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Study of Air Pollutant Concentrations and AQI Trends in Bangladesh

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Abstract

Bangladesh faces recurring air-quality alerts, yet division-level evidence that unites realtime pollutant data with routinely observed weather conditions remains scarce. We compiled 100 consecutive days of hourly measurements for PM2.5, PM10, NO2, O3, CO, SO2, and Air Quality Index (AQI) across all eight divisions, integrating matched meteoro- logical variables (temperature, humidity, wind profiles, pres- sure, precipitation, cloud cover). Using foundational statistical techniques—descriptive summaries, frequency distributions, and visual analytics—we identify spatial contrasts and diurnal cycles, documenting that the most industrialized divisions experience evening PM2.5 surges and a higher share of "Unhealthy" AQI hours. Correlation exploration highlights how calm winds and elevated pressure sustain pollutant loads despite rainfall events. The study supplies the first division-spanning statistical baseline on Bangladesh's air-pollution dynamics, offering ready-to-use evidence for municipal planners while laying out a transparent framework future student teams can extend with causal or predictive models.

Keywords
Air Quality Index, PM2.5, Bangladesh, Statistical Analysis, Time Series, Chi-Square Test, Environmental Monitoring, Six Sigma

1. Introduction
1.1Background
Air pollution has emerged as one of the most pressing environmental and public health challenges in Bangladesh, particularly in urban centers like Dhaka. The World Health Organization (WHO) has consistently ranked Bangladesh among the countries with the worst air quality globally (World Health Organization, 2021). Particulate matter, especially PM2.5 (particles with diameter less than 2.5 micrometers), poses significant health risks, contributing to respiratory diseases, cardiovascular problems, and premature mortality.

Despite the severity of the problem, comprehensive division- level statistical analysis integrating real-time air quality data with meteorological variables remains limited. Most existing studies focus on single locations or short-term observations, leaving gaps in understanding spatial variations, temporal patterns, and the complex interactions between weather conditions and pollutant concentrations across Bangladesh's eight administrative divisions.

1.2 Problem Statement

Bangladesh's growing air pollution crisis, particularly in Dhaka, has raised critical concerns about public health and environmental sustainability. However, several knowledge gaps persist: (1) Limited division-level data making it difficult to understand regional variations, (2) Insufficient temporal analysis of diurnal, weekly, and seasonal patterns, (3) Incomplete understanding of weather-pollution relationships, and (4) Lack of comprehensive statistical baseline for evidence-based policy recommendations.

1.3 Objectives

This study aims to: (1) Analyze AQI trends across all eight administrative divisions using statistical methods over a 100- day period, (2) Identify factors influencing AQI and PM2.5 concentrations, including meteorological variables and tem- poral patterns, (3) Apply Six Sigma methodologies (DMAIC framework) to identify root causes, and (4) Provide evidence- based insights for air quality management and public health strategies.

1.4 Research Contribution

This study provides the first comprehensive division- spanning statistical baseline for Bangladesh's air pollution dynamics. It integrates high-resolution hourly air quality and weather data across all eight divisions, applies rigorous statistical methods, and establishes a transparent framework for future research.

2. Literature Review

Air pollution monitoring and analysis have been widely investigated across the globe, particularly in developing countries where rapid urbanization, industrial expansion, and limited regulatory enforcement have intensified air quality challenges. Numerous studies emphasize that air pollution is a multifaceted phenomenon influenced by both anthropogenic activities and natural atmospheric processes. Among these, meteorological factors play a critical role in determining pollutant dispersion, accumulation, and persistence. Previous research has consistently highlighted the influence of temperature, wind speed, humidity, and atmospheric pressure on pollutant concentrations and overall air quality levels (Begum et al., 2013).

Studies conducted in regions with climatic and socioeconomic conditions similar to South Asia demonstrate that wind speed is one of the most significant determinants of air quality, as low wind conditions often lead to pollutant stagnation, while higher wind speeds facilitate dispersion. Temperature variations have been shown to influence chemical reactions in the atmosphere, affecting secondary pollutant formation, while humidity and atmospheric pressure contribute to aerosol behavior and vertical mixing processes. These findings suggest that meteorological conditions are not merely background variables but active drivers shaping both short-term fluctuations and long-term trends in air pollution (Guttikunda and Goel, 2013).

