



Decentralized Emission Inventories and Traffic Dynamics: A Comprehensive Study on PM_{2.5} and PM₁₀ in the Road Sector of Greater Chennai

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Abstract

In this study, decentralized emission inventories were developed for the road sector in selected areas of Greater Chennai, with a specific focus on PM_{2.5} and PM₁₀ emissions across four distinct periods: pre- and post-lockdowns, semi-lockdowns, and lockdowns. Land use types include residential, commercial, and industrial. It comprises 10 sampling stations: Anna Nagar, Ambattur, T.Nagar, Porur, Valasaravakkam, Koyembedu, Maduravayol, Kilpauk, Alandur, and Kodambakkam. Methodology included primary surveys to assess traffic patterns and mode preferences, monitoring vehicle volumes, and calculating emission rates in grams per second per square meter (g/s-m²). Utilizing primary surveys, the existing travel and transportation features were assessed to understand traffic patterns and mode preferences. Vehicle emission rates in grams per second per square meter (g/s-m²) for both PM_{2.5} and PM₁₀ were determined for all ten stations. The study unveiled that the volume of vehicles commuting to the Koyambedu region is 2.5 to 5 times greater than in other areas. Modal shares varied, with two-wheeled vehicles constituting 33%, buses 25%, four-wheelers and three-wheelers 24%, and Vehicles for hauling goods 18%. Location with the greatest pollutant concentration proved Koyambedu at 0.000158 g/s-m², correlating with its elevated vehicular inventory. Prompted by the current air quality status, this study underscores the necessity to accurately estimate particulate matter emissions from vehicles and understand their impact on air quality.

Keywords Air contamination · Air pollution · Climate change · Air quality

1 Introduction

The pace of urbanization in India is accelerating, particularly in the vicinity of major cities, driven by population growth and economic advancements (Saravanan et al. 2023). This growth has led to a significant increase in vehicle ownership, with approximately 54% of households now owning at least one vehicle (Hung et al. 2010; Wallinton et al. 2022). However, pollution levels vary widely across megacities, and the rise in wealth has contributed to heightened pollution in major urban areas (Horton 2021). While some cities have shown improvements in air quality concerning criteria pollutants such as SPM, SO₂, and NO_x, the overall air pollution status in numerous Indian urban areas remains uncertain and increasingly concerning (Vellaiyan et al. 2024; Tsanakas et al. 2020).

The Central Pollution Control Board sets National Ambient Air Quality Standards yet these limits and those set by the World Health Organization are consistently exceeded in metropolitan areas (Prinz and Richter Mar. 2022). Vehicle

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emissions play a pivotal role in deteriorating air quality, exacerbated by high vehicle-to-population ratios (Saravanan et al. 2023). India's transportation sector consumes 25% of the country's total energy, predominantly derived from oil (Singh et al. , 2023). The shift from rail-based to road-based transportation has significantly increased fuel consumption, leading to elevated pollutant emissions (Muthu et al. 2021). Approximately 30% of the total Suspended Particulate Matter (SPM) pollution load in India's largest urban areas is attributed to vehicles (Gajbhiye et al. 2023).

Cities like Delhi, Mumbai, Chennai, and Kolkata each host over 15% of the nation's automobiles, driven by India's 31% urban population (Iaguno-Munitxa and Bou-Zeid 2023). This concentration poses multiple challenges including air pollution, traffic congestion, and noise (Mohd Shafie and Mahmud 2020). Moreover, more than 45 other metropolitan centers, each with populations exceeding 1 million, collectively account for nearly 10% of all vehicles, with two-wheelers comprising approximately 79% of the total motorized vehicles (Vickram 2023). Megacities are heavily populated, experiencing rapid growth fueled by private vehicles and mass transportation. This urban surge, coupled with extensive automobile use, significantly contributes to environmental degradation through heightened emissions. The resulting impact includes an increased incidence of carcinogenic diseases associated with exposure to these emissions (Vickram 2023).

What sets this situation apart is the simultaneous reliance on both individualized vehicles and mass transit systems, intensifying automobile emissions (Brunekreef and Forsberg 2005). This nuanced perspective underscores the need for comprehensive strategies addressing both individual and collective modes of transportation to mitigate environmental and health risks in burgeoning megacities (Ratanavalachai and Trivitanurak 2023). The term "disease of wealth" aptly characterizes the air pollution stemming from vehicular emissions, particularly prevalent in urban areas (Joo et al. 2023). This study explores global concerns surrounding the surge in automotive emissions, driven by escalating energy consumption, necessitating heightened research and development (Vellaiyan et al. 2024). In Chennai, the exponential growth in vehicle numbers stands out as a primary contributor to elevated Respirable Suspended Particulate Matter (RSPM) and PM10 levels (Ravi et al. 2014). Findings from the NAAQ Monitoring of India (2014–15) indicate that increased PM levels in Chennai correlate with vehicle emissions and traffic dust (Mohan et al. 2011). Since 2005, the number of motorized vehicles has increased twenty-fourfold, with private vehicles constituting over half of daily trips (Xio et al. 2023). The city witnesses a daily influx of at least 700 additional automobiles, significantly impacting pollution levels. The mean annual PM10 concentration exceeds the permissible threshold of 60 $\mu\text{g}/\text{m}^3$ by at least 1.5 times,

leading to degraded air quality (Vickram 2023; Nyhan et al. 2016). This study emphasizes the critical need for emissions monitoring to comprehensively assess the influence of transportation on modeled air pollution (Savio et al. 2022; Ilarri et al. 2022). Driven by concerns over deteriorating air quality, the research aims to accurately estimate vehicle particulate matter (PM) emissions and evaluate their specific impact on the atmospheric conditions in Chennai.

2 Urgency in Characterizing Vehicular Pollution Emissions

Air pollution attributed to vehicular emissions is often referred to as the "disease of wealth," underscoring its prevalence in developed urban areas characterized by high vehicle ownership and usage. The escalating energy consumption linked with increased vehicular emissions has garnered substantial global attention, necessitating extensive research and development efforts. This surge in vehicular emissions, driven by rising energy consumption, has become a matter of global concern, prompting intensified research initiatives. In Chennai, the exponential growth in the number of vehicles stands out as the primary cause behind elevated levels of Respirable Suspended Particulate Matter (RSPM) and Particulate Matter (PM10). According to the National Ambient Air Quality Monitoring of India in 2014–15, vehicle emissions and traffic-related dust are the leading contributors to the high levels of particulate matter observed in the city. Data from the Basic Road Statistics of India and Urban Infrastructure: Twelfth Five-Year Plan indicate a staggering twenty-four-fold increase in motorized vehicles since 2005, with private vehicles accounting for more than half of the total daily trips.

