Air pollution dynamics in two coastal megacities of India amidst COVID-19 pandemic

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Dedication

This doctoral thesis is dedicated with immense love and gratitude to my family- to my father (Jagannath Mandal), for his wisdom and unwavering support, to my mother (Suchitra Mandal), for her boundless love and encouragement, to my wife (Moumita Mandal), for her patience, understanding, and strength, and to my daughter (Aarya Mandal), for being my greatest inspiration and joy.

Certificate from Supervisor

This is to certify that the thesis entitled **"Air pollution dynamics in two coastal megacities of India amidst COVID-19 pandemic"** submitted by **Jayatra Mandal**, who got registered (registration no. **D7/ISLM/76/21, dated 05/01/2022)** his name under the Faculty of Interdisciplinary Studies, Law & Management for the award PhD (Arts) degree of Jadavpur University is absolutely based upon his own work under the supervision of **Dr. Abhra Chanda** and that neither his thesis nor any part of the thesis has been submitted for any degree/diploma or any other academic award anywhere before.

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Statement of Originality

I, **Jayatra Mandal** (Reg. No. **D7/ISLM/76/21, registered on 05/01/2022 do hereby declare that this thesis entitled "Air pollution dynamics in two coastal megacities of India amidst COVID-19 pandemic"** contains literature survey and original research work done by the undersigned candidates as part of Doctoral studies.

All information in this thesis has been obtained and presented in accordance with existing academic rules and ethical conduct. I declare that, as required by thesis rules and conduct, I have fully cited and referred all materials and results that are not original to this work.

I also declare that I have checked this thesis as per the "Policy on Anti Plagiarism, Jadavpur University, 2019", and the level of similarity as checked by iThenticate software is **10%.**

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ABSTRACT

The COVID-19 pandemic led many countries, including India, to implement nationwide lockdowns to halt the virus's spread. India implemented the first lockdown on 24 March 2020 during the first wave. Kolkata and Mumbai experienced subsequent lockdowns due to pandemic surges: Kolkata from 16 May to 30 May 2021 and from 01 January to 15 January 2022, while Mumbai’s lockdowns occurred from 22 April to 1 May 2021 and from 10 January to 19 January 2022. This doctoral thesis examines the impact of COVID-19 lockdowns on air quality in Kolkata and Mumbai, two coastal megacities, using Delhi as a control. The study includes six chapters. One chapter focused on air pollution levels worldwide, and another on air pollution in China, India, and Pakistan. The remaining chapters concentrate on Kolkata, Mumbai, and Delhi. Data were collated from the Central Pollution Control Board (CPCB), Real-time Air Quality Index (AQI), IQAir, and NASA GIOVANNI. The climate datasets used in this research were sourced from Weather Underground and NASA Power. Kolkata has ten, Mumbai has fifteen, and Delhi has thirty-seven ambient air monitoring stations. India’s tropical monsoon climate features distinct wet and dry seasons, with pandemic surges occurring during early pre-monsoon and winter months, which enabled me to study the effect of meteorology on air pollution levels.

Chapter 1 introduced the research topic. The doctoral thesis utilized various methods, including spatial-temporal variation maps generated with the Inverse Distance Weighting (IDW) interpolator using ESRI ArcGIS 10.5, de-weathering through the generalized additive model (GAM) with XLSTAT-R, statistical analysis via the Pearson correlation coefficient in R. Additionally, it employed cartographic techniques and statistical methods, such as point plots, box plots, and sparkline diagrams to illustrate changes in average concentration trends. Chapter 2 detailed the methodology adopted in this doctoral study.

Chapter 3 examines the impact of the COVID-19 lockdown on global atmospheric pollution levels, focusing on ambient NO_2 and Aerosol Optical Depth (AOD) data from NASA’s GIOVANNI portal. Before the lockdowns, China had the highest tropospheric pollution, followed by India, the U.S., Germany, France, and Italy, with the most polluted regions identified in eastern China, India, northern Italy, and western

Germany. The study analyzed four phases for each country: normal phases in 2019 and pre-, during, and post-lockdown phases in 2020. A significant reduction of up to -60% in pollutant levels was observed during the lockdown, with a partial rebound post-lockdown. The findings suggest that periodic short lockdowns could effectively help reduce air pollution and promote a sustainable environment.

Chapter 4 presents a seven-year analysis (2017-2023) of $PM_{2.5}$ data from 760 cities across China, India, and Pakistan, which together represent over 38% of the global population. It reveals that all cities in these countries exceed the WHO's standard limit of 5 $\mu g/m^3$, with $PM_{2.5}$ levels in Pakistani and Indian cities more than double those in China. The study highlights a significant shortage of monitoring stations in Pakistan. Delhi, India, stands out as the most polluted area at 97.5 $\mu g/m^3$. The highest $PM_{2.5}$ concentrations were found in the Indo-Gangetic plain of India, north-central Pakistan, and central-east China. Urgent government intervention is needed to address these levels, as prolonged exposure poses risks to human health and ecological well-being. Continuous monitoring of $PM_{2.5}$ across all cities is essential for effective research and solutions.

Chapter 5 analyzed air quality in three Indian megacities—Mumbai, Kolkata, and Delhi—during the lockdown and compared it to pre-lockdown and post-lockdown periods. Seven major pollutants ($PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, CO, and O_3) were studied using data from 62 AAMSs under the CPCB. Delhi was the most polluted, followed by Kolkata and Mumbai. The lockdown (25 March to 14 April 2020) resulted in significant improvements in air quality compared to the pre-lockdown phase and the same period in 2019. Post-lockdown showed mixed results. Major pollutants reduced as follows: $PM_{2.5}$ by -47% in Mumbai, -52% in Delhi, and -49% in Kolkata; PM_{10} by -41%, -39%, and -37%, respectively; and CO by -27%, -13%, and -21%. This study highlights that short-term lockdowns can refresh air quality in these megacities.

Chapter 6 highlights the differences in air pollution levels during Diwali celebrations in 2020, amid the COVID-19 pandemic, compared to 2019. The concentrations of key pollutants—$PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, CO, and O_3—were significantly higher in 2020. $PM_{2.5}$, PM_{10}, and CO consistently exceeded permissible limits, especially in Delhi, indicating increased firecracker usage during the pandemic. However, pre-

Diwali to Diwali changes in pollutant levels showed lower pollution in Mumbai and Kolkata. Meteorological conditions likely contributed to the heightened pollution in Delhi in 2020, as pollutants lingered for nearly a week after the celebration. The study underscores the need for stricter regulations to reduce pollution from such festivities.

Chapter 7 examines Kolkata's air quality during three pandemic waves. It analyzed seven pollutants ($PM_{2.5}$, PM_{10}, CO, NH_3, NO_2, SO_2, O_3) from 10 monitoring stations. NO_2, NH_3, SO_2, and O_3 were below CPCB standards, but CO exceeded them during all waves. $PM_{2.5}$ and PM_{10} levels fluctuated. Declines of -44%, -34%, -15%, -48%, and -51% in $PM_{2.5}$, PM_{10}, NO_2, SO_2, and O_3 were observed during the second wave compared to the first. The AQI improved by -40% during this period. However, the third wave saw a rise in pollution, making it the highest among the three. Strong positive correlations were found between $PM_{2.5}$, PM_{10}, CO, and NO_2 levels. Seasonal changes affected pollutant concentrations, and specific industrial areas showed compromised air quality. Policymakers should consider short-term lockdowns to improve air quality.

Chapter 8 analyzed air pollutant dynamics in Mumbai during three COVID-19 lockdown phases with varying stringencies: very stringent, moderately stringent, and loose to moderately stringent. Data on $PM_{2.5}$, PM_{10}, CO, NH_3, SO_2, NO_2, O_3, and AQI were sourced from the CPCB. CO consistently exceeded CPCB standards, while $PM_{2.5}$ and PM_{10} were below standards during the first wave but showed mixed results later. During the second wave, pollutants increased by 56% ($PM_{2.5}$), 45% (PM_{10}), 40% (CO), and others compared to the first wave. In the third wave, increases were 89% ($PM_{2.5}$), 15% (PM_{10}), and others compared to the second wave. The findings indicate that lockdowns improved air quality, but as restrictions eased, pollutant levels rose. Lockdowns during winter were more effective in reducing air pollution than those in summer.

Chapter 9 detailed the conclusions and recommendations. To improve air quality in megacities, the following steps are essential: halting construction during high pollution days, expanding electric public transport to reduce private vehicle use, using sweepers and water sprinklers to reduce road dust, implementing the Clean Air Mumbai Initiative, i.e., enforcing monitoring and penalties for non-compliance, planting trees and creating urban green spaces, instituting short-term lockdowns during winter to prevent PM buildup. These actions will help combat air pollution effectively.

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NOMENCLATURE

$(NH_4)_2SO_4$ Ammonium sulphate

AOD Aerosol optical depth

AQI Air quality index

C_6H_6 Benzene

CB Black carbon

CCKP Climate Change Knowledge Portal

CEVD Cerebrovascular disease

CH_4 Methane

CIP China, India, and Pakistan

CNS Central nervous system

CO Carbon monoxide

CO_2 Carbon dioxide

CO_3^{2-} Carbonates

COHb Carboxyhemoglobin

COPD Chronic obstructive pulmonary disease

COVID-19 Coronavirus disease 2019

CPCB Central Pollution Control Board

CVD Cardiovascular disease

DNA Deoxyribonucleic acid

dp Diameters of particles

DPCC Delhi Pollution Control Committee

DU Delhi University

ESA European Space Agency

GAM Generalized additive model

GHG Greenhouse gas

GIS Geographic information system

GoI Government of India

GoM Government of Maharashtra

GoWB Government of West Bengal

GRAP Graded Response Action Plan

H_2 Hydrogen

H_2S Hydrogen Sulphide

H_2SO_4 Sulfuric acid

Hb Haemoglobin

HCl Hydrochloric acid

HMC Howrah Municipal Corporation

HNO_3 Nitric acid

IDW Inverse Distance Weighting

IMD India Meteorological Department

IMF International Monetary Fund

IQ Intelligence quotient

KMC Kolkata Municipal Corporation

LPG Liquid petroleum gas

LULC Land use land cover

mgcv mixed GAM computation vehicles

MODIS Moderate Resolution Imaging Spectroradiometer

MoEF Ministry of Environment and Forest

MoEFCC Ministry of Environment, Forests and Climate Change

MPCB Mumbai Pollution Control Board

N_2 Nitrogen

N_2O Nitrous oxide

NAAQS National Ambient Air Quality Standards

NAQI National Air Quality Index

NASA National Aeronautics and Space Administration

NCAP National Clean Air Programme

NCR National Capital Region

NDMA National Disaster Management Authority

NEERI National Environmental Engineering Research Institute

NH_3 Ammonia

NH_4^+ Ammonium

NH_4Cl Ammonium chloride

NH_4NO_3 Ammonium nitrate

NO Nitric oxide

NO_2 Nitrogen dioxide

NO_3^- Nitrates

NO_x Oxides of nitrogen

NOx Nitrogen oxides

O_2Oxygen

O_3 Ozone

OMI Ozone Monitoring Instrument

PAN Peroxyacylnitrates

Pb Lead

PBL Planetary boundary layer

PCAP Pakistan Clean Air Plan

PM Particulate matter

PM_{10} Particulate matter of 10

$PM_{2.5}$ Particulate matter of 2.5

PPEs Personal protective equipments

PUC Pollution Under Control

RBU Rabindra Bharati University

RD Respiratory disease

RELM REstricted Maximum Likelihood

REML Residual maximum likelihood

RNA Ribonucleic acid

SAR-CoV-2 Severe acute respiratory coronavirus 2

SO_2 Sulphur dioxide

SO_3 Sulfur trioxide

SO_4^{2-} Sulfates

SO_x Sulfur oxides

SPM Suspended particulate matter

States/UTs States and union territories

VOCs Volatile organic compounds

WBPCB West Bengal Pollution Control Board

WHO World Health Organization

Chapter I

Introduction

1.1 Atmospheric air pollution

Air is a mixture of several gases. The main gases are nitrogen (N_2 = 78.09%), oxygen (O_2 = 20.95%), and carbon dioxide (CO_2 = 0.03%) —these are also components of respiratory air. The inhale and exhale ration air the volume % of O_2; N_2; and CO_2 are 20.95:16.4; 79.01:79.5; 0.04:4.1 (Khullar, 2008). Air is considered clean when the ratio remains the same. Often, an unfavourable alteration of the air around us due to drastic variations in its natural composition or the abundance of particulate matter (PM) is air pollution. Both natural and human sources constantly pollute the air. When we breathe, not only O_2 but also some other gases, such as dust particles, sulphur dioxide (SO_2), and carbon monoxide (CO), which are emitted from various natural and man-made sources, enter our respiratory system. About 99% of the global population breathes air that exceeds World Health Organization (WHO) guideline limits (WHO, 2023). Thus, the long-term effects of polluted air include stroke, lung cancer, heart disease, chronic obstructive pulmonary disease, and respiratory infections, such as pneumonia (WHO, 2019; Anwar et al., 2021). Short-term exposure to air pollution is associated with minor breathing discomfort, cough, wheezing, asthma, and respiratory disease (RD) (Manisalidis et al., 2020).

Air pollution has been known as a global problem since the 1930s (Pan et al., 2022). Every year, nearly 7 million premature deaths occur due to air pollution (UNEP, 2022). Air pollution caused an estimated 2 million premature deaths across South Asia in 2022 (IQAir, 2023). The substance that adversely alters the environment is a pollutant. It may be solids, liquids, or gases. The solids include aerosol, mercury, asbestos, lead (Pb), etc. Dissolved solids, urea, ammonia (NH_3), carbonates, nitrates (NO_3^-), fluorides, insecticides, and pesticides are liquid pollutants. CO_2, SO_2, nitrogen dioxide (NO_2), etc., are examples of gaseous pollutants (Khullar, 2008).

1.2 Natural sources of air pollutants in the atmosphere

Sources of air pollutants are mainly two types, natural and human-made or anthropogenic (Pénard-Morand and Annesi-Maesano, 2004; Duffney et al., 2023). Volcanism, forest fires, dust storms, extra-terrestrial material pollution, and decomposition are the natural sources of air pollutants. CO_2, CO, SO_2, and hydrogen sulphide (H_2S) are some of the constituent particles ejected at the time of volcanic eruption that pollute the air (Pénard-Morand and Annesi-Maesano, 2004). Forest fires caused by lightning, hot lava flows, and tree collisions are sources of CO_2, CO, ash, and other airborne pollutants. A dust storm is a source of air particulate matter of 2.5 and 10 μm ($PM_{2.5}$ and PM_{10}). In addition, sea salt in coastal regions, pollen (biological material), and spores (debris of plants and animals) are nature-driven sources of PM (Pénard-Morand and Annesi-Maesano, 2004). A strong wind usually lifts dust particles from bare, dry soils into the atmosphere. Terrestrial material pollution and decomposition of organic matter (i.e., plants, animals, and animal wastes) are significant sources of air pollutants, including methane (CH_4) and NH_3 (EPA, 2023). The secondary pollutant, ozone (O_3), naturally has a low concentration at ground level due to chemical reactions between oxides of nitrogen (NOx) and volatile organic compounds (VOCs) in the presence of sunlight.

1.3 Anthropogenic activities leading to air pollution

UNFPA (2023) opined that more than half of the world's population now lives in towns and cities. It will account for about 5 billion by 2030. This means that more than 70% of the world's population will be urban dwellers by 2030 (UNFPA, 2023). The World Urbanization Prospects Revision (2018) estimated that the megacities of Asia and Africa will account for over 90% of the growth in their current populations in 2050 (World Urbanization Prospects: The 2018 Revision, 2019). Rapid urbanization, fast industrialization, and associated human-made or anthropogenic activities (Chen et al., 2020; Gurjar et al., 2021) (e.g., vehicle movement, land use land cover (LULC) change, and industrial processes) are the prime sources of ground-level air pollution. The burning of fossil fuels in transport assets (land, air, and water mode), electricity generation and industrial processes are the anthropogenic sources of ambient air pollutants (Lestari et al., 2022; Cichowicz and Wielgosiński, 2017; 2015a; 2015b; Lelieveld et al., 2015; Gurney et al., 2012; Nemitz et al., 2002). India ranked eighth most polluted (annual average $PM_{2.5}$ concentrations weighted by population) in 2022 (IQAir, 2023). The report said the transportation sector accounts for 20-35% of $PM_{2.5}$ in Indian cities. Northern India (including Delhi) has witnessed episodic (pre- and during-winter) pollution spikes due to stubble (crop) burning (Abdurrahman et al., 2020). The agriculturally productive states of northern India — Uttar Pradesh, Punjab, Haryana, and West Bengal — account for the highest amount of stubble (IARI, 2012). The coal-mining areas of India account for massive air pollution as coal production has increased 6-7 times in recent years. Simultaneously, the coal import decreased from 234.35 to 208.93 million tonnes during 2018-19 and 2021-22 (DGCI&S, 2023). A recent study mentioned that the industrial sector was responsible for 50% of air pollution (Sharma et al., 2022). Nigam et al. (2021) pointed out that NO_2, SO_2, and PM_{10} originated from vehicular exhaust, road dust, and industrial processes (Nigam et al., 2021). Road traffic exhaust emissions are a significant concern for urban air quality and tropospheric O_3 formation (Colvile et al., 2002; 2001). The commercial practice of agriculture and livestock farming has emitted NH_3, $PM_{2.5}$, PM_{10}, CH_4, and Nitrous oxide (N_2O) (Aneja et al., 2009). The heavy use of fertilizers (particularly N_2-rich) and animal waste, combined with industrial emissions, is responsible for fine particulate air pollution being converted into solid particles (Columbia Climate School, 2016). Lu'ayi and Lestari (2020) have shown the details of agriculture amid pollution levels in Indonesia and across the globe (Lu'ayi and Lestari, 2020). Vadrevu et al. (2017) focused on the effects of air pollution on LULC change in Asia. They established a broad linkage between population, LULC change, and air pollution in this region (Vadrevu et al., 2017). Hong et al. have drawn similar conclusions about urban land use patterns and air quality in the Pearl River Delta, China (Hong et al., 2021).

1.4 Primary air pollutants

An air pollutant emitted directly from a source is a primary pollutant. PM_{10}, $PM_{2.5}$, NO_2, SO_2, tropospheric O_3, CO, NH_3, and Pb are the primary ambient air pollutants.

1.4.1 PM

PM, also known as particle pollution, consists of particles containing a mixture of solid and liquid droplets, commonly found in the troposphere. A few particles are visible to the naked eye (e.g., dust, smoke, dirt, soot), though some are visible only under a microscope; they are so small. Based on aerodynamic diameters of particles (*dp*) of PM National Ambient Air Quality Standards (NAAQS) divided into two categories, ≤10 μm (PM_{10}) and ≤2.5 μm ($PM_{2.5}$) (Chow et al., 2015). They are also known as coarse particles (PM_{10}) and fine particles ($PM_{2.5}$) (Fig. 1.1) (Pan et al., 2022). The big particles (PM_{10}) stay in the air for a few minutes to hours and may travel up to 100 m to 50 km, while fine particles ($PM_{2.5}$) persist for a few days to weeks longer and travel farther (Pénard-Morand and Annesi-Maesano, 2004). Coarse PM poses a lower health risk than fine PM (Wang et al., 2015; Oberdörster et al., 2005). Primary aerosols (PM_{10}) include vehicular exhaust, dust, and sea spray and are directly emitted into the atmosphere. Secondary aerosols ($PM_{2.5}$) are emitted into the air due to reactions of primary and secondary gaseous (Ansari and Pandis, 1998) (e.g., ammonium (NH_4^+), black carbon (CB), NO_3^-, and sulfates (SO_4^{2-})) (IQAir, 2023). Urban areas and regions worldwide suffer from the adverse effects of PM. Based on eight pollutants (PM_{10}, $PM_{2.5}$, CO, NH_3, NO_2, SO_2, O_3, and Pb), the air quality index (AQI) was computed by the Central Pollution Control Board (CPCB), Government of India (GoI) (CPCB, 2014). To compute the AQI, at least three primary pollutant concentrations are required, and either PM_{10} or $PM_{2.5}$ must be used.

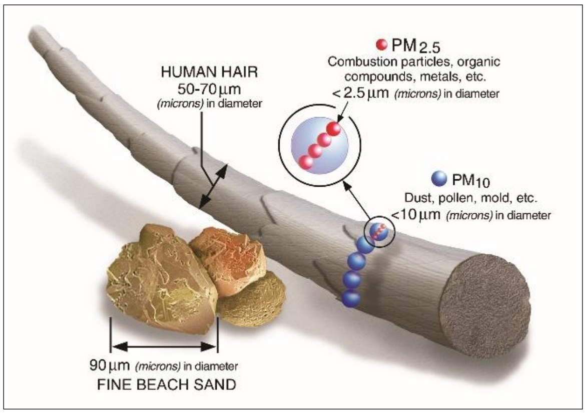


Fig. 1.1 Size comparisons for $PM_{2.5}$ and PM_{10}
Source: EPA, United States Environmental Protection Agency

Table 1.1 National Ambient Air Quality Standards of India
Source: CPCB, 2015

Pollutants	The concentration in ambient air		
	Time weighted average	Industrial Area Residential, Rural & other Areas	Ecologically sensitive area (Notified by Central Govt.)
$PM_{2.5}$ ($\mu g/m^3$)	Annual	40	40
	24 h	60	60
PM_{10} ($\mu g/m^3$)	Annual	60	60
	24 h	100	100
NO_2 ($\mu g/m^3$)	Annual	40	30
	24 h	80	80
NH_3 ($\mu g/m^3$)	Annual	100	100
	24 h	400	400

SO_2 (μg/m^3)	Annual	50	20
	24 h	80	80
CO (mg/m^3)	8 h	02	02
	1h	04	04
O_3 (μg/m^3)	24 h	60	60
	8 h	100	100
	1 h	180	180
Pb	Annual	0.5	0.5
	24 h	1.0	1.0

1.4.1.1 PM_{10}

The ambient air pollutant of PM_{10} has received special scientific and legislative attention due to human health concerns (Shahraiyni and Sodoudi, 2016). The annual and 24-hour (h) concentrations of ambient air should not exceed 60 and 100 μg/m^3, respectively, in industrial, residential (both rural and urban), and ecologically sensitive (notified by the central government) areas of India (Table 1.1). Pollutant substances are derived from natural sources such as forest fires, dust storms, volcanoes, and marine salts, and from anthropogenic sources such as industry, vehicular traffic, construction works, household fuels, etc. (Ni et al., 2012; Brunelli et al., 2007; Vautard et al., 2005). Anthropogenic sources have been more significant than natural ones (Liu et al., 2020). Shahraiyni and Sodoudi (2016) stated that the pollutants have mainly primary and secondary sources. Road traffic and combustion processes are the primary sources in urban areas. At the same time, secondarily, these are emitted through chemical reactions (e.g., atmospheric oxidation of NO_2 to nitric acid (HNO_3) and SO_2 to sulfuric acid (H_2SO_4)) or condensation of vapours (Keary et al., 1998). A study found that traffic-related exhaust (e.g., gases and particles emitted by vehicles when the engine is running) and non-exhaust (e.g., emissions from brake wear, tyre wear, road wear, and road dust resuspension) pollution are principally responsible for PM pollution. They observed that non-exhaust concentrations were six times higher than exhaust emissions for Delhi (Singh et al., 2020). The PM showed significant seasonal oscillation. The maximum increase in pollution levels occurred in the winter season, followed by post-monsoon, summer/pre-monsoon, and monsoon (Sasmita et al., 2022). None of India's megacities met the WHO (2021) annual average PM_{10} concentration of 15 μg/m^3. Mumbai recorded the highest level (216 μg/m^3), followed by Delhi (181 μg/m^3) and Kolkata (116 μg/m^3) (Statista, 2023).

Table 1.2 Typical sources of major air pollutants in Ambient Air

Source: Air Quality Status and Trends in India, CPCB (2000) pp.17-18

Air pollutants	Major sources
$PM_{2.5}$ and PM_{10}	Fuel combustion, power station, construction activities, industrial processes, diesel vehicle exhaust, resuspended road dust, domestic refuse burning, and domestic wood
NO_2	Transport (road, rail, passenger, and commercial), fuel combustion, power station, industrial boilers, chemical processes, waste incinerators, smelters
NH_3	Agricultural field, including animal husbandry and NH_3-based fertilizer applications, industrial processes, and vehicular emissions
SO_2	Fuel combustion, power stations, industrial processes, chemical processes, diesel vehicles, solid waste disposal, smelters
CO	Transport, combustion, industrial processes, solid waste disposal, refuse burning
O_3	Secondary pollutants are formed during the photochemical reaction

1.4.1.2 $PM_{2.5}$

$PM_{2.5}$ has had a higher human health impact than perhaps any other pollutant (Xing et al., 2016). The substance has influenced the atmosphere and regional climate (Pan et al., 2022). The sources of $PM_{2.5}$ are the same as PM_{10} (Table 1.2). Natural forest fires and anthropogenic sources (e.g., burning fuel and chemical reactions) produce atmospheric particles. SO_4^{2-}, NO_3^-, CB, and NH_4^+ are the most common particles that constitute $PM_{2.5}$ (Zhang et al., 2018). Dust storms, wildfires, and sandstorms are the most prevalent natural sources. At the same time, industrial processes, engine combustion, power generation, agricultural processes, wood and coal burning, and building construction are the anthropogenic sources (IQAir, 2023). These tiny particles contribute to urban smog in many major cities worldwide (e.g., Beijing and Delhi). The areas, regions, and territories of Central Asia, South Asia, and Africa are adversely affected by this pollutant.

1.4.2 NO_2

NO_2 is a member of the NO_X family. NO_2 is volatile, reddish to brown, and heavier than air (ILO, 2021). The 24 h permissible limit for the pollutant is 80 µg/m3, with an annual limit of 40 µg/m3, for residential and industrial areas of India (Table 1.1). WHO sets the same annual standard, 40 µg/m^3. The substance is a precursor to $PM_{2.5}$ and ground-level O_3 (Anenberg et al., 2022). Automobile exhaust is one of the largest sources of NO_2 emissions in the ambient air. In addition, industrial emissions, power stations, fuel combustion, chemical processes, waste incinerators, and smelters generate NO_2. Studies show that NO_2 peaks coincide with traffic peaks (Table 1.2). Though the annual mean concentration of NO_2 in most Indian cities is still within tolerance limits, maximum levels in several cities are well above the permissible limits (Khullar, 2008). The megacities of Mumbai, Delhi, and Kolkata had average concentrations of 20-30 $\mu g/m^3$.

1.4.3 SO_2

SO_2 is a colourless gas with a pungent odour. SO_2 is a group member of gaseous sulfur oxides (SO_x) and has a higher mass concentration than other members (e.g., sulfur trioxide, SO3) from the family of SO_x. The component has a significant concern and is usually an indicator of the SO_x family. The 24 h permissible limit of the pollutant is 80 $\mu g/m^3$, with an annual limit of 50 $\mu g/m^3$, for residential and industrial areas of India (Table 1.1). SO_2 emissions come from anthropogenic (e.g., Fuel combustion, industrial processes, road traffic, power stations, and smelters) and natural sources (e.g., bacterial decomposition of organic matter, volcanoes) (Table 1.2). A study by NEERI (National Environmental Engineering Research Institute) found that SO_2 was identified as a critical pollutant during 1960-80 due to high air emissions driven by rapid urbanization and industrialization. Liquid petroleum gas (LPG) replaced wood, coal, and kerosene for cooking fuel, remarkably reducing concentrations (Khullar, 2008). A few metro areas still have a high concentration of traffic and industrial activity.

1.4.4 Tropospheric O_3

O_3 is a bluish gas with an odour that, to a large extent, resembles chlorine. Ground-level or tropospheric O_3 is not emitted directly into the air; it is sourced by chemical reactions between oxides of NO_x and VOSs (EPA, 2023). Emissions from industrial processes, electric utilities, motor vehicle exhaust, gasoline vapours, and chemical solvents are among the primary sources of NO_x and VOS (Table 1.2). O_3 levels are high in urban environments on hot, sunny days, and in colder months, they can reach unhealthy levels. The substance can move farther away due to the wind. Even in rural areas, high O_3 concentrations may be observed. The standard limits for O_3 in India are 180, 100, and 60 $\mu g/m^3$ for 1 h, 8 h, and 24 h, respectively (Table 1.1). Tropospheric O_3 is a key component of urban smog. Asian countries such as India, Bangladesh, and

Pakistan have experienced high seasonal-average population-weighted O_3 concentrations (Climate and Clean Air Coalition, 2017). Tropospheric O_3 is a greenhouse gas (GHG) and an air pollutant that harms human health, ecosystems, and crops.

1.4.5 CO

CO is a deadly poisonous gas. It is a tasteless, colourless, non-irritating and odourless gas. Incomplete combustion of carbon produces CO. Due to its toxicity and high atmospheric concentration, CPCB considers it a primary pollutant for AQI computation. Naturally occurring CO includes volcanic eruptions, smoke from forest fires, natural gases from coal mines, and even lightning (Table 1.2). The anthropogenic sources of CO include motor vehicles, coal combustion, fuel oil combustion, industrial processes, solid waste disposal, and even burning for reuse. Burning firecrackers on festive nights (e.g., Diwali and New Year celebrations) is a significant source of CO during the short-lived phase. Urban road traffic is the leading source of pollutants. It shows significant diurnal variation. From 10 am to 12 noon, and in the early afternoon and evening, CO usually peaks during periods of high traffic. The gas's residence time is about 3 years. Therefore, this pollutant is a prime threat to present society, with an unstoppable rate of increase. The 8 h and 1 h concentrations of ambient air are 2 and 4 mg/m^3, respectively, for industrial, residential (both rural and urban), and ecologically sensitive (notified by the central government) areas of India (Table 1.1).

1.4.6 NH_3

NH_3 is a compound of N_2 and hydrogen (H_2). It is colourless, with a distinct pungent smell, lighter than air, highly reactive, and a soluble alkaline gas. The anthropogenic source is cultivated fields in the form of manure and fertilizer application (Table 1.2). It may last about one week. The gas can be found in air, soil, and water, and it originates mainly from hazardous waste. Biomass burning or fertilizer manufacturing industries are the other sources. Besides that, petrol cars, landfill sites, sewage works, composting of organic materials, combustion, and wild birds are the non-agricultural sources of NH_3 into the air (Wilson et al., 2004; Sutton et al., 2000). In nature, NH_3 is produced in soil by bacterial processes as plants and animal wastes decay. The 24 h and 1 h concentrations of ambient air are 400 and 100 $\mu g/m^3$, respectively, for industrial, residential (both rural and urban), and ecologically sensitive (notified by the central government) areas of India (Table 1.1).

1.4.7 Pb

Pb is a toxic metal. It comprises 0.002% of the Earth's crust (Raj and Das, 2023). In nature, it is rare, but anthropogenic sources such as industry, automobiles, and batteries are the primary sources. About ¾ of the global Pb has been used in motor vehicles (lead-acid) batteries. It has many uses, such as paints, stained glass, ceramic glazes, jewellery, toys, cosmetics, and even traditional medicines. The enormous sources and variety of uses of the gas have adverse health effects, particularly on the human brain and nervous system. The annual and 24 h concentrations of ambient air are 0.5 and 1 $\mu g/m^3$ for industrial, residential (both rural and urban), and ecologically sensitive (notified by the central government) areas of India (CPCB, 2015).

1.5 Air Quality Index

Air quality refers to the overall quality of the air in an area, as measured by pollutant levels. The National Air Quality Index (NAQI) was launched by the GoI on April 6, 2015, for decision-makers and citizens who want to know how well or poorly the air they breathe (NAAQS, 2019). An AQI is an inclusive system that converts the weighted values of individual air pollution-related parameters into a single value or set of numbers (CPCB, 2015). To calculate the AQI, CPCB-India continually monitors the ambient air using the EPA-US method. The CPCB report (CPCB, 2015) has elaborated on all required data processing steps. The Ministry of Environment and Forest (MoEF) revised the national ambient AQI in November 2009 by amending the Environment Protection Rule 1986. They listed a threshold for the air pollutants in the (i) Industrial, Residential, and Rural areas and the (ii) Ecologically Sensitive areas (Table 1.1). AQI formulation mainly includes two steps: (i) Formation of sub-indices (for each pollutant) and (ii) Aggregation of sub-indices to get an overall AQI. They computed the sub-indices for seven pollutants at each station based on 24 h average data (only CO and O_3 had 8 h averages) and the health breakpoint range. AQI computation requires $PM_{2.5}$, PM_{10}, NO_2, SO_2, O_3, CO, NH_3, and Pb as input parameters, of which at least three pollutant concentrations should be available and must include either $PM_{2.5}$ or PM_{10}. The AQI has six categories — good, satisfactory, moderate, poor, very poor, and severe — based on a scale of 0–500 (Table 1.3).

Table 1.3 Major Pollutants concentration, National AQI classes, National AQI categories, and health impacts
Source: CPCB, 2009, 2015

Concentration range*							AQI	AQI category	Health Impact
$PM_{2.5}$ (µg/m^3)	PM_{10} (µg/m^3)	NO_2 (µg/m^3)	NH_3 (µg/m^3)	SO_2 (µg/m^3)	CO (mg/m^3)	O_3 (µg/m^3)			
0-30	0-50	0-40	0-200	0-40	0-1.0	0-50	0-50	Good	Minimal impact
31-60	51-100	41-80	201-400	41-80	1.1-2.0	51-100	51-100	Satisfactory	Minor breathing discomfort to sensitive people
61-90	101-250	81-180	401-800	81-380	2.1-10	101-168	101-200	Moderately polluted	Breathing discomfort to people with lung disease
91-120	251-350	181-280	801-1200	381-800	10.1-17	169-208	201-300	Poor	Breathing discomfort to people with prolonged exposure
121-250	351-430	281-400	1201-1800	801-1600	17-34	209-748	301-400	Very poor	Respiratory illness in people on prolonged exposure
>250	>430	>400	>1800	>1600	>34	>748	401-500	Severe	Respiratory illness in people on prolonged exposure

* *24 h values for $PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, and 8 h values for CO and O_3*

1.6 Impact of meteorology on the air pollution scenario

Meteorological parameters such as rainfall, temperature, relative humidity, wind speed, and air pressure largely control ground-level air pollution. The meteorological variables exhibit significant seasonal variations; January and February comprise the winter season, when the static movement of air increases ground-level air pollution. A reverse scenario occurs in rainy months (June, July, August, and September). The monsoon brings heavy rainfall, resulting in substantially lower air pollution levels. The pre-monsoon (March to May) is characterized by elevated temperatures, high humidity, and low-pressure over land. The transition period between the monsoon and the winter, known as the post-monsoon season, exhibits fluctuating air pollutant concentrations. Tropical cyclones originating in the Bay of Bengal occasionally prevail during this time of the year.

Air pollutants (suspended particulate matter=SPM and SO_2) are correlated with wind speed, temperature, relative humidity, and pressure in Balikesir, Turkey (Ilten and Selici, 2007). Kayes et al. (2019) examined the relationships between meteorological parameters (daily mean temperature, relative humidity, and rainfall) and concentration of air pollutants ($PM_{2.5}$, PM_{10}, CO, NO_X, SO_2, and O_3) in Dhaka megacity, Bangladesh (Kayes et al., 2019). They found that most pollutants negatively correlated with atmospheric temperature and relative humidity.

A rise in ground-level air temperature destabilizes the atmosphere and facilitates enhanced vertical mixing of pollutants (Cichowicz et al., 2017). Thus, increasing air temperature reduced ground-level pollutant concentrations (Ravindra et al., 2019). A stronger negative correlation between temperature and $PM_{2.5}$ than between temperature and NO_2 or SO_2 was observed in four Chinese cities (Gao et al., 2021). A similar, negative correlation between PM_{10} and temperature was observed by many studies (Eliminir, 2005; Ilten and Selici, 2007; Giri et al., 2008). Due to rainfall, the PM may deposit in the ground but then revive in the air as it dries in high summer temperatures. Like higher air temperature, higher wind speed facilitates the dispersal of pollutants (Li et al., 2020), except for some pollutants, such as PM10, which are resuspended at ground level due to higher wind speed (Zhang et al., 2017). Relative humidity influences particle movement, causing PM to settle to the ground. Furthermore, increasing relative humidity reduces air pollutant concentrations (Giri et al., 2008). Like relative humidity, rainfall also helps to decrease air pollutants (Yoo et al., 2014). PM, as well as SO_2 and NO_2, populate the ground-level atmosphere at lower relative humidity (< 40%), and at higher relative humidity, pollutant concentrations usually decrease (Lou et al., 2017; Munir et al., 2017). The ground-level O_3 is produced photochemically. Cloudless skies are prime factors for higher amounts of insolation and photochemical reactions. Thus, high temperatures aggravate O_3 formation. Asif et al. (2022) gave a detailed global review of the spread of COVID-19 under environmental conditions (Asif et al., 2022). Here, I conclude that the governing role of meteorological parameters compelled researchers to deweather the pollutant datasets to examine their variability independent of seasonal fluctuations.

1.7 Human health impacts of air pollutants

1.7.1 Harmful effects of PM

The recent World Air Quality Report (2023) found that Indian cities experienced high levels of PM (IQAir, 2023). The researchers observed that the high concentrations lead to severe health impacts, e.g., premature death, chronic respiratory disease, acute respiratory syndrome, aggravated asthma, lung problems, and emergency hospital admissions. $PM_{2.5}$ is more concerning as it contains a high proportion of various toxic metals and acids, which penetrate deeper into the respiratory system (Table 1.4). The researchers have shown that fine particles ($PM_{2.5}$) pose widespread health risks, including morbidity and mortality, across the globe (Thangavel et al., 2022; Juginović et al., 2021; Segersson et al., 2017; Kim et al., 2015; Russell and Brunekreef, 2009). A study by Sharma et al. (2004) found that $PM_{2.5}$ affects the lower respiratory system (pulmonary region), whereas PM_{10} affects the upper respiratory system (Sharma et al., 2004). The significant association between $PM_{2.5}$ and PM_{10} has acute health effects. Janssen et al. (2013) reported that $PM_{2.5}$ and PM_{10} were significantly ($p < 0.05$) associated with all-cause and cause-specific deaths. In addition, they observed a 10 $\mu g/m^3$ increase in PM levels, with excess risks of 0.8% and 0.6% for $PM_{2.5}$ and PM_{10}, respectively (Janssen et al., 2013). Lu et al. (2015) observed that $PM_{2.5}$ had higher short-term effects than PM_{10}. Moreover, their association is associated with high mortality, but long-term effects and morbidity were inadequate in China (Lu et al., 2015). The details of concentration break and AQI categories for $PM_{2.5}$ and PM_{10} across different regions of the world are provided in Tables 1.5 and 1.6 below.

Table 1.4 Major Pollutants' impact on human health and environment

Source: CPCB ENVIS Control of Pollution Water, Air and Noise, 2015

(http://www.cpcbenvis.nic.in/air_quality_data.html)

Pollutants	Health effects	Environmental effects
PM	Respiratory problems, liver fibrosis, lung/liver cancer, Heart stroke, Bone problems	Visibility reduction
NO_x	Pulmonary disorders increase susceptibility to respiratory infections	The precursor of ozone formation in the troposphere, Aerosol formation
SO_x	Respiratory problems, Heart and lung disorders, Visual impairment	Acid rain
O_3	Respiratory problems, including asthma and bronchitis	O_3 in the upper troposphere causes greenhouse effects, Harmful effects on plants, as it interferes with photosynthesis and results in the death of plant tissues since it assists in the formation of Peroxyacetylnitate (PAN)
CO	Anoxemia leads to various cardiovascular problems. Infants, pregnant women, and elderly people are at higher risk	A major contributor of GHG when it is emitted into the atmosphere, which is linked to climate change and global warming
NH_3	Immediate effects include burning of the eyes, nose, throat, and respiratory tract. Prolonged effects result in blindness, lung damage, or death	atmospheric NH_3 increases the soil acidity when it deposits on plants' surfaces, dissolves, and washes into the soil

Table 1.5 $PM_{2.5}$ concentration and AQI category of States/Territories

Source: CPCB, 2015

India (24 h)		China (24 h)		United States (24 h)		European Union (8 h)	
$PM_{2.5}$ ($\mu g/m^3$)	AQI category	$PM_{2.5}$ ($\mu g/m^3$)	AQI category	$PM_{2.5}$ ($\mu g/m^3$)	AQI category	$PM_{2.5}$ ($\mu g/m^3$)	AQI category
30	Good	35	Excellent	12	Good	10	Very low
60	Satisfactory	75	Good	35	Moderate	20	Low
90	Moderate	115	Lightly polluted	55	Unhealthy for sensitive groups	30	Medium
120	Poor	150	Moderately polluted	150	Unhealthy	60	High
250	Very poor	250	Heavily polluted	250	Very unhealthy	60+	Very high
250+	Severe	250+	Severely polluted	250+	Hazardous		

Table 1.6 PM_{10} concentration and AQI category of States/Territories

Source: CPCB, 2015

India (24 h)		China (24 h)		United States (24 h)		European Union (8 h)	
PM_{10} ($\mu g/m^3$)	AQI category	PM_{10} ($\mu g/m^3$)	AQI category	PM_{10} ($\mu g/m^3$)	AQI category	PM_{10} ($\mu g/m^3$)	AQI category
50	Good	50	Excellent	55	Good	15	Very low
100	Satisfactory	150	Good	155	Moderate	30	Low
250	Moderate	250	Lightly polluted	255	Unhealthy for sensitive groups	50	Medium
350	Poor	350	Moderately polluted	355	Unhealthy	100	High
430	Very poor	420	Heavily polluted	425	Very unhealthy	100+	Very high
430+	Severe	420+	Severely polluted	425+	Hazardous		

1.7.2 Harmful effects of NO_2

The increasing trend in vehicle numbers adversely affected NO_2 concentrations in both rural and urban areas. During the past decades, numerous studies have observed both short-term (hours, days) and long-term (months, years) exposure and its effects on human health. Generally, high exposure over a short period can lead to increased respiratory symptoms (e.g., coughing, breathing difficulties), hospital admissions, and even emergency room visits. Alves et al. (2010) investigated short-term exposures to NO_2 and hospital admission for cardiorespiratory diseases in Lisbon, Portugal (Alves et al., 2010). A study by Costa et al. found that short-term exposure is associated with respiratory hospital admissions and even causes mortality across all age groups (Costa et al., 2014). Khaniabadi et al. (2016) reported that a 10 $\mu g/m^3$ change in concentration increased chronic relative risk and casualties (Khaniabadi et al., 2016). Exposures to high concentrations over more extended periods may contribute to asthma and potentially increase susceptibility to respiratory infections (EPA, 2022). Moreover, asthmatic patients and patients with chronic obstructive pulmonary disease (COPD) (children and elders) are at greater risk for the health effects (CPCB, 2015). The details of the concentration break and the AQI categories for the different regions of the world are given in Table 1.7 below.

1.7.3 Harmful effects of SO_2

The elevated levels of SO_2 in ambient air pose a threat to human health (Cofala et al., 2004). Short-term exposures to SO_2 can harm the respiratory system and cause breathing difficulties. People with sensitive groups, asthmatic patients, and children may be affected more (Table 1.4). The atmospheric concentration of SO_2 leads to the formation of other SO_x. Such SO_x can react with other compounds, forming fine to coarse particles (PM). The small particles may penetrate the lungs and cause various health issues (EPA, 2022). Thus, long-term exposures are responsible for morbidity (respiratory illness) and mortality. Researchers observed that elevated SO_2 levels lead to cardiorespiratory morbidity and mortality (Zhu et al., 2020; Sun and Zhau, 2017; Kanaroglou et al., 2013; Chen et al., 2012). The capital city of China (Beijing) recorded remarkable mortalities due to COPD, cardiovascular disease (CVD), cerebrovascular disease (CEVD), RD, and morbidities like bronchitis, asthma attacks, and even cases of hospital visits per year due to the excessive SO_2 concentration (Wu et al., 2020). In addition, the study assessed the economic cost of health problems. The details of the concentration break and the AQI categories for the different regions of the world are presented in Table 1.8 below.

Table 1.7 NO_2 concentration and AQI category of States/Territories

Source: CPCB, 2015

India (24 h)		China (24 h)		United States (1 h)		European Union (8 h)	
NO_2 (μg/m^3)	AQI category	NO_2 (μg/m^3)	AQI category	NO_2 (μg/m^3)	AQI category	NO_2 (μg/m^3)	AQI category
40	Good	40	Excellent	100	Good	50	Very low
80	Satisfactory	80	Good	190	Moderate	100	Low
180	Moderate	180	Lightly polluted	680	Unhealthy for sensitive groups	200	Medium
280	Poor	280	Moderately polluted	1220	Unhealthy	400	High
400	Very poor	565	Heavily polluted	2350	Very unhealthy	400+	Very high
400+	Severe	565+	Severely polluted	2350+	Hazardous		

Table 1.8 SO_2 concentration and AQI category of states/territories

Source: CPCB, 2015

India (24 h)		China (24 h)		United States (1 h)		European Union (8 h)	
SO_2 (μg/m^3)	AQI category	SO_2 (μg/m^3)	AQI category	SO_2 (μg/m^3)	AQI category	SO_2 (μg/m^3)	AQI category
40	Good	50	Excellent	95	Good	50	Very low
80	Satisfactory	150	Good	200	Moderate	100	Low
380	Moderate	475	Lightly polluted	485	Unhealthy for sensitive groups	350	Medium
800	Poor	800	Moderately polluted	795	Unhealthy	500	High
1600	Very poor	1600	Heavily polluted	1580	Very unhealthy	500+	Very high
1600+	Severe	2620	Severely polluted	1580+	Hazardous		

1.7.4 Harmful effects of O_3

O_3, a secondary pollutant formed in the atmosphere, has significant health impacts. Breathing ground-level O_3 can trigger various health issues, including congestion, chest pain, coughing, and throat irritation. It can worsen Asthma, emphysema, and COPD (Nuvolone et al., 2018; Koman and Mancuso, 2017). Short- and long-term exposures are associated with respiratory and circulatory mortality (Lefohn et al., 2018; Malley et al., 2017; Turner et al., 2016; Jerrett et al., 2009). Long-term exposure to pollutants is likely one of many causes of asthma. The evidence of premature deaths due to O_3-induced respiratory illness is more prominent than that due to other diseases (Nuvolone et al., 2018; Koman and Mancuso, 2017). Healthy people also experience breathing problems when exposed to O_3 pollution. Hot, sunny days in summer are a precursor to O_3 formation; anyone who spends a long time in that air may be affected, especially children and elders. The US EPA recommended that people reduce outdoor activities and stay indoors when O_3 levels are high. Zhang et al. (2019) provided a comprehensive description of O_3 and its health effects (Zhang et al., 2019). About a 60% increase in premature mortalities was observed in 69 Chinese cities during 2013-19 (Lu et al., 2020). The details of the concentration break and the AQI categories for the different regions of the world are presented in Table 1.9 below.

Table 1.9 O_3 concentration and AQI category of States/Territories

Source: CPCB, 2015

India (8 h)		China (8 h)		United States (8 h)		European Union (8 h)	
O_3 ($\mu g/m^3$)	AQI category	O_3 ($\mu g/m^3$)	AQI category	O_3 ($\mu g/m^3$)	AQI category	O_3 ($\mu g/m^3$)	AQI category
50	Good	100	Excellent	120	Good	60	Very low
100	Satisfactory	160	Good	150	Moderate	120	Low
168	Moderate	215	Lightly polluted	190	Unhealthy for sensitive groups	180	Medium
208	Poor	265	Moderately polluted	230	Unhealthy	240	High
748	Very poor	800	Heavily polluted	750	Very unhealthy	240+	Very high
748+	Severe		Severely polluted	750+	Hazardous		

1.7.5 Harmful effects of CO

Haemoglobin (Hb) is a two-way respiratory carrier, transporting O_2 from the lungs to the tissues and facilitating the return transport of CO_2. An elevated CO concentration reduces the O_2 content of red blood cells. About 80-90% of absorbed CO binds with Hb from Carboxyhemoglobin (COHb) (Smithline, 2003). The affinity of Hb for CO is 200-250 times that of O_2 (Hauck, 1984). The high concentration of COHb interferes with O_2 binding and dissociation from Hb, resulting in impaired tissue O_2 delivery or hypoxia (Gorman, 2003). In nonsmokers, COHb stands at <1%; typical cigarette smokers' range 5-10%, but it might exceed (>10%) due to high CO poisoning (Gordon et al., 2014). A 10 mg/m^3 increase in concentration led to a COHb level of about 2% (CPCB, 2014). The CPCB set the CO standard at 2 mg/m^3. High-level CO poisoning may include mental confusion, restlessness, difficulty breathing, rapid heart rate, loss of muscle coordination, loss of consciousness, and bluish skin, leading to Coma or ultimate death. However, the most common effects of low to moderate CO exposure are headache, fatigue, shortness of breath, nausea, and dizziness. If pregnant mothers inhale high CO exposure, their babies are at risk of adverse developmental effects. The common issues include eye, nose, and throat irritation, headaches, diarrhea, cough, chest tightness, nasal congestion, palpitations, shortness of breath, and even asthma (Schiffman and Williams, 2005). A very high concentration in a short time can damage the lungs or even cause loss of life. The details of concentration break and AQI categories for the States/Territories of the World are given below (Table 1.10).

Table 1.10 CO concentration and AQI category of states/territories

Source: CPCB, 2015

India (8 h)		China (24 h)		United States (8 h)		European Union (8 h)	
CO (mg/m^3)	AQI category	CO (mg/m^3)	AQI category	CO (mg/m^3)	AQI category	CO (mg/m^3)	AQI category
1	Good	2	Excellent	5	Good	5	Very low
2	Satisfactory	4	Good	11	Moderate	7.5	Low
10	Moderate	14	Lightly polluted	14	Unhealthy for sensitive groups	10	Medium
17	Poor	24	Moderately polluted	18	Unhealthy	20	High
34	Very poor	36	Heavily polluted	35	Very unhealthy	20+	Very high
34+	Severe	36+	Severely polluted	35+	Hazardous		

1.7.6 Harmful effects of NH_3

The concentration of NH_3 in the air is under the permissible limit. The fertilizer industries and agricultural fields have a notable concentration of NH_3. Atmospheric NH_3 reacts with H_2SO_4, hydrochloric acid (HCl), or HNO_3 and forms ammonium sulphate ($(NH_4)_2SO_4$), ammonium chloride (NH_4Cl), or ammonium nitrate (NH_4NO_3), respectively (Kumar et al., 2019). NH_3 is an irritant, and elevated concentrations can cause several health effects (Sundlad et al., 2004). Moderate exposure (50-150 µg/m3) accounts for health effects such as eye, throat, and skin irritation and mucus buildup. An elevated concentration (>150 µg/m^3) of NH_3 is responsible for pulmonary edema, lower lung inflammation, and death (Agency for Toxic Substances and Disease Registry, 2004; Merchant et al., 2002). Moreover, NH_3 is a precursor of PM formation and has significant health impacts, as it can penetrate deep into the lungs and cause long-term illness (e.g., COPD, Lung cancer) (Wyer et al., 2022). The concentration ranges and AQI categories for NH_3 and Pb are shown in Table 1.11 below.

Table 1.11 Pollutant concentrations and AQI categories of India

India (24 h)		India (24 h)	
NH_3 (µg/m^3)	AQI category	Pb (µg/m^3)	AQI category
200	Good	0.5	Good
400	Satisfactory	1	Satisfactory
800	Moderate	2	Moderate
1200	Poor	3	Poor
1800	Very poor	3.5	Very poor
1800+	Severe	3.5+	Severe

1.7.7 Harmful effects of Pb

Pb is a toxic metal that causes health issues. The low lead poisoning symptoms are headache, irritability, and abdominal pain (Järup, 2003). Elevated concentrations often affect the nervous system, haematological changes, and cardiovascular disease. Occupational lead exposure is associated with anaemia (a lack of healthy red blood cells), increased blood pressure, and hypertension. Moreover, it affects the kidneys, liver, and even reproductive system (Abdulla, 2020). Infants and children exposed to lead can suffer from lower intelligence quotient (IQ), slowed growth and development, hearing and speech problems, and learning and behaviour problems.

1.8 COVID-19 pandemic

Coronavirus disease 2019 (COVID-19) is a deadly, contagious disease caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The symptoms of COVID-19 are variable but often include fever, headache, loss of taste or smell, fatigue, breathing difficulties, and cough. However, the first variant of coronavirus (SARS-CoV-1) was also noted in China in 2000 (Cui et al., 2003; Sangkham et al., 2021). WHO confirmed COVID-19 as a global pandemic in March 2020. The novel COVID-19 has fostered a global health emergency, casting its threat across all countries and marking 2020 as the COVID-19 year. From its centre of origin in Wuhan, China, in late 2019 (Chen et al., 2020; Muhammad et al., 2020), the virus spread through air travel to other major cities in different countries and afterwards from those places further into their hinterlands and adjacent regions (Chakraborty and Maity, 2020). The United States (US) reported its first confirmed case of COVID-19 on January 21, 2020. On January 24, 2020, France informed the WHO of three COVID-19 positives. Within two months (by mid-March 2020), Western Europe had become the epicentre of the pandemic, with more reported active cases and deaths than the rest of the world combined. At present, the outbreak has left its mark everywhere except Antarctica (Acharya, 2020; Nikhat and Fazil, 2020). Afterwards, due to a worldwide spate of cases, the WHO declared COVID-19 a global pandemic on March 12, 2020 (Gautret et al., 2020).

1.9 Lockdowns imposed during the pandemic

The swift spread and ensuing community transmission of COVID-19 since its inception have often overwhelmed local healthcare services quickly. This pandemic left the aged and those with existing health issues particularly vulnerable (MacConnachie et al., 2007). Healthcare officials and governments introduced and widely propagated the concept of 'social distancing' (Manderson and Levine, 2020) and 'lockdowns' to limit the spread of the virus, with cancellations of major sporting and cultural events (Munoz and Meyer, 2020; Parnell et al., 2020) and diplomatic gatherings (Sharfuddin, 2020), closure of religious institutions (Alyanak, 2020), industries and commercial establishments and the suspension of academic conferences and teaching activities (Gallo and Trompetto, 2020). Such lockdowns sought to heavily restrict the movement of those possibly carrying the contagion and stop healthy people from coming into contact with pre-symptomatic/asymptomatic individuals (Imdad et al., 2020). The first restriction/lockdown was imposed in Wuhan city, China, on January 23, 2020, to slow down the spread of infection, followed by other countries (Wang and Su, 2020; Wilder-Smith and Freedman, 2020). After China, Italy was the country most affected by COVID-19. The Italian government imposed the lockdown on March 23, 2020 (Ceylan, 2020). The United States and Western European countries also went into lockdown by early March-April 2020. Nations like India, where the outbreak became potentially threatening after its initial rampage in East Asia and Western Europe, were somewhat quicker to impose such lockdown measures in late March 2020 (Lancet, 2020).

1.10 COVID-19 scenario in India

India has 44,993,186 confirmed COVID-19 cases, with 2067 active cases (0.00%), 44,459,226 recovered cases (98.81%), and 531,893 deaths (1.18%) from January 3, 2020 to June 15, 2023 (MoHFW, 2023; Worldometer, 2023). A total of 2.21 billion vaccine doses have been registered officially as of June 15, 2023. The first cases of novel COVID-19 were observed in Kerala, India, on January 30, 2020, when three medical students travelled from Wuhan, China, the epicentre of COVID-19 (Shivangi and Meena, 2021). In February 2020, there were no new positive cases, though two new positives were detected on March 2, 2020; they travelled from Vienna (Austria) and Dubai (Kumar, 2021). The country reported 50 confirmed cases of novel COVID-19 on March 10, 2020. The first death that occurred due to COVID-19 was on March 12, 2020. WHO declared this novel COVID-19 epidemic a global pandemic (WHO dashboard, 2020; Saha and Chouhan, 2021). Community surveillance, quarantine, isolation wards, adequate personal protective equipment (PPE), trained manpower, and rapid response teams for COVID-19 were strengthened for all states and union territories (States/UTs). The confirmed cases increased from 360 to 8447, with 7 to 273 total deaths in 23 to 31 States/UTs during 21 days, from two days before the nationwide lockdown (March 22, 2020) to two days before the last date of lockdown phase-I (April 12, 2020) (WHO dashboard, 2020). The National Disaster Management Authority (NDMA), chaired by Hon'ble Prime Minister Shri Narendra Modi, has issued an order (dated March 24, 2020) to impose a nationwide lockdown initially for 21 days (25 March-14 April 2020) to combat the spread of the virus through social distancing; was stricter than Janata curfew (people's curfew), announced on March 22, 2020 (Ministry of Home Affairs, 2020). The GoI subsequently imposed a total of 4 lockdown phases from March 25 to May 31, 2020 (phase I for 21 days, phase II for 19 days, and phases

III & IV for 14 days each) and 22 unlock phases (June 1, 2020 to March 31, 2022). Due to the nationwide lockdown, all sectoral activities had stopped except for emergency services. Residential mobility increased by 1.3 billion people to fight against the pandemic (Saha and Chouhan, 2020). At that time, wear face masks, wash hands with soap & water or hand sanitizer, cover your mouth when coughing or sneezing, keep your hands and fingers away from your eyes, nose, and mouth, and consume only thoroughly cooked food and meat, practice social distancing, stay at home, avoid close contact with the people who are infected, clean and disinfect surface regularly –these were the only precaution measures. At the end date of lockdown phase IV (May 31, 2020, 08:00 IST), India had 5164 deaths, 89,995 active cases, and 86,983 cured/discharged cases out of 182,143 confirmed cases (WHO dashboard, 2020). The nation witnessed a concerning growth in the death rate (30%) from March 11 to April 4, 2020; it was the highest COVID-19 death rate for the entire first wave of the pandemic in India. Afterwards, the death rate gradually declined, and the recovery rate improved. India found itself in a horrible situation in September. As of September 28, more than 5.9 million confirmed cases and over 94 thousand deaths from COVID-19 had been reported. Then, a gradual decline in daily new infections was observed until February 2021. India started the largest vaccination drive at 3006 vaccine centres across all States/UTs on January 16, 2021 (WHO, 2021). Only two types of COVID-19 vaccination, Covishield (AstraZeneca-Oxford University, manufactured by the Serum Institute of India Ltd.) and Covaxin (Bharat Biotech, manufactured by Bharat Biotech International Ltd.), have been initiated to aim to vaccinate 300 million people by August 2021 (Deepak et al., 2021). The doses were for the target group of people free of cost for health workers (10 million), 20 million frontline workers (e.g., police, soldiers, municipal workers), and the remaining 270 million elderly people (>50 years) and people with co-morbidities (Bagcchi, 2021). Simultaneously, the COWIN software was operational for vaccine registration, certificate issuance, and monitoring the massive 1.35 billion-person pandemic immunization programme (Choudhary et al., 2023)**.** The COVID-19 infection-tracking device, Aarogya Setu (application software), was launched to protect citizens' safety. As of December 2, 2021, approximately 84% (117 million) of people had received a single dose, and nearly 47% had received a double dose (Bahera et al., 2022).

India experienced a new SARS-CoV-2 variant (now known as B.1.617) in late March 2021. The nation suffered from tremendous health emergencies with a lack of O_2

supply, a crisis for hospital beds, and even basic medicines. As of March 1, India had reported more than 11·12 million confirmed cases and over 1.57 lakh deaths, and reached over 22.92 million confirmed cases and 2.49 lakh deaths on May 12, 2021, amidst the COVID-19 pandemic. India witnessed over 29.57 million confirmed cases and 3.77 lakh deaths on June 16, 2021 (WHO dashboard, 2021). According to Samarasekera (2021), India noted more than 26.4 million confirmed cases and over 2.74 lakh deaths on May 18, 2021 (Samarasekera, 2021). Simultaneously, daily new infection cases jumped 11.5 thousand to 4.14 lakh from March 1 to May 6 and fell again to 43.3 thousand on July 1, 2021. Hence, this is the worst state of the second wave pandemic when daily new cases, active cases, and death tolls have broken all previous records since its inception. The suddenness of the second wave had more severe consequences regarding infection and mortality than the first wave (slowness) (Talukdar et al., 2023).

Finally, the third wave was noted in winter (late December 2021 to February 2022). As of December 29, 2021, India had active cases accounting for less than 1% of total cases — currently 0.22% — the lowest since March 2020, with 1.42 billion vaccinations administered. In just 24 hours, 6358 confirmed cases were noted on December 29, 2021. Still, there was a remarkable change in the scenario on January 18, with 238,018 confirmed cases in the past 24 hours. It was due to the new COVID-19 variant, Omicron. As of February 22, 2022, India accounts for over 42.85 million confirmed cases, over 5.12 lakh deaths, and over 1.76 billion vaccine doses (WHO dashboard, 2022).

1.11 Scholarly observations concerning the impact of lockdown on the air pollution scenario

1.11.1 Global scenario

The novel coronavirus originated in Wuhan, China, in December 2019 and later spread worldwide. The WHO declared in March 2020 that COVID-19 had become a global pandemic and called for a coordinated global response. The most affected countries, like the United States, China, Brazil, India, Russia, Mexico, United Kingdom, Peru, Italy, Germany, and France, recorded millions of infected and lakhs of deaths. Initially, imposing a lockdown was the only solution to combat COVID-19 transmission. Many severely affected countries announced nationwide, state-wide, and zone-wide restrictions on human mobility to break the chain of COVID-19 transmission. Thus, restrictions/lockdowns and the closure of all sectoral activities except emergency services improved ground-level air quality. Researcher documented that past studies found that many countries experienced severe health effects from extreme air pollution (Anenberg et al., 2010; Krewski et al., 2009; Slama et al., 2008). Researchers found a clear link between COVID-19 severity and air pollution. A higher level of air pollution was associated with a higher COVID-19 infection rate in many cities across Asia, Europe, and North America.

Ankan and Coccia (2022) researched concentrations of major pollutants ($PM_{2.5}$, PM_{10}, CO, NO_2, SO_2, and O_3) from 2019 to 2022 across 300 global cities in 19 countries. They indicated that the most significant reductions in pollutants were as follows: $PM_{2.5}$ decreased by over 40% in Germany; PM_{10} dropped by over 150% in Turkey; CO reduced by over 4300% in France; NO_2 decreased by over 150% in China and Australia; SO_2 dropped by over 150% in Israel; and O_3 decreased by over 90% in China due to lockdowns and quarantines (Ankan and Coccia, 2022). A similar study was conducted by Fu et al. (2020) on 20 major cities worldwide. They identified that the reduction in pollutant levels was mainly due to restrictions on transportation, industry, and commercial activities during the lockdown (Fu et al., 2020). Kumari and Toshniwal (2020) evaluated the global impact of the pandemic on air quality using 162 monitoring station datasets from 12 cities worldwide. Their study found that $PM_{2.5}$, $PM_{10,}$ and NO_2 were reduced by 20–34%, 24–47% and 32–64%, respectively, due to restrictions on anthropogenic emission sources during lockdown (Kumari and Toshniwal, 2020). Liu et al. (2020) investigated the impact of lockdown on the air quality in 597 major cities worldwide from January 1 to July 5, 2020. The results show that the concentration of NO_2, $PM_{2.5}$, PM_{10}, SO_2, and CO improved noticeably (Liu et al., 2020). Albayati et al. (2021) reported that air pollutant levels worldwide have decreased due to industrial closures amid the pandemic. In addition, they argued that this reduction reached a level that no political conference or agreement could achieve (Albayati et al., 2021). A review by Ali and Islam (2020) found a strong correlation between air pollution and COVID-19 infections and mortality based on some recent evidence (Ali and Islam, 2020). Most of the reviewed papers demonstrate that both short- and long-term $PM_{2.5}$ and NO_2 may significantly contribute to higher rates of COVID-19 infections and mortality. Silva et al. (2022) conducted a systematic review of 114 papers. Most of the authors paid serious attention to India and China, focusing on urban areas and major air pollutants (e.g., PM_{10}, $PM_{2.5}$, NO_2, O_3, CO, and SO_2) during pre- and post-lockdown periods (Silva et al., 2022). Another systematic review by Bakola et al. (2022) estimated that substantial and robust reductions in NO_2, nitric oxide (NO), CO, CO_2, $PM_{2.5}$, PM_{10}, benzene (C_6H_6), and AQI occurred in pandemic lockdowns in Europe and North America (Bakola et al., 2022). Bray et al. (2021) observed a similar reduction in pollutant concentrations—$PM_{2.5}$, PM_{10}, CO, NO_2, and SO_2—except for O_3—across regional monitoring sites in the USA, China, India, and Europe during March and April 2020, compared to the respective months in 2015-19 (Bray et al., 2021). In addition, four major cities — New York (USA), Milan (Italy), Wuhan (China), and New Delhi (India) — in case studies showed similar reduction trends to those observed at the regional scale. Muhammad et al. (2020) reached a remarkable conclusion based on datasets from the National Aeronautics and Space Administration (NASA) and the European Space Agency (ESA) that some epicentres of COVID-19, such as Wuhan, Italy, Spain, and the USA, have reduced environmental pollution by up to 30% (Muhammad et al., 2020).

A recent study by Zhu et al. (2020) covering 120 cities in China found a critical association between air pollution and COVID-19 (Zhu et al., 2020). A study from the United States shows that increased long-term exposure to $PM_{2.5}$ is associated with a significant increase in COVID-19 mortality (Wu et al., 2020a; 2020b). Garcia et al. (2022) observed the same scenario for California. According to Srivastava (2020), PM and gaseous pollutants have caused more COVID-19 cases and mortality (Srivastava, 2020). Bonilla et al. (2022) observed the same for Latin America. Here, Brazil, Chile, Colombia, and Mexico recorded a 2.7% increase in the COVID-19 mortality rate with a 1 $\mu g/m^3$ increase in long-term exposure to fine particles (Bonilla et al., 2022). A 1 $\mu g/m^3$ increase in the long-term average PM level was associated with a 12% increase in COVID-19 cases in England (Travaglio et al., 2021).

Gao et al. (2021) investigated changes in air pollution before and during the COVID-19 pandemic lockdown in four megacities in China: Wuhan, Beijing, Shanghai, and Guangzhou. They found improvements in air pollution from $PM_{2.5}$, NO_2, and SO_2 (Gao et al., 2021). Gao et al. (2023) examined 336 Chinese cities' air pollutants during 2016-20; they found a decrease in $PM_{2.5}$, PM_{10}, NO_2, SO_2, and CO were 91%, 92%, 75%, 94% and 89% while an increase in O_3 was 87% of cities (Gao et al., 2023). A study by

He et al. (2020) reached a similar conclusion that lockdowns led to a noticeable improvement in air quality in China (He et al., 2020). Lian et al. (2020) found a significant decline in AQI in Wuhan due to the citywide lockdown. Moreover, pollution levels drop sharply in densely populated areas (Lian et al., 2020). Zhang et al. (2021) found that stringent prevention and control measures to combat the spread of COVID-19 led to a decline in concentrations of air pollutants except O_3 in 235 Chinese cities (Zhang et al., 2021). Liang et al. (2023) observed that East China witnessed a dramatic change in aerosol optical depth (AOD) and tropospheric NO_2 during and after the COVID-19 pandemic compared to before (Liang et al., 2023). Xing et al. (2022) reported similar improvements in Shandong Province, China (Xing et al., 2022). Wu et al. (2021) assessed the impact of the COVID-19 lockdown on roadside traffic-related air pollution in Shanghai, China. They identified a nearly 30-40% reduction of pollutants ($PM_{2.5}$, PM_{10}, NO_2, and SO_2) during the pandemic (Wu et al., 2021). A similar traffic reduction is associated with low NO_2 and PM levels in western Europe (Menut, 2020). Skirienė and Stasiškienė (2021) observed that checks on industrial and mobility activities reduced NO_2, $PM_{2.5}$, and PM_{10} emissions by about 20-40% in European countries during pandemic lockdowns (Skirienė and Stasiškienė, 2021). Dursun et al. (2022) studied 30 major cities in Turkey; their results revealed improved air quality following a lockdown (Dursun et al., 2022). Mostafa et al. (2021) examined Egypt amidst COVID-19. They obtained that the absorbing aerosol index decreased by about 30%, NO_2 by 15% and 33%, and CO by 5% over Cairo and Alexandria governorates (Mostafa et al., 2021). Bar et al. (2022) found that the mean tropospheric NO_2 concentration dropped by 18-40% over major urban areas in Europe (e.g., Madrid, Milan, Paris) and the USA (New York, Boston, Springfield) in 2020 due to lockdowns than in 2019 (Bar et al., 2022). Chen et al. (2020) investigated the non-uniform impacts of the COVID-19 lockdown on air quality in the United States. The results showed that NO_2 had the most significant decrease, followed by CO, PM_{10}, O_3, and $PM_{2.5}$ (Chen et al., 2020). Rio de Janeiro (Brazil) recorded a decline in pollutant levels (CO, NO_2, PM_{10}, and O_3) after imposing a partial lockdown (Dantas et al., 2020). The same was noted in the state of São Paulo, Brazil, by Nakada and Urban (2020). The lockdown policy reduced overall air pollutant emissions in California (USA) (Liu et al., 2021). The eastern province of Saudi Arabia experienced reductions of 21-70% in PM_{10}, 5.8-55% in CO, and 8.7-30% in SO_2, though O_3 increased by 6.3-45% during the lockdown phase compared to pre-lockdown (Anil and Alagha, 2021).

