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PM$_{2.5}$ and PM$_{10}$ during COVID-19 lockdown in Kuwait: Mixed effect of dust and meteorological covariates

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**Abstract**

This study investigated the impact of COVID-19 lockdown on particulate matter concentrations, specifically PM$_{2.5}$ and PM$_{10}$, in Kuwait. We studied the variations in PM$_{2.5}$ and PM$_{10}$ between the lockdown in 2020 with the corresponding periods of the years 2017–2019, and also investigated the differences in PM variations between the ‘curfew’ and ‘non curfew’ hours. We applied mixed-effect regression to investigate the factors that dictate PM variability (i.e., dust and meteorological covariates), and also processed satellite-based aerosol optical depth (AOD) to determine the spatial variability in aerosol loads. The results showed low PM$_{2.5}$ concentration during the lockdown (33 μg/m$^3$) compared to the corresponding previous three years (2017–2019); however, the PM$_{10}$ concentration (122.5 μg/m$^3$) increased relative to 2017 (116.6 μg/m$^3$), and 2019 (92.8 μg/m$^3$). After removing the ‘dust effects’, both PM$_{2.5}$ and PM$_{10}$ levels dropped by 18% and 31%, respectively. The mixed-effect regression model showed that high temperature and high wind speed were the main contributors to high PM$_{2.5}$ and PM$_{10}$, respectively, in addition to the dust haze and blowing dust. This study highlights that the reductions of anthropogenic source emissions are overwhelmed by dust events and adverse meteorology in arid regions, and that the lockdown did not reduce the high concentrations of PM in Kuwait.

1. Introduction

The first confirmed case of the coronavirus disease 2019 (COVID-19) was registered in Kuwait on 24 February 2020, about two months after its first detection in Wuhan, China. Reported cases started to increase exponentially, which prompted the government to declare a partial lockdown (referred to as ‘lockdown’ hereafter) beginning from 22 March until 10 May (50 days). Kuwait implemented gradual lockdown restrictions to help control the spread of SARS-CoV-2 (Gasana and Shehban, 2020; Alkhams et al., 2020), and all public and private transport, government and private sectors and non-essential industries were shut down during the ‘curfew’ hours of the lockdown. Private transport, although diminished significantly, was permitted only during the ‘non curfew’ hours. These strict measures resulted in low traffic volume and business activities (Alahmad et al., 2020). Noticeable improvements in visibility were observed during the lockdown days. However, it is unlikely that the lockdown affected the emissions of ‘natural’ dust, where it is normally emitted from land surfaces where land use is less than 30% (Ginoux et al., 2012), as is the case for Kuwait. The dust from the Mesopotamia region is primarily natural (Ginoux et al., 2012), and it is transported down the Arabian Gulf into Kuwait by the north-westerly Shamal, a dust-laden wind that blows from February to October (Ginoux et al., 2012; Middleton and Kappelle, 2020). Exposed loose soil dry surfaces accompanied by high temperatures and wind speed pose an increased risk for wind erosion.

Several studies, both at regional and international levels, have assessed the impact of COVID-19 lockdowns on changes in particulate matter concentrations, specifically coarse and fine particles, with aerodynamic diameters less than 10 μm (PM$_{10}$) and less than 2.5 μm (PM$_{2.5}$), respectively. For instance, compared with the lockdown period, the eastern province of Saudi Arabia and its capital (Riyadh) recorded lower PM$_{10}$ levels, by 27–70% (Anil and Alagha, 2021) and 91% (Aljahdali et al., 2021), respectively. Lower PM$_{10}$ concentrations were also recorded in nine provinces in Turkey (Sahin, 2020) and Tehran, Iran (Broomandi et al., 2020). Several other studies outside the region of the Arabian Peninsula have also reported a significant decline in PM$_{2.5}$ and PM$_{10}$; for instance, Almaty, Kazakhstan (Kerimray et al., 2020), Milan, Italy (Collivignarelli et al., 2020), Barcelona, Spain (Tobías et al., 2020).

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2020), Delhi, India (Mahato et al., 2020), western Europe (Menut et al., 2020), China (Shakoor et al., 2020), and the 50 most polluted cities in the world (Rodríguez-Ureña and Rodríguez-Ureña, 2020). Despite many studies reporting reductions in PM$_{2.5}$ and PM$_{10}$ levels during the lockdowns, some studies reported higher concentrations. For example, the PM$_{2.5}$ level in Baghdad, Iraq, increased by 34–56%, mainly due to dust events (Hashim et al., 2020), while it increased by 27% in five states in the USA due to anthropogenic sources (Shakoor et al., 2020). These contradictory results emphasized the need for further investigation of the effect of lockdowns on PM concentration changes.

