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Meteorological Factors Affecting on $PM_{2.5}$ Concentrations in Bandaraya Melaka

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ABSTRACT

The most hazardous pollutant, $PM_{2.5}$ has caused serious environmental and public health issues. Living in an area with $PM_{2.5}$ pollution can lead to respiratory problems as it can reach the human bloodstream through inhalation. Bandaraya Melaka was chosen to be the study area as it experienced urban tropical environments, where meteorological parameters, including ambient temperature, wind speed, and relative humidity, substantially impact the concentration of $PM_{2.5}$. Hence, this study investigates the relationship between the concentration of $PM_{2.5}$ and these meteorological factors using daily data collected from January to early July 2019. Statistical analyses were conducted after model adequacy checking on the linearity, normality, homoscedasticity, independence of the error term, no multicollinearity, and the absence of an outlier in multiple linear regression fulfilling through five iterations of outlier removal. The F-test revealed a relationship exists between meteorological factors and the concentration of $PM_{2.5}$. The results indicate a moderate positive relationship between meteorological factors and the concentration of $PM_{2.5}$, with only 38% of the total variation in the concentration of $PM_{2.5}$ explained by these factors. In the t-test, all meteorological variables were found to significantly influence the concentration of $PM_{2.5}$, and the final model, containing all factors, was identified as the best-fitting model supported with the lowest AIC and BIC values. This study contributed to better insight into forecasting the quality of the air in tropical urban environments, addressing a research gap in Bandaraya Melaka. These findings are essential for designing effective air quality management strategies, protecting public health, and supporting urban development.

1. INTRODUCTION

Fine particulate matter ($PM_{2.5}$) was among the most hazardous air contaminants. $PM_{2.5}$ is an often-examined particulate matter measure, due to its extensive array of acknowledged detrimental health impacts,

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especially with cardiovascular health concerns (Krittanawong et al., 2023). It comprised minuscule solid particles and liquid droplets with a diameter of 2.5 μg/m^3 (Wang & Ogawa, 2015). The size made it significantly smaller than numerous typical particles, including human hair. $PM_{2.5}$ was approximately 20 times smaller than the diameter of a single hair strand (U.S. Environmental Protection Agency, 2023). It was frequently referred to as dust, soot, dirt, smoke, or aerosols because its tiny size made it visible only under an electron microscope (IQAir, 2022).

Many sources can influence the concentration of $PM_{2.5}$ in the atmosphere. One of the sources was meteorological factors, which were among the significant factors. Kayes et al. (2019) mentioned that meteorological factors have a crucial role in determining the air quality in the atmosphere. Kayes et al. (2019) also mentioned in the study focusing on urban regions that meteorological parameters, specifically ambient temperature, relative humidity, and wind speed, were important contributors to the fluctuation of $PM_{2.5}$ which was the reason this study chose the parameters.

In addition, meteorological factors were chosen in addition to the topography and climate of Bandaraya Melaka, which demonstrated that these meteorological parameters and Bandaraya Melaka were correlated. Unlike other areas, Bandaraya Melaka is located on Peninsular Malaysia's west coast, where the wind from the coast is strong enough to cause an effect on the level of $PM_{2.5}$ (Lim, 2015). In addition, Bandaraya Melaka was selected as it is in a tropical region with high temperature, humidity, and seasonal winds, which could be influential in $PM_{2.5}$ concentration (Latif et al., 2018).

Despite assumptions that urban areas contribute less to fine particulate pollution compared to industrial zones, research by Gao et al. (2018) and Y. Wang et al. (2016) challenges this notion, identifying urban centers as significant contributors to $PM_{2.5}$ pollution. The lack of focused research on meteorological factors in urban tropical environments creates a knowledge gap that this study aims to address. By analysing daily data from January to early July 2019 using multiple linear regression, this research seeks to examine the relationship between ambient temperature, relative humidity, wind speed, and $PM_{2.5}$ concentrations in Bandaraya Melaka.

Wind speed affects $PM_{2.5}$ concentrations as it impacts the dispersion of airborne pollutants. Chen et al. (2020), in China, when studying the relationship between meteorological parameters and the concentration of fine particulate matter, detected a negative association between the concentration of $PM_{2.5}$ and wind speed. They explained that stronger winds have a direct blowing-off force that further promotes the dispersion of particles.

