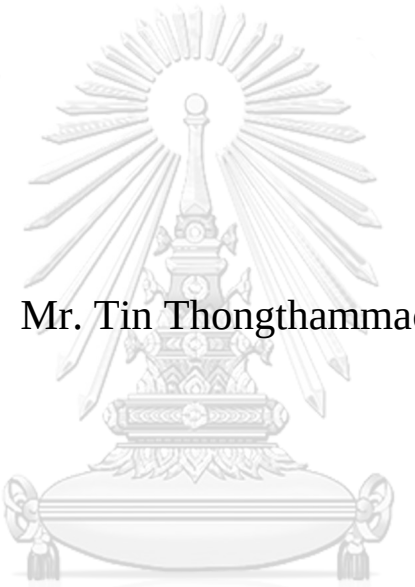
# $PM_{10}$ AND $PM_{2.5}$ CONCENTRATIONS IN BANGKOK OVER 10 YEARS AND IMPLICATIONS FOR AIR QUALITY

Mr. Tin Thongthammachart





A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Science in Hazardous Substance and Environmental Management
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# ฝุ่นละอองขนาดเล็ก $PM_{10}$ และ $PM_{2.5}$ ในกรุงเทพมหานคร ช่วงเวลา 10 ปี และการประเมินคุณภาพอากาศ

นายติณห์ ทองธรรมชาติ



วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
สาขาวิชาการจัดการสารอันตรายและสิ่งแวดล้อม สหสาขาวิชาการจัดการสิ่งแวดล้อม
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| Thesis Title | $PM_{10}$ AND $PM_{2.5}$ CONCENTRATIONS IN BANGKOK OVER 10 YEARS AND IMPLICATIONS FOR AIR QUALITY |
| By | Mr. Tin Thongthammachart |
| Field of Study | Hazardous Substance and Environmental Management |
| Thesis Advisor | Professor Wanida Jinsart, Ph.D. |

Accepted by the Graduate School, Chulalongkorn University in Partial Fulfillment of the Requirement for the Master of Science

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$PM_{10}$ AND $PM_{2.5}$ CONCENTRATIONS IN BANGKOK OVER 10 YEARS AND IMPLICATIONS FOR AIR QUALITY) อ.ที่ปรึกษาหลัก : ศ. ดร.วนิดา จีนศาสตร์

ฝุ่นละอองขนาดเล็กกว่า10 ไมครอน ($PM_{10}$)และฝุ่นละอองขนาดเล็กกว่า 2.5 ไมครอน($PM_{2.5}$)ในอากาศสามารถก่อให้เกิดผลกระทบต่อสุขภาพในมนุษย์ได้ โดยเฉพาะในเขตเมืองใหญ่ที่มีความเข้มข้นของฝุ่นละอองในคุณภาพอากาศสูง เนื่องจากปริมาณการจราจรสูง โดยเป็นแหล่งกำเนิดหลักของฝุ่นละอองนาดเล็ก เช่น เขตธุรกิจของกรุงเทพมหานคร งานวิจัยนี้ มีวัตุประสงค์ เพื่อศึกษาแนวโน้มการเปลี่ยนแปลงของความเข้มข้นฝุ่นละอองของขนาดเล็กในอากาศและประเมินคุณภาพอากาศที่อาจส่งผลต่อความเสี่ยงต่อสุขภาพของประชากรในเขตธุรกิจของกรุงเทพมหานคร การศึกษานี้ใช้ค่าตรวจวัดฝุ่นละอองในอากาศทั่วไปจากกรมควบคุมมลพิษ และสำนักงานกรุงเทพมหานคร ระหว่างปี 2008 ถึง ปี 2017 จากนั้น ค่าตรวจวัดมลพิษทางอากาศระหว่างปี 2015 ถึง ปี 2017 ถูกนำมาสร้างสมการพยากรณ์ค่า $PM_{2.5}$โดยวิธีการประมาณค่าสหสัมพันธ์เส้นตรง (multiple linear regression, MLR) เพื่อใช้เป็นการพยากรณ์ค่า $PM_{2.5}$ในสถานีตรวจวัดฝุ่นคุณภาพอากาศที่ไม่ได้ตรวจวัดค่า $PM_{2.5}$ สมการพยากรณ์ที่ได้ นำไปตรวจสอบด้วยวิธีทางสถิติเพื่อหาความแม่นยำและความถูกต้องของค่าพยากรณ์ ผลการทดสอบทางสถิติด้วยวิธี Q-Q plot พบว่าสมการมีความเชื่อถือได้ทางสถิติอย่างมีนัยสำคัญ หลักจากนั้นค่าความเข้มข้นฝุ่นละลอง $PM_{10}$และ $PM_{2.5}$ที่ได้จากการตรวจวัดและสมการพยากรณ์ นำไปประเมินความเสี่ยงทางสุขภาพจากการได้สัมผัสทางอากาศโดยใช้วิธีการคำนวณ Hazard quotient (HQ) ผลของการประเมินความเสี่ยงนำไปสร้างแผนที่ความเสี่ยงและระบุพื้นที่เสี่ยงโดยใช้โปรแกรมสารสนเทศทางภูมิศาสตร์(GIS) ด้วยวิธี Inverse Distance Weighing (IDW) ผลการสร้างแผนที่ความเสี่ยง พบว่าบริเวณทางตอนใต้ของเขตธุรกิจกรุงเทพมหานคร มีความเสี่ยงสูงกว่าพื้นที่อื่น



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Tin Thongthammachart : $PM_{10}$ AND $PM_{2.5}$ CONCENTRATIONS IN BANGKOK OVER 10 YEARS AND IMPLICATIONS FOR AIR QUALITY. Advisor: Prof. Wanida Jinsart, Ph.D.

Atmospheric particulate matter particles with a diameter less than 10 micron ($PM_{10}$) and less than 2.5 micron ($PM_{2.5}$) have been adverse human health effect. Ambient air pollution data in Central Business District (CBD) of Bangkok monitored by Pollution Control Department and Bangkok Metropolitan Administration were collected over ten years in Bangkok from 2008 to 2017. Trend of the particulate matter concentrations data were investigated over ten year for implications of activities related to air pollution. Daily average air pollution data between year 2015 and year 2017 were used as the dependent variables to develop mathematic models with multiple linear regression (MLR) technique for forecasting $PM_{2.5}$ concentrations in non-monitored areas. The predicted values of $PM_{2.5}$ concentrations were validated by various statistical performance indicators. The Q-Q plots of the measured and predicted values of both selected ambient monitoring data and roadside monitoring data had significant correlations, with $R^2$= 0.88 and 0.96, respectively. The non-carcinogenic health risk assessment of $PM_{10}$ and $PM_{2.5}$ was quantified as the hazard quotient (HQ) from both the measured and predicted data. The risk areas and HQ were compared using the Inverse Distance Weighting (IDW) interpolation technique and illustrated as GIS-based maps. The highest HQ value was discovered in the southern area of the CBD. The risk area could be used for greater precaution propose of public health awareness.



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Tin Thongthammachart

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|---|---|
| AM | Ambient monitoring station |
| AQG | Air Quality Guideline |
| BMA | Bangkok Metropolitan Administration |
| CBD | Central Business District |
| D-W | Durbin and Watson |
| $EC_{inh}$ | Inhalation Exposure Concentration |
| GIS | Geographic Information System |
| HQ | Hazard Quotient |
| HRA | Health Risk Assessment |
| IA | Index of Agreement |
| IDW | Inverse Distance Weighed |
| ITCZ | Inter-Tropical Convergence Zone |
| MAE | Mean Absolute Error |
| MLR | Multiple Linear Regression |
| NAAQS | National Ambient Air Quality Standard |
| NAE | Normalized Absolute Error |
| $O_i$ | Observed sample |
| $\overline{O}$ | Observed mean |
| PA | Prediction Accuracy |
| PCD | Pollution Control Department |
| $P_i$ | Predicted sample |
| $\overline{P}$ | Predicted mean |
| ppb | Part per billion |
| ppm | Part per million |
| $PM_{10}$ | Particulate matter with diameter less than 10 micron |
| $PM_{2.5}$ | Particulate matter with diameter less than 2.5 micron |
| Q-Q | Quotient - Quotient |
| $R^2$ | Coefficient of Determination |
| RfC | Reference Concentration |

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| RMSE | Root Mean Square Error |
| RS | Roadside Monitoring Station |
| $S_{Obs}$ | Standard deviation of the observed values |
| $S_{Prd}$ | Standard deviation of the predicted values |
| SPSS | Statistical Package for Social Science |
| TMD | Thailand Meteorological Department |
| US EPA | United States Environmental Protection Agency |
| VIF | Variance Inflation Factor |
| WHO | World Health Organization |

# CHAPTER I
# INTRODUCTION

## 1.1 Statement of the problems

Airborne particulate matter concentrations have increased in many developing countries, whereas the levels have decreased among some of the developed countries. Several studies related to airborne particulate matter and its implications on public health show that the pollutants have adverse health effects on those exposed to them (WHO, 2016). In addition, many studies have confirmed that fine airborne particulate matter, with an aerodynamic diameter of less than 2.5 μm ($PM_{2.5}$), should be considered more hazardous than suspended particulate matter (SPM) and $PM_{10}$. The smaller size particulate matter has the potential to penetrate the thoracic region of the respiratory system. The ambient guidelines set by the World Health Organization (WHO) for $PM_{2.5}$ are 10 μg/$m^3$, annually, and 25 μg/$m^3$, within a 24-hour period. The respective guidelines for $PM_{10}$ are 20 μg/$m^3$ and 50 μg/$m^3$ (WHO, 2018). The WHO reports that more than 80% of people living in urban areas are exposed to air quality levels that exceed the WHO standard. People who are exposed to fine particulate matter over both short (hours or days) and long periods (months or years) have higher risks of respiratory and cardiovascular morbidity as well as mortality from lung cancer. Southeast Asian countries are one of the countries of concern, where $PM_{2.5}$ levels exceed the WHO air quality guidelines (AQGs) and the trend of $PM_{2.5}$ in these countries has been increasing for over five years (2011-2016). Therefore, this is a very serious issue that the government should be concerned about and thus protect their citizens from exposure to small particulate matter (WHO, 2016). However, the WHO also recommended that government authorities in Southeast Asian countries should launch and promote policies to control ambient small particulate matter so that it does not exceed the safety standard. Many studies have pointed out that the main source of small particulate matter emission in urban areas comes from the traffic and industrial manufacturing processes (Wimolwattanapun *et al.,* 2011). Thus, many policies and regulations to control PM in urban areas regulate source control emissions, the quality of vehicle fuel, and the quality of engine lubricant. There are

also laws that enforce or encourage the use of unleaded petrol and vehicle checkups. However, while these regulations have been effectively regulating some of the suspended particulate matter, they have not been with the small particulate matter ($PM_{10}$ and $PM_{2.5}$) still present in ambient air. The particle sizes of the small particulate matter are difficult to eliminate (Wang *et al.*, 2010). These existing particles are the main cause of urban pollution.

In the case of Bangkok, Thailand, annual average ambient particulate matter concentrations of $PM_{2.5}$ exceeded the WHO AQGs. The excess fine particulate matter concentrations may pose a potential risk to human health. Apart from the excess PM levels, there are few air monitoring stations that can monitor $PM_{2.5}$. These monitoring stations are insufficient to monitor $PM_{2.5}$ in the whole central business district area of Bangkok. Excess $PM_{2.5}$ normally occurs between the rainy and winter seasons, from November to April (PCD, 2018a). However, there are 16 air monitoring stations that can monitor air pollutants and meteorological conditions such as $NO_2$, $SO_2$, CO, $PM_{10}$, ambient temperature, and relative humidity. Therefore, the existing air monitoring data is sufficient to evaluate $PM_{2.5}$ by using a forecasting method such as the statistical distribution technique or a statistical model.

The statistical distribution technique has been used to quantify air pollutant concentrations in a non-detected area. One of the techniques is multiple linear regression (MLR). MLR was applied in the urban areas of several studies for forecasting concentrations of particulate matter (both $PM_{10}$ and $PM_{2.5}$) by using meteorological parameters and co-pollutants as the predictors or the input data (Abdullah *et al.*, 2017; Nazif *et al.*, 2018; Ul-Saufie *et al.*, 2011). The MLR technique has two main advantages: its simple computation and easy implementation. MLR equations have been developed in order to forecast particulate matter in urban areas in different cities such as Finland, Greece, Malaysia, China and Iran (Eldrandaly andAbu-Zaid, 2011; Li andWang, 2017; Ul-Saufie *et al.*, 2012; Vlachogianni *et al.*, 2011). The researchers used the measured ambient air pollutants and meteorological data such as $NO_2$, $SO_2$, CO, $PM_{10}$, ambient temperature, and relative humidity to compute and develop their MLR equations. Their equations have shown to predict air pollutant concentrations with remarkable success. In addition, the development of a model (which includes meteorological factors) can be very useful in predicting

pollutant concentrations and the conventional air pollutants such as $NO_x$, $O_3$ and $SO_2$. Thus, the MLR technique was selected to develop equations for forecasting the $PM_{2.5}$ concentrations in this study. Then, the measured $PM_{2.5}$ concentrations in the monitored areas and predicted $PM_{2.5}$ concentrations in the non-monitored areas were applied to quantify a Health Risk Assessment (HRA). The HRA method was adopted from the regulatory protocol of the USEPA and quantified as the hazard quotient (HQ) for non-carcinogenic substance exposure (US.EPA., 2016a).

Therefore, the aim of this study is to develop MLR equations for estimating $PM_{2.5}$ concentrations and performing a quantitative health risk assessment for Bangkok. MLR was used as a statistical distribution technique to forecast the $PM_{2.5}$ concentrations in the city. The equations utilized the existing air pollution and meteorological values as the predictors. The equations were applied to the air monitoring stations, with non-detected $PM_{2.5}$ data. The $PM_{2.5}$ concentrations were then used to quantify the HRA, and the HRA results were illustrated in $PM_{2.5}$ hazard risk maps of the city.

**1.2 Research objectives**

1.2.1 The first objective aims to study the ambient $PM_{10}$ and $PM_{2.5}$ concentration trends in Bangkok over 10 years and develop a mathematical equation model to forecast fine particulate matter ($PM_{2.5}$) concentrations by using particulate matter concentrations, conventional air pollutants and meteorological factors as the predictor variables.

1.2.2 The second objective aims to complete a health risk assessment of human exposure to particulate matter in Bangkok and create GIS-based maps of the variability of hazard areas in the Central Business District (CBD) of Bangkok.

**1.3 Research hypotheses**

$PM_{2.5}$ concentration in Bangkok would be possibly developed with multiple regression analysis technique by using $PM_{10}$, $O_3$ and ambient humidity as the predicted variables.

**1.4 Scope of the study**

The air monitoring data used in this study came from January 2008 to April 2018 data records. This allowed the particulate matter concentration trends in Bangkok to be investigated. Air monitoring data from 2015 to 2017 were used to develop the MLR equations because the $PM_{2.5}$ has been monitored since 2015. All of the selected monitoring stations are located in the CBD of Bangkok (made up of 31 districts). The air monitoring and meteorological data were collected by the Environment Department of the Bangkok Metropolitan Administration (BMA) and by the Pollution Control Department (PCD) of Thailand. Events and regulations in Thailand were used to discuss the trends of the particulate matter. The measured and predicted particulate matter were then used to quantify the health risk assessment results.

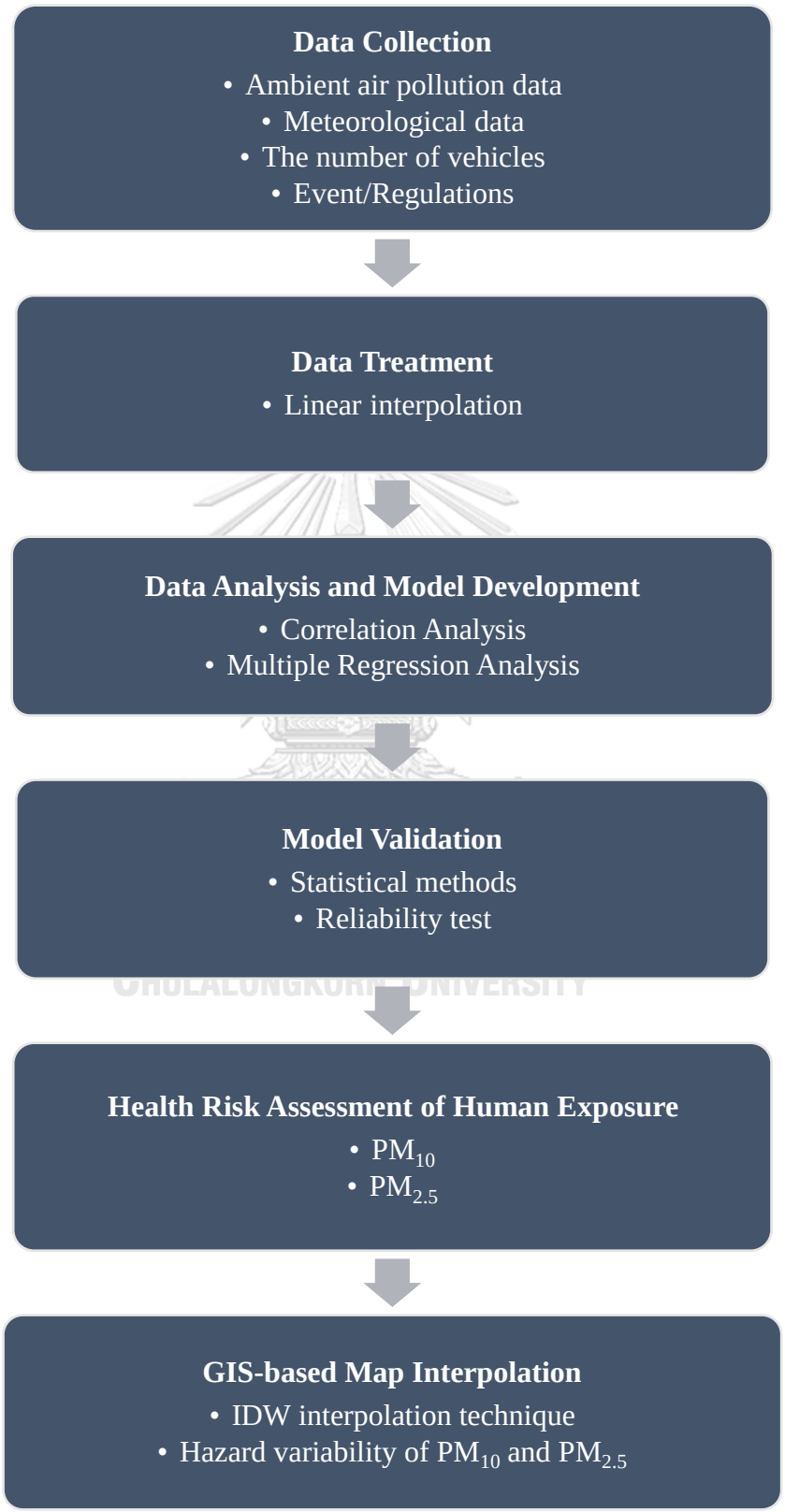
**1.5 Expected outcomes**

1.5.1 Trends of particulate matter can be identified and discussed over a ten-year period.

1.5.2 The developed equations can be used to forecast $PM_{2.5}$ concentrations in both ambient air and roadside air.

1.5.2 GIS-based maps of the $PM_{10}$ and $PM_{2.5}$ concentration distributions and the variability of the hazard area can be used for precautionary purposes in bringing awareness of the human health impacts on the citizens exposed to particulate matter.

## 1.6 Conceptual Framework



# CHAPTER II
# LITERATURE REVIEWS

## 2.1 Bangkok, Thailand

Bangkok is located in central Thailand with a latitude of 13˚44’ North and longitude of 100˚34’ East. The city area is 1,568.737 $km^2$, and there are 5,682,415 registered people in the city, as reported by Department of Provincial Administration Thailand (2017). Though there are 50 districts in the city this study evaluated only the districts in with central business district (CBD) consists of commercial, industrial, and residential areas. Moreover, Thailand has a tropical savanna climate under the Köppen climate classification, which is influenced by the South Asian monsoon system. This region is controlled by a tropical climate zone of three seasons: the rainy season (June–October), winter (November–February) and summer (March–May) (TMD, 2015).

Two major monsoons have a strong influence: from late May to late October, the weather is influenced by the southwest monsoon or East Asian monsoon, and from December till the end of February, the weather is influenced by the northeast monsoon or the East Asian Winter Monsoon. The two different monsoons have influenced the seasonal variation in Thailand, in which atmospheric condition could be affected air pollution. The southwest monsoon from the Indian Ocean generally indicates that it is the wet season, with high rainfall and high ambient relative humidity. This large-scale circulation strengthens the southwest flow when the inter-tropical convergence zone (ITCZ) moves poleward, across the north of Thailand to China in the summer. During the winter, the ITCZ changes into monsoon winds and move into the Southern Hemisphere across Thailand: north-easterly winds bring in air mass that has largely been defined over Southern China. Relative to the rainy season, this air mass has a low humidity and temperature. Rainfall in Bangkok is unusual during the winter monsoon, as any excess moisture would be lost when passing over the mountains to the north and east of the city. Relatively short transition periods exist between the monsoon seasons. In the summer (April and May), there is a transition episode characterized by periods of intense sporadic convection, strong incoming solar radiation and a regional low-pressure regime (Jinsart *et al.*, 2010). The tropical

storms in the summer have affected the precipitation level in the region and decreased the suspended particulate matter in the atmosphere. During this transition episode of the southwest monsoon, the heavy convection of the ITCZ may pass directly over Bangkok. In November and early December, the transition to the winter monsoon takes place, but since the period of strong solar radiation has already passed over Thailand, the winter season does not have as high temperatures or heavy convection (Tran *et al.*, 2006). Therefore, this study takes into account influence of the monsoons and evaluates the particulate matter variations following the seasons and transitional periods in Thailand.

**2.2 Introduction of Air Pollution**

Households, industries, and vehicles release complicated mixtures of air pollutants, many of which are adverse human health and the environment. All of the air pollutants, small particulate matter with a dimeter less than 10 micron and fine particulate matter with a diameter less than 2.5 micron have extreme impact on human health. Most fine particulate matter is emitted from fuel combustion, in both point sources such as power plants, industry, households or biomass burning and mobile sources such as vehicles.

Atmospheric pollution is a main environmental health problem in both developing and developed countries. Air pollution causes both acute and chronic diseases, for instance lung cancer, chronic obstructive pulmonary disease (COPD) and cardiovascular diseases. In 2016, the WHO reported that 4.2 million people died from exposure to ambient air pollution. Worldwide, outdoor air pollution is evaluated to cause about 16% of the lung cancer deaths, 25% of COPD deaths, about 17% of deaths due to coronary heart disease or strokes, and about 26% of respiratory infection deaths.

The citizens in developing and underdeveloped countries excessively occurrence the burden of outdoor air pollution with it being the cause of 88% of the 4.2 million premature deaths that occur in the world each year, and the highest number of deaths are in the Southeast Asia and the Western Pacific countries. The latest burden of its estimation reflected the strong significant role of air pollution is

cardiovascular illness and premature deaths. The estimates are very serious issue and much superior than the scientific proof and understanding.

Several sources of outdoor air pollution are difficult to control with the current technology of its individual. Thus, policy actions and development of the policymakers from cities, national and international are required to resolve the air pollution problems in the areas of transportation, waste management, energy, agriculture and buildings (WHO, 2016).

**2.3 Sources of Air Pollution**

2.3.1 Stationary sources or point sources

Stack emissions or Point source emissions are from industrial boilers, power plants, surface coatings industrial, petroleum refineries, and chemical manufacturing processes.

2.3.2 Mobile sources or line sources

Mobile sources are characterized for on-road sources as well as off-road sources. The on-road sources are from transportation including passenger cars, buses, trucks and other vehicles traveling on the roads either local or highway. The gases emissions from the on-road sources represent 33 percent of the VOCs and 40 percent of the oxides of nitrogen gases ($NO_x$) emissions. Off-road sources are attributed to mobile combustion such as marine industrial, a marine vessel, farming, off-road motorcycles, railroads, and construction) (David andBela, 2000).



2.3.3 Area sources

Area sources include small pollution sources such as gas stations, dry cleaners, and automobile painting shop. Area sources are definite as the sources that release less than 10,000 kg of hazardous air pollutants or less than 25,000 kg of a combination of pollutants in a year. This source also is generally active in commercial buildings such as in the cooling and heating units, and in surface coatings. The residential buildings i.e. fire places, surface coating, and fuel combustion systems in non-road machinery, boats, and railways are also classified as the area sources. Waste disposal in the usage of landfills, open burning and wastewater treatment process are strongly significant area sources (David andBela, 2000).

## 2.4 Particulate Matters

Particulate matter is the term for a mixture of solid particles and liquid droplets found in the air (e.g., black carbon, sodium chloride, nitrates, ammonia, dust and water). Some particles, soot, dust, dirt or smoke, are large enough to be seen with the naked eye (US.EPA., 2016b).

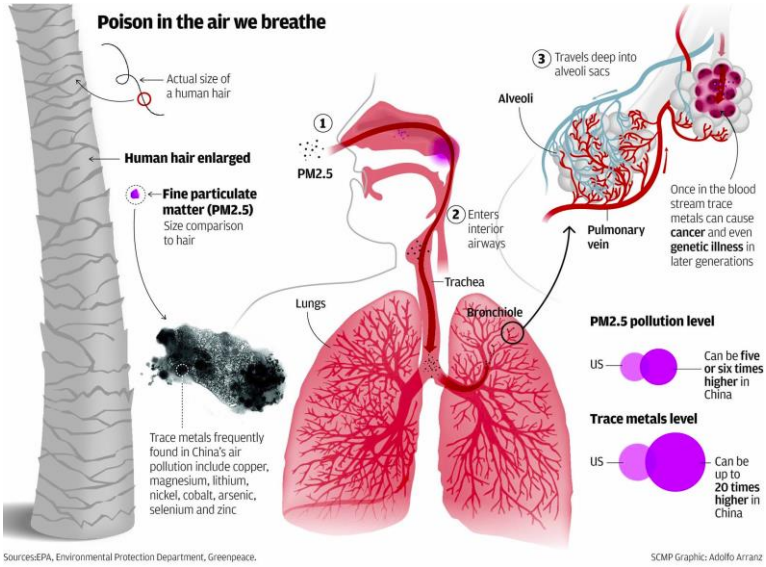



*Figure 2. 1 Rough of exposure to particulate matter (US.EPA., 2016b)*

$PM_{10}$ is an inhalable particle. This particle is generally 10 microns or less. $PM_{2.5}$ can be referred to as fine inhalable particles, with diameters that are generally 2.5 microns or less. $PM_{10}$ and $PM_{2.5}$ are come from the combustion of fossil fuels. Some are emitted directly from their sources, such as construction sites, unpaved roads, fields, smokestacks or fires. Most particles can be formed in the atmosphere because they chemically react with the atmospheric chemicals such as sulfur dioxide and nitrogen oxide that are emitted from industries, automobiles and power plants.

The large particles have a short atmospheric existence, tending to gravitate down quickly under gravity and wind-driven impaction processes. Therefore, only a few particles exceeding 20 microns in diameter can be suspended in the atmosphere, especially in an area that is very close to the source of emission.

$PM_{10}$ and $PM_{2.5}$ have the potential to affect human health and the environment. The particles are directly associated with their ability to cause health problems. This is

because they can penetrate deep into one's lungs, and some may even get into one's bloodstream as shown in Figure. 2.1. Exposure to these particles can affect the lungs and the hearts. Many scientific studies have traced the effect of particulate matter pollution to a variety of problems, which include premature death in people with respiratory problems and heart disease (WHO, 2016) (e.g., irregular heartbeat, nonfatal heart attacks, decreased lung function, aggravated asthma, and increased respiratory symptoms, such as irritation of the airways, coughing or difficulty in breathing). Children, older adults or those with heart or lung diseases are also affected by exposure to particulate matter.

In addition, fine particulate matter ($PM_{2.5}$) have several impacts on the atmospheric environment by reducing visibility. Particles can destroy the environment when it is carried over long distances by wind and then settle on the ground or water. Depending on the chemical compositions of the fine particulate matter, the effects could make lakes and streams acidic, reformation the balance of the nutrient in coastal waters and large river basins, reducing the nutrients in soil, destructive sensitive farm crops and forests, disturbing ecosystems diversity, and causative to acid rain effects (US.EPA., 2016b).

**2.5 Multiple Linear Regression (MLR)**

Multiple Linear Regression (MLR) is applied as the statistical method that allows prediction of variability between independent variables and a dependent variable (Jobson, 1991). The MLR is used by extending the simple linear regression model that there are *P explanatory variables* $X_1, X_2, \ldots, X_p$ which are to be associated to a dependent variable Y. The data matrix is assumed to be derived from a random sample of the observation values ($X_{i1}, X_{i2}, \ldots, X_{ip}, Y_i$), i = 1,2, ... ,n, or equivalently, an n × ($p$ +1) data matrix. The ($P$+1) random variables are assumed to satisfy the linear model as followed:

$$y_i = ß_0 + ß_1x_{i1} + ß_2x_{i2} + \ldots + ß_px_{ip} + u_i \qquad i = 1, 2, \ldots, n$$

Where (1) The $u_i$ $i = 1, 2, \ldots, n$ are the values of an unobserved error term U and are mutually independent and identically distributed; $E[u_i] = 0$; $V[u_i] = \sigma^2_u$ .

(2) The distribution of the error term U is independent of the joint distribution of $X_1, X_2, \ldots, X_p$ and hence the regression function $E[Y \mid X_1, X_2, \ldots, X_p] = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_p x_{ip}$; and $V[Y \mid X_1, X_2, \ldots, X_p] = \sigma^2_{Y \cdot X1, X2, \ldots, Xp} = \sigma^2_u$

(3) The unknown parameters $\beta_0, \beta_1, \beta_2, \ldots, \beta_p$ are constant values.

Because the observations of $y_1, y_2, \ldots, y_n$ are random samples, they are mutually independent and consequently the error terms are also mutually independent. Due to assumption (2), the results are conditional on the observed values of $X_1, X_2, \ldots$, and $X_p$.

MLR is able to be simplified to be clearly understood and widely used in atmospheric forecasting research. MLR is generally applied to investigate the relationship between a response variable and two or more explanatory variables by fitting a linear equation to the observed data (Vlachogianni *et al.*, 2011). MLR equation assumes that the residuals have normal distribution with zero mean, with uncorrelated and constant variance.

