Wildfire Visualization Time Series from 2014-2019 in Phayao Province, Thailand

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Abstract
Wildfire prevention comprises of all the activities that can be performed in order to reduce or prevent wildfire occurrences as well as to minimize wildfire potential impacts and damage. The aim of this research was presented wildfire visualize time series from 2014-2019 using time manager plugin in QGIS software. The study area is Phayao province, that highest of wildfire in northern part of Thailand. Time manager plugin was used to visualize time series during the years 2014 to 2019 with 1,993 hotspots especially 2019 year with 582 hotspots. The highest was shown in Pong district with 779 hotspots (39%) of wildfire during March and April of every year.

1. Introduction

Wildfire monitoring and management in northern part of Thailand is of paramount importance and every summer massive forest wildfires break out in several areas, leaving behind severe destruction in forested and agricultural land, infrastructure and private property, and losses of human lives. Remotely sensed images have a considerable potential for mapping burnt areas and fire regimes, particularly at the regional level. This technology is useful in comparison to other conventional approaches because of its accuracy, repeatability, and speed in data acquisition, longer historical data and ease of combination with other thematic data. Satellite-based burnt area mapping is performed using different sensors (various spatial and temporal resolutions) and classification procedures (Daldegan et al., 2014).

A literature review on the surface fire spread models reveals that fire models can develop from two types of fuel: grassland and shrub land. The fire spread rate depends on three major environmental weather parameters, i.e., wind speed at ground level (Burrows et al., 2006 and Boboulos and Purvis, 2009), moisture control of fuel (Beaza et al., 2002), and moisture content of terrain (Fernandes, 2001). Topographic factors include slope of terrain (Boboulos and Purvis, 2009) and fuel chalacteristics, e.g., high vegetation, vegetation cover, fuel load in the unit area and fuel size (Bilgili and Saglam, 2003)

Recent advances in Geographic Information System (GIS) along with Remote Sensing (RS) have added new dimension to spatial statistics analysis in disaster studies (Jeefoo, 2012). The advances in Free and Open Source Solution for Geoinformatics (FOSS4G) provide an alternative approach to geospatial software development. FOSS4G has become popular as a practical alternative for developers and users and has been successfully used in many applications. The FOSS4G software (QGIS, SAGA GIS, GRASS GIS and so on) stack comprises of system software, data processing tools, data delivery and user interface tools for both desktop and web-based environment (Choosumrong et al., 2016).

Thailand currently faces annual air emission from forest fires during January to May with impact on respiratory health and vision, especially in the upper northern region of the country (Pollution Control Department, 2012 and Junpen et al., 2013). The main reasons for setting fires include the gathering of forest non-timber products, e.g., honey, mushrooms, bamboo, fuel wood, hunting, agricultural residue burning for land clearing before the next crop, incendiary fires, and others. Nearly all forest fires in Thailand are classified as surface fires which combust only surface fuel including twigs, dead leaves, dead plants, grass, and undergrowth (Forest Fire Control Division, 2011). All fires are human caused, especially by rural people living near forested areas. Over the period from 1998-2010, the total frequency of forest fires was approximately 80,767 events corresponding to a burned surface area of 265,472 ha. Approximately 50,872 or 63% of all forest fire events occurred in the Northern part of Thailand and then over a burned area of approximately 122,688 ha, or 46% of all burned areas. Approximately 90% of all forest fire occurrences took place in deciduous forests characterized in to two forest types, mixed deciduous forests and dry dipterocarp forests (Forest Fire Control Division, 2011).

Remote Sensing will provide objective and reliable information that could be useful for solving the burnt detection (Zheentaev, 2016). Regarding fire types of behavior in deciduous forests, the Forest Fire Control Division, Thailand, has reported a surface fire spread rate ranging from 1.70-3.40 m/min which is 1.00-4.00 m of the flame height and 110-250 kW/m of fireline intensity. The fire spread rate might be increased when forest fires occur in steep slope areas. The fire spread rate is a key component in planning and decisions for conducting prescribed fires and suppressing forest fires. However, fire spread rate prediction in the area of the studies is unknown (Pastor et al., 2003 and Forest Fire Control Division, 2011).

