FIRE SPOT IDENTIFICATION BASED ON HOTSPOT SEQUENTIAL PATTERN AND BURNED AREA CLASSIFICATION

NALAR ISTIQOMAH[1], IMAS SUKAESIH SITANGGANG[1] and LAILAN SYAUFINA[2]

[1]*Department of Computer Science, Faculty of Natural Science and Mathematics, Bogor Agricultural University, Indonesia*
[2]*Department of Silviculture, Faculty of Forestry, Bogor Agricultural University, Indonesia*

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ABSTRACT

Indonesia is a country with the world's largest tropical peatlands of about 14.9 million hectares that have important roles that support life. Unfortunately, there were many fires in peatlands. In Kalimantan, peatland fires which are characterized by hotspot occurrences reached an average of 25.1% in this decade. According to experts and field forest fire fighters, fire hotspots that appear in a sequence of two to three days at the same location has a high potential of becoming a forest fire. This study aims to determine the sequential patterns of hotspots occurrence, classify satellite image data and identify the fire spot. Fire spot identification was done using hotspots sequences patterns that were overlaid with burned area classification results. Sequential pattern mining using the Prefix Span algorithm was applied to identify sequences of hotspot occurrence. Meanwhile, classification using Maximum Likelihood method was applied to satellite image Landsat 7 to identify burned areas in Pulang Pisau and Palangkaraya Central Kalimantan and Pontianak in West Kalimantan. Furthermore, sequence patterns were overlaid with image classification results. The results show that in Pulang Pisau, 26.19% of sequences patterns are located in burned areas and 72.62% sequence patterns are in the buffer of burned area within a radius of one kilometer. As for Palangkaraya, there are 62.50% sequences patterns are located in burned areas and 87.50% sequence patterns are in the buffer of burned area with the radius of one kilometer. It is concluded that in Pulang Pisau and Palangkaraya there are respectively 72.62% and 87.50% fire hotspots which are strong indicators of peatland fires.

Keywords: fire spot identification, hotspot, maximum likelihood, Prefix Span, sequential pattern mining

INTRODUCTION

Indonesia is a tropical country that has the world's largest peatlands with 17 to 21 million hectares of peatland forest (Syaufina 2008). Peatlands have important ecological roles, such as the storage of water in the rainy season that will be released as water supply in the dry season. Water absorbed by peatlands in rainy season can also prevent floods. Additionally, peatland is also a habitat for many animals, including fish. Peatlands in Indonesia are spread over several islands including Sumatera, Kalimantan and Papua.

Unfortunately, nowadays many fires happen in peatlands. In Kalimantan, peatland fires which are characterized by hotspot occurrences reached an average of 25.1% in this decade. The number of fire hotspots in peatlands also increased and reached its peak in 2005 (WWF Indonesia 2015). This causes numerous environmental impacts, including loss of biomass and biodiversity, subsidence, loss of ecosystem function including carbon sequestration, and the emergence of smog causing health and transportation problems (Syaufina 2008). Peatland fires are ground or subsurface fires, spreading under the surface with no flaming but smoldering (Syaufina 2008). Compared to other fire types, ground fires may kill trees and shrubs grow on the surface as they burn through and damage the roots. Such fires make firefighting difficult, with the fallen and dead trees that are still standing upright also complicating firefighting. In addition, in the smoldering peat, fires can last longer and produce dense smoke. Based on that, it can be concluded that peatland fire are more dangerous than non-peat fires.