Due to the region’s aridity, frequent dust events have been associated with higher concentrations of PM$_{2.5}$ and PM$_{10}$ in Kuwait (Al-Hemoud et al., 2018, Yuan et al., 2020). The frequent dust events resulted in high PM levels, both indoors (Yuan et al., 2020) and outdoors (Al-Hemoud et al., 2019). Source apportionment in Kuwait showed that dust contributed to 54% of the total PM$_{2.5}$ mass (Alolayyan et al., 2013). Aerosol optical depth (AOD) studies showed lower aerosol loads during the lockdown; both in the region, for example, in the United Arab Emirates (Alqasemi et al., 2020), and globally, for instance, in China (Fan et al., 2020), India (Pathakoti et al., 2020), and Italy (Jain et al., 2020). Meteorological factors were shown to have a considerable effect on PM and AOD (Guo et al., 2017); the high temperature and relative humidity can speed up the atmospheric chemical reactions and produce secondary PM (Wang et al., 2020).

Given that high exposure to PM$_{2.5}$ and PM$_{10}$ lead to detrimental health effects in terms of mortality and morbidity in Kuwait (Al-Hemoud et al., 2018; Al-Hemoud et al., 2019; 2018; Achilleos et al., 2019), it is crucial to know the effects of lockdown on air quality. We hypothesize that the lockdown has led to reductions in PM levels in Kuwait; however, the effect of dust and meteorological covariates remain vague. To our knowledge, no studies have examined the impact of COVID-19 lockdown on air quality in Kuwait. The present study aims to assess the effect of COVID-19 lockdown on air quality in Kuwait, particularly PM$_{2.5}$ and PM$_{10}$ levels, from 22 March to 10 May 2020 (50 days).

A set of analyses were conducted: (1) the comparison of PM$_{2.5}$ and PM$_{10}$ (before and after ‘dust effect’ control) between the 2020 lockdown and the corresponding periods of the years 2017–2019; (2) the comparison of PM$_{2.5}$ and PM$_{10}$ between the curfew and non curfew hours during the lockdown; (3) the assessment of the effect of dust and meteorological factors on PM$_{2.5}$ and PM$_{10}$; (4) the analysis of satellite-based AOD on spatiotemporal variability of aerosol loads during the lockdown.

2. Methods

2.1. Data processing and dust classification

Real-time hourly PM$_{2.5}$ concentrations were obtained from the USA Embassy meteorological station and the Kuwait Environment Public Authority (KEPA) stations (Fig. S1). The USA Embassy station monitors PM$_{2.5}$, and it is located in Bayan, an urban area in the center of Kuwait; hourly PM$_{2.5}$ data were available for the study period (2017–2020). KEPA has 15 monitoring stations that are scattered from the north to the south urban areas and monitor more than 16 pollutants, including six ‘criteria’ air pollutants (PM$_{2.5}$, PM$_{10}$, NO$_2$, SO$_2$, O$_3$, and CO). PM$_{2.5}$ and PM$_{10}$ data were processed in the following ways: First, the hourly concentrations were transformed into daily averages by selecting only the days with more than 75% non-missing values (N $\geq$ 18 out of 24 h) (Pascal et al., 2011). Second, only the values above the fifth percentile of the background concentration were selected (Lim et al., 2012); therefore, we kept only the hourly PM$_{2.5}$ (and PM$_{10}$) values above the minimum background concentration of 8.83 (and 10 $\mu$g/m$^3$). Third, to aggregate the daily data into an annual average, we applied the same rule as the first; that is, only the stations with less than 25% missing values (more than 275 out of 365 days) were selected (Pascal et al., 2011). The fourth condition was related to identifying outliers by transferring the series data into standard scores (i.e., Z scores) and removing any absolute z score larger than Z $\geq$ 4 [Faridi et al., 2018; Barrero et al., 2015]. PM$_{2.5}$/PM$_{10}$ ratios for all stations were checked and resulted within the range of 0.5–0.65, and limits that are considered acceptable in developing countries (USEPA 1996; Ostro, 2004). We compared PM$_{2.5}$ and PM$_{10}$ levels between the lockdown period (22 March–10 May 2020) and the corresponding periods of the years 2017–2019. We used the average of PM concentrations across all stations. We also compared PM$_{2.5}$ and PM$_{10}$ levels between the curfew and non curfew hours during the lockdown. The curfew hours within the lockdowns were from 5 pm to 4 am (22 March - 5 April), 5 pm to 6 am (6 April–23 April), and 4 pm to 8 am (24 April–24 May).

Dust and meteorological data were obtained from Kuwait’s official meteorological station at the meteorological department at Kuwait airport. The meteorological observatory station is located in the center of Kuwait and within 17 km from the USA Embassy station and 48 km from the furthest KEPA station. Six meteorological parameters were collected: temperature (Temp) (°C), relative humidity (RH) (%), precipitation (Prec) (mm), wind speed (WS) (m/s), predominant wind direction (WD) (Deg), and incoming longwave atmospheric radiation (AR) (W/m$^2$).

