Air Pollutant Dispersion and Its Health Impacts in Bukit Rambai, Melaka, and Muar, Johor, Malaysia

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Introduction: Unsafe air quality values (>100) were recorded in Bukit Rambai, Melaka, and Muar, Johor, located in southern Peninsular Malaysia, during forest fires in Sumatera and Kalimantan, Indonesia. This study analyzes the dispersion of atmospheric pollutants in these areas over a four-year period (2015–2018). **Materials and Methods:** Descriptive analysis was performed using SPSS. Wind rose, pollutant rose, and calendar plots were generated using R-Programming and the openair package. Secondary data from the Department of Environment's Air Monitoring Stations at SMK Bukit Rambai, Melaka, and Kolej Vokasional Muar, Johor, from 2015 to 2018 were used. **Results and Discussion:** Wind Direction and Speed: The predominant wind direction in both areas were from the northeast. Bukit Rambai recorded 60% of wind from North-Northeast (NNE) and East-Northeast (ENE) in 2015, with a slight variation over the years. Muar also showed a similar trend with 59% from NNE and ENE in 2018. Wind speed in Muar was higher than Bukit Rambai, with average speeds of 5.6 m/s (SD = 3.074) in 2015, decreasing to 1.2 m/s (SD = 0.688) in 2018. Bukit Rambai showed a decrease in wind speed from 5.3 m/s (SD = 2.66) in 2015 to 1.7 m/s (SD = 1.11) by 2018. Pollutant Concentrations: Higher concentrations of API and PM_{10} were observed with northeast winds. The average API levels at Bukit Rambai were 48.41 (SD = 17.89) and 38.34 (SD = 18.07) at Muar. PM_{10} levels were also higher at Bukit Rambai (45.41 µg/m³, SD = 29.79) compared to Muar (39.42 µg/m³, SD = 26.08). CO levels were higher in Muar (0.76 µg/m³, SD = 0.40) than in Bukit Rambai (0.64 µg/m³, SD = 0.31), while SO_2 and NO_2 levels were low in both areas. API and Outpatient Visits: Unhealthy API days (>100) occurred mainly between September and October 2015. Bukit Rambai had 37 days of unhealthy API levels, while Muar had 19 days. These high pollution days were linked to increased outpatient visits for respiratory issues. **Conclusion:** The study highlights that local emissions are the primary source of pollution, but seasonal factors contribute to higher API levels and respiratory issues. The northeast wind plays a significant role in dispersing pollutants, affecting air quality in both regions.

Keywords: Air Pollution; Air Pollution Index; Pollutants; Wind Rose; Pollutant Rose; Calendar Plot

INTRODUCTION

People generally breathe in air that has been contaminated by local or regional sources. However, depending on atmospheric conditions, air pollution can travel farther and, in some cases, cross international borders (Asian Development Bank, 2022). Transboundary pollution is another source of pollution that has caused haze in Southeast Asia (SEA), particularly Malaysia, nearly every year for the past 30 years (Quah et al., 2021; Khan et al., 2020). During the Sumatera and Kalimantan forests fires in Indonesia, dangerous readings (>100) were recorded in Bukit Rambai, Melaka, and Muar, Johor, in southern Peninsular Malaysia (Sentian et al., 2019). Bukit Rambai was classified as industrial in a previous study because it is located in a heavily industrialized area (Wan Azmi et al., 2024). Meanwhile, Muar, located in northwest Johor, where there are few industries, had the highest recorded API of 663, which is an emergency level (Addiena A Rahim et al., 2023). The objective of this study is to assess the air quality and provide a more comprehensive understanding of the prevailing conditions However, a clear research gap exists in understanding the broader implications of transboundary pollution and

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local emissions, particularly in rural areas. There is a need for more comprehensive long-term studies across different geographical regions in Malaysia to evaluate the cumulative health impacts of air pollution and the role of seasonal changes in influencing pollutant concentrations. Further research should also focus on the effectiveness of cross-border collaboration, especially with neighboring countries like Indonesia, to address transboundary pollution and its associated health risks. This gap in research presents an opportunity for future studies to deepen our understanding of air quality trends and their direct effects on public health.

