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Original Research

Burned Area Evaluation Method for Wildfires in Wildlife Sanctuaries Based on Data from Sentinel-2 Satellite

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Abstract

Wildfire is a kind of disaster that can damage living creatures and environment as well as cause small dust affecting to health of people. Wildfire can be naturally occurred and human's actions. This research aims to evaluate burned areas caused by wildfires in Omkoi Wildlife Sanctuary. The research was conducted by collecting data from Sentinel-2 Satellite for 4 years started from 2017 to 2020. Three formats of spectral indices, i.e., NBR, NDWI, and RBR were used for evaluating burned areas caused by wildfires. Validation was tested by using statistical methods. The results revealed that burned areas from 2017 to 2020 were 0.107 km^2, 1.160 km^2, 0.387 km^2, and 1.031 km^2, respectively. The larges burned area was found in 2018 followed by 2020, 2019, and 2017. For validation, it was found that total accuracy of 2017 was 93.33 % with Kappa statistics of 0.87 whereas total accuracy of 2018 was 78.33 % with Kappa statistics of 0.57. In 2019, total accuracy was 81.67 % with Kappa statistics of 0.63. In 2020, total accuracy was 76.67 % with Kappa statistics of 0.53.

Keywords: remote sensing, digital image processing, burned areas, spectral indices, random forest

Introduction

Wildfire is a kind of fire occurring in forests by whatever causes with free fire spread without control. Theoretically, wildfire is caused by 2 causes, i.e., nature and human activities. During these 3 decades, rapid increase of populations had affected higher need to consume forest resources. Consequently, forests had been destroyed as agricultural areas and locations of communities for expanding communities. Therefore, many forest areas had been destroyed [1]. The remaining forest areas were degenerated and transformed into forests with lower level of moisture, for example, mixed forests, deciduous forests, and forests with large areas of grass or grasslands that can cause wildfire easily. Poverty in rural areas is also another cause forcing more local people to rely on forests for living through foraging, hunting, and forest invasion for agriculture [2]. These activities require fire and become causes of wildfire. Consequently, the frequency and severity of wildfires have been harder than ability of natural mechanism to adjust itself to balance ecosystem of forests [3].

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As a result, wildfire becomes a factor causing severe damages against forest resources and environment. Currently, the level of wildfires in Thailand becomes severe it becomes a factor disturbing balance of ecosystem severely. Important impacts of wildfire are impacts against plant community, soil, forests, water, wild animals and small living creatures in forests, assets, health, and life of humans, economy, society, tourism, and global climate [4]. These impacts cause more crises on drought, off-season rain, rain-shortage, flood, and storm causing wildlife the nationally crucial problem that is currently realized and concerned by all sectors. Most wildfires in Thailand occurred in the north every year started from drought in the beginning of November to the end of April. Most wildfires occurred in the areas of deciduous forests, mixed forests, and forestry plantations [5]. As a result, firebreaks must be constructed in various areas and cooperation from local people must be given to stop burning forests in order to reduce severity of wildfires and reduce smoke caused by forest burning [6].

To evaluate burned areas caused by wildfires in Thailand, besides data from land surveying, it can be currently performed by using data from Remote Sensing Technology [7] because the application of Remote Sensing Technology like data from earth observation satellites, meteorological satellites, and Global Navigation Satellite System (GNSS), during these 4 decades has been developed rapidly with high efficiency [8]. Remote Sensing Technology is able to survey data in wild areas with lower expenses than those of land surveying therefore it has been applied to various fields, for example, forest fire, burned areas drought, flood, and Land Surface Temperatures, etc. [9-11]. From researching on related documents, it was found that some studies on burned areas evaluation were applied to various areas, for example, SW Australian [12], Kurdistan province of western Iran [13], Southeastern Australia [14], and Margalla Hills of Pakistan [15]. They were also applied to some areas of Thailand, for example, Khlong Wang Chao, Khlong Larn, and Mae Wong National Park [2], conservative forests and national forest reserve areas in Mae Hong Son Province [17], and Pai District, Mae Hong Son Province [1], etc.

From the aforementioned importance, the main objective of this research was evaluating burned areas caused by wildfires based on data from Sentinel-2 Satellite with 3 formats of spectral indices including NBR, NDWI, and RBR whereas Omkoi Wildlife Sanctuary was selected as the case study.