The addition of approximately 700 new vehicles onto Chennai's streets each day exacerbates pollution levels, surpassing permissible limits and deteriorating air quality. The average annual concentration of RSPM/PM10 consistently exceeds the recommended threshold of 60 $\mu\text{g}/\text{m}^3$ by at least 1.5 times, highlighting the severity of the air quality issue. Given the alarming state of air quality, there is an urgent need to estimate the emissions of particulate matter pollutants from vehicles and assess their impact on air quality. Monitoring emissions provides crucial insights into the transportation sector's contribution to modeled air pollution, guiding efforts aimed at mitigating the adverse effects on public health and the environment. Thus, our focus is directed towards comprehensively understanding and quantifying vehicular emissions to address the urgent challenges posed by deteriorating air quality in Chennai.

3 Methodology

3.1 City Model

The research focused on thoroughly investigating travel and transport dynamics within the study area, with a primary objective of uncovering intricate traffic patterns and prevalent mode preferences. A screen line survey was pivotal to this investigation, strategically placing imaginary lines (screenlines) to measure traffic volume at critical locations. The survey comprised two main components: a traffic count survey and a vehicle occupancy count survey. Conducted rigorously on weekdays during active hours (8–11 am and 4–7 pm), excluding public holidays, the traffic count survey meticulously tallied vehicular movement in both directions at designated roadside points. Concurrently, the vehicle occupancy count survey observed and recorded the occupancy levels of various vehicle types categorized by mode of transport and route, updated every fifteen minutes on survey sheets. These efforts were executed across 10 diverse study locations chosen to represent varying traffic scenarios.

Vehicle types including buses, two-wheelers, three-wheelers, four-wheelers, taxis, and goods vehicles were systematically classified to provide a comprehensive understanding of the vehicular landscape. The culmination of these surveys yielded a rich dataset, extensively analyzed to identify peak traffic hours, and thoroughly characterize the composition of vehicles traversing the surveyed areas, as detailed in Table 1. This methodological approach not only facilitated accurate estimation of vehicle exhaust emission rates but also provided valuable insights into the dynamics of urban traffic flow essential for effective environmental management and policy-making.

3.2 Urban Transport Issues

The projected population of the Chennai Metropolitan Area (CMA) is expected to reach approximately 12.6 million,

indicating a substantial increase in daily vehicle trips to an estimated 17.3 million, nearly double the current volume. This growth underscores the remarkable proliferation of motor vehicles in recent decades, with the total vehicle population reaching 2.814 million by 2009. Many of the key peripheral arterial routes leading to the city are grappling with severe congestion issues. On average, 7,000 units of passenger cars (PCUs) annually traverse inner cordon sites during peak periods, marking a significant increase over the past decade. The exponential rise in vehicle numbers, coupled with minimal expansion of road infrastructure, has resulted in sluggish traffic speeds, with average speeds of only 10 km/h recorded in the Central Business District (CBD) and 18 km/h on other major thoroughfares.

3.3 Vehicle Emission Rate

Figure 1 depicts the methodology employed to calculate vehicle exhaust emission rates, essential for the AERMOD model used to predict pollutant dispersion in the atmosphere. The process of determining vehicle exhaust emission rates involves a systematic approach that begins with collecting data on current travel and transportation characteristics. This includes gathering information on the number of vehicles, vehicle kilometers traveled (VKT), and emission factors (EF) for various vehicle categories. The vehicle count

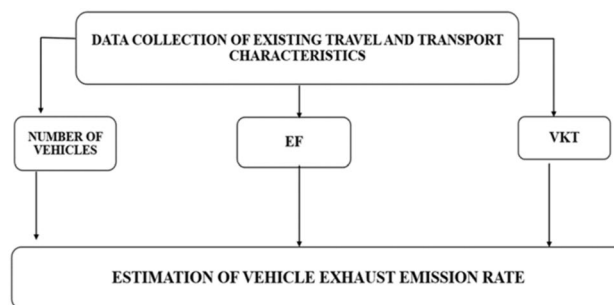


Fig. 1 Estimation of Vehicle Emission Rate

Table 1 Modal share distribution for the study area

Location name	No. of vehicles	BUS	2W	3W/4W/TAXI	GVs
Alandur Bridge	30,182	7613	9971	7171	5420
Porur	93,412	23,559	30,854	22,195	16,777
Kilpauk	67,355	16,987	22,247	16,004	12,097
Anna Nagar	87,647	22,105	28,950	20,825	15,741
Koyambedu	265,591	66,982	87,725	63,104	47,700
Kodambakkam	62,000	15,636	20,479	14,731	11,135
Valasaravakkm	59,862	15,097	19,772	14,223	10,751
Maduravayol-Bridge	104,858	26,445	34,635	24,914	18,832
T.Nagar	104,238	26,289	34,430	24,767	18,721
Ambathur	108,078	27,257	35,698	25,679	19,411

encompasses different classifications such as cars, buses, and trucks, while VKT measures the total distance covered by these vehicles over a specified period. Emission factors, representing the average emissions produced per unit of distance traveled, are obtained from standardized databases. Once the data is collected, it undergoes processing and validation to ensure accuracy. The next step involves using the collected data in the formula: $\text{Total Emissions} = \sum (\text{Number of Vehicles}_i \times \text{VKT}_i \times \text{EF}_i)$, where i represents different vehicle categories. This computation is performed for each category by multiplying the number of vehicles by their corresponding VKT and emission factors. The emissions from all categories are then summed to obtain the total emission rate.

This methodology allows for a comprehensive analysis of vehicle emissions, identifying which vehicle types contribute most significantly to the overall emissions. The results are then analyzed and communicated, providing valuable insights and graphical representations to stakeholders. For example, if data shows that cars, buses, and trucks in a particular area travel 15,000, 40,000, and 30,000 km per year respectively, with emission factors of 0.2, 1.0, and 0.8 g per kilometer, the cumulative emissions can be calculated and analyzed to assess the impact of each vehicle category on total emissions. This systematic approach ensures accurate estimation and helps in developing strategies to reduce emissions.

4 Results and Discussion

4.1 Vehicle Modal Share

Figure 2 illustrates the distribution of various types of vehicles, including BLS (Bus Lane System), 2W (Two-Wheelers), 3W/4W/Taxi, and GV (Goods Vehicles), across several

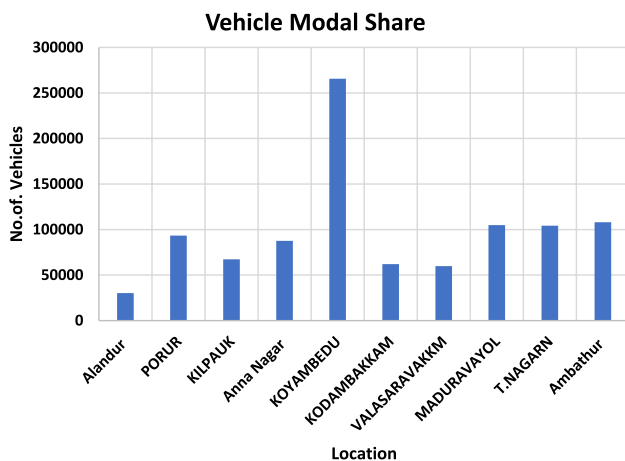


Fig. 2 Vehicle Modal Share

regions. The analyzed areas extend from Alandur Bridge through Gandhi Market to Ashok Nagar, encompassing notable localities such as Porur, Kilpauk, Anna Nagar, Koyambedu, Kodambakkam, Valasaravakkam, Maduravoyal, T Nagar, and Ambattur. The data indicates a significant increase in the use of vehicles, particularly two-wheelers, in the Koyambedu and Kodambakkam sectors. These locations serve as key transportation and business centers.

