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Analysis of Temporal Changes of Air Pollutants Concentrations in Kocaeli, Turkey

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Abstract

Air is an essential requirement for living things to survive. Air pollution is defined as the foreign substances in the air reaching a quantity and density above normal. Regular monitoring and analysis of air pollution is an indispensable step for the measures and policies to be taken. In recent years, the use of open-source software in the evaluation and analysis of air quality data has increased. The R software-based Openair Package developed by the Environmental Research Group at King's College London. This package is used to analyze air quality data, identify potential pollutant sources, and identify correlations and statistical relationships between parameters. In this study, the hourly pollutant parameter (PM, SO_2, and NO_x) measured from two air quality stations between 2018 and 2022 in Kocaeli, were analyzed temporally and statistically with the Openair Package. The study found that the primary sources of pollutants are anthropogenic activities such as vehicle traffic, fossil fuels used for heating, and natural resources. As a result of the analysis, a decrease in PM concentrations and an increase in SO_2 concentrations were observed during the study period. In addition, it was determined that traffic density has a linear relationship with the NO_x parameter.

Keywords
Air Pollution, Time Series, Theil-Sen Estimator, R Project / Openair Package

Hava Kirletici Konsantrasyonlarının Zamansal Değişikliğinin Analizi; Kocaeli Örneği

Özet

Hava, canlıların yaşamlarını sürdürebilmeleri için temel bir gereksinimdir. Hava kirliliği, havadaki yabancı maddelerin normalin üzerinde bir miktar ve yoğunluğa ulaşması olarak tanımlanmaktadır. Hava kirliliğinin düzenli olarak izlenmesi ve analiz edilmesi, alınacak önlemler ve politikalar için vazgeçilmez bir adımdır. Son yıllarda hava kalitesi verilerinin değerlendirilmesi ve analizinde açık kaynak kodlu yazılımların kullanımı artmıştır. King's College London'daki Çevre Araştırma Grubu tarafından R yazılımı tabanlı Openair Paketi geliştirilmiştir. Bu paket, hava kalitesi verilerini analiz etmek, potansiyel kirletici kaynaklarını belirlemek ve parametreler arasındaki korelasyonları ve istatistiksel ilişkileri tespit etmek için kullanılmaktadır. Bu çalışmada, Kocaeli'de 2018-2022 yılları arasında iki hava kalitesi istasyonundan ölçülen saatlik kirletici parametreler (PM, SO_2 ve NO_x) Openair Paketi ile zamansal ve istatistiksel olarak analiz edilmiştir. Çalışma, kirleticilerin birincil kaynaklarının araç trafiği, ısınma için kullanılan fosil yakıtlar ve doğal kaynaklar gibi antropojenik faaliyetler olduğunu ortaya koymuştur. Analiz sonucunda, çalışma dönemi boyunca PM konsantrasyonlarında azalma, SO_2 konsantrasyonlarında ise artış gözlemlenmiştir. Ayrıca trafik yoğunluğunun NO_x parametresi ile doğrusal bir ilişki içinde olduğu tespit edilmiştir.

Anahtar Sözcükler
Hava Kirliliği, Zaman Serisi, Theil-Sen Kestirimi, R Yazılımı / Openair Paketi

1. Introduction

Air pollution is defined as the presence of foreign particles in the atmosphere in such quantity, density, and duration that can harm human health and the ecosystem. This has become an important health and urban problem in recent years, especially in countries with rapid industrialization, urbanization, and population growth (World Health Organization, 2022). Domestic heating, vehicles, industrial plants, and natural sources are the main sources of air pollution (Agustine et al., 2018; Chaurasia & Mohan, 2022). Particulate matter (PM), carbon monoxide (CO), ozone (O_3), nitrogen oxides (NO_X), and sulfur dioxide (SO_2) are the most important pollutants threatening public health (Demirarslan & Zeybek, 2022). World Health Organization (WHO) data shows that almost the entire population (99%) breathes air with an extreme pollutant that exceeds limit values (World Health Organization, 2022).

Today, there is an increase in the number of health problems due to air pollution. The WHO classifies air pollution as the 13th leading cause of death (Yorkor et al., 2021). Short-term exposure to air pollution can lead to infectious respiratory diseases such as coughing, shortness of breath, and wheezing, which damage lung function, as well as lung cancer, asthma, and cardiovascular health problems (Badida & Jayaprakash, 2022; Demirarslan & Zeybek, 2022).

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In 2019, it was estimated that 4.2 million premature deaths worldwide were related to air pollution (Agustine et al., 2018; Sidjabat et al., 2019; World Health Organization, 2022). To minimize the negative impacts of air pollution, the number of air quality monitoring stations has increased significantly in late years. Therefore, a considerable quantity of digital data is stored and made available to users online. Therefore, the necessity of various software tools for processing and analyzing large data sets has gained great importance. One of the software examples used in the evaluation and analysis of air quality data is the Openair Package within the R programming environment. This software package was developed by the Environmental Research Group at King's College London as a Natural Environment Research Council (NERC) project. Each function in the package has a stand-alone analytical method or background, such as linear regression, p-value, and coefficient of determination and decision-making (Carslaw & Ropkins, 2012; Sidjabat et al., 2019; Szulecka et al., 2017). This package includes functions to analyze air quality data, identify correlations of pollutant parameters, define potential pollutant sources using polar plots, and evaluate and analysis of HYSPLIT back trajectories using statistical methods (Carslaw, 2019).

