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An empirical relationship between $PM_{2.5}$ and aerosol optical depth from MODIS satellite images for spatial simulation over Ho Chi Minh city

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Abstract:

Air quality in megacities has been a pressing concern of environmental managers and scientists for decades. Indeed, particulate matter (PM), especially $PM_{2.5}$, is considered a dangerous particle that is harmful to human health. The current sparse monitoring network in Ho Chi Minh city (HCMC) does not accurately reflect the spatial distribution of fine particles in ambient air. Therefore, this research examines the relationship between ground-based station data and aerosol optical depth (AOD) imagery from the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard the Terra/Aqua satellite to establish a $PM_{2.5}$ distribution map of HCMC. $PM_{2.5}$ concentration values monitored from two ground stations were collocated by time and space with Terra/MODIS AOD data from the period of 2016-2020. Pairs of values were checked for correlation and then fit to several regression functions. The most suitable function was chosen to simulate the quantified $PM_{2.5}$ distributions in the study area. A high correlation between $PM_{2.5}$ concentrations and AOD at the wavelength of green light (R^2=0.810) was found with a linear regression model. The results showed that the highest concentration of $PM_{2.5}$ was in February, and the mean value was higher than QCVN 05:2013 (32.5 µg/m^3 compared with 25 µg/m^3, annual mean). These results support the need for essential air quality monitoring in HCMC.

Keywords: **aerosol optical depth (AOD), air pollution, MODIS, $PM_{2.5}$.**

Classification number: **5.1**

Introduction

Fine particles possessing an aerodynamic diameter of less than 2.5 µm, also known as $PM_{2.5}$, are generated by both human-made and natural sources with the majority being from human-made activities like vehicle engines, power generation, and urban heat. (GOV.UK, 2019) [1]. According to World Health Organization (WHO), there is no safe threshold for inhaling these fine particles, either short term or long term, that avoids any adverse effects. Indeed, long-term exposure will increase specific age mortality risks especially to the elderly, children, and those with respiratory or cardiovascular diseases that place these individuals in risky health conditions. Besides this, the WHO report also states that fine particle exposure in high concentration can worsen lung and heart conditions, increase the number of hospital admissions, and even cause death (WHO, 2005) [2]. In HCMC, rapidly increasing transportation density and numerous under-invested industrial parks are raising the air quality index higher year by year. According to the report of Green ID (2018a) [3] about the air quality in HCMC, the number of hours of which the air quality index was classified at an unhealthy level occupied 28.3% of the first trimester of 2018, which is much higher than the same period in 2016 and 2017 (0.6 and 9.6%, respectively). Understandably, the density of dust particle dispersion in the atmosphere continues to grow and become an enormous challenge for local authorities in charge of controlling and monitoring air quality.

In general, megacities of developing countries are still prioritizing economic growth over the environment and, in those cases, networks of fine particle monitoring stations remain limited. HCMC is no exception to this. The installation of only a few $PM_{2.5}$ ground-based stations restricts a thorough assessment of time-space dynamics of fine particles. Therefore, the real-time database of available $PM_{2.5}$ monitoring stations in the research area combined with a remote sensing technique brings a promising method to estimate $PM_{2.5}$ concentrations over the whole city.

An atmospheric remote sensing technique-based index called the AOD is currently being used in scientific research to examine the dispersion of particles of various sizes over large or small areas. AOD, sometimes known as the optical thickness (τ), is a measure of beam solar attenuation due to obstruction from dust or haze. In other words, AOD tells

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us how much direct sunlight reaches the Earth's surface after it is absorbed or scattered by dust particles. AOD is a dimensionless number and is determined by the amount of aerosol in an atmospheric vertical column from the Earth's surface to the top of the atmosphere over different wavelengths (Global Monitoring Laboratory) [4]. From an observer on the ground, an AOD of less than 0.1 is considered clean with characteristics of a clear blue sky, bright sun, and maximum visibility. As AOD increases to 0.5, 1.0, or even greater than 3.0, aerosols become so dense that the sun is obscured (NASA, 2019) [5].