Burnt area maps generated from satellite sensors with high temporal-resolution and coarse spatial-resolution (approximately 1 km.) such as System Pour 1'Observation de la Terra (SPOT-VEGETATION), Advanced Very High Resolution Radiometer (AVHRR), Along Track Scanning Radiometer (ATSR-2), Geostationary Operational Environmental Satellite (GOES) and Moderate Resolution Imaging Spectrometer (MODIS), fail to detect the majority of small and fragmented burnt areas (Schroeder et al., 2008, Simon et al., 2004, Silva et al., 2005 and Daldegan et al., 2014). This study aimed at providing useful information on wildfire hotspots detection and time series management in Phayao province, northern part of Thailand, using QGIS, Time Manager plugin, free and open source software and mapping their patterns and dynamics of wildfire burning.

2. Materials and Methods

2.1 Study Area

Phayao province, a province in the northern part of Thailand, had the high burnt area in the northern in 2019, with 5.16 square kilometers of damaged burnt areas, therefore Phayao province was selected as the study area (Figure 1) because of the highest population ethnics living in the mountain and several types of landscape. Phayao province consists of 9 districts, 68 sub-districts, and 780 villages. The province is located 733 km north of Bangkok, and covered as area of 6,335 square kilometers with geographical location between 18°47′0″N to 19°48′0″N and 100°5′30″E to 100°36′0″E. The province has a population of about 475,215 people (NSO, 2018). The western part of the province is the low water resource of Kwan Phayao lake. The eastern part is mountainous, with an average height of more than 300 m above sea level.

About 28% of the population are predominantly involved in agricultural activities that take place in an extension of approximately 1,852 square kilometers, including paddy fields, fields crop, rambutan, and lychee. The average yearly rainfall is approximately 1,262.40 mm, the highest average monthly rainfall is September with 232.50 mm, and lower average monthly rainfall is January with 2.50 mm (Phayao Provincial Agriculture and Cooperatives Office, 2019).

2.2 Wildfire Hotspots Data

Hotspots burnt detection data, ESRI shape file, during the years of 2014 to 2019 were collected from NASA via FIRMS website [https://firms.modaps.eosdis.nasa.gov]. The data was obtained from the NASA website, with regard to the number of reported wildfire hotspot and confirmed hotspot locations with geometric correction per 24 hour, 48 hour, and 7 day. After the first wildfire hotspots detection were confirmed, all hotspots that had showed in the Phayao province with the following condition: brightness temperature ≥ 295 Kelvin, confidence ≥ 60 %, were considered as expects of wildfire hotspot. Data represented only the hotspots detection in the South East Asia region and have to process using spatial overlay analysis only Phayao province, Thailand by using QGIS open source software.

The data has uploaded by separate comprised of three categories (Shapefiles, Google Earth KML, Text File (CVS)). A dialog of those data and it can be download by MODIS 1km, VIIR 376m / S-NPP, or VIIRS 375 / NOAA-20 respectively. This study was selected shapefiles in South East Asia by 24h. The attribute data of hotspots burnt detection was shown in Table 1, including latitude, longitude, brightness, scan, track, acquisition date, satellite, confidence, version, brightness temperature 31 (Kelvin), fire radiative power (MW - megawatts) and day or night.

2.3 Method

Various software, namely QGIS (https://qgis.org/en/site/) was used in this study. Meanwhile, Time manager plugin have installed. Time manager setting, hotspots detection was calculated for each year from 2014 to 2019, the layer name was generated for each year. The ACQ_DATE (Acquisition Date) field have considered for start and end date of the time series (Figure 2).

