

# Prediction of Hourly Particulate Matter Concentrations in Chiangmai, Thailand Using MODIS Aerosol Optical Depth and Ground-Based Meteorological Data

Thongchai Kanabkaew

Environmental Science Program, School of Engineering and Resources, Walailak University, Nakhon Si Thammarat, Thailand

#### Abstract

Various extreme events recorded over the world have been recognized as scientific-based evidence from possible climate change and variability. The incidence of increasing forest fires and intensive agricultural field burning in Chiangmai and Northern Thailand due to favor conditions may also due to a likely increase of droughts caused by the changing climate. Smog from biomass burning, particularly particulate matter (PM) seriously affects health and the environment. Lack and sparse of ground monitors may cause unreliability for warning information. Satellite remote sensing is now a promising technology for air quality prediction at ground level. This study was to investigate the statistical model for predicting PM concentration using satellite data. Aerosol optical depth (AOD) data were gathered from MODIS-Terra platform while hourly PM<sub>2.5</sub> and PM<sub>10</sub> data were collected from the Pollution Control Department. The relationship between AOD and hourly PM over Chiangmai was addressed by Model I-Simple linear regression and Model II-Multiple linear regression with ground-based meteorological data correction. The data used for the statistical analyses were from smog period in 2012 (January-April). Results revealed that AOD and hourly PM in Model I were positively correlated with the coefficient of determination ( $R^2$ ) of 0.22 and 0.21, respectively for PM<sub>2.5</sub> and PM<sub>10</sub>. The relationship between AOD and hourly PM was improved significantly when correcting with relative humidity and temperature data. The model II gave  $R^2$  of 0.77 and 0.71, respectively for PM<sub>2.5</sub> and PM<sub>10</sub>. To investigate the validity of model, the regression equation obtained from Model II was then applied with smog data over Chiangmai in March 2007. The model performed reasonably with R<sup>2</sup> of 0.74. The model applications would provide supplementary data to other areas with similar conditions and without air quality monitoring stations, and reduce false warning the level of air pollution associated with smog from intensive biomass burning. However, further investigation in different locations should be conducted to confirm the applicability of the model.

Keywords: Particulate matter; Aerosol optical depth; MODIS; Chiangmai

### 1. Introduction

Biomass open burning in Northern Thailand and neighboring countries has been considered as essential sources of high concentrations of particulate matter (PM) during the dry season. Numbers of hotspot detected from satellite data and ground PM measurement data were positively correlated indicating contributions of biomass burning emissions (Kim Oanh and Leelasakultum, 2011). Long dry period could also favor for increasing forest fires and intensive crop residue burning in Chiangmai and Northern Thailand, as well as the neighboring countries. High level of PM concentrations could induce health impacts to those people who exposed the dense haze. The epidemiological study on the association between daily PM<sub>10</sub> concentrations and short-term mortality in Bangkok, Thailand has been published by Ostro et al. (1999) and Vajanapoom et al. (2002). Both studies presented the similar estimate that  $1 \mu g/m^3$  increase in PM<sub>10</sub> will result in 0.10% increase in daily mortality.

Lack and sparse of air quality monitoring in

Chiangmai and Northern Thailand would reduce reliability for PM warning. Nowadays, there are 62 permanent air quality monitoring stations in Thailand of which 31, 14, 3, 9 and 5 stations, respectively are located in Central, Northern, Northeastern, Eastern and Southern Thailand. It is remarkably interested to note that 25 stations are located in Bangkok Metropolitan Region (BMR) and only 2 stations are installed in Chiangmai (PCD, 2011). Applications of satellite data for monitoring the environmental change, including air quality monitoring, particularly ground PM concentrations have been intensively investigated throughout the world (i.e. Wang and Christopher 2003; Engel-Cox *et al.*, 2004; Tian and Chen, 2010).

The objective of this study was to investigate the relationship between AOD and PM data in Chiangmai with and without meteorological data correction. The results retrieved from regression models were expected to be used for predicting PM concentrations in Chiangmai and other areas with similar climate and geography conditions and without air quality monitoring stations.

## 2. Materials and Methods

#### 2.1. Study Area

Chiangmai is located between latitude 17°N to 21°N and longitude 98°E to 100°E (Figure 1). It is the biggest province in Northern region and the second largest province in Thailand (NSO, 2013).

