MODIS-derived fire spatial and temporal distribution during haze season in Southeast Asia using empirical orthogonal function

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Abstract. One of the efforts to control the forest and land fire disasters which affect on the biomass burning haze is fire hotspots monitoring. Biomass burning haze in Southeast Asia (SEA) has become a recurring annual issue. This study aims to determine the spatial and temporal distribution of fire hotspots along SEA, so that it can serve as guidance for efforts to control them. The hotspot data used is derived from NASA’s Fire Information for Resource Management System (FIRMS) MODIS sensors which is collected from 2001-2020. Spatial analysis of the re-gridded data shows the highest burning activities over SEA occurred in Feb-Apr, with >2000 fire events in the Indo-China area and >1000 fire events in Sumatra and Borneo. Empirical Orthogonal Function (EOF) was performed on monthly total hotspot data for 228 months for determining dominant patterns spatially and temporally. Based on the EOF analysis results, the three major modes have achieved a total variance of 71 %. The first mode (EOF1) explains 65 % of the total variance. The second (EOF2) and third (EOF3) modes account for 3.60 % and 2.97 % of the total variance respectively. The first and the third principal component identified high loadings over the Indo-China and Sumatra-Borneo regions respectively. Whereas the second principal component separates the fire areas into China and Indo-China region. Inter-annual pattern is dominant in the EOF1, while the inter-seasonal pattern is dominant in EOF2 and EOF3. ENSO, IOD, and MJO are factors that influence the pattern of the determined principal components. The result of this study provides general understanding on how the fire events varied over the past two decades in SEA.

Keywords: Fire hotspot, Biomass burning haze, Southeast Asia, Empirical Orthogonal Function, Principal Component Analysis

Track Name: Atmospheric Chemistry and Physics
1. Introduction

Widespread burning of forest which leads to transboundary haze has occurred almost every year in Southeast Asia (SEA). Transboundary haze causes various adverse effects in the countries that experience it, including health problems [1][2][3] and economic losses [4][5][6]. The high incidence of pollution due to transboundary haze has also led to an increase in household consumption of water and electricity in Singapore [7]. Recent studies reported that smoke haze occurrence in Malaysia has great negative consequences to human health and economic loss [8][9]. During the Southwest Monsoon period, the biomass burning event has greatly affected the concentration conditions of particulate matter in Southeast Asia [10]. The existence of various negative impacts called for the need to develop the efforts to mitigate the forest fire disaster in SEA. One of the first steps is to understand the condition of fire events that have occurred so far.

The distribution of the burning pollutants cannot be separated from the regional climate and weather characteristics, as in the study conducted in Northern China is also analyzed that various research sites exhibited different variability of aerosols based on meteorological, fuel type, elevation, and biomass burning sources [11]. Another research also studied on the connection of inter-annual climate variability, air quality, and biomass burning in Sumatra, Indonesia found a significant linear relationship between the visibility and ENSO signal as the visibility decrease occurred about 3 months earlier than peak ENSO [12].

This study aims to examine the principal temporal modes of fire activities and their spatial distribution in the Southeast Asia region using EOF to understand the role of the fire activities in the research region. The empirical orthogonal function (EOF) analysis is a method that is often used to study possible spatial modes of environmental variables and climatic data (i.e. patterns) and how they change with time. The fire activities data represented with the total of hotspots is also analyzed across the research area. The fire hotspot data is extracted from the Moderate Resolution Imaging Spectroradiometer (MODIS) data for the analysis of fire regimes in different areas [13]. Study of wildfires in Israel developed mapping methods of fire scars from MODIS imagery to examine the temporal and spatial patterns of wildfires in the 2000s [14]. MODIS hotspots are reliable to detect true burned areas, with only 1.8 % of them are not associated with actual burned patches, except for urban areas where very high commission errors were observed [15]. Spatial analysis to see hotspot distribution using MODIS data has been done in the previous paper [16][17][18]. The result of this study provides general understanding on how varied the fire events from MODIS data has been over the past two decades in SEA. The information of the spatial and temporal distribution of the fire hotspot events in the studied domain can become reference for forest fire disaster management and mitigation in SEA.