METHODS

Air Quality

This study was conducted from 2015 to 2018. Secondary data on Malaysian air quality were obtained from the Department of Environment (DOE), including hourly concentrations of the air pollution index (API) and major pollutants: particulate matter (PM_{10}), ozone (O_3), nitrogen dioxide (NO2), sulfur dioxide (SO2), and carbon monoxide (CO) (NEHAP, 2020). This study did not include $PM_{2.5}$ because it was only monitored starting in August 2018. Bukit Rambai in Melaka and Muar in Johor are coastal towns located on the Straits of Malacca. The air monitoring stations for this study were Kolej Vokasional Muar, Johor (KVM) and SMK Bukit Rambai, Melaka. The monitoring station closed on March 13, 2018, limiting access to the KVM air quality index. Due to changes in the concessionaire firm, data from April to June 2017 were missing from the monitoring stations. Table 1 presents the locations of the monitoring stations.

Table 1 Locations of The Monitoring Stations

Site State	Location	Latitude	Longitude
Johor	Kolej Vokasional Muar	2.0603° N	102.5952° E
Melaka	SMK Bukit Rambai	2.2587° N	102.1729° E

Descriptive analysis by Statistical Packages for the Social Sciences (SPSS 26)

The wind analysis N value represents the number of hours of wind speed data. Another descriptive analysis examines the study area's mean (M) wind speed and standard deviation (SD). The descriptive analysis for pollutants focuses on the mean (M) and standard deviation (SD) of each pollutant in the study areas (Tian et al., 2020).

Wind rose

Color-coded wind roses illustrate the fundamental wind direction and speed. Each spoke around the circle corresponds to the frequency of wind from a specific direction (Poddaeva & Fedosova, 2022; Sundari et al., 2020; Carslaw, 2019). Wind speed characteristics can be analyzed over various time periods, including monthly, annual, seasonal, and decadal intervals, 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 & Fedosova, 2022). Detailed meteorological data on wind speed and direction, including yearly, monthly, daily, and hourly data from monitoring stations, were used.

Pollution rose

Pollution roses show air quality by wind direction and the distribution and strength of emission sources (Zhou et al., 2019). Data on all pollutants, wind speed, wind direction, and meteorological factors (year, month, day, and hourly data) were used. The air pollutant index and the New Malaysia Air Quality Standard's 24-hour limit determined the API and other pollutant breaks. Different pollutants may have different breaks and labels, as concentration readings can vary (Y. Zhang et al., 2021). The new Malaysia Air Quality Standard by the Department of Environment, Malaysia, is presented in Table 2.

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Table 2 New Malaysia Air Quality Standard

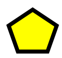
Pollutant	Averaging Time	Ambient Air Quality Standard		
		IT-1 (2015)	IT-2 (2018)	Standard (2020)
		µg/m^3	µg/m^3	µg/m^3
Particulate matter with the size less than 10 micron (PM_{10})	1 year	50	45	40
	24 hours	150	120	100
Particulate matter with the size less than 2.5 micron ($PM_{2.5}$)	1 year	35	25	15
	24 hours	75	50	35
Sulfur Dioxide (SO_2)	1 year	350	300	250
	24 hours	105	90	80
Nitrogen Dioxide (NO_2)	1 year	320	300	280
	24 hours	75	75	70
Ground Level Ozone	1 year	200	200	180
	24 hours	120	120	100
Carbon Monoxide (CO)	1 year	35	35	30
	24 hours	10	10	10

Source: Department of Environment, Malaysia

Calendar plot

The time series values were plotted in a conventional calendar format. This function plots one year of data by month, laid out in a conventional calendar format. Using daily API data, a 12-month calendar for the 2015 to 2018 (4-year) study period was generated to depict the API reading patterns of the study areas and determine the state of the API index in these areas. Each day is colored according to the API of the day. The color range is set using the API values: 0-50 (healthy), 51-100 (moderate), 101-200 (unhealthy), 201-300 (very unhealthy), and over 300 (hazardous). Detailed meteorological data on daily API readings from the monitoring stations were used. The maximum API break value was set to 1000 for all study areas. Table 3 shows the air pollutant index categories by the Department of Environment, Malaysia.

