Suitable Model for Estimation of PM2.5 Concentration Using Aerosol Optical Thickness (AOT) and Ground based Station: Under the Dome in Upper Northern, Thailand

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Abstract
The upper northern areas of Thailand have faced the problem of smog for more than a decade due to open-air burning, geographical features, and climate which all allow the problem to occur continually. One of the air pollutants causing smog is fine particulate matter, less than PM2.5 in diameter, which affects people's health. This research aims at finding a suitable model to be used in estimating PM2.5 concentration from the data collected by the Moderate Resolution Imaging Spectroradiometer, MODIS. The areas of study covering 8 provinces in the upper north of Thailand were used in this research. The data used in this study were Aerosol Optical Thickness (AOT) values, MOD04 data of the MODIS system, which all of these were qualified to be used in detecting this particulate matter in the atmosphere. According to the research methodology, PM2.5 concentrations from 3 ground stations, on the same positions of AOT values from MODO4 produced in a total period of 10 days from February to May 2016, were calculated to examine the suitable model out of 7 models by linear regression and non-linear regression which included Cubic model, S-curve model, Quadratic model, Logarithmic model, Linear model, Power model, and Exponential model. After that, the suitable model was analyzed for its validation and applied in estimating PM2.5 concentration in the areas of upper northern region and Bangkok. The results showed that Cubic model had the highest coefficient of determination (R^2) at 0.770 and its model validation was 83.33%.

1. Introduction

The problem of smog in the north of Thailand occurs every year, especially in the summertime between January and May. There are several main causes of the problem. One is open-air burning such as burning of crop residues and forest fire, another cause is geographical features of the north which are surrounded by the mountain ranges making it appear to be basin-like plain and causing both dust and smoke to float in the atmosphere longer without falling onto the ground, and the other cause of the problem is high atmospheric pressure which affects the smog not to float into higher atmospheric layers making it get detained and cover all over the areas. This has effects on daily life of the inhabitants, tourism and services, both air and land transport as well as social and economic situations. Most importantly, this problem severely results in health problem among people living in the areas because these particulate matter can be inhaled into the lungs and stuck in lower respiratory more easily and deeply than those bigger ones. According to the definition proposed by the US.EPA, particles less than PM2.5 in size are considered fine particles with the diameter smaller than PM2.5, which are originated from car's engine fume, electricity generation plants, industrial factories, and smoke from cooking by firewood. In the study conducted by Institute for Health and Evaluation, University of Washington (Pollution Control Department, 2016), it was found that air pollution is one co-factor causing several diseases, including chronic obstructive pulmonary disease, cerebrovascular disease, ischemic heart disease, lung cancer, and lower respiratory tract infection since there are sorts of chemical substances, both irritants and carcinogens (Krewski et al., 2009, Pope et al., 2002 and 2009, Lepeule et al., 2012 and Miller et al., 2007). This has led to all government and private sectors becoming aware and seeking ways to cure and prevent this existing problem. However, tracking of PM2.5 is currently operated by installation of measuring devices at the ground stations, but the quantity is not enough to be distributed throughout the whole country and this

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makes it difficult for spatial tracking. Moreover, there is no announcement from concerning sectors to allow the use of PM2.5 in order to track and control the air quality while only PM10 is allowed in which course particles are still found. As a result, there was no obvious statistical evidence indicating PM2.5 concentration in the previous time.

Currently, studies of particulate matter in the air have been conducted in many different ways and geo-information technology has also been applied in several studies in order to study air pollution. Those studies include estimation of PM2.5 concentration by using simple linear regression model when AOD value was fixed as independent factor (Engel-Cox et al., 2004 and Wang and Christopher, 2003) together with the use of semi-empirical models (Tian and Chen, 2010, Li et al., 2011 and Lin et al., 2015), artificial neural network models (Gupta and Christopher, 2009b and Wu et al., 2012), linear mixed-effects (LMS) models (Kloog et al., 2011, 2012), geographically weighted regression (GWR) models (Hu et al., 2013 and Song et al., 2014), studies of air quality in Beijing and Wuhan of China, and Saudi Arabia by MODIS (Wang et al., 2013 and Liu et al., 2018), and studies of distribution of burning crop residues and changing in PM2.5 content in China (Yin et al., 2017). A lot of studies in which AOT and AOD values were calculated to examine the relationship with PM2.5 concentration by using statistical method (Chudnovsky et al., 2014, Engle-Cox et al., 2004, Guo et al., 2017 and Li et al., 2018) and the method and products were also compared to find out the most suitable method for examining the relationship between AOT value and PM2.5 concentration (Chen et al., 2017 and You et al., 2015). In this research, AOT values were examined to figure out the most suitable model from those 7 equations, based on PM2.5 concentration collected from the ground stations of the sectors taking responsibility for this matter so that it could benefit to estimation of PM2.5 concentration in the areas where there were no installation of ground stations and it is a way to watch out people's health in these areas. The main objective of this research is to find the suitable model to estimate PM2.5 concentration by using satellite imagery.