Material and Methods

Study Area

This research was conducted by selecting Omkoi Wildlife Santuary (Fig. 1) as the studied area. It was located in the northern part of Thailand in the area of Yang Pieng Sub-District, Mon Jong Sub-District, Omkoi District, Muet Ka Sub-District, Doi Tao District, in Chiang Mai Province, and Banna Sub-District, Sam Ngao District, Tak Province. It is located in 17°17'-17°53'N latitude and 98°25'-98°45'E latitude with approximate area of 1,224 km^2. Its northern part is next to Huai Mae Had and Nam Mae Lai. Its southern part is next to Mae Tuen Wildlife Sanctuary in Tak Province. Its eastern part is next to Ping River and Mae Ping National Park (Mae Hard – Mae Kor), Chiang Mai

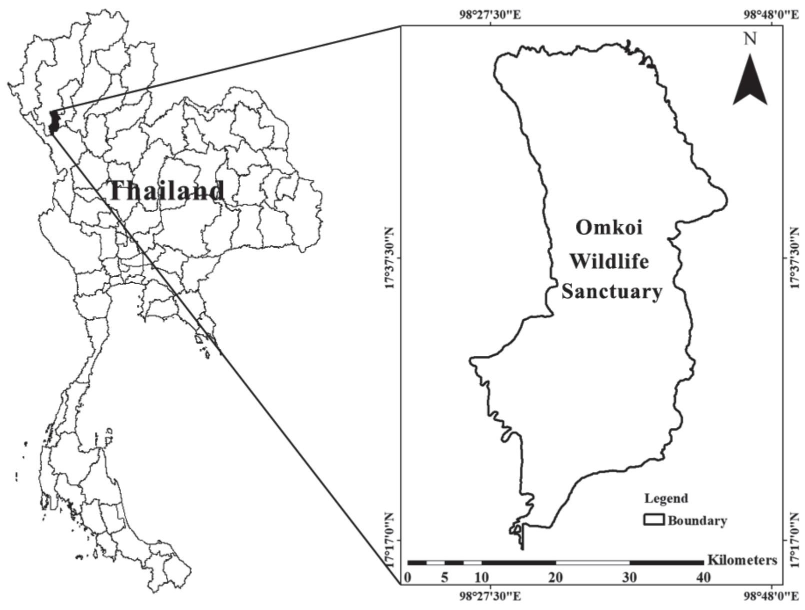

Fig. 1. The study area.

Table 1. The Sentinel-2 satellite band details.

Bands	Central Wavelength (µm)	Resolution (m)
Band 1 - Coastal aerosol	0.443	60
Band 2 - Blue	0.490	10
Band 3 - Green	0.560	10
Band 4 - Red	0.665	10
Band 5 - Vegetation Red Edge	0.705	20
Band 6 - Vegetation Red Edge	0.740	20
Band 7 - Vegetation Red Edge	0.783	20
Band 8 - NIR	0.842	10
Band 8A - Vegetation Red Edge	0.865	20
Band 9 - Water vapour	0.945	60
Band 10 - SWIR - Cirrus	1.375	60
Band 11 - SWIR	1.610	20
Band 12 - SWIR	2.190	20

Province, Lamphun Province, and Tak Province. Its western part is next to Huai Yang Krok Luang and Nam Mae Tuen.

Satellite Data

Sentinel-2 Satellite is a part of Copernicus Program that is considered as the largest Earth Observation Program directed by European Commission (EC) and European Space Agency (ESA). Sentinel-2 Satellite has recorded various data covering Visible (VIS), NIR infrared (NIR), and Short wave infrared (SWIR) with spatial resolution from 10 meters to 60 meters [17]. Data from Sentinel-2 Satellite used in this research are detailed in Table 1.

Indices Used in Research Methodology

Normalized Burn Ratio (NBR)

NBR is designed to find burned areas and evaluate severity of fire. This formula is similar to that of Normalized Difference Vegetation Index (NDVI) but formula of NBR is the use of NIR and SWIR as shown in Equation (1) [18, 19]. Plants will have high reflection in NIR and low reflection in SWIR. On the other hand, burned areas will have low reflection in NIR and high reflection in SWIR. Generally, high NBR indicates small number of plants, empty spaces, and areas that have just been burned.

$$NBR = \frac{(NIR - SWIR)}{(NIR + SWIR)} \tag{1}$$

Normalized Difference Water Index (NDWI)

NDWI is used in inspecting moisture level in soil or plants from content of electromagnetic wave of the sun reflecting from soil or plants in NIR and SWIR as shown in Equation 2 [20]. In the event that water content of soil or plants is high, SWIR will absorb high content of electromagnetic wave leading to lower level of reflection causing high NDWI.

$$NDWI = \frac{(GREEN - NIR)}{(GREEN + NIR)} \tag{2}$$

Relativized Burn Ratio (RBR)