In recent years, the Openair Package has proven its usability in air quality studies. For this reason, this software package has been utilized in many air quality studies in the literature. Dang et al. (2017), analyzed PM_{10} and $PM_{2.5}$ air pollutant parameters in Kaohsiung City, Taiwan with the help of functions in the Openair Package. They investigated the behavior of air pollutant parameters in the study area. Szulecka et al. (2017), analyzed the air quality measurement station data in Krakow, Poland by modeling it with the Openair Package. They pointed out the superiority of the Openair Package in analyzing large data sets and its low processing time. They also mentioned the functionality of this software package and its valuable contributions to the air quality management system. Agustine et al. (2018), investigated the PM_{10} pollutant parameter values in two cities in Indonesia with the Openair Package. They revealed the pollution values of the two cities by extracting the PM_{10} distribution during the study season. Sidjabat et al. (2019), examined the distribution of air pollutant parameters together with meteorological parameters in Jababebeka Industrial Zone in Indonesia in 2015-2018 using the Openair Package. They investigated the distribution around the air monitoring stations using the pollution rose function. Huzlík et al. (2020), examined the parks in Brno, the second largest city of the Czech Republic, in terms of their relationship with air pollutants and meteorological parameters with openair and openairmaps packages. Oleniacz et al. (2021), investigated the air pollutant parameters in the dense industrial and residential areas in the northeast of Krakow, Poland, with the help of the Openair Package. Yorkor et al. (2021), examined the temporal variations of SO_2, NO_2, O_3, and $PM_{2.5}$ air pollutant parameters in Ogoni in the Niger Delta region in Nigeria with the help of an Openair Package. As a result of their analysis, they determined that pollutant parameters increased during the week and decreased at weekends. Yulinawati et al. (2021), determined the indoor and outdoor $PM_{2.5}$ air pollutant value of the women and children's hospital in West Jakarta with the help of low-cost sensors and analyzed it with the Openair Package. According to their results, the pollution value outside the hospital was found to be higher than inside. Demirarslan and Zeybek (2022), analyzed the data of 14 air monitoring and meteorological stations in the Eastern Black Sea region with the polar plot function in the Openair Package. They concluded that the primary pollutant sources are anthropogenic activities. Badida and Jayaprakash (2022), examined the changes in air quality caused by lockdowns in India before and during the Covid-19 pandemic. They concluded that restrictions at the country and state levels positively affected air quality. Beringui et al. (2022), examined the air quality of Rio de Janeiro, one of the most populous cities in Brazil, during the Covid-19 lockdown with the Openair Package. Analyzing pollutant parameters measured at five air quality monitoring stations spread across the city, they found that CO decreased and O_3 increased during the lockdown. They concluded that working from home and distance learning positively affect air quality. Rosianu et al. (2022), investigated the potential relationship and correlation between the main air pollutant parameters, meteorological parameters, and airborne pollen levels in Bucharest between 2014 and 2019 using the Openair Package of R software. Wang et al. (2022), conducted a trend analysis of the $PM_{2.5}$ air pollutant parameter between 2015 and 2019 with the random forest algorithm machine learning method using hourly data from three urban air quality monitoring stations in Xi'an, China. Ropkins et al. (2022), examined the trend analysis and polar graphs of the NO_2 pollutant parameter between 2015 and 2019 by using the data of air quality and meteorology measurement stations in the city of Leeds in the United Kingdom with the help of Openair Package. Iskandaryan et al. (2022), aimed to predict the NO_2 concentration value in Madrid, Spain using machine learning techniques. For this purpose, they tried to learn the behavior of the air pollutant by examining the trend analysis and polar graphs of the hourly values obtained from the air quality measurement stations of 2019 with the Openair Package.

This study aims to analyze the air quality in Kocaeli, an industrial city with the tenth largest population in Turkey, with the help of an Openair Package. Therefore, hourly pollutant parameter values of two air monitoring stations located in the city between 2018–2022 were analyzed temporally and statistically with meteorological (wind speed and direction) data.

2. Materials and Methods

Covid-19 (Coronavirus) disease is an infectious disease caused by the SARS-CoV-2 virus. It was declared a pandemic by the WHO as a result of the rapid spread of the virus, which first emerged in Wuhan, China in December 2019. The Covid-19 pandemic, which first caused a health crisis on a global scale, triggered the economic effects of the crisis with measures such as social distancing practices, lockdowns, closure of production sites, and bans on entry and exit at country borders, which governments put into effect to prevent the spread of the disease (Marangoz & Akçam, 2023; Yener & Demirarslan, 2024). By the end of 2024, the number of Covid-19 cases in the world reached 777 million and the total number of deaths reached 7.1 million. In Türkiye, the number of cases has reached 17 million and the number of deaths has reached 101 thousand (World Health Organization, 2025). Following the first Covid-19 case on March 11, 2020, the Turkish Ministry of Health decided to take various measurements. These measures included school vacations or switching to distance education, postponement of social, cultural and sporting activities, and lockdowns. Education activities in Türkiye were conducted remotely between March 2020 and September 2021. In addition, lockdowns, especially on weekends, were first implemented on April 10, 2020 and continued until May 17, 2021.

2.1. Study area

Kocaeli is an industrial city located in a geographically critical region with a dense population of 2,102,907 people and a daily traffic volume of 57,500 vehicles. The surface area of Kocaeli is 3.613 square kilometers. The number of people per square kilometer in the province is 582, which is the highest population density after İstanbul (Governership of Kocaeli, 2025). Kocaeli is one of the fastest growing industrial regions in Türkiye, with industrial investments intensifying especially between 1960-1975. Kocaeli has 400 first class and approximately 7000 second and third class industrial facilities. Within its borders, there are over 1,000 industrial facilities, 300 of which are large, including three tire factories, an automotive industry, a paper mill, a petrochemical industry, and an oil refinery. When the sectoral distribution of industrial enterprises in Kocaeli is analyzed; It is seen that the first place is the manufacture of fabricated metal products with 19.49%, the second place is the manufacture of machinery and equipment with 12.45%, and the third place is the manufacture of basic metal products with 10.01%. In addition, as of the end of 2019, there are 14 organized industrial zones in Kocaeli province. The most important factors in terms of air pollutants are the city's dense population and related vehicle traffic and the fact that it is an industrial city (Akyürek et al., 2013; Republic of Turkey Ministry of Industry and Technology, 2019).

