Statistical quality control analysis in monitoring air pollution: indoor particulate matters, temperature, and humidity (case study: South Jakarta, Indonesia)

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Abstract. Assessing air quality is essential for minimizing exposure to harmful pollutants and creating strategies for cleaner air. Detailed air quality monitoring offers valuable insights into pollution sources, trends, and potential health risks. Quality Control (QC) is a fundamental component of process monitoring and improvement across various industries. Traditionally applied in manufacturing and industrial settings, QC principles have increasingly been adapted for use in environmental and public health monitoring due to their reliability in ensuring data accuracy and identifying abnormal patterns. Analysis in monitoring air pollution using statistical quality control has an objective to detect patterns and trends in particulate matter levels over time, track variations in air quality to ensure it remains within acceptable limit to identify potential sources of indoor air pollution. Based on the result of quality control analysis it shows that the implementation of Hotelling's T^2 control chart effectively demonstrated all variables indicating that the indoor air quality process is currently stable and under statistical control.

1 Introductions

Air quality is influencing everything from respiratory conditions to overall well-being, making it crucial in maintaining environmental and human health aspects. Air quality can be negatively impacted by various pollutants, including particulate matter, nitrogen oxides, and volatile organic compounds, that are contained in the atmosphere which can pose as significant risks to public health. Poor air quality is often linked to respiratory diseases such as asthma and chronic obstructive pulmonary disease (COPD), as well as cardiovascular complications [1]. Additionally, long-term exposure to polluted air can weaken the immune system and make pre-existing medical conditions worse. With increasing urbanization and

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industrial activity, monitoring and addressing air pollution have become more urgent to ensure sustainable living conditions.

Understanding the effects of air quality on human health and the environment is essential for effective pollution control and mitigation strategies [2]. Airborne pollutants come from both natural processes and human activities, including vehicle emissions, industrial processes, and agricultural activities. These pollutants contribute to environmental degradation by affecting climate patterns, reducing visibility, and disrupting ecosystems. Some pollutants also react with atmospheric compounds, creating secondary pollutants that further worsen air quality. The consequences of poor air quality extend beyond individual health concerns, influencing economic productivity, healthcare costs, and overall quality of life. Therefore, it essential to monitor air quality and understand its implications, so that policymakers and researchers able to implement necessary interventions to reduce the risks and harm.

Measuring air quality is a fundamental step in minimizing exposure to harmful pollutants and developing strategies for cleaner air. A thorough monitoring system helps identify pollution sources, track trends over time, and assess potential health risks. By examining key indicators such as particular matter, humidity, and temperature can detect trends and anticipate pollution spikes, resulting in better preventive actions [3,4]. Reliable data from these assessments also inform air quality regulations, giving governments the basis to implement standards that protect public health [4]. With recent technological developments, air monitoring tools have become more advanced, offering real-time information to support both environmental management and public health initiatives. By prioritizing air quality measurement and analysis, societies can take proactive steps toward ensuring cleaner and healthier environments for future generations. However, despite advancements in monitoring technologies, there remains a lack of studies that systematically apply statistical quality control methods, such as Hotelling's T^2 control charts to assess and interpret multivariate air quality data for detecting abnormal pollution patterns and ensuring reliable environmental assessments.

2 Research Methodology

This research used a quantitative approach, descriptive statistics, and primary data. The research flow began with a literature review to gather insights on air pollution. A normality test is then conducted to ensure the data follows a normal distribution, which is essential for accurate statistical analysis. Next, correlation analysis is used to explore relationships between variables, especially to identify how factors like temperature and humidity affect pollutant levels. These findings support the development of a control chart as part of the statistical process control. By evaluating air quality, we can detect patterns and take corrective actions when pollution levels deviate from the norm.

2.1 Data Collection and Sampling Procedures

The process of collecting data and sampling was performed by placing an IQAir Indoor Air Quality Monitor in an office building in South Jakarta. The data were observed over two months, and 202 observations were made every day, most of them being taken every ten minutes, except the period between 08:00 and 08:10 AM, when the measurements were recorded every ten seconds to test the short-term variability. The monitoring device was left in the same room and configuration throughout the study period, and hence methodological consistency and reliability of data were guaranteed. Instrument relocation and replacement did not take place. Normal office operations were carried out normally, and the dataset could capture the true picture of the indoor air quality scenario when taken during typical

https://doi.org/10.1051/e3sconf/202565002039

occupancy patterns. The raw data was then transformed into daily averages to counter the effects of abnormalities and sudden peaks. These steps made the data set stable, clean and ready to be analyzed statistically.

