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The impacts of COVID-19 lockdown on PM_{10} and SO_2 concentrations and association with human mobility across Turkey

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ABSTRACT

The SARS-CoV-2 virus pandemic (COVID-19) has caused 2.25 million deaths worldwide by February 3, 2021 (JHU, 2021) and still causing severe health and economic disruptions with increasing rates. This study investigates the impact of lockdown measures on ambient air pollution and its association with human mobility in 81 cities of Turkey. We conducted a countrywide analysis using PM_{10} and SO_2 measurement data by the Turkish Ministry of Environment and Urbanization and mobility data derived from cellular device movement by Google. We observed the most significant change in April 2020. PM_{10} and SO_2 concentrations were lower in 67% and 59% of the cities, respectively in April 2020 compared to the previous five years (2015–2019). The correlation results show that Restaurant/Café, Transit, and Workplaces mobility is significantly correlated with PM_{10} and SO_2 concentration levels in Turkey. This study is the first step of a long-term investigation to understand the air quality impacts on population susceptibility to COVID-19.

1. Introduction

COVID-19 is a global infectious disease (Zhu et al., 2020) caused by *severe acute respiratory syndrome coronavirus 2* (WHO, 2020a), which was first reported in Wuhan, China in late 2019 (Lu et al., 2020). On March 11, 2020, the World Health Organization named COVID-19 as a pandemic with more than 118,000 confirmed cases in 114 countries, and 4291 deaths (WHO 2020). COVID-19 has caused 2.25 million deaths worldwide by February 3, 2021 (JHU, 2021). Different countries implemented different lockdown measures to protect public health by minimizing the movement of citizens. As a result, the pandemic caused an estimated global consumption loss of \$3.8 trillion, job losses equivalent to 147 million full-time positions, and a loss of \$2.1 trillion in wages and salaries (Lenzen et al., 2020).

The Ministry of Health of Turkey confirmed the first case of COVID-19 on March 11, 2020 in Istanbul, Turkey (TRT 2020). The Turkish government announced the first restrictions on March 12, 2020, to limit the mobility of citizens, schools were closed starting from March 16, 2020, sports events were canceled and state officers were limited to travel internationally until further notice (BBC 2020). According to the Stringency Index of Oxford COVID-19 Government Response Tracker (Hale et al., 2020), Turkey started with a stringency level of 23.2 on March 11th (Fig. S1). This index is driven by policy indicators (Table S1). The value of the index on a specific day is the average of nine sub-indices. Fig. S1 shows the gradual increase of the stringency index over time until March 28 with 75.9 and decreased to 63.9 on June 2, 2020, in Turkey. The ease on lockdown continued during summer and the index dropped to 42.6 by July 25, 2020. However, restrictions came back by September due to a high number of new cases, the index was as high as 73.6 with the new restriction on September 12, 2020.

Several studies investigated the impact of air quality and meteorological variables on transmission dynamics of COVID-19 (Bashir et al., 2020; Coccia, 2020a, 2021a, 2021b; Srivastava, 2021). Although the environmental impacts of COVID-19 lockdowns are still under investigation by several research groups all around the world, several studies have investigated the change in atmospheric pollution during the pandemic (Archer et al., 2020; Baldasano, 2020; Berman and Ebisu, 2020; Chen et al., 2020; Kerimray et al., 2020; Krecl et al., 2020; Muhammad et al., 2020; Pei et al., 2020). A major decline in Nitrogen dioxide (NO_2) emissions over early 2020 were observed by satellite images from the Centre for Research on Energy and Clean Air (CREA), NASA, and the European Space Agency (ESA) (NASA, 2020). Another study showed a decline in $PM_{2.5}$ (11.3%) and NO_2 (25.5%) during the pandemic in the US (Berman and Ebisu, 2020).

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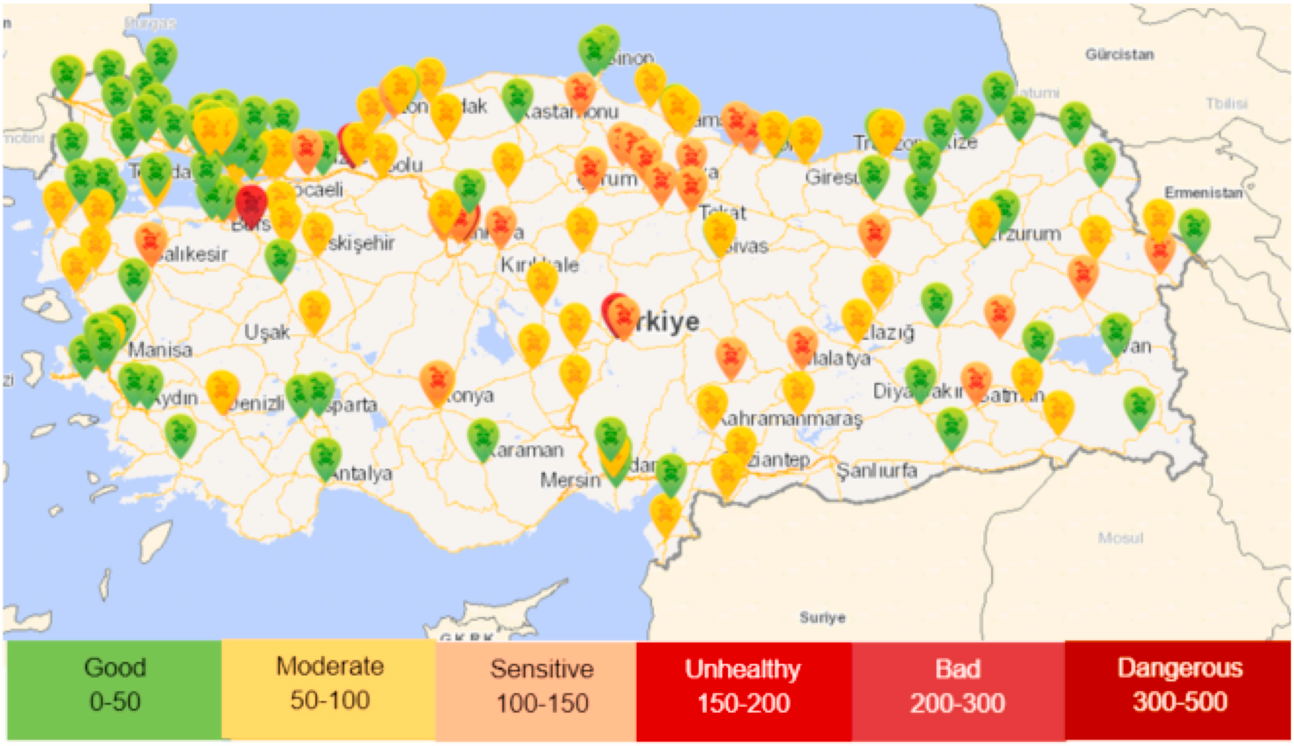

