



Assessment of Air Quality Index and Potential Health Risks Using Meteorological Parameters in Chonburi Province, Thailand

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Abstract

This study assessed seasonal variations in air pollutant concentrations, air quality index (AQI), meteorological influences, and inhalation health risks in an industrially influenced area of Chonburi Province, Thailand, during 2019–2021. Monthly concentrations of NO₂, O₃, PM₁₀, and PM_{2.5} were analyzed by season. AQI was calculated as a screening-level indicator using available monitoring data, excluding SO₂ and CO because complete data were unavailable. Associations between AQI and meteorological variables were examined using Pearson correlation and regression analyses. Non-carcinogenic inhalation risk was assessed using hazard quotient (HQ) values based on a screening-level concentration-based approach. Pollutant concentrations were generally higher in January and February and lower during June–September. Winter showed the highest mean concentrations of NO₂, O₃, PM₁₀, and PM_{2.5} at 16.37 ± 1.64 ppb, 30.73 ± 3.62 ppb, 60.71 ± 11.68 µg/m³, and 31.33 ± 7.53 µg/m³, respectively. AQI was also highest in winter (73.33 ± 32.69), followed by summer (30.22 ± 5.74) and the rainy season (22.67 ± 5.49). AQI was positively correlated with atmospheric pressure ($r = 0.748$, $p < 0.01$) and negatively correlated with relative humidity ($r = -0.621$, $p < 0.01$) and rainfall ($r = -0.524$, $p < 0.01$). Multiple regression showed that atmospheric pressure was the only significant independent predictor of AQI ($B = 8.074$, $p = 0.004$), although this association should be interpreted cautiously due to possible temporal autocorrelation and COVID-19-related activity changes. The HQ results indicated that PM_{2.5} and PM₁₀ were the main contributors to potential non-carcinogenic inhalation risk, particularly during winter, when their HQ values exceeded 1.0. NO₂ and O₃ remained below 1.0 across all seasons. These findings support the need for season-specific air quality management, especially particulate matter control during winter pollution episodes in industrial communities.

Keywords : Air quality index; Meteorological factors; Seasonal variation; Inhalation health risk; Industrial area

Introduction

Air pollution is a major environmental and public health concern worldwide, particularly in rapidly urbanizing and industrializing regions [1]. Exposure to ambient air pollutants can cause a wide range of adverse health effects, from acute symptoms such as coughing, wheezing, respiratory irritation, and difficulty breathing to chronic diseases, including asthma, bronchitis, cardiovascular disease, impaired lung function, and lung cancer [2, 3]. Particulate matter with aerodynamic diameters of less than 2.5 μm and 10 μm ($\text{PM}_{2.5}$ and PM_{10}), together with ground-level ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and carbon monoxide (CO), are among the principal pollutants of public health concern. Fine particulate matter is particularly hazardous because it can penetrate deeply into the respiratory tract and may enter the bloodstream, thereby increasing the risks of respiratory and cardiovascular disorders [4, 5].

The Air Quality Index (AQI) is widely used to communicate ambient air-quality conditions and their potential health implications [6, 7]. It converts pollutant concentrations into a standardized scale that allows the public and regulatory agencies to identify periods of elevated pollution and associated health concerns. In standard AQI calculation, pollutant-specific averaging times are important; for example, $\text{PM}_{2.5}$ and PM_{10} are commonly assessed using 24-hour averages, whereas O_3 and NO_2 may require shorter averaging periods depending on the AQI system applied. Therefore, when only daily monitoring data are available, AQI estimates for some pollutants should be interpreted as screening-level indicators rather than exact regulatory AQI values. However, AQI levels are influenced not only by the intensity of emission sources but also by prevailing meteorological conditions [8]. Consequently, similar emission levels may produce substantially different air-quality conditions depending on atmospheric dispersion, stability, chemical transformation, and pollutant-removal processes.

Meteorological factors play an important role in controlling the concentration, movement, and persistence of air pollutants [9]. Previous studies have shown that wind speed, temperature, relative humidity, rainfall, solar radiation, and pressure-related conditions can substantially influence particulate matter and other air pollutant concentrations [10, 11]. Wind speed

generally promotes atmospheric dispersion, whereas calm conditions can lead to pollutant accumulation near emission sources. Temperature influences atmospheric stability, vertical mixing, and photochemical reactions, while atmospheric pressure may be associated with stagnant air masses and reduced pollutant dispersion. Relative humidity can affect particle growth and atmospheric chemistry, whereas rainfall can remove airborne particles and soluble gases through wet deposition. Solar radiation may also accelerate photochemical reactions that contribute to ozone formation. Because these factors vary seasonally, pollutant concentrations and AQI levels may differ considerably between dry, wet, and transitional periods [12–14].

Chonburi Province is one of Thailand's major industrial, transportation, and logistics centers and forms an important part of the Eastern Economic Corridor [15]. Rapid industrial expansion, urban development, increasing traffic density, and construction activities have introduced multiple sources of air pollution into the area. Bo Win Subdistrict is characterized by a mixture of industrial facilities, residential communities, commercial activities, and heavily trafficked roads. This combination of land uses may increase community exposure to industrial and traffic-related pollutants, particularly during meteorological conditions that limit atmospheric dispersion. In addition, the 2019–2021 study period overlapped with the COVID-19 pandemic, during which changes in traffic volume, industrial activity, and human mobility may have influenced pollutant concentrations. This factor should be considered when interpreting temporal changes in AQI and pollutant levels.

