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Meteorological Impact on Air Pollutants in Malaysia: A Causal Analysis

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KEYWORDS

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ABSTRACT

This study explores the intricate relationships between air pollutants and meteorological parameters across five key locations in Malaysia—Seberang Perai, Shah Alam, Nilai, Larkin, and Pasir Gudang—over the period from 2017 to 2021. Utilizing trend analysis and Granger causality testing, the research found that in Seberang Perai, PM10 is Granger-caused by NO_2 ($p = 0.006$) and CO ($p = 0.004$), indicating a strong causal relationship with 99% and 95% confidence levels, respectively. Temperature significantly influenced ozone levels ($p = 0.047$) with a 95% confidence level, and wind speed showed moderate effects on NO_2 ($p = 0.086$) with a 90% confidence level. In Shah Alam, relative humidity significantly Granger-caused NO_2 ($p = 0.033$) with a 95% confidence level. Urban environments demonstrate multifaceted dynamics involving multiple pollutants and meteorological factors. These insights are critical for air quality management and urban planning in Malaysia, offering a foundation for more targeted and effective strategies to mitigate air pollution. This research contributes to the broader objective of enhancing environmental quality in rapidly developing regions, aligning with global sustainability goals.

1. INTRODUCTION

The contemporary era grapples with a formidable challenge as the changing atmospheric conditions, driven by escalating air pollution, demand urgent attention. Key contributors to this issue include the rapid pace of urbanization, the influence of the industrial revolution, vehicular emissions, human activities, and population growth [1]. A study by Sentian [2] ranked Malaysia as third place in Southeast Asia for pollutant emissions, after Indonesia and Thailand. The expansion of the Malaysian economy has led to pollution in a variety of areas. Air pollution from industrial activity and automobiles, for instance, is currently on the rise. The concentrations of pollution in the atmosphere fluctuate due to weather conditions, pollutant sources, and topography. Nevertheless, meteorological conditions have the greatest influence on fluctuations in ambient air pollution concentrations among these three factors [3].

The phenomena associated with climate change are those that are either directly traceable to natural processes or indirectly attributable to anthropogenic compositional changes. A substantial relationship between climate change and air quality was established. Due to this occurrence, pollutants were prone to be more concentrated in the stratosphere, the lowest layer of the atmosphere, which eventually worsens the level of air quality [4]. Hence, it is necessary to determine the cause-and-effect of PM10 that may contribute to a decline in air quality. In order to overcome these challenges, a study via statistical approach which selected significant parameters as its fundamental element of research was conducted to develop the air pollution model. If the strength of correlation is higher and the causality is significant, the Granger causality will provide some significant information related to cause-and-effect relationship between air pollutants and meteorological parameters [5].

However, with Granger causality, the idea is when the past and present parameters provide significant information to forecast the future, which is commonly used in time series analysis [6]. This study aims to determine cause-and-effect of PM10 using Granger Causality Test. Additionally, the research objectives include identifying types of causal relationships and enhance the understanding of air quality dynamics in Malaysia. This study aligns with environmental initiatives outlined in the Sustainable Malaysia 2030 agenda and contributes to broader goals of environmental sustainability in the country [7], [8].

Granger causality technique was often applied to a series data set to determine the interrelationship between variables which spans up to 150 years [9]. It's important to note that Granger causality does not imply true causation, and the observed relationships may be influenced by other factors. Additionally, the results

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should be interpreted cautiously, considering the assumptions and limitations of the Granger causality test. In this context, the theoretical foundation of Granger causality is grounded in the concept of temporal precedence and the ability of past values of one variable to enhance the prediction of another variable's future values [10]. The approach has found applications not only in economics but also in various fields, including environmental studies, neuroscience, and social sciences.

However, the application of Granger causality in predictive modelling is not without its challenges. One significant challenge is the potential for spurious correlations, where variables may appear to be causally linked due to shared influences or external factors [11]. Careful consideration and rigorous statistical testing are required to mitigate this risk and ensure the validity of the causal relationships identified. Another challenge lies in the assumption of linearity inherent in Granger causality testing, which may limit its applicability in cases where relationships between variables are nonlinear or involve complex interactions [12]. Moreover, Granger causality does not establish the direction of causality definitively and may only reflect statistical associations, necessitating a cautious interpretation of results.

Moreover, a study by Chen [13] further discussed, the application of Granger causality extends beyond predictive modelling to inform policy planning and intervention strategies in air quality management. In this context, understanding the causal relationships between meteorological conditions and air pollution is pivotal for designing targeted measures that address specific contributing factors. Policymakers can use this information to formulate evidence-based strategies aimed at mitigating the impact of certain meteorological conditions on air quality. Additionally, Granger causality facilitates source identification, particularly in urban environments where distinguishing between natural and anthropogenic influences on air quality is challenging [10], [14]. This capability is crucial for effective pollution control measures, aiding in the development of policies that target specific sources of pollution and contribute to sustainable environmental management.

The objective of this study is to determine the cause-and-effect of air pollutants which is PM10 using the Granger causality tests. The data was obtained from the Department of Environment (DOE) and analysed using IBM SPSS Statistical Software Version 29 for descriptive statistics. The descriptive analysis of the air pollutants concentrations, which are PM10, SO2, NO2, O3, and CO, and the meteorological parameters, which are temperature, humidity, and wind speed, was performed at five selected locations of the air monitoring stations in Malaysia between 2017 and 2021.

