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Modelling health implications of extreme $PM_{2.5}$ concentrations in Indian sub-continent: Comprehensive review with longitudinal trends and deep learning predictions

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ABSTRACT

Air pollution poses a critical global challenge, disproportionately impacting public health and the environment in developing nations like India. The review suggests rapid urbanisation, industrialization, and increased energy consumption have worsened air quality, where average annual $PM_{2.5}$ concentration far exceeds World Health Organisation (WHO) guidelines of 5 μg/m^3, leading to high mortality and increased disability-adjusted life years. Indoor air pollution from biomass burning exacerbates the issue, affecting millions of populations in India who rely on traditional fuels. Despite strides in air quality monitoring through National Mission on Air Pollution (NMAP), challenges such as uneven data coverage and limited ground stations for entire country, especially in rural areas, and outdated emission standards hamper effective policy implementation. Therefore, this study utilizes MERRA-2 reanalysis and Global Burden of Disease datasets, this study analysed disease-related mortality influenced by pollution extremes [$MPM_{2.5}$ (Mean Annual Pollution through $PM_{2.5}$), $PM_{2.5}D$ (Polluted days through $PM_{2.5}$), $MAPM_{2.5}$ (Maximum 1-day pollution amount), and $PM_{2.5}99p$ (Heavily polluted regions)]. Single and multilinear regression analyses were conducted between pollution extremes and disease-related mortality, followed by a Convolution Neural Network (CNN) to predict mortality by disease, state, and gender based on pollution extremes. The study revealed significant spatiotemporal variation in $PM_{2.5}$ concentrations across India, with northern states exceeding air quality guidelines and $PM_{2.5}$ levels more than doubling in the Indo-Gangetic Plains between 1980-1990 and 2010–2020. Regression analysis showed correlation between $PM_{2.5}$ and neurological disorders and chronic respiratory diseases, while respiratory infections and tuberculosis had the weakest correlation. Further a dense CNN model improved predictive accuracy, achieving R^2 values between 0.84 and 0.94 across states, diseases, and genders. The study will provide a valuable insight to air quality and health monitoring programme (AQHMP) through suggesting stricter pollution standards, expanded rural monitoring, sector-specific policies, improved emission inventories, and advanced technologies with AI&ML and remote sensing for better data and reduced health risks.

1. Introduction

Air pollution refers to harmful substances in the Earth's atmosphere, resulting from both natural processes and human activities (Kuniyal & Guleria, 2019). These pollutants can be solid particles, liquid droplets, or gases, and they include particulate matter (PM_1, $PM_{2.5}$ and PM_{10}), nitrogen oxides (NO_x), sulphur dioxide (SO_2), carbon monoxide (CO), volatile organic compounds (VOCs), and heavy metals such as lead (Pb) and mercury (Hg) (Kumar et al., 2023). Primary sources of air pollution include industrial emissions, vehicular exhaust, power generation, agricultural activities, and residential heating and cooking (Tomasi & Lupi, 2017). Natural sources such as wildfires, volcanic eruptions, and dust storms also contribute to air pollution, but the significant rise in pollution levels is largely attributable to anthropogenic activities, particularly since the Industrial Revolution (Thangavel et al., 2022). However, continuous urbanisation, industrialization, and increased energy consumption in developing countries such as India have exacerbated the concentration of pollutants in the air, posing a severe threat to

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human health and the environment (Pandey et al., 2021a).

In 2019, a CNN report showed that 21 out of the 30 most polluted cities in the world were in India, with the capital, New Delhi, being the most polluted city globally (CNN and India has 21 of, 2020). Given the regulatory challenges, the surge in economic activities, and rapid industrialization, the ambient air pollution exposure (AAPE) in Indian cities is expected to deteriorate further (Gordon et al., 2018). However, approximately 40% of India's population will continue to face hazardous indoor air pollution exposure (IAPE) far exceeding the World Health Organization (WHO) Air Quality Guidelines (AQG) resulting from traditional cooking fuels (Mottaleb et al., 2022). A recent study also reveals that over 140 million people in India are exposed to air quality that exceeds the WHO safe limit of 5 $\mu g/m^3$ (Yu et al., 2023).

The 2019 subnational burden of disease study estimated that over 10.4% of all deaths in India, roughly 980,000 individuals, and 6.7% of total disability-adjusted life years (DALYs), about 31.1 million, are attributable to exposure to ambient $PM_{2.5}$ (Balakrishnan et al., 2019; de Bont et al., 2024). Although, a recent city-wise study in India found that the risk of death doubles for every 10 $\mu g/m^3$ increase in $PM_{2.5}$ levels (de Bont et al., 2024; The Wire: The Wire News India). When examining data below the Indian air quality standard and utilizing the integrated exposure-response curve, the study observed that 7.2% of all daily deaths could be attributed to $PM_{2.5}$ concentrations exceeding revised WHO guidelines of 5 $\mu g/m^3$ (Brown et al., 2022; de Bont et al., 2024; Pandey et al., 2021b). This positions air pollution as one of the leading risk factors for ill health in the country, potentially surpassing high blood pressure, smoking, child and maternal malnutrition, and diabetes risk factors (de Prado-Bert et al., 2022; Kalra et al., 2023). Given India's current demographic trend, which is skewed towards a younger population, the cumulative cardiovascular and pulmonary effects of air pollution may be masked and only become apparent as latent effects in future decades (Gordon et al., 2018). If $PM_{2.5}$ levels remain at their current levels, it is projected that per-capita mortality attributable to $PM_{2.5}$ in India could increase by 21% by 2030, largely due to the substantial growth in the population over the age of 50 (Apte et al., 2015, 2018). A study on non-smokers has determined that Indians exhibit 30% weaker lung function compared to Europeans (Nandan, 2013). To maintain current achieving a significant reduction in $PM_{2.5}$-attributable mortality rates, especially among the elderly, necessitates a 20–30% decrease in average $PM_{2.5}$ levels over the next 15 years (Xu et al., 2023; Zhang et al., 2022). This ambitious goal underscores the need for substantial improvements in both indoor and outdoor air quality. Addressing this challenge requires a multifaceted approach to tackle pollution sources and enhance air quality standards effectively. Implementing comprehensive strategies is crucial for mitigating the health impacts of fine particulate matter and safeguarding vulnerable populations from increased mortality rates associated with $PM_{2.5}$ exposure.

Efforts to enhance air quality in India face notable obstacles due to insufficient emission inventories and uncertainty about the composition of pollutants in the air (Garaga et al., 2018). Unlike developed Western countries, the nature of pollution in India is influenced by unique factors, including different emission sources and compositions (Beig et al., 2021; Gordon et al., 2018). There is limited research on how various sources and compositions of $PM_{2.5}$ affect health in the Indian context. Early studies suggest that pollutants from fossil fuel combustion may have a more severe health impact per unit of $PM_{2.5}$ compared to those from biomass or windblown sources (Rahman et al., 2021; Yin et al., 2024). However, IAPE from biomass cooking contributes significantly to the country's $PM_{2.5}$ levels, accounting for about one-fourth of the total ambient pollution in India (Sharma & Jain, 2019). This highlights the need for targeted strategies addressing indoor and outdoor pollution sources. In India, indoor and outdoor air pollution are interconnected due to the infiltration of outdoor pollutants indoors and vice versa (Thakur & Patel, 2023). Thus, it is crucial to approach air quality management holistically, considering indoor and outdoor sources together. Effective solutions must address this continuum of pollution to improve health outcomes and comprehensively manage diverse sources of air pollution.

Assessing air pollution exposure and its health impacts is challenging due to significant spatial variability and differences in pollution sources between urban and rural areas (Dias & Tchepel, 2018). In India, while air quality monitoring predominantly focuses on urban centres, rural areas, which also experience high pollution from sources like biomass cooking and trash burning, are often overlooked. This discrepancy complicates the understanding of nationwide exposure patterns. Additionally, the composition of pollutants, such as $PM_{2.5}$, differs between urban and rural areas, influencing the health effects observed in each setting. Urban areas may have higher levels of additional pollutants, including air toxics and heavy metals, further exacerbating health risks (Li et al., 2022). Additionally, both short- and long-term exposure to AAPE and IAPE can result in a variety of health issues, such as stroke, chronic obstructive pulmonary disease, cancers of the trachea, bronchi, and lungs, exacerbated asthma, and lower respiratory infections (Ghorani-Azam et al., 2016). Therefore, comprehensive health assessment must consider both long- and short-term effects of pollutants, emission volumes, exposed populations, and exposure pathways to accurately gauge health outcomes and address the diverse impacts of air pollution.

This review and meta-analysis aim to provide a comprehensive analysis of air pollution, its sources, and its impact on health from an Indian perspective (Fig. 1). Furthermore, the study will examine the evolution, implementation, and effectiveness of air quality regulations across various regions and recommend new policies to mitigate the effects of air pollution. It will define pollution extremes for both long- and short-term exposures in India, and based on this data, regression analysis and deep learning models will be developed to predict mortality rates due to four diseases, categorized by state and gender. The review will also explore major international measures adopted by developed countries, including the United States, the European Union, China, and India. This research will provide valuable insights into the effectiveness of existing policies and guide the development of more targeted and effective strategies to improve public health and air quality in India.

2. Sources of air pollution and exposure scenarios in India

This section offers a background summary of AAPE and IAPE in India, focusing on their major sources and emissions. Gaining insight into these unique exposure profiles is essential for understanding the full extent of air pollution's health effects and formulating effective policies.

2.1. Ambient air pollution exposure (AAPE)

The rapid expansion of industrial, transportation, and power sectors in India, coupled with both planned and unplanned urbanisation, has led to a significant increase in AAPE (Kaur & Pandey, 2021; Parveen et al., 2021). The surge in vehicle numbers and reliance on coal-based power generation are expected to exacerbate this trend in the coming decade (Shakya et al., 2023). Many cities across India are experiencing air pollution levels that frequently surpass the revised WHO's Interim Target-1 thresholds for $PM_{2.5}$ (annual mean < 5 $\mu g/m^3$; 24-h mean < 25 $\mu g/m^3$) and PM_{10} (annual mean < 15 $\mu g/m^3$; 24-h mean < 45 $\mu g/m^3$) and NAAQs threshold's for $PM_{2.5}$ (annual mean < 40 $\mu g/m^3$; 24-h mean < 60 $\mu g/m^3$) and PM_{10} (annual mean < 60 $\mu g/m^3$; 24-h mean < 100 $\mu g/m^3$), indicating a severe and worsening air quality crisis (de Bont et al., 2024; Singh et al., 2021a; Yu et al., 2023). Furthermore, despite a decline in sulphur dioxide (SO_2) levels in some urban areas, pollutants such as nitrogen oxides (NO_x) and carbon monoxide (CO) still need to be more adequately monitored, leaving critical data gaps, particularly in rural regions (Gordon et al., 2018).

