt-journal

Spatial assessment of wildfire risk using remote sensing and environmental variables in Thung Salaeng Luang national park, Thailand

Phurin Makaew[1], Veeranan Chaimanee[2], Wanna Mangkita[1] and Piyapit Khonkaen[1*]
[1]Department of Forest Management, Maejo University Phrae Campus, Phrae, THAILAND
[2]Department of Agro-Industrial Biotechnology, Maejo University Phrae Campus, Phrae, THAILAND
Corresponding author: piyapit@gmail.com

ABSTRACT

This study aims to analyze factors influencing wildfire occurrence and generate a wildfire risk map for Thung Salaeng Luang National Park. Hotspot data were acquired using the satellite sensor of Suomi NPP and the VIIRS system over the study period ranging from 2021 to 2025, having a total of 420 hotspot records. Maximum Entropy Modeling was conducted on the relationship between the presence of wildfire hotspot occurrences and five environmental geographic variables extracted from the remote sensing data such as Elevation Above Sea Level, Slope, Aspect, NDVI, and LST. It is observed that the statistical model performed well in terms of prediction of wildfire risk with an AUC value of 0.812. The most influential factors for wildfire occurrence and spatial distribution were NDVI, LST, Slope, Elevation Above Sea Level, and Aspect. Based on the analysis of the wildfire risk assessment model, the wildfire risk zones of Thung Salaeng Luang National Park were divided into five different levels: very high/extreme risk, high risk, moderate risk, low risk, and lowest risk, which belong to the very low-risk level and cover 724.77 km² (58.22%) of the total area. Following this, there are low-risk areas, which cover an area of 227.16 km² (18.25%), moderate-risk areas, which cover 177.12 km² (14.23%), high-risk areas, which cover 97.47 km² (7.83%), and very high-risk areas, which cover 18.45 km² (1.48%). The very high-risk zones are predominantly distributed in Wang Thong District and Noen Maprang District. These findings provide essential spatial information for wildfire risk management planning by ranking the relative importance of environmental and geographic factors, thereby enabling more efficient mitigation of wildfire occurrence and reducing potential damage and associated impacts within this study area.

Keywords: Wildfire risk assessment, Environmental variables, Spatial distribution analysis, Thung Salaeng Luang National Park, VIIRS hotspot data

INTRODUCTION

Many protected forests in Thailand are subject to periodic forest fires annually. From the information about fires in Thailand from 2013 to 2025 over 13 years, more than 67,000 forest fires occurred, affecting about 2,613.43 square kilometers of forest areas [1]. However, while there is a need for wildfires in some ecosystems, which are capable of adaptation to the effects of wildfires such as stimulating the process of seed germination and forest structure maintenance in deciduous and mixed deciduous forests, the problem of uncontrolled and excessive wildfires results in serious harm to the ecosystem. Forest fires negatively affect biodiversity, water and soil resources, habitats of wildlife [2], and people's health due to the formation of haze and fine particulate matter (PM2.5) [3]. One of the regions that suffer from forest fires is Thung Salaeng Luang National Park, which is located in Phitsanulok and Phetchabun provinces. This region is of extreme significance in terms of preserving natural resources and biodiversity and acting as wildlife habitat. It also helps in the maintenance of natural environment and watershed areas, conducting research and education programs, as well as functioning as a recreational area based on nature. It is therefore imperative to understand the extent and makeup of the park, due to these existing wildfires. The park covers approximately 1,262.40 square kilometers (126,240 hectares) and spans three districts in Phitsanulok Province: Noen Maprang, Wang Thong, and Nakhon Thai, as well as three districts in Phetchabun Province: Khao Kho, Mueang Phetchabun, and Wang Pong.

The forest covers an area of 85.4% (1,063.60 square kilometers). The community land that is provided for by Section 64 of the National Park Act B.E. 2562 (2019) occupies 14.60% (181.84 square kilometers) of the total area of the park [4]. There have been 475 wildfire spots recorded in the last five years (2021-2025). In 2023 (B.E. 2566), the burned area reached a peak of 185.60 square kilometers [1].

©2026 Institute of Research and Development, RMUTT, Thailand

DOI: 10.60101/jarst.2026.268932

JOURNAL OF APPLIED RESEARCH ON SCIENCE AND TECHNOLOGY

The park comprises evergreen forest types (dry evergreen forest, coniferous forest) and particularly deciduous forest (mixed deciduous forest, deciduous dipterocarp forest, savanna forest), which is the area most prone to wildfires during the fire season [5]. Thung Salaeng Luang National Park is therefore an area of importance, suitable and highly necessary for studying the spatial wildfire risk assessment from remote sensing data, for which there has been no research related to fire risk assessment in this area.

This study aimed to 1) to develop a spatial model and evaluate the performance of the model, 2) to analyze the relationship of environmental variables influencing the distribution of wildfires, and 3) to create a wildfire risk map of Thung Salaeng Luang National Park, Phitsanulok Province. Therefore, the study on spatial assessment of wildfire risk using remote sensing and environmental variables in Thung Salaeng Luang National Park can be applied for planning spatial wildfire management.