From Fig. 2, it is evident that two-wheelers constitute a substantial proportion of the overall vehicle distribution, especially in densely populated areas like Koyambedu and Kodambakkam. The BLS and GV categories show a consistent level of stability across all locations, suggesting uniform use of buses and freight vehicles. The 3W/4W/Taxi category exhibits moderate peaks, indicating higher usage in heavily populated or commercially active regions. The distribution pattern highlights the reliance on motorcycles for daily transportation in metropolitan areas, likely due to their convenience and efficiency in navigating crowded city streets. The report also emphasizes the importance of robust public transit networks and effective management of commercial vehicles to enhance the overall transportation infrastructure.

4.2 Estimation of Emission Rate

To calculate traffic emissions, we utilized the number of vehicles, their traveled distances, and the emission factors (EF) detailed in Table 2 of the Indian Emission Inventory

Table 2 Emission Factor for vehicle types

Vehicle mode	PM _{2.5} -EF (gm/km)	PM ₁₀ -EF (gm/km)
Buses	0.8	1.50
Two wheelers	0.05	0.10
Three heelers	0.08	0.20
Four Wheelers	0.03	0.10
Taxis	0.03	0.10
Goods Vehicles	0.5	1.25

Table 3 VKT used for vehicle types

Vehicle type	Fuel	VKT (Km/Day/Vehicle)
Two wheelers	Petrol	75
Auto Rickshaw	Petrol	120
Four Wheelers	Petrol/Diesel	90
Buses	Diesel/CNG*	210
Taxis	Petrol/ Diesel/CNG	120
Goods Vehicles	Diesel	150

Report (<https://www.teriin.org/sites/default/files/files/Indian-Emission-Inventory-Report.pdf>). The daily average Vehicle Kilometers Traveled (VKT) per vehicle category, as shown in Table 3, played a crucial role in determining emissions.

The emission rates were estimated using emission factors provided by the Automotive Research Association of India (ARAI) for Indian vehicles. These factors are specifically tailored to reflect prevailing Indian driving conditions and typical speeds. The computation of emission rates followed a standardized equation, ensuring accuracy and reliability throughout the estimation process (<https://urbanemissions.info/tools/sim-air/> Simple Interactive Models for Better Air Quality: Four Simple Equations for Vehicle Emissions Inventory).

Emissions (tons/year)

$$= \text{Number of Vehicles} * \text{Vehicle km travelled (km/yr)} * \text{Emission factor (gm/km)} * 10^{-6} \text{ (tons/gm)}$$

Vehicle emission rates in g/s for PM_{2.5} and PM₁₀ were computed for all ten sites and listed below by vehicle type.

4.3 Estimated PM_{2.5} and PM₁₀ Emissions

The emission rates were computed by standardizing them through division by the line source area (1000 × 1000 m), resulting in dispersion rates expressed in grams per second per square meter (g/s-m²). This standardization process was conducted for the years 2019, 2020, and 2021, encompassing both periods before and after lockdowns. For precision, the emission rate calculations were refined for alternate time-frames by utilizing ambient data gathered from 10 sampling sites. The calculated emission rates for both PM_{2.5} and PM₁₀ across the years 2019, 2020, and 2021 were analyzed, considering pre-lockdown, post-lockdown, semi-lockdown, and lockdown periods.

Figure 3 depicts the levels of particulate matter (PM) in different regions over various time periods, with a specific

focus on the concentrations of PM_{2.5} and PM₁₀. The analyzed regions include Alandur, Porur, Kilpauk, Anna Nagar, Koyambedu, Kodambakkam, Valasaravakkam, Maduravoyal, T Nagar, and Ambattur. The time periods studied encompass the years before the implementation of lockdown measures (2019 and early 2020), during lockdown measures in 2020 and 2021, and a phase characterized by partial lockdown measures.

The data demonstrates substantial decreases in PM levels during lockdown periods compared to levels before the lockdown. Specifically, there were reductions of 73% and 76% in PM_{2.5} levels in 2020 and 2021, respectively, and reductions of 67% and 84.5% in PM₁₀ levels in the same years. Figure 3 illustrates a significant decline in pollution levels during lockdown periods, highlighting the impact of reduced human activities on air quality. Every region follows a consistent pattern, with the highest levels of PM observed before the implementation of lockdown measures and the lowest levels during the lockdowns. During lockdowns, Koyambedu experiences a significant decrease in PM_{2.5} levels, while areas such as Kodambakkam and Valasaravakkam also show noticeable reductions. In the semi-lockdown period, there is a slight increase in activity compared to the complete lockdown, but PM levels remain below those seen before the lockdown. This suggests that even a partial reduction in activity is beneficial. This data underscores the efficacy of lockdown measures in improving air quality.

Table 4 provides the calculated vehicle emission rates in g/s-m² for PM_{2.5} and PM₁₀ during the pre-lockdown periods of 2019, 2020, and 2021. The ambient pollutant data collected from these stations indicated substantial reductions in PM_{2.5} levels by 73% and 76% during the lockdown periods of 2020 and 2021, respectively. Similarly, PM₁₀ levels exhibited decreases of 67% and 84.5% during the same periods. During the semi-lockdown period in 2020, both PM_{2.5} and PM₁₀ levels experienced a modest decline of 2%.

Table 5 presents the modified emissivity data, which serve as source inputs for the dispersion model in AERMOD software, specifically tailored for the lockdown scenarios.