MLR was applied to this study to forecast $PM_{2.5}$ as the unknown (dependent) variable and the other co-pollutants and meteorological factors as the known (independent) variables. The technique normally used in obtaining the model was stepwise multiple linear regression (stepwise-MLR). This method involves entering independent variables.



**2.6 Health Risk Assessment (HRA)**

Human health risk assessment is the process that can be used to estimate the probability and nature of adverse human health effects. The health risk assessment is used in case of people may potentially be exposed to chemicals in contaminated environmental media, in present or in the future. The methodology for the health risk assessment (HRA) was applied from the publications of the United States Environmental Protection Agency (USEPA) and involved four standard steps, which are shown in Figure 2.

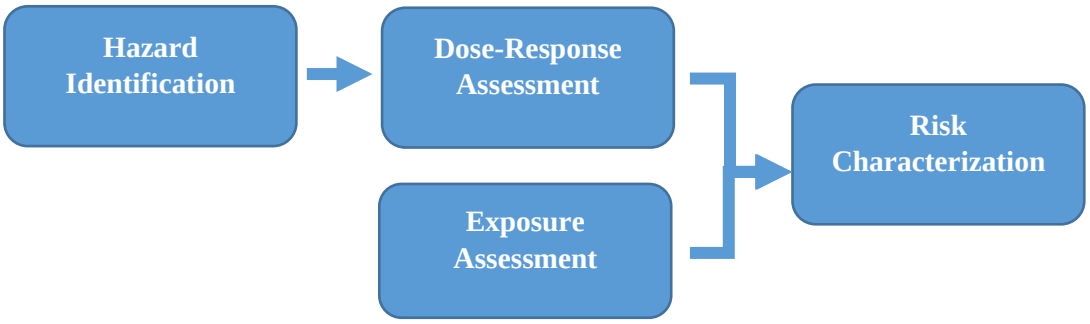



*Figure 2. 2 Health Risk Assessment (HRA) approach*

### 2.6.1 Hazard identification

Hazard identification is the process of determining whether exposure to a contaminated chemical or a stressor could cause and increase the occurrence of specific adverse human health effects such as birth defects or cancer. It also has to do with the likelihood of occurrence of the adverse health effects in humans. In the case of chemical stressors, the hazard identification procedure examines the available scientific data for a given chemical or group of chemicals and develops a weight of evidence to characterize the association between the adverse effects and the chemical agents. Exposure to a hazardous stressor or contaminated chemical agent could generate several different adverse human health impacts such as diseases, tumors formation, reproductive development imperfections, fatality, or other effects.

### 2.6.2 Dose–response assessment

Dose-response assessment for estimating exposure by inhalation is used Reference Concentrations (RfC). The RfC is used as benchmark to evaluate dose-response assessment of non-carcinogenic harmfulness for each vapored and inhaled chemical. Toxicity of non-cancer refers to adverse human health impacts as gene or DNA mutation causing cancer. The RfC was developed from the determination of scientific toxicology and calculation of Acceptable Daily Intake (ADI) values. The RfC is described toxicity for non-carcinogenic substances as the standard concentrations for deriving controlling and safe levels in order to protect populations exposed hazard agents. The methodology of RfC is expanded to interpretation for the

dynamics of the respiratory system as the entry portal and includes dosimetric adjustments to interpretation for the species-specific relationships of exposure concentrations to deposited/delivered doses. The physicochemical characteristics of the inhaled agent are considered as key determinants to its interaction with the respiratory tract and ultimate disposition. Also, the gases and suspended particles are treated separately, and the type of toxicity observed from respiratory tract or toxicity remote to the portal-of-entry influences the dosimetric adjustment applied.

An inhalation reference concentration (RfC) is assessed with a continuous inhalation exposure to the population of human which are included high-sensitive subgroups as children and elder-adults. The RfC development is concerned appreciable risk of non-carcinogenic health effects during the human lifetime.

In addition, the RfC development starts with the identification of a lowest-observed-adverse-effect level (LOAEL) and a no-observed-adverse-effect level (NOAEL). The RfC development is evaluated for the specified adverse human effect from the exposure levels of a given individual study on the several species examination based on toxicology and epidemiology. The NOAEL investigation is the highest level tested at which the specified adverse effect is not occurrence that could be called a “subthreshold level” and the LOAEL is the lowest level tested at which the specified adverse effect is begun occurance. Therefore, The RfC development methodology needs adaptation and conversion by dosimetric modification or adjustment of the LOAELs and NOAELs examination or observed in laboratory with animal experiments, in human epidemiological or occupational studies. The LOAELs and NOAELs were used to calculate human equivalent concentrations (HECs) for ambient exposure conditions. These conditions are presently assumed to be 24 hours per day for a lifetime of 70 years. Therefore, the study of ambient particulate matter affecting human health is used RfC.

Although the dose-response assessment is desirable to use from the study of human experiment, sufficient human data are often unavailable. Thus, the experiment information or data from animal testing is normally used from several animal experiments. The risk evaluator try to develop the animal model which is the most related to human physiology and based on biological effects comparability such as pharmacokinetic, metabolic, and pharmacodynamic data. the most sensitive species is

chosen as the species that displayed the serious negative effect at an exposure level that results in the lowest HEC when dosimetrically adjusted.

The serious toxic effect used in the dose-response assessment step is normally described by the lowest levels of the $NOAEL_{[HEC]}$ which can be the representative of the threshold region (the region where toxicity is apparent from the available data) for the data array. The aim is to choose a prominent toxic effect that is pertinent to the chemical's key mechanism of action. This method assumes that if the serious toxic effect is prevented, then every toxic effect is also prevented. The purpose of the serious toxic effect from all effects in the data array would be necessary to toxicologic judgment because one chemical might produce and express more than a single toxic effect (endpoint) in set of tests in the same or different exposure duration, even in one test species. Furthermore, the NOAEL and LOAEL achieved from experimental studies regarding to the number of subjects or animals examined and on the spacing of the exposure levels. The $NOAEL_{[HEC]}$ value obtained from a single study or several studies that are representative of the threshold region for the overall data array, is the key datum synthesized from an evaluation of the dose- response data. Evaluation of the serious effect characterizes the first scientific determination obligatory by the reference concentrations in the dose-response assessment

The RfC is originated from the $NOAEL_{[HEC]}$ for the critical effect by consistent application of uncertainty factors (UFs). The UFs are applied to account for recognized uncertainties in the extrapolations from the experimental data conditions to an estimate appropriate to the assumed human scenario. Determination of which UFs to apply and the magnitude of each represents the second scientific evaluation required by an RfC dose-response assessment. The standard UFs applied are those for the following extrapolations: (1) effects in average healthy humans to sensitive humans, (2) laboratory animal data to humans, (3) studies of subchronic to chronic duration, (4) a $LOAEL_{[HEC]}$ to a $NOAEL_{[HEC]}$, and (5) an incomplete to complete data base. The UFs are generally an order of magnitude, although incorporation of dosimetry adjustments or other mechanistic data has routinely resulted in the use of reduced UFs for RfCs. The typical reduced UF is three or one-half $\log_{10}$. The composite UF applied to an RfC will alter in magnitude regarding to the number of

extrapolations obligatory. The composite UF when four factors are used is generally reduced from 10,000 to 3,000 in recognition of the lack of independence of these factors. An additional modifying factor (MF) would be applied when scientific uncertainties in the study chosen for operational derivation are not explicitly addressed by the standard UFs. For example, an MF might be applied to account for a statistically minimal or inadequate sample size or for poor exposure characterization. The RfC calculation fron NOAEL were shown in equation 2.1 as follows:

$$RfC = \frac{NOAEL_{[HEC]}}{UF \times MF} \qquad \text{eq. 2.1}$$

Where $NOAEL_{[HEC]}$ = The NOAEL or analogous effect level obtained from the dosimertrically adjusted to a human equivalent concentration (HEC).

UF = Uncertainty factor applied to use for the extrapolations required from characteristics of the experimental regime.

MF = Modifying factor for scientific uncertainty in the study chosen as the basis for the operational derivation.



Confidence levels of high, medium, or low are assigned to the study used in the operational derivation, to the overall data base, and to the RfC itself. Confidence ascribed to the RfC estimate is a function of both the confidence in the quality of the study and confidence in the completeness of the supporting data base together, with the data base confidence taking precedence over that assigned to the study.

High confidence in the RfC is an indication that the data base included investigation of a comprehensive array of noncancer toxicity endpoints established from studies of chronic duration in various mammalian species and that the study (or studies) established an unequivocal NOAEL. Therefore, a high confidence RfC is not likely to change substantially as more data become available, with the exception of additional mechanistic data or sophisticated tests that may change the perspective of the evaluation.

Low confidence in an RfC is usually applied to a derivation that is based on several extrapolations and indicates an estimate that may be especially vulnerable to change if additional data become available. For some chemicals, the data base is so weak that the derivation of a low confidence RfC is not possible. The data base supporting an RfC for a chemical is designated as not-verifiable. Upon the availability of new data, this not-verifiable status would be reexamined. It must be highlighted that the RfC as a quantitative dose-response assessment is not numeric alone. As risk assessments have become a more prevalent basis for decision-making, their scientific quality and clarity of presentation have gained unprecedented importance. Any dose-response assessment, such as the RfC, has inherent uncertainty and imprecision because the process requires some subjective scientific judgment, use of default assumptions, and data extrapolations. A complete dose-response evaluation should include communication of the rationale for data selection, the strengths and weaknesses of the data base, key assumptions, and resultant uncertainties. The rationale for the choice of the data from which the RfC is derived, a discussion of data gaps, and the resultant confidence in the RfC are all outlined in the summary of the RfC entered on the EPA's Integrated Risk Information System (IRIS). A discussion and rationale for the UFs used in the RfC derivation are also provided. This information is an important part of the RfC and must be considered when evaluating the RfC as a dose-response estimate, in addition to assumptions and resultant uncertainties inherent in an exposure assessment, when attempting to integrate the assessments into a risk characterization.



In conclusion, the RfC methods are developed from NOAELs and LOAELs for dosimetric adjustments of particle or gas exposures. The methods represent the currently available science. Uncertainty factors are utilized that allow for RfC derivation in the absence of some data, but the UF and confidence statements explicitly call out prescribed areas of extrapolation in order to communicate data gaps. For example, a UF is used to account for intraindividual variability, an area identified by the NAS as one requiring additional data to more accurately characterize susceptibility of subpopulations. (US.EPA., 1994).

For the study of health risk assessment of $PM_{10}$ and $PM_{2.5}$ exposure, the RfC was obtained from the air quality standard from WHO and Thailand NAAQS by PCD.

The two standard values were compared and quantify health risk in risk characterization step.

### 2.6.3 Exposure assessment

Exposure assessment is the process of measuring or estimating the magnitude, frequency, and duration of human exposure to an agent in the environment or estimating future exposures to an agent that has not yet been released. An exposure assessment includes some discussion of the size, nature, and types of human populations exposed to the agent, as well as discussion of the uncertainties in the above information.

Exposure can be measured directly but more commonly is estimated indirectly through consideration of measured concentrations in the environment, consideration of models of chemical transport and fate in the environment in order to estimate of human intake over time. Depending on the type of chemical agents, it can be divided into two different equations for assessment of both non-carcinogens as shown in Eq. 2.2 and carcinogens as shown in Eq. 2.3.

Exposure assessment for non-carcinogenic substances

$$EC(\mu g/m^3) = \frac{C \times ET \times EF \times ED}{AT} \qquad \text{Eq. 2.2}$$

Exposure assessment for carcinogenic substances

$$CDI(\mu g/m^3) = \frac{C \times ET \times EF \times ED}{AT} \qquad \text{Eq. 2.3}$$

Where, EC = substance exposure concentration per day ($\mu g/m^3$)

CDI = average carcinogen exposure per day ($\mu g/m^3$)

C = toxicity concentration in air

ET = exposure time (24 hours/day)

EF = exposure frequency (350 days/year)

ED = exposure duration (30 years for non-carcinogenic substance exposure and 70 years for carcinogenic exposure)

AT = averaging time (For non-carcinogen used ED x 365 x 24 hour/day and for carcinogen used 70 x 365 x 24 hour/day)

### 2.6.4 Risk Characterization

A risk characterization suggests the risk assessor's decision regarding the nature and presence or absence of risks, along with information about how the risk was assessed (where assumptions and uncertainties still exist). Risk characterization takes place in both human health risk assessments and ecological risk assessments. Risk is normally characterized separately for non-carcinogenic and carcinogenic health risk. For non-carcinogenic health risk due to inhalation, risk characterization is performed by quantifying the hazard using the Hazard Quotient (HQ), which is defined in Eq. 2.4, as follows:

$$HQ = \frac{EC}{RfC} \qquad \text{Eq. 2.4}$$

Where; HQ = Hazard Quotient

EC = inhalation exposure air concentration ($\mu g/m^3$)

RfC = reference concentration ($\mu g/m^3$)

An HQ of less than one (HQ < 1) indicates that the pollutant concentration is below the reference concentration (RfC) value (which means the potential risk is acceptable) with no action required to reduce the pollutant's level. Hence, HQ < 1 is considered safe. However, it can be noted that HQ > 1 does not necessarily suggest a likelihood of adverse effects. It is more suitable to be used as an indication that a potential risk exists for adverse health effects.

For the carcinogenic health effect due to inhalation, the lifetime cancer risk (LCR) is estimated as follows:

$$LCR = EC \times URF \qquad \text{Eq. 2.5}$$

where; LCR = Lifetime cancer risk

EC = exposure air concentration ($\mu g/m^3$)

URF = unit risk factor $(\mu g/m^3)^{-1}$

Some research shows the threshold of cancer risk "acceptability" varies among countries, states, and different cities of the same state. The cancer risk of $10^{-6}$ (1 in a million) is commonly identified as an "acceptable risk." It is also known as minimal

risk, which is described as being very small and negligible, whereas levels of $10^{-6}$ to $10^{-4}$ are deemed as the range of "generally acceptable risk," where $10^{-4}$ may be exceeded in some circumstances, especially when there is a need to balance the costs and benefits of remedial actions (US.EPA., 2016a). This study was applied to the health risk assessment approach to study the hazard exposure to $PM_{10}$ and $PM_{2.5}$ concentrations in Bangkok. The particulate matter exposure assessment used the non-carcinogenic substance approach of the USEPA. The selection of non-carcinogenic health risk assessment was based on the risk characterization of $PM_{10}$ and $PM_{2.5}$ which were not included the other chemicals bound with the particles.

**2.7 Geographic Information System (GIS)**

The geographic information system (GIS) is widely used to work with maps and geographic information. It is used for creating and using maps; compiling geographic data; analyzing mapped information; sharing and discovering geographic information; using maps and geographic information in a range of applications; and managing geographic information in a database. The program that applied the GIS process is called ArcGIS. The main component of ArcGIS that is used to create maps with the raster technique is called ArcMap. This program was applied in this study to evaluate particulate matter distribution.

ArcMap is one of the main interfaces for conducting analyses and creating maps. Here, feature classes and shape files can be populated, data can be edited, calculations can be performed, and finally, maps can be created for displaying the results of the GIS analysis. ArcMap projects are stored as map documents (*.mxd), which save all of the layers added to the map as well as the results of any of the geo-processing tools that were used. It is important to note that **.mxd* does not store the actual data, but only references them and user-defined layer organization and symbols. In addition, the important module in ArcMap is ArcToolBox, which is where all of the geo-processing and spatial analysis tools are located. There are hundreds of tools available and they range from basic to advanced. The ArcMap and ArcToolbox interface are shown in Figure 2.3 and Figure 2.4, respectively.

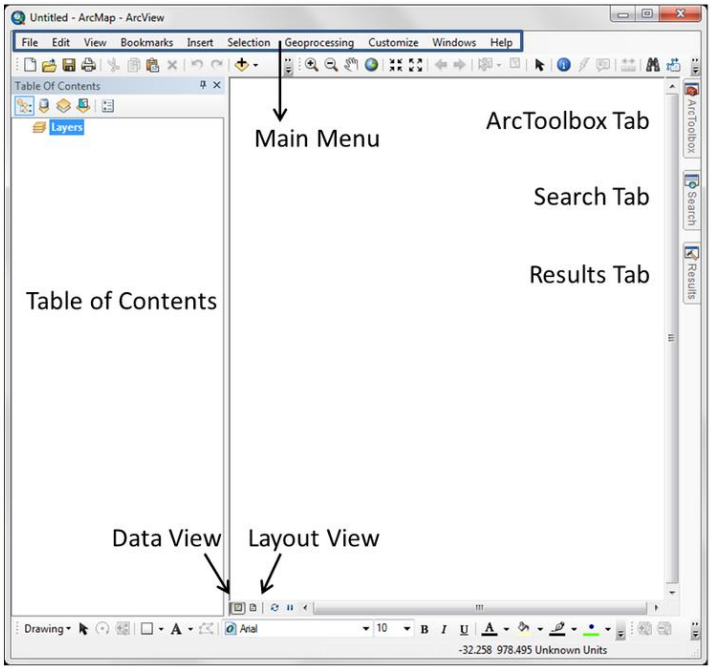



*Figure 2. 3 An overview of the ArcMap interface*

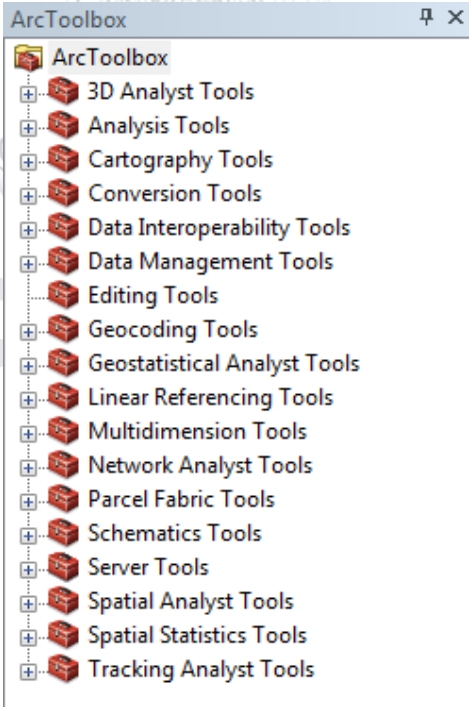



*Figure 2. 4 An overview of the toolboxes in ArcToolbox*

The interpolation methods in GIS are used to create a surface grid in this program and predict the values of the cells at locations that lack sample collection points. It is based on the principle of spatial autocorrelation or spatial dependence, which measures the degree of relationship/dependence between near and distant objects

Spatial autocorrelation determines if values are interrelated in a spatial pattern. This correlation is used to measure the following:

- The similarity of objects within an area.
- The degree to which a spatial phenomenon is correlated to itself in space.
- The level of independence between the variables.
- The nature and strength of the interdependence.

Different interpolation methods will produce different results. There are various methods of the interpolation such as the inverse distance weighted (IDW) tool, spline, and ordinary kriging.

The IDW technique is a method of interpolation that estimates cell values by averaging the values of sample data points in the neighborhood of each processing cell. The closer a point is to the center of the cell being estimated, the more significance it has in the averaging process.

Kriging is an advanced geostatistical procedure that generates an estimated surface from a scattered set of points with z-values. A thorough investigation of the spatial behavior of the phenomenon represented by the z-values should be done before the selection of the best estimation method for generating the output surface.

The Spline tool uses an interpolation method that estimates values using a mathematical function that minimizes overall surface curvature, resulting in a smooth surface that passes exactly through the input points (ESRI, 2016).

## 2.8 Related Research

2.8.1 Ambient particulate matter research

There was a study of drivers' exposure to particulate matter in Bangkok (Jinsart *et al.*, 2012). Exposure to fine particulate matter ($PM_{2.5}$) in public transportation vehicles could have harmful health effects on both drivers and commuters in Bangkok, Thailand, where air pollution from vehicle exhaust is a serious problem. Exposure to fine particulate matter from moving vehicles has not been sufficiently investigated. Thus, the authors measured the levels of $PM_{2.5}$ within various types of vehicles in Bangkok. Their results were the first to demonstrate that the drivers and commuters in Bangkok are exposed to a high level of $PM_{2.5}$, which cannot be detected by current roadside monitoring devices. They suggested the need for further pollution control measures.

The study of decreasing trends of suspended particulate matter and $PM_{2.5}$ concentrations in Tokyo, from 1990 to 2010. The authors reported that, in Tokyo, the annual average SPM concentration declined by 62.6% from 59.4 $\mu g/m^3$ in 1994 to 22.2 $\mu g/m^3$ in 2010, and the concentration of $PM_{2.5}$ declined by 49.8% from 29.3 $\mu g/m^3$ in 2001 to 14.7 $\mu g/m^3$ in 2010. Significant positive correlations were found between traffic volumes and SPM or $PM_{2.5}$, but the average concentrations of SPM and $PM_{2.5}$ concentration per traffic volume have also decreased over the decade studied. These results suggest that reductions in traffic volumes as well as improvements in engine design and the installation of exhaust gas treatment systems might have improved the air quality (Hara *et al.*, 2013).



2.8.2 Multiple linear regression (MLR) analysis with air pollution research

The study on statistical analysis on air pollution using principal component analysis (PCA) and multiple regression analysis in modelling ground-level ozone and factors affecting the air pollution concentrations (Abdul-wahab *et al.*, 2005). Air pollutants including methane ($CH_4$), carbonmonoxide (CO), carbondioxide ($CO_2$), nirogenoxide (NO), nitrogendioxide ($NO_2$) and sulphurdioxide ($SO_2$) and meteorological variables (wind speed and direction, air temperature, relative humidity and solar radiation) were used as parameters for multiple linear and principal component regression techniques analysis. The simulation outcome was applied to

ozone ($O_3$) prediction. For both day and night time, the pollutants were positively correlated; however, they were all negatively correlated with ozone. Multiple regression analysis was applied to fit the ozone data using the conventional pollutants and meteorological factors as predictors. The authors also found the relationship between ozone and the other environmental factors in such a way that the day time ozone concentration tended to increase. Due to the high temperature and high solar radiation, the pollutants NO and $SO_2$ being emitted to the atmosphere induced the secondary ozone concentration. Night time ozone concentrations were affected potentially by NO without the influence of meteorological variables. Nevertheless, the model was able to better predict ozone concentrations in daytime than at night.

In addition, the MLR technique was widely used in air model prediction work. There was the study of performance of MLR for forecasting long-term $PM_{10}$ concentrations using gaseous and meteorological factors as the predicted variables (Ul-Saufie *et al.*, 2012). The study was done in Seberang Perai, Malaysia, to forecast the $PM_{10}$ concentrations. The developed model included $NO_2$, $SO_2$, CO, $PM_{10}$ and meteorological parameters (temperature, relative humidity and wind speed). Five statistical validation tools were used as performance indicators: Prediction Accuracy (PA), Coefficient of Determination ($R^2$), Index of Agreement (IA), Normalized Absolute Error (NAE) and Root Mean Square Error (RMSE). It can be summarized that MLR can be used for accurately predicting long-term $PM_{10}$ concentrations.



Abdullah *et al.* (2017) used MLR to forecast the long-term $PM_{10}$ concentrations during different monsoon seasons in Malaysia. Particulate matter is the pollutant of greatest concern in Peninsular Malaysia because it has the highest API values compared to the other pollutants. Chronic $PM_{10}$ exposure may reduce life expectancy because of an increase in cardiovascular morbidity and lung cancer mortality. The researchers aimed to develop the model that could predict ambient particulate matter concentrations. The predictions could provide important information for taking precautionary measures to avoid exposure to unhealthy ambient pollution. Another benefit was to allow the government or relevant organizations to implement strategic measurements. The purpose of this study was to develop MLR models for different monsoon seasons with meteorological factors as predictors. Daily measurement of $PM_{10}$ concentrations from January 2005 to

December 2011 in Kuala Terengganu, Malaysia, was used as inputs for predicting $PM_{10}$ concentration levels. The developed MLR model performance was remarkable success. Wind speed, rainfall and relative humidity showed negative relationships, whereas temperature and atmospheric pressure were positively correlated with $PM_{10}$ concentrations. Therefore, the researchers concluded that the developed MLR models were appropriate for predicting $PM_{10}$ concentrations at the local level for each monsoon.

Li and Wang (2017) used a regression calculation model to find the relationship between $PM_{2.5}$ and the concentrations of $PM_{10}$, $SO_2$, $NO_2$, $O_3$, CO, temperature and humidity. They used the urban air quality monitoring data as input data in order to find the relationship between $PM_{2.5}$ concentrations and several major air pollutant concentrations. The meteorological elements in the same period were also analyzed respectively. In the results, they found that there was a significant correlation between the concentrations of $PM_{2.5}$ and the others air pollutants that were mentioned before. Therefore, we used these factors as the variables in order to make a multiple linear regression analysis about the $PM_{2.5}$ concentrations and set up the urban $PM_{2.5}$ concentration regression calculation model. For the model validation, two results were principally a good fitting effect between the measured and observed values, which showed that the regression model had a good performance.

Nazif *et al.* (2017) quantified a health risk assessment of particulate matter ($PM_{10}$) exposure by using mathematical models to assess small particulate matter. Meteorological parameters and seasonal variation increase $PM_{10}$ concentrations, especially in the areas that have multiple human activities. Stepwise regression (SR), multiple linear regression (MLR) and principal component regression (PCR) analyses were applied to investigate daily average $PM_{10}$ concentrations. The analyses were carried out using daily average $PM_{10}$ concentrations, temperature, humidity, wind speed and wind direction data from 2006 to 2010. The input data were obtained from an industrial air quality monitoring station in Malaysia. The SR analysis showed that meteorological parameters had less influence on $PM_{10}$ concentrations by having coefficient of determination ($R^2$) results from 23 to 29% based on seasoned and unseasoned analysis. However, the prediction analysis results showed that PCR models had better $R^2$ outcomes than MLR models. The outcomes for the analyses

based on both seasoned and unseasoned data showed that MLR models had $R^2$ result from 0.50 to 0.60, but PCR models had $R^2$ result from 0.66 to 0.89. Additionally, the analysis of model validation using 2016 data also showed that the PCR model performed better than the MLR model, with the PCR model for the seasoned analysis having the best result.

The recent research study has been done in Bahrain. The authors aimed to identify the most important air pollutants based on their individual contribution to air quality index (AQI) and determined the major air pollution sources (Jassima *et al.*, 2018). The air data sets were collected from 17 air quality monitoring sites. XLSTAT 2014 program and Statistical Package for the Social Sciences (SPSS 22) were used to analyze the air data set over six-and-half-year from July 2006 to December 2012. Hierarchical Agglomerative Cluster Analysis (HACA) classified the monitoring stations into three idiosyncratic clusters based on similarities of meteorological parameters and air pollutants characteristics. The principal component analysis (PCA) technique was used to identify major sources of air pollution in each cluster. The PCA analysis established that dust storms, vehicle emissions, manufacturing processes, power plants and airport activities were the main air pollutant emissions. The PCA analysis showed that wind speed and ambient temperature have positive loading, while relative humidity has negative loading. In addition, MLR analysis was applied to develop models for prediction of AQI for every cluster based on the concentrations of key air pollutants. The MLR outcomes showed $PM_{10}$ and $PM_{2.5}$ were closely related to the AQI values. The MLR models showed good performance with $R^2$ values that were higher than 0.7 in every cluster.



2.8.3 GIS Based map for air pollutant distribution research

The evaluation of the spatial variability of the concentrations of ambient air pollution in the Mabtaphud district, Thailand was studied in 2011 (Thepanondh andToruksa, 2011). The measurement of $NO_2$ concentrations used in their study was obtained from 11 ambient monitoring stations in the nearby area. They applied spatial interpolation technique to create the variability of ambient pollutants concentrations using three interpolating techniques: the ordinary kriging, the inverse distance weighted (IDW), and the spline. However, the results showed that the ordinary

kriging interpolation technique performed the best, with less error based on a cross-validation procedure. They also used the ordinary kriging to create a hazard map of nitrogen dioxide. The results showed a small variation of its concentration over the study domain. Nevertheless, spatial interpolation presented that the hotspots (an area with high pollutant concentrations) were located in downwind locations of the industrial estate site. The authors also recommended the further study of air pollution mapping, where it is compared with various interpolating and integrating techniques of secondary data prior to applying the best spatial interpolation technique. In addition, the emissions from the line source played a significant role in increasing the ambient nitrogen dioxide concentrations in the specific location.

In addition, there was a study on GIS performance comparison to find the best interpolation scheme of GIS (Eldrandaly andAbu-Zaid, 2011).The authors compared six GIS-based spatial interpolation methods in order to determine air temperature in Western Saudi Arabia with different interpolation methods. Inverse Distance Weighted (IDW), Global Polynomial, Local Polynomial, Radial Basis Function (Thin-Plate Spline), Ordinary Kriging, and Universal Kriging were applied to this study as interpolation techniques. For the GIS result validation, they used a cross-validation technique to diagnose the performance of the interpolation. The validation showed that Ordinary and Universal Kriging presented the best performance by giving the minimum Root Mean Square Error (RMSE) result.



In Thailand case, GIS was widely used to study air pollution distribution. There was a study of investigation in people living in northern Thailand who were exposed to $PM_{10}$ that was associated with episodes of biomass burning (Mitmark andJinsart, 2017). The authors investigated $PM_{10}$ emissions from natural forest fires and agricultural waste burning. $PM_{10}$ exposures in eight provinces of northern Thailand were investigated by GIS interpolation techniques. They also used daily average ambient $PM_{10}$ concentrations from 10 monitoring stations as the input data for GIS processing. The best interpolation scheme was IDW. The predicted $PM_{10}$ concentrations were validated with the measurement values. GIS-based maps illustrated the variability of $PM_{10}$ distributions and the risk locations that were correlated with forest fire frequency and wind direction.

