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Spatio-Temporal Analysis of Istanbul Air Pollution During the Pandemic using Google Earth Engine and Google Community Mobility Reports

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Abstract

The Covid-19 pandemic has significantly altered people's daily lives and environmental characteristics. All governments have developed specific policies and enforced restrictions that impact people's daily lives to control the pandemic. The traffic index has fallen in numerous cities and countries depending on the restrictions. As a result, restrictions have improved air quality in many cities and countries. In metropolitan cities, however, the contrary has also been observed. This study has looked at how the air quality has changed in Istanbul, considered Turkey's greatest metropolitan city. First, using Sentinel-5P NRTI satellite pictures, the spatio-temporal distribution of air pollutants (NO_2, CO, and SO_2) has been examined. The correlations between these variable groups and air pollutant concentrations were then examined using six independent variable groups (the traffic index of Istanbul, daily deaths in Istanbul, Google community mobility reports of Istanbul, fuel prices, the stringency index of Turkey, two logical attributes regarding the Covid-19 restrictions, and in-class education). The spatial distribution graphs show that when the restrictions are implemented in Turkey, there is a tendency for NO_2, CO, and SO_2 pollution concentrations in Istanbul to fall. Although an improvement in air quality has been noted in several places due to the Covid-19 pandemic restrictions, there was no discernible correlation between the decline in community mobility and pollution concentrations in Istanbul.

Keywords: *Air pollution, Remote sensing, Google community mobility, Data analysis, Spatio-temporal analysis*

Pandemi Sürecinde İstanbul Hava Kirliliğinin Google Earth Engine ve Google Topluluk Hareketlilik Raporları Kullanılarak Mekânsal-Zamansal Analizi

Özet

Covid-19 pandemisi insanların günlük yaşamını ve çevresel faktörleri büyük ölçüde etkilemiştir. Devletler, pandemiyi kontrol altında tutabilmek için kendi ülkelerine özel politikalar izlemiş ve insanların günlük yaşamını etkileyen bazı kısıtlamalar uygulamışlardır. Bu kısıtlamalara bağlı olarak birçok ülke ve şehirde trafik endeksleri azalmıştır. Dolayısıyla birçok ülke ve şehirde kısıtlamalar hava kalitesini olumlu yönde etkilemiştir. Ancak bazı metropol şehirlerde bu durumun tersi de gözlenmiştir. Bu çalışmada, Türkiye'nin en büyük metropol şehri kabul edilen İstanbul'daki hava kalitesinin değişimi araştırılmıştır. Önce hava kirleticilerinin (NO_2, CO ve SO_2)

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zamansal-mekânsal dağılımı Sentinel-5P NRTI uydu görüntüleri kullanılarak analiz edilmiştir. Sonra altı bağımsız değişken grubu (İstanbul trafik endeksi, İstanbul günlük vefat sayıları, İstanbul Google topluluk hareket raporları, Türkiye sıkılık endeksi, Covid-19 kısıtlamalarına ve yüz yüze eğitime ilişkin iki mantıksal öznitelik) belirlenmiş ve bu değişken grupları ile hava kirletici konsantrasyonları arasındaki korelasyonlar araştırılmıştır. Mekânsal dağılım grafiklerine göre, Türkiye'de kısıtlamaların uygulandığı süreçte İstanbul'da hava kirletici konsantrasyonlarında azalma gözlenmektedir. Ancak birçok şehirde Covid-19 pandemisi kısıtlamalarına bağlı olarak hava kalitesinde artış yaşanmasına rağmen, İstanbul topluluk hareketlerindeki azalma ile hava kirletici konsantrasyonları arasında anlamlı bir ilişki bulunamamıştır.

Anahtar Kelimeler: *Hava kirliliği, Uzaktan algılama, Google topluluk hareketlilik, Veri analizi, Zamansal- mekânsal analiz*

1 Introduction

People's daily life and environmental characteristics have undergone drastic changes due to the Covid-19 pandemic, which emerged suddenly and spread rapidly worldwide. All governments have developed specific policies for their countries and enforced restrictions that impact people's daily lives. These restrictions include lockdowns (full or partial), cessation of workplace activities, and closure of restaurants and shopping centers. The traffic index has fallen in numerous cities and countries depending on the restrictions. As a result, an improvement in air quality has been noted. Many studies in the literature analyze the improvements in air quality during the Covid-19 pandemic process. In some of these studies, it is said that the air quality is greatly affected by the restrictions. In others, it has been shown that the restrictions do not severely affect air quality. This study investigated the changes in the concentrations of the pollutants determining the air quality using remote sensing satellite imagery. Then, independent variables associated with the Covid-19 pandemic were defined, and the relationships between pollutant concentration changes and these parameters were investigated.

Developing countries need to control air quality and manage air pollution. Many factors affect air pollution: fossil fuel use, industry, residential activities, manufacturing industry, and rapid urban developments. The entry of these particles into the Earth's atmosphere causes air pollution. The most important of these particles are carbon monoxide (CO), ozone (O3), sulfur dioxide (SO2), nitrogen dioxide (NO2), and particulate matter (PM2.5 and PM10). These pollutants can be released from both fixed and mobile stations. The most important sources of SO2 pollutants are residential sources and industrial sources. The sources of other pollutants are usually vehicles. As the restrictions applied to Covid-19 policies reduced the number of vehicles in traffic, they also severely impacted pollutant concentrations.

The Covid-19 pandemic has led to similar restrictions in many countries and cities. Due to the applied restrictions, vehicle and human mobility have decreased worldwide. In this process, many academic studies have examined the effect of this decrease on air pollution. However, these studies have never examined whether the correlations between these parameters can be used to understand how much people adapt to the rules. The decrease in air pollution due to the decrease in mobility proves that people largely comply with the restrictions imposed. However, the situation in metropolitan cities may show a very different course. In cities considered metropolitan, the situation may show the opposite course. This study investigated the effect of mobility and other relevant parameters on air pollution in Istanbul, a metropolitan city in Turkey. Based on the obtained correlation values, a prediction was made about the extent to which the people in Istanbul obey the rules. In this sense, the study is the first to touch on this point. The findings of this study can be used to monitor whether people follow the rules in possible future pandemic processes. The pseudocode of the methodology is presented in Algorithm 1.

