RESEARCH PAPER

Modelling the Influence of Meteorological Variables on SO_2 and NO_2 Concentrations in Jammu City, India

Gowsiya Mehraj[1], Simerjit Kaur[1]*, Dinesh Kumar[2], Maninder Pal Singh[3]
[1]School of Life Sciences, Rayat-Bahra University, Chandigarh-Mohali, Punjab, India.
Email: dr.simar@rayatbahrauniversity.edu.in (Corresponding Author)
[2]Department of Environmental Science, Central University of Jammu, Bagla Suchani, Jammu and Kashmir, India
[3]University School of Pharmaceutical Sciences, Rayat Bahra Professional University, Hoshiarpur

Abstract

The objective of present study is to examine the concentration of Nitrogen Dioxide (NO_2) and Sulfur Dioxide (SO_2) in an urban area of Jammu (Narwal), India, over a period of one year. The study also takes into consideration the interplay of these gaseous pollutants with meteorological variables in a subtropical monsoon climate. The data reveal ambient NO_2 concentration ranging from 14.17 to 34.47 µg/m³ (mean 23.62 µg/m³) and SO_2 concentration from 2.14–5.63 µg/m³ (mean: 3.45 µg/m³). The seasonal trends exhibit during winter NO_2 and SO_2 concentration peaks out due to thermal inversions and reduced boundary layer heights, while during the monsoon the concentration of gaseous pollutants (NO_2 and SO_2) is lowest due to high precipitation and wind. The Pearson's correlations indicated strong negative associations of gaseous pollutants with wind speed ($r = -0.63$ for NO_2, $r = -0.59$ for SO_2) and high negative correlation with precipitation also ($r = -0.55$ for NO_2, -0.52 for SO_2). The Multiple Linear Regression (MLR) also confirmed wind speed and precipitation are the major predictors ($p < 0.01$) that explain 55% and 56% of variance in gaseous pollutants. Further, the Generalized Additive Models (GAMs) outclassed MLR models with adjusted $R^2 = 0.64$ for NO_2 and $R^2 = 0.59$ for SO_2) indicating existence of a nonlinear associations with sharpest decline in gaseous pollutant when wind speeds is greater than 12 km/h.

Keywords: Statistical modelling, Air pollution, Gaseous Pollutants and Meteorological variables, Jammu.

How to cite this article: Mehraj G, Kaur S, Kumar D, Singh MP. Modelling the Influence of Meteorological Variables on SO_2 and NO_2 Concentrations in Jammu City, India. Int J Drug Deliv Technol. 2026;16(14s): 950-963.
DOI: 10.25258/ijddt.16.14s.106

Introduction

Air pollution is a significant challenge across the globe nowadays. Among various air pollutants Nitrogen Dioxide (NO_2) and Sulfur Dioxide (SO_2) as they present several human health risks and are detrimental to environmental sustainability. These issues become more worrying in urban areas globally and are a serious health hazard in urban areas of India [1–3]. The gaseous pollutants primarily NO_2 and SO_2 are characterized by their highly reactive nature which disrupt atmospheric chemistry and poses major health issues through numerous complex exposure pathways. The major sources of NO_2 and SO_2 pollutants in ambient air are vehicular traffic, industrial processes, and coal-based power plants. These gaseous pollutants are also responsible for various respiratory and cardiovascular diseases that eventually lead to millions of premature deaths annually [4,5]. In India the major sources of SO_2 pollutants are thermal power plants and industrial activity while the major source of NO_2 pollutants is vehicular exhausts particularly in urban centres such as Delhi, Mumbai, and Bengaluru [6–8]. The emission sources exhibit varying spatial and temporal patterns, necessitating urgent development of localized pollution reduction plans. As per Central Pollution Control Board [9] the SO_2 and NO_2 concentrations in urban India have already crossed ambient air quality standards which has resulted in much health related issues and complications. The toxic properties of NO_2 and SO_2 pollutants have detrimental effect on quality of life. The physiological studies have concluded that the prolonged exposure to NO_2 pollutants leads to impaired lung function and higher rates of asthma and chronic obstructive pulmonary disease both among children and senior citizens [10]. Also the exposure to SO_2 and particulate matter leads to increased cardiovascular morbidity and acute respiratory symptoms which can become fatal [11]. As per [12] due to industrial activity in urban areas and environmental degradation on account of gaseous pollutants, an estimated 1.67 million annual deaths occur in India annually. Most of the urban centres in India witness elevated pollution risks from air pollution because these cities have high pollutant levels but they lack effective pollution control systems [13]. While the emission sources generally remain same throughout the year but the concentration of these gaseous pollutants keeps on changing from month to month across various season. These dynamics of air pollution are very complex and linked to several factors particularly atmospheric processes driven by meteorological variables like temperature, wind speed, humidity, and precipitation. These factors critically influence the deposition, dispersion, and transformation of air pollutants in ambient air [14]. The high temperature is generally associated with high photochemical reaction kinetics and formation of secondary pollutants like ozone and peroxyacetyl nitrate [15,16]. On contrary the low wind speeds and low temperature changes trap pollutants near the ground which create stagnant atmospheric conditions and increase the exposure to health risks [17]. Further, with increase in humidity the aqueous-phase reactions increase that expedites the nucleation of sulfate and nitrate aerosols. However, the precipitation acts as a natural cleanser through wet deposition [14]. These interactions between gaseous pollutants and metrological variables are moderated by synoptic-scale atmospheric patterns that last for large areas and many days there by demanding region specific analysis to unravel localized feedback for local mitigation plans [18]. In India the previous research on gaseous pollutants has primarily focused on megacities like Delhi and Mumbai and less attention in literature has been given to smaller urban centres like Jammu which have unique climatic and topographic characteristics that highlight pollutant-meteorology interdependency [19]. The subtropical monsoon climate of Jammu is marked by orographic influences and seasonal inversion layers with proximity to industrial and traffic sources that make it an ideal case study to examining pollutant-meteorological interactions. The previous studies have explored mostly linear relationships between pollutants and meteorological factors using models like multiple linear regressions (MLR) [20]. However, in atmospheric modelling of ambient air, research on gaseous pollutants indicates that non-linear interactions exist, which govern threshold effects and synergistic feedbacks. Limited research exists that have explored such non-linear relationship between pollutants and meteorological variables [21]. In this context, Generalized Additive Models (GAM) offer a dynamic approach to model the complex time-varying non-linear effects demonstrated by particulate matter and meteorological variable interactions [21]. In literature, there exist some critical knowledge gaps that hamper the evidence based policymaking for mitigating of air pollution due to gaseous pollutants. First, some studies simultaneously analyse multiple gaseous pollutants like SO_2 and NO_2 neglecting their interactive effects with metrological variables and their adverse health outcomes [11]. Second, there is a dearth of studies in urban Indian context that have been carried out on application of advanced models to explain non-linear pollutant-meteorological interactions thus only oversimplified air quality forecasting studies have been done mostly [22]. Third, region specific studies, in varied climatic settings like Jammu are scarce. This has led to hampering of development of local air quality management frameworks. The present study addresses these gaps by employing MLR and GAM models to investigate the dynamic interactions between SO_2, NO_2, and meteorological variables in Jammu, India. The study not only aims at advancing atmospheric science but also focuses on informing precision-based regulatory interventions from time to time.