This research makes a significant contribution to the field of environmental science and air quality management by conducting a comprehensive analysis of air pollution trends in Malaysia over a five-year period. It offers valuable insights into the region's air quality dynamics. Utilizing Granger causality analysis, the study goes beyond simple correlations to uncover the complex cause-and-effect relationships between air pollutants and weather conditions. This research aligns with the United Nations' Sustainable Development Goal 11, which aims to minimize the environmental impact of cities by improving air quality [15], [16]. The findings provide a robust basis for developing evidence-based policies and health interventions, enhancing the accuracy of air quality forecasts, and enabling prompt actions to safeguard public health and improve environmental quality in Malaysia [17].

2. EXPERIMENTAL PROCEDURE

2.1 Materials

This study adopts a data-driven approach to examine the relationships between air pollutants and weather conditions in Malaysia from 2017 to 2021, structured into three key phases. The first phase involves collecting and preprocessing data from five selected areas that represent the northern, central, and southern regions of the country. The second phase focuses on analyzing the temporal trends and stationarity of the data. In the third phase, Granger causality tests are employed to explore the cause-and-effect dynamics between pollutants and meteorological factors.

2.2 Methods

The research begins with a descriptive analysis and trend analysis of air pollutant concentrations and meteorological parameters, where box plots and time series graphs were created to visualize the data. Following this, the study moves to the second phase, where Granger causality analysis is used to identify the relationships between air pollutants and meteorological parameters [18]. The causal relationships uncovered are then presented through graphical visualizations, providing a clear depiction of how meteorological factors influence air pollution levels across different regions of Malaysia.

2.3 Site Description

This research focuses on five strategically chosen monitoring stations in Malaysia—Perai, Shah Alam, Nilai, Larkin, and Pasir Gudang as shown in Figure 1. The research area covered the northern, central and southern region. The details and coordinates of the stations are summarized in Table 1.

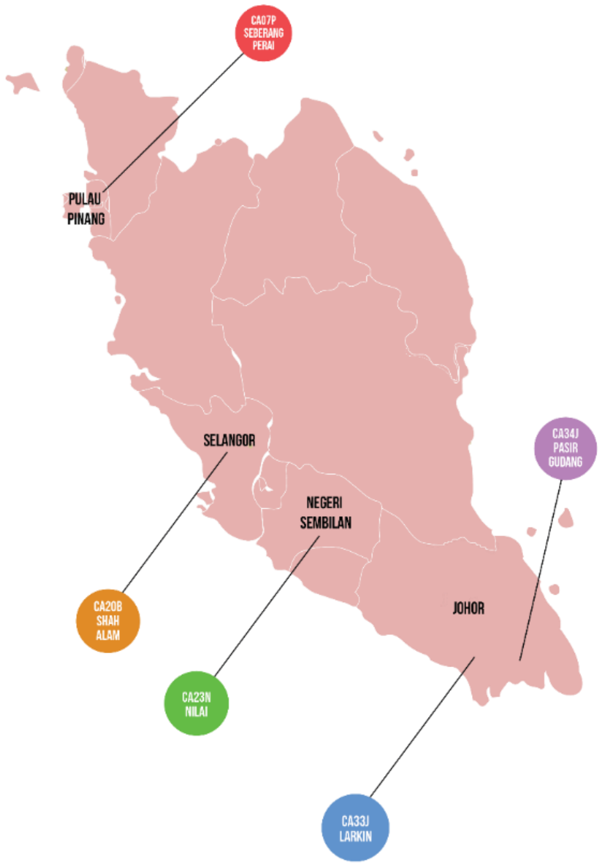


Figure 1. Location of research area.

Table 1 Latitude and Longitude for five monitoring station's location

Station ID	State	Location	Coordinate
CA07P	Seberang Perai, Pulang Pinang	Sek. Keb. Cenderawasih, Taman Inderawasih, Perai	N05° 23.470' E100° 23.213'
CA20B	Shah Alam, Selangor	Sek. Keb. Taman Tun Dr. Ismail Jaya, Shah Alam	N03° 06.287' E101° 33.368'
CA23N	Nilai, Negeri Sembilan	Taman Semarak (Phase II), Nilai	N02° 49.246' E101° 48.877'
CA33J	Larkin, Johor	Teacher Education Temenggong Ibrahim Campus, Larkin, Johor Bahru	N01° 29.815' E103° 43.617'
CA34J	Pasir Gudang, Johor	Sek. Men. Keb. Pasir Gudang 2, Pasir Gudang, Johor Bahru	N01° 28.225' E103° 53.637'

2.4 Data Collection and Preliminary Data Processing

The study utilized secondary data from the Department of Environment Malaysia, covering the period from 2017 to 2021. Data was collected from five air quality monitoring stations, representing urban, suburban, and industrial areas, to analyze five key air pollutants: PM10, SO2, NO2, O3, and CO. Additionally, three meteorological parameters – wind speed, temperature, and relative humidity – were included in the analysis.