Chiangmai occupies an area of 20,107 km<sup>2</sup> with a population of around 1.7 million as of 2011 data. Its terrain mostly consists of forested mountains which are accounted to be around 82.7% of total area, following by agricultural area (12.8%) and urban land (4.4%). In 2011, monthly average temperature ranged 12.5-38.0°C and monthly average relative humidity ranged 52-93% (NSO, 2013). The hottest month is April while the coolest month is January.

## 2.2. Data Collection

## 2.2.1. Air quality and meteorological data

Air quality data which are hourly particulate matter with aerodynamic diameter less than 2.5 and 10 micron ( $PM_{2.5}$  and  $PM_{10}$ , respectively) were gathered from the Pollution Control Department (PCD) of Thailand during the Northern haze episode.  $PM_{10}$  data were collected for January-April, 2007 and January-April, 2012 while  $PM_{2.5}$  data were collected for January-April, 2012 due to availability of the data. Also, hourly meteorological data which are temperature (T) and relative humidity (RH) were gathered from PCD for the same period. The stations used for data collection are 35T (City Hall) and 36T (Yupparaj) located at Muang district, Chiangmai Province (see also Fig. 1).  $PM_{2.5}$  data were available only at 36T station.

#### 2.2.2. Satellite data

Satellite data which are aerosol optical depth (AOD) at 550 nm wavelength and cloud fraction (CF) were gathered from MODIS-Terra platform for March 2007 and January-April 2012 from http://ladsweb.na-scom.nasa.gov/data/search.html. The satellite passed the area at daytime about 10:30 a.m., local standard time.Resolution of AOD data was 10 km x 10 km horizontally. The specific data products used in this study were MOD04 Level 2 Aerosol Product. The data and metadata downloaded were in the form of hierarchical data format (HDF) files for the selected geolocation. HDF files were then extracted by software called HDF explorers.

Satellite-derived AOD data are, in principle, generated by two algorithms depending on the surface:



Figure 1. Study area

over-land or over-ocean. These algorithms allow cloud pixel rejection while maintaining other cloud free pixels. They also allow the corrections for gas ( $O_3$ , water vapor and  $CO_2$ ) absorption by using different bands of satellite sensors. In MODIS procedures, algorithms are applied to individual boxes of 20x20 pixels at 500 m resolution to produce 1 pixel at 10 km resolution of AOD. Out of 400 pixels in the original box, at least 10 pixels must be manipulated by the over-ocean algorithm and 12 by the over-land algorithm. Otherwise, no AOD data were reported (Levy *et al.*, 2009).

It is noteworthy that the 2012 data were used to investigate the correlation between PM and AOD while the 2007 data were used to evaluate the model performance. Both periods were observed to be the intensive biomass open burning with high PM concentrations in Chiangmai (PCD, 2012).

### 2.3. Data Analysis

AOD data under clear sky were used to correlate with ground PM measurements. To select the proximity of MODIS-Terra data to the ambient air stations, a grid size of 30 km x 30 km surrounded the air stations was set up to assign the nearest point. This selection method would reduce the errors related to spatial variation (Engel-Cox *et al.*, 2004). This collocation covers two air quality stations of Chiangmai, 35T and 36T. Hourly average values of PM were used to create the linear relationship between AOD and PM. Data analyses were divided into 2 types of regression models: 1) Simple linear regressions (Model I) and 2) Multiple linear regressions (Model II). Details are summarized as follows.

#### 2.3.1. Model I-Simple linear regression

Simple linear regression was conducted considering only the relationship between AOD and hourly average PM, namely AOD and  $PM_{2.5}$  and AOD and  $PM_{10}$ . This is a simple case to investigate the empirical model explaining how AOD data can represent ground PM data. This method had been done, mostly in previous researches (i.e. Wang *et al.*, 2003; Engel-Cox *et al.*, 2004). Simple linear regression model is indicated in equation (1) where  $b_0$  is an intercept and  $b_1$  is a regression coefficient..