2 Related work

Some studies have shown that air pollution has been reduced in many places, along with reduced human mobility at the global level due to restrictions during the pandemic and, therefore, the use of transport vehicles that produce carbon dioxide.

Algorithm 1. Spatio-Temporary Analysis algorithm of Istanbul Air Pollution During the Pandemic

Input: Air quality pollutant (NO_2, CO, and SO_2) dataset, Istanbul air quality dataset, Istanbul traffic index dataset, daily deaths dataset, Google community mobility reports from Google, fuel prices dataset, stringency index dataset, Covid-19 restrictions dataset, in-class education dataset.

Output: Thematic maps, Correlation of the attributes.

```
1: Collect satellite imagery from GEE for NO2, CO, and SO2 pollutants
2: Create thematic maps for the NO2, CO, and SO2 pollutants
3: Save the thematic maps
4: declare independentVariables[8], pollutants[3]
5: for i=0 To 8
6:    for j=0 To 3
7:    correlation(independentVariables[i], pollutants[j]
8:    endfor
9: endfor
```

Using the Google Earth Engine, Ghasempour and colleagues examined air pollution (GEE) data. Based on TROPOMI data and MODIS-derived Aerosol Optical Depth (AOD), they examined the Spatio-temporal density of NO_2 and SO_2 from January 2019 to September 2020. The study found that NO_2 and AOD levels dramatically dropped. However, SO_2 remained unchanged. They also discovered a strong association between air contaminants and air pressure and temperature [1].

In order to recognize vehicles, Chen et al. used their morphology-based vehicle detection algorithm to examine the pandemic's traffic patterns. They measured traffic density in several cities and assessed how the data showed changes in mobility patterns due to COVID-19 [2].

Singh et al. evaluated the world's air quality and measured the improvement brought on by the reduction in anthropogenic activity during lockdowns. Mean decreases in NO_2, AOD, and $PM_{2.5}$ concentrations over megacities are 19.74 %, 7.38 %, and 49.9 %, respectively, according to the application the authors created using the GEE [3].

Elshorbany et al. used remote sensing for O_3, CO, and tropospheric dioxide column. They assessed the efficacy of reduced traffic volume in enhancing air quality. According to their findings, the reduction in traffic volume during the epidemic improved the air quality [4].

Using ground and satellite data, Bustamante-Calabria et al. examined the lockout's impact on urban light emissions. The quantity of PM_{10} particles and sky brightness were found to be directly correlated [5].

Using satellite data and a network of air quality sensors, Venter et al. investigated the claim that the lockdown has decreased tropospheric and ground-level air pollution concentrations. They discovered proof that there is a connection between the drops in global vehicle transportation and the decrease in ambient NO_2 exposure [6].

Shen et al. examined the relationship between meteorological variations in air pollution. The 2020 lockdown period and the 21-year term means were contrasted. Their investigation found that the large-scale transport of the contaminants demonstrated the significance of meteorology for regional air quality [7].

Using the GEE, Faisal et al. looked at how many contaminants there were concerning the Covid-19 epidemic. They connected the impact of pollution concentrations to BMKG meteorological data using the correlation test method. Their research reveals a significant association between 0.5045 and 0.795 [8].

Using the GEE to analyze images Spatio-temporally, Iqbal et al. examined the NO_2 and CO levels. According to the results, the NO_2 and CO levels were greater in 2019 than in 2021. Likewise, the levels were higher in 2021 than 2020 [9].

On the other hand, several studies show that the Covid-19 lockdowns may not increase the air quality at a high rate. Huang et al. contrasted the monitoring data for air quality from 2017 to 2019 with that from January to April 2020. They assessed how the Covid-19 lockout affected the ambient air quality and the roadside in Hong Kong, China. When comparing the historical data from 2017 to 2019, they discovered a considerable decrease in the roadside and ambient NO_2, PM_{10}, $PM_{2.5}$, CO, and SO_2 in 2020. However, their findings demonstrated an increase in O_3. The reductions during the Covid-19 period were not necessarily bigger than those prior to the Covid-19 period [10].

Liu et al. examined whether intrusive restrictions in the US state of California impact air pollution. Spatio-temporal changes in air pollution before, during, and after the state's quarantine was examined through air quality measurements and patterns. The results show a sudden decrease in air pollution with the entry of the quarantine period and a sudden increase in air pollution with the normalization process. It is stated that the difference in the concentration of NO_2, CO, and $PM_{2.5}$ between the quarantine period and the pre-quarantine period is 38%, 49%, and 31%, respectively [11].

Qiu Z et al., who examined the air pollution changes that are thought to be affected by the restrictions put in place to prevent the spread of the pandemic in Bangladesh, examined aerosol optical depth (AOD), $PM_{2.5}$, PM_{10}, NO_2, O_3 measurements for the 2019 March - 2020 March period. The study results show that the strict lockdown period resulted in 47% AOD reductions in all major cities and $PM_{2.5}$ (37-77%) and PM_{10} (33-70%) across the country. According to the study's conclusion about ozone levels, there is an increase in the national average of 3-12% during the tight closure period and a decrease of 1-3% during the partial closure period [12].

Due to the population's abundance and density, it is impossible to determine the source of air-polluting gases in big cities accurately. Qi Yuan et al., who saw the restriction policies developed to reduce the spread of the pandemic as an opportunity to identify these pollutant sources, stated that PM_{10}, $PM_{2.5}$, NO_2, SO_2 in Hanzhou, a typical Chinese mega city for aerosol particles and gaseous pollutants, and CO decreased by 58%, 47%, 83%, 11%, and 30%, respectively. In addition to this significant decrease, the authors emphasize that the decrease in $PM_{2.5}$ and CO rates is more significant in urban and urban-industrial areas than in suburban areas. It is stated that the most significant decrease among air pollutants is NO_x, with a change of more than 80%. This change is similar in urban, urban-industrial, and suburban areas, while the O_3 rate increases by 102%-125% during the quarantine period. One of the study's most important findings states that long-distance transportation activities in the city cause a significant portion of air pollution, such as 40%-90% [13].