2. Study Site

The areas of upper northern region in this study covered 8 provinces including Chiang Rai, Chiang Mai, Lamphun, Lampang, Phrae, Nan, Mae Hong Son, and Phayao. The geographical features in these areas are generally mountain ranges alternated with valleys. Most of the mountain ranges lie horizontally from the north to the south and they parallel from the west to the east when all valleys, both big and small, lie along with these ranges. There are also areas in basin-like plain which easily causes ventilation with difficulty resulting in compilation of air pollution in this region (Figure1).

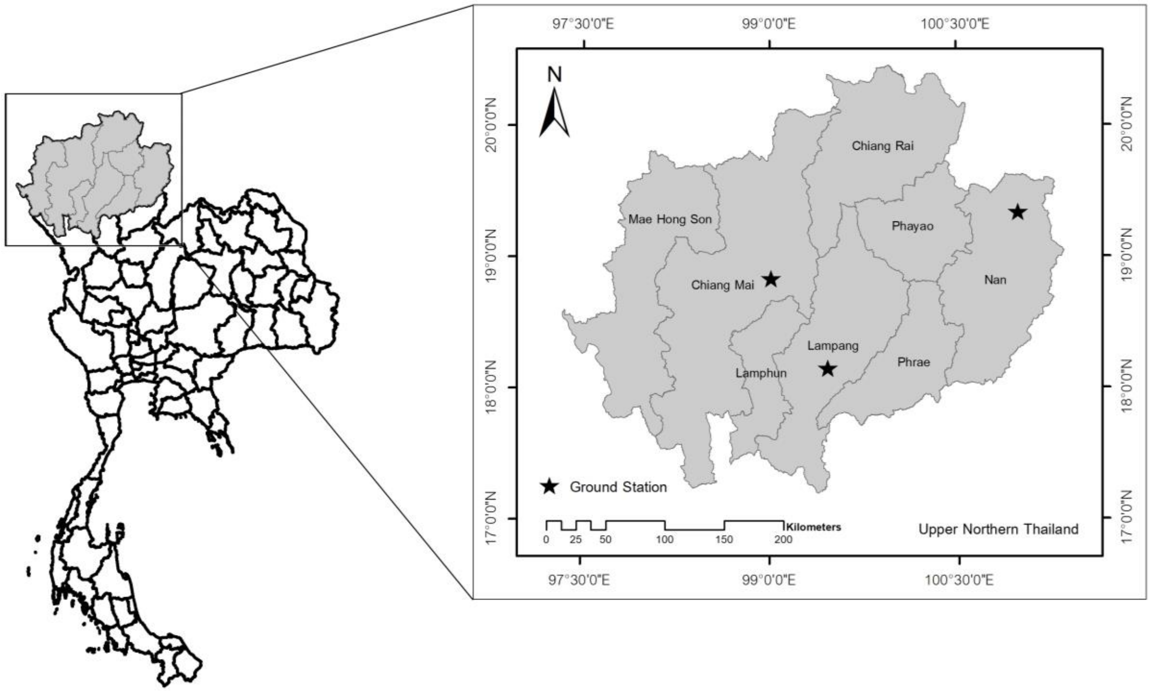


Figure 1: Study site

3. Data and Data Processing

3.1 Data and Data Source

Satellite data: MODIS imagery from TERRA/AQUA satellite had values of Aerosol Optical Thickness (AOT) from the product in MOD04_3K at the spatial resolution at 3 kilometers. Aerosol Optical Thickness (AOT—a synonymous term for AOD used by AERONET) measurements from AERONET sun photometers. For AOD, Multi-Angle Implementation of Atmospheric Correction (MAIAC) retrieval algorithm estimating the Aerosol Optical Depth (AOD) (Just et al., 2018). This data was designed for tracking small particles in the region and it could record data all over the world within 1-2 days. It had the wavelength of 0.4-14 micron which was appropriate for detecting the concentration of dust in the atmosphere (Boys et al., 2014, Ford and Heald, 2013, Gupta and Christopher, 2008a and Reid et al., 2015). The period for the study was 10 days between February and May 2016 (Table 2). The reason for selecting the year 2016 was that it was the period in which the occurrence of smog problem in these areas was highly severe.