1.11.2 Indian Scenario

It is pertinent to note that air pollution is associated with respiratory and CVDs (Zheng et al., 2020). A higher level of air pollution has a far greater impact than COVID-19 (Giani et al., 2020). The GoI initially imposed a nationwide 21-day lockdown on March 24, 2020, to combat the pandemic. All the social gathering places, such as restaurants, cinemas, schools, shopping complexes, and educational institutions, were closed. Staff and students worked from home to maintain a strategic distance from swarms. All transportation services (i.e., rail, road, and air) were suspended, except for emergency services. Besides, almost all production and industrial activities came to a halt (Kumari and Toshniwal, 2020). The total lockdown has adversely influenced the nation's economy. However, limited transportation and economic activity led to a drastic decrease in air pollution (Gautam, 2020). Globally, satellite images and ground data show that air pollution from NO_2 emissions in many regions has decreased, leading to a recovery of the stratospheric O_3 layer (NASA, 2020). This reduction of pollutants brought a blessing to human health and the environment. The high concentration of different air pollutants has varied effects on human health and the environment.

In India, studies on the impact of COVID-19 on air quality are limited, but several studies have examined air quality during nationwide lockdowns (Mahato et al., 2020; Sharma et al., 2020; Mitra et al., 2020). Lowering $PM_{2.5}$ levels has been studied in major cities such as 35-39% in Delhi (Chauhan and Singh, 2020; Mahato et al., 2020), 30-40% in Kolkata (Mitra et al., 2020), and 14-43% in Mumbai (Chauhan and Singh, 2020; Sharma et al., 2020). Several studies show that the nationwide lockdown in India improved air quality (Singh and Chakraborty, 2020). Chinnasamy et al. (2022) examined Kolkata, Delhi, Mumbai, and Bengaluru during the pandemic and found a significant decline in pollutant levels ($PM_{2.5}$, PM_{10}, CO, SO_2, NO_2) (Chinnasamy et al., 2022). Gautam et al. (2021) investigated the eight most polluted Indian cities (Mumbai, Delhi, Bangalore, Hyderabad, Lucknow, Chandigarh, Kolkata, and Ahmedabad) and found significant reductions in pollutant levels (Gautam et al., 2021). Singh and Tyagi (2020) observed Chennai during the COVID-19 Lockdown. They found a revival of the environment with reduced pollutant emissions (Singh and Tyagi, 2020). Chowdhuri et al. (2020) observed a 40-68% reduction in concentration for PM_{10}, NO_2, SO_2, O_3, and aerosol over the Kolkata megacity (Chowdhuri et al., 2020). A similar result was recorded by Chowdhuri et al. (2023) (Chowdhuri et al., 2023). Das et al. (2021a) showed that air pollutant concentrations decreased significantly across 57 urban agglomerations in India during the lockdown (Das et al., 2021a). Das et al. (2021b) reported an 80% reduction in air pollution in Kolkata during the strict lockdown (Das et al., 2021b). It has been found from the study (James-Poetzscher, 2020) in Delhi's metropolitan area that pollution levels have dropped most dramatically; NO_2 concentration fell by 90 μmol/m^2 to 162 μmol/m^2 during the period of March 25 (the day quarantine began) to May 2, and from March 1 to March 24. In 2019, NO_2 levels were also far above this year's levels, averaging 158 μmol/m^2 from March 25 to May 2. In Greater Mumbai and Navi Mumbai, a similar trend has been observed, with NO_2 levels from March 25 to May 2 averaging 77 μmol/m^2, compared to 117 μmol/m^2 from March 1 to March 24. In 2019, NO_2 levels from March 25 to May 2 averaged 122 μmol/m^2. Lately, the CPCB published a report on the effects of the Janata curfew on air quality, finding that a decrease in car traffic led to a 51% reduction in NO_x levels. A 32% decrease in CO_2 levels between 22 and 23 March 2020 compared to March 21, 2020 (Singh and Chakraborty, 2020). Several studies suggest that people with medical problems such as diabetes, chronic respiratory disease, CVD, or even high blood pressure and cancer are at higher risk for coronavirus (Giannis et al., 2020; Fang et al., 2020; Zheng et al., 2020). According to Wu et al. (2020), a person infected with COVID-19 above 59 years has a risk of death 5.1 times higher than only 0.6 times of people below 39 years (Wu et al., 2020).

1.12 Scope of research in Indian megacities

Previous research papers have focused on a few selected parameters or on a single location. A few of them did not account for pollutant concentrations at the same time as the previous year under no lockdown conditions, leading to incomplete inferences. The study on the influence of meteorological conditions on megacities is limited. The deweathering (i.e., the elimination of meteorological parameters such as air temperature, relative humidity, wind speed, and precipitation) of pollutants is also not considered in many studies. The inter-wave lockdown impact on ambient air pollution amidst the COVID-19 pandemic was also not compared by previous researchers. Comparative analyses of three pandemic surges across India's megacities are limited. Moreover, the integration of R, XL-STAT, and a geographic information system (GIS) with a statistical approach was not used in any of the studies mentioned above.

1.13 Study area

Although the present doctoral thesis focused on two coastal cities of India, namely Kolkata and Mumbai, one chapter (Chapter 3) was dedicated to the global scenario. Chapter 4 was dedicated to the air pollution in China, India, and Pakistan (i.e., the most populous region of Asia). Chapter 3 considered select countries worldwide, whereas Chapter 4 focused on the most populous regions of the globe: China, India, and Pakistan.

China, India, and Pakistan (CIP) — these three neighbouring countries — together account for 38% of the global population as of April 2023, according to the UNFPA report (UNFPA, 2023). China lies between east longitudes 73° and 135° and north latitudes 18° and 53°, with a population of 1.42 billion. India's population stands at 142.86 billion in 2023 (Table 1.12). It is situated between longitudes 68°7'E to 97°25'E and latitudes 8°4'N to 37°6'N. Pakistan lies between 23°35'N and 37°5'N latitude and 60°50'E and 77°50'E longitude, with a population of 24.05 billion as of 2023. The urban shares of the CIP are 60.30%, 34.50%, and 36.90%, with a GDP of 14342934, 2891582, and 256996 US$ (UNSD, 2023). CIP spans a wide range of elevations, from the top of the World, Mount Everest, to the Bay of Bengal. The climate of the CIP varies with altitude, latitude, distance from the coast, and the presence of mountains. The region experiences a wide range in temperature and precipitation (Fig. 1.2). The whole of China experiences freezing temperatures, except for the southeast and the southern parts of the Himalayas. The lower Himalayas and the southwest of India account for heavy rainfall. Currently, 495 ambient air monitoring stations (AAMSs) within 31 states/provinces for China, 255 AAMSs within 28 states/provinces for India, and 10 AAMSs within 4 states/provinces for Pakistani cities are in operation (Fig. 1.4). The CO_2 emission estimates are 9809.2/6.8, 2309.1/1.7, and 194.1/0.9 million tons/tons per capita for them in 2021 (UNSD, 2023).

China has four climatic regions, viz., Southwestern, Southern, Central Eastern China, and Inner Mongolia Autonomous and Tibet Autonomous. The Southwestern mountains account for moderate temperatures. Southern China experiences a tropical climate, with heavy rainfall from May to September (the summer season) and year-round high temperatures. Central and Eastern China account for humid summers with minimal climate extremes. The remaining regions have harsh climates, with severe winter cold

Table 1.12 Description profile of China, India and Pakistan

Countries	Avg. elev. (m)	Area (km^2)[1]	% of earth area[1]	Population (billion) 2023[2]	World share (%)[2]	Urban population (% of total population)[3]
China	1840	9600013	6.54	142.57	17.72	60.30
India	621	3287260	2.21	142.86	17.76	34.50
Pakistan	900	881,913	0.59	24.05	2.99	36.90

GDP (million current US$)[3]	Employment in Ag. (% of employed)[3]	Employment in industry (% of employed)[3]	Employment in services (% of employed)[3]	Ambient air monitoring stations[4]	CO_2 emission estimates (million tons/tons per capita)[3]
14342934	24.7	28.2	47.1	524	9809.2/6.8
2891582	41.5	26.2	32.3	202	2309.1/1.7
256996	35.9	25.8	38.3	7	194.1/0.9

[1] *World Population Review, 2023*
[2]*UNFPA, 2023*
[3]*UNSD, 2023*
[4]*IQAir, 2023*

Table 1.13 Some features of the select megacities in India

Megacities	Geographical Position		Avg. elev. (m)	No. of air monitoring stations	Population (million) 2011	Growth rate (%) 2001-11
Mumbai	19°04’33.54 “N	72°52’39.56 “E	14	15	18.4	12.05
Delhi	28°42’14.61 “N	77°06’08.96 “E	216	37	16.3	26.69
Kolkata	22°34’21.53 “N	88°21’50.02 “E	9	10	14.1	6.87

and strong winds (World Bank, 2021a). The highest mean monthly temperature is usually observed in July (20°C), while February accounts for the lowest temperature (-3.6°C) (Fig. 1.3). The mean monthly precipitation ranges from 11.52 mm (December) to 114.17 mm (July) with an annual mean rainfall of 50.71 mm (CCKP, 2021).

The climate of India can be broadly classified as tropical monsoon. According to the India Meteorological Department (IMD), India experiences four seasons: summer or pre-monsoon (March-April-May), monsoon or rainy (June-July-August-September), post-monsoon (October-November), and winter (December-January-February). The nation records a mean monthly temperature range from 17.7°C (January) to 30.5°C (May). Likewise, the mean monthly precipitation varies from 9.96 mm (December) to 283.1 mm (July), with an annual mean of 92.35 mm (Fig. 1.3).

Pakistan experiences a temperate climate. The mountainous Himalayas, the river Indus, the distance from the sea, the undulating topography, and the prevailing wind control Pakistan's climatology. Pakistan experiences four seasons: a hot or dry spring (March-April-May), a rainy summer (June-July-August-September), a retreating monsoon (October-November), and a cool-dry winter (December-January-February) (World Bank, 2021b). Pakistan has a mean monthly temperature range of 9.31°C (January) to 29.73°C (June) and a rainfall range of 7.8 mm (November) to 52.57 mm (July) (CCKP, 2021). Pakistan's annual mean rainfall is 24.75 mm. The summer monsoon of Pakistan accounts for around 60% of the total annual precipitation.

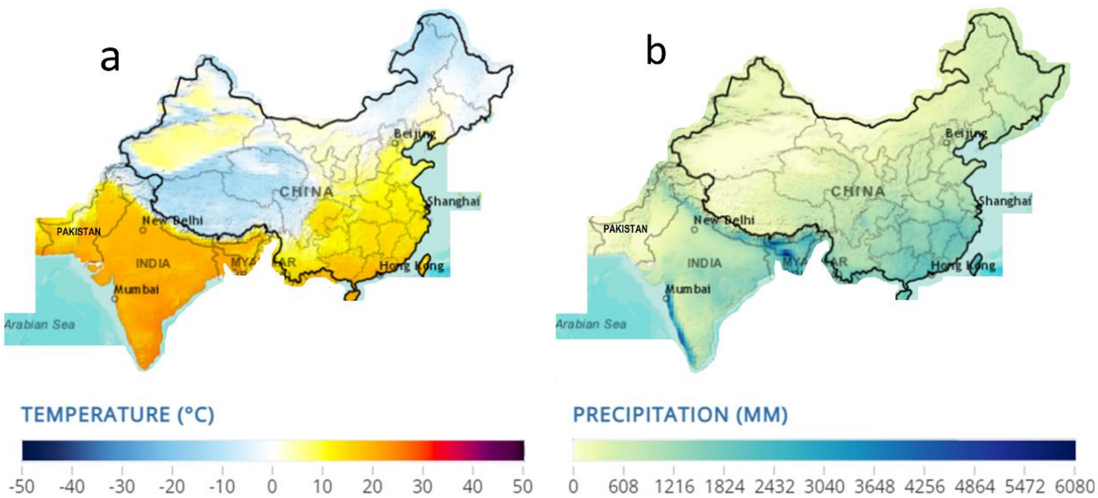


Fig. 1.2 Mean observed (a) temperature and (b) precipitation for the periods of 1991-2020 in China, India, and Pakistan

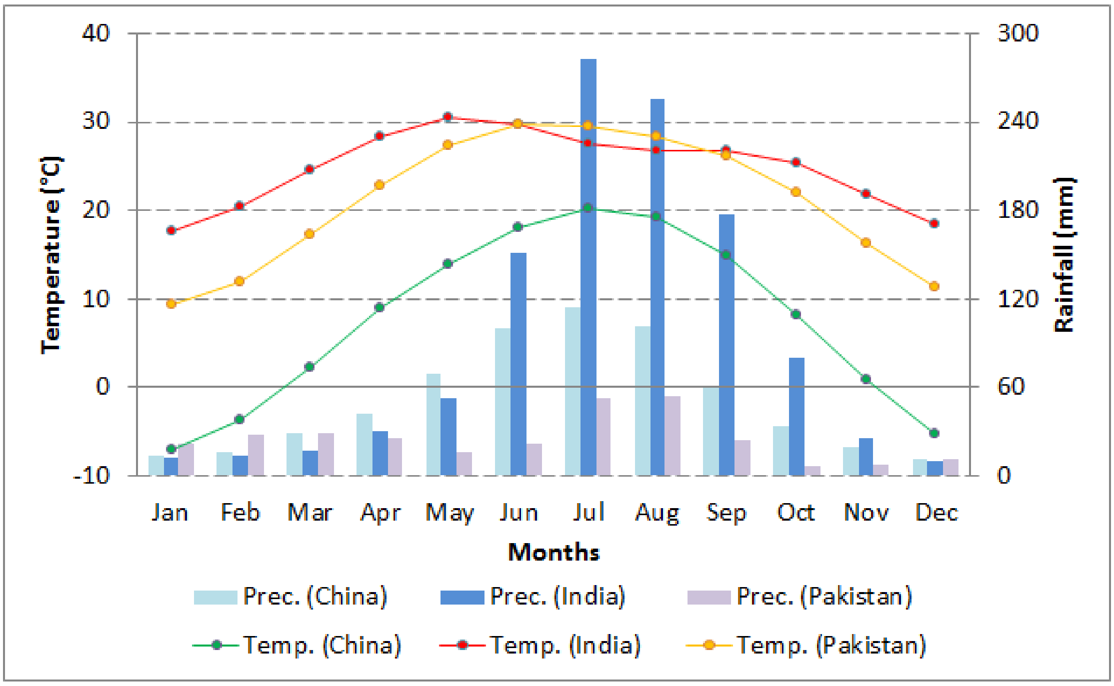


Fig. 1.3 Rainfall temperature graph of China, India, and Pakistan based on three decades of World Bank datasets

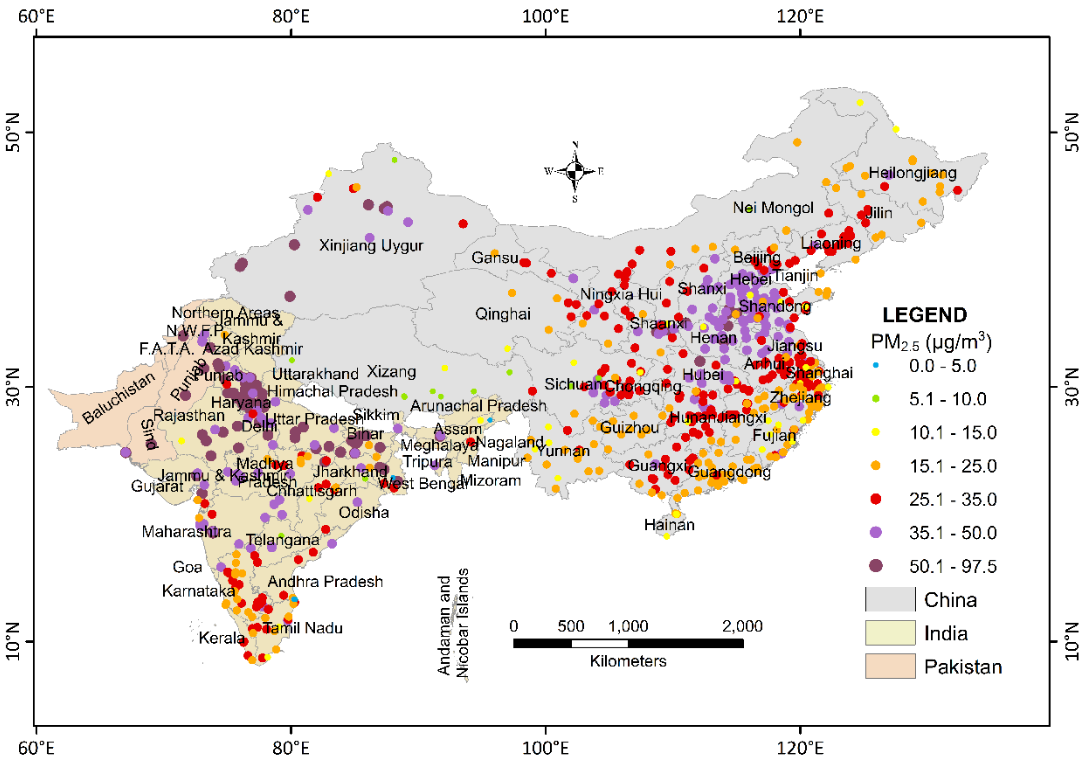


Fig. 1.4 Location of ambient air monitoring stations of China, India, and Pakistan showing historical annual Mean $PM_{2.5}$ concentrations

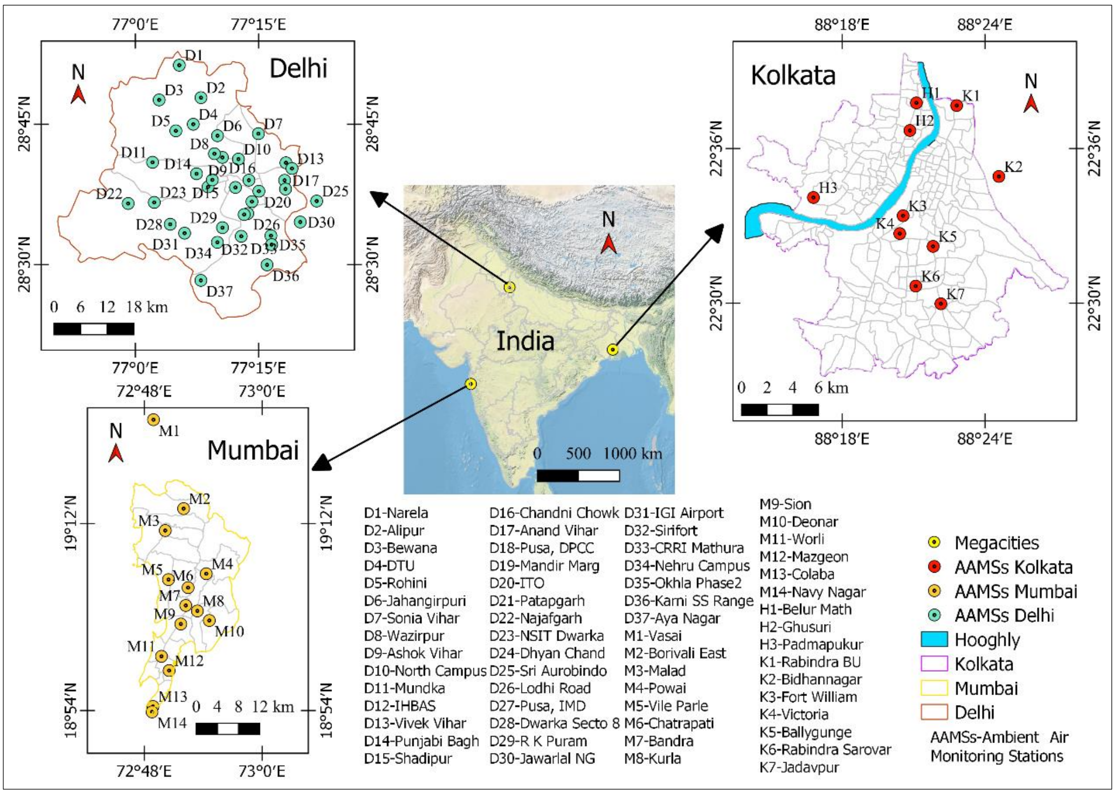


Fig. 1.5 The study area map of Mumbai, Delhi, and Kolkata, showing the locations of the automatic air monitoring stations

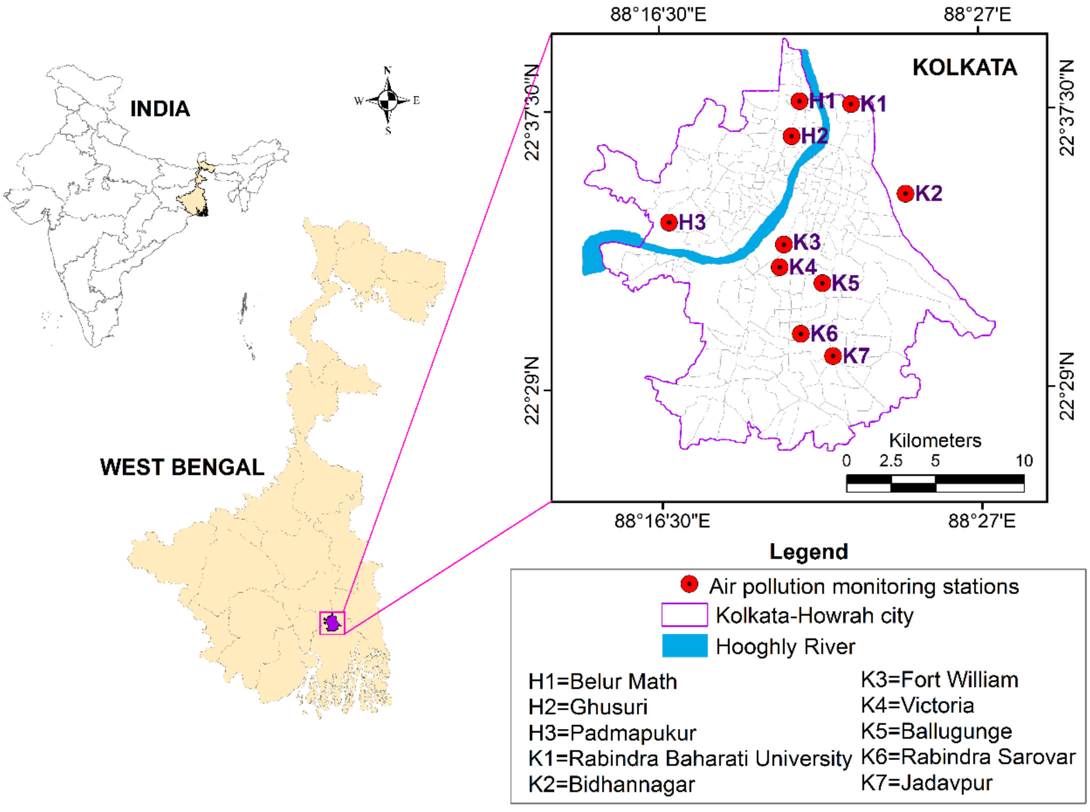


Fig. 1.6 The location of air pollution monitoring stations in Kolkata

The research focused on three megacities of India, namely Mumbai, Kolkata (two coastal megacities), and Delhi, which was considered as a control (Fig. 1.5). Mumbai, the financial capital and the largest megacity of the country, located on the west coast (Arabian Sea), shelters 18.2 million people (Table 1.13). The second-largest megacity in the nation is Delhi (16.3 million), the national capital of India, located in the north. Kolkata, in the north-eastern part of India, has a population of over 14.1 million (Census of India, 2011). Due to the rapid growth rate (27%) observed in the last decade, Delhi is the second leading megacity in the world, with a population of 30.29 million. Mumbai (20.41 million) and Kolkata (14.85 million) rank 9th and 16th in the world, respectively (World Economic Forum, 2016; United Nations, Department of Economic and Social Affairs, Population Division, 2019). The average elevation of the megacities is 14 m for Mumbai, 216 m for Delhi, and only 9 m for Kolkata. Geographical factors such as climate, elevation, and wind direction play a crucial role in regulating air quality in these megacities. In this study, I considered the entire Mumbai megacity, the Kolkata megacity (including the twin cities of Kolkata and Howrah), and the total geographical area of Delhi.

1.13.1 Kolkata

Kolkata and Howrah are twin cities within the megacity of Kolkata (Fig. 1.6). They have populations of 4.50 million and 1.07 million, respectively, and areas of 185 sq. km and 51.7 sq. km, respectively (Census of India, 2011). Geographically, Kolkata Municipal Corporation (KMC) or Kolkata district is situated on the east bank of the river Hooghly. In contrast, Howrah Municipal Corporation (HMC) or Howrah city is in the west. The spatial extension was increased by 205 sq. km and 63.5 sq. km by adding Joka with KMC and Bally with HMC. At present, the megacity of Kolkata ranks 16th globally, with a population of 14.85 million (World Economic Forum, 2016). Kolkata is under a tropical climate (Singh and Chauhan, 2020); it experiences four seasons, viz., winter, summer (pre-monsoon), rainy (monsoon), and autumn (post-monsoon). Winter is the most pleasant time in Kolkata. Here, the lowest temperature stays below 12°C. Winter lasts for three months (December to February). March, April, and May broadly encompass the summer season. High temperatures and humidity characterize the summer/pre-monsoon, and it is also the season of Kal-Baisakhi

(Nor'wester), which brings relief from rain in the afternoon and evening. The Southwest monsoon begins in June and lasts until September. It is the rainy season in Bengal, when the highest rainfall occurs. October and November experience autumn or post-monsoon conditions, characterized by moderate rainfall and moderate temperatures. The days are clear; nights are comfortable in this season. Currently, 10 AAMSs operate over this megacity under the West Bengal Pollution Control Board (WBPCB). The 7 AAMSs (Ballygunge, Bidhannagar, Fort William, Jadavpur, Rabindra Bharati University, Rabindra Sarobar, and Victoria) were within Kolkata, and the remaining 3 (Belur Math, Ghusuri, and Padmapukur) were in Howrah city. Rapid urbanization, the daily increase in vehicle numbers, and the indiscriminate expansion of the Howrah industrial belt are the main drivers of rising air pollution levels in the megacity.

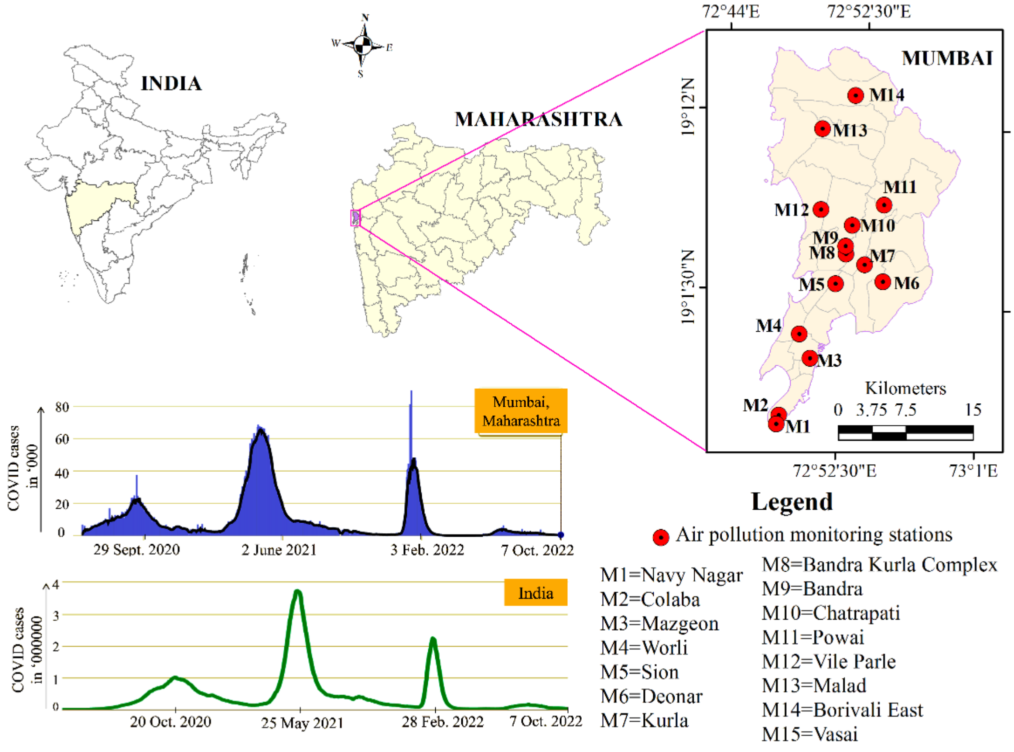


Fig. 1.7 The location of air pollution monitoring stations in Mumbai

1.13.2 Mumbai

Mumbai is situated on the Konkan coast, the west coast of the Arabian Sea of India. The mean elevation of the megacity is 14 m. It is renowned as the country's financial, commercial, and entertainment capital (Das et al., 2022). It had a population of 18.2

million, the largest megacity in the country (Census of India, 2011). An individual has had a 4.5 sq. m living space in the megacity. The megacity experiences a tropical wet and dry climate, a hot summer, heavy monsoonal rainfall, and humidity throughout the year. The western marine wind dominates air circulation. The industrial area lies in the eastern part of the megacity (Gurjar et al., 2016). There are 15 AAMSs, namely Bandra Kurla Complex, Bandra, Borivali East, Chatrapati, Colaba, Deonar, Kurla, Malad, Mazgeon, Navy Nagar, Powai, Sion, Vasai, Vile Parle, and Worli, located in Mumbai city under the control of the Mumbai Pollution Control Board (MPCB) (Fig. 1.7).

1.13.3 New Delhi (as control)

Delhi has a semi-arid climate with extreme dryness, hot summer (March to May), cold and foggy winters (December to February), and moderate rainfall during monsoon (June to September) (Gurjar et al., 2016; Mahato et al., 2020; Singh and Chauhan, 2020). The situation in many industries, power plants, and the increasing vehicular density is leading to extraordinary air pollution in the megacity of Delhi. 37 AAMSs (Alipur, Anand Vihar, Ashok Vihar, Aye Nagar, Bewana, Chandni Chowk, CRRI Mathura, DTU, Dr Karni Singh Shooting Range, Dwarka-sector 8, IGI Airport, IHBAS (Dilshan Garden), ITO, Jahangirpuri, Jawaharlal Nehru Garden, Lodhi Road, Major Dhyan Chand National Stadium, Mandir Marg, Mundka, NSIT Dwarka, Najafgarh, Narela, Nehru campus (Delhi University=DU), North Campus, Okhla Phase-2, Patapganj, Punjabi Bagh, Pusa (Delhi Pollution Control Committee=DPCC), Pusa (IMD), R K Puram, Rohini, Shadipur, Sirifort, Sonia Vihar, Sri Aurobindo, Vivek Vihar, and Wazirpur) monitors the air quality in and around Delhi. Five stations are under the IMD. Another five stations are under the CPCB. The remaining 27 stations are under the DPCC.

1.14 Central queries of the present research

- What is the extent of the country-level spatial impacts of air pollution resulting from the COVID-19 pandemic?
- How closely do cities in China, India, and Pakistan follow the $PM_{2.5}$ guidelines set by the WHO?
- To what degree have air pollutant levels been affected in three major Indian megacities during Diwali amid the COVID-19 pandemic?

- How adverse was the air pollution scenario before and during the pandemic-induced lockdowns in the coastal cities of Kolkata and Mumbai?
- Did pandemic-induced lockdowns improve air pollution levels?
- What were the roles of meteorological parameters in regulating air pollution levels?

1.15 Aims and objectives

- To examine the various country-level spatial impacts of air pollution due to the COVID-19 pandemic.
- To explore the extent to which cities in China, India, and Pakistan adhere to WHO-prescribed $PM_{2.5}$ guidelines.
- To assess the air quality changes in Kolkata and Mumbai during three pandemic waves, along with the spatial distribution of pollutants
- To assess the degree of air pollutant levels from three megacities of India during Diwali amidst the COVID-19 pandemic
- To compare and contrast pollution levels between pandemic and non-pandemic periods and assess the correlations among pollutants in Kolkata and Mumbai
- To assess the impact of meteorological conditions on the air pollution scenarios in pandemic and non-pandemic periods for Kolkata and Mumbai

1.16 A brief outline of the chapters

1. Introduction
2. Data Sources and Research Methods
3. Impact of COVID-19 Lockdowns on Air Pollution
4. $PM_{2.5}$ Levels in China, India, and Pakistan
5. Changes in Air Quality of Indian Megacities During COVID-19
6. Air Pollution During Diwali in Indian Megacities Amid COVID-19
7. Air Quality in Kolkata During Lockdowns
8. Air Quality in Mumbai During Lockdowns
9. Conclusion and recommendations

Chapter II

Data Sources and Research Methods

2.1 Data Sources and Research Methods

This thesis focused on air pollution during the novel COVID-19 pandemic from multiple viewpoints and across various study areas. The Tropospheric AOD and NO_2 were considered for the most polluted countries worldwide (China, India, Italy, France, Germany, and the United States) during the pandemic. The ground-monitored pollutants ($PM_{2.5}$, PM_{10}, CO, NO_2, SO_2, NH_3, and O_3) were considered for India to investigate the impact of the lockdown on air quality in megacities (Mumbai, Delhi, and Kolkata). I analyzed the air quality in pre-lockdown, during-lockdown, and post-lockdown scenarios across the megacities of India and select countries. In addition, I compared air quality during the pandemic phase with the same time window in the previous year (2019) or in normal conditions. The megacities of Mumbai and Kolkata have witnessed three pandemic surges. Wave-wise comparison in the megacity is very crucial. Simultaneously, I analyzed changes in pollution during Dewali and compared them with pre- and post-Dewali pollution levels. In addition, I examined the pandemic year Diwali (2020) with the non-pandemic year (2019). The impact of meteorological parameters, such as temperature, precipitation, relative humidity, air pressure, and wind speed, on air pollution was considered. Above all, I assessed the seasonal change in pollution levels across the different pandemic surges. The research includes weathered and deweathered pollution levels (eliminating the impact of meteorological parameters). The whole study was planned to detect the pollution levels and their health impacts.

2.1.1 AQI

An AQI is an inclusive system that converts the weighted values of individual air pollution-related parameters into a single value or set of numbers (CPCB, 2014). To calculate the AQI, CPCB-India continually monitors the ambient air using the EPA-US method. The CPCB report (CPCB, 2014) has elaborated on all required data processing steps. The MoEF revised the national ambient AQI in November 2009 by amending the Environment Protection Rule 1986. They listed a threshold for the air pollutants in the (i) Industrial, Residential, and Rural areas and the (ii) Ecologically Sensitive areas. AQI formulation mainly includes two steps: (i) Formation of sub-indices (for each pollutant) and (ii) aggregation of sub-indices to get an overall AQI (Fig. 2.1). They computed the sub-indices of seven pollutants at each station based on the 24 h average data (only CO and O_3 were an 8 h average) and health breakpoint range. AQI computation requires $PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, CO, O_3, and Pb as input parameters, with at least three pollutant concentrations available, and at least one of them must include either $PM_{2.5}$ or PM_{10}. The AQI has six categories — good, satisfactory, moderate, poor, very poor, and severe —based on a scale of 0–500 (Table 1.3).

Step 1

Formation of sub-indices (I1, I2,...., In) for n pollutant variables (X1, X2...., Xn) is carried out using sub-index functions that are based on air quality standards and health effects. Mathematically;

$$I_i = f(X_i), i = 1,2 \dots n \qquad \text{Eq. 1}$$

Each sub-index represents a relationship between pollutant concentrations and health effects. The functional relationship between sub-index value (I_i) and pollutant concentrations (X_i) is represented as follows:

$$I = \alpha X + \beta \qquad \text{Eq. 2}$$

Where α =slope of the line, β = intercept at X=0.

The general equation for the sub-index (I_i) for a given pollutant concentration (C_p), as based on the 'linear segmented principle', is calculated as:

$$I_i = [\left\{\frac{(I_{HI} - I_{LO})}{(B_{HI} - B_{LO})}\right\} \times (C_P - B_{LO})] + I_{LO} \qquad \text{Eq. 3}$$

Where,

B_{HI}= Breakpoint concentration greater or equal to given concentration.

B_{LO}= Breakpoint concentration smaller or equal to given concentration.

I_{HI} =AQI value corresponding to B_{HI}

I_{LO} = AQI value corresponding to B_{LO}

C_p = pollutant concentration

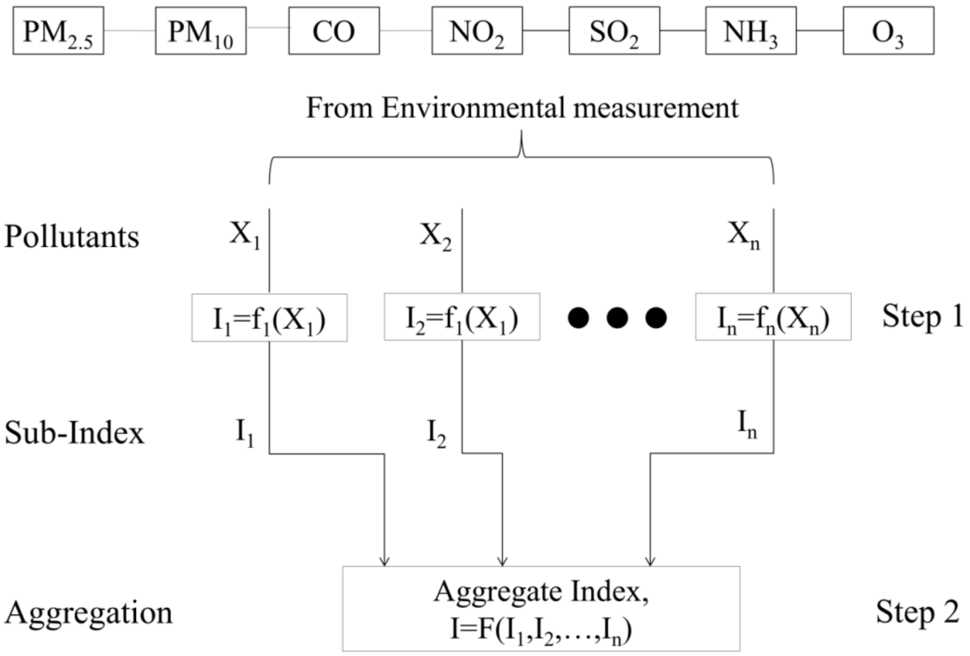


Fig. 2.1 Formation of Air Quality Index

Step 2

The aggregation of sub-indices, Ii, is performed using a mathematical function (described below) to obtain the overall index (I), referred to as the AQI.

$$I = F(I_1, I_2, \dots, I_n) \qquad \text{Eq. 4}$$

Once the sub-indices are formed, they are combined or aggregated in a simple additive form or a weighted additive form:

Weighted Additive Form

$$I = \text{Aggregated Index} = \sum W_i I_i (\text{For } i = 1, \dots\dots, n) \qquad \text{Eq. 5}$$

Where,

$\Sigma W_i = 1$

I_i= sub-index for pollutant i

n = number of pollutant variables

W_i= weightage of the pollutant

Root-Sum-Power Form (nonlinear aggregation form)

$$I = \text{Aggregated Index} = [\sum I_i^p]^{(1/p)} \qquad \text{Eq. 6}$$

Where p is the positive real number >1.

Root-Mean-Square Form

$$I = \text{Aggregated Index} = \{\frac{1}{k}(I^2{}_1 + I^2{}_2 + \ldots I^2{}_k)\}^{0.5} \qquad \text{Eq. 7}$$

Min or Max Operator (Ott, 1978)

$$I = \text{Min or Max}(, I_1 I_2, \ldots I_n) \qquad \text{Eq. 8}$$

2.1.2 GIS interpolation (Inverse Distance Weighting)

The spatial interpolation has been performed using Inverse Distance Weighting (IDW). The interpolation assumes the values of unknown sites/locations based on those of known sites/locations. Things that are close to one another are more alike than things that are farther apart. It assumes that each measured point has a local influence that diminishes with distance. The inverse of the squared distance between the unknown and the known locations forms the weight matrix, based on which the interpolation has been carried out (Lloyd, 2010). The IDW interpolation technique has primarily been used for mapping variables. The CPCB air pollution data was joined to the AAMS shapefile as an Excel file. The values of the unknown points are generated using the megacity's mask layer. The resulting IDW map included $PM_{2.5}$, PM_{10}, CO, NO_2, SO_2, NH_3, O_3, and AQI values depicted by colour stretching from low to high. The IDW method is available in the 'interpolation' of the ArcGIS Spatial Analysis Tools menu. Tapping/clicking on IDW, an IDW window appears. Now, select Input point features data (e.g., Mumbai_$PM_{2.5}$), select the Z value field (e.g., $PM_{2.5}$), and then choose the Output raster destination. Finally, click the OK button. Finally, a raster image (e.g., TIFF) of $PM_{2.5}$ has been generated.

IDW interpolation is easier for the spatial mapping of variables than other tools; no pre-modelling preparation is required to run the programme (Jumaah et al., 2019). It is a pretty user-friendly method. Jha et al. (2011) inferred that the IDW technique is ideal for the Indian air pollution scenario and yields lower error margins than other conventional interpolation approaches. Many scholars and researchers have used the IDW technique to map pollution worldwide (Jha et al., 2011). Jung et al. (2021) investigated the effects of air pollution on patients with chronic kidney disease using the IDW method (Jung et al., 2021). Shukla et al. (2020) used IDW to map the spatial distribution of particulate matter in Delhi (Shukla et al., 2020). Masroor et al. (2020)

examined $PM_{2.5}$ concentrations in Tehran using the IDW method (Masroor et al, 2020). A few researchers, such as Mahato et al. (2020), Bera et al. (2021), Balaji et al. (2022), and Suthor et al. (2023), assessed air pollution in Delhi, Kolkata, Madurai, and Bengaluru during COVID-19, amid lockdown (Mahato et al., 2020; Bera et al., 2021; Balaji et al., 2022; Suthor et al., 2023).

2.1.3 Generalized additive model

A generalized additive model (GAM) is a mathematical model that helps to estimate an association among nonlinear variables. GAM normalizes the restriction by assigning a simple weighted sum. A flexible function, called a spline, allows us to model nonlinear relationships for each variable incorporated into the GAM programme. This model is a user-friendly and explainable machine-learning tool that removes the hindrances posed by nonlinear variations in meteorological conditions to infer the time series variability of air pollutant concentrations (Ropkins and Tate, 2021; Solberg et al., 2021). The flexible approach of this model has made it quite popular among researchers (Dehghan et al., 2018; Li et al., 2019; Ravindra et al., 2019), as it smooths air pollutant data, mitigating the effects of weather variability and seasonal changes.

I used GAM to normalize the air pollutant data, i.e., to remove the effect of meteorological variables on air pollutant concentrations (Munir et al., 2021). The R package is an add-on to XL-STAT that was used to perform the deweathering. Due to limited meteorological data and the unavailability of data for all the AAMSs, I deweathered pollutant data from one station in each of the three megacities —Anand Vihar (Delhi), Chatrapati (Mumbai), and Rabindra Sarobar (Kolkata) — in chapter 6. The normalization or deweathering of air pollutant data was carried out by implementing the mixed GAM computation vehicle (mgcv) data tool (Woods, 2020) in the R programming language (R Core Team, 2020) by taking into consideration six parameters, namely air temperature, relative humidity, wind velocity, wind direction, precipitation, and day of the year. Due to data unavailability, parameters such as solar radiation and cloud cover were excluded. The GAM package is selected from the XLSTAT-R options in MS Excel 2010. A GAM dialogue box will appear; here, General, Options, Missing data, Outputs, and Charts selections are available. In the general part, variables and families were chosen, along with a new sheet for complete output. The smoother (e.g., Cubic spline) and method (e.g., RELM, REstricted Maximum Likelihood) were selected from the Options section. The mean or mode selected for Missing data, all tick on (e.g., descriptive statistics) in the Outputs and Chart (component plots) section.

2.1.4 Scatter plots with Pearson correlation coefficient

A scatter plot is a statistical chart that uses Cartesian coordinates to display values for two variables (e.g., $PM_{2.5}$ and PM_{10}) for a large dataset. The x-axis shows the independent variable, and the y-axis presents the dependent variable. If there is no clear dependent variable in the pairs, either x or y can be plotted. Thus, the situation scatter plots denoted the degree of correlation. Karl Pearson (1920) formulated the Product-Moment Correlation Coefficient, also known as the correlation coefficient. Pearson computed the correlation coefficient based on the arithmetic mean and standard deviation. The relationship is expressed by 'r' or r_{yx}. The formula is given below-

$$\text{ryx} = \frac{\sum XY - \frac{\sum X \times \sum Y}{n}}{\sqrt{\left\{\sum X^2 - \frac{(\sum X)^2}{n}\right\}\left\{\sum YX^2 - \frac{(\sum Y)^2}{n}\right\}}} \qquad \text{Eq. 9}$$

The Pearson correlation coefficient method was used to analyze the association among pollutants during the COVID-19 pandemic waves. The '*r*' value and degree of correlation are classified in Table 2.1.

Table 2.1 The '*r*' value and degree of correlation by Pearson

r	Degree of correlation	*r*	Degree of correlation
+1.0	Perfect positive relation	-1.0	Perfect negative relation
+0.75	Strong positive relation	-0.75	Strong negative relation
+0.50	Moderate positive relation	-0.50	Moderate negative relation
+0.25	Poor positive relation	-0.25	Poor negative relation
r= 0 means no relation			

Here, I used the R programming language to analyze seven pollutants, namely $PM_{2.5}$, PM_{10}, CO, NH_3, NO_2, SO_2, and O_3. The degree of statistically significant correlation between pollutant concentration is denoted by $p < 0.05$= "*"; $p < 0.01$= "**"; and $p < 0.001$= "***".

2.1.5 Box-plots

Box plots (also called box-whisker plots) provide a good visual overview of large datasets. It is constructed from five statistical values: the minimum, the first quartile (or first quartile), the median (or second quartile), the third quartile, and the maximum. The box formed the first quartile to the third quartile. The smallest and largest values are at the ends of the whiskers, with the smallest at the bottom and the largest at the top, known as the minimum and maximum. The ground-monitored ambient pollutant concentrations of $PM_{2.5}$, PM_{10}, CO, NO_2, SO_2, NH_3, O_3, and AQI are shown in these plots. The graphs have two-way comparisons: vertically, inter-pollution levels; horizontally, intra-pollution levels year-wise. Here, I used MS Excel 2010 to compute the box plots.

2.2 Data sources and methods of Chapter 3 (Impact of COVID-19 Lockdowns on Air Pollution)

2.2.1 Data sources

To investigate the environmental effects of coronavirus quarantine periods worldwide on atmospheric quality, two parameters—NO_2 and AOD—have been considered here. Six of the most polluting countries worldwide, where the virus's impact was initially notable, were chosen: China, India, Italy, France, Germany, and the United States. The various periods examined for each of these countries were the pre-lockdown phase (the two prior weeks before the lockdown was imposed in each country in 2020), the lockdown itself (held during 2020), the post-lockdown (the two weeks after lockdown measures were lifted in each country in 2020), and the previous year (the same time windows as the respective nations-wise lockdowns but in 2019- regarded as the normal period) (Table 2.2).

The NO_2 and the AOD datasets were obtained from the NASA GIOVANNI web portal (https://giovanni.gsfc.nasa.gov/giovanni/). The NO_2 Tropospheric Column (30% cloud screened) daily level 3 global 0.25° latitude/longitude grid product of the Aura/Ozone Monitoring Instrument (OMI) and the AOD 550 nm (Deep Blue, Land only) daily L3 global 1° latitude/longitude grid product of the Terra Moderate Resolution Imaging Spectroradiometer (MODIS) were employed here (Table 2.3). Moreover, the NO_2 and AOD datasets were obtained for 2005-19 to examine the spatio-temporal concentrations of these substances across the globe in more normal times (i.e., over the last 15 years, as far back as when both datasets are available). This longer-term view thus depicted the actual usual picture of the pollutants' distribution across the globe, unaffected by lockdowns. The OMI/Aura sensor was launched in 2004, while the Terra/MODIS sensor was launched in 1999. To identify similarities between the datasets, I used the period from 2005 to 2019 to analyze the pre-lockdown period.

To evaluate the accuracy of classified image files obtained from the NASA GIOVANNI web portal, I used ground-station data for NO_2, $PM_{2.5}$, and PM_{10} from the countries under study. This ground-level pollution data was collected from the Air Pollution in the World (Real-time Air Quality Index/AQI) web portal (https://aqicn.org/city/all/). Two ground data stations were selected for each country, viz. Beijing and Wuhan for China; R.K. Puram and Victoria for India; Cornale and Milano Sinato for Italy; Ajaccio-Canetto and Pompidan-Tours for France; Wetzlar and Marburg for Germany; and New York and Ware for the United States. These stations were also chosen to reflect the most polluted zones previously identified in each of the studied countries using NASA data.

2.2.2 Uncertainties of MODIS data

The uncertainties in MODIS data, such as sensor zenith angle and cloud cover, are significant limitations for its spatio-temporal analysis. Few researchers (Li et al., 2016; Li et al., 2019; Muhammad and Thapa, 2020; Muhammad and Thapa, 2021) have effectively discussed these uncertainties in MODIS data. The present study was conducted on datasets collected over 15 years, primarily 15-year-averaged maps of NO_2 and AOD, which seemingly reduce uncertainty to some extent. Clear skies were present during most of the lockdown periods in the respective countries. Urban and industrial regions are the primary source areas of atmospheric pollutants, in contrast to the more sparsely populated rural and mountainous regions.

2.2.3 Methods

To detect the standard (i.e., usual) spatial-temporal concentrations of NO_2 and AOD across the globe, 15-year (2005-19) time-averaged images were prepared from the NASA web portal (Krotkov et al., 2019). The same datasets/images for the six countries mentioned above, covering the previous year, pre-lockdown, lockdown, and post-lockdown periods, were also prepared from the same web portal. The downloaded averaged images were analyzed using ESRI ArcGIS 10.3. To enable visual interpretation of images at the country and global levels, these datasets were appropriately stretched to a fixed range of NO_2 and AOD values. According to the dataset legends on the NASA portal, areas denoted in dark red and blue represent the maximum and minimum concentrations of NO_2. On the other hand, the dark red and yellow tones would depict the maximum and minimum AOD concentrations in a region, respectively.

Table 2.2 The selected countries and their pre-lockdown, lockdown, and post-lockdown durations

Sl. No.	Country	Normal period, 2019	Pre-lockdown period, 2020	Lockdown period, 2020	Post-lockdown period, 2020	Population, 2020*	Urban Population* (%)	World Share* (%)
1	China	23 January-25 March	9 January-22 January	23 January-25 March	26 March-8 April	1,439,323,776	61	18.47
2	India	24 March-14 April	11 March-23 March	24 March-14 April	15 April-28 April	1,380,004,385	35	17.7
3	Italy	9 March-18 May	24 February-8 March	9 March-18 May	19 May-1 June	60,461,826	69	0.78
4	France	17 March-11 May	3 March-16 March	17 March-11 May	12 May-25 May	65,273,511	82	0.84
5	Germany	23 March-20 April	9 March-22 March	23 March-20 April	21 April-4 May	83,783,942	76	1.08
6	United States	3 March-22 April	18 February-2 March	3 March-22 April	23 April-6 May	331,002,651	83	4.25

**as per Worldometer, 2020, based on the latest United Nations Population Division data*

Table 2.3 Dataset Details

Parameter	Agency	Instruments/Platforms	Spatial resolution	Temporal resolution
NO_2	NASA	OMI/Aura	0.25 degree	Daily
AOD	NASA	Terra/MODIS	1 degree	Daily

2.3 Data sources and methods of Chapter 4 ($PM_{2.5}$ Levels in China, India, and Pakistan)

2.3.1 Data sources

To investigate outdoor $PM_{2.5}$ pollution, I extracted annual mean $PM_{2.5}$ concentrations for all 760 cities in China, India, and Pakistan from 2017 to 2023, and monthly mean observed values for these cities in 2023, from the Swiss air quality technology company, IQAir. The Swiss company collects data from government and non-government agencies and non-profit organizations using real-time air quality monitoring instruments and low-cost air quality sensors. Incorporating historical year-end datasets and real-time data, the global dataset was ultimately released. Here, I employed the mean monthly $PM_{2.5}$ concentration of the six most populated cities of China (Beijing, Chengdu, Chongqing, Guangzhou, Shanghai, and Shenzhen), India (Delhi, Kolkata, Mumbai, Hyderabad, Bengaluru, and Chennai), and Pakistan (Lahore, Karachi, Peshawar, Faisalabad, Rawalpindi, and Islamabad). In addition, the capital cities of China (Beijing), India (New Delhi), and Pakistan (Islamabad), annual hours spent in various categories of WHO (WHO, 2022) prescribed $PM_{2.5}$ pollution levels during 2017-23 were incorporated.

2.3.2 Methods

The global air quality report 2023 included 134 countries and therein 7812 locations. I analyzed the spatial distribution of the annual mean concentration of $PM_{2.5}$ using the WHO's (WHO, 2022) annual air quality categories and colour codes in a GIS platform. The WHO assigned seven colour codes to $PM_{2.5}$-related human health risks to better visualize cities: blue, green, yellow, orange, red, purple, and maroon (Table 2.4). The blue colour indicates the level meets WHO guideline limits of 5 $\mu g/m^3$ which is good/healthy for human health concern and exceeds the limits; they are green (5.1-10 $\mu g/m^3$), yellow (10.1-15 $\mu g/m^3$), orange (15.1-25 $\mu g/m^3$), red (25.1-35 $\mu g/m^3$), purple (35.1-50 $\mu g/m^3$), and maroon (>50.1 $\mu g/m^3$). The level of health concern —from good to extremely hazardous — is assigned accordingly.

Table 2.4 World Air Quality Report 2023 Visualization Framework

Source: World Air Quality Report 2022

Annual $PM_{2.5}$ breakpoints based on WHO guidelines and interim targets	$PM_{2.5}$ (µg/m^3)	Colour code	WHO levels	Level of health concern
Meets WHO guideline	0-5	Blue	Air quality guideline	Good
Exceeds by 1 to 2 times	5.1-10	Green	Interim target 4	Moderate
Exceeds by 2 to 3 times	10.1-15	Yellow	Interim target 3	Unhealthy for sensitive groups
Exceeds by 3 to 5 times	15.1-25	Orange	Interim target 2	Unhealthy
Exceeds by 5 to 7 times	25.1-35	Red	Interim target 1	Very unhealthy
Exceeds by 7 to 10 times	35.1-50	Purple	Exceeds target levels	Hazardous
Exceeds by over 10 times	>50.1	Maroon	Exceeds target levels	Extreme Hazardous

Using WHO color schemes, I mapped the annual mean $PM_{2.5}$ concentrations for all 760 cities from 2017 to 23 to visualize the spatial distribution across countries. Point plots depict the temporal trend of $PM_{2.5}$ levels during 2017-23. The variation of mean $PM_{2.5}$ concentrations during 2017-23 over China, India, and Pakistan was also compiled. In addition, I have designed a framework to incorporate different city locations, such as industrial areas, transport hubs, and geographical features (AAMSs cover diverse landscapes, including urban, suburban, and rural areas), as well as weather patterns, including temperature inversions, seasonal variations, fog, smog, etc., from 2017 to 2023. This framework uses two air-monitoring datasets to assess a nation's value across four factors. For industrial locations, the cities considered are Shanghai and Beijing in China, Gurugram and Asansol in India, and Lahore and Karachi in Pakistan. Shenzhen and Guangzhou in China, Delhi and Mumbai in India, and Lahore and Karachi in Pakistan were deployed as transport locations.

Regarding geographical features, the cities are Chengdu and Tianjin in China, Shillong and Siliguri in India, and Faisalabad and Islamabad in Pakistan. Lastly, for weather patterns, the towns include Wuhan and Dongguan in China, Jaipur and Chennai in India, and Peshawar and Lahore in Pakistan. The average values from the two stations are considered for each country.

Likewise, the cities' $PM_{2.5}$ levels were also depicted by point plots using MS Excel based on $PM_{2.5}$ annual mean concentration from 2017 to 2023 of the six most populated cities of China (Beijing, Chengdu, Chongqing, Guangzhou, Shanghai, and Shenzhen), India (Delhi, Kolkata, Mumbai, Hyderabad, Bengaluru, and Chennai), and Pakistan (Lahore, Peshawar, Faisalabad, Karachi, Rawalpindi, and Islamabad). The capital cities of China (Beijing), India (New Delhi), and Pakistan (Islamabad), and the annual hours spent in various categories of WHO-prescribed $PM_{2.5}$ pollution levels during 2019-23, were represented in a bar graph.

I also computed and designed the mean monthly $PM_{2.5}$ concentration for 18 cities (6 cities × 3 nations), column-wise, and the annual average, horizontally, to detect seasonal variation in pollution. The same colour contrast is used for all these figures. The regional differences in pollution levels have been analyzed using mean $PM_{2.5}$ concentrations from the most polluted cities (state- or province-wise) in China, India, and Pakistan. For a state or province of any of these three countries, a single mean value is computed by considering all cities' $PM_{2.5}$ concentrations within that state or province. This approach enabled us to analyze the intra-national and inter-national variability in $PM_{2.5}$ concentrations. The seasonal $PM_{2.5}$ concentrations were computed from data across 760 cities in three nations. The mean observed temperature and precipitation for CIP were prepared from the Climate Change Knowledge Portal (CCKP) of the World Bank using average surface air temperature and precipitation for the period 1991-2020. The spatial distribution and rainfall temperature diagram were generated using these two variables.

2.3.3 Limitations of the study

The present study analyzed the $PM_{2.5}$ pollution scenario using ground-station data from 760 cities: 495 in China, 255 in India, and 10 in Pakistan. These monitoring stations were poorly distributed geographically and unevenly across countries. Moreover, the study was framed based on outdoor air pollution ($PM_{2.5}$). These two are the prime limitations. The emissions from the industry, vehicle movement, and sectoral stubble burning are the principal sources of air pollution. Hence, taking only outdoor monitoring was significant. Though the data stations were unevenly distributed geographically, the zones of human activity were incorporated, and the stations allocated here excluded only the mountainous and desert areas.

Moreover, the number of monitoring stations is adequate for the countries' geographical areas and the population share to be inquired about, and obtain transparent findings. The air monitoring stations in Pakistan — mainly Peshawar, Faisalabad, and Rawalpindi — had a few data gaps, which were a minor limitation. Lahore, Karachi, and Islamabad— these stations' data enabled us to understand the trend of pollution in Pakistan from 2017 to 23; however, given Pakistan's geographic extent and population density, the number of monitoring stations was fewer than in China and India. However, this study did not aim to extrapolate data from the existing dataset to other cities in Pakistan, as that could have led to gross over- or underestimation, which I deliberately avoided and focused solely on the available data to reach my conclusions.

2.4 Data sources and methods of Chapter 5 (Changes in Air Quality of Indian Megacities During COVID-19)

2.4.1 Data used

I collected ground-monitored air pollutant data for $PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, CO, and O_3 from the CPCB web portal (https://app.cpcbccr.com/AQI_India/). Data was gathered from 15 AAMSs in Mumbai, 37 in Delhi, and 10 in Kolkata. The nationwide lockdown in India began on March 24, 2020. I extracted data for three weeks before the lockdown (March 3–23, 2020), three weeks during the lockdown phase (March 25–April 14, 2020), and three weeks after the lockdown (April 15–May 5, 2020). Additionally, I retrieved data from 1 station in Mumbai, 37 in Delhi, and 4 in Kolkata from the CPCB portal during the same period (March 25–April 14) in 2019 to compare air quality between the two years, although data from the other stations in 2019 is unavailable. I analyzed air pollutant data for 12 dates with weekly intervals in 2020: March 3, 10, 17, 23; March 25; March 31; April 7, 14, 15, 21, 28; and May 5. For 2019, data was collected on March 25, 31, April 7, and 14. Daily meteorological data for four parameters—ambient air temperature, relative humidity, wind velocity, and precipitation—from weather stations at airports in these three cities were also retrieved for March, April, and May of 2019 and 2020. Chhatrapati Shivaji International Airport Station (18.97°N, 72.83°E), Safdarjung Airport Station (28.59°N, 77.21°E), and Behala Airport Station (22.54°N, 88.34°E) of Mumbai, Delhi, and Kolkata have been selected for meteorological data, collected from the Weather Underground portal (https://www.wunderground.com/). The Shapiro-Wilk test was conducted to examine the normality of the meteorological data. Based on the outcomes, independent samples of the Student's t-test (for normal data sets) and the Mann-Whitney *U* test (for non-normal datasets) were performed to test the significance of the difference in meteorological parameters between the years 2019 and 2020.

2.4.2 Methods

I analyzed the spatial distribution of the daily average air pollutants data using a GIS platform. To produce a spatial-temporal variation map of all seven air pollutant parameters, I implemented the IDW-based linear combination interpolation technique in ESRI ArcGIS 10.5. The pollutant data for three selected dates, viz., 17 March, 31 March, and 21 April 2020, were mapped to show the spatial distribution of those pollutants under pre-lockdown, lockdown, and post-lockdown scenarios using the same GIS platforms. On the other hand, the point plots, box plots, and sparkline diagrams of the changing trend in average concentrations, and the correlation matrices of pollutants, have been prepared in MS Excel 10. I also computed the AQI to characterize the overall status of air quality in the three megacities.

2.5 Data sources and methods of Chapter 6 (Air Pollution During Diwali in Indian Megacities Amid COVID-19)

2.5.1 Data used

This study considered seven parameters, namely $PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, CO, and O_3. Ground-monitored data on these pollutants were downloaded from the CPCB's official website (https://app.cpcbccr.com/AQI_India/). Delhi, Kolkata, and Mumbai have 37, 10, and 15 AAMSs, respectively. I downloaded the data for all these stations. Diwali was on October 27 and November 14 in 2019 and 2020, respectively. Usually, people burn firecrackers in the evening and continue till midnight. All these AAMSs keep hourly records. I extracted the data on all seven pollutant concentrations at midnight (IST 12:00 am) on both dates. I considered 24 h average data (01:00 am to 12:00 am) for each Diwali date. To understand the rate of increase in pollutant concentrations and their short-term atmospheric residence times, I extracted and analyzed pre- and post-Diwali data for both years. The 24 h average data for October 20, 24, 25, and 26, 2019, and November 7, 11, 12, and 13, 2020, were analyzed to characterize the pre-Diwali pollution situation. Similarly, the 24 h average data for October 28, 29, 30, and November 3, 2019, as well as for November 15, 16, 17, and 21, 2020, were analyzed to understand post-Diwali pollution levels. The logic behind selecting these pre-Diwali and post-Diwali dates was to analyze and compare the pollutant levels just three days ago and just three days after the event. In addition, I considered dates seven days before and seven days after Diwali to examine the residual effects in the atmosphere. Daily meteorological data of five parameters, namely ambient air temperature, relative humidity, wind velocity, wind direction, and precipitation for the exact dates, were retrieved from the weather stations deployed at the Chhatrapati Shivaji International Airport Station (18.97°N, 72.83°E) for Mumbai; Safdarjung Airport Station (28.59°N, 77.21°E) for Delhi, and Maheshtala, Behala

Airport Station (22.54°N, 88.30°E) for Kolkata (Weather Underground portal; https://www.wunderground.com/).

2.5.2 Methods

The net change in each AAMS was computed to analyze changes in pollutant concentrations across different dates within each year. The composite means of the net changes across all AAMSs were further computed for each megacity. The calculation of pre-Diwali to Diwali changes in pollutant concentrations followed two ways: (i) the difference between pollutant concentration on the Diwali date and seven days before Diwali, and (ii) the difference between pollutant concentration on the Diwali date and the average pollutant concentration of three days before Diwali. Similarly, the Diwali to post-Diwali changes were also computed by analyzing (i) the difference between pollutant concentration on the Diwali date and seven days after Diwali, and (ii) the difference between pollutant levels on the Diwali date and the average pollutant concentration of three days after Diwali. The box plots were prepared to show the differences in ambient air pollutant concentrations observed between Diwali 2019 and Diwali 2020 for each parameter. The error bars show the minimum and maximum observed on the respective dates. The intersection of the boxes denotes the median. The lower and the upper ends of the boxes signify the first quartile and the third quartile, respectively.

24 h average data were not available for all AAMSs. Data from two AAMSs (Kurla and Sion) for Mumbai, ten AAMSs (Anand Vihar, Ashok Vihar, Bewana, DTU, Jawaharlal Nehru Garden, Mundka, Patapganj, Pusa DPCC, Rohini, and Sonia Vihar) for Delhi, and three AAMSs for Kolkata (Ballygunge, Fort William, and Ghusuri) were utilized to compute the AQI for the selected dates.

2.5.2.1 Spatial interpolation of data

I analyzed spatial variation in air pollutants and AQI within each megacity using ESRI ArcGIS 10.5. The IDW interpolator and linear combination model were applied. IDW is a deterministic method for computing values at unmeasured locations from measured values at distinct locations (Xie et al., 2021). The interpolation algorithm relies on a probabilistic assumption that the influence of values at nearby locations is greater than that of distant locations on an unknown location (Jumaah et al., 2019). In this method, the weights assigned to an unknown location depend on the distance to other locations with measured data (Vorapracha et al., 2015). The inverse of the squared distance between the unknown and the known locations forms the weight matrix, based on which the interpolation is carried out (Lloyd, 2010). Jha et al. (2011) inferred that the IDW technique is best suited to the Indian air pollution scenario and yields lower error margins than other conventional interpolation approaches (Jha et al., 2011).

2.5.2.2 Deweathering of air-pollutant data

Due to limited meteorological data and the unavailability of meteorological data for all the AAMSs, I deweathered one station's pollutant data from each of the three megacities, namely Anand Vihar (Delhi), Chatrapati (Mumbai), and Rabindra Sarobar (Kolkata). I used a GAM to normalize the air pollutant data, i.e., to remove the effect of meteorological variables on air pollutant concentrations (Munir et al., 2021). This model is a user-friendly and explainable machine-learning tool that removes the hindrances posed by nonlinear variations in meteorological conditions to infer the time series variability of air pollutant concentrations (Ropkins and Tate, 2021; Solberg et al., 2021). The flexible approach of this model has made it quite popular among researchers (Dehghan et al., 2018; Li et al., 2019; Ravindra et al., 2019a), as it smooths air pollutant data, mitigating the effects of weather variability and seasonal changes. The normalization or deweathering of air pollutant data was carried out by implementing the mgcv data tool (Woods, 2020) in the R programming language (R Core Team, 2020) by taking into consideration six parameters, namely air temperature, relative humidity, wind velocity, wind direction, precipitation, and day of the year. Parameters such as solar radiation and cloud cover were excluded due to data unavailability.

2.5.2.3 Statistical analyses

The Shapiro-Wilk test enabled us to assess the normality of the data. An independent-samples Student's t-test indicated a difference in mean air pollutant levels across the cities in the two years. The Pearson correlation coefficient helped us examine the interrelationships among ambient air pollutants. All statistical analyses were conducted using SPSS software (version 16, SPSS Inc.). The results were considered significant at $p < 0.05$.

2.6 Data sources and methods of Chapter 7 (Air Quality in Kolkata During Lockdowns)

2.6.1 Data sources

To investigate the effect of the COVID-19 pandemic-induced lockdown on air quality, I extracted data from all AAMSs in Kolkata and Howrah city. The 24 h averaged ground-level concentrations of $PM_{2.5}$, PM_{10}, CO, NH_3, NO_2, SO_2, and O_3 were collected at 6 pm from the CPCB official website (https://app.cpcbccr.com/AQI_India/). As the study considered the pandemic waves, weekly pollutant concentrations were collected. 25 March, 31 March, 7 April, and 14 April of 2020 were selected for the first wave. Similarly, 16 May, 23 May, and 30 May of 2021, and 1 January, 8 January, and 15 January were used for the second and third waves, respectively. The exact dates, in weekly intervals, for the 2019 data were also collected to assess the non-pandemic pollution level scenario. Meteorological parameters such as temperature (°F), wind speed (mph), relative humidity (%), air pressure (Hg), and precipitation (mm) for 25 March to 14 April 2020, 16 May to 30 May 2021, and 01 January to 15 January 2022 were obtained from the weather stations at Dum Dum Airport (located within the Kolkata megacity).

2.6.2 Methods

The net change in pollutant concentrations was computed and analyzed during the COVID-19 pandemic waves. The wave-wise pollutant concentrations are formulated by following the two steps-

(i) The composite mean was prepared using selected dates of every COVID-19 pandemic wave.
(ii) Difference between COVID-19 pandemic waves and the respective concentration for the normal period.

The box plots presented air pollutant concentrations during the pandemic waves (2020, 2021, and 2022) and the normal phases (2019). Each bar contains minimum, maximum, median, lower quartile, and upper quartile values.