Fig. 3 Estimated PM_{2.5} and PM₁₀ emissions

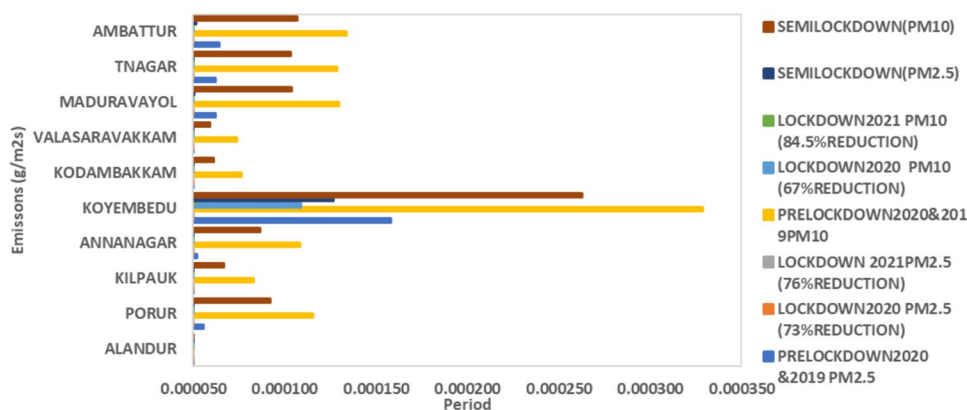


Table 4 Estimated Emission rate in g/s-m²

Location name	Pre lockdown 2020, 2019 & 2021 PM _{2.5}	Pre lockdown 2020, 2019 & 2021 PM ₁₀
Alandur Bridge Near Guindy Industrial Estate	0.000018	0.000037
Porur	0.000056	0.000116
Kilpauk-Pantheon Road Near Cooptex	0.000040	0.000083
Anna Nagar 3Rd Avenue Near K3 Police Station	0.000052	0.000108
Koyambedu	0.000158	0.000329
Kodambakkam-Nsk Salai Near Kodambakkam Railway Station	0.000037	0.000077
Valasaravakkam	0.000035	0.000072
Maduravayol-Bridge Vanagaram—Ambattur Road	0.000063	0.000130
T. Nagar	0.000062	0.000129
Ambathur—Thiruthani Hwy	0.000064	0.000134

Table 5 Emission rates resulting from reductions in vehicular traffic

Location	Pre-lockdown & post lockdown 2019, 2020, 2021 (PM _{2.5})	Lockdown 2020 (73% reduction) (PM _{2.5})	Semi lock-down 2020 (2% reduction) (PM _{2.5})	Lockdown 2021 (76% reduction) (PM _{2.5})	Pre lockdown & post lockdown 2019, 2020, 2021 (PM ₁₀)	Lockdown 2020 (67% reduction) (PM ₁₀)	Semi lock-down 2020 (2% reduction) (PM ₁₀)	Lockdown 2021 (84.5% reduction) (PM ₁₀)
Alandur	0.000017	0.000004	0.000013	0.000003	0.000036	0.000012	0.000030	0.000006
Porur	0.000057	0.000015	0.000045	0.000013	0.000116	0.000038	0.000092	0.000018
Kilpauk	0.000040	0.000011	0.000032	0.000010	0.000083	0.000028	0.000067	0.000013
annanagar	0.000052	0.000014	0.000042	0.000013	0.000108	0.000036	0.000087	0.000017
Koyambedu	0.000158	0.000043	0.000127	0.000038	0.000329	0.000109	0.000263	0.000051
Kodambakkam	0.000037	0.000010	0.000030	0.000009	0.000077	0.000025	0.000061	0.000012
Valasaravakkam	0.000036	0.000010	0.000029	0.000009	0.000074	0.000025	0.000059	0.000011
Maduravayol	0.000063	0.000017	0.000050	0.000015	0.000130	0.000043	0.000104	0.000020
T.nagar	0.000062	0.000015	0.000051	0.000016	0.000129	0.000043	0.000103	0.000020
Ambattur	0.000064	0.000018	0.000052	0.000015	0.000134	0.000044	0.000107	0.000021

These modifications are crucial for accurate modeling and simulation, reflecting the changes in emission patterns during the lockdown periods of 2020 and 2021.

4.4 Emissions In-cooperation

Line source models are widely used tools for estimating the impact of vehicular pollutant emissions and their dispersion (Torrás Ortis and Friedrich 2013). Globally, these dispersion models are extensively applied to predict ambient air quality near roadways. These models integrate cumulative meteorological and traffic characteristics as input variables, highlighting the significant influence of the precision and accuracy of these inputs on forecasting capabilities. The effectiveness of these models depends

on variations in meteorological, topographical, and traffic features across different regions (McDuffie, et al. 2020). Table 5 shows the emission rates resulting from reductions in vehicular traffic.

Figure 4 illustrates an urban area with detailed road networks, waterways, and various key locations such as Ambattur OT, Annanagar Roundana, Maduravoyal, and Koyambedu, among others. Highlighted with blue circles, these locations likely represent specific points of interest or emission sources for a study on vehicular pollutant dispersion. The red boundary outlines the study area, emphasizing regions under investigation for air quality. Using UTM coordinates, the map serves as a tool to visualize the integration of meteorological and traffic data in line

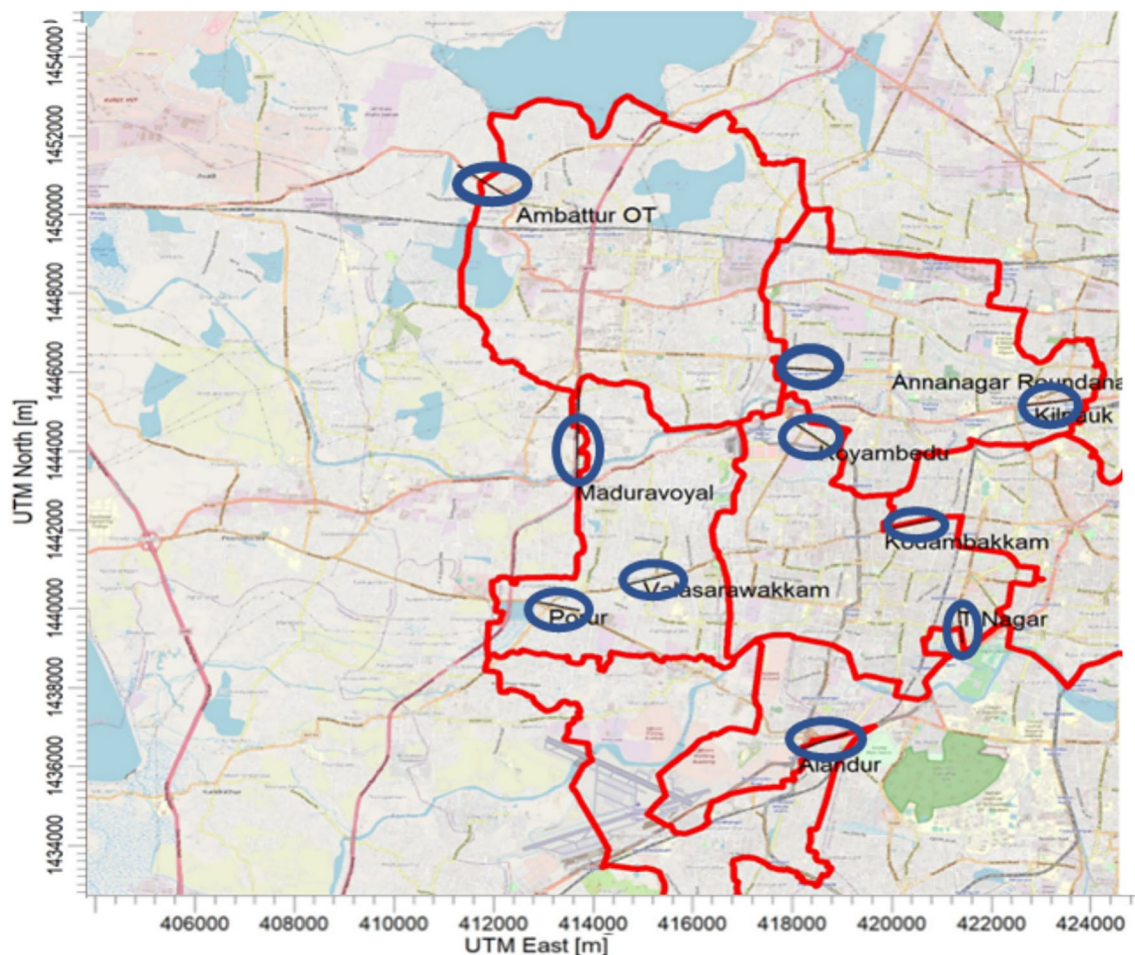


Fig. 4 Line sources of the study area

source models, crucial for predicting ambient air quality near roadways.