Hourly 
$$PM = b_0 + b_1 (AOD)$$
 (1)

#### 2.3.2. Model II-Multiple linear regression

Multiple linear regression was conducted considering the meteorological parameter effects on the relationship between AOD and hourly average PM. Meteorological data were observed to be important factors influencing PM concentrations in Northern Thailand (Kim Oanh and Leelasakultum, 2011). In this study, only surface temperature (T) and surface relative humidity (RH) meteorological factors were used since these two parameters have been found as high significant in the prediction of ground  $PM_{2.5}$  using satellite AOD (Tian and Chen, 2010). Multiple linear regression model is indicated in equation (2) where  $b_0$  is an intercept while  $b_1$ ,  $b_2$  and  $b_3$  are regression coefficients..

Hourly  $PM = b_0 + b_1 (AOD) + b_2 (T) + b_3 (RH)$  (2)

### 3. Results and Discussion

#### 3.1. Current Situation of Haze and PM in Chiangmai

Haze episodes due to biomass open burning in Chiangmai have been observed for more than two decades (Tiyapairat and Sajor 2012) and are recognized as the important sources of high PM concentrations in the area, particularly during the dry season between November to April (Kim Oanh and Leelasakultum, 2011). Emissions of biomass open burning compose of substantial amount of fine PM and toxic substances (Kanabkaew and Kim Oanh, 2011). PM<sub>10</sub> levels during the dry period normally exceed the National Ambient Air Quality Standards of Thailand which is 120  $\mu$ g/m<sup>3</sup> for 24-hour average (Pengchai *et al.*, 2009).

24-hour average concentrations of  $PM_{10}$  were plotted for two periods, January-April, 2007 and January-April 2012 as indicated in Fig. 2. In 2007, haze episode in Chiangmai was found to cause severe air quality deterioration and level of  $PM_{10}$  was found to exceed 350 µg/m<sup>3</sup> (Fig. 2). Recently in early 2012, levels of  $PM_{10}$  were recorded to exceed the National Ambient Air Quality Standards at various locations (PCD, 2012) including Chiangmai as indicated in Fig. 2.

Biomass open burning, including forest fires, crop residue burning and solid waste burning, had been found to be the major cause of haze episodes in Chiangmai and Northern Thailand (Tiyapairat and Sajor 2012). Most forest fires in Northern Thailand were caused by human activities. Based on 1998-2002 data, the biomass open burning was mainly related to the collection and harvest of forest products (37%), hunting (22%), and burning of agricultural crop residue (17%) (Tiyapairat and Sajor 2012).

#### 3.2. Model I

The linear relationships between the ground monitoring data and satellite AOD at clear sky (CF=0) are indicated in Fig.3. The relationship between AOD and



Figure 2. Levels of average PM<sub>10</sub> concentrations during January-April 2007 and January-April 2012 in Chiangmai

 $PM_{2.5}$  showed similar  $R^2$  coefficient in comparison to that between AOD and  $PM_{10}$  that was around 0.20.

The results from this study were compared with the others in U.S. (Engel-Cox *et al.*, 2006) and in China (Wang *et al.*, 2010) in terms of  $b_0$ ,  $b_1$  and  $R^2$ . Magnitude of  $b_1$  values was comparable while  $R^2$  was slightly lower. It is interesting to note that magnitude of  $b_0$  values was considerably higher than the other studies that could be influenced by other factors. The relationship between AOD and PM does not depend only on total mass concentrations but also does depend on a number of influencing factors such as: 1) meteorological factors, 2) PM compositions and 3) AOD vertical profile. These factors are spatially and temporally different in any given regions. Further, in Model II the incorporation of common meteorological parameters, temperature

and relative humidity, was investigated to improve the AOD and PM relationship.

### 3.3. Model II

The model described by equation (2) was fitted using the dataset (PM, AOD, T and RH) to estimate the model coefficients. Overall, the model result performed a considerably significance (p < 0.01) and the model was able to explain 77% and 71% of the variability in the hourly PM<sub>2.5</sub> and PM<sub>10</sub> data, respectively during the 2012 haze episode in Chiangmai (Table 1).