Ambient temperature could influence the phenomenon of temperature inversions in China that block the pollutants from going upward, resulting in excessive concentrations of fine particulate matter (Li et al., 2017). Ma et al. (2021) studies on the $PM_{2.5}$ and O_3 behaviour to meteorological factors in China found that higher temperatures facilitate chemical reactions between vehicle emissions and industrial activities, forming fine particulate matter resulting in high $PM_{2.5}$ levels (Majid et al., 2020). A study by Amil et al. (2016) on the variability of $PM_{2.5}$ in Klang Valley from August 2011 to July 2012 suggests that higher temperatures might form dry conditions that suppress air circulation, trapping pollutants near the surface. The reduced vertical mixing leads to the buildup of $PM_{2.5}$ concentrations at the surface.

How and Ling (2016) explore at Universiti Teknologi Malaysia (UTM) at Skudai, Johor, a region with few rainfalls a year due to high humidity for the rainy season period. Through correlation evaluation, their results showed that temperature and relative humidity aid the aggregation and subsequent removal of particulate matter via precipitation, helping to lower airborne $PM_{2.5}$ concentrations. Studies looking at data from China from 2006 to 2014 found that high relative humidity aided chemical reactions. This process converts sulfur dioxide to sulfate aerosols and consequently enhances the concentration of aerosolised $PM_{2.5}$ in the air (Fang et al., 2017). Ramli et al. (2024) and Dahari et al. (2020) used Pearson Correlation Analysis to examine meteorological influences on air pollutants in Malaysia across seasons. Ramli et al. (2024) found that NO_2, CO, and O_3 correlated with climatic factors, with stronger associations during the

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Southwest monsoon. Dahari et al. (2020) reported a positive correlation between temperature and $PM_{2.5}$ in Skudai, Johor, and a negative correlation with relative humidity and wind speed, with the strongest effects during the Southwest monsoon. Both studies highlight the role of meteorological factors in air pollution variability.

2. METHODOLOGY

The data was collected from 1st January 2019 to 12th July 2019, a total of 193 observations from the Department of Environment (DOE) and the Malaysia Meteorological Department (MET Malaysia). The study was based on $PM_{2.5}$ concentration data from the Department of Environment. Data from an air monitoring station in Bandaraya Melaka in 2019. Met Malaysia provided meteorological data during the same period, such as ambient temperature, relative humidity, and wind speed. This study analysed the dependent variable of $PM_{2.5}$ concentration with independent factors of wind speed, relative humidity, and ambient temperature,

Multiple linear regression was employed in this study because there was more than one predictor variable (Montgomery et al., 2021). This method was used to analyse the relationship between the concentration of $PM_{2.5}$ and meteorological factors, including wind speed, ambient temperature, and relative humidity. Before undergoing multiple linear regression, model adequacy checking should be done. The normality assumption is checked by using the Kolmogorov-Smirnov test, the linearity is assessed through the scatter plots, the homoscedasticity assumption is checked through the scatter plot of residuals against the predicted values, the independence of error term assumption is evaluated through the scatter plot of residuals against date, the multicollinearity assumption is checked through the values of Tolerance (TOL) and Variance Inflation Factor (VIF), and the outliers are detected through the scatter plot of studentized residuals against predicted values. Then, the validity of the test, coefficient of determination, t-test and AIC-BIC were checked to ensure that the model that has a significant relationship is the best-fit model. Data was analysed using SPSS and R-studio.

3. FINDINGS AND DISCUSSION

3.1 Set of variables

This study examined the dependent variable of $PM_{2.5}$ concentration with independent factors of wind speed, relative humidity, and ambient temperature to analyse the relationship between $PM_{2.5}$ concentration with three meteorological factors, which are wind speed, relative humidity, and ambient temperature as shown in Table 1.