Aeolian dust was classified based on two factors: wind speed, and visibility. We adopted a local scale of dust classification based on wind speed and visibility and in-line with the terms defined by the Meteorology Department of the Directorate General of Civil Aviation of Kuwait. Accordingly, dust events were classified based on visibility and wind speed using the following three categories: (1) dust storms (DS): visibility ≤ 1000 m and WS ≥ 8 m/s; (2) rising or blowing dust (BLDS): visibility ≥ 1000 m and WS ≥ 8 m/s; (3) suspended or dust haze (DUHZ): visibility ≤ 5000 m and WS ≤ 8 m/s. The World Meteorological Organization (WMO) defines DS as an ensemble of particles lifted to great heights by strong and turbulent winds and reduced visibility at eye-level (1.8 m) to less than 1000 m (McRae and Piblado, 1987); however, when the visibility at eye-level is reduced but not to less than 1000 m, it is defined as BLDS, while DUHZ resides in the atmosphere from a previous DS (UNEP WMO 2016; WMO 2021). Hoffmann et al. (2008,h) classified DS based on visibility, WS, and PM$_{10}$ and stated that when the average WS is higher than 8 m/s, the average PM$_{10}$ exceeds the dusty air value of 50 $\mu$g/m$^3$. Common definitions of dust events are included in Supplementary Table S1. PM$_{2.5}$ and PM$_{10}$ levels were compared after controlling for the ‘dust effect’; that is, all days classified as DS, BLDS, or DUHZ were removed from the analysis (23 out of 50 days, 46%). In other words, PM comparisons were conducted twice, ‘before’ and ‘after’ removal of the dust days. Moreover, mixed-effect statistical analyses were conducted to estimate the effect of dust and meteorological covariates on the daily variations of PM$_{2.5}$ and PM$_{10}$.

2.2. Satellite AOD

Satellite-based AOD (1 km x 1 km) was compared among the 2020 lockdown and the corresponding periods of the years 2017–2019. The Multi-Angle Implementation of Atmospheric Correction (MAIAC) algorithm was used to process the AOD data (Chudnovsky et al., 2014; Lyapustin et al., 2018; Mawahish et al., 2019). Yearly averages MAIAC at 1km x 1km resolution are presented. AOD is a dimensionless number, and it reflects the number of aerosols present in the vertical profile of the atmosphere (Wang et al., 2020). It represents the amount of radiation eliminated by aerosolized matter (dust, haze, and aerosols). AOD has been widely used to estimate fine (PM$_{2.5}$) (Li et al., 2016; Huang et al., 2018; Lin et al., 2015) and coarse (PM$_{10}$) aerosol loads (Chudnovsky et al., 2020). Lower AOD values (below 0.1) indicate a clear blue sky, while higher values indicate visibility deterioration due to increased aerosol loads (Filonchyk and Yan, 2019; Ogren, 1995).

2.3. Statistical testing (non-parametric and mixed-effects)

Koldamgorov-Smirnov and Shapiro-Wilk tests of normality were statistically significant (p < 0.001), indicating that the PM$_{2.5}$ and PM$_{10}$ data
were not normally distributed. Because of data non-normality, two non-parametric tests were conducted: (1) Kruskal–Wallis one-way analysis of variance (ANOVA) was used to compare the PM$_{2.5}$ and PM$_{10}$ mean concentrations during the 2020 lockdown with the corresponding periods of the years 2017–2019; (2) the Wilcoxon matched-pairs signed-ranks test was used to determine the variations in PM$_{2.5}$ and PM$_{10}$ between the curfew and non-curfew hours during the lockdown. Independently from the lockdown period, to understand the effects of meteorological factors and dust events on PM concentrations in Kuwait, we fitted mixed-effects regression with the calendar year as the grouping variable to predict the PM$_{2.5}$ and PM$_{10}$ variations from a set of covariates (three dust event types and six meteorological parameters). The mixed-effects regression model helps estimates a wide variety of models with single or multivariate outcomes from numerous sampling distributions (e.g., normal, binomial, multinomial, and Poisson) (Heck et al., 2013). The model equation is represented by:

$$
Y_{ij} = \gamma_0 + \gamma_1 \text{Temp}_{ij} + \gamma_2 \text{RH}_{ij} + \gamma_3 \text{PrCp}_{ij} + \gamma_4 W.S_{ij} + \gamma_5 W.D_{ij} + \gamma_6 A.R_{ij} + \gamma_7 D.S_{ij} + \gamma_8 B.L.D_{ij} + \gamma_9 D.U.H.Z_{ij} + u_{ij} + e_{ij}
$$