To address this pressing issue, the use of remote sensing technologies has become increasingly vital (Rautela et al., 2024a). Satellite-based measurements of aerosol optical depth (AOD) (Stirnberg et al., 2018)

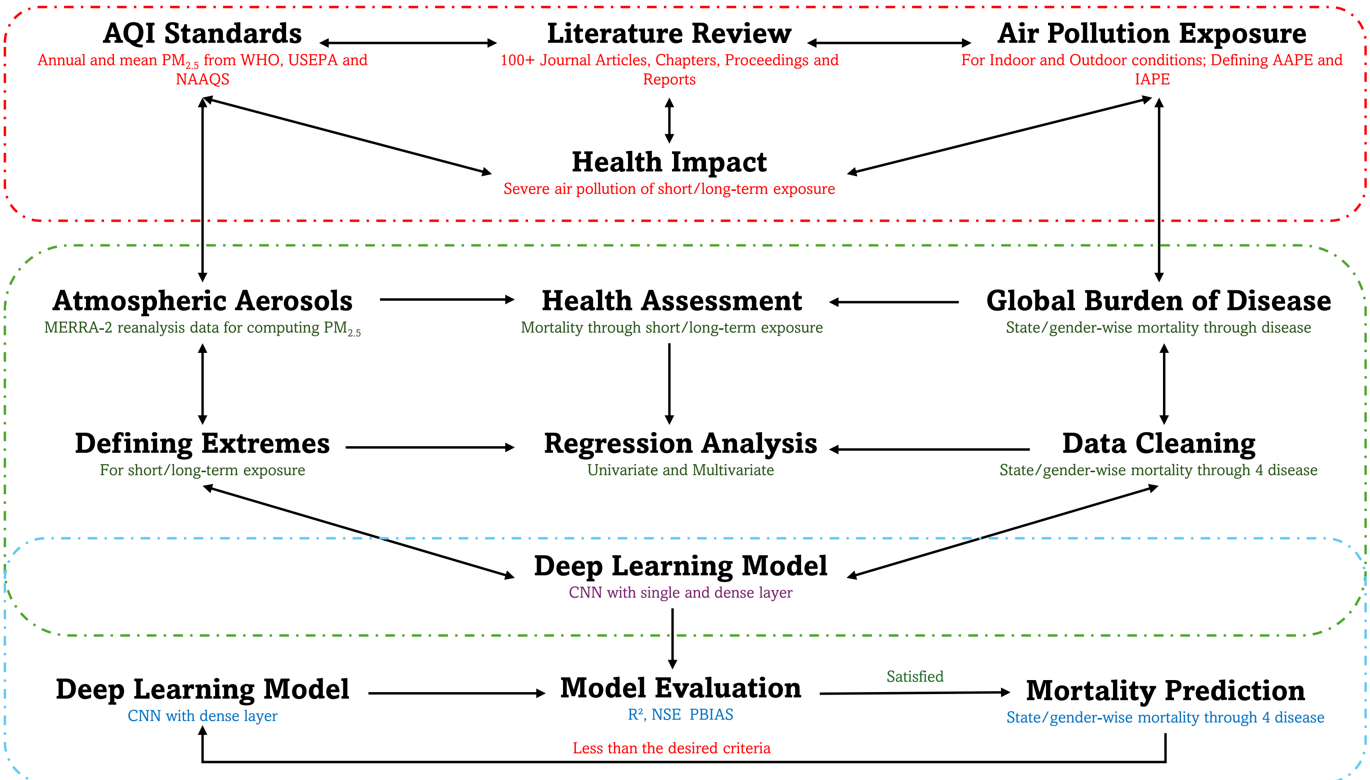

Fig. 1. Comprehensive workflow diagram representing the process for assessing the health impacts of air pollution, integrating data sources, modeling techniques, and mortality estimation.

and reanalysis datasets (Randles et al., 2017) offer a valuable tool for creating national air pollution maps, filling the monitoring gaps in many parts of the country. The Indo-Gangetic Plain, characterised by a mean $PM_{2.5}$ concentration of 50–100 μg/m^3 and $PM_{2.5}$D (days when $PM_{2.5}$ levels exceed 35.5 μg/m^3) ranging from 200 to 250 days annually, experiences alarming pollution levels. With maximum $PM_{2.5}$ concentrations between 300 and 400 μg/m^3, the region endures moderate pollution days ($PM_{2.5}$ concentration between 35.5 and 150.4 μg/m^3) and extreme pollution days ($PM_{2.5}$ levels exceeding 150.4 μg/m^3), highlighting its severity as a public health concern (Rautela & Goyal, 2025; Yu et al., 2023). This severe pollution is attributed to various sources, including biomass and coal combustion, as well as agricultural residue burning. However, leveraging satellite data could significantly enhance efforts to tackle air pollution and its adverse effects on public health and the environment.

2.2. Indoor air pollution exposure (IAPE)

Household practices especially cooking from solid biomass and fuel emissions resulting primarily from incomplete combustion, are the major sources of indoor air pollution. Progress in providing clean and modern cooking fuels for all remains limited. While 57% of the global population had access to clean and modern cooking technologies in 2010, this figure rose only slightly to 66% by 2019 (Küfeoğlu, 2022, pp. 305–330). However, 20% of rural households and 2% of urban households in India rely on biomass burning and soil fuels through traditional stoves, typically operated under insufficient combustion conditions, releasing hazardous substances during burning (Mani et al., 2021). Additionally, as of now, 19% of rural households and 14% of urban households continue to use a mix of traditional biomass and cleaner cooking options such as LPG stoves (Mani et al., 2021). While India's National Air Quality Monitoring Program offers routine air pollution data for numerous urban centres, information on IAPE primarily comes from individual research studies and scientific publications, with limited comprehensive national data available. Over 200+ studies have investigated IAPE in developing countries, with a significant majority focused on India. These studies have utilized various methodologies for exposure assessment, including questionnaire surveys, long-term field measurements, and personal exposure monitoring for women, men, and children (Balakrishnan et al., 2014). Comprehensive quantitative data on IAPE, including findings from India, is compiled in the WHO Global Household Air Pollution Database (Balakrishnan et al., 2014; Chowdhury et al., 2023).

Due to the lack of direct studies quantifying the mortality effects of IAPE, researchers have employed modeling approaches like Integrated-Exposure-Response Curves to connect population-level IAPE exposure estimates with health outcomes (de Bont et al., 2024). However, these models still require validation in real-world settings, as the composition and levels of IAPE in developing countries are distinct from those in developed countries (Gordon et al., 2018). The Global Burden of Disease (GBD) assessment estimated global exposure levels for solid fuel users using a model developed in India (McDuffie et al., 2021; Yin et al., 2024). This model, which integrated $PM_{2.5}$ measurements from rural households with data from the National Family Health Survey, found that $PM_{2.5}$ concentrations could reach up to 337 μg/m^3 (Gordon et al., 2018). These levels far exceed the WHO Air Quality Guidelines Interim Target-1 (35 μg/m^3) and the Indian standard (40 μg/m^3), indicating a severe air quality issue (WHO, 2014).

2.3. Sources of air pollution in India

Air pollution in India stems from a complex mix of sources, both urban and rural, with significant regional variations. In urban areas, vehicular emissions are rapidly becoming the dominant contributor, driven by increasing ownership of motor vehicles and the expansion of highway transport using diesel. The transport sector is estimated to contribute 66% of emissions in Delhi, 52% in Mumbai, and 33% in Kolkata, highlighting its significant impact on air pollution in these major Indian megacities (Dandapat et al., 2020; MoEF, 2010, p. 3). Additionally, Mogno et al.(Mogno et al., 2023) found the contribution of local transport rises 10%–17% to the daily mean $PM_{2.5}$ over Delhi. However, Delhi, where a large portion of the population lives near major roads, the impact of traffic pollution is particularly severe. According to Sahu et al.(Sahu et al., 2023) from 2010 to 2020, there was a marginal decadal growth of 31% in $PM_{2.5}$ and 3% in PM_{10} emissions, with the highest growth observed in BC (57%), OC (34%), and NOx (91%), primarily driven by the transport sector in the Delhi and NCR region. A recent study also found that the primary sources of $PM_{2.5}$ pollution include vehicle exhaust, road and construction dust, and industrial activities, each contributing 10–30% while other contributors are residential activities (under 10% in summer and under 30% in winter), open waste burning (5–15%), power plants outside the city limits (under 7%), dust storms (under 5%), and agricultural residue burning (under 3%) (Guttikunda et al., 2019, 2023a). The eastern states of India, with their extensive coal mines and power plants, are among the most polluted due to a combination of industrial and biomass combustion activities (Tyagi et al., 2021).

Meteorological factors, including seasonal variations in temperature, humidity, and rainfall, play a crucial role in the distribution and severity of air pollution across the country. Maltare et al. (Maltare et al., 2024) found that both $PM_{2.5}$ and PM_{10} strongly correlated with the dew point temperature. Additionally, use of biomass for heating during winter, along with agricultural burning and atmospheric inversions, can lead to significantly increased the concentration of pollutants in large cities like Delhi in Indo-Gangetic Plains (Sahu et al., 2024; Tripathi et al., 2024). Indoor sources, particularly in rural and semi-urban areas, also contribute substantially to outdoor air quality, as pollutants generated indoors can escape and add to ambient pollution levels (Nassikas et al., 2024). However, various past studies shows the average $PM_{2.5}$ concentrations across various Indian cities reveal significant variability, with Delhi having notably high concentrations of AAPE ($PM_{2.5}$ up to140 $\mu g/m^3$) compared to cities like Shimla and Pune, which exhibit lower concentrations (around 25 $\mu g/m^3$). This indicates substantial regional differences in air quality, likely influenced by local sources of pollution and atmospheric conditions (Table 1). The interplay of these various factors makes air pollution in India a multifaceted challenge that requires comprehensive and region-specific strategies to mitigate its impact on public health.

3. Air quality monitoring in India: status and challenges

India's air quality monitoring landscape has evolved significantly in recent years, reflecting the growing recognition of air pollution as a major public health and environmental issue. India's air quality monitoring network includes 1296 stations that cover 473 cities and 7 union territories in 28 states (MoEF&CC, 2022). The country's air quality monitoring efforts are coordinated primarily through the National Air Quality Monitoring Program (NAMP), managed by the Central Pollution Control Board (CPCB), which operates under the Ministry of Environment, Forests and Climate Change (MoEF&CC)(MoEF&CC, 2022). Despite these advancements, several challenges remain in achieving comprehensive and effective air quality assessments in the low and low-middle income counties (Pinder et al., 2019). These challenges include uneven distribution of monitoring stations, gaps in data coverage, lack of real-time data availability in some regions, and the need for improved data integration and analysis to inform policy decisions and public awareness.

In India, CPCB plays a central role in air quality monitoring at the national level, while State Pollution Control Boards (SPCBs) and Pollution Control Committees in Union territories are responsible for state-level monitoring. This multi-tiered approach ensures that air quality data is collected from various geographic and administrative levels. In addition to these institutions, organizations like the National Environmental Engineering Research Institute (NEERI) and certain academic research institutions such as IITs and NITs contribute to air quality assessments. However, their efforts are generally on a smaller scale. In megacities such as Delhi and Pune, dedicated citywide air quality monitoring networks have been established and are administered by the Ministry of Earth Sciences (Board, 2014). These networks operate independently of the NAMP but provide crucial localised data on air pollution levels.

3.1. Air quality standards and monitoring

The CPCB revised the National Ambient Air Quality Standards (NAAQS) in 2009 to include a range of pollutants, including sulphur dioxide (SO_2), nitrogen dioxide (NO_2), particulate matter (PM10 and PM2.5), ozone, lead, arsenic, nickel, carbon monoxide (CO), ammonia (NH3), benzene, and benzo-a-pyrene (BaP) (Gulia et al., 2022; Rautela & Goyal, 2024). The NAAQS set limits for these pollutants to safeguard public health and environmental quality. However, monitoring and reporting practices have been uneven. While the NAMP consistently monitors SO_2, NO_2, and PM_{10}, the monitoring of ozone is limited to a few major cities (CPCB and National Ambient Air Quality Status & Trends, 2019, 2020; Singh et al., 2021b). Pollutants such as air toxics (benzene, toluene, and xylene), BaP, arsenic, and nickel are monitored on a more restricted scale, though efforts to expand these capacities are underway (Gordon et al., 2018). The limited monitoring of ozone, despite its inclusion in the NAAQS, reflects the broader challenges in comprehensively tracking air quality across all pollutants. India's air quality standards, as revised by the CPCB, include annual average limits for PM_{10} and $PM_{2.5}$ that are higher than the guidelines recommended by the World Health Organization (WHO) (de Bont et al., 2024). The CPCB's annual average limit for PM_{10} is set at 60 $\mu g/m^3$, compared to WHO's Interim Target 1 guideline of 70 $\mu g/m^3$. The annual average limit for $PM_{2.5}$ is 40 $\mu g/m^3$, while WHO recommends a lower value of 35 $\mu g/m^3$. These higher limits reflect the severe air pollution challenges faced in India. The discrepancy between national standards and WHO guidelines underscores the need for more localized research to better understand the specific sources and composition of air pollution in India. This includes evaluating the health impacts of different pollutants and their sources, which may differ from those in Europe and North America. Collaborative studies between Indian and international researchers are essential to develop effective strategies for managing air pollution and mitigating its health impacts.

3.2. Data gaps and challenges

Despite these efforts, there are significant data gaps and challenges in air quality monitoring in India. One major issue is the time lag in data reporting, which can delay the availability of crucial information for public health assessments and policy interventions (Nair, 2023). Additionally, the capacity for monitoring $PM_{2.5}$, a critical pollutant due to its health impacts, remains limited in many areas (Agrawal et al., 2021; Thangavel et al., 2022). To address these gaps, hybrid models that combine satellite data with emissions inventories have been developed to estimate ground-level $PM_{2.5}$ concentrations (Rahman & Thurston, 2022; Randles et al., 2017; Shin et al., 2020). These models have provided valuable insights into regional air pollution patterns, instated of cities, particularly for the Indo-Gangetic Plains (Mathew et al., 2023). However, these satellite-based estimates come with their own uncertainties, as the resolution of satellite data is relatively coarse (approximately 10 km), which can affect the precision of the estimates (Alvarado et al., 2019; Ford & Heald, 2016; Gerboles & Reuter, 2010, pp. 1–40; Sorek-Hamer et al., 2020).