Fasso et al. investigated the effects of the Covid-19 pandemic on air pollution. As a result of studies carried out on particulate matter PM_{10}, $PM_{2.5}$, and nitrogen dioxide gases, it was determined that pandemic restrictions were heterogeneous in the region, PM_{10} concentration decreased in metropolitan areas, and nitrogen dioxide decreased near roads closed to traffic. However, the results showing that no significant reductions were detected in rural, industrial and mountainous regions show that $PM_{2.5}$ concentration did not experience a significant decrease regardless of the region in question [14].

NO_2, SO_2, O_3, CO, PM_{10}, and $PM_{2.5}$), which are important air pollutants, are intensely released into the air in daily life. In their study, Kumari et al., investigating the improvement effects of restrictive measures taken in Dublin, Ireland, used Sentinel-5P and Moderate Resolution Imaging Spectroradiometer satellites and ground-based observations. The results show that the most dominant factor of the Air Quality Index (AQI) for Dublin was PM_{10} and $PM_{2.5}$, the NO_2 level decreased by an average of 28%, and AQI improved by 27% [15].

Maghrebi et al. completed another study that looks at the change of air pollutants under pandemic restrictions in Tehran, the capital of Iran. The scientists discovered that the annual average of SO_2 concentration increased throughout the pandemic and linked this to fuels used in power plants by using CO, NO_2, O_3, PM_{10}, SO_2, and AQI air quality data from 14 monitoring stations and Covid-19-related data. Other interesting results of the study show that despite the positive change in AQI around the world, the number of days with a good AQI decreased in Iran, and increased pollution levels across the city were more pronounced in low-income regions [16].

The abnormal change in human mobility has resulted in a positive change in AQI quality at a global level. Addressing $PM_{2.5}$ and NO_2 concentrations within the scope of the US, Berman et al. state that pandemic restrictions cause a 25% decrease in NO_2 and $PM_{2.5}$ concentration decreases in districts where daily life ends in the early evening [17].

Table 1 compares previous studies with the presented study.

3 Study area

Istanbul, often regarded as Turkey's cultural, economic, and historical center, is the subject of this study. Istanbul has 15840900 residents [18]. Istanbul's latitude and longitude are 41.015137 and

28.979530 [19]. Istanbul will be the world's most crowded city in 2021, with a 62 percent average level of congestion, according to the TomTom Annual Traffic Index [20]. In 58 different countries, the traffic index assessed 404 cities. Istanbul's degree of congestion in 2021 has risen 11% from the previous year. Despite full and partial lockdowns because of the Covid-19 pandemic, Istanbul has not seen a significant decrease in transportation congestion. As a result, when compared to research of a similar nature in the literature, Istanbul yields different results. The research area is shown in Figure 1.

Table 1. Comparison of studies in the literature

Study	Examined Variables	Correlation / Association
[1]	NO_2, SO_2, AOD	Yes
[2]	Vehicles and traffic density	Yes
[3]	NO_2, AOD, $PM_{2.5}$	Yes
[4]	NO_2, CO, O_3, AOD	Yes
[5]	PM_{10}	Yes
[6]	NO_2	Yes
[7]	$PM_{2.5}$	Yes
[8]	CO, O_3, SO_2, NO_2	Yes
[9]	NO_2, CO	Yes
[10]	NO_2, PM_{10}, $PM_{2.5}$, CO, SO_2, O_3	Yes except for O3
[11]	NO_2, CO, $PM_{2.5}$	Yes
[12]	AOD, $PM_{2.5}$, PM_{10}	Yes
[13]	PM_{10}, $PM_{2.5}$, NO_2, SO_2, CO, O_3	Yes
[14]	PM_{10}, $PM_{2.5}$, NO_2	Heterogeneous
[15]	AQI, PM_{10}, $PM_{2.5}$, NO_2	Yes
[16]	SO_2	Heterogeneous
[17]	NO_2, $PM_{2.5}$	Yes
Our Study	NO_2, CO, SO_2, the traffic index, daily deaths, Google community mobility reports, fuel prices, the stringency index, Covid-19 restrictions, in-class education	No

Figure 1. Study area

4 Materials and methodology

4.1 Data collection and preprocessing

We have gathered eight different types of data sets for this study in order to examine the impact of the Covid-19 lockdowns on the air quality:

1. Sentinel-5P NRTI daily satellite image data of NO_2, CO, and SO_2 products from the GEE [30, 31, 32, 35]
2. Istanbul air quality data from Istanbul Metropolitan Municipality, The Environment Protection Directorate [21]
3. Istanbul traffic index data from Istanbul Metropolitan Municipality Open Data Portal [22]
4. Daily deaths in Istanbul from Turcovid Open Data Portal [23]
5. Google community mobility reports from Google [24]
6. Fuel prices [25]
7. Stringency index data: This index tracks how stringent lockdown-style regulations are, which largely control people's behavior. All ordinal containment and closure policy indicators are used in its calculation, along with an indicator for public awareness efforts [26]
8. Two logical attributes regarding the Covid-19 restrictions and in-class education.

In the following subsections, we present the preprocessing operations on the data sets and the connections between the data sets. Finally, we explain the methodology to process these six data sets together.

4.1.1 Satellite remote sensing data

Using Sentinel-5P NRTI (Near Real-Time Nitrogen Dioxide, Near Real-Time Carbon Monoxide, and Near Real-Time Sulfur Dioxide) satellite photos, we have examined the Spatio-temporal distribution of air pollutants, specifically NO_2, CO, and SO_2. NRTI Sentinel-5P NO_2 offers high-resolution, almost real-time imaging of NO_2 concentrations. Both the troposphere and the stratosphere contain NO_2. Natural and artificial mechanisms can potentially cause this contaminant to reach the atmosphere. Sentinel-5P NRTI CO provides high-resolution imaging of CO concentrations in virtually real-time. It is a serious air pollutant, especially in some cities. Fossil fuel combustion, biomass burning, and atmospheric oxidation of methane and other hydrocarbons are the primary sources of carbon monoxide. Sentinel-5P NRTI SO_2 offers high-resolution pictures of atmospheric SO_2 concentrations in almost real time. Again, artificial and natural processes may be to blame for introducing this pollution into the atmosphere. The concentrations for the time frame of December 2019 to March 2022 have been depicted. The produced images demonstrate how the Covid-19 epidemic has affected pollution.