To achieve the study's objectives, monthly data on these air pollutants and meteorological factors was gathered and analyzed. Descriptive analysis was conducted using SPSS software, which computed essential statistical metrics such as minimum, maximum, mean, standard deviation, skewness, and kurtosis for each parameter at each station [18]. This provided a comprehensive understanding of the data's characteristics and potential trends, laying the groundwork for further analysis.

2.5 Time Series & Descriptive Analysis

Following data collection, the acquired datasets underwent both descriptive and time series analyses to comprehensively understand their characteristics and temporal dynamics. Descriptive analysis, facilitated by SPSS software, provided key statistical metrics such as minimum and maximum values, mean, standard deviation, skewness, and kurtosis, offering an in-depth understanding of the data from each monitoring station [12]. Subsequently, time series analysis was conducted to examine the stationarity of the data using the Augmented Dickey-Fuller (ADF) test in EViews software.

$$y_t = c + \beta_t + \alpha Y_{t-1} + \emptyset \Delta Y_{t-1} + \emptyset_2 \Delta Y_{t-2} .. + \emptyset_p \Delta Y_{t-p} \quad \text{(Eq 1)}$$

The ADF test, applied to the level form of each series including trend and intercept, was crucial in identifying non-stationarity when p-values exceeded 0.05. In such cases, data differencing was performed to achieve stationarity, ensuring the reliability of further temporal analysis [19]. Together, these analytical steps provided a robust foundation for understanding the data and preparing it for advanced modelling.

2.6 Granger Causality Analysis

The analysis is grounded in the theoretical framework of autoregressive models, which explore how a variable's current value is influenced by its past values. In the context of Granger causality, these models are used to determine whether the past values of one variable (X) significantly improve the prediction of another variable (Y), beyond what Y's own history can predict. While Granger causality doesn't imply true causation, it serves as a powerful statistical tool for identifying predictive relationships in time series data [10], [20]. The test involves comparing models that include and exclude the past values of X to evaluate whether adding X enhances the prediction of Y. This approach is crucial in time series analysis, where understanding the temporal relationships and directional influences between variables is essential for accurate forecasting [9].

$$y_i = \alpha_0 + \sum_{j=1}^{m} \alpha_j y_{i-j} + \sum_{j=1}^{m} \beta_j x_{i-j} + \varepsilon_i \quad \text{(Eq 2)}$$

In the final phase of the study, Granger causality tests were applied to examine the causal relationships between air pollutants and meteorological parameters. Before conducting these tests, the optimal lag length for the analysis was determined using the Akaike Information Criterion (AIC) in EViews software, ensuring a balance between model complexity and goodness of fit. With the selected lag order, an unrestricted Vector Autoregression (VAR) model was estimated. The Granger causality tests were then used to assess whether the past values of one variable provided predictive information about another. A p-value of 0.05 or lower led to the rejection of the null hypothesis of no Granger causality, indicating a significant causal relationship [12]. The results were visualized to illustrate the direction and strength of these causal connections across different monitoring stations.

3. RESULTS AND DISCUSSION

3.1 Descriptive Analysis

A comprehensive analysis of air pollutants and meteorological parameters across five key Malaysian locations—Seberang Perai, Shah Alam, Nilai, Larkin, and Pasir Gudang—reveals distinct patterns and variations that underscore the complex interplay between urbanization, industrial activity, and environmental conditions. Urban areas, particularly Shah Alam and Larkin, consistently exhibit higher mean concentrations of air pollutants such as PM_{10}, SO_2, NO_2, and O_3, reflecting the significant air quality challenges posed by heavy traffic and industrial emissions. In contrast, Pasir Gudang and Larkin recorded some of the lowest minimum concentrations for pollutants like PM_{10} and SO_2, suggesting variability in exposure to pollution sources even within urban and industrial settings. Notably, Larkin also experiences the highest ambient temperatures, indicative of the urban heat island effect, while Pasir Gudang demonstrates better air quality overall, potentially due to effective local environmental management [21].

Table 2 The descriptive analysis of the concentrations from 2017 to 2021

Station	Seberang Perai	Shah Alam	Nilai	Larkin	Pasir Gudang
PM_{10}					
N	54	54	54	54	54
Minimum, µg/m^3	16.185	**20.991**	20.905	17.579	15.502
Maximum, µg/m^3	43.696	89.365	**102.887**	72.508	63.236
Mean, µg/m^3	25.387	32.667	**34.234**	28.194	26.039
Standard Deviation, µg/m^3	6.758	10.138	**12.615**	8.336	8.497
Coefficient of variation	0.266	0.310	**0.368**	0.296	0.326
Skewness	1.153	3.570	**3.379**	3.005	1.787
Kurtosis	1.089	**18.262**	16.227	14.350	5.600

