# Evaluating Air Pollution in Jakarta: A Dynamic Vehicle Age-Based Cohort Emission Models, Meteorological Effects, and COVID-19 Impacts

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# Introduction

## 1.1 Background

Air pollution is a significant environmental concern in the developing countries of the world. International organizations such as WHO (World Health Organization) and UNEP (United Nations Environment Programme) created a network of air pollution monitoring (Mage et al., 1996). Air pollution has severe impacts on public health (Hystad et al., 2020; Syuhada et al., 2023), ecosystem (Sonwani et al., 2022), and climate change (Samani et al., 2021). As stated by WRI Indonesia on September 5, 2023, Jakarta, the capital city of Indonesia, is particularly vulnerable to air pollution due to its rapid urbanization and industrialization. According to a 2023 study (Syuhada et al., 2023), the city's poor air quality has been linked to various health issues, including perspiratory problems, cardiovascular diseases, and even premature mortality. The WRI (World Resources Institute) Indonesia also stated that transportation sector is a significant contributor to air pollution in Jakarta, accounting for a substantial portion of the city's emissions. A recent emissions inventory study (Amri, 2020), conducted in 2020 by Jakarta's Local Government, Bloomberg Philanthropies and Vital Strategies, confirmed the transport sector contributed 67% of $PM_{2.5}$ emissions, 58% of $PM_{10}$ emissions and 84% of Black Carbon emissions in 2019, with the main source being heavy-duty vehicles. Vehicle emissions, in particular, are a major concern due to the large number of vehicles on the road. Based on the BPS/*Badan Pusat Statistik* or National Statistical Agency, the total number of vehicles in Jakarta are more that the total population of Jakarta city (BPS, 2023; BPS DKI Jakarta, 2018, 2020, 2021, 2022, 2023) as shown by Figure 1.1. A similar situation has been observed in Bandung, the capital city of West Java. In 2023, government officials in the transportation sector reported that the total number of vehicles in Bandung had reached approximately 2.2 million, which is nearly equal to the city's population of 2.5 million. This rapid increase in vehicle numbers mirrors the trends seen in Jakarta. In Bandung, the vehicle composition is predominantly motorbike, with about 1.7 million units, while the number of cars is around half million. This significant ratio of vehicles to population underscored the escalating challenges related to traffic congestion, air pollution, and urban planning in Bandung, akin to those faced by Jakarta.

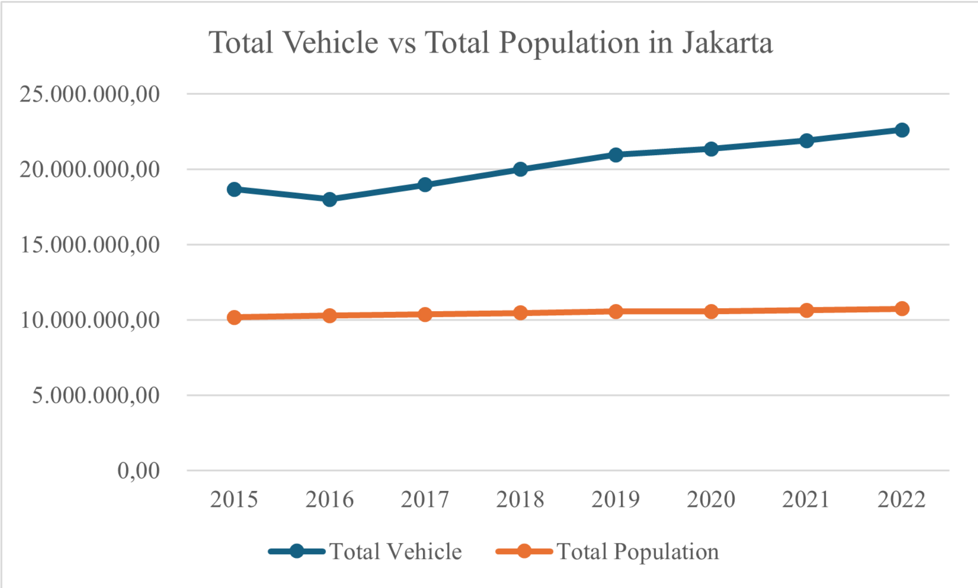


**Figure 1.1** Total Vehicle vs Total Population in Jakarta from 2015 to 2022 (BPS Data)

Understanding the emissions from the transportation sector is crucial for developing effective air pollution mitigation strategies. Recent studies have highlighted the importance of considering the age of vehicles in emissions estimation (Deaton & Winebrake, 2000). A dynamic vehicle age-based cohort model can provide a more accurate estimate of emissions from the transportation sector by accounting for the varying emissions of vehicles of different ages. This approach can help policymakers develop targeted strategies to reduce emissions from the transportation sector. In addition to the transportation sector, meteorological variables such as temperature, humidity, wind speed, and radiation also play a crucial role in air pollution. These variables can affect the dispersion and concentration of pollutants in the atmosphere, making it essential to understand their interactions with air quality. The Coronavirus-19 disease (COVID-19) pandemic has further exacerbated the air pollution problem in Jakarta. The lockdowns and reduced economic activities have led to a significant decrease in air pollution levels, but the pandemic has also highlighted the need for more effective air pollution mitigation strategies. This dissertation aims to contribute to the understanding of air pollution in Jakarta by exploring three interconnected themes which are current update on air pollution or quality and meteorological variables: a review and bibliometric analysis; dynamic vehicle age-based cohort model to estimate the emission from the transportation sector in Jakarta; and correlation between meteorological variables, air quality and COVID-19 pandemic events in Jakarta.

## 1.2 Objectives and Scopes

### *1.2.1 Research Objectives*

Knowing the important of air pollution topic in Jakarta, this study has several aims or objectives to accomplish:

- Providing a review of current research on air pollution and meteorological variables, highlighting key findings, trends, and gaps in the literature.
- Conducting bibliometric analysis to identify research trends, density maps and research gaps in the field of air pollution and meteorological variables.
- Developing a dynamic vehicle age-based cohort model that estimates emissions from the transportation sector in Jakarta.
- Applying the model to estimate emissions from the transportation sector in Jakarta and identify the most significant contributors to air pollution.
- Analysing the impact of different vehicle age distributions on emissions estimates and identify the most effective strategies for reducing emissions.
- Analysing the correlation between the meteorological variables, air quality and COVID-19 death or positive COVID-19 before (2018-2019) and during the pandemic (2020-2021).

### *1.2.2 Research Scope*

In the first chapter, a literature review was conducted to understand the study's objectives concerning air pollution and meteorological variables. This review involved analysing the status of air pollution, meteorological variables, and the COVID-19 pandemic by searching and analysing data from various sources, including Google Scholar and Scopus databases. The second chapter presents a bibliometric analysis to explore research trends related to air pollution or air quality and meteorological variables. In the third chapter, the study focuses on identifying the major contributors to air pollution in Jakarta. Jakarta was chosen as the focused study area due to its status as the most populous city in Indonesia and its frequent mention as one of the most polluted cities in both Indonesia and Southeast Asia. The fourth chapter examines the correlation between meteorological variables, air quality and COVID-19 pandemic event in Jakarta. Finally, the fifth chapter summarizes the study's findings, discusses the study's limitations, and outlines directions for future research.

### 1.3 Methodological Framework

In achieving the research goals, several steps have been taken. First, the literature review was done from a global perspective and countries and then city level. The literature review as described in the second chapter employed bibliometric analysis (BA) and qualitative content analysis. As explained in the third chapter, the second methodology used in this study was developing models for emission inventories can help predict the total emissions from mobile sources. A bottom-up approach using the vehicle kilometer traveled (VKT) was used to calculate the total vehicle emissions in Jakarta. Vehicle emissions were estimated by calculating the sum of the aggregate emissions using vehicle population statistical data, average annual VKT, or average annual vehicle miles traveled (VMT) as emission factors of key air pollutants. For the fourth chapter, air pollutants data collected from Indonesia Government's monitoring stations and $PM_{2.5}$ from IQAir (a Swiss air quality technology company) and meteorological variables data from the Indonesian Agency for Meteorology, Climatology, and Geophysics or BMKG (*Badan Meteorologi, Klimatologi, dan Geofisika*) were analysed by using the Spearman correlation test. Detailed information regarding each research method is described in the following chapters. The research framework can be seen in Figure 1.2.

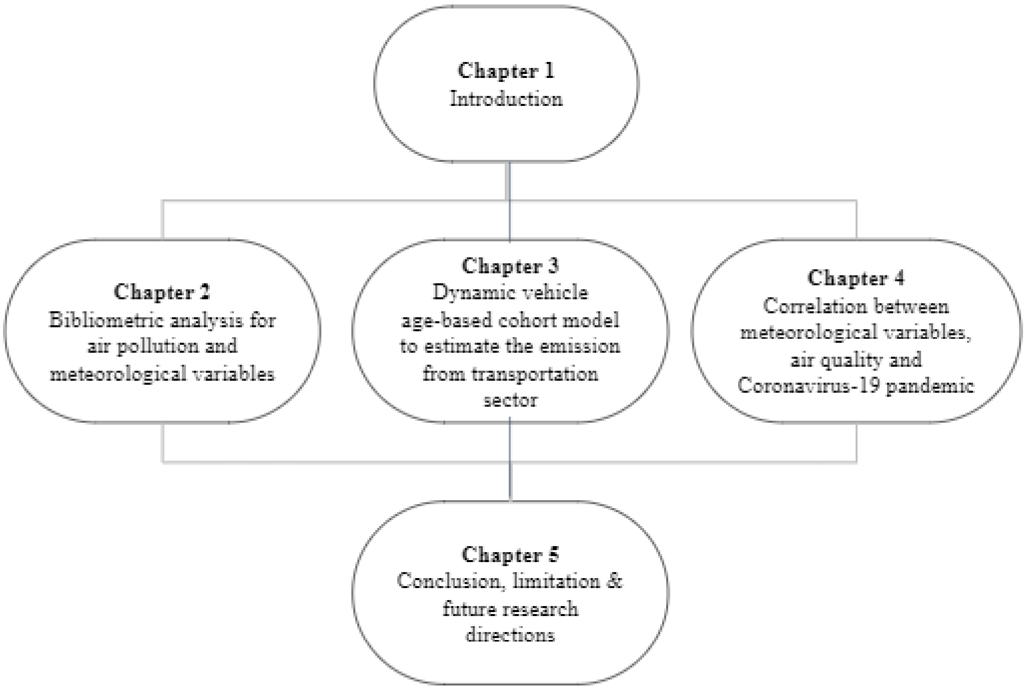


**Figure 1.2** Research framework

## 1.4 Current Status of Air Pollution

### *1.4.1 Air pollution at the global level*

The vast majority of the world's population faces unsafe air pollution levels. Studies show that 7.3 billion people, or 94% of the global population live in areas exposed to $PM_{2.5}$ concentrations over 5 μg/m$^3$ which increases mortality rates by 4% (Rentschler & Leonova, 2023). Air pollution levels are particularly high in middle-income countries, where economies tend to rely more heavily on polluting industries and technologies. For example, China and India alone account for 38% of global exposure to $PM_{2.5}$ concentrations above WHO guidelines (Rentschler & Leonova, 2023). Air pollution poses significant health risks, including increased mortality rates, cardiovascular diseases, respiratory problems, and cancer. It is estimated that air pollution is responsible for 4.9 million deaths annually, with outdoor air pollution being the leading cause of premature mortality (WHO, 2024). The WHO monitors air pollution exposure and health impacts at the national, regional and global levels. They provide detailed national and subnational estimates of air pollution exposure and health impacts, which are used for official reporting and the Sustainable Development Goals (WHO, 2024). According to United States Environmental Protection Agency or EPA (EPA, 2023), despite progress in reducing air pollution, there are still significant challenges to address. These include meeting health-based standards for common air pollutants, limiting climate change, reducing risks from toxic air pollutants, and protecting the stratospheric ozone layer. Table 1.1 below is fifteen top countries in the 2023 Country/region ranking from 2023 IQAir Report (population weighted, 2023 average $PM_{2.5}$ concentration ($\mu g/m^3$) for countries, regions, territories in descending order), while Table 1.2 is for top fifteen capital city.

**Table 1.1** The 2023 Country/region ranking for $PM_{2.5}$ concentration

| | | |
|---|---|---|
| 1 | Bangladesh | 79.9 |
| 2 | Pakistan | 73.7 |
| 3 | India | 54.4 |
| 4 | Tajikistan | 49.0 |
| 5 | Burkina Faso | 46.6 |
| 6 | Iraq | 43.8 |
| 7 | United Arab Emirates | 43.0 |
| 8 | Nepal | 42.4 |
| 9 | Egypt | 42.4 |
| 10 | Dem. Rep. of the Congo | 40.8 |
| 11 | Kuwait | 39.9 |
| 12 | Bahrain | 39.2 |
| 13 | Qatar | 37.6 |
| 14 | Indonesia | 37.1 |
| 15 | Rwanda | 36.8 |

**Table 1.2** The 2023 Regional capital city ranking for $PM_{2.5}$ concentration

| | | |
|---|---|---|
| 1 | New Delhi, India | 92.7 |
| 2 | Dakha, Bangladesh | 80.2 |
| 3 | Ouagadougou, Burkina Faso | 46.6 |
| 4 | Tajikistan, Dushanbe | 46.0 |
| 5 | Baghdad, Iraq | 45.8 |
| 6 | Abuja, Nigeria | 45.4 |
| 7 | Jakarta, Indonesia | 43.8 |
| 8 | Hanoi, Vietnam | 43.7 |
| 9 | Islamabad, Pakistan | 42.4 |
| 10 | Cairo, Egypt | 42.4 |

| | | |
|---|---|---|
| 11 | Katmandu, Nepal | 41.0 |
| 12 | Kinshasa, Dem. Rep. of the Congo | 40.8 |
| 13 | Kuwait City, Kuwait | 39.9 |
| 14 | Manama, Bahrain | 39.2 |
| 15 | Abu Dhabi, United Arab Emirates | 38.2 |

### *1.4.2 Air pollution in Indonesia*

According to the 2023 World Air Quality Report, Indonesia's annual average $PM_{2.5}$ concentration rose sharply in 2023 to 37.1 µg/$m^3$ increased more than 20% compared to 2022 and exceeding the recommended maximum of 10 µg/$m^3$. Major contributors to poor air quality in Indonesia include the mining and oil and gas industries, automobile manufacturing, vehicle emissions, and forest fires. Seasonal variations exist, with the highest levels of air pollution occurring during the dry season (June to October) due to forest fires.

On the website of State of Global Air on $PM_{2.5}$ Exposure, in 2019, India and Niger had $PM_{2.5}$ concentrations between 75 to <85 µg/$m^3$, the highest among all countries in the world. Indonesia was between 15 to <30 µg/$m^3$. As stated in mongabay.com, El Niño events can exacerbate dry conditions and increase the risk of forest fires, which are significant contributor to air pollution in Indonesia. Recent data show that $PM_{2.5}$ levels have been hovering around 60 µg/$m^3$ with readings reaching 322 µg/$m^3$ on September 15, 2023, which is hazardous and can cause serious health effects.

According to wri.com, research consistently points toward the same major sources of air pollution inside Southeast Asia's cities: vehicles, power plants, and industrial emissions. Vehicles contribute significantly to urban air pollution due to the high density of traffic and reliance on fossil fuels, leading to substantial emissions of nitrogen oxides ($NO_X$), carbon monoxide (CO), and particulate matter (PM). Power plants, particularly those burning coal and other fossil fuels, emit large quantities of sulfur dioxide ($SO_2$), $NO_X$ and fine particulate matter, which can travel long distances and affect air quality over wide areas. Industrial emissions, including those from manufacturing, construction, and chemical processing plants, release a variety of pollutants such as volatile organic compounds (VOCs), heavy metals, and other hazardous air pollutants (HAPs) into the atmosphere.

Following is the dashboard of Air Quality in Indonesia in the iqair.com taken on June 17, 2024.

**Most Polluted Cities in Indonesia**

Real-time worst city rankings

| Rank | City | AQI-US |
|---|---|---|
| 1 | Jakarta, Indonesia | 128 |
| 2 | Banda Aceh, Indonesia | 59 |
| 3 | Bandung, Indonesia | 59 |
| 4 | Jambi, Indonesia | 58 |
| 5 | Semarang, Indonesia | 57 |
| 6 | Bandar Lampung, Indonesia | 57 |
| 7 | Palembang, Indonesia | 55 |
| 8 | Pekanbaru, Indonesia | 53 |
| 9 | Pontianak, Indonesia | 53 |
| 10 | Yogyakarta, Indonesia | 53 |

**Figure 1.3** Air Quality dashboard for Indonesia (retrieved June 17, 2024)

### *1.4.3 Air pollution in Jakarta*

On June 17, 2024, based on the AQI dashboard, the status of air quality in Jakarta is considered poor, with $PM_{2.5}$ concentrations at 48 µg/m$^3$, which is 3.2 times above the recommended limit by the WHO. On January 26, 2024, through Antara news, the Governor of Jakarta announced plans to increase the number of air quality monitoring stations to improve accuracy and comprehensiveness of air pollution data collection. By the end of 2024, the local government aims to have approximately 19 air quality monitoring stations in operation. However, the local government has identified that an ideal network would comprise around 25 stations to effectively monitor air quality throughout the city.


**Figure 1.4** Air Quality dashboard for Jakarta (retrieved June 17, 2024)

As stated in the wri.com, in Jakarta, for example, transport contributed 67% of $PM_{2.5}$ emissions, 58% of $PM_{10}$ emissions, and 84% of Black Carbon emissions in 2019. In the recent year, around August 2023, as stated in the Kompas.com, the Minister of Environment and Forestry explained that the sources for air pollution in Jakarta were 44% from transportation and 34% from the PLTU (*Pembangkit Listrik Tenaga Uap*/Thermal Power Plant) and 22% from the households. Global Energy Monitor has revealed that Jakarta has been surrounded by at least 16 PLTU.

According to Syuhada et al., 2023, air pollution in Jakarta has led to more than 10,000 deaths annually, over 5,000 hospitalizations for cardio-respiratory diseases, and more than 7000 adverse health outcomes in children. The total economic burden from air pollution in Jakarta was estimated at USD 2943.42 million in 2019, equivalent to 2.2% of the Gross Regional Domestic Product (GRDP).

The Jakarta provincial government has implemented initiatives to reduce greenhouse gas emissions, such as Governor's regulation No. 90 Year 2021 regarding Regional Low Carbon Development Plan, aiming to reduce emissions by 30% in 2030 and achieve complete emission neutrality in 2050. Jakarta has been operating electric buses since 2022 and plans to transform more than 10,000 fleets by the end of 2030. The government also provides incentives for electric vehicles and supports the electrification of private vehicles through charging stations. According to the Ministry of Energy and Mineral Resources, Indonesia has set ambitious targets for the adoption of electric vehicles by 2030, aiming for 13,000,000 electric motorbikes and 2,000,000 electric cars.

To curb the growing number of vehicles in Jakarta, emission testing has been implemented since 2017. As of September 2023, data from ujiemisi.go.id indicates that only 26% of cars (979,174 out of 2,786,885) in Jakarta have undergone emission testing, while a mere 0.5% of motorbikes (90,776 out of 17,303,671) have been tested.

Emission standards applied by the Government of Indonesia are different from those recommended by the WHO in several key aspects. In terms of regulatory frameworks, Indonesia's emission standards are primarily governed by the Ministry of Environment and Forestry and the Ministry of Energy and Mineral Resources. The Indonesian government began implementing Euro 4 standards for diesel vehicles in April 2022, while the transition for non-diesel vehicles has been phased in since 2018. However, all new vehicles sold in Indonesia from January 1, 2021, onwards are required to comply with Euro 4. Currently, the adoption of Euro 5 standards is under discussion. This Euro 5 is stricter and include lower permissible limits for various pollutants. On the air quality, WHO sets global air quality guidelines to protect public health from the adverse effects of air pollution. These guidelines are not legally binding but serve as a reference for countries to set their own air quality standards. The WHO guidelines are generally more stringent compared to Indonesia's current emission standards (for $PM_{2.5}$ and $PM_{10}$, WHO recommended limits significantly lower that what is often enforced in developing countries, including Indonesia). Due to the gap between these standards and more stringent WHO guidelines, it is important to bridge the gap which will require substantial policy adjustments, technological upgrades, and infrastructural improvements to meet the higher benchmarks set by the WHO, ultimately aiming to better protect public health from the adverse effects of air pollution.

According to tomtom traffic index, in year of COVID-19 (2020 and 2021), Jakarta experienced a better traffic index (36 and 34 respectively) compared to prior 2020 (more than 50). In the year of 2022, the index increased again to almost 50. A 34% congestion level means that on average, travel times were 34% longer than during the baseline non-congested conditions. This means that a 30-minute trip driven in free-flow condition will take 10 minutes longer when the congestion level is at 34%. Featuring 387 cities across 55 countries on 6 continents, the TomTom Traffic Index evaluates cities around the world by their average travel time, fuel costs, and CO2 emissions, providing free access to high-quality and useful information.

Another regulation implemented by the local government of Indonesia to curb the growing number of vehicles was the requirement for vehicle owners to have designated garage. This regulation known as the Local Regulation No. 5 Year 2014 aimed to reduce the number of vehicles on the road by encouraging owners to keep their vehicles in designated areas. However, unfortunately, this regulation has lacked effective enforcement, which has hindered its ability to achieve the intended goal. This is not an isolated issue, as similar regulations have been implemented in other cities such as Depok and Solo, but also faced enforcement challenges.

## 1.5 Current Status of Meteorological Variables

### *1.5.1 Meteorological variables in general*

Meteorological variables play a crucial role in understanding and predicting various environmental phenomena. These variables include temperature, humidity, wind speed, radiation, precipitation and other atmospheric conditions. Other atmospheric conditions include pressure, cloud cover, and precipitation intensity. Weather is an important factor for air quality. The meteorological variables influence the Earth's climate and weather patterns which in turn impact the growth and development of plants, the formation of clouds and precipitation, and the distribution of heat and moisture around the globe.

According to wri.indonesia, periodic surges in air pollution throughout the months of June, July and August are a consistent occurrence in Jakarta. It happens every year when the dry season begins, following the pattern of monsoons. This occurs when a deficiency of moisture in the atmosphere, along with other meteorological factors, combines with elevated emissions, primarily from the transportation and industrial sectors, resulting in alarmingly elevated levels of pollution. In year 2023, the combination of El Niño and continuously increasing human emissions has resulted in a particularly hazardous surge in pollution.

### *1.5.2 Meteorological variables for different areas*

Even though every corner of the Earth has the same type of meteorological variables, the way it impacts each place are different. At a global level, meteorological variables encompass a wide range of climates and weather patterns, from polar regions to tropical zones. This diversity includes various climate zones like equatorial, arid, temperate, and polar. Within specific country, the range of meteorological variables may be more limited, depending on the country's geographical size and location. One big country like United States can have multiple climate zones while Singapore has a relatively uniform tropical climate. At the global level, meteorological variables are influenced by large-scale phenomena such as the El Niño-Southern Oscillation (ENSO) while at the country level, weather patterns are more influenced by regional factors such as proximity to oceans, mountain ranges etc. At the global level, the urban hat island effect is studied and context of global urbanization trends and their impact on local and global climates. Within a country, the urban heat island effect is analysed with a focus on specific cities, comparing urban areas to their rural surroundings and devising localised mitigation strategies.

The key differences in meteorological variables between tropical and non-tropical (temperate) countries are primarily driven by their respective positions relative to the equator and the resultant climatic influences. Tropical regions maintain high and relatively stable temperatures and humidity year-round with distinct wet and dry season, while temperate regions experience pronounced seasonal changes in temperature, humidity, and precipitation, with varied wind patterns and solar radiation levels. These differences significantly influence local weather patterns, ecosystems and human activities in these regions.

Plenty of studies regarding meteorological variables and climate changes were undertaken such as by Deb and Sil, (2014) and Baig et al. (2021). Numerous studies, including those by Huang et al. (2020); Sahoo et al. (2020); Sulaymon et al. (2021), and Sarmadi et al. (2021), have investigated the correlation between air quality, meteorological parameters, and the COVID-19 pandemic. Sarmadi et al. (2021) concentrated on the timeframe spanning from 2020 to 2021, whereas the remaining three studies examined various months within the year 2020.

### 1.6 COVID-19 Pandemic in Indonesia

The initial detection of COVID-19 occurred in China, followed by rapid global transmission to countries including the USA, Russia, UK, France, Germany, Nepal, Australia, Malaysia, Singapore, South Korea, Vietnam, and Taiwan, finally leading to a worldwide spread. Up until beginning of June 2024, the total number of reported COVID-19 cases at the global level was 775,583,309 (WHO Covid-19 dashboard, 2024) out of around 8 billion population in the world. The WHO identified COVID-19 as a global pandemic on March 12, 2020 (Tushabe, 2020). Tushabe (2020) found that the severity of COVID-19 in terms of infection or death was found to be six times higher in countries located in the temperate region (e.g. China, Japan, South Korea) compared to tropical countries (e.g. Thailand, Singapore, Malaysia). Infections in tropical countries accounted for only 4% of global infections, with even fewer deaths (2.5%). Tushabe (2020) further explained that the spread of the disease in temperate regions grew exponentially, while it remained consistently low in tropical regions. This led to the need for different approached for temperate and tropical countries due to varying severity and spread of the disease.

Monnat (2021) found that resident of rural counties adjacent to metro areas faced challenges in various aspects of COVID-19 outcomes, including health, social and financial impacts. Factors such as socioeconomic status, workplace conditions, job types, and political ideology contributed to these disparities, highlighting the complexity of pandemic effects on different populations.

In the time of COVID-19 pandemic, different countries applied different measures and strategies to address the disease. Chen (2021) found that China, Korea, and Singapore, which implemented strict containment measures, had significant outbreak control. Meanwhile, the successful practices in China, Singapore, and South Korea show that the containment strategies were practices that work especially at the individual level identifying and managing the infected patients and their close contacts. In the United States, the United Kingdom, and France, which implemented the mitigation policies, the effect of epidemic prevention and control was not significant that the epidemic continued or even increased epidemic relatively quickly. Kanniah et al. (2020) in their study also highlights significant reductions in pollutants such as $PM_{10}$, $PM_{2.5}$, $NO_2$, $SO_2$, and CO in urban areas, with reductions ranging from 9 to 64%. The study also notes a decrease in tropospheric $NO_2$ levels over urban agglomerations, suggesting that the lockdown measures have resulted in improved air quality in the Southeast Asia region.