MATERIALS AND METHODS

1. Study area

The study site is located in the Thung Salaeng Luang National Park, which can be found in the Phetchabun mountain range that includes parts of the provinces of Phitsanulok and Phetchabun in lower northern Thailand. It was established in 1963 and occupies an area of about 1,262.40 square kilometers with UTM coordinates of 47Q 700262 E 1863061 N. Elevations vary from under 100 meters up to about 1,000 meters. Most of the land was covered by altitude ranges from 500 to 750 meters which formed the largest portion (40.75%), 24.89% from 750 to 1,000 meters, 24.71% from 250 to 500 meters, 8.25% between 100 to 250 meters, and 1.40% Less than 100 meters (Figure 1). It indicates that the elevation is relatively high in this terrain. Weathering and erosion of sandstones have formed sharp mountain tops, cliffs, and difficult slopes. Some parts of this terrain have caves and karst topography due to water erosion along the fractures of rocks that cause variations in the slope of the terrain (Figure 1). Most part of the park has slopes ranging from 15% to 35% (38.28%), then 5%-15% (27.68%), 0%-5% (20.55%), and slopes above 60% (0.66%). These geomorphological characteristics help form headwater streams of some watersheds. Between 1992 and 2021, the average temperature per year was 28°C; the average maximum temperature and minimum temperature were 33.5°C and 23.3°C, respectively. The month of April had the highest average monthly temperature and maximum temperature at 30.7°C and 37.1°C, respectively. However, January had the lowest mean monthly temperature (24.8°C) and minimum temperature (19.1°C). The park averages 9.9 rainy days per month, with August the wettest (20 days) and December the driest (1.4 days). Average annual rainfall is about 110.8 millimeters. September gets the highest precipitation (278.4 millimeters), January gets the lowest (7.5 millimeters), while October experiences the highest daily rainfall (197.1 millimeters).

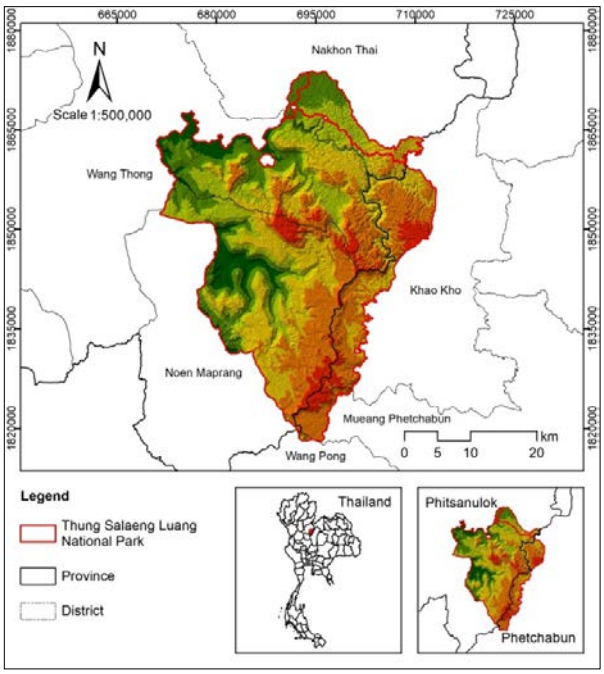


Figure 1 The study area of Thung Salaeng Luang National Park, Phitsanulok, Thailand (Elevation map).

Thung Salaeng Luang National Park covers different kinds of forest areas including dry evergreen, mixed deciduous, deciduous dipterocarp, coniferous, and savanna forests, with a total area of 1,245.44 km². Dry evergreen forest makes up 624.08 km² (50.11%) of the park, while mixed deciduous forest occupies 344.93 km² (27.70%). Secondary forest covers 41.27 km² (3.31%) of the park, while coniferous forest takes up 31.44 km² (2.52%). Savanna forest and open grasslands make up 19.47 km² (1.56%), whereas deciduous dipterocarp forest constitutes 2.41 km² (0.19%) of the park. Moreover, 181.84 km² of the park is designated for residential and agricultural purposes under Section 64 of the National Park Act, B.E. 2562 [4].

Therefore, Thung Salaeng Luang National Park is highly suitable and essential for studying spatial forest fire risk assessment in conjunction with related environmental factors, as it was continuously affected by forest fires every year. In addition, this area also serves as a source of streams and a habitat for wildlife. Spatial risk assessments were used remote sensing data in this area and enable the development of fire risk models and maps that can serve as guidelines for fuel management planning, fire monitoring, and effective firefighting in the future, helping alleviate wildfire impacts in the area.

2. Hotspot data acquisition and preparation

Wildfire hotspot data came from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor

©2026 Institute of Research and Development, RMUTT, Thailand

DOI: 10.60101/jarst.2026.268932

JOURNAL OF APPLIED RESEARCH ON SCIENCE AND TECHNOLOGY

onboard Suomi NPP, and were accessed via the Fire Information for Resource Management System (FIRMS) developed and operated by NASA [6]. This dataset covers 2021–2025, a total of 475 hotspot locations, representing wildfire events in Thung Salaeng Luang National Park (Figure 2)

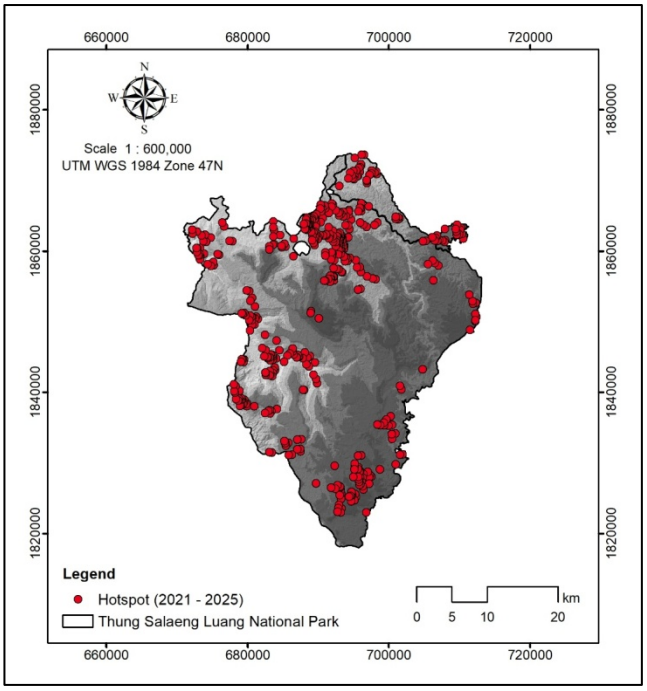


Figure 2 The map of hotspot locations with the period from 2021 to 2025 at Thung Salaeng Luang National Park, Phitsanulok, Thailand (Source: VIIRS sensor onboard the Suomi NPP satellite, NASA FIRMS).