Table 3 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		

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201 to 300	Very Unhealthy		■
>300	Hazardous		▲

(Source: Department of Environment, 2019)

The method described above for statistical validation of pollutant dispersion and health effects has been widely used and validated in environmental health research. Studies such as Liu et al. (2020), Fu et al. (2020), and Meng et al. (2020) have shown that regression models, time series analysis, and spatial analysis are effective tools for analyzing the relationship between air quality and health outcomes. These methods have been rigorously tested in various geographical contexts and have demonstrated the capacity to model complex relationships between environmental factors and public health.

Moreover, the use of R programming for this type of analysis is well-established in the literature due to its powerful data manipulation capabilities and extensive statistical tools. The reproducibility and transparency provided by R also ensure that results can be validated and tested across different study areas, as demonstrated in the work of Al-Harbi et al. (2020) and Coccia (2021).

RESULTS

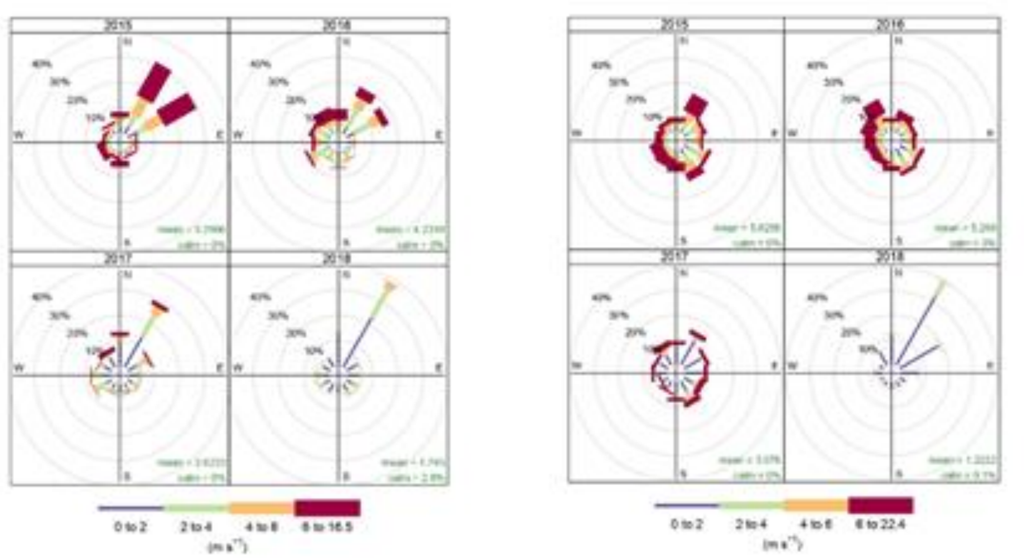

Figure 1 The Wind Rose of SMKBR (A) and KVM (B) Air Monitoring Stations by Year of 2015-2018

Note. Frequency of counts by wind direction (%)

The wind rose diagram (Figure 1) illustrates the frequency of wind direction and speed at the SMKBR and KVM Air Monitoring Stations. To highlight the trends and variations in wind speed and direction over the years, the wind rose for Bukit Rambai from 2015 to 2018 is broken down by year. The diagram for SMKBR shows that the predominant wind direction at Bukit Rambai during this period came from the northeast. The four plots indicate no significant change in wind direction from 2015 to 2018. Specifically, at Bukit Rambai, the two spokes representing North-Northeast (NNE) and East-Northeast (ENE) accounted for 60% of all hourly wind directions in 2015, 35% in 2016, 37% in 2017, and 43% in 2018. The wind rarely came from the southwest.