Table 1. Set of variables

Variable Name	Variable Type	Description
PM2.5 Concentration	Numerical	The reading on the concentration of PM2.5 ($\mu g/m^3$)
Relative Humidity	Numerical	Percentage of Relative Humidity (%)
Wind Speed	Numerical	Speed of the Wind (ms−1)
Ambient Temperature	Numerical	Atmospheric Temperature (◦C)

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3.2 Model equation

The model equation can be expressed as follows:

$$PM_{2.5} = \widehat{\beta_0} + \widehat{\beta_1} x_1 + \widehat{\beta_2} x_2 + \widehat{\beta_3} x_3 + \epsilon$$

where,

y_i : $PM_{2.5}$ concentration
x_1 : Relative Humidity
x_2 : Wind Speed
x_3 : Ambient Temperature
$\widehat{\beta_0}$: the intercept
$\widehat{\beta_1}, \widehat{\beta_2}, \widehat{\beta_3}$: The regression coefficients of the independent variables
ϵ : the error term.

3.3 Model adequacy checking

As per Montgomery et al. (2021), it was essential to go through model adequacy checking before proceeding with the regression analysis since it may help throw light on an error that could cause the analysis not to match the actual scenario and become unreliable.

3.3.1 Before removing outliers

Normality Assumption:

Table 2 shows the result of the Kolmogorov-Smirnov test. The p-value obtained is 0.001, smaller than 0.05 (α). This indicates a significant deviation from the normal distribution, which can be concluded that the normality assumption is not satisfied.

Table 2. Kolomogorov-Smirnov test before the outliers were removed

Kolmogorov - Smirnov	
Statistic	Significance
0.284	0.001

Linearity Assumption:

Fig. 1 shows the scatterplot matrix of $PM_{2.5}$ concentration against ambient temperature, wind speed, and relative humidity. The pattern of the scatterplot appeared to have a randomly scattered point with an increasing pattern between ambient temperature and $PM_{2.5}$ concentration. Other than that, the relative humidity and $PM_{2.5}$ concentration had shown a decreasing pattern with a randomly scattered point. Next, wind speed has a negative relationship with $PM_{2.5}$ concentration as it appears to have a randomly scattered

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plot with a decreasing pattern. Since, the scatterplot between $PM_{2.5}$ concentration and meteorological parameters shows a randomly scattered point, it can be concluded that the linearity assumption is satisfied.

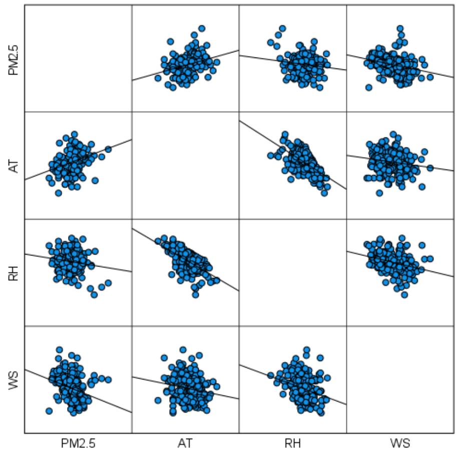

Fig. 1. Scatterplot matrix before the outlier were removed

Homoscedasticity Assumption:

Fig. 2 shows the scatter plot of residuals against the predicted values. The distribution of residuals appears to be randomly distributed, suggesting that the assumption of constant variance is fulfilled.

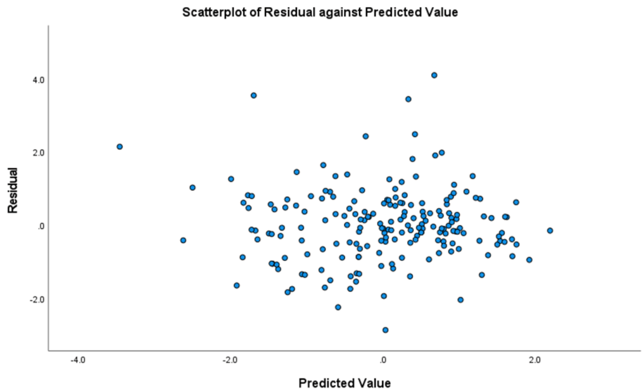

Fig. 2. Scatter plot of residual against predicted value before outliers were removed

Independence of Error Term Assumption:

Fig. 3 shows the scatter plot of residuals against date, illustrating a cyclical pattern. This indicates the presence of autocorrelation, which may violate the assumption of the independence of the error term.