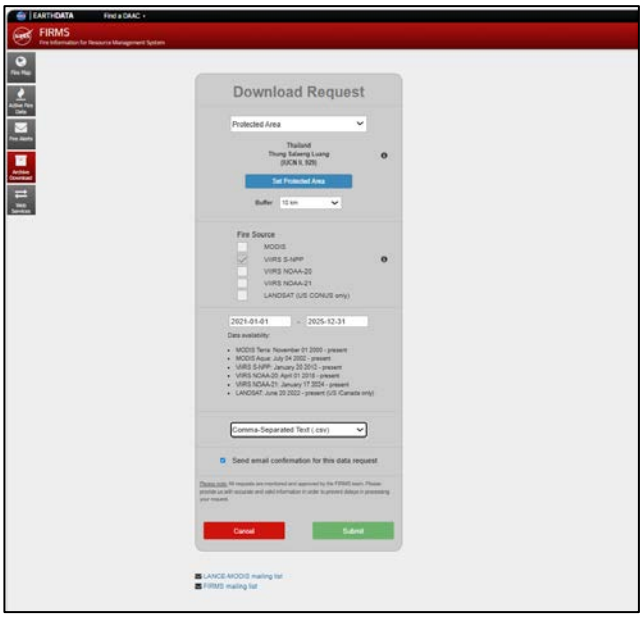


Figure 3 Data download request of the Fire Information for Resource Management System.

VIIRS detected thermal anomalies at about 375-meter resolution, making it good for mapping wildfires. Of the 475 hotspot locations, 420 filtered hotspots were used to build and validate the model [7]. The dataset was randomly divided, where 75% (315 points) was employed for training and modeling, while 25% (105 points) for testing purposes.

Download Request for the Fire Information for Resource Management System (FIRMS) dataset has pre-defined criteria in order to make sure the data is reliable and accurate in terms of its geographic location, time span, and data reliability. Download Criteria were as follows: 1) Area type: Protected Area. 2) Country: Thailand. 3) WPAID: 929 (Thung Salaeng Luang). 4) Buffer = 10 km (to search within 10 km in order to avoid any problems with the boundaries of the study area) [8]. 5) Fire Source: VIIRS S-NPP were used Suomi satellite as a source to identify hot spots. 6) Search period: from January 1, 2021, to December 31, 2025. 7) Choose the file type to download: Shapefile (.shp) or Comma-Separated Values (.CSV) (Figure 3).

3. Environmental variables

In wildfire risk assessment using remote sensing data, the key step that most significantly affects the accuracy of the results is the preparation of data and the management of environmental factor layers. Data obtained from remote sensing had different scales, formats, and coordinate reference systems. Therefore, in order for the model to process them efficiently, all environmental factor layers must be prepared in a uniform format.

The selection of environmental variables was based on a comprehensive literature review of wildfire risk modeling, conducted by selecting 10 environmental factors; elevation, slope, aspect, temperature, normalized difference vegetation index, distance from water body, distance from road, distance from village, land use and land cover, and distance from agriculture that influence the spread of wildfires. Although ten environmental and geographic variables were initially considered, the final model was optimized to retain only the five most influential variables based on their contributions and performance metrics. Pearson Correlation Assessment: It is clear from the analysis that there is significant redundancy among spatial distance variables, namely distance from village and distance from agriculture, as they have very high correlation ($r = 0.911$, $p < 0.001$), whereas moderate to high correlations are seen with distance from road ($r = 0.578–0.604$) and elevation ($r = 0.503–0.578$). Moreover, land use and land cover (land use category) are also correlated with continuous physical parameters like LST ($r = -0.396$) and NDVI ($r = 0.269$). Hence, redundant distance variables and land use were discarded to overcome the issue of multicollinearity. With respect to the VIF analysis for five variables selected, the values are between 1.089 and 1.689, which are below the caution level of 5.0 and the critical level of 10.0, respectively, with all Tolerance values above 0.10 (Table 1).

©2026 Institute of Research and Development, RMUTT, Thailand

DOI: 10.60101/jarst.2026.268932

JOURNAL OF APPLIED RESEARCH ON SCIENCE AND TECHNOLOGY

Table 1 Multicollinearity test results.

Variables	Tolerance	VIF	Assessment
LST	0.59	1.69	No Multicollinearity
Slope	0.77	1.30	No Multicollinearity
Aspect	0.90	1.12	No Multicollinearity
NDVI	0.90	1.11	No Multicollinearity
Elevation	0.92	1.09	No Multicollinearity

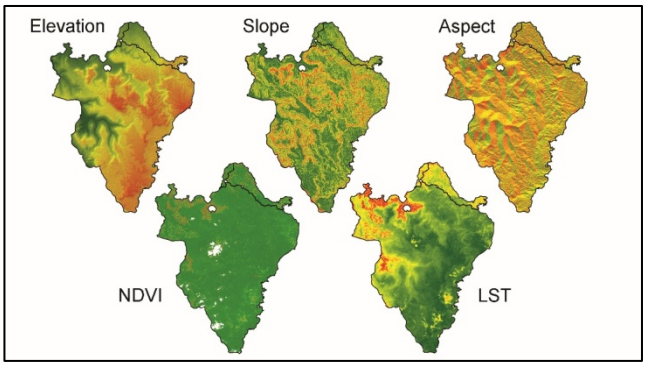


Figure 4 Selected environmental variables for wildfire hotspot analysis using the Maximum Entropy model.

