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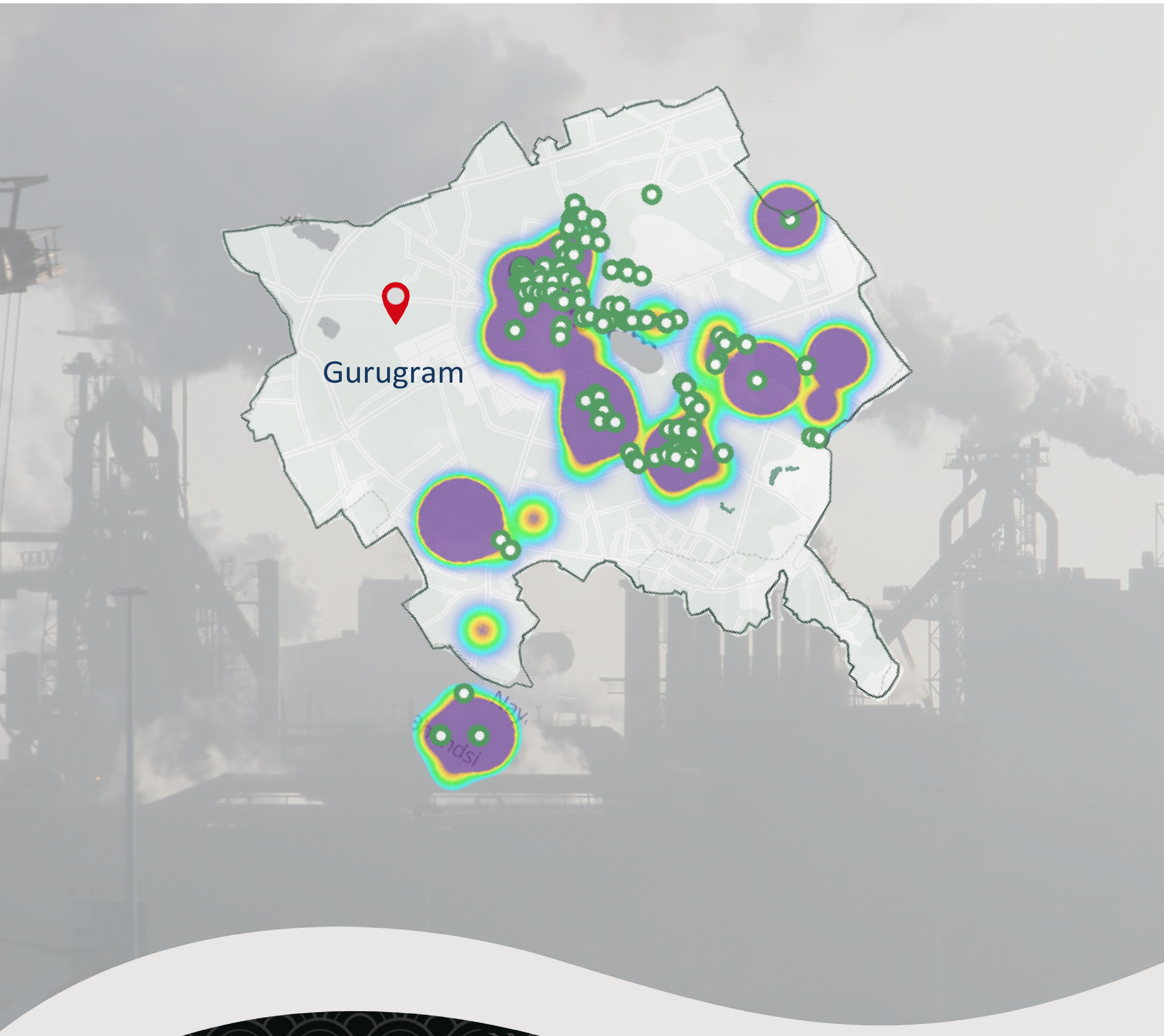

Hyperlocal mapping

of Air Pollution and GHG Emissions in Gurugram, Haryana

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A special note of thanks goes to the **team of citizen scientists** whose energetic participation, commitment, and community engagement were central to the project's success. Their efforts in generating **hyperlocal air quality data** not only enriched the dataset but also demonstrated the power of community-led environmental monitoring.

With this project, the team has been able to demonstrate the efficacy of hyperlocal air quality datasets to measure, analyze and forecast air pollution trends at a local level enabling action by government authorities.

We hope that hyperlocal air quality measurements can soon be adopted by governments around the country to mitigate the severity of the air pollution crisis.

Technology and Action for Rural Advancement,2025

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Executive Summary – Gurugram

This report details a pioneering project focused on hyperlocal mapping of air pollution and Greenhouse Gas (GHG) emissions in Gurugram, Haryana, India, a rapidly urbanizing city facing severe air quality challenges. Recognizing the limitations of traditional air quality monitoring networks in capturing localized pollution variations, the project implemented an innovative approach integrating low-cost Internet of Things (IoT) sensors with active citizen science participation.

The project has been set up by UNDP in collaboration with various partners. It has been guided by the Gurugram Municipal Development Authority (GMDA) since its inception and supported by GIZ/Lacuna Fund for Climate and Energy. GMDA's guidance has been instrumental in the design, implementation, monitoring, and action phases of the project. The setting up of the network of sensors based on the air pollution hotspots in Gurugram, the monitoring through daily and weekly bulletins and the subsequent action were guided by GMDA's knowledge and experience.

The core methodology involved the strategic deployment of 50 IoT-enabled sensors across Gurugram to monitor key pollutants ($PM_{2,5}$, PM_{10}, NO_2, CH_4, CO, and CO_2). Complementing this, twenty trained citizen scientists utilized portable sensors and a dedicated mobile application, VAYU by UNDP, to collect real-time data and geotagged observations of pollution sources across the city. The VAYU digital platform aggregated and analyzed this data using AI and machine learning, providing a dynamic and high-resolution understanding of Gurugram's air quality landscape.

The project successfully generated a substantial hyperlocal dataset, enabling the identification of critical air pollution risk hotspots and the analysis of temporal and spatial pollution trends, particularly during the high-pollution winter months. This detailed risk assessment forms the basis for targeted, evidence-based interventions. Furthermore, the project fostered significant community engagement, empowering citizens to contribute to environmental monitoring and increasing public awareness.

Leveraging the rich dataset and the VAYU platform, the project developed several impactful use cases tailored to Gurugram's specific challenges. These include a real-time air quality intelligence dashboard for public awareness and alerts, a data-driven system for optimizing urban mobility to mitigate vehicular emissions, a forecasting dashboard to enhance the resilience of critical infrastructure during pollution episodes, and an AI-enabled monitoring system for construction dust control and compliance enforcement. The report also outlines policy implications and recommends zone-specific interventions based on the identified hyperlocal hotspots.

While the project achieved significant milestones, it also encountered challenges related to data collection accuracy, technical limitations of low-cost sensors, and operational aspects of managing a citizen science network. The report addresses these limitations and proposes strategies for mitigation, emphasizing the need for rigorous data management, sensor calibration, and sustained community engagement.

Looking ahead, the project lays the groundwork for a more dynamic and responsive air quality management framework in Gurugram. The integration of advanced technologies like AI/ML, the evolution of sensor technology, and the continued engagement of citizens and policymakers are identified as key pathways for future progress. The success of this hyperlocal mapping initiative underscores the potential of combining technological innovation with community participation to address complex environmental challenges in urban centers and offers a scalable model for other cities in India and beyond.

The identification of hyperlocal pollution hotspots in Gurugram offers a critical input into the design of spatially differentiated policy responses. While city-level strategies such as the Graded Response Action Plan (GRAP) have been activated periodically, they often fail to capture the intra-urban variability of exposure risks.