# CHAPTER III
# METHODOLOGY

## 3.1 Study Area

The study area was the Central Business District (CBD) of Bangkok, which contains 31 districts. The district names and the total population of each district in 2017 (BMA, 2018) are shown in Table 3.1 and the location of CBD are shown in Figure 3.1

*Table 3. 1* The number of populations in each district of CBD

| No. | Districts | Population |
|---|---|---|
| 1 | Bang Sue | 125,440 |
| 2 | Chatuchak | 156,684 |
| 3 | Lat Phrao | 120,394 |
| 4 | Bang Kapi | 147,800 |
| 5 | Wang Thonglang | 112,116 |
| 6 | Huai Khwang | 81,515 |
| 7 | Din Daeng | 122,563 |
| 8 | Phaya Thai | 70,238 |
| 9 | Dusit | 95,852 |
| 10 | Ratchathewi | 72,304 |
| 11 | Phra Nakhon | 51,231 |
| 12 | Pom Prap Sattru Phai | 46,581 |
| 13 | Samphanthawong | 24,150 |
| 14 | Bang Phlat | 92,325 |
| 15 | Bangkok Noi | 112,046 |
| 16 | Bangkok Yai | 67,768 |
| 17 | Phasi Charoen | 126,824 |
| 18 | Chom Thong | 152,315 |
| 19 | Thon Buri | 109,482 |
| 20 | Khlong San | 73,263 |
| 21 | Rat Burana | 82,545 |
| 22 | Bang Kho Laem | 89,358 |
| 23 | Yan Nawa | 78,797 |
| 24 | Sathon | 79,624 |
| 25 | Bang Rak | 47,817 |
| 26 | Pathum Wan | 49,121 |
| 27 | Khlong Toei | 102,945 |
| 28 | Vadhana | 84,967 |
| 29 | Suan Luang | 122,534 |
| 30 | Phra Khanong | 90,534 |
| 31 | Bang Na | 90,852 |

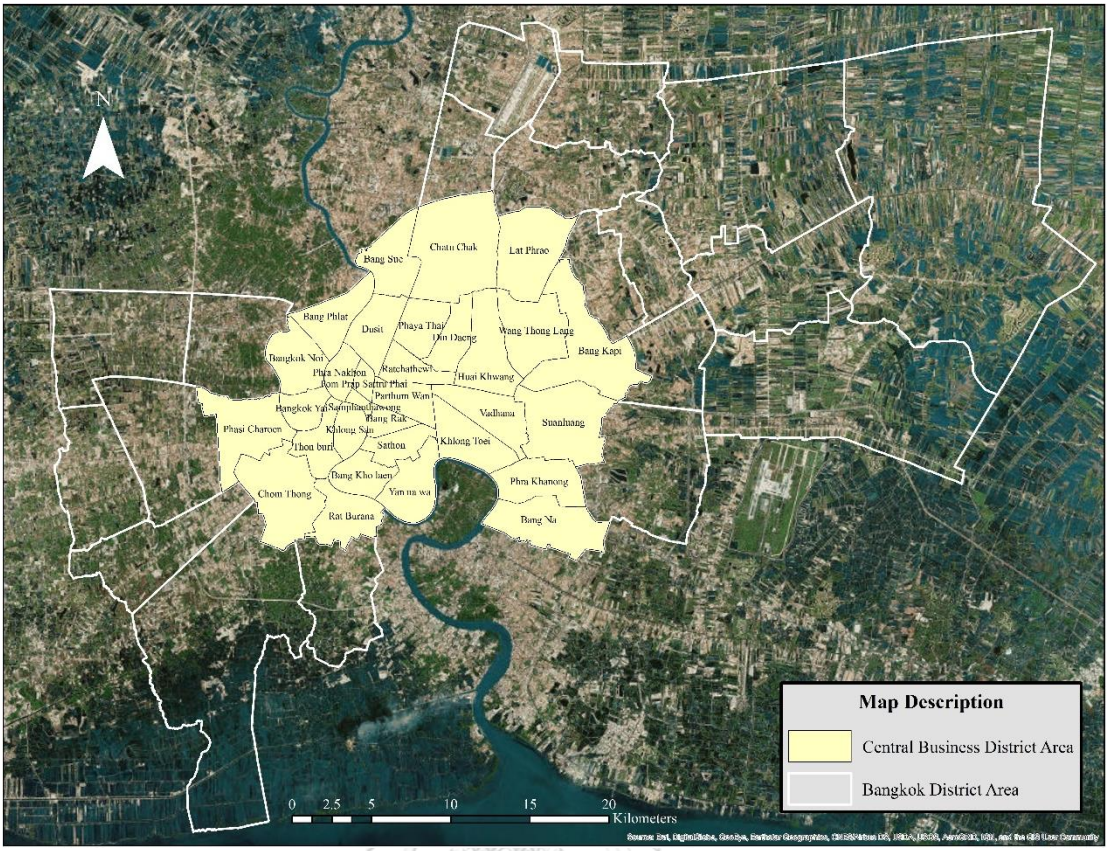



*Figure 3. 1 The location of CBD*

### 3.2 Data Collection

Air pollution and meteorological data in this study were obtained from the Bangkok Metropolitan Administration (BMA) and the Pollution Control Department (PCD). There are 16 air monitoring stations in the CBD. The locations of these monitoring stations were shown in Figure 3.2 and the details of the monitoring stations and their Universal Transverse Mercator (UTM) locations were shown in Table 3.2. The monitoring stations were divided into two types according to their locations: general ambient and roadside monitoring stations. The air pollution and meteorological data measured in this study are as follows: $PM_{10}$, $PM_{2.5}$, CO, NO, $NO_x$, $NO_2$, $O_3$, $SO_2$, wind speed, relative humidity, temperature and rainfall. The data from the monitoring stations for both the general ambient and roadside stations were used to determine the correlation analysis between the $PM_{2.5}$ concentrations and atmospheric variables in CBD of Bangkok. The monitoring stations at the Meteorological Department (5t) and the Public Relations Department (59t) were

selected to develop the MLR equation for the ambient stations. The monitoring stations at Intarapitak (52t), Dindang housing (54t), and Chokchai police office (53t) were selected to develop the MLR equation for the roadside stations. The daily average air pollution and meteorological data from 2015 to 2017 were used as the predicted variables. The selection criteria were based on the monitoring stations with the complete data set and located in a highly polluted area.

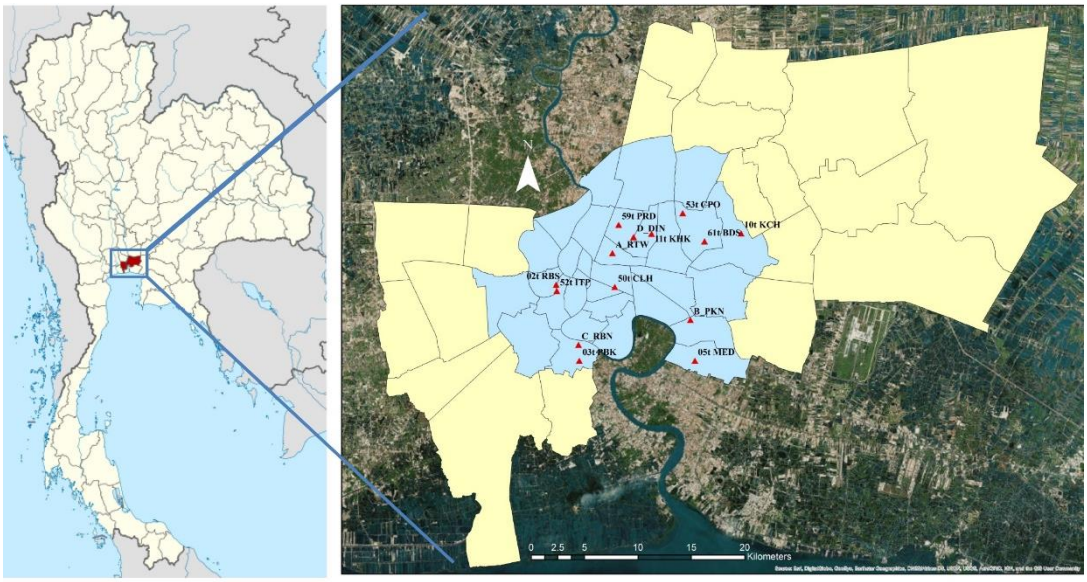



*Figure 3. 2 Air monitoring stations and their locations*

*Table 3. 2 Study sites and monitoring stations coordinate X, Y position in UTM*

| Monitoring Station | | | UTM ZONE 47N | |
|---|---|---|---|---|
| Code | Name | Area type | x | y |
| A_RTW | Ratchathewi District Office | Roadside | 665948 | 1521627 |
| B_PKN | Phrakhanong District Office | Roadside | 673253 | 1515382 |
| C_RBN | Ratburana District Office | Roadside | 662771 | 1513062 |
| D_DIN | Dindang District Office | Roadside | 667927 | 1523135 |
| 02t RBS | Ratjabhat Bansomdej | Ambient | 660676 | 1518679 |
| 03t PBK | Prapadang Bangkae | Ambient | 662848 | 1511579 |
| 05t MED | Meteorological department | Ambient | 673672 | 1511579 |
| 10t KCH | Khlongchan Housing | Ambient | 678005 | 1523487 |
| 11t KHK | Huakwang Housing | Ambient | 669612 | 1523437 |
| 12t NWS | Nonsi wittaya school | Ambient | 667326 | 1515973 |
| 50t CLH | Chulalongkorn Hospital | Roadside | 666169 | 1518468 |

| Monitoring Station | | | UTM ZONE 47N | |
|---|---|---|---|---|
| 52t ITP | Intarapitak | Roadside | 660741 | 1518098 |
| 53t CPO | Chokchai Police Office | Roadside | 672535 | 1525366 |
| 54t DDH | Dindang housing | Roadside | 667907 | 1521979 |
| 59t PRD | Public Relation Department | Ambient | 666536 | 1524275 |
| 61t BDS | Bodindecha School | Ambient | 674574 | 1522729 |

### 3.3 Data Treatment

The hourly average of $PM_{10}$, $PM_{2.5}$, CO, NO, $NO_x$, $NO_2$, $O_3$, $SO_2$, wind speed, relative humidity, temperature and rainfall from the PCD and BMA were treated as follows:

The missing data were replaced prior to calculation of the daily average concentrations. In case of missing data from one hour, data before and after of the missing values were averaged and used to replace the missing data. However, for 2-3 hours of missing data, treatment of the data was carried out by the linear interpolation technique or using data from the previous day as appropriate (Abdullah *et al.*, 2017).

### 3.4 Data Analysis and Model Development

Spearman's correlation coefficient was selected to calculate the correlation coefficient between $PM_{2.5}$ and the observed variables, including CO, NO, $NO_x$, $NO_2$, $O_3$, $SO_2$, wind speed, relative humidity, temperature and rainfall in the ambient air. Spearman's correlation coefficient was selected because the atmospheric variables had non-normal distribution (Hara *et al.*, 2013). The calculation procedure of Spearman's correlation coefficient is as follows (Eq. 3.1):

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} = \frac{\sum_i (X_i - \bar{X})(y_i - \bar{y})}{\sqrt{\sum_i (X_i - \bar{X})^2 \sum_i (y_i - \bar{y})^2}} \qquad \text{Eq. 3.1}$$

Where, ρ is the Spearman rank correlation, di is the difference between the ranks of corresponding variables, n is the number of observations, and x and y are the variables of the sample size. The significant variables related to $PM_{2.5}$ and the other

observed variables were selected as input data for the MLR analysis to develop the mathematical models.

The monitoring stations at the Meteorological Department (5t) and the Public Relations Department (59t) were selected to develop the mathematic equation for the ambient stations. The monitoring stations at Intarapitak (52t), Dindang housing (54t), and Chokchai police office (53t) were selected to develop the mathematic equation for the roadside stations. The daily average air pollution and meteorological data from 2015 to 2017 were used as the input to develop the MLR mathematic model. The selection criteria of air monitoring stations used in model development were based on a complete data set of the monitored data and located in a highly polluted area.

A multiple linear regression (MLR) model is used to determine the relationship between two or more explanatory variables and a response variable by fitting a linear equation to the observed data (Jobson, 1991). This relationship is expressed and simplified in a mathematical equation (Vlachogianni *et al.,* 2011). Generally, an MLR equation is as follows (Eq. 3.2):

$$y = b_0 + \sum_{i=1}^{n} b_i X_i + \varepsilon \qquad \text{Eq. 3.2}$$

Where, $b_i$ and $x_i$ are the regression coefficients and the independent variables respectively, $b_o$ is a constant value at x, and ε is the stochastic error associated with the regression. MLR assumes that the residuals have normal distribution with zero mean, are uncorrelated and have constant variance. The method used in obtaining the equations was stepwise multiple linear regression (Abdullah *et al.,* 2017). Stepwise regression is a method of fitting regression models in which the choice of predicted variables is carried out by an automatic procedure. In each approach, a variable is considered for addition to or subtraction from the set of explanatory variables based on some prespecified criterion. In this study, The MLR equations were constructed by the Statistical Package for Social Science (SPSS) version 22.0.

### 3.5 Model Validation

To validate the model, measured and predicted $PM_{2.5}$ values were used in the statistical analysis of the Variance Inflation Factor (VIF), Durbin-Watson (D-W) Test, Q-Q plots, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Normalized absolute error (NME), Index of Agreement (IA), Prediction Accuracy (PA) and coefficient of determination ($R^2$) (Ul-Saufie *et al.*, 2011; Ul-Saufie *et al.*, 2012; Jinsart *et al.*, 2010; Vlachogianni *et al.*, 2011). Many of them were used to compare and interpret the model performance.

The Variance Inflation Factor (VIF) was used to investigate the multi-collinearity assumption accompanied with the regression output. VIF results can be interpreted in such a way that if a VIF value is less than 10, the regression should be fine. It means there is no multi-collinearity between the independent variables (Abdullah *et al.*, 2017). The VIF calculation is shown in Eq. 3.3.

$$VIF_i = \frac{1}{1- R_i^2} \qquad \text{Eq. 3.3}$$

where $VIF_i$ is the variance inflation factor related with the i*th* predictor and $R_i^2$ is the multiple coefficient of determination in a regression of the i*th* predictor on all other predictors.

The Durbin-Watson (D-W) Test was used to identify autocorrelation. The autocorrelation between the dependent and independent variables essentially reveals the ability of the dependent variables to predict the independent variable ($PM_{2.5}$). Autocorrelation is the similarity of a time series over successive time intervals. It can lead to an underestimation of the standard error in order to evaluate the statistical significance of the predictors' performance. The test outcome can vary from 0 to 4. A value of 2 means that the residual is uncorrelated. The D-W test is described in Eq. 3.4:

$$d = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=2}^{T} e_t^2} \qquad \text{Eq. 3.4}$$

Where T is the number of observations. If one has a lengthy sample, then this can be linearly mapped to the Pearson correlation of the time-series data with its lags. Since *d* is approximately equal to $2(1 - r)$, where r is the sample autocorrelation of the

residuals, d = 2 indicates no autocorrelation. The value of *d* always lies between 0 and 4. If the Durbin–Watson statistic is substantially less than 2, there is evidence of positive serial correlation. As a rough rule of thumb, if Durbin–Watson is less than 1.0, there may be cause for alarm. Small values of *d* indicate successive error terms are positively correlated. If d > 2, successive error terms are negatively correlated (Durbin andWatson, 1950).

Mean Absolute Error (MAE), Normalized absolute error (NME) and Root Mean Square Error (RMSE) range from zero (for the ideal model) to positive infinity (worst model). These statistics are biased toward peak flows. The calculations were shown in Eqs 3.5, 3.6 and 3.7, respectively.

$$MAE = \frac{\sum_{i=1}^{n}|P_i - O_i|}{n} \quad \text{Eq. 3.5}$$

$$NME = \frac{\sum_{i=1}^{n}|P_i - O_i|}{\sum_{i=1}^{n} O_i} \quad \text{Eq. 3.6}$$

$$MSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \quad \text{Eq. 3.7}$$

The Index of Agreement (IA) was developed by Willmott as a standardized measure of the degree of model prediction error and varies from 0 to 1. A computed value of 1 indicates a perfect agreement between the measured and predicted values, and 0 indicates no agreement at all. IA determines the degree to which magnitudes and signs of the observed values (about mean observed value) are related to the predicted deviation about mean predicted values and allows for sensitivity toward difference in the observed and predicted values as well as proportionality changes (Ul-Saufie *et al.,* 2012). The computation of IA is shown in Eq. 3.8.

$$IA = 1 - \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(|P_i - \overline{O}| + |O_i - \overline{O}|)^2}\right] \quad \text{Eq. 3.8}$$

Prediction Accuracy (PA) was used to evaluate the forecasting performance of the model. It has also been used in evaluating the regression and multivariate models for predicting particulate matter concentrations (Nazif *et al.,* 2018). A PA value that is

close to 1 indicates a perfect prediction result. The PA computation is shown in Eq. 3.9.

$$PA = \frac{\sum_{i=1}^{n}(P_i - \overline{O})^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2} \qquad \text{Eq. 3.9}$$

With regard to the coefficient of determination ($R^2$), a correlation value that is close to 1 indicates that the correlation between the observed and the predicted values is perfect. This shows how good the model performance is (Ul-Saufie *et al.*, 2012). The equation is shown as follows (Eq. 3.10):

$$R^2 = \left(\frac{\sum_{i=1}^{n}(P_i - \overline{P})(O_i - \overline{O})}{nS_{prd}S_{Obs}}\right)^2 \qquad \text{Eq. 3.10}$$

where $O_i$ is the observed value (measured value), $P_i$ is the predicted values, $\bar{P}$ is the predicted value mean, $\bar{O}$ is the observed value mean, $S_{prd}$ is the standard deviation of the predicted values, $S_{obs}$ is the standard deviation of the observed values, and n is the number of sample groups.

A statistical analysis for model validation was conducted again and the methods are shown in Table 3.3.

*Table 3. 3 Statistical methods for model validation*

| Indicators | Equation | Description |
|---|---|---|
| MAE | $MAE = \frac{\sum_{i=1}^{n}\lvert P_i - O_i\rvert}{n}$ | MAE value closer to zero indicates good performance. |
| RMSE | $RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}$ | RMSE value ranges from zero (for the ideal model) to positive infinity (worst model). |
| NME | $NME = \frac{\sum_{i=1}^{n}\lvert P_i - O_i\rvert}{\sum_{i=1}^{n}O_i}$ | NME value closer to zero indicates good performance. |
| IA | $IA = 1 - \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(\lvert P_i - \overline{O}\rvert + \lvert O_i - \overline{O}\rvert)^2}\right]$ | IA value closer to one indicates good performance. |
| PA | $PA = \frac{\sum_{i=1}^{n}(P_i - \overline{O})^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2}$ | PA value closer to one indicates good performance. |
| $R^2$ | $R^2 = \left(\frac{\sum_{i=1}^{n}(P_i - \overline{P})(O_i - \overline{O})}{nS_{prd}S_{Obs}}\right)^2$ | $R^2$ value closer to one indicates good performance. |

### 3.6 Health Risk Assessment of Particulate Matters Exposure

A health risk assessment (HRA) associated with particulate matter exposure both $PM_{10}$ and $PM_{2.5}$ was performed. The HRA was evaluated based on the ambient particulate matter concentrations for non-cancer endpoints (USEPA, 2009). The assessment approach was adopted from a USEPA method using the hazard quotient (HQ). The calculations of inhalation exposure concentration ($EC_{inh}$) were calculated from the average ambient particulate matter concentrations (Eq. 11) divided into 4 periods: Inter-monsoon (March 2017 to May 2017), South-west (June 2017 to August 2017), Inter-monsoon (September 2017 to November 2017), and North-east monsoons (December 2017 to February 2018). The evaluated HQs (Eq. 12) of $PM_{2.5}$ were used to create hazard maps with ArcGIS. These maps were compared and divided by following the seasonal variations in Thailand. The reference concentrations of $PM_{10}$ and $PM_{2.5}$ are shown in Table 3.4.

The inhalation exposure concentration ($EC_{inh}$) was quantified as described in Eq. 3.11.

$$EC_{ihn}(\mu g/m^3) = \frac{C \times ET \times EF \times ED}{AT} \qquad \text{Eq. 3.11}$$

Where, C is ambient $PM_{2.5}$ concentrations are from the measured and the predicted values; ET is the exposure time as 24 hours/day; EF is the exposure frequency as 350 days/year; ED is the exposure duration at 30 years for non-carcinogenic substances; AT is the average time (for non-carcinogen; AT = ED (in year) × 365 days × 24 hours/day) (Mokhtar *et al.*, 2014).

Risk characterization of a non-carcinogenic risk was performed by quantifying the hazard quotient (HQ). The calculation of the HQ is shown in Eq. 3.12.

$$HQ = \frac{EC}{RfC} \qquad \text{Eq. 3.12}$$

The HQ were calculated by the daily average RfC and interpret as the daily HQ. Then the daily HQs were average as 3-months average HQ values for interpretation of health risk assessment from PM exposure in each period. A risk

analysis from the HQ values can be identified as follows: if the HQs are greater than 1 (HQs >1), there would be adverse health effects, and if the HQs are less than 1 (HQs < 1), no significant adverse health effects are predicted.

*Table 3. 4 The reference concentration (RfC) of particulate matter*

| Pollutants | RfC ($\mu g/m^3$) | | | |
|---|---|---|---|---|
| | Hourly average | | Annual average | |
| | (WHO, 2018) | (PCD, 2018b) | (WHO, 2018) | (PCD, 2018b) |
| $PM_{10}$ | 50 | 120 | 20 | 50 |
| $PM_{2.5}$ | 25 | 50 | 10 | 25 |

In this study, the HQ values were calculated from WHO for human health risk assessment for sensitive citizen group such as unhealthy people, children and elder people. In addition, the HQs values calculated from Thailand National Air Ambient Quality Standard (NAAQS) developed by PCD were used to quantify health risk for normal citizen group as adults.

### 3.7 GIS-Based Map of PM distribution and Hazard map

$PM_{10}$ and $PM_{2.5}$ concentration distribution and hazard maps (HQ distribution maps) were created by the inverse distance weighted (IDW) technique in the ArcMap program, version 10.4.1. The selection of the interpolation technique was based on the best performance interpolation method for the air pollutants' distribution when compared with those of the Ordinary Kriging and Spline (Mitmark andJinsart, 2017). The IDW interpolating method determines cell values using a linearly weighted combination of a set of sample points. The weight is the functional inverse distance, and the variables being mapped decreases in influence with distance from its sample location. The significant know-point on the interpolated values was based on their distance output point (ESRI, 2016). A general IDW equation is shown in Eq. 3.13.

$$Z_j = \frac{\sum_{i=1}^{n} \left(\frac{Z_i}{d_i^p}\right)}{\sum_{i=1}^{n} \left(\frac{1}{d_i^p}\right)} \qquad \text{eq. 3.13}$$

where *p* is the speed reducer weight control rate obtained from the distance, which is equal to 2; $d_i$ is the distance from an unknown point to a known point; and $z_i$ is the height of the point (ESRI, 2016). The IDW technique was selected for this study to create the GIS-based map for evaluating particulate matter distribution and the health impacts from particulate matter exposure.

For the GIS-based maps of HQ distribution, the input parameters relied on the HQs of particulate matter both $PM_{10}$ and $PM_{2.5}$ divided into four types following different seasonal monsoons: March to May 2017, June to August 2017, September to November 2017 and December 2017 to February 2018. The HQ distribution Maps were illustrated based on the different seasonal variation in Thailand: summer, winter and rainy season. These maps were interpreted trends and distribution of particulate matter risk based on seasonal variation and monsoon difference.

# CHAPTER IV
# RESULTS AND DISCUSSION

This chapter described results and discussion of trend of particulate matter concentration in Bangkok from data collection, data treatment, data analysis and MLR model development. Data used in this study were collected from January 2008 to April 2018; on the other hand, MLR equation for predicting $PM_{2.5}$ concentration were used data from year 2015 to year 2017. The health risk assessment for $PM_{10}$ and $PM_{2.5}$ exposure was quantified and described as the Hazard Quotient (HQ).

## 4.1 Trend of $PM_{10}$ and $PM_{2.5}$ in Bangkok

In Bangkok Thailand, the $PM_{10}$ and $PM_{2.5}$ are not exceed than Thailand National Air Ambient Quality Standard (NAAQS) (PCD, 2018). However, the serious public health issue is the ambient particulate matter concentrations both $PM_{10}$ and $PM_{2.5}$ exceeded than WHO AQGs. The ambient particulate matter standards were shown in Table 3.4. Trend of annual average $PM_{10}$ concentrations from year 2008 to 2017 were displayed in Figure 4.1. The data referred to ambient air monitoring station (AM) and roadside air monitoring station (RS). Events and regulations in Thailand that may be affected the trend of annual particulate matter concentration were shown in Table 4.1 Trend of annual average $PM_{10}$ concentrations were potentially decreased from 2008 to 2012. The decreasing trend during this time was reflected from implementation of new emission standard for new registered vehicles. The implementation of EURO III emission standards of vehicles for heavy-duty diesel vehicles and motorcycles. However, the total number of vehicles still increased from year 2008 to 2011 but the average ambient particulate matter was shown inversed trends due to implementation of Thailand vehicle emission standard regulations as shown in Figure 4.2. Additionally, at the same periods, the trend was dramatically dropped in some areas nearby air quality monitoring stations e.g. 52t, 54t and 59t stations between 2011 to 2012 because of big flooding in Bangkok. This natural disaster directly reflected to the activities that potentially generated fine particulate matter such as driving, manufacturing and construction. Then the trend of $PM_{10}$

slightly had increased again in the next year after flooding event. One of the most conceivable effect came from Thailand's first-car buyer incentive scheme. The incentives offered to those who bought the first car would receive the refund of excise tax. This promotion induced people bought the new car in that year which was reflected to the huge increase of the number of vehicles. The social behavior on the first car buyer scheme reflected to the number of new registered vehicles in Bangkok as shown in Figure 4.3. However, the trends of particulate matter levels had still decreased from 2012 to 2015 because the pollutant exhausting regulation was implemented new vehicle emission standard for new light duty gasoline vehicles and light duty diesel vehicles (EURO 4). This new implementation directly affected the large proportion of vehicles in Bangkok street as passenger cars (sedan), passenger van, pick up, and taxi. This can be seen in Figure 4.2 and Figure 4.3. For the $PM_{10}$ concentration trend after 2014, it has intensely increased since 2015 in several locations as shown in Figure 4.1. The increasing trend were affected from the new and extended construction lines of metro trains in Bangkok. The metro trains projects have begun since 2015 and expected to finish in 2021. This causes high traffic congestion under and nearby constriction sites. The high traffic congestion cause from construction site would be potentially sources of small and fine particulate matter ($PM_{10}$ and $PM_{2.5}$) emissions. The trend of ambient particulate matter would be expected to decrease after the construction being finished.



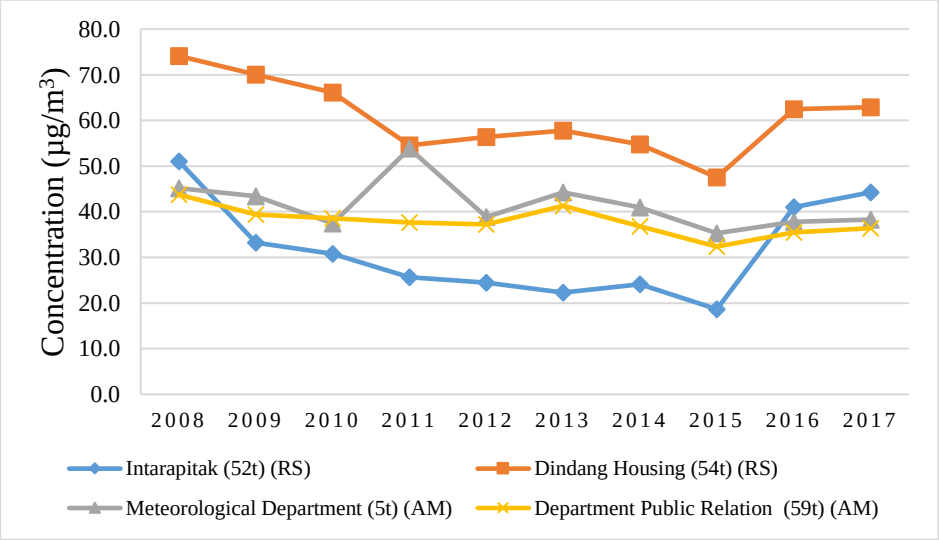



*Figure 4. 1 Trend of annual average $PM_{10}$ in Bangkok*

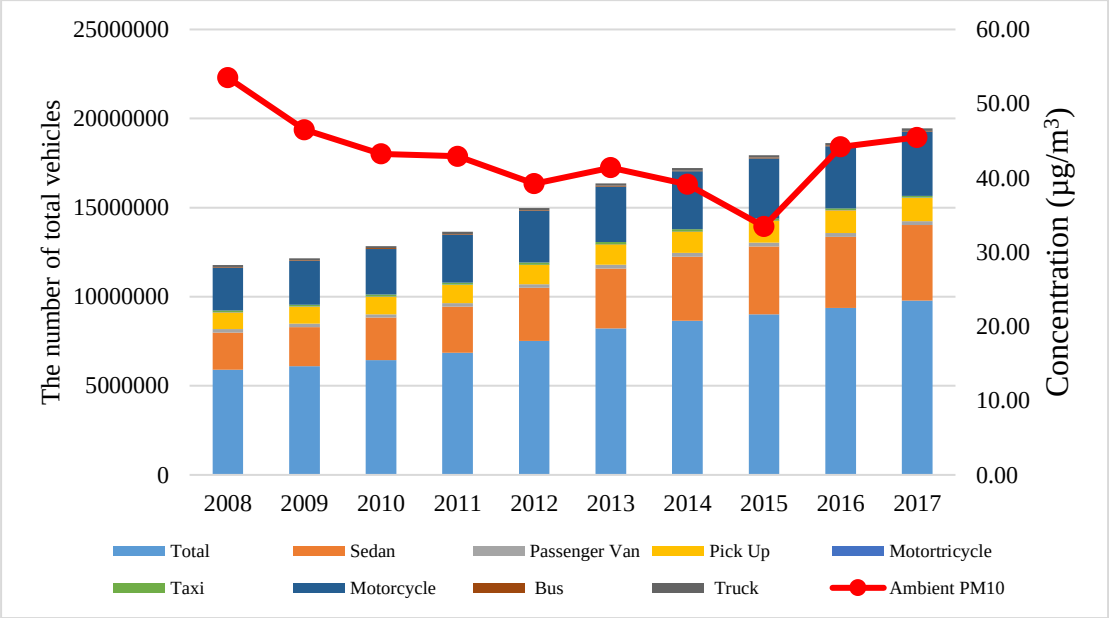



*Figure 4. 2 Annual average $PM_{10}$ concentrations trend and the accumulation number of vehicles in Bangkok between 2008 and 2017*

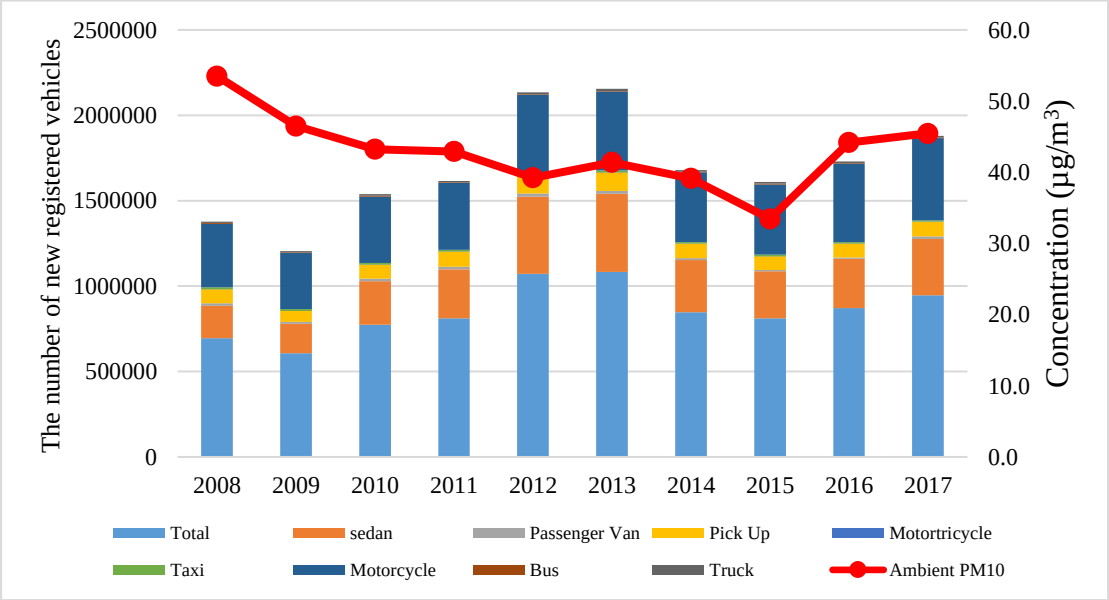



*Figure 4. 3 Annual average $PM_{10}$ concentrations trend and the new registered of vehicles in Bangkok between 2008 and 2017*

The trends of monthly average $PM_{2.5}$ concentrations from May 2016 to April 2018 were shown in Figure 4.4. This trend was indicated season variation of $PM_{2.5}$

levels. According to Thailand climatology, rainy season during May to September was shown the lowest $PM_{2.5}$ concentration because of atmospheric wet deposition reaction. After that, the trends of $PM_{2.5}$ level have been increasing in winter with dry season between September and February. During this season, the atmospheric environment in an area and occasionally the temperature inversion occurred which affected the trapped under the inversion layer with accumulating the high concentration of the particulate matter. The $PM_{2.5}$ concentration trends have been intensely declined from February to May because, during this season, the atmospheric condition is unstable due to the tropical storms and seasonal monsoons occurrences. These caused the decreasing of $PM_{2.5}$ concentration in the ambient atmosphere.