1. Study Area

Jammu city is the winter capital of the Union Territory of Jammu and Kashmir (JKUT, India) located on the banks of the river Tawi (32.7266° N, 74.8570° E, 300 m AMSL) [23]. The city is located between Shivalik hills to the northeast and the Trikuta hills to the northwest. With diverse topography influences, Jammu has unique pollutant dispersion patterns on account of local microclimates (Fig 1). Four distinct meteorological phases can be distinguished in the region's humid subtropical climate: (1) a cool, dry winter from December to March; (2) a transitional pre-monsoon summer from April to June with rising temperatures; (3) a monsoon-dominated rainy season from July to September; and (4) a post-monsoon autumn from October to November with decreasing humidity. The region’s primary rainy season is driven by southwest monsoon that deliver extreme precipitation which collectively accounts for the majority of rainfall in a year. The area exhibits significant seasonal variability with an average annual accumulation of 1,246 mm of rain which is atypical of hydrologic regime. This is also consistent with the general patterns seen in any subtropical monsoon climates. [24]. In the past decade the area has also witnessed huge increase in construction activities, vehicular traffic and small-scale industries that has intensified air pollution challenges and causing elevated levels of gaseous pollutants mostly SO_2 and NO_2. The previous studies on Jammu’s air pollution indicate the air quality frequently violates national ambient air quality standards and these instances are high particularly during winter months when inversion in temperature traps pollutants [25].

Within the Jammu city, Narwal area that represents a mixed industrial cum residential zone was selected for monitoring due to its proximity to major highways heavy vehicular traffic, a fruit & vegetable market, nano industrial units which are primary sources of SO_2 and NO_2 emissions [26]. Narwal's proximity to river Tawi and Shivalik foothills seasonal dust storms aggravate pollution thus presenting itself as an appropriate setting for pollutant-meteorology analysis. During the low winds the pollutants generally get trapped due to city's hilly topography while vehicular and industrial emissions drive recurrent SO_2 and NO_2 emissions causing fluctuations in air quality. Jammu in general and Narwal area in particular is a crucial case study due to its environmental profile as a monitored pollution hotspot and the lack of air quality data from smaller Indian cities make this study more relevant. Further, in order to improve region-specific air quality initiatives, this study looks at the interaction between weather and pollutants.

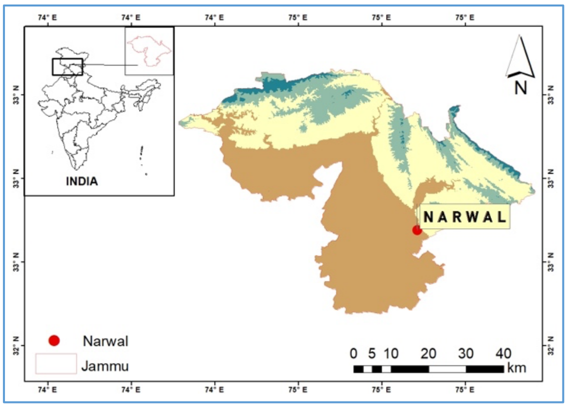


Figure M: Map of study area

2. Materials and Methods

2.1. Data Collection

At the study site (Narwal), the air quality monitoring was conducted over a period of twelve month from December to November in order to capture the seasonal variability across winter, Pre-monsoon, monsoon and post-monsoon months. Sampling was performed biweekly (two days per week), yielding a total of 104 observation days. To capture diurnal variation, six observations were recorded at four-hour intervals over 24 hours on each sample day. Measurements included two gaseous pollutants nitrogen dioxide (NO_2) and sulfur dioxide (SO_2) alongside four meteorological parameters temperature, humidity, wind speed, and precipitation.

2.2. Instruments and Techniques

Nitrogen Dioxide (NO_2) was measured using a Modified Jacob & Hochheiser (NaOH–NaArsenite) method with continuous gas monitoring through a calibrated NO_2 analyzer (APHA, 2017). Sulfur Dioxide (SO_2) was determined via the West and Gaeke colorimetric method employing an SO_2 analyzer equipped with an optical detection system. The monitoring and recording of meteorological variables particularly temperature and humidity was done using a digital thermo-hygrometer with ±0.1 °C, ±2% RH accuracy, For monitoring and recording wind speed a cup anemometer with measurement range of 0.5–50 m/s was used. To ensure consistency and standardization the precipitation data was obtained from the India Meteorological Department (IMD) station in Jammu.

2.3. Quality Assurance and Control (QA/QC)

Prior to deployment of instruments at site, all instruments were calibrated as per the manufacturer requirements for accurate measurements. To confirm the correctness of the analyser various checks particularly regular zero and span checks were carried out. For data reliability duplicate sampling was done at random on 10% of sample days across various seasons. Homogeneity of IMD meteorological data was cross verified by also employing separate field instruments also. Further, during the study period 624 data observations were recorded on 104 sampling days spread across all seasons uniformly with 6 observations each sampling day (104 * 6) providing vigorous meteorological and temporal representation.

3. Statistical Analysis

The data collected during the study period was systematically processed and statistical analysed. The dataset comprised of 104 sampling days (biweekly) spanning over 12 months from December to November across all seasons. In-order to cover all 24 hours on each sampling day six, four-hourly measurements of pollutants (NO_2 and SO_2) and meterological parameters specifically temperature, humidity, wind speed, and rainfall were recorded concurrently. This produced a robust dataset for statistical and both temporal analysis. Multiple Linear Regression (MLR) and Generalized Additive Models (GAM) were employed using SPSS 23 to model the relationships between pollutant concentrations SO_2 and NO_2 as dependent variables and meteorological parameters specifically temperature, wind speed, humidity, and precipitation, as independent interaction variables. MLR is widely used in air pollution studies to compute linear relationships between pollutants and metrological variables assuming the variance of residuals (errors) is constant across different levels of independent variables (homoscedasticity) [27,28]. In this study, MLR coefficients are derived using the least-squares method providing estimates to interpret how each meteorological parameter influences pollutant levels in ambient air. MLR models are being widely used in literature to develop air quality forecasting model to predict the air quality effectively. One such model was developed to forecast NO2 concentrations at Agra [29]. However, air pollution dynamics often exhibit non-linear patterns which MLR models fail to capture. These limitations of MLR model are addressed using GAMs that include smooth functions and have the capability to model non-linear effects of independent variables with greater flexibility in environmental modelling [30]. GAMs are widely used to analyse complex interactions between pollutants and meteorological factors such as PM2.5 , SO_2 and NO_2 across various climate settings [31–33]. In the present study, GAMs have been used to capture non-linear relationships particularly for wind speed and temperature as they are known to exhibit threshold effects in pollutant dispersion [34]. The performance of these GAM models is gauged by computing various estimates particularly the root mean square error (RMSE), coefficient of determination (R^2) and mean absolute error (MAE). The determination of these estimates is consistent with standard practices that are used in air quality modelling worldwide in literature [35]. The R^2 i.e. coefficient of determination measures the proportion of variance explained by the model while RMSE & MAE provide an idea about prediction accuracy of the model providing complementary insights into model fit [36]. Further, these model fit indices also provide any idea about how well the observed data fits the model. To address the model generalizability and prevent overfitting concern which is a critical step in environmental studies with variable meteorological data, cross-validation techniques specifically k-fold cross-validation was applied [37]. These methods and metrics align with methodologies used in recent studies conducted across the world that utilize MLR and GAM to model pollutant-meteorological interactions with higher predictive accuracy [38].