Five spatial variables known to influence wildfire occurrence were selected: 1) Elevation above mean sea level, which affects humidity and forest type. 2) Slope, which directly impacts the direction and speed at which fires spread, with fires on sloped landscapes being more severe and spreading faster than fires on flat lands. 3) Aspect, referring to the direction in which a slope faces; southwest-facing slopes receive sunlight during the day and therefore tend to be drier than slopes facing other directions [9, 10]. The above three variables were obtained from SRTM1 with a 30-meter resolution. 4) Normalized Difference Vegetation Index (NDVI) from Sentinel-2 (MultiSpectral Instrument – MSI) satellite imagery with 10-meter resolution [11, 12], where NDVI is considered as a criterion for the assessment of fuel condition and represents plant greenness, density and biomass. During leaf drop and plants dehydration in the dry season, NDVI will reduce, and this way will correlate with an amount of dry fuel on the ground [12, 13, 14, 15]. 5) Land Surface Temperature (LST) from Landsat 8 (OLI/TIRS) with a 30-meter resolution [8, 16], which is one of the main parameters that affected the moisture in the fuel as an increase in temperature causes reduction in moisture and increases fuel ignitability [17] (Figure 4).

All environmental variables were assigned to a UTM WGS 1984 Zone 47 coordinate system and resampled. They were processed into raster format with a uniform spatial resolution of 300 × 300 meters. Following that, the data set was transformed into ESRI ASCII Grid by means of Geographical Information System (QGIS 3.26.1 / ArcScene 10.4.1) for model creation through a software package Maximum Entropy Species Distribution Modeling (MaxEnt), version 3.4.4.

4. Model development (MaxEnt)

Wildfire occurrence probability was modeled using the Maximum Entropy (MaxEnt) algorithm, a presence-only statistical modeling approach widely used for species distribution and environmental risk analysis [18]. The calculation of spatial probabilities was done by integrating hotspots' presence information with environmental variables. The model was set up based on logistic output where continuous values from 0 to 1 are generated. Calibration and validation of the model were performed through the use of training dataset, which consists of 75% of the total data, while the rest (25%) of the data is used for model testing. Default parameter setting was used in MaxEnt [18, 19, 20].

5. Model performance and environmental variables' importance

The importance of each of the environmental variables was determined through the Jackknife procedure, which evaluates the importance of each variable to the model accuracy. Model evaluation was done using the ROC curve, which displays the sensitivity plotted against 1-specificity. The Area Under the Curve (AUC), ranging from 0 to 1, was used as the primary measure for evaluating the performance of the model [19, 21]. Model accuracy was further classified based on established criteria [22, 23]. To improve classification accuracy, six commonly used threshold methods were applied such as 1) Minimum Training Presence (MTP) 2) 10^{th} Percentile Training Presence (PTP) 3) Equal Training Sensitivity and Specificity (ETRSAS) 4) Maximum Training Sensitivity Plus Specificity (MTRSPS) 5) Equal test sensitivity and specificity (ETESAS) and 6) Maximum Test Sensitivity Plus Specificity (MTESPS). The model with the highest predictive accuracy was selected for wildfire risk mapping [20, 24, 25].

6. Mapping risk of wildfire

For wildfire occurrence, the probabilities were obtained through MaxEnt method and ranged from 0 to 1 for all grid cells. The probability of 0 is an indication that there is low likelihood of wildfire occurrence in the particular grid cell whereas 1 represents high probability, as indicated in Table 2. The probability outputs were classified into five wildfire risk levels using the equal-interval classification method [12]. The final wildfire risk map was generated in a Geographic Information System (GIS) environment and constrained

©2026 Institute of Research and Development, RMUTT, Thailand

DOI: 10.60101/jarst.2026.268932

JOURNAL OF APPLIED RESEARCH ON SCIENCE AND TECHNOLOGY

to the boundary of Thung Salaeng Luang National Park in Phitsanulok, Thailand.

Table 2 Performance evaluation criteria for the MaxEnt model based on AUC values.

Model performance	Weight
Excellent	0.97 – 1.0
Very Good	0.90 – 0.97
Good	0.75 – 0.90
Fair	0.6 – 0.75
Poor	0.5 – 0.6

RESULTS AND DISCUSSION

1. Model performance evaluation

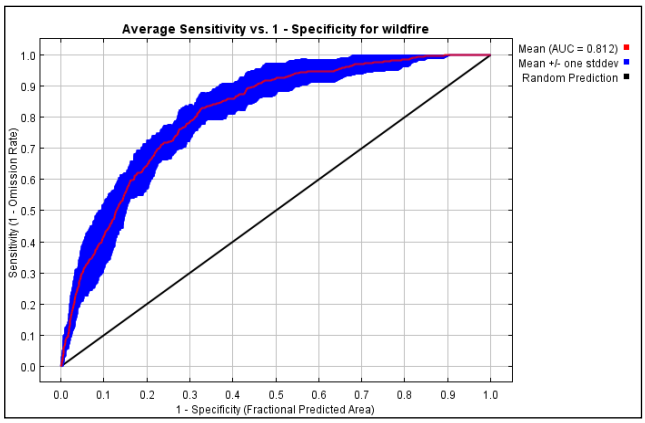


Figure 5 The predictive performance of wildfire risk model in Thung Salaeng Luang National Park.