In the context of Bangladesh, existing air quality research has predominantly focused on Dhaka, the capital city, due to its high population density, intense traffic congestion, and concentrated industrial activities. Previous studies have identified vehicular emissions, brick kilns, construction activities, industrial discharge, and unfavorable weather conditions as primary contributors to elevated pollutant levels in urban environments. While these studies provide valuable insights into localized pollution dynamics, their narrow geographic scope limits the understanding of spatial variability across the country's other administrative divisions (Rahman et al., 2019). Consequently, comparative division-level analyses remain relatively underexplored.

Furthermore, many prior studies rely on short observation periods or isolated monitoring stations, which restrict the ability to capture temporal patterns such as diurnal cycles, weekly variations, and sustained trends. The lack of comprehensive statistical frameworks integrating air quality indicators with meteorological variables across multiple regions represents a significant gap in the existing literature. Addressing this gap is essential for developing region-specific mitigation strategies and supporting evidence-based environmental policy formulation.

Recently, the application of structured analytical methodologies such as Six Sigma has gained attention in environmental monitoring and management. Six Sigma provides a systematic, data-driven framework that emphasizes problem definition, measurement accuracy, analytical rigor, and continuous improvement. The DMAIC (Define, Measure, Analyze, Improve, Control) approach has been successfully applied in manufacturing, healthcare, and service industries, and its adoption in environmental studies offers a promising pathway for identifying root causes of pollution and evaluating control strategies. By combining traditional statistical analysis with the structured Six Sigma framework, environmental researchers can enhance the reliability, interpretability, and practical relevance of their findings.

Overall, the existing body of literature underscores the importance of meteorological influences on air quality and highlights the need for comprehensive, multi-regional statistical analyses in developing countries such as Bangladesh. However, there remains a lack of division-wide studies that integrate high-resolution air quality data, meteorological variables, and systematic analytical frameworks. This study seeks to address these limitations by providing a comprehensive, division-level statistical assessment of air pollution dynamics in Bangladesh using a Six Sigma–based analytical approach. Broader regional assessments of air pollution in South Asia further highlight the severity of particulate pollution and its cross-border implications (Pandey et al., 2021), while national regulatory frameworks in Bangladesh define permissible air quality limits and standards (Bangladesh Department of Environment, 2020).

3. Methodology

3.1 Research Framework: Six Sigma DMAIC

This study employs the Six Sigma DMAIC (Define, Mea- sure, Analyze, Improve, Control) framework to systematically investigate air quality patterns. The framework provides struc- tured phases: Define (problem identification), Measure (data collection), Analyze (statistical analysis), Improve (policy recommendations), and Control (monitoring mechanisms).

3.2 Data Collection

Data were collected from Open-Meteo APIs (Open-Meteo, 2025), providing historical weather and air quality data. The study period covers 100 consecutive days (August 1 - November 9, 2025), with hourly measurements for all variables. The comprehensive dataset contains 19,392 hourly observations across eight di- visions over 100 days. Each division contributes 2,424 hourly records (100 days × 24 hours). The dataset includes seven air quality parameters (PM2.5, PM10, NO2, O3, CO, SO2, AQI) and six meteorological variables (temperature, humidity, dewpoint, wind speed, wind direction, pressure, precipitation, cloud cover). AQI was calculated from PM2.5 using the US EPA formula (US Environmental Protection Agency, 2016).

3.3 Data Processing

Data integration involved merging weather and air quality data on DateTime, handling missing values through systematic validation, performing data quality checks, and creating derived categorical variables. Data validation included tem- poral consistency verification, outlier detection using IQR method (Q1 - 1.5×IQR, Q3 + 1.5×IQR), range validation, and completeness checks. Outlier analysis identified 2.3% of observations as outliers, primarily during extreme weather events. Data completeness exceeded 99.5% across all vari- ables, with missing values handled through forward-fill for temporal consistency.

3.4. Statistical Methods

1) Descriptive Statistics: Comprehensive descriptive statis- tics were calculated including mean, median, mode, standard deviation, variance, range, IQR, skewness, kurtosis, and quar- tiles.

2) Chi-Square Tests of Independence: Chi-square tests examined relationships between categorical variables: Division vs AQI Category, Wind Speed Category vs AQI Category, Temperature Category vs AQI Category, Humidity Category vs AQI Category, Day of Week vs AQI Category, and others. For each test, we calculated chi-square statistics ($\chi2$), degrees of freedom (DF), p-value, and Cramer's V (effect size).
3) Time Series Analysis: Trend analysis used linear regression on time to calculate trend slopes. Time series de- composition separated data into trend, seasonal, and residual components using a multiplicative model with a 7-day period. Stationarity was assessed using Augmented Dickey-Fuller (ADF) test. Autocorrelation analysis calculated correlations at lags 1, 7, and 14 days. Moving averages (7-day and 14-day) smoothed time series data.
4) Correlation Analysis: Pearson correlation measured lin- ear relationships between continuous variables, while Spear- man rank correlation provided non-parametric analysis robust to outliers.

