ASSESSING THE RELATION BETWEEN AIR QUALITY INDICES AND ACUTE RESPIRATORY INFECTION INCIDENCE AT SENTINEL CLINICS IN MELAKA AND JOHOR, MALAYSIA

By

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Chair : Shamarina binti Shohaimi, PhD
Faculty : Science

Pollution is one of the most serious environmental issues confronting the world today, particularly air pollution, which is the focus of this study. The Department of Environment reported hazardous readings during the 2013 Sumatera and Kalimantan Forest fires, particularly at Bukit Rambai, Melaka, with 470, and Muar, Johor, with 750. Bandar Penawar in Johor was selected as the comparative site since it is a coastal town facing the South China Sea while the main study locations located on the Straits of Malacca. Lower respiratory tract infections predicted to account for 13.1% of all fatalities in children aged 5 years worldwide reported by WHO. According to Department of Statisitics, Malaysia, pneumonia was the top cause of mortality among people aged 0-14 years in 2019, accounting for 4.8% of all deaths. The focus of this study is to examine how air contaminants flow and spread throughout the study areas from 2015-2018 and identify the main air pollutants linked to acute respiratory infections in outpatients and age as risk factor. R-Programming and its open-air package were used to construct wind rose, pollutant rose, and calendar plots to depict the pattern of pollutants throughout the study areas. For descriptive analysis, Statistical Product and Service Solutions (SPSS Version 28) were employed, which described the main age group of patients who suffered ARI owing to air pollution and summarized the frequency of visits for ARI by age. It is also used to describe the contaminants and wind speed in the study areas. Correlation determines the association between outpatient visits for ARI at KKBR, KKBM and KKBP with API, SO_2, NO_2, O_3, CO and PM_{10}. One-way ANOVA used to compare age groups. This study used secondary data on pollutants provided by the Department of Environment from SMKBR, KVM, and SMKABP air quality monitoring stations. Secondary data on outpatient visits were obtained from KKBR, KKBM, and KKBP. The overall concentrations of pollutants are governed mainly by north-easterly winds and the average wind speeds were sufficient to aid in the dispersion of air pollutants. The northeast wind sectors recorded the highest value of API and PM_{10} at the three study areas. According to the calendar plot, concluded that local emissions, not transboundary pollution, are the key contributors to the air pollution index found in the study locations, as days with high API show a seasonal pattern. This study found a positive and significant correlation between API, PM_{10}, SO_2 and 0_3 with outpatient visits in KKBR, PM_{10} and outpatient visits in KKBM, API and PM_{10} with outpatient visits in KKBP. Most outpatient visits for acute respiratory infections were made by patients aged 13 to 59, followed by individuals aged 12 and younger and older than 60. The number of outpatient visits for acute respiratory infection at the three clinics varies considerably by age group. The findings of this study are anticipated to contribute to an improvement in air quality in the study areas and inspire further

research in other areas to raise public awareness and promote environmental conservation.

Keywords: Air Pollution, Pollutants, Wind Rose, Pollutant Rose, Calendar Plot

SDG: GOAL 3: Good Health and Well Being, GOAL 11: Sustainable Cities and Communities, GOAL 13: Climate Change

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PENILAIAN HUBUNGAN INDEKS PENCEMARAN UDARA DAN INSIDEN JANGKITAN RESPIRATORI AKUT DI KLINIK SENTINEL DI MELAKA DAN JOHOR, MALAYSIA

Oleh

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Pencemaran adalah salah satu isu alam sekitar yang paling serius yang dihadapi oleh dunia hari ini, terutamanya pencemaran udara, yang menjadi tumpuan kajian ini. Jabatan Alam Sekitar melaporkan bacaan berbahaya semasa kebakaran hutan di Sumatera dan Kalimantan 2013, khususnya di Bukit Rambai, Melaka, dengan bacaan 470, dan Muar, Johor, dengan bacaan 750. Bandar Penawar di Johor dipilih sebagai lokasi perbandingan kerana ia adalah sebuah bandar pantai menghadap Laut China Selatan manakala lokasi kajian utama terletak di Selat Melaka. WHO melaporkan jangkitan saluran pernafasan bawah menyumbang 13.1% daripada jumlah kematian kanak-kanak berumur 5 tahun di seluruh dunia. Menurut Jabatan Perangkaan Malaysia, radang paru-paru adalah penyebab utama kematian dalam kalangan mereka berusia 0-14 tahun pada tahun 2019 dan menyumbang 4.8% daripada jumlah kematian. Fokus kajian ini adalah untuk mengkaji bagaimana bahan pencemar udara bergerak dan merebak ke seluruh kawasan kajian dari tahun 2015-2018 dan mengenal pasti bahan pencemar udara utama yang

dikaitkan dengan jangkitan pernafasan akut di kalangan pesakit luar dan umur sebagai faktor risiko. Pengaturcaraan R dan pakej terbukanya telah digunakan untuk menghasilkan mawar angin, mawar pencemar dan plot kalendar untuk menggambarkan corak pencemaran di seluruh kawasan kajian. Untuk analisis deskriptif, Penyelesaian Produk dan Perkhidmatan Statistik (SPSS Versi 28) telah digunakan untuk menghuraikan kumpulan umur utama pesakit yang mengalami ARI akibat pencemaran udara dan merumus kekerapan lawatan untuk ARI mengikut kumpulan umur. Ia juga digunakan untuk merumuskan bahan cemar dan kelajuan angin di kawasan kajian. Korelasi menentukan hubungan antara lawatan pesakit luar untuk ARI di KKBR, KKBM dan KKBP dengan API, SO_2, NO_2, O_3, CO dan PM_{10}. ANOVA sehala digunakan untuk membandingkan kumpulan umur. Kajian ini menggunakan data sekunder bahan pencemar yang disediakan oleh Jabatan Alam Sekitar dari stesen pemantauan kualiti udara SMKBR, KVM, dan SMKABP. Data sekunder lawatan pesakit luar diperolehi daripada KKBR, KKBM, dan KKBP. Tumpuan keseluruhan bahan pencemar dikawal oleh angin timur laut dan purata kelajuan angin adalah mencukupi untuk membantu dalam penyebaran bahan pencemar udara. Sektor angin timur laut mencatatkan nilai IPU dan PM_{10} tertinggi di ketiga-tiga kawasan. Berdasarkan plot kalendar, kesimpulan dibuat bahawa pencemaran tempatan, bukan pencemaran rentas sempadan merupakan penyumbang utama kepada indeks pencemaran udara yang di lokasi kajian kerana hari dengan IPU tinggi menunjukkan corak bermusim. Kajian ini mendapati terdapat korelasi yang positif dan signifikan antara API, PM_{10}, SO_2 dan 0_3 dengan lawatan pesakit luar di KKBR, PM_{10} dan lawatan pesakit luar di KKBM dan API dan PM_{10} dengan lawatan pesakit luar di KKBP.

Kebanyakan lawatan pesakit luar untuk jangkitan pernafasan akut adalah di kalangan pesakit berumur 13 hingga 59 tahun, diikuti oleh pesakit berumur 12 tahun ke bawah dan lebih daripada 60 tahun. Bilangan lawatan pesakit luar untuk jangkitan pernafasan akut di ketiga-tiga klinik berbeza mengikut kumpulan umur. Penemuan kajian ini diharapkan dapat menyumbang kepada peningkatan kualiti udara di kawasan kajian dan memberi galakan kepada penyelidikan seterusnya di kawasan lain untuk meningkatkan kesedaran orang ramai dan menggalakkan pemuliharaan alam sekitar.

Kata Kunci: Pencemaran Udara, Bahan Pencemar, Mawar Angin, Mawar Pencemar, Plot Kalendar

SDG: MATLAMAT 3: Kesihatan Yang Baik Dan Sejahtera, MATLAMAT 11: Bandar dan Komuniti Mampan, MATLAMAT 13: Perubahan Iklim

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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LIST OF ABBREVIATIONS

API	Air Pollutant Index
APIMS	Air Pollutant Index of Malaysia
ARI	Acute Respiratory Index
CAQM	Continuous Air Quality Monitoring Stations
CVD	Cardiovascular Diseases
DOE	Department of Environment
ENE	East North East
KKBM	Klinik Kesihatan Bandar Maharani
KKBP	Klinik Kesihatan Bandar Penawar
KKBR	Klinik Kesihatan Bukit Rambai
KVM	Kolej Vokasional Muar
LRI	Lower Respiratory Tract Infections
MCAQM	Mobile Continuous Air Quality Monitoring Stations
NEM	Northeast Monsoon
NNE	North of Northeast Direction
SMKABP	Sekolah Menengah Kebangsaan Agama Bandar Penawar
SMKBR	Sekolah Menengah Kebangsaan Bukit Rambai
SWM	Southwest Monsoon
URI	Upper Respiratory Tract Infections

CHAPTER 1

INTRODUCTION

1.1 Introduction

The projected world population of 9.05 billion by 2050 would necessitate a massive increase in energy production and consumption, primarily through the extensive use of natural resources. Rising in energy consumption will to increase greenhouse gas emissions and contribute to climate change (Muzayanah et al., 2022; Erum Rahman and Shazia Rahman, 2022). Such population growth hastens anthropogenic environmental impacts due to rural-urban migration and industrialization, with significant waste generation (Hulkkonen et al., 2022; Torbatian et al., 2020). Both Li et al. (2018) and Hong Chen et al. (2018) agree that fast development and population growth have added to air quality issues. Environmental (soil, air, and water) pollution is a major factor in the severe environmental deterioration and resulting rise in land use that occur as a result (Wu et al., 2022; Dutta and Chatterjee, 2021; Xie et al., 2021). One of the biggest environmental issues currently facing the world is pollution, particularly air pollution (Galimova et al., 2022; Pérez Velasco and Jarosiska, 2022), which is the focus of this study. Climate change has been regarded as one of the twenty-first century's greatest health threats (Daly et al., 2022; Zainuddin et al., 2022; Arnell, 2022; Zhou et al., 2022) with air pollution being the single greatest environmental health risk that is affecting premature deaths annually (Khomenko et al., 2021; Wu et al., 2019) and morbidity worldwide (Dominski et al., 2021). In Uzbekistan, China and France, cardiovascular disease and acute respiratory distress syndrome deaths continue to be primarily caused by air pollution, including indoor and outdoor pollution (Wang et al., 2022; Tian et al., 2022; Gutman et al., 2022).

In accordance with the findings of Fuller et al. (2022), an estimated annual mortality rate of 6.5 million individuals can be attributed to air pollution. Air pollution is a matter of great concern in numerous developing countries because it causes detrimental impacts, such as adverse health consequences, increased mortality rates and impairments experienced by a substantial portion of the population. The impact of disclosing environmental air pollution is more pronounced in developing countries due to the substantial contributions of heavy vehicle emissions and huge industrial emissions resulting global warming (Fuller et al., 2022). According to Fisher et al. (2021), air pollution in Africa, a country in the process of development, led to around 1.1 million fatalities in the year 2019. In 2019, Ethiopia had a financial loss of $3.02 billion, Ghana experienced a loss of $1.63 billion and Rwanda suffered a loss of $349 million due to the adverse effects of morbidity and mortality resulting from air pollution. Pakistan, a developing country, reports that air pollution is responsible for almost 20% of total annual mortality (Cohen et al., 2017). Several major cities in Pakistan, such as Karachi, Lahore, Quetta, Peshawar, Islamabad, and Rawalpindi, have been prone to significant air pollution (Yuan et al., 2020). Environmental damage is unavoidable because the industrial sector is the main engine of economic progress and development. Therefore, it is critical for emerging nations, especially those without environmental policies, to address the problem of the link between mortality, economic advancement, and environmental degradation. (Yuan et al., 2020).

Malaysia, a growing country, hopes to achieve its goal of becoming a developed nation by 2020, with a small delay until 2025 (Afiq et al., 2019). Over a ten-year period, Malaysia's population expanded by 12.9 million. Malaysia's population is expected to increase from 28.6 million in 2010 to 41.5 million in 2040. Despite this, the average annual population growth rate decreases by 0.5%, from 1.8% in 2010 to 0.4% in 2014 (Statistics Malaysia, 2016). Malaysia's urbanization rate will increase to 75.1% in 2020 from 70.9% (19.5 million) in 2010. (24.4 million). The fourth National Physical Plan aims to increase the national urbanisation rate to 85% by 2040. In 2020, six states and 31 administrative districts reached an urbanisation rate of 85% (Department of Statistics Malaysia, 2022b). A total of RM2103.7 million (70.8%) of all environmental protection expenditures was allocated to pollution management. This was followed by waste management, with a total expenditure of RM766.8 million (25.8%) and environmental assessment and fees, which cost RM67.2 million (2%). In 2020, the industrial sector continued to dominate environmental protection expenditures, with expenditures of RM2382.4 million (80.1%) of the total. This was followed by the services sector, which spent RM366.7 million (12.3%), and the mining and quarrying industry, which spent RM100.4 million (3.4%) (Department of Statistics Malaysia, 2022).

The top three causes of air pollution in Malaysia are mobile sources, stationary sources, and open burning (Department of Environment Malaysia, 2020; Lee et al., 2020; Mohd Shafie et al., 2022). Transboundary pollution is another source of pollution that has caused haze in Southeast Asia (SEA), particularly Malaysia, nearly every year for the previous 30 years (Tan et al., 2017; Quah et al., 2021). Haze is associated with high levels of air pollution; it reduces visibility and harms human health. Sumatra and Kalimantan, Indonesia, have been highlighted as contributors to Malaysian transboundary haze due to high-intensity combustions caused by land clearance and burning practices in farming due to their low cost and efficacy, deforestation, and oil palm plantations on peat lands (Purnomo et al., 2018). Due to the southwest monsoon (late May to September), there are more fires throughout the dry season. The winds facilitate the transboundary transport of pollutants from Indonesia's Sumatra and Kalimantan open burning zones to Peninsular Malaysia and Malaysian Borneo, respectively (Khan et al., 2020). The economic effect brought on by the increased healthcare utilization connected to haze-related diseases was enormous (Jaafar et al., 2018; Latif et al., 2018). This occurrence led to a seasonal peak in Malaysia's API reading, which will be described in this study.

One of the first steps Malaysia takes to reduce pollution and protect the environment is to monitor air quality. As part of the new Environmental Quality Monitoring Plan (EQMP), the Department of the Environment (DOE) increased the number of continuous monitoring stations to 65 by the middle of April 2017. These stations are deliberately situated in urban, suburban and industrial areas to monitor significant changes in air quality that may be harmful to the environment and human health (Department of Environment, 2018). Studies carried out globally have examined the connection between air pollution and human health (Orach et al., 2021; Dominski et al., 2021; Karanasiou et al., 2021).

Acute respiratory infections pose an alarming worldwide health issue, which results in significant illness and fatality rates (Mir et al., 2022; Abbafati et al., 2020). ARI is the fourth-leading global cause of mortality, contributing to roughly three million fatalities globally in 2016, according to the World Health Organization (World Health Organization, 2020). Acute lower respiratory infections, encompassing pneumonia and bronchiolitis, have emerged as a significant contributor to hospitalizations and mortality among young children, particularly in countries with fewer economic resources (Troeger et al., 2019). Based on data provided by the Malaysian Ministry of Health, respiratory disease emerged as a prominent cause of hospitalization in the year 2018, reaching 13.86% and 18.73% of total admissions in government and private healthcare facilities, respectively (Ministry of Health, 2019). In the outpatient context, acute respiratory tract infections are also common (Shaver et al., 2019).

In Malaysia, emissions are rising from a variety of sources, including industrial industries, energy production, transportation and open burning (Abdullah et al., 2019; Latif et al., 2014). Bukit Rambai is classified as industrial because it is in a rapidly growing town with heavily industrialized areas that are affected by heavy traffic and seasonal high particulate events (Hasfazilah and Ahmad Shukri, 2016). Muar is a small town in northeastern Johor that has a few industries despite being mainly a residential area (Rani et al., 2018). This could contribute to local emissions.

Vulnerability is a term frequently used in the context of health to describe the degree to which a population or an individual is unable to endure the effects of health hazards (Nikolaos, 2015). Children, the elderly and people in areas with high levels of air pollution are particularly vulnerable (Wang et al., 2022). Those who are more susceptible, exposed or vulnerable may experience more severe health consequences. Due to variances in vulnerability, a change in exposure may have a significant impact on a component of the population even if the overall change in risk is minimal, and a reduction in pollution levels may have a particularly positive impact on the health of those groups of people that are most vulnerable (Makri & Stilianakis, 2008).

The Department of Environment of Malaysia reported hazardous readings during the 2013 Sumatera and Kalimantan Forest fires, particularly at Bukit Rambai, Melaka, with 470, and Muar, Johor, with 750, which were the areas of concern in this study due to air pollutants and outpatient visits for acute respiratory infections. Bandar Penawar, Johor was selected as the comparative site since it is a coastal town facing the South China Sea while Bukit Rambai in Melaka and Muar in Johor are coastal towns located on the Straits of Malacca. Due to the fact that the earth's surface and industries differ, it is anticipated that the selection will have varying results.

1.2 Problem Statement

Children's morbidity and mortality are frequently brought on by acute respiratory infections (ARI). This is notably true in developing countries such as Malaysia, a tropical middle-income nation in Southeast Asia. In 2016, it was estimated that lower respiratory tract infections caused 13.1% of all pediatric deaths worldwide (Wang et al., 2016). In Malaysia, pneumonia was responsible for 4.8% of all 0–14 year old deaths in 2018 (Department of Statistics Malaysia, 2019) and contribute to 14% of all global deaths of children under the age of five, killing 740,180 children in 2019 (World Health Organization, 2022). Acute effects that go untreated can develop to chronic problems. Long-term problems, on the other hand, typically involve several systems and have multiple consequences (Kristen and Carl, 2018). These detrimental impacts on health have had a considerable influence on the health economy, resulting in increases in hospital admission and prescription expenses, the added cost of disease, and the cost of taking medically required breaks, which results in lost opportunities for income (Manan et al., 2018). The findings can be utilized to guide planning and resource allocation.

1.3 Research Questions

This study's primary research issue concerns the air pollution index distribution pattern and outpatient visits for acute respiratory infection in the study areas. The following three sub-research questions are:

1. How are the movement and dispersal of air pollutants in the study areas?
2. What were the main air pollutants positively associated with outpatient visits for acute respiratory infection in the study areas?
3. What is the main age group of patients who suffered acute respiratory infection due to air pollution in the study areas?

1.4 Significance of the Study

Both of these study areas, Bukit Rambai, Melaka and Muar, Johor, have previously reported having the highest API readings in Malaysia during the 2013 Sumatera and Kalimantan Forest fires. It was decided to use Bandar Penawar, Johor, as the comparative site since it is a coastal town facing the South China Sea while Bukit Rambai in Melaka and Muar in Johor are coastal towns located on the Straits of Malacca. The primary age group of patients who have experienced acute respiratory infection owing to air pollution in the research locations is also identified in this study, in addition to the key air pollutants that are positively linked with outpatient visits for acute respiratory infections. Compared to hospital admission, outpatient visits are anticipated to be a more sensitive indicator of acute or short-term health consequences from air pollution. The results of this study should enhance the air quality in the targeted areas and inspire additional research in related fields.

1.5 Scope of the Study

This study will identify the distribution pattern of air pollutant index and outpatient visits for acute respiratory infection in two study areas: Bukit Rambai, which is in Melaka, and Muar, which is in Johor, from 2015 to 2018 (4 years). These study areas previously reported the highest API readings in 2013, which were 750 for Muar and 477 for Bukit Rambai, Melaka. Bandar Penawar, Johor was chosen as the comparative site since it is a coastal town facing the South China Sea while Bukit Rambai in Melaka and Muar in Johor are coastal towns located on the Straits of Malacca.

1.6 The Main Objective of the Study

The objective of this study is to ascertain the presence of an association between the number of outpatients seeking treatment for acute respiratory conditions in sentinel clinics and the air pollution index.

The following are the study's specific objectives:

1. To analyze the movement and dispersal of air pollutants at Bukit Rambai, Melaka and Muar, Johor.
2. To identify the main air pollutants associated with outpatient acute respiratory infection visits at the Bukit Rambai, Melaka and Muar, Johor.
3. To determine the influence of age on the risk of acute respiratory infection due to air pollutants among outpatients in Bukit Rambai, Melaka and Muar, Johor, between 2015 to 2018.

1.6.1 Research Hypotheses

1. Local emissions were the dominant sources instead of transboundary pollution, contributing to the high air pollutant index observed in study areas.
2. Particulate matter is the primary air pollutant related to outpatient visits for acute respiratory infection in the study locations.
3. The age range of <12 experienced the greatest marginal impact of air pollution on outpatient visits, followed by >60 and 13-59.

CHAPTER 2

LITERATURE REVIEW

2.1 Air Pollution

2.1.1 Definition of Air Pollution

Clean air is vital to human health. Clean air is crucial for optimum health and the protection of plants, soils and structures (NEHAP, 2020). Nitrogen (78.0%), oxygen (20.95%) and argon (0.93%) dominate atmospheric gases. Nitrogen and oxygen exist as diatomic (two-atom) molecules as N_2 and O_2, respectively. The monatomic (one atom) gas argon is present in the environment. Due to its noble gas classification, it has a full outer electron shell, which prohibits it from chemically interacting with other atoms. Nitrogen (N_2) and Oxygen (O_2) molecules have an overall form resembling a long capsule with a medial constriction or two partially joined spheres (Daniel Vallero, 2015).

In terms of outdoor air quality, the DOE in Peninsular Malaysia constantly monitors the air quality with a network of sixty-five continuous air monitoring stations (CAMS). The particle matter (PM) level was one of the five factors studied, along with sulphur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO) and ozone (O_3). The air pollution index (API) is calculated using the air quality data taken at each station.

In terms of outdoor air quality, DOE has participated in worldwide environmental discussions and is actively updating the Clean Air Action Plan, in addition to enforcing the Environmental Quality Act (EQA) 1974 and the Environmental Quality (Clean Air) Regulations 2014. The Ministry of Health (MOH) also monitors haze-associated diseases at 52 sentinel health clinics in Malaysia. In addition, the Ministry of Health enforces the Control of Tobacco Product Regulations of 2004 to prohibit smoking and reduce indoor air pollution caused by environmental cigarette smoke. The Department of Occupational Safety and Health (DOSH) helped to improve indoor air quality by developing a Code of Practice (COP 2005) for workplace indoor air quality, which was upgraded to the Industry Code of Practice in 2010 (ICOP 2010). Moreover, the Ministry of Housing and Local Government's Uniform Building By-Law stipulates building ventilation rules (NEHAP, 2020).

2.1.2 Air Pollution and Climate Change

Air pollution and climate change are major environmental hazard to human health and global cause of death and disease (Ferreri et al., 2019; World Health Organization, 2016). Climate change is a serious concern affecting the atmosphere. In terms of spatial and temporal scales, it differs from air pollution. Climate change is mainly caused by greenhouse gases, which have long atmospheric lifetimes and are thus spread uniformly in the atmosphere. On the other hand, air pollution exhibits significant spatiotemporal variability and has a relatively short reaction time regarding the link between emissions and atmospheric concentrations (Seigneur, 2019).

Climate change is increasing the frequency and intensity of wildfires in many places (Mauzerall et al., 2021). Past temperature variations and air pollution produced by climate change substantially impact the mortality or morbidity of human diseases (Lou et al., 2019). Air is considered polluted when contaminants are present at levels that risk human health or degrade ecosystems or other highly valued resources, like buildings and materials. (Ar, 2015; Oke et al., 2021). The air quality in different parts of the country was affected by pollutants emitted from a variety of sources. Any substance, whether solid, liquid or gaseous, that is present in the atmosphere and has the potential to alter its natural properties is considered air pollution. A part of the troposphere or stratosphere is said to be polluted when it deviates from the norm and contains pollutants in amounts that are harmful to both living and nonliving organisms (Carlsen et al., 2021; Zhang et al., 2019; Gajah et al., 2013). Anthropogenic (coal and fuel combustion, industry, automobiles, agriculture) and natural (meteoric, terrestrial, marine, volcanic, erosion and surface winds, forest fires, and biogenic) factors contribute to air pollution (World Health Organization, 2021; de Paula Santos et al., 2021).

Exposure pertains to the manner in which individuals come into contact with atmospheric contaminants, such as through the act of inhaling. In contrast, the dosage pertains to the specific quantity of a substance that is consumed by the body, such as the mass of a pollutant that enters an individual's bloodstream within a specified timeframe (Oke et al., 2021). Outdoor air pollution is recognised as a severe problem due to the elevated concentrations of some pollutants, which have detrimental health and environmental effects

(World Health Organization, 2021). However, realising the health implications of air pollution has led to several international, national, and municipal measures targeting enhancing air quality (Hands, 2022).

2.1.3 Air Pollution Effect

The effects of air pollution can be categorised as either acute or chronic. Acute effects typically affect just one part of the body and can be treated. The definition of an effect as acute does not necessarily address the severity of the effects. It usually only refers to the duration of the effects. In contrast to chronic effects, acute effects have a very rapid onset and or a short course. Acute effects can affect any body's systems (Marcano-Reik, 2013). Untreated acute effects can lead to chronic effects. Long-term conditions without treatment, on the other hand, typically involve multiple systems and have a variety of effects (Kristen and Carl, 2018), including irreversible problems such as respiratory diseases and cardiovascular diseases (Sanyal et al., 2018). According to research by Katoto et al. (2021), whereas one study investigated the impacts of both short- and long-term pollutant exposures, 52% and 48% of the studies evaluated the effects of each respectively. $PM_{2.5}$ (64%), NO_2 (50%), PM_{10} (43%) and O_3 (29%), were the most studied pollutants for acute impacts, whereas $PM_{2.5}$ (85%), NO_2 (39%), O_3 (23%) and PM_{10} (15%) were the most studied for chronic effects.