Some epidemiological studies on the health effects of air pollution were conducted by using measures of $PM_{2.5}$ collected from sparse networks of stationary ground monitors as the exposure metric [6-8]. However, such in-situ $PM_{2.5}$ monitoring stations gives data that represents only a small surrounding zone. Meanwhile, patients could come from other areas, so their acquired particulate-matter related diseases might not originate from the measured area. Therefore, to enhance the reliability of the association between $PM_{2.5}$ and hospital admissions, $PM_{2.5}$ data should be extracted from many more sources. In other words, there should be $PM_{2.5}$ data available for the whole research area and even its vicinity. Nowadays, to build a map of $PM_{2.5}$ dispersions, numerous studies aimed at finding the association between $PM_{2.5}$ and AOD have been conducted using high spatial-temporal coverage of satellite aerosol products. For example, Wijeratne (2003) [9] carried out research to find the relationship between AOD, which was computed from Landsat-7/ETM+, and polluted substances including PM_{10}, CO, NO, NO_2, SO_2, NH_3, O_3 and black particles (BP) and then mapped the urban air pollution dispersion across the Netherlands. Another research project from Kumar (2007) [10] examined the empirical relationship between $PM_{2.5}$ concentrations and MODIS-retrieved AOD (5-km spatial resolution) in the Delhi metropolitan area. A grid of 1×1.5 km^2 overlaid the research area, and $PM_{2.5}$ monitored at 113 sites were collocated by time and space with the AOD computed by using data from MODIS on the Terra satellite. The research showed a significant positive association between $PM_{2.5}$ and AOD, and 1% change in AOD explained the 0.52±0.202% and 0.39±0.15% change in $PM_{2.5}$ monitored within ±45 and 150 min intervals, respectively, of AOD data. The advantage of the above studies in predicting $PM_{2.5}$ concentrations is the support from plenty of real ground-based fine particle data to enhance the accuracy and dependability of the regression model. Besides regression analysis methods, some scientists have utilized simulation models to detect the variation tendency of the $PM_{2.5}$/AOD ratio of research areas, then verifying it by surfaced-measured $PM_{2.5}$ data. The chemical transport model (CTM) has been widely used by many researchers as global scale model [11-13]. Another model called geographically weighted regression (GWR), which is often used on a regional scale, has also been coming up in a lot of research [14-16]. These two models have been employed to construct the map of both horizontal and vertical distributions of $PM_{2.5}$ during the study period, and each model has certain advantages and limitations.

In Vietnam, especially HCMC, there are few studies on $PM_{2.5}$. Due to its distinctive characteristics like small size, light weight, and long retention time, Xuan and Thanh (2017) [17] came up with a comprehensive research plan to investigate the elements in particles and predict the source of $PM_{2.5}$ generations. Nguyen, et al. (2014) [18] has also conducted research to investigate roadside levels and traffic emission rates of $PM_{2.5}$ in HCMC. However, no previous research has simulated $PM_{2.5}$ distributions over that area. Currently, since the in situ $PM_{2.5}$ monitoring stations are very sparsely distributed, there are some limitations like missing input data for simulation models, which typically demand a large amounts and variations of data to obtain an accurate simulation. Therefore, remote sensing technology that has been applied worldwide is used to examine and simulate particles over HCMC. Van, et al. (2014) [19] simulated the spatial distribution of PM_{10} across HCMC on a Landsat image in 2003. The research exploited the correlation of airborne particle - PM_{10} and AOD from Landsat to establish a map of PM_{10} dispersion in the atmosphere. The research rudimentarily showed the potential application of remote sensing technology in monitoring dust particles in the air. Four years after the first trial, to evaluate the increasing level, Van, et al. (2018) [20] expanded the research by building an additional map of PM_{10} distribution in 2015 over HCMC. The 2015 PM_{10} pollution level was more serious when compared with the map from 2003.

In this research, regional ground-based $PM_{2.5}$ concentrations are estimated directly from MODIS-based AOD by regression analysis. Then, $PM_{2.5}$ are simulated on MODIS imagery on 5 representative days for each month in the dry season.

Data and methods

Data

The data for this research comes from 2 main sources: (a) ground-based $PM_{2.5}$ concentrations from 2 in-situ, real-time monitoring stations at the United State (US) Consulate and Environmental Source Samplers, Inc, respectively, in HCMC and (b) MODIS based-AOD extracted from the Terra/Aqua satellite.

Ground-based $PM_{2.5}$ concentrations:

- $PM_{2.5}$ data were extracted from a continuous ambient monitoring station located at the US Consulate in HCMC (coordinates: 10°46'59.9 N, 106°42'03.2 E). Besides this, fine particle concentration was also collected from a different monitoring station invested by the company Environmental

Source Samplers (coordinates: 10°48’54.5 N, 106°43’11.0 E). Both ground-based stations record 24-h atmospheric $PM_{2.5}$ data with high accuracy.

- The Terra satellite housing MODIS circles earth every day and passes over the research area at a certain time interval. The Terra satellite acquires daily images of HCMC at the period of 10:00-11:00 am (Vietnam Time Zone, UTC+7), while the Aqua satellite does so between 2:00-3:00 pm. Therefore, in this research, $PM_{2.5}$ data were extracted within this time interval for data synchronization. Furthermore, MODIS image quality significantly depends on weather and cloud coverage, so dust particle data were collected on clear-sky days of the dry season from January to April (2016-2020).