2. Data and Methods

2.1 Data

This research uses historical data on fire activities for the last 20 years, starting from January 2001 to December 2020. Fire activity data is obtained from NASA's Fire Information for Resource Management System (FIRMS). NASA FIRMS provides historical archive and near-real-time active fire products from the MODIS sensor which uses multiple channels to detect thermal anomalies [19]. The two satellites used are MOD14 (Terra) and MYD14 (Aqua) [20]. The thermal anomalies represent the center of a 1 km pixel that is corrected by the Terra and Aqua using thermal detection algorithm [20]. The daily data for fire activities used in the research are summed from Terra and Aqua satellites. Fire activity data are selected based on the confidence level of the data. Giglio, 2015 developed three confidence levels for hotspot information (Table 1). MODIS hotspots are very reliable to detect true burned areas [15]. As data validation process, it is necessary to filter the data before processing for the next level of analysis. A high level of confidence will result in fewer false alarms [21]. Hence, only data with a confidence level above 80% is used in this study. The research area focuses on the 90° E-130° E and 40° N-10° S domain that covers Southeast Asia and the southern China (Figure 1).
Table 1. Confidence levels of hotspot [20].

| Range          | Confidence Class |
|---------------|------------------|
| 0 % ≤ C < 30 %| Low              |
| 30 % ≤ C < 80 %| Nominal          |
| 80 % ≤ C ≤ 100%| High             |

2.2 Methods

Daily hotspot data in .csv (Comma Separated Values) format is regridded onto 0.5°x0.5° resolution using the R program into monthly data and stored in matrix form in the netCDF format. The monthly data is averaged over 20 years to see the spatial distribution of hotspots. The re-gridded data of fire activities is processed further using Empirical Orthogonal Function (EOF). EOF analysis is a multivariate analysis technique first introduced by [22] and developed independently by [23]. The main purpose of EOF analysis is to filter the large number of data variables to only a few representative variables, without changing most of the variance to describe the data [24].

One way to minimize multicollinearity is spatial dimensions reduction or find new variables which are linear combinations of the original variables provided that the new variables were not correlated, namely EOF method based on the Eigenvalue Problem (EVP). This method is better known as Principal Component Analysis (PCA) method. The latter was used to analyze spatial and temporal variability of PM$_{10}$ concentration across Malaysia [25]. The data were analyzed by means of the rotated principal component analysis and showed the variability of the PM$_{10}$ concentration can be decomposed into four dominant modes in Malaysia. The most recent research on PCA to reduce variance from hotspots was carried out to identify two geographical regions for variance of biomass burning activities in Indo-China [26].

3. Result and Discussion

3.1 Fire Activities Distribution

The results of the spatial map of grid hotspot method with a resolution of 0.5°x0.5° is capable of explaining the distribution of the fire activities within the research area. Hotspots are mapped spatially and cumulatively over 20 years resulting in a varied distribution pattern. The result of MODIS satellite data processing with a confidence level of above 80 % with gridding methods generally shows that hotspots appear each month in different numbers and areas of the hotspot. The number of hotspots for
20 years monthly ranges from 0 up to more than 25,000 hotspots (Figure 2). This is related to the climate phenomenon which also varies in each territory.

Fire activities in January varied from a range of 50 to 5,000 total fire activities. The highest fire activities throughout the research area in January occurred in some parts of Indo-China region (Thailand, Laos, Cambodia, Vietnam, Myanmar). The value decreased gradually in the northern and southern part of Indo-China region. In February, fire activities increased, and it shows that the highest area of fire activities still located in the same location as the previous month. Total fire activities for this month fall in the range of 100 to 10,000 hotspots. Even though the number of burning activities has increased, it does not show a significant expansion of the burning activities area.
March and April were the months with the worst fire activities as we can see from the monthly average throughout the study years, the number of hotspot occurrences is the highest. In April there were more than 15,000 fire activities, while in March there were more than 25,000 fire activities. The areas that had the highest number of burning activities were in Myanmar and Laos, with the number of hotspots over 25,000. In general, the area of Indo-China and the Philippine archipelago had the worst total of fire activities in both March and April. The area of the Malay Peninsula, a small part of Sumatra, and the coast of the Borneo Island also experienced an increase in the incidence of total fire activities reaching a range of total fire activities from 200 to 15,000. These are the months with the highest fire activities in the Malay Peninsula region. The highest hotspot occurrence value in the Malay Peninsula region is concentrated in the eastern part of the Malay Peninsula and gradually decreased to the west of the Peninsula area. The highest number of total hotspots in Sumatra Island is concentrated in the part of Sumatra which borders the Malacca Strait. The southeastern flank of Mainland China also has an increase in the number of total fire activities. The initial condition in January-February in southeast Mainland China only reached 5,000 fire activities, but it increased gradually and reached 15,000 fire activities in March and April.