where $Y_{ij}$ represents the estimated PM concentrations for the $i$th day and $j$th year; $\gamma_0$ is the overall intercept; $u_{ij}$ is the between-year variation in intercepts; $(\gamma_1, \gamma_2, \ldots, \gamma_9)$ is the intercept for each year; and $e_{ij}$ represents the variation in individual days within years. The same model was fitted separately for PM$_{2.5}$ and PM$_{10}$. Dust events were coded as dummy dichotomous variables (i.e., $1 = \text{present}, 0 = \text{not present}$), and the meteorological parameters as continuous variables. The three dust variables (DS, BLDs, and DUHZ) and the six meteorological variables (Temp, RH, Prcp, WS, WD, and AR) are the fixed covariates that estimate the size of the daily variations in PM levels; they are represented by $\gamma_k$ vector with $k \in$ (Gasana and Shehab, 2020; Broomandi et al., 2020). The $\gamma_k$ vector of coefficients from the model can be interpreted as changes in PM concentrations for each one-unit increase in a given $k^{th}$ covariate across all the years adjusted for the rest of the covariates. We selected an unstructured covariance matrix for repeated measures.

3. Results

3.1. Impact of lockdown on PM$_{2.5}$ and PM$_{10}$

The mean PM$_{2.5}$ concentration during the lockdown period in 2020 was 33 $\mu g/m^3$, showing a significant drop compared with the same period of the previous years (2017–2019) (Fig. 1 and Table 1). The PM$_{2.5}$ was reduced by 21% relative to 2019 (33 vs. 41.8 $\mu g/m^3$). The highest mean PM$_{2.5}$ level was recorded in 2018 (52.8 $\mu g/m^3$). Although the mean PM$_{10}$ concentration in 2020 (122.5 $\mu g/m^3$) was 15% lower than in 2018 (145.1 $\mu g/m^3$), it was higher than both 2017 and 2019 by 5% (116.6 $\mu g/m^3$) and 32% (92.8 $\mu g/m^3$), respectively (Fig. 2 and Table 2). The annual variations of PM$_{2.5}$ and PM$_{10}$ showed a nonlinear trend. Kruskal-Wallis one-way ANOVA showed that the changes of PM$_{2.5}$ and PM$_{10}$ levels were statistically significant from 2017 to 2020; ($\chi^2 = 17.55$, df = 3, $p \leq 0.001$) and ($\chi^2 = 24.69$, df = 3, $p \leq 0.001$), respectively. Both PM$_{2.5}$ and PM$_{10}$ concentrations were higher during the non curfew hours: 38.4 vs. 30.2 $\mu g/m^3$ and 149.2 vs. 109.9 $\mu g/m^3$, respectively. However, the Wilcoxon matched-pairs signed-ranks test showed that this difference was not statistically significant for PM$_{2.5}$ ($z = 0.825$, $\text{Sig.} = 0.409$), but it was statistically significant for PM$_{10}$ ($z = 2.302$, $p \leq 0.5$ (Table 3)). The significant variation in PM$_{10}$ between the curfew and non curfew hours is possibly due to the coarse particle emissions related to the special road pavement and asphaltling projects that took place across Kuwait urban areas during the lockdown.

3.2. Dust effect on PM$_{2.5}$ and PM$_{10}$

Both PM$_{2.5}$ and PM$_{10}$ concentrations were compared after removing the ‘dust effect’. The results showed that the PM$_{2.5}$ level was reduced by 18% in 2020 (27.0 vs. 33.0 $\mu g/m^3$) (Fig. 1 and Table 1). The mean difference between the ‘dust’ and ‘no-dust’ events was less prominent during the 2020 lockdown compared to the previous years (Fig. 1), although such years had a roughly similar number of ‘dust events’ (Table S2); this is attributed to the reductions of the major anthropogenic sources (i.e., automobile and industrial emissions). The total dust events for 2018 were the highest (37 days) at 4 DS, 16 BLDs, and 17 days DUHZ, followed by 2017 (25 days) and 2019 (24 days) (Fig. S2). Kruskal–Wallis one-way ANOVA showed that PM$_{2.5}$ levels for the four years were similar after removing the ‘dust effect’ ($\chi^2 = 4.93$, df = 3, $\text{Sig.} = 0.177$). The PM$_{2.5}$ levels were similar between the curfew and non-curfew hours after controlling for the ‘dust effect’ (27.2 vs. 26.8 $\mu g/m^3$), as evidenced by the Wilcoxon matched-pairs signed-ranks test ($z = 0.666$, $\text{Sig.} = 0.431$) (Table 3), so to confirm that the major source of PM$_{2.5}$ during the lockdown was mainly anthropogenic. Although no lockdowns were imposed for the years 2017–2019 the PM$_{2.5}$ levels were also similar between the hours corresponding to the curfew and non-curfew hours for the years 2017–2019 after controlling for the ‘dust effect’ (Table S3). The PM$_{10}$ level was reduced by 31% in 2020 after removal of the ‘dust effect’ (84.1 vs. 122.5 $\mu g/m^3$) (Fig. 2 and Table 2), and Kruskal-Wallis one-way ANOVA showed that the PM$_{10}$ levels were statistically significant different from 2017 to 2020 ($\chi^2 = 31.75$, df = 3, $p \leq 0.001$). The PM$_{10}$ levels were relatively equal between the curfew and non-curfew after controlling for the ‘dust effect’ (83.3 vs. 82.5 $\mu g/m^3$); this was confirmed by the Wilcoxon matched-pairs signed-ranks test ($z = 0.624$, $\text{Sig.} = 0.490$).