3.3. Personal monitoring and emerging technologies

Personal exposure monitoring is an area of growing interest and development, driven by the need to capture more accurate and

Table 1
Summary of $PM_{2.5}$ and PM_{10} concentrations (μg/m^3) in various Indian cities from different studies; The table includes 24-h mean, average, and annual average concentrations, highlighting significant variations across locations.

Study Area	PM Values (μg/m^3)	References
Cities	24-h mean concentration	Gupta and Kumar (2006)
Delhi (Najafgarh, Sarojani, Townhall)	PM_{10} = 188.12, 178.10, 148.77	
Mumbai (Parel, Kalbadevi, Bandra)	PM_{10} = 109.01, 88.49, 120.22	
Kolkata (Cossipore, Dalhousi, Kasha)	PM_{10} = 180.24, 134.18, 93.04	
Chennai (Thiruvottiyar, Gen Hospital, Taramani)	PM_{10} = 66.29, 65.66, 42.18	
City	**Average concentration**	Karar and Gupta (2006)
Kolkata	PM_{10} = 140	
City	**Average concentration**	Kulshrestha and Mishra (2021)
Agra	$PM_{2.5}$ = 104.9 PM_{10} = 154.2	
City	**Average concentration**	Kothai et al. (2011)
Mumbai	$PM_{2.5}$ = 42	
City	**Average mass concentration**	Yadav and Satsangi (2013)
Pune	$PM_{2.5}$ = 72.3 ± 31.3 PM_{10} = 113.8 ± 51.6	
Barapani, foot-hills of NE-Himalaya	Wintertime $PM_{2.5}$ = 39–348	Rajput et al. (2013)
City	**Annual average concentrations (July 2009 to June 2010)**	Deshmukh et al. (2013)
Raipur	$PM_{2.5}$ = 150.9 ± 78.6 PM_{10} = 270.5 ± 105.5 PM_1 = 72.5 ± 39.0	
City	$PM_{2.5}$ = 120.0 ± 103.0	Tiwari et al. (2014)
Delhi	PM_{10} = 222.0 ± 142.0	
City	**Annual mean concentration**	Murari et al. (2015)
Varanasi	$PM_{2.5}$ = 100.0 ± 29.6 PM_{10} = 176.1 ± 85.0 **Monthly average concentration** $PM_{2.5}$ = 43.6–318.5 μg/m^3 PM_{10} = 50.1–154.0 μg/m^3	
City	**Mean mass concentrations**	Tiwari et al. (2015)
Delhi	$PM_{2.5}$ = 118.3 ± 81.7 PM_{10} = 232.1 ± 131.1	
Vishakhapatnam	Annual average concentration PM_{10} = 70.4 ± 29.7	Guttikunda et al. (2015)
City	**Annual average concentration**	
Chennai	$PM_{2.5}$ = 121.5 ± 45.5	
Patiala	$PM_{2.5}$ mass concentration = 60–390 (October–November) $PM_{2.5}$ mass concentration = 18–123 (April–May)	Rajput et al. (2016)
City	**Average concentration**	Sen et al. (2016)
Patiala	$PM_{2.5}$ = 55.4 ± 13.5	
City	**Average concentration**	
Lucknow	$PM_{2.5}$ = 51.5 ± 17.7 PM_{10} = 182.2 ± 58.0	
City	**Average concentration**	
Kolkata	$PM_{2.5}$ = 47.6 ± 9.3 PM_{10} = 66.7 ± 17.0	
City	**Average concentration**	
New Delhi	$PM_{2.5}$ = 61.8 ± 18.6 PM_{10} = 127.4 ± 62.2	
City	**Average concentration**	
Nagpur	$PM_{2.5}$ = 35.2 ± 18.4 PM_{10} = 53.9 ± 23.7	
City	**Average concentration**	
Varanasi	$PM_{2.5}$ = 52.5 ± 28.6 PM_{10} = 139.6 ± 68.0	
Mid-IGP region	Annual mean PM_{10} = 206.2 ± 77.4	Sharma et al. (2016)
City	**24-h mean concentration**	Mahapatra et al. (2018)
Kolkata	PM_{10} = 97.00	
City	**Annual mean concentration**	
Bhubaneswar	$PM_{2.5}$ = 30.6 ± 22.1 PM_{10} = 83.3 ± 30.6	

Table 1 (*continued*)

Study Area	PM Values (μg/m^3)	References
City	**PM_1, average mass concentration**	Rajput et al. (2018)
Kanpur	During non-foggy conditions = 247 ± 113 During foggy conditions = 107 ± 58	
City	**24 h mean concentration**	Islam and Saikia (2020)
Jorhat, Northeast India	$PM_{2.5}$ = 121 ± 49 PM_{10} = 153 ± 45	
City	**24-h mean concentration**	Shaw and Gorai (2020)
Delhi (ITO)	$PM_{2.5}$ = 71.9 PM_{10} = 11.90	
Cities	**24-h mean concentration**	Yadav et al. (2022)
Jaipur	$PM_{2.5}$ = 51 ± 10	
Jodhpur	$PM_{2.5}$ = 78 ± 21	
Kota	$PM_{2.5}$ = 45 ± 13	
Udaipur	$PM_{2.5}$ = 49 ± 12	
Ajmer	$PM_{2.5}$ = 47.3 ± 13	
Alwar	$PM_{2.5}$ = 47.2 ± 8	
Cities	**Average concentration**	Guttikunda and KA (2022)
Jammu	$PM_{2.5}$ = 39.1	
Srinagar	$PM_{2.5}$ = 25.8	
Shimla	$PM_{2.5}$ = 25.7	
Dehra Dun	$PM_{2.5}$ = 35.2	
Amritsar	$PM_{2.5}$ = 66.2	
Ludhiana	$PM_{2.5}$ = 68.7	
Gurgaon	$PM_{2.5}$ = 93	
Meerut	$PM_{2.5}$ = 68.1	
Delhi	$PM_{2.5}$ = 102.1	
Agra	$PM_{2.5}$ = 92.6	
Allahabad	$PM_{2.5}$ = 76.9	
Ghaziabad	$PM_{2.5}$ = 79.1	
Noida	$PM_{2.5}$ = 92.3	
Kanpur	$PM_{2.5}$ = 92.6	
Lucknow	$PM_{2.5}$ = 93	
Varanasi	$PM_{2.5}$ = 84.5	
Patna	$PM_{2.5}$ = 75.8	
Kolkata	$PM_{2.5}$ = 47.3	
Asansol	$PM_{2.5}$ = 55.8	
Ahmedabad	$PM_{2.5}$ = 44.6	
Rajkot	$PM_{2.5}$ = 36.2	
Surat	$PM_{2.5}$ = 32	
Vadodara	$PM_{2.5}$ = 39.4	
Udaipur	$PM_{2.5}$ = 40.2	
Jaipur	$PM_{2.5}$ = 58.6	
Jodhpur	$PM_{2.5}$ = 58.2	
Kota	$PM_{2.5}$ = 54.6	
Kohima	$PM_{2.5}$ = 23.2	
Aizawl	$PM_{2.5}$ = 29.4	
Imphal	$PM_{2.5}$ = 27.4	
Agartala	$PM_{2.5}$ = 59.5	
Dispur	$PM_{2.5}$ = 29.2	
Shillong	$PM_{2.5}$ = 25.2	
Raipur	$PM_{2.5}$ = 53.4	
Durg-Bhilai	$PM_{2.5}$ = 59.4	
Ranchi	$PM_{2.5}$ = 44.3	
Dhanbad	$PM_{2.5}$ = 54.1	
Bokaro	$PM_{2.5}$ = 55.6	
Jamshedpur	$PM_{2.5}$ = 51.5	
Nagpur	$PM_{2.5}$ = 40.6	
Nashik	$PM_{2.5}$ = 26.2	
Pune	$PM_{2.5}$ = 25.2	
Cities	**Average concentration**	de Bont et al. (2024)
Ahmedabad	$PM_{2.5}$ ≈ 50 ± 10 μg/m^3	
Bangalore	$PM_{2.5}$ ≈ 35 ± 10 μg/m^3	
Chennai	$PM_{2.5}$ ≈ 40 ± 10 μg/m^3	
Delhi	$PM_{2.5}$ ≈ 140 ± 50 μg/m^3	
Hyderabad	$PM_{2.5}$ ≈ 60 ± 20 μg/m^3	
Kolkata	$PM_{2.5}$ ≈ 90 ± 30 μg/m^3	
Mumbai	$PM_{2.5}$ ≈ 40 ± 10 μg/m^3	
Pune	$PM_{2.5}$ ≈ 30 ± 10 μg/m^3	
Shimla	$PM_{2.5}$ ≈ 25 ± 10 μg/m^3	
Varanasi	$PM_{2.5}$ ≈ 90 ± 40 μg/m^3	

individualized data on air pollution exposure (Colvile et al., 2001). Traditional fixed-location monitors, while useful for assessing general air quality, often fail to account for the variability in personal exposure resulting from proximity to pollution sources. This limitation can lead to exposure misclassification, which may bias the results of epidemiological studies and affect the accuracy of health impact assessments (Brauer et al., 2002). For example, people living near heavy traffic or industrial areas might experience much higher pollutant levels than what is recorded by stationary monitors in the same region (Brauer et al., 2002; IARC, 2016; Watson et al., 1988).

Recent advancements in microelectronics and manufacturing technologies, such as 3D printing, have facilitated the development of low-cost, wearable air pollution sensors (Bas et al., 2024; Hernández-Gordillo et al., 2021). These sensors represent a significant leap forward in personal exposure monitoring by providing a more personalized approach. Wearable sensors are less burdensome for participants compared to older methods and can more accurately assess individual exposure by accounting for the time-weighted proximity to emission sources (Lin et al., 2022; Tryner et al., 2023; Yun & Licina, 2023). They can track pollutants such as $PM_{2.5}$, volatile organic compounds, NO_2, and ozone in real-time, offering valuable insights into how individuals experience air pollution in their daily lives. These sensors have become available from various manufacturers across North America, Europe, and China. Although their reliability and data quality can vary, they mark a substantial improvement in monitoring personal exposure to air pollutants. Notably, these advancements have also made it feasible to include younger populations, such as children, in exposure studies (Chaudhary et al., 2023). Given that children are particularly vulnerable to the adverse health effects of air pollution, including them in monitoring efforts is crucial for understanding and mitigating the impacts on their health.

3.4. Satellite monitoring and reanalysis datasets

Satellite monitoring has emerged as a valuable tool in the assessment of air quality, complementing traditional ground-based measurements and personal monitoring (Zhu et al., 2023). Satellites provide a broad, global perspective on air pollution, allowing for the observation of large-scale patterns and trends. This capability is particularly useful for areas where ground-based monitoring infrastructure is sparse or non-existent. Satellites equipped with sensors can measure various atmospheric components, including aerosol optical depth (AOD), which serves as a proxy for particulate matter concentrations, particularly $PM_{2.5}$ (Filonchyk et al., 2019; Goyal & Rautela, 2024; Handschuh et al., 2022; Nair et al., 2005). Analysis of these products can estimate ground-level concentrations of pollutants with reasonable accuracy, even in regions with limited monitoring networks (Duc et al., 2022; Li & Zhang, 2019; Zhu et al., 2023). However, satellite measurements come with their own set of challenges. The resolution of satellite data, typically around 0.1° (~10 km), introduces uncertainty in the estimates (Ford & Heald, 2016; Gerboles & Reuter, 2010, pp. 1–40). This spatial resolution may not capture localized pollution hotspots, especially in densely populated urban areas or industrial zones.

