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Effects of the COVID-19 lockdown and recovery on People's mobility and air quality in the United Arab Emirates using satellite and ground observations

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A R T I C L E I N F O

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A B S T R A C T

The stringent COVID-19 lockdown measures in 2020 significantly impacted people's mobility and air quality worldwide. This study presents an assessment of the impacts of the lockdown and the subsequent reopening on air quality and people's mobility in the United Arab Emirates (UAE). Google's community mobility reports and UAE's government lockdown measures were used to assess the changes in the mobility patterns. Time-series and statistical analyses of various air pollutants levels (NO_2, O_3, SO_2, PM_{10}, and aerosol optical depth-AOD) obtained from satellite images and ground monitoring stations were used to assess air quality. The levels of pollutants during the initial lockdown (March to June 2020) and the subsequent gradual reopening in 2020 and 2021 were compared with their average levels during 2015–2019. During the lockdown, people's mobility in the workplace, parks, shops and pharmacies, transit stations, and retail and recreation sectors decreased by about 34%–79%. However, the mobility in the residential sector increased by up to 29%. The satellite-based data indicated significant reductions in NO_2 (up to 22%), SO_2 (up to 17%), and AOD (up to 40%) with small changes in O_3 (up to 5%) during the lockdown. Similarly, data from the ground monitoring stations showed significant reductions in

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NO_2 (49%– 57%) and PM_{10} (19%– 64%); however, the SO_2 and O_3 levels showed inconsistent trends. The ground and satellite-based air quality levels were positively correlated for NO_2, PM_{10}, and AOD. The data also demonstrated significant correlations between the mobility and NO_2 and AOD levels during the lockdown and recovery periods. The study documents the impacts of the lockdown on people's mobility and air quality and provides useful data and analyses for researchers, planners, and policymakers relevant to managing risk, mobility, and air quality.

1. Introduction

According to the World Health Organization (WHO), around 91% of the world's population lives in areas where air quality levels surpass WHO limits (WHO, 2021). Burning fossil fuels for transportation, manufacturing, and power generation is the main contributor

Table 1
Reductions in air pollution due to COVID-19 lockdown reported in selected studies.

Study Area	Study Period	Pollutants Considered	Key Observations	Reference
United Kingdom	100 days post-lockdown compared with the same period during the previous 7 years	NO_2, SO_2, O_3, NO, and $PM_{2.5}$	- NO_2 level decreased by 39%–42% - SO_2 levels more than doubled - O_3 levels increased by ~ 10% - NO levels declined by ~ 55% from 2019 to 61% from the 7-year average - PM2.5 levels decreased by ~ 23% from 2019 and ~ 18% from the 7-year average	Higham et al. (2021)
Florida, USA	Mid-February to mid-April 2015 through 2020	NO_2, CO, O_3, SO_2, and $PM_{2.5}$	- NO_2 and CO reduced by ~ 25% due to restrictions in vehicular emissions - O_3 decreased by ~ 12.4% - SO_2 exhibited spatial variations with a decrease in the range ~ 15.4%–87.2% - $PM_{2.5}$ exhibited no statistically significant difference in most cities	El-sayed et al. (2021)
Spain	March 2nd to April 12th' 2020 compared to March 4th to April 14th, 2019	CO, SO_2, PM_{10}, NO_2, and O_3	- COVID-19 lockdown did not considerably improve air quality - While CO, SO_2, PM_{10}, and NO_2 improved to some extent in some cities, O_3 levels were found to be increasing	Briz-Redón et al. (2021)
Nigeria	January to April 2020 compared to 2005 to 2019	NO_2, SO_2, and O_3	- NO_2 level decreased by ~1.1%−21.8% in the city of Port Harcourt, and slightly increased by ~ 0.3% and 12% in Lagos and Kaduna cities. - While an increase of ~ 54% and 10% in SO_2 levels were observed in Lagos and Kaduna, a decrease by ~ 37% was realized in Port Harcourt - Elevated levels of O_3 were noticed during the COVID-19 lockdown	Fuwape et al. (2021)
India	1 March to May 31, 2020 and 1 June to August 31, 2020	$PM_{2.5}$	- $PM_{2.5}$ decreased dramatically in all megacities up to ~ 26%–62% - Peak hour $PM_{2.5}$ levels declined by ~ 21%–63% during lockdown	Ravindra et al. (2021)
Selection of Cities Worldwide	January to April 2020 compared to the same period during 2016–2019	Air quality index (AQI)	- AQI declined by ~ 8% in Tehran, ~ 22% in Wuhan, ~ 21% in Paris, and ~ 2% in Rome	Yazdani et al. (2021)
Ostrava, Czech Republic	February to June 2020 compared to the same period during 2020.	NO_x and PM_{10}	- NO_x levels decreased by ~ 4.1–5.7% due to the lower traffic intensity during the lockdown - While a decrease of ~ 4.7% was observed in PM_{10} levels in traffic monitoring station, there was no observed decrease in PM_{10} at the rural monitoring station	Bitta et al. (2021)
Ten Cities, China	January 1, 2020 to February 12, 2020	$PM_{2.5}$	- Reduction in PM2.5 levels up to 20% - PM2.5 levels in Beijing, Shanghai, Guangzhou, and Wuhan decreased by 9.23, 6.37, 5.35, and 30.79 μg/m^3, respectively. - The reduction in PM2.5 was attributed to the decrease in anthropogenic emissions (i.e., transportation and industrial activities).	Wang et al. (2020)

to air pollution in urban centers (Borck, 2019; Grondys, 2019; Lelieveld et al., 2015). The use of fossil fuels in the transportation sector is generally recognized as a significant and increasing source of air pollution in urban areas (Colvile et al., 2001; Sicard et al., 2020). In the United Arab Emirates (UAE), a major oil-producing country, most people use personal vehicles rather than public transportation. In a 2019 survey, 22% of road users relied on public transportation and 74% relied on personal vehicles (Sethi, 2020). Air pollution from transportation and other sources has been linked to various health concerns such as respiratory and cardiovascular diseases (Das et al., 2021; Faustini et al., 2014). For instance, long-term exposure to nitrogen dioxide (NO_2) has been associated with heart and cardiovascular diseases, hypertension, diabetes, and increased risk of asthma and poor lung function for middle-aged people (Bowatte et al., 2017; Gan et al., 2012; Shin et al., 2020). Liang et al. (2014) associated ambient concentrations of particulate matter (PM_{10}) with an aerodynamic diameter of 2.5 μm or less ($PM_{2.5}$) with human influenza cases in Beijing.

Monitoring of air quality has become an important activity for public health and environmental protection. In addition to ground monitoring stations, satellites are increasingly being used for monitoring air quality and tracking air pollution sources. The increasing availability of remotely sensed data obtained using advanced sensors with high resolutions made satellite-based data highly useful for monitoring air pollutants and physical conditions of the Earth's surface (Boudriki Semlali and Amrani, 2021; Semlali and Amrani, 2020; Semlali et al., 2021; Semlali and El Amrani, 2021; Weigand et al., 2019). Moreover, metrological and satellite-based derivatives are incorporated in various studies to elucidate the spatiotemporal patterns of air pollutants, biophysical parameters, and the associated respiratory diseases (Alvarez-Mendoza et al., 2020; Chang et al., 2019; Davila Cordova et al., 2020; de Souza, 2019; Sun et al., 2020; Yitshak-Sade et al., 2018).

The outbreak of the COVID-19, which was first reported in late December 2019 in Wuhan, China, escalated into one of the largest health crises in the 21st Century, posing severe risks to all nations (Del Buono et al., 2020; Yu et al., 2020). The wide and rapid spread of the disease and its severe effects led the WHO to declare COVID-19 as a pandemic on March 11, 2020 (Sohrabi et al., 2020). The pandemic triggered global economic and social disruptions and overwhelmed healthcare and education systems in many countries (World Health Organization, 2020). Various drastic measures were adopted worldwide to control and mitigate the rapid dispersion of the virus and reduce its mortality rate by promoting social distancing, banning private and public gatherings, closing schools, places of worships and workplaces, restricting private and public transportation, enforcing stringent quarantine guidelines, imposing nation-wide curfews and even locking down cities (Bashir et al., 2020; Sikarwar and Rani, 2020). Accordingly, the worldwide social and economic activities were disrupted and limited to the essentials. In particular, the transportation sector was severely affected as curfews were imposed because educational institutions, public and private sectors, adopted remote work systems. As a result, people's mobility dramatically changed during the first few months of the pandemic as most people stayed home during business hours. In addition, researchers started to report improvements in air quality based on data obtained from satellite images and ground air quality monitoring stations (Bherwani et al., 2020; Chen et al., 2020; Gautam, 2020; Li et al., 2020; Menut et al., 2020; Muhammad et al., 2020; Rodríguez-Urrego and Rodríguez-Urrego, 2020; Zambrano-Monserrate et al., 2020; Zheng et al., 2020). A summary of selected studies that examined the impact of the COVID-19 lockdown on various air quality parameters, including nitrogen dioxide (NO_2), ozone (O_3), sulfur dioxides (SO_2) particulate matter ($PM_{2.5}$ and PM_{10}), and carbon monoxide (CO) is presented in Table 1. Such improvements in air quality were directly linked to the reductions in traffic and industrial activities (Venter et al., 2021; Fu et al., 2020; Liu et al., 2020).

