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Research article

Air quality index calculation and analysis of pollutant impacts in Ardahan, Türkiye

Hakan Celikten*[1,2]

[1] *Kafkas University, Faculty of Engineering and Architecture, Department of Civil Engineering, 36000, Kars, Türkiye*
[2] *Kafkas University, Institute of Science and Technology, Department of Interdisciplinary Biotecnology, 36000, Kars, Türkiye*

Abstract

This study aims to evaluate air quality in Ardahan, a province located in the northeastern part of Türkiye, based on the pollutants PM_{10}, SO_2, and O_3 measured throughout 2024. Air Quality Index (AQI) values were calculated on an hourly, daily, and monthly scale, and the percentage contribution of each pollutant to the AQI was analyzed. According to the data, a total of 123 risky hours were identified where the AQI exceeded 100, a level considered unhealthy for sensitive groups. In all of these hours, the dominant pollutant was determined to be PM_{10}. The results indicate that PM_{10} was the most influential pollutant on AQI throughout the year, particularly during winter months when high humidity and emissions from heating contributed to increased concentrations. However, from the perspective of daily average AQI values, only 3 days exceeded the threshold of 100. This suggests that while high pollution levels occurred during certain hours of some days, these peaks were not widespread enough to elevate the daily average beyond the threshold. O_3 became more prominent during summer months due to increased photochemical reactions, although it occasionally appeared as the dominant pollutant in certain periods due to data unavailability. The contribution of SO_2 to the AQI remained at a relatively low level. These findings provide important insights for air quality management and environmental policy development. They highlight how critical the issue of missing data is in AQI prediction. Therefore, it is suggested that artificial intelligence and machine learning-based models, which can produce reliable predictions even with incomplete data, are essential tools for improving air pollution early warning systems.

Keywords: *Air quality index; ozone; particulate matter; sulphur dioxide; rural area*

1. Introduction

Air pollution poses a significant threat to both human health and ecological systems across the globe, stemming from diverse anthropogenic sources including industrial processes, transportation emissions, and fossil fuel usage (Ansari and Alam, 2024). With the progress of modern urbanization and industrialization, it has become one of the most significant threats to environmental and public health. According to the World Health Organization (WHO) air pollution program, 91% of the global population is exposed to polluted air, and approximately 4.2 million deaths occur each year due to ambient air pollution (Krishan et al., 2019). In 2019, WHO estimated that more than 15% of all deaths globally were attributable to ambient air pollution (Ansari and Alam, 2024). Air pollution increases the risk of conditions such as asthma, cardiovascular issues, skin infections, eye diseases, throat infections, lung cancer, and bronchitis (Arslan et al., 2024; Natarajan et al., 2024). It has been shown to be responsible for more than one-third of deaths caused by these health problems (Krishan et al., 2019). Prolonged exposure to air pollution not only increases the likelihood of premature death but can also cause developmental problems such as impaired lung function and cognitive development in children (Natarajan et al., 2024).

* Corresponding author.
E-mail address: hakan_celikten@hotmail.com (H. Celikten).
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Monitoring air quality is crucial, especially in environments where pollutant concentrations exceed health-based thresholds. In this regard, the Air Quality Index (AQI), developed by the United States Environmental Protection Agency (USEPA), (Horn and Dasgupta, 2024), serves as a vital indicator that quantifies the intensity of air pollutants and helps assess their health impacts (Janarthanan et al., 2021). The Air Quality Index informs the public about the level of air quality in their environment and warns vulnerable groups such as children, the elderly, and individuals with cardiovascular or respiratory diseases about potential health hazards (Kingsy and Manju, 2019). The AQI is calculated based on measurements of pollutants such as $PM_{2.5}$, PM_{10}, CO, SO_2, NO_2, and O_3 and expresses air quality as a single numerical value. The AQI, which spans a scale from 0 to 500, classifies air quality into six distinct categories: Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, Very Unhealthy, and Hazardous (Janarthanan et al., 2021; Oruc, 2022). More precisely, AQI scores ranging from 0 to 50 indicate “Good” air quality, while values from 51 to 100 correspond to “Moderate” conditions. Levels between 101 and 150 signal air that is “Unhealthy for Sensitive Groups,” 151 to 200 reflect “Unhealthy” status, 201 to 300 are labeled “Very Unhealthy,” and scores from 301 to 500 fall under the “Hazardous” category. Index values exceeding 500 are classified as “Beyond AQI,” yet still considered within the Hazardous range (Horn and Dasgupta, 2024). Given the severe harm air pollution inflicts on both human health and agricultural economies, accurate air quality forecasting is critically important for assisting governments with atmospheric early warning systems and emergency planning (Qiao et al., 2022). The AQI enables individuals-especially the elderly, children, and those with respiratory diseases-to take protective measures based on daily air quality levels. Additionally, local authorities and environmental agencies can utilize AQI data to develop anti-pollution policies and respond through early warning systems in situations that threaten public health.

