Assessment of Wildfire Risk at Recreational Sites in Sri Lanna National Park, Chiang Mai, Northern Thailand, using Remote Sensing and GIS Techniques

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Abstract
Wildfires have had massive impacts on recreational areas in national parks in Thailand that have seen a decline in tourism activities due to fire damage. Therefore, prevention and control of wildfires can minimize fire damage at recreation sites for existence of national parks. This study integrates remote sensing and geographic information system (GIS) techniques for modeling and mapping wildfire risks to evaluate the potentials for fires at recreational sites. The factors comprehensively recognized as influencing wildfire occurrence, namely leaf fuel load, slope, aspect, elevation, distance from roads, and proximity to settlements were selected for establishing a wildfire risk model. A differenced normalized burn ratio (dNBR) was used to rate wildfire sensitivity for subclasses of each factor. All factors were then weighted using pairwise comparison, where the leaf fuel load was the most important factor and we show that soil moisture can be used as a new factor for modeling wildfire risk. Our model correctly classified 74.67% of real wildfire instances, confirming that the selected factors could be used for mapping wildfire-prone areas. The mapping showed three different categories of wildfire risk; 22.15% of the study area was predicted to be a high wildfire risk zone, and 42.25% and 35.60% were categorized as moderate and low risk, respectively. A map of wildfire risk zones was overlaid with recreation sites in Sri Lanna national parks, revealing that 6 of 22 recreation sites were at high risk from wildfires. Hence, this study contributes to reducing wildfire threats to recreational areas and can help develop appropriate method for accessing areas prone to wildfires.

1. Introduction

National parks in Thailand are protected forest areas that contain natural resources, biodiversity, and appealing scenery and landscape that attracts tourism. Recreation and tourism plays an important role in the life of the national park because most visitors cite scenery and landscape as their main reasons for visiting a national park. Recreation areas in the national park have a wide variety of natural places and landscapes that enable activities for tourism such as camping, boating, walking and climbing trails, and wildlife viewing. Such recreational areas are increasingly threatened and damaged by wildfires, resulting in a decline in tourism activities. Wildfires are complicated events that occur as a result of natural processes and human activities (Vasilakos et al., 2009). Statistical evidence demonstrates increasing trends in fire frequency and area burned within Thai protected forest areas from 2014 to 2016, with 4,207, 4,982, and 6,685 wildfires, accounting for 50,723, 60,453 and 125,896 ha of burned area in 2014, 2015, and 2016, respectively (Forest Fire Control Division, 2016). These numbers imply that the wildfires are occurring more frequently and are burning larger areas, expanding into recreational zones. Most wildfires in Thailand occur in national parks, especially in the north, and are mainly attributed to human activities.

Wildfires occur when three requirements needed for ignition and combustion are met, the so-called fire triangle: fuel to burn, air to supply oxygen, and a heat source to ignite the fire. After a fire starts, a wide range of factors determines the fire duration and intensity. These factors include the quantity and type of fuel, topographic characteristics (slope, aspect, and elevation), favorable environmental conditions (e.g., extreme drought and low soil moisture), which can accelerate fire combustion and result in uncontrollable spread of fire over large areas. Hence, factors influencing fire behavior need to be analyzed when mapping wildfire risk zones (Chuvieco and Congalton, 1989).

Satellite remote sensing and geographic information system (GIS) techniques have been widely used in wildfire assessment, such as predicting wildfire severity based on vegetation indices (VI), establishing wildfire risk models, and analyzing factors responsible for wildfire. Topography, anthropogenic data, and the characteristics of vegetation or fuel have been used as the most important factors influencing wildfire occurrence. Many studies have integrated these factors to establish wildfire risk models. Jaiswal et al., (2002) undertook a wildfire risk assessment for areas in India. They used the vegetation type, slope, aspect, and distance from roads and settlements to establish a wildfire risk model that showed strong agreement with actual fire-affected sites. Adab et al., (2013) applied vegetation moisture, slope, aspect, elevation, distance from roads, and vicinity to settlements as factors influencing accidental fires. Moreover, the quality, size, and shape of vegetation or fuel were used with other wildfire potential factors (slope, elevation, aspect, weather, land cover/use map, etc.) to establish a wildfire risk and hazard model (Yakubu et al., 2013). In addition to fuel type and moisture input, the quantity of fuel should also be analyzed, since large amounts of fuel result in higher intensity fires. Additionally, soil moisture should be considered as a wildfire factor because it is positively correlated with fuel moisture content (Burapapol and Nagasawa, 2016a). The present study integrated remote sensing and GIS techniques for modeling and mapping wildfire risk and evaluating recreation sites at risk from wildfires. To achieve these goals, data were obtained from Landsat 8 operational land imager (OLI) and thermal infrared sensor (TIRS), and moderate-resolution imaging spectroradiometer (MODIS) images, and were integrated with GIS data to establish a wildfire risk model for mapping wildfire-prone areas in Sri Lanna national park. This study introduces soil moisture as a new factor for establishing a wildfire risk model, and proposes a differenced normalized burn ratio (dNBR) to rate wildfire sensitivity for subclasses of each risk factor. A wildfire risk map produced from this model was used to assess potential wildfire risk at recreation sites. Authors propose that a wildfire risk map produced by their model can be used as a complementary data for local officials and other decision makers dealing with wildfires, in developing appropriate plans for preventing wildfires in national parks and recreational areas.