Simultaneously, to characterize the overall pollution scenario, I have used the AQI (CPCB, 2014). The AQI is calculated based on (i) the sub-index of $PM_{2.5}$, PM_{10}, NH_3, NO_2, SO_2, 24 h average, and 8 h average of CO and O_3, and (ii) identifying the highest amount among the said pollutants that serve as AQI. AQI computation must require pollutants $PM_{2.5}$ and PM_{10}, and at least three pollutant concentrations should be available out of seven pollutants ($PM_{2.5}$, PM_{10}, CO, NH_3, NO_2, SO_2, and O_3) and Pb. Based on pollutant concentrations and six AQI categories, CPCB prepared a health breakpoint range that considers the human health impacts of these pollutants (Table 1.3).

2.6.2.1 The IDW method

The spatial distribution of pollutants was generated using the IDW interpolation model. The IDW is a commonly used method for computing unknown points from known point data (Xie et al., 2017). The method is widely accepted for spatial mapping of air pollution at the city scale compared to other conventional interpolation methods (Jha et al., 2011). In this study, I processed this approach for the pandemic waves using the ESRI ArcGIS 10.5 platform.

2.6.2.2 Deweathering of air pollutant data

The research focused exclusively on an area of only 269.5 sq. km within the Kolkata megacity. Hence, it was safe to assume that the meteorological parameters at a given time remained unchanged within this area. I used only one station's pollutant data, which was Rabindra Bharati University (RBU). The GAM in XL-STAT was used to remove the effects of meteorological variables on air pollutant concentration. There is a model in the R programming language, RStudio (R Core Team, 2020), known as mgcv (Wood, 2020), used to perform normalization or deweathering of pollutants. The model failed to run when all five parameters were used, resulting in a "execution was halted" error. So, I have selected the three most effective parameters: temperature, rainfall, and wind speed. The relative humidity and air pressure were excluded from the model because they had more coefficients than the data.

2.6.2.3 Statistical Correlation

The Pearson correlation coefficient method was used to analyze the association among pollutants during the COVID-19 pandemic waves. It is a linear correlation between variables or two sets of data, diagrammatically represented by scatter plots. Here, I used RStudio to analyze seven pollutants: $PM_{2.5}$, PM_{10}, CO, NH_3, NO_2, SO_2, and O_3. The degree of statistically significant correlation between pollutant concentration is denoted by p <0.05= "*"; p <0.01= "**"; and p <0.001= "***". Many researchers have used this method to compute correlations among air pollutants (Mahato et al., 2020; Sarkar et al., 2021).

2.7 Data sources and methods of Chapter 8 (Air Quality in Mumbai During Lockdowns)

2.7.1 Data sources

The present study focused on the Mumbai megacity based on available AAMSs of the Pollution Control Board of India. I considered the available 24 h-averaged ground-level concentrations of $PM_{2.5}$, PM_{10}, CO, NH_3, SO_2, NO_2, O_3, and AQI at 6 pm. I retrieved the data from the CPCB, Ministry of Environment, Forests and Climate Change (MoEFCC), GoI web portal (https://app.cpcbccr.com/AQI_India/). Since the study focused on three surges of the pandemic, I considered extracting pollutant concentration data for these dates: March 25, March 31, April 7, and April 14, 2020, for the first wave; April 22, April 27, and May 1, 2021, for the second wave; and January 10, January 15, and January 19, 2022, for the third wave. I extracted pollutant data for the exact dates in 2019, when there was no pandemic, to assess non-pandemic pollution levels in the megacity.

The weather station at the Chhatrapati Shivaji International Airport Station (18.97°N, 72.83°E) in Mumbai provided meteorological data, including temperature, precipitation, relative humidity, air pressure, and wind speed, for the dates mentioned above. The meteorological data were retrieved from the weather underground portal (https://www.wunderground.com/). The daily precipitation data were collected from the NASA Power portal (https://power.larc.nasa.gov/data-access-viewer/).

2.7.2 Data limitations

There were some constraints on data availability. I compared pollutant concentrations between the pandemic waves (2020, 2021, and 2022) and the non-pandemic period in 2019, which served as the normal phase. Bandra is the only AAMS where all data were available, except for NH_3 in 2019 (https://airquality.cpcb.gov.in/ccr/#/caaqm-dashboard-all/caaqm-landing). Bandra (MPCB) AAMS was selected for the deweathering of pollutants for the first wave (2020) and the second wave (2021). However, due to data constraints, Bandra Kurla Complex (IITM) is considered for the third wave. Due to data gaps for NH_3 and O_3 in Bandra and Bandra Kurla Complex for the first and second waves, I used Chhatrapati Shivaji International Airport (MPCB) for these two pollutants. However, I am confident that given the total quantity of data analyzed in the present study, these data gaps should not hamper the overall results.

2.7.3 Methods

This study focused on a comparative analysis of concentrations of $PM_{2.5}$, PM_{10}, CO, NH_3, NO_2, SO_2, and O_3, and the AQI, across three different waves and at the same time during a non-pandemic phase. AQI is a tool that combines various pollutants into a single number (an index value). Hence, it affects the overall air quality in a specific area. To carry out this research and fulfil the objectives of this study, I computed

(i) Air monitoring station-wise, each pollutant's mean concentration for the first wave (2020), the second wave (2021), and the third wave (2022)

(ii) Wave-wise (first, second, and third) pollutants' mean concentration based on available air monitoring datasets

CPCB prepared the formulation of AQI. AQI calculation is based on the pollutant/sub-index of eight pollutants in 24 h concentrations, viz., $PM_{2.5}$, PM_{10}, NO_2, SO_2, CO, O_3, NH_3, and Pb. $PM_{2.5}$, $PM_{10,}$ and at least three pollutant concentrations are required to calculate the AQI. The pollutant concentrations, National AQI classes, National AQI categories, and health impacts are shown in Table 1.3. Here, a low concentration of the substance in the air indicates minimal health impacts; a high concentration can cause prolonged suffering.

2.7.3.1 IDW model

I have applied the IDW interpolator model to characterize the spatial distribution scenarios implied by several previous studies. In this method, a few unknown points are computed from a dataset of known points (Xie et al., 2017). Air pollution mapping using the IDW method is widely accepted nowadays (Jha et al., 2011; Jumaah et al., 2019; Mahato et al., 2020; Sarkar et al., 2021). This study analyzed the wave-wise spatial distribution of pollutants using ESRI ArcGIS 10.5.

2.7.3.2 Generalized additive model

The GAM allows the modelling of nonlinear attribute predictions. The GAM function was developed in XLSTAT-R and programmed through the mgcv package in R (Wood, 2020). The model is user-friendly and configured with a machine-learning tool that removes the meteorological parameters' impact on pollutants (Ropkins and Tate, 2021). Here, temperature, humidity, wind speed, and precipitation were considered for the deweathering of $PM_{2.5}$, PM_{10}, CO, NO_2, SO_2, NH_3, and O_3. In GAM, pollutants are taken as dependent variables, and the selected four meteorological drivers are independent variables. Cubic splines for data smoothing and residual maximum likelihood (REML) techniques are used in GAM options.

2.7.3.3 Correlation coefficient method

The Pearson correlation coefficient was computed from scatter plots to analyze the interrelationships among pollutants during COVID-19 surges. Previous research found that the combined impact of substances was more harmful. I performed a correlation (r) analysis in RStudio using seven pollutants. Here, the "r" value ranges from +1 to -1, meaning strong positive to strong negative. Simultaneously, the degree of significance level three, viz., p <0.05= "*"; p <0.01= "**"; and p <0.001= "***", is considered. The Correlation coefficient method is widely accepted for air pollutant concentration nowadays (Mahato et al., 2020; Sarkar et al., 2021).

Chapter III

Impact of COVID-19 Lockdowns on Air Pollution

3.1 Introduction

The swift spread and ensuing community transmission of COVID-19 since its inception have often overwhelmed local healthcare services quickly, leaving the aged and those with existing health issues particularly vulnerable (MacConnachie et al., 2007). Healthcare officials and governments introduced and widely propagated the concept of 'social distancing' (Manderson and Levine, 2020) and 'lockdowns' to limit the spread of the virus, with cancellations of major sporting and cultural events (Munoz and Meyer, 2020; Parnell et al., 2020) and diplomatic gatherings (Sharfuddin, 2020), closure of religious institutions (Alyanak, 2020), industries and commercial establishments and the suspension of academic conferences and teaching activities (Gallo and Trompetto, 2020).

Such lockdowns sought to heavily restrict the movement of those possibly carrying the contagion and stop healthy people from coming into contact with pre-symptomatic/asymptomatic individuals (Imdad et al., 2020). The Chinese government declared its lockdown period in late January 2020 to slow down the spread of infection (Wilder-Smith and Freedman, 2020). The United States and Western European countries also went into lockdown by early March 2020. Nations like India, where the outbreak became potentially threatening after its initial rampage in East Asia and Western Europe, were somewhat quicker to impose such lockdown measures in late March 2020 (Lancet, 2020).

Such a complete shutdown of industry and vehicular movements and the substantial decrease in all but essential services inevitably left its imprint on the environment. The ESA (2020) and NASA (2020) released satellite image products in April 2020 that showed a marked improvement in air quality resulting from COVID-19-induced lockdowns, and Muhammad et al. (2020) briefly highlighted the global picture in this regard (Muhammad et al., 2020). There have also been several studies that have examined the localized impact of the above lockdowns in different parts of the world and particularly across large cities and regions, on the environmental (primarily air) quality (Mahato et al., 2020; Kumari and Toshniwal, 2020; Anil and Alagha, 2020; He et al., 2020c; Singh and Chauhan, 2020; Collivignarelli et al., 2020; Kerimray et al., 2020; Kumari and Managi, 2020; Menut et al., 2020; Baldasano, 2020; Giani et al., 2020; Sahoo et al., 2020; Patel et al., 2020; Wang et al., 2020) or brought forth the strong correlation between the improvement of air quality and the COVID-19 induced lockdown (Ghosh and Ghosh, 2020; Mahato and Ghosh, 2020; Sarkar et al., 2020). However, relatively few studies have mapped and analysed the lockdown's effect on air quality at the national level, comparing its relative impact across different nations.

An attempt has thus been made here to draw attention to the multiple country-level spatial impacts of this occurrence across the globe in a single, succinct account, based on available NASA satellite datasets of NO_2 and AOD. Aerosols are solid and liquid particles suspended in the atmosphere, and their primary sources include windblown dust, sea salts, volcanic ash, smoke from wildfires, factory pollution, and vehicular combustion (NASA, 2020). Traffic pollution is the primary source of tropospheric NO_2 (He et al., 2020a, 2020b). Such air pollutants generate short-term as well as long-term morbidity, with about seven million people worldwide dying from such respiratory-induced illnesses (WHO, 2020), and they markedly impact the economies of the most affected nations. Therefore, discerning the extent of reduction of these pollutants is important, as it can provide insights into how much the local atmosphere can self-purify when lower levels of pollutants are continuously added. This can help frame guidelines to periodically curtail such emissions and achieve some measure of sustainability that less affects the health of the residents of these regions.

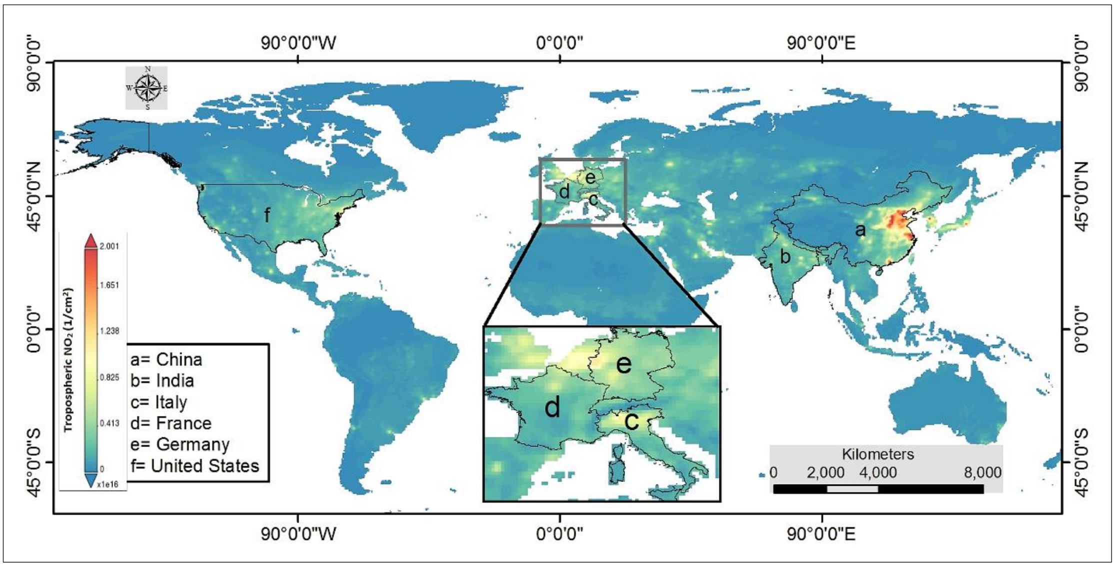


Fig. 3.1 15-year averaged map of NO_2 distribution across the globe

3.2 Results and discussion

3.2.1 Spatiotemporal concentration of NO_2 across the globe

The 15-year time-averaged map of NO_2 concentrations worldwide is shown in Fig. 3.1. The United States, China, India, France, Germany, and Italy all have a high concentration of NO_2, with this being particularly high in a few pockets within each of these countries. These areas thus pose considerable risks to human health. China was the worst-affected country, having the highest NO_2 concentration levels, followed by India, the United States, Italy, France, and Germany (Fig. 3.1). The tropospheric NO_2 column amount has particularly increased during this time over the new and rapidly developing regions of China and in other parts of South Asia (Ghude et al., 2009). NO_2 is usually emitted into the troposphere through vehicular emissions, industrial activities, and the burning of domestic fuels. Since the COVID-19 lockdowns in these countries had effectively halted vehicular movement and industrial activity, it was expected that a discernible improvement in air quality would be observed in their most affected regions.

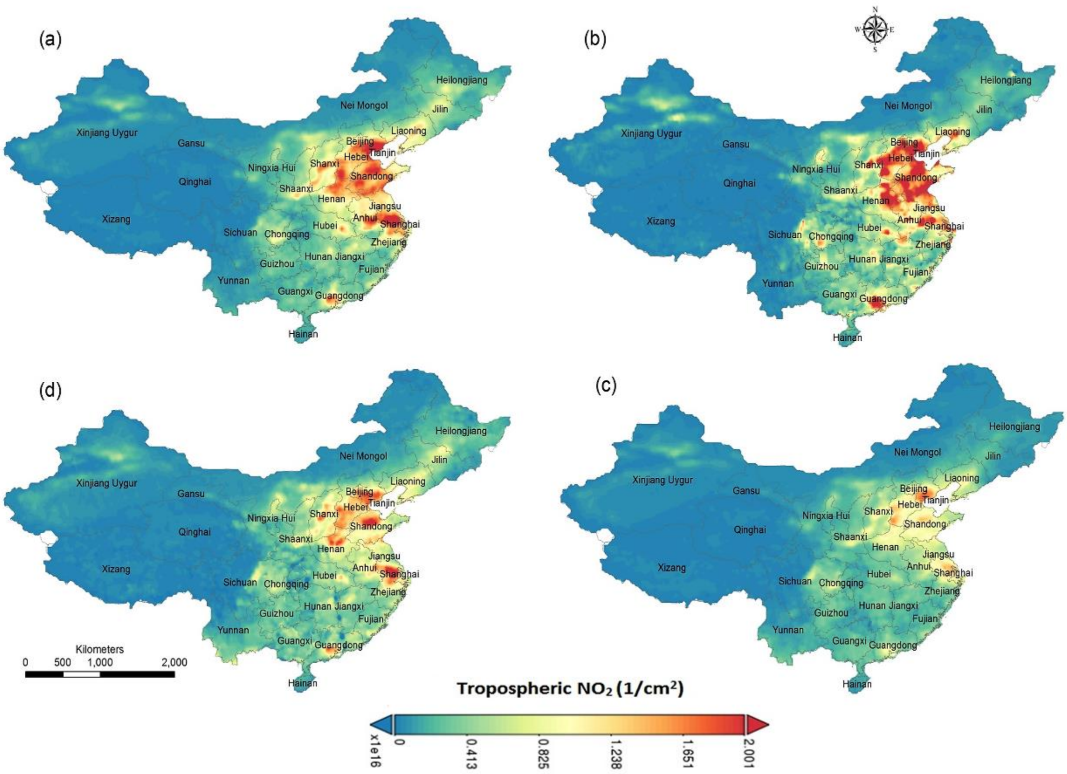


Fig. 3.2 Status of NO_2 concentration over China, in - (a) the previous year (23 January - 25 March 2019), (b) Pre-lockdown phase, (c) During lockdown phase, and (d) Post-lockdown phase

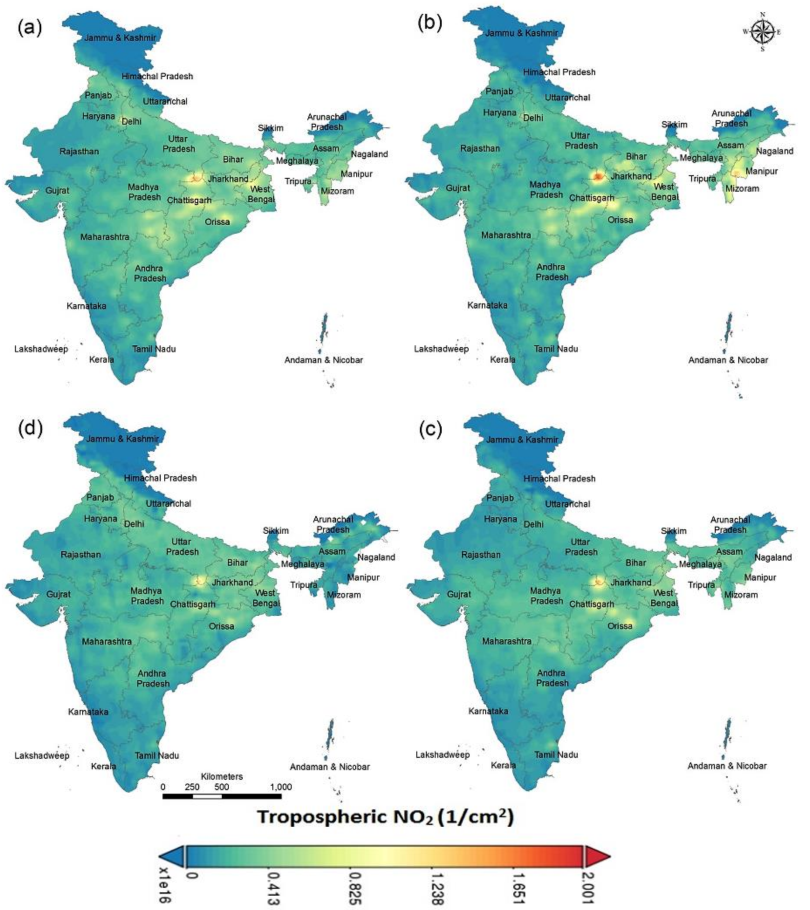


Fig. 3.3 Status of NO_2 concentration over India in - (a) the previous year (24 March - 14 April 2019), (b) Pre-lockdown phase, (c) During lockdown phase, and (d) Post-lockdown phase

3.2.2 Spatiotemporal concentration of NO_2 in the six nations

The eastern part of China, i.e., the areas of Beijing, Tianjin, Hebei, Shandong, Shanghai, Anhul, Henan, Jhangsu, Shanx, Shaanxi, and Hejian were highly polluted, with more than 2.001×10^{15} molecules/cm^2 NO_2 levels in the previous year (Fig. 3.2a) and pre-lockdown periods (Fig. 3.2b). This concentration level had reduced significantly during the lockdown period (Fig. 3.2c). Still, it had then also increased sharply in the post-lockdown era (Fig. 3.2d). However, contaminant levels in the Tianjin and Shanghai areas remained quite notable, even during the lockdown period, and were markedly higher than those in the other regions mentioned above. Overall, up to an 85% reduction in the NO_2 levels was witnessed in the country during the lockdown period. Still, the falling pollutant levels increased soon thereafter (a nearly 35% increase) just after the lockdown. Most countries recorded a 50% reduction in NO_2 in their urban areas, with built-up neighbourhoods showing a 33% reduction during the restriction phase (Singh et al., 2020). The reopening of industries and resumption of vehicular movement no doubt added more pollution in the post-lockdown period. On the other hand, there was almost 75% less concentration of this pollutant during the lockdown than during the same period the previous year.

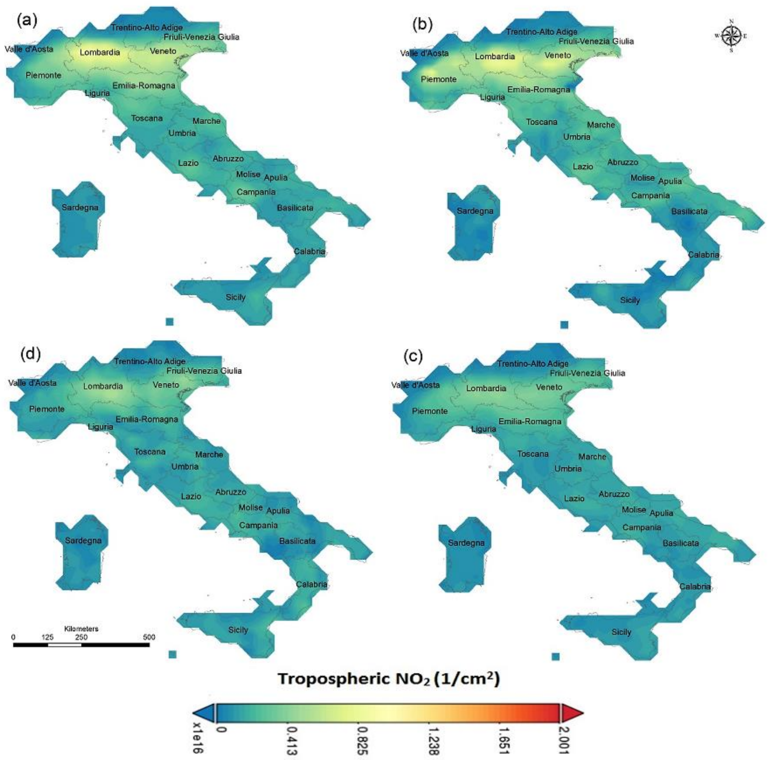


Fig. 3.4 Status of NO_2 concentration over Italy in - (a) the previous year (9 March - 18 May 2019), (b) Pre-lockdown phase, (c) During lockdown phase, and (d) Post-lockdown phase

A few pockets in the eastern part of India (primarily its states along/around the Ganga plains, e.g., Uttar Pradesh, Chhattisgarh, Jharkhand, West Bengal, Madhya Pradesh, Orissa, and Delhi) were the notable polluted zones (Fig. 3.3). This region witnessed an up to 65% reduction in the concentration of NO_2 during the lockdown period. India also witnessed a remarkable fall in the NO_2 column density in 2020 compared to the 2017-19 average for the month of April-May (Biswas and Ayantika, 2020; Pathakoti et al., 2020; Sharma et al., 2020; Singh et al., 2020). Similar inferences of a fall in NO_2 emissions over South Asia were reported by Shafeeque et al. (2021) (Shafeeque et al., 2020). This diminished level was also about 40% lower than the level in the normal period of 2019. The NO_2 level remained almost unchanged even after two weeks into the post-lockdown phase (Fig. 3.3d). Only one pocket was observed with a NO_2 level exceeding 2.001×1015 molecules/cm^2 during the pre-lockdown period, which subsequently decreased to 0.825×1015 molecules/cm^2. The partial relaxation in the transport and industrial sectors during the unlock period obviously contributed to increased air pollution.

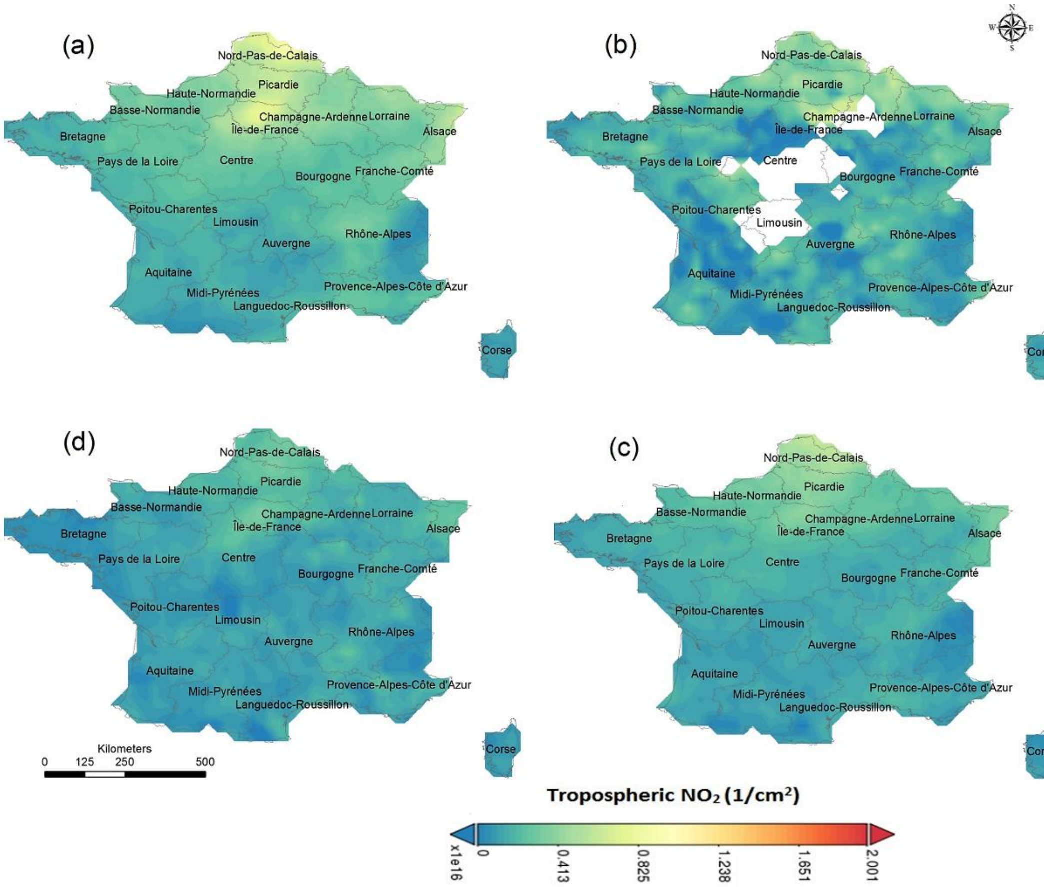


Fig. 3.5 Status of NO_2 concentration over France in - (a) the previous year (17 March - 11 May, 2019), (b) Pre-lockdown phase, (c) During lockdown phase, and (d) Post-lockdown phase

Italy had reported a nominal NO_2 concentration (below 0.825×1015 molecules/cm^2) in its previous normal year period of 2019 and also during the pre-lockdown period, with the most polluted areas being the northern provinces of the country, e.g., Lombardia and Veneto. About a 55% reduction in the contaminant level was noted in the lockdown period (Fig. 3.4). At the same time, the post-lockdown scenario remained relatively similar to the lockdown phase. Similar inferences for major cities in European countries were drawn by Singh et al. (2020) (Singh et al., 2020).

The northern part of France, i.e., the provinces of Nord-Pas-de-Calais, Picardie, and Ile-de-France, was the most polluted with respect to NO_2 concentration in the previous normal year and in the pre-lockdown phase (Figs. 3.5a, 3.5b), with levels ranging from 0.825×10^{15} to 1.238×10^{15} molecules/cm^2. This concentration level had decreased significantly during the lockdown period (Fig. 3.5c), with the entire country reporting a 50% decrease. The continued post-lockdown reduction in the NO_2 concentration is shown in Fig. 3.5d.

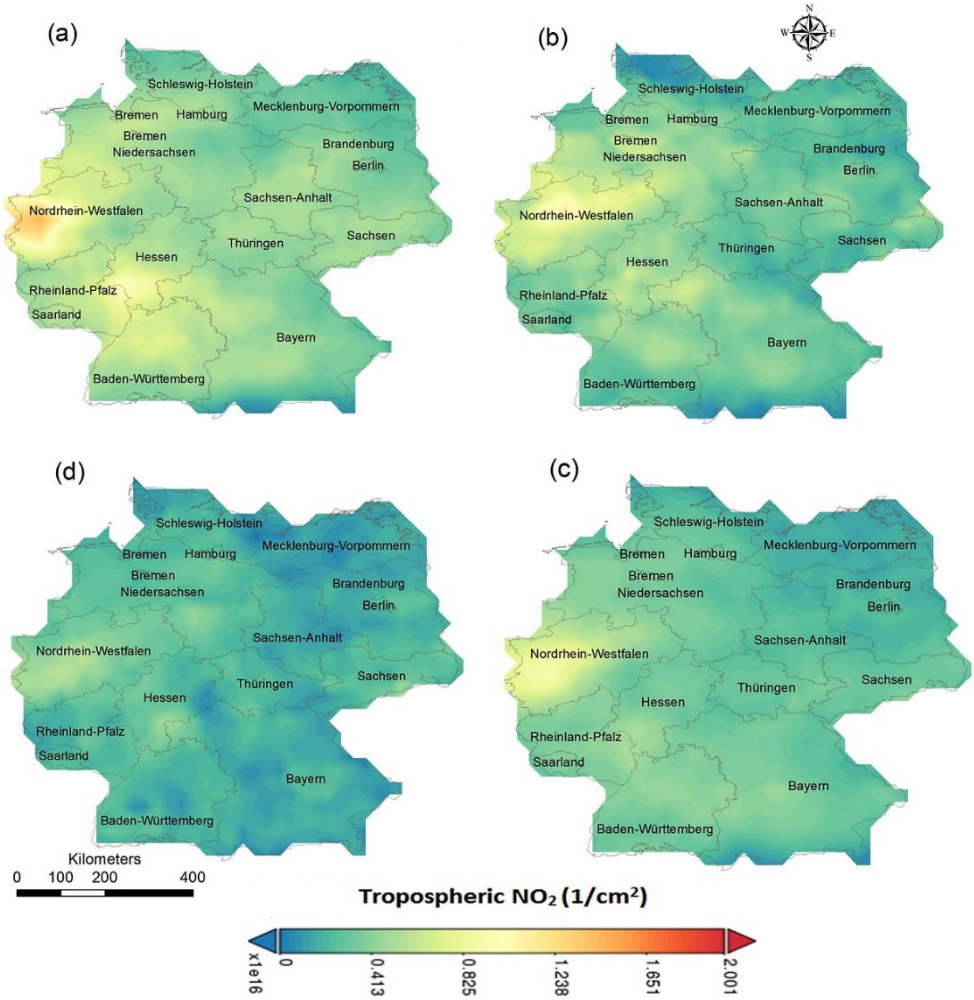


Fig. 3.6 Status of NO_2 concentration over Germany in - (a) the previous year (23 March - 20 April, 2019), (b) Pre-lockdown phase, (c) During lockdown phase, and (d) Post-lockdown phase

The NO_2 concentration levels recorded in Germany during the normal period (2019) and the pre-lockdown phase were the highest in Western Europe. Its western portions were markedly more polluted than the rest of the country. Nordrhein-Westfalen was the only state to record a concentration of about 1.852×1015 molecules/cm^2 of NO_2 in both the normal and pre-lockdown periods. The states of Hessen, Rheinland-Pfalz and Baden-Wurttemberg also had moderate concentrations of this pollutant. Germany witnessed a drop of about 60-70% in its NO_2 levels during the lockdown period (Fig. 3.6) compared to these two periods. This decrease continued into the post-lockdown phase (Fig. 3.6d).

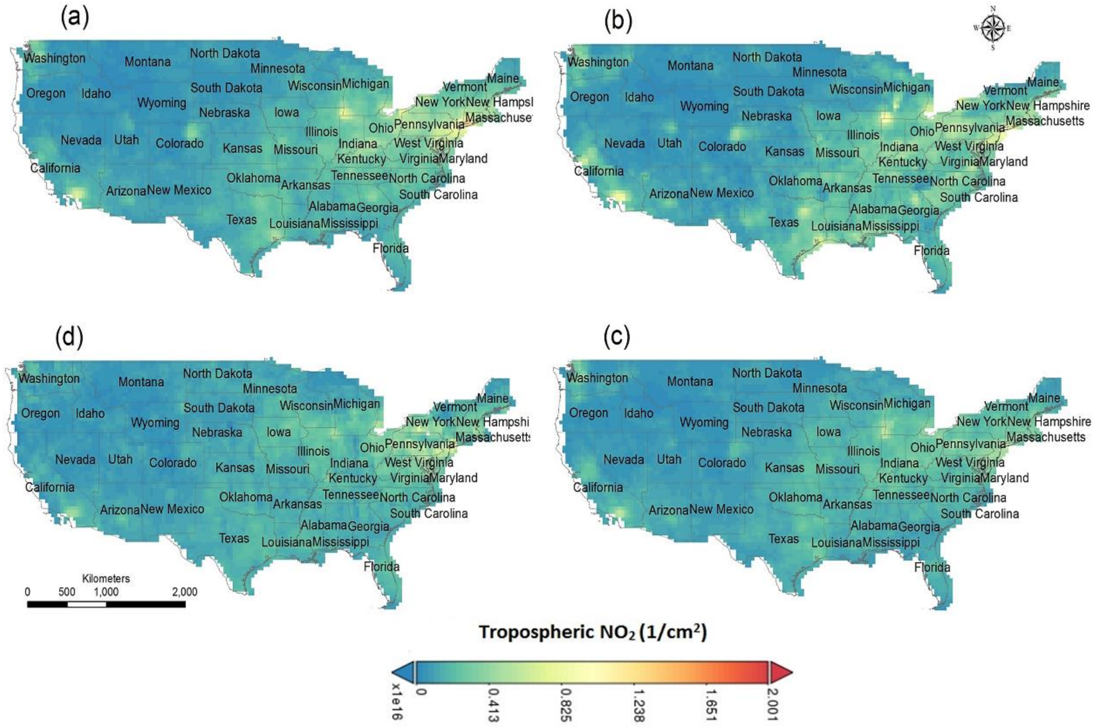


Fig. 3.7 Status of NO_2 concentration over the United States in - (a) the previous year (3 March - 22 April, 2019), (b) Pre-lockdown phase, (c) During lockdown phase, and (d) Post-lockdown phase

In the United States, the states in its eastern part and in the upper mid-east, such as New York, New Jersey, Pennsylvania, Michigan, and Connecticut, were considerably polluted as per the ambient NO_2 concentration levels in the normal and pre-lockdown periods (Fig. 3.7). These levels dropped by up to 65% once the lockdown ensued. The highest concentration in a single pocket was about 1.238×1015 molecules/cm^2 during the normal period, while the remaining areas were near 0.413×10^{15} molecules/cm^2. The lockdown reduced the average NO_2 concentration by about 0×1015 molecules/cm^2 across the US.

3.2.3 Spatial pattern of AOD worldwide

Fig. 3.8 shows the spatial distribution (based on the 15-year averaged datasets) of the aerosol amounts in the troposphere. Higher aerosol levels occur over African and Southeast Asian countries. As this map consists of datasets collected over the whole year, the aerosol amounts reported were linked to different processes, generated in different places and at different times of the year (NASA, 2020). Land clearing and agricultural fires were the major contributors to aerosol formation in Africa and South America (Tosca et al., 2013; Martin et al., 2010; De Oliveira et al., 2019; Morgan et al., 2019), along with the dust particles being blown off the Sahara, Arabian, and other deserts. Such dust storms transport particles into the troposphere over the Arabian countries and elevate the aerosol levels along the fringes of the Thar Desert in India (Ghosh et al., 2018) and the periphery of the Gobi Desert in eastern China (Yang et al., 2017). The burning of field stubble also increases dust levels in the winter months across the foothills of the Himalayan region in the Gangetic plains and across China (Chen et al., 2017; Sharma et al., 2017). These elevated aerosol amounts worsen the pollution effect, adding to that being produced by vehicular and industrial exhausts and severely impairing respiration and health (NRC, 2010).

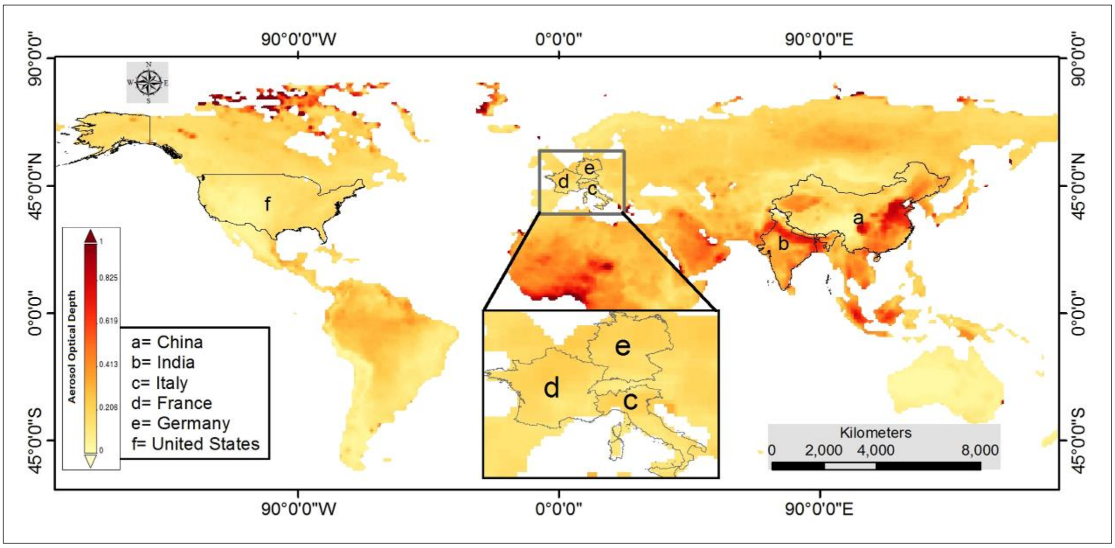


Fig. 3.8 15-year averaged map of AOD concentration across the globe

3.2.4 Spatiotemporal concentration of AOD across the six examined countries

Fig. 3.9 shows aerosol concentrations in the normal and pre-lockdown phases, and during the lockdown and post-lockdown in China. The AOD concentration reduced significantly during the lockdown due to the complete shutdown of the industry and transport sectors. The eastern part of the country, i.e., the provinces of Hebei, Beijing, Henan, Shandong, Shanghai, and Jhangsu recorded AOD values of nearly 1. At the same time, Shanx, Shaanxi, Liaong, Jilian, Heilongjiang, Guangxi, and Sichuan had lower values, around 0.619 AOD. Overall, China witnessed about a 70% reduction in AOD levels during the lockdown period compared to the normal period (i.e., the same period in 2019) and the pre-lockdown phase. There was a 50% reduction in Shanghai, parts of South Korea, Beijing, and regions around Xi'an in East Asia during the lockdown period (Singh et al., 2020). A massive reduction in the AOD was similarly observed in the northern part of South Asia in April 2020 (Shafeeque et al., 2020; NASA, 2020). The reopening of industries and renewed movement of vehicles are expectedly to add more pollution in the post-lockdown phase. Hence, a revival of AOD levels was observed (Fig. 3.9d).

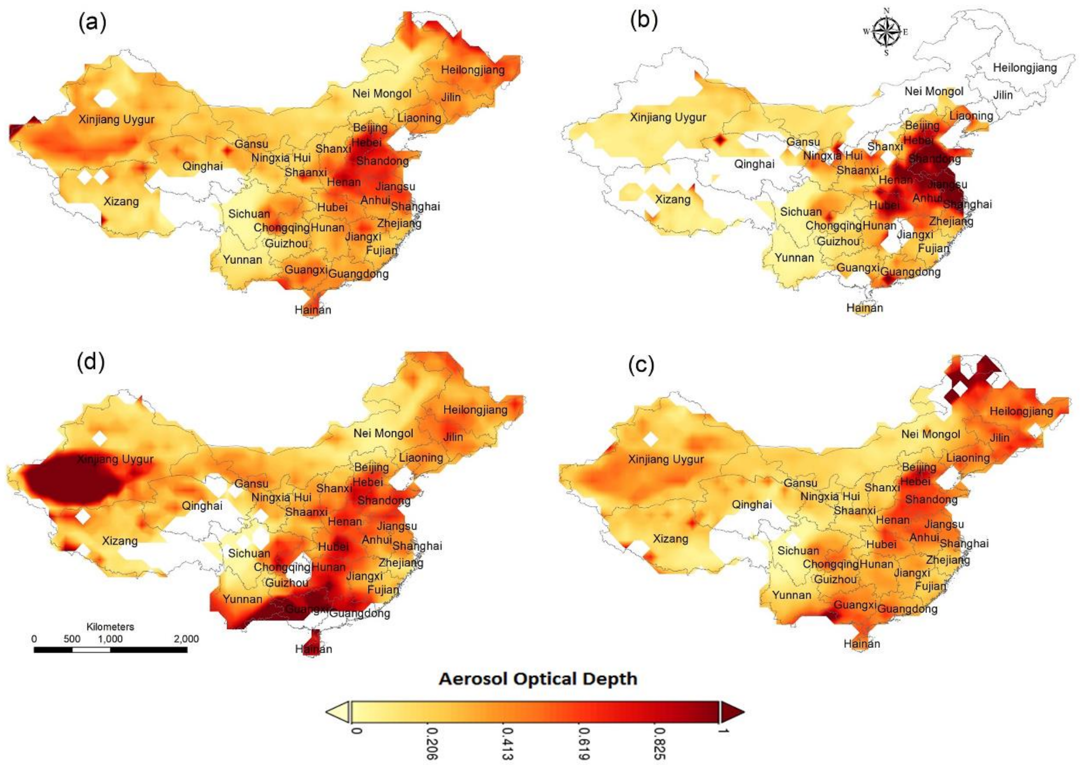


Fig. 3.9 Status of AOD concentration over China in (a) the previous year, (b) the Pre-lockdown period, (c) the during lockdown period, and (d) the Post-lockdown period

Fig. 3.10 shows aerosol concentrations over India during the four phases mentioned above. The Gangetic Plains usually record the highest aerosol concentrations during normal times, i.e., in the previous year and pre-lockdown phases, due to industrial pollution, field stubble burning, and heavy vehicular emissions (Sharma et al., 2017; Ghosh et al., 2018). Thus, the northern to eastern states of Haryana, Delhi, Uttar Pradesh, Bihar, West Bengal, and Assam showed high AOD aerosol concentrations

(AOD being nearly 1). At the same time, Orissa, Chhattisgarh, and Andhra Pradesh also reported quite elevated levels (Fig. 3.10a, 3.10b). During the lockdown period, the AOD was reduced by about 75%, while the post-lockdown increase was about 60%. A similar reduction in AOD over India during the pre-monsoon period of 2020 was reported by Biswas and Ayantika (2020) and Pathakoti et al. (2020) (Biswas and Ayantika, 2020; Pathakoti et al., 2020).

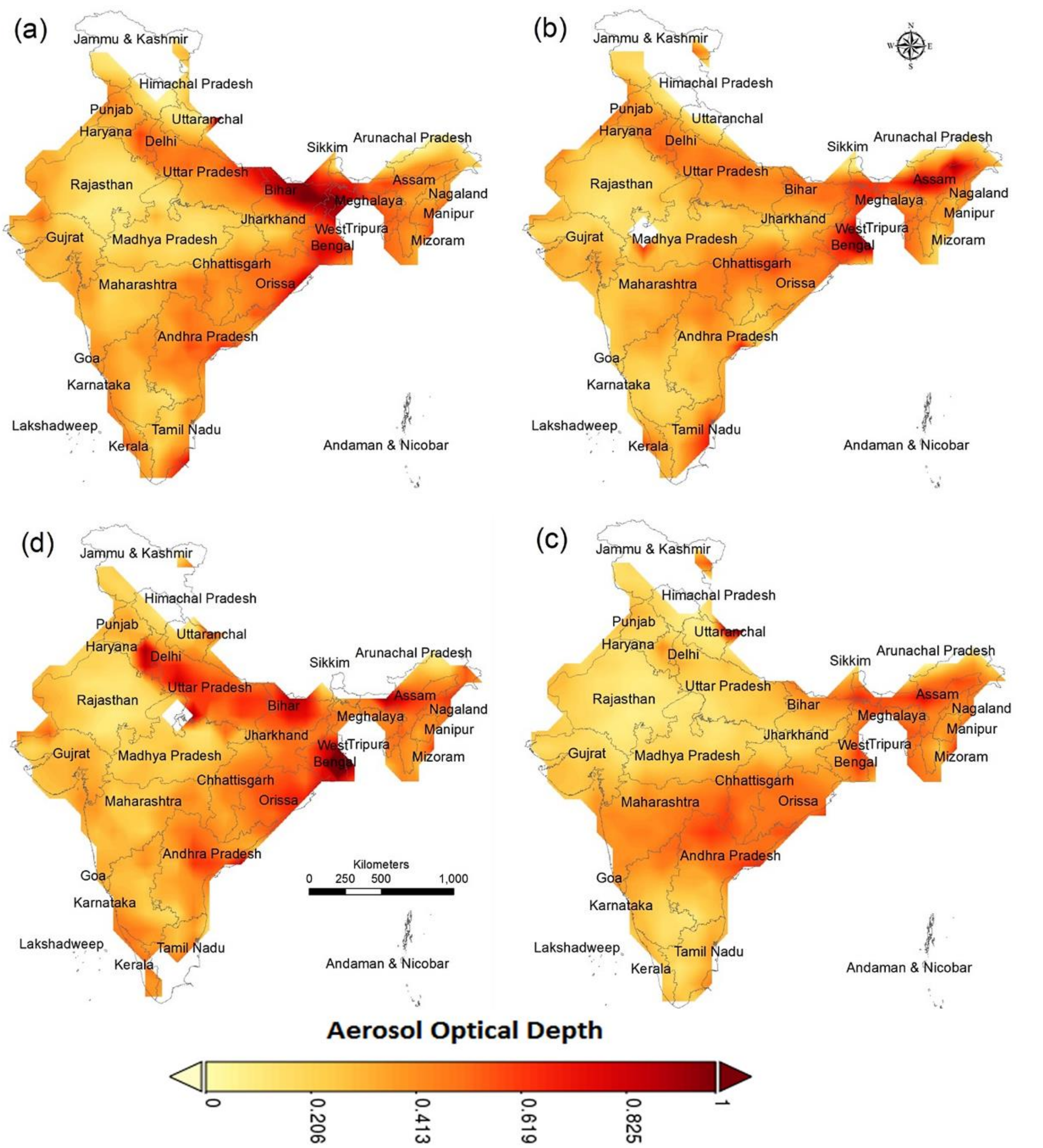


Fig. 3.10 Status of AOD concentration over India in (a) the previous year, (b) the Pre-lockdown period, (c) during the lockdown period, and (d) the Post-lockdown period

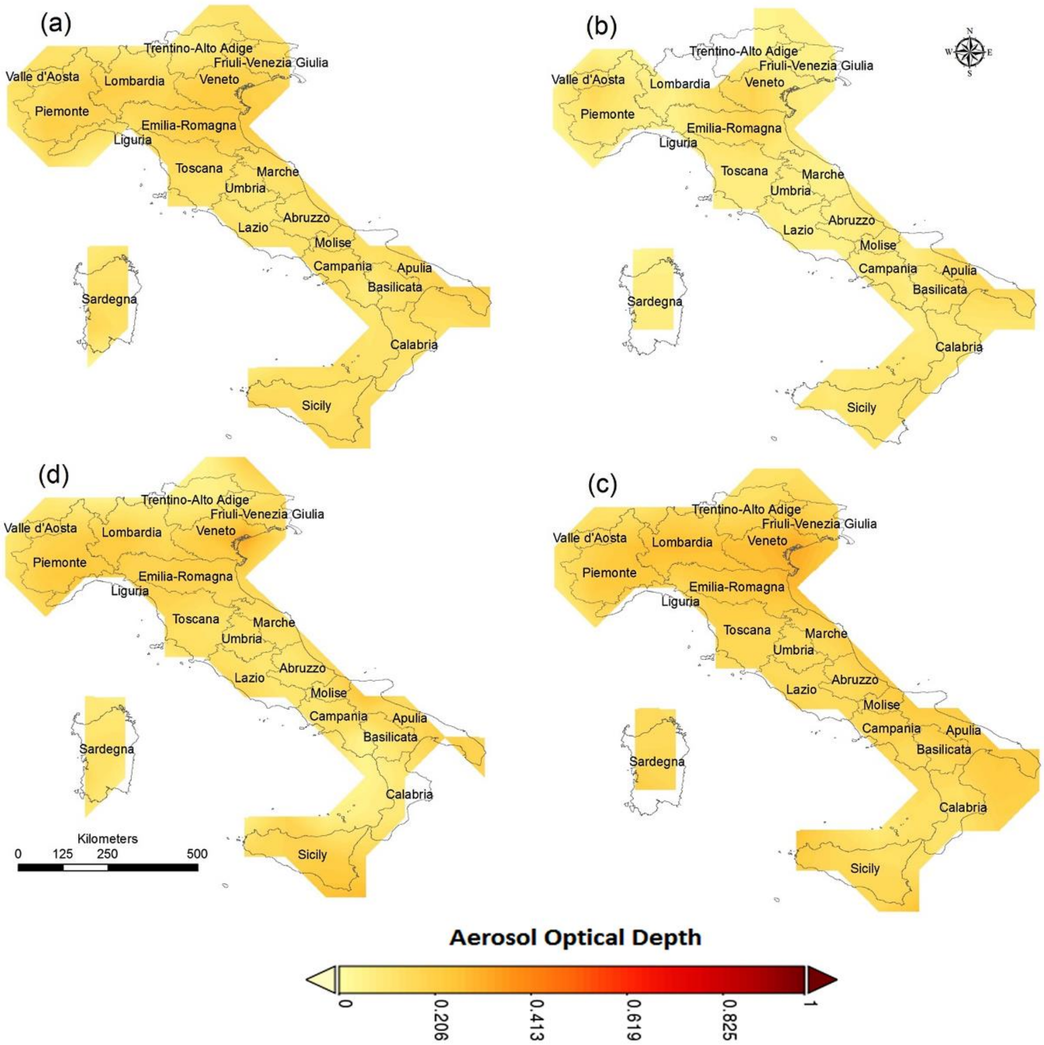


Fig. 3.11 Status of AOD concentration over Italy in (a) the previous year, (b) the Pre-lockdown period, (c) the lockdown period, and (d) the Post-lockdown period

In Italy, France, and Germany, the respective AOD levels were very low in both the normal and pre-lockdown phases (Fig. 3.11, 3.12, 3.13). The northern part of Italy and the northwest regions of both France and Germany recorded slightly higher AOD concentrations than the rest of these countries. The normal-time AOD concentration was also the highest in Germany among the three nations. Slight improvements in the above were noted in the lockdown phase. The post-lockdown scenario is almost the same as during the lockdown. In the United States, the northern states, such as Utah, South Dakota, Colorado, and Maine, had relatively higher AOD concentrations during the normal period in 2019 (Fig. 3.14a). Only a partial dataset was available for the pre-lockdown period. During the lockdown period, the AOD reduced by about 45%, while the post-lockdown levels remained similar to those during the lockdown phase (Fig. 3.14c, 3.14d).

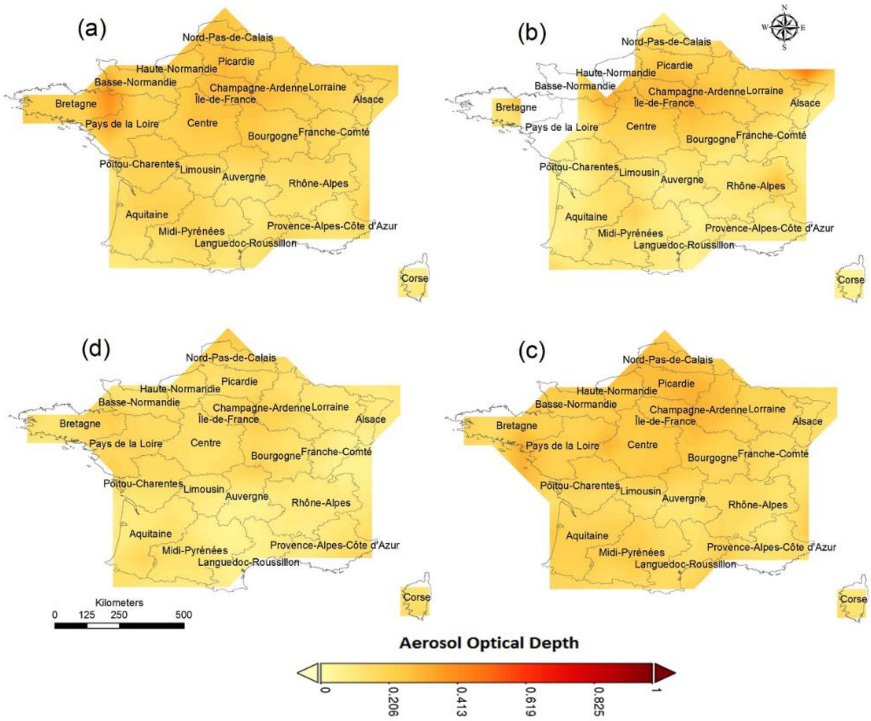


Fig. 3.12 Status of AOD concentration over France in (a) the Previous year, (b) the Pre-lockdown period, (c) the lockdown period, and (d) the Post-lockdown period

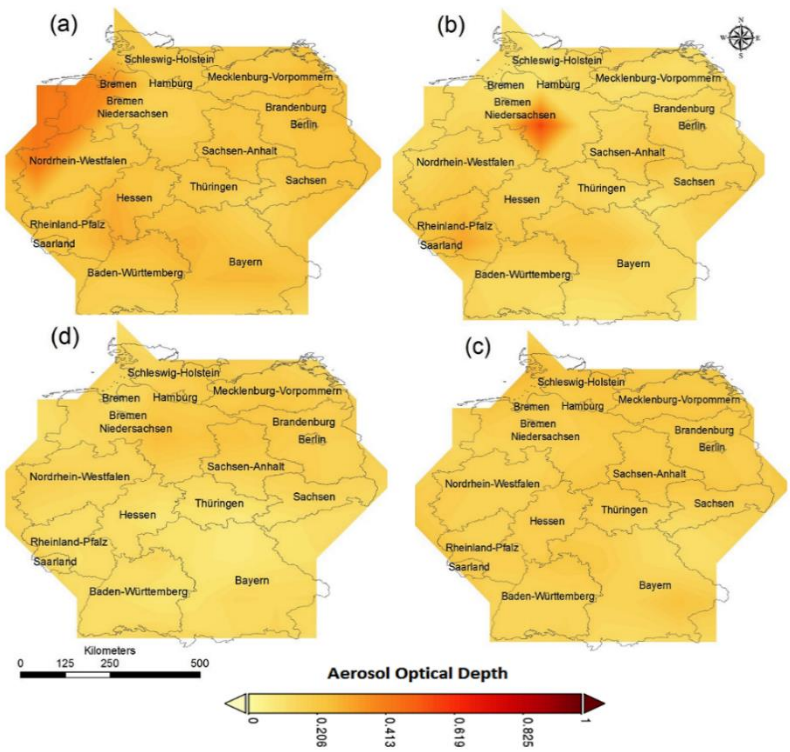


Fig. 3.13 Status of AOD concentration over Germany in (a) the Previous year, (b) the Pre-lockdown period, (c) the lockdown period, and (d) the Post-lockdown period

Table 3.1: The studied countries and their pre-lockdown, lockdown, and post-lockdown levels of air pollutants at select stations

***(**Source: Air Pollution in the World (Real-time Air Quality Index/AQI), https://aqicn.org/city/all/)*

Pollutants	Periods	China		India			Italy		France		Germany	United Sates	
		Beijing	Wuhan	R. K. Puram, Delhi	Victoria, Kolkata	Cornale, Lombardia	Milano Sinato, Lombardia	Ajaccio-canetto	Pompidan-tours	Wetzlar	Marburg	New York	Ware
NO_2 ($\mu g/m^3$)	Pre-lockdown	19.14	23.07	27.30	21.77	16.00	33.36	5.00	12.64	9.43	7.71	19.67	2.46
	Lockdown	12.85	13.77	8.06	5.91	8.33	21.62	3.05	6.37	10.76	7.34	11.74	1.35
	Post-lockdown	12.81	18.00	9.00	4.21	6.71	22.00	2.71	7.21	7.86	5.78	10.14	1.00
$PM_{2.5}$ ($\mu g/m^3$)	Pre-lockdown	107.93	153.21	123.46	118.38	NM	76.58	38.00	31.14	33.57	29.36	36.21	40.29
	Lockdown	117.87	127.60	98.05	95.22	NM	59.46	38.85	44.92	49.10	45.62	26.22	31.39
	Post-lockdown	74.58	106.42	103.43	58.64	NM	43.58	31.14	34.07	34.07	30.93	19.71	23.79
PM_{10} ($\mu g/m^3$)	Pre-lockdown	47.93	66.28	90.69	68.07	101.00	29.82	14.43	13.35	13.36	10.50	NM	NM
	Lockdown	41.80	49.09	68.05	46.59	61.92	24.28	13.96	17.43	19.93	20.55	NM	NM
	Post-lockdown	57.90	47.09	66.83	30.29	52.35	18.64	14.14	13.85	12.92	12.35	NM	NM

*NM = Not Measured

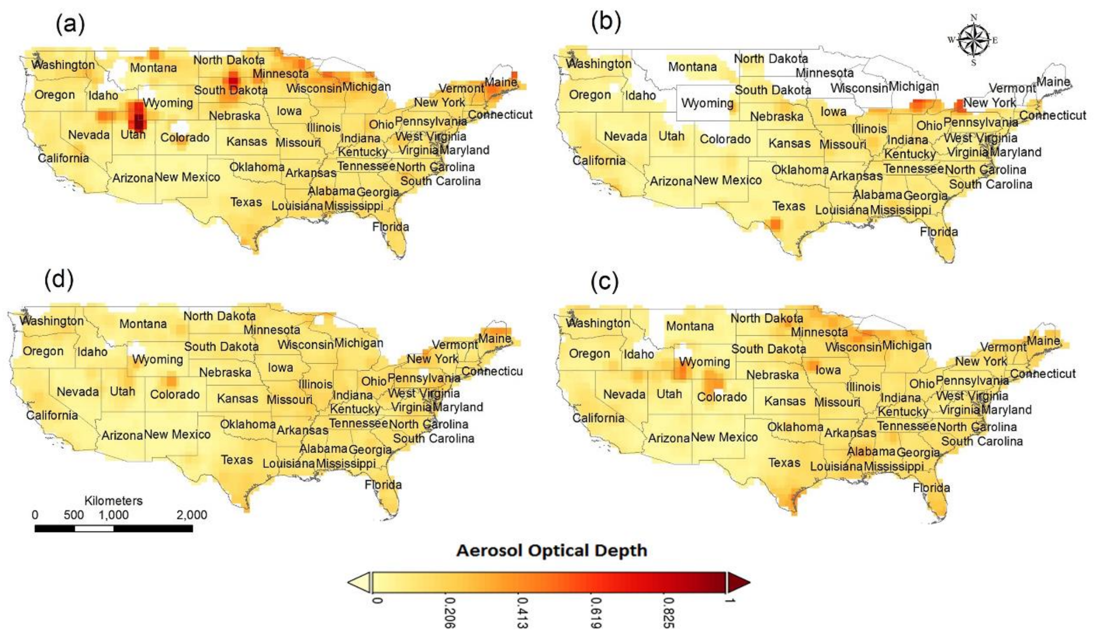


Fig. 3.14 Status of AOD concentration over the United States, in (a) the Previous year, (b) the Pre-lockdown period, (c) during the lockdown period, and (d) the Post-lockdown period

3.2.5 Comparison of satellite-derived parameter trends with ground-measured information

To further examine whether the satellite image captured decreases in NO_2 and AOD levels, I examined similar data from a select few stations in each of the examined countries/regions. The ground-based NO_2 measurements also showed a sharp decrease in this pollutant's levels during the lockdown phase, with a slight increase once the lockdown was lifted (Table 3.1). Some of the sharpest reductions in this regard were observed at the R.K. Puram station in New Delhi, India, and at the Victoria station in Kolkata, India. More minor changes were apparent at stations in China, the USA, Italy, and France. Strangely, the Wetzlar station in Germany actually reported an increase in the NO_2 levels during the lockdown. At the same time, that country's Marburg station also reported only a very slight decline in this pollutant, possibly due to partial operation of the industries there, which are centres of precision engineering and manufacturing. What was observed across the board, however, was that in the post-lockdown period, NO_2 levels did not immediately return to their pre-lockdown levels but remained mostly near the levels attained during the lockdown, or even declined slightly in some cases. This is significant because it highlights the marked effect on the atmosphere that a short lockdown period can have, and it also indicates the window during which this condition can persist. Therefore, temporary stoppages of short duration at the regional level could be a sustainable way to partially improve ambient air quality.

For the AOD comparison, I used the available $PM_{2.5}$ and PM_{10} data for the above stations. Again, it was apparent that the concentration of aerosol or atmospheric particulate matter declined during the lockdown period in almost all the observed stations. Their respective values were at lower levels than before, even in the post-lockdown phase. Thus, there was a significant decline in both pollutants' levels between the pre-lockdown and the lockdown, as well as the post-lockdown periods. This reveals the similarity of trends recorded between the compared datasets and validates our analysis.

Chapter IV

$PM_{2.5}$ Levels in China, India, and Pakistan

4.1 Introduction

With each passing day, the severity and impact of air pollution are increasing worldwide, especially in urban areas (Sicard et al., 2023). Recent reports indicate that millions of people are facing premature death due to the surge in air pollutants in rural and urban sectors (Vos et al., 2020). WHO stated that 99% of the world's population lived amidst polluted air in 2019 (WHO, 2022). People living in low- and middle-income countries (mainly in Southeast Asia and the Western Pacific Regions) are disproportionately affected by air pollution. These regions faced 89% of the 4.2 million ill-timed expiries (WHO, 2022).

PM concentrations that often remain suspended in the air, with diameters less than 2.5 µm ($PM_{2.5}$) and between 2.5 µm and 10 µm (PM_{10}), pose the most significant air quality threat worldwide (Kanawade et al., 2020). Motorized vehicles and industrial factories are the primary sources of both $PM_{2.5}$ and PM_{10}. However, of the two types of PM based on their diameter, $PM_{2.5}$ is considered far more lethal to human health owing to its ability to penetrate deep into the lungs and even the bloodstream (Xing et al., 2016). It is a standard indicator of air pollution and causes adverse health impacts with its elevated levels in the air (WHO, 2022). $PM_{2.5}$ is usually measured using an aerosol sampler that draws in air and filters particles, recording data as µg per unit volume of air (usually m^3). It is a time-consuming technique that cannot provide real-time data; however, it is the most accurate for measuring $PM_{2.5}$ levels in the air.

To reduce the $PM_{2.5}$ in outdoor air, the United Nations WHO has set an annual interim target of $PM_{2.5}$, which is divided into four sub-targets (1, 2, 3, 4), i.e., 35 $\mu g/m^3$, 25 $\mu g/m^3$, 15 $\mu g/m^3$, and 10 $\mu g/m^3$, respectively. Vulnerable groups such as children, individuals suffering from COPD, pregnant women, and diabetic patients have more significant health risks due to rising levels of air pollution (WHO, 2021). Almost every living organism and human community worldwide is experiencing, or will experience, the severe and harmful effects of air pollution.

Indoor air pollution has also become a matter of growing concern (Cetin, 2016; Aisha and Cetin, 2023); however, this piece of research exclusively focused on outdoor $PM_{2.5}$ levels. Particulate matter in the open environment not only imposes harmful effects owing to its own presence but also aids in spreading other pollutants like heavy metals (Cetin and Aisha, 2023; Cetin and Jawed, 2021; 2024). Anthropogenic activities, such as mining and heavy traffic, lead to the proliferation and spread of such metal pollutants, using $PM_{2.5}$ as carrier particles (Bozdogan Sert et al., 2019; Cetin et al., 2022a; 2022b; 2023). Thus, $PM_{2.5}$ plays a dual negative role in deteriorating human health.

China's $PM_{2.5}$ concentrations depict an uncertain scenario. Although many cities have experienced significant improvements, several regions of China continue to face poor air quality, with $PM_{2.5}$ concentrations as high as 120 µg/m^3, primarily due to the burning of solid fuels and vehicular emissions (Gautam et al., 2019). According to the WHO, China's average annual $PM_{2.5}$ concentration in 2022 was 35.5 µg/m^3, well above the recommended level of 5 µg/m^3 or less. However, air quality in several areas has improved noticeably over the past few years. For instance, the $PM_{2.5}$ concentration decreased in Beijing from 90 µg/m^3 in 2013 to 35 µg/m^3 in 2022. More than 64% of the cities have seen a decline in annual $PM_{2.5}$ concentrations. Due to the significant likelihood of cardiorespiratory-related mortality, a study in Northern China found that life expectancy was reduced by almost six years (Chen et al., 2013; Anwar et al., 2021). According to Liu et al. (2021), air pollution poses a significant threat to the male and elderly age groups in China, who account for 58% and 61% of hospital admissions, respectively (Liu et al., 2021). Economically backward and highly urbanized areas make women and children more susceptible to air-related short- and long-term health effects (Chuwah et al., 2017; Anwar et al., 2021). Government initiatives to minimize air pollution, like the shutdown of coal-fired power plants and the promotion of electric vehicles, are to thank for this improvement. However, air pollution is a prime issue in northern and northeast China. These areas frequently have $PM_{2.5}$ concentrations above 100 µg/m^3, which are dangerous to human health.

The recent $PM_{2.5}$ pollution situation in India is concerning. According to the World Air Quality Report (2022), annual $PM_{2.5}$ levels in almost 60% of Indian cities were at least 7 times higher than recommended levels. Several Indian cities consistently confront high $PM_{2.5}$ concentrations. Based on $PM_{2.5}$ concentrations, Delhi, the nation's capital, has regularly been listed among the world's most polluted cities. 'Severe' to 'emergency' levels of $PM_{2.5}$ pollution have been observed in Delhi with increasing frequency in recent years, particularly during winter. Although the severity may vary, cities like Mumbai, Kolkata, Chennai, and Bangalore all experience high $PM_{2.5}$ concentrations. According to the most recent Global Burden of Disease (IHME, 2019), the mean population-weighted $PM_{2.5}$ concentration is estimated to be 74.3 µg/m^3. Exposure to degraded air quality is associated with 133.5 fatalities per 100,000 persons/year. In India, $PM_{2.5}$ pollution is estimated to cause 1.67 million premature deaths/year. According to Chatterjee et al. (2023), the high concentration of $PM_{2.5}$ costs India $36.8 billion annually in lost productivity and medical expenses (Chatterjee et al., 2023). Though several studies have indicated the impact of multifarious natural and anthropogenic drivers that amplify $PM_{2.5}$ levels, not only in India but also in the Asian context, the assessment of the degree of personal exposure and health risk requires significant interventions (Chelani and Gautam, 2023; Gautam et al., 2016; 2020; Gupta et al., 2022).

Children are more susceptible to the consequences. Furthermore, they tend to have lower IQs and a higher risk of respiratory issues. In addition to the adverse effects on health, air pollution costs Indian businesses roughly $94 billion annually, which equates to about 3% of India's total GDP, 50% of all taxes paid, and 150% of the country's healthcare budget (Sharma, 2021). According to Dalberg Advisors, there is a significant negative correlation between labour productivity and the AQI, with lower productivity at higher AQI values. Additionally, poor air quality makes it less likely for people to go outside, which decreases customer flow in retailers and thereby causes businesses that serve customers to experience a $22 billion decline in revenue (Sharma, 2021). An emission inventory is required to assess the effects of policy and technological interventions on India's emission load, even though the National Clean Air Programme (NCAP) objectives have set a target of a 20 to 30% decrease in $PM_{2.5}$ concentrations by 2024 (Ganguly et al., 2021).

According to the WHO, the annual average $PM_{2.5}$ concentration in Pakistan is 52.1 µg/m^3, which exceeds the WHO guideline of 10 µg/m^3. Pakistan ranked third-highest in the world for pollution, with an average $PM_{2.5}$ concentration 14.2 times above the WHO annual air quality guideline value in 2022. Among cities in Pakistan, Lahore recorded the highest $PM_{2.5}$ concentrations and showed a gradual increase from 2017 to

2022. Lahore, Peshawar, Faisalabad, Bahawalpur, Karachi, Rawalpindi, and Islamabad are the seven major cities in Pakistan with the highest $PM_{2.5}$ concentrations in 2022. People in the middle-income group noted more respiratory disorders in Quetta (Anwar et al., 2021). Due to $PM_{2.5}$ exposure, Pakistan recorded 91.22 deaths per 1 lakh population in 2017, though the rate increased to 94.42 deaths in 2019 (IHME, 2019). To identify air pollution mitigation strategies and set targets to reduce air pollution, Pakistan has implemented the 'Pakistan Clean Air Plan' (PCAP). The initiative aims to reduce various air pollutants (including CB) at the national and regional levels.

