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Influence of Weather on Pollutant Concentrations: An Empirical Evidence from Nnamdi Azikiwe International Airport

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ABSTRACT

Airports are major contributors to air pollution, which can adversely affect local air quality and public health. This study investigates the influence of weather conditions on pollutant levels at Nnamdi Azikiwe International Airport, focusing on Nitrogen Dioxide (NO_2), Sulphur Dioxide (SO_2), and Carbon Monoxide (CO). The study aims to analyze how weather variables such as temperature, wind speed, and wind direction affect pollutant concentrations. Data collection spanned from October 2021 to September 2023 using the MSA Altair 5X Multi Gas Detector, with measurements taken eight times a month at three different times of day. The analysis involved time series and multiple regression models to evaluate the impact of weather on pollutant levels. Results revealed significant variations in pollutant concentrations related to different wind directions and temporal trends. Specifically, temperature and wind direction were found to significantly influence CO, SO_2, and NO_2 levels, with high explanatory power in the regression models. The study concludes that weather conditions play a critical role in determining pollutant concentrations at the airport. Recommendations include incorporating weather variables into air quality management strategies, optimizing flight schedules based on weather forecasts, and enhancing emission control technologies.

Keywords: Aircraft Emission, Air Quality, Environment, Pollutants, Weather.

1.0. Introduction

The environment, encompassing air, soil, and water, serves as humanity's fundamental life support system. Historically, these components were pristine and undisturbed, forming a complex web of relationships connecting humans to the natural world. Despite significant scientific and technological advances, humanity remains utterly dependent on the environment for essential resources such as air, water, food, shelter, and energy (Tyler et al., 2010). The natural environment consists of four interlinked systems: the atmosphere, hydrosphere, lithosphere, and biosphere, which are in a state of constant change, primarily due to human activities (Tyler et al., 2010). The intensification of human activities has led to numerous adverse effects on these systems, particularly the hydrosphere and atmosphere. The present-day atmosphere, significantly different from the Pre-Industrial Revolution Era, has seen substantial changes in chemical composition due to intense human activities (Ahuti, 2015).

Furthermore, pollution, as defined by Wiwanitkit (2011), is "the unwanted destruction of the natural environment by human and naturally induced insults," and it has become a global problem exacerbated by population growth and urbanization. As cities expand and industrial activities increase, so does the consumption of energy and the discharge of waste, leading to severe environmental pollution. This pollution manifests in various forms, including air pollutants like smoke, smog, and gases such as carbon monoxide (CO), nitrogen oxides (NOx), and sulphur oxides (SOx), which pose significant health risks and environmental challenges (Wiwanitkit, 2011; Kelishadi, 2012; WHO, 2015, 2016). Among these pollutants, particulate matter with a diameter of 2.5 micrometers or less (PM2.5) has gained considerable attention due to its adverse effects on health and the environment (Cheng et al., 2021). Studies have shown that meteorological factors such as temperature, humidity, wind speed, and air pressure significantly affect the variation of PM2.5 concentrations (Cheng et al., 2021; Ma et al., 2020; Yousefian et al., 2020).

Nitrogen dioxide (NO_2), another major pollutant, has been linked to the formation of secondary fine particles and tropospheric ozone (Shen et al., 2021). Changes in NO_2 concentrations are influenced by both emissions and meteorological conditions, with seasonal and spatial variations observed across different regions (Shen et al., 2021). Ozone (O_3) pollution, a growing concern, is also significantly influenced by synoptic weather patterns and regional transport of pollutants (Hu et al., 2024). For instance, high-concentration ozone pollution events in the Yangtze River Delta were found to be driven by evolving weather patterns that facilitated the transport of ozone-rich air masses (Hu et al., 2024).

Aviation is one of the sectors significantly contributing to air pollution. Airports, seen as hubs of human and aircraft-related mechanical activities, emit substantial amounts of pollutants into the environment (Kliengchuay et al., 2021). Studies from various regions have demonstrated that the interaction between meteorological conditions and pollutants like PM10, NO_2, and CO plays a critical role in pollution episodes (Kliengchuay et al., 2021; Grigorieva & Lukyanets, 2021). For instance, in Lamphun, Thailand, PM10 concentrations were shown to be strongly influenced by temperature, humidity, and wind speed (Kliengchuay et al., 2021), while in Russia, hot weather and air pollution were found to have a synergistic effect on respiratory health (Grigorieva & Lukyanets, 2021).