2. Materials and Methods

2.1 Study area

The study area was Sri Lanna National Park, located in Chiang Mai province, northern Thailand (Figure 1). The national park covers 140,600 ha, with an elevation range of 400–1,718 m, and includes a mountain range running north to south. The climate is tropical and the weather is generally hot and humid. The mean annual temperature is 26.7 °C, with minimum and maximum temperatures of 10.0 °C (January) and 41.6 °C (April), respectively (Thai Meteorological Department, 2015). Dry season begins in December and lasts through April, with a minimum average precipitation of 4.10 mm in February (Department of National Parks, Wildlife, and Plant Conservation [DNP], 2003).

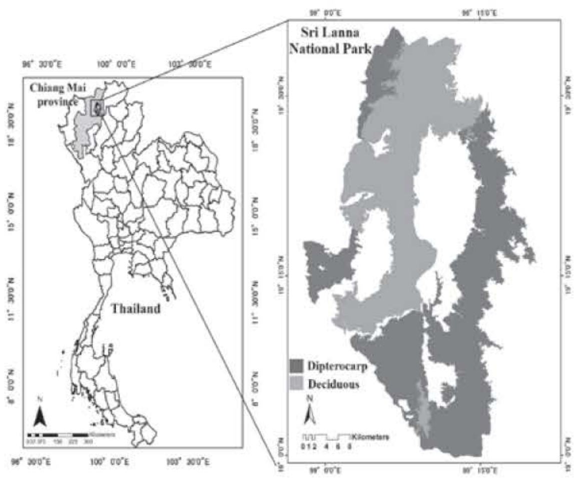

Figure 1: Study site in Sri Lanna National Park, Thailand

The park encompasses numerous forest types, including deciduous, dipterocarp, dry evergreen, hill evergreen, and pine forests. The soil characteristics in the park are closely related to the slope; 92.2% of the total forest area is classified as a soil slope complex series, which is found in areas with slopes that exceed 35%. Sandy and sandy loam soils are dominant (DNP, 2003). Due to the large range of elevations and diverse forest types, the national park features various attractions, such as fertile forests, waterfalls, freshwater springs, caves, and mountains. These attractions have become well-known recreational and tourism locations. Moreover, many forms of recreation are available in this park, such as campsites, natural study trails, and a reservoir. Unfortunately, some of the recreation areas have been damaged by wildfires which occur annually during the dry season, peaking in February and March, and mainly occur in the dipterocarp and deciduous forests. Most wildfires in the park are classified as surface fires. Fires start during the dry season, when there is the greatest leaf accumulation on the ground surface from dipterocarp and deciduous trees, providing the largest proportion of fuel load. Thus, this study was limited to such areas of the national park with the highest potential for wildfires.

2.2 Datasets

The datasets and overall methodology used in the present study are presented in Figure 2, where the corresponding data sources are shown in Table 1. The parameters involved in wildfire occurrence and those influencing wildfire behavior were selected as described in the following sub-sections:

2.2.1 Leaf fuel load

The fuel plays a major role in the initial stage of wildfires (fire ignition), and the fuel load also contributes to fire intensity. Higher fuel loads create longer flames and more intense fires for a given rate of spread. The largest component of surface fuel is dead leaves, which provide an efficient fuel for surface wildfires. In this study, we therefore focused on analyzing leaf fuel load. Fuel load can be assessed using the greenness index, especially the normalized difference vegetation index (NDVI) which has been tested to predict leaf fuel load (Burapapol and Nagasawa, 2016b). Their predictions were applied here to estimate the spatial distribution of leaf fuel load. Seasonal NDVI values were calculated from the Landsat 8 OLI.

2.2.2 Soil moisture

A low degree of soil moisture can indicate drought conditions, which influence the likelihood of wildfires. Soil moisture is positively correlated with fuel moisture. Under dry conditions, areas with low soil moisture and resulting low fuel moisture are more prone to wildfires and fires spread quickly. Therefore, soil moisture should be considered as a factor in wildfire models. A soil moisture model established by Burapapol and Nagasawa (2016a) was used to estimate the spatial distribution of soil moisture in the study area.

2.2.3 Topographic data

The topography is the most stable variable in fire behavior. The slope can be a primary influence on wildfire behavior (Weise and Biging, 1997) and affects both the rate and direction of fire spread. Fires generally tend to move faster up, rather than down, a slope (Adab et al., 2011). Steeper slopes result in faster fires due to more aggressive wind action. The aspect (slope direction) determines how much radiated heat a slope will receive from the sun. South to southwest aspects receive the most solar radiation, with comparatively higher temperature and lower humidity.

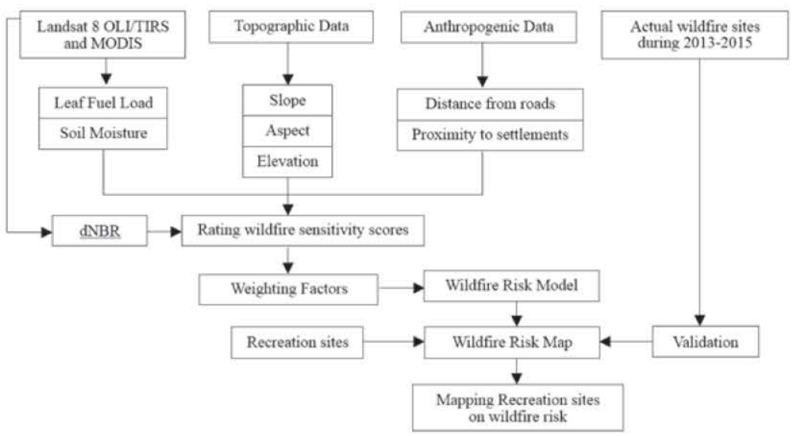

Figure 2: Overall methodology

Table 1: Data sources of parameters used for modeling and mapping wildfire risk and evaluating wildfire risk to recreational sites

