ISLAMIC UNIVERSITY OF TECHNOLOGY

DHAKA, BANGLADESH

ORGANIZATION OF ISLAMIC COOPERATION

TEMPORAL ANALYSIS OF AQI AND METEOROLOGICAL INFLUENCE ON AIR QUALITY IN GAZIPUR

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October 2025

TEMPORAL ANALYSIS OF AQI AND METEOROLOGICAL INFLUENCE ON AIR QUALITY IN GAZIPUR

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Submitted to the

DEPARTMENT OF CIVIL AND ENVIRONMENTAL ENGINEERING (CEE)

ISLAMIC UNIVERSITY OF TECHNOLOGY (IUT)

In partial fulfillment of the requirement for the award of the degree of

BACHELOR OF SCIENCE IN CIVIL ENGINEERING

October 2025

DECLARATION OF CANDIDATES

We hereby declare that the thesis work under the supervision of Dr. Amimul Ahsan entitled "Temporal Analysis of AQI And Meteorological Influence on Air Quality in Gazipur", has been performed by us and this work has not been submitted elsewhere for reward of any degree or diploma (except for publication).

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October 01,2025

ABSTRACT

This study explores the long-term trends of air quality and their relationship with meteorological conditions in Gazipur, Bangladesh, using data from the Department of Environment (DoE) collected between 2013 and 2024. The analysis focused on six key air pollutants — SO_2, NO_x, CO, O_3, $PM_{2.5}$, and PM_{10} — through exceedance evaluation, temporal trend analysis, and correlation with meteorological parameters. Among all pollutants, $PM_{2.5}$ was found to be the most critical, exceeding the WHO 2021 24-hour guideline (15 µg/m³) on about 89.92% of days and the national standard on 81.35% of days. The 12-year average $PM_{2.5}$ concentration was 94.43 µg/m³, with the highest monthly average of 220.88 µg/m³ in January and the lowest of 19 µg/m³ in July, showing strong seasonal variation. The annual average AQI ranged from 176 to 271, which corresponds to "Unhealthy" to "Very Unhealthy" conditions. Meteorological analysis for 2020–2024 revealed that wind speed ($r = -0.48$) and rainfall ($r = -0.42$) had the strongest negative relationships with $PM_{2.5}$, while temperature ($r = -0.19$) and relative humidity ($r = -0.27$) also contributed moderately. The combined influence of these factors explained about 58% ($R^2 = 0.58$) of the variation in $PM_{2.5}$ levels. Seasonal assessment showed that winter had the highest pollution levels due to low wind speed, temperature inversion, and minimal rainfall, whereas monsoon conditions helped to dilute and wash out pollutants. The results highlight Gazipur's ongoing air quality crisis, mainly driven by rapid industrialization, dense traffic, and unfavorable weather conditions. These findings underline the need for stronger emission control strategies, better urban air management, and the integration of meteorological forecasting in air pollution mitigation plans.

ACKNOWLEDGMENTS

We would like to express our deepest gratitude to the Almighty Allah, whose endless mercy and blessings have enabled us to successfully carry out this study and complete the preparation of our project and thesis.

The project/thesis entitled "Temporal Analysis of AQI and Meteorological Influence on Air Quality of Gazipur" has been carried out in partial fulfillment of the requirements for the degree of Bachelor of Science (B.Sc.) in Civil Engineering. This work has been made possible through the kind support and cooperation of many individuals to whom we are deeply grateful.

We express our sincere appreciation to our supervisor, Dr. Amimul Ahsan, Associate Professor, Department of Civil and Environmental Engineering (CEE), Islamic University of Technology (IUT), Bangladesh, for his patient guidance, valuable time, insightful suggestions, and continuous encouragement throughout the preparation and completion of this study.

We would also like to extend our heartfelt gratitude to the Department of Environment (DoE) for providing the air quality data and to the Bangladesh Meteorological Department (BMD) for providing essential meteorological data, which were fundamental to the successful execution of this research.

Finally, we express our heartfelt gratitude to the respected faculty members of the Department of Civil and Environmental Engineering (CEE), IUT, for their kind advice, valuable suggestions, and encouragement, which greatly contributed to the successful completion of this project/thesis.

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CHAPTER I

INTRODUCTION

1.1 Background

Air pollution is a major problem for the environment and public health all over the world. Cities are having more and more trouble meeting air quality standards because of rapid urbanization, industrial growth, and traffic emissions that keep getting worse (Kim, Kabir and Kabir 2015). Rapid economic growth has often come at the cost of deteriorating air quality, and urban centers in developing nations remain at the forefront of this crisis. Dhaka, the capital of Bangladesh, has been named one of the most polluted cities in the world time and time again. Levels of important pollutants often go above both national and international standards. Although numerous studies have focused on assessing the air quality of Dhaka city, insufficient attention has been given to the surrounding areas. These peri-urban and industrial areas are also going through a lot of urbanization and infrastructure growth, which makes their air quality just as important for a full environmental assessment and public health planning.

Particulate matter (PM) has become one of the most dangerous pollutants for people and the environment. PM is a complicated mix of solid particles and liquid droplets that are floating in the air. It is split into fine particles ($PM_{2.5}$, <2.5 µm) and coarse particles (PM_{10}, <10 µm) (Hou, et al. 2019), (Pope III , et al. 2002). They can come from two places: primary sources, like cars, brick kilns, burning biomass, road dust, and industrial processes, or secondary sources, like sulfate from SO_2 oxidation or nitrate from NO_x (USEPA 2022). In Dhaka, $PM_{2.5}$ makes up almost half of the PM_{10} load, which means it is the most dangerous air pollutant in terms of exposure and risk (Guttikunda, Begum and Wadud 2012).

There is a lot of evidence that being around high levels of PM can have a lot of bad effects on health. Fine and ultrafine particles can infiltrate the alveolar regions of the lungs and enter the bloodstream, resulting in chronic respiratory diseases, bronchitis, cardiovascular disease and potentially premature mortality (Dockery, Schwartz and Spengler 1992); (Pope III , et al. 2002). Epidemiological studies have demonstrated significant correlations between $PM_{2.5}$ exposure and lung cancer, ischemic heart disease, and stroke (Braga, Zanobetti and Schwartz 2002). In addition to harming health, particulate matter makes it harder to see, changes the climate in a region by trapping heat, and adds to the problem of localized warming (Ramanathan, et al. 2001)

This research designates Gazipur City as the principal area of emphasis. Over the years, Dhaka has consistently exhibited critically high levels of air pollution with severe winter peaks, while Gazipur, though historically less monitored, has shown a rapidly worsening trend driven by accelerated industrialization and urban expansion. Gazipur is undergoing rapid urbanization and industrial advancement, emerging as a developing urban center characterized by the swift expansion of built and industrial zones, while maintaining elements of its natural environment. An examination of land cover and land-use alterations from 1990 to 2020 demonstrated that Gazipur saw significant urban growth, leading to considerable reductions in wooded regions and aquatic systems, signifying environmental deterioration due to unregulated urbanization. (Arifeen, et al. 2021). Over the past two decades, urbanization in Gazipur has risen by over 44%, whilst forest cover has declined by about 21% and water bodies have reduced by approximately 6%. Over the past five years, urban expansion has surpassed 28%, leading to a reduction of around 26% in forest areas and 9% in aquatic bodies. (Akhi, et al. 2021)

This shift is driven by substantial industrialization and an increase in in-migration, especially from rural areas seeking work prospects. A geospatial analysis (2000–2020) indicates that the built-up area expanded by roughly 12%, while the population nearly doubled, reflecting vertical growth and increased population density; this development is propelled by economic opportunities, strategic connectivity to Dhaka, and low land prices (Das, Joye and Ahmed 2024). Collectively, these dynamics have contributed to a steady deterioration of air quality in Gazipur over the years, with rising pollutant concentrations (specially $PM_{2.5}$) posing increasing environmental and public health risks.

Meteorological parameters are crucial in affecting PM levels and their fluctuations. Wind speed and direction, ambient temperature, relative humidity, rainfall intensity and duration, solar radiation, and boundary layer height all work together to determine how pollutants spread, change chemically, and are removed (Pateraki, et al. 2012); (Leung, et al. 2018); (Liu, et al. 2019)). Despite their significance, the quantitative impact of meteorological variables on PM dynamics in Bangladesh is inadequately investigated, with most current studies focused solely on Dhaka city (Islam, et al. 2016).

In this situation, it is necessary to do a more thorough evaluation that includes both the city center of Dhaka, Gazipur and the areas around them. Monitoring pollutants like $PM_{2.5}$, PM_{10}, CO, SO_2, and O_3 not only helps us understand what makes up and how bad air pollution is, but it also lets us look at how these pollutants change over time and with the weather. The objective of this study is to assess the air quality in Gazipur city and its adjacent areas from 2013 to 2024, utilizing data gathered from strategically positioned air quality and meteorological monitoring stations. This is an important step for protecting public health, lowering environmental risks, and making sure that cities in one of the world's most crowded and polluted areas can grow in a way that is good for the long term.

1.2 Objective

1. To assess the long-term trends and variations in $PM_{2.5}$ concentrations and Air Quality Index (AQI) in Gazipur over the past 12 years (2013-2024)
2. To examine the annual & seasonal correlation between meteorological parameters (temperature, relative humidity, wind speed, rainfall, rain days) and $PM_{2.5}$ concentrations

1.3 Organization of Thesis

The thesis has been presented in five chapters.

Chapter One presents background and objective of the study.

Chapter Two presents a review of the present conditions of Gazipur air quality, role of PM on deteriorating the air quality, characteristics of PM, adverse effects of PM on health and environment, link between meteorology and PM, National Studies on PM in Bangladesh etc. and the existing literature gap.

Chapter Three describes the methodology followed in this research. It analyses yearly average (2013-2024) and daily average air quality data (2020–2024) from Continuous Air Monitoring Stations, focusing on $PM_{2.5}$, PM_{10}, and meteorological parameters through statistical testing, correlation, and regression to evaluate temporal and seasonal trends. Exceedance analysis against national and WHO standards, alongside multi-pollutant assessment (SO_2, NO_2, CO, O_3), was performed to comprehensively understand temporal variations and health-related risks.

Chapter Four presents the results derived from the analysis of air quality data collected during the mentioned time period. The observed patterns, statistical findings, and key insights obtained through the various analytical approaches applied in this study are thoroughly discussed here.

Finally, Chapter Five summarizes the major conclusions from the present research and presents recommendations for future study.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

This section reviews existing national-scale studies on air quality in Bangladesh, with a particular focus on particulate matter (PM) and other key pollutants. It highlights the findings from earlier works on sources, seasonal patterns, and transboundary contributions, while also examining methodological approaches. Finally, the section identifies limitations in the current body of research and outlines the gaps that necessitate further investigation.

2.2 Origin & Characteristics of PM

Particulate matter (PM) in the atmosphere originates from both natural and human-made sources. Natural contributors include soil dust, sea spray, pollen, volcanic emissions, and wildfires (Morakinyo et al., 2016). In contrast, anthropogenic sources include vehicle exhaust, industrial emissions, residential heating with solid fuels, and biomass burning(Hime et al., 2018). Although natural processes contribute a large fraction of PM mass globally, particles from human activities are considered more hazardous due to their smaller aerodynamic size and their tendency to remain concentrated in urban areas rather than being uniformly dispersed(Thangavel et al., 2022). Moreover, anthropogenic PM often contains heavy metals such as lead, nickel, and arsenic, along with carbonaceous material and sulphates, which have been strongly associated with respiratory and cardiovascular diseases.

2.3 Adverse Impact of PM

2.3.1 Impact of PM on human health

Exposure to particulate matter (PM), especially fine particles such as $PM_{2.5}$, poses significant risks to human health. In Dhaka, Bangladesh, time-series data show that every 10 µg/m³ increase in $PM_{2.5}$ concentration was associated with a 0.27% rise in cardiovascular emergency visits, a 0.32% increase in hospital admissions, and nearly a 0.87% increase in cardiovascular deaths(Rahman et al., 2021). Another hospital-based study in Dhaka reported that an interquartile increase in $PM_{2.5}$ (about 103 µg/m³) elevated cardiovascular emergency room visits by roughly 12%, with stronger effects among older adults and during winter (Khan et al., 2019). Similarly, extremely high concentrations of $PM_{2.5}$ and PM_{10} have been recorded in Khulna City, reaching levels more than six times higher than WHO guidelines, implying serious risks of respiratory illnesses and reduced lung function among residents (Saju et al., 2023)

Globally, $PM_{2.5}$ exposure has been strongly associated with respiratory diseases such as asthma and chronic obstructive pulmonary disease (COPD), as well as cardiovascular morbidity, lung cancer, and premature mortality (Cohen et al., 2017). The toxic effects are largely driven by fine particles' ability to penetrate deep into the lungs, enter the bloodstream, and deliver harmful compounds such as heavy metals and black carbon throughout the body.

2.3.2 Impact of PM on Environment

Particulate matter (especially fine $PM_{2.5}$) carries trace and potentially toxic elements which get deposited onto leaves; studies in Dhaka show that leaves of higher plants accumulate these elements, indicating soil and vegetation contamination (Jashim et al., 2024). The deposition of PM also reduces light penetration in plant canopies, lowering photosynthetic rates; for example, a study in Beijing found that plant communities with grass or shrub understories had higher $PM_{2.5}$ levels under the canopy than those with tree-shrub-grass mixes, showing that vegetation structure matters for PM reduction(Pan et al., 2024). In

Bangladesh's Khulna City, ambient PM concentrations ($PM_{2.5}$, PM_{10}) are multiple times above WHO guidelines, increasing dust deposition on buildings and vegetation, degrading surfaces and likely altering urban micro-climates(Saju et al., 2023). Also, acidification associated with $PM_{2.5}$, through wet deposition, slows down the breakdown of leaf litter in species such as willow, magnolia, and camphor trees, signalling disruption of nutrient cycling and ecosystem functioning(Wu & Zhang, 2018)

2.4 National & International Standards of Ambient Air Quality

The Bangladesh National Ambient Air Quality Standards (BNAAQS) were first introduced under the Environment Conservation Rules (ECR), 1997 and later revised in 2005 to regulate major air pollutants including particulate matter (PM_{10}, $PM_{2.5}$), Sulphur dioxide (SO_2), Nitrogen dioxide (NO_2), Carbon monoxide (CO), Ozone (O_3), and lead (Pb). These standards were established to protect public health and the environment by setting permissible limits for each pollutant in Bangladesh.

Table 2.1 : National Ambient Air Quality Standards (NAAQS) for Bangladesh

Pollutant	Objective	Average
CO	10 mg/m^3 (9 ppm)	8 hours(a)
	40 mg/m^3 (35 ppm)	1 hour(a)
Pb	0.5 µg/m^3	Annual
NO_x	100 µg/m^3 (0.053 ppm)	Annual
PM10	50 µg/m^3	Annual (b)
	150 µg/m^3	24 hours (c)
PM2.5	15 µg/m^3	Annual
	65 µg/m^3	24 hours
O_3	235 µg/m^3 (0.12 ppm)	1 hour (d)
	157 µg/m^3 (0.08 ppm)	8 hours
SO_2	80 µg/m^3 (0.03 ppm)	Annual
	365 µg/m^3 (0.14 ppm)	24 hours (a)

Notes:

(a) Not to be exceeded more than once per year 24 hours

(b) The objective is attained when the annual arithmetic mean is less than or equal to 50 µg/m3

(c) The objective is attained when the expected number of days per calendar year with a 24- hour average of 150 µg/m3 is equal to or less than 1

(d) The objective is attained when the expected number of days per calendar year with the maximum hourly average of 0.12 ppm is equal to or less than 1 (Source: AQMP, DOE).

The Air Quality Index (AQI) is a standardized tool used to communicate the level of air pollution and its potential health impacts. It categorizes air quality into six color-coded levels, ranging from "Good" to "Hazardous," making it easier for the public to understand pollution risks and take necessary precautions

Table 2.2 : Air quality index (AQI) in Bangladesh

AQI Value	Level of Health Concern	Colors
	English	
0-50	Good	Green
51-100	Moderate	Yellow
101-150	Unhealthy for Sensitive Group	Orange
151-200	Unhealthy	Red
201-300	Very Unhealthy	Purple
301+	Hazardous	Maroon

The World Health Organization (WHO) released the updated *Global Air Quality Guidelines* in September 2021 to provide evidence-based recommendations on safe exposure levels for major air pollutants, including $PM_{2.5}$, PM_{10}, O_3, NO_2, SO_2, and CO. These guideline values and interim targets aim to protect human health by encouraging countries to adopt stricter air quality standards in line with scientific evidence (WHO, 2021).

Table 2.3 : WHO recommended Air Quality Guideline levels & Interim Targets

(WHO global air quality guidelines. Particulate matter ($PM_{2.5}$ and PM_{10}), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide. Geneva: World Health Organization; 2021. Licence: CC BY-NC-SA 3.0 IGO.)

Pollutant	Averaging time	Interim target				AQG level
		1	2	3	4	
$PM_{2.5}$, µg/m³	Annual	35	25	15	10	5
	24-hour[a]	75	50	37.5	25	15
PM_{10}, µg/m³	Annual	70	50	30	20	15
	24-hour[a]	150	100	75	50	45
O_3, µg/m³	Peak season[b]	100	70	–	–	60
	8-hour[a]	160	120	–	–	100
NO_2, µg/m³	Annual	40	30	20	–	10
	24-hour[a]	120	50	–	–	25
SO_2, µg/m³	24-hour[a]	125	50	–	–	40
CO, mg/m³	24-hour[a]	7	–	–	–	4

[a] 99th percentile (i.e. 3–4 exceedance days per year).
[b] Average of daily maximum 8-hour mean O_3 concentration in the six consecutive months with the highest six-month running-average O_3 concentration.

2.5 Seasonal Variation of air pollutants

This section presents a detailed analysis of the seasonal variations of air pollutants ($PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3) in three major cities of Bangladesh—Chittagong, Dhaka, and Gazipur—which helps in understanding the past patterns of seasonal fluctuations in air quality-

2.5.1 Seasonal Variation of $PM_{2.5}$

In Chittagong, Hoque et al. (2022) found that $PM_{2.5}$ ranged from 14.6 µg/m³ in July to 93.5 µg/m³ in January, with an annual average of 53.8 µg/m³—over four times the national standard of 15 μg/m³. Elevated winter levels were linked to increased emissions from biomass and fossil fuel combustion, combined with unfavorable meteorological conditions (Hoque et al., 2020).

In Gazipur, $PM_{2.5}$ increased from October to a peak of 208 μg/m³ in January 2018 and then declined to 28 μg/m³ in July. The annual average of 94.43 μg/m³ exceeded the national standard by over six times, largely due to nearby brick kilns and winter emissions, as well as limited pollutant dispersion (Mukta et al., 2020). Over the past decade, dry-season $PM_{2.5}$ has consistently surpassed national standards, while rainy-season levels remain lower (Islam et al., 2015).

Similarly, in Dhaka, $PM_{2.5}$ rose steadily from October 2016, peaking at 183.87 μg/m³ in January 2017, and declined to 29.6 μg/m³ by June 2017 (Hoque et al., 2020).

2.5.2 Seasonal Variation of PM_{10}

In Chittagong, Hoque et al. (2022) analysed data from August 2017 to July 2018 and found an annual average of 111.43 μg/m³—over twice the national standard of 50 μg/m³—with a peak of 210 μg/m³ in January and a minimum of 26.9 μg/m³ in July.

In Gazipur, between October 2017 and September 2018, PM_{10} concentrations ranged from 50.79 μg/m³ in August to 300 μg/m³ in January 2018, with an average of 141.80 μg/m³, nearly three times the national standard. Elevated winter levels were attributed to emissions from diesel vehicles and nearby brick kilns (Mukta et al., 2020; Hoque et al., 2015).

Similarly, in Dhaka, during October 2016 to September 2017, PM_{10} increased from October, peaking at 303 μg/m³ in February 2017, and declined to 56.6 μg/m³ by June 2017 (Hoque et al., 2020).

2.5.3 Seasonal Variation of SO_2

In Chittagong, Hoque et al. (2022) analyzed data from August 2017 to July 2018 and found SO_2 levels peaked at 12.81 ppb during the 2018 monsoon, with the lowest concentration of 3.24 ppb in winter 2017.

In Gazipur, between August 2017 and July 2018, SO_2 increased during October–November and again from May to July, reaching a maximum of 15.9 ppb in July 2018 and a minimum of 1.40 ppb in December 2017. Values remained below the national standard, with seasonal differences attributed to motor vehicle, brick kiln, and industrial emissions (Mukta et al., 2020).

Similarly, in Dhaka, from October 2016 to September 2017, SO_2 rose from October, peaking at 37.1 ppb in February, and declined steadily through May. Dry-season concentrations (October–February) averaged 21.7 ppb, higher than the wet season (13.4 ppb), likely due to coal-fired brick kilns, lower temperatures, and atmospheric conditions that limit dispersion (Hoque et al., 2020).

2.5.4 Seasonal Variation of NO_2

In Chittagong, during August 2017–July 2018, NO_2 peaked at 63.90 ppb in the pre-monsoon season and reached a minimum of 24.38 ppb during the monsoon (Hoque et al., 2022).

In Gazipur, from October 2017 to September 2018**,** the highest NO_2 level (42.17 ppb) occurred in the winter (December–February), while the lowest (8.17 ppb) was recorded during the monsoon of 2018. These emissions primarily originate from fossil fuel combustion in vehicles, power plants, industrial boilers, and other equipment (Mukta et al., 2020; Kgabi & Sehloho, 2012).

Similarly, in Dhaka, during October 2016–September 2017, NO_2 peaked in November 2016 (81.5 ppb) and February 2017 (63.3 ppb), declining steadily thereafter to 12.6 ppb in June. Average winter concentrations (October–April) were nearly three times higher than summer values (May–September), likely due to increased coal combustion in nearby brick kilns (Hoque et al., 2020).

2.5.5 Seasonal Variation of O_3

In Chittagong, during August 2017–July 2018, O_3 concentrations peaked at 5.34 ppb in the post-monsoon season and were lowest (3.58 ppb) in the pre-monsoon, declining from March to August. Levels were up to eighteen times higher than the national standard (Hoque et al., 2022).

In Gazipur, from October 2017 to September 2018, O_3 peaked at 4.03 ppb in winter 2017 and fell to 1.53 ppb in August. Following the winter peak, concentrations declined to 2.92 ppb during the monsoon 2018. The national standard for O_3 is 17.81 times higher than the observed average annual concentration of 4.49 ppb (Mukta et al., 2020).

Similarly, in Dhaka, during October 2016–September 2017, O_3 rose at the onset of winter, peaking at 26.7 ppb in February, then declining to 1.53 ppb in August. Winter concentrations (October–February) were nearly four times higher than summer levels, likely due to air transport from northern brick kilns and a lower atmospheric boundary layer trapping pollutant (Hoque et al., 2020).

2.5.6 Seasonal Variation of CO

In Chittagong, during August 2017–July 2018, CO peaked at 1.26 ppm in winter and was lowest (0.60 ppm) in the pre-monsoon, influenced by industrial emissions, vehicular activity, and low wind speeds (Rouf et al., 2012). Levels remained well below the national annual standard (Hoque et al., 2022).

In Gazipur, from October 2017 to September 2018, CO reached 2.37 ppm in winter 2017 and declined to 0.73 ppm in monsoon 2018**,** reflecting emissions from industrial activity, high vehicle density, and meteorological factors such as lower wind speeds and atmospheric mixing height (Mukta et al., 2020).

