Evaluating Spatial and Temporal Variations of Aerosol Optical Depth and Biomass Burning over Southeast Asia Based on Satellite Data Products

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ABSTRACT

Many severe air quality problems in the major cities of Southeast Asia (SEA) are related to atmospheric aerosols, and these are mainly caused by smoke haze from biomass burning. To better understand the cause and effect relationships for the tempo-spatial distributions of atmospheric aerosols in SEA, a variety of satellite-based Moderate Resolution Imaging Spectroradiometer (MODIS) products of aerosol optical depth (AOD), precipitation, burned area (BA) and fire pixel counts (FC, derived from the active fire product) were collected and processed to evaluate the spatial and temporal variations among atmospheric aerosol, climate factors, and biomass burning in SEA during 2002–2011. High AOD zones (HAZs) located in the continental and maritime portion of SEA are identified through hotspot analysis of AOD maps. The peak AOD, BA and FC months are concentrated in the dry seasons of each HAZ. Although BA and FC are mostly identified in Indochina, the HAZ located in maritime SEA has a comparable level of AOD which may be contributed by the fire-related emissions from peatland in Indonesia. Compared to the commonly used fire-effected area dataset (MCD45 product), BA derived from a hybrid approach (MCD64 product) that considers both active fire (AF) and land change information has higher correlation coefficients with AOD in both HAZs. Linear regression models are then developed for the Indochina and the maritime HAZs, to estimate the level of AOD from the MODIS monthly fire datasets. In general the empirical models can better explain the temporal trends of AOD in HAZs by using AF-based products. The links between regional aerosol and local burning in Indochina SEA are relatively complex due to the cross-boundary transport of aerosol from Southern China.

Keywords: MODIS; Aerosol optical depth; Southeast Asia; Burned area; Active fire.

INTRODUCTION

Biomass burning in tropical Asia emits large amounts of gaseous pollutants and particulate matter, which play an important role in global climate change (Seiler and Crutzen, 1980), and have caused considerable concerns with regard to regional air quality (Marlier et al., 2015). Many severe air quality problems in Southeast Asia (SEA), such as dust, smog and haze pollution, are associated with the smoke aerosol particles originating from fire-related emissions (Streets et al., 2003; Tahir et al., 2013; Aouizerats et al., 2015). For example, emissions from deforestation and land clearing fires in the Sumatra and Kalimantan of Indonesia, triggered a record-breaking smoke-haze episode in Singapore during June 2013 (Velasco and Rastan, 2015). The temporal trend of PM10 in Kuala Lumpur, Malaysia, is dependent on the amount of biomass burning from Sumatra, Indonesia, during south-westerly monsoons (Khan et al., 2015). In Indochina (the continental portion of SEA), a trajectory analysis showed that the tropospheric ozone column in northern Thailand during dry season is enhanced by biomass burning in surrounding regions, including Myanmar, Laos and India (Sonkaew and Macatangay, 2015). Air quality degradation in the neighboring countries of Indonesia or Myanmar has significantly raised the attention of the scientific community with regard to transboundary air pollution (Aouizerats et al., 2015). Examining the links between the spatial-temporal variability patterns of aerosols and fires in SEA is useful for obtaining reliable cause-and-effect relationships in relation to transboundary pollution issues. However, the spatial distribution of smoke aerosol particles in transboundary basins is often driven by regional atmospheric transport patterns, which can be very different from the distribution of fire sources (Freitas et al., 2009; Longo et al., 2010). Additionally, emission events produced by long- or short-lived fires can also lead to different haze conditions, lasting from weeks to several months. Selecting a monitoring dataset which is representative of both temporal and spatial
Satellite remote sensing can be used to monitor atmospheric aerosols, and currently provides the only information available for investigating the spatial-temporal patterns of complex aerosol systems, such as SEA (Reid et al., 2013). Satellite sensors characterize key aerosol properties, such as the aerosol optical thickness or depth (AOD) and the aerosol effective radius, by measuring light extinction in an atmospheric column. Specifically, AOD data produced from the Moderate resolution Imaging Spectroradiometer (MODIS, on board the NASA platform Terra and Aqua) has been widely applied to examine the seasonal and regional variability of trace gases and aerosol particles (Alpert et al., 2012; Indira et al., 2013; Lalitporn et al., 2013; Zheng et al., 2013; Mehta, 2015), and to evaluate its relation to air pollution (Zhu et al., 2011) or significant emission sources, such as burning activities (Koren et al., 2007; Bevan et al., 2009; Vadrevu et al., 2011). In view of the important impacts on global climate and regional air quality, the scientific community has developed a number of operational fire products based on the detection of thermal anomalies (i.e., active fires, abbreviated to AF) and land surface changes (i.e., burned areas, abbreviated to BA). The AF products provide key response information about the locations of fires that are burning when the satellite passes by (Chalbot et al., 2013; Zha et al., 2013). The satellite-derived BA products are key data that are used to support the global greenhouse gases (GHGs) emissions inventory and climate modeling. Our knowledge about the spatial and temporal distributions of fire sources and aerosols has thus been extended with the increased application of satellite-based observations, and this has also encouraged the scientific community to make more efforts to improving the products by continuously updating the retrieval algorithms and collecting reliable field data for validation.

