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Spatio-temporal analysis of air quality and its relationship with COVID-19 lockdown over Dublin

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ABSTRACT

Air pollution has become one of the biggest challenges for human and environmental health. Major pollutants such as Nitrogen Dioxide (NO_2), Sulphur Dioxide (SO_2), Ozone (O_3), Carbon Monoxide (CO), and Particulate matter (PM_{10} and $PM_{2.5}$) are being ejected in a large quantity every day. Initially, authorities did not implement the strictest mitigation policies due to pressures of balancing the economic needs of people and public safety. Still, after realizing the effect of the COVID-19 pandemic, countries around the world imposed a complete lockdown to contain the outbreak, which had the unexpected benefit of causing a drastic improvement in air quality. The present study investigates the air pollution scenarios over the Dublin city through satellites (Sentinel-5P and Moderate Resolution Imaging Spectroradiometer) and ground-based observations. An average of 28% reduction in average NO_2 level and a 27.7% improvement in AQI (Air Quality Index) was experienced in 2020 compared to 2019 during the lockdown period (27 March–05 June). We found that PM_{10} and $PM_{2.5}$ are the most dominating factor in the AQI over Dublin.

1. Introduction

In early 2020, the deadliest coronavirus disease 2019 (COVID-19) started to spread rapidly across the globe. As a result of the COVID-19 outbreak, human health has become at the forefront of our collective concerns and, on March 11, 2020, it was declared a global pandemic by the World Health Organization (WHO). Due to its high transmissibility and high infectivity, countries across the globe implemented strict lockdowns to contain the outbreak (Siddiqui et al., 2020). This is because lockdown and pollution control measures constrain many anthropogenic activities in terms of transport, industrial and other socio-economic (Shen et al., 2011). The drastic shutdowns have made the impact of human activities on air quality more visible (Kaloni et al., 2022, 2021) and provided an abrupt opportunity to understand what we can do better to address air pollution.

Around half the world's population is exposed to the worst air quality (Health Effects Institute and of Disease project, 2020; Alparslan et al., 2021). Numerous studies have already proved the direct association of air pollution with multiple health issues such as respiratory and cardiovascular diseases (Flegal et al., 2007; Franklin et al., 2007; Gent et al., 2009; Kappos et al., 2004). Air pollution has become one of the biggest risks to human health (Pedersen et al., 2013; Danesi et al., 2021a; Sun et al., 2019;

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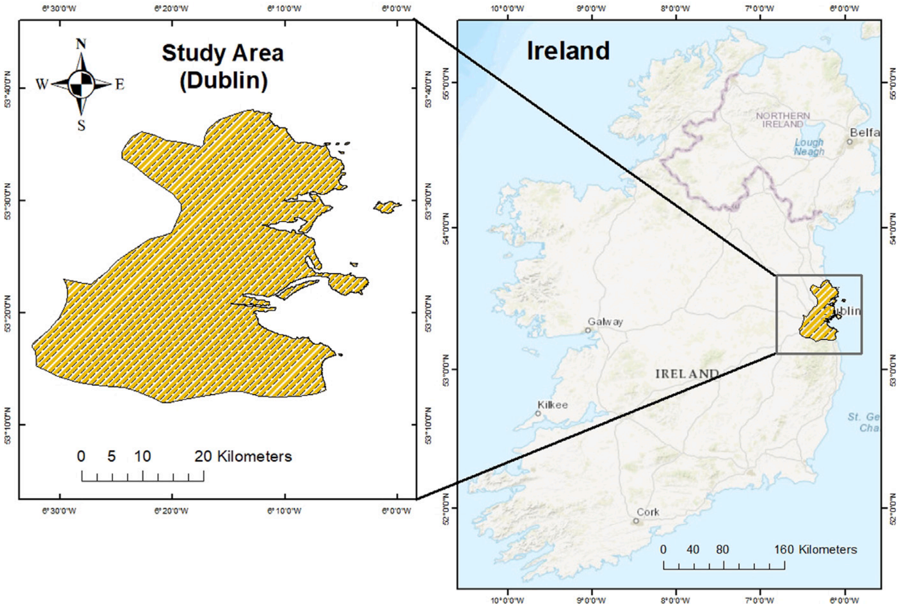

Fig. 1. We demonstrate the study area of Dublin, Ireland in this illustration.

Weinmayr et al., 2015), resulting in great loss of life. Several studies (Danesi et al., 2021b; Pak et al., 2020) are therefore focused on accurately predicting the pollutant concentration at the ground-level, along with the prediction of other atmospheric contributing factors including temperature (Akrami et al., 2021), precipitation (Pathan et al., 2022, 2021) and solar irradiance (Fathima et al., 2019). In 2019, air pollution moved up from the 5th to the 4th leading contributor to overall premature deaths (6.67 million), only after high blood pressure, tobacco and poor diet (Health Effects Institute and of Disease project, 2020).

A substantial reduction in air pollution has been experienced during the COVID-19 lockdown across the world (Dantas et al., 2020; Otmani et al., 2020; Sarkar et al., 2021; Tobías et al., 2020). Venter et al. (2020) analysed both ground and tropospheric air pollution levels using more than 10,000 ground stations and satellite observations across the globe. They depicted a 29%, 11% and 9% reduction in NO_2, O_3 and $PM_{2.5}$ respectively during the first two weeks of lockdown. In a similar study, Bao and Zhang (2020) examined the air quality data for the 44 cities in northern China and concluded a 7.80% improvement in air quality with a 69.85% reduction in human mobility strongly associated with the COVID-19 lockdown. Mahato et al. (2020) reported a 40%–50% improvement in air quality during the first week of lockdown over Delhi, one of the most polluted cities in the world. Numerous other studies were conducted in the U.S. (Chen et al., 2020), Brazil (Kondo Nakada and Urban, 2020), Australia (Duc et al., 2021), Italy (Collivignarelli et al., 2020) and Egypt (Mostafa et al., 2021). All the studies revealed a significant improvement in air quality during the COVID-19 lockdown. Due to large volumes of traffic, many areas of Dublin experiencing poor air quality and frequently breach the EU limits. According to the Google mobility data (Reports, 2021), a 39% reduction in public transport is observed during the lockdown period in Dublin County compared to the baseline (January 3–February 6, 2020).