Anwar et al. (2021) observed that China, India, and Pakistan, a conglomeration with the highest population density in Central Asia, suffer severely from air pollution and its health impacts. They recommended that profound spatio-temporal air pollution monitoring has become an urgent need of the hour in China, India, and Pakistan (Anwar et al., 2021). According to Kanawade et al. (2020), about 6 million people die prematurely each year due to air pollution (Kanawade et al., 2020). There is strong evidence that both short- and long-term exposure to air pollution is often associated with poor lung function in children (Zhang et al., 2022a). Although the number of child deaths worldwide has declined from 3.8 million in 2000 to 2.4 million in 2019, the first 28 days of life in the last two decades are still a dangerous time, especially for surviving children (Paulson et al., 2021). During this period, ambient air may increase the risk of infant death and disease (Lin et al., 2023). Exposure to $PM_{2.5}$ is the leading cause of death worldwide, causing approximately 4.2 million deaths annually in 2015, mostly in Asian countries, particularly Pakistan, India, and China (Anwar et al., 2021). Reviewing the above, these papers mainly discuss the concentration and harmful effects of $PM_{2.5}$, a central air pollutant.

Thus, keeping the background outlined above in mind, this study analyzed $PM_{2.5}$ levels in outdoor air using a dataset from the Swiss air quality technology company IQAir from 2017 to 2023. The study strived to analyze data from 760 cities across three countries: China, India, and Pakistan. The main objective of the current study was to explore the extent to which these cities comply with the WHO-prescribed $PM_{2.5}$ guidelines. This study also aimed to explain the overall $PM_{2.5}$ pollution scenario in China, India, and Pakistan (CIP) (based on the available data) and the spatiotemporal $PM_{2.5}$ dynamics and characterize the seasonal changes of $PM_{2.5}$ across the major cities of these countries, their trend and annual hours spent by the pollutant as per WHO assigned classes/codes based on human health risks.

4.2 Results

4.2.1 Non-compliance with the WHO guidelines

The countries and territories in Asia (central and south) and Africa have witnessed the worst air quality globally (Fig. 4.1). India, Pakistan, and China, Asian countries, are highly populated. The regions/territories have also suffered from high $PM_{2.5}$ concentrations. Oceania and other countries achieved the WHO guidelines in 2023. Among the Asian and African countries counted (only 24 of 54), Iraq, Saudi Arabia, Chad, Egypt, Nigeria, and Uganda have recorded poor air quality. Territories and countries in Europe and North and South America have minimal average annual $PM_{2.5}$ concentrations.

Not a single one of 760 cities has met the WHO annual guideline of 5 $\mu g/m^3$ (Table 3.1). Only 10 Chinese cities have annual mean $PM_{2.5}$ concentrations of 5.1-10 $\mu g/m^3$. 16 cities in China and 2 in India that recorded $PM_{2.5}$ concentrations ranging from 10.1 $\mu g/m^3$ to 15 $\mu g/m^3$. Likewise, 1, 81, and 303 cities in Pakistan, India, and China recorded $PM_{2.5}$ concentrations ranging between 15.1 $\mu g/m^3$ and 35 $\mu g/m^3$. About 172 cities in India exceeded the WHO target level, followed by 166 in China and 9 in Pakistan. Although the number of cities studied in Pakistan (10) was far fewer than in India and China, the results show that all 10 cities exhibit very poor $PM_{2.5}$ concentrations in ambient air. This study inferred that, except for 10 Chinese cities, all other 750 cities across CIP have experienced unhealthy to extremely hazardous air quality.

The central and eastern parts of China and the Gangetic Plain of India have higher pollution levels than the rest of the region (Fig. 4.2). The southwest of China, the north and northeast of India, and the west and central parts of Pakistan lack ambient air monitoring stations. Hence, it was not easy to comment on these regions.

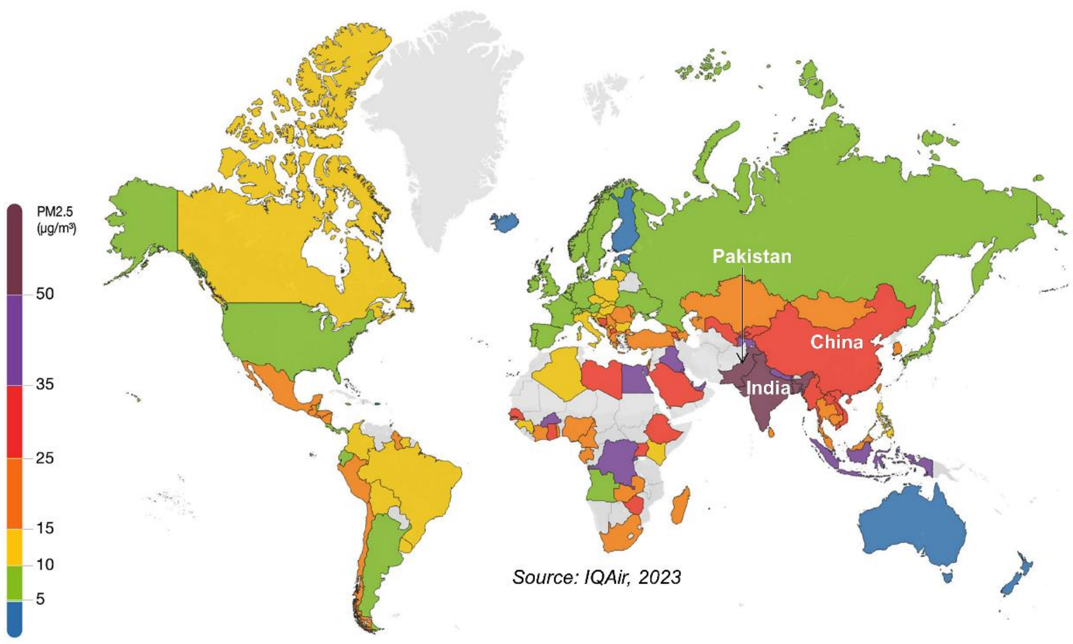


Fig. 4.1 Country-wise annual mean $PM_{2.5}$ concentration of 2023

Table 4.1 Annual mean $PM_{2.5}$ concentrations of cities in 2023

$PM_{2.5}$ (µg/m^3)	China (count)	India (count)	Pakistan (count)
0-5	0	0	0
5.1-10	10	0	0
10.1-15	16	2	0
15.1-25	138	27	0
25.1-35	165	54	1
35.1-50	155	71	3
>50.1	11	101	6
Total	495	255	10

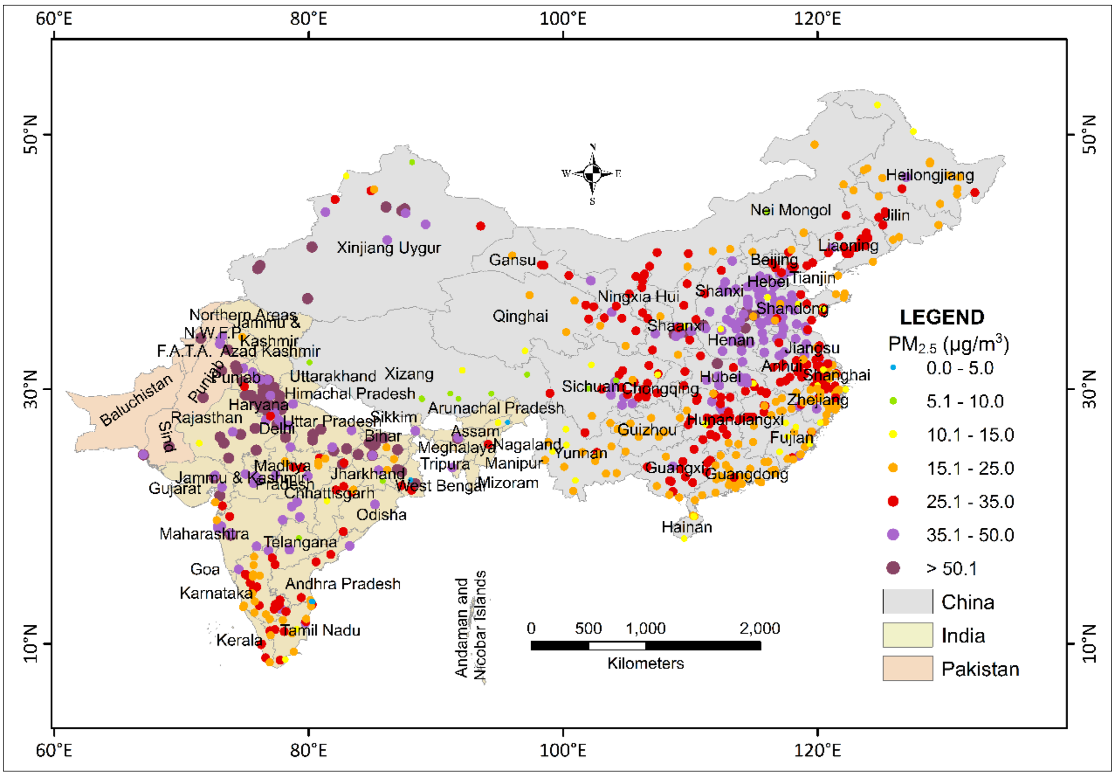


Fig. 4.2 Location of ambient air monitoring stations of China, India and Pakistan showing historical annual mean $PM_{2.5}$ concentrations

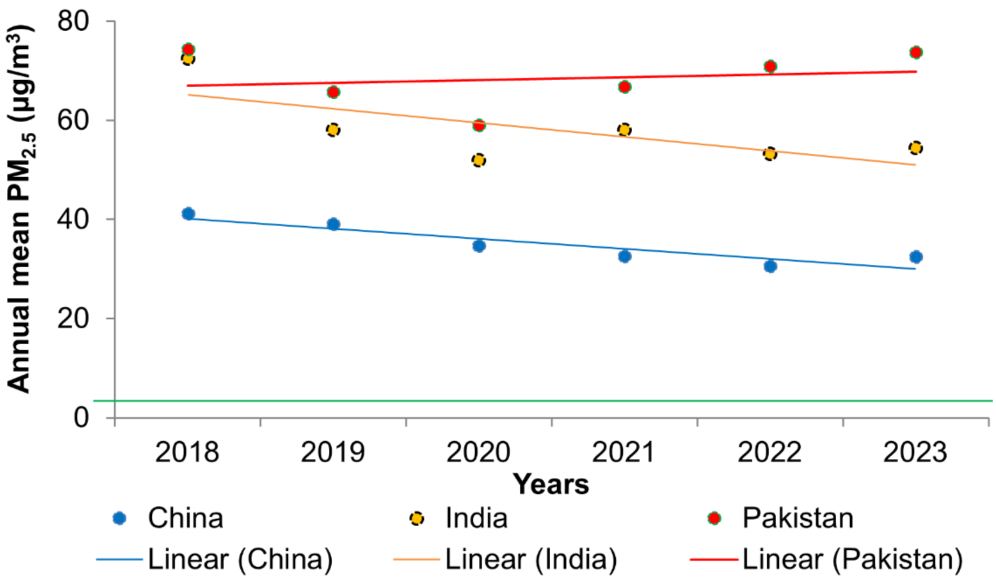


Fig. 4.3 Temporal change of annual mean $PM_{2.5}$ concentration for China, India and Pakistan

4.2.2 PM2.5 concentration variability across the nations

According to the World Air Quality Report 2023, Pakistan and India rank 2nd and 3rd, respectively, among the world's most polluted countries, while China ranks 19th. The present analysis indicated a gradual decline in $PM_{2.5}$ concentrations in China and India; in contrast, Pakistan has shown a rising trend (Fig. 4.3). However, the annual mean $PM_{2.5}$ concentration for CIP was higher in 2023 compared to 2022 by 6.21%, 2.06%, and 3.95%, respectively (Table 4.2). India and China have improved their city-level air quality (as measured by $PM_{2.5}$ concentrations) from 2021 to 2023 by -0.31% and -6.37%, respectively. Pakistan has experienced a 10.33% decline in city-level air quality. Additionally, the annual mean $PM_{2.5}$ concentration in Chinese and Indian cities improved by 8.81% and 7.45%, respectively, in 2023 compared to the historical average of 2018-22. Pakistani cities have seen a 9.41% increase, remaining unhealthy.

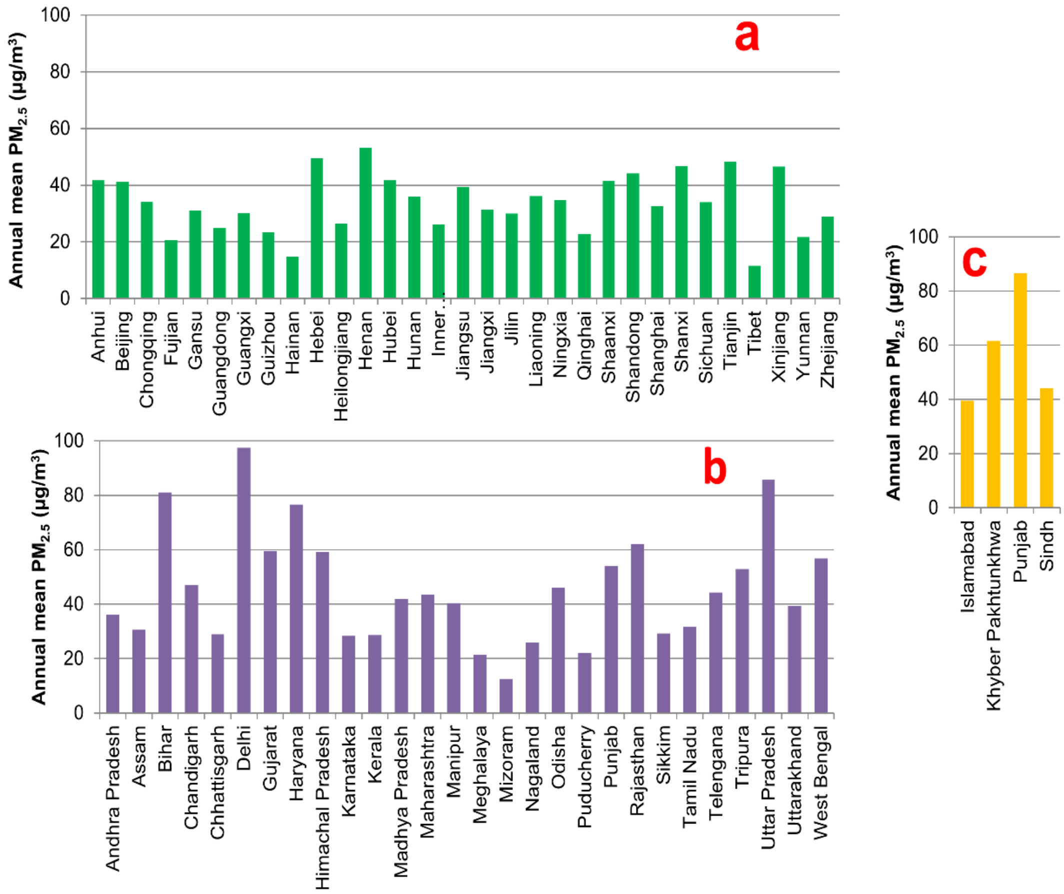


Fig. 4.4 State-wise cities' historical annual mean $PM_{2.5}$ concentrations for (a) China, (b) India and (c) Pakistan

Table 4.2 Variation of mean $PM_{2.5}$ concentrations during 2018-23 over China, India and Pakistan

Countries	2023	2022	2021	Average of 2018-22	2022 and 2023		2021 and 2023		Average of 2018-22 and 2023	
					Net variation	% of variation	Net variation	% of variation	Net variation	% of variation
China	32.5	30.6	32.6	35.6	1.9	6.21	-0.1	-0.31	-3.1	-8.81
India	54.4	53.3	58.1	58.8	1.1	2.06	-3.7	-6.37	-4.4	-7.45
Pakistan	73.7	70.9	66.8	67.4	2.8	3.95	6.9	10.33	6.3	9.41

Table 4.3 Summary statistics of locational variation of mean $PM_{2.5}$ concentrations during 2018-23 over China, India and Pakistan

Locations	States	$PM_{2.5}$ ($\mu g/m^3$)
Industrial	China	34.5 ± 7.0
	India	74.6 ± 23.1
	Pakistan	69.8 ± 27.6
Transport	China	22.6 ± 5.0
	India	72.5 ± 27.7
	Pakistan	69.8 ± 27.6
Geography	China	43.4 ± 5.5
	India	35.1 ± 14.1
	Pakistan	67.7 ± 32.4
Weather	China	35.0 ± 11.1
	India	42.2 ± 14.2
	Pakistan	88.9 ± 13.9

The study focused on the historical (2017-23) annual mean $PM_{2.5}$ ($\mu g/m^3$) concentration in the most polluted cities in different states. According to the data (Fig. 4.4), the National Capital Region (NCR) of Delhi, India, ranked first with a concentration of 97.5 $\mu g/m^3$, followed by Punjab (Pakistan) with 86.6 $\mu g/m^3$ and Uttar Pradesh with 85.7 $\mu g/m^3$, ranking second and third, respectively. Tibet (China) and Mizoram (India) were noted with minimal pollution levels of nearly 12 $\mu g/m^3$. In China, 19 out of 31 states (approximately 61%) had pollution levels ranging from 20 to 40 $\mu g/m^3$. In comparison, about 31% (10 states) had concentrations ranging from 40 to 60 $\mu g/m^3$. In India, 39% (11 states) of the regions had pollution concentrations ranging from 20-40 $\mu g/m^3$, and 39% (11 states) had concentrations ranging from 40-60 $\mu g/m^3$, with five states having levels exceeding 60 $\mu g/m^3$. There are only two Pakistani provinces that recorded a mean $PM_{2.5}$ concentration of nearly 40 $\mu g/m^3$, one with nearly 60 $\mu g/m^3$, and another with nearly 80 $\mu g/m^3$. Chinese provinces such as Hebei and Henan were found to exceed the WHO-recommended levels by over 10 times, i.e., >50 $\mu g/m^3$. States in India, such as Bihar, Delhi, Haryana, Rajasthan, and Uttar Pradesh, reported pollution levels exceeding 60 $\mu g/m^3$. Every reported state in Pakistan also faced extremely high $PM_{2.5}$ concentrations. The study highlighted the variations in $PM_{2.5}$ mean concentrations across industrial, transport, geographical, and weather locations in three distinct countries. They found that the highest concentration was observed in India (almost 75 $\mu g/m^3$) in industrial and transport cities, followed by Pakistan (approximately 70 $\mu g/m^3$) and China (approximately 30 $\mu g/m^3$) (Table 4.3). In Pakistan, the concentration was highest in both geographic locations (almost 70 $\mu g/m^3$) and weather patterns (approximately 90 $\mu g/m^3$). India and China had concentrations of 40 $\mu g/m^3$ (approximately) each. In addition, from the perspective of maximum and minimum regional variations within a country, China showed variations in geography and transport; India, in industry and geography; and Pakistan, in weather and geography. Hence, this indicates that $PM_{2.5}$ concentrations vary across cities nationwide.

4.2.3 Seasonal variability of $PM_{2.5}$ concentrations

The residents of the three countries faced significant challenges due to high $PM_{2.5}$ ($\mu g/m^3$) levels during the winter season. The $PM_{2.5}$ concentrations in winter were as follows: China, 47.8 ± 22.6 $\mu g/m^3$; India, 70.2 ± 41.5 $\mu g/m^3$; and Pakistan, 98.0 ± 45.5 $\mu g/m^3$ (Table 4.4). Even after the monsoon season, the concentrations in Indian and Chinese cities remained elevated at 64.3 ± 43.2 $\mu g/m^3$ and 89.1 ± 59.1 $\mu g/m^3$, respectively. However, there was a noticeable decrease in $PM_{2.5}$ levels during the pre-monsoon and monsoon seasons in Indian and Pakistani cities. A similar trend was observed in Chinese cities during the monsoon season (17.3 ± 6.9 μg/m^3). The highest mean monthly $PM_{2.5}$ concentration was recorded in December for Pakistan (136.6 ± 44.1 μg/m^3), November for India (80.3 ± 52.6 μg/m^3), and January for China (53.6 ± 26.7 μg/m^3). The lowest mean monthly $PM_{2.5}$ concentration was observed in July for all three countries: China 15.2 ± 5.7 μg/m^3, India 23.2 ± 11.5 μg/m^3, and Pakistan 29.0 ± 6.7 μg/m^3. I calculated the monthly mean $PM_{2.5}$ concentration for the six most populous cities in each country, revealing that the highest and lowest concentrations were in December (92.5 ± 63.1 μg/m^3) and July (22.8 ± 11.3 μg/m^3) (Fig. 4.5). Furthermore, city residents experienced adverse effects primarily during the winter season, followed by the post-monsoon, pre-monsoon, and monsoon seasons, respectively.

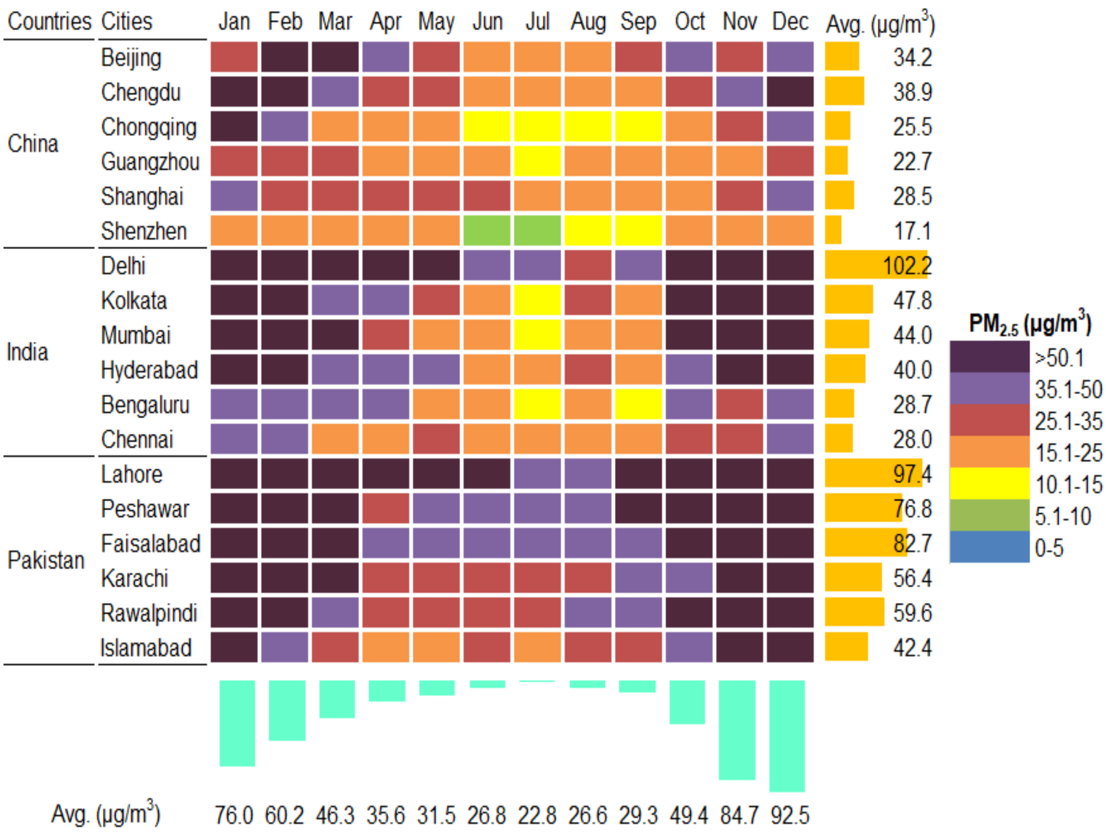


Fig. 4.5 Annual mean monthly $PM_{2.5}$ concentration in the cities of China, India and Pakistan

Table 4.4 Seasonal pattern of $PM_{2.5}$ ($\mu g/m^3$) concentration over China, India and Pakistan

Seasons	Months	China		India		Pakistan	
		Monthly average	Seasonal average	Monthly average	Seasonal average	Monthly average	Seasonal average
Pre-monsoon	March	38.5 ± 14.3	32.1 ± 13.5	48.7 ± 23.2	42.5 ± 20.7	45.4 ± 16.3	34.8 ± 14.8
	April	33.6 ± 13.7		42.3 ± 20.2		29.5 ± 11.4	
	May	24.1 ± 7.0		36.7±16.3		29.7 ± 11.2	
Monsoon	June	17.9 ± 6.4	17.3 ± 6.9	29.8 ± 12.5	26.7 ± 12.4	32.1 ± 9.4	34.9 ± 9.9
	July	15.2 ± 5.7		23.2 ± 11.5		29.0 ± 6.7	
	August	16.8 ± 6.8		27.5 ± 11.7		35.5 ± 7.8	
	September	19.5 ± 8.0		26.4 ± 12.7		42.4 ± 10.7	
Post-monsoon	October	27.6 ± 11.6	30.4 ± 12.0	48.3 ± 21.5	64.3 ± 43.2	58.1 ± 29.3	89.1 ± 59.1
	November	33.2 ± 11.7		80.3 ± 52.6		120.1 ± 66.3	
Winter	December	45.4 ± 19.6	47.8 ± 22.6	71.5 ± 41.6	70.2 ± 41.5	136.6 ± 44.1	98.0 ± 45.5
	January	53.6 ± 26.7		79.3 ± 47.7		88.3 ± 36.5	
	February	44.5 ± 19.6		60.2 ± 32.1		69.1 ± 26.5	

4.2.4 $PM_{2.5}$ concentrations across the most polluted cities

I identified each nation's six most populated cities' annual mean $PM_{2.5}$ ($\mu g/m^3$) concentration trend, China (Beijing 34.2 ± 13.0 $\mu g/m^3$, Chengdu 38.9 ± 19.8 $\mu g/m^3$, Chongqing 25.5 ± 14.3 $\mu g/m^3$, Guangzhou 22.7 ± 6.9 $\mu g/m^3$, Shanghai 28.5 ± 8.9 $\mu g/m^3$, and Shenzhen 17.1 ± 6.3 $\mu g/m^3$), India (Delhi 102.2 ± 73.4 $\mu g/m^3$, Kolkata 47.8 ± 27.6 $\mu g/m^3$, Mumbai 44.0 ± 25.9 $\mu g/m^3$, Hyderabad 40.0 ± 14.8 $\mu g/m^3$, Bengaluru 28.7 ± 10.8 $\mu g/m^3$, and Chennai 28.0 ± 8.6 $\mu g/m^3$) and Pakistan (Lahore 97.4 ± 52.4 $\mu g/m^3$, Peshawar 76.8 ± 48.7 $\mu g/m^3$, Faisalabad 82.7 ± 59.2 $\mu g/m^3$, Karachi 56.4 ± 34.4 $\mu g/m^3$, Rawalpindi 59.6 ± 36.0 $\mu g/m^3$, and Islamabad 42.4 ± 23.0 $\mu g/m^3$) (Fig. 4.5). Delhi is the most polluted city (102.2 ± 73.4 $\mu g/m^3$) out of eighteen cities of these three countries and followed by Lahore, Faisalabad, and Peshawar. Monthly mean concentrations in Pakistani cities are always 16 times higher than the WHO target levels. Islamabad was in a better position (42.4 ± 23.0 $\mu g/m^3$) than other cities in Pakistan. However, it exceeds the permissible standard by 8 times. Lahore scored the second-highest with a concentration of 97.4 ± 52.4 $\mu g/m^3$ out of eighteen cities. All the months remained to exceed the WHO's target level. Chennai is far better (interim target 1, annual mean 35 $\mu g/m^3$) than the other five cities in India. The Chinese cities were far better than those in India and Pakistan. Beijing, Chongqing, Guangzhou, Shanghai, and Shenzhen achieved the WHO interim target level one (below 35 $\mu g/m^3$) except for Chengdu (38.9 ± 19.8 $\mu g/m^3$) in China. Shenzhen has the liveliest air among eighteen cities.

All six Chinese cities showed a gradual decrease in $PM_{2.5}$ concentrations (Fig. 4.6a). Shenzhen showed the lowest concentration among the six cities. Chengdu has experienced the highest $PM_{2.5}$ concentration on a temporal scale. The capital city, Beijing, demonstrated the most significant continuous reduction in concentrations. However, none of the Chinese cities met the WHO guideline (less than 5 $\mu g/m^3$/year). However, cities' overall $PM_{2.5}$ levels have been improving. Likewise, Indian cities have mixed results. Here, the concentration of $PM_{2.5}$ decreased during the COVID-19 pandemic amid lockdown periods, then increased again. Chennai has shown a minimal trend in concentration over the past six years. Delhi had the worst conditions throughout the period. Pakistani cities showed a similar trend, with a decline in levels during the pandemic in Lahore, Faisalabad, and other cities (Fig. 4.6c). Rawalpindi, Karachi, Islamabad, and Peshawar have noted a continuous slow rise in levels. A few instances of insufficient data for other cities were noted. Here, we can conclude that the cities of Pakistan were the worst polluted (nearly 30-140 μg/m^3/year), followed by Indian (25-120 μg/m^3/year) and Chinese cities (15-60 μg/m^3/year).

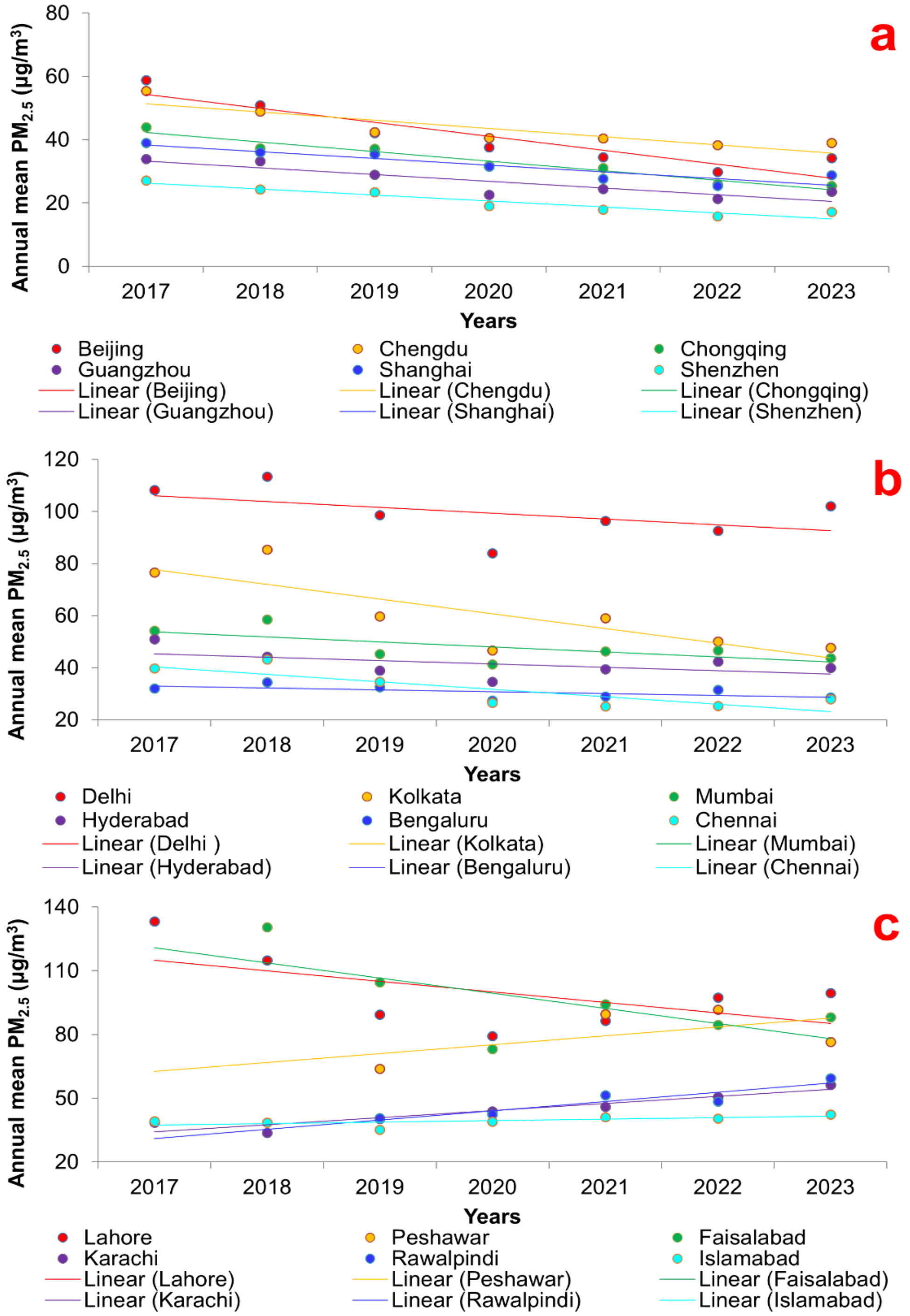
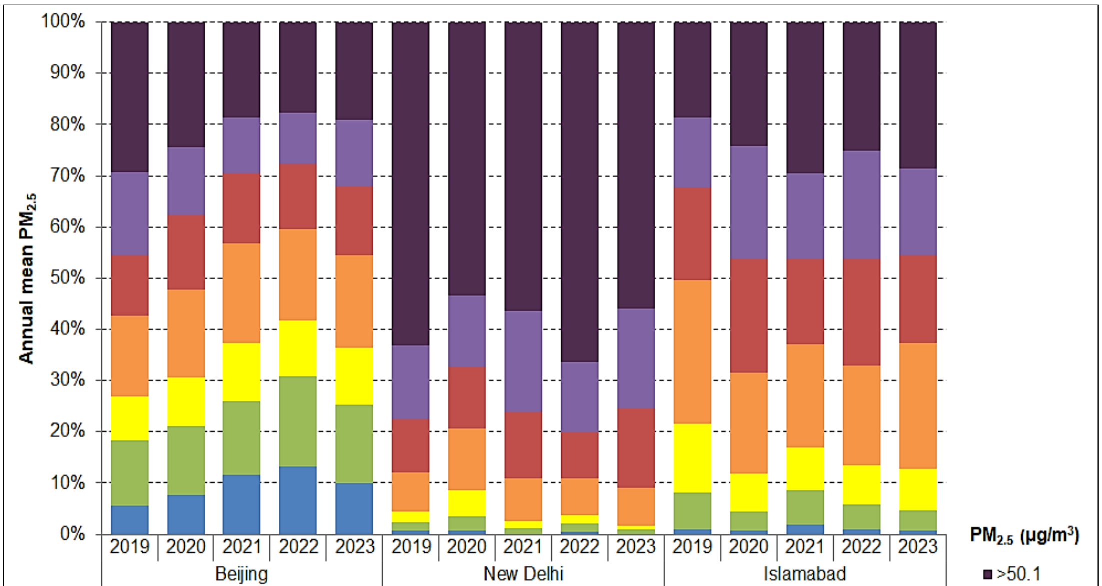


Fig. 4.6 Annual $PM_{2.5}$ mean concentration of (a) China, (b) India and (c) Pakistan over 7 years for the select 18 cities

The residence time of pollutants is crucial for city dwellers. Here, I compared the three capital cities' residence time during 2019-23 (Fig. 4.7). Beijing improved air quality over the years and maintained the WHO guideline of 5 μg/m^3 stringently. In 2019, it was 5.5% to 13.2% for 2022 and a slow rise for 2023 (9.9%). In addition, the heights of the green and orange colour bars have developed over the years. Simultaneously, the number of violet and maroon colour bars decreased in Beijing during 2019-22, with a steady decline in residence time, except in 2023, when a slow rise was observed. New Delhi suffered adversely from poor air quality during these periods. The concentration improved during the pandemic year compared to pre-pandemic levels and was again revitalized, only to worsen due to poor air quality in the post-pandemic years. The air was unhealthy; the cumulative concentrations of violet and maroon bars were 67%, 80%, and 75% for 2020, 2022, and 2023, respectively. In terms of air quality, the air that Delhi's residents breathe is heavily polluted. Similarly, Islamabad (Pakistan's capital) spent less than 1% of its hours in a healthy atmosphere. The green bar (near the WHO guideline) hours were mixed, though about 45% of the hours were spent in hazardous or extremely hazardous air.



	Beijing 2019	Beijing 2020	Beijing 2021	Beijing 2022	Beijing 2023	New Delhi 2019	New Delhi 2020	New Delhi 2021	New Delhi 2022	New Delhi 2023	Islamabad 2019	Islamabad 2020	Islamabad 2021	Islamabad 2022	Islamabad 2023
>50.1	29.4	24.4	18.7	17.6	19.1	63.1	53.5	56.3	66.3	56	18.6	24.2	29.6	25.1	28.6
35.1-50	16.2	13.3	10.8	10	12.9	14.5	13.7	19.9	13.7	19.3	13.8	22.0	16.5	21.1	16.8
25.1-35	11.7	14.6	13.6	12.8	13.5	10.3	12.1	12.8	9.2	15.6	18	22.3	16.9	20.8	17.2
15.1-25	15.8	17.1	19.5	17.9	18.1	7.6	12.2	8.4	7	7.4	28	19.7	20.1	19.6	24.7
10.1-15	8.7	9.4	11.4	10.9	11.2	2.2	5.0	1.51	1.8	0.8	13.4	7.4	8.2	7.6	8.1
5.1-10	12.8	13.6	14.4	17.6	15.3	1.6	2.8	1.1	1.4	0.8	7.2	3.7	6.8	4.9	3.8
0-5	5.5	7.6	11.5	13.2	9.9	0.7	0.7	0	0.6	0.1	1	0.7	1.9	0.9	0.8

Cities

Fig. 4.7 Annual hours spent at different $PM_{2.5}$ pollution levels of capital cities of China, India and Pakistan

4.3 Discussion

Coal usage is the main challenge in Chinese cities (Pui et al., 2014). China is one of the world's leading countries and has served many nations. In addition to household, vehicular, and industrial emissions, coal combustion contributed further $PM_{2.5}$ to the air (Zheng et al., 2017). To combat the issues, the Chinese used renewable resources. According to Abbasi-Kangevari et al. (2023), India had the world's highest population-weighted average ambient $PM_{2.5}$ levels (Abbasi-Kangevari et al., 2023). India witnessed 1.67 million deaths in 2019 (Pandey et al., 2021). It was the highest number of air pollution-related deaths in any country in the world. Vehicular emissions account for about 40% of $PM_{2.5}$ in Indian cities (Singh et al., 2017). The northern plain contains high levels of $PM_{2.5}$ due to stubble (crop) burning, the location of the Agra-Delhi-Kalka-Saharanpur industrial belt, and heavy vehicular emissions. In 2023, 13 of the 15 most polluted cities were in India (IQAir, 2023). Simultaneously, India is the world's most populous country, with a population of 1.42 billion (UNFPA, 2023). Hence, indoor emissions added more pollution to the existing outdoor pollution. Pakistan was the second most polluted country in the world in 2023 (IQAir, 2023). House and forest fires led to Pakistan's poor air quality last year. Besides that, stubble (crop) burning in winter, vehicular emissions, and factories contributed significantly to $PM_{2.5}$ levels. Severe smog in Punjab Province results from winter temperatures and temperature inversions, along with crop-burning smoke, industrial and vehicular emissions, and brick kiln activity (Ashraf et al., 2022). Regional factors such as geography, climate, and socio-economic conditions are crucial in influencing air quality in China. Studies have shown that meteorological factors, such as precipitation, temperature, and wind direction, and socio-economic factors, such as per capita GDP, industrialization rate, and urbanization, significantly impact air quality (Zhou et al., 2023; Zhang et al., 2022b; Yan et al., 2023).

Additionally, air pollutant concentrations across regions were influenced by factors such as carbon emission intensity, energy consumption, and industrial activity. Emissions are positively correlated with electricity generation, urban population density, and steel production and negatively correlated with disposable income and gross construction output (Yan and Sun, 2023; Tian, 2023). Studies have shown significant spatial heterogeneity in $PM_{2.5}$ concentrations globally, with developed regions experiencing decreases, while developing regions, such as India, see increases

(Xu et al., 2023). Meteorological parameters such as temperature, surface pressure, and relative humidity have been identified as key drivers of $PM_{2.5}$ levels in India, accounting for a significant portion of the variability across the country (Maheshwarkar et al., 2022). Additionally, changes in meteorological variables such as wind speed, temperature inversions, and boundary layer height have been observed to affect $PM_{2.5}$ concentrations in Indian cities, with emissions playing a dominant role in the increase in $PM_{2.5}$ levels over the years (Hancock et al., 2023). Research indicates that $PM_{2.5}$ levels in urban areas such as Lahore are influenced by sources such as vehicle emissions, combustion sources, and dust. Both regional and local pollution sources contribute to elevated $PM_{2.5}$ levels (Ahmad et al., 2022). Analysis of data shows that $PM_{2.5}$ concentrations have increased over the years, especially in provinces such as Punjab and Sindh, and in cities such as Lahore, Faisalabad, and Karachi, where levels have risen significantly (Mariam et al., 2021). A study during the COVID-19 period revealed varying impacts on $PM_{2.5}$ levels in Lahore and Karachi, indicating a correlation between air quality and lockdown policies (Sipra et al., 2021). Additionally, a global study emphasizes the role of socioeconomic factors in shaping $PM_{2.5}$ concentrations, with regions at different stages of development showing diverse impacts on air quality. This suggests that countries can achieve better air quality through sustainable development practices (Xu et al., 2023).

Rapid urbanization has increased $PM_{2.5}$ pollution from transportation, energy production, and industry, all of which are concentrated in densely populated areas (Gurjar et al., 2008). Studies conducted in China have shown that urban areas with high land-use intensity tend to have higher $PM_{2.5}$ concentrations. This suggests a correlation between urbanization and air pollution (He et al., 2023; Yang et al., 2023a). Additionally, a global analysis spanning from 2000 to 2020 indicates that as urbanization progresses, $PM_{2.5}$ concentrations are expected to rise. Significant increases have been observed in Asian and African countries compared with Europe and the Americas (Zhou et al., 2023). The interaction between natural environments, socio-economic factors, and urbanization is crucial in influencing $PM_{2.5}$ pollution levels. Elevation, precipitation, population density, and economic factors impact the intensity of urban PM islands found in Chinese cities (Peng et al., 2022).

Furthermore, the effects of urban expansion and emission growth on $PM_{2.5}$ and O_3 pollution in highly urbanized cities such as Chengdu underscore the complex relationship between urbanization and air quality. This underscores the importance of sustainable urban development in mitigating the health risks associated with air pollution (Zhan et al., 2023). The rapid urbanization in India has led to a significant increase in $PM_{2.5}$ pollution levels, affecting air quality in cities such as Coimbatore and the Delhi-NCR. Studies have shown that urban growth and industrialization contribute to higher $PM_{2.5}$ concentrations, with vehicular emissions, industrial activities, and residential areas as significant sources of pollution (Arunkumar et al., 2022; Misra et al., 2019; Verma, 2020). The spatial-temporal distribution of PM in Indian cities has been found to exceed national air quality standards, highlighting the adverse effects of urbanization on air quality (Arunkumar et al., 2022). Lockdown measures put in place during the COVID-19 pandemic resulted in a significant reduction in $PM_{2.5}$ levels in Chennai, indicating the direct impact of urban activities on air pollution levels (Badida and Jayaprakash, 2022). Understanding the sources and pathways of $PM_{2.5}$ dispersion through modelling and assessment can help in developing targeted interventions to mitigate air pollution in rapidly urbanizing regions like India (Verma, 2020).

Most cities in Southeast and Southern Asia suffer from heavy vehicular emissions that cause smog in winter and haze in other seasons. These lead to extensive cardiovascular and respiratory problems among the city dwellers, especially the infant populations. The combustion of fossil fuels in cities and megacities increased $PM_{2.5}$ levels in the air, and the particles travel regionally and across continents (Ravindra et al., 2016; Anwar et al., 2021). Urban biomass burning affects regional PM concentrations, contributing approximately 85% and 89% to PM_{10} and $PM_{2.5}$ (Pimonsree et al., 2018). A recent study in India shows no such impact of air pollution during the monsoon season. Weather conditions also fall into the very good and satisfactory category of AQI (Kumar et al., 2018). Air pollution gets worse due to heavy traffic in the subcontinent during the winter months. Also, low temperatures and high humidity in winter tend to create smog and haze, creating unfavourable conditions for the inhabitants.

Further, the daily average concentration and AQI for $PM_{2.5}$ show a peak in winter. In contrast, a minimum is observed during the monsoon season (Mamta et al., 2010). Other studies have shown that $PM_{2.5}$ concentrations in the air increase with changes in wind direction, as well as with factors such as temperature reversal, large-scale deposition, advection, and radiative cooling (Shi et al., 2020). The above results and discussion lead to an approach for ambient air monitoring and management. It is evident that during the COVID-19 pandemic, when lockdowns or quarantines were in effect across the country, NO_2 and $PM_{2.5}$ levels in the air were 2.5 times lower than in non-pandemic scenarios. There was very little traffic on the roads, and factories were closed. Here, we can conclude that fewer lives are lost when $PM_{2.5}$ levels are low; otherwise, it has a significant impact on people's lives. The cities experience low temperatures, wind speeds, relative humidity, and precipitation in winter, which prolongs the residence time of air pollution and increases ground-level air pollution. The monsoon season is characterized by moderate temperature and wind speed, high relative humidity, and maximum precipitation. As a result, the air pollution level decreased. The pollutant spent minimal residence time in the air. The pre-monsoon norwester brings rain/storms in the afternoon/evening, which was the reason for the moderate concentration of that substance. A few western disturbances with moderate levels of all climatic parameters are expected post-monsoon, keeping pollution levels medium.

Air pollution from coal mining, vehicle emissions, and industrial operations has a significant impact on human health and the environment. Coal mining contributes to the release of harmful gases such as CO_2, CO, NO_2, and $PM_{2.5}$, which affect air quality and can lead to health issues like respiratory infections and lung cancer (Kumar and Rajput, 2022; Zhang et al., 2022c). Vehicle emissions, mainly from transportation activities, are a significant source of pollutants such as CO_2, NO_2, and $PM_{2.5}$, which can cause adverse health effects, including asthma and cardiovascular disease (Li, 2020; Nawaz et al., 2023). Industries also play a crucial role in air pollution, contributing to the degradation of air quality and posing risks to human health, particularly in densely populated areas like Santiago, Chile (Nawaz et al., 2023). Studies have demonstrated that exposure to $PM_{2.5}$ is linked with increased risks of cardiovascular and respiratory diseases, lung cancer, stroke, pneumonia, depression, and diabetes (Sukuman et al., 2023).

Additionally, exposure to $PM_{2.5}$ has been associated with oxidative stress, inflammation, mitochondrial dysfunction, neuronal apoptosis, synaptic damage, deoxyribonucleic acid (DNA) methylation, and metabolic disturbance in the central nervous system (CNS) (Ye et al., 2023). Furthermore, a study on the combined effects of $PM_{2.5}$ and arsenic found elevated lung inflammation and heart damage, driven by oxidative stress, in animal models (Rivas-Santiago et al., 2024). An ecological study also revealed varying chronic health effects from different $PM_{2.5}$ sources, with lung cancer and circulatory disease mortality risks closely correlated with specific emissions (Zhang et al., 2023b). These findings collectively underscore the urgent need to mitigate $PM_{2.5}$ pollution to protect public health. Addressing these sources of pollution is vital to mitigate their harmful impacts on human health and the environment, highlighting the need for sustainable practices and regulatory measures (Le et al., 2024).

The impact of policy interventions and mitigation strategies for $PM_{2.5}$ in CIP goes beyond the effects of the pandemic. In China, the COVID-19 lockdown led to a significant reduction in $PM_{2.5}$ levels, demonstrating the effectiveness of emergency emission control measures (Yang et al., 2022; Wang et al., 2020). The study also stresses the importance of long-term emission control strategies to reduce $PM_{2.5}$ concentrations, particularly in heavily populated areas with high anthropogenic emissions, such as megacities (Wang et al., 2020). In India, the nationwide lockdown improved air quality by reducing industrial, commercial, and transportation activities, highlighting the potential benefits of strict regulatory measures (Biswas et al., 2022). Additionally, in Pakistan, although explicit data were not provided, similar strategies, such as implementing emission control measures and conducting spatial-temporal analyses, could be essential for mitigating $PM_{2.5}$ pollution and improving air quality in urban areas.

Various research findings can guide effective policy interventions to reduce $PM_{2.5}$ concentrations in CIP. In China, the implementation of carbon trading policies has resulted in a significant reduction in $PM_{2.5}$ levels. This underscores the importance of market-based tools such as carbon trading (Weng et al., 2022). Additionally, the "Clean Heating" policy in north China has shown positive impacts on $PM_{2.5}$ concentrations, highlighting the effectiveness of region-specific interventions such as clean energy initiatives (Li et al., 2023). Furthermore, the use of air purifiers in urban areas is cost-effective, especially when targeting specific indoor $PM_{2.5}$ concentration levels. This indicates the importance of indoor air quality management strategies (Zhang et al., 2023b). These findings emphasize the importance of a multifaceted approach that combines market mechanisms, regional policies, and indoor air quality management to reduce $PM_{2.5}$ pollution in these countries effectively.

Effective policies for reducing outdoor $PM_{2.5}$ concentrations in CIP involve a combination of environmental protection measures, economic development strategies, and targeted regulations. In China, region-specific policies focusing on vegetation protection, SO_2 emission reduction, and balancing industrial growth with environmental sustainability show promise in combating $PM_{2.5}$ pollution (Li et al., 2024). Additionally, air purifiers have been highlighted as a cost-effective intervention, especially in urban areas, to reduce exposure to $PM_{2.5}$ and improve health outcomes (Zhang et al., 2023). Furthermore, the "Clean Heating" policy in China has demonstrated positive impacts on $PM_{2.5}$ levels, emphasizing the importance of domain-specific interventions and coal-banning measures (Li et al., 2023). Urban agglomeration development plans in China have also proven effective in reducing $PM_{2.5}$ pollution through industrial agglomeration, technological innovation, and environmental regulation (Jiang et al., 2022). These findings suggest that a holistic approach encompassing environmental, economic, and technological dimensions is crucial for successful $PM_{2.5}$ reduction strategies in these countries. Policy interventions and mitigation strategies for $PM_{2.5}$ in CIP involve a multifaceted approach. In China, the execution of policies, such as the Air Pollution Prevention and Control Action Plan and the Three-Year Action Plan for Winning the Blue-Sky Defense Battle, has led to progress in reducing $PM_{2.5}$ concentrations. This progress is achieved by technological advancements and differentiated control strategies among cities (Shu et al., 2023; Yang et al., 2023b). Similarly, in India and Pakistan, measures such as stringent industrial emission standards, the promotion of cleaner technologies, and the adoption of renewable energy sources are crucial for mitigating $PM_{2.5}$ pollution. Urban planning initiatives emphasizing efficient public transportation systems and green spaces to reduce vehicular emissions are also important (Akomolafe et al., 2024). Additionally, addressing regional transport contributions to $PM_{2.5}$ pollution through cross-province source-receptor matrices and climate change mitigation strategies is essential for improving air quality and environmental equality in these regions (Li et al., 2023).

Chapter V

Changes in Air Quality of Indian Megacities During COVID-19

5.1 Introduction

The coronavirus (COVID-19) pandemic poses a significant threat to the global human population. Coronaviruses are single-stranded ribonucleic acid (RNA) viruses that can infect not only humans but also a variety of animals as well (Kooraki et al., 2020). The mode of transmission of this coronavirus requires exhaustive studies; however, maintaining social distance is recognized as one of the most effective ways to prevent its rapid spread (Lipsitch et al., 2020). The WHO declared in March 2020 that COVID-19 had become a global pandemic and called for a coordinated global response. The most affected countries, like the United States, Brazil, United Kingdom, Mexico, Italy, India, France, Spain, Peru, Iran, and Russia, recorded millions of infected and thousands of deaths (Docherty et al., 2020). The COVID-19 pandemic severely affected the world economy, especially in developing countries. Gita Gopinath of the International Monetary Fund (IMF) noted that the COVID-19 pandemic would lead to a global recession in 2020. The economic growth rate would drop to −3% (Gopinath, 2020). Researchers found a clear link between COVID-19 severity and air pollution. A higher level of air pollution was associated with a higher COVID-19 infection rate in many cities across Asia, Europe, and North America. A study by Xie and Zhu (2020) covering 120 cities in China found a strong association between air pollution and COVID-19. Moreover, studies from the United States show that increased long-term exposure to $PM_{2.5}$ is associated with a significant increase in COVID-19 mortality (Wu et al., 2020a; b).

Each year, anthropogenic pollutant emissions contribute to poor air quality in India (Balakrishnan et al., 2019). The major cities in India, such as Chennai, Delhi, Hyderabad, Kolkata, and Mumbai, are among the most populous, and ambient $PM_{2.5}$ concentrations remain above the WHO annual guideline value of 10 $\mu g/m^3$ (WHO, 2016). Several studies indicated that air quality in India has deteriorated beyond measures in recent times (Chauhan and Singh, 2020; Sarkar et al., 2018; Sarkar et al., 2019). New Delhi, the capital of India, has stable air quality, with pollution levels much higher than those in Beijing (Zheng et al., 2017). India is one of the most populous countries in the world, and due to its high urban population density, air pollution levels remain significantly high. The principal sources of pollutants are vehicular emissions, industrial activities, and domestic fuel burning (Mor et al., 2021). Except for O_3, the others, such as $PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, and CO, are the primary air pollutants (Table 1.2). It is pertinent to note that air pollution is associated with respiratory and CVDs (Zheng et al., 2020). A higher level of air pollution has a greater impact than COVID-19 (Giani et al., 2020). The GoI initially imposed a nationwide 21-day lockdown on 24 March 2020 to combat the pandemic. All the social gathering places, such as restaurants, cinemas, schools, shopping complexes, and educational institutions, were closed. Staff and students worked from home to maintain a strategic distance from swarms. All transportation services, including rail, road, and air, were suspended, except for emergency services. Besides, almost all production and industrial activities came to a halt (Kumari and Toshniwal, 2020). The total lockdown has adversely influenced the nation's economy. However, limited transportation and economic activity led to a drastic decrease in air pollution (Gautam, 2020). Globally, satellite images and ground data show that air pollution from NO_2 emissions in many regions has decreased, allowing the stratospheric O_3 layer to recover (NASA, 2020). This reduction of pollutants brought a blessing to human health and the environment. The high concentration of different air pollutants has varied effects on human health and the environment (Table 1.5).

In India, studies of the impact of COVID-19 on Air Quality are limited (Mahato et al., 2020; Sharma et al., 2020; Mitra et al., 2020). A reduction in $PM_{2.5}$ levels has been observed in major cities, such as 35–39% in Delhi (Chauhan and Singh, 2020; Mahato et al., 2020), 30–40% in Kolkata (Mitra et al., 2020), and 14–43% in Mumbai (Chauhan and Singh, 2020; Sharma et al., 2020) due to the lockdown. It is evident from several pieces of research that the nationwide lockdown in India improved the air quality (Singh and Chakraborty, 2020). However, most papers focused on a few selected parameters or on a single location. Moreover, most of these studies did not consider pollutant concentrations at the same time of year under no lockdown conditions, leading to incomplete inferences. The meteorological conditions were also overlooked in many of these papers. This chapter aimed to show changes in air quality in three megacities (Mumbai, Delhi, and Kolkata) in India during the lockdown, compare the observations with those in the previous year (under no lockdown restrictions), and characterize the role of meteorological variables. For the present study, I considered seven air pollutants: $PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, CO, and O_3. I also analyzed four meteorological parameters: ambient air temperature, relative humidity, wind velocity, and precipitation. I implemented statistical and model-based approaches to examine changes in the AQI during the lockdown through a comparative analysis. I believe this type of study can help policymakers address rising air pollution in urban areas and implement action plans to reduce it.

5.2 Results and discussion

5.2.1 Changes in the concentration of Particulate matter ($PM_{2.5}$ and PM_{10})

PM is a significant pollutant, particularly in urban and industrial areas (Santra, 2015). $PM_{2.5}$ and PM_{10} levels declined significantly across India's megacities after the lockdown was imposed (Fig. 5.1a and Fig. 5.1c). The pre-lockdown concentration was substantially higher compared to the permissible limit of 60 $\mu g/m^3$ for $PM_{2.5}$ and 100 $\mu g/m^3$ for PM_{10} across all the megacities. The $PM_{2.5}$ concentrations during lockdown in Mumbai dropped below the permissible limit. Still, in the other two megacities, it remained above the limit. However, PM_{10} levels fell below the specified permissible limit across all India's megacities during the lockdown. The post-lockdown concentration of $PM_{2.5}$ in Mumbai and Kolkata remained below the permissible limit, following a declining trend over time, whereas Delhi exhibited the opposite trend. Here, $PM_{2.5}$ concentrations exhibited an increase in the post-lockdown phase (Fig. 5.1b). Similarly, PM_{10} levels declined significantly in Mumbai and Kolkata, whereas in Delhi exhibited a rising trend (Fig. 5.1d). Post-lockdown PM_{10} levels were consistently below the permissible limit.

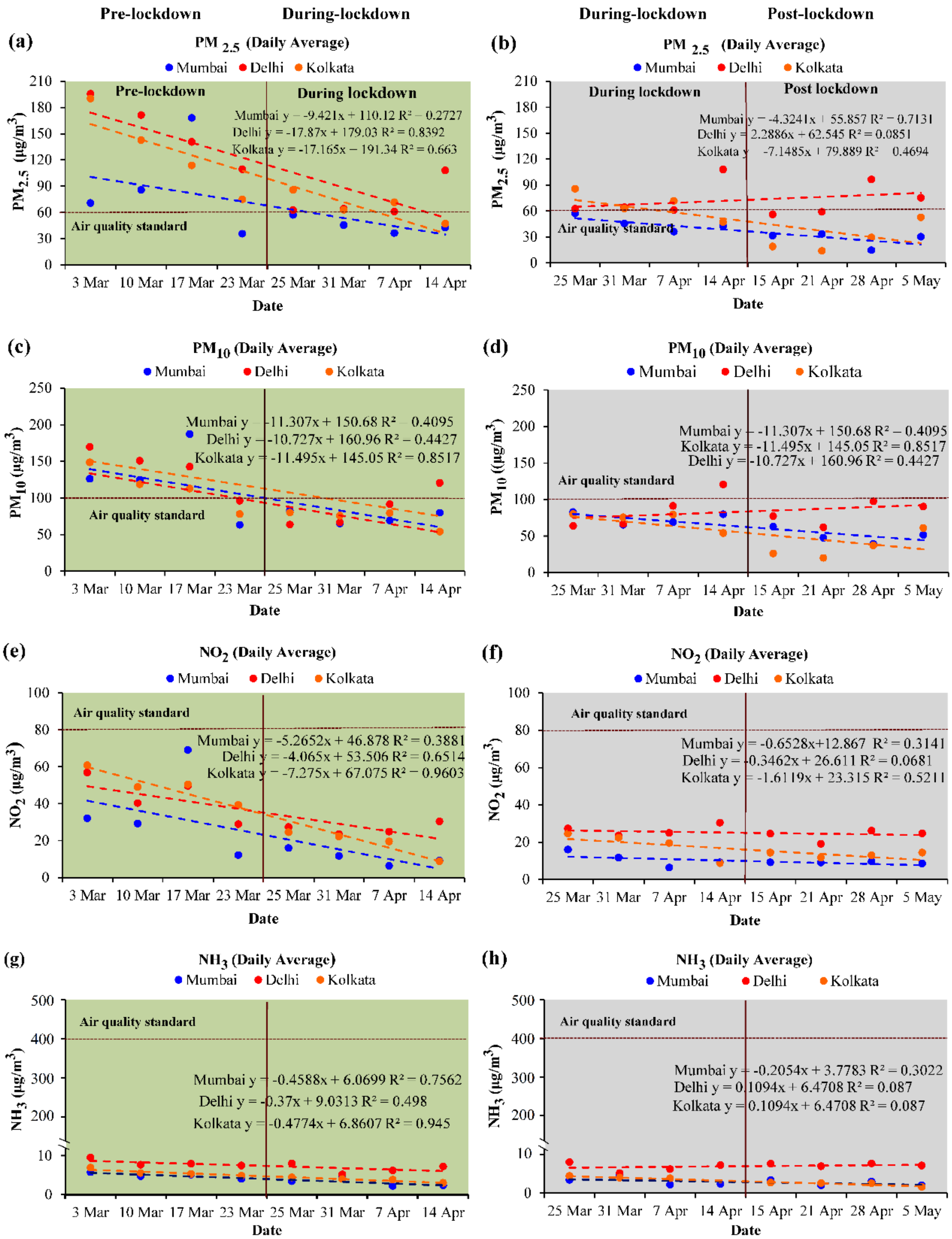


Fig. 5.1 The trend of average concentrations of (a; b) $PM_{2.5}$, (c; d) PM_{10}, (e; f) NO_2, (g; h) NH_3 between 3 March to 14 April 2020 and 15 April to 5 May 2020 in all three megacities of India

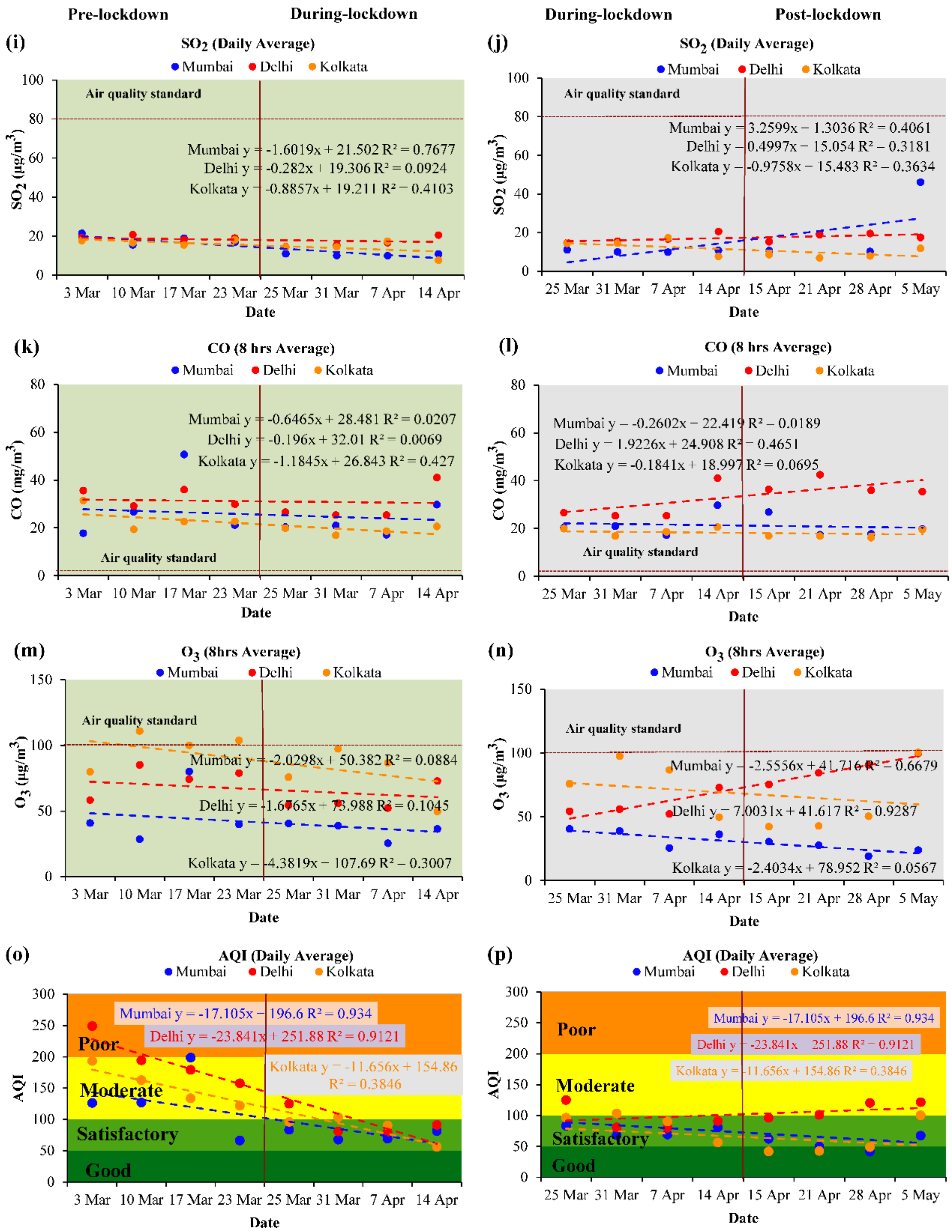


Fig. 5.2 The trend of average concentrations of (i; j) SO_2, (k; l) CO (m; n) O_3, and (o; p) AQI between 3 March to 14 April 2020 and 15 April to 5 May 2020 in all three megacities of India

Table 5.1 Weekly descriptions of air pollutants in pre-lockdown, during-lockdown, and post-lockdown across all three megacities of India

Pollutants	Megacities	Pre-lockdown				During-lockdown				Post-lockdown			
		3 March	10 March	17 March	23 March	25 March	31 March	7 April	14 April	15 April	21 April	28 April	5 May
$PM_{2.5}$	Mumbai	70.88±13.94	85.70±40.59	168.13±39.03	35.63±4.21	57.22±7.46	45.38±8.75	36.25±7.80	42.67±11.68	31.60±9.45	33.33±15.12	14.57±3.95	30.17±20.61
	Delhi	195.28±41.55	171.80±38.71	141.36±45.39	108.69±37.94	62.06±31.60	64.28±31.00	60.93±21.20	108.00±47.86	56.11±17.78	59.06±23.51	96.37±32.68	75.38±17.45
	Kolkata	190.30±66.78	142.70±57.56	113.90±30.16	74.90±40.36	85.60±21.01	63.00±22.39	71.50±14.58	47.00±6.78	18.89±7.73	13.78±4.27	29.50±6.65	52.50±7.99
PM_{10}	Mumbai	126.13±20.39	124.70±32.06	187.25±57.96	63.38±8.81	82.89±13.15	65.25±13.23	69.17±10.53	79.60±8.99	62.67±13.09	47.63±11.78	39.00±15.44	51.50±12.36
	Delhi	168.75±38.28	150.53±24.65	143.88±33.33	95.66±17.66	63.21±13.44	66.55±16.15	91.35±17.90	120.66±27.98	77.22±16.36	61.89±20.22	97.44±28.59	90.25±18.24
	Kolkata	148.50±34.39	118.50±29.87	112.60±19.36	77.90±35.83	80.00±15.68	75.70±11.64	79.40±10.79	54.00±8.72	25.90±5.74	20.00±6.42	37.10±7.88	61.00±13.15
NO_2	Mumbai	32.00±19.80	29.20±18.08	69.00±49.78	12.11±9.24	16.00±10.42	11.67±7.07	6.33±2.80	9.17±3.92	9.17±8.11	9.00±5.86	9.60±5.68	8.50±7.05
	Delhi	57.58±21.93	41.03±17.25	50.88±20.27	28.97±12.99	27.64±16.04	23.53±17.81	24.90±19.47	30.42±12.41	24.50±17.40	19.04±12.10	26.13±14.10	24.63±8.52
	Kolkata	60.80±29.37	49.10±19.84	50.40±22.56	39.30±28.29	24.50±9.77	22.30±9.30	19.50±10.73	8.80±4.66	14.40±6.19	11.67±4.82	12.90±5.78	14.43±7.16
NH_3	Mumbai	5.75±3.37	4.67±4.27	5.13±3.14	4.00±2.33	3.38±1.69	4.63±5.21	2.17±0.98	2.33±1.21	3.33±2.58	2.00±1.22	3.00±0.00	2.00±0.00
	Delhi	9.62±3.76	7.62±2.76	7.92±2.71	7.54±2.60	8.15±3.94	5.17±1.50	6.14±3.48	7.20±4.05	7.55±4.22	6.91±2.76	7.65±4.30	7.13±3.08
	Kolkata	6.90±2.69	5.50±1.58	5.30±2.75	4.80±1.93	4.4±2.32	4.00±2.16	3.80±2.10	3.00±2.05	2.70±1.95	2.56±1.81	2.50±1.43	1.57±0.79

Cont……

SO_2	Mumbai	21.38±34.48	15.50±17.30	18.89±12.35	16.89±23.32	11.00±9.10	10.00±8.38	9.86±10.88	10.83±10.01	10.67±9.61	19.29±28.99	10.14±11.35	46.00±41.27
	Delhi	19.43±8.74	21.17±10.75	18.19±8.17	19.11±7.72	14.48±7.14	15.44±6.40	16.64±7.12	20.52±10.33	15.30±7.78	18.96±17.80	19.47±10.30	17.48±10.24
	Kolkata	17.70±11.68	16.70±8.55	15.50±4.55	18.10±9.92	14.40±5.15	15.44±4.38	17.30±7.32	7.60±3.75	8.50±3.98	6.78±1.72	7.80±2.35	11.86±2.41
CO	Mumbai	17.78±11.23	26.70±29.16	50.70±25.53	21.22±13.55	20.33±13.54	21±14.00	17.13±14.54	29.71±26.87	26.86±24.79	17.38±16.54	17.75±13.60	19.83±14.02
	Delhi	37.53±25.46	30.69±25.58	36.51±26.91	30.78±25.43	24.85±15.23	26.36±19.12	27.10±22.83	41.43±29.66	36.37±27.29	42.40±27.42	35.96±25.14	35.44±25.92
	Kolkata	31.40±12.59	19.40±8.85	22.60±10.73	22.70±13.57	19.90±17.36	16.90±10.05	18.60±3.81	20.60±5.78	16.90±4.31	16.78±7.46	16.10±6.38	19.57±4.58
O_3	Mumbai	40.75±15.42	28.50±15.97	80.10±42.76	39.78±19.98	40.44±24.15	38.78±24.11	25.43±12.38	36.20±22.04	30.50±14.77	27.57±22.22	19.00±15.57	23.80±15.58
	Delhi	57.31±34.18	84.94±53.89	71.94±54.79	78.06±49.12	54.77±40.97	54.63±32.97	50.89±35.60	74.57±44.14	75.36±49.08	84.45±55.28	90.46±68.59	99.50±69.50
	Kolkata	79.90±31.34	110.78±58.93	100.00±47.27	103.67±51.64	75.78±29.06	97.33±46.71	86.67±12.68	49.67±8.57	42.22±16.25	42.67±9.26	50.33±5.52	100.43±6.63

In the pre-lockdown phase, the concentration of $PM_{2.5}$ in Mumbai, Delhi, and Kolkata varied from 35.63 to 168.13 μg/m^3, 108.69 to 195.28 μg/m^3, and 74.90 to 190.30 μg/m^3, respectively. In contrast, during the lockdown, these ranges were 36.25-57.22 μg/m^3, 60.93-108.00 μg/m^3, and 47.00-85.60 μg/m^3, respectively (Table 5.1). The post-lockdown concentrations ranged from 14.57 to 33.33 μg/m^3 in Mumbai, 56.11 to 96.37 μg/m^3 in Delhi, and 13.78 to 52.50 μg/m^3 in Kolkata. The pre-lockdown and lockdown ranges of PM_{10} in Mumbai were 63.38 to 187.25 μg/m^3 and 65.25 to 82.89 μg/m^3, respectively. In Delhi, the pre-lockdown PM_{10} ranged from 95.66 to 168.75 μg/m^3, and lockdown PM_{10} varied from 63.21 to 120.66 μg/m^3. In Kolkata, the pre-lockdown and lockdown ranges of PM_{10} were 77.90 to 148.50 μg/m^3 and 54.00 to 80.00 μg/m^3, respectively. The post-lockdown PM_{10} ranges were 39.00 to 62.67 μg/m^3 for Mumbai; 61.89 to 97.44 μg/m^3 for Delhi; and 20.00 to 61.00 μg/m^3 for Kolkata. To break the chain of COVID-19 transmission, the government had to rely on maintaining social distancing and completely closing all sectoral activities. Therefore, the movement of vehicles, the closure of industries, administrative centres, shopping malls, and all other allied services, except emergency services, remained closed during those days. Such widespread closure has caused a drastic improvement in ground-level air quality (NASA, 2020; Muhammad et al., 2020; Bera et al., 2020; Sharma et al., 2020; Mahato et al., 2020; Singh and Chauhan, 2020; Srivastava et al., 2020; Lancet, 2020). After the completion of the lockdown phase (24 March-14 April), the bus services and industrial activities were restricted, as the earlier scenario did not begin. The railway service was completely shut down. The post-lockdown new normal included mostly work-from-home, except for emergencies and online services. $PM_{2.5}$ during the lockdown reduced by about -46.61% (41.87 μg/m^3), -51.84% (80.06 μg/m^3), and -48.81% (63.68 μg/m^3) for Mumbai, Delhi, and Kolkata, respectively, compared to the pre-lockdown concentrations (Table 5.2). Similarly, PM_{10} was reduced by about -40.70% (51.00 μg/m^3), -38.95% (54.42 μg/m^3), and -36.81% (42.10 μg/m^3) in Mumbai, Delhi, and Kolkata, respectively. The post-lockdown average concentrations of $PM_{2.5}$ were reduced by about -42.83% (20.54 μg/m^3), -3.56% (2.65 μg/m^3), and -57.07% (38.11 μg/m^3) compared to the lockdown concentrations in Mumbai, Delhi, and Kolkata, respectively (Table 5.3). PM_{10} was reduced by about -32.46% (24.12 μg/m^3), -4.20% (3.58 μg/m^3), and -50.19% (36.28 μg/m^3) in Mumbai, Delhi, and Kolkata, respectively.