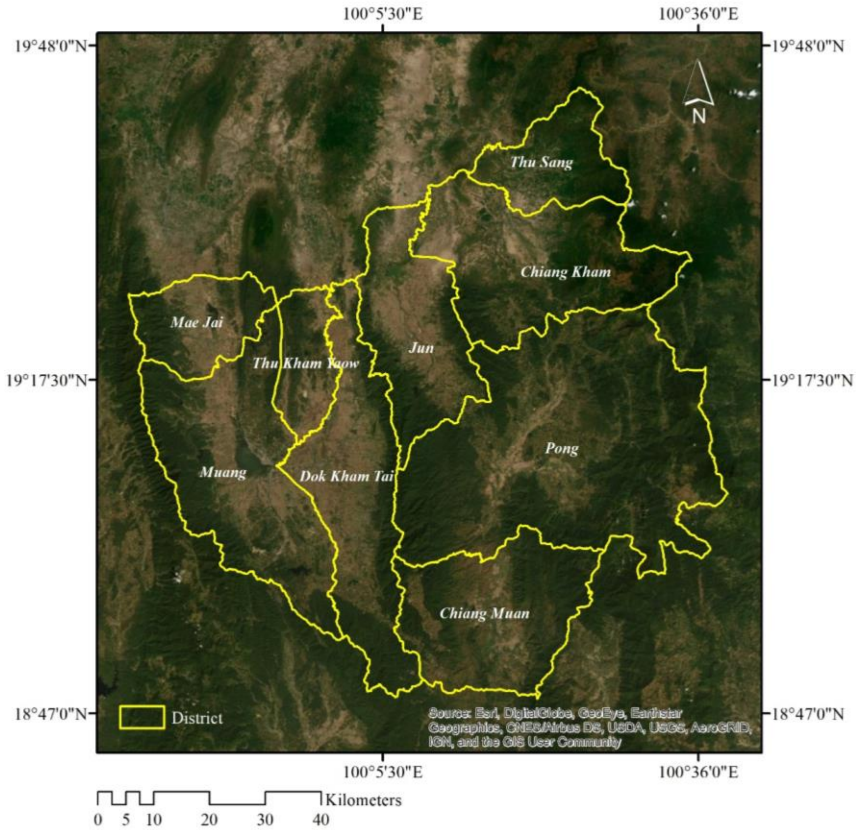

Figure 1: Study area, Phayao Province

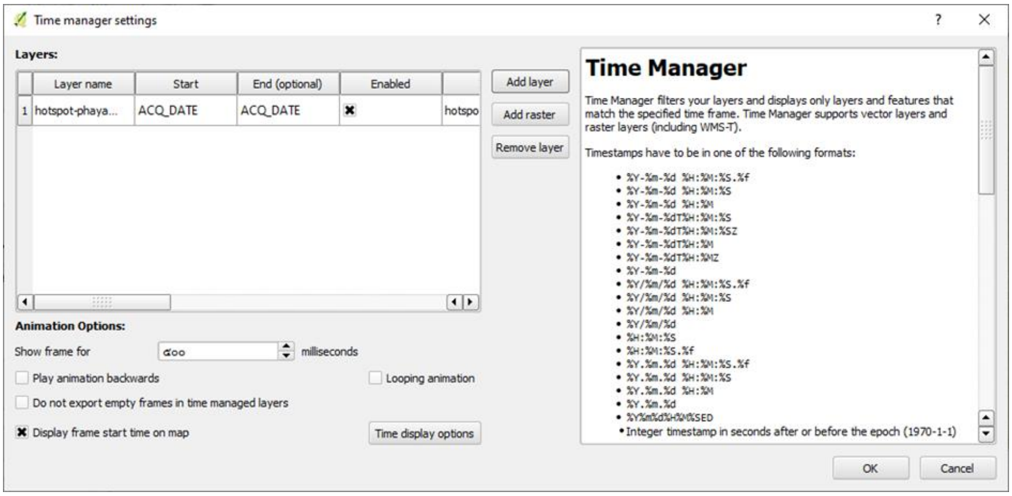

Figure 2: Time manager plugin in QGIS

3. Results

Hotspot of wildfire detected in most area of Phayao province, causing severe make a living problems and financial tolls on the population affected. In 2019, the total number was 582 points, which is the highest recorded of hotspot detection for the current decade. After 2014 (459 points), a gradual decrease was seen in the number of hotspots detection until 2019 (in 2016, increase again with 408 points), and again a regular decrease was seen in the number of hotspots detection until 2019. The lowest occurrence was in 2018 (140 points). As shown in Table 2, in total 1,993 points were reported. Wildfire hotspots detection based on month of the hotspots was also determined. The highest hotspot was in March with a percentage of 45.01% (897 points), while hotspot in the April was 30.96% (617 points) (Table 3).