4.1.2 Istanbul air quality data

The objective is to investigate the factors influencing how pollutant concentrations change after the images have been taken. Data on daily pollution concentrations were needed for this. This information was obtained from the Environment Protection Directorate of the Istanbul Metropolitan Municipality. We also used the NO_2, CO, and SO_2 concentration readings from 31 monitoring stations. Then, average monthly concentrations for all of Istanbul were determined. This data collection covers the period from December 2019 to March 2022.

4.1.3 Istanbul traffic index data

We predict that air quality factors are the Covid-19 process, changes in community mobilities, and traffic index parameters. We have gathered the Istanbul traffic index data from Istanbul Metropolitan Municipality Open Data Portal. The period of this data set is from December 2019 to March 2022.

4.1.4 Daily deaths data

Partial or complete lockdowns during the Covid-19 process have decreased air pollution in many countries. In order to analyze the situation in Turkey, the relationship between Istanbul's confirmed case numbers and pollutant concentrations should be investigated. However, the Turkish Ministry of Health did not share the daily number of confirmed cases by province. Due to this, a new parameter was added: the daily death toll in Istanbul (total number of deaths with or without Covid-19). This dataset is gathered from Turcovid Open Data Portal. The period of this data set is from December 2019 to March 2022.

4.1.5 Google community mobility reports

Google's reports on community mobility demonstrate how Covid-19 is causing communities to move in diverse ways. These data can show how visitation to locations like parks and grocery stores is changing relative to a baseline in particular regions. The places include grocery & pharmacies (GP), parks (P), transit stations (T), retail & recreation (RR), residential (R), and workplaces (W). The mobility patterns for locations such as supermarkets, food distribution centers, farmers' markets, specialized food shops, pharmacy stores, and pharmacies are shown by GP. T displays the mobility patterns for neighborhood parks, national parks, open-air beaches, marinas, dog parks, plazas, and public gardens. P displays the mobility patterns for locations such as public transport hubs, such as subway, bus, and train stations. The mobility trends for locations like eateries, cafes, shopping malls, theme parks, museums, libraries, and movie theaters are presented by RR. The mobility trends for residential locations are shown by R. Finally, W presents the mobility trends for places of work. The baseline is the median value, for the corresponding day of the week, during the five weeks, Jan 3–Feb 6, 2020. The period of this dataset is from March 2020 to March 2022.

4.1.6 Fuel prices

Since there was no significant relationship between partial or complete lockdowns applied during the Covid-19 process and air pollution and traffic data, we also included the fuel prices parameter in the study. In addition, we investigated whether the exorbitant increases in fuel prices in the past two years affected the traffic index. The period of this data set is from November 2019 to March 2022.

4.1.7 Stringency index data

In order to better understand how local government limits on air pollution during the Covid-19 pandemic in Istanbul affected the city's air quality, we included this dataset in the analysis. Data regarding the stringency index were taken from [27]. This data set's time frame spans from January 2020 to March 2022.

4.1.8 Logical attributes

We have added two logical attributes to the study: (1) the logical variable indicating whether there was a Covid-19 restriction in the relevant month (1: any restriction, 0: no restriction), (2) continuing in-class education in the relevant month (1: means continuing in-class education at all levels or some levels, 0: means interruption of education or distance education at all levels). The period of this data set is from November 2019 to March 2022.

4.2 Methodology

We applied two steps to detect the change in pollutant concentrations due to Covid-19. First, we visualized the pollutant concentrations with the remote sensing method and analyzed the Spatio-temporal distributions of the air pollutants. Then we investigated the correlation between the independent parameters predicted to affect the concentrations and the pollutants.

4.2.1 Spatio-temporal distribution of air pollutants and visualization

With the aid of satellite image sets, we examined the Spatio-temporal distributions of air contaminants. The GEE [28] offers a multi-petabyte database of geospatial resources and satellite pictures. The platform also has tools for planetary-scale study. The GEE platform enables rapid and efficient development of change detection apps, trend calculating applications, and applications for quantifying differences on the Earth's surface.

ESA's Sentinel-5 Precursor observes atmospheric trace gases and aerosol products. It is possible to develop air quality, climate, and stratospheric ozone applications using the data provided by this satellite [29]. The Tropospheric Monitoring Instrument (TROPOMI), the single payload instrument of the satellite, allows global daily coverage since it is a push-broom imaging spectrometer with a wide field of view. The instrument swath width is approximately 2600 km on the ground. It has a high spatial resolution (7x7 km2). The Sentinel-5 Precursor Level-2 products are accessible in Near Real-Time (NRT). We used Sentinel-5P NRTI NO_2 [30], Sentinel-5P NRTI CO [31], and Sentinel-5P NRTI SO_2 [32] datasets in this study. We created a Javascript program in the GEE to gather, rectify, and visualize the pollutant concentrations from the chosen image collections. JavaScript source codes are available at [33]. The processes described below are used to process the chosen photographs.

- We clipped region of interest (Istanbul),
- We uploaded the boundaries of Istanbul in shapefile format to the GEE platform,
- We collected the Sentinel-5P NRTI images from the GEE platform,
- We extracted the images by mosaicking the overlapping scenes over Istanbul region,
- We prepared monthly Spatio-temporal maps.
- We created thematic maps that show the concentrations for each month. Figure 2 shows the distribution of the pollutant concentrations.

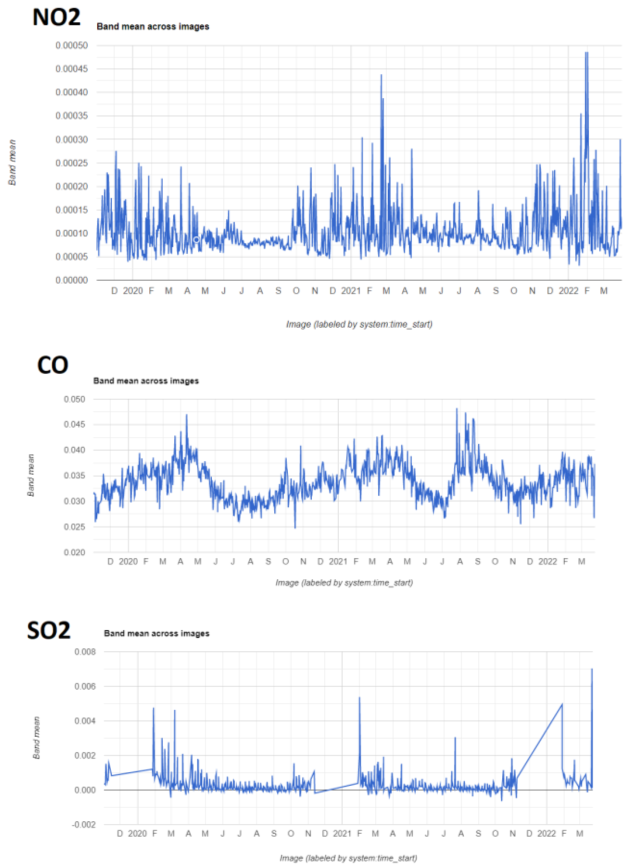

Figure 2. Distribution of the pollutant concentrations.