In rural areas, the use of fossil fuels for heating and the incineration of waste contribute significantly to the deterioration of air quality by releasing harmful pollutants into the atmosphere, such as carbon monoxide (CO), sulfur dioxide (SO_2), nitrogen oxides (NO_x), and particulate matter (PM) (Natarajan et al., 2024). Among the six air pollutants considered in AQI calculations, $PM_{2.5}$ and O_3 are particularly critical for human health. Ozone, a secondary pollutant formed through photochemical reactions between NO_x and volatile organic compounds (VOCs), has been shown to significantly reduce crop yields and is a major component of smog, which poses toxic risks to both animal and plant life (Wang et al., 2019). Long-term exposure to $PM_{2.5}$ is a major environmental risk factor for cardiopulmonary and lung cancer-related mortality (Pope et al., 2002).

Although global interest in air quality has intensified in recent decades, the majority of scholarly investigations continue to concentrate on densely populated metropolitan areas and highly industrialized urban centers. Within the context of Türkiye, empirical research on air quality has similarly exhibited a spatial bias, predominantly prioritizing regions characterized by elevated levels of industrial activity and demographic concentration. Notable examples include Istanbul, Çanakkale, Adıyaman, Antalya, and Mersin, which have frequently constituted the focal points of monitoring initiatives and analytical assessments. (Eke et al., 2024; Kara et al., 2024; Oguz and Pekin 2024; Ozdemir et al., 2024; Yavuz 2025). The emphasis of previous research can be ascribed to the fact that air pollution in these urban centers is capable of affecting larger segments of the population and of giving rise to considerable public health concerns. Nevertheless, this research orientation has led to the underrepresentation, within the existing literature, of smaller-scale regions with limited industrial activity, which may nonetheless be subject to episodic air pollution risks due to particular meteorological and geographical conditions. For this reason, Ardahan Province, situated in northeastern Türkiye, was selected in the present study as a representative case of a smaller region with restricted industrial development. The province is characterized by prolonged and severe winters, frequent meteorological inversions, and elevated levels of fuel consumption for residential heating, all of which contribute significantly to air pollution risks especially during the winter months.

Despite its limited industrial activity, Ardahan is exposed to high particulate matter (PM) levels in winter due to increased fuel usage for heating and meteorological inversions. In this study, Air Quality Index (AQI) values were calculated on an hourly, daily, and monthly basis based on the measured concentrations of pollutants such as PM_{10}, SO_2, and O_3. In addition, the relative contributions of these pollutants to AQI values were also determined. The findings of this analysis are expected to make a significant contribution to environmental planning and policy development processes in provinces like Ardahan, which are especially vulnerable to air quality issues during the winter season.

2. Material and methods

2.1. Monitoring location

Located in the northeastern part of Türkiye, Ardahan Province lies between 42.70° east longitude and 41.11° north latitude. Geographically, it shares international borders with Georgia and Armenia to the northeast, and is surrounded by the provinces of Kars to the south and southeast, Erzurum to the southwest, and Artvin to the west (Barlik et al., 2024). The data used in this study comprise hourly measurements for the year 2024, obtained from the Ardahan Air Quality Monitoring Station (Ardahan/City Center, coordinates: latitude 41.110816, longitude 42.7010571), which operates under the National Air Quality Monitoring Network of the Ministry of Environment, Urbanization and Climate Change of the Republic of Türkiye (SIM, 2025). The analysis focused on the parameters PM_{10}, SO_2, O_3, NO_x, and NO. The measurement period spans from January 1, 2024, to December 31, 2024. The location of the province and the monitoring station is presented in Fig. 1.

In all air quality monitoring stations affiliated with the central authority, sulfur dioxide (SO_2) and particulate matter (PM_{10}, $PM_{2.5}$) are measured alongside nitrogen oxides (NO, NO_2, NO_x), carbon monoxide (CO), and ozone (O_3) using fully automated systems. The measurement data collected at these stations are transmitted via GSM modems to the Data Processing Center of the Environmental Reference Laboratory, which operates under the Ministry of Environment, Urbanization, and Climate Change. The data, received as hourly averages from the stations, are subjected to verification procedures (Sahin, 2025). Subsequently, the validated data from the air quality monitoring stations are made publicly accessible through the website www.havaizleme.gov.tr and the National Air Quality Monitoring Network mobile application.

