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ANALYSIS AND ASSESSMENT OF AIR QUALITY IN ASTANA: COMPARISON OF POLLUTANT LEVELS AND THEIR IMPACT ON HEALTH

Abstract: This study presents an in-depth analysis of air quality in Astana, Kazakhstan, utilizing both mobile and stationary air monitoring systems over a two-year period. The research focuses on tracking key air pollutants, namely carbon monoxide (CO), nitrogen dioxide (NO_2), particulate matter (PM2.5 and PM10), and sulfur dioxide (SO_2), providing a comparative assessment of seasonal trends and the sources of pollution, which include transportation, industrial emissions, and domestic heating during the cold season. The study emphasizes the significance of monitoring systems in urban environments to understand better the impact of air pollution on public health and the effectiveness of sustainable interventions. One of the major insights from this research is the comparison between seasonal variations in pollutant levels and the city's transition toward sustainable energy practices, such as increased gasification and the use of electric transportation, which has already demonstrated a positive impact on reducing emissions during peak heating periods. The results show that while Astana has improved air quality, air pollution remains a concern, especially in winter due to the increased use of solid fuel. This paper emphasizes the importance of real-time data from mobile sensors and suggests their wider use to complement stationary sensors for better monitoring. In addition to pollutant tracking, the study delves into the health implications of prolonged exposure to air pollutants, particularly in urban areas. The study concludes by advocating for expanded use of mobile monitoring systems and advanced data analytics to provide actionable insights for policymakers, urban planners, and public health officials.

Keywords: Air pollution; data analysis; air quality, air monitoring; smart city; health impact.

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Introduction

Air pollution in Kazakhstan has become an increasingly pressing problem in recent years. Despite significant investments in the public health system, the country continues to lag behind other states in terms of life expectancy and various health indicators.

Scientists claim that the CO_2 content in the Earth's atmosphere is currently at a record high. Every year about 40 billion tonnes of carbon dioxide are added to the atmosphere [1]. Residents of cities near motorways are more exposed to the negative effects of polluted air than those living in rural areas.

Developed countries (UK, Japan and USA) are characterized by longer life expectancy and significantly less mortality among the population. But at the same time, these countries have several problems related to respiratory diseases and declining immunity. In 2019, the estimated life expectancy of the US population was 78.9 years, but due to the COVID-19 pandemic, this indicator decreased by 1.5 years, and in the UK by 1.3 [2], [3].

Climate of Astana characterized by strong winds, favors the natural weathering of particulate matter from the atmosphere. Without this phenomenon, the level of air pollution could be significantly higher, which negatively affects human health. Effective utilization of this climatic condition requires the development of environmentally sustainable solutions to air pollution problems. Astana lags far behind Almaty in the number of stationary sensors, as their installation and maintenance require significant financial costs.

According to international ratings of air pollution, the city of Astana is constantly on the list with poor indicators, which causes the high relevance of the study. Astana is in the 67th place among 119 large cities on the level of air pollution in real-time. This indicator is not accurate and insufficient to assess the level of air pollution based on data from 4 stationary sensors [4].

According to the head of the Ministry of Ecology of the Republic of Kazakhstan, residents of areas with gas supply still prefer solid fuel for heating, which contributes to air pollution, and one of the reasons for this is the high cost of connecting to gas, which ranges from 700 to 900 thousand tenge; in addition, emissions from cars also have a significant impact on air quality. In this regard, the paper proposes the introduction of mobile sensors for monitoring, visualization, and analysis of urban air pollution data [5].

About 16 thousand deaths related to diseases caused by poor air quality are recorded annually in Kazakhstan. Such data was presented by Yakup Berish, a representative of the United Nations Development Programme in Kazakhstan. According to the CORE studies conducted to assess the level of morbidity of upper respiratory diseases, the results of spirometric analysis revealed that 6.7% of the population of Kazakhstan suffer from chronic obstructive pulmonary disease [6].

The main sources of significant air pollution are combined heat and power plants, autonomous boiler houses, private furnaces and road transport. The main pollutants include particulate matter PM2.5 and PM10 [7], [8], [9], [10], [11], [12], [13], carbon monoxide [14], [15], nitrogen oxides [16], [17], [18], sulfur dioxide [19], carbon dioxide [20], [21], [22], [23], [24] and heavy metals.

Literature Review

Air pollution in cities in Kazakhstan, such as Almaty, Astana and Ust-Kamenogorsk, is a serious environmental problem, exacerbated by seasonal changes and industrial activities. The main sources of pollution, including transport, coal combustion, and industrial plants, result in increased concentrations of pollutants, especially in winter, highlighting the need for innovative monitoring technologies to track air quality changes in real-time, as emphasized in studies [25] and [26].

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The research methods described in [27], [28], [29] and [30] include the use of modern technologies and machine learning to improve air pollution monitoring. Studies from International Information Technologies University [27] and the Technical University of Catalonia [28] demonstrate how systems based on IoT, LoRaWAN and graphical methods help to reduce costs, simplify data collection and improve monitoring accuracy, including consideration of climatic and seasonal changes. Authors from India [29] present an ETAPM-AIT system that uses sensors to measure the levels of eight pollutants, transmitting the data to a cloud server for processing using the Elman Neural Network (ENN) model and Artificial Algae Algorithm (AAA) to efficiently classify pollutants and predict air quality. In turn, the authors of [30] apply machine learning techniques such as random forest regression, AdaBoost and multilayer perceptron to build models of pollutant dependence on environmental parameters and analyze the data using correlation coefficients and model quality indicators such as MSE and MAE.

Also, studies [31] have used IoT-based systems that utilise fog computing for data processing. These systems quickly process air quality data and transfer it to the cloud for further analysis, which speeds up the response to changes in pollution levels. The introduction of such technologies, together with methods for recovering missing data [32], have enabled more accurate and timely tracking of air pollution, even with limited resources.

Studies [33] and [34] used air quality and meteorological data analysis techniques to assess the impact of the COVID-19 lockdown on pollution. In the first study, the authors found a decrease in PM2.5 concentrations due to reduced transport activity, which emphasized the need to expand the monitoring network in countries with an insufficient number of stations. In the second study, the authors conducted a comparative analysis of air in eight cities in Kazakhstan, using monitoring data and statistical analysis to identify changes in pollutant concentrations and their relationship to seasonal and weather conditions. The main findings indicated a reduction in transport emissions as a result of the lockdown, but no significant improvement in air quality was observed in industrial cities.

The improvement of the monitoring system proposed in [35] implies a more accurate distribution of stationary and mobile stations, which will help to monitor changes in pollutant concentrations more effectively. This will allow for a more rapid response to the occurrence of critical levels of pollutants and timely action.

Studies [36] and [37] emphasize the importance of improving air quality monitoring methods for better pollution management. The [36] study emphasizes the need to raise standards and develop more affordable methods, such as mobile monitoring, as traditional methods, including gas chromatography and mass spectrometry, are too expensive. In turn, the [37] study demonstrates that mobile monitoring effectively identifies localized areas of high pollution and optimizes resource allocation, which helps to overcome the limitations of traditional methods and makes monitoring more accessible and cost-effective. Thus, combining these approaches can significantly improve air quality management and provide more accurate data for developing targeted pollution reduction strategies.