Although previous studies have examined air pollution, meteorological conditions, and health risks, several important gaps remain. Prior research has demonstrated that the relationships between $\text{PM}_{2.5}$ and meteorological variables vary across regions and seasons, highlighting the importance of season-specific analysis [16]. In Thailand, Kliengchuay, Srimanus [17] integrated meteorological parameters with $\text{PM}_{2.5}$ -related health impact assessment using AirQ+, while Vongruang, Suppoung [18] examined meteorological criteria for $\text{PM}_{2.5}$ risk classification in a coastal industrial province. However, these studies primarily focused on $\text{PM}_{2.5}$ rather than AQI as an integrated air quality indicator. In addition, age-specific health risk assessment has been

applied to PM_{2.5} exposure among children in northern Thailand [19], but less attention has been given to multiple age groups within industrially influenced communities. Therefore, this study does not claim to introduce a fundamentally new analytical method; rather, it provides a locally contextualized integrated screening assessment that combines seasonal AQI variation, meteorological associations, and age-specific inhalation health risk estimation in an industrial community of eastern Thailand.

Although previous studies in Thailand have examined PM_{2.5} variation, meteorological effects, and health risk assessment, most have focused on individual pollutants or single analytical components. The present study differs by integrating seasonal AQI characterization, meteorological association analysis, regression-based screening, and age-specific inhalation health risk assessment within the same industrially influenced community in Chonburi Province. Therefore, the contribution of this study is a locally contextualized integrated screening assessment for air-quality management in an industrial area of eastern Thailand.

Addressing this gap is important because an integrated assessment can provide a more complete understanding of how meteorological conditions influence air quality and how resulting exposure may affect different population groups. Such evidence can support the identification of high-risk seasons, vulnerable age groups, and meteorological conditions associated with elevated pollution levels. It can also strengthen local air-quality surveillance, public-health warnings, and environmental management strategies in rapidly developing industrial areas. However, source attribution was beyond the scope of this study because wind-direction analysis, back-trajectory modelling, boundary-layer information, and detailed emission inventory data were not available. Future studies should incorporate these data to better distinguish local industrial sources from regional transport and meteorologically driven accumulation.

Accordingly, this study aimed to: (1) characterize the seasonal variations in AQI and meteorological factors in Bo Win Subdistrict, Chonburi Province, during 2019–2021; (2) determine the relationships between AQI and key meteorological variables using correlation and regression analyses; and (3) assess seasonal inhalation health risks among different age groups using the U.S. EPA hazard quotient approach. The findings are expected

to provide local screening evidence for air-quality monitoring, seasonal risk communication, and environmental health management, rather than definitive source attribution or causal prediction of AQI.

Materials and Methods

Study Area and Data Collection

The study was conducted in Bowin Subdistrict, Si Racha District, Chonburi Province, Thailand (approximately 13.1°N, 101.0°E), which lies within the EEC's designated industrial promotional zone [16]. The location of the monitoring sites and the study area are presented in **Fig. 1**. The subdistrict is home to one of Thailand's largest integrated industrial estates, accommodating over 600 factories engaged in petrochemical processing, electronics manufacturing, automotive assembly, and logistics operations. The area is subject to a tropical monsoon climate with three distinct seasons: (i) the cool-dry (winter) season from November to February, dominated by the northeast monsoon with low humidity and minimal precipitation; (ii) the hot-dry (summer) season from March to May, characterised by high solar radiation and elevated temperatures; and (iii) the wet (rainy) season from June to October, driven by the southwest monsoon with high rainfall and humidity. These seasonal meteorological contrasts provide an ideal natural experiment for examining the meteorological modulation of ambient air quality. The study period covered 2019–2021, which overlapped with the COVID-19 pandemic and associated changes in traffic, industrial activity, and human mobility. Therefore, temporal variations in pollutant concentrations and AQI during 2020–2021 were interpreted cautiously, as they may reflect both meteorological effects and changes in anthropogenic emissions during the pandemic period.

Data Analysis

The data used in the analysis comprised meteorological and air pollution data. Meteorological data were obtained from the Meteorological Department, Chonburi Province, consisting of relative humidity, atmospheric pressure, rainfall, temperature, and wind speed. Air pollution data were obtained from the Bowin Subdistrict Monitoring Station, Si Racha District, Chonburi Province, operated by the Pollution Control Department. The air pollutants included in the analysis were NO₂, O₃, PM₁₀, and PM_{2.5}.

SO₂ and CO were not included because complete and consistent data for these pollutants were not available from the selected monitoring station throughout the study period. Their exclusion was therefore considered a limitation because the maximum sub-index AQI may be underestimated on days when SO₂ or CO would otherwise contribute the dominant AQI sub-index.