For Muar, the wind primarily blew from the northeast during the study period, except in 2015, when the predominant wind came from the northwest. The four plots reveal variations in wind direction over the years. In Muar, the NNE and ENE directions accounted for 24% of all hourly wind directions in 2015, 35% in 2016, 37% in 2017, and 59% in 2018. In 2016, the two spokes representing West-Northwest (WNW) and Northwest (NW) made up 24% of all hourly wind directions. The wind rarely came from the northwest in 2015 or from the southwest in 2016, 2017, and 2018.

Table 4 Descriptive Analysis for The Wind Speed (m/s) at SMKBR and KVM monitoring station for 2015-2018

Year	***N***		***Min***		***Max***		***M***	
	SMKBR	**KVM**	**SMKBR**	**KVM**	**SMKBR**	**KVM**	**SMKBR**	**KVM**
2015	4782	8746	0.7	1.0	16.5	16.9	5.3 ± 2.66	5.6 ± 3.07
2016	8688	8767	1.4	1.0	13.5	16.9	4.2 ± 2.26	5.3 ± 3.08
2017	6475	6562	0.0	0.0	11.0	22.4	2.6 ± 2.07	3.1 ± 3.44
2018	8759	1685	0.0	0.0	8.7	4.8	1.7 ± 1.11	1.2 ± 0.67

A descriptive analysis was performed (Table 4). The results show that the average wind 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 (SD = 1.11), respectively. The average wind speed in Bukit Rambai was highest in 2015, gradually decreasing in 2016, 2017, and 2018. This area demonstrated a downward trend in wind speed. However, the incomplete data for April to June 2017 may affect the accuracy of this analysis.

For Muar, the average wind speed 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 (SD = 0.688), respectively. The average wind speed in Muar was highest in 2017 compared to 2015, 2016, and 2018.
The lack of complete data for the API and other pollutants from April to June 2017, as well as the closure of the KVM monitoring station after March 12, 2018, may also impact the results of this analysis.

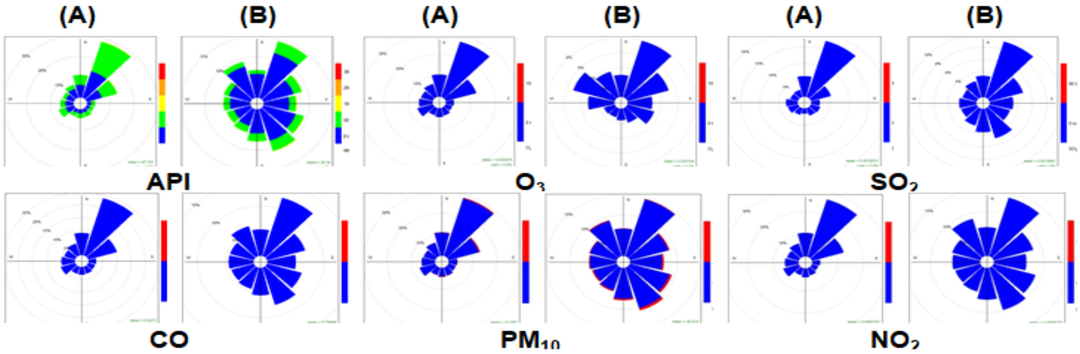

Figure 2 The Pollutant Rose of API, O_3, SO_2, CO, PM_{10} and NO_2 at (A) SMKBR and (B) KVM Air Monitoring Stations from 2015-2018

The pollution rose plots shown in Figure 2 further support the analysis by illustrating the concentrations of API, O_3, CO, NO_2, PM_{10}, and SO_2 by wind direction in Bukit Rambai and Muar. The figures display pollution roses for all major pollutants monitored by the DOE, except for $PM_{2.5}$, from 2015 to 2018. The pollutant rose analysis suggests that the visual examination of the plots indicates that northeast winds play a dominant role in influencing the overall pollutant concentrations in both study areas. Specifically, in both areas, the northeast wind sectors are associated with the highest concentrations of API and PM_{10} compared to the other pollutants.