The research demonstrates the wide application of both traditional and state-of-the-art methods in this area. Paper [38] focuses on comparing different regression methods for predicting air pollution in smart cities, emphasizing the importance of model accuracy and real-time data processing efficiency using Apache Spark. While [38] work focuses on improving prediction accuracy and data processing speed, paper [39] presents an overview of the application of clustering techniques such as k-means and hierarchical agglomeration to the analysis of air pollution data over the last three decades. These methods help in spatio-temporal analysis and identification of pollution sources.

Continuing the theme of data processing techniques, the study [40] reviews bias correction and other techniques to estimate pollution at the local level, providing more accurate data based on ground measurements. In turn, the paper [41] introduces the TL-BLSTM deep learning method to improve prediction over large time intervals, overcoming the limitations of traditional methods and showing a significant improvement in accuracy.

Paper [42] focuses on the use of wireless sensors installed on buses to complement fixed systems and assess the quality of communication and data transmission. In contrast, paper [43] describes a web application that integrates air quality data from different sources, such as sensors and informative websites and plans to use neural networks for prediction. While [42], [43] papers focus on data collection and analysis, paper [44] proposes an innovative approach using environmental drones that not only monitor but also actively manage pollution by creating air quality maps and indices for long-term analyses.

One of the solutions to reduce air pollution could be to gradually reduce the amount of burning solid fuel and connect private homes and combined heat and power plants (CHPPs) to gas. The issue of gasification of Astana city was initiated in 2014 at the meeting of the interdepartmental commission for the development of oil, gas and energy sectors [45], and in December 2016 a feasibility study of the project was completed [46]. The implementation of Astana gasification projects faced a number of obstacles and was suspended indefinitely [47] and the first stage of gasification started in 2020.

In 2021, the first phase of gasification in Astana was completed, bringing gas to 8,429 private homes and 8 apartment buildings [48], [49]. By 2022, the number of subscribers with access to gas increased to 12,000, covering about 200,000 residents [50]. In 2023, the second phase of gasification was completed, bringing more than 8,500 homes connected to gas [51]. The Minister of Energy confirmed that the completion of the gasification of Astana is scheduled for 2025 [52].

In Astana, a connection of CHPPs to gas started in 2023. In this year, the first stage of construction of CHPP-3 was completed, and the gas-fired heat stations "South-East" and "Turan" were commissioned. These facilities were the first gas-fired thermal power plants in Kazakhstan and allowed to significantly improve heat supply to the city [53], [54].

There is also a slight, but still noticeable increase in the number of electric vehicles in the city of Astana. Currently, about 1.1 thousand electric vehicles are registered, and 134 electric buses have been put into operation [55], [56]. Moreover, the entry of new operators into the electric scooter rental market contributes to the growing demand for environmentally friendly modes of transportation.

The levels of air pollutants in Astana vary significantly based on seasonal and geographic factors, directly impacting public health. It is hypothesized that phased gasification and the increasing number of electric vehicles in Astana will positively affect the reduction of harmful substances in the air, contributing to an overall improvement in the city's environmental conditions.

Methods and Materials

For the study, a systematic search of the scientific literature was conducted using the following electronic databases: Mendeley [57], PubMed [58], Scopus [59], and Web of Science [60]. The search included both peer-reviewed journal articles and conference proceedings published between 1968 and 2023. The search query included keywords related to the study topic, such as Air pollution health effects, PM2.5 and respiratory health, Systemic inflammation, Cardiovascular risks from pollution, CO_2 and cognitive function, Particulate matter and diabetes, Heavy metals neurodegeneration, NO_2, SO_2 respiratory impact, CO exposure health risks, Airborne pollutants and cancer. The literature was selected based on the relevance of the materials to the issues under study.

Within the framework of the study on air pollution monitoring in the cities of Kazakhstan, it was concluded that the most appropriate approach is to use a combination of descriptive, comparative, and statistical methods of data analysis. The descriptive method is chosen for a detailed description of the current state of air pollution, which will allow us to visualize the scale and nature of the problem. Comparative analysis is used to assess differences in pollution levels between different cities and regions, as well as to analyze changes over time. Statistical analysis on open data sources provides quantitative estimates of pollutant levels and reveals statistical relationships between different variables, such as seasonal variations and the impact of industrial activities. This integrated approach allows not only a deeper understanding of pollution dynamics but also the development of more effective strategies to improve air quality based on objective data.

To proceed with the comparison of the CO gas values for January and July 2023, statistical methods were used:

1. Descriptive Statistics
2. Visual Analysis (Given at *Hourly Mean Co Concentrations In January And July 2023, Fig.16*)
3. Two sample t-test.

The descriptive statistics and t-test results are given in Table 1.

Table 1. Descriptive statistics and two sample t-test

№	Measures	Statistical formulas	Value	Conclusion
1	Mean (μ)	$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$ Where: 1) xi is the CO value at each hour; 2) N is the total number of hours.	January Mean (777.00 μg/m³) vs July Mean (440.79 μg/m³)	The mean CO concentration in January is significantly higher than in July.
2	Variance (σ^2)	$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2$	January Variance (366,559.81) vs July Variance (73,365.41)	The CO concentrations in January fluctuate much more than in July, indicating greater variability in CO levels during the winter.
3	Standard Deviation (σ)	$\sigma = \sqrt{\sigma^2}$	January Standard Deviation (605.44) vs July Standard Deviation (270.86)	The standard deviation confirms that January's CO concentrations are not only higher on average but also more spread out from the mean. This further supports the idea of higher day-to-day or hour-to-hour variations in CO levels during the colder months.
4	Coefficient of Variation (CV)	$CV = \frac{\sigma}{\mu}$	Coefficient of Variation (CV) January CV (0.779) vs July CV (0.614)	January's CO concentrations are more variable ($CV = 0.779$) than those in July ($CV = 0.614$). Even though July has a lower standard deviation, the smaller mean makes its variation less significant relative to January.
5	T-test for Comparison of Means (t)	$t = \frac{\mu_1 - \mu_2}{\sqrt{\frac{\sigma_1^2}{N_1} + \frac{\sigma_2^2}{N_2}}}$	T-statistic: $t = 13.75$	The t-test result shows that the difference between the mean CO concentrations in January and July is statistically significant.