2.2. Air quality and meteorological data

Data obtained from two air quality monitoring stations were used in the study. The first one is located in the city center in a region with a high density of commercial areas and vehicle traffic where people spend time all day long. The second is located in the Alikahya neighborhood in an area with dense residential and industrial facilities such as tire factories. PM_{10} ($\mu g/m^3$), SO_2 ($\mu g/m^3$), and NO_X ($\mu g/m^3$) air pollutant parameters obtained hourly between January 01, 2018, and November 30, 2022, published online by the Ministry of Environment, Urbanization and Climate of the Republic of Turkey were used as a data set. Pollutant parameters are measured according to the methods and sampling methods determined by the Ministry of Environment, Urbanization, and Climate Change (2023). Measurements at the stations have been carried out with fully automatic devices since 1984 in a way to give hourly averages.

Hourly wind direction and speed data of the Izmit/Tepetarla meteorological station in the Meteostat database (Lamprecht, 2023), which is the closest distance to the measurement stations, were obtained and used to help analyze air pollutant parameters. Among the 12 air quality monitoring stations located within the boundaries of the province of Kocaeli, the primary rationale for selecting only two stations (as detailed in Table 1) for the analysis is their proximity to the Izmit/Tepetarla station, where meteorological data is collected. It is deemed suitable to utilize the data from the air pollutant stations in closest proximity to this station, which is the sole station within the boundaries of Kocaeli province that provides meteorological data as open data, for the analysis to be conducted.

Figure 1 shows the locations of the air monitoring stations and Table 1 shows the information about the stations and measured pollutant values.

Table 1: Information on air quality monitoring stations

Station No	Stations	Geographical coordinates		Measured pollutants
		Latitude	Longitude	
AQM_1	Merkez	40.7658	29.9512	PM_{10}, SO_2, NO_x
AQM_2	Alikahya	40.771	30.0077	PM_{10}, SO_2, NO_x

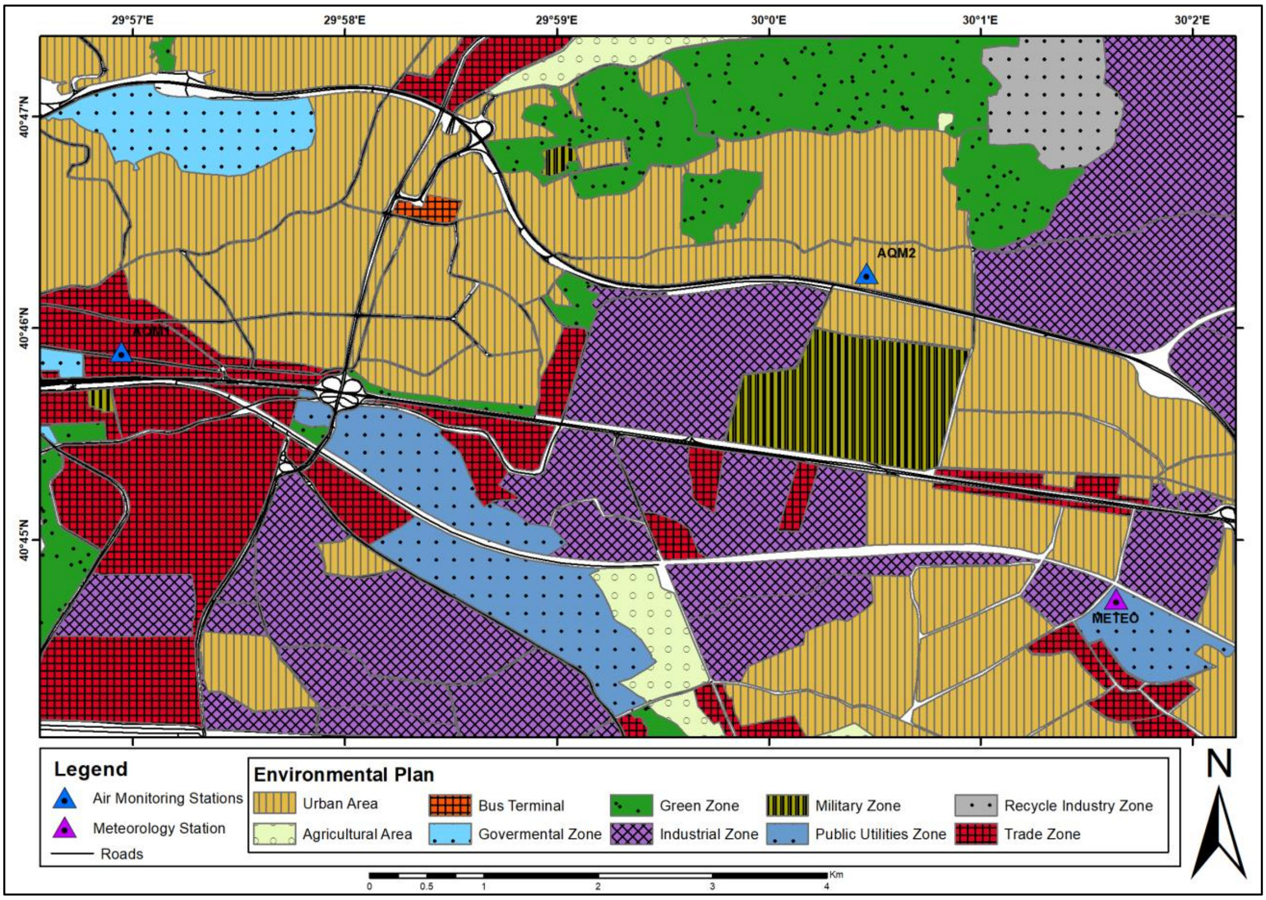

Figure 1: Air monitoring/meteorology station and environmental plan of study area

2.3. Data analysis

Open-source R software is preferred by different disciplines for many different studies (R Core Team, 2019). It is useful software for air quality research with data editing, statistical analysis with many functions, creating high-quality graphics capability, and visualization characteristic parameters (Demirarslan & Zeybek, 2022). The Openair Package of the open-source R software developed by Carslaw and Ropkins (2012) was used for the interpretation, visualization, and analysis of air pollutant and meteorological parameters obtained in this study. With the help of the Openair Package, time series and time variation technique analysis procedures were applied to air pollutant parameters and graphs of these methods were created. The change in the average concentrations of air pollutants over time was determined at a 95% confidence interval. All openair codes used in the analyzes were run with a default value of 0.99 percentile. In other words, the top 1% of the data set was removed so that outliers would not affect the analysis. Daily and monthly averages were obtained using the *timeAverage* function in the relevant code blocks of the Openair Package.