SO_2					
N	54	54	54	54	54
Minimum, ppm	0.001	0.001	0.001	0.001	0.001
Maximum, ppm	0.002	0.002	0.004	0.003	**0.010**
Mean, ppm	0.001	0.001	0.001	**0.002**	**0.002**
Standard Deviation, ppm	0.0003	0.0002	0.0005	0.0005	**0.0013**
Coefficient of variation	0.3	0.2	0.5	0.25	**0.65**
Skewness	0.473	0.187	4.234	0.063	**4.269**
Kurtosis	-0.757	0.746	23.370	0.223	**23.504**
NO_2					
N	54	54	54	54	54
Minimum, ppm	0.005	**0.007**	0.006	0.004	0.004
Maximum, ppm	0.015	**0.022**	0.018	0.018	0.018
Mean, ppm	0.009	**0.016**	0.013	0.012	0.011
Standard Deviation, ppm	0.002	0.003	0.003	0.003	**0.004**
Coefficient of variation	0.22	0.19	0.23	0.25	**0.36**
Skewness	**0.483**	-0.408	0.040	0.036	-0.495
Kurtosis	**1.314**	0.290	-0.845	-0.788	-0.863
O_3					
N	54	54	54	54	54
Minimum, ppm	0.004	**0.014**	0.005	0.009	0.008
Maximum, ppm	0.031	**0.038**	0.024	0.026	0.025
Mean, ppm	0.016	**0.020**	0.010	0.015	0.014
Standard Deviation, ppm	**0.007**	0.005	0.004	0.004	0.004
Coefficient of variation	**0.44**	0.25	0.4	0.27	0.29
Skewness	0.075	1.306	**1.451**	0.667	0.517
Kurtosis	-0.734	1.860	**2.074**	0.863	-0.032
CO					
N	54	54	54	54	54
Minimum, ppm	0.473	**0.531**	0.372	0.188	0.410
Maximum, ppm	1.023	**1.263**	1.184	0.975	0.905
Mean, ppm	0.715	**0.829**	0.594	0.601	0.657
Standard Deviation, ppm	0.101	0.150	0.127	**0.218**	0.122
Coefficient of variation	0.14	0.18	0.21	**0.36**	0.19
Skewness	0.348	0.240	**1.888**	-0.152	0.080
Kurtosis	0.678	-0.158	**7.703**	-1.313	-0.871

The descriptive statistics for these locations from 2017 to 2021 further illustrate in the Table 2 is the impact of broader environmental factors on air quality. For instance, the 2020 Movement Control Order (MCO) led to a significant decrease in NO_2 levels across urban areas like Shah Alam, as reduced transportation and industrial activities resulted in lower emissions [22], [23]. However, the data also highlight the vulnerability of these areas to extreme pollution events, such as the spikes in PM_{10} and SO_2 concentrations observed in October 2019, largely driven by seasonal weather changes and industrial activities. These findings emphasize the importance of continuous monitoring and targeted interventions to manage air pollution, particularly in industrial and urban areas [24]. The variability in pollutant concentrations across different locations and time periods underscores the need for localized strategies to address specific pollution sources and mitigate the impact of extreme events on the environment.

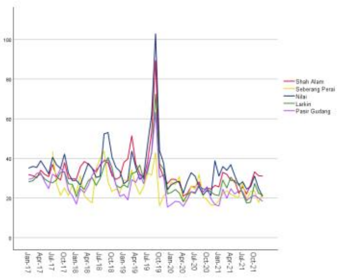
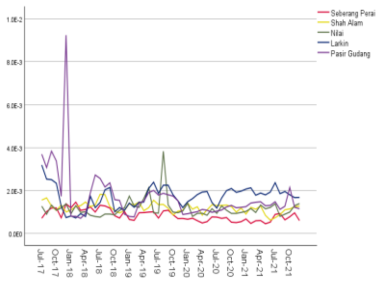
3.2 Trend Analysis

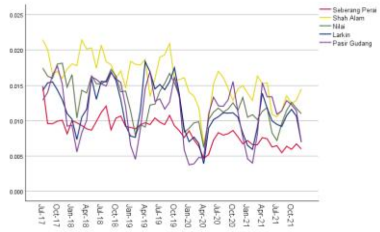
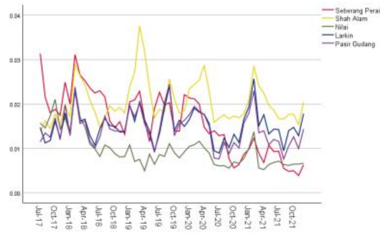
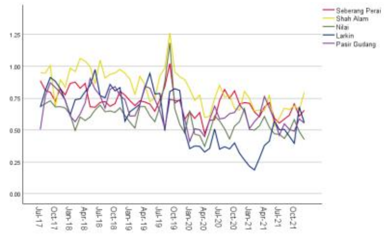
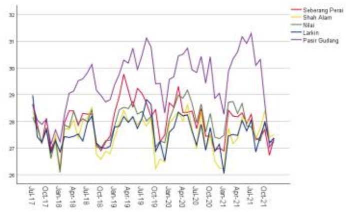
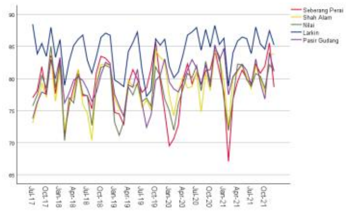
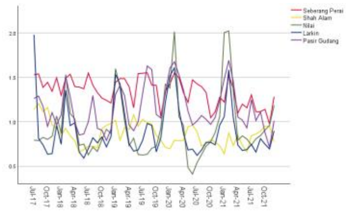
From 2017 to 2021, air quality in Malaysia generally remained within acceptable limits, with occasional fluctuations influenced by both seasonal variations and human activities. Particulate matter (PM_{10}) levels were predominantly in the "Good" to "Moderate" range, except during the 2019 haze episode, which saw a significant spike in concentrations. This event highlighted the vulnerability of the region to transboundary pollution. Conversely, the Movement Control Order (MCO) implemented in 2020 due to the COVID-19 pandemic led to a notable decrease in PM_{10} levels, underscoring the impact of reduced industrial activities and vehicular emissions on air quality. Sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and carbon monoxide (CO) concentrations remained consistently low throughout this period, well below the Malaysian Ambient Air Quality Guidelines (MAAQG) limits [25]. These findings reflect the effectiveness of ongoing regulatory measures and industrial controls in managing these pollutants. However, ozone (O_3) levels, while still within permissible limits, emerged as a pollutant of concern, particularly during periods of high solar radiation, which is known to catalyze ozone formation [9].