Fig. 1. Ardahan province and station location where air quality data were obtained.

2.2. Air quality index

The AQI provides a standardized numerical representation of air quality by evaluating the concentration levels of various atmospheric pollutants. Commonly included in AQI computations are $PM_{2.5}$, PM_{10}, sulfur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), and ozone (O_3). As outlined by the United States Environmental Protection Agency (EPA) under the National Ambient Air Quality Standards (NAAQS), the AQI for each pollutant is determined through a specific formula designed to translate pollutant concentrations into index values (Bishoi et al., 2009):

$$AQI_i = \frac{I_{Hi} - I_{Lo}}{C_{Hi} - C_{Lo}}(C_i - C_{Lo}) + I_{Lo}$$

Definition of variables:

AQI_i: The calculated AQI value for pollutant *i*; it represents the air quality index for that specific pollutant. C_i: The measured concentration of the pollutant (e.g., in µg/m³ for PM_{10} and SO_2, or in ppb for O_3). C_{Lo} and C_{Hi}:

The lower and upper bounds of the concentration range that includes C_i. These breakpoints are determined based on national or international air quality standards. I_{Lo} and I_{Hi}: The corresponding AQI values for C_{Lo} and C_{Hi}, defining the AQI range into which the concentration falls. The ranges shown in Table 1 are used: (0-50, 51-100, 101-150, 151-200, 201-300 and 301-500).

Table 1
Pollutant-Based AQI breakpoints categorized by health risk levels and color indicators.

AQI Category, Pollutants and Health Markers				
PM_{10} (µg m^{-3}) 24-hr	SO_2 (ppb) 1-hr	O_3 (ppb) 8-hr	AQI	AQI Category
	C_{Lo}- C_{Hi}		I_{Lo}- I_{Hio}	
0-54	0-35	0-54	0-50	Good
55-154	36-75	55-70	51-100	Moderate
155-254	76-185	71-85	101-150	Unhealty for sensitive groups
255-354	186-304	86-105	151-200	Unhealty
355-424	305-604	106-200	201-300	Very Unhealty
425-604	605-1004	-	301-500	Hazardous

The analysis was performed using measurements obtained from the air quality monitoring station, focusing on PM_{10}, SO_2, and O_3, which are primary contributors to AQI calculations. Since the pollutant concentration values such as $PM_{2.5}$, NO_2, and CO were not available in the data obtained from the monitoring station, they were excluded from the calculations. In this context, AQI calculations were performed using 24-hour average concentrations for PM_{10}, 8-hour rolling averages for O_3, and hourly measurements for SO_2. The AQI breakpoint values for each pollutant, determined according to EPA's color-coded standards, are presented in Table 1.

3. Results

3.1. Statistical analysis

The data were obtained in Excel format, and the preprocessing phase was conducted using both Python (pandas, numpy libraries) and Microsoft Excel. Out of the hourly measurements recorded over the course of one year, 72.53% of PM_{10}, 71.94% of SO_2, and 98.22% of O_3 data were valid. While O_3 data demonstrates high reliability in terms of data completeness, there are significant gaps in PM_{10} and SO_2 measurements. Since the calculation of the National Air Quality Index (NAQI) requires valid data from at least three pollutants, these deficiencies may limit the ability to compute the index during certain time periods. During preprocessing, missing data (represented by "–") were cleaned and filtered to retain only statistically meaningful entries. For each pollutant, only valid (measurable) hourly values were included in the analysis. The pollutant data were structured in separate columns, and a unified dataset was created for further evaluation. Descriptive statistics for each measured pollutant parameter are presented in Table 2.

Table 2
Descriptive statistical properties of pollutant parameters.

Pollutants	Min.	Max.	Mean	Std. Dev.
PM_{10} (µg/m³) 24-hr	13.83	179.07	44.08	22.55
SO_2 (ppb) 1-hr	0.18	9.25	1.99	1.12
O_3 (ppb) 8-hr	3.29	78.75	33.82	15.17
NO (µg/m³) 1-hr	0.33	96.62	7.35	7.40
NO_X (µg/m³) 1-hr	0.0	198.64	32.07	24.77

Among the air pollutants evaluated in this study, PM_{10} exhibited the highest average concentration, with a mean value of 44.08 µg/m³ and a standard deviation of 22.55, indicating a broad dispersion. O_3 ranked second with an average concentration of 33.82 ppb; however, its maximum value reached a remarkable 78.75 ppb. SO_2, on the other hand, demonstrated a relatively stable distribution, characterized by a low average (1.99 ppb) and a narrow range of variation. The NO parameter remained at a low level with a mean concentration of 7.35 µg/m³, but its temporal fluctuations were supported by a standard deviation of 7.40. The NO_x data, despite having a modest average value, included one of the most extreme maximum values recorded 198.64 µg/m³. The high standard deviation and the substantial gap between the average and maximum values indicate the occurrence of sporadic but severe pollution events. These statistical indicators provide critical insights into the air quality observed in Ardahan Province throughout 2024, highlighting the need for targeted mitigation policies, particularly concerning PM_{10}, NO_x, and O_3 pollutants.