Fig. 1. Localization of the monitoring stations in Turkey and air quality for 08.12.2020 13:00 (UHKIA, 2020).

Similarly, 30% reduction in NO_2 during the month of March in the urban northeastern US was observed by satellite data (Blumberg, 2020). Bao and Zhang (2020) showed that the air quality index decreased by 7.80% and SO_2, $PM_{2.5}$, PM_{10}, NO_2, and CO decreased by 6.76%, 5.93%, 13.66%, 24.67%, and 4.58%, respectively as an average of 44 cities in China due to lockdown measures. Another study estimated a decrease in the carbon footprint burden by 20% compared with 2015–2019 in Italy (Rugani and Caro, 2020). In Brazil, researchers observed significant reductions (30.3–48.5) in CO levels and limited reductions for PM_{10} levels during the first week of the lockdown (Dantas et al., 2020). Another group analyzed the air quality impacts in São Paulo, where drastic reductions observed for NO, NO_2, and CO by 77.3%, 54.3%, and 54.3%, respectively compared to the five-year monthly mean. On the other hand, the researchers observed an approximately 30% increase in ozone concentrations in urban areas (Nakada and Urban, 2020). In Kazakhstan, $PM_{2.5}$, CO, and NO_2 concentrations were reduced by 21%, 49%, and 35%, respectively during the first lockdown period between mid-March and mid-April compared to the average on the same days in 2018–2019 (Kerimray et al., 2020). In India, where a nationwide lockdown was imposed initially for three weeks from 24th March to 14th April 2020, PM_{10} and $PM_{2.5}$ were reduced more than 50% compared to the pre-lockdown phase (Mahato et al., 2020). Similarly, NO_2 and CO concentration levels were reduced by 52.68% and 30.35%, respectively. In Salé City, Morocco, 75%, 49%, and 96% reductions for PM_{10}, SO_2, and NO_2 were observed, respectively (Otmani et al., 2020). In the United Arab Emirates, Nitrogen Dioxide (NO_2), Aerosol Optical Depth, and Surface Urban Heat Island Intensity variables were examined during lockdown periods and the levels declined by 23.7%, 3.7%, and 19.2%, respectively, compared to the same period in 2019 (Alqasemi et al., 2021). The majority of these studies focus on the first lockdown period between March and April of 2020. In literature, mobility data is mainly used to investigate the spread of COVID-19 in societies (Chang, 2020).

In this study, we explore the continuous change in air quality between January 2020 and November 2020, especially March and April, in 81 cities of Turkey by an extensive database of ground monitoring stations. Besides, we investigate the associations between air quality parameters and mobility trends to understand the impact of lockdown measures on air quality.

2. Methods

We obtained 24-h average PM_{10}, $PM_{2.5}$, SO_2, CO, O_3, NOx, and NO_2 concentration data for 2015 through 2020 from the public air quality monitoring network designed by the Turkish Ministry of Environment and Urbanization (UHKIA, 2020). Each city has at least one station for air quality measurement (Fig. 1). However, only PM_{10} and SO_2 parameters were selected for the analysis due to being the only available parameters for 81 cities between January 2015 and November 2020. There are several missing data for other air quality parameters in smaller cities. We aim to investigate the change in all cities in TR compared to five years before lockdown; therefore, we only selected two parameters for this study.

Mobility measure is the most important statistical parameter to define the distance and movement of a person in a society. The aim of mobility data is to capture general patterns in human mobility based on mobile device utilization. Even though the government set social distancing guidance and limitations, which is the same for all 81 cities of Turkey, we observed different behavior in each region. Therefore, we aim to capture actual patterns of human mobility by using datasets from Google (GoogleLLC, 2020). The importance of the dataset is showing a relative trend of how the movement of people in Turkey changes day after day. Google's mobility dataset is based on users' location information, which is classified into Workplaces, Residential, Retail and Recreation, Grocery and Pharmacy, Transit, Stations, Parks, and Restaurant/Café. We have used six categories, Workplaces, Residential, Grocery and Pharmacy, Transit, Stations, Parks, and Restaurant/Café, which can have direct effects on air quality.

We have also obtained car-purchasing data from the Turkish Statistical Institute reports (TUIK, 2020) to interpret the results.