To address these challenges, satellite data are often combined with ground-based observations and advanced statistical models to improve accuracy. For example, the reanalysis datasets (Chakraborty et al., 2021, 2022; Randles et al., 2017; Rautela et al., 2024a), which integrate observations from various sources, including satellites, ground-based measurements, and meteorological models, offer a more comprehensive view of air quality. These datasets provide historical and near-real-time estimates of atmospheric conditions and pollutant concentrations, allowing for more detailed spatial and temporal analyses. Reanalysis datasets, such as those produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), the National Oceanic and Atmospheric Administration (NOAA) and NASA Goddard Earth Sciences Data and Information Services Centre (GES DISC), incorporate vast amounts of observational data into a coherent framework (Rautela et al., 2024b; Rautela & Goyal, 2024; Singh et al., 2023). They use assimilation techniques to combine satellite observations with numerical weather prediction models, resulting in high-resolution datasets that can be used to study air quality trends, identify pollution sources, and assess the effectiveness of regulatory measures. The integration of satellite monitoring and reanalysis datasets with personal exposure data enhances the understanding of air pollution impacts. By linking individual exposure assessments from wearable sensors with broad-scale satellite and reanalysis data, researchers can gain insights into how localized pollution sources contribute to overall exposure and health outcomes. This comprehensive approach can inform more targeted and effective air quality management strategies.

4. Impact of air pollution on public health in India

In recent years, India has consistently ranked among the countries with the highest levels of air pollution globally (Yu et al., 2023). According to the Global Burden of Disease (GBD) study, air pollution is a leading risk factor for disease burden in India, contributing to millions of deaths annually (McDuffie et al., 2021). The GBD 2019 report estimated that over 1.67 million deaths in India were attributable to air pollution, including ambient (outdoor) and household air pollution, making it the second leading risk factor for mortality in the country, after high blood pressure (Yadav et al., 2021).

Epidemiological studies in India have provided substantial evidence linking air pollution to a wide range of health effects, particularly respiratory and cardiovascular diseases (Lee et al., 2014; Yadav et al., 2021). Fine particulate matter ($PM_{2.5}$) is of particular concern due to its ability to penetrate deep into the lungs and enter the bloodstream, leading to systemic inflammation and oxidative stress (Behinaein et al., 2023; Jiang et al., 2016; Larkin & Hystad, 2017; Yadav et al., 2021). The high levels of $PM_{2.5}$ in Indian cities, often exceeding the WHO guidelines, are associated with increased rates of respiratory infections, chronic obstructive pulmonary disease (COPD), asthma, and lung cancer. A recent study showed Delhi was one of the most polluted cities in the world, found that long-term exposure to high $PM_{2.5}$ levels was associated with a 54% increase in the risk of all-cause mortality, a 43% increase in cardiovascular mortality, and a 58% increase in respiratory mortality. Additionally, a city-level health assessment in India reveals that 7.2% of daily deaths in these urban areas are attributable to $PM_{2.5}$ levels exceeding the WHO guidelines, with Delhi experiencing the highest fraction of deaths linked to $PM_{2.5}$ pollution (de Bont et al., 2024). The impact of air pollution on cardiovascular health is particularly alarming, as numerous studies have established a strong connection between high air pollution exposure and an elevated risk of heart attacks, strokes, hypertension, and other cardiovascular diseases (Jalali et al., 2021; Palacio et al., 2023; Pope et al., 2004). Fine particulate matter, such as $PM_{2.5}$, can provoke cardiovascular events by causing systemic inflammation, oxidative stress, and endothelial dysfunction (Krittanawong et al., 2023). A large cohort study found that long-term exposure to $PM_{2.5}$ significantly increased the risk of ischemic heart disease, stroke, and heart failure, with every 10 μg/m^3 rise in $PM_{2.5}$ concentration leading to a 12–14% increase in the risk of cardiovascular mortality (Alexeeff et al., 2021; Hayes et al., 2020; Krittanawong et al., 2023).

In addition to respiratory and cardiovascular diseases, air pollution has been linked to adverse pregnancy outcomes. Pregnant women exposed to high levels of air pollution are at an increased risk of complications such as low birth weight, preterm birth, and developmental delays (Fu et al., 2024). These adverse outcomes are believed to result from the effects of pollutants like $PM_{2.5}$ and NO_2 on placental function and fatal development (Fussell et al., 2024). A study conducted in Tamil Nadu state found that pregnant women exposed to high levels of $PM_{2.5}$ were more likely to give birth to infants with decrease in low birth weight of 4g per 10-μg/m^3 increase in $PM_{2.5}$ exposures (Balakrishnan et al., 2018). Similarly, a study in China found that for each interquartile range (IQR) increase in $PM_{2.5}$ exposure, the risk of preterm birth rose by 4.84%, while the excess risk associated with SO_2 exposure was 3.65% (Liu et al., 2018).

The burden of air pollution is not evenly distributed across the population, with certain groups being more vulnerable to its effects. Children, the elderly, and individuals with pre-existing health conditions are particularly susceptible to the adverse effects of air pollution (Pandey et al., 2021a). Children are at a higher risk due to their developing respiratory systems and higher rates of physical activity, which increase their exposure to air pollutants (Aithal et al., 2023). Studies have shown that children living in highly polluted areas are more likely to suffer from respiratory infections, asthma, and impaired lung function (Aithal et al., 2023; Esposito et al., 2014). A recent study conducted in Lanzhou, China found that 1 μg/kg-d increase in the 5-year average daily dose (ADD) of $PM_{2.5}$ was associated with significant decreases in forced vital capacity (FVC) by 10.49 mL and in forced expiratory volume in 1 s (FEV1) by 7.68 mL, with the strongest impact observed in the year immediately preceding the lung function tests, particularly among girls (Li et al., 2020).

The Global Burden of Disease (GBD) datasets have played a crucial role in quantifying the health impacts of air pollution in India (Pandey et al., 2021a). The GBD project, a comprehensive effort led by the Institute for Health Metrics and Evaluation (IHME), provides estimates of mortality and disability-adjusted life years (DALYs) attributable to various risk factors, including air pollution (GBD & Global Burden of Disease, 2021). The GBD 2019 report estimated that air pollution was responsible for 17.8% of all deaths in India, with ambient $PM_{2.5}$ being the leading contributor (Pandey et al., 2021a). The report also highlighted the significant burden of household air pollution, particularly in rural areas where biomass fuels are commonly used for cooking. Household air pollution was estimated to contribute to 26.4% of all deaths in children under five years old, primarily due to lower respiratory infections.

The health impacts of air pollution in India are not limited to urban areas. Rural areas, where a significant portion of the population resides, also face substantial exposure to air pollutants, particularly from household sources (Manisalidis et al., 2020). The use of solid fuels such as wood, dung, and crop residues for cooking and heating is a major source of household air pollution in rural India. Recent studies found that 0.5 to 1.35 million deaths are attributed to IAPE globally (Chowdhury et al., 2023), with approximately 0.8 million of these deaths occurring in India (CAPC, 2019). The health effects of household air pollution are particularly severe for women and children, who spend more time indoors and are therefore more exposed to indoor air pollution. However, death rate is decrease due to IAPE is decrease by 64·2% from 1990 to 2019 (Pandey et al., 2021a)

One of the major challenges in addressing the health impacts of air pollution in India is the lack of comprehensive and reliable data on air quality and health outcomes (Gurjar et al., 2016). While air quality monitoring networks have been established in several cities, there is still a significant gap in data coverage, particularly in rural and remote areas (Guttikunda, Ka, et al., 2023). This lack of data makes it difficult to accurately assess the exposure of different populations to air pollution and to evaluate the effectiveness of interventions. Moreover, health data in India is often incomplete or not systematically collected, which limits the ability to conduct robust epidemiological studies (Narain, 2016; Selvaraj et al., 2022). To address these challenges, there is a need for greater investment in air quality monitoring and health data collection in India. Expanding the network of air quality monitoring stations to cover more regions, including rural areas, would provide a more accurate picture of air pollution levels and their spatial distribution. Additionally, integrating air quality data with health data would enable researchers to conduct more detailed and comprehensive studies on the health impacts of air pollution. This would require collaboration between different government agencies, research institutions, and public health organizations.

In recent years, there have been several initiatives aimed at reducing air pollution in India and mitigating its health impacts. The National Clean Air Programme (NCAP), launched by the MoEF&CC in 2019, aims to reduce $PM_{2.5}$ and PM_{10} levels by 20–30% by 2024, relative to 2017 levels (Dahiya & Sivalingam, 2023). The NCAP includes measures such as strengthening the air quality monitoring network, promoting cleaner technologies, and raising public awareness about the health risks of air pollution. However, the effectiveness of these measures will depend on their implementation and the level of commitment from all stakeholders. Despite these efforts, significant challenges remain in addressing the health impacts of air pollution in India. One of the key challenges is the enforcement of existing regulations and policies. While there are strict emission standards for industries and vehicles, compliance with these standards is often weak, particularly in smaller cities and rural areas. Strengthening the enforcement of environmental regulations and ensuring that industries and vehicles adhere to emission standards is crucial for reducing air pollution levels and protecting public health.

5. Case study on the health assessment through short- and long-term air pollution in India

5.1. Datasets

This study leverages MERRA-2 reanalysis data obtained from the NASA GESDISC DATA ARCHIVE application (Randles et al., 2017; Rautela & Goyal, 2024), focusing on datasets with spatial-temporal resolutions of 0.5° × 0.625° and an hourly interval, spanning from January 1, 1980, to December 31, 2023. The analysis includes fifty distinct variables related to atmospheric aerosols, encompassing three dimensions with time, latitude, and longitude. Specifically, dimensions such as time (t), latitude (ϕ), longitude (λ), and variables such as black carbon surface mass concentration (BCSMASS), dust surface mass concentration-$PM_{2.5}$ ($DUSMASS_{25}$), organic carbon surface mass concentration (OCSMASS), sea salt surface mass concentration-$PM_{2.5}$ (SSSMASS25), and SO_4 surface mass concentration (SO_4SMASS) were extracted using a climate data operator (CDO). To adapt the data for daily analysis, the mean of 24-h observations was computed, converting the original hourly temporal resolution into a daily temporal resolution. The $PM_{2.5}$ concentration (μg/m^3) for each grid cell was then calculated as per Buchard et al. (Buchard et al., 2016) and Provençal et al., (Provençal et al., 2017) (Eq. (1)):

$$PM_{2.5} = (BCSMASS + DUSMASS25 + OCSMASS + SSSMASS25 + 1.375 \times SO_4SMASS) \times 10^9 \quad (1)$$

Where, BCSMASS, $DUSMASS_{25}$, OCSMASS, $SSSMASS_{25}$, and SO_4SMASS represent the surface mass concentrations of black carbon, dust, organic carbon, sea salt, and sulfates, respectively, in kg/m^3. The multiplication by 10^9 is applied to convert these mass concentrations from kg/m^3 to μg/m^3, as the variables' concentration values are fractional. The result, $PM_{2.5}$, represents the particulate matter concentration in μg/m^3, providing a critical measure for assessing air quality.

The Global Burden of Disease (GBD) data, an extensive and comprehensive source for assessing global health trends, was utilized in this study to analyse the prevalence and impact of several critical health conditions across India (GBD & Global Burden of Disease, 2021). The data was thoroughly sourced from the Global Health Data Exchange (GHDx) platform, specifically from the GBD 2021 dataset (GBD and Global Burden of Disease, 2021) (https://ghdx.healthdata.org/gbd-2021). The focus of this analysis was on four significant categories of mortality due to 'respiratory infections and tuberculosis,' 'neurological disorders,' 'cardiovascular diseases,' and 'chronic respiratory diseases' (Fig. S1). These categories were selected due to their substantial burden on public health and their relevance to ongoing healthcare challenges in India. The dataset spans a comprehensive

Table 2
Definition of extreme pollution indices (Rautela & Goyal, 2025).

Indicator	Indicator name	Indicator definitions	Units
$MPM_{2.5}$	Mean Annual Pollution through $PM_{2.5}$	Mean annual total pollution through $PM_{2.5}$	μg/m^3
$PM_{2.5}D$	Polluted days through $PM_{2.5}$	Number of days when $PM_{2.5}$ > 40 μg/m^3	days
$MAPM_{2.5}$	Maximum 1-day pollution amount	Annual maximum 1-day pollution through $PM_{2.5}$	μg/m^3
$PM_{2.599p}$	Heavily polluted regions	When total annual pollution >99th percentile	μg/m^3

period from 1980 to 2021, allowing for an in-depth longitudinal analysis of these health conditions over more than four decades. This temporal range is crucial for understanding the trends, improvements, or deteriorations in public health over time, and how various socio-economic, environmental, and healthcare interventions may have influenced these trends. The data encompasses all states and union territories of India, ensuring a wide geographical coverage that includes diverse population groups with varying socio-economic statuses, healthcare access levels, and environmental conditions. This granularity is essential for identifying state-specific health challenges and formulating targeted public health interventions. Moreover, the analysis was conducted separately for both male and female populations, acknowledging the gender-specific health disparities within these disease categories.