MODIS Imagery based-AOD: the aerosol optical depth of the MODIS’s Terra and Aqua satellites is computed by the National Aeronautics and Space Administration (NASA) through two important algorithms, namely, Dark Target and Deep Blue. AOD retrieved from MODIS imagery has a spatial resolution of 3 km and is stored online for free download. On the satellite, there are seven spectral bands with wavelengths of 0.47, 0.55, 0.66, 0.865, 1.24, 1.64 and 2.13 µm measured by MODIS. However, scattering and absorption of both molecules and aerosols in the atmosphere are only important and occur in visible and near-infrared regions (Gustavo Camps-Valls, et al., 2011) [21]. Besides, research works by Van, et al. (2012, 2014) [19, 22] on PM_{10} distribution from SPOT 5 and Landsat satellite imagery also stated that airborne particulate matter showed better scattering at visible wavelengths. Therefore, this research focused on measuring and assessing the strength of the relationship between MODIS-AOD at 3 wavelengths, namely, 0.47, 0.55 and 0.66 µm, and the corresponding $PM_{2.5}$ concentration data.

Methods

There are two types of spatial resolutions for MODIS-AOD, which are 10 km and 3 km. In this research, since the simulated area was a city and not an entire region, 3-km spatial resolution was used to ensure the highest accuracy for the correlation investigation.

In this study, MODIS-based AOD at the coordinates of 2 ground-based continuous $PM_{2.5}$ monitoring stations in HCMC were extracted. Besides this, $PM_{2.5}$ data from the two stations at the time the MODIS satellite passed and scanned the research area were collected. The majority of the acquired data was in the dry season when the weather was cloudless. Since the resolution of MODIS imagery was quite low (3 km in space), some retrieved AOD values were not located exactly at the coordinates of the $PM_{2.5}$ stations, but they were not greater than a distance of 1.5 km. Additionally, since the monitoring device gives 1 h worth of data, there is a slight discrepancy compared with the time the MODIS imagery was acquired (less than 30 min).

The main research method in this work is correlation analysis, which is a statistical technique that is used to measure how strongly a pair of 2 variables are related to each other. In this research, 2 variables were specifically determined by real-time measurement values of $PM_{2.5}$ and AOD from MODIS. An advantageous result in correlation analysis allowed the next step of using a regression function to simulate $PM_{2.5}$ concentration distributions across the study area. The dataset was divided into two parts: training data (55 values in the stage of 2016-2019) to establish the model and testing data (8 values in 2020) to check the reliability and accuracy of the model.

Firstly, a Q-Q test was conducted to check the normal distribution of all datasets. All data that included real-time $PM_{2.5}$ concentrations and MODIS-AOD of 3 different wavelengths (0.47, 0.55 and 0.66 µm) were tested to assess if they are normally distributed.

Pearson analysis is the next step to check the correlation between two quantitative and continuous variables, which are $PM_{2.5}$ data and AOD, in this research. The purpose of employing the Pearson analysis was to check the strength of the relationship between $PM_{2.5}$ and AOD at the 3 types of wavelengths mentioned above. The Pearson coefficient (R) ranges from -1 to +1. The closer R is to +1 or -1, the more closely AOD and $PM_{2.5}$ are related (SPSS tutorial) [23].

Based on the Pearson’s coefficient of correlation analysis, any wavelengths that show AOD is not correlated with $PM_{2.5}$ are removed. Conversely, the remaining AODs that show high correlation with $PM_{2.5}$ are applied to build the regression model using the least squares method. Besides, in our research, we examined the test not only with linear models, but other regression models (Table 1), to find the best-fit function. All steps were conducted by statistical software (SPSS). In SPSS analysis, selecting the best model that mathematically describes the relationship between two variables is based on three criteria. Here, the Sig Anova and Sig coefficient (or p-value) results from SPSS must be less than 5% (significant level). This means the null hypothesis can be discarded and that there exists an association between the two variables. After that, R^2 was the final criterion used to determine the best model.

Finally, to verify the feasibility of the regression model, root mean square error (RMSE) in Eq. 1 was used to compare the deviation between $PM_{2.5}$ computed by the regression model and the real $PM_{2.5}$ data from the testing dataset. Keep in mind that AOD represents a vertical column of aerosol from the Earth’s surface to the satellite, which includes both particle and liquid droplets, and that $PM_{2.5}$ is mainly concentrated and dispersed near the ground and is almost always in particle form. Therefore, the elucidated relationship would be affected by these factors. RMSE is given by:

$$RMSE = \sqrt{\frac{1}{n}\sum(P_{cal} - P_{meas})^2} \quad (1)$$

where n is the number of samples, P_{cal} was the value of $PM_{2.5}$ calculated from the regression function and P_{meas} was the $PM_{2.5}$ that was measured by the ground-based monitoring stations.

