HEALTH EFFECTS OF $PM_{2.5}$ ON CHILDREN AND HEALTH BURDEN AND ASSOCIATED ECONOMIC BURDEN OF $PM_{2.5}$ IN HO CHI MINH CITY, VIETNAM

BY

TINH HO HUU

A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF THE DOCTOR OF PHILOSOPHY IN (OCCUPATIONAL AND ENVIRONMENTAL HEALTH)

FACULTY OF PUBLIC HEALTH

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ABSTRACT

Ambient fine particulate matter ($PM_{2.5}$) is a growing issue in Ho Chi Minh City (HCMC), the most populous province in Vietnam. Study on the adverse health effects, particularly on children, caused by exposure to $PM_{2.5}$ has still been sparse in the city. This study aimed to evaluate the health effects of $PM_{2.5}$ on children and estimate the burdens of $PM_{2.5}$, including health and associated economic burdens, among the whole population in HCMC, Vietnam.

The study collected the daily $PM_{2.5}$ concentrations from the United State Consulate in HCMC and the Vietnam National University in HCMC (two fixed monitoring stations) from 2016 – 2019. The health database was collected from hospitals and commune health stations.

First, the study collected computerized records of children hospitalized by acute lower respiratory infections – ALRI (61,204 records) and asthma (11,223 records) in all pediatric hospitals. The generalized linear models with the family of quasi-Poisson distribution were used to determine the association between daily exposure to $PM_{2.5}$ and hospital admissions for respiratory diseases (ALRI, asthma).

Second, the study collected data from 163,868 women with singleton pregnancies from three maternity hospitals in HCMC. Linear regression and logistic regression were employed to determine the association between exposure to $PM_{2.5}$ and birth weight (BW), preterm birth (PTB), and term low birth weight (LBW). The adverse effects of $PM_{2.5}$ were estimated during five different periods of $PM_{2.5}$ exposure, including the first month of pregnancy, the first trimester, the second trimester, the third trimester, and the entire pregnancy.

Third, 28,837 deaths recorded in 2019 were analyzed to calculate the death rate. The Environmental Benefits Mapping and Analysis Program - Community Edition (BenMAP-CE) was applied to estimate the health and economic benefits in three controlling scenarios of annual average $PM_{2.5}$ concentration in 2019. The three scenarios were rolling back to the World Health Organization's annual average Air Quality Guideline values of 5 $\mu g/m^3$ (guideline value in 2021) and 10 $\mu g/m^3$ (guideline value in 2005 which becomes Interim Target 4 of 2021 WHO Air Quality Guideline), and the Vietnamese annual average standard of 25 $\mu g/m^3$.

The study found that the mean of daily average $PM_{2.5}$ concentration in HCMC from 2016-2019 was 28.0 $\mu g/m^3$, exceeding the Vietnamese standard and the WHO guidelines. Each 10 $\mu g/m^3$ increase in $PM_{2.5}$ posed an excess risk of 1.86% (95% CI: 0.24% ~ 3.52%) ALRI admission after six days of exposure (lag_6). Exposure to $PM_{2.5}$ resulted in more hospital admissions in male children and the age group from 2 to under 5 years old than in females and the age group one or under, respectively. Similarly, ambient $PM_{2.5}$ is associated with hospital admissions for asthma among children under 5 years old. The excess risk of hospital admission was 3.86% (95% CI: 0.44%~7.4%) per 10 $\mu g/m^3$ increase in $PM_{2.5}$ level (4-day average exposure), females are sensitive than males and age group from 2-5 are more vulnerable than the age group 1 or under.

The study also indicated that prenatal exposure to $PM_{2.5}$ decreased BW and increased the risk of PTB. Each 10 $\mu g/m^3$ increase in $PM_{2.5}$ during the second trimester lowered with 11.8 g the BW (95% confident interval - CI: 5.2 – 18.3) and increased with 23.1% the risk of PTB (Odds ratio – OR = 1.23, 95%CI: 1.14 – 1.34). However, the association between maternal exposure to $PM_{2.5}$ and the risk of term LBW was not statistically significant.

Applying the BenMAP-CE, the pooled number of avoided deaths of all causes were 3,785 (1,179-6,335), 3,195 (982-5,468), and 1,300 (384-2,386) for three scenarios, respectively. The associated economic benefits were \$ 0.8-6.2, \$ 0.6-5.4, and \$ 0.2-2.3 billion, respectively.

Overall, the study findings show that the annual average concentration of $PM_{2.5}$ in HCMC exceeded the Air Quality Guideline of the World Health Organization and significantly contributed to increasing respiratory diseases among children. Additionally, maternal exposure to $PM_{2.5}$ shows a risk of a decrease in BW and the risk of PTB. Meanwhile, controlling $PM_{2.5}$ greatly benefits health and the economy; thus, the city should have action plans for mitigating the $PM_{2.5}$ pollution.

Keywords: Air pollution, Fine particulate matter, Particulate matter, Lower respiratory infection, ALRI, Low birth weight, Preterm birth, Health benefits, Economic benefits, BenMAP, Value of statistical life, VSL

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LIST OF ABBREVIATIONS

Symbols/Abbreviations	Terms
AAP	Ambient air pollution
AED	Aerodynamic equivalent diameter
ALRI	Acute lower respiratory infections
AQG	Air Quality Guidelines
AQMS	Air quality monitoring system
BenMAP-CE	Environmental Benefits Mapping and Analysis Program - Community Edition
CAP	Criteria air pollutants
CI	Confident interval
CHS	Commune health station
COI	Cost of illness
COPD	Chronic obstructive pulmonary disease
CPI	Consumer price index
C-R	The concentration-response
EBD	Environmental Burden of Disease Assessment tool
EC	Elemental carbon
USEPA	The United States Environmental Protection Agency
ESCAPE	European Study of Cohorts for Air Pollution Effects
FEV1	Forced expiration volume in 1s
FVC	Forced vital capacity
DALY	Disability-adjusted life year
GAINS	Greenhouse Gas and Air Pollution Interactions and Synergies
GDP	Gross Domestic Product
IARC	The International Agency for Research on Cancer
ICD-10	International Classification of Diseases, 10th revision
IHD	Ischemic heart disease
IPF	Idiopathic pulmonary fibrosis
IT	Interim target

Symbols/Abbreviations	**Terms**
HAP	Household air pollution/Indoor air pollution
HAPIT	Household Air Pollution Intervention Tool
HCMC	Ho Chi Minh City
HIF	Health impact function
HR	Hazard ratio
LEAP-IBC	The Long-range Energy Alternatives Planning Integrated Benefits Calculator
LBW	Low birth weight
NAAQS	National Ambient Air Quality Standards
OR	Odds ratio
PAHs	Polycyclic aromatic hydrocarbons
PM	Particulate matter
PPP	Purchasing Power Parity index
PTB	Preterm birth
PTD	Preterm, delivery
RH	Relative humidity
RR	Relative risk
SIM-air	Simple Interactive Models for better air quality
SDGs	Sustainable development goals
SGA	Small for gestational age
TSP	Total suspended particle
US	The United State
VNUHCM	Vietnam National University Ho Chi Minh City
VSL	Value of Statistical Life
VOCs	Volatile organic compounds
WHO	World Health Organization
WTP	Willingness to pay
YLL	Year of life loss

CHAPTER 1
INTRODUCTION

1.1 Background

Air pollution has been a contemporarily global public health issue. Exposure to air pollution may cause a wide range of health effects, varying from mild to severe conditions and from acute effects to chronic outcomes. Around 7 million deaths were attributable to air pollution globally (WHO, 2018b), amongst those particulate matter not larger than 2.5 µm ($PM_{2.5}$) contributed to about 2.9 million deaths (5.2% of total) and loss of 83 million Disability-Adjusted Life Years (DALY) (3.3% of all) (Health Effects Institute, 2019). Particulate matter is a general term for microscopic particles and liquid droplets in the atmosphere. It is categorized by its aerodynamic equivalent diameter (AED), such as PM_{10} (AED $\leq$ 10 µm) and $PM_{2.5}$ (AED $\leq$ 2.5 µm). Particulate matter penetrates the body through respiration, located in the respiratory tract (PM_{10}) or circulation system ($PM_{2.5}$), resulting in various adverse health effects such as exacerbating lung and heart conditions, increasing the age-specific mortality risk, and hospital admissions.

Air pollution has become a hot issue in Vietnam, especially in megacities such as Ha Noi and Ho Chi Minh City (HCMC). The annual mean ambient $PM_{2.5}$ and PM_{10} in HCMC in 2016 were 42 µg/m^3 and 90 µg/m^3, respectively (WHO, 2021a). These results far surpassed the air quality guidelines recommended by the World Health Organization (WHO) of 10 µg/m^3 and 20 µg/m^3 for $PM_{2.5}$ and PM_{10}, respectively (WHO, 2005), and the Vietnamese standard of 25 µg/m^3 and 50 µg/m^3 for $PM_{2.5}$ and PM_{10}, respectively (MONRE, 2013b). Recently, the WHO recommended a lower guideline value for an annual $PM_{2.5}$ concentration of 5 µg/m^3 (WHO, 2021c).

The representative and sufficient particulate matter database has still been a challenge in Vietnam due to lacking monitoring stations, especially for $PM_{2.5}$. Although the WHO report on $PM_{2.5}$ might be outdated (WHO, 2021a), the decline in air quality in HCMC was undebatable due to the rapid population growth, high density of vehicles, industrial parks, and constructions.

Environmental studies relating to $PM_{2.5}$ and associated adverse health impacts have been relatively sparse in Vietnam, especially in HCMC. Some of those are obsoleted due to being conducted before 2010 (Mehta et al., 2011; Phung et al., 2016). The newest one focused on $PM_{2.5}$ and acute lower respiratory infections (ALRI) among children in only one hospital (Luong et al., 2020); this may not provide a complete picture of HCMC. Another study conducted in 2012 also focused on only PM_{10} and used models to assess health impacts (Ho, 2017). Besides, there is no study on the birth effects of ambient air pollutants and a lack of scientific evidence on the burdens of disease and the economic burdens caused by air pollution.

Children are one of the groups vulnerable to air pollution. Children have incomplete growth lungs, active and playing close to the ground, breathing a great deal of air (Gasana et al., 2012). Thus, children have some unique risks compared to adults. Worldwide, 93% of all children have lived in environments with air pollution levels above the WHO air quality guidelines. Around 25% of deaths of children under five years were directly or indirectly related to environmental risks. Air pollution contributes to respiratory tract infections that resulted in 543,000 deaths of children under five years in 2016 (WHO, 2018a). Thus, it is urgent to investigate further the effects of air pollutants on children's health, especially $PM_{2.5}$ in HCMC – the most populous city in Vietnam.

This study aimed to evaluate the health effects of $PM_{2.5}$ on children and estimate the burdens of $PM_{2.5}$, including health and associated economic burdens, among the whole population in Ho Chi Minh City, Vietnam.

1.2 Study area and scope

HCMC was chosen for implementing the study because this was the unique province in southern Vietnam that has a $PM_{2.5}$ database. HCMC is not only the most populous city in Vietnam but also the center of the economy, culture, and education in Vietnam. The city's total area was around 2,095 km^2, consisting of 19 urban and five suburban districts, and is home to approximately 9 million people (51.3% female, 6.1% under 5 years old, 79.2% urban) (GSO Vietnam, 2020). The HCMC's altitude is 19m above sea level, surrounded by Sai Gon River and contiguous to the sea. The city climate was hot and humid year-round, and the two main seasons included the rainy season (May to November) and the dry season (December to April the following year).

HCMC has a crowded number of vehicles, with 8.2 million, including around 782 thousand automobiles and 7.5 million motorcycles, in Oct 2020 (Department of Transportation Ho Chi Minh City, 2020), and a large number of vehicles from neighboring provinces commuting in the city daily. The city has 20 industrial parks with 4,217 hectares (VietinBank Securities JSC, 2021) and shares the border with four provinces with a high density of industrial parks. Therefore, the local emission and emissions in neighboring provinces affected the air quality in HCMC.

HCMC owns 12 central hospitals that belong to ministries, and more than 100 hospitals belong to the HCMC Department of Health. There were several specialized hospitals (the highest level in the health system), including those two maternity hospitals (Tu Du hospital and Hung Vuong hospital) and three children's hospitals (Children's hospital 1, Children's hospital 2, and Children's City hospital). All these five hospitals belong to the HCMC Department of Health. Besides, there are 319 commune health stations (CHSs), the lowest level in the governmental health sector. Figure 1.1 illustrates the network of health stations in HCMC:

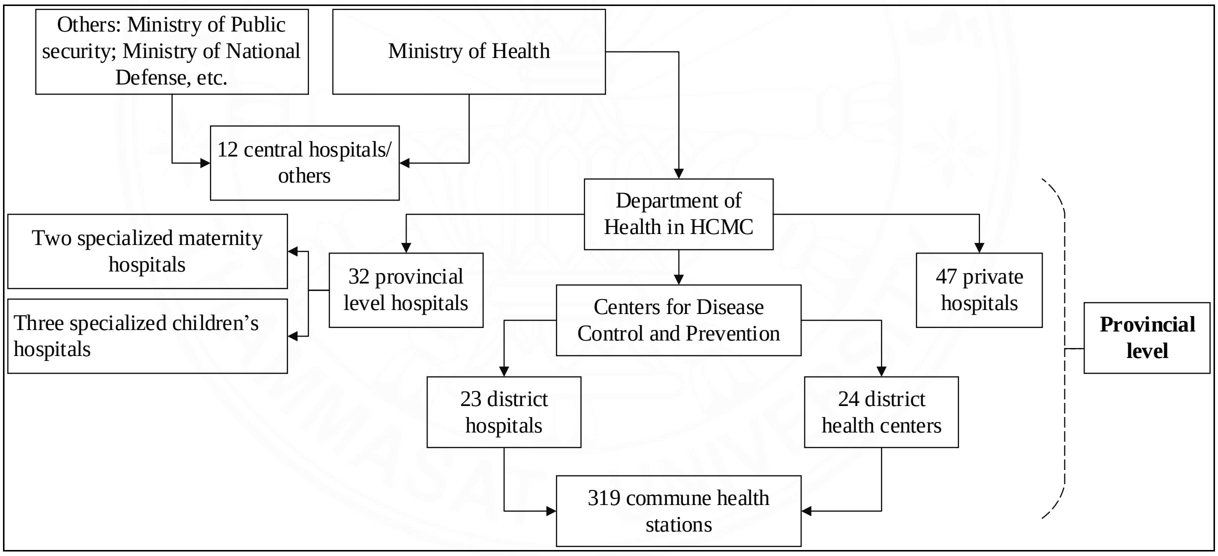


Figure 1.1. The network of health stations in Ho Chi Minh City

Firstly, the study collected a morbidity database of respiratory diseases among children at three children's hospitals. Other general and private hospitals provide services for children's respiratory diseases; however, it was a modest percentage compared to the three children's hospitals mentioned.

Secondly, regarding the infant dataset, according to a report by the Reproductive Health Care Center, 184,554 babies (among those, 53,687 was HCMC resident) were born in the year 2019 at 52 hospitals in HCMC. Three hospitals accounted for 65.7% of babies born, including Tu Du hospital (37%), Hung Vuong hospital (23.5%), and Gia Dinh hospital (5.2%). Correspondingly, this study collected data from these hospitals to represent HCMC data. General information about the selected hospital is presented in Table 1.1

Concerning estimating the disease burden and associated economic burden caused by $PM_{2.5}$, a mortality database from 319 CHSs at 24 districts in HCMC was collected. On average, there were 5 – 10 staff per CHS, including one doctor and other staff (nurse, technician). Each CHS is responsible for community health at its commune/ward, including primary health care and health management (number of deaths, number of infants, population). The number of people in each CHS differed depending on location (rural or urban), square, and density, ranging from below 5 thousand to above 50 thousand people.

Table 1.1 The general information of the selected hospitals

Hospital	Established year	Medical field	No. staff	No. beds	Average outpatients daily	Average daily hospitalized patients	Average babies born monthly
Children's hospital 1	1954	Children	1626	na	na	na	na
Children's hospital 2	1978	Children	> 2600	1.400	>5000	310	na
Children's City hospital	2017	Children	1100	1092	>1400	na	na
Tu Du	1923	Maternity	3000	> 1000	na	na	> 5600
Hung Vuong	1958	Maternity	1200	900	na	na	> 3600
Gia Dinh hospital	1945	General	1800	1500	>4500	>800	> 800

Na: not available

1.3 Research questions, hypotheses, and objectives

The research question was how does exposure level to $PM_{2.5}$ affect the number of daily children hospitalized due to respiratory diseases; adverse effects on infants, including birth weight and pre-term birth; and health and economic burdens?

The research hypotheses are:

1. $PM_{2.5}$ positively correlates with daily hospitalization due to respiratory diseases among children in Ho Chi Minh City.
2. $PM_{2.5}$ positively correlates with birth weight decrease, term low birth weight, and preterm birth among newborn babies.
3. $PM_{2.5}$ contributes to enormous mortality and economic burdens in the HCMC population.

General objective: To determine adverse health effects, health and economic burdens caused by $PM_{2.5}$.

Specific objectives:

1. To describe $PM_{2.5}$ concentrations and meteorological parameters (temperature, relative humidity) from 2016 to 2019.
2. To determine the correlation of $PM_{2.5}$ concentrations and meteorological parameters (temperature, relative humidity) from 2016 to 2019.
3. To determine the association between $PM_{2.5}$ concentrations with daily hospital admission due to respiratory diseases among children under 5 years old from 2016 to 2019.
4. To determine the association between maternal exposure to $PM_{2.5}$ and birth weight decrease among newborn babies from 2016 to 2019.
5. To determine the association between maternal exposure to $PM_{2.5}$ with the risk of term low birth weight and the risk of pre-term birth among newborn babies from 2016 to 2019.
6. To estimate the number of avoided deaths and economic benefits of controlling $PM_{2.5}$ in HCMC under various scenarios.

CHAPTER 2
REVIEW OF LITERATURE

2.1 Background of air pollution

Air pollution has become a critical public health problem affecting millions of people worldwide and resulting in detrimental environmental issues such as global warming and poor visibility. Globally air quality has deteriorated seriously in the past few decades with economic development, population escalation, traffic growth, modern industrialization, and reduction in the forest (Akimoto, 2003; Chan and Yao, 2008; B. M. Kim et al., 2015; Kulshrestha et al., 2009; Pascal et al., 2014; Raaschou-Nielsen et al., 2013; Rashki et al., 2013; Sharma et al., 2014; Shen et al., 2010), causing a significant rising of adverse health effects (West et al., 2016). The air is polluted by one or more substances at a concentration or for a duration above their natural levels, potentially producing an adverse effect (IARC, 2016).

Air pollution includes outdoor or ambient air pollution (AAP) and indoor or household air pollution (HAP). They are strongly interconnected. There are primarily two sources of air pollution in the atmosphere, including natural and anthropogenic emissions. Natural forest fires, volcanic and soil eruptions are prevalent in natural sources; meanwhile, human activities far exceed natural sources resulting in air pollution. Human activities contribute much to air pollution, such as fuel combustion from vehicles; heat and power generation; industrial facilities; municipal and agricultural waste sites and waste incineration/burning; and residential cooking, heating, and lighting with polluting fuels (Manisalidis et al., 2020).

Air pollution is also divided into primary and secondary air pollution. Primary air pollutants are phenomena applied to pollutants emitted directly from a source such as exhaust of automobile emissions, industries, burning of fossil fuels, or construction sites. Secondary air pollutants are generated in the ambient air through reactions between primary pollutants or water vapor and sunlight, such as sulfate and nitrate particles, sulfur acid, ozone, and peroxy-acyl-nitrate (Vallero, 2014).

The components polluting the air are called air pollutants. Air pollutants can be classified into different categories based on their characteristics such as three classes, including coarse particulate matter (PM), aerosol class, and gases (Hocking, 2005) or gaseous compounds, volatile organic compounds (VOCs), and PM (IARC, 2016). The United States Environmental Protection Agency (USEPA) has identified six criteria air pollutants (CAP) comprising carbon monoxide (CO), lead (Pb), nitrogen dioxides (NO_2), ground-level ozone (O_3), PM, and sulfur dioxides (SO_2) (Esworthy, 2014). PM is considered a key indicator of air pollution by various natural and human activities, causing many diseases that significantly reduce human life expectancy. The potential for causing health problems is reversed with the particle size (K. H. Kim et al., 2015).

Exposure to air pollution can increase the risks of mortality and morbidity worldwide (Q. Li et al., 2019). The International Agency for Research on Cancer (IARC) classified both outdoor air pollution and particulate matter as carcinogenic to humans (Group I) (IARC, 2016). It is estimated that 91% of the world's population (93% of its children) were exposed to fine PM at levels that exceeded the WHO-recommended guideline (WHO, 2018c). Globally, 7 million deaths were attributable to the combined effects of HAP and AAP in 2016. Notably, about 94% of these deaths occur in low and middle-income countries. The Southeast Asian and Western Pacific regions bear most of the burden, with 2.4 and 2.2 million deaths, respectively (WHO, 2018b).

2.2 Background of particulate matter

2.2.1 General definition and classification

Particulate matter is a complex mixture of gaseous and particulate pollutants, varying spatially and temporally in concentration, source, composition, atmospheric lifetime, and other physical and chemical properties (WHO, 2006a). The health effects of particulate matter depend on the particle size, concentration, surface composition, exposure duration, and sensitivity of the exposed individual (K. H. Kim et al., 2015; Kunzli and Tager, 2005; Ostro et al., 2011).

According to the AED, atmospheric particles can be divided into total suspended particulate (TSP: AED $\leq$ 100 µm), inhalable particles or coarse particles (PM_{10}: AED $\leq$ 10 µm), respirable particles or fine particles ($PM_{2.5}$: AED $\leq$ 2.5 µm), and ultrafine particles (AED $\leq$ 0.1 µm) (Esworthy, 2014; Vallero, 2014). Most fine PM is secondary particles.

PM_{10} is an indicator of inhalable particles that can penetrate the thoracic region of the lung, including fine particles and a subset of coarse particles (Pope and Dockery, 2006).

PM_{10} and $PM_{2.5}$ can include chemical components such as sulfates, nitrates, acids, metals, and particles with various chemicals adsorbed onto their surfaces (IARC, 2016). Concerning $PM_{2.5}$, different toxicological and physiological considerations suggest that fine particles may significantly affect human health (Pope and Dockery, 2006). The size of particles is associated with their potential to cause health problems. Smaller diameter particles pose more significant human health problems as they penetrate deeply into the lungs. $PM_{2.5}$ can be breathed more deeply into the lungs, remain suspended in the air for extended periods, penetrate more readily into indoor environments, and be transported over longer distances (Wilson and Suh, 1997). Fine particles also affect the ecosystem by decreasing visibility (haze) (Vallero, 2014) or deteriorating the environment. Comparing general properties and size distinguishing $PM_{2.5}$ and PM_{10} mode particles are summarized in Table 2.1 and Figure 2.1.

Most particulate matter people inhale can be generally removed by cilia and mucus in the human respiratory tract; however, the $PM_{2.5}$ fraction is retained mainly in the lung and accounts for 96% of particles observed in the human pulmonary parenchyma. $PM_{2.5}$ can penetrate the lung's air exchange region, enter the circulatory system, and spread to the whole body (Figure 2.2 and Figure 2.3). Due to their specific surface, $PM_{2.5}$ can easily combine with some toxic compounds, such as transition metals and polycyclic aromatic hydrocarbons (PAHs). $PM_{2.5}$ is, therefore, more harmful to population health than larger particles (Q. Li et al., 2019). Because numerous studies have shown that fine $PM_{2.5}$ particle levels can be linked to premature mortality and adverse health effects, $PM_{2.5}$ levels are often used as a prominent surrogate for air pollution (Dockery et al., 1993; Kurt et al., 2016; Peters and Pope, 2002; Pope and Dockery, 2006; Pope et al., 2009).

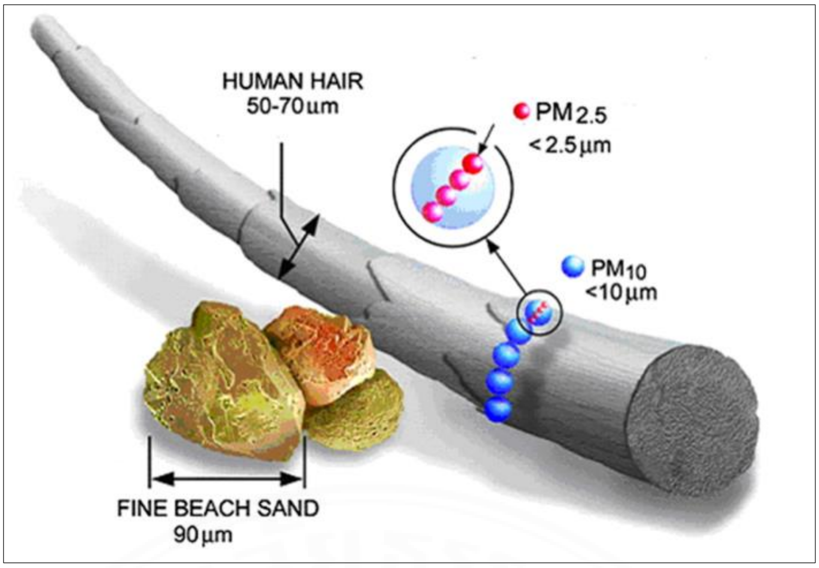


Figure 2.1. Size comparison of $PM_{2.5}$ and PM_{10} against the average diameter of a human hair (~70 µm) and fine beach sand (~90 µm) (Guaita et al., 2011; K. H. Kim et al., 2015)

Table 2.1. Comparison of the fundamental properties $PM_{2.5}$ versus PM_{10}

Characteristics	**$PM_{2.5}$**	**PM_{10}**	**Reference**
Diameter	Not larger than 2.5 µm	Not larger than 10 µm	(Atkinson et al., 2010)
Composition	SO_{2-4}; NO_{-3}; NH_{+4}; H+; elemental carbon; organic compounds; PAH; metals, Pb, Cd, V, Ni, Cu, Zn; particle-bound water; and biogenic organics	Resuspended dust, soil dust, street dust; coal and oil fly ash; metal oxides of Si, Al, Mg, Ti, Fe, $CaCO_3$, NaCl, sea salt; pollen, mold spores, and plant parts.	(Cheung et al., 2011)
Sources	Combustion of coal, oil, gasoline; transformation products of NO_x, SO_2, and organics including biogenic organics, e.g., terpenes; high-temperature processes; smelters, and steel mills	Resuspension of soil tracked onto roads and streets; Suspension from disturbed soils, e.g., farming and mining; resuspension of industrial dust; construction, coal and oil combustion, and ocean spray.	(Srimuruganandam and Shiva Nagendra, 2012)
Lifetimes	Days to weeks	Minutes to hours	(Cheung et al., 2011)
Travel distance (kilometers)	100 to 1000	1 to 10	(Srimuruganandam and Shiva Nagendra, 2012)

Figure 2.2 illustrates the general toxicological pathways of particulate from lung exposure to cardiovascular and cerebrovascular diseases. Particulate matter can induce or exacerbate lung diseases, including chronic obstructive pulmonary disease (COPD), asthma, lung infection, and lung cancer. Ultrafine particles could translocate from the lung into the bloodstream, causing systemic inflammation and oxidative stress that negatively impact blood and blood vessels, heart function, and the brain (Xia et al., 2016).

Figure 2.3 shows the predicted fractional deposition of inhaled particles in three locations. Different particulate matter diameters will locate various sites in the body, such as nasal, pharyngeal, laryngeal, tracheobronchial, and alveolar (Oberdörster et al., 2005).

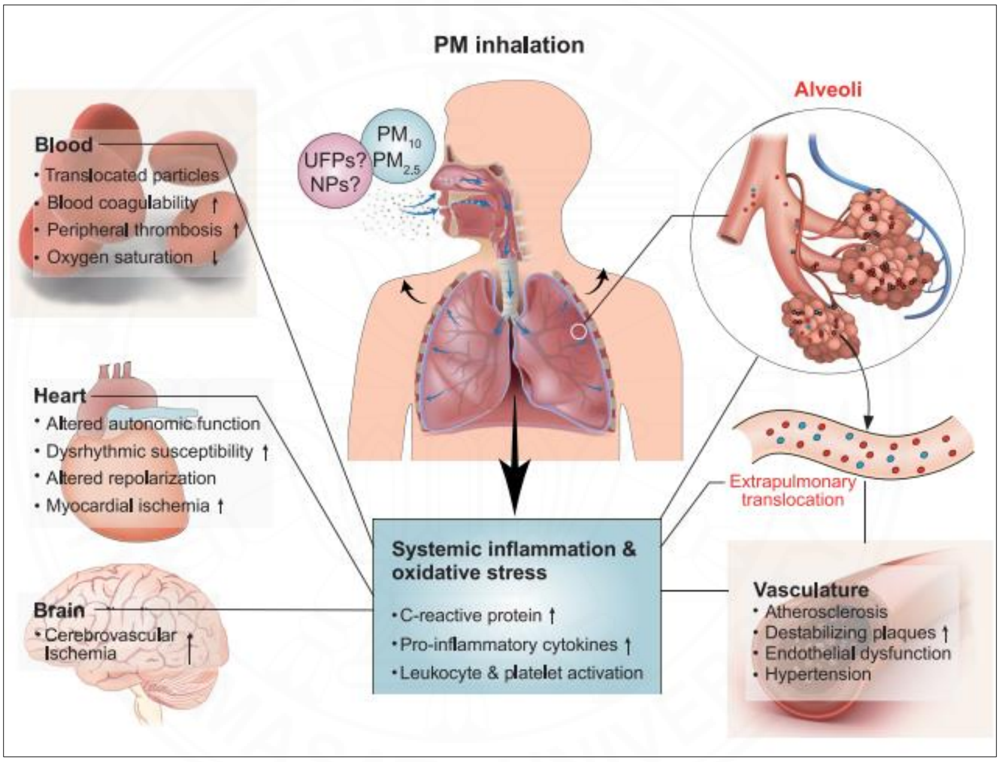


Figure 2.2. General toxicological pathways linking particulate matter lung exposure to cardiovascular and cerebrovascular diseases (Xia et al., 2016)

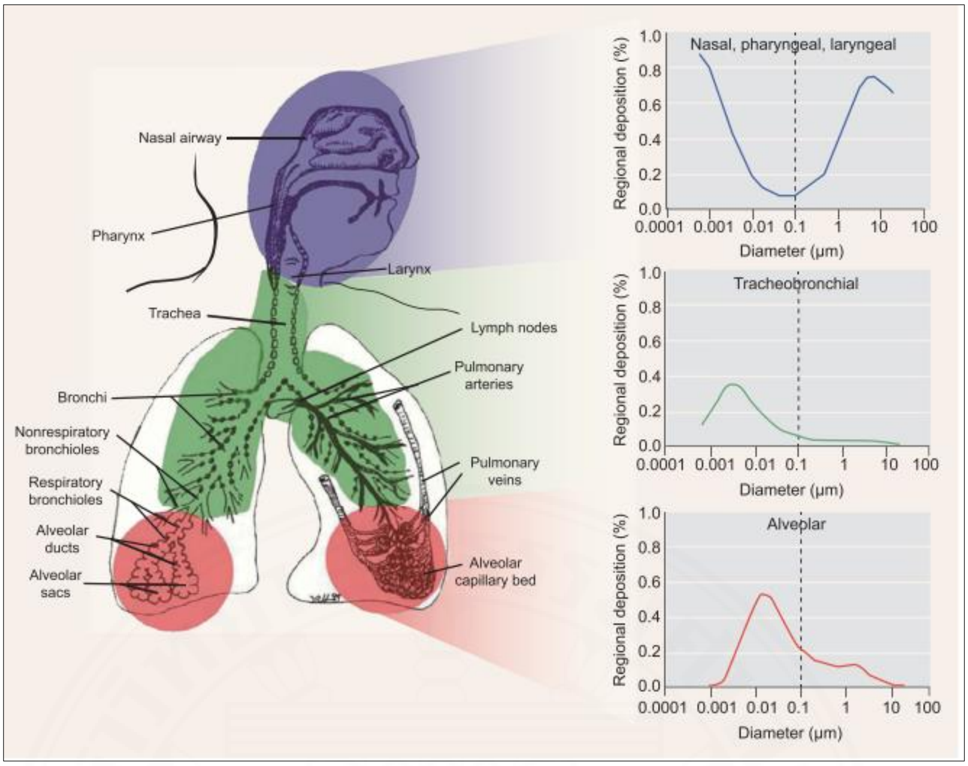


Figure 2.3. Predicted fractional deposition of inhaled particles (Oberdörster et al., 2005)

2.2.2 Sources and components

Particulate matter primarily comes from various sources, including anthropogenic and natural sources. Anthropogenic sources include all human activities which generate pollutants, such as vehicles, constructions, power generation, agriculture, and industrial activities. Natural sources are windblown soil, pollens, molds, forest fires, volcanic emissions, and sea spray (Brook et al., 2004; Juda-Rezler et al., 2011).

