

STUDY OF ACTIVE FIRE EVOLUTION IN NORTHERN THAILAND USING KERNEL DENSITY ESTIMATION (KDE)

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Abstract

Biomass burning is one of the major causes of air pollution in Northern part of Thailand releasing toxic compounds especially particulate matters causing adverse health effects, socio-economic impacts, and poor visibility. Patterns and causes of biomass burning remain unclear especially within the reserved forest areas, where thoroughly field survey is almost impossible. Currently, active fires can be near real-time monitored by satellites, mainly from Moderate Resolution Imaging Spectroradiometer (MODIS) and a newer system called Visible Infrared Imaging Radiometer Suite (VIIRS) which can provide better resolution on both time and space. In this paper, Space-Time Kernel Density Estimation (ST-KDE) was used to analyze historical active fire data from VIIRS during 1th December 2019 and 4th April 2020. The algorithm can reveal possible dense areas as well as frame periods and temporal dynamic of the fire. The 3D space-time visualization of the result allows users to compare between different time so it can reveal the spatial change of active fire areas especially how small areas built up larger areas. Possible ignition areas can also be identified. The comparison of the results with news and field surveys collected from the government was also reported. The information is useful for fire prevention and fire forecasting. *Keywords: VIIRS, Kernel Density Estimation, Spatio-temporal, Active fire*

1. INTRODUCTION

The Northern part of Thailand is facing severe air pollution especially during Winter between December and April. The previous studies have shown that the two main sources of small particulate matters (PM10 and PM2.5) are from vehicular exhausts and open biomass burning, especially from forest fire and combustion of agricultural residues [1, 2]. Although various schemes including fire bans, fire restriction and prescribed burns are strictly implemented in Northern area, forest fire is becoming worse during the last 10 years.

Understanding fire regime, including ignition points and size of fires, especially where the area is hardly to be reached by field observation, is important to fire management. Nowadays, active fire can be detected and monitored by satellite sensors. One is from Moderate Resolution Imaging Spectroradiometer (MODIS), which is installed on Terra and Aqua EOS satellites. The newer one is Visible Infrared Imaging Radiometer Suite (VIIRS) on Suomi-NPP and NOAA-20 satellites which can provide better resolutions on both space and time. The data is available through NASA's website. This research used VIIRS since the system provides better resolution then it can better detect fires that have been overlooked.

Several studies applied clustering analysis to analyze spatial-temporal forest fire data. The result from cluster analysis can reveal hotspots with ignition date. Artés, et al. [3] creates a quick map of real-time MODIS and VIIRS data using DBSCAN technique with concave hull to cluster fires. Similar work has been done by [4]. Tonini, et al. [5] and Nhongo, et al. [6] employed KDE to visualize clusters of forest fire as a smooth surface. Koutsias, et al. [7] applied KDE to identify ignition points from coarse data.

This research applied space-time KDE similar to [4] and [3] with forest fire data in Northern part of Thailand. The result of space-time KDE will be discussed.

2. DATA

Our active fire data was VIIRS NOAA-20 active fire data from NASA's Fire Information for Resource Management System (FIRMS) website (https://firms.modaps.eosdis.nasa.gov/active_fire/#firms-shapefile). The data was in shape file format (.shp) with approximately 375 meters spatial resolution. Pixels of active fires were marked as points at their centroids. Only nominal and high confidence pixels were selected to avoid sun glint



misdetection.

The data between 12th December 2019 and 30th April 2020 were considered because it was the period of haze season. The satellite took photos twice a day—around 6 am and 6 pm.

The Northern part of Thailand, including 9 provinces which are: Chiang Rai, Chiang Mai, Lamphun, Phayao, Lampang, Mae Hong Son, Nan, and Uttaradit, were focused in this study. Most of the area in Northern part is dominated by mountainous areas with reserved forest. The area of the data covers nine provinces as shown in Fig.1.



Figure 1 The nine provinces study area with reserved forest area highlighted (in green)

3. METHODS

The data, containing both location and time, was processed using space-time kernel density estimation method (STKDE) [8]. The STKDE enhanced the visualization by highlighting dense areas. The space-time KDE is defined as:

$$\hat{f}(x, y, t) = \frac{1}{nh_s^2 h_t} \sum_{i=1}^n K_s(\frac{x - x_i}{h_s}, \frac{y - y_i}{h_s}) K_t(\frac{t - t_i}{h_t}) \quad (1)$$

where $\hat{f}(x, y, t)$ is the density estimate at location (x, y, t), h_s and h_t are the spatial and temporal bandwidths, n is the total number of points, x is any point on a space, x_i is ith observation. $i; i = 1,2,3,...,n, K_s$ and K_t are the spatial and temporal kernel functions.