PM2.5 concentration data: Data related to PM2.5 concentrations from the ground stations was supported by Air Quality and Noise Management Bureau, Pollution Control Department, Thailand on the same date as the products of MOD04 were provided by the three ground stations; Yupparaj Wittawalai School Station in Chiang Mai (36t) (coordinates of 18°79′11″ and 98°99′00″), Mae Moh Provincial Waterworks Authority Station in Lampang (40t) (coordinates of 18°28′27″ and 99°65′99″), and Chaloem Phra Kiat Hospital Station in Nan (75t) (coordinates of 19°32′124″ and 101°02′54″). In this study, there was complete imagery in 10 days which could provide 30 datasets to be used. Other spatial data: Other spatial data included the scope of governance in 8 provinces in upper northern Thailand, which was used to examine the best model in calculating for PM2.5 concentration and the scope of governance in central region of Thailand which was used in the application process (Figure 2).

3.2 Data Processing

Part 1: It was the process of adjusting geometric data of the satellite imagery because the data of the product MOD04_3K from MODIS was in HDF-EOS (.hdf) and the coordinate system was Geographic Lat/Long which was necessary to be adjusted into WGS84 UTM zone 47N. The type of file also needed to be adjusted into DAT (.dat). In addition, because there was only one SDS to be used in calculating PM2.5 concentration, which was Optical_Depth_Land_And_Ocean containing data of Aerosol Optical Thickness (AOT) regarding rate of absorption and reflection of thermal energy in dust and smog in the atmosphere, so the validation had to be adjusted and bad value in AOT values had to be eliminated before cutting off the data with the study areas.

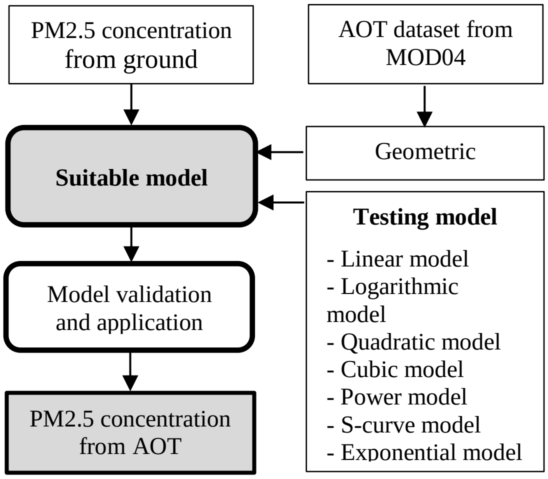


Figure 2: Work Process

Part 2: The process of examining the suitable model for estimation of PM2.5 concentration was conducted to determine the relationship between PM2.5 concentrations form the ground stations and data of AOT satellite imagery by using 7 models of linear regression including Linear model, Logarithmic model, Quadratic model, Cubic model, Power model S-curve model, and Exponential model so as to discover the suitable model by considering coefficient of determination (R^2).

Part 3: Process of evaluating the validation of the suitable model was tested with the actual values measured from the ground stations. Then the model was used to calculate PM2.5 concentration based on AQI breakpoints of the U.S. Environmental Protection Agency (2016). After that, AQI breakpoints at the ground station were checked by the use of 6 levels in evaluating accuracy if they were accurate or incorrect compared with the PM2.5 concentrations found in the study.

4. Finding Suitable Model

4.1 Define Variables

Available techniques for finding suitable model was based on independent variables (X) and dependent variable (Y). In this research, independent variable was digital number obtained at the same point as that of the ground stations from AOT values of MOD04 while dependent variable was PM2.5 concentrations from the ground stations.

Such suitable statistical models with variable types are as the next subtopic. All were selected to retrieve the best model to develop the model.

4.2. Testing Model

It was the analysis of relationship between PM2.5 concentrations from the ground stations and AOT values from satellite imagery at the same time and the same position by selecting dataset for creating 30 correlation models as previously mentioned. After that, the relationship was examined by 7 models of linear regression. When testing all 7 models, coefficient of determination (R^2) values were found and used as an index to select the most suitable model for estimation of PM2.5 concentration.

1) Linear model: Y = aX + b
Linear model is a linear approach to modelling the relationship between a dependent variable and independent variables.

2) Logarithm model: Y = aln (X) + b
Logarithm model is used to model situations where growth or decay accelerated rapidly at first and then slows over time.

3) Quadratic model: $Y = aX^2 + bX + c$
Quadratic model is used to model situation where values decrease then increase or values increase then decrease.

4) Cubic model: $Y = aX^3 + bX^2 + cX + d$
Cubic model is a process in which the third-degree equation is identified for the given set of data.