We performed unpaired Welch's two-sample *t*-test analysis by R-software (RStudio Team, 2020) in order to determine the significant reductions in PM_{10} and SO_2 concentrations in 2020. In this analysis, we

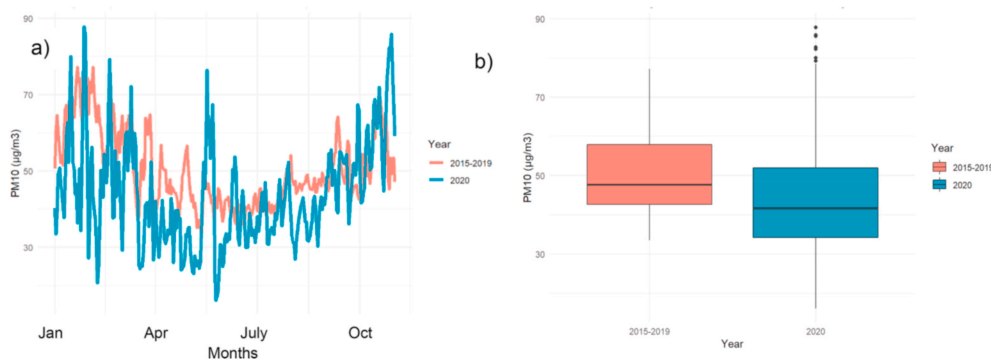

Fig. 2. (a) Daily average concentrations (b) distribution of PM_{10} (μg/m^3) for 2015–2019 and 2020.

assumed the samples follow normal distribution due to the sufficient number of observations in each sample. Then, we performed F- test to check the variance assumption of the *t*-test. F-statistic is defined as:

$$F = \frac{s_1^2}{s_2^2} \sim F_{n1,n2}$$

where $n1$ and $n2$ are the sample sizes of the samples.

The formula for t-statistics varies based on the variance equality. If the variance of both samples are statistically equal

$$t = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{s_p^2\left(\frac{1}{n_1} - \frac{1}{n_2}\right)}}$$

where $s_p^2 = \frac{(n_1-1)s_1^2+(n_2-1)s_2^2}{n_1+n_2-2}$ is the pooled variance. In this equation, $\overline{X_1}$ and $\overline{X_2}$ are the means of the samples, $n1$ and $n2$ are the sample sizes, s_1^2 and s_2^2 are the variances.

If the variance equality is not satisfied,

$$t = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{\frac{s_1^2}{n_1} - \frac{s_2^2}{n_2}}}$$

Here $\overline{X_1}$ and $\overline{X_2}$ are the means of the samples, $n1$ and $n2$ are the sample sizes, s_1^2 and s_2^2 are the variances.

We divided the data set into two groups, mean of 2015–2019 and 2020. H_0 represents there is no significant effect of COVID-19 on air quality, where H_1 represent the significant difference between the means of the two groups.

We performed Pearson's correlation analysis to measure the relationship between air pollutants and mobility data sets. Pearson's correlation coefficient is a number ranging between −1 and +1, which shows a negative to a positive correlation between variables. The formula for Pearson's correlation is:

$$\rho_{x_1 x_2 = \frac{Cov(x_1, x_2)}{\sigma_{x_1}\sigma_{x_2}}}$$

where $Cov(x_1, x_2)$ is the covariance between two variables in the scenario, σ is the standard deviation of x_1 *and* x_2.

In this study, we aim to test the difference between PM_{10} and SO_2 concentrations in 2020 and 2015–2019. Therefore, we performed unpaired or independent Welch's two-sample t statistic, which is based on comparing two groups based on their average. Another reason for selecting this parametric test rather than the nonparametric test is the sample size of the dataset allows us to approach normality by Central

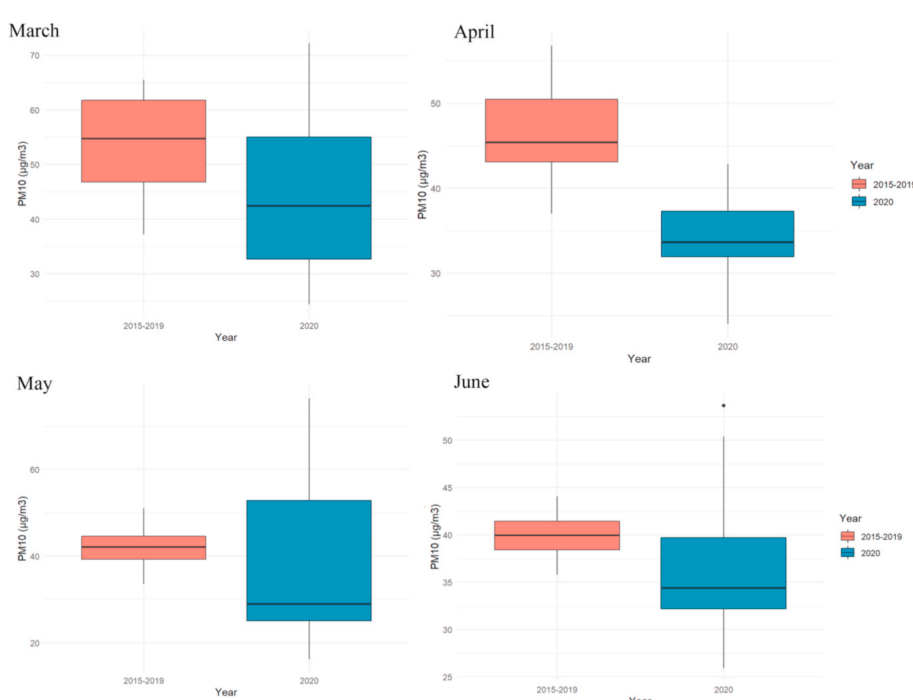

Fig. 3. The distribution of average PM_{10} concentrations (μg/m^3) in March, April, May, and June of 2020 and 2015–2019.