Satellite-based observations offer great opportunities to look for spatial and temporal variability patterns in aerosols, as well as in relation to fires. A sharp reversal trend for both aerosols and biomass burning over the Amazon Basin, which may be linked to a tri-national policy shift that was implemented in 2006, was identified through trend analysis of the satellite-based AOD and fire counts (FC, summarized from the AF product) dataset (Koren et al., 2007). The spatial and temporal distributions of biomass burning activities in South America are also well represented by ground-based observation of AOD, with this dataset correlating well with the MODIS AOD data (Hoelzemann et al., 2009). Recently, a joint statistical analysis of satellite derived fire and smoke loading (represented by AOD) data shows strong inter-annual correlation between AOD and two MODIS fire products in the Amazon Basin (Mishra et al., 2015) during the peak burning season. Although the emissions from forest, cropland and savanna maintenance fires have long been recognized as the main anthropogenic sources of carbonaceous aerosol and trace gas in SEA, the correlations between fire activities and the resulting aerosol loading have rarely been examined at a larger scale using satellite data products.

This study explored the link between the spatio-temporal patterns of MODIS derived AOD and fire products, as well as with the environmental factors of precipitation and land cover, in the SEA region for the 10-year period between 2002 and 2011. First, the spatial hotspots and seasonal patterns of AOD have been identified, and compared with the El Niño-Southern Oscillation (ENSO) cycle. Second, the time series of zonal statistics obtained from four MODIS fire products within each high AOD zone, e.g., the MCD14 AF, MCD45 BA, GFED4 BA and the recently released GFED4 BA with small fires (GFED4s), have been examined and compared. Finally, the links between MODIS fire products and the resulting AOD within the hotspot zones were studied using correlation and regression analyses.

MATERIALS AND METHODS

Study Area

Southeast Asia is located between the Pacific and Indian Ocean and consists of two geographic regions, i.e., the mainland and maritime SEA, generally encompassing the area from (30°N, 95°E) to (10°S, 142°E) (Fig. 1). The mainland part of SEA (hereinafter referred to as “Indochina”) studied in this work includes Vietnam, Laos, Cambodia, Thailand, and Myanmar, while the maritime part of SEA (hereinafter referred to as “maritime SEA”) includes Brunei, Indonesia, Malaysia, Philippines, and Singapore. The total land and sea area of the SEA region is about 4,646,139 km² and 18,776,000 km², respectively.

The Indochina and maritime SEA are both located in a tropical monsoon climate zone, in which the weather is mainly influenced by seasonal monsoons and there are distinct wet and dry seasons. The climate in maritime SEA is warmer and more humid because it is surrounded by oceans and at lower latitudes. Generally, the temperature in SEA is high (> 35°C) during dry seasons, resulting in a higher risk of wild fires and natural forest burning than during wet seasons.

The climate in SEA is very suitable for the growing of paddy rice and a number of valuable crops, e.g., oil palm trees and rubber trees. Fire burning is the only known method in Indonesia to clear land for the introduction of croplands (Streets et al., 2003). Additionally, most of the agricultural wastes in the Indochina Peninsula, mainly rice straw, are burned in the open during harvest seasons. Research indicates that this agricultural burning may contribute more aerosol emissions to the atmosphere than that seen from natural fires (Kondo, 2004).

Satellite-Based Data Products

Consider the proper spatial and temporal resolutions given by the MODIS, and the study period during which data can be entirely covered, the MODIS data products were found to be optimum and used in this work. Several MODIS earth observation products associated with the aerosol mass concentration and burning activities are applied in this study. First, the spatial and temporal patterns of aerosols are evaluated by the AOD products. Second, the ranges and locations of possible fire affected areas are mapped by the satellite-based BA products. Third, in addition to BA,
Fig. 1. The geographical location and countries included in the study area.

Table 1. Summary of satellite-based data products employed in this study.

<table>
<thead>
<tr>
<th>Product</th>
<th>Product name</th>
<th>Satellite sensor</th>
<th>Algorithm</th>
<th>Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>AOD</td>
<td>MOD08_M3</td>
<td>Terra MODIS</td>
<td>(Remer et al., 2005)</td>
<td>1° monthly</td>
</tr>
<tr>
<td>Active fire</td>
<td>MCD14ML</td>
<td>Terra MODIS</td>
<td>Giglio et al. (2003)</td>
<td>1 km monthly</td>
</tr>
<tr>
<td>Burned area</td>
<td>MCD45A1</td>
<td>Terra MODIS</td>
<td>Roy et al. (2005)</td>
<td>500 m monthly</td>
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<td></td>
<td>GFED4</td>
<td>Aqua MODIS</td>
<td>Giglio et al. (2009, 2013)</td>
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<td></td>
<td>GFED4s</td>
<td>Aqua MODIS</td>
<td>Randerson et al. (2012)</td>
<td></td>
</tr>
<tr>
<td>Land cover</td>
<td>MCD12Q1</td>
<td>Terra MODIS</td>
<td>–</td>
<td>500 m yearly</td>
</tr>
<tr>
<td></td>
<td>Aqua MODIS</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Precipitation</td>
<td>GPCP 2.2</td>
<td>Multiple satellites</td>
<td>–</td>
<td>2.5° monthly</td>
</tr>
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</table>

the FC summarized from the AF product is also used to indicate the burning activities. Finally, some environmental variables that may affect the distribution of aerosols and burning, such as precipitation and land-cover products, are considered in this study. A summary of satellite-based data products is listed in Table 1.