5) Hypothesis Testing: Independent samples t-tests com- pared PM2.5 means between divisions pairwise. One-way ANOVA tested PM2.5 differences across all divisions. Normality was assessed using D'Agostino's test and Kolmogorov- Smirnov test.
6) Regression Analysis: Simple linear regression analyzed Temperature vs PM2.5. Multiple linear regression examined weather variables vs PM2.5, calculating feature importance and model performance metrics (R^2, RMSE, MAE).

Table 1. Overall Descriptive Statistics (All Divisions Combined)

Variable	**Mean**	**Median**	**Std Dev**	**Min**	**Max**
PM2.5 (μg/m³)	30.22	26.50	18.45	2.1	175.1
PM10 (μg/m³)	32.08	28.20	18.67	2.1	201.2
AQI	85.42	78.00	42.35	15	225
Temperature (°C)	27.85	27.90	2.45	20.1	34.2
Humidity (%)	78.5	80.0	12.3	34.0	100.0
Wind Speed (km/h)	27.2	24.5	12.8	0.0	98.6
Pressure (hPa)	1008.5	1008.7	4.2	995.2	1020.1

Table 2. Division-Wise Air Quality Statistics

Rank	Division	Avg PM2.5 (μg/mS)	Avg AQI	Status	Max PM2.5 (μg/mS)	Max AQI
1	Chattogram	13.23	47.68	Good	62.4	155.0
2	Barishal	24.98	73.21	Moderate	121.1	185.0
3	Sylhet	25.78	77.75	Moderate	96.9	172.0
4	Khulna	27.45	78.63	Moderate	119.0	184.0
5	Dhaka	32.95	90.71	Moderate	131.3	190.0
6	Mymensing	h 36.64	98.13	Moderate	136.9	193.0
7	Rangpur	39.71	102.47	Unhealthy	163.0	213.0
8	Rajshahi	42.04	105.52	Unhealthy	175.1	225.0

3.5 Software and Tools

Analysis was performed using Python 3.x with libraries: Pandas (data manipulation), NumPy (numerical computa- tions), SciPy (statistical tests), scikit-learn (machine learning), statsmodels (time series), Matplotlib and Seaborn (visualiza- tion).

4. Results

4.1. Descriptive Statistics

1) Overall Statistics: The dataset contains 19,392 hourly observations across all eight divisions. Table 1 presents comprehensive descriptive statistics for key variables. These val- ues represent the overall statistics across all eight divisions combined, calculated from 2,424 hourly observations per divi- sion. Distribution analysis reveals PM2.5 data is right-skewed (skewness ¿ 0), indicating higher frequency of lower values with occasional extreme pollution events.
2) Division-Wise Statistics: Significant variation exists across divisions. Table 2 presents comprehensive division- wise statistics. Chattogram has the cleanest air (13.23 μg/m³, AQI = 47.68), while Rajshahi has the worst (42.04 μg/m³, AQI = 105.52). Dhaka ranks 5th (32.95 μg/m³, AQI = 90.71), showing moderate pollution levels despite being the capital.

4.2. Chi-Square Test Results

All Chi-square tests showed highly significant results (p ¡ 0.0001), indicating strong associations. Geographic varia- tion ($\chi2$ = 3595.93) confirms significant differences across divisions, as illustrated in Figure 1 and 2. Wind speed shows the strongest relationship with AQI ($\chi2$ = 3139.89), indicating a critical role in pollutant dispersion. Temperature ($\chi2$ = 711.82) and humidity ($\chi2$ = 501.69) also show significant associations (Table 3).