This study recommends the implementation of zone-specific interventions such as:

a) Deployment of mobile enforcement and dust suppression units in identified hotspots,
b) Temporal restrictions on high-emission construction and transportation activities during peak hours,
c) Installation of vegetative buffers and air filtration systems in and around sensitive locations such as schools and healthcare facilities,
d) Enhanced public access to real-time air quality data through digital dashboards and SMS alerts, and
e) Inclusion of citizen-generated data and community monitoring under the Vayu platform to augment municipal capacity.

UNDP India, TARA and other partners, with financial support from the GIZ/Lacuna Fund for Climate and Energy, undertook a project to develop hyperlocal datasets on targeted point sources of air pollution and measure emissions in localized environments across Gurugram. STS Global provided the data science inputs, MistEO set up and managed the VAYU portal which hosted more than 1.4 million hyperlocal datasets, and Airshed Planning Professionals designed, manufactured, and maintained the Low-Cost Sensors.

1. Introduction

Air pollution is one of the most inescapable environmental challenges of the present day, having far-reaching repercussions for public health, ecosystems, biodiversity, and climate patterns. It is a pervasive and expanding global issue, affecting both rural and urban regions around the globe. As air quality declines, it poses grave risks to human health, contributing to cardiovascular and respiratory diseases, early mortality, and decreased life expectancy. According to the estimates of the World Health Organization (WHO), 99% of the world population breathes air that surpasses WHO's recommended air quality standards, making air pollution a silent but fatal threat to human well-being (WHO, 2021). According to a report by WHO, more than seven million people worldwide lose their lives due to diseases linked with PM2.5 pollution (WHO, 2015). PM2.5 was identified as the primary cause of respiratory and cardiovascular diseases. Low and middle-income nations accounted for 94% of premature deaths in 2016 caused by air pollution (WHO, 2018d). According to the United Nations Development Program (UNDP), climate change and air pollution have a firm association. Short-lived climate pollutants like methane, black carbon, and ground-level ozone have a major influence on global warming despite their shorter lifespan in the atmosphere compared to CO_2. Reducing these pollutants can reduce the present pace of warming by half (UNEP,2021). Since air pollution is a transboundary problem, tackling it calls for strict enforcement of laws, robust international collaboration, and a shift to cleaner energy and sustainable urban growth.

Air Pollution, according to the UNEP, is the result of particulate and gas emissions and the chemical processes they undergo in the atmosphere. The drivers behind escalating air pollution and associated greenhouse gas (GHG) emissions are complex and deeply rooted in modern development patterns, particularly urbanization and associated land-use changes (Li et al., 2024).Urban areas, serving as epicenters of socio-economic activity, are also major contributors to global emissions and environmental degradation (National Centre for Biotechnology Information [NCBI], n.d.). The rapid expansion of cities globally fuels increased energy consumption, places greater demands on transportation systems, concentrates industrial activities, and generates vast amounts of waste (NCBI, n.d.). Cities are estimated to be responsible for 70-75% of global energy consumption and carbon dioxide (CO2) emissions, underscoring their critical role in driving climate change (NCBI, n.d.).

Land Use Land Cover (LULC) change is a fundamental driver linked intrinsically to urbanization. Global data synthesized over 29 years (1992-2020) demonstrate a dramatic expansion of artificial surfaces (133%) and croplands (6%), at the expense of pasture and forest areas. This conversion, particularly the increase in artificial surfaces associated with urban growth, is significantly correlated with rising GHG emissions, primarily driven by the associated increase in energy consumption. Projections based on current trends suggest global GHG emissions could reach 76 ± 8 GtCO2eq by 2050 if these land-use patterns persist(Li et al., 2024). This transformation of the Earth's surface is not merely a transient issue; the conversion to urban uses represents one of the most irreversible human impacts on the biosphere. It permanently alters landscapes, hastens the loss of productive farmland, fragments habitats, reduces biodiversity, and modifies hydrological and biogeochemical cycles. This permanence amplifies the long-term consequences of current development trajectories. Furthermore, the pressure extends beyond the urban boundary itself; urbanization often intensifies agriculture on remaining undeveloped land and can drive agricultural expansion into new areas, creating cascading pressures on land resources far removed from the city (Seto Lab. (n.d.).

A critical aspect of urban environmental impact is the Urban Heat Island (UHI) effect, where cities experience higher temperatures than surrounding rural areas due to the prevalence of heat-absorbing surfaces like concrete and asphalt and the lack of vegetation. This phenomenon directly increases energy demand for cooling, particularly in warmer climates, leading to higher electricity consumption and associated emissions if the energy source is fossil fuel based. This creates a detrimental feedback loop: urban form drives higher temperatures, which increases energy use, which in turn exacerbates emissions and potentially worsens local air quality (e.g., through ozone formation), further contributing to warming (NCBI, n.d.).

The relationship between air pollution, climate change, and human health forms a critical nexus, with profound implications, especially for rapidly developing nations like India. These issues are deeply interconnected. Many sources, particularly the combustion of fossil fuels, release both health-damaging air pollutants (like particulate matter (PM), nitrogen oxides (NOx), sulfur dioxide (SO2)) and GHGs (like CO2) simultaneously (United Nations Environment Program [UNEP], n.d.). Furthermore, some air pollutants, such as tropospheric ozone and certain aerosols like black carbon, function as short-lived climate forces, directly contributing to warming or altering climate processes. Conversely, climate change itself can exacerbate air pollution problems. Rising temperatures can accelerate the chemical reactions that form ground-level ozone, a major respiratory irritant (Singh et al., 2024).
Changes in weather patterns influenced by climate change can also affect the dispersion and concentration of pollutants, potentially leading to more frequent and severe pollution episodes. Recent air modelling studies specifically indicate that climate warming could worsen PM2.5 pollution across India UNEP, n.d.).

The human health consequences of this nexus are severe, particularly in India, which faces some of the world's highest air pollution levels. In 2019 alone, an estimated 1.67 million deaths in India were attributable to air pollution, representing 17.8% of all deaths in the country. The majority stemmed from ambient particulate matter pollution (0.98 million deaths) and household air pollution (0.61 million deaths) (WHO, 2021).

Climate change adds another layer of health risk through direct impacts like heat stress. Research by Akhtar (2007) highlights that global warming has contributed to increased frequency and intensity of heat waves in India, leading to a rise in heat-related mortality, particularly in northwestern, southern, and southeastern regions(Akhtar, 2007). Heat waves, defined in India based on temperature deviations from the norm, can persist for days and disproportionately affect the elderly and those living in poor urban conditions with inadequate water supply. A lag effect is often observed, where mortality peaks slightly after the heat wave event(Akhtar, 2007),(Kushwaha & Sen Roy, 2012). Looking ahead, projections by Dholakia et al. (2015) paint a concerning picture for urban India. Their study, covering fifty-two major urban areas, predicts a substantial increase in heat-related mortality by the late 21st century under plausible climate change scenarios (RCP 4.5 and 8.5), potentially doubling or more compared to baseline levels. Critically, this projected rise in heat deaths is expected to overshadow any potential decline in cold-related mortality during winter months. Cities like Delhi, Ahmedabad, Mumbai, Kolkata, and Bengaluru are projected to face the highest absolute increases (Dholakia et al., 2015). These studies underscore the compounded vulnerability of India's population, facing the dual threats of severe air pollution and increasing heat stress, amplified by climate change (WHO,2021). The risks are particularly acute for urban populations, especially the poor, elderly, and those residing in informal settlements who often lack resources for adaptation (Gao et al., 2024).