Unlike other criteria pollutants, particulate matter is not a specific chemical entity but a mixture of particles from different sources and different sizes, compositions, and properties. The chemical composition of particulate matter is critical and highly variable. A study of $PM_{2.5}$ reported that organic compounds accounted for 18–70% of the particulate matter mass, sulfate ions accounted for 10–67%, nitrate ions accounted for a few percent to 28%, and ammonium ions accounted for 7–19% of the particulate matter mass (Zhang et al., 2007). Elemental carbon (EC) and crustal materials are important contributors to $PM_{2.5}$, 5–10% and 5–20% of the $PM_{2.5}$ mass, respectively (Belis et al., 2013; Chow and Watson, 2012). Also, sulfate ion in $PM_{2.5}$ and $PM_{0.1}$ is predominantly from the oxidation of SO_2, mainly from the combustion without emission controls of sulfur-containing fossil fuels (IARC, 2016).

Different sizes of particles often come from different emission sources. The identification of these particles can help identify their source. The ratio of $PM_{2.5}$ to PM_{10} ($PM_{2.5}/PM_{10}$) gives valuable information about the sources as natural or anthropogenic. Anthropogenic sources produce more fine particles due to traffic emissions or burning activities resulting in a higher $PM_{2.5}/PM_{10}$ ratio. In contrast, natural sources such as windblown or road dust mostly have a higher contribution of coarse particles resulting in a lower value (Q. Li et al., 2019).

2.2.3 Association between particulate matter and other pollutants, meteorology parameters

Particulate matter is significantly correlated with other pollutants and meteorological parameters. $PM_{2.5}$ and PM_{10} concentrations were reported to have a positive correlation to O_3, NO_2, and air pressure and a negative correlation to temperature, relative humidity, wind speed, and precipitation (Jiang et al., 2020; Karagiannidis et al., 2014; Luong et al., 2017; Mehta et al., 2011; Prakash et al., 2009).

2.3 Human effects associated with exposure to particulate matter

Air pollution has been a significant risk factor for global health. One of the critical drivers of adverse health effects is ambient $PM_{2.5}$ which ranked as the 6^{th}-highest risk factor for early death in 2016 (Health Effects Institute, 2019). Negative health consequences of air pollution can occur due to short- or long-term exposure. Mortality attributed to AAP is identified as an indicator of sustainable development goals (SDGs) (WHO, 2016). $PM_{2.5}$ was attributable to over 4 million deaths from cardiopulmonary and respiratory diseases in 2016. The deaths attributable to $PM_{2.5}$ were ranked equivalent to high cholesterol and high body mass index but significantly higher than other well-known risk factors (such as alcohol use, physical inactivity, or high sodium intake) (Health Effects Institute, 2019). In 2015, $PM_{2.5}$ was estimated as the fifth-ranking mortality risk factor, causing 4.2 million and 103.1 million DALYs (Cohen et al., 2017; Forouzanfar et al., 2016). Deaths caused by ambient $PM_{2.5}$ increased from 3.5 million in 1990 to 4.1 million in 2016 (Cohen et al., 2017; Health Effects Institute, 2019), and it is estimated that 92% of the world's population resides in areas exceeding the WHO's Air Quality Guidelines (AQG) (Shaddick et al., 2016).

Exposure to particulate matter can lead to many adverse health effects, such as premature death, nonfatal heart attacks, irregular heartbeat, aggravated asthma, and problems in lung function and respiratory (Atkinson et al., 2010; Cadelis et al., 2014; Correia et al., 2013; Fang et al., 2013; Meister et al., 2012). Short-term and long-term exposure to $PM_{2.5}$ can increase the risk of mortality due to all causes, non-accidental causes, cardiovascular diseases, IHD, and lung cancer (Cesaroni et al., 2013; Crouse et al., 2012; Krewski et al., 2009; Laden et al., 2006; Pope et al., 2002; Pope et al., 2004). It is estimated that every 10-$\mu g/m^3$ increase in $PM_{2.5}$ exposure results in a 2.8% increase in particulate matter-related mortality (95% CI: 2.0–3.5) in short-term exposure and 1.6 (95% CI: 1.5–1.8) in long-term exposure (Kloog et al., 2013).

Besides, many studies identified associations between particulate matter levels and adverse birth outcomes, although results are inconsistent regarding which pollutants or which trimester of exposure is most relevant (Ebisu and Bell, 2012). Recently, several studies have shown that maternal exposure to air pollution can affect the developing fetus, causing adverse birth outcomes such as infant death, stillbirth, term low birth weight (LBW), preterm birth (PTB), and small for gestational age (SGA) (Dibben and Clemens, 2015; P.-C. Lee et al., 2013; Vinikoor-Imler et al., 2014).

2.3.1 Respiratory diseases and particulate matter

When $PM_{2.5}$ is inhaled, it deposits in the lung and affects it first. $PM_{2.5}$ elicits oxidative stress in various ways and triggers a series of adverse effects on the normal functions of those cells or even causes them to die by apoptosis, autophagy, or others. At the same time, $PM_{2.5}$ will lead to inflammation and ultimately significantly reduce lung function, even for healthy subjects. Persistent oxidative and inflammatory injury attributable to chronic $PM_{2.5}$ exposure would be responsible for developing and maintaining chronic bronchitis, COPD, asthma, and lung cancer. Besides, $PM_{2.5}$ may alter and impair the lung's normal immune, rendering it susceptible to infections. These effects would lead to a decline in pulmonary immunity and facilitate infectious disease.

In general, particulate matter has wide-range influences on the respiratory system, such as increasing overall respiratory symptoms, the incidence of malignant tumors, the incidence of chronic respiratory diseases, mortality; exacerbation of COPD and asthma; causing temporary loss of lung function in normal people; reducing lung function growth in children and pulmonary diffusing capacity in lung function (Kyung and Jeong, 2020). The mechanism deteriorating the health of $PM_{2.5}$ can be reducing antimicrobial activity in the respiratory tract (S. Zhang et al., 2019), modifying immune response and inflammation (Lambert et al., 2003), or conveying microorganisms from the environment (Cao et al., 2014).

Exposure to particulate matter, especially $PM_{2.5}$, can increase the risk of hospitalization due to deterioration of COPD, particularly significant for the 14–90-day period prior to hospital admission (relative risk – RR = 1.06–1.32) (Atkinson et al., 2014; Zieliński et al., 2018). It is estimated that air pollution caused 1.6 million deaths from COPD (Schraufnagel et al., 2019). Exposure to particulate matter can also cause allergic sensitization and asthma exacerbation (Guarnieri and Balmes, 2014; Thurston et al., 2017). $PM_{2.5}$ was significantly associated with the increasing incidence and prevalence of asthma. Every 10 µg/m^3 $PM_{2.5}$ concentration increment increased by 0.67%, 0.65%, and 0.49% the total number of hospitals, out-patient, and emergency room visits, respectively (Tian et al., 2017).

Particulate matter has been identified as a culprit of lung cancer. Long-term exposure to particulate matter can increase the risk of COPD, lung cancer, and a decline in pulmonary function. $PM_{2.5}$ exposure resulted in a long recovery time, increasing the burden of the disease (Kyung and Jeong, 2020). Several studies reported that the hazard ratio of lung cancer was 1.22 and 1.18 for an increase in PM_{10} concentration of 10 µg/m^3 and $PM_{2.5}$ of 5 µg/m^3, respectively (MacIntyre et al., 2014; Raaschou-Nielsen et al., 2013). In a meta-analysis study in Korea, the risk of lung cancer increased by 1.09-fold (95% CI: 1.01–1.14) when the concentration of $PM_{2.5}$ increased by 10 µg/m^3. A similar result was observed in PM_{10} (1.08-fold increased risk; 95% CI: 1.00–1.17) (Kyung and Jeong, 2020). About 500,000 lung cancer deaths are estimated to be attributed to air pollution (Guarnieri and Balmes, 2014). Both PM_{10} and $PM_{2.5}$ were reported to significantly increase the mortality rate in lung cancer patients in the 2017 and 2018 meta-analyses (Kim et al., 2018).

Particulate matter also increases hospital admission due to pneumonia. A recent meta-analysis showed that the incidence rate of pneumonia in children increased by 1.5% and 1.8% for every 10 µg/m^3 increase in PM_{10} and $PM_{2.5}$, respectively (Nhung et al., 2017). The overall mortality rate (RR=1.02) of respiratory disease patients was significantly increased per

10 µg/m^3 increase in $PM_{2.5}$ in fine dust (Fajersztajn et al., 2017). The concentration of PM_{10} and $PM_{2.5}$ were also reported to significantly increase the idiopathic pulmonary fibrosis (IPF) mortality rate. Each 10 µg/m^3 PM_{10} and $PM_{2.5}$ increase leads to 2.01- and 7.93-fold IPF, respectively (Sesé et al., 2018).

Air pollution can threaten human health of all ages and places; however, children are most vulnerable. Children have immature immune systems, a higher breathing rate, and narrower airways, which are advantageous factors for the adverse effects of air pollution (DeFlorio-Barker et al., 2019; Ostro et al., 2009). Children usually play close to the ground, spend much time outside, and physically engage in potentially polluted air (WHO, 2018a). Air pollution caused around 0.54 million deaths in children under five years and 52,000 deaths in children aged 5–15 in 2016. Of the deaths attributable to the combined effects of HAP and AAP worldwide in 2016, 9% were in children (WHO, 2018a).

Exposure to air pollution has adversely affected children's lung function. In the European Study of Cohorts for Air Pollution Effects (ESCAPE), Gehring and others found an association between $PM_{2.5}$ levels at the current address and a slight decrease in lung function in children aged 6–8 years (Gehring et al., 2013). A prospective cohort study of children in Taiwan showed that increased exposure to ambient $PM_{2.5}$ was associated with lower rates of development in some measures of lung function, including forced vital capacity (FVC) and forced expiration volume in 1s (FEV1), and with reduced development of FVC (Hwang et al., 2015). Reduced lung function was also seen in school children in Hong Kong who had long-term exposure to higher levels of AAP (Gao et al., 2013). In four cities in China, comprising Chongqing, Guangzhou, Lanzhou, and Wuhan, exposure to ambient particulate matter was associated with decreased lung function development in children (Roy et al., 2012). The magnitude of the effects on lung function differs by study, perhaps because of spatial differences in particulate matter mass, number, and composition. In a study of five European birth cohorts, Eeftens and others found a more consistent association between increased particulate matter mass and reduced lung function than with individual components of particulate matter (Eeftens et al., 2014). They also found minor adverse effects associated with exposure to nickel and sulfur in particulate matter. These findings suggest that particulate matter mass, rather than specific components, is more helpful in assessing risks from exposure to air pollution to lung development and function in children.

Short-term exposure to AAP exacerbates acute respiratory infections. Nhung and others conducted a meta-analysis of 17 studies on the acute effects of AAP on childhood pneumonia (Nhung et al., 2017). They concluded that short-term increases in AAP are significantly associated with increased hospital admissions for pneumonia. Darrow and colleagues investigated the association between short-term changes in ambient air pollutant concentrations and visits to emergency departments for respiratory infections (Darrow et al., 2014). They found that exposure to air pollutants such as $PM_{2.5}$, NO_2, and O_3 exacerbates upper respiratory diseases and pneumonia among children under five years.

Long-term exposure to AAP may also increase the risk of pneumonia in early life. In a meta-analysis of 10 European birth cohorts, MacIntyre and others reported the association between the incidence of pneumonia and long-term exposure to traffic-related air pollution (MacIntyre et al., 2014). Vehicle traffic is one of the primary sources of exposure to AAP. Rice and others examined the association between prenatal exposure to traffic-related air pollution in Boston, the USA, and the risk of respiratory infection (including pneumonia, bronchiolitis, and croup) in early life (Rice et al., 2015). Reduced distance from roadways and higher traffic density was correlated with a higher risk of respiratory infection, suggesting that living close to a major road during pregnancy heightens the risk for respiratory infections in early life.

Several studies documented that exposure to particulate matter significantly affected acute respiratory infections. Jedrychowski and others assessed the effect of prenatal exposure to $PM_{2.5}$ on acute bronchitis and pneumonia between birth and seven years (Jedrychowski et al., 2013). They found that the incidence of recurrent pulmonary infections was significantly correlated with prenatal $PM_{2.5}$ exposure in a dose-dependent manner. Fuertes and others combined the results for seven birth cohorts to investigate the effects of various components of particulate matter on the development of pneumonia in early childhood (Fuertes et al., 2014). All the components (iron, potassium, copper, nickel, sulfur, silicon, vanadium) except zinc from PM_{10} were associated with a higher risk of pneumonia in early life.

Although most studies showed a positive association between air pollution and respiratory diseases among children, several studies reported that the relationship was not statistically significant (Darrow et al., 2014; Karr et al., 2006a; Karr et al., 2009; Nenna et al., 2017). Several explanations can partly lead to this inconsistency, such as residual confounding inherent in conventional observational study designs (Darrow et al., 2014; Karr et al., 2009), the effect of the causal modeling approach, which uses suitable surrogates of unobserved potential outcomes under alternative exposure scenarios and by comparing the counterfactual outcomes and observed outcomes (Rubin, 1991).

2.3.2 Adverse birth outcomes and particulate matter

2.3.2.1 General information on adverse birth outcomes

The health impacts of exposure to air pollution during the prenatal period are often overlooked but can be significant. Several studies provided evidence of an association between maternal exposure to air pollution and adverse birth outcomes, including stillbirth, preterm birth, low birth weight, and being small for gestational age (WHO, 2018a).

According to the WHO definition, stillbirth is fetal death occurring at a birth weight equal to or above 1000g, or at least 28 completed weeks of gestation; meanwhile, preterm birth is infants born alive before 37 weeks of gestation, compared to normal one from 37 – 42 weeks (WHO, 2006b, 2018d). Low birth weight is a phenomenon of weight at birth of under 2500g (UNICEF, 2018; WHO, 2015). Small for gestational age is commonly defined as having a weight below the 10th percentile of the recommended sex-specific birth weight for gestational age (WHO, 1995).

Adverse birth outcomes have still been a challenge for many countries, and preterm birth is one of the significant challenges in perinatal health care. Most perinatal deaths occur in preterm infants, and preterm birth is a considerable risk factor for neurological impairment and disability. Preterm birth not only affects infants and their families – providing care for preterm infants, who may spend several months in hospital, has increased cost implications for health services. Preterm birth rates were estimated from 9.8% in the year 2000 to 10.6% in 2014, equally 14.8 million alive infants in the year 2014 (Beck et al., 2010; Chawanpaiboon et al., 2019), and around 1.1 million babies died from complications of preterm birth every year (WHO, 2014). South Asia and sub-Saharan Africa contributed about 52% of the global live births but accounted for nearly two-thirds (60%) of the global preterm infants (Blencowe et al., 2012). Among 7.6 million deaths in children under five years in 2010, preterm birth complications accounted for 14.1% (1.078 million, uncertainty range 0.916-1.325) (Liu et al., 2012). Health complications resulting from preterm birth are considered the leading cause of death among children under five years of age, resulting in over one million deaths in 2016 (Liu et al., 2016; WHO-MCEE, 2018; WHO, 2018d).

Besides, it was estimated that around 2.6 million infants were stillbirths globally in 2015. The stillbirth rate decreased by 25.5%, from 24.7 per 1000 births in 2000 to 18.4 per 1000 births in 2015. Notably, 98% of all stillbirths occurred in low and middle-income countries, 77% in South Asia and sub-Saharan Africa (Blencowe et al., 2016).

Along with preterm birth and stillbirths, low birth weight is another major public health issue worldwide and is associated with a range of short and long-term health effects. Birth weight is an essential indicator for estimating fetal growth, and low birth weight was associated with perinatal morbidity and mortality and health issues during adolescence and beyond. The prevalence of low birth weight was estimated at around 20 million yearly (WHO, 2014). Low birth weight was estimated at 15.3% globally in 2000, then significantly decreased to 10.6% in 2010 (World Bank, 2019). The impact of low birth weight is not the only disease, low growth (WHO, 2014) and death among infants, but also increases the risk for noncommunicable diseases such as diabetes, cardiovascular disease, and chronic kidney diseases later in life (Andersson et al., 2000; Eriksson et al., 2018; Johansson et al., 2008; Larroque et al., 2001; Risnes et al., 2011).

Another adverse birth outcome is small for gestational age. In low-income and middle-income countries was estimated that 32.4 million infants with born small for gestational age (27% of live births) in 2010 (A. C. Lee et al., 2013). Small gestational age and low birth weight are associated with preterm birth (Etzel RA, 2012). Thus, preterm birth and small for gestational age can occur independently or together, resulting in low birth weight (Cohen et al., 2017; Etzel RA, 2012). Adverse birth outcomes can increase the risks of premature death and disability, including cardiovascular morbidity, chronic lung disease, obesity, and metabolic syndrome (Etzel RA, 2012; Zheng et al., 2016). Emerging evidence suggests an increased risk for developmental delays and poorer cognitive performance (Etzel RA, 2012; Lundgren and Tuvemo, 2008). Children with adverse birth outcomes may require more health care after birth, placing demands on health facilities and resources with broader social impacts (Etzel RA, 2012).

2.3.2.2 The association between adverse birth outcomes and pollutants

Numerous studies have shown a significant association between exposure to AAP and adverse birth outcomes, especially exposure to PM, SO_2, NO_x, O_3, and CO. Exposure to particulate matter, especially to fine particulate matter, was documented as a risk factor for preterm birth, stillbirth and infants born small for gestational age (Q. Li et al., 2019; WHO, 2018a).

Maternal exposure to air pollution has been figured out as a risk factor for preterm birth (Hansen et al., 2006; Le et al., 2012; Wilhelm et al., 2011), especially in particulate matter effects (Brauer et al., 2008; Darrow et al., 2011; Q. Li et al., 2019; Pedersen et al., 2016; Pereira et al., 2016; Twum et al., 2016). It was estimated that 2.7–3.4 million preterm birth globally in 2010 was associated with exposure to $PM_{2.5}$ during gestation (Malley et al., 2017). Preterm birth has been consistently associated with SO_2 levels (Stieb et al., 2016), while the evidence for associations with CO, NO, NO_2, and O_3 remains inconclusive (Malley et al., 2017; Shah and Balkhair, 2011). Similarly, several meta-analyses performed between 2012 and 2016 consistently showed positive associations between exposure to $PM_{2.5}$ during pregnancy and low birth weight and suggested that late pregnancy may be a critically vulnerable time (Li et al., 2017; Sapkota et al., 2012; Shah and Balkhair, 2011; Stieb et al., 2012; Sun et al., 2016).

Several meta-analysis studies reported that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ was positively associated with a 5% - 10% excess risk of low birth weight (Dadvand et al., 2013; Guo et al., 2018; Stieb et al., 2012; Sun et al., 2016; Zhu et al., 2015), 10% excess risk of preterm birth and 15% excess risk of small for gestational age, and the pooled estimate of the decrease in birth weight was 14.6 g (Zhu et al., 2015) and 15.9 g (Sun et al., 2016). Exposure to $PM_{2.5}$ during the second trimester and the third trimester significantly decreased birth weight by –12.6 g and –10.0 g, respectively (Sun et al., 2016). However, another study reported that the most substantial effect was in the first trimester (Z. Li et al., 2019).

Individual chemical elements of particulate matter may be involved in its toxic effect. Studies on $PM_{2.5}$ chemical components and birth outcomes have been limited. A study conducted in Atlanta reported that $PM_{2.5}$, EC, and water-soluble $PM_{2.5}$ metals, such as copper, are associated with low birth weight (Darrow et al., 2011). Associations were also reported between $PM_{2.5}$ components of aluminum, EC, Ni, Si, vanadium, and zinc and the risk of low birth weight (Bell et al., 2010). In an extensive study of eight pooled European cohorts, the sulfur component on the $PM_{2.5}$ surface was reported to increase the risk of low birth weight (Pedersen et al., 2016). As the chemical components of particulate matter differ widely by source, this may explain some of the inconsistencies in the findings of different studies (Sun et al., 2016). In an extensive systematic review of studies in China (Jacobs et al., 2017), SO_2 was consistently associated with low birth weight. There is less evidence of associations between exposure during pregnancy to PM_{10}, PAH, and other elements of AAP, such as CO and NO_2, and low birth weight (Aguilera et al., 2009; Sapkota et al., 2012; Stieb et al., 2012).

In contrast, the association between stillbirth and particulate matter is unclear. Several studies reported a non-statistically significant risk of stillbirth per 10 $\mu g/m^3$ increase in $PM_{2.5}$ (Bobak and Leon, 1999; Faiz et al., 2012; Pearce et al., 2010; Zhu et al., 2015). Other studies documented a modestly increased risk associated with exposure to $PM_{2.5}$ throughout pregnancy (Green et al., 2015; Yang et al., 2018) or at specific stages, such as the third trimester (DeFranco et al., 2015) or the week before delivery (Faiz et al., 2013). PM_{10} was also found as a small significant risk (Hwang et al., 2011; Kim et al., 2007; Yang et al., 2018). In most studies, the most substantial effect for PM_{10}, SO_2, CO, and O_3 was in the third trimester (Green et al., 2015; Hwang et al., 2011; Kim et al., 2007; Siddika et al., 2016; Yang et al., 2018). Acute exposure to AAP in the week before delivery has been the subject of relatively few studies. New evidence suggests that such exposure increases the risk of stillbirth. Faiz and colleagues (Faiz et al., 2012) found an increased risk of stillbirth when mothers were exposed to high levels of CO, SO_2, NO_2, or $PM_{2.5}$ in the 6 days before delivery. In a retrospective cohort study of 223,375 births in the USA, exposure to O_3 during the week before delivery increased the risk of stillbirth by 13–22% (Mendola et al., 2017).

Few studies have explored the association between exposure to air pollution and infants born small for gestational age. Maternal exposure to $PM_{2.5}$ and PM_{10} has been associated with small gestational age births (Pereira et al., 2016; Shah and Balkhair, 2011). Le and colleagues found an association between small for gestational age at term and exposure to high CO and NO_2 levels in the first month and exposure to O_3 and PM_{10} >35 $\mu g/m^3$ during the third trimester (Le et al., 2012). Another study of 2.5 million births in Canada between 1999 and 2008 re-confirmed the statistically significant association between exposure to NO_2 during pregnancy and infants born small for gestational age at term (Stieb et al., 2016).

Overall, many studies reported the detrimental impacts of $PM_{2.5}$ and adverse birth outcomes, especially preterm birth and low birth weight. However, several studies reported that this relationship was non-statistically significant (Gehring et al., 2011; Madsen et al., 2010; Sapkota et al., 2012). Inconsistencies might result from differences in study populations or study design, such as control for confounders, exposure assessment, statistical methods, and sample size. Other possible explanations are variations in the exposure period and collinearity among pollutants (Maisonet et al., 2004). Additionally, the chemical composition of particles can be another critical reason, varying by region and season and associated with adverse health effects (M. L. Bell et al., 2007; Michelle L. Bell et al., 2007; Bell et al., 2008; Zhou et al., 2011).

2.4 Application of BenMAP-CE tool to estimate the burden of diseases and economic burden

2.4.1 General introduction of BenMAP-CE

The USEPA released BenMAP *(Environmental Benefits Mapping and Analysis Program)* in 2003 to quantify the health burden and health economic with the air quality changes. In 2015, BenMAP was transformed into an open-source software called BenMAP-CE *(BenMAP-Community Edition),* enabling a broadly accessible (Sacks et al., 2018). Several tools share similar functions with BenMAP-CE, such as LEAP-IBC (The Long-range Energy Alternatives Planning Integrated Benefits Calculator), AirQ+, GAINS (Greenhouse Gas and Air Pollution Interactions and Synergies), Environmental Burden of Disease Assessment tool for ambient air pollution (EBD), Simple Interactive Models for better air quality (SIM-air) or HAPIT (Household Air Pollution Intervention Tool) (Anenberg et al., 2016). BenMAP-CE has several strengths, such as the ability to analyze many different pollutants, calculate morbidity and mortality, estimate health economics, analyze at various geographical levels, and adjust parameters when necessary.

The BenMAP-CE operates based on four main components comprising (i) Air quality database; (ii) Population database; (iii) Incidence rates of disease or death; (iv) Risk estimate (generally the coefficient from a statistical model that measures the response of a health effect for a one-unit change in an air pollutant concentration (e.g., per $\mu g/m^3$), which referred to as a beta – ß coefficient) (Sacks et al., 2018). Besides, BenMAP-CE needs maps at different levels of the study area.

2.4.2 Estimating health effects

Firstly, based on baseline data of air pollution and control scenarios, BenMAP-CE will determine the change in ambient air pollution. Then, BenMAP-CE relates the change in pollution concentration with specific health effects (health endpoints). This association is often called the health impact function (HIF) or the concentration-response (C-R) function. These HIFs are derived from epidemiology studies relating pollutant concentrations to health outcomes. BenMAP-CE applies that relationship to the population experiencing the change in pollution exposure to calculate health impacts with the following equation:

$$\Delta Y = Y_0 * Pop * (1 - e^{-\beta * \Delta PM})$$

Where $\triangle Y$ refers to the estimated health impact attributed to pollutants, ß is the beta coefficient from an epidemiologic study, $\triangle PM$ defines the change in air quality, Y_0 is the baseline rate (incidence) for the health effect of interest, Pop is the population exposed to air pollution (Sacks et al., 2018).

2.4.3 Health economic estimation

Air quality improvement decreases negative health impacts such as mortality and morbidity for the community. From an economic aspect, an avoided premature death will be worth a certain amount of money. After calculating the health changes, BenMAP-CE can estimate the health economic value by multiplying the reduction of the health effect by an estimate of the economic value per case (Figure 2.4) (EPA, 2022):

Economic Value = Health effect * Value of health effect

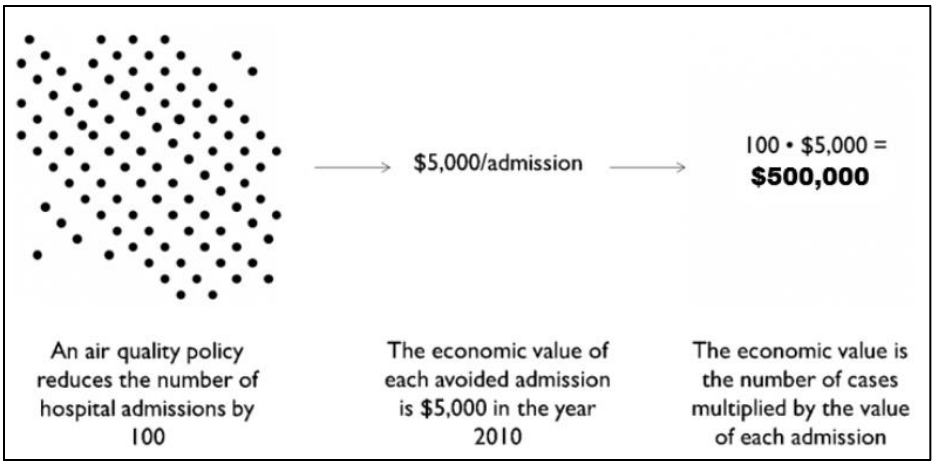


Figure 2.4. Estimating the economic value of human health effects

There are several different ways of calculating the value of the health effect. BenMAP-CE can calculate the economic value of air quality change using the Cost of illness (COI), or Willingness to pay (WTP), or Value of Statistical Life (VSL). The COI metric is the amount of money that a patient must bear for hospital admissions and other outcomes due to air pollution-related causes; this value comprises the medical expenses and work lost but does not count the value individuals place on pain and suffering associated with the event. By contrast, WTP metrics include the COI plus the expense calculated for pain and suffering, loss of satisfaction, and leisure time (Q. Li et al., 2019). The value of an avoided premature mortality is generally calculated using the VSL. The VSL is the amount of money that a group of people agrees to pay to slightly decrease the risk of premature death in the population (EPA, 2022).

The VSL value is not the monetary value of individual lives. Instead, it reflects the amount individuals are willing to pay to incrementally reduce their risks of death from adverse health conditions that may be caused by environmental pollution.

For instance, if every person in a population of 100,000 people was asked how much he or she agreed to pay for a reduction in their risk of dying of 1 per 100,000 (0.001%) for the following year. This reduction in risk means that one fewer death among the sample of 100,000 people would be expected over the next year on average, sometimes described as “one statistical life saved”. Suppose the answer to the question was $100 per person. Then the total amount of money that the population would be willing to pay to save one statistical life in a year was $10 million ($100 per person among 100,000 people). This is the “value of a statistical life”. If that population can prevent 10 avoided deaths, the economic benefit would be $100 million (or 10 avoided death * $10 million VSL).

In the case of a country that is not available an estimated VSL, an indirect method to calculate is transferring from USA VSL and adjusting for differences in income levels.

2.5 Burden of air pollution

Air pollution can result in a considerable threat to health worldwide. The association between air pollution and adverse health impacts, such as increased mortality and morbidity, has been reported in many studies. WHO estimated that in 2016, 7 million deaths were attributable to air pollution, and 94% occurred in low and middle-income countries (WHO, 2018b). In 2017, air pollution (ambient $PM_{2.5}$, indoor air pollution, ozone) caused around 5 million deaths (nearly 150 million years of healthy life lost), accounting for 8.7% of all deaths globally (5.9% of all DALYs globally). The countries with the highest mortality burden attributable to air pollution in 2017 were China (1.2 million) and India (1.2 million) (Figure 2.5) (IHME, 2019). Focusing on $PM_{2.5}$, long-term exposure to ambient $PM_{2.5}$ contributed to 2.9 million deaths (83 million DALYs) in 2017, responsible for 5.2% of all global deaths (3.3% of all global DALYs). China and India were still the highest burdens globally (852,000 deaths, 19.8 million DALYs, 673,000 deaths, and 21.3 million DALYs, respectively) (IHME, 2019).

Air pollution was the leading environmental risk factor, ranked fifth among global risk factors for mortality. Air pollution far surpassed environmental risks such as unsafe water and lack of sanitation, which were the main focus of public health measures. Chronic noncommunicable diseases contributed to 82% of the disease burden attributable to air pollution. Air pollution accounted for 41% of global deaths from COPD, 20% from type 2 diabetes, 19% from lung cancer, 16% from IHD, and 11% from stroke. Air pollution also contributes to infectious diseases (35% of deaths from lower-respiratory infections). These contributions vary among countries with different relative levels of ambient and household air pollution (IHME, 2019).

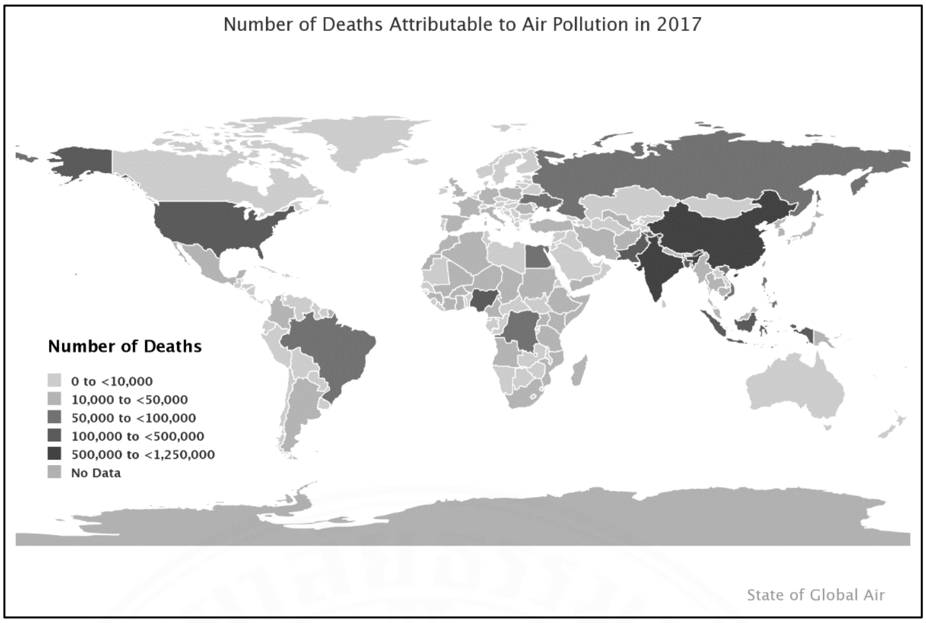


Figure 2.5. Numbers of deaths attributable to air pollution in countries around the world in 2017 (IHME, 2019)

The impacts of air pollution exposure on life expectancy are substantial. Figure 2.6 compares the reductions in life expectancy among significant risk factors. Air pollution can reduce 1.8 years of life expectancy on average worldwide. This means a child born today can die 20 months sooner, on average, than expected in the absence of air pollution. Among 1.8 years of life lost, exposure to ambient $PM_{2.5}$ contributed slightly over one year, followed by indoor air pollution with almost nine months and ozone with less than one month. The global map of life expectancy loss attributable to existing levels of $PM_{2.5}$ exposure in 2016 is illustrated in Figure 2.7. In case of the air quality is improved, such as the concentration of ambient $PM_{2.5}$ was limited to 35 µg/m^3 or lower, the global life expectancy gains increase from about three months on average to 7 months if the $PM_{2.5}$ level is at least 10 µg/m^3 (Figure 2.8).