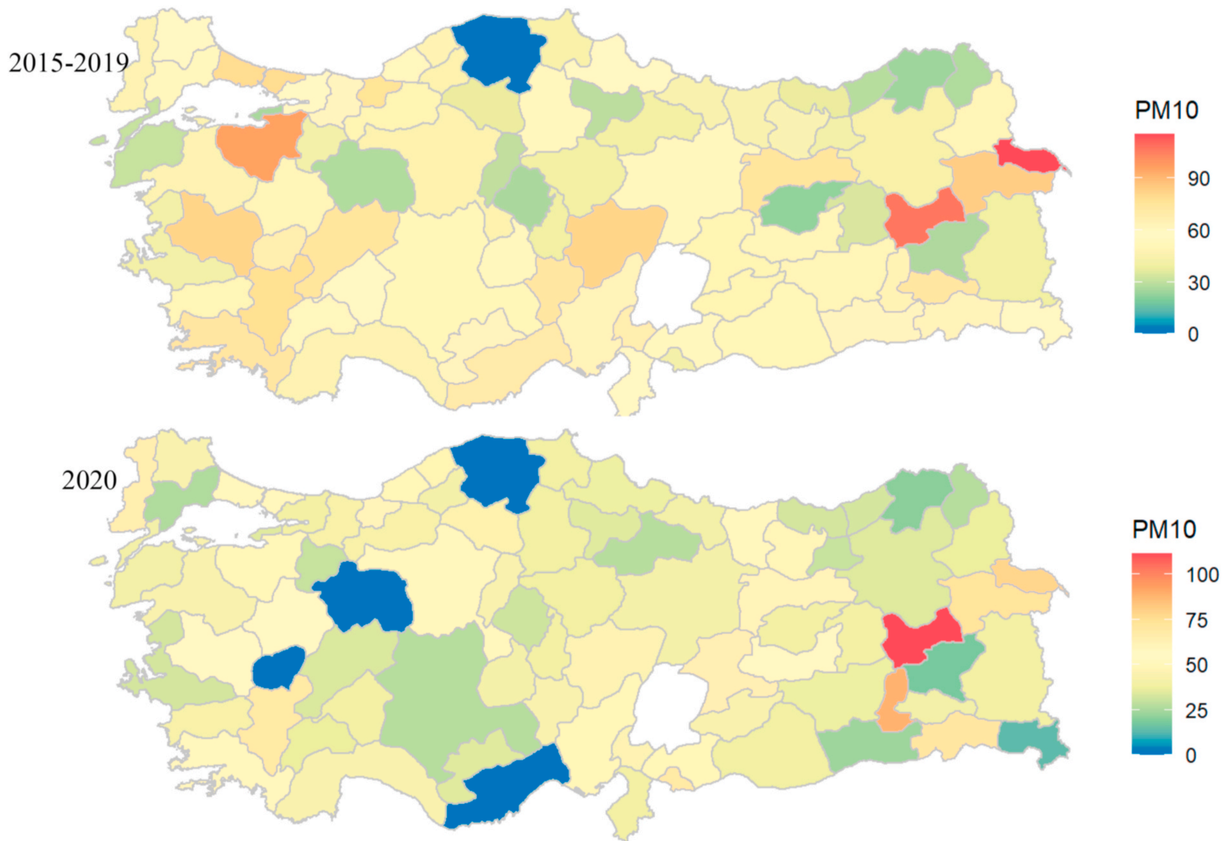

Fig. 4. Heat map of average PM_{10} concentrations (μg/m^3) for January–November 2020 and 2015–2019 mean.

Limit Theorem. The second aim is to check the relationship between PM_{10} and SO_2 concentrations. For this purpose, we performed Pearson correlation coefficients between related variables to find out the strength and direction of the relationship if it exists.

3. Results and discussion

We compared daily average concentrations of PM_{10} and SO_2 of 2020 to the average of the daily concentrations of the years 2015 through 2019 (Fig. S2). We did not take monthly averages to be able to provide the most accurate variability that represents the lockdown restrictions, which were updated weekly not monthly. In addition, we used the average of five-year data (2015–2019) to provide meaningful baseline data to be able to compare with the associated dates in 2020. Second, we investigated the association between air quality parameters and mobility data in each city.

- **The Reduction of Air Pollutants due to COVID-19 Lockdown**

There is a general lower concentration trend for PM_{10} throughout 2020 compared to the 2015–2019 average at the ground monitoring sites in Turkey (Fig. 2a). However, we observe a sharp decrease in March as a result of lockdown measures. The average concentration for March 2020 is 43.75 μg/m^3 while the average concentration is 53.90 μg/m^3 for the baseline. We see the real impact of lockdown in the month of April, approximately 67% of cities had lower average PM_{10} concentrations in April 2020 compared to the associated dates in all of the previous five years. The gap between the two trends narrows down during the summer months, which can be a result of ease in lockdown restrictions starting from June 2020. Fig. 2b shows the difference between the daily average concentrations of PM_{10} (μg/m^3) between 2020 and 2015–2019. The median concentration for 2020 is significantly lower than 2015–2019. There are outliers for 2020 due to occasional very high concentrations related to sudden changes in restriction policy.