The current study aims to examine the lockdown effect on improving the air quality levels across Dublin using satellite-derived spatiotemporal data sets and ground-based measurements. This study could help the researchers and policymakers to understand and implement the multidimensional approach towards air pollution.

2. The study area

The present study is focused on Dublin (Fig. 1), the capital and largest city of Ireland. Dublin, a centre of Irish education, art and culture, administration, and industry, has been listed under the top thirty cities globally (Globalization and Network, 2020). Geographically, it is situated on a bay on the east coast, at the mouth of the Liffey river, surrounded by a low mountain range to the south and flat farmland to the north and west. The city experiences a maritime climate (Cfb) with mild-hot summers, cool winters, and a lack of temperature extremes. It records the lowest average temperature (6–8 °C) in Jan–Feb, while highest in Jul–Aug, peaking at about 20–22 °C. The average annual rainfall is 700–800 mm. The city holds a total area of 117.8 km square and has a total of 1,347,359 population according to the 2016 census (Office, 2016). The city has 22 national and local air quality monitoring stations (Council, 2021). In 2019 total of 2 805 839 new vehicles were registered in the transport department Ireland, and the highest number (59 003) of vehicles registered in Dublin city (Office, 2019).

3. Air pollutant data

The long term status of pollutants (NO_2, SO_2, O_3 and CO) and their spatio-temporal variation before and during the lockdown over the Dublin city were derived using the European Space Agency's (ESA) Sentinel-5 precursor satellite data available through

Table 1
Data used and its specification.

Platform	Sensors	Parameters	Band	Resolution	Product level
Satellite data	MODIS Terra and Aqua combined data	AOD	Green band (0.55 μm)	1000 m	Level 2 product
–	Sentinel-5P Near Real -Time (NRTI)	NO_2	Total vertical column of NO_2	1113.2 m	Level 2 product
–	–	SO_2	SO_2 vertical column density at ground level	1113.2 m	Level 2 product
–	–	O_3	Total atmospheric column of O_3 between the surface and the top of the atmosphere	1113.2 m	Level 2 product
–	–	CO	Vertically integrated CO column density.	1113.2 m	Level 2 product
Ground Station data		NO_2		24 h composite	
–		SO_2		24 h composite	
–		O_3		8 h composite	
–		$PM_{2.5}$		24 h composite	
–		PM_{10}		24 h composite	
–		AQI		24 h composite	

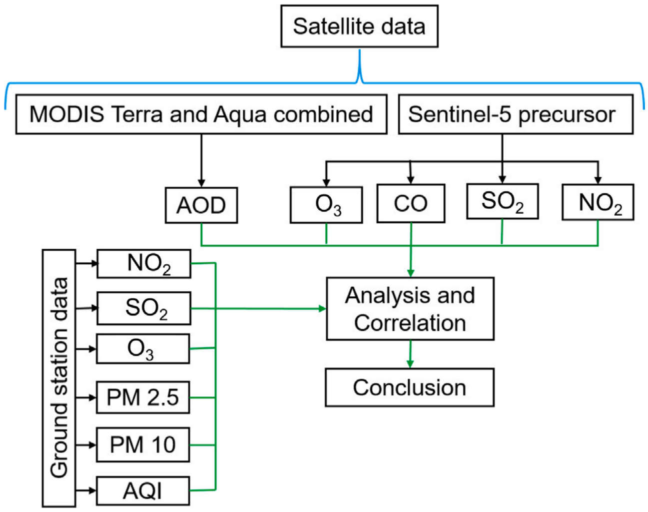

Fig. 2. Methodology for pollution analysis using satellite and ground data.

TROPOspheric Monitoring Instrument (TROPOMI). This investigation uses Near Real-Time/level-3 (NTRI-L3) S5P products. A detailed specification of datasets is mentioned in Table 1. All datasets used for the analysis are directly imported from the Google Earth Engine (GEE) Image Collection. GeeMap (Wu, 2020), a Python package for interactive mapping with Google Earth Engine (Ferrari and Cribari-Neto, 2004) API is used for the analysis.

According to the Irish Daily Mirror newspaper,[1] the Republic of Ireland confirmed its first case on February 29, 2020. As cases continued to surge, on March 27, 2020, the government of Ireland imposed a complete lockdown for two weeks except for the essentials, and on April 10, 2020, it was further extended for 3 weeks until May 5, 2020. On May 5, 2020, the first ease in restrictions was announced by the government and on May 18, 2020, phase one of easing the COVID-19 restrictions placed over the country (Mirror, 2021).

Therefore considering these dates, the investigation is designed for a series of timelines, such as; pre-lockdown (March 01–26, 2020), phase-I lockdown (March 27–April 10, 2020), phase-II lockdown (April 11–May 05, 2020), phase-III lockdown (May 06–18, 2020), and phase-IV lockdown (May 19–June 05, 2020) (Mirror, 2021).