Data Acquisition

The original dataset consists of 466,165 rows and 4 columns. Descriptive statistics were calculated for the air pollution monitoring data in Astana, the results of which are presented in Figure 1.

code	count	mean	std	min	25%	50%	75%	max
CO	99109.0	534.10	617.44	0.0	262.82	381.27	577.19	14332.85
NO2	92559.0	70.18	147.31	0.0	6.12	15.97	47.84	989.32
PM10	87579.0	54.03	89.23	0.0	9.81	21.47	59.12	1325.76
PM2.5	87794.0	42.69	87.20	0.0	2.22	8.29	38.82	1317.78
SO2	99124.0	64.43	255.37	0.0	3.47	13.76	23.48	2000.00

Figure 1. Summary Statistics by Code

For further investigation, average values of the "code" for each month from December 2021 to April 2024 were taken, as the rest of the data was not available, or was not complete for the various stations. Open data sources initially provided 220 monitoring stations across Kazakhstan, of which 9 were located in Astana city and were intended to measure air pollution levels. However, only 5 of these stations were selected for our study, as the data from the remaining 4 stations were incomplete for the pollutants we selected. The final dataset contains 715 rows x 4 columns. There are 5 stations (k4, k7, k8, k9, k12) with 5 different pollutant codes each (CO, NO_2, PM2.5, PM10, SO_2) registered in the dataset.

During the analysis of air quality data, mean values for certain pollutant codes were missing for some monitoring stations (stationId) in the dataset. To address this problem, a systematic approach was taken to correct missing values to ensure the completeness and reliability of the data for subsequent analysis.

A method was used to impute these missing values, which involved calculating the overall average value for the pollutant code in question for all available monitoring stations for a given month. This is done using (1), where the average values of the pollutant code for all stations were summed, and then the sum was divided by the number of stations for which data are available:

$$\bar{M}s,m,c = \frac{1}{N_m}\sum_{s\in S_m} Ms,m,c. \tag{1}$$

The resulting value was then used to replace the missing mean value for a particular station identifier (2):

$$Ms,m,c \ = \ \bar{M}m,c \ \text{ if } Ms,m,c \text{ is absent,} \tag{2}$$

Where:

- Ms, m, c the average value for station s in a month m for code c.
- Sm the set of all stations for which data are available in the month m.
- Nm number of stations in Sm.

Replacing missing data with mean values is a technique used to handle incomplete datasets. This method keeps the overall dataset unbiased compared to methods such as deletion, which can skew the results by removing certain data points. Moreover, instead of discarding incomplete records, the imputation of missing values preserves the complete data set and ensures that no information is lost, thus increasing the validity of the analyses. Calculating and replacing by the mean is computationally inexpensive and easy to implement, especially for large datasets.

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The final dataset contains information for 5 stations collected from the Kazhydromet open data source in Astana, including their geographic coordinates and current status. The data was visualized in the form of an interactive map showing the stations, where each station is labeled with a marker that displays additional information about the station (Fig. 2).

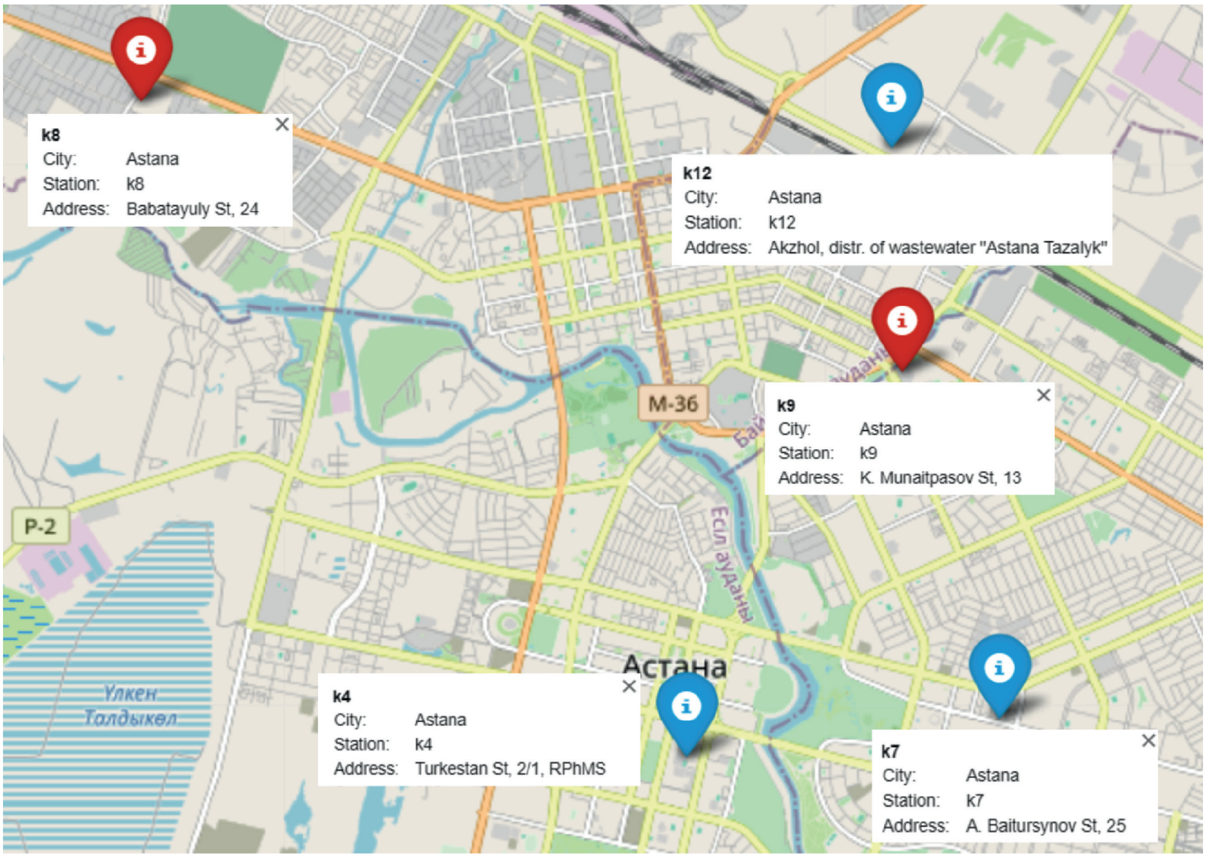

Figure 2. Air quality monitoring stations in Astana

During data analysis, the table (Fig. 3) with air quality indices was used to construct heatmaps using the US EPA formula based on the maximum work function [61]. In plotting the graphs, CO values (Fig. 3) were converted from mg/m³ to µg/m³. The report [61] identified 6 AQI categories namely "Good", "Satisfactory", "Moderate", "Poor", "Very poor", and "Severe", and takes into account 8 air pollutants. Figure 3 is a tool to inform people about the status of air quality and possible health effects.

AQI Category (Range)	PM_{10} 24-hr	$PM_{2.5}$ 24-hr	NO_2 24-hr	O_3 8-hr	CO 8-hr (mg/m³)	SO_2 24-hr	NH_3 24-hr	Pb 24-hr
Good (0-50)	0-50	0-30	0-40	0-50	0-1.0	0-40	0-200	0-0.5
Satisfactory (51-100)	51-100	31-60	41-80	51-100	1.1-2.0	41-80	201-400	0.6 –1.0
Moderate (101-200)	101-250	61-90	81-180	101-168	2.1- 10	81-380	401-800	1.1-2.0
Poor (201-300)	251-350	91-120	181-280	169-208	10.1-17	381-800	801-1200	2.1-3.0
Very poor (301-400)	351-430	121-250	281-400	209-748*	17.1-34	801-1600	1201-1800	3.1-3.5
Severe (401-500)	430 +	250+	400+	748+*	34+	1600+	1800+	3.5+

**One hourly monitoring (for mathematical calculation only)*

Figure 3. Values for AQI Scale (units: µg/m³, unless otherwise specified)

Results and Discussions

To compare pollutant concentration levels in 2022 and 2023, graphs were constructed calculating average pollutant values for each month by station. The red line separated the two years for visual comparison and presentation of data.