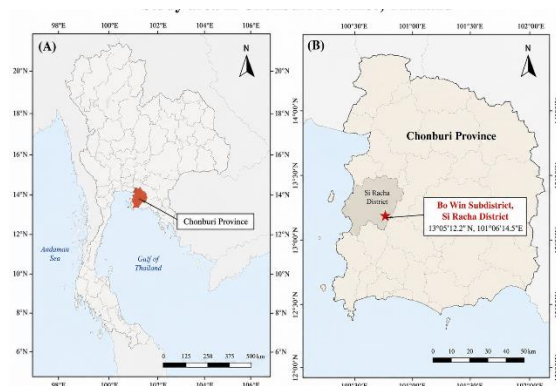


Figure 1 Location of the study area in Si Racha District, Chonburi Province, eastern Thailand

Daily average concentrations were used as the available routine monitoring dataset for the study period. However, the U.S. EPA AQI system applies pollutant-specific averaging times, including 24-hour averages for PM_{2.5} and PM₁₀, 8-hour or 1-hour averages for O₃, and 1-hour averages for NO₂. Therefore, AQI values derived from daily average NO₂ and O₃ data in this study should be interpreted as screening-level estimates rather than exact regulatory AQI values. The meteorological data and air pollution data covered the study period of 2019–2021.

Air Quality Index

The AQI was calculated for each pollutant following the U.S. EPA AQI Technical Assistance Document, using the linear interpolation formula [20]:

$$AQI^i = \frac{(AQI^{HI} - AQI^{LO}) / (Conc^{HI} - Conc^{LO})}{(Conc^i - Conc^{LO}) + AQI^{LO}} \quad (1)$$

where Concⁱ is the measured concentration of pollutant *i*; Conc^{LO} and Conc^{HI} are the lower and upper concentration breakpoints bracketing Concⁱ; and AQI^{LO} and AQI^{HI} are the corresponding AQI breakpoint values. The overall AQI was determined as the

highest pollutant-specific sub-index among the available pollutants, namely NO₂, O₃, PM₁₀, and PM_{2.5}. SO₂ and CO were excluded because complete and consistent monitoring data were not available from the selected station throughout the study period. Since the U.S. EPA AQI framework uses pollutant-specific averaging times, the AQI values calculated from daily average O₃ and NO₂ concentrations should be interpreted as screening-level estimates rather than regulatory AQI values. AQI categories were classified according to U.S. EPA standards (Table 1).

Statistical Analysis

Pearson's correlation coefficient (*r*) was used to evaluate bivariate associations between AQI and each meteorological variable. Prior to correlation analysis, data were screened for normality using the Shapiro–Wilk test. When normality assumptions were not met, Spearman's rank correlation was considered as a sensitivity analysis to confirm the direction and robustness of the associations. The strength of correlation was interpreted as: $|r| < 0.3$ (weak), $0.3 \leq |r| < 0.7$ (moderate), and $|r| \geq 0.7$ (strong). Statistical significance was set at $\alpha = 0.05$ and $\alpha = 0.01$, two-tailed.

Table 1 Air Quality Index (AQI) classification scheme

AQI Range	Category	Health Implications
0 – 50	Good	Air quality is satisfactory; poses little or no risk.
51 – 100	Moderate	Acceptable quality; some concern for unusually sensitive individuals.
101 – 150	Unhealthy for Sensitive Groups	Sensitive populations (elderly, children, asthmatics) may experience health effects.
151 – 200	Unhealthy	Everyone may begin to experience health effects.
201 – 300	Very Unhealthy	Health alert: serious effects for all population groups.

AQI Range	Category	Health Implications
301 – 500	Hazardous	Health warning of emergency conditions; entire population likely to be affected.

Correlation and regression analyses were performed using monthly mean observations for the 2019–2021 period, yielding an analytical sample size of $N = 36$. Simple linear regression models were constructed for each meteorological predictor individually to assess the independent predictive capacity of each variable:

$$AQI = \beta_0 + \beta_1 X^I + \varepsilon^I \quad (2)$$

where X^I represents each meteorological variable and ε is the random error term. Model performance was evaluated using the coefficient of determination (R^2) and p -value of the regression coefficient.

A multiple linear regression (MLR) model was subsequently developed incorporating all meteorological predictors simultaneously to assess their joint influence on AQI:

$$AQI = \beta_0 + \beta_1 Ra + \beta_2 T + \beta_3 RH + \beta_4 Pa + \beta_5 Ws + \varepsilon \quad (3)$$

where Ra is rainfall, T is temperature, RH is relative humidity, Pa is atmospheric pressure, and Ws is wind speed. Before interpreting the regression results, model assumptions were examined. Multicollinearity among predictors was assessed using the variance inflation factor (VIF), and VIF values were reported to evaluate the stability of regression coefficients, particularly because relative humidity, rainfall, and atmospheric pressure may be intercorrelated. VIF values were reported to evaluate the stability of regression coefficients, particularly because relative humidity, rainfall, and pressure may be intercorrelated. Model assumptions (normality of residuals, homoscedasticity, linearity) were verified through residual diagnostic plots [21]. Because monthly AQI data may exhibit temporal dependence, the Durbin–Watson statistic was also used to assess residual autocorrelation. Regression results were interpreted as statistical associations rather than causal effects. All analyses were performed using SPSS Statistics version 28.0.