Data/Parameters	Source of data	Creation of data	Acquisition date	Purpose
Leaf fuel load	Landsat 8 OLI (30m)	NDVI in normal season NDVI in dry season	14 Oct 2014 19 Feb 2015	Modeling wildfire risk
Soil moisture	Landsat 8 OLI/TIRS (30m) MODIS (1km)/ MOD11A2	NDDI and TVDI LST	19 Feb 2015 18–25 Feb 2015	Modeling wildfire risk
Slope	DEM (30 m)	Slope map	–	Modeling wildfire risk
Aspect	DEM (30 m)	Aspect map	–	Modeling wildfire risk
Elevation	DEM (30 m)	Elevation map	–	Modeling wildfire risk
Distance from roads	Shapefile	Lines	–	Modeling wildfire risk
Proximity to settlements	Shapefile	Points	–	Modeling wildfire risk
dNBR	Landsat 8 OLI (30m)	NBR *pre fire* NBR *post fire*	14 Oct 2014 19 Feb 2015	Rating wildfire sensitivity scores
Actual wildfire sites	Shapefile	Points	2013–2015	Validating wildfire risk map
Recreation sites	Shapefile	Points	–	Evaluating risk of wildfire

Therefore, fuels tend to dry out sooner, ignite more thoroughly, and burn longer on south-facing slopes (Noonan, 2003 and Iwan et al., 2004). The elevation influences the amount of precipitation, wind exposure, temperature, and moisture that an area receives. Thus, elevation plays a large role in determining the condition of the fuel (Castro and Chuvieco, 1998). At lower elevations, fuels tend to dry out fast because of higher temperatures and lower precipitation. In this study, the slope, aspect, and elevation data were extracted from a digital elevation model (DEM), provided by the Royal Thai Survey Department.

2.2.4 Anthropogenic data

Wildfires can be caused by the movements of humans and vehicles. Human activities are often linked to the occurrence of fires (Dong et al., 2005). Forests that are near centers of human activity, such as roads and settlements, can be more prone to fires, especially accidental man-made fires and hence, the distance from roads and settlements are important variables. For the proposed model, distances from roads and settlements were obtained from the DNP and were available in the GIS database in vector format (Shapefile).

2.2.5 dNBR

The dNBR is calculated from the normalized burn ratio (NBR) of pre-fire and post-fire events. Initially, the dNBR and NBR estimated from remotely sensed data were developed to identify burned from unburned areas (Lopez-Garcia and Caselles, 1991). Both indices were accepted for their ability to distinguish levels of burn severity within a fire-affected region (Bisson et al., 2008 and Key and Benson, 2006). We therefore applied the dNBR to evaluate the wildfire sensitivity rating scores for subclasses of each factor. An NBR dataset was generated from the reflectances of the near-infrared (NIR) and shortwave infrared (SWIR) bands of Landsat 8 OLI images, as expressed by Equation 1. A final dNBR dataset was derived from NBR values of pre-fire and post-fire images, as described by Equation 2.

$$NBR = \frac{NIR - SWIR}{NIR + SWIR}$$

Equation 1

$$dNBR = NBR\textit{pre fire} - NBR\textit{post fire}$$

Equation 2

2.3 Methodology

The study methodology comprised two main parts: modeling and mapping wildfire risk, and evaluating recreational sites for wildfire risk. These are presented in the following sections in more detail.

2.3.1 Preprocessing remotely sensed data

Landsat 8 and MODIS images acquired for the study area are shown in Table 1. The Landsat 8 data were converted from digital numbers (DNs) to reflectance values before calculating the VI values. The DN conversion followed the steps of the USGS (2013). The Landsat 8 dataset used were L1G-level products, which were geographically corrected and projected into the UTM (Zone 47N, WGS 84 datum) coordinate system. Then, MODIS imagery was co-registered to Landsat 8 imagery to reduce potential geometric errors. Finally, both Landsat 8 and MODIS data were clipped within the boundary of the study area, and clouds and cloud shadows were removed.

2.3.2 Preparing GIS data

Leaf fuel load and soil moisture were classified into three intervals on thematic maps. Slope, aspect, and elevation computed from the DEM (30 m resolution) were clipped based on the corresponding study area, and then categorized into different intervals on thematic maps. Settlement and road locations were buffered at specified distances. Buffer zones of 2,000 m and 4,000 m were created around the settlement locations, and 1,000 m and 2,000 m were used around roads. The stratification of each factor is presented in Table 2.

Table 2: Subclasses of each factor

Factors	Subclasses
Leaf fuel load (kg ha^{-1})	<1000, 1000–2500, >2500
Soil moisture (%)	<5 , 5–10 , >10
Slope(degrees)	<15 , 15–35 , >35
Aspect	north, east, south, west
Elevation (m)	<700, 7000–1400, >1400
Distance from roads (m)	< 1000, 1000 – 2000, > 2000
Proximity to settlements (m)	< 2000, 2000 – 4000, > 4000

2.3.3 Rating wildfire sensitivity scores

The dNBR of the thematic map was assigned a value of 1 for burned areas and 0 for non-burned. The stratified subclasses of each factor were overlaid with the dNBR. The frequency of burned areas was used to assign different wildfire sensitivity scores to subclasses. For each class, the total number of burned pixels was calculated as a percentage of the total class area. The percentage was ordered to evaluate its susceptibility to wildfire (3 = high, 2 = moderate, and 1 = low). The subclass with the highest percentage of burned area was labelled as high wildfire risk and was given the highest ranking of 3. Next, the class with a smaller percentage was assigned a moderate risk of score 2, and the class with lowest percentage was rated as low risk with a score of 1.