Aerosol Product

The MODIS sensor is a science instrument on-board the Terra and Aqua satellites (launched in December 1999 and May 2002, respectively), which measures the radiances at the top-of-atmosphere (TOA) in a total of 36 spectral channels. Information associated with the radiation reflected by the Earth’s surface, such as that from the land, ocean, cloud and aerosols, is collected by 19 reflected solar bands (RSBs) ranging from 0.41 to 2.1 µm. For the retrieval of aerosol properties in an atmosphere from the measured TOA reflectance (Remer et al., 2009), e.g., aerosol loading (AOD), Ångstrom exponent, and aerosol effective radius, it is assumed that: (1) the TOA reflectance for clear-sky (no cloud) pixels is mainly contributed by the surface, the atmospheric molecules, and the aerosols; (2) the scattering properties of the surface for some specific RSBs can be neglected or accurately inferred; and (3) sufficient a priori knowledge of the expected aerosol optical properties is provided. Generally, the availability of satellite-derived aerosol information is limited by cloud fractions, and its uncertainty mainly comes from variations in the scattering properties of the Earth’s surface. Separate retrieval algorithms and RSB combinations are thus used for each surface type (Remer et al., 2005, 2009). The MODIS derived aerosol products have been validated against a variety of ground-based observations (More et al., 2013; Tiwari and Singh, 2013), and widely used for climate modelling. For example, the MODIS AOD retrievals are routinely compared to measurements from the Aerosol Robotic Network, and show better correlation over open oceans than the surface of the land (Remer et al., 2008).
The primary MODIS AOD product is derived at RSB 550 nm with 10 × 10 km resolution (Level 2 product). While aerosol retrieval algorithms are identical for both MODIS instruments, the Terra-MODIS Level 3 AOD global gridded dataset was applied in this study (MOD08_M3), over both continent and ocean, and computed from the Level 2 product at a 1° × 1° spatial resolution and monthly temporal resolution.

Active Fire

Compared to the RSBs used for deriving AOD, fire products are often obtained from channels showing the optical features of vegetation or hotspots. Fire products can thus also be derived from the MODIS sensor, but are commonly based on different sets of bands and the use of completely different retrieval approaches. Additionally, the channels used for land surface products, such as land-cover and fire spots, have been atmospherically corrected and are independent of the AOD algorithm. The MODIS Fire Team developed AF and BA products to provide information with regard to both climate change and practical applications, including global biomass burning and wildland fire monitoring.

First, the AF product provides information about the “location of burning fires at the time of the satellite overpass” (Justice et al., 2002), which is derived by exploiting different responses of the middle-infrared (MIR, 4 µm MODIS channel with 1-km resolution) and longwave-infrared (LIR, 11 µm MODIS channel with 1-km resolution) bands to scenes containing hot subpixel targets (Giglio et al., 2003). In this study, the global-monthly-fire-location product entitled MCD14ML (collection 5) is used, which contains the date and time of satellite overpass, sensor platform (Terra or Aqua), geographic location (center of a fire pixel), algorithm information, and detection confidence for each fire pixel detected (Giglio et al., 2013). The MCD14ML AF product is derived using data inputs from both Terra and Aqua, and has a native resolution of 1-km. In order to compare this with the AOD product, we calculate the fire pixel counts (FCs) as the sum of individual 1-km AF pixels at the 1° × 1° scale.

Burned Area

Second, the BA product gives information on the “spatial extent of burn scars over a specified time period” (Justice et al., 2002). Based on the burn scar index (BSI) that uses the normalized difference between MIR and near-infrared (NIR), Roy (1999) first developed a burn scar detection algorithm to map changed pixels (potential burned areas) by identifying a large BSI change value for each co-located pixel from multi-temporal imagery. However, the accuracy of the global BA products derived from the burn scar detection algorithm is often limited by the availability of robust multi-temporal data (Boschetti et al., 2009). Note that the AF information was used in the BSI algorithm to locate pixels in a change map to derive confidence thresholds for the classification of potential BA.

With the better georeferenced, atmospherically corrected and cloud screened data provided by MODIS, Roy et al. (2005) developed a new algorithm which directly derives BA based on the changes in daily surface reflectance of each geo-located pixel, without the use of AF information. This direct-mapping algorithm was adapted by the MODIS Fire Team to routinely generate global BA, with the codenames of the products starting with MCD45. In contrast to the former BSI algorithm, the AF information is no longer used in the new algorithm producing MCD45. MCD45 products are the most commonly used BA data for biomass burning studies, and have been widely compared to other datasets (Ruiz et al., 2014), and shown reasonable results globally (Roy et al., 2008).