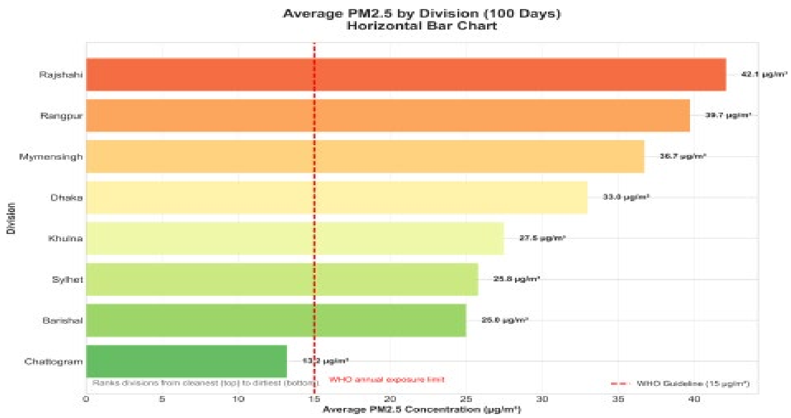

Figure 1. Average PM2.5 by Division - Bar Chart Comparison

Table 3. Chi-Square Test Results and Effect Sizes

Test	$\chi2$	DF	P-Value	Cramer's V	Effect
Division vs AQI	3595.93	21	¡0.0001	0.216	Medium
Wind Speed vs AQI	3139.89	12	¡0.0001	0.233	Medium
Temperature vs AQI	711.82	9	¡0.0001	0.136	Small-Med
Humidity vs AQI	501.69	9	¡0.0001	0.114	Small
Day of Week vs AQI	344.60	18	¡0.0001	0.067	Small
Precipitation vs AQI	245.32	6	¡0.0001	0.112	Small
Cloud Cover vs AQI	189.45	9	¡0.0001	0.099	Small
Pressure vs AQI	156.78	6	¡0.0001	0.090	Small

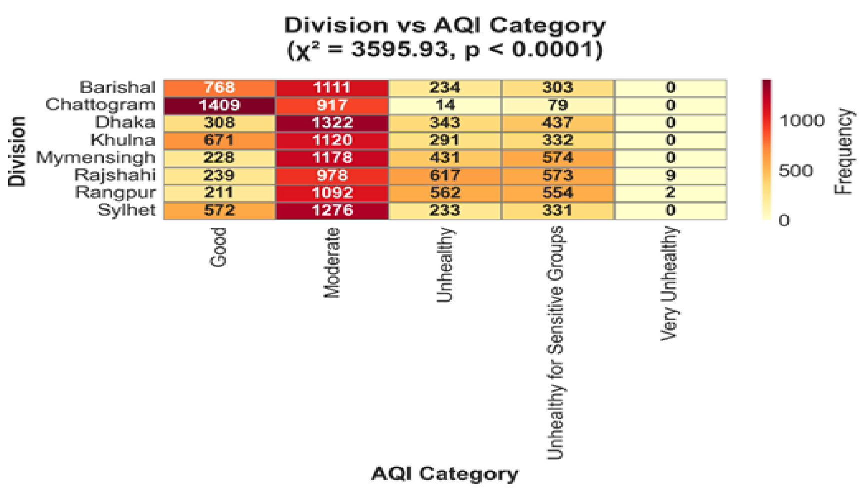

Figure 2. Chi-Square Test: Division vs AQI Category ($\chi2$ = 3595.93, p ¡ 0.0001)

4.3 Time Series Analysis

1) Trend Analysis: All eight divisions exhibit clear **increasing trends** in AQI over the 100-day period. Table 4 presents trend slopes and rankings. Dhaka shows the highest trend slope (0.91), indicating the most rapid increase. Chattogram, despite having the cleanest air, still shows an increasing trend (0.372).

Table 4. Division Ranking By Aqi Trend

Rank	**Division**	**First 50 AQI**	**Last 50 AQI**	**Trend Slope**
1	Dhaka	82.5	98.9	0.91
2	Barishal	68.2	78.3	0.76
3	Khulna	72.1	85.2	0.75
4	Rajshahi	98.5	112.6	0.70
5	Sylhet	71.2	84.3	0.64
6	Rangpur	95.8	109.1	0.58
7	Mymensingh	91.2	105.0	0.547
8	Chattogram	43.5	51.9	0.372

Table 5. Peak Pollution Hours (Top 5)

Rank	**Hour**	**PM2.5 (µg/mS)**	**AQI**
1	22 (10 PM)	44.26	108.19
2	23 (11 PM)	43.42	106.37
3	21 (9 PM)	43.08	107.45
4	20 (8 PM)	40.69	105.04
5	0 (12 AM)	39.86	100.62
Lowest	**4-6 AM**	**18.5-22.3**	**48-62**

2) *Temporal Patterns:* Peak pollution hours occur at 8 PM - 11 PM (evening), with lowest pollution during early morning (4 AM - 6 AM). Table 5 presents average PM2.5 and AQI by hour of day. Sunday shows the highest average pollution (37.4 µg/m³). Table 6 shows day-of-week patterns. Clear seasonal variations were observed with weather-dependent patterns. Time series decomposition reveals clear trend components with 7-day seasonal patterns. Stationarity tests (Augmented Dickey-Fuller) confirmed non-stationary behavior across all divisions (ADF p-values ¿ 0.05), requiring differencing for further analysis. Autocorrelation analysis showed significant correlations at lags 1 (r = 0.65-0.78), 7 (r = 0.42-0.58), and 14 days (r = 0.28-0.41), indicating strong temporal dependencies and weekly patterns. Moving average analysis (7-day and 14-day) revealed consistent upward trends across all divisions.