Table 1. Equations of the different regression models between $PM_{2.5}$ and AOD (IBM) [24].

	Curve estimation regression models	Regression models $PM_{2.5}$ = f(AOD)
1.	Linear	$PM_{2.5}$=×AOD+β
2.	Logarithmic	$PM_{2.5}$=α×ln(AOD)+β
3.	Inverse	$PM_{2.5}=\frac{\alpha}{AOD}+\beta$
4.	Quadratic	$PM_{2.5}=\alpha\times AOD^2+\beta\times AOD+\gamma$
5.	Cubic	$PM_{2.5}=\alpha\times AOD^3+\beta\times AOD^2+\gamma\times AOD+\varepsilon$
6.	Power	$PM_{2.5}=AOD^{\alpha}\times\beta$
7.	Compound	$PM_{2.5}=\alpha^{AOD}\times\beta$
8.	S-curve	$\ln(PM_{2.5})=\frac{\alpha}{AOD}+\beta$
9.	Logistic	$PM_{2.5}=\frac{1}{\alpha^{AOD}\times\beta+\frac{1}{\gamma}}$
10.	Growth	$\ln(PM_{2.5})=\alpha\times AOD+\beta$
11.	Exponential	$\ln(PM_{2.5})=\alpha\times AOD+\ln(\beta)$

Results and discussion

Normal distribution test for $PM_{2.5}$ and AOD data

The probability Q-Q plot was used to check if $PM_{2.5}$ and AOD data were normally distributed. The results are shown in Fig. 1.

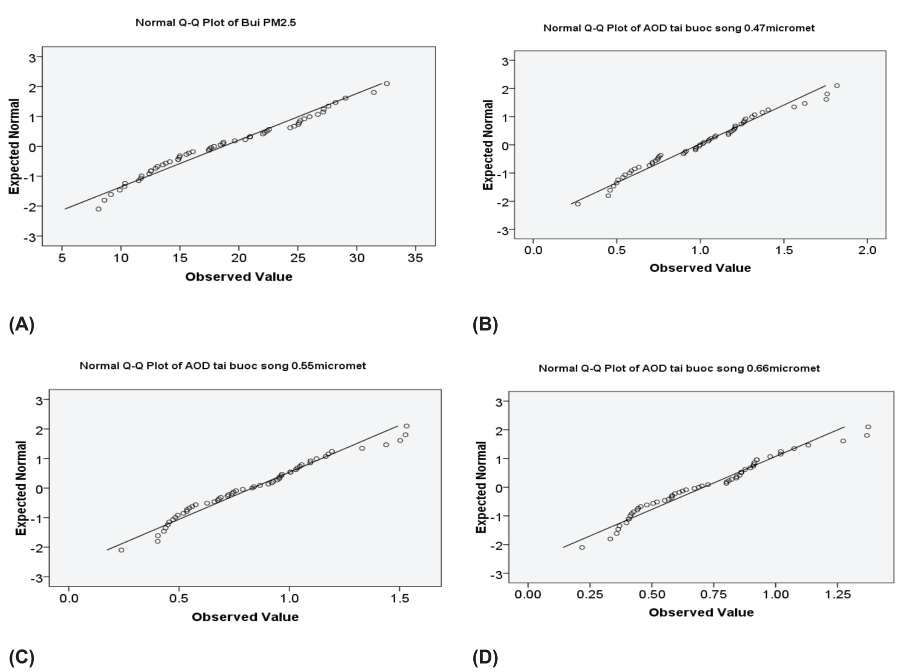


Fig. 1. Normal Q-Q Plot of (A) $PM_{2.5}$, (B) AOD-470 μm, (C) AOD-550 μm, and (D) AOD-660 μm.

If the datasets are closely distributed along the line in the Q-Q plots, it can be concluded that they have a normal distribution. In contrast, if the data points are scattered far from the line, it is obvious that the dataset is not normally distributed. The Q-Q plot for $PM_{2.5}$ and AOD in the 3 wavelengths (470, 550 and 660 μm) in Fig. 1 are dispersed very closely along the diagonal line in each case. Therefore, it was concluded that the dataset of $PM_{2.5}$ and the 3 AODs were normally distributed.

Pearson test to find the correlation between $PM_{2.5}$ and AOD

The correlation analysis between MODIS-AOD and $PM_{2.5}$ at 3 wavelengths (0.47, 0.55 and 0.66 μm) was a crucial and decisive stage of the research. In this step, since the datasets were quantitative variables, the Pearson test was selected to evaluate the correlation. The testing results are shown in Table 2.

Table 2. Correlation between $PM_{2.5}$ and AOD by Pearson test.