Figure 3, Figure 4, and Figure 5 present the thematic maps of the distributions for the pollutant concentrations NO_2, CO, and SO_2, respectively. The period of these maps is between November 2019 and March 2022.
We created GIF images using these images to show more clearly how the pollutant concentration changed by month between November 2019 and March 2022. These GIF images are available at [33].

4.2.2 Correlation between the independent parameters and the air pollutant concentrations

This step combined all independent variables and pollutant concentration values into a data set and analyzed correlations between variables. Since the variables' units are different, we first normalized all the variable values. Then, normalization was carried out according to the min-max method, the formula of which is given in Equation 1.

$$X' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

First, we analyzed how air pollutants are affected by the traffic index. Figure 6 shows the relationship between traffic index and air pollutant concentrations.

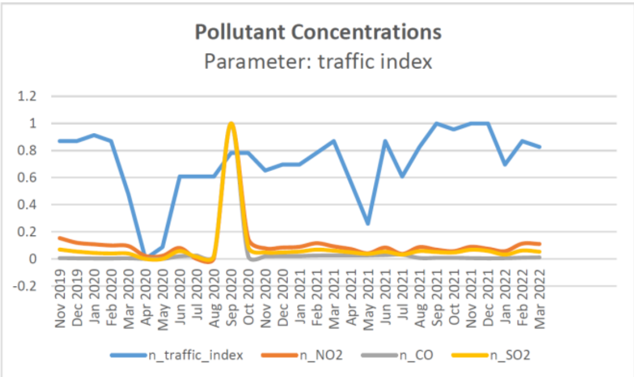

Figure 3. Traffic index and air pollutant concentrations.

Then, we analyzed how air pollutants are affected by the daily deaths. Figure 7 shows the relationship between daily deaths and air pollutant concentrations.

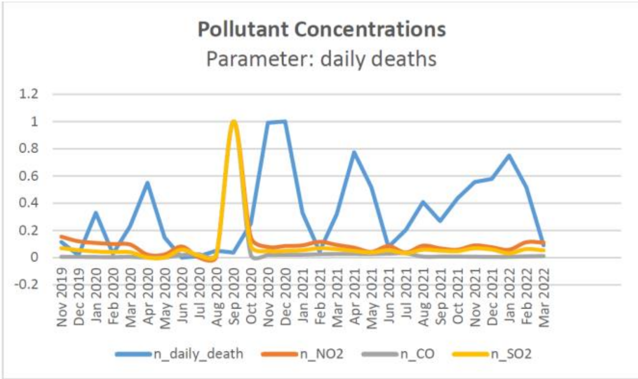

Figure 4. Daily deaths and air pollutant concentrations.

Then, we analyzed how air pollutants are affected by the community mobility trends. Figure 8 shows the relationship community mobility items and air pollutant concentrations.

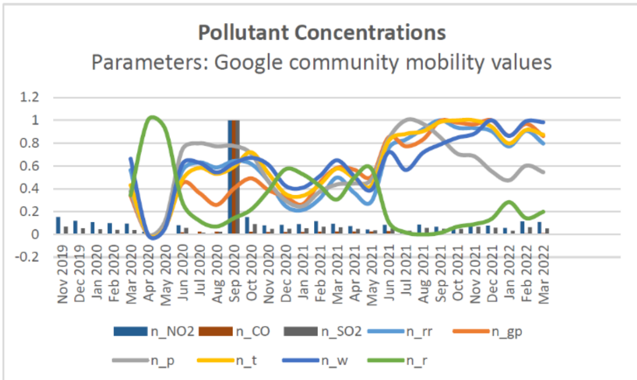

Figure 5. Community mobility and air pollutant concentrations.

Then, we analyzed how air pollutants are affected by the fuel prices. Figure 9 shows the relationship between fuel prices and air pollutant concentrations.

