Applied Environmental Research
- RESEARCH FOR SUSTAINABLE PLANET -

Research Article

# Estimation of Respiratory Disease Burden Attributed to Particulate Matter from Biomass Burning in Northern Thailand Using 1-km Resolution MAIAC-AOD

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## Abstract

The upper northern Thailand suffers from air pollution due to open burning, which has been known for a long time. It was also found that different respiratory diseases were attributed to air pollution, especially particulate matter. This study estimated the health impacts attributed to $PM_{10}$ between 2014 and 2016 using the burden of disease in terms of the disability adjusted life year (DALYs). The spatial correlation was evaluated based on applicable remote sensing data using the geographically weighted regression (GWR) model. The average measured $PM_{10}$ concentrations for the summer and annual periods between 2014 and 2016 were 73 and 89 μg $m^{-3}$, respectively, exceeded the national standard (50 μg $m^{-3}$). In the months of March and April, when $PM_{10}$ concentrations were at their highest, the maximum values of the Multi-Angle Implementation of Atmospheric Correction (MAIAC-AOD), 2.70 and 3.48, were recorded. There was a strong correlation between the MAIAC-AOD and the ground-based AOD measurements (AERONET stations), with R of 0.8468, 0.8396, and 0.8334 between 2014–2016. The correlation coefficients for the 3,208 co-located gridded of $PM_{10}$ emissions vs. measured $PM_{10}$, measured $PM_{10}$ vs. MAIAC-AOD, and MAIAC-AOD vs. $PM_{10}$ emissions were 0.6656, 0.6446, and 0.5580, respectively. The spatial correlation between the interpolated measured $PM_{10}$ and 1-km MAIAC-AOD was 0.5979, 0.3741, and 0.7584 as an outcome of GWR. The total DALYs of chronic obstructive pulmonary disease (COPD) attributable to $PM_{10}$ in 2014–2016 were 115,930 years per 100,000 population, with the relative risk of COPD related to $PM_{10}$ at a 95% confidence interval of 1.2045–1.2107.

## ARTICLE HISTORY

Received: 4 Jan. 2023
Accepted: 35 Apr. 2023
Published: 15 May 2023

## KEYWORDS

COPD;
DALYs;
Disease burden;
MAIAC-AOD;
$PM_{10}$

## Introduction

Air pollution is a major environmental problem in the upper northern of Thailand, especially in the dry season (February–May) for over a decade. Recently, there are many studies that have been examined for the primary emission source and importance air pollutant in this area [1–2]. They found that the major air pollutants in the upper norther Thailand are $PM_{10}$ emitted from biomass burning which is usually caused by agriculture, forest fire, savanna and grass land, respectively [3]. Those phenomenal cause $PM_{10}$ concentration in this area exceed the national ambient air quality standard of 120 μg $m^{-3}$ $day^{-1}$, during summer period of every year, it can be exceeded the standard for nearly 50 days from 120 measured days [4]. Due to the rise in air pollution over the past ten years, satellite remote sensing data have been used in various studies to estimate ground-level particulate matters (PM: $PM_{10}$, $PM_{2.5}$). Most PM estimations are only presented at spatial resolutions of 3–10 km to monitor air quality in the impacted areas. Here, we propose a spatially continuous, high-resolution (1 km) AOD dataset for further PM estimates across northern Thailand to minimize spatiotemporal heterogeneities and enhance

https://doi.org/10.35762/AER.2023008

the overall estimate accuracy of ground-level PM concentrations. The MODIS Multi-Angle Implementation of Atmospheric Correction (MAIAC) is a novel, cutting-edge technique that combines pixel- and image-based processing with time series analysis [5]. In comparison to MODIS AOD's 3 km resolution, MAIAC-AOD's 1 km resolution might produce many more AOD-PM pairings, depict PM's comprehensive geographic distribution characteristics, and have a greater degree of accuracy [6]. By incorporating ground-based PM monitoring, meteorological data, land use, and a demographic, the MAIAC AOD examined the daily ground PM concentration at a spatial resolution of 1 km and demonstrated a good AOD-PM correlation [7–9], as well as forecasting emission inventories using satellite AOD data [10]. The MAIAC-AOD was validated using the Aerosol Robotic Network (AERONET), a ground-based AOD monitoring system. The results demonstrated a significant correlation between MAIAC-AOD and AERONET data of R = 0.83, RMSE = 0.04 [11], and R = 0.867–0.929, RMSE = 0.130–0.287, MAE = 0.091–0.198 [12].

The relationship between hourly PM from the air monitoring station and MODIS-AOD was examined using relative humidity and temperature. It was discovered that R for $PM_{2.5}$ and $PM_{10}$ was around 0.77 and 0.71, respectively [13]. And the comparison of ground based $PM_{10}$ and CO concentrations over northern Thailand for the years 2014 to 2017 using satellite data with a 10 km resolution revealed that the high levels of air pollutants during March and April and the temporal variability were in good accordance [14]. Additionally, the average correlation coefficients (R) between ground-based $PM_{10}$ observations and MODIS-AOD 10 km resolution in Bangkok Metropolitan Region were 0.46 for Terra and 0.38 for Aqua AOD, respectively. However, it was noted that a MODIS-AOD resolution of 10 km might be too coarse to account for change in $PM_{10}$ concentration if the monitoring stations were located closer to local sources in densely populated urban areas [15].