This study focuses on Nnamdi Azikiwe International Airport, investigating the intricate relationships between weather variables and pollutant concentrations over a two-year period from October 2021 to September 2023. The primary aim of this article is to explore how weather conditions influence the levels of various pollutants at the airport. Specifically, the study involves an in-depth analysis of the proportions of cardinal wind directions across defined intervals to understand their distribution and variability over time and forecast same. Additionally, it tests the null hypothesis (H0) that there is no discernible temporal trend in the individual concentrations of nitrogen dioxide (NO_2), sulphur dioxide (SO_2), and carbon monoxide (CO) over the study period. The research also evaluates the null hypothesis (H0) that weather factors such as temperature, wind speed, and wind direction have no significant impact on the concentrations of these pollutants.

2.0 Methodology

2.1. Materials

This study employs an empirical analytical approach to investigate the influence of weather variables on pollutant concentrations at Nnamdi Azikiwe International Airport from October 2021 to September 2023. The data collection focused on monitoring three key pollutants: carbon monoxide (CO), sulphur dioxide (SO_2), and nitrogen dioxide (NO_2). Ground-level pollution concentrations were measured using the MSA Altair 5X Multi Gas Detector, a high-precision environmental monitoring device equipped with advanced MSA cell sensors and various optional infrared sensors, ensuring rapid response times and high reliability.

To ensure accurate measurements, the MSA Altair 5X was calibrated prior to data collection using certified standard gas mixtures. The calibration process followed the manufacturer's guidelines and involved zero and span calibration using clean air and calibration gases for CO, SO_2, and NO_2. Calibration was performed biannually to maintain measurement precision, and the device was subjected to compensation algorithms that adjusted for environmental factors such as temperature, humidity, and pressure. These algorithms compensated for sensor drift and ensured the data accurately reflected pollutant concentrations under varying atmospheric conditions.

Pollution samples were collected eight times a month, with each site visited twice and sampled for three minutes per site. Sampling occurred at three different times of day: morning (8:00-11:30 am), afternoon (12:30-3:30 pm), and evening (4:00-6:45 pm), to capture variations in pollutant levels throughout the day. The instrument was recalibrated every six months, ensuring consistent data quality. Calibration checks were performed before and after each sampling session to verify that the device remained within its specified accuracy range.

2.2. Methods

After data collection, the pollutant concentration readings were processed using statistical analysis tools. The analysis involved time series decomposition to identify seasonal trends and patterns in the pollutant levels. Additionally, ordinal regression models were applied to assess the relationship between weather variables (such as temperature, wind speed, and wind direction) and pollutant concentrations. Residual diagnostic tests were conducted to ensure the robustness of the regression models. The analysis further included the use of compensation algorithms to correct for the effects of environmental noise, sensor drift, and cross-sensitivity between different gases.

The general form of the ordinal regression model fitted in the study can be expressed as:

$$\text{logit}[\mathbb{P}(Y \leq j)] = \alpha_j - \beta_1 X_1 - \beta_2 X_2 - \beta_3 X_3 - \cdots - \beta_k X_k \quad (1)$$

Where:

- Y is the ordinal response variable (pollutant concentration levels: CO, SO_2, NO_2).
- j refers to the cut-off points (or thresholds) for the ordinal categories.
- α_j is the threshold (cut-off) parameter for category j.
- $X_1, X_2, \dots, X_k$ are the predictor variables (temperature, wind speed, cardinal wind direction).
- $\beta_1, \beta_2, \dots, \beta_k$ are the coefficients (parameters) to be estimated for each predictor.

3.0 Result and Discussion

3.1. Analysis of Wind Direction Proportions Across Intervals

Table 1: Proportions of Cardinal Wind Directions Across Specified Intervals

Count of Cardinal-Wind-Direction						
Intervals Labels	**ESE (%)**	**S (%)**	**SE (%)**	**SSE (%)**	**SSW (%)**	**Grand Total (%)**
3.47-4.47	9.13	19.88	0.00	30.53	3.05	62.60
4.47-5.47	8.69	17.40	9.14	0.00	0.00	35.23
366.47-367.47	0.00	0.00	0.00	0.00	2.17	2.17
Grand Total	**17.82**	**37.28**	**9.14**	**30.53**	**5.22**	**100.00**

Source: Field Survey, 2023

The analysis of cardinal wind directions (ESE, S, SE, SSE, and SSW) across different intervals provides insight into the variability and distribution of wind patterns. These wind patterns play a significant role in pollutant dispersion, influencing local air quality at Nnamdi Azikiwe International Airport. Studies have established strong links between meteorological factors such as wind direction, wind speed, and air pollution dispersion. For instance, Ma et al. (2020) highlighted the critical role of wind speed and direction in the transport and dispersion of tropospheric ozone (O_3) in Lanzhou, China, showing that certain wind patterns can exacerbate or mitigate pollution levels. Similarly, Hu et al. (2024) found that evolving synoptic weather patterns influence the transport and sources of high-concentration ozone in the Yangtze River Delta, China, indicating that wind plays a key role in the spread of pollutants over multiple regions. In the current analysis, the dominance of the S and SSE wind directions in the 3.47-5.47 intervals suggests that these directions are more prevalent in carrying pollutants across the area.