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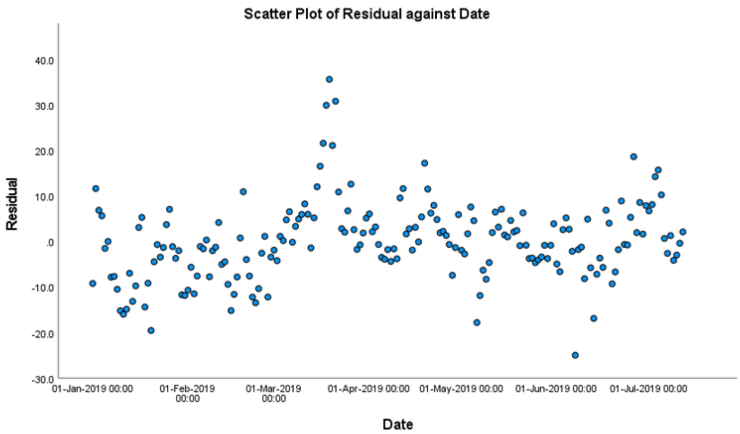

Fig. 3. Scatter plot of residual against date before outliers were removed

Multicollinearity Assumption:

Table 3 shows the values of Tolerance (TOL) and Variance Inflation Factor (VIF). The tolerance values obtained are 0.485 for ambient temperature, 0.456 for relative humidity, and 0.709 for wind speed. All the meteorological factors have TOL values greater than 0.2, suggesting that multicollinearity does not exist. Meanwhile, the VIF values are 2.060 for ambient temperature, 2.193 for relative humidity, and 1.410 for wind speed, which were below 10, further confirming that there is no multicollinearity exists between them.

Table 3. Multicollinearity test

Variables	**Tolerance**	**VIF**	**Presence of Multicollinearity**
Ambient Temperature (AT)	0.485	2.060	No
Relative Humidity (RH)	0.456	2.193	No
Wind Speed (WS)	0.709	1.410	No

Presence of Outlier Assumption:

Fig. 4 shows the scatter plot of studentized residuals against predicted values. Three points are beyond the cutoff point (±3), which indicates the presence of outliers in the concentration of $PM_{2.5}$ (Montgomery et al., 2021). These outliers may excessively influence the regression model, which can reduce its predictive accuracy.

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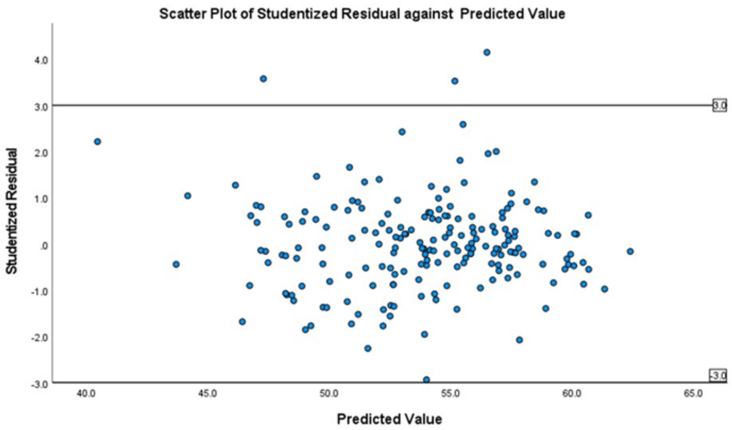

Fig. 4. Scatter plot of studentized residual by predicted value before the outliers were removed

Fig. 5 shows the scatter plot of studentized residuals against leverage values. This plot indicates the presence of outliers, as some points exceed the cutoff of $\frac{2\,(4)}{193} = 0.04145$. This suggests that the assumption of the regression model is violated due to the presence of outliers in the meteorological factors (x).

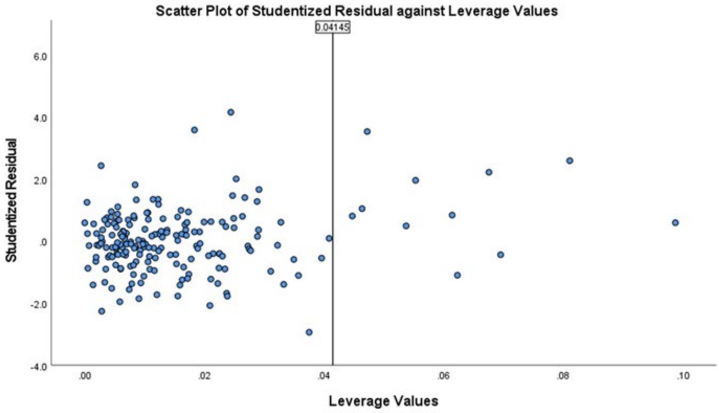

Fig. 5. Scatter plot of studentized residual by leverage before the outliers were removed

3.3.2 Outlier detection

Based on Table 4, after analysing the data, 24 observations are identified as influential points, which require approximately five iterations to be excluded from the analysis.