In addition, the measurement of $PM_{2.5}$ concentration at Intarapitak (52t) station was shown the highest concentration comparing with the other stations. The 52t monitoring station is roadside monitoring purpose which may be directly affected from traffic emission in order to induce $PM_{2.5}$ emission from non-point sources to ambient atmosphere. However, there are only 7 $PM_{2.5}$ air monitoring stations operated by PCD and BMA in the Central Business District. These monitoring stations are insufficient to cover whole air environment to monitor $PM_{2.5}$ concentration. The author would like to generate $PM_{2.5}$ mathematic equations to forecast $PM_{2.5}$ in the non-detected locations by using co-pollutants and meteorological conditions as the predicted variables.



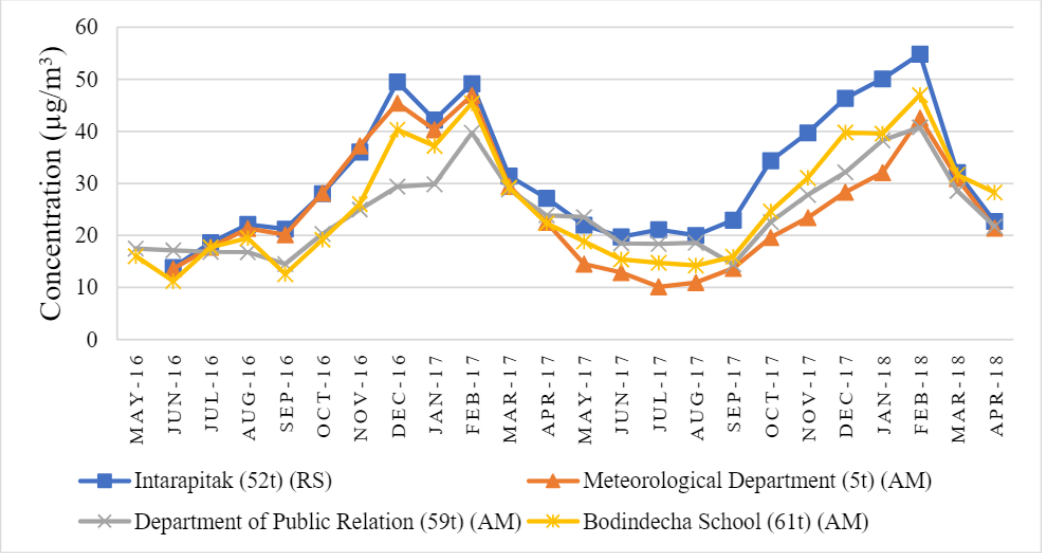



*Figure 4. 4 Trend of monthly average $PM_{2.5}$ in Bangkok from May 2016 to April 2018*

*Table 4. 1 Events and regulations in Thailand.*

| Year | Event / Regulation Implementation |
|---|---|
| 2007 | • Implementation of emission standards for new Heavy-Duty Diesel Vehicles (EURO 3)[1] |
| 2008 | • Implementation of emission standards for new Motorcycles (EURO 3) [1] |
| 2011 | • Thailand's first-car buyer incentive scheme from government policy.[2] |
| | • Thailand huge flooding event. The flooding event occurred during rainy season in Thailand. The event began at the end of July triggered by the landfall of Tropical Storm Nock-ten. These floods soon spread through the provinces from northern, northeastern, to central Thailand along the Mekong and Chao Phraya river basins. Flooding persisted until mid-January 2012 in some areas of Bangkok and central Thailand.[3] |
| 2012 | • Implementation of emission standards for new Light Duty Gasoline Vehicles and Light Duty Diesel Vehicles (EURO 4) [1] |
| 2015 | • The beginning of new construction of Bangkok Metro Train. There are four lines including green, blue, red and purple that has been constructed and these projects are expected to be done in 2019.[4] |
| 2016 | • The beginning of new construction of Bangkok Metro Train. There are three lines including yellow, pink and green that has been constructed and these projects are expected to be done in 2021.[4] |
| 2018 | • Implementation of emission standards for new Motorcycles (EURO IV) [1] |

1. (PCD, 2018a)
2. (National Legislative Assembly, 2014)
3. (Promchote *et al.*, 2015)
4. (Realist Solution Company, 2015)

**4.2 Correlation analysis between particulate matter and other observed elements.**

Spearman correlation analysis between $PM_{2.5}$ and other observed elements was shown in Table 4.2. For the ambient stations, $PM_{2.5}$ has positive correlated with $PM_{10}$, CO, $NO_2$, $NO_X$, $O_3$, $SO_2$ and windspeed whereas it has negative corelated with temperature, relative humidity and rainfall amount. For the roadside monitoring stations, $PM_{2.5}$ has positive correlated with $PM_{10}$, CO, $NO_2$, $NO_X$, $SO_2$ and $O_3$ whereas it has negative corelated with wind speed, relative humidity and rainfall amount. However, NO and windspeed for ambient monitoring stations and temperature for roadside monitoring stations have no correlated with $PM_{2.5}$. The statistic was analyzed at the 0.01 level P<0.01 (2-tailed). The variables that has correlated with $PM_{2.5}$ would be used as the input variables for model construction by using stepwise multiple regression analysis.

*Table 4. 2 Spearman correlation analysis results of $PM_{2.5}$ and other observed variables*

| $PM_{2.5}$ & Variables | Ambient monitoring station | | | Roadside monitoring station | | |
|---|---|---|---|---|---|---|
| | Correlation coefficient | Significant level | Sample Size | Correlation coefficient | Significant level | Sample Size |
| $PM_{10}$ | 0.874 | 0.000 | 1469 | 0.853 | 0.000 | 1222 |
| CO | 0.219 | 0.000 | 1469 | 0.422 | 0.000 | 1079 |
| NO** | -0.061 | 0.020 | 1465 | 0.082 | 0.090 | 1010 |
| $NO_2$ | 0.476 | 0.000 | 1467 | 0.731 | 0.000 | 1010 |
| $NO_X$ | 0.344 | 0.000 | 1465 | 0.418 | 0.000 | 1010 |
| $O_3$ | 0.537 | 0.000 | 1494 | 0.339 | 0.000 | 930 |
| $SO_2$ | 0.369 | 0.000 | 525 | 0.292 | 0.000 | 843 |
| Wind speed*** | -0.047 | 0.084 | 1378 | -0.367 | 0.000 | 1167 |
| Temperature**** | -0.188 | 0.000 | 1491 | -0.031 | 0.277 | 1220 |
| Relative Humidity | -0.323 | 0.000 | 1491 | -0.376 | 0.000 | 1220 |
| Rainfall amount | -0.300 | 0.000 | 1491 | -0.337 | 0.000 | 1220 |

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

** No significant correlation with $PM_{2.5}$ for ambient and roadside monitoring data

*** No significant correlation with $PM_{2.5}$ for ambient monitoring data

**** No significant correlation with $PM_{2.5}$ for roadside monitoring data

The analysis of NO and windspeed are no significant correlation with $PM_{2.5}$ at P<0.01 for ambient monitoring station and Temperature is no significant correlation with $PM_{2.5}$ at P<0.01 for roadside monitoring station.

### 4.3 MLR Analysis to formulate an equation for predicting $PM_{2.5}$

#### 4.3.1 MLR equation for ambient area

The analysis of the air quality data and meteorological data sets for formulating an $PM_{2.5}$ predicting equation in general ambient area were used Multiple Linear Regression (MLR) with stepwise input data technique. The model summary was shown in Table 4.3 and the regression of $PM_{2.5}$ and the predicted variables for general ambient air was shown in Table 4.4. It was found that the parameters included $PM_{10}$ ($\mu g/m^3$), CO (ppm), $NO_2$ (ppb), $O_3$ (ppb) $SO_2$ (ppb), temperature ($^oC$) and relative humidity (%RH) could provide the best performance of the regression equation. The rest of parameters such as solar radiation was not play significant role to provide better model performance.

*Table 4. 3 The summarization of MLR model for ambient area*

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Durbin-Watson |
|---|---|---|---|---|---|
| 1 | .891[a] | .794 | .793 | 6.76243 | |
| 2 | .901[b] | .812 | .811 | 6.46765 | |
| 3 | .904[c] | .817 | .816 | 6.38077 | |
| 4 | .908[d] | .824 | .822 | 6.27276 | |
| 5 | .913[e] | .833 | .831 | 6.11238 | |
| 6 | .915[f] | .837 | .835 | 6.05085 | |
| 7 | .916[g] | .839 | .836 | 6.01794 | .323 |

a. Predictors: β, $PM_{10}$
b. Predictors: β, $PM_{10}$, $O_3$
c. Predictors: β, $PM_{10}$, $O_3$, $SO_2$
d. Predictors: β, $PM_{10}$, $O_3$, $SO_2$, CO
e. Predictors: β, $PM_{10}$, $O_3$, $SO_2$, CO, HUM
f. Predictors: β, $PM_{10}$, $O_3$, $SO_2$, CO, HUM, $NO_2$
g. Predictors: β, $PM_{10}$, $O_3$, $SO_2$, CO, HUM, $NO_2$, TEMP
β=constant value

*Table 4. 4 Regression of $PM_{2.5}$ and the predicted variables for ambient area*

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. | Collinearity Statistics | |
|---|---|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | | Tolerance | VIF |
| 1 | β | -4.619 | .757 | | -6.105 | .000 | | |
| | $PM_{10}$ | .775 | .018 | .891 | 43.135 | .000 | 1.000 | 1.000 |
| 2 | β | -5.808 | .745 | | -7.801 | .000 | | |
| | $PM_{10}$ | .679 | .022 | .780 | 30.481 | .000 | .595 | 1.680 |
| | $O_3$ | .304 | .045 | .174 | 6.785 | .000 | .595 | 1.680 |
| 3 | β | -6.992 | .799 | | -8.752 | .000 | | |
| | $PM_{10}$ | .629 | .026 | .724 | 24.632 | .000 | .440 | 2.273 |
| | $O_3$ | .349 | .046 | .199 | 7.613 | .000 | .556 | 1.798 |
| | $SO_2$ | 1.375 | .365 | .086 | 3.770 | .000 | .727 | 1.375 |
| 4 | β | -4.884 | .932 | | -5.242 | .000 | | |
| | $PM_{10}$ | .661 | .026 | .760 | 25.217 | .000 | .404 | 2.474 |
| | $O_3$ | .322 | .045 | .184 | 7.092 | .000 | .546 | 1.832 |
| | $SO_2$ | 1.548 | .361 | .097 | 4.288 | .000 | .718 | 1.393 |
| | CO | -6.403 | 1.522 | -.088 | -4.208 | .000 | .835 | 1.197 |
| 5 | β | -21.300 | 3.314 | | -6.426 | .000 | | |
| | $PM_{10}$ | .694 | .026 | .798 | 26.352 | .000 | .380 | 2.632 |
| | $O_3$ | .426 | .049 | .243 | 8.760 | .000 | .451 | 2.215 |
| | $SO_2$ | 1.821 | .356 | .114 | 5.120 | .000 | .702 | 1.425 |
| | CO | -8.426 | 1.534 | -.116 | -5.493 | .000 | .780 | 1.281 |
| | HUM | .194 | .038 | .133 | 5.150 | .000 | .523 | 1.912 |
| 6 | β | -23.267 | 3.335 | | -6.976 | .000 | | |
| | $PM_{10}$ | .768 | .034 | .883 | 22.294 | .000 | .218 | 4.594 |
| | $O_3$ | .389 | .049 | .222 | 7.862 | .000 | .428 | 2.337 |
| | $SO_2$ | 1.767 | .352 | .111 | 5.012 | .000 | .700 | 1.428 |
| | CO | -7.785 | 1.531 | -.107 | -5.085 | .000 | .768 | 1.302 |
| | HUM | .222 | .038 | .152 | 5.806 | .000 | .497 | 2.013 |
| | $NO_2$ | -.171 | .052 | -.092 | -3.285 | .001 | .434 | 2.302 |

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. | Collinearity Statistics | |
|---|---|---|---|---|---|---|---|---|
| 7 | β | -7.524 | 7.121 | | -1.057 | .291 | | |
| | $PM_{10}$ | .748 | .035 | .860 | 21.254 | .000 | .206 | 4.847 |
| | $O_3$ | .394 | .049 | .225 | 7.996 | .000 | .427 | 2.341 |
| | $SO_2$ | 1.902 | .355 | .119 | 5.361 | .000 | .684 | 1.462 |
| | CO | -8.168 | 1.530 | -.113 | -5.338 | .000 | .760 | 1.316 |
| | HUM | .208 | .038 | .143 | 5.420 | .000 | .487 | 2.055 |
| | $NO_2$ | -.178 | .052 | -.096 | -3.428 | .001 | .433 | 2.308 |
| | TEMP | -.494 | .198 | -.051 | -2.498 | .013 | .819 | 1.221 |

*Dependent variable is $PM_{2.5}$

The MLR equation predicting $PM_{2.5}$ for ambient monitoring stations can be described as $PM_{2.5}$ (µg/$m^3$) = -7.524 + 0.75$PM_{10}$ (µg/$m^3$) + 0.39 $O_3$ (ppb) +1.90 $SO_2$ (ppb) – 8.17 CO (ppm) - 0.21Relative Humidity (% RH) - 0.49 Temperature (ºC). This equation was shown well performance with $R^2$ is 0.84. The VIF values was 1.22 (less than 10) meaning no multi-collinearity between the independent variables. The Durbin-Watson analysis can be interpreted that this equation has no any first autocorrelation problem. Q-Q plots of observed and predicted $PM_{2.5}$ concentration during January to April 2018 illustrated in Figure 4.5 was perform well agreement with $R^2$ = 0.88.



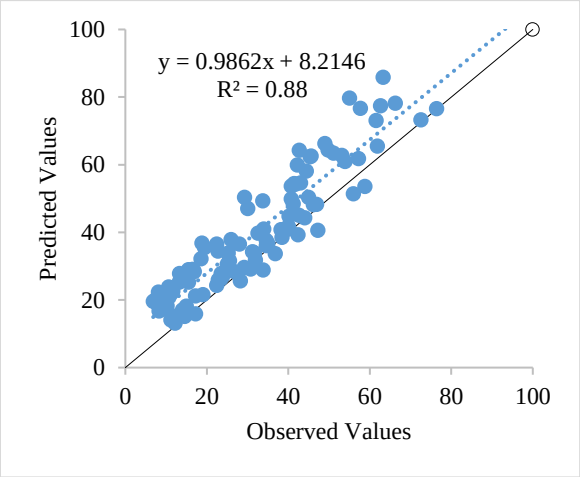



*Figure 4. 5 Q-Q plot validation for ambient area equation*

### 4.3.2 MLR equation for roadside area

The analysis of the air quality data and meteorological data sets for formulating an $PM_{2.5}$ predicting equation in roadside area were used MLR with stepwise independent data technique. The model summary was shown in Table 4.5 and the regression of $PM_{2.5}$ and the predicted variables for general ambient air was shown in Table 4.6. It was found that the parameters included $PM_{10}$ ($\mu g/m^3$), $NO_2$ (ppb), $O_3$ (ppb), CO (ppm), Relative Humidity (%RH) and Windspeed (m/s) could provide the best performance of the regression equation. The rest of parameters such as $SO_2$, solar radiation or ambient temperature was not play significant role to provide better model performance.

*Table 4. 5 The summarization of MLR model for roadside area*

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Durbin-Watson |
|---|---|---|---|---|---|
| 1 | .939[a] | .882 | .882 | 5.73219 | |
| 2 | .945[b] | .894 | .893 | 5.45390 | |
| 3 | .950[c] | .903 | .902 | 5.22139 | |
| 4 | .951[d] | .905 | .904 | 5.17249 | |
| 5 | .952[e] | .906 | .905 | 5.15384 | |
| 6 | .952[f] | .906 | .905 | 5.14107 | 1.106 |

a. Predictors: β, $PM_{10}$
b. Predictors: β, $PM_{10}$, $NO_2$
c. Predictors: β, $PM_{10}$, $NO_2$, $O_3$
d. Predictors: β, $PM_{10}$, $NO_2$, $O_3$, CO
e. Predictors: β, $PM_{10}$, $NO_2$, $O_3$, CO, HUM
f. Predictors: β, $PM_{10}$, $NO_2$, $O_3$, CO, HUM, WS
g. Dependent Variable: $PM_{2.5}$
β = Constant value

*Table 4. 6 Regression of $PM_{2.5}$ and the predicted variables for roadside area*

| | Model | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. | Collinearity Statistics | |
|---|---|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | | Tolerance | VIF |
| 1 | β | -2.768 | .541 | | -5.119 | .000 | | |
| | $PM_{10}$ | .768 | .011 | .939 | 71.622 | .000 | 1.000 | 1.000 |
| 2 | β | -3.057 | .516 | | -5.929 | .000 | | |
| | $PM_{10}$ | .672 | .015 | .822 | 44.265 | .000 | .451 | 2.216 |
| | $NO_2$ | .194 | .023 | .158 | 8.513 | .000 | .451 | 2.216 |
| 3 | β | -4.367 | .520 | | -8.391 | .000 | | |
| | $PM_{10}$ | .604 | .017 | .738 | 35.661 | .000 | .333 | 3.002 |
| | $NO_2$ | .244 | .023 | .199 | 10.757 | .000 | .416 | 2.403 |
| | $O_3$ | .222 | .028 | .112 | 7.943 | .000 | .712 | 1.405 |
| 4 | β | -5.660 | .621 | | -9.113 | .000 | | |
| | $PM_{10}$ | .589 | .017 | .721 | 34.252 | .000 | .317 | 3.159 |
| | $NO_2$ | .224 | .023 | .182 | 9.660 | .000 | .393 | 2.547 |
| | $O_3$ | .250 | .029 | .126 | 8.707 | .000 | .665 | 1.504 |
| | CO | 2.553 | .684 | .053 | 3.733 | .000 | .685 | 1.460 |
| 5 | β | -10.490 | 2.077 | | -5.049 | .000 | | |
| | $PM_{10}$ | .597 | .017 | .730 | 34.275 | .000 | .307 | 3.258 |
| | $NO_2$ | .235 | .024 | .191 | 9.983 | .000 | .378 | 2.645 |
| | $O_3$ | .276 | .031 | .140 | 9.033 | .000 | .581 | 1.722 |
| | CO | 2.183 | .698 | .046 | 3.127 | .002 | .653 | 1.532 |
| | HUM | .063 | .026 | .037 | 2.435 | .015 | .595 | 1.681 |
| 6 | β | -12.846 | 2.359 | | -5.446 | .000 | | |
| | $PM_{10}$ | .597 | .017 | .730 | 34.368 | .000 | .307 | 3.258 |
| | $NO_2$ | .249 | .024 | .204 | 10.185 | .000 | .346 | 2.886 |
| | $O_3$ | .292 | .031 | .148 | 9.294 | .000 | .549 | 1.823 |
| | CO | 2.685 | .737 | .056 | 3.645 | .000 | .583 | 1.714 |
| | HUM | .070 | .026 | .041 | 2.686 | .007 | .585 | 1.708 |
| | WS | 1.126 | .538 | .032 | 2.092 | .037 | .588 | 1.700 |

*Dependent variable is $PM_{2.5}$

The MLR equation for predicting $PM_{2.5}$ in ambient area can be described as $PM_{2.5}$ = -12.85 + 0.597 $PM_{10}$ (µg/$m^3$) + 0.25 $NO_2$ (ppb) + 0.29 $O_3$ (ppb) + 2.68 CO (ppm) + 0.07 Relative Humidity (% RH) + 1.13 Windspeed (m/s). This equation was shown well performance with $R^2$ is 0.91. The VIF values range 1.70-3.26 (less than 10) meaning no multi-collinearity between the independent variables. The Durbin-Watson analysis can be interpreted that this equation has no any first autocorrelation problem. Q-Q plots of observed and predicted $PM_{2.5}$ concentration during January to April 2018 illustrated in Figure 4.6 was perform well agreement with $R^2$ = 0.96.

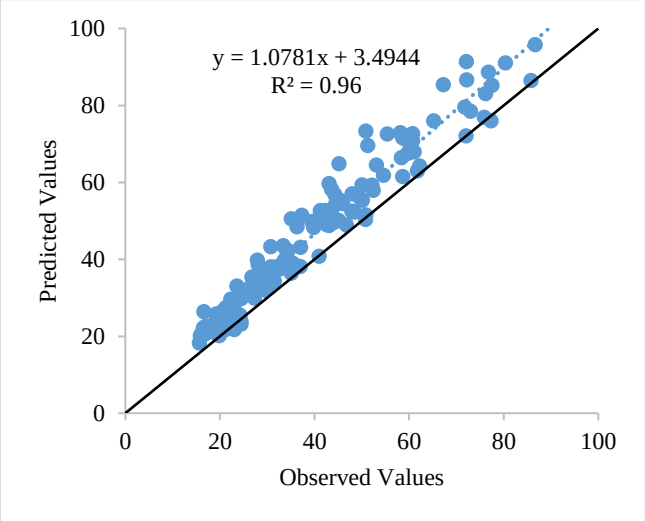



*Figure 4. 6 Q-Q plot validation for roadside equation*



The summary equations for $PM_{2.5}$ forecasting in ambient and roadside areas were described in Table 4.7. Overall, $PM_{10}$ and gases air pollutants have positive influence on $PM_{2.5}$ concentrations. $PM_{2.5}$ in urban area mostly comes from traffic emission. $PM_{10}$ and gases air pollution including $NO_x$, $NO_2$, $O_3$, and CO come from vehicle emission in urban area (Watson *et al.*, 1998). These co-pollutants were also confirmed with the correlation analysis between $PM_{2.5}$ and the conventional air pollutants in Tokyo. The results indicated that were statistically significant positive correlations between the annual average suspended particulate matter concentrations and $NO_x$, $SO_2$, and CO at air monitoring stations and traffic volume (Hara *et al.*, 2013). These variables related to $PM_{2.5}$ concentration because of the same pollutant emitted source. On the other hand, temperature, wind speed and relative humidity have inverted relationship with $PM_{2.5}$ concentrations in the atmosphere as shown in

Table 4.2. The meteorological factors were ascertained that decreasing wind speed as well as increasing temperature and humidity can support the accumulation of ambient particulate matter. Temperature has negative influence correlation with $PM_{2.5}$ because when the atmospheric temperature is high, the air convection at the surface area will increase, which lead beneficial the upward transport of the particulate matter (Li andWang, 2017). Wind speed also showed an invert influence on $PM_{2.5}$ which means the concentration of $PM_{2.5}$ tend to be lower in high wind speed area than calm area because the pollutants are diluted by dispersion (Turalıoğlu *et al.*, 2005). It can be quantified that the numerous meteorological parameters have peculiar influence on $PM_{2.5}$ concentration levels.

*Table 4. 7 The summary MLR equations*

| Area type | Model | $R^2$ | VIF | D-W |
|---|---|---|---|---|
| Ambient | $PM_{2.5}$ (µg/m$^3$) = -7.524 + 0.75$PM_{10}$ (µg/m$^3$) + 0.39 $O_3$ (ppb) +1.90 $SO_2$ (ppb) – 8.17 CO (ppm) - 0.21Relative Humidity (%RH) - 0.49 Temperature ($^o$C) | 0.84 | 1.22- 4.85 | .323 |
| Roadside | $PM_{2.5}$ (µg/m$^3$) = -12.85 + 0.597 $PM_{10}$ (µg/m$^3$) + 0.25 $NO_2$ (ppb) + 0.29 $O_3$ (ppb) + 2.68 CO (ppm) + 0.07 Relative Humidity (%RH) + 1.13 Windspeed (m/s) | 0.91 | 1.70-3.26 | 1.106 |



## 4.4 Model Validation

### 4.4.1 Statistical Validation

Model performance statistical validation for $PM_{2.5}$ prediction was shown in Table 4.8 with MAE, RMSE, NME, IA, PA and $R^2$. Differences between observed and predicted values were also acceptable with IA, PA and $R^2$. Generally, it was found that the error between the observed and predicted values also perform well according to MAE, RMSE and MAE results are not exceeded than their standard deviation of observed and predicted values. This model can perform well in predicting of overall concentration of $PM_{2.5}$ for ambient area and roadside area as determined by $R^2$ = 0.88 and 0.96, respectively. Index of agreement (IA) can be acceptable as the results were over than 0.5 and very close to 1 (IA > 0.5).

*Table 4. 8 Performance indicators for model validation*

| Performance indicators | Model | |
|---|---|---|
| | Ambient station | Roadside station |
| Observed Mean ($O_i$) | 30.67 | 39.36 |
| Predicted Mean ($P_i$) | 38.46 | 45.93 |
| Observed Standard Deviation ($O_{std}$) | 18.58 | 19.59 |
| Predicted Standard Deviation ($P_{std}$) | 19.50 | 22.30 |
| Mean Absolute Error (MAE) | 8.38 | 21.57 |
| Root Mean Square Error (RMSE) | 10.19 | 8.04 |
| Normalized absolute error (NME) | 0.27 | 0.17 |
| Index of Agreement (IA) | 0.93 | 0.96 |
| Prediction Accuracy (PA) | 1.28 | 1.19 |
| Coefficient of determination ($R^2$) | 0.88 | 0.96 |

**4.4.2 Reliability Validation**

From January 1st, 2018 to April 30th, 2018, the observed data were evaluated the reliability of predicting results. The reliability was divided into 2 types: the reliability of $PM_{2.5}$ at the selected monitoring stations and the reliability of $PM_{2.5}$ test against with the other monitoring stations. Reliability results at the selected monitoring stations were validated with the observed data from the monitoring stations at Meteorological Department (5t) and the Department of Public Relation (59t) for ambiebt area representatives as shown in Figure 4.7, and the monitoring stations Intarapitak (52t) and Chokchai police office (53t) for the roadside area representatives as shown in Figure 4.8. The outcomes performed well agreement between the observed and predicted values. The interpretation can be described that the model can achieve a good fitting effect. In addition, this study investigated model performance by testing reliability by cross-validation technique. The MLR equations that would be developed from the selected station were tested with the other monitoring stations. The monitoring station at Bodindecha School (61t) was tested with the MLR equation for ambient areas and the monitoring station at Ratchathewi Office District (A_RTW) was tested with the MLR equation for roadside areas. The

cross against reliability validation results were shown in Figure 4.9. The validating results of cross-validation performed well agreement between the observed and predicted values.