3.3. AOD (2017–2020)

AOD data analysis highlighted the substantial reductions of aerosol loads over Kuwait and the surrounding region during the lockdown period in 2020 relative to the corresponding periods in 2017 and 2018 (Fig. S3). The urban areas of Kuwait showed lower AOD during the 2020 lockdown compared to the three previous years (Fig. 3), except in specific locations where special construction projects related to road

### Table 1
PM$_{2.5}$ mass concentrations ($\mu g/m^3$) during the lockdown (22 March–10 May 2020) and the corresponding periods of the years 2017–2019: Before and after removing the ‘dust effect’.

| Year     | Mean | Median | Minimum | Maximum | SD   | Kruskal–Wallis$^*$ |
|----------|------|--------|---------|---------|------|-------------------|
| Before removal of ‘dust effect’ |      |        |         |         |      |                   |
| 2017     | 49.6 | 41.0   | 12.3    | 302.6   | 48.3 |                   |
| 2018     | 52.8 | 44.8   | 3.3     | 179.4   | 39.2 | $\chi^2 = 17.55$, df = 3, $p \leq 0.001$ |
| 2019     | 41.8 | 35.7   | 18.9    | 211.6   | 29.7 |                   |
| 2020     | 33.0 | 27.8   | 12.3    | 199.7   | 27.7 | $\text{Sig.} = 0.001$** |
| After removal of ‘dust effect’ |      |        |         |         |      |                   |
| 2017     | 33.5 | 29.7   | 12.3    | 68.5    | 15.4 |                   |
| 2018     | 33.3 | 31.3   | 3.3     | 63.3    | 16.8 | $\chi^2 = 4.93$, df = 3, $p \leq 0.001$ |
| 2019     | 31.6 | 30.8   | 19.5    | 50.1    | 9.1  |                   |
| 2020     | 27.0 | 24.1   | 12.3    | 53.6    | 9.9  | $\text{Sig.} = 0.177$ |

$^*$ Kruskal–Wallis ANOVA; ** $p$-value $\leq 0.001$.  

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asphalting were carried out. The non-urban areas that go from the west (above Al-Mutla) to North of Kuwait Bay and Bubiyan Island had higher AOD values (> 0.6) (Fig. S4). The evaporate-saline deposits from tidal mudflats (Sabkhas) characterize large areas of Bubiyan Island and contribute greatly to the dust haze (Fig. S5). Haze ‘dusty air’ was classified by Hoffman when hourly mean PM10 concentrations are higher than 50 μg/m³ (Hoffmann et al., 2008a,b).

3.4. Mixed-effects

Estimating the effect of all covariates (three dusty types and six meteorological parameters) showed that mainly four covariates (two dust types and two meteorological parameters) significantly influence PM variations. Across all the years, PM2.5 increased by 3.2 μg/m³ (CI: 1.91–4.49) when the temperature is raised by 1 °C; similarly, the PM2.5 increased by 0.37 μg/m³ (CI: 0.15–0.59) when the relative humidity is increased by 1% (Table 4). The occurrences of blowing dust and dust haze led to an increase in PM2.5 by 9.3 μg/m³ (CI: 3.24–15.36) and 18.47 μg/m³ (CI: 12.70–24.23), respectively. Wind speed, blowing dust, and dust haze were significant predictors for PM10 (Table 5). Across all years, PM10 increased by 9.4 μg/m³ (CI: 2.86–16.01) when the wind speed is increased by 1 m/s. The occurrences of blowing dust and dust haze led to an increase of PM10 by 50.8 μg/m³ (CI: 26.58–75.01) and 62.1 μg/m³ (CI: 40.70–83.51), respectively.
Table 2
PM$_{10}$ mass concentrations ($\mu$g/m$^3$) during the lockdown (22 March–10 May 2020) and the corresponding periods of the years 2017–2019: Before and after removing the ‘dust effect’.