RBR is index of severity of burning that can represent difference between NBR before and after wildfire based on satellite data for calculating dNBR or ΔNBR. It can be used for estimating severity of burning (Equation 3) and change of value between NBR before and after wildfire would be small. In this case, Relativized Burn Ratio as shown in Equation 4 [21] and Table 2 [19] would be used for processing.

$$dNBR = NBR_{pre-fire} - NBR_{post-fire} \tag{3}$$

$$RBR = \left(\frac{dNBR}{NBR_{pre-fire} + 1.001} \right) = \left(\frac{NBR_{pre-fire} - NBR_{post-fire}}{NBR_{pre-fier} + 1.001} \right) \tag{4}$$

Methodology

In this study, the researcher divided procedures of research methodology as detailed in Fig. 2 and procedures of research methodology could be explained as follows:

Analysis on Burned Area

Data from Sentinel-2 Satellite were downloaded via https://earthexplorer. usgs.gov/ based on studied areas and defined duration. Data from Sentinel-2 were input into SNAP software through Batch Processing and Collocation. NBR was used for extracting burned areas whereas NDWI was used for removing cloud spaces mixed in satellite data. RBR was used for extracting severity of burned areas by extracting burned areas with burning from moderate level or reflection of 0.27 and higher as shown in Table 2. After those procedures, the obtained result was burned areas in the form of raster data. Subsequently, the outcome was converted from raster data to be vector data for calculating burned areas in Omkoi Wildlife Sanctuary.

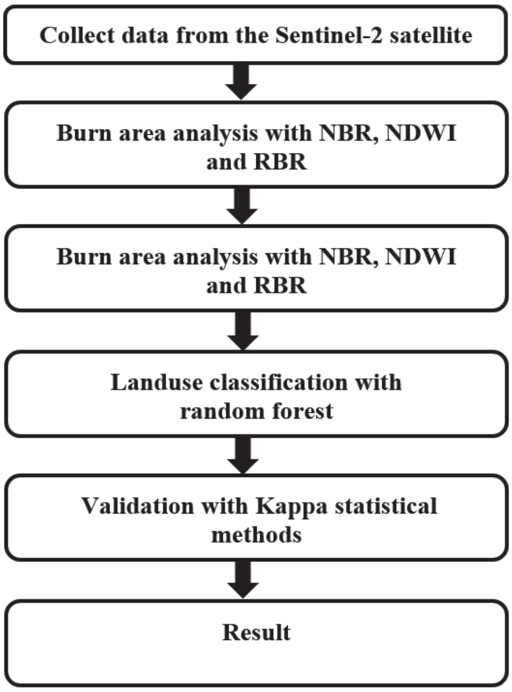

Fig. 2. Flowchart of the study.

Table 2. Classification of severity level.

Severity level	ΔNBR Range
Enhanced Regrowth, high (post-fire)	-0.500 to -0.251
Enhanced Regrowth, low (post-fire)	-0.250 to -0.101
Unburned	-0.100 to +0.099
Low Severity	+0.100 to +0.269
Moderate-low Severity	+0.270 to 0.439
Moderate-high Severity	+0.440 to +0.659
High Severity	+0.660 to +1.000

Classification of Land Use

It is classification of data from Sentinel-2 by using ArcGIS Program through supervised classification with training area as representative of statistical value of each type of land used shown in satellite data. The result of visual interpretation was used for creating training area. Subsequently, training area was selected randomly via systematic random point through systematical distribution in all data layers that could cover areas as many as possible. Training area point was converted to be polygon for performing statistical calculation of data of each type of land use as the representative of data classification for supervised classification through random forest.

Evaluation of Accuracy

Binomial Probability: It is the procedure to calculate the sample size. Subsequently, the training areas of the studied areas were sampled by using automatic random point via ArcGIS program. Subsequently, data layers of the sample group were classified into 2 types including burning point and non-burning point for testing accuracy. To calculate the sample size, binomial probability was used as shown in Equation (5).

$$n = \frac{z^2(p)(q)}{e^2} \tag{5}$$

Where;
n = Minimum number of samples (exploration points)
p = chance of accuracy (values between 0 – 1)
q = chance o
f error (it is equal to 1-p)
z = values from the standard normal distribution table Z
e = random error

False Color Composite

In this research, false color composite was performed through 2 formats including:

- To test accuracy of land use - Data from Sentinel-2 Satellite were used for false color composite by mixing colors in red, green, and dark blue spectral with NIR Red and Green (R G B: 8 4 3) (see in Fig. 7a). This color mixing method could represent land use clearly, i.e., forests were represented by red, agricultural areas were represented by pinkish red, miscellaneous areas were represented by green, and urban areas were represented by white [22].