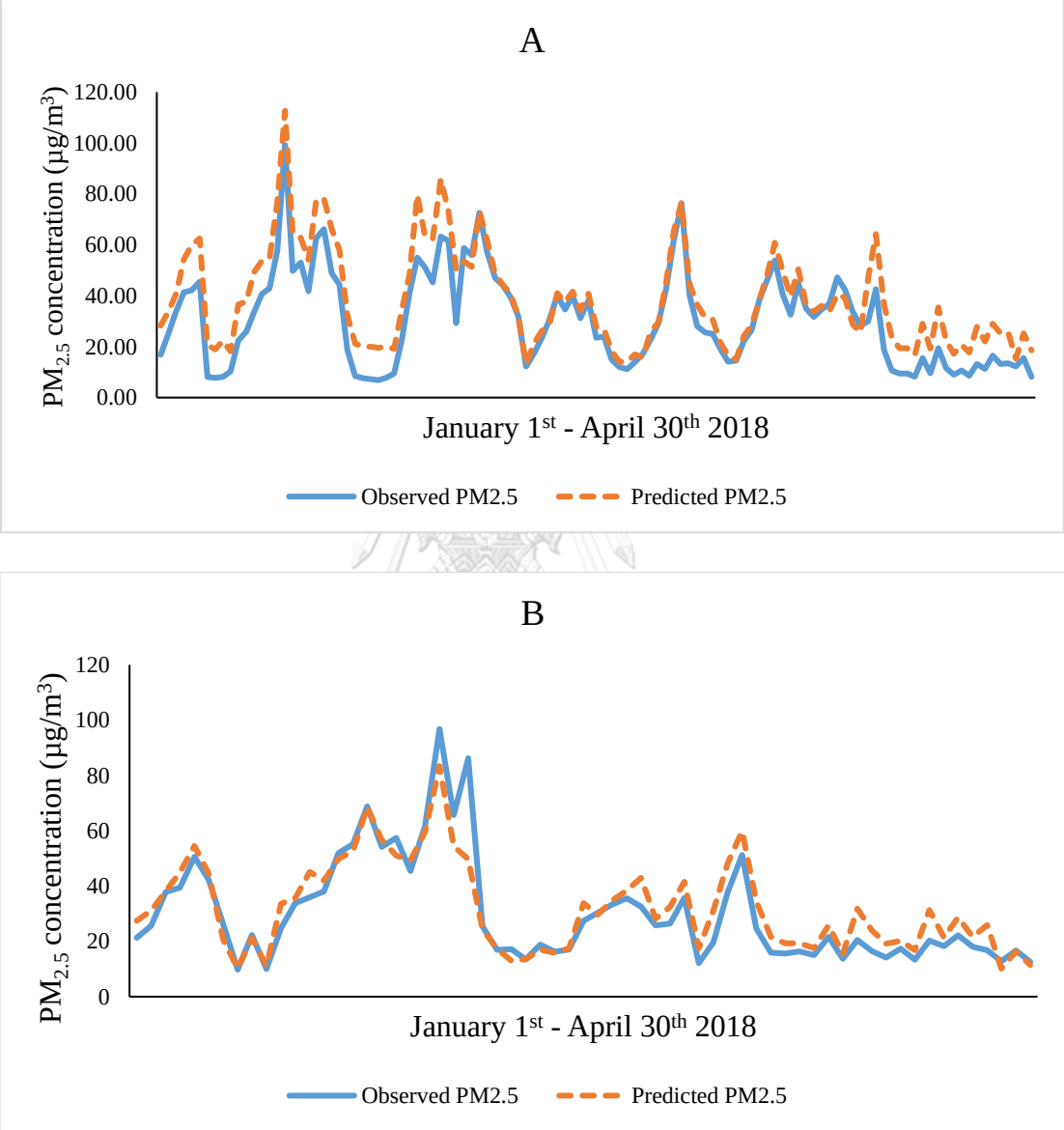



*Figure 4. 7 $PM_{2.5}$ of ambient monitoring data at (A) Meteorological Department (5t) and (B) at The Department of Public Relations (59t) from January 1st - April 30th 2018*

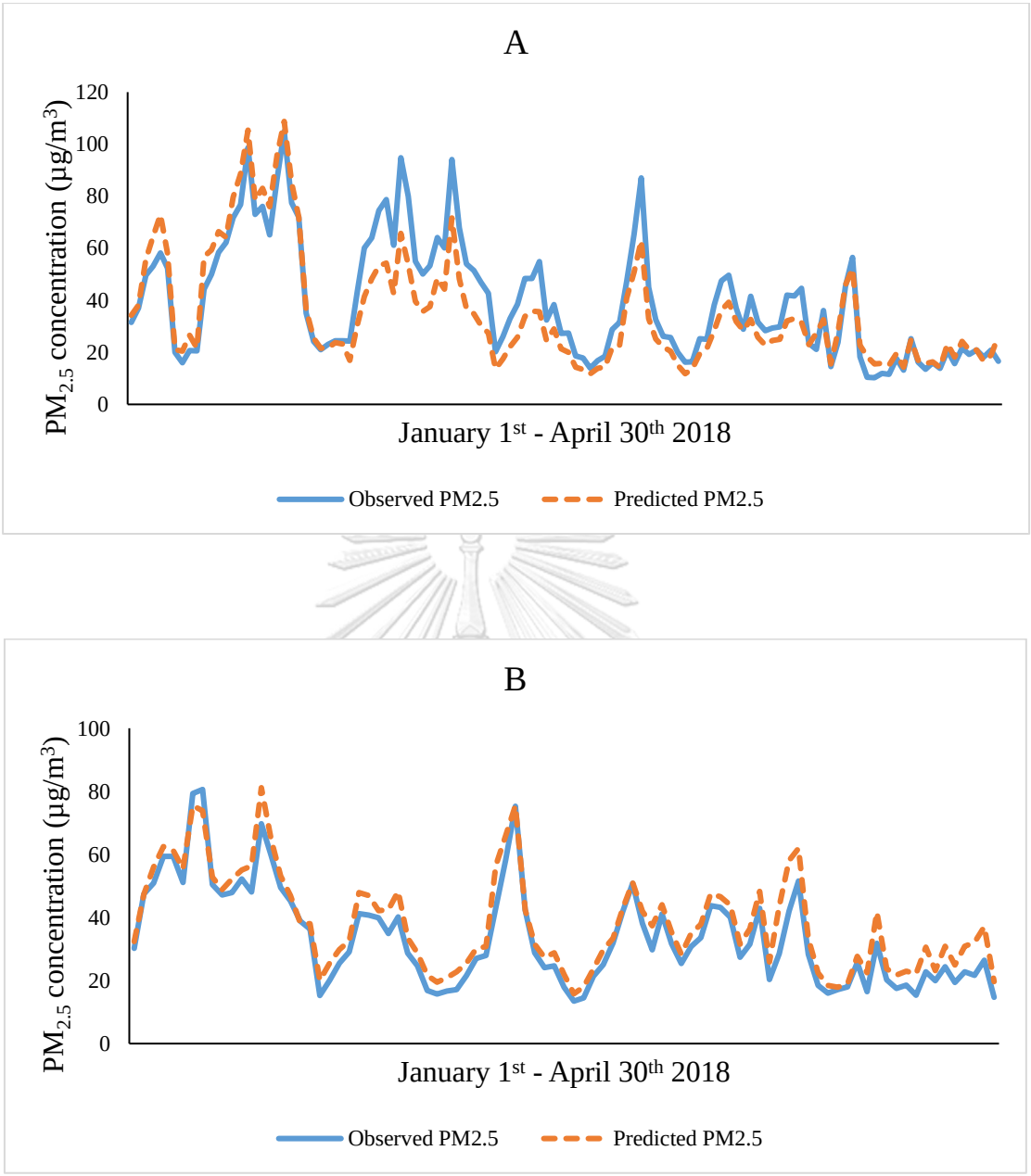



*Figure 4. 8 $PM_{2.5}$ of roadside monitoring data at (A) Intarapitak (52t) and (B) Chokchai Police station from January 1st - April 30th 2018*

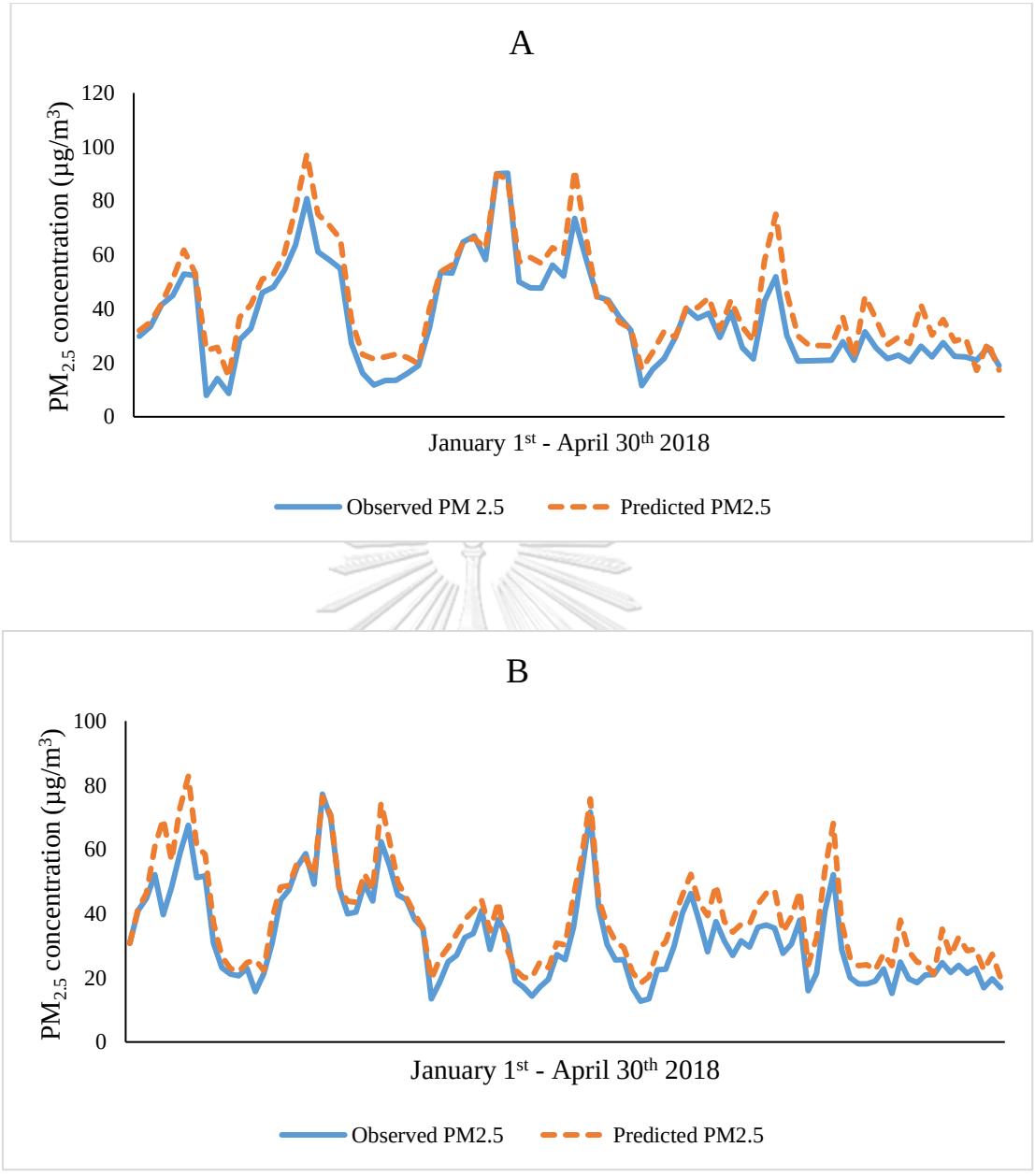



*Figure 4. 9 Test against reliability of $PM_{2.5}$ with developed MLR equtions for ambient area and roadside area, respectively from January 1st - April 30th 2018*
*(A) Ambient monitoring station at Bodindecha School (61t)*
*(B) Roadside monitoring station at Ratchathewi District Office (A_RTW)*

Focusing on the extreme $PM_{2.5}$ events that are indicative of health concerns, Figure 4.10 displays the match between both sets of simulations and the observations for all four measurement sites. In general, the simulations showed skill at the $90^{th}$ and $95^{th}$ percentiles but have some difficulty in capturing the frequency of the extreme events at or above the $99^{th}$ percentile. The predicted results were greatly overestimated the $PM_{2.5}$ concentration and show little skill with the observations. The predicted results at Intarapitak (52t) was underestimated average $PM_{2.5}$ concentration levels because there are other potential sources of $PM_{2.5}$ emission. Three crematories are surrounded and temples with crematories located within 1 km radius from the monitoring station. Therefore, the emission from these crematories may potentially affect $PM_{2.5}$ concentration in the atmosphere. Despite the $PM_{2.5}$ was high level, the composition of PM from cremation can be harmful to residents and workers in the area. For example, the study in China and Thailand reported that the process of corpse cremation produces several dangerous air pollutants and greenhouse gases, including fine particulate matter, sulfur dioxide ($SO_2$), carbon dioxide ($CO_2$), carbon monoxide (CO) nitrogen oxides ($NO_x$), volatile organic compounds (VOCs), and heavy metals which could have affected surrounded environment and human health (Achawangkul *et al.*, 2016; Xue *et al.*, 2018). Moreover, the predicted results at the public relation department was underestimated only in predicting the extreme $PM_{2.5}$ concentration but the average predicted $PM_{2.5}$ was close with the measured results. This can be suggested that there were the extreme atmospheric inversion phenomena occur in the day of February 2018, in which the particulate matter was accumulated and suspended in the atmosphere; therefore, the high concentrations of particulate matter were detected with exceeded the Thailand NAAQS over Bangkok area (Lefevre, 2018). The unusual atmospheric phenomena would affect the predicted result inaccurately. Normally the atmospheric inversion phenomena occur in February and March in every year in Thailand because of the gap between seasonal monsoons changing. The northeastern monsoon has been calming down and the southern monsoon has become strong and taken replacement. The effect of the monsoon changing led the atmosphere stable condition. This stable condition induced the strong atmospheric inversion.

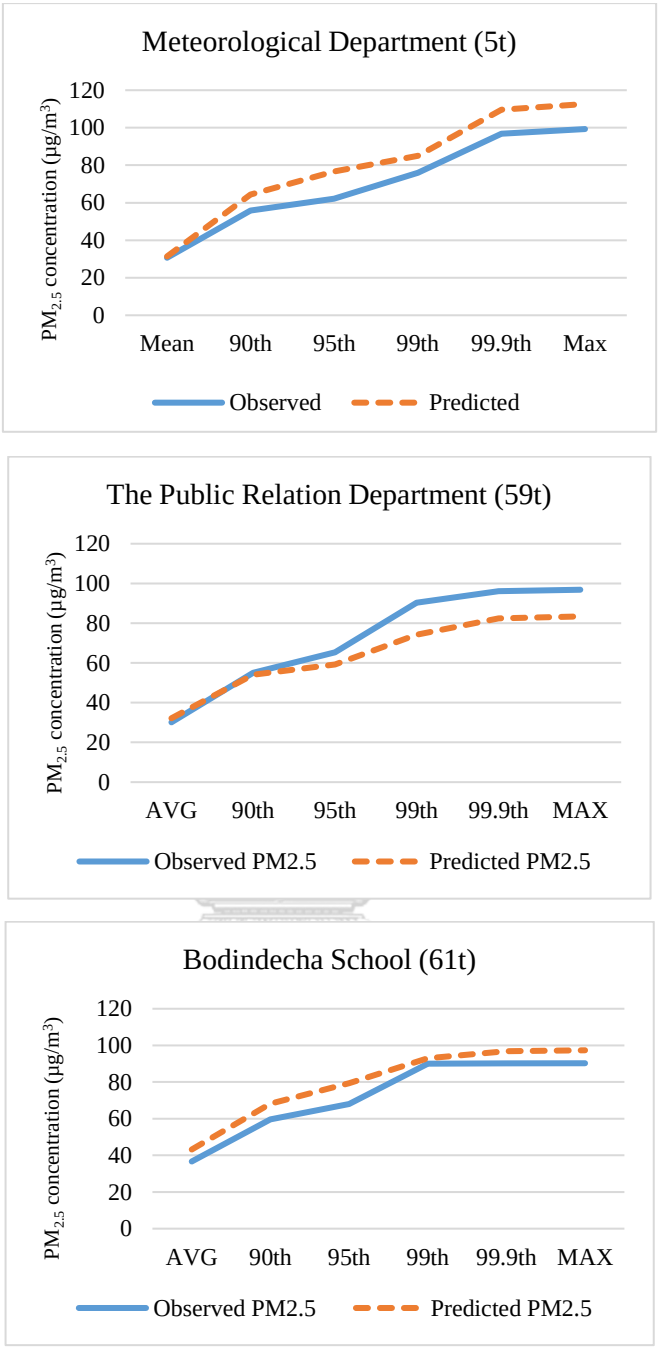



*Figure 4. 10 Comparison of $PM_{2.5}$ concentration from 3 ambient monitoring stations between observation data against the model predicted data from January to April 2018*

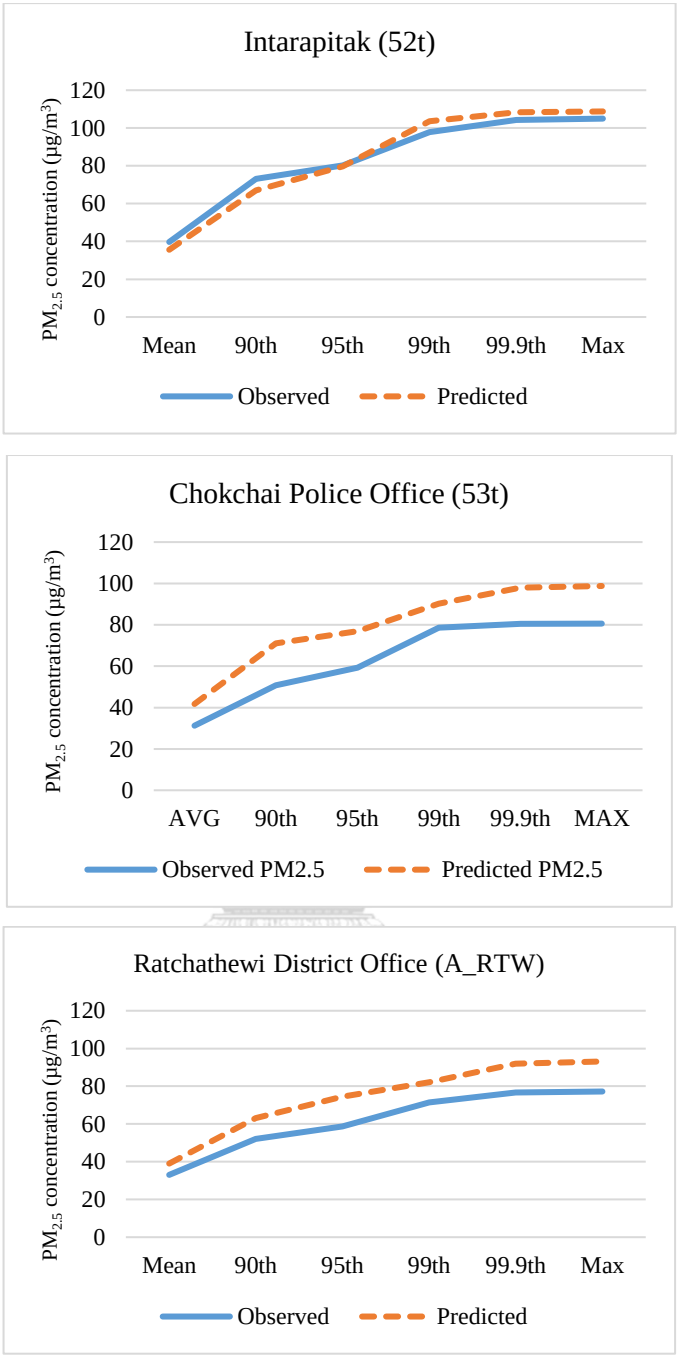



*Figure 4. 11 Comparison of $PM_{2.5}$ concentration from 3 roadside monitoring stations between observation data against the model predicted data from January to April 2018*

## 4.5 Health Risk Assessment of Particulate Matter Exposure

### 4.5.1 Health Risk Assessment of $PM_{10}$ Exposure

The ambient monthly average $PM_{10}$ concentrations from the measurement as were shown in Table 4.9. $PM_{10}$ average concentrations less than 120 $\mu g/m^3$ meaning acceptable concentration levels for daily average concentration and less than 50 $\mu g/m^3$ meaning acceptable concentration levels for annual average concentration. The $PM_{10}$ concentrations almost all areas of CBD were acceptable concentrations whereas the $PM_{10}$ levels nearby 03t PBK, B_PKN, C_RB and D_DIN stations as marked with yellow label were exceeded than Thailand NAAQS. Also, the exceeding concentration levels occur during December to February as the gap between regional monsoon change.

The HQs values of $PM_{10}$ were calculated to investigate health risk assessment of $PM_{10}$ exposure. The RfC used in HQ calculation were obtained from WHO standard for sensitive citizens case e.g. children, elders, those with respiratory problems; and obtained from Thailand NAAQS for the normal citizens case e.g. adult. The HQs of $PM_{10}$ exposure were divided into 4 episodes regarding to seasonal variation: from March to May 2017, from June to August 2017, from September to November 2017 and from December 2017 to February 2018. The HQs of $PM_{10}$ exposure based on the HQs of $PM_{10}$ exposure based on Thailand NAAQS were shown in Table 4.10. and based on WHO air quality standard were shown in Table 4.11.

*Table 4. 9 $PM_{10}$ Ambient concentrations based on seasonal variations*

| Stations | $PM_{10}$ Ambient Concentrations ($\mu g/m^3$) | | | | |
|---|---|---|---|---|---|
| | Mar 17 – May 17 | Jun 17 - Aug 17 | Sep 17 – Nov 17 | Dec 17 – Feb 18 | Annual 2017 |
| 02t RBS | 34.51 | 21.86 | 26.18 | 50.91 | 35.88 |
| 03t PBK | 51.98 | 64.2 | 63.13 | 73.48 | 60.92 |
| 05t MED | 31.6 | 27.36 | 38.17 | 60.91 | 38.29 |
| 10t KCH | 32.84 | 22.27 | 33.53 | 56.76 | 34.93 |
| 11t KHK | 17.37 | 26.89 | 37.14 | 49.37 | 27.32 |
| 12t NWS | 44.88 | 30.84 | 37.24 | 61.16 | 43.63 |
| 50t CLH | N/D | 42.66 | 53.11 | 68.72 | N/D |
| 52t ITP | 38.6 | 32.01 | 43.51 | 68.74 | 44.21 |
| 53t CPO | N/D | 30.2 | 48.76 | 69.92 | N/D |
| 59t PRD | 34.52 | 26.22 | 31.38 | 53.75 | 36.32 |
| 61t BDS | 33.11 | 22.43 | 34.27 | 57.54 | 35.43 |
| A_RTW | 42.85 | 33.5 | 43.69 | 61.39 | 43.64 |
| B_PKN | 76.85 | 58.79 | 77.14 | 108.49 | 79.67 |
| C_RB | 83.57 | 73.41 | 67.76 | 90.61 | 79.75 |
| D_DIN | 91.53 | 62.59 | 81.45 | 90.09 | 80.48 |

N/D mean non-detected data.

The average $PM_{10}$ concentrations shown in Table 4.9 can be described that the monthly average ambient $PM_{10}$ concentrations were acceptable level at all area of Central Business District (CBD) of Bangkok. However, the annual average ambient $PM_{10}$ concentration can be acceptable almost all areas but there are a few areas at 03t_PBK, B_PKN, C_RB and D_DIN was discovered the average concentrations were exceeded than Thailand NAAQs. These four areas are located at southern CBD of Bangkok. This area should be marked as the high-risk areas and greater precaution.

Quantitative health risk assessment of $PM_{10}$ exposure were shown in Table 4.10 and Table 4.11. The average HQs values based on Thailand NAAQS for quantifying health risk in the normal citizens case could be interpreted that those living in CBD of Bangkok were acceptable risk from exposure to $PM_{10}$ in all seasons. The HQs values were less than 1 (HQs < 1) at all four episodes meaning that normal people would be safe all year round. In addition, the average HQs values based on WHO standard for quantifying health risk in the sensitive citizens case could be

described that almost areas of CBD were acceptable risk of people exposure to $PM_{10}$ for those in sensitive groups as the average HQs values less than 1 (HQs <1). Nevertheless, the areas nearby 03t_PBK, B_PKN, C_RB and D_DIN monitoring stations were discovered the average HQ values exceeding than 1 (HQs >1) meaning that the sensitive people in these areas could be adversely affected by exposure to $PM_{10}$. According to seasonal variation, during December 2017 to February 2018 described as winter with dry season, The average HQs values exceeded than 1 almost all areas of CBD of Bangkok.

This can be explained that, during winter and dry season, those in sensitive groups could be risk from exposure to $PM_{10}$. This could be suggested that, during winter with dry season, sensitive unhealthy people should be cautioned to protect themselves and stay away from high concentration of particulate matter. However, the average HQ values during September to November displayed the lowest levels comparing with the other periods because of high levels of precipitation in rainy season.

*Table 4. 10 The average HQs of $PM_{10}$ Exposure based on Thailand NAAQS*

| **Stations** | **Mar 17 – May 17** | | **Jun 17 - Aug 17** | | **Sep 17 – Nov 17** | | **Dec 17 – Feb 18** | |
|---|---|---|---|---|---|---|---|---|
| | EC | HQ | EC | HQ | EC | HQ | EC | HQ |
| 02t RBS | 33.09 | 0.28 | 20.96 | 0.17 | 25.10 | 0.21 | 48.82 | 0.41 |
| 03t PBK* | 49.84 | 0.42 | 61.56 | 0.51 | 60.54 | 0.50 | 70.46 | 0.59 |
| 05t MED | 30.30 | 0.25 | 26.24 | 0.22 | 36.60 | 0.31 | 58.41 | 0.49 |
| 10t KCH | 31.49 | 0.26 | 21.35 | 0.18 | 32.15 | 0.27 | 54.43 | 0.45 |
| 11t KHK | 16.66 | 0.14 | 25.78 | 0.21 | 35.61 | 0.30 | 47.34 | 0.39 |
| 12t NWS | 43.04 | 0.36 | 29.57 | 0.25 | 35.71 | 0.30 | 58.65 | 0.49 |
| 50t CLH | N/D | N/D | 40.91 | 0.34 | 50.93 | 0.42 | 65.90 | 0.55 |
| 52t ITP | 37.01 | 0.31 | 30.69 | 0.26 | 41.72 | 0.35 | 65.92 | 0.55 |
| 53t CPO | N/D | N/D | 28.96 | 0.24 | 46.76 | 0.39 | 67.05 | 0.56 |
| 59t PRD | 33.10 | 0.28 | 25.14 | 0.21 | 30.09 | 0.25 | 51.54 | 0.43 |
| 61t BDS | 31.75 | 0.26 | 21.51 | 0.18 | 32.86 | 0.27 | 55.18 | 0.46 |
| A_RTW | 41.09 | 0.34 | 32.12 | 0.27 | 41.89 | 0.35 | 58.87 | 0.49 |
| B_PKN* | 73.69 | 0.61 | 56.37 | 0.47 | 73.97 | 0.62 | 104.03 | 0.87 |
| C_RBN* | 80.14 | 0.67 | 70.39 | 0.59 | 64.98 | 0.54 | 86.89 | 0.72 |
| D_DIN* | 87.77 | 0.73 | 60.02 | 0.50 | 78.10 | 0.65 | 86.39 | 0.72 |

*Table 4. 11 The average HQs of $PM_{10}$ Exposure based on WHO air quality standard*

| Stations | Mar 17 – May 17 | | Jun 17 - Aug 17 | | Sep 17 – Nov 17 | | Dec 17 – Feb 18 | |
|---|---|---|---|---|---|---|---|---|
| | EC | HQ | EC | HQ | EC | HQ | EC | HQ |
| 02t RBS | 33.09 | 0.66 | 20.96 | 0.42 | 25.10 | 0.50 | 48.82 | 0.98 |
| 03t PBK* | 49.84 | 1.00 | 61.56 | 1.23 | 60.54 | 1.21 | 70.46 | 1.41 |
| 05t MED | 30.30 | 0.61 | 26.24 | 0.52 | 36.60 | 0.73 | 58.41 | 1.17 |
| 10t KCH | 31.49 | 0.63 | 21.35 | 0.43 | 32.15 | 0.64 | 54.43 | 1.09 |
| 11t KHK | 16.66 | 0.33 | 25.78 | 0.52 | 35.61 | 0.71 | 47.34 | 0.95 |
| 12t NWS | 43.04 | 0.86 | 29.57 | 0.59 | 35.71 | 0.71 | 58.65 | 1.17 |
| 50t CLH | N/D | N/D | 40.91 | 0.82 | 50.93 | 1.02 | 65.90 | 1.32 |
| 52t ITP | 37.01 | 0.74 | 30.69 | 0.61 | 41.72 | 0.83 | 65.92 | 1.32 |
| 53t CPO | N/D | N/D | 28.96 | 0.58 | 46.76 | 0.94 | 67.05 | 1.34 |
| 59t PRD | 33.10 | 0.66 | 25.14 | 0.50 | 30.09 | 0.60 | 51.54 | 1.03 |
| 61t BDS | 31.75 | 0.63 | 21.51 | 0.43 | 32.86 | 0.66 | 55.18 | 1.10 |
| A_RTW | 41.09 | 0.82 | 32.12 | 0.64 | 41.89 | 0.84 | 58.87 | 1.18 |
| B_PKN* | 73.69 | 1.47 | 56.37 | 1.13 | 73.97 | 1.48 | 104.03 | 2.08 |
| C_RBN* | 80.14 | 1.60 | 70.39 | 1.41 | 64.98 | 1.30 | 86.89 | 1.74 |
| D_DIN* | 87.77 | 1.76 | 60.02 | 1.20 | 78.10 | 1.56 | 86.39 | 1.73 |

N/D mean non-detected data.

### 4.5.2 Health Risk Assessment of $PM_{2.5}$ Exposure

The ambient $PM_{2.5}$ from the measured and predicted concentrations were shown in Table 4.12. The Thailand NAAQS were compared with the average fine particulate matter concentrations. $PM_{2.5}$ average concentrations less than 50 $\mu g/m^3$ meaning acceptable concentration levels for daily average concentration and less than 25 $\mu g/m^3$ meaning acceptable concentration levels for annual average concentration. Nevertheless, a few areas as marked with yellow highlight in Table 4.12 were discovered $PM_{2.5}$ concentrations exceeding than air quality standard. The average $PM_{2.5}$ were normally higher during December through February than the other periods because of the climatographic condition.