Delhi had the highest average concentrations of $PM_{2.5}$ and PM_{10} compared to the other two megacities of India. According to the WHO, Delhi was the most polluted city among 4,300 cities worldwide based on $PM_{2.5}$ concentrations (World Economic Forum, 2018).

Mumbai had air quality ranging from moderately polluted (89.82 μg/m^3) to satisfactory (47.96 μg/m^3), while Delhi and Kolkata were very poor to moderately polluted by $PM_{2.5}$ during the lockdown (Table 1.3). On the other hand, the megacities of Mumbai (125.32 to 74.32 μg/m^3), Delhi (139.70 to 85.28 μg/m^3), and Kolkata (114.38 to 72.28 μg/m^3) have recorded very healthy air quality due to a decline in PM_{10} levels. Post-lockdown, $PM_{2.5}$ and PM_{10} levels were well within the permissible limits in Mumbai and Kolkata, whereas in Delhi, they exceeded the permissible limit. Hence, breathing discomfort has taken place among people in sensitive groups and those with lung diseases, instead of prolonged suffering with lung diseases during lockdown. The post-lockdown impacts were minimal for Mumbai and Kolkata. In addition, horizontal visibility in the surface air improved during the COVID-19 pandemic.

Table 5.2 Variation of air pollutants in pre-lockdown and during-lockdown periods across all three megacities of India

Pollutants	Megacities	Pre-lockdown (3 March to 23 March)	Lockdown (25 March to 14 April)	Total variation Avg.	% of variation
$PM_{2.5}$ (μg/m^3)	Mumbai	89.82±55.75	47.96±11.22	-41.87	-46.61
	Delhi	154.44±52.23	74.38±39.75	-80.06	-51.84
	Kolkata	130.45±64.79	66.78±2.86	-63.68	-48.81
PM_{10} (μg/m^3)	Mumbai	125.32±54.39	74.32±13.75	-51.00	-40.70
	Delhi	139.70±39.85	85.28±30.45	-54.42	-38.95
	Kolkata	114.38±38.81	72.28±15.79	-42.10	-36.81
NO_2 (μg/m^3)	Mumbai	35.50±35.50	11.24±11.24	-24.26	-68.33
	Delhi	44.66±21.23	26.64±16.60	-18.02	-40.36
	Kolkata	49.90±25.53	18.78±10.53	-31.13	-62.37
NH_3 (μg/m^3)	Mumbai	4.88±3.29	3.25±3.04	-1.63	-33.39
	Delhi	8.16±3.07	6.74±5.57	-1.42	-17.39
	Kolkata	5.63±2.34	3.80±2.14	-1.83	-32.44
SO_2 (μg/m^3)	Mumbai	18.00±21.88	10.42±9.03	-7.58	-42.11
	Delhi	19.52±8.90	16.80±8.019	-2.72	-13.91
	Kolkata	17.00±8.77	13.45±6.26	-3.55	-20.88
CO (mg/m^3)	Mumbai	29.61±24.62	21.73±17.22	-7.88	-26.61
	Delhi	33.88±25.77	29.73±22.84	-4.15	-12.25

	Kolkata	24.03±12.00	19.00±10.29	-5.03	-20.92
O_3 (μg/m^3)	Mumbai	47.84±32.81	35.73±21.34	-12.10	-25.30
	Delhi	72.99±49.16	58.85±39.35	-14.14	-19.37
	Kolkata	98.08±47.40	77.36±32.68	-20.72	-21.13
AQI	Mumbai	129.29±55.42	75.50±13.33	-53.79	-41.61
	Delhi	164.53±50.61	96.42±39.69	-68.11	-41.39
	Kolkata	152.78±53.46	86.48±27.37	-66.30	-43.40

Table 5.3 Variation of air pollutants during the lockdown and post-lockdown periods across all three megacities of India

Pollutants	Megacities	During-lockdown (25 March to 14 April)	Post-lockdown (15 April to 5 May)	Total variation Avg.	% of variation
$PM_{2.5}$	Mumbai	47.96±	27.42±13.15	-20.54	-42.83
	Delhi	74.38±	71.73±23.42	-2.65	-3.56
	Kolkata	66.78±	28.67±23.42	-38.11	-57.07
PM_{10}	Mumbai	74.32±	50.20±25.55	-24.12	-32.46
	Delhi	85.28±	81.70±34.83	-3.58	-4.20
	Kolkata	72.28±	36.00±34.83	-36.28	-50.19
NO_2	Mumbai	11.24±	9.07±1.79	-2.17	-19.35
	Delhi	26.64±	23.57±6.67	-3.07	-11.51
	Kolkata	18.78±	13.35±6.67	-5.43	-28.90
NH_3	Mumbai	3.25±	2.58±1.40	-0.67	-20.51
	Delhi	6.74±	7.31±2.29	0.57	8.40
	Kolkata	3.80±	2.33±2.29	-1.47	-38.64
SO_2	Mumbai	10.42±	21.52±17.12	11.10	106.57
	Delhi	16.80±	17.80±3.46	1.00	5.96
	Kolkata	13.45±	8.73±3.46	-4.72	-35.07
CO	Mumbai	21.73±	20.45±5.70	-1.27	-5.86
	Delhi	29.73±	37.54±5.65	7.81	26.28
	Kolkata	19.00±	17.34±5.65	-1.66	-8.75
O_3	Mumbai	35.73±	25.22±6.13	-10.52	-29.43
	Delhi	58.85±	87.44±18.53	28.59	48.59
	Kolkata	77.36±	58.91±18.53	-18.45	-23.85
AQI	Mumbai	75.5±	55.2±	-20.3	-26.89
	Delhi	96.42±	109.89±	13.47	13.97
	Kolkata	86.48±	58.47±	-28.01	-32.39

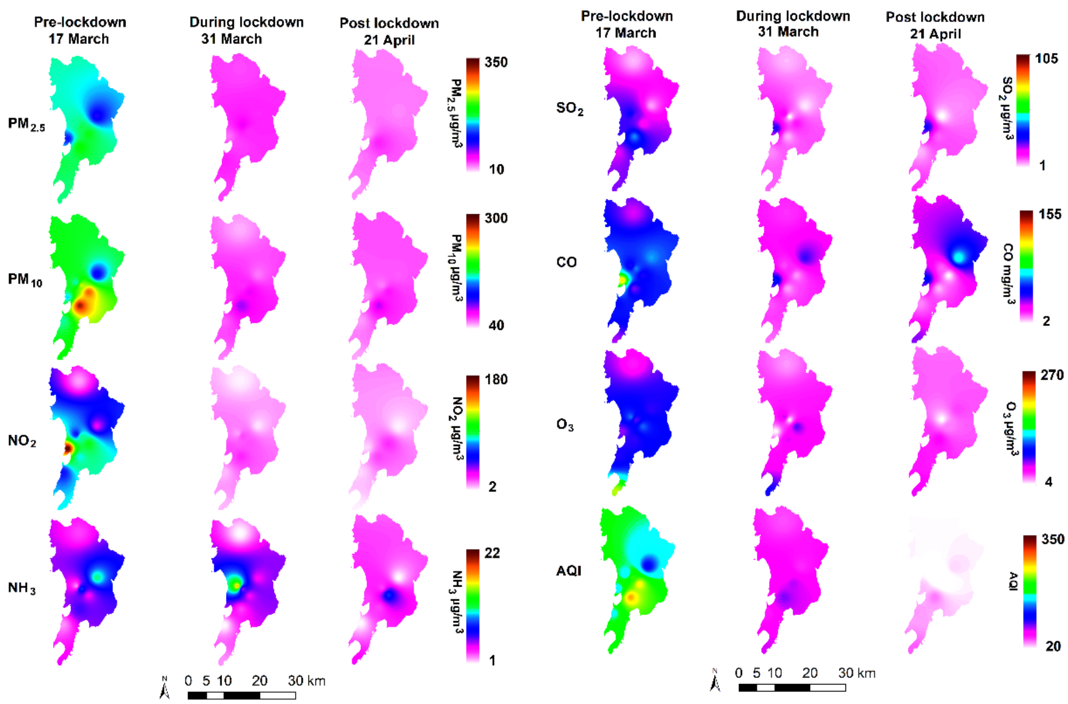


Fig. 5.3 The spatiotemporal variability of pollutants over the megacity of Mumbai

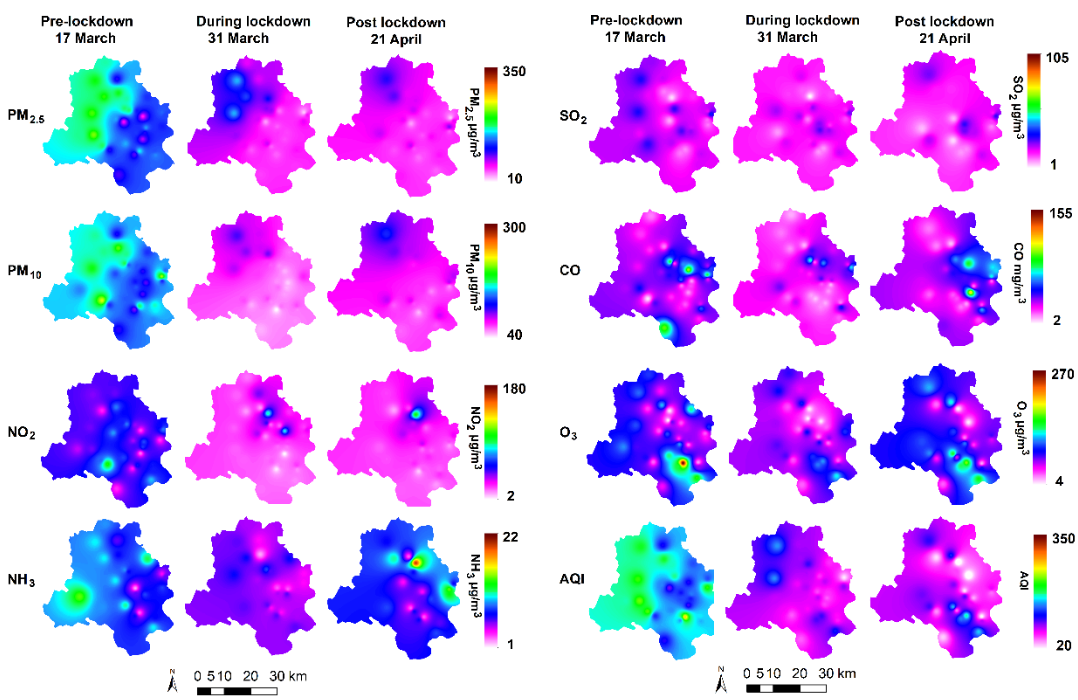


Fig. 5.4 The spatiotemporal variability of pollutants over the megacity of Delhi

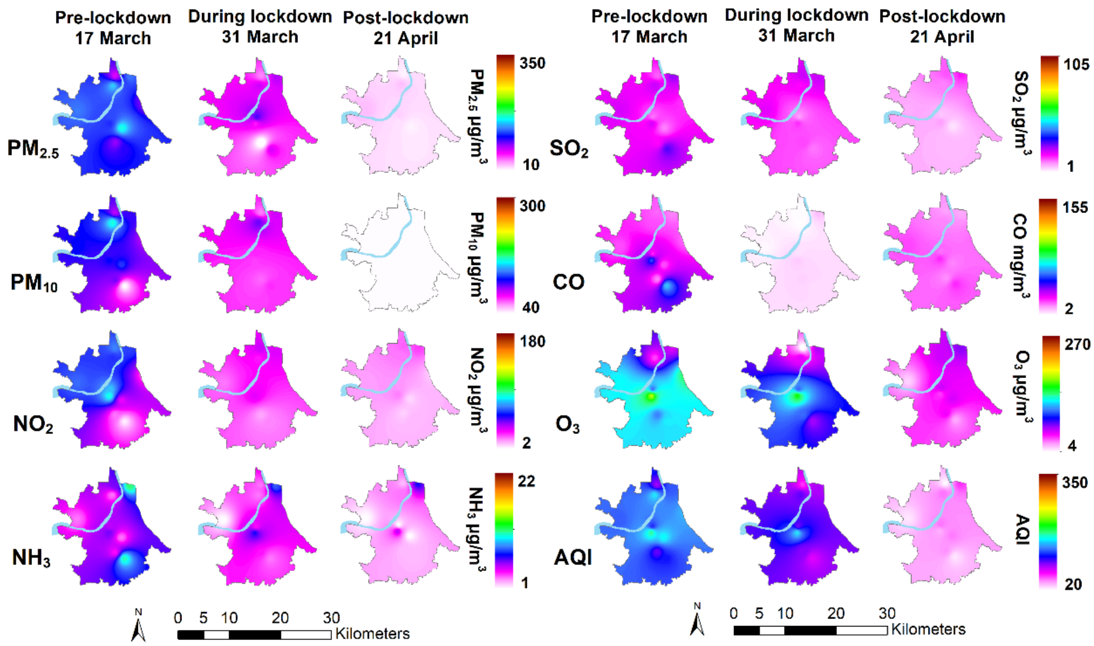


Fig. 5.5 The spatiotemporal variability of pollutants over the megacity of Kolkata

The spatial distributions of $PM_{2.5}$ and PM_{10} across all three megacities of India have been shown (Figs. 5.3, 5.4, 5.5). Significant improvements in air quality have been detected in the Lockdown phase, and it continued to post-lockdown. The eastern parts of the megacities of Delhi and Kolkata had better air quality than their western parts. There were more industrial activities and vehicular emissions in the western part than in the eastern part. The marine wind refreshed the western part of Mumbai. Therefore, the scenario was the opposite here; the eastern part was more contaminated than the western part. However, in the latter few weeks, deteriorations in air quality were recorded due to partial relaxation in the transport service and industry sectors.

Delhi recorded the highest $PM_{2.5}$ and PM_{10} in 2019 and 2020, except for PM_{10} of 2020 during the period of 25 March-14 April (Figs. 5.6a, 5.6b). Mumbai recorded the lowest levels of $PM_{2.5}$ and PM_{10}, while Kolkata recorded moderate concentrations. Compared to the 2019 scenario, the PM_{10} level in Delhi has shown the most considerable reduction (-51.78%) during the COVID-19 lockdown. $PM_{2.5}$ exhibited the highest reduction (-34.67%) for Mumbai compared to Delhi and Kolkata (Table 5.4).

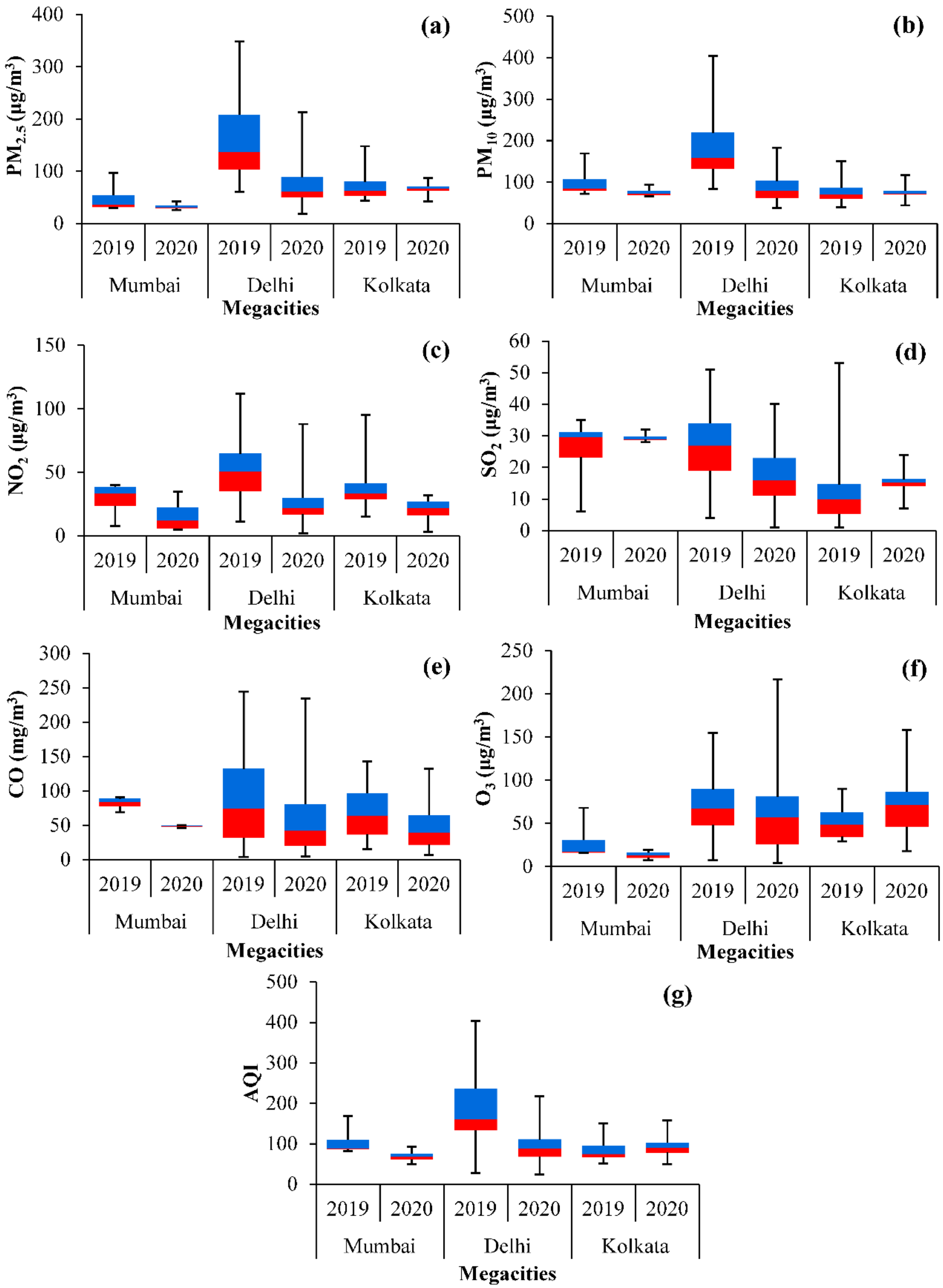


Fig. 5.6 Changes in average concentrations of (a) $PM_{2.5}$, (b)PM_{10}, (c) NO_2, (d) SO_2, (e) CO, (f) O_3, and (g) AQI between 25 March to 14 April 2019 and 25 March to 14 April 2020 observed in all three megacities. The lower and upper end of the box represents the first (Q_1) and the third (Q_3) quartile. The divider of the box represents the median. The error bars represent the minimum and the maximum values.

Table 5.4 Average concentration of air pollutants in Mumbai (Bandra), Delhi (ITO), and Kolkata (RBU) for the period of 25 March to 14 April during 2019 and 2020

Pollutants	Megacities	25 March to 14 April 2019	25 March to 14 April 2020	Total variation Avg.	% of variation
$PM_{2.5}$ (µg/m^3)	Mumbai	49.75±31.79	32.50±6.81	-17.25	-34.67
	Delhi	177.00±86.92	147.33±76.05	-29.67	-16.76
	Kolkata	128.75±91.02	87.75±36.09	-41.00	-31.84
PM_{10} (µg/m^3)	Mumbai	102.25±44.89	76.00±11.92	-26.25	-25.67
	Delhi	161.25±85.18	77.75±26.55	-83.50	-51.78
	Kolkata	115.00±54.72	79.75±24.45	-35.25	-30.65
NO_2 (µg/m^3)	Mumbai	28.75±14.64	16.00±13.98	-12.75	-44.35
	Delhi	28.00±14.44	29.75±13.67	1.75	6.25
	Kolkata	75.25±56.02	30.75±9.46	-44.50	-59.14
NH_3 (µg/m^3)	Mumbai	NM*	NM	NM	NM
	Delhi	5.00±1.22	3.75±1.50	-1.25	-25.00
	Kolkata	4.00±0.82	8.50±1.00	4.50	112.50
SO_2 (µg/m^3)	Mumbai	25.00±12.94	29.50±1.73	4.50	18.00
	Delhi	22.75±13.30	19.75±4.35	-3.00	-13.19
	Kolkata	10.75±10.56	17.25±2.75	6.50	60.47
CO (mg/m^3)	Mumbai	82.00±9.83	48.50±1.91	-33.50	-40.85
	Delhi	39.00±18.17	46.00±33.18	7.00	17.95
	Kolkata	18.75±2.63	10.50±3.11	-8.25	-44.00
O_3 (µg/m^3)	Mumbai	29.50±25.68	13.00±8.49	-16.50	-55.93
	Delhi	24.50±4.80	60.50±8.19	36.00	146.94
	Kolkata	58.75±23.17	66.50±16.38	7.75	13.19

*NM=not measured

5.2.2 Changes in the concentration of NO_2

NO_2 helps in the O_3 formation in the troposphere, and it also leads to aerosol formation. The concentration of NO_2 substantially reduced in India during the lockdown period (NASA, 2020; ESA, 2020; Muhammad et al., 2020; Bera et al., 2020; Ghosh and Ghosh, 2020; Mahato et al., 2020). Fig. 5.1e shows a significant decline in NO_2 in megacities due to the COVID-19 lockdown. The same decline was also noticed in the post-lockdown phase (Fig. 5.1f). NO_2 concentration was below the permissible limit of 80 µg/m^3 in all three phases of pre-lockdown, lockdown, and post-lockdown.

The NO_2 concentration in the pre-lockdown for Mumbai, Delhi, and Kolkata were 12.11–69.00 μg/m^3; 28.97–57.58 μg/m^3; and 39.30–60.80 μg/m^3, whereas during the lockdown those were 6.33–16.00 μg/m^3; 23.53–30.42 μg/m^3; and 8.80–24.50 μg/m^3. During the post-lockdown period, the NO_2 concentrations varied from 8.50–9.60 μg/m^3, 19.04–26.13 μg/m^3, and 11.67–14.43 μg/m^3, respectively (Table 5.1). The pre-lockdown concentrations were higher, while during lockdown, a significant drop was noted across the megacities. The continuous fall was also noted in the post-lockdown period. Hence, improvements in air quality (NO_2) were observed across India's megacities during the COVID-19-induced lockdown.

The average concentration of NO_2 was reduced by about -68.33%, -40.36%, and -62.37% in lockdown for Mumbai, Delhi, and Kolkata, respectively (Table 5.2). Their post-lockdown reduction was -19.35%, -11.51%, and -28.90% for those megacities (Table 5.3). Therefore, the highest reduction was recorded in Kolkata (-31.13 & -5.43 μg/m^3), followed by Mumbai (-24.26 & -2.17 μg/m^3) and Delhi (-18.02 & -3.07 μg/m^3) during both the lockdown and post-lockdown phases. Nationwide, strict lockdowns and the new normal post-lockdown checked NO_2 levels. Hence, with the lower concentration of this pollutant, the impact on human health was nominal, i.e., good air quality (Table 1.3). On the other hand, this may reduce the precursor of O_3 formation and aerosol formation in the troposphere.

The sharp improvement in air quality across all three megacities during lockdown and post-lockdown, compared to pre-lockdown, is shown here (Figs. 5.3, 5.4, 5.5). I found that just one day after the nationwide lockdown began, a remarkable improvement in NO_2 levels was observed compared to pre-lockdown levels in all three megacities. It lasted up to 14 April 2020. The western part of Delhi, Kolkata, and the eastern part of Mumbai have experienced unhealthy air quality.

The box plots (Fig. 5.6c) show that NO_2 levels have decreased in megacities in India during the lockdown year (2020). The high range, 30.75–75.25 μg/m^3, with the highest average concentration in Kolkata, was at the top, followed by Mumbai and Delhi during the same time the previous year (2019). Mumbai and Kolkata experienced decreases of approximately -44.35% and -59.14%, respectively, during the lockdown period compared to 2019, while Delhi recorded a slight increase of 6.25% (Table 5.4).

5.2.3 Changes in the concentration of NH_3

NH_3 is a highly reactive and soluble alkaline gas. The agricultural fields, the additional amount added from petrol cars, industry, and sewage are the principal sources of NH_3 (Sutton et al., 2000; Wilson et al., 2004). The nationwide lockdown played a significant role in regulating its concentration. Its concentration substantially declined in all three megacities during the lockdown period (Fig. 5.1g). The same decline was also observed in post-lockdown Mumbai and Kolkata, except in Delhi (Fig. 5.1h). The average NH_3 concentrations were very low, not only during the lockdown phase but also in the pre-lockdown and post-lockdown periods, compared to the permissible limit of 400 $\mu g/m^3$ across India's megacities.

The pre-lockdown concentrations of NH_3 in Mumbai, Delhi, and Kolkata were 4.00–5.75 $\mu g/m^3$, 7.54–9.62 $\mu g/m^3$, and 4.80–6.90 $\mu g/m^3$, respectively. During the lockdown, those ranges were 2.17–4.63 $\mu g/m^3$, 5.17–8.15 $\mu g/m^3$, and 3.00–4.40 $\mu g/m^3$, respectively (Table 5.1). The post-lockdown concentrations were 2.00–3.33 $\mu g/m^3$, 6.91–7.65 $\mu g/m^3$, and 1.57–2.70 $\mu g/m^3$ for those megacities. Hence, NH_3 concentrations in Delhi were slightly higher compared to the other two megacities.

During the lockdown, Mumbai, Delhi, and Kolkata witnessed a reduction of -33.39%, -17.39%, and -32.44% in NH_3 levels, respectively (Table 5.2). The post-lockdown reductions were -20.51% and -38.64% in Mumbai and Kolkata, respectively, while Delhi recorded an increase of 8.40% (Table 5.3). Therefore, Kolkata recorded the maximum decline (-1.83 and -1.47 $\mu g/m^3$), followed by Mumbai (-1.63 and -0.67 $\mu g/m^3$) and Delhi (-1.42 and 0.57 $\mu g/m^3$). Such a nominal concentration of NH_3 in all the phases is a healthy sign for the lower tropospheric atmosphere.

The spatial maps showing the gradual decrease in NH_3 levels in all three phases (pre-lockdown, lockdown, and post-lockdown) are illustrated in Figs. 5.3, 5.4, 5.5. However, the scenario changed slightly after two to three weeks due to partial relaxation of necessary transportation and controlled industrial activity outside the COVID-19-infected or containment zones declared by the Government for Delhi (Mahato et al., 2020; Srivastava et al., 2020; Kumar et al., 2020).

NH_3 records for Mumbai in 2019 were not available on the CPCB website due to a technical error. Delhi witnessed a decline from 5.00 to 3.75 $\mu g/m^3$ during the lockdown year 2020 compared to the previous year 2019 (Table 5.4). On the other hand, Kolkata witnessed an increase (4.00 to 8.50 μg/m^3) from 2019 to 2020. Therefore, NH_3 showed mixed results in India's megacities between 2019 and 2020.

5.2.4 Changes in the concentration of SO_2

SO_2 is a colourless gas that is very harmful to plant, animal, and human health. People with lung diseases, children, older people, and those who are more exposed to SO_2 are at higher risk of skin and lung diseases (Ghorani-Azam et al., 2016). The COVID-19 lockdown led to a decline in SO_2 levels in India's megacities (Fig. 5.2i). Compared with pre-lockdown concentrations, lockdown-phase concentrations were lower in all three megacities. However, the post-lockdown trend changed, except for Kolkata. Mumbai and Delhi exhibited a rising trend during the post-lockdown phase (Fig. 5.2j). The concentration of SO_2 was very low compared to the permissible limit of 80 μg/m^3 for all three phases, pre-lockdown, during-lockdown, and post-lockdown.

The pre-lockdown concentration of SO_2 in Mumbai, Delhi, and Kolkata varied as 15.50–21.38 μg/m^3; 18.19–21.17 μg/m^3; and 15.50–18.10 μg/m^3, respectively, whereas during the lockdown those were 9.86–11.00 μg/m^3; 14.48–20.52 μg/m^3; and 7.60–17.30 μg/m^3; and during the post-lockdown phase, the ranges were 10.14–46.00 μg/m^3; 15.30–19.47 μg/m^3; and 6.78–11.86 μg/m^3, respectively (Table 5.1). The pre-lockdown concentrations were higher, but during the lockdown, a significant decline was observed across the megacities. The continuous drop was also noted in post-lockdown, only in Kolkata. Overall, significant improvements in air quality, reflected in reduced SO_2 levels, were observed across India's megacities during the COVID-19 lockdown.

The average SO_2 concentration was reduced by about -42.11%, -13.91%, and -20.88% in Mumbai, Delhi, and Kolkata, respectively, during the lockdown (Table 5.2). The only post-lockdown reduction was -35.07% in Kolkata. In comparison, the rise in Mumbai and Delhi was 106.57% and 5.96%, respectively (Table 5.3). The concentration of SO_2 in Delhi was higher compared to the other two megacities. For that reason, Delhi can occasionally experience acid rain in the central city and the suburbs. However, due to low overall SO_2 concentrations below the threshold, the megacities of India enjoyed good-quality air with no health impact (Table 1.3).

The spatial patterns of SO_2 are illustrated in Figs. 5.3, 5.4, 5.5. The box plots (Fig. 5.6d) show that SO_2 levels fluctuated in megacities of India (2020). The maximum average concentration was in Mumbai, followed by Delhi and Kolkata. Delhi recorded a decline (-13.19%), while Mumbai (18.00%) and Kolkata (60.47%) recorded increases in SO_2 compared to the previous year, 2019 (Table 5.4).

5.2.5 Changes in the concentration of CO

CO is a colourless and odourless gas. Its excessive concentrations can lead to headaches, dizziness, weakness, nausea, vomiting, and loss of consciousness, which affect human health (Ghorani-Azam et al., 2016). The concentration of CO has remarkably reduced in India during the lockdown period (Bera et al., 2020). Fig. 5.2k shows a significant decline in CO in megacities due to the pandemic-induced lockdown. The post-lockdown trend has remained the same (a decline) in Mumbai and Kolkata; however, Delhi has remained an exception (Fig. 5.2l). All recorded values were well above the permissible limit (2 mg/m^3), with a noticeable impact on human health and the environment.

The CO concentrations during the pre-lockdown phase for Mumbai, Delhi, and Kolkata varied as 17.78–50.70 mg/m^3; 30.69–37.53 mg/m^3; and 19.40–31.40 mg/m^3, respectively, whereas during the lockdown those were 17.13–29.71 mg/m^3; 24.85–41.43 mg/m^3; and 16.90–20.60 mg/m^3, respectively (Table 5.1). The megacities in the same order exhibited a post-lockdown variation of 17.38–26.86 mg/m^3, 35.44–42.43 mg/m^3, and 16.10–19.57 mg/m^3, respectively.

The average CO concentration decreased by about -26.61%, -.25%, and -20.92% in Mumbai, Delhi, and Kolkata, respectively (Table 5.2). Mumbai (-5.86%) and Kolkata (-8.75%) continued to show a steady decline in concentration. In contrast, Delhi experienced a rise (26.28%) again in the post-lockdown phase. The spatial pattern map for the megacities of Mumbai and Delhi recorded a fall in lockdown (Figs. 5.3, 5.4). The megacity Kolkata has noted a gradual decline from 17 March to 31 March and from 21 April (Fig. 5.5). Overall, CO levels did not improve significantly due to the lockdown. High CO levels can cause Anoxemia, which, in turn, can lead to various cardiovascular problems; infants, pregnant women, and older people are at high risk due to its high concentration in the lower troposphere.

In a similar period to the previous year, 2019, and the lockdown period of 2020, the average CO concentrations have reduced by about -40.85% and -44.00% in Mumbai and Kolkata, respectively. However, in Delhi, the CO concentrations increased (17.95%) (Table 5.4). Hence, Kolkata witnessed extreme change, followed by Mumbai and Delhi in 2019–2020 (Fig. 5.6e).

5.2.6 Changes in the concentration of O_3

O_3 is a colourless gas produced by a chemical reaction between NO_x and VOCs emitted from natural sources and domestic activities (Ghorani-Azam et al., 2016). With rising ground-level O_3, the risk of respiratory diseases, particularly asthma, increases. The declining trend of O_3 is illustrated in Fig. 5.2m. The post-lockdown trend has remained the same (decline) for Mumbai, Kolkata, and Delhi, as in the case of many other pollutants, which exhibited an increase (Fig. 5.2n). Except for Kolkata, the other two megacities had O_3 levels below the CPCB-permissible limit (60 $\mu g/m^3$) in both the pre-lockdown and lockdown phases. Post-lockdown concentrations were below the limit in Mumbai, whereas concentrations were inconsistent in Delhi and Kolkata. High concentrations lead to various health problems, such as asthma and bronchitis, and harmful effects on plants, as they interfere with photosynthesis and cause the death of plant tissues by facilitating the formation of PAN.

The O_3 varied as 28.50–80.10 $\mu g/m^3$; 57.31–84.94 $\mu g/m^3$; and 79.90–110.78 $\mu g/m^3$ for Mumbai, Delhi, and Kolkata in pre-lockdown, whereas during the lockdown the ranges were 25.43–40.44 $\mu g/m^3$; 50.89–74.57 $\mu g/m^3$; and 49.67–97.33 $\mu g/m^3$ respectively (Table 5.1). The post-lockdown variation was 19.00–30.50 $\mu g/m^3$, 75.36–99.50 $\mu g/m^3$, and 42.22–100.43 $\mu g/m^3$ for the megacities in the same order.

The average O_3 concentrations were reduced by about -25.30%, -19.37%, and -21.13% during the lockdown phase in Mumbai, Delhi, and Kolkata, respectively (Table 5.2). The megacity of Delhi noted a rising (48.59%) concentration, and the rest of the two have remained the same, -29.43% and -23.85%, respectively, in the post-lockdown period (Table 5.3). Therefore, Mumbai and Kolkata experienced a continuous drop in O_3 concentration, whereas Delhi experienced an increase during the post-lockdown phase.

I found a steady increase in O_3 from 17 March to 14 April in the spatial distribution maps for Mumbai and Kolkata (Figs. 5.3, 5.5). Megacity Delhi has recorded a sequential fall and rise in lockdown and post-lockdown conditions (Fig. 5.4). The partial relaxation of transport services and industry sectors in Delhi increased O_3 levels.

Compared to the previous year (2019), the average O_3 concentration during the COVID-19 period (2020) decreased by about 55.93% in Mumbai (Table 5.4). Delhi and Kolkata, in contrast, showed increases in O_3 levels (Fig. 5.6f).

5.2.7 Changes in the AQI

The declining trend of AQI is shown for the period of lockdown in Fig. 5.2o. The post-lockdown trend has remained the same (a decline) in Mumbai and Kolkata, with Delhi as an exception (Fig. 5.2p). Mumbai air quality ranged from moderate to satisfactory; Delhi, from poor to satisfactory; and Kolkata, from moderate to good (according to CPCB standards). Overall, the temporal change in AQI in 2020 showed significant improvement in air quality during the lockdown and post-lockdown phases compared to the pre-lockdown phase.

Spatial changes in AQI for all three megacities are shown in Figs. 5.3, 5.4, 5.5 on the selected dates of 17 March, 31 March, and 21 April. I found that Mumbai had better air quality than the other two megacities across all three phases (pre-, during-, and post-lockdown). The southeastern part of the megacities Delhi and Kolkata, as well as the western part of Mumbai, had better air quality. Hence, the lockdown appeared to improve air quality to varying degrees across all three megacities.

The average magnitude of AQI in all three phases (pre-lockdown, lockdown, and post-lockdown) were very close to each other (Table 5.2). The AQI range in pre-lockdown and lockdown was highest for Delhi (164.53–96.42), followed by Kolkata (152.78–86.48) and Mumbai (129.29–75.50). The post-lockdown variations were 75.5–55.2, 96.42–109.89, and 86.48–58.47 for Mumbai, Delhi, and Kolkata, respectively (Table 5.3). Therefore, Delhi was in the worst condition. Kolkata was the second most polluted megacity in India. Mumbai had lower air pollution levels.

The box plots (Fig. 5.6g) show that the AQI level decreased in megacities of India during the lockdown year 2020 compared to the previous year, 2019. Delhi was the worst megacity in the high range, with maximum average concentrations, followed by Kolkata and Mumbai.

5.2.8 Correlation between ambient air pollutants

Pearson correlation coefficient matrices with scatter plots for air pollutants were derived for all three megacities of India for the period from 3 March to 5 May 2020. The daily average concentration of $PM_{2.5}$, PM_{10}, and NO_2 had a strong significant positive relationship in Mumbai (r = 0.97**, 0.97**, and 0.95**); Delhi (r = 0.96**, 0.91**, and 0.91**) and Kolkata (0.98**, 0.92**, and 0.91**) (Fig. 5.7a, b, c) (* denotes $p < 0.05$; ** denotes $p < 0.01$). The combined concentrations of air pollutants affected not only human health but also the environment. The correlations between ambient air pollutants were not always strong. A weak positive relationship was also detected often. The daily (24 h) average concentration of $PM_{2.5}$ moderately correlated with the daily (24 h) average NH_3 concentration in Mumbai (r = 0.63) and Delhi (r = 0.66); however, the relationships were not significant. In Kolkata, the same couple exhibited a significant positive correlation (r = 0.91*). The relationship between $PM_{2.5}$ and SO_2 was near zero or absent in Mumbai, whereas in Kolkata, a significant positive relationship was observed (r = 0.77*). Likewise, $PM_{2.5}$ and CO were strongly correlated in Mumbai and Kolkata (r = 0.85*, r = 0.82*), but in Delhi, the relationship was weakly positive. $PM_{2.5}$ and O_3 were strongly correlated (r = 0.89**) in Mumbai but showed no relationship (r = 0.04) in Delhi.

The daily (24 h) average concentration of PM_{10} moderately correlated with the daily (24 h) average NH_3 in Mumbai (r = 0.71) and Delhi (r = 0.60), whereas in Kolkata it showed a strongly significant positive relationship (r = 0.90*). The relationships between PM_{10} and SO_2 were moderately positive (r = 0.67) in Delhi, strongly significant and positive (r = 0.85*) in Kolkata, but no relationship was noted in Mumbai. Likewise, PM_{10} and CO showed strong correlations (r = 0.77*, r = 0.78*) in Mumbai and Kolkata, whereas Delhi showed a very poor positive correlation. The PM_{10} and O_3 showed a strong correlation

(r = 0.82*) in Mumbai, a moderate one (r = 0.69) in Kolkata, and no correlation (r = 0.03) in Delhi.

The relationships between NO_2 and NH_3 were moderately positive in Mumbai and Delhi. At the same time, there was a very strong positive correlation (r = 0.93**) in Kolkata. The NO_2 with pollutants of SO_2 strongly and significantly correlated (r = 0.77*) in Kolkata. At the same time, moderate and almost no relations took place in Delhi and Mumbai. The relationships between NO_2 and CO were strongly significant (r = 0.81*, r = 0.77*) in Mumbai and Kolkata, while Delhi had a weak relation. The NO_2 and O_3 were strongly and significantly correlated (r = 0.87*) in Mumbai and moderately correlated (r = 0.61) in Kolkata. However, there was a very weakly negative correlation in Delhi.

On the other hand, a strong, significant positive relation (r = 0.84*) between CO and O_3 was observed in Mumbai. Likewise, NH_3 and SO_2; SO_2 and O_3 were also noted strong significant positive relationship (r = 0.77*, r = 0.84*) in Kolkata. Hence, except for the daily average concentrations of $PM_{2.5}$, PM_{10}, and NO_2, the remaining four pollutants (NH_3, SO_2, CO, and O_3) showed a 100% positive correlation; they were not always significantly correlated across all three megacities.

(a)

Mumbai	$PM_{2.5}$	PM_{10}	NO_2	NH_3	SO_2	CO	O_3
$PM_{2.5}$							
PM_{10}	0.97**						
NO_2	0.97**	0.95**					
NH_3	0.63	0.71	0.69				
SO_2	0.03	0.00	0.08	-0.15			
CO	0.846*	0.769*	0.810*	0.37	-0.03		
O_3	0.89**	0.82*	0.87*	0.59	-0.04	0.84*	

(b)

Delhi	$PM_{2.5}$	PM_{10}	NO_2	NH_3	SO_2	CO	O_3
$PM_{2.5}$							
PM_{10}	0.96**						
NO_2	0.91**	0.91**					
NH_3	0.66	0.60	0.70				
SO_2	0.68	0.67	0.39	0.31			
CO	0.21	0.27	0.15	0.32	0.55		
O_3	0.04	0.03	-0.20	0.08	0.49	0.53	

(c)

Kolkata	$PM_{2.5}$	PM_{10}	NO_2	NH_3	SO_2	CO	O_3
$PM_{2.5}$							
PM_{10}	0.98**						
NO_2	0.92**	0.91**					
NH_3	0.91**	0.90**	0.93**				
SO_2	0.770*	0.835*	0.772*	0.777*			
CO	0.82*	0.78*	0.77*	0.75	0.56		
O_3	0.59	0.69	0.61	0.49	0.840*	0.31	

Fig. 5.7. The Pearson correlation coefficient matrices show the relationship between the different air pollutants across the megacities of (a) Mumbai, (b) Delhi, and (c) Kolkata. The dots represent the scatter plots between the respective parameters. [*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed)].

5.2.9 Role of meteorological parameters

The mean ± standard deviation of air temperature, relative humidity, wind speed, and total rainfall observed from 3 March to 23 March, 25 March to 14 April, and 15 April to 5 May for the years 2019 and 2020 are illustrated in Fig. 5.8. Air temperature exhibited an increasing trend from March to May in all three megacities; however, the trend was most prominent in Delhi. The same trend was observed in both 2019 and 2020. An increase in ground-level air temperature destabilizes the atmosphere and facilitates greater vertical mixing of pollutants (Cichowicz et al., 2017). Thus, increasing air temperature reduces pollutant concentrations at ground level (Ravindra et al., 2019). From Fig. 5.8, it is evident that air temperature increased during the lockdown period compared to the pre-lockdown phase. Hence, a fraction of the reduction in pollutant concentration can be attributed to this increase in temperature. However, the degree of increase in air temperature during the same period was the same in the previous year (2019) ($p > 0.05$). Despite similar increases in temperature in 2019 and 2020, the concentration of several pollutants was lower during the 2020 lockdown. Thus, the effect of lockdown cannot be ignored.

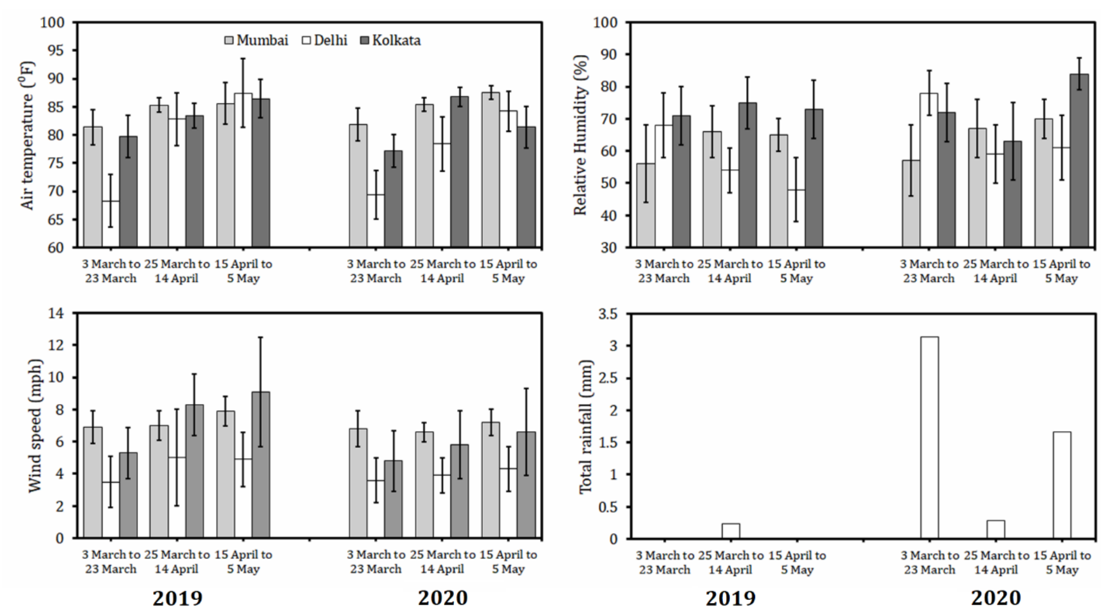


Fig. 5.8 The column graph showing the monthly mean of the meteorological parameters (air temperature, relative humidity, and wind speed) and total rainfall observed during March, April, and May in the years 2019 and 2020 in Mumbai, Delhi, and Kolkata. The error bars denote the standard deviation from the mean.

Like higher air temperature, higher wind speed also facilitates the dispersal of pollutants (Li et al., 2020), except for some pollutants, such as PM_{10}, which are resuspended at ground level due to higher wind speed (Zhang et al., 2018). Mumbai did not exhibit a significant difference in wind speed between the pre-lockdown and lockdown phases; however, the difference was noticeable in Kolkata and Delhi. However, the overall mean wind speed for 2019 and 2020 did not differ significantly between Delhi and Mumbai ($p > 0.05$). The wind speed in Kolkata for the year 2019 was significantly higher than that observed in the year 2020. If wind speed had played a crucial role in governing the pollutant concentrations, an increase in pollutant levels could have been expected in Kolkata. However, except for O_3 and NH_3, all the other pollutants were reduced in 2020 compared to 2019. Thus, it can be inferred that wind speed played a negligible role in reducing the pollutant level during the lockdown.

PM, as well as SO_2 and NO_2, are present in the ground-level atmosphere at lower relative humidity (< 40%), and at higher relative humidity, pollutant concentrations usually decrease (Lou et al., 2017; Munir et al., 2017). However, during the study period in both years, the mean relative humidity never fell below 55% in any phase. Except for Mumbai, relative humidity decreased marginally in Kolkata and Delhi between the pre-lockdown and lockdown phases. Given that relative humidity affects pollutant concentrations, this decrease in relative humidity should have increased pollutant concentrations. However, the present observations indicated otherwise. Thus, it can be inferred that relative humidity also played a negligible role in the reduction in pollutant concentrations during the 2020 lockdown. Like relative humidity, rainfall also helps reduce air pollutants (Yoo et al., 2014); however, there was no rainfall in Mumbai or Kolkata in either year. In Delhi, there was negligible rainfall in both years. Thus, overall, we can infer that, except for air temperature, the other meteorological parameters did not significantly reduce pollutant concentrations during the 2020 lockdown.

Chapter VI

Air Pollution During Diwali in Indian Megacities Amid COVID-19

6.1 Introduction

Diwali, also known as Deepavali, is a festival of lights. In India, people celebrate this auspicious occasion during the post-monsoon months of October or November (Ambade, 2018; Mukherjee et al., 2018). The date of the festival in a particular year varies according to the Hindu lunisolar calendar (Dershowitz and Reingold, 2009). Diwali symbolizes the spiritual victory of light over darkness, good over evil, and wisdom over ignorance (Mathur, 2021), and its celebration involves burning firecrackers and sparklers (Sateesh et al., 2018; Ghei and Sane, 2018). Several festivals in different corners of the world, like the New Year celebrations, the Lantern Festival in China, the Sky Fest in Ireland, and others, include firecrackers (Ambade, 2018, and the references therein). However, Diwali deserves special mention, as hundreds of millions of people usually participate in burning 26 firecrackers. Across the length and breadth of India, several townships, cities, and metropolises, like Ahmedabad (Ganguly et al., 2019), Bangalore (Gowda et al., 2020), Bhopal (Choudhry et al., 2018), Bhubaneswar (Mandal et al., 2020), Chennai (Prakash et al., 2019), Dehradun (Prabhu et al., 2019), Delhi (Mukherjee et al., 2018, Saxena et al., 2020; Singh and Srivastava, 2020; Patel et al., 2021), Faridabad (Sharma et al., 2018), Guwahati (Garaga and Kota, 2018), Hyderabad (Chen et al., 2020), Jabalpur (Srivastava et al., 2014), Jaisalmer (Mahecha et al., 2012), Jamshedpur (Ambade, 2018), Jhansi (Chauhan et al., 2014), Kolkata (Sahu, 2019), Lucknow (Barman et al., 2009), Mumbai (Nanda et al., 2018), Nagpur (Kumar et al., 2017), Nashik (Dhanwate, 2017), Sambalpur (Sahu et al., 2020), Udaipur (Chittora and Kapoor, 2015), Varanasi (Kumar et al., 2016), and Vishakapatnam (Ganguly et al., 2019) recorded a significant rise in air pollutants in the lower troposphere during the Diwali celebrations.

The burning of firecrackers releases an array of harmful chemical compounds (barium nitrate; potassium chlorate, nitrate, and perchlorate; sodium oxalate; strontium nitrate), metals (aluminium, iron oxides, and manganese), metalloids (arsenic), and non-metals (sulphur) into the ambient atmosphere (Kulshrestha et al., 2004; Rajendran et al., 2021). Several flying firecrackers introduce highly toxic VOCs like polychlorinated dibenzodioxins and dibenzofurans into the lower troposphere (Camilleri and Vella, 2010). These compounds have a high residence time in the atmosphere and travel long distances from the place of emission (Klima et al., 2020). The several constituents in the firecrackers, upon burning, lead to an increment in $PM_{2.5}$ levels (Liu et al., 2019). The perturbations caused by the fireworks explosions enhance the PM_{10} and CB levels in the atmosphere (Majumdar et al., 2017). Aerosol concentrations, SO_2, and NO_2 exhibit a sharp increase after firecrackers are lit (Chhabra et al., 2020). Attri et al. (2001) emphasized that the explosion of firecrackers produces O_3 gas even in the absence of NO_X (Attri et al., 2001). Other byproducts, such as CO, CO_2, and NH_3, could significantly pollute the atmosphere from these fireworks (Sawlani et al., 2019). Several pieces of research indicated the human health risks associated with the celebration using firecrackers (Garaga and Kota, 2018; 2020; Prabhu et al., 2019; Gowda et al., 2020; Sahuet al., 2020). High levels of particulate matter (PM_{10} and $PM_{2.5}$) in ambient air cause a range of respiratory problems and cardiovascular disorders (Yunesian et al., 2019). Different types of asthma and obstructive pulmonary diseases are associated with pollutants like SO_2 and NO_2 (Greenberg et al., 2017). Moreover, many of these air pollutants are active carcinogens (Gadi et al., 2019; Kulshreshtha et al., 2021).

At present, the novel coronavirus (COVID-19) is the biggest threat to human society across the globe (Khot and Nadkar, 2020; Rahimi and Abadi, 2020; Zheng, 2020). As of May 2021, the outbreak of this virus had resulted in almost 3.5 million official deaths (https://www.worldometers.info/coronavirus), and many remain uncounted (Wang et al., 2021). The spread of various strains of this virus has worsened the situation globally (Bappy et al., 2021; Duggan et al., 2021; Sarkar et al., 2021). The associated invasive fungal coinfections, such as Black, White, and Yellow fungus, have become another primary concern in combating this pandemic (Moorthy et al., 2021; Nori et al., 2021). Recent studies suggest that air pollution aggravates COVID-19 infectivity and mortality (Coccia, 2021). Travaglio et al. (2021) established a strong link between $PM_{2.5}$ and the spread of coronavirus (Travaglio et al., 2021). Recent research suggests that NO_2 may increase the fatality rate of COVID-19 infections (Ogen, 2020) and that O_3 acts as a carrier and incubator for coronaviruses (Zoran et al., 2020). India is among the worst-affected countries, struggling to cope with this pandemic (Kumari et al., 2021).

To disrupt the spread of COVID-19, the GoI announced a nationwide lockdown on 24 March 2020. Initially, the lockdown was for three weeks (Phase 1); however, the GoI extended it for three more phases, till 31 May 2020 (Soni, 2021). Keeping in mind the economic requirements, from 1 June 2020, some relaxations came into the scenario, and through several unlock phases, society started resuming the pre-COVID-19 life (Gangwar and Roy, 2021). Several studies found that the COVID-19-induced nationwide lockdown significantly improved air quality nationwide (Bera et al., 2021; Naqvi et al., 2021; Ravindra et al., 2021; Sathe et al., 2021). The complete stop of vehicular traffic and a halt to all industrial activities reduced pollutant levels below thresholds in many Indian cities during the lockdown phases. In the year 2020, Diwali was on 14 November. During this time in 2020, India was slowly but steadily recovering from the first wave of COVID-19 spread. Keeping in view the adversities that enhanced air pollution can cause, the Honourable Supreme Court imposed an embargo on the sale or use of all kinds of firecrackers from midnight of 9 November 2020 to 30 November 2020 in all cities and towns across the country.

Despite many such initiatives, the nation witnessed an unexpected second wave from March 2021 (Mallapaty, 2021), peaking in May 2021, when daily infections reached 0.4 million. However, previous studies reported a 34% decline in pollutants during Diwali due to a similar environment-friendly ban on the free sale of firecrackers in 2018 (Kulshreshtha et al., 2021). Concerning this background, the present study aimed to analyze and compare the air quality of three megacities of India (Mumbai, Delhi, and Kolkata) on the auspicious day of Diwali in the year 2020 (in the presence of the COVID-19 pandemic) and the previous year 2019 (in the absence of the pandemic). These three megacities are the most populous and most polluted in the entire country. The scientific literature indicates that the burning of firecrackers in these densely populated regions significantly deteriorates the ambient air quality (Chatterjee et al., 2013; Anand et al., 2019; Sawlani et al., 2019; Chattopadhyay and Shaw, 2021). I hypothesized that, amid an ongoing pandemic, many people must have refrained from burning firecrackers during Diwali, leading to a lower degree of increase in pollutant levels than observed the previous year, when there was no pandemic in the nation. Several studies focused on the effect of burning firecrackers on the air quality during Diwali. Similarly, air pollution levels during a pandemic-induced lockdown have also received substantial attention from the scientific community in recent years. However, none of these studies considered the effects of Diwali celebrations amidst a pandemic scenario. This study reports, for the first time, air pollutant levels in three Indian megacities during Diwali amid the COVID-19 pandemic. The findings of this study are expected to guide policy managers in populous, polluted cities in seeking avenues to create a sustainable urban atmospheric environment. Since air quality management in urban settings has become a challenge for contemporary urban planners, studies like this can serve as eye-openers for both stakeholders and policymakers.

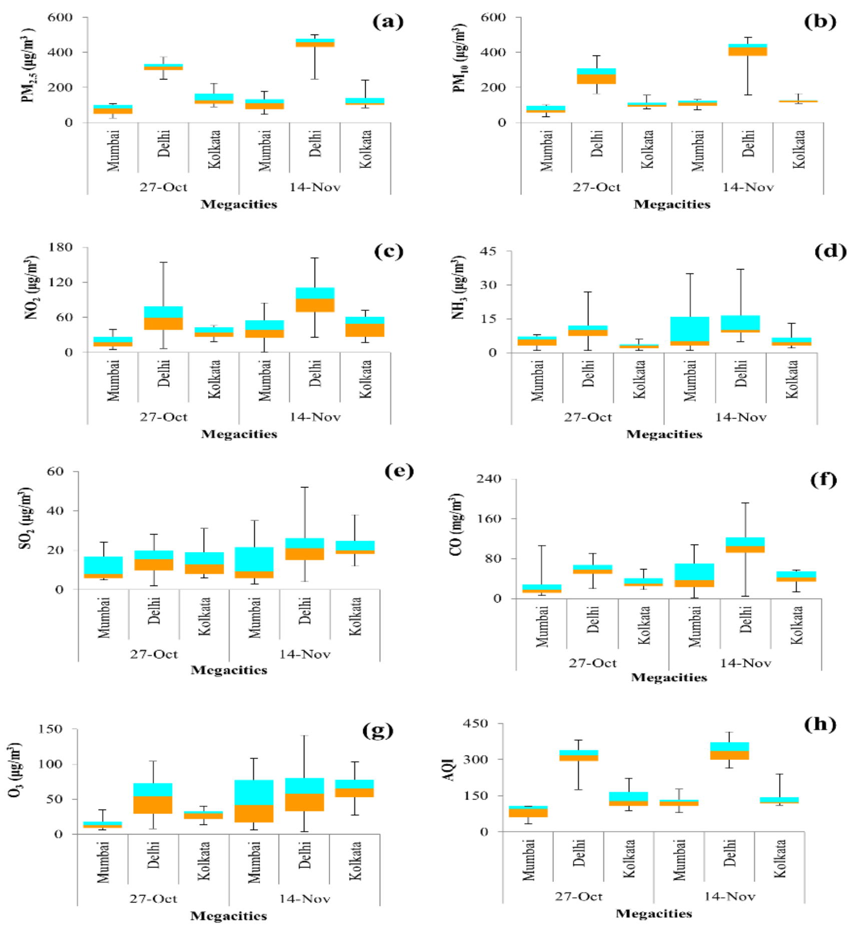


Fig. 6.1 The box plot showing the concentrations of (a) $PM_{2.5}$, (b) PM_{10}, (c) NO_2, (d)NH_3, (e) SO_2, (f) CO, (g) O_3, and (h) AQI at Mumbai, Delhi, and Kolkata on the day of Diwali in two consecutive years (27 October of 2019 and 14 November 2020). The error bars show the maximum and minimum values. The boxes show the first quartile, median, and third quartile from bottom to top.

Table 6.1 Average concentration of air pollutants in Diwali of the previous year (2019) and the lockdown year (2020) across three megacities of India

Source: CPCB (2019; 2020)

Pollutants	Mumbai				Delhi				Kolkata				Permissible Limit*
	27 Oct., 2019	14 Nov., 2020	Net Variation	%	27 Oct., 2019	14 Nov., 2020	Net Variation	%	27 Oct., 2019	14 Nov., 2020	Net Variation	%	
$PM_{2.5}$ ($\mu g/m^3$)	72.88	106.13	33.25	31.33	317.00	442.89	125.89	28.42	138.70	128.20	-10.50	-8.19	60
PM_{10} ($\mu g/m^3$)	72.00	108.80	36.80	33.82	265.97	408.81	142.84	34.94	105.50	128.50	23.00	17.90	100
NO_2 ($\mu g/m^3$)	20.00	41.86	21.86	52.22	62.03	91.68	29.65	32.34	33.60	45.10	11.50	25.50	80
NH_3 ($\mu g/m^3$)	5.25	10.69	5.44	50.90	10.07	13.74	3.67	26.71	3.10	5.20	2.10	40.38	400
SO_2 ($\mu g/m^3$)	11.67	13.92	2.25	16.17	15.03	21.59	6.56	30.38	14.56	22.20	7.64	34.43	80
CO (mg/m^3)	28.00	45.57	17.57	38.56	58.69	111.53	52.84	47.38	33.60	42.00	8.40	20.00	2
O_3 ($\mu g/m^3$)	15.44	48.07	32.63	67.87	54.38	59.11	4.73	8.00	27.90	66.10	38.20	57.79	60
AQI	81.13	122.77	41.64	33.92	314.66	455.61	140.95	30.94	138.70	139.40	0.70	0.50	

* 24 h values for $PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, and 8 h values for CO and O_3

6.2 Results and discussion

6.2.1 Air pollutant concentrations in Diwali 2019 and 2020

To break the chain of COVID-19 transmission, the GOI announced a nationwide lockdown, initially for 21 days, starting on 24 March 2020. Diwali was on 14 November 2020, during the sixth unlock phase, after four successive lockdown periods and five unlock phases. The average concentrations of PM_{10} and CO during Diwali were above the respective permissible limits in all three cities in 2019 and 2020 (Table 6.1). Such high concentrations of PM_{10} prevailed in other cities of India, like Varanasi (Kumar et al., 2020), Nagpur (Rao et al., 2012), and Guwahati (Garaga and Kota, 2018), when there was no pandemic. $PM_{2.5}$ was also beyond the limit in 2019 and 2020. The only exception was Mumbai, which showed a concentration below the threshold during Diwali 2019. Fireworks consist of several fuels, oxidants, agglutinants, propellants, and colouring agents, which, upon burning, enhance the PM load in the ground-level atmosphere (Hoyos et al., 2020). Recent research strongly indicates that both PM_{10} and $PM_{2.5}$ facilitate the spread of coronavirus (Setti et al., 2020) and increase casualties (Yao et al., 2020). Tropospheric O_3 was below the permissible limit in all the instances except for Kolkata, which experienced a higher concentration on Diwali 2020. Similarly, NO_2 levels were within the threshold limits on all occasions, except for Delhi during Diwali 2020. O_3 is usually produced during the daytime through photochemical reactions involving NO_2. However, Attri et al. (2001) argued that several fireworks produce sufficient light to facilitate nighttime photochemical oxidation of NO_2 to produce O_3 (Attri et al.,2001). Preliminary research indicated a high likelihood of enhanced coronavirus spread under elevated NO_2 and O_3 concentrations in respirable air (Ogen, 2020; Zoran et al., 2020). NH_3 and SO_2 were below the permissible limit in all three cities in both years. These observations indicate that there was no significant reduction in air pollutant levels during Diwali amidst the pandemic. On the contrary, to our surprise, almost all the pollutants showed elevated concentrations in Diwali 2020 compared to Diwali 2019. The only exception was Kolkata, where the mean $PM_{2.5}$ concentration in 2020 was lower than in 2019. The difference in $PM_{2.5}$ between Diwali 2019 and Diwali 2020 was statistically significant in Delhi and Mumbai ($p < 0.05$). For PM_{10}, NO_2, CO, and O_3, this difference was significant in all three cities ($p < 0.01$). The increase in NH_3 concentrations in 2020 was significant only in Mumbai ($p < 0.05$). In contrast, for SO_2, the increase was significant for Delhi and Kolkata ($p < 0.05$). Delhi witnessed the highest increment in $PM_{2.5}$ (125.89 μg/m^3), PM_{10} (142.84 μg/m^3), and CO (52.84 mg/m^3). In comparison, Kolkata recorded the highest O_3 level (38.20 μg/m^3) between Diwali 2019 and 2020. The elevated O_3 concentration in Kolkata indicates that large numbers of firecrackers that produce light were burnt, thereby facilitating O_3 production during the nighttime. Similar observations were reported in previous studies (Attri et al., 2001; Nishanth et al., 2012). However, some conflicting opinions suggest that burning firecrackers produces several VOCs, such as phenol and C_6H_6, that mimic O_3 at night (Xu et al., 2018). The percentage of increase (in 2020 compared to 2019) in CO was 47% in Delhi, followed by Mumbai (39%) and Kolkata (20%). Though O_3 did not exceed the permissible limit in Mumbai and Delhi, the increase in its concentration during Diwali in the pandemic year was 68% in Mumbai, followed by Kolkata (58%) and Delhi (8%). $PM_{2.5}$ and PM_{10} recorded a nearly 30% increase in Mumbai and Delhi. CPCB computes the AQI from all pollutant concentrations and serves as a holistic indicator of air pollution. The AQI levels indicate that Delhi was the most polluted megacity, followed by Kolkata and Mumbai, during Diwali in both years. Fig. 6.1 shows the minimum, first quartile, median, third quartile, and maximum values of ambient air pollutants on the day of Diwali in 2019 and 2020. Fig. 6.1a shows that all five $PM_{2.5}$ statistical measures increased in 2020 for Mumbai and Delhi, except in Kolkata. Figs. 6.1b, 6.1c, 6.1d show an overall increase of PM_{10}, NO_2, and NH_3 during Diwali 2020 in all three cities. Fig. 6.1e shows that the first and third quartiles of SO_2 were nearly identical in Mumbai in 2019 and 2020. Kolkata and Delhi showed a similar pattern for CO (Fig. 6.1f) and O_3 (Fig. 6.1g), respectively. Fig. 6.1h shows the descriptive statistics of AQI.