3.2. Temporal distribution of AQI at hourly, daily, and monthly scales

Extensive research has been devoted to investigating the health impacts of air pollution and to advancing predictive and control strategies for air quality management, with ongoing efforts continuing in this domain. In this study, data obtained from the National Air Quality Monitoring Station were analyzed on an hourly, daily, and monthly basis. Fig. 2 illustrates the maximum hourly AQI values measured throughout 2024 in Ardahan, along with the dominant pollutant types identified on an hourly scale. Each pollutant type is represented by a distinct color and symbol in the figure. In general, hourly AQI values fluctuated between 30 and 100, though they occasionally exceeded 120. These time periods may pose potential risks, especially for sensitive groups. It is evident that air quality can vary significantly within a day on an hourly basis. PM_{10} frequently appeared as the dominant pollutant in the hourly data. According to the report published by the Turkish State Meteorological Service, the average relative humidity in Ardahan ranged between 66.7% and 70.5% between the years 1970 and 2024 (MGM, 2024). Higher relative humidity levels enhance the adhesion of particulate matter to water vapor, increasing the mass concentration of particles (Zhang et al., 2017). The elevated humidity levels in Ardahan appear to significantly contribute to the increased concentration and dominance of PM_{10}.

In addition, O_3 also emerged as a dominant pollutant during specific hours and days. Incomplete fuel combustion results in a direct increase in CO, NO_2, and particulate matter emissions. The photochemical reactions between emitted NO_2 and volatile organic compounds (VOCs) subsequently lead to ozone formation. These ozone-producing photochemical reactions can peak during the summer months, when solar radiation is more intense (Horn and Dasgupta, 2024). This phenomenon can be associated with elevated ozone levels driven by sunlight exposure during summer. Notably, on the evenings of August 4 and 5, 2024 (between 18:00 and 20:00), AQI values exceeded 120, with O_3 identified as the dominant pollutant during those hours. Furthermore, reduced fossil fuel consumption for heating during the summer in Ardahan likely leads to decreased PM_{10} concentrations, thereby allowing O_3 to become the prevailing pollutant.

During the sampling period, the daily average maximum AQI values measured in Ardahan and the dominant pollutant types for each day are presented in Fig. 3. The daily AQI values

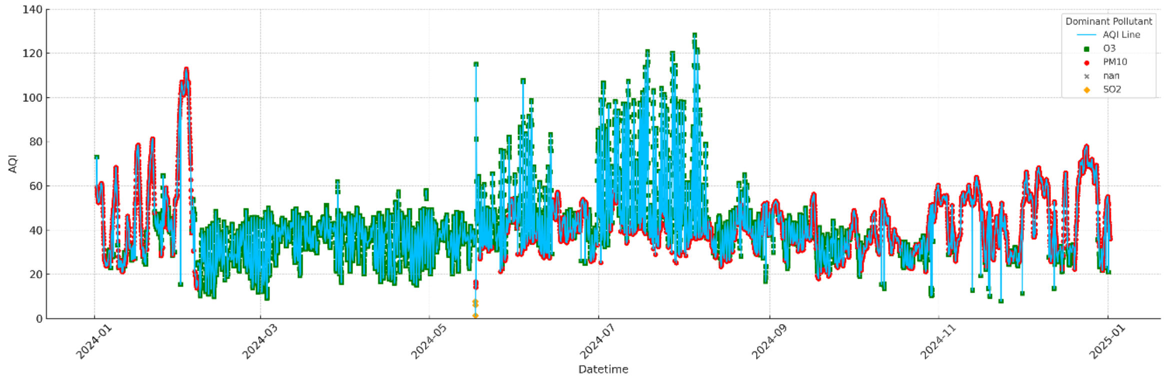

Fig. 2. Hourly AQI trends by time of day.