Similarly, in Dhaka, during October 2016–September 2017, CO rose from October, peaking at 5.82 ppm in February, then declined to 0.85 ppm in August. Winter concentrations were more than twice the summer levels, highlighting strong seasonal fluctuations (Hoque et al., 2020).

2.6 Correlation among air pollutants

Several studies in Bangladesh have examined the relationships among key air pollutants. In Dhaka, during December 2021–January 2022, Pearson's correlation analysis showed a strong positive correlation between $PM_{2.5}$ and PM_{10} ($r = 0.74$, $p < 0.01$), and moderate positive correlations between NO_2 and CO ($r = 0.60$), NO_2 and $PM_{2.5}$ ($r = 0.60$), and NO_2 and PM_{10} ($r = 0.59$), all significant at $p < 0.05$. These results suggest that the pollutants share common sources such as vehicular emissions, industrial activities, and road dust (Hoque et al., 2025).

In Chittagong, from August 2017 to July 2018, $PM_{2.5}$ and PM_{10} were strongly correlated ($r = 0.822^{**}$, $p < 0.01$), with a regression equation of $PM_{10} = 2.125 \times PM_{2.5} + 3.017$ ($R^2 = 0.676$). In contrast, SO_2 showed moderate negative correlations with $PM_{2.5}$ ($r = –0.745^{*}$) and PM_{10} ($r = –0.735^{*}$), with regression equations $PM_{2.5} = –4.060 \times SO_2 + 84.21$ ($R^2 = 0.5551$) and $PM_{10} = –10.35 \times SO_2 + 196$ ($R^2 = 0.5404$), indicating differing source pathways or atmospheric behavior (Hoque et al., 2022).

Similarly, in Gazipur, $PM_{2.5}$ and PM_{10} exhibited a very strong linear relationship ($R^2 = 0.9802$), with the regression equation $PM_{2.5} = 0.9848 \times PM_{10} + 79.797$, suggesting common sources such as traffic and industrial emissions (Islam et al., 2023).

2.7 Relationship between Meteorological Parameters & $PM_{2.5}$

Several studies in Bangladesh have examined the influence of meteorological parameters on $PM_{2.5}$ concentrations. In Chittagong, during August 2017–July 2018, $PM_{2.5}$ exhibited a negative correlation with rainfall and temperature. Concentrations dropped significantly during the monsoon (June–September) due to heavy precipitation, while limited rainfall in winter (December–February) led to increased levels. Higher temperatures enhanced atmospheric turbulence and pollutant dispersion, reducing $PM_{2.5}$, whereas lower winter temperatures favored accumulation. PM_{10} showed similar seasonal trends (Hoque et al., 2022).

Across six major urban cities from 2013–2018, cross-correlation and multiple non-linear regression analyses revealed that wind speed had the strongest negative correlation with $PM_{2.5}$ and PM_{10}, aiding pollutant dispersion. Temperature generally showed a negative correlation due to increased boundary layer height, though positive correlations in vegetated areas like Sylhet and Chittagong were observed, likely due to enhanced NVOC emissions. Relative humidity, rainfall amount, and rainfall duration negatively influenced PM levels through wet deposition, with rainfall duration particularly effective in regions with consistent rainfall, such as Sylhet. Solar radiation showed a positive correlation with PM, especially PM_{10}, by enhancing secondary aerosol formation (Islam et al., 2023).

Seasonal analysis at the CAMS-4 station in Gazipur revealed that wind speed had the strongest negative correlation with $PM_{2.5}$ during the monsoon (–0.518), followed by winter (–0.480), post-monsoon (–0.400), and pre-monsoon (–0.376). Temperature was negatively correlated in winter (–0.191) but positively in monsoon (0.274), while relative humidity maintained a consistent negative correlation across all seasons. Rainfall duration had a stronger negative effect during the monsoon and post-monsoon (Islam et al., 2023).

Similarly, in Gazipur, during October 2017–September 2018, $PM_{2.5}$ concentrations increased during post-monsoon and winter due to limited rainfall, and decreased during pre-monsoon and monsoon due to wet deposition. Temperature also negatively correlated with $PM_{2.5}$, with higher temperatures promoting atmospheric mixing and lower winter temperatures favoring accumulation. PM_{10} followed the same seasonal pattern (Mukta et al., 2020).

2.8 Importance of Exploring link between PM & Meteorology

Particulate matter (PM) interacts closely with meteorological conditions, significantly influencing both air quality and climate. Two important PM components are sulfate aerosols (SO_2-derived) and black carbon (BC), which have contrasting impacts on atmospheric temperature. Sulfates are typically concentrated near the surface, where they scatter solar radiation and create localized cooling effects. In contrast, BC is more widely distributed in the atmosphere and absorbs solar radiation, contributing to atmospheric warming. The combination of scattering by sulfates and absorption by BC is referred to as direct radiative forcing (Hansen et al., 1997; Ramanathan et al., 2001).

Beyond direct effects, PM also influences cloud microphysics and precipitation. Higher PM levels increase cloud condensation nuclei, producing more but smaller droplets. This enhances cloud cover without increasing total water mass, reducing the likelihood of rainfall and reflecting more solar radiation back into space—a process termed first indirect radiative forcing**.** Additionally, smaller droplet sizes increase cloud lifetime and albedo, further cooling the climate, which is known as second indirect radiative forcing (Ramanathan et al., 2001).

Understanding how meteorological parameters modulate particulate matter (PM) levels is essential for both air quality management and climate resilience. A recent six-year (2013-2018) analysis across major Bangladeshi cities (Dhaka, Gazipur, Chittagong, Sylhet, Rajshahi, and Barishal) demonstrated that wind speed, temperature, relative humidity, rainfall, and rainfall duration significantly influence $PM_{2.5}$ and PM_{10} concentrations, with wind speed showing the strongest negative correlation.(Islam et al., 2023)

2.9 AQI Condition in Bangladesh

Majumder et al. (2023) analysed the air quality of six major districts in Bangladesh between 2014 and 2019, classifying AQI into six categories (A–F). The results showed significant seasonal variation, with the highest AQI levels recorded in winter (December–February) and the lowest during the monsoon (July–September). In Gazipur, for example, extremely unhealthy air (Class F) was dominant in winter (67%), while during monsoon, 43% and 40% of days fell under Good (Class A) and Moderate (Class B), respectively. Post-monsoon and pre-monsoon periods exhibited intermediate pollution levels. The variation is largely explained by particulate matter, which increases during dry months and is reduced by rainfall in the wet season. One-way ANOVA confirmed significant station-wise differences, with strong positive correlations between PM2.5 and AQI across all sites (R^2 ranging from 0.8173 in Chattogram to 0.9214 in Gazipur). Overall, AQI levels followed the seasonal order: Winter > Pre-Monsoon > Post-Monsoon > Monsoon. Narayanganj (77%), Gazipur (67%), and Dhaka (45%) recorded the highest proportions of extremely unhealthy air. In contrast, Sylhet (554 days) and Barisal (510 days) experienced the most Good AQI days, while Dhaka had the fewest (157 days).

2.10 24-hour Fluctuation of PM2.5 concentration

A study on 24-hour variations of PM2.5 in Gazipur and Mymensingh (Feb–Apr 2019) showed that concentrations steadily rose from morning to evening, with the lowest levels at 1:00 AM in both cities. Peak concentrations occurred at 1:00 PM in Gazipur and 7:00 PM in Mymensingh (Hasan et al., 2020).

2.11 National Air Quality Studies & Existing Literature Gaps

A considerable number of studies have been conducted to investigate particulate matter (PM) and air pollution trends in Bangladesh, with emphasis on major urban centers such as Dhaka, Chittagong, Rajshahi and Khulna. These works have established brick kilns, motor vehicles, industrial sources, and road dust as primary contributors to $PM_{2.5}$ and PM_{10} concentrations (B. Begum et al., 2014). Seasonal and transboundary influences on PM variability have also been highlighted, with studies showing elevated $PM_{2.5}$ during winter due to regional haze formation and temperature inversion effects that trap pollutants over northern India and Bangladesh (B. A. Begum et al., 2016). Variations in pollutant ratios (e.g., $PM_{2.5}/PM_{10}$ and $BC/PM_{2.5}$) further underscore the influence of meteorological conditions, particularly wind regimes and rainfall, on dispersion and accumulation of pollutants.

Most existing works, however, are concentrated on Dhaka and a handful of other major cities. For example, air quality monitoring at the US Embassy in Dhaka and in Chattogram has been used to investigate correlations between PM and meteorological parameters through linear regression and simple statistical analyses (Razib et al., 2020). Machine learning methods have also been applied to predict PM variability in Dhaka, Chittagong, Sylhet, and Rajshahi (Shahriar et al., 2020), while back-trajectory and conditional probability function analyses were conducted for multiple cities to assess long-range pollutant transport (M. Rana & Khan, 2020). Collectively, these studies confirm strong seasonal and spatial variation in PM levels across Bangladesh, yet they seldom extend to Gazipur in a systematic manner.

Only a few works explicitly included Gazipur in their assessments, such as short-term studies evaluating seasonal variation of $PM_{2.5}$ and gaseous pollutants (Mukta et al., 2020; Hasan et al., 2020). Other multi-city investigations that covered Dhaka, Gazipur, and Narayanganj examined pollutant correlations and wind trajectories (Rana et al., 2016), but these did not rigorously evaluate the role of meteorological parameters like wind speed, humidity, or rainfall in shaping long-term $PM_{2.5}$ variation. As a result, while Gazipur is consistently reported among the most polluted districts due to its concentration of brick kilns, textile factories, and heavy traffic flows, the literature on its air quality remains relatively sparse compared to Dhaka. Furthermore, most available studies rely on short monitoring periods (seasonal or annual), limiting the ability to detect multi-year trends or to disentangle emission-driven versus meteorologically-driven changes.

Therefore, the primary research gap lies in the lack of long-term, Gazipur-specific analyses that integrate both pollutant trends ($PM_{2.5}$ and AQI) and meteorological influences. Addressing this imbalance is critical because Gazipur, as one of Bangladesh's rapidly industrializing hubs, contributes significantly to national emissions and experiences some of the country's highest $PM_{2.5}$ levels. The present study is designed to fill this gap by conducting a multi-year trend analysis of $PM_{2.5}$ and AQI in Gazipur and examining the statistical relationships between $PM_{2.5}$ and key meteorological parameters**.** Such an approach will provide new insights into the drivers of air pollution in Gazipur and strengthen the evidence base for policy interventions aimed at improving local and national air quality.

CHAPTER III

METHODOLOGY

3.1 Introduction

This chapter presents an in-depth analysis process on yearly and monthly air quality data from 2013 to 2024 and daily air quality data from 2020 to 2024 obtained from Continuous Air Monitoring Stations in Gazipur. Key pollutants ($PM_{2.5}$, PM_{10}, SO_2, NO_x, CO, and O_3) along with meteorological parameters (temperature, humidity, rainfall, and wind speed) were analyzed. Statistical tests, correlation analysis, exceedance evaluation, and regression modeling were employed to examine temporal and seasonal variations, pollutant exceedances against national and WHO standards, and the influence of meteorology on air quality.

3.2 Site Description

3.2.1 Study Area

Gazipur is a significant district in central Bangladesh, situated in the Dhaka Division, and is acknowledged as a key industrial and residential center of the nation. The district encompasses 1,806.36 square kilometers, including 273.42 square kilometers of forested land. The 2022 Population Census reported that Gazipur's total population was 5,263,450, and the literacy rate was 81.42%. Geographically, it is bordered by Mymensingh and Kishoreganj to the north, Kishoreganj and Narsingdi to the east, Dhaka and Narayanganj to the south, and Dhaka and Tangail to the west. The district is administratively divided into five upazilas: Gazipur Sadar, Sreepur, Kapasia, Kaliganj, and Kaliakair, and encompasses three pourashavas: Kaliganj, Sreepur, and Kaliakair. Gazipur was designated a City Corporation in 2013, making it the largest in Bangladesh, indicative of the district's swift urbanization and its crucial significance in the national textile and garment sectors.

This study concentrates solely on Gazipur Sadar due to its rapid urbanization, industrial significance, and distinctive socio-economic dynamics, despite the national importance of Gazipur District as a whole. Gazipur Sadar covers an area of 141.19 square kilometers, situated between 23°53′ and 24°11′ north latitudes and 90°20′ and 92°30′ east longitudes. It is adjacent to Sreepur Upazila to the north, Savar and Rupganj Upazilas and Uttara Thana to the south, Kaliganj and Rupganj Upazilas to the east, and Kaliakair and Savar Upazilas to the west. The 2022 Population Census indicates that Gazipur Sadar has a total population of 345,801, consisting of 181,602 males, 164,158 females, and 41 hijra individuals, with a population density of 2,449 individuals per square kilometer. The annual population has changed 4% during the time period of 2011-2022 (Population & Housing Census 2022 2022). Its strategic proximity to the capital Dhaka, along with its high population density and significant concentration of textile industries, highlights its function as both an industrial hub and a residential extension of the Greater Dhaka metropolitan area.

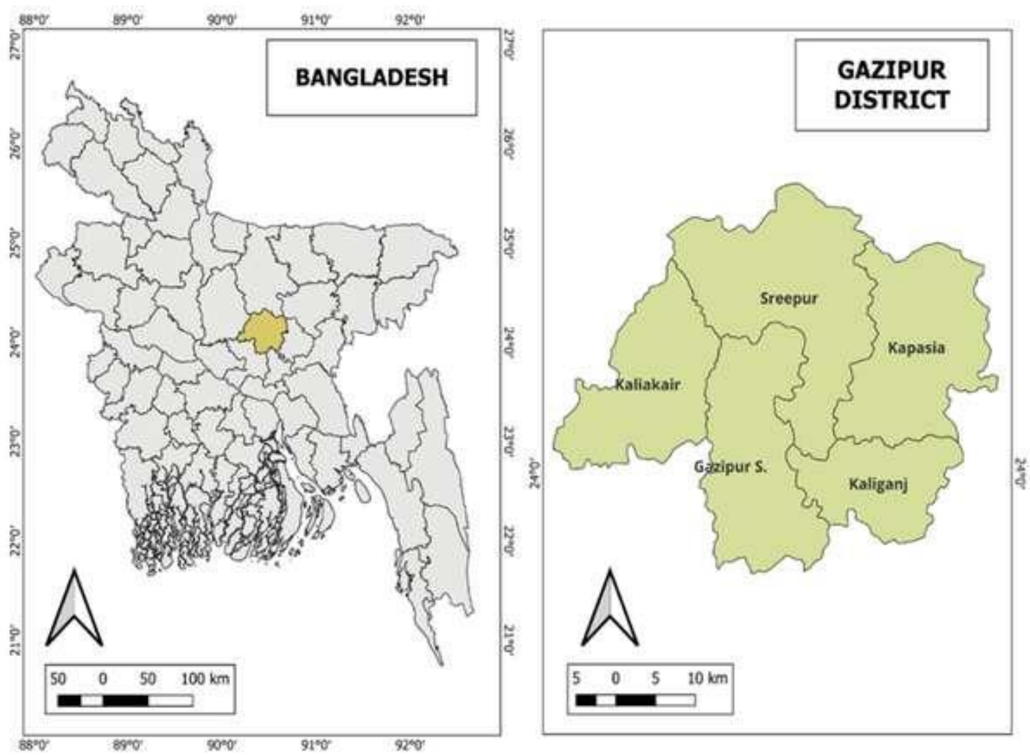


Figure 3.1 Map of Gazipur District

3.2.2 CAMS-4

The Department of Environment (DoE) in Bangladesh has instituted a nationwide air quality monitoring (AQM) network. Continuous surveillance of six criterion pollutants ($PM_{2.5}$, PM_{10}, SO_2, CO, NO_x, and O_3) is conducted by 31 Continuous Air Monitoring Stations (CAMS) and Compact Continuous Air Monitoring Stations (C-CAMS) situated in the divisional and industrial regions of the nation. CAMS-4 is a single station located at 23°.99’41.28” N, 90°.42’23.15” E in Gazipur. The CAMS is implemented in the Graveyard of the Gazipur City Corporation, which is located near East Chandana. The site is situated approximately 15 meters from a low-traffic road, 500 meters from a rail tract, and 4 kilometers from the Gazipur Chowrasta Intersection, a significant intersection for all vehicles traveling in the northern region (Rana, et al. 2016). In the vicinity, there are an estimated 100 illicit brick kilns, in addition to the 199 legal brick kilns (CCCA 2019). Furthermore, there is an ongoing initiative to construct a four-lane express highway in Gazipur city (Rahman and Lateh 2016). Consequently, moderate traffic emissions, large emissions from brick kilns, road dust re-suspension, and road construction are all significant sources of pollution in this region (Rana, et al. 2016).

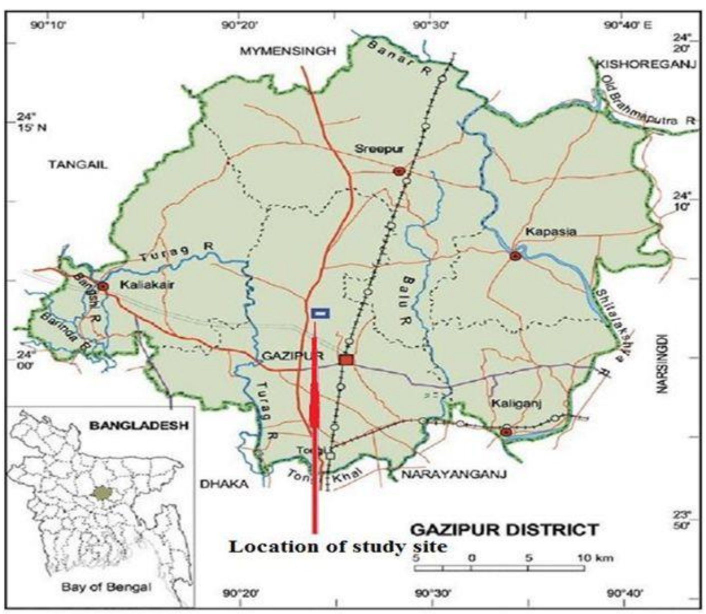


Figure 3.2 Map of the CAMS-4 in Gazipur city.

3.3 Data Collection

To guarantee accuracy and thorough coverage, data for this study on Gazipur's air quality were gathered from both domestic and foreign sources.

The Department of Environment (DoE), Bangladesh, which uses its Continuous Air Monitoring Stations (CAMS-4) to track air pollutants, provided the data on air quality. The main markers of ambient air quality, PM_{10}, $PM_{2.5}$, SO_2, NO_2, and O_3, are among the pollutants that are measured.

Meteorological parameters were gathered from the Bangladesh Meteorological Department (BMD) to supplement this dataset. BMD obtains its data from a variety of sources, such as radar systems, satellite imagery, and ground-based observational networks. These platforms collectively offer reliable and verified meteorological data that is crucial for analyzing air quality.

Secondary meteorological data were gathered from a number of well-known international weather databases in addition to these institutional sources. Utilized were data from three websites: Weather api, Weather & Climate, Time and Date, all of which incorporate sub-sources like NASA's Modern-Era Retrospective Analysis for Research and Applications (MERRA-2), the World Meteorological Organization (WMO), and weather satellite imagery. From 2013 to 2024, these sources provided long-term meteorological data on temperature, precipitation, wind speed, relative humidity, and precipitation days.

Additionally, information was obtained from World Weather Online for the daily meteorological datasets spanning 2020–2024. The World Meteorological Organization (WMO) datasets, global satellite imagery from both polar-orbiting and geostationary satellites, and outputs from the ECMWF (European Centre for Medium-Range Weather Forecasts) atmospheric model are among the reliable sources of meteorological data that are compiled on this platform. By combining these various datasets, the study's analytical framework is strengthened and daily atmospheric conditions are accurately represented.

3.4 Exceedance Analysis of Ambient Pollutants

In the initial stage of analysis, air quality data for six major pollutants—$PM_{2.5}$, PM_{10}, SO_2, NO_x, CO, and O_3—were examined against both the Bangladesh National Ambient Air Quality Standards (NAAQS) and the World Health Organization (WHO) guideline values. This process, also known as exceedance analysis, was used to assess how frequently observed pollutant concentrations exceeded the predetermined threshold limits. For each pollutant, the proportion of observations exceeding the respective standard value was calculated as:

$$\%Exceedence = \frac{N_{Exceed}}{N_{Total}} \times 100$$

where N_{exceed} represents the number of recorded instances where pollutant concentration exceeded the relevant guideline, and N_{total} denotes the total number of valid observations.

This assessment showed that $PM_{2.5}$ had the highest number of exceedances when compared to both national and international standards. As a result, $PM_{2.5}$ was found to be the most dangerous pollutant in Gazipur and was chosen for more in-depth study in later stages of this research.

3.5 Data Processing

There are a significant number of outliers and missing values in the raw hourly dataset of the chosen CAMS. To ensure accuracy, reliability, and consistency, a thorough pretreatment of the dataset was carried out before statistical analysis and modeling were started. Outliers and missing values are common in meteorological and air quality data, which can be caused by errors in the instruments, problems with data transmission, or environmental anomalies. These anomalies have the potential to significantly skew trend analysis, correlation, and regression modeling if left unchecked. Preprocessing was therefore divided into two main stages: (i) Identifying and removing outliers and (ii). Handling missing values.

3.5.1 Identifying and Removing Outliers

Outliers are extreme data points that deviate significantly from the general distribution of the dataset. Their presence can skew interpretations of pollutant–meteorology relationships by having an unfair effect on statistical measures like the mean, correlation coefficients, and regression slopes. To solve this problem, the Interquartile Range (IQR) method was used. This method is widely seen to be robust and non-parametric approach.

The process included calculating the first quartile (Q_1) and the third quartile (Q_3), which are the 25th and 75th percentiles of the dataset. The interquartile range (IQR) is the space between the first and third quartiles.

$$IQR = Q_3 - Q_1$$

Any observation x_i was marked as an outlier if it met the following condition:

$$x_i < Q_1 - 1.5 \times IQR \ or \ x_i > Q_3 + 1.5 \times IQR$$

We took out data points that met this criterion from the dataset. The reason for this method is that values above this threshold are not in the expected range of natural variability and are most likely due to mistakes or unusual events. By getting rid of these outliers, the dataset better reflected the real weather conditions in Gazipur.

3.5.2 Handling Missing Values

The presence of missing values can compromise the continuity of time series analysis and reduce the robustness of regression models. To address this issue, a combination of interpolation and extrapolation techniques was employed.

Interpolation was applied when missing data occurred between two valid observations. Linear interpolation was chosen for its simplicity and effectiveness in environmental data analysis. The missing value $x_{(t)}$ at time $t_{(t)}$ was estimated as:

$$x_{(t)} = x_{(t_0)} + \frac{(t - t_0)}{(t_1 - t_0)} \times (x(t_1) - x(t_0))$$

where $x_{(t_0)}$ and $x_{(t_1)}$ are the known values at times $t_{(0)}$ and $t_{(1)}$, respectively. This method assumes a linear transition between two known points and is suitable for filling short gaps without altering long-term variability.

Extrapolation was used in cases where missing values appeared at the boundaries of the dataset, at the start or end of the time series. In such cases, linear extrapolation was employed, given by:

$$x_{(t)} = x_{(t_n)} + (t - t_n) \times \frac{(x_{(t_n)} - x_{(t_{n-1})})}{(t_n - t_{n-1})}$$

where $x_{(t_n)}$ *and* $x_{(t_n-1)}$ represent the last two observed values in the series. This method extends the existing trend to estimate boundary values, ensuring continuity in the time series.