Badida et al. (2022) discovered a statistically significant positive relationship between PM_{10} and overall non-accidental, respiratory, cardiovascular disease (CVD) and lung cancer mortality by analyzing the long-term effects of ambient air pollution on all-cause and cause-specific mortality. In two investigations, SO_2 was also linked to deaths from cardiovascular and respiratory conditions. Despite the dearth of study on the relationship between respiratory and CVD Mortality and NO_2, a favourable association was observed between the two variables. Short-term exposure to PM_{10}, $PM_{2.5}$, NO_2, and SO_2 was linked to several morbidity outcomes. PM_{10} and stroke, NO_2 and stroke, and O_3 and respiratory hospital admissions were the only relationships not shown to be statistically significant. Zhang et al case-crossover's study from 2022 in China showed that short-term exposure to $PM_{2.5}$ was strongly linked to under-5 mortality from all naturals causes and from diseases such preterm birth, diarrhoea, pneumonia, and digestive disorders. Apart for cancer and memory-related problems, household air pollution from solid fuel consumption is linked to an increased incidence of chronic multi-morbidity in Chinese people, which includes digestive disorders, heart diseases, hypertension, and asthma (Shi et al., 2022).

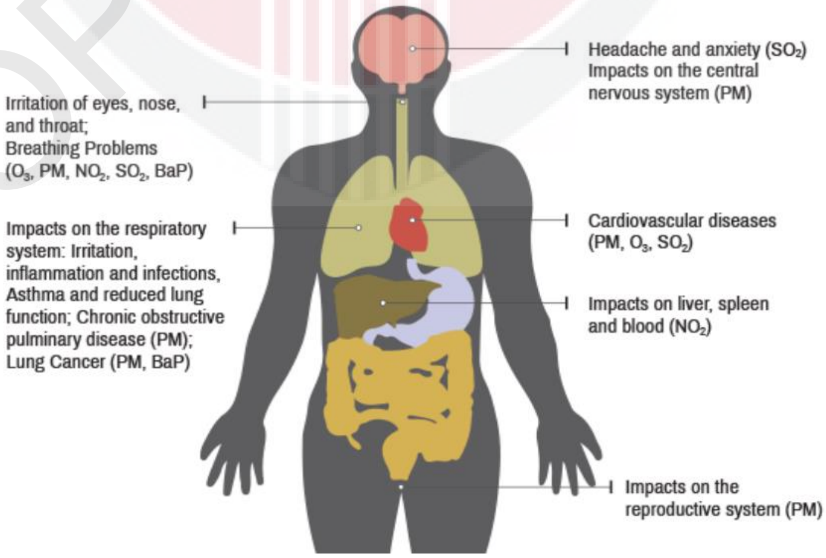


Figure 2.1: Health Impact on Air Pollution
(Source: globalactionplan.org.uk)

An analysis of air mass transport using backward trajectories for all regions in Malaysia in October and November 2015 identified biomass burning in Sumatera, Indonesia, as an associated source of transboundary air pollution (Sentian et al., 2019). Smoke has a harmful influence on the health of our country and our neighbours. These negative effects on health have had a significant impact on the health economy, leading to rises in hospital admission and prescription costs, the extra cost of disease, and the price of taking medically required leaves, which results in lost earning opportunities (Manan et al., 2018).

According to an analysis by Murnira Othman et al. (2022) particle deposition in the human respiratory tract revealed higher total deposition fraction values during haze days than on non-haze days, the average $PM_{2.5}$ and PM_{10} ratio during haze days was higher than the average for normal days for all sites, indicating higher $PM_{2.5}$ concentrations during haze days compared to normal days. According to the findings of this study, biomass-burning activities during the dry seasons and the Southwest monsoon significantly impacted Malaysia and Thailand. Due to higher pollutant concentrations from the fires, more than 60% of the population living in the densely populated Greater Klang Valley was exposed to harmful and hazardous air quality conditions during the 2015 wildfires. In September and October 2015, PM_{10} concentrations in Malaysia were above average, exposing nearly 40% of the population to those levels (Mead et al., 2018). Abdullah and Alias (2018) and Khan et al. (2020), who discovered that the concentration of PM_{10} was roughly twice as high during the haze period as it was during the non-haze period in 2015, came to a similar conclusion.

Malaysia stated that for four years in a succession, the percentage of haze episodes recorded across all stations was greater (67%) than the number of non-haze incidents (33%) (2012-2015). Acute exacerbation of bronchial asthma (AEBA) and chronic obstructive pulmonary disease (AECOPD) inpatient and outpatient patients showed significantly higher means during haze episodes than inpatient and outpatient cases during non-haze episodes (Jaafar et al., 2021). Hanafi et al. (2019) contend that for all age groups, the health risks during haze seasons were greater than those during non-haze seasons. Outpatient morbidity in medical clinics increased as the amount of haze in Johor Bahru increased. The average yearly economic losses in Pasir Gudang and Larkin due to the impact of haze on outpatient health were estimated to be RM83,233 and RM107,486. According to Jaafar et al. (2018), the economic impact of the rise in healthcare utilisations connected with haze-related illnesses was substantial.

The number of haze episodes was greater than the number of non-haze events (haze episodes were defined as monthly PM_{10} levels of ≥50μg^{-3}). The average rate of inpatient, outpatient, and total healthcare utilisation was much greater during haze occurrences. The four-year cumulative differences in direct medical costs for haze and non-haze periods were approximately RM13.1 million for inpatient cases, RM1.4 million for outpatient cases, and RM14.5 million for total cases. The Asian haze episode in 1997 increased the number of hospitalizations and premature deaths among adults with respiratory problems, and subsequent haze occurrences increased the number of hospitalizations. Between 2005 and 2013, the cost of hospital admission ranged from RM1.8 million to RM118.9 million. The incremental cost of sickness (COI) was RM21 million during the haze in 1997, while it rose to RM410 million during the haze in 2013 (Manan et al., 2018).

2.2 Local Emission

People generally breathe in air that has been contaminated by local or regional sources. According to atmospheric circumstances, air pollution can, however, go farther and, in some cases, cross international borders (Asian Development Bank, 2022). Since motor vehicles were a major contributor to the air pollution, development must be carefully planned to maintain low levels. Lower levels of air pollutants will be maintained through the use of green technology-based management to reduce emissions from local burning and waste combustion (Abdul Halim et al., 2018).

2.3 Respiratory Infection

2.3.1 Definition of Acute Respiratory Infection

An acute respiratory infection (ARI) is characterized by the sudden onset of at least one of the symptoms listed. The first four symptoms include a cough, a sore throat, trouble breathing, coryza and an infection-related diagnosis from a doctor. ARI may present with or without fever (World Health Organization, 2009). According to MISP, 2015, severe acute respiratory infection (SARI) is a respiratory infection that has started within the last ten (10) days, has a history of fever or a recorded fever of less than 38°C, coughs, and necessitates hospitalisation. In a study by Mabahwi et al. (2018), hospital admissions in Petaling Jaya increased again on days 7 and 8 after initially declining on days 3 and 4. This link was found to be significant. Considering this, it may be said that a 10 μg/m^3 rise has a larger short-term impact on admissions for respiratory health. In 2014 and 2015, the incidence of upper respiratory tract infections in Johor was proportionate to the PM concentration and API value (Hanafi et al., 2018). In 2015, according to Ortega-García et al. (2020), the paediatric emergency care unit got 12,354 visits from Murcia residents suffering from acute upper or lower respiratory tract disease. Hospitalization for respiratory symptoms increased with increasing mean daily NO_2 and O_3 levels and reduced with increasing age. Asthma, bronchitis, and pneumonia account for the majority of deaths attributable to air pollution in Delhi from 2001 to 2012, and there has been an increase in the number of deaths attributable to respiratory illness among children (Singh and Grover, 2018).

A study by Sam et al. (2021) revealed that the expected costs of ARI hospitalisations for children younger than 5 years are substantial. The same results were reached by Li et al. (2022), who reported an extrapolated estimate of 2.5 to 4.1 million hospitalisations caused by respiratory syncytial virus in children aged 0 to 60 months worldwide in 2019. In addition, prices rise as children become older, and comorbidities, premature birth, the finding of a respiratory virus, and ARI are all known to be major causes of death for kids in developing countries.

In the Philippines, deaths from ARI are far more prevalent among children than adults. In developed countries, this trend is inverted, where the elderly was the highest incidence of ARI-related mortality. Delhi, India, has also reported this by Singh and Grover (2018) for the age group greater than 60 years old. According to the Global Burden of Disease Survey, child wasting was responsible for 53.0% of lower respiratory infection (LRI) fatalities in men and 56.4% of LRI deaths in women among children under the age of five worldwide. More than 25% of LRI mortality in children aged 5 to 14 years was attributed to household air pollution, which can be caused by the use of solid fuels, with a population-attributable percentage of 26.0% for males and 25.8% for women. Smoking was a factor in 20.4%, 30.5%, and 21.9% of male LRI deaths between the ages of 15 to 49, 50 to 69, and 70 and older, respectively. Female LRI deaths from household air pollution were linked to 21.1% of those aged 15 to 49, and 18.2% of those aged 50 to 69. Ambient particulate matter was the main risk factor for LRI mortality in women aged 70 and older, accounting for 1.17% of such deaths (Globally and Bill, 2022). Throughout recorded history, viral respiratory infections have plagued humans. Unfortunately, there has been little progress in preventing the spread of viral respiratory infections worldwide (Davidse et al., 2021).

2.3.2 Classification of Acute Respiratory Infection

Acute respiratory infections (ARI) include upper and lower respiratory tract infections (URI and LRI). The upper respiratory tract consists of the airways between the nostrils and the voice cords in the larynx, as well as the paranasal sinuses and middle ear. Airways stretch from the trachea and bronchi to the bronchioles and alveoli in the lower respiratory tract (Ghimire et al., 2022). Patients with ARI experience various symptoms. When ARI is severe, it presents as a lower respiratory tract infection, which can lead to wheezing illnesses, including bronchiolitis, pneumonia, and asthma. ARI manifests as URI symptoms such as a cough, fever, and runny nose in moderate cases. ARI can cause movement and dispersal of air pollutants in the study areas and all bodily systems, possibly resulting in mortality (Yao et al., 2022). LRI consist of pneumonia, acute bronchiolitis, and bronchitis resulting from bacterial and viral infections (Álvaro-Meca et al., 2022). As the fourth leading cause of mortality worldwide, particularly among children, lower respiratory infections ranked the deadliest communicable disease (Wacharachaisurapol et al., 2021). However, the number of fatalities has significantly decreased; in 2019, 2.6 million lives were affected, 460 000 fewer than in 2000. (WHO, 2020). Air pollution, in addition to causing respiratory illnesses, can harm the eyes, skin, lungs and other respiratory organs. In severe cases, it might lead to cancer mortality and breathing problems. The circulatory system may become weaker as a result of air pollution, increasing the likelihood of failure. (Singh and Grover, 2018).

2.4 Sentinel Clinics

2.4.1 Definition of Sentinel Clinics

According to MISP (2015), a sentinel surveillance system comprises one or more designated healthcare facilities that collect epidemiologic data and laboratory specimens from patients with an illness that meets a certain case definition. Sentinel surveillance systems are a cost-effective method for collecting high-quality data from a small number of locations in relatively common circumstances. Ministry of Health monitors air pollution-related disorders such as conjunctivitis, asthma and acute respiratory infection at 52 sentinel health clinics around Malaysia on every month (DOE, 2020).

2.4.2 WHO's Guideline for the Selection of the Sentinel Clinics

Murray and Cohen (2016) stated that sentinel site surveillance provides useful epidemiological information on proportions caused by various diseases, age distribution, and risk factors; it may also be used for tracking trends of hospitalised cases within a health institution, assuming healthcare patterns and population remain stable. Demographic representativeness, regional representativeness, and climatic representativeness should be taken into account while determining the location of sentinel sites (World Health Organization, 2014).

2.5 Ambient Air Quality Monitoring Programme in Malaysia

2.5.1 Definition of Air Quality Monitoring Station

The usual method for managing air quality, determining trends, and estimating exposure for epidemiological analysis has been to measure air pollutant concentrations at fixed-location monitoring sites. However, despite an increase in the number of monitoring sites worldwide, coverage is insufficient and frequently limited to big cities to reliably assess exposure in the many varied locales where people live (World Health Organization, 2021). According to Yatkin et al., 2020 in research and epidemiological studies, monitoring and sampling air pollutants are typically done at locations considered representative of the surrounding area. However, especially in metropolitan regions with numerous sources, ambient air concentrations at monitoring stations may differ significantly from those at neighbouring sites. The European Union (2008) proposed that cities with less than 0.25 million population build at least two monitoring sites to measure the annual average of ambient particulate matter, and one more station for every 0.25 million residents up to 1.5 million. The guidelines also suggested 13 sites for cities with fewer than 6.0 million people and 15 sites for cities with more than 6.0 million people. There are two significant gaps in detecting air pollution levels: The first is a global lack of monitoring, as well as inadequate monitoring in rural areas or outside of big cities; the second is an inability to quantify the spatial variation in particular air pollutants within cities. (WHO, 2021).

2.5.2 Air Quality Monitoring Stations in Malaysia

The Department of Environment's Environmental Quality Monitoring Programme (EQMP) monitors the nation's environmental quality using a network of environmental monitoring stations to detect any significant changes that could be detrimental to both the environment and human health. The EQMP network includes 65 Continuous Air Quality Monitoring Stations (CAQM), 14 Manual Air Quality Monitoring Stations (MAQM) and 3 Mobile Continuous Air Quality Monitoring Stations (MCAQM) for monitoring the nation's air quality. The Environmental Data Center will receive almost real-time air quality information from the CAQM station (EDC). The CAQM station provides near real-time air quality data scheduled to be transmitted to the Environmental Data Centre (EDC). The CAQM network is divided into the following categories: suburban; urban; industrial; rural. The background air quality characteristics are represented by the CAQM station. Data from the CAQM network generate hourly Air Pollutant Indexes, which are made available to the public via the APIMS (Air Pollutant Index of Malaysia) website and the MyIPU mobile application. The MAQM network employs a high-volume sampler, which collects PM_{10} and $PM_{2.5}$ on a predetermined schedule. The collected particulate matter is sent to a contract laboratory for heavy metal and hydrocarbon analysis. The DOE instructs the MCAQM station to be deployed in situations of pollution events or when a specific study is required. The MCAQM station is outfitted with the full complement of equipment to measure a comprehensive list of air quality parameters as with the fixed CAQM station (Department of Environment, 2019a).

2.5.3 Factors of Air Quality Monitoring Stations Selection

Malaysia constructed state-wide air quality monitoring networks to measure air quality in various locations, including residential areas, industrial regions, commercial areas, roadside areas, and reference sites. According to USEPA (2008) and DENR (2021) the following criteria in Table 2.1 should be used to select monitoring sites:

Table 2.1: Criteria of the Monitoring Sites Selection

No	Criteria	Justification
1	Results of past and current monitoring	To ensure that each monitoring station is representative of the targeted areas as feasible for evaluating trends data, past and current monitoring results must be accessible.
2	Representativeness	The priority area is the zone with the highest concentration of pollution in the region, and monitoring should also be conducted in planned growth regions to identify the environmental effects of future development.
3	Accessibility	Accessibility is the process of acquiring, maintaining, and transporting equipment and staff for a monitoring operation.
4	Availability of support services (power, telephone line and so forth)	The power supply to the equipment shelter must be designed to accommodate all operating and starting conditions; the supply for the equipment shall be divided into two separate circuits, one for indoor equipment and one for outdoor equipment. All circuits must be secured by an Earth Leakage Circuit Breaker (ELCB) or a Residual Current Device (RCD); all electrical wiring must be regarded as a permanent installation; all outdoor wiring must be protected; and there must be appropriate lighting and an internet network.
5	Security	The necessity for equipment shelters in which all structures created, including but not limited to equipment hut, must be typhoon-proof; all metal parts must be painted, rust-resistant, and well-insulated; and all construction materials utilised must be asbestos-free.
6	Effect of any specific topography	Topographical factors exacerbate problems with both the transport and distribution of air pollution. Smaller topographical features may have only localised effects, whereas larger ones, such as broad river basins or towering mountain ranges, may have far-reaching consequences. Before settling on a monitoring site, topographic considerations should be considered to avoid jeopardising the monitoring's aims.

2.5.4 Air Pollutant Index

An air quality standard is a specific amount of an air pollutant adopted as enforceable (for instance, a concentration or deposition threshold). Unlike an air quality guideline level, an air quality standard must incorporate additional components in addition to the effect-based level and average time. These are the methods and strategies for measuring things, the data handling procedures (such as quality assurance and quality control), and the statistics used to get the value from measurements that may be compared to the standard (WHO, 2021). Many countries now use several different air quality index systems, including the Air Pollutant Index (API), the Pollutant Standard Index (PSI), the Air Quality Index (AQI), and the Air Quality Health Index (AQHI). Because each statistic uses a unique approach and intensity in relation to the nation's economy, lifestyles, and other aspects, the indexes could not be comparable (Payus et al., 2022). Malaysia adopted API as an indicator of the air quality in a specific location (refer Table 2.2). The index values range from 0 to 500. Five API categories within this range are determined based on a specific subrange of index values and are connected to potential health issues.

Particulate matter (PM_{10} and $PM_{2.5}$), ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2) and carbon monoxide (CO) are the criterion pollutants tracked and included in API calculations. The API sub-index value of each pollutant is derived based on its concentration, and the sub-index with the highest value is chosen as the hourly API value. The pollutant concentration used as input in API sub-index computations varies depending on the averaging hour. For example, the hourly $PM_{2.5}$ sub-index is calculated from 24-hour running averages, whereas the hourly NO_2 sub-index is produced from 1-hour averages. Therefore, even when the air appears contaminated, as it may during a haze incident with high $PM_{2.5}$ concentrations, the API value may not show unhealthy or very unhealthy values for several hours after an occurrence. One reason for the variation in the averaging hour utilised as an input value for API is that health consequences related to the specific pollutant are linked to exposure length. The API is concerned with the potential health effects on the public. As the API value rises, the increasing health impact indicates how much awareness and mitigation would be required in problem areas. The API, mostly related to human health, can determine which days have good or poor air quality. Lower values are linked to better air quality and fewer health concerns (Department of Environment Malaysia, 2020).

Table 2.2: Air Pollutant Index Category

Air Pollutant Index (API)	Air Pollution Status	Colour Code	Shape
0 to 50	Good		○
51 to 100	Moderate		⬡
101 to 200	Unhealthy		⬠
201 to 300	Very Unhealthy		□
>300	Hazardous		△

(Source: Department of Environment, 2019)

2.5.5 Five Main Pollutants Globally

2.5.5.1 Ozone

When a single oxygen atom (O) joins with dioxygen (O_2), the regular oxygen molecule, in the presence of a third-body molecule that can absorb the heat from the process, ozone, a triplet oxygen (O_3), is formed. When nitrogen oxides (NO_x) and volatile organic compounds (VOCs) react in the presence of sunlight, O_3 pollutants are formed. During hot and sunny days, the formation of O_3 is accelerated. The primary sources of VOCs and NO_x emissions are industries and motor vehicle emissions, particularly in urban areas (Department of Environment Malaysia, 2020). Ozone can negatively impact a person's overall respiratory health, causing airway inflammation and breathing difficulties such as shortness of breath and discomfort when taking deep breaths. These effects can exacerbate respiratory diseases such as asthma, emphysema and chronic bronchitis. This disease is referred to as chronic obstructive pulmonary disease (COPD) (Zhang et al., 2019). In Asia and the Middle East, population-weighted ozone concentrations range from 30 to 50 µg/m^3 to 120 to 140 µg/m^3 primarily in small island countries Population-weighted seasonal ozone concentrations in southern Asian nations with high populations can reach 130 µg/m^3. Megacities in Africa; Cairo in Egypt, Kinshasa in The Democratic Republic of Congo and Lagos in Nigeria are likewise anticipated to have high concentrations, but there is currently limited information available (World Health Organization, 2021).

2.5.5.2 Carbon Monoxide

Due to its absence of colour, odour, and taste, Carbon Monoxide (CO) is a gas that poses an unnoticeable threat. It results from the incomplete combustion of hydrocarbons (Reumuth et al., 2019; Payus et al., 2019; Chen et al., 2021). According to long-term measurements, CO pollution in Malaysia has shown small but decreasing trends in the northern and central regions. In contrast, the southern region has shown small but increasing trends in the southern region. El Niño occurrences in 1997 and 2015 were most likely connected to CO concentrations at all stations in all five regions; northern, central, southern and eastern Malaysian Peninsula and Malaysian Borneo (Sentian et al., 2019). Chen et al. (2021) show evidence that exposure to ambient CO, despite its lower levels than current air quality regulations, may still pose a danger to public health. This is based on a cross-country analysis of time series. According to research conducted in China by Wang et al. (2021), short-term exposure to CO is linked to an increased risk of death from non-accidental causes, cardiovascular diseases, respiratory diseases, coronary diseases, heart disease, stroke and chronic obstructive pulmonary disease.

2.5.5.3 Sulphur Dioxide

Conventionally, the natural sources of Sulphur Dioxide (SO_2) come from processes such as biological degradation, forest fires, oceans, volcanoes, and other industrial processes. Since there are no volcanic eruptions in Malaysia, a significant amount of SO_2 is produced by automobiles and power plants burning coal and petroleum (Mohamad et al., 2015). SO_2 and outpatient visits for respiratory diseases were congruent with existing studies in the literature.

2.5.5.4 Particulate Matter

Particulate matter (PM) is a mixture of liquid and solid airborne particles, categorised by aerodynamic diameter, that are too tiny to fall to the ground under the force of gravity World Health Organization (2021). About 51% of the PM comprises carbon and other earth's crust elements (Karthik et al., 2017). Due to their size, wide distribution and high activity, PM is a major factor in the development of heavy hazes and is more likely to have severe health consequences than other inhalable particles, leading to an increase in the number of patients with upper respiratory tract infections (Hanafi et al., 2018). For the long-term measuring period for PM_{10} pollution in Malaysia, all regions, northern, central, southern and eastern Malaysian Peninsula and Malaysian Borneo, have displayed inconsistent trends. The highest daily PM_{10} at all stations in all five regions were most likely linked to El Niño events in 1997 and 2015 (Sentian et al., 2019). From 2009 to 2011, it was determined that PM_{10} concentrations in Muar were higher than those in Larkin, despite Larkin's higher population density. This is because of the haze occurrence that occurred during that time. The wind has carried smoke from a forest fire in Sumatra, Indonesia, resulting in transboundary issues. This transboundary has resulted in the declaration of a haze emergency in the district of Muar (Khir et al., 2018). In a Pearson correlation analysis performed by Zizi et al. (2018), the ambient temperature was found to have the strongest positive correlation to the PM_{10} concentration among the meteorological parameters, demonstrating that ambient temperature tends to contribute significantly to higher PM_{10} concentrations, even those as high as in Southwest monsoon. During the Southwest Monsoon, the yearly average PM_{10} concentration surpassed the Malaysia Ambient Air Quality Guidelines (50µg/m^3). However, the PM_{10} concentration during the Northeast Monsoon was below the permitted threshold (Abdul Hamid et al., 2018). Even though more concentrations appear to be below the limit over the past decade, concentrations for all locations increased in 2015 due to the haze that occurred in Malaysia from August to September as a result of massive land and forest fires in Sumatra and Kalimantan, Indonesia, which caused many schools to close due to extremely poor air quality (Khir et al., 2018).The particle size of PM is classified as follow:

a. Particulate Matter Less Than 10 (PM_{10})

The PM_{10} designation refers to coarse particles with a diameter of 2.5 to 10 micrometers. Usually, these bigger particles are found close to busy industrial areas and dusty roads (Pizzorno and Crinnion, 2017). Largely filtered out by the nose and upper airway, particles larger than 10m have a relatively short suspension half-life. Ultrafine ($PM_{0.1}$), fine ($PM_{0.1\text{-}2.5}$), and coarse ($PM_{2.5\text{-}10}$) fractions are all included in PM_{10} (Anderson et al., 2012). A study of Zahrotul Hayati and Utami Iriani (2018) found a strong association between PM_{10} concentration and ARI symptoms in children under the age of five in Rawa Terate Health Centre, Indonesia. Other than that, prenatal exposure to high levels of ambient PM_{10}, according to a study by Zhao et al. (2018), increased the likelihood of abnormal fetal growth. Aside from that, relationships between mental health or well-being determinants and PM_{10} have been discovered by Petrowski et al. (2021).

b. Particulate Matter Less Than 2.5 ($PM_{2.5}$)

$PM_{2.5}$ refers to fine particles with a diameter between 0.1 and 2.5 micrometers (Pizzorno and Crinnion, 2017). $PM_{2.5}$ may absorb a wide range of poisonous and hazardous compounds due to its huge surface area. Small particle size allows it to enter the lungs deeply, deposit in the terminal bronchioles, alveoli and even cross the gas-blood barrier to reach the circulatory system (Hsu et al., 2016). Recent research by Strosnider et al. (2019) revealed a correlation between exposure to $PM_{2.5}$ and visits to the emergency room for a variety of respiratory conditions, including respiratory infections. The relationship between acute respiratory infection hospitalizations and short-term exposure to $PM_{2.5}$ was discovered by Xia et al. (2017), who also investigated the relationship between various forms of air pollution and respiratory hospitalization. Supported by a study by Li et al. (2021). Other further investigation (Zhang et al., 2019) also supported a strong positive association between $PM_{2.5}$ and the quantity of hospitalizations for URTI and LRTI.

c. Particulate Matter Less Than 0.1 ($PM_{0.1}$)

Less than 0.1 micrometers in diameter are considered ultrafine particles, also referred to as nanoparticles. They are referred to as $PM_{0.1}$ and are more soluble than bigger particles (Pizzorno and Crinnion, 2017). The negative impact of $PM_{0.1}$ on cases of influenza-like illness has been demonstrated by a study by Lu et al. (2023). $PM_{0.1}$ was found to be causally related with greater morbidity in total respiratory illnesses and chronic obstructive lung disorders, but not with asthma (Lv et al., 2023).