5.2. Computation of short- and long-term pollution extremes

The present study proposed novel four major air pollution extremes (APE) to address the short and long-term effects of air pollution on health (Rautela & Goyal, 2025). The proposed APEs are mean annual $PM_{2.5}$ concentrations ($MPM_{2.5}$) and days when $PM_{2.5}$ concentrations are greater than 40 μg/m^3 ($PM_{2.5D}$) for long-term and maximum annual $PM_{2.5}$ concentrations ($MAPM_{2.5}$) and 99th percentile for $PM_{2.5}$ concentrations ($PM2.5_{99p}$) for short term over India during 1980–2023 (Table 2). These APEs provide a comprehensive framework to evaluate the health impacts of air pollution by distinguishing between long-term and short-term exposure effects. $MPM_{2.5}$ and $PM_{2.5}D$ focus on sustained exposure, which is critical for understanding chronic respiratory and cardiovascular diseases, while $MAPM_{2.5}$ and $PM_{2.599p}$ capture acute exposure episodes, aiding in the assessment of short-term health crises, such as respiratory distress and hospital admissions. Further, $PM_{2.5}$ statistics and filtering the data for 1980–1990 and 2010–2020. Ten-year rolling averages for $PM_{2.5}$ extremes ($MPM_{2.5}$, $PM_{2.5D}$, $MAPM_{2.5}$ and $PM_{2.599p}$) are calculated for each state and UTs. These averages are then compared between the two periods to determine percentage changes.

5.3. Interrelationships between pollution extremes and mortality through diseases

To examine the relationship between $PM_{2.5}$ extremes and mortality through these diseases' linear regression and multi-linear analysis were carried out. The analysis is conducted separately for male and female populations to account for potential gender-specific differences in disease susceptibility. For each disease, the methodology explores its relationship with 4 p.m.$_{2.5}$ variables: MPM_{25}, PM_{25D}, $MAPM_{25}$ and $PM_{2599p.}$ Linear regression models are then fitted for each gender and mortality through various disease combinations. However multi-linear regression uses the combined impact of these $PM_{2.5}$ variables on disease-specific mortality rates for each gender. The regression models used the $PM_{2.5}$ metrics as independent variables and mortality rates as the dependent variable. The model's fit was evaluated using the R^2 statistic, which measures the proportion of variance in mortality explained by $PM_{2.5}$ variables. This approach provides insights into the complex interactions between air pollution and public health, highlighting the necessity of gender-specific and disease-specific strategies in addressing $PM_{2.5}$-related health risks.

5.4. Deep learning model for the modelling of mortality

Deep learning models, such as CNNs and LSTMs, can predict or forecasting variables by learning complex, non-linear patterns and dependencies within data, enabling them to effectively handle high-dimensional inputs, temporal sequences, and spatial relationships (Shaikh et al., 2022a, 2022b). These models are mostly used in the healthcare sector for disease prediction, patient outcome forecasting, medical image analysis, drug discovery, and personalized treatment planning, leveraging their ability to analyse complex datasets with high accuracy (Ayub Khan Benazir Bhutto Shaheed University Lyari Karachi et al., 2022; Shaikh et al., 2022c). This study used, a CNN model to predict mortality through various diseases by the extremes based on $PM_{2.5}$ data. It merges state-wise $PM_{2.5}$ statistics and health data, focusing on four diseases: cardiovascular diseases, neurological disorders, respiratory infections, and chronic respiratory diseases. The data is filtered for each disease, and features (MPM_{25}, PM_{25D}, $MAPM_{25}$ and PM_{2599p}) are standardised. A sliding window approach generates data sequences, which are then split into training and testing sets. The model, a combination of a 1D Convolutional Neural Network (Conv1D) and a Dense layer, is trained to predict mortality for each disease and for males and females, respectively (Fig. 2). The convolutional layer captures temporal patterns by applying filters across sequences of 5 consecutive data points, followed by a max-pooling layer that reduces the data's dimensionality while preserving important features. After the convolutional operations, the flattened output is passed through a fully connected Dense layer with 50 units, allowing the model to learn complex relationships between the features. The final output layer is a single neuron that predicts the mortality value for each state-year pair, corresponding to the specific disease and gender. After training, the model's predictions are scaled back to their original values, and the absolute values are used to ensure non-negative predictions (Rautela et al., 2024a).

Further, a different CNN architecture used in this study is designed to effectively model the complex relationships between environmental factors and health outcomes (Fig. 2). It begins with a series of 1D convolutional layers, each designed to capture local patterns within the data. The first convolutional layer utilizes 64 filters, followed by batch normalisation to stabilise the training process and dropout to mitigate overfitting (Meghani et al., 2023; Singh & Goyal, 2023). The second block contains 128 filters, continuing the process of learning more abstract features, with additional dropout layers to enhance model robustness (Rautela et al., 2024a). A max-pooling layer follows, which helps reduce the dimensionality of the feature maps while preserving important information. The third convolutional layer, with 256 filters, deepens the model's ability to learn intricate patterns in the data. After the convolutional layers, the model is flattened, transforming the output into a format suitable for dense layers. The dense layers employ L_2 regularization and dropout to prevent overfitting, providing a more generalised model that can adapt to new data (Rautela et al., 2024b). The model is compiled with the Adam optimizer, known for its adaptive learning rate, and trained using the mean squared error loss function, which is appropriate for regression tasks. The training process runs for ~150 epochs with a batch size of 16, during which the model's performance is continually assessed using a validation split of 10% (Table 3). This ensures the model's weights are optimised for training data and generalisation to unseen data.

5.5. Model evaluation

The evaluation of models is conducted through a detailed process that involves calculating and analysing several key performance metrics: Mean Squared Error (MSE: loss function), R-squared (R^2), Nash-Sutcliffe Efficiency (NSE), and Percent Bias (PBIAS) (Rautela et al., 2022; Sofi

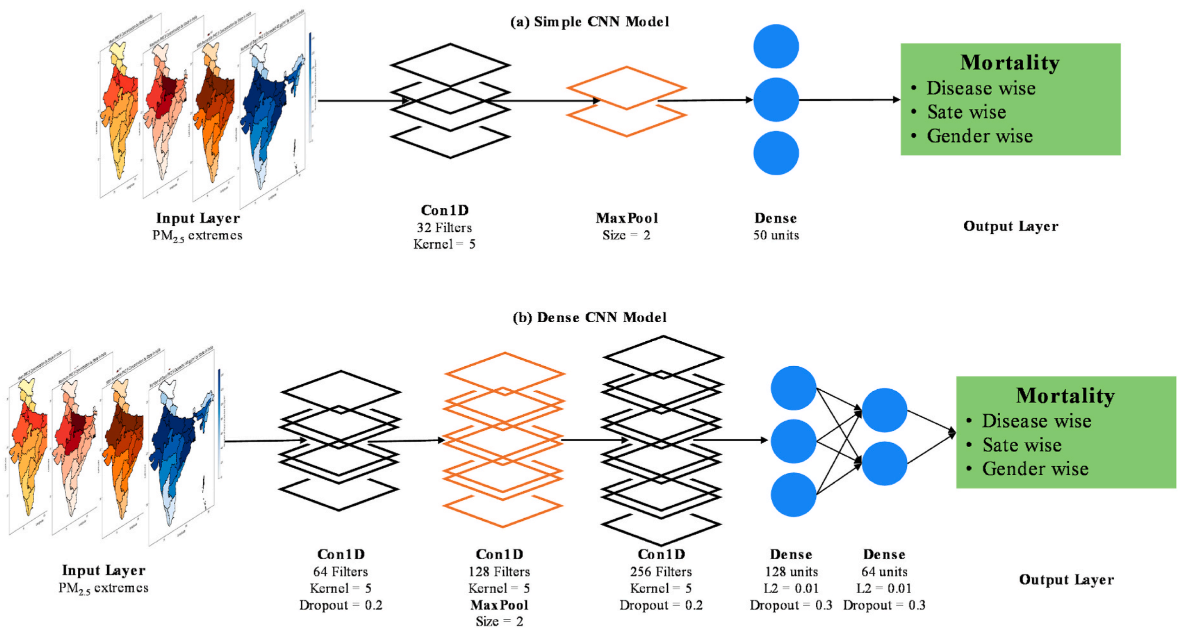

Fig. 2. CNN architecture for the prediction of mortality.

et al., 2023). These metrics are computed for both training and testing datasets to assess the model's accuracy and predictive performance. The MSE measures the average error magnitude between observed and predicted values, while the R^2 indicates the proportion of variance explained by the model. NSE evaluates the model's predictive power relative to a mean-based model, with values closer to 1 indicating better performance. PBIAS quantifies the overall bias of the predictions, with positive values suggesting underestimation and negative values indicating overestimation.

Table 3
Hyperparameters used in the CNN model for disease prediction.

S. No.	Hyperparameters	Description	Value used
1	Batch size	The number of images processed per training iteration.	16
2	Kernel size	The size of the convolutional filter for the Conv1D layers.	3
3	Learning rate	Step size for weight updates during training.	0.0002
4	Optimizer	Algorithm refining model parameters based on gradients.	Adam
5	β1	Controls the decay rate for the first moment estimate of the gradient.	0.9
6	β2	Controls the decay rate for the second moment estimate of the gradient.	0.99
7	Loss function	Measures prediction accuracy.	Mean Squared Error (MSE)
8	Number of hidden layers	Depth of the neural network architecture.	6 (3 Conv1D layers + 1 Flatten layer + 2 Dense layers)
9	Activation function	Introduces non-linearity.	ReLU (in Conv1D and Dense layers)
10	Pooling size	The size of the pooling window in the MaxPooling1D layer.	2
11	Regularization	Regularization technique to reduce overfitting.	$L_2(0.01)$
12	Epochs	Number of training iterations.	150
13	Validation split	Fraction of data to be used for validation during training.	0.1

5.6. *Results and discussion*

5.6.1. *Extreme pollution indices*

In the Indian subcontinent, there is significant spatiotemporal variation in $PM_{2.5}$ concentrations (Fig. 3). From 1980 to 2023, the $MPM_{2.5}$ concentrations across all Indian states exceeded the World Health Organization (WHO) revised guidelines of 5 μg/m^3 and the U.S. Environmental Protection Agency (USEPA) guidelines of 12 μg/m^3 (EPA, 2020; IHME, 2018; van Donkelaar et al., 2010; van Donkelaar et al., 2015; Yu et al., 2023). However, according to the Central Pollution Control Board (CPCB) and National Ambient Air Quality Standards (NAAQS) guidelines, only the northern states exceeded the threshold of 40 μg/m^3 (Board, 2014). In terms of population exposure, 99.36% of the Indian population is exposed to $MPM_{2.5}$ levels above WHO recommendations. The rolling averages between 1980-1990 and 2010–2020 indicate a rapid increase in $PM_{2.5}$ concentrations across India, especially in the Indo-Gangetic Plains (IGP) and eastern states (Fig. 4a). In these regions, $PM_{2.5}$ concentrations have more than doubled, showing an increase of over 200% compared to the 1980–1990 decade (Guttikunda & KA, 2022). The higher $PM_{2.5}$ concentrations are primarily due to a combination of anthropogenic activities and regional meteorological conditions (Bran & Srivastava, 2017). Northern India, particularly the Indo-Gangetic Plain, suffers from severe air pollution due to dense industrial activities, high vehicular emissions, extensive agricultural stubble burning, and widespread biomass use for cooking, driven by the region's high population density (Tripathi et al., 2024). Additionally, the topography and meteorological conditions, such as low wind speeds and winter temperature inversions, trap pollutants close to the ground, worsening air quality (Zhou et al., 2024). States like Delhi, Uttar Pradesh, Punjab, and Haryana are particularly affected by these factors. Conversely, southern and northeastern states generally show lower $PM_{2.5}$ concentrations, likely due to lower levels of industrialization, better air circulation, and more extensive green cover, which aids in dispersing pollutants. However, in rural areas, indoor air pollution from biomass burning still significantly contributes to overall $PM_{2.5}$ concentrations.