5) Power model: Y = aXb
Power model is one in which the dependent variable is proportional to the independent variable raised to a power.

6) S-curve model: Y = e(a/X) + b
where: e is natural log, S-curve or logistic model is used to describe data and to explain the relationship between one dependent binary variable and one or more independent variables.

7) Exponential model: Y = abX
Exponential model is a variable grows exponentially. Exponential decay occurs when the factor is less than one.

4.3 Model Validation

Model validation refers to the processes that the model represents the reality-based system. It is to a sufficient level of accuracy. For this study, this step was the process of evaluating the model validation when the most suitable model was used to estimate PM2.5 concentration in upper northern areas. Then it was analyzed with PM2.5 concentrations measured at the ground stations. The validation was from the percentage of dataset quantity between the level of PM2.5 concentrations from the ground stations and PM2.5 concentration obtained from the estimation.

4.4 Model Application

The most suitable model was applied in estimating PM2.5 concentrations in other areas where the areas chosen in this study was the central region of Thailand. The geographic features were large plain in the middle of the country where both the eastern and western mountain ranges parallel from the north to the south before flowing into the Gulf of Thailand. These areas were regarded as the economic center of the country as well as the location of the industrial estate, with a lot of big factories, and these areas also faced the problem of PM2.5 concentration, especially in the beginning of 2018.

5. Results

5.1 Suitable Model for Estimation of PM2.5

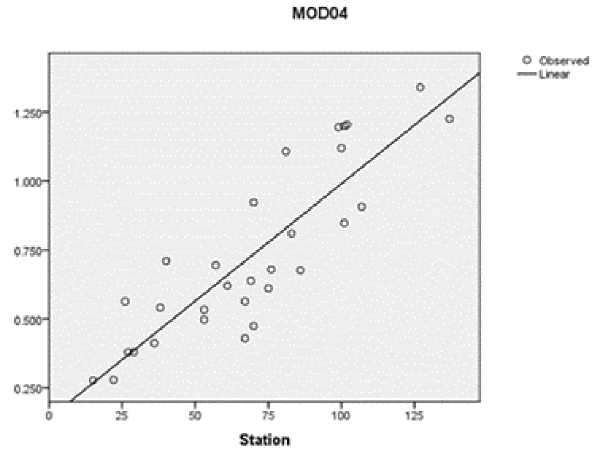
Finding the suitable model for estimation of PM2.5 concentrations from the ground stations and AOT values from satellite imagery was conducted at the same time and the same positions as shown in the following 30 datasets (Table 1). All 30 datasets were later analyzed to discover the relationship with 7 models of linear regression in order to acquire the most suitable model used in estimation of PM2.5 concentration. The analysis showed that Cubic model provided the best value of relationship between the two data sets (Figure 3). As shown in the figure, both datasets of Cubic model conformed to each other and was more likely to move into the same direction than any other model. However, the three highest coefficient of determination (R^2) values were Cubic model with R^2=0.770, followed by S-curve model with R^2=0.764, and quadratic model with R^2=0.759, respectively (Table 2). According to model consideration, it could be concluded that suitable model to be used in estimation of PM2.5 was Cubic model (Equation 1) of which the accuracy would be later analyzed.

$$PM2.5 = 135.53*(AOT)^3 - 346.876*(AOT)^2 + 359.549*(AOT) - 58.143 \quad (R^2 = 0.770)$$

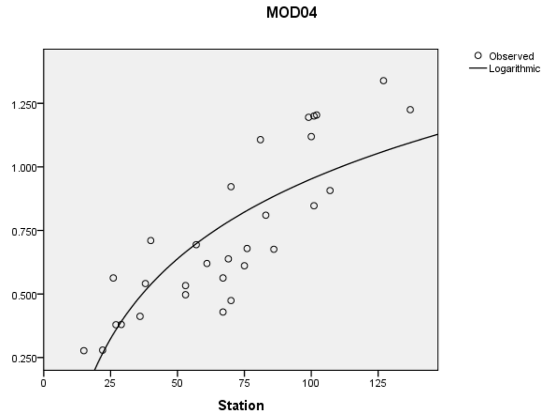
Equation 1

Table 1: Relationship between PM2.5 concentration from ground station and AOT value