Despite the severity of these challenges, there is also significant potential for positive change. Climate mitigation policies, such as transitioning from fossil fuels to clean, renewable energy sources, offer substantial health co-benefits by simultaneously reducing GHG emissions and emissions of health-harming air pollutants (UNEP, n.d.). Given India's high baseline levels of air pollution and numerous pollution hotspots, the country stands to gain some of the greatest health co-benefits globally from such mitigation efforts. Achieving India's stated goal of net-zero emissions by 2070, announced at COP26, could therefore yield immediate and significant improvements in public health alongside long-term climate objectives (Ashoka Centre for People-centric Energy Transition [ACPET], n.d.).

Air pollution and climate change are deeply connected, as they originate from similar sources and collectively contribute to greenhouse gas emissions (WHO,2021). Both natural processes and anthropogenic activities can lead to air pollution. Natural causes such as lightning, sea spray, and volcanic eruptions can all contribute to air pollution. However, the bulk is brought on by five categories of human activity: waste, industry, transportation, agriculture, and households. Particulate matter (PM2.5 and PM10), nitrogen oxides (NOx), sulfur dioxide (SO_2), carbon monoxide (CO), ozone (O_3), volatile organic compounds (VOCs), and methane (CH_4) constitute the major air pollutants. Air pollutants are classified as primary or secondary. Primary pollutants, such as emissions from factories, vehicles, and wildfires, are released directly into the atmosphere, while secondary pollutants result from chemical reactions occurring in the air. As per a recent World Bank analysis, the worldwide cost of health harm brought on by exposure to air pollution is $8.1 trillion, or 6.1% of the world's gross domestic product (World Bank, 2022). On the far side of human health, poor air quality also disrupts agriculture, lowering crop yields due to increased atmospheric pollutants and reduced sunlight penetration.

Air pollution is a global issue because it is an intricate, multifaceted problem that transcends national and political borders. The parts that follow examine its transboundary character, underlining how pollutants move beyond regions, aggravating global health and environmental concerns. To provide a thorough grasp of the issue and the necessity for immediate action, we lastly examine the main causes of air pollution in India and evaluate their effects on the environment, the economy, and public health.

1.1 Air pollution – A transboundary issue

Air pollution brings about serious threats to the health of the environment worldwide and crosses national boundaries. Since pollutants may transcend borders and impact areas far from their original origins, it is a severe transboundary concern. Due to their ability to travel great distances via air currents, pollutants like nitrogen oxides and particulate matter (PM2.5) can have a detrimental effect on areas that are distant from the sources of their earliest emissions. A 2024 World Bank bulletin reports that over 50% of air pollution in major South Asian cities is transboundary, traveling across city, state, and national borders. In the Indo-Gangetic Plain and Himalayan Foothills region, key sources include household cooking, transport, crop burning, industry, and power plants. Managing these emissions is challenging as responsibilities are spread across multiple government ministries (World Bank, 2024).

The European Environment Agency (EEA) states that energy production and transportation activities are the main sources of emissions of important air pollutants, including sulfur oxides (SO_x), nitrogen oxides (NO_x), carbon monoxide (CO), methane (CH_4), non-methane volatile organic compounds (NMVOCs), certain heavy metals, and polycyclic aromatic hydrocarbons. These pollutants can persist in the atmosphere long enough to be transported over thousands of kilometers, contributing to transboundary air pollution (Dholakia et al., 2015).

The complexity of managing transboundary air pollution is significant. As highlighted by Abas et al. (2019), unlike issues such as ozone depletion (Montreal Protocol) or global climate change (Kyoto Protocol/Paris Agreement), there are no universally binding conventions specifically governing the broad range of transboundary air pollutants, although regional agreements exist (Abas et al.,2019). Traditional environmental policy principles like the 'polluter-pays' principle are often difficult to apply across borders, typically being restricted to the source country (Sprinz, 2004) . This limitation underscores the critical need for international cooperation and regional frameworks to address shared air quality problems effectively (NEASPEC, n.d.). Abas et al. suggest that cooperative control mechanisms, potentially involving mutual supervision, joint standard-setting, or even extending the polluter-pays principle through international environmental law, are necessary (Abas et al.,2019). Regional integration initiatives, by fostering collaboration and shared governance structures, can potentially strengthen environmental regulations and curb transboundary pollution flows.

The Indo-Gangetic Plain (IGP) and the Himalayan region provide a stark example of transboundary air pollution dynamics in South Asia. The IGP is one of the world's most significant agricultural zones and a major air pollution hotspot. A major contributor, particularly during the post-monsoon season (October-November), is the large-scale open burning of agricultural residues (ARB), primarily rice straw, in the northwestern Indian states of Punjab and Haryana. This practice releases vast quantities of pollutants, including particulate matter (PM2.5, PM10), black carbon (BC), carbon monoxide (CO), and volatile organic compounds (VOCs)(Saikia, 2024).

A study by Khanal et al. (2022) specifically investigated an air pollution episode in Kathmandu, Nepal, during November 2020. Their analysis, using in-situ measurements, satellite data, and back-trajectory modelling, demonstrated that transboundary transport of smoke plumes from ARB in northwest India was the primary cause of a rapid doubling of PM2.5 concentrations in the Kathmandu Valley over just a few days. This research revealed a crucial aspect: while ARB emissions are widespread during the season, the significant transport of these pollutants across the plains and into the central Himalayas (beyond the Mahabharat range) is episodic. Specific synoptic and mesoscale meteorological conditions, particularly favorable wind patterns often channeled through river valleys, are required to lift and transport the polluted air masses from the plains into higher altitude regions like Kathmandu. This episodic nature presents a distinct challenge for mitigation and management. It implies that simply reducing overall seasonal emissions, while necessary, might not be sufficient to prevent these high-impact transboundary events (Khanal et al., 2022).

Effective management requires enhanced forecasting capabilities to predict high-risk transport periods and potentially implement targeted, temporary, emission controls during those windows, demanding a sophisticated level of regional coordination and data sharing. The findings from studies like Khanal et al. (2022) and the broader analysis by Abas et al. (2019) strongly reinforce the inadequacy of purely national approaches to air quality management in regions like South Asia. The documented impact of ARB emissions from India on Nepal's air quality highlights the interconnectedness of the regional airshed(Khanal et al., 2022).Addressing such challenges effectively necessitates robust regional frameworks for collaboration. This includes establishing mechanisms for sharing monitoring data, developing joint modelling capabilities to understand source-receptor relationships (as pursued by groups like NEASPEC in East Asia), coordinating emission inventories, and developing harmonized or cooperative policy interventions (NEASPEC, n.d.).

While regional bodies like the South Asia Co-operative Environment Program (SACEP) and initiatives like the South Asian Nitrogen Hub (SANH) exist and work on related environmental issues (South Asia Co-operative Environment Program [SACEP], 2021), a dedicated and comprehensive framework for managing transboundary *air pollution* across South Asia appears less developed compared to other regions or issues, representing a critical gap that needs addressing (Talukdar et al., 2020). As Khanal et al. suggest, scientific evidence of transboundary impact can serve as a vital starting point for initiating the necessary multilateral dialogue and cooperation (Khanal et al., 2022).

The transboundary nature of air pollution underscores the need for global collaboration in formulating and enforcing effective policies and regulations. By acknowledging the collective responsibility in managing air quality, nations can unite to address the far-reaching environmental and health consequences of air pollution. While international cooperation is vital, it is equally important to focus on localized pollution hotspots. A deeper understanding of air quality at the hyperlocal level—such as within urban areas and industrial zones—is crucial for crafting targeted mitigation strategies, enhancing public health, and ensuring the successful implementation of policies.