2.5.5.5 Nitrogen Dioxide

Nitrogen Dioxide (NO_2), released mainly by motor vehicles, construction, and industrial pollution, is a major ambient air pollutant and a crucial precursor of ozone and other photochemical secondary pollutants. (Du et al., 2022; Serio et al., 2022). At low concentrations, NO_2 exposure has been linked to mild respiratory symptoms, while over exposure in a small space has been linked to death. WHO (2021) reports that high-income North American countries saw a dramatic reduction of -4.7% per year compared to relatively more moderate declines of -2.5% and -2.1% in western Europe and high-income Asia-Pacific countries respectively while Eastern Asia, on the other hand, saw a strong rise in population-weighted NO_2 concentrations throughout this time, at a rate of 6.7% annually. While in Malaysia, in the east and southern regions, NO_x pollution has shown rising patterns, but the central region has seen declining trends. High NO_x levels were linked to automobile emissions and nearby industrial operations, particularly in urban and industrial areas (Sentian et al., 2019).

Zhang et al. (2021) reported that NO_2 and SO_2 were the main air pollutants that affected the daily frequency of URI clinic visits. Years of life lost (YLL) due to non-accidental diseases, cardiovascular diseases, and respiratory diseases, respectively, were found to increase by 0.64%, 0.47%, and 0.68% relative increases for every 10 g/m^3 increase in two days moving average NO_2 concentrations in China, according to a multi-city study (Li et al., 2021). Short and long-term NO_2 exposure in children at all stages of development demonstrates that this group is particularly vulnerable. Effects include neonatal weight loss in moms who are exposed during the third trimester, as well as asthma morbidity in preschool children. Furthermore, NO_2 exposure has been associated to asthma exacerbations in primary school-aged children and decreased lung function in paediatrics. Finally, long-term NO_2 exposure has been associated to an increased incidence of lung illness (Beckwith et al., 2019).

2.5.6 Malaysia Ambient Air Quality Standard

By averaging the annual air quality data from the monitoring sites and using the Malaysia Ambient Air Quality Standard, the air quality trend for 2010 to 2020 was determined, as shown in Table 2.3. For 2020, Malaysia Ambient Air Quality Standard IT-2 is used. To replace the Malaysia Ambient Air Quality Guideline, which has been in operation since 1989, a new Ambient Air Quality Standard was established.

Table 2.3: New Malaysia Air Quality Standard

Pollutant	Averaging Time	Ambient Air Quality Standard		
		IT-1 (2015)	IT-2 (2018)	Standard (2020)
		μg/m³	μg/m³	μg/m³
Particulate matter with a size of less than 10 microns (PM_{10})	1 year 24 hours	50 150	45 120	40 100
Particulate matter with a size less than 2.5 microns ($PM_{2.5}$)	1 year 24 hours	35 75	25 50	15 35
Sulfur Dioxide (SO_2)	1 year 24 hours	350 105	300 90	250 80
Nitrogen Dioxide (NO_2)	1 year 24 hours	320 75	300 75	280 70
Ground Level Ozone	1 year 24 hours	200 120	200 120	180 100
Carbon Monoxide (CO)	1 year 24 hours	35 10	35 10	30 10

Source: Department of Environment, Malaysia

2.5.7 Other Elements Monitored by Air Quality Monitoring Station

2.5.7.1 Wind Speed

Wind speed characteristics can be analyzed using a variety of time periods, including monthly, annual, seasonal and decadal, as well as peak or extreme values for each period (Ren et al., 2022). Standard wind classifications are as follows: weak (up to 5 m/s), medium (5-10 m/s), severe (10-20 m/s) and hurricane (above 20 m/s) (Poddaeva and Fedosova, 2022). Wind speed and direction significantly impact pollutant transport and atmospheric dispersion in the atmosphere (Perugu et al., 2016). In atmospheric modelling, the amounts of pollutants due to the dilution effect typically decrease as the distance from sources increases (Atamaleki et al., 2019). According to Zhang et al. (2023), the presence of concentrated air contaminants might diminish the efficacy of strong winds in removing them, hence compromising atmospheric visibility even when wind speed conditions are consistent. It is crucial to acknowledge that densely populated areas with high wind speeds exhibit a reduced frequency of illnesses, suggesting that elevated wind speeds facilitate the dissemination of airborne pollutants. Poor public health can result from the stagnation of contaminated air containing viral agents and the spread of infectiousness (Coccia, 2021). In the event of a weak wind, a higher level of energy consumption would result in urban heat island and pollution heat island phenomena, which could have an impact on the quality of urban life, including energy consumption, human health, human comfort, urban rainfall and urban sustainability (Abbassi et al., 2022; Xu et al., 2018).

2.5.7.2 Wind Direction

The direction of the wind is shown by a weathervane, also known as a wind vane, which rotates freely. A wind vane directs the wind's direction. When describing wind direction, it is important to note that this is the direction from which the wind blows, not the direction in which it moves. A north wind blows toward the south (Intermediate Energy, 2017). Massive land burning in Indonesia led to the fog and haze that affected the state of Johor in 2015, with the haze occurring during the monsoon season and being affected by wind direction. Because of this, the winds are expected to circulate over the Southern region's atmosphere.

Consequently, PM_{10} concentrations surged rapidly (Azman et al., 2021; Khir et al., 2018). A seasonal shift in wind direction causes a monsoon. The transition between seasons is accompanied by changes in both ocean and land temperatures, consequently inducing shifts in wind patterns. The weather patterns in Malaysia are influenced by two different monsoons, namely the Southwest Monsoon (SWM) and the Northeast Monsoon (NEM). The SWM occurs from late May to September, while the NEM takes place from November to March (Idris et al., 2020). The cold surge flowing toward the equatorial region causes NEM to produce high winds, rough seas, and heavy rainfall. This cyclonic vortex might produce heavy rains for three to eight days (Azman et al., 2021). The SWM is characterised by low precipitation, less clouds, high outgoing long-wave radiation (OLR), and dry epochs frequently (Chenoli et al., 2018). North-easterly winds predominate during the wet seasons, whereas south-westerly winds prevail during the dry seasons (Dominick et al., 2015). Malaysia experiences a monsoon transition period in addition to the NEM and SWM, which normally starts in April–May and September–October. During the monsoon transition, the wind direction will shift for a short duration, with generally weak wind conditions and speeds not reaching 10 knots. Furthermore, the weather is humid, and the temperature rises, particularly in the afternoon (Masseran and Razali, 2016).

2.5.8 Air pollution and human health

A review was conducted by the authors on 72 articles investigating the association between air pollution (led by $PM_{2.5}$, PM_{10}, CO, NO_2, SO_2 and O_3) and human health (mainly respiratory followed by cardiovascular effects).

Potentials relevant studies were published in English language and identified through database searching, Science Direct and PubMed, from 2016 to 2021. The findings were presented in Table 2.4.

Table 2.4: Association Between Air Pollution and Human Health Categorized by Effect, Pollutants and Health Effects

No	Author	Effect	Pollutants	Respiratory	Ulcerative Colitis	Psychiatric	ED Admissions	Migraine	Cardiovascular	Amyotrophic Lateral	Brain structure	Otitis Media	Hospitalization and ED Visits	Peptic Ulcer Bleeding	Substance Abuse	Vascular Disease	Diabetic Problems
1	Brkamp et al., 2019	Acute	$PM_{2.5}$			X											
2	Brønnum-Hansen et al., 2018	Chronic	NO_2	X					X								X
3	Byrwa-Hill et al., 2020	Acute	O_3, NO_2 and CO	X													
4	Chang et al., 2017	Acute	$PM_{2.5}$	X													
5	Cheng et al., 2019	Acute	$PM_{2.5}$ and NO_2	X													
6	Croft et al., 2020	Acute	$PM_{2.5}$	X													
7	Cromar et al., 2020	Acute	NO_2, O_3, and $PM_{2.5}$	X													
8	Cserbik et al., 2020	Chronic	$PM_{2.5}$								X						
9	Daitao Zhang et al., 2019	Acute	$PM_{2.5}$	X													

Table 2.4 (continued)

No	Author	Effect	Pollutants	Respiratory	Ulcerative Colitis	Psychiatric	ED Admissions	Migraine	Cardiovascular	Amyotrophic Lateral	Brain structure	Otitis Media	Hospitalization and ED Visits	Peptic Ulcer Bleeding	Substance Abuse	Vascular Disease	Diabetic Problems
10	DeVries et al., 2016	Acute	SO_2						X								
11	Duan et al., 2021	Acute	$PM_{2.5}$		X												
12	Elliot et al., 2016	Acute	$PM_{2.5}$, PM_{10}										X				
13	Elser et al., 2021	Acute	NO_2 and $PM_{2.5}$					X									
14	Garcia-Olivé et al., 2018	Acute	SO_2	X													
15	Ghada et al., 2021	Acute	PM_{10} and NO										X				
16	Godri Pollitt et al., 2016	Acute	$PM_{2.5}$	X													
17	Gongbo Chen et al., 2017	Acute	$PM_{2.5}$, PM_{10}											X			
18	Goodman et al., 2017	Acute	O_3	X													

Table 2.4 (continued)

No	Author	Effect	Pollutants	Respiratory	Ulcerative Colitis	Psychiatric	ED Admissions	Migraine	Cardiovascular	Amyotrophic Lateral	Brain structure	Otitis Media	Hospitalization and ED Visits	Peptic Ulcer Bleeding	Substance Abuse	Vascular Disease	Diabetic Problems
19	Goodman et al., 2017	Acute	NO_2						X								
20	Hao Zhang et al., 2018	Acute	$PM_{2.5}$, PM_{10}, NO_2, CO, and O_3	X													
21	Hopke et al., 2021	Acute	$PM_{2.5}$										X				
22	Huang et al., 2019	Chronic	$PM_{2.5}$	X													
23	Hwang et al., 2017	Acute	$PM_{2.5}$	X					X								
24	Hyewoon Lee et al., 2018	Acute	$PM_{2.5}$, PM_{10}, CO, and O_3					X									
25	Hyunmee Kim et al., 2018	Acute	NO_2														X
26	John et al., 2018	Acute	NO_2, O_3 and $PM_{2.5}$						X								
27	Kate Shannon et al., 2016	Acute	O_3	X													

Table 2.4 (continued)

No	Author	Effect	Pollutants	Respiratory	Ulcerative Colitis	Psychiatric	ED Admissions	Migraine	Cardiovascular	Amyotrophic Lateral	Brain structure	Otitis Media	Hospitalization and ED Visits	Peptic Ulcer Bleeding	Substance Abuse	Vascular Disease	Diabetic Problems
28	Keet et al., 2018	Chronic	$PM_{2.5}$ and PM_{10}	X													
29	Kim et al., 2019	Chronic	PM_{10}, NO_2	X													
30	Kovacevic et al., 2020	Acute	PM_{10}, NO_2 and SO_2	X													
31	Liang et al., 2017	Acute	$PM_{2.5}$										X				
32	Linwei Tian et al., 2017	Acute	NO_2											X			
33	Liu et al., 2017	Acute	$PM_{2.5}$	X					X								
34	Lu et al., 2020	Acute	$PM_{2.5}$, PM_{10}, NO_2, SO_2 and O_3			X											
35	Ma et al., 2020	Acute	$PM_{2.5}$, NO_2 and SO_2	X													
36	Malig et al., 2016	Acute	O_3	X													
37	Martín Martín et al., 2018	Acute	SO_2, CO and NO_x	X													
38	Masoumi et al., 2017	Acute	NO and SO_2	X													

Table 2.4 (continued)

No	Author	Effect	Pollutants	Respiratory	Ulcerative Colitis	Psychiatric	ED Admissions	Migraine	Cardiovascular	Amyotrophic Lateral	Brain structure	Otitis Media	Hospitalization and ED Visits	Peptic Ulcer Bleeding	Substance Abuse	Vascular Disease	Diabetic Problems
39	Mazenq et al., 2017	Acute	PM_{10}, NO_2, and O_3	X													
40	Myung et al., 2019	Acute	$PM_{2.5}$, PM_{10}, CO							X							
41	Niu et al., 2020	Acute	$PM_{2.5}$, PM_{10}, CO, NO_2, SO_2 and O_3			X											
42	Noh et al., 2016	Acute	O_3, NO_2 and PM_{10}	X													
43	Oh et al., 2020	Acute	$PM_{2.5}$									X					
44	Olstrup et al., 2019	Acute	PM_{10} and O_3	X													
45	Ortega-García et al., 2020	Acute	PM_{10}, NO_2, and O_3	X													
46	Ou et al., 2019	Acute	$PM_{2.5}$	X													
47	Oudin et al., 2018	Acute	NO_2, O_3, and PM_{10}			X											
48	Oudin et al., 2018	Acute	NO_2, O_3, and PM_{10}			X											
49	Pan et al., 2019	Acute	$PM_{2.5}$						X								

Table 2.4 (continued)

No	Author	Effect	Pollutants	Respiratory	Ulcerative Colitis	Psychiatric	ED Admissions	Migraine	Cardiovascular	Amyotrophic Lateral	Brain structure	Otitis Media	Hospitalization and ED Visits	Peptic Ulcer Bleeding	Substance Abuse	Vascular Disease	Diabetic Problems
50	Pel-Chih Wu et al., 2020	Acute	$PM_{2.5}$													X	
51	Peng et al., 2016	Acute	$PM_{2.5}$														X
52	Pothirat et al., 2019	Acute	$PM_{2.5}$	X					X								
53	Qian Zhang et al., 2016	Acute	$PM_{2.5}$ and PM_{10}						X								
54	Qin Xu et al., 2017	Acute	$PM_{2.5}$						X								
55	Reid et al., 2019	Acute	$PM_{2.5}$, PM_{10}	X													
56	Rodrígue-Villamizar et al., 2018	Acute	NO_2, PM_{10}, and $PM_{2.5}$	X													
57	Solimini et al., 2017	Acute	PM_{10}, NO_2						X								
58	Stowell et al., 2019	Acute	$PM_{2.5}$						X								

Table 2.4 (continued)

No	Author	Effect	Pollutants	Respiratory	Ulcerative Colitis	Psychiatric	ED Admissions	Migraine	Cardiovascular	Amyotrophic Lateral	Brain structure	Otitis Media	Hospitalization and ED Visits	Peptic Ulcer Bleeding	Substance Abuse	Vascular Disease	Diabetic Problems
59	Suji Lee et al., 2021	Acute	$PM_{2.5}$ and PM_{10}						X								
60	Sun Hyun Kim et al., 2020	Acute	$PM_{2.5}$			X											
61	Szyszkowicz et al., 2016	Acute	O_3, $PM_{2.5}$, and SO_2			X											
62	Szyszkowicz et al., 2018	Acute	$PM_{2.5}$, NO_2, O_3, and SO_2	X													
63	Szyszkowicz et al., 2018	Chronic	NO_2, and $PM_{2.5}$, PM_{10}												X		
64	Szyszkowicz et al., 2020	Acute	$PM_{2.5}$ and NO_2			X											
65	Tétreault et al., 2016	Chronic	$PM_{2.5}$, NO_2 and O_3	X													
66	Tapia et al., 2020	Acute	$PM_{2.5}$						X								
67	Yang et al., 2020	Acute	$PM_{2.5}$						X								

Table 2.4 (continued)

No	Author	Effect	Pollutants	Respiratory	Ulcerative Colitis	Psychiatric	ED Admissions	Migraine	Cardiovascular	Amyotrophic Lateral	Brain structure	Otitis Media	Hospitalization and ED Visits	Peptic Ulcer Bleeding	Substance Abuse	Vascular Disease	Diabetic Problems
68	Yaohua Tian et al., 2018	Acute	O_3										X				
69	Ye et al., 2018	Acute	$PM_{2.5}$						X								
70	Yuxia Ma et al., 2016	Acute	PM_{10}, SO_2 and NO_2	X													
71	Zhang et al., 2021	Acute	$PM_{2.5}$, PM_{10}, and SO_2	X													
72	Zhaom et al., 2020	Acute	$PM_{2.5}$							X							

Note. **x** = The primary contaminants in included studies cause the diseases listed.

This review found a gap regarding acute and chronic effects on humans caused by air pollution. The recorded 65 acute and 7 chronic cases showed that cardiovascular diseases are the main contributor to acute cases. Short-term or acute effects refer to exposure to pollution from several hours to 7 days (Zheng et al., 2021). This review discovered that respiratory and cardiovascular diseases would have an acute effect.

In comparison, the chronic effects are asthma, brain structure and substance abuse. Chronic effects are symptoms of long-term or recurring illnesses or diseases. Chronic effects emerge gradually, sometimes due to repeated exposure to low concentrations of a health hazard. The latency period is when a health effect develops after the first exposure to a hazard (Kirch, 2008).

2.5.8.1 Type of pollutants

There was ozone, nitrogen dioxide (NO_2), sulphur dioxide (SO_2), particulate matter less than 2.5 m ($PM_{2.5}$), and particulate matter less than 10 m (PM_{10}) (O_3). Twenty-five studies looked at exposure to PM_{10}, 48 looked at exposure to $PM_{2.5}$, 27 looked at NO_2, 12 looked at SO_2, 6 looked at CO, and 20 looked at O_3. These pollutants were all determined to be the main ones that fuel-powered vehicles, thermoelectric power plants, and industrial sites emitted into the atmosphere (de Paula Santos et al., 2021)

2.5.8.2 Particulate matter and human health

Instead of being a single, self-contained pollution, particulate matter includes components, including chemical and biological fractions (Morakinyo et al., 2016). This study demonstrates a stronger association between air pollution and the development or deterioration of respiratory illnesses such as asthma and cardiovascular disease. (Suji Lee et al., 2021; Zhaom et al., 2020; V Tapia et al., 2020; Yang et al., 2020; Ye et al., 2018; Xu et al., 2017). In a previous multi-city time-series analysis it was found that children's asthma and combined respiratory disease had positive age-specific relationships with smoke $PM_{2.5}$, while adults' asthma, bronchitis, chronic obstructive pulmonary disease, and combined respiratory disease had positive age-specific relationships with smoke $PM_{2.5}$ (Stowell et al., 2019; Daitao Zhang et al., 2019; Xu et al., 2017). According to epidemiological research, particulate matter is associated with digestive issues, including ulcerative colitis (Duan et al., 2021). This study demonstrated that short-term exposure to ambient $PM_{2.5}$ was strongly associated with an increased likelihood of daily outpatient visits for ulcerative colitis, particularly among younger patients under 65. Few studies suggest that pollutants especially particulate matter, are associated with mental disorders, such as depression (Szyszkowicz et al., 2016), which may result in substance abuse even at low levels (Niu et al., 2020; Szyszkowicz et al., 2020; Kim et al., 2020; Oudin et al., 2018). (Szyszkowicz et al., 2018). Particulate matter, which may trigger the sympathetic nervous system, had the greatest impact on migraines of all the pollutants (Lee et al., 2018), especially on days with high temperatures. According to Cserbik et al. (2020), even at relatively low levels, present $PM_{2.5}$ may be a significant environmental factor impacting children's structural brain development patterns. Brief exposure to $PM_{2.5}$ and PM_{10} is likely to increase children's odds of acquiring acute otitis media during the summer season (Oh et al., 2020). It was observed that short- and medium-term $PM_{2.5}$ exposure increased non-diabetic individuals' fasting blood sugar levels (Peng et al., 2016). Particulate matter comes in various sizes (refer Figure 2.2), with those smaller than 10 micrometers having the ability to penetrate our lungs and cause severe health problems (European Environment Agency, 2022).

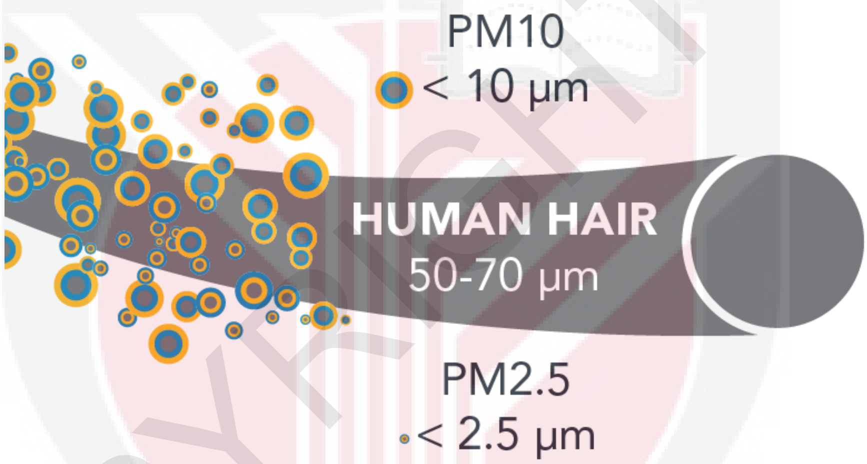


Figure 2.2: Particulate Size Comparison
(Source: California Air Resources Board)

2.5.8.3 Nitrogen dioxide and human health

Short-term exposure to high NO_2 triggered asthma and other respiratory diseases related to emergency department visits (Byrwa-Hill et al., 2020; Solimini et al., 2017; Mazenq et al., 2017; Noh et al., 2016) and long-term exposure will cause prevalent migraine and migraine severity (Elser et al., 2021). In addition, Hyunmee Kim et al. (2018) suggest that NO_2 is explicitly associated with emergency department visits for diabetic coma.

2.5.8.4 Sulphur dioxide and human health

The major health problem associated with sulphur dioxide exposure is acute upper and lower respiratory diseases (Zhang et al., 2021; Ma et al., 2020; Kovacevic et al., 2020; Szyszkowicz et al., 2018; Martín Martín et al., 2018), mental disorder (Niu et al., 2020; Lu et al., 2020), emergency department visits for depression between 1-7 days after exposure for females and 1 and 5 and 8 days after exposure for males (Szyszkowicz et al., 2016), ascending trend for bronchospasm (Garcia-Olivé et al., 2018; Masoumi et al., 2017) and exacerbation of existing chronic obstructive pulmonary disease following by short-term exposure (DeVries et al., 2016).

2.5.8.5 Ozone and human health

Ozone exposure, even at relatively low levels, can result in trips to the emergency room for upper and lower acute respiratory illnesses (Cromar et al., 2020; Olstrup et al., 2019; Szyszkowicz et al., 2018) and cause the need for respiratory outpatient visits (Zhang et al., 2018; Malig et al., 2016; Kate Shannon et al., 2016; Tian et al., 2018). In addition, it is worth noting that ozone has been found to contribute to the prevalence of mental problems, even in areas characterized by comparatively low levels of this pollutant. However, it is important to acknowledge that the available research on this topic is currently limited (Niu et al., 2020; Lu et al., 2020; Oudin et al., 2018). The synergistic effect of ozone can also trigger migraine, especially on high-temperature days (Lee et al., 2018), emergency visits for asthma (Ortega-García et al., 2020; Goodman et al., 2017; Mazenq et al., 2017; Noh et al., 2016; Tétreault et al., 2016) and exacerbate asthma in asthmatic children (Tétreault et al., 2016). Children living in low socioeconomic status environments appear to be especially vulnerable to ozone in each city in the United States, with positive odd ratios and high underlying rates of respiratory morbidity (O' Lenick et al., 2017). Ozone also had cardiorespiratory effects (John et al., 2018), associated with an increased risk of emergency room visit for depression between 1 and 7 days after exposure for females and between 1 and 5 or 8 days after exposure for males (Szyszkowicz et al., 2016).

2.5.8.6 Carbon Monoxide and human health

The presence of elevated levels of carbon monoxide in inhaled air impedes the capacity of the bloodstream to transport oxygen effectively The authors (Byrwa-Hill et al., 2020), Zhang et al. (2018), Lee et al. (2018) and Myung et al. (2019) discovered that brief exposure to heightened levels of carbon monoxide can result in visits to the emergency department for asthma-related issues, visits to respiratory outpatient clinics for pediatric patients and the emergence of amyotrophic lateral sclerosis, which ultimately leads to respiratory failure. Additionally, individuals may get migraines during periods of hot weather. Mental illnesses can result from long-term carbon monoxide exposure in environments with low and high air temperatures (Niu et al., 2020) and respiratory disease in children (Martín Martín et al., 2018).

This review by the authors presented evidence on the effects of pollutants on human health. Nearly half of the evidence was from studies on the daily number of respiratory disease admissions or visits. This review also showed that particulate matter has a stronger influence on outpatient or emergency visits, either in cardiovascular or respiratory disease, than the other air pollutants.

CHAPTER 3

GENERAL MATERIALS AND RESEARCH METHODOLOGY

3.1 Description of the Study Areas

All the 3 study areas are in Peninsular Malaysia. For this study, three locations were selected: Muar, Johor, and Bukit Rambai, Melaka are two residential areas with minor industries with high API values (Halim et al., 2020; Rani et al., 2018; Jamal Othman et al., 2014). Bandar Penawar, Johor, chosen as a comparative site in this study, never recorded a hazardous API value. These three study areas are all located in the southern region, which is a resemblance. The landscape is mostly flat in the southern part of the country. However, because of the summit of Titiwangsa Ridge, the northern part of this region is slightly elevated. The region’s main economic activity is manufacturing, including fisheries, wood-based industries, and palm oil plantations. (Mohtar et al., 2022).

3.1.1 Air Quality Data

Secondary air quality data were gathered from the Department of Environment (DOE) continuous air quality monitoring (CAQM) stations situated closest to the chosen sentinel clinic from 2015 to 2018 (4 years). There were no accessible statistics on the air quality near the patients' homes. Therefore, it was assumed that the air quality data acquired from the monitoring station nearest to the hospital sampled likewise applied to the area of the patients.

The Department of Energy (DOE) utilizes a network of 65 air quality monitoring sites to collect data on the hourly levels of significant pollutants, including particulate matter ($PM_{2.5}$ and PM_{10}), ozone (O_3), nitrogen dioxide (NO_2), sulphur dioxide (SO_2) and carbon monoxide (CO). The purpose of constructing these monitoring stations is to establish a continuous process of data collection, measurement, and monitoring of the stipulated ambient air quality. $PM_{2.5}$ was excluded from this study since its concentration was only added to API calculations in Malaysia beginning in August 2018. Since there was a change in the concessionaire company, the records for April to June 2017 have been cancelled. Except for the SMKABP air quality monitoring station, all selected continuous air quality monitoring sites face the Malacca Strait to the west. Selected monitoring sites are as Table 3.1.