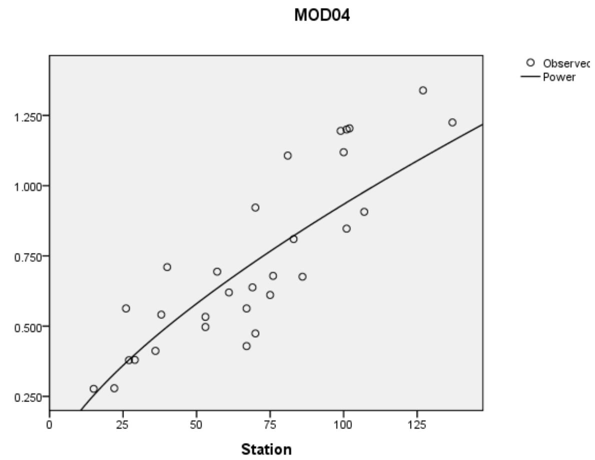
No.	Date	Time	Station					
			36t		40t		75t	
			PM2.5 from Ground sta.	PM2.5 from AOT value	PM2.5 from Ground sta.	PM2.5 from AOT value	PM2.5 from Ground sta.	PM2.5 from AOT value
1	16 February 2016	03.35	86	0.676	27	0.379	53	0.533
2	18 February 2016	03.40	75	0.611	67	0.429	38	0.541
3	17 March 2016	04.05	67	0.563	26	0.563	69	0.638
4	19 March 2016	03.50	76	0.679	29	0.380	81	1.107
5	21 March 2016	03.40	107	0.907	57	0.694	99	1.195
6	9 April 2016	04.10	101	0.847	53	0.497	36	0.412
7	14 April 2016	04.30	83	0.810	15	0.277	127	1.339
8	16 April 2016	04.15	100	1.119	102	1.204	137	1.225
9	4 May 2016	04.05	101	1.200	40	0.710	70	0.474
10	8 May 2016	03.40	70	0.922	61	0.620	22	0.279



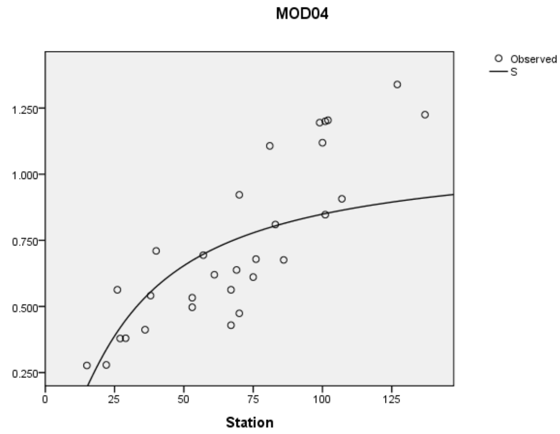
Linear



Logarithmic

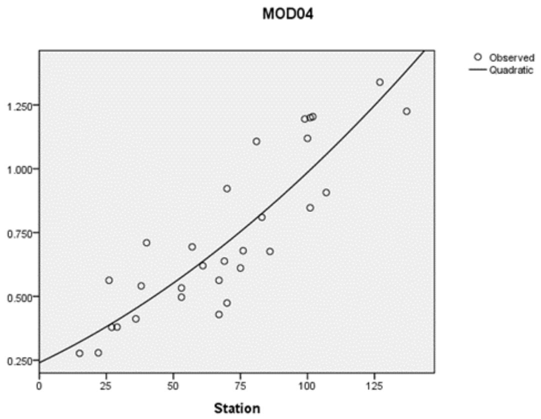


Power

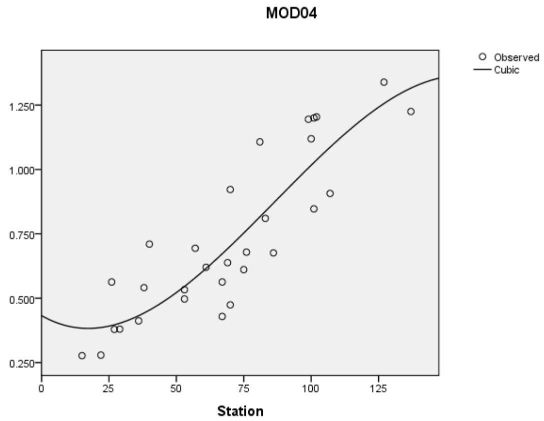


S-curve

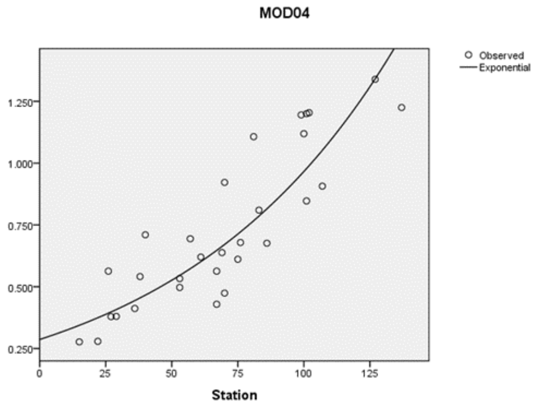
Figure 3: Graph of testing results for each model (Continue next page)