El-Kenawy et al. (2021) assessed the changes in NO_2, CO, CH_4, SO_2, aerosols, and AOD during the 2020 COVID-19 lockdown (March to June 2020) in 21 metropolitan cities covering 14 countries across the Middle East using Sentinel-5 satellite data. Considerable reductions were observed in SO_2, NO_2, and CO levels, mainly in small cities and, to a lesser extent in megacities. Other researchers assessed the impact of the COVID-19 lockdown on air quality in the Middle East, including Saudi Arabia (Aljahdali et al., 2021; Anil and Alagha, 2020; Morsy et al., 2021), Kuwait (Al-Hemoud et al., 2021), Iraq (Hashim et al., 2021a; 2021b), Iran (Aghashariatmadari, 2021), and the UAE (Kaied et al., 2021; Shanableh et al., 2022; Teixidó et al., 2021). However, the available regional studies focused on the early stages of the pandemic and did not adequately represent the reopening phase nor present comprehensive and quantitative analyses of the changes in various air pollutants and mobility patterns. In this study, which is focused on the UAE, we assessed the impact of COVID-19 initial lockdown (March to June 2020) and subsequent reopening on people's mobility patterns across different mobility sectors in the UAE. We also assessed the spatial and temporal variations of various air pollutants (NO_2, SO_2, O_3aerosol optical depth, AOD, and PM_{10}) using satellite data (see Table 2) and ground-based observations. The current study documents the impact of COVID-19 lockdown and subsequent reopening on mobility and air quality in the UAE, presents a comparison of the impact of the lockdown on air quality as reflected by satellite data and ground-based observations and correlates the people's mobility patterns with the observed changes in air quality during lockdown and subsequent recovery.

Table 2
Description of the satellite dataset used in this study.

Variable	Source of Data	Spatial Resolution	Temporal Resolution	Reference
Aerosols Optical Depth (AOD)	MODIS-Terra	1°	daily	Levy et al. (2015)
NO_2 Total Column	OMI	0.25°	daily	Lamsal et al. (2021)
	TROPOMI Sentinel-5p	0.01°	daily	ESA (2021)
O_3 daytime	AIRS	1°	daily	Airs and Teixeira (2013)
SO_2 Concentration	MERRA-2	0.5 × 0.625°	daily	Global Modeling and Assimilation Office (2015)

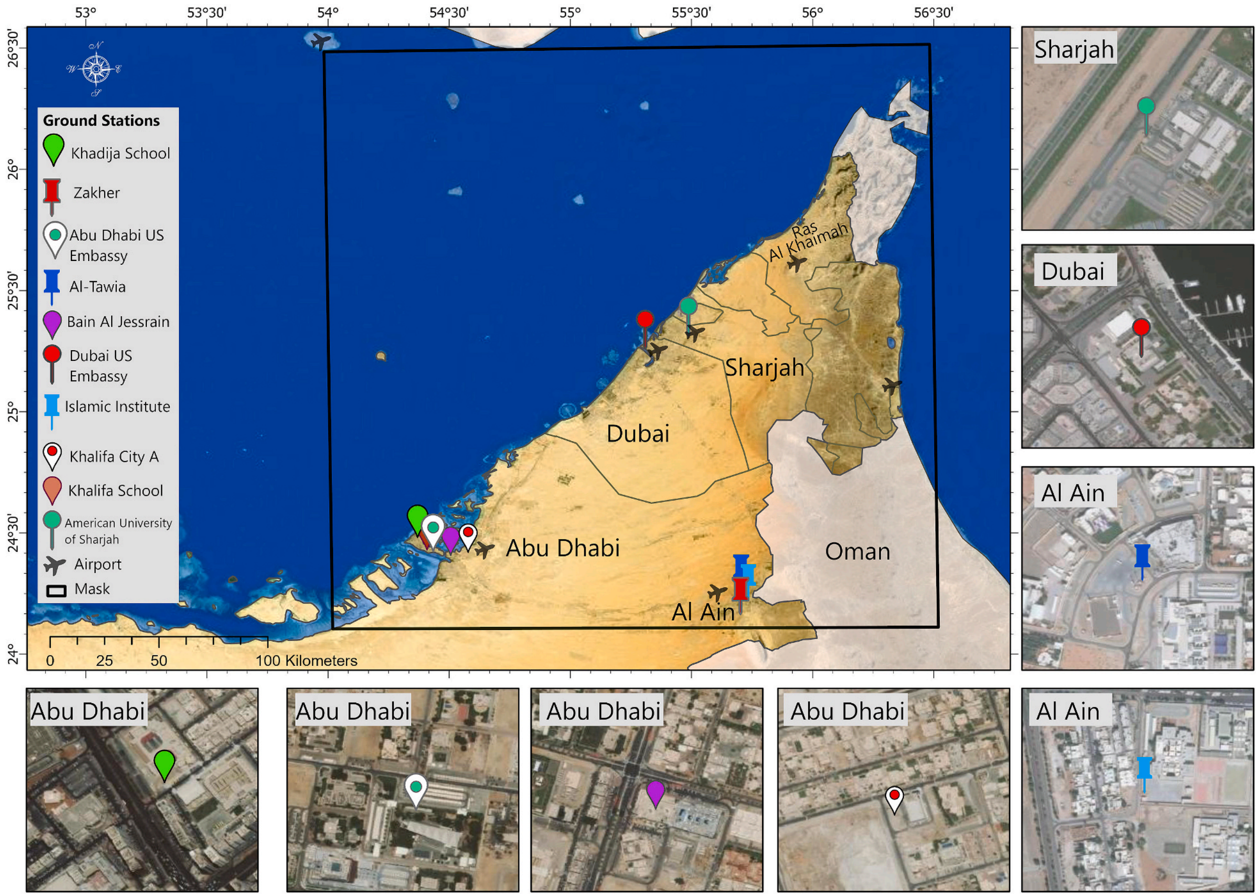

Fig. 1. Location of the study area and the distribution of the nine air quality ground monitoring stations.

2. Materials and methods

2.1. Study area

The study area covers the major cities in UAE, including Abu Dhabi (1.5 M people), Dubai (3.3 M), Sharjah (1.3 M), and Al-Ain (0.8 M). The mean annual temperature of the study area ranges from 18 °C to 37 °C, with summer temperatures reaching as high as 50 °C. The mean relative humidity varies from 52% to 69% and reaches as high as 80%. Rainfall is scarce and infrequent and occurs from December to March ranging between 80 mm and 140 mm/year. The location of the UAE and its major cities is shown in Fig. 1. Fig. 1 also shows the locations of the nine-ground air quality monitoring stations used in the study, which are positioned in various urban and suburban areas of the country.

2.2. Methods

The methodological framework of this study is summarized in Fig. 2. First, time-series mobility and air pollution data were generated from various sources and preprocessed. Second, the lockdown measures undertaken by the UAE's authorities to contain the COVID-19 outbreak and the subsequent relaxation of such measures were identified and correlated with the Oxford's stringency index (SI). Third, the SI was correlated with the mobility trends observed in the various population mobility sectors, including retail and recreation, grocery and pharmacy, parks transit stations, workplace, and residential. Moreover, time-series analyses of air pollutants levels, including NO_2, SO_2, O_3, AOD, and PM_{10} were performed using satellite and ground-based observations. The satellite and ground-based air pollution levels were also compared and correlated to the lockdown measures as indicated by the people's mobility patterns.

2.3. Data sources and analysis

2.3.1. People's mobility and stringency index

The community mobility data used in this study were acquired from Google's COVID-19 Mobility Reports (COVID-19 Community Mobility Reports, CMR, 2020). Google's CMR is anonymized and aggregated data from mobile or portable devices that permit recording of the location history from those who use Google applications (Aktay et al., 2020). The data describe different activity patterns on the basis of time, geographical location, and sectors. In this study, daily changes in people's mobility patterns were compared to baseline values for various sectors in the UAE, including retail and recreation (i.e. restaurants, cafes, malls, and museums), groceries and pharmacies (i.e. markets, food warehouses, and pharmacies), parks (i.e. parks, public beaches, and marinas), transit stations (i.e. subway, bus and train stations), workplaces and residential areas. Given the differences in weekday and weekend routines, the utilized Google's CMR baseline periods provided a normal value for each day of the week, expressed as the median value for the five-week period from January 3 to February 6, 2020 (Google, 2020; Hannah, 2020; Warren and Skillman, 2020). Weekly averages of Google's CMR mobility data were also estimated for the various user sectors before, during, and after COVID-19 lockdown.

The UAE government response SI was evaluated on the basis of the data obtained from the Oxford COVID-19 Governments Response Tracker (OxCGRT) (Hale and Webster, 2020). The OxCGRT maintains a comprehensive record of governments' policies, restrictions, and interventions to contain COVID-19. The SI was used in this study as a proxy to assess the degree of the strictness of

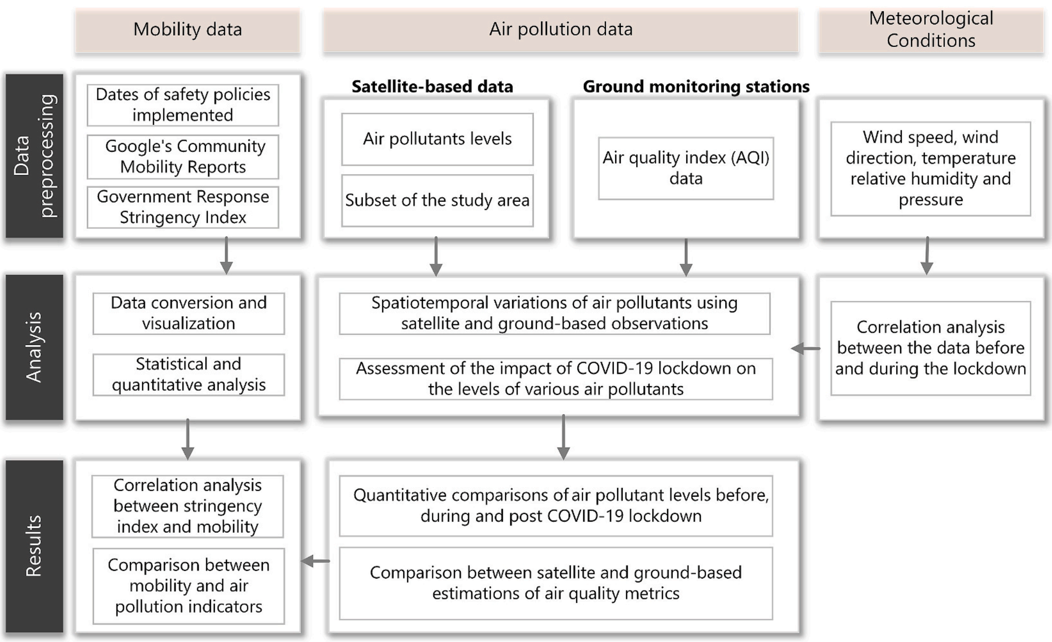

Fig. 2. Framework of the methodology used in the study.