3.6 Data Calculation

The Air Quality Index (AQI) was used to figure out the air quality in Gazipur by measuring the amount of fine particulate matter ($PM_{2.5}$) in the air. The Air Quality Index (AQI) is a standardized indicator developed by governmental and environmental agencies to convey the current or forecasted level of air pollution and its associated health implications to the general public. It transforms complex pollutant concentration data into a single, easy-to-understand score, often supplemented by color coding, to facilitate risk communication. AQI values were calculated following the methodology adopted by the United States Environmental Protection Agency (USEPA 2022), which has also been widely applied in Bangladesh.

For each 24-hour average concentration of $PM_{2.5}$, the corresponding AQI value was determined by linear interpolation between the breakpoints defined by the EPA. The AQI was calculated using the following equation:

$$I_p = \frac{(I_{Hi} - I_{LO})}{(BP_{Hi} - BP_{Lo})}(BP_{L0}) + I_{LO}$$

`

Here, I_p is the index for pollutant p, C_p is the truncated concentration of pollutant p, BP_{HI} is the concentration breakpoint greater than or equal to C_p, BP_{LO} is the concentration breakpoint that is less than or equal to $C_{p,}$ I_{Hi} is the AQI value corresponding to BP_{HI}, I_{Lo} is the AQI value corresponding to BP_{L0}.

3.7 Data Visualization

Graphical studies were conducted to depict daily and long-term air quality trends in Gazipur. The data encompassed graphs of daily and monthly AQI values, illustrating short-term variations and overarching temporal averages. Monthly and Annual trend graphs were produced to illustrate the evolution of $PM_{2.5}$ concentrations across time, offering insights into long-term fluctuations in air quality. Graphs depicting seasonal variations of $PM_{2.5}$ revealed unique patterns during the pre-monsoon, monsoon, post-monsoon, and winter periods. These plots collectively provided a comprehensive overview of $PM_{2.5}$ dynamics and AQI fluctuations in the research area.

3.8 Data Analysis

3.8.1 Correlation Analysis

To better understand how air quality in Gazipur is influenced by weather conditions, Pearson's correlation analysis was applied between $PM_{2.5}$ concentrations and selected meteorological parameters (temperature, humidity, precipitation, and wind speed). This method quantifies the degree of linear association between two continuous variables, producing a coefficient (r) that ranges from –1 to +1, where positive values indicate a direct relationship and negative values indicate an inverse relationship. The coefficient was calculated using the following expression:

$$r = \frac{\sum(xi\text{-}\bar{x})(yi - \bar{y})}{\sqrt{\sum\ (x_{\text{i}}\ - x\bar{x})^2} * \sqrt{\sum\ (y_{\text{i}}\ - \ \bar{y})^2}}$$

Here, x_{i} and y_{i} denote paired observations of $PM_{2.5}$ and the meteorological variable under consideration, while $\bar{x}$ and $\bar{y}$ represent their respective mean values.

In addition to the standard correlation, the analysis was extended through the use of time-lagged correlation. This means that the meteorological variables were shifted forward by one or more days, and the correlation with $PM_{2.5}$ was recalculated. The reasoning behind this step is that weather conditions do not always affect pollution levels instantly. For instance, a change in wind speed or rainfall may influence pollutant concentrations with a delay, as it can take time for atmospheric dispersion or deposition to occur. By testing correlations with and without lag periods, the analysis was able to capture both immediate and delayed relationships, offering a more complete picture of how meteorology interacts with $PM_{2.5}$ in the study area.

3.8.2 Simple Linear Regression Analysis

To further explore the relationship between $PM_{2.5}$ concentrations and individual meteorological parameters, Simple Linear Regression (SLR) analysis was performed. Unlike correlation, which only quantifies the strength and direction of an association, regression analysis also provides a predictive model that expresses how changes in a meteorological factor influence variations in $PM_{2.5}$ levels.

The general form of the regression equation applied in this study is:

$$Y = \beta_0 + \beta_1 X + \epsilon$$

In this equation, Y represents the dependent variable, which in this case is the $PM_{2.5}$ concentration, while X denotes the independent variable, referring to a meteorological factor such as temperature, humidity, wind speed, or precipitation. The intercept of the regression line is represented by β_0, whereas β_1 indicates the slope coefficient, capturing the rate of change in $PM_{2.5}$ relative to variations in X. Finally, ϵ accounts for the error term, which represents the portion of variability in $PM_{2.5}$ not explained by the model.

In practice, this meant fitting a straight line through the observed data points to determine how strongly and in what direction each meteorological factor influenced $PM_{2.5}$. For example, a negative slope (β_1) would indicate that as the meteorological parameter increases (e.g., wind speed or rainfall), $PM_{2.5}$ concentrations tend to decrease due to greater dispersion or removal of particles. Conversely, a positive slope would suggest that rising values of a variable, such as temperature, may be linked with higher $PM_{2.5}$ levels under certain atmospheric conditions.

Model Evaluation

The performance of the regression model was evaluated using the coefficient of determination (R^2), which measures the proportion of variability in $PM_{2.5}$ explained by the meteorological factor. It is expressed as:

$$R^2 = \frac{Explained\ Variation\ (SSR)}{Total\ Variation\ (SST)} = 1 - \frac{SSE}{SST}$$

where SST is the total sum of squares, SSR is the regression sum of squares, and SSE is the residual sum of squares. An R^2 value closer to 1 indicates a stronger explanatory power of the independent variable.

Hypothesis Testing (ANOVA and t-test)

To determine whether the regression relationship was statistically meaningful, an Analysis of Variance (ANOVA) was performed. The test compared the variation explained by the regression model to the unexplained residual variation. The resulting F-statistic was calculated as:

$$F = \frac{MSR}{MSE} = \frac{\frac{SSR}{df_{reg}}}{\frac{SSE}{df_{res}}}$$

where MSR is the mean square regression and MSE is the mean square error. A large F-value with a very small significance level (p-value < 0.05) confirmed that the regression model was significant.

At the individual coefficient level, the t-test was used to check whether the slope coefficient β_1 differed significantly from zero. The t-statistic was calculated as:

$$t = \frac{\beta_1}{SE(\beta_1)}$$

where SE(β_1) is the standard error of the slope. The associated p-value indicated whether the predictor had a statistically significant effect on $PM_{2.5}$. Confidence intervals at the 95% level were also reported to provide a range within which the true coefficient value was expected to lie.

Visualization

To complement the statistical findings, regression outputs were visualized using scatter plots of $PM_{2.5}$ against each meteorological parameter, overlaid with fitted regression lines. The regression equation and corresponding R^2 value were displayed directly on the plots to provide an immediate interpretation of the strength and direction of the relationship. Residual distributions were also examined to check whether the assumptions of linear regression—such as linearity, independence, and homoscedasticity—were reasonably satisfied.

3.8.3 Multiple Linear Regression Analysis

While simple linear regression allowed the relationship between $PM_{2.5}$ and each meteorological parameter to be explored individually, it does not account for the fact that multiple factors may act simultaneously on air quality. To address this, Multiple Linear Regression (MLR) analysis was applied. This approach enables the combined effects of several meteorological parameters to be assessed within a single model, providing a more realistic representation of the atmospheric processes influencing $PM_{2.5}$ concentrations.

The general form of the MLR equation used in this study is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n + \epsilon$$

In this expression, Y denotes the dependent variable ($PM_{2.5}$ concentration), and $X_1, X_2, X_3, \ldots, X_n$ represent the independent variables corresponding to the different meteorological parameters, such as temperature, humidity, wind speed, and precipitation. The intercept of the regression line is represented by β_0 , while each coefficient β_i reflects the expected change in $PM_{2.5}$ associated with a one-unit change in the respective meteorological parameter, holding all other factors constant. The error term ϵ captures the unexplained variability not accounted for by the predictors.

Model Fit Statistics

The strength of the relationship between the predictors and $PM_{2.5}$ was first evaluated using correlation and determination coefficients. The multiple correlation coefficient (R) measures the overall strength of association between observed and predicted $PM_{2.5}$ values, and is given as:

$$R = \sqrt{\frac{Regression\ Sum\ of\ Squares(SSR)}{Total\ Sum\ of\ Squares(SST)}}$$

The coefficient of determination (R^2) shows the proportion of variation in $PM_{2.5}$ explained by the model:

$$R^2 = \frac{SSR}{SST}$$

To account for the number of predictors, the adjusted R^2 was also calculated:

$$R^2_{Adj} = 1 - \frac{(1 - R^2)(n - 1)}{n - k - 1}$$

Where n is the sample size and k is the number of predictors. This statistic is more reliable when comparing models with different numbers of explanatory variables.

ANOVA (Analysis of Variance)

To test whether the predictors collectively had a significant effect on $PM_{2.5}$, ANOVA was conducted. In this framework, the total variation in $PM_{2.5}$ (SST) was partitioned into explained variation (SSR) and unexplained variation (SSE):

SST=SSR+SSE

The F-statistic was then computed as:

$$F = \frac{MSR}{MSE} = \frac{SSR/k}{SSE/(n-k-1)}$$

where MSR is the mean square regression and MSE is the mean square error. A high F-value with a corresponding significance level (p-value) close to zero indicated that the regression model as a whole was statistically significant.

Residual Analysis

Finally, residuals (the differences between observed and predicted $PM_{2.5}$) were examined to evaluate model assumptions. Line fit plots compared predicted and observed $PM_{2.5}$ values for each predictor, while residual plots assessed whether the errors were randomly distributed without systematic patterns. This step confirmed the appropriateness and robustness of the regression model.

CHAPTER IV

RESULTS AND DISCUSSIONS

4.1 Introduction

The results begin with an exceedance analysis of pollutant concentrations against Bangladesh standards for 2013–2024, from which $PM_{2.5}$ was identified as the most critical pollutant. Based on this, monthly and yearly trend analyses of $PM_{2.5}$ and AQI were conducted for the same period. A more detailed investigation was then carried out for 2020–2024, including overall pollutant analysis, $PM_{2.5}$ exceedance against both Bangladesh and WHO guidelines, AQI exceedance assessment, seasonal variation, Pearson's correlation, and regression analyses (SLR and MLR).

4.2 Overview of long-term Air Quality and Meteorological Parameters Analysis (2013–2024)

4.2.1 Overall Pollutant Assessment

A summary of the annual averages of all considered pollutants (SO_2, NO_x, CO, O_3, $PM_{2.5}$, and PM_{10}) for Gazipur, calculated from the DoE CAMS-4 monitoring station (DoE, 2024) during the period of 2013–2024, is presented in Table 4.1.and graphical representation in Figure 4.1.

Table 4.1 : Annual Average Concentrations (µg/m³) of Major Air Pollutants in Gazipur (2013–2024)

Year	SO_2	NOx	CO	O_3	$PM_{2.5}$	PM_{10}
2013	8.27	26.9	1.52	14.21	84.53	134.79
2014	5.03	46.81	1.62	2.99	96.36	158.19
2015	11.35	16.46	1.59	4.79	87.54	149.38
2016	9.65	24.41	1.31	4.2	87.07	143.56
2017	36.97	42.15	2.69	7.71	92.33	144.74
2018	4.74	23.6	1.2	8.46	112.29	157.86
2019	5.56	38.87	2.02	7.8	103.23	162.11

2020	4.69	33.83	4.09	7.72	53.88	195.85
2021	3.65	20.51	10.78	4.82	100.43	247.33
2022	6.05	5.81	8.57	5.68	94.64	144.78
2023	10.78	4.57	6.46	17.57	98.69	172.51
2024	12.56	5.28	1.56	10.81	96.9	134.15

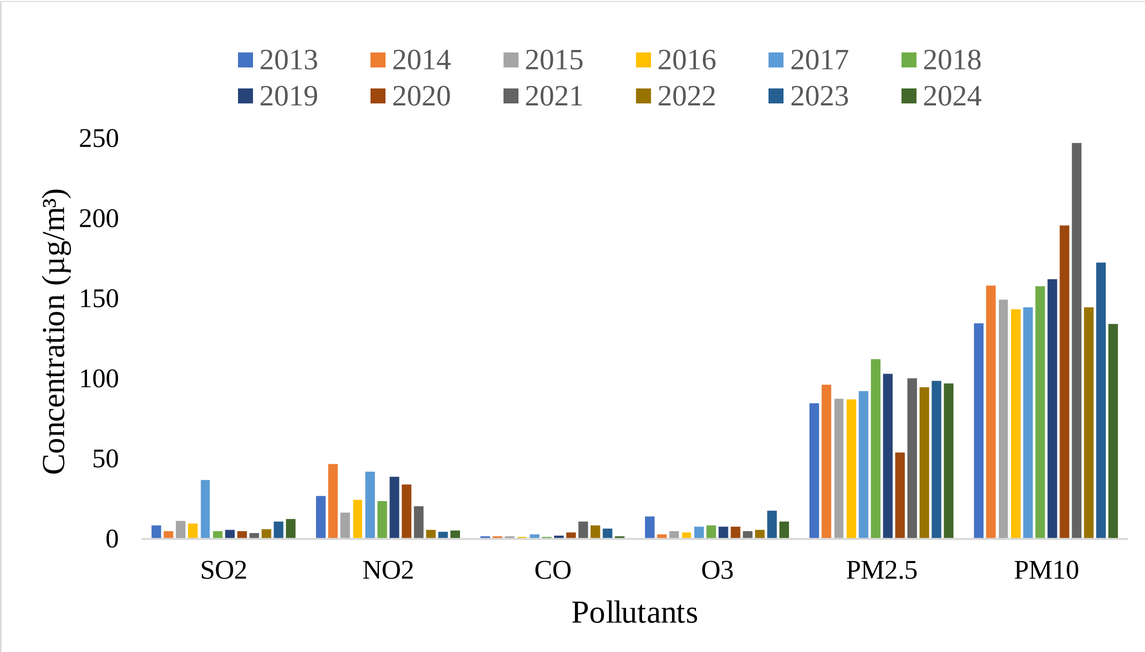


Figure 4.1 Yearly Average Concentrations(µg/m³) of Major Air Pollutants in Gazipur (2013–2024)

Figure 4.1 shows the yearly average amounts of SO_2, NO_2, CO, O_3, $PM_{2.5}$, and PM_{10} in Gazipur from 2013 to 2024. The results show that the air quality in the area is mostly affected by particulate pollutants, while gaseous pollutants are still present but not as much.

During the study period, SO_2 levels usually stay below 15 µg/m³, with slightly higher peaks in 2017 and 2024. The main sources of SO_2 in Gazipur are emissions from brick kilns and the burning of fossil fuels in factories. These sources are in line with the gas's occasional changes. NO_2 levels are more variable, with higher values from 2014 to 2016 and more moderate levels in the years that followed. Because Gazipur is a heavily industrialized area with a lot of traffic, these changes are probably caused by vehicle exhaust from rapid urbanization and industrial combustion processes.

CO is not a major pollutant in the area, as shown by the fact that CO levels are always low, usually below 6 µg/m³. This is because car exhaust and incomplete burning in brick kilns both add to the CO emissions. The amount of O_3 is also low, usually between 5 and 15 µg/m³. Even though there are precursors, the moderate amount of ozone in Gazipur suggests that photochemical smog formation is not as bad as particulate matter pollution. This is because ozone is a secondary pollutant that is made when NO_x and Volatile Organic Compounds (VOCs) react with each other.

On the other hand, the levels of $PM_{2.5}$ and PM_{10} are very high and always higher than both the Bangladesh National Ambient Air Quality Standards (BNAAQS) and the World Health Organization (WHO) guidelines. $PM_{2.5}$ levels are usually between 80 and 110 µg/m³, which is a lot higher than the WHO's yearly limit of 5 µg/m³. There is a big jump in 2018, which is in line with the rise in construction work, such as the building of the Dhaka–Gazipur Expressway and metro rail, as well as the growth of industrial operations. In Gazipur, $PM_{2.5}$ comes from things like road dust that gets stirred up again, emissions from factories, car exhaust, and brick kilns that are everywhere.

PM_{10} levels are even higher, ranging from 130 to 250 µg/m³. In 2021, when it went over 240 µg/m³, it was at its highest. This could be due to things like industrial growth, dust from unpaved roads, large-scale construction, and seasonal changes, like dust coming in from other countries. The prevalence of coarse particulate matter in Gazipur shows that both local and regional sources add to the PM_{10} burden.

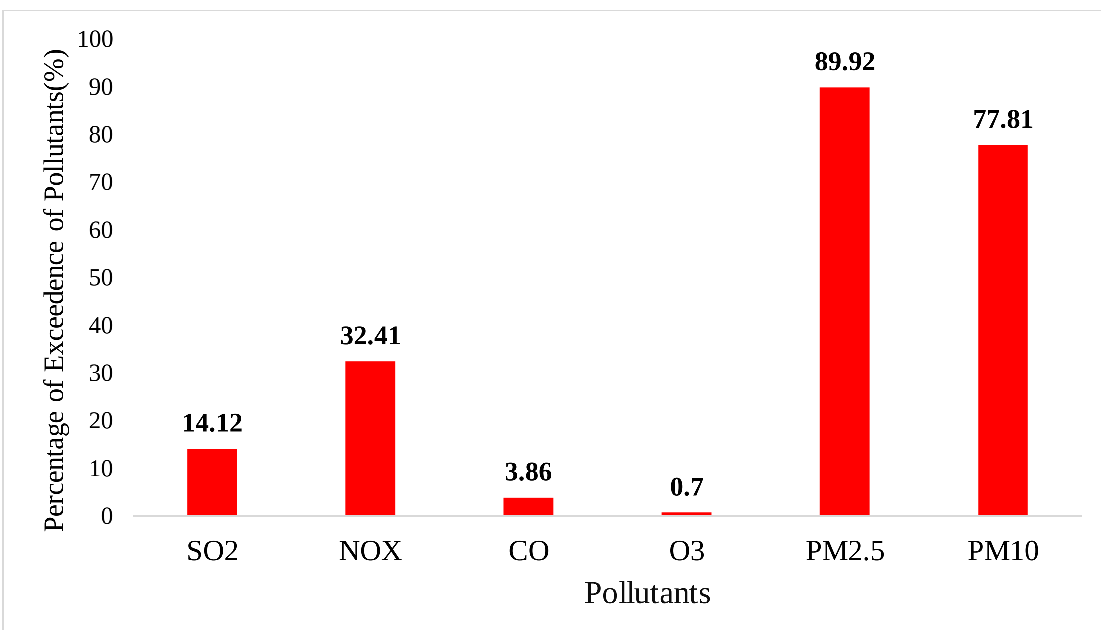


Figure 4.2: Exceedance Percentage of Pollutants (2013 to 2024)

For the period 2013–2024, an exceedance analysis (Appendix-1) of major air pollutants was conducted using daily monitoring data (Figure 4.2). The exceedance test was performed against the World Health Organization (WHO) Air Quality Guidelines (AQGs) of 2021, which provide threshold limits for both short-term (24-hour) averaging periods. These standards serve as critical benchmarks to evaluate the severity of air pollution and its potential impacts on public health.

The findings demonstrate that particulate matter ($PM_{2.5}$ and PM_{10}) was clearly the most significant pollutant in Gazipur during the analysis period. The pollutant $PM_{2.5}$ had an exceedance frequency of 89.92%, which means that on almost 9 out of every 10 days of monitoring, the levels were higher than what the WHO says is safe. This shows how much fine particulate matter pollution is in the area, which is especially worrying because $PM_{2.5}$ gets deep into the lungs and into the bloodstream, which can cause heart and lung diseases. PM_{10} also had a very high exceedance rate of 77.81%, which shows how common coarse particles are in the air. There are many sources of fine and coarse particulate matter in Gazipur. These include emissions from thousands of brick kilns, industrial activities, burning biomass, resuspended road dust, and ongoing construction projects like the expansion of highways and urban infrastructure.

NOx, on the other hand, was above the WHO limits on 32.41% of days. This shows that combustion-related sources like vehicles and burning industrial fuel are a big part of the problem. SO_2 went over the limit on 14.12% of the days, at much lower than particulate matter and NOx. Carbon monoxide (CO) exceedances were infrequent, occurring merely 4% of the time, indicating that CO pollution is less significant in Gazipur under present circumstances. Lastly, ozone (O_3) never went above the guideline levels during the whole study period. This means that photochemical smog and secondary ozone formation are not yet the biggest air quality problems in this area.

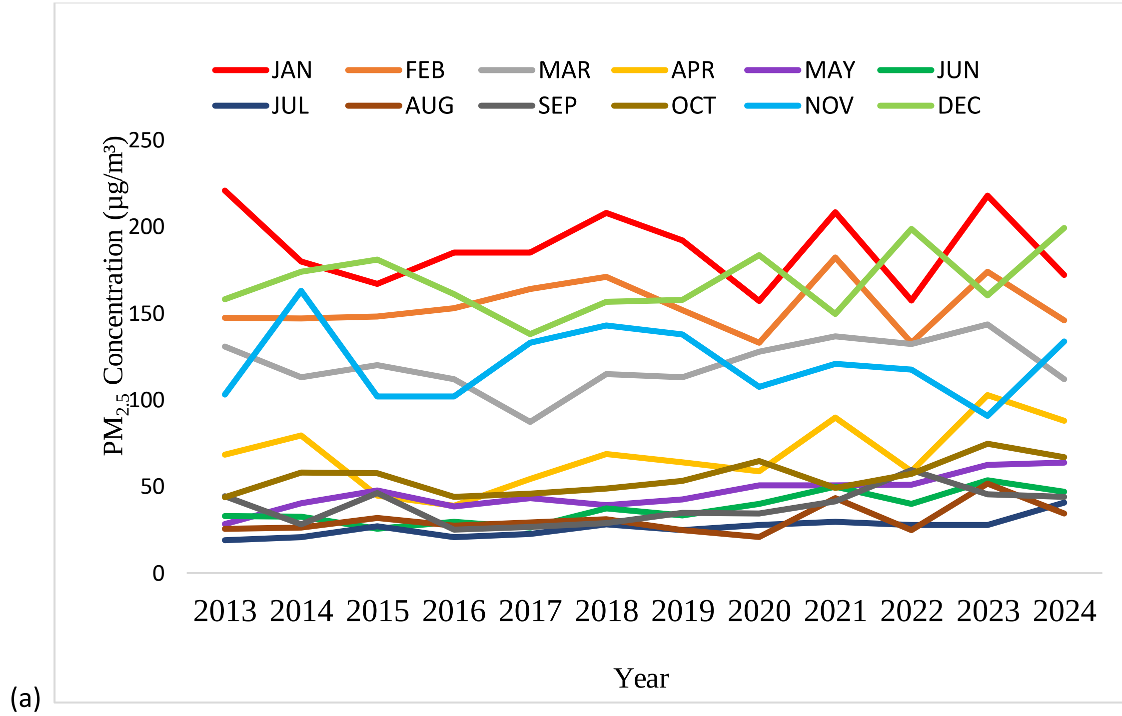
The exceedance analysis shows that the air pollution in Gazipur is mostly caused by particulate matter, with $PM_{2.5}$ being the worst pollutant. The very high exceedance rates for $PM_{2.5}$ and PM_{10} show that these pollutants often stay well above safe levels, which is bad for both people and the environment. Consequently, the research emphasized a more comprehensive examination of $PM_{2.5}$, concentrating on its long-term trends, seasonal fluctuations, and statistical correlations with meteorological variables. This choice is based on the fact that $PM_{2.5}$ not only has the highest exceedance percentage, but it is also the most harmful pollutant to health among those studied.