A decrease in the occurrence of total fire activities in the research areas occurred in May and June, in addition to a decrease in total fire activities in the Indo-China region and the Philippine archipelago, there was also a reduction in the area affected. Fire activities that occur in the Indo-China region only occur in coastal areas, namely Vietnam and Cambodia. The difference compared to the previous months
is that there has been a shift in areas that have high fire activities, which moved from the Indo-China region to the Sumatera region. In contrast to the decrease in area in the Indo-China and China regions, the total fire activities in the Borneo area began to expand in July and August. In July, the total fire activities that occurred in the research area were in the range of 50 to 5000, with the highest total fire activities occurring in Sumatra and the west part of Borneo. Fire activities in Java, Bali, Nusa Island, and Sulawesi began to emerge. In August, the area of fire activities in the Borneo area expanded and experienced an increase in total fire activities. The highest fire activities occurred in the Sumatera and Borneo regions with a total range of total fire activities reaching a range of 1,000 to 5,000. Fire activities on the Malay Peninsula ranged from 100 to 5,000 fire activities, while the occurrence of total fire activities in Indo-China was decreasing.

September is the peak of total fire activities in the regions of Borneo and Sumatra. The total range of fire activities occurs up to a range of 15,000. While the conditions of fire activities on the Malay Peninsula are in the same condition as the previous month, there have been occurrences of fire activities in eastern of China with a range of 100-2,000 total fire activities. Total fire activities were gradually reduced again in the Sumatera and Borneo region in October until December. In October, fire activities in China and the eastern coast of Indo-China began to re-emerge. The total value of its fire activities continued to increase from October to December in these areas and it expanded to Indo-China in December.

March and April are months with the highest number of hotspots, and it is located in the Indo-China region. The fire activities not only have an impact in the Indo-China region, but also have an impact on the surrounding area. Burning activities will create haze and how the haze will affect the surrounding environment depends on the conditions of the atmosphere.

### Table 2. Statistic for the first three PC.

|        | PC1   | PC2   | PC3  |
|--------|-------|-------|------|
| Variance explained (%)| 65.04 % | 3.60 % | 2.96 % |
| Cumulative variance (%)| 65.04 % | 68.64 % | 71.6 % |

#### 3.2 EOF Spatial – Temporal Distribution

To see how the variation of the total hotspots in this area, EOF analysis was performed. The variances explained by the first three principal components are shown in Table 2. The first four principal components explained 71.60 % of the total variances. A large portion of the total variability was captured by the first principal component (PC1). PC1 explained the largest fraction of variance of approximately 65.04 %. The second mode (PC2) explaining 3.60 % of the total variance followed by the third principal component (PC3) explained 2.96 % of the total variance. Subsequent principal components with a lower fraction of explained variance were not considered for further analysis.
Figure 3 shows the principal mode of the EOF. The principal component score of the EOF mode shows the value or contribution of each major component to each unit of observation. The principal component value can range between positive and negative. A high positive (negative) value means that the EOF mode makes a large contribution and has a positive (negative) effect on the unit of observation. Figure 3a shows the principal mode of total fire hotspot for PC1 in the study area. The variability of total fire hotspots has a scale ranging from 0 to -0.04. The result identified high loadings over the Indo-China region and decreased gradually to the southern part of Indo-China. The EOF1 results indicate that Indo-China region has the large contribution to variability of the total of fire hotspots during 2001-2020.