UAE government lockdown measures. SI is an overall composite score derived on the basis of nine response indicators that entail the closure of schools, workplaces, cancellation of public events, restrictions on gatherings, closure of public transportation, stay-at-home orders, restrictions on internal movements, international travel restrictions, and public information campaign (Bourdin et al., 2022; Chan et al., 2021; Liang et al., 2021; Piquero and Kurland, 2021). Daily SI was obtained and converted into weekly averages. Similar to Wielechowski et al. (2020), SI values were interpreted in the following manner: (i) SI values lower than 40 was considered 'low', (ii) SI values that ranged from 41 to 70 were considered 'medium' and (iii) SI values greater than 71 were considered 'high'. In addition to the SI, a record of the main UAE Government's measures and events that affected the mobility trends were compiled and used to explain some of the variations in the mobility trends.

2.3.2. Air pollution datasets

The levels of various air pollutants, including NO_2, SO_2, O_3, PM_{10}, and AOD, were used in this study to assess the effect of the lockdown imposed by the UAE authorities on air quality. The levels of air pollutants were retrieved from various satellite-based systems, including ozone monitoring instrument (OMI), atmospheric infrared sounder (AIS), modern-era retrospective analysis for research and applications, Version 2 (MERRA-2), moderate resolution imaging spectroradiometer (MODIS), and Tropospheric Monitoring Instrument (TROPOMI). The atmospheric information is derived from the satellite-based measurements of the solar light backscattered by the atmosphere and the Earth's surface. Table 2 briefly describes the utilized datasets. NO_2 levels were acquired from Sentinel-5P TROPOMI level 2 for four months (March to June) in 2019, 2020, and 2021. Sentinel-5P TROPOMI, launched on October 13, 2017, measures the solar radiation reflected by and radiated from the earth and records atmospheric concentrations of various pollutants, and cloud characteristics at a spatial resolution of 0.01 arc degrees. Furthermore, the levels of NO_2, O_3, SO_2, $PM_{10,}$ and AOD were acquired from the NASA's Giovanni website (https://giovanni.gsfc.nasa.gov/giovanni/). NASA-Giovanni is a web application that offers a simple and user-friendly interface for visualizing, analyzing, and accessing a wide range of remotely sensed data. Monthly time-series products of NO_2, SO_2, O_3, and AOD were downloaded from the NASA-Giovanni website and averaged for the region of interest (ROI) using ArcGIS Pro Software. The ROI (mask), which covers the main cities of the UAE, was used as a reference to evaluate trends and compare the levels of each atmospheric pollutant before, during, and after the lockdown. Overall, the monthly averaged product was derived for each pollutant between 2015 and 2021 (a total of 79 images for each pollutant). The quantitative assessment was performed by comparing the average pollutants levels (APL) pre-lockdown (2015–2019) with the levels during 26 March 2020 to 24 June 2020 and post-lockdown by computing the percentage change using Equation (1).

$$\%\ change\ in\ APL = \frac{(APL\ in\ the\ year\ 2020\ -\ APL\ average\ of\ the\ years\ 2015\ to\ 2019)}{(APL\ in\ the\ year\ 2020)} \times 100. \tag{1}$$

Hourly concentrations of four major pollutants, including NO_2, SO_2, O_3, and PM_{10}, were obtained from nine air quality monitoring ground stations between 2018 and 2021 and used to evaluate lockdown and subsequent reopening effects on air quality in the UAE. As shown in Fig. 1 and Table 3, the stations are located in the Abu Dhabi Emirate (stations located in Bain Al Jessrain, Khalifa High School, Khadija Primary School, United States Embassy (US-ABD) and Khalifa city A (KC-A), Al Ain city (stations located in Al-Tawia, Islamic Institute (ISIN), and Zakher), Dubai Emirate (Dubai US embassy) and Sharjah (American University of Sharjah, AUS-SHJ). The datasets were acquired from the World Air Quality Index (AQI) website (https://waqi.info/). Timely averaged concentrations of the pollutants were computed for each station, and the averages for years 2018–2019 and for 2020 and 2021 were compared. The impacts of the implemented lockdown measures on air quality were assessed by analyzing the levels of pollutants from satellite- and ground-based observations using different functions and packages in R-statistics (i.e., Openair, Tidyverse, ggplot, and Corrplots). Finally, comparisons between the satellite- and ground-based observations and correlation analysis were performed to assess the compatibility of the data obtained from the two sources for the years 2018–2021.

2.3.3. Ancillary data

Sample meteorological data including wind speed, wind direction, temperature, relative humidity, and average pressure were obtained from three ground monitoring stations located at the American University of Sharjah (AUS-SHJ), Abu Dhabi, and Ras Al Khaimah (RAK) airports for the period 2018–2020 (Fig. 1). Spearman's correlation test was conducted on the meteorological data obtained before and during the lockdown to establish the significance of changes in the meteorological conditions before and during

Table 3
Description of the ground monitoring stations.

Station	Emirate	Coordinates		Measured air pollutants	Land use type
		Longitude	Latitude		
Al-Tawia	Al-Ain	55° 42′ 17.53″	24° 15′ 33.06″	NO_2, O_3, SO_2 and PM_{10}	Suburban
Bain Al Jessrain	Abu Dhabi	54° 30′ 21.91″	24° 24′ 26.3″	NO_2, O_3, SO_2 and PM_{10}	Urban
Dubai US Embassy	Dubai	55° 18′ 32.9″	25° 15′ 30.54″	O_3 and $PM_{2.5}$	Urban
Islamic Institute	Al-Ain	55° 44′ 5.51″	24° 13′ 8.61″	NO_2, O_3, SO_2 and PM_{10}	Suburban
Khalifa School	Abu Dhabi	54° 24′ 30.35″	24° 25′ 48.33″	NO_2, O_3, SO_2 and PM_{10}	Suburban
Khadija School	Abu Dhabi	54° 22′ 9.59″	24° 28′ 53.61″	NO_2, O_3, SO_2 and PM_{10}	Urban
Khalifa City A	Abu Dhabi	54° 34′ 41.5″	24° 25′ 11.7″	NO_2, O_3, SO_2 and PM_{10}	Suburban
US Embassy	Abu Dhabi	54° 26′ 1.36″	24° 25′ 27.81″	NO_2, O_3, SO_2 and PM_{10}	Urban
Zakher	Al-Ain	55° 42′ 7.58″	24° 9′ 48.48″	NO_2, O_3, SO_2 and PM_{10}	Urban
AUS-SHJ	Sharjah	55° 29′ 14.64″	25° 18′ 46.44″	NO_2, O_3, SO_2 and PM_{10}	Urban

the pandemic and consequently assess the general impact of such changes on measured air quality parameters.

Moreover, yearly utility consumption data for Sharjah, including electricity, water, and gas consumption, were acquired from Sharjah Electricity, Water, and Gas Authority (SEWA). The yearly averages of the utility consumption data before the pandemic (2016–2019) were compared with the average consumption of the year of the pandemic (2020) to assess the overall changes in utility consumption, particularly consumption of energy and its potential contribution to air quality.

3. Results and discussion

3.1. Mobility and COVID-19

Since the COVID-19 outbreak in the UAE in March 2020, the UAE took not only robust actions to control but also ensured continuity of education and economic activity. The COVID-19-related measures and events affecting mobility commenced on 3rd March 2020 through the closure of schools and universities by implementing a national disinfection program that involved a daily closure of 10 h for disinfecting public facilities and in urban areas. On 23rd March 2020, shopping centers, malls, and public facilities were closed, and on 26th March 2020, a 10-h travel restriction was imposed. On 4th April 2020, the Emirate of Dubai enacted a 24-h travel restriction to curb the rapid spread of the virus. Relaxation of the lockdown measures began towards the middle of April when malls and shopping centers were allowed to operate at 60% capacity. On 24th June 2020, the travel restrictions were lifted, and the national disinfection program was ceased. In addition to the lockdown measures, mobility was affected by many factors, such as self-imposed community restrictions, restrictions on international travel, and public holidays. Other factors, especially extended ones such as the four-day Eid-Al-Fitr holiday starting 24th May 2020 and the five-day Eid-Al-Adha holiday starting 7th July 2020. Table A (Appendix A) lists major COVID-19-related measures and events affecting mobility in the UAE.

Fig. 3 depicts the changes in mobility during the COVID-19 lockdown based on Google's CMR coupled with the SI starting from 16th February 2020 until August 21, 2021 for six main mobility sectors: retail and recreation; grocery and pharmacy; parks; transit stations; workplace; and residential. The vertical purple lines in Fig. 3 show the dates of the major events. The data in Fig. 3 clearly show the relationship between the SI and Google's CMR during the lockdown, thereby the changes in the SI were accompanied by opposite changes in the mobility for all mobility sectors, except the residential. During the early period of the pandemic and starting March 2020, the mobility in all sectors (except the residential) declined rapidly in response to a rapid increase in the SI. Meanwhile, changes in mobility in the residential sector were directly proportional to the changes in the SI, reflecting that more people stayed at homes during the most stringent periods of the lockdown.