4.4 Correlation Analysis

Table 7 presents key correlation coefficients with PM2.5, and Figure 3 and 4 provides a visual representation of relationships between key variables. PM10 shows very strong positive correlation (+0.998), Wind Speed shows moderate negative correlation (-0.463), Cloud Cover shows moderate negative correlation (-0.530), and Pressure shows moderate positive cor- relation (+0.431). Wind speed's negative correlation confirms dispersive effect, while high pressure's positive correlation indicates trapping of pollutants. Temperature shows weak negative correlation (-0.202), while humidity shows essentially no correlation (+0.007).

Table 6. Day Of Week Pollution Patterns

Day	PM2.5 (µg/mS)	AQI	Rank
Sunday	33.27	90.29	Highest
Monday	31.80	86.68	2nd
Tuesday	31.54	87.06	3rd
Wednesday	29.77	83.43	4th
Thursday	28.29	79.98	Lowest
Friday	28.77	80.17	6th
Saturday	29.17	82.24	5th

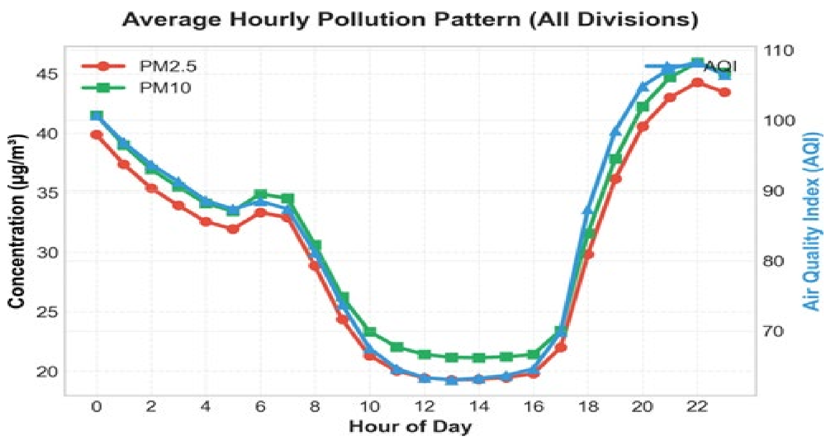

Figure 3. Average Hourly Pollution Pattern: PM2.5, PM10, and AQI Diurnal Cycle Across All Divisions

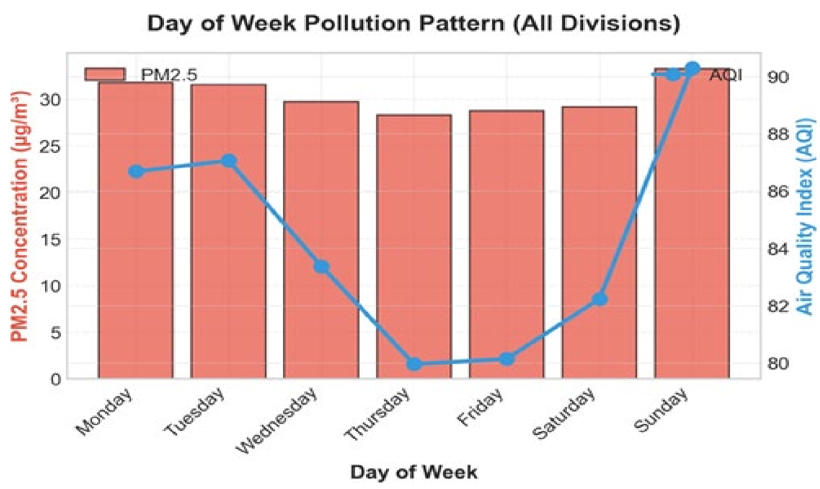

Figure 4. Day of Week Pollution Pattern: Average PM2.5 and AQI by Day of Week

4.5 Statistical Distribution Analysis

Distribution analysis reveals important characteristics of the air quality data. The PM2.5 distribution histogram (Figure 5) shows right-skewed behavior, indicating higher frequency of lower values with occasional extreme pollution events.