The first process applied for the analysis of air pollutants is the polar plot function. This function provides a useful visualization tool to study the behavior of pollutant parameters and for pollutant source characterization (Ropkins & Carslaw, 2012). Two-variable polar graphs are an effective graphical tool used to distinguish between different types of sources and their properties. It shows how the intensity of a pollutant parameter changes with wind speed and direction in polar coordinates (Szulecka et al., 2017). According to Carslaw and Beevers (2013), the following steps should be followed to create bivariate polar plots. Pollutant intensities are separated into 'bins' according to wind speed-direction values, and the average pollutant concentration values of the values corresponding to these 'bins' are calculated. To obtain sufficient information from the concentration distribution, the wind speed should be 30 m/s and the wind direction should be 10°. Wind speeds above this value cannot be used in the analysis due to the decreasing accuracy of the measuring instruments in obtaining wind speeds higher than 30 m/s.

Wind components u and v values;

$$u = \bar{u}.\sin\left(\frac{2\pi}{\theta}\right), \quad v = \bar{u}.\cos\left(\frac{2\pi}{\theta}\right) \tag{1}$$

is calculated by the formula. Here $\bar{u}$ is the hourly average wind speed and θ is the average wind direction, where 90° indicates east.

As a result of these processes, we have u, v, and the concentration (C) of the pollutant parameter measured at the surface. The Generalized Additive Model (GAM) is used to calculate a point on the graph. GAM is a practical model approximation for predicting air pollution. Since the relationships between variables are not linear, their relationships with each other are essential. GAM approach is as follows;

$$\sqrt{C_i}=\beta_0+\sum_{j=1}^{n} s_j\left(x_{ij}\right)+e_i \quad (2)$$

where C_i is the i th pollutant concentration, β_0 is the overall mean of the response, $s_j(x_{ij})$ is the smooth function of i th value of covariate j, n is the total number of covariates, and e_i is the i th residual.

The second process applied to air pollutant parameters is the Theil-Sen function. This function is used to show the time trends of pollutant parameters. The Theil-Sen approach is commonly used for long-term trend analysis (Wang et al., 2022). According to Carslaw (2019), the method works as follows. The slopes between all points in the dataset are calculated. As the size of the dataset increases, the value of the calculated slope increases rapidly. The Thil-Sen estimate is the median value of the calculated slopes in the data set. The advantage of this method is that it is capable of providing accurate confidence intervals even for data sets that are not normally distributed and have variable variances. It is also robust against possible outliers. These two advantages can be important in air pollution forecasting.

3. Results

In this study, the air quality of the study area between 2018 and 2022 was analyzed using the data obtained from the air quality measurement stations whose location and measured air pollutant parameters are given in Table 1. Figure 2 shows the time series graph of the daily averages of the data obtained from air quality measurement stations. The area shown in gray in the graph shows the Covid-19 period, which affected the whole world. During the Covid-19 period, various restrictions (lockdowns, distance education, work, and so on) were also imposed in Turkey, as they were all over the world. After the first case was reported in Turkey in March 2020, restrictions were imposed in the following months to reduce the impact of Covid-19. As can be seen in Figure 2, Covid-19 has had a positive impact on air quality as mentioned in many studies in the literature (Lv et al., 2022; Matthias et al., 2021; Shen et al., 2022). During the Covid-19 period, there was a noticeable decrease, especially in SO_2 and NO_X values. In the period after the restrictions were lifted, pollutant parameter concentrations increased.

Figure 2: Time series of daily means of air pollutants by 2018 – 2022 in Kocaeli

Figure 3 shows the time variation graph of air pollutant parameters. From this graph, it is possible to examine the weekly, monthly, and hourly distributions of pollutant parameters during the study period. Accordingly, it is seen that NO_X values of AQM_1 station located in the city center where vehicle traffic is intense reach the highest values (120 µg/m^3) during the midday hours (10:00-14:00) on weekdays. Especially when the Sunday section is examined, the decrease in NO_X values at noon due to the lack of vehicle traffic is striking. Likewise, at the AQM_2 station, which is close to industrial facilities, NO_X values were found to be high (80 µg/m^3) during the same hours. It is observed that NO_X values are at high levels, especially in spring and winter months, and decrease in summer months. When the PM_{10} pollutant parameter is analyzed, it is seen that it is at similar levels in both monitoring stations. It was determined that the highest levels during the day reached in the afternoon hours (14:00-15:00). It is seen that PM_{10} pollutant reaches the highest levels, especially in November. When the SO_2 pollutant parameter is analyzed, it is seen that the highest values are in the evening hours (18:00-20:00). The reason for this is generally thought to be due to the need for heating. As it is known, the biggest source of SO_2 is fossil fuels burned for heating purposes. For this reason, SO_2 values are higher at the AQM_2 station, which is closer to industrial and residential areas. Especially in December, February, March, and April, which are the months with the lowest temperatures due to the climate of the study area, it was determined that SO_2 values due to heating are high.