Fig. 3 shows the distribution of average PM_{10} concentrations (μg/m^3) in March, April, May, and June of 2020 and 2015–2019. Box-plots for March show the impact of the first restrictions, which were set on March 11th with the stringency level of 23.2. The median concentration decreased by 13 μg/m^3 in 2020 compared to the previous years. The stringency index drastically increased to 75.9 by March 28, which explains the high variability of concentration in March 2020. In April, we see the main impact of lockdown measures, which had a more constant stringency level throughout the month. The gap between average PM_{10} concentration levels for 2020 and the baseline increased in April (Fig. S3, Table S4). The variability for average 2020 decreased compared to the previous month. In May, we see a similar concentration level for 2020 but higher variability due to starting fewer restrictions by the end of the month (Fig. 3). The stringency level decreased to 63.9 by June 2, 2020. As a result, we see an increasing trend in PM_{10} concentrations in June with lower variability. Fig. 4 shows the spatial variability of average PM_{10} concentrations. We see a general betterment in PM_{10} concentrations across the country. Kastamonu city is excluded from 2015 to 2019; Kastamonu, Eskişehir, Uşak, Mersin, and Osmaniye cities were excluded from the 2020 data set due to data availability. The highest pollution occurred in Muş (106.8 μg/m^3), Iğdır (115.3 μg/m^3), Bursa (95.8 μg/m^3), and Ağrı (83.3 μg/m^3) cities in average between 2015 and 2019. In 2020, the highest decreases were observed in Hakkari (−300%), Mardin (−162%), Afyon (−117%), Tekirdağ (−102%), Konya (−93%), and Bursa (−91%) cities. There are noticeable exceptions from decreasing trend of concentrations for several cities such as Tunceli, Kilis, Kırıkkale, and Batman cities (Table 1).

We observe a more drastic change in April. In Hakkari city, the average PM_{10} concentration decreased by 521% compared to the previous years in April (Fig. S2). However, we see a significant increase in a

Table 1
Average concentration of PM_{10} ($\mu g/m^3$) from largest to smallest change by city for the years 2015–2019 and 2020. Change indicates the percent change in 2020 with respect to the 2015–2019 mean.

City	2015–2019	2020	Change (%)	City	2015–2019	2020	Change (%)
Hakkari	55.7	13.9	−300%	Bolu	49.2	42.4	−16%
Mardin	60.8	23.2	−162%	Ağrı	83.3	72.1	−16%
Afyon	73.6	33.9	−117%	Sinop	44.5	38.8	−15%
Tekirdağ	53.0	26.3	−102%	Ordu	46.3	40.4	−15%
Konya	52.4	27.2	−93%	Denizli	77.2	67.8	−14%
Bursa	95.8	50.1	−91%	Karabük	46.5	41.6	−12%
Siirt	72.2	40.2	−80%	Adıyaman	49.3	44.5	−11%
Karaman	61.5	34.7	−77%	Gaziantep	54.8	50.3	−9%
Kayseri	80.8	45.9	−76%	Balıkesir	47.4	43.8	−8%
Niğde	72.2	44.7	−62%	Yozgat	40.6	38.3	−6%
Burdur	60.2	37.3	−61%	Antalya	47.4	44.8	−6%
İstanbul	78.6	50.9	−55%	Bartın	48.1	47.6	−1%
Bitlis	26.6	17.7	−51%	Nevşehir	40.1	39.7	−1%
Iğdır	115.3	77.6	−49%	Ardahan	27.2	27.1	−1%
Tokat	40.6	27.4	−48%	Van	39.6	39.4	0%
Samsun	55.9	38.2	−47%	K.Maras	59.3	60.1	1%
Kocaeli	57.3	39.2	−46%	Gümüşhane	47.2	48.3	2%
Osmaniye	66.7	45.9	−45%	Muş	106.8	111.3	4%
Sakarya	60.8	41.9	−45%	Elazığ	50.6	53.6	6%
Manisa	80.9	56.0	−44%	Kütahya	50.7	54.2	6%
Bilecik	42.5	29.6	−43%	Ankara	46.9	50.9	8%
Isparta	57.1	39.8	−43%	Şırnak	61.9	69.6	11%
Muğla	72.6	51.4	−41%	Giresun	45.7	52.5	13%
Hatay	55.6	39.4	−41%	Rize	28.6	32.9	13%
Bayburt	42.5	30.4	−40%	Bingöl	34.4	40.0	14%
Çorum	53.7	38.5	−40%	Amasya	29.3	34.5	15%
Kars	49.5	36.9	−34%	Çankırı	37.9	44.8	16%
Şanlıurfa	51.1	38.3	−33%	Kırşehir	26.5	31.7	16%
Kırklareli	57.0	43.6	−31%	Malatya	49.4	63.2	22%
İzmir	41.9	32.1	−30%	Çanakkale	30.8	40.6	24%
Diyarbakır	49.6	38.2	−30%	Yalova	26.2	34.8	25%
Sivas	53.5	41.3	−30%	Edirne	47.4	64.0	26%
Erzurum	43.8	34.0	−29%	Batman	63.4	88.0	28%
Aksaray	53.0	41.6	−27%	Kırıkkale	30.1	44.0	32%
Düzce	75.2	59.4	−27%	Kilis	43.1	67.8	36%
Adana	62.7	50.1	−25%	Tunceli	22.5	39.7	43%
Erzincan	73.7	60.1	−23%	Eskişehir	27.4	0.0	NA
Zonguldak	59.9	49.9	−20%	Kastamonu	0.0	0.0	NA
Aydın	50.5	42.3	−19%	İçel	69.0	0.0	NA
Artvin	24.2	20.4	−19%	Uşak	66.4	0.0	NA
Trabzon	37.6	32.0	−18%				

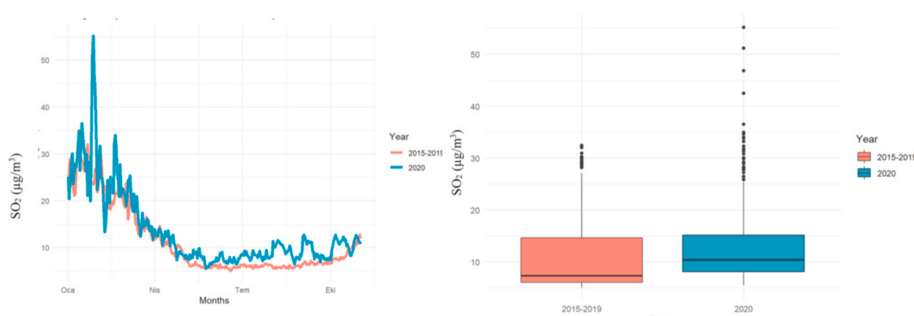

Fig. 5. (a) Daily average concentrations (b) distribution of SO_2 ($\mu g/m^3$) for 2015–2019 and 2020.