Table 5 Mean and Standard Deviations of Pollutants for Bukit Rambai and Muar Air Monitoring Stations for 2015-2018

Pollutants	**Bukit Rambai**	**Muar**
API	48.91 ± 17.89	38.34 ± 18.07

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PM_{10}	45.41 ± 29.79	39.42 ± 26.08
O_3	0.02 ± 0.02	0.02 ± 0.01
CO	0.64 ± 0.31	0.76 ± 0.40
SO_2	0.00 ± 0.002	0.00 ± 0.001
NO_2	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

A descriptive analysis was performed on selected pollutants: API, PM_{10}, O_3, CO, SO_2, and NO_2, with the results presented in Table 5. The average API levels at Bukit Rambai and Muar from 2015 to 2018 were 48.41 (SD = 17.89) and 38.34 (SD = 18.07), respectively. The average PM_{10} levels at Bukit Rambai and Muar were 45.41 (SD = 29.79) and 39.42 (SD = 26.08). The average O_3 levels at Bukit Rambai and Muar were 0.02 (SD = 0.02) and 0.02 (SD = 0.01), respectively. The average CO levels at Bukit Rambai and Muar were 0.64 (SD = 0.31) and 0.76 (SD = 0.40). The average SO_2 levels at Bukit Rambai and Muar were 0.00 (SD = 0.002) and 0.00 (SD = 0.001). The NO_2 levels in Bukit Rambai and Muar were 0.01 (SD = 0.01) and 0.01 (SD = 0.01), respectively. The incomplete data from April to June 2017 may affect the accuracy of this analysis, and the KVM data were only available until March 12, 2018, as the monitoring station is no longer operational.

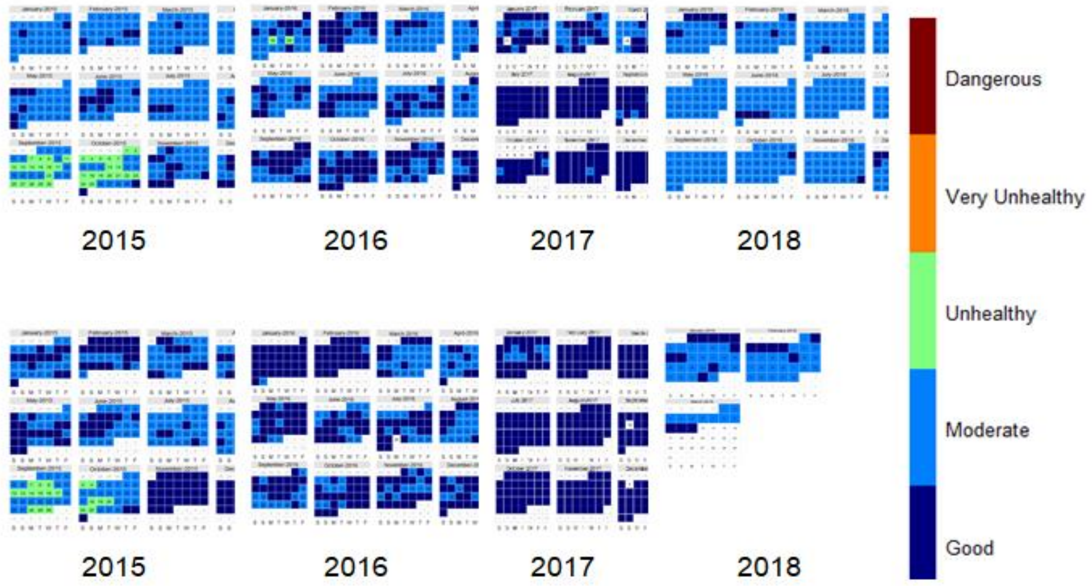

Figure 3 Calendar plot for SMKBR Monitoring Station from 2015-2018

A calendar plot for the period from 2015 to 2018 was generated for both study areas and is presented in Figure 3. The profiling reveals that days with an API level greater than 100 (unhealthy) were concentrated in Bukit Rambai during the following periods: September 7–9, 2015; September 11–17, 2015; September 23, 2015; September 26–October 7, 2015; October 13–14, 2015; October 17–25, 2015; and December 10, 2015. Additionally, January 18 and 20, 2016, had two days with an unhealthy API level. In total, Bukit Rambai experienced 37 days with an unhealthy API level between 2015 and 2018.