In the study and analysis of the distribution of wildfire-risk areas in Thung Salaeng Luang National Park, the researchers applied the Maximum Entropy Model (MaxEnt), a highly efficient tool for analyzing the spatial distribution of events. Based on the evaluation of the model's prediction accuracy through the analysis of the Area Under the Receiver Operating Characteristic Curve (AUC), it was found that the developed model has a good ability to predict the risk of forest fires (0.75–0.90), with an AUC value of 0.812, which is significantly higher than the random baseline threshold (Figure 5) [23]. When examining the details of the results shown in Figure 5, the red curve representing the model average (Mean AUC = 0.812) always lies above the black diagonal line, which is the benchmark for random prediction (Random Prediction) with an AUC of 0.50. This result demonstrates the model's reliability in predicting wildfire risk. Additionally, the blue band surrounding the red curve represents the standard deviation (Mean ± 1 stddev), which is narrow and clustered, indicating that the model has low variance and high stability when tested repeatedly. Based on these results, the MaxEnt model can effectively detect and learn spatial relationship patterns between various environmental factors and wildfire occurrence points and can accurately and reliably distinguish between high- and low-risk areas.

2. Model validation and threshold optimization

Model validation was conducted using 25% of hotspot data, including both presence and pseudo-absence points. Since the logistic output of MaxEnt produces continuous probability values (0–1), it was necessary to define a threshold to convert these values into binary predictions (presence/absence of wildfire occurrence). The number of points in the validation data set was 210, with an equal number of presence (P = 105) and pseudo-absence (A = 105), referring to data absence generated from sites other than the sites affected by wildfire. In this case, the Smart Patrol data were collected randomly at survey points having wildlife in the Thung Salaeng Luang National Park. Six commonly applied threshold criteria were considered in this analysis based on previous research works [20, 24, 26]. Among these, the 10th Percentile Training Presence (PTP) threshold yielded the highest classification accuracy, with an overall accuracy of 73.81% by correctly identifying 92 presence points and 63 absence points (Table 3). This result indicates that the PTP threshold provides an optimal balance between omission and commission errors, making it the most appropriate threshold for wildfire risk classification in this study. The use of multiple threshold criteria enhances the reliability of model interpretation and reduces uncertainty associated with binary classification, where selecting an appropriate threshold is another crucial step in producing accurate MaxEnt predictions and subsequently generating wildfire risk map.

Table 3 The accuracy assessment of threshold-based contingency model analysis.

Types of data	Hotspots		Threshold (%)
	P	A	O
Total	105	105	210
MTP	103	14	55.71
PTP	92	63	73.81
ETRSAS	73	71	68.57
MTRSPS	81	66	70.00
ETESAS	75	68	68.10
MTESPS	80	67	70.00

Note: P = presence points; A = absence points; O = observed values derived from totals and overall accuracy (%).

3. Impact of environmental variables on wildfire events

The impact analysis of the environmental variables showed that the most impactful variable is NDVI, with 66.8% contribution and 70.3% permutation importance. The next most influential environmental

©2026 Institute of Research and Development, RMUTT, Thailand

DOI: 10.60101/jarst.2026.268932

factors in wildfire occurrence are Land Surface Temperature (LST), Slope, Elevation, and Aspect, respectively. Aspect appeared the lowest correlation with wildfire risk (Table 4).

Table 4 The correlation analysis of environmental factors influencing wildfire distribution.

Environmental factors	Percentage of correlation	Percentage of importance factors changes (%)
NDVI	66.8	70.3
LST	15.3	11.9
Slope	13.8	11.8
Elevation	3.1	5.1
Aspect	1.0	0.9

The Jackknife test showed that NDVI is the most important predictor in the model. Only NDVI gave the highest training gain, and removing it caused the biggest drop in gain. It implies that NDVI offers the necessary information for predicting wildfires. This variable is significant due to the relevance of vegetation because NDVI is an indicator of canopy greenness and plant biomass growth, which have a link to the dry fuel volume during the dry season. The second most significant predictor was the Land Surface Temperature (LST), as it was indicated the surface temperature and the dryness of the fuel. High LST implies dryness, hence the higher chance of ignition and fire spread. Lastly, slope and elevation showed moderate significance in line with the fire behavior theory [27, 28]. Aspect had the least effect in this area, matters less than vegetation and temperature (Figure 6).

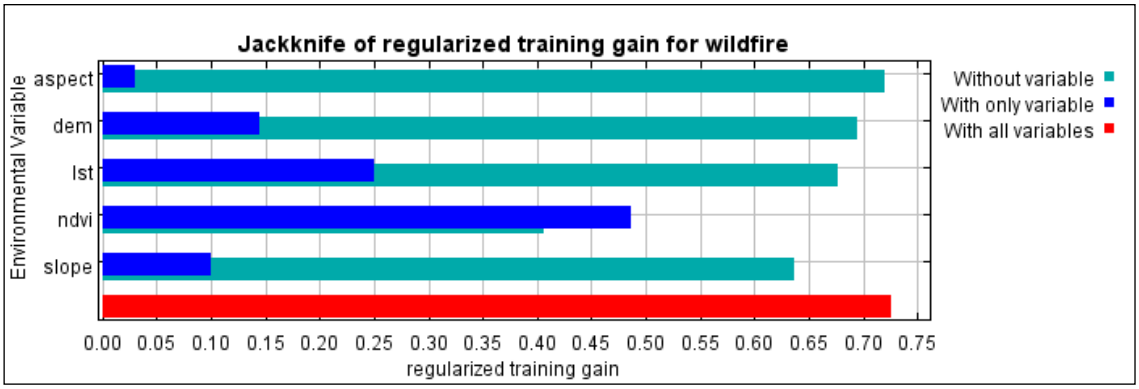


Figure 6 The results of jackknife test to measure the relationship between environmental factors and wildfire occurrence.