Fig. 2 depicts the methodology used for the present study. We have primarily used satellite data in our pollution analysis for the city of Dublin, Ireland. The satellite data are obtained from MODIS (Terra and Aqua) and Sentinel-5 precursor. The AOD is obtained from MODIS data; whereas the other pollutants O_3, CO, SO_2 and NO_2 are obtained from Sentinel-5P. The variation in significant pollutants are analysed at both spatial and temporal scales. A correlation matrix also has been generated to determine the impact of these pollutants on the Air Quality. For correlation analysis, satellite AOD data is extracted after averaging the values in a 2 km buffer around the ground station location (53.354N, –6.278W). This is further validated via a time series analysis of pollutant data

[1] https://www.irishmirror.ie/news/irish-news/year-covid-ireland-timeline-incredible-23585166

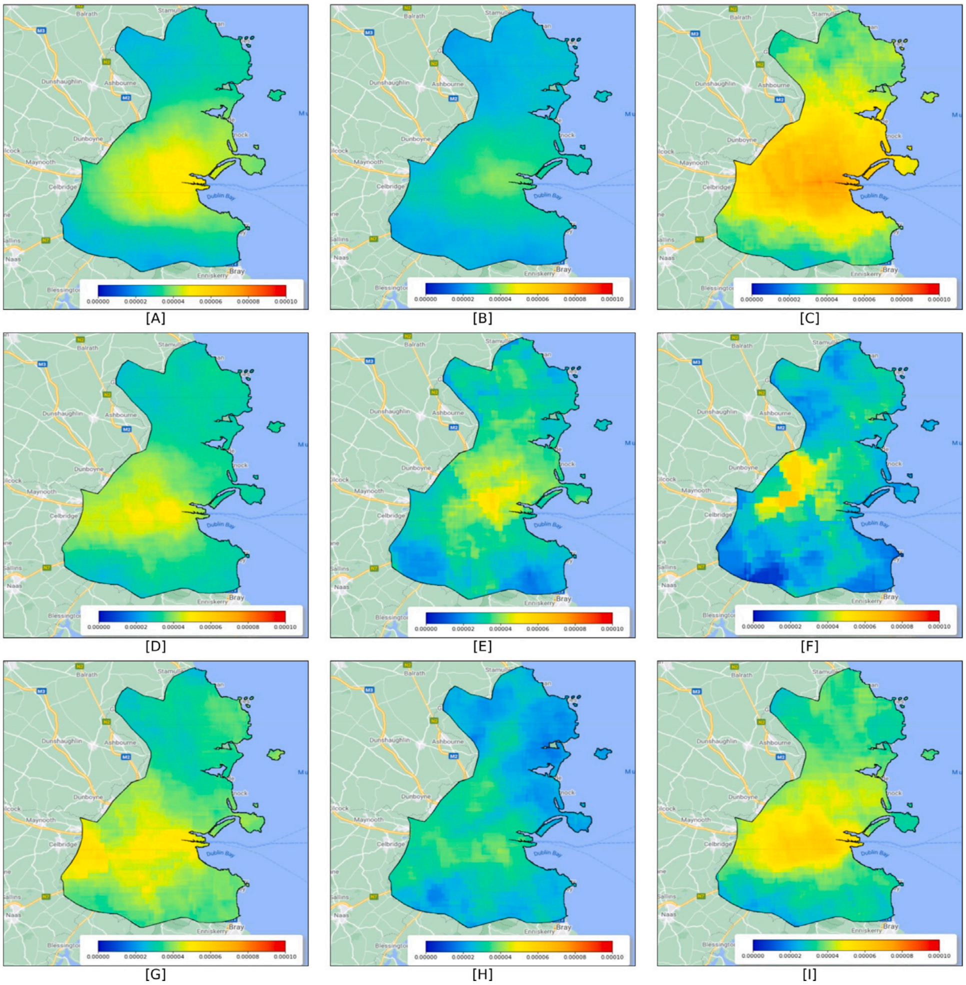

Fig. 3. NO_2, [A] 2019, average NO_2 [B] 2020, average NO_2 [C] 2019, During lockdown period [D] 2020, During lockdown period [E] 2020, Prelockdown [F] Phase-I [G] Phase-II [H] Phase-III [I] Phase-IV.

obtained from ground-based stations. These ground-based observations are correlated with their satellite counterparts to observe the effect of the lockdown.

4. Analysis & results

In this section, we demonstrate the changes in concentrations of significant pollutants for the pre-lockdown and lockdown period. The aim of the spatial plots is to quantify the effect of lockdown on air quality during the different phases of lockdown and before the lockdown. The area averaged maps of significant pollutants are generated for the study periods and are explained below.

4.1. Nitrogen dioxide

NO_2 is an essential trace gas in the earth's atmosphere. It enters the atmosphere due to different anthropogenic activities and natural processes such as biomass burning, fossil fuel combustion, wildfires and lightning (Das et al., 2021). A considerable reduction (28%) in NO_2 levels has been observed during the lockdown period (March 27–June 5) in 2020 compared to 2019 for the same period (Table 2). Although the lockdown was imposed for a shorter period, the impact resulted in a sharp decline in average annual tropospheric column NO_2 levels over Dublin (Fig. 3).

A sharp decline (21.75%) in average tropospheric column NO_2 concentration is observed in 2020 compared to the previous year 2019 (Table 2). A detailed analysis of the NO_2 levels before and during the different phases of lockdown has been analysed. A maximum drop in NO_2 levels is observed during the phase-I (−13.7%) and phase-III lockdown (−15.5%). However, phase-II (+19.7%) and phase-IV (+20.8%) showed an increase in NO_2 levels compared to the pre-lockdown period. The reduction in vehicular emissions caused by Covid-19 restrictions led to a dramatic fall in NO_2 concentration (Collivignarelli et al., 2021; Jephcote et al.,

Table 2
All analysed pollution parameters during the lockdown.