In 2022 (Fig. 4), there are marked fluctuations with high CO levels at the beginning and a significant peak in December, followed by a decline in between. But at the same time, CO concentrations do not exceed the "Satisfactory". In 2023, CO levels can be characterized as more stable, with no sharp peaks. The increase of carbon monoxide concentration in winter is due to the heating season: in summer the main source of gas is motor vehicle exhaust, and in winter the concentration increases due to the combustion of solid fuels by private houses and CHPPs in the city.

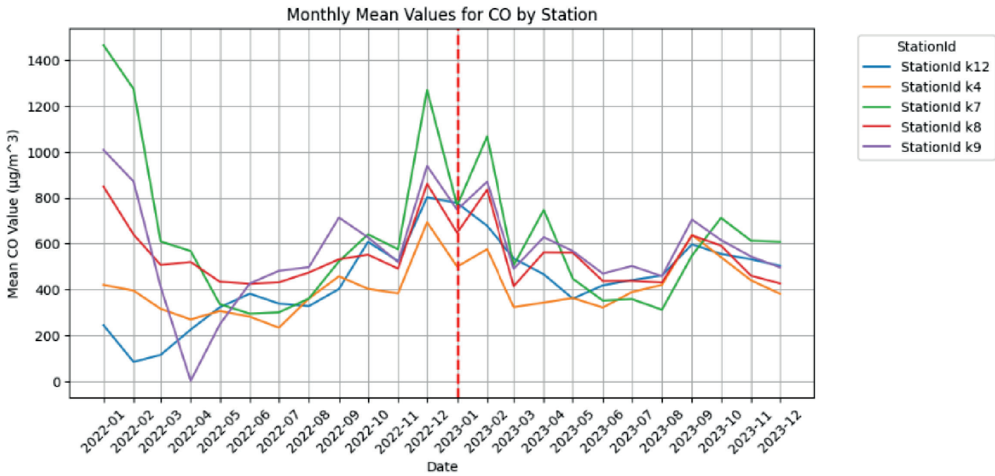

Figure 4. Monthly Mean Values for CO by Station

In 2022 and 2023 (Fig. 5), there are marked fluctuations in NO_2 levels at all stations. However, at station ID k4 (represented by the orange line) NO_2 levels are particularly high. NO_2 values at this station in 2022 reach a significant peak in May and July, reaching about 400 µg/m^3, while in August and September 2023, increases up to 500 µg/m^3 can be observed.

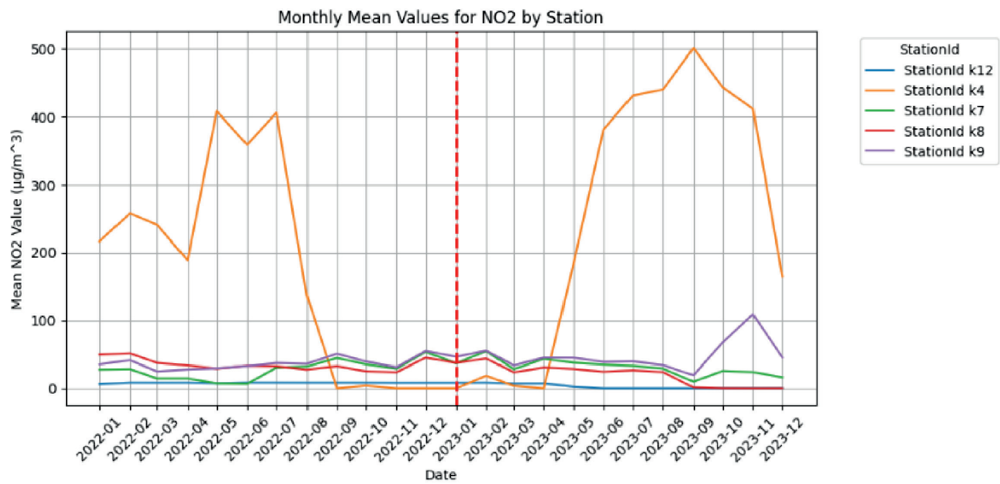

Figure 5. Monthly Mean Values for NO_2 by Station

On the heat map (Fig. 6) of NO_2 concentrations at station k4, dark red cells show levels in the "Severe" category, i.e. NO_2 concentrations of more than 400 µg/m^3. Mostly the increase in

NO_2 concentrations at station k4 is observed during the summer period and may be due to a local feature - the station is located near a highway or industry. Nitrogen oxide concentrations of other stations are within the range of “Good”, “Satisfactory”, and in some cases “Moderate”.

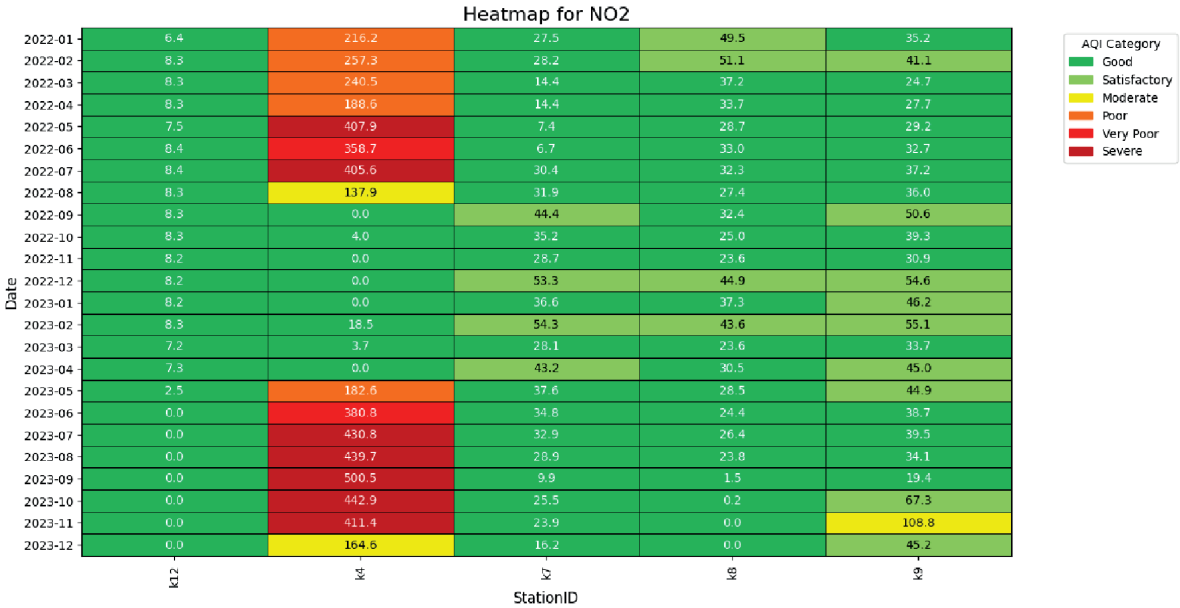

Figure 6. Heat map of monthly mean NO_2 values (μg/m^3)

In 2022 (Fig. 7), there are significant fluctuations in PM2.5 levels, especially for stations k12 (blue line) and k4 (orange line). Station k12 shows a sharp peak in March 2022, reaching over 300 μg/m^3, followed by a sharp decline. Station k4 shows a similar trend with a major peak in September 2022 reaching over 400 μg/m^3.