This Model II performance was better than Model I by a significant increase of  $R^2$  of 55% and 50%, respectively for  $PM_{2.5}$  and  $PM_{10}$ . The inclusion of meteorological parameters, i.e. surface temperature



Figure 3. Predicting PM data using AOD data (Model I: Simple linear regression)

| Table | 1. Multiple | linear regression | model of AOD | and PM inc | luded r | meteorological | factors |
|-------|-------------|-------------------|--------------|------------|---------|----------------|---------|
|       | 1           | 0                 |              |            |         | Ũ              |         |

| Parameter         | Regression model  | <i>p</i> value |
|-------------------|---|----------------|
| PM <sub>2.5</sub> | Hourly $PM_{2.5} = 367 + 46 (AOD) - 6.6 (T) - 2.6 (RH), R^2 = 0.77$ | 8.95E-09**     |
| $PM_{10}$         | Hourly $PM_{10} = 706 + 75 (AOD) - 15.8 (T) - 3.5 (RH), R^2 = 0.71$ | 1.65E-07**     |
| Remark: **p<0.01  |   |                |



Figure 4. Observed and simulated hourly PM10 in Chiangmai using dataset in March 2007

and relative humidity, could enhance the predictive performance of the model.

## 3.4. Model Evaluation

To test the validity of regression model, Model II was used to simulate hourly average  $PM_{10}$  in Chiangmai during the 2007 haze episode (Fig. 4). Model results were slightly underestimated the observed  $PM_{10}$  and were not able to capture the peak concentrations. Statistical regression models normally tend to predict means better than the tails of distribution (Kim Oanh and Leelasakultum, 2011). However, the model was able to explain around 74% of the variability in hourly average  $PM_{10}$ . Due to the unavailability of  $PM_{2.5}$  data in 2007, only the regression model for  $PM_{10}$  was evaluated.

Several studies discussed the influence of aerosol mass concentration profile on the relationship between AOD and PM (Corbin et al., 2002; Wang and Christopher, 2003; Engel-Cox et al., 2004; Engel-Cox et al., 2006; Wang et al., 2010) and revealed that the aerosol profile was as high important for enhancing the use of satellite data for PM air quality studies. PM ground measurement is normally restricted to the surface layer or planetary boundary layer (PBL). AOD below PBL could be more appropriate to represent PM in a wellmixed condition. Obtaining aerosol profile, for example, from LIDAR or chemical transport models could help split the whole column of AOD to at least above and below the PBL. Engel-Cox et al. (2006) and Wang et al. (2010) showed that the linear regression correlation between AOD and PM increased significantly when including the LIDAR data. Thus, without AOD vertical profile, the relationship between AOD and PM could have a limited meaning.

However, only meteorological variables were incorporated in this study since the temperature and relative humidity are common parameters with a strong influence on the AOD and PM relationship (Tian and Chen, 2010) and can be basically monitored elsewhere. For AOD, the data are readily available from NASA website as mentioned earlier in section 2.2. Thus, the multiple linear regression model would be simply used to predict the concentrations of PM. Incorporation of AOD vertical profile would require additional tools, i.e. LIDAR and chemical transport models which are, on the contrary, not readily available for use. However, for long term PM air quality monitoring, further study should apply the aerosol vertical profile to improve AOD and PM relationship. The validity test should be also investigated for other areas to confirm the reliability and applicability of the model.

## 4. Conclusions

Simple linear regression (Model I) was conducted to identify the relationship between AOD retrieved from MODIS and ground PM during the 2012 haze occurrence in Chiangmai. Results acquired from this research showed positive correlations between AOD and  $PM_{2.5}$ , and AOD and  $PM_{10}$  with R<sup>2</sup> of 0.22 and 0.21, respectively. Incorporation of surface temperature and relative humidity improved significantly the relationship between AOD and PM. The R<sup>2</sup> obtained from multiple linear regression (Model II) were around 0.77 and 0.71, respectively for PM<sub>2.5</sub> and PM<sub>10</sub>. The model validity for March 2007 confirmed possibility to apply the regression correlation between AOD and PM in Chiangmai. For further study, the validity should be investigated to ensure the applicability of the model for other areas.

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## **Correspondence to**

Dr. Thongchai Kanabkaew Environmental Science Program, School of Engineering and Resources, Walailak University, 222 Thai Buri, ThaSala, Nakhon Si Thammarat, 80161 Thailand Email: thongchai.ka@wu.ac.th