- To test accuracy of burned areas caused by wildfires - Data from Sentinel-2 Satellite were used for false color composite by mixing colors in red, green, and dark blue spectral with SWIR, NIR, and Red (R G B: 12 8 4) (see in Fig. 3). This color mixing method could represent land use clearly, i.e., forests were represented by purple with intensity of color shade consistent with severity of burning. In other areas, fire points were represented by orange, areas with plants were represented by green, empty spaces and agricultural areas were represented by white, pink, and light purple [2, 23].

Random Forest

It is a kind of model of Machine Learning that was developed from Decision Tree but Random Forest is increasing number of trees to be several trees for higher efficiency of operation and more accuracy. Random Forest Model is highly preferred in using Machine Learning. The principle of Random Forest is creating several sub-models from Decision Tree (from 10 models to over than 1000 models). Each model

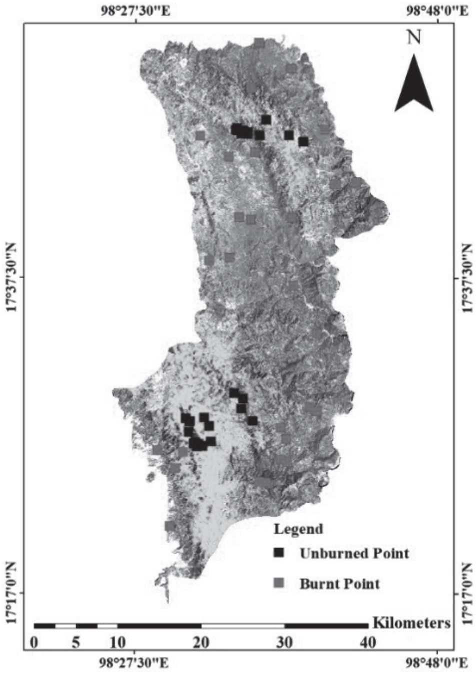

Fig. 3. False color composite (R G B: 12 8 4).

obtained different data set that was subset of all data sets. While performing prediction, each Decision Tree has to perform its own prediction whereas the results of prediction are calculated by using vote output that is mostly selected by Decision Tree (in case of classification) or by using mean from output of each Decision Tree (in case of regression) [24, 25].

Results and Discussion

Results of Analysis on Burned Areas

These are the results of NBR analysis on burned areas from 2017 to 2020 based on calculation with SNAP and ArcGIS software (Examples of burned areas are shown in Fig. 4. Form the Fig. 4 of this study is classification of severity of burning that is divided into 3 levels: (1) high severity ranged from +0.660 to 1.000; (2) moderate-high severity ranged from +0.440 to +0.659; and (3) moderate-low severity ranged from +0.270 to +0.439. From RBR processing (Fig. 5) to find sizes of burned areas caused by wildfires, it was found that burned areas caused by wildfires from 2017 to 2020 were calculated to be 0.107 km^2, 1.160 km^2, 0.387 km^2, and 1.031 km^2, respectively. From analysis, it was found that burned areas occurred in those 4 periods of time had the same characteristic, i.e., spreading was occurred throughout the area but there were some differences on direction and density of spreading. It could be said that these 4 periods of time had spreading throughout the area but wildfires of 2018 covered wide areas with the highest density of burning.

Results of Classification of Land Use

Since land use in Thailand was slightly changed in this research, data from Sentinel-2 Satellite on December 12th, 2020, were selected to classify land use. In this research, supervised classification was used through random forest. Land use was classified into 4 types including water sources, forests, miscellaneous areas, and urban. After classifying, obtained data of classification were colors, i.e., water sources (dark blue), forests (green), miscellaneous areas (orange), and urban (red) as shown in Fig. 6. The researcher input data obtained from classification into ArcGIS software in order to find areas of each type of land and data were shown in table form as shown in Table 3. Fig. 6 is Land Use Map of Omkoi Wildlife Sanctuary on December 12th, 2020, with land use classified by using data from Sentinel-2 Satellite with the use of colors as types of land. From such map, it was found that forest had the largest area calculated to be 72.20% of total areas representing that Omkoi Wildlife Sanctuary is surrounded by forests, followed by miscellaneous areas, urban, and water sources calculated to be 20.80%, 6.30%, and 6.30%, respectively.