| Year     | Mean  | Median | Minimum | Maximum | SD   | Kruskal–Wallis* |
|----------|-------|--------|---------|---------|------|-----------------|
| Before removal of ‘dust effect’ |       |        |         |         |      |                 |
| 2017     | 116.6 | 103.9  | 43.2    | 380.7   | 64.7 | $\chi^2 = 24.69$, df = 3, sig. = 0.001* |
| 2018     | 145.1 | 113.5  | 63.9    | 457.5   | 88.2 |                 |
| 2019     | 92.8  | 65.6   | 40.8    | 344.6   | 73.2 |                 |
| 2020     | 122.5 | 93.1   | 46.4    | 606.7   | 105.1|                 |
| After removal of ‘dust effect’ |       |        |         |         |      |                 |
| 2017     | 96.5  | 83.7   | 43.2    | 201.8   | 40.8 | $\chi^2 = 31.75$, df = 3, sig. = 0.000** |
| 2018     | 107.2 | 99.4   | 67.9    | 180.9   | 33.8 |                 |
| 2019     | 61.0  | 57.6   | 40.8    | 89.6    | 12.2 |                 |
| 2020     | 84.1  | 75.3   | 46.3    | 140.7   | 29.1 |                 |

* Kruskal–Wallis ANOVA; ** p-value < 0.001.

Table 3
PM$_{2.5}$ and PM$_{10}$ mass concentrations ($\mu$g/m$^3$) for the curfew and non curfew during the lockdown (22 March–10 May 2020): Before and after removing ‘dust effect’.

| Dust Effect | Period | Mean  | Median | Minimum | Maximum | SD   | Wilcoxon* |
|-------------|--------|-------|--------|---------|---------|------|-----------|
| PM$_{2.5}$  | Before | 30.2  | 26.6   | 8.6     | 93.7    | 14.7 | z = 0.825, sig. = 0.409 |
|            | Non curfew | 38.4  | 27.3   | 9.5     | 404.1   | 57.1 | z = 0.666, sig. = 0.431 |
|            | Curfew  | 27.2  | 25.8   | 8.6     | 58.7    | 10.6 |                   |
|            | After   | 26.8  | 23.0   | 9.5     | 47.5    | 10.8 |                   |
|            | Non curfew | 46.9  | 40.1   | 44.7    | 447.3   | 81.4 |                   |
|            | Curfew  | 108.9 | 90.1   | 44.7    | 447.3   | 81.4 |                   |
| PM$_{10}$  | Before  | 149.2 | 95.5   | 41.4    | 1278.0  | 209.4| z = 2.302, sig. = 0.021** |
|            | Non curfew | 149.2 | 95.5   | 41.4    | 1278.0  | 209.4|                   |
|            | Curfew  | 83.3  | 70.9   | 44.7    | 150.3   | 32.4 |                   |
|            | After   | 82.5  | 73.6   | 41.4    | 155.8   | 30.7 |                   |

* Wilcoxon matched-pairs signed-ranks test; ** p-value ≤ 0.05.

Table 4
Estimates of fixed effects for PM$_{2.5}$ mass concentrations ($\mu$g/m$^3$).

| 95% CI | Parameter | Estimate | Sig. | lower | upper |
|--------|-----------|----------|------|-------|-------|
|        | Temperature | 3.20     | .000 | 1.91  | 4.49  |
| Meteorological | RH | 0.37     | .001* | 0.15  | 0.59  |
|        | WS | 1.56     | .104 | -.33  | 3.45  |
|        | WD | 0.00     | .428 | -.01  | 0.02  |
|        | Prcp | 0.59    | .543 | 1.35  | 2.54  |
|        | AR | -0.00    | .707 | 0.01  | 0.02  |
| Dust | DS | -11.03   | .285 | -31.54| 9.47  |
|        | BLD | 9.30     | .003 | 3.24  | 15.36 |
|        | DUHZ | 18.47   | .000* | 12.70 | 24.23 |

* p-value ≤0.01
* Temperature
* RH: Relative Humidity
* WS: Wind Speed
* WD: Wind Direction
* Prcp: Precipitation
* AR: Atmospheric Radiation
* DS: Dust Storm
* BLD: Blowing Dust
* DUHZ: Dust Haze.
4. Discussion

This study was the first that examined the effect of COVID-19 lockdown on air quality, particularly PM$_{2.5}$ and PM$_{10}$, in Kuwait. We compared the PM$_{2.5}$ and PM$_{10}$ levels (before and after removal of ‘dust effect’) between the lockdown (2020) and the corresponding periods of the years 2017–2019. We analyzed satellite-based AOD so to investigate the spatial variability of aerosol loads. We also used a mixed-effects regression to determine the factors (dust types and meteorological parameters) that estimate PM variability.