2.3.4 Weighting factors on wildfire

A pairwise comparison method developed by Saaty (1980) in the context of the analytic hierarchy process (AHP) decision making process, was applied to prioritize the factors for wildfire risk in the study area. The pairwise comparison was weighted by decision makers to make comparative judgments. This method has been tested theoretically and empirically for a variety of decision situations and multi-criteria decision making problems, including spatial decision making (Malczewski, 1999). It has been effectively adopted into GIS-based decision making on wildfires (Vasilakos et al., 2007, Vadrevu et al., 2010 and Yakubu et al., 2013). Each factor was compared pairwise and weighted on a scale of 1 to 9. According to Saaty's ranking scale, a scale of 1 indicates equal importance between two factors, whereas a scale of 9 indicates that one factor is 9 times more important than the other. Three wildfire experts and stakeholders from the DNP (a fire specialist, a fire planner, and a wildfire fighter), who are involved in wildfire management in Thailand, were asked to weight the importance and priority of these pairwise comparisons. Then, a decision matrix (comparison table) was constructed using a ratio matrix. The relative weights were normalized to sum to 1, and finally averaged among the three experts.

2.3.5 Establishing and validating wildfire risk model and map

The weighted factors (layers), which were rated in different subclasses, were integrated using the GIS union process to establish a wildfire risk model. The model used to determine wildlife risk areas is shown in Equation 3:

$$WFR = W_1(F_{i=1\text{-}3}) + W_2(SM_{i=1\text{-}3}) + W_3(S_{i=1\text{-}3}) + W_4(A_{i=1\text{-}4}) + W_5(E_{i=1\text{-}3}) + W_6(R_{i=1\text{-}3}) + W_7(ST_{i=1\text{-}3})$$

Equation 3

Where WFR is the numerical index of wildfire risk; $W_{1\text{–}7}$ are the weighting values of each factors based on the pairwise comparison; F, SM, S, A, E, R and ST are the factors influencing wildfire, namely: leaf fuel load, soil moisture, slope, aspect, elevation, distance from roads, and proximity to settlements, respectively. The superscript i indicates subclasses based on rating the wildfire sensitivity scores using the dNBR. Authors then defined the interval size of the WFR value to classify wildfire risks into three risk categories; low, medium, and high. Finally, a map showing the wildfire risk zones in different categories was obtained.

The accuracy of the wildfire risk map was tested against actual wildfire occurrences during 2013–2015. A confusion matrix, showing the correspondence between predicted and actual classifications (Congalton, 1991), was adopted to verify the map. The actual wildfire points were used as ground-truth data for the high risk class only. Both the actual and predicted wildfire points were evaluated in the matrix (Table 3) and the accuracy was calculated from the percentage of correctly classified instances, as described by Equation 4:

$$\text{\% of correctly classified instances} = \frac{A + D}{(A+B+C+D)} \times 100$$

Equation 4

Table 3: Confusion matrix modified from Congalton (1991)

Actual wildfire points	Predicted wildfire points		
		H	M or L
	H	A	B
	M or L	C	D

Note: H = High risk, M = Moderate risk and L = Low risk

2.3.6 Assessment of wildfire risk at recreational sites

The verified wildfire risk map was further used to evaluate the risk of wildfire to recreational sites within Sri Lanna national park. Buffers of 500 m were created around recreational sites and overlaid with the wildfire risk map. From the buffered areas, the fraction of each area prone to wildfire was assessed based on the wildfire risk categories. Finally, a map was produced showing wildfire risk within the buffered areas, which can help in wildfire prevention at these locations.

3. Results and Discussion

The burned areas in 2015 (Figure 3a) detected by dNBR covered 4,489.38 ha (5.40% of total area). The dNBR in the thematic map was overlaid with each factor assigned to different subclasses. The relative frequencies of burned areas in each subclass were calculated to evaluate the wildfire sensitivity of each subclass, as illustrated in Table 4.

Areas with leaf fuel load >2,500 kg ha^{-1} showed the highest percentage of burned area, indicating greatest sensitivity to wildfire (score of 3). In comparison, leaf fuel loads of 1,000–2,500 kg ha^{-1} and <1,000 kg ha^{-1} had lower percentages of burned areas, and were ranked as having moderate (score of 2) and low (score of 1) wildfire sensitivity, respectively (Figure 3b). Hence, the risk of wildfire is a function of the amount of leaf fuels. The results showed that soil moisture levels were inversely related to the number of burned areas. Areas with soil moisture <5% showed a high percentage of burned area, and therefore categorized as having high wildfire sensitivity (score of 3). Areas with soil moisture of 5–10% and >10% had lower percentages of burned areas and were classified as having moderate (score of 2) and low (score of 1) wildfire sensitivity, respectively (Figure 3c). This implies that lower soil moisture is associated with increased wildfire risk, and vice versa. This supports the findings of previous research, which showed that low soil moisture was associated with large wildfires during the vegetation growing season (Krueger et al., 2015).

A large percentage of burned areas occurred in areas with slopes less than 15 degrees, which was therefore classified as having high wildfire sensitivity (score of 3). It was found that most of the areas with slopes less than 15 degrees were close to settlements and agricultural areas, which might account for their high sensitivity to wildfire. Areas with the slopes of 15–35 degrees and slopes steeper than 35 degrees were evaluated as having moderate (score of 2) and low (score of 1) wildfire sensitivity, respectively (Figure 3d). South-facing areas showed the highest percentage of burned areas (approximately 48%), and were therefore rated as having high wildfire sensitivity (a score of 3). This is because south-facing areas usually receive more sunlight resulting in higher temperatures and fuel with a lower moisture content.