4.5 Wind Speed and Wind Direction During the Study Periods

Air pollution exhibits a predominant downwind dispersion pattern, making wind the foremost meteorological factor influencing its transport and dispersal (Denier van der Gon, et al. 2013; Tsanakas et al. 2020). The horizontal spread of a plume is notably influenced by wind shear, denoting a change in wind direction over the plume depth (Winkler et al. 2018). A wind rose is a graphical representation of wind speeds and the direction from which the wind blows (Dhanalakshmi and Radha 2021) is instrumental in recording and visualizing wind speed data. Utilizing WRPLOT View, wind roses were plotted to illustrate discrete changes in wind patterns during the study periods as shown in Figs. 5, 6, 7, 8. Wind rose diagram showing the distribution of wind speed and direction at a specific location. Figures indicates that the prevailing

winds predominantly come from the west, with wind speeds mainly in the range of 1.0–2.0 m/s, as represented by the yellow and orange bars. Higher wind speeds (up to 5.0 m/s) are less frequent. The wind blows from the west for 37.45% of the recorded time, with calm conditions (less than 0.5 m/s) occurring 27.47% of the time. The peak emission concentration detected in the Koyambedu area led to forecasts of PM_{2.5} and PM₁₀ period concentrations for the years 2019, 2020, and 2021. The USEPA AERMOD modelling revealed that the predicted pollutant concentration was highest during the post-lockdown period of 2021.

4.6 Modelling Output for PM_{2.5} and PM₁₀

Figure 9 shows the Modelling output of post lockdown period during 2021 for PM_{2.5}. The image is a concentration map depicting the dispersion of pollutants across a specified urban area, with key locations such as Ambattur OT, Maduravoyal, Koyambedu, and Annanagar Roundana. The pollutant concentrations in micrograms per cubic