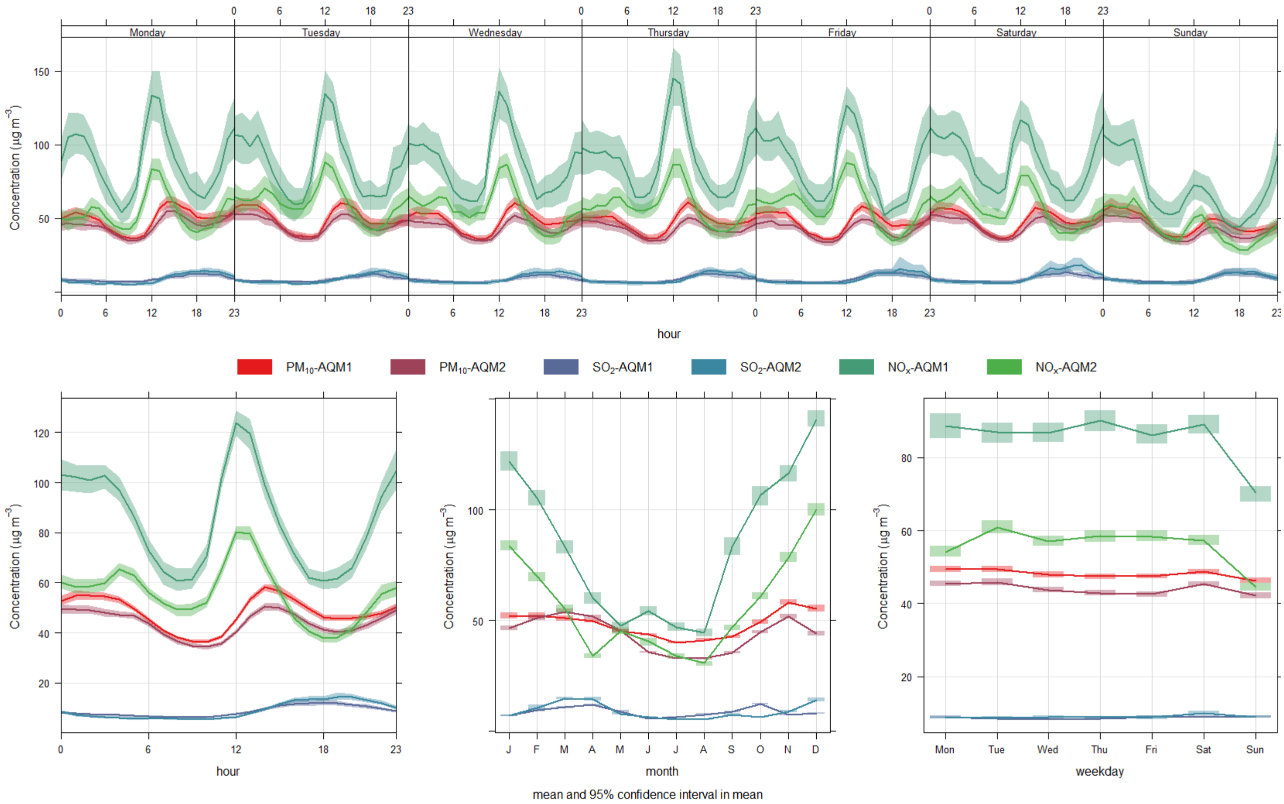

Figure 3: Time variations of air pollutants in hours, weekdays, and months between 2018–2022

Figure 4 shows bivariate polar plots by using PM_{10}, SO_2, and NO_X pollutant parameters measured at air monitoring stations and wind speed and direction parameters. In the graphs created, the starting point of the axes indicates the location of the measuring station. When Figure 4 is analyzed, the most obvious situation for PM_{10} is that pollutant values are also at low levels at low wind speeds. As the wind speed increases (8-12 m/s), pollutant parameter values also increase. Especially in 2018, the highest values were detected in the east direction at the AQM_1 station located in the city center. Also in 2022, high concentrations are observed in the northwest direction at station AQM_2, which is located in the area of industrial facilities. The reason for this situation is thought to be the transport of PM10 pollutant from different regions to the study area due to high wind speed. When the graphs created for SO_2 are examined, it is determined that the highest values were reached in the east direction in the region where industrial facilities are located in 2021. In both stations, pollutant values, which were at low levels in the first years of the study, have shown an increasing trend in recent years. Especially for AQM_2 in 2022, it is seen that high pollutant values are reached with westerly winds at high wind speeds. When the NO_X pollutant is analyzed, it is seen that the AQM_1 station, where there is heavy vehicle traffic, has higher pollutant values in all years. Especially in 2018, the highest pollutant values were reached at low wind speeds.

Figure 5 shows the correlation coefficients of pollutant parameters and wind speed and direction. When Figure 5 is analyzed, it is seen that PM_{10} and NO_X values have low negative correlation and SO_2 parameter has low positive correlation value. This situation is in parallel with the SO_2 polar plot values shown in Figure 4.

In Figure 4, SO_2 values are at low levels at low wind speeds and their distribution increases as the wind speed increases. Similar situation can be said for NO_X values, NO_X values, which have a negative correlation with wind speed in Figure 5, are shown as high pollutant values at low wind speeds and low pollutant values at high wind speeds in the polar plot graphs given in Figure 4. However, the same is not the case for PM pollutant values. The pollutant values in Figure 5, which have a negative correlation with wind speed, do not show similar characteristics in Figure 4. In this case, as mentioned above, it strengthens the belief that high wind speed carries PM values from different regions to the study area.