This aligns with findings by Cheng et al. (2021), who demonstrated that static or high-speed winds could contribute to higher particulate matter (PM2.5) concentrations due to limited dispersion in certain areas. Shen et al. (2021) further corroborated the role of unfavorable weather conditions, including wind, in increasing nitrogen dioxide (NO_2) concentrations in urban agglomerations, highlighting the significant impact of meteorological factors on air quality. Interestingly, the absence of wind in the interval 366.47-367.47 and the minor presence of SSW suggests a near-stagnant condition. This kind of stagnation can contribute to the accumulation of pollutants, as noted by Kliengchuay et al. (2021), who observed that low wind speeds, coupled with certain pollutant levels, contribute to the persistence of PM10 concentrations in Lamphun, Thailand, particularly during the dry season. Therefore, wind direction and speed, as reflected in Table 1, directly influence pollutant levels, supporting existing literature on the interaction between weather and air quality. This interaction emphasizes the need for a comprehensive understanding of wind patterns in pollution studies to effectively model and mitigate the impact of harmful emissions.

3.2. Temporal trend in the individual concentrations of pollutants over the study periods

This section presents the trend analysis of pollutants—Carbon Monoxide (CO), Sulphur Dioxide (SO_2), and Nitrogen Dioxide (NO_2)—across different months, providing a comprehensive overview of the mean concentrations during the study periods (October 2021 – September 2023).

3.2.1 Carbon Monoxide (CO) Trend

Figure 1 illustrates the forecast for Carbon Monoxide (CO) concentrations extending to September 2024, incorporating forecasted values alongside lower and upper confidence intervals. This forecast is generated using the Exponential Smoothing (ETS) model, a robust time series forecasting method integrated into Microsoft Excel. The ETS model, which is particularly effective for handling data characterized by trends and seasonality, has been applied in numerous studies on environmental forecasting (Ahuti, 2015; López et al., 2019).

Beginning with the observed value for August 2023 (1.4331), the model provides monthly forecasted values from October 2023 to September 2024. These values are accompanied by corresponding lower and upper confidence bounds, which reflect the inherent uncertainty in such projections. The forecast suggests a gradual rise in CO concentrations throughout the forecast period, with the values increasing progressively toward mid-2024. However, the flattening of the forecast curve towards the latter part of the period should not be misconstrued as an indication of stable CO levels. Instead, this pattern highlights the model's increasing uncertainty over time, a common limitation in long-term predictions (Tyler et al., 2010; Wiwanitkit, 2011).

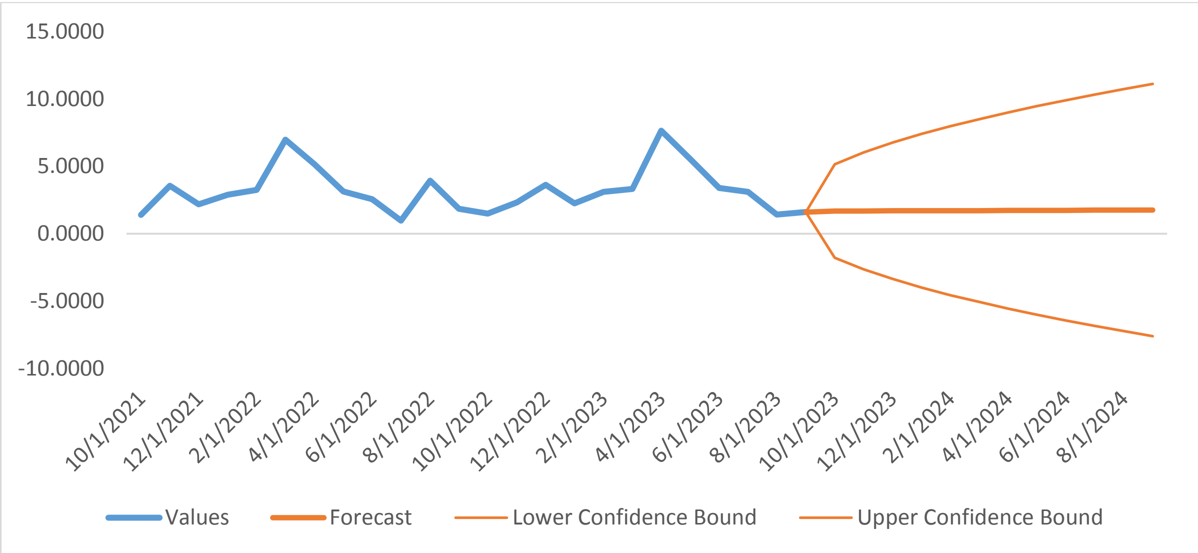

Figure 1: Forecast for Carbon Monoxide (CO)