Similarly, the $MAPM_{2.5}$ exhibits greater variations than $MPM_{2.5}$ (Fig. 3b). States with higher forest cover, such as Madhya Pradesh and the northeastern states, show $MAPM_{2.5}$ levels between 300 and 400 μg/m^3, likely due to wildfires. The study also observed a drastic change in rolling average $MAPM_{2.5}$ between the two decades, with increases of up

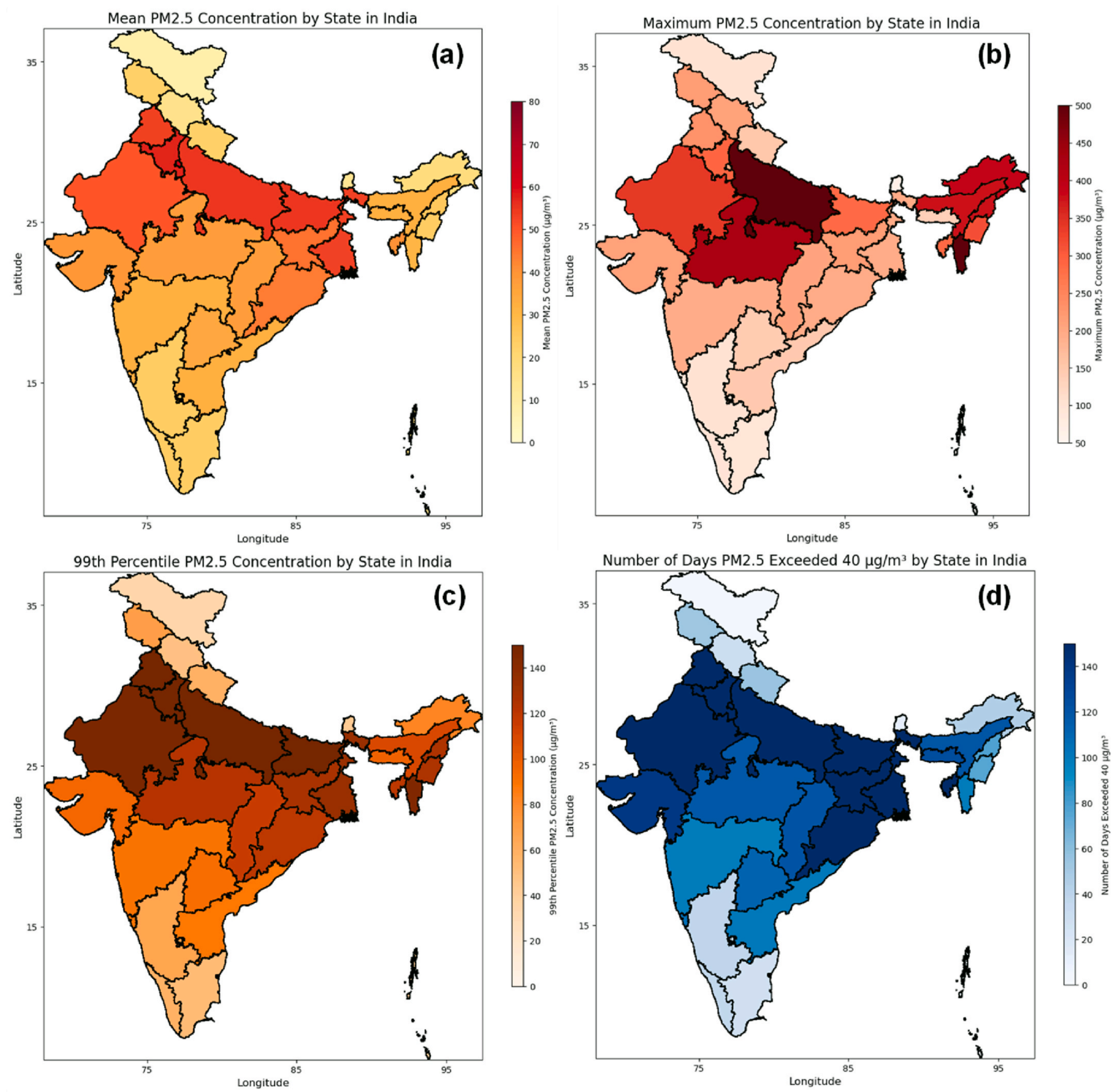

Fig. 3. State-wise pollution extremes (a) Mean Annual $PM_{2.5}$ (b) Maximum Annual $PM_{2.5}$ (c) 99th Percentile of $PM_{2.5}$ and (d) Number of days when $PM_{2.5}$ > NAAQS limit (40 μg/m^3).

to 400% in the eastern and northeastern regions of India (Fig. 4b). In terms of extreme polluted days, $PM_{2.599p}$ shows higher values in central and northern to northeastern regions compared to southern states (Fig. 3c). Similarly, the rolling average changes are also higher in these states (Fig. 4c). Regarding exposure ($PM_{2.5D}$), the IGP and eastern regions experience 120–150 days annually where $PM_{2.5}$ levels exceed the NAAQS limit, while central regions have 80–100 days, and southern and northern states have 20–40 days (Fig. 3d). However, there has been a drastic increase in polluted days across India, with a sixfold rise from 1980 to 1990 to 2010–2020 (Fig. 4d). The rising number of extreme polluted days, predominantly in central and northern states, demonstrates the growing public health risk from sustained air quality deterioration (Yu et al., 2023). The substantial increase in $PM_{2.5}$ concentrations, particularly in the IGP and eastern states, underscores the interplay between anthropogenic activities and climatic factors, necessitating region and sector-specific policy responses as highlighted by Ganguly et al. (Ganguly et al., 2020).

5.6.2. $PM_{2.5}$ effect on health

The regression analysis of the $MPM_{2.5}$ reveals that neurological disorders and chronic respiratory diseases exhibit the strongest correlations with R^2 values ranging from 0.18 to 0.21 for both males and females (Fig. S2). Conversely, respiratory infections and tuberculosis show the weakest correlations, with R^2 values between 0.07 and 0.09. Cardiovascular diseases fall in between, displaying a moderate correlation with R^2 values of 0.15–0.16 (Fig. S2). However, the R^2 values for the

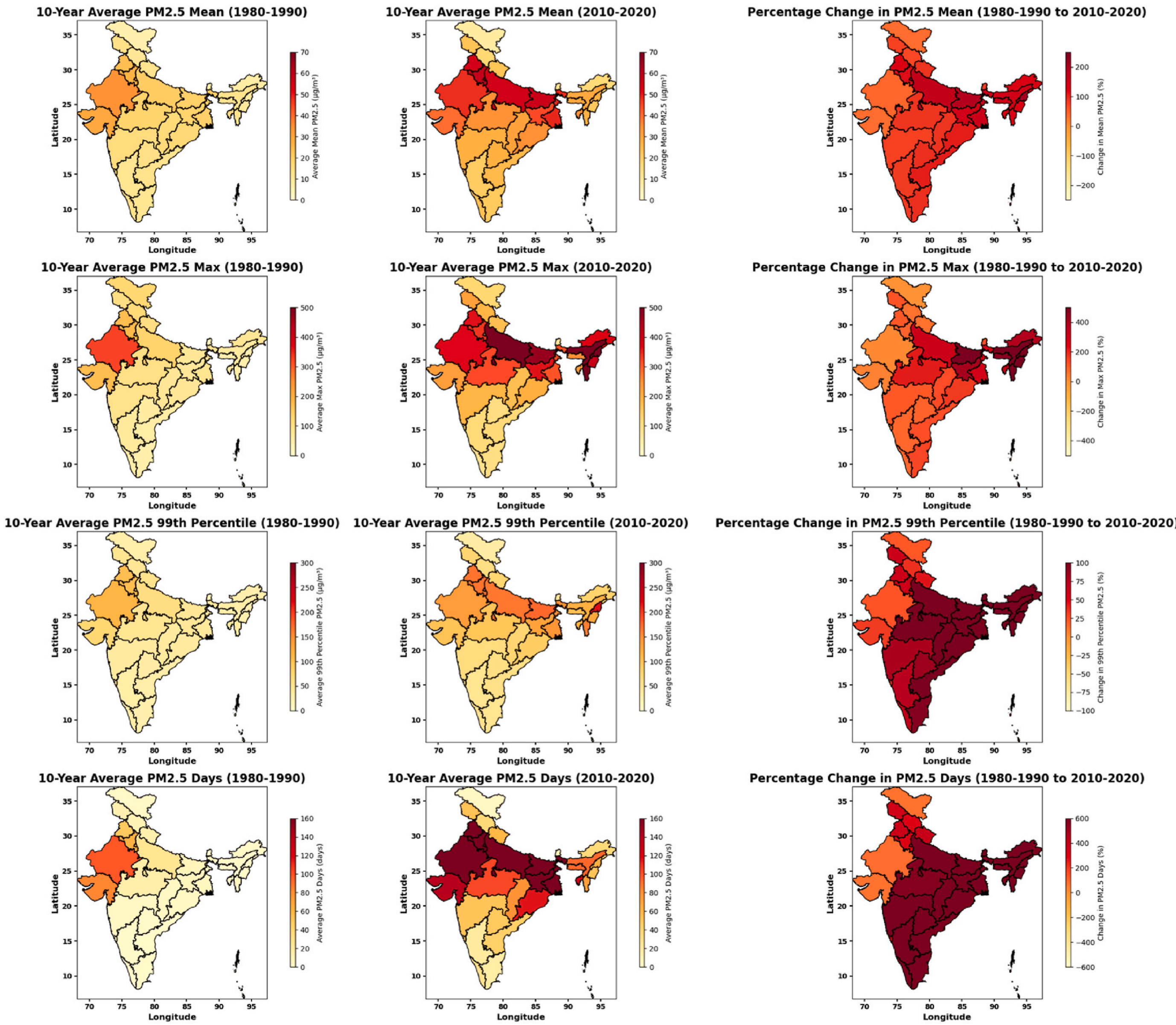

Fig. 4. State-wise decadal rolling averages [(1980–1990) and (2010–2020)] of various $PM_{2.5}$ extremes and their percentage change.

$MAPM_{2.5}$ suggest generally weak relationships across all health outcomes, ranging from 0.01 to 0.06 (Fig. S3). Chronic respiratory diseases present the highest correlation with $R^2 = 0.06$, while cardiovascular diseases show the lowest, with R^2 values between 0.01 and 0.02 (Fig. S3). For $PM_{2.599p}$, R^2 values suggest weak to moderate correlations across all health outcomes for both genders (Fig. S4). Chronic respiratory diseases show the strongest relationship with R^2 values between 0.09 and 0.10, while respiratory infections and tuberculosis display the weakest correlation with R^2 values between 0.02 and 0.03 (Fig. S4). The wide scattering of data points underscores significant variability, with minimal gender differences observed in R^2 values and trend line slopes across health outcomes. In the case of $PM_{2.5D}$, the R^2 values indicate moderate correlations, with chronic respiratory diseases and neurological disorders showing better relationships ($R^2 = 0.14$ to 0.16) (Fig. S5). Cardiovascular diseases and respiratory infections/tuberculosis exhibit weaker correlations with R^2 values from 0.04 to 0.10 (Fig. S5). Despite this, the trend lines display a positive slope throughout all the extremes are associated with increased rates of these health conditions. The data points, although scattered, generally follow the upward trend, with consistent relationships observed between males and females.

Combining all indices through multivariate analysis reveals some improvements in R^2 values but still indicates limited predictive accuracy (Fig. S6). Specifically, respiratory infections and tuberculosis exhibit weak predictive relationships with R^2 values of 0.17 for males and 0.15 for females. Neurological disorders show a slightly better performance, with R^2 values of 0.32 for males and 0.30 for females. Cardiovascular diseases and chronic respiratory diseases exhibit moderate predictive power, with R^2 values of 0.30 and 0.24 to 0.26, respectively, for both genders. The red diagonal line in each plot illustrates the ideal scenario where predicted values perfectly match actual values. However, the data points' spread around this line highlights the model's limited predictive accuracy, particularly for respiratory infections and tuberculosis. To enhance predictive accuracy, we developed a CNN model with one dense layer. This model achieved an impressive R^2 value of 0.776 across all plots, demonstrating robust predictive capability (Fig. 5). The model's performance is stratified by state, gender, and individual disease, with data points generally clustering along the diagonal. This indicates a reasonable fit across various regions, though some regional disparities in prediction accuracy remain.

