PhD Thesis

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AIR POLLUTION DYNAMICS IN TWO COASTAL MEGACITIES OF INDIA AMIDST COVID-19 PANDEMIC

THESIS

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Nomenclature

$(NH_4)_2SO_4$ Ammonium sulphate

AOD Aerosol optical depth

AQI Air quality index

BMC Brihanmumbai Municipal Corporation

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 diseases

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

HNO_3Nitric 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_2Nitrogen dioxide

NO_3^- Nitrates

NO_x Oxides of nitrogen

NOx Nitrogen oxides

O_2Oxygen

O_3 Ozone

OMI Ozone Monitoring Instrument

PAN Peroxyacylnitrates

Pb Lad

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 1 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 respiratory air too. The inhale and exhale ration air volume % of O_2; N_2; and CO_2 are 20.95:16.4; 79.01:79.5; 0.04:4.1 (Khullar, 2008). The atmospheric air is recognized as clean when the ratio remains the same. Often, an unfavourable alteration of our surrounding air due to drastic variations in its natural composition or fullness of any particulate matter (PM) is air pollution. The air is constantly being polluted both by nature and man. 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 are stroke, lung cancer, heart diseases, chronic obstructive pulmonary problems and respiratory infections, like pneumonia (WHO, 2019; Anwar et al., 2021). Short-term exposure to air pollution is responsible for minor breathing discomfort in sensitive people, 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 (CO_3^{2-}), 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 molten lave flow, and collision between trees are sources of CO_2, CO, and ash, which are pollutants in the air. 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 the bare and dry soils into the atmosphere. The terrestrial material pollution and decomposition of organic matter (i.e. plants, animals and animal wastes) are the significant sources of air pollutants for methane (CH_4) (EPA, 2023) and NH_3. The secondary pollutant, ozone (O_3), usually has a low concentration at ground level naturally due to chemical reactions between oxides of nitrogen (NO_x) and volatile organic compounds (VOCs) with the help 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% growth of their current population 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 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 is ranked as the 8th most polluted (annual average $PM_{2.5}$ concentrations weighted by population) country in 2022 (IQAir, 2023). The report said the transportation sector contributes to $PM_{2.5}$ from 20-35% across Indian cities. Northern India (including Delhi) has witnessed an episodic (pre- and during-winter) pollution boom by stubble (crop) burning (Abdurrahman et al., 2020). The agriculture-productive states of northern India, Uttar Pradesh, Punjab, Haryana, and West Bengal account for the highest quantity of stubble (IARI, 2012). The coal mining areas of India account for massive air pollution as coal production has increased 6-7 times more in recent years. Simultaneously, the coal import decreased from 234.35 to 208.93 million tonnes during 2018-19 & 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. Road traffic exhaust emissions are the prime concern of 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 are responsible for fine-particulate air pollution to solid particles (Columbia Climate School, 2016). Lu'ayi & Lestari (2020) have shown a detail of agriculture amid pollution levels in Indonesia and across the globe (Lu'ayi and Lestari, 2020). Vadrevu et al. (2017) focused on the change in LULC with air pollution 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 is also known as particle pollution, which consists of particles with a mixture of solid and liquid droplets commonly found in the troposphere. A few particles are seen with the naked eye (e.g., dust, smoke, dirt, soot, etc.), though some are visible only by 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 at a distance of 100 m to 50 km, while fine particles ($PM_{2.5}$) last for a few days to weeks longer and travel far away (Pénard-Morand and Annesi-Maesano, 2004). Coarse PM poses less health risk than fine (Wang et al., 2015; Oberdörster et al., 2005). Primary aerosols (PM_{10}) include vehicular exhaust, dust and sea spray and are discharged into the atmosphere directly from sources. 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/regions across the globe suffer adversely from the 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

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 concentrations of ambient air should not be higher than 60 and 100 µg/m³ for industrial, residential (both rural and urban), and ecologically sensitive (notified by the central government) areas of India (Table 1.1). The pollutant substances account for natural sources such as forest fires, dust storms, volcanoes, and marine salts, and anthropogenic sources like industry, vehicular traffic, construction works, household fuels, etc. (Ni et al., 2012; Brunelli et al., 2007; Vautard et al., 2005). Anthropogenic sources' have had greater significance than natural ones (Liu et al., 2020). Shahraiyni and Sodoudi (2016) stated that the pollutants have mainly primary and secondary sources. The 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 pointed out the 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 of traffic principally responsible for PM pollution. They observed that non-exhaust concentrations were six times more than exhaust emissions for Delhi (Singh et al., 2020). The PM showed significant seasonal oscillation. The maximum rise in pollution level was in the winter season, followed by post-monsoon, summer/pre-monsoon, and monsoon (Sasmita et al., 2022). None of the megacities of India met the WHO (2021) PM_{10} annual average concentration of 15 µg/m³. Mumbai recorded a maximum (216 µg/m³), followed by Delhi (181 µg/m³) and Kolkata (116 µg/m³) (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

1.4.1.2 $PM_{2.5}$

$PM_{2.5}$ has had a higher human health impact than perhaps any other pollutants (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 causes (e.g., burning fuel and chemical reactions) form the particles in the atmosphere. 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, and industrial processes, combustion of engines, power generation, agricultural processes, wood and coal burning, and building construction are the anthropogenic sources (IQair, 2023). These tiny particles cause urban smog in many metro cities across the globe (e.g., Beijing, Delhi, etc.). The areas, regions, and territories of central Asia, south Asia, and Africa suffer adversely from this pollutant.

1.4.2 NO_2

NO_2 is one of the family members of NO_X. NO_2 is volatile, reddish to brown and heavier than air (ILO, 2021). The 24 h permissible limit of the pollutant is 80 µg/m³ with an annual of 40 µg/m³ for residential and industrial areas of India (Table 1.1). WHO sets the same annual standard, 40 µg/m³. 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 emission 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 an annual mean concentration of NO_2 in most Indian cities is still within limits of tolerance, 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 to 30 μg/m^3.

1.4.3 SO_2

SO_2 is colourless with pungent odour gas. 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=SO_3) from the family of SO_x. The component has vast concern and usually accounts for an indicator of the SO_x family. The 24 h permissible limit of the pollutant is 80 μg/m^3 with an annual of 50 μg/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, volcanos) (Table 1.2). A study by NEERI (National Environmental Engineering Research Institute) identified that SO_2 was denoted as a critical pollutant during 1960-80 for high emissions in the air due to the rapid growth of urbanization and industrialization. Liquid petroleum gas (LPG) replaced wood, coal, and kerosene for cooking fuel remarkably checked concentrations (Khullar, 2008). A few metro areas still have a high concentration due to road 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). The emission from industrial processes, electric utilities, motor vehicle exhaust, gasoline vapours, and chemical solvents are some of the prime sources of NO_x and VOSs (Table 1.2). O_3 level is high in urban environments on hot sunny days, but colder months experience the same, reaching unhealthy levels. The substance can move further away by the wind. Even rural areas may observe similar high O_3 concentrations. The standard limit of O_3 in India is 180, 100 and 60 μg/m^3 for 1 h, 8 h and 24 h (Table 1.1). The tropospheric O_3 is a prime component of urban smog. Asian countries like India, Bangladesh, and Pakistan have witnessed high seasonal average population-weighted O_3 concentrations (Climate and Clean Air Coalition, 2017). Tropospheric O_3 is a greenhouse gas (GHG) and air pollutant that harms human health, the ecosystem, and crops.

1.4.5 CO

CO is a deadly poisonous gas. It's a tasteless, colourless, non-irritating and odourless gas. The incomplete combustion processes of carbon result in the production of CO. Due to toxicity and maximum share level in the atmosphere, 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 are motor vehicles, coal combustion, fuel oil combustion, industrial processes, solid waste disposal, and even reusing burning. Burning firecrackers on festive nights (e.g., Diwali and New Year celebrations) act as a prime source of CO in 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 early afternoon/evening hours, CO usually peaks coinciding with peak traffic pressure. The residence time of the gas is about three 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 for industrial, residential (both rural and urban), and ecologically sensitive (notified by 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 featured as colourless with a distinct pungent smell, lighter than air, highly reactive and soluble alkaline gas. The anthropogenic source is cultivated field in the form of manures and fertilizer application (Table 1.2). It may last about one week. The gas can be found in air, soil, and water, originating mainly from hazardous wastes. 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 occurs in soil from bacterial processes when plants and animal wastes decay. The 24 h and 1 h concentrations of ambient air are 400 and 100 µg/m^3 for industrial, residential (both rural and urban), and ecologically sensitive (notified by 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 major sources. About ¾ th of the global Pb has been used for 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 µg/m³ 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 denotes the overall quality of air in any area from the perspective of pollutants in general. 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 bad the air they breathe (NAAQS, 2019). An AQI is an inclusive system that changes the weighted values of the individual air pollution-connected parameters into one variety 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 of seven pollutants at each station based on the 24 h average data (only CO and O_3 had an 8 h average) and health break-point range. AQI computation needs $PM_{2.5}$, 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 category, and health impacts
Source: CPCB, 2009, 2015

1.6 Impact of meteorology on 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 variations over seasons; January and February comprise the winter season when the static movement of air increases the degree of ground-level air pollution. A reverse scenario occurs in rainy months (June, July, August, and September). The monsoon accounts for heavy rainfall, resulting in substantially decreasing air pollution levels. The pre-monsoon (March to May) is characterized by elevated temperature with high humidity and low pressure on 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. They found that most pollutants negatively correlated with atmospheric temperature and relative humidity.

A rise in air temperature at the ground level destabilizes the atmosphere and facilitates enhanced vertical mixing of pollutants (Cichowicz et al., 2017). Thus, increasing air temperature regulated the reduction of pollutant concentration at the ground level (Ravindra et al., 2019). A stronger negative correlation between temperature and $PM_{2.5}$ than NO_2 and SO_2 was recorded 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 revive again into the air by drying up in high summer temperatures. Like higher air temperature, higher wind speed facilitates the dispersal of pollutants (Li et al., 2020), except for some pollutants like PM_{10}, which gets resuspended at the ground level due to higher wind speed (Zhang et al., 2017). Relative humidity influences the particle movement and settles down PM on 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, populates the ground-level atmosphere at a lower relative humidity (< 40%), and at higher ranges, the pollutant concentration usually decreases (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. Here, we can conclude that the governing capability of the meteorological parameters compelled researchers to deweather the pollutant datasets to see their variability irrespective of seasonal fluctuations.

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

1.7 Human health impacts of air pollutants

1.7.1 Harmful effects of PM

The recent World Air Quality Report (2023) has shown that Indian cities suffered adversely from the high PM. 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 the fine particles ($PM_{2.5}$) have had widespread health risks of both 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) pointed out that $PM_{2.5}$ impacts the lower respiratory system (pulmonary region) while PM_{10} takes place in the upper part. The significant association between $PM_{2.5}$ and PM_{10} has acute health effects. Janssen et al. (2013) stated that $PM_{2.5}$ and PM_{10} were significantly ($p < 0.05$) associated with all causes and cause-specific deaths. In addition, they observed a 10 µg/m^3 increase in PM level, increased 0.8% and 0.6% excess risk for $PM_{2.5}$ and PM_{10} (Janssen et al., 2013). Lu et al. (2015) observed that $PM_{2.5}$ had higher short-term effects than PM_{10}. Moreover, their association poses high mortality, but long-term influences and morbidity were inadequate for China (Lu et al., 2015). The details of concentration breaks and the AQI category of $PM_{2.5}$ and PM_{10} for the different regions of the world are given below in Table 1.5 & 1.6.

Table 1.5 $PM_{2.5}$ concentration and AQI category of States/Territories
Source: CPCB, 2015

Table 1.6 PM_{10} concentration and AQI category of States/Territories
Source: CPCB, 2015

1.7.2 Harmful effects of NO_2

The increasing trend of vehicles adversely altered the concentration of NO_2 in both rural and urban areas. During 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 in a short span includes augmenting respiratory diseases, particularly asthma, leading to respiratory symptoms (e.g., coughing, breathing difficulties), hospital admissions and even visits to emergency rooms. Alves et al. (2010) investigated short-term exposures to NO_2 and hospital admission for cardiorespiratory diseases in Lisbon, Portugal. A study by Costa et al. found that short-term exposures account for respiratory hospital admission and even cause mortality for all age groups (Costa et al., 2014). Khaniabadi et al. (2016) pointed out that a 10 $\mu g/m^3$ change in concentration aggravated chronic relative risk and casualties (Khaniabadi et al., 2016). Longer exposures to mass concentrations may contribute to asthma and potentially increase susceptibility to respiratory infections (EPA, 2022). Moreover, asthmatic and patients with chronic obstructive pulmonary diseases (COPD) (children and elders) are at greater risk for the health effects (CPCB, 2015). The details of concentration breaks and the AQI categories for the different regions of the world are given below in Table 1.7.

Table 1.7 NO_2 concentration and AQI category of States/Territories
Source: CPCB, 2015

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 and lead to 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 attack, and even hospital visits cases 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 concentration breaks and the AQI categories for the different regions of the world are given below in Table 1.8.

Table 1.8 SO_2 concentration and AQI category of states/territories
Source: CPCB, 2015

1.7.4 Harmful effects of O_3

O_3, a secondary pollutant formed in the atmosphere, has significant health impacts. Breathing with ground-level O_3 can trigger various health issues like congestion, chest pain, coughing, and throat irritation. It can worsen Asthma, emphysema and COPD (Nuvolone et al., 2018; Koman and Mancuso, 2017). The short-term and long-term exposures pose 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 to be one of the 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 of O_3 formation; anyone who spends a long time in that ambient air may be affected, especially children and elders. US EPA recommended that people should reduce outdoor activities and stay indoors when the O_3 concentration is high. Zhang et al.

(2019) gave a complete description of O_3 amid health problems. About a 60% increase in premature mortalities was observed in 69 Chinese cities during 2013-19 (Lu et al., 2020). The details of concentration breaks and the AQI categories for the different regions of the world are given below in Table 1.9.

Table 1.9 O_3 concentration and AQI category of States/Territories
Source: CPCB, 2015

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. The elevated concentration of CO reduces the amount of O_2 in 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 concentration increase led to a percentage COHb level, which could be about 2% (CPCB, 2014). The CPCB set the standard of CO as 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, headache, diarrhoea, cough, chest tightness, nasal congestion, palpitation, 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 life loss. The details of concentration breaks 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

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 form 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 its elevated concentration could cause several health impacts (Sundlad et al., 2004). Moderate exposure (50-150 μg/m3) accounts for the health effects of irritation of the eye, throat, and skin and mucus build-up. An elevated concentration (>150 $\mu g/m^3$) of NH_3 is responsible for pulmonary oedema, 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 vast health impacts, which 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 of NH_3 and Pb are given below in Table 1.11.

Table 1.11 Pollutants concentration and AQI category of India

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 concentration often affects the nervous system, haematological changes and CVD. Occupational lead exposure accounts for anaemia (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 a virus, the severe acute respiratory coronavirus 2 (SAR-CoV-2). The symptoms of COVID-19 are variable but often include fever, headache, loss of taste, loss of 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 the spate of cases worldwide, 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 the COVID-19 pandemic since its inception often overwhelmed local healthcare services quite 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 restrictions/lockdown was imposed in Wuhan city, China, on January 23, 2020, to slow down the spread of infection and followed by other countries (Wang and Su, 2020; Wilder-Smith and Freedman, 2020). After China, Italy was the country most affected by COVID-19. Italian government imposed the lockdown by March 23, 2020 (Ceylan, 2020). The United States and countries in Western Europe 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 cases of COVID-19 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 novel COVID-19 cases 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 words, adequate personal protective equipments (PPEs), 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/UTSs 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 sectorial 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 session in India. Afterwards, the death rate gradually declined, and the recovery rate improved. India reached 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 gradually decreasing trend of 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 by Serum Institute of India Ltd.) and Covaxin (Bharat Biotech by Bharat Biotech International Ltd.), have been initiated to aim at vaccinating 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 peoples with co-morbidities (Bagcchi, 2021). Simultaneously, COWIN software was in action for vaccine registration, issuing certificates and monitoring the 1.35 billion massive people pandemic immunization programme (Choudhary et al., 2023). The COVID-19 infection tracking device, Aarogya Setu (application software), was launched for citizens' safety. As of December 2, 2021, approximately 84% (117 million) people had been vaccinated with their single dose and nearly 47% with double doses (Bahera et al., 2022).

India experienced a new variant of SARS-CoV-2 (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. 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 that accounted for less than 1% of total cases, currently 0.22%, the lowest since March 2020, with 1.42 billion vaccinations given. 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 the impact of the new variant of COVID-19, 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 have registered officially (WHO dashboard, 2022).

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

1.11.1 Global scenario

The novel coronavirus originated in Wuhan, China, in December 2019 and spread across all nations later. The WHO declared in March 2020 that COVID-19 has turned into a global pandemic and called for a forceful worldwide reaction. 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-wise restrictions for human mobility to break the chain of COVID-19. Thus, restrictions/lockdowns and closure of all sectorial activities except emergency services improved the ground-level air quality. Researchers documented from past studies that many countries suffered severe health issues due to extreme air pollution (Anenberg et al., 2010; Krewski et al., 2009; Slama et al., 2008). 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 in Asia, Europe, and North America.