The year 2023 appears more stable compared to 2022, although there are still notable peaks in PM2.5 levels for stations k12 and k4. At station k12 there is a noticeable increase around April 2023, exceeding 200 μg/m^3, and another peak at station k4 is observed around May 2023.

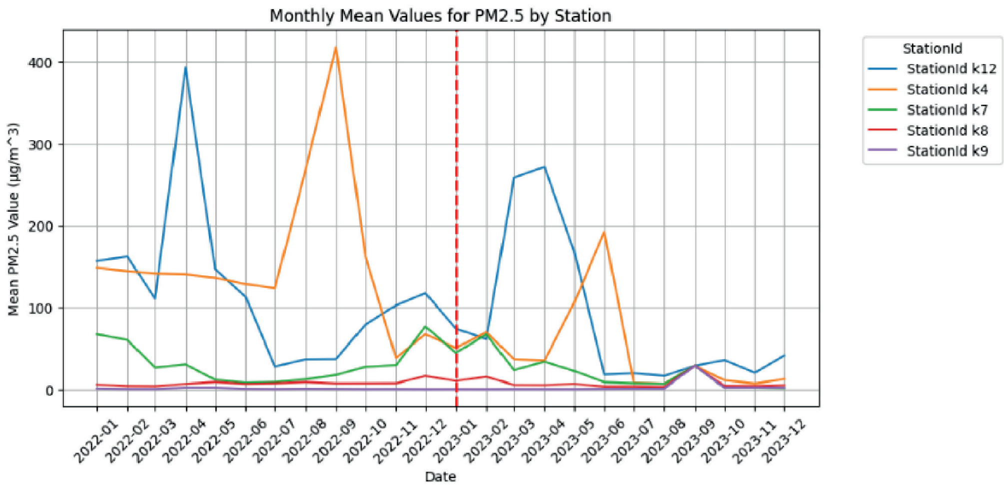

Figure 7. Monthly Mean Values for PM2.5 by Station

According to the results of the heat map (Fig. 8) of values for the period from January 2022 to December 2023, a deterioration of PM2.5 concentrations can be observed at stations k4 and k12, especially in the first half of 2022, when values often exceed the permissible limits

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and reach the Severe level. Improvements can be observed at station k8 and especially k9, where values remain at good levels throughout the period.

Significant increase in PM2.5 concentration at some stations (k12 and k4) can be related to the increased content of ash particles in the air during the heating season, as well as to the formation of construction dust during the summer period as a result of the construction of residential buildings and structures.

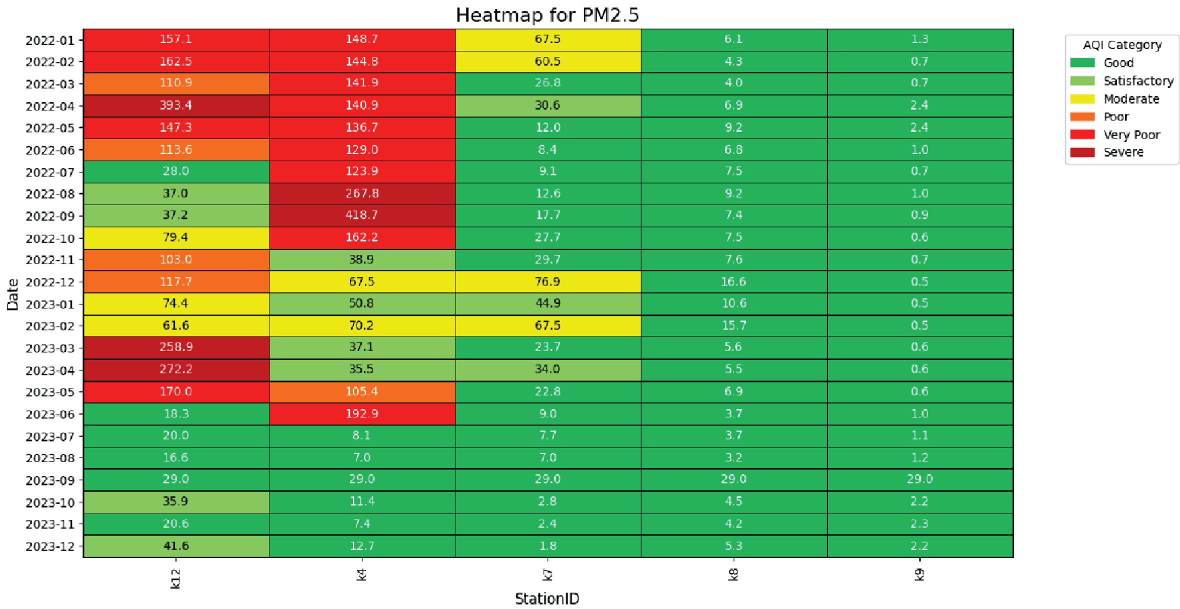

Figure 8. Heat map of monthly mean PM2.5 values (μg/m³)

In 2022 (Fig. 9), there are significant fluctuations in PM10 levels, especially for stations k12 (blue line) and k4 (orange line). At station k12, there is a sharp peak in March 2022, reaching over 300 μg/m³, followed by a decline. At station k4, the main peak occurs in September 2022, when levels exceed 400 μg/m³.

At stations k12 and k4, there is a noticeable increase in PM10 levels, especially in April 2023 for station k12 and May 2023 for station k4. However, these levels are lower than the peaks observed in 2022. The second half of 2023 shows a more stable trend at all stations, with minimal fluctuations and generally lower PM10 levels, indicating an overall improvement in air quality compared to the previous year.