Health Risk Assessment

Health risk from exposure to air pollutants through inhalation was assessed using the hazard quotient (HQ), which is commonly applied to evaluate potential non-carcinogenic health effects. The HQ represents the ratio between the estimated exposure concentration and the reference concentration for inhalation exposure [22]. An HQ value less than or equal to 1 indicates that the estimated exposure is within an acceptable level and that adverse non-carcinogenic health effects are unlikely to occur. In contrast, an HQ value greater than 1 suggests that the exposure level exceeds the reference threshold, indicating a potential health concern from inhalation exposure [19]. The non-carcinogenic hazard quotient for inhalation exposure was calculated as follows:

$$HQ = \frac{EC}{Rfc} \quad (4)$$

where HQ is the hazard quotient, EC is the exposure concentration of the pollutant in air ($\mu\text{g}/\text{m}^3$) and RfC is the pollutant-specific inhalation reference concentration ($\mu\text{g}/\text{m}^3$). The exposure concentration was estimated using the following equation:

$$EC = \frac{C \times ET \times EF \times ED}{AT} \quad (5)$$

where C is the measured concentration of the air pollutant ($\mu\text{g}/\text{m}^3$), ET is the exposure time (h/day)(h/day)(h/day), EF is the exposure frequency (days/year), ED is the exposure duration (years), and AT is the averaging time (h). Exposure was assumed to occur for 24 h/day and 350 days/year, representing a long-term residential exposure scenario in the study area. For non-carcinogenic risk assessment, AT was calculated as $ED \times 365 \times 24$. Under this formulation, the exposure duration term is cancelled algebraically by the averaging time; therefore, the HQ values were interpreted as overall pollutant-specific screening estimates rather than age-specific dose-based risk estimates.

Prior to HQ calculation, NO_2 and O_3 concentrations reported in ppb were converted to $\mu\text{g}/\text{m}^3$, while PM_{10} and $\text{PM}_{2.5}$ concentrations were directly used in $\mu\text{g}/\text{m}^3$. The RfC values used in this study were 57, 120, 25, and 50 $\mu\text{g}/\text{m}^3$ for NO_2 , O_3 , $\text{PM}_{2.5}$, and PM_{10} , respectively.

Results and Discussion

Seasonal Meteorological Characteristics

Table 2 presents the mean meteorological parameters disaggregated by season across the 2019–2021 study period. The winter season was distinguished by the lowest mean rainfall (20.75 mm), the lowest relative humidity (66.65%), the highest atmospheric pressure (1002.84 hPa), and the lowest wind speed (4.15 knots). These meteorological conditions are characteristic of the prevailing northeast monsoon, which delivers continental air masses with low moisture content and suppresses vertical atmospheric mixing through high-pressure subsidence. In contrast, the rainy season recorded the highest rainfall (156.19 mm), the greatest relative humidity (77.12%), the lowest atmospheric pressure (999.20 hPa), and the highest wind speed (5.22 knots)—conditions that collectively facilitate the dispersion and wet deposition of air pollutants. The summer season represented an intermediate regime with the highest temperature (30.39°C) and moderate precipitation.

Air Pollutant and Air Quality Index

Monthly concentrations of NO₂, O₃, PM₁₀, and PM_{2.5} showed a clear temporal pattern (**Figure 2**). The highest concentrations were generally observed in January and February. In January, NO₂, O₃, PM₁₀, and PM_{2.5} concentrations were 18.56 ppb, 32.44 ppb, 70.62 µg/m³, and 40.00 µg/m³, respectively.

Similarly, high concentrations were observed in February, with values of 15.38 ppb, 32.56 ppb, 68.67 µg/m³, and 34.33 µg/m³, respectively. In contrast, lower concentrations were generally recorded during June–September, with minimum values observed for NO₂ in August (8.00 ppb), O₃ in August (15.00 ppb), PM₁₀ in June (31.34 µg/m³), and PM_{2.5} in August (11.33 µg/m³).

When grouped by season, winter showed the highest average concentrations for all pollutants (**Table 3**). The mean concentrations of NO₂, O₃, PM₁₀, and PM_{2.5} during winter were 16.37 ppb, 30.73 ppb, 60.71 µg/m³, and 31.33 µg/m³, respectively. These values decreased during summer to 12.10 ppb, 22.53 ppb, 40.47 µg/m³, and 17.89 µg/m³, respectively, and were lowest during the rainy season at 10.21 ppb, 17.61 ppb, 33.30 µg/m³, and 13.28 µg/m³, respectively. This seasonal pattern indicates that winter was the most critical period for air pollution in the study area, particularly for particulate matter.

The higher pollutant concentrations during winter may be associated with stable atmospheric conditions, reduced vertical mixing, and limited rainfall, which can promote pollutant accumulation near the ground surface. Conversely, the lower concentrations during the rainy season may reflect the effect of atmospheric washout and wet deposition.