Accuracy Test

Accuracy Test of Classification by Using Kappa Statistics

To test accuracy of land use, the researcher used binomial probability (Equation 5) to find surveying points and 100 surveying points were obtained. After perceiving surveying points, random point was performed by classifying land use into 4 types including water sources, forests, miscellaneous areas, and urban. The obtained points were 25 points per class that could be represented by reference point map. Accuracy test of land use is shown in Fig. 7. Fig. 7 represents reference point map of accuracy test of land use through colors of class classified into 4 colors including green for forests, dark blue for water sources, orange for miscellaneous areas, and red for urban. Accuracy test based on Kappa statistics is shown in Table 4.

From studying, it was found that type of land use with the highest level of accuracy was: 1) water sources, i.e., from accuracy test of 25 points, there were 22 points of classification that were the same whereas the remaining 3 points were urban; 2) forests, i.e., from accuracy test of 25 points, there were 21 points of classification that were the same whereas the remaining 4 points were miscellaneous areas; 3) miscellaneous areas, i.e., from accuracy test of 25 points, there were 20 points of classification that were the same whereas the remaining 5 points were forests. Land type with the lowest level of accuracy was 4) urban, i.e., from accuracy test of 25 points, there were 18 points of classification that were the same whereas the remaining 7 points were miscellaneous areas, respectively.

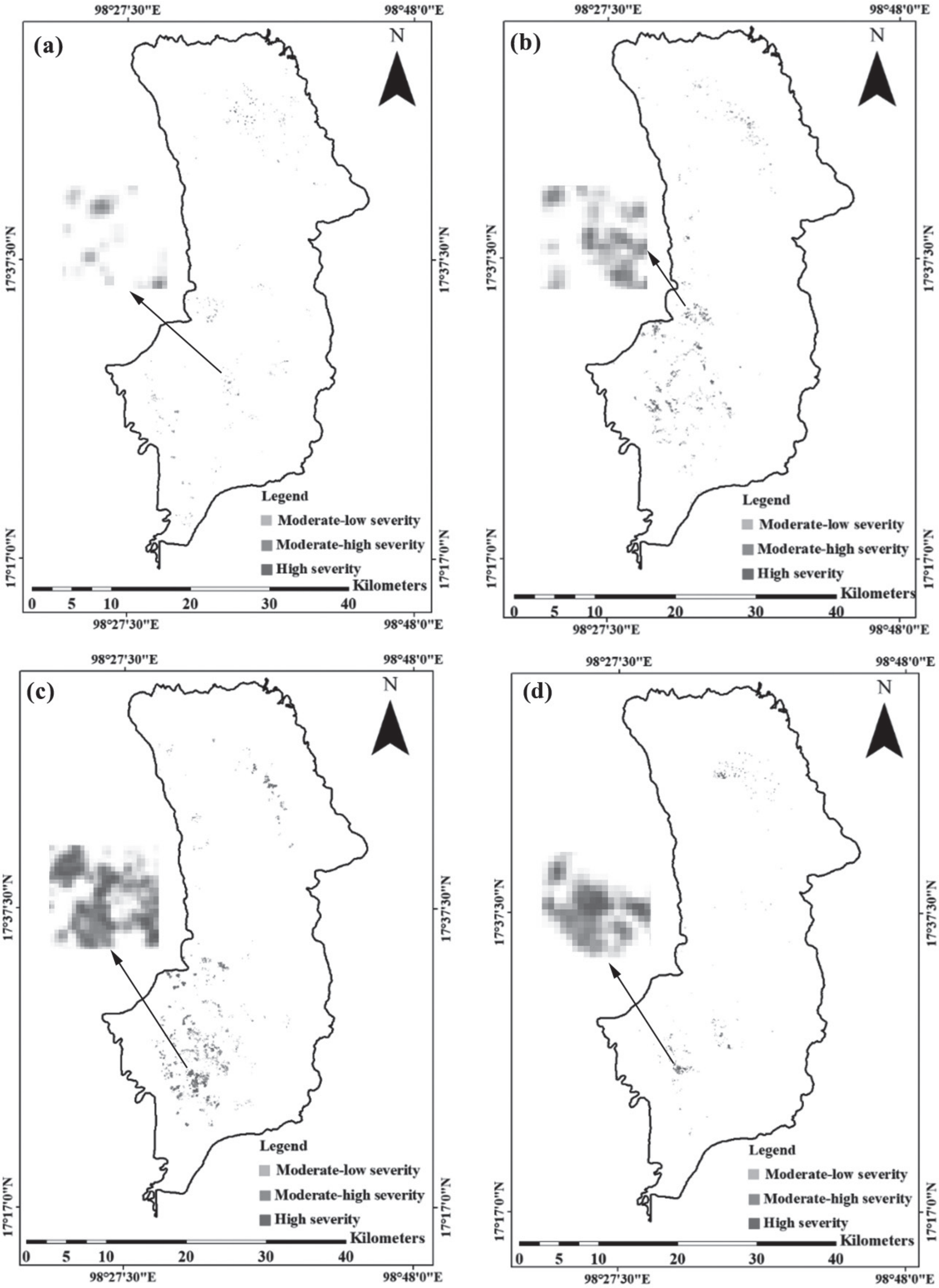

Fig. 4. Burned areas from NBR analysis a) 2017, b) 2018, c) 2019, and d) 2020.