The lockdown measures eased towards the middle of April 2020 and the SI declined gradually from its peak value at the start of the month. The SI continued to decline until the middle of May 2020, then remained constant up towards the end of June. Following cessation of the UAE's national disinfection program, a sharp drop in SI occurred towards the end of June 2020, then the SI trend remained constant for about seven weeks, up to September 2020. The SI then gradually fluctuated with an overall increasing trend up to the end of 2020. Meanwhile, the CMR mobility in all sectors (except the residential) gradually increased starting April as the restrictions were eased and continued to increase until the end of the year, with fluctuations and spikes reflecting temporary actions and special events in the country. In the residential sector, the mobility declined gradually following its peak in April. By the end of 2020, school and institutions of higher education remained closed with education conducted online while most of the other officially imposed mobility restrictions were eased. On the other hand, self and workplace-imposed mobility restrictions and requirements

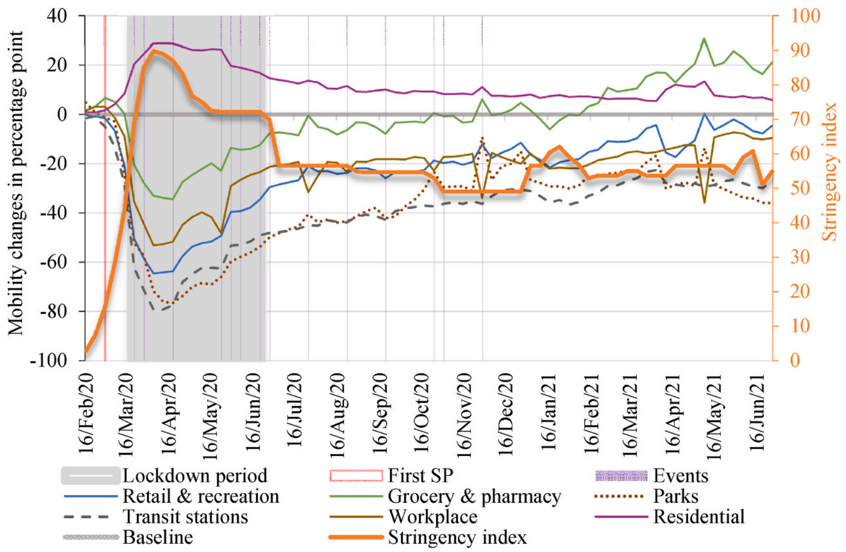

Fig. 3. Stringency index (SI) and people's mobility during lockdown and recovery in the UAE various sectors including retail and recreation, grocery and pharmacy, parks transit stations, workplace and residential.

remained as residents and businesses-maintained efforts to curb the spread of disease. The data in Fig. 3 show near complete mobility recovery in the grocery and pharmacy sectors towards the end of the year, with the other sectors showing varying degrees of recovery.

The spikes and rapid changes in CMR mobility in Fig. 3 reflect specific COVID-19-related measures and events in the UAE. The partial re-opening of malls, shopping centers and public facilities and public festivities in the last week of April 2020 contributed to rapid changes in retail and recreation mobility. By the end of May, the return to work increased workplace mobility, which resulted in a corresponding decrease in residential mobility. By the end of July, the change in transit stations' mobility kept increasing after lifting the travel restrictions and resuming public transport facilities.

The stringency index (SI) in Fig. 4 reflects the UAE's government actions taken to contain and control the spread of the disease. The initial stringent response to the COVID-19 outbreak in March and April 2020 was not sustained for a long period despite the increase in COVID-19 cases towards the end of 2020 (Fig. 4). The need to maintain business activity and ease restrictions on the community and increased awareness and vaccination rate partially shifted the responsibility of following the required health and safety measures to individuals, businesses, and government departments. Furthermore, the lockdown measures became more selective and targeted, such as imposing restrictions on travel from certain destinations rather than all destinations. The data in Fig. 4 also indicate the initial and the subsequent waves of COVID-19 infections corresponding to the COVID-19 Alpha, Beta and Delta variants. Overall, the changes in the numbers of COVID-19 infections reflected the infectivity of the virus rather then the stringency measures, which remained stable following initial lockdown.

3.2. Impacts of COVID-19 lockdown on air quality

3.2.1. Satellite-based assessment

The reduction in people's mobility during the lockdown reduced transportation emissions, especially during the first four months following the COVID-9 breakdown in March 2020. Time-series analyses of satellite-based monthly average levels of NO_2 (retrieved from OMI and TROPOMI Sentinel-5p satellite data), O_3 (retrieved from AIRS satellite data), SO_2 (retrieved from MERRA-2 satellite data), and AOD (retrieved from MODIS-Terra satellite data) were performed before (2015–2019), during (March 2020 to June 2020) and after the lockdown (see Table 2). For instance, Fig. 5 provides a comparison of the monthly average NO_2 levels, obtained from TROPOMI Sentinel-5p satellite data, during the main lockdown months (March to June 2020) and during the same period in 2019 and 2021. Fig. 5a–d compared to Fig. 5e–h shows a gradual decline in NO_2 levels during the lockdown months of April to June, indicating that the imposed travel restrictions contributed to reducing the NO_2 levels in the UAE. The gradual return to normal life in 2021 corresponded with increased NO_2 levels, as shown in Fig. 5i-l.

Quantification of the impact of COVID-19 was performed by comparing the weighted averages of pollutants levels within the masked study area. Fig. 6 displays the differences and changes in the daytime average monthly levels of NO_2, SO_2, O_3 and AOD. The time-series analysis showed significant reductions in the levels of the various pollutants during 2020 compared with their averages for the years 2015–2019. Particularly, the levels of NO_2 in Fig. 6a, were obtained from OMI satellite data, exhibited clear reduction trends up to 22%. Globally, NO_2 reductions due to COVID-19 were estimated to be in the range of 13%–23% (Keller et al., 2021). NO_2 accumulates in the air mainly because of the combustion of fossil fuels in vehicles and industrial and power generation facilities (US EPA, 2021). In the UAE, which is lightly industrialized, the transportation sector suffered the most disruption, and the decline in mobility due to COVID-19 is likely to be the main contributor to NO_2 reduction. In 2021, the monthly average NO_2 levels generally increased beyond their levels during the stringent lockdown months in 2020, however remained below their pre-pandemic levels in 2019.

In terms of SO_2, the trends established by the data in Fig. 6b, which were obtained from MERRA-2 satellite data, suggest that the monthly levels remained low and nearly steady over the years during 2015–2019. The data also show noteworthy reductions in SO_2

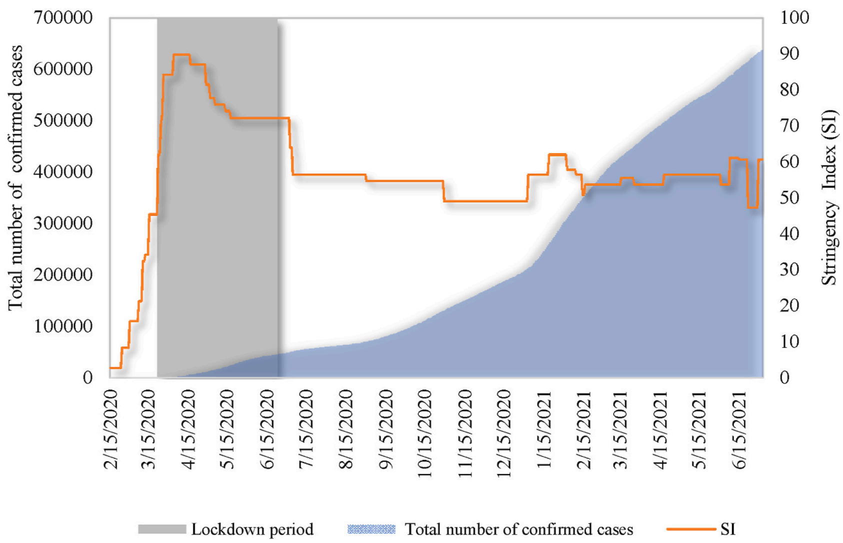

Fig. 4. Stringency index vs the total number of confirmed cases in the UAE during the study period.