2.2 Normality Test

An assessment of the normality data is a prerequisite for many statistical tests because normal data is an underlying assumption in parametric testing. There are four variables tested in this research: $PM_{2.5}$, PM_{10}, Humidity, and Temperature. Both $PM_{2.5}$ and visibility are important parameters to measure the situation of air pollution [3]. The multivariate normality test is divided into two types: univariate normality test (each data individually) and multivariate normality test (simultaneously). One of the tests can be used to observe the distribution of a data set is the Kolmogorov-Smirnov test, which compares the empirical cumulative distribution of a sample to a reference from normal distribution. If the p-value is high, it means there's not enough evidence to reject the assumption that the data are normally distributed [4].

2.3 Correlation Analysis

Correlation analysis evaluates relationships between environmental factors like particulate matter, humidity, and temperature. Using Pearson correlation, it can be measured how strongly the association between these variables, for example whether changes in humidity and temperature significantly influence particulate matter concentrations. A strong positive or negative correlation indicates how weather conditions influence on pollutant behaviours, such as how they spread, build up, or form. This approach identifies causal links, improves air quality forecasting, and informs pollution control strategies. Understanding these correlations is crucial for developing effective mitigation measures and ensuring a healthier atmosphere.

2.4 Statistical Quality Control

Quality Control (QC) plays an essential role in monitoring and improvement across various industries. Traditionally applied in manufacturing and industrial settings, QC principles are now widely applied in environmental and public health monitoring because of their effectiveness in ensuring data accuracy and spotting unusual patterns [5]. In environmental analysis, Quality assurance (QA) typically involves rigorous procedures for sample collection, preservation, and analysis to maintain data integrity and traceability. In the context of air quality, QC frameworks are instrumental in establishing thresholds, detecting deviations, and supporting evidence-based interventions [6].

To apply statistical tools accurately in QC processes, it is essential first to evaluate the distribution characteristics of environmental data. Control charts are a key part of statistical process control and are commonly used to monitor variation in processes [7]. Normality testing plays a crucial role in determining whether the distribution of a data set follows a normal distribution or not. Once normality is confirmed, multivariate quality control such as Hotelling's T^2 control chart may be applied to monitor multiple interrelated variables simultaneously. This method is especially helpful for identifying what's causing variation and for improving the process overall. It monitors changes in the average of several variables and can detect small shifts in the system [8]. Since Hotelling's T^2 takes into account the relationships between variables, it's particularly effective in environmental studies where factors like $PM_{2.5}$ and humidity are interdependent.

To perform Hotelling's T^2, it begins by squaring the t-statistic which is typically used when testing a hypothesis regarding a univariate mean. When the null hypothesis is assumed to be true, the *t* follows a distribution with $n-1$ degrees of freedom [9].

$$t^2 = \frac{(\overline{x} - \mu_0)^2}{\frac{s^2}{n}} = (\overline{x} - \mu_0)\left(\frac{1}{s^2}\right)(\overline{x} - \mu_0) \sim F_{1,n-1} \tag{1}$$

When a *t*-distributed random variable with $n-1$ degrees of freedom squared, it becomes an F-distributed random variable with 1 and $n-1$ degrees of freedom

$$t^2 > F_{1,n-1,\alpha} \tag{2}$$

$$T^2 = n(\overline{x} - \mu_0)' S^{-1} (\overline{x} - \mu_0) \tag{3}$$

3 Results and Discussions

3.1 Descriptive Approach

Descriptive methods provide a foundational way to understand how particulate matter, humidity, and temperature vary over time. These methods help establish baseline conditions and identify trends within the dataset. By examining measures such as mean, variance, skewness, and kurtosis, it allows evaluation of pollutant behaviours and meteorological fluctuations, highlighting potential environmental influences. Table 1 shows descriptive statistics of the cleansed data.