The lockdown in 2020 lowered the PM$_{2.5}$ mean concentrations in urban areas by 21% relative to 2019. However, the PM$_{10}$ level increased by 32%. Also, the PM$_{2.5}$ levels in 2020 were lower than in 2017 and 2018. It is apparent that PM$_{2.5}$ has been reducing gradually since 2017.
Reduced emissions from anthropogenic sources (e.g., traffic, industrial operations, and petrol stations) may have contributed to the reductions of PM$_{2.5}$. The background concentrations of fine particulate pollution (PM$_{2.5}$) in Kuwait are quite large. Sources’ apportionment of fine particles (PM$_{2.5}$) in Kuwait showed that 11% and 12% were attributed to the traffic and petrochemical industry, respectively (Alolayan et al., 2013), while regional pollution accounted for 43% (Alahmad et al., 2021). Some fractions of PM$_{2.5}$ reductions during lockdowns might have been caused by low secondary chemical reactions (sulfates, nitrates, and secondary VOCs) (Kroll et al., 2020). However, the response of PM$_{2.5}$ to lockdown-induced emissions is not straightforward and depends on complex chemical reactions between precursors and hydroxyl radicals (OH) and peroxy radical intermediates (HO$_2$ and RO$_2$) (Kroll et al., 2020). The increase of PM$_{10}$ in urban areas during the lockdown is to be attributed to both natural dust and anthropogenic sources. Similar findings were recorded in other countries; for instance, dust events were attributed to an increase of 34–56% in PM$_{10}$ levels in Iraq (Hashim et al., 2020), and anthropogenic sources were attributed to an increase of 27% in PM$_{10}$ levels in the USA (Shakoor et al., 2020) during lockdowns, compared to pre-lockdowns. A strong relationship was determined between high PM$_{10}$ levels and dust events in Kuwait (Al-Hemoud et al., 2018). Road asphaltling, street scraping and pavement mixing operations continued during the lockdown, and might have attributed considerably to PM$_{10}$ levels.

No significant differences in PM$_{2.5}$ were detected between the curfew and non curfew hours during the lockdown even after controlling for the ‘dust effect’, and indicate that the major sources of PM$_{2.5}$ during the lockdown were mainly of anthropogenic type (mobile sources of emission and power plant emissions). Another explanation of the similarity in PM$_{2.5}$ between the curfew and non curfew hours might be due to pollution attenuation and saturation decay of PM$_{2.5}$ ascribed to lower impacts from local and regional pollution sources. During the non curfew hours, vehicle traffic was reduced considerably, and activities of major industrial operations slowed down, and consequently, the pollution ‘carry-over effect’ toward the curfew hours was marginal. Yet, this conclusion must be interpreted with caution as there is an inherent difference between diurnal and nocturnal variations in the boundary layer and mixing height (Al-Hemoud et al., 2019). The statistically significant (and insignificant) differences between the curfew and non curfew hours in PM$_{10}$ before and after the removal of the ‘dust effect’ indicate the substantial contribution of natural dust emission to coarse particles in the urban areas. The PM$_{2.5}$ and PM$_{10}$ levels were roughly similar between the hours corresponding to the curfew and non curfew for the years 2017–2019 after controlling for the ‘dust effect’ (Table S3) and provides further evidence of the sizeable contribution of background dust effect on PM levels in Kuwait.

The mixed-effects model showed that high temperature and high wind speed were the main drivers for blowing dust (BLDS), and as a result, aerosols can be suspended as dust haze (DUHZ) for most of the days. High wind speed can lift large quantities of particles into the air (BLDS), where they can be transported from their source and become suspended for days (DUHZ) (Al-Hemoud et al., 2020). DUHZ was associated with the highest increase in PM$_{2.5}$ and PM$_{10}$. The high temperature in Kuwait causes intensive surface heating (Alahmad et al., 2020) by the sun and breakdown of nocturnal temperature gradients that result in soil loosening and ejection of air-laden fine particles (PM$_{2.5}$). High wind speed causes surface bombardment of particles, wind shear stress, and turbulent eddies, causing detachment and short-term suspension of coarse particles (PM$_{10}$). Kuwait recorded the highest temperature and wind speed in the region (vs. Iraq, Saudi Arabia, Iran, Syria) in the years 2001–2017 (Li et al., 2020). Both wind speed and temperature have a large role in soil erosion and aerosol emission (UNEP WMO 2016; Shi et al., 2004).