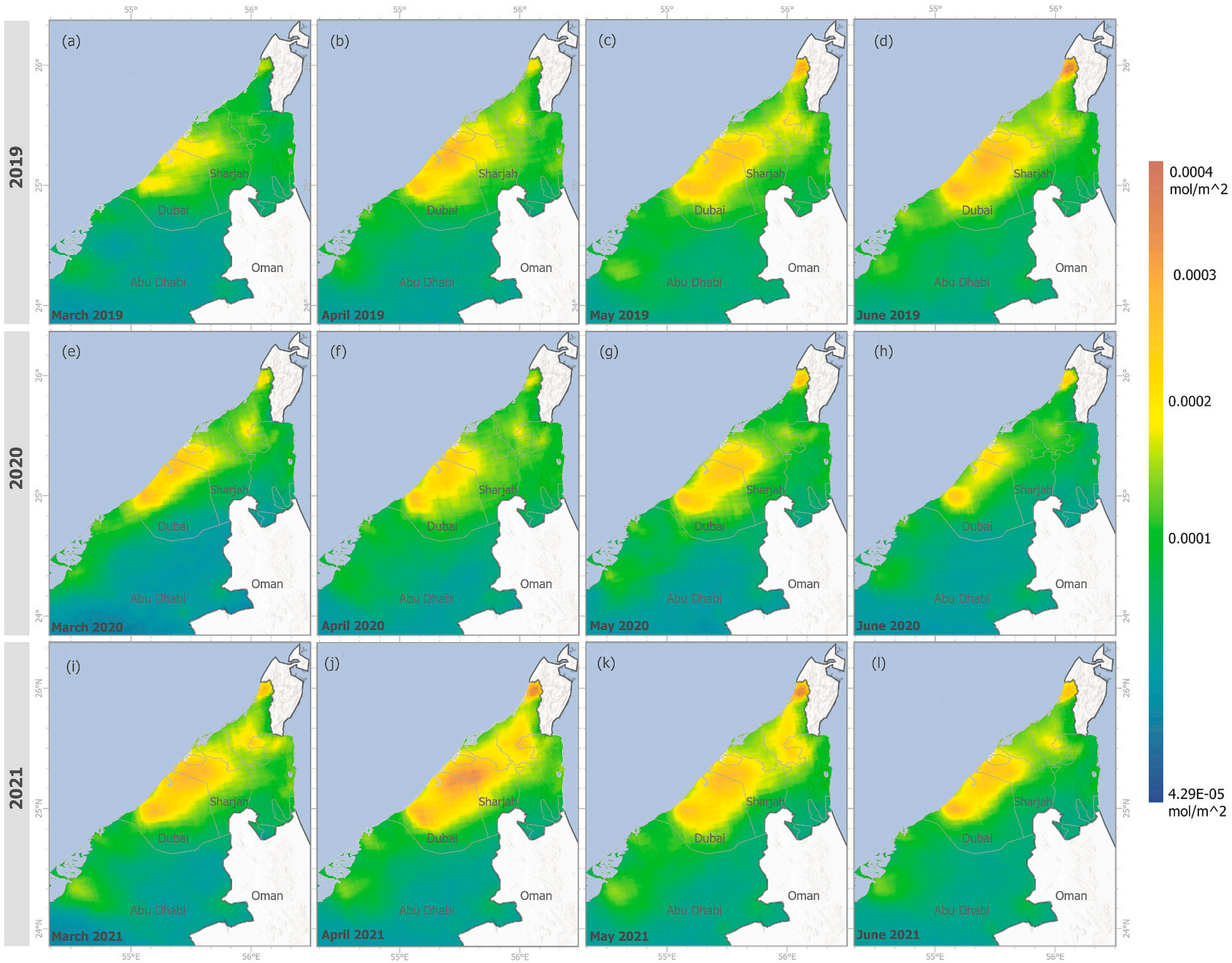

Fig. 5. Changes in NO_2 levels using TROPOMI Sentinel-5p for NO_2 expressed in mol/m^2: (a–d) before; (e–g) during; and (h–l) post-initial COVID-19 lockdown.

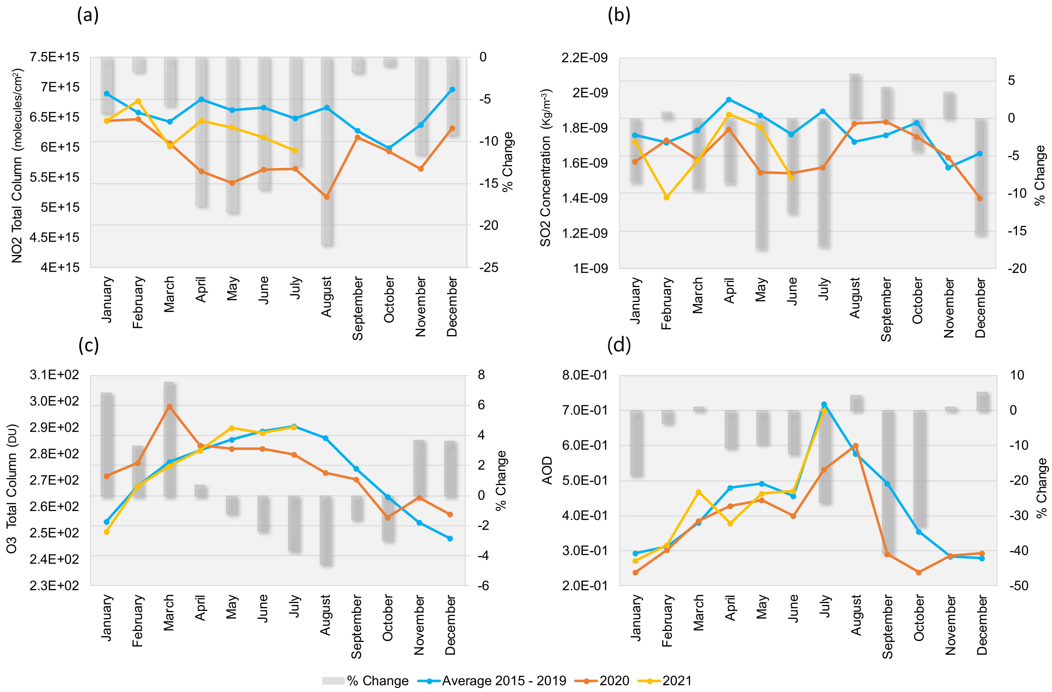

Fig. 6. Monthly averages and percentage change of the different pollutant concentrations: (a) NO_2; (b) SO_2; (c) O_3 daytime; and (d) AOD.

levels ranging from 8% to over 17% during the lockdown months of the pandemic. SO_2 is mainly emitted from power plants and industries that burn fuels with high sulfur content, such as coal and diesel. In the UAE, natural gas and diesel are used for power generation, and ultra-low-sulfur diesel is used in large commercial vehicles and light industrial facilities. As a result, the SO_2 levels in the UAE and their variations remain relatively low.

The ground-level O_3, which is formed by a set of photochemical reactions between man-made emissions of nitrogen oxides (NOx) and volatile organic compounds (VOCs) in the presence of sunlight and heat, is considered a harmful air pollutant because of its associated adverse effects on human health, vegetation, and ecosystems (Alvarez-Mendoza et al., 2019; Geddes and Murphy, 2012; Sicard et al., 2017; Zoran et al., 2014). The ground level O_3 levels are dependent on various factors, including the availability of precursors, such as nitrogen oxides and volatile organic compounds (VOCs), wind, seasonal changes in temperature, humidity, sunlight intensity, and O_3 sinks. According to the trend established in Fig. 6c in the UAE for years 2015–2019, the average O_3 level, which was obtained from AIRS satellite data, showed a steady increase from January to July, followed by a drop during the following months. The O_3 level is typically low in winter and high in summer, with minimum and maximum levels occurring in the UAE in December and July, respectively (Al Katheeri et al., 2012; Kharbat et al., 2019; Tolba and Saab, 2009). During 2020, the O_3 levels increased in January and February, then exhibited a sharp increase in March followed by a sharp decline in April 2020, then continued to decline afterward until October. The data indicate a clear deviation in the O_3 trends during 2020 compared to the average trend during 2015–2019, especially the sharp changes in March and April. Such trends may be attributed to the observed reduction in NO_2 levels and the expected reduction in VOCs emissions from vehicles and industry (Gkatzelis et al., 2021; Omidvarborna et al., 2018). The data also indicate that in the first half of 2021, the O_3 levels matched their observed levels during 2015–2019.

Aerosols are liquid and solid particles suspended in the air that is caused by both natural (i.e., dust, fog, sea salt) and anthropogenic emissions (Wei et al., 2020). Aerosols can affect the climate system by absorbing and scattering incoming shortwave radiation, (Samset et al., 2018). They can alter the optical and micro-physical properties of clouds, the patterns of atmospheric circulation, and affect the temperature of the air (Storelvmo, 2017; Wei et al., 2020). The satellite-based aerosols optical depth (AOD), a measure of aerosol loading in the atmosphere (Mehta, 2015), for the study area is shown in Fig. 6d. The AOD levels in the UAE rise from January to May, slightly dips in June, exhibit a sharp peak in July, then decline to their lowest value in December, which is part of the rainy season. The AOD trends in the UAE reflect the contributions of primary emissions, such as dust and emissions from transportation and industry, but also contributions from photochemical reactions that produce aerosols from gaseous precursors, including nitrogen oxides (Liu et al., 2019; Seinfeld and Pandis, 2008). The data in Fig. 6d show that the monthly AOD levels in 2020 were significantly lower than their corresponding average values during 2015–2020, with reductions up to over 40% in September. Furthermore, the monthly average AOD trends during 2020 deviated from the average trends observed for 20150-2019. In 2021, the AOD levels increased and followed the trend observed during 2015–2019.

Overall, the data in Fig. 6 indicate significant changes in all assessed air pollutants levels and their average monthly trends during the lockdown year of 2020 compared to 2015–2019 and 2021. The changes in air pollutants levels can be linked to the observed changes in people's mobility as the associated traffic reduction represented a major reduction in pollutants' emissions from the transportation sector during 2020. The weather conditions can also influence the observed changes in air quality; however, the changes in the general weather patterns, as discussed in the following section, do not exclude the impact of the pandemic on the observed improvement in air quality.

3.2.2. *Ground-based air quality assessment*

Fig. 7 shows daily boxplots of the air quality index (AQI) of four air quality constituents (NO_2, SO_2, O_3, and PM_{10}) measured at four ground stations during the two years before the lockdown (2018–2019) and for the years 2020 (during the lockdown) and 2021 (after the lockdown). The data show that the medians of the NO_2 and PM_{10} levels were lower in all monitoring stations during the lockdown (2020) compared to the same periods during 2018–2019 and 2021. On the other hand, the SO_2 and O_3 levels declined in some stations and increased in others.