Therefore, wildfires can more easily ignite and spread more rapidly. Hence, south-facing areas are the most critical in terms of the initiation and spread of wildfires. East- and west-facing areas were assigned moderate wildfire sensitivity (score of 2). Lastly, north-facing areas had lower percentage of burned area (approximately 17%), and were therefore evaluated as having low wildfire sensitivity (a score of 1) (Figure 3e). According to the percentage of burned area, high elevation areas were less susceptible to wildfires. Most of the burned area occurred at elevations below 700 m which was assigned a score of 3. This is probably because there is much more moisture in the air and less oxygen at higher elevations, so wildfires are less likely to occur. Meanwhile, areas at 700–1,400 m elevation had the second-highest percentage of burned area, and were assigned moderate wildfire sensitivity (a score of 2). The smallest percentage of burned area was found at elevations higher than 1,400 m, which were evaluated as having low wildfire sensitivity with a score of 1 (Figure 3f).

Table 4: Rating wildfire sensitivity scores assigned to subclasses for wildfire risk modeling

Factor	Subclass	Burned area (ha)	Total area (ha)	Percentage of burned area	Rating	Wildfire sensitivity
Leaf fuel load (kg ha^{-1})	<1000	171.99	25,532.37	3.84%	1	Low
	1000–2500	1,034.55	45,253.98	23.04%	2	Moderate
	>2500	3,282.84	12,407.94	73.12%	3	High
Soil moisture (%)	<5	4,188.06	36,952.02	93.29%	3	High
	5–10	299.43	38,757.60	6.67%	2	Moderate
	>10	1.89	7,484.67	0.04%	1	Low
Slope (degrees)	<15	2,641.05	35,957.97	58.83%	3	High
	15–35	1,579.41	44,394.30	35.18%	2	Moderate
	>35	268.92	28,42.02	5.99%	1	Low
Aspect	North	678.06	19,524.15	17.79%	1	Low
	East	1,028.92	19,827.63	27.00%	2	Moderate
	South	1,834.20	22,371.84	48.13%	3	High
	West	948.24	21,470.67	24.88%	2	Moderate
Elevation (m)	<700	3,355.29	46,425.24	74.74%	3	High
	700–1400	1,133.10	36,749.61	25.24%	2	Moderate
	>1400	0.99	19.44	0.02%	1	Low
Distance to roads (m)	<1000	1,796.76	28,714.86	40.02%	3	High
	1000–2000	982.08	22,721.31	21.88%	1	Low
	>2000	1,710.54	31,758.12	38.10%	2	Moderate
Proximity to settlements (m)	<2000	1,749.60	26,458.38	38.97%	3	High
	2000–4000	1,623.06	40,861.71	36.16%	2	Moderate
	>4000	1,116.72	15,874.2	24.87%	1	Low