few cities, such as Batman city (+53%). One of the reasons can be agricultural burning practices, which is common for example in Batman city. In metropolitan cities, the impact of stay-at-home order on PM_{10} concentration is slightly lower but causes a significant decrease such as in Istanbul city (−55%), which can be a direct result of reduced road traffic. On the other hand, we do not see this impact in the capital city, Ankara, where people's actual mobility is different from the state ordinances. This can be related to characteristics of the city where more state offices locate than private businesses.

Fig. 5 shows the average daily SO_2 concentrations throughout 2020 compared to 2015–2019 mean across Turkey. We see a gradual decrease from March to May for both trends, which is parallel to the domestic heating season. The average SO_2 concentration for 2020 is slightly higher compared to the previous five years based on a two-tailed *t*-test ($p < .02$) where both datasets are right-skewed with outliers. The occurrence of more outliers is closely related to the sudden changes in mobility restrictions, which corresponds to high variation in data.

In March and April 2020, the average concentrations of SO_2 are slightly higher than 2015–2019; however, the differences are not significant (Table S2). On the other hand, we observe significantly higher concentrations in May and June of 2020 as shown in Fig. 6 ($p < .001$). The month of May serves as a transition period, as a result, we see higher

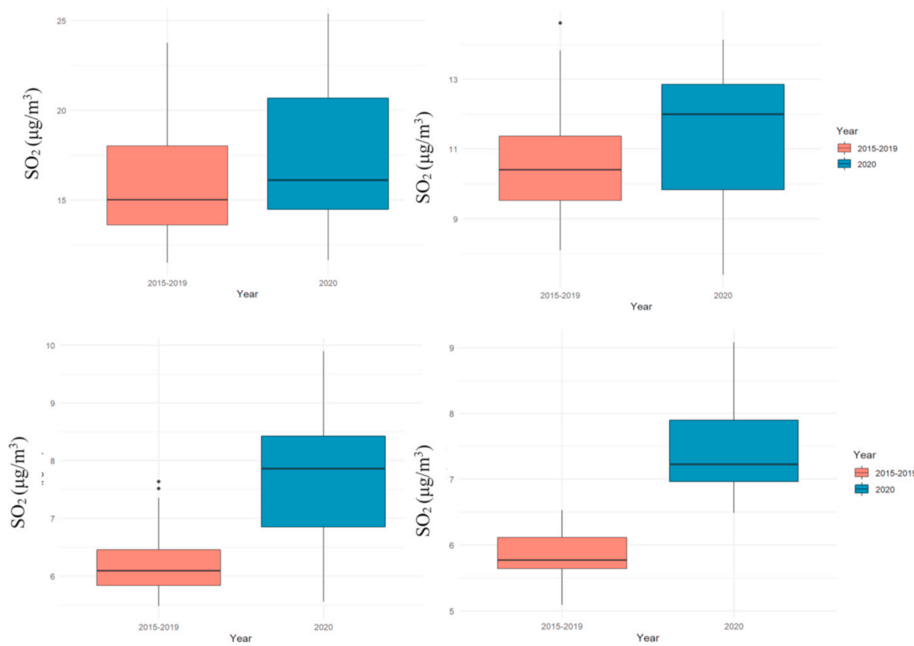

Fig. 6. The distribution of average SO_2 concentrations (μg/m^3) in March, April, May, and June of 2020 and 2015–2019.