		AOD at the wavelength of 0.47 μm	AOD at the wavelength of 0.55 μm	AOD at the wavelength of 0.66 μm
$PM_{2.5}$	Pearson correlation	0.870**	0.900**	0.886**
	Sig. (2-tailed)	0.000	0.000	0.000

** Correlation is significant at the 0.01 level (2-tailed).

In general, the Pearson correlation analysis in Table 2 demonstrates positive relationships between $PM_{2.5}$ and AODs at 3 wavelengths with p=0.000. However, the $PM_{2.5}$ concentrations and AOD of green light (0.55 μm) indicated the most significant correlation at the 0.01 level (2-tailed) with R=0.900, while blue and red lights showed lower correlation levels of R=0.870 and 0.886, respectively. Therefore, we chose the green light AOD (0.55 μm) to build the regression model for $PM_{2.5}$.

Building the regression model for $PM_{2.5}$

After the Pearson correlation test, regression analysis was the next step to determine the most adequate model for this correlation. The regression models of $PM_{2.5}$ and AOD-0.55 μm built by SPSS are shown in Table 3.

Table 3. The regression models between $PM_{2.5}$ and AOD at wavelength of 0.55 µm.

Number	Models	R^2	Sig. (Anova)	Sig. (Coefficients)	
1	Linear	0.810	0.000	AOD Constant	0.000 0.003
2	Logarithmic	0.766	0.000	ln(AOD) Constant	0.000 0.000
3	Inverse	0.608	0.000	1/AOD Constant	0.000 0.000
4	Quadratic	0.812	0.000	AOD AOD^2 Constant	0.01 0.583 0.413
5	Cubic	0.821	0.000	AOD AOD^2 AOD^3 Constant	0.501 0.123 0.105 0.070
6	Power	0.773	0.000	ln(AOD) Constant	0.000 0.000
7	Compound	0.773	0.000	AOD Constant	0.000 0.000
8	S-curve	0.647	0.000	1/AOD Constant	0.000 0.000
9	Logistic	0.773	0.000	AOD Constant	0.000 0.000
10	Growth	0.773	0.000	AOD Constant	0.000 0.000
11	Exponential	0.773	0.000	AOD Constant	0.000 0.000

From Table 3, we could conclude that all models were suitable to use at a confidence of 95% because all sig. Anova results were less than 5%. However, the sig. coefficients of the quadratic and cubic models were greater than 5%, so these models were rejected. Among the remaining models, the inverse had the lowest R^2 (0.608) while linear had the highest value (0.810). Therefore, the linear model was selected to build the regression model with the standard error of 5.93 µg/m^3 (Eq. 2, Fig. 2) and it is given by:

$$PM_{2.5}=36.684\times AOD+6.839 \qquad (2)$$

Equation 2 is applied to the testing dataset (8 values) to check the reliability of the regression model. The calculated $PM_{2.5}$ and the ground-based measured $PM_{2.5}$ are displayed in Table 4.

Table 4. Calculated and measured $PM_{2.5}$ of testing dataset.

Number	Date of simulation	Calculated $PM_{2.5}$ (µg/m^3)	Measured $PM_{2.5}$ (µg/m^3)
1	5-Jan 2020; 10:00	48.6	49.4
2	13-Jan 2020; 14:00	22.4	28.0
3	13-Feb 2020; 10:00	19.3	20.9
4	24-Feb 2020; 13:00	45.3	48.3
5	26-Feb 2020; 10:00	50.9	60.2
6	27-Feb 2020; 11:00	23.7	25.4
7	12-Mar 2020; 9:00	14.9	18.8
8	1-May 2020; 10:00	16.0	15.7

From Eq. 1, the RMSE of the testing dataset was 4.3 µg/m^3, which demonstrated that the deviation between calculated and measured $PM_{2.5}$ was not significant.

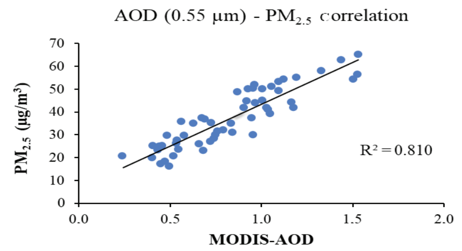


Fig. 2. Linear regression model between $PM_{2.5}$ and AOD at wavelength of 0.55 µm.