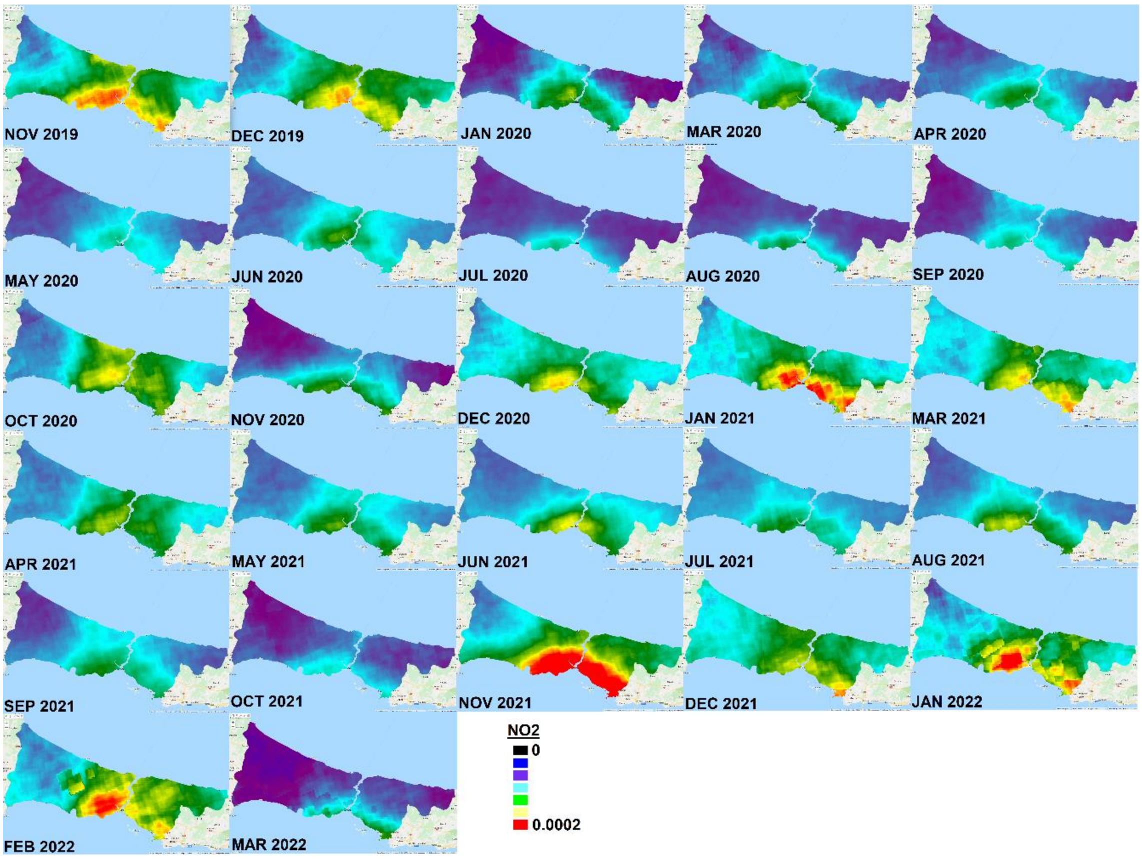

Figure 6. Thematic map of the NO_2 concentration distribution.

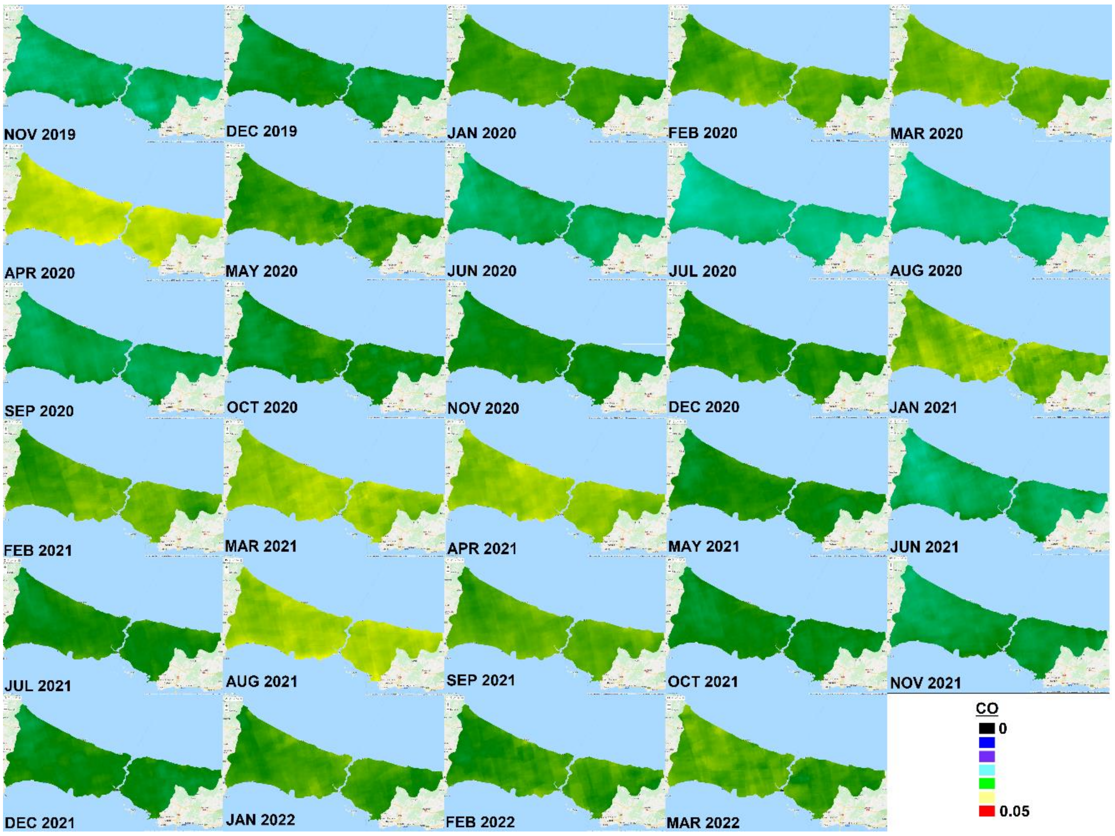

Figure 7. Thematic map of the CO concentration distribution.