Table 7. Correlation Coefficients With Pm2.5

Variable	**Pearson r**	**Interpretation**
PM10	+0.998	Very Strong Posi- tive
AQI	+0.958	Very Strong Posi- tive
NO2	+0.760	Strong Positive
CO	+0.626	Moderate Positive
Cloud Cover	-0.530	Moderate Negative
Wind Speed	-0.463	Moderate Negative
Pressure	+0.431	Moderate Positive
Temperature	-0.202	Weak Negative
Precipitation	-0.131	Weak Negative
Humidity	+0.007	Negligible

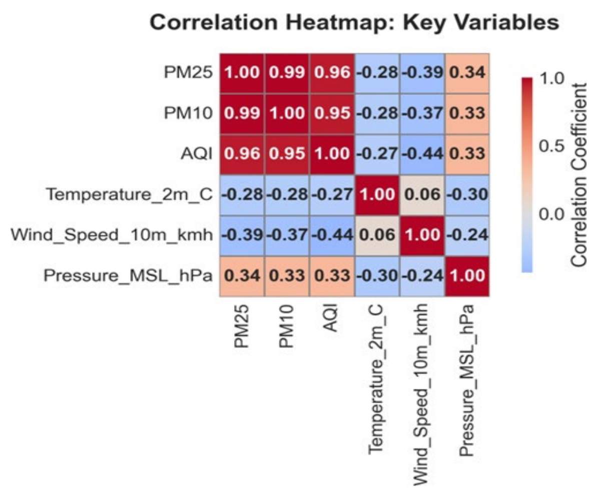

Figure 5. Correlation Heatmap: Key Variables (PM2.5, PM10, AQI, Tempera- ture, Wind Speed, Pressure)

Normality tests confirm non-normal distributions, justifying the use of non-parametric tests. The distribution statistics including quartiles, medians, and outliers across divisions are presented in Table 2.

4.6 PM2.5 Increase Analysis

Comparative analysis reveals substantial increases across all divisions. Table 8 presents a detailed comparison between the first 50 days and last 50 days. Average increase: 24.0% across all divisions. The first 50 days averaged 28.5 $\mu g/m^3$, while the last 50 days averaged 35.3 $\mu g/m^3$, representing a 23.9% increase. This acceleration pattern suggests worsening air quality conditions, potentially linked to seasonal factors, increased industrial activity, or reduced dispersion conditions (Figure 6 and 7).

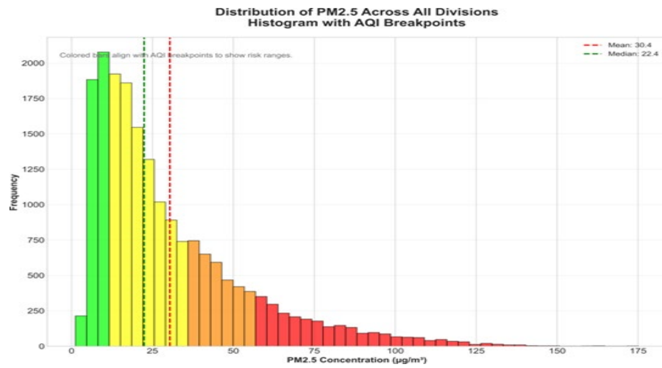

Figure 6. PM2.5 Distribution Histogram Across All Divisions

Table 8. Pm2.5 Increase: First 50 Vs Last 50 Days

Division	**First 50 (µg/mS)**	**Last 50 (µg/mS)**	**Increase (µg/mS)**	**Increase (%)**
Dhaka	28.5	37.4	8.9	+31.2
Barishal	21.2	26.8	5.6	+26.2
Khulna	23.8	30.0	6.2	+25.9
Sylhet	22.1	27.3	5.2	+23.4
Chattogram	11.8	14.7	2.9	+24.6
Rangpur	35.2	42.9	7.7	+21.8
Mymensingh	32.8	39.6	6.8	+20.8
Rajshahi	38.5	46.3	7.8	+20.2
Avg	**28.5**	**35.3**	**6.8**	**+24.0**