On June 21, 2023, Indonesia officially lifted its pandemic status, as announced by President Joko Widodo. This decision followed a series of preparatory steps, beginning with the termination of the PPKM/*Pemberlakuan Pembatasan Kegiatan Masyarakat* (Community Activity Restrictions) regulation at the end of December 2022. Three months later, the mandate to wear facial masks was also lifted. In June 2023, after securing agreement within the Cabinet regarding the country's readiness to transition to endemic status, the end of pandemic status was formally declared. The WHO had lifted the pandemic status a month earlier. According to data from Ministry of Health's COVID-19 portal (covid19.go.id), by May 2023, Indonesia has recorded a total of 161,352 deaths out of 6,779,631 positive COVID-19 cases.

Mahendradhata et al., 2021 evaluated the capacity of Indonesia's healthcare system based on four elements of surge capacity which are staff, stuff, structure and system. At the time of evaluation, the available medical staffs are insufficient to deal with potentially increasing demands as the pandemic. The pandemic has exposed the fragility of medical supply chains. Surges in the number of patients requiring hospitalization have led to depleted medical supplies. The existing healthcare infrastructure is still inadequate to deal with the rise of COVID-19 cases, which has also exposed the limited capacity of the healthcare infrastructure to manage medical waste. The COVID-19 pandemic has further exposed the weakness of the patient referral system and the limited capacity of the healthcare system to deliver essential health services under prolonged emergencies.

The survey conducted by the SMERU with the support from the UNICEF, UNDP and Prospera in May 2021, has resulted the key recommendations to address the social and economic impacts of the COVID-19 pandemic on vulnerable groups. The pandemic has significantly impacted vulnerable groups, including children, lower-middle and middle-income groups, and the social protection system. The recommendations were to ensure children continue their education, support schools, provide social protection solutions, and temporarily relax conditionalities in programs, to expand food assistance programs, monitor food availability and affordability, and to support workers during the pandemic. Finally, to implement fiscal assessments, streamline programs, expand coverage, and reform the social protection system to build resilience and mitigate long-term scarring.

Aside from the above aspects, the COVID-19 pandemic has impacted human behaviour in various aspects of daily life quite significantly. One of the most obvious changes has been in the public health practices. The widespread adoption of behaviours such as wearing masks, frequent handwashing, and the use of hand sanitizers. The pandemic also has affected the increased acceptance and utilization of digital activities, including the digital health services like telemedicine which allowed people to seek medical advice and care without the need for in-person visits, thereby minimizing the risk of infection. This shift not only transformed the health care delivery model but also expanded access to medical services. The pandemic has also significantly altered work and social behaviours. The necessity of social distancing led to a rapid and widespread adoption of remote work, fundamentally changing the traditional office environment. Companies and employees alike have had to adapt to new technologies and virtual collaboration tools, leading to a rethinking of productivity, work-life balance, etc. This shift has resulted in a more flexible work culture that many predict will persist beyond the pandemic. Social interactions have also been affected, with a move towards virtual gatherings and a reduction in large, in-person events. The way people shop has similarly evolved, with a marked increase in online shopping and digitalization and convenience, reshaping consumer behaviour and expectations. Overall, the pandemic has accelerated several pre-existing trends and introduced new dynamics that continue to influence societal behaviour in significant ways.

In conclusion, the COVID-19 pandemic has illustrated the varied impacts and responses across different regions, socioeconomic groups, and healthcare systems globally. Therefore, it is important to tailor public health strategies for each country. For Indonesia, it is also important to improve its healthcare system in the pandemic situation, particularly in surge capacity and infrastructure to avoid big impact to its social and economic system.

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**Chapter 2**

# Current Update on Air Pollution and Meteorological Variables: A Review and Bibliometric Analysis

## 2.1 Introduction

As cited in the World Resources Institute in November 2023, Jakarta was again ranked the most polluted in the world. At the same time, the poor air quality has threatened its citizen's health. The majority of the population in Southeast Asia resides in the areas where air pollution levels surpass the clean air guidelines set by the WHO. Most of the source of air pollution comes from vehicles, power plants and industrial emissions. According to the 2023 World Air Quality Report, only seven countries managed to meet the WHO $PM_{2.5}$ annual guideline (annual average of 5 $\mu g/m^3$ or less). The countries listed in the report are Australia, Estonia, Finland, Grenada, Iceland, Mauritius, and New Zealand. The report also indicated that climate conditions and transboundary haze were significant contributors in Southeast Asia, where $PM_{2.5}$ concentrations increased across almost all countries in the region (IQAir, 2024).

Air pollution is a crucial environmental concern that has unfortunate effects on human health, ecosystems, and climate change (Manisalidis et al., 2020; Sarkar et al., 2023). There are plenty of studies that have investigated the relationship between air pollution or air quality and meteorological variables such as temperature, humidity, wind speed, radiation, etc. (Huang et al., 2020; Sahoo et al., 2021; Sarmadi et al., 2021; Sulaymon et al., 2021). Understanding the complex interactions between air pollution or air quality and meteorological variables is important for effective air quality management and policy development.

Bibliometric analysis refers to the application of statistical techniques on published literature in order to analyse publication patterns over time and get valuable insights on prominent scientists, nations, and organizations. Bibliometric is a valuable tool for visualizing the literature and conducting quantitative analysis of developments and growth in scientific publications (Y. Li et al., 2023). Multiples bibliometric studied on air pollution have been published (Ansari & Quaff, 2024; Chen et al., 2024; Jain et al., 2022; Y. Li et al., 2023; Olutola & Phoobane, 2023;

J. Sun et al., 2020; Sweileh et al., 2018). These studies demonstrate the growing interest in bibliometric analysis of air pollution research, which helps to identify key trends, hotspots, and areas of focus in the field. On meteorological variables, there have been several publications also (Adisa et al., 2020; J. Li, 2018).

Evaluating research output is a crucial process for showcasing the impact and cooperation of a country or region in a specific field. Hence, the objective of this study was to examine internationally published literatures on air pollution and meteorological variables. The study will include a variety of relevant research articles, conference papers, and other scientific publications. Additionally, to acquire diverse publication attributes, such as types of publications, subject categories, institutions or affiliations, countries, year trends, and content analysis of keywords, abstract and article titles. However, the search limits for English publications only.

The focus will be on exploring current knowledge about air pollution and meteorological variables related. The study also aims to identify and evaluate research trends, research gap and variables for air pollution research in the Scopus database using VOSviewer software that research air pollution and meteorological variables influential.

## 2.2 Materials and Methods

### *2.2.1 Data Collection and Screening*

Data sources in this study are taken using Scopus Database. From previous research, Scopus was selected to obtain information from digital libraries and offer various queries through institutional subscriptions (Klapka & Slabý, 2020). The keywords used in this study are “Air Pollution” or “Air Quality” and “Meteorological Variables”. The data used was the literature published over the last 10 years, from 2014 to 2024. The article selection or screening process for this study took several stages or filters that can be seen in the flow chart image (Figure 2.1). Stage 1 involves the identification of papers with the keywords above, with a total of 1,576 articles analysed. After applying Stage 2 filtering based on the publication year, we acquired a total of 996 documents as the results. After applying stage 3 filtering, which includes criteria such as document kind (article, conference paper and book chapter), publishing stage, and English language, a total of 907 items were filtered as eligible articles.

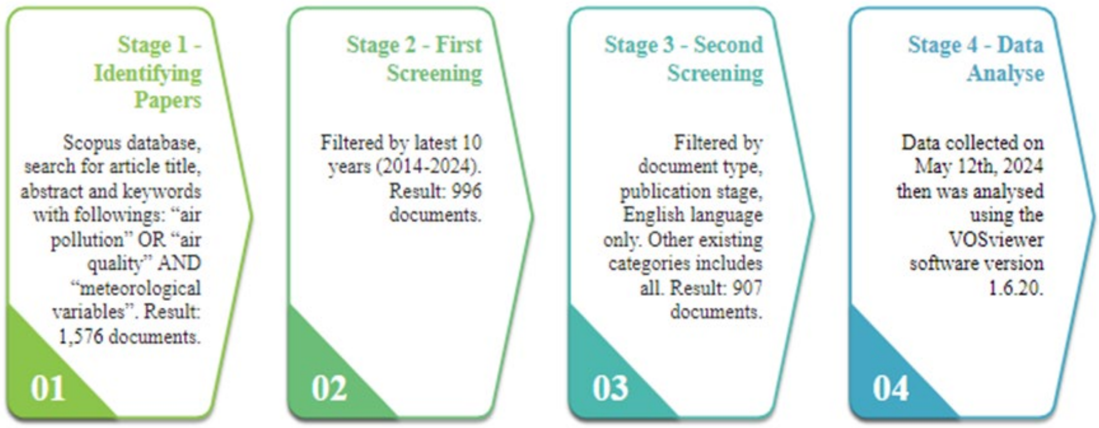


**Figure 2.1** Flow diagram for article selection process

### *2.2.2 Data Analysis*

Documents selected in the Scopus database of 907 articles are then downloaded in the csv format and included in the qualitative content analysis using VOSviewer software. In bibliographic metadata, the term "keyword" contains important information in scientific work and is usually used for indexing purposes (Ramadan et al., 2022; Harfadli et al., 2024).

Furthermore, VOSviewer is used to illustrate trends in the form of bibliometric (Effah et al., 2023), i.e. publication maps with keywords or terms (term co-occurrence maps) will form a network (co-citation) that is connected based on related research. The more links between keywords or terms, the stronger the relationship between the terms. In this study, for network visualization and overlay analysis, bibliometric data was analysed using a binary approach for text data and a fractional approach for bibliographic data. The analysis aimed to provide a qualitative understanding of research trends, gaps, and variables in air pollution research through visual representation and network connections between keywords or terms.

## 2.3 Results and Discussion

In this section, the bibliometric analysis results are discussed based on research trends, research gaps and variables for air pollution research.

### *2.3.1 Research Trends*

As demonstrated in the Figure 2.2, there are four clusters formed based on the co-occurrence of keywords. The first cluster describes Air Pollution and Health Impact: Analysing Meteorological and Pollutant Data. This cluster focuses on the intersection of air pollution, meteorological variables, and their impacts on public health. It covers a wide range of topics including air quality, particulate matter, nitrogen dioxide, ozone, and sulphur dioxide. The cluster also explores the effects of air pollution on COVID-19, mortality, hospital admissions, and respiratory diseases such as asthma. It explores into the application of machine learning, artificial neural networks, and data mining for prediction, forecasting, and modelling the impact of atmospheric pollutants. The role of lockdowns, temporal variations, and low-cost sensors in air quality management are also highlighted.

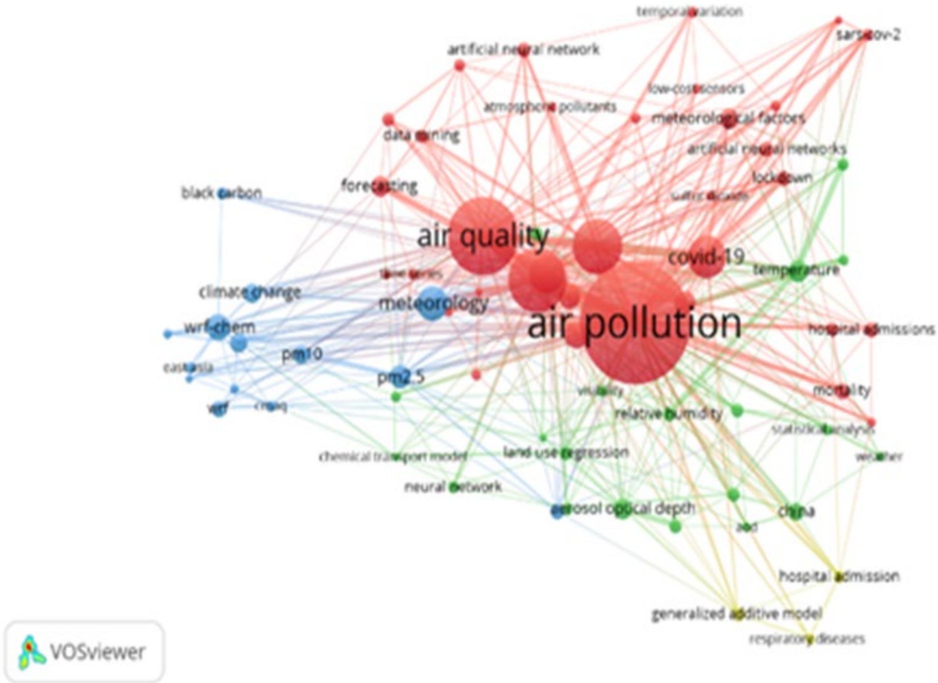


**Figure 2.2** Map of research cluster

The second cluster describes Meteorological Parameters and Public Health: Insights and Implications. This cluster examines the relationship between meteorological parameters and public health outcomes. It includes studies on the influence of relative humidity, wind speed, and visibility on health. The use of land use regression, MODIS (Moderate Resolution Imaging Spectroradiometer) data, and statistical analysis to understand surface ozone, aerosol, and weather patterns is also covered. The cluster emphasizes the importance of public health epidemiology and the application of neural networks and random forests in analysing these parameters. It also investigates the chemical transport model (CTM) and aerosol optical depth (AOD) as significant factors in this domain.

Further, the third cluster explains Advanced Air Quality Modelling and Atmospheric Studies. This cluster is dedicated to advanced air quality modelling and the study of atmospheric processes. It includes topics such as meteorology, $PM_{2.5}$, $PM_{10}$, black carbon, and tropospheric ozone. The cluster features the use of models like WRF-Chem (Weather Research and Forecasting model coupled with

Chemistry), CMAQ (Community Multiscale Air Quality model), and WRF (Weather Research and Forecasting) to simulate air quality and atmospheric circulation. The impact of climate change on air quality in regions like East Asia is also discussed. It highlights the application of these models in understanding fine particulate matter and improving air quality management strategies.

The fourth cluster portrays Statistical Methods in Assessing Health Outcomes from Air Pollution. This cluster focuses on the application of statistical methods to evaluate the health outcomes associated with air pollution. It includes the use of generalized additive models and other statistical tools to analyse hospital admissions and respiratory diseases. The cluster provides insights into how statistical analysis can help in understanding the correlation between air quality and health outcomes, guiding public health interventions and policies.

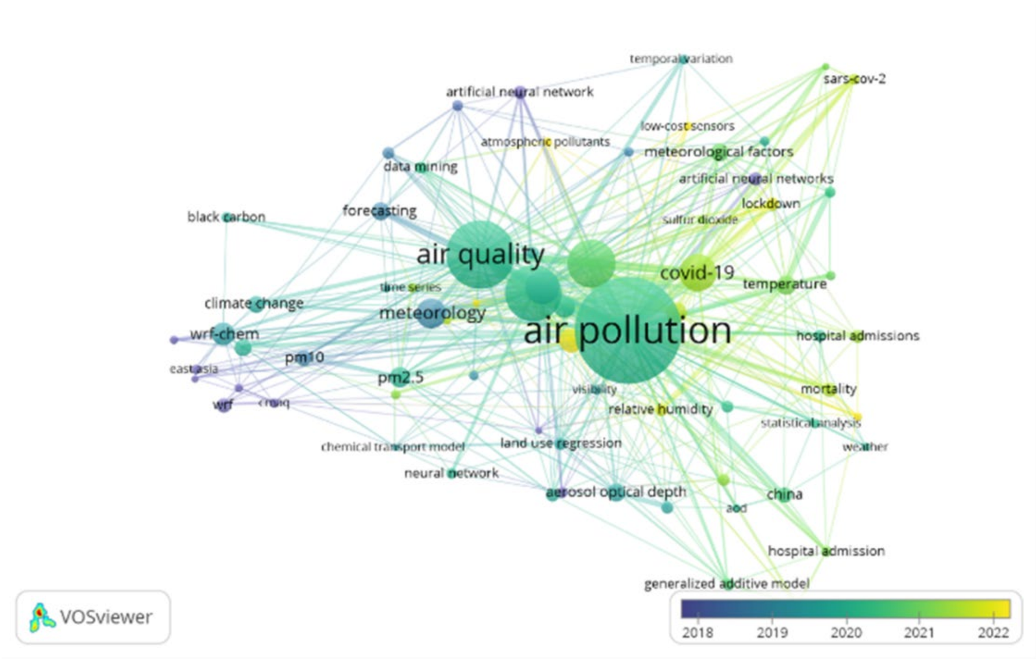


**Figure 2.3** Overlay map of research year

As demonstrated in Figure 2.3, there is a relationship among labels (topics), clusters (thematic groupings), the weight of occurrences (frequency or emphasis), and the year of publication. Emerging focus in the first cluster is air pollution (weight 195), air quality (weight 103), and particulate matter (weight 80). They were the most frequently occurring topics, particularly around 2020. This period coincides with increased global awareness of air pollution and its health impacts, likely influenced by the COVID-19 pandemic. Further, COVID-19 Impact label such as COVID-19 (weight 44), sars-cov-2/severe acute respiratory syndrome coronavirus 2 (weight 8), and related terms like lockdown (weight 11) showed a significant increase in 2020 and 2021, reflecting research into how the pandemic influenced air quality and public health.

Next research trend in the second cluster has shown topics such as temperature (weight 18), humidity (weight 8), and relative humidity (weight 9). These topics have gained attention, especially in 2020 and 2021. This indicates a growing interest in understanding how weather and climate factors impact air quality and health. In addition, public health integration is also an issue raised, as seen from terms such as public health (weight 10) and epidemiology (weight 8) highlight an increasing focus on the intersection of environmental science and public health.

Research trends in the third cluster revealed that advanced modelling is an issue that is often raised by some researchers as seen from several terms such as WRF-chem (weight 22), CMAQ (weight 7), and chemical transport model (weight 5). This topic shows a steady increase, with significant research activity around 2019. This indicates advancements in using sophisticated models to study air quality. Climate Change and Pollutants is an interesting topic like climate change (weight 15), $PM_{2.5}$ (weight 20), and black carbon (weight 8) reflect ongoing concerns and research into how these factors influence atmospheric conditions and public health.

The fourth cluster which focuses on statistical analysis on basic topics around 2017-2018. The use of methods like generalized additive model (weight 10) and statistical analysis (weight 7) points to a robust approach in assessing the health impacts of air pollution. Health Implications: Labels such as hospital admission (weight 8) and respiratory diseases (weight 7) highlight the direct health consequences being studied, particularly in the context of air pollution.

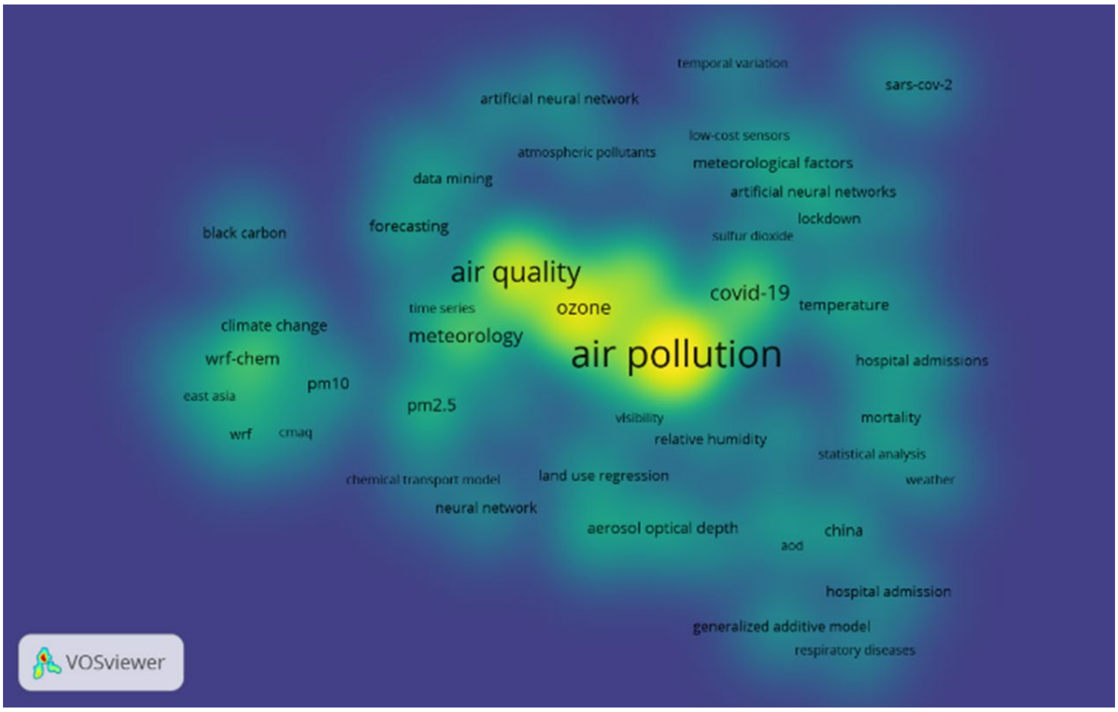


**Figure 2.4** Research density map

The density analysis of the research data revealed concentrated periods of intense study, particularly around 2020 and 2021, largely driven by the global impact of the COVID-19 pandemic. The first cluster, focusing on air pollution and health impacts, demonstrated the highest density, with significant emphasis on topics like air pollution, air quality, and particulate matter. This cluster also showed increased research on the effects of COVID-19, machine learning, and meteorological variables during these years. The second cluster which covers meteorological parameters and public health, also showed notable density in 2019 and 2020, highlighting the integration of weather factors and public health studies. The third cluster focused on air quality modelling and atmospheric studies, exhibited dense occurrences in 2019, reflecting advancements in modelling techniques and climate change research.  The fourth cluster, dealing with statistical methods and health outcomes, exhibited increased density in 2020 and 2021, emphasizing the application of statistical analysis to health impacts related to air pollution. The overall density trends indicate key periods of research intensity and the evolving focus areas within the field.

### *2.3.2 Research Gap*

The bar chart provides a visual representation of lowest the weight of total link strength and occurrences for various research labels. This chart can be used to identify potential research gaps and areas that may require more focus. From Figure 5, relative humidity, land use regression, sars-cov-2 and humidity have high connectivity but relatively fewer studies. More frequent and diverse studies in these areas could fill this gap. Neural networks, hospital admission, and coronavirus, and data mining has been consistently studied but additional research could enhance understanding, especially in the context of air pollution and health. Modes, prediction, temporal variation, statistical analysis, CMAQ, modelling, wind speed, Sulphur Dioxide, chemical transport models, aerosols and random forest are terms that have received less emphasis in research, showing potential for new discoveries and wider study. The below research gap was based on the weight of total link strength and occurrences. The biggest gap or highest weight is inside red box, the moderate one is inside the green box and the smallest gap or lowest weight is inside the black box.

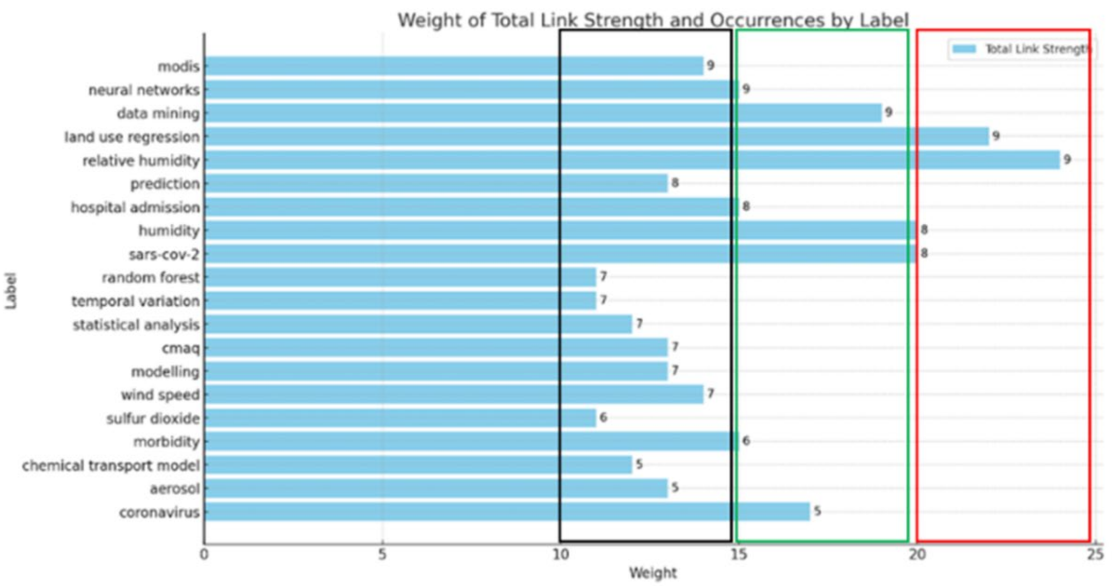


**Figure 2.5** Research Gap on Air Pollution

The Figure 2.5 explained about 20 labels under the air pollution and meteorological variables analysed. Each label has different weight of total link strength and occurrences. Total link strength of a label represents the cumulative strength of its connections with other labels in the network. A higher weight indicates stronger or more numerous connections. The number of occurrences of a label represents how frequently it appears within the dataset. The number on the right of the label indicates the level of occurrences of the label. While the number in the horizontal axis indicates the weight of the total link strength. For example, the label of coronavirus has 17 for its weight of the total link strength and appears 5 times in the dataset, while humidity has 21 for its weight of the total link strength and appears 8 times in the dataset. The visualization through the Figure 2.5 helps in understanding the significance and connectivity of various labels related to air pollution and meteorological variables within research context.

### *2.3.3 Variables for air pollution research*

To identify the important variables for air pollution modelling from data of VOSviewer, the observation can focus on the labels associated with high weights of occurrences and total link strength. These labels often represent key variables and factors frequently studied and considered crucial in the context of air pollution modelling. The following are the variables in Table 2.1.