	NO_2 (μmol/m^2)	SO_2 (μmol/m^2)	O_3 (μmol/m^2)	CO (μmol/m^2)	AOD	AQI
Annual (2019)	35.31	264.68	150161.2	32019.85	0.10	
Annual (2020)	27.63	399.95	147379	32552.34	0.10	
Lockdown (2019)	49.07	326.86	165154.6	35193.33	0.11	52.7
Lockdown (2020)	35.35	471.71	156146.4	35366.89	0.10	38.1
Pre-lockdown	32.38	710.8	170008.3	35697.41	0.10	
Phase-I	27.95	1287.05	152334.7	37571.74	0.09	
Phase-II	38.76	469.34	161927.4	35893.02	0.09	
Phase-III	27.34	295.52	159673.6	35101.79	0.07	
Phase-IV	39.13	264.03	150326.9	32350.64	0.17	

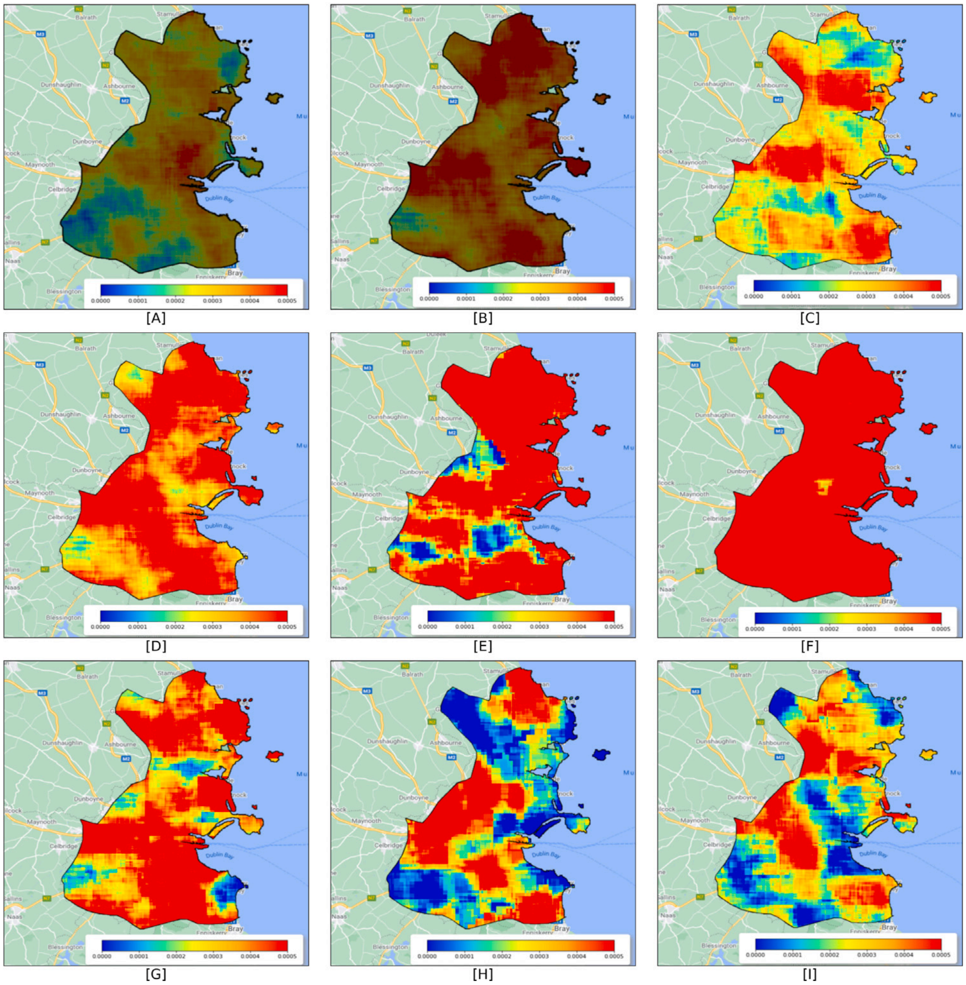

Fig. 4. SO_2 [A] 2019, average SO_2 [B] 2020, average SO_2 [C] 2019, During lockdown period [D] 2020, During lockdown period [E] 2020, Pre-lockdown [F] Phase-I [G] Phase-II [H] Phase-III [I] Phase-IV.

2021), but burning solid fuel and meteorological conditions may sometimes dominate vehicular emissions. These discrepancies can also be attributed to the nature of the lockdown and its implementation. In a similar study, Dacre et al. (2020) observed an increase in NO_2 concentration during the lockdown and cited that this change could be due to meteorology.