In this research, SciPy, a Python library was employed. Gaussian was chosen as a kernel function on both space and time. Optimal bandwidth was calculated automatically by the library. The result from the library are density values assigned on every input location, which are different from other libraries that interpolate density over small grid intervals within the specified region.

RESULTS

Fig.2 shows the daily number of active fire spots. The number of spots increased significantly since February 2020 and remained high until the end of April 2020. The fluctuation of the graph also reveals the difference number of fires between daytime and nighttime.



Figure 2 Daily number of active fire spots

The result of STKDE in space-time cube is shown in Fig.3. The density was represented as color brightness. The dense areas are the areas in which points of active fire were contiguous. The figure highlighted the dense area of fires around the regions of Lamphun, Mae Hong Son, Chiang Mai, and some part of Chiang Rai.



Top view





Figure 3 The result of STKDE in 3D space-time cube

To make it clearer, the result of STKDE was divided into time intervals as shown in Fig.4. During December 2019 and January 2020, the active fires scattered with low density. The fires were mostly located in Chiang Rai and a part of Phayao district and they were scattered. There were also some low-density spots in the Southern part (Lampoon and Uttradit) as well. The fires the Southern part spread out and were denser during 19 January 2020 and 13 February 2020 covered the areas of Southern Chiang Mai, most areas in Lampoon, Lampang, and Phrae. The fire also spread in Southern part of Nan. Then, the dense fire areas in the West (Mae Hongson) and Northern part of Chiang Mai (Chaiprakarn, Chiangdao, Phrao, and Mae Tang subdistricts) occurred the mid of February 2020. It was possible that the fire in Mae Hongson spread from Myanmar border. There were still fires in Uttradit in the mid of February, but the fires moved to the North, which are forest reserve areas. Between 9 March 2020 and 3 April 2020 seemed to be the most severe fire period. The fire spread dramatically on the Northern part of Thailand. The high-density values in Mae Hongson, the North of Chiangmai (Sameong and Pai subdistricts), and Northern part of Nan (Tung Chang and Chaloem Phra Kiat subdistricts) indicates there were persistent fire areas. However, the fire spots did not spread into municipal areas. Most of the fire spots disappeared in April 2020 but the high density of fires in Northern part of Chiang Mai were still remained.





To highlight the densest area, the areas where the density was higher than 0.8 quantile is shown in Fig. 5. The top view in Fig.5 suggests the three very dense areas. The earliest dense fire area occurred in Hot subdistrict of Chiang Mai province in January 2020. The biggest dense area covered Mae Hong Son and Northern part of Chiang Mai province. There were also dense fire areas occurred in March covered the areas of Thung Chang and Chaloem Phra Kiat subdistricts of Nan province.











SIDE VIEW

Figure 5 KDE result with more than 0.8 quantile

5. CONCLUSIONS AND DISCUSSIONS

Northern part of Thialand faces severe air pollution every year causing by forest fire and crop residue burning. This study applied STKDE to analyze active fire data from VIIRS. The density calculated from STKDE highlights dense area of fire in both space and time, so the result suggests contiguous and persistent area of fire.

The result shows that the fire scattered in December in two areas. One was on the Southern part of Northern Thailand. Another area covered Chiang Rai and Phayao district. The fires spread out to Central part in the following month. STKDE highlights dense fire area in Mae Hong Son and a part of Chiangmai starting after the mid of February until the beginning of March. Another dense fire area was in Mae Hong Son, which might spread from Myanmar border. The result of this study pointed out that Samoeng, Pai, and Chiang Dao subdistrict in Chiang Mai were the biggest dense fire areas which occurred for many days and it should be focused on during March. The result highlighted that cross-boundary fires is one of an important issue, especially the Thai - Myanmar border in Mae Hong Son province. The result also reveals heterogenous fire pattern over time, which might be the result from burning ban applied in different time. The reason of such space-time patterns should be further explored.

The result of this study can be used in fire management. It can allow firefighters to evaluate fire areas for preparing firefighting equipment. The result can also point out the area that should be focused. By comparing the result with other years, fire-prone areas can be identified.

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