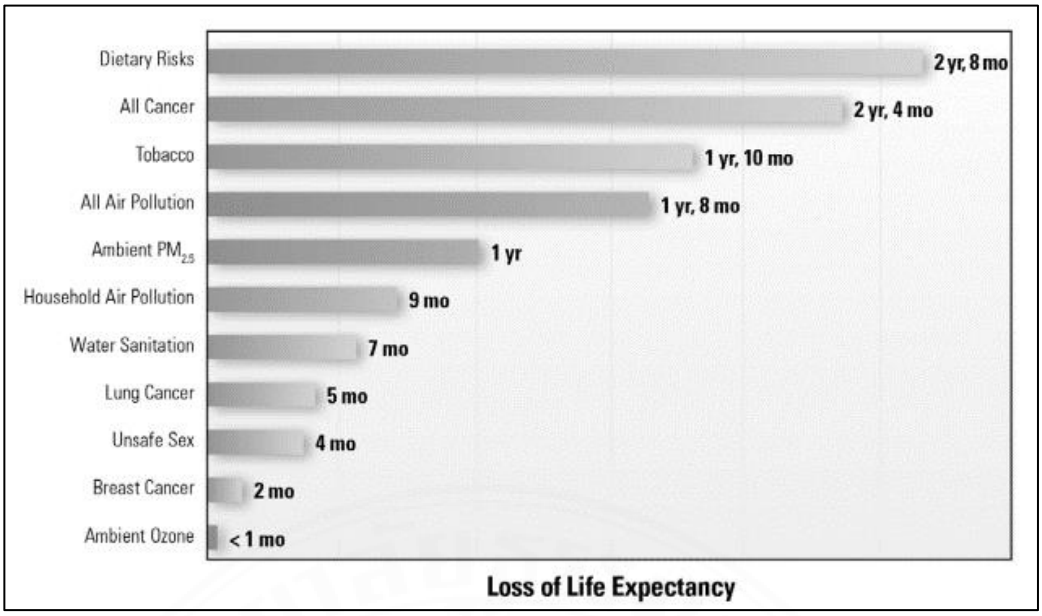


Figure 2.6. Major risk factors for loss of life expectancy (IHME, 2019)

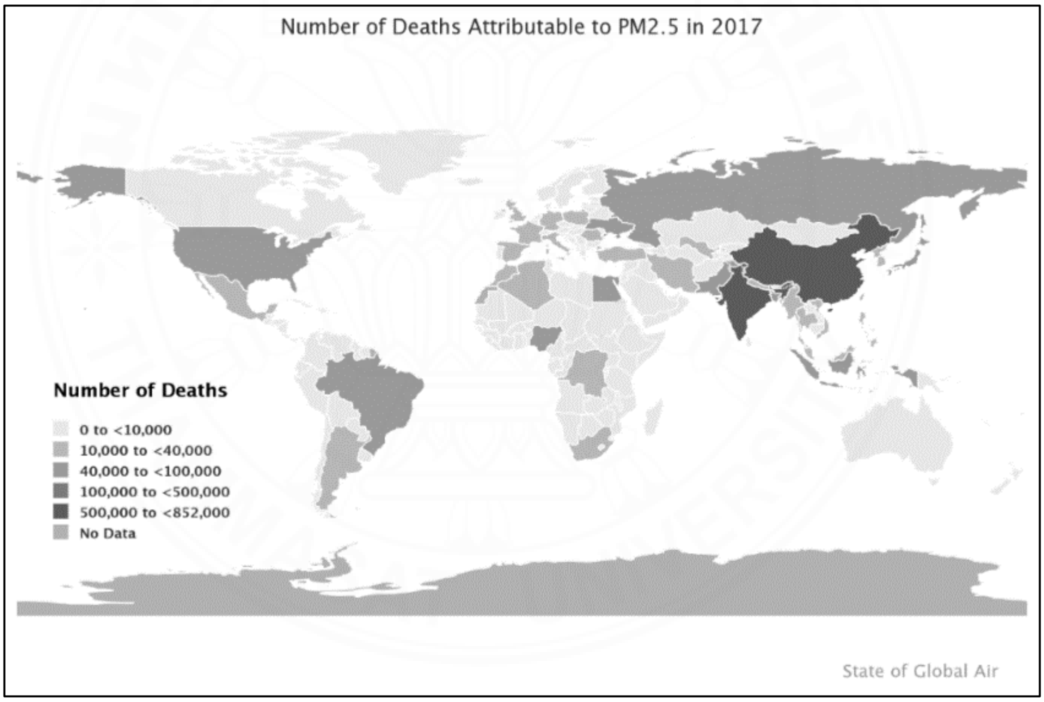


Figure 2.7. Global map of life expectancy loss attributable to existing levels of $PM_{2.5}$ exposure in 2016 (IHME, 2019)

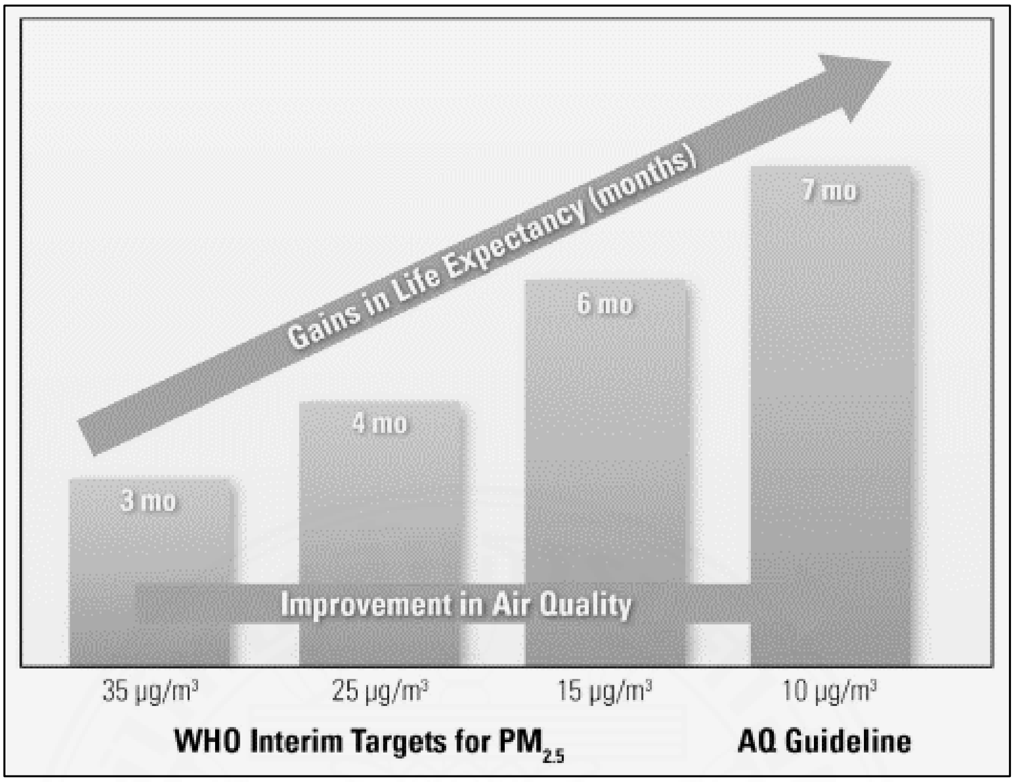


Figure 2.8. Hypothetical global gains in life expectancy if air quality had met WHO interim targets or the Air Quality Guideline (IHME, 2019)

Most studies estimated the number of deaths or hospital admissions caused by air pollution to determine the disease burden. These estimations were typically gained by calculating the number of avoided deaths when the air pollution concentration was pulled back to the standard level. Then, the health economics of air pollution can be measured using the disease burden. There are two common metrics to estimate the monetary value of life, comprising the VSL and the value of a life year (Franchini et al., 2015). The value of statistical life and the value of a life year are correlated, and often the latter is derived from the former.

A study in 25 European cities found that in case of complying with the WHO guideline of annual mean $PM_{2.5}$ (10 $\mu g/m^3$) resulted in 22 additional months of life expectancy at age 30, corresponding to a total of 19,000 deaths delayed (around 400,000 life-years), with a 31 billion Euros health economic (Pascal et al., 2013). The Organization for Economic Co-operation and Development (OECD) estimated that the economic burden from premature deaths from ambient air pollution among 34 OECD countries increased by approximately 7% from 2005 to 2010, reaching 1.6 trillion US dollars in 2010 (OECD, 2014). During the Beijing 2008

Olympic Games, China implemented the enforcement of measures to control the PM_{10} limit of 100 μg/m^3, significantly reducing 38% of health-related economic costs compared with the periods before and after the Games (Hou et al., 2010).

Air pollution has greatly burdened all countries, especially in populous countries such as China and India. In China, a study conducted in 2014 (Chen et al., 2017) reported that if the annual $PM_{2.5}$ level meets the WHO IT-1 with 35 µg/m^3 (WHO, 2005), the number of avoided premature deaths due to cardiovascular, respiratory, and lung cancer were 89,000 people, 47,000 people, and 32,000 people, respectively. The economic benefit was 260 billion China's currency (using WTP to estimate) or 72 billion China currency (using human capital to estimate), making up 0.4% - 0.11% of China's GDP in 2014. Another study using $PM_{2.5}$ mass concentrations from 1,382 national air quality monitoring stations in 367 cities from January 2014 to December 2016 suggested that $PM_{2.5}$ in 2015 contributed 40.3% to total stroke deaths, 33.1% to ALRI under 5-year-old deaths, 26.8% to IHD deaths, 23.9% to lung cancer deaths, 18.7% COPD deaths, 15.5% to all-cause deaths. If the $PM_{2.5}$ concentrations meet the WHO IT-1, IT-2, IT-3, and AQG, the mortality benefits will be 24.0%, 44.8%, 70.8%, and 85.2% of the total mortalities (Song et al., 2017). Similarly, a study in China using air pollutant concentrations in 338 cities in 2017 reported that all air pollutants were attributable to 1.35 million premature deaths for all causes (17.2% of total deaths). Among pollutants, NO_2, $PM_{2.5}$, $PM_{2.5\text{-}10}$, SO_2, O_3 and CO were 28.9%, 11.1%, 5.2%, 9.6%, 23.0%, and 22.2%, respectively. Short-term exposure to air pollutants is associated with nearly 8.0 million cardiovascular and respiratory disease hospital admissions. The overall economic loss due to premature mortality and hospital admissions was 2.5% of China's GDP in 2017 (Yao et al., 2020).

A study in 24 cities in Brazil using a database from 2000 to 2017 illustrated that if the annual $PM_{2.5}$ is 10 µg/m^3, 28,874 – 82,720 premature deaths in Sao Paulo city can be avoided due to all-cause mortality. It was estimated that 2,378 – 6,282 premature death (all causes) could be avoided in all 15 cities in 2017, including 1,373 – 3,428 for cardiovascular diseases, 927 – 2,514 for IHD, and 101 – 264 for lung cancer (Andreao et al., 2018). Similarly, 5,372 premature deaths (all causes) in Iran in 2017 could have been delayed if the $PM_{2.5}$ concentration had been 10 µg/m^3 (Bayat et al., 2019). In Sydney, $PM_{2.5}$ caused 430 premature deaths, resulting in a 5,800-year life loss in 2007. Besides, 630 hospitalized cases due to cardiovascular and respiratory diseases were estimated to be associated with $PM_{2.5}$ (R. A. Broome et al., 2015).

2.6 Air quality standards

In order to protect human health, ecosystems, and other aspects, air quality standards for specific pollutants were set up. However, these standards are slightly different depending on organizations and countries. Table 2.2 provides several pollutant standards. The EPA also set the standards into two levels: primary and secondary. The former was applied for public health protection, including protecting the health of vulnerable groups such as asthmatics, children, and older adults. The latter provides public welfare protection, including protection against decreased visibility and damage to animals, crops, vegetation, and buildings.

Table 2.2 Air quality standards for six principal pollutants according to NAAQS (EPA), WHO (WHO, 2006a, 2021c), European Commission (European Commission, 2018), Thailand (Transport Policy), and Vietnam (MONRE, 2013b)

Pollutant	**Averaging time**	**USEPA NAAQS**	**WHO 2005** (µg/m^3)	**WHO 2021** (µg/m^3)	**EU Commission** (µg/m^3)	**Thailand** (µg/m^3)	**Vietnam** (µg/m^3)
CO	15 minutes	.	100,000 *		.	.	.
	30 minutes	.	60,000 *		.	.	.
	1 hour	35 ppm ^{P}	30,000 *		.	34,200	30,000
	8 hours	9 ppm ^{P}	10,000 *		10	10,260	10,000
	24 hours			4 mg/m^3			
Pb	1 month	.	.		.	.	1.5
	3 months	.	.		.	1500	.
	1 year	0.15 µg/m$^{3\ PS}$	.		.	.	.
	1 hour	.	0.5 *		0.5	.	0.5
NO_2	24 hours	100 ppb ^{P}	200		200	320	200
	1 year	.	.	25	.	.	100
	1 hour	53 ppb ^{PS}	40	10	40	57	40
O_3	8 hours	.	.			200	200
	1 year	0.07 ppm ^{PS}	100	100	120	140	120
$PM_{2.5}$	1 year	12.0 µg/m$^{3\ P}$	10	5	25	25	25
	24 hours	15.0 µg/m$^{3\ S}$	25	15	.	.	.
	1 year	35 µg/m$^{3\ PS}$	25	15		50	50
PM_{10}	24 hours	.	20	15	40	50	50
	10 minutes	150 µg/m$^{3\ PS}$	50	45	50	120	150
SO_2	1 hour	.	500		.	.	.
	3 hours	75 ppb ^{P}	.		350	780	350
	24 hours	0.5 ppm ^{S}	.		.	.	.
	1 year	.	20		125	300	125
	15 minutes	.	.		.	100	50

P: Primary S: Secondary PS: Primary and Secondary

2.7 Prevention and management of particulate matter

Pollution profoundly affects health; therefore, reducing pollution positively impacts health, particularly the health of susceptible individuals. Many studies reported the remarkable effectiveness of measures cutting air pollutant levels. Reducing $PM_{2.5}$ concentrations significantly improved life expectancy (Pope et al., 2009). Reducing black carbon and O_3 levels would prevent over 3 million premature deaths and increase crop yields by around 50 million tons annually (Shindell et al., 2012). If air pollution levels in heavy traffic areas were reduced, asthma and other respiratory diseases would significantly reduce (Kim et al., 2004).

Different interventions are available to reduce exposure to air pollution. Interventions range from national or regional regulations to particular local actions involving single or multiple governmental sectors (Van Erp et al., 2012). Pollution prevention and emission control measures can minimize airborne particulate matter emissions. It should be emphasized that prevention is always better and more cost-effective than control. Reducing PM emissions at sources is far more cost-effective than trying to remove them from the ambient air. Particular attention should be given to pollution abatement measures in areas where toxics associated with particulate emissions may pose a significant environmental health risk.

2.8 $PM_{2.5}$ monitoring network in HCMC, Vietnam

The Vietnam Environment Administration (VEA) of the Ministry of Natural Resources and Environment (MONRE) has established an agency, the Center for Environmental Monitoring (CEM), for monitoring environmental quality in 2018 with two sub-centers, one is responsible for the northern provinces, and the other is for the southern provinces. While the CEM in the north was completely established and implementing monitoring activities, the CEM in the south was still under the establishment and had few databases until 2020. The northern CEM was installed automatic, real-time monitoring systems in Hanoi, Quang Ninh, Viet Tri, Hue, Da Nang, and Nha Trang in 2010 (one station per province, exception for Ha Noi 2 stations). In 2017, Ha Noi installed an additional 10 Air Quality Monitoring Systems (AQMS). The CEM monitoring data of the northern provinces are available to the public at the *cem.gov.vn* website. Provinces such as HCMC belong to the southern CEM, are still without the air quality monitoring network. Recently, HCMC approved a plan for the installation of several AQMS.

Correspondingly, the $PM_{2.5}$ database in HCMC has been relatively limited due to a shortage of automatic monitoring stations. Regarding the governmental sector, The Environmental Monitoring and Analysis Center in HCMC was established around seven years ago; however, they have been operating traditional monitoring. From 2016 to 2019, the sufficient dataset was 2019; however, this dataset was traditionally collected 10 days per month (daily $PM_{2.5}$ concentration) from 6 monitoring stations.

Regarding the non-governmental site, the monitoring station of the US Consulate in HCMC has been established and provided free access to the hourly $PM_{2.5}$ dataset from 2016 to the present. Besides, the Vietnam National University Ho Chi Minh City (VNUHCM) also built a monitoring station in the university several years ago. In general, the potential $PM_{2.5}$ dataset which can be collected in HCMC during the last four years are from the US Consulate and the VNUHCM.

2.9 Studies on adverse health impacts of particulate matter in Vietnam

Overall, several epidemiological studies have shown that exposure to poor air quality results in significant adverse health effects in Vietnam (Table 2.3). Most of the studies were conducted in Ha Noi and HCMC, the two most populated cities in Vietnam, with the availability of the air quality database. However, the number of studies on the health impacts of air pollution in Vietnam has been relatively sparse, especially among children in HCMC.

Six studies were conducted on respiratory diseases and air pollution (Luong et al., 2017; Luong et al., 2020; Mehta et al., 2011; Nhung et al., 2019; Nhung et al., 2018; Phung et al., 2016), 3 in HCMC and 3 in Ha Noi. Two out of three studies in HCMC may be obsoleted due to data collected before 2010 (Mehta et al., 2011; Phung et al., 2016). Besides, the only study of Mehta and others focused on children under 5 years old; meanwhile, Phung and others studied all ages. The newest one (Luong et al., 2020) focused on $PM_{2.5}$ and ALRI among children under 5 years old hospitalized in only one children's hospital from Feb 2016 to Dec 2017; hence it may not fully represent HCMC.

In Ha Noi city, increasing in 10 $\mu g/m^3$ PM was documented with an increase in the risk of admission with respiratory disease (J00-99) among children under 5-year-old of 1.4% (PM_{10}), 2.2% ($PM_{2.5}$), and 2.5% (PM_1) on the same day of exposure (Luong et al., 2017). A higher result was reported in ALRI among children from one to five-year-old. The attributable excess risk for an interquartile range increase in PM was 5.6% (PM_{10}), 6.3% ($PM_{2.5}$), 7.7% (PM_1), and 10.1% (NO_x) (Nhung et al., 2018). In HCMC, $PM_{2.5}$ was reported as a cause of increasing 3.51% risk of ALRI hospital admission among children under 5-year-old, the male seemed to be more sensitive to exposure to $PM_{2.5}$ than females, and acute bronchiolitis was the most popular (Luong et al., 2020). Additionally, NO_2 and SO_2 have been associated with ALRI admissions among children during the dry season, with excess risks of 8.5% and 5.85% (Mehta et al., 2011).

There were four health impact assessment studies in terms of health economic and the health burden of air pollution (Dhondt et al., 2010; Hieu et al., 2013; Ho, 2017; Vu et al., 2020). Ho and others applied the emission sensitivity model to conduct air emission inventory for the transportation sector, i.e., FVM (Finite Volume Model), and TAPOM (Transport and Photochemistry Mesoscale Model) to simulate the meteorology and the spatial distribution of PM_{10} in HCMC. Then, the BenMAP was applied to calculate the number of deaths and estimate economic losses due to PM_{10}. The study reported that a high concentration of PM_{10} causes 204 deaths per year in HCMC, making economic losses of 1.84 billion USD. This study may have a limitation since mortality was collected by interviewing 200 households in 15 wards of District 5. Then the results were interpreted for District 5 and generated for HCMC (24 districts). Hieu and others conducted a study in Ha Noi and reported 3,200 extra deaths caused by traffic-related PM_{10}, and each person lost around 12-14 working days per year from 2007 to 2009 due to $PM_{2.5}$. Dhondt and others implemented a study in Hai Phong City (the north of Vietnam) with the conclusion that the PM_{10} situation in 2007 contributed to 1,287 deaths, and the estimated number of death was 2,741 for the year 2020. The hospital admissions due to PM_{10} rose from 44,954 in 2007 to 51,467 in 2020, and the restricted-activity days due to $PM_{2.5}$ accounted for 852,352 per year. In general, HCMC still lacks studies on health burdens and health economics caused by air pollution, especially $PM_{2.5}$, which can represent the city well. The latest one, the study of Vu and others, reported that if the annual $PM_{2.5}$ concentration in HCMC in 2017 met the WHO guideline of 10 $\mu g/m^3$ (WHO,2005), 1,136 deaths could be avoided from cardiopulmonary diseases (715 deaths), ischemic heart disease – IHD (357 deaths), and lung cancer (64 deaths) (Vu et al., 2020). This study could have been more comprehensive if providing the estimated of avoided deaths due to all causes and calculated monetary benefit.

There is no study in Vietnam concerning the adverse impacts of air pollution on pregnant women and their newborn babies. Vietnam is considered the country with the lowest low birth weight rate in Southeast Asia and Oceania, estimating 8.2% in 2015 (UNICEF-WHO, 2019). The preterm birth rate in Vietnam in 2014 was 6.53%, compared to 12.2% in 2000 (WHO, 2020).

This study aims to provide additional information which may be gaps in previous studies, update the association between $PM_{2.5}$ and health impacts in HCMC, contribute to the growing literature on the health effects of air pollution in Vietnam, and support scientific evidence for a new action program.

Table 2.3. Review of studies regarding ambient air pollution and health impacts in Vietnam

Author	Location	Study design	Study period	Health outcome	Exposure	Main finding
(Mehta et al., 2011)	HCMC (Children 1 Hospital and Children 2 Hospital)	• Case crossover	• 2003 -2005	• Daily hospital admissions for ALRI (J13-J18, J21) amongst children < 5	Daily PM_{10}, NO_2, SO_2, O_3	• ALRI admissions were associated with NO_2 and SO_2 during the dry season, with excess risks of 8.5% (95% CI 0.80 – 16.79) and 5.85% (95% CI 0.44 – 11.55). • PM_{10} could be associated with increased admissions, but PM_{10} and NO_2 showed a strong correlation (0.78), and the study was unable to distinguish.
(Phung et al., 2016)	HCMC (Gia Dinh hospital and 115 People's hospital)	• Times series	• 2/2004 – 12/2007	• Daily hospital admissions for respiratory diseases (J00-99, exclusion J60-70) and CVD (I00-99, exclusion I00-02, I05-09)	Daily PM_{10}, NO_2, SO_2, O_3	• NO_2 and PM_{10} were significantly associated with hospital admissions for respiratory and cardiovascular diseases; SO_2 was moderately associated. • 10 $\mu g/m^3$ increase in each air pollutant increased 0.7%-8% the risk of respiratory admissions and 0.5%-4% the risk of CVD admissions. • People under 65 years old had a higher risk of hospital admissions caused by air pollutants than the older group (except for cardiovascular risk). • Females were more sensitive than males to air pollutants with respiratory diseases.
(Ho, 2017)	HCMC	• Health impact assessment	• 2012	• Extra deaths due to PM_{10}	PM_{10}	• The high concentration of PM_{10} causes 204 deaths per year and making economic losses of 1.84 billion USD
(Luong et al., 2020)	HCMC	• Times series	• 2/2016 - 12/2017	• ALRI (J13 – J18, J21) among children aged < 5	$PM_{2.5}$	• Each 10 $\mu g/m^3$ $PM_{2.5}$ increase was associated with a 3.51% risk of ALRI admission. • Males are more vulnerable than females.

						• Exposure to $PM_{2.5}$ was more likely to be infected with acute bronchiolitis than pneumonia.
(Hieu et al., 2013)	Ha Noi	• Health impact assessment	• 2007-2009	• The mortality effect of PM_{10} • Number of restricted activity days due to $PM_{2.5}$	PM_{10}, $PM_{2.5}$	• 3,200 extra deaths by traffic-related PM_{10}. • Each person lost around 14 days in 2007, 12 days in 2008, and 13 days in 2009 due to $PM_{2.5}$ pollution.
(Nhung et al., 2018)	Ha Noi	• Time series	• 2007-2014	• Daily pneumonia (J12-J18), bronchitis, and asthma (J20, J21, J45) of children 0-17	• Daily PM_{10}, $PM_{2.5}$, PM_1, NO_2, NO_X, SO_2, CO, O_3	• The positive association between air pollutants and pneumonia hospitalization (except O_3, SO_2) for age 0-17, and CO for bronchitis and asthma
(Nhung et al., 2019)	Ha Noi	• Time series	• 2007 – 2016	• ALRI	• Daily PM_{10}, $PM_{2.5}$, PM_1, NO_2, NO_X, SO_2, CO, O_3	• Increased levels of O_3 before admission predicted prolonged hospitalizations. • 85.8 mg/m^3 O_3 increase decreased 5% (2%-8%) in the odds of discharge from the hospital among children with ALRI.
(Nhung et al., 2020)	Hanoi, Quang Ninh, Phu Tho	• Case-crossover study	• 2011 – 2016	• Hospital admissions due to cardiovascular diseases	• Daily PM_{10}, $PM_{2.5}$, PM_1, NO_2, NO_X, SO_2, CO, O_3	• PM was positively associated with daily hospital admissions due to most cardiovascular conditions. • An IQR (34.4 mg/m^3) increment in the two-day average (lag_{1-2}) level of $PM_{2.5}$ was associated with a 6.3% (3.0%–9.8%) increase in the daily count of admissions for IHD and 23.2% (11.1%–36.5%) for cardiac failure. • Hospitalizations for stroke in Hanoi and cardiac failure in Phu Tho showed strong positive associations with SO_2.
(Luong et al., 2017)	Ha Noi	• Time-stratified case-crossover	• 9/2010-9/2011	• Daily hospital admissions for respiratory disease (J00-99) children < 5 years	• PM_1, $PM_{2.5}$, PM_{10}	• 10 μg/m^3 increase in PM_{10}, $PM_{2.5}$, or PM_1 increased 1.4%, 2.2%, and 2.5% the risk of admission on the same day of exposure, respectively.

(Dhondt et al., 2010)	Hai Phong City	• Health impact assessment	• 2007, estimated to 2020	• Extra deaths due to PM_{10} • Extra COPD hospitalization due to PM_{10} • Number of restricted activity days due to $PM_{2.5}$	PM_{10}, $PM_{2.5}$	• 1,287 deaths per year were attributable to the PM_{10} situation in 2007, and the estimated number of deaths by 2020 doubled (2741 cases). • Hospital admissions due to PM_{10}: 44,954 in 2007 to 51,467 in 2020. • The restricted-activity days due to $PM_{2.5}$: 852,352 per year

** Restricted-activity days: the average annual number of days a person experienced staying in bed or a work-loss day or school-loss day or cut-down*

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research design

A time-series study was conducted in Ho Chi Minh City (HCMC) in the south of Vietnam. The study collected morbidity data from three children's hospitals and newborn data from two maternity hospitals and one general hospital, which accounted for most of the newborn babies in HCMC. The mortality database was collected at all 319 commune health stations (CHS) in HCMC. The study collected daily $PM_{2.5}$ concentration data from two monitoring stations in HCMC, i.e., US Consulate and Vietnam National University Ho Chi Minh City.

The health database was collected from 2016 to 2019 because the daily $PM_{2.5}$ concentration data has been available in HCMC since 2016.

3.2 Research method

The secondary data, including hospital records and other stored information, and daily PM2.5 concentration data were used for the study.

3.3 Sample size

The study applied the total population sampling technique. All hospital records that met the inclusion criteria were collected.

3.4 Health outcome database and recruitment process

3.4.1 Morbidity database of respiratory diseases among children

The database was collected at the three specialized children's hospitals (Children's Hospital 1, Children's Hospital 2, and Children's City Hospital). There were three hospitals for children in HCMC and other provinces adjacent to HCMC. Therefore, this dataset was sufficiently representative of HCMC children.

This study focused on acute lower respiratory infection (ALRI) and asthma among children. ALRI was defined as the principal diagnosis of hospital admission based on the International Classification of Diseases, 10th revision code (ICD-10) from J12–J18 or J21

(Horne et al., 2018; Luong et al., 2020; Mehta et al., 2013; Z. Zhang et al., 2019). The diseases were divided into subgroups, such as pneumonia (J12–J18) and bronchitis or bronchiolitis (J21) (Darrow et al., 2014; Nhung et al., 2019). Asthma is a condition in which the airways swell and narrow and may produce extra mucus. It can cause combinate cough, wheeze, shortness of breath, and chest tightness. A database of asthma was extracted using the ICD-10 code from J45-J46.

Information about children equal to or under five years of age from 1.1.2016 to 31.12.2019 was extracted from computerized records of the hospitals. Extracted information included name, gender, age, address, hospitalization date, discharge date, and ICD-10 discharge diagnosis.

The inclusion criteria are the following:

- Children from 0 – 5 ages with the address in HCMC;
- Hospitalized for treating respiratory diseases from 1.1.2016 to 31.12.2019.
- Discharge diagnosis with ALRI based on ICD-10 code from J12 – J18, J21, or asthma (J45-J46).

The exclusion criteria:

- Neonatal admissions (<28 days) were likely to be influenced by perinatal conditions; thus, they were removed (Mehta et al., 2013).
- Repeated hospital admission within 14 days to avoid double counting (Mehta et al., 2013).

3.4.2 Database of newborn babies

There are around 52 hospitals in HCMC that are able to provide delivery services for pregnant women; however, only Tu Du Hospital and Hung Vuong Hospital are the two central specialized maternity hospitals (the highest level) in HCMC. These hospitals are in high priority for most pregnant women for delivery services. In the year 2019, these two hospitals accounted for 60.5% of the total number of babies born in HCHC (184,554 babies), divided into 68,210 babies in Tu Du Hospital (37% of the total) and 43,404 babies in Hung Vuong Hospital (23.5% of the total). Also, another hospital that accounted for a remarkable number of babies born in 2019 is Gia Dinh Hospital (9,520 babies – 5.2% in total). In 2019, the number of newborn babies in these three hospitals accounted for around 66% of the total number of babies born in HCMC.

This study extracted the database of newborn babies delivered in the three hospitals from the hospital's computerized records from 2016 to 2019. Extracted information included baby information, including gender, number of weeks, birth order, weight, and date of birth, and mother information, including age and gestation week. Other mother information, i.e., education, weight, occupation, smoking, and drinking alcohol status, was unavailable in the hospital records.

The inclusion criteria were cases that the baby's mothers had an address in HCMC and delivered a baby in 2016 – 2019. The exclusion criteria were cases lacking newborn information (weight, gender), twins or more, and stillbirth.

3.4.3 Mortality database among the whole population

In HCMC, CHS is the lowest level in the health system. They provide essential health services for the community and monitor community health, including recording the number of people who die annually. There were 319 CHSs in total, and this study collected all mortality databases from all CHSs.

The information was collected, including gender, age, year of death, address, and cause of death (categorized in the ICD-10 code).

The inclusion criteria were people who had an address in HCMC and died from 2016 to 2019. There were no exclusion criteria.

3.5 Ambient air $PM_{2.5}$ concentrations and meteorological data recruitment process

The $PM_{2.5}$ database was collected at two monitoring stations in the center of HCMC, shown in Figure 3.1. The first source of $PM_{2.5}$ data was the Ho Chi Minh City US Consulate (10.7835°N, 106.7006°E, hourly value) (AirNow, 2020). Outlier values were detected using median absolute deviation within a running window of 6 hours (Singh et al., 2021). Values noted with invalid or suspected values and detected outliers were treated as missing. Valid values which were under the limit of detection (LOD) of the monitoring instrument (Beta-ray Attenuation Monitor, BAM 1020) were replaced by the LOD of the instrument (4.8 $\mu g/m^3$). Daily mean $PM_{2.5}$ concentration was then calculated using the criteria of at least 75% valid hourly values. The daily average concentration was assigned as missing when hourly concentration data was lower than 18 hours (Nandar et al., 2020). Another source of $PM_{2.5}$ data was from the University of Science - Vietnam National University HCMC (10.7626°N, 106.6819°E, daily value).