3.1. Descriptive Statistics of Pollutants and Meteorological Variables

This study provides a detailed analysis of ambient concentrations of Nitrogen Dioxide (NO_2) and Sulfur Dioxide (SO_2) over a complete annual cycle from December to November. Data was collected at a high temporal resolution, with 104 observation days (two per week) and six recordings per day at 4-hour intervals yielding a total of 624 observations. This sampling design was used to ensure the sampling design is capable of capturing both intense seasonal shifts and diurnal fluctuations. The region's climate is characterised by four distinct periods: the cool, stable winter (December–February), the hot, dry pre-monsoon (March–May); the wet, windy monsoon (June–September); and the transitional post-monsoon (October–November). The sample annual descriptive statistics are summarized in the Table 1. It can be observed from the table that several key patterns on pollutant profiles and metrological variations can be deducted. The NO_2 concentrations shows a considerable range of 14.17 – 34.47 µg/m^3 centred around a mean of 23.62 µg/m^3 while this mean is well below the India's 24 hour National Ambient Air Quality Standard (NAAQS) of 80 µg/m^3. Although the NO_2 pollution concentration in ambient air is under control but the persistent exposure of population to chronic moderate-level of NO_2 raises concerns for long-term cardiovascular and respiratory health. In contrast SO_2 levels were in the range of 2.14 – 5.63 µg/m^3 with mean average of 3.45 µg/m^3 which is also within the permissible NAAQS limit of 80 µg/m^3. This glaring difference is a testament to successful national policies such as the reduced reliance on high-sulfur industrial fuels and the introduction of stricter emission norms for vehicles and industry [39]. Although the gaseous pollutant concentrations in ambient air are changing but they are not extremely erratic as suggested by the modest coefficients of variation of 20.7% for NO_2 and 22.9% for SO_2. This suggests a combination of generally stable emission sources and modifying weather forces. Nevertheless these pollutant concentration also show a consistent trend across seasons

Table 1. Descriptive statistics of NO_2 and SO_2 concentrations (µg/m^3).

Pollutant	**Minimum**	**Maximum**	**Mean**	**Std. Dev.**	**CV (%)**
NO_2	14.17	34.47	23.62	4.88	20.7
SO_2	2.14	5.63	3.45	0.79	22.9

The temporal trends of these gaseous pollutants showed a clear and consistent seasonal pattern without abrupt discontinuities as shown in figure 1 & figure 1a and figure 2 and figure 2a. NO_2 concentrations exhibited a pronounced peak during the winter months, a phenomenon widely attributed to the high frequency of thermal inversions and a significantly reduced boundary layer height that traps and concentrates pollutants near the surface. SO_2 concentrations were more stable throughout the year but showed a subtle yet consistent elevation during the post-monsoon period. This minor peak likely coincides with increased local emissions from coal combustion for heating and widespread agricultural biomass burning (stubble burning) in the surrounding semi-urban and rural landscapes.

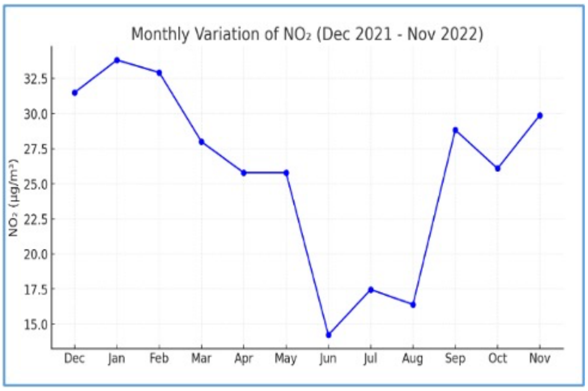


Figure 1: Temporal Variation of Nitrogen Dioxide (NO_2) Concentration in Ambient Air

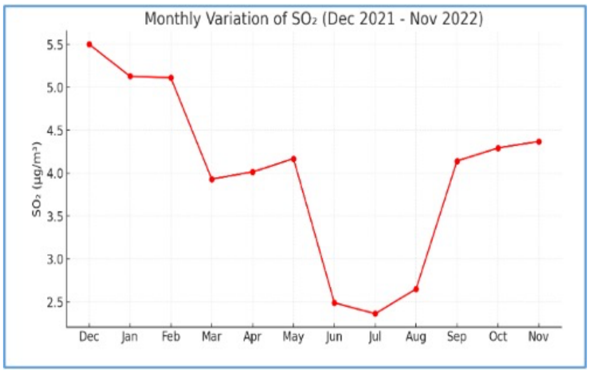


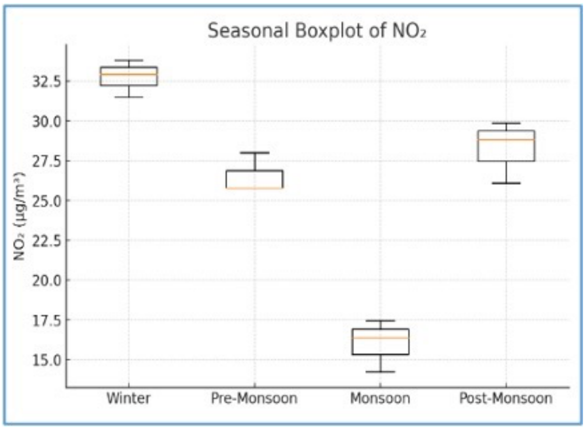
Figure 2: Seasonal Variation of SO_2 Concentration in Ambient Air

These pollutant dynamics cannot be interpreted in isolation; they are intrinsically linked to the prevailing meteorological conditions. The various seasons present a unique set of metrological condition for studying the diverse interactions between pollutants and varying metrological variables as shown in Table 2. The metrological conditions vary largely from season to season with little variation within the season also. The winters are particularly characterized by cool, moderately humid conditions with low wind speed that offer ideal conditions for pollution to aggravate. In contrast, the pre-monsoon season is hot, dry, and windy, often with dust storms, although this promotes the dispersion of pollutants but at the same time it also introduces particulate matter. While the monsoon which is defined by its extreme rainfall, high humidity, and strong winds, facilitate the condition for cleansing mechanism of gaseous pollutants. The post-monsoon season that offers mild temperatures and moderate rainfall mark a transition back towards winter stability and provide conditions for steady accumulation of pollutants, although lower than winters. This understanding about the meteorological conditions is very essential for understanding the statistical relationships explored between gaseous pollutants and metrological variables in the subsequent sections.

Table 2. Meteorological characteristics during different seasons.