Table 6.2 Average concentration of ambient air pollutants in a normal year (2019) of three megacities in India

Source: CPCB (2021)

Normal year, 2019							Variation							
Pollutants	Megacity	20-Oct	Avg. of 24-26 Oct	27 October, 2019	Avg. of 28-30 Oct	03-Nov	27 October and 20 October		27 October and Avg. of 24-26 Oct		Avg. of 28-30 Oct and 27 October		3 November and 27 October	
							Net	%	Net	%	Net	%	Net	%
$PM_{2.5}$ ($\mu g/m^3$)	Mumbai	29.00	48.67	102.00	144.17	39.00	73.00	71.57	53.33	52.29	42.17	29.25	-63.00	-43.70
	Delhi	227.40	316.50	329.90	418.83	461.20	102.50	30.95	13.40	3.92	88.93	21.38	131.30	27.18
	Kolkata	203.00	77.67	176.00	226.89	186.33	-27.00	-15.34	98.33	55.87	50.89	22.43	10.33	4.55
PM_{10} ($\mu g/m^3$)	Mumbai	37.00	69.67	98.00	121.00	85.00	61.00	62.24	28.34	28.91	23.00	19.01	-13.00	-10.74
	Delhi	181.40	280.03	296.00	414.87	435.11	114.60	37.81	15.97	6.10	118.87	26.38	141.33	30.97
	Kolkata	135.67	75.56	121.00	170.33	159.67	-14.67	-12.12	45.44	37.56	49.33	28.96	38.67	22.70
NO_2 ($\mu g/m^3$)	Mumbai	44.50	46.17	36.00	46.25	34.50	-8.50	-23.61	-10.17	-28.25	10.25	22.16	-1.50	-3.24
	Delhi	62.60	74.90	68.70	77.65	69.90	6.10	10.27	-6.20	-8.28	8.95	11.03	1.20	3.89
	Kolkata	39.00	30.00	33.67	35.78	42.33	-5.33	-15.84	3.67	10.89	2.11	5.90	8.67	24.22
NH_3 ($\mu g/m^3$)	Mumbai	6.00	3.67	8.00	5.34	7.00	2.00	25.00	4.34	54.19	-2.67	-49.95	-1.00	-18.74
	Delhi	8.90	10.50	11.70	14.20	15.20	2.80	24.71	1.20	10.49	2.50	14.83	3.50	18.58
	Kolkata	3.67	4.22	4.33	5.33	6.33	0.67	15.38	0.11	2.56	1.00	18.75	2.00	37.50
SO_2 ($\mu g/m^3$)	Mumbai	16.50	18.00	19.00	17.34	17.50	2.50	13.16	1.00	5.25	-1.67	-9.60	-1.50	-8.65
	Delhi	13.89	16.83	15.40	16.23	11.56	1.22	4.53	-1.43	-8.53	0.83	8.00	-4.22	-23.59
	Kolkata	9.00	8.33	14.33	18.89	22.67	5.33	37.21	6.00	41.86	4.56	24.12	8.33	44.12
CO (mg/m^3)	Mumbai	32.00	30.33	12.00	17.67	21.00	-20.00	-166.67	-18.33	-152.78	5.67	32.07	9.00	50.95
	Delhi	52.00	72.27	61.80	108.23	89.60	9.80	14.14	-10.47	-11.66	46.43	40.83	27.80	23.13

	Kolkata	39.67	29.78	35.33	35.11	32.33	-4.33	-12.26	5.56	15.73	-0.22	-0.64	-3.00	-8.54
O_3 ($\mu g/m^3$)	Mumbai	10.00	10.83	20.00	42.42	14.50	10.00	50.00	9.17	45.84	22.42	52.85	-5.50	-12.97
	Delhi	42.30	69.03	52.90	34.33	21.70	10.60	18.56	-16.13	-25.25	-18.57	-35.49	-31.20	-50.65
	Kolkata	48.00	23.44	28.00	39.22	41.33	-20.00	-71.43	4.56	16.27	11.22	28.61	13.33	33.99
AQI	Mumbai	44.50	71.50	102.00	144.17	85.00	57.50	55.95	30.50	29.52	42.17	29.11	-17.00	-16.67
	Delhi	227.40	312.43	331.30	417.27	479.80	103.90	31.19	18.87	5.69	114.67	21.22	148.50	31.02
	Kolkata	203.00	87.67	176.00	226.89	186.33	-17.00	-10.88	78.00	49.97	42.67	21.68	4.00	3.63

Table 6.3 Average concentration of ambient air pollutants for COVID-19 year (2020) of three megacities in India

Source: CPCB (2021)

COVID-19 year, 2020							Variation							
Pollutants	Megacity	07-Nov	Avg. of 11-13 Nov	14-Nov	Avg. of 15-17 Nov	21-Nov	14 November and 7 November		14 Nov and Avg. of 11-13 Nov		Avg. of 15-17 Nov and 14 Nov		21 November and 14 November	
							Net	%	Net	%	Net	%	Net	%
$PM_{2.5}$ ($\mu g/m^3$)	Mumbai	128.00	169.17	120.50	170.50	197.50	-7.50	-5.29	-48.67	-39.85	50.00	28.49	77.00	39.05
	Delhi	432.00	348.93	473.00	258.93	265.90	41.00	8.67	135.33	28.61	-235.67	-49.82	-245.00	-51.80
	Kolkata	247.00	103.89	130.33	222.45	226.67	-116.67	-89.51	26.44	20.29	92.11	41.41	96.33	42.50
PM_{10} ($\mu g/m^3$)	Mumbai	168.50	168.84	127.00	152.50	190.50	-41.50	-32.52	-41.84	-33.13	25.50	16.51	63.50	33.27
	Delhi	410.60	329.00	437.10	183.92	202.60	26.50	5.93	108.10	25.13	-253.18	-57.92	-234.50	-53.65

	Kolkata	139.33	121.33	138.33	182.00	164.33	-1.00	-0.72	17.00	12.29	43.67	23.99	26.00	15.82
NO_2 ($\mu g/m^3$)	Mumbai	82.50	67.00	58.50	55.67	82.50	-24.00	-46.79	-8.50	-15.44	-2.84	-2.49	24.00	29.78
	Delhi	83.60	80.07	91.90	54.60	56.90	8.30	7.42	11.83	10.57	-37.30	-40.59	-35.00	-38.08
	Kolkata	48.33	55.00	50.00	67.55	50.33	1.67	-2.18	-5.00	-9.71	17.55	24.98	0.33	0.53
NH_3 ($\mu g/m^3$)	Mumbai	33.00	36.33	18.50	17.17	13.50	-14.50	-36.88	-17.83	-41.66	-1.33	-2.05	-5.00	-32.07
	Delhi	12.00	12.90	12.80	11.65	7.90	0.80	5.38	-0.10	-2.11	-1.91	-7.49	-4.90	-31.19
	Kolkata	3.33	9.44	5.00	5.11	5.67	1.67	33.33	-4.44	-88.89	0.11	2.22	0.67	11.76
SO_2 ($\mu g/m^3$)	Mumbai	8.50	9.50	9.50	9.83	12.00	1.00	11.67	0.00	0.00	0.33	3.38	2.50	20.63
	Delhi	20.40	19.53	20.90	19.33	14.80	0.50	1.04	1.37	5.33	-1.57	-8.44	-6.10	-30.48
	Kolkata	32.67	23.44	26.00	36.22	30.00	-6.67	-25.64	2.56	9.83	10.22	28.22	4.00	13.33
CO (mg/m^3)	Mumbai	44.00	39.84	26.50	35.50	43.50	-17.50	-73.61	-13.34	-51.59	9.00	25.90	17.00	38.95
	Delhi	90.10	104.33	114.00	55.03	60.30	23.90	19.52	9.67	7.36	-58.97	-88.46	-53.70	-45.33
	Kolkata	56.33	36.78	43.00	46.00	79.67	-13.33	-31.01	6.22	14.47	3.00	6.52	36.67	46.03
O_3 ($\mu g/m^3$)	Mumbai	33.00	67.33	74.50	74.50	62.00	41.50	52.93	7.17	7.56	0.00	0.12	-12.50	-21.37
	Delhi	45.20	53.47	72.30	43.10	43.90	27.10	38.02	27.00	24.70	-43.67	-36.77	-43.00	-37.63
	Kolkata	78.33	48.56	70.67	59.55	18.33	-7.67	-10.85	22.11	31.29	-11.11	-18.66	-52.33	-285.45
AQI	Mumbai	168.50	186.67	128.00	178.67	197.50	-40.50	-24.04	-58.67	-31.43	50.67	28.36	69.50	34.95
	Delhi	429.30	351.33	472.40	262.73	265.90	43.10	9.08	135.33	26.54	-235.67	-44.21	-245.00	-43.65
	Kolkata	247.00	118.11	139.67	223.44	226.67	-126.00	-50.17	18.17	14.52	80.00	38.84	93.00	42.64

6.2.2 Changes in air pollutant concentrations between pre-Diwali and post-Diwali

Tables 6.2 and 6.3 show the changes in air pollutant concentrations during the pre-Diwali and post-Diwali phases in 2019 and 2020, respectively. $PM_{2.5}$ increased substantially during Diwali 2019 relative to pre-Diwali levels, and concentrations remained elevated for three days after Diwali 2019. In Mumbai and Kolkata, $PM_{2.5}$ levels after 7 days of Diwali were almost back to pre-Diwali levels. However, in Delhi, the concentration continued to increase even 7 days after Diwali (Table 6.2). Earlier studies showed Delhi suffers from elevated $PM_{2.5}$ concentrations, which hampers the air quality and visibility at the ground level (Kumar et al., 2007; Sahu and Kota, 2017). In 2020, the opposite trend prevailed. The $PM_{2.5}$ concentrations increased in the post-Diwali phases in Mumbai and Kolkata. They decreased in Delhi after seven days from Diwali (Table 6.3). PM_{10} concentrations overall significantly increased during Diwali in both years compared to pre-Diwali levels, and remained high even 1 week after Diwali. Delhi was the only exception in 2020, where concentrations one week later reached pre-Diwali levels. NO_2 concentrations were higher during the three days after Diwali 2019 than those observed on the day of Diwali. The increase in motor vehicles already leads to higher NO_2 levels in Delhi, and firecrackers add to that pre-existing load (Ganguly, 2009; Singh, 2010). However, in 2020, Delhi was the only city with higher NO_2 levels on Diwali than on either pre- or post-Diwali days. Mumbai and Kolkata showed no significant difference between the pre-Diwali and post-Diwali phases. NH_3 and SO_2 concentrations increased consistently from pre-Diwali to Diwali and post-Diwali in 2019 and 2020 in Delhi and Kolkata; however, in Mumbai, concentrations decreased gradually after Diwali. CO concentrations declined steadily from pre-Diwali to post-Diwali in Mumbai and Kolkata; however, in Delhi, concentrations increased consistently in both years. O_3 increased in Delhi and Mumbai during the same timeframe; however, Kolkata recorded a steady decrease. AQI, which indicates the overall air pollution level, showed a consistent increase in Delhi even 7 days after Diwali in 2019; however, in the other two cities, the AQI gradually decreased after the event. Diwali 2020 highlights fall for Delhi seven days after the event, while Mumbai and Kolkata gradually increased. Among the changes in air pollutant concentrations observed across different phases, the one between the pre-three-day average and the day of Diwali serves as a proxy for the degree of fireworks. This difference was substantial for all pollutants in Delhi during Diwali 2020, except NH_3.

These results suggest that during the sixth unlock phase, vehicular and industrial emissions were substantially high. These emissions enhanced the pollutant loads in the lower atmosphere even before Diwali (Maji et al., 2021; Ravindra et al., 2021). During Diwali 2020, the general mass believed that India had already seen the worst and was steadily overcoming the pandemic. This perception might have led people to celebrate Diwali as they did in earlier years.

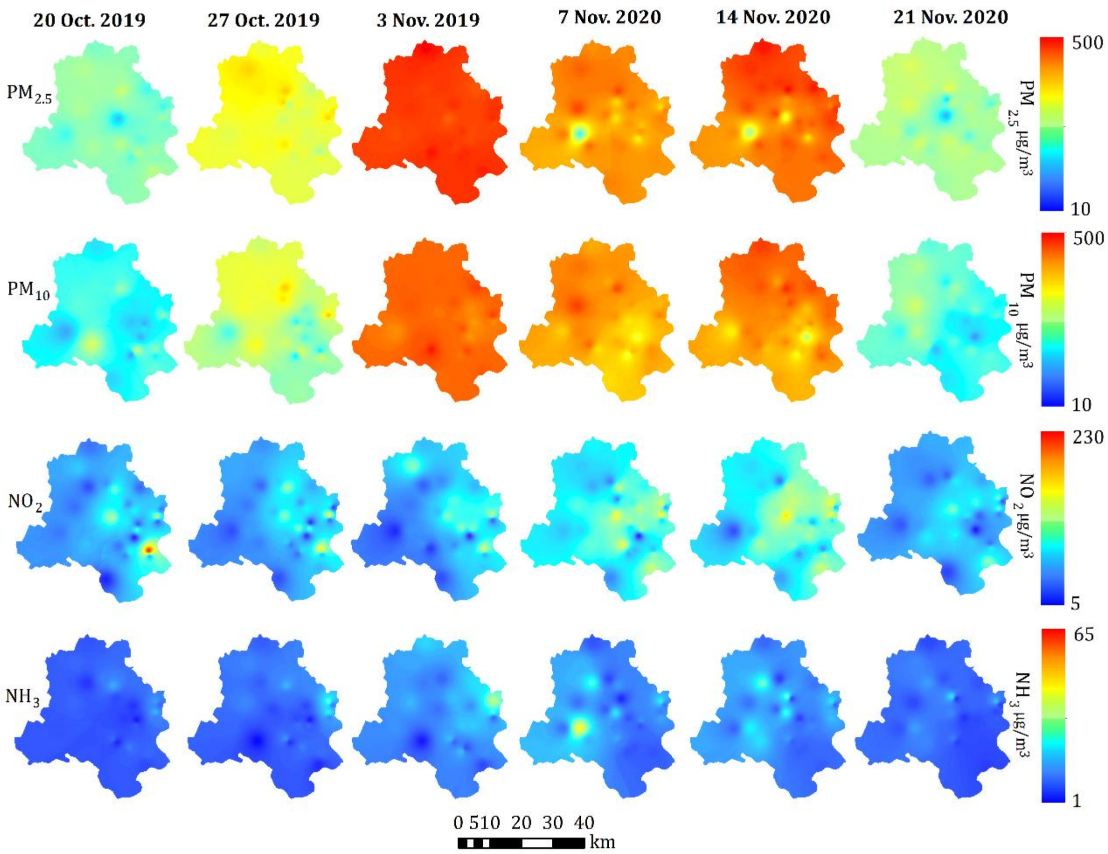


Fig. 6.2 The spatial distribution of $PM_{2.5}$, PM_{10}, NO_2, and NH_3 in Delhi on the seventh day before Diwali, on Diwali, and on the seventh day after Diwali of 2019 and 2020.

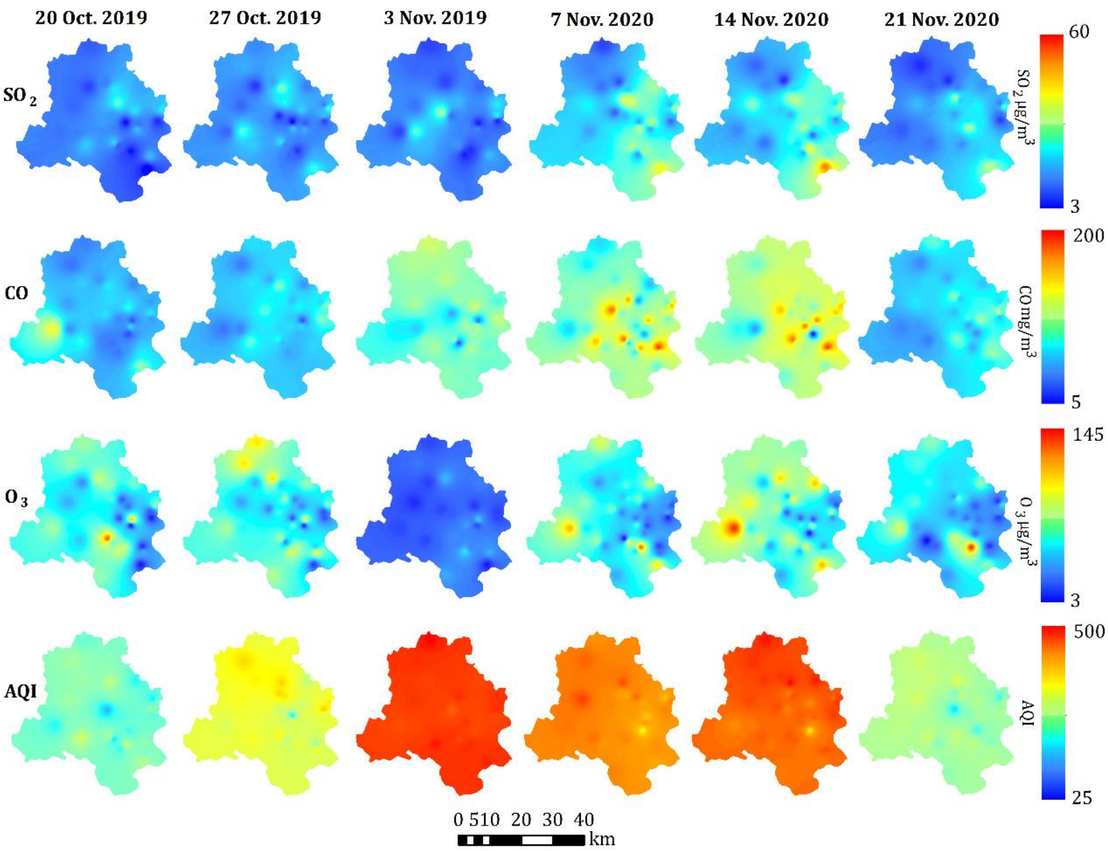


Fig. 6.3 The spatial distribution of SO_2, CO, O_3, and AQI in Delhi on the seventh day before Diwali, on Diwali, and on the seventh day after Diwali of 2019 and 2020.

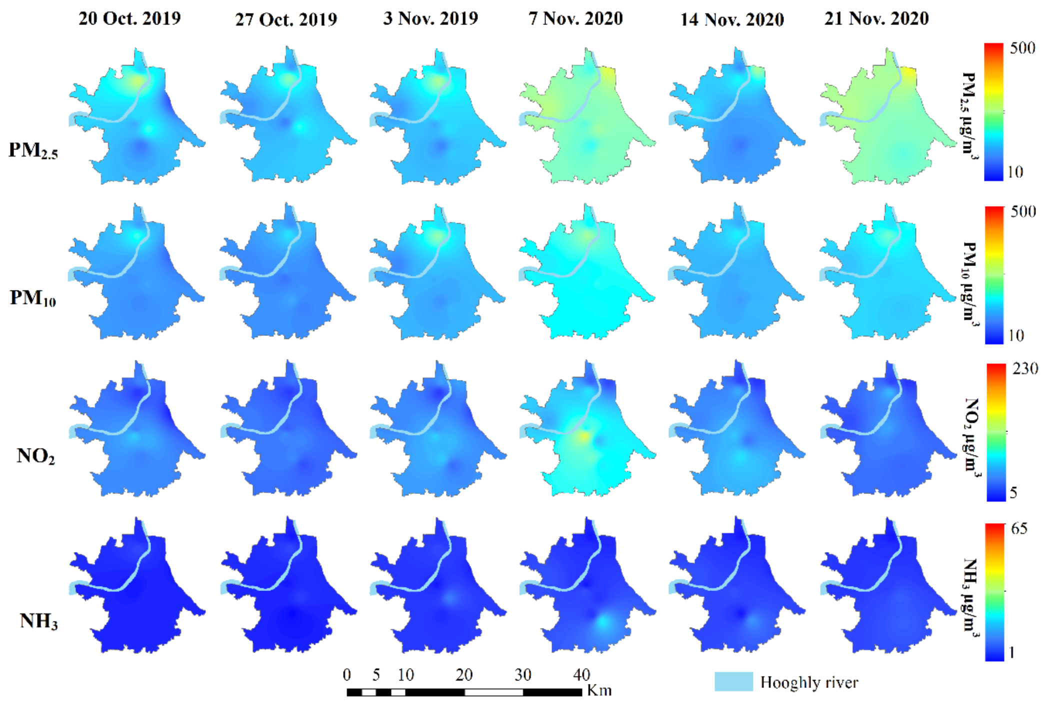


Fig. 6.4 The spatial distribution of $PM_{2.5}$, PM_{10}, NO_2, and NH_3 in Kolkata on the seventh day before Diwali, on Diwali, and on the seventh day after Diwali of 2019 and 2020.

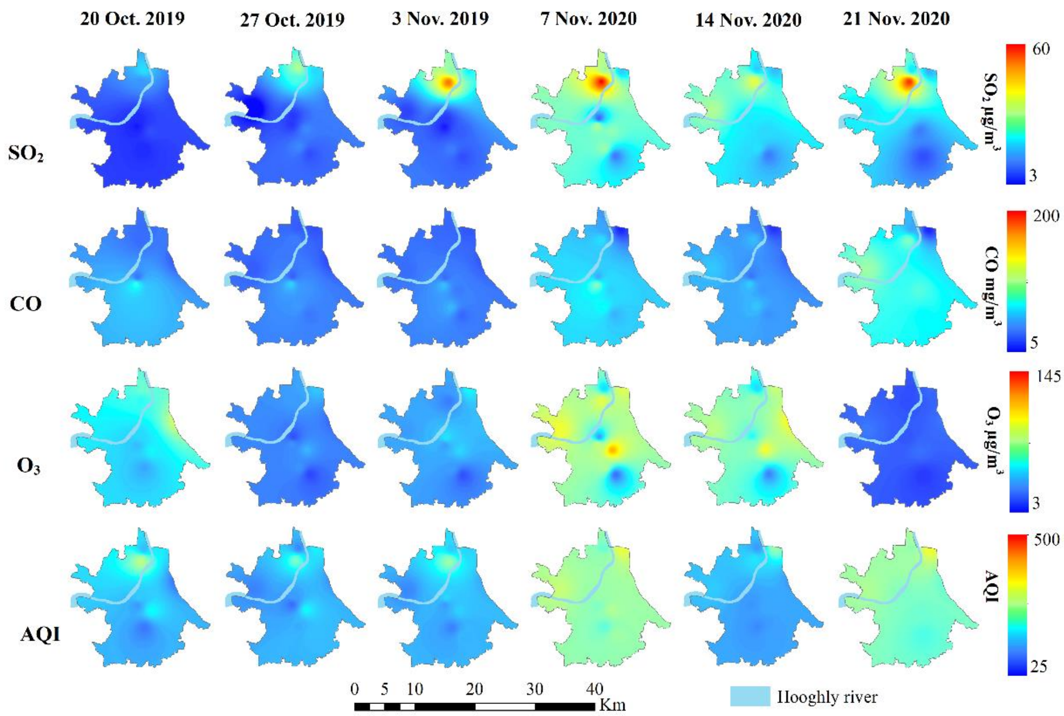


Fig. 6.5 The spatial distribution of SO_2, CO, O_3, and AQI in Kolkata on the seventh day before Diwali, on Diwali, and on the seventh day after Diwali of 2019 and 2020.

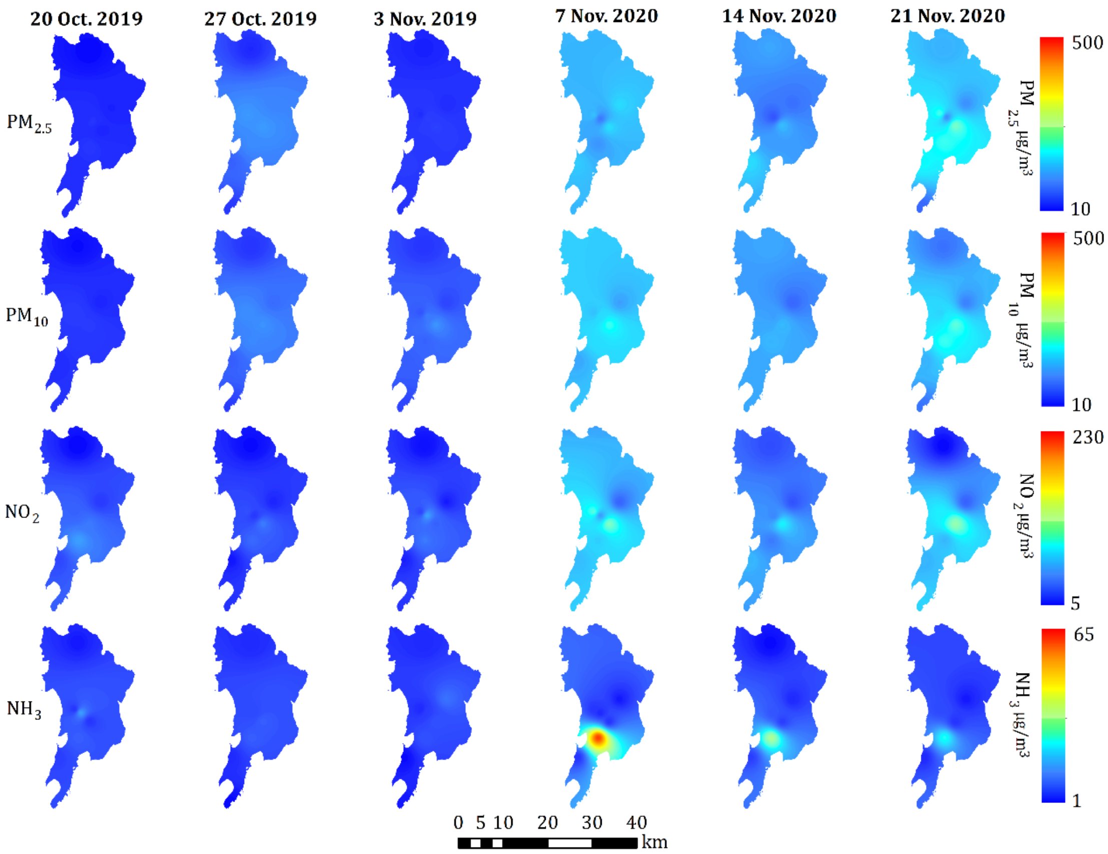


Fig. 6.6 The spatial distribution of SO_2, CO, O_3, and AQI in Mumbai on the seventh day before Diwali, on Diwali, and the seventh day after Diwali of 2019 and 2020

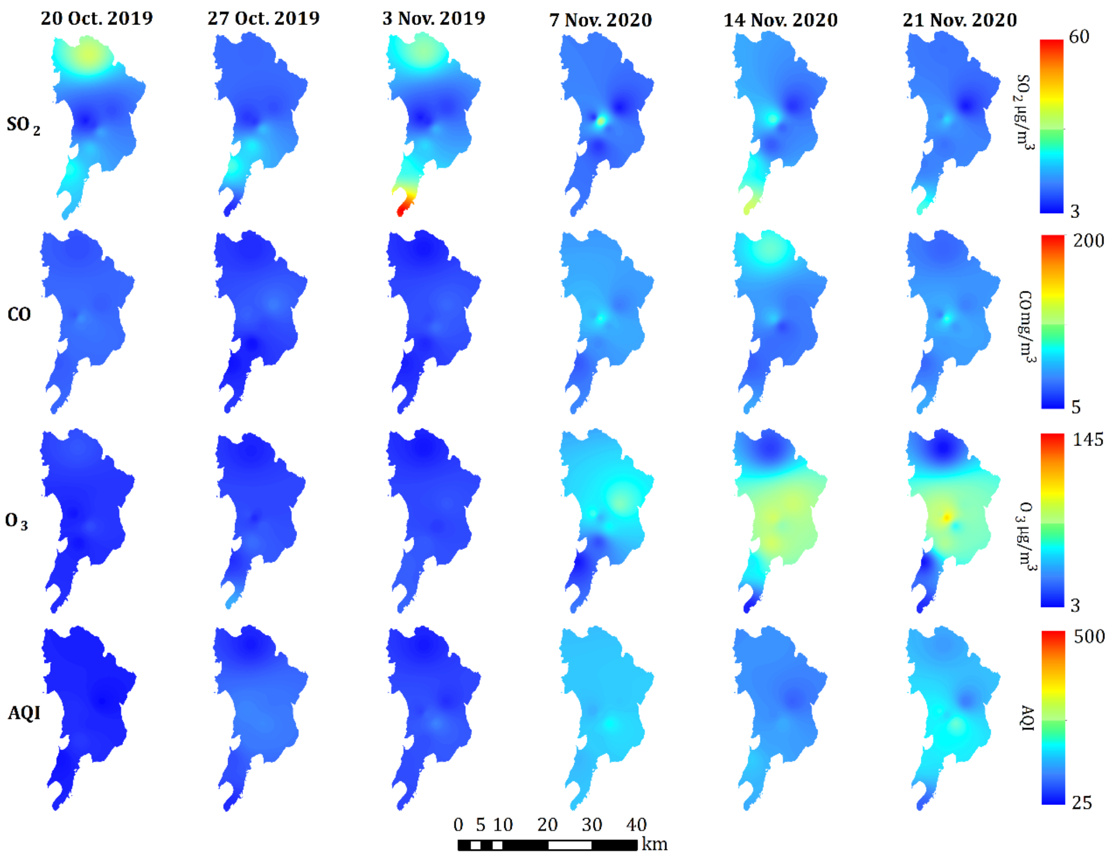


Fig. 6.7 The spatial distribution of SO_2, CO, O_3, and AQI in Mumbai on the seventh day before Diwali, on Diwali, and on the seventh day after Diwali of 2019 and 2020.

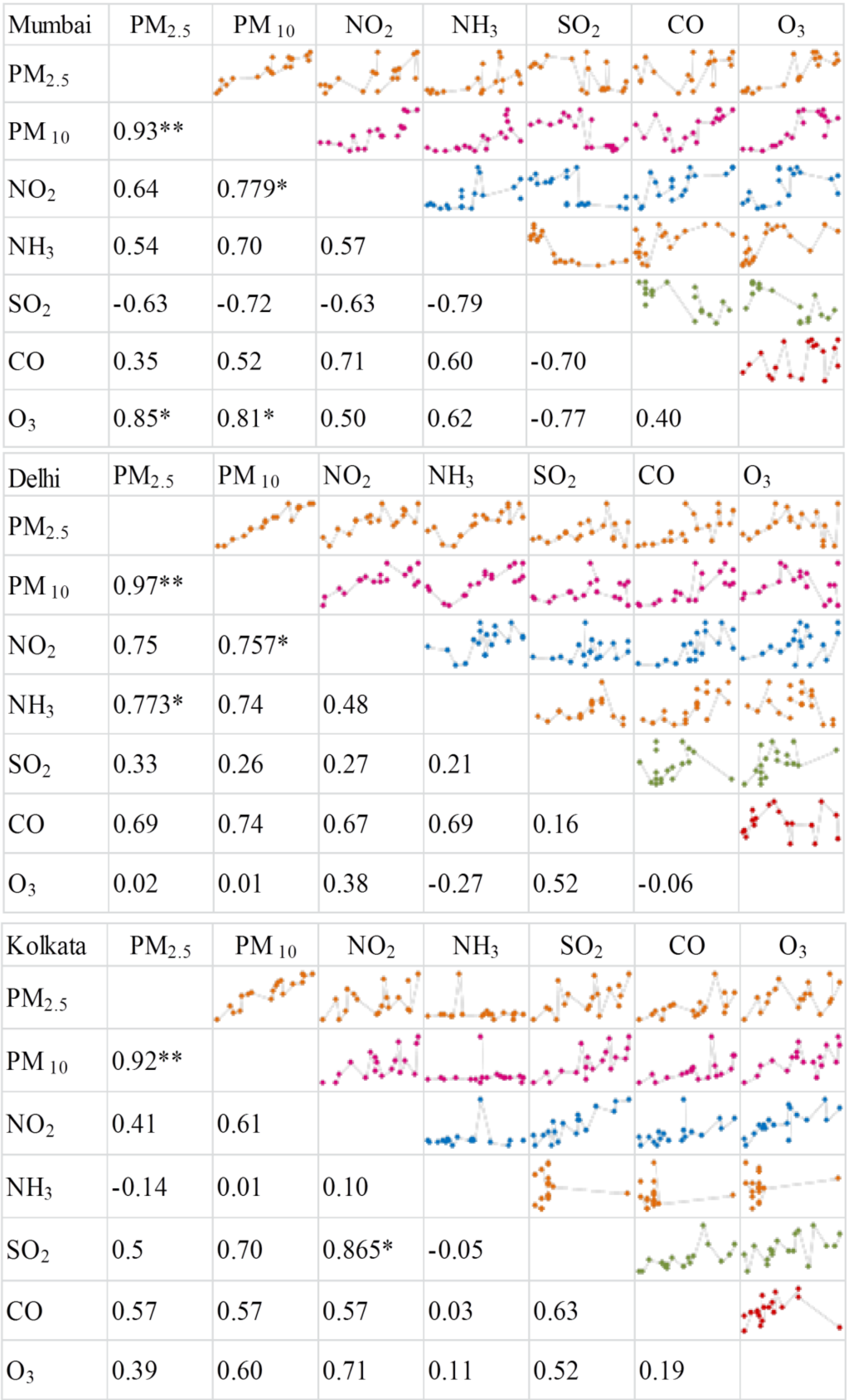
6.2.3 Spatial distribution of AQI

Figs. 6.2 and 6.3 show the spatial distribution of all pollutants in Delhi on pre-Diwali, Diwali, and post-Diwali days in 2019 and 2020. A visual inspection of these maps shows that the northern and eastern parts had higher pollutant concentrations than the rest of the city. This observation could be due to the high population density in these areas. Tyagi et al. (2016) and Garg et al. (2019) observed similar spatial variability of several air pollutants in Delhi (Tyagi et al., 2016; Garg et al., 2016). These maps also show that Delhi has a higher residence time of pollutants. Padmanabhamurty et al. (1990) and Guttikunda and Gurjar (2012) observed lower pollutant dispersal capacity in Delhi, especially during the post-monsoon season (Padmanabhamurty et al., 1990; Guttikunda and Gurjar, 2012). Almost all the parameters showed higher colour bars in the post-Diwali phase. These figures also show a significant increase in pollutant levels during the pre-Diwali-to-Diwali transition in both years. This observation indicates no noticeable change in firecracker burning during the pandemic-stricken Diwali of 2020.

There was a marked difference in the transition phases of 2019 and 2020 in Kolkata (Figs. 6.4, 6.5) and Mumbai (Figs. 6.6, 6.7). All pollutants, except PM_{10}, showed lower colour bars during Diwali 2020 than in the pre-Diwali scenario. This observation shows that the restricted burning of firecrackers occurred to some extent in Kolkata and Mumbai. The northern and eastern parts of Kolkata had higher pollution levels due to their high population density. The western part of Mumbai had lower air pollution, likely due to the adjacent sea breeze, which quickly dilutes pollutants.

6.2.4 Correlation between air pollutants

Considering the pollutant data for both years, PM_{10} and $PM_{2.5}$ showed a significant positive correlation ($p < 0.01$) in all three megacities (Fig. 6.8). Zhou et al. (2016) observed a similar correlation all through China. They observed that these two different-sized particulate matters have almost similar compositions (Zhou et al., 2016). O_3 and NO_2 showed a significant positive correlation with particulate matter levels in Mumbai. NO_2 is the principal catalyst in tropospheric O_3 production. Hence, these two should usually exhibit a negative correlation or no correlation at all. However, reports of positive and negative correlations between these pollutants exist in Indian cities (Venkitaswamy and Bhaskar, 2015). NO_2 and NH_3 showed similar correlations with PM_{10} and $PM_{2.5}$ ($p < 0.05$), respectively. However, no such correlation existed with O_3. In Kolkata, SO_2 and NO_2 showed a significant positive correlation ($p < 0.05$). These two gases can severely deteriorate lung activity and affect the bronchioles (Moseholm et al., 1993), which leads to complications in COVID-19-infected patients.



a

Mumbai	$PM_{2.5}$	PM_{10}	NO_2	NH_3	SO_2	CO	O_3
$PM_{2.5}$							
PM_{10}	0.93**						
NO_2	0.64	0.779*					
NH_3	0.54	0.70	0.57				
SO_2	-0.63	-0.72	-0.63	-0.79			
CO	0.35	0.52	0.71	0.60	-0.70		
O_3	0.85*	0.81*	0.50	0.62	-0.77	0.40	

b

Delhi	$PM_{2.5}$	PM_{10}	NO_2	NH_3	SO_2	CO	O_3
$PM_{2.5}$							
PM_{10}	0.97**						
NO_2	0.75	0.757*					
NH_3	0.773*	0.74	0.48				
SO_2	0.33	0.26	0.27	0.21			
CO	0.69	0.74	0.67	0.69	0.16		
O_3	0.02	0.01	0.38	-0.27	0.52	-0.06	

c

Kolkata	$PM_{2.5}$	PM_{10}	NO_2	NH_3	SO_2	CO	O_3
$PM_{2.5}$							
PM_{10}	0.92**						
NO_2	0.41	0.61					
NH_3	-0.14	0.01	0.10				
SO_2	0.5	0.70	0.865*	-0.05			
CO	0.57	0.57	0.57	0.03	0.63		
O_3	0.39	0.60	0.71	0.11	0.52	0.19	

Fig. 6.8 The correlation matrices and scatter plots between the seven air pollutants across the megacities of (a) Mumbai, (b) Delhi, and (c) Kolkata [*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed)].

Table 6.4 Meteorological parameters (air temperature, relative humidity, and wind speed) and total rainfall observed during Diwali 2019 and 2020 in Mumbai, Delhi, and Kolkata
Source: https://www.wunderground.com/

Megacity	Date	Temperature (° F)			Humidity (%)			Wind Speed (mph)			Rainfall (inch)
		Max	Avg	Min	Max	Avg	Min	Max	Avg	Min	Total
Mumbai	27 October 2019	90	84.2	77	89	70.6	52	13	6.1	0	0
	14 Nov 2020	95	86.3	79	74	58.5	41	13	6	0	0
Delhi	27 October 2019	89	74.9	65	90	66.4	34	9	3.3	0	0
	14 Nov 2020	82	63.9	54	97	82.1	53	2	0.6	0	0
Kolkata	27 October 2019	84	76.6	70	94	86.7	66	9	4.4	0	0
	14 Nov 2020	88	77.3	66	83	61.5	43	10	4.2	0	0

6.2.5 Role of meteorological parameters and interrelationship between pollutants

Table 6.4 shows the average, minimum, and maximum air temperature, relative humidity, wind speed, and total rainfall for the three megacities during Diwali 2019 and 2020. There was no statistically significant difference in the mean air temperature between Mumbai and Kolkata on Diwali in the two consecutive years. However, Delhi recorded a significantly lower air temperature in 2020 than in 2019. Tiwary et al. (2015; 2018) observed that low temperatures facilitated higher pollutant loads in Delhi, which could be one of the reasons for the higher concentration during the pre-Diwali phase of 2020 than in 2019 (Tiwary et al. 2015; 2018). Increased air temperature leads to an unstable atmosphere, which facilitates higher pollutant loads in Delhi, which could be one of the reasons for the higher concentration during the period, allowing the pollutants to dilute quickly (Cichowicz et al., 2017; Ravindra et al., 2019b). Relative humidity was lower in Mumbai and Kolkata (during Diwali) in 2020 than in 2019. Lower air moisture content facilitates the enhancement of pollutants and vice versa (Lou et al., 2017; Munir et al., 2017). Delhi recorded an elevated relative humidity during Diwali in the pandemic year. This increased humidity should have significantly reduced the pollutant load. However, a pre-Diwali-to-Diwali increase in pollutant concentrations, despite high moisture levels, indicates rampant firecracker burning in Delhi. Wind speed showed no significant difference between the 2019 and 2020 Diwali phases in Mumbai and Kolkata. Usually, higher wind speeds dissipate pollutant concentrations, whereas a reverse scenario indicates a stable atmosphere that retains them (Li et al., 2020). In Delhi, the wind speed was much less in the 2020 Diwali than in the 2019 Diwali. This low wind speed could have worsened the scenario in Diwali 2020.

The wind direction showed significant changes between pre-Diwali and Diwali dates in a few instances (Figs. 6.9, 6.10). In 2019, the predominant northeastern winds in pre-Diwali shifted to the northwest on Diwali in Mumbai. The wind from the western end came over the sea, thereby helping dilute air pollutant concentrations. In 2020, during the pandemic, no such wind reversal was observed in Mumbai. Delhi witnessed a change in wind direction from south-southeast to north-northwest during the pre-Diwali to Diwali period. The wind from the north, which comes from the Himalayas, is usually cold, leading to a drop in temperature. This reduction in temperature might have led to higher levels of air pollution in Delhi during Diwali. There was no rainfall in any of the cities in the 2019 and 2020 Diwali phases. Precipitation usually reduces pollutant loads (Yoo et al., 2014); however, it did not play any role in regulating pollutant loads in either year. Thus, analyzing the observations as a whole could partially support the hypothesis for Mumbai and Kolkata. However, the results from Delhi outrightly rejected the same framework I framed for this study.

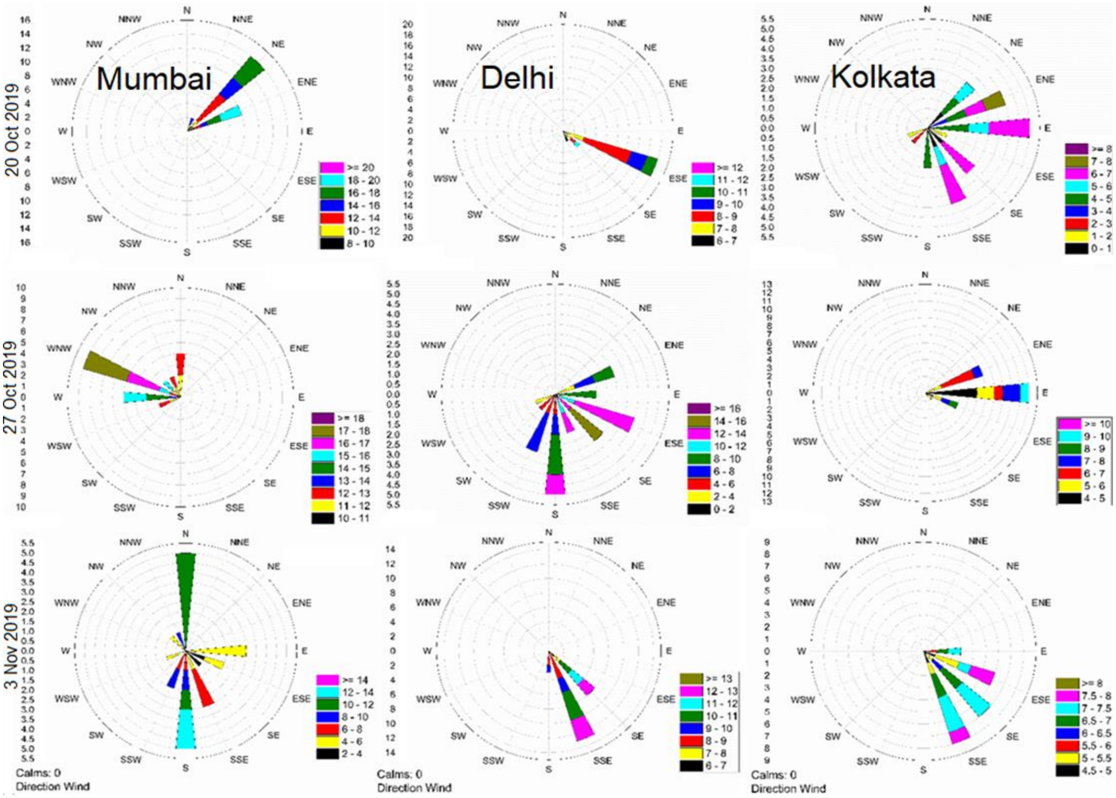


Fig. 6.9 The wind rose diagram for the three cities on the seventh day before Diwali, on the day of Diwali, and the seventh day after Diwali during the year 2019

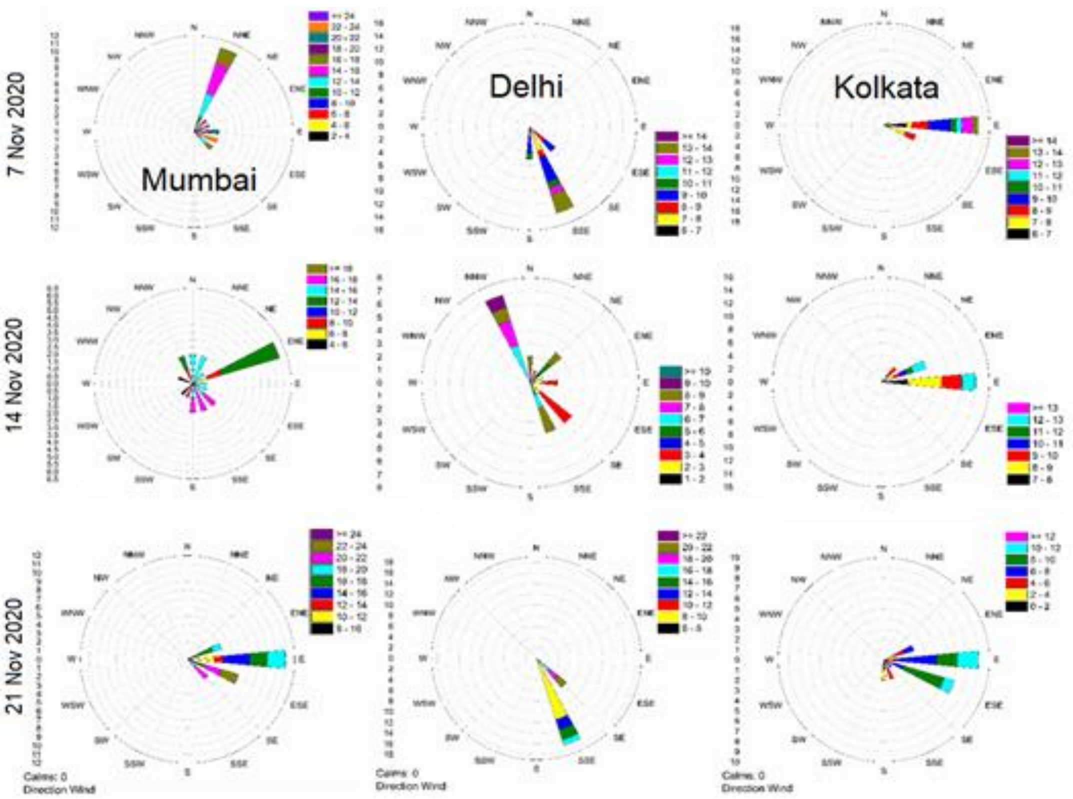


Fig. 6.10 The wind rose diagram for the three cities on the seventh day before Diwali, on the day of Diwali, and the seventh day after Diwali during the year 2020

6.2.6 Interpretation of changes in deweathered air pollutant data

The deweathered data from one station for 2019 and 2020 are listed in Table 6.5. Due to the unavailability of the complete meteorological dataset, I had to restrict myself to only one station. However, the deweathered data also showed a similar trend to that observed in the unprocessed data sets across all stations. Deweathered $PM_{2.5}$ and PM_{10} showed a significant increase from pre-Diwali (the seventh day before Diwali) to Diwali in Delhi in the pandemic year 2020. Mumbai and Kolkata also showed increases in these two parameters. However, the magnitude of the increase was much lower than that of Delhi. NO_2 did not show a significant increase between pre-Diwali and Diwali in any of the megacities in 2020, but NH_3 increased in Mumbai and Delhi. SO_2 increased substantially from pre-Diwali to Diwali in Delhi and Kolkata during the 2020 pandemic. CO did not show any significant variation. However, SO_2 and O_3 increased substantially on Diwali 2020 in Delhi. O_3 levels, in particular, increased in all three cities during Diwali in the pandemic year. Data from only one station is insufficient to infer for the entire city. However, the deweathered data also indicate that Delhi is the worst affected among the three megacities considered in this study.

Table 6.5 Deweathered air pollutant data of Delhi (Anand Vihar), Mumbai (Chhatrapati), and Kolkata (Rabindra Sarobar) on the seventh day before Diwali, on Diwali, and the seventh day after Diwali in the year 2019 and 2020

Megacities	Phases	$PM_{2.5}$ (µg/m^3)	PM_{10} (µg/m^3)	NO_2 (µg/m^3)	NH_3 (µg/m^3)	SO_2 (µg/m^3)	CO (mg/m^3)	O_3 (µg/m^3)
Delhi 2019	20.10.2019 (Pre-Diwali)	147.3	312.5	105.2	68.4	7.0	32.0	21.5
	27.10.2019 (Diwali)	282.7	479.7	115.4	94.9	15.8	32.6	12.6
	03.11.2019 (Post-Diwali)	425.6	575.1	114.2	103.8	15.6	33.0	8.5
Delhi 2020	07.11.2020 (Pre-Diwali)	288.7	525.8	139.1	54.3	13.1	54.0	27.4
	14.11.2020 (Diwali)	363.0	608.4	121.5	57.1	19.7	54.0	31.9
	21.11.2020 (Post-Diwali)	131.5	251.6	83.9	25.4	15.0	52.3	31.5
Mumbai 2019	20.10.2019 (Pre-Diwali)	22.5	37.2	19.4	47.2	5.7	22.9	7.8
	27.10.2019 (Diwali)	39.0	98.3	20.8	24.1	5.2	22.8	9.4
	03.11.2019 (Post-Diwali)	34.0	98.3	59.3	21.7	4.7	22.7	13.6
Mumbai 2020	07.11.2020 (Pre-Diwali)	36.9	153.9	39.5	14.7	29.2	25.7	45.0
	14.11.2020 (Diwali)	43.8	160.1	39.3	21.8	20.8	25.6	61.8
	21.11.2020 (Post-Diwali)	52.3	148.1	38.5	26.2	16.2	25.6	51.3
Kolkata 2019	20.10.2019 (Pre-Diwali)	51.6	97.0	37.7	12.4	4.7	31.7	36.6
	27.10.2019 (Diwali)	93.7	130.4	41.2	7.4	9.4	32.8	27.2
	03.11.2019 (Post-Diwali)	75.5	150.2	61.6	10.0	11.3	33.0	34.3
Kolkata 2020	07.11.2020 (Pre-Diwali)	82.6	182.0	84.3	16.3	20.9	32.5	41.1
	14.11.2020 (Diwali)	51.0	115.1	60.9	10.2	20.2	32.9	48.5
	21.11.2020 (Post-Diwali)	75.6	137.2	64.9	15.5	13.2	32.1	21.0

Chapter VII

Air Quality in Kolkata During Lockdowns

7.1 Introduction

The novel COVID-19 pandemic has wreaked havoc throughout the world since the onset of 2020, leading to an estimated casualty of 5.4 million people (Msemburi et al., 2023). The cataclysmic impacts of the pandemic still continue to manifest across the social, economic, health, education, and many other sectors directly linked to the lives and livelihoods of the global population (Adedoyin and Soykan, 2023; Alabi and Ngwenyama, 2023; Chow et al., 2023; Gurney, 2023). In March 2020, the WHO declared the COVID-19 outbreak a global pandemic. Until 2022, imposing lockdowns was the only measure adopted by almost all countries worldwide to combat the surge and spread of COVID-19, as COVID-19 infection rates rose (Minu et al., 2023). The social distancing and the forcefully imposed restrictions on mobility to curb the spread of the virus have had severe repercussions throughout society, especially the socio-economically weaker sections (Husain et al., 2023; Li et al., 2023). However, one of the most positive aspects of these lockdowns was the worldwide recovery in air quality (Aboagye et al., 2023; Drikvandi et al., 2023; Han et al., 2023).

The intention behind imposing the lockdowns was to prevent human contact and thus avert the spread of the contagious COVID-19 virus. However, the lockdowns enabled us to understand that air pollution due to multifarious anthropogenic activities, including fossil fuel burning, actually helped in spreading the virus, acting as carriers, and also enhancing the COVID-19 lethality and mortalities throughout the world (Magazzino et al., 2020; 2021; 2022; Mele et al., 2021). Indian megacities have been one of the worst-affected instances in this regard (Mele and Magazzino, 2021). Even now, as the pandemic recedes, the ever-deteriorating air quality in many urban areas worldwide has become a severe health concern (Monoson et al., 2023; Vyas et al., 2023). The inevitable pollution of the air due to manifold emissions from the industrial sector, which cannot be avoided at the cost of hampering development, has prompted present-day atmospheric scientists and environmentalists to seek amicable solutions, both in terms of policies and preventive measures (Bonilla et al., 2023; Wu et al., 2023). Thus, this study sought to understand the roles of lockdowns, their stringency, and meteorological factors in shaping pollutant concentrations, keeping the research question at the forefront: Can transient lockdowns truly help us alleviate the pollution load in the atmosphere?

Due to the COVID-19 pandemic, as in many countries, India was also compelled to declare several nationwide lockdowns. On 24 March 2020, the Indian Government imposed the first lockdown during the first surge of infections. This lockdown was maintained with utmost stringency in sheer desperation to arrest the outbreak, as all industries, commercial centres, and academic and religious institutions were shut down (Alyanak, 2020; Sharfuddin, 2020). All planned local, regional, and international events were cancelled (Duarte Muñoz and Meyer, 2020; Gallo and Trompetto, 2020; Parnell et al., 2020). Such lockdowns and closure of all sectoral activities except emergency services improved the ground-level air quality. Several researchers have observed a concomitant improvement in air quality during the imposed lockdowns (Mahato and Ghosh, 2020; Sarkar et al., 2021). Almost all megacities in India, like Ahmedabad, Bangalore, Chennai, Delhi, Hyderabad, Mumbai, and Kolkata, witnessed significant improvement in air quality during the lockdown imposed in the first wave (Bera et al., 2021; Sharma et al., 2020; Singh and Chauhan, 2020; Singh and Tyagi, 2021; Eregowda et al., 2021; Mahato et al., 2020; Roy and Balling, 2021; Sarkar et al., 2021; Simret and Gupta, 2022).

The world economy was severely affected by these lockdowns; however, the improvement in the air pollution scenario was undeniable (Gautam, 2020). Such pollution reduction brought a prolonged blessing to the environment, including less aerosol formation, lower levels of greenhouse gases linked to global climate change and global warming, reduced acid rain, protection of plant tissue, and more. The high concentration of gases with a long residence time has led to enormous health issues that have caused morbidity in the form of various cardiovascular problems, respiratory problems, lung cancer, visual impairment, etc. (Wang and Li, 2021). Latif et al. (2021) noted that lockdown measures simultaneously slowed the spread of COVID-19, thereby reducing morbidity and mortality (Latif et al., 2021). Benchrif et al. (2021) examined the effects of these lockdowns in cities with populations of more than a million. They observed significant improvements in air quality across all cities and lockdowns they studied (Benchrif et al., 2021). These observations compel us to question whether short-term lockdowns can actually alleviate air pollution in densely populated cities and sustain their ambience in the long run.

In India, the CPCB continuously monitors ground-level concentrations of NH_3, CO, NO_2, O_3, $PM_{2.5}$, PM_{10}, and SO_2. Several studies, as mentioned above, used this crucial dataset; however, most papers focused only on the lockdown phase during the first wave and the corresponding changes in air quality. The state governments of different cities across the nation also declared similar lockdowns. The Government of West Bengal (GoWB) (Kolkata megacity falls under its jurisdiction) announced a two-week lockdown during the second wave to prevent the spread of the virus (16 May to 30 May 2021; pre-monsoon season). Many sectors were completely closed, including academic institutions and public entertainment venues such as swimming pools, spas, gyms, beauty parlours, salons, parks, zoos, and tourist attractions. The restrictions during this lockdown were tight enough, but not as stringent as during the first wave. Another lockdown during the third wave was imposed by GoWB in the city from 01 January to 15 January 2022 (winter season) to combat the rapid spread of the new COVID-19 variant, "Omicron". However, most services operated at 50% capacity during the third wave, indicating a much lower degree of stringency than in the first and second waves. Thus, these lockdowns provided us with a platform to study changes in air pollutant levels across several lockdowns with varying degrees of stringency and seasons, to understand the role of meteorology as well.

Meteorological parameters such as rainfall, temperature, relative humidity, wind speed, and air pressure largely control ground-level air pollution. Asif et al. (2022) gave a detailed global review of the spread of COVID-19 under varying environmental conditions (Asif et al., 2022). Given the governing role of meteorological parameters, special attention was paid to deweathered pollutant datasets. The said meteorological variables usually exhibit significant seasonal changes. January and February are the winter months when the static movement of air increases ground-level air pollution. The reverse scenario occurs in rainy months (June, July, August, and September). During this monsoon season, with heavy rainfall, air pollution levels decrease substantially. High temperatures, high humidity, and low land pressure characterize the pre-monsoon (March to May). The winter months of December and January mark a static air environment, with occasional inversion conditions that often elevate air pollutant levels. However, the transition period between the monsoon and the winter, known as the post-monsoon season, exhibits fluctuating air pollutant concentrations.

Tropical cyclones originating in the Bay of Bengal occasionally prevail during this time of the year.

This study is unique because air quality levels during all three waves amid lockdowns were continuously monitored. Moreover, the concentration of pollutants during the non-pandemic period of 2019 was analyzed, when there were no lockdowns or restrictions in the city. The comparison between lockdown and no-lockdown, and the monitoring of them through the implementation of down states and deweathered pollutant levels datasets, were considered in this study. Machine learning tools, such as R programming and GIS technology, combined with a statistical approach, added a new dimension of analysis to pollution datasets across weathered and deweathered scenes. Hence, this study will be fruitful for policymakers in combating and reducing seasonal collective air pollution concentrations in metro areas, and in monitoring them through the implementation of specific action plans. The results of this study can show us avenues to improve ambient air quality in cities and metropolises, especially those that are overpopulated and polluted.

7.2 Results and discussion

7.2.1 Fluctuating dynamics of PM_{10} and $PM_{2.5}$

The concentration of $PM_{2.5}$ was below the standard (60 μg/m^3) of CPCB for the second wave. The first and third waves' concentrations of $PM_{2.5}$ were substantially higher than the CPCB permissible limit (Fig. 7.1a). The PM_{10} level was higher for the third wave. In contrast, the concentrations in the first two waves were lower than the CPCB standard (100 μg/m^3). Thus, both $PM_{2.5}$ and PM_{10} concentrations decreased in the second wave, followed by a rising trend in the third wave.

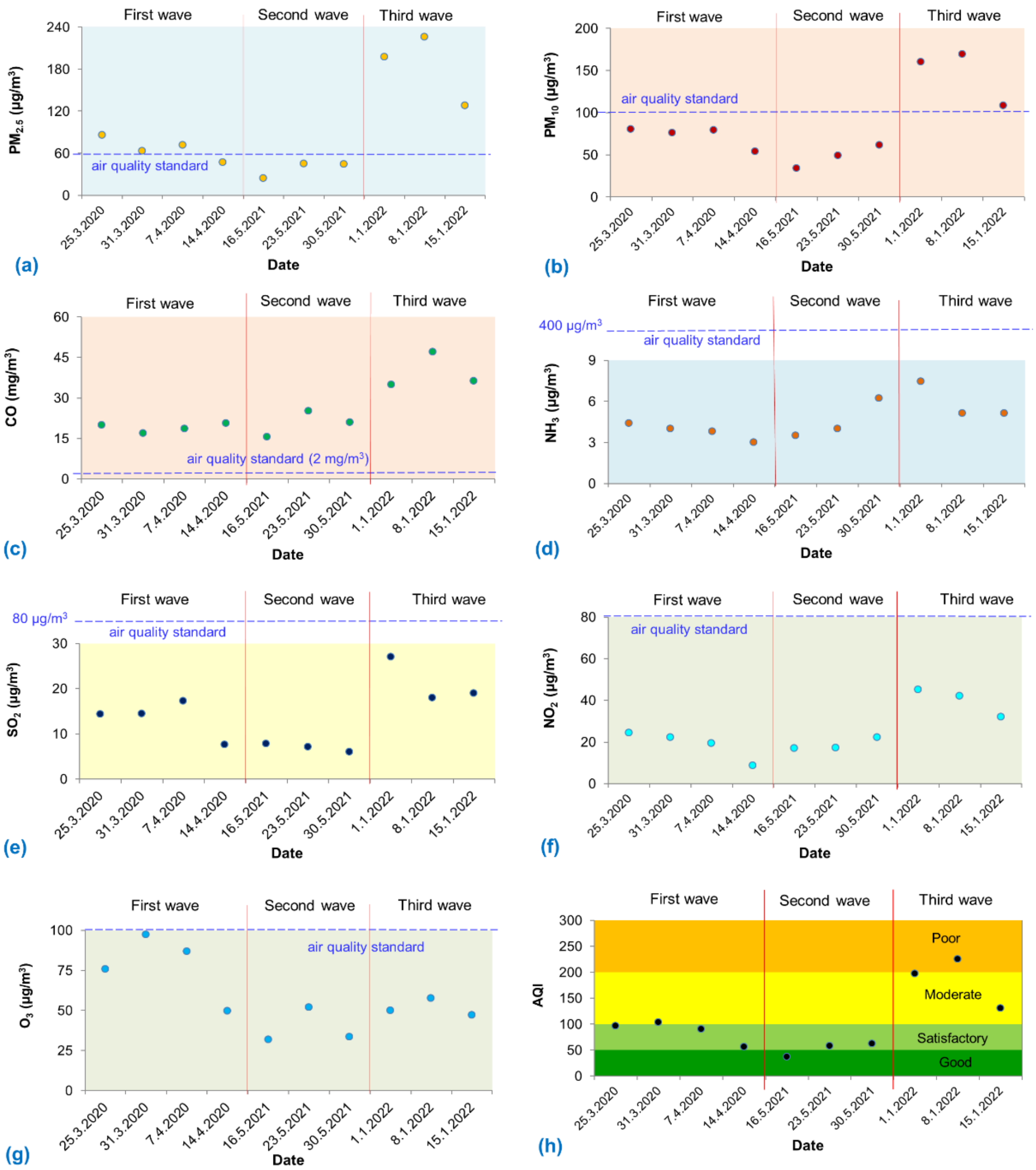


Fig. 7.1 Weekly average atmospheric levels of (a) $PM_{2.5}$, (b) PM_{10}, (c) CO, (d) NH_3, (e) SO_2, (f) NO_2, (g) O_3 and (h) AQI in Kolkata megacity during COVID-19-induced lockdowns across the first wave (2020), second wave (2021), and third wave (2022)

Table 7.1 Weekly data of ambient air pollutants in COVID-19 amid lockdowns for first, second and third wave
Source: CPCB web portal, https://airquality.cpcb.gov.in/AQI_India_Iframe/)

Pollutants	First wave lockdown				Second wave lockdown			Third wave lockdown			Permissible limit of CPCB
	25.3.2020	31.3.2020	7.4.2020	14.4.2020	16.5.2021	23.5.2021	30.5.2021	1.1.2022	8.1.2022	15.1.2022	
$PM_{2.5}$ (µg/m^3)	85.60±21.01	63.00±22.39	71.50±14.58	47.00±6.78	24.33±7.70	44.89±11.40	43.88±10.97	197.20±60.93	225.50±54.16	127.63±65.45	60
PM_{10} (µg/m^3)	80.00±15.68	75.70±1.64	79.40±10.76	54.00±8.72	34.10±7.71	48.90±11.82	61.56±11.31	159.80±38.62	169.20±40.09	108.38±27.98	100
CO (mg/m^3)	19.90±17.36	16.90±10.05	18.60±3.81	20.60±5.78	15.50±8.36	25.20±10.41	21.00±9.67	34.90±24.05	47.10±21.70	36.33±26.51	2
NH_3 (µg/m^3)	4.40±2.32	4.00±2.16	3.80±2.10	3.00±2.05	3.50±1.35	4.00±1.63	6.22±6.08	7.44±7.38	5.13±5.64	5.14±2.54	400
SO_2 (µg/m^3)	14.40±5.15	14.50±4.38	17.30±7.32	7.60±3.75	7.80±2.57	7.10±2.64	6.00±3.00	27.00±15.09	18.00±12.38	19.00±8.57	80
NO_2 (µg/m^3)	24.50±9.77	22.30±9.30	19.50±10.73	8.80±4.66	17.10±7.00	17.20±5.53	22.22±16.46	45.22±27.78	42.13±29.53	32.00±20.91	80
O_3 (µg/m^3)	75.78±29.06	97.33±46.71	86.67±12.68	49.67±8.57	31.67±13.55	51.89±19.78	33.33±3.51	49.89±19.37	57.50±24.33	47.00±16.04	100
AQI	96.10±22.71	103.20±32.03	90.40±13.03	56.20±8.56	37.30±8.84	58.00±11.41	62.44±10.51	197.20±60.93	225.50±54.16	130.50±63.99	

Air pollutants are reported as mean ± standard deviation.

Table 7.2 Variation of air pollutants in First wave & Second wave lockdown and Second wave & Third wave lockdown periods

Pollutants	First wave lockdown (25 Mar-14 Apr, 2020)	Second wave lockdown (16 May-30 May, 2021)	Total variation Avg.	% of variation	Second wave lockdown (16 May-30 May, 2021)	Third wave lockdown (1 Jan-15 Jan, 2022)	Total variation Avg.	% of variation
$PM_{2.5}$ (µg/m^3)	66.78±21.86	37.46±13.76	-29.31	-43.90	37.46±13.76	187.43±7041	149.97	400.32
PM_{10} (µg/m^3)	72.28±15.79	47.72±15.13	-24.55	-33.97	47.72±15.13	148.46±43.81	100.74	211.09
CO (mg/m^3)	19.00±10.29	20.55±10.04	01.55	08.17	20.55±10.04	39.55±23.87	19.00	92.45
NH_3 (µg/m^3)	03.80±02.14	04.52±03.66	00.72	18.87	04.52±03.66	06.00±05.63	01.48	32.82
SO_2 (µg/m^3)	13.45±06.26	07.00±02.74	-06.45	-47.96	07.00±02.74	21.42±12.64	14.42	206.04
NO_2 (µg/m^3)	22.10±10.53	18.72±10.43	-03.38	-15.28	18.72±10.43	40.33±26.07	21.61	115.41
O_3 (µg/m^3)	77.36±32.68	37.92±18.29	-39.44	-50.98	37.92±18.29	39.55±20.14	01.63	04.29
AQI	86.48±27.37	52.24±14.95	-34.23	-39.59	52.24±14.23	188.25±69.34	136.01	260.35

First-wave and second-wave lockdowns are reported as mean ± standard deviation.

In the first, second, and third waves, the concentration of $PM_{2.5}$ varied from 47.00 to 85.60 μg/m^3, 24.33 to 44.89 μg/m^3, and 127.63 to 225.50 μg/m^3, respectively (Table 7.1). The PM_{10} range was 54.00 to 80.00 μg/m^3, 34.10 to 61.56 μg/m^3, and 108.38 to 169.20 μg/m^3, respectively. To arrest the pandemic during the first wave, the GoI forcefully implemented social distancing. Barring emergency services, all sectors, such as academia, industry, shopping malls, and administrative centres, were closed. The widespread and stringent implementation of lockdowns inevitably reduced atmospheric pollutant loads (Bera et al., 2021; Mahato et al., 2020; Muhammad et al., 2020; Sharma et al., 2020). The lockdown during the second wave was more relaxed compared to the first wave. GoWB again decided to curtail people's mobility by issuing government orders on the pandemic. So, GoWB announced the selective containment zone approach w.e.f. 6 am on 16 May 2021 to 6 pm on 30 May 2021 in the public and collective interest. All industries, manufacturing units, government offices, private establishments, educational/academic institutions, train services, and bus services were restricted. Still, a few essential and emergency services were allowed to open for a decent period. Such practice and people's awareness considerably reduced the pollutant load. The rapid spreading rate of the Omicron variant compelled GoWB to announce another lockdown during the third wave in 2022. Schools, Colleges, and Universities were strictly closed; however, administrative activities were allowed to operate at 50% employee strength. Almost all private and Government offices operated at 50% capacity, and work-from-home was encouraged. Similarly, local train and metro services were restricted to operate only between 5 am and 7 pm. All kinds of human and vehicular activities were stopped from 10 pm to 5 am; however, during this time, traffic is usually minimal. Such lax practices contributed to ground-level air pollution. As a result, $PM_{2.5}$ and PM_{10} concentrations were high during the COVID-19 first-wave lockdown (Table 7.3). These two pollutant concentrations for the third-wave lockdown were increased by 400.32% (149.97 μg/m^3) and 211.09% (100.74 μg/m^3) compared to the second-wave lockdown.

Fig. 7.2 shows the spatial distribution of PM_{10} and $PM_{2.5}$ in the Kolkata megacity during the study. Significant improvement in air quality was detected during the second wave compared to that observed in the first wave. During the third wave of lockdown, air pollution levels rose again. The northern and western parts of the region were more polluted, while the central part was the least polluted. There were higher levels of vehicular emissions and industrial activity in those pockets. The remaining zone was moderately polluted.