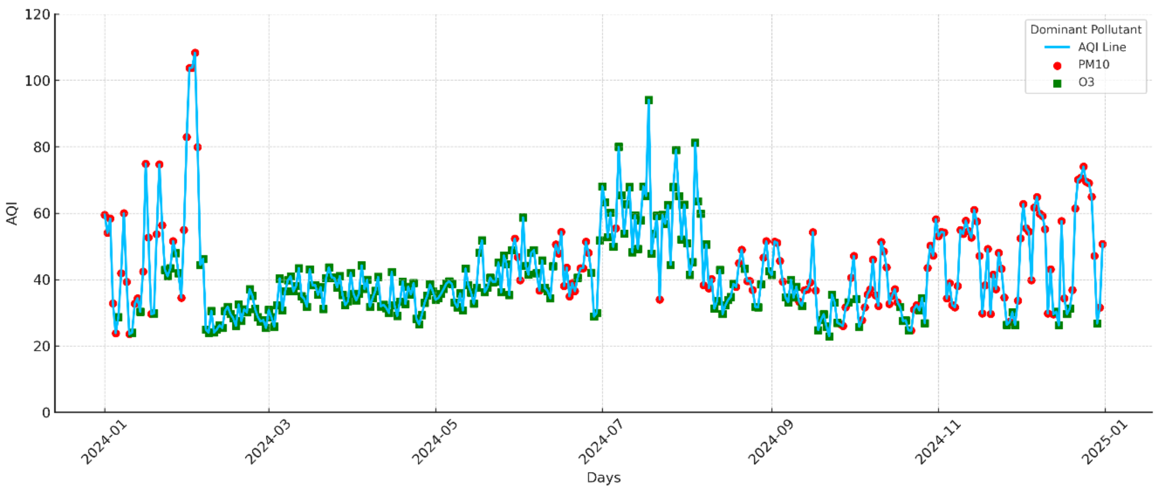

Fig. 3. Daily average AQI trends for 2024.

generally ranged between 30 and 80, indicating that air quality in Ardahan was mostly at a moderate level. Only on a few days did the AQI exceed 100, reaching levels considered unhealthy for sensitive groups. PM_{10} was observed as the most frequently dominant pollutant in the graph, suggesting that particulate matter pollution is a significant issue in Ardahan. PM_{10} is typically associated with residential fuel combustion, dust transport, and road traffic emissions. It was also observed that ozone (O_3) appeared as the dominant pollutant on certain days. Similarly, between 2019 and 2023, a marked increase in ozone concentrations was reported, particularly on hot days (Barlik et al., 2024). Although ozone is generally known to be more prominent during warmer months, the analysis revealed several instances during the winter months where ozone appeared as the dominant pollutant. Further investigation indicated that these occurrences often coincided with the unavailability of PM_{10} data. However, attributing the prevalence of ozone solely to missing PM_{10} concentrations may lead to a misleading interpretation. Therefore, to ensure a more reliable assessment, data were re-evaluated using weekly and monthly averages. This approach helps mitigate the influence of short-term data gaps and provides a more robust representation of pollutant dominance across seasons. Fluctuations in AQI values were more pronounced during the winter months. In contrast, during the summer months, air quality was more stable and generally at better levels.

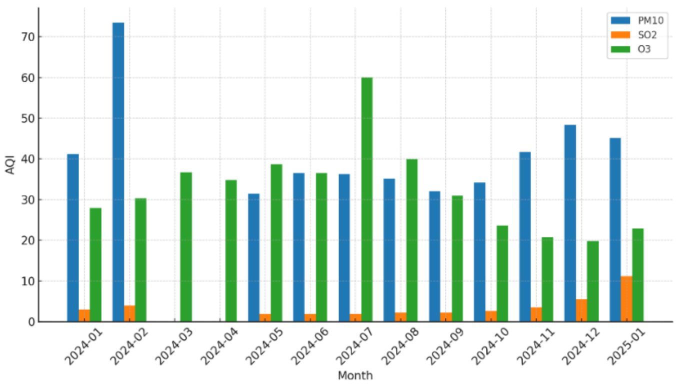

Fig. 4. Monthly average AQI values for 2024.

Fig. 4 displays the monthly average AQI values for Ardahan throughout the year 2024. PM_{10} (represented by blue bars) was the most dominant pollutant across the entire year. Notably, PM_{10} levels were particularly high in January (2024-01) and February (2024-02), exceeding values of 45 and 70, respectively In a study conducted in areas close to the region based on data between 2010 and 2018, it was observed that PM10 concentrations generally reached higher values in the winter months (Ghale et al., 2021). This suggests that emissions from heating and stagnant atmospheric conditions in winter contribute significantly to increased PM_{10} pollution.

O_3 (represented by green bars) exhibited a pronounced increase in July (2024-07), reaching an AQI value approaching 60, which constituted the highest recorded O_3 level of the year. This increase highlights the intensification of ozone formation due to higher temperatures and increased solar radiation during the summer months. SO_2 (represented by orange bars) remained at generally low levels throughout the year. A slight increase was observed only in November (2024-11) and December (2024-12). This rise can be attributed to the use of fossil fuels such as coal during the winter months.