Season	Temperature (°C)	Humidity (%)	Wind Speed (km/h)	Precipitation (mm)
Winter	4–21	50–60	5–10	50–100
Pre-Monsoon	17–44	26–45	10–15	40–80
Monsoon	23–46	75–85	20–25	600–800
Post-Monsoon	12–30	50–60	5–10	30–60

Figure 1a: Seasonal Boxplot of Nitrogen Dioxide (NO_2) Concentration in Ambient Air



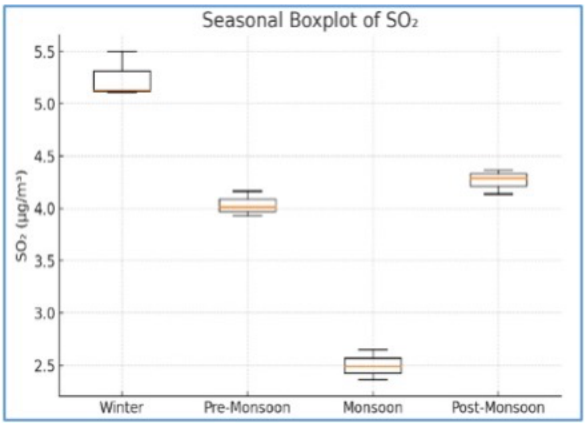


Figure 2a: Temporal Variation of SO_2 Concentration in Ambient Air

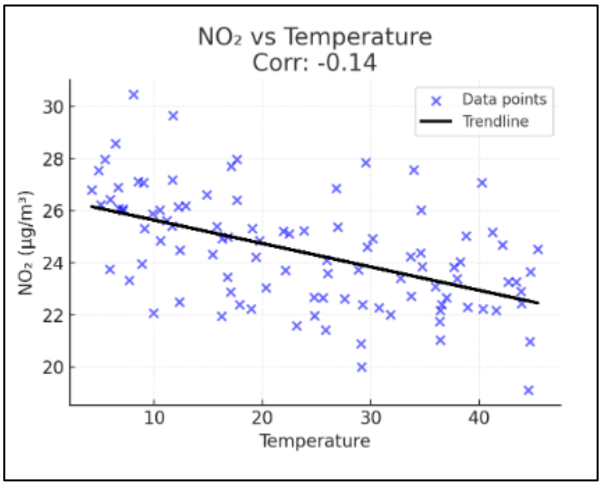
Correlation Analysis

The correlation analysis is a statistical technique to determine the strength and direction between two variables in a relationship which are interchangeable while as regression establishes dependent and independent variables. For present study to analyse the linear relationships between gaseous pollutants and meteorological parameter, the Pearson's correlation coefficients were calculated using the complete dataset of 624 observations across all seasons. The results of correlation coefficients between gaseous pollutants concentration and meteorological parameter are presented in Table 3. These values of correlation coefficients vary from high to low impact however with consistent direction (negative). This present a clear picture of varying impact of metrological variables on pollutant concentration.

Table 3. Pearson's correlation coefficients (r) between pollutants and meteorological variables.

Pollutant	**Temperature**	**Humidity**	**Wind Speed**	**Precipitation**
NO_2	–0.14	–0.41	**–0.63**	**–0.55**
SO_2	–0.12	–0.39	**–0.59**	**–0.52**

The correlation analysis between meteorological variables and gaseous pollutants (SO_2 & NO_2) reveals consistent negative associations highlighting the influence of metrological parameters on pollutant dispersion and removal processes as shown in Figures 3 to Figure 10. The figure 3 shows the scatter plot between NO_2 and temperature. It can be observed from figure 3 a weak negative correlation (r = –0.14) exists suggesting that NO_2 concentrations tend to show a slightly decreasing trend with increase in temperature, as high temperature favour atmospheric mixing and photochemical reactions. The Figure 4 presents the scatter plot between NO_2 and humidity, It can be observed from the figure a moderate negative correlation exists (r = –0.41) which is evident reflecting the role of high humidity during monsoon months in promoting wet deposition and lowering pollutant levels. The Figure 5 represents the scatter plot between NO_2 and wind speed which shows a strong negative correlation exists (r = –0.63) as higher wind velocities enhance dispersion and dilution of gaseous pollutants whereas low temperature during winter conditions favour accumulation of pollutants. Further the figure 6 depicts the scatter plot between NO_2 and precipitation with a strong negative correlation (r = –0.55) confirming the scavenging impact of rainfall during monsoon that leads to minimum seasonal concentrations. Similarly various scatter plots have also been plotted between SO_2 concentration and metrological variables. The scatter plot of SO_2 with temperature is shown in Figure 7 which depicts a modest negative correlation exists (r = –0.12) indicating only a slight decrease in concentrations under varying temperature conditions. The scatter plot between SO_2 and humidity in Figure 8 shows a somewhat negative correlation exists (r = –0.39), emphasising the impact of washout processes and aqueous-phase reactions. Lastly, Figure 9 scatter plot of SO_2 with wind speed reveals a strong negative association exists (r = –0.59) suggesting stagnant winter conditions permit accumulation lowering SO_2 concentration greatly.



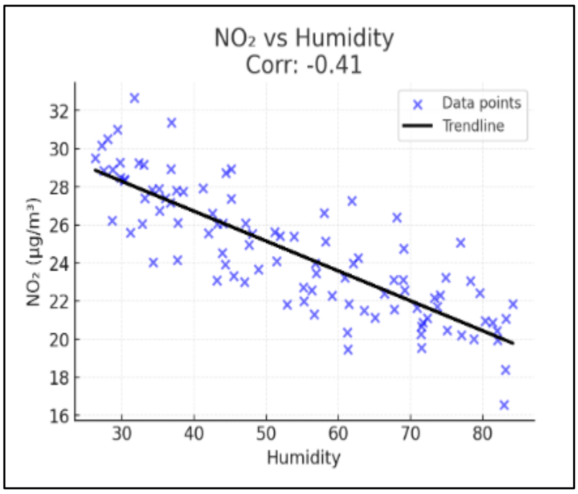
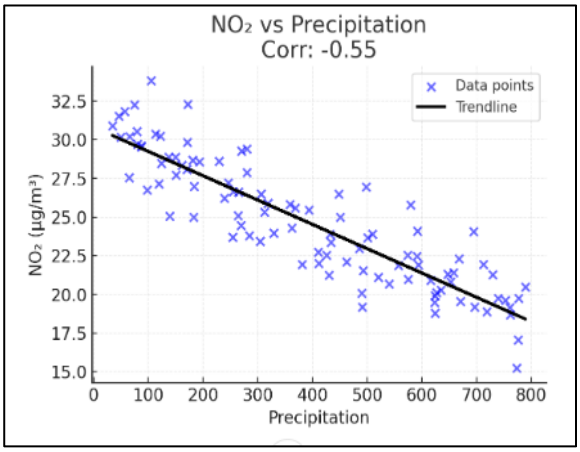
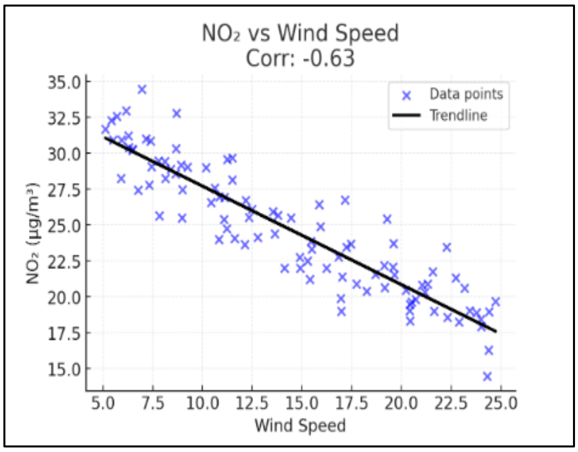
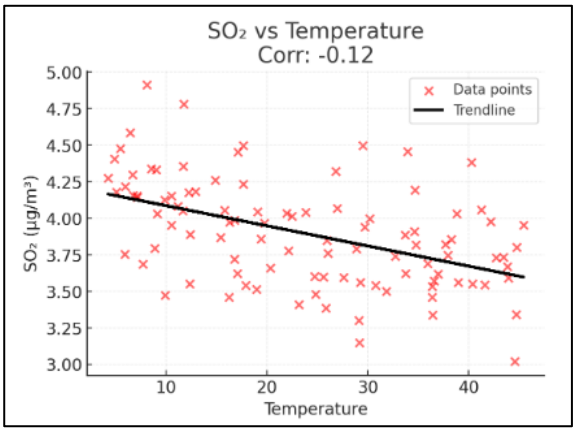