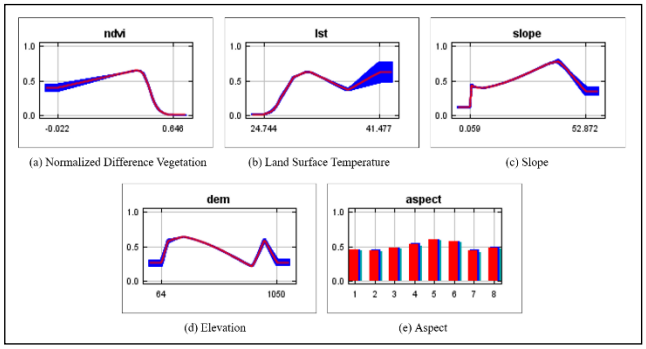


Figure 7 Environmental variables and their relation with wildfire occurrences.

Wildfire hotspots showed clear patterns across different environmental factors. The highest number of hotspots appeared where NDVI values ranged from about 0.25 to 0.58 (Figure 7a). This implies that regions with a moderate amount of vegetation cover were more likely to be affected by the wildfire as there would be enough dry fuel to cause fires when the dry season occurs. Majority of the hotspots for LST temperatures were within the range of 30- 37°C (Figure 7b); these were temperatures which increase probability of ignition. Majority of the fires occurred on land with slope values of 35- 42% (Figure 7c), similar to what previous literature indicated where fires can be easily propagated by steeper slopes [29]. Maximum hotspots were located at elevations from 150 to 400 meters above sea level (Figure 7d). This was in agreement with past literature which indicates that low lying areas are more prone to wildfires due to their high temperature. Lastly, majority of the hotspots were located on south-facing slopes (Figure 7e) which were sunnier and therefore prone to fires (Figure 7) [27, 28, 30].

4. Mapping of wildfire risks

The best model which was chosen based on MaxEnt analysis was employed to make a wildfire risk map. This model utilizes a training presence threshold of 10th percentile value with a cutoff value of 0.218. Wildfire risk zones in Thung Salaeng Luang National Park have been classified into five classes: extremely/ very high risk, high risk, moderate risk, low risk, and lowest risk. Thung Salaeng Luang National Park were classified as having the lowest risk level, with an area of 724.77 square kilometers (58.22% of the whole area). The findings are similar to those found in other researches indicating lower risks for wildfires [12, 29, 31]. The low-risk areas cover 227.16 square kilometers (18.25%), while the moderate-risk areas cover 177.12

©2026 Institute of Research and Development, RMUTT, Thailand

DOI: 10.60101/jarst.2026.268932

JOURNAL OF APPLIED RESEARCH ON SCIENCE AND TECHNOLOGY

square kilometers (14.23%). High-risk areas account for 97.47 square kilometers (7.83%), and very high-risk areas cover about 18.45 square kilometers (1.48%) of the national park. High- and very-high-risk areas are mainly found in the upper and certain boundary zones of the park. Spatial analysis shows that wildfire risk density is highest along the western boundary, especially in the upper area. Next is the northern aspect, where risk areas cluster in the upper region. The southern aspect has limited risk areas at its lowest point, and the eastern aspect has the lowest wildfire risk (Figure 8).

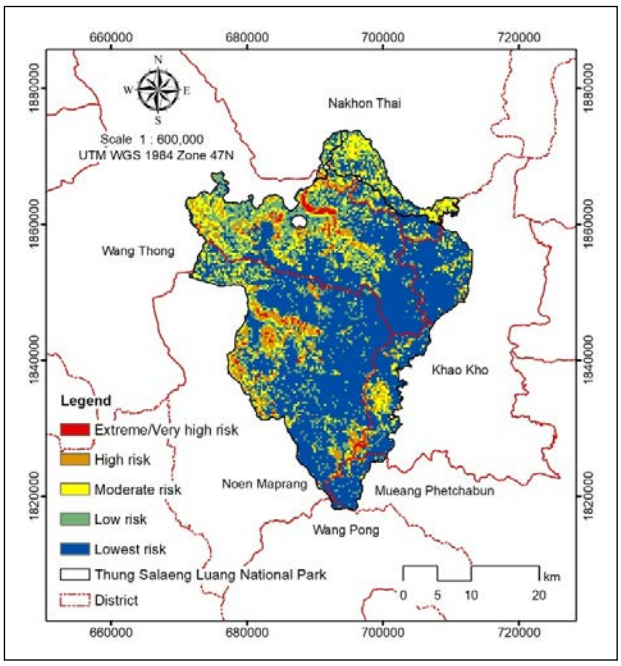


Figure 8 Map of wildfire risk areas in Thung Salaeng Luang National Park, Phitsanulok Province.

The spatial pattern is determined by variation in the environmental factors in terms of the vegetation attributes, topographical complexities, and micro-climatic variation in the landscape. The high-risk zone in the northern and western parts could be due to the dryness in these regions, availability of more fuels, and high solar exposure, increasing the possibility of wildfire ignition and spread. The zones of high risk for wildfire need to be prioritized for management of wildfires through fuel management, surveillance, and early warning systems.