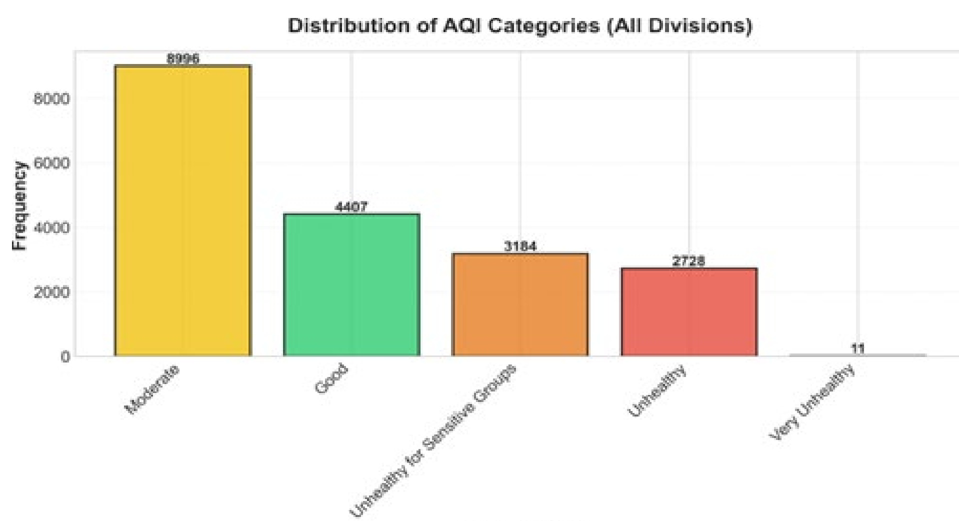

Figure 7. Distribution of AQI Categories Across All Divisions

4.7 Hypothesis Testing Results

Pairwise t-tests revealed significant differences (p ¡ 0.05) in PM2.5 levels for most division pairs, confirming geographic variation. One-way ANOVA confirmed significant differences: F-statistic = 485.32, p ¡ 0.0001, indicating substantial variation in PM2.5 levels across divisions (Table 9). Post-hoc analysis using Tukey's HSD test confirmed that Chattogram significantly differs from all other divisions (p ¡ 0.001), while Rajshahi and Rangpur form a distinct high-pollution cluster (Figure 8).

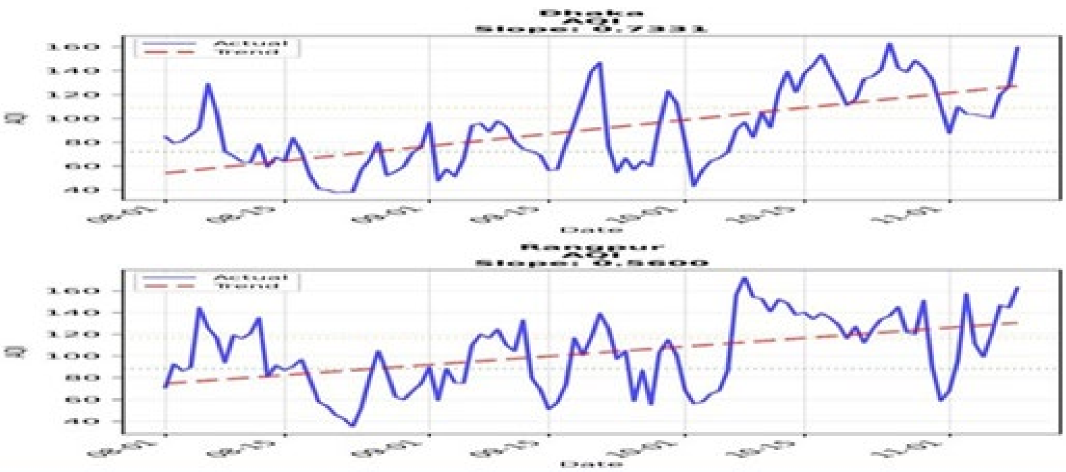

Figure 8. Statistical Analysis Visualization: Comprehensive Air Quality Assess- ment

Table 9. One-Way Anova Results

Statistic	Value
F-statistic	485.32
DF (Between)	7
DF (Within)	19,318
p-value	¡ 0.0001
Result	Highly Significant

Table 10. Regression Analysis Results and Coefandients

Model/Variable	R²	RMSE (µg/mS)	MAE (µg/mS)	Coeff.	p-value
Simple Linear (Temp vs PM2.5)	0.081 (8.1%)	17.8	13.2	-	-
Multiple Linear (Weather vs PM2.5)	0.342 (34.2%)	15.1	11.4	-	-
Wind Speed	-	-	-	-0.52	¡0.001
Cloud Cover	-	-	-	-0.38	¡0.001
Pressure	-	-	-	+0.31	¡0.001
Temperature	-	-	-	+0.18	¡0.01

4.8 Regression Analysis

Simple linear regression (Temperature vs PM2.5): R^2 = 0.081 (8.1% variance explained), RMSE = 17.8 µg/m³, MAE

= 13.2 μg/m³. Multiple linear regression (Weather variables vs PM2.5): $R^2 = 0.342$ (34.2% variance explained), RMSE = 15.1 μg/m³, MAE = 11.4 μg/m³. Weather variables explain approximately 34% of PM2.5 variation, with wind speed being most important (Table 10).