In northern Thailand, liver cancer, ischemic heart disease, chronic obstructive pulmonary disease (COPD), and traffic accidents are the top five deaths of men (the mortality rate is adjusted at the base of 89, 75, 70, 53 and 49 per 100,000 population, respectively). Women are more likely to suffer vascular disease, brain ischemia, heart disease, COPD, diabetes, nephritis, and renal impairment (the mortality rate is adjusted at the base of 88, 50, 46, 33 and 24 per 100,000 population, respectively) [16]. In 2014, there were 7,193 incidents of deaths attributed to the risk of air pollution. The number of years lost to illness, disability, or premature mortality is a measure of overall disease burden known as the Disability Adjusted Life Year (DALYs), through including comparable years of life lost even while healthy because of illness or disability, it broadens the definition of years of life lost leading to premature death. Smoking (46.0%), pollution from ambient particulate matter (20.7%), and occupational exposure to particulate matter, gases, and fumes (15.6%) were the factors most responsible for the DALYs rates for COPD. Thailand accounted for 645,448 DALYs, or 3.3% of all DALYs, in 2018, that had a significant relation to ambient air pollution. In 1999 and 2004, COPD was one of top ten causes of death, while in 2009, 2011, and 2014, it was in the top twenty. [17], [26] found contribution of $PM_{10}$ and $PM_{2.5}$ related to COPD exacerbations. The current study clarification the association between $PM_{10}$ emission and measured $PM_{10}$ using the MAIAC-AOD product with 1-km resolution. The disability adjusted life year for COPD caused by $PM_{10}$ was then estimated.

## Material and methods

### 1) $PM_{10}$ data and MAIAC-AOD products

The nine northern Thai provinces which comprise the study area are Chiang Mai, Chiang Rai, Lampang, Lamphun, Phreae, Nan, Phayao, Mae Hong Son, and Tak as shown in Figure 1a. Comparing MAIAC-AOD with the emission rate from our prior work was carried out using hourly measured PM10 concentrations at eleven air monitoring stations from Pollution Control Department (PCD) [18]. The product of MAIAC-AOD at 1-km resolution with 550 nm in HDF4 format was obtained from the Level-1 and Atmosphere Archive & Distribution System (LAADS) Distributed Active Archive Center (DAAC) as shown in Figure 1b. It was discovered that there was a significant correlation between the Aerosol Robotic Network's (AERONET) surface-based monitoring and the MAIAC-AOD product [19–22]. In this study, the Chiang Mai Meteorology Station, Angkhang, and Omkoi district's AERONET Level 2.0 were used to validate the MAIAC-AOD. While our MAIAC-AOD was at 550 nm, the closest AERONET-AOD data was at a wavelength between 500 and 675 nm. The 550 nm of AERONET-AOD was interpolated based on the 500 and 675 nm data employing the Angstrom Exponent to enable it to be compared with MAIAC-AOD at 550 nm, and the average daily correlation coefficient (R) between AERONET-AOD and MAIAC-AOD was determined.

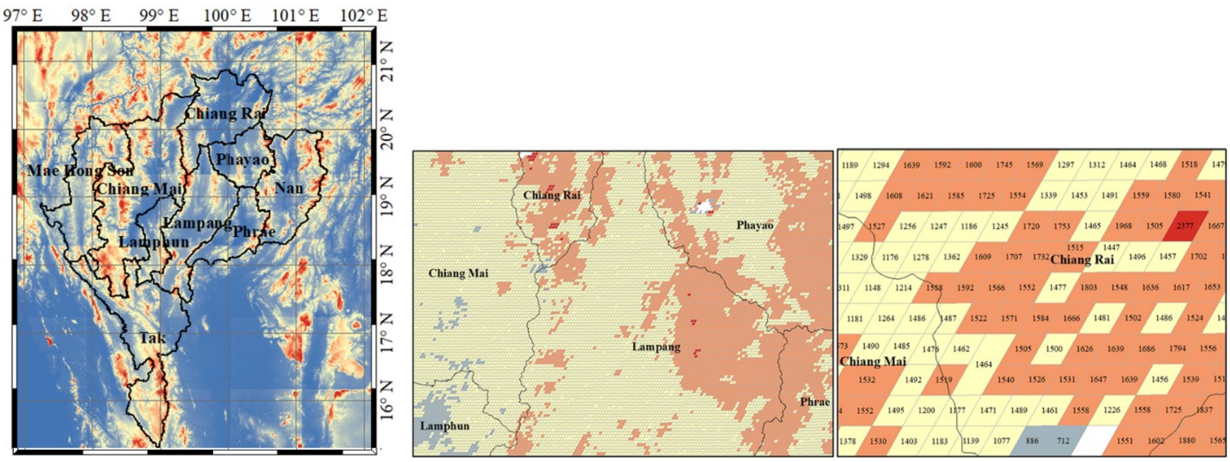


**Figure 1** (a) study domain and (b) MAIAC-AOD 1-km resolution and its grid value.

### 2) Distribution and relationship between $PM_{10}$ emissions, measured $PM_{10}$, and MAIAC-AOD

To assess the temporal trend, the average daily measured $PM_{10}$ from PCD monitoring stations, the average daily estimated $PM_{10}$ emission from our previous research [18], and the average daily of the 1-km resolution of MAIAC-AOD from the LAADS at the same site of PCD monitoring station between 2014 and 2016 were all plotted on the same graph, and the average, maximum, and standard deviation of these variables were elaborated. The daily correlation between $PM_{10}$ emission and measured $PM_{10}$, measured $PM_{10}$ and MAIAC-AOD, as well as MAIAC-AOD and $PM_{10}$ emission in the same colocation of the monitoring station between 2014 and 2016 was investigated. Because the emission estimated from the VIIRS hot spot from our previous study was with high resolution product (375 m) and greater able to detect small fires than the other hot spot product, a significant correlation between $PM_{10}$ emission and measured $PM_{10}$ was determined. GIS software was used to carry out the spatial distribution of associated parameters; the cell statistics approach was employed to establish a 1 km grid cell for the MAIAC-AOD for the seasonal and annual. And the inverse distance weighted (IDW) technique was used to generate the measured $PM_{10}$ distribution of the non-monitoring station [23]. The Geographically Weighted Regression (GWR) tool was then applied to establish the spatial correlation between the measured $PM_{10}$ and MAIAC-AOD [24–25]. In accordance with the sequential method depicted in Figure 2, the spatial predicted $PM_{10}$ concentration in each grid cell of each subdistrict was averaged to continue assessing the disease burden.