Table 3.1: Details of the Air Quality Monitoring Stations

Site State	Location	Latitude	Longitude
Johor	Kolej Vokasional Muar (KVM)	2.0603° N	102.5952° E
Johor	SMKA Bandar Penawar (SMKABP)	1.5636° N	104.2262° E
Melaka	SMK Bukit Rambai (SMKBR)	2.2587° N	102.1729° E

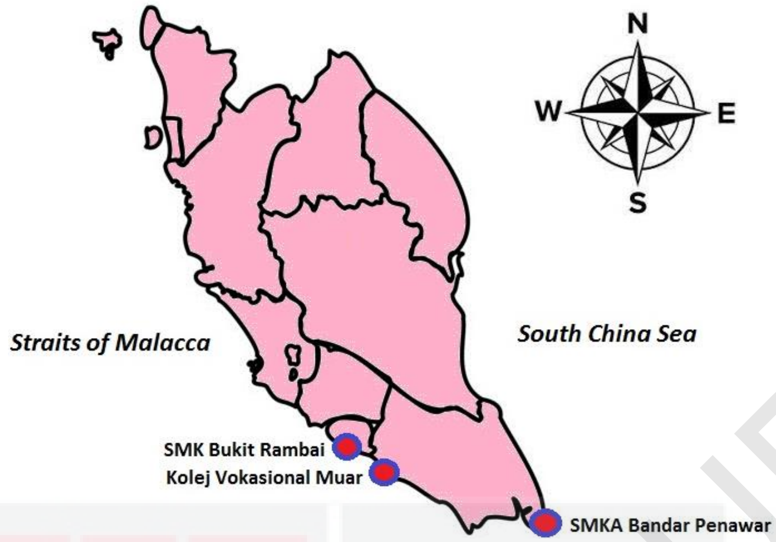


Figure 3.1: The Locations of Monitoring Stations of The Study

The two main monitoring sites, SMKBR and KVM, were separated by 61.2 kilometres. These air quality monitoring stations are strategically situated in industrial and residential areas to identify and monitor any significant changes in air quality that could endanger human health and the environment (Department of Environment, 2010). The air quality index KVM data were only available until March 12, 2018, as the monitoring station is no longer used. The data for all monitoring stations in 2017 was incomplete because the data for April to June was cancelled due to concessionaire company changes

3.1.2 Outpatient Visits Data

Data on ARI was obtained from daily outpatient visits report from 2015 to 2018 (4 years). The selected sentinel clinics were as Table 3.2.

Table 3.2: Details on Selected Sentinel Clinics

Site State	Location	Latitude	Longitude
Johor	Klinik Kesihatan Bandar Maharani (KKBM)	2.0581° N	102.5766° E
Johor	Klinik Kesihatan Bandar Penawar (KKBP)	1.5532° N	104.2332° E
Melaka	Klinik Kesihatan Bukit Rambai (KKBR)	2.2549° N	102.1800° E

Infection was diagnosed by a doctor based on a physical examinations and symptoms. Acute respiratory infection cases were counted based on patient reports of throat discomfort, nasal block, cough, nasal discharge, painful throat, and loss of voice lasting shorter than 14 days (less than 14 days is considered acute infection) (Meltzer et al., 2010). The days with no patients will have a value of zero for outpatient visits because the clinics are not located in the same state and have different operating hours and holidays, notably in Johor, where Friday and Saturday are the official days of rest compared to other states in Malaysia.

3.2 Data Analysis

3.2.1 Statistical Product and Services Solutions (SPSS Version 28)

3.2.1.1 Descriptive Analysis

Descriptive statistics are employed for the purpose of summarizing the data. The data were collected, verified, and inputted into the software. The result from the descriptive analysis describing the main age group of patients who suffered ARI due to air pollution and summarizes the frequencies of visits for

ARI by age range from 2015 to 2018 (4 years) at the KKBR, KKBM and KKBP. The N value will represent the number of days with data of outpatient visits for ARI. Another descriptive analysis focuses on the mean (M) and standard deviation (SD) for the main age group of patients, which is divided into 3 age ranges; under 12 years old, 13 to 59 years old and over 60 years old who visited the clinics with ARI (Yu et al., 2020; Masoumi et al., 2017; Darrow et al., 2014). The age range was determined using the State Health Department's monthly report template to the Ministry of Health. Descriptive analysis was also employed to describe the study areas' pollutants and wind speed. The N value for the wind analysis will represent the number of hours with wind speed data. The subjects of another descriptive analysis are the mean (M) and standard deviation (SD) of the wind speed for the research areas from 2015 to 2018. The descriptive analysis for the pollutants analysis concentrates on the mean (M) and standard deviation (SD) for each pollutant for the study areas from 2015 to 2018. Data were presented as mean ± standard deviation (SD)(Hu et al., 2020).

3.2.1.2 Pearson's rank correlation coefficient

The dataset exceeds a size of n>50, prompting the utilization of the Kolmogorov-Smirnov test to assess the normality of the data. Pearson's Correlation Coefficient analysis was employed to determine the correlation between outpatient visits for ARI at KKBR, KKBM and KKBP with of API, SO_2, NO_2, O_3, CO and PM_{10} from 2015 to 2018, spanning a period of four years. The selection of analysis was prompted by the normal distribution of the data.

Statistical significance was defined as $p<0.001$ (Hu et al., 2020; Mohd Zizi et al., 2018).

3.2.1.3 One-way ANOVA

The One-way ANOVA was applied to assess the age groups in relation to the parameter of 'frequency of outpatient visits,' revealing statistically significant differences among the age groups. Given the variation in sample sizes throughout the different study areas, a post-hoc Bonferroni analysis was conducted in order to identify any significant differences that may exist between the age groups. (Yu et al., 2020; Mendy et al., 2019; Lothrop et al., 2017)

3.2.2 R-Programming

3.2.2.1 Wind Rose

A wind rose was plotted and analysed to identify the pattern of wind distribution and the direction of the dominant wind. The wind rose gives an information-laden view of how wind direction and speed are typically distributed at the study location. Colour-coded wind roses illustrate the fundamental wind direction and speed caused by the wind. The wind rose represents the ranges of wind speeds in various parts of the area. The length of each spoke around the circle is proportional to the frequency with which the wind blows from a specific direction. Each concentric circle represents a different frequency, with the centre representing zero and the outer circles representing increasing frequencies (Ren et al., 2022; Poddaeva and Fedosova, 2022; Muhammad Hisyam et al., 2016). To undertake the analysis, detailed meteorological data on wind speed and wind direction, including year, month, day, and hourly data for SMKBR, KVM, and SMKABP monitoring stations from 2015 to 2018 (4 years) were imported in excel format into the R-Programming. The wind rose was generated using the following code using data on Bukit Rambai from 2015-2018 as an example:

```
> windRose (BUKIT_RAMBAI_1518)
> library (readxl)
> BUKIT_RAMBAI_1518 <- read_excel ("E:/DATA BARU KAJIAN/R BUKIT
RAMBAI/BUKIT RAMBAI 1518.xlsx",
+     col_types = c ("date", "numeric", "numeric",
+         "numeric", "numeric", "numeric",
+         "numeric", "numeric", "numeric",
+         "numeric"))
> View (BUKIT_RAMBAI_1518)
> windRose (BUKIT_RAMBAI_1518)
```

Using the same data, the following code was used to generate the 2x2 wind rose plot for Bukit Rambai, split by year:

```
> windRose (BUKIT_RAMBAI_1518, type = "year", layout = c (2, 2), cols =
"default")
```

BUKIT_RAMBAI_1518 was a data frame with ws and wd fields, and cols were colours for plotting. Options include "default," "increment," "heat," "jet," "hue," and user defined. For user-defined, the user can supply a list of colour names recognised by R. 'default' was used in this analysis. 'type' determines how the data is split, conditioned, and plotted. The default will generate a single plot from all of the data. ‘type’ can be one of the built-in types described in cutData, such as "season", "year", "weekday", and so on. In this analysis, ‘year’ was used to plot the wind rose of the study areas from 2015 to 2018.

3.2.2.2 Pollution Rose

Pollution rose is a variation of wind rose that is useful in analysing pollutant concentrations based on wind direction, specifically the proportion of time the concentration is within a specified range. Pollution rose to provide two vital data elements: the air quality for each wind direction and the distribution and strength of emission sources. Pollution roses were drawn in this study to identify and estimate the impact of likely source regions of alternative air pollutants detected by diverse wind direction sectors in the study areas. This further aids in reducing the impact of meteorological variables on pollution trends, increasing the robustness of the results. Furthermore, this study highlights the proportional contribution to the mean while drawing pollution rose plots to acquire important insight into the wind directions that most contribute to total air pollutants concentrations. Different pollutants may have different breaks and labels as the concentration readings differ (Youzu Zhang et al., 2021; Sung et al., 2014; Said, 2012). To undertake the analysis, detailed meteorological data on wind speed, wind direction and all pollutants, including year, month, day, and hourly data for SMKBR, KVM, and SMKABP monitoring stations from 2015 to 2018 (4 years), were used. The API breaks were adjusted based on the air pollutant index, and the other pollutant breaks were adjusted based on the permissible limit for 24 hours of the New Malaysia Air Quality Standard. Using Bukit Rambai data from 2015 to 2018 in Excel format as an example, the pollution rose was generated using the following code:

```
> breaks <- c (0, 50, 100, 200, 300, 1000)
> labels <- c ("0-50", "51-100", "101-200", "201-300", “301-1000”)
> pollutionRose (BUKIT_RAMBAI_1518, pollutant = "api", breaks = breaks,
labels = labels,cols = c("blue", "green", "yellow", "orange", “red”), statistic =
"max")
```

'breaks' and ‘labels’ was used to specify specific break points while BUKIT_RAMBAI_1518 was a data frame with pollutants fields. ‘cols’ was the colours used for plotting in this analysis. The colour was defined using a list of colour names recognised by R, which was blue, green, yellow, orange and red, which was adjusted based on the air pollutant index colours code adopted by Malaysia.

3.2.2.3 Calendar Plot

Plot time series values in conventional calendar format description will be used. This function will plot one year of data by month laid out in a conventional calendar format. Utilizing daily API data, a 12-month calendar for the 2015 to 2018 (4-year) study period was generated to depict the API reading pattern of the study areas to determine the state of the API index of the study areas. Each day is coloured according to the API of the day. The colour range is set using the API, which is 0-50 (healthy), 51-100 (moderate), 101-200 (unhealthy), 201-300 (very unhealthy), and over 300 (hazardous). This will depict the air pollution levels in the study areas. To undertake the analysis, detailed meteorological data on daily API data for SMKBR, KVM, and SMKABP monitoring stations from 2015 to 2018 (4 years) were used. The API break maximum value was set to 1000 for all study areas. Using Bukit Rambai

API data from 2015 in Excel format as an example, the calendar plot was created with the following code:

```
> breaks <- c (0, 50, 100, 200, 300, 1000)
> labels <- c ("Good", "Moderate", "Unhealthy", "Very Unhealthy",
"Dangerous")
>calendarPlot (BUKIT_RAMBAI_2018, pollutant = "api", breaks = breaks,
labels = labels,cols = c("blue", "green", "yellow", "orange", "red"), statistic =
"max", layout = c(4, 3))
```

Similarly, this calendar plot analysis used 'breaks' and 'labels' to specify specific breakpoints. At the same time BUKIT_RAMBAI_2015 was a data frame with API fields. 'cols' were the colours used for plotting in this analysis. The colour was defined using a list of R-recognised names, including blue, green, yellow, orange, and red. It was adjusted based on Malaysia's air pollutant index colours code. A 4x3 layout was used for this calendar plan. To separate between years the bold line will be used to differentiate between years.

CHAPTER 4

MOVEMENT AND DISPERSAL OF AIR POLLUTANTS IN THE STUDY AREAS

4.1 Introduction

Air pollution has a negative impact on the environment and the well-being of a given population. This is due to the fact that air is polluted by numerous sources, and its complexity is primarily determined by meteorological conditions, topography as well the nature of the pollutants emitted (Hamza and Azman, 2015). Wind transports air pollutants away from their source and disperses them elsewhere, implying that pollution in one area can affect air quality in a large area (Manisalidis et al., 2020). From 2015 to 2018, this study will determine the distribution pattern of air pollutant index and outpatient visits for acute respiratory infection in two study areas: Bukit Rambai in Melaka and Muar in Johor (4 years). In 2013, these study areas had the highest API readings, which were 750 for Muar and 477 for Bukit Rambai, Melaka. Bandar Penawar in Johor was selected as the comparative site since it is a coastal town facing the South China Sea while Bukit Rambai in Melaka and Muar in Johor are coastal towns located on the Straits of Malacca. Given that the earth's surface and industries vary, it is anticipated that the outcome of the selection will vary. This was intended to demonstrate that transboundary or local pollution. To achieve the first objective, wind roses, pollutant rose and calendar plot was plotted and analysed to determine the pattern of wind distribution and the predominant wind direction in Bukit Rambai, Melaka; Muar, Johor; and Bandar Penawar, Johor. $PM_{2.5}$ was excluded from this study since its concentration was only added to API calculations in Malaysia beginning in August 2018.

4.2 Material and Method

4.2.1 Air Quality Data of Study Areas

This study utilised hourly concentrations of major pollutants measured by DOE, including particulate matter (PM_{10}), ozone (O_3), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), and carbon monoxide (CO). Since there was a change in the concessionaire company, the records for April to June 2017 have been cancelled. Except for the SMKABP air quality monitoring station, all selected continuous air quality monitoring sites face the Malacca Strait to the west.

4.2.2 Wind Rose of The Study Areas

Colour-coded wind roses illustrate the fundamental wind direction and speed caused by the wind. The wind rose represents the ranges of wind speeds in various parts of the area. The length of each spoke around the circle is proportional to the frequency with which the wind blows from a specific direction. Each concentric circle represents a different frequency, with the centre representing zero and the outer circles representing increasing frequencies. Include the reference. To undertake the analysis, detailed meteorological data on wind speed and wind direction, including year, month, day, and hourly data for SMKBR, KVM, and SMKABP monitoring stations from 2015 to 2018 (4 years) were imported in excel format into the R-Programming.

The wind roses were generated using the following code using data on Bukit Rambai from 2015-2018:

```
> windRose (BUKIT_RAMBAI_1518)
> library (readxl)
> BUKIT_RAMBAI_1518 <- read_excel ("E:/DATA BARU KAJIAN/R BUKIT
RAMBAI/BUKIT RAMBAI 1518.xlsx",
+     col_types = c ("date", "numeric", "numeric",
+        "numeric", "numeric", "numeric",
+        "numeric", "numeric", "numeric",
+        "numeric"))
> View (BUKIT_RAMBAI_1518)
> windRose(BUKIT_RAMBAI_1518)
```

Using the same data, the following code was used to generate the 2x2 wind rose plot for Bukit Rambai, split by year:

```
> windRose (BUKIT_RAMBAI_1518, type = "year", layout = c (2, 2), cols =
"default")
```

The wind roses were generated using the following code using data on Bandar Maharani from 2015-2018:

```
> windRose (BANDAR_MAHARANI_1518)
> library (readxl)
> BANDAR_MAHARANI_1518 <- read_excel("E:/DATA BARU KAJIAN/R
BANDAR MAHARANI/BANDAR MAHARANI 1518.xlsx",
+     col_types = c ("date", "numeric", "numeric",
+        "numeric", "numeric", "numeric",
+        "numeric", "numeric", "numeric",
+        "numeric"))
> View (BANDAR_MAHARANI_1518)
> windRose(BANDAR_MAHARANI_1518)
```

Using the same data, the following code was used to generate the 2x2 wind rose plot for Bandar Maharani, split by year:

```
> windRose (BANDAR_MAHARANI_1518, type = "year", layout = c (2, 2),
cols = "default")
```

The wind roses were generated using the following code using data on Bandar Penawar from 2015-2018:

```
> windRose (BANDAR_PENAWAR_1518)
> library (readxl)
> BANDAR_PENAWAR_1518 <- read_excel("E:/DATA BARU KAJIAN/R
BANDAR PENAWAR/BANDAR PENAWAR 1518.xlsx",
+     col_types = c ("date", "numeric", "numeric",
+         "numeric", "numeric", "numeric",
+         "numeric", "numeric", "numeric",
+         "numeric"))
> View (BANDAR_PENAWAR_1518)
> windRose(BANDAR_PENAWAR_1518)
```

Using the same data, the following code was used to generate the 2x2 wind roses plot for Bandar Penawar, split by year:

```
> windRose (BANDAR_PENAWAR_1518, type = "year", layout = c (2, 2),
cols = "default")
```

4.2.3 Calendar Plot of The Study Areas

The calendar plot function effectively visualises data in this approach by displaying daily concentrations of API in a calendar layout. Using the daily API data, 12 months calendar was generated for the 2015 to 2018 (4 years) study period. Each day is coloured according to the API of the day. The colour range is set using the API, which is 0-50 (healthy), 51-100 (moderate), 101-200 (unhealthy), 201-300 (very unhealthy), and over 300 (hazardous). To undertake the analysis, detailed meteorological data on daily API data for SMKBR, KVM, and SMKABP monitoring stations from 2015 to 2018 (4 years) were used. The API break maximum value was set to 1000 for all study areas.

Using Bukit Rambai API data from 2015 to 2018 in Excel format, the calendar plot was created with the following code:

```
> breaks <- c (0, 50, 100, 200, 300, 1000)
> labels <- c ("Good", "Moderate", "Unhealthy", "Very Unhealthy", "Dangerous")
>calendarPlot (BUKIT_RAMBAI, pollutant = "api", breaks = breaks, labels = labels,cols = c("blue", "green", "yellow", "orange", "red"), statistic = "max", layout = c(4, 3))
```

Using Bandar Maharani API data from 2015 to 2018 in Excel format, the calendar plot was created with the following code:

```
> breaks <- c (0, 50, 100, 200, 300, 1000)
> labels <- c ("Good", "Moderate", "Unhealthy", "Very Unhealthy", "Dangerous")
>calendarPlot (BANDAR_MAHARANI, pollutant = "api", breaks = breaks, labels = labels,cols = c("blue", "green", "yellow", "orange", "red"), statistic = "max", layout = c(4, 3))
```

Using Bandar Penawar API data from 2015 to 2018 in Excel format, the calendar plot was created with the following code:

```
> breaks <- c (0, 50, 100, 200, 300, 1000)
> labels <- c ("Good", "Moderate", "Unhealthy", "Very Unhealthy", "Dangerous")
```

```
>calendarPlot (BANDAR_PENAWAR, pollutant = "api", breaks = breaks, labels = labels,cols = c("blue", "green", "yellow", "orange", "red"), statistic = "max", layout = c(4, 3))
```

The API breaks were adjusted based on the air pollutant index, and the other pollutant breaks were adjusted based on the permissible limit for 24 hours of the New Malaysia Air Quality Standard. Using Bukit Rambai data from 2015 to 2018 in Excel format as an example, the pollution rose was generated using the following code:

```
> breaks <- c (0, 50, 100, 200, 300, 1000)
> labels <- c ("0-50", "51-100", "101-200", "201-300", “301-1000”)
> pollutionRose (BUKIT_RAMBAI_1518, pollutant = "api", breaks = breaks,
labels = labels,cols = c("blue", "green", "yellow", "orange", “red”), statistic =
"max")
```

4.2.4 Pollution Rose of The Study Areas

The API breaks were adjusted based on the air pollutant index, and the other pollutant breaks were adjusted based on the permissible limit for 24 hours of the New Malaysia Air Quality Standard.

Using Bukit Rambai data from 2015 to 2018 in Excel format, the pollution rose for API was generated using the following code:

```
> breaks <- c (0, 50, 100, 200, 300, 1000)
> labels <- c ("0-50", "51-100", "101-200", "201-300", “301-1000”)
> pollutionRose (BUKIT_RAMBAI_1518, pollutant = "api", breaks = breaks,
labels = labels,cols = c("blue", "green", "yellow", "orange", “red”), statistic =
"max")
```

Using Bukit Rambai data from 2015 to 2018 in Excel format, the pollution rose for O_3 was generated using the following code:

```
> breaks <- c (0, 100, 150)
> labels <- c ("0-100", "101-150")
> pollutionRose (BUKIT_RAMBAI_1518, pollutant = "o3", breaks = breaks,
labels = labels,cols = c("blue", "red"), statistic = "max")
```

Using Bukit Rambai data from 2015 to 2018 in Excel format, the pollution rose for CO was generated using the following code:

```
> breaks <- c (0, 10, 100)
> labels <- c ("0-10", "11-100")
> pollutionRose (BUKIT_RAMBAI_1518, pollutant = "co", breaks = breaks,
labels = labels,cols = c("blue", "red"), statistic = "max")
```

Using Bukit Rambai data from 2015 to 2018 in Excel format, the pollution rose for SO_2 was generated using the following code:

```
> breaks <- c (0, 80, 100)
> labels <- c ("0-80", "81-100")
> pollutionRose (BUKIT_RAMBAI_1518, pollutant = "so2", breaks = breaks,
labels = labels,cols = c("blue", "red"), statistic = "max")
```

Using Bukit Rambai data from 2015 to 2018 in Excel format, the pollution rose for PM10 was generated using the following code:

```
> breaks <- c (0, 100, 350)
> labels <- c ("0-100", "101-350")
> pollutionRose (BUKIT_RAMBAI_1518, pollutant = "pm10", breaks = breaks,
labels = labels,cols = c("blue", "red"), statistic = "max")
```

Using Bukit Rambai data from 2015 to 2018 in Excel format, the pollution rose for NO_2 was generated using the following code:

```
> breaks <- c (0, 70, 100)
> labels <- c ("0-70", "71-100")
> pollutionRose (BUKIT_RAMBAI_1518, pollutant = "no2", breaks = breaks, labels = labels,cols = c("blue", "red"), statistic = "max")
```

Based on their respective data, this process created the pollution rose for each pollutant at Bandar Maharani and Bandar Penawar.

4.2.5 Descriptive Analysis on Pollutants and Wind Speed

Descriptive analysis was also employed to describe the study areas' pollutants and wind speed. The N value for the wind analysis will represent the number of hours with wind speed data. The subjects of another descriptive analysis are the mean (M) and standard deviation (SD) of the wind speed for the research areas from 2015 to 2018. The descriptive analysis for the pollutants analysis concentrates on the mean (M) and standard deviation (SD) for each pollutant for the study areas from 2015 to 2018.

4.3 Results and Discussion

A descriptive analysis was conducted to check the validity, and the findings are presented in Table 4.1. From the descriptive analysis, the average speed at Bukit Rambai, Muar and Bandar Penawar from 2015 to 2018 was 3.3 m/s (SD=2.413), 4.6 m/s (SD=3.367) and 4.5 m/s (SD=4.262) respectively. Bandar Penawar has the highest wind speed, followed by Muar and Bukit Rambai.

Table 4.1: Descriptive Analysis for The Wind Speed (m/s) at The Study Areas for 2015-2018

Study Site	*N*	*Min*	*Max*	*M*
Bukit Rambai	28701	0.0	17.0	3.3 ± 2.41
Muar	25760	0.0	22.0	4.6 ± 3.37
Bandar Penawar	49674	0.0	23.0	4.5 ± 4.26

Note: *N* = Hours with Wind Speed Reading

The wind roses diagram (Figure 4.1 – Figure 4.3) depicts wind direction and speed frequency at SMKBR, KVM and SMKABP Air Quality Monitoring Stations. These wind roses demonstrate that the study areas winds blew mainly from the northeast. These three plots showed that no difference in wind direction from 2015 to 2018 for all the study areas. In fact, in Bukit Rambai 2 spokes around the northeast direction, north of northeast direction (NNE) and east northeast (ENE) comprise 43% of all hourly directions, 24% of all hourly directions in Muar and 36% of all hourly directions in Bandar Penawar.