According to the results of a comparison between MCD14 AF and MCD45 BA, Roy et al. (2008) suggested that the estimation of BA may benefit from the use of both AF and BA information, due to the complementary nature of MODIS fire products. Therefore, based on the hybrid concept that was used in the earlier BSI algorithm (Roy, 1999), Giglio et al. (2009) developed an AF based BA mapping algorithm which detects persistent changes in a daily vegetation-index time series derived from surface reflectance observations. Specifically, the AF maps are used to generate regional probability density functions for classifying the persistent changes as either burned or unburned areas. Burned areas mapped by this hybrid algorithm are included in the MODIS Collection 5.1 direct-broadcast monthly products and versions three and four of the Global Fire Emission Database (abbreviated as GFED3 and GFED4). A new test dataset was recently released at May 2015, which combines the 1-km MCD14 AF and 500-m GFED4 BA observations to estimate small fire burned areas based on the difference in normalized burn ratio (Randerson et al., 2012). The test dataset was called GFED4s to distinguish the BA with small fires from the standard GFED BA without small fires, i.e., GFED4.

Consequently, in addition to the MCD14ML FC product, three BA products (all produced based on both Aqua and Terra data) are applied in this study to represent fire burning activities in order to evaluate their tempo-spatial variations with AOD, including: (1) the monthly 500-m MCD45A1 BA product reporting the approximate date of burning between eight days before and after the calendar month period (16 day overlap). All confidence levels of BA detection are considered; (2) the monthly 500-m GFED4 BA product, also named as MCD64A1 (Randerson et al., 2012; Ruiz et al., 2014); and (3) the monthly 500-m GFED4s BA product.

Precipitation and Land-Cover

The monthly mean precipitation data of the study area was obtained from the Global Precipitation Climatology Project version 2.2 (GPCP 2.2). The GPCP 2.2 precipitation has a standard spatial resolution of 2.5°, and is derived from multiple satellite sources and gauge measurements (Huffman and Huffman, 1997).

The Global Land Cover Facility (GLCF) develops and distributes satellite-based observation data and products to support land-cover studies that range from the local to global scales. The MODIS land-cover type product (MCD12Q1) with International Geosphere-Biosphere Programme (IGBP) classes is spatially aggregated and georeferenced by the GLCF for each year from 2001–2012 (GLCF). The native
resolution MCD12Q1 product in the GLCF tile framework (close to 500 m) for regional studies was applied in this work. Because of the longer time-span and higher frequency of global mapping, the MCD12Q1 is appropriate for showing important land cover changes over time (Yang and Lo, 2010). We reduce the number of land cover types in MCD12Q1 from IGBP’s 17 classes to nine, by merging five types of forest (evergreen needle leaf, evergreen broadleaf, deciduous needle leaf, deciduous broadleaf and mixed), two types of shrub land (closed and open), two types of savanna (woody and not woody), two types of croplands (croplands and croplands with natural vegetation mosaic) and two types of water body (water and permanent wetland) into ‘Forest’, ‘Shrub lands’, ‘Savannas’, ‘Croplands’, and ‘Water’, respectively.

Spatial Statistics Analysis

The spatial distributions of the monthly AOD, FC, BA and precipitation datasets during 2002–2011 are summarized using zonal statistic tools in ESRI ArcGIS 10.2, which calculates statistics based on the values of a dataset within each defined zone or field. The zonal boundary was based on the country borders first, and then this was refined to high AOD zones (HAZs) after hotspot analysis.

The hotspot analysis tool in ArcGIS calculates the Getis-Ord statistic ($G_i^*$) for each weighted field in a dataset, and assesses whether the high- or low-value fields cluster spatially. For example, the $G_i^*$ value for field $i$ of the country-based AOD dataset can be calculated as:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{x} \sum_{j=1}^{n} w_{i,j}}{S^2 \sqrt{\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2}}$$

where $w_{i,j}$ is the spatial weight between country polygon $i$ and $j$, which is evaluated by the Euclidean distance between their centroids; $x_j$ is the mean AOD level for country $j$; $n$ is the number of country polygons; $\bar{x}$ is the mean AOD value of the dataset; and $S$ is the standard deviation of AOD values in the dataset. Based on the calculated $G_i^*$, the hotspot analysis tool will return a GiZ-score for each country. The larger the GiZ-score is, the more intense the clustering of high AOD values is (i.e., there is hotspot).

RESULTS AND DISCUSSION

Spatial-Temporal Variations of Aerosol Optical Depth in Southeast Asia

AOD Hotspots

The spatial and temporal variations of AOD in SEA countries are shown in Fig. 2. This figure is drawn with a 1 degree spatial resolution, and month-averaged levels of AOD for the 10-year period examined in this work (2002–2011). As shown in Fig. 2, it is evident that high AOD pixels tend to cluster near other high value pixels, and form high AOD regions in both Indochina and maritime SEA. The high AOD region in Indochina is approximately located in the northern Indochina Peninsula during January to April (Figs. 2(a)–2(d)); and that in the maritime SEA is located at Kalimantan (Indonesia), during August to October (Figs. 2(b)–2(j)). In Indochina the level of AOD gradually increases from November, peaking in the following March and slowly declining after April. This seasonal pattern was also found in the maritime SEA, in which the level of AOD begins to increase in May, peaks in October, and slowly falls after November.