Ankan and Coccia (2022) researched major pollutants ($PM_{2.5}$, PM_{10}, CO, NO_2, SO_2, and O_3) concentration from 2019 to 2022 across 300 global cities of 19 countries. They depicted that the maximum reduction in pollutants was as follows, $PM_{2.5}$ over 40% in Germany; PM_{10} over 150% in Turkey; CO over 4300% in France; NO_2 over 150% in China and Australia, SO_2 over 150% in Israel, O_3 over 90% in China due to lockdown and quarantines. A similar study was done by Fu et al. (2020) on 20 major cities around the world. They identified that pollutant deduction was noted mainly due to restrictions on transportation, industry, and commercial activities during the lockdown. Kumari and Toshniwal (2020) evaluated the global impact of the pandemic on air quality based on 162 monitoring station datasets from 12 cities across the globe. Their study found $PM_{2.5}$, 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. 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. Albayati et al. (2021) mentioned that air pollutant levels have decreased worldwide due to industrial closure amidst the pandemic. In addition, they argued that this reduction reached a level that all political conferences and agreements could not reach. 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. Most of the reviewed papers demonstrate that both the short and long-term $PM_{2.5}$ and NO_2 may significantly contribute to higher rates of COVID-19 infections and mortalities. Silva et al. (2022) did a systematic review of a total of 114 papers. Most of the authors paid serious attention to India and China, usually urban areas and therein major air pollutants (e.g. PM_{10}, $PM_{2.5}$, NO_2, O_3, CO, and SO_2) levels during pre- and post-lockdown periods. Another systematic review by Bakola et al. (2022) estimated that substantial and robust reduction 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. Bray et al. (2021) observed a similar reduction trend of pollutants, $PM_{2.5}$, PM_{10}, CO, NO_2, and SO_2 concentrations except O_3 for regional monitoring sites in the USA, China, India and Europe during March and April 2020 compared to respective month for 2015-19. In addition, four major cities, New York (USA), Milan

(Italy), Wuhan (China), and New Delhi (India) case studies revealed similar reduction trends as observed on a regional scale. Muhammad et al. (2020) made a remarkable conclusion based on National Aeronautics and Space Administration (NASA) and European Space Agency (ESA) datasets that some of the epicentres of COVID-19, such as Wuhan, Italy, Spain and the USA, have reduced up to 30% of environmental pollution.

A recent study by Zhu et al. (2020) covering 120 cities in China showed a critical relationship between air contamination and COVID-19 disease. A study from the United States shows that an increase in long-term exposure to $PM_{2.5}$ results in a significant rise in the death rate from COVID-19 (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. Bonilla et al. (2022) observed same for Latin America. Here, Brazil, Chile, Colombia, and Mexico recorded a 2.7% increase in the COVID-19 mortality rate with an increase in long-term exposure of 1 $\mu g/m^3$ of fine particles. A 1 $\mu g/m^3$ increase in the long-term average of PM was responsible for 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 lockdown of the COVID-19 pandemic in four megacities of China, Wuhan, Beijing, Shanghai, and Guangzhou. They found an improvement in air pollution by $PM_{2.5}$, NO_2, and SO_2. Gao et al. (2023) examined 336 Chinese cities' air pollutants during 2016-20; they got a decrease in $PM_{2.5}$, PM_{10}, NO_2, SO_2, and CO were 91%, 92%, 75%, 94% and 89% while an increase of O_3 was 87% of cities. A study by He et al. (2020) drew a similar conclusion that lockdowns led to a noticeable improvement in air quality in China. Lian et al. (2020) found a significant fall in AQI in Wuhan city due to city scale lockdown. Moreover, pollution levels fall rigorously in densely populated areas. 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. 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. Xing et al. (2022) depicted similar improvements in the Shandong Province of China. 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 in 2018-19. A similar traffic reduction accounts for low NO_2 and PM levels in west Europe (Menut, 2020). Skirienė and Stasiškien˙e (2021) observed that checks of industrial and mobility activities restrict the NO_2, $PM_{2.5}$, and PM_{10} emissions by about 20-40% in European countries during pandemic lockdowns. Dursun et al. (2022) studied 30 major cities in Turkey; the result revealed improved air quality levels after imposing a lockdown. 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. Bar et al. (2022) study revealed that 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 lockdown than that of 2019. Chen et al. (2020) investigated the non-uniform impacts of the COVID-19 lockdown on air quality in the United States. The result revealed that the NO_2 drop was highest and followed by CO, PM_{10}, O_3 and $PM_{2.5}$. Rio de Janeiro (Brazil) recorded a fall in pollutant (CO, NO_2, PM_{10} and O_3) levels for imposing a partial lockdown (Dantas et al., 2020). The same was noted for the São Paulo state of Brazil by Nakada and Urban (2020). The lockdown policy reduced the overall emissions of air pollutants in California (USA) (Liu et al., 2021). The eastern province of Saudi Arabia experienced a reduction of PM_{10}, CO, and SO_2 by 21-70%, 5.8-55%, and 8.7-30% though O_3 increased exceptionally by 6.3-45% in 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 degree of air pollution has far more impact than COVID-19 (Giani et al., 2020). The GoI initially imposed a complete lockdown all over the country for 21 days to combat the critical pandemic on March 24, 2020. 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. Suspension of all transportation services (i.e. rail, road, and air) took place, except for the 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, it has been proven by satellite images and ground data that air pollution in the form of NO_2 emissions in many parts has dropped in a way that the stratospheric O_3 layer is recovering (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, the study of the impact of COVID-19 on Air Quality is limited, but there are several studies on air quality during nationwide lockdowns (Mahato et al., 2020; Sharma et al., 2020; Mitra et al., 2020). Lowering $PM_{2.5}$ levels have 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). It is evident from several pieces of research that the nationwide lockdown in India improved the air quality (Singh and Chakraborty, 2020). Chinnasamy et al. (2022) examined Kolkata, Delhi, Mumbai and Bengaluru during the pandemic states, and results showed a significant decline trend of pollutants ($PM_{2.5}$, PM_{10}, CO, SO_2, NO_2). Gautam et al. (2021) investigated the eight most polluted Indian cities (Mumbai, Delhi, Bangalore, Hyderabad, Lucknow, Chandigarh, Kolkata, and Ahmedabad), and the result shows a significant reduction of pollutants. Singh and Tyagi (2020) observed Chennai during the COVID-19 Lockdown. They found a revival of an environment with reduced emissions of pollutants. Chowdhuri et al. (2020) observed a 40-68% reduction of concentration for PM_{10}, NO_2, SO_2, O_3, and aerosol over the Kolkata megacity. A similar result was recorded by Chowdhuri et al. (2023). Das et al. (2021a) showed that the concentration of air pollutants decreased remarkably across 57 urban agglomerations in India during lockdown. Das et al. (2021b) noted an 80% reduction in air pollution in Kolkata due to the strict lockdown. It has been found from the study (James-Poetzscher, 2020) in Delhi's metropolitan area, pollution levels have dropped most dramatically; NO_2 concentration fell by 90 $\mu mol/m^2$ to 162 $\mu mol/m^2$ during the period of March 25 (the day quarantine began) to May 2 and March 1 to March 24. In 2019, NO_2 levels were also far above this year's levels, averaging 158 $\mu mol/m^2$ from March 25 to May 2. In Greater Mumbai and Navi Mumbai, a similar trend has been observed as NO_2 levels from March 25 to May 2 averaged 77 $\mu mol/m^2$ compared to 117 $\mu mol/m^2$ from March 1 to March 24. In 2019, NO_2 levels from March 25 to May 2 averaged 122 $\mu mol/m^2$. Lately, the CPCB published a report on the air quality effects of the Janata curfew and found that a decrease in the number of cars on the road led to a 51% reduction in NO_x levels in the air. 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 for people below 39 years.

1.12 Scope of research in Indian megacities

The previous research papers have concentrated on a few selected parameters or only one specific location. A few of them did not account for the pollutant concentrations during the same time of the previous year under no lockdown condition, which led to incomplete inferences. The study on the influence of meteorological conditions over the megacities is limited. The deweathering (i.e. elimination of meteorological parameters like air temperature, relative humidity, wind speed, and precipitation) of pollutants is also not taken into account by many of the studies. The inter-wave lockdown impact on ambient air pollution amidst the COVID-19 pandemic was also not compared by previous researchers. Comparative analyses based on three pandemic surges among megacities of India are limited. Moreover, the incorporation of R programming, XL Stat, and geographic information system (GIS) with a statistical approach was not incorporated in any studies mentioned above.

1.13 Study area

Though the present doctoral thesis focused on two coastal cities of India, namely Kolkata and Mumbai, one chapter of this thesis (Chapter 3) was dedicated to the global scenario and the other chapter (Chapter 4) was dedicated to the air pollution scenario of China, India, and Pakistan (i.e., the most populated region of Asia). Chapter 3 considered select countries from all over the world, whereas Chapter 4 focussed on the most populated regions of the globe: China, India, and Pakistan.

China, India, and Pakistan (CIP), these three neighbouring countries hold 38% of the global population as of April 2023, according to the UNFPA report (UNFPA, 2023). China geographically lies between east longitudes 73° to 135° and north latitudes 18° to 53° with a population of 1425.7 million. India's population stands at 1428.6 million 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 to 37°5'N latitude and 60°50'E to 77°50'E longitude with a population of 240.5 million 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 has a wide range of elevations, from the top of the World, Mount Everest, to the Bay of Bengal. The climate of the CIP varies according to the altitude, latitude, distance from the coast, and presence of the mountain. The region experiences a wide range in terms of temperature and precipitation (Fig. 1.2). The whole of China experiences freezing temperatures except the southeast and southern parts of the Himalayas. The lower Himalayas and southwest of India account for heavy rainfall. Currently, 495 ambient air monitoring stations (AAMS) within 31 states/provinces for China, 255 AAMS within 28 states/provinces for India, and 10 AAMS 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 and 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 (summer seasons) and high temperatures throughout the year. Central and Eastern China accounts for humid summers with minimum climate extremes. The remaining regions have harsh climates with heavy cold in winter and strong breezes (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).

Table 1.12 Description profile of China, India and Pakistan

The climate of India can broadly be classified as a tropical monsoon type. 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, river Indus, distance from the sea, undulating topography, and prevailing wind control Pakistan's climatology. Pakistan experiences four seasons, and they are hot or dry spring (March-April-May), summer rainy (June-July-August-September), retreating monsoon (October-November), and cool-dry winter (December-January-February) (World Bank, 2021b). Pakistan accounts for a mean monthly temperature and rainfall ranging from 9.31°C (January) to 29.73°C (June) and 7.8 mm (November) to 52.57 mm in 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

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, situated in the northern part. 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) hold the 9^{th} and 16^{th} position 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 parameters such as climate, elevation, and wind direction play a crucial role in regulating the air quality of these megacities. In this study, we considered the entire Mumbai megacity, the Kolkata megacity, including the twin cities of Kolkata and Howrah, and the total geographical area of Delhi.

Table 1.13 Some features of the select megacities in India

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

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

1.13.1 Kolkata

Kolkata and Howrah are the twin cities located within the megacity of Kolkata (**Fig. 1.6**). They have a population of 4.50 million and 1.07 million, with an area 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 river Hooghly. In contrast, Howrah Municipal Corporation (HMC) or Howrah city is on 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 holds the 16th position in the world, 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. The summer/pre-monsoon is characterized by high temperatures with high humidity, and it is also the season of Kal-Baisakhi (Norwester), which brings relief from rain during the afternoon and evening. Southwest monsoon enters in June and stays up to September. It is the rainy season in Bengal when maximum rainfall occurs. October and November experience autumn or post-monsoon, which is characterized by moderate rain with moderate temperature. The days are clear; nights are comfortable in this season. Currently, ten AAMSs operate over this megacity under West Bengal Pollution Control Board (WBPCB). The seven AAMSs (Ballygunge, Bidhannagar, Fort Willam, Jadavpur, Rabindra Bharati University, Rabindra Sarobar, and Victoria) were within Kolkata, and the remaining three (Belur Math, Ghusuri, and Padmapukur) in Howrah city. The fast urbanization, day-by-day increasing number of vehicles, and the indiscriminate growth of the Howrah industrial belt are the main reasons for the rising air pollution level 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, 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 fifteen 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 of many industries, power plants, and increasing vehicular density are leading to extraordinary air pollution in the megacity of Delhi. 36 AAMSs (Alipur, Anand Vihar, Ashok Vihar, Aye Nagar, Bewana, 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 Indian Meteorological Department. Another five stations are under the CPCB. The remaining 26 stations are under the Delhi Pollution Control Board.

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. Materials and Methods
    (a) Data Sources
    (b) Methods
3. Gauging the effects of the COVID-19 pandemic lockdowns on atmospheric pollution content in select countries
4. Outdoor $PM_{2.5}$ pollution levels in China, India, and Pakistan
5. Effects of the COVID-19 pandemic on the air quality of three megacities in India
6. Air pollution in three megacities of India during the Diwali festival amidst COVID-19 pandemic
7. Characterizing the air quality of the Kolkata megacity amidst COVID-19 waves-induced lockdowns
8. Characterizing the air quality of the Mumbai megacity amidst COVID-19 waves-induced lockdowns
9. Conclusions

Chapter 2 Data Sources and Research Methods

This thesis focused on air pollution during the novel COVID-19 pandemic from various viewpoints and different study areas. The Tropospheric AOD and NO_2 were taken into account for the most polluting countries (China, India, Italy, France, Germany, and the United States) worldwide during the pandemic. The ground-monitored seven 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 lockdown on megacities (Mumbai, Delhi, and Kolkata) air. 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 the air quality during the pandemic phase with the same window frame of the previous year (2019) or normal conditions. The megacity of Mumbai and Kolkata has witnessed three pandemic surges. Wave-wise comparison in the megacity is very crucial. Simultaneously, I analyzed the change in pollution during Dewali and compared it with the pre-Dewali and post-Dewali pollution. In addition, I examined the pandemic year Diwali (2020) with the non-pandemic (2019). The impact of meteorological parameters like 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 the wethered and deweathered (eliminate the impact of meteorological parameters) pollution levels. 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 changes the weighted values of the individual air pollution-connected parameters into one variety 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 needs

$PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, CO, O_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).

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;

$I_i = f(X_i), i = 1,2 \dots n$ 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:

$I = \alpha X + \beta$ 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:

$I_i = \left[\left\{\frac{(I_{HI} - I_{LO})}{(B_{HI} - B_{LO})}\right\} \times (C_P - B_{LO})\right] + I_{LO}$ 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 AQI

Step 2

The aggregation of sub-indices, Ii, is carried out with some mathematical function (described below) to obtain the overall index (I), which is referred to as AQI.

$I = F(I_1, I_2, \dots, I_n)$ Eq. 4

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

Weighted Additive Form

$I = \text{Aggregated Index} = \sum W_i I_i (\text{For } i = 1, \ldots, n)$ 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)

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

Where p is the positive real number >1.

Root-Mean-Square Form

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

Min or Max Operator (Ott, 1978)

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

2.1.2 GIS interpolation (Inverse Distance Weighting)

The spatial interpolation has deployed using Inverse Distance Weighting (IDW) interpolation. The interpolation assumes unknown sites/locations value based on some known sites/locations value. 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). IDW interpolation technique has largely been used in the mapping of variables. The air pollution data collected by the CPCB was joined as an Excel file with the shapefile of AAMS. The unknown points' values are generated using the mask layer of the megacity. 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 low to high values. 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 quite a user-friendly method. Jha et al. (2011) inferred that the IDW technique is ideal for the Indian air pollution scenario and leads to fewer error margins than other conventional interpolation approaches. Many scholars and researchers have used the IDW technique to map pollution across the globe. Jung et al. (2021) investigated the effects of air pollution on chronic kidney disease patients using the IDW method. Shukla et al. (2020) incorporated IDW for spatial distribution mapping of particulate matter in Delhi. Masroor et al. (2020) examined $PM_{2.5}$ concentrations in Tehran using the IDW method. A few researchers, like 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 amidst lockdown.

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 is called a spline that allows us to model nonlinear relationships for each variable incorporated in 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 smoothens the air pollutant data negating the effect of weather variability and seasonal change.

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 in XL-STAT by which the deweathering was carried out. Due to limited meteorological data and 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). The normalization or deweathering of air pollutant data was carried out by implementing the mixed GAM computation vehicles (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 the unavailability of data, parameters like solar radiation and cloud cover were excluded. The GAM package is chosen from 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

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

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

The Pearson correlation coefficient method was conducted 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

Here, Iused the R programming language by considering 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) give a good visual inspection of large data sizes. It's constructed from five statistical values, the minimum value, the first value, the median (or second quartile), the third quartile, and the maximum value. The box formed the first quartile to the third quartile. The smallest and largest values are situated at the end of the whiskers, the smallest/bottom and the largest/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, while horizontally, intra-pollution levels year-wise. Here, I used MS Excel 2010 to compute the box plots.

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

2.2.1 Data sources

To investigate the environmental effects of the coronavirus quarantine periods across the globe on atmospheric quality, two parameters, i.e. NO_2 and AOD, have been considered here. Six of the most polluting countries worldwide, where the impact of the virus was notable initially, 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 the AOD datasets were also obtained for 2005-19 to examine the spatio-temporal concentration of these substances across the globe in more normal times (i.e. over the last 15 years, which is as far back as when both these datasets can be obtained). 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 samples of the ground station data of NO_2, $PM_{2.5}$ and PM_{10} of the studied countries. 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 keep in mind the previously ascertained most polluted zones of each studied country from the NASA data.

2.3.2 Uncertainties of MODIS data

The uncertainties of MODIS data, such as sensor zenith angle and cloud cover, are the major limitations in 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 the datasets collected over a 15-year time period, which were primarily the 15-year averaged maps of NO_2 and AOD, which seemingly decreases the uncertainty to some extent. Clear skies were present during most of the lockdown periods in the respective countries. Urban and industrial regions are the major source areas of atmospheric pollutants in contrast to the more sparsely populated rural and mountainous regions.