Table 1: FIRM data description

Item	Detail	Description
Latitude	Latitude	Center of 1km fire pixel but not necessarily the actual location of the fire as one or more fires can be detected within the 1km pixel.
Longitude	Longitude	Center of 1km fire pixel but not necessarily the actual location of the fire as one or more fires can be detected within the 1km pixel.
Brightness	Brightness temperature 21 (Kelvin)	Channel 21/22 brightness temperature of the fire pixel measured in Kelvin.
Scan	Along Scan pixel size	The algorithm produces 1km fire pixels, but MODIS pixels get bigger toward the edge of scan. Scan and track reflect actual pixel size.
Track	Along Track pixel size	The algorithm produces 1km fire pixels, but MODIS pixels get bigger toward the edge of scan. Scan and track reflect actual pixel size.
Acq_Date	Acquisition Date	Data of MODIS acquisition.
Acq_Time	Acquisition Time	Time of acquisition/overpass of the satellite (in UTC).
Satellite	Satellite	A = Aqua and T = Terra.
Confidence	Confidence (0-100%)	This value is based on a collection of intermediate algorithm quantities used in the detection process. It is intended to help users gauge the quality of individual hotspot/fire pixels. Confidence estimates range between 0 and 100% and are assigned one of the three fire classes (low-confidence fire, nominal-confidence fire, or high-confidence fire).
Version	Version (Collection and source)	Version identifies the collection (e.g. MODIS Collection 6) and source of data processing: Near Real-Time (NRT suffix added to collection) or Standard Processing (collection only). "6.0NRT" - Collection 6 NRT processing. "6.0" - Collection 6 Standard processing. Find out more on collections and on the differences between FIRMS data sourced from LANCE FIRMS and University of Maryland.
Bright_T31	Brightness temperature 31 (Kelvin)	Channel 31 brightness temperature of the fire pixel measured in Kelvin.
FRP	Fire Radiative Power (MW - megawatts)	Depicts the pixel-integrated fire radiative power in MW (megawatts).
Daynight	Day or Night	Day (D), Night (N)