3.3. Contribution of PM_{10}, SO_2, and O_3 to the air quality index

Since the AQI is determined based on the pollutant with the highest concentration at a given time, the percentage contributions of each pollutant type to the AQI were calculated in this study. Fig. 5 illustrates the hourly contribution percentages of PM_{10}, SO_2, and O_3 pollutants to the AQI throughout 2024. PM_{10} emerged as the most dominant pollutant year-round, with its contribution to the AQI concentrated mostly within the 40%-90% range. A previous study also reported similar findings, indicating that PM_{10} was the most influential parameter affecting the 24-hour average AQI with a contribution rate of 88.5% (Barlik et al., 2024). This phenomenon was found to be associated with data gaps in PM_{10} measurements during those specific periods. Missing data can significantly compromise the accuracy and reliability of AQI calculations. When only one pollutant is available, the AQI becomes overly sensitive to that particular pollutant.

To address this issue, the literature suggests various approaches, including statistical imputation techniques, time series analyses, artificial neural networks, and machine learning-based prediction and alert systems (Peng et al., 2017; Mo et al., 2019; Gogikar et al., 2019; Han et al., 2023; Durán Boneth et al., 2024). These methods aim to mitigate the impact of missing data and to produce more balanced and reliable AQI estimations. SO_2, in contrast, generally contributed less than 10% to the AQI, indicating that it was not a primary determinant of air quality in the case of Ardahan.

Fig. 6 presents the daily contribution percentages of PM_{10}, SO_2, and O_3 to the AQI throughout the year 2024. PM_{10} consistently appears as the dominant pollutant, contributing between 40% and 80% across the year. O_3, on the other hand, emerged as the dominant pollutant on certain days, particularly during the early months of the year and in the summer. The contribution of SO_2 remained quite low, generally below 10%. It is noteworthy that the significant data gaps in the chart (especially between February and March) are due to incomplete measurements. During this period, O_3 appears to contribute 100% to the AQI, which is a technical artifact caused by the absence of data from other pollutants. This visualization clearly highlights the dominant influence of PM_{10} on AQI in Ardahan, while also indicating that ozone can be seasonally significant, and that the overall contribution of SO_2 is limited.

Fig. 7 illustrates the monthly percentage contributions of PM_{10}, SO_2, and O_3 to the AQI for the year 2024. The chart clearly demonstrates the extent to which each pollutant influenced AQI throughout the year. PM_{10} consistently emerged as the primary contributor to AQI, with contribution rates exceeding 60% in January, February, November, and December. This suggests that emissions from heating and stagnant atmospheric conditions during the winter months significantly increased PM_{10} accumulation. O_3 contributed 100% to AQI in March and April, likely due to missing data from other pollutants during those months, resulting in a technically induced dominance. In other months, ozone contributed between 30% and 60%, which can be attributed to increased photochemical reactions during the warmer seasons. SO_2, by contrast, had a very limited impact on AQI throughout the year. Its contribution generally remained below 5%, reaching close to 10% only in a few months. This indicates that SO_2 is not a determining pollutant in Ardahan's air quality. Overall, PM_{10} was the most influential pollutant on AQI throughout the year. While O_3 was significant during spring and summer months, its apparent dominance in certain months is