1.2 India and Air Quality

India is grappling with severe air quality issues, as many of its cities rank among the most polluted globally. The rapid pace of urbanization, industrial expansion, and a rising population have all played a significant role in worsening air pollution throughout the country. According to IQAir's World Air Quality Report (2020), South Asian cities rank among the most polluted globally, with India frequently recording some of the highest PM2.5 levels (IQAir, n.d.). Seasonal biomass burning, building dust, and vehicle emissions are the main causes of the severe air pollution episodes that often occur in cities like Beijing, Jakarta, and New Delhi. Forty-two of the fifty most polluted cities in the world are in India, according to the World Air Quality Report 2020. Cities like Delhi, Kanpur, and Varanasi often record dangerously elevated levels of particulate matter (PM2.5) and other dangerous pollutants (IQAir, 2020). India experiences some of the highest air pollution levels globally, significantly impacting public health and the economy. Prolonged exposure to PM 2.5 is linked to severe health conditions, including lung cancer, heart disease, and strokes. The WHO estimates that 1.67 million deaths in India in 2019 were caused by air pollution, accounting for 17.8% of all fatalities in the nation (World Bank, 2023). Air pollution originates from several key sectors, including transportation, industry, agriculture, power generation, waste management, biomass burning, residential activities, and construction and demolition processes. Furthermore, air pollution has a significant negative impact on quality of life, healthcare expenses, and productivity. India's National Clean Air Program (NCAP) is a significant initiative aimed at addressing the country’s worsening air quality. It establishes a time-bound target for air quality improvement, prioritizing approximately 131 "non-attainment" cities where pollution levels exceed permissible limits. However, consistent local, regional, and national initiatives, as well as improved environmental regulatory monitoring and enforcement, will prove essential to achieving substantial improvements in air quality.

1.3 Sources of air pollution in India and its impact

India's air pollution stems from both natural and human-induced sources, posing serious risks to public health, the environment, and the economy. Key contributors include emissions from vehicles and industries, biomass combustion, construction dust, and the burning of crop residues. Additionally, wind-blown dust, including dust from natural sources like construction sites, roadways, and industrial facilities, can contribute to PM 2.5 levels.

The World Bank (2024) reports that over half of India’s PM 2.5 emissions form in the upper atmosphere when ammonia (NH_3) reacts with sulfur dioxide (SO_2) and nitrogen oxides (NO_x). Agriculture, industry, power plants, households, and transport are key contributors. Unlike primary PM 2.5, its secondary form spreads widely, crossing cities, states, and borders.

According to a report by the Council of Scientific and Industrial Research (CSIR), road traffic emissions are a significant source of air pollution in urban India. Road dust contributes to PM emissions in major cities, accounting for 37% in Delhi, 30% in Mumbai, and 61% in Kolkata. Similarly, road transport is the leading source of PM2.5 pollution in Bengaluru (41%), Chennai (34%), Surat (42%), and Indore (47%) (CSIR-NIScPR, 2022) (Kanaujia et al., 2022). According to NASA Earth Observatory (2024), satellite data showed increased fire activity in northern India each November as farmers, particularly in Punjab, burned excess straw after the rice harvest. This quick, low-cost field-clearing method contributed to severe air pollution across the Indo-Gangetic Plain, worsening air quality in October and November (NASA Earth Observatory, n.d.).

The World Health Organization (WHO) states that air pollution can impact every organ in the body. Tiny airborne pollutants can pass through the lungs into the bloodstream, circulate throughout the body, and contribute to systemic inflammation and cancer risks (World Health Organization [WHO], n.d.). According to The State of Global Air (2024), air pollution was the second most significant cause of mortality globally in 2021, accounting for 8.1 million fatalities, including those of children under five (Health Effects Institute [HEI], 2024). In 2021, air pollution accounted for about 18% of all deaths in India, according to The State of Global Air (2024). With more than 2.09 million deaths attributed to air pollution, it continues to be the nation's top health concern. Moreover, 62% of Indians live in regions with PM2.5 concentrations higher than the WHO's least strict Interim Target for healthy air (35 $\mu g/m^3$)(Health Effects Institute [HEI], n.d.). UNEP states that, in addition to harming human health, air pollution also has an impact on ecosystems and food production, and it also contributes to climate change (UNEP, n.d.).

While global initiatives emphasize emission reductions through clean energy adoption and stringent regulations, India confronts distinct challenges stemming from rapid urbanization, industrial growth, and widespread biomass fuel usage. Combating air pollution necessitates a comprehensive strategy that combines policy reforms, technological advancements, and active community involvement.

2. Hyperlocal Air Quality

2.1 Air pollution in cities and its sources

India's economy is among the fastest growing in the world, yet this rapid advancement comes with the pressing challenge of air pollution. An amalgamation of waste burning, automobile emissions, and industrial activity, along with construction dust causes some of the worst levels of air pollution in urban areas. According to the IQAir 2023 report, cities such as Begusarai, New Delhi, Guwahati, Greater Noida, Gurugram, and Gurugram rank among the most polluted, consistently recording hazardous PM2.5 levels (IQAir, n.d.). This alarming trend is attributed to their dense populations and substantial energy consumption. Urban environments are home to a wide range of pollution sources. Traditional contributors to air pollution include vehicle emissions, coal-fired power plants, industrial fossil fuel consumption, and certain agricultural practices like fertilizer use and crop residue burning. Air pollutants can originate naturally or result from human activities. Examples include emissions from brick kilns burning raw wood, agricultural waste, or low-quality coal, roadside burning of organic and plastic waste, biomass or cow dung used for cooking, accidental landfill fires, and pollution from construction activities (Kumar et al., 2015). Figure 1 illustrates the major sources of air pollution in six Indian cities, highlighting the contribution of road dust, transport, industries, and waste burning (Guttikunda, 2018) (Kumar et al., 2015).

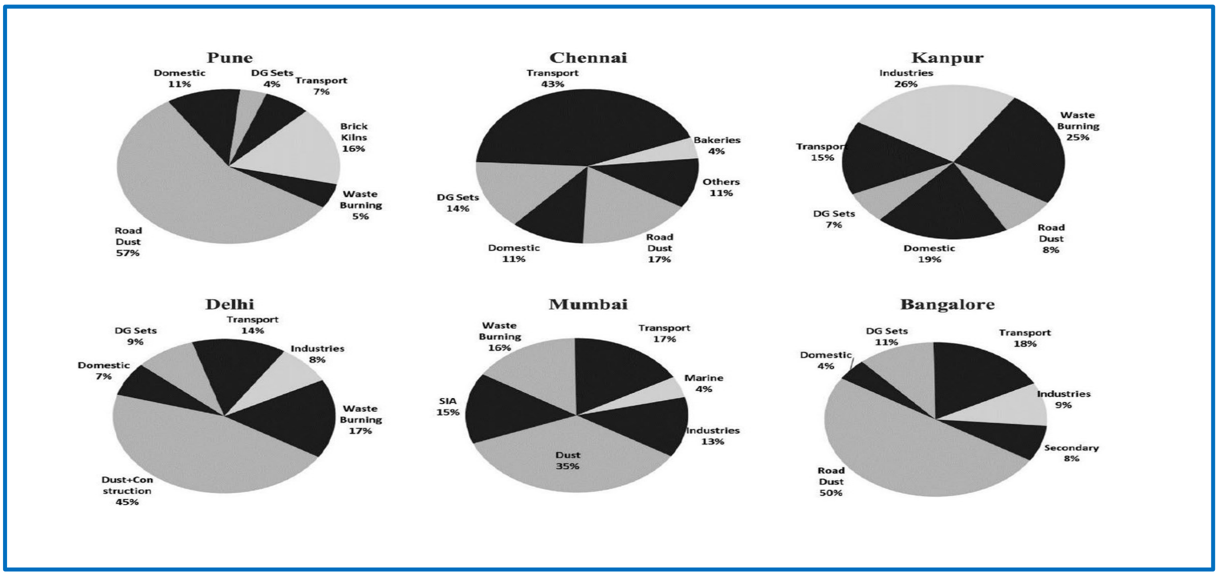


Figure 1 :*Source: Guttikunda, S. (2018). Air Pollution in India: Status and Challenges. Indian Science, Technology, and Innovation Portal***.**

According to a 2021 report by the Council on Energy, Environment and Water (CEEW) titled *What is Polluting India's Air*, the power sector was the largest contributor to nitrogen oxides (NO_x) and sulfur dioxide (SO_2) emissions in India. These pollutants underwent atmospheric reactions, forming secondary particulate matter, which elevated ambient particulate pollution levels. Additionally, the residential sector, which was the highest contributor to particulate emissions, was a major factor in air pollution-related mortality in the country and required urgent attention (Council on Energy, Environment and Water, 2021).