Quadratic



Cubic



Exponential

Figure 3: Graph of testing results for each model

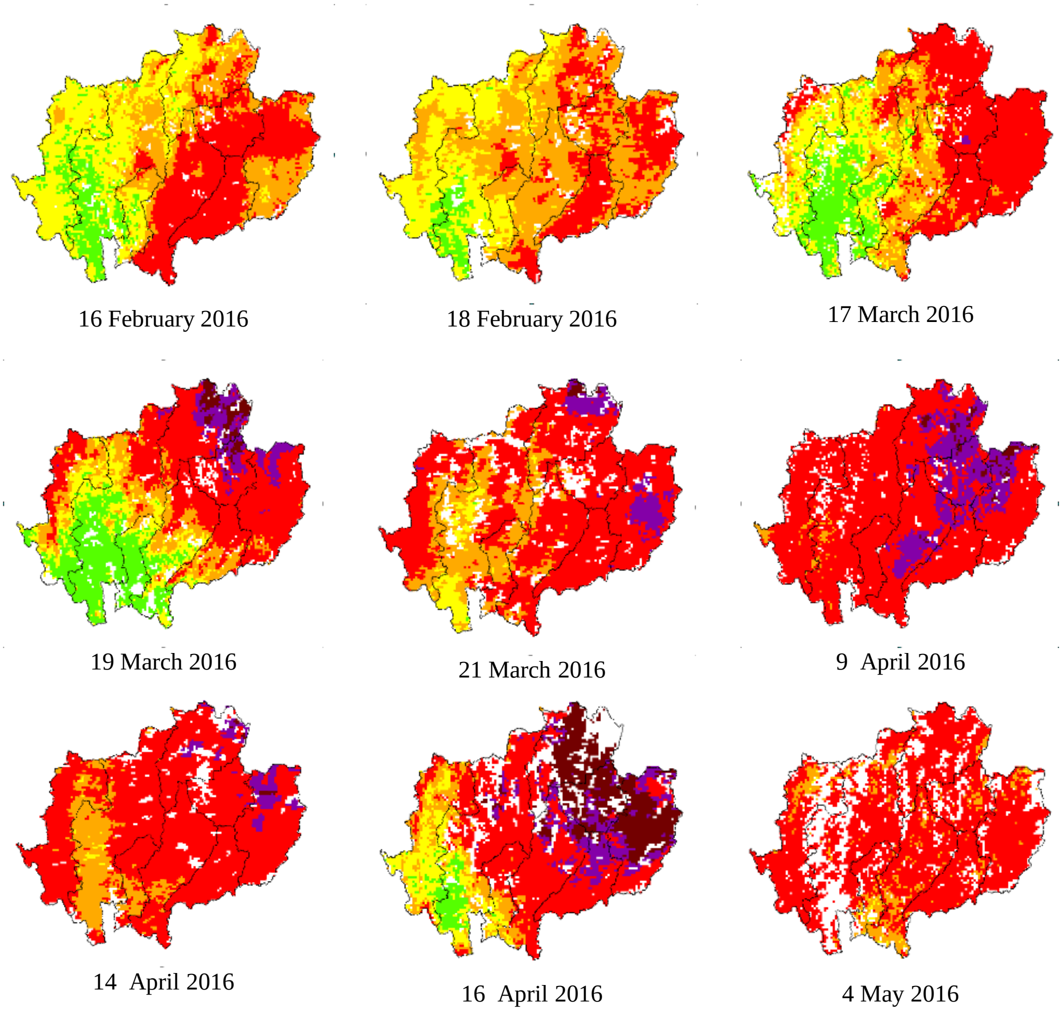
Table 2: Testing model and coefficient determination (R^2)

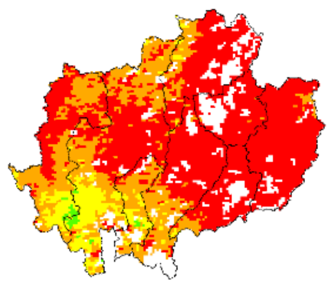
Model	Equation	R^2
Cubic	$Y = 135.53*x^3 – 346.876*x^2 + 359.549*x - 58.143$	0.770
S-Curve	$Y = e^{(-0.634/x) + 5.160}$	0.764
Quadratic	$Y = -32.272*x^2 + 140.217*x - 12.767$	0.759
Logarithmic	$Y = 62.295 \ln(x) + 94.659$	0.757
Linear	$Y = 88.436*x + 4.815$	0.752
Power	$Y = 95.549\ x^{1.0752}$	0.738
Exponential	$Y = 21.349\ e^{1.4404x}$	0.653
when Y is PM2.5 concentration (µg/m^3) X is AOT value		