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

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

Table 2.3 Dataset Details

2.3.3 Methods

To detect the normal (i.e. usual) spatial-temporal concentration of the NO_2 and AOD attributes across the globe, the 15-year (2005-19) time-averaged images were prepared from the NASA web portal (Krotkov et al., 2019). The same respective datasets/images of the six countries mentioned above, for the previous year, pre-lockdown phase, lockdown, and post-lockdown periods were also prepared from the same web portal. The downloaded averaged images were analyzed using the ESRI ArcGIS 10.3 platform. For visual interpretation of the images at the country level and for the world as a whole, these datasets were properly stretched using a fixed range of NO_2 and AOD values. As per the dataset legends provided by the NASA portal, areas denoted with dark red and blue tones would 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 concentration of the AOD, respectively, in a region.

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

2.3.1 Data sources

To investigate outdoor $PM_{2.5}$ pollution, Iextracted the annual mean concentration of $PM_{2.5}$ for all 760 cities of China, India, and Pakistan from 2017 to 2023 and the monthly mean observed in these cities for 2023 from the Swiss air quality technology company IQAir. The Swiss company collects data from government & non-government agencies and non-profit organizations using real-time air quality monitoring instruments and low-cost air quality sensors. Incorporating the historical year-end datasets and collected real-time data, ultimately, global data was released. Here, Iemployed 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, Peshawar, Faisalabad, Rawalpindi, and Islamabad). In addition, the capital cities of China (Beijing), India (New Delhi), and Pakistan's (Islamabad) annual hours spent in various categories of WHO (WHO, 2022) prescribed $PM_{2.5}$ pollution levels during 2017-23 were incorporated.

Table 2.4 World Air Quality Report 2023 Visualization Framework

Source: World Air Quality Report 2022

2.3.2 Methods

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

Using WHO colour schemes, Ideployed all 760 cities with $PM_{2.5}$ averaged annual mean concentration (2017-23) for spatial mapping of the countries. The temporal trend of $PM_{2.5}$ levels during 2017-23 is depicted by point plots. The variation of mean $PM_{2.5}$ concentrations during 2017-23 over CIP was also compiled. In addition, I have designed a framework for incorporating different city locations, such as industrial, transport, geographical features (AAMSs cover diverse landscapes, including urban, suburban, and rural areas), and weather patterns, including temperature inversions, seasonal variations, fog, smog, etc. from 2017 to 2023. This framework utilizes two air monitoring datasets to assess the value of a nation based on these four factors. For industrial location, the cities considered are Shanghai and Beijing for China, Gurugram and Asansol for India, and Lahore and Karachi for Pakistan. Shenzhen and Guangzhou for China, Delhi and Mumbai for India, and Lahore and Karachi for Pakistan were deployed for transport locations.

Regarding geographical features, the cities are Chengdu and Tianjin for China, Shillong and Siliguri for India, and Faisalabad and Islamabad for Pakistan. Lastly, for weather patterns, the towns include Wuhan and Dongguan for China, Jaipur and Chennai for India, and Peshawar and Lahore for 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's (Islamabad) annual hours spent in various categories of WHO-prescribed $PM_{2.5}$ pollution levels during 2019-23 were represented by a bar graph.

Ialso computed and designed the mean monthly $PM_{2.5}$ concentration of 18 (6 cities × 3 nations) cities column-wise and annual average horizontally to detect the seasonal variation of pollution. The same colour contrast is used for all these figures. The regional differences in pollution levels have been analyzed using the mean $PM_{2.5}$ concentration data 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-nation variability in $PM_{2.5}$ concentrations. The seasonal $PM_{2.5}$ concentrations were computed based on the 760 cities across three nations. The mean observed temperature and precipitation of CIP were prepared from the Climate Change Knowledge Portal (CCKP) of Worldbank using the variables of average mean surface air temperature and precipitation for the periods of 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 based on ground station data of 760 cities, 495 for China, 255 for India and 10 for Pakistan. These monitoring stations were geographically not well distributed and country-wise uneven. 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 sectorial stubble burning are the principal sources of air pollution. Hence, taking only outdoor monitoring was significant. Though the data stations were uneven geographically, the zones of human activities were incorporated, and the stations allocated here only excluded the mountainous and desert areas.

Moreover, the number of monitoring stations is adequate for geographical areas of the countries and population share to inquire about and get transparent findings. The air monitoring stations of Pakistan, mainly Peshawar, Faisalabad, and Rawalpindi, had a few data gaps that 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, compared to the stretch of Pakistan and its population density, the number of monitoring stations was fewer in comparison to Chain and India. However, this study didn't aim to extrapolate data for other cities in Pakistan from the existing dataset as that could have led to gross over or underestimation, which I deliberately avoided and focused only on the available data to draw conclusions.

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

2.4.1 Data used

Iextracted the ground-monitored air pollutants data of $PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, CO, and O_3 from the CPCB web portal (https://app.cpcbccr.com/AQI_India/). Icollected data from 15 AAMS of Mumbai, 37 AAMS of Delhi, and 10 AAMS of Kolkata. The nationwide lockdown started in India on 24 March 2020. Iextracted the data for three weeks before the lockdown (3 March to 23 March 2020), three weeks during the lockdown phase (25 March to 14 April 2020), and three weeks post-lockdown (15 April to 5 May 2020). I also extracted the data of one station from Mumbai, 36 stations from Delhi, and four stations from Kolkata from the CPCB web portal during the same time window period (25 March to 14 April) of the previous year, 2019, to compare the air quality between two years. The data from the rest of the stations for the year 2019 is unavailable. Iextracted and analyzed the air pollutants data for twelve dates having weekly intervals for the year 2020: 3 March, 10 March, 17 March, 23 March, 25 March, 31 March, 7 April, 14 April, 15 April, 21 April, 28 April, and 5 May. For the year 2019, Iextracted the data for the dates 25 March, 31 March, 7 April, and 14 April. Daily meteorological data of four parameters, namely ambient air temperature, relative humidity, wind velocity, and precipitation for March, April, and May (of the years 2019 and 2020), were retrieved from the weather stations deployed at the airports of these three megacities. 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 selected for meteorological data, collected from Weather Underground portal (https://www.wunderground.com/). 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 Methodology

Ianalyzed the spatial distribution of the daily average air pollutants data using a GIS platform. To produce a spatial-temporal variation map of all the seven air pollutant parameters, Iimplemented the interpolation technique based on the IDW interpolator by linear combination model using ESRI ArcGIS 10.5 platform. The pollutant data for three selected dates, viz., 17 March, 31 March, and 21 April 2020, were mapped to show the spatial distribution for pre-lockdown, lockdown, and post-lockdown scenarios of those pollutants using the same GIS platforms. On the other hand, the point plots, box plots, and sparklines diagram for changing trend change in average concentration and correlation matrixes of pollutants have been prepared by MS Excel 10. Ialso computed the AQI to characterize the overall status of air quality in the three megacities.

2.5 Data sources and methodology 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. The ground-monitored data on these pollutants were downloaded from the official website of the CPCB (https://app.cpcbccr.com/AQI_India/). Delhi, Kolkata, and Mumbai have 37, 10, and 15 AAMSs, respectively. I downloaded the data for all 135 of these stations. Diwali was on 27 October and 14 November in 2019 and 2020, respectively. Usually, people burn firecrackers in the evening and continue till midnight. All these AAMSs keep a record of hourly data. Iextracted the data on all seven pollutant concentrations at midnight (IST 12:00 am) on both of the dates. Iconsidered 24-hour 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 residence time in the atmosphere, Iextracted and analyzed the pre-Diwali and post-Diwali data on the pollutant concentration for both years. The 24-hour averaged data for the dates 20, 24, 25, and 26 October 2019 and 07, 11, 12, and 13 November 2020 were analyzed to characterize the pre-Diwali pollution scenario. Similarly, the 24-hour averaged data for the dates 28, 29, 30 October, and 03 November 2019, as well as 15, 16, 17, and 21 November 2020, were analyzed to understand the 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, Iconsidered a date that was seven days before and seven days after the Diwali date to examine the residual effect in the atmosphere. Daily meteorological data of five parameters, namely ambient air temperature, relative humidity, wind velocity, wind direction, and precipitation for the same 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 Mohestola, Behala Airport Station (22.54°N, 88.30°E) for Kolkata (Weather Underground portal; https://www.wunderground.com/).

2.5.2 Methodology

The net change in each of the AAMS was computed to analyze the changes in pollutant concentrations between the different dates within the respective years. The composite means of the net changes observed in all the 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 in the Diwali date and seven days before Diwali and (ii) the difference between pollutant concentration in 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 represent the difference in ambient air pollutant concentration observed between Diwali 2019 and Diwali 2020 for each of the parameters. 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 end of the boxes signify the first quartile and third quartile, respectively.

24-hour average data was not available for all the AAMSs. Data from two AAMS (Kurla and Sion) for Mumbai, ten AAMS (Anand Vihar, Ashok Vihar, Bewana, DTU, Jawaharlal Nehru Garden, Mundka, Patapganj, Pusa, DPCC, Rohini, and Sonia Vihar) for Delhi and three AAMS 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

Ianalyzed the spatial variation in the air pollutants and AQI within each of the megacities using the ESRI ArcGIS 10.5 platform. The interpolation technique based on the IDW interpolator and linear combination model was applied. IDW is a deterministic approach to compute 76 the values at unmeasured locations based on the measured values at distinct locations (Xie et al., 2021). The interpolation algorithm depends on a probabilistic logic that the influence of the values at a nearer location is higher than that of a distant location to an unknown location (Jumaah et al., 2019). In this method, the weights assigned to an unknown location are a function of the distance from the other locations having measured data (Vorapracha et al. 2015). 118 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 for the Indian air pollution scenario and leads to fewer error margins than other conventional interpolation approaches.

2.5.2.2 Deweathering of air-pollutant data

Due to limited meteorological data and unavailability of meteorological data for all the AAMS, Ideweathered one station's pollutant data from each of the three megacities, namely Anand Vihar (Delhi), Chatrapati (Mumbai), and Rabindra Sarobar (Kolkata). Iused 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 189 (Dehghan et al., 2018; Li et al., 2019; Ravindra et al., 2019a), as it smoothens the air pollutant data negating the effect of weather variability and seasonal change. 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 like solar radiation and cloud cover were excluded due to the unavailability of data.

2.5.2.3 Statistical analyses

Shapiro-Wilk test enabled us to check the normality of the data. An independent sample Students' t-tests indicated the difference in mean air pollutant levels among the cities over the two different years. Pearson correlation coefficient facilitated us to examine the inter-relationship between the 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 methodology 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, Iextracted data from all AAMS of Kolkata-Howrah city in Kolkata. 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 & 14 April of 2020 were selected for the first wave. Likewise, 16 May, 23 May, & 30 May of 2021 and 1 January, 8 January, & 15 January have been used for the 2nd and 3rd waves respectively. The same dates in weekly intervals for the year 2019 data were also collected to assess the non-pandemic pollution level scenario. The 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 retrieved from the Dum Dum airport (the airport within the Kolkata megacity) weather stations.

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 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 concentration and six AQI categories, CPCB prepared a health breakpoint range considering the human health impact of such pollutants (Table 1.3).

2.6.2.1 The IDW method

The spatial distribution of pollutants was prepared by using the IDW interpolator model. The IDW is a commonly used method to compute unknown points based on known points' data (Xie et al., 2017). The method is widely accepted for the spatial mapping of air pollution on a city scale compared to other conventional interpolation methods (Jha et al., 2011). In this study, Iprocessed this approach for the pandemic waves using the ESRI ArcGIS 10.5 platform.

2.6.2.2 Deweathering of air pollutant data

The research exclusively focused on an area of only 269.5 sq. km of Kolkata megacity. Hence, it was safe to assume that the meteorological parameters at a particular time remained unchanged within this area limit. I used only one station's pollutant data, which was Rabindra Bharati University (RBU). The GAM of XLSTAT was used to remove the effect of the meteorological variables on the air pollutant concentration.

There is a model configured in the R programming language of R studio (R core team, 2020) known as mgcv (Wood, 2020), used for performing the normalization or deweathering of pollutants. The model failed to perform by taking all five parameters, resulting in "execution was halted". So, I have taken the most effective three parameters, temperature, rainfall, and wind speed. The relative humidity and air pressure were excluded from the model due to having more coefficients than the data.

2.6.2.3 Statistical Correlation

The Pearson correlation coefficient method was conducted to analyze the association among pollutants during the COVID-19 pandemic waves. It's a linear correlation between variables or two sets of data diagrammatically represented by scatter plots. Here, I used the R programming language by taking into account 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 $p < 0.001$ = "***". Many researchers have used this method for computing air-pollutants correlation (Mahato et al., 2020; Sarkar et al., 2021).

2.7 Data sources and methodology 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. Iconsidered available 24 h averaged ground-level concentrations of $PM_{2.5}$, PM_{10}, CO, NH_3, SO_2, NO_2, O_3, and AQI for 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/). As the study focused on three surges of the pandemic, I considered extracting the pollutant concentration data for the following dates; 25 March, 31 March, 7 April, and 14 April 2020 for the first wave; 22 April, 27 April, and 1 May 2021 for the second wave, and 10 January, 15 January, and 19 January 2022 for the third wave. I extracted the pollutant data for the exact dates of 2019 when there was no pandemic to assess the non-pandemic pollution level scenarios in the megacity.

The weather station set up at the Chhatrapati Shivaji International Airport Station (18.97° N, 72.83° E) of Mumbai facilitated the meteorological data such as 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 the pollutant concentrations between the pandemic waves (2020, 2021, and 2022) and the regular phase in 2019 under no pandemic situation. 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 1st wave (2020) and 2nd wave (2021). However, due to data constraints, Bandra Kurla Complex (IITM) is considered for the third wave. Due to the data gap of NH_3 and O_3 in Bandra and Bandra Kurla Complex for the first and second waves, I considered 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 between three different waves and between these waves at the exact same time during a non-pandemic phase. AQI is a tool that represents various pollutants in a single number (index value). Hence, it exerts an overall air quality status on people 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 first wave (2020), second wave (2021), and 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, and NH_3. $PM_{2.5}$, PM_{10}, and a minimum of three pollutant concentrations must be required to find the AQI. The pollutant concentration, National AQI classes, National AQI categories, and health impacts have been shown in Table 1.3. Here, a low amount of substance in the air indicates minimal health impacts; a high concentration exerted prolonged suffering.

2.7.3.1 IDW model

I have applied the IDW interpolator model to characterize the spatial distribution scenarios as implied in several previous studies. In this method, a few unknown points are computed based on a few known points dataset (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's wave-wise spatial distribution of pollutants was processed using the ESRI ArcGIS 10.5 platform.

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 a mgcv package in R (Wood, 2020). The model is user-friendly and configured with a machine-learning tool that removes the meteorological parameter's 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 as independent variables. The cubic spine for smoothening data and residual maximum likelihood (REML) techniques are adapted in GAM options.

2.7.3.3 Correlation coefficient method

The Pearson correlation coefficient with scatter plots was computed to analyze the interrelationship between the pollutants during COVID-19 surges. The previous research detected that the combined impact of substances was more harmful. I performed the correlation (r) method through R studio based on seven pollutants. Here, the "r" value ranges from +1 to -1 means strong positive to strong negative. Simultaneously, the degree of significant level three, viz. $p < 0.05$= "*"; $p < 0.01$= "**"; and $p < 0.001$= "***" considered. The Correlation coefficient method is widely accepted for air pollutant concentration nowadays (Mahato et al., 2020; Sarkar et al., 2021).

Chapter 3 Impact of COVID-19 Lockdowns on Air Pollution

3.1 Introduction

The swift spread and ensuing community transmission of the COVID-19 pandemic since its inception often overwhelmed local healthcare services quite quickly. They 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 (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 NASA (2020) released a few satellite image products in April 2020 that showed a 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; 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 analyzed the lockdown's effect on air quality at the entire country level while 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 NO_2 and the AOD. Aerosols are solid and liquid particles suspended in the atmosphere, and their major sources are windblown dust, sea salts, volcanic ash, smoke from wildfires, 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 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 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.

Fig. 3.1 15-years 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 added to the tropospheric air column through vehicular emission, industrial activities and burning of domestic fuel. Since the COVID-19 lockdowns in each of these countries had effectively halted vehicular movement and industrial activity, it was expected that a discernable improvement in the air quality would likely be observed in each of 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, the contaminant levels in the Tianjin and Shanghai areas were still quite notable, even during the lockdown period, being markedly higher than the levels in the other regions mentioned above. Overall, up to 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 of NO_2 in their urban areas, with the built-up neighbourhoods characterizing a reduction of 33% 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 2017-2019 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 showing a fall in the NO_2 emissions over South Asia were elicited by Shafeeque et al. (2021). This diminished level was also about 40% less than what had existed in the normal period of 2019. The NO_2 level remained almost the same even after two weeks of the post-lockdown phase (Fig. 3.3d). Only one pocket was witnessed with a more than 2.001×10^{15} molecules/cm^2 NO_2 level in the pre-lockdown period, which reduced up to 0.825×10^{15} molecules/cm^2 thereafter. The partial relaxation in the transport and industrial sectors in the unlock period obviously added to the air pollution subsequently.

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 just a nominal amount (below 0.825×10^{15} molecules/cm^2) of NO_2 concentration 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 55% reduction in the contaminant level was noted in the lockdown period (Fig. 3.4). At the same time, the post-lockdown scenario remained quite similar to the lockdown phase. Similar inferences for major cities in European countries were drawn by Singh et al. (2020).