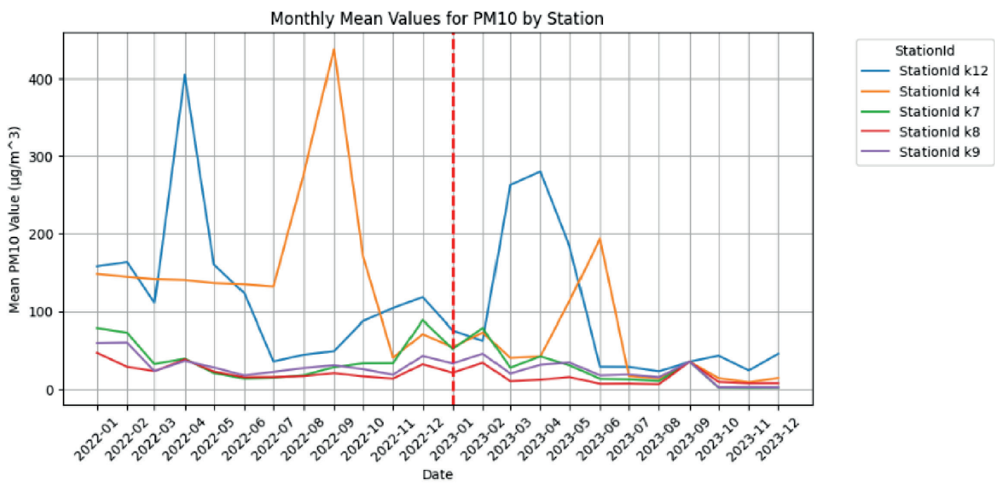

Figure 9. Monthly Mean Values for PM10 by Station

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Figure 10 shows an increasing trend in PM10 concentrations at stations k4 and k12. Station k4 requires the most attention, as it shows periodic exceedances of PM10, which has a negative impact on air quality. Stations k8 and k9 show a good tendency to maintain stable air quality throughout the period.

Figure 10. Heat map of monthly mean PM10 values (μg/m^3)

In 2022 (Fig. 11), there are significant spikes in SO_2 levels for station k12 (blue line). Several notable peaks are observed, with the highest occurring in January 2022 when SO_2 levels exceed 700 μg/m^3. Additional peaks are observed in May, October, and December 2022, each time reaching between 200 μg/m^3 and 400 μg/m^3.

The year 2023 is dramatically different from 2022 in terms of SO_2 levels. For most of the year, SO_2 levels at all stations, including station k12, remain very low and stable, with no significant spikes. However, in November 2023, there was a sudden and dramatic increase in SO_2 levels at station k12, suggesting an isolated event or anomaly in that month.

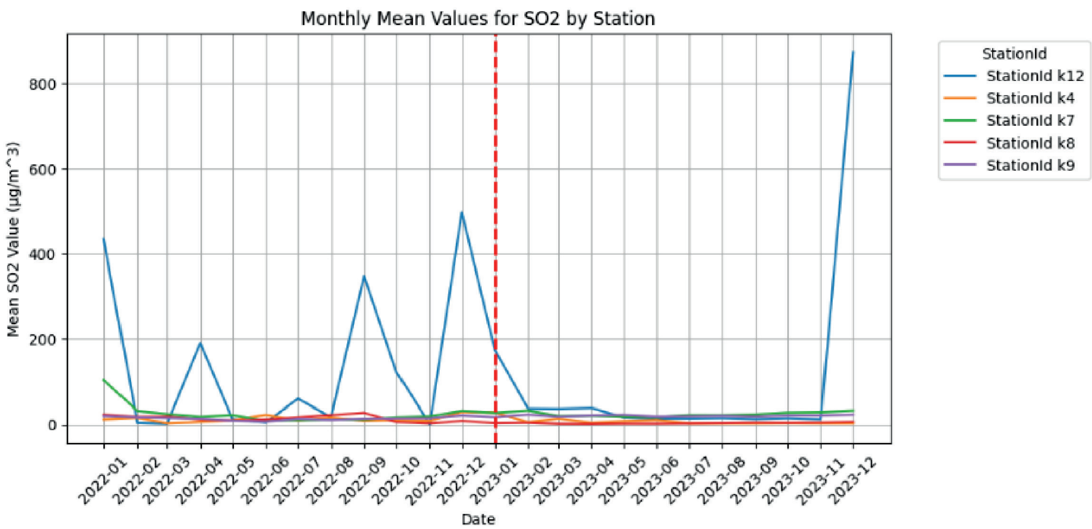

Figure 11. Monthly Mean Values for SO_2 by Station

Station k12 shows the strongest fluctuations in SO_2 levels (Fig. 12) with sharp pollution peaks in January and December 2022, as well as in December 2023, where the most significant deterioration is recorded. In contrast, stations k4, k8, and k9 show stable and good air quality with minimal pollution levels throughout the period. The increase in sulfur dioxide concentrations in winter can be attributed to the location of station k12 at a distance of 3 km from the municipal combined heat and power plant, whose emissions contain sulfur dioxide (SO_2).

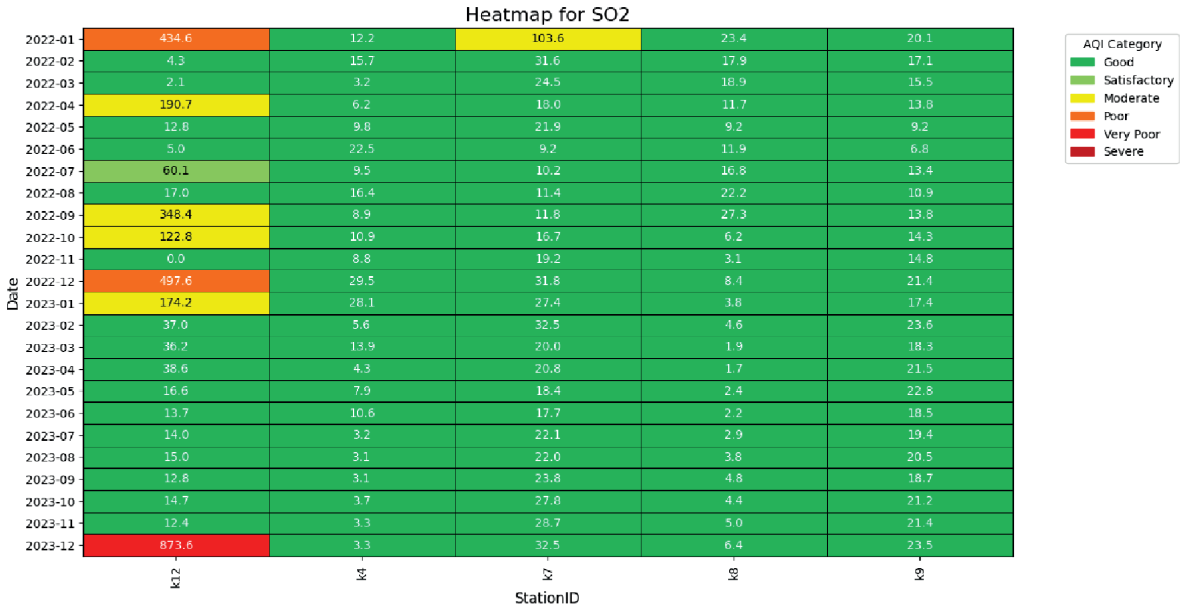

Figure 12. Heat map of monthly mean SO_2 values (μg/m3)

From this graph (Fig. 13), it can be concluded that the annual mean values of the pollutants CO and NO_2 increased from 2022 to 2023. Levels of PM2.5, PM10 and SO_2 decreased in 2023 compared to 2022, indicating an improvement in air quality for these pollutants.