The country-polygon based GiZ-scores for each monthly AOD map (Fig. 2) are calculated and shown in Fig. 3. High aerosol zones (HAZs) are identified by selecting the polygons with GiZ-scores greater than 1.65 (p-value < 0.1), and are highlighted in orange (1.65 < GiZ-score < 1.96, p-value < 0.1) and red (GiZ-score > 1.96, p-value < 0.05) in Fig. 3. High aerosol zones in the mainland portion of SEA, abbreviated as Indochina HAZ, are significant from January to June, which consists of Myanmar, Vietnam, Laos, Thailand, and Cambodia. The maritime HAZ including Malaysia, Singapore, Sumatra, Java and Kalimantan, is significant during the peak AOD months of June to December. The outlines of the identified HAZs are highlighted in Fig. 2, e.g., the Indochina and maritime HAZ are outlined in blue and purple, respectively, to indicate the hotspots of AOD in SEA. In general, these hotspots are very close to our observations in Fig. 2. Note that the remaining analyses in this study will focus on the two HAZs separately to investigate the relationships between fire products and the resulting levels of AOD.

Temporal Trends of AOD in HAZs

As shown in Fig. 4(a), the fluctuations in monthly AOD and precipitation for the Indochina HAZ both follow a sine-wave pattern, in which the peaks and troughs of monthly AOD time series are always located in dry and wet seasons, respectively. Compared to the Indochina HAZ, it is relatively difficult to detect the peaks and troughs of AOD values from the monthly precipitation of the maritime HAZ (Fig. 4(b)). In general, the levels of monthly AOD show an inverse relationship to precipitation in both HAZs ($r = -0.43$).

The annual baseline/trough level of AOD over the maritime HAZ is around 150 (Fig. 4(b)), which is slightly higher than that within the Indochina HAZ (Fig. 4(a)). However, the fluctuations in monthly AOD for the maritime HAZ are less severe when the four unusual annual AOD peaks are excluded, e.g., 2002, 2004, 2006 and 2009 (circled on Fig. 4(b)). The monthly Oceanic Niño Index (ONI) obtained from the historical NOAA weather dataset was used to determine whether the El Niño or La Niña climate patterns actually occurred (Fig. 4). The ONI is a measurement of the deviations from normal sea-surface temperatures that El Niño and La Niña produce in the east-central Pacific Ocean. As defined by NOAA (NOAA, 2015), an ONI score higher than 0.5 indicates the possible occurrence of El Niño (relatively dry and warm weather in the maritime SEA), and lower than −0.5 denotes the possibility of La Niña (relatively wet and cold weather in the maritime SEA). The
Fig. 2. Maps of month-averaged AOD from the MOD03_M8 dataset during 2002–2011. The Indochina and maritime HAZ are outlined in blue and purple, respectively.
Fig. 3. The spatial and temporal distributions of the month-averaged GIZ scores for each SEA country polygon during 2002–2011.
results showed that the four unusually high peaks of the AOD time series all occurred in El Niño periods (Fig. 4(b)), when the climate in the maritime HAZ was relatively dry and warm. As a result, during these excessively dry times it is more likely that Malaysia, Singapore and Indonesia will experience increased AOD levels and more fire affected areas. However, the ONI does not seem to be a significant factor with regard to the timing of AOD peaks in Indochina.

**Spatial-Temporal Variations of Fire Burning in Southeast Asia**

**Spatial-Temporal Distribution of GFED4s Burned Areas**

Based on the GFED4s BA dataset, the spatial and temporal distributions of fire burning are examined in this section. The GFED4s was chosen because it contains hybrid information of large burn scars (MCD45) and active fires (MCD14 and GFED4), as well as the small cropland fires which may be significant in SEA countries. The month-merged (accumulated for each month) GFED4s BA maps for the period of 2002–2011 are shown on Fig. 5. The burned areas in Indochina start to develop from November (Fig. 5(k)), peak during the following February to April (Figs. 5(b)–5(d)), and decrease from May (Fig. 5(e)). In the maritime SEA, BA are distributed in the western part of the Malay Archipelago, including Malaysia, Sumatra, Kalimantan and Java, during May to October. It is significant that high BA regions are spatially clustered around the AOD hotspots (Figs. 2 and 3), showing the potential spatial linkages between the GFED4s BA and the level of AOD. With regard to the temporal distribution, the occurrence of fire burning events is consistent with the dry seasons and high AOD months.

To further examine the temporal relationships between fire burning and AOD, the monthly averaged time series of GFED4s BA and AOD are compared in Fig. 6. In the Indochina HAZ (Fig. 6(a)), the overall interaction between local fire burning and AOD is not clear, even though the highest BA and AOD both occur in March, and other three high BA months (January, February and April) seem to follow the same trend. As shown in Fig. 5, a large number
Fig. 5. Spatial and temporal distributions of month-merged GFED4s burned area data.
Comparisons between MODIS Fire Products

The monthly distributions of AOD and different BA products in the Indochina and maritime HAZ for the 10 years between 2002–2011 are compared in Figs. 7(a) and 7(b), respectively. The GFED4s product contains higher BA than GFED4 as it also considers small fires; MCD45 is the only dataset derived from the non-AF guided algorithm, and provides the lowest BA estimates in both HAZs. The monthly time series of three BA products show similar trends in the Indochina HAZ. In the maritime HAZ, the MCD45 does not match the occurrence of peak AOD levels during El Niño periods, despite the fact that these were perfectly matched by GFED4, GFED4s and MCD14 (circled in Figs. 7(b) and 7(d)). Countries within the maritime HAZ experienced both increased AOD levels and fire activities during four excessively dry periods (2002–2003, 2004–2005, 2006–2007, and 2009–2010). Additionally, the fire counts provided by MCD14 have almost the same trends (Figs. 7(c) and 7(d)) as GFED4 and GFED4s (Figs. 7(a) and 7(b)), and thus the AF information plays a dominant role in the algorithm (MCD64) used to derive the GFED products.