*Table 4. 12 $PM_{2.5}$ Ambient concentrations based on seasonal variations*

| Stations | $PM_{2.5}$ Ambient Concentrations (µg/$m^3$) | | | | |
|---|---|---|---|---|---|
| | Mar 17 – May 17 | Jun 17 - Aug 17 | Sep 17 – Nov 17 | Dec 17 – Feb 18 | Annual 2017 |
| 02t RBS* | 22.23 | 12.33 | 15.67 | 34.83 | 23.19 |
| 03t PBK* | 31.55 | 38.62 | 39.91 | 48.73 | 37.94 |
| 05t MED | 25.33 | 11.34 | 17.42 | 33.69 | 23.27 |
| 10t KCH* | 24.14 | 14.48 | 24.08 | 42.91 | 25.15 |
| 11t KHK* | 14.53 | 16.93 | 24.42 | 37.93 | 22.52 |
| 12t NWS* | 30.16 | 19.28 | 24.24 | 42.78 | 29.2 |
| 50t CLH | N/D | 17.90 | 26.88 | 41.8 | N/D |
| 52t ITP | 26.88 | 20.6 | 31.38 | 50.28 | 31.14 |
| 53t CPO | N/D | 14.38 | 19.96 | 31.67 | N/D |
| 59t PRD | 25.44 | 18.53 | 20.51 | 36.95 | 24.77 |
| 61t BDS | 23.58 | 14.81 | 23.99 | 41.99 | 25.44 |
| A_RTW | 21.36 | 19.61 | 28.38 | 38.21 | 25.05 |
| B_PKN* | 57.54 | 40.82 | 56.68 | 79.09 | 58.02 |
| C_RBN* | 58.36 | 51.67 | 48.99 | 64.96 | 56.50 |
| D_DIN* | 64.15 | 44.45 | 59.46 | 64.78 | 57.63 |

N/D mean non-detected data

* Meaning used the predicted $PM_{2.5}$ concentrations from developed MLR equations.

*The yellow highlight means the average concentrations exceeded than Thailand NAAQS.



The average HQs of $PM_{2.5}$ exposure was shown in Table 4.13 and Table 4.14. The average HQs values based on Thailand NAAQS for quantifying health risk for the normal citizens case and based on WHO air quality standard for quantifying health risk for sensitive citizen case.

For health risk assessment for normal citizen case as shown in Table 4.13, the average HQ values almost all areas in CBD were acceptable as the HQs less than 1 (HQs < 1). However, the areas near by the air monitoring stations of B_PKN, C_RBN and D_DIN were displayed the average HQs exceeded than 1 (HQs >1). These could be described that these locations have adversely potential risk to the people living nearby.

For health risk assessment for sensitive citizen case as shown in Table 4.14, Almost all areas of CBD were acceptable risk but the areas nearby 03t PBK, 12t

NWS, 52t IPT, A_RTW B_PKN, C_RBN and D_DIN were displayed the average HQs exceeded than 1 (HQs >1) in some seasons. In addition, during December 2017 through February 2018, the average HQs values exceeded than 1 (HQs > 1) all stations meaning that all area in CBD of Bangkok were potentially adverse health effect by exposure to $PM_{2.5}$. During this period, the climatology induced particulate matter extreme accumulating in the atmosphere. However, the average HQ values during September to November displayed the lowest levels comparing with the other periods. Hence, during winter with dry season, the sensitive people including children, elders, and unhealthy people would be at risk from fine particulate matter exposure. They should wear personal protected equipment during the high $PM_{2.5}$ concentration occurrence or they should stay away from the high-risk areas.

*Table 4. 13 The average HQs of $PM_{2.5}$ Exposure based on Thailand NAAQS*

| **Stations** | **Mar 17 – May 17** | | **Jun 17 - Aug 17** | | **Sep 17 – Nov 17** | | **Dec 17 – Feb 18** | |
|---|---|---|---|---|---|---|---|---|
| | EC | HQ | EC | HQ | EC | HQ | EC | HQ |
| 02t RBS | 21.32 | 0.43 | 11.82 | 0.24 | 15.03 | 0.30 | 33.40 | 0.67 |
| 03t PBK* | 30.25 | 0.61 | 37.03 | 0.74 | 38.27 | 0.77 | 46.73 | 0.93 |
| 05t MED | 24.29 | 0.49 | 10.87 | 0.22 | 16.70 | 0.33 | 32.31 | 0.65 |
| 10t KCH | 23.15 | 0.46 | 13.88 | 0.28 | 23.09 | 0.46 | 41.15 | 0.82 |
| 11t KHK | 13.93 | 0.28 | 16.23 | 0.32 | 23.42 | 0.47 | 36.37 | 0.73 |
| 12t NWS | 28.92 | 0.58 | 18.49 | 0.37 | 23.24 | 0.46 | 41.02 | 0.82 |
| 50t CLH | N/D | N/D | 17.16 | 0.34 | 25.78 | 0.52 | 40.08 | 0.80 |
| 52t ITP | 25.78 | 0.52 | 19.75 | 0.40 | 30.09 | 0.60 | 48.21 | 0.96 |
| 53t CPO | N/D | N/D | 13.79 | 0.28 | 19.14 | 0.38 | 30.37 | 0.61 |
| 59t PRD | 24.39 | 0.49 | 17.77 | 0.36 | 19.67 | 0.39 | 35.43 | 0.71 |
| 61t BDS | 22.61 | 0.45 | 14.20 | 0.28 | 23.00 | 0.46 | 40.26 | 0.81 |
| A_RTW | 20.48 | 0.41 | 18.80 | 0.38 | 27.21 | 0.54 | 36.64 | 0.73 |
| B_PKN | 55.18 | 1.10 | 39.14 | 0.78 | 54.35 | 1.09 | 75.84 | 1.52 |
| C_RBN | 55.96 | 1.12 | 49.55 | 0.99 | 46.98 | 0.94 | 62.29 | 1.25 |
| D_DIN | 61.51 | 1.23 | 42.62 | 0.85 | 57.02 | 1.14 | 62.12 | 1.24 |

*Table 4. 14 The average HQs of $PM_{2.5}$ Exposure based on WHO air quality standard*

| Stations | Mar 17 – May 17 | | Jun 17 - Aug 17 | | Sep 17 – Nov 17 | | Dec 17 – Feb 18 | |
|---|---|---|---|---|---|---|---|---|
| | EC | HQ | EC | HQ | EC | HQ | EC | HQ |
| 02t RBS | 21.32 | 0.85 | 11.82 | 0.47 | 15.03 | 0.60 | 33.40 | 1.34 |
| 03t PBK* | 30.25 | 1.21 | 37.03 | 1.48 | 38.27 | 1.53 | 46.73 | 1.87 |
| 05t MED | 24.29 | 0.97 | 10.87 | 0.43 | 16.70 | 0.67 | 32.31 | 1.29 |
| 10t KCH | 23.15 | 0.93 | 13.88 | 0.56 | 23.09 | 0.92 | 41.15 | 1.65 |
| 11t KHK | 13.93 | 0.56 | 16.23 | 0.65 | 23.42 | 0.94 | 36.37 | 1.45 |
| 12t NWS | 28.92 | 1.16 | 18.49 | 0.74 | 23.24 | 0.93 | 41.02 | 1.64 |
| 50t CLH | N/D | N/D | 17.16 | 0.69 | 25.78 | 1.03 | 40.08 | 1.60 |
| 52t ITP | 25.78 | 1.03 | 19.75 | 0.79 | 30.09 | 1.20 | 48.21 | 1.93 |
| 53t CPO | N/D | N/D | 13.79 | 0.55 | 19.14 | 0.77 | 30.37 | 1.21 |
| 59t PRD | 24.39 | 0.98 | 17.77 | 0.71 | 19.67 | 0.79 | 35.43 | 1.42 |
| 61t BDS | 22.61 | 0.90 | 14.20 | 0.57 | 23.00 | 0.92 | 40.26 | 1.61 |
| A_RTW | 20.48 | 0.82 | 18.80 | 0.75 | 27.21 | 1.09 | 36.64 | 1.47 |
| B_PKN* | 55.18 | 2.21 | 39.14 | 1.57 | 54.35 | 2.17 | 75.84 | 3.03 |
| C_RBN* | 55.96 | 2.24 | 49.55 | 1.98 | 46.98 | 1.88 | 62.29 | 2.49 |
| D_DIN* | 61.51 | 2.46 | 42.62 | 1.70 | 57.02 | 2.28 | 62.12 | 2.48 |

***** The monitoring stations presented the HQs levels exceed than 1 (HQs > 1) all episodes.

Overall, the ecological risk assessment of $PM_{10}$ and $PM_{2.5}$ exposure was gradually acceptable risk in almost areas of CBD. There were a few areas in southern CBD discovered high risk to human health. The human health risk for those with healthy and normal group as the adulthood citizen were acceptable risk for exposure to $PM_{10}$ and $PM_{2.5}$ almost all area of Bangkok. However, the human health risk for those with unhealthy or sensitive groups would be risk from exposure to $PM_{10}$ and $PM_{2.5}$ in some areas in CBD. In addition, the high-risk duration would be normally occurred in the winter with dry season during November through February. During the high-risk period, the citizens especially sensitive group should protect themselves by using the air personal protective equipment (PPE) or should stay safely in the indoor area. After the health risk assessment were evaluated by modelled and computed with the US. EPA. equation, the HQs values based on WHO air quality standard were used to create GIS-based maps by ArcMap programs to investigate the

distribution of HQs and specify the high-risk locations in case of savior scenario especially for those with sensitive health condition in CBD of Bangkok.

### 4.6 Hazard Map Analysis

The average HQs values based on WHO air quality standard computation were used to illustrated GIS-based map. The IDW interpolation technique was selected to demonstrate HQ distribution. This GIS technique was applied because it was the smooth surface of data in the simulation of IDW and the technique was discovered the better interpolation scheme comparing with the ordinary kriging and spline (Mitmark and Jinsart, 2017). Levels of the average HQ as shown in **Figure 4.12** were classified into 12 classes from **HQ < 0.5** to **HQ > 3.25** as increasing 0.25 in each step.

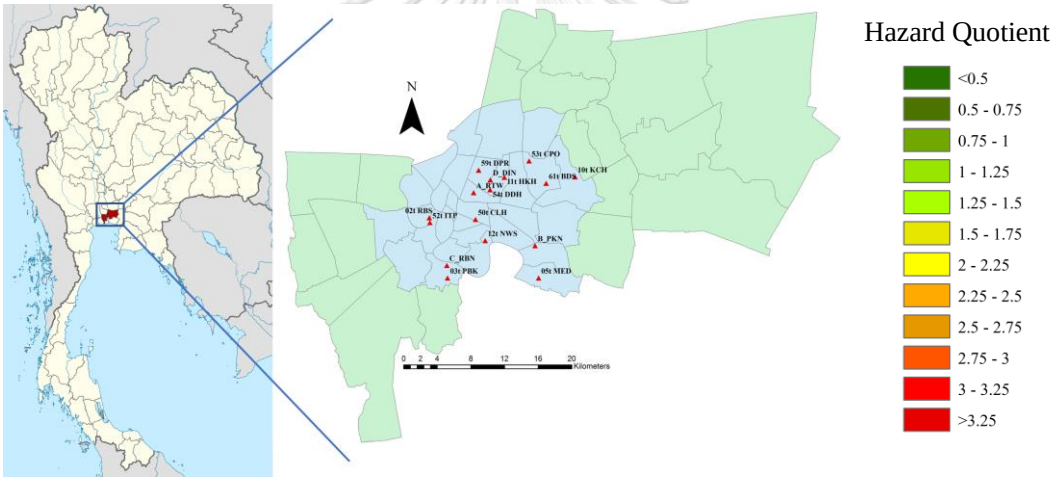





*Figure 4. 12 HQ classification and location of Central Business District*

#### 4.6.1 Hazard Map of $PM_{10}$

Mapping HQ values of $PM_{10}$ from the set of measurement data was performed using ArcGIS 10.4. A raster map from spatial interpolation depicting the distribution of the average HQ of $PM_{10}$ distribution in four stages: March to May 2017, from June to August 2017, from September to November 2017 and from December 2017 to February 2018 was illustrated by performing the IDW method. The GIS-based maps of the average HQ of $PM_{10}$ inhalation exposure as shown in Figure 4.13 to Figure 4.16 were discovered that the average HQ were higher during December to February than the other periods. However, the other periods in the study year were gradually

found acceptable risk. Almost area of CBD was covered with green area as shown in the mentioned figures indicating no adverse health effect. Nevertheless, the southern CBD covered by three monitoring stations: 03t PBK, C_RBN and B_PKN would be indicated high risk location because the color classification was shown the average HQ values exceeding than 1 (HQ >1).


*Figure 4. 13 GIS-based maps of the HQs of $PM_{10}$ and wind rose plot during March – May 2017*


*Figure 4. 14 GIS-based maps of the HQs of $PM_{10}$ and wind rose plot during June - August 2017*


*Figure 4. 15 GIS-based maps of the HQs of $PM_{10}$ and wind rose plot during September - November 2017*

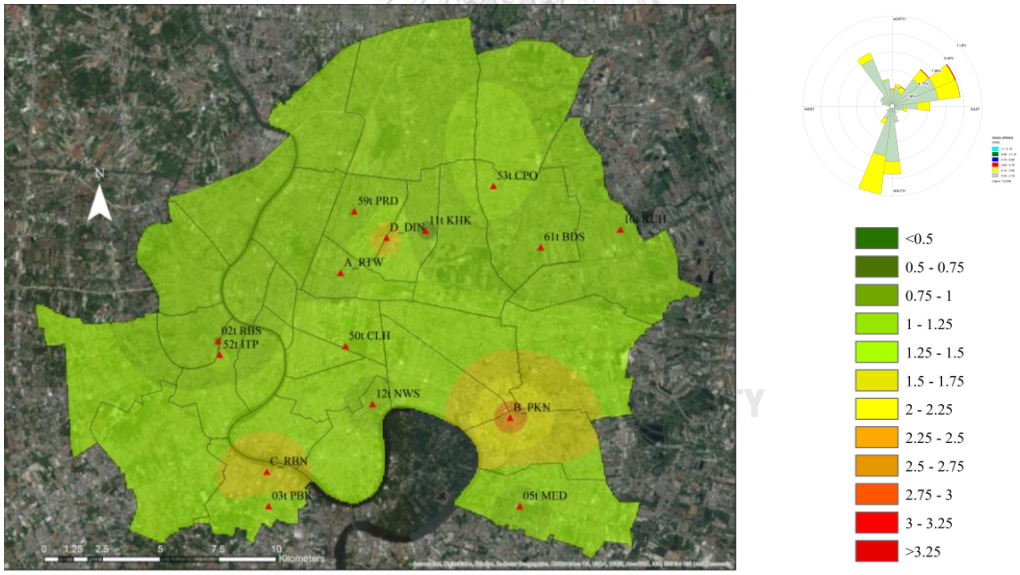



*Figure 4. 16 GIS-based maps of the HQs of $PM_{10}$ and wind rose plot during December 2017 – February 2018*

### 4.6.2 Hazard Map of $PM_{2.5}$

Mapping HQ values of $PM_{2.5}$ was performed using ArcGIS 10.4. A raster map from spatial interpolation depicting the distribution of the average HQ of $PM_{2.5}$ distribution following the seasonal variations in four stages: March to May 2017, from June to August 2017, from September to November 2017 and from December 2017 to February 2018 was illustrated by performing the IDW technique.


*Figure 4. 17 GIS-based maps of the HQs of $PM_{2.5}$ and wind rose plot during March – May 2017*

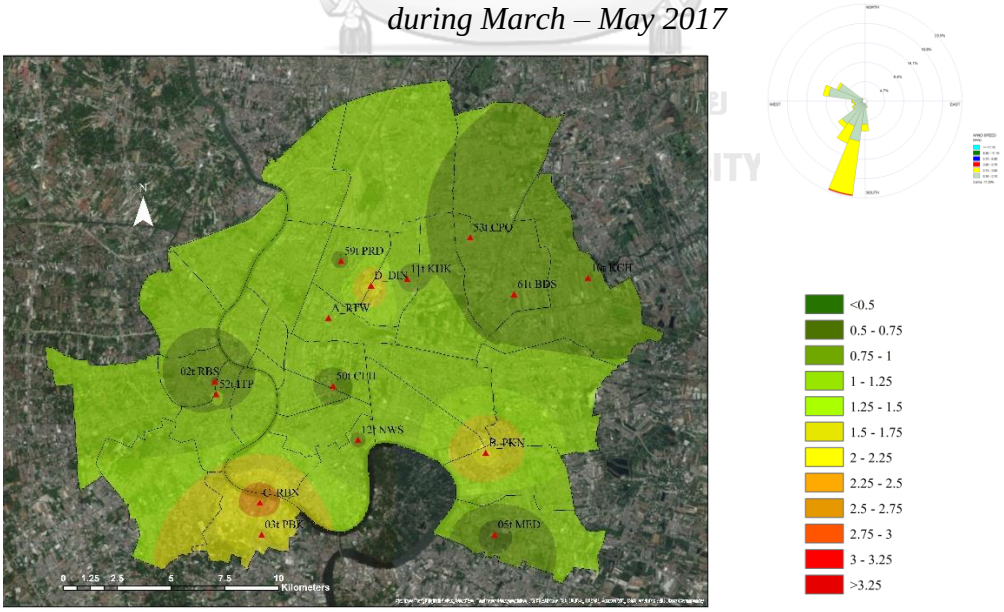



*Figure 4. 18 GIS-based maps of the HQs of $PM_{2.5}$ and wind rose plot during June - August 2017*

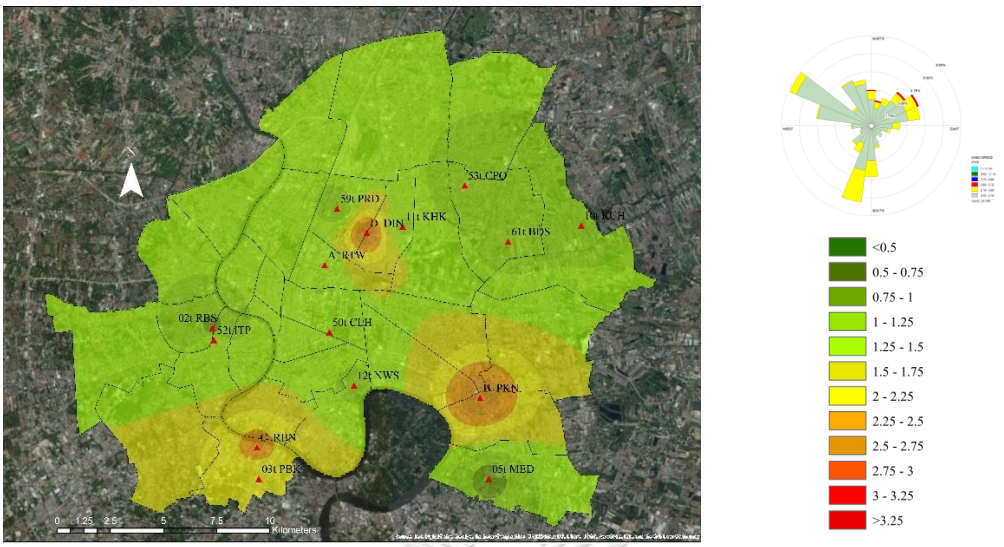



*Figure 4. 19 GIS-based maps of the HQs of $PM_{2.5}$ and wind rose plot during September - November 2017*

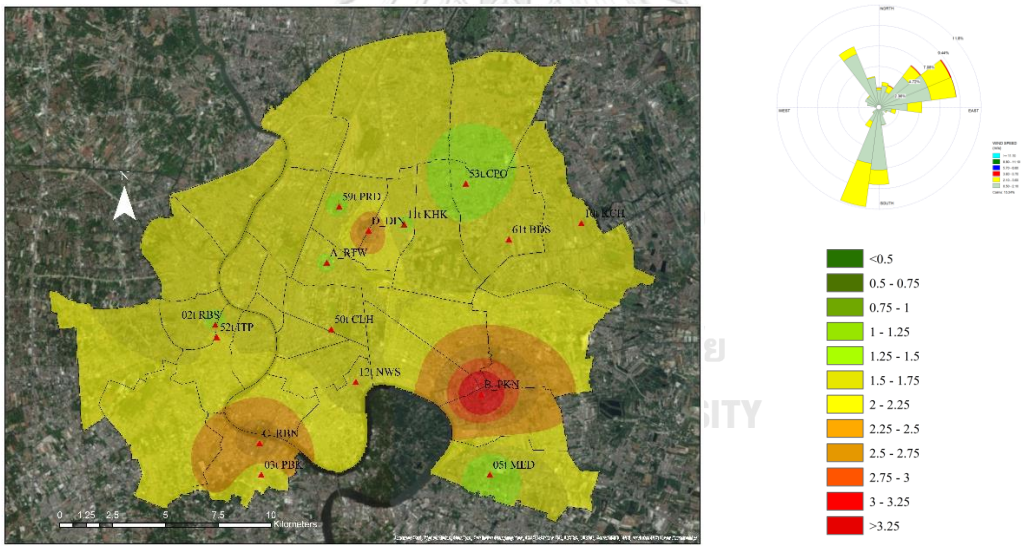



*Figure 4. 20 GIS-based maps of the HQs of $PM_{2.5}$ and wind rose plot during December 2017 – February 2018*

A raster map from spatial interpolation depicting the distribution of the average HQs of $PM_{2.5}$ concentrations was produced and compared as shown in GIS-based maps in Figure 4.17 to Figure 4.20. It was found that distribution of the average HQs was higher in during December 2017 to February 2018 than during March to May 2017, during June to August 2017, and during September to November 2017.

The climatology of winter between December and February (Figure 4.20) induces the pollutants are trapped in the urban atmosphere because there is temperature inversion that is thin layer of the atmosphere where the normal decrease in temperature with height switches to the temperature increasing with height. So, the pollutants will be trapped under the inversion layer and accumulating with high concentration under the layer (Wimolwattanapun *et al.*, 2011). Therefore, during this season, people in Bangkok would potentially be adverse highest health risk impact from exposure to $PM_{2.5}$. The tropical storms occurrence in summer during March to May (Figure 4.17) and the atmospheric precipitation in rainy season during June to August and September to November (Figure 4.18 and Figure 4.19) affect $PM_{2.5}$ concentration levels by wet deposition reaction and leaching the suspended particles. The highest HQ value was found over the southern area of central business district of Bangkok. The high-risk area in southern CBD were found at the areas nearby B_PKN and C_RBN monitoring stations. At the C_RBN, there are Rajburana Temple and Thailand glass industry located within 2 km nearby the air monitoring station as shown in Figure 4.21. The activity in temple such as cremation and industrial process would potentially be generated $PM_{10}$ and $PM_{2.5}$ emissions. This would affect ambient particulate matter concentration levels. In addition, there are refinery petroleum plants and the wharf transportation pier located within 5 km radius from the B_PKN monitoring station as shown in Figure 4.22. These also would be the potential sources of fine particulate matter emission. It could be noted that the high-risks areas of $PM_{2.5}$ exposure require greater precaution.



In summary, the high-risk location of $PM_{10}$ and $PM_{2.5}$ were at the southern CBD. People with unhealthy physical living nearby high-risk areas should be concerned of the hazardous of particulate matter and avoid outdoor activities in the day with high concentration of small particulate matters. Especially, during winter with dry season, people should use personal protective equipment such as masks and stay in indoors.

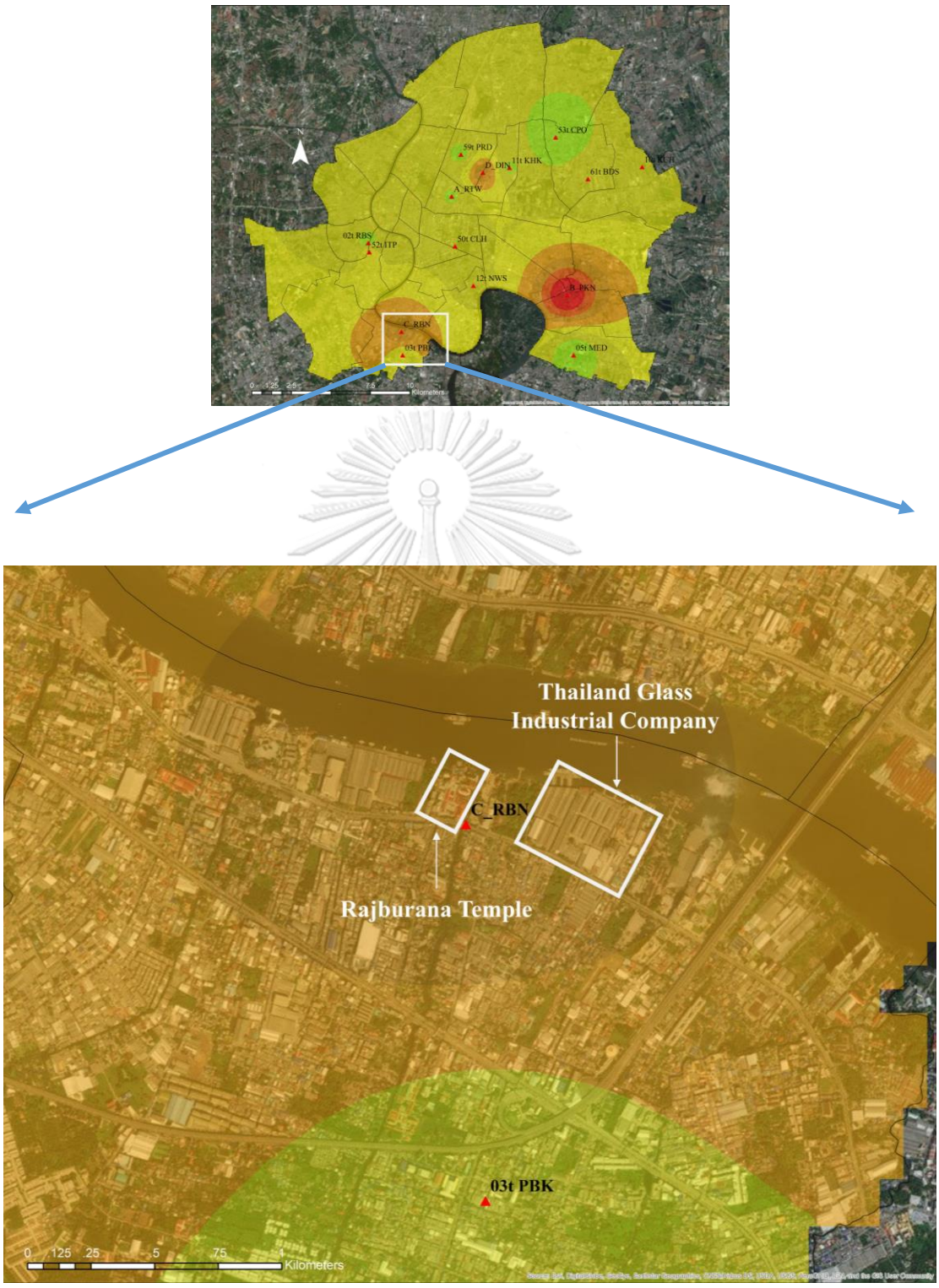



*Figure 4. 21 Possibly potential sources of particulate matter emission nearby C_RBN*

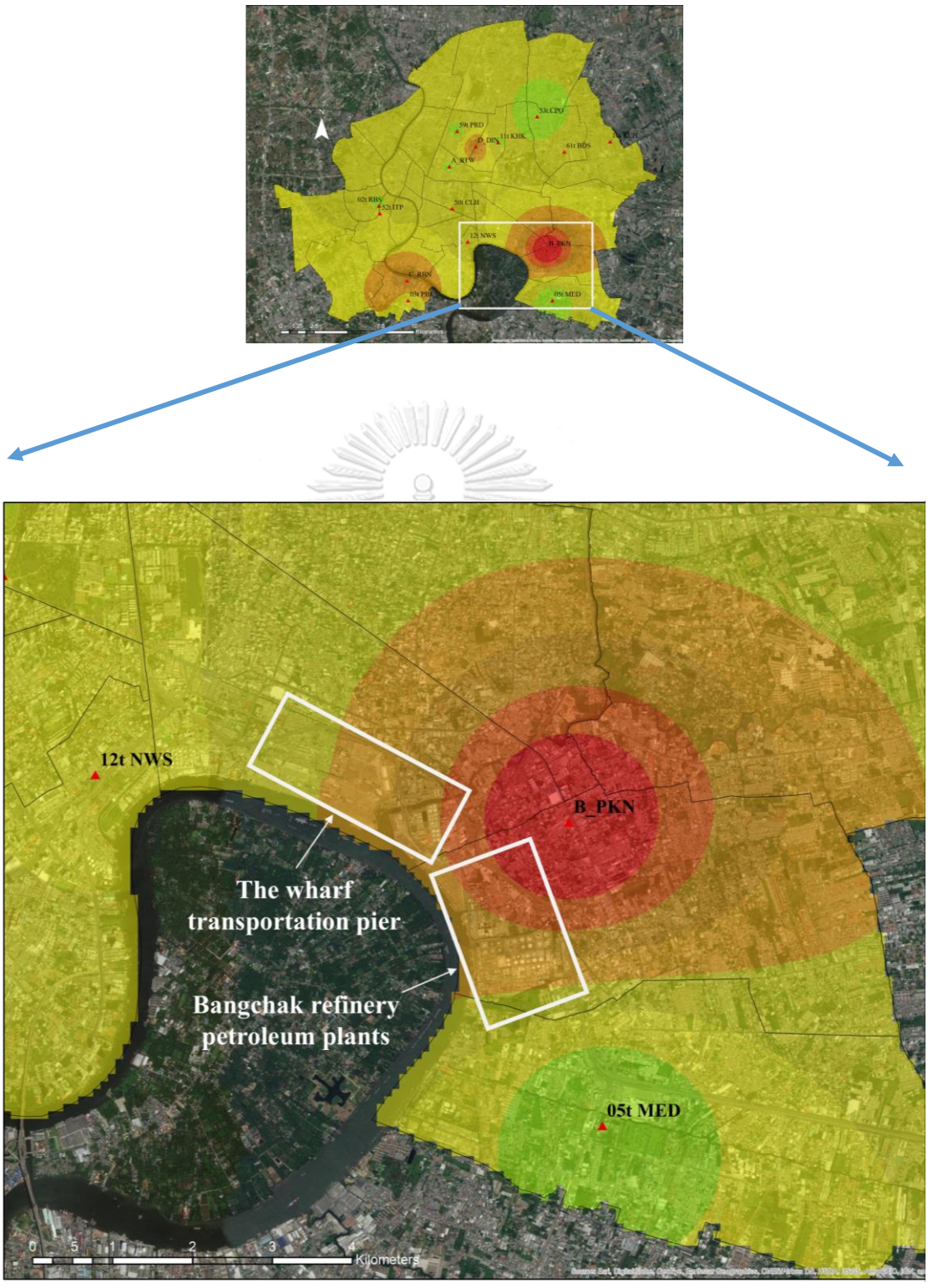



*Figure 4. 22 Possibly potential sources of particulate matter emission nearby B_PKN*

# CHAPTER V
# CONCLUSIONS

The overall results were findings from this study are summarized in this chapter. Conclusions with respect to the objectives of the study were presented. The mathematical equation and health risk assessment of $PM_{10}$ and $PM_{2.5}$ in the study were demonstrated. This chapter also provided recommendation for further study and their limitations.