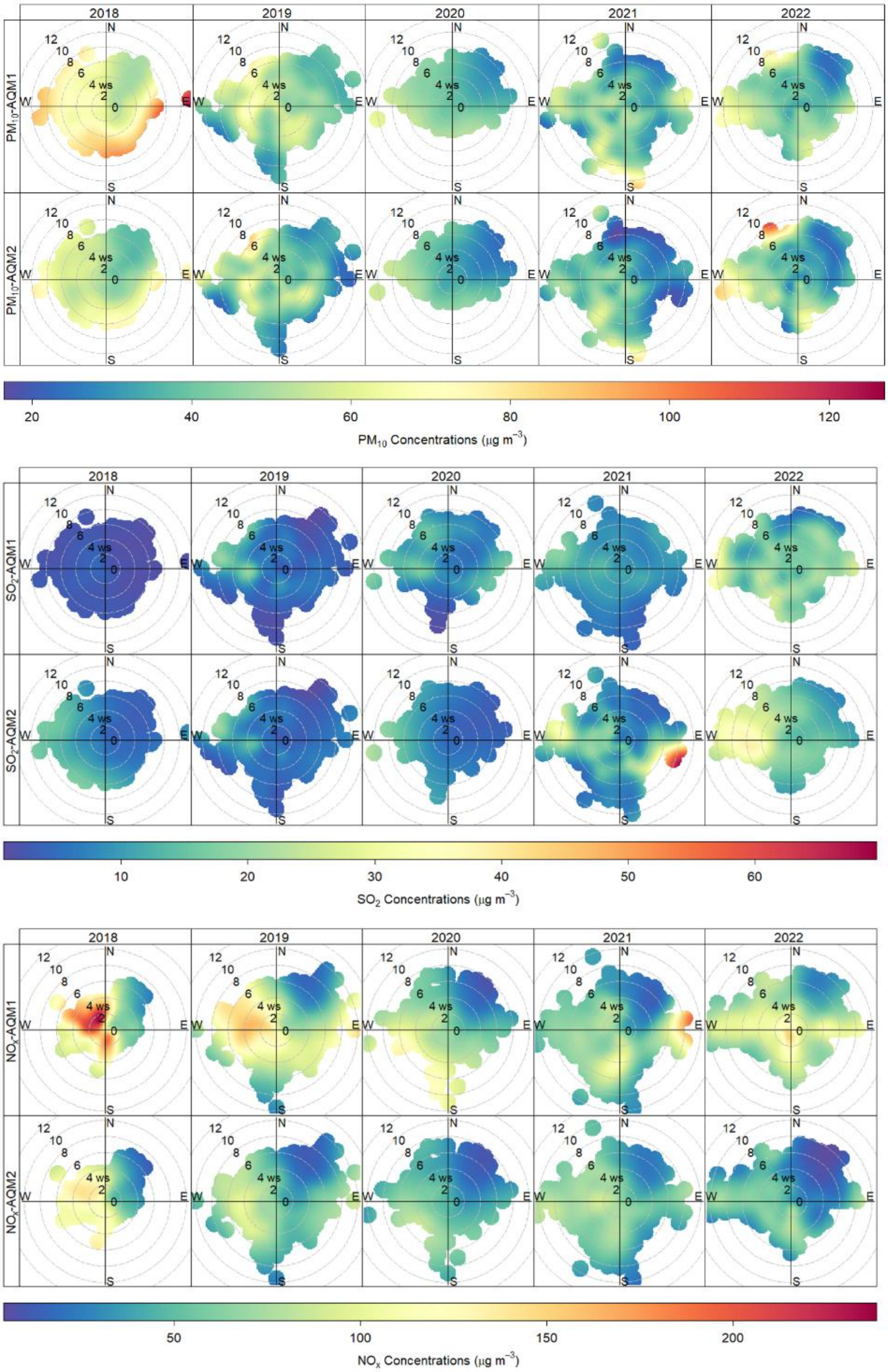

Figure 4: The identification of potential source contribution for wind speed for air pollutants at the monitoring stations

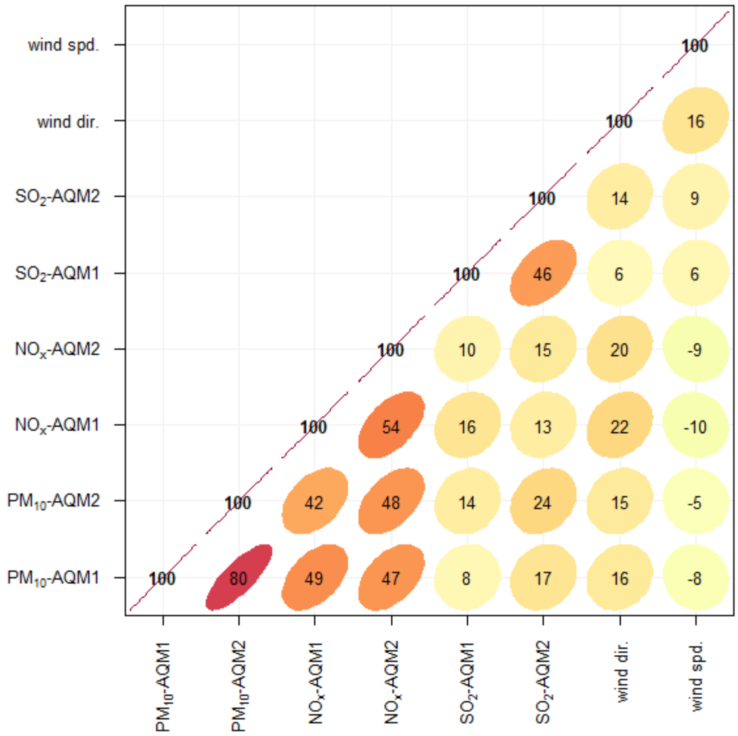

Figure 5: Statistical correlation coeffients of pollutant parameters and wind parameters

A non-parametric Mann-Kendall method using the Theil-Sen function was used to determine the statistical significance of the trends of air pollutants at the monitored stations. Figure 6 shows the graphs generated with the Thil-Sen function. Thil-Sen graphs were created based on monthly averages in three categories: before, during and after the pandemic. Therefore, hourly data were first converted to monthly averages. Then, since air pollutants show strong seasonal variations, the data were subjected to de-seasonalization, a feature of the Openair Package (Carslaw & Ropkins, 2012). The graphs in Figure 6 show the de-seasonalized monthly average concentrations of air pollutant parameters. The solid red line represents the trend of the pollutants. The leftmost value shown in green at the top of each graph represents the overall trend for each time period. The 95% confidence interval values of the slope are shown in square brackets. The * symbols at the end of the trend values indicate how statistically significant the estimate is: $p < 0.001$ = ∗∗∗, $p < 0.01$ = ∗∗, $p < 0.05$ = ∗ , and $p < 0.1$ = +. The absence of a symbol means that there is no statistically significant slope detected.