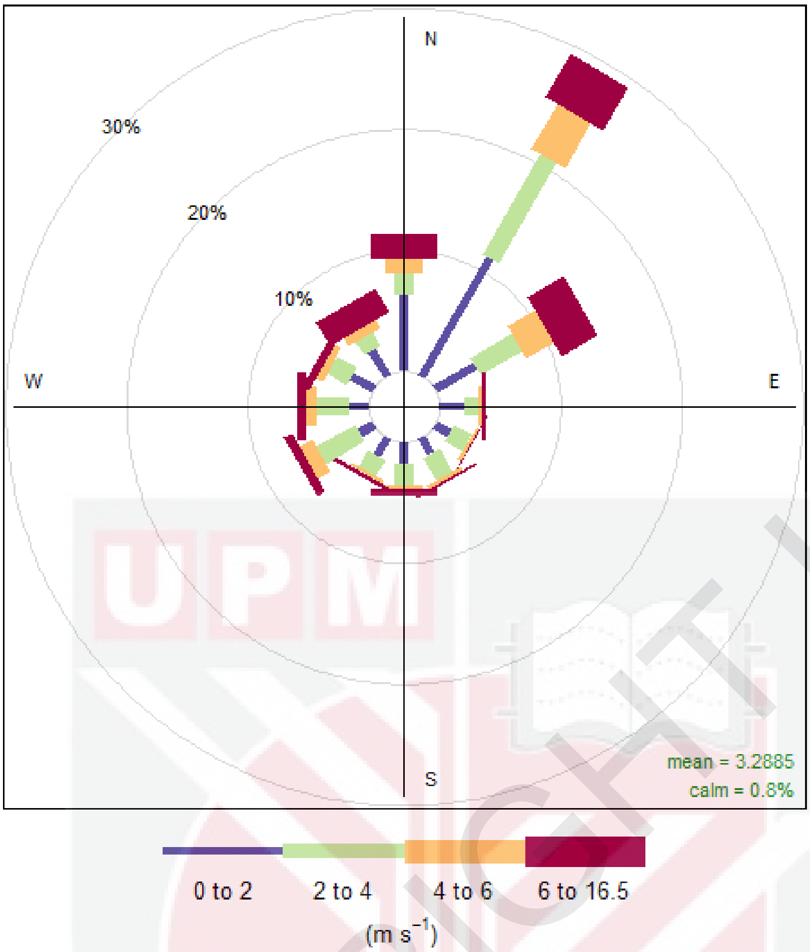


Figure 4.1: The Wind Rose of SMKBR Bukit Rambai Air Quality Monitoring Station from 2015 – 2018
Note. Frequency of counts by wind direction (%)

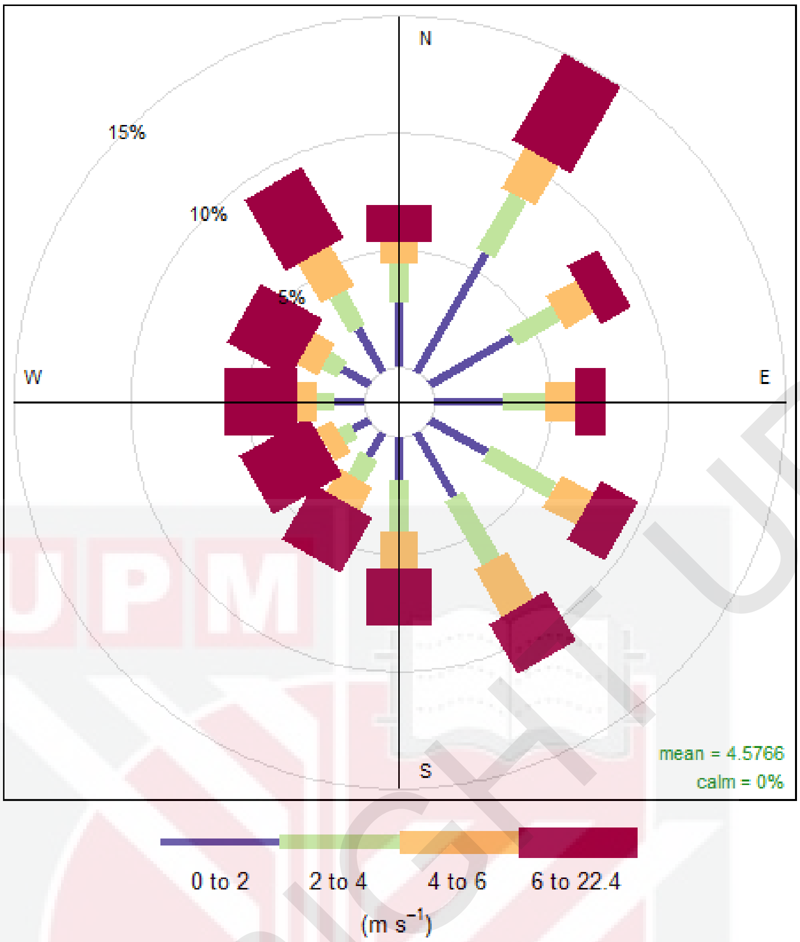


Figure 4.2: The Wind Rose of KVM Muar Air Quality Monitoring Station from 2015 – 2018
Note. Frequency of counts by wind direction (%)

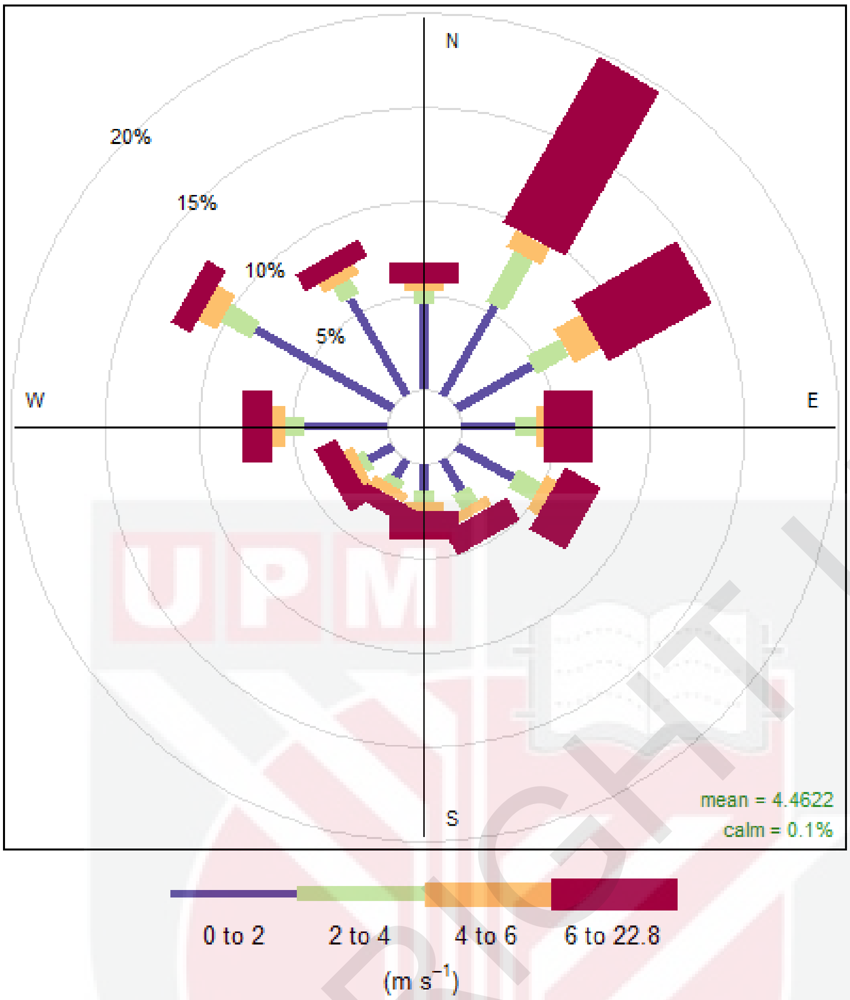


Figure 4.3: The Wind Rose of SMKABP Bandar Penawar Air Quality Monitoring Station from 2015 – 2018
Note. Frequency of counts by wind direction (%)

A descriptive analysis was conducted to check the validity, and the findings are presented in Table 4.2. From the descriptive analysis, the average speed at Bukit Rambai from 2015 to 2018 was 5.3 m/s (SD=2.66), 4.2 m/s (SD=2.26), 2.6 m/s (SD=2.07) and 1.7 m/s (1.11) respectively. The average wind speed in Bukit Rambai was greater in 2015 than in 2016, 2017 and 2018. This area exhibited a decreasing wind speed trend. The incomplete data may impact this analysis for April to June 2017.

Table 4.2: Descriptive Analysis for The Wind Speed (m/s) at SMKBR Bukit Rambai monitoring station for 2015-2018

Year	*N*	*Min*	*Max*	*M*
2015	4782	0.7	16.5	5.3 ± 2.66
2016	8688	1.4	13.5	4.2 ± 2.26
2017	6475	0.0	11.0	2.6 ± 2.07
2018	8759	0.0	8.7	1.7 ± 1.11

Note: *N* = Hours with Wind Speed Reading

This wide picture of wind rose in Bukit Rambai from 2015 to 2018 was split into years, as shown below, to demonstrate the trend and variations of wind speed and wind direction of each year for each study area. The wind rose (Figure 4.4) diagram depicts wind direction and speed frequency at SMKBR Air Quality Monitoring Station. This wind rose demonstrates that the Bukit Rambai wind blew mainly from the northeast during the period. These four plots showed that there was no difference in wind direction from 2015 to 2018. In fact, in Bukit Rambai, 2 spokes around the North-Northeast (NNE) and East-Northeast (ENE) comprised 60% of all hourly directions in 2015, 35% of all hourly directions in 2016, 37% of all hourly directions in 2017 and 43% of all hourly directions in 2018. The wind rarely blows from the southwest direction.

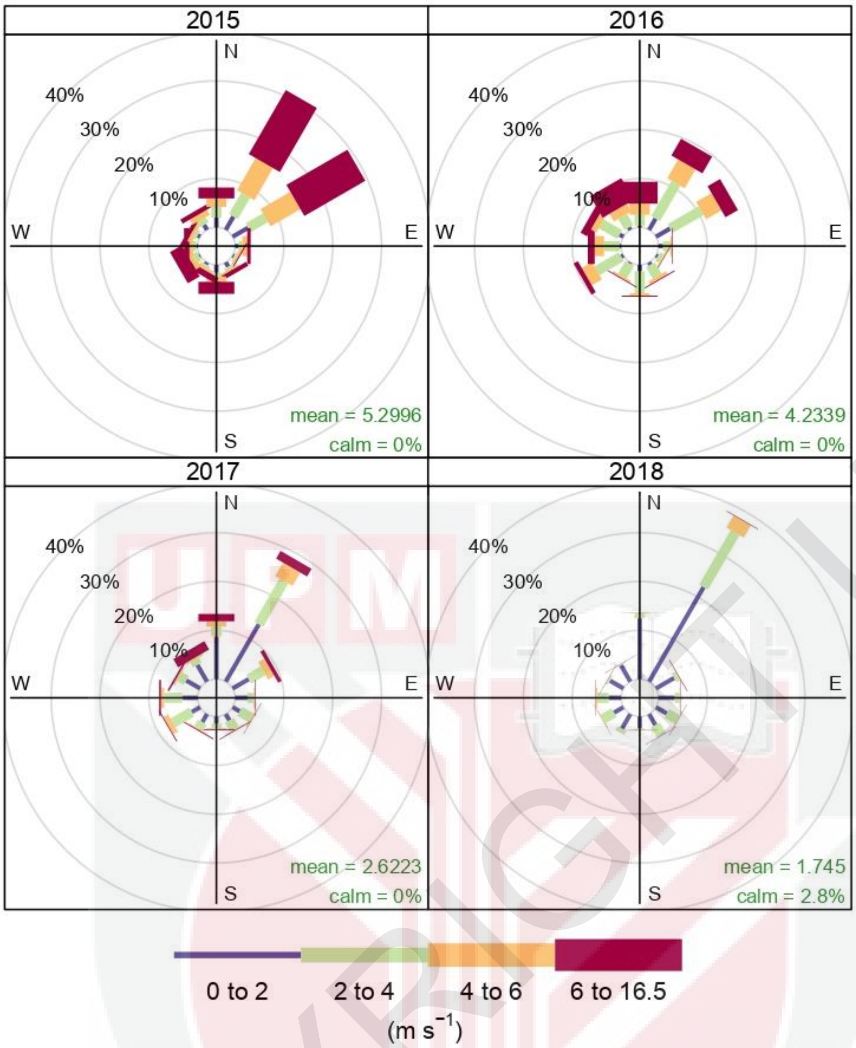


Figure 4.4: The Wind Rose of SMKBR Bukit Rambai Air Quality Monitoring Stations for 2015-2018
Note. Frequency of counts by wind direction (%)

A descriptive analysis was conducted to check the validity, and the findings are presented in Table 4.3. From the descriptive analysis, the average speed at Muar from 2015 to 2018 was 5.6 m/s (SD=3.074), 5.3 m/s (SD=3.075), 3.1 m/s (SD=3.444) and 1.2 m/s (0.688) respectively. The average wind speed in Muar was greater in 2017 than in 2015, 2016 and 2018. The lack of complete data for API and other pollutants from April to June 2017 and the fact that KVM data were only available until March 12, 2018, because the monitoring station is no longer in operation, could impact this analysis.

Table 4.3: Descriptive Analysis for the Wind Speed (m/s) at KVM Muar Air Quality Monitoring Station for 2015-2018

Year	*N*	*Min*	*Max*	*M*
2015	8746	1.0	16.9	5.6 ± 3.07
2016	8767	1.0	16.9	5.3 ± 3.08
2017	6562	0.0	22.4	3.1 ± 3.44
2018	1685	0.0	4.8	1.2 ± 0.67

Note: *N* = Hours with Wind Speed Reading

The wind rose (Figure 4.5) diagram depicts wind direction and speed frequency at the KVM Air Quality Monitoring Station. This wind rose demonstrates that the wind at Muar during the period blew mainly from the northeast, except for 2015, when the wind blew mostly from the northwest. These four plots showed that there was a difference in wind direction from 2015 to 2018. In fact, in Muar, 2 spokes around the NNE and ENE comprised 24% of all hourly directions in 2015, 35% of all hourly directions in 2017 and 59% of all hourly directions in 2017. In 2016, 2 spokes around the west-northwest (WNW) and northwest (NW) comprised 24% of all hourly directions. The wind rarely blew from the northwest in 2015 and southwest in 2016, 2017 and 2018.

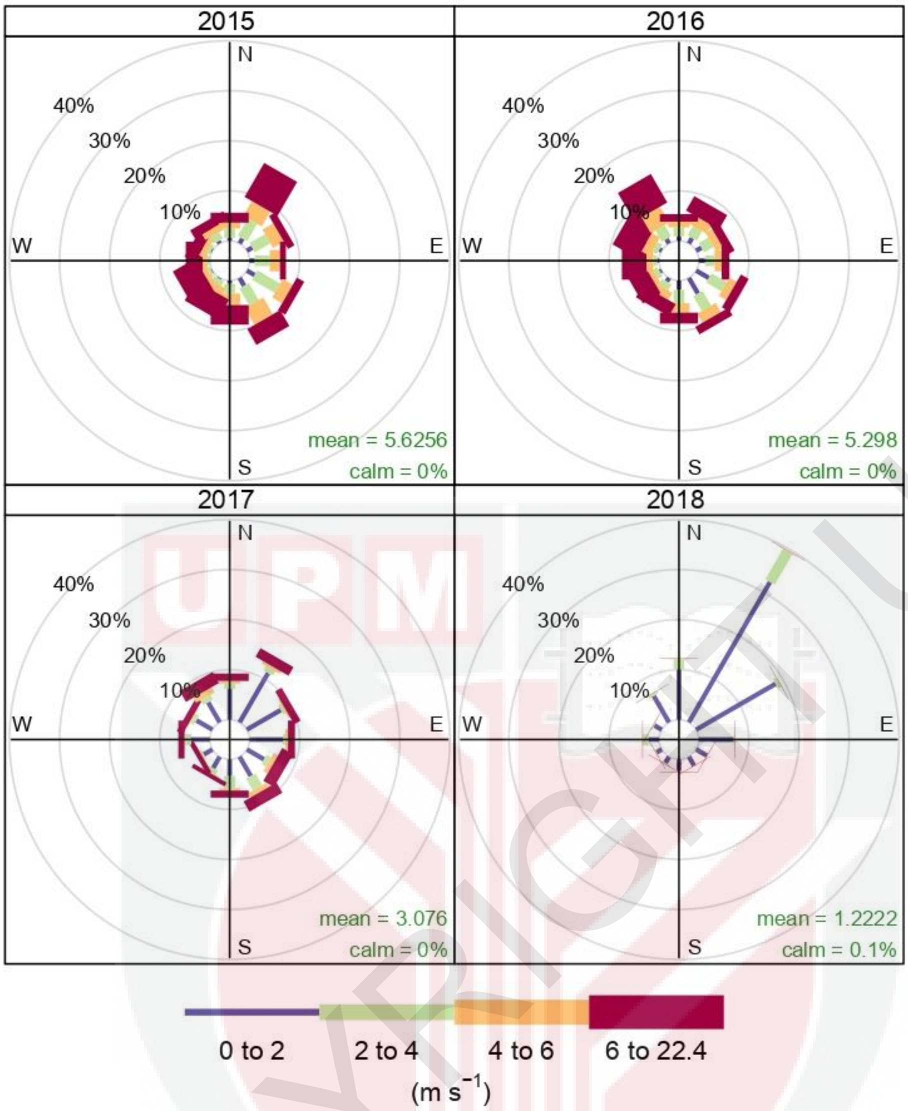


Figure 4.5: The Wind Rose of KVM Muar Air Quality Monitoring Stations by the Year 2015-2018
Note. Frequency of counts by wind direction (%)

A descriptive analysis was conducted to check the validity, and the findings are presented in Table 4.4. From the descriptive analysis, the average speed at Bandar Penawar from 2015 to 2018 was 5.7 m/s (SD=4.502), 4.8 m/s (SD=4.218), 3.3 m/s (SD=3.99) and 1.2 m/s (0.958) respectively. The average wind speed in Bandar Penawar was greater in 2015 than in 2016, 2017 and 2018. This area exhibited a declining wind speed trend. The incomplete data may impact this analysis for April to June 2017.

Table 4.4: Descriptive Analysis for the Wind Speed (m/s) at SMKABP Bandar Penawar Air Quality Monitoring Station for 2015-2018

Year	*N*	*Min*	*Max*	*M*
2015	8727	1.0	22.8	5.7 ± 4.50
2016	8743	1.0	19.9	4.8 ± 4.22
2017	5973	0.0	19.6	3.3 ± 4.00
2018	8748	0.0	6.8	1.2 ± 0.96

Note: *N* = Hours with Wind Speed Reading

The wind rose (Figure 4.6) diagram depicts wind direction and speed frequency at SMKABP Monitoring Station. This wind rose demonstrates that the winds at Bandar Penawar during the period blow mainly from the northeast. These four plots showed that there was no difference in wind direction from 2015 to 2018. In fact, in Bandar Penawar, 2 spokes around the North-Northeast (NNE) and East-Northeast (ENE) comprised 36% of all hourly directions in 2015, 41% of all hourly directions in 2016, 35% of all hourly directions in 2017 and 32% of all hourly directions in 2018. The wind rarely blows from the southwest direction.

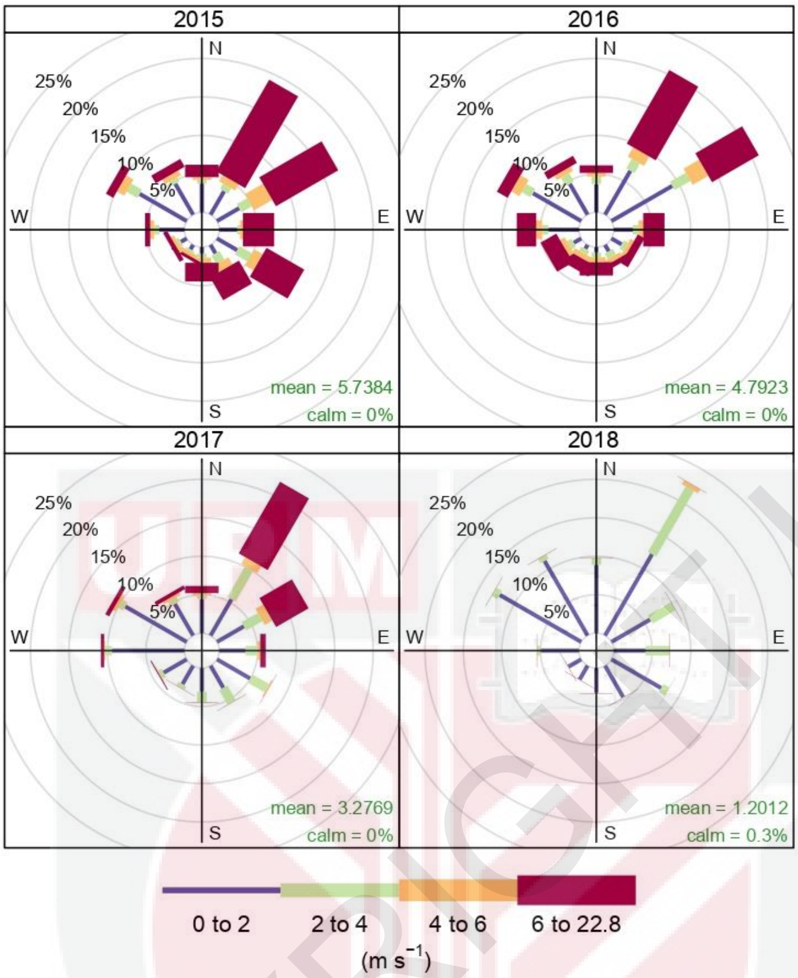


Figure 4.6: The Wind Rose of SMKABP Bandar Penawar Air Quality Monitoring Stations for 2015-2018
Note. Frequency of counts by wind direction (%)

The wind rose demonstrates that the wind in the study areas during the period blew mainly from the northeast, except for 2015 in Muar, which blew mostly from the northwest. Satari et al. (2015) stated that the wind predominantly came from a certain direction during a particular monsoon. Still, wind direction has been gradually changing over the ten years. The study areas' average wind speeds from 2015 to 2018 are sufficient to aid in the dispersion of air contaminants. The fact that fewer infections occur in densely populated locations with high wind speeds, showing that high wind speeds enhance the distribution of air contaminants, must be taken into consideration (Perugu et al., 2016). Wind speeds in Peninsular Malaysia were persistent but averagely low (Satari et al., 2015). Little wind can promote the stagnation of contaminated air containing viral agents and aid in spreading viral infectivity, causing problems for public health (Coccia, 2021).

All study areas had a decreasing wind speed trend over time, which should increase outpatient visits due to the stagnation of contaminated air. Still, according to this analysis, only Muar had an increase in outpatient visits year after year. In contrast, the outpatient visits trend due to acute respiratory infection in Bukit Rambai and Bandar Penawar fluctuated yearly. According to Kim et al. (2015), the average concentration of particle-bound polycyclic aromatic hydrocarbons, which include carbon, hydrogen, oxygen, nitrogen, and sulphur, on the road decreased as the prevailing wind speed increased at the neighbourhood scale when the wind speed was greater than 2.0 m/s. In another instance, it was discovered that NO, NO_2, and SO_2 had negative associations with wind speed, showing that wind diluted these air contaminants (Al-Harbi et al., 2020). When particulate matter pollution processes occur, the wind speed slows down. In comparison to other cities, Urumqi, Lhasa, Beijing, Zhengzhou, Nanning, and Guangzhou see increased dispersion of $PM_{2.5}$ when the wind speed increases. Yet, due of regional transportation, an increase in wind speed might lead to $PM_{2.5}$ accumulation in some places, like as Wuhan (Luo et al., 2021). According to Linda et al. (2022), at a height of 2 metres above the ground, the average threshold wind speed that causes PM_{10} resuspension is 1.58 m/s. Significant pollution ($PM_{2.5}$ > 150 g m^{-3}) occurs in China when the wind speed is less than 10.29 m/s, the planetary boundary layer is less than 500 metres, and the temperature inversion is greater than 6°C (Meng et al., 2020).

However, in this study, the API was still within the normal and moderate range in the study areas, which were 3.3 m/s (SD=2.413) for Bukit Rambai, 4.6 m/s (SD=3.367) for Muar, and 4.5 m/s (SD=4.262) for Bandar Penawar from 2015 to 2018. This was true even though the average wind speed was less than 10.29 m/s. Certain atmospheric characteristics, such as temperature and the planetary boundary layer, pressure and relative humidity are not taken into account in this study (Luo et al., 2021; Meng et al., 2020). Considering the different climates in China and Malaysia, different results may occur. This is in line with a study by Qi et al. (2021) and Liu et al. (2020), which found that the concentration of various toxins is significantly influenced by the diverse climatic conditions. Felda Sungai Mas in 2015 to 2017, about 11.4 km from the monitoring station, reported information that was more or less accurate than the study's findings, including the fact that the wind there primarily came from the northeast and south, in accordance with Malaysia's monsoon season. Wind speeds typically range from 0.3 to 3.3 m/s, and the maximum wind speed was recorded at 3.4 to 5.4 m/s (EnviroSolutions and Consulting Sdn Bhd, 2021). The four plots of Muar showed that there was a difference in wind direction from 2015 to 2018. This can be explained by a study by Rajagopalan et al. (2014) which stated that unplanned and rapid urbanisation in Muar can potentially alter the microclimate of this tropical city, altering the air temperature and wind pattern. In some areas, unplanned vertical and horizontal development obstructed wind flow, worsening the urban environment's thermal conditions. In Malaysia, even though the mean direction of the wind or its concentration parameter is high, the mean wind speed is low. Hence, it suggested that the direction of the wind does not influence the speed of wind in Peninsular Malaysia regardless of where it blows (Satari et al., 2015).

A descriptive analysis was conducted on selected pollutants: API, PM_{10}, O_3, CO, SO_2, NO_2, and the findings are presented in Table 4.6. From the descriptive analysis, the average API level at Bukit Rambai, Muar and Bandar Penawar from 2015 to 2018 was 48.41 (SD=17.89), 38.34 (SD=18.07) and 41.12 (SD=14.40), respectively. The average PM_{10} level at Bukit Rambai, Muar and Bandar Penawar were 45.41 (SD=29.79), 39.42 (SD=26.08) and 35.78 (SD=21.25). The average O_3 level at Bukit Rambai, Muar and Bandar Penawar was 0.02 (SD=0.02), 0.02 (SD=0.01) and 0.02 (SD=0.02). The average level of CO at Bukit Rambai, Muar and Bandar Penawar was 0.64 (SD=0.31), 0.76 (SD=0.40) and 0.45 (SD=0.20). The average level of SO_2 at Bukit Rambai, Muar and Bandar Penawar was 0.00 (SD=0.002), 0.00 (SD=0.001) and 0.00 (SD=0.001). The NO_2 levels in Bukit Rambai, Muar, and Bandar Penawar were 0.01 (SD=0.01), 0.01 (SD=0.01), and 0.01 (SD=0.01), respectively. The incomplete data may impact this analysis for April to June 2017, and KVM data were only available until March 12, 2018, because the monitoring station is no longer in operation.