## 5.1 Conclusions

Trends of $PM_{10}$ were investigated over ten year from 2008 to 2017. Overall, the trend of ambient particulate matter concentration levels had decreased from 2008 to 2015. Then the trends have been rising again since 2017. The increasing trends could be reflected from the construction of metro trains over all area of Bangkok and vicinity area. The construction of metro could be affected traffic congestion under and above construction sites.

For the MLR model development for estimating $PM_{2.5}$, concentrations in central business district of Bangkok, daily average air pollution data and meteorological factors from 2015 to 2017 were used to develop MLR equations using stepwise multiple linear regression. The predicted equations were used to estimate $PM_{2.5}$ concentrations in non-monitored areas. The model result was divided to predict $PM_{2.5}$ into two types: ambient area model and roadside area model.

The ambient area model can be written as **$PM_{2.5}$ ($\mu g/m^3$) = -7.524 + 0.75$PM_{10}$ ($\mu g/m^3$) + 0.39 $O_3$ (ppb) +1.90 $SO_2$ (ppb) – 8.17 CO (ppm) - 0.21Relative Humidity (%RH) - 0.49 Temperature (°C).**

The roadside area model can be written as **$PM_{2.5}$ ($\mu g/m^3$) = -12.85 + 0.597 $PM_{10}$ ($\mu g/m^3$) + 0.25 $NO_2$ (ppb) + 0.29 $O_3$ (ppb) + 2.68 CO (ppm) + 0.07 Relative Humidity (%RH) + 1.13 Windspeed (m/s).**

The model validation by statistical evaluation of MAE, NME, RMSE, IA, PA, $R^2$ and Q-Q plots showed the model performance with remarkable results.

The measured values of $PM_{10}$ and $PM_{2.5}$ as well as the predicted values of $PM_{2.5}$ concentrations were used to investigate health risk assessment of people exposure to these particulate matters by using the average HQ. Overall, the average HQ values were acceptable risk during summer and rainy season; however, the average HQ values of $PM_{10}$ and $PM_{2.5}$ in winter could be adversely affected human health. During December through February, the particulate matter in atmosphere is higher than the other periods according to the atmospheric conditions and seasonal monsoons. The average HQ of both $PM_{10}$ and $PM_{2.5}$ were illustrated by GIS and compared by following the seasonal variation. The highest HQ value in GIS-based maps were discovered over the southern area of Central Business District of Bangkok. There are a few potential sources of particulate matter emission such as crematory in the temple, refinery petroleum plants and wharf transportation pier. These sources are located near monitoring stations with 5 km, in which they could be reflected to ambient particulate matter. It could be noted that the high-risks areas of $PM_{2.5}$ exposure require greater precaution. However, the high-risk area should be installed the $PM_{2.5}$ monitoring stations in order to validated with the predicted values.

**5.2 Recommendations**

Multiple Linear Regression was applied to this model because of simple and remarkable prediction results supported by many studies. However, there are many mathematical techniques to do forecasting on atmospheric pollution but they require more complex data than the MLR technique. Once the input data could be available, the other mathematical techniques could be done. In addition, the MLR equations were developed by ambient air pollution and meteorological condition data. It would be better to add the other predicted variables if the variables could be the potential sources of particulate matter emission and their data are sufficient to develop model; for example, if there is the real-time number of vehicles nearby the air monitoring stations, model developers can use these data as the predicted variables to develop MLR equation. Moreover, the monitoring site representatives are crucial parameter in developing and accessing air pollution situation particularly when health impact is

needed to be evaluated. It could be described that whole area of central business district of Bangkok should be added more the air monitoring stations to cover the area. In addition, the MLR equations would be examined again with the measured data when the detected data is available is non-monitored sites. For the GIS based maps of health risk assessment, it could be claimed that only southern of Bangkok is at risk because they have more monitoring stations. This study could be a preliminary study to indicate the high-risk location and government should be greater precaution. Also, the health risk assessment should be investigated again when the air pollutant measurement data is available.

**5.3 Limitations**

The limitation of the MLR equation included that it inherently assumes of persistence of the both meteorological and air quality situation. This model would be not worked to forecast $PM_{2.5}$ in the location with existing potential serval $PM_{2.5}$ sources such as industrial estate or factories. However, there are many kinds of mathematic models like Box model, Gaussian plume model are able to forecast air pollution from the point sources. The MLR equation were used the environment in Bangkok, in which it would be imprecise and inaccurate with the other cities. The model is specified to use in the specific location. In addition, the model could be inaccurate in case of fluctuating weather conditions, such as those associated with meteorological conditions.

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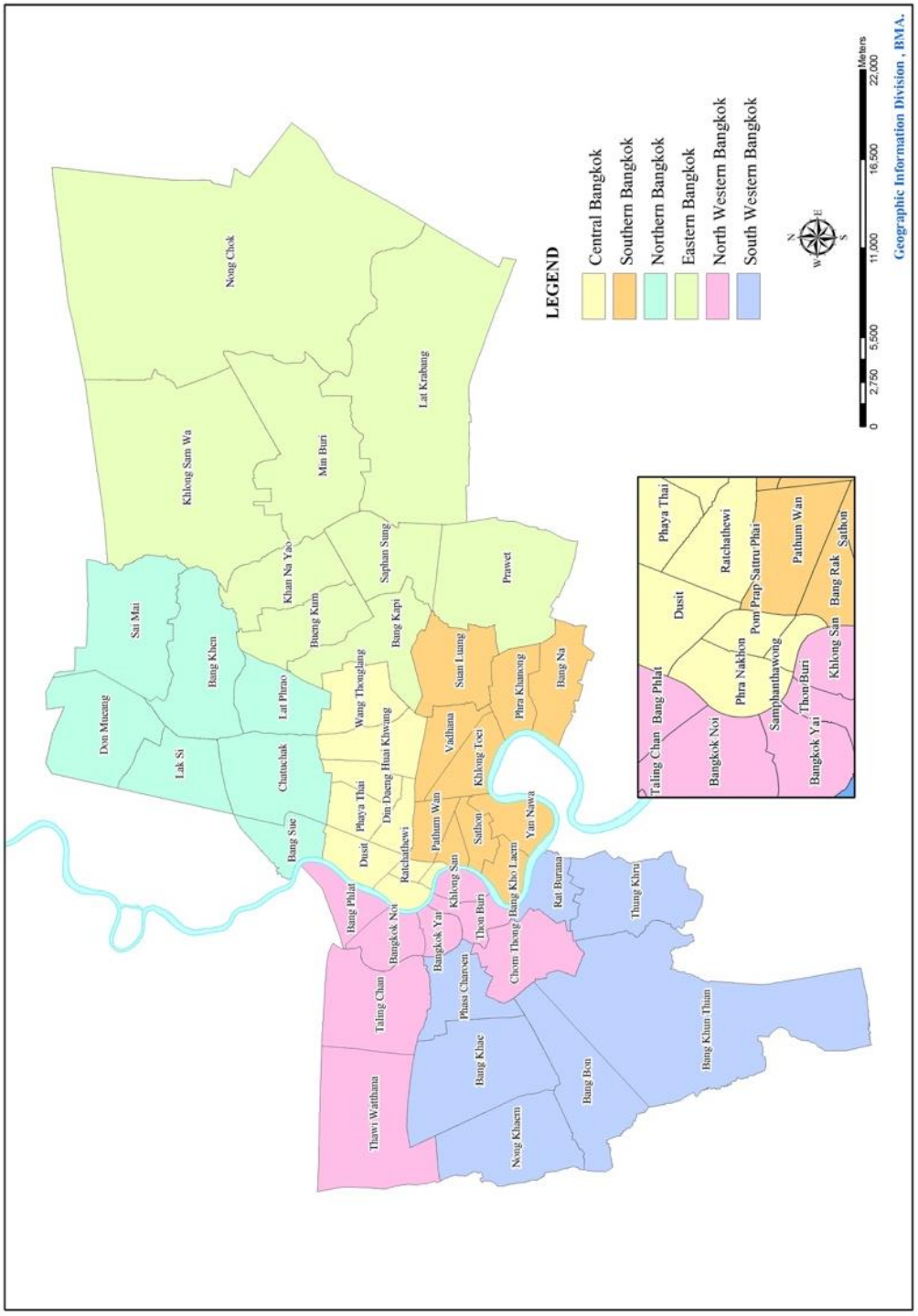
# APPENDICES

## APPENDIX A

Districts in Bangkok

| Code No. | Districts | Code No. | Districts |
|---|---|---|---|
| 01 | Phra Nakhon | 26 | Din Daeng |
| 02 | Dusit | 27 | Bueng Kum |
| 03 | Nong Chok | 28 | Sathon |
| 04 | Bang Rak | 29 | Bang Sue |
| 05 | Bang Khen | 30 | Chatuchak |
| 06 | Bang Kapi | 31 | Bang Kho Laem |
| 07 | Pathum Wan | 32 | Prawet |
| 08 | Pom Prap Sattru Phai | 33 | Khlong Toei |
| 09 | Phra Khanong | 34 | Suan Luang |
| 10 | Min Buri | 35 | Chom Thong |
| 11 | Lat Krabang | 36 | Don Mueang |
| 12 | Yan Nawa | 37 | Ratchathewi |
| 13 | Samphanthawong | 38 | Lat Phrao |
| 14 | Phaya Thai | 39 | Watthana |
| 15 | Thon Buri | 40 | Bang Khae |
| 16 | Bangkok Yai | 41 | Lak Si |
| 17 | Huai Khwang | 42 | Sai Mai |
| 18 | Khlong San | 43 | Khan Na Yao |
| 19 | Taling Chan | 44 | Saphan Sung |
| 20 | Bangkok Noi | 45 | Wang Thonglang |
| 21 | Bang Khun Thian | 46 | Khlong Sam Wa |
| 22 | Phasi Charoen | 47 | Bang Na |
| 23 | Nong Khaem | 48 | Thawi Watthana |
| 24 | Rat Burana | 49 | Thung Khru |
| 25 | Bang Phlat | 50 | Bang Bon |




Map of Bangkok district

# APPENDIX B

## Ambient Monitoring Data Analysis

Correlations Analysis of ambient monitoring station data

| | | | CO | NO | NO2 | NOX | O3 | SO2 | PM10 | PM2.5 | WS | TEMP | HUM | RAIN |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Spearman's rho | CO | Correlation Coefficient | 1.000 | .227** | .480** | .444** | .153** | .334** | .259** | .219** | -.633** | -.274** | .009 | .082** |
| | | Sig. (2-tailed) | . | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .720 | .002 |
| | | N | 1503 | 1487 | 1489 | 1487 | 1497 | 543 | 1464 | 1469 | 1381 | 1494 | 1494 | 1494 |
| | NO | Correlation Coefficient | .227** | 1.000 | .389** | .730** | -.567** | .334** | .031 | -.061* | -.221** | -.334** | .488** | .409** |
| | | Sig. (2-tailed) | .000 | . | .000 | .000 | .000 | .000 | .233 | .020 | .000 | .000 | .000 | .000 |
| | | N | 1487 | 1499 | 1499 | 1499 | 1493 | 551 | 1460 | 1465 | 1377 | 1490 | 1490 | 1490 |
| | NO2 | Correlation Coefficient | .480** | .389** | 1.000 | .893** | .140** | .304** | .581** | .476** | -.436** | -.523** | .010 | .036 |
| | | Sig. (2-tailed) | .000 | .000 | . | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .700 | .161 |
| | | N | 1489 | 1499 | 1503 | 1499 | 1495 | 553 | 1462 | 1467 | 1379 | 1492 | 1492 | 1492 |
| | NOX | Correlation Coefficient | .444** | .730** | .893** | 1.000 | -.149** | .398** | .468** | .344** | -.388** | -.555** | .215** | .204** |
| | | Sig. (2-tailed) | .000 | .000 | .000 | . | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .000 |
| | | N | 1487 | 1499 | 1499 | 1499 | 1493 | 551 | 1460 | 1465 | 1377 | 1490 | 1490 | 1490 |
| | O3 | Correlation Coefficient | .153** | -.567** | .140** | -.149** | 1.000 | .026 | .482** | .537** | -.063* | .158** | -.633** | -.488** |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 | . | .550 | .000 | .000 | .019 | .000 | .000 | .000 |
| | | N | 1497 | 1493 | 1495 | 1493 | 1528 | 550 | 1490 | 1494 | 1407 | 1519 | 1519 | 1519 |
| | SO2 | Correlation Coefficient | .334** | .334** | .304** | .398** | .026 | 1.000 | .391** | .369** | -.336** | -.106* | -.218** | -.080 |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 | .550 | . | .000 | .000 | .000 | .014 | .000 | .061 |
| | | N | 543 | 551 | 553 | 551 | 550 | 555 | 534 | 525 | 547 | 547 | 547 | 547 |
| | PM10 | Correlation Coefficient | .259** | .031 | .581** | .468** | .482** | .391** | 1.000 | .874** | -.004 | -.233** | -.365** | -.319** |
| | | Sig. (2-tailed) | .000 | .233 | .000 | .000 | .000 | .000 | . | .000 | .889 | .000 | .000 | .000 |
| | | N | 1464 | 1460 | 1462 | 1460 | 1490 | 534 | 1495 | 1469 | 1374 | 1487 | 1487 | 1487 |
| | PM2.5 | Correlation Coefficient | .219** | -.061* | .476** | .344** | .537** | .369** | .874** | 1.000 | -.047 | -.188** | -.323** | -.300** |
| | | Sig. (2-tailed) | .000 | .020 | .000 | .000 | .000 | .000 | .000 | . | .084 | .000 | .000 | .000 |
| | | N | 1469 | 1465 | 1467 | 1465 | 1494 | 525 | 1469 | 1500 | 1378 | 1491 | 1491 | 1491 |
| | WS | Correlation Coefficient | -.633** | -.221** | -.436** | -.388** | -.063* | -.336** | -.004 | -.047 | 1.000 | .222** | -.151** | -.40** |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 | .019 | .000 | .889 | .084 | . | .000 | .000 | .000 |
| | | N | 1381 | 1377 | 1379 | 1377 | 1407 | 547 | 1374 | 1378 | 1412 | 1412 | 1412 | 1412 |
| | TEMP | Correlation Coefficient | -.274** | -.334** | -.523** | -.555** | .158** | -.106* | -.233** | -.188** | .222** | 1.000 | -.291** | -.311** |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 | .000 | .014 | .000 | .000 | .000 | . | .000 | .000 |
| | | N | 1494 | 1490 | 1492 | 1490 | 1519 | 547 | 1487 | 1491 | 1412 | 1525 | 1525 | 1525 |
| | HUM | Correlation Coefficient | .009 | .488** | .010 | .215** | -.633** | -.218** | -.365** | -.323** | -.151** | -.291** | 1.000 | .710** |
| | | Sig. (2-tailed) | .720 | .000 | .700 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | . | .000 |
| | | N | 1494 | 1490 | 1492 | 1490 | 1519 | 547 | 1487 | 1491 | 1412 | 1525 | 1525 | 1525 |
| | RAIN | Correlation Coefficient | .082** | .409** | .036 | .204** | -.488** | -.080 | -.319** | -.300** | -.240** | -.311** | .710** | 1.000 |
| | | Sig. (2-tailed) | .002 | .000 | .161 | .000 | .000 | .061 | .000 | .000 | .000 | .000 | .000 | . |
| | | N | 1494 | 1490 | 1492 | 1490 | 1519 | 547 | 1487 | 1491 | 1412 | 1525 | 1525 | 1525 |

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

*. Correlation is significant at the 0.05 level (2-tailed).

## STEPWISE MULTIPLE LINEAR REGRESSION FOR AMBIENT DATA EQUATION

**Descriptive Statistics**

| | Mean | Std. Deviation | N |
|---|---|---|---|
| PM2.5 | 25.2076 | 14.88073 | 485 |
| CO | .4985 | .20503 | 485 |
| NO2 | 14.8139 | 7.99712 | 485 |
| O3 | 16.0648 | 8.49505 | 485 |
| PM10 | 38.4940 | 17.11221 | 485 |
| TEMP | 28.3596 | 1.53030 | 485 |
| HUM | 72.2353 | 10.20657 | 485 |
| SO2 | 1.7234 | .93238 | 485 |

**Correlations**

| | | PM2.5 | CO | NO2 | O3 | PM10 | TEMP | HUM | SO2 |
|---|---|---|---|---|---|---|---|---|---|
| Pearson Correlation | PM2.5 | 1.000 | .232 | .530 | .670 | .891 | -.306 | -.496 | .452 |
| | CO | .232 | 1.000 | .396 | .106 | .359 | -.245 | .022 | .294 |
| | NO2 | .530 | .396 | 1.000 | .232 | .677 | -.323 | -.150 | .343 |
| | O3 | .670 | .106 | .232 | 1.000 | .636 | -.127 | -.624 | .125 |
| | PM10 | .891 | .359 | .677 | .636 | 1.000 | -.325 | -.557 | .471 |
| | TEMP | -.306 | -.245 | -.323 | -.127 | -.325 | 1.000 | .000 | -.048 |
| | HUM | -.496 | .022 | -.150 | -.624 | -.557 | .000 | 1.000 | -.258 |
| | SO2 | .452 | .294 | .343 | .125 | .471 | -.048 | -.258 | 1.000 |
| Sig. (1-tailed) | PM2.5 | . | .000 | .000 | .000 | .000 | .000 | .000 | .000 |
| | CO | .000 | . | .000 | .010 | .000 | .000 | .317 | .000 |
| | NO2 | .000 | .000 | . | .000 | .000 | .000 | .000 | .000 |
| | O3 | .000 | .010 | .000 | . | .000 | .003 | .000 | .003 |
| | PM10 | .000 | .000 | .000 | .000 | . | .000 | .000 | .000 |
| | TEMP | .000 | .000 | .000 | .003 | .000 | . | .500 | .147 |
| | HUM | .000 | .317 | .000 | .000 | .000 | .500 | . | .000 |
| | SO2 | .000 | .000 | .000 | .003 | .000 | .147 | .000 | . |
| N | PM2.5 | 485 | 485 | 485 | 485 | 485 | 485 | 485 | 485 |
| | CO | 485 | 485 | 485 | 485 | 485 | 485 | 485 | 485 |
| | NO2 | 485 | 485 | 485 | 485 | 485 | 485 | 485 | 485 |
| | O3 | 485 | 485 | 485 | 485 | 485 | 485 | 485 | 485 |
| | PM10 | 485 | 485 | 485 | 485 | 485 | 485 | 485 | 485 |
| | TEMP | 485 | 485 | 485 | 485 | 485 | 485 | 485 | 485 |
| | HUM | 485 | 485 | 485 | 485 | 485 | 485 | 485 | 485 |
| | SO2 | 485 | 485 | 485 | 485 | 485 | 485 | 485 | 485 |

**Model Summary[h]**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | | Durbin-Watson |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change | |
| 1 | .891[a] | .794 | .793 | 6.76243 | .794 | 1860.626 | 1 | 483 | .000 | |
| 2 | .901[b] | .812 | .811 | 6.46765 | .018 | 46.031 | 1 | 482 | .000 | |
| 3 | .904[c] | .817 | .816 | 6.38077 | .005 | 14.214 | 1 | 481 | .000 | |
| 4 | .908[d] | .824 | .822 | 6.27276 | .007 | 17.707 | 1 | 480 | .000 | |
| 5 | .913[e] | .833 | .831 | 6.11238 | .009 | 26.520 | 1 | 479 | .000 | |
| 6 | .915[f] | .837 | .835 | 6.05085 | .004 | 10.792 | 1 | 478 | .001 | |
| 7 | .916[g] | .839 | .836 | 6.01794 | .002 | 6.242 | 1 | 477 | .013 | .323 |

a. Predictors: (Constant), PM10
b. Predictors: (Constant), PM10, O3
c. Predictors: (Constant), PM10, O3, SO2
d. Predictors: (Constant), PM10, O3, SO2, CO
e. Predictors: (Constant), PM10, O3, SO2, CO, HUM
f. Predictors: (Constant), PM10, O3, SO2, CO, HUM, NO2
g. Predictors: (Constant), PM10, O3, SO2, CO, HUM, NO2, TEMP
h. Dependent Variable: PM2.5

**ANOVA[a]**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 85087.294 | 1 | 85087.294 | 1860.626 | .000[b] |
| | Residual | 22087.812 | 483 | 45.730 | | |
| | Total | 107175.106 | 484 | | | |
| 2 | Regression | 87012.809 | 2 | 43506.404 | 1040.064 | .000[c] |
| | Residual | 20162.297 | 482 | 41.830 | | |
| | Total | 107175.106 | 484 | | | |
| 3 | Regression | 87591.537 | 3 | 29197.179 | 717.124 | .000[d] |
| | Residual | 19583.568 | 481 | 40.714 | | |
| | Total | 107175.106 | 484 | | | |
| 4 | Regression | 88288.276 | 4 | 22072.069 | 560.951 | .000[e] |
| | Residual | 18886.830 | 480 | 39.348 | | |
| | Total | 107175.106 | 484 | | | |
| 5 | Regression | 89279.110 | 5 | 17855.822 | 477.925 | .000[f] |
| | Residual | 17895.996 | 479 | 37.361 | | |
| | Total | 107175.106 | 484 | | | |
| 6 | Regression | 89674.221 | 6 | 14945.703 | 408.211 | .000[g] |
| | Residual | 17500.885 | 478 | 36.613 | | |
| | Total | 107175.106 | 484 | | | |
| 7 | Regression | 89900.276 | 7 | 12842.897 | 354.624 | .000[h] |
| | Residual | 17274.830 | 477 | 36.216 | | |
| | Total | 107175.106 | 484 | | | |

# MLR EQUATION CONSTRUTION

| Model | | Unstandardized Coefficients | | Standardized Coefficients | | | 95.0% Confidence Interval for B | | Correlations | | | Collinearity Statistics | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | t | Sig. | Lower Bound | Upper Bound | Zero-order | Partial | Part | Tolerance | VIF |
| 1 | (Constant) | -4.619 | .757 | | -6.105 | .000 | -6.105 | -3.132 | | | | | |
| | PM10 | .775 | .018 | .891 | 43.135 | .000 | .740 | .810 | .891 | .891 | .891 | 1.000 | 1.000 |
| 2 | (Constant) | -5.808 | .745 | | -7.801 | .000 | -7.271 | -4.345 | | | | | |
| | PM10 | .679 | .022 | .780 | 30.481 | .000 | .635 | .722 | .891 | .811 | .602 | .595 | 1.680 |
| | O3 | .304 | .045 | .174 | 6.785 | .000 | .216 | .392 | .670 | .295 | .134 | .595 | 1.680 |
| 3 | (Constant) | -6.992 | .799 | | -8.752 | .000 | -8.562 | -5.423 | | | | | |
| | PM10 | .629 | .026 | .724 | 24.632 | .000 | .579 | .680 | .891 | .747 | .480 | .440 | 2.273 |
| | O3 | .349 | .046 | .199 | 7.613 | .000 | .259 | .438 | .670 | .328 | .148 | .556 | 1.798 |
| | SO2 | 1.375 | .365 | .086 | 3.770 | .000 | .658 | 2.092 | .452 | .169 | .073 | .727 | 1.375 |
| 4 | (Constant) | -4.884 | .932 | | -5.242 | .000 | -6.714 | -3.053 | | | | | |
| | PM10 | .661 | .026 | .760 | 25.217 | .000 | .609 | .712 | .891 | .755 | .483 | .404 | 2.474 |
| | O3 | .322 | .045 | .184 | 7.092 | .000 | .233 | .411 | .670 | .308 | .136 | .546 | 1.832 |
| | SO2 | 1.548 | .361 | .097 | 4.288 | .000 | .838 | 2.257 | .452 | .192 | .082 | .718 | 1.393 |
| | CO | -6.403 | 1.522 | -.088 | -4.208 | .000 | -9.393 | -3.413 | .232 | -.189 | -.08 | .835 | 1.197 |
| 5 | (Constant) | -21.300 | 3.314 | | -6.426 | .000 | -27.813 | -14.787 | | | | | |
| | PM10 | .694 | .026 | .798 | 26.352 | .000 | .642 | .746 | .891 | .769 | .492 | .380 | 2.632 |
| | O3 | .426 | .049 | .243 | 8.760 | .000 | .331 | .522 | .670 | .372 | .164 | .451 | 2.215 |
| | SO2 | 1.821 | .356 | .114 | 5.120 | .000 | 1.122 | 2.520 | .452 | .228 | .096 | .702 | 1.425 |
| | CO | -8.426 | 1.534 | -.116 | -5.493 | .000 | -11.440 | -5.412 | .232 | -.243 | -.103 | .780 | 1.281 |
| | HUM | .194 | .038 | .133 | 5.150 | .000 | .120 | .268 | -.496 | .229 | .096 | .523 | 1.912 |
| 6 | (Constant) | -23.267 | 3.335 | | -6.976 | .000 | -29.821 | -16.714 | | | | | |
| | PM10 | .768 | .034 | .883 | 22.294 | .000 | .700 | .836 | .891 | .714 | .412 | .218 | 4.594 |
| | O3 | .389 | .049 | .222 | 7.862 | .000 | .292 | .486 | .670 | .338 | .145 | .428 | 2.337 |
| | SO2 | 1.767 | .352 | .111 | 5.012 | .000 | 1.074 | 2.459 | .452 | .223 | .093 | .700 | 1.428 |
| | CO | -7.785 | 1.531 | -.107 | -5.085 | .000 | -10.793 | -4.777 | .232 | -.227 | -.094 | .768 | 1.302 |
| | HUM | .222 | .038 | .152 | 5.806 | .000 | .147 | .297 | -.496 | .257 | .107 | .497 | 2.013 |
| | NO2 | -.171 | .052 | -.092 | -3.285 | .001 | -.274 | -.069 | .530 | -.149 | -.061 | .434 | 2.302 |
| 7 | (Constant) | -7.524 | 7.121 | | -1.057 | .291 | -21.517 | 6.469 | | | | | |
| | PM10 | .748 | .035 | .860 | 21.254 | .000 | .679 | .817 | .891 | .697 | .391 | .206 | 4.847 |
| | O3 | .394 | .049 | .225 | 7.996 | .000 | .297 | .491 | .670 | .344 | .147 | .427 | 2.341 |
| | SO2 | 1.902 | .355 | .119 | 5.361 | .000 | 1.205 | 2.599 | .452 | .238 | .099 | .684 | 1.462 |
| | CO | -8.168 | 1.530 | -.113 | -5.338 | .000 | -11.175 | -5.161 | .232 | -.237 | -.098 | .760 | 1.316 |
| | HUM | .208 | .038 | .143 | 5.420 | .000 | .133 | .284 | -.496 | .241 | .100 | .487 | 2.055 |
| | NO2 | -.178 | .052 | -.096 | -3.428 | .001 | -.280 | -.076 | .530 | -.155 | -.063 | .433 | 2.308 |
| | TEMP | -.494 | .198 | -.051 | -2.498 | .013 | -.882 | -.105 | -.306 | -.114 | -.046 | .819 | 1.221 |