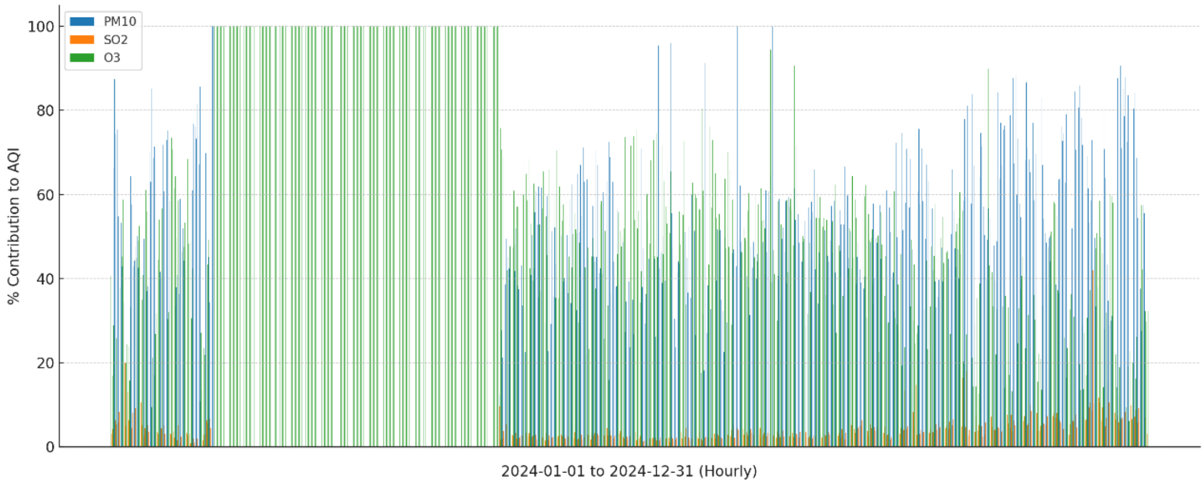

Fig. 5. Hourly percentage contribution of PM10, SO_2, and O_3 to AQI during 2024.

Fig. 6. Daily percentage contribution of PM_{10}, SO_2, and O_3 to AQI during 2024.

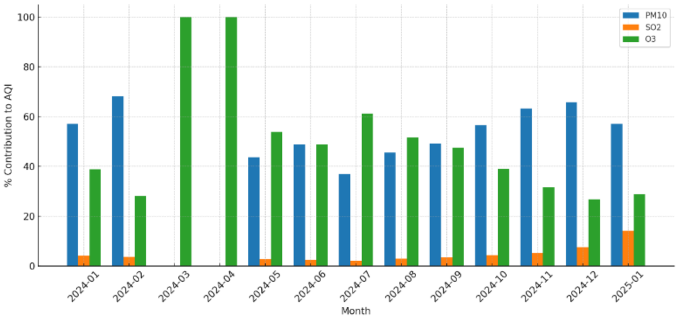

Fig. 7. Monthly percentage contribution of PM_{10}, SO_2, and O_3 to AQI during 2024.

largely due to the absence of data for other pollutants. The contribution of SO_2 remained negligible across the entire period.

The results obtained demonstrate the critical importance of seasonal variations and data availability in determining the dominant pollutant in AQI calculations. In addition to seasonal and technical influences, data availability plays a key role in shaping AQI assessments. Particularly during periods when ozone appears as the dominant pollutant, it can be assumed that other parameters were not measured. If such data gaps occur in metropolitan areas where urbanization and industrialization are intense, this may significantly hinder the accurate prediction of public health risks associated with air pollution.

4. Discussion

After excluding missing data points (when fewer than three pollutant measurements (PM_{10}, SO_2, O_3) were available), hourly National Air Quality Index (NAQI) values were calculated based on valid observations. The computed NAQI values demonstrate temporal variability in air quality throughout the measurement period. PM_{10} was frequently identified as the dominant pollutant, particularly in periods where elevated particulate levels corresponded with higher index values. In contrast, SO_2 and O_3 generally contributed to lower index values, reflecting relatively lower ambient concentrations and lesser impact on the overall index.

The dominance of PM_{10} in the index calculations suggests that particulate pollution remains a critical concern in the studied region, particularly during winter months, due largely to increased domestic heating and meteorological conditions that restrict atmospheric dispersion. While periods of generally moderate to good air quality have been recorded, intermittent elevations in NAQI (mostly due to PM_{10}) highlight the need for targeted air quality management strategies aimed at reducing particulate matter emissions.

According to the 2021 World Health Organization (WHO) air quality guidelines, the recommended 24-hour mean limit for PM_{10} is 45 µg/m³, while the annual mean should not exceed 15 µg/m³. For SO_2, WHO suggests a 24-hour average limit of 40 µg/m³, and for ozone (O_3), the 8-hour maximum daily average should remain below 100 µg/m³ (Matar et al., 2024) .The descriptive statistics in Table 2 indicate notable variability in pollutant levels. PM_{10} reached a peak value of 179.07 µg/m³, which significantly exceeds the daily limit value of 45 µg/m³ set by both WHO. This suggests the occurrence of short-term pollution episodes with potentially adverse health impacts, particularly for sensitive populations such as children, the elderly, and individuals with respiratory conditions (Mushtaq et al., 2024). SO_2 peaked at 9.25 ppb, which remains well below the hourly standard of 75 ppb (according to EPA guidelines). This indicates that sulfur dioxide pollution is generally not a dominant concern in the study area during the monitoring period. O_3 showed a maximum concentration of 78.75 ppb, which is close to or slightly above the 8-hour average standard of 50 ppb recommended by WHO (Donzelli and Suarez-Varela, 2024). This suggests that during certain periods, ozone levels may have posed moderate health risks, particularly during warm and sunny days conducive to photochemical reactions. While PM_{10} appears to be the most critical pollutant, frequently exceeding acceptable limits, SO_2 levels remained consistently low, and O_3 levels occasionally approached or surpassed threshold values, potentially contributing to elevated air quality index scores during specific episodes. These thresholds are designed to protect public health, especially vulnerable groups such as children, the elderly, and individuals with respiratory conditions. Exceedances of these values, as observed in certain periods of the dataset, indicate potential health risks and highlight the need for targeted air quality management strategies.