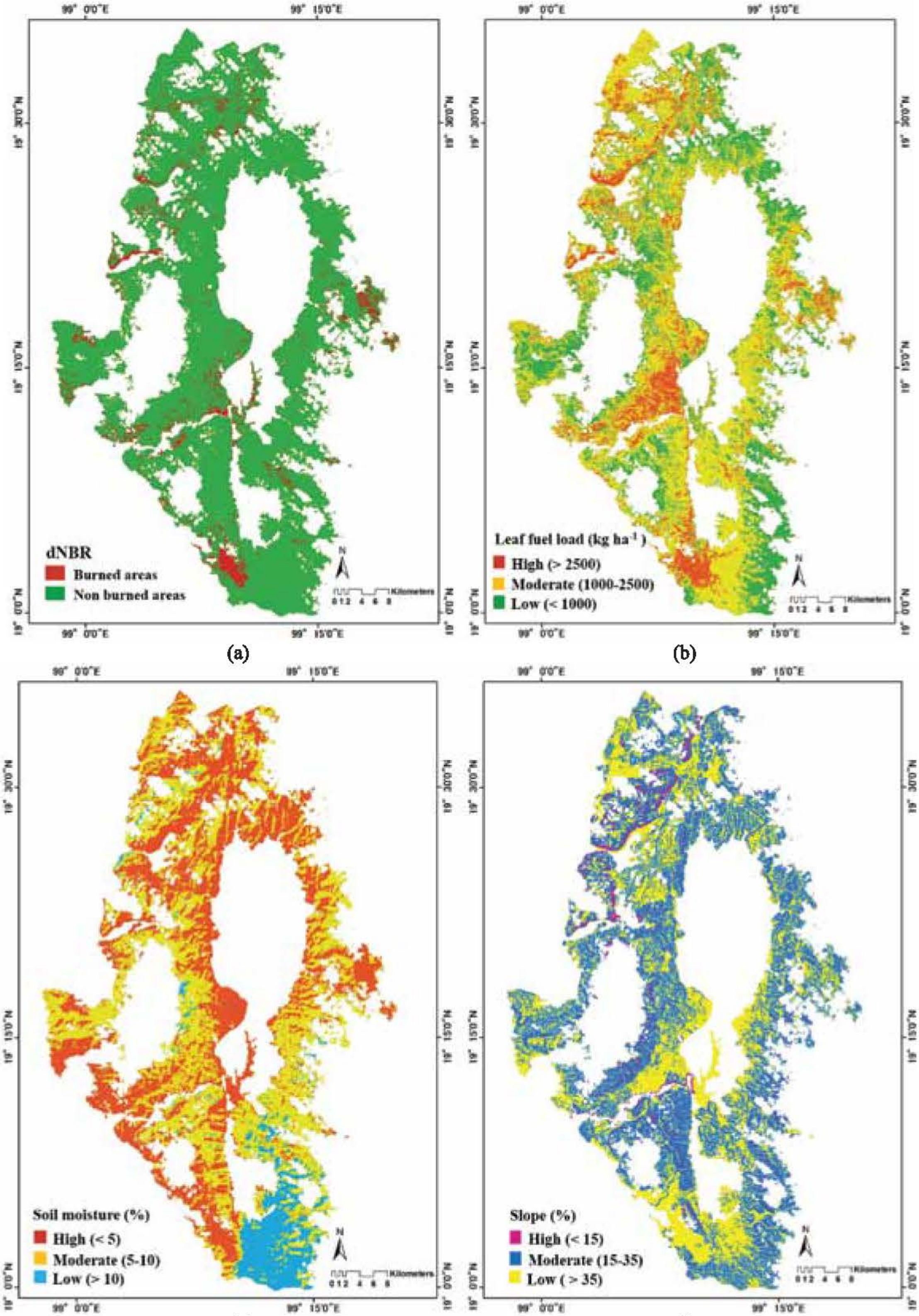

Figure 3: Continued next page

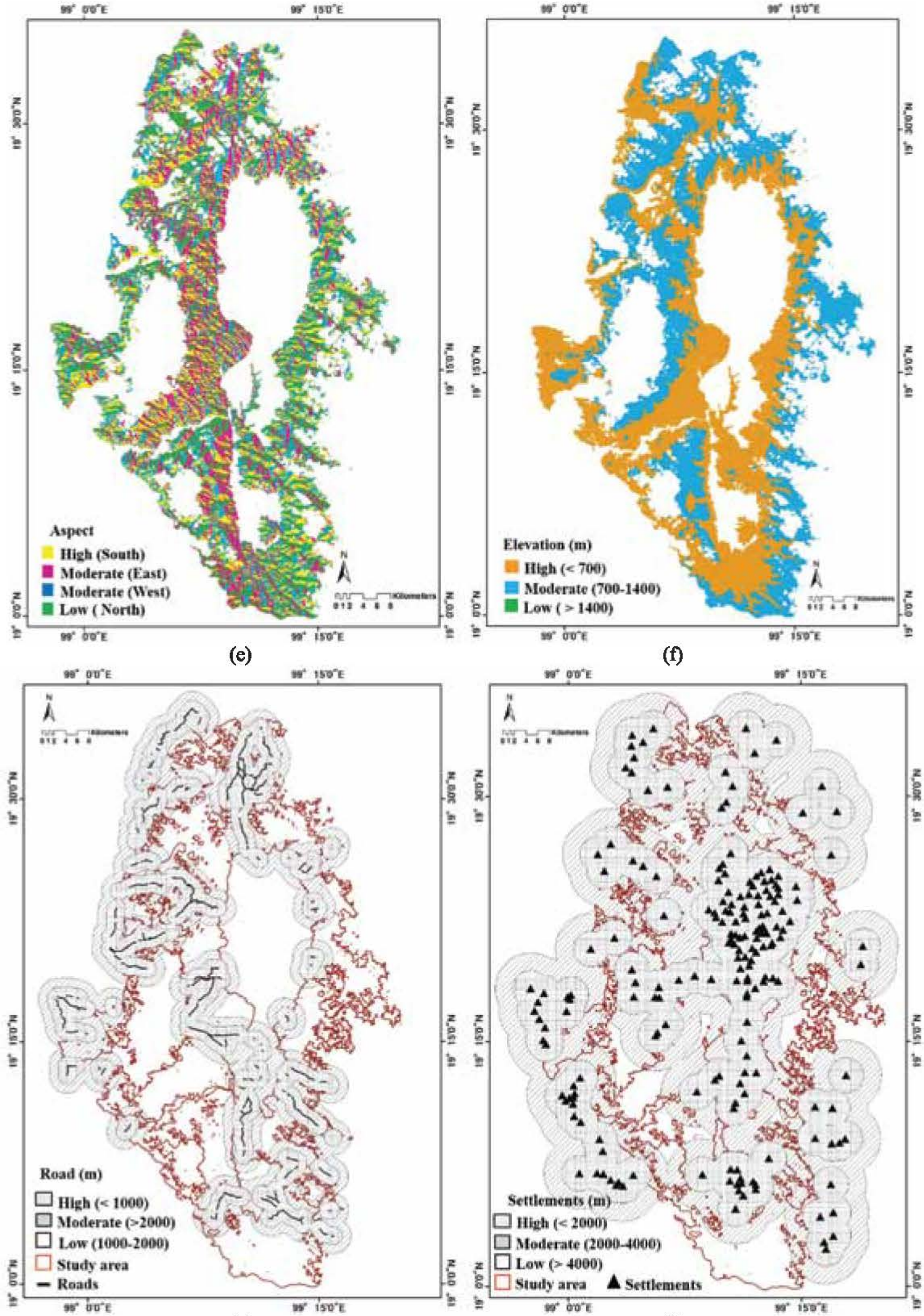

Figure 3: (a) The dNBR in Sri Lanna National Park obtained from Landsat 8 OLI images; (b) leaf fuel load with rated subclasses; (c) soil moisture with rated subclasses; (d) slope with rated subclasses; (e) aspect with rated subclasses; (f) elevation with rated subclasses; (g) road buffer with rated subclasses, and (h) settlement buffer with rated subclasses

Areas <1,000 m from road networks had the highest percentage of burned area and were assigned a high wildfire sensitivity of 3, while areas 1,000–2,000 m and >2,000 m from roads were classified as having low and moderate wildfire sensitivity, respectively (Figure 3g). The largest percentage of burned areas was found at distances <2,000 m from settlements (highly sensitive to wildfire). Those areas at distances of 2,000–4,000 m and >4,000 m from settlements were classified as having moderate and low wildfire sensitivity, respectively (Figure 3h). Hence, forest areas located close to roads and settlements are at highest risk from wildfires. According to the results of rating scores, dNBR can be appropriately applied to all factors to evaluate the levels of wildfire sensitivity. This is because factors assigned a wildfire sensitivity by the dNBR followed the same trends as the physical theory of wildfire behavior and interactions in the fire environment.