When calculating overall accuracy, it was found that overall accuracy was 81% with Kappa statistics of consistency at 0.75. When classifying classes of forests, water sources, miscellaneous areas, and urban, it was found that producer's accuracy was 80.77%, 100%, 64.52%, and 85.71%, respectively, with omission error at 19.23%. There was no error of missing parts that was calculated to be 35.48% and 14.29% with user's accuracy at 84%, 88%, 80%, and 72%, respectively. Commission error was 16%, 12%, 20%, and 28%, respectively.

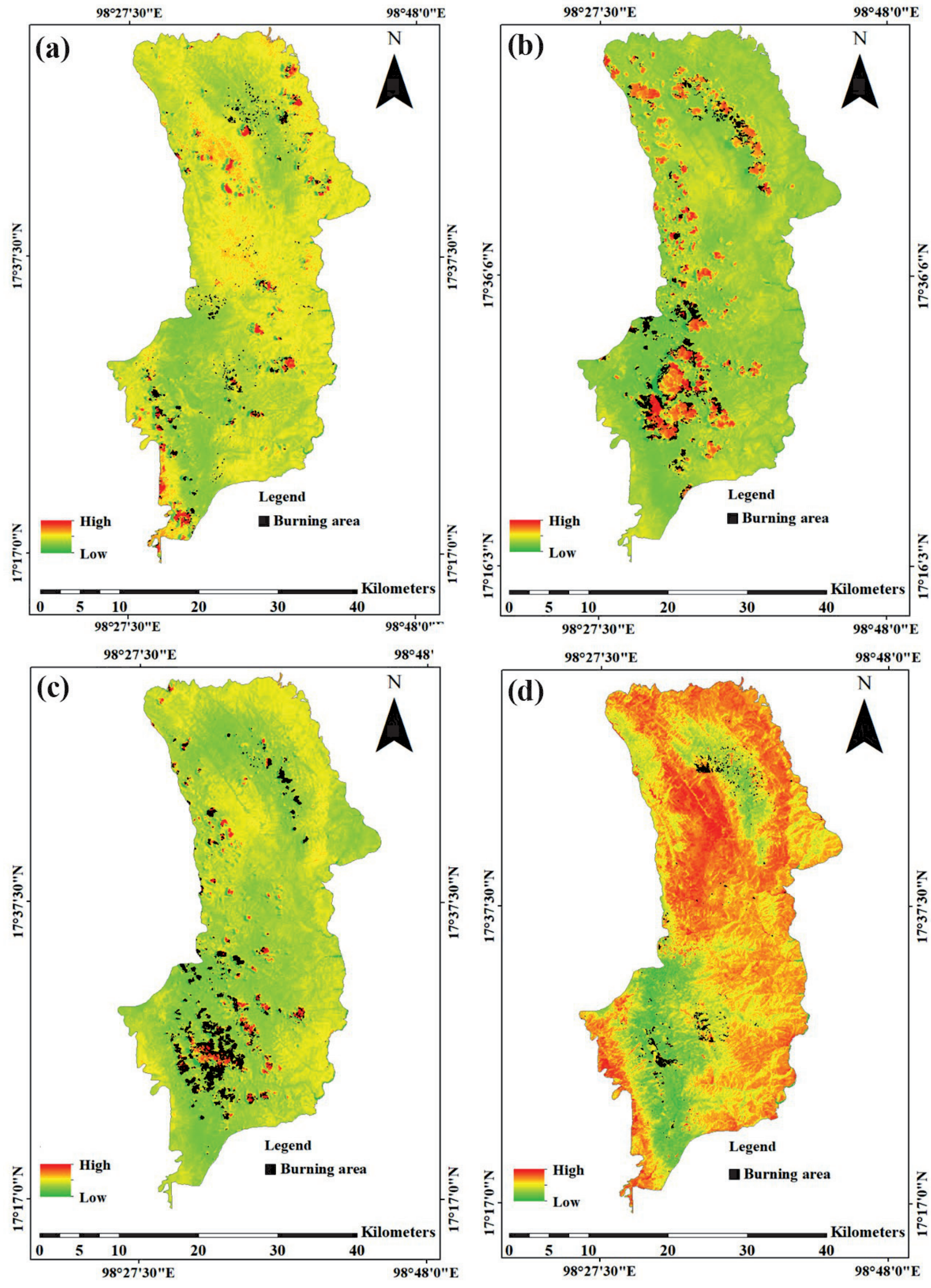

Fig. 5. Burned areas from RBR analysis a) 2017, b) 2018, c) 2019, and d) 2020.