Table 4.5: Mean and Standard Deviations of Pollutants for Bukit Rambai, Muar and Bandar Penawar Air Quality Monitoring Stations for 2015-2018

Pollutants	Bukit Rambai	Muar	Bandar Penawar
API	48.91 ± 17.89	38.34 ± 18.07	41.12 ± 14.40
PM_{10}	45.41 ± 29.79	39.42 ± 26.08	35.78 ± 21.25
O_3	0.02 ± 0.02	0.02 ± 0.01	0.02 ± 0.02
CO	0.64 ± 0.31	0.76 ± 0.40	0.45 ± 0.20
SO_2	0.00 ± 0.002	0.00 ± 0.001	0.00 ± 0.001
NO_2	0.01 ± 0.01	0.01 ± 0.01	0.01 ± 0.01

Note: API = Air Pollutants Index; PM_{10} = Particulate Matter <10 micron; SO_2 = Sulphur Dioxide; NO_2 = Nitrogen Dioxide; O_3 = Ozone; CO = Carbon Monoxide

The analysis was extended to include the pollution rose of each pollutant in the study areas. The pollution rose plots shown in Figures 4.7, Figure 4.8, Figure 4.9, Figure 4.10 and Figure 4.11 then supplement the analysis by highlighting API, O_3, CO, NO_2, PM_{10} and SO_2 concentrations by wind direction in Bukit Rambai, Muar, and Bandar Penawar. The figures depict pollution roses for all primary pollutants monitored by the DOE, with the exception of $PM_{2.5}$ from 2015 to 2018. In Bukit Rambai, the northeast winds dominate in controlling overall pollutant concentrations, which this study discovered was potentially from the industrial and residential areas to the monitoring station. The average concentrations of API and PM_{10} were 48.91 and 45.41, respectively, higher than the other pollutants. In Muar, the northeast winds dominate in controlling overall pollutant concentrations, which this study discovered was potentially from the industrial and residential area to the monitoring station. The average concentrations of API and PM_{10} were 38.34 and 39.42, respectively, higher than the other pollutants. In Bandar Penawar, the northeast winds dominate in controlling overall pollutant concentrations, which this study discovered was potentially from the rubber plantation and residential area to the monitoring station. The average concentrations of API and PM_{10} were 42.55 and 38.66, respectively, higher than the other pollutants.

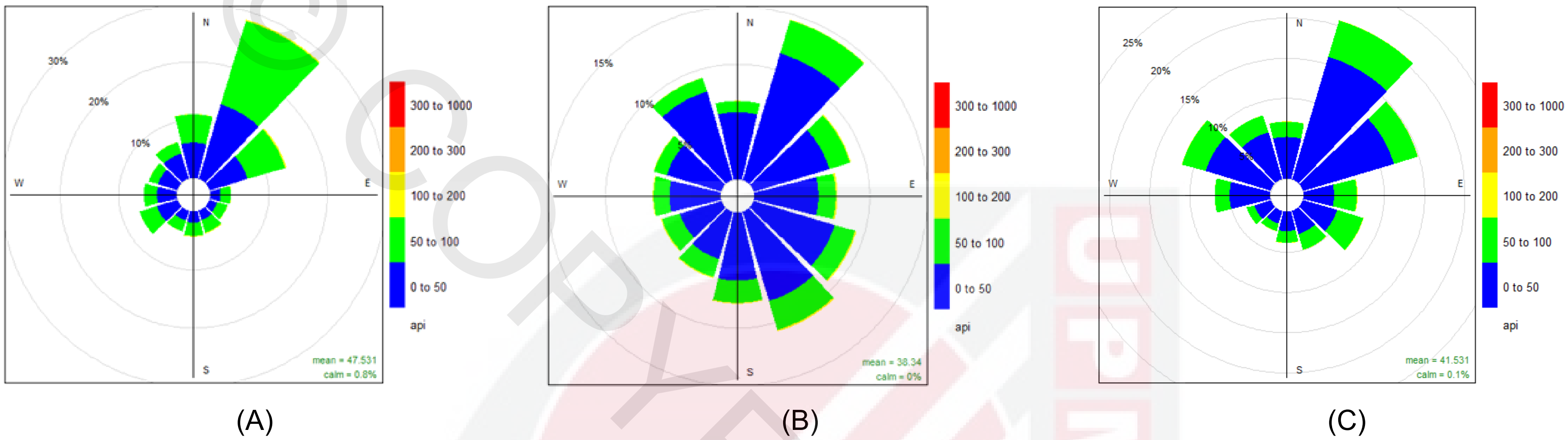
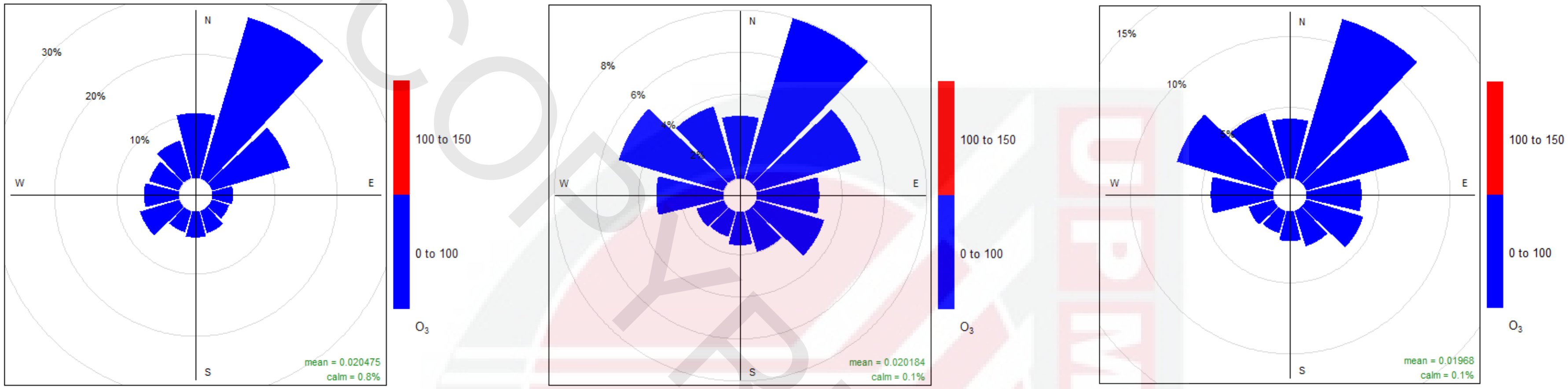
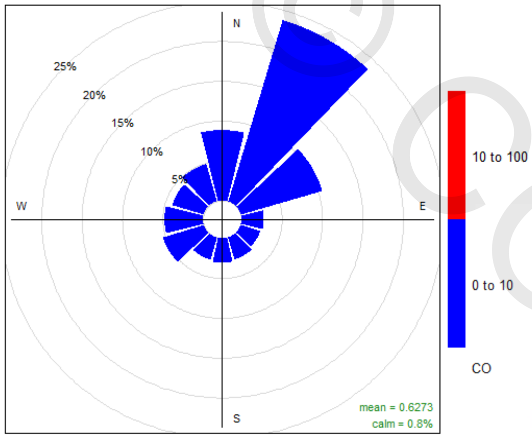


Figure 4.7: The Pollutant Rose of API at (A) SMKBR Bukit Rambai (B) KVM Muar (C) SMKABP Bandar Penawar Air Quality Monitoring Stations from 2015-2018
Note. Frequency of counts by wind direction (%)

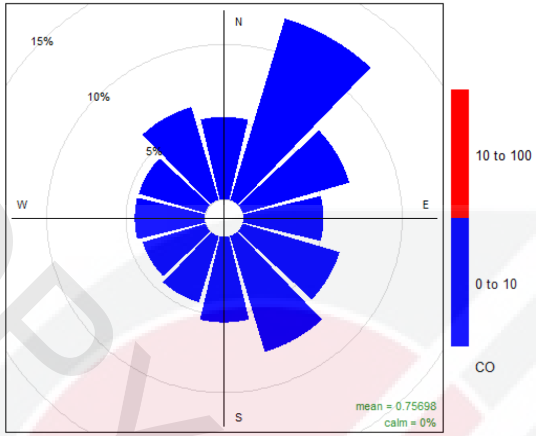


(A) (B) (C)

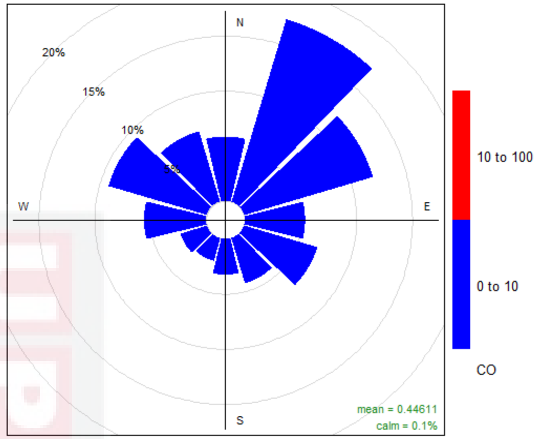
Figure 4.8: The Pollutant Rose of Ozone (O_3) at (A) SMKBR Bukit Rambai (B) KVM Muar (C) SMKABP Bandar Penawar Air Quality Monitoring Stations from 2015-2018
Note. Frequency of counts by wind direction (%)



(A)

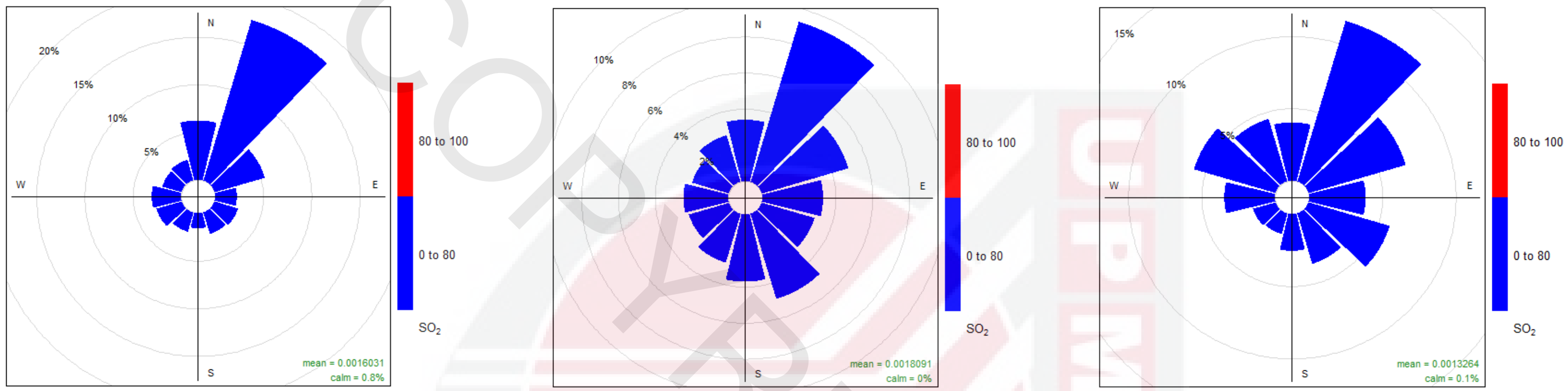


(B)



(C)

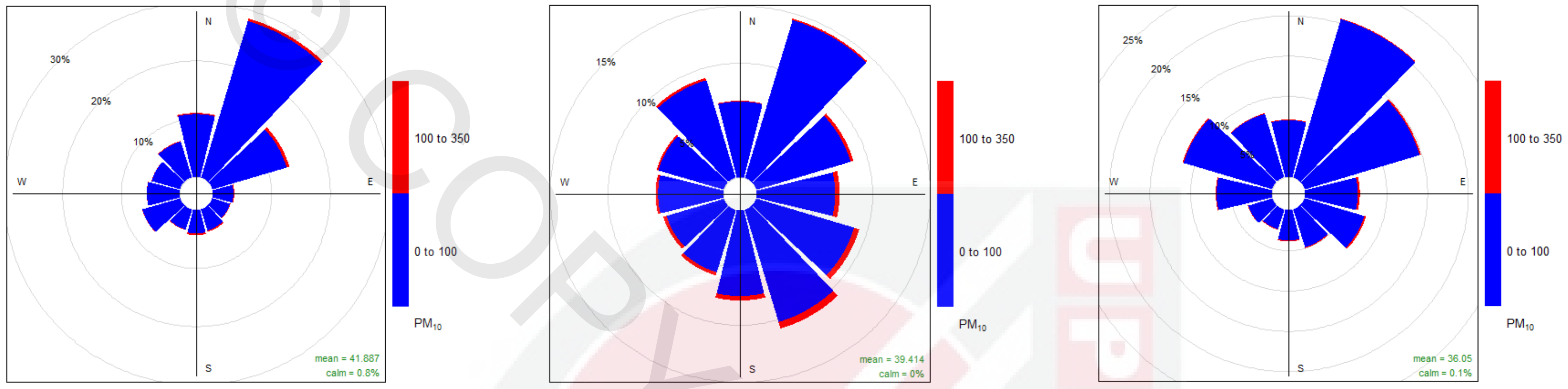
Figure 4.9: The Pollutant Rose of Carbon Monoxide (CO) at (A) SMKBR Bukit Rambai (B) KVM Muar (C) SMKABP Bandar Penawar Air Quality Monitoring Stations From 2015-2018
Note. Frequency of counts by wind direction (%)



(A) (B) (C)

Figure 4.10: The Pollutant Rose of Sulphur Dioxide (SO_2) at (A) SMKBR Bukit Rambai (B) KVM Muar (C) SMKABP Bandar Penawar Air Quality Monitoring Stations From 2015-2018

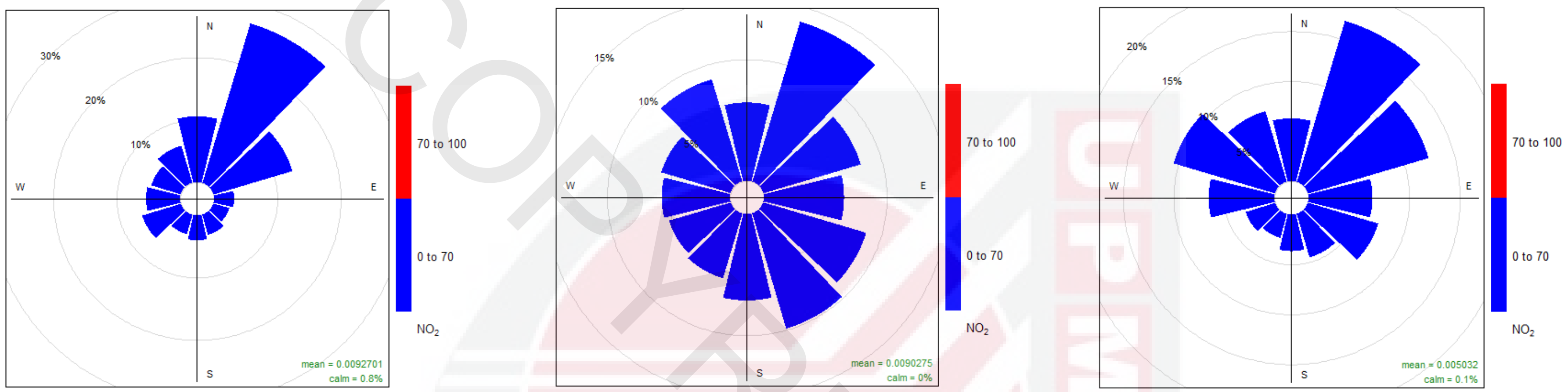
Note. Frequency of counts by wind direction (%)



(A) (B) (C)

Figure 4.11: The Pollutant Rose of Particulate Matter Less Than 10 (PM_{10}) at (A) SMKBR Bukit Rambai (B) KVM Muar (C) SMKABP Bandar Penawar Air Quality Monitoring Stations From 2015-2018

Note. Frequency of counts by wind direction (%)



(A) (B) (C)

Figure 4.12: The Pollutant Rose of Nitrogen Dioxide (NO_2) at (A) SMKBR Bukit Rambai (B) KVM Muar (C) SMKABP Bandar Penawar Air Quality Monitoring Stations From 2015-2018

Note. Frequency of counts by wind direction (%)

From pollutant rose analysis, it could be suggested that the visual inspection of the pollution rose plots reveals that northeast winds dominate in controlling the overall concentrations of pollutants in all three study areas. In fact, for all three study sites, the northeast wind sectors indicate the highest concentrations of API and PM_{10} than the other pollutants. As the days with high API are limited to seasonal conditions, this study found that local emissions, rather than transboundary pollution, are the primary contributors to the air pollution index observed in the study areas. The local breathed in air that has been contaminated by local or regional sources. The residential area does not significantly contribute to the API. Nevertheless, the analysis indicates that the residential area also contributes to the API value in the study areas.

According to Payus et al., 2022, Bukit Rambai was previously identified as a hotspot area from 2011 to 2013 due to its consistently high percentage of exceedance. Likewise, Bukit Rambai had the highest daily maximum mean API concentration in the Southern Peninsular Region of 397 and an overall moderate mean API value of 53 from 2010 to 2016. It may be contributed by factories in Bukit Rambai that manufacture furniture and wood, which may emit pollutants that have both short and long-term adverse effects on human health.

Muar, where few industries are located, recorded API readings between the range of normal and moderate from 2000 to 2009 but were impacted by seasonal biomass-burning activities in Sumatera, Indonesia (Rahman et al., 2016). The mean API reading recorded at Muar's sub-urban station was 51.61 μgm^{-3} (29.77 - 105.56 μgm^{-3}), which was higher than in the industrial area of

Pasir Gudang with 49.86 μgm^{-3} (30.32 - 83.76 μgm^{-3}) and residential area of Johor Bahru with 42.12 μgm^{-3} (23.05 - 109.14 μgm^{-3}).

PM_{10} and O_3 are considered to be the most likely factors influencing API variations (Rahman et al., 2016). In Bandar Penawar, no substantial sources of air pollution were discovered. The northeast of the Bandar Penawar Monitoring Station was covered with palm plantations; hence the findings of this study conflicted with Diener and Mudu (2021) and Janhäll (2015), which vegetation and green spaces should show reductive effects on air-borne pollutants concentrations, especially of PM. Green spaces intended to optimise the deposition and net removal of PM or certain PM size ranges have demonstrated the ability to decrease local concentrations, especially during periods of high pollution levels. These pollution peaks have been found to be particularly significant for short-term health impacts. This occurrence may be attributed to the dispersion of air pollution.

According to Rani et al. (2018), wind speed, wind direction, and solar radiation affect the distribution of air pollution. This supports the claim that meteorological conditions determine outflow strength and depend on the geographical location and the season during the emission period. Despite the fact that more concentrations appear to be below the limit than in the previous ten years, concentrations for all locations increased in 2015 as a result of the haze brought on by the massive land and forest fires in Sumatra and Kalimantan, Indonesia, which forced many schools to close due to the extremely poor air quality. The haze occurred in Malaysia from August to September (Khir et al., 2018).

In addition, it is stated that pollutants experience long-distance transport due to their longer lifetimes. For example, O_3 and PM have a lifetime ranging from a few hours to a few weeks, whereas CO has a lifetime measured in years. Despite being situated in a residential, this may be one of the contributing factors. The monsoon seasons are primarily responsible for the seasonal variations in PM_{10} levels that frequently exceed the Malaysian Ambient Air Quality Standard (MAAQS) and the National Ambient Air Quality Standard (NAAQS) in the study areas. Burning tropical plants during the southwest monsoon causes elevated PM_{10} levels (Mohtar et al., 2022). Furthermore, this study highlights the proportional contribution to the mean while drawing pollution rose plots to acquire important insight into the wind directions that most contribute to total air pollutants concentrations. However, pollutant rose alone cannot pinpoint the location of the upwind source.

The profiling is shown in Figure 4.13, indicating that days with an API level greater than 100 (unhealthy) were concentrated in Bukit Rambai from 7 to 9 September 2015, 11 to 17 September 2015, 23 September 2015, 26 September to 7 October 2015, 13–14 October 2015, 17–25 October 2015, and 10 December 2015. On January 18 and 20, 2016, there were two days with an unhealthy API level. The total number of days with an unhealthy API level at Bukit Rambai was 37 from 2015 to 2018.

The profiling is shown in Figure 4.14, indicating that days with an API level greater than 100 (unhealthy) were concentrated in Muar from 7 to 9 September 2015, 12 to 17 September 2015, 28 to 30 September 2015, 3 to 4 October

2015, 18–20 October 2015 and 23–25 October 2015. The total number of days with an unhealthy API level at Muar was 19 from 2015 to 2018.

The profiling is shown in Figure 4.15, indicating that days with an API level greater than 100 (unhealthy) were concentrated in Bandar Penawar on 11 September 2015, 24 to 25 September 2015, 29 September to 2 October 2015, 6 October 2015, 23 to 25 October 2015 and 5 November 2015. In 2016, there were 4 days with an unhealthy level of API, which occurred on May 17 and 22 and August 6 and 7. The total number of days with an unhealthy API level at Bandar Penawar was 16 from 2015 to 2018.

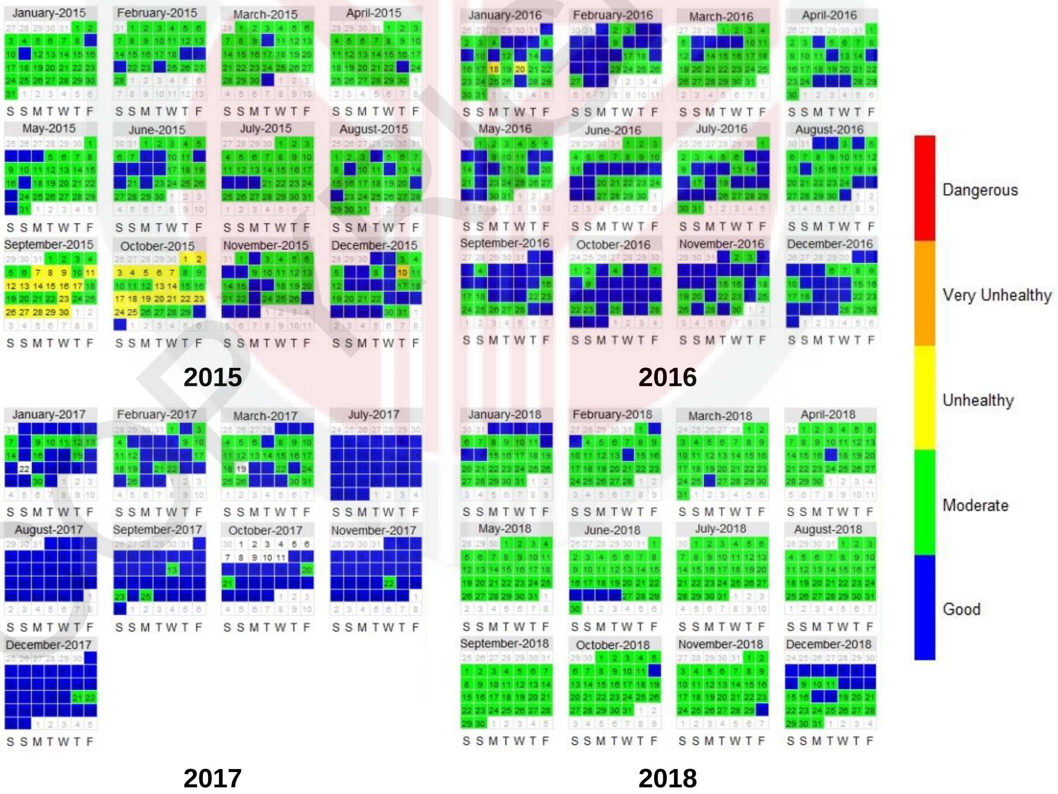


Figure 4.13: Calendar plot for SMKBR Monitoring Station from 2015-2018

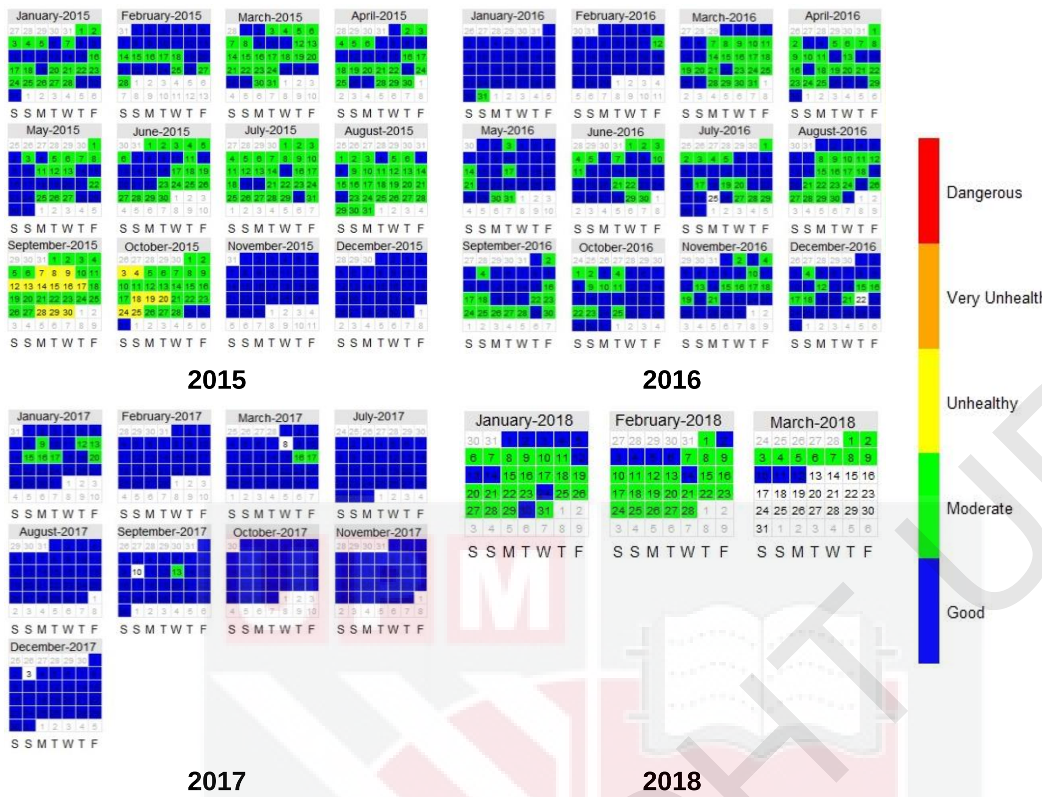


Figure 4.14: Calendar plot for KVM Monitoring Station from 2015-2018

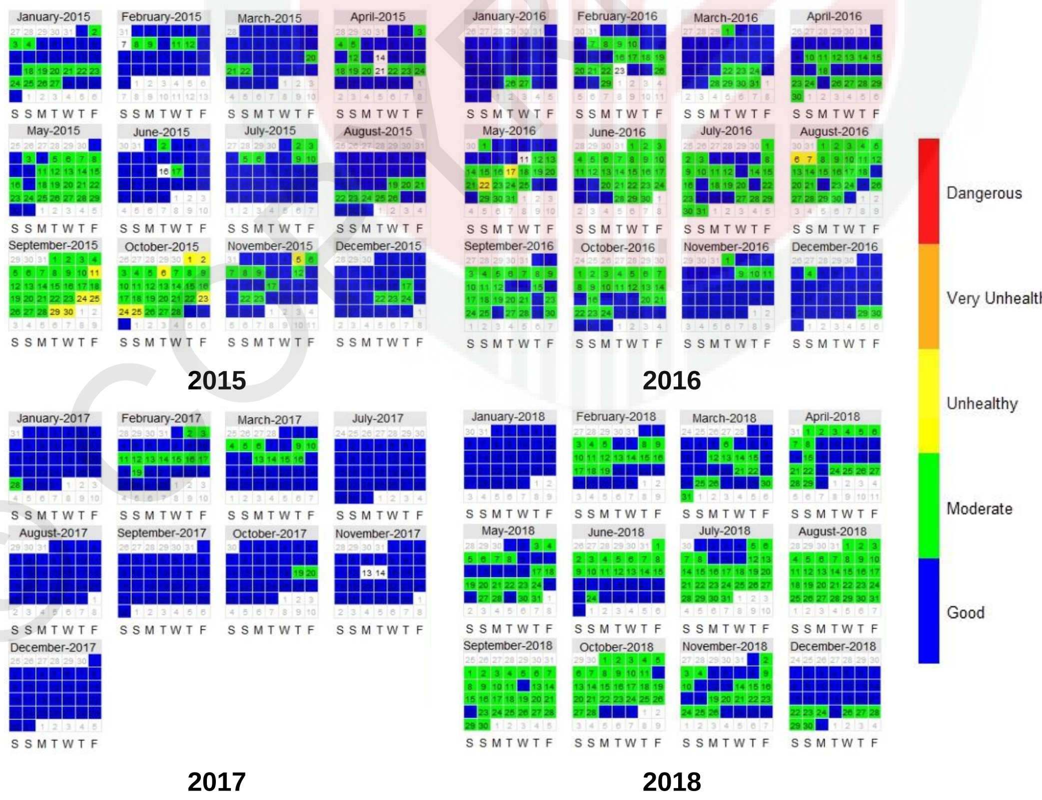


Figure 4.15: Calendar plot for Bandar Penawar Monitoring Station from 2015-2018

The calendar plot analysis used the four-year daily air pollutant index of the study areas to better the detection using visual data profiling. The results show that the developed approach can easily pinpoint months and years with poor air quality. The arrangement of the data into a 4x3 monthly grid represents the concentration of API from 2015 to 2018. Residents in the three study areas have normal (0-50) and moderate (51-100) API levels over the years.