Meteorological parameters exhibited distinct seasonal patterns shown in Table 3. Wind speeds increased significantly during monsoonal periods, especially at coastal monitoring stations, contributing to the dispersion of pollutants. Relative humidity consistently remained high, ranging between 80-90%, with slight decreases during the Northeast Monsoon, possibly due to drier air masses. Ambient temperatures followed a predictable seasonal cycle, with higher temperatures observed during the Southwest Monsoon and cooler temperatures during the Northeast Monsoon [26]. The 2020 MCO period provided a unique case study, where significant improvements in air quality were observed across all monitored pollutants. This period of reduced human activity, including limited industrial operations and transportation, offered a glimpse into the potential for sustained air quality improvements with concerted efforts in pollution control [4].

These findings underscore the need for continuous monitoring and adaptive policy-making to address the dynamic nature of air quality in Malaysia, particularly in the context of seasonal changes and episodic events such as haze. Future strategies should focus on maintaining low levels of key pollutants while addressing emerging concerns like ozone, ensuring that air quality remains within safe limits for public health and the environment [21].

Table 3 The time series trend analysis of the concentrations from 2017 to 2021

<table>
<tr><th>Concentration</th><th>Time Series Trend Analysis</th></tr>
<tr><td>PM_{10}</td><td>
</td></tr>
<tr><td>SO_2</td><td>
</td></tr>
</table>

NO_2	
O_3	
CO	
Temperature	
Humidity	
Wind Speed	

3.3 Granger Causality Analysis

Granger causality occurs when the past and present values of a specific characteristic provide valuable information for predicting its future behavior in a time series. To explore the causal relationships among the parameters PM_{10}, SO_2, NO_2, CO and O_3, a Granger causality test was conducted. The results of these tests for each monitoring station are presented in Tables 4-8.

Table 4 Granger causality for Seberang Perai monitoring station

Monitoring Station: Seberang Perai, Pulau Pinang		
Dependent Parameter: PM_{10}		
Independent Parameter	Chi-Sq	p-value
SO_2	0.27548	0.600
NO_2	7.46433	0.006*
O_3	0.05908	0.808
CO	8.33552	0.004*
Temperature	0.06056	0.806
Wind Speed	0.37567	0.540
Humidity	0.04410	0.834
Dependent Parameter: SO_2		
PM_{10}	0.70308	0.402
NO_2	0.75367	0.385
O_3	0.58565	0.444
CO	0.81203	0.368
Temperature	0.09796	0.754
Wind Speed	0.38388	0.536
Humidity	0.20211	0.653
Dependent Parameter: NO_2		
PM_{10}	0.56086	0.454
SO_2	8.32492	0.004*
O_3	0.38846	0.533
CO	0.07306	0.787
Temperature	0.19442	0.659
Wind Speed	0.86435	0.353
Humidity	0.00803	0.929
Dependent Parameter: O_3		
PM_{10}	10.3228	0.001*
SO_2	1.17158	0.279
NO_2	10.6869	0.001*
CO	2.83435	0.092**
Temperature	3.94086	0.047*
Wind Speed	2.7845	0.095**
Humidity	0.17181	0.679
Dependent Parameter: CO		
PM_{10}	0.43881	0.508
SO_2	1.23403	0.267
NO_2	2.38014	0.123***
O_3	0.63427	0.426
Temperature	0.7021	0.402
Wind Speed	5.13726	0.023*
Humidity	0.36855	0.544
Dependent Parameter: Temperature		
PM_{10}	0.3439	0.558

SO_2	0.70477	0.401
NO_2	1.91067	0.167
O_3	2.02246	0.155
CO	0.82515	0.364
Wind Speed	0.53066	0.466
Humidity	0.46584	0.495
Dependent Parameter: Wind Speed		
PM_{10}	1.52507	0.217
SO_2	0.36673	0.545
NO_2	2.94965	0.086**
O_3	4.26101	0.039*
CO	2.70516	0.100**
Temperature	2.59238	0.107***
Humidity	3.08547	0.079**
Dependent Parameter: Humidity		
PM_{10}	6.05225	0.014*
SO_2	0.45877	0.498
NO_2	7.67461	0.006*
O_3	1.37195	0.242
CO	2.55233	0.110***
Temperature	10.4196	0.001*
Wind Speed	0.11611	0.733
* Indicates significant at 5% level ** Indicates significant at 10% level *** Indicates significant at 15% level		