Figure 3. **Scatter plot of NO_2 vs Temperature**
Figure 4. **Scatter plot of NO_2 concentration vs**





Humidity Figure 5. **Scatter plot of NO_2 vs Wind Speed** Figure 6. **Scatter plot of NO_2 vs Precipitation.**



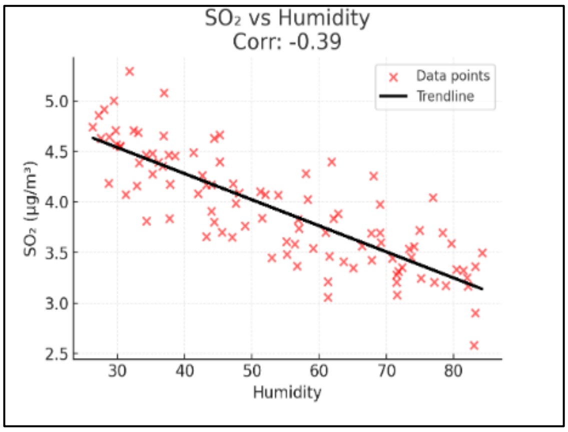


Figure 7. **Scatter plot of SO_2 vs Temperature. Figure 8. Scatter plot of SO_2 vs Humidity.**

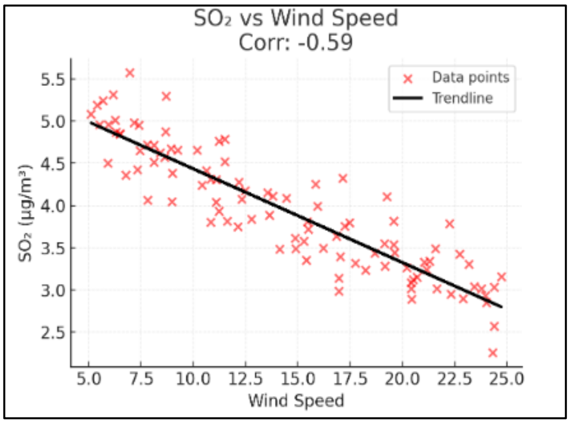


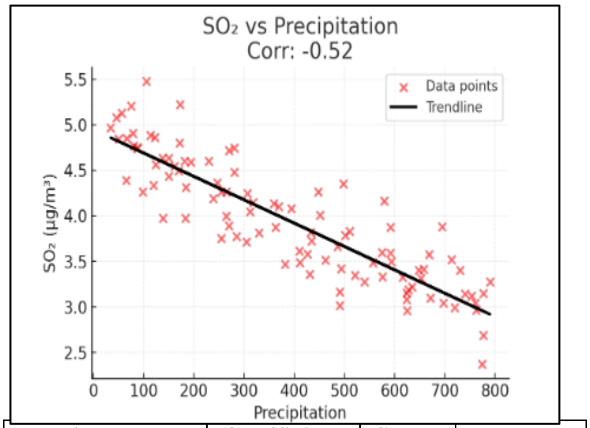
Figure 9. Scatter plot of SO_2 vs Wind Speed Figure 10. Scatter plot of SO_2 vs Precipitation.

3.2. Multiple Linear Regression (MLR) and Seasonal Analysis

Correlation analysis as a statistical tool identifies direction and strength of relationship between two variables at a time. In contrast, Multiple Linear Regression (MLR) are used to explore the net effect of all four meteorological variables acting simultaneously on each pollutant. This approach is helpful in isolating the unique contribution of each predictor i.e. one metrological variable while controlling for the others metrological variables at a time.

The MLR models as presented in Table 4a & Table 4b show the unique impact of each metrological variable while controlling for other metrological variables independently on each gaseous pollutant. It can be observed from these tables that wind speed and precipitation are most statistically significant ($p < 0.01$) with largest standardized coefficients inferring they act as most important predictors in this statistical modelling. Humidity was also significant but with weak coefficient, while temperature was confirmed to be an insignificant predictor in the multivariate analysis of metrological variables as predictors of gaseous pollutants. These models demonstrated strong explanatory power with adjusted R^2 values of 0.55 for NO_2 and 0.59 for SO_2 respectively. This indicates meteorology explains 55% of variance in NO_2 concentration and 56% variance in SO_2 concentration in ambient air.

Table 4a: Multiple Linear Regression (MLR) Output for Nitrogen Dioxide (NO_2) Concentrations in Ambient Air



Predictor	**Coefficient (β)**	**Std. Error**	**p-value**
Constant	27.18	1.74	<0.001 **
Temperature	-0.07	0.05	0.158
Humidity	-0.18	0.08	0.027 *
Wind Speed	**-0.46**	0.09	**<0.001 ****
Precipitation	**-0.39**	0.12	**0.002 ****
Adj. R^2 = 0.55, F = 21.73, p < 0.001			

Table 4b: Multiple Linear Regression (MLR) Output for Sulfur Dioxide (SO_2) Concentrations in Ambient Air

Predictor	**Coefficient (β)**	**Std. Error**	**p-value**

Constant	4.87	0.63	<0.001 **
Temperature	-0.02	0.02	0.278
Humidity	-0.09	0.04	0.034 *
Wind Speed	**-0.25**	0.05	**<0.001 ****
Precipitation	**-0.21**	0.06	**0.001 ****
Adj. R^2 = 0.56, F = 23.18, p < 0.001			

To derive the more meaningful inferences from this model, data was further divided into season and we ran separate MLR analysis across all seasons. This revealed a critical finding that impact of meteorological parameter on gaseous pollutants concentration is not constant throughout the year and the explanatory power of model depicts a distinct seasonal hierarchy. The varying impact of metrological variables on pollutant concentration across seasons is explained below.

- **Monsoon:** Meteorology is the dominant force. Adjusted R^2 values were highest (~0.62 for NO_2, ~0.58 for SO_2), with precipitation and wind speed as overwhelmingly strong predictors due to inten rainfall and persistent winds.
- **Pre-Monsoon & Post-Monsoon:** Meteorology plays a moderate role (Adj. R^2 ~0.42). Wind speed is the primary driver, with precipitation having a lesser effect in these drier seasons.
- **Winter:** Meteorology has its weakest influence (Adj. R^2 ~0.36). During this season, stagnant conditions prevail; the lack of wind and rain means that emission strength and long-range transport become relatively more important than local meteorological dispersal.