To realize why the under-detection of BA by the MCD45 product is particularly significant in the maritime SEA (Fig. 7(b)), it is of interest to further investigate the differences in BA between the direct mapping approach (MCD45) and the hybrid method (GFED4 and GFED4s). Several studies have examined the differences between MCD45 BA and the AF generated BA estimates. Roy et al. (2005) indicated that AF detection (MCD14) provides greater total BA estimates than direct mapping approach (MCD45) in forested environments. In contrast, under-detections of the AF product were reported in studies carried out in Australia and Southern Africa, as some fires were not actively burning at the time when MODIS passed overhead (Giglio, 2007). The direct mapping approach may under-detect BA in cases or places where burn scars are often too small and dispersed to appear in the MODIS 500 m pixel resolution (Roy and Landmann, 2005), or
when the burn scared obscured by vegetation (Giglio et al., 2009). Furthermore, a comprehensive spatial and temporal correlation analysis regarding different land cover classes at the global scale concluded that MCD14 gives greater BA estimations than MCD45 in croplands, evergreen forest and deciduous needleleaf forest classes, with such regions generally showing higher tree cover and leaf area indexes (Roy et al., 2008). It is thus postulated that the under-detection of BA by MCD45 (or the overestimation of AF-based products) in SEA was because the fires in this region were mostly small and occurred in forested areas. Our results support the postulation made by the previous works, in which the AF were mostly detected in the forest and savanna areas of the Indochina HAZ (Fig. 7(e)), and in forest and cropland areas of the maritime HAZ (Fig. 7(f)).

Fire Emissions from Peatland Burning in the Malay Archipelago

Although the strength of local fire burning in the Indochina HAZ was almost seven times larger than that of maritime HAZ (Figs. 6 and 7), the baseline levels of AOD in both HAZs were comparable (Fig. 6), ranging from 180–400, except for some peak AOD levels during dry and excessive burning months (February and March in the Indochina HAZ; August to October in the maritime HAZ). It was thus postulated that the fire emissions of the southern HAZ originated from land classes with higher emission factors or fuel loads. Based on a spatial distribution analyses of fire products (Fig. 3) and the national soil maps from the Food and Agriculture Organization of the United Nations (UNFAO, 2015), we confirmed that there are relatively more burned peatlands in Indonesia. The aerosol particle emissions from Indonesian peatland fires have been shown to be significant in a number of studies, and have been identified as one of the largest near-surface reserves of terrestrial organic carbon (Page et al., 2002), contributing to a large amount of GHGs emissions and having negative impacts on human health, transport, tourism, and economic activity in Southeast Asia (Gaveau et al., 2014). Indonesian peatland fires are mostly anthropogenic and implemented
for land clearance activities, including small-scale disposal of agricultural waste, and large-scale forest cleaning before establishing valuable economic crops (Page et al., 2002).

The air pollutant emission factors for peatland fires are found to be several times higher than those for fires in other land classes (van der Werf et al., 2010), as shown on Table 2. Although the CO₂ emission factor for peat fires is comparable to that seen with other land classes, its emission factors in CO, CH₄ and NOₓ are significantly higher than those of the others. For the two major land use categories in the maritime HAZ (Fig. 7(f)), e.g., forest and cropland, the emission factor for peatland is about two times higher than those for forest and cropland in CO₂; nine and three times higher than those for cropland and forest in CH₄; and 32 and 10 times higher than those for cropland and forest in NOₓ. As a result of emissions from peatland burning, although fewer local fire spots were detected in the maritime HAZ, this can still lead to a high level of AOD.

**Associations between AOD and Fire Products in High Aerosol Areas**

**Correlations between AOD and Fire Products**

The temporal correlations between AOD and fire variables, including AOD, MCD45 BA, GFED4 BA, GFED4s BA, MCD14 FCs, precipitation, MCD14 FCs on savannas, MCD14 FCs on forests and MCD14 FCs on croplands, were evaluated using a correlation matrix, as shown in Table 3. All fire products as well as the AOD show weak to negative medium correlations to monthly precipitation in both HAZs, which indicates that the overall variations of AOD in SEA cannot be captured by one natural factor only, and so it is also necessary to consider anthropogenic factors.

A comparison between the correlations of AOD and fire products within two HAZs confirms that the Indochina HAZ should have a more complicated aerosol sources, such as cross-boundary air pollution, which may influence the regional AOD fluctuations and reduce the correlations between AOD and local fires. The correlations between AOD and the BA product generated by a non-AF guided approach (MCD45) are not significant in either the Indochina HAZ (R = 0.26) nor maritime HAZ (R = 0.58). However, the other three fire products are all highly correlated (Pearson’s correlation coefficient R > 0.8) to AOD in the maritime HAZ, while only MCD14 FCs have a higher correlation with AOD in the Indochina HAZ (R = 0.76). The results indicate that the temporal trends of AOD in SEA can be best explained by the FCs derived from MCD14 AF, followed by two AF-based BA products, GFED4s and GFED4.