When examining studies conducted in Turkish provinces with higher levels of industrial activity and population density compared to Ardahan, it has been reported that the average PM_{10} concentration over a three-month period in Adana was 12.54 µg/m³ (Pekdogan et al., 2024). In another study conducted in Adıyaman, the annual average concentrations of PM_{10} and SO_2 were found to be 45.6 µg/m³ and 8.9 µg/m³, respectively; while the maximum concentrations reached 751.81 µg/m³ for PM_{10} and 562.27 µg/m³ for SO_2 (Kara et al., 2024). In a study covering 12 different districts of Istanbul, ozone (O_3) concentrations ranged between 7.04 and 39.69 µg/m³, while PM_{10} concentrations varied between 28.27 and 125.41 µg/m³ (Ozdemir et al., 2024). In the present study, the annual average concentrations of O_3, PM_{10}, and SO_2 were calculated as 39.67 µg/m³, 43.98 µg/m³, and 24.23 µg/m³, respectively. When compared with findings from other regions in Türkiye, these values reveal the spatial variability of air pollution levels. The fact that the PM_{10}, SO_2, and O_3 concentrations observed in this study are similar to or occasionally higher than those recorded in major metropolitan areas indicates that air pollution is not solely attributable to industrial or traffic-related sources. Instead, residential heating, meteorological conditions, and regional factors also play a significant role in determining pollutant levels. Consequently, these factors can periodically lead to unhealthy levels in the Air Quality Index (AQI).

Additionally, during the measurement period, it was observed that pollutant concentrations could not be detected at certain time intervals based on the data obtained from the air quality monitoring station. In recent years, the use of artificial intelligence (AI) and machine learning (ML) techniques in air pollution forecasting has gained significant momentum, primarily due to their superior capacity to model complex and nonlinear interactions among variables (Liu et al., 2021). Among the commonly applied models are artificial neural networks (ANNs), support vector machines (SVMs), and fuzzy logic systems (FLMs), as well as their more sophisticated variants such as the Backpropagation Neural Network (BPNN). Artificial neural networks (ANNs), support vector machines (SVMs), and fuzzy logic systems (FLM), along with their advanced versions such as BPNN Backpropagation neural network (BPNN) (Kamal et al., 2006), Radial basis function neural network (RBFNN) (Wahid et al., 2011), LSSVM (Least squares support vector machine) (Li and Yang, 2010), and ANFIS (Adaptive neural network fuzzy inference system), offer high prediction accuracy. In addition to deep learning models such as Long Short-Term Memory (LSTM), classical machine learning methods such as Autoregressive Integrated Moving Average (ARIMA), Decision Trees, K-Nearest Neighbors (KNN), Gradient Boosting (GB), AdaBoost, Huber Regressor, and Dummy Regressor are also widely used in air quality prediction and have proven to be effective in handling complex data structures (Mishra and Gupta, 2024). This study has demonstrated the importance of applying alternative modeling approaches to improve the reliability of Air Quality Index (AQI) predictions in cases of technical failures or data gaps at air quality monitoring stations in Türkiye.

5. Conclusion

The findings of this study indicate that, throughout 2024, air quality in Ardahan was frequently at “moderate” and “unhealthy for sensitive groups” levels, particularly during the winter months due to PM_{10}-related pollution. Ozone (O_3), on the other hand, was found to become dominant during the summer as a result of photochemical processes intensified by higher temperatures and solar radiation. However, its dominance during winter months was identified as a technical artifact caused by data gaps. The contribution of SO_2 to the AQI was found to be minimal, suggesting that it is not a major pollutant influencing air quality in the Ardahan region. Furthermore, the study revealed that data gaps in AQI calculations can lead to misleading identification of the dominant pollutant. This highlights the necessity of addressing missing data in air quality assessments. Therefore, the applicability of artificial intelligence (AI) and machine learning (ML)-based models is considered crucial for reducing the impact of incomplete datasets and for achieving more accurate AQI predictions. In conclusion, hybrid and deep learning-based approaches offer higher predictive accuracy compared to classical methods. These models are particularly valuable as decision-support tools for local administrations in regions such as Ardahan, which may face significant air quality challenges during the winter season.

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