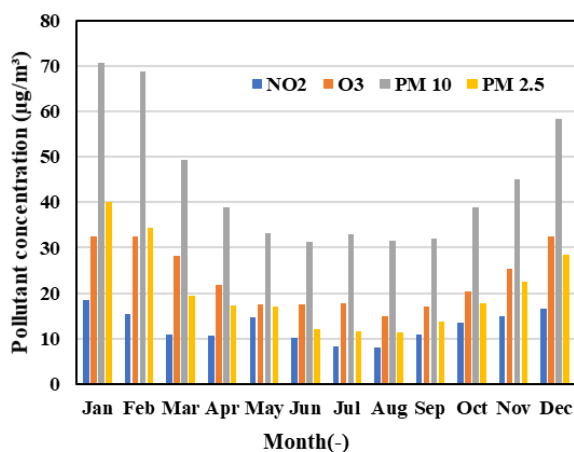


Figure 2 Monthly variation in NO₂, O₃, PM₁₀, and PM_{2.5} concentrations during the study period

Table 2 Seasonal mean meteorological parameters at Bowin Subdistrict, Chonburi Province

Season	Ws (knot)	Ra (mm)	T(°C)	Pa (hPa)	RH (%)
Winter	4.15	20.75	28.88	1002.84	66.65
Summer	4.93	87.16	30.39	1000.72	73.53
Rainy	5.22	156.19	29.40	999.20	77.12

Table 3 Seasonal variation in air pollutant concentrations in the study area

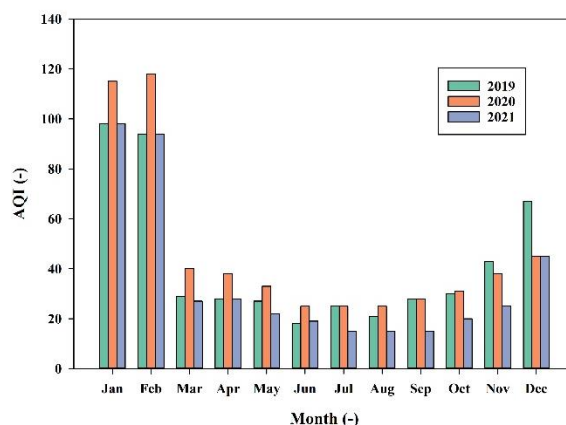
Season	NO ₂ (ppb)	O ₃ (ppb)	PM ₁₀ (µg/m ³)	PM _{2.5} (µg/m ³)
Winter	16.37 ± 1.64	30.73 ± 3.62	60.71 ± 11.68	31.33 ± 7.53
Summer	12.10 ± 2.23	22.53 ± 5.43	40.47 ± 8.23	17.89 ± 1.26
Rainy	10.21 ± 2.23	17.61 ± 1.97	33.30 ± 3.12	13.28 ± 2.65
Overall Mean ± SD	12.74 ± 3.36	23.21 ± 6.73	44.23 ± 14.49	20.45 ± 9.30

This finding is consistent with Watcharaviton, Chio [23], who reported clear monthly and seasonal variations of PM₁₀, NO₂, SO₂, and O₃ in Bangkok, with higher concentrations during winter and lower levels during the rainy period. Similarly, Li, Shao [24] found that PM_{2.5}, PM₁₀, and NO₂ were generally higher during the winter/heating period in Beijing, reflecting the influence of seasonal emissions and meteorological conditions. Shelton, Liyanage [25] also demonstrated that urban air pollutants, including PM_{2.5}, PM₁₀, NO₂, SO₂, and O₃, varied seasonally and were associated with meteorological parameters. Therefore, the monthly pollutant concentrations were subsequently converted into AQI values to provide an integrated indicator of air quality and to support health-risk interpretation in the following section.

Figure 3 illustrates the temporal variation in monthly AQI during 2019–2021. The results revealed pronounced seasonal fluctuations in air quality across the study area. Overall, AQI values ranged from 15 to 118, indicating that air quality varied from good conditions to levels that may affect sensitive population groups. The annual mean AQI values were 42.33 ± 28.12 , 46.75 ± 33.23 , and 35.25 ± 29.56 in 2019, 2020, and 2021, respectively. Although the mean AQI values generally remained within the good air quality category, substantial monthly fluctuations were observed, suggesting that short-term meteorological and emission-related factors played an important role in determining air quality conditions.

A distinct increase in AQI was observed during December to February in each year, with the highest AQI recorded in January 2020. This peak value of 118 indicates a level of air pollution that may pose health risks to sensitive groups, particularly children, older adults, and individuals with respiratory diseases. The elevated AQI during this period may be

attributed to the combined influence of seasonal meteorological conditions and local emission sources. During the winter season, relatively stable atmospheric conditions, lower mixing height, reduced rainfall, and weaker pollutant dispersion can promote the accumulation of air pollutants near the ground surface. These conditions may be particularly relevant in areas influenced by industrial activities, transportation networks, and urban expansion.

**Figure 3** Monthly Air Quality Index analysis from 2019 to 2021

In contrast, the lowest AQI values were recorded from June to September 2021, with a minimum value of 15, reflecting good air quality and minimal health risk. This period corresponds largely to the rainy season, during which frequent rainfall and higher atmospheric moisture can enhance pollutant removal through wet deposition and reduce the resuspension of particulate matter. Rainfall can also improve atmospheric cleansing by washing out airborne particles and soluble pollutants, thereby contributing to lower AQI levels.