Table 5 Granger causality for Shah Alam monitoring station

Monitoring Station: Shah Alam, Selangor		
Dependent Parameter: PM_{10}		
Independent Parameter	Chi-Sq	p-value
SO_2	0.265915	0.6061
NO_2	0.36214	0.5473
O_3	0.7682	0.3808
CO	0.13059	0.7178
Temperature	0.8573	0.3545
Wind Speed	0.25011	0.617
Humidity	1.30993	0.2524
Dependent Parameter: SO_2		
PM_{10}	0.93613	0.3333
NO_2	0.47725	0.4897
O_3	6.49885	0.0108*
CO	0.81203	0.368
Temperature	0.09796	0.754
Wind Speed	0.04149	0.8386
Humidity	5.25909	0.0218*

Dependent Parameter: NO_2		
PM_{10}	0.04903	0.8248
SO_2	1.14396	0.2848
O_3	2.16246	0.1414***
CO	0.00000	0.9988
Temperature	4.16959	0.0412*
Wind Speed	1.48254	0.2234
Humidity	3.42587	0.0642**
Dependent Parameter: O_3		
PM_{10}	0.03081	0.8607
SO_2	4.11517	0.0425*
NO_2	2.45781	0.1169***
CO	0.03068	0.861
Temperature	9.75627	0.0018*
Wind Speed	8.92796	0.0028*
Humidity	1.50687	0.2196
Dependent Parameter: CO		
PM_{10}	0.25866	0.611
SO_2	0.00017	0.9897
NO_2	4.00726	0.0453*
O_3	1.25323	0.2629
Temperature	1.76683	0.1838
Wind Speed	1.75085	0.1858
Humidity	1.55784	0.212
Dependent Parameter: Temperature		
PM_{10}	2.61517	0.1058***
SO_2	0.38199	0.5365
NO_2	0.05352	0.8170
O_3	0.06365	0.8008
CO	0.55323	0.4570
Wind Speed	0.79587	0.3723
Humidity	0.44362	0.5054
Dependent Parameter: Wind Speed		
PM_{10}	0.50807	0.4760
SO_2	1.94103	0.1636
NO_2	2.49409	0.1143***
O_3	1.43348	0.2312
CO	0.84585	0.3577
Temperature	0.61697	0.4322
Humidity	3.63526	0.0566**
Dependent Parameter: Humidity		
PM_{10}	4.54342	0.033*
SO_2	0.75312	0.3855
NO_2	0.38076	0.5372
O_3	0.3154	0.5744
CO	2.58462	0.1079***

Temperature	0.78545	0.3755
Wind Speed	4.02767	0.0448*
* Indicates significant at 5% level ** Indicates significant at 10% level *** Indicates significant at 15% level		

Table 6 Granger causality for Nilai monitoring station

Monitoring Station: Nilai, Seremban		
Dependent Parameter: PM_{10}		
Independent Parameter	Chi-Sq	p-value
SO_2	17.3825	0.0000*
NO_2	2.65213	0.1034
O_3	0.12296	0.7258
CO	0.08302	0.7732
Temperature	0.93289	0.3341
Wind Speed	0.02122	0.8842
Humidity	0.02725	0.8689
Dependent Parameter: SO_2		
PM_{10}	0.29853	0.5848
NO_2	0.00926	0.9233
O_3	1.05435	0.3045
CO	0.10762	0.7429
Temperature	0.0836	0.7725
Wind Speed	0.10636	0.7443
Humidity	0.22171	0.6377
Dependent Parameter: NO_2		
PM_{10}	0.05751	0.8105
SO_2	0.3871	0.5338
O_3	4.31398	0.0378*
CO	1.27003	0.2598
Temperature	3.97136	0.0463*
Wind Speed	2.50175	0.1137***
Humidity	2.17022	0.1407***
Dependent Parameter: O_3		
PM_{10}	0.85759	0.3544
SO_2	0.65904	0.4169
NO_2	0.19946	0.6552
CO	0.46569	0.495
Temperature	6.39771	0.0114*
Wind Speed	0.05283	0.8182
Humidity	1.21675	0.27
Dependent Parameter: CO		
PM_{10}	10.1566	0.0014*
SO_2	4.14503	0.0418*
NO_2	0.43911	0.5076

O_3	0.032	0.858
Temperature	1.28169	0.2576
Wind Speed	0.18107	0.6705
Humidity	0.21399	0.6437
Dependent Parameter: Temperature		
PM_{10}	1.07442	0.2999
SO_2	0.5214	0.4702
NO_2	5.10253	0.0239*
O_3	0.72542	0.3944
CO	0.12099	0.728
Wind Speed	1.57351	0.2097
Humidity	5.49687	0.0191*
Dependent Parameter: Wind Speed		
PM_{10}	0.20797	0.6484
SO_2	0.15761	0.6914
NO_2	2.15878	0.1418***
O_3	10.4632	0.0012*
CO	1.3272	0.2493
Temperature	20.0355	0.0000*
Humidity	2.18803	0.1391***
Dependent Parameter: Humidity		
PM_{10}	5.04776	0.0247*
SO_2	1.09402	0.2956
NO_2	0.71872	0.3966
O_3	5.41697	0.0199*
CO	0.1454	0.703
Temperature	11.116	0.0009*
Wind Speed	0.00193	0.9649
* Indicates significant at 5% level ** Indicates significant at 10% level *** Indicates significant at 15% level		