The implications of this forecast are significant, as prolonged elevated CO levels pose considerable health risks, particularly in areas adjacent to major transportation hubs like airports (Kelishadi, 2012; WHO, 2016). Should the forecasted upward trend materialize, there could be a notable exacerbation of respiratory and cardiovascular diseases, particularly in vulnerable populations. This trend underscores the necessity for proactive mitigation strategies aimed at reducing CO emissions from aviation and related activities, including advancements in fuel efficiency and the adoption of stricter emissions regulations (WHO, 2015, 2016).

The uncertainty captured by the confidence bounds further emphasizes the critical need for immediate intervention. Should CO concentrations approach the upper confidence limits, the environmental and health impacts could be more severe than anticipated. Integrating meteorological factors—such as wind direction and speed—into these forecasts is essential, given their established influence on pollutant dispersion patterns (Ahuti, 2015; López et al., 2019).

3.2.2 Sulphur Dioxide (SO_2) Trend

Figure 2 presents the forecast for Sulphur Dioxide (SO_2) concentrations up to September 2024, employing the Exponential Smoothing (ETS) model, a time series forecasting model available in Microsoft Excel. The ETS method is known for its capacity to accommodate trends and seasonal variations, making it a suitable

tool for environmental forecasting, particularly in studies examining the effects of pollutant concentrations over time (Ahuti, 2015; López et al., 2019).
Starting with the observed value for September 2023 (0.0135), the model provides monthly forecasts for SO_2 levels from October 2023 to September 2024, complete with lower and upper confidence bounds. These confidence bounds highlight the uncertainty inherent in the forecasting process and offer a range within which the actual SO_2 concentrations are expected to fall. The forecast indicates a relatively stable trend in SO_2 concentrations throughout the forecast period, with only minor fluctuations observed month-to-month.

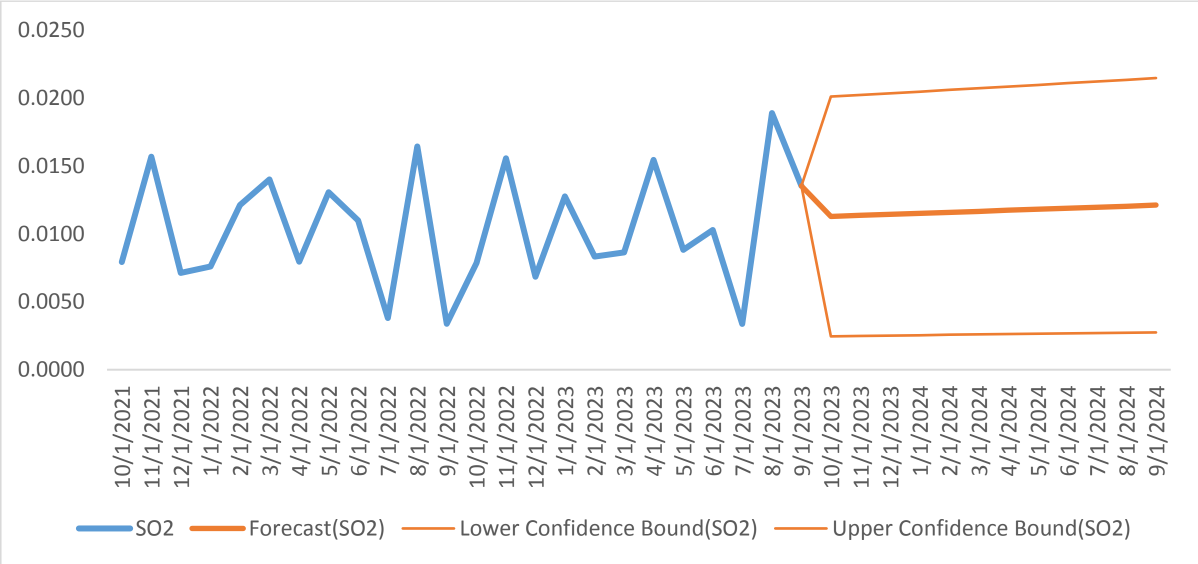

Figure 2: Forecast for Sulphur Dioxide (SO_2)