### 3) Quantifying of disease burden

The health endpoint for our investigation was chosen based on the DALYs value of the health endpoint attributable to air pollution, the availability of the exposure-response coefficient (β), and the baseline incidence rate of the health endpoint. Since COPD (J40–J44) was one of the twenty top causes of disability-adjusted life years (DALYs) in the Thailand Burden of Disease Reports from 2009, 2011, and 2014, it was primary as the study's selected health endpoint. In northern Thailand during the seasonal haze, an increase in COPD was correlated with a rise in $PM_{10}$ [26]. Additionally, an increase in $PM_{10}$ was consistently related to mortality and the years of life lost (YLL) [27].

An exposure–response coefficients (β) of COPD for $PM_{10}$ was 2.7E-06 per 1 µg $m^{-3}$ [28]. Population distribution of exposure (Pe) was assessed by divided number of populations in each subdistrict with total population in Thailand. The age group of burden of disease quantification was classified as same as the Provincial Public Health Office with 15–39, 40–49, 50–59, and 60+ years for each subdistrict. Baseline number of death for COPD was gathered from Provincial Public Health Office. The standard life expectancy of each age group was obtained from the standard life of WHO.

The provincial public health office of the research area provided the CODP incidences. The number of years a person has suffered from a COPD symptom is used to calculate their disability year [29]. Relative risk (RR) was calculated using the following Eq. 1, which employs an exponential relationship between the exposure-response coefficient (β) and the varying concentrations of predicted and background $PM_{10}$ in ambient air. The first step was subtraction of predicted $PM_{10}$ by the background $PM_{10}$, getting the change of $PM_{10}$ concentration (ΔC). The background concentration was to indicated degree of exposure to $PM_{10}$ which contributed by the local emission sources that was added to the background concentration which could be affected to the local population [30].

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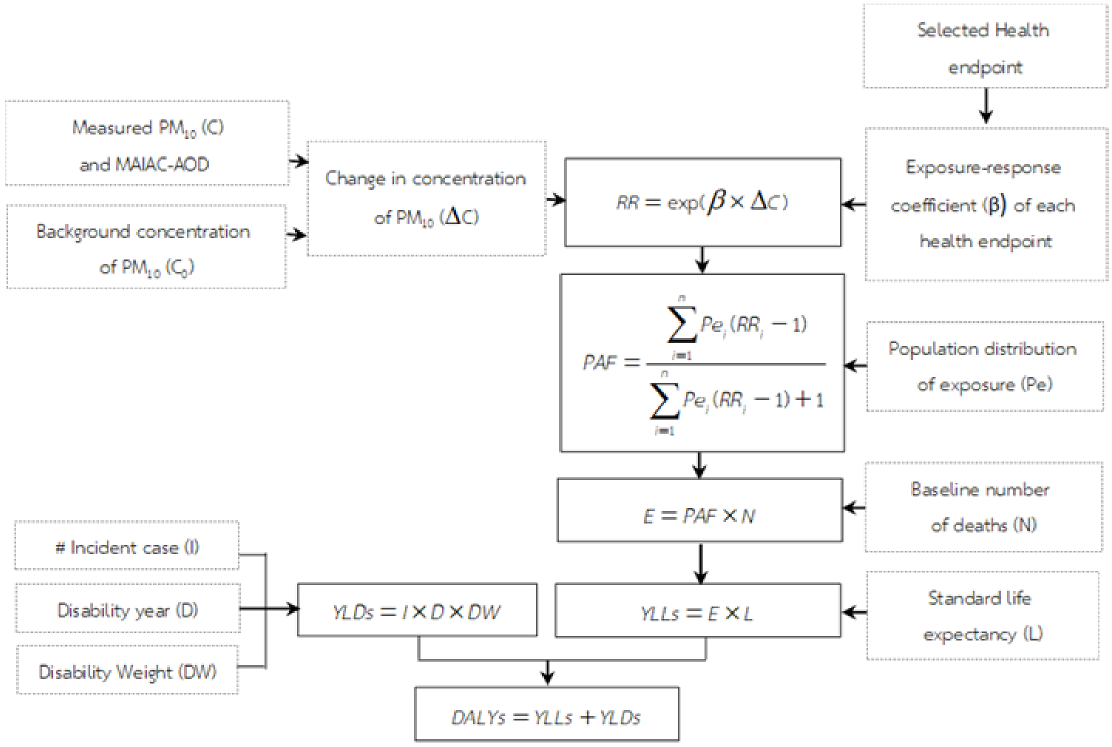


**Figure 2** Quantification of disease burden.

$$RR = \exp\left[\beta\left(C_a - C_0\right)\right] \quad \text{(Eq. 1)}$$

where; $\beta$ is the exposure–response coefficients of $PM_{10}$ (per 1 µg $m^{-3}$) of COPD, Ca is the average concentration of $PM_{10}$ and $C_0$ is the background level of $PM_{10}$ (10 µg $m^{-3}$) [31].