4.2. Sulphur dioxide

SO_2 is a key pollutant, adversely affecting human health and air quality. The majority of the emitted SO_2 comes from anthropogenic sources and plays a vital role in climate through radiative forcing and atmospheric chemistry. Fig. 4 indicates that the tropospheric column SO_2 levels are not aligning with the lockdown restrictions and are more localized. Despite the lockdown

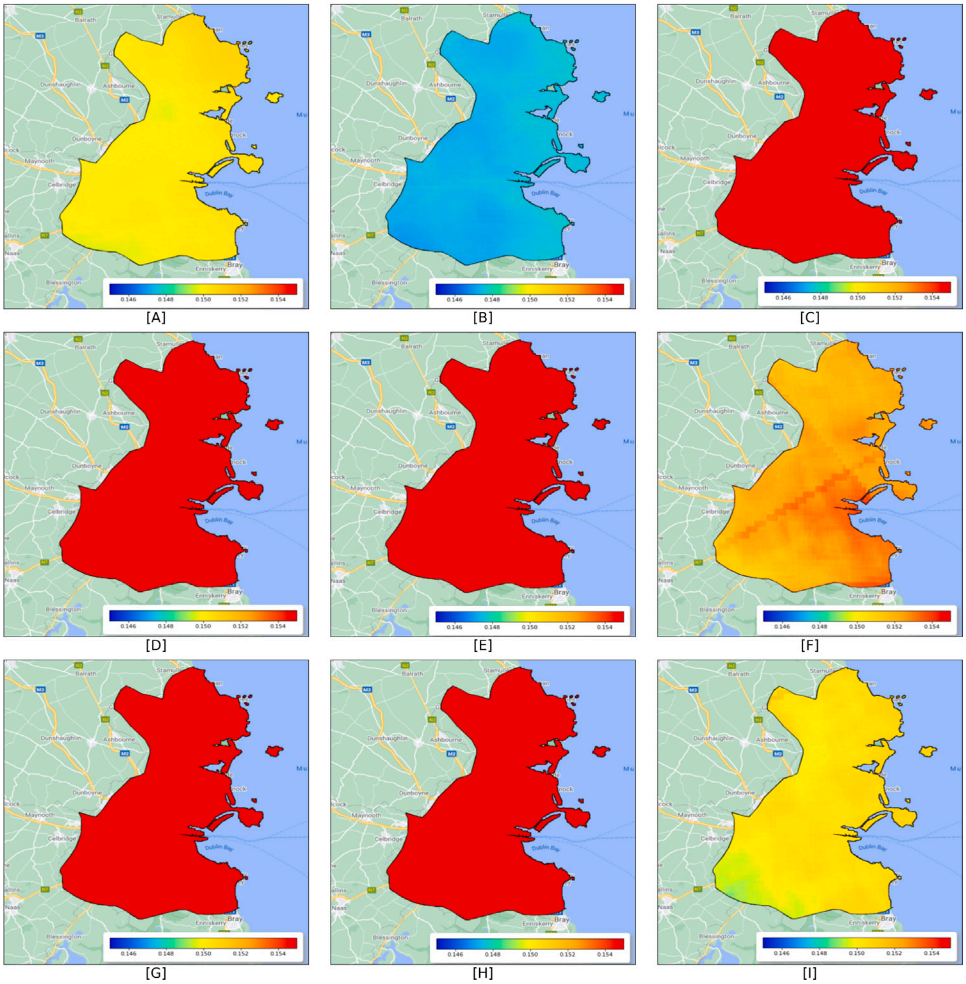

Fig. 5. O_3 [A] 2019, average O_3 [B] 2020, average O_3 [C] 2019, During lockdown period [D] 2020, During lockdown period [E]2020, Pre-lockdown [F] Phase-I [G] Phase-II [H] Phase-III [I] Phase-IV.

impact in 2020, Dublin showed a high-level SO_2 compared to 2019. During the different phases, it is observed that the SO_2 increased from the pre-lockdown period to the first phase of lockdown and again started decreasing and reaching the lowest level in the fourth phase of lockdown (Table 2, Fig. 4).

4.3. Ozone

Ozone (O_3) is also an important greenhouse gas. The stratosphere, it protects the biosphere from dangerous ultraviolet radiation. However, In the troposphere, it acts as an efficient cleansing agent, but at high concentrations, it also becomes harmful to the health of humans and the environment. Sentinel-5P; Near Real-Time Ozone, observations showed a lower level concentration in 2020 compared to 2019 (Fig. 5).

Short term analysis clearly revealed a significant reduction in ozone level during the most and least restricted phases of the lockdown and started increasing during the second and third phases, while a high level in the intermediate phases of lockdown (Fig. 5, Table 2). Ozone, a secondary pollutant, is formed by the ozone precursors (nitrogen oxides and volatile organic compounds) in solar radiation. Traffic is the major source of ozone precursors. Ozone has the unique property of being degraded by the compounds (NOx) formed by it. A reduction in traffic, resulting in a diminution of ozone precursors, can increase ozone concentration. Additionally, new ozone formation may continue by the volatile organic compounds (VOCs) emitted by trees and other sources. This might be a reason for the high ozone concentration despite the traffic restrictions.

4.4. Carbon monoxide

Carbon monoxide (CO), a prominent atmospheric pollutant, and trace gas, plays a vital role in atmospheric chemistry, e.g., the formation of tropospheric ozone. The primary sources of CO are biomass burning, combustion of fossil fuels and atmospheric oxidation.