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | Tolerance | VIF | Minimum Tolerance |
| 1 | CO | -.100[b] | -4.622 | .000 | -.206 | .871 | 1.148 | .871 |
| | NO2 | -.135[b] | -4.934 | .000 | -.219 | .542 | 1.846 | .542 |
| | O3 | .174[b] | 6.785 | .000 | .295 | .595 | 1.680 | .595 |
| | TEMP | -.018[b] | -.844 | .399 | -.038 | .895 | 1.118 | .895 |
| | HUM | .001[b] | .046 | .963 | .002 | .690 | 1.450 | .690 |
| | SO2 | .042[b] | 1.782 | .075 | .081 | .778 | 1.285 | .778 |
| 2 | CO | -.078[c] | -3.679 | .000 | -.165 | .846 | 1.182 | .509 |
| | NO2 | -.081[c] | -2.863 | .004 | -.129 | .475 | 2.104 | .299 |
| | TEMP | -.034[c] | -1.635 | .103 | -.074 | .884 | 1.131 | .535 |
| | HUM | .084[c] | 3.231 | .001 | .146 | .567 | 1.762 | .490 |
| | SO2 | .086[c] | 3.770 | .000 | .169 | .727 | 1.375 | .440 |
| 3 | CO | -.088[d] | -4.208 | .000 | -.189 | .835 | 1.197 | .404 |
| | NO2 | -.076[d] | -2.683 | .008 | -.122 | .474 | 2.111 | .246 |
| | TEMP | -.048[d] | -2.297 | .022 | -.104 | .861 | 1.161 | .386 |
| | HUM | .097[d] | 3.759 | .000 | .169 | .560 | 1.787 | .426 |
| 4 | NO2 | -.056[e] | -1.971 | .049 | -.090 | .457 | 2.187 | .244 |
| | TEMP | -.063[e] | -3.019 | .003 | -.137 | .842 | 1.188 | .367 |
| | HUM | .133[e] | 5.150 | .000 | .229 | .523 | 1.912 | .380 |
| 5 | NO2 | -.092[f] | -3.285 | .001 | -.149 | .434 | 2.302 | .218 |
| | TEMP | -.047[f] | -2.298 | .022 | -.105 | .821 | 1.218 | .338 |
| 6 | TEMP | -.051[g] | -2.498 | .013 | -.114 | .819 | 1.221 | .206 |

a. Dependent Variable: PM2.5

b. Predictors in the Model: (Constant), PM10

c. Predictors in the Model: (Constant), PM10, O3

d. Predictors in the Model: (Constant), PM10, O3, SO2

e. Predictors in the Model: (Constant), PM10, O3, SO2, CO

f. Predictors in the Model: (Constant), PM10, O3, SO2, CO, HUM

g. Predictors in the Model: (Constant), PM10, O3, SO2, CO, HUM, NO2

**Collinearity Diagnostics[a]**

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | (Constant) | PM10 | O3 | SO2 | CO | HUM | NO2 | TEMP |
| 1 | 1 | 1.914 | 1.000 | .04 | .04 | | | | | | |
| | 2 | .086 | 4.716 | .96 | .96 | | | | | | |
| 2 | 1 | 2.818 | 1.000 | .02 | .01 | .02 | | | | | |
| | 2 | .117 | 4.904 | .78 | .01 | .44 | | | | | |
| | 3 | .065 | 6.596 | .20 | .97 | .55 | | | | | |
| 3 | 1 | 3.655 | 1.000 | .01 | .01 | .01 | .01 | | | | |
| | 2 | .197 | 4.307 | .00 | .01 | .27 | .46 | | | | |
| | 3 | .099 | 6.073 | .99 | .07 | .07 | .16 | | | | |
| | 4 | .049 | 8.610 | .00 | .92 | .66 | .37 | | | | |
| 4 | 1 | 4.536 | 1.000 | .00 | .00 | .01 | .01 | .01 | | | |
| | 2 | .206 | 4.694 | .00 | .01 | .31 | .27 | .05 | | | |
| | 3 | .141 | 5.670 | .08 | .02 | .02 | .45 | .35 | | | |
| | 4 | .073 | 7.866 | .75 | .15 | .00 | .01 | .38 | | | |
| | 5 | .044 | 10.160 | .16 | .81 | .66 | .26 | .22 | | | |
| 5 | 1 | 5.437 | 1.000 | .00 | .00 | .00 | .00 | .00 | .00 | | |
| | 2 | .229 | 4.874 | .00 | .04 | .22 | .01 | .04 | .01 | | |
| | 3 | .184 | 5.442 | .00 | .01 | .04 | .59 | .00 | .01 | | |
| | 4 | .101 | 7.342 | .01 | .02 | .01 | .12 | .78 | .01 | | |
| | 5 | .045 | 10.981 | .00 | .87 | .51 | .24 | .15 | .00 | | |
| | 6 | .004 | 36.102 | .99 | .06 | .22 | .04 | .03 | .97 | | |
| 6 | 1 | 6.302 | 1.000 | .00 | .00 | .00 | .00 | .00 | .00 | .00 | |
| | 2 | .231 | 5.219 | .00 | .02 | .15 | .01 | .04 | .01 | .01 | |
| | 3 | .195 | 5.681 | .00 | .00 | .12 | .30 | .00 | .01 | .08 | |
| | 4 | .149 | 6.505 | .00 | .00 | .03 | .48 | .03 | .00 | .29 | |
| | 5 | .090 | 8.353 | .01 | .00 | .01 | .00 | .90 | .01 | .11 | |
| | 6 | .028 | 15.049 | .00 | .86 | .53 | .18 | .01 | .00 | .46 | |
| | 7 | .004 | 39.792 | .99 | .12 | .14 | .03 | .02 | .97 | .05 | |
| 7 | 1 | 7.251 | 1.000 | .00 | .00 | .00 | .00 | .00 | .00 | .00 | .00 |
| | 2 | .262 | 5.256 | .00 | .02 | .06 | .01 | .01 | .01 | .05 | .00 |
| | 3 | .206 | 5.935 | .00 | .00 | .22 | .24 | .02 | .00 | .05 | .00 |
| | 4 | .150 | 6.956 | .00 | .00 | .03 | .52 | .05 | .00 | .25 | .00 |
| | 5 | .095 | 8.735 | .00 | .00 | .02 | .00 | .87 | .00 | .14 | .00 |
| | 6 | .028 | 16.110 | .00 | .81 | .55 | .18 | .01 | .00 | .45 | .00 |
| | 7 | .007 | 32.477 | .02 | .06 | .12 | .04 | .05 | .77 | .06 | .11 |
| | 8 | .001 | 87.862 | .98 | .10 | .01 | .01 | .00 | .21 | .00 | .88 |

a. Dependent Variable: PM2.5

**Residuals Statistics[a]**

| | Minimum | Maximum | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Predicted Value | 3.7825 | 73.1499 | 25.2076 | 13.62881 | 485 |
| Residual | -18.33227 | 14.66118 | .00000 | 5.97426 | 485 |
| Std. Predicted Value | -1.572 | 3.518 | .000 | 1.000 | 485 |
| Std. Residual | -3.046 | 2.436 | .000 | .993 | 485 |

a. Dependent Variable: PM2.5

# Roadside Monitoring Data Analysis

Spearman's Correlations Analysis of Roadside monitoring station data

| | | | CO | NO | NO2 | NOX | O3 | SO2 | PM10 | PM2.5 | WS | TEMP | HUM | RAIN |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Spearman's rho | CO | Correlation Coefficient | 1.000 | .523** | .626** | .681** | -.152** | .411** | .528** | .422** | -.467** | -.090** | -.089** | .001 |
| | | Sig. (2-tailed) | . | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .001 | .001 | .969 |
| | | N | 1281 | 1124 | 1124 | 1124 | 987 | 1002 | 1272 | 1079 | 1214 | 1273 | 1273 | 1273 |
| | NO | Correlation Coefficient | .523** | 1.000 | .440** | .875** | -.598** | .355** | .364** | .082** | -.165** | -.151** | .040 | .161** |
| | | Sig. (2-tailed) | .000 | . | .000 | .000 | .000 | .000 | .000 | .009 | .000 | .000 | .166 | .000 |
| | | N | 1124 | 1185 | 1185 | 1185 | 923 | 926 | 1176 | 1010 | 1134 | 1177 | 1177 | 1177 |
| | NO2 | Correlation Coefficient | .626** | .440** | 1.000 | .785** | .024 | .367** | .744** | .731** | -.501** | -.026 | -.354** | -.179** |
| | | Sig. (2-tailed) | .000 | .000 | . | .000 | .475 | .000 | .000 | .000 | .000 | .368 | .000 | .000 |
| | | N | 1124 | 1185 | 1185 | 1185 | 923 | 926 | 1176 | 1010 | 1134 | 1177 | 1177 | 1177 |
| | NOX | Correlation Coefficient | .681** | .875** | .785** | 1.000 | -.349** | .419** | .605** | .418** | -.417** | -.128** | -.118** | .047 |
| | | Sig. (2-tailed) | .000 | .000 | .000 | . | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .104 |
| | | N | 1124 | 1185 | 1185 | 1185 | 923 | 926 | 1176 | 1010 | 1134 | 1177 | 1177 | 1177 |
| | O3 | Correlation Coefficient | -.152** | -.598** | .024 | -.349** | 1.000 | .069* | .154** | .339** | -.069* | -.114** | -.296** | -.347** |
| | | Sig. (2-tailed) | .000 | .000 | .475 | .000 | . | .034 | .000 | .000 | .025 | .000 | .000 | .000 |
| | | N | 987 | 923 | 923 | 923 | 1116 | 960 | 1107 | 930 | 1064 | 1108 | 1108 | 1108 |
| | SO2 | Correlation Coefficient | .411** | .355** | .367** | .419** | .069* | 1.000 | .317** | .292** | -.146** | -.238** | -.197** | -.042 |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 | .034 | . | .000 | .000 | .000 | .000 | .000 | .174 |
| | | N | 1002 | 926 | 926 | 926 | 960 | 1054 | 1045 | 843 | 1025 | 1046 | 1046 | 1046 |
| | PM10 | Correlation Coefficient | .528** | .364** | .744** | .605** | .154** | .317** | 1.000 | .853** | -.477** | -.028 | -.383** | -.252** |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 | .000 | .000 | . | .000 | .000 | .290 | .000 | .000 |
| | | N | 1272 | 1176 | 1176 | 1176 | 1107 | 1045 | 1437 | 1222 | 1371 | 1430 | 1430 | 1430 |
| | PM2.5 | Correlation Coefficient | .422** | .082** | .731** | .418** | .339** | .292** | .853** | 1.000 | -.367** | -.031 | -.376** | -.337** |
| | | Sig. (2-tailed) | .000 | .009 | .000 | .000 | .000 | .000 | .000 | . | .000 | .277 | .000 | .000 |
| | | N | 1079 | 1010 | 1010 | 1010 | 930 | 843 | 1222 | 1228 | 1167 | 1220 | 1220 | 1220 |
| | WS | Correlation Coefficient | -.467** | -.165** | -.501** | -.417** | -.069* | -.146** | -.477** | -.367** | 1.000 | .178** | .052 | -.057* |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 | .025 | .000 | .000 | .000 | . | .000 | .056 | .036 |
| | | N | 1214 | 1134 | 1134 | 1134 | 1064 | 1025 | 1371 | 1167 | 1379 | 1379 | 1379 | 1379 |
| | TEMP | Correlation Coefficient | -.090** | -.151** | -.026 | -.128** | -.114** | -.238** | -.028 | -.031 | .178** | 1.000 | -.360** | -.297** |
| | | Sig. (2-tailed) | .001 | .000 | .368 | .000 | .000 | .000 | .290 | .277 | .000 | . | .000 | .000 |
| | | N | 1273 | 1177 | 1177 | 1177 | 1108 | 1046 | 1430 | 1220 | 1379 | 1438 | 1438 | 1438 |
| | HUM | Correlation Coefficient | -.089** | .040 | -.354** | -.118** | -.296** | -.197** | -.383** | -.376** | .052 | -.360** | 1.000 | .638** |
| | | Sig. (2-tailed) | .001 | .166 | .000 | .000 | .000 | .000 | .000 | .000 | .056 | .000 | . | .000 |
| | | N | 1273 | 1177 | 1177 | 1177 | 1108 | 1046 | 1430 | 1220 | 1379 | 1438 | 1438 | 1438 |
| | RAIN | Correlation Coefficient | .001 | .161** | -.179** | .047 | -.347** | -.042 | -.252** | -.337** | -.057* | -.297** | .638** | 1.000 |
| | | Sig. (2-tailed) | .969 | .000 | .000 | .104 | .000 | .174 | .000 | .000 | .036 | .000 | .000 | . |
| | | N | 1273 | 1177 | 1177 | 1177 | 1108 | 1046 | 1430 | 1220 | 1379 | 1438 | 1438 | 1438 |

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

*. Correlation is significant at the 0.05 level (2-tailed).

**STEPWISE MULTIPLE LINEAR REGRESSION FOR ROADSIDE DATA EQUATION**

**Descriptive Statistics**

| | Mean | Std. Deviation | N |
|---|---|---|---|
| PM2.5 | 32.6357 | 16.71023 | 685 |
| CO | .8034 | .34945 | 685 |
| NO | 31.4608 | 31.65323 | 685 |
| NO2 | 24.2720 | 13.63714 | 685 |
| NOX | 55.3775 | 41.00363 | 685 |
| O3 | 14.6642 | 8.45819 | 685 |
| SO2 | 1.6819 | .90267 | 685 |
| PM10 | 46.0805 | 20.43197 | 685 |
| WS | .8095 | .47625 | 685 |
| HUM | 65.4614 | 9.86311 | 685 |
| RAIN | .2225 | .58813 | 685 |

| | | PM2.5 | CO | NO | NO2 | NOX | O3 | SO2 | PM10 | WS | HUM | RAIN |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Pearson Correlation | PM2.5 | 1.000 | .456 | .310 | .767 | .495 | .502 | .446 | .939 | -.486 | -.478 | -.177 |
| | CO | .456 | 1.000 | .284 | .509 | .388 | -.044 | .367 | .437 | -.510 | -.005 | .046 |
| | NO | .310 | .284 | 1.000 | .593 | .960 | -.381 | .272 | .336 | -.065 | -.061 | .034 |
| | NO2 | .767 | .509 | .593 | 1.000 | .791 | .189 | .390 | .741 | -.544 | -.384 | -.089 |
| | NOX | .495 | .388 | .960 | .791 | 1.000 | -.224 | .336 | .504 | -.234 | -.179 | -.008 |
| | O3 | .502 | -.044 | -.381 | .189 | -.224 | 1.000 | .106 | .477 | -.235 | -.531 | -.193 |
| | SO2 | .446 | .367 | .272 | .390 | .336 | .106 | 1.000 | .482 | -.256 | -.272 | -.065 |
| | PM10 | .939 | .437 | .336 | .741 | .504 | .477 | .482 | 1.000 | -.480 | -.503 | -.190 |
| | WS | -.486 | -.510 | -.065 | -.544 | -.234 | -.235 | -.256 | -.480 | 1.000 | .151 | -.057 |
| | HUM | -.478 | -.005 | -.061 | -.384 | -.179 | -.531 | -.272 | -.503 | .151 | 1.000 | .416 |
| | RAIN | -.177 | .046 | .034 | -.089 | -.008 | -.193 | -.065 | -.190 | -.057 | .416 | 1.000 |
| Sig. (1-tailed) | PM2.5 | . | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .000 |
| | CO | .000 | . | .000 | .000 | .000 | .125 | .000 | .000 | .000 | .445 | .113 |
| | NO | .000 | .000 | . | .000 | .000 | .000 | .000 | .000 | .045 | .056 | .190 |
| | NO2 | .000 | .000 | .000 | . | .000 | .000 | .000 | .000 | .000 | .000 | .010 |
| | NOX | .000 | .000 | .000 | .000 | . | .000 | .000 | .000 | .000 | .000 | .420 |
| | O3 | .000 | .125 | .000 | .000 | .000 | . | .003 | .000 | .000 | .000 | .000 |
| | SO2 | .000 | .000 | .000 | .000 | .000 | .003 | . | .000 | .000 | .000 | .045 |
| | PM10 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | . | .000 | .000 | .000 |
| | WS | .000 | .000 | .045 | .000 | .000 | .000 | .000 | .000 | . | .000 | .068 |
| | HUM | .000 | .445 | .056 | .000 | .000 | .000 | .000 | .000 | .000 | . | .000 |
| | RAIN | .000 | .113 | .190 | .010 | .420 | .000 | .045 | .000 | .068 | .000 | . |
| N | PM2.5 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 |
| | CO | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 |
| | NO | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 |
| | NO2 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 |
| | NOX | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 |
| | O3 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 |
| | SO2 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 |
| | PM10 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 |
| | WS | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 |
| | HUM | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 |
| | RAIN | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 | 685 |

**Model Summary[g]**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | | Durbin-Watson |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change | |
| 1 | .939[a] | .882 | .882 | 5.73219 | .882 | 5129.737 | 1 | 683 | .000 | |
| 2 | .945[b] | .894 | .893 | 5.45390 | .011 | 72.479 | 1 | 682 | .000 | |
| 3 | .950[c] | .903 | .902 | 5.22139 | .009 | 63.092 | 1 | 681 | .000 | |
| 4 | .951[d] | .905 | .904 | 5.17249 | .002 | 13.936 | 1 | 680 | .000 | |
| 5 | .952[e] | .906 | .905 | 5.15384 | .001 | 5.931 | 1 | 679 | .015 | |
| 6 | .952[f] | .906 | .905 | 5.14107 | .001 | 4.375 | 1 | 678 | .037 | 1.106 |

a. Predictors: (Constant), PM10

b. Predictors: (Constant), PM10, NO2

c. Predictors: (Constant), PM10, NO2, O3

d. Predictors: (Constant), PM10, NO2, O3, CO

e. Predictors: (Constant), PM10, NO2, O3, CO, HUM

f. Predictors: (Constant), PM10, NO2, O3, CO, HUM, WS

g. Dependent Variable: PM2.5

**ANOVA[a]**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 168552.621 | 1 | 168552.621 | 5129.737 | .000[b] |
| | Residual | 22441.978 | 683 | 32.858 | | |
| | Total | 190994.599 | 684 | | | |
| 2 | Regression | 170708.511 | 2 | 85354.255 | 2869.533 | .000[c] |
| | Residual | 20286.088 | 682 | 29.745 | | |
| | Total | 190994.599 | 684 | | | |
| 3 | Regression | 172428.587 | 3 | 57476.196 | 2108.223 | .000[d] |
| | Residual | 18566.012 | 681 | 27.263 | | |
| | Total | 190994.599 | 684 | | | |
| 4 | Regression | 172801.438 | 4 | 43200.360 | 1614.686 | .000[e] |
| | Residual | 18193.161 | 680 | 26.755 | | |
| | Total | 190994.599 | 684 | | | |
| 5 | Regression | 172958.990 | 5 | 34591.798 | 1302.303 | .000[f] |
| | Residual | 18035.609 | 679 | 26.562 | | |
| | Total | 190994.599 | 684 | | | |
| 6 | Regression | 173074.633 | 6 | 28845.772 | 1091.377 | .000[g] |
| | Residual | 17919.966 | 678 | 26.431 | | |
| | Total | 190994.599 | 684 | | | |

## MLR EQUATION CONSTRUCTION

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. | 95.0% Confidence Interval for B | | Correlations | | | Collinearity Statistics | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | | Lower Bound | Upper Bound | Zero-order | Partial | Part | Tolerance | VIF |
| 1 | (Constant) | -2.768 | .541 | | -5.119 | .000 | -3.829 | -1.706 | | | | | |
| | PM10 | .768 | .011 | .939 | 71.622 | .000 | .747 | .789 | .939 | .939 | .939 | 1.000 | 1.000 |
| 2 | (Constant) | -3.057 | .516 | | -5.929 | .000 | -4.069 | -2.044 | | | | | |
| | PM10 | .672 | .015 | .822 | 44.265 | .000 | .643 | .702 | .939 | .861 | .552 | .451 | 2.216 |
| | NO2 | .194 | .023 | .158 | 8.513 | .000 | .149 | .238 | .767 | .310 | .106 | .451 | 2.216 |
| 3 | (Constant) | -4.367 | .520 | | -8.391 | .000 | -5.388 | -3.345 | | | | | |
| | PM10 | .604 | .017 | .738 | 35.661 | .000 | .570 | .637 | .939 | .807 | .426 | .333 | 3.002 |
| | NO2 | .244 | .023 | .199 | 10.757 | .000 | .200 | .289 | .767 | .381 | .129 | .416 | 2.403 |
| | O3 | .222 | .028 | .112 | 7.943 | .000 | .167 | .277 | .502 | .291 | .095 | .712 | 1.405 |
| 4 | (Constant) | -5.660 | .621 | | -9.113 | .000 | -6.879 | -4.440 | | | | | |
| | PM10 | .589 | .017 | .721 | 34.252 | .000 | .556 | .623 | .939 | .796 | .405 | .317 | 3.159 |
| | NO2 | .224 | .023 | .182 | 9.660 | .000 | .178 | .269 | .767 | .347 | .114 | .393 | 2.547 |
| | O3 | .250 | .029 | .126 | 8.707 | .000 | .193 | .306 | .502 | .317 | .103 | .665 | 1.504 |
| | CO | 2.553 | .684 | .053 | 3.733 | .000 | 1.210 | 3.895 | .456 | .142 | .044 | .685 | 1.460 |
| 5 | (Constant) | -10.490 | 2.077 | | -5.049 | .000 | -14.57 | -6.411 | | | | | |
| | PM10 | .597 | .017 | .730 | 34.275 | .000 | .563 | .631 | .939 | .796 | .404 | .307 | 3.258 |
| | NO2 | .235 | .024 | .191 | 9.983 | .000 | .188 | .281 | .767 | .358 | .118 | .378 | 2.645 |
| | O3 | .276 | .031 | .140 | 9.033 | .000 | .216 | .336 | .502 | .328 | .107 | .581 | 1.722 |
| | CO | 2.183 | .698 | .046 | 3.127 | .002 | .812 | 3.553 | .456 | .119 | .037 | .653 | 1.532 |
| | HUM | .063 | .026 | .037 | 2.435 | .015 | .012 | .114 | -.478 | .093 | .029 | .595 | 1.681 |
| 6 | (Constant) | -12.846 | 2.359 | | -5.446 | .000 | -17.477 | -8.214 | | | | | |
| | PM10 | .597 | .017 | .730 | 34.368 | .000 | .563 | .631 | .939 | .797 | .404 | .307 | 3.258 |
| | NO2 | .249 | .024 | .204 | 10.185 | .000 | .201 | .297 | .767 | .364 | .120 | .346 | 2.886 |
| | O3 | .292 | .031 | .148 | 9.294 | .000 | .230 | .353 | .502 | .336 | .109 | .549 | 1.823 |
| | CO | 2.685 | .737 | .056 | 3.645 | .000 | 1.239 | 4.131 | .456 | .139 | .043 | .583 | 1.714 |
| | HUM | .070 | .026 | .041 | 2.686 | .007 | .019 | .121 | -.478 | .103 | .032 | .585 | 1.708 |
| | WS | 1.126 | .538 | .032 | 2.092 | .037 | .069 | 2.183 | -.486 | .080 | .025 | .588 | 1.700 |

a. Dependent Variable: PM2.5

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | Tolerance | VIF | Minimum Tolerance |
| 1 | CO | .056[b] | 3.847 | .000 | .146 | .809 | 1.236 | .809 |
| | NO | -.007[b] | -.476 | .634 | -.018 | .887 | 1.127 | .887 |
| | NO2 | .158[b] | 8.513 | .000 | .310 | .451 | 2.216 | .451 |
| | NOX | .030[b] | 1.948 | .052 | .074 | .746 | 1.340 | .746 |
| | O3 | .070[b] | 4.759 | .000 | .179 | .772 | 1.295 | .772 |
| | SO2 | -.009[b] | -.593 | .553 | -.023 | .768 | 1.302 | .768 |
| | WS | -.046[b] | -3.072 | .002 | -.117 | .770 | 1.299 | .770 |
| | HUM | -.007[b] | -.463 | .644 | -.018 | .747 | 1.338 | .747 |
| | RAIN | .002[b] | .126 | .900 | .005 | .964 | 1.037 | .964 |
| 2 | CO | .021[c] | 1.473 | .141 | .056 | .733 | 1.364 | .409 |
| | NO | -.097[c] | -6.292 | .000 | -.234 | .624 | 1.602 | .318 |
| | NOX | -.122[c] | -6.022 | .000 | -.225 | .360 | 2.776 | .218 |
| | O3 | .112[c] | 7.943 | .000 | .291 | .712 | 1.405 | .333 |
| | SO2 | -.016[c] | -1.103 | .270 | -.042 | .765 | 1.306 | .407 |
| | WS | -.008[c] | -.509 | .611 | -.020 | .691 | 1.447 | .405 |
| | HUM | -.005[c] | -.321 | .748 | -.012 | .747 | 1.339 | .395 |
| | RAIN | -.007[c] | -.529 | .597 | -.020 | .958 | 1.044 | .436 |
| 3 | CO | .053[d] | 3.733 | .000 | .142 | .685 | 1.460 | .317 |
| | NO | -.036[d] | -1.847 | .065 | -.071 | .382 | 2.621 | .313 |
| | NOX | -.040[d] | -1.568 | .117 | -.060 | .223 | 4.483 | .199 |
| | SO2 | .001[d] | .055 | .956 | .002 | .748 | 1.337 | .294 |
| | WS | .005[d] | .318 | .750 | .012 | .683 | 1.464 | .332 |
| | HUM | .048[d] | 3.172 | .002 | .121 | .624 | 1.602 | .328 |
| | RAIN | .003[d] | .255 | .799 | .010 | .948 | 1.055 | .329 |
| 4 | NO | -.021[e] | -1.071 | .285 | -.041 | .363 | 2.753 | .282 |
| | NOX | -.020[e] | -.790 | .430 | -.030 | .213 | 4.704 | .179 |
| | SO2 | -.008[e] | -.545 | .586 | -.021 | .729 | 1.372 | .287 |
| | WS | .027[e] | 1.759 | .079 | .067 | .598 | 1.673 | .316 |
| | HUM | .037[e] | 2.435 | .015 | .093 | .595 | 1.681 | .307 |
| | RAIN | -.002[e] | -.144 | .885 | -.006 | .937 | 1.067 | .311 |
| 5 | NO | -.018[f] | -.908 | .364 | -.035 | .362 | 2.766 | .278 |
| | NOX | -.016[f] | -.607 | .544 | -.023 | .211 | 4.732 | .178 |
| | SO2 | -.003[f] | -.184 | .854 | -.007 | .713 | 1.403 | .282 |
| | WS | .032[f] | 2.092 | .037 | .080 | .588 | 1.700 | .307 |
| | RAIN | -.014[f] | -1.097 | .273 | -.042 | .816 | 1.226 | .305 |
| 6 | NO | -.035[g] | -1.703 | .089 | -.065 | .322 | 3.108 | .230 |
| | NOX | -.037[g] | -1.376 | .169 | -.053 | .188 | 5.308 | .146 |
| | SO2 | -.003[g] | -.201 | .841 | -.008 | .713 | 1.403 | .282 |
| | RAIN | -.012[g] | -.890 | .374 | -.034 | .807 | 1.239 | .305 |

a. Dependent Variable: PM2.5
b. Predictors in the Model: (Constant), PM10
c. Predictors in the Model: (Constant), PM10, NO2
d. Predictors in the Model: (Constant), PM10, NO2, O3
e. Predictors in the Model: (Constant), PM10, NO2, O3, CO
f. Predictors in the Model: (Constant), PM10, NO2, O3, CO, HUM
g. Predictors in the Model: (Constant), PM10, NO2, O3, CO, HUM, WS

**Collinearity Diagnostics[a]**

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | (Constant) | PM10 | NO2 | O3 | CO | HUM | WS |
| 1 | 1 | 1.914 | 1.000 | .04 | .04 | | | | | |
| | 2 | .086 | 4.726 | .96 | .96 | | | | | |
| 2 | 1 | 2.821 | 1.000 | .02 | .01 | .01 | | | | |
| | 2 | .132 | 4.629 | .76 | .02 | .30 | | | | |
| | 3 | .048 | 7.681 | .23 | .98 | .69 | | | | |
| 3 | 1 | 3.645 | 1.000 | .01 | .00 | .01 | .01 | | | |
| | 2 | .205 | 4.217 | .00 | .01 | .19 | .49 | | | |
| | 3 | .113 | 5.686 | .96 | .02 | .07 | .21 | | | |
| | 4 | .037 | 9.871 | .02 | .97 | .73 | .28 | | | |
| 4 | 1 | 4.522 | 1.000 | .00 | .00 | .00 | .01 | .00 | | |
| | 2 | .241 | 4.330 | .00 | .00 | .05 | .46 | .09 | | |
| | 3 | .139 | 5.703 | .25 | .04 | .25 | .01 | .14 | | |
| | 4 | .061 | 8.586 | .74 | .00 | .09 | .19 | .74 | | |
| | 5 | .037 | 11.072 | .00 | .96 | .60 | .34 | .03 | | |
| 5 | 1 | 5.409 | 1.000 | .00 | .00 | .00 | .00 | .00 | .00 | |
| | 2 | .247 | 4.682 | .00 | .01 | .00 | .39 | .07 | .01 | |
| | 3 | .226 | 4.891 | .01 | .02 | .17 | .03 | .01 | .02 | |
| | 4 | .075 | 8.471 | .01 | .00 | .22 | .10 | .87 | .01 | |
| | 5 | .037 | 12.109 | .00 | .93 | .58 | .30 | .03 | .00 | |
| | 6 | .005 | 31.682 | .99 | .04 | .04 | .18 | .02 | .97 | |
| 6 | 1 | 6.053 | 1.000 | .00 | .00 | .00 | .00 | .00 | .00 | .00 |
| | 2 | .502 | 3.471 | .00 | .01 | .03 | .01 | .01 | .00 | .17 |
| | 3 | .245 | 4.965 | .00 | .00 | .02 | .39 | .07 | .00 | .00 |
| | 4 | .108 | 7.492 | .00 | .04 | .27 | .07 | .22 | .01 | .21 |
| | 5 | .052 | 10.795 | .02 | .07 | .10 | .00 | .55 | .07 | .37 |
| | 6 | .035 | 13.136 | .00 | .85 | .50 | .30 | .15 | .01 | .09 |
| | 7 | .005 | 36.040 | .98 | .03 | .08 | .23 | .00 | .90 | .15 |

a. Dependent Variable: PM2.5



**Residuals Statistics[a]**

| | Minimum | Maximum | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Predicted Value | 6.3598 | 96.3534 | 32.6590 | 15.96884 | 695 |
| Residual | -23.74317 | 45.30427 | -.00511 | 5.22520 | 695 |
| Std. Predicted Value | -1.652 | 4.006 | .001 | 1.004 | 695 |
| Std. Residual | -4.618 | 8.812 | -.001 | 1.016 | 695 |

a. Dependent Variable: PM2.5

# APPENDIX C

The 10th Better Air Quality Conference

Kuching Malaysia

14 – 16 November 2018

**Poster Presentation**

## Mathematic Model Prediction of Fine Particulate Matter Concentrations in Bangkok: Implications for Air Quality and Health

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**ABSTRACT**
Atmospheric particulate matter particles with a diameter less than 10 micron ($PM_{10}$) and less than 2.5 micron ($PM_{2.5}$) have been adverse human health effect. Ambient air pollution data in central area of Bangkok monitored by Pollution Control Department, Thailand were collected over ten years in Bangkok from 2008 to 2017. The daily average air pollution data were used as the input data to develop mathematic models by stepwise multiple regression technique. The equations divided for general air and roadside air were applied to forecast $PM_{2.5}$ concentration in Bangkok from 2018 to 2020. The predicted results were validated by statistical methods. The validated equations were effectively used to predict $PM_{2.5}$ concentration in Bangkok with the existing atmospheric variables. The $PM_{2.5}$ from the observed and predicted values was interpolated with GIS with Inverse Distance Weighted (IDW) technique to create PM distribution maps in Bangkok. GIS-based maps illustrated the variability and risk area of ambient $PM_{2.5}$. These outcomes could be support national policy for the awareness of human health impact from fine particulate matter.

**Keywords:** *$PM_{10}$, $PM_{2.5}$, GIS, Atmospheric particulate matter, Multiple regression analysis*

E-Abstract book: https://baq2018.org/wp-content/uploads/2018/11/BAQ-E-ABSTRACT_COMPILATION.pdf

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**Oral Presentation**

The 2nd International Conference on Environment, Livelihood, and Services (ICELS 2018)
19 – 22 November 2018

**AO008**

# Statistical Distribution Techniques for Estimating $PM_{2.5}$ Concentrations and Assessing Quantitative Health Risks in Bangkok.

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## Abstract

Daily average air pollution data in 2015-2017, as monitored by the Bangkok Metropolitan Administration (BMA) and Pollution Control Department (PCD), were used as the dependent variables to develop multiple linear regression (MLR) equations. $PM_{2.5}$ in non-detected areas was estimated from the ambient air quality equation and roadside air quality equation. The generated $PM_{2.5}$ concentrations were validated by various statistical performance indicators. The Q-Q plots of the measured and observed values of both selected ambient monitoring data and roadside monitoring data had significant correlations, with $R^2$ = 0.88 and 0.96, respectively. The non-carcinogenic health risk assessment of $PM_{2.5}$ was quantified as the hazard quotient (HQ) from both the measured data and predicted data. The risk areas and HQ were compared using inverse distance weighting interpolation and illustrated with GIS-based maps. The highest HQ value was discovered in the southern area of the central business district of Bangkok.

**Keywords:** $PM_{2.5}$, Multiple linear regression, HQ, GIS

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