The stability in the forecasted SO_2 levels suggests that significant changes in emission sources are unlikely, barring unforeseen industrial developments or shifts in aviation-related activities at the study site (Kelishadi, 2012). However, the relatively narrow range of confidence bounds signifies that the model predicts minimal variability, suggesting a continued low but steady presence of SO_2 in the atmosphere near Nnamdi Azikiwe International Airport. Given the health risks associated with prolonged SO_2 exposure, particularly in relation to respiratory conditions (WHO, 2015, 2016), even small increases could exacerbate local air quality concerns.
Moreover, meteorological factors such as wind direction and speed, which have been shown to influence the dispersion of pollutants, play a crucial role in determining SO_2 concentration levels (Tyler et al., 2010). Given the relatively low forecasted concentrations, future models might benefit from incorporating weather data to enhance accuracy and account for fluctuations in pollutant dispersion (López et al., 2019). This consideration is vital, as certain wind patterns—particularly those identified in earlier sections—may contribute to localized pollution events or mitigate the impact of emissions depending on seasonal variations (Wiwanitkit, 2011).
The forecasted stability of SO_2 concentrations has implications for environmental management and health policy. While the predicted levels remain low, maintaining this status requires continued efforts to control emissions from both aviation and surrounding industrial activities. Without stringent environmental regulations, there is a risk that even small upward trends, especially those near the upper confidence bounds, could lead to adverse health effects over time (WHO, 2016).

3.2.3 Nitrogen Dioxide (NO_2) Trend
Figure 3 presents the forecast for Nitrogen Dioxide (NO_2) concentrations through September 2024, using the Exponential Smoothing (ETS) model, a widely recognized time series forecasting technique embedded in Microsoft Excel. The ETS model, known for its ability to account for seasonality and trends, provides a reliable method for forecasting pollutant concentrations over time (Ahuti, 2015; López et al., 2019).
Beginning with the observed value in September 2023 (0.1459), the forecast provides monthly projections for NO_2 concentrations from October 2023 to September 2024. Each forecasted value is accompanied by lower and upper confidence bounds, offering a measure of the uncertainty inherent in the predictions. The forecast indicates a steady upward trend in NO_2 concentrations over the forecast period, with values gradually increasing month by month. This trend may be influenced by seasonal factors, traffic patterns, and aviation-

related activities at Nnamdi Azikiwe International Airport, as identified in prior studies on air pollution dynamics (Wiwanitkit, 2011; Kelishadi, 2012).

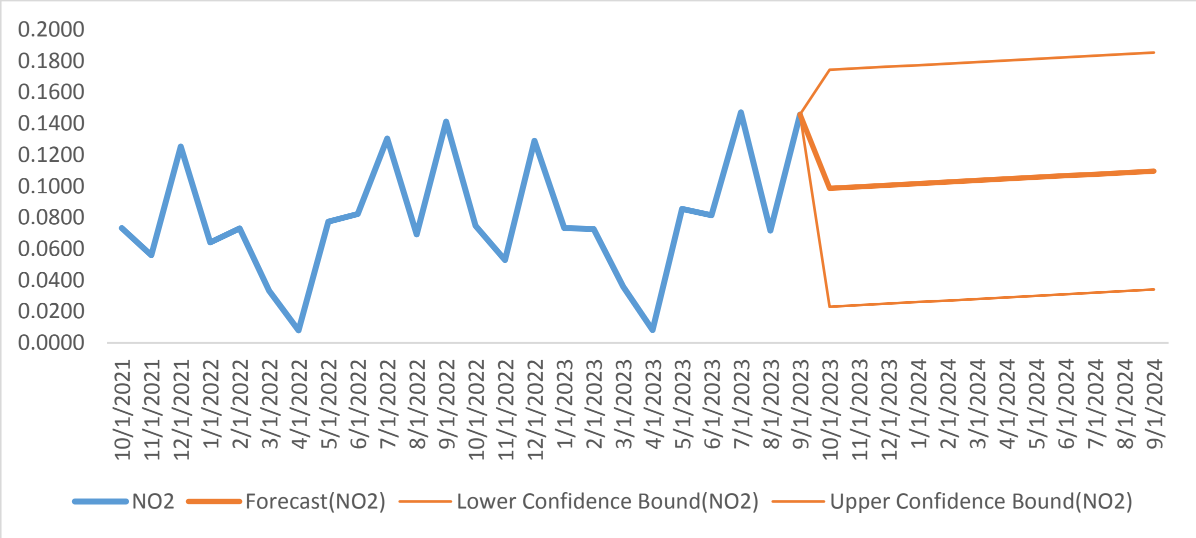

Figure 3: Forecast for Nitrogen Dioxide (NO_2)

The projected rise in NO_2 concentrations is of particular concern given its known health impacts, including respiratory issues and cardiovascular diseases (WHO, 2015, 2016). NO_2 is a major contributor to urban air pollution, and increases in its concentrations, even within the bounds predicted by the model, could exacerbate health risks, particularly for vulnerable populations (WHO, 2016). The relatively narrow range of the confidence bounds suggests that while the forecast is reliable, even slight deviations near the upper bounds could have significant public health implications.