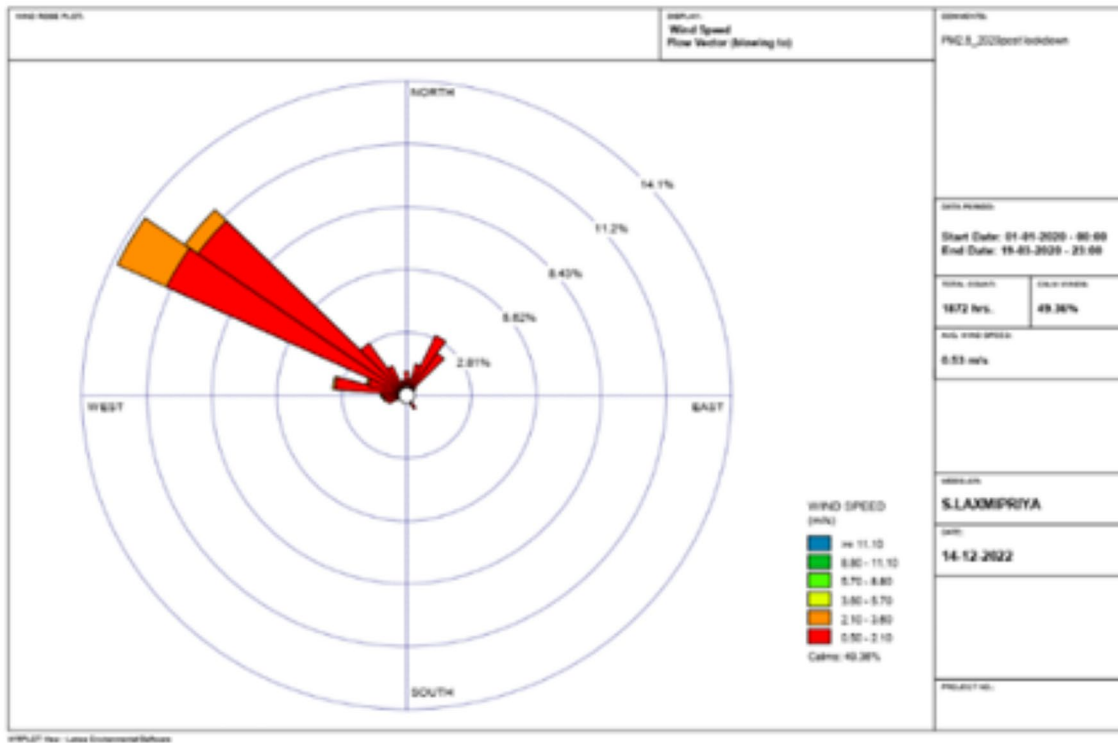


Fig. 5 Wind speed and wind direction during 2020 pre-lockdown period

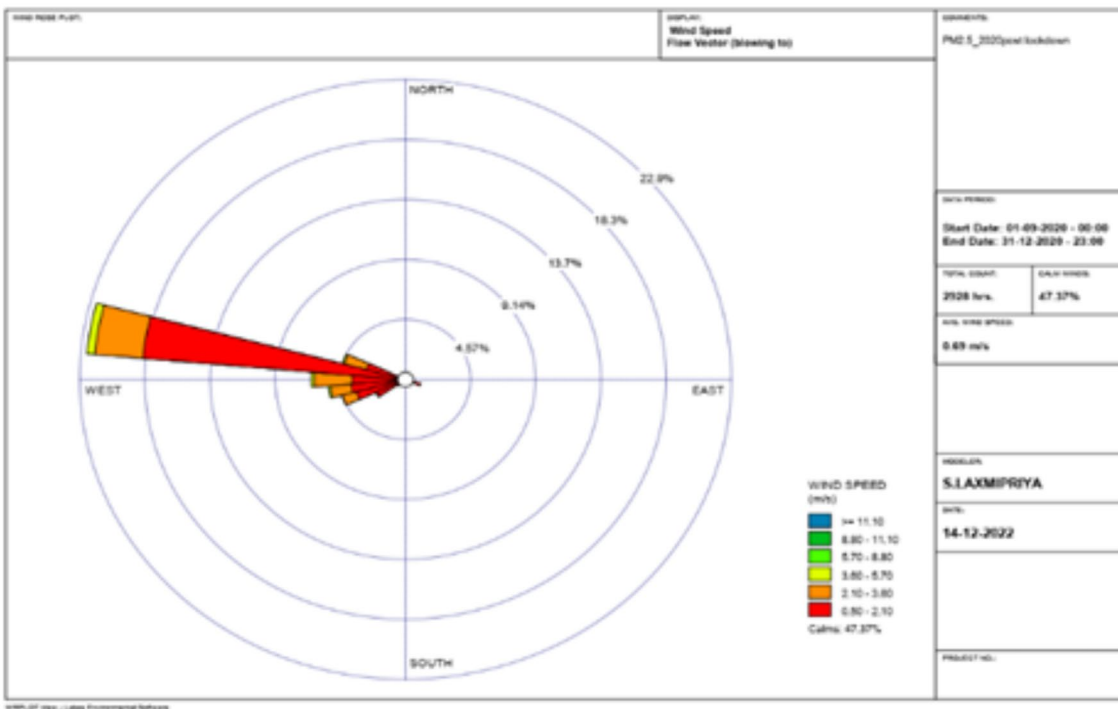


Fig. 6 Wind speed and wind direction during 2020 post-lockdown period

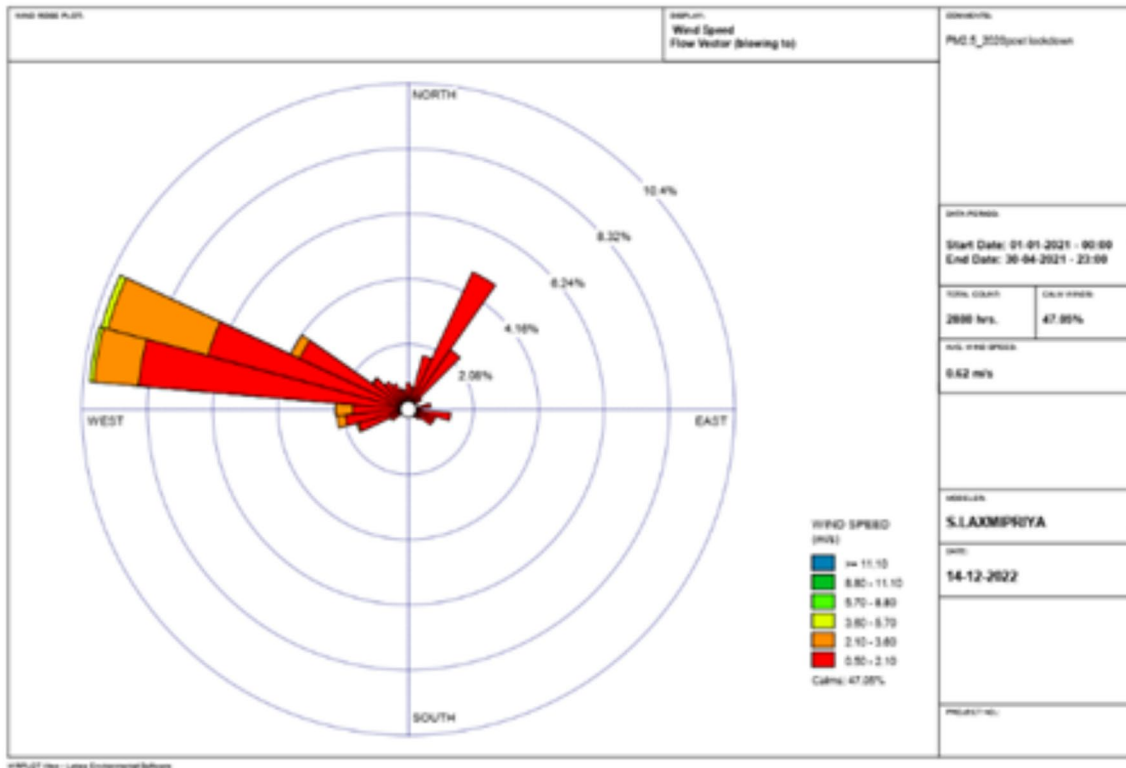


Fig. 7 Wind speed and wind direction during 2021pre-lockdown period

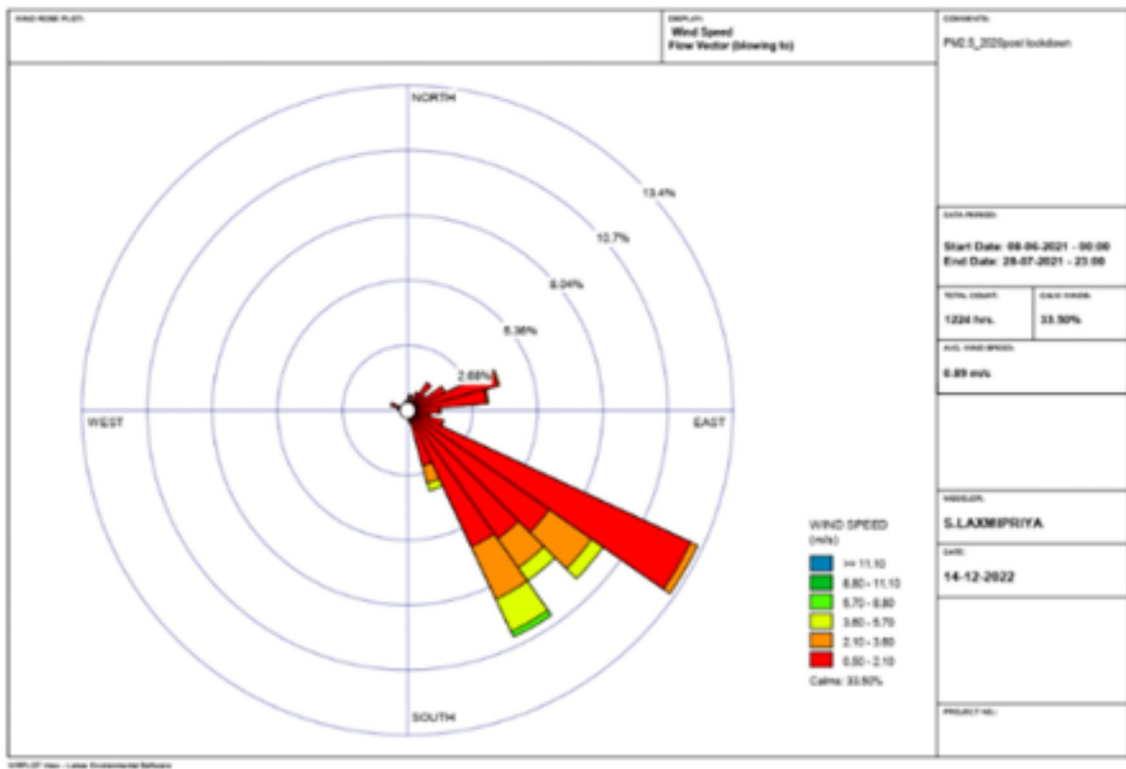


Fig. 8 Wind speed and wind direction during 2021post-lockdown period

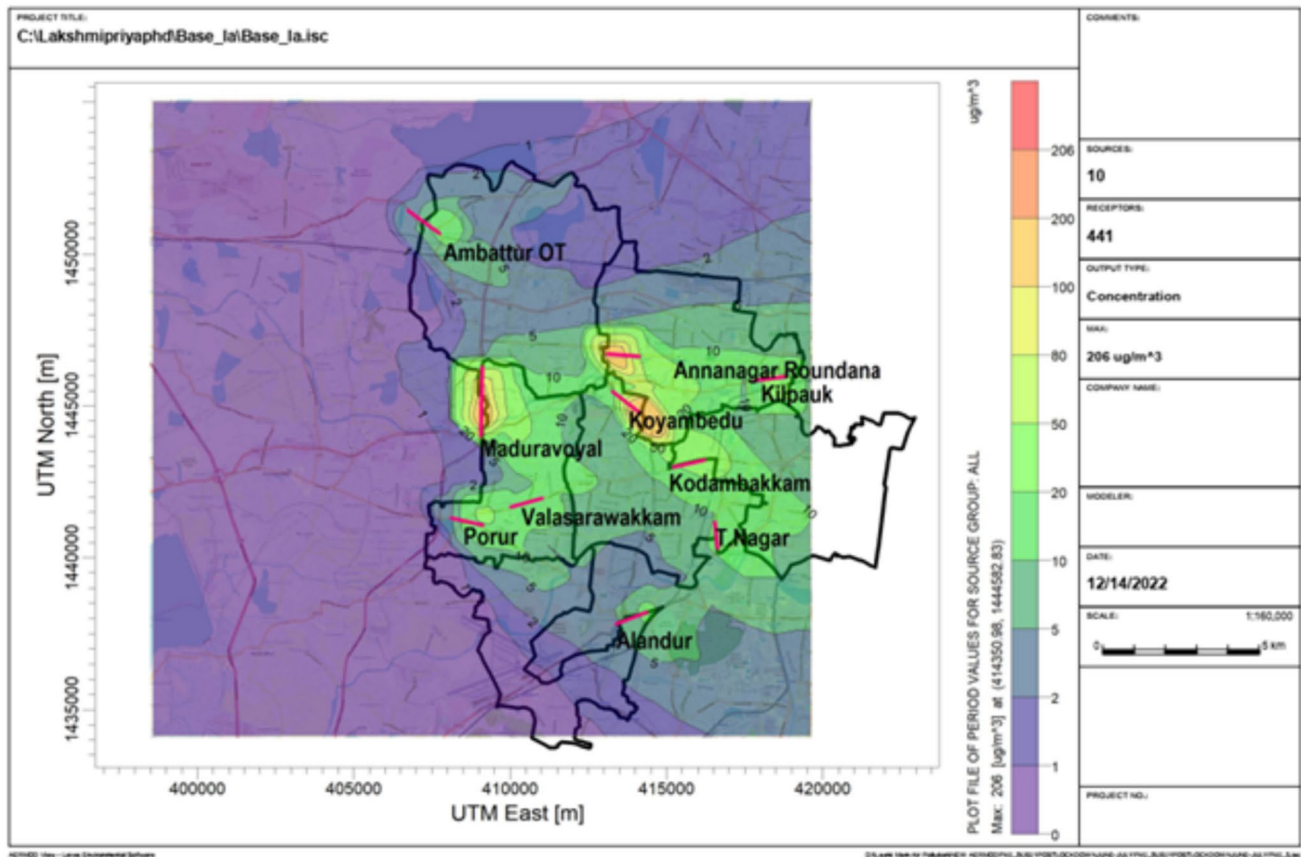


Fig. 9 Modelling output of post lockdown period during 2021 for $PM_{2.5}$

meter ($\mu\text{g}/\text{m}^3$), with values ranging from low (green areas) to high (red areas). The highest concentration recorded is $206 \mu\text{g}/\text{m}^3$, primarily in regions like Koyambedu and Annanagar Roundana, indicating significant pollution hot-spots. The map incorporates data from 10 sources and 441 receptors, providing a comprehensive view of pollutant spread influenced by vehicular emissions and other factors. This visualization is crucial for understanding air quality patterns and addressing environmental health concerns in the area.

Figure 10 depicts air pollution concentration levels in a specific urban area, with regions during 2021 post lockdown period for PM_{10} . The color gradient, ranging from blue to red, indicates varying levels of pollution, with red representing the highest concentration ($428 \mu\text{g}/\text{m}^3$) and blue the lowest. Figure 10 uses the UTM coordinate system to denote specific locations within the mapped area. Key information includes the presence of 17 pollution sources and contour intervals set at 20, offering a detailed spatial representation of pollution intensity. Figure 10 serves as a critical tool for environmental management, urban planning, and public health awareness. It highlights areas with high pollution levels (in red), which demand immediate intervention to

mitigate health risks, particularly for vulnerable populations. Moderately polluted regions (in yellow and orange) require monitoring and potential preventive measures.

4.7 Health and Environmental Impact

Spatial disparities in air quality within Greater Chennai are heavily influenced by variations in traffic patterns, types of vehicles, and meteorological conditions. Areas with high traffic volumes, like Koyambedu, experience elevated levels of $PM_{2.5}$ and PM_{10} emissions, leading to poorer air quality compared to less congested regions. Additionally, the concentration and dispersion of pollutants are affected by differences in land use types, such as residential, commercial, and industrial zones. Industrial areas tend to have higher emissions due to the presence of additional pollution sources.

The health and environmental consequences of these spatial disparities in air quality can be significant. Elevated concentrations of $PM_{2.5}$ and PM_{10} are linked to respiratory and cardiovascular diseases, increased hospital admissions, and higher mortality rates. Vulnerable populations, such as the elderly, infants, and individuals with preexisting health conditions, are particularly susceptible. Long-term exposure