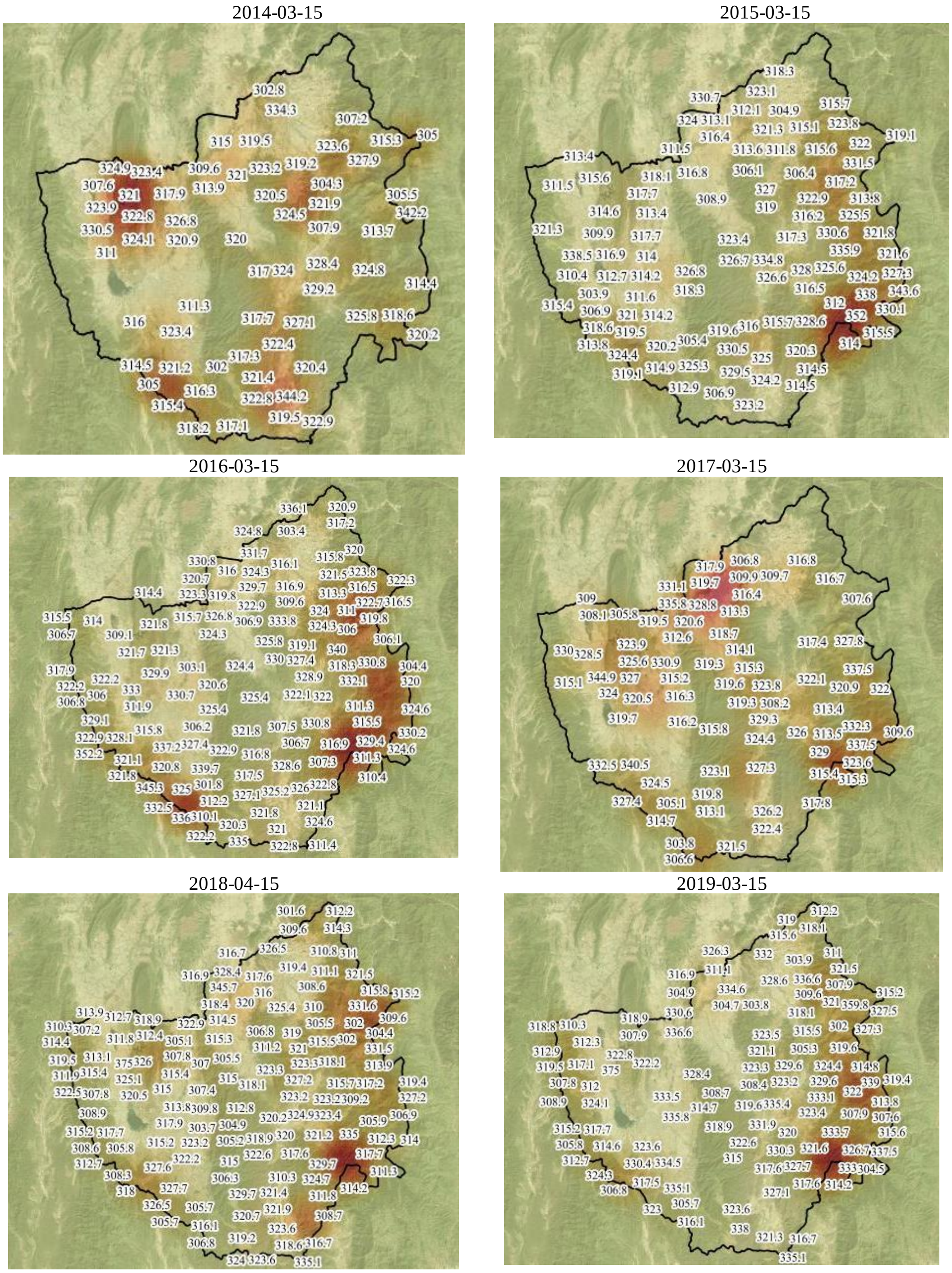

Figure 3: Hotspot time series from 2014 - 2019

Table 2: Number of hotspot detection from the year of 2014 – 2019 in Phayao province

Year	Number of hotspot detection	Percent (%)
2014	459	23.03
2015	262	13.15
2016	408	20.47
2017	142	7.12
2018	140	7.02
2019	582	29.20
Total	**1,993**	**100.00**

Source: Fire Information for Resource Management System, NASA

Table 3: Number of hotspot detection by month from 2014 – 2019

Mount	Number of Hotspot Detection in Phayao province, Thailand						%	Total
	2014	2015	2016	2017	2018	2019		
January	14	8	16	2	12	14	3.31	66
February	54	21	23	11	7	41	7.88	157
March	**278**	**135**	135	**71**	26	**252**	**45.01**	**897**
April	85	76	**211**	20	**37**	188	30.96	617
May	6	5	14	10	3	34	3.61	72
June	2	0	0	1	0	2	0.25	5
July	0	0	0	0	0	1	0.05	1
August	0	0	0	1	0	0	0.05	1
September	0	1	0	0	0	0	0.05	1
October	0	0	0	0	0	0	0.00	0
November	1	4	2	0	27	28	3.11	62
December	19	12	7	26	28	22	5.72	114

Source: Fire Information for Resource Management System, NASA

The wildfire hotspots detection was illustrated by interpolating the value over the space, using Kernel Density Estimation as interpolation method, as shown in Figure 3. Maps of monthly hotspots detection were generated, which indicated the dynamics of wildfire hotspots distribution through time during 6 years for the month of March and April (2018) for the years of 2014 to 2019. The number of hotspot detection by month showed that the spatial distribution of wildfire hotspot was clustered (red color). Maps showed that the hotspot occurred everywhere in the province, even in area in the northern part of the province, which is more rural with a lower density of villages (Figure 3).

Time manager for each year represented the absolute global position and created brightness temperature trend in direction and extent for all wildfire radius area. Brightness temperature of each location was observed mainly in agriculture areas (Mae Jai and Pong districts) of the Phayao province. The purpose of the map was to compare the global distribution of wildfire brightness temperature for 6 serial years. The global pattern was observed almost same in each year. Maps of monthly hotspots were generated, which indicated the dynamics of wildfire brightness temperature through time during January to July for the year 2019. A total of 532 hotspots detection and wildfire brightness temperature were recorded and geo-referenced (Figure 4). The highest number of hotspots per day were 32 hotspots (date 2019-03-12) in Chiang Kham district.

Figure 5 represents the results for 2019 by month. The hotspots in Phayao province spread rapidly in all the study area during January and the wide spatial hotspot distribution was conserved during the peak of the epidemic, at February to April 2019. A hotspots detection map was built from the brightness temperature (Kelvin) of each point for each day during the complete burn, and MODIS sensor was confirmed that hotspots were spread all around the province showing a hotspot with red colored areas in the west and north of the province. This apparent cluster was due to a notification effect in the native location, where spatial resolution of hotspots was lower. The highest brightness temperature was shown 405.7 Kelvin (date: 2019-04-15) in Pong district and lowest brightness temperature was shown 301.2 Kelvin (date: 2019-03-29) in Chiang Kham district.

In Pong, there was 779 points of hotspot detection, affecting 39.09% of the total summary hotspot. Approximately 58.01% (Chiang Kham and Pong districts) of the occurred in the west of province, with the highest number occurring in Pong district and the second highest in Chiang Kham district (377 points). While Thu Kham Yaow had the lowest number with only 40 points (2.01%). The summary of hotspot from 2014 – 2019 by district is shown in Table 4 and Figure 6.