The northern part of France, i.e. the provinces of Nord-Pas-de-Calais, Picardie and Ile-de-France, were the most polluted with respect to NO_2 concentration in the previous normal year and in the pre-lockdown phase (Fig. 3.5a, 3.5b), with levels ranging from 0.825×10^{15} to 1.238×10^{15} molecules/cm^2. This concentration level had reduced significantly in the lockdown period (Fig. 3.5c), with the entire country reporting an overall 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 (of 2019) and the pre-lockdown phases 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 that recorded about 1.852×10^{15} molecules/cm^2 concentration of NO_2 in 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 one pocket was noted to be about 1.238×10^{15} molecules/cm^2 in the normal period, while the remaining areas were near 0.413×10^{15} molecules/cm^2. The lockdown had reduced about 0×10^{15} molecules/cm^2 of NO_2 concentration on average overall in 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 amounts occur over African countries and over the countries of Southeast Asia. As this map consists of datasets taken for the whole year, the aerosol amounts reported were linked to different processes in different places that generated them 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 to the troposphere in 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 raises the dust content in the winter months along 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 represents the aerosol amounts 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 its AOD levels during the lockdown period compared to the normal (i.e., the same period in 2019) and 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 expectedly added more pollution in the post-lockdown phase. Hence, a revival of the AOD level was detected (Fig. 3.9d).

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

Fig. 3.10 represents the aerosol concentration over India during the four phases mentioned above. The Gangetic Plains usually record the highest amounts of aerosol concentration 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 the AOD over India in the pre-monsoon period of 2020 was detected by Biswas and Ayantika (2020) and Pathakoti et al. (2020).

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

Fig. 3.11 Status of AOD concentration over Italy in - (a) the previous year, (b) Pre-lockdown period, (c) During lockdown period, and (d) 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 parts of both France and Germany recorded slightly higher AOD concentrations than the remaining areas of these respective countries. The normal-time AOD concentration was also the highest in Germany compared to the other two nations. Slight improvements in the above were noted in the lockdown phase. The post-lockdown scenario is almost similar to that during the lockdown times. In the United States, the states in its northern part, such as Utah, South Dakota, Colorado and Maine, had relatively higher concentrations of AOD in 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) Previous year, (b) Pre-lockdown period, (c) During lockdown period, and (d) Post-lockdown period

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

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

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

For an added examination of whether the satellite image captured information regarding the decrease in the NO_2 and the AOD levels was truly reflected in the ground conditions, we 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 noted for the R.K. Puram station in New Delhi, India and also for the Victoria station in Kolkata, India. Lesser degrees of change were apparent for 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 a partial operation of the industries herein as they are centres of precision engineering and manufacturing. What was observed across the board, however, was that in the post-lockdown period, NO_2 levels immediately did not go back up to their pre-lockdown levels but continued to remain mostly near the levels attained during the lockdown or even declined slightly in some cases. This is significant as it highlights the marked effect of cleansing the atmosphere that a short lockdown period can have and is also indicative of the window for which this condition can last. Therefore, temporary, such stoppages of short duration at the regional level could be a sustainable way of partially improving the ambient air quality.

For the AOD comparison, we used the $PM_{2.5}$ and PM_{10} data that was available 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 declining trend in both the pollutants' levels between the pre-lockdown and the lockdown as well as post-lockdown periods. This reveals the similarity of trends recorded between the compared datasets and validates our analysis.

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/)

*NM = Not Measured

Chapter 4 $PM_{2.5}$ 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 the urban sectors (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 Southeast Asia and Western Pacific Regions) unduly experience the adverse effects of air pollution. These regions faced 89% of the 4.2 million ill-timed expiries (WHO, 2022).

Particulate matter concentrations that often remain suspended in the air with a diameter of less than 2.5 μm ($PM_{2.5}$) and a diameter between 2.5 μm and 10 μm (PM_{10}) are 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, out of the two different types of particulate matter based on their diameter, $PM_{2.5}$ is considered far more lethal to human health owing to their capability to penetrate deep into the lungs or even blood streams (Xing et al., 2016). It's 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 by using an aerosol sampler that draws in air and filters the particles to record the data in μg per unit volume of air passed through the sampler (usually m^3). It is a time-consuming technique and can not provide real-time data; however, it is the most accurate technique to measure $PM_{2.5}$ 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 μg/m^3, 25 μg/m^3, 15 μg/m^3, and 10 μg/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 in the world 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. Particular matter in the open environment not only imposes harmful effects owing to their own presence but also aids in spreading other pollutants like heavy metals (Cetin and Aisha, 2023; Cetin and Jawed, 2021; 2024). Anthropogenic activities like 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 are dealing with poor air quality, with $PM_{2.5}$ concentrations as high as 120 $\mu g/m^3$ 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 $\mu g/m^3$, significantly higher than the recommended level of less than 5 $\mu g/m^3$. However, the air quality in several places has improved noticeably in the past few years. For instance, the $PM_{2.5}$ concentration decreased in Beijing from 90 $\mu g/m^3$ in 2013 to 35 $\mu g/m^3$ 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 is a remarkable threat to the male and elderly age group of China, who make up 58% and 61% of hospital admissions, respectively. Economically backward and heavily urbanized areas make women and children more susceptible to air-induced short-term 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 places frequently have $PM_{2.5}$ concentrations above 100 $\mu g/m^3$, which is dangerous for human health.

The recent $PM_{2.5}$ pollution situation in India is concerning. According to the World Air Quality Report (World Air Quality Report, 2022), annual $PM_{2.5}$ levels in almost 60% of Indian cities were at least seven times higher than recommended values. 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 as one of this planet's most polluted cities. 'Severe' to 'emergency' levels of $PM_{2.5}$ pollution has been seen in Delhi frequently in recent years, particularly during the winter. Although the degree of severity may vary, other cities like Mumbai, Kolkata, Chennai, and Bangalore all experience problems with high $PM_{2.5}$ concentrations. According to the most recent Global Burden of Disease (GBD) (IHME, 2019), the mean population-weighted $PM_{2.5}$ concentration is estimated to be 74.3 $\mu g/m^3$. Exposure to degraded air quality is associated with 133.5 fatalities per 100,000 persons/year. In India, $PM_{2.5}$ pollution is held accountable for 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. 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 and or equal to 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 when the AQI value is higher. Additionally, poor air makes it less likely for people to go outside, which decreases customer flow in retailers and thereby causes the fall of businesses that serve customers to experience a decline in $22 billion 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 concentration of $PM_{2.5}$ in Pakistan is 52.1 $\mu g/m^3$, which is above the WHO guideline of 10 $\mu g/m^3$. Pakistan ranked 3rd highest polluted nation in the world with a 14.2 times higher average $PM_{2.5}$ concentration of the WHO annual air quality guideline value in 2022. Among the cities in Pakistan, Lahore recorded the highest $PM_{2.5}$ concentrations and has a gradually increasing trend from 2017 to 2022. Lahore, Peshawar, Faisalabad, Bahawalpur, Karachi, Rawalpindi, and Islamabad are the seven major cities in Pakistan concerning $PM_{2.5}$ concentrations in

2022. People in the medium-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 a revised program called the 'Pakistan Clean Air Plan' (PCAP). The initiative has been taken to dilute the various air pollutants (blank carbon and others) at national and regional levels.

Anwar et al. (2021) observed that China, India, and Pakistan, a conglomeration of the highest population density in the centre of Asia, suffer terribly due to air pollution and its health impacts. They recommended that profound spatiotemporal air pollution monitoring has become an urgent need of the hour in China, India, and Pakistan. According to Kanawade et al. (2020), about six million individuals suffer premature deaths yearly due to air pollution. There is good evidence that long-term and short-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, it can be said that these papers mainly discuss the concentration and harmful effects of $PM_{2.5}$ as one of the central air pollutants.

Thus, keeping in view the background mentioned above, this study analyzed $PM_{2.5}$ levels in outdoor air from the dataset furnished by 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 to what extent these cities are abiding by WHO-prescribed $PM_{2.5}$ guidelines. This study also aimed to explain the overall $PM_{2.5}$ pollution scenario in 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 of 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 suffered adversely with high $PM_{2.5}$ concentrations, too. Oceania and other countries achieved the WHO guidelines in 2023. Out of the counted Asian and African countries (only 24 out of 54), Iraq, Saudi Arabia, Chad, Egypt, Nigeria, and Uganda have recorded poor air quality. Territories and countries of Europe and North and South America have minimal annual average $PM_{2.5}$ concentrations.

Not a single out of 760 cities have met the WHO annual guideline of 5 $\mu g/m^3$ (Table 3.1). Only 10 Chinese cities have 5.1 to 10 $\mu g/m^3$ annual mean $PM_{2.5}$ concentrations. There are 16 and 2 cities in China and India that recorded $PM_{2.5}$ concentrations ranging between 10.1 $\mu g/m^3$ and 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 China exceeded the WHO target level, followed by 166 in India and 9 in Pakistan. Though the number of cities studied for Pakistan (10 only) was way fewer than India and China, the results show that all ten cities suffer from very poor $PM_{2.5}$ concentration in the ambient air. It was inferred from this study that, with the exception of 10 Chinese cities, all other 750 cities across China, India and Pakistan have suffered from unhealthy to extremely hazardous air.

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

The central eastern part of China and the Gangetic Plain of India have witnessed 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 have no ambient air monitoring stations. Hence, it was difficult to comment on these regions.

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 $PM_{2.5}$ concentration variability across the nations

According to the World Air Quality Report 2023, Pakistan and India are ranked 2nd and 3rd in the list of the world's most polluted countries, while China is ranked 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 (through a reduction in $PM_{2.5}$ concentrations) from 2021 to 2023 by -0.31% and -6.37%. Pakistan has experienced a city-level air quality degradation of 10.33%. Additionally, Chinese and Indian cities' annual mean $PM_{2.5}$ concentration improved by -8.81% and -7.45% in 2023 compared to the historical average of 2018-22. Pakistani cities have shown a rise of 9.41%, remaining unhealthy.

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

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

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

The study focused on the historical (2017-2023) 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) Delhi of India ranked 1 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 2 and 3 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) and 39% (11 states) of the regions had pollution concentrations ranging from 20-40 $\mu g/m^3$ and 40-60 $\mu g/m^3$, respectively, with 5 states having levels exceeding 60 $\mu g/m^3$. There are only 2 Pakistani provinces that recorded a mean $PM_{2.5}$ concentration of nearly 40 $\mu g/m^3$, 1 with nearly 60 $\mu g/m^3$ and another with nearly 80 $\mu g/m^3$. Chinese provinces such as Hebei and Henan were noted to have over 10 times the WHO-recommended levels, i.e., >50 $\mu g/m^3$. States in India such as Bihar, Delhi, Haryana, Rajasthan, and Uttar Pradesh noted 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 3.3). In Pakistan, the concentration in terms of geographical locations (almost 70 $\mu g/m^3$) and weather patterns (approximately 90 $\mu g/m^3$) was highest among the three countries studied. India and China had concentrations of 40 $\mu g/m^3$ (approx) each. In addition, from the perspective of maximum and minimum regional variations within a country, China showed variations in geography and transport, India showed variations in industry and geography, and Pakistan showed variations in weather and geography. Hence, this indicates that the concentration of $PM_{2.5}$ varies with the city's location of their nation.

4.2.3 Seasonal variability of $PM_{2.5}$ concentrations

The residents of the three countries experienced 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 μg/m^3 and 89.1 ± 59.1 μg/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. We 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 $PM_{2.5}$ (μg/m^3) concentration over China, India and Pakistan

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

We 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. Lahore, Peshawar, and Faisalabad. Pakistani cities' monthly mean concentrations always remain 16 times higher than WHO target levels. Islamabad was in a better position (42.4 ± 23.0 $\mu g/m^3$) than other cities in Pakistan. However, it stands 8 times more than the permissible standard. Lahore scored second highest with a concentration of 97.4 ± 52.4 $\mu g/m^3$ out of eighteen cities. All the months remained to exceed 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 compared to 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 is a city that has more lively air out of eighteen cities.

All six Chinese cities recorded a gradually decreasing trend of $PM_{2.5}$ concentration (Fig. 4.6a). Shenzhen noted a minimal concentration out of the six cities. Chengdu has witnessed a maximum concentration of $PM_{2.5}$ on a temporal scale. The capital city, Beijing, demonstrated a maximum continuous reduction of 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 $PM_{2.5}$ had reduced during the COVID-19 pandemic amid the lockdown periods, thereby increasing again. Chennai is a city that has recorded a minimal trend of concentration over six years. Delhi had the worst conditions throughout the period. Pakistani cities' had a similar trend, with a drop in levels during the pandemic for Lahore, Faisalabad, etc. (Fig. 4.6c). Rawalpindi, Karachi, Islamabad, and Peshawar have noted a regular slow rise in levels. There were a few insufficient data for other cities 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, we 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 was reduced in Beijing during 2019-22, a regular falling residence time except in 2023, when a slow rise was noted. New Delhi suffered adversely from poor air quality during the periods. The concentration was improved in the pandemic year compared to pre-pandemic and again revitalized, with poor air quality in post-pandemic years. The healthy air was nominal; the cumulative concentrations of violet and maroon bars were 67%, 80% and 75% for 2020, 2022 and 2023. In inference, the air breathed by dwellers of Delhi is massively polluted. Similarly, Islamabad (Pakistan's capital) spent less than 1% of its hours in a healthy atmosphere. The green bar (near WHO guideline) hours were mixed though about 45% of hours spent by the hazardous to extreme hazardous to air.

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

4.3 Discussion

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Coal usage is the main challenge in Chinese cities (Pui et al., 2014). China is one of the leading countries in the world and has served many nations. Besides household, vehicular, and industrial emissions, coalier combustion added additional $PM_{2.5}$ into 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 leading ambient $PM_{2.5}$ levels on a population-weighted average. India witnessed 1.67 million deaths in 2019 (Pandey et al., 2021). It was the highest air pollution-related death by any country in the world. Vehicular emission contributes to $PM_{2.5}$ about 40% across 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 out of 15 of the most polluted cities are situated in India (IQAir, 2023). Simultaneously, India is the world's most populous country, with 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 combustion, and factories added a high amount of $PM_{2.5}$. Severe smoggy conditions in Punjab Province result 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 socioeconomic conditions are crucial in influencing air quality in China. Studies have shown that meteorological factors like precipitation, temperature, and wind direction, along with socioeconomic factors such as per capita GDP, industrialization rate, and urbanization, significantly impact air quality levels (Zhou et al., 2023; Zhang et al., 2022b; Yan et al., 2023).

Additionally, the concentration of air pollutants in different regions was influenced by factors like carbon emission intensity, energy consumption, and industrial activities. 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 like India see increases (Xu et al., 2023). Meteorological parameters like temperature, surface pressure, and relative humidity have been identified as key influencers of $PM_{2.5}$ levels in India, explaining a significant portion of variability across the country (Maheshwarkar et al., 2022). Additionally, changes in meteorological variables like wind speed, temperature inversions, and boundary layer height have been observed to impact $PM_{2.5}$ concentrations in Indian cities, with emissions playing a dominant role in the increase of $PM_{2.5}$ 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 high levels of $PM_{2.5}$ (Ahmad et al., 2022). Analysis of the data shows that $PM_{2.5}$ concentrations have increased over the years, especially in provinces like Punjab and Sindh and in cities like 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 influencing $PM_{2.5}$ concentrations, with regions at different development stages 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 concentrated in densely populated areas (Gurjar et al., 2008). Studies conducted in China have demonstrated that urban areas with high levels of land-use intensity tend to have higher concentrations of $PM_{2.5}$. 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 to Europe and America (Zhou et al., 2023). The interaction between natural environments, socioeconomic factors, and urbanization is crucial in influencing $PM_{2.5}$ pollution levels. Elevation, precipitation, population density, and economic factors impact the intensity of urban particulate matter 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 emphasizes the importance of sustainable urban development to mitigate 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-National Capital Region. Studies have shown that urban growth and industrialization contribute to higher concentrations of $PM_{2.5}$, with vehicular emissions, industrial activities, and residential areas being major sources of pollution (Arunkumar et al., 2022; Misra et al., 2019; Verma, 2020). The spatial-temporal distribution of particulate matter in Indian cities has been found to exceed national air quality standards, highlighting the negative 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 of the cities of southeast and southern Asia suffer from massive vehicular emissions that cause smog in winter and haze in other periods of the year. These lead to extensive cardiovascular and respiratory problems among the city dwellers, especially the infant populations. The combustion processes of fossil fuel in cities and megacities lead to increased $PM_{2.5}$ in the air, and the particles travel regionally and between continents (Ravindra et al., 2016; Anwar et al., 2021). Urban biomass burning affects regional particulate matter 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 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 that cause unfavourable conditions for the inhabitants.

Further, the daily average concentration and AQI for $PM_{2.5}$ show a maximum pollutant concentration during winter. In contrast, a minimum is observed during monsoon season (Mamta et al., 2010). Other studies have shown that the concentration of $PM_{2.5}$ in the air increases due to changes in wind direction and features such as temperature reversal, large-scale deposition, advection and radiative cooling (Shi et al., 2020). The above results and discussion lead us to an ambient air monitoring and management approach. It is evident that during the COVID-19 pandemic, when the lockdown or quarantine was in action across the country, nitrogen dioxide (NO_2) and $PM_{2.5}$ were 2.5 times less in the air compared to non-pandemic scenarios. There was very little traffic on the roads, and factories were closed. Here, we can conclude that the loss of life is less if the amount of $PM_{2.5}$ is minimal in the air; otherwise, it has a vast impact on people's lives. The cities experience low temperatures, wind speed, relative humidity, and precipitation in winter, increasing ground-level air pollution due to high residence time. 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 the moderate presence of all said climatic parameters are featured post-monsoon, resulting in pollution levels remaining medium.