The missing daily values were replaced with the mean concentration of the day before and the day after (Mohamed Noor et al., 2008). In the case of two or more consecutive days with missing $PM_{2.5}$ concentration, these days were left blank. The city's daily level concentration of $PM_{2.5}$ was calculated by averaging the 24-h hourly data from the two monitoring stations.

Figure 3.1. The geographical location of Ho Chi Minh City and the location of the $PM_{2.5}$ monitoring stations in HCMC

Temperature and relative humidity data were collected from the National Centers for Environmental Information (https://www.ncei.noaa.gov). A real-time monitoring station was located at the HCMC's Tan Son Nhat international airport. The recorded dataset comprises daily minimum, maximum, and average temperatures (°F) and daily average dew point (°F). The daily relative humidity data were calculated from ambient and dewpoint temperatures based on the following equation:

$$\textbf{Relative humidity (RH)} \approx \mathbf{100 - 5}(\boldsymbol{T - T_{dp}})$$ (Lawrence, 2005).

Where T is the temperature (^{0}C), and T_{dp} is dew point temperature (^{0}C).

Temperature and relative humidity were also collected from the National Center for Hydro-Meteorological Forecasting in HCMC. The final temperature and relative humidity dataset was the two sources' average.

3.6 Variable definition

3.6.1 Dependent variables

a) In terms of the morbidity database, the dependent variables were:

- The number of daily hospitalized children due to ALRI: the total daily number of children had discharged diagnosis according to ICD-10 from J12 – J18 (pneumonia) and J21 – J22 (bronchitis) at three children's hospitals.
- The number of daily hospitalized children due to asthma: the total daily number of children had discharged diagnosis according to ICD-10 from J45 – J46 at three children's hospitals.

b) Regarding variables relating to newborn babies, there were three variables:

- Weight of newborn babies: This was a continuous variable.
- Newborn babies diagnosed with term-low birth weight: This was a binary variable; a baby was diagnosed with low birth weight when weight was below 2500g.
- Newborn babies diagnosed with pre-term birth: This was a binary variable; a baby was diagnosed with pre-term birth when they were born alive before 37 weeks of gestation.

c) Regarding the mortality database, the dependent variable was the number of daily deaths due to total causes and specific death causes.

d) Relating to the burden of PM2.5, there were two variables calculated by the BenMAP-CE tool:

- The number of premature deaths can be avoided.
- The amount of money was lost due to premature deaths.

3.6.2 Independent variables

The independent variables included:

- Daily $PM_{2.5}$ concentration.
- Weather parameters (temperature, relative humidity), season.
- Personal characteristics: gender, age.

3.6.3 Conceptual frameworks

The conceptual frameworks of this study, including the conceptual framework of study objectives, the conceptual framework of health data collection sites, the conceptual framework of variables, and the framework of the study, are shown in Figures 3.2 to 3.5, respectively.

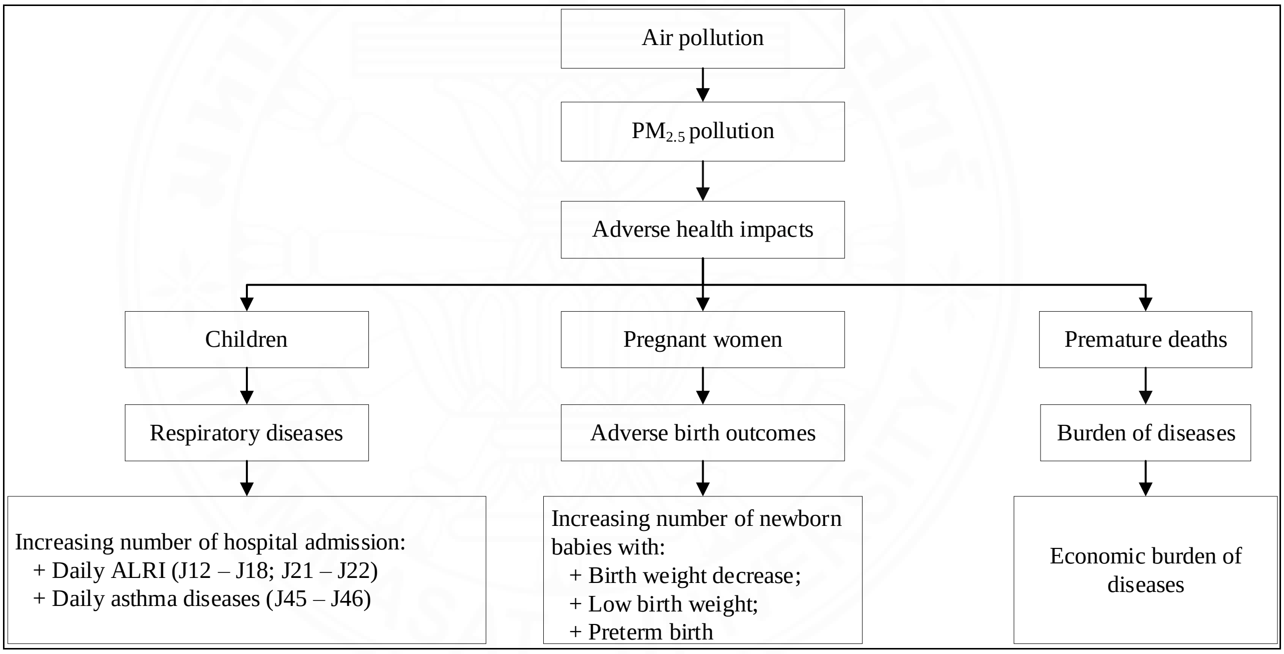


Figure 3.2. Conceptual framework of study objectives

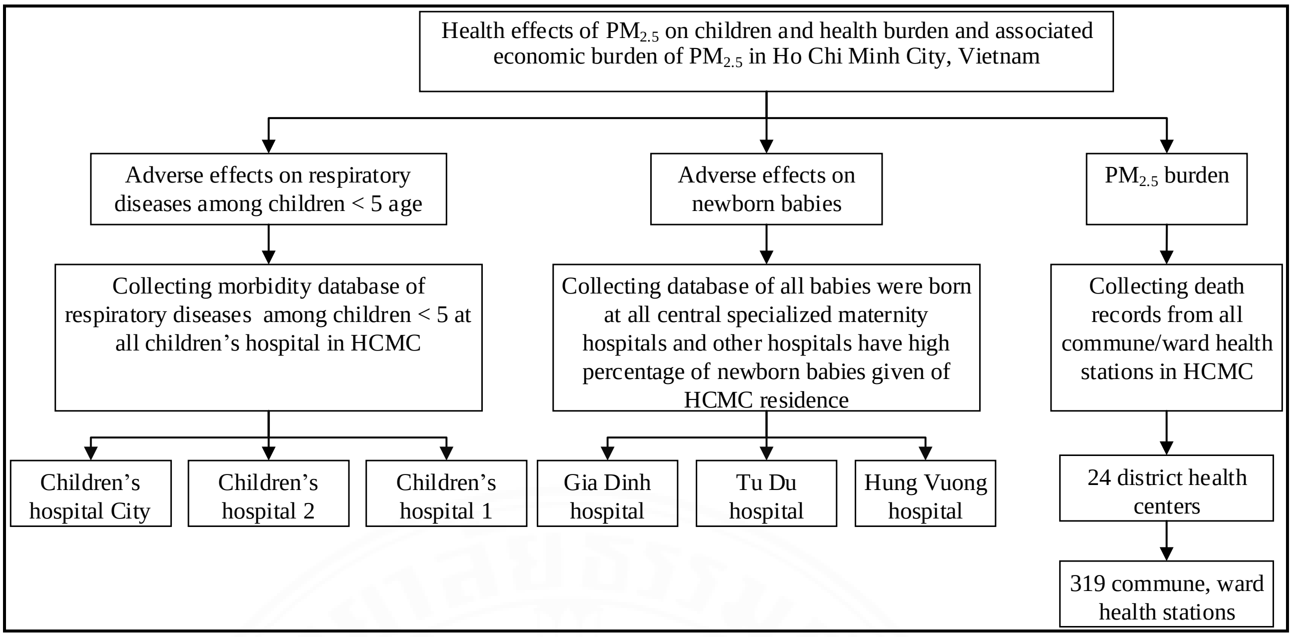


Figure 3.3. Conceptual framework of health data collection sites

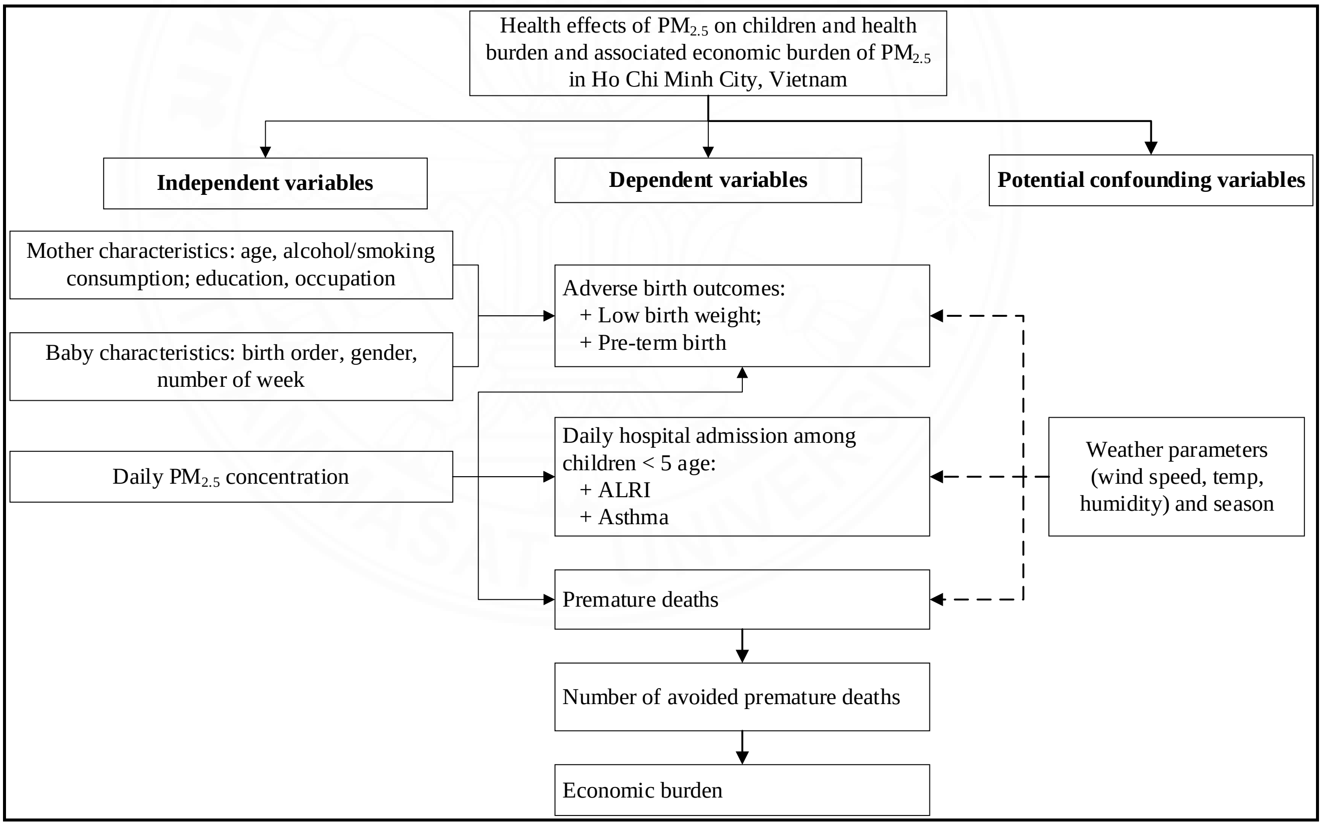


Figure 3.4. Conceptual framework of variables

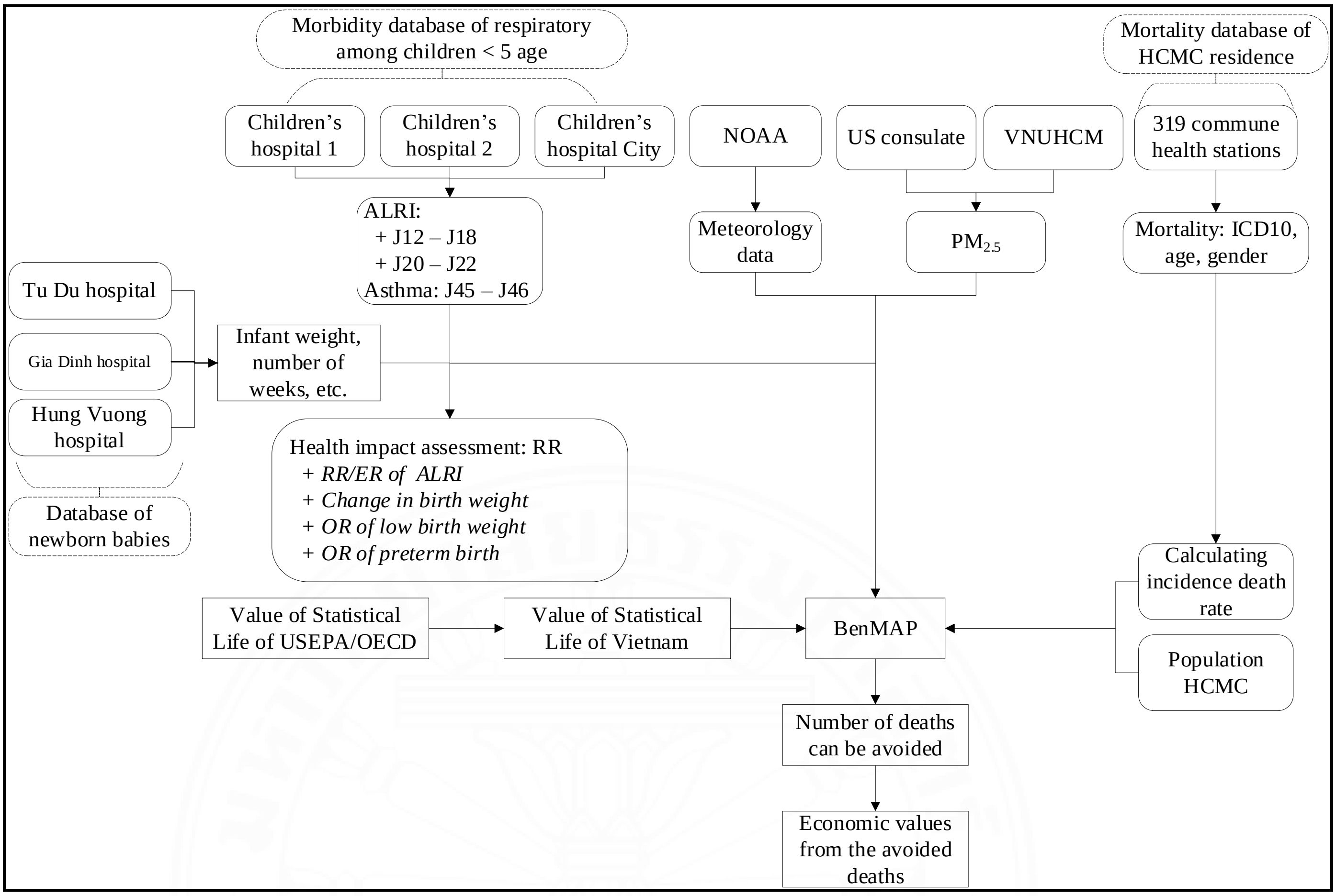


Figure 3.5. Conceptual framework of the study

3.7 Data cleaning

3.7.1 Data cleaning of health outcomes

ALRI and asthma

The data cleaning process is shown in Figure 3.6. The raw data from each hospital were selected using the ICD-10 code from J12 – J18, J21 – J22, and J45 – J46. Then, data were continuously removed from hospitalized cases before 1/1/2016 or after 31/12/2019; age out of range from 28 day-olds to under 5-year-old; and did not have an address in HCMC. Cases with multiple hospital admissions during 14 consecutive days were selected for the first-time hospital admission.

After cleaning data in each hospital, data from three hospitals were combined and checked the repeat hospital admission for 14 consecutive days again. The final data were categorized by gender, age group (<2 and from 2 - < 5), and ICD-10 code of ALRI (pneumonia: J12 – J18, bronchitis: J21 – J22).

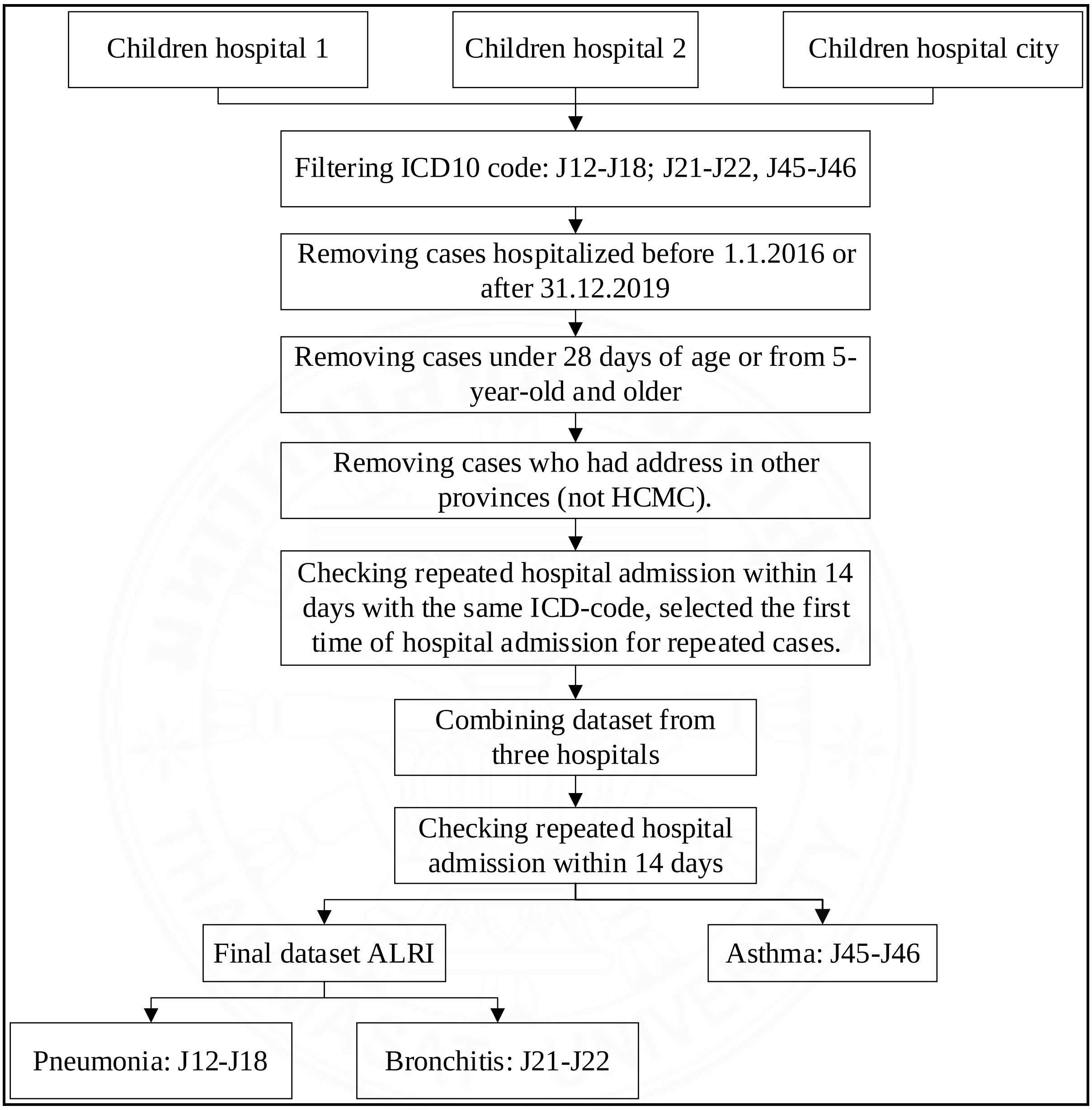


Figure 3.6. The process of data cleaning the ALRI database and asthma disease database

Infant database

The study defined the term LBW as an infant having a gestational period from 37 – 44 weeks and weighing less than 2500 g (Hyder et al., 2014). A PTB case was a baby born alive before 37 weeks (WHO, 2018d). The combined newborn database from the three hospitals was cleaned by removing cases with missing information on the mother's age and cases with multiple pregnancies; stillbirths; undetermined or missing infant gender; mother's age lower than 15 or higher than 59-year-old; missing infant weight; infant weight lower than 1,000 g or higher than 5,500 g (Hyder et al., 2014; Z. Li et al., 2019). The database was subsequently cleaned regarding three birth outcomes, including BW decrease, PTB, and term LBW. For BW decrease, only infants with a gestational period from 32 – 44 weeks were selected for analysis (Z. Li et al., 2019). For term LBW, only cases with gestation lengths from 37 – 44 weeks were selected (Hyder et al., 2014; Rappazzo et al., 2014). Regarding PTB, cases with gestation periods lower than 20 weeks or higher than 44 weeks were removed (Hyder et al., 2014; Rappazzo et al., 2014).

Mortality database

The mortality database was cleaned to retain data on cases that had the address in HCMC and died during 2016-2019.

3.7.2 Data cleaning of $PM_{2.5}$ concentration and weather parameters

The data cleaning process of $PM_{2.5}$ and meteorological parameters is presented in Figure 3.7. For the hourly value of $PM_{2.5}$ from the US monitoring station, values noted as invalid and suspected were treated as missing. Outlier values were detected using median absolute deviation within a running window of 6 hours (Singh et al., 2021) and then were treated as missing values. Valid values which were under the lower detection limit (LOD) of the monitoring instrument (BAM 1020) were replaced by LOD (4.8 $\mu g/m^3$). Daily mean $PM_{2.5}$ was calculated with at least 75% valid hourly values. The daily average concentration was assigned as missing when hourly concentration data was lower than 18 hours (Wong et al., 2008). The missing values of daily $PM_{2.5}$ concentration could be converted from the daily PM_{10} concentration as an alternative method; however, daily PM_{10} data was unavailable. Therefore, missing values were filled using the mean-before-after method (Mohamed Noor et al., 2008). If two or more consecutive days were missing the daily $PM_{2.5}$ value, those days were left blank (missing).

The daily mean $PM_{2.5}$ calculated from the US consulate was combined with a daily $PM_{2.5}$ concentration of the VNUHCM station to get a final daily $PM_{2.5}$. If a missing daily value was encountered at either one of the two monitoring stations, the daily data of the other was used. If they were encountered at both stations, that day was left blank.

There were two data sources regarding meteorological parameters, including the NOAA and the National Center for Hydro-Meteorological Forecasting in HCMC. The average daily temperature and relative humidity were taken from the two sources.

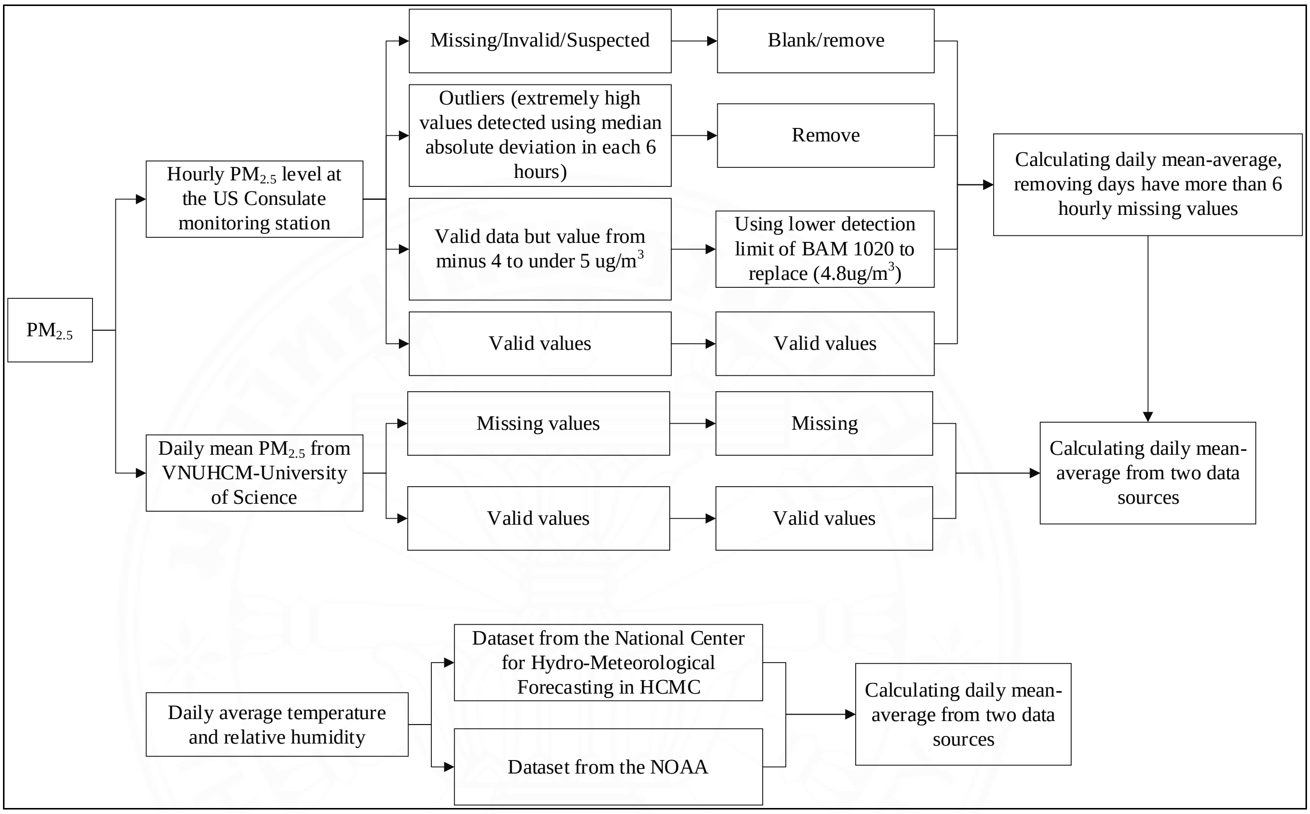


Figure 3.7. The process of data cleaning $PM_{2.5}$ and the meteorological parameters dataset

3.8 Statistical analysis

3.8.1 Descriptive analysis

The health outcome database was described using frequency and mean (standard deviation). The daily concentration of $PM_{2.5}$ and other weather parameters were presented with mean and standard deviation (or median and interquartile range). Several graphs, such as line – and – bar plots, were also employed to illustrate daily $PM_{2.5}$ levels and numbers of health outcomes.

3.8.2 Determining the association between $PM_{2.5}$ and respiratory diseases among children

3.8.2.1 ALRI

The generalized linear models with the family of quasi-Poisson distribution were applied to assess the association between daily concentration $PM_{2.5}$ and ALRI. Potential confounding factors, including temperature, relative humidity, day of the week, and national holidays were controlled by integrating them into the model.

Health outcomes are the counted data and follow Poisson distribution. The Poisson model was a commonly applied statistical model for counting data. However, one of the assumptions of the Poisson model was that the mean and the variance were equal. In practice, the observed data was usually overdispersion meaning that the observed variance was larger than the assumed variance (Lee et al., 2012). Applied the traditional Poisson model for the overdispersion could result in an inaccurate conclusion by underestimating the variability of the data (Cox, 1983). Therefore, the quasi-Poisson model was a remedy for overdispersion data (Ver Hoef and Boveng, 2007).

This study estimated the lagged effects of $PM_{2.5}$ up to 7 days (Croft et al. 2019; I.-S. Kim et al. 2020; Luong et al. 2020; Nenna et al. 2017) applying the distributed lag linear models (DLM) (Gasparrini 2011). The single-day lag models were used to assess the delayed effects of individual lagged exposure. In the DLM, the different lag effects were adjusted for each other by adding all lag effects into the model. The DLM overcame the possible limitations of the single-day lag models, which estimated the lag effect separately (Zheng et al. 2017).

In the DLMs models, three cross-basis matrices for the three predictors ($PM_{2.5}$, temperature, and relative humidity) were built and then put in the model formula of a regression function. The effect of $PM_{2.5}$ exposure was assumed linear with the health outcomes, and the lag structures were set up to 7 days with an integer function. The cross-basis matrices of temperature and relative humidity were fitted in the model with B-spline function and strata for lags (0-1, 1-3, 3-5, and 5-7 days).

The study controlled seasonal and long-term trends using a natural spline with 7 df-degrees of freedom per year (Bhaskaran et al., 2013). The plot of residuals over time and the Dickey-Fuller test were used to examine the stationary of the model after control. The day of the week was put in the models as a categorical variable, and a dummy variable was used for a national holiday in years. The population in HCMC from 2016 to 2019 was assumed to be stable. The general analytical model was as follows:

$$Y_{s,t} \sim quasi - Poisson\ (\mu_t)$$

$$Ln(\mu_{s,t}) = \alpha + spl(time, df = 28) + \gamma_1 PM_{s,t} + \gamma_2 Temp_{s,t} + \gamma_3 RH_{s,t} + \gamma_4 Dow + \gamma_5 Hol$$

where $Y_{s,t}$ was the observed daily count of hospital admissions in spatial unit *s* and period time *t*; α was the intercept; *spl* was the flexible spline function of time, using a cubic B-spline; *df* was the degree of freedom. $PM_{s,t}$ was the $PM_{2.5}$ levels at each lag single-day lag model or a cross-basis matrix of $PM_{2.5}$ levels at each lag day in DLMs. $Temp_{s,t}$, and $RH_{s,t}$ were temperature values, and relative humidity was categorized for 10 deciles in the single-day lag models or cross-basis matrix of daily mean temperature and relative humidity in DLMs, respectively. *Dow* was the categorical day of the week; *Hol* was the binary variable for a national holiday (1 for a holiday and 0 for a non-holiday).

The reliability of the model was checked with sensitivity analysis. The controlling seasonality and long-term were tested with different degrees of freedom, 6 df per year and 8 df per year. Time-stratified models with a stratum for each month nested in a year were also applied instead of the cubic B-spline to control seasonality and long-term.

The results were reported as excess risk - ER (ER = (RR – 1) *100), and its 95% confidence interval (CI) for daily hospitalization for ALRI per 10 µg/m^3 increase in $PM_{2.5}$. R software version 3.5.3 (http://www.r-project.org) was used for all analysis, applying the packages including lubridate, tsModel, ggplot2, ggfortify, ggthemes, gridExtra, Epi, dlnm, and splines.

3.8.2.2 Asthma

The association between daily $PM_{2.5}$ and the number of asthma hospitalizations among children was calculated with the Generalized additive models (GAM) with quasi-Poisson regression (Chang et al., 2019). The time trend was controlled with the natural spline function with 7 df per year. The model was controlled for possible confounding variables of temperature and relative humidity by a natural spline function with 6 df for temperature and 3 df for relative humidity. The day in the week and holidays were fitted into the model as a categorical variable (day of the week) and dummy variable (holidays).

The association between $PM_{2.5}$ and asthma was estimated up to 4 lag-days of $PM_{2.5}$ using the moving average. The average of the present day and the previous days were lag_{01} (previous day), lag_{02} (previous 2 days), lag_{03} (previous 3 days), and lag_{04} (previous 4 days).

The results were reported as excess risk and its 95% CI for daily hospitalization for asthma per 10 $\mu g/m^3$ increase in $PM_{2.5}$. R software version 3.5.3 (http://www.r-project.org) was used for all analysis, applying the packages including Epi, splines, tsModel, and mgcv.

3.8.3 Determining the association between $PM_{2.5}$ and adverse birth outcomes

Linear regression was employed to determine the association between BW and $PM_{2.5}$; logistic regression was used to estimate the relationship between binary variables (PTB and term LBW) and $PM_{2.5}$. Models were adjusted for several covariates, including infant gender, maternal age (under 20, 20-29, 30-39, over 39 years), length of gestation week (32-36, 37- 40, 41-44 weeks), birth order (first, second or more), year of pregnancy (2015, 2016, 2017, 2018 and 2019), pregnant season (rainy season and dry season), average temperature, average relative humidity throughout the pregnancy-specific period (Michelle L. Bell et al., 2007; Stieb et al., 2016). Other factors could affect birth outcomes, such as education, occupation, alcohol, and smoking history consumption of the mother; however, these factors were not available in the hospital record.