* Corresponding author: nalar.istiqomah23@gmail.com

Several studies of peatland have been conducted. Sitanggang *et al.* (2014) applied a spatial decision tree algorithm on spatial data of forest fires. The result of this study is a pruned spatial decision tree with 122 leaves with accuracy of 71.66%. From this study it was also foundthat the spatial tree produced a higher accuracy than the non-spatial trees that were created using the ID3 and C4.5 algorithm. The ID3 had accuracy of 49.02% and the accuracy of C4.5 was 65.24%. Sitanggang (2013) also conducted study to discover the possible influence factors on the occurrence of fire events using Apriori algorithm in Rokan Hilir Riau Province Indonesia. The Apriori algorithm was applied on a forest fire dataset which contained data on physical environment, socio-economic, weather and peatlands. The results show that there are strong relationships between hotspot occurrence and influential factors for the support about 12.42%, the confidence of 1, and the lift of 2.26. Support of association between hotspot occurrence and an influential factor is the percentage of transaction in a dataset that contain both hotspot occurrence and the influential factor. Confidence is the percentage of transactions in a dataset containing hotspot occurrence that also contain an influential factor. Lift measures the correlation between hotspot occurrence and an influential factor in the association rule *hotspot occurrence influential factor*. Moreover, Annisa *et al.* (2015) used Kulldorff's Scan Statistics (KSS) method with Poisson model to recognize the distribution pattern of hotspot clusters in the Sumatra peatland areas in 2014. Results showed that the method is reliable to detect the clusters of hotspots which have the accuracy of 95%.

The occurrence of fire hotspots is used as forest fire indicator. Hotspot data have been widely collected by various institutions. Meanwhile, experts and practitioners stated that the hotspots that appear two or three days in sequence at the same location have a high potential of becoming a forest fire. Therefore, sequential pattern mining can be applied to obtain hotspot sequence patterns for fire identification.

Research on sequential pattern mining has been carried out by Nurulhaq and Sitanggang (2015). This study conducted sequential pattern mining of data hotspots in Riau Province in 2000 until 2014 using the PrefixSpan algorithm. The occurrences of a sequential pattern of hotspots were generated each year with several values of the minimum support. The sequential pattern of hotspot in 2013 and 2014 were analyzed because its number of hotspot occurrences is greater than other years. This study produced patterns that have length up to 4 hotspot occurrences (in 2013) and 3 hotspot occurrences (in 2014).

However, hotspot occurrences do not necessarily indicate the occurrence of forest fires. So land managers typically have to check hotspots into the field to find out if the hotspot is a forest fire or not. This requires much time and cost, especially for areas that are difficult to reach. Therefore, there is a need for a easy and efficient validation method of sequence patterns of hotspot occurrence.

To observe the extent and impact of the peatland fires, technologies can provide information that cover large areas as needed. One of them is remote sensing, usually done from satellites, but also from aircraft and increasingly from drones. Location of fires, intensity of fires and burned area can be determined easily and effectively from satellite (Justice 1993). One of method that can be used is sattelite imagery classification. Several studies have been conducted in this field, one of them is study by Mitri and Gitas (2002) using object-oriented classification model. In this study, satellite imagery from Mediterania Spanyol was classified to identify burned area. This identified a total burned area of 6900 ha, with a 90% accuracy.

Khaira *et al* (2016) also performed satellite image classification using SVM. In this study, Landsat 5 and 7 images were classified to determine the land cover changes, the accuracy of classification was 98.2%. Then, Thariqa *et al.* (2016) conducted a comparison of decision tree algorithms to classify satellite imagery. From this study is known that the best algorithms for image classification of forest fires are the C5.0 with an accuracy of 99.79%.

Moreover, Sitanggang *et al.* (2015) processed Landsat TM image to determine the radius of a hotspot such that random points are generated outside a hotspot buffer as false alarm data. Clustering and majority filtering were performed to extract burn scars in Rokan Hilir, Riau Province Indonesia. It resulted the radius of a hotspot 0.907 km. Beside the ID3 algorithm, C4.5 and extended spatial ID3 have been applied. The results are decision trees for modeling hotspot occurrence which have the accuracy of 49.02% for the ID3 decision tree, 65.24% for the C4.5 decision tree, and 71.66% for the extended spatial ID3 decision tree.

In addition, there are other image classification algorithms that can be used (Lu 2007). One of them is the per-pixel classification approach that can be done with maximum likelihood method. This method has advantages such as its robustness and wide availability in almost all image processing software (Lu 2007). Maximum likelihood estimates less parameters, so that this method can classify images very quickly (Canty, 2010). The results of the classification of satellite imagery can be used to validate the hotspots sequence pattern. By overlaying the results of image classification with the hotspots sequences pattern, we can identify whether sequence patterns are located in burned areas or not. Hotspots sequence pattern in burned areas are called the true fire occurrences.