All factors with subclasses rated the scores were weighted according to their corresponding risk for wildfire, based on the judgments of wildfire experts and stakeholders (Table 5). Leaf fuel load had the highest weighting (therefore contributing greatly to wildfire), followed by slope, proximity to settlements, distance from roads, aspect, and soil moisture, whereas elevation was the least important. It can be concluded that, among these factors, fuel load is highly influential for wildfire and is considered the most important factor because it contributes both stages of wildfire occurrence (ignition and spread/intensity). The averaged weighting of each factor was substituted in the wildfire risk model using Equation 3. The wildfire risk map produced from the model shows the estimated possibility of wildfires in the study area (Figure 4a).

Model validation is an essential part in any natural hazards assessment, where the predictions are compared to a real-world dataset (Begueria, 2006). Therefore, in this study, we used wildfire site data to validate our wildfire risk maps. The number of wildfire sites in each risk class was determined and the fraction of correctly classified instances. The results shown in Figure 4a demonstrate that the actual wildfire sites are mostly found in the high risk zone (56) as classified by the model. In addition, the confusion matrix showed that the map achieved 74.67% classification accuracy (Table 6). Hence, the proposed model can reliably estimate wildfire risk. The use of the seven factors generated from remotely sensed and GIS data was effective for predicting wildfire-prone areas.

Table 5: Weightings assigned to factors influencing wildfire, based on the judgments of wildfire experts and stakeholders using a pairwise comparison method

Factors	Weighting scores			
	Wildfire specialist	**Wildfire planner**	**Wildfire-fighter**	**Average**
Leaf fuel load	0.301	0.406	0.082	0.263
Soil moisture	0.020	0.084	0.077	0.060
Slope	0.073	0.108	0.417	0.200
Aspect	0.048	0.034	0.142	0.075
Elevation	0.043	0.040	0.093	0.059
Distance from roads	0.163	0.164	0.134	0.154
Proximity to settlements	0.353	0.164	0.054	0.191
Sum	1.000	1.000	1.000	1.000

Table 6: Accuracy assessment of wildfire risk map based on the confusion matrix

Actual wildfire points	**Predicted wildfire points**			**% of correctly classified instances**
		H	M or L	
	H	56	0	74.67%
	M or L	19	0	

Table 7: Results of the wildfire risk map

WFR value	**Description of the value**	**Number of pixels**	**Total area prone to wildfire**	
			ha	**%**
0.5 – 1.9	Low-risk wildfire area	209,640	30,330	35.60
2.0 – 2.4	Moderate-risk wildfire area	399,889	35,990	42.25
2.5 – 3.0	High -risk wildfire area	336,998	18,868	22.15
	Total	946,527	85,188	100

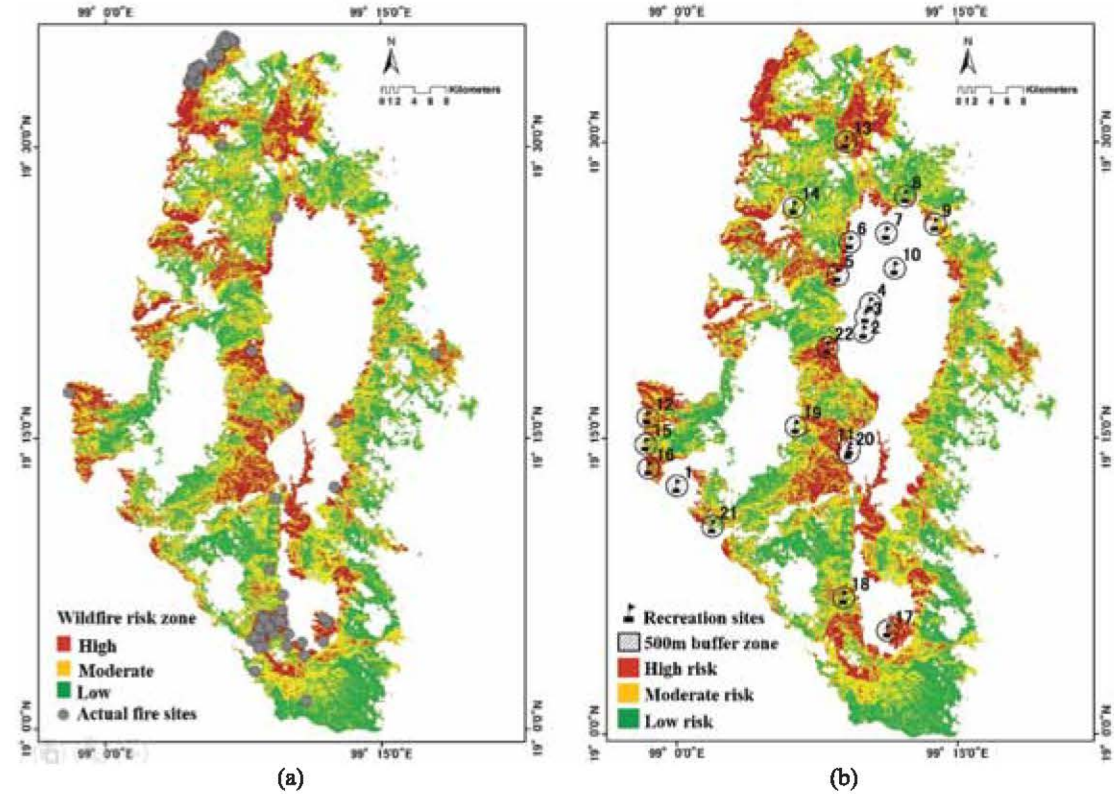

Figure 4: (a) Spatial map of wildfire risk and actual wildfire sites and (b) Recreational sites overlaid onto zones of estimated wildfire risk