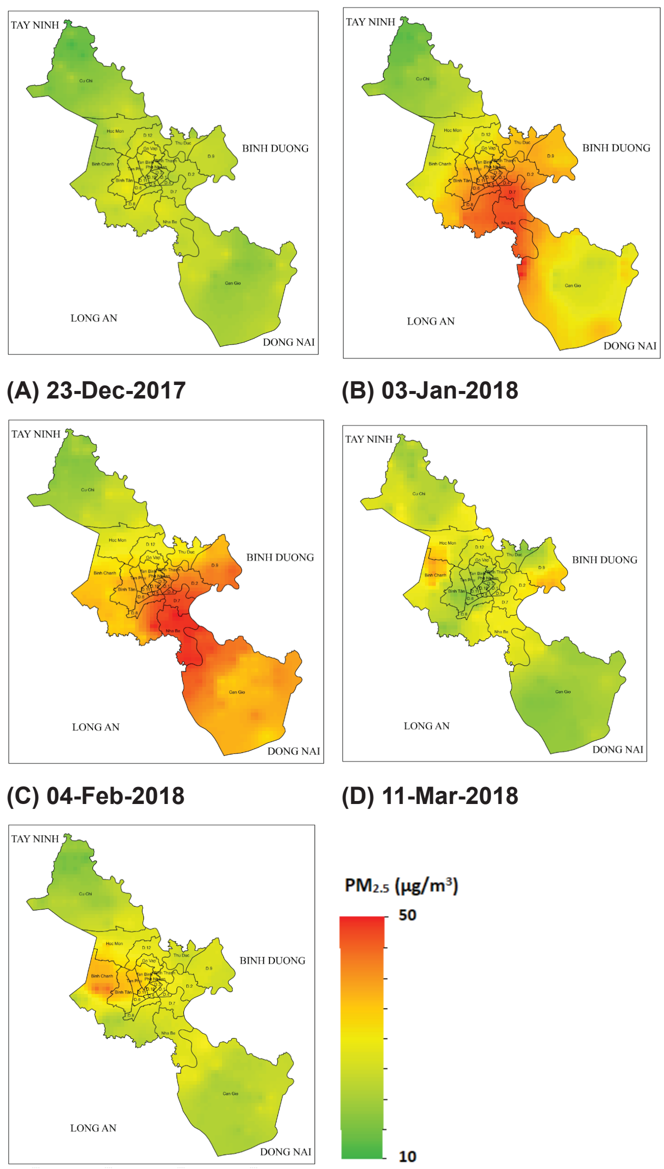
Mapping $PM_{2.5}$ distributions across HCMC

The regression model of $PM_{2.5}$ and AOD in the wavelength of 0.55 µm was employed to build a $PM_{2.5}$ map by ArcGIS. For an objective assessment, $PM_{2.5}$ was simulated at representative days in each month from December 2017 to April 2018.

The map of $PM_{2.5}$ distributions in HCMC was established on a MODIS satellite image at 10:00 am on representative days of each month in the dry season (Table 5). At this time, the industry was working, the traffic density was already high, and a circulation of trucks was allowed in the city; so 10:00 am could be considered as one of the largest dust generation times in a day. The map of Fig. 3 shows that $PM_{2.5}$ concentrations are higher at existing central districts such as districts 1, 3, 5, Tan Binh, Phu Nhuan and Go Vap. This could be explained by the tremendous intensity of transportation on main roads and infrastructure density in each section, especially at rush hour. Besides, some existing factories in industrial parks such as the Tan Binh, Tan Tao, and Le Minh Xuan industrial parks, have degraded emission treatment systems and discharge a large amount of gas that includes fine particles. In contrast, in suburban territories/districts such as Cu Chi, Binh Chanh, and Can Gio that have small traffic density and fewer construction, $PM_{2.5}$ tended to be lower. Especially, in the Can Gio district, the development of mangrove forests proved advantageous to the prevention of invading $PM_{2.5}$ from other areas.

Table 5. Statistics of $PM_{2.5}$ concentrations by representative days.

Dates	Mean	Max	Min
23-Dec-2017	19.9	28.9	10.34
03-Jan-2018	26.6	44.1	11.6
04-Feb-2018	32.5	49.7	16.6
11-Mar-2018	25.2	37.8	16.5
09-Apr-2018	24.1	41.7	14.1



(A) 23-Dec-2017 (B) 03-Jan-2018

(C) 04-Feb-2018 (D) 11-Mar-2018

(E) 09-Apr-2018

Fig. 3. $PM_{2.5}$ distributions over HCMC on (A) 23-Dec-2017, (B) 03-Jan-2018, (C) 04-Feb-2018, (D) 11-Mar-2018, and (E) 09-Apr-2018.

Binh Chanh and Cu Chi are known as two extensive land areas of HCMC where many industrial parks are on the plan of investment, so they can potentially become more and more polluted in the near future.