4.2.2 Temporal Trend Analysis of $PM_{2.5}$

After the yearly analysis of all pollutants was carried out, it was found that $PM_{2.5}$ consistently exhibited the highest levels of exceedance compared to both national and international standards. On this basis, $PM_{2.5}$ was identified as the most critical pollutant for further investigation. Consequently, $PM_{2.5}$ was selected for a more in-depth study to better understand its behavior across different timescales. In this extended analysis, monthly variations of $PM_{2.5}$ concentrations between 2013 and 2024 were examined with the objective was to identify seasonal patterns, inter-annual changes, and potential associations with meteorological conditions and anthropogenic activities, gaining a clearer understanding of how $PM_{2.5}$ pollution evolves over the course of the year was achieved, highlighting the periods of highest pollution that demand greater attention in air quality management. A summary of the annual averages of PM during the period of 2013–2024, the data of which is collected from DoE, is presented in Table 4.2.and graphical representation in Figure 4.3.

Table 4.2 : Monthly Variations of $PM_{2.5}$ Concentrations($\mu g/m^3$) in Gazipur (2013–2024) (DoE, 2024)

Month	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
JAN	220.88	180	167	185	185.25	208	192	157.151	208.41	157.5	218	172.1
FEB	147.35	147	148	153	164	171	152	133.048	182.26	133	173.9	145.9
MAR	130.77	113	120	112	87.3	115	113	127.878	136.91	132.3	143.6	112.1
APR	68.39	79.5	44.85	38.9	54.4	68.73	64	58.733	90.35	58.7	102.8	87.8
MAY	28.34	40.3	47.6	38.6	43.2	39.1	42.7	50.796	50.56	50.9	62.4	63.8
JUN	33	32.6	25.65	29.8	26.2	37.5	33.5	39.853	50.84	39.9	53.6	46.9
JUL	19	20.6	26.9	20.9	22.6	28	25	27.6365	29.5	27.6	27.6	40.7
AUG	25.5	26.2	31.8	27.5	29.17	31.13	24.96	20.88	43.19	25	51.7	34.4
SEP	44.4	28.1	46.2	25.1	26.7	29	34.73	34.46	41.53	59.5	45.6	44.1
OCT	43.8	58	57.7	44.2	46	49	53.13	64.56	49.29	57.5	74.7	66.8
NOV	103	163	102	102	133	143	137.76	107.58	121.02	117.7	90.8	133.9
DEC	158	174	181	161	138	156.74	157.85	183.62	149.626	198.7	160.2	199.3



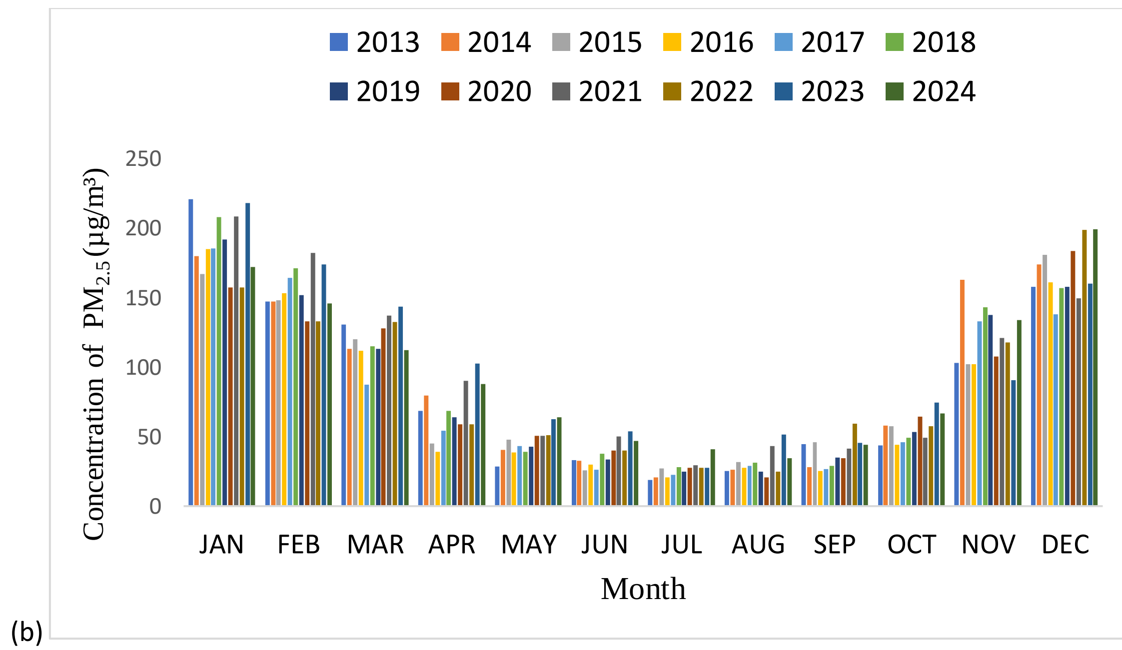


Figure 4.3(a): Year-wise Monthly Trends in $PM_{2.5}$ Concentrations (2013–2024) ;

(b): Month-wise Comparative Distribution of $PM_{2.5}$ Concentrations across Different Years (2013–2024)

The twelve-year period from 2013 to 2024 is shown in this line graph in Figure 4.3(a), which shows the monthly trends in $PM_{2.5}$ concentration. Each line shows how $PM_{2.5}$ levels changed over the course of a year in that month. There is a very clear seasonal pattern, with the highest concentrations always happening in the winter months (December, January, February, and to some extent November and March). January is the most polluted month, with levels often above 200 µg/m³ and sometimes even close to 220 µg/m³ (2013 and 2023). December and February also show high levels, usually between 150 and 200 µg/m³. This makes winter the worst time for pollution.

On the other hand, $PM_{2.5}$ levels are much lower in the summer and monsoon months (May to September). July and August are the months with the lowest concentrations, which are often below 30–40 µg/m³. This difference shows how seasonal weather affects pollution levels. For example, heavy rain and high humidity during the monsoon help wash away pollutants, while temperature inversions and calm winds in the winter cause pollutants to build up. April and October are transitional months, and their values are usually between 50 and 100 µg/m³. This shows the gradual change from clean to polluted seasonal regimes. The overall graph shows that $PM_{2.5}$ pollution is more common in the winter than in the summer, even though it changes from year to year.

This bar chart in Figure 4.3(b) goes along with the last graph by showing the $PM_{2.5}$ distribution for each month of each year. The figure also supports the seasonal cycle: $PM_{2.5}$ levels are always high in December, January, and February, with January often being the month with the highest levels. For instance, January 2013 had more than 220 µg/m³, and January 2023 had similarly high level, showing that winter pollution episodes last for a long time.

In contrast, the months of June, July, and August always have the lowest levels of $PM_{2.5}$, usually staying below 40 µg/m³ for all years. The months of May to September, when the summer monsoon is in full swing, show how rain and more mixing in the atmosphere can clean things up. October and November are interesting transition months. After the monsoon, concentrations start to rise a lot, which sets the stage for winter pollution events. In the same way, pollution levels start to go down slowly in March and April after the winter.

This figure shows not only the seasonal cycle but also changes from year to year by putting the yearly data for each month next to each other. $PM_{2.5}$ levels were much higher than usual in February 2021, but they were lower than usual in some summers (like 2015–2016). The graph shows that there are yearly changes, but the seasonal cycle is strong. The winter peaks and summer lows are a consistent and defining feature of $PM_{2.5}$ pollution in Gazipur from 2013 to 2024.

4.2.3 Temporal Trend Analysis of AQI

After identifying $PM_{2.5}$ as the most critical pollutant due to its consistently high exceedance levels, an extended analysis was carried out using the Air Quality Index (AQI) framework. The AQI is a standardized tool that translates pollutant concentrations into a single value, thereby providing a clear picture of air quality in terms of human health risks. By applying the USEPA methodology with the established breakpoints, the monthly $PM_{2.5}$ concentrations for the period 2013–2024 were converted into corresponding AQI values (Appendix-2). Table 4.3 and Table 4.4 presents the summary of annual average AQI for the years 2013–2024, while Figure 4.4 provides their graphical illustration.

Table 4.3 : Monthly Variations of AQI in Gazipur (2013–2024)

Month	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
JAN	271	230	217	235	235	258	242	208	258	208	268	222
FEB	198	198	199	203	214	221	202	191	232	191	224	198
MAR	190	181	184	180	167	182	181	188	193	191	196	180
APR	158	163	124	109	148	158	155	153	169	153	175	168
MAY	85	113	131	109	120	110	119	139	138	139	155	155
JUN	95	94	79	88	81	106	96	112	137	112	146	129
JUL	66	69	82	70	73	84	78	84	88	84	84	114
AUG	79	81	92	83	87	91	78	69	120	78	141	98
SEP	123	85	127	78	82	87	99	98	116	153	126	122
OCT	121	152	152	122	127	134	144	156	135	152	161	157
NOV	176	213	175	175	191	196	193	178	185	183	169	191
DEC	208	224	231	211	194	207	208	234	200	249	211	249

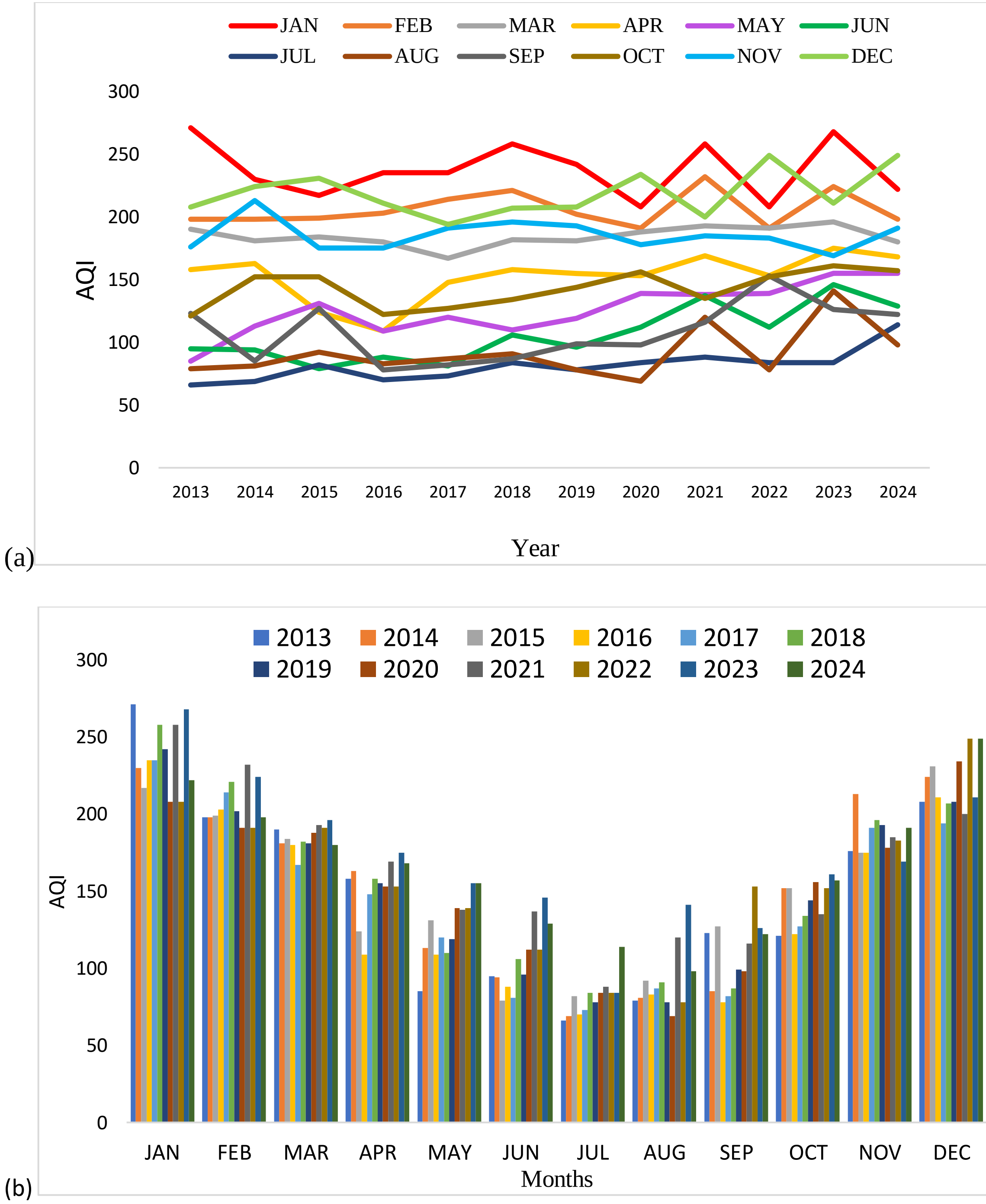


Figure 4.4(a): Year-wise Monthly Trends in AQI (2013–2024) ; (b): Month-wise Comparative Distribution of AQI across Different Years (2013–2024)

The line graph in Figure 4.4(a) shows that the AQI changes with the seasons from 2013 to 2024, with different levels of pollution severity in different months. The AQI values are always highest in the winter months (December, January, and February), and they often range from 200 to 300 or higher. This puts the air quality in the "Very Unhealthy" (201–300) or even "Hazardous" (301–500) range during some years, according to AQI breakpoints. Being exposed to these levels is dangerous for everyone's health, not just for sensitive groups like kids, old people, and people with pre-existing conditions.

The months of June, July, and August, on the other hand, always have the lowest AQI values, which are mostly between 50 and 100, which is the "Moderate" range. Values sometimes drop to around 50, which is the lower end of the "Good" range. This time of year, the air is much cleaner because it rains a lot and the atmosphere cleans itself. March, April, and October are examples of transitional months that usually fall into the "Unhealthy for Sensitive Groups" (101–150) to "Unhealthy" (151–200) categories, which means there is a moderate risk level.

There are also changes from year to year. For instance, the AQI values in January 2021 and 2023 are very high and close to the Hazardous range. In contrast, the AQI values in January 2014 and 2016 are lower but still Unhealthy to Very Unhealthy. These changes point to a mix of weather effects and rising emissions from human activities.

The bar chart in Figure 4.4(b) shows the AQI for each month over all the years, which makes it easier to compare the health risks of different times of the year. January is the most polluted month in almost every year. It consistently goes over 250, which puts it in the "Very Unhealthy" category and, in some cases, close to the "Hazardous" level. This means that the air in Gazipur during the winter is not safe to breathe outside and can have serious health effects on everyone. December and February have similar patterns, with values often between 200 and 250. This shows that the air quality is dangerous all winter long.

On the other hand, the AQI levels in June and July stay between 60 and 90, which is the "Moderate" level. Air pollution doesn't pose a big threat to the general public during these months, but some people who are very sensitive may still feel some effects. May and September are mostly in the "Unhealthy for Sensitive Groups" range. October and

November are transitional months, when AQI values quickly rise toward the Unhealthy (151–200) and Very Unhealthy levels. The bar chart also shows a long-term trend that is getting worse, which is important. December and January AQI values have been consistently higher in recent years, especially from 2022 to 2024. In some cases, they have even gotten close to the Hazardous range. This is because of more human activities, like construction, industrial work, and car emissions, as well as bad air flow in the winter.

Tables 4.3 and 4.4 present the annual average Air Quality Index (AQI) for Gazipur between 2013 and 2024, along with the corresponding health categories.

Table 4.4: Annual Average of AQI and Their Category in Gazipur (2013–2024)

Year	AQI	Category
2013	148	Unhealthy for Sensitive Groups
2014	151	Unhealthy
2015	149	Unhealthy for Sensitive Groups
2016	139	Unhealthy for Sensitive Groups
2017	143	Unhealthy for Sensitive Groups
2018	153	Unhealthy
2019	150	Unhealthy for Sensitive Groups
2020	151	Unhealthy
2021	164	Unhealthy
2022	158	Unhealthy
2023	171	Unhealthy
2024	165	Unhealthy

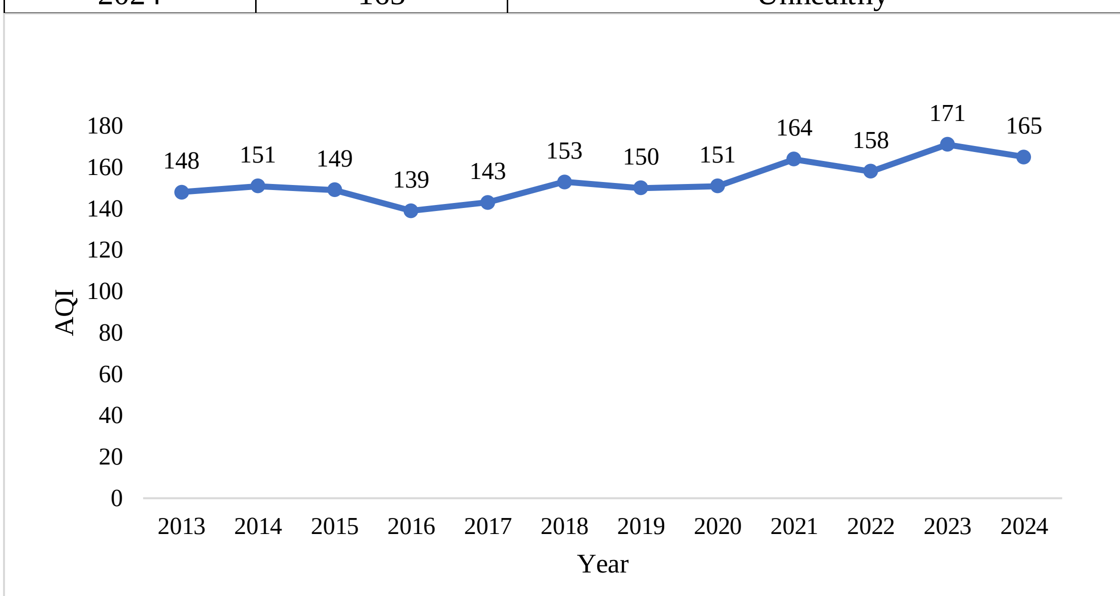


Figure 4.5 : Annual Average of AQI (2013-2024)

The line graph in Figure 4.5 shows that AQI values stayed high throughout the study period, from 139 in 2016 to 171 in 2023. The trend has some ups and downs, but it mostly goes up, especially after 2020, when AQI values went above 160 and peaked at 171 in 2023. This shows that the air quality has gotten worse in the last few years compared to the first part of the decade.

The table 4.4 shows the health risk groups that go with each AQI level. Most of the time from 2013 to 2017, AQI values were in the "Unhealthy for Sensitive Groups" range (101–150). This means that the general public was less affected, but groups that are more likely to get sick, like children, the elderly, and people with respiratory or cardiovascular diseases, were at a higher risk of getting sick. But the AQI values for some of these years (2013, 2014, 2015, and 2017) were very close to the limit of 151, which means they were on the edge of the "Unhealthy for Sensitive Groups" and "Unhealthy" categories.

Starting in 2018, Gazipur's AQI started to fall more and more into the "Unhealthy" range (151–200). This means that everyone was at risk for health problems, and sensitive groups were at even more risk. Long-term exposure at this level is linked to worse breathing problems, lower lung function, and a higher chance of making asthma or other long-term lung and heart problems worse. The years 2021 to 2024 are especially worrying because the AQI values stayed above 160, which means that air quality was getting worse over time. The fact that "Unhealthy" levels were more common in later years indicates that, in the absence of more stringent air quality management, the population will continue to experience progressively severe health consequences.

4.2.4 Meteorological Parameters

After conducting the $PM_{2.5}$ and AQI analyses, it was considered important to further investigate how these air quality indicators may relate to meteorological parameters. The Table 4.5 provides annual values of $PM_{2.5}$ that was derived from DoE, alongside key climatic variables including wind speed, temperature, relative humidity, rainfall, and number of rainy days.

Table 4.4 : Annual Average of $PM_{2.5}$ (µg/m³) and Meteorological Parameters in Gazipur (2013–2024) (DoE, 2024)

Year	$PM_{2.5}$ (µg/m³)	Wind speed(km/h)	Temperature(°c)	Relative Humidity	Rainfall(mm)	Rain Days
2013	85.2	11.12	25.75	77.33	6.25	142
2014	88.53	9.77	26.09	77.16	4.41	125
2015	92.82	10.75	26.19	76.21	8.3	166
2016	78.17	10.56	26.83	76.66	6.26	157
2017	82.71	10.74	26.48	76.14	9.26	173
2018	95	10.03	26.48	74.58	5.99	159
2019	83.3	12.48	26.58	70.59	6.1	148
2020	94.6	12.63	26.33	77.67	7.79	170
2021	89.8	7.97	26.25	78	6.62	147
2022	88.19	7.87	25.83	81.75	5.9	139
2023	100.41	10.01	26.5	77.92	6.8	118
2024	95.65	14.83	26.25	77.58	4.91	52

The meteorological data gives us some hints about what causes $PM_{2.5}$ fluctuations. For example, years with more rain and more rain days, like 2015 (8.3 mm and 166 rain days) and 2017 (9.26 mm and 173 rain days), have slightly lower $PM_{2.5}$ levels. This could mean that wet deposition has a cleaning effect. In contrast, 2024 had only 52 days of rain and 4.91 mm of rain, which is one of the higher $PM_{2.5}$ averages (95.65 µg/m³).

Wind speed seems to be important for how pollutants spread as well. Wind speeds were over 12 km/h in 2019–2020, which may have helped spread pollutants, even though $PM_{2.5}$ levels were still high, probably because there were strong local sources of pollution. On the other hand, in 2021–2022, wind speeds dropped below 8 km/h and pollutant levels stayed high, showing that the atmosphere doesn't mix as well during calmer years. The temperature and relative humidity also change a little from year to year, but their effects don't seem to be as direct as those of rain and wind speed.

Although precipitation and rainy days exhibit the most significant correlation with pollution reduction, variations in wind speed also affect pollutant dispersion. However, due to the small size of the dataset, these assumptions are only suggestive, not definitive. This recognition the intention to conduct a thorough investigation using data from 2020 to

2024, a period marked by more extensive records and significant variability in meteorological indicators.

4.3 In-Depth Air Quality Evaluation (2020–2024)

4.3.1 Major pollutants and AQI assessment

A thorough study of all major air pollutants was done from 2020 to 2024 in order to better understand trends in air quality and the health risks that come with them. Before going into a detailed analysis of each pollutant, an exceedance test was done as the first step. This test compared the recorded levels of pollutants (SO_2, NO_2, CO, O_3, PM_{10}, and $PM_{2.5}$) to the 2021 WHO Air Quality Guideline (AQG) standards. These are internationally accepted standards for measuring air quality. The goal of this step was to find out how often each pollutant went over the safe limits, which would help identify which pollutants were the most dangerous.