4. Discussion

When it comes to wildfire management, GIS provides accurate and comprehensive information to analyse, visualize, and prioritize values at risk, such as housing developments, utility infrastructure, wildfire, and natural or cultural resources. Within the scope of wildfire management, wildfire prevention comprises of all the activities that can be performed in order to reduce or prevent wildfire occurrences as well as to minimize wildfire potential impacts and damage. For the purpose of mitigation, a GIS plays a vital role in mapping fire-prone areas, monitoring fuel load and risk modelling; for preparedness and response it helps in fire detection, predicting spread/direction of fire, early warning and coordinate fire-fighting efforts.

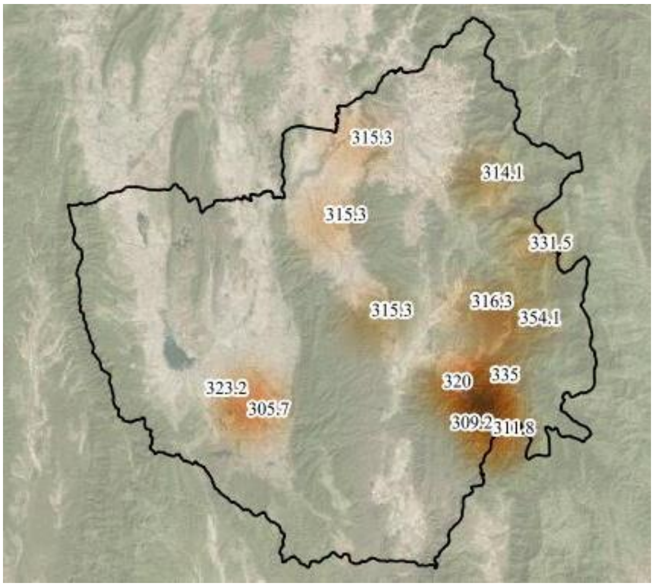

Figure 4: Wildfire time series in January 2019 (532 points)