The study aimed to determine the adverse effects of $PM_{2.5}$ during five different periods of $PM_{2.5}$ exposure, i.e., the first month of pregnancy; the first trimester (1^{st} – 13^{th} weeks); the second trimester (14^{th} – 26^{th} week); the third trimester (27^{th} – week of birth) and the entire pregnancy (1^{st} week – week of birth) (Z. Li et al., 2019). The average concentration of $PM_{2.5}$ exposure, temperature, and relative humidity were estimated for each pregnant woman corresponding with each period for analysis. Based on the date of birth and gestation length (weeks) in the hospital record, the study estimated the first day of pregnancy using the date of birth minus the gestational period. Then, the average exposure was calculated for every week until delivery.

The associations between $PM_{2.5}$ exposure and PTB and term LBW were reported using OR and its 95%CI for 10 $\mu g/m^3$ increase in $PM_{2.5}$. For BW, the results showed the average weight change for every 10 $\mu g/m^3$ increase in $PM_{2.5}$. Sensitivity analysis for the linear gestational exposure models restricting the data set to first births only was executed. A P-value <0.05 implied the statistical significance of associations when comparing.

3.8.4 Estimating health effects using the BenMAP-CE tool

3.8.4.1 BenMAP-CE

The USEPA released BenMAP in 2003 to quantify the health burden and health economics with the air quality changes. In 2015, BenMAP was transformed into an open-source software called BenMAP-CE (BenMAP-Community Edition), enabling a broadly accessible (Sacks et al., 2018). Compared to other tools with similar functions, BenMAP-CE was considered the most comprehensive tool (Anenberg et al., 2016).

The BenMAP-CE operates based on four main components comprising (i) Air quality database; (ii) Population database; (iii) Incidence rates of health endpoints; (iv) Health effect function (the response of a health effect for a unit change in an air pollutant concentration, which referred to as a beta – ß coefficient) (Sacks et al., 2018). Besides, BenMAP-CE needs maps at different levels of the study area.

Based on the baseline air pollution data and the control scenarios, BenMAP-CE would determine the change in pollutant concentration. Then, BenMAP-CE related the risk of change in pollutant concentration with specific health endpoints (ß coefficients). BenMAP-CE applied ß coefficients to the population experiencing the change in pollutant exposure to calculate health impacts with the following equation:

$$\Delta Y = I_0 * Pop * (1 - e^{-\beta * \Delta PM})$$

Where △Y referred to the estimated health impact attributed to pollutants, ß was the coefficient from an epidemiological study, △PM defined change in air quality, I_0 was the baseline incidence rate for the health effect of interest, and Pop was the population exposed to air pollution (Sacks et al., 2018).

3.8.4.2 Counterfactual scenarios

The air quality change (△PM) was the difference between the starting air pollution level (the baseline) and the concentration after some modification, such as a new regulation (the control). This study assumed three control scenarios for the annual concentration of $PM_{2.5}$, including the WHO AQG in 2021 of 5 μg/m^3 (the first scenario) and the WHO AQG in 2005 of 10 μg/m^3 (the second scenario)(WHO, 2005, 2021c), and the Vietnamese standards of 25 μg/m^3 (the third scenario) (MONRE, 2013a). BenMAP-CE was used to estimate the number of avoided deaths associated with changing $PM_{2.5}$ concentration between the baseline ($PM_{2.5}$ concentration in 2019) and the control scenarios.

3.8.4.3 Exposed population

The exposed population was the number of people affected by air pollution reduction. In this study, the exposed population was the HCMC population. HCMC's population was aggregated from reports of all 22 districts and categorized by each 5-year age group (0-4, 5-9, 10-14, …, 80 up), gender, and district. During 2019-2019, HCMC had only population data for 2019; thus, the BenMAP-CE was only applied to calculate the health and economic benefits for the HCMC in 2019. The HCMC population in 2019 was 8.9 million, female accounted for 51%, and 40% was under 30 years old.

3.8.4.4 The baseline death rate and health endpoints

The baseline incidence rate (I_0) was the mortality rate calculated from the total number of deaths in HCMC in 2019. The mortality rate was calculated in detail for each health endpoint using the International Classification of Diseases of 10th revision (ICD-10), age group (each 5-year-group), gender, and 22 districts. This study estimated the number of avoided deaths due to six health endpoints, including all causes (A00-R99), all causes (non-accident), cardiopulmonary diseases (I00-I99 and J00-J99), cardiovascular diseases (I00-I99), IHD (I20-I25) and lung cancer (C33-C34).

3.8.4.5 Concentration-response functions (ß coefficient)

ß coefficient was the relationship between $PM_{2.5}$ and a particular health endpoint. It was estimated using a health impact or concentration-response function (Burnett et al., 2014; Lim et al., 2012). ß coefficient reflected the percentage change in the risk of an adverse health effect due to a one-unit change in ambient air pollution. ß coefficients could be estimated by models, such as Integrated Exposure-Response (Burnett et al., 2014) and Global Exposure Mortality Model (Burnett et al., 2018). ß coefficients could also be derived from relative risk –

RR or Odds ratio – OR or Hazard ratio – HR in epidemiological studies (typically cohort studies with an extended follow-up and large population) (Cao et al., 2011; Cesaroni et al., 2013; Crouse et al., 2012; Krewski et al., 2009; Laden et al., 2006; Pope et al., 2002; Pope et al., 2004; Yin et al., 2015) and systematic review (Hoek et al., 2013; Janssen et al., 2011). The equation of ß calculation and standard error of ß ($ß_{se}$) was followed (EPA, 2022):

$$\beta = \frac{\ln(\text{RR or OR or HR})}{\Delta\ \text{pollution}} \qquad \beta_{se} = \frac{\frac{\ln(\text{UCL})}{\Delta\ \text{pollution}} - \frac{\ln(\text{LCL})}{\Delta\ \text{pollution}}}{2*1.96}$$

$$\text{LCL} = \frac{\beta - \beta_{2.5\ percentile}}{1.96} \qquad \text{UCL} = \frac{\beta_{97.5\ percentile} - \beta}{1.96}$$

Where: ln is natural log; UCL is upper confidence limit; LCL is lower confidence limit.

Ideally, this study should use the ß coefficients estimated for the Vietnamese or HCMC populations; however, no such studies were available. Therefore, this study applied ß coefficients of other countries (Table 3.1).

ß coefficients calculated from the study of Krewski et al. (2009) have been used in numerous studies to estimate the health impacts of $PM_{2.5}$ (Altieri and Keen, 2019; Andreao et al., 2018; Richard A. Broome et al., 2015; Hassan et al., 2021; Manojkumar and Srimuruganandam, 2021; Nandar et al., 2020; Yang et al., 2019). Krewski et al. (2009) analyzed data from the extended follow-up study of the American Cancer Society (ACS). This study followed up 552,138 people aged 30 and older from 1982 – 2000 in all 50 states of the United States (US). The study reported a significant association between $PM_{2.5}$ concentration and increased mortality risk due to all causes, cardiopulmonary diseases, IHD, and lung cancer (Krewski et al., 2009). Another cohort study was Havard Six Cities – H6C conducted from 1974 – 2009 among 8,096 people aged 25 – 74 in six east cities of the US. The study reported a significant association between $PM_{2.5}$ and death due to all causes, cardiovascular diseases, and lung cancer (Lepeule et al., 2012).

Applying ß coefficients from the studies of the US population to other populations, such as HCMC, could limit a generation-representative result due to several factors. They could be the difference in characteristics of populations, the annual average $PM_{2.5}$ concentration, the constituents of $PM_{2.5}$, and other topography and climate factors. Therefore, our study used ß coefficients calculated from different areas, including studies in the US (Krewski et al., 2009;

Lepeule et al., 2012), Italy (Cesaroni et al., 2013), China (Cao et al., 2011), Thailand (Fold et al., 2020), and a meta-analysis (Hoek et al., 2013) to provide wide-range possible results.

The meta-analysis of Hoek et al. (2013) combined many studies globally, including studies from America, Europe, and Asia, to determine the association between $PM_{2.5}$ and mortality risk of all causes and cardiovascular diseases. Therefore, its ß coefficients could be acceptably reliable compared to a single epidemiological study for reference. Applying ß coefficients of study in China (Cao et al., 2011) and Thailand (Fold et al., 2020) could be more consistent for HCMC because of several similar patterns of country and population. However, these studies had several limitations. The study in China indirectly estimated $PM_{2.5}$ through a ratio of total suspended particulate, and the result only reported the significance between $PM_{2.5}$ and mortality due to cardiovascular diseases. The study in Thailand also reported the significance between $PM_{2.5}$ and mortality of all causes (non-accident). Besides, the study in Thailand did not control any potential confounding factor.

In this study, we estimated the number of avoided deaths using ß coefficients calculated from various studies in Table 3.1 and then pooled the results with random effect in BenMAP (Altieri and Keen, 2019).

Table 3.1. ß coefficients and its standard error ($ß_{se}$) for increasing 10 μg/m^3 $PM_{2.5}$ of long-term exposure

Studies	Location	Time	Age	$ß \pm ß_{se}$					
				All-cause	**All-cause (non-accidental)**	**Cardiopulmonary**	**Cardiovascular**	**IHD**	**Lung cancer**
Krewski et al. (2009)	USA	1982-2000	30-99	0.002956 ± 0.000991	*na*	0.008618 ± 0.001405	*na*	0.013976 ± 0.001989	0.010436 ± 0.003222
Lepeule et al., (2012)	USA	1974-2009	25-74	0.013103 ± 0.003347	*na*		0.023111 ± 0.005241	*na*	0.031481 ± 0.01255
Cesaroni et al. (2013)	Italy	2001-2010	30-99	*na*	0.003922 ± 0.000491	*na*	0.005827 ± 0.000963	0.009531 ± 0.001631	0.004879 ± 0.002178
Hoek et al. (2013)	Systematic review		30-99	0.006015 ± 0.001033	*na*	*na*	0.010075 ± 0.002445	*na*	*na*
Cao et al. (2011)	China	1991-2000	15-99	*na*	*na*	*na*	0.002762 ± 0.000919	*na*	*na*
Fold et al. (2020*)	Thailand	2007-2016	30-99	*na*	0.001743 ±0.0007458	*na*	*na*	*na*	*na*

na.: Not available

3.8.5 Estimating health economics using the BenMAP-CE tool

Air quality improvement decreases negative health impacts such as mortality and morbidity for the community. In economics, an avoided death is worth a certain amount of money. After calculating the health benefits, BenMAP-CE could estimate the health economic value by multiplying the reduction of avoided deaths with an estimated economic value per case (EPA, 2022).

This study applied VSL to calculate the economic benefit. The Vietnamese VSL in 2019 was calculated by converting from the VSL reference of the USEPA and the Organization for Economic Cooperation and Development (OECD) using the following formula:

$$\mathbf{VSL_{VN,2019} = VSL_{base} * (Y_{VN,2019}/Y_{base,2019})^{\varepsilon}}$$ (EPA, 2022; World Bank and IHME, 2016)

Where $VSL_{VN,2019}$: The Vietnamese VSL in 2019

VSL_{base}: The base VSL of the reference. The VSL of OECD was 3,832,843$ (2011 US $, PPP) (World Bank and IHME, 2016), and the VSL baseline of USEPA was 8,700,000$ (2011 US $, PPP) (EPA, 2022; World Bank, 2020).

$Y_{base,2019}$ and $Y_{VN,2019}$: Gross domestic product (GDP) per capita of OECD or the US and the Vietnamese GDP per capita in 2019, adjusted with PPP. GDP per capita (PPP adjusted) in 2019 of Viet Nam, USA, and OECD were 10,134, 62,459, and 44,628 (2017 US $), respectively (World Bank, 2020).

ε: The VSL inflation coefficient. It was suggested for the developing countries from 1.0 – 1.4. This study used an average value of 1.2 (World Bank and IHME, 2016).

Hence, the Vietnamese VSL was 647,050$ and 981,200$ (2011 US $, PPP) using the VSL reference of OECD and the USEPA, respectively.

3.8.6 Analysis using the Vietnamese mortality incidence rate from Global Burden Diseases

The analysis was executed with the mortality incidence rate from Global Burden Diseases (GBD) (IHME, 2020). The GBD provided an estimation of the mortality incidence rate for each country; thus, this study assumed the mortality incidence rate in HCMC was similar to Viet Nam. The purpose of this analysis is to compare the results when using the mortality incidence rates calculated from the mortality database of the Ho Chi Minh City population.

3.9 Ethical study

The Thammasat University Ethics Committee approved this study's ethical approval, COA No. 071/2564, project No. 059/2564, on 29 June 2021.

CHAPTER 4

RESULTS

4.1 Daily $PM_{2.5}$ concentration and meteorological parameters in Ho Chi Minh City from 2016 to 2019

In Table 4.1, the daily concentration of $PM_{2.5}$ in HCMC from 2016-2019 was 8.6 µg/m^3 to 76.9 µg/m^3 with an annual average of 28.2 µg/m^3. The annual average of temperature and relative humidities were 28.6 (^{0}C) and 72.5 (%).

Table 4.1. Descriptive statistics of daily $PM_{2.5}$ concentration and weather parameters in Ho Chi Minh City from 2016-2019 (n=1461)

Parameters	**Frequency distribution**			**Mean (SD)**	**Min – Max**
	25th	**50th**	**75th**		
$PM_{2.5}$ (µg/m^3)	19.8	25.6	35.3	28.2 ± 11.2	8.6 – 76.9
Temperature (^{0}C)	27.7	28.6	29.3	28.6 ± 1.3	22.6 – 32.5
Relative humidity (%)	68.0	72.7	77.8	72.5 ± 7.3	51.5 – 93.3

Out of the total of 1461 days from 2016-2019, 758 days (52%) and 1,342 days (92%) had the daily average $PM_{2.5}$ level exceeded the WHO guideline values of 2005 (25 µg/m^3) and 2021 (15 µg/m^3), respectively. For the Vietnamese daily average standard of 50 µg/m^3, 66 days (4.5%) had the daily average $PM_{2.5}$ concentration exceeded the standard (Table 4.2).

Table 4.2. Number of days on which the daily average $PM_{2.5}$ concentration exceeded the WHO guidelines/Vietnamese standard

Guidelines/standards	**Year**				
	2016	**2017**	**2018**	**2019**	**2016 – 2019**
WHO air quality guidelines of 2005 was updated in 2015 (24-hour average)					
≤ 25 µg/m^3 (n, %)	187 (51.1%)	139 (38.1%)	193 (52.9%)	184 (50.4%)	703 (48.1%)
> 25 µg/m^3 (n, %)	179 (48.9%)	226 (61.9%)	172 (47.1%)	181 (49.6%)	758 (51.9%)
WHO air quality guidelines of 2021 (24-hour average)					
≤ 15 µg/m^3 (n, %)	14 (3.8%)	14 (3.8%)	39 (10.7%)	53 (14.5%)	120 (8.2%)
> 15 µg/m^3 (n, %)	352 (96.2%)	351 (96.2%)	326 (89.3%)	312 (85.5%)	134 (91.8%)
Vietnamese $PM_{2.5}$ standard (24-hour average)					
≤ 50 µg/m^3 (n, %)	354 (96.7%)	350 (98.6%)	345 (94.5%)	336 (92.1%)	1395 (95.5%)
> 50 µg/m^3 (n, %)	12 (3.3%)	5 (1.4%)	20 (5.5%)	29 (8.0%)	66 (4.5%)

Overall, the daily $PM_{2.5}$ concentration showed seasonal fluctuation over a year. The high concentration was from the last months of the year to the early months of the following year, then gradually declined to the lowest level in the middle of the year before rising again (Figure 4.1). Similarly, there was a clear seasonal signal in temperature and relative humidity. The daily average temperature started increasing from the beginning of the year, peaked in the middle year, and then decreased. The daily average relative humidity contrasted with temperature (Figure 4.1). The daily $PM_{2.5}$ concentrations showed a negative correlation to the daily average temperature (-0.31) and a positive correlation to relative humidity (0.02) (Figure 4.2).

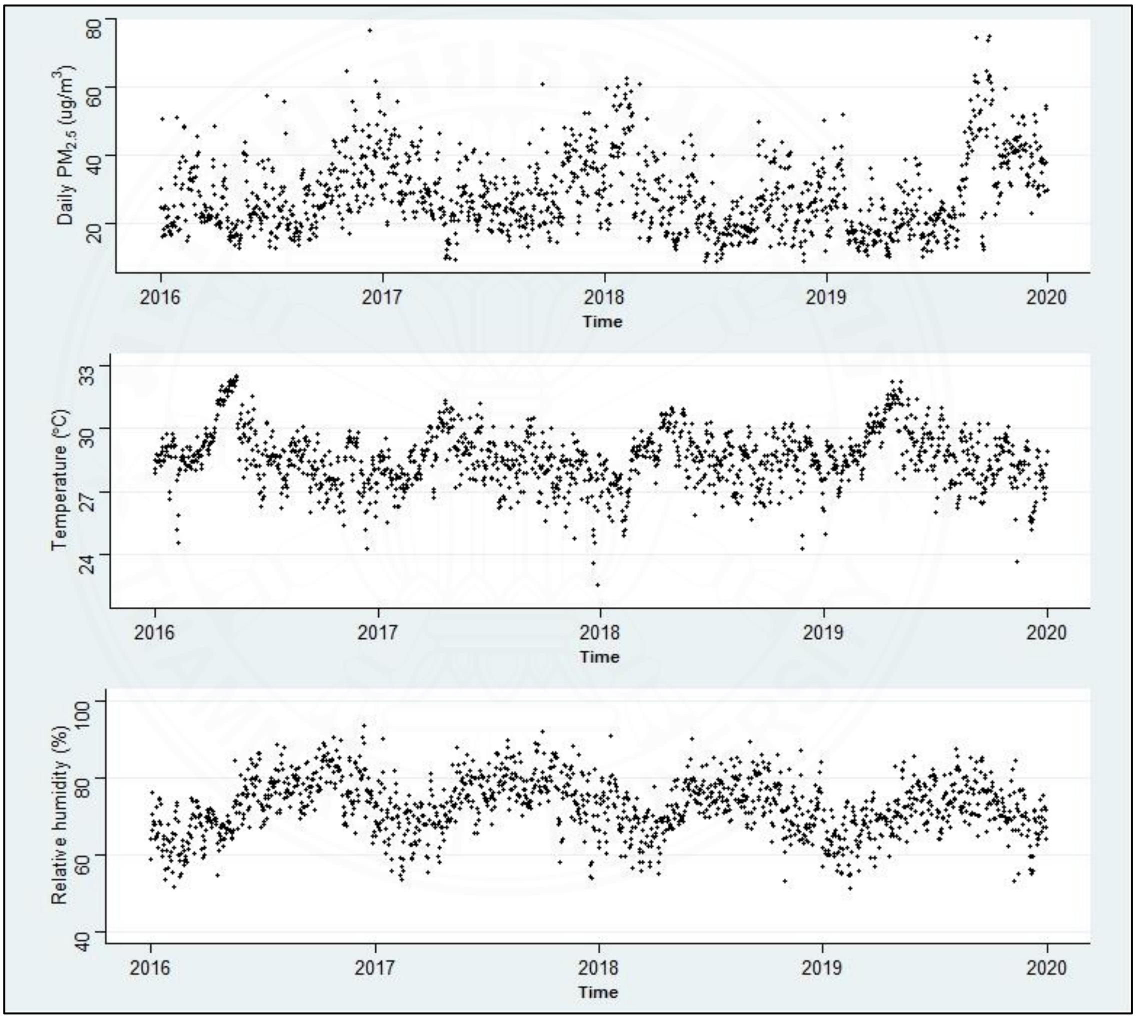


Figure 4.1. Plotting daily average $PM_{2.5}$, temperature, and relative humidity over time from 2016 to 2019 in Ho Chi Minh City

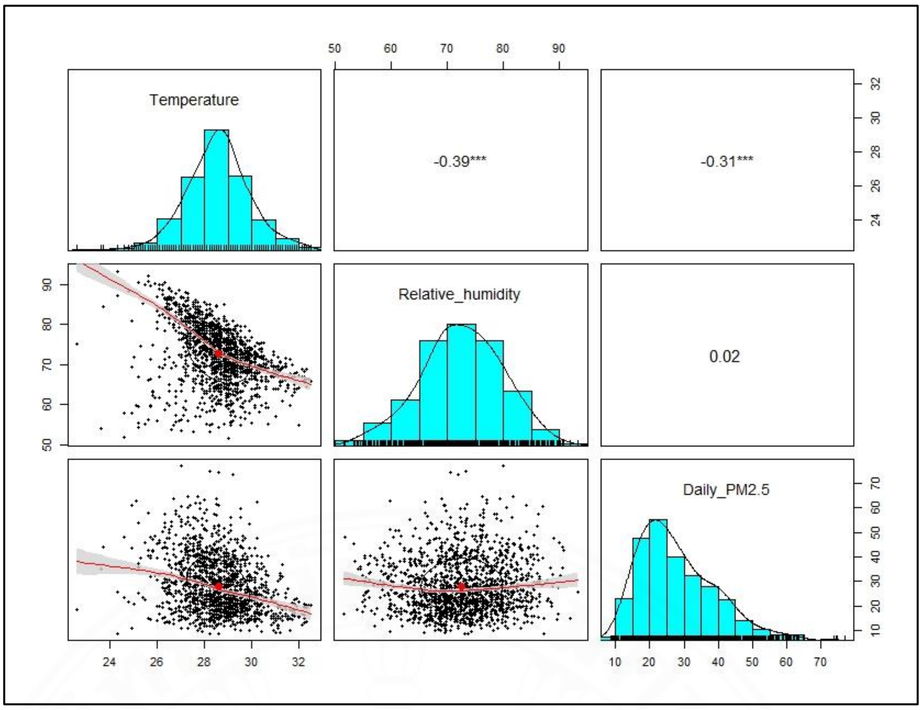


Figure 4.2. Correlation between daily $PM_{2.5}$ concentration, temperature, and relative humidity during 2016 – 2019 in Ho Chi Minh City

4.2 Effect of $PM_{2.5}$ on the acute lower respiratory infection (ALRI) and asthma among children under 5-year-old in HCMC

4.2.1 General distribution of daily hospital admissions for ALRI and asthma among children under 5-year-old

As shown in Table 4.3, there were 50,778 ALRI cases admitted to three children's hospitals in HCMC from 2016 to 2019. The daily average of admitted ALRI cases was 35 patients, with males being dominant over females (21 cases vs. 14 cases). Most ALRI cases were under 2 years old (35,004 cases of 50,778 cases). The average daily number of admitted cases was 24 cases among this group compared to 11 cases from 2 to under 5 years old. The total case of pneumonia was 2 times higher than bronchitis (33,900 vs. 16,878), resulting in the average number of daily admitted pneumonia cases being 23 patients compared to 12 patients with bronchitis.

A total of 11,223 children were hospitalized from 2016-2019 due to asthma, 8 cases per day on average. The male gender cases were nearly 2 times higher than female (7,232 vs.

3,991), and most cases were in groups 2 to under 5 years old (7,853 cases), as shown in Table 4.3.

Table 4.3. Descriptive statistics of daily hospital admissions for ALRI and asthma among children under 5 years old in Ho Chi Minh City from 2016-2019.

Characteristics	**Frequency**			**Mean (SD)**	**Min – Max**
	25th	**50th**	**75th**		
Daily average hospital admissions for ALRI *(n=50,778)*	26	33	42	34.7 ± 12.1	2 – 77
Gender groups					
Male *(n=30,432)*	15	20	26	20.8 ± 7.8	1 – 53
Female *(n=20,346)*	10	13	17	13.9 ± 5.7	1 – 45
Age groups					
< 2 *(n=35,004)*	16	22	31	23.9 ± 10.8	2 – 67
2 – <5 *(n=15,774)*	8	10	13	10.8 ± 4.3	0 – 27
ICD code groups					
Bronchitis (J22) *(n=16,878)*	7	11	15	11.6 ± 5.6	0 – 37
Pneumonia (J12 – J18) *(n=33,900)*	17	23	28	23.2 ± 8.1	2 – 55
Daily average hospital admissions for asthma *(n=11,223)*	5	7	10	7.7 ± 3.8	0 – 24
Gender groups					
Male *(n=7,232)*	3	5	7	5.0 ± 2.8	0 – 17
Female *(n=3,991)*	1	2	4	2.7 ± 1.9	0 – 12
Age groups					
< 2 *(n=3,370)*	1	2	4	2.3 ± 2.0	0 – 11
2 - <5 *(n=7,853)*	3	5	7	5.4 ± 2.8	0 – 20

4.2.2 Distribution of daily admitted cases of ALRI, asthma, and daily $PM_{2.5}$ concentration over time

Figure 4.3 shows the distribution of daily admitted cases of ALRI and asthma among children under 5 years old in HCMC from 2016 to 2019. A seasonal fluctuation of admitted cases in a year was observed. ALRI and asthma cases had a low number of daily admitted cases in months of the first quarter, then gradually increased, peaked in the early months of the third quarter, and steadily decreased thereafter.

Daily $PM_{2.5}$ concentration also showed seasonal fluctuation. The high concentration was from the last months of the year to the early months of the following year, then gradually declined to the lowest level in the middle of the year before rising again.

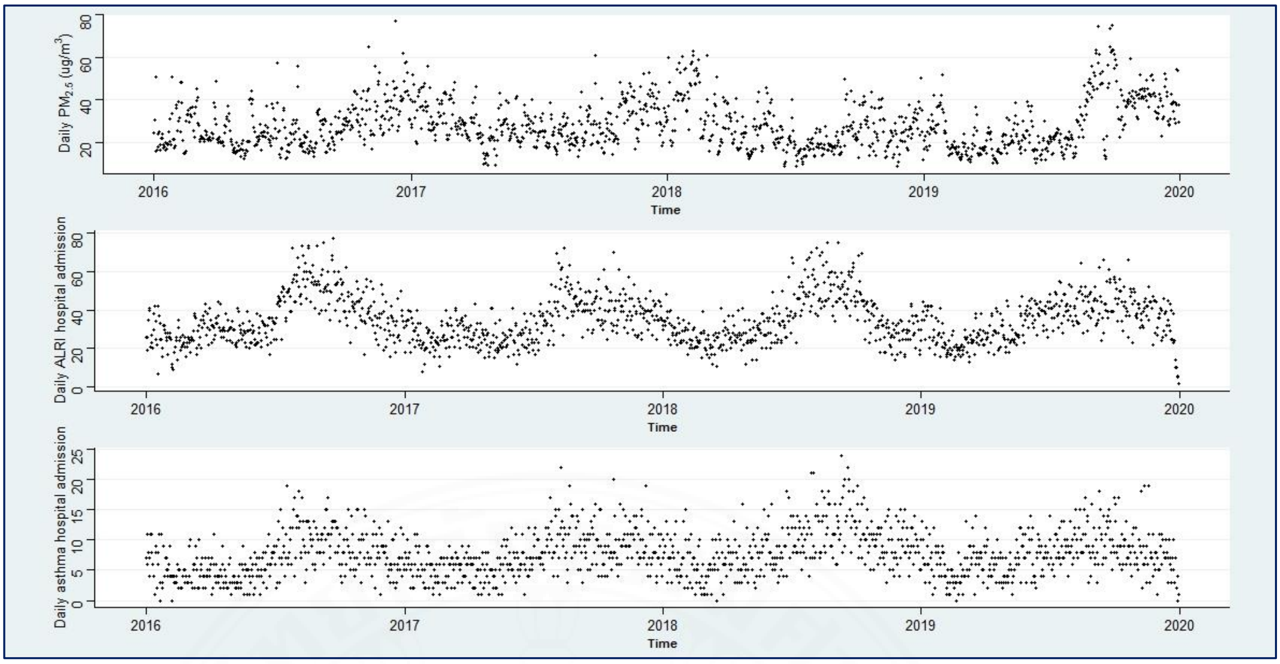


Figure 4.3. Daily hospital admission for ALRI and daily $PM_{2.5}$ concentration from 2016 to 2019 in Ho Chi Minh City.

4.2.3 The association between daily $PM_{2.5}$ concentration and hospital admission due to ALRI among children under 5-year-old in Ho Chi Minh City

4.2.3.1 Controlling seasonality and cycle of ALRI cases using cubic B-spline

The health outcome data required stationary data to detect the association between the health outcomes and predicted variables (no seasonal and cyclic signal). Therefore, a natural spline controlled the ALRI database for seasonality and cycle.

Figure 4.4 presented the seasonal and cyclic signal detected by the cubic B-spline (red line) compared to the plotting of the ALRI case over time (blue dot). Figure 4.5 reported the residual of ALRI data after controlling with the cubic B-spline; the model residual showed stationary with a mean was around 0 value. Dickey-Fuller test reported -10.919 and p-value < 0.01; thus, the model residual was stationary.