**Table 2.1** Variables for air pollution

| Category | Variable | Description |
|---|---|---|
| Meteorological Variables | Humidity | The amount of water vapor present in the air. |
| | Wind Speed | The rate at which air is moving horizontally past a given point. |
| | Relative Humidity | The ratio of the amount of water vapor present in the air to the maximum amount that the air could hold at that temperature. |
| Pollutants | Sulphur Dioxide | A colourless gas with a pungent odour, primarily emitted from burning fossil fuels. |
| | Black Carbon | Fine particulate matter consisting of black carbon particles, primarily emitted from incomplete combustion of fossil fuels and biomass. |

| | | |
|---|---|---|
| | Particulate Matter ($PM_{2.5}$ & $PM_{10}$) | Fine particles suspended in the air, with diameters of 2.5 micrometres or smaller ($PM_{2.5}$) and 10 micrometres or smaller ($PM_{10}$). |
| | Ozone | A gas molecule composed of three oxygen atoms, often formed through chemical reactions between nitrogen oxides and volatile organic compounds in the presence of sunlight. |
| Health Impact Indicators | Morbidity | The incidence of disease within a population. |
| | Hospital Admission | The number of individuals admitted to hospitals due to health issues, often related to air pollution exposure. |
| | Respiratory Diseases | Disorders affecting the lungs and respiratory system, including conditions such as asthma, bronchitis, and chronic obstructive pulmonary disease (COPD). |
| Modelling and Analytical Methods | Machine Learning | A field of artificial intelligence that enables computer systems to learn from data and make predictions or decisions without being explicitly programmed. |
| | Neural Networks | Computational models inspired by the structure and functioning of the human brain, capable of learning complex patterns and relationships from data. |
| | Random Forest | A machine learning algorithm consisting of multiple decision trees, used for classification and regression tasks. |
| | Statistical Analysis | Techniques for analysing and interpreting data to uncover patterns, trends, and relationships, often used for hypothesis testing and inference. |
| | Generalized Additive Model | A statistical model used to explore relationships between predictors and a response variable, allowing for nonlinear and nonparametric relationships. |

| | | |
|---|---|---|
| Data Sources and Tools | MODIS (Moderate Resolution Imaging Spectroradiometer) | in the Earth's environment, including air quality parameters. |
| | CMAQ (Community Multiscale Air Quality model) | A computational tool used for simulating air quality at regional and local scales, integrating meteorological, emission, and chemical transport processes. |
| | WRF-Chem (Weather Research and Forecasting model coupled with Chemistry) | A numerical weather prediction model coupled with a chemistry module, used for simulating atmospheric composition and air quality. |
| Temporal Factors | Temporal Variation | Changes in air pollution levels and other variables over time, influenced by factors such as diurnal patterns, seasonal variations, and long-term trends. |
| | Time Series Analysis | Statistical methods for analysing sequential data collected at regular intervals over time, used to identify patterns, trends, and anomalies. |

Some of the limitations of this study of usage of bibliometric analysis on the air pollution or quality and meteorological variables are:

1. In terms of scope and coverage of databases: this study relies on specific databases which do not include all relevant journals especially those in languages other than English or those not indexed comprehensively. This also means there could be a publication bias from well-established journals, potentially overlooking valuable insights from lesser-known or regional publications.
2. Quantitative focus: It emphasizes on quantitative measures such as citation counts, publication frequency, and co-authorship networks, which may not fully capture the qualitative aspects of research contributions, methodologies and findings.

## 2.4 Conclusions

The results of the bibliometric analysis reveal insightful patterns of air pollution and meteorological variables research. The study explores research trends related to air pollution and meteorological variables. Four clusters were identified based on keyword co-occurrence, covering various aspects such as air pollution, health impacts, meteorological parameters, and advanced air quality modelling. The clusters delve into topics like air quality, particulate matter, nitrogen dioxide, ozone, sulphur dioxide, health outcomes, statistical analysis, and modelling techniques. Significant research activity was noted around 2019-2021, particularly influenced by the COVID-19 pandemic. Emphasis was placed on machine learning, artificial neural networks, statistical methods, and models like WRF-Chem (Weather Research and Forecasting model coupled with Chemistry) and CMAQ (Community Multiscale Air Quality model) in studying air quality and health impacts. The research gaps identified may include areas where further investigation is needed to enhance understanding, prediction, and management of air pollution and its impacts on public health. Specific gaps in the literature could involve novel methodologies, emerging pollutants, understudied health outcomes, or unexplored interactions between air pollutants and meteorological factors. The study identified emerging focus areas in air pollution research, including the impact of climate change on air quality, statistical methods for assessing health outcomes, and advancements in air quality modelling. Notable topics such as climate change, $PM_{2.5}$, black carbon, statistical analysis, and health implications were emphasized in the clusters.

Future research in the field of air pollution and meteorological variables could focus on several key areas. Firstly, there is a need for further investigation into the impact of climate change on air quality, particularly considering the evolving environmental conditions and their effects on pollutant levels. Additionally, exploring the application of advanced statistical methods in assessing health outcomes related to air pollution could provide valuable insights into the effectiveness of different analytical approaches. Furthermore, future studies could delve into the integration of machine learning techniques with meteorological data to enhance predictive models for air quality monitoring and forecasting. Lastly, examining the long-term trends and patterns in air pollution, especially in relation to changing meteorological variables, could offer a comprehensive understanding of the dynamics between atmospheric conditions and pollutant concentrations.

Some of the research gap stated above have been addressed in the remaining chapters of this dissertation. Humidity, relative humidity and sars-cov-2 are of three of the four topics mentioned as the weakest research gap found in air pollution and meteorological variables. Humidity is a significant meteorological variable than can influence air quality and the spread of airborne pathogens, including sars-cov-2. Studies have shown that humidity can affect the concentration and dispersion of pollutants as well as the survivability and transmissibility of viruses. Chapter 4 address this by exploring the specific correlations between humidity levels and air quality parameters during the COVID-19 pandemic. This can add valuable insights into how humidity influences air pollution and viral transmission dynamics.

The relationship between air pollution and the spread or severity of COVID-19 has been a critical area of Chapter 4. Air pollution can exacerbate respiratory conditions, potentially increasing susceptibility to COVID-19 and worsening outcomes for infected individuals. Chapter 4 directly addresses the correlation between air quality and COVID-19 events. This can contribute to understanding how air pollution might have influenced the pandemic's progression and severity.

The high connectivity between these variables (e.g. humidity, relative humidity and sars-cov-2) and relatively fewer studies addressing them together highlight the importance of comprehensive research in this area. Chapter 4, in particular, by examining the correlation between meteorological variables, air quality, and COVID-19 events, provides a holistic view that integrates these elements. This approach can uncover complex interactions and contribute to filling the research gap.

Hospital admission and coronavirus were mentioned in moderate research gap. Chapter 4 examined changes in air quality due to meteorological conditions correlate with fluctuations in hospital admissions for COVID-19 cases. Chapter 4 also directly addressed the coronavirus and the interplay between air pollution and COVID-19. In addressing the gap, Chapter 4 also investigated how air quality and meteorological factors influence the spread and severity of COVID-19.

Statistical analysis, wind speed, sulphur dioxide, prediction and temporal variation were mentioned in the lowest research gap in air pollution and meteorological variables. The cohort model in Chapter 3 can potentially predict emissions over time, addressing temporal variation. This can contribute to the prediction aspect, particularly because in Chapter 3, a model developed to forecast future emissions based on vehicle age trends. Analysis of temporal changes in air quality and meteorological variables in Chapter 4, before and during pandemic lockdowns can provide valuable insights. Statistical analysis, Spearman's correlation in particular was used in Chapter 4 to understand the correlations between meteorological variables, air quality and COVID-19 cases. Wind speed plays a critical role in the dispersion and concentration of air pollutants. Wind speed was one of meteorological variables analysed in Chapter 4 to understand how wind speed affects air quality during the pandemic or to understand pollutant behaviour. Sulphur dioxide in Chapter 4 was one of the pollutants analysed to examine the impact of this pollutant on COVID-19 cases and the correlation of this pollutant with meteorological variables.

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## Chapter 3
## Dynamic Vehicle Age-Based Cohort Model to Estimate Emissions from Transportation Sector in Jakarta

### 3.1 Introduction

Jakarta is one of the top cities with the worst air pollution in Southeast Asian countries and Asia in 2021. The particulate matter ($PM_{10}$), ozone ($O_3$), and carbon monoxide (CO) in 2018 were above the international standardized limits based on WHO standards (Kusumaningtyas et al., 2018). From 2001 to 2015, the index of $PM_{10}$ concentration in Jakarta, according to the Air Quality Management System (AQMS), had a yearly average about three times higher than the WHO standard values, which was 20 $\mu g/m^3$ on average (Rita et al., 2016). Although the WHO recommends an annual mean value of less than 20 $\mu g/m^3$ for $PM_{10}$ and 10 $\mu g/m^3$ for $PM_{2.5}$, the latest data retrieved in April 2018 for Jakarta demonstrated that $PM_{10}$ was 82 and $PM_{2.5}$ was 45 µg/m3. Based on air quality data from Open Data Jakarta from January to October 2018, the CO, $PM_{10}$, and $O_3$ concentrations were above the WHO standards limit (Kusumaningtyas et al., 2018). Vehicles burn gasoline or diesel fuel in their engines and emit CO, nitrogen oxides ($NO_x$), unburned hydrocarbons (HC), and air toxics. The amount of PM is higher in diesel engines than in gasoline ones (Rita et al., 2016).

The transportation sector is the primary source of air pollution in cities because it emits nitric oxide (NO) and carbon dioxide ($CO_2$) at least 30% and 14% of the total global air pollution emissions, respectively (Réquia et al., 2015). Jin et al. (2019) revealed that vehicular emissions are the most significant contributors to air pollution in China, which has arisen due to the increasing number of vehicles in the last decade owing to economic development and urbanization. Moreover, PM emissions from vehicles are produced during fuel burning in vehicle machines. While the increase in the population (approximately 1%) and road length (less than 1%) is low, the number of vehicles has increased significantly (approximately 10%) in Jakarta (BPS Catalogue, 2010-2017). The total number of vehicles in Jakarta exceeds the total human population, as shown in Figure 3.1 (BPS Catalogue, 2010, 2013, 2018). The data from the following figure was derived from *Badan Pusat Statistik*/National Statistical Agency (BPS) and Samsat Polda Metro Jaya

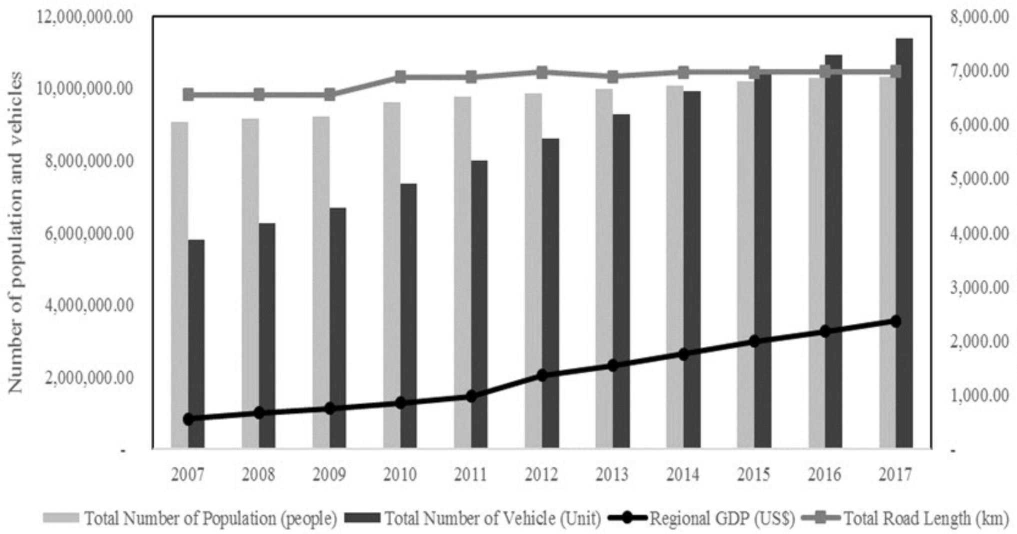


**Figure 3.1** Total number of populations, vehicle, and GDP of Jakarta (2007–2017)

Energy consumption in the transportation sector is estimated to increase at an average rate of 5.9% per year in 2012–2035, driven by the rising demand for mobility and subsidies. The low quality of public transport is expected to underlie the significant expansion in vehicle ownership. According to previous studies, transportation has the highest contribution to the emission inventory of $CO_2$ in Jakarta, in particular (Mungkasa, 2018; Rahmawati, 2009). The data for the following figure was based on data from Samsat Polda Metro Jaya (received Aug 2019).

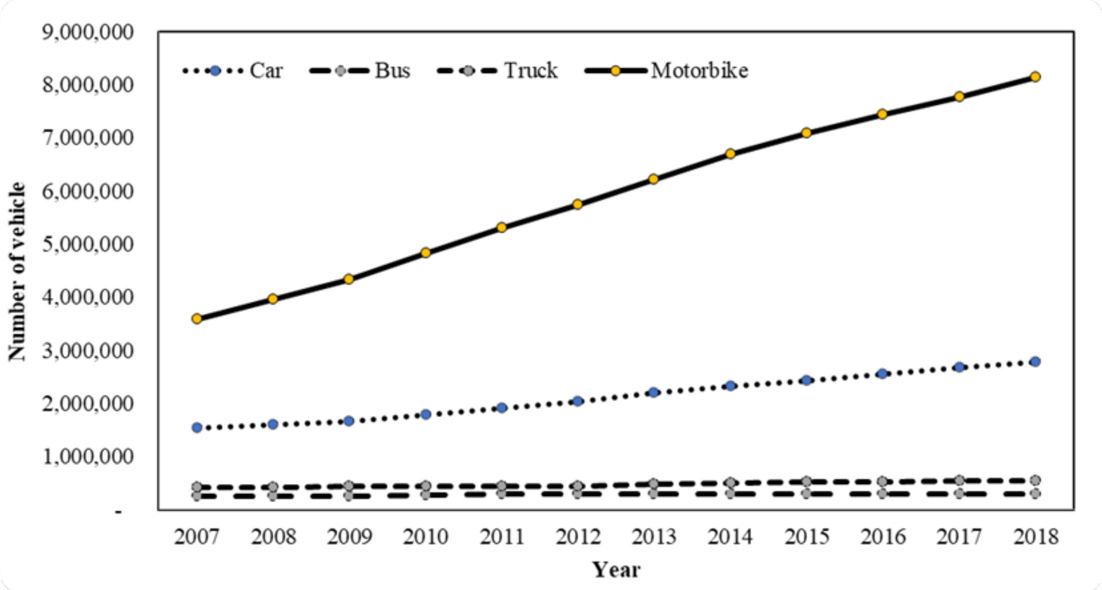


**Figure 3.2** Total number of vehicles registered in Jakarta (2007–2018)

An emission test conducted in Jakarta in 2005 found that 57% of vehicles did not pass the emission standard. In 2017, emission tests conducted on approximately 12,024 vehicles in Jakarta (92% with a vehicle age range of 1–10 years, 7% 11–20 years, and 1% over 20 years old) found that almost 12% (approximately 1,400) of vehicles did not pass the standard. More than 50% of the cars tested with more than 10 years of age failed the test. Vehicles aged > 40 years were also observed on the road (Open Data Jakarta). This situation arises from the absence of regulations concerning the age of vehicles, particularly for private vehicles, in Indonesia. In 2015, there was public discourse about implementing a 10-year vehicle age limit in Jakarta, but it did not result in any concrete action, except for public transportation such as bus or taxi for inner city usage. In recent years, this discussion has resurfaced. The local government of Jakarta has drafted a regulation to impose a maximum private vehicle age of 10 years starting in the year 2025. However, this proposal has elicited negative reactions from the public. The results obtained from one of research (Sitinjak, 2023) show that public awareness and acceptance of the application of end-of-life vehicle (ELV) are still very low. In addition, the regulations that have been applied to check the feasibility of vehicles (e.g. emission test) are proven unable to cut down the number of old vehicles. ELV vehicles in Indonesia are still managed poorly by some workshops and some scrap iron collector companies. These workshops are privately managed, and the demolition activities do not follow the correct standards (Sitinjak, 2023).

End-of-life vehicles refer to vehicles that have reached the end of their useful life due to age, wear, or damage, making them no longer roadworthy or economically repairable. These vehicles are often directed to scrappage programs, where they are dismantled, recycled, or disposed of in an environmentally responsible manner. Scrappage programs aim to remove older, less efficient, and more polluting vehicles from the road, promoting environmental sustainability and improving overall vehicle fleet quality. Implementing this ELV policy requires the cooperation of all stakeholders (government, automotive industry, and the community).

The Government attempted to reduce air pollutants by introducing Euro 4 to replace Euro 2 fuel for passenger cars starting in October 2018, as stated in the Environment Minister's Regulation No. 20/Setjen/Kum.1/3/2017, and by implementing massive vehicle emission tests. Therefore, applying strict policy standards for vehicle emissions could reduce these levels (Huo et al., 2012).

Converting to the Euro standard for all vehicles, including those over ten years old, CO, $NO_x$, HC, and PM emissions will significantly be decreased (Bayasgalan & Matsumoto, 2017). The change from Euro 2 to Euro 4 is considered an essential solution for decreasing air pollutants. The emission level declines significantly as vehicle technology improves (Huo et al., 2012). The better the technology and the newer the vehicles, the better the emission levels. Therefore, vehicle emission tests are also essential for reducing the pollutants released by vehicles to preserve the air quality of the environment.

Before moving forward on whether the change from Euro 2 to Euro 4 will result in better air quality in Jakarta, identifying and understanding the significant contributors to the current air pollution is crucial. Most studies in Indonesia calculated $CO_2$ emissions using total fuel consumption (Adhi, 2018; Bayasgalan & Matsumoto, 2017; PT Delima Laksana Tata, 2012). The vehicle age is rarely included as a critical factor in calculating $CO_2$ emissions. Therefore, this study used dynamic models that imply the vehicle age cohort using the STELLA application to calculate the total emissions of key air pollutants. With this model, the emissions inventory for important air pollutants, particularly CO, HC, $NO_x$, and $PM_{10}$, could be calculated in more detail. Air pollutant emissions in 2040 were also predicted. To assess whether the current strategy is effective enough and to identify a possible new strategy to enable the Local Government of Jakarta to reach its goal in $CO_2$ emission and other essential air pollutant reduction, this study aimed to (1) know the main contributor of air pollution from road transportation sources in Jakarta from 2007 to 2018; (2) analyse the total air pollutant emissions from road transportation sources in Jakarta in 2040 under the business-as-usual (BAU) scenario; and (3) understand the current implementation of Euro 4 standard emissions.

### 3.2 Material and Methods

Mobile emissions are influenced by several factors, including machine characteristics, driving patterns, and vehicle usage (maintenance and fuel characteristics). Developing models for emission inventories can help predict the total emissions from mobile sources. These models should test and evaluate regulatory mechanisms for mobile source pollution control (Rita et al., 2016).

There are several ways to calculate vehicle emissions. However, in this study, a bottom-up approach using the vehicle kilometer travelled (VKT) was used to calculate the total vehicle emissions in Jakarta. Vehicle emissions were estimated by calculating the sum of the aggregate emissions using vehicle population statistical data, average annual VKT, or average annual vehicle miles travelled (VMT) as emission factors of key air pollutants. The following formula was used to calculate the emissions:

$$E_i = \sum_{j} V_j . VKT_j EF_{ij} \tag{1}$$

where $E_i$ is the total emissions of pollutant i (grams/year); $V_j$ is the total number of vehicles of type j on the road during that year (vehicles); $VMT_j$ or $VKT_j$ is the average annual miles/km traveled by vehicles of type j (mile/vehicle/year or kilometer/vehicle/year); $EF_{ij}$ is the average emissions of pollutant i for vehicle type j (g/mile or g/km).

Note: EF is often referred to as the vehicle “emission factor” (Deaton & Winebrake, 2000).

Deaton (2000) stated that vehicle age could significantly impact emissions because when the vehicle gets older, the chances of the efficiency loss of the catalytic converters increase, which may produce higher emissions. The increase in emissions over the lifetime of a vehicle is called emissions deterioration (Deaton & Winebrake, 2000). Age cohorts were used to capture the relationship between vehicle age and dynamic modeling. The VKT was used according to the cohort models since vehicle emissions are mainly influenced by the emission factor of the vehicle and the frequency of vehicle usage. However, several other factors also influence vehicle emissions, which are included in the dynamic model, such as the emission standards in the studied areas, vehicle speed, fuel quality, and vehicle type.

The total vehicle population data was collected from SAMSAT Polda Metro Jaya from 2007 to 2018, whereas vehicle categories in Jakarta were retrieved from the *Badan Pusat Statistik*/National Statistical Agency (BPS). Based on the local regulation, the vehicle categories consisted of passenger cars (gasoline and diesel), motorbikes (gasoline), trucks (diesel), and buses (diesel). The vehicle population and the scrapped rate were divided into three cohorts, including “age type 1” (from 2018 to 2014), “age type 2” (from 2013 to 2010), and “age type 3” (from 2009 to 2007). These cohorts of the vehicle population were determined based on the study conducted by Bayasgalan and Matsumoto (2017) in Ulaanbaatar. The emission standards utilized for this study derived from references in Japan. Given the underlying data for the vehicle population spanned from 2007 to 2018 (refer to Figure 3.2), the emission standards selected were anchored to three basis years in the Japan emission standards, namely 2005, 2009 and 2018. Because finding the annual VKT and purchase rate data is difficult, it was determined by the average value of the VKT and purchase rate in the studied years.

The leakages in the auto cohort model represent untimely vehicle scrappage, either due to accidents or breakdowns (Deaton, 2000), making them no longer roadworthy or economically repairable. Jakarta faces a significant challenge due to the lack of dedicated facilities for vehicle scrappage. This deficiency hampers the efficient and environmentally responsible disposal of end-of-life vehicles, leading to potential environmental hazards and inefficiencies in managing obsolete vehicles. The absence of such facilities results in a lack of data on vehicle scrappage, further complicating efforts to implement effective scrappage programs aimed at reducing pollution and improving the quality of the vehicle fleet in the city. Therefore, the leakages in the auto cohort model in this calculation uses the data of vehicles that move out from Jakarta.

In this study, vehicle population, age, and leakage (moved out of Jakarta) were acquired from the *Sistem Administrasi Manunggal Satu Atap*/One Roof Administration System (SAMSAT Office) of Polda Metro Jaya or the Police Corps of the Jakarta area. Owing to the lack of data on detailed vehicle accidents or scrapped vehicles, we used only the total number of vehicles that moved out from Jakarta (Data Information on Vehicles in Jakarta, SAMSAT). A constant VKT across all cohorts was used to determine VKT owing to the lack of data on VKT for each vehicle cohort category. The VKT number for passenger cars and motorbikes was acquired from the website of a major car dealer called Carmudi Indonesia (Carmudi.co.id), focusing on used cars and motorbikes sold in Jakarta. VKT of buses and trucks was derived from the previous research conducted by Adhi (2018).

Under the regulations of the Indonesian Government, emissions standards are differentiated only by vehicle category and not by vehicle age. Therefore, Emission Standards of Japan from dieselnet.com were used as emission standards for cars, buses, and trucks (DieselNet). Motorbike emission standards were obtained from the transport policy.net. The accuracy of vehicle emissions calculations is highly dependent on the age distribution of the vehicle. Some regulations state vehicles scrappage when vehicles reach a certain age or have been used for a specific number of kilometers in certain areas. An increase in the number of scrapped vehicles usually follows an increase in the vehicle population. Changes in the population of vehicles result in changes in the vehicle age distribution annually. In this study, STELLA, utilized as a dynamic modelling software, has played an important role to understand the influence of the environment and make predictions of how it will evolve in the future. Leveraging the available vehicle population data and emission inventories, the software supported the development of vehicle age cohort modelling when estimating emissions. The emissions sub model in the analysis was used to calculate the total emissions produced by each type of vehicle more accurately. For this study, STELLA used 20 similar dynamic models (five vehicle categories assessing four key pollutants).

## 3.3 Results and Discussion

### *3.3.1 The contributors of air pollution from road transportation*

Table 3.1 lists the input data of the STELLA application for each vehicle classification. The data in Table 3.2 were used to estimate the number of emissions emitted by each vehicle type and age. As shown in Table 3.1, the highest VKT values was from bus. However, this was not as significant as that for motorbikes and gasoline cars. Therefore, motorbikes have the highest purchase rate among vehicles. The older the vehicle, the higher the scrap rate. The three cohorts were determined based on the available vehicle data and chosen emission standards. "Flow 1," "Flow 2," and "Final scrap" are the leakage fraction, meaning the number of vehicles being scrapped either due to accidents or breakdown or moved to other areas. Based on the age cohorts, the youngest vehicles contributed to emissions per kilometer. For instance, type 1 motorbikes produce half the lower emissions of CO, $NO_x$, and HC than types 2 and 3 motorbikes. The type 1 gasoline cars, diesel cars, buses, and trucks have lower $NO_x$ emissions. These vehicles have lower PM emissions than motorbikes. The dynamic model presented in Figure 3.3 was used to determine and connect the impact of each factor on the pollutants emitted. In this study, the key pollutants emitted from vehicles, including CO, HC, $NO_x$, and $PM_x$ were calculated. Table 3.1 summarizes the contributions of each vehicle category/classification level to the key pollutant emissions.