Analysis of the spatial variation of wildfires risks within the six districts of Thung Salaeng Luang National Park indicated an uneven distribution of the very high-risk areas. It was found that Wang Thong District located in Phitsanulok Province had the largest wildfire risk, which covered 9.45 square kilometers or 51.22% of the entire very high-risk area. Another district, Noen Maprang in Phitsanulok Province ranked second in terms of very high-risk area coverage at 7.38 square kilometers (40%). Overall, these two districts made up over 90% of the entire high-risk areas, thus being the main target of wildfire prevention measures. Khao Kho District accounts for 1.17 square kilometers (6.34%), followed by Mueang Phetchabun District with 0.27 square kilometers (1.46%). Nakhon Thai District contributes 0.18 square kilometers (0.98%), and Wang Pong District has the lowest wildfire risk (Table 5). However, what this research did not do was compare the results obtained through the analysis of the application of a single model of the MaxEnt algorithm model to the results of other models on the risk of wildfires. This would have been an important recommendation for future research that could have compared the results from other models as well in order to verify and compare test results and reduce errors in spatial models.

Table 5 Wildfire risk levels in Thung Salaeng Luang National Park classified by district.

Wildfire risk levels	Unit	Wang Thong	Noen Maprang	Khao Kho	Mueang Phetchabun	Nakhon Thai	Wang Pong	Total
Very High risk	km^2	9.45	7.38	1.17	0.27	0.18	0.00	18.45
	%	51.22	40.00	6.34	1.46	0.98	0.00	100.00
High risk	km^2	32.40	44.73	11.88	1.89	6.48	0.09	97.47
	%	33.24	45.89	12.19	1.94	6.65	0.09	100.00
Moderate risk	km^2	65.61	50.94	18.90	0.90	40.77	0.00	177.12
	%	37.04	28.76	10.67	0.51	23.02	0.00	100.00
Low risk	km^2	94.95	82.26	19.89	4.05	26.01	0.00	227.16
	%	41.80	36.21	8.76	1.78	11.45	0.00	100.00
Lowest risk	km^2	180.63	334.8	134.28	24.84	48.60	1.62	724.77
	%	24.92	46.19	18.53	3.43	6.71	0.22	100.00

CONCLUSIONS

1. Model performance and accuracy

In the analysis of the wildfire risk modeling performance in the Thung Salaeng Luang National Park, it is evident that the model was able to attain an AUC value of 0.812, indicating good predictive performance. Model accuracy was further evaluated on 25% of the test data, including both wildfire-present and wildfire-absent cases. Six different logistic threshold criteria were tested. The results indicate that the 10th Percentile Training Presence (PTP) threshold is the most suitable

©2026 Institute of Research and Development, RMUTT, Thailand

DOI: 10.60101/jarst.2026.268932

for generating the wildfire risk map. From this criterion, a cutoff value of 0.218 was arrived at, producing the highest accuracy of the models at 73.81%.

2. Significant environmental factors contributing to wildfires

The analysis of the environmental factors using the Jackknife test revealed that NDVI is the most significant environmental variable contributing to the distribution of wildfires. This highlights the significance of vegetative characteristics such as the amount of fuel and moisture content in determining fire risks. Some of the variables influencing fires include LST, slope, and elevation, which determine the fuel dryness, heat accumulation, and topographic configuration of the landscape. Aspect was found to have the least contribution to the wildfire occurrence, thus pointing out the limited significance of this variable in the studied environment.

3. Spatial distribution of wildfire risk

In this research, the wildfire risk areas in Thung Salaeng Luang National Park were divided into five levels. Most of these areas were classified as very low wildfire risk areas and consisted of 724.77 km2 (58.22% of the total area). This is followed by low and moderate risk of wildfire with 18.25% and 14.23% respectively. The high wildfire risk covers a total of 97.47 square kilometers (7.83%), while the very high wildfire risk covers around 18.45 square kilometers (1.48%). Based on the district-level analysis done for the six districts located in Thung Salaeng Luang National Park, it was found out that the two districts with the highest risk of wildfires are Noen Maprang and Wang Thong. More than 90% of the total area of wildfire risk belongs to those two districts.

In this study, a complete analysis of fire risk mapping and its influencing parameters in Thung Salaeng Luang National Park was conducted. The combination of remote sensing data with the MaxEnt model is an efficient approach that could be used for detecting high-risk regions and environmental factors responsible for wildfires. The wildfire risk map developed in this study could help in managing the wildfire in a spatially distributed way by providing the necessary tools for prioritizing those high-risk regions for preventive actions. Such preventive actions could include management of fuel, monitoring of vegetative environment, development of early warning systems, etc. In conclusion, this work can be considered as an important step towards improving forest fire risk management. However, this study relies solely on the MaxEnt model. Future research should use comparisons of multiple models to increase prediction accuracy and reduce errors in generating wildfire risk maps.

ACKNOWLEDGEMENT

The authors would like to express their sincere gratitude to Thung Salaeng Luang National Park for generously providing essential data and facilitating access to information used in this study. Their support was instrumental in enabling the analysis and successful completion of this research.