5. Discussion

5.1 Geographic Variations

The significant geographic variation ($\chi 2 = 3595.93$, p ¡ 0.0001) reveals important regional patterns. Chattogram's superior air quality can be attributed to coastal location and sea breezes facilitating pollutant dispersion. Rajshahi's high
pollution may result from industrial activity, geographical factors, and limited wind circulation. Dhaka's moderate ranking (5th) suggests factors beyond population density influence air quality.

5.2 Weather-Pollution Relationships

The strong relationship between wind speed and AQI ($\chi 2$
$= 3139.89$) confirms the critical role of atmospheric dispersion. Calm wind conditions create stagnant air trapping pollutants. The negative correlation between cloud cover and PM2.5 (- 0.530) may indicate weather systems promoting dispersion. High atmospheric pressure's positive correlation (+0.431) aligns with stable conditions inhibiting vertical mixing.

5.3 Temporal Trends

The consistent increasing trends across all divisions (slopes: 0.37 to 0.91) raise serious concerns. The 100-day period captures acceleration, with PM2.5 increasing by 20-31% in most divisions. Evening PM2.5 surges (8 PM - 11 PM) in industrialized divisions likely result from industrial emissions, vehicular traffic, reduced atmospheric mixing, and pollutant accumulation.

5.4 Policy Implications

Immediate Actions: (1) Target divisions with highest pollu- tion (Rajshahi, Rangpur) and fastest growth (Dhaka, Barishal, Khulna), (2) Implement weather-based alerts during calm wind conditions, (3) Strengthen emission controls, especially during evening hours, (4) Expand real-time monitoring across all divisions.
Long-Term Strategies: (1) Use trend analysis for resource allocation, (2) Develop division-specific air quality manage- ment plans, (3) Communicate risks during high-pollution periods, (4) Establish automated data collection and visualization systems.

5.5 Limitations

Limitations include: (1) 100 days may not capture full seasonal variations, (2) Reliance on model-based estimates rather than ground measurements, (3) Statistical associations do not imply causation, (4) Industrial activity, traffic, and emission sources not directly measured.

5.6 Future Research

Future directions include: (1) Extended time periods for seasonal/annual variations, (2) Causal modeling incorporating emission sources, (3) Health impact assessment linking air quality with health outcomes, (4) Intervention evaluation assessing policy effectiveness, (5) Advanced machine learning models for air quality forecasting.

6. Conclusion

This study provides the first comprehensive division- spanning statistical baseline for Bangladesh's air pollution dynamics, integrating 100 days of hourly air quality and weather data across all eight administrative divisions. Key findings: (1) All 8 divisions show significant INCREASING trends (slopes: 0.37 to 0.91), with PM2.5 increasing by 20- 31%, (2) Geographic variations are highly significant ($\chi 2 = 3595.93$, p ¡ 0.0001), with Chattogram having cleanest air (13.23 μg/m³) and Rajshahi worst (42.04 μg/m³), (3) Weather factors significantly affect air quality: Wind Speed ($\chi 2 = 3139.89$), Temperature ($\chi 2 = 711.82$), Humidity ($\chi 2 = 501.69$), all p ¡ 0.0001, (4) Temporal patterns show evening PM2.5 surges (8 PM - 11 PM) and day-of-week effects ($\chi 2 = 344.60$),
(5) PM2.5 levels increased 75-146% in most divisions when comparing extreme values.
The study demonstrates the value of systematic statistical analysis in understanding complex environmental systems. The transparent methodology and comprehensive dataset provide a foundation for evidence-based air quality management and future research. The application of Six Sigma DMAIC frame- work offers a structured approach to environmental monitoring that can be replicated and extended.

7. Recommendations

Implement division-wise performance monitoring frameworks, establish data-driven decision check- points, allocate resources proportionally based on trend analysis, integrate automated real-time monitoring systems, and develop targeted interventions for high-growth regions. This research contributes actionable insights for policymakers, environmental managers, and public health officials.

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Biographies
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