The gradual increase in NO_2 concentrations, as forecasted, aligns with previous research indicating that airports and their surrounding areas are significant sources of nitrogen oxides due to aircraft emissions, ground operations, and associated traffic (Tyler et al., 2010). Additionally, weather patterns such as wind speed and direction play a key role in the dispersion of NO_2 and other pollutants (López et al., 2019). The cardinal wind directions identified in earlier sections, particularly those from the southeast and south, may contribute to pollutant dispersion or accumulation in specific areas, further influencing local NO_2 levels.

The model's ability to forecast a gradual increase in NO_2 concentrations through 2024 underscores the need for proactive environmental policies aimed at mitigating pollutant emissions. Without such interventions, the projected rise in NO_2 could exceed safe thresholds, leading to deteriorating air quality in the vicinity of the airport. Implementing stricter regulations on aviation emissions and improving traffic management in surrounding areas could help curb the anticipated increase in NO_2 concentrations (Wiwanitkit, 2011; Kelishadi, 2012).

3.3. Impact of weather factors concentrations of these pollutants

3.3.1 Model Performance Pseudo R-Square

The Table 2 presents the Pseudo R-Square values for the ordinal regression models predicting the concentrations of Carbon Monoxide (CO), Sulphur Dioxide (SO_2), and Nitrogen Dioxide (NO_2) based on weather variables.

Table 2: Pseudo R-Square

Pseudo R-Square	**CO**	**SO_2**	**NO_2**
Cox and Snell	0.682	0.708	0.561
Nagelkerke	0.701	0.616	0.569
McFadden	0.62	0.612	0.529

Link function: Logit.

Source: Field Survey, 2023

For Carbon Monoxide (CO), the Cox and Snell Pseudo R-Square value is 0.682, indicating that approximately 68.2% of the variance in CO concentration is explained by the weather variables in the model. The Nagelkerke Pseudo R-Square value is slightly higher at 0.701, suggesting a strong explanatory power of about 70.1%.

The McFadden Pseudo R-Square value is 0.62, which also indicates a substantial proportion of variance explained. These values suggest that the model is quite effective in explaining the variation in CO concentrations based on temperature, wind speed, and wind direction. Given the high levels of CO observed at the airport, it is crucial to consider its impact on both human health and operational efficiency. High CO concentrations can impair cognitive and physical performance, posing risks to airport staff and travelers. According to Grigorieva and Lukyanets (2021), exposure to high CO levels, especially combined with high temperatures, can exacerbate respiratory issues, increasing the risk of acute health problems. Therefore, implementing air quality monitoring systems and enhancing ventilation in high-traffic areas are essential precautionary measures to mitigate CO-related health risks.

For Sulphur Dioxide (SO_2), the Cox and Snell Pseudo R-Square value is 0.708, the highest among the three pollutants, indicating that 70.8% of the variance in SO_2 concentration is explained by the model. The Nagelkerke Pseudo R-Square value is 0.616, suggesting a more moderate explanatory power. The McFadden Pseudo R-Square value is 0.612, supporting the notion that the model explains a significant portion of the variance in SO_2 levels. The slightly lower Nagelkerke value compared to Cox and Snell might be due to the differences in how these measures adjust for the number of predictors and the sample size. SO_2 exposure at the airport can lead to respiratory issues, particularly for individuals with pre-existing conditions such as asthma. According to Shen et al. (2021), SO_2 concentrations are influenced by both emission sources and meteorological conditions. Precautions should include regular maintenance of emission control systems, ensuring compliance with air quality standards, and providing adequate health monitoring for those working in or frequently visiting areas with high SO_2 levels.