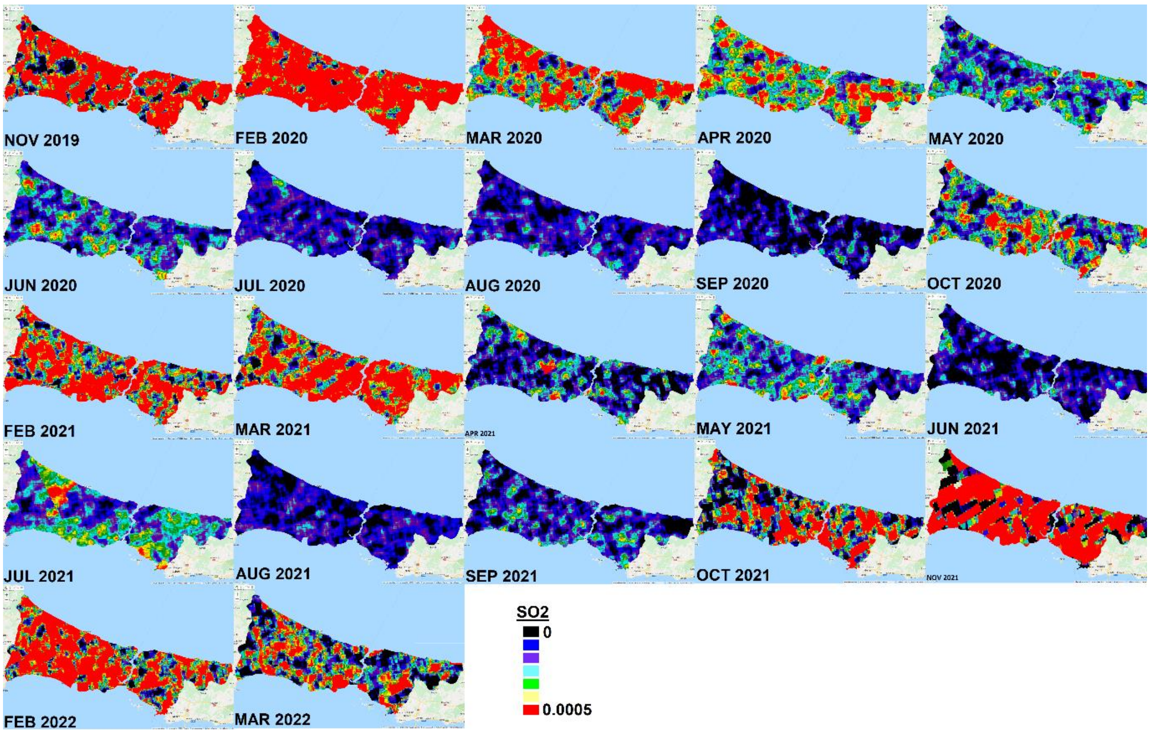

Figure 8. Thematic map of the SO_2 concentration distribution.

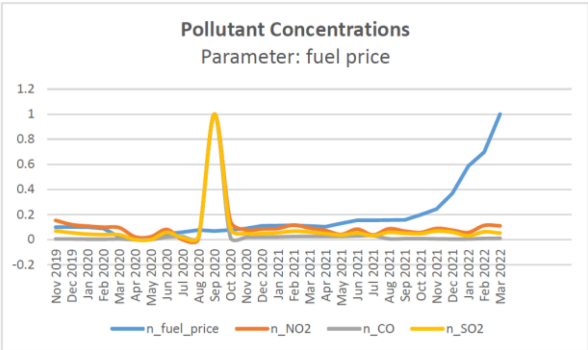

Figure 9. Fuel prices and air pollutant concentrations.

Then, we analyzed how air pollutants are affected by the stringency index of Turkey. Figure 10 shows the relationship between stringency index and air pollutant concentrations.

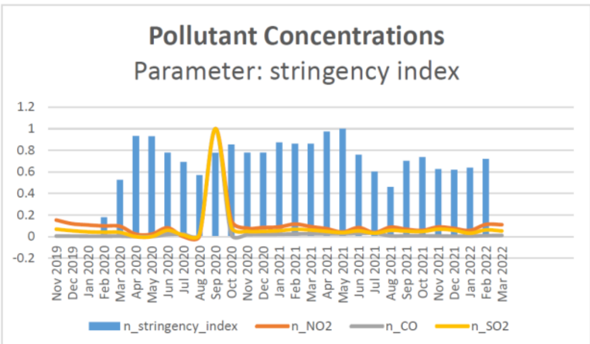

Figure 10. Stringency index and air pollutant concentrations

Finally, we analyzed how air pollutants are affected by the restrictions and in-class education. Figure 11 shows the relationship between restriction, in-class education, and air pollutant concentrations.

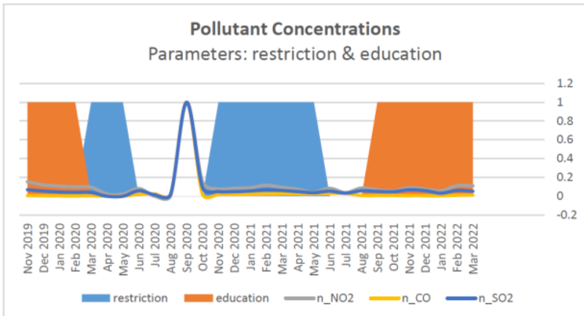

Figure 11. Restrictions - in-class education and air pollutant concentrations.

There was no apparent relationship between the parameters predicted to affect air pollutants and the concentrations. Therefore, we examined their correlations better to reveal the relationship between independent variables and concentrations. The correlation coefficient is a value between -1 and +1. It reveals the degree to which two variables are correlated with one another. A perfect positive connection is indicated by a correlation coefficient of 1. On the other hand, a correlation coefficient of -1 denotes a completely adverse correlation. The correlation coefficient can be calculated using the formula given in Equation 2.

$$r = \frac{\sum(x - m_x)(y - m_y)}{\sqrt{\sum(x - mx)^2 \sum(y - my)^2}} \quad (2)$$

As a result, the variables and their correlations were found, as shown in Figure 12.

	rest.	edu.	s_index	t_index	d_death	f_price	rr	gp	p	t	w	r	NO_2	CO	SO_2
rest.	1														
edu.	-0.56713	1													
s_index	0.545591	-0.56153	1												
t_index	-0.59855	0.586769	-0.447	1											
d_death	0.400358	0.008231	0.236822	-0.08737	1										
f_price	-0.33623	0.542333	-0.2999	0.321035	0.133482	1									
rr	-0.83582	0.660114	-0.66952	**0.785364**	-0.10998	0.474236	1								
gp	-0.63461	**0.764371**	-0.46921	**0.775621**	0.106768	0.601428	**0.884603**	1							
p	**-0.80501**	0.15172	-0.47108	0.581312	-0.35486	0.082433	**0.797934**	0.584045	1						
t	**-0.77132**	0.684377	-0.58489	**0.838682**	-0.00828	0.525082	**0.96874**	**0.944548**	**0.755164**	1					
w	-0.67584	**0.713334**	-0.6349	**0.85287**	0.009952	0.653428	**0.895462**	**0.86151**	0.578935	**0.90349**	1				
r	**0.803488**	-0.39284	0.62748	-0.8075	0.266423	-0.29079	**-0.92067**	**-0.72572**	**-0.90776**	**-0.88783**	**-0.82067**	1			
NO_2	-0.1658	-0.06972	0.027142	0.174623	-0.20546	-0.0525	0.077347	-0.05895	0.170228	0.032989	0.081212	-0.15702	1		
CO	-0.12561	-0.18161	0.097117	0.051982	-0.19537	-0.10585	0.029013	-0.1304	0.182403	-0.02813	-0.00809	-0.13043	-	1	
SO_2	-0.16233	-0.12114	0.071483	0.133912	-0.19096	-0.07517	0.081662	-0.06853	0.201966	0.031504	0.06077	-0.17187	-	-	1

Figure 12. Correlation coefficients (rest: restrictions, edu:in-class education, s_index: stringency index, t_index: traffic index, d_death: daily death, f_price: fual price, rr: retail and recreation , gp: grocery and pharmacy, p: parks, t: transit, w: workplace, r: residential)

5 Results and discussion

5.1 Results of Spatio-temporal distribution of air pollutants

Spatial maps show a decreasing trend of NO_2, CO, and SO_2 pollutant concentrations when restrictions are in place in Turkey. It is observed that the values in 2019 and 2020, when schools are partially closed, are at lower levels compared to 2021 and 2022. The regions with the most significant increases in NO_2, CO, and SO_2 concentrations are close to the Bosphorus. Therefore, a decrease in pollutant concentrations as one goes to the inner parts. This shows that the pollution in coastal areas is at higher levels.