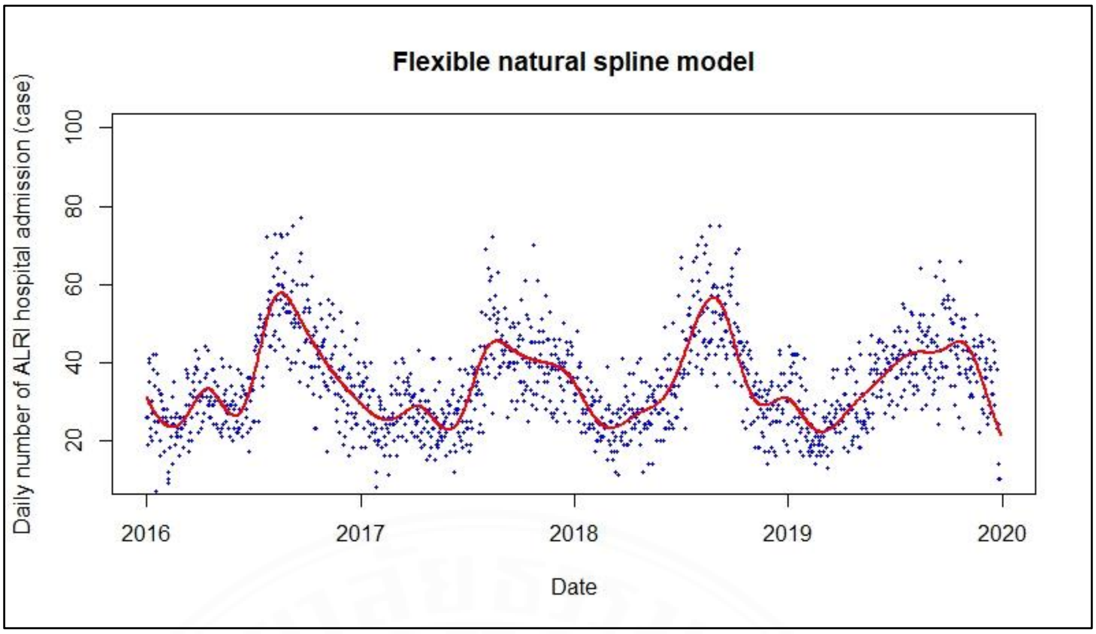


Figure 4.4. Using a natural spline model with 7 degrees of freedom per year for controlling seasonality and cycle among ALRI cases in Ho Chi Minh City from 2016 to 2019

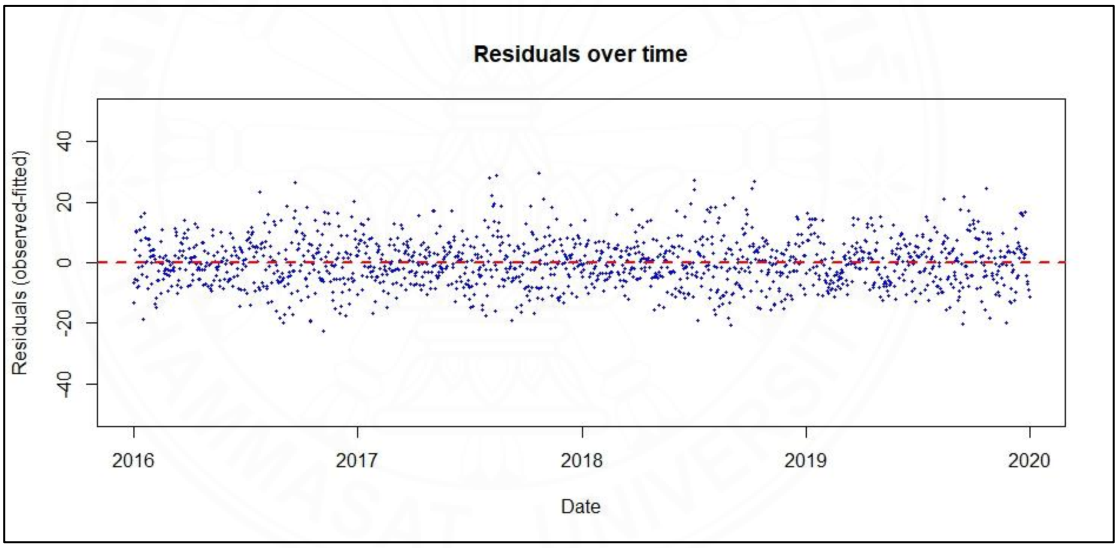
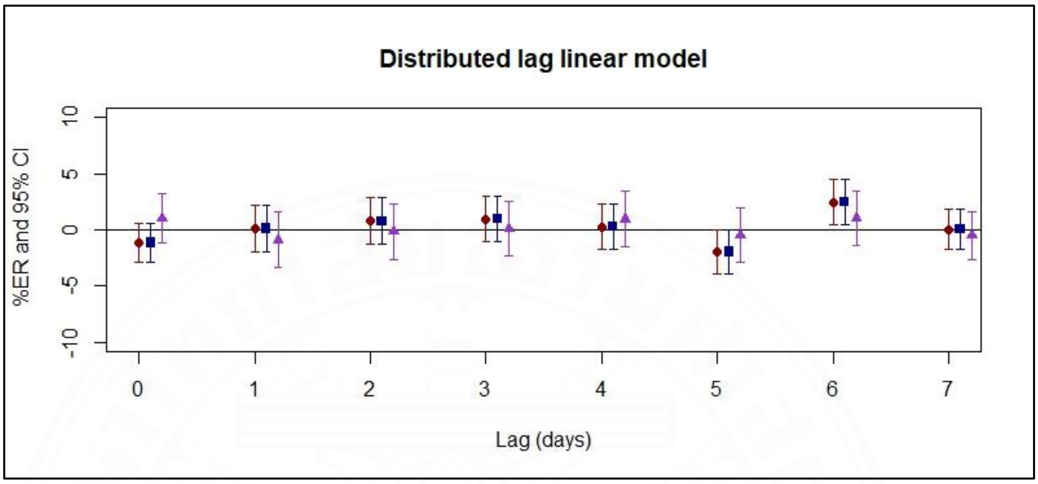


Figure 4.5. Residual of natural spline model with 7df per year applied for controlling seasonality and cycle among ALRI cases in Ho Chi Minh City from 2016 – 2019

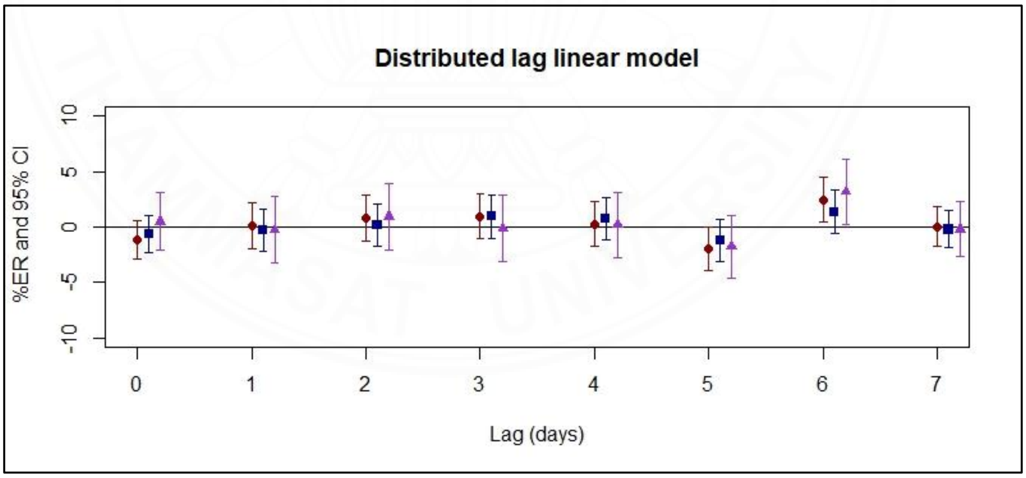
4.2.3.2 Estimating the association between $PM_{2.5}$ and hospital admission due to ALRI among children under 5-year-old using the distributed lag linear model

The effect of each 10 µg/m³ increase in $PM_{2.5}$ to ALRI hospital admissions when all lag terms modeled together using the DLMs were presented in, Figure 4.6, Figure 4.7, and Table 4.4. A significant effect of each 10 µg/m³ $PM_{2.5}$ increment to the number of ALRI admission was found at lag_6 with the excess risk of 1.79% (0.14%~3.46%). In subgroup analysis, the significant associations were found in the male gender at lag_6 (ER=2.37, 95% CI: 0.33~4.45), the age group from 2 to under 5 at lag_6 (ER=3.07, 95% CI: 0.12~6.10).



●: All ALRI ■: ALRI in male ▲: ALRI in female

Figure 4.6. The excess risk of each 10 µg/m³ increase in $PM_{2.5}$ to hospital admissions for ALRI by gender



●: All ALRI ■: ALRI in age group < 2 ▲: ALRI in age group 2-<5

Figure 4.7. The excess risk of each 10 µg/m³ increase in $PM_{2.5}$ to hospital admissions for ALRI by age group

4.2.3.3 Sensitivity analysis

All sensitivity analyses showed consistent results of the significant association between each 10 μg/m^3 increase in $PM_{2.5}$ with a total of ALRI, ALRI in the male gender, and the age group from 2 to under 5 years old. Specifically, when using 6 df per year instead of 7 df per year for controlling the time trend in the cubic B-spline, the excess risk of total ALRI, ALRI in the male gender, and ALRI in the age group 2 to under 5 at lag_6 were 1.87% (0.20%~3.57%); 2.49% (0.43%~4.59%); 3.05% (0.10%~6.09%) (Table 4.5). These excess risk numbers were 1.85% (0.24%~3.49%); 2.42% (0.40%~4.48%), and 3.19% (0.30%~6.17%) when applying 8 df per year in the cubic B-spline (Table 4.6).

Applying the time–stratified model for seasonality control instead of the cubic B-spline model, each 10 μg/m^3 increase in $PM_{2.5}$ was significantly associated with the excess risk at lag_6 of total ALRI, ALRI in the male gender and ALRI in the age group from 2 to under 5 were 1.89% (0.22%~3.59%); 2.48% (0.43%~4.57%); and 3.45% (0.58%~6.40%) (Table 4.7).

Table 4.4. The excess risk (ER) in the distributed lag linear model between each 10 μg/m^3 $PM_{2.5}$ increase and hospital admissions due to ALRI among children under 5 years old after controlling seasonality, trend, temperature, and humidity.

	Total ALRI	ALRI in male	ALRI in female	Age < 2	Age 2 to <5	Bronchitis	Pneumonia
Lag (day)	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**
0	-0.33 (-1.76~1.13)	-1.17 (-2.94~0.62)	0.95 (-1.22~3.17)	-0.66 (-2.34~1.05)	0.46 (-2.12~3.11)	-0.24 (-2.56~2.14)	-0.37 (-2.08~1.37)
1	-0.32 (-1.95~1.34)	0.10 (-1.93~2.17)	-0.94 (-3.37~1.55)	-0.34 (-2.25~1.61)	-0.27 (-3.20~2.74)	-1.82 (-4.42~0.86)	0.44 (-1.52~2.44)
2	0.40 (-1.24~2.08)	0.78(-1.26~2.87)	-0.16 (-2.61~2.35)	0.15 (-1.77~2.11)	0.91 (-2.04~3.96)	-0.27 (-2.91~2.44)	0.71 (-(1.25~2.72)
3	0.60 (-1.05~2.26)	0.95 (-1.09~3.03)	0.07 (-2.37~2.56)	0.93 (-1.00~2.90)	-0.17 (-3.08~2.82)	0.90 (-1.76 3.62)	0.47 (-1.48~2.47)
4	0.53 (-1.11~2.18)	0.26 (-1.76~2.32)	0.93 (-1.51~3.43)	0.70 (-1.22~2.65)	0.17 (-2.73~3.16)	1.67 (-0.97~4.39)	-0.04 (-1.98~1.94)
5	-1.39 (-2.98~0.23)	-1.98 (-3.94~0.02)	-0.51 (-2.89~1.94)	-1.20 (-3.07~0.71)	-1.81 (-4.61~1.07)	-1.25 (-3.80~1.38)	-1.46 (-3.35~0.48)
6	**1.86 (0.24~3.52)**	**2.43 (0.40~4.49)**	1.03 (-1.39~3.50)	1.33 (-0.58~3.28)	**3.15 (0.25~6.14)**	1.99 (-0.63~4.68)	1.80 (-0.14~3.78)
7	-0.20 (-1.61~1.23)	0.01 (-1.74~1.79)	-0.53 (-2.63~1.62)	-0.24 (-1.91~1.45)	-0.23 (-2.72~2.32)	0.14 (-2.14~2.48)	-0.36 (-2.04~1.35)

Table 4.5. The excess risk in the distributed lag linear model between each 10 μg/m^3 $PM_{2.5}$ increasing and hospital admissions due to ALRI among children under 5-year-old using 6 df per year for controlling time trend

	Total ALRI	ALRI in male	ALRI in female	Age < 2	Age 2 to <5	Bronchitis	Pneumonia
Lag	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**
0	-0.42 (-1.89~1.07)	-1.16 (-2.95~0.66)	0.70 (-1.48~2.93)	-0.65 (-2.35~1.08)	0.15 (-2.46~2.84)	0.06 (-2.30~2.47)	-0.66 (-2.39~1.10)
1	-0.24 (-1.93~1.47)	0.22 (-1.85~2.34)	-0.93 (-3.39~1.59)	-0.21 (-2.16~1.78)	-0.38 (-3.37~2.70)	-1.57 (-4.22~1.15)	0.42 (-1.58~2.46)
2	0.45 (-1.24~2.18)	0.85 (-1.24~2.98)	-0.13 (-2.61~2.41)	0.24 (-1.72~2.24)	0.92 (-2.10~4.04)	-0.12 (-2.81~2.64)	0.71 (-1.30~2.76)
3	0.67 (-1.02~2.40)	1.07 (-1.01~3.19)	0.09 (-2.38~2.62)	1.04 (-0.93~3.04)	-0.27 (-3.24~2.79)	1.13 (-1.57~3.90)	0.47 (-1.52~2.51)
4	0.51 (-1.17~2.22)	0.29 (-1.76~2.40)	0.83 (-1.63~3.36)	0.70 (-1.25~2.69)	0.27 (-2.71~3.33)	1.84 (-0.85~4.59)	-0.15 (-2.12~1.87)
5	-1.45 (-3.08~0.21)	-1.98 (-3.98~0.05)	-0.65 (-3.06~1.82)	-1.20 (-3.10~0.74)	-2.07 (-4.92~0.87)	-1.10 (-3.69~1.56)	-1.62 (-3.55~0.35)
6	**1.87 (0.20~3.57)**	**2.49 (0.43~4.59)**	0.96 (-1.48~3.46)	1.39 (-0.55~3.37)	**3.05 (0.10~6.09)**	2.21 (-0.45~4.94)	1.71 (-0.26~3.72)
7	-0.47 (-1.91~0.98)	-0.19 (-1.95~1.60)	-0.90 (-3.01~1.25)	-0.37 (-2.04~1.34)	-0.89 (-3.39~1.68)	0.21 (-2.09~2.56)	0.80 (-2.49~0.92)
Net	0.9 (-1.02~2.86)	1.53 (-0.83~3.95)	-0.05 (-2.87~2.84)	0.93 (-1.32~3.22)	0.71 (-2.65~4.18)	2.61 (-0.49~5.81)	0.05 (-2.2~2.35)

Table 4.6. The excess risk in the distributed lag linear model between each 10 μg/m^3 $PM_{2.5}$ increasing and hospital admissions due to ALRI among children under 5-year-old using 7 df per year for controlling time trend

	Total ALRI	**ALRI in male**	**ALRI in female**	**Age < 2**	**Age 2 to <5**	**Bronchitis**	**Pneumonia**
Lag	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**
0	-0.50 (-1.93~0.94)	-1.35 (-3.10~0.44)	0.77 (-1.39~2.99)	-0.79 (-2.45~0.91)	0.28 (-2.29~2.91)	-0.37 (-2.69~2.01)	-0.58 (-2.27~1.15)
1	-0.22 (-1.84~1.43)	0.20 (-1.83~2.26)	-0.83 (-3.26~1.66)	-0.21 (-2.11~1.73)	-0.27 (-3.18~2.73)	-1.71 (-4.31~0.97)	0.53 (-1.42~2.51)
2	0.48 (-1.16~2.14)	0.85 (-1.18~2.93)	-0.08 (-2.52~2.42)	0.25 (-1.66~2.20)	1.02 (-1.92~4.05)	-0.19 (-2.83~2.53)	0.78 (-1.17~2.77)
3	0.62 (-1.00~2.28)	0.99 (-1.04~3.06)	0.09 (-2.35~2.58)	0.96 (-0.96~2.91)	-0.22 (-3.11~2.76)	0.93 (-1.72~3.66)	0.49 (-1.44~2.47)
4	0.44 (-1.18~2.08)	0.19 (-1.82~2.24)	0.82 (-1.61~3.31)	0.61 (-1.29~2.54)	0.29 (-2.61~3.27)	1.60 (-1.03~4.31)	-0.14 (-2.06~1.82)
5	-1.41 (-2.99~0.19)	-2.00 (-3.95~-0.01)	-0.53 (-2.91~1.91)	-1.25 (-3.11~0.64)	-1.77 (-4.56~1.10)	-1.26 (-3.81~1.36)	-1.49 (-3.37~0.43)
6	**1.85 (0.24~3.49)**	**2.42 (0.40~4.48)**	1.01 (-1.40~3.48)	1.33 (-0.57~3.26)	**3.19 (0.30~6.17**)	1.98 (-0.64~4.68)	1.78 (-0.14~3.75)
7	-0.53 (-1.92~0.89)	-0.33 (-2.07~1.43)	-0.81 (-2.91~1.33)	-0.46 (-2.11~1.21)	-0.69 (-3.16~1.84)	-0.11 (-2.40~2.22)	-0.73 -2.40~0.96)
Net	0.7 (-1.34~2.79)	0.89 (-1.64~3.5)	0.41 (-2.66~3.59)	0.41 (-1.98~2.87)	1.77 (-1.92~5.6)	0.83 (-2.49~4.27)	0.61 (-1.82~3.11)

Table 4.7. The excess risk in the distributed lag linear model between each 10 μg/m^3 $PM_{2.5}$ increasing and hospital admissions due to ALRI among children under 5-year-old using time–stratified model for controlling time trend

	Total ALRI	**ALRI in male**	**ALRI in female**	**Age < 2**	**Age 2 to <5**	**Bronchitis**	**Pneumonia**
Lag	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**
0	-0.27 (-1.75~1.23)	-1.05 (-2.84~0.78)	0.90 (-1.33~3.17)	-0.66 (-2.38~1.08)	0.66 (-1.89~3.27)	-0.13 (-2.49~2.30)	-0.35 (-2.09~1.42)
1	-0.41 (-2.08~1.29)	0.03 (-2.02~2.13)	-1.08 (-3.55~1.46)	-0.54 (-2.48~1.44)	-0.12 (-2.99~2.83)	-1.91 (-4.54~0.79)	0.34 (-1.65~2.36)
2	0.20 (-1.48~1.90)	0.63 (-1.43~2.73)	-0.45 (-2.93~2.10)	-0.09 (-2.03~1.89)	0.84 (-2.05~3.82)	-0.46 (-3.12~2.27)	0.50 (-1.49~2.52)
3	0.56 (-1.12~2.26)	0.93 (-1.13~3.03)	0.01 (-2.47~2.55)	0.77 (-1.19~2.76)	0.00 (-2.85~2.93)	0.93 (-1.75~3.68)	0.39 (-1.58~2.41)
4	0.31 (-1.35~2.00)	0.07 (-1.96~2.14)	0.68 (-1.80~3.22)	0.56 (-1.38~2.53)	-0.17 (-3.01~2.75)	1.57 (-1.09~4.30)	-0.31 (-2.27~1.68)
5	-1.40 (-3.03~0.25)	-1.96 (-3.94~0.06)	-0.56 (-3.00~1.93)	-1.19 (-3.09~0.74)	-1.93 (-4.68~0.90)	-1.17 (-3.75~1.48)	-1.52 -3.44~0.44)
6	**1.89 (0.22~3.59)**	**2.48 (0.43~4.57**	1.02 (-1.45~3.55)	1.25 (-0.69~3.22)	**3.45 (0.58~6.40)**	2.10 (-0.56~4.83)	1.78 (-0.19~3.79)
7	-0.77 (-2.21~0.70)	-0.43 (-2.19~1.37)	-1.28 (-3.42~0.91)	-0.76 (-2.45 0.95)	-0.83 (-3.26 1.66)	-0.31 (-2.63~2.05)	-0.98 (-2.68~0.74)
Net	0.07 (-2.06~2.25)	0.63 (-1.99~3.32)	-0.79 (-3.94~2.47)	-0.7 (-3.17~1.83)	1.84 (-1.85~5.67)	0.55 (-2.86~4.08)	-0.19 (-2.71~2.39)

4.2.4 Estimating the association between $PM_{2.5}$ and hospital admission due to asthma among children under 5-year-old using the moving average

Table 4.8 shows the excess risk (ER) of hospital admissions for asthma per each 10 μg/m^3 $PM_{2.5}$ increase in different lag days. The positive association was demonstrated in all lags. However, a significant association was found in lag_{04} with the ER of 3.86% (95% CI: 0.44%~7.40%). For subgroups, the significant association was in females at lag_{04} with an ER of 5.91% (95% CI: 0.27%~11.86%), and age group from 2 to under 5 years old at lag_{02}, lag_{03}, and lag_{04} with an ER of 3.68% (95% CI: 0.145~7.35%), 4.32% (95% CI: 0.50%~8.29%), and 5.02% (95% CI: 0.90%~9.30%), respectively.

Table 4.8. The excess risk (ER) in the distributed lag linear model between each 10 μg/m^3 $PM_{2.5}$ increase and hospital admissions due to asthma among children under 5 years old after controlling seasonality, trend, temperature, and humidity.

Lag (day)	Asthma				
	Total	**Male**	**Female**	**Ages < 2**	**Ages 2 - <5**
	%ER (95% CI)	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**	**%ER (95% CI)**
Lag_{01}	1.44 (-1.25~4.19)	1.14 (-2.06~4.44)	2.02 (-2.34~6.58)	-1.10 (-5.62~3.64)	2.42 (-0.80~5.75)
Lag_{02}	2.46 (-0.48~5.49)	1.80 (-1.69~5.41)	3.72 (-1.09~8.77)	-0.67 (-5.60~4.52)	**3.68 (0.14~7.35)**
Lag_{03}	3.15 (-0.03~6.43)	2.41 (-1.37~6.33)	4.56 (-0.65~10.03)	0.15 (-5.20~5.79)	**4.32 (0.50~8.29)**
Lag_{04}	**3.86 (0.44~7.40)**	2.79 (-1.26~7.00)	**5.91 (0.27~11.86)**	0.89 (-4.85~6.99)	**5.02 (0.90~9.30)**

4.3 Effects of maternal exposure to $PM_{2.5}$ and adverse birth outcomes

4.3.1 General descriptive information of the study population

One hundred seventy-three thousand two hundred ten infants were born from 2016 to 2019 at three selected maternity hospitals. After data cleaning, 9,342 cases were removed (5.4%), and data of 163,868 remaining infants was used for analysis.

Table 4.9 shows that among 163,868 infants, the number of male babies was slightly higher than that of female babies, the average birth weight was 3,135 g, and the average male gender's weight at birth was around 100 g higher than that of the female gender. Regarding the gestation period, most infants were 37 – 40 weeks (89.6%), and 9% were lower than 37 weeks (PTB). The male gender was more predominant in PTB than the female (9.8% vs. 8.2%). Of 149,023 term births, 2.3% were term LBW. The female gender had a higher percentage of term LBW than the male gender (2.3% vs. 1.9%).

Table 4.9. General information on investigated infants, the average concentration of $PM_{2.5}$, temperature, and relative humidity in Ho Chi Minh City between 2016-2019

Characteristics	**Mean ± SD or N (%)**
Gender (n=163,868)	
Male	85,059 (51.9)
Female	78,809 (48.1)
Birth weight (g)	3,135.4 ± 477.4
Male	3,170.0 ± 476.0
Female	3,098.2 ± 456.5
Pre-term birth (PTB)	14,845 (9.1)
Male	8,357 (9.8)
Female	6,488 (8.2)
Term low birth weight (LBW) (total number of infants with gestation lengths from 37 – 44 weeks =149,023)	3,374 (2.3)
Male	1,362 (1.9)
Female	2,012 (2.3)
Maternal age (year)	30.0 ± 5.2
Under 20	3,785 (2.3)
20 – 29	76,367 (46.6)
30 – 39	77,352 (47.2)
Over 39	6,364 (3.9)
Length of gestation (weeks)	38.4 ± 1.6
Under 37	14,845 (9.1)
37 – 40	147,846 (89.6)
41 – 43	2,177 (1.3)
Birth order	
First	72,333 (44.1)
Second or more	91,535 (55.7)
Year of pregnancy	
2015	19,375 (11.8)
2016	45,644 (27.8)
2017	43,075 (26.3)
2018	42,754 (26.1)
2019	13,020 (8.0)
Season of pregnancy	
Dry season (May – Nov)	74,720 (45.6)
The rainy season (Dec-Apr)	89,148 (54.4)

The average daily $PM_{2.5}$ concentration during the entire pregnancy period was 27.2 $\mu g/m^{3,}$ and the difference in $PM_{2.5}$ level between each specific pregnancy period was negligible, as shown in Table 4.10. The average daily temperature and relative humidity were 28.6 ^0C and 75.4%, respectively, during the entire pregnancy period, as shown in Table 4.10.

Table 4.10. The average daily $PM_{2.5}$ concentration, temperature, and relative humidity during each specific period for pregnancy of 163,868 births

Period of exposure to $PM_{2.5}$	Mean ± SD	Median (min-max)	IQR
First month (n=144,493)			
$PM_{2.5}$ (µg/m^3)	27.2 ± 6.5	26.4 (15.3 – 48.8)	8.0
Temperature (^{0}C)	28.6 ± 0.9	28.4 (26.8 – 31.8)	0.9
Relative humidity (%)	73.8 ± 7.4	75.4 (56.9 – 85.9)	12.9
First trimester (n=144,493)			
$PM_{2.5}$ (µg/m^3)	27.0 ± 5.5	25.4 (17.2 – 39.9)	6.4
Temperature (^{0}C)	28.6 ± 0.8	28.4 (27.2 – 30.4)	1.1
Relative humidity (%)	74.3 ± 6.2	75.1 (60.4 – 82.4)	10.9
Second trimester (n=155,234)			
$PM_{2.5}$ (µg/m^3)	26.7 ± 5.4	25.2 (17.2 – 43.8)	5.9
Temperature (^{0}C)	28.7 ± 0.7	28.5 (27.02 – 30.4)	1.0
Relative humidity (%)	75.0 ± 5.8	76.5 (60.4 – 82.4)	9.5
Third trimester (n=163,868)			
$PM_{2.5}$ (µg/m^3)	27.8 ± 6.4	25.5 (12.6 – 64.8)	8.6
Temperature (^{0}C)	28.6 ± 0.7	28.4 (25.6 – 31.9)	0.9
Relative humidity (%)	75.4 ± 5.7	77.1 (53.4 – 85.8)	9.0
Entire pregnancy (n=144,493)			
$PM_{2.5}$ (µg/m^3)	27.2 ± 3.2	27.3 (19.1 – 35.5)	6.3
Temperature (^{0}C)	28.6 ± 0.3	28.5 (27.7 – 29.6)	0.6
Relative humidity (%)	75.4 ± 2.2	75.6 (65.6 – 81.2)	2.5

SD: Standard deviation *min-max: minimum-maximum* *IQR: Interquartile range*

4.3.2 The relationship between birth weight (BW) and $PM_{2.5}$ concentration

Table 4.11 shows the results of several variables in the linear model with BW, except $PM_{2.5}$, temperature, and relative humidity. The BW decrease was associated with female infants, young mothers, short gestation, and first birth. Women who were pregnant in 2015 resulted in infants with significantly lower BW than those who were pregnant between 2016-2018. The data also revealed that BW was slightly higher among women who were pregnant during the rainy season (May – Nov.), although this difference was not statistically significant, as shown in Table 4.11.

Table 4.11. Coefficients for covariates after adjustment of potential confounders[a] for the entire pregnancy period

Covariate	**Coefficient of birth weight (BW) (g) (95% CI)**
Gender	
Female	Ref.
Male	85.47 (81.62 ~ 89.32)
Maternal age (year)	
20 – 29	Ref.
Under 20	-132.00 (-145.04 ~ -118.95)
30 – 39	34.98 (30.67 ~ 39.29)
40 or above	7.30 (-3.06 ~ 17.66)
Length of gestation (weeks)	
37 – 40	Ref.
Under 37	-683.93 (-690.92 ~ -676.94)
Over 40	174.45 (157.71 ~ 191.18)
Birth order	
First	Ref.
Second or more	67.07 (62.80 – 71.33)
Year of pregnancy	
2015	Ref.
2016	14.48 (7.75 ~ 21.21)
2017	28.33 (21.53 ~ 35.13)
2018	20.18 (13.38 ~ 26.99)
2019	8.15 (-1.26 ~ 17.57)
Season of pregnancy	
Dry	Ref.
Rainy	1.74 (-2.39 ~ 5.87)

[a]*: The model was adjusted for infant gender, maternal age, gestation length, birth order, year of pregnancy, and the season of pregnancy throughout the pregnancy.*

Table 4.12 presents linear model results for the correlations of gestational exposure to $PM_{2.5}$ and change in BW at the different pregnancy periods of exposure. $PM_{2.5}$ significantly affected the BW decrease for the second trimester, i.e., every 10 $\mu g/m^3$ increase in the average daily $PM_{2.5}$ concentration of the second semester lowered 11.771 g in BW with all births (P-value <0.001, 95% CI: -18.296 ~ -5.246). For the entire pregnancy period, $PM_{2.5}$ negatively affected BW with a 4 g decrease per every 10 $\mu g/m^3$ increase in the average daily $PM_{2.5}$; however, the association was insignificant. Similar results were reported for the first trimester and third trimesters.

Results from the analysis with only the first birth were similar to all birth. Exposure to $PM_{2.5}$ significantly affected BW for the second trimester, with a decrease of 18.604 g per 10 μg/m^3 increase in the average daily $PM_{2.5}$ for the semester (P-value <0.001, 95% CI: -28.464 ~ -8.745) as shown in Table 4.12.

Table 4.12. Change in birth weight (g) (95% CI) per 10 μg/m^3 increase in the average daily $PM_{2.5}$ for each gestational period after adjustment of covariates in the regression model[a]

Period of exposure to $PM_{2.5}$	**Birth weight (BW) change (95% CI)**	
	All birth	First birth
Exposure to $PM_{2.5}$ during the first month *(n=143,185 all births, n=62,776 first birth)*	0.242 (-4.763 ~ 5.247)	0.087 (-7.419 ~ 7.594)
Exposure to $PM_{2.5}$ during the first trimester (1st week – 13th week) *(n=143,185 all births, n=62,776 first birth)*	-2.173 (-9.315 ~ 4.969)	-2.512 (-13.239 ~ 8.215)
Exposure to $PM_{2.5}$ during the second trimester (14th week – 26th week) *(n=153,860 all births, n=67,848 first birth)*	-11.771 (-18.296 ~ -5.246)**	-18.604 (-28.464 ~ -8.745)**
Exposure to $PM_{2.5}$ during the third trimester (27th week – week of birth) *(n=162,465 all births, n=71,767 first birth)*	-1.401 (-5.667 ~ 2.865)	-4.578 (-11.066 ~ 1.909)
Exposure to $PM_{2.5}$ during the entire period of pregnancy *(n=143,185 all births, n=62,776 first birth)*	-3.947 (-13.631 ~ 5.736)	-11.500 (-26.376 ~ 3.374)

[a]: The model was adjusted for infant gender, maternal age, gestation length, birth order, year of pregnancy, the season of pregnancy, average temperature, and average relative humidity.
***P-value < 0.001*

4.3.3 The relationship between term low birth weight (LBW) and $PM_{2.5}$ concentration

Every 10 μg/m^3 increase in the average daily $PM_{2.5}$ for each gestational period seems to be a risk for term LBW; however, the associations were not statistically significant. Moreover, the results of all birth analyses and firth birth analyses suggested an inconsistency, as shown in Table 4.13. In the all-birth analyses, the strongest association with $PM_{2.5}$ exposure was in the second trimester (OR = 1.063), followed by the third trimester and the entire period of pregnancy (OR=1.052), while the first birth analysis revealed that exposure to $PM_{2.5}$ during the first trimester had the strongest association with term LBW (OR = 1.059).

Table 4.13. Odds ratio (95% CI) per 10 μg/m^3 increase in the average daily $PM_{2.5}$ of each gestational period and term low birth weight after adjustment of covariates in the logistic regression model[a]

Period of exposure to $PM_{2.5}$	**OR (95% CI)**	
	All birth	**First birth**
Exposure to $PM_{2.5}$ during the first month *(n=131,184 all births, n=57,426 first birth)*	1.008 (0.927 ~ 1.098)	1.033 (0.922 ~ 1.157)
Exposure to $PM_{2.5}$ during the first trimester (1^{st} week – 13^{th} week) *(n=131,184 all births, n=57,426 first birth)*	1.003 (0.888 ~1.132)	1.059 (0.899 ~ 1.248)
Exposure to $PM_{2.5}$ during the second trimester (14^{th} week – 26^{th} week) *(n=141,027 all births, n=62,094 first birth)*	1.063 (0.951 ~ 1.188)	1.030 (0.886 ~ 1.198)
Exposure to $PM_{2.5}$ during the third trimester (27^{th} week – week of birth) *(n=149,023 all births, n=65,716 first birth)*	1.052 (0.979 ~ 1.129)	1.043 (0.946 ~ 1.151)
Exposure to $PM_{2.5}$ during the entire period of pregnancy *(n=131,184 all births, n=57,426 first birth)*	1.045 (0.889 ~ 1.230)	1.014 (0.811 ~ 1.267)

[a]: The model was adjusted for infant gender, maternal age, gestation length, birth order, year of pregnancy, season of pregnancy, average temperature, and average relative humidity.

4.3.4 The relationship between preterm birth (PTB) and $PM_{2.5}$ concentration

The analysis of all births and the $PM_{2.5}$ exposure during the first month, the first and second trimester of pregnancy showed a risk of PTB. The Odds ratio was 1.010 (95% CI: 1.029 ~ 1.175), 1.121 (95% CI: 1.020 ~ 1.233), and 1.231 (95% CI: 1.136 ~ 1.336), respectively. The risk of PTB was only found for the exposure to $PM_{2.5}$ during the second trimester when analyzing only the first births (OR: 1.203, 95% CI: 1.071 – 1.350), as shown in Table 4.14.

Table 4.14. Odds ratio (95% CI) per 10 μg/m^3 increase in the average daily $PM_{2.5}$ of each gestational period and PTB after adjustment of covariates in the logistic regression model[a]

Period of exposure to $PM_{2.5}$	**OR (95% CI)**	
	All birth	**First birth**
Exposure to $PM_{2.5}$ during the first month *(n=144,493 all births, n=63,299 first birth)*	1.010 (1.029 ~ 1.175)*	1.093 (0.996 ~ 1.200)
Exposure to $PM_{2.5}$ during the first trimester (1st week – 13th week) *(n=144,493 all births, n=63,299 first birth)*	1.121 (1.020 ~ 1.233)*	1.119 (0.979 ~ 1.280)
Exposure to $PM_{2.5}$ during the second trimester (14th week – 26th week) *(n=155,234 all births, n=68,402 first birth)*	1.231 (1.136 ~ 1.336)**	1.203 (1.071 ~ 1.350)*
Exposure to $PM_{2.5}$ during the third trimester (27th week – week of birth) *(n=163,821 all births, n=72,314 first birth)*	0.991 (0.940 ~ 1.045)	1.001 (0.932 ~ 1.084)
Exposure to $PM_{2.5}$ during the entire period of pregnancy *(n=144,493 all births, n=63,299 first birth)*	1.091 (0.966 ~ 1.231)	1.080 (0.905 ~ 1.287)

[a]: The model was adjusted for infant gender, maternal age, gestation length, birth order, year of pregnancy, season of pregnancy, average temperature, and average relative humidity.
**P-value < 0.05. **P-value < 0.001*

4.4 Assessment of the health and economic benefit of improving the $PM_{2.5}$ pollution

4.4.1 Mortality in Ho Chi Minh City in 2019

There were 28,837 deaths recorded in HCMC in 2019. The crude mortality death rate was 321 per 100,000 population (pop). The adjusted mortality death rate according to age groups and gender of the Vietnamese population in 2019 was 432 per 100,000 pops, and the male gender was higher than the female (454/per 100,000 pops vs. 410 per 100,000 pops). The average age of death was 69 years old, and 55 percent were male gender. Nearly 50 percent of deaths were under 70 years old (premature death) (WHO, 2021b) (Table 4.15).