Seasonal comparison further confirmed that winter was the most critical period for air quality deterioration (see **Table 4**). The mean

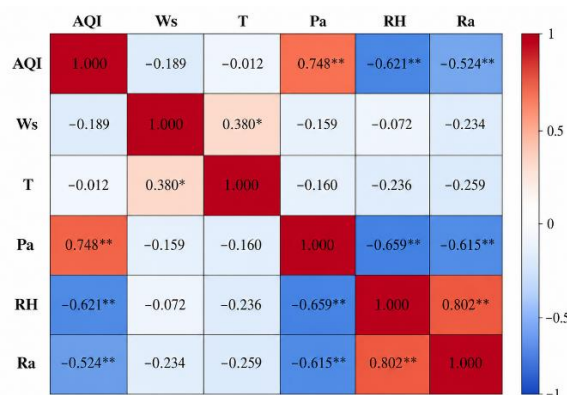
AQI during winter was 73.33 ± 32.69 , which was approximately 2.43 times higher than that observed in summer and 3.23 times higher than that observed in the rainy season. These findings indicate that seasonal meteorological conditions strongly influenced AQI variation in the study area. Although summer and rainy seasons were both classified as good air quality periods, the rainy season showed the lowest mean AQI, supporting the role of precipitation in reducing ambient pollutant concentrations.

Table 4 Seasonal AQI variation (2019–2021)

Season	AQI (Mean $\pm$ SD)	Degree
Winter	73.33 ± 32.69	Moderate
Summer	30.22 ± 5.74	Good
Rainy	22.67 ± 5.49	Good

Correlation Between AQI and Meteorological

Pearson's correlation analysis was performed to evaluate the relationships between AQI and meteorological factors. As presented in **Figure 4**, atmospheric pressure showed the strongest positive association with AQI ($r = 0.748$, $p < 0.01$). This result indicates that periods of higher atmospheric pressure tended to coincide with higher AQI values. High-pressure conditions are generally associated with greater atmospheric stability, weaker vertical mixing, and limited pollutant dispersion, which may promote the accumulation of pollutants near the ground.



* Correlation significant at $p < 0.05$ (two-tailed); ** Correlation significant at $p < 0.01$ (two-tailed).

Figure 4 Heatmap of Pearson correlation coefficients between AQI and meteorological variables

Relative humidity exhibited a strong and statistically significant negative correlation with AQI ($r = -0.621$, $p < 0.01$). Rainfall also demonstrated a significant inverse association with AQI ($r = -0.524$, $p < 0.01$). These findings suggest that higher relative humidity and greater rainfall were generally associated with lower AQI values. Rainfall may reduce atmospheric pollutant concentrations through wet deposition, while humid and rainy conditions may also suppress the resuspension of road dust and enhance atmospheric cleansing.

Wind speed showed a weak negative correlation with AQI, but the relationship was not statistically significant ($r = -0.189$, $p > 0.05$). Although the direction of the relationship is consistent with the dispersive effect of wind, its weak magnitude suggests that wind speed alone did not substantially explain AQI variability during the study period. This may be related to the limited variability of wind speed, differences in wind direction, local topographic conditions, or the influence of nearby industrial and traffic-related emission sources.

Temperature showed almost no relationship with AQI ($r = -0.012$, $p > 0.05$), indicating that temperature alone was not an important determinant of AQI during the study period. This negligible association may reflect competing atmospheric processes, as higher temperatures can enhance vertical mixing while also promoting photochemical reactions and secondary pollutant formation. The influence of temperature may therefore vary according to pollutant type, season, solar radiation, and its interaction with other meteorological variables.

The correlation matrix also revealed significant relationships among the meteorological variables. Wind speed was positively correlated with temperature ($r = 0.380$, $p < 0.05$). Atmospheric pressure was negatively correlated with relative humidity ($r = -0.659$, $p < 0.01$) and rainfall ($r = -0.615$, $p < 0.01$), whereas relative humidity was strongly positively correlated with rainfall ($r = 0.802$, $p < 0.01$). The significant interrelationships among meteorological variables indicate that these factors did not operate independently. Therefore, multiple linear regression analysis was subsequently performed to evaluate the independent contribution of each meteorological variable to AQI after simultaneous adjustment for the other variables. This analytical approach

is important because the observed bivariate associations may partly reflect shared meteorological processes, such as atmospheric stability, moisture conditions, and precipitation-related pollutant removal.

These findings are consistent with previous studies showing that meteorological conditions can jointly influence air pollutant dispersion, accumulation, and removal. Zhang, Zhang [26] reported that $PM_{2.5}$ concentrations were negatively associated with wind speed, suggesting that stronger winds enhance pollutant dispersion. Wang, Cao [27] found that particulate matter concentrations were closely related to wind speed, surface pressure, and relative humidity. Similarly, Yu, Zhong [28] demonstrated that AQI was associated with wind speed, relative humidity, and precipitation, with wind and rainfall contributing to lower AQI through atmospheric dispersion and pollutant washout.