Table 7 Granger causality for Pasir Gudang monitoring station

Monitoring Station: Pasir Gudang, Johor		
Dependent Parameter: PM_{10}		
Independent Parameter	Chi-Sq	p-value
SO_2	0.34408	0.8419
NO_2	2.40257	0.3008
O_3	2.12515	0.3456
CO	3.14377	0.2077
Temperature	1.35877	0.5069
Wind Speed	1.07842	0.5832
Humidity	0.1096	0.9467
Dependent Parameter: SO_2		
PM_{10}	4.82275	0.0897**

NO_2	3.21985	0.1999
O_3	2.2273	0.3284
CO	8.51814	0.0141*
Temperature	7.58611	0.0225*
Wind Speed	2.68239	0.2615
Humidity	2.6471	0.2662
Dependent Parameter: NO_2		
PM_{10}	5.08789	0.0786**
SO_2	1.80519	0.4055
O_3	0.89026	0.6407
CO	5.32211	0.0699**
Temperature	7.71731	0.0211*
Wind Speed	1.05749	0.5893
Humidity	1.11196	0.5735
Dependent Parameter: O_3		
PM_{10}	3.673	0.1594
SO_2	0.16266	0.9219
NO_2	2.52949	0.2823
CO	7.76301	0.0206*
Temperature	1.7852	0.4096
Wind Speed	6.05544	0.0484*
Humidity	4.19207	0.1229***
Dependent Parameter: CO		
PM_{10}	1.24136	0.5376
SO_2	4.16605	0.1246***
NO_2	7.35129	0.0253*
O_3	7.07622	0.0291*
Temperature	3.32216	0.1899
Wind Speed	0.89244	0.64
Humidity	11.565	0.0031*
Dependent Parameter: Temperature		
PM_{10}	0.04821	0.9762
SO_2	1.36199	0.5061
NO_2	2.0086	0.3663
O_3	0.62318	0.7323
CO	0.11285	0.9451
Wind Speed	1.61012	0.4471
Humidity	3.0286	0.22
Dependent Parameter: Wind Speed		
PM_{10}	2.71378	0.2575
SO_2	7.91984	0.0191*
NO_2	9.66931	0.0079*
O_3	6.00789	0.0496*
CO	9.16854	0.0102*
Temperature	2.61201	0.2709
Humidity	3.11237	0.2109

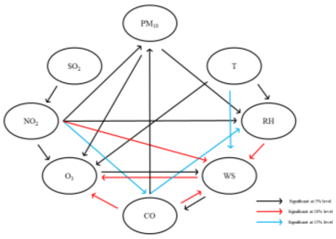
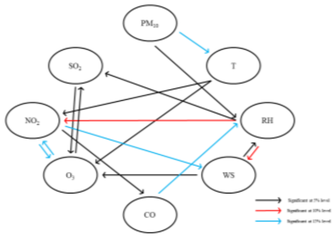
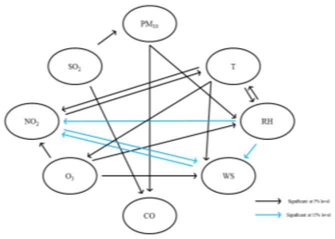
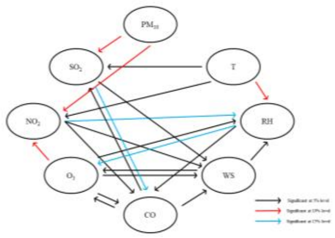
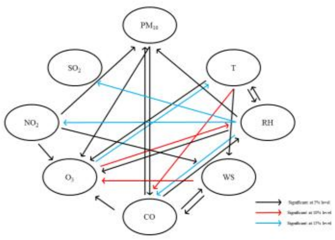
Dependent Parameter: Humidity		
PM_{10}	0.70876	0.7016
SO_2	0.45195	0.7977
NO_2	4.39832	0.1109***
O_3	8.44162	0.0147*
CO	0.85217	0.6531
Temperature	5.29491	0.0708**
Wind Speed	7.87386	0.0195*
* Indicates significant at 5% level ** Indicates significant at 10% level *** Indicates significant at 15% level		