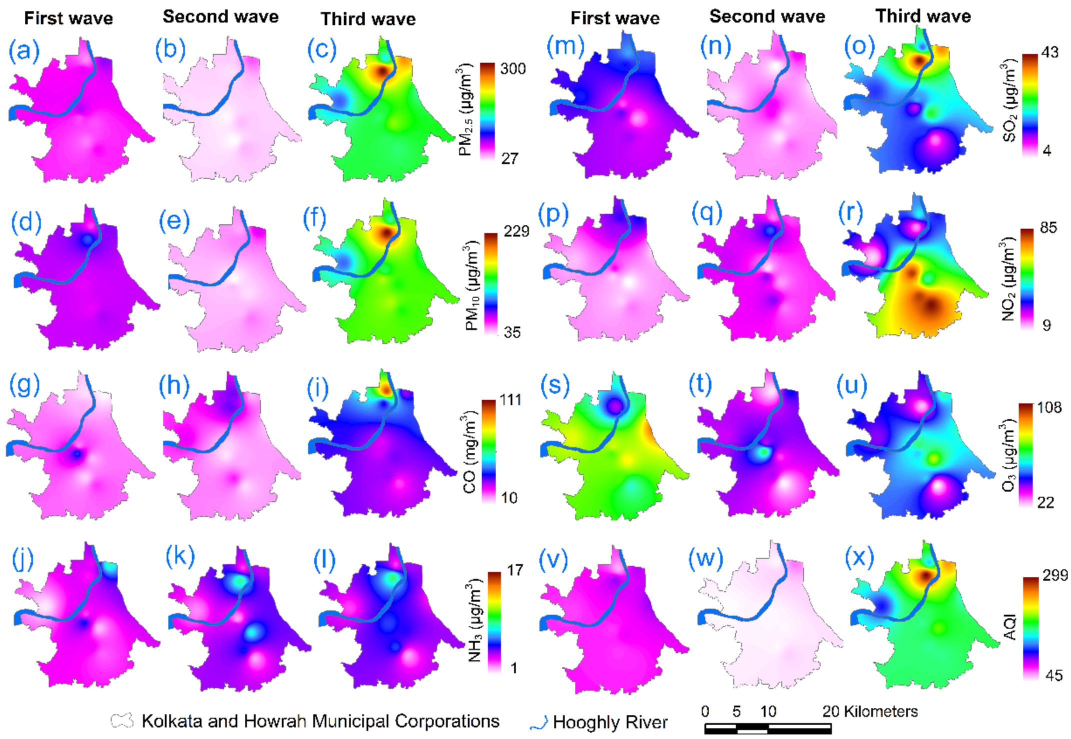


Fig. 7.2 Spatial distribution of (a-c) $PM_{2.5}$; (d-f) PM_{10}; (g-i) CO; (j-l) NH_3; (m-o) SO_2; (p-r) NO_2; (s-u) O_3 and (v-x) AQI in Kolkata and Howrah Municipal Corporations during COVID-19-induced lockdowns across the first wave (2020), second wave (2021), and third wave (2022)

$PM_{2.5}$ and PM_{10} decreased during the pandemic, particularly during lockdown phases, compared to the 2019 baseline, as shown in the box plots (Figs. 7.3a, 7.3b). The normal periods (2019) average concentrations of $PM_{2.5}$ were 81.42, 67.00, and 330.78 µg/$m^{3,}$ while their corresponding lockdown phase concentrations were 72.58 (first wave), 41.38 (second wave), and 241.44 µg/m^3 (third wave), respectively. Therefore, the results indicate moderately polluted air during the first and second waves, which may cause breathing discomfort for people with lung diseases. However, severe air pollution was observed during the third wave, leading to respiratory illness among people exposed to prolonged exposure (Table 1.3). Likewise, the PM_{10} concentrations during the non-pandemic period were 88.58, 82.40, and 265.11 µg/m3, while during the pandemic waves they were 81.42, 55.25, and 174.78 µg/m^3, respectively. Hence, it was satisfactory for the first two waves but had poor air quality during the third-wave lockdown amid the pandemic.

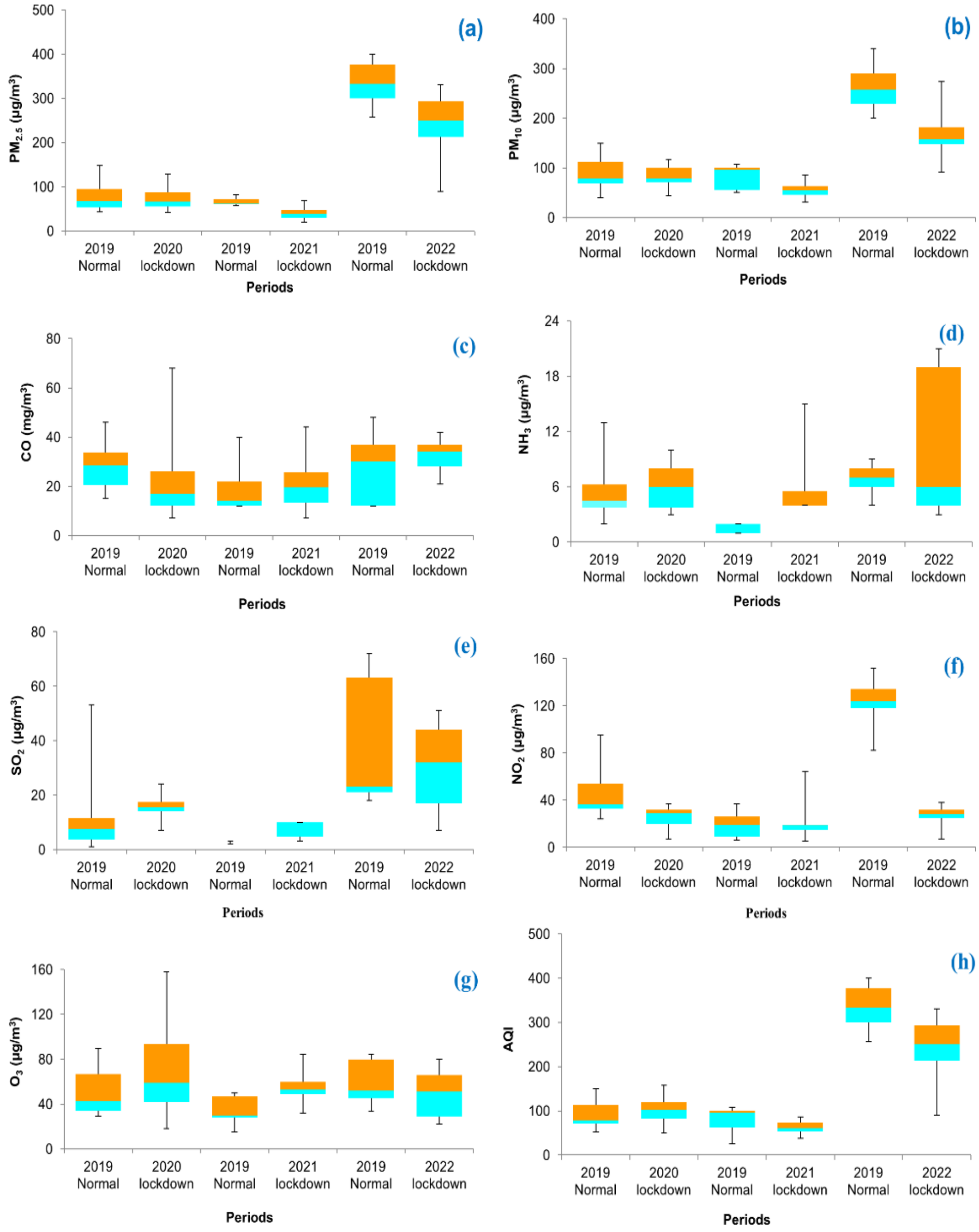


Fig. 7.3 Box plots portraying the atmospheric levels of (a) $PM_{2.5}$), (b) PM_{10}, (c) CO, (d) NH_3, (e) SO_2, (f) NO_2, (g) O_3 and (h) AQI in Kolkata megacity during the normal period (2019) and COVID-19-induced lockdowns across the first wave (2020), the second wave (2021), and third wave (2022). The box contains the third quartile, median, and first quartile. The cyan and orange colours represent the ranges from the first quartile to the median and from the median to the third quartile. The error bars have a minimum and maximum value at the bottom and top, respectively.

Table 7.3 Average concentration of air pollutants in Kolkata megacity for the Normal periods* and COVID-19 amid lockdown periods

Pollutants	$PM_{2.5}$ (µg/m^3)	PM_{10} (µg/m^3)	CO (mg/m^3)	NH_3 (µg/m^3)	SO_2 (µg/m^3)	NO_2 (µg/m^3)	O_3 (µg/m^3)	AQI
Normal period (25 Mar-14 Apr, 2019)	81.42±37.17	88.58±33.64	27.92±9.26	5.50±3.26	11.75±14.35	46.33±22.73	50.17±20.81	107.33±57.63
First wave lockdown (25 Mar-14 Apr, 2020)	72.58±24.82	81.42±22.01	22.67±17.43	5.83±2.41	15.42±4.68	26.08±9.60	71.25±41.68	100.83±31.06
Total variation Avg.	-8.83	-7.17	-5.25	0.33	3.67	-20.25	21.08	6.00
% of variation	-10.85	-8.09	-18.81	6.06	31.21	-43.71	42.03	6.33
Normal period (16 May-30 May, 2019)	67.00±9.90	82.40±26.78	20.00±13.47	1.60±0.55	2.80±0.45	19.40±12.67	34.00±14.47	86.50±18.19
Second wave lockdown (16 May-30 May, 2021)	41.38±17.43	55.25±17.19	21.88±13.46	5.88±3.83	7.75±3.15	21.00±18.47	55.60±18.93	62.88±16.43
Total variation Avg.	-25.63	-27.15	1.88	4.28	4.95	1.60	21.60	-15.73
% of variation	-38.25	-32.95	9.38	267.19	176.79	8.25	63.53	-20.01
Normal period (1 Jan-15 Jan, 2019)	330.78±47.67	265.11±45.12	28.89±14.00	7.00±1.73	36.33±23.43	123.56±21.88	57.56±19.02	328.89±55.06
Third wave lockdown (1 Jan-15 Jan, 2022)	241.44±72.85	174.78±56.93	32.67±6.32	10.11±7.46	30.22±16.54	25.44±10.63	50.67±21.37	241.44±72.85
Total variation Avg.	-89.33	-90.33	3.78	3.11	-6.11	-98.11	-6.89	-89.33
% of variation	-27.01	-34.07	13.08	44.44	-16.82	-79.41	-11.97	-27.01

Air pollutants are reported as mean ± standard deviation.

** Normal period data were available for the ambient air monitoring stations of Rabindra Bharati University, Victoria, and Ghusuri*

The COVID-19 pandemic waves' mean concentrations of $PM_{2.5}$ were reduced by about -27.01% (89.33 $\mu g/m^3$) for the third wave, -38.25% (25.63 $\mu g/m^3$) for the second wave, and -10.85% (8.83 $\mu g/m^3$) for the first wave compared to the normal phase of 2019 (Table 7.3). Similarly, the drop in PM_{10} was -8.09% (7.17 $\mu g/m^3$), -32.95% (27.15 $\mu g/m^3$), and -34.07% (90.33 $\mu g/m^3$) across the three waves, respectively. The lockdown during the third wave occurred during the winter. So, the static movement of air and cold air had a high capacity to hold ground-level air pollution. The lockdown during the first and second waves occurred in the pre-monsoon or summer season.

A similar drop in the concentration of $PM_{2.5}$ and PM_{10} was recorded during the pandemic amid the first phase of lockdown (first wave 2020) compared to pre-lockdown and the same window period of the previous year (2019) (Mahato et al., 2020; Bera et al., 2021; Sarkar et al., 2021; Sangkham et al., 2021; Pal et al., 2022; Kapse et al., 2023). The same scenario was noted in the first phase of the lockdown (second wave 2021) by Gregory et al. (2024) (Gregory et al., 2024). Similar observations, i.e., reductions of −30.6% and −34.9% in $PM_{2.5}$ and PM_{10}, have been reported in the review paper by Navaratnam et al. (2024) (Navaratnam et al., 2024). Another recent study in Portugal found that PM_{10} levels decreased by -21.1% during the lockdown period compared to historical periods (2015-19) (Silva et al., 2024).

7.2.2 CO dynamics in the atmosphere

A previous study found that CO levels were unusually low in India during the lockdown phase. Fig. 7.1c shows that all recorded values were well above the CPCB permissible limit (2 mg/m^3). Its high concentration is inclined to various cardiovascular problems, and infants, pregnant women, and older people are at risk. The pandemic period concentrations were 16.90-20.60 mg/m^3, 15.50-25.20 mg/m^3, and 34.90-47.10 mg/m^3 for the first, second, and third waves, respectively (Table 7.1).

The spatial distribution of CO across the Kolkata megacity is shown in Fig. 7.2. Temporal maps indicate a gradual decrease in air quality. The third wave was the most polluted of the three. The northern parts of Kolkata were more polluted than the rest of the city. More industrial activities and vehicular emissions were in those pockets. The remaining zone was less polluted. The rise in concentration in the second wave was 8.17% (1.55 mg/m^3) compared to the first wave, and 92.45% (19.00 mg/m^3) for the third wave compared to the second wave phase concentrations (Table 7.2).

The average CO concentration during the COVID-19 pandemic was reduced by about -18.81% (from 5.25 mg/m^3) during the first wave lockdown period compared to the normal phase. The latter two waves gained 9.38% (1.88 μg/m^3) and 13.08% (3.78 mg/m^3) during the normal phases (Table 7.3). Partial relaxation of vehicular movement restrictions, industrial closures, and seasonal factors contribute to such a high concentration of air pollution. CO itself is a major contributor to GHGs when it is emitted into the atmosphere, which is linked to climate change and global warming. The inter-lockdown and normal periods of CO concentration are depicted in Fig. 7.3c. A mixed scenario is detected here.

The same observation (−21.7% fall) was reported in the review paper by Navaratnam et al. (2024) (Navaratnam et al., 2024). Mokarram et al. (2024) have the same results in their study of the Isfahan region (Iran), a volume decreases due to lockdown stringency (Mokarram et al., 2024).

7.2.3 Negligible role of NH_3 observed in air pollution

Several studies indicated that NH_3 originates from cultivated land, petrol cars, industry, and sewage (Wilson et al., 2004; Sutton et al., 2000). The concentration of NH_3 was very low across all three waves, well below the CPCB permissible limit (400 μg/m^3). Therefore, it is unlikely to cause any health issues at such a low concentration. The sequential NH_3 ranges during the three waves were 3.00-4.40 μg/m^3, 3.50-6.22 μg/m^3, and 5.13-7.44 μg/m^3, respectively (Table 7.1).

The spatial distribution of NH_3 is shown in Fig. 7.2. The northern and central parts have higher concentrations than the rest of the region. The city has witnessed increases of 18.87% (0.72 μg/m^3) and 32.82% (1.48 μg/m^3) in the second and third waves, respectively (Table 7.2). It was due to agricultural field waste, NH_3-based fertilizer applications, industrial processes, and vehicular emissions.

The box plots show a steady increase in NH_3 concentration during lockdowns amid pandemic waves compared to the normal period (Fig. 7.3d). The COVID-19 pandemic wave average concentrations of NH_3 increased by about 6.06% (0.33 μg/m^3) for the first wave, 267.19% (4.28 μg/m^3) for the second wave, and 44.44% (3.11 μg/m^3) for the third wave compared to the normal phase of 2019 (Table 7.3). A recent paper scrutinized the pandemic during the lockdown and changes in pollutant concentrations, noting lower concentrations recorded due to reduced industrial activity and vehicular movement (Mokarram et al., 2024).

7.2.4 SO_2 dynamics in the atmosphere

The concentration of SO_2 was also below the permissible limit (80 μg/m^3) during all three pandemic waves (Fig. 7.1e). The concentration of this gas fell with time in each phase. The government's transportation and industrial policy closures, along with people's awareness, led to this variation. The low concentration indicates minimal health impact. The magnitude of SO_2 was different in each wave: 7.60-17.30 μg/m^3 for the first wave, 6.00-7.80 μg/m^3 (second wave), and 18.00-27.00 μg/m^3 (third wave) (Table 7.1).

The spatial distribution of SO_2 is illustrated in Fig. 7.2. A significant improvement in air quality during the second wave phase lockdown, compared to the first wave phase, and a remarkable gain during the third wave phase were noted. A few pockets of the northern part have witnessed a higher concentration than the rest of the region. There was a reduction of about -47.96% (6.45 μg/m^3) from the first wave to the second wave. However, a gain of 206.04% (14.42 μg/m^3) occurred from the second wave to the third wave. Hence, there were mixed results in inter-lockdown phases (Table 7.2).

The box plots (Fig. 7.3e) show that SO_2 concentration was unstable and fluctuated across the city. There were gains in concentration during the lockdown waves (first and second) compared to the normal phases of 2019. It decreased during the third wave, amid the lockdown, compared to the 2019 normal period. The average values of lockdown and normal periods were 15.42, 7.75, and 30.22, and 11.75, 2.80, and 36.22 μg/m^3. A high rise (176.79%) in the second wave phase lockdown and a fall (-16.82%) in the third wave were detected (Table 7.3). The varying degrees of relaxation and strictness of the lockdown resulted in mixed results.

A study by Sun and Li (2024) identified a -12% drop in concentration due to restricted anthropogenic activities and lockdown stringency across Handan, China (Sun and Li, 2024). The same observation (−14.7% fall) has been reported in the review paper by Navaratnam et al. (2024) (Navaratnam et al., 2024). Mokarram et al. (2024) experienced the same (Mokarram et al., 2024).

7.2.5 Fluctuation of NO_2

The concentration of NO_2 leads to aerosol formation and is closely linked to the tropospheric O_3 Layer. The concentration of NO_2 markedly dropped in India during the pandemic amid the first wave of lockdown (Bera et al., 2021; Ghosh and Ghosh, 2020; Mahato et al., 2020; Muhammad et al., 2020; NASA, 2020; ESA, 2020). NO_2 concentration was below the standard (80 μg/m^3) for all three waves (Fig. 2f). The gradual decline trend for the first wave phase was followed by a slight increase for the second wave phase, and, thereby, a decline for the third wave phase was noted. During the pandemic waves, the concentration of NO_2 varied from 8.80 to 24.50 μg/m^3 (first wave), 17.10 to 22.22 μg/m^3 (second wave), and 32.00 to 45.22 μg/m^3 (third wave), respectively (Table 7.1). A significant improvement in air quality (NO_2) during the COVID-19 lockdown phases compared to 2019 was observed across all three waves. The strict regulations on transportation and industrial activity in the city led to substantial improvements in air quality.

Fig. 7.2 shows the spatial distribution of NO_2 in the city during the COVID-19 pandemic wave lockdown. Visual inspection of these maps shows that the north-western part of the first two waves and the southern part of the third wave exhibited higher pollution levels (NO_2) than the rest of the region. Similar to $PM_{2.5}$ and PM_{10}, the improvement (-15.28% with 3.38 μg/m^3) of air quality in the second wave phase compared to the first wave, and then a fall in air quality with 115.41% (21.61 μg/m^3) in the third wave phase was detected (Table 7.2).

The box plots (Fig. 7.3f) show the maximum, median, and minimum values of the pollutants of normal phases compared to pandemic wave phases. A significant drop in air pollution has been detected for all three waves. The most significant fall occurred in the third wave (-79.41%, 98.11 μg/m^3), followed by the first wave (-43.71%, 20.25 μg/m^3). The second wave was exceptional, with a slight rise (8.25% with 1.60 μg/m^3) in NO_2 pollution level compared to a normal period (Table 7.3). However, the overall result was quite satisfactory. The concentration of NO_2 always remained low and had no such health impact in both periods of normality and the pandemic.

A study by Sun and Li (2024) found a -55% drop in concentration due to reduced anthropogenic activities and increased lockdown stringency in Handan, China (Sun and Li, 2024). Likewise, reductions of -34.3% and -39.1% in NO_2 were observed by Silva et al. (2024) and Navaratnam et al. (2024), respectively (Silva et al., 2024; Navaratnam et al, 2024). Mokarram et al. (2024) reported the same in the Isfahan region of central Iran (Mokarram et al., 2024).

7.2.6 O_3 dynamics

The Tropospheric O_3 layer plays a significant role in protecting the environment against harmful ultraviolet rays. However, its lower volume can cause several effects not only in humans (respiratory diseases and skin cancer) but also in plants (plant death). The city had O_3 levels below the permissible limit (100 μg/m^3) for all three waves (Fig. 7.1g).

The O_3 varied as 49.67-97.33 μg/m^3, 31.67-51.89 μg/m^3, and 47.00-57.50 μg/m^3 for the first, second, and third waves, respectively (Table 7.1). The intra-lockdown variation was recorded with time, from the first wave to the third wave. A gradual improvement in the O_3 level was observed from the first wave to the second wave, and then to the third wave, in the spatial distribution map (Fig. 7.2).

Air pollution dropped by -50.98% (39.44 μg/m^3) during the second wave compared to the first wave (Table 7.2). The reverse scenario was detected in the third wave phase compared to the second wave phase. However, air pollution rose by 4.29% (1.63 μg/m^3) during the third wave phase compared to the second wave.

Compared to the normal period, the mean O_3 concentration decreased in the first two pandemic lockdown waves and increased in the third wave (Fig. 7.3g). The volume increased by 42.03% (21.08 μg/m^3) and 63.53% (21.60 μg/m^3) in the first and second waves compared to the normal periods of 2019. The volume of O_3 was improved by -11.97% (6.89 μg/m^3) for the third wave phase than normal (Table 7.3). Therefore, the city has satisfactory air quality with minimal health issues.

Navaratnam et al. (2024) reported a 16% increase in mean O_3 concentration (Navaratnam et al., 2024). The opposite results also showed a -0.82% decline in the level in Portugal, according to the study by Silva et al. (2024) (Silva et al., 2024). Another study identified a rising trend of concentration in Kolkata (Kapse et al., 2023).

7.2.7 AQI dynamics during the lockdowns

The level of AQI values also varied from well to satisfactory for the first two waves and thereby moderate to poor for the third wave (Fig. 7.1h). The first wave phase value ranged from 56.20 to 103.20, 37.30 to 62.44 for the second wave, and 130.50 to 225.50 for the third wave (Table 7.1).

The spatial distribution map showed a significant improvement, with a -39.59% (34.23) decrease in AQI in the second wave phase compared to the first wave phase. The third-wave phase's ground-level air pollution was the highest among the three (Fig. 7.2). The north-western part was more polluted due to the location of industry and heavy vehicular traffic. The concentration of AQI in the third wave phase was increased by 260.35% (136.01) compared to the second wave (Table 7.2). The relaxation and fewer restrictions measures came into force compared to the previous two waves. All offices operated at 50% capacity, and local train and metro services operated with a few restrictions.

The box plots (Fig. 7.3h) show that the AQI level increased slightly (6.33%) in the first wave. The level dropped in the second wave (-20.01%) and the third wave (-27.01%) compared to the normal period. Hence, breathing discomfort affects sensitive people and can lead to prolonged exposure to health issues. Moreover, a sharp improvement in the recent two waves of COVID-19 amid lockdown was noted compared to normal periods in 2019.

7.2.8 Association between the air pollutant concentrations

The daily average (24 h) concentration of $PM_{2.5}$ and PM_{10}; $PM_{2.5}$ and CO; $PM_{2.5}$ and NO_2; PM_{10} and NO_2 had a very robust positive relationship (r=0.99***, 0.90***, 0.93***, and 0.94***) (Fig. 7.4) (*denotes p <0.05; **denotes p <0.01; and ***denotes p <0.001). Likewise, $PM_{2.5}$ and SO_2; PM_{10} and SO_2; PM_{10} and CO; NO_2 and NH_3; NO_2 and SO_2 had a strong positive relationship (0.81**, 0.85**, 0.87**, 0.80**, and 0.82**) at 99% level of confidence. These results indicate that vehicular movement and industrial exhaust fumes, the primary sources of PM, are closely associated with other pollutants. The combined concentrations of ambient air pollutants have significant health and environmental impacts. A few moderate, weak, and sometimes no relations between ambient air pollutants were also noted. The daily average $PM_{2.5}$ concentration was moderately correlated with the daily average (24 h) NH_3 concentration (r=0.62). The relationships between NH_3 and the daily average (24 h) concentrations of SO_2 and CO were moderate and positive (r=0.57 and 0.53, respectively). SO_2 and CO are also moderately correlated (r=0.58). On the other hand, the city exhibited a few poor (positive) relationships between ambient pollutants such as O_3 and $PM_{2.5}$, O_3 and PM_{10}; O_3 and SO_2 (r=0.04, 0.10, 0.31), and a few negative (r=-0.03, -0.28, and -0.21) relationships with O_3 and pollutants of NO_2, NH_3, and CO, respectively.

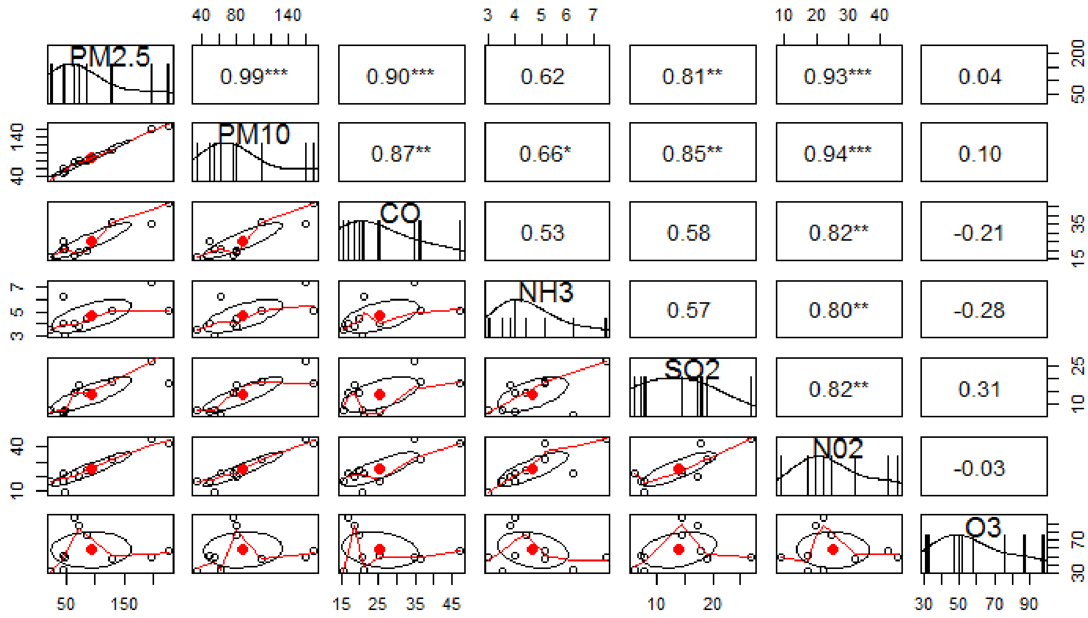


Fig. 7.4 Correlation coefficient matrices (after Pearson) between the air pollutants over the Kolkata megacity. The scatter plots presented the correlation. Here, ***stands for *p* <0.001, **stands for *p* <0.01, and *stands for *p* <0.05

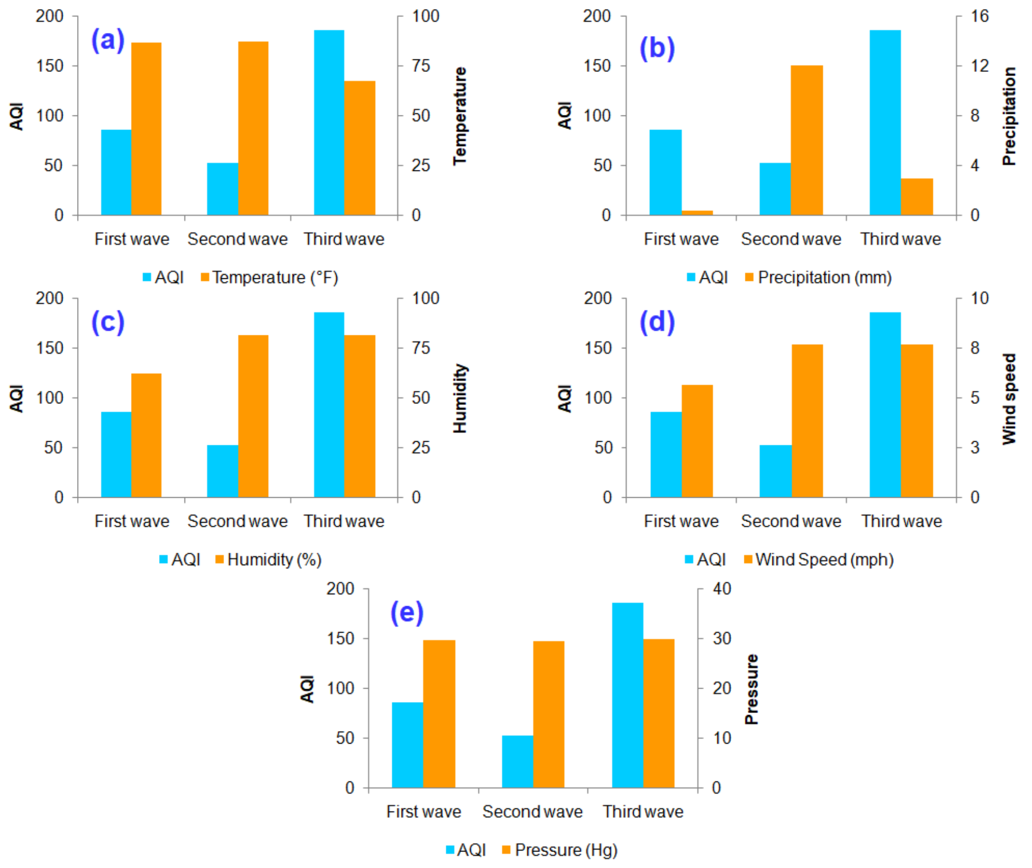


Fig. 7.5 The concentration of air temperature and the AQI (a); precipitation and AQI (b); humidity and AQI (c); wind speed and AQI (d); and air pressure and AQI (e) in the Kolkata megacity during the COVID-19-induced lockdowns across the first wave (2020), the second wave (2021), and the third wave (2022)

Table 7.4 Summary Statistics of meteorological parameters (air temperature, relative humidity, wind speed, air pressure, and precipitation) observed during COVID-19 pandemic amid lockdown waves

Parameter	Temperature (°F)			Humidity (%)			Wind Speed (mph)			Pressure (Hg)			Precipitation (mm)		
	First wave	Second wave	Third wave	First wave	Second wave	Third wave	First wave	Second wave	Third wave	First wave	Second wave	Third wave	First wave	Second wave	Third wave
Min.	82.6	80.9	63.60	42.30	71.20	74.00	3.30	1.10	2.00	29.70	29.30	29.90	0.00	0.00	0.00
Max.	89.2	91.1	72.10	83.90	93.20	89.30	9.00	14.60	6.30	29.80	29.70	30.00	5.90	91.2	43.00
Mean	86.84	87.57	67.43	62.48	81.73	81.73	5.68	7.71	7.71	29.78	29.57	29.97	0.36	12.05	3.01
Std. dev.	1.73	3.41	2.67	11.92	6.94	4.48	1.91	4.03	1.38	0.04	0.10	0.05	1.28	25.93	10.69

7.2.9 Influences of meteorological variables in governing air pollutant levels

The minimum, maximum, mean, and standard deviation of air rainfall (precipitation), temperature, wind speed, relative humidity, and air pressure for the COVID-19 lockdown amid pandemic waves are portrayed in Table 7.4. The mean air temperature was 87.57°F for the second wave, followed by 86.84°F (first wave) and 67.43°F (third wave). The high air temperature creates low pressure with inclined humidity and wind speed, thereby increasing the chances of precipitation. These conditions have led to a decline in ground-level air pollution. Increased air temperature indicates an unbalanced atmosphere, which allows pollutants to mix rapidly and, hence, be diluted (Cichowicz et al., 2017; Ravindra et al., 2019). Here, the COVID-19 lockdown during the second wave was similar. As a result, the city experienced low air pollution. High temperatures, low humidity, and lower wind speeds, with minimal rainfall, characterize the first wave. Lower air moisture content is associated with higher pollution levels (Lou et al., 2017; Munir et al., 2017).

Previous research indicates that high humidity can enhance the persistence of certain pollutants in the atmosphere (Xian et al., 2021). However, in this study, none of the lockdowns coincided with the monsoon peak, which could have allowed us to shed light on this aspect. In contrast, increased wind speed helps disperse air pollutants, reducing their concentration and potential health impacts (Zhou et al., 2020), as observed to some extent during the pre-monsoon season. Cao et al. (2021) noted that higher temperatures are generally associated with lower COVID-19 transmission rates, as evidenced by a negative correlation between temperature and virus spread (Cao et al., 2021). Additionally, changes in air pressure can influence weather patterns, which, in turn, affect temperature and humidity, thereby impacting air quality and health outcomes during the pandemic (Zhou et al., 2020). In line with these observations, our dataset shows that even a bit of relaxation during the lockdown led to significant pollution in the winter months, when temperatures and relative humidity were lower than those usually observed during other times of the year.

Sarkar et al. (2021) noted that elevated aerosol layers and low wind speeds contributed to higher AOD, suggesting higher PM levels in central India during the lockdown (Sarkar et al., 2021). Kuttippurath et al. (2023) noted that the lockdown led to a 1-3°C drop in temperature and reduced wind speeds, thereby affecting local weather patterns (Kuttippurath et al., 2023). Changes in humidity levels were also observed, contributing to overall meteorological shifts during the lockdown period. A synoptic visualization of these parameters and pollution levels for Kolkata is shown in Fig. 7.5.

Such less rainfall due to the abnormality of Kalbaisakhi (nor'wester) increased ground-level air pollution in the first wave compared to the second wave. The third wave occurred in winter, when lower temperatures and moderate wind speeds, along with dispersed rainfall from western disturbances, helped concentrate pollutants (Li et al., 2020). During winter, the planetary boundary layer (PBL) lowers, facilitating the trapping of pollutants closer to Earth's surface. In contrast, during the pre-monsoon (summer) months, enhanced atmospheric instability increases the PBL height, facilitating the dispersion of pollutants (Arregocés et al., 2021). Therefore, it can be inferred that all meteorological parameters played a significant role in controlling ground-level pollution concentrations, as determined by their seasonal characteristics. Hence, the winter lockdown (third wave) had the highest pollution levels, followed by the early pre-monsoon lockdown (first wave) and the late pre-monsoon lockdown (second wave). Table 7.5 presents a comparative analysis of the present findings with those of previous studies on Indian megacities, which largely corroborate the present findings.

Table 7.5 Previous research related to the effect of COVID-19 pandemic amid lockdown on air pollutants

Change in concentration of air pollutants								Cities	Periods	References
$PM_{2.5}$ (µg/m^3)	PM_{10} (µg/m^3)	CO (mg/m^3)	NH_3 (µg/m^3)	SO_2 (µg/m^3)	NO_2 (µg/m^3)	O_3 (µg/m^3)	AQI			
16.02%, 17.99% and 20.04%↓	8.94%, 11.75%, 20.91%↓	1.61%, 6.34%, and 6.88%↓	-	5.08%, 9.49%, and 17.93%↓	22.79%, 15.19%, and 8.04%↓	5.59%, 9.73%, and 17.93%↑	-	Kolkata	March, April, and May for the years 2019 and 2020	Bera et al., 2021
-	51.01%↓	-	-	40.38%↓	68.38%↓	42.58%↓	-	Kolkata Metropolitan Region	Pre-lockdown (17 February-23 March 2020) to lockdown (24 March-20 May 2020, i.e., during the first wave)	Chowdhuri et al., 2020
58.71%↓	57.92%↓	↓	192%↓	4 times reduction↓	55.203%↓	352%↑	↓	Kolkata	Pre-lockdown (22 February-21 March 2020) to lockdown (24 March-3 May 2020, i.e., during the first wave)	Sarkar et al., 2021
51.85%↓	53.11%↓	30.35%↓	12.33%↓	17.97%↓	52.68%↓	0.78%↑	60.95%↓	Delhi	Pre-lockdown (2 March-21 March, 2020) to lockdown (25 March-14 April,	Mahato et al., 2020

									2020 i.e. first wave)	
38.68%↓	60.46%↓	-	-	-	-	-	-	Nehru Nagar, Delhi	Previous year (2019), same window (25 March-14 April) and lockdown (first wave, 2020)	
18.43%↑	3.17%↑	23.00%↑	-	42.16%↑	39.02%↑	0.02%↑	11.56%↓	Bangkok Metropolitan Region	Previous year (2019), same window (1 January-30 March) and lockdown (first wave, 2020)	Sangkham et al., 2021
2.14%↓ 15.52%↑ 16.92%↑ 8.49%↓	13.39%↓ 18.17%↑ 25.55%↑ 8.64%↓	38.89%↓ 9.28%↑ 46.38%↑ 34.65%↓	- - - -	8.75%↑ 11.89%↓ 29.83%↑ 30.57%↑	15.11%↓ 39.39%↓ 10.04%↑ 89.21%↓	9.44%↓ 9.13%↑ 12.55%↑ 22.52%↓	- - - -	Bangalore Delhi Kolkata Mumbai	Pre-Covid period (26 April 2019 to 25 April 2020) and during COVID-19 (26 April 2020 to 25 April 2021)	Kapse et al., 2023
41%↓	52%↓	29%↓	-	-	50%↓	7%↑	-	Delhi	Pre-lockdown (10 March-20 March 2020) and during lockdown (25 March-6 April 2020)	Jain and Sharma, 2020

45%↓	52%↓	41%↓	-	-	48%↓	14%↑	-		20 March to 10 April for 2019 and 2020
33%↓	47%↓	46%↓	-	-	75%↓	8%↑	-	Mumbai	Pre-lockdown (10 March-20 March 2020) and during lockdown (25 March-6 April 2020)
DNA*	DNA*	DNA*	-	-	DNA*	DNA*	-		20 March to 10 April for 2019 and 2020
14%↓	DNA*	25%↓	-	-	32%↓	3%↑	-	Chennai	Pre-lockdown (10 March-20 March 2020) and during lockdown (25 March-6 April 2020)
39%↓	DNA*	23%↓	-	-	43%↓	73%↑	-		20 March to 10 April for 2019 and 2020
22%↓	34%↓	16%↓	-	-	60%↓	11%↓	-	Bangalore	Pre-lockdown (10 March-20 March 2020) and during lockdown (25 March-6 April 2020)
47%↓	40%↓	15%↓	-	-	56%↓	21%↓	-		20 March to 10 April for 2019 and 2020

23%↓	34%↓	29%↓	-	-	60%↓	17%↑	-	Kolkata	Pre-lockdown (10 March-20 March 2020) and during lockdown (25 March-6 April 2020)	
27%↓	32%↓	16%↓	-	-	66%↓	87%↑	-		20 March to 10 April for 2019 and 2020	
50.20%	39.25%↓	14.34%↓	0.06%↑	8.89%↓	25.59%↓	59.58%↑	-	Delhi	Pre-lockdown (before 24 March 2020) and After complete lockdown (After 24 March 2020)	Pal et al., 2022
70.08%↓	56.30%↓	24.24%↓	70.52%↓	5.47%↓	76.88%↓	2.86%↑	-	Mumbai		
81.02%↓	68.93%↓	57.57%↓	45.95%↓	61.77%↓	56.95%↓	40.67%↑	-	Kolkata		
50.81%↓	41.11%↓	45.78%↓	61.35%↓	67.64%↓	23.67%↓	191.71%↑	-	Chennai		
46.61%↓	40.70%↓	26.61%↓	33.39%↓	42.11%↓	68.33%↓	25.30%↓	41.61%↓	Mumbai	Pre-lockdown (3 March-23 March. 2020) and during lockdown (25 March-14 April, 2020)	My observation
51.84%↓	38.95%↓	12.25%↓	17.39%↓	13.91%↓	40.36%↓	19.37%↓	41.39%↓	Delhi		
48.81%↓	36.81%↓	20.92%↓	32.44%↓	20.88%↓	62.37%↓	21.13%↓	43.40%↓	Kolkata		
42.83%↓	32.46%↓	5.86%↓	20.51%↓	106.57%↑	19.35%↓	29.43%↓	26.89%↓	Mumbai	During lockdown (25 March-14 April, 2020)) and post- lockdown (15 April-5 May, 2020)	
3.36%↓	4.20%↓	26.28%↑	8.40%↑	5.96%↑	11.51%↓	48.59%↑	13.97%↑	Delhi		
57.07%↓	50.19%↓	8.75%↓	38.64%↓	35.07%↓	28.90%↓	23.85%↓	32.39%↓	Kolkata		
34.67%↓	25.67%↓	40.85%↓	DNA*	18.00%↑	44.35%↓	55.93%↓	-	Bandra, Mumbai	Previous year (2019), same	

16.76%↓	51.78%↓	17.95%↑	25.00%↓	13.19%↓	6.25%↑	146.94%↑	-	ITO, Delhi	window (25 March-14 April) and lockdown (first wave, 2020)
31.84%↓	30.65%↓	44.00%↓	112.50%↑	60.47%↑	59.14%↓	13.19%↑	-	Rabindra Bharati University, Kolkata	

↑& ↓=positive and negative change; DNA=data not available*

Table 7.6 Average concentration of air pollutants in Kolkata megacity for the weathered and deweathered datasets during the three lockdown phases

Pollutants		$PM_{2.5}$ (µg/m^3)	PM_{10} (µg/m^3)	CO (mg/m^3)	NH_3 (µg/m^3)	SO_2 (µg/m^3)	NO_2 (µg/m^3)	O_3 (µg/m^3)
First wave lockdown (25 Mar-14 Apr, 2020	Weathered	87.75±36.94	79.75±24.45	10.50±3.11	8.50±1.00	17.25±2.75	30.75±9.46	66.50±16.38
	Deweathered	69.30±25.04	70.46±13.41	13.48±0.96	6.81±1.20	15.01±3.18	24.80±4.30	57.37±5.71
	Total variation Avg.	-18.45	-9.29	2.98	-1.69	-2.24	-5.95	-9.13
	% of variation	-21.03	-11.65	28.42	-19.87	-13.01	-19.35	-13.74
Second wave lockdown (16 May-30 May, 2021)	Weathered	58.67±13.80	68.33±17.04	15.33±7.37	4.00±0.00	10.00±0.00	18.33±0.58	47.00±14.11
	Deweathered	142.55±116.87	106.68±60.56	20.97±14.01	6.23±2.08	24.51±14.68	28.85±4.87	60.20±1.20
	Total variation Avg.	83.88	38.34	5.64	2.23	14.51	10.52	13.20
	% of variation	142.98	56.11	36.75	55.76	145.09	57.39	28.09
Third wave lockdown (1 Jan-15 Jan, 2022)	Weathered	254.67±40.10	162.67±23.16	32.00±4.58	4.33±0.58	37.00±11.36	31.33±3.06	63.00±10.82
	Deweathered	285.73±12.22	189.11±19.66	36.43±1.71	4.08±0.13	40.73±1.02	34.69±1.92	62.46±2.95
	Total variation Avg.	31.07	26.45	4.43	-0.25	3.73	3.36	-0.54
	% of variation	12.20	16.26	13.84	-5.87	10.08	10.72	-0.86

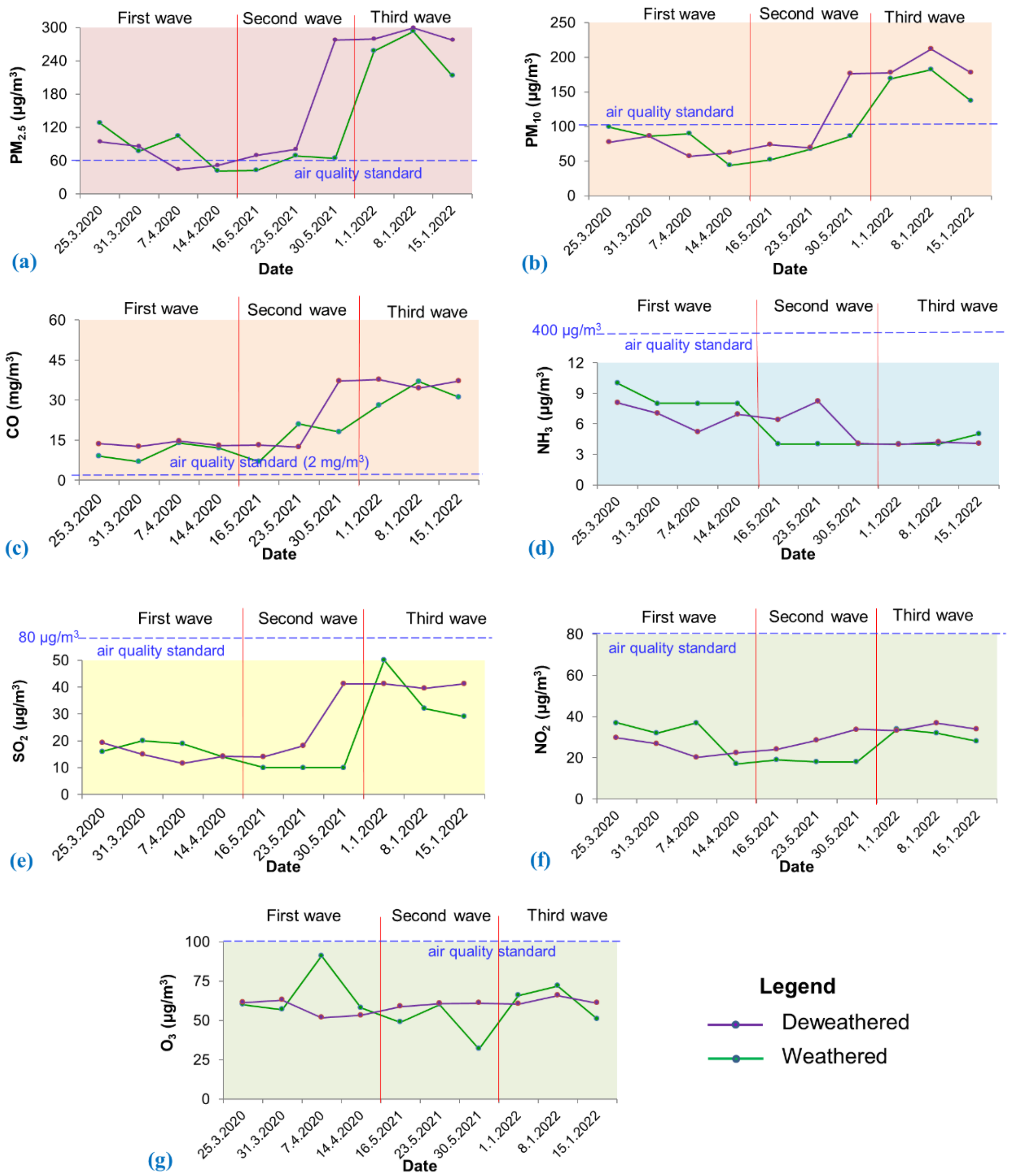


Fig. 7.6 Comparative analysis of deweathered and weathered data of atmospheric pollutant levels in megacity during COVID-19-induced lockdowns across the first wave (2020), second wave (2021), and third wave (2022)

7.2.10 Comparison between weathered and deweathered conditions of air pollutants

To normalize the weather dataset, the pollutant data were deweathered. Here, three meteorological parameters, viz., temperature, rainfall, and wind speed, have been taken for deweathering. The weathered and deweathered line graphs are shown in Fig. 7.6. A similar trend in pollutants was observed for both weathered and deweathered conditions. A sharp increase in the third wave from the second wave phase was observed for $PM_{2.5}$, PM_{10}, CO, and SO_2. Likewise, NO_2 increased in the third wave compared with the second wave.

Moreover, improvement in air quality ($PM_{2.5}$, PM_{10}, CO, SO_2, and NO_2) was highest in the second wave amid lockdown, followed by the first and third waves for both weathered and deweathered conditions. The NH_3 showed a decreasing trend from the first wave to the second wave and, thereby, the third wave for the weathered dataset. A slight increase was observed in the second-wave deweathered dataset. However, the trend was a gradual decrease or regular improvement in air quality (NH_3). The O_3 trend was mixed for both weathered and deweathered datasets. The one-station (RBU) dataset is insufficient to characterize a city's meteorological conditions fully. However, the deweathered data also portrayed a similar trend for the city. This observation indicates that meteorological conditions, though they regulated pollutant concentrations across the different seasons, did not regulate the trend of increases or decreases in air pollution levels.

The weathered-to-deweathered mean concentrations of $PM_{2.5}$ and PM_{10} decreased by -21.03% and -11.65% during the first wave, but increased by 142.98% and 56.11% during the second wave, and by 12.20% and 16.26% during the third wave (Table 7.6). Similarly, SO_2 and NO_2 levels decreased during the first wave (-13.01% and -19.35%) but increased during the second wave (145.09% and 57.39%) and the third wave (10.08% and 10.72%). However, NH_3 and O_3 concentrations increased during the second wave (55.76% and 28.09%). Still, they decreased during the first wave (-19.87% and -13.74%) and the third wave (-5.87% and -0.86%) after deweathering. CO showed a consistent increase across all three waves, with increases of 28.42%, 36.75%, and 13.84%, respectively. These results indicate mixed trends across weathered-to-deweathered datasets for all three pandemic waves, highlighting the significant role of meteorology. The variation between weathered and deweathered pollutant levels was evident. The third wave had the least variation during the winter season, while the second wave showed the most variation during the pre-monsoon period. Both the first and second waves occurred during the pre-monsoon period. Still, the second wave exhibited greater variation due to the lockdown's greater stringency.

A few areas of Handan (China) recorded a significant increase in deweathered O_3 levels due to a robust decline of NO_2 gas (Sun and Li, 2024). Ghaffarpasand et al. (2024) studied $PM_{2.5}$ levels in the regular phase and deweathered phase in Kampala City (Africa). The result revealed that the deweathered $PM_{2.5}$ level showed approximately 5.5% greater reduction than the regular phase (Ghaffarpasand et al., 2024). Saleem et al. (2024) argued that meteorological drivers make a minor contribution to reducing air pollution levels compared with lockdown stringency (Saleem et al., 2024). Another recent study found that unfavourable weather factors reduced pollution levels during the COVID-19 pandemic (Si et al., 2024). Verma et al. (2024) stated that meteorological factors influenced PM_{10} more than human activities (Verma et al., 2024).

Chapter VIII

Air Quality in Mumbai During Lockdowns

8.1 Introduction

The novel coronavirus (COVID-19) disease was declared a pandemic on 12 March 2020, and the global health emergency it fostered lingered from 2020 to 2022 (Hammad et al., 2023; Naseer et al., 2023). Among the several countries, India had its fair share of the impact of this deadly pandemic that ravaged its economy and led to several casualties (Junuguru and Singh, 2023). The megacities of India, with very high population density, were severely impacted by the pandemic (Desai, 2020). Both central and respective state governments of India had to impose lockdowns to arrest the spread of the virus in several phases whenever the number of COVID-19-infected cases rose (Ravindran and Shah, 2023).
Despite the many ill effects this pandemic introduced, the brighter side of the COVID-19-induced lockdowns was the significant improvement in air quality observed worldwide (Das et al., 2023; Pathak et al., 2023). Several scholarly pieces of literature unequivocally showed that air quality in Indian cities and metropolises has also witnessed a remarkable improvement owing to these lockdowns (Chinnasamy et al., 2023; Kashyap et al., 2023; Persis and Amar, 2023). Megacities like Delhi, Kolkata, and Mumbai have received substantial attention in this regard (Dhar, 2023; Chinnasamy et al., 2023; Yeasin et al., 2023; Pal et al., 2022; Meo et al., 2022).

Mumbai, the business capital of India and home to more than 25 million people, was one of the hard-hit megacities, having witnessed three prominent lockdown phases in 2020 (during the first wave), 2021 (second wave), and 2022 (third wave). Chattopadhyaya and Shaw (Chattopadhyaya and Shaw, 2021) investigated the association between air pollutants and COVID-19 spread in Mumbai. They found that pollutant concentrations were correlated mainly with COVID-19 deaths, with higher COVID-19 case counts observed where PM_{10}, NO_2, and SO_2 exposures were high. A significant improvement in air quality was observed in Mumbai during the lockdown phase (first phase of the first wave) of 2020 compared to the pre-lockdown and the same window of the previous year, 2019 (Kumari and Toshniwal, 2022). Das et al. (2022) examined changes in air quality between the first and second waves amid lockdown in Mumbai. The result shows that air quality declined by 32% in the second wave, following the imposition of a regional lockdown (2021), compared with the nationwide lockdown (2020) (Das et al., 2022).

However, while most of the studies focused on the impact of lockdowns on the level of air pollutants, meteorological conditions were ignored in many studies while comparing the pandemic and non-pandemic scenarios (Chattopadhyaya and Shaw, 2021; Shehzad et al., 2021). Moreover, most of the literature focused on the lockdowns during the first wave (Kumari and Toshniwal, 2022; Meo et al., 2022) and a few on the second wave of the surge in COVID-19 infected cases (Das et al., 2022; Nath et al., 2022). Studies encompassing all three significant waves of COVID-19 case surges, while accounting for differences in meteorological conditions, are scarce to date. The present study was thus focused on Mumbai, with a view to addressing the shortcomings of earlier studies and developing a holistic understanding of how air pollutant dynamics changed with varying levels of lockdown stringency and their interrelationships with meteorological conditions.

Mumbai is India's second most populous city (after Delhi). This megacity witnessed many confirmed cases and deaths during the multi-wave of the COVID-19 pandemic. The reason this megacity has been chosen for the present study is that the three successive waves witnessed by this city featured distinct lockdown restrictions and seasonal conditions. The first wave had no known medicines and zero vaccinations. People were scared enough during the onset of the pandemic. The second wave occurred during the early stages of vaccination, and people had the mindset that they had to live with the virus. The third wave featured single- and double-dose vaccination rates of 90% and 60%, respectively, among the megacity's population (Nagarajan, 2022), and city-wide immunity was also prominent. From a seasonal perspective, the first and second waves occurred in the early summer/pre-monsoon and late summer, respectively, whereas the third wave occurred in winter. Hence, meteorological drivers, viz., wind speed, temperature, humidity, and rainfall, were different in these lockdown phases.

Thus, this city offered us a suitable platform to study the dynamics of air quality under varying lockdown restrictions and seasonal conditions. The primary objective of this study was to investigate changes in air quality during COVID-19 pandemic surges, while accounting for natural seasonality in meteorological conditions. The second objective of the study was to assess whether the stringency of lockdowns imposed had a role in regulating the air quality. This study's assessment involved deweathering the pollutant data and correlating air pollutant levels with one another and with meteorological drivers. The outcomes from studies like this might guide decision-makers and planners on how climatic variables control pollution levels during the pandemic surge. In addition, these observations might help us in the future to improve the air quality of the otherwise polluted megacities of India.

8.2 Results

8.2.1 Changes in the concentration of $PM_{2.5}$ and PM_{10}

The megacity of Mumbai has witnessed three consecutive lockdowns. The first wave concentrations of $PM_{2.5}$ and PM_{10} were below the standard (60 μg/m^3 and 100 μg/m^3) of CPCB (Figs. 8.1a, 8.1b). The weekly $PM_{2.5}$ and PM_{10} levels were higher during the third wave and were below the standard during the second wave. Hence, the decline was observed in the first wave, followed by a mixed trend in the second wave, and, again, a rise in the third wave. The three surges in $PM_{2.5}$ concentrations varied from 37.40 to 57.22 μg/m^3, 42.33 to 131.86 μg/m^3, and 58.83 to 183.00 μg/m^3, respectively (Table 8.1). The PM_{10} ranges were 65.25-82.89 μg/m^3, 67.73-181.82 μg/m^3, and 74.60-147.82 μg/m^3. Overall, increases of 55.84% (26.53 μg/m^3) and 88.80% (65.73 μg/m^3), as well as 44.82% (32.73 μg/m^3) and 14.71% (15.56 μg/m^3), were observed for $PM_{2.5}$ and PM_{10} during the transition from the first to second wave and the second to third wave (Table 8.2). The spatial dispersions are shown in Figs. 8.2a and 8.2b. $PM_{2.5}$ and PM_{10} ranged from 32.51 to 226.97 μg/m^3 and 31.16 to 161.75 μg/m^3, respectively. These observations show that $PM_{2.5}$ had a greater impact on the residents of Mumbai than PM_{10}. Wave-wise, the third wave was the worst for air quality, and the first wave showed potentially good air quality. During the second wave, the megacity's air was moderately polluted. The south and south-eastern parts detected more pollution than the city's western parts. The study exhibited that $PM_{2.5}$ and PM_{10} have dropped (-34.67% & -22.13%, and -25.67% & -38.62%) in the first and third waves amid lockdown phases compared to normal (Table 8.3). The scenario was the opposite during the second wave. According to the World Air Quality Report 2021, last year (2021), the $PM_{2.5}$ annual average (46.4 μg/m^3) was more than in 2019 (45.3 μg/m^3) for Mumbai. One of the prime reasons for this observation could be that most people felt reckless about resuming their jobs during the second wave to overcome the financial constraints the first wave imposed on millions. Compared to their regular phase concentration, 20.54% and 5.24% increases in $PM_{2.5}$ and PM_{10} were observed during the second wave amid lockdown phases. The boxplots (Fig. 8.3a) show that the average $PM_{2.5}$ concentration was 36, 36, and 176 $\mu g/m^3$ in the normal phase, while in the pandemic phase, it was 31, 45, and 129 $\mu g/m^3$. Likewise, PM_{10} levels were 84, 87, and 209 $\mu g/m^3$, and 72.5, 87, and 120.5 $\mu g/m^3$, for the regular and pandemic phases (Fig. 8.3b). Hence, both $PM_{2.5}$ and PM_{10} showed similar changes in concentration. The first and second waves, both during the pandemic and in the non-pandemic period, were within the satisfactory AQI range for both $PM_{2.5}$ (31-60 $\mu g/m^3$) and PM_{10} (51-100 $\mu g/m^3$). The third wave recorded very poor AQI levels for particulate matter, which could have increased the risk of breathing discomfort and respiratory illness among megacity dwellers.

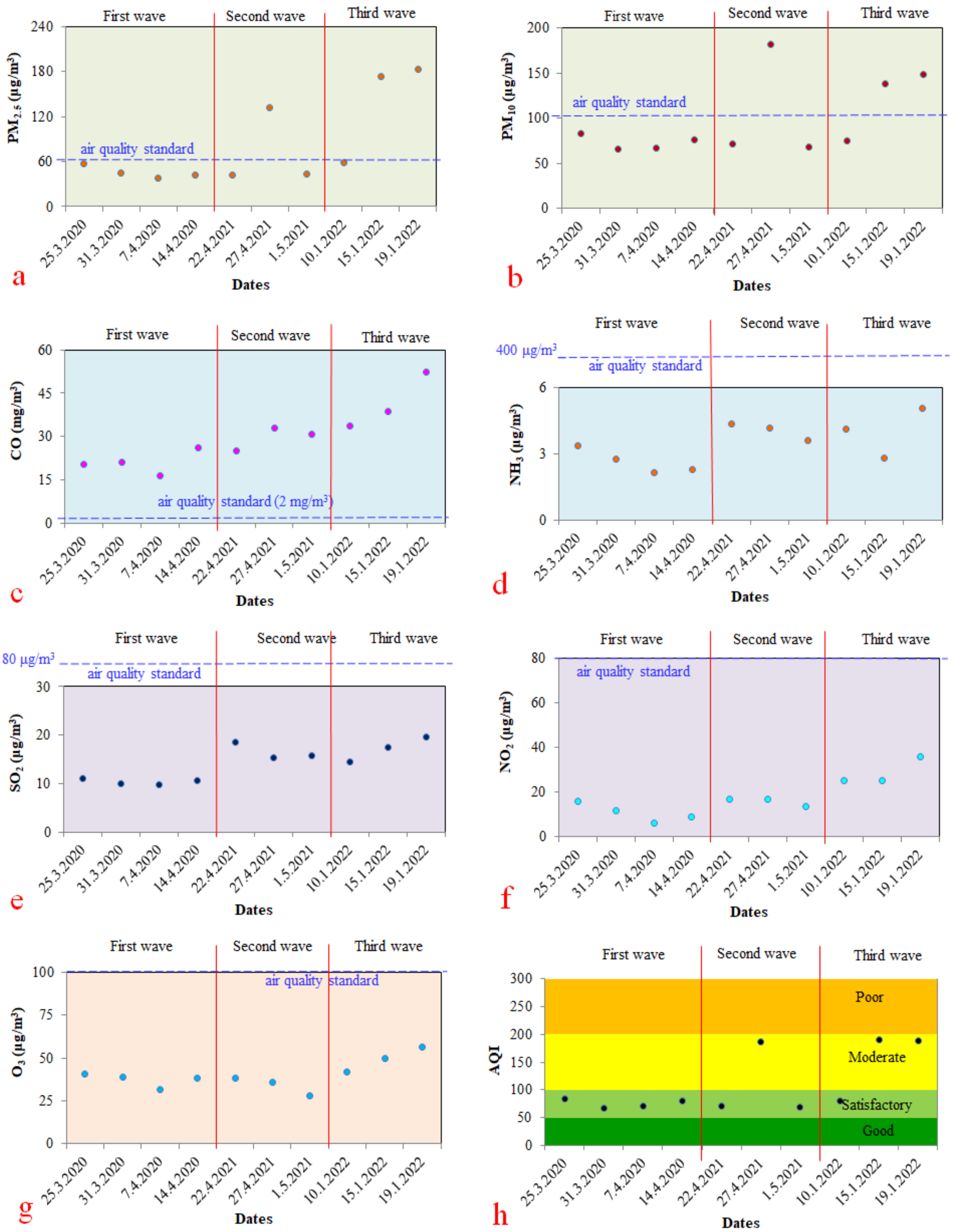


Fig. 8.1 Daily average concentrations of (a) $PM_{2.5}$, (b) PM_{10}, (c) CO, (d) NH_3, (e) SO_2, (f) NO_2, (g) O_3 and (h) AQI during COVID-19 amid lockdown periods

Table 8.1 Weekly data of ambient air pollutants in COVID-19 amid lockdowns for the first, second, and third waves

Source: CPCB web portal, https://airquality.cpcb.gov.in/AQI_India_Iframe/

Pollutants	First wave lockdown				Second wave lockdown			Third wave lockdown			Permissible limit of CPCB
	25.3.2020	31.3.2020	7.4.2020	14.4.2020	22.4.2021	27.4.2021	1.5.2021	10.1.2022	15.1.2022	19.1.2022	
$PM_{2.5}$ (μg/m^3)	57.22±7.46	45.38±8.75	37.40±7.23	42.50±9.54	42.00±13.85	131.86±123.94	43.77±21.03	58.83±22.14	173.83±81.96	183.00±59.95	60
PM_{10} (μg/m^3)	82.89±13.15	65.25±13.23	67.14±11.01	75.50±12.86	70.92±20.26	181.82±58.79	67.73±17.61	74.60±15.33	137.45±19.90	147.82±26.82	100
CO (mg/m^3)	20.33±13.54	21.00±14.00	16.67±13.67	26.22±24.29	25.00±25.85	33.00±27.83	30.93±23.11	33.83±31.20	38.77±15.76	52.43±25.77	2
NH_3 (μg/m^3)	3.38±1.69	2.75±1.49	2.14±0.90	2.29±1.11	4.36±4.78	4.18±5.10	3.64±3.93	4.15±6.19	2.83±1.53	5.08±5.60	400
SO_2 (μg/m^3)	11.00±9.10	10.00±8.38	9.75±10.08	10.57±9.16	18.64±21.12	15.42±19.97	15.7±18.49	14.45±14.14	17.42±18.03	19.69±18.43	80
NO_2 (μg/m^3)	16.00±10.42	11.67±7.07	6.43±2.57	8.86±3.67	16.86±13.01	16.93±13.21	13.57±10.35	25.31±17.72	25.42±20.97	35.92±27.85	80
O_3 (μg/m^3)	40.44±24.15	38.78±24.11	31.75±21.24	38.43±26.07	38.54±27.76	36.15±23.92	28.31±18.63	41.92±21.72	49.46±34.41	56.38±47.68	100
AQI	83.44±12.88	67.88±12.99	70.14±9.96	80.17±8.16	70.77±19.57	186.62±109.92	69.38±22.21	80.36±19.59	190.83±58.49	188.92±50.21	

Air pollutants are reported as mean ± standard deviation.