Air pollution resulting from coal mining activities, 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, especially from transportation activities, are a major source of pollutants like CO_2, NO_2, and $PM_{2.5}$, which can cause adverse health effects such as asthma and CVDs (Li, 2020; Nawaz et al., 2023). Industries also play a crucial role in air pollution, with their emissions 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 effect of $PM_{2.5}$ and arsenic showed high levels of lung inflammation and heart damage due to 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 resulted in improved air quality due to decreased industrial, commercial, and transportation activities, highlighting the potential benefits of strict regulatory actions (Biswas et al., 2022). Additionally, in Pakistan, although explicit data was not provided, similar strategies, such as implementing emission control measures and conducting spatial-temporal analysis, could be essential in mitigating $PM_{2.5}$ pollution and enhancing air quality in urban areas.

Various research findings can guide effective policy interventions to reduce $PM_{2.5}$ concentrations in China, India, and Pakistan. In China, the implementation of carbon trading policies has resulted in a significant reduction in $PM_{2.5}$ levels. This emphasizes the importance of market-based tools like 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 has been shown to be 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 significance of a multifaceted approach that combines market mechanisms, regional policies, and indoor air quality management to effectively reduce $PM_{2.5}$ pollution in these countries.

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, the use of air purifiers has 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 policies such as the Air Pollution Prevention and Control Action Plan and the Three-Year Action Plan for Winning the Blue Sky Defense Battle have shown 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 like stringent emission standards for industries, promotion of cleaner technologies, and 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 5 Changes in Air Quality of Indian Megacities During COVID-19

5.1 Introduction

The pandemic caused by the 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 WHO declared in March 2020 that COVID-19 has turned into a global pandemic and called for a forceful worldwide reaction. 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 from the International Monetary Fund (IMF) pointed out that due to the impact of COVID-19, the global economy would experience a recession in 2020. 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 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 $PM_{2.5}$ results in a significant rise in the death rate from COVID-19 (Wu et al., 2020a, Wu et al., 2020b).

Each year, the emission of anthropogenic pollutants contributes to undesirable air quality levels in India (Balakrishnan et al., 2019). The major cities in India, like Chennai, Delhi, Hyderabad, Kolkata, and Mumbai, are among the most populated, where ambient concentrations of $PM_{2.5}$ remain above WHO annual guideline values 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, suffers from stable air quality with much higher levels of pollution than Beijing (Zheng et al., 2017). India is one of the most populated countries in the world, and due to its high population density in urban areas, the air pollution level remains 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 degree of air pollution has more impact than COVID-19 (Giani et al., 2020). The GoI initially imposed a complete lockdown all over the country for 21 days to combat the critical pandemic on 24 March 2020. 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. Suspension of all transportation services, including rail, road, and air, took place, except for the 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, it has been proven by satellite images and ground data that air pollution in the form of NO_2 emissions in many parts has dropped in a way that the stratosphere O_3 layer is recovering (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 of the papers concentrated on a few selected parameters or only one specific location. Moreover, most of these studies did not take into account the pollutant concentrations during the same time of the year under no lockdown conditions, which led to incomplete inferences. The meteorological conditions were also overlooked in many of these papers. This paper aimed to show the changes in the air quality of three megacities (Mumbai, Delhi, and Kolkata) in India during the lockdown, compared the observations with the scenario in the previous year (under no lockdown restrictions) and characterized the role of the meteorological variables. For the present study, we took into account seven air pollutants: $PM_{2.5}$, PM_{10},

NO_2, NH_3, SO_2, CO, and O_3. We also analyzed four meteorological parameters: ambient air temperature, relative humidity, wind velocity, and precipitation. We implemented statistical and model-based approaches for this study to examine the changes in the AQI during the lockdown through a comparative analysis. We believe that this type of study can help policymakers cope with the increasing air pollutants in urban areas and seek some path through action plans to reduce the level of pollution.

5.2 Results and discussion

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

Particulate matter is one of the major pollutants, particularly in urban and industrial areas (Santra, 2015). $PM_{2.5}$ and PM_{10} levels declined significantly across the megacities of India after imposing the lockdown (Fig. 5.1a and Fig. 5.1c). The pre-lockdown concentration was substantially higher compared to the permissible limit of 60 µg/m^3 for $PM_{2.5}$ and 100 µg/m^3 for PM_{10} across all the megacities. The concentrations of $PM_{2.5}$ during lockdown dropped below the permissible limit in Mumbai. Still, on the other two megacities, it remained above the limit. However, the PM_{10} levels went below the said permissible limit across all the megacities of India during the lockdown. The post-lockdown concentration of $PM_{2.5}$ for Mumbai and Kolkata remained below the said permissible limit, following a decreasing trend over time, whereas Delhi exhibited the opposite. 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, it exhibited a rising trend (Fig. 5.1d). The post-lockdown amounts of PM_{10} were always 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

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 to 57.22 µg/m^3, 60.93 to 108.00 µg/m^3, and 47.00 to 85.60 µg/m^3, respectively (Table 5.1). The post-lockdown concentrations ranged from 14.57 to 33.33 µg/m^3 for Mumbai, 56.11 to 96.37 µg/m^3 for Delhi, and for Kolkata, it was 13.78 to 52.50 µg/m^3. The pre-lockdown and lockdown ranges of PM_{10} in Mumbai were 63.38 to 187.25 µg/m^3 and 95.66 to 168.75 µg/m^3, respectively. In Delhi, the pre-lockdown PM_{10} ranged from 77.90 to 148.50 µg/m^3, and lockdown PM_{10} varied from 65.25 to 82.89 µg/m^3. In Kolkata, the pre-lockdown and lockdown ranges of PM_{10} were 63.21 to 120.66 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 for Kolkata, it was 20.00 to 61.00 µg/m^3. To break the chain of the spread of COVID-19, maintaining social distancing among people and completely closing all sectorial activities was the only way for the government to do this. Therefore, the movement of vehicles, closing 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 under a complete shutdown. The post-lockdown new normal included mostly work-from-home activities except for any emergency 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} 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 WHO, Delhi was the most polluted city among 4300 cities in the world based on the concentration of $PM_{2.5}$ (World Economic Forum, 2018).

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

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

Mumbai had moderately polluted (89.82 μg/m^3) to satisfactory (47.96 μg/m^3) air quality, while Delhi and Kolkata were very poor to moderately polluted by $PM_{2.5}$ in lockdown (Table 1.3). On the other hand, the megacity 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 noted very healthy air due to fall of PM_{10}. The post-lockdown $PM_{2.5}$ and PM_{10} were well in Mumbai and Kolkata, whereas in Delhi, it was above the permissible limit. Hence, breathing discomfort to the people of a sensitive group and people with lung diseases has taken place instead of prolonged suffering with lung diseases in lockdown. The post-lockdown impacts were minimal for Mumbai and Kolkata. Besides that, horizontal visibility in surface air was also improved due to the COVID-19 pandemic.

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 (Fig. 5.3, Fig. 5.4, and Fig. 5.5). Significant improvements in air quality have been detected in the Lockdown phase, and it continued to post-lockdown. The eastern part of the megacities of Delhi and Kolkata had better air quality compared to the western part. There were more industrial activities and vehicular emissions in the western part than in the east. The marine wind refreshed the western part of Mumbai. Therefore, the scenario was the opposite here; the eastern part was more contaminated compared to the western part. However, in the later 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} for 2019 and 2020 except the PM_{10} of 2020 during the period of 25 March-14 April (5.6a, 5.6b). Mumbai recorded the lowest amount of $PM_{2.5}$ and PM_{10}, while Kolkata noted a moderate amount concentration. Compared to the 2019 scenario, the PM_{10} value of Delhi has witnessed the highest reduction (58.60%) during the COVID-19 lockdown. $PM_{2.5}$ also exhibited the highest reduction (34.67%) compared to Mumbai 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 Avg. 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

*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 the significant declining trend of NO_2 in the 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 39.40–60.80 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, the NO2 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 post-lockdown. Hence, improvements in air quality (NO_2) were observed across the megacities of India due to the COVID-19-induced lockdown.

The average concentration of NO_2 was reduced in lockdown by about 68.33%, 40.36%, and 62.37% 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), respectively, in both during-lockdown and post-lockdown phases. Nationwide strict lockdown and new-normal post-lockdown checked the level of NO_2. 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 of air quality for all three megacities during-lockdown and post-lockdown compared to pre-lockdown has been mapped here (Fig. 5.3, Fig. 5.4, Fig. 5.5). We found that just one day after the commencement of nationwide lockdown the remarkable improvement of NO_2 has been noted compared to pre-lockdown in all three megacities. It lasted up to 14 April 2020. The west part of Delhi and Kolkata and the east part of Mumbai have witnessed healthy air.

The box plots (Fig. 5.6c) have shown that the NO_2 level has dropped in megacities in India during the lockdown year (2020). The high range, 30.75–75.25 µg/m^3, with maximum average concentrations of Kolkata, was on top, followed by Mumbai and Delhi during the same time of the previous year (2019). Mumbai, Delhi, and Kolkata witnessed a reduction of about 44.35%, 42.77%, and 39.45% in the lockdown period compared to the 2019 scenario (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 noticed in post-lockdown for the megacities of Mumbai and Kolkata, except for Delhi (Fig. 5.1h). The average NH_3 concentrations were very nominal not only in the lockdown phase but also in the pre-lockdown and post-lockdown period, compared to the permissible limit of 400 µg/m^3 across the megacities of India.

The pre-lockdown concentrations of NH_3 in Mumbai, Delhi, and Kolkata were 4.00–5.75 µg/m^3, 7.62–9.62 µg/m^3, and 4.80–6.90 µg/m^3, respectively. During the lockdown, those ranges were 2.17–4.63 µg/m^3, 5.17–8.15 µg/m^3, and 3.00–4.40 µg/m^3, respectively (Table 5.1). The post-lockdown concentrations were 2.00–3.33 µg/m^3, 6.91–7.65 µg/m^3, and 1.57–2.70 µg/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 28.64% for Mumbai and Kolkata, while Delhi exhibited an increase of 8.40% (Table 5.3). Therefore, Kolkata recorded the maximum decline (1.83 & 1.47 µg/m^3), followed by Mumbai (1.63 & 0.67 µg/m^3) and Delhi (1.42 & 0.57 µg/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 Fig. 5.3, Fig. 5.4, Fig. 5.5. However, the scenario was slightly different after two to three weeks due to partial relaxation on necessary transportation and controlled industrial activity outside the COVID-19 infected zone or containment zone declared by the Government for Delhi (Mahato et al., 2020; Srivastava et al., 2020; Kumar et al., 2020).

NH_3 records of Mumbai for the year 2019 were not available on the CPCB website due to some technical error. Delhi witnessed a declining trend from 8.95 to 3.75 μg/m^3 in the lockdown year 2020 compared to the previous year 2019 (Table 5.4). On the other hand, Kolkata witnessed an increase (5.21 to 8.50 μg/m^3) from 2019 to 2020. Therefore, NH_3 exhibited mixed results in the megacities of India 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). COVID-19 lockdown led to a declining trend of SO_2 in megacities of India (Fig. 5.2i). Compared to the pre-lockdown concentrations, the 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 period, a significant fall was noted across the megacities. The continuous drop was also noted in post-lockdown only for Kolkata. Overall, significant improvements in air quality in the form of SO_2 reduction were observed across the megacities of India due to the blessing of COVID-19 amid the lockdown.

The average concentration of SO_2 was reduced during the lockdown by about 42.11%, 13.91%, and 20.88% for Mumbai, Delhi, and Kolkata, respectively, in the lockdown phase

(Table 5.2). The only post-lockdown reduction was 35.07% in the case of 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 main city and the suburbs. However, due to the overall low concentrations of SO_2 below the threshold, the megacities of India relished good quality air with zero health impact (Table 1.3).

The spatial pattern of SO_2 is illustrated in Fig. 5.3, Fig. 5.4, Fig. 5.5. The box plots (Fig. 5.6d) have shown that the SO_2 level was fluctuating in megacities of India (2020). The maximum average concentration was in Mumbai, followed by Delhi and Kolkata. Delhi recorded a decline (26.93%), while Mumbai (18.00%) and Kolkata (27.11%) observed an increase 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 has shown the significant declining trend of CO in the megacities due to the pandemic-induced lockdown. The post-lockdown trend has remained the same (decline trend) for Mumbai and Kolkata; however, Delhi remained an exception (Fig. 5.2l). All the recorded values were very high compared to the permissible limit (2 mg/m^3), which has 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 concentration of CO reduced during the lockdown by about 26.61%, 12.25%, and 20.92% for Mumbai, Delhi, and Kolkata, respectively (Table 5.2). Mumbai (5.86%) and Kolkata (8.75%) maintained a continuous drop in the concentration. In contrast, Delhi experienced a rise (26.28%) again in the post-lockdown phase. The spatial pattern map for the megacity of Mumbai and Delhi recorded a fall in lockdown (Fig. 5.3, 5.4). The megacity Kolkata has noted a gradual fall from 17 March to 31 March and 21 April, respectively (Fig. 5.5). Overall, the CO levels did not improve to a large extent due to the effect of the lockdown. High CO levels can cause Anoxemia, which, in turn, can lead to various cardiovascular problems; infants, pregnant women, and old people will be at high risk due to its dense concentration in the lower troposphere.

In a similar period to the previous year, 2019, and the lockdown period of 2020, the average concentrations of CO have reduced by about 40.85% and 61.72% for Mumbai and Kolkata, respectively. However, in Delhi, the CO concentrations slightly increased (3.06%) (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 the increase in ground-level O_3, an increased risk of respiratory diseases, particularly asthma, prevails. The declining trend of O_3 is illustrated in Fig. 5.2m. The post-lockdown trend has remained the same (decline trend) for Mumbai, Kolkata, and Delhi, like the case of many other pollutants, exhibited an increase (Fig. 5.2n). Except for Kolkata, the other two megacities had O_3 levels below the permissible limit (60 μg/m^3) of CPCB in both pre-lockdown and during the lockdown phase. The post-lockdown concentration was below the limit in Mumbai, whereas the concentrations were not consistent in Delhi and Kolkata. The high concentrations lead to various health problems like asthma and bronchitis and harmful effects on plants as it interferes with photosynthesis and result in the death of plant tissues since it assists in the formation of PAN.

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

The average concentrations of O_3 were reduced in the lockdown phase by about 25.30%, 19.37%, and 21.13% for Mumbai, Delhi, and Kolkata, respectively (Table 5.2). The megacity of Delhi noted a rising (48.39%) concentration, and the rest of the two have remained the same, 29.43% & 23.85%, respectively, in the post-lockdown (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.

We found a regular improvement of O_3 from 17 March to 14 April in the spatial distribution map for Mumbai and Kolkata (Fig. 5.3, 5.5). Megacity Delhi has recorded a sequential fall and rise in lockdown and post-lockdown (Fig. 5.4). The partial relaxation on transport service and industry sectors in Delhi increased the O_3 level.

Compared to the previous year (2019), the average concentration of O_3 during the COVID period (2020) was reduced by about 55.93% in Mumbai, followed by 13.51% in Delhi (Table 5.4). Kolkata, on the contrary, exhibited an increase in O_3 level (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 (decline trend) for Mumbai and Kolkata, Delhi being an exception (Fig. 5.2p). Mumbai air quality levels ranged from moderate to satisfactory; Delhi ranged from poor to satisfactory; and Kolkata moderate to good category (according to the standards of CPCB). Overall, the temporal change in AQI in the year 2020 exhibited a significant improvement in air quality during the lockdown and post-down phases compared to the pre-lockdown phase.

Spatial change in AQI for all three megacities is shown in Figs. 5.3, 5.4, and 5.5 on the selected dates of 17 March, 31 March, and 21 April. We found that Mumbai had better air quality compared to the other two megacities in all three phases (pre-during-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 seemed to improve the air quality to a varying extent in 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 a comparatively lower pollution level in the air.

The box plots (Fig. 5.6g) have shown that the AQI level dropped 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 matrixes with scatter plots were derived between the air pollutants for all three megacities of India 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^{**}, & 0.95^{**}); Delhi ($r = 0.96^{**}$, 0.91^{**}, & 0.91^{**}) and Kolkata (0.98^{**}, 0.92^{**}, & 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 in Mumbai ($r = 0.63$) and Delhi ($r = 66$); however, the relationship was 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 noted to be near zero or no in Mumbai, while in Kolkata, a significant positive relationship was observed ($r = 0.77^{*}$). Likewise, $PM_{2.5}$ and CO were also strongly correlated in Mumbai & Kolkata ($r = 0.85^{*}$, $r = 0.82^{*}$), but Delhi exhibited a poor positive relationship. The $PM_{2.5}$ and O_3 were strongly correlated ($r = 0.89^{**}$) in Mumbai and exhibited 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 ($r = 0.60$), while in Kolkata, it was a strong significant positive ($r = 0.90^{*}$) relationships. The relationships of PM_{10} and SO_2 were moderately positive ($r = 0.67$) in Delhi, while in Kolkata, it was a strong significant positive (r = 0.85*), but no relationship was noted in Mumbai. Likewise, PM_{10} and CO strongly (r = 0.77*, r = 0.78*) correlated in Mumbai & Kolkata, while Delhi has counted a very poor positive correlation. The PM_{10} and O_3 had a strong (r = 0.82*) correlation in Mumbai and Kolkata. It was moderate ($r = 0.69$), while no relations ($r = 0.03$) were noted for Delhi.

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)].

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 (0.93**) correlation in Kolkata. The NO_2 with pollutants of SO_2 strongly 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 strong and 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 & SO_2; SO2 & O_3 were also noted strong significant positive relationship (r = 0.77*, r = 0.84*) in Kolkata. Hence, except for the daily average concentration of $PM_{2.5}$, PM_{10}, and NO_2, the rest of the four pollutants (NH_3, SO_2, CO, and O_3) had a cent per cent positive correlation; they were not always significantly correlated in all three megacities some times.