5.2 Results of the correlation analysis

The Covid-19 epidemic has been linked to a drop in pollution concentrations and an improvement in air quality, according to numerous research studies. On the other hand, there are also studies in metropolitan cities where the opposite is observed. This situation has also been observed in Istanbul, which is considered to be Turkey's largest metropolitan city. Although a general increase in air quality was observed, it was found that this increase was not related to the predicted independent parameters.

Restrictions were introduced in Turkey for the first time in April 2020. Accordingly, a decrease was observed in the traffic index in April 2020. However, there was a rapid increase in the traffic index after a while. One possible reason for this increase may be the implementation of the restrictions at certain times and the fact that people in Istanbul did not comply with the restrictions for a long time. Accordingly, there was an increase in pollutant concentrations (see Figure 6).

The Turkish Ministry of Health has not announced the daily number of deaths and the number of confirmed cases by provinces. For this reason, it was impossible to analyze the change in pollutant concentrations according to the Covid-19 parameters. However, the daily death rates in Istanbul can be considered an indicator as it includes the number of deaths caused by Covid-19. Therefore, we created a graph of the variation in daily death numbers and pollutant concentrations in Istanbul. It has been observed that there are small decreases in pollutant concentrations during the peak periods of daily death numbers (see Figure 7).

The Google community mobility reports include numerical data showing the change in the shopping dynamics of communities, the change in using public transport, the change in being in the workplace, and the change in the length of stay at home. However, when these data and the graph showing the change in pollutant concentrations were examined, no significant relationship was observed between mobility items and the changes in pollutant concentration (see Figure 8).

It is predicted that the increase in fuel prices will affect the number of vehicles on the road and indirectly lead to a positive change in pollutant concentrations. However, as of April 2021, no significant relationship was observed between increasing fuel prices in a nearly linear trend and changes in pollutant concentration (see Figure 9).

When the stringency index, which serves to present the policies implemented by the governments, and the graph showing the change in pollutant concentrations are examined, it is observed that there are partial decreases in pollutant concentrations during the periods when the policies are tightened. Increasing restrictions can reduce air pollution, albeit partially (see Figure 10).

Considering the logical variables (restrictions and in-class education) included in the study, there was a partial decrease in pollutant concentrations with the cessation of in-class education and the onset of restrictions. However, no significant change in pollutant concentrations was observed during the partial restrictions applied between November 2020 and June 2021. Furthermore, although there was a slight increase in concentrations with the start of in-class education, there were also decreases in the following period (see Figure 11).

We took the lower limit of 0.7 as a basis for the correlation coefficients obtained from the correlation analysis. Accordingly, coefficients in the range of 0.7&1 were accepted as significant positive correlations, and coefficients in -1&-0.7 were accepted as significant negative correlations. No significant relationship was observed between the pollutant concentration parameters and the independent variables based on these ranges. Significant positive relationships were observed as follows; restrictions and residential mobility (0.803488), in-class education and grocery&pharmacy mobility (0.764371), in-class education and workplace mobility (0.713334), traffic index and retail&recreation mobility (0.785364), traffic index and grocery&pharmacy mobility (0.775621), traffic index and transit mobility (0.838682) , traffic index and workplace mobility (0.85287), retail&recreation mobility and grocery&pharmacy mobility (0.884603), retail&recreation mobility and parks mobility (0.797934), retail&recreation mobility and transit mobility (0.96874), retail&recreation mobility and workplace mobility (0.895462), grocery&pharmacy mobility and transit mobility (0.944548), grocery&pharmacy mobility and workplace mobility (0.86151) , parks mobility and transit mobility (0.755164), transit mobility and workplace mobility (0.90349). Significant negative relationships were observed as follows; restrictions and parks mobility (-0.80501), restrictions and transit mobility (-0.77132), retail&recreation mobility and residential mobility (-0.92067), grocery&pharmacy mobility and residential mobility (-0.72572), parks mobility and residential mobility (-0.90776), transit mobility and residential mobility (-0.88783), and workplace mobility and residential mobility (-0.82067).

The parameter that negatively affects NO_2 concentration is the daily death parameter (-0.20546), and the most positive parameter is the traffic index parameter (0.174623). The parameter that negatively affects the CO concentration is the daily death parameter (-0.19537), and the most positive parameter is the parks mobility parameter (0.182403). The parameter that negatively affects SO_2 concentration is the daily death parameter (-0.19096), and the most positive parameter is the parks mobility parameter (0.201966). Since these correlation coefficients are pretty low, it cannot be said that there is a strong significant relationship between pollutant concentrations and these independent variables. However, the fact that the daily death number variable has the highest negative value for all three parameters indicates a significant result.

6 Conclusion

In this study, spatial distributions of pollutant concentrations were examined within the boundaries of Istanbul, using several different data sets, and then the factors affecting the pollutant changes were investigated. In many of the studies on similar topics in the literature, it is stated that the restrictions imposed by the governments due to the Covid-19 pandemic have a positive effect on air quality. However, when the situation within the borders of Istanbul was examined, no significant relationship was found between the parameters associated with the Covid-19 pandemic and the pollutant concentrations. The reasons include people's less obedience to rules in metropolitan cities, the uninterrupted business life, and the fact that there are too many people. In some news published during the long restrictions period, it was reported that the traffic in Istanbul did not decrease but, on the contrary, increased during some closures [34]. The findings of the presented study also support this argument.

Supplementary material

All supporting material for the study is available at [33]: The GEE source codes, datasets, thematic maps, and GIF images.

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