On 23-Dec-2017, since this is the transition time between the rainy and dry seasons, the average $PM_{2.5}$ over the entire HCMC was low (19.9 $\mu g/m^3$) (Table 5). However, $PM_{2.5}$ concentrations gradually increased over the next few months. At the peak of the dry season in February, the $PM_{2.5}$ mean was 32.5 $\mu g/m^3$, which is higher than the threshold specified in the National Technical Regulation on Ambient Air Quality, QCVN 05:2013 (25 $\mu g/m^3$, average in a year) [25]. In February, almost the entire south region of HCMC was ranked as a serious pollution area. The $PM_{2.5}$ concentrations at some places were at a high level with the highest value reached being 49.7 $\mu g/m^3$ (Table 5). Although these data are only for a few representative days for each month in the dry season, it showed that inside HCMC there are still areas that $PM_{2.5}$ concentrations exceeded Vietnamese standards every month (Fig. 3). With the rapid development of industry and economy, this is a serious warning of declining air quality in HCMC.

At present, the air quality in HCMC receives more and more concern from environmental management authorities and scientists alike. Many non-governmental organizations have been established with the purpose to prevent overwhelming air pollution and especially eliminate fine particles like $PM_{2.5}$ from the air. Although HCMC has been evaluated to be less polluted than Hanoi, the capital of Vietnam (Green ID, 2018b) [26], it is necessary to control and diminish the gas emissions generated from vehicles and industrial plants. Tackling the air pollution in HCMC is difficult to work and a long-term effort must be established and resolved in specific stages. Polluted substance dispersion surveillance is one of the first steps. In recent years, remote sensing has been demonstrated to be a distinctive tool for pollution monitoring.

In this research, remote sensing technology has been applied to simulate $PM_{2.5}$ concentrations on MODIS satellite images. Despite the low spatial resolution of MODIS satellite images, a daily image is nonetheless supplied so the progress of $PM_{2.5}$ distributions can be monitored, which allows time to find an appropriate treatment solution. Besides, to get more detailed $PM_{2.5}$ map, other higher resolution satellite images like Landsat or Sentinel can be used to build a city-level perspective of $PM_{2.5}$ dispersions.

The map of $PM_{2.5}$ distribution based on satellite images temporarily play an important role as the basis for environmental managers in HCMC to monitor the progress of fine particle generation in the atmosphere. Then, planning reasonable policies to firstly minimize the impact of $PM_{2.5}$ on human health and finally cut the sources of $PM_{2.5}$ emissions as much as possible for the purpose of sustainable development.

One more advantage of this research, when compared with others, is the accuracy. Since this research is based on the correlation between continuous quantitative variables, $PM_{2.5}$ data are being measured by continuous monitoring stations and AOD values from MODIS satellites are also being derived every day. Therefore, the more data received, the greater the accuracy of the model.

Conclusions

In this paper, the simulation of $PM_{2.5}$ via AOD from MODIS satellite imagery was derived from a simple regression model combined with remote sensing technology. Remote sensing is not a new tool to map particulate matter, but it is a cutting-edge technology that can be applied to many cities with sparse ground monitoring stations like HCMC. This research has had an initial success in verifying the assumption of an association between $PM_{2.5}$ concentrations and AOD. According to the correlation analysis result, $PM_{2.5}$ showed the best correlation with AOD at the green wavelength (0.55 µm) in form of linearity (R^2=0.810). On the scientific side, this research serves as a basis for further studies that apply remote sensing to air quality monitoring. For society, this research will help environmental managers as a reference source to issue policies that mitigate and prevent $PM_{2.5}$ emissions in HCMC.

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COMPETING INTERESTS

The authors declare that is no conflict of interest regarding the publication of this article.

REFERENCES

[1] GOV.UK (2019), *Public Health: Sources and Effect of $PM_{2.5}$, Local Air Quality Management (LAQM) Support*, Department for Environment Food & Rural Affairs.

[2] WHO (2005), *Air Quality Guidelines, Global Update 2005*, 496pp, WHO regional office for Europe.

[3] Green Innovation and Development Centre (2018a), *Current Status of Ambient Air Quality in HCMC - Quarter 1*, 3pp.

[4] Global Monitoring Laboratory, *SURFRAD Aerosol Optical Depth*, https://gml.noaa.gov/grad/surfrad/aod/.

[5] NASA (2019), *Dark Target, Aerosol Retrieval Algorithm*, https://darktarget.gsfc.nasa.gov/.

[6] T. Lokman, A. Omar, K. Ferhat, E. Nilufer (2008), "Particulate matter ($PM_{2.5}$, $PM_{10-2.5}$, and PM_{10}) and children's hospital admissions for asthma and respiratory diseases: a bidirectional case-crossover study", *Journal of Toxicology and Environmental Health, Part A*, **71(8)**, pp.512-520.