The population distribution of exposure (Pe) and relative risk (RR) values as stated in Eq. 2 were used to calculate the fraction of disease burden attributable by $PM_{10}$ (PAF). The population distribution of exposure (Pe) in a subdistrict level was determined using the population ratio of each subdistrict to the total population of Thailand. Information on the northern population was provided by Thailand's Department of Provincial Administration. We assume that the population in the same subdistrict was subjected to the same levels of pollution.

$$PAF = \frac{\sum_{i=1}^{n} Pe_i\left(RR_i - 1\right)}{\sum_{i=1}^{n} Pe_i\left(RR_i - 1\right) + 1} \quad \text{(Eq. 2)}$$

Where; PAF is the proportion of disease burden caused by $PM_{10}$, $Pe_i$ is the proportion estimates of the population in exposure to $PM_{10}$, including the unexposed and $RR_i$ is the relative risk in exposure to $PM_{10}$.

Eq. 3 was used to estimate the expected number of fatalities attributed to $PM_{10}$, and it was then used to determine the DALYs.

$$E = PAF \times N \quad \text{(Eq. 3)}$$

Where; E is the expected number of deaths due to $PM_{10}$ and N is the baseline number of deaths for COPD.

Years lived with a disability (YLDs) were determined using a formula that multiplied the number of incidents, the disability year, and the disability weight, which ranged from 0 (perfect health) to 1 (worst health condition). For this study, the disability weight of COPD associated with $PM_{10}$ was 0.284 [32].

$$YLDs = I \times D \times DW \quad \text{(Eq. 4)}$$

Where; I is the number of COPD incident (case), D is the disability year (year) and DW is the disability weight.

Eq. 5 was used to calculate the YLLs from the standard life expectancy YLLs to premature death.

$$YLLs = E \times L \quad \text{(Eq. 5)}$$

Where; E is the number of COPD premature mortalities attributed to $PM_{10}$ and L is the standard life expectance.

After combining YLLs and YLDs, the DALYs were determined using the Eq. 6.

$$DALYs = YLLs + YLDs \quad \text{(Eq. 6)}$$

## Results and discussions

First, the association between daily AERONET-AOD and MAIAC-AOD at 550 nm was examined, and it was found that all three AERONET sites; the Chiang Mai Meteorology Station, Angkhang, and Omkoi district showed a strong correlation, with R values of 0.8468, 0.8396, and 0.8334 for the years 2014–2016, respectively. The total derived MAIAC-AOD in upper-northern Thailand from 2014 to 2016 was 3208. Summer was the season in which the MAIAC-AOD was found most frequently (62.5%), followed by the winter (34.8%) and the rainy season (2.7%). The optimum levels of the MAIAC-AOD, 2.70 and 3.48, were observed in the months of March and April, respectively, which was consistent with the highest measured $PM_{10}$ concentration and emission. But in July and September, there were remarkably fewer observations of the MAIAC-AOD. The seasonal trends of $PM_{10}$ emission, measured $PM_{10}$, and MAIAC-AOD were highest in summer and lowest in rainy season as shown in Table 1. Nevertheless, the study found that the annual average $PM_{10}$ concentration in northern Thailand was 73 μg $m^{-3}$ from 2014 to 2016, which is higher than national limit of 50 μg $m^{-3}$.

### 1) Relationship of $PM_{10}$ emissions, measured $PM_{10}$, MAIAC-AOD

Figure 3 displayed the 3,208 data that were available for each province and the entire northern area between 2014 and 2016 in terms of emissions rate, measured $PM_{10}$, and MAIAC-AOD. All three variables peaked in the summer months (Feb–May) [33], then started to decline in the rainy months (Jun-Sep), when there was a drop in $PM_{10}$ emission and AOD detected. According to Pearson correlation statistics, the three pair variables; $PM_{10}$ emission vs measured $PM_{10}$, measured $PM_{10}$ vs MAIAC-AOD, and $PM_{10}$ emission vs MAIAC-AOD among northern region between 2014 and 2016 exhibited average correlations of 0.6656, 0.6446, and 0.5580, respectively. While the correlation coefficient for each season was determined according to the season's month, with summer from February to May, rainy from June to September, and winter from October to January, as shown in Table 2 and Figure 4.

**Table 1** Average daily, seasonal, and annual MAIAC-AOD, measured $PM_{10}$, and $PM_{10}$ emission in northern Thailand from 2014 to 2016

| Month | No. of days | $PM_{10}$ emission (ton $ha^{-1}$) *[18] | | | Measured $PM_{10}$ (μg $m^{-3}$) | | | MAIAC-AOD | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | S.D. | Max. | Mean | S.D. | Max. | Mean | S.D. | Max. |
| Jan | 470 | 1.36 | 0.81 | 7.10 | 56 | 54 | 142 | 0.37 | 0.21 | 1.60 |
| Feb | 485 | 2.42 | 1.78 | 8.43 | 81 | 33 | 203 | 0.51 | 0.24 | 1.53 |
| Mar | 600 | 4.14 | 2.20 | 8.43 | 127 | 62 | 449 | 1.03 | 0.47 | 2.70 |
| Apr | 556 | 2.87 | 2.39 | 8.43 | 84 | 49 | 456 | 0.98 | 0.50 | 3.48 |
| May | 364 | 0.56 | 0.30 | 3.00 | 47 | 24 | 163 | 0.55 | 0.27 | 1.35 |
| Jun | 31 | 0.81 | 0.11 | 1.00 | 26 | 19 | 82 | 0.39 | 0.17 | 0.85 |
| Oct | 55 | 0.93 | 0.09 | 1.04 | 35 | 11 | 56 | 0.47 | 0.19 | 0.82 |
| Nov | 278 | 0.95 | 0.21 | 3.50 | 33 | 11 | 62 | 0.24 | 0.13 | 0.65 |
| Dec | 369 | 0.99 | 0.29 | 4.30 | 44 | 15 | 90 | 0.28 | 0.16 | 1.10 |
| Summer | 2005 | 2.87 | 2.23 | 8.43 | 89 | 54 | 456 | 0.80 | 0.47 | 3.48 |
| Rainy | 86 | 0.89 | 0.11 | 1.04 | 32 | 15 | 82 | 0.44 | 0.18 | 0.85 |
| Winter | 1117 | 1.13 | 0.59 | 7.10 | 46 | 20 | 142 | 0.30 | 0.18 | 1.60 |
| Annual | 3208 | 2.21 | 1.99 | 8.43 | 73 | 50 | 456 | 0.62 | 0.45 | 3.48 |