PC2 has a positive and negative variability of total fire hotspots with the range of the variability of total fire hotspots from -0.06 to 0.06 (Figure 3b). The second principal component separates the different fire areas, positive loadings is located in the southeast China and southeast part of the Borneo Island; and the opposite loadings is on the Indo-China region. The result in this mode shows the high variability of total fire hotspots with a positive contribution in the southeast part of the China region and southeast part of the Borneo Island; and negative contribution in the Indo-China region. Loadings in the southern part of Sumatra, southern part of Borneo, and the eastern coast of Vietnam are shown in PC3, while Indo-China showed weak loadings (Figure 3c). The variability of total fire hotspots has a positive scale ranging from 0 to 0.06. In EOF3 mode, these areas contribute the most to the variability of total fire hotspots.
Figure 4 shows the principal component time series of PC1 that the PC1 region is dominated by negative variables throughout the years. In this first mode of principal component, an annual pattern occurs. Although it recurs every year in the cycle, the magnitude fluctuates every year. The peak always occurs at the beginning of the years and the strongest were in 2004, 2007, and 2010. To see what factors influenced the incidence of fire activities, it is necessary to look at the system that can give strong effect to the weather and climate over the Indo-China region.
The second and third PC give an inter-seasonal variability (figure 4b and 4c). There are positive and negative variations in PC2. However, similar to PC1, there was a high negative variable value for PC2 and PC3 in 2010. Looking at the PC2 area which the negative loading is also located in the Indo-China area, it can be said that the strong factor that influences PC1 also becomes an influence on PC2. PC3 was more dominant in having a high variable value in its positive value throughout the period except in 2010.

3.3 Hotspots and Weather Anomalies in Southeast Asia
The variability of fire activities is formed by similar factors that shape climate patterns. El Niño Southern Oscillation (ENSO) is known to dominate the inter-annual fire signal in Indo-China and Maritime Continent (MC). ENSO, as well as Indian Ocean Dipole (IOD), contributed as the inter-annual factor for the incidence of fire activities in Indonesia [27]. Warm phase ENSO conditions trigger the negative summertime precipitation anomalies in the MC. Fire activity increases dramatically with decreases of the precipitation. Likewise, IOD can be an indirect factor in fire activity, because of its effect on precipitation. During the strong ENSO years and a positive phase of the IOD, precipitation is less than usual in the Indo-China region. Conversely, during the La Niña years and a negative phase of the IOD, rainfall throughout the Indo-China Peninsula is above normal, except in parts of central Laos and northern Vietnam [28]. Likewise in the MC, the mixed diversity of ENSO and IOD events leads autumn droughts and is linked to frequent rampant forest wildfires [29].

Time series indices of ENSO and IOD; and the amplitude of MJO phases 4 and 5 are presented in the 4d-f graph to see the pattern similarity between the indices and PC value. By comparing the patterns, it can be seen whether the climate indices affect the PC value. On PC1 conditions, where the main contributors are in the Indo-China region, can be related to ENSO or IOD. The highest score for principal component on PC1 at the beginning of 2010 reached -6.10 when the ENSO moderate occurs in the end of 2009 until the beginning of 2010 (Figure 4d), coupling with the strong positive IOD (Figure 4e). Likewise at the end of 2002, early of 2007, 2016, and 2019, when the ENSO event occurred, there was also an increase in the signal of PC1. In early 2007, the score reached more than -5.00 which was influenced by the existence of a moderate El Nino scale that was active in those years and a positive IOD at the beginning of 2007. The signal fire was weakest from 2017 to 2018 within the study period, non-ENSO and non-IOD year occurred. Previous study reported that the increase in biomass burning activities over northern Indo-China is related to the intensification of the India-Burma Trough in the lower and middle troposphere as the result of the increase in north westerly wind behind the India-Burma Trough which could advect dryer air from the higher latitude to northern Indo-China. Dryer condition can help promote the local biomass burning activities. Furthermore, 2010 was a year with strong India-Burma Trough and SCSA so that the amount of biomass burning over northern Indo-China is greater than other years [26].