[7] Y. Guo, Y. Jia, Y. Pan, L. Liu, H. Wichmann (2009), "The association between fine particulate air pollution and hospital emergency room visits for cardiovascular diseases in Beijing, China", *Science of the Total Environment*, **407(17)**, pp.4826-4830.

[8] C. Feng, J. Li, W. Sun, Y. Zhang, Q. Wang (2016), "Impact of ambient fine particulate matter ($PM_{2.5}$) exposure on the risk of influenza like-illness: a time-series analysis in Beijing, China", *Environmental Health*, **15(1)**, pp.1-12.

[9] I. Wijeratne (2003), *Mapping of Dispersion of Urban Air Pollution Using Remote Sensing Techniques and Ground Station Data*, Master Thesis, International Institute for Geo-Information Science and Earth Observation Enschede, The Netherlands.

[10] N. Kumar (2007), "An empirical relationship between $PM_{2.5}$ and aerosol optical depth in Delhi Metropolitan", *Atmos. Environ.*, **41(21)**, pp.4492-4503.

[11] Y. Liu, P. Koutrakis, R. Kahn (2007), "Estimating fine particulate matter component concentrations and size distributions using satellite-retrieved fractional aerosol optical depth: part 2 - a case study", *J. Air Waste Manag. Assoc.*, **57(11)**, pp.1360-1369.

[12] A. Van Donkelaar, R.V. Martin, M. Brauer, R. Kahn, R. Levy, C. Verduzco, P.J. Villeneuve (2010), "Global estimates of ambient fine particulate matter concentrations from satellite-based aerosol optical depth: development and application", *Environ. Health Perspect.*, **118(6)**, pp.847-855.

[13] W. Di Nicolantonio, A. Cacciari (2010), "Modis multiannual observations in support of air quality monitoring in northern Italy", *Italian Journal of Remote Sensing*, **43(3)**, pp.97-109.

[14] X. Hu, L.A. Waller, M.Z. Al-Hamdan, W.L. Crosson, M.G. Estes Jr, S.M. Estes, D.A. Quattrochi, J.A. Sarnat, Y. Liu (2013), "Estimating ground-level $PM_{2.5}$ concentrations in the southeastern U.S. using geographically weighted regression", *Environmental Research*, **121**, pp.1-10.

[15] Z. Ma, X. Hu, L. Huang, J. Bi, Y. Liu (2014), "Estimating ground-level $PM_{2.5}$ in China using satellite remote sensing", *Environ. Sci. Technol.*, **48(13)**, pp.7436-7444.

[16] W. Song, H. Jia, J. Huang, Y. Zhang (2014), "A satellite-based geographically weighted regression model for regional $PM_{2.5}$ estimation over the Pearl river delta region in China", *Remote Sens. Environ.*, **154**, pp.1-7.

[17] V.D. Xuan, T.C. Thanh (2017), "$PM_{2.5}$ personal exposure and sources of population living near 2 environment monitoring station in HCMC", *Science & Technology Development*, **20(M1)**, pp.26-34.

[18] Nguyen Tran Huong Giang, Nguyen Thi Kim Oanh (2014), "Roadside levels and traffic emission rates of $PM_{2.5}$ and BTEX in HCMC, Vietnam", *Atmospheric Environment*, **94**, pp.806-816.

[19] T.T. Van, N.P. Khanh, H.D.X. Bao (2014), "Remoted sensed aerosol optical thickness determination to simulate PM_{10} distribution over urban area of HCMC", *Journal of Science*, **30(2)**, pp.62-72.

[20] Tran Thi Van, Nguyen Hang Hai, Vo Quoc Bao, Ha Duong Xuan Bao (2018), "Remote sensing-based aerosol optical thickness for monitoring particular matter over the city", *Proceedings*, **2(7)**, DOI: 10.3390/ecrs-2-05175.

[21] Gustavo Camps-Valls, Devis Tuia, Luis Gómez-Chova, Sandra Jiménez, and Jesús Malo (2011), *Remote Sensing Image Processing*, 192pp, Morgan & Claypool Publishers.

[22] T.T. Van, T.T. Binh, H.D.X. Bao (2012), "Study of dust pollution detecting ability in urban areas by remote sensing technology to support air environment observation", *Journal of Science and Technology Development*, **15(M2)**, pp.32-47.

[23] SPSS tutorial, *Pearson Correlations - Quick Introduction*, https://www.spss-tutorials.com/pearson-correlation-coefficient/.

[24] IBM SPSS Statistics documentation, *Curve Estimation Regression*, https://www.ibm.com/docs/en/spss-statistics.

[25] National Technical Regulation on Ambient Air Quality (2013), *QCVN 05:2013*.

[26] Green Innovation and Development Centre (2018b), *Update on Status of Air Quality in 1st quarter 2018, Air Quality Report*, 3pp.