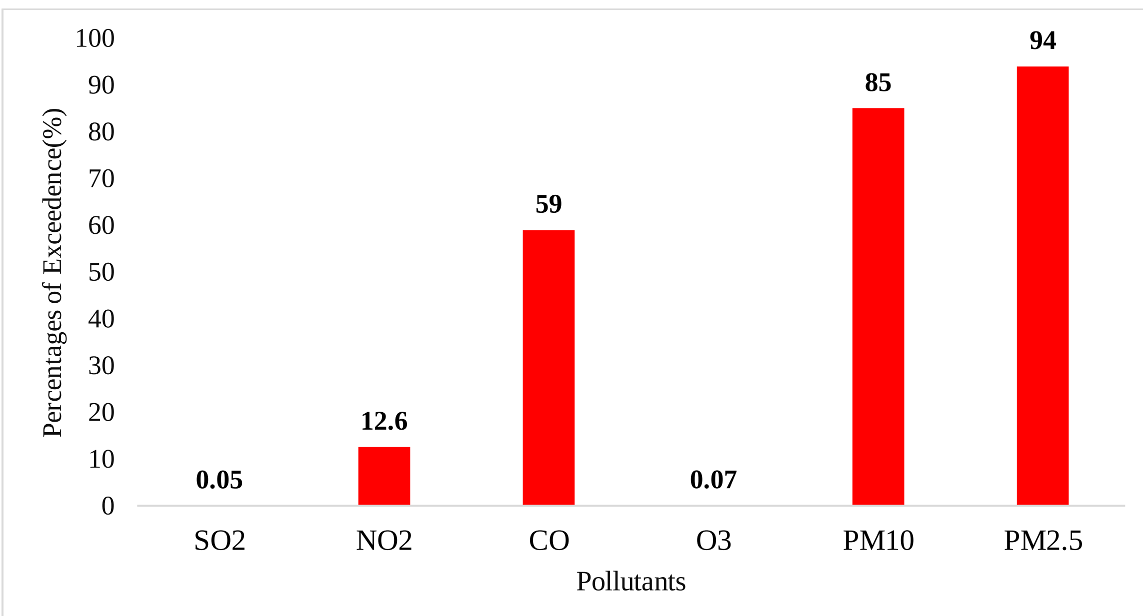


Figure 4.6 : Exceedance of Pollutants (2020-2024)

Figure 4.6 illustrates the results of this exceedance analysis. $PM_{2.5}$, a fine particulate matter that penetrates deep into the lungs and even enters the bloodstream, emerged as the most critical pollutant, with an exceedance rate of about 94%. This means nearly all of the observed concentrations were higher than the guideline value of 15 μg/m³ for the 24-hour average. $PM_{2.5}$ consistently showed the highest exceedance in both analyses, with 89.92% (2013–2024) and an even higher 94% (2020–2024). This indicates that fine particulate matter pollution has not only remained severe but has also intensified in recent years. This trend especially concerning as $PM_{2.5}$ links to cardiovascular, respiratory, and long-term health risks.

PM_{10} also showed a very high exceedance rate of 85%, reflecting widespread levels above the AQG value of 45 μg/m³ (24-hour average). While PM_{10} particles are larger than $PM_{2.5}$, they still affect human health, primarily by irritating the respiratory tract and aggravating lung conditions. PM_{10} also exhibited very high exceedance levels in previous long-term analysis (2013-2024), with 77.81%. The combined high exceedance of $PM_{2.5}$ and PM_{10} shows that particulate matter pollution is the main problem with air quality and makes it the hardest to meet air quality standards.

Nitrogen Dioxide (NO_2), a key traffic-related pollutant, exceeded the guideline about 12.6% of the time. Between 2013 and 2024, nitrogen oxides (NO_x) exceeded standards 32.41% of the time, compared to just 12.6% between 2020 and 2024. This decline implies that NO_x levels may have decreased recently, perhaps as a result of improved combustion efficiency or more stringent vehicle emission standards. However, despite this decrease, NO_2 still presents a risk of exacerbating asthma and irritating the lungs, particularly in areas with high traffic.

Sulfur Dioxide (SO_2) showed an extremely low exceedance rate of only 0.5%. Between 2013–2024, SO_2 exceeded the guideline value about 14.12% of the time, suggesting that it was once a moderately concerning pollutant in the region. However, during the more recent period of 2020–2024, this rate dropped sharply to just 0.5%, indicating that SO_2 pollution has largely come under control. The near elimination of exceedance in recent years suggests that SO_2 is no longer a major pollutant of concern in Gazipur. There could be a number of reasons for this big drop. For instance, stricter environmental rules and more use of cleaner alternatives in industries and brick kilns may have led to a gradual shift away from high-sulfur fuels. Such changes, along with desulfurization techniques in industrial plants and better fuel quality standards, may have helped lower SO_2 emissions.

A significant difference in Carbon Monoxide (CO) levels existed between the two time periods. During the extended timeframe of 2013 to 2024, the exceedance rate was comparatively modest at 4%, but it surged to 59% from 2020 to 2024. This rise may have been caused by Gazipur's rapid urbanization and industrial growth in the last few years, along with more traffic congestion. Also, lower wind speeds and fewer rainy days in recent years would have made it harder for the atmosphere to spread out, which would have let CO build up at higher levels. The big difference between the two periods shows that while other pollutants like SO_2 have gotten better because of control measures, CO has become a new and important pollutant that needs specific ways to be reduced. The increasing exceedance rate of CO, which impairs the blood's capacity to transport oxygen, presents significant short-term health hazards, including headaches, dizziness, and cardiovascular strain.

The WHO 2021 AQG limit for ozone (O_3) concentrations was never exceeded during the study period, which means that the levels stayed within the limit. This means that ground-level ozone pollution is not a big problem in the area right now. Ozone, on the other hand, is a secondary pollutant that comes from photochemical reactions between NO_x and VOCs. Its levels can change depending on the weather. Although it is not a concern in this dataset, monitoring should continue to identify potential future risks, particularly during warmer months.

Following the pollutant exceedance analysis, Air Quality Index (AQI) categorization was carried out based on $PM_{2.5}$ concentrations for the period 2020–2024. The results, presented in Figure 4.7, provide an overview of how frequently the air quality in Gazipur fell into different health-related categories as defined by the AQI system. The majority of days were associated with groups linked to health concerns. The scarcity of "Good" air quality days indicates limited opportunities for inhaling clean air. The high number of numerous "Hazardous" days indicates that pollution constitutes a significant issue necessitating urgent public health intervention and more stricter emission regulations.

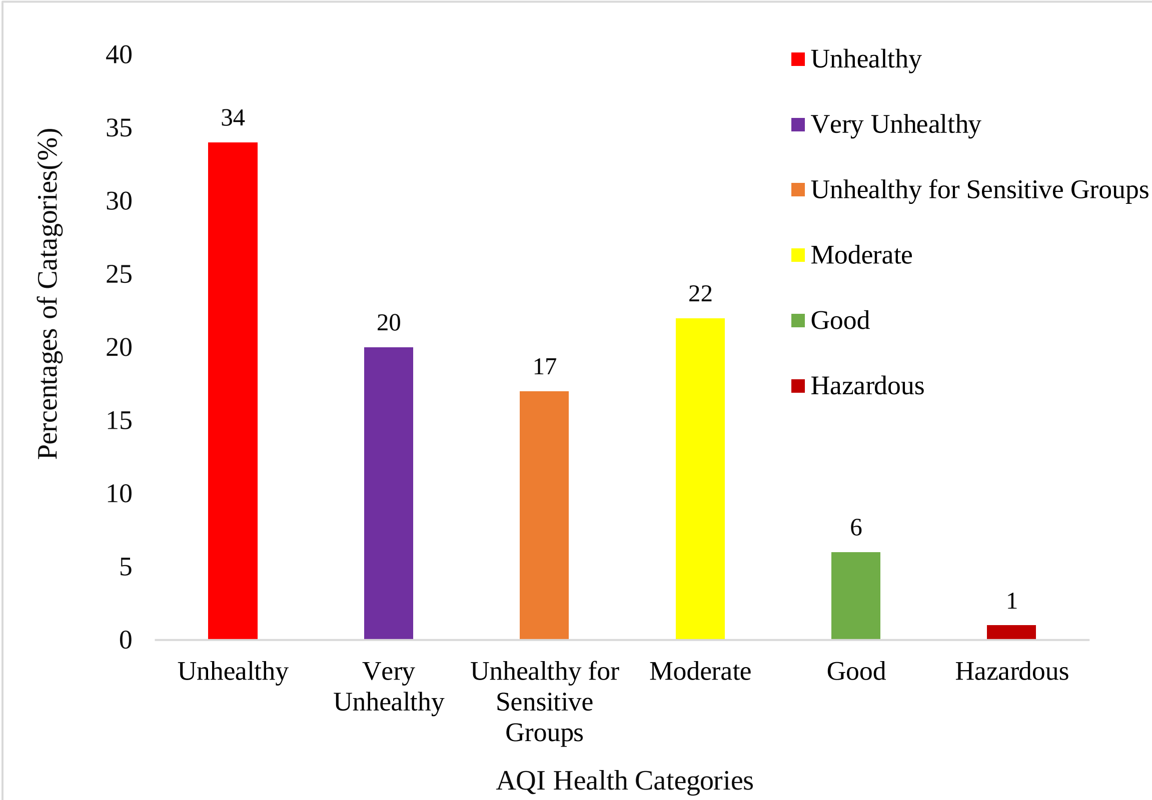


Figure 4.7 : AQI Health Categories (2020-2024)

During the study period, the "Unhealthy" category made up 34% of all days, which is a lot. People in this group (AQI: 151–200) may start to have health problems like eye, nose, and throat irritation, as well as worsening respiratory problems like asthma. People who are more likely to get sick are children, the elderly, and people with long-term respiratory or heart problems.

The second most common category was "Moderate" (22%), which means that the air quality is generally acceptable but can still cause minor irritation for people who are very sensitive. The "Very Unhealthy" category (20%) came next, which means that the conditions are very bad for everyone's health. During these times, emergency health warnings are needed, and the chances of people going to the hospital for respiratory and cardiovascular diseases go up a lot.

Another 17% of the days were marked as "Unhealthy for Sensitive Groups" (AQI: 101–150). People who are sensitive to this range may have trouble breathing and their chronic health problems may get worse, which lowers their overall quality of life.

Only 6% of the days were in the "Good" category, which means that clean, healthy air was present but not very often during this five-year period. The most troubling finding, though, is that 1% of the days were rated as "Hazardous" (AQI >300). This is the most serious category, which means that everyone is at risk of serious health problems, such as sudden respiratory symptoms, worsening of chronic illnesses, and even death in extreme cases.

4.3.2 Exceedance Analysis of $PM_{2.5}$ Against Bangladesh and WHO Standards

After completing the AQI analysis, we focused specifically on $PM_{2.5}$ exceedance trends, as this pollutant had already been identified as the most critical contributor to poor air quality. To better understand the severity of pollution and its compliance with regulatory standards, exceedance was assessed for each year from 2020 to 2024 using both the Bangladesh National Ambient Air Quality Standards (BNAAQS) and the updated WHO Air Quality Guidelines (2021).

The BNAAQS currently establishes the annual $PM_{2.5}$ limit at 15 $\mu g/m^3$ and the 24-hour standard at 65 $\mu g/m^3$. Conversely, the WHO (2021) standards are significantly more rigorous, establishing an annual limit of 5 $\mu g/m^3$ and a 24-hour limit of 15 $\mu g/m^3$, which highlights the most recent global scientific findings indicating that even minimal levels of fine particulate matter can pose severe health risks,

Figure 4.8(a) illustrates the daily $PM_{2.5}$ concentration profile over the study period, plotted alongside the threshold limits for both standards. The Bangladesh 24-hour standard (65 $\mu g/m^3$) is represented by the red line, while the much stricter WHO 24-hour guideline (15 $\mu g/m^3$) is represented by the yellow line. From the graph, it is evident that daily $PM_{2.5}$ concentrations frequently fluctuate above both thresholds, with far more frequent exceedances when compared against the WHO benchmark.

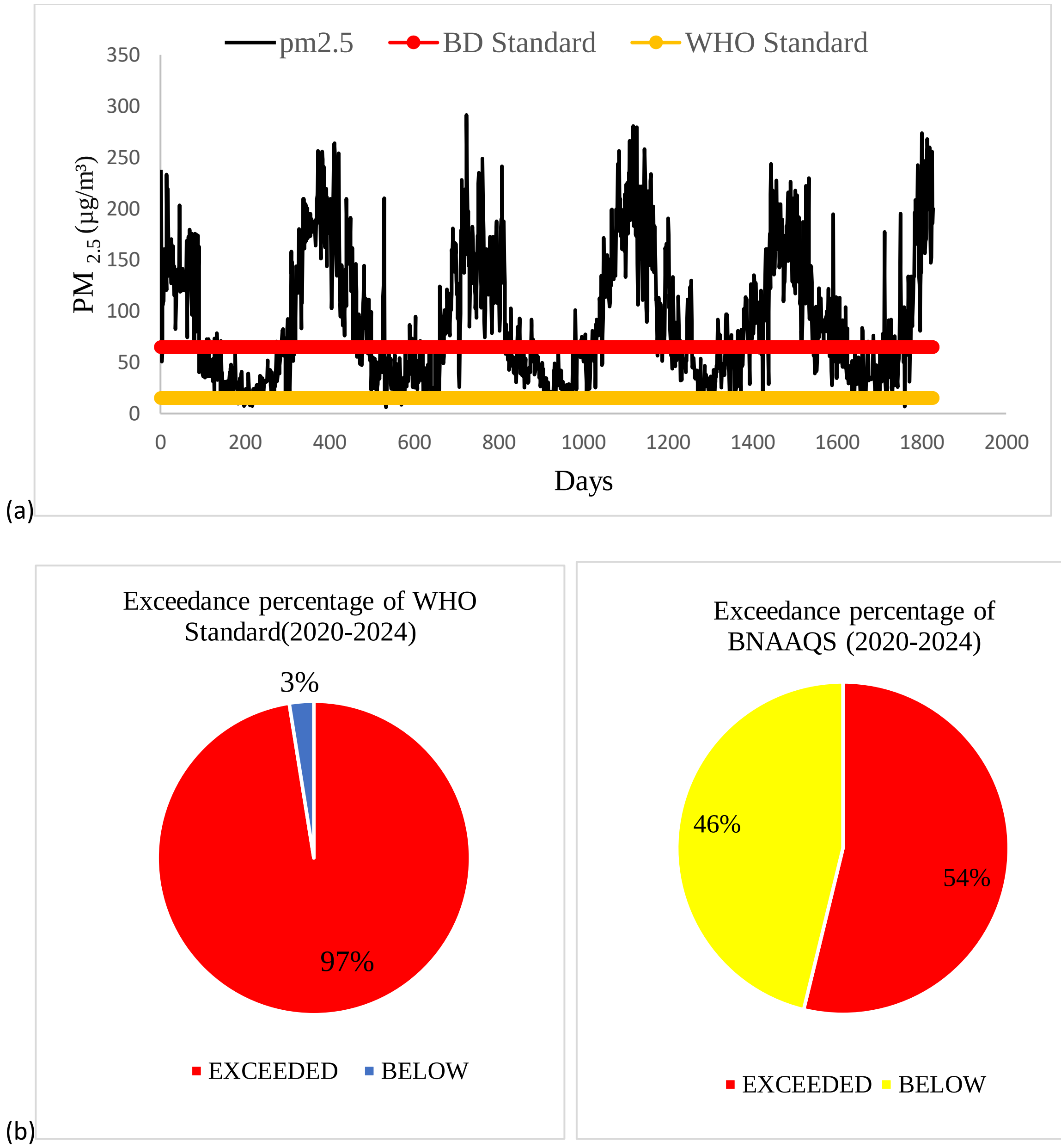
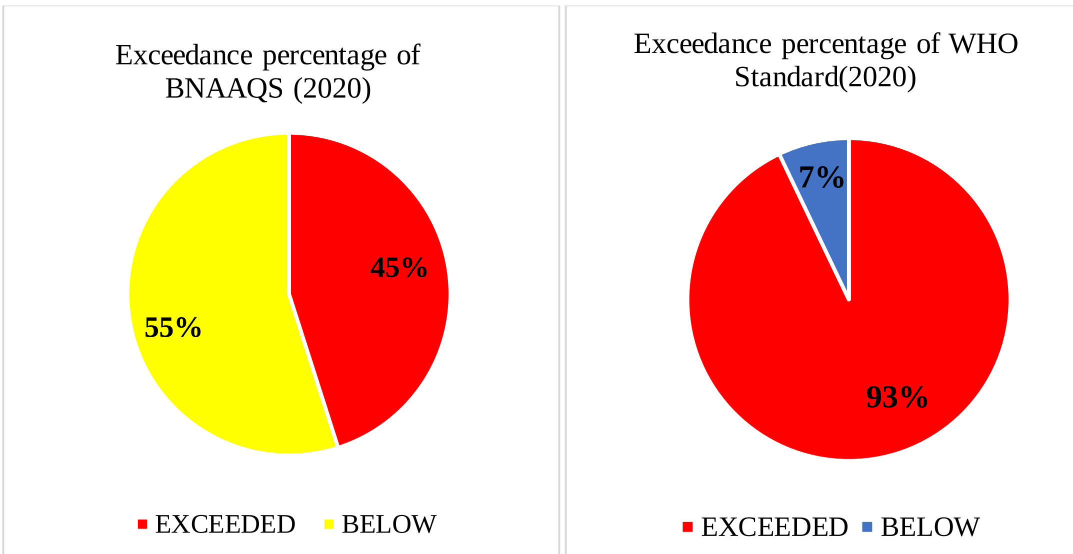


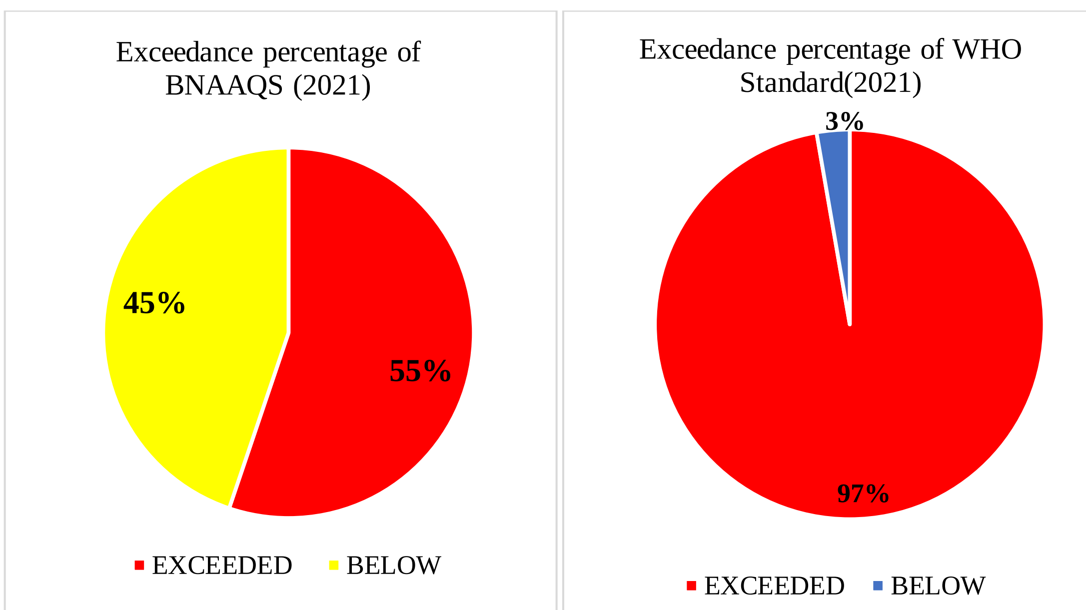
Figure 4.8 (a) : Daily Variation of $PM_{2.5}$ Concentration with Respect to Bangladesh and WHO Standards (2020–2024) ; (b) : Exceedance percentage of BNAAQS and WHO Standard(2020-2024)

This observation is shown quantitatively in Figure 4.8(b). In violation of WHO standards, exceedances were recorded on 97% of the days, indicating that merely 3% of the days conformed to the global health-based safe level. This underscores the gravity of $PM_{2.5}$ pollution in the area and its potential for significant health repercussions, particularly as the WHO criteria aim to mitigate risks associated with cardiovascular, respiratory, and other pollution-related ailments.

Conversely, exceedances of the Bangladesh national norm are somewhat lower yet still significant. Approximately 54% of the days over the BNAAQS level, but 46% of the days remained within the permitted limits. This signifies that, even under the less permissive local norm, over fifty percent of the monitored days presented threats to air quality.



(a)



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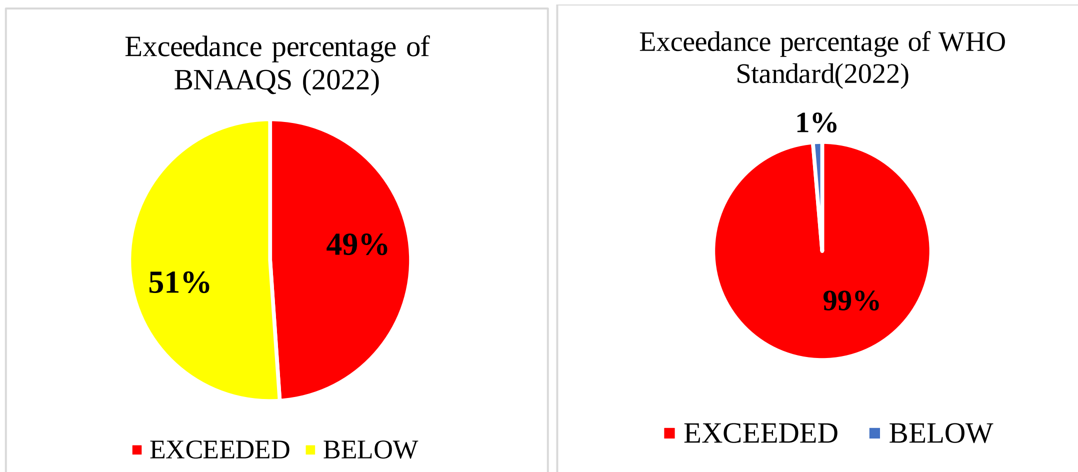
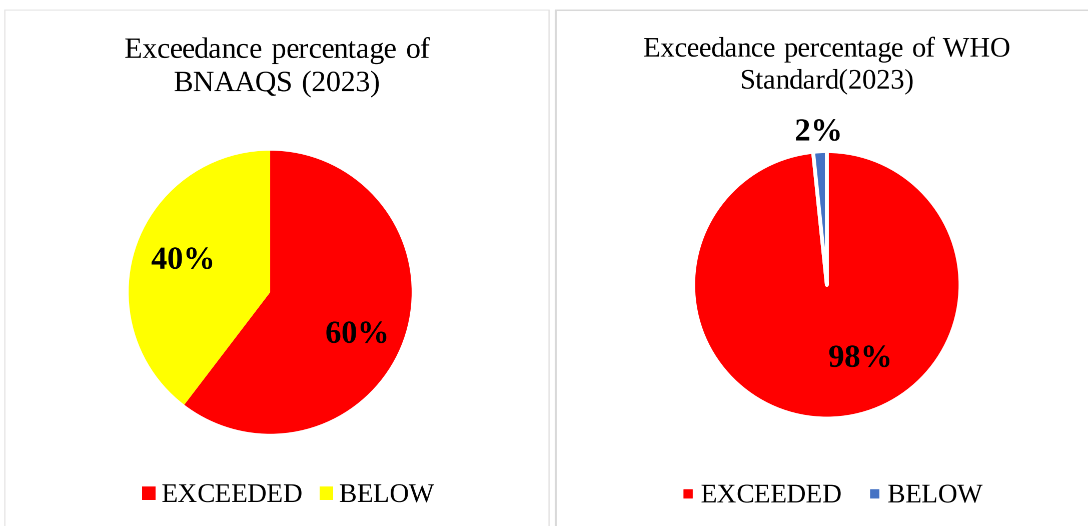


(d)


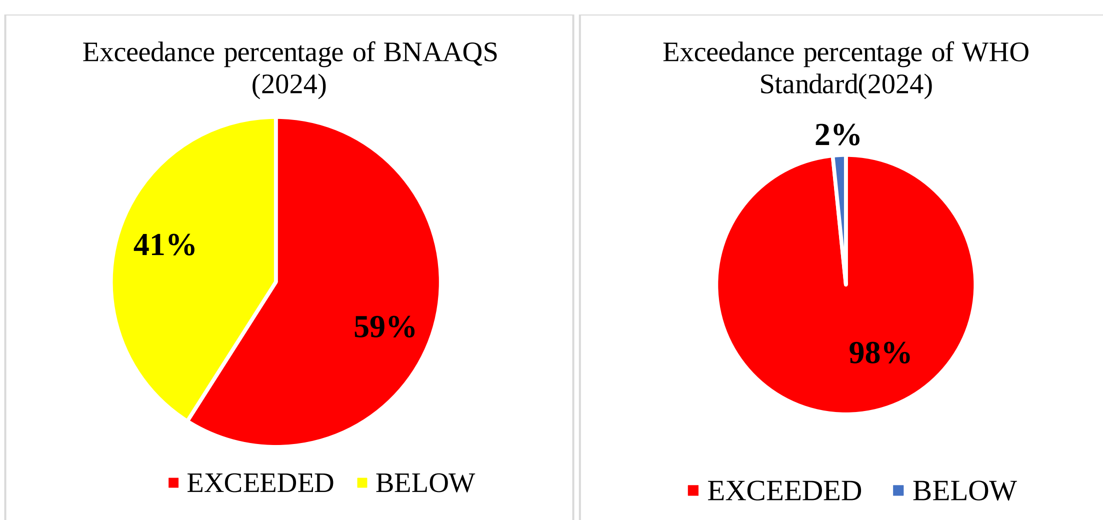
(e)


Figure 4.9 : Exceedance percentage of BNAAQS and WHO Standard (a)2020 (b)2021 (c)2022 (d)2023 (e)2024

Figure 4.9 shows five pie charts that show the annual exceedance percentages of $PM_{2.5}$ concentrations compared to the World Health Organization (WHO) guideline values and the Bangladesh National Ambient Air Quality Standard (BNAAQS) for the years 2020–2024. When taken as a whole, these graphics show the sharp disparities between national and international standards and the concerning degree to which air quality norms are being exceeded.