**Table 2** Average daily, seasonal, and annual MAIAC-AOD, measured $PM_{10}$, and $PM_{10}$ emission in northern Thailand from 2014 to 2016

| Season | Days | R between EI and measured $PM_{10}$ | R between Measured $PM_{10}$ and AOD | R between EI and AOD |
|---|---|---|---|---|
| Dry season | 2,005 | 0.6084 | 0.5614 | 0.4652 |
| Rainy season | 86 | 0.2696 | 0.3762 | 0.3048 |
| Winter season | 1,117 | 0.2882 | 0.4101 | 0.1363 |
| Annual | 3,208 | 0.6656 | 0.6446 | 0.5580 |

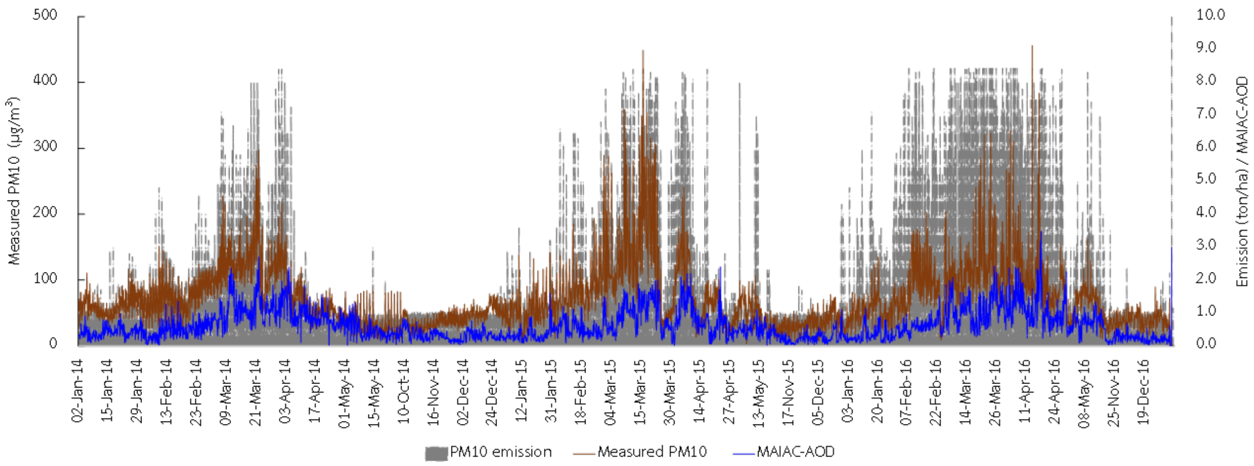


**Figure 3** Daily temporal distribution $PM_{10}$ emissions, measured $PM_{10}$, and MAIAC-AOD.

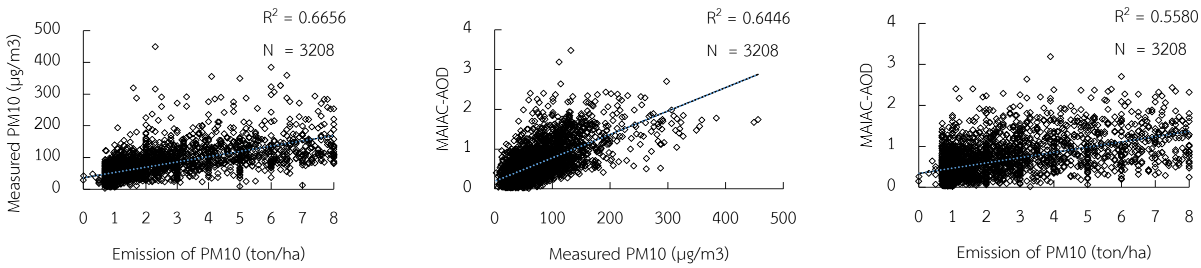


**Figure 4** The correlations of $PM_{10}$ emission, measured $PM_{10}$, and MAIAC-AOD in the northern Thailand during 2014–2016 at the same co-location of air monitoring station.

The high value of correlation between measured $PM_{10}$ and $PM_{10}$ emission was consistent with our previous study and several other studies since the ground-based emissions data were matched by the VIIRS approach with a high correlation value because VIIRS has a remarkable ability to detect small fires and high resolution (375 m), which occur throughout summer months [34–35]. According to the missing of the AOD data on some days, which are typically brought on by cloud and high surface reflectance, the lower correlation value between the pair of measured $PM_{10}$ vs. MAIAC-AOD and $PM_{10}$ emission vs. MAIAC-AOD could have been caused by meteorological variables such relative humidity, planetary boundary layer height, wind, and cloud interference [7, 10, 36]. However, the high correlation score was noticed in the summer months due to the availability of MAIAC-AOD, which was about 52–69%, corresponding with the high level of emissions and measured $PM_{10}$ during the summer.