Similarly, the profiling indicates that days with an API level greater than 100 (unhealthy) were concentrated in Muar during the following periods: September 7–9, 2015; September 12–17, 2015; September 28–30, 2015; October 3–4, 2015; October 18–20, 2015; and October 23–25, 2015. Muar had a total of 19 days with an unhealthy API level from 2015 to 2018.

DISCUSSION

Except for Muar in 2015, the wind rose analysis indicates that winds predominantly came from the northeast in both study areas. It was observed that wind patterns vary by area and season and do not follow a consistent direction. Malaysia is known for having lower wind speeds compared to countries like Denmark and the Netherlands, with average wind speeds typically below 3 m/s, limiting its potential for generating stable wind energy. However, the highest wind speeds recorded range between 6 and 12 m/s (Noman et al., 2020). The average wind speeds in the studied areas from 2015 to 2018 were sufficient to assist in the dispersion of air pollutants. High wind speeds help disperse air pollutants, and areas with higher wind speeds tend to have fewer health issues (Yang et al., 2020). In contrast, minimal air movement can cause the accumulation and spread of virus particles, leading to public health concerns regarding viral infections (Coccia, 2021).

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.

It is anticipated that outpatient visits will provide a more responsive indicator for evaluating the acute or short-term health effects associated with exposure to air pollution, as compared to hospital admissions (Guo et al., 2021).

The Ministry of Health continuously monitors illnesses related to haze, such as asthma, conjunctivitis, and acute respiratory infections. Both study areas showed a downward trend in wind speed, which would typically lead to increased outpatient visits due to polluted air. However, only Muar showed a consistent increase in outpatient visits, while Bukit Rambai's acute respiratory infection cases remained steady. The combined effects of anthropogenic sources and meteorological factors contribute to variations in air pollution concentrations (Ma et al., 2022). Coccia suggests that high concentrations of air pollutants, combined with low wind speeds, can increase the duration that virus particles remain in the air, leading to prolonged exposure in urban areas (Coccia, 2021). Even when wind speeds are steady, the presence of concentrated air pollutants can reduce the ability of strong winds to disperse them, resulting in decreased atmospheric visibility. It is important to note that densely populated areas with higher wind speeds tend to experience fewer health issues, as higher wind speeds facilitate the dispersion of airborne pollutants (X. Zhang et al., 2023). During periods of weak wind, urban heat islands and pollution heat islands can form, leading to increased energy consumption and negatively impacting urban quality of life, including human health, comfort, rainfall patterns, and overall urban sustainability (Abbassi et al., 2022; Xu et al., 2018).

Wind speed was found to be negatively correlated with NO, NO_2, and SO_2, indicating that wind dilution helps reduce the concentrations of these pollutants (Al-Harbi et al., 2020). During PM pollution events, wind speeds typically decrease. Linda et al. (2022) found that the average wind speed required to resuspend PM_{10} particles at a height of 2 meters is 1.58 m/s. Despite the average wind speed in this study being less than 10.29 m/s, the API values remained within the normal and moderate ranges in both study areas. The average wind speed for Bukit Rambai was 3.3 m/s (SD = 2.413), and for Muar, it was 4.6 m/s (SD = 3.367) from 2015 to 2018. However, other atmospheric factors, such as temperature, the planetary boundary layer, pressure, and relative humidity, which were not considered in this study, may have influenced the results (Luo et al., 2021; Meng et al., 2020). Differences in atmospheric conditions between China and Malaysia could also explain variations in the results, as noted in studies by Qi and Liu, which concluded that different meteorological conditions have distinct effects on pollutant concentrations (Qi et al., 2021; Liu et al., 2020). The wind direction in Muar showed more variation from 2015 to 2018. Rajagopalan (2014) found that rapid, unplanned development in Muar could alter the microclimate of this tropical city, disrupting wind flow and air temperature, which worsens urban thermal conditions.