As cities continue to expand, addressing urban air pollution requires a targeted, data-driven approach that incorporates hyperlocal monitoring to identify pollution hotspots and implement precise mitigation strategies.

2.2 Context: Air pollution and GHG emissions in Gurugram

Gurugram is a metropolitan city in the Delhi-NCR region. It is home to major companies, offices, and malls, and has become a city of major importance in modern India. It inhabits a population of 15,14,432 people as per the 2011 Census(https://gurugram.gov.in/) and has major roads and highways stretching through. The older regions of Gurugram are also home to many industries and manufacturing units.

Air Quality in Gurugram

One of the cities most severely impacted by air pollution in India is Gurugram. Barring the interruption from the COVID-19 pandemic, it has consistently been named as one of the most polluted cities in India, as well as the world.

The most defining characteristic of Gurugram in recent decades has been its explosive urban growth and the consequent dramatic transformation of its Land Use Land Cover (LULC) (Rajesh & Kumari, 2022). Historically agricultural, the area underwent rapid development, particularly after India's economic liberalization in the early 1990s (Ganga Maheshwari & Suganya, 2021).Proximity to Delhi, coupled with state government policies facilitating private investment, attracted multinational corporations (MNCs), IT companies, and major real estate developers like DLF Group, Unitech, and Ansal Properties (Preeti, 2024). This private sector-led boom transformed Gurugram into a 'Millennium City' or 'Cyber City', characterized by modern office spaces, high-rise residential complexes, shopping malls, and associated infrastructure(Rajesh & Kumari, 2022).

This rapid urbanization has come at the cost of other land uses. Studies using satellite imagery document a drastic decline in agricultural land – from potentially over 80% in the early 1970s to around 26.5% by 2003(Rajesh & Kumari, 2022) , and further down to approximately 43.4% of the district area by 2017(Seema et al., 2019). Correspondingly, built- up areas expanded significantly; one study noted an increase from 11.36 sq. km to 84.2 sq. km between 1971 and 2003(Rajesh & Kumari, 2022), while another calculated a 1076% increase in built-up area between 1990 and 2017(Yadav & Rai, 2023). This expansion also led to decreases in vegetation cover and the area occupied by water bodies (Office of the Principal Scientific Adviser to the Government of India, n.d.). This pattern of rapid, often private developer-driven sprawl, while generating economic growth, has placed immense pressure on the region's resources and environment, contributing to infrastructure deficits and significant environmental challenges, including severe air pollution (Preeti, 2024).

The population-dense city of Gurugram mostly comprises the working population, who need to commute to and from their working locations, resulting in heavy vehicular emissions. Gurugram also has one of the highest vehicle ownership rates in the country, with 232 cars for every 1,000 people whereas Delhi has just 120 cars for every 1,000 people(Daga 2016). The region of Gurugram also has a severe lack of public transport which increases the reliance on private vehicles. The lack of public transport in the city, combined with the heavy reliance on private vehicles to commute has led to extremely elevated levels of vehicular pollution, combined with others.

Due to the unreliable supply of electricity in the city, many residential apartments and apartment buildings have started relying on diesel generators. DG sets alone are responsible for increasing the PM2.5 and PM10 concentrations by 30%. Some other major sources of pollution in the city apart from vehicular emissions and DG sets are construction waste, soil dust, biomass, refuse burning, and landfills.

PM2.5- Measured by Dispersion and Receptor Modelling

- Vehicular Emissions- Ranges between 16- 27%.
- Dust Emissions- Ranges between 15-49%.
- Biomass Emissions- Ranges between 14-27%.
- Industrial Emissions- Ranges between 13-30%.
- Other Emissions (Residential, accidental)- Ranges between 8-15%.

PM10- Measured by Dispersion and Receptor Modelling

- Vehicular Emissions- Ranges between 14- 23%.
- Dust Emissions- Ranges between 30-52%.
- Biomass Emissions- Ranges between 13-19%.
- Industrial Emissions- Ranges between 13-26%.
- Other Emissions (Residential, accidental)- Ranges between 6-8%.

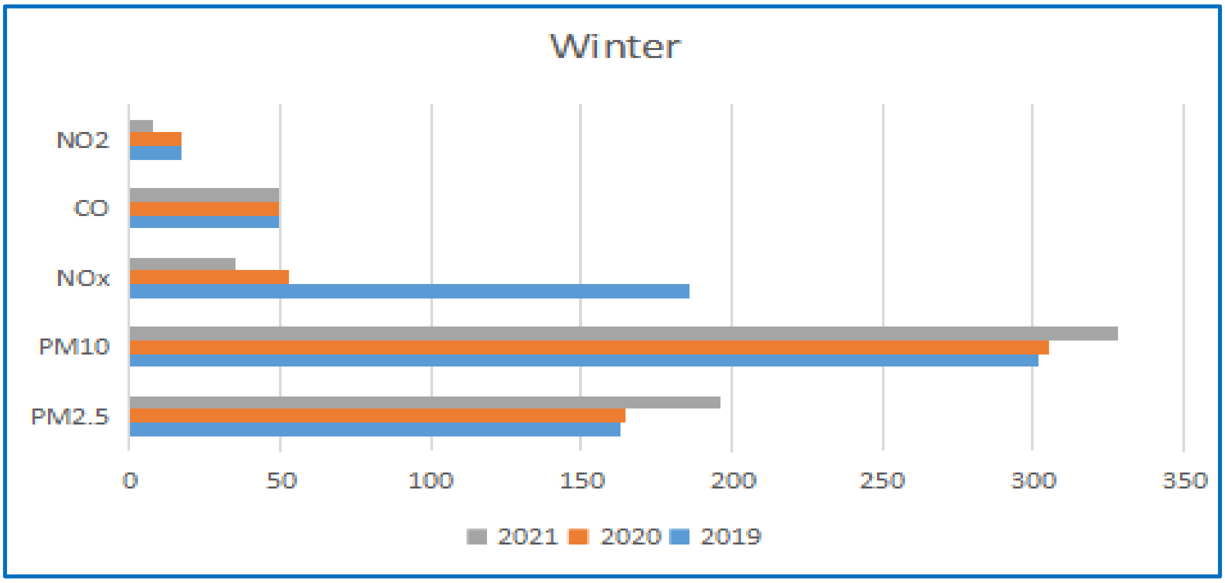


Figure 2 : *Trends of Gurugram pollutant parameters over the years 2019, 2020, and 2021 in the Winter season*