Accuracy Test of Burned Areas

To test accuracy of burned areas, the researcher used binomial probability (Equation 5) to find surveying points and 60 surveying points were obtained. After perceiving surveying points, random point was performed by dividing into 30 burning points and 30 non-burning points. From surveying reference points, it was found that most reference points met with occurred burned areas that could be represented as Table of Accuracy Test of tested points that met with burned areas of both periods of time as shown in Table 5, 6, 7, and 8.

Table 3. Land Use Classification.

Type of Land Use	Area (km²)	%
Forests	883.728	72.2
Water	8.568	0.70
Miscellaneous	254.592	20.80
Urban	77.112	6.30

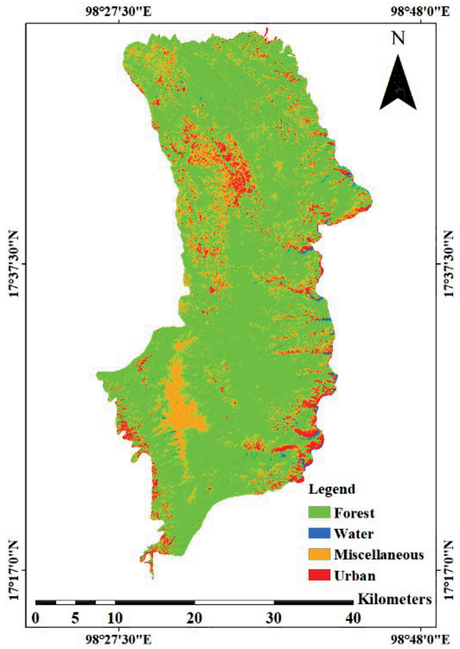

Fig. 6. Classification of Land use of Omkoi Wildlife Sanctuary.

Table 5 represented the accuracy test of reference points of 2017 by determining 60 random points divided into 30 burning points and 30 non-burning points. From analysis on data in tables, it was found that there were 2 points of burning points that were not burned areas and there were 2 points of non-burning points that were burned areas. Overall, there were 4 different points between results and reference points. Overall accuracy was 93.33% with Kappa statistics of consistency at 0.87.

Table 6 represented accuracy test of reference points of 2018 by determining 60 random points divided into 30 burning points and 30 non-burning points. From analysis on data in tables, it was found that there were 6 points of burning points that were not burned areas and there were 7 points of non-burning points that were burned areas. In overall, there were 13 different points between results and reference points. Overall accuracy was 78.33% with Kappa statistics of consistency at 0.57.

Table 7 represented accuracy test of reference points of 2019 by determining 60 random points divided into 30 burning points and 30 non-burning points. From analysis on data in tables, it was found that there were 3 points of burning points that were not burned areas and there were 8 points of non-burning points that were burned areas. In overall, there were 11 different points between results and reference points. Overall accuracy was 81.67% with Kappa statistics of consistency at 0.63.

Table 8 represented accuracy test of reference points of 2020 by determining 60 random points divided into 30 burning points and 30 non-burning points. From analysis on data in tables, it was found that there were 5 points of burning points that were not burned areas and there were 9 points of non-burning points that were