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Table 4. Removed observation detected as outliers

Days	Cook's Distance	DFFITS	DFB0	DFB1	DFB2	DFB3
1	0.0220	-	-	0.2461	-	-
26	-	0.4993	7.7319	-	-	-
27	-	-	3.2687	-	-	-
42	-	-	3.6710	-	-	-
43	-	-	1.2218	-	-	-
45	-	-	3.1235	-	-	-
50	0.0354	0.5785	-	-	-	-
60	0.0363	0.5804	-	-	-	-
73	0.0377	0.6439	7.3495	-	-	-
74	0.1313	1.1447	22.2615	-	-	-
75	0.0614	1.0591	14.6419	-	-	-
76	0.1578	2.0278	22.9148	-	-	-
77	0.1717	1.6490	23.2676	-	-	-
78	0.1311	1.0834	7.4278	-	-	-
79	0.0247	-	-	-	-	-
80	0.0770	0.7340	8.4760	-	-	-
130	-	-	1.9026	-	-	-
158	0.1795	-	-	0.4897	-	0.2057
162	-	0.5606	-	0.1579	-	-
163	0.1288	1.1251	22.1357	-	-	-
166	-	-	2.4425	-	-	-
168	-	0.3574	-	-	-	-
173	-	0.4793	-	-	-	-
177	0.0961	1.4538	-	-	-	0.1664

3.3.3 After removing outlier

Normality Assumption

Table 5 shows the results of the Kolmogorov-Smirnov test after the outliers were removed. The p-value is 0.2, which is greater than 0.05 (α), indicating that the normality assumption is satisfied.

Table 5. Kolmogorov - Smirnov test after outliers were removed

Kolmogorov - Smirnov	
Statistic	Significance
0.045	0.2

Linearity Assumption:

Based on Fig. 6, the scatter plot matrix of $PM_{2.5}$ against ambient temperature, wind speed, and relative humidity. The scatter plot between the concentration of $PM_{2.5}$ and the ambient temperature appears to have a randomly scattered point with an increasing pattern. Next, the scatterplot of $PM_{2.5}$ against relative humidity shows an increasing pattern with a randomly scattered point. Then, the scatter plot of $PM_{2.5}$ concentration against the wind speed shows a decreasing pattern. Since, the scatterplot between $PM_{2.5}$ concentration and meteorological parameters shows a randomly scattered point, it can be concluded that the linearity assumption is satisfied.

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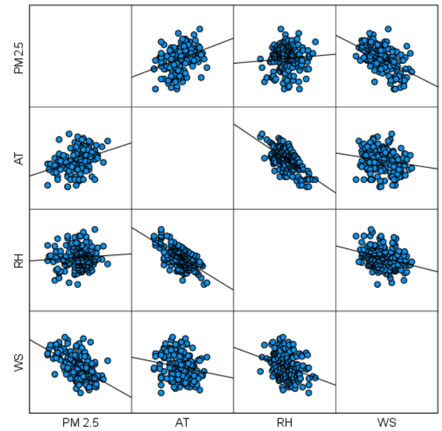

Fig. 6. Scatter plot matrix after the outliers were removed

Homoscedasticity Assumption:

Fig. 7 shows the scatter plot of residuals against predicted values, representing the assumption of homoscedasticity. After removing the outlier, the scatter plot displays a more even distribution of residuals across the predicted values, indicating that the homoscedasticity assumption is satisfied.