Based on explanation above, the question arises how to identify fire spots on the hotspots sequences pattern and satellite image burned area classification? To answer these questions, a study was conducted to do sequential pattern mining of hotspot data using the Prefix Span algorithm. The results of hotspot sequences pattern were then evaluated using satellite image data that were classified by the maximum likelihood method. The purpose of this study is to obtain sequential patterns of hotspots occurrence using the Prefix Span algorithm, to apply the maximum likelihood method to classify satellite image data of burned area and, ultimately to identify the fire spots. Fire spot identification was done using hotspots sequences patterns that overlaid with burned area classification results.

MATERIALS AND METHODS

Studi Area and Datasets.

The study area of this research is peatland in West Kalimantan and Central Kalimantan, Indonesia, focused on provinces that have many peatland fires. This study used satellite imagery Landsat 7, peatland map data, and hotspots for 2014 and 2015. Hotspot data were collected from the Fire Information for Resource Management System Moderate Resolution Imaging Spectrometer National Aeronautics and Space Administration (FIRMS MODIS NASA, https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms). The satellite imagery used for the classification process is Landsat 7 in Pulang Pisau and Palangkaraya, Central Kalimantan province. Landsat 7 image were taken from United States Geological Survey (USGS). Image acquisition date is adjusted to the date of sequences of hotspot and availability of image at the USGS, which is dated October 14, 2015. Peatland map in 2002 was used to select the peat land cover on Landsat satellite imagery. Mapping of peatland areas was obtained from Wetlands International.

Research Methods

This study consists of three major parts as depicted in Figure 1: 1) determine sequence patterns of hotspots in 2014 and 2015 using Prefix Span algorithm, 2) classify satellite image of burn area, and 3) identify fire spots.

1 Data Preprocessing
Data preprocessing consists of data selection, data cleaning, data transformation and

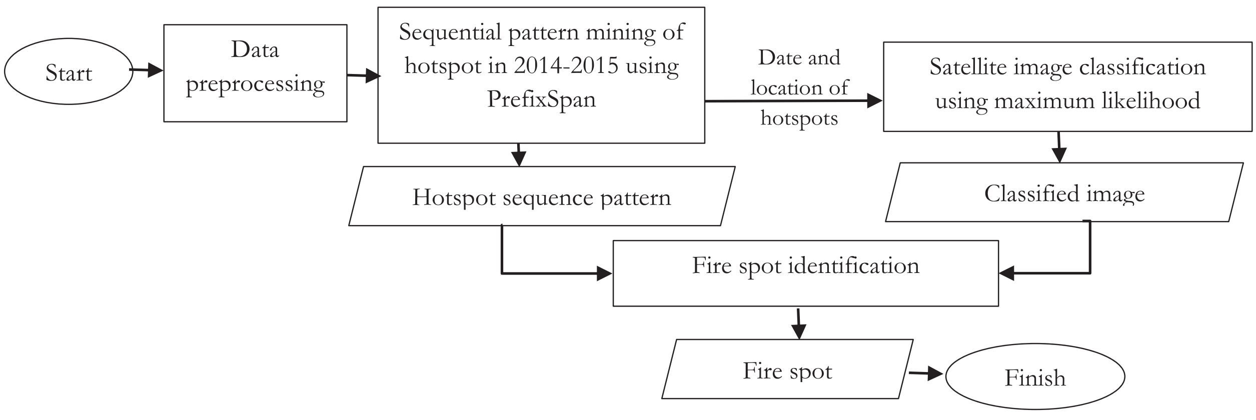


Figure 1 Research steps

generation of data sequential using the R software. In data selection attributes that will be used in this study were selected. Data cleaning was done by removing the attributes or data that have missing value or noise. In data transformation we transform the attributes types. Sequential data were generated by sorting the data by longitude, latitude and date attribute.

Data preprocessing was also performed on satellite image Landsat 7. Filling the gap on the image, band combination, and subseting image were done in preprocessing stage. Filling the gap was performed to fill part of image that have no value. Filling the gap was done using gap mask to determine the location of the pixel to be filled. This task was done using Quantum GIS. Moreover, band combination was performed to get the RGB color from the image. Color Red is represented by band 7, Green is represented by band 4 and Blue is represented by band 2. Furthermore, satellite images were selected to determine area of interest which is peatland.