Table 8 Granger causality for Larkin monitoring station

Monitoring Station: Larkin, Johor		
Dependent Parameter: PM_{10}		
Independent Parameter	Chi-Sq	p-value
SO_2	0.15787	0.9241
NO_2	7.40993	0.0246*
O_3	0.48319	0.7854
CO	6.85545	0.0325*
Temperature	2.72915	0.2555
Wind Speed	0.59571	0.7424
Humidity	10.1513	0.0062*
Dependent Parameter: SO_2		
PM_{10}	1.19689	0.5497
NO_2	0.14098	0.9319
O_3	3.53898	0.1704
CO	0.00484	0.9976
Temperature	2.69656	0.2597
Wind Speed	1.16637	0.5581
Humidity	4.1847	0.1234***
Dependent Parameter: NO_2		
PM_{10}	1.98644	0.3704
SO_2	1.21659	0.5443
O_3	2.98602	0.2247
CO	0.754	0.6859
Temperature	2.04233	0.3602
Wind Speed	0.63395	0.7283
Humidity	4.27402	0.118***
Dependent Parameter: O_3		
PM_{10}	8.04246	0.0179*
SO_2	1.1476	0.5634
NO_2	12.4574	0.002*
CO	8.15554	0.0169*
Temperature	5.91208	0.052*

Wind Speed	5.00742	0.0818**
Humidity	19.7155	0.0001*
Dependent Parameter: CO		
PM_{10}	1.07	0.5857
SO_2	2.29789	0.317
NO_2	9.19884	0.0101*
O_3	2.32634	0.3125
Temperature	5.03124	0.0808**
Wind Speed	6.26311	0.0436*
Humidity	4.05392	0.1317***
Dependent Parameter: Temperature		
PM_{10}	1.05693	0.5895
SO_2	0.9288	0.6285
NO_2	1.1508	0.5625
O_3	4.49174	0.1058***
CO	2.06483	0.3561
Wind Speed	0.69235	0.7074
Humidity	9.18115	0.0101*
Dependent Parameter: Wind Speed		
PM_{10}	1.38829	0.4995
SO_2	0.65156	0.722
NO_2	7.33653	0.0255*
O_3	1.96176	0.375
CO	13.0422	0.0015*
Temperature	10.9037	0.0043*
Humidity	3.37888	0.1846
Dependent Parameter: Humidity		
PM_{10}	2.30743	0.3155
SO_2	0.08511	0.9583
NO_2	2.62454	0.2692
O_3	5.72441	0.0571**
CO	8.91539	0.0116*
Temperature	8.99964	0.0111*
Wind Speed	0.84879	0.6542
* Indicates significant at 5% level ** Indicates significant at 10% level *** Indicates significant at 15% level		

Table 9 The result Granger Causality Diagram for all the monitoring stations

Monitoring Stations	**Granger Causality Diagram**
Seberang Perai, Pulau Pinang	
Shah Alam, Selangor	
Nilai, Seremban	
Pasir Gudang, Johor	
Larkin, Johor	

*Black lines indicate causality relationships with p-values less than 0.05
*Red lines represent relationships with p-values between 0.05 and 0.10
*Blue lines indicate causality relationships with p-value more than 0.10

In sub-urban and urban areas, meteorological factors significantly influenced pollutant levels, revealing distinct interaction patterns across various locations. In Seberang Perai, ambient temperature exhibited a strong relationship with ozone (O_3), while SO_2 and NO_2 showed moderate correlations with temperature. Shah Alam demonstrated that relative humidity Granger-caused NO_2 and moderately influenced O_3, while temperature was a moderate cause of NO_2 levels [27]. These findings align with Table 9, existing research that underscores the crucial role of temperature and humidity in shaping air quality dynamics, particularly in ozone formation and nitrogen dioxide concentrations [28].

In industrial and urban areas, more complex pollutant interactions were observed. Nilai displayed a bidirectional causality between SO_2 and PM_{10}, with wind speed also playing a significant role in SO_2 levels. Larkin, an urban center, showed that NO_2 and CO Granger-caused PM_{10}, while relative humidity influenced both PM_{10} and O_3

concentrations. Pasir Gudang revealed diverse interactions, where O_3 influenced SO_2, wind speed affected SO_2, and PM_{10} had an impact on NO_2, O_3, and CO levels [2]. These findings highlight the intricate dynamics of air pollution in urban and industrial settings, emphasizing the importance of understanding the multifaceted relationships between pollutants and meteorological factors for effective air quality management.

4. CONCLUSION

This study provides critical insights into the relationships between air pollutants and meteorological parameters across various regions in Malaysia. Descriptive analysis reveals that urban areas, such as Shah Alam and Larkin, consistently exhibit higher pollutant concentrations, particularly PM_{10} and NO_2, due to industrial activities and traffic emissions. In contrast, Pasir Gudang recorded lower levels of PM_{10} and SO_2, reflecting effective local management. The trend analysis from 2017 to 2021 highlights key events such as the 2019 haze, which caused significant PM_{10} spikes, and the 2020 Movement Control Order (MCO), which led to a noticeable reduction in NO_2 and PM_{10} due to decreased industrial and vehicular activities.

The Granger causality analysis uncovers significant cause-and-effect relationships, particularly in Seberang Perai, where NO_2 ($p = 0.006$) and CO ($p = 0.004$) significantly influence PM_{10}, and ozone (O_3) is affected by temperature ($p = 0.047$). In Shah Alam, relative humidity ($p = 0.033$) significantly impacts NO_2 levels. These findings highlight the pivotal role of meteorological factors in influencing air quality dynamics. The study underscores the importance of targeted interventions based on regional characteristics to mitigate air pollution, supporting broader goals of environmental sustainability and public health protection in Malaysia.

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