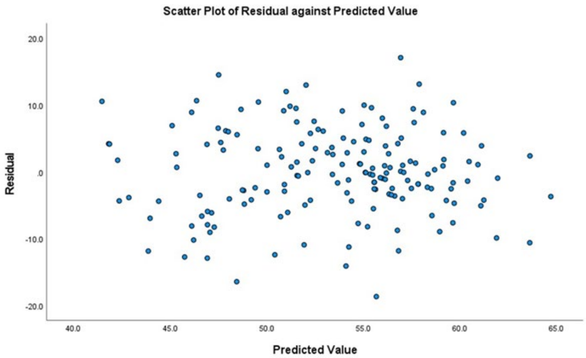

Fig.7. Scatter plot of residual against predicted value after the outliers were removed

Independence of an Error Term Assumption:

Fig. 8 presents the scatter plot of residuals against the dates after removing the outlier. The plot appears to be scattered randomly. This indicates that the independence of the error term is satisfied.

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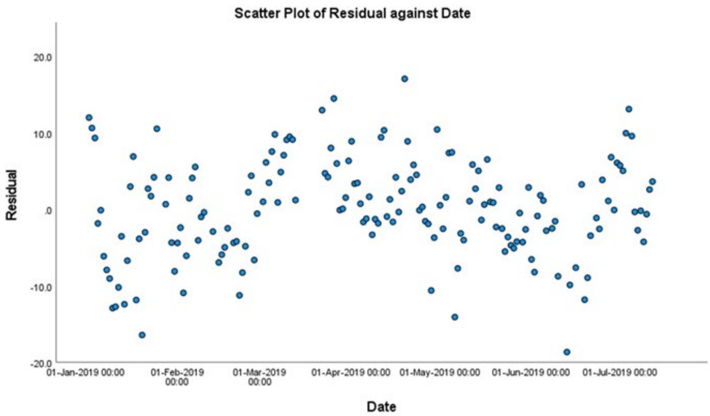

Fig. 8. Scatter plot of residual by date after the outliers were removed

Multicollinearity Assumption:

Table 6 shows the values of Tolerance (TOL) and Variance Inflation Factor (VIF). The tolerance values obtained are 0.429 for ambient temperature, 0.401 for relative humidity, and 0.663 for wind speed. All the meteorological factors have TOL values greater than 0.2, suggesting that multicollinearity does not exist. Meanwhile, the VIF values are 2.333 for ambient temperature, 2.495 for relative humidity, and 1.509 for wind speed, which were below 10, further confirming that no multicollinearity exists between them.

Table 6. Multicollinearity among the variables after the outliers were removed

Variables	Tolerance	VIF	Presence of Multicollinearity
Ambient Temperature	0.429	2.333	No
Relative Humidity	0.401	2.495	No
Wind Speed	0.663	1.509	No

Scatterplot of Studentized Residual against Predicted Value:

Based on Fig. 9 shows the scatter plot of studentized residuals against predicted values. The plot shows that no points exceed the cutoff point for *y*, indicating that the absence of outliers in *y* is satisfied.

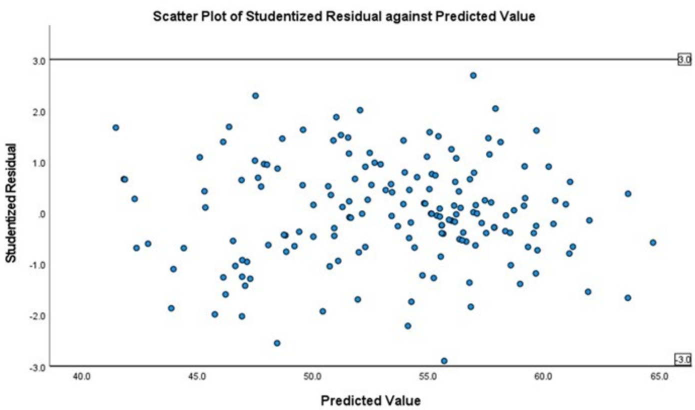

Fig. 9. Scatter plot of studentized residual by predicted value after the outliers were removed

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Scatter Plot of Studentized Residual against Leverage Value:

Fig. 10 shows the scatter plot of studentized residuals against leverage values. The plot identifies approximately four points that exceed the cutoff point, which is $\frac{2\,(4)}{169} = 0.04734$. However, further analysis confirms that these points are not influential and do not significantly affect the regression results. Consequently, no additional observations are removed at this stage, and there are no remaining outliers in this iteration. Hence, the assumption about the absence of outliers is fulfilled.