**Table 3.1** Vehicle population by age cohort, and purchased and scrapped rates by age cohort

| Vehicle Classification | VKT (km/ year) | Vehicle population by age cohort (V) | | | Purchased rate | Scrapped rate by age cohort | | |
|---|---|---|---|---|---|---|---|---|
| | | Type 1 | Type 2 | Type 3 | | Type 1 | Type 2 | Type 3 |
| Motorbike | 2,203.24 | 37,111,977 | 26,432,833 | 7,548,371 | 0.075 | 0.00015 | 0.00153 | 0.00291 |
| Passenger car - gasoline | 10,631.06 | 11,962,622 | 8,987,522 | 2,954,544 | 0.053 | -0.00042 | 0.00137 | 0.00317 |
| Passenger car - diesel | 12,741.47 | 824,788 | 619,663 | 203,707 | 0.053 | 0.00048 | 0.00187 | 0.00326 |
| Bus | 60,590.00 | 1,178,379 | 1,180,049 | 1,045,830 | 0.013 | 0.00048 | 0.00187 | 0.00326 |
| Truck | 12,775.00 | 2,642,949 | 2,255,341 | 841,637 | 0.024 | 0.00106 | 0.00163 | 0.00220 |

**Table 3.2** Emission factor by vehicle type and ag

| Vehicle classification | Type of age | Emission factor (g/km) | | | |
|---|---|---|---|---|---|
| | | CO | $NO_x$ | HC | PM |
| Motorbike | Type 1 | 2.000 | 0.150 | 0.800 | 0.100 |
| | Type 2 | 5.500 | 0.300 | 1.200 | 0.100 |
| | Type 3 | 5.500 | 0.300 | 1.200 | 0.200 |
| Passenger car – gasoline | Type 1 | 1.150 | 0.050 | 0.100 | 0.005 |
| | Type 2 | 1.150 | 0.050 | 0.050 | 0.005 |
| | Type 3 | 1.150 | 0.050 | 0.050 | 0.005 |
| Passenger car – diesel | Type 1 | 0.630 | 0.150 | 0.024 | 0.005 |
| | Type 2 | 0.630 | 0.080 | 0.024 | 0.005 |
| | Type 3 | 0.630 | 0.150 | 0.024 | 0.014 |
| Bus | Type 1 | 2.220 | 0.400 | 0.170 | 0.010 |
| | Type 2 | 2.220 | 0.700 | 0.170 | 0.010 |
| | Type 3 | 2.220 | 2.000 | 0.170 | 0.027 |
| Truck | Type 1 | 2.220 | 0.400 | 0.170 | 0.010 |
| | Type 2 | 2.220 | 0.700 | 0.170 | 0.010 |
| | Type 3 | 2.220 | 2.000 | 0.170 | 0.027 |

**Table 3.3** Order of vehicle types contributing to air pollution in Jakarta

| Order | 2018 | | | | 2040 | | | |
|---|---|---|---|---|---|---|---|---|
| | CO | HC | NO | PM | CO | HC | NO | PM |
| 1st | Motorbike | Motorbike | Bus | Motorbike | Motorbike | Motorbike | Bus | Motorbike |
| 2nd | Car gasoline | Bus | Motorbike | Car gasoline | Car gasoline | Car gasoline | Motorbike | Car gasoline |
| 3rd | Bus | Car Gasoline | Truck | Bus | Bus | Bus | Truck | Bus |
| 4th | Truck | Truck | Car Gasoline | Truck | Truck | Truck | Car Gasoline | Truck |
| 5th | Car diesel | Car diesel | Car diesel | Car diesel | Car diesel | Car diesel | Car diesel | Car diesel |

Table 3.3 shows that the significant contributors to the air pollutants measured from 2007 to 2018 were motorbikes for CO, HC, and PM and buses for NO pollutants. The major contributors for CO in Jakarta among all types of vehicles from 2007 to 2018 were motorbike, a type 1 or the youngest age group due to their biggest unit number compared to other vehicle age cohorts. Réquia et al. (2015) showed that light-duty vehicles (LDV) were the major contributor to CO emissions, resulting in as much as 68.9%, and heavy-duty vehicles (HDV) were the major contributor for NO emission, resulting in as much as 90.7%. Therefore, the primary contributor to air pollutants in Jakarta will be CO, among the other pollutants in 2040, using the BAU scenario. Gasoline cars will be the second contributor to CO, HC, and PM pollutants until 2040. Diesel cars have the lowest number of emissions compared to other vehicle categories. Therefore, they will be the minor contributor to all pollutants. Similar models such as below are drawn for other types of pollutants and vehicle categorization.

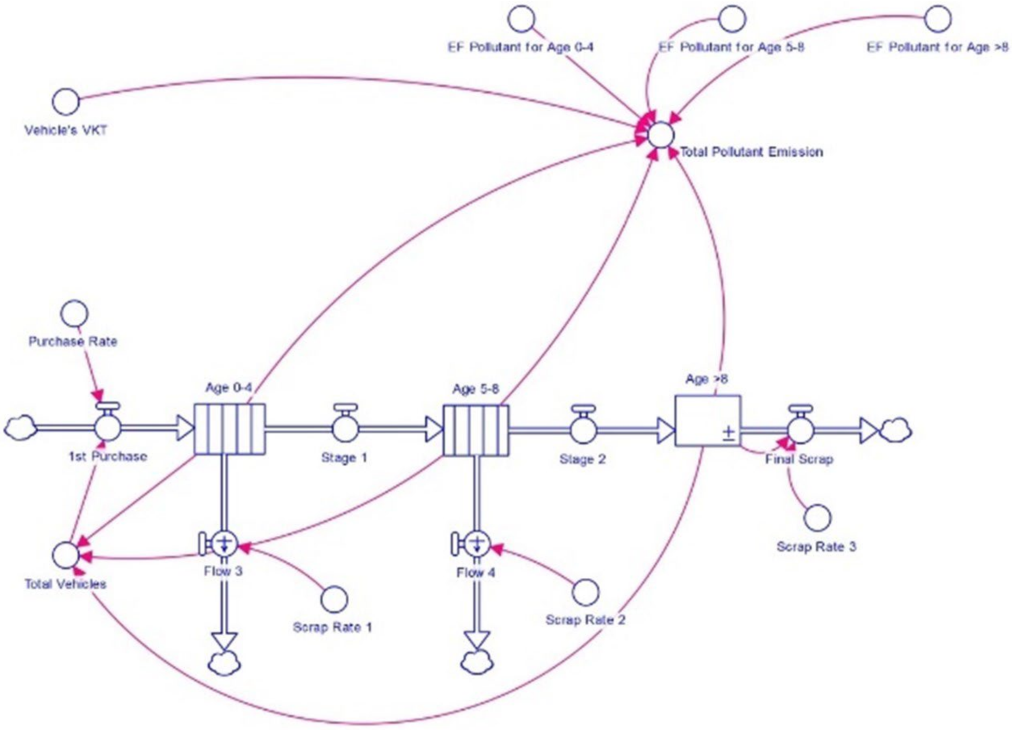


**Figure 3.3** The dynamics sub-models of a vehicle using carbon monoxide (CO) as the key pollutant

From 2007 to 2018, the CO emissions from motorbikes were the highest of the total CO emissions in Jakarta, followed by those from gasoline, buses, trucks, and diesel cars. The relationship between the total number of vehicles and their contribution to air pollution was relatively strong. Between 2007 and 2018, motorbikes accounted for almost 67% of all vehicles in Jakarta, followed by gasoline cars (approximately 23%), trucks, buses, and diesel cars, consecutively. Among all types of vehicles, the major contributors were motorbikes and buses, followed by trucks. In 2040, buses will be the primary contributor to NO emissions. However, car gasoline is predicted to produce higher HC emissions in 2040 than buses in 2018. This situation may be due to the annual increasing number of gasoline-passenger cars and the decreasing number of buses, because most buses are considered public transportation, and they need to follow the regulation on age limitation for the bus to operate, which is a maximum of 10 years. Table 3.4 shows the significant contributors of air pollutants in 2007, 2018, and 2040.

**Table 3.4** Major contributors to CO, HC, NO, and PM in Jakarta in 2007, 2018, and 2040

| Year | Parameter | Bus | Car Diesel | Car Gasoline | Motorbike | Truck |
|---|---|---|---|---|---|---|
| 2007 | CO | 30.2% | 0.9% | 19.4% | 38.8% | 10.7% |
| | HC | 15.8% | 0.2% | 8.6% | 69.8% | 5.6% |
| | NO | 65.9% | 0.8% | 4.1% | 11.4% | 17.7% |
| | PM | 13.5% | 0.5% | 5.5% | 76.5% | 3.9% |
| 2018 | CO | 20.9% | 0.8% | 17.5% | 52.7% | 8.2% |
| | HC | 10.8% | 0.2% | 5.1% | 79.6% | 4.2% |
| | NO | 63.9% | 0.6% | 2.6% | 10.0% | 23.0% |
| | PM | 0.4% | 0.0% | 24.8% | 74.7% | 0.1% |
| 2040 | CO | 7.4% | 1.0% | 21.3% | 70.2% | 8.9% |
| | HC | 3.2% | 0.1% | 3.6% | 91.4% | 1.6% |
| | NO | 44.7% | 1.1% | 4.4% | 27.4% | 22.4% |
| | PM | 0.1% | 0.0% | 17.0% | 82.9% | 0.1% |

CO, carbon monoxide; HC, hydrocarbons; NO, nitric oxide; PM, particulate matter.

### *3.3.2 Total emission estimation from transportation sources*

From 2007 to 2040, LDVs, such as cars and motorbikes, are significant contributors to CO emissions (61.29%). The significant contributors to NO pollutant emissions were HDV, such as buses, accounting for 44.70% (S. Sun et al., 2019). Previous studies also showed similar results, where HDV contributed to 50% of NO pollutant emissions. Air emissions are directly correlated with the dominant vehicle type (Jia et al., 2018; Zhou et al., 2019). If the vehicle type with the highest number of vehicles is HDV, the highest emissions will be from the pollutants $NO_x$ and PM. Souza et al. (2013) stated that gasoline vehicles were the most significant contributors to CO pollutants (74%), whereas diesel vehicles were the most significant contributors to PM (91%). These vehicles were the most significant contributors to total hydrocarbons (THC) by as much as 61.4%24. Bellasio et al. (2007) stated that gasoline-fuelled cars were the most significant contributors to CO pollutant (72.7%), PM (36.5%), and $NO_x$ (32.1%), whereas motorbikes were minor contributors to CO pollutants.

However, the use of alternative fuels does not significantly reduce the number of pollutants. Gasoline-fuelled LDVs were minor contributors of $NO_x$ pollutants, and passenger cars with liquid petroleum gas (LPG) as a fuel were minor contributors of PM (Bellasio et al., 2007). Mishra et al. (2014) concluded that cars with alternative fuels to methane, such as compressed natural gas (CNG), were the most significant contributors to $NO_x$ pollutant (29.38%) in 2012. In this research, the total number of motorbikes (LDV) increased significantly compared to buses (HDV) and other vehicle types (see Figure 4[a–d]), and it can be predicted that the most significant contributor of air pollutants in DKI Jakarta will be motorbikes until the end of the predicted year.

From 2007 to 2018, the major contributor to CO in the motorbike category among the three age cohorts was type 1 or the younger/newest motorbikes. Younger motorbikes had enormous numbers among the other two age cohorts, based on vehicle population data. If there are no interventions for the population, the air pollution contributors will be the same. Dill (2004) stated that a scrapping program for vehicles based on vehicle age could reduce emissions, but not as much as was predicted. In the worst-case scenario, the CO emissions reduction could only reach 20%. In Jakarta, there was already a local regulation issued in 2019 by the governor on limiting the age of vehicles to 10 years for private vehicles starting in 2025. If implemented, this regulation will undoubtedly help reduce CO emissions in Jakarta. However, national laws need to be revised to enable the implementation of local regulations in the field.

Moral et al. (2019) demonstrated that the emission of $NO_x$ from a new vehicle was lower than that from a scrapped vehicle (assumed to be the same as that of 10-year-old cars). The total emission of $NO_x$ for a new car was 12.63 tons while that for the scrapped car was 18.65 ton (Laborda & Moral, 2019). Lumbreras et al. (2008) also mentioned that vehicle renewal was the most effective alternative policy for decreasing $NO_x$ emissions (24.70%), $PM_{10}$ (17.63%), $PM_{2.5}$ (21.19%), and CO (21.19%). The older the vehicle, the higher the emissions which will be resulted by the vehicle.

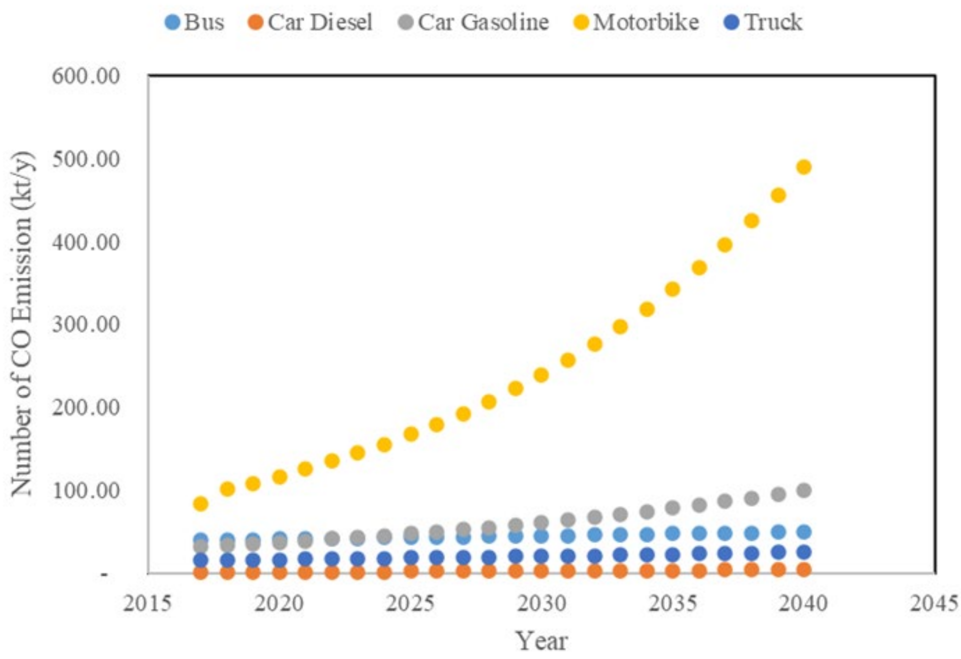


**Figure 3.4** Predicted CO emission in Jakarta from 2018 to 2040.

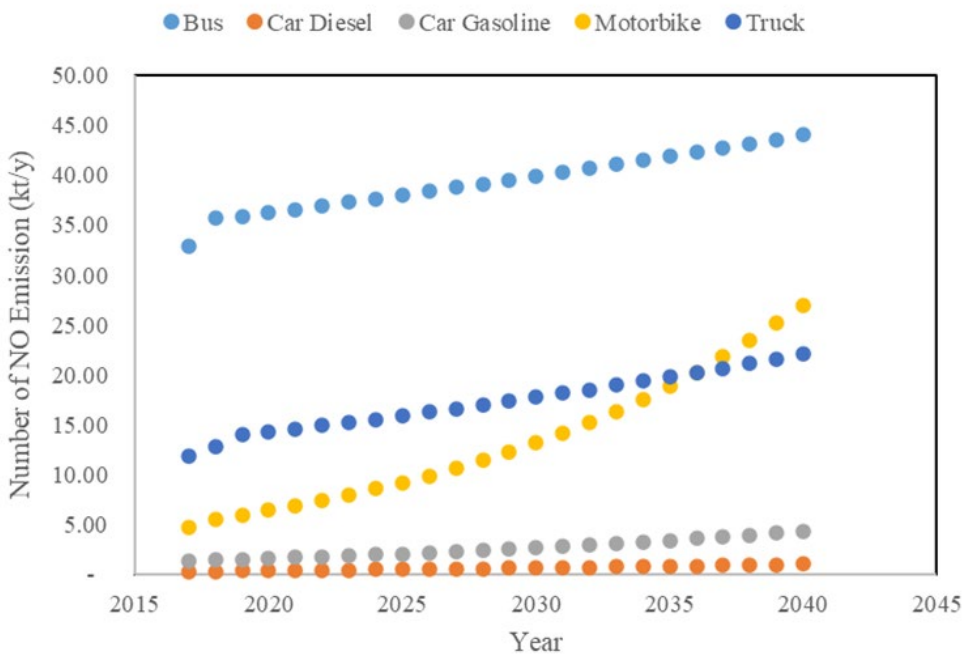


**Figure 3.5** Predicted NO emission in Jakarta from 2018 to 2040.

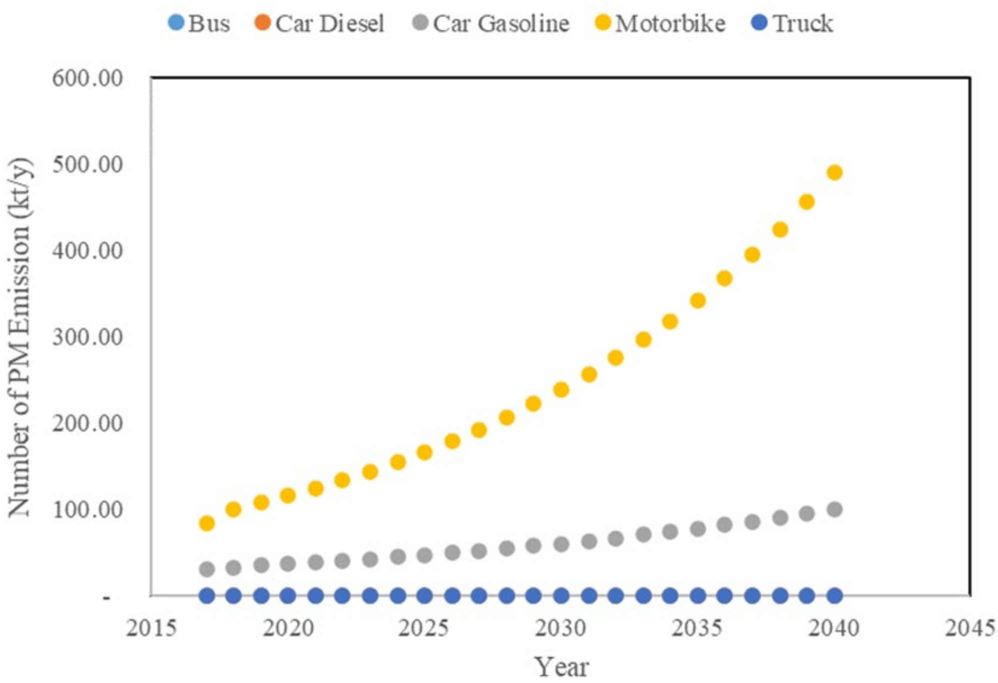


**Figure 3.6** Predicted PM emission in Jakarta from 2018 to 2040.

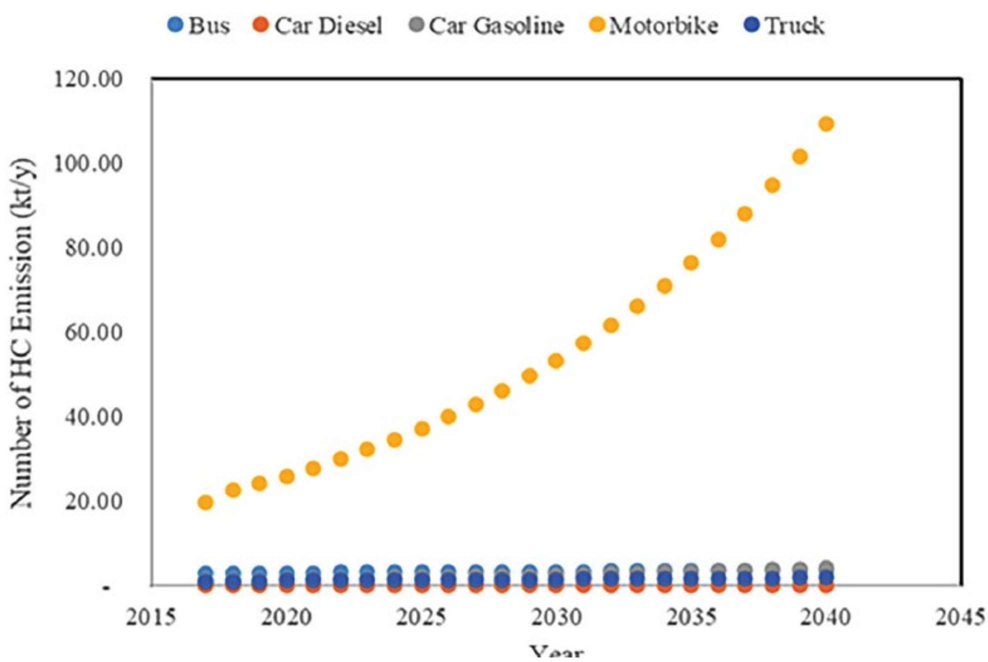


**Figure 3.7** Predicted HC emission in Jakarta from 2018 to 2040.

Wang et al. (2019) found that a policy for scrapping yellow tags decreased air pollution emissions. The yellow-tagged vehicle (TVs) is an LDV that fulfills the emission standards of China III. The implementation of TVs saw decreased emission of $PM_{2.5}$, $PM_{10}$, $NO_x$, CO, and HC as much as 16.46 kt (kilotons), 18.12 kt, 174.44 kt, 669.11 kt, and 91.64 kt, respectively, from year 2008 to 2015 (S. Sun et al., 2019). Wee et al. (2011) demonstrated that the scrappage policy for vehicles is effective because of its the low cost. This policy can be applied to areas with a high population and to vehicles with old technology for emission control. Limiting old private vehicles running on the streets of Jakarta would be an excellent intervention for improving air quality.

From 2007 to 2040, gasoline cars will be the second-largest contributors to CO and PM pollutants after motorbikes [Figure 3.4 (a, d)]. The total number of cars using gasoline was considerably lower than that of motorbikes. The total number of cars in Jakarta in 2018 was four times that in 2007, whereas the number of motorbikes was five. The percentage of motorbikes increasing annually is also much higher than that of gasoline-powered cars. Therefore, even though car emissions are more significant than those of motorbikes, the total number of pollutants from motorbikes remains far higher than that of gasoline cars. If there is no intervention to decrease the number of vehicles (cars or motorbikes), pollution in Jakarta will worsen.

Vehicle age and number are significant factors when recommending policies to reduce emissions. Pastorello et al. (2017) stated that PM emissions from vehicles with gasoline and diesel as fuels would decrease by approximately 20% after applying the vehicle scrapping policy with a certain VKT. They also found in their study that the average mileage traveled for a 10-year-old car was approximately 40% of the same car (gasoline or diesel) in its first year or decreased to 10% of the 20-year-old car (Pastorello et al., 2017). Consequently, the PM emissions of a passenger vehicle decrease by more than 20% because the average kilometers traveled by an older car decrease. This finding demonstrates the importance of estimating the average kilometers traveled for every vehicle category and age.

Several policies have been implemented to improve the air quality and reduce air pollution in cities. These policies are implemented by limiting the number of vehicles on the streets, applying odd and even vehicle plate numbers, limiting the type of vehicles passing on certain roads, improving fuel quality, limiting vehicle age, or applying scrappage policies. Li et al. (2018) explained the policy to limit the number of vehicles in Langfang, China, based on vehicle plate numbers or License plate recognition (LPR), which was implemented by two methods, one-day-per-week (ODPW) and odd-and-even (OAE). The shift from the ODPW policy to the OAE has significantly increased the vehicle speed on the more prominent streets, whether during peak hours or not. This policy has also directly influenced a reduction in traffic volumes. Traffic volume was reduced by approximately 8.74% after the implementation of the OAE policy (replacing the previous ODPW policy). Jakarta has already regulated odd and even numbers of vehicles since 2016. This is due to the increasing number of vehicles, particularly LDV. Jakarta may need to learn from other countries, such as Brazil, and their programs. Szwarcfiter et al. (2005) demonstrated that the Brazilian Motor Vehicle Air Pollution Control Program (PROCONVE) policy implemented from 2003 to 2010 targeted LDV. The program reduced the CO, HC, and NOx emissions by 51%, 47%, and 50%, respectively (Szwarcfiter et al., 2005).

### *3.3.3 The current situation of Euro 4 implementation in Jakarta*

Full implementation of the Euro 4 standard fuel was postponed until 2022 in Jakarta. Although all gas stations in Jakarta have Euro 4, there is insufficient fuel to meet this demand. Moreover, a facility for conducting emission tests on vehicles is under construction. The residents of Jakarta are not following the local government regulation to switch to Euro 4 gasoline because its promotion by the local government is lacking; there are many residents who do not know the emission impact of using Euro 4 gasoline on air quality and weak law enforcement by the local government (Purwanto, 2021).

As reported by Hirota and Kashima (2020), the introduction of Euro 4 was postponed twice: in 2013 and 2017. The implementation of Euro 4 standard vehicles was also postponed twice, from 2018 to 2022. Simultaneously, the share of production was relatively low. It seems impossible for only 1.4% of the Indonesian fuel market to achieve the national target in the following years (Hirota & Kashima, 2020). Therefore, if the total number of gasoline cars and motorcycles used the Euro 4 standard in Jakarta in 2018 and the emission factors were collected from Huo et al. (2012), then the CO, HC, and $NO_x$ emissions in 2022 would be nine times lower (Fu et al., 2013). Because data on the current implementation of Euro 4 is lacking and the entire project implementation has been postponed, this research was limited to the existing use of Euro 2 standard vehicles.

Fu et al. (2013) found that the emission of $NO_x$ from HDV became the primary pollutant source influencing air quality in Chinese cities. The emission factors of $NO_x$ measured from buses were 1,60-, 1,16-, 1,77-, 1,27-; 2,49- and 2,44-times higher than the $NO_x$ predicted by the Euro 4 model for vehicles in the city, suburb, and highway (Huo et al., 2012). Therefore, adjusting the essential emission factor from a local study is highly encouraged in the Euro 4 model to improve emission estimation. Yang et al. (2018) found that the elimination of old vehicles and upgrading fuel quality contributed to a decrease in emissions in Tianjin, Beijing, and Hebei City, China (Yang et al., 2018). Lee et al. (2019) stated that the emission factor of $NO_x$ for Euro 4 for LDV only estimated–27-31% of the $NO_x$ emissions on the street. This weak representation was caused by low acceleration during the driving cycle and limited monitoring tools (valve degradation of EGR/exhaust gas recirculation). This condition also proved that the standard emission for Euro 4 for the LDV was highly dependent on vehicle age. If the vehicle is already old (as is the case in Korea today), then the measurement of emission of $NO_x$ with this standard would be accurate and helpful in increasing the effectiveness of emission control. If the vehicle is still new, then a complete change is required to the diagnostic system and the valve tools for its EGR. Therefore, the Euro 4 emissions policy for passenger cars has high uncertainty (Kraan et al., 2012).