2 Sequential Pattern Mining on Hotspot Data

Sequential data generated from preprocessing stage were used to determine sequential pattern using the PrefixSpan algorithm. PrefixSpan applies a 'divide and conquer' approach that recursively projects the database into a set of smaller data base based on repetitive pattern at the time. Then the projection is used to obtain the patterns. PrefixSpan project only prefix of the pattern, so the size of the projected database will continue to shrink and redundancy tests on every possible position of potential candidate will be reduced (Pei *et al* 2014).

3 Satellite Image Classification using Maximum Likelihood

Stages of image classification are image preprocessing, classification using maximum likelihood and filtering classified image. The images as the result of data preprocessing then were classified using the maximum likelihood method. Classification was done utilizing the ILWIS software. Before performing classification, data sampling is necessary for each image. Samples contain examples of burned and not burned pixels. In this study, sampleswas taken from the pixel image with band combination of 7, 4, and 2. Red pixel represents burned area, while other pixels represent not burned area. Furthermore, the classification results were filtered. Classification results have salt-and-pepper noises. Noise was removed using the smoothing filter. This study uses a majority filter for smoothing image as the results of classification.

4 Fire spot identification

According to the results of satellite image classification, pixels which indicate burned and not burned area are identified. Meanwhile, from the results of sequential pattern mining using PrefixSpan, sequences pattern of hotspot occurrences in Kalimantan were extracted from the hotspot dataset. Furthermore, the hotspot sequence patterns were compared with the classified image to identify sequences patterns that are located in burned areas. Hotspot sequence pattern that are occurred in burned area are considered as fire spots.

RESULTS AND DISCUSSION

Data Preprocessing

In preprocessing stage, data selection, data transformation and data sequential generation were performed. Data selection was done by selecting attributes that will be used in this study. The selected attributes of a hotspot are longitude, latitude and date of acquisition of hotspot. Furthermore, hotspots were selected in the study area namely peatlands in Kalimantan.

In data transformation, the type of attribute acquistiondate is converted to integer denoted as date code. In this study, the code is assigned to 1 until 730, code 1 represents1 January 2014 and so on until date code 730 representing 31 December 2015. In addition, in the data transformation, the decimal digits of longitude and latitude were rounded into 2 significant digits. Rounding was performed to obtain more than one hotspot occurrences in a radius of 1 km.

The last data preprocessing stage is sequential data generation. One sequence is a series of events in one location. Table 1 is an example of sequence of hotspots. According to Table 1, it can be seen that in a location with longitude of 109.48 and latitude of -0.53, there are hotspot

Table1 Sample of hotspot sequences

Longitude	Latitude	Sequence
108.94	0.80	728 -2
109.48	-0.53	629 -1 622 -2
109.12	0:32	622 -1 627 618 -1 628 -1 630 -1 -2

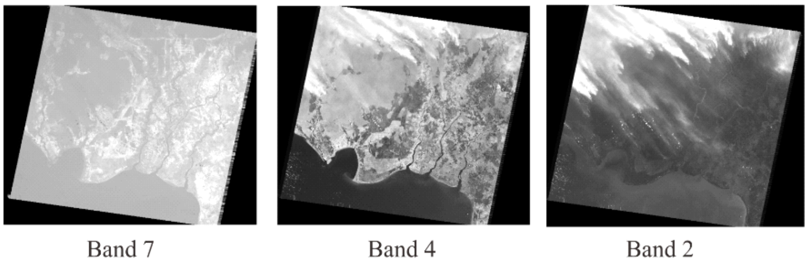


Figure 2 Example of filling gap on band 7, 4 and 2

occurrences on day of 622 (which is 14 September 2015) and day of 629 (which is 21 September 2015). This sequence means that hotspot occurrence at that location has a span of eight days.

Satellite images used in this step were collected from USGS website which can be accessed onhttp://earthexplorer.usgs.gov/. Satellite images were selected based on district where sequence patterns took place and date when sequence patterns occurred.

There are two images that are suitable for the sequences namely for the area Pontianak on 8 September 2015, Pulang Pisau and Palangkaraya on 14 October 2015. Both the images were preprocessed, classified and filtered to get burned area. Filling the gap, band combinations and subsets of images were done in the preprocessing stage.