The BNAAQS exceedance rate for 2020 is 45%, meaning that nearly half of the days under observation went over the national threshold while the other half stayed within allowable bounds. On the other hand, the exceedance percentage sharply increases to 93% when the WHO's more stringent standard is used, leaving only 7% of the days in compliance. This glaring discrepancy shows that following national standards does not always equate to following international health-based recommendations.

The exceedance rate against BNAAQS rose marginally to 55% in 2021, indicating that most days had $PM_{2.5}$ levels above the national safe limit. However, 97% of the days were in excess of WHO standards, with only 3% falling within the permissible range. This highlights how difficult it is becoming to maintain air quality, even at the national level, while meeting international standards is continuously impossible.

Although the BNAAQS showed a slight improvement in 2022, with exceedance dropping to 49%, almost half of the days still went against national guidelines. WHO exceedance, however, remained startlingly high at 99%, while compliance fell to just 1%. According to this year's results, achieving WHO compliance is nearly impossible under the current circumstances, even though there may be short-term improvements in comparison to BNAAQS.

With exceedance reaching 60%, the highest level during the study period, 2023 shows a worsening trend by national standards. Conversely, the WHO exceedance rate was 98%, indicating a nearly universal violation of international standards. This implies that the long-term trajectory is still unfavorable even though year-to-year performance varies.

Ultimately, BNAAQS exceedance decreased slightly to 59% in 2024, indicating a slight improvement over the year before but still showing that more than half of the days were above the national threshold. Only 2% of days were in compliance, with WHO exceedance remaining critically high at 98%. This supports the trend that WHO's stricter limits are nearly always broken, while Bangladesh's national standards, despite being less strict, still report frequent violations.

The fluctuations in compliance with BNAAQS from 2020 to 2024 can be attributed to a mix of seasonal factors, changes in the weather, and changes in emissions. The air quality in Bangladesh is very sensitive to the weather. In the winter, for example, the $PM_{2.5}$ levels are usually higher because the air is still, the wind is weak, and the temperature often changes. These things make it harder for pollutants to spread out, which lets fine particles build up near the surface. On the other hand, during the monsoon season, more rain and stronger winds wash away and spread pollutants, which lowers their concentrations. Because of this strong seasonality, exceedance levels naturally change from year to year, making it hard to follow BNAAQS consistently.

Along with weather-related factors, human-made factors also had a big effect on compliance patterns. Years with more industrial activity, brick kiln activity, or big construction projects usually had more $PM_{2.5}$ exceedances. On the other hand, times when people were less active, like during the COVID-19 lockdown in 2020, saw short-term improvements in air quality. Also, transboundary air pollution and regional dust transport events from nearby countries sometimes caused spikes in $PM_{2.5}$, which made compliance trends even more difficult to follow.

Overall, the inconsistent compliance with BNAAQS shows how seasonal weather patterns, local emissions, and pollutants from outside sources all work together to affect air quality. This shows how hard it is to keep air quality improvements steady in places like Bangladesh, where natural and human-made factors work together in complex ways (Sarwar, et al. 2023). This variability indicates that enduring mitigation strategies must incorporate both emission control policies and meteorological factors to guarantee more consistent adherence to national standards.

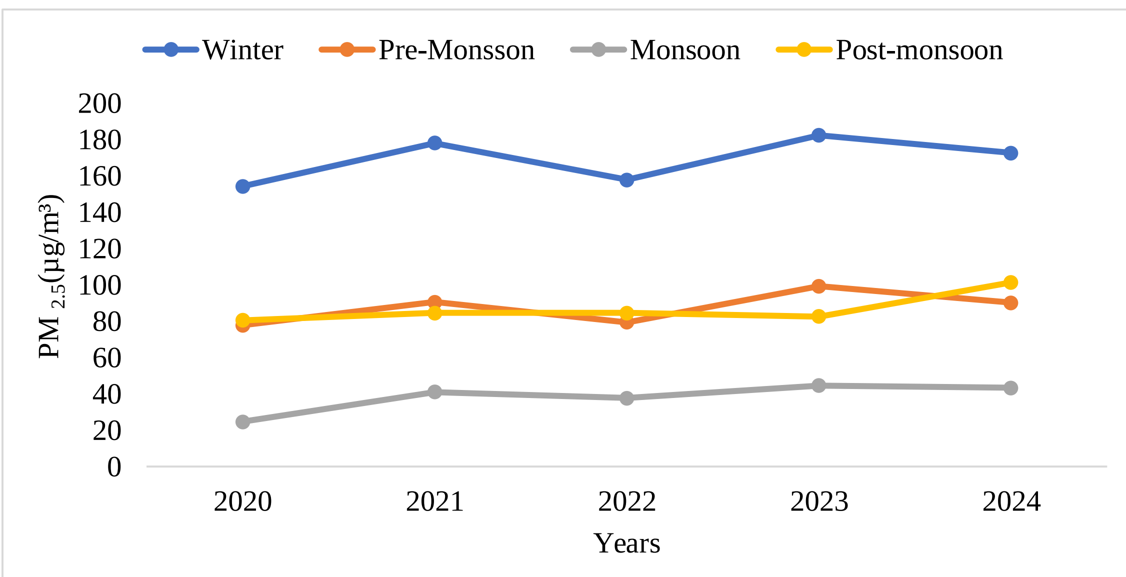
4.3.3 Seasonal Trend Analysis of $PM_{2.5}$

For the next stage of analysis, the seasonal variation of $PM_{2.5}$ was examined by dividing the year into four phases: Winter (December–February), Pre-monsoon (March–May), Monsoon (June–September), and Post-monsoon (October–November). This classification helps to capture how changing meteorological conditions across seasons influence pollution levels and reveal periods of highest and lowest air quality. Table 4.5 and Figure 4.10 presents the seasonal average concentrations and time-series of $PM_{2.5}$(µg/m³) respectively across the four seasons for the years 2020 to 2024.

Table 4.5: Seasonal Average $PM_{2.5}$ Concentrations (µg/m³) in Gazipur (2020–2024)

Seasons	2020	2021	2022	2023	2024
Winter	154.278	178.089	157.848	182.346	172.533
Pre-Monsson	77.82	90.603	79.357	99.303	90.25
Monsoon	24.72	40.967	37.7146	44.54	43.26
Post-monsoon	80.45	84.56	84.623	82.628	101.35

(a)



(b)

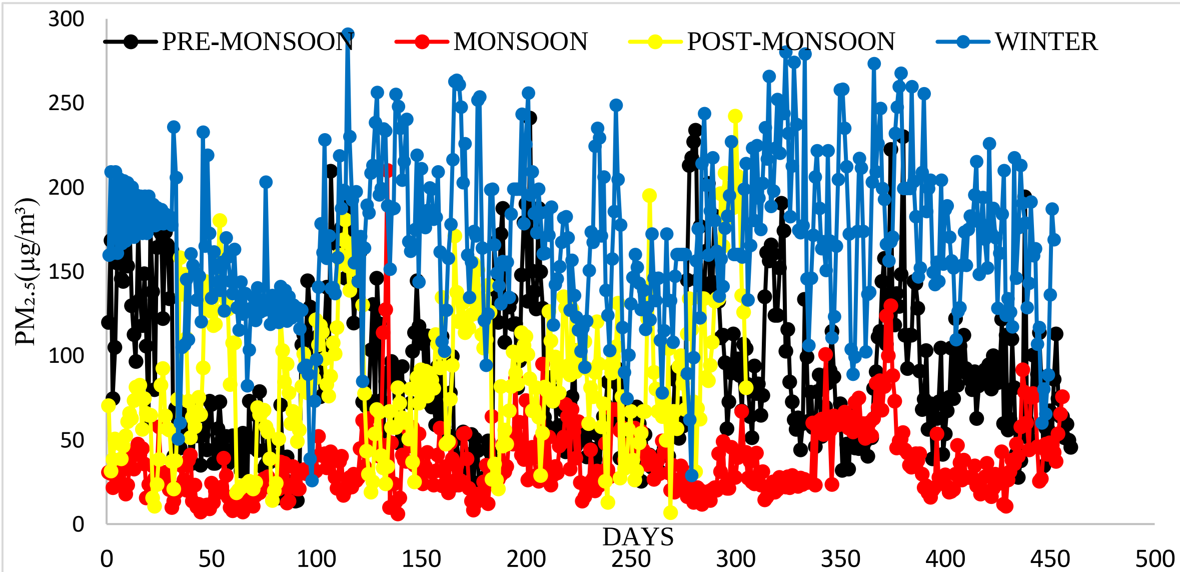


Figure 4.10 :(a) Yearly Average of Seasonal Variation in Gazipur (2020-2024) (b) Time-Series Representation of Seasonal $PM_{2.5}$ Variation in Gazipur (2020–2024)

There is a clear seasonal cycle in the tabulated averages and the time-series plot. Winter always has the highest $PM_{2.5}$ concentrations, followed by post-monsoon and pre-monsoon. Monsoon is the cleanest time, with the lowest values.

The table 4.5 shows that $PM_{2.5}$ levels in the winter ranged from 154.3 µg/m³ in 2020 to 182.3 µg/m³ in 2023, and then they dropped a little to 172.5 µg/m³ in 2024. These numbers are much higher than those of other seasons, often more than twice the pre-monsoon averages and almost five to six times higher than the monsoon averages. The time-series graph backs this up by showing that there are many peaks in the winter months, when concentrations often go above both the national and WHO guidelines. The high levels in winter are mostly caused by a mix of weather and human activity. In the colder months, the planetary boundary layer is shallow, vertical mixing is less, and temperature inversions occur. These all keep pollutants close to the surface (Mukta, et al. 2020). Also, lower wind speeds in the winter make dispersion even less likely. Anthropogenic sources like increased biomass burning, industrial fuel use, and brick kiln operations during the dry season make this problem worse. As a result, winter has the worst air quality problems

The post-monsoon season also has moderately high $PM_{2.5}$ levels, with averages between 80.5 µg/m³ in 2020 and 101.4 µg/m³ in 2024. During the time between the wet monsoon and the start of the cooler months, the rain stops and the air gets drier, which lets pollutants build up. Burning agricultural waste and the return of industrial work during the dry season make the concentrations even higher during this time. (Saju, et al. 2023)

The months before the monsoon have lower $PM_{2.5}$ levels than the winter and after the monsoon, but they are still high, averaging between 77.8 µg/m³ in 2020 and 99.3 µg/m³ in 2023. The weather is more unstable during these months because the temperatures are rising, which makes vertical mixing stronger (Rahman and Meng 2024) But higher dust resuspension, vehicle emissions, and burning of crop residues before the monsoon season keep $PM_{2.5}$ levels at worrying levels.

The monsoon season, on the other hand, always has the lowest $PM_{2.5}$ levels, with averages ranging from 24.7 µg/m³ in 2020 to 44.5 µg/m³ in 2023. The main reason for this big drop is the combination of heavy rain and high relative humidity, which effectively remove particulate matter from the air through wet deposition and washout processes. The wind speeds are stronger during the monsoon, which also makes the air less dense. The time-series plot makes this very clear: $PM_{2.5}$ levels dropped to their lowest points and stayed pretty stable during the monsoon.

The seasonal analysis shows that pollution levels in Gazipur follow a pattern that happens again and again (Mukta, et al. 2020). Winter is the most dangerous season because the levels are always dangerous. Monsoon, on the other hand, is a time when the air naturally cleans itself. The pre- and post-monsoon seasons are transitional periods with concentrations that are moderately high. This seasonal pattern shows how important it is to think about how the weather changes when looking at air quality data and making policy decisions. This is because the same sources of pollution can have very different effects depending on the time of year.

4.4 Annual Correlation Between Meteorological Parameters & $PM_{2.5}$ (2020-2024)

The relationship between $PM_{2.5}$ concentrations and meteorological parameters (temperature, precipitation, wind speed, and relative humidity) was examined using the Pearson correlation coefficient**.** The analysis was carried out both year-wise (2020–2024, each with 365 daily records) and for the entire study period (1825 days in total) to capture both annual and long-term variations. The resulting correlation matrices were visualized with a three-color conditional formatting scale, where values close to –1 (red) indicated strong negative correlation, 0 (yellow) denoted no correlation, and +1 (green) reflected strong positive correlation.

Table 4.6 : Annual Correlation between meteorological parameters & $PM_{2.5}$(µg/m³) for 2020

Year-2020	$PM_{2.5}$(µg/m³)	Temp (˚C)	Precipitation (mm)	Wind Speed (Km/h)	Humidity (%)
$PM_{2.5}$(µg/m³)	1.00	-0.76	-0.45	-0.58	-0.74
Temp (˚C)	-0.76	1.00	0.23	0.43	0.52
Precipitation (mm)	-0.45	0.23	1.00	0.45	0.49
Wind Speed	-0.58	0.43	0.45	1.00	0.53
Humidity	-0.74	0.52	0.49	0.53	1.00

In 2020, $PM_{2.5}$ concentrations showed a strong negative correlation with all meteorological parameters. The highest negative associations were observed with temperature (r = –0.76) and humidity (r = –0.74)**,** indicating that higher temperatures and relative humidity were generally linked with lower $PM_{2.5}$ levels. Similarly, wind speed (r = –0.58) and precipitation (r = –0.45) also exhibited negative correlations, suggesting that enhanced atmospheric mixing and wet deposition contributed to pollutant reduction. On the other hand, meteorological parameters were positively correlated with each other, with particularly strong relationships between humidity and temperature (r = 0.52)**,** humidity and wind speed (r = 0.53)**,** and precipitation and wind speed (r = 0.45)**.** These results highlight the significant influence of meteorological variability on air quality dynamics during 2020.

Table 4.7 : Annual Correlation between meteorological parameters & $PM_{2.5}$(µg/m³) for 2021

Year-2021	$PM_{2.5}$(µg/m³)	Temp (˚C)	Precipitation (mm)	Wind Speed (Km/h)	Humidity (%)
$PM_{2.5}$(µg/m³)	1.00	-0.68	-0.33	-0.50	-0.80
Temp (˚C)	-0.68	1.00	0.10	0.39	0.42
Precipitation (mm)	-0.33	0.10	1.00	0.25	0.43
Wind Speed	-0.50	0.39	0.25	1.00	0.45
Humidity	-0.80	0.42	0.43	0.45	1.00

In 2021, $PM_{2.5}$ levels again exhibited a negative association with all meteorological parameters. The strongest negative correlation was found with humidity (r = –0.80)**,** followed by temperature (r = –0.68) and wind speed (r = –0.50), highlighting the strong role of atmospheric moisture and dispersion in reducing particulate concentrations. Precipitation also showed a weaker but still negative relationship with $PM_{2.5}$ (r = –0.33), indicating limited washout effects compared to other factors. Meanwhile, meteorological variables remained positively correlated among themselves, with notable relationships between humidity and precipitation (r = 0.43)**,** humidity and wind speed (r = 0.45) and temperature and wind speed (r = 0.39)**.** These findings suggest that, similar to 2020, meteorological conditions exerted a considerable influence on $PM_{2.5}$ variations during 2021, with humidity emerging as the most influential factor.

Table 4.8 : Annual Correlation between meteorological parameters & $PM_{2.5}$(µg/m³) for 2022

Year 2022	$PM_{2.5}$(µg/m³)	Temp (˚C)	Precipitation (mm)	Wind Speed (Km/h)	Humidity (%)
$PM_{2.5}$(µg/m³)	1.00	-0.76	-0.32	-0.50	-0.74
Temp (˚C)	-0.76	1.00	0.15	0.44	0.53
Precipitation (mm)	-0.32	0.15	1.00	0.32	0.44
Wind Speed	-0.50	0.44	0.32	1.00	0.42
Humidity	-0.74	0.53	0.44	0.42	1.00

In 2022, $PM_{2.5}$ concentrations showed a consistently negative correlation with all meteorological variables, most strongly with temperature (r = –0.76) and humidity (r = –0.74)**.** Wind speed (r = –0.50) also maintained a moderate negative relationship, while precipitation (r = –0.32) exhibited the weakest influence, indicating that rainfall played a comparatively smaller role in pollutant removal that year. Positive associations were again observed among meteorological factors, with relatively strong correlations between humidity and temperature (r = 0.53)**,** humidity and precipitation (r = 0.44), and temperature and wind speed (r = 0.44)**.** These results reinforce the finding that atmospheric conditions, particularly temperature and humidity, were the dominant regulators of $PM_{2.5}$ variability during 2022.

Table 4.9 : Annual Correlation between meteorological parameters & $PM_{2.5}$(μg/m³) for 2023

Year 2023	$PM_{2.5}$(μg/m³)	Temp (˚C)	Precipitation (mm)	Wind Speed (Km/h)	Humidity (%)
$PM_{2.5}$(μg/m³)	1.00	-0.63	-0.41	-0.55	-0.79
Temp (˚C)	-0.63	1.00	0.18	0.41	0.38
Precipitation (mm)	-0.41	0.18	1.00	0.37	0.53
Wind Speed	-0.55	0.41	0.37	1.00	0.47
Humidity	-0.79	0.38	0.53	0.47	1.00

In 2023, $PM_{2.5}$ again displayed a negative correlation with all meteorological factors, with the strongest association observed with humidity (r = –0.79), followed by temperature (r = –0.63) and wind speed (r = –0.55)**.** Precipitation showed a weaker but still negative link (r = –0.41), suggesting a relatively smaller role in reducing particulate matter. As in previous years, meteorological parameters were positively interrelated, particularly between precipitation and humidity (r = 0.53)**,** wind speed and humidity (r = 0.47)**,** and temperature and wind speed (r = 0.41)**.** These findings emphasize that humidity continued to be the most influential factor in $PM_{2.5}$ reduction during 2023, while precipitation remained the least effective among the variables considered.

Table 4.10 : Annual Correlation between meteorological parameters & $PM_{2.5}$(µg/m³) for 2024

Year 2024	$PM_{2.5}$(µg/m³)	Temp (˚C)	Precipitation (mm)	Wind Speed (Km/h)	Humidity (%)
$PM_{2.5}$(µg/m³)	1.00	-0.68	-0.32	-0.56	-0.74
Temp (˚C)	-0.68	1.00	0.08	0.48	0.44
Precipitation (mm)	-0.32	0.08	1.00	0.26	0.46
Wind Speed	-0.56	0.48	0.26	1.00	0.53
Humidity	-0.74	0.44	0.46	0.53	1.00

In 2024, $PM_{2.5}$ concentrations maintained a negative correlation with all meteorological parameters, most notably with humidity (r = –0.74) and temperature (r = –0.68). Wind speed (r = –0.56) also showed a moderate negative influence, while precipitation (r = –0.32) again appeared as the weakest controlling factor. Positive correlations were observed among the meteorological variables themselves, with relatively stronger links between wind speed and temperature (r = 0.48), humidity and wind speed (r = 0.53) and humidity and precipitation (r = 0.46). These results further confirm that humidity and temperature consistently played dominant roles in $PM_{2.5}$ variation, whereas precipitation contributed least to pollutant reduction during 2024.

Table 4.11: Annual Correlation between meteorological parameters & $PM_{2.5}$(µg/m³) for 2020- 2024

Year 2020-2024	$PM_{2.5}$(µg/m³)	Temp (˚C)	Precipitation (mm)	Wind Speed (Km/h)	Humidity(%)
$PM_{2.5}$(µg/m³)	1.00	-0.69	-0.36	-0.53	-0.76
Temp (˚C)	-0.69	1.00	0.14	0.43	0.45
Precipitation (mm)	-0.36	0.14	1.00	0.31	0.47
Wind Speed	-0.53	0.43	0.31	1.00	0.48
Humidity	-0.76	0.45	0.47	0.48	1.00

For the entire study period (2020–2024), $PM_{2.5}$ concentrations exhibited a strong negative correlation with all meteorological variables. The most pronounced associations were with humidity (r = –0.76) and temperature (r = –0.69), confirming their dominant role in regulating particulate matter levels. Wind speed also showed a moderate negative correlation (r = –0.53), indicating the influence of atmospheric dispersion on pollutant reduction. In contrast, precipitation (r = –0.36) demonstrated the weakest negative link, suggesting that rainfall had a comparatively limited impact on $PM_{2.5}$ removal over the long term. Meanwhile, meteorological factors were positively correlated with one another, with notable relationships between humidity and precipitation (r = 0.47), humidity and wind speed (r = 0.48), and temperature and wind speed (r = 0.43). Overall, the five-year dataset highlights that humidity and temperature consistently acted as the key meteorological drivers of $PM_{2.5}$ variability, whereas precipitation played the least significant role.