Table 1. Descriptive Statistics

	$PM_{2.5}$ (µg/m^3)	**PM_{10} (µg/m^3)**	**Temperature (°C)**	**Humidity (%RH)**
Mean	26.78 ± 6.94	26.88 ± 7.04	24.04 ± 1.12	64.19 ± 5.28
Sample Variance	48.22	49.55	1.25	27.92
Kurtosis	2.60	2.80	-0.63	-0.80
Skewness	1.30	1.35	0.64	0.69

The air quality data presented in the table provides key insights into the concentration of particulate matter ($PM_{2.5}$ and PM_{10}) and environmental factors like temperature and humidity. The mean concentration of $PM_{2.5}$ is 26.78 µg/m³ with a standard deviation of 6.94, while PM_{10} shows a very similar mean of 26.88 µg/m³ with a slightly higher standard deviation of 7.04. These values indicate moderate levels of air pollution, which could pose some health risks, particularly for sensitive individuals. The temperature is relatively stable, averaging 24.04°C with minimal fluctuation, suggesting that the climate remains comfortable. Humidity, with a mean of 64.19%, indicates a relatively humid environment, potentially affecting pollutant dispersion and human comfort.

The sample variance values show how spread out the data points are. $PM_{2.5}$ and PM_{10} have relatively high variance values of 48.22 and 49.55, respectively, indicating some fluctuation in pollutant levels over time. Temperature variance is significantly lower at 1.25, meaning the temperature remains consistent without extreme variations. Humidity has a variance of 27.92, reflecting some variability in atmospheric moisture, which can influence air quality dynamics, particularly pollutant accumulation and dispersion.

Kurtosis and skewness provide further statistical insights into the data distribution. The positive kurtosis values for $PM_{2.5}$ (2.60) and PM_{10} (2.80) suggest a relatively sharp distribution with more extreme values, meaning periods of higher pollution levels might be observed occasionally. Temperature and humidity, however, have negative kurtosis values (-

0.63 and -0.80), indicating a more evenly distributed dataset with fewer extreme variations. The skewness values reveal that all four parameters are positively skewed, meaning they are slightly inclined towards higher values rather than lower ones. The moderate skewness of $PM_{2.5}$ (1.30) and PM_{10} (1.35) further supports the idea of occasional spikes in pollution levels.

To gain deeper insights, breaking down the data by month or season can help identify when pollution levels are highest. This can reveal patterns linked to human activities or weather changes. Comparing weekday and weekend trends, along with hourly data, can also give a more detailed view of daily pollution fluctuations. The coefficient of variation (CV), calculated by dividing the standard deviation by the mean, shows how much the data varies. For PM2.5, the CV is about 25.9%, and for PM10, it's 26.2%, both indicating moderate variability. These values help assess how reliable the average pollution levels are. In comparison, humidity has a higher CV (8.2%) than temperature (5.2%), suggesting that moisture in the air plays a stronger role in how pollutants spread. Understanding these patterns can help forecast air quality and implement measures to mitigate pollution effects, ensuring better environmental and health outcomes.

3.2 Weekends vs Weekdays

Analysing air quality differences between weekends and weekdays provides valuable insights into how human activity influences atmospheric pollution levels [10]. Urban environments experience fluctuating air pollution patterns based on varying traffic volumes, industrial operations, and meteorological conditions, which differ between workdays and leisure days. Understanding these variations can reveal significant trends in pollutant accumulation, dispersion rates, and the impact of environmental factors. This type of temporal analysis helps identify behavioural or policy-related interventions needed to manage peak pollution days effectively. The result can be identified in peak pollution times by comparing air quality metrics during different periods. Table 1 shows a comparison between weekends and weekdays.

Table 2. Weekends vs Weekdays

	$PM_{2.5}$ (μg/m³)	**PM_{10} (μg/m³)**	**Temperature (°C)**	**Humidity (%RH)**
Weekdays	24.41	24.47	23.58	61.47
Weekends	32.92	33.09	25.23	71.22
Daily	26.78	26.88	24.04	64.19