The entire Landsat 7 satellite imagery began on 3 May 2003 has a gap due to damage on the SLC. The gap causes pixels to have no value. Such a gap will also lead to low quality of classification results. For these reasons, it is necessary to fill the gap by estimating the value of the missing pixels. This study conducted gap filling using the QGIS software and gap mask that are obtained from the USGS. Filling gap was done on each band using the gap mask for band that operated. Figure 3 show the result of filling gap on band 7, 4 and 2.

Sequential Patterns using Prefix Span Algorithm

In this study, sequential pattern mining was performed on the sequence dataset of hotspot in Kalimantan in 2014 and 2015. The value of minimum support used is 1%. The resulting pattern has length of 1 event to 3 events. For further analysis we use only sequences pattern of length 2 to 3 events because these patterns are considered to become fire spots.

Table 2 shows number of sequence patterns of hotspots for each dataset generated using PrefixSpan algorithm that is available in the sequential pattern mining framework (SPMF) framework (http://www.philippe-fournier-viger.com/spmf/).

Table 2 explains that the sequence patterns in 2014, are widely occurred in East Kalimantan. As in 2015, the sequence patterns are common in West Kalimantan and Central Kalimantan. In West Kalimantan, there are 14 sequences with the length of 2 events while in Central Kalimantan, there are 10 sequences with the length of 2 events and 1 sequence with the length of 3 events.

Table 2 Number of sequence pattern of hotspots

	West Kalimantan		South Kalimantan		Central Kalimantan			East Kalimantan			Kalimantan Island	
event	1	2	1	2	1	2	3	1	2	3	1	2
2014	49	6	28	6	30	3	0	40	21	2	32	2
2015	35	14	31	5	45	10	1	42	1	0	45	7

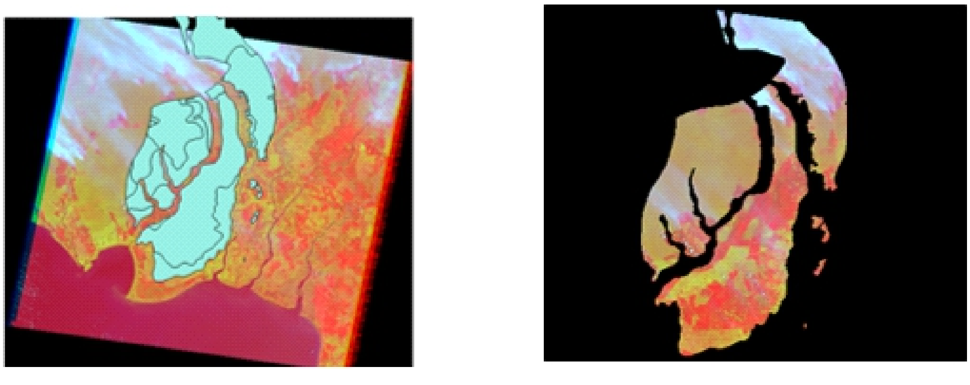
In this study, the sequence patterns in West Kalimantan and Central Kalimantan in 2015 were analyzed further. Table 3 represents the results of sequence patterns in 2015 in West and Central Kalimantan with the length of 2 and 3 events. Those patterns are mostly found in Kubu Raya and Pontianak, West Kalimantan and also Pulang Pisau and Palangkaraya, Central Kalimantan.

As many as 23 sequence patterns with lengths of 2 or 3 events generated in 2014 were mostly found in East Kalimantan, especially in the area of Ketapang and Sambas in 26th September 2014. In addition, sequence pattern of hotspots was frequently found in West Kalimantan and Central Kalimantan in 2015. As many 14 sequences with length of 2 events were found in West Kalimantan especially in the area of Ketapang and Kayong Utara on the 10th and 21st September 2015. Furthermore, there are 11 sequences with length of 2 or 3 events found in Central Kalimantan, especially in the areas of Kapuas and Katingan on the 9th and 14th October 2015.