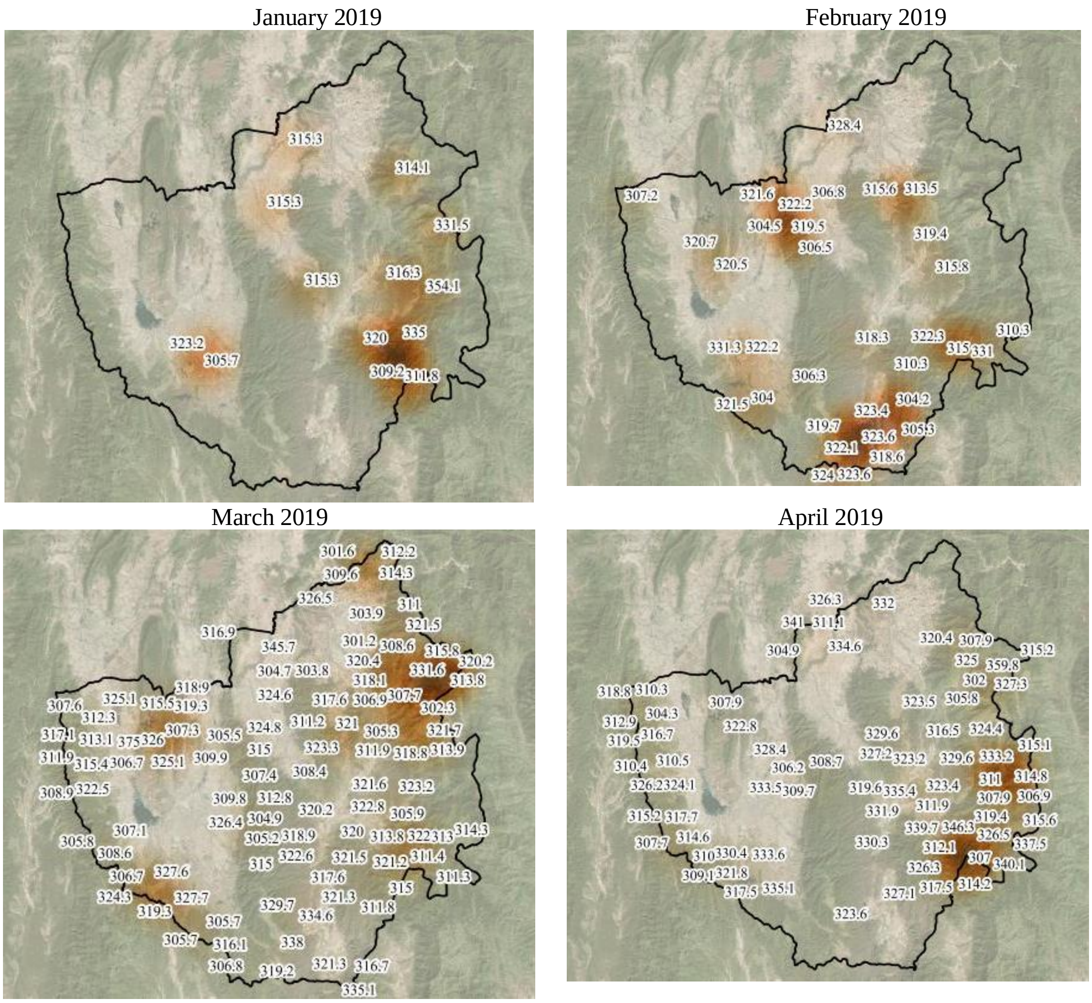

Figure 5: Wildfire time series in the year of 2019 with totally 532 of hotspots (cont. next page)

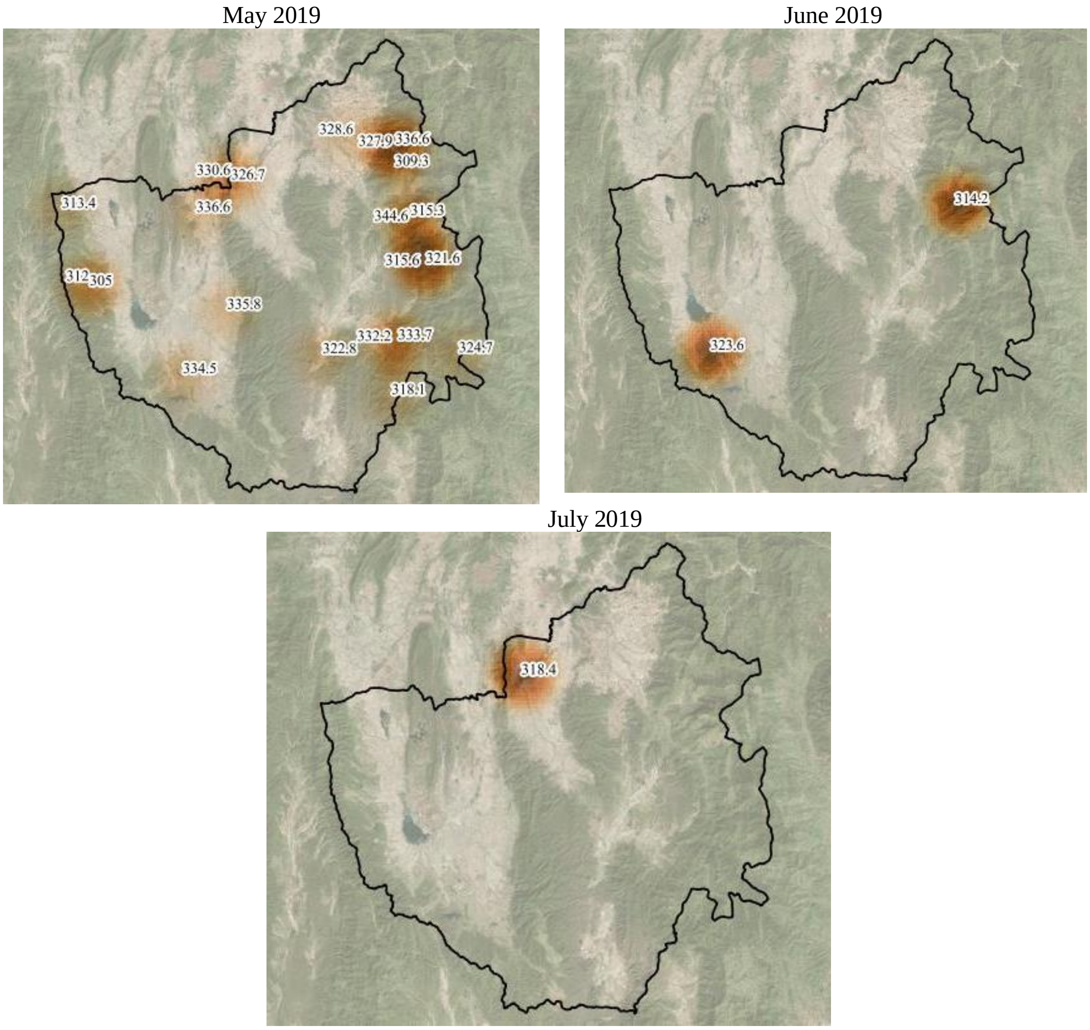

Figure 5: Wildfire time series in the year of 2019 with totally 532 of hotspots

For recovery a GIS can be used as a damage assessment tool useful for mapping the extent of burn, understanding biological responses due to differential surface heating (i.e. fire severity) and quantifying extent and pattern of burned areas (SANPA, 2012). This article aimed at providing useful information on wildfire hotspots detection and time series management using QGIS and mapping their patterns and dynamics of wildfire burning. Time manager plugin proved to be a valuable tool to analyze the space-time change over time.