Fig. 8 presents the variations and percentage changes of the monthly averages of the air quality parameters during the Lockdown period in 2020 compared to their monthly averages during the 2018–2019 and 2021 in four monitoring stations. The data in Fig. 8a show that, in 2020, the monthly average NO_2 levels were consistently and significantly lower than their corresponding averages for 2018–2019, with reductions reaching as high as 57%. Even the available 2021 trends showed reduced levels compared to their levels during 2018–2019. The differences among the stations reflect location-specific conditions, including weather conditions and proximity to NO_2 sources, mainly roads and industrial areas.

Similarly, the monthly average PM_{10} levels generally declined during 2020 and 2021 compared to the averages of 2018–2019 (Fig. 8b), with reductions reaching up to 64%. The level of PM_{10} in the atmosphere is influenced by natural and man-made sources (Amato et al., 2014; Samara and Voutsa, 2005). PM_{10} can experience significant variations according to weather conditions and emissions from nearby sources. On the other hand, the monthly average O_3 levels (Fig. 8c) increased in some stations and decreased in others over different periods. Based on the trends observed in Fig. 8c, the O_3 data in two of the stations showed consistent reductions in O_3 levels in the range of 12%–56% during 2020 compared to 2018–2019. Meanwhile, the monthly average O_3 levels in the other two stations declined in some months and increased in others during 2020 compared to the average levels in 2018–2019. Overall, the observed variability in O_3 trends reflect its dependency on the local conditions in the areas surrounding the monitoring stations.

For SO_2 (Fig. 8d), the data show inconsistent trends among the various stations, with the monthly average SO_2 levels increasing in some stations and decreasing in others over different periods of time. A significant increase was observed in the SO_2 levels in ABD-US and ISIN stations during 2020 compared to the average of 2018–2019, except for the period from June to August. Conversely, a consistent and significant reduction in SO_2 levels was observed in the KC-A in 2020 compared with the average of SO_2 in 2018–2019. As mentioned earlier, traffic is not the main source of SO_2 and the observed trends may not directly reflect the significant changes in

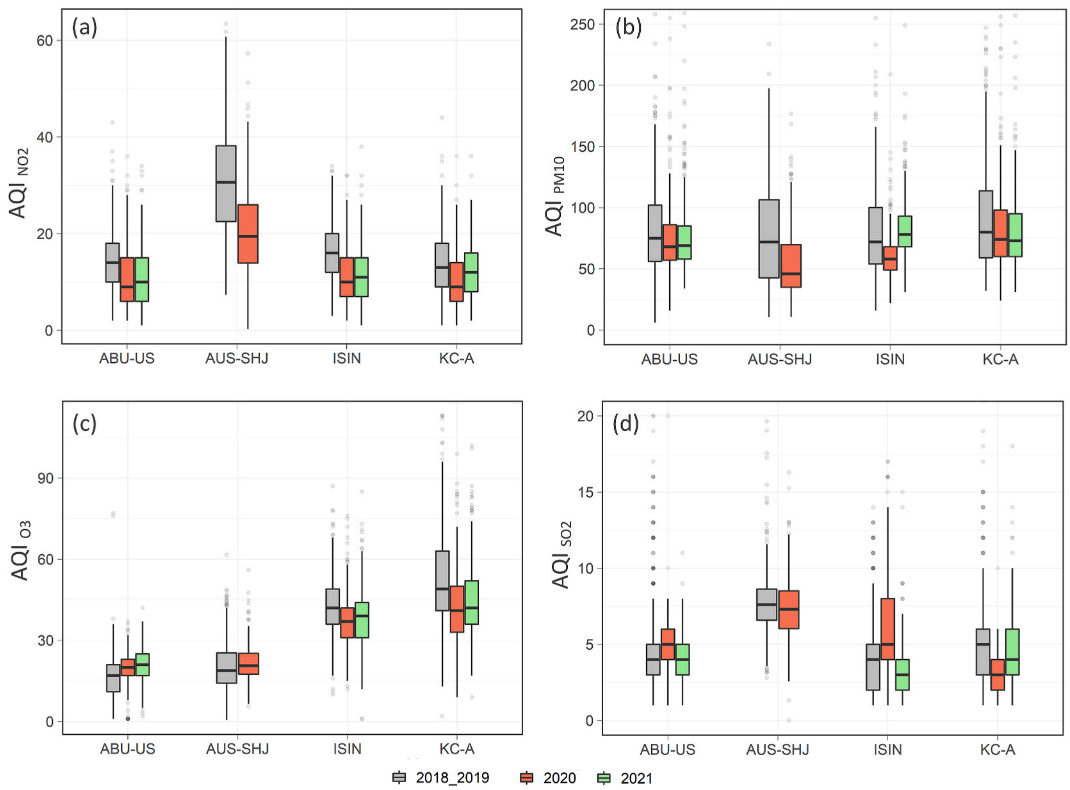

Fig. 7. Boxplots of daily AQI for (a) NO_2, (b) PM_{10}, (c) O_3, (d) SO_2 levels recorded at four monitoring stations (ABU-US, AUS-SHJ, ISIN, and KC-A).

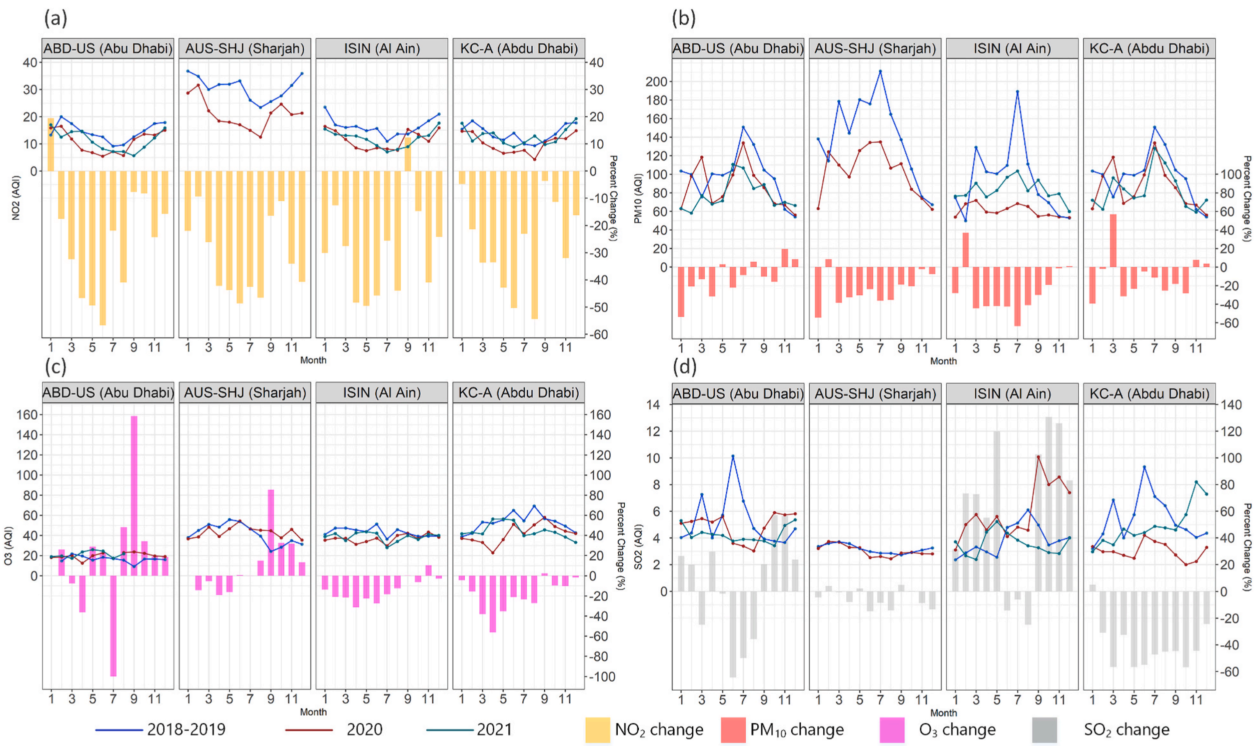

Fig. 8. Variations and percent changes in (a) NO_2, (b) PM_{10}, (c) O_3, (d) SO_2 concentrations, recorded in ABU-U S, AUS-SHJ, ISIN, and KC-A stations, during 2018–2019, 2020 and 2021.

mobility.

Ground-based air pollutants measurements are highly influenced by the meteorological conditions (He and Lu, 2012; Yen et al., 2013), pollution sources, and proximity to such sources. Therefore, the comparison of pollutants levels measured at different times at the same station requires careful consideration of such influencing factors. Fig. 9 presents an example of the wind conditions at the AUS-SHJ station during 2018, 2019, and 2020, indicating that the general wind patterns over the three years showed some variability but were generally consistent. For instance, most of the observed moderate and high wind speeds across the three years (about 10–15%) appeared to have come from the west, northwest and south (i.e., 15%). On the other hand, most of the observed low wind speeds across the three years was found to come from northeast and southeast directions (i.e., about 5–10%). However, the yearly wind patterns are not reflective of the variations at the times of measurements. Additional analysis of the changes in the local meteorological conditions (i.e. wind speed, wind direction, temperature, and relative humidity) before and during the pandemic was based on Spearman's correlation test, as shown in Table 4. The data of the local metrological condition was obtained from three stations situated in Sharjah (AUS), Abu Dhabi (ABD), and Ras Al Khaimah (RAK) airports. Based on Spearman's correlation test, the data in Table 3 suggest that there were no significant (P-value > 0.05) differences between the wind speed before and during the pandemic in the three stations. Similarly, the wind direction did not change significantly during and after the pandemic. On the other hand, significant differences (P-value < 0.05) existed for temperature, humidity, and pressure. The closeness of the wind speed and direction results before and after the pandemic enhances the validity of the comparisons of the averages of the air quality parameters for both the satellite and ground-based observations.