For Nitrogen Dioxide (NO_2), the Cox and Snell Pseudo R-Square value is 0.561, indicating that 56.1% of the variance in NO_2 concentration is accounted for by the weather variables. The Nagelkerke Pseudo R-Square value is 0.569, suggesting a similar level of explanatory power. The McFadden Pseudo R-Square value is 0.529, which, while lower than the other two measures, still indicates that over half of the variance in NO_2 concentration is explained by the model. These values imply that the model is moderately effective in explaining NO_2 concentrations. High NO_2 levels at the airport can adversely affect respiratory health, particularly for vulnerable populations like children and the elderly (Cheng et al., 2021). To address this, it is important to implement air quality improvement measures such as controlling emissions from ground support equipment and ensuring that the airport's air filtration systems are functioning optimally. Additionally, regular air quality assessments and timely public health advisories can help manage exposure risks.

3.3.2 Model Parameter Estimates

Table 3: Parameter Estimates for Ordinal Regression

Variables		CO			SO_2			NO_2		
		β	Wald	p-value	β	Wald	p-value	β	Wald	p-value
Temperature (C)		0.038	129.88	0.000	-0.032	32.163	0.000	0.008	5.948	0.015
Wind Speed		0.001	1.636	0.201	-0.005	17.137	0.000	0.002	21.653	0.000
Cardinal Wind Direction	ESE	0.24	3.369	0.066	-0.904	24.257	0.000	0.731	34.238	0.000
	S	0.953	57.62	0.000	-0.61	13.021	0.000	-0.566	22.046	0.000
	SE	0.73	27.923	0.000	-0.726	12.954	0.000	-0.353	6.921	0.009
	SSE	-0.145	1.308	0.253	-0.533	9.736	0.002	-0.152	1.563	0.211
	SSW	0[a]			0[a]			0[a]		

Source: Field Survey, 2023

The fitted model with specific parameter estimates for each pollutant concentration (CO, SO_2, NO_2) is thus given below:

For Carbon Monoxide (CO):

$$\text{logit}[\mathbb{P}(Y_{\text{CO}} \leq j)] = \alpha_j + 0.038 \cdot \text{Temp} + 0.001 \cdot \text{Wind Speed} + 0.240 \cdot \text{ESE} + 0.953 \cdot \text{S} + 0.730 \cdot \text{SE} - 0.145 \cdot \text{SSE} \quad (2)$$

For Sulfur Dioxide (SO_2):

$$\text{logit}\left[\mathbb{P}\left(Y_{\text{SO}_2} \leq j\right)\right] = \alpha_j - 0.032 \cdot \text{Temp} - 0.005 \cdot \text{Wind Speed} - 0.904 \cdot \text{ESE} - 0.610 \cdot \text{S} - 0.726 \cdot \text{SE} - 0.533 \cdot \text{SSE} \quad (3)$$

For Nitrogen Dioxide (NO_2):

$$\text{logit}\left[\mathbb{P}\left(Y_{\text{NO}_2} \leq j\right)\right] = \alpha_j + 0.008 \cdot \text{Temp} + 0.002 \cdot \text{Wind Speed} + 0.731 \cdot \text{ESE} - 0.566 \cdot \text{S} - 0.353 \cdot \text{SE} - 0.152 \cdot \text{SSE} \quad (4)$$

Where**:**

- SSW is the reference category for the wind direction, hence it is omitted from the model.
- Each β coefficient shows the effect of the corresponding predictor on the likelihood of the pollutant concentration being in a particular category.
- The significance of each predictor is indicated by the p-values (predictors with p-values < 0.05 are considered statistically significant).

3.4 Discussion of Findings

Starting with Carbon Monoxide (CO), the analysis reveals that temperature has a significant positive effect on CO concentration, with a beta coefficient (β) of 0.038 and a p-value of 0.000. This finding aligns with the study by Grigorieva and Lukyanets (2021), which suggests that elevated temperatures can enhance chemical reactions and emissions from various sources, thus increasing CO levels. However, wind speed does not have a significant effect on CO concentration (β = 0.001, p-value = 0.201), indicating that variations in wind speed alone are insufficient to influence CO levels significantly. Regarding wind direction, winds from the south (S) and southeast (SE) significantly increase CO concentrations, with beta coefficients of 0.953 and 0.73, respectively, both with p-values of 0.000. These findings are supported by Chen et al. (2021), who observed that specific wind directions can lead to higher pollutant levels due to the accumulation of emissions in particular areas. Conversely, winds from the east-southeast (ESE) show a positive but marginally non-significant effect (β = 0.24, p-value = 0.066), while south-southeast (SSE) winds have a non-significant negative effect (β = -0.145, p-value = 0.253). The south-southwest (SSW) direction serves as the reference category.