The air quality data shows a notable difference between weekdays and weekends, particularly in particulate matter ($PM_{2.5}$ and PM_{10}) concentrations. On weekdays, $PM_{2.5}$ levels average 24.41 μg/m³, while PM_{10} averages 24.47 μg/m³. These values indicate moderate air pollution, likely influenced by regular human activities such as traffic and industrial operations. However, $PM_{2.5}$ and PM_{10} concentrations rise significantly on weekends to 32.92 μg/m³ and 33.09 μg/m³, respectively, suggesting increased pollution levels. This could be attributed to increased recreational and domestic activities, traffic patterns, or meteorological influences [11]. The daily mean values of 26.78 μg/m³ for $PM_{2.5}$ and 26.88 μg/m³ for PM_{10} reflect a moderate pollution level but mask the variations between weekdays and weekends. The difference in particulate matter levels between weekend and weekdays is substantial which represents a relative increase of approximately 35%. This indicates that air pollutions instensify during weekends, possibly due to household emissions, market activity, or reduced regulation enforcement. The standard deviation for daily PM levels also higher during the

https://doi.org/10.1051/e3sconf/202565002039

weekeds as shown in Table 1, which confirming increased variability and instability in air quality during non-working days.

Temperature patterns also show a clear distinction between weekdays and weekends. On weekdays, the mean temperature is 23.58°C, whereas on weekends, it rises to 25.23°C, resulting in a higher daily average of 24.04°C. This increase during weekends could be linked to changes in urban heat island effects, human activities, or seasonal factors influencing temperature fluctuations. The slightly higher temperature might impact atmospheric stability, affecting pollutant dispersion and air quality. Warmer conditions could intensify specific chemical reactions in the air, leading to secondary pollutant formation, further impacting air quality. The 1.65°C increase in weekend temperature (approximately +7.0%) may accelerate photochemical reactions, particularly those forming ozone or secondary aerosols. These reactions further compound pollution risks, especially in tropical urban regions like Jakarta.

Humidity levels vary substantially between weekdays and weekends. The weekday humidity averages 61.47%, indicating a relatively stable atmospheric moisture level. However, it increases to 71.22% on weekends, showing a much more humid environment. The daily mean humidity of 64.19% reflects this variation. Elevated humidity levels on weekends can influence pollutant behaviour, potentially enhance aerosol formation, and limit dispersion, leading to the accumulation of pollutants. High humidity may also contribute to a perceived decline in air quality due to the increased moisture content, making the atmosphere feel heavier and less breathable. The 9.75 percentage point increase in humidity during weekends translates to a 15.9% rise from the weekday level, which can promote particulate matter agglomeration and reduce vertical mixing in the lower atmosphere. This combination of high humidity and higher temperatures may reinforce pollution build-up.

The data suggests that air pollution worsens during weekends, accompanied by increased temperature and humidity. Shifts in human activities, traffic patterns, and meteorological conditions may drive these changes [12]. These findings underscore the need for targeted pollution control strategies during weekends, such as vehicle usage restrictions, public awareness campaigns, or emission caps for high-activity zones. Understanding these variations can help design more effective air pollution management strategies, such as tailored interventions targeting peak pollution periods. Further analysis of pollutant sources and environmental conditions could provide deeper insights into the mechanisms behind these fluctuations, ultimately guiding policies to improve air quality and health outcomes.

3.3 Normality Test

Based on four of the variables, the result of the normality test are as follows:

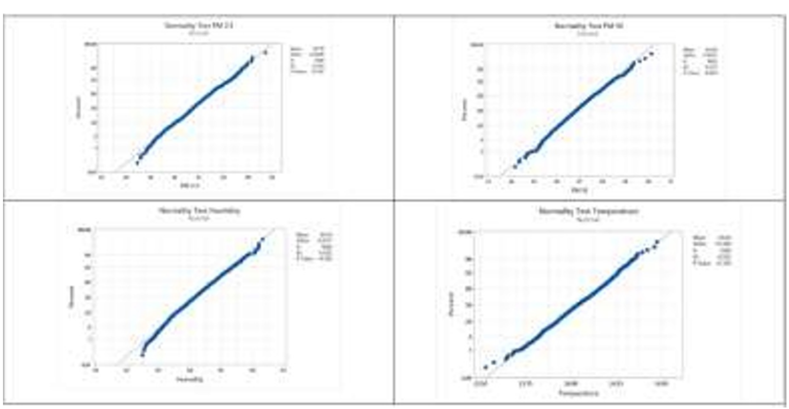

Fig. 2. Normality Test of $PM_{2.5}$ PM_{10} Humidity and Temperature

The normality test for the $PM_{2.5}$, PM_{10}, humidity and temperature data in figure 2 is based on the Kolmogorov-Smirnov (KS) test [13]. For all four variables, the KS statistics were low (ranging from 0.020 to 0.027) and the p-values were high (above 0.083), indicating that the data follows a normal distribution. In hypothesis testing, a high p-value (above 0.05) means there is no strong reason to reject the assumption that data is normally distributed. $PM_{2.5}$ showed a KS statistic of 0.020 and p-value > 0.150. Its skewness (1.30) and kurtosis (2.60) suggest moderate asymmetry but still withing normal range. PM_{10} had a KS statistic of 0.027 and a p-value > 0.083 with similar skewness (1.35) and kurtosis (2.80), indicating occasional extreme values but a generally bell-shaped distribution. Humidity also passed the normality test as well as temperature confirming a normal distribution.

3.4 Correlation Analysis

Scatter plot arranged in a figure 3 with four types of variables being compared and the 95% confidence interval of Pearson correlation. The top left plot on figure 6 shows the relationship between $PM_{2.5}$ levels and humidity, which shows any pattern or trends such as a positive or negative correlation. The top right plot shows the relationship between $PM_{2.5}$ levels and temperature, observe the distribution of points to determine if there is a correlation. The bottom left plot shows the relationship between PM_{10} levels and humidity, and the same with the other plot, the visible trends that indicate a correlation between these variables. The bottom right plot shows the relationship between PM_{10} levels and temperature. Overall, the strength and direction of the correlation can be inferred from the scatter plots. Since the points are closely clustered around a line, it indicates a strong correlation. This is also supported by the r coefficient of correlation, and the direction (positive or negative) can be determined by the slope of the line.

The direction and magnitude of these correlations are crucial for modeling pollutant behavior and forecasting air quality. High correlations between PM2.5 and PM10 support joint monitoring, while the moderate links with temperature and humidity suggest the need to consider weather data in pollution mitigation strategies. This multivariate understanding serves as a foundation for the subsequent application of Hotelling's T^2 control charts, where the interplay between pollutants and environmental variables must be evaluated jointly rather than independently.

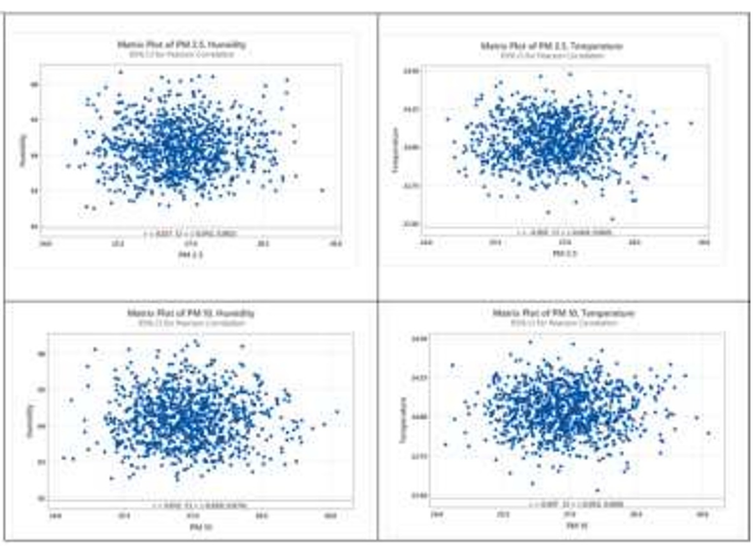

Fig. 3. Correlation Analysis between $PM_{2.5}$, PM_{10}, Temperature and Humidity

3.5 Hotelling T^2 Control Chart

The Hotelling T^2 control chart is a control chart used when a process involves monitoring multiple characteristics simultaneously. The Hotelling T^2 control chart is used when two or more characteristics are technically dependent or suspected to be related. There are two forms of the Hotelling T^2 control chart [14], which is the Hotelling T^2 control chart for subgroup data and the Hotelling T^2 control chart for individual observations.