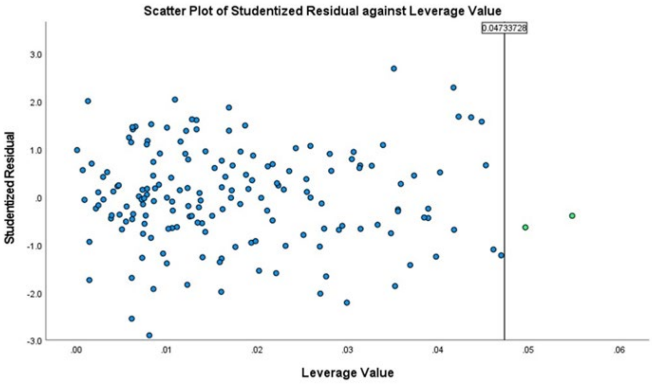

Fig. 10. Scatter plot of studentized residual by leverage value after the outliers were removed

3.4 Modelling data

3.4.1 Testing the validity of the model (F-Test)

Based on the results in Table 7, the value of the F test is 33.749 from the division of MSR and MSE. The value obtained is higher than the critical F value, which is 2.60, and the p-value of 0.001 is lower than the significance level of 0.05. Both the F test and the p-value results indicate that there is a significant relationship between the concentration of $PM_{2.5}$ and meteorological factors, which are wind speed, relative humidity and ambient temperature.

Table 7. F-Test of the model

MSR	MSE	F	$F_{3,165,0.05}$	p-value
1420.294	42.084	33.749	2.60	0.001

3.4.2 Coefficients of determination (R^2)

Table 8 illustrates the association between meteorological factors and the concentration of $PM_{2.5}$. The strength of the relationship is 0.617, which indicates a moderate positive relationship. Then, the coefficient of determination obtained is 0.380. This suggests that approximately 38% of the total variation in the concentration of $PM_{2.5}$ is explained by meteorological factors, while the remaining 62% is attributed to other factors.

Table 8. Coefficient of determination

R	Strength	R-Square
0.617	Moderate Positive	0.380

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3.4.3 Testing the significance of the model (T-test)

Based on Table 9, the p-values for ambient temperature, relative humidity, and wind speed are 0.001, 0.011, and 0.001. All meteorological factors have a p-value less than the significance level of 0.05. This indicates that all three variables are significant predictors of $PM_{2.5}$ concentration.

Table 9. T-test of the model

Model	t	Significance
Constant	-2.480	0.014
Ambient Temperature	4.749	0.001
Relative Humidity	2.561	0.011
Wind Speed	-5.051	0.001

3.4.4 The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC)

Table 10 presents the AIC and BIC values for each model. As shown, Model 2 has the highest AIC and BIC values, while Model 7 has the lowest. According to Kimura and Waki (2016), the model with the smallest AIC and BIC values is considered the best among the candidates. Therefore, the best model is Model 7, which includes a combination of all predictor variables which is $PM_{2.5} =$ -104.264 + 4.821AT + 0.470RH - 1.793WS.

Table 10. AIC & BIC for choosing the best model

Model	Predictors	Model Equation	AIC	BIC
Model 1	AT only	-104.264 + 4.821AT	1171.933	1181.323
Model 2	RH only	-104.264 + 0.470RH	1193.369	1202.758
Model 3	WS only	-104.264 - 1.793WS	1137.171	1146.560
Model 4	AT + WS	-104.264 + 4.821AT - 1.793WS	1122.144	1134.663
Model 5	AT + RH	-104.264 + 4.821AT + 0.470RH	1139.851	1152.371
Model 6	WS + RH	-104.264 + 0.470RH - 1.793WS	1137.210	1149.730
Model 7	AT + WS +RH	-104.264 + 4.821AT + 0.470RH - 1.793WS	1117.556	1133.205

3.4.5 Model equation

$$PM_{2.5} = -104.264 + 0.470 * \text{Relative Humidity} - 1.793 * \text{Wind Speed} + 4.821 * \text{Ambient Temperature} \quad (1)$$

Regarding the regression coefficient of constant, it can be said that on average, when the meteorological factors are zero, the reading of $PM_{2.5}$ concentration will be $-104.264\mu gm^{-3}$. While the coefficient of relative humidity represents that with all other variables remaining constant, on average, when relative humidity increases by 1%, the reading of $PM_{2.5}$ concentration increases by $0.470\mu gm^{-3}$. Although the coefficient of wind speed represents that with all other variables held constant, on average, when wind speed increases by $1ms^{-1}$, the reading of $PM_{2.5}$ concentration decreases by $1.793\mu gm^{-3}$. While the coefficient of ambient temperature represents that with all other variables remaining constant, on average, when the ambient temperature increases by 1°C, the reading of $PM_{2.5}$ concentration increases by $4.821\mu gm^{-3}$.

