Quantifying ENSO and IOD impact to hotspot in Indonesia based on Heterogeneous Correlation Map (HCM)

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Abstract. Land and forest fires in Indonesia have a long history. Several major land and forest fires in Indonesia such as in 2002, 2006, 2009, 2015, and 2019 were associated impacts of the ENSO and IOD phenomena. This research aims to find out how much ENSO and IOD impact to land and forest fires in Indonesia. This research used Sea Surface Temperature (SST) anomalies in the Nino 3.4 index region and DMI region as indicators for ENSO and IOD, while hotspot was used as an indicator of land and forest fires in Indonesia. Heterogeneous Correlation Map (HCM) was used to describe the correlation of hotspots with ENSO variance and IOD variance on spatial patterns. The HCM obtained from Singular Value Decomposition (SVD) analysis used to identify the variances. The result showed that anomalies SST in Nino 3.4 index region had greater correlation with hotspot in Provinces of South Kalimantan, East Kalimantan, and Central Kalimantan than those of other regions in Indonesia. Anomalies SST in DMI region had greater correlation with hotspot in Provinces of Lampung, South Sumatera, West Kalimantan, South Kalimantan and Central Kalimantan, than those of other regions in Indonesia. Temporal analysis showed that the largest variance of hotspot in Indonesia mostly in the mid of the year.

1. Introduction

Land and forest fires in Indonesia have a long history. Several major land and forest fires in Indonesia such as in 2002, 2004, 2006, 2009, 2015, and 2019 were associated impacts of ENSO and IOD phenomena. This research aims to find out how much ENSO and IOD impact to land and forest fires in Indonesia. This research used Sea Surface Temperature (SST) anomalies in the Nino 3.4 index region and DMI region as indicators for ENSO and IOD, while hotspot was used as an indicator of land and forest fires in Indonesia. Heterogeneous Correlation Map (HCM) was used to describe the correlation of hotspots with ENSO variance and IOD variance on spatial patterns. The HCM obtained from Singular Value Decomposition (SVD) analysis used to identify the variances. The result showed that anomalies SST in Nino 3.4 index region had greater correlation with hotspot in Provinces of South Kalimantan, East Kalimantan, and Central Kalimantan than those of other regions in Indonesia. Anomalies SST in DMI region had greater correlation with hotspot in Provinces of Lampung, South Sumatera, West Kalimantan, South Kalimantan and Central Kalimantan, than those of other regions in Indonesia. Temporal analysis showed that the largest variance of hotspot in Indonesia mostly in the mid of the year.
Figure 1. Time series (a) Hotspot, (b) Nino 3.4 Index and dipole mode index.

Figure 1(a) shows a time series of hotspots average in Indonesia as an indicator of land and forest fires. Figure 1(b) provides a time series of Nino 3.4 index as an indicator of ENSO and time series of DMI as an indicator of IOD. Figure 1(b) shows that Nino 3.4 index has value larger than 1 in 2002, 2006, 2009, and 2015. In those years where the Nino 3.4 index larger than 1, simultaneously, the number of hotspots are larger than 10000. There were also several years where the number of hotspots are larger than 10000, along with the Nino 3.4 index and DMI larger than 1 in 2006 and 2016. In 2019, the number of hotspots are larger than 10000, along with the DMI larger than 1. This fact could indicate the impact of ENSO and IOD to hotspot in Indonesia. This research is to characterize the impact of ENSO and IOD to hotspots occurrence in Indonesia.

This research utilizes the analysis of Singular Value Decomposition (SVD) to characterize the impacts of ENSO and IOD to hotspot in Indonesia. The results of the SVD analysis are presented in Heterogeneous Correlation Map (HCM) to illustrate the correlation of variances hotspots in Indonesia with ENSO and IOD. SVD results will also be analyzed temporally.

2. Methods

2.1. SVD analysis

Analysis of Singular Value Decomposition (SVD) generally was used to identify spatial and temporal patterns that are independent of a data, where SVD analysis explains the fraction of the covariance of data [5].

This research uses the OISST dataset from the National Oceanic and Atmospheric Administration (NOAA) and hotspot dataset in Indonesia in the area of 6°N-11°S, 95°E-141°E, that has 0.25°×0.25° degree with time series monthly from 2001 to 2019 obtained from the Agency from Meteorology Climatology and Geophysics (BMKG). SVD analysis was applied on the cross-covariance matrix that was constructed from the matrix of hotspot data (P) and the matrix of ENSO or IOD data (S). The cross-covariance is obtained from the product of P and S^T as follows

\[ C = P S^T. \]

Applying the SVD, the temporal average of C was filtered out, to facilitate easier interpretation of the results in terms of their anomalies. SVD reduction on the cross-covariance matrix C will result in

\[ C = U \Sigma V^T. \]
where $\mathbf{U}$ is singular vector of hotspot matrix and $\mathbf{V}$ is singular vector of ENSO or IOD matrix, while $\mathbf{\Sigma}$ is diagonal matrix that contains singular values of cross-covariance matrix $\mathbf{C}$ [5].