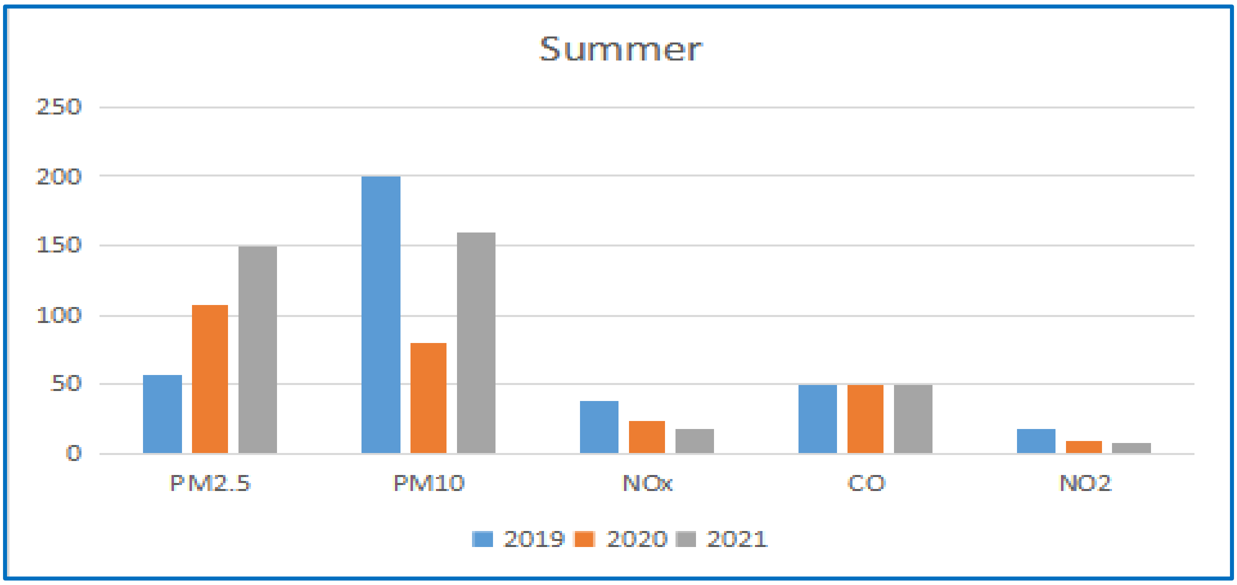


Figure 3: *Trends of Gurugram pollutant parameters over the years 2019, 2020, and 2021 in the summer season*

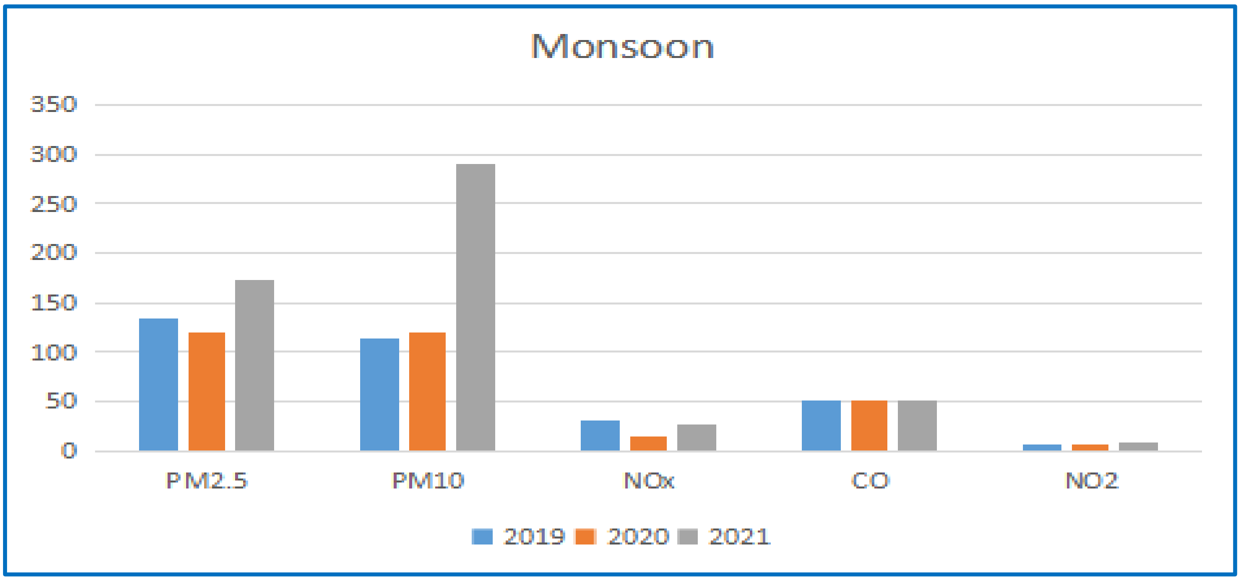


Figure 4 : *Trends of Gurugram pollutant parameters over the years 2019, 2020, and 2021 in the Monsoon season*

3. The Project

The project implemented by UNDP India in collaboration with TARA (an enterprise of the Development Alternatives group) and other partners, and supported by the GIZ-LACUNA Fund, focuses on addressing the pervasive air pollution challenges in Gurugram. It has successfully generated a hyperlocal dataset on air pollution sources, encompassing both point and nonpoint sources, through the integration of IoT sensors, citizen science, and societal intelligence. The real-time air quality data collected has facilitated the mapping of spatio-temporal pollution patterns, offering a comprehensive understanding of local pollution hotspots across these urban centers.

This data-driven approach has equipped local authorities with the insights necessary to develop targeted, site-specific action plans aimed at mitigating air pollution. The project has also fostered significant community engagement, with citizen scientists playing an active role in data collection and validation, thereby ensuring a collaborative and inclusive effort in addressing the issue. By advancing science-based solutions, the initiative has contributed to enhanced public health outcomes and provided a foundation for informed decision-making in long-term environmental management.

3.1 Rationale for Hyperlocal Air Quality Measurement

Traditional air quality monitoring networks, typically composed of sophisticated, regulatory-grade monitors (RGMs) operated by agencies like the CPCB, form the backbone of air quality assessment and compliance verification. However, these networks face inherent limitations, particularly in capturing the complex, dynamic nature of air pollution within urban environments (UNDP GCTISD, 2023).RGMs are expensive to purchase, operate, and maintain, and require significant technical expertise, which often restricts the number of monitoring stations that can be deployed (UNDP GCTISD, 2023). Consequently, these networks are often sparse, providing data representative of broader areas but potentially missing significant pollution variations that occur over short distances (tens to hundreds of meters) and timespans (Patel et al., 2023). This spatial and temporal granularity is crucial for understanding actual human exposure, identifying localized pollution hotspots (e.g., near busy roads, industrial facilities, construction sites), and evaluating the effectiveness of targeted interventions (Asian and Pacific Centre for Transfer of Technology [APCTT], 2024). The lack of dense monitoring networks is particularly acute in low- and middle-income countries (LMICs) due to resource constraints (UNDP Global Centre for Technology, Innovation and Sustainable Development, 2023).

This gap necessitates approaches that can provide air quality information at a much finer, or "hyperlocal," scale. The primary rationale for hyperlocal monitoring is to move beyond city-wide averages and understand the variations in air quality at the neighborhood, street, and even individual level, where people live, work, and commute.

Such granular data offers several potential benefits:

a) **Improved Exposure Assessment:** Providing more accurate estimates of pollutant concentrations individuals are exposed to,
b) **Hotspot Identification:** Pinpointing specific locations with consistently high pollution levels,
c) **Source Identification:** Helping to infer local emission sources by correlating pollution peaks with specific activities or locations,
d) **Targeted Interventions:** Enabling more focused and efficient mitigation strategies directed at identified hotspots or sources,
e) **Urban Planning:** Informing decisions related to land use, transportation design, and green space allocation,
f) **Community Awareness and Engagement:** Empowering citizens with information about their local environment and fostering participation in solutions.

Literature Review: Hyperlocal Monitoring as a Solution

The feasibility and adoption of hyperlocal air quality monitoring have been significantly advanced by the emergence of low-cost sensor (LCS) technologies over the past decade. These sensors, measuring pollutants like PM, CO, NO2, O3, and meteorological parameters, offer several advantages that make denser monitoring networks possible:

a) **Lower Cost:** LCS units can be orders of magnitude cheaper than RGMs, allowing for the deployment of many more sensors for a given budget.
b) **Smaller Size and Portability:** Their compact nature facilitates easier deployment in diverse locations, including mobile monitoring platforms or personal devices (Patel et al., 2023).
c) **Ease of Deployment:** Installation and setup can often be simpler than for complex RGM stations.