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 the years 2019 and 2020. An increase in air temperature at the ground level destabilizes the atmosphere and facilitates enhanced vertical mixing of pollutants (Cichowicz et al., 2017). Thus, increasing air temperature facilitates the reduction of pollutant concentration at the ground level (Ravindra et al., 2019). From Fig. 5.8, it is evident that the air temperature increased during the lockdown period compared to that observed in the pre-lockdown phase. Hence, a fraction of the reduction in the concentration of pollutants can be accounted for by 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 a similar increase in temperature in the years 2019 and 2020, the concentration of several pollutants was lower in the lockdown phase of 2020. Thus, the effect of lockdown can not 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 like PM_{10}, which gets resuspended at the ground level due to higher wind speed (Zhang et al., 2018). Mumbai did not exhibit any significant difference in wind speed between the pre-lockdown and lockdown phases; however, the difference was noticeable in the case of Kolkata and Delhi. However, the overall mean wind speed for the years 2019 and 2020 did not show any statistically significant difference 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.

Particulate matters, as well as SO_2 and NO_2, populate the ground-level atmosphere at a lower relative humidity (< 40%), and at higher ranges, the pollutant concentration usually decreases (Lou et al., 2017; Munir et al., 2017). However, during the study period in both years, the mean relative humidity never went below 55% in any of the phases. Except for Mumbai, a marginal decrease in relative humidity was observed in Kolkata and Delhi between the pre-lockdown phase and the lockdown phase. The way relative humidity affects pollutant concentrations, this lowering in relative humidity should have increased the pollutant's concentrations. However, the present observations indicated otherwise. Thus, it can be deduced that relative humidity also played a negligible role in the reduction in pollutant concentrations during the lockdown phase of 2020. Like relative humidity, rainfall also helps in decreasing air pollutants (Yoo et al., 2014); however, there was no rain in Mumbai and Kolkata in either of the years. In Delhi, there was negligible rainfall in both of the years. Thus, on the whole, we can infer that except for the air temperature, the other meteorological parameters did not play a significant role in reducing the pollutant concentrations during the lockdown of 2020.

Chapter 6 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). The aerosol concentrations, SO_2 and NO_2 exhibit a sharp increase after the burning of firecrackers (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. Other resultant gases like CO, CO_2, and NH_3 could significantly pollute the atmosphere due to 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 (both PM_{10} and $PM_{2.5}$) in the ambient air cause an array 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 led to almost 3.5 million official casualties (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 like Black, White, and Yellow fungus have become another point of severe concern while combatting 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. Recent research suggests that NO_2 potentially enhances the fatality rate due to COVID-19 infections (Ogen, 2020), and O_3 acts as a carrier and an incubator for coronaviruses (Zoran et al., 2020). India is one of the worst-affected countries struggling to cope with this pandemic (Kumari et al., 2021).

With an intent to disrupt the spread of COVID-19 viruses, the GoI announced a nationwide lockdown on 24 March 2020. Initially, the lockdown was for three weeks (Phase 1); however, the GoI extended the lockdown 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 indicated that the COVID-19-induced nationwide lockdown drastically improved the air quality in all corners of the country (Bera et al., 2021; Naqvi et al., 2021; Ravindra et al., 2021; Sathe et al., 2021). The complete stop of vehicular locomotion and a halt to all sorts of industrial activities reduced the pollutant levels below the 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 Honorable Supreme Court made 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 unpredicted second wave from March 2021 (Mallapaty, 2021), reaching a peak in May 2021 when infection cases were 0.4 million people per day. However, previous studies reported a 34% decline in pollutants during Diwali due to a similar environment-friendly ban imposed on the free sale of firecrackers in the year 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 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). We hypothesized that amidst an ongoing pandemic, people in large numbers must have restrained from burning firecrackers during Diwali, which led to a lower degree of enhancement in pollutant levels than the observations in 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, the air pollution levels under a pandemic-induced lockdown have also received substantial attention from the scientific community in the recent past. However, none of these studies considered the effects of Diwali celebrations amidst a pandemic scenario. This study reports for the first time the degree of air pollutant levels from three megacities of India during Diwali amidst the COVID-19 pandemic. The findings of this study are expected to guide the policy managers of such populous and polluted cities to look for avenues to create a sustainable urban atmospheric environment. Since air quality management in urban setups has become a challenge for present-day urban planners, studies like this can act 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 lockdown year (2020) across three megacities of India Source: CPCB (2019; 2020)

* 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 the spread of COVID-19 viruses, the GOI announced a nationwide lockdown, initially for 21 days, starting from 24 March 2020. Diwali was on 14 November 2020, during the sixth unlock phase, after four successive periods of lockdown and five unlock periods. 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 exhibited a concentration below the threshold during the Diwali of 2019. Fireworks consist of several fuels, oxidants, agglutinants, propellants, and colouring agents, which enhance the PM load in the ground-level atmosphere on burning (Hoyos et al., 2020). Recent pieces of research strongly indicated that both PM_{10} and $PM_{2.5}$ facilitate the spread of coronavirus (Setti et al., 2020) and lead to increased 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. Usually, O_3 production takes place during the daytime due to the 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. Preliminary research indicated a high possibility of enhanced spread of coronavirus 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 of the 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 240 was Kolkata, where the mean concentration of $PM_{2.5}$ in 2020 was lower than that observed 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 during 2020 was significant only in the case of 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 $PM_{2.5}$ (125.42 μg/m^3), PM_{10} (142.84 μg/m^3), and CO (52.84 mg/m^3). In comparison, Kolkata recorded the highest in O_3 (38.20 μg/m^3) between the Diwali of 2019 and 2020. Enhanced O_3 concentration in Kolkata indicates that firecrackers that produce light were burnt in plenty, which, in turn, facilitated the production of O_3 during nighttime. Similar observations were reported in previous studies (Attri et al., 2001; Nishanth et al., 2012). However, some contradicting opinions suggest that the burning of firecrackers produces several VOCs like phenol and C_6H_6 that mimic the O_3 during nighttime (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 cross the permissible limit in Mumbai and Delhi, the increase in its concentration during the Diwali of 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 the pollutant concentrations, and it serves as a holistic air pollution indicator. The AQI magnitudes indicate that it was the most polluted megacity, followed by Kolkata and Mumbai during the Diwali of both years. Fig. 6.2 shows the ambient air pollutants' minimum, first quartile, median, third quartile, and maximum values on the day of Diwali in 2019 and 2020. Fig. 6.2a shows that all these five statistical measures of $PM_{2.5}$ increased in 2020 for Mumbai and Delhi, except for Kolkata. Fig. 6.2b, 6.2c, and 6.2d show an overall increase of PM_{10}, NO_2, and NH_3 during Diwali 2020 in all three cities. Fig. 6.2e shows that the first and third quartiles of SO_2 were almost the same in Mumbai in 2019 and 2020. Kolkata and Delhi showed a similar scenario in the case of CO (Fig. 6.2f) and O_3 (Fig. 6.2g), respectively. Fig. 6.2h 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)

Table 6.3 Average concentration of ambient air pollutants for COVID-19 year (2020) of three megacities in India
Source: CPCB (2021)

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

Table 5.2 and Table 5.3 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 from the pre-Diwali levels, and the concentrations remained elevated even three days after Diwali 2019. In Mumbai and Kolkata, the $PM_{2.5}$ levels after seven days of Diwali almost went back to the pre-Diwali scenario. However, in Delhi, the concentration kept on increasing even after seven days from Diwali (Table 5.2). 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 5.3). PM_{10}, on the whole, significantly increased during Diwali in both years compared to their pre-Diwali levels, and the concentrations remained high even after one week from Diwali. Delhi was the only exception in 2020, where the one week later concentrations reached the pre-Diwali levels. NO_2 concentrations were higher during the three days after Diwali 2019 than those observed on the day of Diwali. The increment in motor vehicles already leads to enhanced NO_2 levels in Delhi, and the firecrackers add to that pre-existing load (Ganguly, 2009; Singh, 2010). However, in the year 2020, Delhi was the only city to have higher NO_2 levels on the day of Diwali compared to both pre-Diwali and post-Diwali days. Mumbai and Kolkata did not record any significant variation across the pre-Diwali to post-Diwali phases. NH_3 and SO_2 concentrations showed a consistently increasing trend from pre-Diwali to Diwali to post-Diwali transitions of 2019 and 2020 in Delhi and Kolkata; however, Mumbai showed a gradual decrease after Diwali. CO showed a steady decline in concentration from pre-Diwali to post-Diwali in Mumbai and Kolkata; however, Delhi showed a consistent increase during 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 scenario, showed a consistent increase in Delhi even after seven days of Diwali in 2020; however, in the other two cities, the AQI gradually decreased after the event. Among the changes in air pollutant concentrations observed between different phases, the one between the pre-three-day average and the day of Diwali acts as a proxy of the degree of fireworks. This difference was substantially high for all the pollutants in Delhi during the Diwali of 2020, except for 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 the people to celebrate Diwali like 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. 6.6 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

Fig. 6.2 and Fig. 6.3 show the spatial distribution of all the pollutants in Delhi during the pre-Diwali, Diwali, and post-Diwali days of 2019 and 2020. Visual inspection of these maps portrays that the northern and eastern parts exhibited more 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. These maps also show that Delhi has a higher residence time of pollutants. Padmanabhamurty et al. (1990) and Guttikunda and Gurjar (2012) observed the lower dispersal capacity of pollutants in

Delhi, especially during the post-monsoon season. Almost all the parameters showed higher colour bars in the post-Diwali phase. These figures also exhibit a significant increase in pollutant levels during the pre-Diwali to Diwali transition in both years. This observation indicates no noticeable change in the burning of firecrackers during the pandemic-stricken Diwali of 2020. There was a marked difference in the transition phases of 2019 and 2020 in Kolkata (Fig. 6.4 and Fig. 6.5) and Mumbai (Fig.6.6 and Fig. 6.7). Many of the pollutants, except for PM_{10}, showed a lower colour bar in the Diwali of 2020 than the pre-Diwali scenario. This observation illustrates that the restricted burning of firecrackers took place to some extent in Kolkata and Mumbai. The northern and eastern parts of Kolkata showed higher pollution owing to the high population density. The western part of Mumbai exhibited lesser air pollution, which could be due to adjacent sea breezes that help in the quick dilution of the pollutants.

6.2.4 Correlation between air-pollutants

Taking into account 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 matter have almost similar compositions. 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 correlation 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 complexities in COVID-19-infected patients.

Fig. 6.7 The correlation matrices and scatter plots between the seven 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/

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 of Mumbai and Kolkata between the Diwali of two consecutive years. However, Delhi recorded a significantly lower air temperature in 2020 than in 2019. Tiwary et al. (2015; 2018) observed that low temperature facilitated higher pollutant load in Delhi, which could be one of the reasons behind higher concentration in the pre-Diwali phase of 2020 than in 2019. Increased air temperature leads to an unstable atmosphere, which allows the pollutants to dilute quickly (Cichowicz et al., 2017; Ravindra et al., 2019b). Relative humidity was comparatively lower in Mumbai and Kolkata (during Diwali) in the year 2020 compared to that 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 increment in pollutant concentrations, despite having high moisture, indicates the rampant burning of firecrackers in Delhi. Wind speed showed no significant difference between the 2019 and 2020 Diwali phases in Mumbai and Kolkata. Usually, higher wind speeds dissipate the pollutant concentrations, and a reverse scenario indicates a stable atmosphere that retains the pollutants (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 exhibited significant changes between pre-Diwali and Diwali dates in a few instances (Fig. 6.8 and Fig. 6.9). In the year 2019, the predominant northeastern winds in pre-Diwali changed to the northwest on the Day of Diwali in Mumbai. The wind from the western end came over the sea, thus helping to dilute the air pollutant concentrations. In the pandemic year 2020, no such wind reversal was observed in Mumbai. Delhi witnessed a change in wind direction from the south-southeast to the north-northwest during the pre-Diwali to Diwali. The wind that flows from the north comes from the Himalayas and is usually cold, leading to a drop in temperature. This reduction in temperature might have facilitated enhanced air pollutant levels in Delhi during Diwali. There was no rainfall in any of the cities in the 2019 and 2020 Diwali phases. Precipitation usually dampens the pollutant loads (Yoo et al., 2014); however, it could not play any role in regulating the pollutant load in any of the two years. Thus, analyzing the observations altogether, we could partially accept our hypothesis for Mumbai and Kolkata. However, the results from Delhi outrightly rejected the same we framed for this study.

Fig. 6.8 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. 6.9 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 2020

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.

6.2.6 Interpretation of changes in deweathered air pollutant data

The deweathered data from one station each for both the years 2019 and 2020 is listed in Table 6.5. Due to the unavailability of the complete meteorological dataset, we had to restrict ourselves to only one station. However, the deweathered data also portrayed a similar trend to that observed in the case of unprocessed data sets for all the 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 exhibited an increase in these two parameters. However, the magnitude of the increase was much lower than that of Delhi. NO_2 did not show any significant increase between the pre-Diwali and Diwali in any of the megacities during 2020, but NH_3 exhibited an increase 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 the Diwali day of 2020 in Delhi. O_3 levels, in particular, exhibited an increase in all three cities during Diwali in the pandemic year. Only one station’s data is not sufficient to infer for the entire city. However, the deweathered data also indicates that Delhi is the worst affected among the three megacities considered in this study.

Chapter 7 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 more 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 as a global pandemic. Up to 2022, imposing lockdowns has been the only means adopted by almost all countries in the world to combat the surge and spread of this virus, depending on the surge of COVID-19 infection rates (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 that these lockdowns introduced to us was the recovery of air quality that has been observed throughout the world (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, to 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 lethalities 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, when the pandemic is already over, the ever-deteriorating air quality across several urban setups throughout the world has become a point of severe health concern (Monoson et al., 2023; Vyas et al., 2023). The inevitable pollution of air due to manifold emissions from the industrial sector that cannot be shunned at the cost of hampering development has urged present-day atmospheric scientists and environmentalists to look for amicable solutions, both in terms of policies and preventive measures (Bonilla et al., 2023; Wu et al., 2023). Thus, this study strived to understand the role of lockdowns and their stringency and meteorological factors in governing 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 outbreak of the COVID-19 pandemic, like 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 sectorial 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 betterment 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 reduction of pollution brought a prolonged blessing to environments, like less aerosol formation, reduction of the volume of greenhouse gases which are linked to global climate change and global warming, a decline in acid rains, protection of plant tissue, and many more. The high concentration of gases with a long residence time has had enormous health issues that lead to morbidity in the form of various cardiovascular problems, respiratory problems, lung cancer, visual impairment, etc. (Wang and Li, 2021). Latif et al. (2021) pointed out that the practice of lockdown stopped the COVID-19 spread simultaneously, slowing down morbidity and mortality therein. Benchrif et al. (2021) examined the effect of these lockdowns in cities with a population of more than a million. They observed significant improvement in air quality in all the cities and across all the lockdowns they studied. These observations compel us to argue whether short-term lockdowns can actually alleviate the air pollution scenario in populated cities to sustain their ambience in the longer run.

In India, the ground-level concentrations of NH_3, CO, NO_2, O_3, $PM_{2.5}$, PM_{10}, and SO_2, and are constantly monitored by the CPCB. Several pieces of research, as mentioned above, utilized this crucial dataset; however, most of the papers/research concentrated on the lockdown phase during the first wave only and the corresponding change in air quality. The state governments of different cities across the nation also declared similar lockdowns. The Government of West Bengal (GoWB) (Kolkata megacity fall under its jurisdiction) announced a lockdown during the second wave to prevent the spread of the virus for two weeks (16 May to 30 May 2021; pre-monsoon season). Many sectors were completely closed, such as academic institutions and public entertainment venues like swimming pools, spas, gyms, beauty parlours, salons, parks, zoos, and tourist places. The tightness in the restrictions during this lockdown was good enough but not as stringent as observed 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 fast transformation rate of a new COVID-19 variant of "Omicron". However, most of the services functioned with a 50% working capacity during the third wave, which implies a much lesser degree of stringency compared to the first and second waves. Thus, these lockdowns provided us with a platform to study the changes in air pollutant levels across several lockdowns with varying degrees of stringency and varying 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. Keeping in mind the governing capability of the meteorological parameters, special attention was paid to deweathered pollutant datasets. The said meteorological variables usually exhibit significant changes over seasons. January and February are the winter seasons when the static movement of air increases the degree of 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. The pre-monsoon (March to May) is characterized by high temperatures with high humidity and low pressure on land. The winter months of December and January mark a static air environment with occasional inversion conditions that usually elevate the 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 the changes in air quality levels during all three waves amid lockdowns were continuously monitored. Moreover, the concentration of the pollutants for the non-pandemic period of 2019 was analyzed when there were no lockdowns and restrictions in the city. The comparison between lockdown and no-lockdown states and deweathered pollutant level data were considered in this study. Machine learning tools like R programming and GIS technology with a statistical approach added a new dimension of analysis on pollution datasets with weathered and deweathered scenes. Hence, this study will be fruitful for policymakers to combat and reduce the seasonal collective air pollution concentration in metro areas and check them by implementing certain action plans. The results obtained from this study can show us avenues to improve the 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 concerning the CPCB permissible limit (Fig. 7.1a). The PM_{10} level was higher for the third wave. In contrast, the first two waves' concentrations were lower than the standard of CPCB (100 µg/m^3). Thus, both $PM_{2.5}$ and PM_{10} concentrations exhibited a decrease 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/)

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

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 ranges of PM_{10} were 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. Such widespread and stringent implementation of lockdowns inevitably reduced the load of atmospheric pollutants (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 cut down people's mobility by issuing government orders regarding 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 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 time duration. 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, administration activities were allowed to operate at 50% employee strength. Almost all private and Government offices worked with 50% strength, 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, usually traffic remains minimal. Such loose practices promoted 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 pollutants concentrations for third-wave lockdown concentrations were increased by 400.32% (149.97 μg/m^3) and 211.09% (100.74 μg/m^3) compared to second-wave lockdown.