### *3.3.4 The current progress of Electric Vehicles in Jakarta*

The global electric vehicle market is growing rapidly with electric cars accounted for around 18% of all cars sold in 2023, a significant increase from 14% in 2022 (Global EV Outlook 2024: Moving towards Increased Affordability, 2024), driven by policy support, investment in the EV supply chain, and the need to reduce greenhouse gas emissions.

ASEAN countries, including Indonesia, are key players in this market where in the year 2023, in the vehicle global production, Indonesia ranks as number 15 (while Thailand as number 10) and in the vehicle global market, Indonesia ranks as number 17 (while Thailand as number 18) (Prasetyo, 2024). Indonesia has been actively promoting EV adoption through government initiatives and private sector investments. However, Indonesia faces challenges in infrastructure development, cost and affordability, and policy consistency. Despite these challenges, Indonesia has opportunities to develop its EV market through government support, private sector investment, and international collaboration. The transition to EVs is crucial for reducing emissions and improving air quality and Indonesia is well-positioned to play a significant role in this transition.

Indonesia is poised to become a significant player in the global EV market, leveraging its vast reserves of nickel and other critical minerals. Indonesia's target for decarbonization increased from 29% to 31.8% (with its own ability) or from 41% to 43.2% (with international aid) by 2030. Energy sector roadmap towards net zero emission is targeted to be achieved in 2060. The government has set ambitious targets, aiming for 2 million EV passenger cars and 13 million electric motorcycles on the roads by 2030, with an expected market value of $20 billion by 2030, 22 million EV passenger cars and 101 million electric motorcycles by 2040, 65 million EV passenger cars and 175 million electric motorcycles by 2050 (Indonesian Ministry of Energy and Mineral Resources, 2022). Another target is all motorcycles will be electric in the period of 2051-2060 (Bappenas, 2021). However, the country faces several challenges, including a lack of robust charging infrastructure, high EV costs, and concerns over battery range and after-sales services. Despite these hurdles, Indonesia is actively promoting EV adoption through incentives such as tax breaks and subsidies, and by attracting major manufacturers like Hyundai, Mitsubishi, and BYD to establish production facilities. The country's commitment to transitioning to cleaner energy sources and its strategic positioning as a hub for EV production and supply chains make it well-positioned for growth, though it must navigate domestic and international challenges to fully realize its EV potential. As stated by a Professor of Environmental Engineering from ITB in the CNN Indonesia's interview in July 2024, the use of EVs in Indonesia can reduce emissions by up to 20% by 2030, which would have a substantial impact on air quality.

### 3.4 Conclusion

Identifying the specific contributors of each pollutant is essential to better address the air pollution problem. Based on the results of this study, motorbikes were the primary contributors to the emission of air pollutants CO, HC, and PM, and buses were the primary contributors to NO from 2007 to 2018 in Jakarta. If there is no intervention to address this issue shortly or until 2040, the primary contributor will still be motorbikes, followed by passenger gasoline cars. This study also concluded that LDVs are major contributors to air pollutants in Jakarta. Significant interventions to reduce LDVs in Jakarta will improve the air quality.

Using the auto cohort with emission sub-model enabled this study to confirm that the age of the vehicles is essential. However, the increased number of vehicles in Jakarta is an even more critical issue to address. Knowing the source of the problem will help produce a better solution to address each specific problem. For instance, if the source of the problem is the increasing number of motorbikes, then some regulations, such as the limitation of motorbike ownership, limiting the area where people can ride a motorbike, and intensive emission tests for motorbikes produced before 2013, can be applied.

The author also believes that the Indonesian Government needs to produce more detailed emission factors that fit the local situation. Implementing Euro 4 will likely decrease the air pollution caused by private passenger cars because some of the data used in this study were collected from references from other countries. Therefore, a future study is required to determine the actual emissions of different vehicle categories and fuels. Future studies should focus on how the implementation of the Euro 4 in Indonesia could work as planned.

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# Chapter 4
# Correlation Between Meteorological Variables, Air Quality, and the COVID-19 Pandemic Events

## 4.1 Introduction

The problem of air quality and air pollution has been a concern not only for individual cities or countries but also at a global level. Air pollution has negative effects on the economy and health of people residing in affected areas (Rodríguez-Urrego and Rodríguez-Urrego, 2020; Isaifan, 2020). Climate change has the potential to impact air quality through changes in weather patterns and meteorological conditions that create environments favorable for the accumulation of pollutants. This can result in an increased frequency, severity, and duration of heat waves, air stagnation events, and precipitation (X. Sun et al., 2022). For instance, a study revealed that droughts in the southwestern region of the United States of America have the potential to escalate wildfires and dust, consequently exacerbating the levels of particulate matter (PM) pollution (Berman et al., 2017). Additionally, warming climates can intensify ozone ($O_3$) pollution (Xu et al., 2023). Scientists have discovered that air quality can be influenced by climate change and extreme weather events, and conversely, these events can also be impacted by air quality. Heatwaves, droughts, wildfires, cold waves, snowfall, and flooding have all been identified as factors that can have an effect on the quality of both air and water. For instance, stagnant air during heatwaves traps pollutants, leading to increased surface $O_3$ levels, whereas drought and heat can fuel wildfires and produce hazardous smoke. In contrast, cold waves can cause air pollution to accumulate (Peterson et al., 2014). Pollutants released into the atmosphere have the potential to induce alterations in climate patterns, whereby $O_3$ plays a role in promoting warming, while PM can have either warming or cooling impacts. Furthermore, air temperature and precipitation can exert an influence on the overall quality of the air (Melamed et al., 2016). The correlation between air pollution and climate change emphasizes the necessity for collaborative endeavours in tackling these concerns. The 2020 World Air Quality Report stated that in previous years, South and East Asia had the highest levels of pollution, with Bangladesh, China, India, and Pakistan accounting for almost all of the 50 most polluted cities worldwide (Mishra & Kulshrestha, 2021). The COVID-19 pandemic of 2019 had a significant impact on the air quality during the year 2020. The implementation of lockdown measures resulted in temporary reductions in the consumption of fossil fuels, which in turn led to a decrease in air pollution levels. As a result, 65 percent (%) of cities and 84% of countries saw improvements in air quality in 2020. Nevertheless, the enhancements achieved may prove to be temporary since the levels of pollutants are expected to bounce back (Tian et al., 2021). Additionally, extreme air pollution events, such as wildfires and dust storms, in 2020 that were linked to climate change and agricultural practices resulted in significant air pollution spikes and greenhouse gas emissions. Despite the ongoing contribution of burning fossil fuels and industrialization to global air pollution, the pursuit of addressing climate change and air pollution is progressively proving advantageous (Raihan et al., 2022). Many studies have reported a significant reduction in air pollutant concentrations owing to the lockdown implemented in the country. The cities that had better air quality in 2020 were Singapore (-38%), Wuhan (-18%), Seoul (-16%), and Delhi (-15%) (Adam et al., 2021; Ali et al., 2021; Karuppasamy et al., 2020). Numerous studies, including those by Huang et al. (2020); Sahoo et al. (2020); Sulaymon et al. (2021), and Sarmadi et al. (2021), have investigated the correlation between air quality, meteorological parameters, and the COVID-19 pandemic. Sarmadi et al. (2021) concentrated on the timeframe spanning from 2020 to 2021, whereas the remaining three studies examined various months within the year 2020. A significant portion of the research articles that were published stemmed from brief observations conducted during the lockdown period. However, they did not consider long-term meteorological variables in the long run (He et al., 2020; Linares et al., 2021). Rapid population growth and economic development in Southeast Asia have led to significant challenges of air pollution. Fine particulate matter ($PM_{2.5}$) emissions originate from diverse sources across different countries, such as construction, industry, and transportation. Additionally, Southeast Asia is susceptible to wildfires, further contributing to the presence of $PM_{2.5}$ in the region (Phairuang et al., 2020). However, in 2020, there were fewer fires than in 2019 because the dry season was wetter. This led to a 70% improvement in air quality in

Southeast Asian cities by 2020 (Kanniah et al., 2020). There is also a specific case in Indonesia where the air quality of every city worsened between 2018 and 2019 (Benchrif et al., 2021). Due to the COVID-19 pandemic restrictions, the yearly levels of $PM_{2.5}$ in each urban area showed enhancement in 2020 when contrasted with those in 2018. For instance, the local government of Jakarta introduced many regulations related to air quality, such as odd and even number rules (starting September 9, 2019); limiting the mobility of older vehicles; more choices of public transportation; and new regulations such as mandatory emission tests, developing bigger pedestrian walkways, and more parks (Purwadi et al., 2020). Despite the endeavours made by the local government to enhance the air quality, Jakarta still grapples with poor air quality. This predicament poses a significant challenge for the provincial government of Jakarta and other key stakeholders who are dedicated to enhancing the air quality in the region. It should also be noted that the slow implementation of Euro 4 is related to the several reasons described above. The lack of enforcement and socialization of residents has also slowed implementation (Greenstone & Fan, 2019). Identifying the cause or source of air pollution is also essential; the Government of Indonesia can then choose effective strategies to resolve air pollution and develop and implement effective policies to reduce emissions (Gunawan et al., 2017). The current study was initiated due to the deteriorating air quality in Jakarta. Despite the many ongoing efforts of the government to resolve air quality issues, from improving public transportation to issuing air-quality-related regulations, the results are yet to be elucidated. A comprehensive comprehension of the circumstances can aid in assessing whether the existing strategies will successfully accomplish the government's objective of diminishing air pollutant emissions, or if alternative approaches should be explored. The objective of this study was to examine the potential associations between meteorological variables and air pollution or air quality in a city, as well as the impact of the COVID-19 pandemic-related regulations on vehicle mobility. The objective of the current study was to examine the impact of mobility limitations implemented during the pandemic period spanning from 2020 to 2021 on the quality of air, while also conducting a comparative analysis of air quality data from Jakarta over a four-year period, encompassing 2018 to 2019 (pre-pandemic) and

2020 to 2021 (pandemic period). Additionally, this study aimed to analyse other factors, such as weather conditions, which may have influenced the air quality in Jakarta between 2018 and 2021.

## 4.2 Materials and Methods

### 4.2.1 Study area and data Collection

Jakarta, the capital region of Indonesia, is divided into five cities and one municipality (Figure 4.1). The total area of Jakarta is 7,659.02 km$^2$, and the total population in 2019, 2020, and 2021 was 10,557,810, 10,562,088, and 10,609,681, respectively. Jakarta is renowned for its high population density, with a projected figure surpassing 16,000 individuals per square kilometer (km$^2$). A commuter survey carried out by the National Statistics Agency of Jakarta revealed that around 2.43 million commuters journey within, to, and from the city on a daily basis.

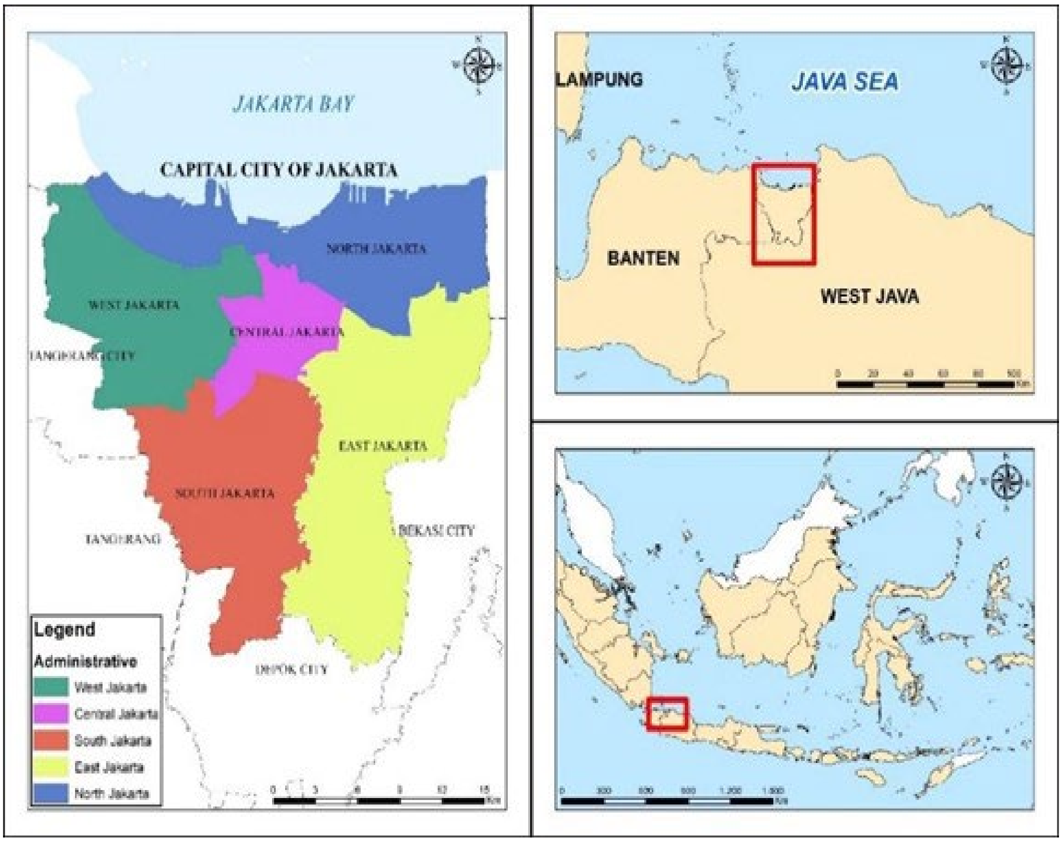



**Figure 4.1** Geographic location of the study area in Jakarta, the capital region of Indonesia

Limited mass public transportation has increased vehicle ownership, in contrast to the growth in the length of roads. Traffic congestion in Jakarta typically arises during peak hours, such as in the morning as individuals commence their workday and, in the evening, as they make their way back home. Air quality in Jakarta has been one of the worst among Asian countries in recent years, owing to the significant number of vehicles and traffic jams. Air pollution stemming from automobiles is an inescapable reality in urban areas. The five types of mass public transportation in Jakarta are commuter lines, TransJakarta buses, mass rapid transit (MRT), and light rail transit (LRT) managed by the local government in Jakarta; taxis; and online transportation (operated by private companies such as Gojek and Grab) (Oktorini & Barus, 2022). The key pollutants considered in this study were carbon monoxide (CO), hydrocarbon (HC), nitric oxide ($NO_x$), particulate matter 10 ($PM_{10}$), carbon dioxide ($CO_2$), and sulphur dioxide ($SO_2$) as measured by the local government of Jakarta at five monitoring stations: Bundaran HI, Kelapa Gading, Kebun Jeruk, Jagakarsa, and Lubang Buaya (Figure 4.2). Given that the monitoring stations failed to gather $PM_{2.5}$ data in both 2018 and 2019, the essential $PM_{2.5}$ data was acquired from the Swiss Air Quality Technology Company (IQAir), a Swiss company specializing in air quality technology. Daily temperature, rainfall, wind speed, humidity, and sunshine hours in Jakarta were obtained from the Indonesian Agency for Meteorology, Climatology, and Geophysics (*Badan Meteorologi, Klimatologi, dan Geofisika*) located in Jakarta. All the meteorological and air quality data, collected on a daily basis, spanning from 2018 to 2021 were acquired. The Health Office of Jakarta provided information regarding the implemented restriction measures and the count of COVID-19 victims on daily basis.

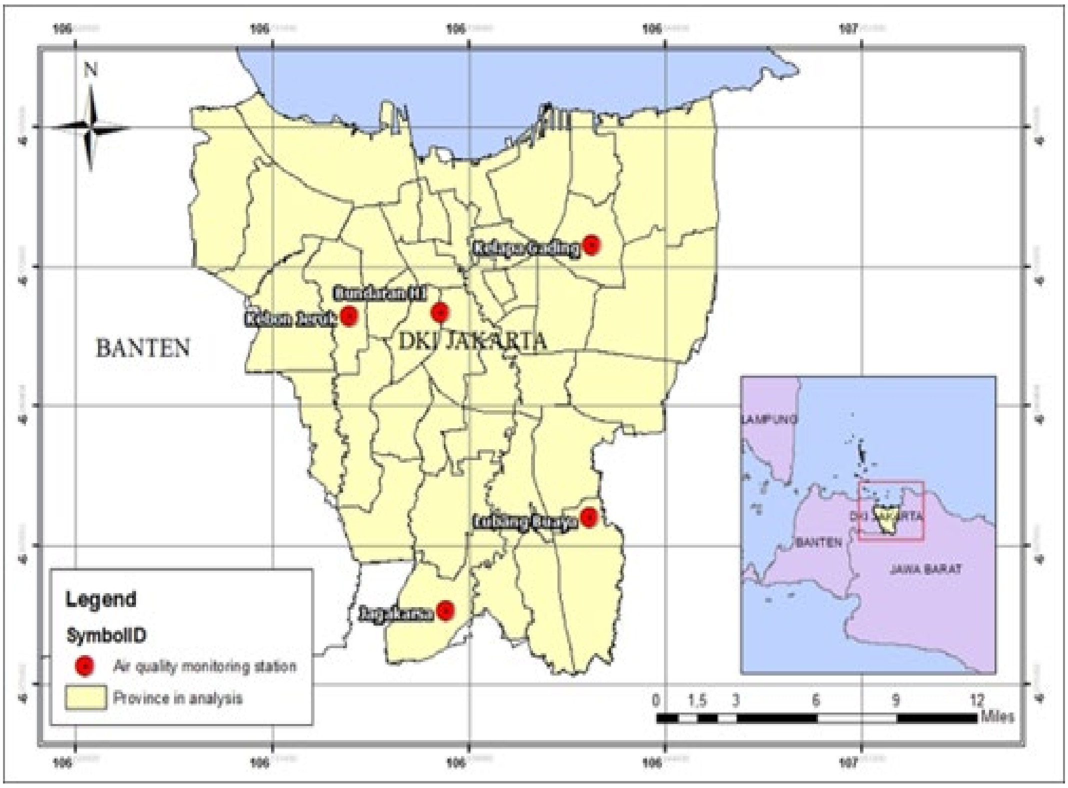



**Figure 4.2** Map of the sampling locations and air quality monitoring stations in Jakarta

### *4.2.2 Data analysis*

Microsoft excel (Microsoft 365, version 2309) was utilized to summarize all the data collected. Scatter plots were employed to detect the initial connections between (Khan & Khan, 2009). Statistical package for the social sciences (SPSS) software (version 16.0) was used to analyse meteorological characteristics, air quality data, and pandemic events. As the data used for this research project did not follow a normal distribution, the Spearman correlation test was employed as an empirical method to examine the relationship between air pollutants, meteorological variables, and COVID-19 in Jakarta. The Spearman correlation technique possesses ample strength to evaluate the direction and extent of the monotonic relationship between variables (Bashir et al., 2020).

## 4.3 Results and Discussion

### *4.3.1 Overview of the Study Area*

According to the annual report by BMKG, (2020), the Indonesian Agency for Meteorology, Climatology, and Geophysics, the extreme temperature change in Jakarta in 2020 was much higher than the average temperature from 1981 to 2010. December and January are the months when Java experiences the highest amount of rainfall. When analysing the average rainfall data between 1981 and 2010, it is evident that the precipitation levels were greater in the present year compared to previous years. News reports mentioned Jakarta multiple times as one of the cities with the poorest air quality in Asia and Southeast Asia. Air quality data from Jakarta, as reported in IQAir, showed that on Monday, June 20, 2022, Jakarta ranked second after Santiago, Chile, as the city with the worst air quality. The concentration of $PM_{2.5}$ in Jakarta was 27 times higher than that recommended by the World Health Organization. IQAir, (2018) identified Jakarta as one of the most polluted cities in Southeast Asia. In the report by IQAir, (2019), Jakarta was classified as the most polluted capital city in the region. Jakarta showed a higher ranking this year compared to the previous year and experienced enhanced air quality as a result of measures taken during the COVID-19 pandemic, as reported by IQAir (2020). A year later, IQAir, (2021) stated that Jakarta's ranking improved even further compared to 2020. The Government of Indonesia monitors the quality of critical air pollutants, including $PM_{10}$, $SO_2$, CO, $O_3$, and $NO_2$ (nitrogen dioxide), as mandated by the Environment Ministry Regulation No.12/2010. The transportation sector was the primary source of the following air pollutant parameters: $NO_x$ (84%), $PM_{10}$ (76%), and CO (90%). Despite the relatively modest growth in population (around 1%) and road length (less than 1%), the surge in the number of vehicles was substantial, surpassing 10%. In fact, the total number of vehicles in Jakarta in 2020 was twice the population count of the city. Heavy traffic congestion caused by the high volume of vehicles and inadequate infrastructure leads to elevated levels of air pollutants. The age limitation for vehicles in Indonesia is only applied to vehicles used for public transportation and not to privately owned cars or motorcycles (Local regulation No. 5 Year 2014). Private car owners are not required by any regulations to have garages. This is one reason that owning cars is easy for people in Jakarta. The demand for mobility and subsidies is expected to drive an annual increase of 5.9% in energy consumption in the transportation sector from 2012 to 2035. The insufficiency of trustworthy public transportation is projected to sustain the increase in private vehicle ownership. The number of passenger light-duty vehicles in Indonesia grew from 10.4 million in 2012 to 21.3 million in 2020 and is projected to reach 37.5 million in 2035. Emission tests conducted on approximately 12,024 vehicles in Jakarta in 2017 (92% with an age range of 1–10 years, 7% between 11–20 years, and 1% over 20 years old) found that almost 12% (or approximately 1,400) of vehicles did not pass the test. More than 50% of the cars over 10 years of age failed the test (Open Data Jakarta, 2018). Vehicles with operation periods exceeding 40 years are still in use. In spite of surpassing a 40-year operational span, there are still vehicles that remain in active service. With regards to the assessment of emissions, a total of 9,581 vehicles underwent testing in 2019. Among these, a notable 3.4% (322 vehicles) failed to meet the required standards and did not pass the test. Based on Regulation of Jakarta's Governor No. 66 Year 2020, vehicles over 3 years of age must carry out and pass emission tests. In the first semester of 2020, of the 3,869 vehicles tested, 2.5 percent of the vehicles (98 vehicles) did not pass the test.

#### *4.3.2 COVID-19 Countermeasures Policy in Jakarta*

Indonesian patients with COVID-19 were first identified on February 14, 2020 in Jakarta. Subsequently, there has been a rise in the number of COVID-19 cases among patients in Jakarta, a city considered as one of the epicenters of the pandemic. According to the Government of Indonesia data, there were more than six million cases and approximately 157,000 deaths as of June 19, 2022, attributed to COVID-19. Until June 21, 2022, the total cumulative number of positive COVID-19 cases in Jakarta was 1,258,665, with 1,238,059 declared cured, 15,309 dead, and 5,297 hospitalized. The Indonesian Government has implemented various measures to limit transportation and industrial operations in light of the pandemic. The following is a chronology of the regulations regarding the limitations on vehicle usage in Jakarta (Anugerah et al., 2021):

a. On March 14, 2020, all tourist places were closed for two weeks.

b. On March 16, 2020, all schools were closed for two weeks.

c. On March 16, 2020, all TransJakarta buses, MRT, and LRT were limited to running only from 06.00 a.m. (before noon) to 06.00 p.m. (after noon) and with specific numbers of fleets (TransJakarta, 248 routes reduced to 13 routes; MRT, 16 fleets to only 4 fleets with arrival only every 20 minutes instead of 5 to 10 minutes; and LRT, from every 10 minutes to 30 minutes) for two weeks.

d. On March 17, 2020, all TransJakarta buses, MRT, and LRT resumed their regular working hours and fleet sizes; however, they limited the total number of passengers per fleet.

e. On March 16, 2020, the rules for odd and even numbered vehicles in a wider area were stopped, but applied again on August 3, 2020.

f. On March 16, 2020, letters from the Jakarta local government regarding suggestions for working from home were disseminated to all companies in Jakarta, and approximately 220 companies, including ministries and government agencies, immediately applied the work-from-home system.

g. On March 16, 2020, all religious events were suspended.

h. Indonesia's large-scale social restrictions (PSBB - *Pembatasan Sosial Berskala Besar*) were effectively implemented on April 10, 2020, based on the local government of Jakarta regulation No. 33, Year 2020 and the Ministry of Health Regulation No.9, Year 2020 Article 13 on the limitation of transportation mode.

i. The PSBB Transition was effectively applied from June 5 to June 18, 2020, and another PSBB Transition from June 19 to July 2, 2020. Two additional extensions of the PSBB Transition were applied until July 30, 2020. Other extensions were from July 31 to August 13, 2020. Odd and even numbered vehicles were used again starting August 3, 2020. The MRT began to normalize again on June 3, 2020. The critical period in which transportation limitations in Jakarta were applied was from March 16 to the end of May 2020.

j. Community activities restriction enforcement (PPKM; *Pemberlakuan Pembatasan Kegiatan Masyarakat*) Levelling represents the culmination of previous government policies and is implemented according to specific conditions in each region. This policy was introduced as previous policies were deemed unsuccessful in managing the increasing number of COVID-19 cases, which continued to rise in Indonesia. This policy was applied from January 11, 2021 to December 30, 2022.