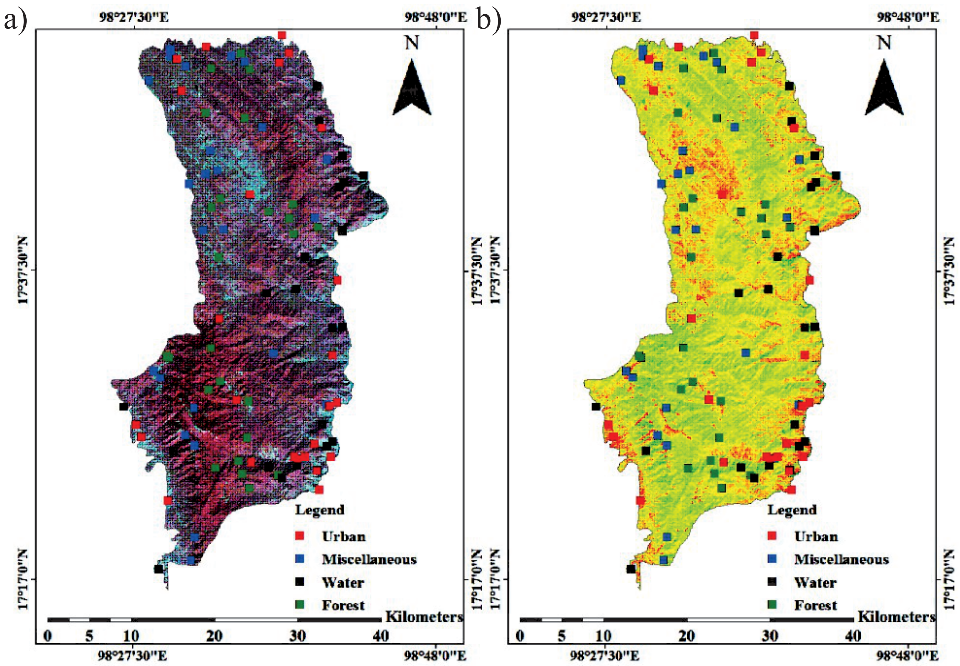

Fig. 7. Accuracy assessment based on Kappa statistics between a) false color composite (R G B: 8 4 3) and b) Land use classification from Sentinel-2 data.

Table 4. Accuracy Test of Classification.

Type of Land Use	Forests	Water	Miscellaneous	Urban	Sum	User's accuracy (%)
Forests	21	0	4	0	25	84
Water	0	22	0	3	25	88
Miscellaneous	5	0	20	0	25	80
Urban	0	0	7	18	25	72
Sum	26	22	31	21	100	
Producer's accuracy (%)	80.77	100	64.52	85.71		
Overall accuracy 81						
Kappa statistics 0.75						

Table 5. Accuracy test of reference points of 2017.

Class	Burning points	Non-burning points	Sum	%
Burning points	28	2	30	93.33
Non-burning points	2	28	30	93.33
Sum	30	30	60	
%	93.33	93.33		
Overall accuracy 93.33				
Kappa statistics 0.87				

Table 6. Accuracy test of reference points of 2018.

Class	Burning points	Non-burning points	Sum	%
Burning points	24	6	30	76.67
Non-burning points	7	23	30	80.00
Sum	31	29	60	
%	77.42	79.31		
Overall accuracy 78.33				
Kappa statistics 0.57				

Table 7. Accuracy test of reference points of 2019.

Class	Burning points	Non-burning points	Sum	%
Burning points	27	3	30	73.33
Non-burning points	8	22	30	90.00
Sum	35	25	60	
%	77.14	88.00		
Overall accuracy 81.67				
Kappa statistics 0.63				

Table 8. Accuracy test of reference points of 2020.

Class	Burning points	Non-burning points	Sum	%
Burning points	25	5	30	70.00
Non-burning points	9	21	30	83.33
Sum	34	26	60	
%	73.53	80.77		
Overall accuracy 76.67				
Kappa statistics 0.53				

burned areas. Overall, there were 14 different points between results and reference points. Overall accuracy was 76.67% with Kappa statistics of consistency at 0.53.

Conclusions

Wildfires have caused damages against living creatures and non-living things in the world and they may be caused by humans or nature. With this reason, the problem on wildfires must be solved in order to prevent impacts against humans and living creatures. Therefore, it is necessary to plan and manage wildfire detection system by using land surveying, semi-air wildfire detection, air wildfire detection, and wildfire detection based on satellite data. This research was conducted to find burned areas based on data from Sentinel-2 Satellite in Omkoi Wildlife Sanctuary, Yang Pieng Sub-District, Mon Chong Sub-District, Omkoi District, Muet Ka Sub-District, Doi Tao District, Chiang Mai Province, and Banna Sub-District, Sam Ngao District, Tak Province, from 2017 to 2020. This study found that data from Sentinel-2 satellites can be effectively applied to evaluate burned areas caused by wildfires in Omkoi Wildlife Sanctuary. During the duration of this study, there were different burned areas in each period of time, i.e., burned area of 2017 were 0.107 km^2. Burned areas of 2018 were 1.160 km^2. Burned areas of 2019 were 0.387 km^2. Burned areas of 2020 were 1.031 km^2. In 2018, burned areas were in the highest level followed by 2020, 2019, and 2017, respectively. This research used 3 formats of spectral indices to find burned areas including NBR, NDWI, and RBR. The results revealed that those spectral indices were able to classify burned areas from wildfires properly.

Acknowledgments

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Conflict of Interest

The authors declare no conflict of interest.

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