Table 4.15. The mortality rate and general characteristics of deaths in Ho Chi Minh City in 2019

Characteristics	**Frequency**	**Percent**
Total deaths	28,837	
The mortality rate (/100,000 population)		
Crude rate	321	
The adjusted rate*	432	
The adjusted rate in males*	454	
The adjusted rate in females*	410	
The average age of deaths	68.8 ± 18.0	
Age groups of deaths		
0 – 9	187	0.7
10 – 19	175	0.6
20 – 29	429	1.5
30 – 39	1,048	3.6
40 – 49	2,130	7.4
50 – 59	4,201	14.6
60 – 69	5,711	19.8
70 – 79	5,251	18.2
≥ 80	9,544	33.1
Age missing	161	0.6
Gender		
Male	15,795	54.8
Female	13,042	45.2
Premature death		
<70 years old	13,881	48.4

**: The rate was directly standardized according to the age group and gender of the Vietnamese population in 2019 (Naing, 2000).*

Of the total deaths, the ICD-10 code of R00-R99 (unclear causes) accounted for 48%, followed by diseases of the circulatory system (20%), neoplasms (12%), diseases of the respiratory system (7.5%), and group of accident and injury (4.1%) (Table 4.16).

Table 4.16. The distribution of total deaths in Ho Chi Minh City in 2019 by causes, age group, and gender

Group causes of death	**ICD-10 code**	**All (n=28,837)**	**Age <70 (n=13,881)**	**Age ≥ 70 (n=14,795)**	**Male (n=15,795)**	**Female (n=13,042)**
		n (%)	**n (%)**	**n (%)**		
Diseases of the circulatory system	I00-I99	5,857 (20.3)	3,873 (27.9)	1,958 (13.2)	3,579 (22.7)	2,728 (17.5)
Cerebrovascular diseases	*I60-I69*	*2,832 (9.8)*	*1,971 (14.2)*	*846 (5.7)*	*1,758 (11.1)*	*1,074 (8.2)*
Ischaemic heart diseases	*I20-I25*	*1,013 (3.5)*	*640 (4.6)*	*369 (2.5)*	*626 (4.0)*	*387 (3.0)*
Other forms of heart disease	*I26-I52*	*813 (2.8)*	*417 (3.0)*	*390 (2.6)*	*442 (2.8)*	*371 (2.8)*
Hypertensive diseases	*I10-I15*	*305 (1.1)*	*180 (1.3)*	*125 (0.8)*	*170 (1.1)*	*135 (1.0)*
The remaining other ICD-10 codes		*894 (3.1)*	*665 (4.8)*	*228 (1.5)*	*583 (3.7)*	*311 (2.4)*
Neoplasms	C00-D48	3,245 (11.9)	2,770 (20.0)	626 (4.2)	2,124 (13.5)	1,301 (0.0)
Liver and gallbladder	*C22-C24*	*1,192 (4.1)*	*953 (6.9)*	*223 (1.5)*	*863 (5.5)*	*329 (2.5)*
Larynx, trachea, bronchus, and lung	*C32-C34*	*632 (2.2)*	*490 (3.5)*	*135 (0.9)*	*442 (2.8)*	*190 (1.5)*
Oesophagus, stomach, small intestine	*C15-C17*	*311 (1.1)*	*249 (1.8)*	*59 (0.4)*	*185 (1.2)*	*126 (1.0)*
Others		*1,290 (4.5)*	*1,078 (7.8)*	*209 (1.4)*	*634 (4.0)*	*656 (5.0)*
Diseases of the respiratory system	J00-J99	2,159 (7.5)	1,202 (8.7)	949 (6.4)	1,268 (8.0)	891 (6.8)
Accident and injury	S00-T98; V01-Y98	1,190 (4.1)	1,032 (7.4)	154 (1.0)	862 (5.5)	328 (2.5)
Certain infectious and parasitic diseases	A00-B99	760 (2.6)	611 (4.4)	142 (1.0)	549 (3.5)	211 (1.6)
Diseases of the digestive system	K00-K93	523 (1.8)	408 (2.9)	110 (0.7)	368 (2.3)	155 (1.2)
Diseases of the genitourinary system	N00-N99	499 (1.7)	351 (2.5)	147 (1.0)	278 (1.8)	221 (1.7)
Endocrine, nutritional, and metabolic diseases	E00-E90	471 (1.6)	270 (2.0)	201 (1.4)	234 (1.5)	237 (1.8)
Other causes		216 (0.8)	190 (1.4)	24 (0.2)	137 (0.9)	79 (0.6)
Unclear causes	R00-R99	13,737 (47.6)	3,174 (22.9)	10,484 (70.9)	6,396 (40.5)	7,341 (56.3)

4.4.2 Assessment of the health benefit of improving the $PM_{2.5}$ pollution

Table 4.17 presents the number of deaths that could have been avoided in case the $PM_{2.5}$ concentration in 2019 achieved three control scenarios. The first scenario was the assumption that the $PM_{2.5}$ concentration in HCMC met the 2021 WHO annual average AQG for $PM_{2.5}$ of 5 µg/m^3. The second scenario was the assumption that the $PM_{2.5}$ met the 2005 WHO annual average AQG for $PM_{2.5}$ of 10 µg/m^3, and the Vietnamese annual average standard for $PM_{2.5}$ of 25 µg/m^3 was the third scenario. The study found that the lower the $PM_{2.5}$ concentration was controlled, the higher health benefits were produced. The table also indicated the different β coefficients from various studies that resulted in different estimated health benefits.

In the first scenario, 3,785 (1,179–6,335) deaths from all causes could have been avoided, accounting for 43 per 100,000 pop and 13 percent of total deaths in 2019. The avoided deaths attributable to all causes (non-accident), cardiopulmonary diseases, cardiovascular diseases, IHD, and lung cancer, were 2,092 (485–3,406); 1,511 (1,059–1,925); 1,140 (231–1,925); 276 (162–379); and 151 (28–365), respectively.

In the second scenario, the health benefits of avoided deaths from all causes were 3,195 (982-5,468) cases (36/100,000 pop and 11 percent of total deaths in 2019). If the $PM_{2.5}$ concentration reached the third scenario, the total avoided deaths due to all causes were 1,300 (384 – 2,386) cases (15/100.000 pop and 4.5 percent of total deaths in 2019). For gender analysis, the female gender had more avoided deaths than the male gender (around 57% vs. 43% of total avoided deaths, respectively).

In sub-district analysis, the top four districts with a high number of avoided deaths were Thu Duc City, District 8, Cu Chi District, Hoc Mon District, and Binh Thanh District. In contrast, the lowest number of avoided deaths were the Can Gio district, District 7, and Nha Be district (Table 4.18 and Figure 4.8).

Controlling the annual average $PM_{2.5}$ concentration produced a considerable economic benefit for HCMC, as indicated in Table 4.19. The monetary benefits which could be obtained through 3,785 (1,179-6,335) avoided death in the first scenario was 2.4 (0.4-4.1) billion US$ (2011 US$, PPP) in accordance with the reference of the OECD VSL and 3.7 (1.2 – 6.2) billion US$ (2011 US$, PPP) in accordance with the reference of the USEPA VSL. This amount of money was lowered to 2.1 (0.6-3.5) billion US$ (2011, US$, PPP) (the OECD VSL reference) and 3.1 (1.0-5.4) billion US$ (2011 US$, PPP) (the USEPA VSL reference) in the second scenario. Controlling the $PM_{2.5}$ to reach the third scenario would save 841 (248-1,544) million US$ (2011 US$, PPP) (the OECD VSL reference) and 1,276 (377-2,341) million US$ (2011 US$, PPP) (the USEPA VSL reference).

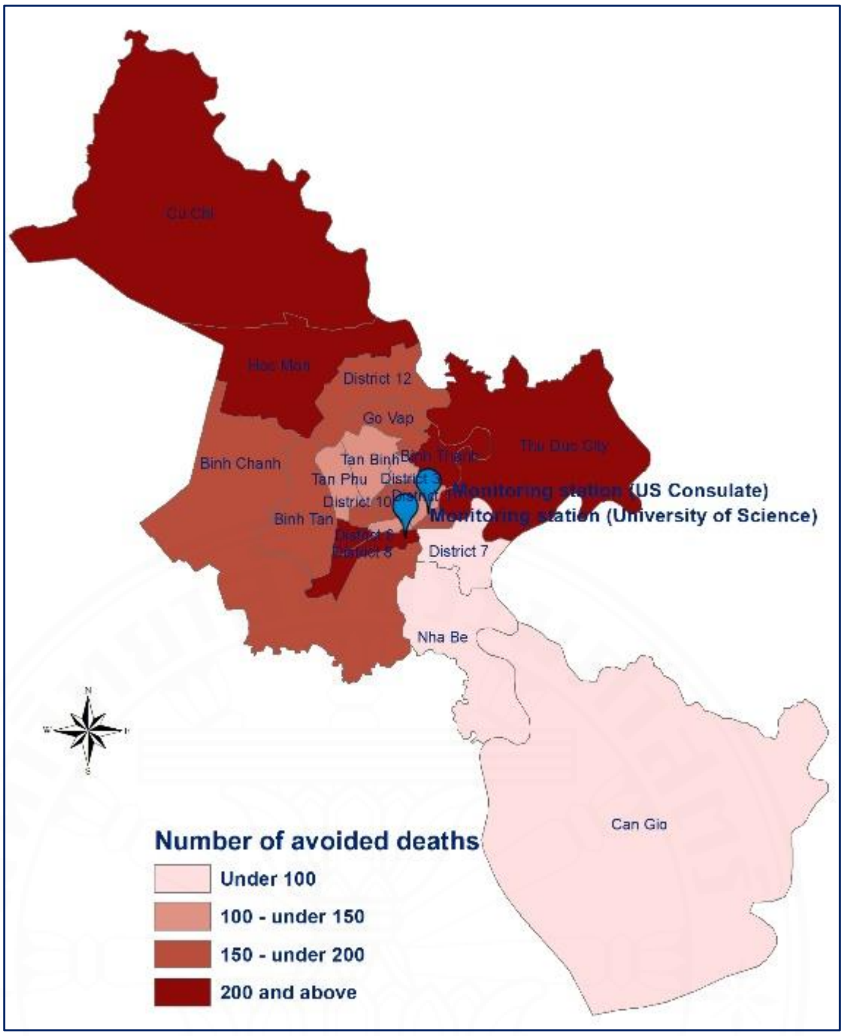


Figure 4.8. The number of avoided deaths by districts in the scenario of the $PM_{2.5}$ concentration in 2019 in Ho Chi Minh City met the World Health Organization of 5 µg/m^3

Table 4.17. Estimated number of avoided deaths attributable to $PM_{2.5}$ among the Ho Chi Minh City population in 2019

Control scenario of $PM_{2.5}$ / Study referred	**Number of avoided deaths**					
	All-cause	**All-cause (non-accidental)**	**Cardiopulmonary diseases**	**Cardiovascular diseases**	**IHD**	**Lung cancer**
The first scenario 2021 WHO annual average AQG for $PM_{2.5}$ (5 μg/m^3)						
Lepeule et al. (2012)	4,884 (2,630-6,795)	*na*	*na*	2,070 (1,305-2,671)	*na*	282 (81-400)
Krewski et al. (2009)	2,243 (759-3,631)	*na*	1,511 (1,059-1,925)	*na*	326 (246-397)	150 (63-224)
Cesaroni et al. (2013)	*na*	2,772 (2,107-3,406)	*na*	877 (603-1,133)	235 (162-302)	75 (8-135)
Hoek et al. (2013)	4,396 (2,973-5,724)	*na*	*na*	1,425 (787-1,987)	*na*	*na*
Cao et al. (2011)	*na*	*na*	*na*	438 (150-708)	*na*	*na*
Fold et al. (2009)	*na*	1,261 (182-2,279)	*na*	*na*	*na*	*na*
Pooled	3,785 (1,179-6,335)	2,092 (485-3,406)	1,511 (1,059-1,925)	1,140 (231-2,453)	276 (162-379)	151 (28-365)
Male	*1,625 (489-2,870)*	*863 (200-1,405)*	*646 (453-823)*	*505 (101-1,125)*	*120 (70-164)*	*68 (13-169)*
Female	*2,160 (690-3,465)*	*1,229 (285-2,001)*	*865 (606-1,102)*	*635 (130-1,328)*	*156 (92-215)*	*83 (15-196)*
The second scenario 2005 WHO annual average AQG for $PM_{2.5}$ (10 μg/m^3)						
Lepeule et al. (2012)	4,180 (2,216-5,885)	*na*	*na*	1,805 (1,113-2,369)	*na*	251 (68-367)
Krewski et al. (2009)	1,877 (632-3,049)	*na*	1,278 (890-1,637)	*na*	278 (208-342)	128 (53-193)
Cesaroni et al. (2013)	*na*	2,323 (1,762-2,861)	*na*	737 (505-956)	199 (136-257)	63 (7-114)
Hoek et al. (2013)	3,702 (2,491-4,840)	*na*	*na*	1,209 (660-1,702)	*na*	*na*
Cao et al. (2011)	*na*	*na*	*na*	366 (125-593)	*na*	*na*
Fold et al. (2009)	*na*	1,052 (152-1,907)	*na*	*na*	*na*	*na*
Pooled	3,195 (982-5,468)	1,752 (404-2,861)	1,278 (890-1,637)	962 (193-2,160)	234 (136-326)	128 (23-330)
Male	*1,367 (407-2,477)*	*723 (167-1,180)*	*547 (380-700)*	*427 (84-990)*	*101 (59-141)*	*58 (10-153)*
Female	*1,828 (575-2,991)*	*1,029 (237-1,681)*	*731 (510-937)*	*535 (109-1,170)*	*133 (77-185)*	*70 (13-177)*
The third scenario (The Vietnamese annual average standard for $PM_{2.5}$ (25 μg/m^3)						
Lepeule et al. (2012)	1,777 (897-2,595)	*na*	*na*	808 (464-1,121)	*na*	119 (27-195)
Krewski et al. (2009)	743 (246-1,221)	*na*	518 (354-675)	*na*	115 (84-145)	53 (21-82)
Cesaroni et al. (2013)	*na*	927 (698-1,148)	*na*	293 (198-384)	80 (53-105)	25 (3-47)
Hoek et al. (2013)	1,495 (991-1,979)	*na*	*na*	496 (261-717)	*na*	*na*
Cao et al. (2011)	*na*	*na*	*na*	143 (48-234)	*na*	*na*
Fold et al. (2009)	*na*	414 (59-757)	*na*	*na*	*na*	*na*
Pooled	1,300 (384-2,386)	692 (157-1,148)	518 (354-675)	385 (74-998)	94 (53-137)	51 (9-159)
Male	*556 (158-1,078)*	*285 (64-472)*	*221 (151-288)*	*169 (32-457)*	*40 (23-59)*	*22 (4-69)*
Female	*744 (226-1,308)*	*407 (93-676)*	*297 (203-387)*	*216 (42-541)*	*54 (30-78)*	*29 (5-90)*

na: Not available *Pooled: Using random effects in BenMAP-CE*

Table 4.18. Estimated number of avoided deaths from all causes attributable to $PM_{2.5}$ among the HCMC population in 2019 by districts

No.	District	Pop in 2019	Number of avoided deaths		
			5 μg/m³	10 μg/m³	25 μg/m³
1.	Thu Đuc	1.169.967[1]	343 (105-596)	288 (87-509)	105 (31-200)
2.	District 8	424.667	272 (84-462)	232 (71-403)	104 (31-194)
3.	Cu Chi	462.047	236 (75-378)	199 (63-326)	80 (24-140)
4.	Binh Thanh	499.164	232 (73-380)	191 (60-321)	62 (18-111)
5.	Hoc Mon	542.243	208 (65-350)	175 (54-302)	70 (21-130)
6.	District 6	233.561	206 (64-355)	176 (54-310)	79 (23-149)
7.	Gò Vap	676.899	195 (62-317)	163 (51-272)	62 (19-111)
8.	District 11	209.867	189 (58-326)	162 (49-285)	74 (22-140)
9.	District 10	234.819	187 (60-296)	161 (51-260)	77 (24-133)
10.	District 12	620.146	177 (53-317)	149 (44-272)	57 (16-113)
11.	District 4	175.329	172 (52-306)	146 (43-265)	60 (17-117)
12.	Binh Tan	784.173[2]	170 (52-299)	145 (44-260)	62 (18-119)
13.	Binh Chanh	705.508[3]	167 (53-273)	142 (44-237)	61 (18-108)
14.	District 3	190.375	157 (51-246)	131 (42-208)	52 (16-88)
15.	Tan Phu	485.348	146 (44-258)	123 (37-224)	52 (15-101)
16.	District 5	159.073	133 (42-217)	116 (36-192)	58 (18-104)
17.	District 1	142.625	132 (41-223)	108 (33-187)	30 (9-56)
18.	Tan Binh	474.792	131 (41-215)	110 (34-185)	44 (13-80)
19.	Phu Nhuan	163.961	121 (39-191)	101 (32-162)	37 (11-63)
20.	District 7	360.155	90 (29-146)	76 (24-126)	31 (9-55)
21.	Nha Be	206.837	64 (20-107)	55 (17-92)	23 (7-41)
22.	Can Gio	71.526	46 (14-84)	39 (11-73)	16 (4-32)

5 μg/m³ and 10 μg/m³: WHO guidelines of annual $PM_{2.5}$ concentration of 2021 and 2005, respectively

25 μg/m³: The Vietnamese standard of annual $PM_{2.5}$ concentration

Table 4.19. Estimated economic benefits in three scenarios of $PM_{2.5}$ achievement in 2019 in Ho Chi Minh City

Control scenario of $PM_{2.5}$	**Cause of deaths**					
	All-cause	**All-cause (non-accidental)**	**Cardiopulmonary diseases**	**Cardiovascular diseases**	**IHD**	**Lung cancer**
The first scenario 2021 WHO annual average AQG for $PM_{2.5}$ (5 µg/m^3) (WHO, 2021c)						
Total number of avoided deaths (pooled)	3,785 (1,179-6,335)	2,092 (485-3,406)	1,511 (1,059-1,925)	1140 (231-2,453)	276 (162-379)	151 (28-365)
Economic benefits of applying the OECD VSL (billion US$)	2.4 (0.8-4.1)	1.4 (0.3-2.2)	1 (0.7-1.2)	0.7 (0.1-1.6)	0.18 (0.1-0.25)	0.1 (0.02-0.24)
Economic benefits of applying the USEPA (billion US$)	3.7 (1.2-6.2)	2.1 (0.5-3.3)	1.5 (1-1.9)	1.1 (0.2-2.4)	0.27 (0.16-0.37)	0.15 (0.03-0.36)
The second scenario 2005 WHO annual average AQG for $PM_{2.5}$ (10 µg/m^3) (WHO, 2006a)						
Total number of avoided deaths (pooled)	3,195 (982-5,468)	1,752 (404-2,861)	1,278 (890-1,637)	962 (193-2,160)	234 (136-326)	128 (23-330)
Economic benefits of applying the OECD VSL (billion US$)	2.1 (0.6-3.5)	1.1 (0.3-1.9)	0.83 (0.58-1.06)	0.62 (0.12-1.4)	0.15 (0.09-0.21)	0.08 (0.01-0.21)
Economic benefits of applying the USEPA (billion US$)	3.1 (1.0-5.4)	1.7 (0.4-2.8)	1.25 (0.87-1.61)	0.94 (0.19-2.12)	0.23 (0.13-0.32)	0.13 (0.02-0.32)
The third scenario (The Vietnamese annual average standard for $PM_{2.5}$ (25 µg/m^3) (MONRE, 2013a)						
Total number of avoided deaths (pooled)	1,300 (384-2,386)	692 (157-1,148)	518 (354-675)	385 (74-998)	94 (53-137)	51 (9-159)
Economic benefits of applying the OECD VSL (Million US$)	841 (248-1,544)	448 (102-743)	335 (229-437)	249 (48-646)	61 (34-89)	33 (6-103)
Economic benefits of applying the USEPA (Million US$)	1,276 (377-2,341)	679 (154-1,126)	508 (347-662)	378 (73-979)	92 (52-134)	50 (9-156)

The estimated Value of Statistical Life (VSL) of Viet Nam was 647,050 (2011 US$ PPP), applying the OECD VSL and 981,200 (2011 US$ PPP) using the USEPA VSL.

4.4.3 Analysis using the Vietnamese mortality incidence rate from Global Burden Diseases

Applying the mortality rate from the Global Burden Disease to BenMAP-CE instead of the mortality rate calculated from the total deaths in HCMC showed a higher result in the number of avoided deaths and the estimated economic benefit (Table 4.20 and Table 4.21). The pooled of avoided deaths of all causes were 7,741 (2,389-13,308) cases, 6,541 (1,989-11,478) cases, and 2,634 (770-4,970) cases for three scenarios of controlling $PM_{2.5}$ concentration. The estimated economic benefit was 5.0 (1.5-8.6), 4.2 (1.3-7.4), 1.7 (0.5-3.2) billion US$ (2011, US$, PPP) (the OECD VSL reference) and 7.6 (2.3-13.1), 6.4 (2-11.3), 2.6 (0.8-4.9) billion US$ (2011 US$, PPP) (the USEPA VSL reference). These estimated results were around two times higher than those using the incidence rate calculated from total deaths in HCMC.

Table 4.20. The estimated number of avoided deaths attributable to $PM_{2.5}$ among the Ho Chi Minh City population in 2019 adopted the incidence rate from the global burden of disease

Control scenario of $PM_{2.5}$ / Study referred	**Number of avoided deaths**			
	All-cause	**Cardiopulmonary diseases**	**IHD**	**Lung cancer**
WHO guideline (5 μg/m³)				
Lepeule et al. (2012)	10,257 (5,522-14,275)	5,485 (3,458-7,076)	*na*	1,119 (321-1,585)
Krewski et al. (2009)	4,548 (1,538-7,363)	*na*	2,405 (1,817-2,933)	625 (263-934)
Cesaroni et al. (2013)	*na*	3,506 (2,413-4,530)	1,737 (1,197-2,230)	314 (35-562)
Hoek et al. (2013)	8,915 (6,028-11,609)	5,699 (3,147-7,947)	*na*	*na*
Cao et al. (2011)	*na*	1,734 (594-2,802)	*na*	*na*
Fold et al. (2020)	*na*	*na*	*na*	*na*
Pooled	7,741 (2,389-13,308)	3,937 (916-7,076)	2,037 (1,197-2,801)	620 (116-1,447)
Male	3,374 (1010-6143)	1,693 (380-2,928)	838 (493-1,152)	280 (51-668)
Female	4,367 (1379-7165)	2,244 (536-4,148)	1,199 (704-1,649)	340 (65-779)
WHO guideline (10 μg/m³				
Lepeule et al. (2012)	8,772 (4,649-12,354)	4785 (2950-6279)	*na*	994 (270-1,455)
Krewski et al. (2009)	3,801 (1,279-6,176)	*na*	2,058 (1,542-2,528)	532 (220-804)
Cesaroni et al. (2013)	*na*	2,948 (2,019-3,823)	1,473 (1,007-1,902)	264 (29-476)
Hoek et al. (2013)	7,499 (5,043-9,806)	4,839 (2641-6,809)	*na*	*na*
Cao et al. (2011)	*na*	1,448 (494-2,349)	*na*	*na*
Fold et al. (2020)	*na*	*na*	*na*	*na*
Pooled	6,541 (1,989-11,478)	3,345 (762-6,279)	1,730 (1,007-2,410)	529 (97-1,310)
Male	2,862 (841-5,297)	1,431 (316-2,739)	712 (414-992)	239 (43-605)
Female	3,679 (1,148-6,181)	1,914 (446-3,540)	1,018 (593-1,418)	290 (54-705)
The Vietnamese standard (25 μg/m³)				
Lepeule et al. (2012)	3,701 (1,868-5,407)	2,151 (1,235-2,982)	*na*	477 (108-780)
Krewski et al. (2009)	1,490 (493-2,448)	*na*	867 (631-1,089)	220 (87-345)
Cesaroni et al. (2013)	*na*	1,176 (794-1,543)	602 (402-793)	105 (11-195)
Hoek et al. (2013)	2,998 (1,987-3,969)	1,990 (1,048-2,879)	*na*	*na*
Cao et al. (2011)	*na*	566 (190-928)	*na*	*na*
Fold et al. (2020)	*na*	*na*	*na*	*na*
Pooled	2,634 (770-4,970)	1,374 (295-2,773)	711 (402-1,032)	215 (38-667)
Male	1,152 (325-2,291)	586 (122-1,218)	292 (165-424)	97 (17-308)
Female	1,482 (445-2,679)	788 (173-1,555)	419 (237-608)	118 (21-359)

na: Not available *Pooled: Using random effects in BenMAP-CE*

Table 4.21. Estimated economy benefit in three scenarios of $PM_{2.5}$ achievement in 2019 in Ho Chi Minh City adopted the incidence rate from the global burden of disease

Control scenario of $PM_{2.5}$	**Cause of deaths**			
	All-cause	**Cardiovascular diseases**	**IHD**	**Lung cancer**
WHO guideline (5 μg/m^3)				
Total number of avoided deaths (pooled)	7,741 (2,389-13,308)	3,937 (916-7,076)	2,037 (1,197-2,801)	620 (116-1,447)
Economy benefit applied OECD VSL (trillion $)	5 (1.5-8.6)	2.5 (0.6-4.6)	1.32 (0.77-1.81)	0.4 (0.08-0.94)
Economy benefit applied USEPA (trillion $)	7.6 (2.3-13.1)	3.9 (0.9-6.9)	2 (1.17-2.75)	0.61 (0.11-1.42)
WHO guideline (10 μg/m^3)				
Total number of avoided deaths (pooled)	6,541 (1,989-11,478)	3,345 (762-6,279)	1,730 (1,007-2,410)	529 (97-1,310)
Economy benefit applied OECD VSL (trillion $)	4.2 (1.3-7.4)	2.16 (0.49-4.06)	1.12 (0.65-1.56)	0.34 (0.06-0.85)
Economy benefit applied USEPA (trillion $)	6.4 (2-11.3)	3.28 (0.75-6.16)	1.7 (0.99-2.36)	0.52 (0.1-1.29)
The Vietnamese standard (25 μg/m^3)				
Total number of avoided deaths (pooled)	2,634 (770-4,970)	1,374 (295-2,773)	711 (402-1,032)	215 (38-667)
Economy benefit applied OECD VSL (million $)	1,704 (498-3,216)	889 (191-1,794)	460 (260-668)	139 (25-432)
Economy benefit applied USEPA (million $)	2,584 (756-4,877)	1,348 (289-2,721)	698 (394-1,013)	211 (37-654)

The estimated value of statistical life (VSL) of Viet Nam was 647,050 (2011 US $) applying OECD VSL and 981,200 (2011 US $) using USEPA VSL.

CHAPTER 5
DISCUSSION

The study analyzed the database of 62,001 children under 5-year-old hospitalized in all three pediatric hospitals in HCMC due to acute lower respiratory infections – ALRI (50,778 records) and asthma diseases (11,223 records) from 2016 to 2019 and the $PM_{2.5}$ dataset in the same period to determine the association between $PM_{2.5}$ exposure and the risk of hospital admission for ALRI and asthma. Additionally, the study analyzed the database of 163,868 HCMC infants born in 2016 – 2019 to determine the associations between maternal $PM_{2.5}$ exposure and adverse birth outcomes. The health and economic benefits of controlling $PM_{2.5}$ concentration were also estimated.

The annual average concentration of $PM_{2.5}$ from 2016 to 2019 in HCMC was 28.2 µg/m^{3,} which exceeded the WHO's Air Quality Guideline in 2021 of 5 µg/m^3 (WHO, 2021c), and the Vietnamese standard of 25 µg/m^3 (MONRE, 2013a). Generally, the study finding presents a negative impact of $PM_{2.5}$ exposure on babies and children. Controlling the annual concentration of $PM_{2.5}$ to meet the WHO guidelines or the Vietnamese standard shows massive health and economic benefits.

5.1 Effect of $PM_{2.5}$ on hospitalization for acute lower respiratory infections (ALRI) among children under 5-year-old in HCMC

The study found a positive association between the daily $PM_{2.5}$ level and the number of ALRI hospital admission. Each 10 µg/m^3 increase in daily $PM_{2.5}$ had an excess risk of 1.86% (95% CI: 0.24% ~ 3.52%) ALRI admission after six days of exposure (lag_6). The particulate matter has been reported as a risk of hospital admission among children due to lower respiratory infections. Its effect was different in magnitude and individual lagged effect in various studies. In a time-stratified case-crossover study in Ha Noi – a northern city in Viet Nam, a 10 µg/m^3 increase in daily $PM_{2.5}$ was reported to increase 2.2% risk of respiratory diseases (J00 – J99) admission among children under five years on the same day of exposure (lag_0) (Luong et al., 2017). Meanwhile, a time-series study in HCMC reported that a 10 µg/m^3 increase in daily $PM_{2.5}$ increased the 3.51% risk of ALRI admission at lag_3 using the distributed lag linear models (DLMs) with constraint (Luong et al., 2020). Each 10 µg/m^3 increase in daily $PM_{2.5}$ was also reported to increase 1.5% risk of ALRI hospital admission after two cumulative days of exposure among children under 14 years (Zheng et al., 2017), 0.79% risk of lower respiratory infection (J10 – J22) after three cumulative days of exposure among children under 18 years in 18 cities of China (Pu et al., 2021). Several studies also reported an insignificant association between lower respiratory diseases with acute exposure to $PM_{2.5}$ (Karr et al., 2006b; Karr et al., 2009). The explanation for this difference could be from several reasons, such as study design, target population, the applied models for analysis, $PM_{2.5}$ components of the study site, pathogen epidemiology, and other characteristics of the population studied.

Regarding gender, around 60 percent of children in our study were boys. We had a comparable result with the previous research in HCMC that the male gender was more sensitive to $PM_{2.5}$ impact than the female (Luong et al., 2020). While each 10 $\mu g/m^3$ increase in daily $PM_{2.5}$ posed a risk of hospital admission among the male group with an excess risk of 2.43% (95% CI: 0.40% ~ 4.49%), the female was insignificant. The possible explanation could be that male children are more attracted to outside activities than girls, leading to a high risk of exposure to outdoor pollutants (Telford et al., 2016). The difference in health responses to susceptibility to air pollution between the two genders could be another reason (Clougherty, 2010). Besides, boys own other factors that facilitate a higher rate of respiratory infection, such as a smaller airway to lung (Bjornson and Mitchell, 2000), smooth muscle, vascular functions, and hormonal status (Jensen-Fangel et al., 2004). A study in China reported a similar finding that $PM_{2.5}$ effects were only seen in boys (Wang et al., 2021).

For the age group, 69 percent of children in this study were aged one or below. However, the impact of $PM_{2.5}$ on ALRI hospital admission among this age group was insignificant. Whereas, each 10 $\mu g/m^3$ increase in daily $PM_{2.5}$ increased 3.15% (95% CI: 0.25% ~ 6.14%) excess risk of hospital admission at lag_6 among the age group from 2 to under 5 years. Stronger associations with $PM_{2.5}$ in older children were reported in several studies (Luong et al., 2020; Wang et al., 2021; Zheng et al., 2017). Older children may have frequent exposure to outdoor air, thus increasing their chance to expose ambient air pollutants. Meanwhile, younger children could be less exposed because they were mostly kept indoors. In Viet Nam, infants are usually breastfed from 12 to 24 months, which could be another protective factor from air pollution and other biological agents (Cheng et al., 2013; Nhung et al., 2018).