5.2 Model Validation

Result from examining suitable model in equation (1) was used to enquire PM2.5 concentration from satellite imagery in the areas of the upper north of Thailand for 10 days between February and May 2016. The selection of date providing complete images was the same as the date on which PM2.5 concentrations were considered to find suitable model, according to previous section. Findings from PM2.5 concentration analysis by Cubic model were shown in Figure 4 and the maps displaying PM2.5 concentrations were based on PM2.5 AQI breakpoints of the U.S.EPA in 2018. Maps of PM2.5 concentrations from suitable model determination were later tested for model validation when these PM2.5 concentrations were analyzed together with 30 datasets of PM2.5 concentrations from the three ground stations. Air Quality Index

(AQI) was used to test the validation and the results were shown in Table 3.





Color	PM2.5 (μg/m^3)	Category
	0-12	Good
	12.1-35.4	Moderate
	35.5-55.4	Unhealthy for sensitive groups
	55.5-150.4	Unhealthy
	150.5-250.4	Very unhealthy
	>250.5	Hazardous
	-	No data

Figure 4: Estimation of PM2.5 concentration in Upper Northern, Thailand

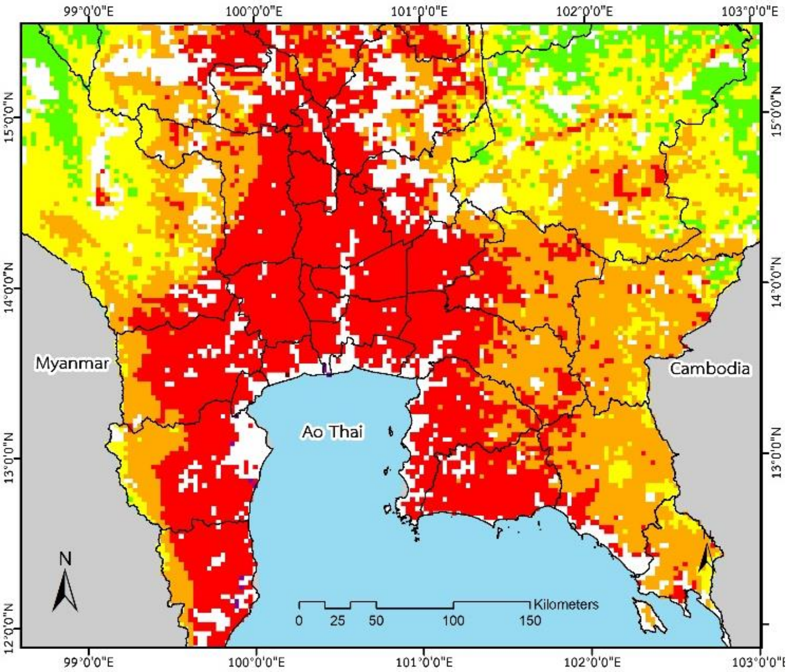
Evaluation of model validation from the relationship between PM2.5 concentrations from the ground stations and those from the Cubic model revealed that the validation was 83.33%.

5.3 Model Application

The model was also applied to estimate PM2.5 concentration in the central region of Thailand in 2018 as the problem of smog was extremely more severe than any other year. All significant causes included transport, electricity generation, industrial factories, and open-air burning activities together with no ventilation, both vertical and horizontal, in the area. This study consequently chose this area to try model application for estimation of PM2.5 concentration on February 5, 2018 and the analysis was shown as in Figure 5. The results from this analysis were compared with those of quality measurement of PM2.5 in the area conducted by the Pollution Control Department of Thailand. It showed that both results conformed to each other in the same direction. At 8.00 pm on February 5, 2018, the department reported that PM2.5 concentration was higher than standard level (>50 μg/m^3) at every ground station. However, there were only 6 ground stations in Bangkok including Bang Na district, Wang Thong Lang district, Pa Thum Wan district (by the side of Pra Ram 3 road), Thon Buri district (by the side of Intdhra Phitak road), Wang Thong Lang district (by the side of Lad Phrao road), and Raja Dhevi district (by the side of Pha Ya Thai road).