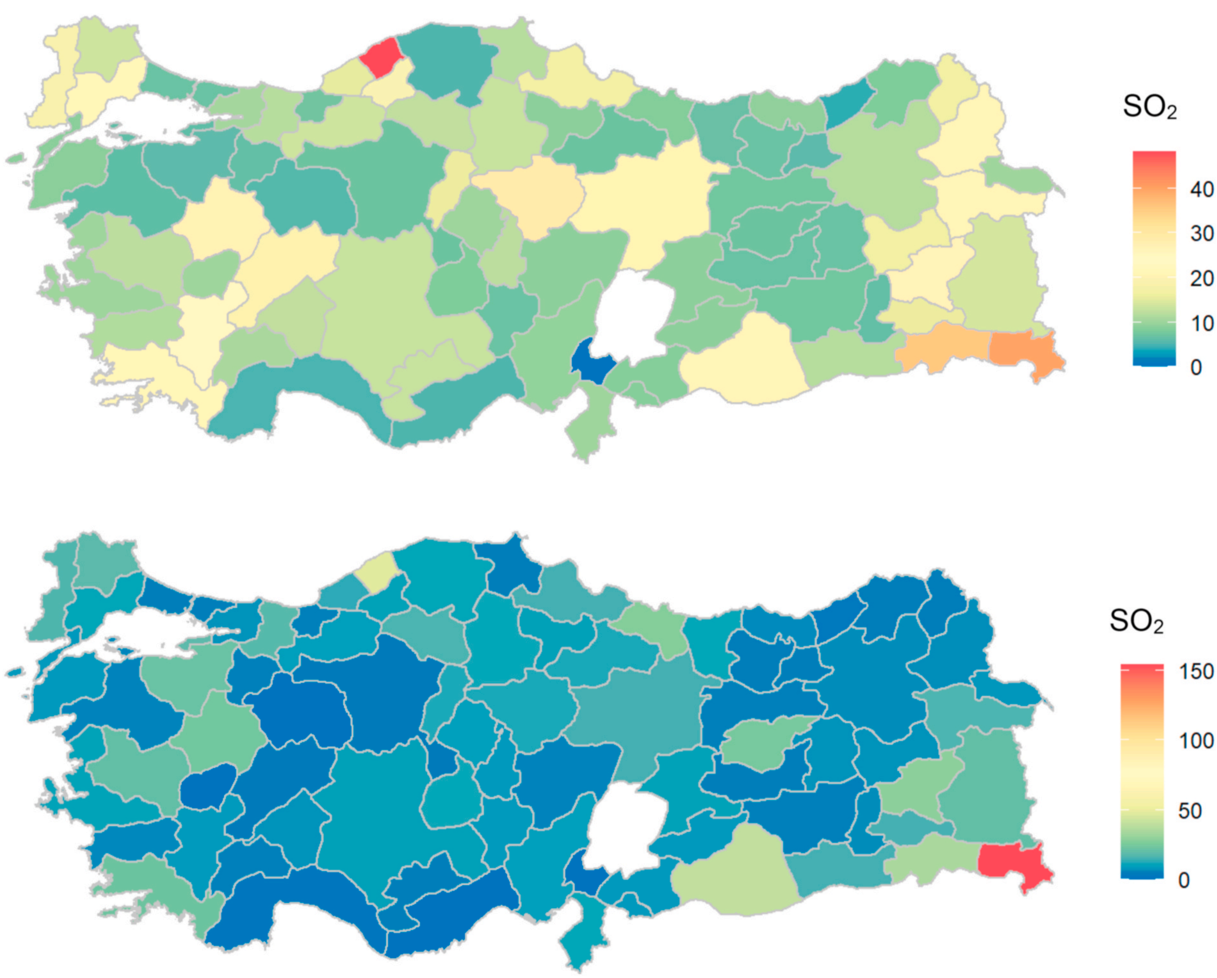

Fig. 7. Heat map of average SO_2 concentrations (μg/m^3) for January–November 2020 and 2015–2019 mean.

Table 2
Average concentration of SO_2 (μg/m^3) from largest to smallest change by city for the years 2015–2019 and 2020. Change indicates the percent change in 2020 with respect to the 2015–2019 mean.

City	2015–2019	2020	Change (%)	City	2015–2019	2020	Change (%)
Afyon	19.6	5.0	−291%	Adıyaman	9.1	8.8	−3%
Ardahan	16.7	5.2	−222%	Siirt	15.8	15.4	−3%
Kars	20.7	6.8	−203%	Kırşehir	10.0	9.8	−3%
Denizli	23.2	8.9	−161%	Şırnak	35.6	35.0	−2%
Yozgat	28.5	12.0	−137%	Bayburt	5.9	5.8	−1%
Muş	16.8	7.4	−127%	Çanakkale	8.8	8.7	−1%
Karaman	12.9	5.7	−126%	Gaziantep	8.6	8.6	0%
Sinop	11.8	5.5	−114%	Balıkesir	6.1	6.2	0%
Tekirdağ	21.8	11.3	−92%	Kilis	8.6	8.7	1%
Karabük	19.7	10.6	−85%	Bartın	48.1	48.7	1%
Burdur	10.9	6.0	−82%	Adana	9.6	9.7	1%
Aydın	11.4	6.4	−79%	Muğla	21.7	22.9	5%
Antalya	5.0	2.8	−75%	Bingöl	6.8	7.3	7%
Isparta	12.4	7.2	−71%	Bitlis	26.4	28.7	8%
Erzurum	11.6	6.9	−68%	İzmir	10.1	11.2	9%
Artvin	8.2	5.2	−57%	Batman	6.2	6.9	9%
Ankara	7.1	4.7	−53%	Amasya	9.0	10.1	11%
Kayseri	9.1	6.3	−46%	Hatay	10.1	11.6	13%
Bolu	13.7	9.5	−44%	Malatya	9.1	10.9	16%
Kocaeli	10.5	7.3	−43%	Mardin	11.7	14.7	20%
Sivas	20.5	14.6	−41%	Çankırı	12.4	16.0	22%
Nevşehir	12.2	8.7	−40%	Niğde	6.9	8.9	23%
Rize	4.3	3.1	−39%	Kırklareli	13.7	18.1	24%
Trabzon	9.2	6.7	−38%	Van	14.2	19.9	29%
Konya	13.0	10.0	−30%	Aksaray	8.3	11.7	29%
Ağrı	20.8	16.1	−29%	Sakarya	11.9	18.3	35%
Iğdır	10.3	8.0	−28%	Manisa	12.3	19.8	38%
Gümüşhane	6.8	5.3	−28%	Tokat	7.0	12.2	43%
Kırıkkale	15.8	12.6	−26%	Giresun	6.6	11.5	43%
Düzce	7.3	5.9	−23%	Şanlıurfa	21.2	40.0	47%
Diyarbakır	7.4	6.0	−23%	Kastamonu	5.1	11.4	55%
Erzincan	7.4	6.0	−23%	Yalova	6.1	18.4	67%
İstanbul	6.8	5.5	−22%	Ordu	8.5	27.3	69%
Zonguldak	15.5	12.9	−20%	Tunceli	7.1	24.5	71%
Elazığ	6.7	5.7	−17%	Bursa	6.0	21.6	72%
Samsun	17.0	14.7	−16%	Hakkari	39.6	154.2	74%
Kütahya	26.7	23.5	−14%	Eskişehir	5.5	0.0	NA
Edirne	18.7	16.6	−13%	Mersin	5.2	0.0	NA
Çorum	12.9	11.8	−9%	Osmaniye	0.0	0.0	NA
K.Maras	20.8	19.9	−5%	Uşak	10.2	0.0	NA
Bilecik	6.4	6.1	−4%				

variability in data. The significant increase in May and June can be a result of behavioral change. People tend to use more private vehicles during the COVID-19 pandemic. Vehicle exhaust emissions are a major contributor to SO_2 emissions. According to Turkey Statistical Institute (TUIK), the number of the newly registered automobiles increased 55% between January–August in 2020 compared to 2019 (Table S3). 48.5% is petrol and 42.9% is diesel-fueled vehicles out of the newly registered cars in 2020. As a consequence, we see higher average daily SO_2 concentration levels throughout 2020 (Fig. 5a). There might be two reasons for high variability in May and June; first, weekly changes in lockdown measures, second is the movement of air masses before arriving at the monitoring sites.