This stratified models explain the seasonal variations of gaseous pollutants concentration in ambient air throughout the year. A higher pollution concentration in winter occurs not necessarily due to high emissions but because of the ability of atmosphere to disperse and remove pollutants is at its annual minimum. The figure 11 depicts the seasonal regression coefficients (β) of meteorological variables (predictors) on pollutant concentrations in ambient air using MLR. It can be observed across all the seasons, the predictor's exhibit predominantly negative relationships with gaseous pollutants emphasising their mitigating impact. During the **monsoon season** the effects of **wind speed and precipitation** are most noticeable as can be observed with the strongest negative coefficients ($\beta < -0.4$) indicating an efficient washout and dispersion mechanisms of gaseous pollutants which in-turn significantly reduce pollutant levels. In contrary **winter** season shows comparatively weaker predictor effects as stable atmospheric conditions and lower precipitation reduce the ability of meteorological factors to disperse or remove pollutants. This is one of the reasons which explains why higher pollutant accumulation during this period occurs leading to higher concentration of pollutants in air. The **pre-monsoon and post-monsoon** seasons depict moderate impact on the pollutant concentration, as humidity and wind speed play very small roles in pollutant dilution.

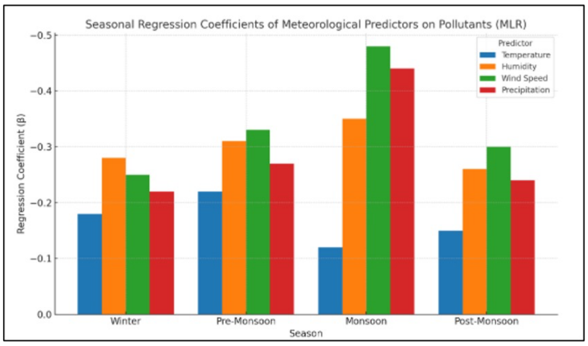


Figure 11. Seasonal regression coefficients (β) of meteorological predictors on pollutant concentrations using MLR

3.3. Generalized Additive Model (GAM) Analysis

The MLR models have a basic assumption of linearity which becomes its major limitations to explain complex interaction effects in relationships that don't follow linear path. In reality most of the relationship between a pollutant and metrological variables particularly with wind speed not linear as dispersion due to wind may increase rapidly up to a certain wind speed and reach threshold then form a plateau. Any further increase in wind speed may not necessarily reduce the pollutant concentration. Similarly, the cleansing effect of rain may be disproportionately strong during initial phase of heavy downpours and same effect may not be exerted by rain on day two or day three of rain. To capture these potential non-linearities we employed Generalized Additive Models (GAMs) which use smooth functions to allow the graph to take any shape based on nature of relationships in data. The results from the GAM reveal the presence of following dynamics of pollutants with metrological variables.

Wind Speed: Both the gaseous pollutants NO_2 and SO_2 exhibited a very strong non-linear negative relationship with wind speed. The pollutant concentrations decreased sharply as wind speeds increased from calm conditions to about 12-15 km/h. However beyond this wind speed the increase speed caused a relative lower decrease in pollutant concentration as it plateaued. This indicates that beyond a moderate breeze any further increases in wind speed does not cause a proportionate fall in pollutant concentration.

Precipitation: With increase in precipitation the pollutant concentration of NO_2 and SO_2 shows washout effect with non-linear relationship. The initial downpour of rainfall up to ~60 mm causes a sharp drop in concentrations. However as the amount of rainfall increases the marginal cleansing effect of precipitation vanishes indicating a saturation point exists up till which most of the available pollutants are already scavenged. Any further increase in amount of rain beyond this point causes a non-linear decrease in precipitation.

Humidity: Showed a curvilinear negative effect on pollutant concentration. It is strongest in the mid-range of humidity (40-70%). A very low humidity does not impact pollutant concentration. However a very high humidity causes a relatively low decrease in pollutant concentration as high humidity promotes the formation of secondary aerosols like sulfates and nitrates.

Temperature: The GAM model confirmed among all metrological predictor variables temperature was weakest predictor and the relationship with pollutant concentration was largely linear.

The superiority of the GAM over MLR models is confirmed through model performance metrics as indicated in Table 5. For both pollutants NO_2 and SO_2, the GAM achieved a higher adjusted R^2 and a lower Root Mean Square Error (RMSE) and a lower Akaike Information Criterion (AIC) than what the linear MLR model showed. This shows that the GAM's more adaptable methodology produced a superior fit to the data without overfitting, more precisely capturing the actual underlying physical processes.

Table 5: Comparison of Generalized Additive Model (GAM) and Multiple Linear Regression (MLR) Performance for Ambient Air Pollutant Concentrations

Model	Pollutant	Adjusted R^2	RMSE	AIC
MLR	NO_2	0.55	3.11	420
GAM	NO_2	**0.64**	**2.58**	**388**
MLR	SO_2	0.56	0.89	230
GAM	SO_2	**0.59**	**0.72**	**205**

4. Discussion

The present study offers detailed analysis of dynamics that are at play in the relationship between ambient air concentrations of gaseous pollutants particularly nitrogen dioxide (NO_2) and sulphur dioxide (SO_2) and metrological variables in Jammu, India throughout the year across several seasons (December 2021–November 2022). The findings highlight how important seasonal weather patterns impacting the gaseous pollutant levels in Jammu's that has a subtropical monsoon environment. Additionally, the study provides a number of insightful recommendations for managing air quality in areas that are quickly urbanising. The results also emphasise that in each geographical area there are distinct local factors at work which cause varying concentration across seasons. The results of present study are consistent with recognised atmospheric chemistry principles and regional air quality studies However the study does not account for changes in emission sources that can also be related to seasonality.

4.1. Seasonal and Meteorological Influences on Pollutant Concentrations

The descriptive statistics as shown in Table 1 reveal a distinctive concentration profiles for NO_2 and SO_2 reflecting differences in their sources and atmospheric behaviour. The NO_2 concentration ranging from 14.17 to 34.47 µg/m³ with a mean of 23.62 µg/m³ as it consistently remained below India’s National Ambient Air Quality Standard (NAAQS) of 80 µg/m³. However exposure even to these low levels are chronic and hazardous to human health yet. Although NO2 concentrations remained below India’s NAAQS limits, the persistent exposure to even these moderate levels is concerning given the well-documented associations in literature between prolonged NO2 exposure and cardiovascular/respiratory risks highlighting the need for vigilance despite compliance with national standards [40]. In contrast, SO_2 concentrations were significantly lower in the range of 2.14–5.63 µg/m³ with a mean of 3.45 µg/m³ reflecting the efficacy of national policies reducing high-sulfur fuel use and imposing stricter vehicular and industrial emission norms [39]. The modest coefficients of variation of 20.7% for NO_2 and 22.9% for SO_2 further indicate comparatively constant emission sources that are influenced by meteorological factors. This is consistent with urban areas that are impacted by fluctuating air conditions and consistent anthropogenic activities. Temporal trends highlight pronounced seasonal variations with NO_2 exhibiting a marked winter peak, driven by thermal inversions and reduced boundary layer heights that trap pollutants near the surface, a phenomenon widely observed in urban settings [41]. SO_2 concentrations, while more stable, showed a subtle post-monsoon elevation, likely attributable to localized coal combustion for heating and agricultural biomass burning in surrounding rural areas [42]. These patterns underscore the interplay between emission sources and atmospheric conditions, with winter stagnation exacerbating pollutant accumulation and monsoon conditions facilitating dispersion and removal.