Table 8.2 Variation of air pollutants in First wave & Second wave lockdown and Second wave & Third wave lockdown periods

Pollutants	First wave lockdown (25 Mar-14 Apr, 2020)	Second wave lockdown (22 Apr-1 May 2021)	Total variation Avg.	% of variation	Second wave lockdown (22 Apr-1 May 2021)	Third wave lockdown (10 Jan- 19 Jan 2022)	Total variation Avg.	% of variation
$PM_{2.5}$ (µg/m^3)	47.50±10.88	74.03±84.64	26.53	55.84	74.03±84.64	139.76±81.52	65.73	88.80
PM_{10} (µg/m^3)	73.03±14.14	105.76±64.27	32.73	44.82	105.76±64.27	121.32±38.06	15.56	14.71
NO_2 (µg/m^3)	10.97±7.45	15.79±12.06	4.82	43.93	15.79±12.06	28.97±22.58	13.19	83.54
NH_3 (µg/m^3)	2.67±1.37	4.06±4.49	1.39	52.27	4.06±4.49	4.05±4.92	-0.01	-0.20
SO_2 (µg/m^3)	10.33±8.75	16.49±19.27	6.15	59.55	16.49±19.27	17.33±16.75	0.85	5.14
CO (mg/m^3)	21.06±16.62	29.53±25.30	8.48	40.27	29.53±25.30	42.15±25.54	12.62	42.73
O_3 (µg/m^3)	37.45±22.99	34.33±23.52	-3.12	-8.33	34.33±23.52	49.45±36.01	15.11	44.02
AQI	75.53±12.86	104.62±83.28	29.09	38.51	104.62±83.28	155.34±67.53	50.72	48.48

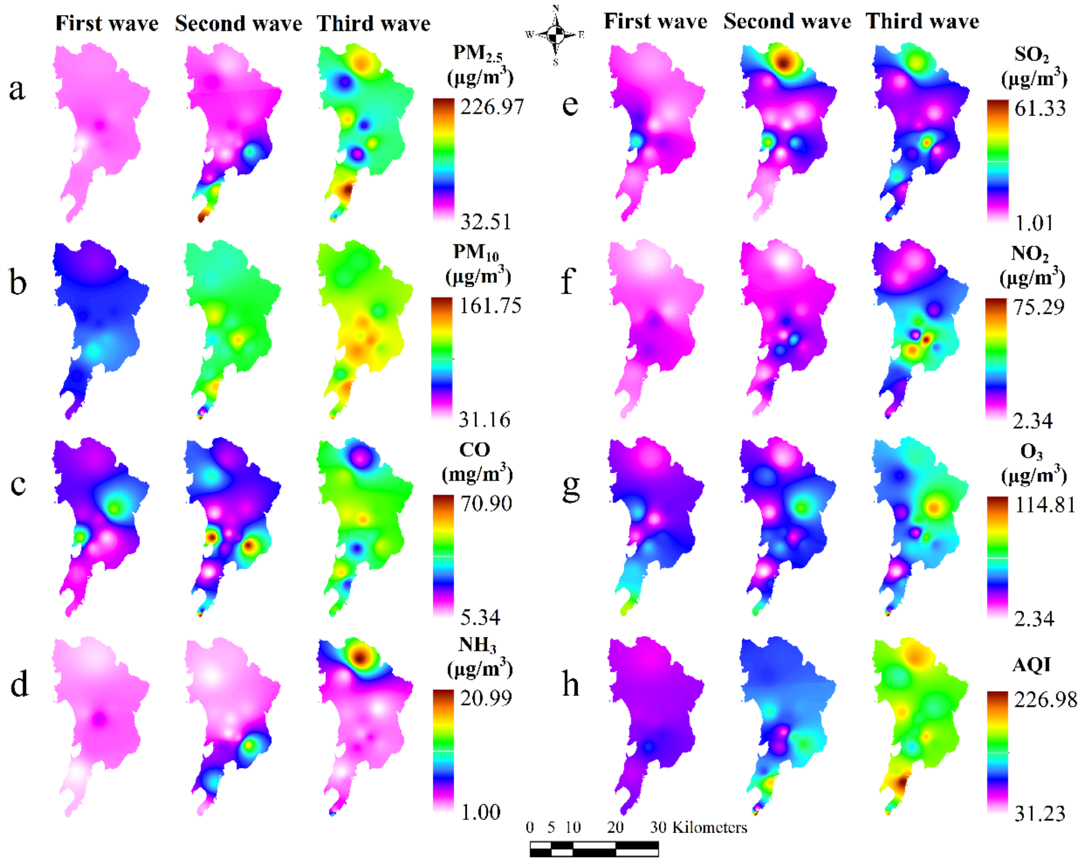


Fig. 8.2 The spatial distribution of (a) $PM_{2.5}$, (b) PM_{10}, (c) CO, (d) NH_3, (e) SO_2, (f) NO_2, (g) O_3, and (h) AQI in Mumbai during COVID-19 amid inter-lockdown periods

Table 8.3 Average concentration of air pollutants in Mumbai megacity for the Normal periods and COVID-19 amid lockdown periods[1]

Pollutants	$PM_{2.5}$ (μg/m^3)	PM_{10} (μg/m^3)	CO (mg/m^3)	NH_3 (μg/m^3)	SO_2 (μg/m^3)	NO_2 (μg/m^3)	O_3 (μg/m^3)	AQI
Normal period (25 Mar-14 Apr 2019)	49.75±31.79	102.25±44.86	82.00±9.83	NDA*	25.00±12.94	28.75±14.64	29.50±25.68	107.50±41.17
First wave lockdown (25 Mar-14 Apr, 2020)	32.50±6.81	76.00±11.92	48.50±1.91	NDA*	29.50±1.73	16.00±13.98	13.00±8.49	76.00±11.92
Total variation Avg.	-17.25	-26.25	-33.50	-	4.50	-12.75	-16.50	-31.50
% of variation	-34.67	-25.67	-40.85	-	18.00	-44.35	-55.93	-29.30
Normal period (22 Apr-1 May 2019)	37.33±6.11	82.67±8.39	91.33±3.79	NDA*	29.00±2.00	27.33±10.02	29.00±15.52	91.33±3.79
Second wave lockdown (22 Apr-1 May 2021)	45.00±0.00	87.00±0.00	70.00±0.00	NDA*	41.00±0.00	12.00±0.00	41.00±1.00	87.00±0.00
Total variation Avg.	7.67	4.33	-21.33	-	12.00	-15.33	12.00	-4.33
% of variation	20.54	5.24	-23.36	-	41.38	-56.10	41.38	-4.74
Normal period (10 Jan-19 Jan 2019)	165.67±28.92	196.33±29.14	101.67±6.43	NDA*	33.33±12.22	61.67±2.52	54.00±22.11	196.33±29.14
Third wave lockdown (10 Jan- 19 Jan 2022)	129.00±79.20	120.50±45.96	39.00±35.76	NDA*	22.00±4.58	6.67±4.43	16.33±8.02	136.50±68.59
Total variation Avg.	-36.67	-75.83	-62.67	-	-11.33	-55.00	-37.67	-59.83
% of variation	-22.13	-38.62	-61.64	-	-34.00	-89.19	-69.75	-30.48

Air pollutants are reported as mean ± standard deviation

[1]Bandra Kurla Complex was considered for 2019, 2020, 2021, and 2022 *NDA = No data available for NH_3

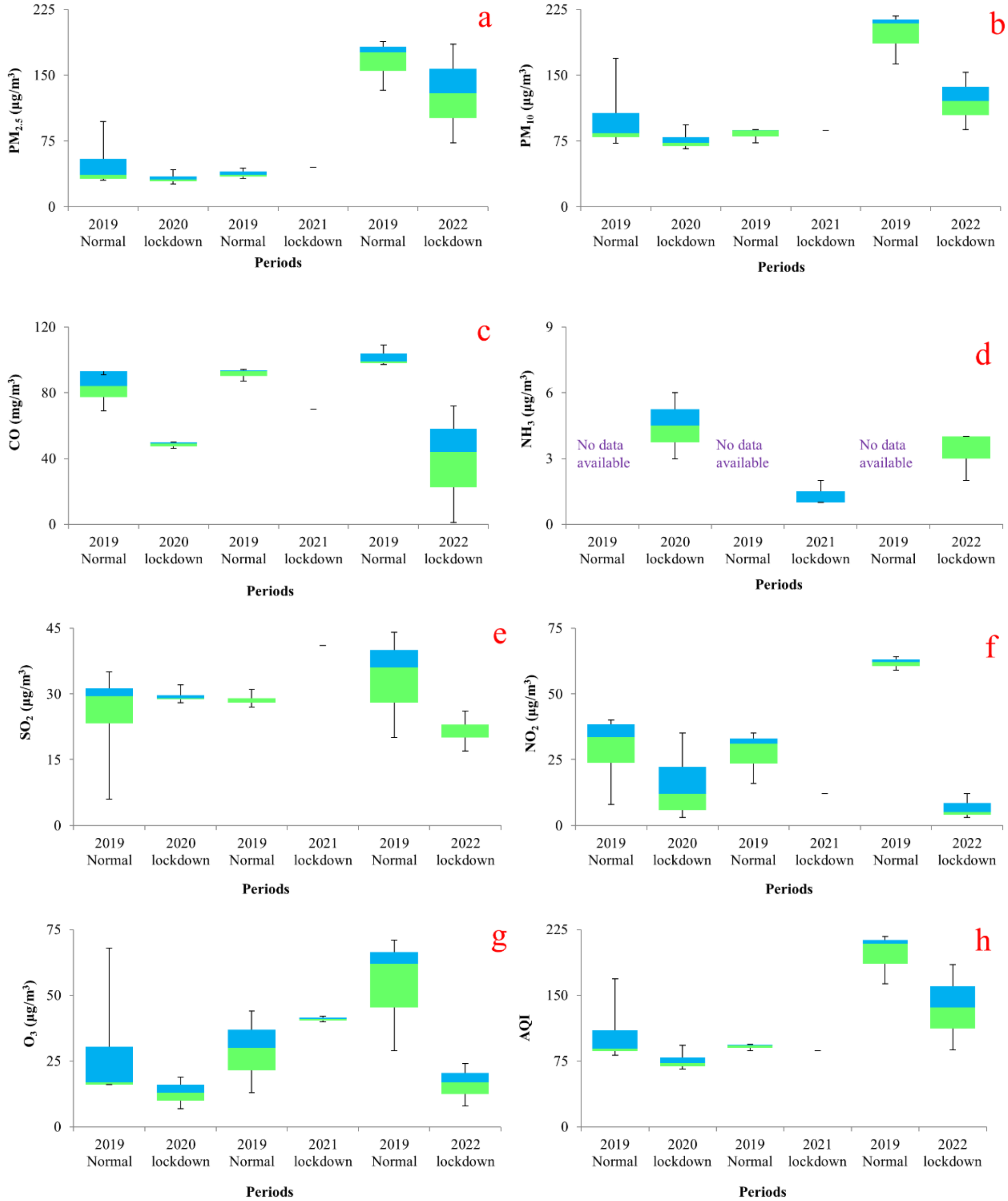


Fig. 8.3 The box plot showing the concentrations of (a) $PM_{2.5}$, (b) PM_{10}, (c) CO, (d) NH_3, (e) SO_2, (f) NO_2, (g) O_3, and (h) AQI at Mumbai during the normal period (2019) and three consecutive waves amid lockdown phases

8.2.2 Changes in the concentration of CO

CO is a colourless, odourless, and tasteless air pollutant that remains abundant in urban areas. Industrial processes, transport, combustion, solid waste disposal, and refuse burning are the prime sources of ground-level CO. CO is a GHG linked with global climate change. In addition to environmental impacts, elevated CO concentrations can cause harmful health effects, including neurological, neurobehavioural, and cardiovascular disorders in humans (WHO, 2000). The recorded concentration of CO was higher than the standard of CPCB (2 mg/m^3) (Fig. 8.1c). The megacity has witnessed a sharp increase in the inter-wave trend in CO levels. It indicates unhealthy air with various human health risks. The pandemic period concentrations were 16.67-26.22 mg/m^3, 25.00-33.00 mg/m^3, and 33.83-52.43 mg/m^3 for the first wave, second wave, and third wave, respectively (Table 8.1). Fig. 8.2c shows that CO levels ranged from 5.34 to 70.90 mg/m^3. The first wave observed the lowest CO levels. The second wave yielded mixed results, and the third wave broke the records set by the first two. The megacity noted a 40.27% (8.48 mg/m^3) increase in concentration during the second wave compared to the first. Likewise, a 42.73% (12.62 mg/m^3) increase was observed in the third wave compared to the second wave (Table 8.2). Looking into the concentrations of normal phases when no pandemic-induced lockdown occurred and comparing them with lockdown waves, I recorded a -40.85% (33.50 mg/m^3), -23.56% (21.33 mg/m^3), and -61.64% (62.67 mg/m^3) reduction during the three successive waves (Table 8.3). Hence, the pandemic amid lockdowns brought long-term blessings to environmental air quality. Fig. 8.3c depicted a similar scenario. The average CO concentrations were 84, 93, and 99 mg/m^3 for normal phases, while the pandemic-phase concentrations were 49, 70, and 44 mg/m^3. However, all these values (>34 mg/m^3) are in the severe AQI category, which can cause severe respiratory illness in people with prolonged exposure.

8.2.3 Changes in the concentration of NH_3

According to the CPCB, the standard limit of NH_3 is 400 μg/m^3. Concentrations lower than this standard were recorded in all three COVID-19-induced waves (Fig. 8.1d). NH_3 concentrations varied from 2 to 5 μg/m^3 for the waves (Table 8.1). The intra-wave comparison shows a 52.27% (1.39 μg/m^3) increase in NH_3 levels in the second wave compared to the first. The second-to-third wave variation was only -0.20% (0.85

μg/m^3), indicating almost no change (Table 8.2). The spatial distribution map portrayed similar scenarios of low NH_3 concentrations across the megacity for all three waves (Fig. 8.2d). Intra-wave comparisons indicated that the first wave was best for the citizens, followed by the second and third waves in terms of NH_3 concentrations. A few pockets of the south and north exerted a relatively higher concentration in the second and third waves. I could not portray the concentration of NH_3 in both the normal and pandemic phases because the 2019 data were insufficient. Hence, I depicted only pandemic-surge concentrations in the box plots (Fig. 8.3d).

8.2.4 Changes in the concentration of SO_2

The SO_2 concentration was also below the standard limit (80 μg/m^3) during all three pandemic surges (Fig. 8.1e). However, a rising trend persisted from the first day of the first wave to the last day of the recent wave. The wave-wise ranges were 9.75-11.00 μg/m^3, 15.42-18.64 μg/m^3, and 14.45-19.69 μg/m^3 for the first, second, and third wave, respectively (Table 8.1). The spatial pattern of the substance is illustrated in Fig. 8.2e. Lower SO_2 levels were recorded in the first wave amid lockdown, compared to the second and third waves across the city. The second and third waves gradually reduced SO_2 levels. The northern part of Mumbai had higher concentrations than the rest of the region. There was an upsurge of 59.55% (6.15 μg/m^3) and 5.14% (0.85 μg/m^3) for the first wave-second wave and the second wave-third wave, respectively (Table 8.2). Hence, there was a continuous increment in SO_2 levels in the inter-lockdown phases. The average values of COVID-19 phases and normal phases were 29 & 29.5, 41 & 29, and 23 & 36 μg/m^3 (Fig. 8.3e). Hence, good quality (< 40 μg/m^3) air with minimal health impact prevailed during both pandemic and non-pandemic phases. The boxplots exhibited that the substances were unstable and fluctuated. The city has witnessed increases in SO_2 concentration during the first (18.00%) and second wave (41.38%) pandemic surges, compared to normal periods (Table 8.3). The third wave witnessed a reverse scenario, a reduction of -34% (11.33 μg/m^3).

8.2.5 Changes in the concentration of NO_2

NO_2 concentration was below the permissible limit (80 μg/m^3) of CPCB for all three waves (Fig. 8.1f). A rising trend has been noted from the point plot graph. NO_2 varied from 6.43-16.00 μg/m^3 (first wave), 13.57-16.93 μg/m^3 (second wave), and 25.31-35.92 μg/m^3 (third wave) in COVID-19 phases (Table 8.1). The megacity also witnessed a continuous increase in NO_2 concentrations from the first wave to the second wave with a 43.93% (4.82 μg/m^3) increase, and from the second wave to the third wave with an 83.54% (13.19 μg/m^3) increase (Table 8.2). Fig. 8.2f shows the distribution of NO_2 during the pandemic wave's lockdown. Visual inspection of these maps shows that the central part exhibited more pollution levels (NO_2) during all three waves than the rest of the region. The concentrations gradually reduced from the core towards the periphery. The box plots (Fig. 8.3f) showed a significant drop in NO_2 during COVID-19 waves compared to normal periods in 2019. The third wave noted a maximum fall in concentration with -89.19% (55.00 μg/m^3), followed by the second wave at -56.10% (15.33 μg/m^3) and the first wave at -44.35% (12.75 μg/m^3) (Table 8.3).

8.2.6 Changes in the concentration of O_3

The city witnessed the O_3 levels below the permissible limit (100 μg/m^3) during all three waves (Fig. 8.1g). A marginal increase in O_3 has been observed from the first wave to the third wave. The O_3 ranges were 31.75-40.44 μg/m^3, 28.31-38.54 μg/m^3, and 41.92-56.38 μg/m^3 for the first, second, and third waves, respectively (Table 8.1). The intra-lockdown variation has been noted with time. I found a drop in average O_3 concentration from the first wave to the second wave with a volume of -8.33% (-3.12 μg/m^3) and, followed by a noticeable rise in O_3 levels from the second wave phases to the third wave, 44.02% (15.11 μg/m^3) (Table 8.2). The wave-wise spatial distribution has been shown in Fig. 8.2g. Uneven patterns of concentration have been observed. During the COVID-19 pandemic, the O_3 concentration dropped by -55.93% and -69.75% in the first and third waves, respectively, though it increased by 41.38% in the second wave compared to the 2019 normal year level (Table 8.3). The boxplots (Fig. 8.3g) show that the range of substances was greater in normal phases than in pandemic phases. The mean concentrations in the pandemic and non-pandemic phases were 13 & 17, 41 & 30, and 17 & 62 μg/m^3 for the first, second, and third waves, respectively. Therefore, the city has good air quality with minimal health issues except for one satisfactory level.

8.2.7 Changes in the AQI

The megacity's AQI was excellent during the pandemic waves. The first wave witnessed a satisfactory AQI, followed by satisfactory to moderate AQI for the second and third waves (Fig. 8.1h). We may conclude that air pollution levels rose with the withdrawal of lockdowns and that poor air quality persisted for a couple of months thereafter. The AQI ranged from 70.14 to 83.44 for the first, 69.38 to 186.62 for the second, and 80.36 to 190.83 for the third wave (Table 8.1). The visual inspection of AQI maps showed a gradual increase in poor-quality air from the first wave to the third wave, peaking in the second wave (Fig. 8.2h). No particular pattern in spatial distribution could be observed. The first and third waves showed a similar pattern, with pollution levels rising from the core to the periphery. The southern part has higher pollution than the rest of the regions. The positive variation of inter-wave was remarkable; the first-second wave stood at 38.51% (29.09), while the second-third wave was at 48.48% (50.72) (Table 8.2). Likewise, for other pollutants, AQI levels were higher for normal phases than in pandemic phases (Fig. 8.3h). A steady drop in concentration has been revealed for pandemic waves compared to normal periods (2019). The mean AQIs for the lockdown and non-lockdown phases were 72.5 & 89.5, 87 & 93, and 136.5 & 209 across the three successive waves. A similar variation was exhibited in Table 18.3. A fall of -29.30% (31.50), -4.74% (4.33), and -30.48% (59.83) has been recorded for three pandemic waves compared to the normal phase concentrations.

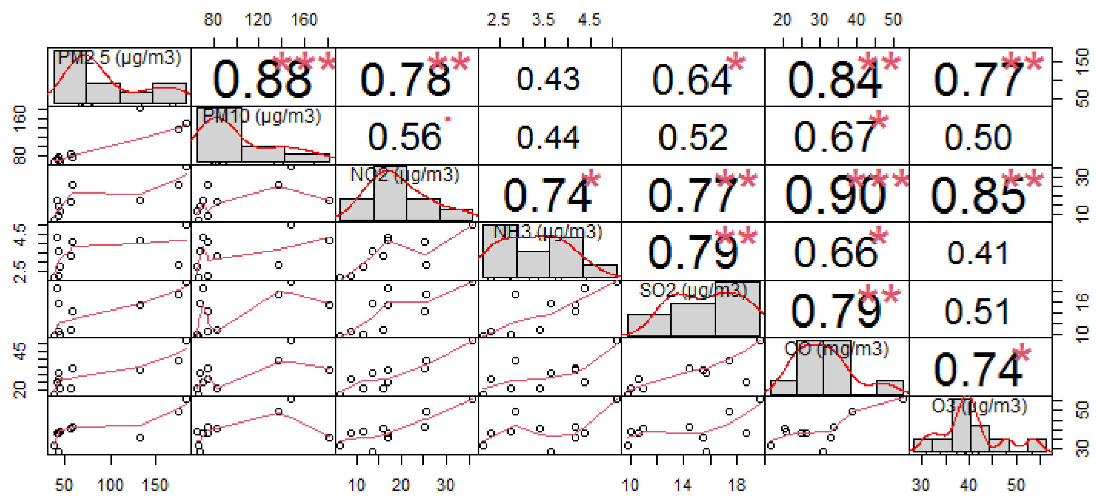


Fig. 8.4 The correlation coefficient matrices (after Pearson) between the air pollutants over Mumbai. The scatter plots presented the correlation.

8.2.8 Correlation between ambient air pollutants

To analyze the relationships among pollutants, I have prepared a correlation matrix using Karl Pearson's coefficient and scatter plots for the COVID-19 periods (three waves). The degree of significance between parameters was denoted as p <0.05 (95%)*, p <0.01 (99%)**, and p <0.001 (99.99%)***. The results revealed that $PM_{2.5}$ and PM_{10}; NO_2 and CO –these two pairs of pollutants have had a very robust positive relationship (r=0.88***, 0.90***) (Fig. 8.4). Likewise, $PM_{2.5}$ and NO_2; $PM_{2.5}$ and CO; $PM_{2.5}$ and O_3; NO_2 and SO_2; NO_2 and O_3; NH_3 and SO_2; SO_2 and CO noted a strong positive relationship (r=0.78**; 0.84**; 0.77*; 0.77**, 0.85**, 0.79**, 0.79**) at 99% level of confidence. A few moderate relations between $PM_{2.5}$ and SO_2 (r=0.64*); PM_{10} and NO_2 (r=0.56); PM_{10} and SO_2 (r=0.52); NO_2 and NH_3 (r=0.74*); NH_3 and CO (r=0.66*); SO_2 and O_3 (r=0.51); CO and O_3 (0.74*) also noted. The city has observed a few pairs ($PM_{2.5}$ and NH_3; PM_{10} and NH_3; NH_3 and O_3; SO_2 and O_3) with low-to-moderate correlations (r = 0.50). Not a single poor or statistically insignificant relationship was recorded through this analysis.

8.2.9 Variations in meteorological parameters

The synoptic description of meteorological parameters such as air temperature, humidity, wind speed, air pressure, and precipitation of all three pandemic waves has been depicted in Table 8.4. The second wave recorded the highest mean temperature (30.69°C), followed by the first (29.59°C) and the third wave (24.42°C). Likewise, the second wave recorded higher humidity, wind speed, and precipitation than the first and third waves. The recorded humidity was 66.46%, 70.18%, and 59.13% for the first, second, and third waves. The maximum wind speed was noted at the second wave (7.19 mph), followed by the first wave (6.96 mph) and the third wave (5.23 mph). The minimum precipitation occurred in the third wave (0.01 mm) and the maximum in the second wave (0.34 mm). The air pressure was almost similar for all three waves.

Table 8.4 Summary Statistics of meteorological parameters (air temperature, relative humidity, wind speed, air pressure, and precipitation) observed during COVID-19 pandemic amid lockdown waves

Parameter	Temperature (°C)			Humidity (%)			Wind Speed (mph)			Pressure (Hg)			Precipitation (mm)		
	First wave	Second wave	Third wave	First wave	Second wave	Third wave	First wave	Second wave	Third wave	First wave	Second wave	Third wave	First wave	Second wave	Third wave
Min.	28.06	29.83	21.50	46.50	60.30	51.90	5.50	6.30	4.20	29.70	29.70	29.80	0.00	0.01	0.00
Max.	31.28	31.50	26.78	74.90	76.10	69.00	9.20	8.10	6.00	29.90	29.80	29.90	1.07	0.65	0.06
Mean	29.59	30.69	24.42	66.46	70.18	59.13	6.96	7.19	5.23	29.80	29.76	29.89	0.25	0.34	0.01
Std. dev.	-17.07	-17.28	-15.89	7.94	4.28	5.91	0.84	0.50	0.54	0.03	0.05	0.03	0.31	0.22	0.02

Table 8.5 Average concentration of air pollutants in Mumbai megacity for the weathered and deweathered datasets during the three lockdown phases

Pollutants		$PM_{2.5}$ (µg/m^3)	PM_{10} (µg/m^3)	CO (mg/m^3)	NH_3 (µg/m^3)	SO_2 (µg/m^3)	NO_2 (µg/m^3)	O_3 (µg/m^3)
First wave lockdown (25 Mar-14 Apr, 2020	Weathered	32.50±6.81	76.00±11.92	48.50±1.91	4.50±1.29	29.50±1.73	16.00±13.98	8.00±0.00
	Deweathered	35.33±5.32	74.23±9.65	52.98±7.24	3.79±1.54	32.05±3.38	14.61±7.55	14.92±10.97
	Total variation Avg.	2.83	-1.77	4.48	-0.71	2.55	-1.39	6.92
	% of variation	8.71	-2.33	9.25	-15.69	8.65	-8.67	86.44
Second wave lockdown (22 Apr-1 May, 2021)	Weathered	45.00±0.00	87.00±0.00	70.00±0.00	1.33±0.58	41.00±0.00	12.00±0.00	41.00±1.00
	Deweathered	41.24±2.18	86.99±1.16	65.77±1.46	1.58±0.46	38.12±2.46	11.82±2.84	33.85±2.59
	Total variation Avg.	-3.76	-0.01	-4.23	0.25	-2.88	-0.18	-7.15
	% of variation	-8.35	-0.01	-6.04	18.60	-7.03	-1.51	-17.44
Third wave lockdown (10 Jan-19 Jan, 2022)	Weathered	133.67±56.58	120.33±32.50	56.67±14.19	2.00±1.00	22.00±4.58	6.67±4.73	16.33±8.02
	Deweathered	159.56±54.06	135.10±27.52	56.93±8.88	1.86±0.86	18.81±1.16	7.38±2.18	16.27±2.94
	Total variation Avg.	25.89	14.77	0.27	-0.14	-3.19	0.72	-0.06
	% of variation	19.37	12.27	0.47	-6.92	-14.48	10.75	-0.40

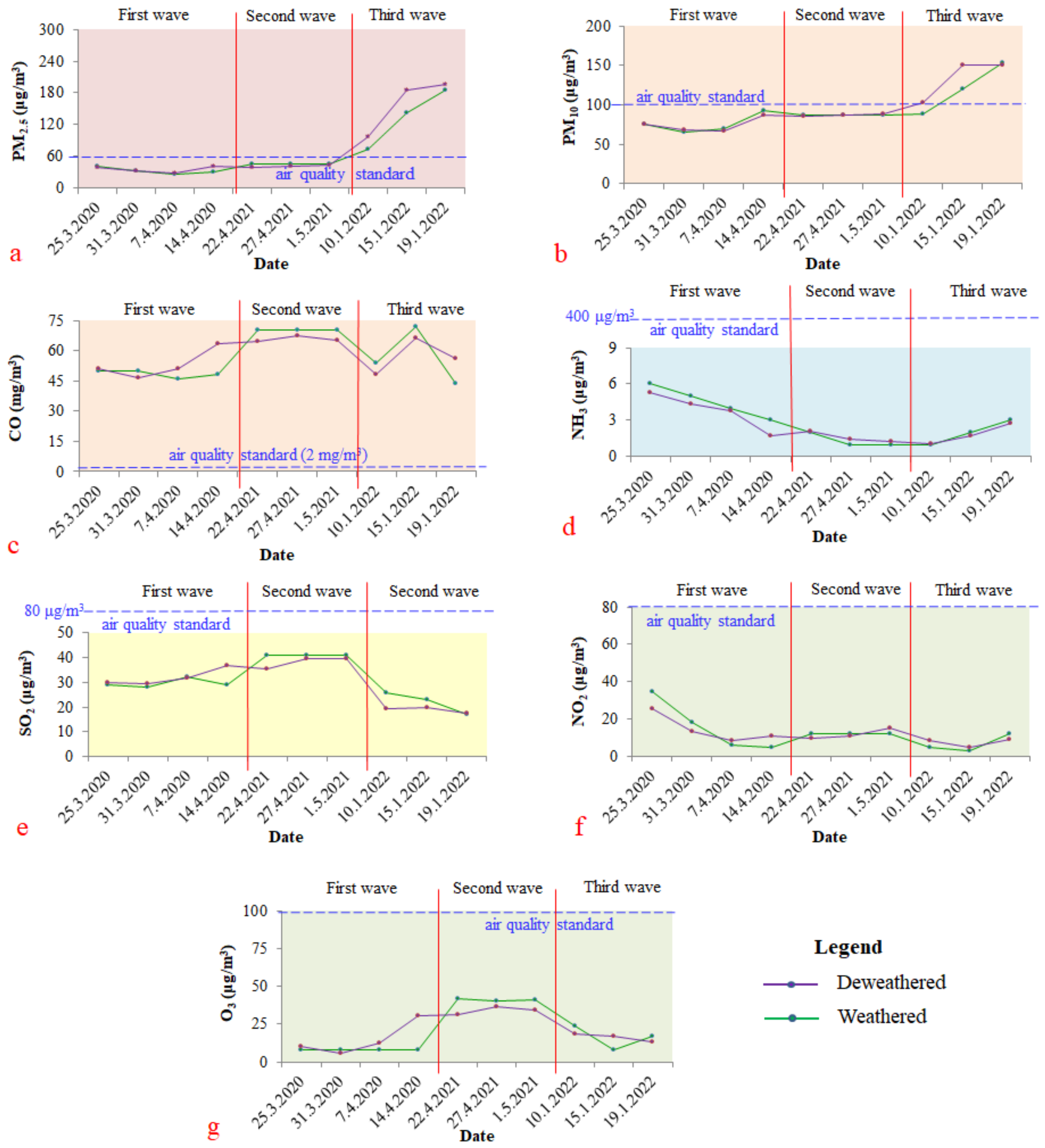


Fig. 8.5 Comparative analysis of deweathered and weathered data of atmospheric pollutant levels in megacity during COVID-19-induced lockdowns across the first wave (2020), second wave (2021), and third wave (2022)

8.2.10 Comparison between weathered and deweathered conditions of air pollutants

I have deweathered (removed the effect of weather parameters) the select pollutants. Temperature, humidity, wind speed, and precipitation are the four most influential meteorological parameters considered to eliminate meteorological influence on air pollutant concentrations. The comparison-contrast of weathered and deweathered pollutants is shown in Fig. 8.5. The concentrations of $PM_{2.5}$ and PM_{10} were above the CPCB standard during the third wave. However, they were below the limit for the first and second waves amid lockdowns. Overall, they noted a gradual rising trend from the first wave to the third wave. NO_2 and NH_3 showed the opposite trend to PM. These two noted a regular decline trend from the first wave to the third wave. Unlike others, SO_2, CO, and O_3 showed a rising trend in the first-second wave, then dropped in the second-third wave. We can summarize that a few parameters showed a regular rise, a regular fall, and an initial fall-rise followed by a fall again. Hence, weathered and de-weathered line graphs had similar trends for seven pollutants. I used the GAM function, selecting only one AAMS data point, Bandra. As I considered only the city area, one AAMS portrayed quite perfect results for analysis.

The mean concentrations of $PM_{2.5}$ and PM_{10} decreased by -8.35% and -0.01%, respectively, during the second wave. In contrast, during the first wave, $PM_{2.5}$ increased slightly, while PM_{10} decreased by 2.33%. However, both $PM_{2.5}$ and PM_{10} levels surged during the third wave, increasing by 19.37% and 12.27%, respectively (Table 8.5). The concentration of CO exhibited minor variations between the weathered and deweathered phases. Nevertheless, the levels of $PM_{2.5}$, PM_{10}, and CO were significantly above the permissible limits for the third wave, which are set at 60 $\mu g/m^3$ for $PM_{2.5}$, 100 $\mu g/m^3$ for PM_{10}, and 2 mg/m^3 for CO. The levels of $PM_{2.5}$ and PM_{10} were below the standard for the first and second waves, though CO was above the limit. Other pollutants, such as NH_3, SO_2, NO_2, and O_3, remained well below permissible standards, with few changes observed between the weathered and deweathered phases. These results indicate mixed trends in the weathered-to-deweathered datasets across all three pandemic waves, highlighting the significant influence of meteorology. The variation in pollutant levels between the two phases was evident, with the third wave showing the least variation during winter for $PM_{2.5}$ and PM_{10}. The first and second waves exhibited the most tremendous variation during the pre-monsoon period. It appears that the stringency of the lockdown had a more crucial impact on these variations than meteorological factors.

8.3 Discussion

The first COVID-19-positive cases were reported in late January in Kerala, India. Three medical students returned to India from the epicentre of the pandemic (Wuhan, China) (Andrews et al., 2020). The Kerala Government announced lockdowns on 23 March 2020. To stop the rapid spread of that virus, the GoI imposed a nationwide 21-day lockdown. That was the first wave amid lockdowns when ground-level air quality improved significantly. GoI also instructed the complete closure of all regular services, including academic institutions, social and political gatherings, industry, recreational activities, and almost all other services, except emergency services. The present study included the surge phases and pollution levels therein. The lockdown significantly reduced pollutant levels and AQI during the first wave. The city's researchers identified similar air quality improvements to the megacity scale (Sharma et al., 2020; Lancet, 2020; Mahato et al., 2020). NASA (2020) and ESA (2020) released a few images that drew similar conclusions about improvements in air quality (NASA, 2020; ESA, 2020). Infection rates began to fall in September 2020. After a few months, the second wave of the pandemic surged in March 2021. The nation was again struggling with vaccines, hospital beds, oxygen cylinders, and other medical goods. Simultaneously, the financial crisis was another big issue for the people and the GoI. As a result, the Central and state governments were less strict than during the first wave to protect the livelihoods and incomes of the common people. To break the chain of COVID-19 transmissions, the Government of Maharashtra (GoM) declared a ten-day lockdown from 8 pm 22 April 2021 to 7 am 1 May 2021. Specific areas within the megacity that recorded the most cases were declared containment zones. GoM has set a group of guidelines for said pandemic periods, such as the office attendance should not be more than 15% of employees at a time; a single event in a single hall with a gathering of 25 persons only for the marriage ceremony; private passenger transport should be availed only with 50% of seating capacity with no standing travellers; and public passenger transport allowed for emergency services only. The second wave amid lockdowns and changes in air quality is depicted above. The new COVID-19 infection rates began to fall in August-September 2021. Quarantine for travellers and a few restrictions were applied, especially for those who were not yet vaccinated (vaccine certificate). During this phase, people could stabilize themselves slightly, and India learned a lesson that they have to live with the virus (COVID-19) like other viruses. The third wave amid lockdowns was announced on 8 January 2022 by the GoM, w.e.f. 10 January 2022 at 00.00 hours, for the public and collective interest. The new COVID-19 variant, "Omicron", was spreading rapidly. Schools, colleges, and coaching institutions remain closed till 15 February 2022, except for major Boards (10^{th} and 12^{th} standard students) and GoI-advised online mode study. Entertainment parks, zoos, museums, forts, and other ticketed places/events for the general public remain closed. Government offices functioned only online. Private offices advised that not more than 50% of employees' regular attendance. Saloons, shopping malls, market complexes with restricted entry, restaurants, eateries, and cinemas were permitted to operate at 50% capacity at a time. Fully vaccinated persons (internal travellers) travelled only for that period, though international travellers should follow the GoI guidelines. The marriages and social/religious/cultural/political gatherings have allowed a maximum of 50 persons, and the funeral and last rites have allowed a maximum of 20 persons. The industries were open to maintaining COVID-appropriate norms, such as wearing masks and regularly sanitizing workplaces, and only double-vaccinated workers were allowed to enter the work sites. Those loose practices led to greater ground-level air pollution than in the previous two waves amid lockdowns. The relaxation and a few sectors' (industry and mass vehicles) activity due to economic perspectives boosted the areas with an anomaly in the spatial distribution of pollutants and overall AQI level. Simultaneously, ground-level air pollution increased significantly in recent lockdown periods. The first phase of the first wave of the pandemic was reported as the most stringent lockdown, with a score of 100, and in the later phases, pollutant concentrations gradually declined (Hale et al., 2020; Kumar and Managi, 2020). Srivastava et al. (2021) drew a similar conclusion on the Delhi megacity. The degree of stringent lockdown (from very strict to relaxed) worsens pollution levels in the megacity (Srivastava et al., 2021). Mahato and Pal (2022) assessed the second wave amid changes in air quality in Delhi. They argued that the improvement in air quality was greater in the first wave than in the second, due to higher lockdown stringency (Mahato and Pal, 2022).

Previous studies have shown that combined pollutant concentrations have significant negative impacts on human health and the environment. Zhou et al. (2016) depicted a similar correlation for China (Zhou et al., 2016). A positive correlation among the pollutants was identified for Kolkata (Sarkar et al., 2021), Mumbai (Chattopadhyay and Shaw, 2021), and Delhi (Mahato et al., 2020). The principal pollutants of the area were $PM_{2.5}$ and PM_{10}. Hence, the AQI range was the same as that of PM concentrations. High temperatures, high humidity, and high wind speeds, with moderate rainfall, were typical of the pre-monsoon season and characterized the first two pandemic waves. Generally, more precipitation in a specific place means a controlled pollution level.

High wind speeds also dilute pollution levels. The degree of pandemic relaxation was much higher for the second wave than for the first, and the resultant elevated pollution level for the second wave was higher than that of the first. The third wave includes low temperatures, minimal humidity, low wind speed, and high air pressure, with the least precipitation, which is typical of the winter period. Those salient features focus on ground-level pollution levels. Rahaman et al. (2020) observed similar scenarios over the Indo-Gangetic plain. They observed higher pollution levels in the winter and lower levels in the summer (Rahaman et al., 2020). Grange et al. (2016) reported that concentrations of $PM_{2.5}$, PM_{10}, NO_2, SO_2, and CO reached their maximum during the winter months, while decreasing during the monsoon (June-August) months (Grange et al., 2016). Verma et al. (2023) examined major Indian cities, and their results showed higher seasonal variability in Delhi and Kolkata and lower seasonal variability in Chennai and Mumbai (Verma et al., 2023).

Sandeep et al. (2013) noted similar seasonal variations and pollutant concentrations for Mumbai (Sandeep et al., 2013). Karar et al. (2006) examined the seasonal variations of pollutants in Kolkata. The result revealed a higher winter concentration of pollutants than in other seasons, due to the static movement of air and longer residence times (Karar et al., 2006). Kumar and Dash (2018) have had similar experiences: summer or pre-monsoon periods have lower pollution levels than winter (Kumar and Dash, 2018). Likewise, Sellamuthu and Jeyadharmarajan (2022) examined this in their research on the urban environment. They mentioned that energy use and atmospheric stability lead to higher pollutant concentrations during winter (Sellamuthu and Jeyadharmarajan, 2022). Hence, greater relaxation during the lockdown phase heavily polluted the megacity. The standard deviation of parameters detected mixed results. Besides that, a few local influences, such as the Arabian Sea to the west and the activities of surrounding landlocked states to the east, played a crucial role in the spatial distribution of pollution levels.

Chapter IX

Conclusion and Recommendations

9.1 Global scenario

The present study assessed the extent to which improvements in two air quality parameters (NO_2 and AOD) occurred following COVID-19-induced shutdowns across select countries worldwide. Before such lockdowns were put in place, China had the highest levels of tropospheric air pollution, followed by India, the United States, Germany, France, and Italy. Specifically, the eastern parts of China, India, and the United States, the northern provinces of Italy and France, and the western portions of Germany were the most polluted regions worldwide. Thus, four-time phases were re-examined for each country: their respective normal phases, i.e., periods corresponding to the 2020 lockdowns in the previous year (2019), and the country-wise pre-lockdown, lockdown, and post-lockdown phases of 2020. Despite using datasets with relatively coarse resolutions and limitations, an overall reduction of nearly 60% in pollutant levels was observed in these countries during the lockdown period. These levels varied across the individual nations examined in this study, as did the rate at which the contaminants approached their pre-lockdown levels after restrictions were lifted. However, it was evident that restricting anthropogenic activities can help us restore atmospheric pollutant levels to pre-industrial levels. This research also showed that curbing air pollution can help us combat several types of ailments and chronic health issues in the near future. These results warrant considering intermittent lockdowns in the near future, especially in heavily industrialized and urbanized areas, to combat air pollution.

9.2 $PM_{2.5}$ pollution in China, India, and Pakistan

Air pollution has devastating consequences that should deeply concern us all. The present thesis shows that 100% of the cities of China, India, and Pakistan exhibit $PM_{2.5}$ > 5 $\mu g/m^3$, the WHO-prescribed standard limit. This situation is highly alarming as almost 40% of the global population resides in these three countries. The $PM_{2.5}$ concentrations in the ambient air of Pakistani and Indian cities were more than double that observed in Chinese cities. The developed urban and industrial belts in the three countries showed the highest concentrations of $PM_{2.5}$. The present situation warrants immediate government intervention to reduce $PM_{2.5}$ levels, given the rapid rate of urbanization across these three countries. Prolonged exposure to such high levels of

$PM_{2.5}$ could harm humans and the overall ecological health of these regions. The emission of $PM_{2.5}$ should be prevented, and greater attention should be paid to prevent its mixing in the air. If unchecked, mankind and its environment may soon face greater health impacts from the burgeoning populations that thrive in these countries.

9.3 Air Quality of Indian Megacities During COVID-19

The nationwide lockdown has had significant impacts on air quality in India's megacities. Seven air pollutants were studied to assess AQI during the COVID-19 lockdown. $PM_{2.5}$, PM_{10}, and CO are the major pollutants across the megacities. Meanwhile, concentrations of remaining pollutants, such as NO_2, NH_3, SO_2, and O_3, were below CPCB standards during both the pre-lockdown and lockdown phases. $PM_{2.5}$, PM_{10}, and CO recorded declines of 47%, 41%, and 27% in Mumbai; 52%, 39%, and 12% in Delhi; and 49%, 37%, and 21% in Kolkata during the lockdown phase. These pollutants showed similar declining trends: 43%, 32%, and 19% for Mumbai; 4%, 4%, and 12% for Delhi; and 57%, 50%, and 29% in the post-lockdown phase. The AQI declined during the COVID-19 lockdown period (25 March-14 April 2020) compared to the same period in 2019.

Delhi was in the worst condition, with average pollutant concentrations, even compared to last year's (2019) scenario, followed by Kolkata and Mumbai. The megacities of Delhi and Kolkata showed higher pollution in the western parts than in the east, whereas Mumbai showed the opposite spatial pattern. The meteorological parameters played a negligible role in reducing pollutant concentrations during the lockdown period, except for the increase in air temperature. Among the seven pollutants, only three, $PM_{2.5}$, PM_{10}, and NO_2, were significantly (positively) correlated across the megacities. The other pollutants showed inconsistent correlations. To stop the spread of this global pandemic, social distancing, i.e., the prevention of mass gatherings, was the only option. All sectoral lockdowns, including vehicle movement, industry, domestic, and allied services, except emergency services, were closed entirely. As a result, improvements in air quality were recorded in the megacities of Mumbai, Delhi, and Kolkata. These observations indicate that environmental managers and policymakers should implement intermittent, well-planned lockdowns in the future to safeguard the urban outdoor environment without compromising economic growth.

9.4 Air Pollution During Diwali in Indian Megacities Amid COVID-19

The present thesis compared the air pollution levels (during Diwali) of three megacities of India, namely Delhi, Mumbai, and Kolkata, between a non-pandemic year (2019) and a pandemic-stricken year (2020). Previous studies indicate that burning firecrackers causes severe air pollution and that air pollution facilitates the transmission of COVID-19. These generalized observations prompted us to examine differences in air pollution levels during Diwali 2020, amid the COVID-19 pandemic, and compare them with those of the previous year's Diwali, when there was no pandemic. The study revealed elevated concentrations of $PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, CO, and O_3 on Diwali 2020 in all three cities, with very few exceptions. This observation primarily indicates that people celebrated Diwali with greater vigour even amid pandemic conditions. However, analyzing the pre-Diwali-to-Diwali changes in air pollutant concentrations for both years showed a minor increase for most pollutants in Mumbai and Kolkata. Delhi was an exception, where the enhancement in pollutant levels during Diwali in 2020 was much higher than that observed in 2019.

Earlier studies showed that Delhi is the worst sufferer of air pollution throughout the year. The present study indicated that despite air pollution problems, people in Delhi did not refrain from burning firecrackers even during a pandemic, which can significantly worsen the pandemic and lead to more casualties. Moreover, Diwali in the pandemic year took place at such a time when the sixth unlock phase was in action. The nation was steadily returning to pre-pandemic norms. The terror of the coronavirus had slowly dissipated by this point, which might have prompted people to celebrate Diwali as before. In addition, a lack of awareness of the causal effects of burning firecrackers in promoting the spread of the virus might have played a crucial role. In 2020, Diwali fell in mid-November, when air temperature and wind speed were lower than during Diwali in October 2019. This difference in meteorological conditions might have led to a partial enhancement in the overall pollutant load in Delhi's ground-level atmosphere. However, the pre-Diwali-to-Diwali changes in pollutant concentrations showed a dramatic increase, which could be attributed solely to firecracker burning. Mumbai and Kolkata did not record such an increase in pollutant concentrations from pre-Diwali to Diwali. It is more concerning that Delhi retained pollutant loads in the atmosphere even a week after Diwali in 2020. The stable atmosphere over Delhi prolongs the residence time of air pollutants, especially during the winter months following Diwali. The PM_{10},

$PM_{2.5}$, and CO levels exceeded the permissible limits in all three megacities during Diwali 2019 and 2020. Besides Delhi, elevated concentrations are also a concern in Mumbai and Kolkata. However, the concentrations were almost twice as high in Delhi as in Mumbai and Kolkata. Recent studies indicated a sharp decline in air pollution levels during the nationwide lockdown. Diwali in 2020 was concomitant with the sixth unlock phase, when the country was almost back on track, recovering from the pandemic. In the next few months, India witnessed a deadly second wave of COVID-19 infections. Though Diwali is a one-day event, burning firecrackers for even a single day can worsen the air pollution and deteriorate the ground-level atmosphere.

These observations compel us to rethink burning firecrackers, given their harmful impacts on the atmosphere. However, as the festival of Diwali, like many others around the world, is widely celebrated by millions, there is no justification for hurting the religious sentiments of these people. Thus, green, water-based, and biodegradable crackers should be promoted to avoid atmospheric pollution. Hence, they can be burnt without impacting the celebrations. Further innovations should be nurtured, leveraging the proactive involvement of such a large number of people in the Diwali celebration to reduce air pollution rather than aggravate it. For example, if water-based crackers are devised, their burning can actually help reduce particulate matter pollution by coalescence and subsequent deposition on land surfaces.

9.5 Air pollution scenario in Kolkata

The present study aimed to examine the effects of lockdowns imposed during the COVID-19 pandemic (of varying stringency across seasons) on ambient air quality in Kolkata, India. Data on seven air pollutants were retrieved from India's CPCB during three lockdowns imposed in pre-monsoon 2020, pre-monsoon 2021, and winter 2022. The air pollutant concentrations during the lockdown phases in the respective years were also compared with those of the same time windows in a non-pandemic year (2019). The significant findings that emerged from this study were i) lockdowns inevitably helped in reducing the air pollutant levels, ii) the degree of reduction of air pollutants depended on the stringency of the lockdowns imposed (the greater the stringency, the higher the reduction in air pollutant levels), iii) meteorological factors governed the concentrations of air pollutants and iv) the winter season coupled with the least stringent lockdown showed significant levels of air pollutants in the ambient air of the city. The study showed that restrictions on vehicle movement, industry sectors, households, and associated services, excluding emergency services, played a crucial role in the first two waves. The relaxation of the third-wave lockdown increased the pollution level. Remarkable improvements in $PM_{2.5}$, PM_{10}, NO_2, and AQI were observed across all lockdown phases compared to normal phases (2019).

Seasonal changes in meteorological parameters affect air pollutant concentrations, and the winter season, when atmospheric stability remains significantly higher than in other seasons, is the most susceptible to air pollution. The spatial distribution map showed that a few pockets of the industry and transport sectors compromised air quality. The outcomes from the present study are intended to draw the attention of policymakers, planners, and decision-makers to the fact that implementing short-term planned lockdowns can really improve the ambient air quality of cities all over the world, especially during those seasons when the atmospheric vis-à-vis the meteorological conditions aid in building up air pollutants in the lower troposphere. This would not only reduce human health risks but also help alleviate climate change to some extent. In an era when townships are rapidly becoming cities worldwide, steps like this can enhance the sustainability of cities and the societies that reside therein. However, the present study provides a significant scientific rationale for better understanding this dynamic and crucial natural phenomenon: air pollution. Based on the results of this study, the researcher stresses the need to predict spatially explicit pollution scenarios for the megacity of Kolkata, especially after the monsoon, when the dry winter prevails. It can help us identify zones that need improvement in air quality. The present study showed that, despite high pollution levels in this twin city, pollution is not ubiquitous and exhibits significant spatial variability. To curb pollution levels, given the business-as-usual growth of both the human population and small- to medium-scale industries in the peripheries of this busy metropolis, zone-based intermittent lockdowns can be considered an avenue to alleviate the atmospheric pollutant load. As PM concentrations are found to be the most lethal factor in this study area, a temporary ban on construction activities during the two winter months (mid-December to mid-February) can also be placed on the table for discussion, as these activities contribute to particulate matter pollution. With the wind shifting from north to south during the dry winter months, the industrial sectors in the area's northern belt pose a significant threat to city dwellers. However, more intensive studies are required to obtain a clear understanding of environmental pollution dynamics in the study region and to better cope with this natural hazard for a more resilient and sustainable urban environment.

9.6 Air pollution scenario in Mumbai

The findings of this study unequivocally indicate that the lockdowns imposed during the three prominent COVID-19 surges in the business capital of India (Mumbai) significantly reduced air pollution levels in this megacity. $PM_{2.5}$ and PM_{10} were the principal points of concern, as these two pollutants exhibited higher concentrations, followed by CO. Other pollutants, such as NH_3, SO_2, NO_2, and O_3, were consistently below CPCB standards; however, their concentrations varied with seasons and depended on the lockdown timings. This study indicated that improvements in air quality during the lockdown phases depended entirely on the level of law enforcement. The stringent imposition of lockdowns led to better results, as significant declines in air pollutant levels accompanied them. However, over time, the Government relaxed the stringency of lockdowns, mindful of the economic crisis it had imposed on people. The inter-wave changes in pollutant levels and the comparison of pollutant data between pandemic and non-pandemic phases showed that lockdowns can act as potent regulators of air quality. Seasonal changes also play a crucial role in governing air quality. This study indicated that low temperatures and relative humidity levels favour the accumulation of air pollutants in the city's environment. COVID-19-induced lockdowns provided us with a real-world platform to experiment with the effects of curbs on anthropogenic activities on air quality. These results should encourage decision-makers, policymakers, and planners to devise tactical strategies for short-term lockdowns in the future, especially during periods when air quality is most degraded. With the ongoing anthropogenic activities, air pollution is inevitable, especially in densely populated pockets of the world. However, the ever-degrading air quality in those regions is taking a heavy toll on their health. It is time I reflected on our activities and explored possible avenues to improve the city's air quality, which is also an essential component of the Sustainable Development Goals.

9.7 Overall Recommendations

Several measures can be taken to effectively reduce emissions. First, it is essential to adopt alternative methods for waste incineration, such as composting household waste, recycling, and proper landfill disposal. Encouraging the use of public transportation and investing in public transport infrastructure is crucial to minimizing reliance on private vehicles. Additionally, promoting bicycling and walking can make a significant contribution. Like many Western countries, a separate lane for cyclists can be a brilliant innovation to encourage short-distance travellers.

According to conservative projections by the Pew Research Center, China has reached its peak population, which is expected to decline by the end of this century. In contrast, India and Pakistan have not yet peaked, and population growth is anticipated over the coming decades. This growth signals potential industrial expansion in these countries, underscoring the need to prioritize non-conventional energy sources over fossil fuels.

Furthermore, installing air purifiers in homes and offices can help mitigate the harmful effects of $PM_{2.5}$ particles in the indoor air. Investments in research and innovation to develop new technologies to control $PM_{2.5}$ pollution should be prioritized. It is also vital to adhere to the latest recommendations of the WHO Global Air Quality Guidelines (AQGs), which advocate for reducing air pollution to protect public health and combat climate change. Effective implementation requires rigorous monitoring and strict enforcement of laws, with penalties for violators in both the industrial and transportation sectors.

Controlling activities that generate $PM_{2.5}$ particles, such as open-cast mining and construction, is essential. Initiatives such as frequent water spraying by both the Government and the private sector (as part of corporate social responsibility) can help lower $PM_{2.5}$ concentrations, especially during dry winter months. Occasionally implementing short-term lockdowns, perhaps for 3-5 days each month, could also prove effective in reducing $PM_{2.5}$ levels, ultimately saving lives and fostering a more sustainable environment.

This approach aligns with the concept of ‘neo-determinism’ or ‘stop-and-go determinism’ proposed by Griffith Taylor, which suggests that nature responds to human impact on the environment. These improvements in air quality indicate that nature can revitalize itself when human activities remain within ecological limits, leading to sustainable development.

To enhance air quality in megacities, several actions are necessary year-round, including operating only LPG-fueled three-wheelers, procuring natural gas-powered buses, upgrading auto emission testing centres (Pollution Under Control, PUC), creating artificial rain during dry periods, and water sprinkling on roads during winter months. Roadside eateries should transition from solid fuels to LPG, and construction sites need to remain covered. Furthermore, awareness programs should start at the school level.

Diwali is a significant religious and cultural event for millions of people in India. The Government should promote non-polluting firecrackers to protect the environment while allowing for traditional celebrations. Beyond Diwali, many other events involve the use of firecrackers, and such initiatives can significantly improve ambient air quality.

A multifaceted approach is necessary to combat air pollution in megacities like Kolkata and Mumbai. Here are some recommendations for each of these coastal megacities:

Kolkata

1. Implement the Graded Response Action Plan: This plan involves immediate actions based on the AQI levels. Actions may include halting construction activities, mechanically sweeping roads, and suspending schools when pollution levels are high.
2. Restrict Vano Cars: Vano cars, which run on adulterated fuels, are a significant source of pollution. Limiting the use of these vehicles can help reduce emissions.
3. Enhance Public Transport: Improve and expand public transportation options to decrease the number of private vehicles on the road.
4. Promote Green Spaces: Increase the number of parks and green areas to help absorb pollutants and improve air quality.
5. Raise Public Awareness: Educate citizens about the health impacts of air pollution and encourage preventive measures, such as using air purifiers indoors and limiting outdoor activities on high-pollution days.

Mumbai

1. Clean Air Mumbai Initiative: The Brihanmumbai Municipal Corporation (BMC) has launched a seven-step strategy to reduce air pollution. This includes

sustainable construction practices, measures to reduce road dust, and sustainable waste management.

2. Electrification of Vehicles: Promote the use of electric vehicles (EVs) and provide the necessary charging infrastructure to reduce emissions from traditional vehicles. However, unless and until a complete switchover from non-renewable to green energy is achieved, pollution will be generated elsewhere, if not within cities.
3. Mechanical Sweeping and Water Sprinkling: Utilize mechanical sweepers and water sprinklers to minimize road dust, which is a major contributor to air pollution.
4. Waste Management: Implement sustainable waste management practices, such as banning waste burning and promoting waste-to-energy plants.
5. Urban Greening Projects: Plant more trees and create urban green spaces to enhance air quality and provide a healthier environment for residents.

Both cities are taking steps to address air pollution. Still, continued efforts and community involvement are crucial for long-term improvement. Some data limitations imposed minor constraints on this research; more AAMSs need to be established within megacities to effectively study the spatial dynamics of these pollutants, given current predictions that the population in these cities will increase in this century.

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Gauging the effects of the COVID-19 pandemic lockdowns on atmospheric pollution content in select countries

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1. Introduction

The swift spread and ensuing community transmission of the COVID-19 pandemic since its inception often overwhelmed local healthcare services quite quickly and left the aged and those with existing health issues particularly vulnerable (MacConnachie et al., 2007). Healthcare officials and governments introduced and widely propagated the concept of 'social distancing' (Manderson and Levine, 2020) and 'lockdowns' to limit the spread of the virus, with cancellations of major sporting and cultural events (Munoz and Meyer 2020; Parnell et al., 2020) and diplomatic gatherings (Sharfuddin, 2020), closure of religious institutions (Alyanak, 2020), industries and commercial establishments and the suspension of academic conferences and teaching activities (Gallo and Trompetto, 2020). Such lockdowns sought to heavily restrict the movement of those possibly carrying the contagion and stop healthy people from coming into contact with pre-symptomatic/asymptomatic individuals (Imdad et al., 2020). The Chinese government declared its lockdown period in late January 2020, to slow down the spread of infection (Wilder-Smith and Freedman, 2020). The United States and countries in Western Europe also went into lockdown by early March 2020. Nations like India, where the outbreak became potentially threatening after its initial rampage in East Asia and Western Europe, were somewhat quicker to impose such lockdown measures in late March 2020 (The Lancet, 2020).

Such a complete shutdown of industry and vehicular movements and the substantial decrease in all but essential services inevitably left its imprint on the environment. The European Space Agency (ESA, 2020) and the National Aeronautics and Space Administration (NASA, 2020) released a few satellite image products in April 2020 that showed the marked improvement in air quality as a result of the COVID-19 induced lockdowns and Muhammad et al. (2020) briefly highlighted the global scenario in this respect. There have also been a number of studies that have examined the localized impact of the above lockdowns in different parts of the world and particularly across large cities and regions on the environmental (primarily air) quality (Mahato et al., 2020; Kumari and Toshniwal, 2020; Anil and Alagha, 2020; He et al., 2020c; Singh and Chauhan, 2020; Collivignarelli et al., 2020; Kerimray et al., 2020; Kumar and Managi, 2020; Menut et al., 2020; Baldasano, 2020; Giani et al., 2020; Sahoo et al., 2020; Patel et al., 2020; Wang et al., 2020; Mandal et al., 2021) or brought forth the strong correlation between the improvement of air quality and the COVID-19 induced lockdown (Ghosh and Ghosh, 2020; Mahato and Ghosh, 2020; Sarkar et al., 2020). However, there have been relatively fewer studies (e.g. Acharya et al., 2021) that have mapped and analyzed the lockdown's effect on the air quality at the entire country level, while at the same time comparing its relative impact across different nations.

An attempt has thus been made here to draw attention to the multiple country-level spatial impacts of this occurrence across the globe within one succinct account, based on the available NASA satellite datasets of Nitrogen Dioxide (NO_2) and the Aerosol Optical Depth (AOD). Aerosols are the solid and liquid particles suspended in the atmosphere and their major sources are windblown dust, sea salts, volcanic ash, smoke from wildfires and pollution from factories and vehicular combustion (NASA, 2020). Traffic pollution is the primary source of tropospheric NO_2 (He et al., 2020a, 2020b). Such air pollutants generate short term as well as long term morbidity, with about seven million people worldwide dying from such respiratory induced illnesses (WHO, 2020), and it markedly impacts upon the economies of the most affected nations. Therefore, discerning the extent in reduction of these pollutants is important, as it can provide insights into the how much the local atmosphere can self-purify if no/lesser proportions of pollutants are constantly added to it. This can help frame guidelines to periodically curtail such emissions and achieve some measure of sustainability that less affects the health of the residents of these regions.

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Outdoor $PM_{2.5}$ pollution levels and their degree of compliance with WHO air quality guidelines across 760 cities in China, India, and Pakistan

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Abstract

Particulate matter ($PM_{2.5}$) has long been recognized as a lethal air pollutant. Multifarious anthropogenic activities, especially in the urbanized belts, lead to this pollution, and the humans and other life forms thriving in these regions suffer the worst. In this regard, the present study collated the $PM_{2.5}$ data for seven years (2017–2023) across 760 cities, encompassing three neighbouring countries, China, India, and Pakistan, that comprise more than 38% of the global population in the present date. Analyzing this comprehensive dataset, it could be inferred that 100% of the three countries' cities exhibit $PM_{2.5} > 5$ μg/m^3, the WHO-prescribed standard limit. The $PM_{2.5}$ load in Pakistani and Indian cities was more than double that observed in Chinese cities. However, this study also noted a lack of an adequate number of monitoring stations in Pakistan compared to those in China and India. The national capital region of Delhi (India) was the worst polluted region (97.5 μg/m^3) out of 63 states/provinces of these three nations. The developed belt in the Indo-Gangetic plain of India, the north-central parts of Pakistan, and the central-east regions of China showed the highest concentrations of $PM_{2.5}$. The present situation warrants immediate intervention from government levels to reduce the $PM_{2.5}$ levels, given the rate of urbanization witnessed throughout these three countries. Prolonged exposure to such high $PM_{2.5}$ levels could harm humans and these regions' overall ecological health. Real-time $PM_{2.5}$ concentrations in all the major and minor metropolises, cities, and townships should be seriously monitored by the respective countries to prioritize research and propose effective solutions.

Highlights

- Only a single city met WHO limits of < 5 μg/m^3 out of 760 cities.
- Delhi (India) noted the highest pollution level (97.5 μg/m^3) among the 63 provinces.
- The central-east of China and the Gangetic plain of India suffered the worst.
- Pakistani and Indian cities showed higher $PM_{2.5}$ levels than the Chinese cities.

Keywords $PM_{2.5}$ · WHO limit · China · India · Pakistan

Abbreviations

Extended author information available on the last page of the article

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Effects of COVID-19 pandemic on the air quality of three megacities in India

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ABSTRACT

COVID-19 pandemic compelled many countries in the world to go for a nationwide lockdown to prevent the spread of the coronavirus. India started the lockdown on 24 March 2020. We analyzed the air quality of three megacities of India, namely Mumbai, Delhi, and Kolkata, during the lockdown phase and compared it with the pre-lockdown and post-lockdown scenarios. We considered seven major air pollutants: $PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, CO, and O_3. We analyzed the data acquired from 56 automatic air-monitoring stations (AAMS) under the Central Pollution Control Board (CPCB) spread across the megacities. The air pollution level in the eastern part of Mumbai and the western part of Delhi and Kolkata usually remains high. Delhi was the worst polluted megacity, followed by Kolkata and Mumbai. The stop of vehicular movements and industrial lockdown across the nation has substantial effects on the environment, especially in the atmosphere near the Earth's surface. Our analysis showed significant improvements in air quality during the period of lockdown (25 March to 14 April 2020) compared to the pre-lockdown phase (3 March to 23 March 2020) and the same time window of the previous year (25 March to 14 April 2019). The post-lockdown (15 April to 5 May) phase exhibited mixed results. We mapped the spatial pattern of these pollutants and the air quality index (AQI). According to CPCB, $PM_{2.5}$, PM_{10}, and CO are the major air pollutants in India that reduced by 47%, 41%, and 27% in Mumbai; 52%, 39%, and 13% in Delhi; and 49%, 37%, and 21% in Kolkata, respectively, in the lockdown phase. $PM_{2.5}$, PM_{10}, and NO_2 exhibited significant correlations across the three megacities. This study shows that occasional short-term lockdowns can effectively refresh the air in these megacities.

1. Introduction

The pandemic caused by a coronavirus (COVID-19) poses a significant threat to the human population throughout the world. Coronaviruses are single-stranded ribonucleic acid (RNA) viruses that can infect not only humans but also a variety of animals as well (Kooraki et al., 2020). The mode of spread of this coronavirus requires exhaustive studies; however, maintaining social distance is recognized as one of the most fruitful solutions to prevent its rampant spread (Lipsitch et al., 2020). The World Health Organization (WHO) declared in March 2020 that the COVID-19 has turned out into a global pandemic and called for a forceful worldwide reaction. The most affected countries like United States, Brazil, United Kingdom, Mexico, Italy, India, France, Spain, Peru, Iran, and Russia recorded millions of infected and thousands of deaths (Docherty et al., 2020). The COVID-19 pandemic severely affected the world economy, especially in developing countries. Gita Gopinath from the International Monetary Fund (IMF) pointed out that due to the impact of the COVID-19, the global economy would experience a recession in 2020, and the economic growth rate would drop to −3% (Gopinath, 2020). Researchers found an undeniable link between the effectiveness of COVID-19 and polluted air. A higher level of air pollution led to a higher rate of COVID-19 infection in many polluted cities of Asia, Europe, and North America. A recent study by Xie and Zhu (2020) covering 120 cities in China showed a critical relationship between air contamination and COVID-19 disease. Moreover, studies from the United States show that an increase in long-term exposure to particulate matter ($PM_{2.5}$) results in a significant rise in the death rate from COVID-19 (Wu et al., 2020a, 2020b).

Each year the emission of anthropogenic pollutants contributes to undesirable air quality levels in India (Balakrishnan et al., 2019). The

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Air pollution in three megacities of India during the Diwali festival amidst COVID-19 pandemic

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ABSTRACT

The present study characterized the difference in air pollution levels between Diwali celebrations amidst the Covid-19 pandemic (14 November 2020) and the previous year (27 October 2019). The concentration of seven principal air pollutants, namely $PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, CO, and O_3, was substantially higher in 2020 Diwali than in 2019 Diwali. $PM_{2.5}$, PM_{10}, and CO were always above the permissible limits in all three megacities, with the highest concentrations observed in Delhi. This observation indicates that amidst the pandemic, people burnt more firecrackers than the preceding year. However, the pre-Diwali to Diwali changes in pollutant concentrations suggested that Mumbai and Kolkata had lower pollution levels due to the fireworks. The firework-induced air pollutant load in Delhi was enhanced by a higher margin in the pandemic year. The difference in meteorological conditions between the two consecutive year's Diwali might have led to the enhanced pollutant load in 2020, especially in Delhi. Delhi showed a tendency to retain the pollutants in the ground-level atmosphere for almost one week after the event. Thus, this study implies the need for stringent law enforcement to ameliorate the pollution levels due to such celebrations.

1. Introduction

Diwali, also known as Deepavali, is a festival of lights. In India, people celebrate this auspicious occasion during the post-monsoon months of October or November (Ambade, 2018; Mukherjee et al., 2018). The date of the festival in a particular year varies according to the Hindu lunisolar calendar (Dershowitz and Reingold, 2009). Diwali symbolizes the spiritual victory of light over darkness, good over evil, and wisdom over ignorance (Mathur, 2021), and its celebration involves burning firecrackers and sparklers (Sateesh et al., 2018; Ghei and Sane, 2018). Several festivals in different corners of the world like the New Year celebrations, the Lantern Festival in China, Sky fest in Ireland, and others, include firecrackers (Ambade (2018) and the references therein). However, Diwali deserves a special mention, as hundreds of millions of people participate in burning firecrackers. Across the length and breadth of India, several townships, cities, and metropolises, like Ahmedabad (Ganguly et al., 2019), Bangalore (Gowda et al., 2020), Bhopal (Choudhry et al., 2018), Bhubaneswar (Mandal et al., 2020), Chennai (Prakash et al., 2019), Dehradun (Prabhu et al., 2019), Delhi (Mukherjee et al., 2018, Saxena et al., 2020; Singh and Srivastava, 2020; Patel et al., 2021), Faridabad (Sharma et al., 2018), Guwahati (Garaga and Kota, 2018), Hyderabad (Chen et al., 2020), Jabalpur (Srivastava et al., 2014), Jaisalmer (Mahecha et al., 2012), Jamshedpur (Ambade, 2018), Jhansi (Chauhan et al., 2014), Kolkata (Sahu, 2019), Lucknow (Barman et al., 2009), Mumbai (Nanda et al., 2018), Nagpur (Kumar et al., 2017), Nashik (Dhanwate, 2017), Sambalpur (Sahu et al., 2020), Udaipur (Chittora and Kapoor, 2015), Varanasi (Kumar et al., 2016), and Vishakapatnam (Ganguly et al., 2019) recorded a significant rise in air pollutants in the lower troposphere during the Diwali celebrations.

The burning of firecrackers releases an array of harmful chemical compounds (barium nitrate; potassium chlorate, nitrate, and perchlorate; sodium oxalate; strontium nitrate), metals (aluminum, iron oxides, and manganese), metalloids (arsenic), and non-metals (sulfur) into the ambient atmosphere (Kulshrestha et al., 2004; Rajendran et al., 2021). Several flying firecrackers introduce highly toxic volatile organic compounds like polychlorinated dibenzodioxins and dibenzofurans into the lower troposphere (Camilleri and Vella, 2010). These compounds have a high residence time in the atmosphere and travel long distances from the place of emission (Klima et al., 2020). The several constituents in the firecrackers on burning lead to an increment in particulate matter < 2.5 micrometer ($PM_{2.5}$) levels (Liu et al., 2019). The perturbations caused by the firework explosions enhance the particulate matter < 10 micrometer

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Characterizing the air pollution dynamics amidst three COVID-19-induced lockdowns during the first wave (2020), second wave (2021), and third wave (2022) in the Kolkata and Howrah Municipal Corporations, India

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Abstract

This study characterized India's Kolkata and Howrah Municipal Corporations' air quality during three prominent waves of the coronavirus pandemic (25 March–14 April 2020; 15 May–30 May 2021; and 1 January–15 January 2022). The primary aim was to examine the role of these COVID-19 pandemic-induced lockdowns and their stringency and meteorological factors in governing the pollutant concentrations, namely, CO, NH_3, NO_2, O_3, PM_{10}, $PM_{2.5}$, SO_2, and monitored by ten automated air pollution monitoring stations (AAMS) of the Central Pollution Control Board (CPCB). A total of 20 days of pollutant data from ten AAMS across four years were analyzed in this study. CO was above the CPCB standard, while $PM_{2.5}$ and PM_{10} varied during all three waves. $PM_{2.5}$, PM_{10}, NO_2, SO_2, and O_3 levels were −44%, −34%, −15%, −48%, and −51% less during the second wave than the first wave. The third wave witnessed a rise in air pollution levels compared to the second wave, as the stringency of lockdown was relaxed. Air pollution was the highest during the third wave among the three waves. The daily average (24 h) concentrations of PM_{10}, CO, and NO_2 showed a significantly strong positive correlation with $PM_{2.5}$. The results indicated that the meteorological conditions played a central role in governing air pollutant concentration. The spatial distribution map portrayed that the pockets of industrial/transport sectors compromised the overall air quality. Policymakers, planners, and decision-makers must note that the results showed that the city's air pollution level can be alleviated by implementing occasional short-term lockdowns.

Keywords COVID-19 pandemic · Lockdown · Air pollution · Air quality index · Municipality · Meteorology

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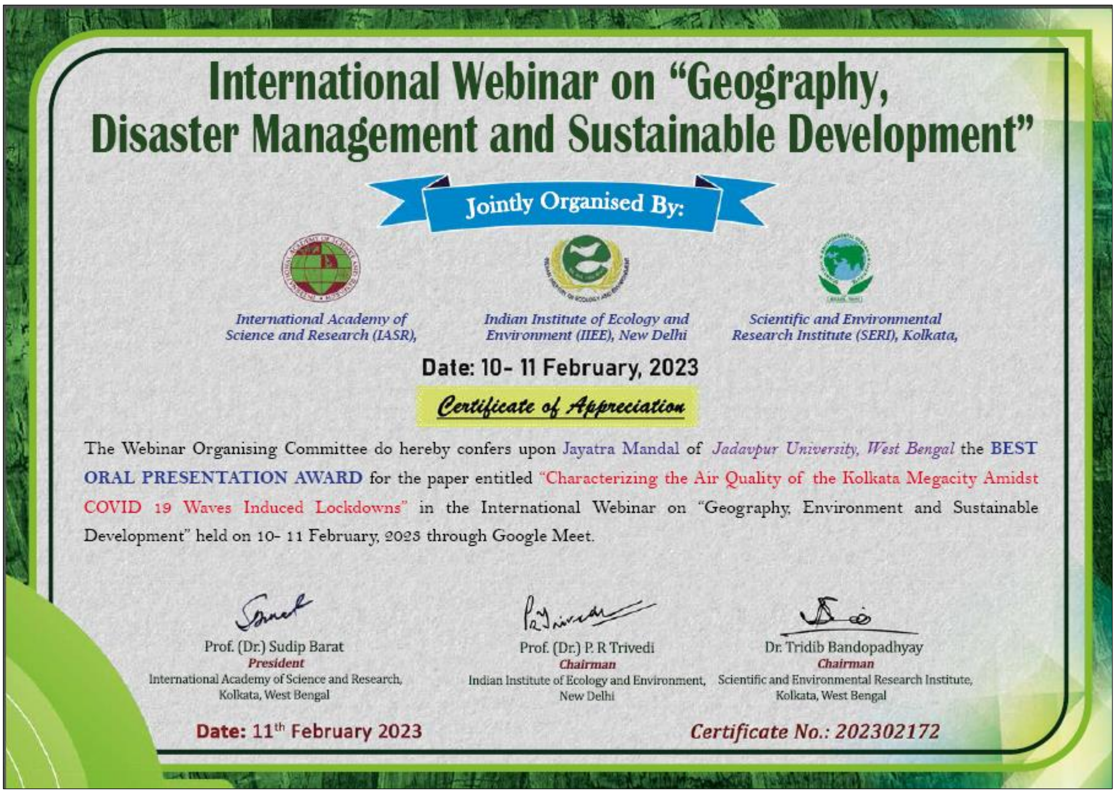

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The Webinar Organising Committee do hereby confers upon Jayatra Mandal of *Jadavpur University, West Bengal* the **BEST ORAL PRESENTATION AWARD** for the paper entitled "Characterizing the Air Quality of the Kolkata Megacity Amidst COVID 19 Waves Induced Lockdowns" in the International Webinar on "Geography, Environment and Sustainable Development" held on 10- 11 February, 2023 through Google Meet.

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