Simple and Multiple Linear Regression Models:

Following Pearson's correlation analysis, simple linear regression was conducted to quantify the individual effects of meteorological variables on AQI. The regression results were consistent with the correlation analysis (see **Table 5**). Atmospheric pressure was the strongest individual predictor of AQI and explained 55.9% of its variability ($R^2 = 0.559$, $p < 0.001$). Relative humidity also showed a significant inverse association with AQI and

explained 38.6% of the variability ($R^2 = 0.386$, $p < 0.001$). Rainfall was likewise significantly and negatively associated with AQI, accounting for 27.4% of the variability ($R^2 = 0.274$, $p = 0.002$). In contrast, wind speed ($R^2 = 0.036$, $p = 0.293$) and temperature ($R^2 < 0.001$, $p = 0.945$) were not statistically significant predictors of AQI. The use of simple linear regression and the coefficient of determination (R^2) in the present study is consistent with previous air quality studies that applied regression-based approaches to explain or predict AQI. Bortnick, Coutant [29] used regression models to relate continuous $PM_{2.5}$ monitoring data to AQI reporting and demonstrated that simple linear regression could provide strong model fit, with (r^2) values of 0.96 and 0.86 across different metropolitan areas. Similarly, Alruwaili [30] applied simple linear regression to examine the relationship between traffic volume and AQI, reporting an (R^2) value of 0.71 for AQI. More recently, Ajaj, Awad [31] used linear regression models to predict AQI during severe dust periods in Iraq based on $PM_{2.5}$ concentrations and reported high explanatory performance, with monthly (R^2) values up to 0.85 and validation (R^2) values exceeding 0.90. These studies support the use of simple linear regression and (R^2) as appropriate statistical tools for evaluating the explanatory contribution of individual environmental or meteorological predictors to AQI variability.

Table 5 Simple linear regression models between meteorological variables and AQI

Predictor	Regression model	<i>r</i>	R^2	p-value
Wind speed (Ws)	$AQI = 61.016 - 4.588Ws$	-0.189	0.036	0.293
Temperature (T)	$AQI = 45.576 - 0.298T$	-0.012	<0.001	0.945
Atmospheric pressure (Pa)	$AQI = -10,027.097 + 10.057Pa$	0.748	0.559	<0.001
Relative humidity (RH)	$AQI = 234.794 - 2.710RH$	-0.621	0.386	<0.001
Rainfall (Ra)	$AQI = 51.367 - 0.143Ra$	-0.524	0.274	0.002

Multiple linear regression was performed to evaluate the independent effects of meteorological variables on AQI, as presented in **Table 6**. The model was statistically significant and explained 60.7% of AQI variability ($R^2 = 0.607$, adjusted $R^2 = 0.534$, $p < 0.001$), indicating that meteorological conditions substantially contributed to changes in air quality during the study period. Among the predictors, atmospheric pressure was the only significant independent factor associated with AQI

($B = 8.074$, $\beta = 0.600$, $p = 0.004$). This finding suggests that higher atmospheric pressure may promote pollutant accumulation, likely due to more stable atmospheric conditions, reduced vertical mixing, and limited pollutant dispersion. Such conditions can increase near-surface pollutant concentrations, particularly in areas influenced by industrial activities and traffic emissions. Although relative humidity and rainfall were significantly associated with AQI in the correlation analysis, they were no longer

significant in the adjusted model. This may reflect overlapping effects among meteorological variables, particularly the interrelationships between atmospheric pressure, humidity, and rainfall. Similarly, wind speed and temperature were not significant predictors after adjustment, suggesting that their effects on AQI may depend on other factors such as wind direction, emission sources, atmospheric stability, and seasonal conditions.

The present findings are consistent with previous studies indicating that meteorological conditions play an important role in regulating air pollution levels. Kliengchuay, Cooper Meeyai [32] reported that meteorological variables, including relative humidity, temperature, and atmospheric pressure, were associated with PM₁₀ concentrations in Mae Hong Son Province, Thailand. Similarly, Lv, Li [33] found that wind speed was negatively associated with PM_{2.5} and NO₂ concentrations, while rainfall contributed to the reduction of several air pollutants. In addition, Wang, Cui [34] demonstrated that precipitation generally reduced AQI and PM_{2.5} concentrations

through atmospheric washout and wet deposition. These findings support the results of the present study, in which atmospheric pressure was the dominant independent predictor of AQI, while relative humidity and rainfall showed inverse associations with AQI in the bivariate analysis.

Human Health Risk Assessment:

Table 6 summarizes the results of the inhalation health risk assessment based on the screening-level concentration-based approach. The HQ values varied by pollutant and season, with the highest values generally observed during winter. Among the pollutants, PM_{2.5} and PM₁₀ were the dominant contributors to potential non-carcinogenic inhalation risk. The highest HQ value was observed for PM_{2.5} during winter (HQ = 1.202), followed by PM₁₀ during winter (HQ = 1.164). Both values exceeded the benchmark value of 1.0, indicating potential non-carcinogenic health concerns associated with particulate matter exposure during the winter season.

Table 6 Multiple linear regression analysis of meteorological variables associated with AQI

Predictor	B	SE	Standardized β	t	p	95% CI for B
Constant	-8012.901	2630.886	—	-3.046	0.005	-13,411.034 to -2614.768
Ws	-3.349	3.386	-0.138	-0.989	0.331	-10.296 to 3.597
T	2.100	3.501	0.087	0.600	0.554	-5.084 to 9.284
Pa	8.074	2.554	0.600	3.161	0.004	2.834 to 13.314
RH	-1.019	0.976	-0.233	-1.043	0.306	-3.022 to 0.985
Ra	0.006	0.061	0.023	0.103	0.919	-0.119 to 0.131

In contrast, NO₂ and O₃ showed HQ values below 1.0 across all seasons. The HQ values for NO₂ ranged from 0.323 in the rainy season to 0.518 in winter, while those for O₃ ranged from 0.276 in the rainy season to 0.482 in winter. PM₁₀ and PM_{2.5} also showed lower HQ values during summer and the rainy season, with values below 1.0. These findings indicate that particulate matter, particularly PM_{2.5} and PM₁₀ during winter, represented the main contributors to potential inhalation health risk in the study area. The results should be interpreted as screening-level pollutant-specific risk estimates rather than age-specific dose-based risk estimates.