REFERENCES

1. Department of National Parks, Wildlife and Plant Conservation. Burned forest areas within protected areas [Internet]. 2025 [cited 2026 Mar 6]. Available from: https://catalog.dnp.go.th/dataset/fire1. (in Thai).
2. Akka-akra S. Forest fire control in Thailand. Bangkok: Royal Forest Department; 2000.
3. World Health Organization. Wildfires [Internet]. 2023 [cited 2025 Jul 10]. Available from: https://www.who.int/health-topics/wildfires.
4. National Park Office. Management plan for Thung Salaeng Luang National Park (2023–2027). Department of National Parks, Wildlife and Plant Conservation; 2022.
5. Makaew P, Mangkita W, Chaimanee W, Khonkaen P. Development of a wildfire risk mapping model based on forest type and land use characteristics in Thung Salaeng Luang National Park, Phitsanulok Province [in Thai]. In: Jaradrattanapaiboon A, editor. Proceedings of the 6th national and the 4th international MJU-Phrae Conference; 2026 Jul 24; Phrae Nakara Hotel, Phrae, Thailand. Phrae: Maejo University-Phrae Campus; 2026. p. 298-312.
6. National Aeronautics and Space Administration (NASA). Fire Information for Resource Management System (FIRMS) [Internet]. Washington (DC): NASA; c2026 [cited 2027 Jul 12]. Available from: https://firms.modaps.eosdis.nasa.gov/.
7. Paudel GP, Lamsal K, Bhattarai P, Bhattarai A, Tripathi S. Geospatial forest fire risk assessment and zoning by integrating MaxEnt in Gorkha District, Nepal. Heliyon. 2024;10(11):e31305.
8. Thamrongrat T, Kamyo T, Haopinjai I, Chueasa-ard T. Wildfire risk assessment using satellite imagery in Doi Phu Kha National Park, Nan Province. Thai J For. 2024;43(1):98-110.
9. U.S. Geological Survey. SRTM 1 Arc-Second Global [Entity ID: SRTM1N16E100V3] [Internet]. 2014 [cited 2026 Mar 6]. Available from: https://earthexplorer.usgs.gov.
10. Dontree S. Forest Fire and Haze Management: Lessons Learned from the Multi-stakeholder Collaborative Management in Chiang Mai Province. *J Soc Sci Chiang Mai Univ* [Internet]. 2019;27(2):121-55. Available from: https://so04.tci-thaijo.org/index.php/jss/article/view/171653

©2026 Institute of Research and Development, RMUTT, Thailand

DOI: 10.60101/jarst.2026.268932

11. Muangphet P. Application of geographic information systems and remote sensing for wildfire risk assessment in Mae Chaifa National Forest Reserve, Lampang Province [dissertation]. Nonthaburi: Sukhothai Thammathirat Open University; 2017.
12. Kamyo T, Kamyo P, Panthong K, Howpinjai I, Kamton R, Asanok L. Assessing Fire Risk Zones in Phrae Province, Northern Thailand, Using a MaxEnt Model. Geographies. 2025;5(3):51.
13. Chuvieco E, Cocero D, Riaño D, Martin P, Martínez-Vega J, de la Riva J, Pérez F. Combining NDVI and surface temperature for the estimation of live fuel moisture content in forest fire danger rating. *Remote Sens Environ*. 2004 Aug 30;92(3):322-31.
14. Pettinari CA, Chuvieco E. Fire danger assessment from remote sensing. Curr For Rep. 2016;2(3): 159-70.
15. Jaiswal RK, Mukherjee S, Raju KD, Saxena R. Forest fire risk zone mapping from satellite imagery and GIS. Int J Appl Earth Obs Geoinformation. 2002;4(1):1-10.
16. Maimaun P, Charoenpanyanet A. Development of a wildfire occurrence prediction model based on climate variability using geoinformatics in Omkoi District, Chiang Mai Province. Burapha Sci J. 2023;28(2):949-75.
17. U.S. Geological Survey. Landsat 8 collection 2 Level 2 science product [Internet]. 2020 [cited 2026 Mar 6]. Available from: https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LC08_C02_T1_L2.
18. Phillips SJ, Anderson RP, Schapire RE. Maximum entropy modeling of species geographic distributions. Ecol Model. 2006;190(3-4):231-59.
19. Phillips SJ, Dudík M. Modeling of species distributions with MaxEnt: New extensions and a comprehensive evaluation. Ecography. 2008; 31(6):756-69.
20. Trisurat Y, Kanchanasaka B, Kreft H. Assessing potential effects of land use and climate change on mammal distributions in northern Thailand. Wildl Res. 2014;41(6):522-8.
21. Baldwin RA. Use of maximum entropy modeling in wildlife research. Entropy. 2009;11(4):854-66.
22. Swets JA. Measuring the Accuracy of Diagnostic Systems. Science. 1988;240(4857):1285-93.
23. D'Souza J. Let's learn about AUC ROC curve! Medium. 2018 [cited 2026 Mar 6]. Available from: https://medium.com/greyatom/lets-learn-about-auc-roc-curve-4a94b4d88152.
24. Liu C, Berry PM, Dawson TP, Pearson RG. Selecting thresholds of occurrence in the prediction of species distributions. Ecography. 2005;28(3):385-93.
25. Phalanisong K, Traisurat Y, Bhumpakphan N, Sukchaloem D, Phochong S. Spatial distribution models for overlapping habitats of gaur and wild elephant in Phu Khieo Wildlife Sanctuary, Chaiyaphum Province. Thai J Sci Technol. 2019;8(2):116-26.
26. Trisurat Y, Toxopeus AG. Modeling species distribution. In: Trisurat Y, Shrestha RP, Alkemade R, editors. Modeling species distribution. IGI Global; 2011. p. 171-97.
27. Rothermel RC. A mathematical model for predicting fire spread in wildland fuels. U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station; 1972. Report No.: Research Paper INT-115.
28. Albini FA. Estimating wildfire behavior and effects. U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station; 1976.
29. Thamrongrat T. Application of geographic information systems for wildfire risk assessment in Doi Phu Kha National Park, Nan Province [dissertation]. Chiang Mai: Maejo University; 2024.
30. Holden ZA, Morgan P, Evans JS. A predictive model of burn severity based on 20-year satellite-inferred burn severity data in a large southwestern US wilderness area. Forest Ecol Manage. 2009; 258(11):2399-406.
31. Laksanamaphan R, Wanthongchai K, Mianmit N. Forest fire risk area analysis in Khao Yai National Park using MaxEnt model. In: The 25th National Forestry Conference: Thai Forestry towards Green Economy; 2023; Kasetsart University. p. 21-30.

©2026 Institute of Research and Development, RMUTT, Thailand

DOI: 10.60101/jarst.2026.268932