PC2 and PC3 have seasonal patterns during the study period. The peak of the PC of fire events occurs typically once or twice per season. PC2 is dominated by negative principal component. Furthermore, PC2 and PC3 in the year 2010 has a strong negative value as in PC1, means that of the El Nino-positive IOD years have increased the fire event occurrences in all cases. This is similar to the previous study where the combined effect of El Nino and positive IOD events are stronger compared to individual event, but depending on the season [30].

The time series of PC2 generally has two signal peaks, namely a positive signal at the beginning of the year and a negative signal at the end of the year. Recent research on the Inter Tropical Convergence Zone (ITCZ) mentioned that seasonal migration of ITCZ is related to the fire events in the MC [31]. Winter monsoon is formed by southern extent of ITCZ and lead the fire activity in Indo-China. Otherwise, northward extent of the ITCZ will form a Summer Monsoon and lead fire activity in the MC.

PC3 has a positive value of PC scale ranging from 0 to 0.06. The inter-seasonal pattern of the burning events that occurs can be caused by the MJO. If ENSO phase is the strongest indicator of fire events, the MJO often dictates when observed burning occurs in any given season [31]. El Nino events at the end of 2002, early of 2005, early of 2010, end of 2015, and early of 2019 caused an increase in positive
signal on PC3. Sumatra and western Borneo are influenced by the phase of the MJO more than the other regions. Observed burning activity on the islands of Sumatra was more influenced by the phase and strength of the MJO [32]. Figure 4f shows the amplitude of the MJO during the study period. MJO is a tropical disturbance that propagates eastward along the tropics with a cycle of 30-60 days. The MJO phases which are related to climatic conditions in the Maritime Continent are MJO phases 4 and 5. A strong positive value for PC3 occurred in September of 2015 and a strong negative value in March of 2010. MJO entered phases 4 and 5 in September in 2015 with a strong MJO in the middle of the month, while MJO entered phases 4 and 5 in end of March 2010 with a strong MJO (Figure 4f). In August 2002 and September 2019, the principal component value was valued at more than 4.00, along with the entry of strong MJO into phases 4 and 5 that month (Figure 4f).

The highest variable value that occurred in 2015 can be affected by the ENSO activities as the PC3 region which is located in the southeast part of Sumatra and Borneo have known in many studies has correlation with ENSO activity [33][34][35]. PC scores give positive value above 3.00 in March 2004, August-October 2006, and September 2019 at the same time with strong MJO, while August 2004 and October 2015 occurred during non-MJOs. Knowing how the variability of hotspot events and the complexity of meteorology and climatology elements that can influence the variability of the hotspot need to be studied in more detail for each phenomenon. Furthermore, to see in more detail related to factors that affect hotspot occurrences, future study is suggested to use anomaly data of hotspots. By using the anomaly data, the influence factors are expected to be caught more clearly. Better understanding from the study with lead to mitigation measures which are important under a changing climate in the future.

4. Conclusion
The distribution of hotspot data for 2001-2020 in the study area is analyzed. The results shows that the distribution of hotspots vary each month over the Southeast Asia. EOF analysis conducted on monthly total hotspot data determines three dominant patterns spatially and temporally. The first mode (EOF1) explains 65% of the total variance and identify high loadings over the Indo-China. The second (EOF2) and third (EOF3) EOF methods account for 3.60% and 2.97% of the total variance respectively. The second principal component separates the fire areas into China and Indo-China region, however the third principal component identify high loading in Sumatra-Borneo region. Annual pattern is dominant in the EOF1, while the inter-seasonal pattern is dominant in EOF2 and EOF3. Coupling of El Nino and positive IOD are factors that form the annual pattern on EOF1 which shows that loading is concentrated in the Indo-China region. Meanwhile, EOF2 and EOF3 that show the loading for MC, are more influenced by the presence of inter-seasonal factors such as MJO, although in certain years, the annual factor is stronger and still affects the incidence of fire events, as we know that MC climate system also linked with ENSO and IOD. Future studies need to discuss in more detail what driven factors influence the pattern of the determined principal components.

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