Table 4.12: Summary of Year-wise Pearson Correlation Coefficients between $PM_{2.5}$(µg/m³) and Meteorological Parameters (2020–2024)

$PM_{2.5}$ vs	**$PM_{2.5}$ (µg/m³)**	**Temp (˚C)**	**Precipitation(mm)**	**Wind Speed (Km/h)**	**Humidity (%)**
2020	1	-0.76	-0.45	-0.58	-0.74
2021	1	-0.68	-0.33	-0.499	-0.805
2022	1	-0.76	-0.32	-0.504	-0.74
2023	1	-0.63	-0.41	-0.55	-0.79
2024	1	-0.68	-0.32	-0.56	-0.74

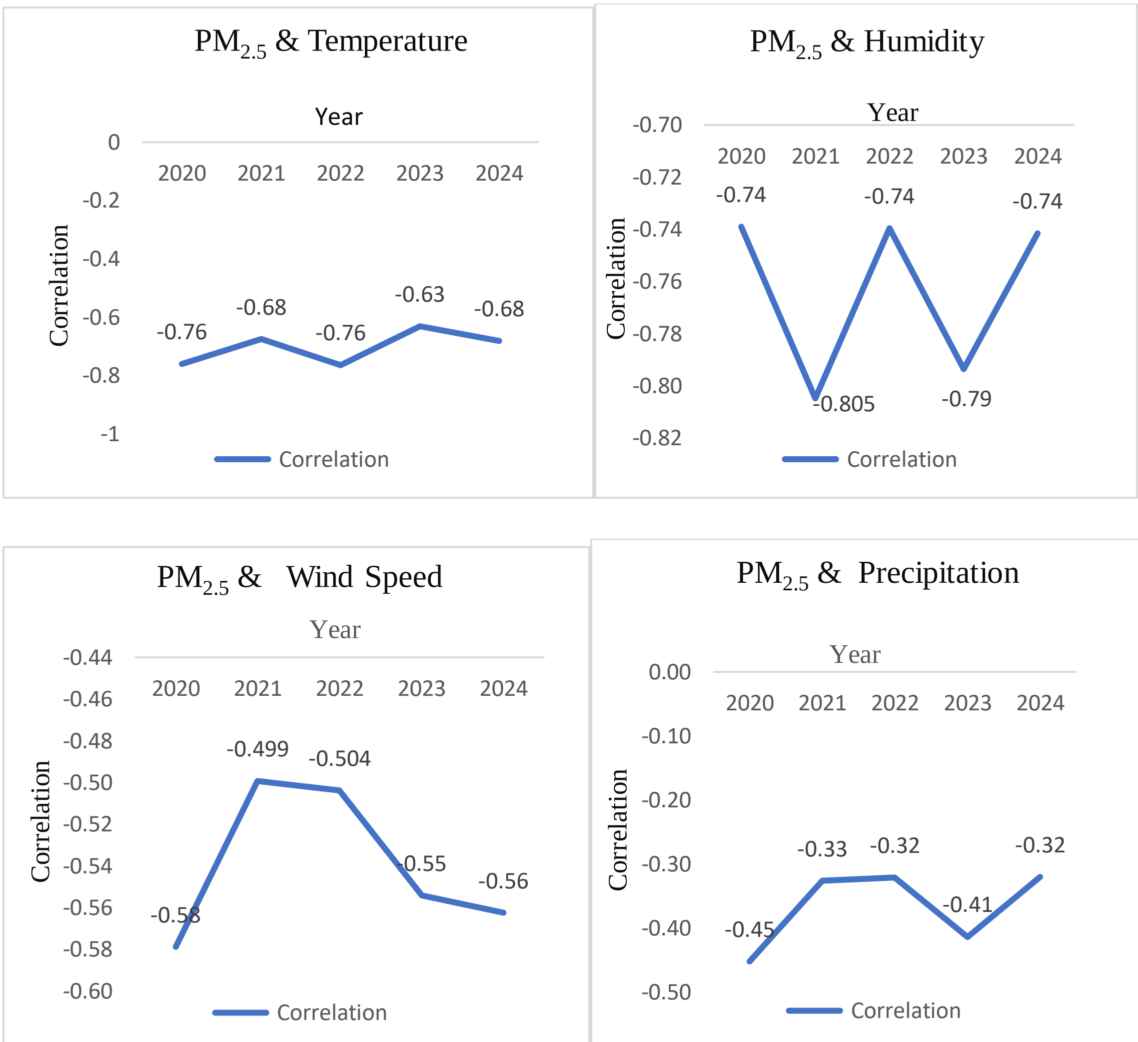


Figure 4.11 : Annual correlation between (a) $PM_{2.5}$ & Temperature (b) $PM_{2.5}$ & Humidity (c) $PM_{2.5}$ & Wind Speed (d) $PM_{2.5}$ & Precipitation

From 2020 to 2024, $PM_{2.5}$(µg/m³) consistently showed negative correlations with all meteorological factors. The strongest associations were with humidity (r up to –0.81) and temperature (r up to –0.76), while wind speed showed moderate influence and precipitation remained the weakest determinant. These results indicate that temperature and humidity were the primary drivers of $PM_{2.5}$ variability across the study period.

4.5 Lagged Correlation Analysis

To investigate the temporal relationship between $PM_{2.5}$ concentrations and meteorological parameters, Pearson correlation analysis with lag periods was conducted. Since the analysis is based on daily data, a lag of **'0'** indicates that the ambient parameter of a specific day is correlated with the $PM_{2.5}$ concentration on the same day. A positive lag (e.g., +1) signifies that the parameter of a given day is associated with the $PM_{2.5}$ concentration of the following day, implying that the parameter leads $PM_{2.5}$. Conversely, a negative lag (e.g., –1) denotes that the parameter of a particular day is related to the $PM_{2.5}$ concentration of the previous day, meaning that $PM_{2.5}$ leads the parameter. In this manner, the lagged correlation analysis allows for understanding whether changes in meteorological conditions precede or follow variations in particulate matter concentrations, and how the correlation strength varies with different lag periods.

Table 4.13 *:* Annual Correlation with Lag (2020)

Lag	Temp(˚C)	Precipitation (mm)	Wind Speed (Km/h)	Humidity(%)
-4	-0.75	-0.40	-0.52	-0.73
-3	-0.75	-0.40	-0.55	-0.73
-2	-0.76	-0.38	-0.55	-0.73
-1	-0.76	-0.42	-0.56	-0.73
0	-0.76	-0.45	-0.58	-0.74
1	-0.77	-0.43	-0.59	-0.72
2	-0.77	-0.42	-0.59	-0.68
3	-0.78	-0.42	-0.58	-0.66
4	-0.79	-0.39	-0.58	-0.65

Table 4.14 presents the annual Pearson correlation between $PM_{2.5}$ and meteorological parameters at different lag periods for 2020. At lag 0, which corresponds to the same-day interaction, the correlation values match the Pearson correlation coefficients reported earlier (temperature: r = –0.76, humidity: r = –0.74, wind speed: r = –0.58, precipitation: r = –0.45). As the lag increases from –4 to +4 days, correlations with temperature and wind speed slightly strengthen, with temperature reaching –0.79 at lag +4, while humidity gradually weakens from –0.73 to –0.65. Precipitation correlations remain comparatively

weaker and relatively stable across the lags. These results indicate that temperature and wind speed have a leading influence on PM2.5, whereas the effect of humidity and precipitation is less sensitive to lag, highlighting the temporal dynamics between meteorological factors and particulate matter concentrations.

Table 4.14 : Annual Correlation with Lag (2021)

Lag	Temp(˚C)	Precipitation (mm)	Wind Speed (Km/h)	Humidity(%)
-4	-0.63	-0.25	-0.37	-0.73
-3	-0.64	-0.28	-0.39	-0.74
-2	-0.65	-0.29	-0.43	-0.76
-1	-0.66	-0.29	-0.44	-0.79
0	-0.68	-0.33	-0.50	-0.80
1	-0.69	-0.34	-0.49	-0.80
2	-0.69	-0.30	-0.46	-0.78
3	-0.70	-0.26	-0.42	-0.75
4	-0.71	-0.21	-0.37	-0.73

Table 4.15 presents the annual Pearson correlation between $PM_{2.5}$ and meteorological parameters at different lag periods for 2021. At lag 0, corresponding to the same-day interaction, the correlation values match the Pearson correlation coefficients reported earlier (temperature: r = –0.68, humidity: r = –0.80, wind speed: r = –0.50, precipitation: r = –0.33). As the lag varies from –4 to +4 days, temperature and wind speed correlations slightly increase, with temperature reaching –0.71 at lag +4, while humidity shows a slight weakening from –0.73 to –0.80 across the lags. Precipitation remains the weakest and most variable factor throughout the lag periods. These results suggest that temperature and wind speed tend to lead PM2.5 variations, whereas humidity and precipitation show less sensitivity to lag, reflecting the temporal relationship between meteorological factors and particulate matter concentrations in 2021.

Table 4.15 : Annual Correlation with Lag (2022)

Lag	Temp(˚C)	Precipitation (mm)	Wind Speed (Km/h)	Humidity(%)
-4	-0.75	-0.27	-0.42	-0.69
-3	-0.75	-0.27	-0.43	-0.70

-2	-0.75	-0.28	-0.44	-0.71
-1	-0.75	-0.28	-0.47	-0.72
0	-0.76	-0.32	-0.50	-0.74
1	-0.78	-0.32	-0.50	-0.73
2	-0.80	-0.28	-0.46	-0.72
3	-0.80	-0.26	-0.46	-0.70
4	-0.79	-0.23	-0.45	-0.69

Table 4.16 presents the annual Pearson correlation between $PM_{2.5}$ and meteorological parameters at different lag periods for 2022. At lag 0, corresponding to the same-day interaction, the correlation values match the Pearson correlation coefficients reported earlier (temperature: r = –0.76, humidity: r = –0.74, wind speed: r = –0.50, precipitation: r = –0.32). As the lag varies from –4 to +4 days, correlations with temperature and wind speed generally strengthen, with temperature reaching –0.80 at lag +3, while humidity shows slight weakening from –0.69 to –0.74. Precipitation remains comparatively weaker across the lag periods. These results indicate that temperature and wind speed have a leading influence on $PM_{2.5}$, whereas humidity and precipitation are less sensitive to lag, reflecting the temporal interactions between meteorological factors and particulate matter concentrations in 2022.

Table 4.16 : Annual Correlation with Lag (2023)

Lag	**Temp(˚C)**	**Precipitation (mm)**	**Wind Speed (Km/h)**	**Humidity(%)**
-4	-0.62	-0.37	-0.40	-0.71
-3	-0.62	-0.38	-0.42	-0.72
-2	-0.62	-0.37	-0.44	-0.74
-1	-0.62	-0.39	-0.50	-0.78
0	-0.63	-0.41	-0.55	-0.79
1	-0.66	-0.42	-0.55	-0.78
2	-0.69	-0.39	-0.50	-0.74
3	-0.71	-0.34	-0.46	-0.71
4	-0.72	-0.33	-0.46	-0.70

Table 4.17 presents the annual Pearson correlation between $PM_{2.5}$ and meteorological parameters at different lag periods for 2023. At lag 0, which corresponds to the same-day

interaction, the correlation values match the Pearson correlation coefficients reported earlier (temperature: r = –0.63, humidity: r = –0.79, wind speed: r = –0.55, precipitation: r = –0.41). As the lag varies from –4 to +4 days, temperature and wind speed correlations generally increase, with temperature reaching –0.72 at lag +4, while humidity gradually weakens from –0.71 to –0.70. Precipitation correlations remain relatively weak throughout the lag periods. These results suggest that temperature and wind speed tend to lead $PM_{2.5}$ variations, whereas humidity and precipitation are less sensitive to lag, reflecting the temporal relationship between meteorological factors and particulate matter concentrations in 2023.

Table 4.17 : Annual Correlation with Lag (2024)

Lag	**Temp(˚C)**	**Precipitation (mm)**	**Wind Speed (Km/h)**	**Humidity(%)**
-4	-0.70	-0.28	-0.46	-0.67
-3	-0.70	-0.25	-0.47	-0.68
-2	-0.68	-0.28	-0.47	-0.69
-1	-0.67	-0.31	-0.53	-0.72
0	-0.68	-0.32	-0.56	-0.74
1	-0.70	-0.32	-0.56	-0.72
2	-0.71	-0.30	-0.52	-0.70
3	-0.71	-0.29	-0.49	-0.67
4	-0.70	-0.29	-0.50	-0.67

Table 4.18 presents the annual Pearson correlation between $PM_{2.5}$ and meteorological parameters at different lag periods for 2024. At lag 0, representing the same-day interaction, the correlation values match the Pearson correlation coefficients reported earlier (temperature: r = –0.68, humidity: r = –0.74, wind speed: r = –0.56, precipitation: r = –0.32). Across lags from –4 to +4 days, temperature and wind speed correlations generally strengthen slightly, with temperature reaching –0.71 at lag +3, while humidity shows a gradual weakening from –0.67 to –0.74. Precipitation remains the weakest and most stable factor across the lags. These results indicate that temperature and wind speed tend to lead $PM_{2.5}$ variations, whereas humidity and precipitation are less sensitive to lag, reflecting the temporal interactions between meteorological parameters and particulate matter concentrations in 2024.

4.6 Simple Linear Regression Analysis

4.6.1 $PM_{2.5}$ VS Precipitation

The regression analysis between $PM_{2.5}$ concentration and precipitation show a statistically significant negative relationship. The regression coefficient of precipitation is -1.76 ($p < 0.001$), which means for every 1 mm increase in rainfall the $PM_{2.5}$ concentration decreases by about 1.76 µg/m³. The R^2 value of 0.13 indicates that precipitation explains around 13% of the variation in $PM_{2.5}$ levels. The intercept of 101.64 suggests that in the absence of rainfall, the average baseline $PM_{2.5}$ concentration remains high at about 101 µg/m³. This outcome implies that rainfall has a cleansing or washout effect on particulate matter, supporting the role of precipitation in reducing ambient air pollution. However, the relatively low R^2 value also highlights that precipitation alone cannot capture the full dynamics of $PM_{2.5}$ variation, since other meteorological factors such as wind speed, humidity, and temperature, along with local emission sources, contribute significantly. The persistence of high baseline values even during dry conditions suggests strong influence of anthropogenic emissions and indicates that rainfall, although effective, cannot fully counterbalance pollution episodes in highly polluted urban environments.

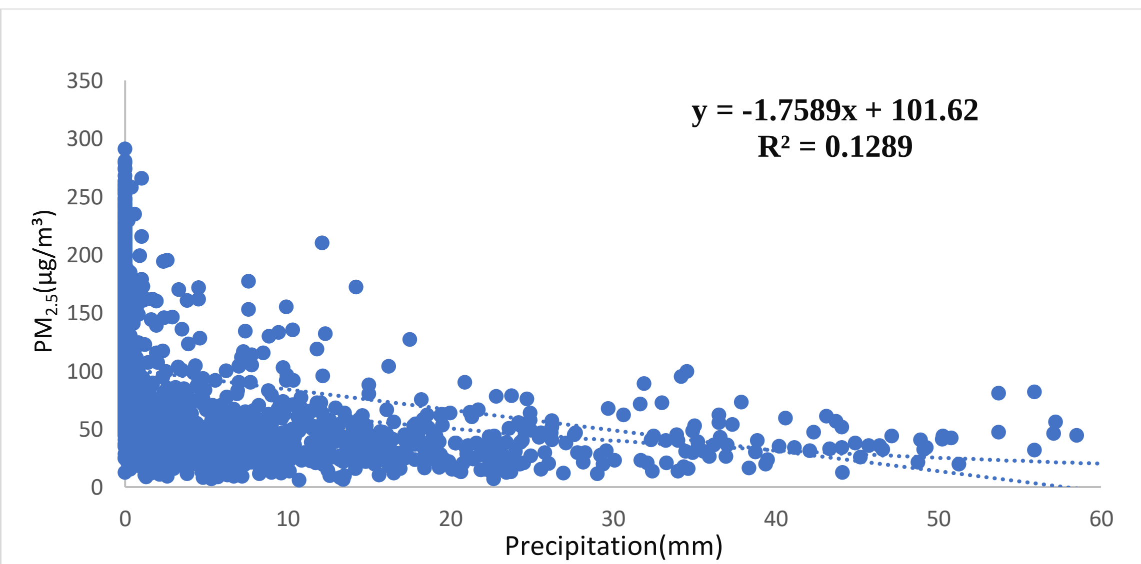


Figure 4.12 : Scatter plot of $PM_{2.5}$(µg/m³) vs Precipitation(mm)

4.6.2 $PM_{2.5}$ VS Wind Speed

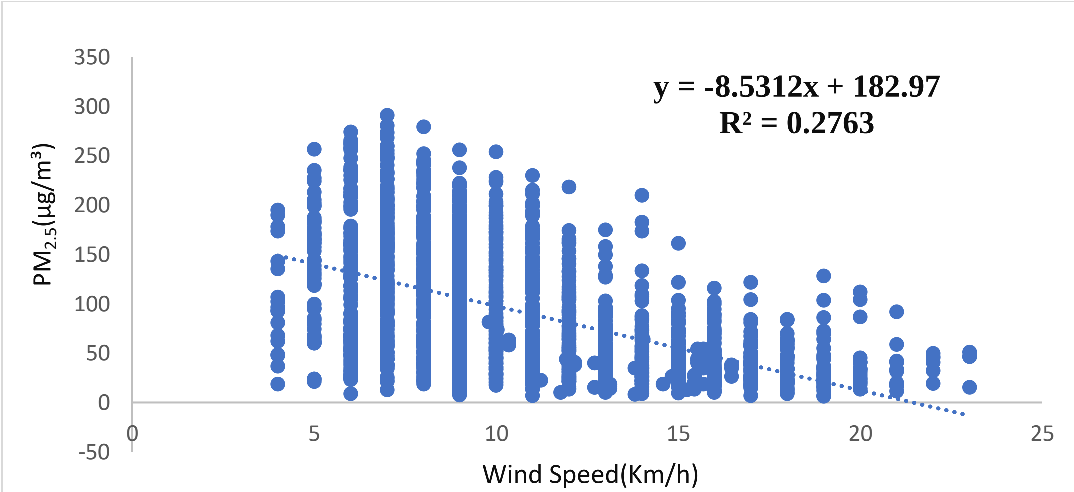


Figure 4.13 : Scatter Plot of PM $_{2.5}$ vs Wind Speed(Km/h)

The simple linear regression analysis was conducted to investigate the relationship between wind speed and $PM_{2.5}$ concentration levels, using a sample size of 1,827 observations. The results indicate a statistically significant negative relationship between wind speed and $PM_{2.5}$ levels, with a regression coefficient of -8.5312, suggesting that for every 1 unit increase in wind speed, $PM_{2.5}$ concentration decreases by approximately 8.53 units. The regression model is statistically significant as evidenced by the F-value of 696.82 and a significance F (p-value) of 2.44E-130, which is far below the standard alpha level of 0.05, indicating a highly significant model. The R Square value of 0.2763 implies that approximately 27.63% of the variance in $PM_{2.5}$ concentration can be explained by wind speed alone, while the remaining variation is likely influenced by other factors. The intercept of the model is 182.97, which represents the estimated $PM_{2.5}$ value when wind speed is zero. The p-value for the slope (wind speed) is also extremely small (2.44E-130), confirming that the effect of wind speed on $PM_{2.5}$ is statistically significant. Additionally, the confidence interval for the wind speed coefficient ranges from -9.17 to -7.90, reinforcing the reliability of the negative relationship. Overall, the analysis supports the conclusion that increasing wind speed is associated with a reduction in $PM_{2.5}$ levels, although the R^2 indicates that other variables should also be considered for a more comprehensive model.

4.6.3 $PM_{2.5}$ VS Humidity

The regression analysis shows a significant inverse relationship between humidity and $PM_{2.5}$ concentration, with an R square of 0.583 indicating that 58.3% of the variation in $PM_{2.5}$ can be explained by humidity. The regression equation $PM_{2.5}$ = 259.64 – 2.77(Humidity) suggests that for every one-unit increase in humidity, $PM_{2.5}$ decreases by about 2.77 units. The model is highly significant, as confirmed by the F-statistic (2556.65) and p-value (0), while the negative coefficient of humidity is supported by its narrow confidence interval (-2.87 to -2.66). The scatter plot also demonstrates this negative trend, showing that higher humidity levels are generally associated with lower $PM_{2.5}$ concentrations, likely due to atmospheric processes such as particle settling and wet deposition.

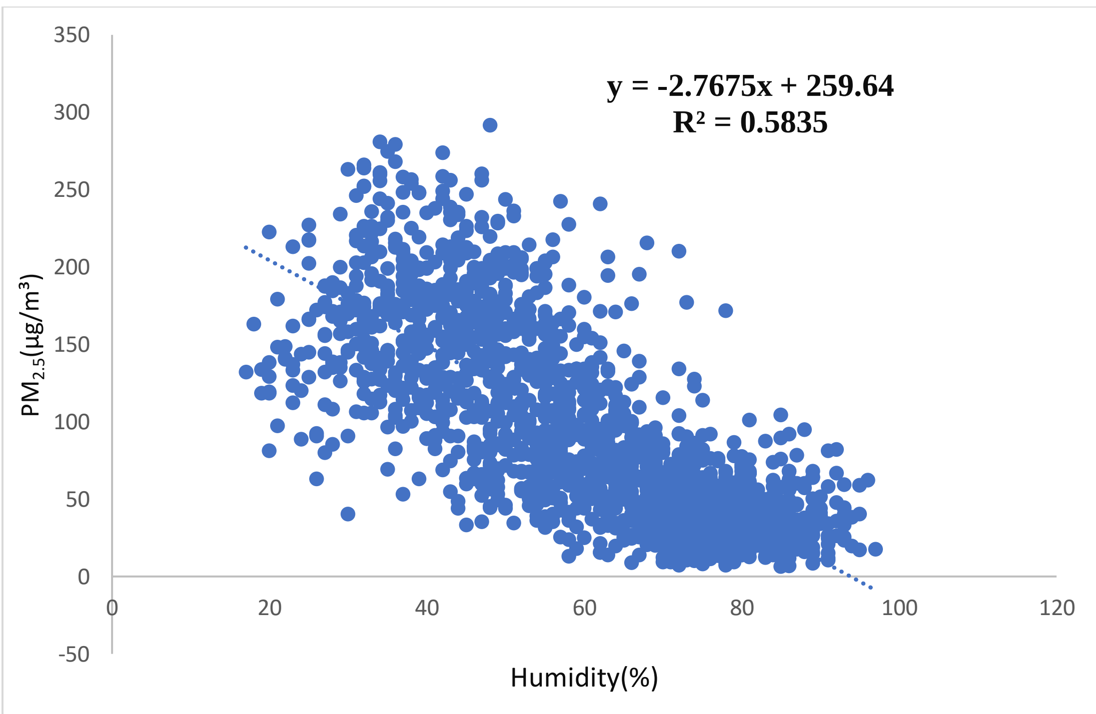


Figure 4.14: Scatter Plot of $PM_{2.5}$(μg/m³) vs Humidity(%)

4.6.4 $PM_{2.5}$ VS Temperature

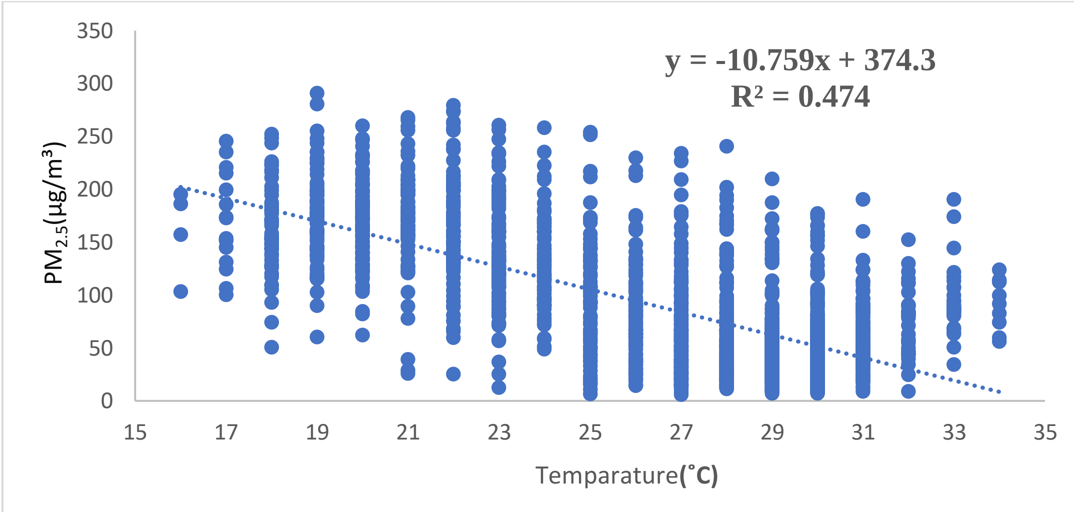


Figure 4.15 : Scatter Plot of $PM_{2.5}$ vs Temperature(˚C)

The regression analysis between $PM_{2.5}$ and temperature indicates a strong negative relationship, with an R square value of 0.474 showing that 47.4% of the variation in PM $_{2.5}$ can be explained by temperature. The regression equation $PM_{2.5}$ = 374.30 – 10.76(Temperature) suggests that for every one-degree Celsius increase in temperature, $PM_{2.5}$ concentration decreases by about 10.76 units. The model is statistically significant, as shown by the F-statistic (1644.86) and the extremely low p-value (<0.001). The confidence interval for the temperature coefficient (-11.28 to -10.24) confirms the robustness of this negative association. These findings indicate that higher temperatures are generally associated with lower $PM_{2.5}$ concentrations, which may be related to enhanced atmospheric mixing and dispersion of pollutants under warmer conditions.