In both study areas, the highest concentrations of API and PM_{10} were found in the northeast wind sectors. While API is not significantly influenced by residential areas, the analysis suggests that residential areas do have an effect on API levels. From 2011 to 2013, Bukit Rambai was a hotspot for pollution due to its high exceedance rate. Bukit Rambai recorded the highest daily maximum API concentration in the Southern Peninsular Region, 397, and a moderate mean API value of 53 from 2010 to 2016. This pollution may be attributed to emissions from Bukit Rambai's furniture and wood industries (Payus et al., 2022), which can have short- and long-term health impacts. In contrast, Muar, which has fewer industries, recorded API levels within the normal to moderate range between 2000 and 2009 but was affected by seasonal biomass burning in Sumatera, Indonesia. The mean API levels recorded at Muar's suburban station were higher than those in the industrial area of Pasir Gudang and the residential area of Johor Bahru. PM_{10} and O_3 were the primary factors influencing variations in the API (Rahman et al., 2016). According to Fu et al. (2020), wind speed and precipitation influence the distribution of air pollution, supporting the idea that meteorological conditions, geographical location, and season play a role in determining pollutant dispersion. Different pollutants have different lifespans, with O_3 and PM_{10} lasting from hours to weeks and CO remaining in the air for years, which may explain the impact of pollution even in residential areas. PM_{10} levels in the study areas often exceeded Malaysia's National Ambient Air Quality Standards (MAAQS) due to seasonal changes brought on by the monsoon seasons. During the southwest monsoon, tropical plant burning increases PM_{10} levels (Mohtar et al., 2022). However, the pollution rose analysis cannot pinpoint the exact location of the upwind pollution sources. The calendar plot of the air pollutant index for the study areas shows that residents typically experience normal (0-50) and moderate (51-100) API levels over the years. The 2015 haze from large-scale land and forest fires in Sumatra and Kalimantan, Indonesia, caused widespread poor air quality, raising API levels in both study areas. During August and September, Malaysia experienced haze (Sentian et al., 2019). No days with very unhealthy or hazardous API levels were recorded in either study area between 2015 and 2018. The profiling shown in Figure 3 indicates that Bukit Rambai was more prone to air pollution, as the number of days with an unhealthy API level was higher than in Muar. The calendar plot map suggests that local emissions, rather than transboundary pollution, were the primary drivers of air pollution, as the high API days were seasonal.

CONCLUSION

Numerous anthropogenic and natural variables in various ambient conditions and geographic locations of the study areas resulted in varying pollutant levels. The control should commence from the local source. 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. 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.

Malaysia should strengthen collaboration with neighboring countries, such as Indonesia and Thailand, to effectively manage and mitigate transboundary air pollution, particularly from forest fires. Establishing a more comprehensive regional framework would promote shared responsibility and coordinated efforts in addressing cross-border air pollution. Additionally, Malaysia could collaborate with these nations to enforce more stringent fire prevention policies, including the monitoring and regulation of agricultural practices, such as the prohibition of open burning.

The study emphasizes the need for targeted air quality management strategies, with a focus on mitigating seasonal pollution spikes and reducing local emissions.

Due to their ability to penetrate deep into the lungs and even reach the bloodstream, it is crucial to consider $PM_{2.5}$ particles in future studies. These tiny particles can be inhaled and cause serious health problems. The results are anticipated to enhance the air quality in the studied areas and stimulate further investigation in other areas facing the same issue.

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Ethical Declaration

This research does not involve using animals or personal information from human participants.

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Consent to Publish

The Authors hereby consents to publication in this journal.

Authors' contribution

Noor Aniza Ibrahim, Shamarina Shohaimi, Juliana Jalaludin and Mohd Noor Hisham Mohd Nadzir contributed to the study conception and design; material preparation and data collection were performed by Noor Aniza Ibrahim; data analysis was conducted by Noor Aniza Ibrahim supervised by Shamarina Shohaimi, Juliana Jalaludin and Mohd Noor Hisham Mohd Nadzir. The first draft of the manuscript was written by Noor Aniza binti Ibrahim. Shamarina Shohaimi, Juliana Jalaludin and Mohd Noor Hisham Mohd Nadzir commented on the manuscript. All authors read and approved the final manuscript.

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