### *4.3.3 Correlation between Air Quality Parameters*

This study identified various correlations between air quality parameters such as $PM_{2.5}$, $PM_{10}$, CO, $O_3$, $SO_2$, and $NO_2$. Positive linear correlations were observed between $PM_{2.5}$– $PM_{10}$ ($R^2$ or R-squared = 0.53), $PM_{10}$–CO ($R^2$ = 0.03), $PM_{10}$– $O_3$ ($R^2$ = 0.11), and CO– $NO_2$ ($R^2$ = 0.50) concentrations. The levels of $PM_{2.5}$ and PM10, which are parameters used to measure ambient air quality, exhibit a strong positive correlation. This can be attributed to the fact that they originate from the same source and are influenced by similar meteorological conditions (Zoran et al., 2020). $PM_{2.5}$ and $PM_{10}$ are fine particulate matter; however, $PM_{10}$ includes larger particles that can be inhaled into the upper respiratory tract, whereas $PM_{2.5}$ includes smaller particles that can reach the lower respiratory tract and enter the bloodstream, causing more severe health effects (Ramadan et al., 2023). Strong correlations were also noted between CO and $NO_2$. These two indicators of air quality are typically linked to shared origins, including vehicle emissions, industrial discharges, and biomass combustion. Both CO and $NO_2$ are produced during the incomplete combustion of fuels and are emitted from the same sources, leading to their co-occurrence in the atmosphere (Shao et al., 2022). Positive nonlinear correlations were observed between $PM_{10}$– $SO_2$ ($R^2$ = 0.03), $PM_{2.5}$ – $SO_2$ ($R^2$ = 0.39), $PM_{2.5}$ – CO ($R^2$ = 0.29) and – $NO_2$ ($R^2$ = 0.46), and $SO_2$ – $NO_2$ ($R^2$ = 0.38) and – CO ($R^2$ = 0.51). In contrast, a negative linear correlation was observed between CO and $O_3$ ($R^2$ = 0.27). Negative nonlinear correlations were observed in $PM_{2.5}$– $O_3$ ($R^2$ = 0.42) and $SO_2$– $O_3$ ($R^2$ = 0.40) and – $NO_2$ ($R^2$ = 0.38). The levels of the atmospheric pollutants CO and $O_3$ exhibit an inverse relationship due to the fact that CO can serve as a reservoir for $O_3$ by undergoing a chemical reaction with it to produce $CO_2$, thereby impeding the generation of $O_3$. Additionally, CO has the ability to diminish the quantity of sunlight necessary for the formation of $O_3$, which is a photochemical process reliant on sunlight (Yao et al., 2023). Therefore, high levels of CO can limit $O_3$ formation in the atmosphere, leading to a negative correlation between these two pollutants (Liu et al., 2020). The formation mechanisms of ground-level $O_3$ and PM differ, resulting in an inverse relationship between the two. Particulate matter is generated mainly by the combustion of fossil fuels and industrial activities, whereas $O_3$ is formed by the photochemical reaction of volatile organic compounds and $NO_x$ in the presence of sunlight. Ozone production escalates during sunny weather due to photochemical reactions, while particulate matter concentration decreases as a result of dispersion and dilution by atmospheric mixing. In contrast, during cloudy weather, the concentration of PM increases because it is trapped near the surface in the absence of atmospheric mixing, whereas the production of $O_3$ decreases because of the lack of sunlight. As a result, there tends to be a reverse association between $O_3$ and PM levels (Ravina et al., 2022; S. Zhao et al., 2020). The scatterplots of all air pollutants from 2018 to 2021 are shown in Figure 4.3.

The first four graphics in Figure 4.3 are positive linear correlations. The linear regression lines indicating the strength and direction of their correlations. In summary, $PM_{2.5}$–$PM_{10}$ and CO–$NO_2$ shows stronger correlations compared to $PM_{10}$–CO and $PM_{10}$–$O_3$.

$PM_{2.5}$–$PM_{10}$ ($R^2 = 0.53$): This scatter plot would show a moderately strong positive linear relationship, indicating that as $PM_{2.5}$ concentrations increase, $PM_{10}$ concentrations also tend to increase. The $R^2$ value of 0.53 suggests that 53% of the variation in $PM_{10}$ concentrations can be explained by variations in $PM_{2.5}$ concentrations.

$PM_{10}$–CO ($R^2 = 0.03$): This scatter plot would show a very weak positive linear relationship, indicating that there is little to no linear association between $PM_{10}$ and CO concentrations. The $R^2$ value of 0.03 suggests that only 3% of the variation in CO concentrations can be explained by variations in $PM_{10}$ concentrations.

$PM_{10}$– $O_3$ ($R^2 = 0.11$): This scatter plot would show a weak positive linear relationship, indicating a slight tendency for $PM_{10}$ and $O_3$ concentrations to increase together. The $R^2$ value of 0.11 suggests that 11% of the variation in $O_3$ concentrations can be explained by variations in $PM_{10}$ concentrations.

$CO–NO_2$ ($R^2 = 0.50$): This scatter plot would show a moderately strong positive linear relationship, indicating that as CO concentrations increase, $NO_2$ concentrations also tend to increase. The $R^2$ value of 0.50 suggests that 50% of the variation in $NO_2$ concentrations can be explained by variations in CO concentrations.

The fifth graphics in Figure 4.3 with a downward-sloping linear regression line indicates a negative linear correlation. The downward-sloping line would visually represent this inverse relationship. $CO–O_3$ ($R^2 = 0.27$): This scatter plot would show a negative linear relationship, indicating that as CO concentrations increase, $O_3$ concentrations tend to decrease. The $R^2$ value of 0.27 suggests that 27% of the variation in $O_3$ concentrations can be explained by variations in CO concentrations.

The sixth until eleventh graphics in Figure 4.3 display scatter plots for each pair of pollutants, with curves indicating the nature of their nonlinear correlations. Unlike linear correlations, these relationships would not be represented by straight lines but by curves that best fit the data points, showing the strength and direction of their nonlinear associations.

$PM_{10}–SO_2$ ($R^2 = 0.03$): This scatter plot would show a very weak positive nonlinear relationship, indicating that there is little to no association between $PM_{10}$ and $SO_2$ concentrations. The $R^2$ value of 0.03 suggests that only 3% of the variation in $SO_2$ concentrations can be explained by variations in $PM_{10}$ concentrations.

$PM_{2.5}–SO_2$, $PM_{2.5}–CO$, and $PM_{2.5}–NO_2$ ($R^2 = 0.0002$): These scatter plot showed very weak positive nonlinear relationships, indicating that as $PM_{2.5}$ concentrations increase, $SO_2$, CO, and $NO_2$ concentrations also tend to increase in a nonlinear manner. The $R^2$ value of 0.0002 suggests that only 0.02% of the variation in $SO_2$, CO, and $NO_2$ concentrations can be explained by variations in $PM_{2.5}$ concentrations.

$SO_2$–$NO_2$ ($R^2$ = 0.38): This scatter plot would show a moderate positive nonlinear relationship, indicating that as $SO_2$ concentrations increase, $NO_2$ concentrations also tend to increase in a nonlinear manner. The $R^2$ value of 0.38 suggests that 38% of the variation in $NO_2$ concentrations can be explained by variations in $SO_2$ concentrations.

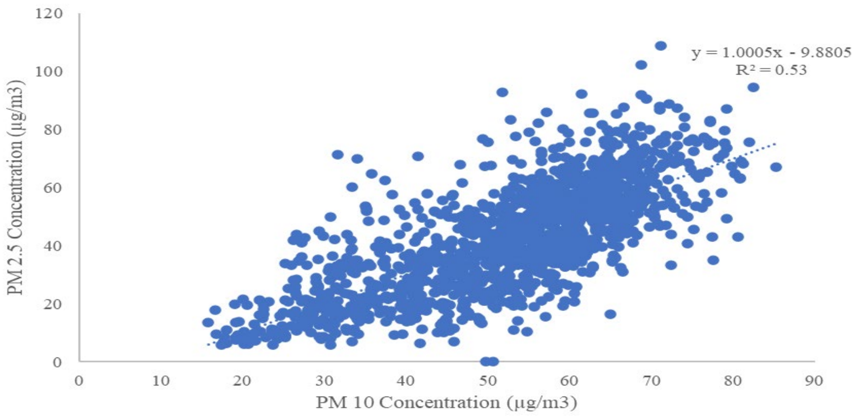
$SO_2$–CO ($R^2$ = 0.51): This scatter plot would show a relatively strong positive nonlinear relationship, indicating that as $SO^2$ concentrations increase, CO concentrations also tend to increase in a nonlinear manner. The $R^2$ value of 0.51 suggests that 51% of the variation in CO concentrations can be explained by variations in $SO_2$ concentrations.

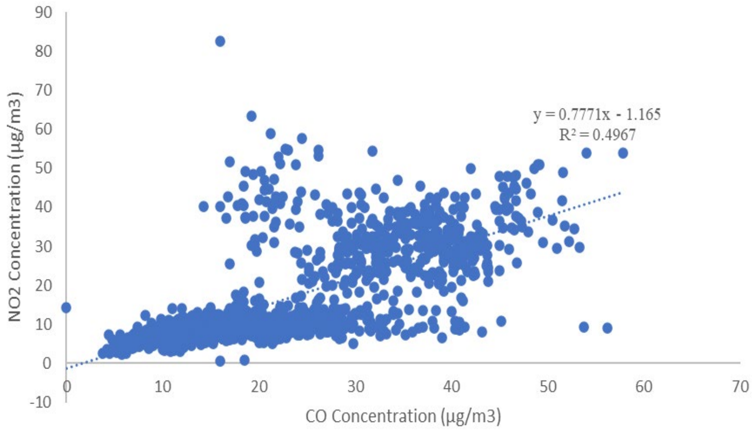
The last three graphics in Figure 4.3 display scatter plots for each pair of pollutants, with curves indicating the nature of their negative nonlinear correlations. These relationships would not be represented by straight lines but by curves that best fit the data points, showing the strength and direction of their nonlinear associations. In summary, the graphics would illustrate that higher levels of $PM_{2.5}$ and $SO_2$ are generally associated with lower levels of $O_3$ and $NO_2$, respectively, with moderate degrees of explanatory power as indicated by the $R^2$ values. The curved lines on the scatter plots would represent these inverse nonlinear relationships.

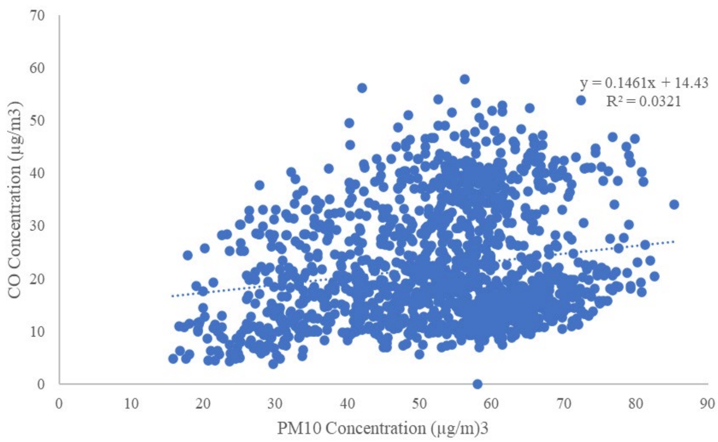
$PM_{2.5}$ – $O_3$ ($R^2$ = 0.213): This scatter plot would show a negative nonlinear relationship, indicating that as $PM^{2.5}$ concentrations increase, $O_3$ concentrations tend to decrease in a nonlinear manner. The $R^2$ value of 0.213 suggests that 21% of the variation in $O_3$ concentrations can be explained by variations in $PM_{2.5}$ concentrations.

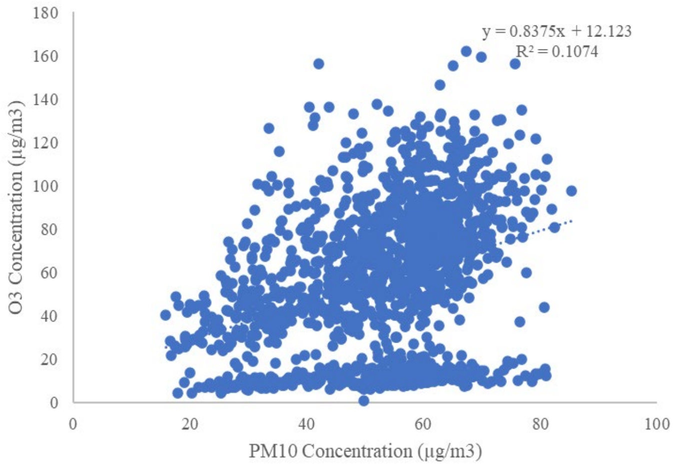
$SO_2$ – $O^3$ ($R^2$ = 0.40): This scatter plot would show a negative nonlinear relationship, indicating that as $SO_2$ concentrations increase, $O^3$ concentrations tend to decrease in a nonlinear manner. The $R^2$ value of 0.40 suggests that 40% of the variation in $O^3$ concentrations can be explained by variations in $SO_2$ concentrations.

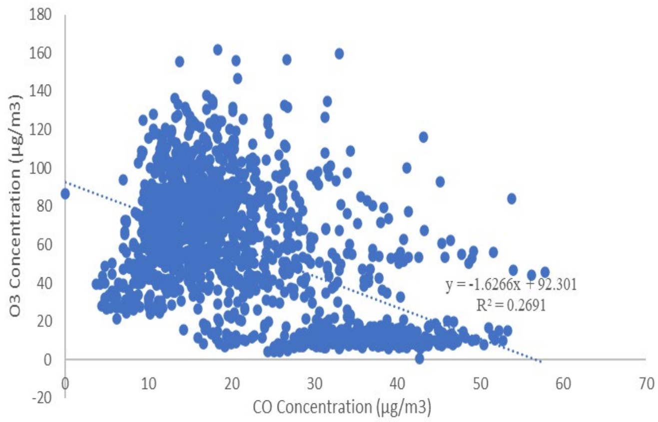
$O_3$ – $NO_2$ ($R^2$ = 0.36): This scatter plot would show a negative nonlinear relationship, indicating that as $O_3$ concentrations increase, $NO_2$ concentrations tend to decrease in a nonlinear manner. The $R^2$ value of 0.36 suggests that 36% of the variation in $NO_2$ concentrations can be explained by variations in $O_3$ concentrations.

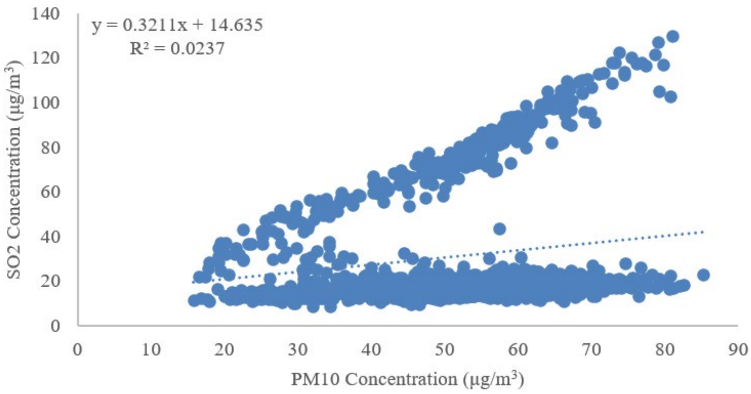


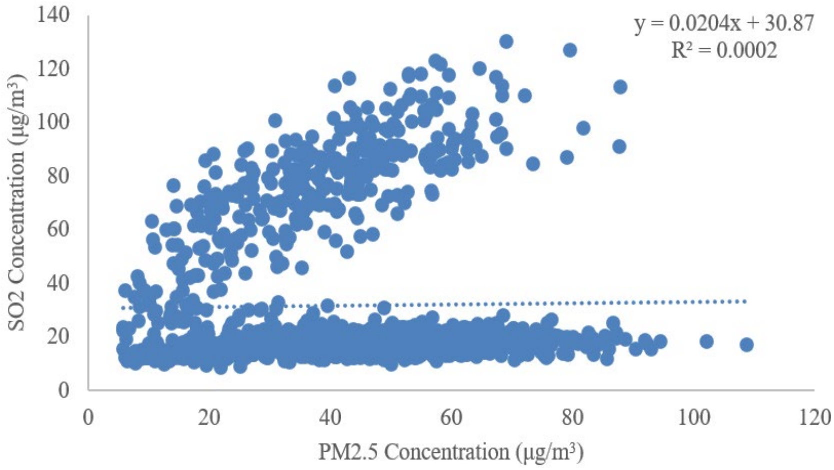



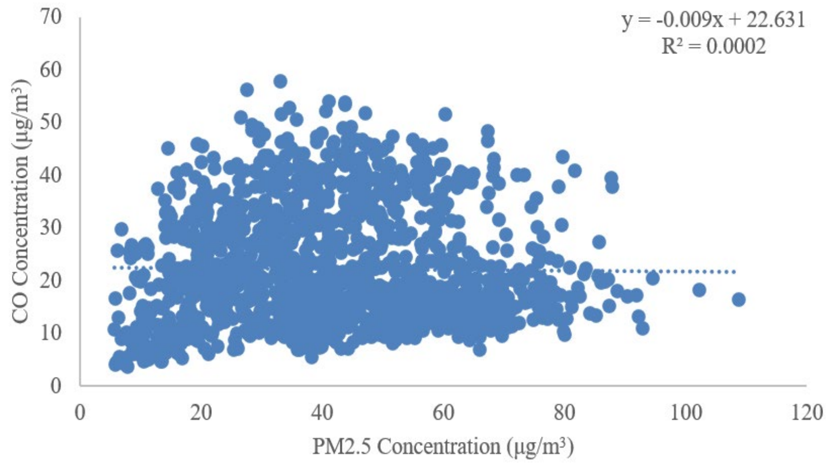



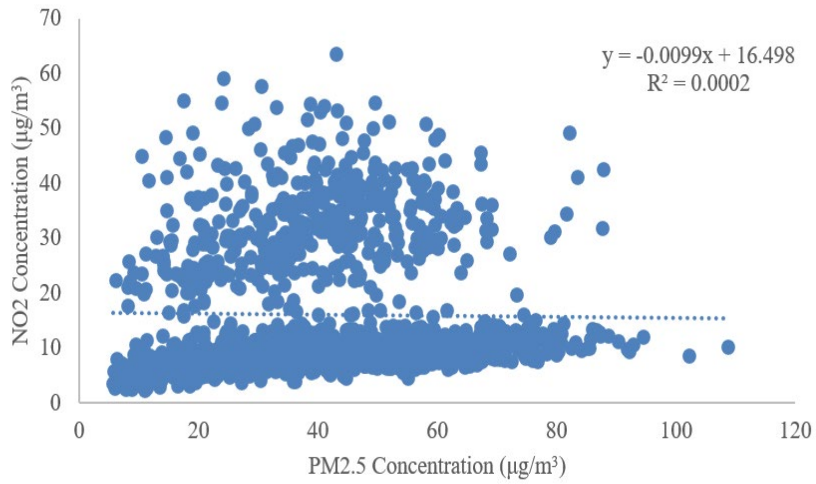

y = 0.8375x + 12.123
R² = 0.1074
O3 Concentration (µg/m3)
PM10 Concentration (µg/m3)
0
20
40
60
80
100
120
140
160
180
0
20
40
60
80
100

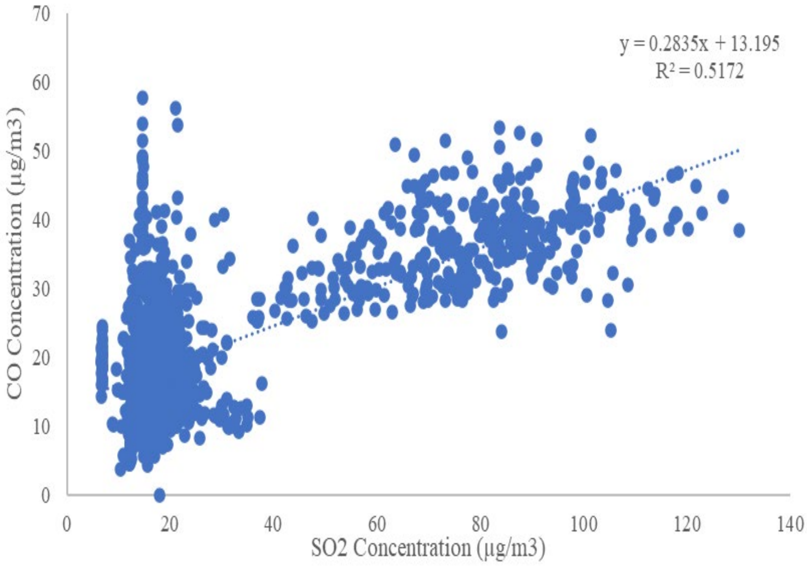

y = -1.6266x + 92.301
R² = 0.2691
O3 Concentration (µg/m3)
CO Concentration (µg/m3)
-20
0
20
40
60
80
100
120
140
160
180
0
10
20
30
40
50
60
70


y = 0.3211x + 14.635
R² = 0.0237
SO2 Concentration (µg/m³)
PM10 Concentration (µg/m³)
0
20
40
60
80
100
120
140
0
10
20
30
40
50
60
70
80
90

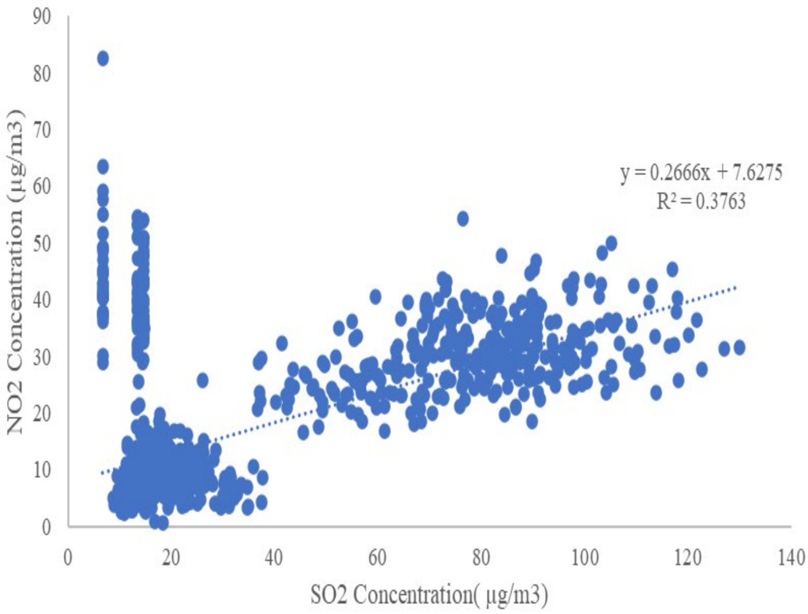

y = 0.0204x + 30.87
R² = 0.0002
SO2 Concentration (μg/m³)
PM2.5 Concentration (μg/m³)


y = -0.009x + 22.631
R² = 0.0002
CO Concentration (μg/m³)
PM2.5 Concentration (μg/m³)


y = -0.0099x + 16.498
R² = 0.0002
NO2 Concentration (μg/m³)
PM2.5 Concentration (μg/m³)



y = 0.2835x + 13.195
R² = 0.5172
CO Concentration (µg/m3)
SO2 Concentration (µg/m3)
0
10
20
30
40
50
60
70
0
20
40
60
80
100
120
140

y = 0.2666x + 7.6275
R² = 0.3763
NO2 Concentration (µg/m3)
SO2 Concentration( µg/m3)
0
10
20
30
40
50
60
70
80
90
0
20
40
60
80
100
120
140

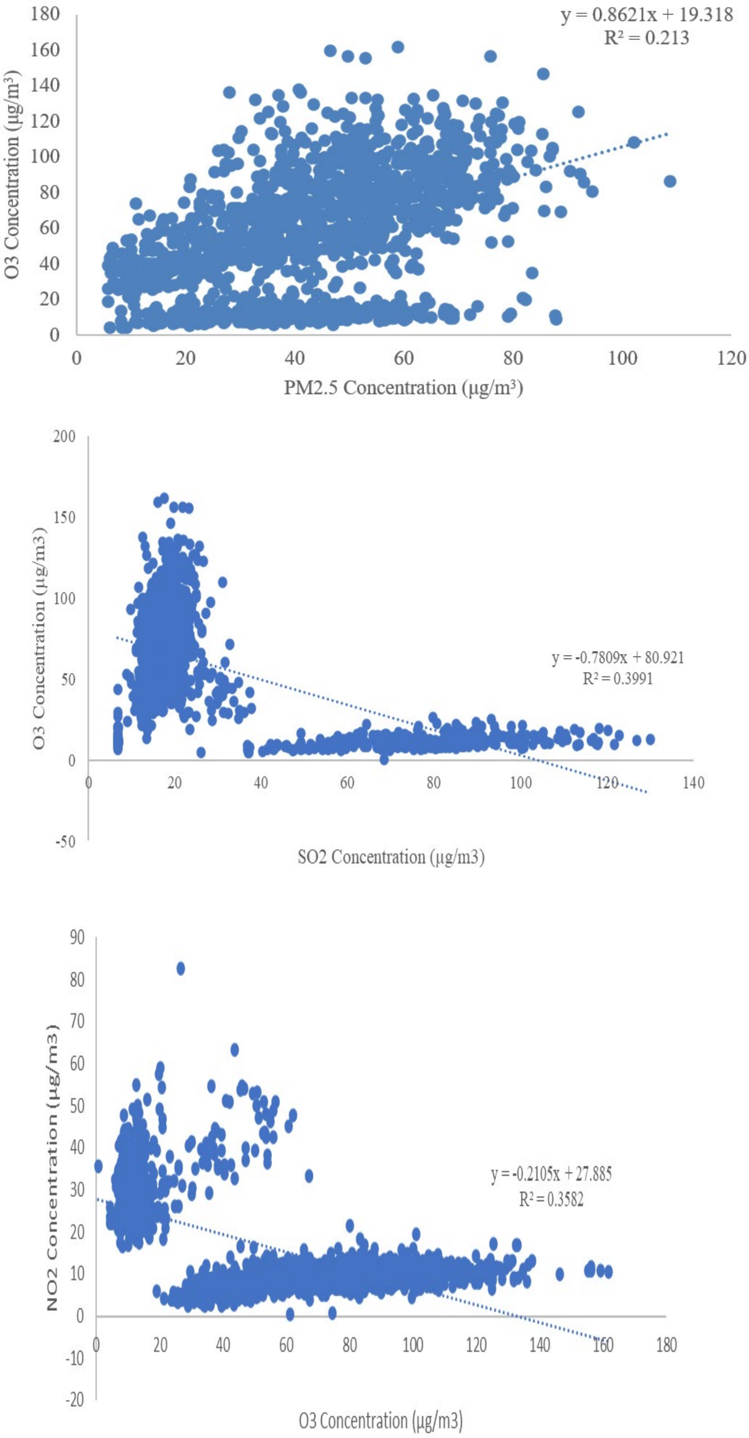



**Figure 4.3** Scatterplots of all air quality parameter during 2018–2021

To understand more about the non-linear correlation graphics, Figure 4.4 demonstrate the different results of graphics for $PM_{10}$ - $SO_2$ when data from 2018 to 2021 was calculated separately between Before COVID and During COVID. Before COVID, $PM_{10}$–$SO_2$ ($R^2$ = 0.0014) calculation resulted a scatter plot that would show a very weak positive nonlinear relationship, indicating that there is little to no association between $PM_{10}$ and $SO_2$ concentrations. The $R^2$ value of 0.0014 suggests that only 0.14% of the variation in $SO_2$ concentrations can be explained by variations in $PM_{10}$ concentrations. During COVID, $PM_{10}$–$SO_2$ ($R^2$ = 0.1193) calculation resulted a scatter plot would show also a very weak positive nonlinear relationship, however, the $R^2$ value during COVID was bigger than before COVID. The same results also occurred for correlation of $PM_{2.5}$–$SO_2$ as shown in the Figure 4.5.