3.3. Mobility trends versus air pollution levels

Given the restrictions imposed on people's mobility during the early months of the pandemic, air quality improvements were observed from both satellites and ground monitoring stations. In addition to transportation, the other major source of air pollution in the UAE is power generation. However, analysis of utility consumption data (electricity, gas, and water) obtained from the Sharjah Electricity, Water and Gas Authority (SEWA) for Sharjah, one of the seven emirates of the UAE, did not show a significant change in power consumption during the 2020 (Fig. 10a–c). On the other hand, the satellite images indicated a significant reduction in NO_2 levels over Sharjah during 2020 as compared to 2019 and 2021 (Fig. 10a–c). Therefore, reduction in mobility during the lockdown was the major contributor to the observed improvement in air quality.

To assess the links between people's mobility in the different sectors and the examined air pollutants (NO_2, O_3, SO_2, and AOD) obtained from the satellite observations, Pearson's correlation analysis was estimated and shown in Fig. 11a. The results show significant positive correlations among the various mobility sectors and similar significant positive correlations ranging between 0.55 and 0.7 between the NO_2 and mobility patterns in the various sectors except for the residential sector, which as expected showed, a significant negative correlation with NO_2 variations. The AOD showed some correlation with the mobility sectors, but correlations for O_3 and SO_2 were low. The data also show significant correlations between the levels of O_3 and AOD and NO_2 and AOD. Fig. 11b visually shows the trends assumed by people's mobility in the various sectors and the average monthly NO_2 levels obtained from the satellite images. The visual trends confirm the significant correlations indicated by the Pearson's correlation test coefficients.

In Fig. 12, we show a comparison of the ground-based and satellite-based measurements for NO_2 and PM_{10}/AOD. The satellite data, in this case, were obtained from the immediate area surrounding each station (i.e. pixel surrounding each station is $1^\circ \times 1^\circ$), which covers a wider area compared to the point measurements done at the monitoring stations. The data in Fig. 12 suggest that both, satellite

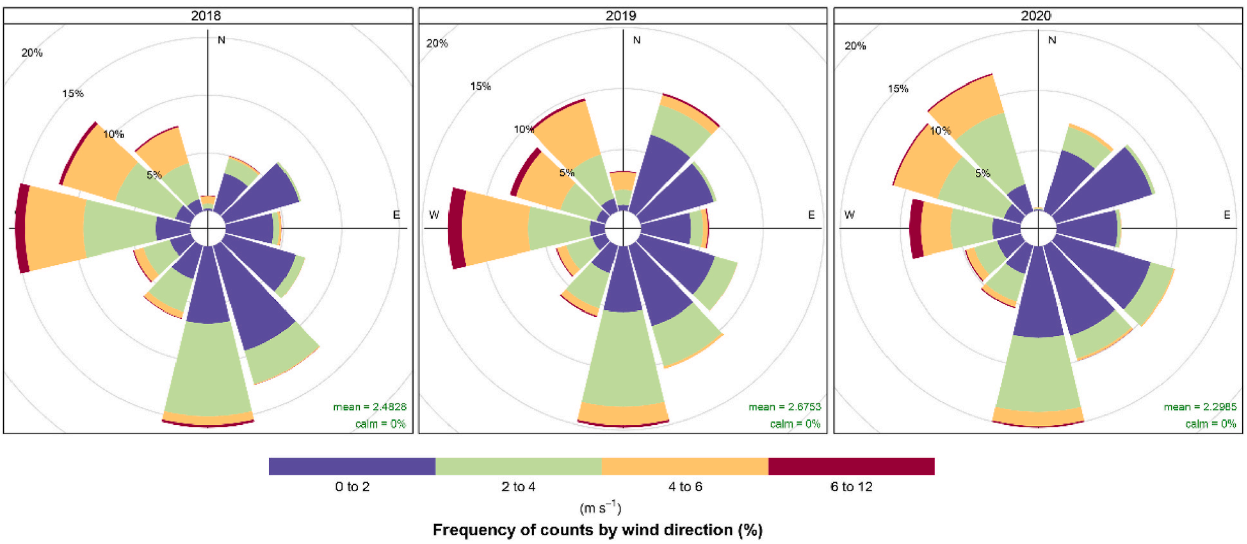

Fig. 9. Example wind rose trends observed before and during COVID-19 lockdown from the AUS-SHJ (Sharjah) station: (a) 2018; (b) 2019; and (c) 2020.

Table 4
Assessment of changes in the meteorological parameters during the lockdown (January–June 2020) and the average of the same period before the pandemic (2018–2019).

Station	Item	Wind Speed (ms^{-1})	Wind direction (degree)	Temperature (C̊)	Relative humidity (%)	Pressure (mm)
AUS-SHJ	January–June 2018–2019	2.79	202	26.2	47.4	1006
	January–June 2020	2.49	199	25.7	50.6	1006
	Spearman's Rho	–0.012	–0.104	0.899	0.433	0.911
	P-value	0.87	0.16	<2.2E-16	1.022E-09	<2.2E-16
ABD	January–June 2018–2019	3.88	207	27.06	50.87	1005.72
	January–June 2020	4.16	200	27.04	54.02	1006.53
	Spearman's Rho	-0.084	NA[a]	0.8631703	0.2162354	0.756
	P-value	0.2621	NA[a]	<2.2e-16	0.00337	<2.2e-16
RAK	January–June 2018–2019	3.21	208	26.05	50.64	1006.39
	January–June 2020	3.03	203	25.80	56.35	1006.87
	Spearman's Rho	0.059	NA[a]	0.89	0.56	0.84
	P-value	0.4318	NA[a]	<2.2e-16	<2.2e-16	<2.2e-16

[a] NA: numerical values are not available for wind direction in Abu Dhabi and RAK airports stations.

and ground-based observations, indicated relatively similar trends in the levels of NO_2, particulate matter (ground-based PM_{10} and satellite-based AoD) in response to the COVID-19 lockdown during 2020 compared to the same periods before and after the lockdown. However, the trends were not consistent for the other air quality parameters, SO_2 and O_3. It should be noted that the available monitoring stations are not uniformly distributed and do not represent the same areas covered by the satellite images. Nevertheless, statistical comparisons of the correlations between the satellite and ground data, as well as the correlations among the various air quality parameters in Fig. 13 which helps in understanding the degree to which the various compared variables are related. The satellite and ground-based estimations of NO_2, and AOD (PM_{10}) levels were highly correlated (correlation coefficient of 0.83), while SO_2 and O_3 showed low correlations of 0.22 and 0.19, respectively.

4. Conclusion

The current study presents an assessment of the impact of COVID-19 lockdown and subsequent reopening on people's mobility patterns across different mobility sectors in the UAE, as well as the spatial and temporal variations of selected air pollutants (NO_2, SO_2, O_3, PM_{10}, and AOD) from satellite and ground-based observations. The initial COVID-19 lockdown measures in the UAE starting March 2020 resulted in significant reductions (34%–79%) in the people's mobility in the workplace, parks, shops and pharmacies, transit stations, and retail and recreation sectors. On the other hand, people's mobility in the residential increased by approximately 29%. The reductions in mobility and associated traffic reductions contributed to the achievement of significant improvements in air quality, as confirmed using extensive satellite and ground-based air quality observations. Based on the satellite data, the achieved reductions reached 22% for NO_2, 17% for SO_2, 5% for O_3, and 40% for AOD. NO_2 and PM_{10} levels observed from nine ground-monitoring stations demonstrated significant reductions in the range of 49%–57%, and 19%–64%, respectively; however, the levels of SO_2 and O_3 exhibited inconsistent trends. The data indicated strong positive correlations between the satellite and ground-based stations for NO_2 and AOD/PM_{10}, but poor correlations for SO_2 and O_3. The results also indicated significant correlations between the mobility and the NO_2 and AOD/PM_{10} trends, demonstrating the impact of mobility on air pollution. Following the initial 2020 lockdown, the mobility and air quality indicators generally started to regain their pre-pandemic levels and trends. It should be noted that unlike satellite-based observations, the limited number of ground stations in the study area did not provide adequate spatial coverage of air quality in the UAE. In addition, the coarse resolution of the satellite-based observations did not provide sufficient information to assess the local air quality conditions. Overall, the study provides an analysis framework for assessing and managing air quality in relation to people's mobility and documents the impact of COVID-19 on people's mobility and air quality in the UAE.

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Author statement

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, data acquisition, analysis, validation, and writing, or revision of the manuscript.

Ethical statement

We declare that all ethical practices have been followed in relation to the development, writing, and publication of the article.