In terms of spatial variability, SO_2 reductions were recorded in 59% of the cities in Turkey (Fig. 7), the highest decreases were observed in Afyon (−291%), Ardahan (−222%), Kars (−203%), Denizli (−161%), Yozgat (−137%), Muş (−127%), Karaman (−126%), and Sinop (−114%) cities (Table 2). Noticeable increases occurred in Hakkari (+74%), Bursa (+72%), Tunceli (+71%), and Ordu (+69%) cities. Fig. 7 shows the average SO_2 concentrations between January–November in 2020 and 2015–2019 mean. We see a stronger change in April compared to the average concentration levels in 2020 (Table S5, Fig. S4).

- **Correlations between Air Quality and Mobility**

It is important to investigate the actual mobility of people in Turkey to capture the effect of COVID-19 on local air quality because there was no complete compliance with the government restrictions. We used six classes to analyze the relationship between mobility and PM_{10} concentration levels; Restaurant/Café, Grocery and Pharmacy, Park, Transit, Workplaces, and Residential. We calculated the Pearson's product-moment correlation coefficient for the concentration levels and mobility data in each category.

Table S5 shows the average mobility values of the six categories for Turkey and each city. The negative values represent the decrease in the percentage of mobility while the positive ones show the increase in the percentage of mobility with respect to baseline denoted by 0. NA values in the table mean that those cities have no information for the related category. Fig. S5 shows the average change in mobility for the whole country. Results show that the mobility in Restaurant/Café, Grocery and Pharmacy, Transit, Workplaces decreased in Turkey during the given time period while the mobility in both Parks and Residential increased as expected.

On the other hand, we can see that the highest decrease in the mobility at Restaurant/Café is in Hakkari city while the lowest one is in Muğla city. The main differences between these two cities are population and characteristics. Muğla city is a holiday town with a population of more than three times of Hakkari city. If we look at the mobility in Grocery and Pharmacy, Tunceli has the most reduction in mobility while Ağrı has the most increase.

The most decrease in the mobility at Parks is in Gümüşhane while the highest increase is in Muğla. The results for the Transit category shows that the highest decrease occurred in Karabük while the lowest was in the eastern city of Van. The mobility in workplaces for provinces shows that Istanbul has the highest decrease while the Hakkari has the lowest one. Lastly, Istanbul has the highest positive change in Residential mobility while Artvin has the highest decrease.

Fig. S6 shows that the Restaurant/Café mobility and the average concentration of PM_{10} are positively correlated ($r = 0.39$, $p < .001$). We see a similar trend for the average concentration and Grocery&Pharmacy mobility ($r = 0.32$, $p < .001$), Parks ($r = 0.18$, $p = .002$), Transit ($r = 0.43$, $p < .001$), and Workplaces ($r = 0.40$, $p < .001$). On the other hand, we detect a negative correlation between Residential and mobility ($r = -0.32$, $p < .001$), which is expected.

The results show that the strongest positive impact on average SO_2 concentration is Restaurant/Café mobility ($r = 0.32$, $p < .001$), Transit mobility ($r = 0.26$, $p < .001$), and Workplaces mobility ($r = 0.39$, $p < .001$) (Fig. S7). We observe a negative correlation between stay-at-home and average SO_2 concentration ($r = -0.16$, $p = .007$), which shows that the main source of SO_2 is related to traffic emissions. However, we need data on industrial activities for further investigation, because SO_2 is a common air pollutant to describe industry emissions.

4. Conclusion

This study investigated the effects of COVID-19 restrictions on PM_{10} and SO_2 concentrations across Turkey. All cities of Turkey (81) implemented the same lockdown measures. The state set the first mobility restrictions in March 2020; however, the rules have been updated weekly throughout the year. First, we analyzed the daily average concentrations of both pollutants between January and November of 2020, compared to the previous five years, 2015–2019 based on public air quality monitoring network data. We analyzed the correlation between mobility and air quality by obtained mobility data from Google.

The presented results in this study are critically important for future investigations of air quality and mortality rates. Several studies explored the impact of air quality on mortality rates all around the world (Buonanno et al., 2020; Coker et al., 2020; Giani et al., 2020; Holshue et al., 2020; Liang et al., 2020; Liu et al., 2020; Ogen 2020). Mortality rates by the city are not available yet in Turkey; however, we will be able to continue the next step when this information is available in 2021. As we know, this is the first study that investigates the effect of COVID-19 on ambient air quality across Turkey and the relationship with mobility. Also, 2020 provides a rare opportunity to experiment and analyze how human behavior can affect PM_{10} and SO_2 concentrations. The results can help policymakers to understand the impact of lockdown measures on air quality in different cities with different characteristics, which provides a comprehensive air quality picture of the region that can be used in future studies on air quality and infectious diseases.

Credit author statement

Nur H. Orak: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Ozancan Ozdemir: Methodology, Formal analysis, Visualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no actual or potential competing financial interests.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2021.111018.

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