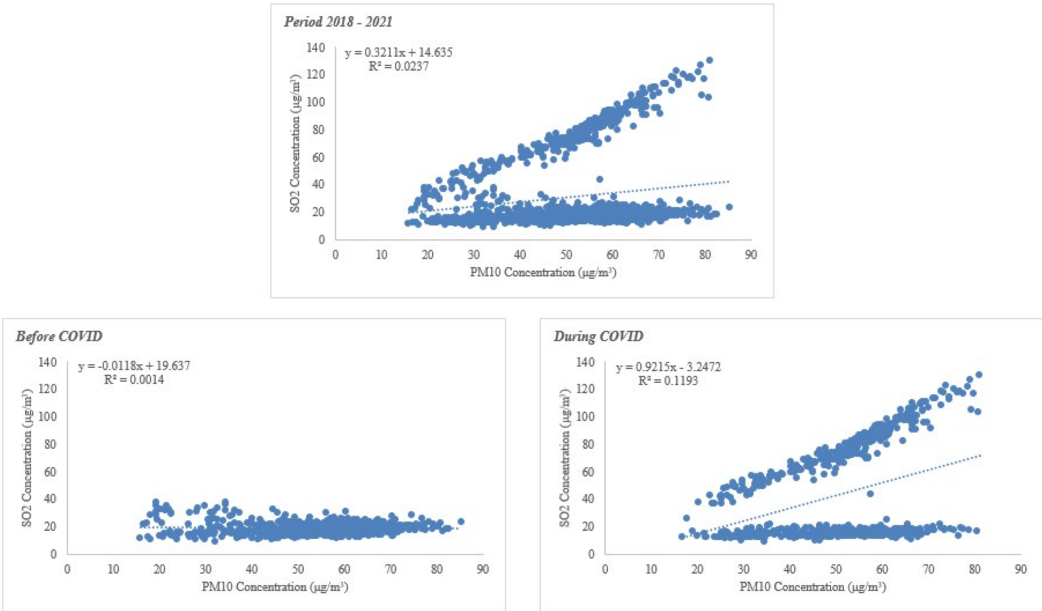



**Figure 4.4** Scatterplots of $PM_{10}$– $SO_2$ Before and During COVID

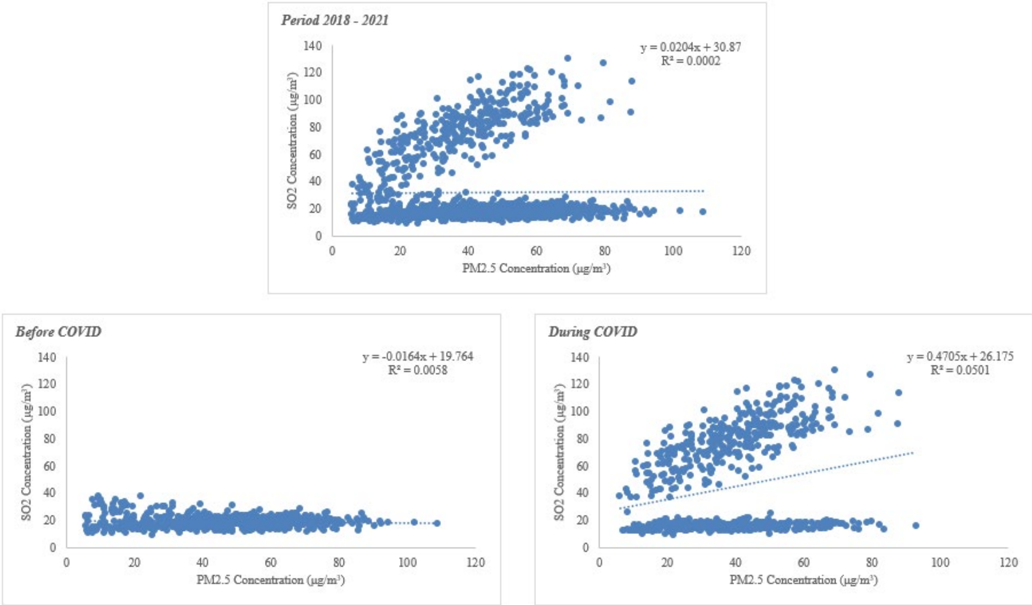



**Figure 4.5** Scatterplots of $PM_{2.5}$– $SO_2$ Before and During COVID

The average concentrations of CO, NO, and $SO_2$ before the COVID-19 pandemic remained mostly constant. However, during COVID-19, the average concentrations were higher than before COVID-19. As shown in Figure 4.6, $PM_{10}$ and $PM_{2.5}$ before and during the COVID-19 episode, had similar average concentrations. However, during the pandemic, there was a noticeable decline in the levels of $PM_{2.5}$ and $O_3$. This decline can be attributed to the decrease in traffic and industrial activities, which in turn resulted in a reduction in the concentration of $PM_{2.5}$. With the implementation of lockdowns and quarantine measures, traffic and industrial activities decreased, leading to low air pollutant emissions. In addition, lower energy usage and variations in weather conditions, such as increased precipitation, wind intensity, and humidity, can also contribute to the decrease in levels of $PM_{2.5}$ and $O_3$ in the air (Anugerah et al., 2021).

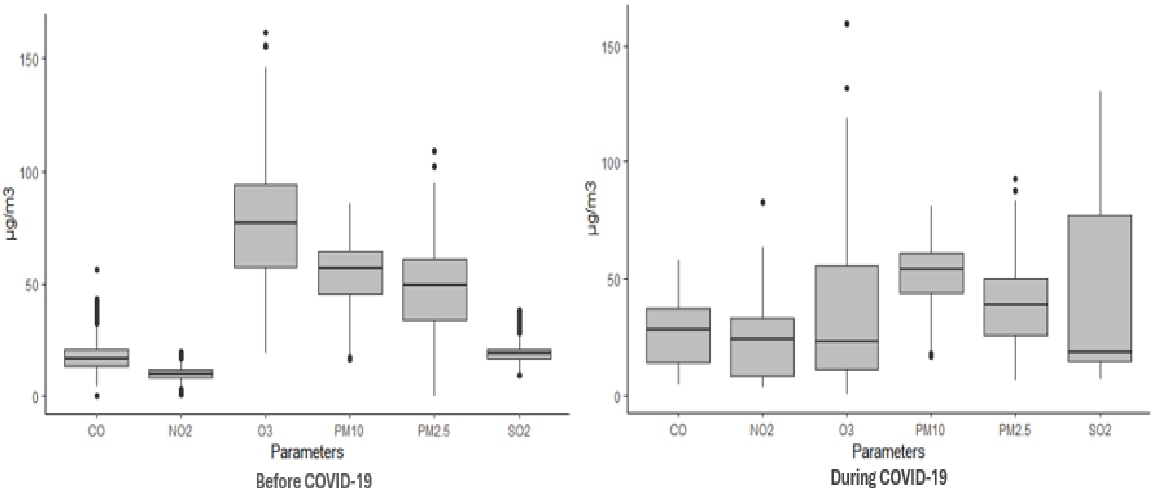



**Figure 4.6** Average concentration of ambient air quality parameter before and during COVID-19

### *4.3.4 Air Quality Parameters in Different Seasons*

Before and during the pandemic, similar average levels of $PM_{10}$ were observed in ambient air during the rainy and dry seasons. However, $PM_{2.5}$ and $O_3$ levels decreased during the pandemic in both the dry and rainy seasons. Moreover, $SO_2$, CO, and $NO_2$ concentrations increased during the pandemic in both seasons. Generally, all air quality parameters were higher during the dry season than during the rainy season (Figure 4.7). As per the Air Quality Report that encompasses the timeframe of 2020 to 2021, there was an observed drop of roughly 5% in $PM_{2.5}$ concentrations in the area. An improvement in air quality was observed in six countries, with Indonesia contributing the most by demonstrating a 16% decrease in annual $PM_{2.5}$. The application of the PPKM level regulation amid the COVID-19 pandemic had consequences on the mobility of people. With reduced vehicle and human activity during COVID-19, but also less improvement in green open spaces, the level of $O_3$ decreased (Stratoulias & Nuthammachot, 2020).

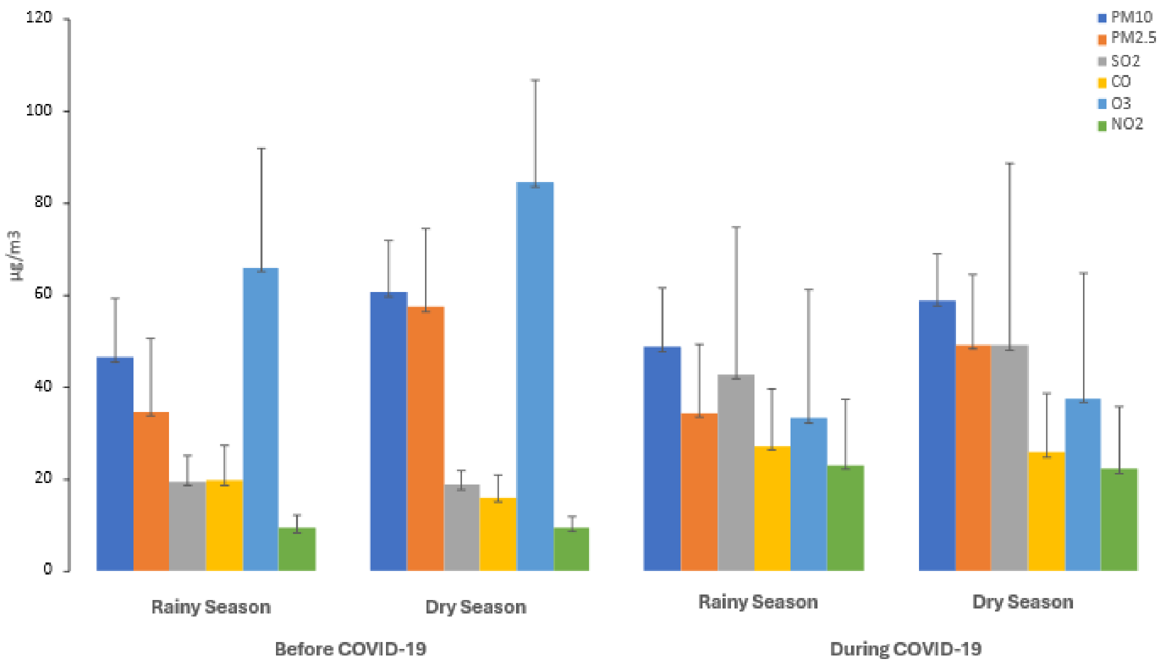



**Figure 4.7** Average level of ambient air quality parameters in different seasons

The decrease in $O_3$ could also be explained by the effect of increased $NO_2$ during COVID-19. According to Li et al. (2014), $NO_x$ and volatile organic compounds are critical precursors to ground-level $O_3$. A negative relationship between $NO_2$ and $O_3$ was also found by Hashim et al. (2021), who explained that the presence of large amounts of NO in the air exerts considerable influence on $O_3$ to form $NO_2$. The research conducted by Wyche et al. (2021) provides evidence to support the idea that a decrease in titration is associated with a significant reduction in $NO_x$ concentrations, especially in the early stages of the pandemic. They also explained that a decrease in total $NO_x$ compared to total non-methane hydrocarbons was a significant factor in the increase in $O_3$ levels in urban areas in Asia and Europe. The rise in levels of $SO_2$, CO, and $NO_2$ observed during the COVID-19 pandemic can be attributed to various factors such as the combustion of household waste, the release of pollutants from coal burning, and the heightened reliance on private vehicles due to perceived hygiene concerns compared to public transportation. The result is also consistent with the findings of Wibowo et al. (2020), who indicated that the use of private vehicles, as well as the implementation of strict health protocols in outdoor areas, led to continued vehicle mobility during the pandemic in Jakarta, rather than a reliance on public transportation. The increase in CO and $NO_2$ is also consistent with the findings of Rendana et al. (2022); concentrations increased owing to the migration of pollution carried in the cardinal directions from east and southeast Jakarta.

### *4.3.5 Description of Meteorological Parameters*

The temperature and wind speed before and during the COVID-19 pandemic were similar at 28–29 degrees Celsius (°C) and 1.3–1.6 speed per strength (m/s), respectively. The humidity before the pandemic in the dry season (71.323%) was lower than that during the pandemic (75.094%), whereas during the rainy season (77.638%), the humidity was only slightly lower than that before the pandemic (78.086%). The rainfall intensity exhibited a significant surge during the pandemic in comparison to the period preceding it. In the dry season, the precipitation escalated from 0.859 mm to 3.132 mm, while in the rainy season, it rose from 8.785 mm to 12.654 mm. This heightened intensity of rainfall during the pandemic highlights the potential impact of global events on weather patterns. The duration of radiation showed a slight decrease during the dry season, from 5.414 h (hour) before the pandemic to 4.440 h during the pandemic. A summary of the meteorological parameters is presented in Table 4.1.

**Table 4.1** Summary of meteorological parameters in Jakarta before and during COVID-19

| Year | Season | Temperature (°C) | Humidity (%) | Rainfall Intensity (mm) | Duration of Radiation (h) | Wind Speed (m/s) |
|---|---|---|---|---|---|---|
| Before COVID-19 Pandemic (2018-2019) | Dry | 28.916 ± 0.825 | 71.323 ± 5.088 | 0.859 ± 3.799 | 5.414 ± 1.982 | 1.300 ± 0.558 |
| | Rainy | 28.317 ± 1.034 | 78.086 ± 5.301 | 8.785 ± 16.098 | 4.264 ± 2.656 | 1.468 ± 0.568 |
| During COVID-19 Pandemic (2020-2021) | Dry | 28.871 ± 0.837 | 75.094 ± 4.829 | 3.132 ± 6.185 | 4.440 ± 2.217 | 1.360 ± 0.528 |
| | Rainy | 28.415 ± 1.033 | 77.638 ± 6.170 | 12.654 ± 22.720 | 4.216 ± 2.557 | 1.535 ± 0.658 |

### *4.3.6 Correlation of Meteorological and Air Quality Parameters*

As shown in Table 4.2, negative correlations were found between humidity or rainfall and $PM_{10}$ or $PM_{2.5}$, indicating that when humidity or rainfall is high, $PM_{10}$ or $PM_{2.5}$ will be low. The data revealed a direct relationship between temperature and $PM_{10}$ as well as $PM_{2.5}$, showing that an increase in temperature leads to higher levels of these particulate matters. No correlation was observed between $NO_2$ and any of the meteorological characteristics. Weak correlations observed among various meteorological parameters and $SO_2$, CO, ground-level ozone $O_3$, radiation, and wind speed to PM. Moderate correlations were found between temperature, humidity, and rainfall and $PM_{10}$ (0.29, 0.38, and 0.36, respectively) and $PM_{2.5}$ (0.30, 0.34, and 0.35, respectively).

**Table 4.2** Correlation of meteorological and air quality parameters

| Parameters | $PM_{10}$ | $PM_{2.5}$ | $SO_2$ | CO | $O_3$ | $NO_2$ |
|---|---|---|---|---|---|---|
| Temperature | 0.299** | 0.303** | 0.060* | -0.076** | 0.153** | -0.032 |
| Humidity | -0.375** | -0.335** | -0.204** | 0.168** | -0.174** | 0.012 |
| Rainfall | -0.363** | -0.346** | -0.100** | 0.149** | -0.166** | 0.039 |
| Radiation | 0.198** | 0.236** | 0.127** | -0.086** | 0.144** | 0.015 |
| Wind speed | -0.134** | -0.200** | -0.063* | -0.080** | -0.085** | -0.033 |

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

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

Notes: White, grey, green, and blue boxes indicate no correlation and weak, moderate, and strong correlations, respectively.

Inhalation of particulate matter, which consists of tiny solid and liquid particles, can lead to negative health impacts due to its complex composition. The concentrations of both $PM_{10}$ and $PM_{2.5}$ in ambient air were found to be affected by a variety of factors, including weather conditions such as temperature, humidity, and rainfall. Previous studies have shown that the concentration of PM is positively correlated with temperature, which means that as temperature increases, so does the concentration of PM in air. Elevated temperatures have the potential to enhance the chemical processes responsible for generating particulate matter (PM). This can result in a rise in the occurrence and severity of wildfires and dust storms, both of which have the capacity to release substantial quantities of PM into the atmosphere (Srivastava, 2021; Zhu et al., 2020). However, the concentration of PM was negatively correlated with humidity and rainfall, indicating that as humidity and rainfall increased, the concentration of PM in the air decreased. The presence of higher humidity and greater rainfall has a significant impact on the elimination of particulate matter (PM) from the air. This is primarily attributed to the role of these environmental factors in increasing the size of PM particles, thereby enhancing their susceptibility to removal through precipitation and deposition mechanisms (X. Zhao et al., 2020).

### *4.3.7 Correlation of Meteorological Parameters and COVID-19 Events*

Despite improved air quality during the COVID-19 pandemic and related lockdown measures, the contribution of air pollutants and meteorology to the transmission of the virus remains unclear. According to Kolluru et al. (2021), several air pollutants and meteorological variables, including $PM_{2.5}$, $PM_{10}$, CO, $O_3$, temperature, relative humidity, and wind speed, promoted COVID-19 transmission in five Indian megacities. During the lockdown period, a notable correlation was discovered between the levels of pollutants, meteorological factors, Air Quality Index (AQI), and the number of confirmed cases and fatalities, as indicated in a prior investigation (Kolluru et al., 2021). The correlation between COVID-19 cases and deaths was most pronounced with temperature compared to other meteorological variables, whether during lockdown or when restrictions were not in place (Chelani & Gautam, 2022). Ozone and temperature explained most of the variability in COVID-19 cases and deaths, whereas the AQI was not significant. Wind speed and relative humidity had less explanatory power. The data implies that meteorological factors, specifically temperature, might contribute to the transmission of COVID-19.

### *4.3.8 Correlation of Air Quality Parameters and COVID-19 Events*

In contrast to the study conducted by Huang et al. (2020), which found a substantial association between COVID-19 mortality rates and average temperature as well as air quality index in 12 Chinese cities, the current research, as outlined in Table 3, indicates only a minor correlation between confirmed COVID-19 deaths and the various air quality parameters measured. Moderate correlations were found between positive COVID-19 cases and $SO_2$ ($R^2$ = 0.39), whereas a strong correlation was found between $PM_{10}$ ($R^2$ = 0.68), $PM_{2.5}$ ($R^2$ = 0.56), CO ($R^2$ = 0.67), and $O_3$ ($R^2$ = 0.67). A possible explanation for this correlation is that exposure to air pollution can weaken the immune system and increase the susceptibility to respiratory infections, including COVID-19. Furthermore, air pollution has the potential to trigger inflammation in the lungs and other organs, worsening the symptoms of COVID-19 and resulting in more serious consequences (Wu et al., 2020). An alternative explanation could be that air pollution serves as a vehicle for the virus, enabling it to spread over greater distances and linger in the air for extended durations. This, in turn, raises the chances of transmission (Botto et al., 2023). Although the PPKM level was determined by the number of positive cases, death rate, and number of hospitalized COVID patients, it seems that the number of positive cases is strongly related to the level of almost all air quality parameters.

**Table 4.3** Correlation of air quality parameters and COVID-19 events

| Events | $PM_{10}$ | $PM_{2.5}$ | $SO_2$ | CO | $O_3$ | $NO_2$ |
|---|---|---|---|---|---|---|
| Confirmed death | 0.247** | 0.206** | 0.202** | 0.078* | 0.078* | 0.084* |
| Recovered | 0.127** | 0.216** | 0.194** | 0.022 | 0.022 | 0.139** |
| Positive cases | 0.680** | -0.558** | 0.385** | 0.668** | 0.669** | 0.067 |

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

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

Notes: White, grey, green, and blue boxes indicate no correlation and weak, moderate, and strong correlations, respectively.

#### *4.3.9 Correlation of Air Quality Parameter Before and During COVID-19*

The concentrations of PM and $SO_2$ during the pandemic moderately correlated with their concentrations before the pandemic. A similar trend was also observed in the relationship between $PM_{2.5}$ levels prior to the pandemic and $O_3$ levels post-pandemic, as well as $O_3$ levels prior to the pandemic and $SO_2$ levels post-pandemic. $SO_2$ before the pandemic and $NO_2$ after the pandemic had a moderately negative correlation (Table 4.4). One possible reason for the correlation between PM and $SO_2$ is that their sources, such as industrial emissions and transportation, are generally persistent and remain relatively stable over time (Hilker et al., 2021). Therefore, their levels can be impacted by various short- and long-term factors like weather patterns, air mass movements, and seasonal fluctuations. Moreover, the concentrations of PM and $SO_2$ are influenced by meteorological factors, such as wind speed and direction, temperature, humidity, and rainfall (Adha & Hadi, 2021). For instance, the velocity and orientation of wind can impact the movement and scattering of contaminants from their origins, while the temperature and humidity can influence the chemical reactions that result in the creation of PM and $SO_2$. The existence of regulatory policies aimed at decreasing the emissions of these pollutants could also be a contributing factor to the moderate correlation (Lu et al., 2021). Although the effects of these policies may not be immediately visible, their long-term impacts can be observed through changes in air quality over time. The negative correlation between $SO_2$ and $NO_2$ may be attributed to the different sources of these pollutants. $SO_2$ primarily originates from industrial activities, whereas transportation is the main source of $NO_2$. As a result of the lockdowns implemented during the pandemic, transportation activities experienced a notable decline, potentially resulting in a reduction in $NO_2$ concentrations. However, industrial activities were not affected as much; therefore, the $SO_2$ concentrations may have remained relatively stable. This difference in source reduction may explain why the correlation between $SO_2$ and $NO_2$ changed from positive before the pandemic to negative during the pandemic (Filonchyk et al., 2020; Kolluru et al., 2021).

**Table 4.4** Correlation of air quality parameters before and during COVID-19

| | | During COVID-19 Pandemic (2018-2019) | | | | | |
|---|---|---|---|---|---|---|---|
| | | $PM_{10}$ | $PM_{2.5}$ | $SO_2$ | CO | $O_3$ | $NO_2$ |
| Before COVID-19 Pandemic (2020-2021) | $PM_{10}$ | 0.383** | 0.430** | 0.363** | 0.226** | -0.112** | 0.169** |
| | $PM_{2.5}$ | 0.441** | 0.488** | 0.364** | 0.190** | -0.03972 | 0.167** |
| | $SO_2$ | 0.027 | 0.028 | -0.223** | -0.188** | 0.432** | -0.324** |
| | CO | -0.084* | -0.043 | -0.078* | 0.031 | -0.000 | 0.114** |
| | $O_3$ | 0.294** | 0.320** | 0.167** | 0.073 | 0.048 | 0.134** |
| | $NO_2$ | 0.080* | 0.121** | 0.250** | 0.203** | **-0.266 | 0.244** |

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

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

Notes: White, grey, green, and blue boxes indicate no correlation and weak, moderate, and strong correlations, respectively.

### *4.3.10 Limitation of the study*

At the time of this study, data from the post-pandemic period were not yet available. To enhance the robustness and depth of the findings, future study should consider incorporating more comprehensive data. This can be achieved by comparing the findings with other cities that are experiencing similar conditions and restrictions. Additionally, exploring more potential factors such as socio-economic factors and utilizing more advanced statistical methods will contribute to a more comprehensive analysis. Given the limitations related to geography, limited air quality monitoring numbers, data availability, and statistical methodologies, it is anticipated that future studies will provide a more nuanced and insightful conclusion.

## 4.4 Conclusions

Based on the findings of this study, there was a weak correlation between confirmed deaths because of COVID-19 and all air quality parameters. The findings of the study highlighted a distinct relationship between positive COVID-19 cases and particular pollutants. Positive cases of COVID-19 were strongly correlated with

$PM_{10}$, $PM_{2.5}$, CO, and $O_3$, whereas $PM_{2.5}$ alone, showed a negative correlation. The positive correlation that existed between positive COVID-19 cases and $PM_{10}$, CO, and $O_3$ indicated that higher levels of these pollutants may indicate higher citizen mobility, which is a potential risk factor for COVID-19 transmission. The data indicates that air pollution might intensify the effects of the COVID-19 pandemic. Pollutants like $PM_{10}$ and $PM_{2.5}$ can impair lung function and weaken immune system defenses, making individuals more susceptible to respiratory infections, including COVID-19. Furthermore, CO and $O_3$, known for their adverse effects on respiratory health, may also contribute to increased vulnerability. The study also analysed air quality parameters before and during the pandemic, uncovering intriguing trends. PM and $SO_2$ concentrations during the pandemic showed moderate correlations with their pre-pandemic levels, indicating that existing pollution trends continued despite the pandemic. However, over the time, the interplay among pollutants has undergone changes. $PM_{2.5}$ concentrations before the pandemic correlated with $O_3$ and $SO_2$ levels after the pandemic, suggesting changes in atmospheric chemistry and pollution dynamics due to altered environmental factors and human activities. Furthermore, a modestly adverse association was identified between pre-pandemic $SO_2$ levels and post-pandemic $NO_2$ concentrations. This inverse relationship underscores the complex interplay between different pollutants and highlights the possible effect of modified emission sources and environmental regulations during the pandemic. This study pinpointed various important meteorological factors such as wind speed, wind direction, temperature, humidity, and rainfall, which play a crucial role in influencing the levels of PM and $SO_2$ concentrations. Temperature was positively correlated with $PM_{10}$ and $PM_{2.5}$, while humidity and rainfall showed negative correlations. It is important for individuals to be mindful of the heightened risk of PM exposure during hot weather, as it can result in long-term health issues. This suggests that temperature variations can affect virus transmission rates and severity. This highlights the necessity for additional research in order to unravel the intricacies of air quality, meteorology, and the dynamics of infectious diseases. Further study that includes more data and advanced statistical methods is needed since understanding the complex relationships between the meteorological variables, air quality parameters and COVID-19 events is crucial for developing effective public health strategies and environmental policies to protect communities from both air pollution and infectious diseases.