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3.5 Discussion

This study used multiple linear regression to examine the impact of meteorological factors on $PM_{2.5}$ concentrations in Bandaraya Melaka. The F-test confirmed the model's statistical significance ($p = 0.001$), indicating that ambient temperature, relative humidity, and wind speed influence $PM_{2.5}$ levels. The coefficient of determination ($R^2 = 0.38$) indicates that 38% of the total variation in $PM_{2.5}$ is explained by meteorological factors. This aligns with Wise and Comrie (2005), who reported low R^2 values (12% to 49%) in similar studies, suggesting that other factors, such as emissions and transboundary pollutants, could be the main contributor to the total variation in $PM_{2.5}$. Although meteorological factors are not the primary contributor to $PM_{2.5}$ levels, their role in facilitating pollutant transport, transformation, and deposition underscores their relevance in this study.

The t-test showed all parameters were significant: temperature ($p = 0.001$, $r = 0.353$) and humidity ($p = 0.011$, $r = 0.079$) had weak positive relationships with $PM_{2.5}$, while wind speed ($p = 0.001$, $r = -0.536$) had a moderate negative relationship. These findings are consistent with previous studies attributing $PM_{2.5}$ increases to photochemical reactions and the presence of moisture causing accumulation of the pollutants, while atmospheric mixing processes (both horizontal advection and vertical convection) facilitate the dispersion of pollutants to another area (How & Ling, 2016; Dahari et al., 2020).

AIC and BIC confirmed that the full model, including all meteorological parameters, provided the best fit. The final model suggests that temperature and humidity positively influence $PM_{2.5}$, while wind speed has a negative effect. These findings highlight the role of meteorological factors in air quality but also emphasize the need to consider non-meteorological contributors. Other factors such as emissions, human activities may be considered in future research.

4. CONCLUSION

This study investigates the relationship between $PM_{2.5}$ concentration and meteorological factors in Bandaraya Melaka using multiple linear regression. The results confirm that ambient temperature, relative humidity, and wind speed significantly impact $PM_{2.5}$ levels, collectively explaining 38% of its variation. While meteorological factors are not the primary contributors, they still play a role in $PM_{2.5}$ fluctuation. The final model suggests that temperature and humidity positively influence $PM_{2.5}$, whereas wind speed has a negative effect. Though this model may not be ideal for direct prediction, it provides valuable insights into the interaction between meteorology and air pollution. Additionally, this study highlights the importance of meteorological factors in mitigating air pollution, particularly in scenarios such as transboundary haze. Understanding how these parameters influence $PM_{2.5}$ can help authorities implement preventive measures, such as cloud seeding, to reduce pollution levels. Moreover, public awareness of these relationships can aid in environmental planning and air quality management.

To enhance future research, several aspects should be considered. Expanding the study to different regions of Malaysia would provide comparative insights into $PM_{2.5}$ behaviour and help identify location-specific pollution sources. Incorporating additional meteorological variables such as rainfall, atmospheric pressure, and wind direction could improve model accuracy and offer a more comprehensive understanding of $PM_{2.5}$ fluctuations. Furthermore, extending the study duration to 12 months or multiple years would allow for a better understanding of seasonal variations and long-term trends in $PM_{2.5}$ levels. By addressing these aspects, future studies can provide stronger evidence for air pollution management strategies and contribute to more effective environmental policies.

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6. CONFLICT OF INTEREST STATEMENT

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

7. AUTHORS' CONTRIBUTIONS

Nur Alya Adriana Abdullah Sani: Conceptualisation, methodology, formal analysis, investigation, and writing- original draft; **Nurkhairany Amyra Mokhtar**: Conceptualisation, supervision, writing- review and editing, and validation.

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