This technological shift has coincided with the rise of **Citizen Science (CS)** in the environmental field (Kumar & Rivas, 2022). While CS does not necessitate LCS use , the accessibility and lower cost of these sensors have enabled broader public participation in air quality monitoring projects. Citizen science initiatives leverage community involvement to collect data, often expanding monitoring coverage into areas previously unmeasured. Beyond data collection, CS can play a vital role in democratizing environmental information, increasing public understanding of air pollution issues and their links to health and climate change, fostering community engagement, and potentially advocating for policy action.

Various **implementation strategies** for hyperlocal monitoring using LCS have been explored. These include deploying networks of stationary sensors across a city, using sensors mounted on vehicles (e.g., buses, waste collection trucks) for mobile mapping, and equipping individuals with personal sensors to measure exposure during daily activities.

The design of the monitoring network (e.g., grid-based, source-oriented, volunteer-hosted), sensor placement considerations, robust data management systems (including transmission and storage), and rigorous calibration and validation protocols are critical for successful implementation.

However, it is crucial to acknowledge the **challenges and limitations** associated with LCS. Data quality can be variable and is often lower than that of RGMs. LCS performance can be affected by environmental factors like temperature and humidity, sensor drift over time, cross-interferences from other pollutants, and limitations in sensitivity or robustness at exceptionally low or high concentrations. Therefore, careful calibration (often involving co-location with reference instruments) and ongoing quality assurance/quality control (QA/QC) procedures are essential to ensure data reliability. The overall cost of an LCS project extends beyond the initial sensor purchase to include resources for maintenance, calibration, data infrastructure, analysis, and personnel.

A key concept emerging from literature is "fitness for purpose". The required level of data accuracy and reliability depends heavily on the intended application. Data for raising public awareness or identifying general trends might tolerate greater uncertainty than data intended for scientific research on health effects, regulatory compliance assessment, or detailed source apportionment. This highlights that there is no single standard for LCS data quality; rather, projects must clearly define their objectives and ensure the chosen sensors and data management practices meet the requirements of that specific application.

Furthermore, LCS are viewed as **complementary** to, rather than replacements for traditional RGM networks. RGMs provide the high-accuracy, legally defensible data needed for compliance and tracking long-term trends against standards. LCS networks excel at filling the spatial and temporal gaps left by sparse RGM networks, providing insights into local variations and exposure patterns. Effective air quality management increasingly involves hybrid approaches that leverage the strengths of both RGM and LCS technologies, often using RGMs as anchors for calibrating and validating the denser LCS networks (UNDP GCTISD, 2023).

Table 1: Comparison of Traditional (RGM) vs. Hyperlocal (LCS-based) Air Quality Monitoring

Feature	Traditional Monitoring (RGM)	Hyperlocal Monitoring (LCS-based)
Cost per Unit	Rs.3.5-4.0 Lakhs (approx.)	Rs. 0.7 Lakhs (approx.)
Spatial Coverage	Sparse / Low Density	Potentially High Density / Dense Networks 12
Temporal Resolution	Typically High (e.g., hourly)	Often High (e.g., minutes)
Data Accuracy/Reliability	High / Reference Standard	Variable / Lower than RGM / Requires Calibration & QA/QC
Maintenance Needs	High / Requires Skilled Technicians	Moderate to High (calibration, replacement)
Typical Applications	Regulatory Compliance, Trend Analysis, Research	Hotspot ID, Exposure Assessment, Awareness, Citizen Science
Key Limitations	High Cost, Limited Spatial Detail, Infrastructure Needs [12]	Data Quality Variability, Calibration Needs, Lifespan

The geographical spread and complexity of pollution sources pose a significant challenge to successful intervention. The International Energy Agency (IEA) has identified fossil fuel combustion as a primary contributor to both air pollution and greenhouse gas (GHG) emissions in India. Critical pollutants such as NOx, SO_2, and PM2.5 primarily originate from energy-related fuel combustion, which is also the country's primary source of CO_2 emissions. This overlap necessitates an integrated approach to address both air pollution and climate change. However, because they are so diffuse and extensive, it is still difficult to identify individual emission sources. Major contributors such as vehicular emissions, biomass and waste burning, industrial activities, construction dust, and agricultural residue burning complicate targeted mitigation efforts. Without localized, high-resolution data, policy solutions run the danger of being ineffectual and too general.

In response to this challenge, UNDP India, in collaboration with TARA and other partners, and with financial support from GIZ/Lacuna Fund for Climate and Energy, has taken a crucial step in creating hyperlocal datasets for air pollution and GHG emissions. This initiative focuses on Gurugram, a city that has been grappling with severe air pollution. The project has employed innovative methodologies, such as citizen science and the deployment of IoT sensors, to collect granular, real-time data on air quality. The data collected from these sensors has provided invaluable insights into pollution hotspots, enabling a more nuanced understanding of local air quality challenges. Hyperlocal air quality data enables local administrations to take targeted actions to contain the pollution.

By deploying 50 IoT sensors across Gurugram, the project has been able to monitor critical pollutants such as PM10, PM2.5, NO_2, CH_4, CO, and CO_2. These sensors have been integrated with mobile and web applications, allowing for real-time data visualization. Moreover, citizen scientists have played an essential role in data collection, ensuring that the community is actively engaged in understanding and addressing local air quality issues. The collaborative approach has led to better data validation and strengthened partnerships with local government agencies and civil society organizations.

Through these efforts, the project has created a foundation for more effective air quality management strategies in Gurugram. The work done so far demonstrates the power of integrating innovative technology with community engagement, providing a clear path toward addressing the pressing air pollution challenges in India's urban centers.

3.2 Objectives

UNDP India and TARA, with financial support from the GIZ/Lacuna Fund for Climate and Energy, undertook a project to develop hyperlocal datasets on targeted point sources of air pollution and measure emissions in localized environments across Gurugram. The project focused on:

a) Conducting hyperlocal air pollution data collection using innovative methodologies such as citizen science and societal intelligence.

b) Implementing data processing, quality assurance, and analytical techniques to establish correlations and explore modelling potential between field data and remote sensing observations.

c) Developing use-case pathways to translate data insights into tangible impact, working in close collaboration with government stakeholders to ensure scalability and applicability across diverse geographic regions.

The overarching objective of this initiative was to conduct hyperlocal mapping of air pollution and greenhouse gas (GHG) emissions in Gurugram, enabling evidence-based decision-making and targeted interventions for improved air quality management. These objectives are designed to ensure a comprehensive and integrated approach to the air pollution challenges faced by both cities. By systematically working towards these goals, the project intends to generate a robust, actionable dataset that can significantly enhance air quality management and contribute to long-term environmental improvements.

3.3 Approach and Methodology

This project aimed to address the limitations of conventional air quality monitoring in Gurugram by implementing a hyperlocal monitoring strategy. The overarching goal was to generate high-resolution spatial and temporal data on key air pollutants within the city, moving beyond the insights available from the existing sparse regulatory network. The core strategy involved deploying a network of Internet of Things (IoT)-enabled low-cost air quality sensors across different land-use areas and microenvironments within Gurugram. This technological approach was integrated with a citizen science component, engaging residents in hosting sensors, contributing observations, and participating in the interpretation of findings. The intended outcomes included the creation of detailed hyperlocal air pollution maps, identification of localized pollution hotspots, enhanced understanding of pollution dynamics within the city, and the provision of accessible data to empower community members and inform potential mitigation actions by local authorities. This approach sought to leverage the complementary strengths of LCS technology for dense spatial coverage and citizen science for community engagement and localized knowledge.

In line with our approach, the methodology for mapping air pollution in India is tailored to address the complexities of air quality monitoring and source identification. By integrating advanced technology, active citizen participation, and strategic collaboration with local government agencies, the project ensures a comprehensive and effective execution of its objectives.