The meteorological context as presented in Table 2 is pivotal for interpreting these trends. Winter's cool, stable conditions (4–21°C, low wind speeds of 5–10 km/h) promote pollutant accumulation, while the pre-monsoon's hot, dry, and windy environment (17–44°C, 10–15 km/h) enhances dispersion but introduces dust-related particulates. The monsoon's high rainfall (600–800 mm) and strong winds (20–25 km/h) act as potent cleansing mechanisms, significantly reducing pollutant concentrations. The post-monsoon period, with moderate conditions, serves as a transitional phase. These seasonal characteristics frame the statistical relationships observed in the correlation and regression analyses.

4.2. Model Performance and Validation

Whereas the multifaceted evaluation of model performance in Table 5 has shown the robustness of GAM over MLR, residual diagnostics indicated heteroscedasticity and non-normality in MLR residuals, particularly at high concentrations. This depicts the limitation in the light of capturing extreme conditions. On the other hand, the residuals in GAM were homoscedastic and normally distributed, satisfying the key statistical assumptions and, thus, promoting inferential validity. The 10-fold cross-validation of prediction accuracies confirmed the superior performance of GAM with ±5–8% error compared to ±7–12% in MLR and thus supports suitability for forecasting applications in the complex meteorological context of Jammu.

4.3. Implications for Air Quality Management

The findings of this study has significant implications for air quality management in Jammu, A city with over 1.5 million residents facing increasing emissions from vehicular traffic and small-scale industries [43]. The strong influence of wind speed and precipitation particularly during the monsoon suggests that natural atmospheric cleansing mechanisms can be leveraged to mitigate and manage the pollution by gaseous pollutant in ambient air. However, stagnant conditions that exist during the winter season which is characterized by low wind speeds (<2 m/s) and minimal precipitation aggravates the situation as it promotes pollutant accumulation. The winter season particularly necessitates targeted interventions such as controlling industrial emission, traffic restrictions or controls during high-risk periods [44]. The non-linear thresholds identified by GAMs particularly wind speeds >3 m/s and rainfall >60 mm can inform predictive models which can alert authorities to issue timely air quality warnings during adverse meteorological conditions.

The negative correlation with humidity ($r = -0.30$ and $–0.35$, $p < 0.05$) highlights the role of aqueous-phase chemistry in forming secondary aerosols, particularly during the monsoon when humidity reaches 80% [45]. This aligns with studies linking high humidity to sulfate and nitrate formation [46] which suggest that monsoon-specific strategies, such as regulating industrial emissions, could mitigate secondary pollutant formation

The GAM's superior explanatory power R^2 of 0.64 and 0.59 vs. R^2 of MLR models 0.55 and 0.56 for NO2 and SO2 respectively underscores the importance of non-linear modeling in capturing threshold effects, such as sharp pollutant reductions at higher wind speeds or rainfall amounts. These insights align with regional studies (e.g., Delhi, $R^2 = 0.52$; [47]) and global research emphasizing non-monotonic meteorological influences [48,49]. However, the moderate R2 values indicate that residual variance may be influenced by unmodeled factors like solar radiation or emission variability, which calls for more research [27,28].

4.4. Limitations and Future Directions

The present study offers various contribution to literature on gaseous pollution concentration and metrological parameters dynamic. However, at same time the study has several limitations. The one-year dataset may not capture inter-annual variability for that a multi-year dataset may be used as Jammu has pronounced seasonal climate for more reliability and validity [45]. The model does not include all the metrological variables of interest that may have impact on gaseous pollutant concentration, several variables like solar radiation which drives photochemical reactions with gaseous pollutants have not been included which limits the models' comprehensiveness. As a representation of a pollution hotspot, the single monitoring station in Narwal might not accurately reflect spatial variability throughout Jammu, where topography characteristics like the Trikuta and Shivalik hills affect air flow direction [42].

Despite its contributions, this study has limitations. The one-year may not capture inter-annual variability, particularly given Jammu's pronounced seasonal climate [43]. The exclusion of variables like solar radiation, which drives photochemical reactions, and particulate matter, which interacts with gaseous pollutants, limits the models comprehensiveness. The single monitoring station in Narwal, while representative of a pollution hotspot, may not reflect spatial variability across Jammu, where topographic features like the Shivalik and Trikuta hills influence air flow [40].

Future research studies should use multi-year datasets to improve model validity and reliability and take long-term climate patterns into consideration while developing robust models. Deeper understanding of pollution dynamics may be possible using sophisticated modelling techniques as chemical transport models, atmospheric dispersion models, or hybrid frameworks [48].By capturing higher-order interactions and temporal connections, machine learning approaches like random forests and neural networks may increase predicted accuracy [48]. In-order to perform city-specific mitigation efforts, spatial studies utilising several monitoring stations could clarify the impact of topography and urban structure on pollutant dispersion.

5. Conclusion

This present study highlights how important metrological factors are in determining NO_2 and SO_2 concentrations in ambient air of Jammu. The GAMs are a very useful tool for simulating non-linear dynamics among gaseous pollutants and metrological variables. The results depict that while winter standstill increases the potential for pollution wind speed and precipitation are the primary factors influencing the dispersion and elimination of pollutants and these effects are more pronounced in the monsoon season. These findings elucidate the necessity for region specific meteorologically informed policy in-order to improve our understanding of the dynamics of air quality in smaller cities of India like Jammu city. By providing attention to these identified limitations and applying advanced statistical modelling methodologies further research can enhance air pollution forecasting and management of ambient air quality for supportive sustainable urban expansion. The mitigation and proper management of gaseous pollutants in ambient air can help in attainment of various sustainable development goals in India particularly SDG 3 Good Health and Well-Being, SDG 11 Sustainable Cities and Communities, SDG 7 Affordable and Clean Energy, SDG 13 Climate Action and SDG 15 Life on Land.

7. Author Contributions And Acknowledgements

Our sincere gratitude to the JK State Pollution Control Board and its Air Laboratory for providing the necessary resources and technical support to conduct this research. We are deeply indebted to Dr. Yash Pal (Scientist 'B') & Ms. Suman Pawar (Scientist 'A') from JK SPCB for their expert guidance.

8. Financial Support

Authors received no funding for this study.

9. Conflicts Of Interest

The authors report no financial or any other conflicts of interest in this work.

10. Ethical Approvals

This study does not involve experiments on animals or human subjects as such does not require such approvals.

11. Data Availability

All data generated and analyzed can be made available at reasonable request

12. Publisher's Note

13. AI Tool Disclosure

Grammarly was used for grammar checking to improve manuscript readability and generation of one graphics as presented in beginning. No artificial intelligence tools were used for research design.