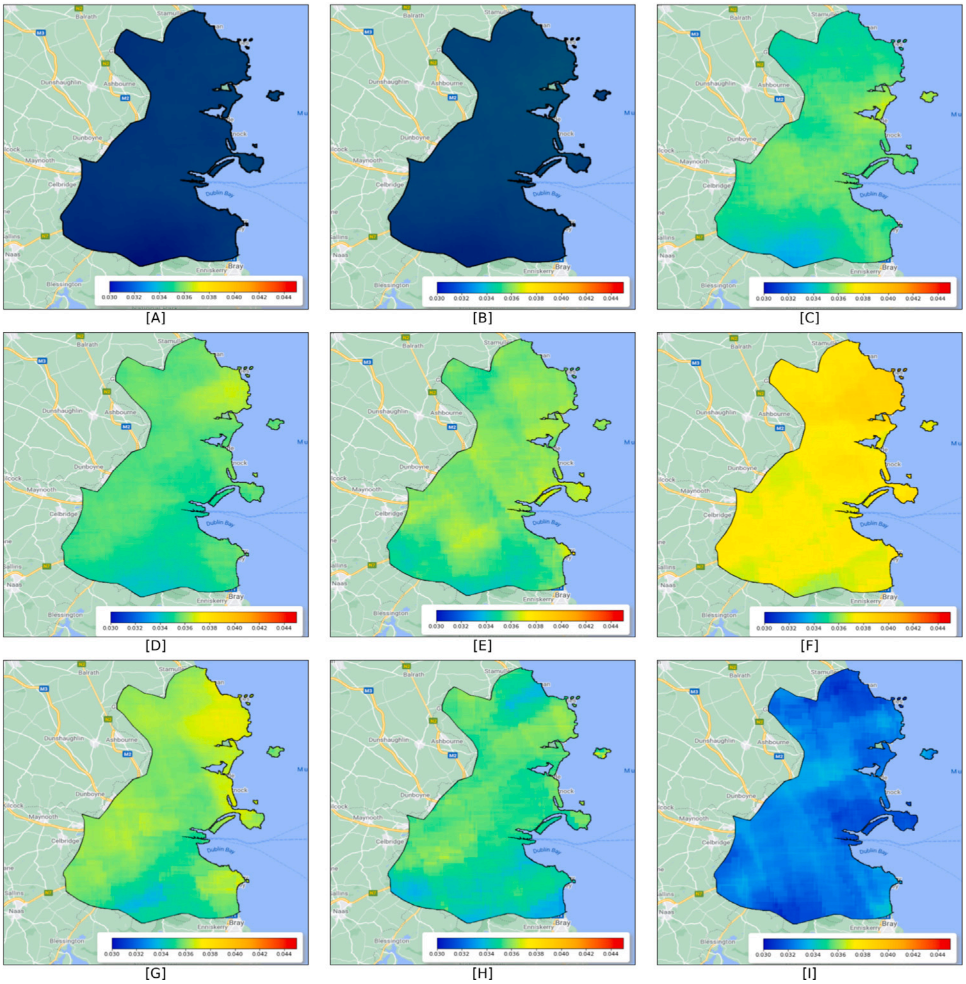

Fig. 6. CO [A] 2019, average CO [B] 2020, average CO [C] 2019, During lockdown period [D] 2020, During lockdown period [E] 2020, Pre-lockdown [F] Phase-I [G] Phase-II [H] Phase-III [I] Phase-IV.

At the annual level, 2020 appeared as a slight increase in tropospheric column CO levels. CO showed the opposite results from the most restricted to the minor restricted phases of the lockdown (Fig. 6, Table 2). The increased CO concentration could be attributed to the emission transported from other regions and the higher emission tendency of people residing in their homes during the lockdown.

4.5. Aerosol Optical Depth (AOD)

Aerosol Optical Depth (AOD) is a measure of the extinction of solar radiation by atmospheric particles. In other words, it tells us how much direct sunlight is prevented from reaching the ground due to the atmospheric particles. Moderate Resolution Imaging Spectroradiometer (MODIS) observations showed that AOD is almost at the same levels throughout the study period (Fig. 7, Table 2). Phase-IV revealed a sudden rise in AOD level (Fig. 7, Table 2), which may be attributed to the dust and other particles blown with air from other continents.

4.6. Correlation analysis between parameters

The correlation coefficient is a measure of linear correlation between two sets of data. It is the ratio between the covariance of two variables and the product of their standard deviations. Pearson's correlation coefficient is used to correlate the pollution parameter to each other, and it is given by Benesty et al. (2009)