Spatial patterns and temporal patterns can be obtained from the modes of singular vectors $\mathbf{U}$ and $\mathbf{V}$. This research used only two modes to be analyzed, and are considered sufficient to describe the hotspot variability in Indonesia [5,6].

2.2. Temporal analysis
Temporal analysis was performed on the expansion coefficients of each data matrix. The expansion coefficient for hotspots in Indonesia was obtained from the product of the matrix $\mathbf{U}^T$ and matrix $\mathbf{P}$, and the expansion coefficient of ENSO or IOD was obtained from the product matrix $\mathbf{V}^T$ and matrix $\mathbf{S}$. In detail these are given as follows

$$
\mathbf{E}_1 = \mathbf{U}^T \mathbf{P} \\
\mathbf{E}_2 = \mathbf{V}^T \mathbf{S},
$$

where $\mathbf{E}_1$ is temporal pattern of hotspot matrix for each mode, and $\mathbf{E}_2$ is temporal pattern of ENSO or IOD matrix for each mode [7].

2.3. Spatial analysis
Spatial analysis used the Heterogeneous Correlation Map (HCM) to describe the correlation of hotspots in Indonesia with varying values of the ENSO or IOD. HCM hotspots in Indonesia were obtained from the correlation expansion coefficient of variance ENSO or IOD with hotspots matrix in Indonesia $r(\mathbf{E}_2, \mathbf{P})$ [7].

2.4. Variances of data
Variance explained of the mode is a proportion of the singular value of the particular mode to the total sum of the singular values. This is often interpreted as a percentage of which a mode is representing the variability of the total phenomenon [5].

In this research, the temporal average of the cross-covariance matrix was removed. So, the data has reduced its variance to facilitate the SVD decomposition process in capturing the significant variability from the expected mean [7].

3. Results and discussion

3.1. SVD analysis of hotspot in Indonesia with Sea Surface Temperature (SST) Anomalies in Nino 3.4 Region
The El Nino Southern Oscillation (ENSO) significantly influence the Indonesian rainfall [8]. Therefore, ENSO had an impact to land and forest fires in Indonesia during El Nino episode. SVD decomposition of the cross-covariance matrix in the Nino 3.4 region ($5^\circ$N-5$^\circ$S, 170$^\circ$W-90$^\circ$W) [9] was performed in coupling with the hotspot data in Indonesia. The SVD also consider the influence of several different time lags for the analysis. We found that the best result was given by time lag of 2 months. The results of this are shown in Figure 2 below with time lag of 2 months.
Figure 2. (a) HCM of first mode hotspot in Indonesia with SST anomalies in Nino 3.4 region with lag 2 months, (b) HCM of second mode hotspot in Indonesia with SST anomalies in Nino 3.4 region with lag 2 months, (c) temporal patterns of first mode hotspot in Indonesia with SST anomalies in Nino 3.4 region with lag 2 months, (d) temporal patterns of second mode hotspot in Indonesia with SST anomalies in Nino 3.4 region with lag 2 months.

Figure 2(a) shows pattern with variance explained 79.69%. Figure 2(a) shows that most of the Kalimantan has greater correlation than the correlation of other regions in Indonesia, especially in the Provinces of South Kalimantan, East Kalimantan, and Central Kalimantan with the highest correlation ranges from 0.25-0.5. Figure 2(b) shows pattern with variance explained 11.67%. The highest correlation in Figure 2(b) was in the range of 0-0.25. The hotspot correlation with SST anomalies in Nino 3.4 region in the second mode pattern was smaller than first mode pattern, which means that the first mode is more sensitive with SST anomalies in the Nino 3.4 region than the second mode. Figure 2(c) shows the temporal pattern of the first mode variance of hotspot in Indonesia, which mostly occurred in the mid of the year. The highest peak was in 2015, where strong ENSO phenomena occurred during that year as showed in Figure 1. Figure 2(d) shows the temporal patterns second mode of hotspot in Indonesia, which shows the occurrence hotspots in the beginning of the year.

Table 1. Variances and correlations of temporal hotspot patterns of each mode with average of SST anomalies in Nino 3.4 region.

| Modes | Variance  | Correlation |
|-------|-----------|-------------|
| 1     | 79.69%    | 0.291       |
| 2     | 11.67%    | 0.023       |

Table 1 summarizes temporal patterns of hotspots that are more correlated with SST anomalies in Nino 3.4 region. The first mode was the mode with the highest variance and highest correlation with SST anomalies in Nino 3.4 region. This means that SST anomalies in Nino 3.4 was more sensitive on the variance of hotspot in first mode that mostly occurred in the middle of the year, than the variance of hotspots in the second mode that occurred in the beginning of the year. The first mode had greater correlation, so SST anomalies in Nino 3.4 region was more sensitive on HCM patterns in first mode than the second mode. Moreover, SST anomalies in nino 3.4 region was more sensitive in its impact to the Provinces South Kalimantan, East Kalimantan, and Central Kalimantan than other regions in Indonesia.
3.2. SVD hotspot analysis in Indonesia with Sea Surface Temperature (SST) anomalies in DMI Region