4.7 Multiple Linear Regression Analysis

The regression model developed to estimate $PM_{2.5}$ from meteorological parameters performed strongly, with an R^2 value of 0.739. This means that about 74 percent of the variability in PM2.5 concentrations can be explained by the four predictors: temperature, precipitation, wind speed, and humidity. The adjusted R^2 (0.738) is very close to the R^2, confirming that the model is not overfitted despite the large sample size (1827 observations). The overall F-statistic of 1291.46 with a significance level of $p < 0.001$ shows that the model is statistically significant, meaning at least one predictor has a meaningful relationship with PM2.5. Based on the regression coefficients, the following predictive equation was obtained:

$PM_{2.5}$ = 391.55 – 6.41 *(Temperature) – 0.15*(Precipitation) – 1.47*(Wind Speed) – 1.89*(Humidity)

Looking at the coefficients, the intercept (391.55) represents the baseline $PM_{2.5}$ concentration when all predictors are zero. The coefficient for temperature is -6.41, meaning that for every 1°C increase , $PM_{2.5}$ decreases by about 6.41 µg/m³, holding other factors constant. Precipitation has a coefficient of -0.15, showing that each additional millimeter of rainfall lowers $PM_{2.5}$ slightly through particle washout. Wind speed has a coefficient of -1.47, suggesting that faster winds help disperse pollutants. Humidity has the largest effect with a coefficient of -1.89, indicating that higher relative humidity significantly reduces $PM_{2.5}$, likely due to enhanced particle deposition. The p-values for all variables are below 0.05, confirming that these effects are statistically significant.

Overall, the results indicate that meteorological conditions have a strong influence on $PM_{2.5}$ levels. Higher temperature, humidity, wind speed, and precipitation all contribute to lowering pollutant concentrations. Among these, temperature and humidity are the dominant factors, while precipitation plays a smaller but still measurable role. These findings highlight the importance of weather variability in shaping urban air quality and should be considered when designing pollution control and management strategies.

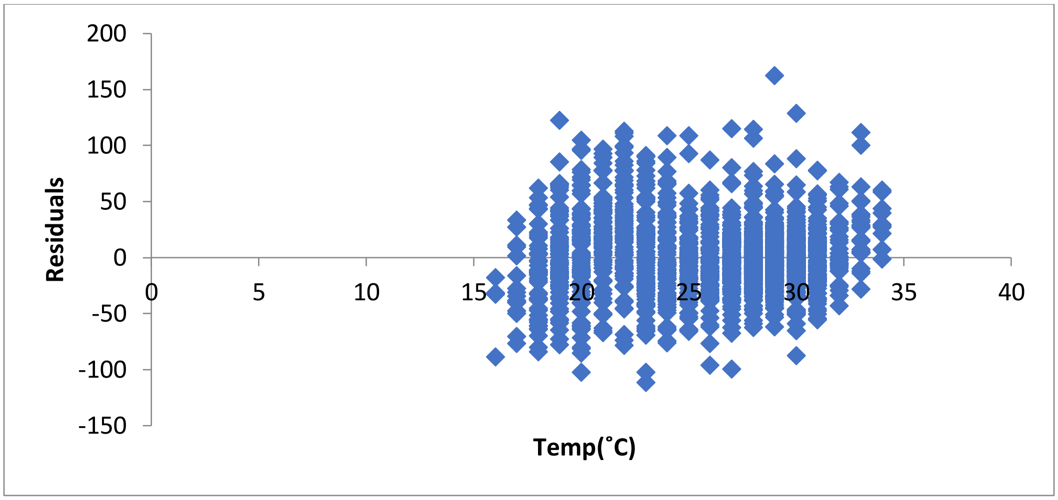


Figure 4.16 : Residual Plot of Temperature

The residual plot for temperature indicates that the residuals are randomly distributed around zero with no clear trend, suggesting that the linearity assumption of the regression model is satisfied. The spread of residuals remains relatively constant across the range of temperature, implying homoscedasticity, although a few outliers are present.

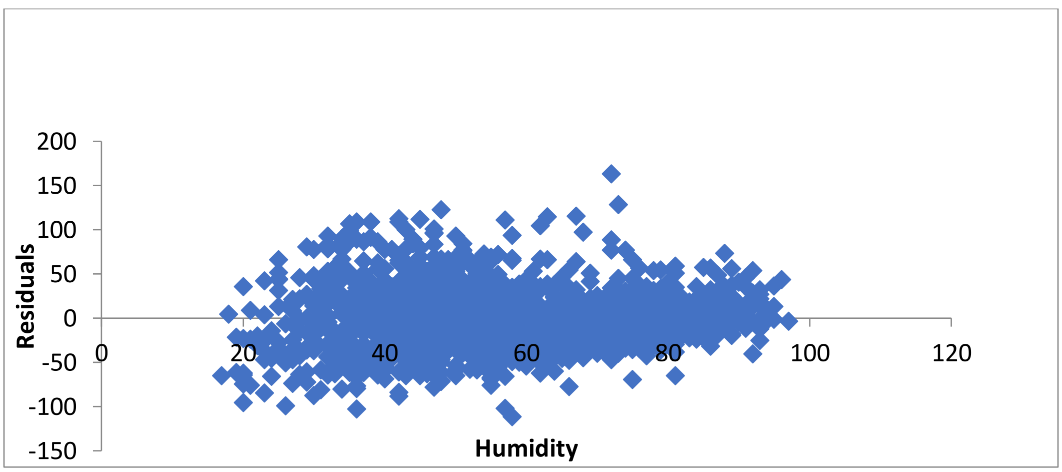


Figure 4.17 : Residual Plot of Humidity

The residual plot for humidity shows that the residuals are randomly scattered around zero with no clear pattern, suggesting that the linearity assumption is met. While the spread of residuals is relatively wide, no strong evidence of heteroscedasticity is observed.

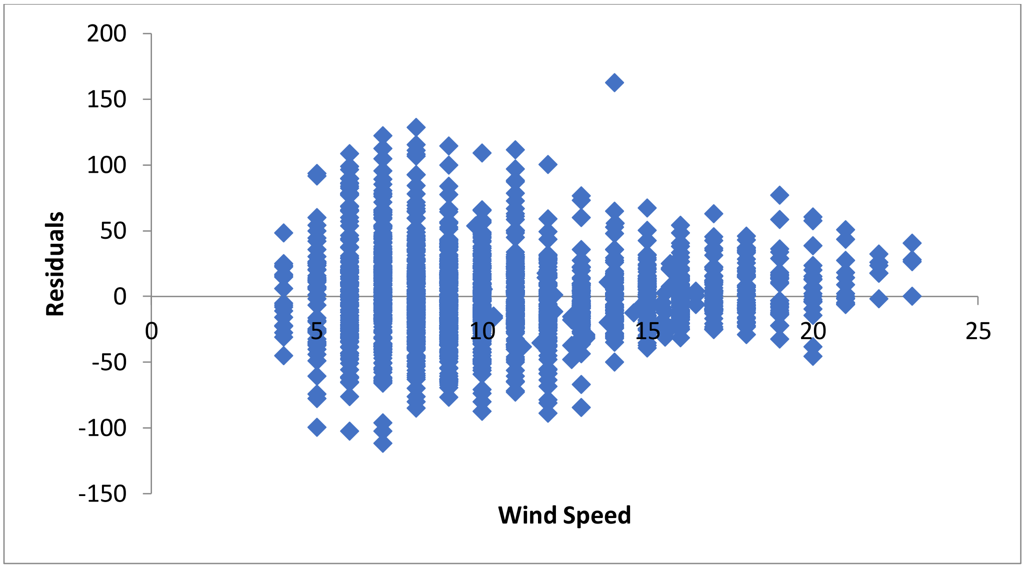


Figure 4.18 : Residual Plot of Wind Speed

The residual plot for wind speed shows that the residuals are dispersed around zero without a distinct trend, indicating that the linearity assumption is reasonably satisfied. The spread of residuals appears relatively consistent across different wind speed values, suggesting no strong evidence of heteroscedasticity. However, the residuals display a wide vertical range, implying that the model does not fully capture all variability associated with wind speed.

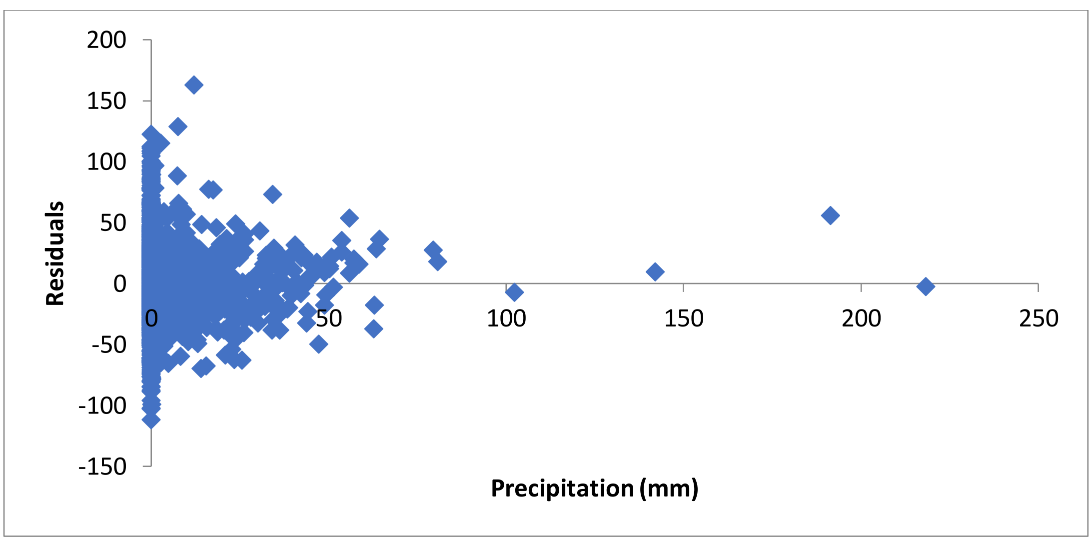


Figure 4.19 : Residual Plot of Precipitation(mm)

The residual plot for precipitation shows that most residuals are clustered near lower precipitation values, with fewer data points at higher levels. The residuals are centered around zero without a strong systematic trend, which suggests that the linearity assumption is reasonably satisfied. However, the plot indicates heteroscedasticity, as the spread of residuals is larger at lower precipitation levels and narrows as precipitation increases. This implies that the model explains variability less effectively at lower precipitation values.

CHAPTER V

CONCLUSION AND FUTURE WORK

5.1 Conclusion

This study thoroughly evaluated the long-term air quality state of Gazipur City Corporation and its correlation with climatic data from 2013 to 2024, with an in-depth analysis of the years 2020 to 2024. We conducted a sequential analysis, commencing with annual and monthly pollutant trends, an evaluation of compliance with both the Bangladesh National Ambient Air Quality Standards (BNAAQS) and World Health Organization (WHO) guidelines. This was followed by an analysis of the Air Quality Index (AQI) and advanced statistical modeling to ascertain the meteorological factors influencing particulate matter ($PM_{2.5}$) variability. The main points are as follows:

Persistent $PM_{2.5}$ pollution: Long-term study showed that $PM_{2.5}$ was always above national and international requirements and was the main pollutant of concern for Gazipur. It was one of the pollutants that were monitored (SO_2, NO_x, CO, O_3, $PM_{2.5}$, and PM_{10}).

Annual and seasonal dynamics: Monthly and yearly trend analysis showed that winter always has the highest $PM_{2.5}$ levels, often over 150–200 µg/m³. This is because to increased moist deposition and atmospheric cleaning during the monsoon season. Throughout the research period, the yearly averages of $PM_{2.5}$ stayed substantially over the limits set by the BNAAQS (15 µg/m³) and the WHO (5 µg/m³).

AQI risk levels: The AQI test showed that the air quality in Gazipur often falls into the "Unhealthy" to "Very Unhealthy" categories. This is a big health risk for the general public, especially for sensitive groups like kids, the elderly, and people with heart or respiratory problems.

Meteorological influence: Analyses of correlation and regression showed that wind speed, rainfall, and relative humidity are very important for moving and removing pollutants. During the winter, low wind speeds and dry, stagnant air caused $PM_{2.5}$ to build up. During the monsoon, rain and humidity lowered the levels. But these weather benefits are becoming less important because of the fast rise of cities and industries.

Effects of urban and industrial activity: The study connects the decline in Gazipur's air quality to the growth of the textile and manufacturing industries, brick kilns, heavy traffic on key highways, and big construction projects like the Dhaka–Gazipur Expressway. These local sources of pollution often have a bigger influence than the natural cleaning effects of weather cycles.

5.2 Future Work and Research Directions

This study offers a thorough evaluation of long-term air quality and climatic impacts in Gazipur; nonetheless, significant research gaps persist that future inquiries should explore to enhance understanding and inform policy development.

The integration of land use and urban expansion data does not clearly examine the impact of land use and land cover (LULC) changes on air quality. Future research should incorporate high-resolution satellite imagery and urban development maps to analyze the impact of industrial growth, urban sprawl, vegetation loss, and alterations in wetlands on pollutant concentration over time.

The current investigation examined city-level averages of pollution without distinguishing between residential, industrial, commercial, and mixed-use zones. Spatially resolved monitoring and zonal analysis will elucidate the impact of land use patterns and emission hotspots on local exposure levels, hence facilitating more effective intervention targeting.

This study utilized daily and monthly averages; however, the diurnal fluctuations of $PM_{2.5}$ and other contaminants have not been investigated. This analysis may reveal rush-hour peaks, nocturnal accumulation at low mixing heights, and variations in meteorological control during the day.

Advanced data analytics and predictive modeling predominantly employed classical statistical methodologies, including correlation and both simple and multiple linear regression. Integrating programming tools and machine learning models (e.g., random forest, LSTM networks, chemical transport modeling) could more effectively elucidate intricate non-linear interactions among emissions, meteorology, and PM fluctuation, facilitating the development of early warning systems.

Rectifying these deficiencies would enhance this fundamental study into a more geographically and temporally nuanced, predictive, and implementable framework for air quality management in Gazipur and analogous rapidly expanding urban areas.

APPENDIX

1. Exceedance Analysis for SO_2 (WHO AQG 2021, 24-hour standard = 40 µg/m³)

Data span: January 2013–December 2024 (daily observations; days with valid SO_2 data only).

Let N be the total number of valid daily observations, E the number of days exceeding the standard, and W the number of days within (or equal to) the standard. Then $N = E + W$ and the exceedance fraction f_e and percentage (%) Exceedance are:

$$f_e = E / N$$

$$\%Exceedance = (E / N) \times 100$$

Here, E = 1978 days, W = 12024 days, so N = 14002 days.

$f_e = 1978 / 14002 = 0.1413$

%Exceedance = (1978 / 14002) × 100 = 14.13%

Correspondingly, the compliance (within-standard) percentage is $\%Within = (W / N) \times 100 = (12024 / 14002) \times 100 = 85.87\%$.

So, over the 2013–2024 period, 1,978 out of 14,002 valid days exceeded the WHO 2021 SO_2 24-hour guideline, yielding an exceedance rate of approximately 14.12%.

2. Formal AQI Calculation for a 24-hour $PM_{2.5}$ Concentration of 220.88 µg/m³

Measured 24-h $PM_{2.5}$ concentration: 220.88 µg/m³

According to the AQI breakpoints, $PM_{2.5}$ Concentration of 150.5–250.4 µg/m³ maps to an AQI of 201–300 (Very Unhealthy).

BP_{LO} = 150.5 µg/m³, BP_{HI} = 250.4 µg/m³

I_{LO} = 201, I_{HI} = 300

$$I_p = \frac{(I_{Hi} - I_{LO})}{(BP_{Hi} - BP_{LO})} (BP_{Lo}) + I_{LO}$$

By doing numeric substitution

$$I = [(300 - 201) / (250.4 - 150.5)] \times (220.8 - 150.5) + 201$$

$$= (99 / 99.9) \times 70.3 + 201$$

$$\approx 0.990991 \times 70.3 + 201$$

$$\approx 69.60 + 201 = 270.60$$

So, we have got AQI value (nearest integer) and category

AQI = 271 (Very Unhealthy, range 201–300)

3.Annual Correlation with Lag Analysis in Excel :

The annual correlation with lag (2020) analysis presented in Table 4.14 was performed using Microsoft Excel. The objective of this analysis was to determine the relationship between $PM_{2.5}$ concentration and temperature while considering different lag values.

To calculate the lagged Pearson correlation coefficients, a custom Excel formula was applied using the LET and CORREL functions. The formula dynamically adjusts the data ranges based on the specified lag value and computes the corresponding correlation coefficient.

For example, when the lag value (L) was –4, the computed correlation between Temperature and $PM_{2.5}$ was –0.75, as reported in Table 4.14.

The Excel formula used is shown below:

```
=LET(
   L,$H3,
   N,COUNTA($B$2:$B$367),
   pm,$B$2:INDEX($B$2:$B$367,N),
   x,$C$2:INDEX($C$2:$C$367,N),
   r,
   IF(L=0,
      CORREL(pm,x),
      IF(L>0,
         CORREL(INDEX(pm,1+L):INDEX(pm,N), INDEX(x,1):INDEX(x,N-L)),
         CORREL(INDEX(pm,1):INDEX(pm,N+L), INDEX(x,1-L):INDEX(x,N))
      )
   ),
   r
)
```

4.Single Linear Regression Analysis -Summary Output for $PM_{2.5}$ vs Precipitation

Regression Statistics	
Multiple R	0.36
R Square	0.13
Adjusted R Square	0.13
Standard Error	58.63
Observations	1827.00

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	928478.40	928478.40	270.12	1.03282E-56
Residual	1825	6273074.57	3437.30		
Total	1826	7201552.97			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	101.64	1.51	67.19	0.00	98.67	104.61	98.67	104.61
Precipitation (mm)	-1.76	0.11	-16.44	0.00	-1.97	-1.55	-1.97	-1.55

5. Single Linear Regression Analysis -Summary Output for $PM_{2.5}$ vs Wind Speed

Regression Statistics	
Multiple R	0.525658775
R Square	0.276317148
Adjusted R Square	0.275920609
Standard Error	53.43868791
Observations	1827

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	1989912.576	1989912.576	696.8229152	2.4419E-130
Residual	1825	5211640.393	2855.693366		
Total	1826	7201552.969			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	182.9703127	3.696001803	49.50493058	0	175.7214748	190.2191506	175.7214748	190.2191506
Wind Speed	-8.531249129	0.323185161	-26.39740357	2.4419E-130	-9.16510078	-7.897397479	-9.16510078	-7.897397479

6. Single Linear Regression Analysis -Summary Output for $PM_{2.5}$ vs Humidity

Regression Statistics	
Multiple R	0.763865607
R Square	0.583490666
Adjusted R Square	0.583262442
Standard Error	40.54095869
Observations	1827

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	4202038.94	4202038.94	2556.654508	0
Residual	1825	2999514.03	1643.569331		
Total	1826	7201552.969			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	259.6359708	3.464404268	74.94390107	0	252.8413569	266.4305846	252.8413569	266.4305846
Humidity	-2.767492095	0.05473314	-50.56337121	0	-2.874838272	-2.660145919	-2.874838272	-2.660145919

7. Single Linear Regression Analysis -Summary Output for $PM_{2.5}$ vs Temperature

Regression Statistics	
Multiple R	0.688506971
R Square	0.47404185
Adjusted R Square	0.473753653
Standard Error	45.55722266
Observations	1827

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	3413837.49	3413837.49	1644.857818	6.3247E-257
Residual	1825	3787715.48	2075.460537		
Total	1826	7201552.969			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	374.3010849	7.06230868	52.99981944	0	360.4500281	388.1521416	360.4500281	388.1521416
Temp(˚C)	-10.75902548	0.265282593	-40.55684675	6.3247E-257	-11.27931487	-10.2387361	-11.27931487	-10.2387361

8.Multiple Linear Regression Analysis

Regression Statistics	
Multiple R	0.859802901
R Square	0.739261029
Adjusted R Square	0.738688605
Standard Error	32.10272267
Observations	1827

ANOVA					
	df	SS	MS	F	Significance F
Regression	4	5323827.459	1330956.865	1291.45788	0
Residual	1822	1877725.51	1030.584803		
Total	1826	7201552.969			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	391.5491284	5.039438787	77.69697083	0	381.6654442	401.4328126	381.6654442	401.4328126
Temp(˚C)	-6.406050171	0.21957098	-29.1753044	7.1409E-154	-6.836687455	-5.975412887	-6.836687455	-5.975412887
Precipitation (mm)	-0.146852879	0.067249673	-2.183696555	0.029111714	-0.278747433	-0.014958325	-0.278747433	-0.014958325
Wind Speed	-1.47391848	0.232316793	-6.344433665	2.80949E-10	-1.929553705	-1.018283256	-1.929553705	-1.018283256
Humidity	-1.890135281	0.056497216	-33.45537056	1.0148E-191	-2.000941397	-1.779329165	-2.000941397	-1.779329165

Sample Residual Output-

Observation	Predicted $PM_{2.5}$	Residuals	Standard Residuals
1	151.7816646	84.10833541	2.622849499
2	142.0115607	63.96843934	1.994803349
3	120.6327911	-69.85279109	-2.178302034
4	137.7009689	-77.51096891	-2.417116033
5	142.9318351	-37.71183509	-1.176012666
6	177.1805972	-70.62059719	-2.202245439
7	183.9087047	-38.64870472	-1.205228178
8	167.6357613	-57.85576134	-1.804184495
9	156.8716856	3.768314361	0.117511795
10	143.2549514	10.60504859	0.330709748
11	145.5613035	4.098696511	0.127814491
12	148.9253573	-15.82535725	-0.493500794
13	159.0175185	-11.80751854	-0.368207787
14	161.2297112	-40.77971117	-1.271681867
15	156.7137963	76.23620372	2.377363525
16	159.7584225	5.561577487	0.173433235
17	153.030315	66.36968501	2.069684226
18	146.208048	26.67195198	0.831742961
19	151.4622371	-16.91223706	-0.52739425
20	147.2631599	14.50684015	0.452383919
21	189.259683	-36.92968303	-1.151621896
22	190.7336015	-46.81360151	-1.459843792
23	194.0976553	-54.99765527	-1.7150568
24	187.3695478	-31.62954775	-0.986341521
25	188.0110326	-61.16103263	-1.907256671
26	184.6469789	-14.35697887	-0.447710618
27	177.0864377	-18.41643774	-0.574301516
28	171.7380893	-27.51808925	-0.858129058
29	162.6742591	-25.69425907	-0.801254409
30	144.1183264	19.29167355	0.601595027
31	153.7365887	-25.17658874	-0.785111284
32	179.9057959	-64.5857959	-2.014055107
33	189.259683	-45.40968303	-1.416063745
34	201.336139	-76.43613905	-2.383598344
35	200.6004947	-63.36049472	-1.975845094

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