API concentrations increased in 2015 across all locations, including the three study areas, due to the haze caused by massive land and forest fires in Sumatra and Kalimantan, Indonesia, which forced many schools to close due to extremely poor air quality. From August to September, Malaysia experienced haze (Sentian et al., 2019; Khir et al., 2018). For the three study locations between 2015 and 2018, there were no days with a very unhealthy and dangerous API level.

The profiling shown in Figure 4.14 indicates that Bukit Rambai is more prone to air pollution since the days with unhealthy level was higher than the other study areas. The calendar plot map showed that local emissions, rather than transboundary pollution, are the primary contributors to the air pollution index observed in the study areas, as the days with high API are limited to seasonal conditions.

4.4 Conclusion

In this study, the wind direction in each area over time is remarkably stable in each of the study areas overall. There was no difference in wind direction from

2015 to 2018 for all the study areas. Northeast winds control the overall concentrations of pollutants in all three study areas. The study areas' average wind speeds from 2015 to 2018 are sufficient to aid in the dispersion of air contaminants. Bandar Penawar has the highest wind speed, followed by Muar and Bukit Rambai. The presence of wind can facilitate the dispersion of contaminants. In fact, for all three study sites, the northeast wind sectors indicate the highest concentrations of API and PM_{10} than the other pollutants. In order to effectively mitigate the sources of pollution, it is imperative to recognise that the primary pollutants of concern are PM_{10} and API. Consequently, appropriate measures ought to be implemented to regulate and manage these sources. From the calendar plot, this study showed that local emissions, rather than transboundary pollution, are the primary contributors to the air pollution index observed in the study areas, as the days with high API are limited to seasonal conditions. Numerous anthropogenic and natural variables in various ambient conditions and geographic locations of the study areas resulted in varying pollutants levels. The control should commence from the local source.

CHAPTER 5

MAIN AIR POLLUTANTS THAT ARE POSITIVELY ASSOCIATED WITH OUTPATIENT VISITS FOR ACUTE RESPIRATORY INFECTION IN THE STUDY AREAS

5.1 Introduction

This study, in addition to the previous studies, identifies the primary air pollutants associated with outpatient visits for acute respiratory infection in Bukit Rambai, Melaka and Muar, Johor. Bandar Penawar in Johor was chosen as the comparative site due to its geographical location as a coastal town facing the South China Sea. In contrast, Bukit Rambai in Melaka and Muar in Johor are also coastal towns, but they are situated along the Straits of Malacca. The presence of various environmental circumstances, such as hazy and non-hazy days, as well as diverse geographic locations, such as semi-rural and rural areas, are subject to significant influence from a combination of natural and human-induced causes. Consequently, the levels of pollutants are expected to exhibit variability (Nadiah et al., 2018). It is expected that outpatient visits will serve as a more sensitive measure for assessing acute or short-term health effects caused by exposure to air pollution compared to hospital admissions (Guo et al., 2021). To achieve the second objective, correlation analysis examined the relationship between API, PM_{10}, SO_2, NO_2, O_3 and CO and outpatient visits for ARI in Bukit Rambai, Melaka; Muar, Johor; and Bandar Penawar, Johor. It is anticipated that the results indicate a potential for enhancing human health through effective management of urban development and its associated environmental quality.

5.2 Materials and Method

5.2.1 Air Quality Data of The Study Areas

This study utilised hourly concentrations of major pollutants measured by DOE, including particulate matter (PM_{10}), ozone (O_3), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), and carbon monoxide (CO). $PM_{2.5}$ was excluded from this study since its concentration has only been added to API calculations in Malaysia beginning in August 2018. Since there was a change in the concessionaire company, the records for April to June 2017 have been cancelled. Except for the SMKABP air quality monitoring station, all selected continuous air quality monitoring sites face the Malacca Strait to the west.

5.2.2 Outpatient Visits Data on Sentinel Clinics

Data on ARI was obtained from daily visit outpatient visits report from 2015 to 2018 (4 years) at KKBR, KKBM and KKBP.

5.2.3 Pearson Rank-Order Correlation

Since the sample size is larger than 50 (n>50), the Kolmogorov-Smirnov test determine whether the data are normally distributed. Due to the normal data distribution, Pearson's Correlation Coefficient analysis was used to determine the association between outpatient visits for ARI at KKBR, KKBM and KKBP with API, SO_2, NO_2, O_3, CO and PM_{10} from 2015 to 2018 (4 years) to ensure the reliability of the study's findings. Statistical significance was defined as $p<0.001$.

5.3 Results and Discussion

Pearson's rank-order correlation was run to examine the relationship between API, PM_{10}, SO_2, NO_2, O_3, CO and outpatient visits for ARI at Bukit Rambai, Melaka; Muar, Johor and Bandar Penawar, Johor from 2015-2018. The findings were shown in Tables 5.1, 5.2, and 5.3.

Table 5.1: Pearson Rank-Order Correlation between API, PM_{10}, SO_2, NO_2, O_3, CO and Outpatient Visits for ARI at Bukit Rambai from 2015-2018

	API	PM_{10}	SO_2	NO_2	O_3	CO	ARI Outpatient Visits
API	1.000						
PM_{10}	.673**	1.000					
SO_2	.081**	.048**	1.00				
NO_2	.326**	.417**	-.047**	1.00			
O_3	.496**	.296**	.236**	.181**	1.00		
CO	.197**	.245**	.068**	.288**	.124**	1.00	
ARI Outpatient Visits	.134**	.043**	.226**	-.100**	.035**	-.047**	1.000

**. Correlation is significant at the 0.01 level (2-tailed) ($p<0.01$).
Note. API = Air Pollutants Index; PM_{10} = Particulate Matter <10 micron; SO_2 = Sulphur Dioxide; NO_2 = Nitrogen Dioxide; O_3 = Ozone; CO = Carbon Monoxide; ARI = Acute Respiratory Infection

Table 5.2: Pearson Rank-Order Correlation between API, PM_{10}, SO_2, NO_2, O_3, CO and ARI Outpatient Visits at Muar from 2015-2018

	API	PM_{10}	SO_2	NO_2	O_3	CO	ARI Outpatient Visits
API	1.000						
PM_{10}	.249**	1.000					
SO_2	.055**	-.377**	1.00				
NO_2	.273**	-.272**	.535**	1.00			
O_3	.315**	-.404**	.547**	.631**	1.00		
CO	.054**	-.385**	.674**	.633**	.577**	1.00	
ARI Outpatient Visits	-.077**	.178**	-.414**	-.283**	-.152**	-.326**	1.000

**. Correlation is significant at the 0.01 level (2-tailed) ($p<0.01$).
Note. API = Air Pollutants Index; PM_{10} = Particulate Matter <10 micron; SO_2 = Sulphur Dioxide; NO_2 = Nitrogen Dioxide; O_3 = Ozone; CO = Carbon Monoxide; ARI = Acute Respiratory Infection

Table 5.3: Pearson Rank-Order Correlation between API, PM_{10}, SO_2, NO_2, O_3, CO and Outpatient Visits at Bandar Penawar from 2015-2018

	API	PM_{10}	SO_2	NO_2	O_3	CO	ARI Outpatient Visits
API	1.000						
PM_{10}	.285**	1.000					
SO_2	.177**	-.274**	1.00				
NO_2	.197**	-.400**	.641**	1.00			
O_3	.483**	-.212**	.484**	.539**	1.00		
CO	.273**	-.421**	.518**	.718**	.556**	1.00	
ARI Outpatient Visits	.074**	.487**	-.172**	-.306**	-.173**	-.460**	1.000

**. Correlation is significant at the 0.01 level (2-tailed) ($p<0.01$).
Note. API = Air Pollutants Index; PM_{10} = Particulate Matter <10 micron; SO_2 = Sulphur Dioxide; NO_2 = Nitrogen Dioxide; O_3 = Ozone; CO = Carbon Monoxide; ARI = Acute Respiratory Infection

Bukit Rambai, Melaka, and Muar, Johor, have residential and industrial areas. As stated by Abdullah et al., 2016 that most of the air pollution comes from the combustion of fossil fuels in vehicles and industries. Bukit Rambai, Melaka experiences good (0-50), moderate pollution (50 to 100) and only 37 days of an unhealthy level of API (101 to 200) throughout the years (2015-2018). The correlation study demonstrated that, except for the NO_2 and CO, the daily concentration of API and air pollutants showed a significant positive connection with the daily outpatient visits for acute respiratory infections. The strongest relationship was observed between API and PM_{10}. A positive correlation between API and PM_{10} was also found in this study, which can be explained by a study by Hanafi et al. (2018) which identified a direct association between the PM_{10} concentration and API in Johor in 2014 and 2015 and the number of cases of upper respiratory tract infections yet consistent with the findings of Zhang et al. (2021) and Azid et al. (2016), which determined that PM_{10} is the primary contributor to API variability and the main source of air pollution measurements.

While this study does not incorporate the association with ambient temperature, a Pearson Correlation analysis by Mohd Zizi et al. (2018) shows that ambient temperature is the largest positive correlation to the PM_{10} concentration among the meteorological factors. By adding this related data in future, we can give a better and more convincing explanation of the relationship or correlation between the air pollutants and the related factor that affected how the air quality changed in that area. The negative and significant correlation between SO_2 and CO with daily outpatient visits can be explained using the study by Szyszkowicz et al. (2018) that demonstrates even in a context with modest levels of air pollution, exposure to pollution can increase the incidence of emergency room visits for upper and lower respiratory diseases, which may help to explain the negative correlation between pollutants and outpatient visits.

Muar, Johor experiences good (0-50), moderate pollution (50 to 100) and only 19 days of an unhealthy level of API (101 to 200) throughout the years (2015-2018). This study indicated a negative and significant relationship between API, SO_2, NO_2, 0_3 and CO, except for PM_{10} with outpatient visits. PM_{10} was a significant aspect of air pollution in most case studies (Zhang et al., 2021; Li et al., 2023). The study conducted by Szyszkowicz et al. (2018) provides evidence that even in environments with relatively low levels of air pollution, exposure to pollutants can lead to an increase in emergency room visits for both upper and lower respiratory diseases. This finding offers an explanation for the observed contrary relationship between pollutants and outpatient visits. Furthermore, a strong positive correlation was observed between the API and other pollutants, SO_2 and CO, NO_2 and O_3, NO_2 and CO, as well as O_3 and CO. Furthermore, a weak yet significant negative correlation was observed between SO_2, NO_2, O_3, CO and PM_{10}.

In Muar, Johor, the strongest relationship was observed between CO and SO_2. This is consistent with a study conducted in Petaling Jaya, Selangor, which discovered a significant positive correlation between CO and SO_2 by Azmi et al. (2010), citing the influence of heavy traffic. Muar is one of Johor's major cities. Compared to Selangor and Wilayah Persekutuan, Johor came in third with 42,923 new motor vehicle registrations in 2019 and 35,394 in 2020, according to the statistics (Ministry of Transport Malaysia, 2021).

Bandar Penawar, Johor experiences good (0-50), moderate pollution (50 to 100) and only 16 days of an unhealthy level of API (101 to 200) throughout the years (2015-2018). The result of this study indicated that there was a negative and significant correlation between pollutants with outpatient visits, except for API and PM_{10}. Moreover, there was also a negative and significant correlation between PM_{10} with SO_2, NO_2, 0_3 and CO. There was a positive and significant correlation between API and SO_2, NO_2, O_3 and CO, and between SO_2 with NO_2, O_3 and CO, between NO_2 with O_3 and CO, between O_3 and CO.

In Bandar Penawar, Johor, the strongest relationship was observed between NO_2 and CO. Incomplete combustion from gasoline and diesel engines produces the potentially hazardous airborne gases CO and NO_2. The most common source of these gases is motor vehicles. Other instances include using generators, propane or wood-burning cooking and heating appliances, cigarettes, and even natural events like lightning and forest fires (Du et al., 2022; Chen et al., 2021; Reumuth et al., 2019; Payus et al., 2019).

5.4 Conclusion

This study found a positive and significant correlation between API, PM_{10}, SO_2 and 0_3 with outpatient visits for ARI in KKBR, PM_{10} and outpatient visits for ARI in KKBM, API and PM_{10} with outpatient visits for ARI in KKBP. These findings suggest a potential contribution from local pollution to the occurrence of ARI cases in those areas and this should be the primary point of control. The study findings indicate that outpatient visits for ARI were associated with pollutants and their interactions in all three study areas. These correlations were found to be both positive and negative, and were statistically significant. It is important to note that these associations were observed within the context of the local activities specific to each study area. The presence of a little contradiction in the findings across the three study areas can be attributed to variations in the composition of pollutants, which may be influenced by factors such as industrial processes and local activities. The presence of diverse environmental circumstances, such as haze and non-haze days, and the existence of distinct geographic locations, such as semi-rural and rural areas, are subject to significant influences from a multitude of anthropogenic and natural factors. Consequently, these conditions and locations will exhibit varying amounts of pollutants. The study's findings indicate that particulate matter is expected to be the primary air pollutant linked to outpatient visits for acute respiratory infection in the areas under study. The hypothesis has been validated.

CHAPTER 6

THE MAIN AGE GROUP OF PATIENTS WHO SUFFERED ACUTE RESPIRATORY INFECTION DUE TO AIR POLLUTION IN THE STUDY AREAS

6.1 Introduction

A multitude of research studies have been conducted to examine the impacts of ambient air pollution on human health, focusing on the associations between certain air contaminants and particular health outcomes. The majority of these incidents pertained to children (He et al., 2022; Ibrahim et al., 2022; Song et al., 2018). In Malaysia, the main diseases under surveillance in relation to air pollution include conjunctivitis, asthma and acute respiratory infections (DOE, 2020). However, the main emphasis of this study is on acute respiratory infection. The third objective of this study was to determine the influence of age on the risk of acute respiratory infection due to air pollutants among outpatients in Bukit Rambai, Melaka and Muar, Johor between 2015 to 2018. Bandar Penawar, located in the state of Johor, was chosen as the comparative site due to its geographical positioning as a coastal town facing the South China Sea. In contrast, Bukit Rambai in Melaka and Muar in Johor are also coastal towns, but they are situated along the Straits of Malacca. It is expected that outpatient visits will serve as a more sensitive measure for assessing the acute or short-term health effects resulting from air pollution, in comparison to hospitalisation. (Guo et al., 2021). This will enable the implementation of preventive and medical strategies for the effective management of ARI among individuals within vulnerable age groups.

6.2 Materials and Method

6.2.1 Outpatient Visits Data on Sentinel Clinics

Data on ARI was obtained from daily visit outpatient visits report from 2015 to 2018 (4 years). The selected sentinel clinics were KKBR, KKBM and KKBP.

6.2.2 Descriptive Analysis on Age Group

The descriptive analysis described the main age group of patients who suffered ARI due to air pollution and summarizes the frequencies of visits for ARI by age range from 2015 to 2018 (4 years) at the KKBR, KKBM and KKBP. The N value will represent the number of days with data of outpatient visits for ARI. Another descriptive analysis focuses on the mean (M) and standard deviation (SD) for the main age group of patients, which is divided into 3 age ranges; under 12 years old, 13 to 59 years old and over 60 years old who visited the clinics with ARI.

6.2.3 One-Way ANOVA

The One-way ANOVA was used to compare age groups for the parameter of 'frequency of outpatient visits,' and statistically significant differences were found between the age groups. Since the sample size of each study area differs, a post-hoc Bonferroni analysis was performed to find differences between the age groups.

6.3 Results and Discussion

Table 6.1 showed that in 2015, outpatient visits in the age group 13-59 (M=10.97, SD=4.83) were higher than outpatient visits in the age group of <12 (M=8.80, SD=4.44) and outpatient visits in the age group of >60 (M=6.28, SD=2.74). In 2016, outpatient visits in the age group of 13-59 (M=13.32, S =4.58) were higher than outpatient visits in the age group of <12 (M=11.24, SD=4.48) and outpatient visits in the age group of >60 (M=2.63, SD=1.18). In 2017, outpatient visits in the age group of 13-59 (M=13.05, SD=6.38) were higher than outpatient visits in the age group of <12 (M=9.61, SD=5.97) and outpatient visits in the age group of >60 (M=2.80, SD=1.11). In 2018, outpatient visits in the age group of >60 (M=10.75, SD=19.22) were higher than outpatient visits in the age group of 13-59 (M=12.37, SD=7.26) and outpatient visits in the age group of <12 (M=10.14, SD=5.46).

A one-way ANOVA in Table 6.1 revealed that in 2015, 2016, 2017 and there was a statistically significant difference in age groups between at least three groups (F (2,4481) = 346.60, p = <0.001) in 2015, (F (2,5173) = 398.93, p = <0.001) in 2016, (F (2,4130) = 483.17, p = <0.001) in 2017 and (F (2,4521) = 30.60, p = <0.001) in 2018 which the age group of <12 and >60 do not differ significantly from each other.

As shown in Figure 6.1, in 2015, there were 4,484 total outpatient visits for acute respiratory conditions at Klinik Kesihatan Bukit Rambai, with a higher proportion among the age range of 13-59 years old with 2,127 (47.44%) total visits and maximum visits of 28 persons per day, followed by the age range of

<12 years old with 1,583 (35.30%) total visits and maximum visits of 29 persons per day, and the age range of >60 years old with 774 (17.26%) total visits and maximum visits of 16 persons per day. In 2016, there were 5,176 total outpatient visits for acute respiratory conditions, with a higher proportion among the age range of 13-59 years old, with 2,816 (54.40%) total visits and maximum visits of 26 persons per day, followed by the age range of <12 years old with 2,246 (43.39%) total visits and maximum visits of 24 persons per day, and the age range of >60 years old with 114 (2.20%) total visits and maximum visits of 5 persons per day. In 2017, there were 4,133 total outpatient visits for acute respiratory conditions, with a higher proportion among the age range of 13-59 years old, with 2,338 (56.57%) total visits and maximum visits of 30 persons per day, followed by the age range of <12 years old with 1,468 (35.52%) total visits and maximum visits of 24 persons per day, and the age range of >60 years old with 327 (7.91%) total visits and maximum visits of 5 persons per day. In 2018, there were 4,524 total outpatient visits for acute respiratory conditions, with a higher proportion among the age range of 13-59 years old, with 2,082 (46.02%) total visits and maximum visits of 32 persons per day, followed by the age range of <12 years old with 1,877 (41.49%) total visits and maximum visits of 31 persons per day, and the age range of >60 years old with 565 (12.49%) total visits and maximum visits of 64 persons per day. From 2015 to 2018, Klinik Kesihatan Bukit Rambai received 18,317 outpatient visits for acute respiratory infections, with the highest proportion among the age range of 13-59 years old, followed by the age range of <12 years old and the age range of > 60 years old.

As shown in Table 6.1, in 2015, outpatient visits in the age group of 13-59 (M=79.67, SD=63.16) were higher than outpatient visits in the age group of >60 (M=79.67, SD=63.16) and outpatient visits in the age group of <12 (M=33.83, SD=16.09). In 2016, outpatient visits in the age group of >60 (M=46.63, SD=61.06) were higher than outpatient visits in the age group of 13-59 (M=71.73, SD=52.25) and outpatient visits in the age group of <12 (M=29.69, SD=15.33). In 2017, outpatient visits in the age group of 13-59 (M=125.02, SD=35.46) were higher than outpatient visits in the age group of >60 (M=65.84, SD=26.04) and outpatient visits in the age group of <12 (M=58.97, SD=20.23). outpatient visits in the age group of >12 (M=98.45, SD=43.86) were higher in 2018 than outpatient visits in the age group of >60 (M=86.79, SD=37.13) and outpatient visits in the age group of 13-59 (M=130.86, SD=37.07).

A one-way ANOVA in Table 6.1 revealed that in 2015, 2016, 2017 and there was a statistically significant difference in age groups between at least three groups ($F (2,23897) = 1800.99$, $p = <0.001$) in 2015, ($F (2,25892) = 2393.57$, $p = <0.001$) in 2016, ($F (2,61740) = 33094.63$, $p = <0.001$) in 2017 and ($F (2,15133) = 2088.07$, $p = <0.001$) in 2018.

As shown in Figure 6.2, in 2015, there were 23,900 total outpatient visits for acute respiratory conditions at Klinik Kesihatan Bandar Maharani, with a higher proportion among the age range of 13-59 years old with 13,738 (55.25%) total visits and maximum visits of 330 persons per day, followed by the age range of <12 years old with 6,256 (28.91%) total visits and maximum visits of 80 persons per day, and the age range of >60 years old with 3,906 (15.84%) total visits and maximum visits of 261 persons per day. In 2016, there were 25,895 total outpatient visits for acute respiratory conditions, with a higher proportion among the age range of 13-59 years old, with 14,308 (57.48%) total visits and maximum visits of 341 persons per day, followed by the age range of <12 years old with 7,486 (26.18%) total visits and maximum visits of 112 persons per day, and the age range of >60 years old with 4,101 (16.34%) total visits and maximum visits of 147 persons per day. In 2017, there were 61,743 total outpatient visits for acute respiratory conditions, with a higher proportion among the age range of 13-59 years old, with 31,921 (51.70%) total visits and maximum visits of 225 persons per day, followed by the age range of >60 years old with 15,448 (25.02%) total visits and maximum visits of 135 persons per day and the age range of <12 years old with 14,374 (23.28%) total visits and maximum visits of 135 persons per day. In 2018, there were 69,674 total outpatient visits for acute respiratory conditions, with a higher proportion among the age range of 13-59 years old, with 32,558 (46.73%) total visits and maximum visits of 215 persons per day, followed by the age range of >60 years old with 18,775 (26.95%) total visits and maximum visits of 167 persons per day, and the age range of <12 years old with 18,341 (26.32%) total visits and maximum visits of 192 persons per day. From 2015 to 2018, Klinik Kesihatan Bandar Maharani received 181,212 outpatient visits for ARI, with the highest proportion among the age range of 13-59 years old, followed by the age range of <12 years old and the age range of >60 years old.

As shown in Table 6.1, in 2015, outpatient visits in the age group of 13-59 (M=22.48, SD =8.32) were higher than outpatient visits in the age group of >60

(M=4.02, SD=3.15) and outpatient visits in the age group of <12 (M=5.06, SD=2.89). In 2016, outpatient visits in the age group of 13-59 (M=9.23, SD=3.14) were higher than outpatient visits in the age group of >60 (M=2.51, SD=1.91) and outpatient visits in the age group of <12 (M=3.08, SD=1.32). In 2017, outpatient visits in the age group of 13-59 (M=10.76, SD=3.64) were higher than outpatient visits in the age group of <12 (M= 4.13, SD=2.21) and outpatient visits in the age group of >60 (M=3.58, SD=1.65). Outpatient visits in the age group of 13-59 (M=8.04, SD=3.18) were also higher in 2018 than outpatient visits in the age group of <12 (M=4.10, SD=2.58) and outpatient visits in the age group of >60 (M=2.05, SD=0.97).