### 2) Spatial distribution

### 2.1) Spatial distribution of $PM_{10}$ emissions

The distribution of biomass emissions were 0.5 to 50 tons of emissions per hectare in the study area. It was discovered that Mae Hong Son, Tak, and Chiang Mai, which were areas with a majority of forest, had a high distribution of $PM_{10}$ emission (more than 30 tons per hectare). Throughout a three-year period, it was found that Mae Hong Son province produced significant average $PM_{10}$ emissions, with emissions above 10 tons $ha^{-1}$ in every subdistrict. Furthermore, it was found that provinces with most of the agricultural area, such Chiang Rai, Phare, and Nan, tended to have lower $PM_{10}$ emissions (10 tons $ha^{-1}$) in the three years as shown in Figure 5.

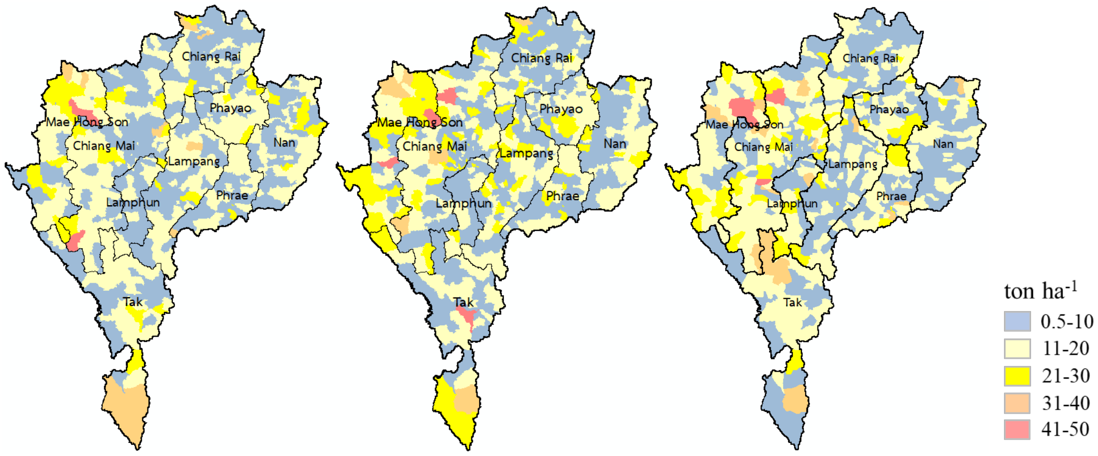


**Figure 5** Emission of $PM_{10}$ 2014–2015.

### 2.2) Spatial distribution of MAIAC-AOD

Figure 6 displays the spatial distribution of MAIAC-AOD for each season and year from 2014 to 2016. The MAIAC-AOD was more prevalent in the summer (Feb-May) and winter (Oct-Jan) compared to the rainy (Jun-Sep), however the high AOD (>0.75) was only seen during the summer months, according to studies, mixed deciduous woods shed their leaves during the dry season, and fires in savannas and grasslands may have been ignited by trash accumulation in places where trees have been abnormally dense. Additionally, the time for harvesting and cleaning the field for the following planting was carried out during summertime [37]. The high value of MAIAC-AOD was observed in the east (Chiang Rai, Phayao, Nan, Phrae, and Lampang) as opposed to the west, which is consistent to our previous study's discovery of a high fire hot spot, and many maize residues burned in the field in these areas [38], which was associated to the emission of particulate matter that could be detected by the MAIAC-AOD instrument.

### 3) Burden of disease

According to the good temporal correlation between the emissions rate, measured PM10, and MAIAC-AOD at the eleven monitoring stations in northern Thailand between 2014 and 2016 was observed with the range between 0.5338–0.8101. Along with the good spatial correlation between MAIAC-AOD and PAF of COPD that was demonstrated by use of Geographic Weight Regression approach in GIS that was estimated from differences in background and measured $PM_{10}$ concentrations, together with  and exposed population, the correlation between MAIAC-AOD and PAF for the years 2014 to 2016 was 0.5979, 0.3741, and 0.7584, respectively. Based on the considerations, we decided to predict the disease burden in terms of DALYs for every province in the study area using the interpolated measured $PM_{10}$ concentration. The average PAF during 2014–2016 was 3.01E-05, 2.42E-05, and 2.37E-05, respectively, the spatial distribution of PAF was shown in Figure 7. The relative risk of COPD during 2014–2016 was 1.2090, 1.2062, and 1.2079 which was consistent with the PAF that was highest in the year 2014.

The overall DALYs of COPD attributable to $PM_{10}$ between 2014 and 2016 were 115,930 years per 100,000 populations, with 3,528 years for those between the ages of 15 and 39, 6,866 years for those between the ages of 40 and 49, 19,826 years for those between the ages of 50 and 59, and 85,710 years for those over 60. Nan, Phayao, and Chiang Mai were the top three provinces with the highest DALYs of COPD, with 21,364 (18%), 15,132 (13%), and 13,421 (12%) years per 100,000 populations, respectively, while Lamphun has the lowest with 8,353 (7%) years as shown in Table 4. Since Phayao province had the largest agricultural areas in the north and produced a substantial portion of PM10 from such areas (927 tons between 2012 and 2016) [18]. The 2018 Air Quality Assessments for Health and Environment Policies found that the DALYs of chronic lower respiratory diseases (J40–J47) caused by $PM_{2.5}$, $PM_{10}$, and $O_3$ in Chiang Mai ranged from 3,283–17,612 years per 100,000 populations. Thailand reported 645,448 DALYs from ambient (outdoor) air pollution per 100,000 people in 2018 [39]. In comparison to other years, 2016 had the highest DALYs of COPD with 46,317 years per 100,000 populations with an average PM10 concentration of 45 $\mu g\ m^{-3}$. While in 2014, the DALYs of COPD was 26,039 years per 100,000 populations with an average $PM_{10}$ concentration of 44.7 $\mu g\ m^{-3}$. The DALYs from this study were compared to those from a study by Chulabhorn Research Institute that discovered the DALYs of cancer, eye diseases, cardiovascular diseases, and respiratory diseases associated by $PM_{2.5}$, $PM_{10}$, and ozone during the period of

https://doi.org/10.35762/AER.2023008

2012 to 2016 ranged from 3,283 to 16,612 years per 100,000 people in the Chiang Mai area [40]. While our study which focused on COPD attributed to only $PM_{10}$ found that the DALYs were 13,421 years per 100,000 population during 2014–2016.