$$\rho(X,Y) = \frac{cov(X,Y)}{\sigma X \sigma Y} \quad (1)$$

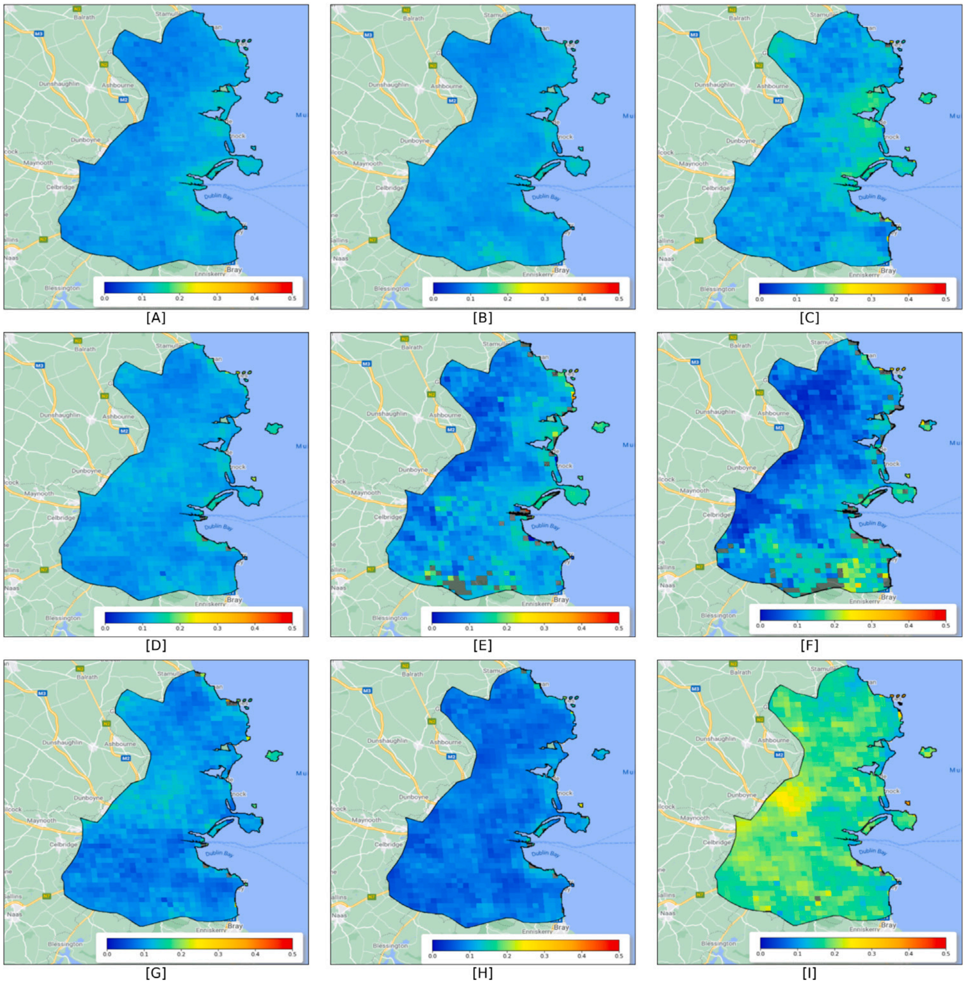

Fig. 7. AOD [A] 2019, average AOD [B] 2020, average AOD [C] 2019, During lockdown period [D] 2020, During lockdown period [E] 2020, Pre-lockdown [F] Phase-I [G] Phase-II [H] Phase-III [I] Phase-IV.

Table 3
Pearson correlation coefficient between all pollution parameters.

	AOD	NO_2	SO_2	O_3	PM_{10}	$PM_{2.5}$	AQI
AOD	1.00	−0.03	0.07	0.15	0.06	0.12	0.16
NO_2	−0.03	1.00	0.81	−0.59	0.66	0.66	0.56
SO_2	0.07	0.81	1.00	−0.43	0.61	0.63	0.48
O_3	0.15	−0.59	−0.43	1.00	−0.19	−0.25	−0.12
PM_{10}	0.06	0.66	0.61	−0.19	1.00	0.97	0.81
$PM_{2.5}$	0.12	0.66	0.63	−0.25	0.97	1.00	0.82
AQI	0.16	0.56	0.48	−0.12	0.81	0.82	1.00

Where, cov is the covariance, σ X, is the standard deviation of X, σ Y, is the standard deviation of Y.

Table 3 showed that the Particulate matters (PMs) are the most dominating factors to the Air Quality over Dublin. It is also observed that NO_2 and SO_2 are also highly correlated with air quality. The correlation matrix with colour scale is also represented in Fig. 8, where blue side of the colour scale shows the highest correlation and the red side shows the lowest.

4.7. Time-series analysis

Ground observations for different pollutants (NO_2, SO_2, O_3, PM_{10} and $PM_{2.5}$) also have been analysed for the pre and post-lockdown duration (Fig. 9). These ground-based pollutant data were accessed from the OpenAQ Platform and originate from European Environmental Agency (EEA) over the Dublin city at location Id 4837. OpenAQ is the world's first real-time and

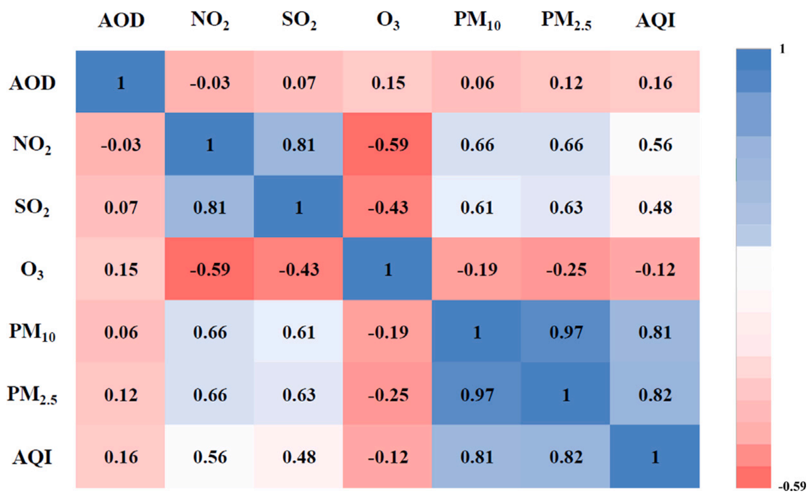

Fig. 8. Visual representation of correlation matrix. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

historical air quality data platform, aggregating government-measured and research-grade data entirely open-source (Anon, 2020). A continuous decreasing trend has been observed in NO_2 concentrations from pre lockdown to during the lockdown period, while SO_2 showed no trend during the same period. Ozone showed a continuously increasing trend from the pre-lockdown to during the lockdown period. AQI remains under the 'Good' and 'Satisfactory' categories throughout the study period.