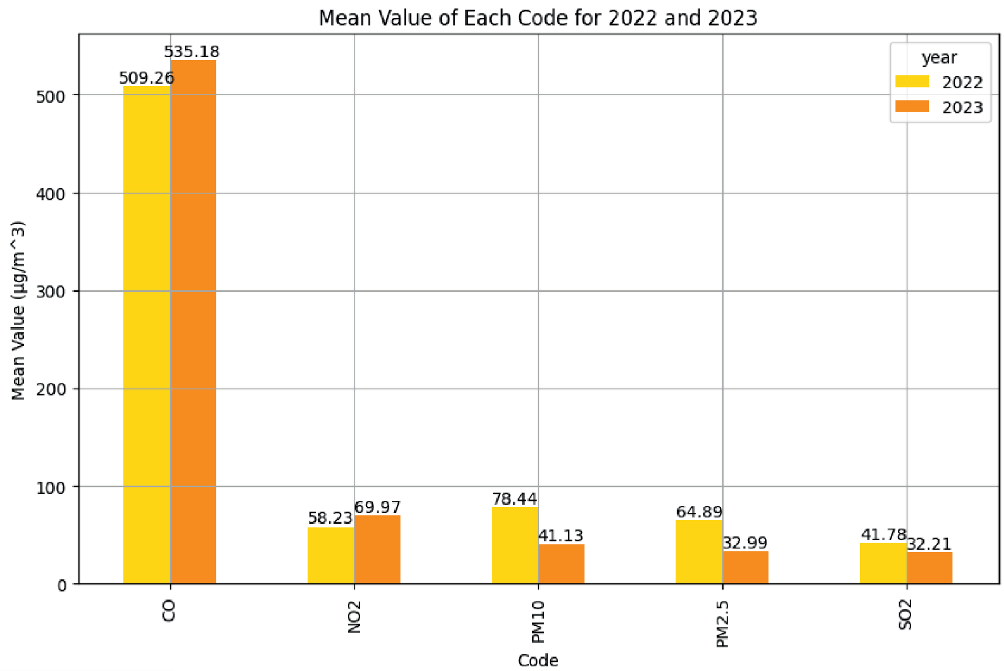

Figure 13. Comparison of Mean Pollutant Concentrations for 2022 and 2023

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Mean Co Values In Heating Seasons

The plot of mean CO values during the heating seasons (Fig. 14) reflects a pattern: CO concentrations are higher in the winter months (December through February), reach a maximum in the middle of the heating season, and then gradually decrease at the end of the heating season. The period from December 2021 to April 2022 is characterized by the highest peak (913.69 μg/m^3 in April 2022), while the other two periods show more moderate peaks in December or January. It is assumed that the decrease in carbon monoxide concentrations at the beginning of the 2023-2024 heating season (max. 711.61μg/m^3) compared to the 2022-2023 season (max. 913.69 μg/m^3) is due to the completion of the second phase of gasification in the city and the commissioning of the "Southeast" and "Turan" gas-fired heating plants.

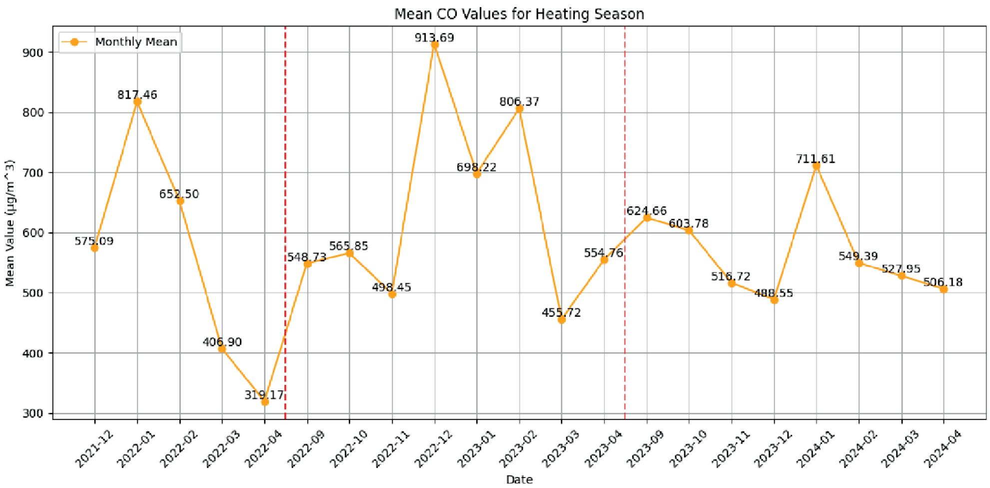


Figure 14. Mean CO (μg/m^3) values for Heating Seasons

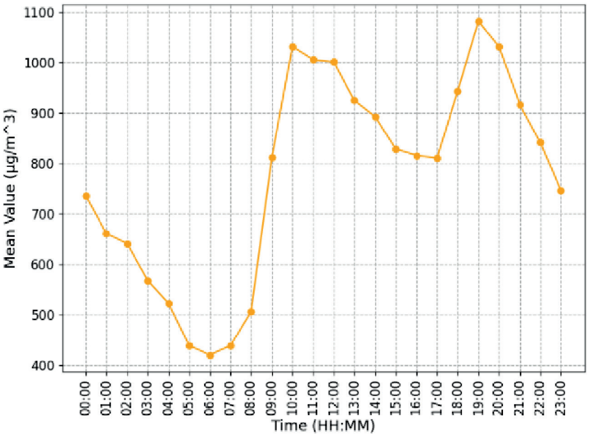
Hourly Mean Co Concentrations In January And July 2023

Data for January and July 2023 were analyzed to provide a **visual comparison** of changes in carbon monoxide concentrations throughout the day during the winter heating season and during the summer season (Fig. 15).

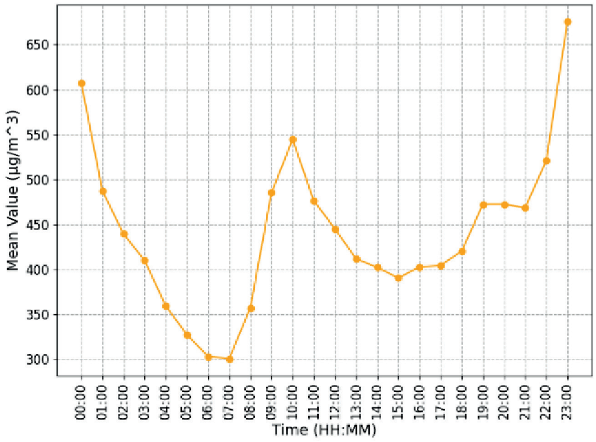
Figure 16.a presents the mean values of carbon monoxide concentrations by hour during January 2023. The data analysis shows that there is a minimum level of CO concentrations between 5:00 AM and 7:00 AM. Meanwhile, at 10:00 and 19:00 maximum concentration values are recorded, which may indicate the influence of various factors, such as traffic activity and meteorological conditions, on the level of air pollution during these time intervals.