Furthermore, we developed denser CNN model with 3 layers to

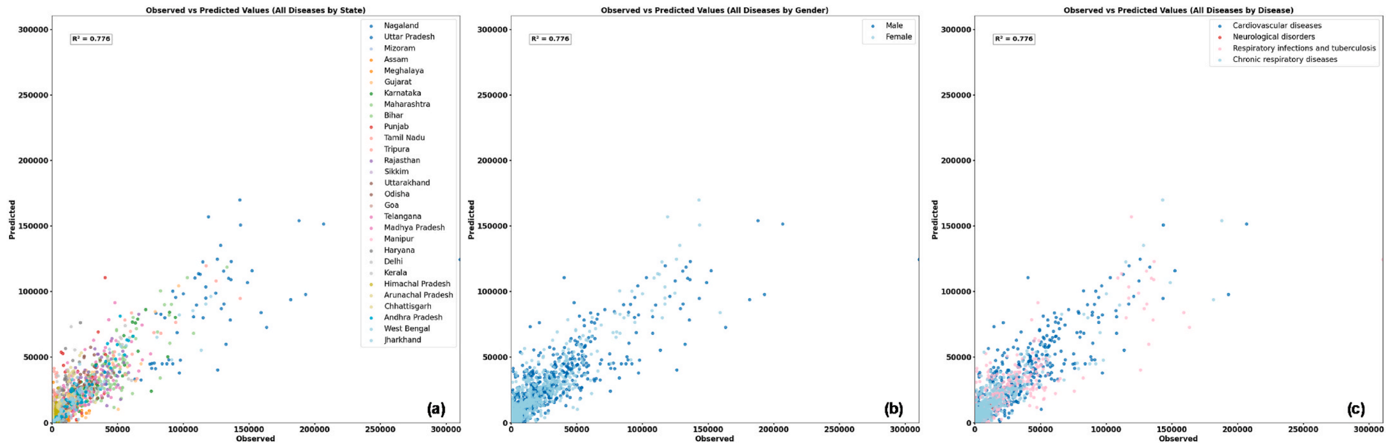

Fig. 5. Observed and Predicted values of mortality based on CNN model (a) State-wise (b) Gender-wise and (c) Disease-wise.

predict spatio-temporal gender-wise mortality rate through various disease for each state. For all the disease the model shows R^2 value ranges in between 0.84-0.94 and 0.84–0.94 for males and females respectively. Figs. S6–S9 shows scatter plots and temporal variations for each disease and respective gender. The time series graphs reveal fluctuations in mortality rates, with some notable spikes, particularly in recent years. There are slight differences between training and testing data predictions, especially visible in the females. However, the spatial variations showed a clear north south divide with northern states, particularly Uttar Pradesh, consistently showing higher mortality rates (dark red) compared to southern states for respiratory infections and tuberculosis and chronic respiratory for both training and testing phase (Fig. 6). Additionally, neurological disorders and cardiovascular mortality patterns show a more complex distribution. Several states, including Uttar Pradesh in the north, Maharashtra in the west, and Tamil Nadu in the south, consistently display high mortality rates. The model's predictions closely match the observed data for both genders and in both training and testing sets, indicating good performance. There are slight variations between genders, with some states showing different intensities of mortality rates. The consistency in patterns between genders implies that geographical factors may play a significant role in mortality rates. While subtle differences exist between observed and predicted maps, especially for smaller states, the overall spatial distribution remains consistent.

Apart from the visual interpretations we have also used the statistical indices to judge the model efficiency of dense CNN using, R^2, NSE and PBIAS respectively. The R^2 values, ranging from 0.84 to 0.96, indicate a strong fit between the predicted and actual values, with particularly high accuracy in the testing phase for Respiratory Infections and Tuberculosis in males ($R^2 = 0.96$) and females ($R^2 = 0.95$). The NSE (Nash-Sutcliffe Efficiency) values mirror the R^2, reinforcing the model's strong predictive performance (Table 4). However, the PBIAS values reveal some biases: negative PBIAS for males in the testing phase of Respiratory Infections and Tuberculosis (−1.94 %) suggests slight overestimation, while a positive PBIAS in other cases, like 15.54 % for females in Neurological Disorders, indicates underestimation (Table 4). The moderate to high PBIAS in certain cases, such as Chronic Respiratory Diseases in males during training (12.31%), suggests that while the model is generally accurate, there is room for improvement in reducing bias and achieving better balance between underestimation and overestimation (Table 4).

The health impacts of $PM_{2.5}$ are evident through its correlation with various diseases, where chronic respiratory conditions and neurological disorders exhibit the strongest relationships. Although individual pollution indices like $MPM_{2.5}$, $MAPM_{2.5}$, and $PM_{2.5}99p$ show varying degrees of association with health outcomes, the overall trends indicate a direct link between high pollution levels and increased disease prevalence. Similar findings have been reported in several studies conducted across India and its surrounding regions, highlighting that exposure to $PM_{2.5}$ poses a significant mortality risk, contributing to approximately one million deaths annually (Chatterjee et al., 2023; de Bont et al., 2024). However, a positive correlation was also observed between specific disease-related mortality rates and air pollution, with a 9% increase in stroke mortality for every 10 μg/m^3 rise in $PM_{2.5}$ levels (Adar & Pant, 2022). The multivariate analysis, despite modest improvements in R^2 values, highlights the complexity of predicting health outcomes solely based on pollution indices. The development and deployment of CNN models have significantly enhanced predictive capabilities, achieving strong R^2 values in most cases. A denser CNN model further refines predictions, demonstrating high accuracy for spatio-temporal, gender-specific mortality forecasts.

Assessing the health impacts of air pollution, discrepancies in estimates are often observed due to the continuous evolution of data, methodologies, and exposure assessment techniques (Rautela & Goyal, 2025). These discrepancies, arising from changes in population dynamics, exposure levels, and epidemiological evidence, can lead to confusion and a lack of credibility in the findings (Evangelopoulos et al., 2020). Such variations in estimates highlight the challenges that policymakers, governments, and the public face when interpreting air pollution data. For example, the approaches taken by major institutions such as the WHO and the Institute for Health Metrics and Evaluation (IHME) to estimate exposure and health outcomes have evolved over time (IHME, 2018; WHO, 2021). These agencies are working towards producing a unified Global Burden of Disease (GBD) study, with a more consistent methodology to reduce confusion and improve clarity. However, these discrepancies underline the need for transparent communication of new methods and updates, ensuring that they are presented at a level of detail accessible to all stakeholders. Recent studies have pointed out the uncertainties in the current risk functions used in the GBD estimates, highlighting areas where further improvement is needed (Burnett & Cohen, 2020; Pope et al., 2018; Shaffer et al., 2019). These studies identified the limitations in existing methods and provided suggestions for refining risk assessments (Amnuaylojaroen & Parasin, 2023; de Bont et al., 2024; GBD & Global Burden of Disease, 2021; Pandey et al., 2021a). While significant progress has been made, these uncertainties continue to challenge the accuracy of health estimates linked to air pollution (de Bont et al., 2024). Despite these challenges, DL models offer a promising solution to enhance the predictive power of mortality and disease outcomes. DL's ability to handle large and complex datasets enables the generation of more precise predictions, which can play a crucial role in developing effective strategies for mitigating the health impacts of air pollution. In this context, utilizing DL models to assess mortality rates can offer new insights into the relationship between air pollution and health outcomes, aiding the

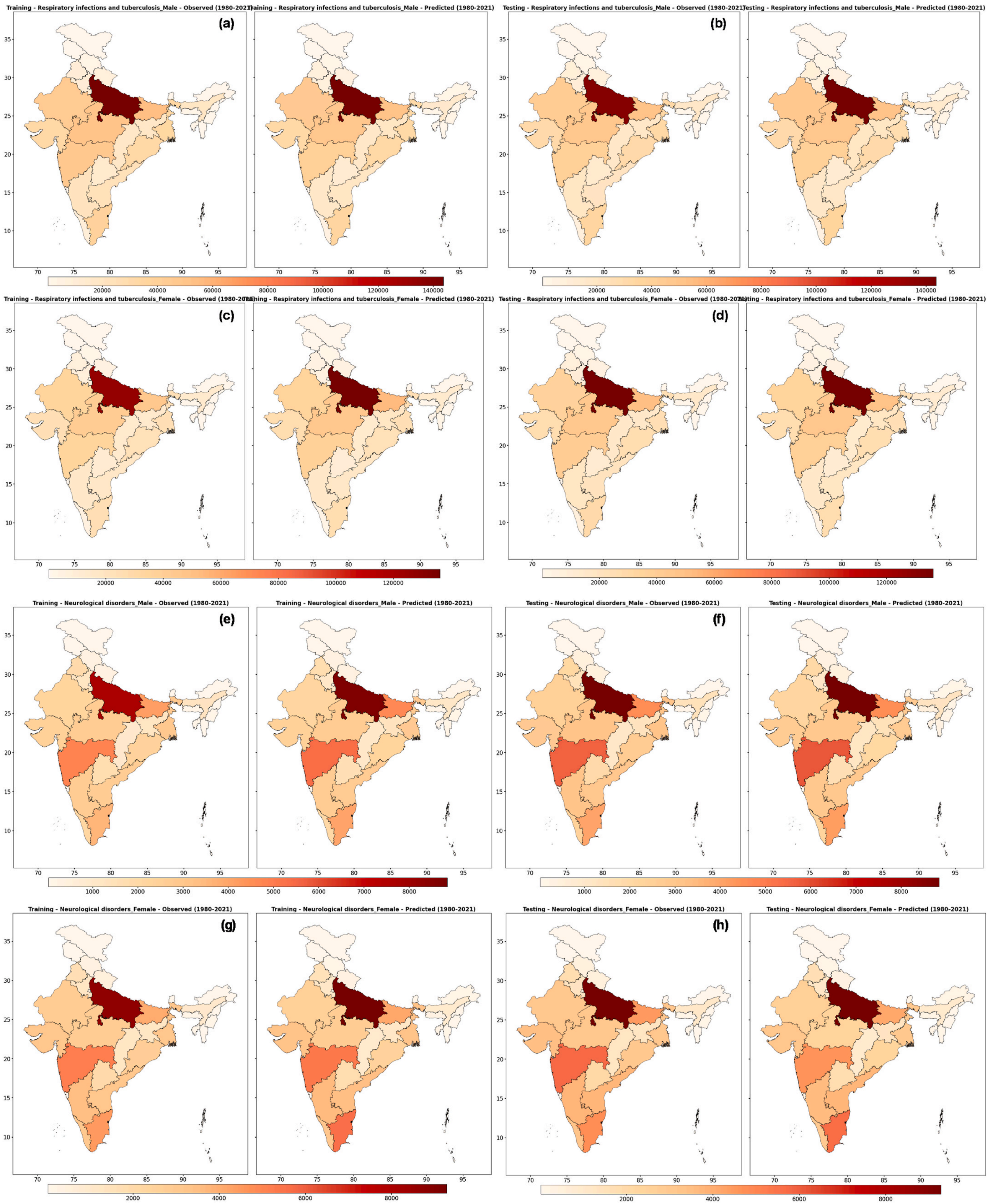

Fig. 6. Observed and predicted mortality rates for various diseases in India (1980–2021). Panels show results for respiratory infections and tuberculosis: (a) training, (b) testing for males, (c) training, and (d) testing for females; neurological disorders: (e) training, (f) testing for males, (g) training, and (h) testing for females; chronic respiratory diseases: (i) training, (j) testing for males, (k) training, and (l) testing for females; and cardiovascular diseases: (m) training, (n) testing for males, (o) training, and (p) testing for females. Colour intensity indicates mortality rates, with darker red representing higher rates. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