AOD values in 2020 were below 0.4 in urban areas, where all the ground monitoring stations are located; an indication of lower aerosol loads during the lockdown. Nevertheless, all AOD values in the urban areas from 2017 to 2019 were higher (0.4–0.6). The highest aerosol load was recorded in 2018, similarly it had the highest number of dust events. Toward the end of 2018, Kuwait had severe flash floods from the heaviest rain ever recorded since 1962 (271.5 mm in November and December). As a result, wet deposition of suspended particles and high surface moisture lowered the 2019 AOD tremendously. During the lockdown, there appears to be a distinct spatial pattern of aerosols; the highest AOD values were located in Bubiyan Island and along the coastlines. The high AOD load to the north of Kuwait Bay above Al-Mutla was mainly attributed to natural dust. This vast area encompasses topographical cliffs, sand dunes, and scarce vegetation cover. The open topography includes three large desert areas: Al-Suba‘a, Al-Butanah/Al-Arafajiah, and Khur Al-Subiya‘Al-Sabriya. The construction of roads and interchanges for access to the ‘future Al-Mutla city’ had also contributed to the intense AOD loads. The spatial trend of AOD loads was shown to be higher for Kuwait relative to surrounding countries (Li et al., 2020), with maximum AOD recorded in the spring (Kokkalis et al., 2018). The annual dust fallout in Kuwait Bay was estimated at 283,172 t (Neelamani and Al-Dousari, 2016). From fine to very fine sand fractions (63–250 μm) and silt (≤ 63 μm) compromise 56% and 37% of dust deposits (Al-Awadhi and AlShuaibi, 2013), and clay (≤ 3 μm) constitutes most of the dust in the coastal areas (Al-Dousari et al., 2017). Soils with fine particle size are most erodible, especially with very fine sand and silt (Borselli et al., 2012; Le Bissonnais, 2016). The intensity of aeolian activity (dust emission) in Bubiyan Island is remarkable, and it is enhanced by the presence of ‘Sabkhas’ and sediments supplied from the wide intertidal zone (Al-Dousari and Al-Awadhi, 2012). The island is situated within shallow waters that carry an active broad wash plain of ‘Shat Al-Arab’ in northern Iraq. The large quantities of mud-size particles (silt and clay) act as favorable loads for high wind speed. Fluvial and aeolian erosion in the Wadis (dry flash-waterbeds) to the west of Bubiyan Island contributed to barren grounds and became the main source of sediment retention (particle lifting by wind erosion). The continuous disturbance of the soil surface from vehicles, through the use of various unstructured tracks in the desert increased soil erodibility, which in turn led to an increase in dust emissions. As described above and shown in the analysis of the data presented, Kuwait experiences aerosols from both natural and anthropogenic sources, and from the local and transboundary origin.

There are some limitations to this study. First, we were unable to assess to what extent the lockdown had suppressed the regional background pollution, and to what extent this had affected the reductions in PM$_{2.5}$ in Kuwait. Gaseous pollutants that are heavily linked to anthropogenic sources, such as SO$_2$, NO$_2$ and O$_3$, were not examined due to lack of data. Therefore, readers must be cautioned as it is hard to disentangle reductions in natural and anthropogenic sources of pollution during the lockdown period using only mass measurements of particulate matter of different size fractions. Second, we have not examined the impact of the transboundary dust emission on the concentrations of PM$_{10}$. It is imperative to examine source apportionment using specified PM data to account for local and regional pollution. This data was not available due to logistical restrictions of the lockdown. Third, AOD above areas with high surface reflectance (i.e., deserts) is challenging because of the small upwelling radiance due to scattering by atmospheric particles. Finally, in estimating the effects of meteorological factors on PM concentrations we assumed linearity in the functional forms of these variables. This may not provide the best fit; however, it provides better interpretability of the coefficients compared to the generalized additive models.

5. Conclusion

We investigated the effect of the COVID-19 lockdown on air quality in Kuwait. We generated interesting results in terms of parsing out the difference between lockdown-associated PM reductions and other reductions that had to do with ‘dust events’ that are unlikely to be related to the lockdown at all. We compared the PM$_{2.5}$ and PM$_{10}$ levels.
during the 2020 lockdown to the corresponding periods of the years 2017–2019. Under normal conditions (before removal of the ‘dust effect’), the lockdown was associated with a 21% drop in PM$_{2.5}$ and a 32% increase in PM$_{10}$ compared to 2019. The increase in mean PM$_{10}$ level relative to 2019 is unsurprising because it is a direct consequence of the dust effect and meteorological variability. Removal of the ‘dust effect’ reduced the PM$_{2.5}$ and PM$_{10}$ by 18% and 31%, respectively. The mix-effect statistics incorporated all dust events and meteorological parameters into the model and the results showed that high temperature and high wind speed contribute significantly to PM$_{2.5}$ and PM$_{10}$ respectively. Blowing dust and dust haze also have a significant contribution to PM levels. Low aerosol loads were observed during the lockdown compared to the previous three years, however high aerosol loads were always present around Bubiyan Island and to the north of Kuwait Bay. COVID-19 lockdown provided an unprecedented opportunity to better understand air pollution in Kuwait. The extents of PM variations are dictated not only by anthropogenic source emissions but also by dust meteorological covariates. Overlooking this complex relationship undermines our full understanding of the high PM levels in Kuwait.

Ethics approval and consent to participate

Not Applicable.

Consent for publication

All authors agreed to publish the manuscript.

Authors’ contributions

AHA analyzed the data and wrote the manuscript. AAK performed the mix-effect using SPSS. HAD supplied the meteorological data and interpreted output. JLD supplied and interpreted the AOD maps. BA revised the manuscript. PK approved the research methodology.

Declaration of Competing Interest

The authors declare that they have no competing interests.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.envsci.2021.100215.

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