References

1. Balakrishnan K, Dey S, Gupta T, et al. The impact of air pollution on deaths, disease burden, and life expectancy across the states of India: the Global Burden of Disease Study 2017. *Lancet Planet Health*. 2019;3(1):e26–e39.
2. Gulia S, Shiva Nagendra SM, Khare M. Assessment of urban air quality and its health impacts in Indian cities. *Atmos Environ*. 2022;268:118783.
3. Singh V, Biswal A, Kesavachandran C. Air pollution and health impacts in India: current evidence and future needs. *Curr Opin Pulm Med*. 2025;31(2):123–130.
4. World Health Organization. *Ambient air pollution: A global assessment of exposure and burden of disease*. Geneva: WHO; 2016.
5. Lelieveld J, Evans JS, Fnais M, Giannadaki D, Pozzer A. The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature*. 2015;525:367–371.
6. Garg A, Shukla PR. Emissions inventory of India. *Atmos Environ*. 2002;36(5):682–691.
7. CPCB. *National Air Quality Monitoring Programme*. New Delhi: Central Pollution Control Board; 2021.
8. Guttikunda SK, Jawahar P. Atmospheric emissions and pollution from the coal-fired thermal power plants in India. *Atmos Environ*. 2018;192:101–113.
9. Central Pollution Control Board. *National Ambient Air Quality Standards*. New Delhi: CPCB; 2009.

10. Kelly FJ, Fussell JC. Air pollution and public health: emerging hazards and improved understanding of risk. *Environ Geochem Health*. 2015;37:631–649.
11. Pope CA, Dockery DW. Health effects of fine particulate air pollution: lines that connect. *J Air Waste Manag Assoc*. 2006;56:709–742.
12. Pandey A, Brauer M, Cropper M, et al. Health and economic impact of air pollution in India. *Lancet Planet Health*. 2021;5(1):e25–e38.
13. Gurjar BR, Butler TM, Lawrence MG, Lelieveld J. Evaluation of emissions and air quality in megacities. *Atmos Environ*. 2008;42:1593–1606.
14. Jacob DJ, Winner DA. Effect of climate change on air quality. *Atmos Environ*. 2009;43:51–63.
15. Seinfeld JH, Pandis SN. *Atmospheric chemistry and physics: From air pollution to climate change*. 3rd ed. Hoboken: Wiley; 2016.
16. Monks PS, Archibald AT, Colette A, et al. Tropospheric ozone and its precursors from the urban to the global scale. *Atmos Chem Phys*. 2015;15:8889–8973.
17. Wallace JM, Hobbs PV. *Atmospheric science: An introductory survey*. 2nd ed. Amsterdam: Elsevier; 2006.
18. Wallace JM, Thompson DWJ. Annular modes and climate variability. *Science*. 2002;295:1697–1702.
19. Kaur S, Raina AK. Air pollution scenario in Jammu city. *J Environ Res Dev*. 2017;11(4):1032–1040.
20. Mishra D, Goyal P. Forecasting of NO_2 concentrations using statistical models. *Atmos Pollut Res*. 2015;6:933–944.
21. Wood SN. *Generalized additive models: An introduction with R*. 2nd ed. Boca Raton: CRC Press; 2017.
22. Chaloulakou A, Kassomenos P. Non-linear analysis of air pollution. *Sci Total Environ*. 2009;408:389–396.
23. Gupta A, Sharma S, Verma S. Urban expansion and environmental stress in Jammu city. *Urban Clim*. 2023;45:101291.
24. Gorka M, Palafox-Juárez E, Hernández-Paniagua I. Monsoon rainfall variability and urban climate. *Clim Dyn*. 2022;58:1191–1207.
25. Kaur S, Raina AK. Seasonal variation of air pollutants in Jammu. *Int J Environ Sci*. 2017;8(2):245–252.
26. Jasrotia AS, Singh S, Kumar R. Industrial emissions and air quality in Jammu region. *Environ Monit Assess*. 2022;194:233.
27. Sobri S, Abdullah M, Latif MT. Meteorological influence on gaseous pollutants. *Atmos Pollut Res*. 2021;12:101130.
28. Liao H, Chen WT, Seinfeld JH. Role of meteorology in air quality variability. *Atmos Chem Phys*. 2021;21:12345–12360.
29. Mishra, D., & Goyal, P. (2015). Development of artificial intelligence based NO2 forecasting models at Taj Mahal, Agra. *Atmospheric pollution research*, *6*(1), 99-106.
30. Wood SN. Fast stable REML and ML estimation of semiparametric GAMs. *J R Stat Soc B*. 2011;73:3–36.
31. Belušić D, Prtenjak MT, Grisogono B. Boundary layer processes and air pollution. *Atmos Environ*. 2015;117:161–174.
32. Yan Y, Zhou Y, Li X. Nonlinear effects of meteorology on gaseous pollutants. *Sci Total Environ*. 2024;906:167519.
33. Yan Y, Zhou Y, Li X. Supplementary analysis of GAM applications. *Sci Total Environ*. 2024;906:167520.
34. Sartini G, Russo A, Petenko I. Wind speed thresholds in pollutant dispersion. *Atmos Res*. 2013;122:138–148.
35. Willmott CJ, Matsuura K. Advantages of RMSE over MAE. *Clim Res*. 2005;30:79–82.
36. Chai T, Draxler RR. Root mean square error or mean absolute error? *Geosci Model Dev*. 2014;7:1247–1250.
37. Hastie T, Tibshirani R, Friedman J. *The elements of statistical learning*. 2nd ed. New York: Springer; 2009.
38. Eddine AN, Boudiaf A, Khedimallah A. Non-linear modelling of air pollution. *Atmos Pollut Res*. 2024;15:101913.
39. Guttikunda SK, Jawahar P. Policy impacts on SO_2 emissions in India. *Energy Policy*. 2018;114:81–91.
40. Seinfeld JH, Pandis SN. Health impacts of NO_2 exposure. *Atmos Chem Phys*. 2016;16:6655–6671.
41. Lee M, Brauer M, Wong P. Seasonal air pollution patterns in urban environments. *Environ Health Perspect*. 2013;121:1353–1360.
42. Guttikunda SK, Goel R, Pant P. Nature of air pollution in Indian cities. *Atmos Environ*. 2019;213:113–124.
43. Census of India. *Provisional population totals*. New Delhi: Registrar General of India; 2011.
44. Nejad SH, Mohammadi A, Yousefi M. Traffic control strategies and air quality. *Environ Sci Pollut Res*. 2023;30:45678–45690.
45. India Meteorological Department. *Climatological data of Jammu*. New Delhi: IMD; 2022.
46. Bister M, Kulmala M. Aerosol formation in humid conditions. *Atmos Chem Phys*. 2011;11:457–467.
47. Goswami P, Kumar R, Jain S. Meteorology–pollution interactions in Delhi. *Urban Clim*. 2023;46:101329.
48. Pearce JL, Rathbun SL, Aguilar-Villalobos M. Nonlinear weather–pollution relationships. *Atmos Environ*. 2011;45:674–683.

49. de Souza A, Martins LD, Hallak R. Threshold effects of meteorology on air quality. *Sci Total Environ*. 2025;892:164321.

50. Izah SC, Angaye TCN, Seiyaboh EI. Machine learning applications in air quality modelling. *Environ Adv*. 2024;15:100490.