Table 3: Model validation

Predicted		**Observed**		**Predicted**		**Observed**	
PM2.5 (μg/m^3)	**AQI**	**AQI**	**PM2.5 (μg/m^3)**	**PM2.5 (μg/m^3)**	**AQI**	**AQI**	**PM2.5 (μg/m^3)**
68.26	4	4	86	17.71	2	2	15
62.96	4	4	75	70.78	4	4	40
61.62	4	4	67	51.50	3	3	53
83.73	4	4	107	63.73	4	4	61
68.49	4	4	76	40.58	3	3	36
79.89	4	4	101	55.47	3	3	53
77.53	4	4	83	56.30	4	4	38
99.74	4	4	100	18.11	2	2	22
108.01	4	4	101	65.25	4	4	69
58.52	4	2	26	98.65	4	4	81
84.71	4	4	70	107.45	4	4	99
42.96	3	4	67	110.91	4	4	137
35.34	2	2	29	129.74	4	4	127
108.46	4	4	102	34.67	2	2	27
69.61	4	4	57	48.78	3	4	4



Color	PM2.5 (μg/m^3)	Category
	0-12	Good
	12.1-35.4	Moderate
	35.5-55.4	Unhealthy for sensitive groups
	55.5-150.4	Unhealthy
	150.5-250.4	Very unhealthy
	>250.5	Hazardous
	-	No data

Figure 5: Model application for estimation of PM2.5 concentration in Central zone, Thailand

This revealed that the number and location of the ground stations used for measuring PM2.5 concentration clustered in the central zone of Bangkok and it was not enough for estimation of PM2.5 concentration as spatial data of the whole area. This study, therefore, allowed the researcher to acquire the distribution and PM2.5 concentration in other areas where there was no report of air quality or there were no ground stations for measuring PM2.5 concentration.

6. Conclusion and Further Research

Determining suitable technique and method used for estimation of PM2.5 concentration with AOT values from MODIS was conducted by testing in all 7 models of regression. It was revealed that the relationship between PM2.5 concentrations from the ground stations and those from AOT values of cubic model provided the highest coefficient of determination (R^2) value at 0.770. Consequently, it was considered the suitable model for estimation of PM2.5 concentration and this method was used to evaluate model validation when this cubic model was used to estimate PM2.5 concentration in the areas of upper northern region for 10 days. Later, the results were compared with PM2.5 concentrations from the three ground stations and there were totally 30 datasets. The results revealed that the model contained the validation at 83.33 % based on PM2.5 AQI breakpoints of the U.S.EPA. In addition, model application in the central zone of Thailand was conducted in 2018 and found that PM2.5 concentrations in Bangkok areas conformed to PM2.5 concentrations from the ground stations. This study was also found that the findings were similar to previous studies which aimed at examining the best and most suitable method for estimation of PM2.5 concentration although the differences in model were found in the end (Engle-Cox et al., 2004, Wang et al., 2013, Chudnovsky et al., 2014, You et al., 2015, Guo et al., 2017, Chen et al., 2017 and Li et al., 2018).

This study corresponded to the finding of Wang et al., (2013), You et al., (2015) and Li et al., (2018). They used non-linear regression models to investigate the relationship between AOT data and PM2.5 concentration. By regression analysis and their correlations are R^2= 0.818, R^2= 0.830, and R^2= 0.600, respectively. Moreover, there are some studies used specific models to predict PM2.5 concentration. Mixed effect model including temperature, relative humidity, and boundary later height (BLH) on daily PM2.5 (R^2=0.90), Aerosol Type Analysis Method (ATAM) that combined atmospheric boundary layer height (BLH), relative humidity, and effective radius of the aerosol size distribution (Ref) (R^2=0.792), and Geographically and Temporally Weight Regression (GTWR) model that can account for spatial and temporal variability (R^2=0.75) were used by Chudnovsky et al., (2014), Chen et al., 2017) and Guo et al., (2017), respectively. However, linear regression model was used to model and estimate PM2.5 concentration (R^2=0.428) (Engle-Cox et al., 2004).

According to the main problem of PM2.5 situation is poor information to allocate the concentration of PM2.5. The outcome of this study therefore to solve this problem. It would be useful to estimate PM2.5 concentration in the other area especially the remote areas that lack of ground station. A spatial concentration pattern of PM2.5 would be estimated from satellite imagery. Related organization could use this outcome to warn people in each area for protection of themselves from toxic haze especially in the sensitive groups. This is also helpful to the budget allocation for setting ground station to monitor PM2.5.

However, this study was only the trial to examine a spatial estimation of PM2.5 concentration which was suitable for the areas without installation of ground stations. For future study, in order to bring more benefits in monitoring and preventing causes of the problem, it is necessary to examine the relationship or causes of PM2.5 origins and check if PM2.5 is more or less from each of the origins. Determining physical factors including wind direction, relative humidity, and temperature at that time should be also examined to see if it is related to PM2.5 concentration or not and how it is.

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