For Sulphur Dioxide (SO_2), temperature has a significant negative impact, with a beta coefficient of -0.032 and a p-value of 0.000. This suggests that as temperature increases, SO_2 levels decrease, possibly due to enhanced dispersion and dilution at higher temperatures, consistent with the findings of Shen et al. (2021). Wind speed also significantly affects SO_2 concentrations negatively (β = -0.005, p-value = 0.000), implying that higher wind speeds facilitate the dispersion of SO_2, reducing its concentration. This observation is corroborated by research from Wiwanitkit (2011), which highlights the role of wind in dispersing air pollutants. Wind direction plays a crucial role as well. Winds from the ESE significantly reduce SO_2 levels (β = -0.904, p-value = 0.000), as do winds from the south (β = -0.61, p-value = 0.000), southeast (β = -0.726, p-value = 0.000), and south-southeast (β = -0.533, p-value = 0.002). These findings suggest that winds from these directions help disperse SO_2, lowering its concentration compared to the reference wind direction (SSW), supporting the observations made by Kelishadi (2012).

In the case of Nitrogen Dioxide (NO_2), temperature again shows a significant positive effect (β = 0.008, p-value = 0.015), indicating that NO_2 levels increase with rising temperatures. This aligns with the study by Cheng et al. (2021), which found that higher temperatures can lead to increased NO_2 levels due to enhanced photochemical reactions. Wind speed, on the other hand, has a significant positive effect on NO_2 concentrations (β = 0.002, p-value = 0.000), suggesting that higher wind speeds might contribute to increased NO_2 levels, possibly due to the transportation of NO_2 from other areas, as discussed by Ahuti (2015). Regarding wind direction, winds from the ESE significantly increase NO_2 concentrations (β = 0.731, p-value = 0.000), while winds from the south (β = -0.566, p-value = 0.000) and southeast (β = -0.353, p-value = 0.009) significantly decrease NO_2 levels. Winds from the south-southeast (SSE) have a non-significant effect (β = -0.152, p-value = 0.211), with the south-southwest (SSW) serving as the reference. These results indicate that wind direction can have a significant impact on NO_2 levels, consistent with findings by Tyler et al. (2010) on the influence of atmospheric conditions on pollutant distribution.

4.0. Conclusions

This study revealed varying patterns in cardinal wind direction proportions, temporal trends in pollutants such as Nitrogen Dioxide (NO_2), Sulphur Dioxide (SO_2), and Carbon Monoxide (CO), and the influence of weather factors on these pollutant concentrations.
Among the pollutants studied, CO was found to have the highest concentration variability, influenced significantly by temperature and specific wind directions. The positive relationship between temperature and

CO levels ($\beta = 0.038$, p-value = 0.000) suggests that higher temperatures can enhance emissions from sources like aircraft engines (Grigorieva & Lukyanets, 2021). Aircraft exhaust, known for its CO emissions, is a major contributor at airports, which aligns with findings by Kelishadi (2012) regarding CO levels around aviation hubs.

SO_2 levels were also notably affected by wind direction, with significant reductions in SO_2 concentrations observed with winds from directions like ESE, S, SE, and SSE. The negative impact of temperature on SO_2 levels ($\beta = -0.032$, p-value = 0.000) suggests enhanced dispersion and dilution at higher temperatures (Shen et al., 2021). This could indicate that SO_2 emissions, possibly from ground-based operations or industrial activities near the airport, are influenced by weather patterns.

NO_2 levels showed significant variability with temperature ($\beta = 0.008$, p-value = 0.015) and wind speed ($\beta = 0.002$, p-value = 0.000), which could be due to the complex interaction of NO_2 emissions from both aircraft and other sources (Cheng et al., 2021; Ahuti, 2015). The significant increase in NO_2 concentrations with ESE winds further underscores the role of specific wind directions in pollutant dispersion.

4.1 Recommendation

Given these findings, the study therefore suggests the following recommendations to the airport authority:

- Implement comprehensive air quality monitoring systems that integrate weather data with pollutant measurements. This will enable real-time tracking of pollutant levels and their relationship with weather conditions, facilitating better decision-making in air quality management (Tyler et al., 2010).
- Develop weather-based emission control strategies. More like a stricter regulation on aircraft emissions during periods of high temperatures could help mitigate CO levels, as aircraft are significant sources of CO at airports (Wiwanitkit, 2011; Grigorieva & Lukyanets, 2021).
- Consider operational adjustments to reduce SO_2 emissions, particularly during unfavorable wind conditions. Such as optimizing ground operations and using cleaner technologies could help decrease SO_2 concentrations (Kelishadi, 2012).
- Launch public awareness campaigns to educate individuals about the impact of weather patterns on air quality. Informing the public about actions they can take to protect their health during periods of high pollutant levels will be beneficial (Cheng et al., 2021).

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