Fig. 7.2 shows the spatial distribution of PM_{10} and $PM_{2.5}$ in 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, revived air pollution was detected. The northern and western parts of the region were more polluted, while the central part was the least polluted. There were more vehicular emissions and industrial activities 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} dropped during the pandemic amid lockdown phases compared to the normal periods of 2019, as shown in the box plots (Fig. 7.3a, 7.3b). The normal periods (2019) average concentrations of $PM_{2.5}$ were 81.42, 67.00, and 330.78 $\mu g/m^{3,}$ while their corresponding lockdown phase concentrations were 72.58 (first wave), 41.38 (second wave), and 241.44 $\mu g/m^3$ (third wave), respectively. Therefore, the results indicate moderately polluted air during the first and second waves, which means breathing discomfort to people with lung diseases. However, severe air pollution was noted for the third wave, which induced respiratory illness in people exposed to prolonged air (Table 1.1). Likewise, the PM_{10} non-pandemic period's concentration was recorded at 88.58, 82.40, and 265.11 $\mu g/m^3$ while the concentrations during the pandemic waves were 81.42, 55.25, and 174.78 $\mu g/m^3$ respectively. Hence, it was a satisfactory type for the first two waves but had poor air quality for 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 range 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

Air pollutants are reported as mean±standard deviation.

** Normal period data was 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 μg/m^3) for the third wave, -38.25% (25.63 μg/m^3) for the second wave, and -10.85% (8.83 μg/m^3) for the first wave compared to the normal phase of 2019 (Table 7.3). Similarly, the amount of drop of PM_{10} was -8.09% (7.17 μg/m^3), -32.95% (27.15 μg/m^3), and -34.07% (90.33 μg/m^3), respectively, for three waves. The lockdown during the third wave was in the winter period. So, the static movement of air and cold air had a high magnitude of ground-level air pollution holding capacity. 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). Similar observations, i.e., −30.6% & −34.9% dropped for $PM_{2.5}$ & PM_{10}, have been witnessed by the review paper of Navaratnam et al. (2024). Another recent study in Portugal scrutinized PM_{10} levels as reduced by 21.1% in the lockdown period compared to historical periods (2015-19) (Silva et al.,2024).

7.2.2 CO dynamics in the atmosphere

A previous study has witnessed that CO has unusually reduced in India during the lockdown phase. Fig. 7.1c shows that all recorded values were extraordinary compared to the CPCB permissible limit (2 mg/m^3). Its high concentration is inclined to various cardiovascular problems, and infants, pregnant women, and old ages 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 distributions of CO across the Kolkata megacity have been portrayed in Fig. 7.2. A gradual decrease in air quality has been detected from temporal maps. The third wave was the most polluted compared to the first two waves. The northern parts of Kolkata were more polluted than the rest. 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 COVID-19 pandemic average concentration of CO was reduced by about -18.81% (5.25 mg/m^3) for 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, industrial closure, and seasonal impact leads to such a high concentration of air pollution. CO itself is a major contributor to greenhouse gasses (GHGs) when it is emitted into the atmosphere, which is linked to climate change and global warming. The inter-lockdown and normal periods of concentration of CO have been depicted in Fig. 7.3c. A mixed scenario is detected here.

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

7.2.3 Negligible role of NH_3 observed in air pollution

Several pieces of research 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 nominal for all three waves as per the CPCB permissible limit (400μg/m^3). Therefore, it is less likely to impart any health issues with such little 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 more concentration than any other part of the region. The city has witnessed a rise of 18.87% (0.72 μg/m^3) and 32.82% (1.48 μg/m^3) for the second and third waves (Table 7.2). It was because of the sources of agricultural field waste, NH_3-based fertilizer applications, industrial processes, and vehicular emissions.

The box plots exhibit a steady increase in the concentration of NH_3 for 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 0.06% (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 third wave compared to the normal phase of 2019 (Table 7.3). A recent paper scrutinized the pandemic amid the lockdown and the change in the concentration of pollutants and dropped concentrations recorded due to checked industrial activities 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 transportation and industrial closure of the government policy and people's awareness made 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 pattern of SO_2 has been illustrated in Fig. 7.2. The significant improvement of air quality in the second wave phase lockdown compared to the first wave phase and, thereby, remarkable gain during the third wave phase was noted. 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 was a mixed result in inter-lockdown phases (Table 7.2).

The box plots (Fig. 7.3e) have shown that the SO_2 concentration was unstable and fluctuated in the city. There were gains in concentration in lockdown waves (first and second) compared to normal phases of 2019. It reduced in the third wave amid the lockdown phase compared to the normal period of 2019. The average values of lockdown and normal periods were 15.42, 7.75, & 30.22 and 11.75, 2.80, & 36.22 μg/m^3. High rise (176.79%) in the second wave phase lockdown and fall (-16.82%) for the third wave 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 witnessed by the review paper of Navaratnam et al. (2024). Mokarram et al. (2024) experienced the same.

7.2.5 Fluctuation of NO_2

The concentration of NO_2 leads to aerosol formation, and it is highly interlinked with 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). The significant improvement in air quality (NO_2) due to COVID-19 amid lockdown phases compared to normal phases of 2019 was noted for all three waves. The strictness put into practice on transportation and industrial activity for the city resulted in substantial improvement in the 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 portrays that the north-western part for the first two waves and the southern part for the third wave exhibited more 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) have shown 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 maximum fall was in the third wave with -79.41% (98.11 μg/m^3), followed by the first wave (-43.71% with 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) identified a 55% drop in concentration due to restricted anthropogenic activities and lockdown stringency across Handan, China. Likewise, 34.3% and 39.1% reduction of NO_2 were observed by Silva et al., 2024 and Navaratnam et al., 2024. Mokarram et al. (2024) experienced the same for the Isfahan region in central Iran.

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 thinner volume can cause several effects not only for humans (respiratory diseases and skin cancer) but also for plants (death of plants). 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 regular improvement in the O_3 level was observed from the first wave to the second wave phase and the third wave in the spatial distribution map (Fig. 7.2).

There was a drop in air pollution by -50.98% (39.44 µg/m^3) in the second wave phase than in the first wave (Table 7.2). The reverse scenario was detected in the third wave phase compared to the second wave phase. However, a rise in air pollution was recorded by 4.29% (1.63 µg/m^3) for the third wave phase compared to the second wave.

Compared to the normal period, the mean amount of O_3 during the pandemic lockdown waves dropped for the first two waves and improved for 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 well to satisfactory air quality with minimal health issues.

Navaratnam et al. (2024) have shown a 16% mean concentration increase for the O_3 substance. The opposite results also found a 0.82% fall in level for Portugal, according to the study of 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 exhibited significant improvement with -39.59% (34.23) of 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 movement. 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 functioned with 50% workers, and local train and metro services operated with few restrictions.

The box plots (Fig 7.3h) have revealed that the AQI level slightly increased (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 to sensible people and prolonged exposure to health issues in waves. Moreover, a sharp improvement in the recent two waves of COVID-19 amid lockdown was noted compared to normal periods in 2019.

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

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, which are the fundamental sources of particulate matter, showed a close association with the 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 concentration of $PM_{2.5}$ was moderately correlated (r=0.62) with the daily average (24 h) NH_3. The relationship between NH_3 and the daily average (24 h) concentration of SO_2 and CO was noted as a moderate positive (r=0.57 and 0.53) relationship. 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, CO respectively.

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

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 were 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 declined ground-level air pollution. Increased air temperature indicates an unbalanced atmosphere, which allows the pollutants to undergo rapid mixing and, hence, dilution (Cichowicz et al., 2017; Ravindra et al., 2019). Here, the COVID-19 lockdown amid the second wave was in similar conditions. As a result, low air pollution prevailed in the city. The first wave is characterized by high temperature, low humidity, and less wind speed with minimal rainfall. The lower air moisture content facilitates the pollution level (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 peak of monsoons, 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), which was, to some extent, observed 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. Additionally, changes in air pressure can influence weather patterns, which in turn affect temperature and humidity, impacting air quality and health outcomes during the pandemic (Zhou et al., 2020). In line with these observations, our data set shows that even only a bit of relaxation during the lockdown led to significant pollution in the winter months when the temperature and relative humidity were lower than what usually remains during the other time of the year.

Sarkar et al. (2021) pointed out that elevated aerosol layers and low wind speeds contributed to increased AOD, which may indicate increased PM levels in central India during the lockdown. Kuttippurath et al. (2023) highlighted that the lockdown resulted in a temperature drop of 1-3 °C and reduced wind speeds, which affected local weather patterns. 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 was in winter, where lower temperatures and moderate wind speed with dispersed rainfall due to western disturbances helped concentrate the pollutants (Li et al., 2020). During the winter, the planetary boundary layer (PBL) lowers, which facilitates trapping the pollutants closer to the earth's surface. In contrast, during the pre-monsoon (summer) months, the enhanced atmospheric instability increases the height of the PBL, facilitating the dispersion of pollutants (Arregocés et al., 2021). Therefore, it could be inferred that all meteorological parameters played a significant role in controlling the ground-level pollution concentrations as per their seasonal character. Hence, the winter lockdown (third wave) had the highest pollution, followed by the early pre-monsoon lockdown (first wave) and late pre-monsoon lockdown (second wave). Table 7.5 shows the comparative analysis of the present findings with that of previous studies conducted in this regard on Indian megacities, which majorly corroborated the present findings.

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

↑& ↓=*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

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 dataset from the weather, 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 graph is plotted in Fig. 7.6. A similar trend of 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 also increased in the third wave from the second wave.

Moreover, improvement of 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 wave and third wave 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 noted in the second wave deweathered dataset. However, the trend was a gradual decrease or regular improvement in air quality (NH_3). The trend of O_3 was mixed for both weathered and deweathered datasets. The one station (RBU) dataset is not well enough to conclude a whole city's meteorological effect. However, the deweathered data also portrayed a similar trend for the city. This observation indicates that meteorological conditions, though they regulated the concentrations of the pollutants across the different seasons, did not regulate the trend of increase/decrease in air pollution levels.

The weathered to deweathered mean concentrations of $PM_{2.5}$ and PM_{10} were reduced 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 in concentration during all three waves, with rises of 28.42%, 36.75%, and 13.84%, respectively. These results indicate mixed trends in 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 a higher magnitude of variation due to the stringency of the lockdown.

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 had approximately 5.5% more reduction than that of the regular phase. Saleem et al. (2024) argued that meteorological drivers have less contribution compared to lockdown stringency in restricting air pollution levels. Another recent study observed that unfavourable weathered factors checked the pollution level during the COVID-19 pandemic period (Si et al., 2024). Verma et al. (2024) stated that meteorological factors influenced PM_{10} more than human activities.

Chapter 8 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, where population density is very high, were severely impacted due to 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).

Keeping aside the many ill facets that this pandemic introduced, the brighter side of the COVID-19-induced lockdowns was the significant improvement in air quality witnessed throughout the world (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, which shelters more than 25 million people, was one of the hard-hit megacities of India, which 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 pollutant concentrations largely correlated with COVID-19 deaths, as the number of COVID-19 cases increased 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 same window of the previous year, 2019 (Kumari and Toshniwal, 2022). Das et al. (2022) examined the air quality change between the first wave and second wave amid lockdown in Mumbai. The result shows that there was a 32% degradation in terms of air quality change in the second wave due to the imposition of a regional lockdown (2021) compared to that observed during the nationwide lockdown (2020).

However, while most of the studies focussed 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 focussed on the lockdowns during the first (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 cases surge vis-à-vis considering the difference in meteorological conditions scarcely exist to date. The present study was thus focused on Mumbai, keeping in view the shortfalls of the earlier studies and developing a holistic understanding of how the air pollutant dynamics changed with the altered levels of lockdowns in terms of stringency and their interrelationship with meteorological conditions.

Mumbai is India's second most populous city (after Delhi). This megacity witnessed many confirmed cases and death tolls 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 had three distinct features in terms of lockdown restrictions and seasonal conditions. The first wave had no known medicines and zero vaccination. People were scared enough during the onset of the pandemic. The second wave was amidst the initial stages of vaccination, and people had a mindset that they had to live with the virus. The third wave featured almost 90% and 60% of single and double doses of vaccination of the people of the megacity (Nagarajan, 2022), and city-scale immunity was also prominent. From the seasonal perspective, the first and second waves took place in the early summer or pre-monsoon and late summer, whereas the third wave was 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 with varying lockdown restrictions vis-à-vis varying seasonal conditions. The primary objective of this study was to investigate the air quality changes during the COVID-19 pandemic surges, keeping in view the natural seasonalities 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 the air pollutant levels amongst themselves and meteorological drivers. The outcomes from studies like this might guide decision-makers and planners on how climatic variables controlled 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 (Fig. 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 declining trend was in the first wave, followed by mixed in the second wave, and again, a rise in the trend was noted in the third wave. The three surges in concentrations of $PM_{2.5}$ varied from 37.40 to 57.22 µg/m^3, 42.33 to 133.86 µg/m^3, and 58.83 to 183.00 µg/m^3, respectively (Table 8.1). The ranges of PM_{10} were 65.25 to 82.89 µg/m^3, 67.73 to 181.82 µg/m^3, and 74.60 to 147.82 µg/m^3. Overall, a 55.84% (26.53 µg/m^3) and 88.80% (65.73 µg/m^3) rise was observed for $PM_{2.5}$ and PM_{10} during the first to second wave and the second to third wave (Table 8.2). The spatial dispersions are shown in Fig. 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 $PM_{2.5}$ badly influenced the dwellers of Mumbai compared to PM_{10}. Wave-wise, the third wave was noted as the worst in terms of 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 World Air Quality Report 2021, last year (2021) $PM_{2.5}$ annual average (46.4 µg/m^3) was more than 2019 (45.3 µg/m^3) for Mumbai. One of the prime reasons behind this observation could be that most people felt reckless about resuming their jobs during the second wave to overcome the financial constraints that the first wave introduced to millions. Compared to their regular phase concentration, 20.54% and 5.24% increases in $PM_{2.5}$ and PM_{10} were observed during the pandemic phase. The boxplots (Fig. 8.3a) have shown that the average amount of $PM_{2.5}$ was 36, 36, and 176 μg/m^3 for the normal phase, while in the pandemic phase, they were 31, 45, and 129 μg/m^3. Likewise, PM_{10} levels were 84, 87, & 209 μg/m^3 and 72.5, 87, & 120.5 μg/m^3 for regular and pandemic phases (Fig. 8.3b). Hence, both $PM_{2.5}$ and PM_{10} exhibited a similar type of concentration change. The first and second waves amid the pandemic and non-pandemic amounts were under satisfactory AQI category for both $PM_{2.5}$ (31-60 μg/m^3) and PM_{10} (51-100 μg/m^3). The third wave noted very poor AQI from the perspective of particulate matter, which could have led to a high chance of breathing discomfort and respiratory illness for 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 first, second and third wave (Source: CPCB web portal, https://airquality.cpcb.gov.in/AQI_India_Iframe/)

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

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]

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 any urbanized sector. 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. Besides environmental impacts, elevated concentrations of CO can cause harmful health impacts such as neurological, neurobehavioural, and cardiovascular disorders in human beings (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 portrays that the CO levels varied from 5.34 to 70.90 mg/m^3. The first wave observed the lowest CO levels. The second wave noted mixed results, and the third wave broke the record of the initial two waves. The megacity noted a 40.27% (8.48 mg/m^3) gain in concentration in the second wave compared to the first wave phase. Likewise, a 42.73% (12.62 mg/m^3) gain was recorded for the third wave compared to the second wave phase (Table 8.2). Looking into the concentrations of normal phases when no pandemic-induced lockdown occurred and comparing it with lockdown waves, we 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 blessings to environmental air quality. Fig. 8.3c depicted a similar scenario. The average concentrations of CO were 84, 93, and 99 mg/m^3 for normal phases, while their 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 causes severe respiratory illness in people on 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) rise in NH_3 level in the second wave compared to the first wave. 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 comparison indicated that the first wave was best for the citizens, followed by the second and third waves from the perspective of NH_3 concentrations. A few pockets of south and north exerted a relatively higher concentration in the second and third waves. We could not portray the concentration of NH_3 in both the normal and pandemic phases due to insufficient data for 2019. Hence, we depicted only pandemic surge concentrations in box plots (Fig. 8.3d).

8.2.4 Changes in the concentration of SO_2

The amount of SO_2 was also below the standard limit (80 µg/m^3) during all three pandemic surges (Fig. 8.1e). However, a rising trend followed from day one 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 in the first wave amid lockdown were recorded compared to the second and third waves all through the city. The second and third waves deteriorated SO_2 levels gradually. 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 a gain in SO_2 concentration during pandemic surges of first (18.00%) and second wave (41.38%) 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 plots 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 first wave to second wave with a 43.93% (4.82 µg/m^3) increase, and second wave to third wave with 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) exhibited a significant drop of NO_2 in COVID-19 amid waves than in 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. We 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. The uneven patterns of concentrations have been observed. During the COVID-19 pandemic, the O_3 concentration has dropped by -55.93% and -69.75% for the first and third waves, though it has improved by 41.38% for the second wave compared to their normal year level of 2019 (Table 8.3). The boxplots (Fig. 8.3g) have shown that the range of the substances was more in normal phases than in pandemic phases. The mean amount of pandemic and non-pandemic phase concentrations were 13 & 17, 41 & 30, and 17 & 62 μg/m^3 from the first, second, and third waves. 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 remarkably good 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 revived with the withdrawal of lockdowns aided by bad air quality within a couple of months. 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 detected a gradual upsurge of poor-quality air from the first wave to the third wave through the second wave (Fig. 8.2h). No particular pattern in spatial distribution could be observed. The first and third waves witnessed a similarity, with a low to high pollution level 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 AQI for lockdown and non-lockdown phases were 72.5 & 89.5, 87 & 93, and 136.5 & 209 for 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 than the normal phase concentrations.