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# Chapter 5
# Conclusions and Further Studies

## 5.1 Conclusions

There are several important findings from the study in the previous chapters:

1. The study explored air pollution and meteorological variables research trends, identified four clusters based on keyword co-occurrence. It highlights topics such as air quality, health impacts, meteorological parameters, and advanced air quality modelling. The research in the studied period between 2019 and 2021 was influenced by the COVID-19 pandemic and focuses on machine learning, artificial neural networks, statistical methods, and models like WRF-Chem and CMAQ.
2. The study identified emerging focus areas in air pollution research, including climate change's impact on air quality, statistical methods for assessing health outcomes, and advancements in air quality modelling. Future research should focus on key areas such as climate change's impact on air quality, advanced statistical methods for assessing health outcomes, and long-term trends in air pollution.
3. The study also found that motorbikes were the primary contributors to air pollutants CO, HC, and PM in DKI Jakarta from 2007 to 2018, followed by buses. Interventions to reduce LDVs in DKI Jakarta could improve air quality. The author believes that the Indonesian Government needs to produce more detailed emission factors that fit the local situation.
4. The study also highlighted a distinct relationship between positive COVID-19 cases and specific pollutants, suggesting that air pollution might intensify the effects of the pandemic. Pollutants like $PM_{10}$ and $PM_{2.5}$ can impair lung function and weaken immune system defenses, making individuals more susceptible to respiratory infections. The study also identified important meteorological factors such as wind speed, wind direction, temperature, humidity, and rainfall, which play a crucial role in influencing PM and $SO_2$ concentrations.

Further research is needed to understand the complex relationships between meteorological variables, air quality parameters, and COVID-19 events, which is crucial for developing effective public health strategies and environmental policies.

## 5.2 Limitation of This Study

The study focuses on the dynamic vehicle age-based cohort model to estimate emissions from the transportation sector in Jakarta, which relies on data availability and precision. However, the model assumes vehicle usage patterns, maintenance practices, and technological advancements, which may not fully capture real-world variability. The study is limited to Jakarta and may not be applicable to other cities with different transportation infrastructures, vehicle compositions, or regulatory environments. Technological advancements may outpace the data and assumptions used in the study, potentially leading to outdated conclusions. The correlation between meteorological variables, air quality, and the COVID-19 pandemic events in Jakarta is temporal and data-dependent, with limitations in the Spearman correlation test and the unique nature of the pandemic. The review and bibliometric analysis are limited to the scope and selection of literature, and the regional focus may not reflect global variations in air pollution and meteorological research.

## 5.3 Future Research Directions

Future studies on air pollution should consider the following points:

1. The research on dynamic vehicle age-based cohort model can be expanded to other cities with different traffic patterns, vehicle compositions, and regulatory environments. Real-time data integration through IoT (Internet of Things) devices and sensors could improve the model's accuracy and responsiveness.
2. The study can be enhanced by conducting policy impact analysis to analyse the impact of various measures on emission reductions. This study can analyse the impact of various policy measures such as scrappage schemes, emission standards, and alternative fuel adoption.

3. Longitudinal studies can track changes in emissions over time and assess the long-term effectiveness of interventions. This study can provide deeper insights into emission trends and mitigation strategies.
4. Comparative studies across regions can understand the similarities and differences in how meteorological variables and air quality interact with COVID-19 pandemic events or any other diseases.
5. Employing advanced statistical methods and extended study periods can provide more robust insights.
6. Investigating the role of public health interventions by exploring the impact of additional variables, such as socioeconomic factors, public health infrastructure, and behavioural changes can inform better health policies and strategies.
7. Regular updates to the review and bibliometric analysis can identify emerging trends and gaps in the literature including enable the study more relevant and current.

# Appendices

## 1 Equations Submitted to Stella Applications for Chapter 3

```
Top-Level Model:
"Age_0-4"(t) = "Age_0-4"(t - dt) + ("1st_Purchase" - Stage_1 - Flow_3) * dt
  INIT "Age_0-4" = 697
    TRANSIT TIME = 1
    CAPACITY = INF
    INFLOW LIMIT = INF
  INFLOWS:
    "1st_Purchase" = Purchase_Rate*Total_Vehicles
  OUTFLOWS:
    Stage_1 = CONVEYOR OUTFLOW
    Flow_3 = LEAKAGE OUTFLOW
      LEAKAGE FRACTION = 1-(1-Scrap_Rate_1)
"Age_5-8"(t) = "Age_5-8"(t - dt) + (Stage_1 - Stage_2 - Flow_4) * dt
  INIT "Age_5-8" = 36999
    TRANSIT TIME = 1
  INFLOWS:
    Stage_1 = CONVEYOR OUTFLOW
  OUTFLOWS:
    Stage_2 = CONVEYOR OUTFLOW
    Flow_4 = LEAKAGE OUTFLOW
      LEAKAGE FRACTION = 1-(1-Scrap_Rate_2)
"Age_>8"(t) = "Age_>8"(t - dt) + (Stage_2 - Final_Scrap) * dt
  INIT "Age_>8" = 257905
  INFLOWS:
    Stage_2 = CONVEYOR OUTFLOW
  OUTFLOWS:
    Final_Scrap = Scrap_Rate_3*"Age_>8"
"EF_Pollutant_for_Age_0-4" = 2.22
"EF_Pollutant_for_Age_5-8" = 2.22
"EF_Pollutant_for_Age_>8" = 2.22
Purchase_Rate = 0.013
Scrap_Rate_1 = 0.00048
Scrap_Rate_2 = 0.00187
Scrap_Rate_3 = 0.00326
Total_Pollutant_Emission = ((Vehicle's_VKT*"Age_0-4"*"EF_Pollutant_for_Age_0-
4")+(Vehicle's_VKT*"Age_5-8"*"EF_Pollutant_for_Age_5-
8")+(Vehicle's_VKT*"Age_>8"*"EF_Pollutant_for_Age_>8"))
Total_Vehicles = "Age_0-4"+"Age_5-8"+"Age_>8"
Vehicle's_VKT = 60590
{ The model has 19 (19) variables (array expansion in parens).
 In root model and 0 additional modules with 0 sectors.
 Stocks: 3 (3) Flows: 6 (6) Converters: 10 (10)
 Constants: 10 (10) Equations: 6 (6) Graphicals: 0 (0)
 }
```

# 2 Number of Population and Vehicles by Year for Chapter 3

| Year | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Total Number of Population | 9,064,600 | 9,146,181 | 9,223,000 | 9,607,800 | 9,758,100 | 9,862,100 | 9,969,900 | 10,075,300 | 10,177,900 | 10,277,600 | 10,305,408 |
| Total Number of Vehicle | 5,800,009 | 6,266,401 | 6,690,922 | 7,342,793 | 7,981,994 | 8,593,687 | 9,259,814 | 9,904,931 | 10,415,989 | 10,907,549 | 11,362,662 |
| Regional GDP (US$) | 566.45 | 677.41 | 757.02 | 861.99 | 982.52 | 1,369.43 | 1,546.88 | 1,762.32 | 1,989.33 | 2,177.12 | 2,365.36 |
| Total Road Length (km) | 6,544 | 6,544 | 6,544 | 6,866 | 6,866 | 6,956 | 6,876 | 6,956 | 6,956 | 6,973 | 6,973 |

| Year | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Car | 1,547,336 | 1,610,915 | 1,661,795 | 1,789,458 | 1,919,891 | 2,040,394 | 2,195,647 | 2,331,933 | 2,437,935 | 2,559,388 | 2,668,777 | 2,789,377 |
| Bus | 256,766 | 257,37 | 257,905 | 273,789 | 294,628 | 295,613 | 294,904 | 294,141 | 294,005 | 294,587 | 294,186 | 295,601 |
| Truck | 414,278 | 427,359 | 435,654 | 441,886 | 451,469 | 446,31 | 480,022 | 509,718 | 524,138 | 529,595 | 538,123 | 541,375 |
| Motorbike | 3,579,622 | 3,968,749 | 4,333,559 | 4,835,650 | 5,313,995 | 5,738,262 | 6,211,367 | 6,687,375 | 7,076,249 | 7,438,432 | 7,773,511 | 8,136,410 |
| Special Vehicle | - | - | - | - | - | 71,096 | 75,861 | 79,75 | 81,647 | 83,531 | 86,048 | 89,332 |
| Total Number of Vehicle | 5,798,002 | 6,264,393 | 6,688,913 | 7,340,783 | 7,979,983 | 8,591,675 | 9,257,801 | 9,902,917 | 10,413,974 | 10,905,533 | 11,360,645 | 11,852,095 |

# 3 Predicted Vehicles Population and Emission for Chapter 3

| Year | Number of Cars | | | | | Total CO Emission (kt/y) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Bus | Car Diesel | Car Gasoline | Motorbike | Truck | Bus | Car Diesel | Car Gasoline | Motorbike | Truck |
| 2017 | 295,601 | 179,915 | 2,609,462 | 8,136,410 | 541,375 | 39.76 | 1.44 | 31.90 | 83.74 | 15.35 |
| 2018 | 298,529 | 189,161 | 2,744,191 | 8,745,787 | 553,353 | 40.16 | 1.52 | 33.55 | 101.13 | 15.69 |
| 2019 | 301,46 | 198,814 | 2,884,709 | 9,397,390 | 565,555 | 40.55 | 1.60 | 35.27 | 108.67 | 16.04 |
| 2020 | 304,424 | 208,933 | 3,031,913 | 10,096,259 | 578,008 | 40.95 | 1.68 | 37.07 | 116.75 | 16.39 |
| 2021 | 307,416 | 219,566 | 3,186,630 | 10,847,102 | 590,736 | 41.35 | 1.76 | 38.96 | 125.43 | 16.75 |
| 2022 | 310,438 | 230,741 | 3,349,241 | 11,653,783 | 603,744 | 41.76 | 1.85 | 40.95 | 134.76 | 17.12 |
| 2023 | 313,489 | 242,484 | 3,520,150 | 12,520,457 | 617,038 | 42.17 | 1.95 | 43.04 | 144.78 | 17.50 |
| 2024 | 316,571 | 254,825 | 3,699,781 | 13,451,583 | 630,625 | 42.58 | 2.05 | 45.23 | 155.55 | 17.88 |
| 2025 | 319,683 | 267,795 | 3,888,578 | 14,451,956 | 644,511 | 43.00 | 2.15 | 47.54 | 167.11 | 18.28 |
| 2026 | 322,825 | 281,424 | 4,087,009 | 15,526,724 | 658,703 | 43.42 | 2.26 | 49.97 | 179.54 | 18.68 |
| 2027 | 325,998 | 295,747 | 4,295,566 | 16,681,422 | 673,207 | 43.85 | 2.37 | 52.52 | 192.90 | 19.09 |
| 2028 | 329,203 | 310,798 | 4,514,765 | 17,921,993 | 688,031 | 44.28 | 2.49 | 55.20 | 207.24 | 19.51 |
| 2029 | 332,439 | 326,616 | 4,745,151 | 19,254,823 | 703,181 | 44.72 | 2.62 | 58.01 | 222.65 | 19.94 |
| 2030 | 335,706 | 343,239 | 4,987,292 | 20,686,773 | 718,665 | 45.16 | 2.76 | 60.97 | 239.21 | 20.38 |
| 2031 | 339,006 | 360,708 | 5,241,790 | 22,225,215 | 734,49 | 45.60 | 2.90 | 64.08 | 257.00 | 20.83 |
| 2032 | 342,339 | 379,066 | 5,509,274 | 23,878,069 | 750,663 | 46.05 | 3.04 | 67.35 | 276.11 | 21.29 |
| 2033 | 345,704 | 398,358 | 5,790,408 | 25,653,842 | 767,193 | 46.50 | 3.20 | 70.79 | 296.65 | 21.76 |
| 2034 | 349,102 | 418,632 | 6,085,888 | 27,561,678 | 784,086 | 46.96 | 3.36 | 74.40 | 318.71 | 22.24 |
| 2035 | 352,534 | 439,938 | 6,396,447 | 29,611,396 | 801,351 | 47.42 | 3.53 | 78.20 | 342.41 | 22.73 |
| 2036 | 355,999 | 462,328 | 6,722,853 | 31,813,548 | 818,997 | 47.89 | 3.71 | 82.19 | 367.88 | 23.23 |
| 2037 | 359,498 | 485,858 | 7,065,915 | 34,179,470 | 837,031 | 48.36 | 3.90 | 86.39 | 395.23 | 23.74 |
| 2038 | 363,032 | 510,586 | 7,426,483 | 36,721,343 | 855,462 | 48.83 | 4.10 | 90.79 | 424.63 | 24.26 |
| 2039 | 366,6 | 536,571 | 7,805,451 | 39,452,250 | 874,299 | 49.31 | 4.31 | 95.43 | 456.21 | 24.80 |
| **2040** | **370,204** | **563,88** | **8,203,757** | **42,386,251** | **893,551** | **49.80** | **4.53** | **100.30** | **490.13** | **25.34** |

| Year | Number of Cars | | | | | Total HC Emission (kt/y) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Bus | Car Diesel | Car Gasoline | Motorbike | Truck | Bus | Car Diesel | Car Gasoline | Motorbike | Truck |
| 2017 | 295,601 | 179,915 | 2,609,462 | 8,136,410 | 541,375 | 3.04 | 0.06 | 1.39 | 19.81 | 1.18 |
| 2018 | 298,529 | 189,161 | 2,744,191 | 8,745,787 | 553,353 | 3.07 | 0.06 | 1.46 | 22.57 | 1.20 |
| 2019 | 301,46 | 198,814 | 2,884,709 | 9,397,390 | 565,555 | 3.11 | 0.06 | 1.53 | 24.25 | 1.23 |
| 2020 | 304,424 | 208,933 | 3,031,913 | 10,096,259 | 578,008 | 3.14 | 0.06 | 1.61 | 26.05 | 1.26 |
| 2021 | 307,416 | 219,566 | 3,186,630 | 10,847,102 | 590,736 | 3.17 | 0.07 | 1.69 | 27.99 | 1.28 |
| 2022 | 310,438 | 230,741 | 3,349,241 | 11,653,783 | 603,744 | 3.20 | 0.07 | 1.78 | 30.07 | 1.31 |
| 2023 | 313,489 | 242,484 | 3,520,150 | 12,520,457 | 617,038 | 3.23 | 0.07 | 1.87 | 32.31 | 1.34 |
| 2024 | 316,571 | 254,825 | 3,699,781 | 13,451,583 | 630,625 | 3.26 | 0.08 | 1.97 | 34.71 | 1.37 |
| 2025 | 319,683 | 267,795 | 3,888,578 | 14,451,956 | 644,511 | 3.29 | 0.08 | 2.07 | 37.29 | 1.40 |
| 2026 | 322,825 | 281,424 | 4,087,009 | 15,526,724 | 658,703 | 3.33 | 0.09 | 2.17 | 40.07 | 1.43 |
| 2027 | 325,998 | 295,747 | 4,295,566 | 16,681,422 | 673,207 | 3.36 | 0.09 | 2.28 | 43.04 | 1.46 |
| 2028 | 329,203 | 310,798 | 4,514,765 | 17,921,993 | 688,031 | 3.36 | 0.10 | 2.40 | 46.25 | 1.49 |
| 2029 | 332,439 | 326,616 | 4,745,151 | 19,254,823 | 703,181 | 3.39 | 0.10 | 2.52 | 49.69 | 1.53 |
| 2030 | 335,706 | 343,239 | 4,987,292 | 20,686,773 | 718,665 | 3.42 | 0.10 | 2.65 | 53.38 | 1.56 |
| 2031 | 339,006 | 360,708 | 5,241,790 | 22,225,215 | 734,49 | 3.46 | 0.11 | 2.79 | 57.35 | 1.60 |
| 2032 | 342,339 | 379,066 | 5,509,274 | 23,878,069 | 750,663 | 3.49 | 0.12 | 2.93 | 61.61 | 1.63 |
| 2033 | 345,704 | 398,358 | 5,790,408 | 25,653,842 | 767,193 | 3.53 | 0.12 | 3.08 | 66.20 | 1.67 |
| 2034 | 349,102 | 418,632 | 6,085,888 | 27,561,678 | 784,086 | 3.56 | 0.13 | 3.23 | 71.12 | 1.70 |
| 2035 | 352,534 | 439,938 | 6,396,447 | 29,611,396 | 801,351 | 3.60 | 0.13 | 3.40 | 76.41 | 1.74 |
| 2036 | 355,999 | 462,328 | 6,722,853 | 31,813,548 | 818,997 | 3.63 | 0.14 | 3.57 | 82.09 | 1.78 |
| 2037 | 359,498 | 485,858 | 7,065,915 | 34,179,470 | 837,031 | 3.70 | 0.15 | 3.76 | 88.20 | 1.82 |
| 2038 | 363,032 | 510,586 | 7,426,483 | 36,721,343 | 855,462 | 3.74 | 0.16 | 3.95 | 94.76 | 1.86 |
| 2039 | 366,6 | 536,571 | 7,805,451 | 39,452,250 | 874,299 | 3.78 | 0.16 | 4.15 | 101.80 | 1.90 |
| **2040** | **370,204** | **563,88** | **8,203,757** | **42,386,251** | **893,551** | **3.81** | **0.17** | **4.36** | **109.37** | **1.94** |

| Year | Number of Cars | | | | | Total NO Emission (kt/y) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Bus | Car Diesel | Car Gasoline | Motorbike | Truck | Bus | Car Diesel | Car Gasoline | Motorbike | Truck |
| 2017 | 295,601 | 179,915 | 2,609,462 | 8,136,410 | 541,375 | 32.84 | 0.31 | 1.39 | 4.74 | 11.8 |
| 2018 | 298,529 | 189,161 | 2,744,191 | 8,745,787 | 553,353 | 35.75 | 0.33 | 1.46 | 5.57 | 12.85 |
| 2019 | 301,46 | 198,814 | 2,884,709 | 9,397,390 | 565,555 | 35.85 | 0.37 | 1.53 | 5.99 | 13.96 |
| 2020 | 304,424 | 208,933 | 3,031,913 | 10,096,259 | 578,008 | 36.20 | 0.39 | 1.61 | 6.43 | 14.27 |
| 2021 | 307,416 | 219,566 | 3,186,630 | 10,847,102 | 590,736 | 36.56 | 0.41 | 1.69 | 6.91 | 14.58 |
| 2022 | 310,438 | 230,741 | 3,349,241 | 11,653,783 | 603,744 | 36.92 | 0.43 | 1.78 | 7.43 | 14.90 |
| 2023 | 313,489 | 242,484 | 3,520,150 | 12,520,457 | 617,038 | 37.28 | 0.45 | 1.87 | 7.98 | 15.23 |
| 2024 | 316,571 | 254,825 | 3,699,781 | 13,451,583 | 630,625 | 37.65 | 0.48 | 1.97 | 8.57 | 15.57 |
| 2025 | 319,683 | 267,795 | 3,888,578 | 14,451,956 | 644,511 | 38.02 | 0.50 | 2.07 | 9.21 | 15.91 |
| 2026 | 322,825 | 281,424 | 4,087,009 | 15,526,724 | 658,703 | 38.39 | 0.53 | 2.17 | 9.89 | 16.26 |
| 2027 | 325,998 | 295,747 | 4,295,566 | 16,681,422 | 673,207 | 38.77 | 0.55 | 2.28 | 10.63 | 16.62 |
| 2028 | 329,203 | 310,798 | 4,514,765 | 17,921,993 | 688,031 | 39.15 | 0.58 | 2.40 | 11.42 | 16.98 |
| 2029 | 332,439 | 326,616 | 4,745,151 | 19,254,823 | 703,181 | 39.53 | 0.61 | 2.52 | 12.27 | 17.36 |
| 2030 | 335,706 | 343,239 | 4,987,292 | 20,686,773 | 718,665 | 39.92 | 0.64 | 2.65 | 13.18 | 17.74 |
| 2031 | 339,006 | 360,708 | 5,241,790 | 22,225,215 | 734,49 | 40.31 | 0.67 | 2.79 | 14.16 | 18.13 |
| 2032 | 342,339 | 379,066 | 5,509,274 | 23,878,069 | 750,663 | 40.71 | 0.71 | 2.93 | 15.22 | 18.53 |
| 2033 | 345,704 | 398,358 | 5,790,408 | 25,653,842 | 767,193 | 41.11 | 0.74 | 3.08 | 16.35 | 18.94 |
| 2034 | 349,102 | 418,632 | 6,085,888 | 27,561,678 | 784,086 | 41.52 | 0.78 | 3.23 | 17.56 | 19.35 |
| 2035 | 352,534 | 439,938 | 6,396,447 | 29,611,396 | 801,351 | 41.92 | 0.82 | 3.40 | 18.87 | 19.78 |
| 2036 | 355,999 | 462,328 | 6,722,853 | 31,813,548 | 818,997 | 42.34 | 0.86 | 3.57 | 20.27 | 20.21 |
| 2037 | 359,498 | 485,858 | 7,065,915 | 34,179,470 | 837,031 | 42.75 | 0.91 | 3.76 | 21.78 | 20.66 |
| 2038 | 363,032 | 510,586 | 7,426,483 | 36,721,343 | 855,462 | 43.17 | 0.95 | 3.95 | 23.40 | 21.11 |
| 2039 | 366,6 | 536,571 | 7,805,451 | 39,452,250 | 874,299 | 43.60 | 1.00 | 4.15 | 25.14 | 21.58 |
| **2040** | **370,204** | **563,88** | **8,203,757** | **42,386,251** | **893,551** | **44.03** | **1.05** | **4.36** | **27.01** | **22.05** |

| Year | Number of Cars | | | | | Total PM Emission (kt/y) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Bus | Car Diesel | Car Gasoline | Motorbike | Truck | Bus | Car Diesel | Car Gasoline | Motorbike | Truck |
| 2017 | 295,601 | 179,915 | 2,609,462 | 8,136,410 | 541,375 | 0.44 | 0.01 | 31.90 | 83.74 | 0.16 |
| 2018 | 298,529 | 189,161 | 2,744,191 | 8,745,787 | 553,353 | 0.48 | 0.01 | 33.55 | 101.13 | 0.17 |
| 2019 | 301,46 | 198,814 | 2,884,709 | 9,397,390 | 565,555 | 0.49 | 0.01 | 35.27 | 108.67 | 0.19 |
| 2020 | 304,424 | 208,933 | 3,031,913 | 10,096,259 | 578,008 | 0.49 | 0.01 | 37.07 | 116.75 | 0.19 |
| 2021 | 307,416 | 219,566 | 3,186,630 | 10,847,102 | 590,736 | 0.49 | 0.01 | 38.96 | 125.43 | 0.20 |
| 2022 | 310,438 | 230,741 | 3,349,241 | 11,653,783 | 603,744 | 0.50 | 0.01 | 40.95 | 134.76 | 0.20 |
| 2023 | 313,489 | 242,484 | 3,520,150 | 12,520,457 | 617,038 | 0.50 | 0.02 | 43.04 | 144.78 | 0.21 |
| 2024 | 316,571 | 254,825 | 3,699,781 | 13,451,583 | 630,625 | 0.51 | 0.02 | 45.23 | 155.55 | 0.21 |
| 2025 | 319,683 | 267,795 | 3,888,578 | 14,451,956 | 644,511 | 0.51 | 0.02 | 47.54 | 167.11 | 0.22 |
| 2026 | 322,825 | 281,424 | 4,087,009 | 15,526,724 | 658,703 | 0.52 | 0.02 | 49.97 | 179.54 | 0.22 |
| 2027 | 325,998 | 295,747 | 4,295,566 | 16,681,422 | 673,207 | 0.52 | 0.02 | 52.52 | 192.90 | 0.23 |
| 2028 | 329,203 | 310,798 | 4,514,765 | 17,921,993 | 688,031 | 0.53 | 0.02 | 55.20 | 207.24 | 0.23 |
| 2029 | 332,439 | 326,616 | 4,745,151 | 19,254,823 | 703,181 | 0.54 | 0.02 | 58.01 | 222.65 | 0.24 |
| 2030 | 335,706 | 343,239 | 4,987,292 | 20,686,773 | 718,665 | 0.54 | 0.02 | 60.97 | 239.21 | 0.24 |
| 2031 | 339,006 | 360,708 | 5,241,790 | 22,225,215 | 734,49 | 0.55 | 0.02 | 64.08 | 257.00 | 0.25 |
| 2032 | 342,339 | 379,066 | 5,509,274 | 23,878,069 | 750,663 | 0.55 | 0.02 | 67.35 | 276.11 | 0.25 |
| 2033 | 345,704 | 398,358 | 5,790,408 | 25,653,842 | 767,193 | 0.56 | 0.03 | 70.79 | 296.65 | 0.26 |
| 2034 | 349,102 | 418,632 | 6,085,888 | 27,561,678 | 784,086 | 0.56 | 0.03 | 74.40 | 318.71 | 0.26 |
| 2035 | 352,534 | 439,938 | 6,396,447 | 29,611,396 | 801,351 | 0.57 | 0.03 | 78.20 | 342.41 | 0.27 |
| 2036 | 355,999 | 462,328 | 6,722,853 | 31,813,548 | 818,997 | 0.57 | 0.03 | 82.19 | 367.88 | 0.27 |
| 2037 | 359,498 | 485,858 | 7,065,915 | 34,179,470 | 837,031 | 0.58 | 0.03 | 86.39 | 395.23 | 0.28 |
| 2038 | 363,032 | 510,586 | 7,426,483 | 36,721,343 | 855,462 | 0.58 | 0.03 | 90.79 | 424.63 | 0.29 |
| 2039 | 366,6 | 536,571 | 7,805,451 | 39,452,250 | 874,299 | 0.59 | 0.03 | 95.43 | 456.21 | 0.29 |
| **2040** | **370,204** | **563,88** | **8,203,757** | **42,386,251** | **893,551** | **0.60** | **0.04** | **100.30** | **490.13** | **0.30** |

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