Figure 16.b presents data on mean carbon monoxide concentrations by hour throughout July 2023. Analysis of the data shows that carbon monoxide concentrations are significantly lower at 6:00 a.m. compared to the rest of the day. Concentrations remain at moderate levels throughout the day, but the highest values are observed at 23:00, which may be due to increased vehicle activity and other emission sources during the evening hours.

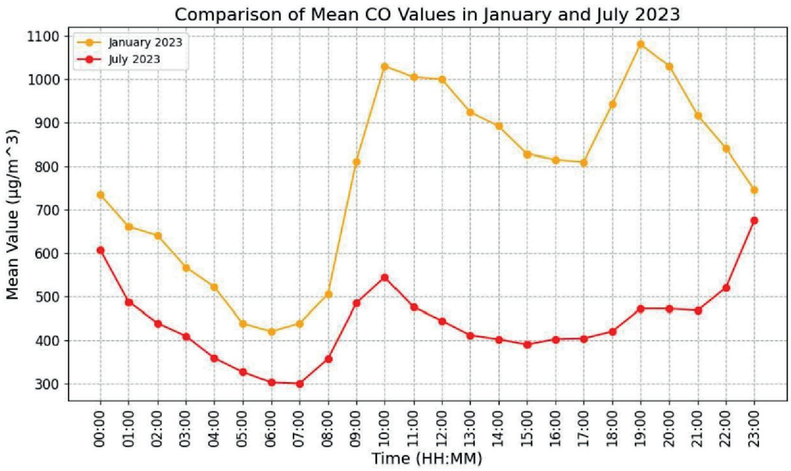
Comparing the carbon monoxide concentrations for January and July 2023, it can be noted that summertime pollution levels are significantly lower considering the peaks. In some time intervals, for example, in the afternoon, carbon monoxide concentrations in July are half as high as in January. This indicates cleaner ambient air conditions in summer than in winter. One of the key factors contributing to the higher CO concentrations in January is emissions associated with solid fuel combustion. Minimum concentrations of carbon monoxide in January are observed between 5 and 7 a.m., amounting to 410-430 μg/m^3, while in July during the same period CO concentrations do not exceed 300 μg/m^3.



a) Hourly CO Concentrations (μg/m³) in January 2023 at Station k12



b) Hourly CO Concentrations (μg/m³) in July 2023 at Station k12



c) Comparison of CO Levels: January vs July 2023 at Station k12

Figure 15. Hourly CO Concentrations

The Impact Of Air Pollutants On Human Health

Particulate matter, especially PM2.5, penetrates deeply into the lungs, causing inflammation and exacerbation of asthma, bronchitis, and other diseases. In people with chronic diseases, contact with particulate matter, SO_2, NO_2 and O_3 increases the risk of exacerbations and hospitalizations [62], [63], [64]. Particulate matter causes systemic inflammation and oxidative stress, increasing the risk of hypertension, atherosclerosis and heart attacks. CO exposure also contributes to coronary diseases [65]. Heavy metal particles can cause neuroinflammation and neurodegenerative changes, affecting cognitive function, especially in children and the elderly [66]. Certain particulate components, including polycyclic aromatic hydrocarbons and heavy metals, initiate cancer in organs such as the lungs and bladder [67], [68]. The link between PM2.5 and diabetes are supported by studies. Particles cause systemic inflammation and disrupt insulin signaling, which contributes to insulin resistance and elevated blood sugar levels [69], [70]. Particles affect metabolic processes, contributing to diabetes through inflammation and stress, which requires strict measures to reduce contaminant levels [71], [72], [73], [74], [75], [76], [77], [78], [79]. NO_2 can irritate the respiratory tract and contribute to asthma and other respiratory diseases. It can also reduce the ability of the lungs to clear contaminants, which increases the risk of infections and chronic lung disease [80], [81].

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Sulfur dioxide (SO_3), sulphuric acid (HSO_3), and sulphuric acid (H_2SO_4) are formed when oxygen interacts with the atmosphere. The effects of sulfur dioxide (SO_2) are extremely detrimental to human and plant health. High concentrations of SO_2 lead to the destruction of chlorophyll in plants, causing chlorosis. Exposure to significant amounts of SO_2 can cause respiratory problems, respiratory and lung diseases, and deterioration of the respiratory and cardiovascular systems. SO_2 is especially dangerous for people with asthma and chronic lung or heart disease. In addition, sulfur dioxide contributes to the formation of fine acid aerosols, which have serious health impacts and contribute to climate change [82].

It has been observed that this gas irreversibly binds to the iron core of hemoglobin, a red blood component that is involved in oxygen transport. Because of this binding, oxygen can no longer be absorbed by the blood, reducing cellular respiration and posing a threat to human life. According to the National Air Quality Standards, it is acceptable to be exposed to carbon monoxide concentrations of up to 10 ppm (11,456 μg/m^3) in the atmosphere for up to 8 hours, which is considered safe [83]. However, even low levels of CO, below the Immediately Dangerous To Life and Health standard, can be dangerous to humans [84].

Although CO_2 is not toxic at low concentrations, elevated levels can cause headaches, dizziness, and, in extreme cases, fainting and death due to lack of oxygen. Carbon dioxide (CO_2) can have significant effects on human health, especially when chronically exposed to elevated levels of CO_2. An article [85] discusses that when CO_2 concentrations increase in the atmosphere and in enclosed spaces, the pH in the human body can decrease. This change in pH can lead to dysfunctions of proteins in the body, causing them to clot and aggregate improperly. These changes can contribute to a variety of diseases, including obesity, diabetes, respiratory diseases, osteoporosis, cancer, and neurological disorders.

In [21] the effects of carbon dioxide on human health in an indoor environment were considered. Carbon dioxide concentrations between 500-5,000 ppm (900,004–9,000,045 μg/m^3) lead to increased blood flow, pressure changes, and increased heart rate [86]. Increased CO_2 levels above 1000 ppm (1,800,009 μg/m^3) can decrease the activity of cognitive functions, such as decision-making, and be the cause of dry cough, and rhinitis [87]. Higher indoor carbon dioxide levels, above 10,000 ppm (18,000,090 μg/m^3), cause headaches, and loss of concentration [88], [89], [90].

Conclusion

The study revealed an urgent need to improve the air quality monitoring and control system in the cities of Kazakhstan, especially in Astana. The main air pollutants affecting public health remain particulate matter (PM2.5 and PM10), nitrogen oxides (NO_2), carbon monoxide (CO) and sulfur dioxide (SO_2). Concentrations of these substances, especially in winter, often exceed permissible limits, which can lead to significant health effects, including respiratory and cardiovascular disease.

One of the key drivers of pollution is the use of solid fuels for heating and emissions from road transport. Gasification of Astana, initiated in recent years, has already shown positive results but needs to be accelerated to reach more homes and businesses. The introduction of mobile sensors and improved monitoring infrastructure will allow more accurate real-time monitoring of air quality changes.

To protect public health, comprehensive measures are needed to minimize emissions, including the development of electric transportation, reducing the use of solid fuels, and improving environmental monitoring.

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