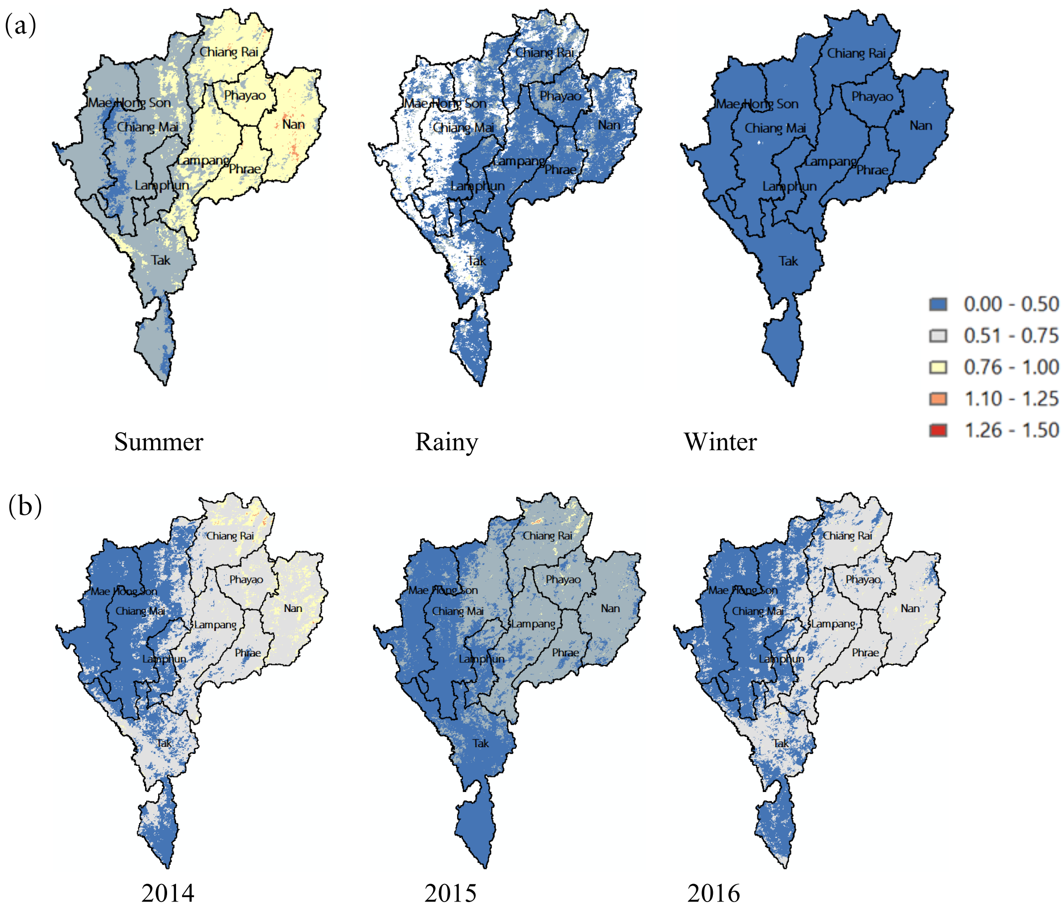


**Figure 6** Distribution of (a) average seasonal MAIAC-AOD (3 years), and (b) average annual MAIAC-AOD.

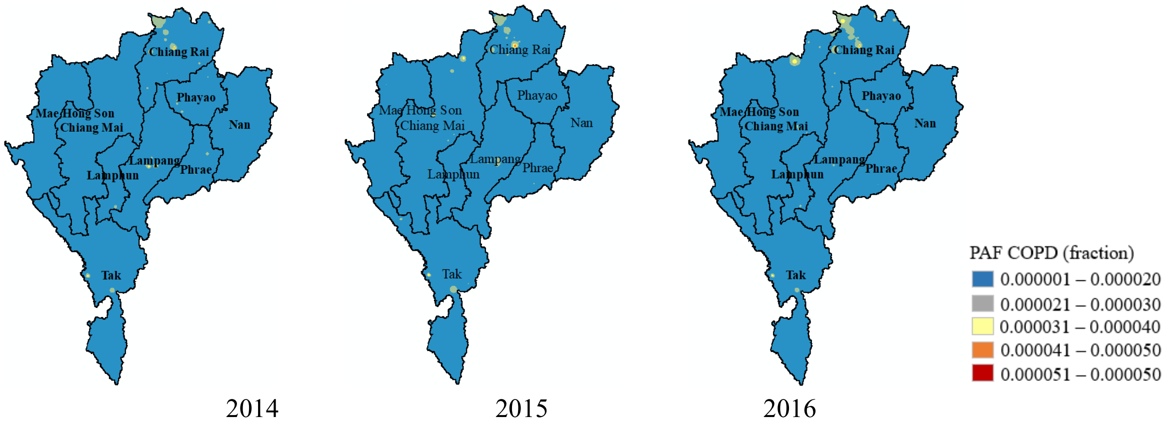


**Figure 7** PAF of COPD during 2014-2016.

**Table 3** Relative risk and proportion of disease burden caused by COPD based on monitored $PM_{10}$ concentration, 2014–2016

| Year | Average $PM_{10}$ ($\mu g\ m^{-3}$) | Average AOD (per 1-km grid) | RR | | PAF | |
|---|---|---|---|---|---|---|
| | | | Mean | 95% CI | Mean | 95% CI |
| 2014 | 44.7 | 0.60 | 1.2090 | 1.2073–1.2107 | 3.01E-05 | 2.69E-05-3.33E-05 |
| 2015 | 42.4 | 0.58 | 1.2062 | 1.2045–1.2079 | 2.42E-05 | 2.31E-05-2.52E-05 |
| 2016 | 45.0 | 0.68 | 1.2079 | 1.2068–1.2091 | 2.37E-05 | 2.27E-05-2.47E-05 |