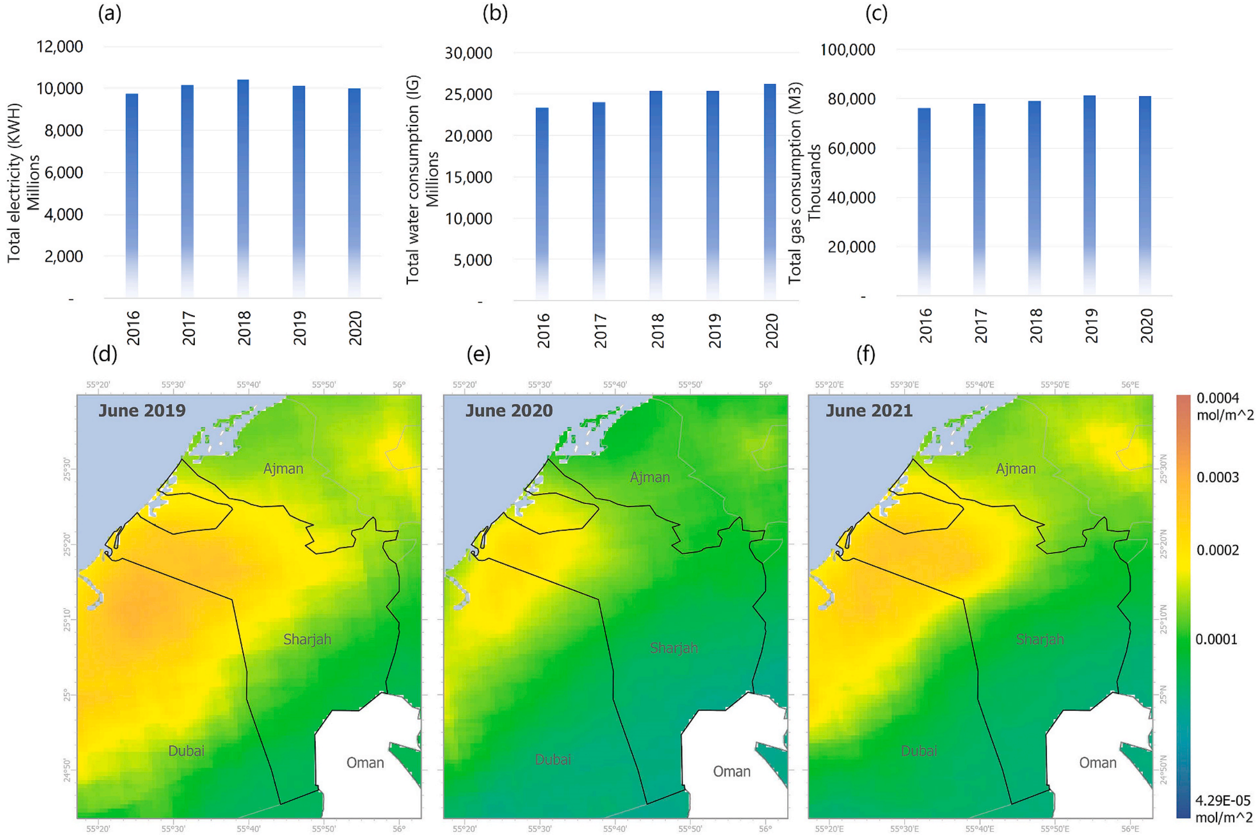

Fig. 10. NO_2 levels and the temporal total electricity, water and gas consumptions in the Emirate of Sharjah during 2016–2020.

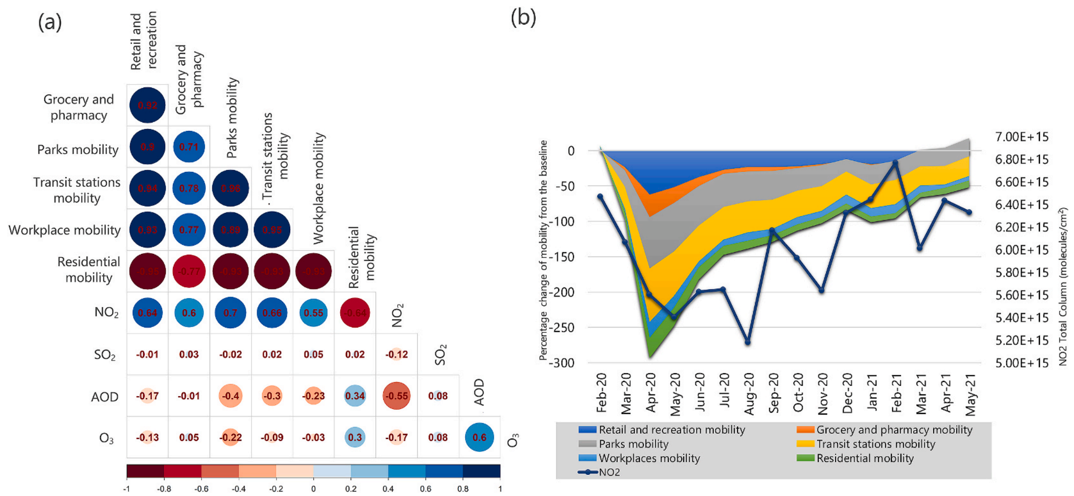

Fig. 11. (a) Correlation analysis between mobility patterns and the evaluated air pollutants obtained from satellite observations, and (b) people's mobility patterns vs. NO_2 levels before, during and after COVID-19 lockdown.

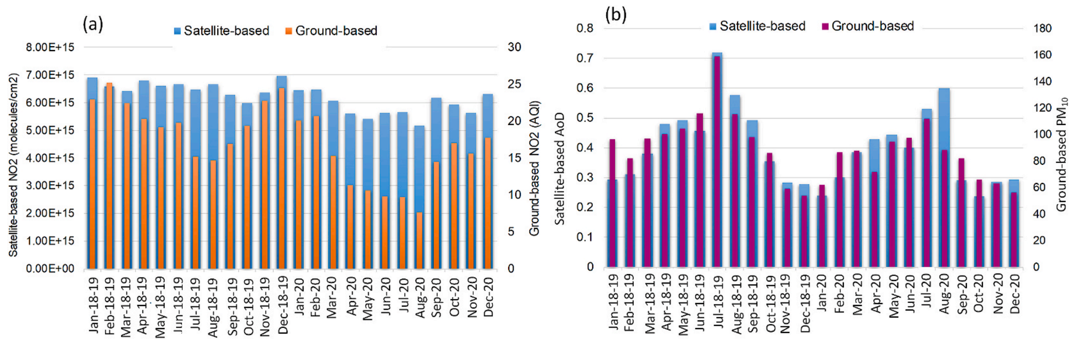

Fig. 12. (a) Satellite vs ground-based NO_2; b) Satellite-based AOD vs ground-based PM_{10} and AOD obtained from satellite and average of all ground monitoring stations before, during and after COVID-19 lockdown.

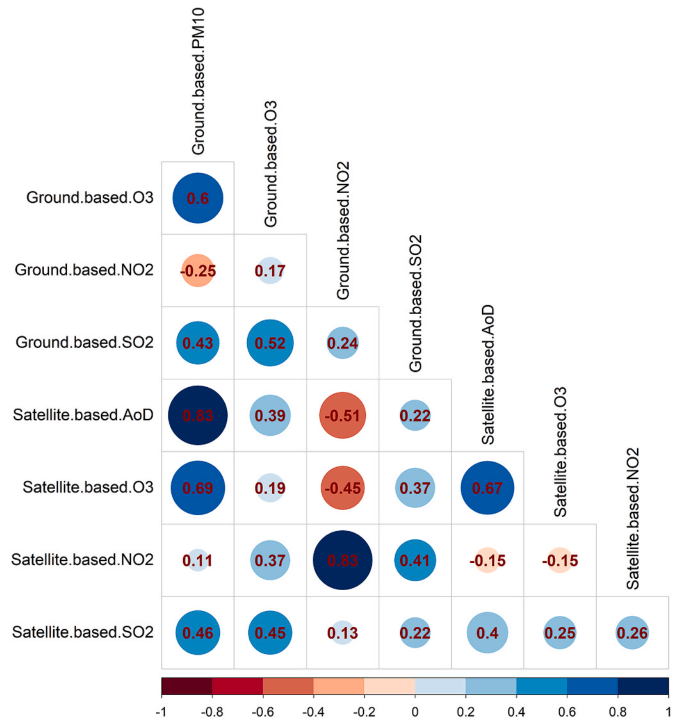

Fig. 13. Pearson's correlation matrix between satellite and ground-based observations.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A1
Record of major COVID-19-related measures and events affecting mobility in the UAE.

Dates	Safety policies implemented
March 3, 2020	Closure of schools and universities
March 23, 2020	Closure of malls, shopping centers, public facilities and restaurants
March 26, 2020	Imposing 10-h travel restrictions
March 29, 2020	UAE activates remote work system, allowing only 30% work capacity at offices
April 4, 2020	Imposing 24-h travel restrictions in Dubai
April 24, 2020	Re-opening malls and shopping centers at 60% capacity
May 24, 2020	Beginning of Eid-Al-Fitr 4-day holiday
June 3, 2020	Dubai private sector to operate at 100% capacity
June 7, 2020	UAE government hikes staff capacity at offices to 50%
June 24, 2020	Internal travel restrictions lifted
June 29, 2020	UAE announces gradual re-opening of mosques and other places of worship
July 2, 2020	Abu Dhabi re-opens some public beaches and parks
July 30, 2020	Beginning of Eid-Al-Adha 5-day holiday
August 23, 2020	New Islamic year, public holiday
August 27, 2020	Nurseries and childcare centers can re-open
September 24, 2020	Entry permits into the country resumed
October 29, 2020	Public holiday
November 1, 2020	Resumption of social events in Sharjah
December 1, 2020	Commemoration day
January 5, 2021	UAE announces mandatory PCR testing every 14 days for government employees
January 24, 2021	PCR test required every seven days for non-vaccinated federal government employees
January 27, 2021	Federal Authority for Government Human Resources (FAHR) announces new quarantine rules for federal government employees
February 7, 2021	Capping operating capacity of commercial, economic and tourism activities in Abu Dhabi
May 11, 2021	Beginning of Eid-Al-Fitr 5-day holiday

(continued on next page)

Table A1 (*continued*)

Dates	Safety policies implemented
May/June	UAE announces the suspension of entry for travels from a set of countries
June 6, 2021	UAE announces only vaccinated people with a negative test result can attend events
July 20, 2021	Beginning of Eid-Al-Adha 4-day holiday

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