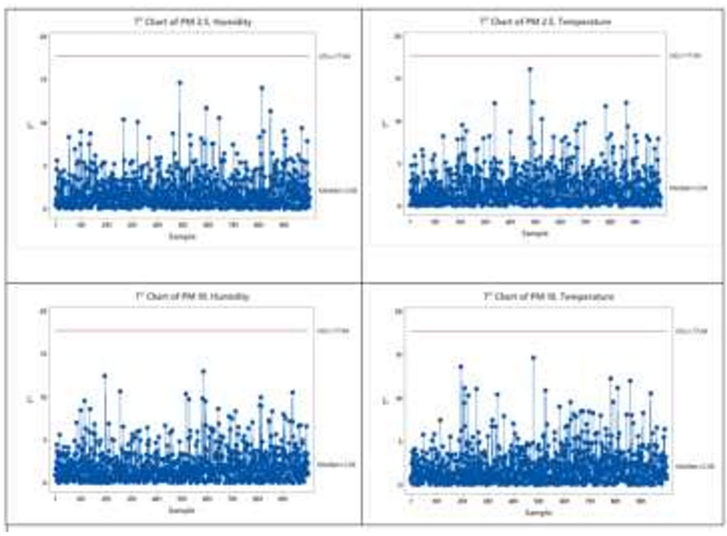

Fig. 4. Hotelling T^2 Control Chart for $PM_{2.5}$, PM_{10}, Humidity and Temperature

The Hotelling T^2 control chart in figure 4 shows the multivariate relationship between $PM_{2.5}$ concentrations and humidity levels. Each data point on the chart represents a sample, with the T^2 statistic showing how far the combined values of $PM_{2.5}$ and humidity deviate from the multivariate mean while taking correlation into account. The Upper Control Limit (UCL) sets at 17.64, where in this chart none of the data points exceed the line. It indicates that all observed variations fall within the acceptable range and the process is statistically in control. This demonstrates that the interaction between $PM_{2.5}$ and humidity remained consistent and did not exhibit abnormal behaviour throughout the data period. The median suggests that most of the samples are close to the average relationship between the two variables. While several peaks can be observed, these do not surpass the control limit, meaning no out-of-control behaviour. This suggests that even with visible fluctuations, the relationship stays within expected environmental variation. The right column on Figure displays the Hotelling T^2 control chart for monitoring the multivariate relationship between $PM_{2.5}$ and temperature. Although some samples show relatively high T^2 values, none exceed the UCL at 17.64. This implies that throughout the observation period, the interaction between $PM_{2.5}$ and temperature remained within statistically controlled limits. The chart demonstrates a stable process without any significant deviation.

Monitoring PM_{10} levels using control charts, especially using the Hotelling T^2 control chart, helps in identifying periods when particulate matter concentrations exceed acceptable limits [15]. The UCL in the chart indicates the threshold above which PM_{10} levels are considered problematic. The data show that PM_{10}, temperature, and humidity around Jakarta are in control since the data are between UCL and LCL. This suggests that the air pollution is within an acceptable range, indicating that the air quality is under control and within the expected limits. This range is considered normal and does not typically require immediate action. This approach not only ensures advanced pollution tracking but also helps detect subtle changes in the overall air quality system that may not be visible in univariate analysis.

4 Conclusions and Suggestions

This study applies statistical quality control (SQC) to assess indoor air pollution in South Jakarta by analysing key variables such as $PM_{2.5}$, PM_{10}, temperature, and humidity. The descriptive statistics reveal moderate but fluctuating pollution levels, with a notable increase during weekends, suggesting behavioural or activity-based influences on indoor air quality. The normality tests confirmed that all variables follow a normal distribution, validating the use of parametric control tools for further analysis. The correlation analysis highlights significant relationships between particulate matter and meteorological factors, particularly humidity and temperature, indicating that indoor pollutant behaviour is strongly influenced by environmental conditions. The use of Hotelling's T^2 control chart effectively demonstrated the multivariate control status of particular matter concentrations with environmental variables. All observations for $PM_{2.5}$ and PM_{10} paired with temperature and humidity remained within the Upper Control Limit (UCL), indicating that the indoor air quality process is currently stable and under statistical control.

To improve future monitoring, it is suggested that further studies incorporate longer observation periods and include outdoor air quality data for comparative analysis. Extending the observation period to capture seasonal variations and long-term trends, integrating real-time IoT sensors and control mechanisms may enhance data granularity and responsiveness. Developing predictive models using machine learning to anticipate pollution spikes and optimize mitigation strategies. Moreover, implementing targeted interventions during weekends, while pollution levels tend to rise, should be considered. Overall, this integrated statistical approach supports data-driven environmental monitoring and offers a replicable model for broader urban air quality assessment.

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