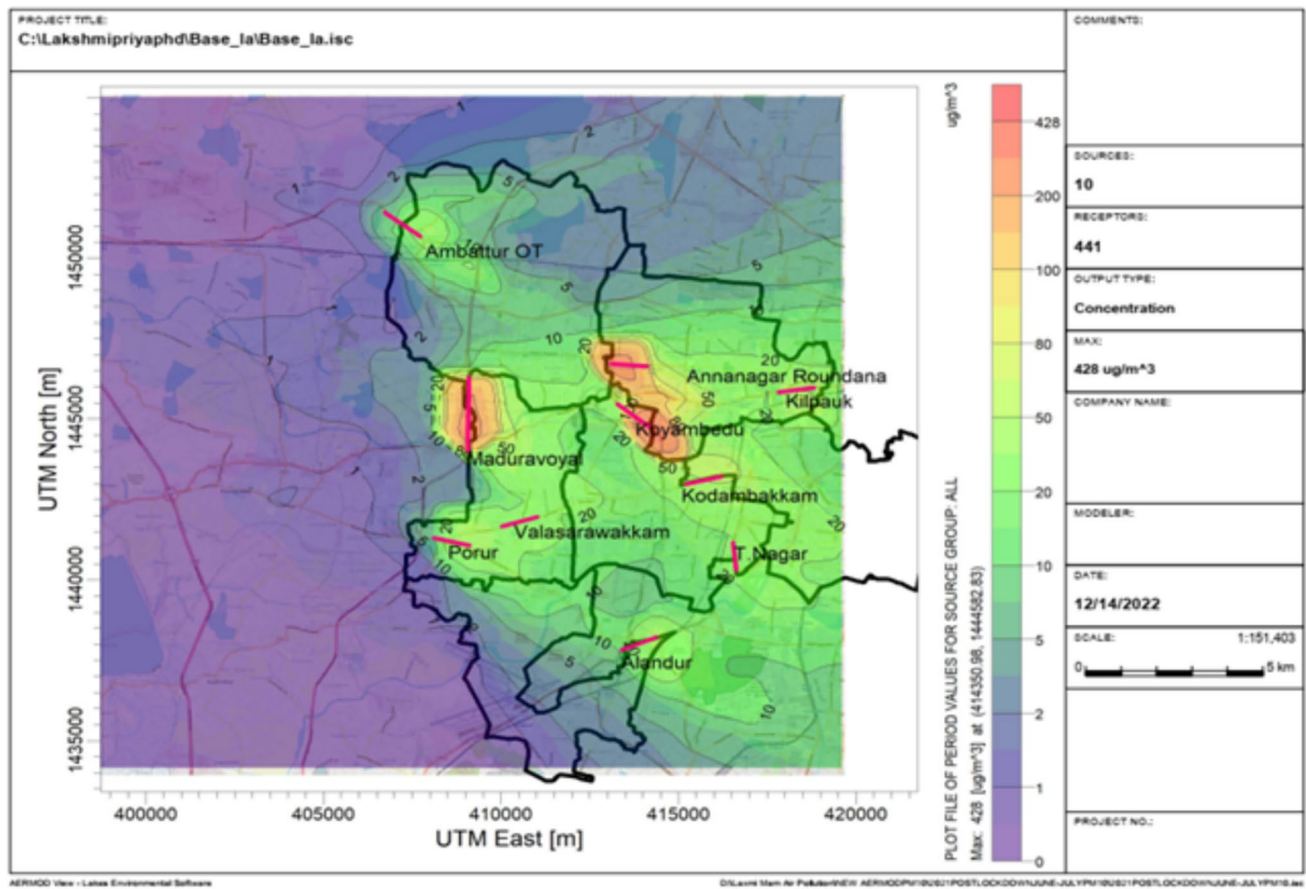


Fig. 10 Modelling output of post lockdown period during 2021 for PM_{10}

to high levels of particulate matter can lead to chronic health conditions such as asthma, bronchitis, and lung cancer.

High levels of particulate matter can also degrade ecosystems. $PM_{2.5}$ and PM_{10} settling on soil and water bodies can affect the growth of plants and contaminate water supplies. This deposition can disrupt nutrient balance in soils and water, impacting aquatic life and agricultural productivity. In summary, the significant spatial disparities in air quality across Greater Chennai result from variations in traffic dynamics and emission factors, posing severe implications for public health and the environment. Targeted interventions and policies that consider the unique characteristics and needs of different regions within the city are essential to address these disparities.

5 Conclusion

Field assessments indicate that the volume of automobiles traveling to the Koyembedu study location is notably higher, fluctuating between 2.5 to 5 times more than in various other regions. Analysis of modal share reveals that vehicles

represent a substantial portion of transportation: 33% for two-wheelers, 25% for buses, 24% for three- and four-wheelers, and 18% for load vehicles. During the semi-lockdown and lockdown periods, there was a significant reduction in particulate matter pollution, particularly evident when comparing pre- and post-lockdown periods. The concentration of particulate matter during these periods notably decreased, with Koyembedu exhibiting the highest emission concentration at 0.000158 g/s-m^2 , closely aligning with the vehicular inventory for the region.

Analysis of PM_{10} and $PM_{2.5}$ levels during pre- and post-lockdown periods revealed that PM_{10} levels were consistently twice as high as $PM_{2.5}$ levels in a significant portion of the study region. The concentration of PM_{10} increased by a factor of two or three compared to $PM_{2.5}$ levels across all other stations. The prevailing wind direction post-lockdown in 2021 predominantly indicated winds blowing towards the ESE to S directions, accounting for approximately 38% of all hourly winds. The average wind speed during this period was recorded at 0.85 m/s, with approximately 29.25% of winds blowing between 0.5 to 2.1 m/s (up to 7.56 km/h), 6.26% blowing between 2.1 to 3.6 m/s (up to 12.96 km/h),

and 1.04% with speeds ranging from 3.6 to 5.7 m/s (up to 20.52 km/h). Utilizing AERMOD modeling, the study predicted the dispersion of particulate matter. Results showed that during June to July 2021 (post-lockdown), the concentration of PM_{2.5} and PM₁₀ was primarily distributed in the ESE to S directions. Notably, Koyembedu exhibited the highest concentrations of PM during June 2021, with levels reaching 206 µg/m³ for PM_{2.5} and 428 µg/m³ for PM₁₀, identifying it as a hotspot compared to other stations and surpassing the prescribed norms of the CPCB for the analyzed period.

5.1 Limitation of the Study

The study on PM_{2.5} and PM₁₀ emissions in Greater Chennai, although comprehensive, is subject to numerous inherent uncertainties and limitations. The reliance on primary surveys to evaluate traffic patterns and mode preferences can introduce sampling biases and inaccuracies in data collection. The methodology used assumes uniform emission factors across various vehicle types and driving conditions to calculate emission rates in grams per second per square meter (g/s-m²). This approach may overlook variations due to engine efficiency, maintenance levels, and driving behavior. Furthermore, the study's focus on specific sampling stations may not adequately represent the spatial variability of emissions throughout the entire urban area. Seasonal variations and meteorological conditions are simplified into four broad periods, which may not fully capture transient fluctuations that significantly influence pollutant dispersion and concentration. Additionally, the assumptions regarding vehicle types and their respective contributions may not account for future changes in traffic composition and technological advancements. These factors introduce uncertainties that can impact the generalizability and accuracy of the emission inventories and subsequent air quality assessments.

5.2 Scope of Future Work

Conducting a longitudinal study to evaluate the influence of particulate matter pollutants over an extended duration would involve gathering on-site data for several years. This would allow for an examination of trends and associations between pollutant levels and health outcomes, providing a foundation for future research.

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Code availability Not applicable.

Declarations

Conflict of interest Not applicable.

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