The study revealed useful information on brightness temperature time series during 2014 – 2019 risk assessment to wildfire. In 2019, the total number was 532 points, which is the highest recorded of hotspot detection for the current decade and the lower in 2018 with hotspots detection 140 points. Moreover, the highest hotspot was in March with a percentage of 46.17%, while hotspot in the April was 31.76% respectively. In Thailand, wildfire is occurred in summer season especially February to May.

The wildfire hotspots detection by using brightness temperature (Kelvin) also plays important role and it was seen that wildfire hotspots is generally prevalent in the Phayao province during the months of March to April 2019. The highest brightness temperature was shown 405.7 Kelvin (date: 2019-04-15) in Pong district and lowest brightness temperature was shown 301.2 Kelvin (date: 2019-03-29) in Chiang Kham district. Approximately 323.20 Kelvin is averaged of brightness temperature in the province during 2014 – 2019. However, the limitation in the study was the wildfire hotspots detection data. Due to boundary of administrative line, some hotspots point near the territorial of Phayao province were moved and wildfire hotspots data for these areas was not available for small area.

Table 4: Summary of hotspot from 2014 – 2019 by district

District	Summary of hotspot from 2014 - 2019	Percent (%)
Chiang Kham	377	18.92
Chiang Muan	217	10.89
Dok Kham Tai	112	5.62
Jun	96	4.82
Mae Jai	46	2.31
Muang	269	13.50
Pong	779	39.09
Thu Kham Yaow	40	2.01
Thu Sang	57	2.86
Total	**1,993**	**100.00**

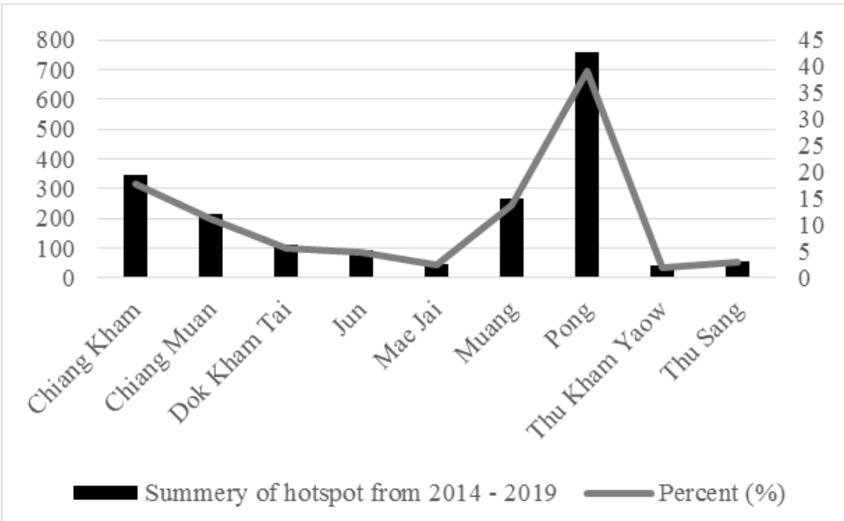

Figure 6: Wildfire hotspot by district from 2014 – 2019

5. Conclusions

The results showed that proposed methods and tools can be beneficial for forest fire control officers to visualize and appreciate the distribution and trends of diffusion shapes of hotspots and to prepare warning and awareness to the atmosphere. Wildfire hotspots detection diffusion patterns by using brightness temperate (Kelvin) may provide useful information to support forest fire control officers to control and predict wildfire spread over hotspot areas only rather than for a whole province. Forest fire control officers may service the model to plan an approach to control hotspot by the information received on supply and hotspots for various day or week. This may save cost and time and make Ministry of Natural Resources and Environment efforts more efficient. In future it would be important to have regular daily analysis for several years to converge faster at hotspots locations and be equipped for deterrent trials. The criteria were acquisition date and time of wildfire detection of each year very important to predict burn area. The methodology is based on notions on general principles of geostatistics and has the potential for application for other disaster.

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