Regarding the subgroups of ALRI, nearly 67% of children in our study were hospitalized due to pneumonia (J12 – J18). This study found a positive association between $PM_{2.5}$ and pneumonia and between $PM_{2.5}$ and bronchitis at several lags. However, all associations were not statistically significant. Several studies reported the relationship between each daily 10 $\mu g/m^3$ increase in $PM_{2.5}$ and pneumonia diseases among children, with the risk ranging from around 1% to more than 10% (Cheng et al., 2019; Lv et al., 2017; Nhung et al., 2017; Nhung et al., 2018; Sherris et al., 2021; Wang et al., 2021). Some studies revealed a contrasting result that reported a significant association between $PM_{2.5}$ and bronchitis or bronchiolitis (J20–J21; J20-J22) (Kim et al., 2020; Luong et al., 2020; Zheng et al., 2017).

5.2 Effect of $PM_{2.5}$ on hospitalization for asthma diseases among children under 5-year-old in HCMC

Eleven thousand two hundred twenty-three children in HCMC were hospitalized from 2016 – 2019 for asthma disease. The study documented that ambient $PM_{2.5}$ are associated with hospital admissions for asthma among children under 5 years old in HCMC. The increase in the rate of hospital admission was 3.86% (95% CI: 0.44%~7.4%) per 10 $\mu g/m^3$ increase in daily $PM_{2.5}$ level (4-day average exposure). Our study consolidated the evidence of the impact of $PM_{2.5}$ on asthma among children in previous studies, which indicated the risk of hospital admission on asthma per 10 $\mu g/m^3$ increase in daily $PM_{2.5}$ of 2.2% - 2.3% (Zhang et al., 2016; Zheng et al., 2015). Our results are also comparable to a study in Denmark which indicated the excess risk of hospital admission per IQR increase of daily $PM_{2.5}$ (4.8 $\mu g/m^3$) of 9% (95% CI: 4%~13%) (Iskandar et al., 2012).

Study on the association between exposure to $PM_{2.5}$ and hospital admissions for asthma is relatively sparse, especially among children under 5 years old. Previously studies were mainly conducted among children 0-18 and reported a positive association between the increasing $PM_{2.5}$ level and hospital admission for asthma. A case-crossover study of 2,507 outpatients and inpatients in Chongqing, China, reported a significant association for each 10 ug/m^3 increase in daily $PM_{2.5}$ and hospital visits among male gender of 2.9% (95% CI: 1.2%~4.6%), children aged 2-5 of 2.8% (95% CI: 1.2%~4.4%). The risk of hospital visits was significant among outpatients at 1.6% (95% CI: 0.1%~3.0%); meanwhile, the risk of inpatients was not statistically significant (Ding et al., 2017). A study of 17,227 asthma admissions during 2015–2016 in Hefei City, China, documented a higher result. The risk of hospital admission was 19.4% (95% CI: 7.4%~32.6%) at lag_1, 27.5% (95% CI: 12.3%~44.9%) at lag_{01}, 26.6% (95% CI: 8.9%~47.2%) at lag_{02}, 21.1% (95% CI: 2.7%~42.8%) at lag_{03} for each IQR of $PM_{2.5}$ (40 µg/m^3) increase (Y. Zhang et al., 2019). A study in Shanghai, China, reported the risk of hospital admission for asthma was 6.0% (95% CI: 5.3%~6.8%) at lag_4, 6.1% (95% CI: 5.1%~7.2%) among the age group of ≤ 2 years at lag_5, and 7.1% (95% CI: 5.8%~8.4%) among the age group of 3-5years old at lag_4 (Yu et al., 2021). However, the number of pediatric asthma hospital visits in this study was relatively small, 169, 79, and 61, for all age groups; age group of ≤ 2 years old, and age group of 3-5 years old, respectively (Yu et al., 2021).

Some studies in Europe indicated a higher excess risk of hospitalization for asthma among children than our findings. The excess risk from a study in Turkey was reported from 25% (95% CI: 5%–50%) per 10-µg/m^3 rise in daily $PM_{2.5}$ levels (Tecer et al., 2008). A study in Denmark reported an excess risk of 15% (95% CI: 0%–32%) per IQR of daily $PM_{2.5}$ (5 µg/m^3) among school children (aged 5–18 years) (Andersen et al., 2008). The excess risk of admission for asthma was 26% (95% CI: 10%–44%) to the intensive care unit (ICU) and 19% (95% CI: 12%–27%) in non-ICU per 12-µg/m^3 increase in $PM_{2.5}$ among children aged 6 to 18 years in New York (Silverman and Ito, 2010). A significant relationship was observed on warm and cool days with the excess risk of 6.87% and 1.72% per 10 µg/m^3 increment in the 3-day moving average (lag_2) concentrations of $PM_{2.5}$ (Silverman and Ito, 2010).

The adverse effect of exposure to $PM_{2.5}$ and hospital admission for asthma have been inconsistent results. $PM_{2.5}$ concentration has been indicated as a risk factor for hospital admission for asthma in some studies (Andersen et al., 2008; Bouazza et al., 2018; Cheng et al., 2014; Ding et al., 2017; Iskandar et al., 2012; Silverman and Ito, 2010; Tecer et al., 2008; Zhang et al., 2016; Y. Zhang et al., 2019; Zheng et al., 2015). Several studies reported a non-relationship between hospitalization for asthma and $PM_{2.5}$ (Lin et al., 2002; Xu et al., 2016). Hospital admissions for asthma were also reported to have a significant relationship to other pollutants such as coarse matter (PM from 2.5 to 10 µm in diameter) (Lin et al., 2002), PM_{10} (Nastos et al., 2010; Yu et al., 2021), O_3 (Silverman and Ito, 2010), NO_2 (Ding et al., 2017; Y. Zhang et al., 2019) or CO (Ding et al., 2017).

The mechanism of asthma exacerbation due to $PM_{2.5}$ has not been understood fully. Particulate matter deposits in the airways and can result in airway inflammation, mucosal edema, and cytotoxicity (Zheng et al., 2015). Particulate matter can also induce oxidative stress in dendritic cells and their interactions, triggering asthma exacerbations (Li and Buglak, 2015). For asthma disease, the genetic aspects could play a particular role and have been widely studied. However, further studies are required to explore this point further (Toskala and Kennedy, 2015).

Smoking and other indoor pollutants can trigger asthma. Our study did not control these factors due to the unavailability of data. These factors are unlikely as confounding factors between $PM_{2.5}$ levels and admissions for asthma because of the present association since day-to-day variations in indoor emissions may not be correlated with $PM_{2.5}$ air pollution (Cheng et al., 2014).

The particulate effect can vary by season. The concentration can be high during the cold season and low in the warm season (Bell et al., 2008; Zanobetti et al., 2009). During the cold season, people are less likely to go outdoors; thus, using the $PM_{2.5}$ concentration at fixed monitoring stations can limit extrapolating personal exposure. There is no cold season in HCMC. The yearly average temperature is 28.6 ± 1.3; thus, our study can overcome this limitation.

Our study could provide more information if the outpatients were taken into account. In Vietnam, the patient visit to the treatment units are usually unscheduled and are first come, first served. Conceptually, hospital outpatient records may provide reliable morbidity information for a defined population. However, people can quickly access private clinics or drug stores when unwell. They usually come to the hospitals when the conditions become worse. The reporting system has not covered these units. Therefore, the outpatient database in hospitals does not reflect the comprehensive status of community health.

To the best of our knowledge, this study is the first work that investigated the association between exposure to $PM_{2.5}$ and hospital admissions for asthma in Vietnam. Our findings may have implications for asthma prevention in Vietnam and contribute to the limited scientific literature about the acute effects of $PM_{2.5}$ on asthma morbidity outcomes in developing countries.

5.3 Effects of maternal exposure to $PM_{2.5}$ and adverse birth outcomes

Overall, the study showed that maternal $PM_{2.5}$ exposure significantly decreased birth weight (BW) and increased the risk of preterm birth (PTB). Meanwhile, the results showed no significant risk for term low birth weight (LBW).

The decrease in BW might be attributed to maternal exposure to $PM_{2.5}$ more in the second trimester. Our study found that every 10 μg/m^3 increase in average daily $PM_{2.5}$ concentration exposure during the second trimester significantly lowered BW by 11.77 g (95% CI: 5.25 g ~ 18.30 g). A meta-analysis reported a similar result with a BW decrease of 12.6 g (95% CI: 3.1 g ~ 21.7 g) (Sun et al., 2016). A study of 10,915 singleton live births conducted in Suzhou, China, concluded that gestational exposure to $PM_{2.5}$ at 10 μg/m^3 increments in the second trimester lowered BW by 4.94 g (95% CI: 0.05 g ~ 9.83 g) (Han et al., 2018). However, the significant association between BW decrease and the level of maternal exposure to $PM_{2.5}$ during the first trimester and the third trimester were also reported in several studies (Z. Li et al., 2019; Sun et al., 2016).

Our study also found a 3.95 g decrease in BW associated with 10 μg/m^3 increase in average daily $PM_{2.5}$ exposure for the entire pregnancy period, although the association was not statistically significant. Previous studies reported some evidence that exposure to $PM_{2.5}$ during the whole pregnancy period could result in a BW decrease (Balakrishnan et al., 2018; Hao et al., 2016; Hyder et al., 2014; Kloog et al., 2012; Z. Li et al., 2019; Savitz et al., 2013). A study of 170,008 live births conducted in the Ningbo city of Zhejiang, China, reported that every 10.55 μg/m^3 increase in average daily $PM_{2.5}$ concentration exposure throughout the entire pregnancy period was associated with a 3.65 g decrease in BW (95% CI: 1.29 g ~ 6.02 g) (Z. Li et al., 2019). A similar conclusion with a 3.92 g decrease in BW (95% CI: 1.08 g ~ 6.76 g) was documented in a follow-up study conducted among 1,285 pregnant women in India (Balakrishnan et al., 2019; Balakrishnan et al., 2018). Another study in China showed a higher result with a 12.8 g decrease in term BW (95% CI: 7.3 g ~18.4 g) (Xiao et al., 2018). Similar results were reported in studies on the American population and from a meta-analysis study. Every 10 μg/m^3 increase in average daily $PM_{2.5}$ exposure during the entire pregnancy could result in a 12.8 g to 15.9 g in the BW decrease (Kloog et al., 2012; Morello-Frosch et al., 2010; Sun et al., 2016). However, all studies did not have a common agreement on the association between maternal exposure to $PM_{2.5}$ and BW decrease. The null statistical associations appeared in some studies (Bonzini et al., 2010; Darrow et al., 2011; Gehring et al., 2011; Jacobs et al., 2017; Lamichhane et al., 2015; Laurent et al., 2013; Lavigne et al., 2016; Madsen et al., 2010).

Concerning the risk of term LBW, our findings suggest maternal exposure to $PM_{2.5}$ could pose a risk of term LBW. Exposure to average daily $PM_{2.5}$ at 10 μg/m^3 increments during the first, second, third, and entire pregnancy increases the risk of term LBW by 0.3%, 6.3%, 5.2%, and 4.5%, respectively. However, all these associations are not statistically significant. In some previous studies, maternal $PM_{2.5}$ exposure was reported significantly increase the risk of term LBW from 1% to 9% (Hao et al., 2016; Hyder et al., 2014). Higher results were reported in studies conducted in China with the risk of term LBW from 22% to 38% (Wu et al., 2018; Xiao et al., 2018). Exposure to $PM_{2.5}$ during the third trimester could substantially impact the risk of term LBW by 17% (95% CI: 5% ~ 29%) (Wu et al., 2018). Nevertheless, several studies had similar results as ours, which reported the insignificant association between maternal $PM_{2.5}$ exposure and the risk of term LBW (Brauer et al., 2008; Gehring et al., 2011; Madsen et al., 2010). The relatively small number of term LBW in our study (3,374 term LBW infants) compared to 81,797 terms LBW infants in the study in New York (Hao et al., 2016) or 11,641 term LBW infants in the study in Connecticut and Massachusetts (Hyder et al., 2014) could be a limitation in determining the association.

In terms of PTB, our study found that every 10 $\mu g/m^3$ increase in the average daily $PM_{2.5}$ concentration exposure during the second trimester had the most substantial impact on PTB with a significantly increased risk of 23.1% (95% CI: 13.6% ~ 33.6%), followed by exposure during the first trimester with the risk of 12.1% (95% CI: 2.0% ~ 23.3%). Our findings agreed with previous studies that documented the significant association between the risk of PTB and maternal exposure to $PM_{2.5}$ (Bachwenkizi et al., 2022; Guo et al., 2018; He et al., 2022; Kloog et al., 2012; Lavigne et al., 2016; Xiao et al., 2018).

A cross-sectional study from 15 countries in Africa reported an increase of 8% risk of PTB (95% CI: 1% ~ 16%) for every 10 $\mu g/m^3$ $PM_{2.5}$ increment (Bachwenkizi et al., 2022). Similarly, every 10 $\mu g/m^3$ increase in average daily $PM_{2.5}$ exposure during the entire pregnancy period was found to increase the risk of PTB by 6% - 8% in a study in the USA (Kloog et al., 2012) and China (Guo et al., 2018; He et al., 2022). A study conducted in Shanghai, among 132,783 singleton live births, showed a risk of PTB up to 27% (95% CI: 20% ~ 36%) (Xiao et al., 2018). Interestingly, a study conducted in Ontario, Canada, among 818,400 singleton live births, revealed that every 2 $\mu g/m^3$ increase in maternal exposure to $PM_{2.5}$ over the entire pregnancy period could pose a PTB risk of 4.0% (95% CI: 2.4% ~ 5.6%) (Lavigne et al., 2016). However, some studies reported a non-statistically significant association between $PM_{2.5}$ and the risk of PTB (Fleischer et al., 2014; Gehring et al., 2011; Hyder et al., 2014; Rudra et al., 2011).

The inconsistent association between $PM_{2.5}$ exposure and adverse birth outcomes, including BW decrease, term LBW, and PTB in different studies, could be partly due to several factors. First, exposure assessment methods can play an important role. Data on $PM_{2.5}$ collected from various sources such as the ground fixed monitoring stations, satellite prediction, or using models can show slightly different results (Fleischer et al., 2014; Hyder et al., 2014; Xiao et al., 2018). Second, the background of $PM_{2.5}$ and the $PM_{2.5}$ constituents could also be other factors. The different $PM_{2.5}$ components (such as zinc, elemental carbon, silicon, and aluminum) may have various effects (Bell et al., 2010; Xiao et al., 2018; Xue et al., 2018). $PM_{2.5}$ with dominant carbonaceous components could have a higher PTB risk than SO_4^{2-}, NH_4^+, and NO_3^- (He et al., 2022; Xue et al., 2018). Additionally, the adverse effects could not be observed in relatively cleaner study areas, so the adverse effects did not appear. Third, controlling potential confounding factors and co-exposures could be another factor. PM_{10}, NO_2, and O_3 were also reported as risk factors of PTB (Fleischer et al., 2014; Lavigne et al., 2016). Besides, the susceptibilities of local populations and other customs could contribute to the $PM_{2.5}$ effect (M. L. Bell et al., 2007; Morello-Frosch et al., 2010; Xue et al., 2018). Other factors, such as geographic location and characteristics of the mother (such as age, education, occupation, history of alcohol consumption, and smoking), may play a role in the occurrence of adverse birth effects (Guo et al., 2018; Hao et al., 2016).

This study found an association between $PM_{2.5}$ exposure and birth outcomes; however, the exact biological mechanisms of the associations have not been well-established. It is speculated that pollutants may increase the risk of adverse birth outcomes through processes related to inflammation, oxidative stress, endocrine disruption, impaired oxygen transport across the placenta, respiratory epithelial injury, genetic and epigenetic changes (Guo et al., 2022; Slama et al., 2008). $PM_{2.5}$ exposure could lead to increased intrauterine inflammation and decreased placental DNA methylation, which are considered risk factors for adverse birth outcomes (Janssen et al., 2013; Nachman et al., 2016).

5.4 Assessment of the health and economic benefit of improving the $PM_{2.5}$ pollution

5.4.1 Health benefit of $PM_{2.5}$ reduction

Air pollution has adverse health effects, including morbidity and mortality. In the scenario of the annual average $PM_{2.5}$ concentration of HCMC in 2019 meeting the 2021 WHO annual average AQG of 5 μg/m^3, our study estimated that the health benefits are 4,884 (95% CI: 2,630-6,795) avoided all-cause mortalities using the concentration-response functions (ß coefficients) of the H6C reanalysis (Lepeule et al., 2012), 3,702 (2,491-4,840) using the Hoek meta-analysis (Hoek et al., 2013), and 2,243 (759-3,631) using the ACS reanalysis (Krewski et al., 2009). Similarly, there are various estimated results of other health endpoints, including all-causes (non-accidental), cardiopulmonary diseases, cardiovascular diseases, IHD, and lung cancer. The variability in the estimated health benefits across ß coefficients highlights the importance of selecting ß coefficients for analysis in BenMAP-CE. Ideally, ß coefficients should be calculated for the target population, but such studies have been lacking in Viet Nam. Applying ß coefficients from other populations, such as in the ACS study or H6C study, to the population of HCMC can introduce limitations. Our study used ß coefficients from various global studies in different countries and pooled the results by combining the studies with the same health endpoint. This could generate a more representative result for HCMC than using ß coefficients from a single study.

Our study estimated that the pooled health benefits were 3,785 (0.042% of the total population) avoided all-cause deaths in the scenario of annual average $PM_{2.5}$ meeting 5 μg/m^3. The benefit was predominant in the female gender accounting for 57% of total avoided deaths. This can be due to the higher female population structure of the city (51% vs. 49%) (GSO Vietnam, 2020), and women were more vulnerable to ambient air pollution than men (Liu et al., 2020). In the scenario of $PM_{2.5}$ controlling to attain the 2005 WHO annual average AQG of 10 μg/m^3, the avoided deaths were 3,195 cases (0.036% of the total population). This result could be comparable to a study in Teheran where the $PM_{2.5}$ baseline was 30.7 μg/m^3 (slightly higher than our study - 28.9 μg/m^3) and the control scenario of 10 μg/m^3. The health benefit from the Teheran study was higher than ours (5,372 avoided deaths, 0.06% of the total population).

The health benefits calculated between countries could be difficult to compare because of the different input parameters of BenMAP-CE. The difference could be the $PM_{2.5}$ concentration (the baseline and the control scenario), ß coefficients, and mortality incidence rate of health endpoints. In India and China, where the annual average $PM_{2.5}$ concentration is usually high, the health benefit of controlling $PM_{2.5}$ will be huge. The result from a study in Wuhan, China, estimated that 21,384 all-cause deaths (0.19% of the total population) could be avoided if the annual average $PM_{2.5}$ concentration was improved from 94 μg/m^3 to 53 μg/m^3 (Qu et al., 2020).

The annual $PM_{2.5}$ concentration in Uttar Pradesh, India, was 89 ±12 μg/m^3 in 2019, and the health benefits of achieving the WHO AQG of 10 μg/m^3 was 0.57 (0.67% of the state population) million cases in all-cause mortality (Manojkumar and Srimuruganandam, 2021).

Our findings were also comparable to a study in Bangkok, Thailand, where the annual average $PM_{2.5}$ was not much different (28.9 μg/m^3 in HCMC vs. 27.9 μg/m^3 in Bangkok) and other similar characteristics of the population, geography, climate, and socio-economic status. Applying the β coefficients of the ACS (Pope et al., 2002) and the controlling scenario $PM_{2.5}$ of 10 μg/m^3, the health benefits of Bangkok were 2,772, 1,686, and 291 avoided deaths for all causes, cardiopulmonary diseases, and lung cancer, respectively (Fold et al., 2020). This study also used β coefficients from the study of Cao et al. (Cao et al., 2011) in China. These results were much lower, with 374, 316, and 67 avoided deaths, respectively. Correspondingly, choosing the β coefficient was crucial to the estimated result. Although using the β coefficients from the ACS, our study applied the updated β coefficients of the re-analysis with the follow-up time from 1982-2000 (Krewski et al., 2009). The Bangkok study used β coefficients from the period between 1982-1998 (Fold et al., 2020). Our findings were 1,877, 1,278, and 128 avoided deaths, respectively. These numbers were lower than the results in the Bangkok study (Fold et al., 2020). One possible explanation was our study's low mortality rate. The mortality incidence rate in Bangkok was nearly two times higher than in HCMC. Forty-six thousand deaths from all causes were reported in Bangkok in 2017 (Fold et al., 2020) compared to 28,000 deaths for all causes in HCMC in 2019.

In Southeast Asia countries like Thailand and Vietnam, applying the β coefficients from the study in China (Cao et al., 2011) to estimate the health benefits could be more reliable than the ACS study because of some similar characteristics between countries. However, the study in China had several limitations. Due to the unavailability of $PM_{2.5}$ monitoring data, $PM_{2.5}$ concentrations were estimated from a ratio to total suspended dust concentration. Besides, this study only reported a significant association between $PM_{2.5}$ and mortality risk due to cardiovascular diseases. Meanwhile, the association between $PM_{2.5}$ and mortality risk due to all causes and lung cancer were not statistically significant.

Regarding the mortality incidence rate, several studies calculated these rates from the number of deaths of the study population; others used an alternative method by adapting the rates from the Global Burden of Disease (GBD). Our study applied the former approach, categorized by gender, age group (5-year group), and 22 districts. This method could provide a more representative estimation of the study population. Our study also used the mortality incidence rates from the GBD for sensitivity analysis, and the results from this method were much higher. The GBD provided the estimated rates for a whole country; hence applying them to a specific place in a country could be a limitation.

In HCMC, a previous study estimated that if the annual average $PM_{2.5}$ concentration in 2017 met 10 μg/m^3, the health benefits were 715, 357, and 64 avoided deaths due to cardiopulmonary diseases, IHD, and lung cancer, respectively (Vu et al., 2020). This study used the mortality incidence rates calculated from the number of deaths in 2017 in HCMC and applied the β coefficients from the ACS study (Krewski et al., 2009). However, this study did not estimate the health benefit of the all-cause mortality endpoint and the economic benefit. Applying the same β coefficients and the $PM_{2.5}$ control scenario, our results of the health benefits in 2019 for all causes, cardiopulmonary diseases, IHD, and lung cancer were 1,877, 1,278, 278, and 128, respectively. The difference in estimated results could be partly due to our study's $PM_{2.5}$ annual average of 28.9 μg/m^3 in 2019 compared to 23.0 μg/m^3 in the previous one in 2017 (Vu et al., 2020). There might be an inter-annual variation of $PM_{2.5}$ concentration; therefore, health impacts will vary following the variation of $PM_{2.5}$ concentration. The different concentrations of $PM_{2.5}$ measured in fixed monitoring stations and calculated by models could also be another explanation. The $PM_{2.5}$ level in 2017 at the monitoring station of the US Consulate (AirNow, 2020) was 28.5 μg/m^3, higher than the $PM_{2.5}$ concentration estimated by models in the previous study (23 μg/m^3) (Vu et al., 2020).

Additionally, our findings showed that nearly 48% of deaths in HCMC in 2019 were recorded as the unclear cause. Therefore, estimated health benefits in terms of avoided deaths based on the mortality rates of several specific causes of death (lung cancer, cardio-pulmonary, and IHD, can be significantly underestimated. Meanwhile, estimating health benefits based on the mortality rate of all causes, as also applied in our study, will give more reasonable estimates. Our study recorded 8,016 deaths related to cardiopulmonary diseases (I00-I99 and J00-J99) (27.8% of total deaths), 1,013 deaths due to IHD (I20-I25) (3.5% of total deaths) and 632 deaths due to lung cancer (C32-C34) (2.2% of total deaths). These mortality rates were slightly different from the previous study, which calculated that the death rates due to cardiopulmonary disease, IHD, and lung cancer were 30.1%, 15.0%, and 2.0% of total deaths, respectively (Vu et al., 2020). All these calculations were based on the database recorded in the Vietnamese A6 mortality reporting system;

however, the quality of this system was a challenge, especially in recording the specific cause of death. Recently, the Vietnamese Ministry of Health released Circular No. 37/2019/TT-BYT in 2019, requiring several critical pieces of information to record the mortality database to improve the reporting system quality.

5.4.2 Economic benefit valuation

The Vietnamese VSL in 2019 was estimated to be US$ 647,050, according to the OECD VSL reference, and US$981,200, according to the USEPA VSL reference. Therefore, the economic benefits of three scenarios of $PM_{2.5}$ controlling in 2019 in HCMC would be US$ 2.4 - 3.7 billion (scenario of 5 $\mu g/m^3$), US$ 2.1 - 3.1 billion (scenario of 10 $\mu g/m^3$), and US$ 841 - 1,276 million (scenario of 25 $\mu g/m^3$). Compared to the total Gross Regional Domestic Product (GRDP) of HCMC in 2019 of $ 58.3 billion (The Communist Party of Vietnam, 2020), these associated economic benefits accounted for 4.1% - 6.3%, 3.6% - 5.3%, and 1.4% - 2.2% of the GRDP, respectively.

Improving the $PM_{2.5}$ concentration could result in a considerable amount of monetary benefit. Reducing by 0.6 $\mu g/m^3$ of $PM_{2.5}$ concentration in Sydney would be worth AUS$ (Australian Dollars) 2.6 trillion (Richard A. Broome et al., 2015). A study in Wuhan, China, reported the associated economic benefit of reducing annual $PM_{2.5}$ concentration from 94 $\mu g/m^3$ to 53 $\mu g/m^3$, accounting for 4.8% of the GDP of Wuhan in 2017 (Qu et al., 2020). Of the controlling scenario of the annual average $PM_{2.5}$ concentration in 2019 attaining 10 $\mu g/m^3$, our estimated economic benefit (3.6% - 5.3% of GRDP) was similar to a study in South Africa which reported the monetary benefit of 4.5% of the country's GDP (US$ 29.1 trillion), using OECD VSL reference (Altieri and Keen, 2019). The monetary amount of US$ 1.9 trillion (the OECD VSL reference) was the benefit in case Teheran succeeded in maintaining an annual average $PM_{2.5}$ concentration at 10 $\mu g/m^3$ (Bayat et al., 2019).

A shortage of the VSL for Vietnamese people would affect the precision of the economic benefit estimation. In this study, the VSL derived from the OECD and USEPA reference was slightly different, around US$ 0.65 million and US$ 0.98 million, respectively. The VSL of USEPA relied on wage-risk studies, whereas the OECD had a different approach, focusing on stated-preference studies conducted globally and using meta-analysis to combine the results (Robinson et al., 2019). The VSL value of Viet Nam calculated from the OECD estimate was likely similar to the VSL of Thailand (US$ 0.65 million vs. US$ 0.66 million) (Gibson et al., 2007), a country in South East Asia like Viet Nam. Therefore, the VSL calculated from the OECD reference could be more suitable for Viet Nam; meanwhile, the VSL calculated from the USEPA reference might be overestimated.

5.5 Strength and limitations

This study enriched scientific evidence of the adverse health impact of $PM_{2.5}$ in HCMC. Regarding the association between exposure to $PM_{2.5}$ and ALRI among children under 5, the study collected a health database from all three pediatric hospitals to provide a representative result for the HCMC children. This could be a strength compared to the previous study in HCMC. Additionally, to the best of our knowledge, our study is the first to determine the adverse effects of maternal exposure to $PM_{2.5}$ and birth outcomes.

Regarding estimating health and economic benefits, the study completed aspects not looked at in the previous HCMC study (Vu et al., 2020). They were the estimated health benefit in terms of avoided deaths based on the mortality rate of all causes and their economic benefits. In the case of HCMC, with a high percentage, nearly 48%, of deaths in 2019 recorded as the unclear cause, the use of the mortality rate of all causes in estimating health benefits will give a more reasonable estimate than the use of the mortality rates of several specific causes of deaths. Additionally, the city authority could use the monetary benefits from this study to decide on action plans for the city based on cost-benefit analysis.

However, we had several limitations in this study. Therefore, our findings should be interpreted with caution, and additional studies are warranted to examine the independent health effect of $PM_{2.5.}$ The first limitation is that this study used the $PM_{2.5}$ database from two fixed monitoring stations to extrapolate to the city. The two monitoring stations were in the city's center, surrounded by compact houses, narrow streets, high population density, and vehicle density, with no industrial park. The $PM_{2.5}$ concentration in the city center tended to be higher than in rural districts, and the primary source of $PM_{2.5}$ in HCMC was transportation sources, accounting for 45% of total emissions (Vu et al., 2020). Therefore, the $PM_{2.5}$ concentration extrapolated from the two monitoring stations in the city center could be considered the most representative estimate of population exposure. In previous studies, the concentration of pollutants from the fixed monitoring station could be acceptable as a proxy for personal exposure among residents living around the monitoring station below 40 kilometers (Dockery et al., 2005; Tian et al., 2017; Wellenius et al., 2012; Xie et al., 2015). In quality assurance for air pollution measurement systems, the monitoring station's representativeness scale could differ depending on the monitoring objective. The urban scale with dimensions of 4 to 50 kilometers was applied to determine background concentration levels (EPA, 2013). All 22 districts of HCMC were within a 40 kilometers radius of the monitoring stations; thus, our results could be reliable.

Second, the study did not have any control for other pollutants such as PM_{10}, O_3, NO_x, CO, and SO_x due to the unavailability of their dataset. The insufficient information of the study objects due to using the secondary health data is another limitation (such as children's information and mother's characteristics). Thus, the study could not control them in models for more accurate results. Some studies indicated that the risk of adverse birth outcomes when exposed to pollutants, could also be higher among mothers with comorbidities like diabetes, eclampsia, or asthmatic (Lavigne et al., 2016). Low education, a history of smoking or alcohol consumption, and a household with low income could negatively affect births (Hao et al., 2016; Z. Li et al., 2019).

Regarding estimating health and economic benefits, the study used β coefficients from other countries, which might insufficiently represent the HCMC. The limited quality of death records was a challenge in calculating the mortality rates. A large percentage of deaths with unclear causes affected the accuracy of the mortality incidence rate of specific causes. The shortage of value of a statistical life for Vietnamese people was another challenge when calculating the economic benefits.

CHAPTER 6
CONCLUSION AND RECOMMENDATION

Ambient fine particulate matter significantly burdens public health in Ho Chi Minh City. From 2016 to 2019, the average $PM_{2.5}$ concentration in Ho Chi Minh City, Viet Nam, was high compared to the Air Quality Guideline recommended by the World Health Organization and the National Technical Regulation on Ambient Air Quality. Our study indicated that increasing $PM_{2.5}$ potentially poses an excess risk of hospital admission due to respiratory diseases among children under 5 years old. Maternal exposure to $PM_{2.5}$ may cause adverse birth effects, including birth weight decrease and an increased risk of preterm birth, particularly exposure to $PM_{2.5}$ during the second trimester.

Controlling $PM_{2.5}$ showed massive benefits for health and the economy. Suppose the annual average $PM_{2.5}$ concentrations in 2019 achieved three control scenarios, i.e., 5 $\mu g/m^3$ (2021 WHO annual average AQG) and 10 $\mu g/m^3$ (2005 WHO annual average AQG which became Interim Target 4 in 2021), and the Vietnamese annual average standard of 25 $\mu g/m^3$. In that case, the avoided deaths could be 3,785, 3,195, and 1,300, respectively. The economic benefits were 2.4, 2.1, and 0.84 trillion US$ (2011 US$, PPP) using the OECD VSL reference and 3.7, 3.1, and 1.3 trillion US$ (2011 US$, PPP) using the USEPA VSL reference.

The study documented a considerable benefit when improving the $PM_{2.5}$ concentration. Thus, the current Vietnamese standard of $PM_{2.5}$ should be revised to protect community health better, such as using the World Health Organization Interim Target 3 or 4 (15 $\mu g/m^3$ or 10 $\mu g/m^3$) instead of the current standard of $PM_{2.5}$ (25 $\mu g/m^3$).

The study findings indicate that Ho Chi Minh City should implement more robust public policies for mitigating $PM_{2.5}$ pollution. The city should prioritize action plans to improve the air quality and raise public awareness to protect their health. More air monitoring stations should be invested in providing representative data for each district and cover all criteria pollutants to give spatial representativeness for the city. Using remote sensing from satellites, air pollution dispersion modelings, or validated low-cost sensors to estimate $PM_{2.5}$ concentration is also a solution for the limited number of monitoring stations. A reporting system that can record the health databases from all hospitals and clinics should be developed to provide a comprehensive database for health monitoring and research activities.

Future studies that collect more years of data should be conducted, and the generalized linear models applied for analysis must minimize the random parameter. The effect of seasonal variation on the health of pregnant women should be carefully studied, and proposing the most appropriate time for starting the pregnancy period. Other studies could evaluate the role of multiple pollutants in the effects on health, calculating the specific health response functions and the value of a statistical life for Vietnamese people.

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