5. Conclusions and future work

Although the pandemic and associated restrictions came with high societal and personal costs, at the same time, many places worldwide experienced the blue sky, starry nights, and snow-capped mountains from a far distance, often for the first time in several decades. It is not possible to maintain these changes permanently, but the lessons accrued highlight the possibilities in future environmental management. As the shutdown ended, emissions have increased quickly, wiping out any gains in air quality. Undoubtedly, the COVID-19 shutdown has made the human influence on air quality more visible. During the lockdown, a substantial reduction in nitrogen dioxide (NO_2) was reported worldwide. However, few studies reported increased ozone (O_3) levels and a modest decrease in fine-particle air pollution. Almost all studies have revealed a substantial reduction in air pollution with a significant improvement in air quality across the globe. However, these studies are limited to comparing the situation without and with lockdown measures regardless of seasonal effects, different atmospheric conditions, and several other factors, such as our efforts to reduce the anthropogenic emissions year after year. Additionally, the weather modelling system must be utilized to better estimate the improvement in air quality due to lockdown measures only. Furthermore, we intend to use knowledge graph technologies (Wu et al., 2022, 2021) to combine diverse pollution and weather data to understand these pollutant patterns in this atmosphere. Overall, the outcomes of this study highlight the trade-offs between human interventions and environmental health and inspire renewed demands for better air quality in the longer term.

Computer code availability

The source code related to this manuscript is available via: https://github.com/Sushma7870-git/Air-Quality-analysis-over-Dublin.

CRediT authorship contribution statement

Sushma Kumari: Conceptualization, Methodology, Software, Data curation, Writing – original draft, Visualization, Investigation, Writing – review & editing. **Avinash Chand Yadav:** Methodology, Software, Data curation, Writing – original draft, Investigation, Writing – review & editing. **Manabendra Saharia:** Methodology, Writing – original draft, Investigation, Validation, Writing – review & editing. **Soumyabrata Dev:** Conceptualization, Methodology, Supervision, Writing – original draft, Investigation, Validation, Writing – review & editing.

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.

Data availability

Data will be made available on request.

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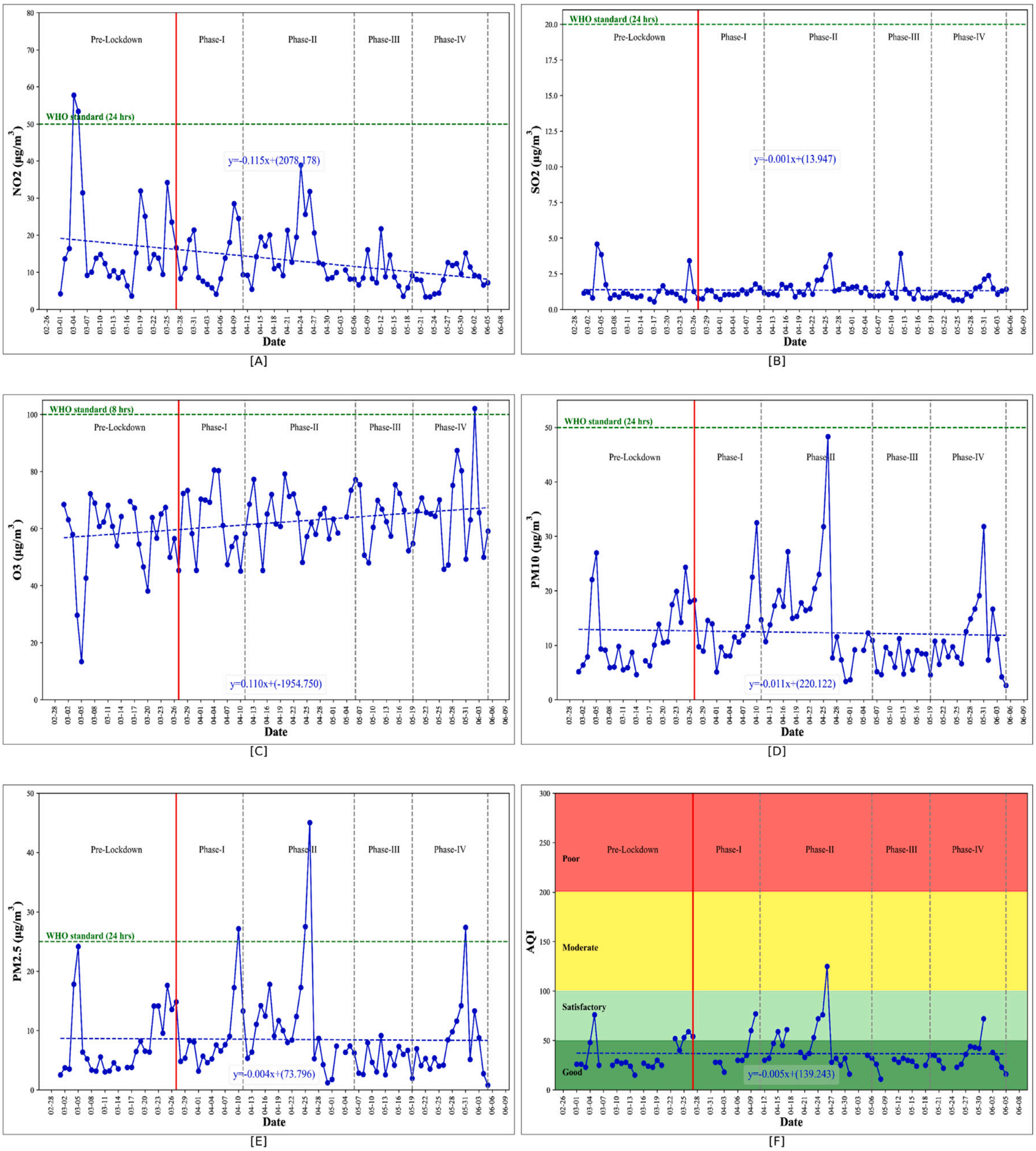

Fig. 9. Time-series analysis before and during lockdown period [A] NO_2 (μg/m^3) [B] SO_2 (μg/m^3) [C] O_3 (μg/m^3) [D] PM_{10} (μg/m^3) [E] $PM_{2.5}$ (μg/m^3) [F] Air Quality Index.

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