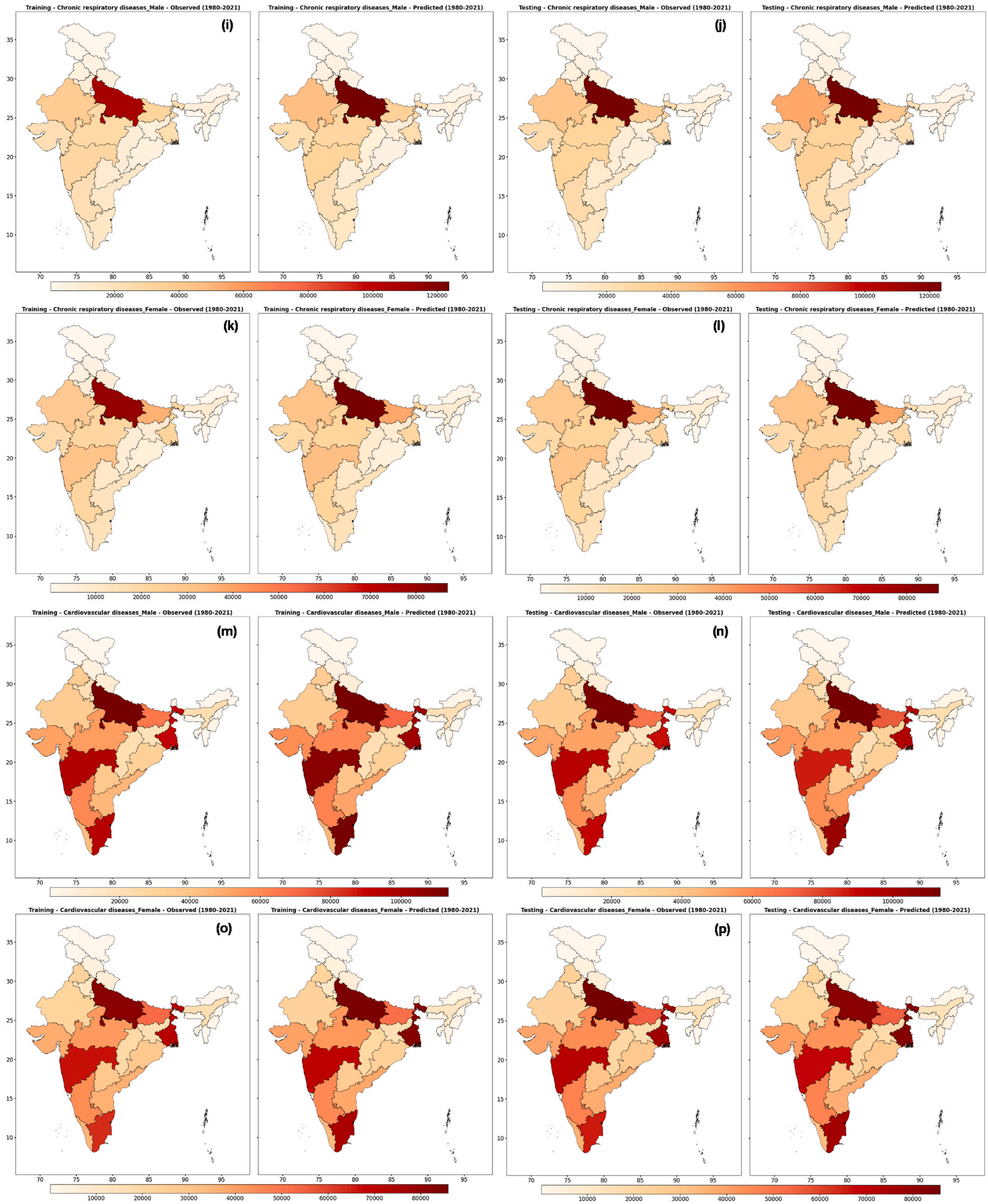

Fig. 6. (*continued*).

Table 4
Model performance metrics for various diseases by gender for training and testing phase.

Disease	Gender	Set	R^2	NSE	PBIAS (%)
Respiratory infections and tuberculosis	Male	Training	0.84	0.84	−3.74
Respiratory infections and tuberculosis	Male	Testing	0.96	0.96	2.60
Respiratory infections and tuberculosis	Female	Training	0.95	0.95	9.45
Respiratory infections and tuberculosis	Female	Testing	0.86	0.86	−1.94
Neurological disorders	Male	Training	0.93	0.93	7.14
Neurological disorders	Male	Testing	0.93	0.93	1.83
Neurological disorders	Female	Training	0.91	0.91	10.98
Neurological disorders	Female	Testing	0.87	0.87	15.54
Cardiovascular diseases	Male	Training	0.91	0.91	8.39
Cardiovascular diseases	Male	Testing	0.85	0.85	15.09
Cardiovascular diseases	Female	Training	0.91	0.91	7.60
Cardiovascular diseases	Female	Testing	0.88	0.88	9.13
Chronic respiratory diseases	Male	Training	0.94	0.94	12.31
Chronic respiratory diseases	Male	Testing	0.93	0.93	7.78
Chronic respiratory diseases	Female	Training	0.94	0.94	9.90
Chronic respiratory diseases	Female	Testing	0.89	0.89	11.60

Table 5
Overview of air pollution prevention policies, year of implementation, key details, and advantages in various countries.

Country	Air Pollution Prevention Policies	Year of Implementation	Details	Advantages
United States	Clean Air Act	1970	Sets regulations to control air pollution	Reduces emissions of harmful pollutants, protects public health, improves air quality, supports innovation in clean energy technologies
	National Ambient Air Quality Standards (NAAQS)	1970	Establishes limits for common pollutants	Provides clear standards for compliance, facilitates monitoring and enforcement, guides pollution control efforts
	Acid Rain Program	1990	Addresses acid rain through emissions trading program	Achieves pollution reductions cost-effectively, fosters innovation in emissions reduction strategies
	Clean Power Plan (now repealed)	2015 (repealed in 2019)	Aimed to reduce greenhouse gas emissions from power plants (repealed, but influenced industry practices)	Encouraged transition to cleaner energy sources, promoted investment in renewable energy and energy efficiency measures
China	Air Pollution Action Plan	2013	Targets specific pollutants and regions	Addresses severe pollution issues, promotes regional cooperation, encourages technology innovation, enhances public awareness
	National Ambient Air Quality Standards (NAAQS)	1982	Sets standards for air quality	Establishes benchmarks for pollution control, guides regulatory actions, protects public health
	Air Pollution Control Zones	2000	Designates areas for focused pollution control measures	Enables targeted interventions, optimizes resource allocation, mitigates localized pollution impacts
India	National Clean Air Programme (NCAP)	2019	Aims to reduce air pollution in urban areas	Focuses on source-specific action plans, integrates air quality monitoring, facilitates timely response to pollution events, promotes public awareness
	Air Quality Index (AQI)	2014	Provides real-time air quality information	Raises public awareness, enables informed decision-making, promotes behavior changes towards pollution reduction
	Graded Response Action Plan (GRAP)	2017	Implements actions based on severity of air pollution levels	Enhances emergency preparedness, ensures coordinated response to pollution episodes, minimizes health impacts
European Union	Ambient Air Quality Directive	1996	Sets limits for pollutants	Harmonizes air quality standards across member states, supports transboundary cooperation, drives innovation in clean technologies
	National Emission Ceilings Directive (NECD)	2001	Establishes emission reduction targets	Guides emission reduction efforts, ensures progress towards pollution reduction goals, supports international commitments
	Clean Vehicle Directive	2009	Regulates emissions from vehicles	Promotes adoption of cleaner vehicle technologies, reduces transportation-related pollution emissions
Japan	Air Pollution Control Law	1968	Regulates emissions from specified sources	Strengthens regulatory framework, enhances data availability, promotes pollution prevention, fosters corporate accountability
	Pollutant Release and Transfer Register (PRTR)	2001	Increases transparency of emissions	Empowers public and stakeholders, promotes corporate responsibility, facilitates pollution reduction planning
Canada	Canadian Environmental Protection Act	1999	Regulates air pollutants	Facilitates multi-stakeholder collaboration, supports evidence-based policymaking, promotes public participation, drives continuous improvement
	National Air Pollution Surveillance Network (NAPS)	1969	Monitors air quality across the country	Provides data for informed decision-making, supports targeted pollution control measures, enables trend analysis
	Clean Air Regulatory Agenda	2012	Sets out a comprehensive framework for air quality management	Streamlines regulatory processes, ensures consistency in pollution control efforts, facilitates stakeholder engagement
Australia	National Clean Air Agreement	1992	Coordinates air quality management	Promotes national consistency in air quality management, provides legal framework for pollution control, protects human health and environment
	National Environment Protection (Ambient Air Quality) Measure	1998	Sets standards for pollutants	Safeguards public health, guides pollution control efforts, ensures compliance with international obligations

formulation of targeted policies that aim to reduce air pollution exposure and its associated health risks.

6. Global policies to reduce the air pollution

Several air pollution prevention policies across several countries, highlighting their implementation years, objectives, and benefits in Table 5. The United States' Clean Air Act and NAAQS, established in 1970, set the foundation for controlling harmful emissions and setting clear air quality standards, influencing global practices (Summary of the Clean Air). China's National Air Quality Action Plan (2013) and similar standards focus on targeted regional interventions and technological innovation to combat severe pollution. India's NCAP (2019) emphasizes urban air quality with source-specific action plans and integrates real-time monitoring through AQI and emergency measures like GRAP (China: National Air Quality Action). The European Union's directives harmonize air quality standards across member states, promoting innovation and transboundary cooperation (EU, 2020). Japan's Air Pollution Control Law (1968) (Ministry of the Environment, 1968) and PRTR enhance regulatory frameworks and corporate accountability, while Canada's Environmental Protection Act (1999) and monitoring networks support collaborative, evidence-based policymaking (Barton-Maclaren et al., 2022). Australia's National Clean Air Agreement (1992) coordinates air quality management nationwide, ensuring consistency in pollution control (Chiodo, 2015). Each country designs its approach to local challenges, balancing regulation, innovation, and public engagement to improve air quality and protect public health.

India introduced its air pollution policies relatively late compared to other nations, largely due to rapid industrialization, urbanization, and economic growth that outpaced environmental regulations (Guttikunda, Ka, et al., 2023). Findings of this study also underline the urgent need for policymakers to implement region-specific and sector-targeted policies to mitigate the growing health impacts of $PM_{2.5}$ pollution in India. The NCAP should be strengthened by integrating stricter air quality standards, particularly in the Indo-Gangetic Plains and northern states, where pollution levels are highest. Policy frameworks like the State Action Plans for Air Quality Management (SAPs) must be tailored to address localized sources such as agricultural stubble burning and industrial emissions, particularly in Uttar Pradesh, Punjab, and Haryana. To address the health impacts, the National Health Policy (NHP) should incorporate air pollution mitigation as a core element, with special emphasis on chronic respiratory diseases, neurological disorders, and cardiovascular health. This includes ensuring access to early diagnostics and treatments in highly polluted areas. In the agriculture sector, the Pradhan Mantri Fasal Bima Yojana (PMFBY) could be enhanced by promoting cleaner, sustainable farming practices and the reduction of biomass burning, which is a significant contributor to $PM_{2.5}$ levels. Urban planning policies under the Smart Cities Mission should integrate green infrastructure, public transport expansion, and industrial relocation to reduce urban air pollution. Regional policies focusing on the northeastern and central states should incorporate better forest fire management practices under the National Afforestation Programme to curb wildfires, a significant source of pollution. Furthermore, the Integrated Disease Surveillance Programme (IDSP) must prioritize air pollution-related health conditions, with guidelines for monitoring and reporting morbidity and mortality linked to $PM_{2.5}$ exposure. However, there is a need to establish clear guidelines for public awareness campaigns under the Swachh Bharat Mission, focusing on educating the population about the dangers of indoor air pollution and promoting the use of cleaner cooking technologies.

7. Conclusion

This study presents a comprehensive assessment of the health impacts of air pollution in India, focusing on $PM_{2.5}$ exposure and its correlation with various health outcomes. Air pollution, particularly in the form of $PM_{2.5}$, has emerged as a significant environmental health hazard, exacerbated by rapid urbanization, industrialization, and vehicular emissions. The analysis, using MERRA-2 reanalysis data and Global Burden of Disease (GBD) data from 1980 to 2021, reveals pronounced spatial and temporal variations in air pollution levels across India. Northern and eastern regions experience the highest concentrations and the most polluted days, with drastic increases in $PM_{2.5}$ levels over the decades, especially in the Indo-Gangetic Plains and eastern states. The correlation analysis between $PM_{2.5}$ levels and health outcomes show moderate to strong associations for neurological disorders and chronic respiratory diseases, while weaker correlations are observed for respiratory infections and tuberculosis. The deep learning models, including the CNN architecture, demonstrate robust predictive capabilities with high R^2 values for forecasting disease-related mortality. Regional disparities are evident, with northern states like Uttar Pradesh exhibiting persistently high rates of respiratory infections and cardiovascular diseases. The enhanced CNN model, with improved accuracy and reduced bias, offers valuable insights into spatiotemporal disease mortality patterns across India, highlighting the need for targeted public health interventions. The findings underscore the urgency of implementing comprehensive air quality management policies to mitigate health impacts, focusing on emission reduction, cleaner technologies, and enhanced public awareness.

CRediT authorship contribution statement

Kuldeep Singh Rautela: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Manish Kumar Goyal:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Methodology, Data curation, Conceptualization.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techsoc.2025.102843.

Data availability

Data will be made available on request.

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