When the PM_{10} pollutant parameter is analyzed from the graphs in Figure 6, it is seen that this parameter shows a downward trend in both stations. Only AQM_2 showed a significant increase in pollutant values after the pandemic. In AQM_1, the upper and lower limit values before, during and after pandemic of -13.06 – -6.86, -7.24 – 8.21, -19.09 – 10 µg/m^3 with a 95% confidence interval, respectively. In addition, a decrease of -10.69, -0.59 and -1.15 µg/m^3 before, during and after the period was determined, respectively. In AQM_2, the upper and lower limit values before, during and after pandemic of -7.36 – -1.08, -21.52 – 12.67, -35.61 – 20.82 µg/m^3 with a 95% confidence interval, respectively. Also, a decrease of -4.91, -2.66 µg/m^3 before, during the period were determined, respectively, and an increase of 3.12 µg/m^3 after the period was determined. A significant increase in the PM_{10} pollutant parameter was observed only at the AQM_2 station, which is located in a dense industrial and residential area after the pandemic. When the SO_2 pollutant parameter graphs are analyzed, it is seen that there is an increasing trend in both stations. It is observed that there is a decrease in pollutant parameter values during the pandemic at AQM_1 station and before the pandemic at AQM_2 station. AQM_1, the upper and lower limit values before, during and after pandemic of 0.84 – 3.77, -5.91 – 8.68, -13.28 – 20.82 µg/m^3 with a 95% confidence interval, respectively. In addition, an increase of 2.09 µg/m^3 before the period was determined, and a decrease of -0.42 and -4.28 µg/m^3 during and after the period were determined, respectively. In AQM_2, the upper and lower limit values before, during and after pandemic of -2.6 – -0.04, -2.08 – 7.46, -21.83 – 15.69 µg/m^3 with a 95% confidence interval, respectively. In addition, a decrease of -1.58 µg/m^3 before the period was determined, also an increase of 1.29 and 0.63 µg/m^3 during and after the period were determined, respectively. We can relate the decrease in AQM_1 during the pandemic to the restriction of mobility. This area, where dense commercial areas are located, has decreased in terms of SO_2 pollutant with the closure decisions taken within the scope of pandemic measures. The same cannot be said for AQM_2. As a result of the continued operation of industrial facilities during the pandemic process, no decrease was observed during the pandemic process.

Finally, when the graphs of the NOx pollutant parameter are examined, it is determined that there are increasing trends at the AQM_1 station located in the city center around heavy vehicle traffic and decreasing trends at the AQM_2 station located near industrial and residential areas. In AQM_1, the upper and lower limit values before, during and after pandemic of -6.38 – 44, -59.76 – 27.39, -71.99 – 164.78 µg/m^3 with a 95% confidence interval, respectively. In addition, an increase of 12.69 and 57.47 µg/m^3 before and after the period were determined, respectively, and also a decrease of -10.73 µg/m^3 during the period was determined. In AQM_2, the upper and lower limit values before, during and after pandemic of -6.01 – 5.96, 12.25 – 68.59, -123.98 – -2.47 µg/m^3 with a 95% confidence interval, respectively. In addition, an increase of 0.5 and 37.57 µg/m^3 before and during the period were determined, respectively, and also a decrease of -73 µg/m^3 after the period was determined. It is thought that the biggest reason for the decrease in the NO_X pollutant parameter at AQM_1 station during the pandemic is the decrease in vehicle traffic in the relevant region. The increases before and after the pandemic support this situation. In the AQM_2 region, where industrial and residential areas are dense, the intense increase in the pandemic process and the rapid downward trend afterwards are thought to be related to the ozone-NO_X chemical transformation in the atmosphere. However, no investigation on this chemical transformation was performed in this study.