An examination of the inter-correlations between fire products shows that the two BA products generated by hybrid approaches (GFED4 and GFED4s) have a similar pattern to MCD45 (R = 0.85 and 0.89) in the Indochina HAZ, but are more related to MCD14 (R = 0.83 and 0.89) in the maritime HAZ. It is concluded that the fire affected areas in the Indochina HAZ are mostly detectable by using a direct mapping approach only, while in the maritime HAZ the detection of BAs was mostly guided by the AF information, which tends to derive more small fires in forested regions.

Although the correlations between AOD and the fire variables were not further increased after dividing the FCs into three land cover classes, some interesting changes in their correlations were found in the Indochina HAZ. Fire counts for forests within the Indochina HAZ have a significantly higher correlation to AOD (R = 0.79) than the fire counts for savanna and cropland (R = 0.62 and 0.59), and relatively lower correlations to other fire products, e.g.,

<table>
<thead>
<tr>
<th>Category</th>
<th>CO₂</th>
<th>CO</th>
<th>CH₄</th>
<th>NOₓ</th>
<th>N₂O</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peat fire</td>
<td>1703</td>
<td>210</td>
<td>20.8</td>
<td>2.26</td>
<td>0.2</td>
<td>van der Werf et al. (2010)</td>
</tr>
<tr>
<td>Savanna/Grassland</td>
<td>1613 ± 95</td>
<td>65 ± 20</td>
<td>2.3 ± 0.9</td>
<td>0.21 ± 0.10</td>
<td>3.9 ± 2.4</td>
<td>IPCC (2006)</td>
</tr>
<tr>
<td>Agriculture residues</td>
<td>1515 ± 177</td>
<td>92 ± 84</td>
<td>2.7</td>
<td>0.07</td>
<td>2.5 ± 1.0</td>
<td></td>
</tr>
<tr>
<td>Tropical forest</td>
<td>1580 ± 90</td>
<td>104 ± 20</td>
<td>6.8 ± 2.0</td>
<td>0.2</td>
<td>1.6 ± 0.7</td>
<td></td>
</tr>
<tr>
<td>Extra tropical forest</td>
<td>1569 ± 131</td>
<td>107 ± 37</td>
<td>4.7 ± 1.9</td>
<td>0.26 ± 0.07</td>
<td>3.0 ± 1.4</td>
<td></td>
</tr>
<tr>
<td>Biofuel burning</td>
<td>1550 ± 95</td>
<td>78 ± 31</td>
<td>6.1 ± 2.2</td>
<td>0.06</td>
<td>1.1 ± 0.6</td>
<td></td>
</tr>
</tbody>
</table>

**Table 2.** Emission factors for different kinds of burning (g kg⁻¹ dry matter burnt).

**Table 3.** Correlation matrix between AOD and fire variables in the HAZ. Pearson’s correlation coefficients for variables in the Indochina and maritime HAZ are listed in the upper and lower triangular matrix, respectively.
R = 0.35, 0.43 and 0.62 to MCD45, GFED4 and GFED4s, respectively. The results indicate that the variations of AOD in the Indochina are strongly related to FCs in forest areas. Even though the FCs give a more varied BA estimates in forested regions compared to the other three BA products, using FCs alone or FCs for forest areas only are still better approaches with regard to relating the fire product to the temporal variations of AOD in Indochina. Forest burning is the primary technique in SEA to remove deforested areas for further human development (Ziegler et al., 2011). For example, farmers burn the deforested site to shift to cropland; and forest plantation companies burn the forest site to prepare for the next planting after forest logging (Miettinen et al., 2011).

Quantification of the Linkage between AOD and Fire Products

Based on the results of temporal correlation analyses for AOD and fire products, linear regression models are further developed to quantify the linkage between the levels of AOD and fire products. Two empirical models, including a general model and dry season model, were developed for each HAZ. The general model was established based on all monthly AOD and fire product data during 2002–2011 (N = 120). The annual dry period data were used to develop the dry season model (N = 60), which contains the monthly data collected between November to the following April in the Indochina HAZ, and from May to October in the maritime HAZ. The level of monthly mean AOD within a HAZ was dependent variables in the regression analysis and the independent variables, which were automatically chosen using the stepwise regression approach (SPSS Statistics 17.0), contained five satellite-based products (MCD45 BA, MCD14 FCs, GFED4 BA, GFED4s BA, and monthly mean precipitation) and their log-transformed values. The optimal model was chosen based on the least number of potential explanatory variables and the largest determination coefficient of the regression model.

Empirical models developed for the estimation of mean AOD levels in the HAZ based on the selected fire products are list in Table 4. The independent variables selected for the Indochina HAZ were MCD14 FCs, GFED4 BA and monthly mean precipitation. In the maritime HAZ, the GFED4s BA and monthly mean precipitation were used. Because of a lower correlation with the temporal variation of AOD, the most commonly used MODIS BA product, i.e., MCD45, is not used with any of the four models developed in this work. The results suggest that the association between regional mean AOD levels and fire burning can better be captured by fire products that are more sensitive to small forested fires.