A one-way ANOVA in Table 6.1 revealed that in 2015, 2016, 2017 and there was a statistically significant difference in age groups between at least three groups (F (2,1092) = 323.68, p = <0.001) in 2015, (F (2,2803) = 1584.08, p = <0.001) in 2016, (F (2,3267) = 1510.04, p = <0.001) in 2017 and (F (2,2558) = 821.27, p = <0.001) in 2018.

As shown in Figure 6.3, in 2015, there were 5,935 total outpatient visits for acute respiratory conditions at Klinik Kesihatan Bandar Penawar, with a higher proportion among the age range of 13-59 years old with 4,626 (77.94%) total visits and maximum visits of 45 persons per day, followed by the age range of <12 years old with 848 (14.29%) total visits and maximum visits of 14 persons per day, and the age range of >60 years old with 461 (7.77%) total visits and maximum visits of 16 persons per day. In 2016, there were 2,806 total outpatient visits for acute respiratory conditions, with a higher proportion among the age range of 13-59 years old, with 1,944 (69.28%) total visits and maximum visits of 18 persons per day, followed by the age range of <12 years old with 597 (21.28%) total visits and maximum visits of 7 persons per day, and the age range of >60 years old with 265 (9.44%) total visits and maximum visits of 7 persons per day. In 2017, there were 3,270 total outpatient visits for acute respiratory conditions, with a higher proportion among the age range of 13-59 years old, with 2,273 (69.51%) total visits and maximum visits of 19 persons per day, followed by the age range of <12 years old with 748 (22.87%) total visits and maximum visits of 12 persons per day and the age range of >60 years old with 249 (7.61%) total visits and maximum visits of 8 persons per day. In 2018, there were 2,568 total outpatient visits for acute respiratory conditions, with a higher proportion among the age range of 13-59 years old, with 1,611 (62.73%) total visits and maximum visits of 19 persons per day, followed by the age range of <12 years old with 661 (25.74%) total visits and maximum visits of 13 persons per day, and the age range of >60 years old with 296 (11.53%) total visits and maximum visits of 5 persons per day. From 2015 to 2018, Klinik Kesihatan Bandar Penawar received 14,579 outpatient visits for ARI, with the highest proportion among the age range of 13-59 years old, followed by the age range of <12 years old and the age range of >60 years old.

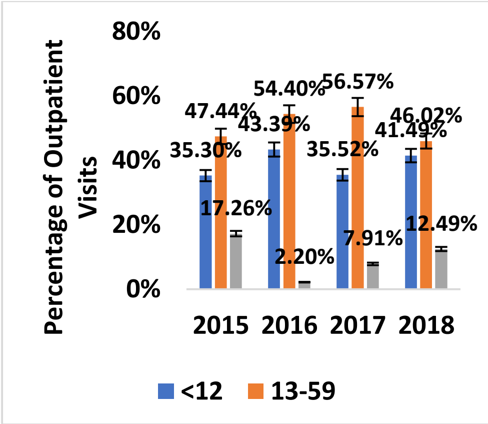


Figure 6.1: Percentage distribution of outpatient visits based on the main age group of patients who suffered ARI at Klinik Kesihatan Bukit Rambai from 2015-2018

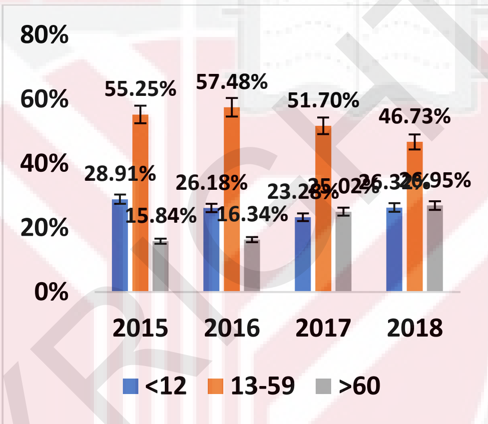


Figure 6.2: Percentage distribution of outpatient visits based on the main age group of patients who suffered ARI at Klinik Kesihatan Bandar Maharani from 2015-2018

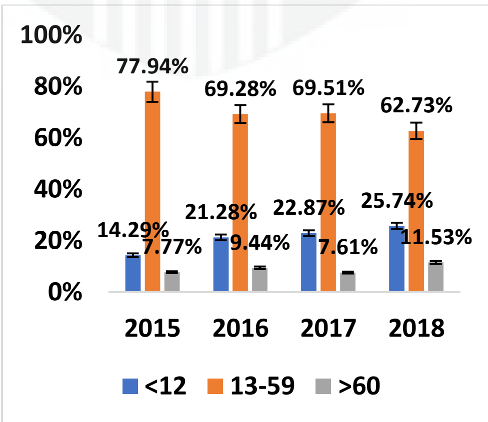


Figure 6.3: Percentage distribution of outpatient visits based on the main age group of patients who suffered ARI at Klinik Kesihatan Bandar Penawar from 2015-2018

Table 6.1: Means and standard deviations of daily outpatient visits based on the age group of patients who suffered ARI at KKBR Melaka, KKBM Muar and KKBP Bandar Penawar from 2015-2018

		Daily Outpatient Visits KKBR		Daily Outpatient Visits KKBM		Daily Outpatient Visits KKBP	
Year	**Age Range**	***N***	***Mean ± SD***	***N***	***Mean ± SD***	***N***	***Mean ± SD***
	<12	1583	$8.80_b \pm 4.44$	7486	$33.83_a \pm 16.09$	848	$5.06_b \pm 2.89$
2015	13-59	2127	$10.97_c \pm 4.83$	14308	$79.67_c \pm 63.16$	4626	$22.48_c \pm 8.32$
	>60	774	$6.28_a \pm 2.74$	4101	$42.53_b \pm 36.24$	461	$4.02_a \pm 3.15$
	<12	2246	$11.24_b \pm 4.48$	6256	$29.69_a \pm 15.24$	597	$3.08_b \pm 1.32$
2016	13-59	2816	$13.32_c \pm 4.58$	13738	$71.73_c \pm 52.25$	1944	$9.23_c \pm 3.14$
	>60	114	$2.63_a \pm 1.18$	3906	$46.63_b \pm 61.06$	265	$2.51_a \pm 1.91$
	<12	1468	$9.61_b \pm 5.97$	14374	$58.97_a \pm 20.23$	748	$4.13_b \pm 2.21$
2017	13-59	2338	$13.05_c \pm 6.38$	31921	$125.02_c \pm 35.46$	2273	$10.76_c \pm 3.64$
	>60	327	$2.80_a \pm 1.11$	15448	$65.84_b \pm 26.04$	249	$3.58_a \pm 1.65$
	<12	1877	$10.14_a \pm 5.46$	18341	$33.83_b \pm 16.09$	661	$4.10_b \pm 2.58$
2018	13-59	2082	$12.37_b \pm 7.26$	32558	$79.67_c \pm 63.16$	1611	$8.04_c \pm 3.18$
	>60	565	$10.75_a \pm 19.22$	18775	$42.53_a \pm 36.24$	296	$2.05_a \pm 0.97$

Note. Means with different subscripts differ at the $p=0.05$ level by Duncan's new multiple range test.

According to the analysis, only Muar experienced an increase in outpatient visits year after year. In contrast, the trend of outpatient visits due to acute respiratory infection in Bukit Rambai and Bandar Penawar fluctuates yearly. All these three sentinel clinics received the highest proportion among the 13-59 years old age range, followed by <12 and >60. The vulnerability of children to the adverse health consequences of air pollution arises from their underdeveloped immune systems, immature lung and metabolic systems, and concurrent respiratory illnesses (Lee, 2021).

A lot of study has been conducted on the associations between air pollutants and specific health impacts within the context of studies investigating the impact of ambient air pollution on human well-being. The majority of these cases involved children as those who suffered. The impact of NO_2 on emergency department visits for acute upper respiratory tract infections was shown to be more pronounced among children aged 0 to 5 years, whereas the influence of PM_{10} was more significant in the age group of 6 to 14 years. In a study conducted by Song et al. (2018) in Shijiazhuang, China, a significant correlation was observed between levels of ambient NO_2 and SO_2 and hospital outpatient visits among children with respiratory disease. This finding indicates a strong association between ambient air pollution and respiratory hospitalisations in children aged 0 to 4 years in Bintulu. Similarly, in Poland, short-term fluctuations in O_3 levels were found to be linked to an increase in absences from school due to respiratory illness among children aged 9 to 10. Ratajczak et al. (2021) also discovered that moderate-term exposure to air pollution was associated with a heightened risk of upper respiratory infections in children aged 3 to 12 years. Furthermore, a study conducted in 2018 revealed that all ambient air pollutants were associated with an increased risk of upper respiratory infections. Multiple studies indicate that children who have been exposed to higher levels of pollutants are likely to experience persistent impairment in lung function compared to those who have been exposed to lower levels, as evidenced by previous longitudinal research on the trajectory of lung function over time. This trend becomes more prominent as long as these children remain exposed to pollutants (Schultz et al., 2017). All the studies contradict the result of this study.

In a study by Mohd Shafie et al. (2022), Klang was identified by the AirQ+ model as a significantly high-risk location for chronic bronchitis in the adult population in 2009, with 804,240 residents (with a relative risk of 1.85). Most areas were contaminated with annual PM_{10} levels exceeding the recommended Department of Environment and the World Health Organization Global Air Quality Guidelines level. The study's age range, however, was not identified. All the identified studies ran afoul of this study's conclusion that the highest proportion of outpatient visits for acute respiratory infection was among the 13 to 59 years old. The elderly was less likely than younger persons to seek therapy because they relied more on family members and were possibly less informed about current events. Even though children are familiar with social media and current events, they may be unable to filter out irrelevant material and may be unaware of the need for treatment (Aamir et al., 2022). Adults confront a challenge as they are proportionally exposed to environmental pollutants when they are at work. Adults are a subpopulation believed to be particularly susceptible to exposure to air pollution, according to studies on the health effects of air pollution on adult populations. This was revealed by Achilleos et al. (2019) in Kuwait, where the acute impacts of air pollution resulted in the deaths of the following age groups: 32,044 elderly people, 33,250 adolescents/adults (12,938 Kuwaitis and 20,312 non-Kuwaitis), and 8,454 children (4,781 Kuwaitis and 3,673 non-Kuwaitis) (21,670 Kuwaitis and 10,374 non-Kuwaitis). The correlation between these findings and lung function may contribute to an increase in outpatient visits among 13- to 59-year-olds.

Numerous studies have discovered a relationship between pollution and both adult and child lung function. A linear mixed-effects model was used to analyze the effects of air pollution on lung function, inflammation and oxidative stress in 30 healthy young adults from China. The most prevalent markers of inflammation are interleukin-6 (IL-6) and C-reactive protein (CRP), while malondialdehyde (MDA), a stable byproduct of lipid peroxidation, has been frequently used as a biomarker of overall oxidative stress. Increased C-reactive protein (CRP), malondialdehyde, and lung function were found to be associated with higher $PM_{2.5}$ exposure (MDA). Every 10 g/m^3 rise in $PM_{2.5}$ (lag 2 days) is associated with a decrease in forced expiratory volume (FEV1), a decrease in peak expiratory flow (PEF) of 46.34 ml/s, an increase in CRP of 2.86% (95% CI: 1.47%, 4.27%), and an increase in MDA of 1.63% (95% CI: 0.14%, 3.14%) (Xu et al., 2022). According to longitudinal observational data from the Dutch Lifelines cohort study, which followed 49,705 adults aged 18 and over between 2006 and 2015, higher exposure to $PM_{2.5}$, but not black carbon, was associated with higher cognitive processing time (CPT) and slower cognitive processing speed [Total Effect $PM_{2.5}$: FEV1 model = 8.31 103, force forced capacity (FVC) model = 8.30 103 (95% CI: 5.69 103, 10.91 103)]. More than 97% of the effect was directly connected with $PM_{2.5}$ (Aretz et al., 2021).

Although $PM_{2.5}$ likely contributed to increase in adult outpatient visits in the study areas, this aspect was not considered in this analysis because the DOE did not collect $PM_{2.5}$ data until 2019. People with diabetes and predisposing heart or lung disease, particularly asthma, are vulnerable populations who should be aware of health-protection measures. Even on days with low air pollution, the health of vulnerable and sensitive individuals can be negatively affected (Manisalidis et al., 2020). Other studies link the effect of air pollution on adult and older age groups with other illnesses caused by air pollution, Alzheimer's disease and related dementia by Trevenen et al. (2022) and Mork et al. (2023) also impair physical and mental health, as described by Ju et al. (2022).

At Klinik Kesihatan Bukit Rambai, a one-way ANOVA in Table 6.2 showed that there was a statistically significant difference in age groups across at least three groups ($F (2,18314) = 750.57$, $p = 0.001$).

According to the Bonferroni test for multiple comparisons, the mean value for the age group under 12 ($M=10.08$, $SD=5.15$) differed substantially from that of the age groups between 13 and 59 ($M=12.51$, $SD=5.86$), and the age group over 60 ($M=6.82$, $SD=11.39$). The age range of 13-59 exhibited outpatient visits for acute respiratory infection compared to <12 and >60 at this sentinel clinic.

Table 6.2: Analyses for the Age Groups of Outpatients Visits for Acute Respiratory Infection at Klinik Kesihatan Bukit Rambai from 2015-2018

Measure	<12	13-59	>60	*F* ratio	*p*	η2
	M ± SD	M ± SD	M ± SD			
Age Groups	10.08_b ± 5.15	12.51_c ± 5.86	6.82_a ± 11.39	720.57*	<.001	0.08

Note. Means with different subscripts differ at the *p*=0.05 level by Duncan's new multiple range test.

A one-way ANOVA in Table 6.3 revealed that there was a statistically significant difference in age groups between at least three groups (F (2,126671) = 17448.19, p = <0.001) at Klinik Kesihatan Bandar Maharani.

Bonferroni test for multiple comparisons indicated that the mean value of the <12 age group (M=53.38, SD=31.55) was significantly different than 13-59 age group (M=104.88, SD=52.75) and >60 age groups (M=63.58, SD=37.88). The age range of 13-59 exhibited outpatient visits for acute respiratory infection compared to <12 and >60 at this sentinel clinic.

Table 6.3: Analyses for the Age Groups of Outpatients Visits for Acute Respiratory Infection at Klinik Kesihatan Bandar Maharani from 2015-2018

Measure	<12	13-59	>60	*F* ratio	*p*	η2
	M ± SD	M ± SD	M ± SD			
Age Groups	53.38a ± 31.55	104.88c ± 52.75	63.58b ± 37.88	17448.19*	<.001	0.22

Note. Means with different subscripts differ at the *p*=0.05 level by Duncan's new multiple range test.

A one-way ANOVA in Table 6.4 revealed that there was a statistically significant difference in age groups between at least three groups ($F(2,14861) = 3530.73$, $p = <0.001$) at Klinik Kesihatan Bandar Penawar.

Bonferroni test for multiple comparisons indicated that the mean value of the <12 age group (M=4.18, SD=2.48) was significantly different than 13-59 age group (M=15.24, SD=8.90) and >60 age groups (M=3.18, SD=2.28). The age range of 13-59 exhibited outpatient visits for acute respiratory infection compared to <12 and >60 at this sentinel clinic.

Table 6.4: Analyses for the Age Groups of Outpatients Visits for Acute Respiratory Infection at Klinik Kesihatan Bandar Penawar from 2015-2018

Measure	<12	13-59	>60	*F* ratio	*p*	η2
	M ± SD	M ± SD	M ± SD			
Age Groups	4.18b ± 2.48	15.24c ± 8.90	3.18a ± 2.28	3530.72*	<.001	0.32

Note. Means with different subscripts differ at the *p*=0.05 level by Duncan's new multiple range test.

A one-way ANOVA was performed to compare the three different age groups of outpatient visits for ARI at Klinik Kesihatan Bukit Rambai, Klinik Kesihatan Bandar Maharani and Klinik Kesihatan Bandar Penawar. For the three clinics, the outpatient visits for acute respiratory infection vary significantly by age group. The age range of 13-59 exhibited outpatient visits for acute respiratory infection compared to <12 and >60 in this study area. Age and symptoms showed different influences on healthcare-seeking behaviour (Gabrani et al., 2021; Zhang et al., 2020; Lee et al., 2018). According to Zhang et al. (2020), older adults with symptoms such as fever, sore pharynx and headache had a significantly higher consultation rate compared to other age groups. This study's findings are in stark contrast with the prior findings. The 30-day incidence rates for ILI (influenza-like illness) and ARI (acute respiratory disease) were 0.8% and 7.2%, respectively, and 91% and 64% of those affected sought medical attention.

According to a national study of persons with incident severe acute respiratory syndrome coronavirus 2 (SARS-Cov-2) infections (Kojima et al., 2022), those over 65 had a greater likelihood of seeking treatment. According to a study by Barua et al. (2017), 56.1% of the elderly had a positive attitude toward receiving medical care, while others were compelled to self-medicate due to financial constraints. While there are also cases in Tamil Nadu where there was a positive correlation between mothers' awareness of the danger signs of ARI in children and treatment-seeking behaviour despite having the most high-risk districts (p=0.254; p=0.008) (Challa et al., 2016). In contrast, a study conducted in China by Zhong et al. (2021) indicated that self-medication was the primary form of home treatment (36.28% utilised only self-medication; 27.92% combined self-medication with physical cooling measures), while 36.5% accepted advice from medical specialists. In Nigeria, there is a lack of care-seeking for fever in children under five, with 3,632 (12.6%) children under five having a fever in the prior two weeks. Of these, 1142 (31.4%) had been treated at an appropriate health facility for treatment (Baba and Zainab, 2017). Logistic regression analyses were used to evaluate data from 1,408 children under 5 who had experienced ARI symptoms in Indonesia two weeks before the survey from 2012 to 2017. Of these children, about 25% did not obtain medical treatment (Titaley et al., 2020). Other cases reported the proportion of people using a hospital to initiate care was 40% among those aged 18-59 and 28% among those aged >60 ($p<0.01$) (Gabrani et al., 2021). From February 8, 2012, to March 1, 2012, 2,520 homes in the districts of East Jakarta and Bogor participated in a survey. Nearly half (47%) of households reported treating severe respiratory diseases at home, with 24% receiving just home care and 23% purchasing medication from a pharmacy or shop. A similar proportion (47%) sought treatment at a health facility: 37% at a health clinic, 10% at a hospital, and 6% elsewhere, such as with a traditional healer.

There were no disparities in care-seeking based on educational level, either globally or by district (Praptiningsih et al., 2016). They concluded that different age groups might have different treatment preferences. Paternal education, religion, geographic location of residency, age, and female empowerment significantly impacted care-seeking behaviour (Baba and Zainab, 2017). The decision to handle a severe sickness at home, with or without pharmacy medication, or to visit a government or private clinic are some of the reasons for choosing against going to the hospital (Praptiningsih et al., 2016).

6.4 Conclusion

The outpatient visits for acute respiratory infections at the three clinics differ significantly by age group. Compared to the age ranges of 12 and >60 in this study area, outpatient visits for acute respiratory infections were more common in people aged 13 to 59. Age and symptoms showed different influences on healthcare-seeking behaviour. The bias occurs when conclusions about individuals are erroneously derived from findings about the group to which those individuals belong. In the present context, it was anticipated that individuals belonging to the <12 and > 60 age groups would exhibit a higher susceptibility to air pollution. However, the findings of the study contradict this assumption, as it was observed that individuals between the ages of 13 and 59 were more susceptible to the adverse effects of air pollution. The hypothesis rejected and this finding suggests that an association that emerged from an ecological study is prone to the ecological fallacy; a logical error that happens when a group's traits are assigned to an individual.

CHAPTER 7

CONCLUSION

There was no difference in wind direction from 2015 to 2018 for all the study areas. Northeast winds control the overall concentrations of pollutants in all three study areas. The study areas' average wind speeds from 2015 to 2018 are sufficient to aid in the dispersion of air contaminants. Bandar Penawar has the highest wind speed, followed by Muar and Bukit Rambai. In fact, for all three study sites, the northeast wind sectors indicate the highest concentrations of API and PM_{10} than the other pollutants. From the calendar plot, this study showed that local emissions, rather than transboundary pollution, are the primary contributors to the air pollution index observed in the study areas, as the days with high API are limited to seasonal conditions. This study found a positive and significant correlation between API, PM_{10}, SO_2 and 0_3 with outpatient visits in KKBR, PM_{10} and outpatient visits in KKBM, API and PM_{10} with outpatient visits in KKBP. PM_{10} is the primary contributor to API variability and the main source of air pollution measurements. Most of outpatient visits for acute respiratory infections between 2015 and 2018 were among 13-59 years old patients, followed by the young under 12 and elderly over 60. For the three clinics, the outpatient visits for acute respiratory infection vary significantly by age group.

7.1 Strengths and Limitations of the Study

This study was undertaken to tackle a shortage of prior studies explicitly examining the relationship between acute respiratory infections and outpatient visits in the areas of Muar, Johor and Bukit Rambai, Melaka. By carrying out this study, we aim to contribute to the existing body of research on acute respiratory infections and outpatient visits in Malaysia. This study has some limitations. To estimate the impacts of air pollutants, the outpatient visits data for ARI data was retrieved for only three sentinel clinics, KKBR, KKBM, and KKBP. Since different clinics may have different disease constitutions in outpatients, and the number of outpatient visits in three sentinel clinics is relatively small for a whole study area, a possible selection bias could affect the result. However, with the high population mobility in the study areas, the data from three government clinics could at least partially reflect the overall impact of the air pollutants. In the near future, it will be necessary to incorporate additional climatic variables, including temperature, humidity and pressure, into the analysis of pollution movement and dispersion within areas of study. Presently, only the impact of wind has been looked at. The scope of this study was confined to acute respiratory illness, and it is important to include additional health conditions associated with air pollution, such as conjunctivitis (Nam et al., 2022; Lu et al., 2019) and asthma (Madaniyazi and Xerxes, 2021; Cuneo et al., 2019) in future study. Consequently, it does not provide a comprehensive picture of the effects of air pollution on human health in the study areas.

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APPENDIX D

INTELLECTUAL PROPERTIES

INTELLECTUAL PROPERTIES

PROJECT TITLE : The Relationship Between Air Pollution Index and Daily Clinic Visits for Acute Respiratory Infection at the Sentinel Clinics.

2. OWNERSHIP

2.1 The thesis belongs to Jabatan Kesihatan Negeri Melaka and Universiti Putra Malaysia

2.2 Other institutions (if applicable) are allowed to access the thesis. Permission is needed from the main supervisor if the data is to be used for any purposes.

2.3 Should the data is to be reproduced by third party for any purpose, authors of the thesis are required to be cited.

2.4 Data sharing among collaborative institution will be decided accordingly based on mutual consent from each parties.

3.0 PATENT

3.1 Not applicable

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4.0 PUBLICATION POLICY

4.1 Authorship should be decided by the project leader, taking into account of the scientists most involved in designing and executing the research, preferably at the beginning of the study. Author(s) must take full responsibility for the content of the publication and defend its critism. Persons who had input little intellectual content but contributed in other ways need not be included in authorship but acknowledged in the appropriate section of the publication.

4.2 Authors have ethical responsibilities to ensure honest reporting, which implies complete description of how their data is collected and reporting honest relation of their work to others. Authors must follow institutional procedures for approval of their manuscripts (to protect the institution scientific reputation).

4.3 Unpublished data drawn from the other sources should be identified as such and be appropriately credited, with indication that such acknowledgement is with the consent of the person being credited.

4.4 The same manuscript must not be published twice, unless the data is updated and conclusions modified. For example, a paper published in proceedings must not be sent to another journal for publication unless its content has changed substantially.

4.5 The editors and reviewers must treat manuscripts as confidential communication and not divulge their contents without consent of the author(s). Reviewers are responsible not only for unbiased, objective critical analysis of manuscripts but also completing their task within the time allowed.

4.6 The sub-project leader (if applicable) will decide on the authorship (and ranking of authors) of any publications arising from the sub-projects taking into account of the scientists most involved in designing and executing the research.

4.7 All publication must include name of the project leader, and the relevant sub-project leader (if applicable).

4.8 Proceedings of scientific meetings (workshops, conference, symposia, etc) may carry the names of scientific editors and others who may have made substantial contributions to the production of the volume on its cover. It is recommended that the names of the organizing committee members, language editor(s), and translator(s) (if applicable) be placed on the inside of the inner title page.

4.9 The books, reference books, and research report written/edited by individual scientist(s) will carry the names of authors of scientific editors, as applicable, on the

BIODATA OF STUDENT

Noor Aniza binti Ibrahim earned a master's degree in Environmental Health and Safety from Universiti Teknologi MARA in 2018. She is an Assistant Environmental Health Officer at Jabatan Kesihatan Negeri Melaka and a part-time lecturer at Consist College. She holds Train the Trainer (TTT1) and Training Management for Business (TTT2) certifications from the National Institute for Occupational Safety and Health (NIOSH), a Certificate of Exemption for Train the Trainer from the Human Resources Development Fund (HRDF), and a Graduate Technologist Certificate from the Malaysia Board of Technologists (MBOT). She is also an invited examiner for the Bachelor in Environmental Health and Safety (Hons), Faculty of Health Sciences, Universiti Teknologi MARA poster presentation seminar on industrial attachment (2017, 2018, 2019 and 2022). In addition, she is a speaker for the Conference and Dialogue of Environmental Health Officers/ Assistant Environmental Health Officers with Melaka State Health Director and State Health Deputy Melaka (Public Health). During her master's degree, she studied the association between the air pollution index and outpatient visits for acute respiratory infection, which she has continued in this doctoral study.

LIST OF PUBLICATIONS

Noor Aniza Ibrahim, Shamarina Shohaimi, Juliana Jalaludin, M. N. H. M. N. (2025). Air Pollutant Dispersion and Its Health Impacts in Bukit Rambai, Melaka, and Muar, Johor, Malaysia. IX(III), 675–685. https://doi.org/10.47772/IJRISS

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