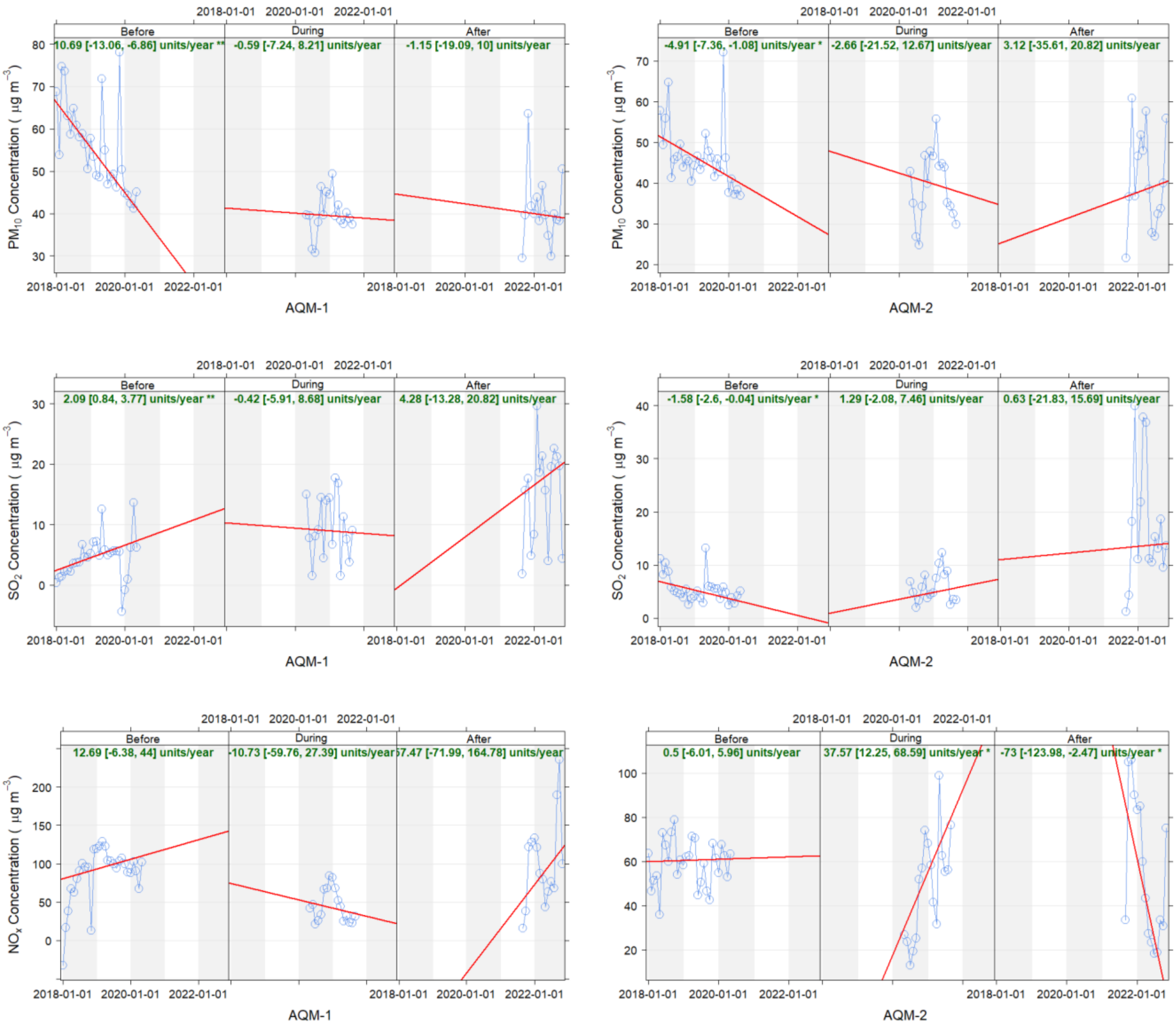

Figure 6: Trends in the air pollutants at the monitoring stations before, during and after the Covid-19 pandemic

4. Discussion

In this study, the air quality of Kocaeli province, which has intensive industrial facilities and therefore a dense population, has been investigated for 5 years between 2018 and 2022. For this purpose, hourly data from two air quality monitoring stations in the city center, where commercial areas and heavy traffic flow are located, and around the city center, where industrial facilities and residential areas are located, were used.

Studies by Badida and Jayaprakash (2022), Beringui et al. (2022), Habeebullah et al. (2022), Ngo et al. (2022) and Yener and Demirarslan, (2024) show that there has been a decrease in air pollutant values due to the lockdowns imposed during Covid-19. In this study, there is a decrease in pollutant values during the Covid-19 period in the time series graphs.

In addition, in the Thil-Sen trend graphs, it can be said that the pollutants show a downward trend with the effect of the Covid-19 period, or the pollutants that have an increasing trend causes the rate of increase to remain at low levels.

In the PolarPlot graphs, high PM_{10} concentrations are observed at high wind speeds as reported by Dang et al. (2017), Demirarslan and Zeybek (2022), Beddows et al. (2015), Carslaw et al. (2006), Grange et al. (2016) and Bousiotis et al. (2022). Similar results were obtained in this study as well. In the graphs, PM_{10} concentrations measured at both stations show an increase at high wind speeds. According to Huzlík et al. (2020), Iskandaryan et al. (2022), Ropkins et al. (2022), and Uria-Tellaetxe and Carslaw (2014) showed that NO_X values were high in measurements made in areas adjacent to heavy vehicle traffic. In the present study, similar results were obtained at the station located in the city center (AQM_1) due to traffic.

When the time-variation graphs are examined, Dang et al. (2017), Yorkor et al. (2021), Szulecka et al. (2017), Chaurasia and Mohan (2022) and Demirarslan and Akıncı, (2018) emphasized that pollutant parameter concentrations increase in winter months. In the current study, it was determined that the concentrations of all parameters measured at air quality stations increased in winter months. In addition, NO_X concentrations were found to be lower on Sundays compared to other days of the week in all studies in the literature (such as Carslaw & Beevers (2013)) as well as in this study. In addition, Yener and Demirarslan (2022) and Demirarslan and Akıncı (2018) stated in their study that the negative effect of anthropogenic factors on O_3 can be attributed to increased NO_2 due to motor vehicle use, industrial activities and population growth. The biggest reason for this is that the vehicle density is much less on Sunday, which is a holiday, compared to other days.

The Openair Package, a package of open source R software used in the literature and in this study, is shown to be a useful tool for temporal and statistical analysis of air pollutants. Sidjabat et al. (2019), Oleniacz et al. (2021) and Uria-Tellaetxe and Carslaw (2014) highlighted that the Openair Package is particularly useful in analyzing pollutant parameters around industrial areas. The R software, which is open-source and utilizes the Openair Package, is capable of running on all operating systems, thus negating the necessity for specialized hardware. A critical distinguishing feature of Openair is its capacity to facilitate the examination of large data sets in a remarkably short period of time through its functions and visualization methods, which are the most significant aspect of the software. It facilitates the determination of relationships between the parameters that constitute the data set, the definition of complex spatial analyses, and the creation and verification of distribution models.

5. Conclusion

Air pollution is a very important factor in human health and climate change. To minimize the harmful effects of air pollution, it needs to be continuously monitored and intervened when necessary. Air quality monitoring stations are established by countries to monitor air pollution regularly and various environmental policies are produced with the data obtained from these stations. It is important for the institutions that produce policies to overcome air pollution to access the correct information as soon as possible. For this reason, the data obtained from monitoring stations should be analyzed reliably in a short time.

Openair, a package of R, open-source software used in this study, is an important tool for the analysis of air pollution. As a result of the analysis made with the Openair Package in the study, it is seen that air pollutant sources are mostly anthropogenic. It has been determined that high values of wind speed, which is one of the meteorological parameters, increase the density of particulate matter in the air. In addition, it was observed that the Covid-19 pandemic period within the study period had a positive effect on air pollution by reducing the concentrations of PM_{10} and NO_X air pollutants. On the contrary, an increase in SO_2 pollutant values was observed. It was also revealed that traffic density has a linear relationship with NO_X. Several measures can be taken with various policies to reduce these pollutants. Reducing fossil fuels used to meet the heating needs of homes, expanding the use of electric vehicles, and improving the filter systems used in industrial facilities can be shown as a few examples of measures that can be taken.

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