Satellite Image Classification using Maximum Likelihood

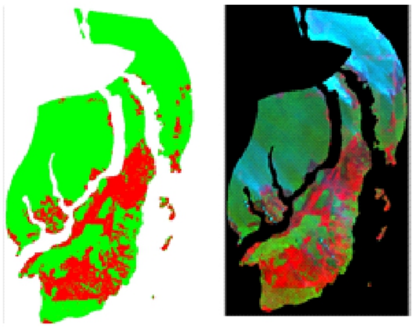
Table 3 Hotspot sequence patterns in West and Central Kalimantan 2015

Province	Sequence 2-*events* *(in date code)*	Sequences date	Sequence 3-*events* *(in date code)*	Sequences date
West Kalimantan	549 -1 552 -1 #SUP: 8	03/07/2015 – 06/07/2015	-	-
	549 -1 550 -1 #SUP: 8	03/07/2015 – 04/07/2015		
	608 -1 609 -1 #SUP: 8	31/08/2015 – 01/09/2015		
	609 -1 616 -1 #SUP: 13	01/09/2015 – 08/09/2015		
	609 -1 611 -1 #SUP: 11	01/09/2015 – 03/09/2015		
	613 -1 616 -1 #SUP: 10	05/09/2015 – 08/09/2015		
	616 -1 618 -1 #SUP: 14	08/09/2015 – 10/09/2015		
	617 -1 618 -1 #SUP: 11	09/09/2015 – 10/09/2015		
	618 -1 659 -1 #SUP: 8	10/09/2015 – 21/10/2015		
	618 -1 622 -1 #SUP: 9	10/09/2015 – 14/09/2015		
	622 -1 629 -1 #SUP: 9	14/09/2015 – 21/09/2015		
	629 -1 630 -1 #SUP: 20	21/09/2015 – 22/09/2015		
	629 -1 659 -1 #SUP: 10	21/09/2015 – 21/10/2015		
	634 -1 659 -1 #SUP: 16	26/09/2015 – 21/10/2015		
Central Kalimantan	615 -1 616 -1 #SUP: 52	07/09/2015 – 08/09/2015	647 -1 652 -1 654 -1 #SUP: 47	09/10/2015 – 14/10/2015 – 16/10/2015
	622 -1 629 -1 #SUP: 49	14/09/2015 – 21/09/2015		
	629 -1 631 -1 #SUP: 134	21/09/2015 – 23/09/2015		
	640 -1 652 -1 #SUP: 48	02/10/2015 – 14/10/2015		
	645 -1 647 -1 #SUP: 61	07/10/2015 – 09/10/2015		
	647 -1 652 -1 #SUP: 106	09/10/2015 – 14/10/2015		
	647 -1 654 -1 #SUP: 66	09/10/2015 – 14/10/2015		
	652 -1 654 -1 #SUP: 150	14/10/2015 – 16/10/2015		
	652 -1 657 -1 #SUP: 72	14/10/2015 – 19/10/2015		
	659 -1 661 -1 #SUP: 63	21/10/2015 – 23/10/2015		



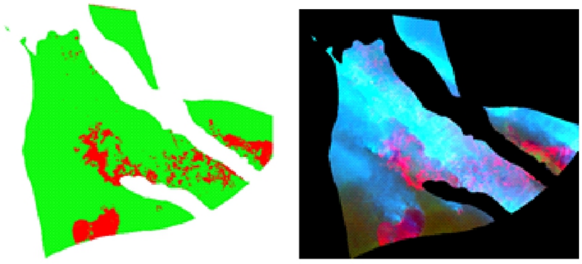
(a) Overlay the image (b) Clipping the image

Figure 3 Overlay (a) and clipping (b) the image with peatland map



(a) (b)

Figure4 Pulang Pisau image: classification results (a) and original image (b)



(a) (b)

Figure 5 Palangkaraya image: classification results (a) and original image (b)