The performance of the empirical models used to derive the AOD levels is shown in Fig. 8. In general, the AOD levels derived by the empirical models for the maritime HAZ (Figs. 8(c) and 8(d)) provide tighter and stronger relationships with the observed AOD in terms of having lower relative percentage deviations (RPD) and higher R² values. The results indicate that the levels of AOD in Indochina were not only contributed by local fires, but also the cross-boundary sources of pollution, as mentioned in the previous sections. In contrast, the linkage between AOD and fire products in the maritime SEA is relatively straightforward. The dry season models (Figs. 8(b) and 8(d)) perform better than the general models (Figs. 8(a) and 8(c)) in both HAZs, as fire burning is more closely related to the decline in regional AOD during dry seasons.

CONCLUSION

The spatial and temporal statistical analysis of MODIS derived fire products and AOD in the SEA region during the 10-year period of 2002–2011 shows associations between fire burning and the levels of mean AOD within the hotspot zones identified in this study. The AOD hotspot zone located in the Indochina Peninsula consists of Myanmar, Vietnam, Laos, Thailand, and Cambodia, where the peak AOD months are during January to April. Another hotspot zone identified in the Malay Archipelago, which contains Malaysia, Singapore, and the western islands of Indonesia, has significantly high AOD months between August and October.

The peak burning months are generally consistent with the peak AOD months within each HAZ. Specifically, the burning season almost coincides the high AOD season in the maritime HAZ, and is about one month earlier in the Indochina HAZ. The AOD variations are relatively steady during wet seasons (baseline), when there are almost no local fires in the HAZs. As a result of high emissions from peat fires on Indonesia, the AOD levels in the maritime HAZ are slightly higher than those in the Indochina HAZ, even though much fewer local fire spots were detected.

Apart from the steady baseline, the fluctuations of AOD in the maritime HAZ are strongly correlated to the results of satellite-based fire detection, as well as with the occurrence of the El Niño climate pattern. Because there are no significant fire sources in the maritime HAZ other than the Indonesia, the result from regression analysis shows a direct impact of Indonesia biomass burning on the hotspot zone AOD levels.

Table 4. Linear regression models for the prediction of monthly AOD levels in the SEA HAZ using selected regional fire products.

<table>
<thead>
<tr>
<th>HAZ</th>
<th>Period</th>
<th>Linear regression model</th>
<th>N</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indochina</td>
<td>All</td>
<td>$\log(AOD) = 1.098 + 0.222 \cdot \log(MCD45) + 0.268 \cdot \log(Prep)$</td>
<td>120</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>Dry</td>
<td>$\log(AOD) = 1.404 + 0.423 \cdot \log(MCD45) - 0.202 \cdot \log(GFED4)$</td>
<td>60</td>
<td>0.69</td>
</tr>
<tr>
<td>Maritime SEA</td>
<td>All</td>
<td>$\log(AOD) = -0.578 + 0.49 \cdot \log(GFED4s) + 0.66 \cdot \log(Prep)$</td>
<td>120</td>
<td>0.66</td>
</tr>
<tr>
<td></td>
<td>Dry</td>
<td>$\log(AOD) = -0.753 + 0.581 \cdot \log(GFED4s) + 0.593 \cdot \log(Prep)$</td>
<td>60</td>
<td>0.83</td>
</tr>
</tbody>
</table>

Variable units: AOD (unitless); GFED4s (km$^2$); GFED4 (km$^2$); Prep (precipitation, mm month$^{-1}$); MCD14 (AF counts).
Fig. 8. Comparing the mean regional AOD simulated by linear regression models to the observed AOD within (a) Indochina HAZ during all seasons, (b) Indochina HAZ during dry seasons, (c) maritime HAZ during all seasons, and (d) maritime HAZ during dry seasons.

during both dry-season ($R^2 = 0.83$) and wet-season ($R^2 = 0.66$). Furthermore, the biomass burning in Indonesia may mainly be contributed by small peatland and forest fires. This association between AOD and fire products was not so noticeable in the Indochina HAZ, because of potential cross-boundary pollution sources and the influence of seasonal monsoons.

Fire products derived from or based on the detection of thermal anomalies have stronger associations with AOD and are better explanatory variables of AOD, as compared to the BA derived by the direct mapping approach. It is evident that fires mapped by the AF-based algorithms in the maritime HAZ are commonly small and within forested regions, and these have general no been detected by the commonly used MCD45 product. In contrast, the recently released GFED4s BA product is a better indicator of smoke loading in the maritime HAZ, due to the consideration of both AF information and small-fire effected areas. This study thus suggests the use of FCs or GFED4s BA for more accurate assessments of the effects of fire on smoke aerosols in the SEA region.

ACKNOWLEDGMENTS

The authors thank the Ministry of Science and Technology, Taiwan ROC, for the financial support provided for this study through grants NSC-101-2221-E-006-153 and MOST-103-2221-E-006-014. This research was supported in part by funding received from the Headquarters of University Advancement at National Cheng Kung University, which is sponsored by the Ministry of Education, Taiwan ROC.

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Received for review, October 25, 2015

Revised, November 22, 2015

Accepted, November 22, 2015