**Table 4** DALYs of COPD attributable to PM10 (per 100,0000) during 2014–2016

| Province | Annual DALYs | | | Total 3 years of DALYs for COPD (per 100,000) | | | | Total DALYs for 3 years | % of all DALYs |
|---|---|---|---|---|---|---|---|---|---|
| | 2014 | 2015 | 2016 | 15-39 yrs. | 40-49 yrs. | 50-59 yrs. | 60+ yrs. | | |
| Chiang Mai | 3,785 | 4,174 | 5,462 | 555 | 853 | 2,514 | 9,499 | 13,421 | 12 |
| Lamphun | 1,844 | 5,180 | 1,329 | 335 | 528 | 1,536 | 5,953 | 8,353 | 7 |
| Lampang | 3,162 | 5,955 | 6,570 | 281 | 670 | 2,175 | 12,561 | 15,687 | 14 |
| Phrae | 1,503 | 4,526 | 4,849 | 294 | 627 | 1,937 | 8,021 | 10,878 | 9 |
| Nan | 3,851 | 8,414 | 9,100 | 330 | 863 | 2,958 | 17,213 | 21,364 | 18 |
| Phayao | 4,583 | 4,833 | 5,716 | 420 | 803 | 2,429 | 11,480 | 15,132 | 13 |
| Chiang Rai | 1,553 | 3,040 | 4,416 | 236 | 434 | 1,515 | 6,825 | 9,009 | 8 |
| Mae Hong Son | 2,236 | 3,270 | 3,898 | 410 | 571 | 1,934 | 6,488 | 9,404 | 8 |
| Tak | 3,522 | 4,183 | 4,977 | 667 | 1,518 | 2,828 | 7,669 | 12,682 | 11 |
| Total | 26,039 | 43,574 | 46,317 | 3528 | 6,866 | 19,826 | 85,710 | 115,930 | 100 |

## Conclusion

The concentration of $PM_{10}$ along with the exposure-response coefficient, population distribution, baseline mortalities, standard life expectancy, number of COPD incidence case, and disability weight were used to predict relative risk and proportion of disease burden to quantify the burden of disease attributable to $PM_{10}$. By comparing the $PM_{10}$ emission from our previous research with the measured $PM_{10}$ from the PCD monitoring station and the 1-km of MAIAC-AOD, we examined the relationship between the quantity of $PM_{10}$ in the air and its emission. The total MAIAC-AOD was calculated for 3,208 in the study region between 2014 and 2016, and the results showed that it was observed more frequently (62.5%) in summer, with the highest values of 2.70 and 3.48 being recorded in the months of March and April, respectively. The findings also revealed that there was a good temporal correlation between the emissions, measured $PM_{10}$, and MAIAC-AOD at the eleven monitoring stations during 2014 to 2016. The maximum recorded $PM_{10}$ concentration and emission were also consistent with those findings. Therefore, we estimate the disease burden in terms of DALYs attributable to $PM_{10}$ using the spatially measured $PM_{10}$ concentration. In the northern region, the overall number of DALYs attributable to $PM_{10}$ for COPD was 115,930 years per 100,000 populations, with Nan having the highest percentage (18%) and Lamphun having the lowest (7%), which is linked to the coverage of MAIAC-AOD detected. Furthermore, during the years 2014–2016, the correlation between MAIAC-AOD and PAF was 0.5979, 0.3741, and 0.7584, respectively. To enhance the precision of the prediction of PM10 concentration using the 1-km resolution of MAIAC-AOD, the future research must integrate meteorological parameters such as wind direction, wind speed, planetary boundary layer, and temperature. Adequate air quality management is currently required to reduce air pollution urgently and effectively, particularly for $PM_{10}$ and $PM_{2.5}$ pollutants. In the northern region, emissions from transportation, biomass burning, and agricultural activities make up the majority of the sources of $PM_{10}$. The findings of the present study demonstrate the value of local evaluation and assessment of COPD related to air quality to protect population health. This study is based on the assumption that the entire population of northern Thailand is exposed to the high level of PM10 concentration at an average annual level of 73 $\mu g\ m^{-3}$ which exceed the annual standard level (50 $\mu g\ m^{-3}$). The finer resolution of MAIAC-AOD would be great for future research to achieve finer resolution when quantifying the burden of disease.

## Acknowledgement

This work has been supported by the Faculty of Public Health, Thammasat University. The Thailand Pollution Control Department provided accurate data on daily $PM_{10}$ concentrations. The Atmosphere Archive & Distribution System (LAADS) Distributed Active Archive Center (DAAC) stored appropriated MAIAC-AOD data. The AERONET (AErosol RObotic NETwork) data were recorded by the NASA, and the health endpoint was obtained from the Provincial Public Health Office of Chiang Mai, Chiang Rai, Lampang, Lamphun, Phreae, Nan, Phayao, Mae Hong Son, and Tak Province.

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