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

8.2.8 Correlation between ambient air pollutants

To analyze the relationship among pollutants, we have prepared Karl Pearson's coefficient of correlation matrix with scatter plots for 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=0.67*); 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 witnessed a few pairs ($PM_{2.5}$ and NH_3; PM_{10} and NH_3; NH_3 and O_3; SO_2 and O_3) of low to moderate correlations (nearer to 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 have been depicted in Table 8.4. The second wave recorded the highest mean temperature (31.50 °C), followed by the first (31.28 °C) and the third wave (24.42 °C). Likewise, the second wave noted high humidity, wind speed, and precipitation, followed by 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.

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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

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

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

We have deweathered (removed the effect of weather parameters) the select pollutants. Temperature, humidity, wind speed, and precipitation are the four most influencing meteorological parameters that were considered to eliminate the influence of meteorology on air pollutant concentrations. The comparison-contrast of weathered and deweathered pollutants has been shown in Fig. 8.5. The concentration of $PM_{2.5}$ and PM_{10} were above the standard of CPCB for the third wave. However, they were below the limit for 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 recorded the reverse scenario of PM. These two noted a regular decline trend from the first wave to the third wave. Unlike others, SO_2, CO, and O_3 had a rising trend for the first-second wave, dropping in the second-third wave. We can summarize that a few parameters noted a regular rise, a regular fall, and an initial fall-rise and fall again. Hence, weathered and de-weathered line graphs had similar trends for seven pollutants. We conducted the GAM function by choosing only one AAMS data of Bandra. As we considered only the city area, one AAMS portrayed quite perfect results for analysis.

The mean concentrations of $PM_{2.5}$ and PM_{10} showed a decrease of -8.35% and -0.01%, respectively, during the second wave. In contrast, during the first wave, $PM_{2.5}$ slightly increased while PM_{10} decreased by -2.33%. However, both $PM_{2.5}$ and PM_{10} levels surged during the third wave, with increases of 19.37% and 12.27% (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 higher than the permissible limits, which are set at 60 µg/m^3 for $PM_{2.5}$, 100 µg/m^3 for PM_{10}, and 2 mg/m^3 for CO. 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 greatest 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 pandemic's epicentre (Wuhan, China) (Andrews et al., 2020). Kerala Government announced lockdowns on 23 March 2020. To stop the rapid spread of that virus, the GoI declared strict lockdowns across the nation for 21 days. That was the first wave amid lockdowns when ground-level air quality improved significantly. GoI also instructed the complete closure of all regular services such as academic institutions, social and political gatherings, industry, recreational activities, and almost all services except emergency services. The present study included the surge phases and pollution levels therein. The lockdown significantly improved pollutant and AQI levels in the first wave phase. The city's researchers identified similar air quality improvements to the megacity scale (Sharma et al., 2020; Lancet, 2020; Mahato et al., 2020). The NASA (2020) and the ESA (2020) released a few images that drew similar conclusions of improvement in air quality. The infection rates started to fall in September 2020. After a few months, the second pandemic wave surged in March 2021. The nation was again struggling with vaccines, hospital beds, oxygen cylinders, and other medicinal goods. Simultaneously, the financial crisis was another big issue for the people and the GoI. As a result, Central and state governments were less strict compared to the first wave for the sake of the livelihood and income of the commons. 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 air quality changes has been portrayed above. The new COVID-19 infection rates began to fall in August-September 2021. The concept of quarantine for travellers and a few restrictions on travellers were applied, especially for those who were not vaccinated yet (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 GoM and w.e.f. 10 January 2022 at 00.00 hours for the public and collective interest. The new variant of COVID-19, “Omicron”, was spreading rapidly. Schools, colleges, and coaching institutions remain closed till 15 February 2022 except for major Boards (10th and 12th standard students) and GoI-advised online mode study. Entertainment parks, zoos, museums, forts, and other ticketed places/events for the general public remain closed. The Government offices functioned through online mode only. Private offices advised that not more than 50% of regular attendance of employees. Saloons, shopping malls, market complexes with restricted entry, restaurants, eateries, and cinemas were permitted at 50% of 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 funeral and last rites with a maximum of 20 persons. The industries were open to maintaining COVID-appropriate norms, such as wearing masks and regular sanitization of workplaces, and only double-vaccinated workers were allowed to enter the work sites. Those loose practices promoted ground-level air pollution compared to the previous two waves amid lockdowns. The relaxation and a few sectors’ (industry and mass vehicles) activeness 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 lockdown phases) deteriorates the pollution level for the megacity. Mahato and Pal (Mahato and Pal, 2022) assessed the second wave amid air quality change in Delhi. They argued that the air quality improvement was greater in the first wave than in the second due to the imposing degree of stringency of lockdown.

Previous studies have identified that the combined concentrations of pollutants have massive negative impacts on human health and the environment. Zhou et al. (2016) depicted a similar correlation for China. 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. The first two pandemic waves were characterized by high temperatures, high humidity, and high wind speed with moderate rainfall, which are the typical features of the pre-monsoon season. Generally, more precipitation in a specific place means a controlled pollution level.

The high wind speed dilutes the pollution level as well. 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 temperature, minimal humidity, low wind speed, and high air pressure with the least precipitation that was the typical winter period. Those salient features concentrate on the ground-level pollution level. Rahaman et al. (2020) observed similar scenarios over the Indo-Gangetic plain. They observed a high pollution level for the winter season and less in the summer. Grange et al. (2016) mentioned that the concentrations of $PM_{2.5}$, PM_{10}, NO_2, SO_2, and CO reached their maximum during the winter months while decreasing in the monsoon (June-August) months. Verma et al. (2023) examined major Indian cities, and the result reflected a higher seasonal variability for Delhi and Kolkata and less for Chennai and Mumbai.

Sandeep et al. (2013) noted similar seasonal variations and pollutant concentrations for Mumbai. Karar et al. (2006) examined the seasonal variations of pollutants in Kolkata. The result revealed a higher winter concentration of pollutants compared to other seasons due to static movement of air and longer residence time. Kumar and Dash (2018) have had similar experiences, namely that summer or pre-monsoons have lower pollution levels than winter. Likewise, Sellamuthu and Jeyadharmarajan (2022) analyzed the same in their research on the urban environment. They mentioned that energy use and atmospheric constancy lead to higher pollutant concentrations during winter. Hence, more relaxation in the lockdown phase highly polluted the megacity. The standard deviation of parameters detected mixed results. Besides that, a few local influences, like the situation of the Arabian Sea on the west and the location of surrounding landlock states' activities on the east, played a crucial role in the spatial distribution of the pollution level.

Chapter 9 Conclusion and Recommendations

9.1 Global scenario

The present study has assessed the extent to which the improvement in two parameters of air quality occurred as a result of the COVID-19-induced shutdowns across select countries of the world. 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. Despite using quite coarser resolution datasets and having some dataset limitations, an overall nearly 60% reduction in pollutant levels was witnessed in these countries during the lockdown period. These levels varied for the individual nations examined in this study, as well as the rate at which the contaminants reached close to their pre-lockdown levels after restrictions were lifted. However, it was prominent that restricting anthropogenic activities can help us revive the atmospheric pollutant levels to a pre-industrial revolution state. 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 that intermittent lockdowns need to be considered in the near future, especially in heavily industrial and urbanized setups, 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 CIP exhibit $PM_{2.5} > 5$ μg/m^3, the WHO-prescribed standard limit. This situation is extremely 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 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. The emission of $PM_{2.5}$ should be prevented, and more attention should be paid to avoid mixing $PM_{2.5}$ in the air. If it remains unchecked, soon, mankind and its environment may invite greater health impacts on the burgeoning population that thrives in these countries.

9.3 Air pollution scenario in three megacities of India during the COVID-19 pandemic

The nationwide lockdown has had significant impacts on the air quality of the megacities of India. Seven air pollutants were studied to assess the AQI due to the effect of the COVID-19 lockdown. $PM_{2.5}$, PM_{10}, and CO are the major pollutants across the megacities. Meanwhile, remaining pollutants, such as NO_2, NH_3, SO_2, and O_3 concentrations, were below the CPCB standards during both the pre-lockdown and the lockdown phases. $PM_{2.5}$, PM_{10} & CO recorded a decline of 47%, 41%, & 27% for Mumbai; 52%, 39%, & 13% for Delhi; and 49%, 37%, & 21% for Kolkata during the lockdown phase. These pollutants exhibited the same decline trend with 43%, 32% & 19% for Mumbai, 4%, 4% & 12% for Delhi, and 57%, 50% & 29% in the post-lockdown phase. The declining trend of AQI was observed during the COVID-19 lockdown period (25 March-14 April 2020) compared to the same window of the previous year, 2019.

Delhi was in the worst condition as per average concentrations of pollutants, even when compared to last year's (2019) scenario, followed by Kolkata and Mumbai. The megacities of Delhi and Kolkata had more pollution in the western part compared to the east, whereas Mumbai exhibited an opposite spatial pattern. The meteorological parameters had a negligible role in reducing the pollutant concentrations during the lockdown period, except for the increasing air temperature. Among the seven pollutants, only three, $PM_{2.5}$, PM_{10}, and NO_2, were significantly (positive) 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 sectorial lockdowns, such as vehicle movement, industry, domestic, and allied services, except the emergency services, were completely closed. 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 place intermittent and well-planned lockdowns in the future to safeguard the urban outdoor atmosphere without comprising economic growth.

9.4 Air pollution during Diwali in the three megacities

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 indicated that burning firecrackers leads to intense air pollution and that air pollution aids in the transmission of COVID-19 viruses. These generalized observations prompted us to examine the difference in air pollution levels during the Diwali of 2020 amidst the COVID-19 pandemic and compare the scenario with that of the previous year's Diwali when there was no pandemic. The study revealed elevated $PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, CO, and O_3 concentrations in Diwali 2020 in all three cities, with very few exceptions. This observation primarily indicates that people celebrated Diwali with more vigour even under a pandemic-stricken condition. However, analyzing the pre-Diwali to Diwali changes in air pollutant concentrations for both years portrayed a lesser increase for most of the 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, the people of Delhi did not restrict themselves from burning firecrackers even in a pandemic situation, which can significantly aggravate 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 going back to the pre-pandemic norms. The terror of the coronavirus slowly dissipated at this point, which might have triggered the people to celebrate Diwali like before. In addition, an absence of awareness regarding the causal effects of burning firecrackers to promote the spread of the virus might have played a crucial role. In 2020, Diwali was in mid-November when air temperature and wind speed were lower than the Diwali held 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 indicated a dramatic increase, which could be possible only because of burning firecrackers. Mumbai and Kolkata did not record such an increase in pollutant concentrations from pre-Diwali to Diwali. It is more concerning that Delhi retained the pollutant loads in the atmosphere even after one week of Diwali in 2020. The stable atmosphere of Delhi enhances the residence time of air pollutants, especially in the winter months, which come just after Diwali. The PM_{10}, $PM_{2.5}$, and CO levels were above the permissible limit in all three megacities during the Diwali of 2019 and 2020. Besides Delhi, such elevated concentrations are a point of concern for Mumbai and Kolkata. However, the concentrations were almost double in Delhi compared to those observed 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 one day can aggravate the infection scenario and deteriorate the ground-level atmosphere.

These observations compel us to rethink burning firecrackers, keeping in view the harmful impacts they have on the atmosphere. However, as the festival of Diwali, like many other festivals all over the world, is proactively celebrated by millions, there is no call to hurt the religious sentiments of these people. Thus, green crackers, water-based crackers, and biodegradable crackers should be promoted so that they do not pollute the atmosphere. Hence, they can be burnt without impacting the celebrations. Further innovations should be nurtured, where the proactive involvement of such a huge number of people in the Diwali celebration can be effectively used to reduce air pollution instead of aggravating 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 intended to observe the effect of lockdowns imposed during the COVID-19 pandemic (of varying stringency under different seasons) on the ambient air quality of the 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 post-monsoon 2022. The air pollutant concentrations of the lockdown phases in the respective years were also compared with the air pollutant concentrations of the same time windows in a non-pandemic time (the year 2019). The major 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 the restriction on vehicle movement, industry sector, household, and associated services, excluding emergency services, played a crucial role in the first two waves. The relaxation for the third-wave lockdown increased the pollution level. The remarkable improvement of $PM_{2.5}$, PM_{10}, NO_2, and AQI was noted for all the lockdown phases compared to normal phases (2019).

Seasonal changes in meteorological parameters lead to changes in air pollutant concentration, and the winter season, when the atmospheric stability remains significantly higher than the other seasons, remains the most susceptible to air pollution. The spatial distribution map portrayed that a few pockets of the industry and transport sector compromised the air quality level. The outcomes from the present study 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 the health risks for humans but can alleviate climate change to some extent. In an era when townships are rapidly converting to cities all through the world, steps like this can enhance the sustainability of the cities as well as the societies that reside therein. However, a significant scientific rationale has been outlined through the present study to understand this very dynamic and crucial natural phenomenon, air pollution. Based on the results generated from this study, the authors stress predicting spatially explicit pollution scenarios for the city of Kolkata and Howrah Municipal Corporation areas, especially after the monsoon when the dry winter prevails. It can enable us to locate the zones that are in dire need of improving air quality. The present study showed that despite high pollution levels existing in this twin city, it is not ubiquitous and shows significant spatial variability. To curb the pollution levels, keeping in view 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 thought of as an avenue to alleviate the atmospheric pollutant load. As the particulate matter 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-Februray) can also be placed on the table for discussion as these activities essentially lead to particulate matter pollution. With the wind direction changing from flowing north to flowing south during the dry winter months, the industrial sectors in the northern belt of this area pose a major threat to the city dwellers. However, more intensive studies are required to have a precise view of environmental pollution dynamics in the study region to cope with this natural hazard for a better 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 surges in the COVID-19 cases witnessed by the business capital of India (Mumbai) significantly reduced the 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 like NH_3, SO_2, NO_2, and O_3 were consistently below the standards of CPCB; however, their concentrations varied with seasons and depended on the lockdown timings. This study indicated that the improvement in air quality during the lockdown phases depended entirely on the degree of law enforcement. Stringent imposition of lockdown led to better results as significant declines in air pollutant levels accompanied them. However, with time, the Government relaxed the stringency in implementing lockdowns, keeping in view the economic crisis that these lockdowns exerted on the people. The inter-wave changes in pollutant levels and the comparison of pollutant data between pandemic and non-pandemic phases exhibited that lockdowns can act as a potent regulator 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 furnished us with a real-life platform to experiment with the effect of curbs on anthropogenic activities on air quality. These results should encourage the decision-makers, policymakers, and planners to devise tactical strategies for short-term lockdowns in the future, especially during those times of the year when air quality remains the most degraded. With the ongoing anthropogenic activities, air pollution is inevitable, especially in densely populated pockets of the world. However, the ever-degrading quality of air that the people of those regions breathe is taking a heavy toll on their health. It is time that we introspected our activities and looked for possible avenues to regulate the city's air quality, which is also an essential component of the sustainable development goals.

9.7 Overall Recommendation

Several measures can be undertaken to effectively reduce emissions. First, it is essential to adopt alternative methods to open incineration of waste, such as composting household waste, recycling, and proper waste disposal in landfills. Encouraging the use of public transportation and investing in public transport infrastructure is crucial to minimize reliance on private vehicles. Additionally, promoting bicycling and walking can contribute significantly. Like many Western countries, a separate lane for cyclers 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 it is anticipated that population increases will occur over the coming decades. This growth signifies potential industrial expansion in these countries, highlighting the need to emphasize non-conventional energy sources instead of 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 for the development of 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, 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 like frequent water spraying by both Government and private sectors (as part of corporate social responsibility) can help lower $PM_{2.5}$ concentration, 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 the air quality in megacities, several actions are necessary throughout the year, including operating only LPG-fueled three-wheelers, procuring natural gas-driven 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 firecracker use, and such initiatives can significantly improve ambient air quality.

A multi-faceted approach is necessary to combat air pollution in highly populated 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 has launched a seven-step strategy to reduce air pollution. This includes sustainable construction practices, road dust reduction measures, and sustainable waste management.
2. Electrification of Vehicles: Promote the use of electric vehicles 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 created somewhere else, if not within the 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 imparted minor constraints in this research; more automatic air monitoring stations need to be established within the boundary of megacities to effectively study the spatial dynamics of these pollutants, given the current predictions that the population in these cities are expected to increase in this century.

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---

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65 amt.copernicus.org — 27 words — < 1%
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---

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---

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---

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---

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Zeyang Zhang. "Reprint of: The spatial-temporal characteristics and health impacts of ambient fine particulate matter in China", Journal of Cleaner Production, 2017
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---

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Crossref 18 words — < 1%

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112	Mengfan Yan, Han Ge, Liwen Zhang, Xi Chen et al. "Long-term PM2.5 exposure in association with chronic respiratory diseases morbidity: A cohort study in Northern China", Ecotoxicology and Environmental Safety, 2022 Crossref	18 words — < 1%
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---

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---

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Crossref

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---

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Crossref

9 words — < 1%

---

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Crossref

9 words — < 1%

---

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Crossref

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Publications

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Crossref

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