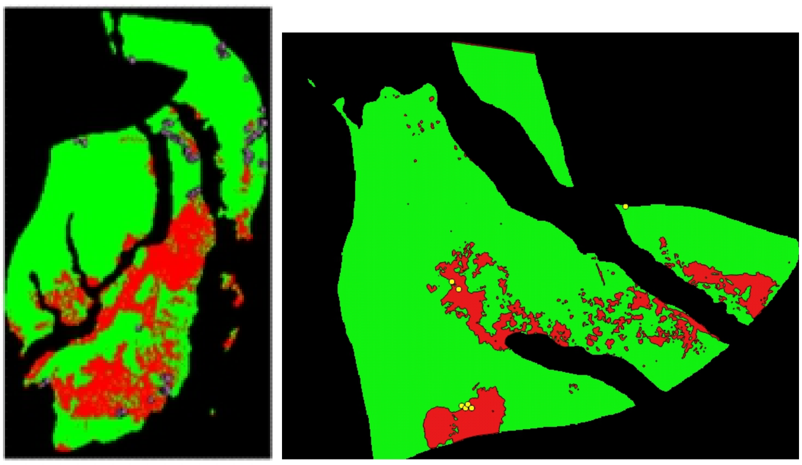
This study use the band combination of 7, 4 and 2. This combination is valid to be used to detect the burned area (Quinn 2001). To get the image in peatlands, it is necessary to process the image subset. In order to obtain the image subset we did image overlay and clipping using peatlands map. Overlay was conducted to determine the area of peatland, and clipping process was done to take part of peatland only. Figure 4 illustrates the overlay and clipping process.

To perform image classification, sampling was necessary. In this study, red pixels were taken as samples of burned class, while other colours were taken as the samples of not burned class. Then the samples were used to perform the image classification using ILWIS software (https://www.itc.nl/ilwis/). Figure 5 shows the result of image classification for area of Pulang Pisau compared to its original image. Figure shows the result of image classification for area of Palangkaraya compared to its original image.

In Figure 5 and 6, the red color represents burned areas, while green represents unburned areas. As can be seen in Figures 5 and 6, the classification results close to the original images. Therefore, classification results are good enough. Image classification results were used in the fire spot identification.

Fire Spot Identification

To get accurate locations of hotspot sequences, values of longitude and latitude of sequence patterns were restored to 3 decimal places. Furthermore, patterns that occur in the same period of the imagery were selected. The classified image was overlaid with selected sequence pattern. Figure 7 shows sequence patterns overlaid with classified image for area of Pulang Pisau and Palangkaraya.



(a) Pulang Pisau (b) Palangkaraya

Figure 6 Sequences pattern of hotspots overlaid with classified images for the area of (a) Pulang Pisau and (b) Palangkaraya

Table 4. Percentages of sequence patterns of hotspots in burned and buffer areas

Area	In burned area	In burned and buffer area
Pulang Pisau	26.19%	72.62%
Palangkaraya	62.50%	87.50%

Sequences patterns in burned area and not burned area were determined by executing the SQL statements. If a pattern is in the area on fire, then it is labeled as "yes" otherwise it is labeled as "no". Identification also done in buffer with the radius of 1 km around burned area.

The sequence patterns of hotspot located in the burned area represents fire spots. The sequence patterns of hotspot located in the buffer of burned areas represent sequence patterns around area of peatland fires. Table 5 shows percentage of sequence patterns of hotspots in burned area and in the buffer area.

From Table 5, it is known that percentage of sequence patterns in burned and buffer area is greater than those only in burned area. It is caused by inability of the classification algorithm to identify burned area in the image where there is much smoke. With this taken into account, it can be concluded that in Pulang Pisau there were 72.62% sequence patterns that become forest fire. Meanwhile in Palangkaraya, there were 87.50% sequence patterns that become forest fire.

CONCLUSIONS

The Prefix Span algorithm was successfully applied to determine the sequence patterns of hotspots in two peatland areas in Kalimantan for 2014 and 2015. Sequence patterns with lengths of 2 or 3 events generated in 2014 were mostly found in the area of Ketapang and Sambas East Kalimantan. In addition, sequences with length of 2 events were found in especially in the area of Ketapang and Kayong Utara West Kalimantan in 2015. In Central Kalimantan, hotspot sequences with length of 2 or 3 events were mostly found in the areas of Kapuas and Katingan in 2015.

The experimental result shows that for the area of Pulang Pisau, there are 26.19% and 72.62% sequence patterns that are located in burned areas and in the buffer area respectively. As for Palangkaraya, there are 62.50% and 87.50% sequence patterns that are located in burned areas and in the buffer area respectively. This study shows that about 72.62% and 87.50% hotspots sequentially occurred in Pulang Pisau and Palangkaraya respectively. Those hotspots are considered as fire spots that become strong indicator for peatland fires.

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