Table 8: Evaluation of wildfire potential at recreational sites based on the wildfire risk map

ID (Figure 4)	Name of recreational site	Type of recreation	Areas prone to wildfire		
			Risk level	%	ha
1	Wat Mae Pang	Temple site	None	0.00	0.00
2	Wat Tham Doi Kham	Temple site	None	0.00	0.00
3	Nam Ru Conservation Forest	Natural learning site	None	0.00	0.00
4	Wat Phra Chao Lan Thong	Temple site	None	0.00	0.00
5	Mae Wa Reservoir	Rest viewpoint	High	77.68	24.75
6	Ban Nong Krok Hot Spring	Hot spring	High	65.63	5.67
7	Wat Phrathat Doi Nang Lae	Temple site	None	0.00	0.00
8	Huai Pa Phlu Waterfall	Waterfall	Low	50.39	35.10
9	Mae Kon Reservoir	Rest viewpoint	Moderate	74.44	29.88
10	Wat Phrathat Jai Klang Muang	Temple site	None	0.00	0.00
11	Mae Pang Reservoir	Rest viewpoint	None	0.00	0.00
12	Huay Kum Nature Trail and Camping site	Nature trail and campsite	Moderate	54.12	40.77
13	Pha Daeng Cave	Cave	High	51.89	40.77
14	Pla Prung Reservoir	Rest viewpoint	Moderate	63.41	37.44
15	The Elephant Training Center, Chiang Dao	The Elephant Training Center	Moderate	72.71	39.33
16	The Elephant Training Center, Mae Ping	The Elephant Training Center	High	53.38	29.88
17	Wat Phrathat Muang Noeng	Temple site	High	76.76	22.59
18	Nang Lae Waterfall	Waterfall	Moderate	60.71	47.7
19	Mon Hin Lai Waterfall	Waterfall	Moderate	65.37	18.18
20	Mon Hin Lai Viewpoint	Rest viewpoint	None	0.00	0.00
21	Sri Lanna office area, Mae Ngad Reservoir	Rest viewpoint and campsite	Moderate	46.92	17.82
22	Doi Jom Hod	Rest viewpoint	High	72.36	56.07

Table 7 shows the verified wildfire risk zones corresponding to levels of wildfire risk. The map identified low, moderate, and high risk levels. An area of 18,868 ha (22.15%) was estimated as having high wildfire risk, followed by 42.25% moderate and 35.60% low risk. The high-risk zones were mostly located around the boundary of the national park, adjacent to roads and settlements, and generally had large amounts of leaf fuel. Finally, the verified map was overlaid with the 500 m buffer zones created around recreational sites, producing a map of sites susceptible to wildfire risk (Figure 4b), where the potential effects of wildfires on these sites was evaluated (Table 8). The majority of recreational sites had a moderate to high risk of wildfire. Six recreational sites had high risk of being affected by wildfire, especially sites 5, 17, and 22, which had >70% risk. A further seven sites showed moderate risk and only one recreational site was in the low-risk category. Eight recreation sites had negligible probability of wildfire risk. The resulting map contributes to minimizing wildfire impacts at recreational sites and can help in planning and decision making regarding the prevention and control of wildfires. Moreover, the findings of this study can help develop appropriate method for accessing areas prone to wildfires.

4. Conclusion

The present study proposes integrating remote sensing and GIS techniques to identify areas prone to wildfires in forest areas of Sri Lanna National Park, northern Thailand. GIS and remotely sensed data were combined to model wildfire risk based on leaf fuel load, soil moisture, slope, aspect, elevation, distance from roads, and proximity to settlements. The findings revealed that using dNBR as an evaluator was appropriate for rating the wildfire sensitivity of factor subclasses. The selected factors produced a reliable model for mapping wildfire-prone areas, with the resulting risk map showing strong agreement with actual wildfire sites. The leaf fuel load showed the greatest influence on wildfires, and we proposed soil moisture as a new factor for predicting wildfires. The resulting map of wildfire risk can be used for evaluating recreational sites under threat of potential fires, which is helpful for preventing fire damage at such sites. The findings of this study could improve wildfire risk assessment in Thai national parks and other similar locations.

Moreover, the map can be used to develop basic guidelines for relevant local officials and decision makers, to enable appropriate fire management for high-risk areas in order to protect recreational areas from wildfire damage and support the sustainable operation of national parks. The results of this study show that remote sensing and GIS technologies that make use of spatial data integrated with appropriate algorithm or model can provide information sets that can be used to produce wildfire risk maps. However, the subjective weight of each factor was developed only for the dipterocarp and deciduous forests. Hence, we cannot use the same weighting values for other regions because the forest types and wildfire characteristics in each region are different. Therefore, to apply this method more generally, the factors affecting the wildfire need to be weighted for each region appropriately. Finally, the future study on wildfire risk could be assessed by using higher resolution remote sensing data; and could be added other significant factors driving wildfire occurrence such as fuel moisture in order to increase the precision of wildfire risk assessment.

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