Seasonal differences were evident, with HQ values generally highest in winter and

lowest during the rainy season. This pattern may reflect increased pollutant accumulation under stable winter meteorological conditions, reduced vertical mixing, and limited atmospheric dispersion. In contrast, lower values during the rainy season may be partly associated with atmospheric washout and wet deposition, which reduce particulate concentrations in ambient air.

These findings are consistent with previous studies reporting seasonal differences in particulate matter exposure and health risk. Wu, Lu [35] found that PM_{2.5} and associated heavy metal concentrations were highest in winter, and that non-carcinogenic health risks increased during periods of elevated particulate pollution in Ningbo, China. Duan, Yan [36] similarly reported seasonal variations in

PM_{2.5}-bound trace metals and source-specific health risks in an industrial city in China. Roy, Singh [37] also demonstrated that PM₁₀-

and PM_{2.5}-bound metals contributed to non-carcinogenic risks among both adults and children in a polluted mining area.

Table 6 Seasonal hazard quotient values for non-carcinogenic inhalation risk

Pollutant	Winter	Summer	Rainy
NO ₂	0.518	0.383	0.323
O ₃	0.482	0.353	0.276
PM ₁₀	1.164	0.776	0.639
PM _{2.5}	1.202	0.686	0.509

Note: NO₂ and O₃ concentrations reported in ppb were converted to µg/m³ prior to HQ calculation.

Limitations and Future Directions:

This study has several limitations. First, the analysis was based on monitoring data from a single industrially influenced area during 2019–2021, which may limit generalization to areas with different emission sources, land-use characteristics, and meteorological conditions. Second, the statistical analyses focused mainly on seasonal patterns and linear associations between AQI and meteorological variables; therefore, short-term fluctuations, nonlinear relationships, lag effects, and temporal autocorrelation may not have been fully captured. The study period also overlapped with the COVID-19 pandemic, during which changes in traffic and industrial activity may have influenced air quality patterns.

Third, AQI was calculated using available pollutants, including NO₂, O₃, PM₁₀, and PM_{2.5}, while SO₂ and CO were excluded due to incomplete data. In addition, daily average O₃ and NO₂ concentrations were used; therefore, the AQI values should be interpreted as screening-level estimates rather than exact regulatory AQI values. Fourth, the health risk assessment was based on a screening-level concentration-based approach using pollutant-specific reference concentrations. Thus, HQ values should be interpreted as pollutant-specific screening estimates rather than individual clinical risk or age-specific dose-based risk estimates.

Future studies should include longer monitoring periods, additional monitoring sites, SO₂ and CO data, pollutant-specific time-series models, nonlinear and lag-effect analyses, and threshold-based approaches. Incorporating wind direction, boundary layer height, source apportionment, emission inventory data, personal

exposure monitoring, and health-outcome data would strengthen causal interpretation and improve the design of targeted air quality management strategies.

Conclusions

This study assessed seasonal AQI variation, meteorological influences, and inhalation health risks in the study area. The results showed that AQI varied by season, with higher levels during winter and lower levels during the rainy season. Pearson's correlation and simple linear regression indicated that atmospheric pressure was positively associated with AQI, whereas relative humidity and rainfall were negatively associated with AQI. In the multiple linear regression model, atmospheric pressure remained the only significant independent predictor, suggesting that high-pressure or stable atmospheric conditions may be associated with pollutant accumulation. However, this finding should be interpreted cautiously because the analysis was based on monthly time-series observations and may be influenced by autocorrelation, multicollinearity among meteorological variables, and changes in anthropogenic activity during the COVID-19 period.

The inhalation health risk assessment showed that potential non-carcinogenic risk varied by pollutant and season. PM_{2.5} and PM₁₀ were the dominant contributors to the estimated risk, particularly during winter, when their HQ values exceeded the benchmark value of 1.0. In contrast, NO₂ and O₃ showed HQ values below 1.0 across all seasons. Since the assessment was based on a screening-level

concentration-based approach, the HQ results should be interpreted as pollutant-specific screening estimates rather than age-specific dose-based risk estimates. These findings highlight the importance of season-specific air quality management, particularly during winter pollution episodes, with priority attention to particulate matter control.

Future studies should incorporate longer-term air quality monitoring, pollutant-specific source apportionment, wind direction, boundary layer height, emission inventory data, and spatial exposure assessment. The integration of personal exposure monitoring and age-specific activity patterns would also improve the accuracy of inhalation health risk estimation. In addition, advanced statistical or machine-learning models could be applied to better predict AQI variation and identify key drivers of air pollution in industrially influenced communities. Future work should also include SO₂ and CO where complete data are available, apply pollutant-specific AQI averaging conventions, and evaluate threshold-based prediction models, such as logistic regression or ROC analysis, to identify meteorological conditions associated with unhealthy AQI levels.

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