IOD was defined by two regions, the western IOD area and the eastern IOD area. The western IOD is defined as SST anomalies in western of Indian Ocean ($10^\circ$S-$0^\circ$, $70^\circ$E-$110^\circ$E) and the eastern IOD is defined as SST anomalies in eastern of Indian Ocean ($10^\circ$S-$10^\circ$N, $50^\circ$E-$70^\circ$E), while the DMI the differences between the western IOD and the eastern IOD [10]. Land and forest fires in Indonesia is more intensive when IOD was positive than when the IOD was negative [11]. Generally, IOD was positive when the western IOD larger than eastern IOD.

In this part of the analysis, we also consider several time lags for the influence of the phenomena. Here we find that the best result was given by lag 0 month. Following this result, Figure 3 below showed the result of SVD with lag 0 month.

![Figure 3](image)

Figure 3. (a) HCM of first mode hotspot in Indonesia with SST anomalies in DMI region with lag 0, (b) HCM of second mode hotspot in Indonesia with SST anomalies in DMI region with lag 0, (c) temporal patterns of first mode hotspot in Indonesia with SST anomalies in DMI region with lag 0, (d) temporal patterns of second mode hotspot in Indonesia with SST anomalies in DMI region with lag 0

Figure 3(a) shows pattern with variance explained 48.44%. Figure 3(a) shows that the correlation in Provinces of Lampung, South Sumatra, West Kalimantan, South Kalimantan and Central Kalimantan was greater than the correlation of other regions in Indonesia. The highest correlation was in the range of 0.25-0.5. Figure 3(b) shows pattern with variance explained 20.88%. In Figure 3(b) the highest correlation was in range of 0-0.25. The hotspot correlation with SST anomalies in DMI region in second mode pattern was smaller than first mode pattern, means the first mode pattern was more sensitive with SST anomalies in DMI region. Figure 3(c) shows the temporal pattern first mode of hotspot in Indonesia, which mostly occurred in the middle of the year. The hotspots with the highest peak also occurred in 2015. Figure 3(d) shows the temporal patterns of second mode hotspot in Indonesia, which there were several years that hotspot occurred in the beginning of the year.

Table 2. Variances and correlations of temporal hotspot patterns of each mode with average of SST anomalies in DMI region.

| Modes | Variance  | Correlation |
|-------|-----------|-------------|
| 1     | 48.44%    | 0.338       |
| 2     | 20.88%    | 0.176       |

Table 2 summarizes temporal patterns of hotspot that are most correlated with SST anomalies in DMI region. The first mode was the mode with the highest variance and highest correlation with SST anomalies in DMI region. This means that SST anomalies in DMI region was more sensitive on variance
of hotspot in first mode that mostly occurred at the middle of the year, than the variance of hotspots in the second mode that occurred at the beginning of the years. The first mode had larger variance, so SST anomalies in DMI region was more sensitive to the HCM patterns in first mode than the second mode. Moreover, SST anomalies in DMI region was more sensitive to the hotspots of Provinces Lampung, South Sumatra, West Kalimantan, South Kalimantan and Central Kalimantan, than other regions in Indonesia.

4. Conclusion
We have analyzed and quantify the impacts of ENSO and IOD events to land and forest fires in Indonesia, mostly on land and forest fires that occurred in the mid of the years. Nino 3.4 index as an indicator of ENSO had more influence to the number of hotspots in the Provinces of South Kalimantan, East Kalimantan, and Central Kalimantan than the other regions in Indonesia. Whilst for the indicator of IOD, DMI had more influence to the number of hotspot in the Provinces of Lampung, South Sumatra, West Kalimantan, South Kalimantan and Central Kalimantan than other regions in Indonesia. The regional coverage that is influenced in its land and forest fire by of ENSO, is less that influenced by IOD, however the opposite is the case in terms of their hotspots as it is indicated by the variance explained of the first mode analysis ENSO (76.69%) is larger than that by IOD (48.44%). Therefore, although region impacted by ENSO was less than IOD, ENSO had more impact to land and forest fires in Indonesia in the context of hotspots numbers or magnitude.

As a consequence of the seasonal climate pattern and annual variability in Indonesia, most of the land and forest fires in Indonesia occurred during the dry season in the middle of the year especially in Provinces of South Kalimantan, East Kalimantan, West Kalimantan, Central Kalimantan, Lampung, and South Sumatra. However, there were also land and forest fire episodes in the beginning of the year in several regions, such as Riau. The result of this research showed that significant/major land and forest fires event that occurred in the middle of the year is more correlated with ENSO and IOD, than land and forest fires events that occurred in the beginning of the years. Knowledge of ENSO and IOD forecasting is therefore important to provide early warnings of land and forest fires, and fire management [11,12].

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