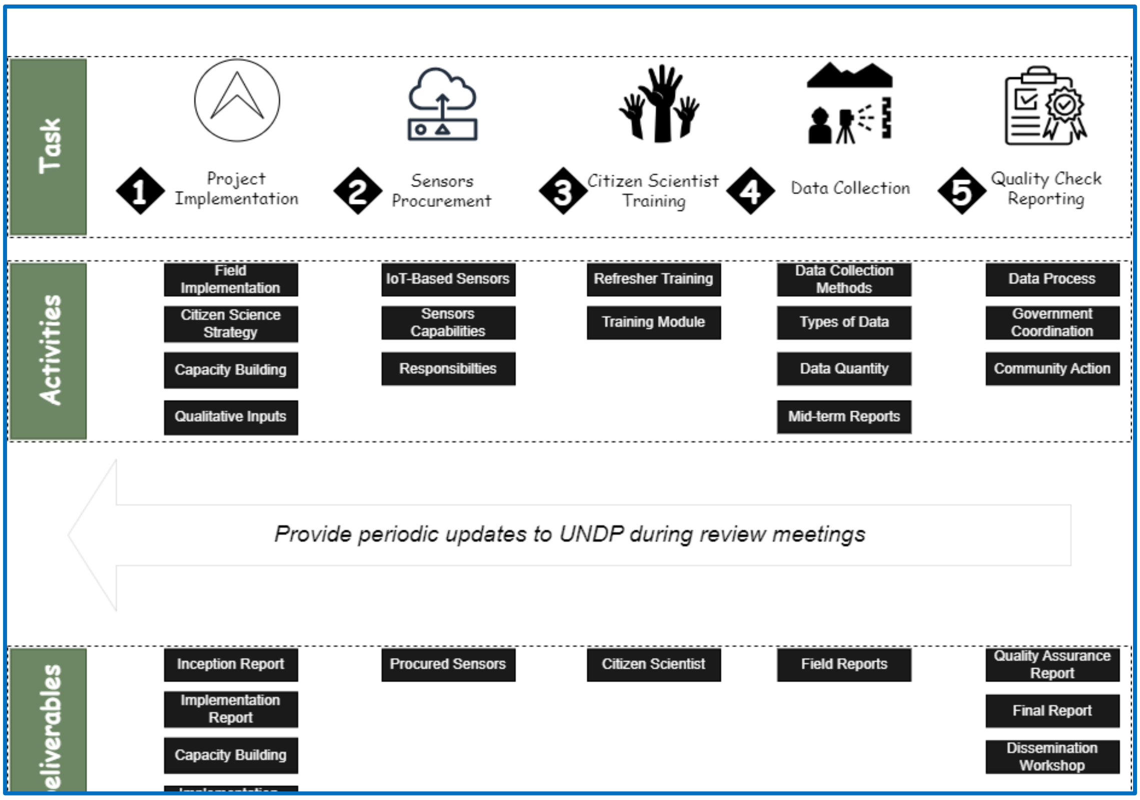


Figure 5 : *Tasks, Activities and Deliverables in the Project*

From the beginning, the project received guidance from the GMDA in selection of sites, approvals for installing sensors, their unhampered maintenance as well as review and follow up action.

A detailed breakdown of our methodology is as follows:

1. **IoT Devices/Air Pollution Sensors Procurement:** The deployment of IoT devices and air pollution sensors was a critical component of the project's methodology for hyperlocal air pollution mapping in Indian cities. These devices are essential for

collecting real-time data on air quality, allowing us to identify pollution sources and make data-driven decisions.

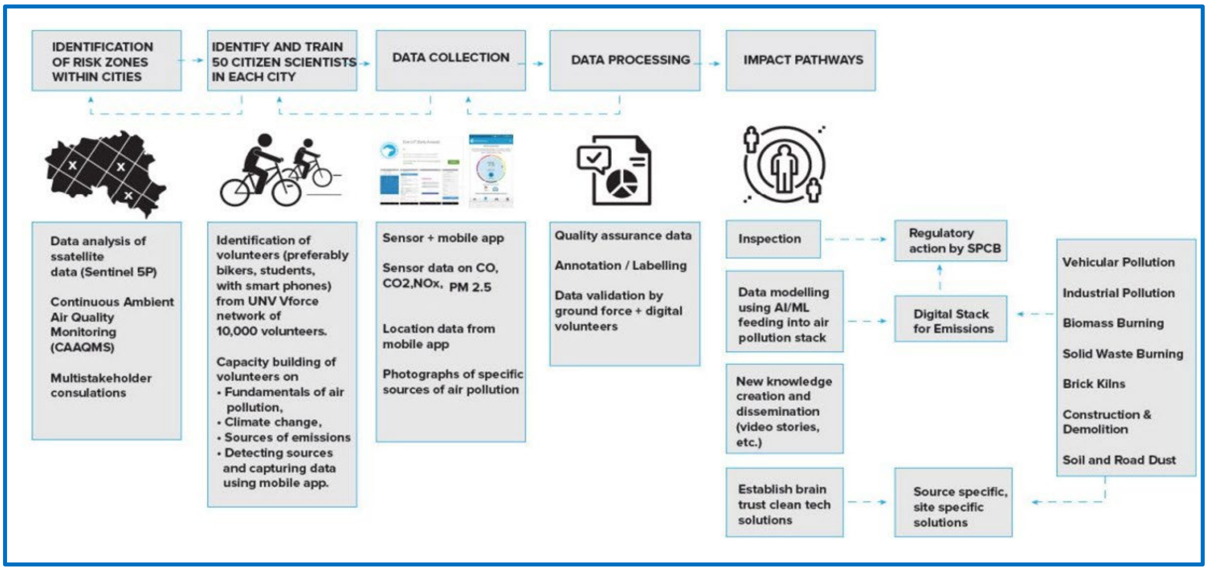


Figure 6 : *Detailed Task Breakdown*

2. **Deployment of IoT Devices and Air Pollution Sensors:** The methodology involved procuring, installing, and maintaining fifty low-cost air quality sensors. These sensors measured key air pollutants, including CO, CO_2, NO_x, CH_4, $PM_{2.5}$, and PM_{10}, with a minimum data refresh rate of 15 minutes. As the service provider, DA was responsible for managing the entire lifecycle of these sensors, ensuring their effective operation and maintenance throughout the project duration.
3. **Engagement of Citizen Scientists:** A crucial aspect of the project's approach was the engagement of citizen scientists. DA identified and trained twenty volunteers across Gurugram , equipping them with the necessary skills to contribute to data collection. These volunteers played a pivotal role in gathering air pollution data using IoT sensors and mobile applications. They documented various pollution sources, including industrial emissions, vehicular pollution, biomass burning, solid waste burning, brick kilns, construction and demolition activities, and soil and road dust.

The process of identifying and training citizen scientists in each city followed these steps:

Step 1: Volunteer Selection

DA collaborated with the United Nations Volunteers (UNV) Program to identify and recruit twenty volunteers in Gurugram. Volunteers were selected from diverse socio-economic backgrounds to ensure broad representation. We benefited from GMDA's backing as a key government organization, in choosing volunteers with the right profile.

Step 2: Eligibility Criteria

The selected citizen scientists were required to be residents of the respective cities, possess an Android smartphone, demonstrate basic digital literacy, have access to a personal vehicle for commuting, and show a genuine interest in improving air quality in their community.

Step 3: Gender Balance and Diversity

A key criterion in the selection process was maintaining gender balance, with at least 50% of the chosen citizen scientists being women. Additionally, diversity in socio-economic status and background was ensured.

Step 4: Data Collection Period and Appreciation Certificates

Data collection activities were conducted between June 2024 and April 2025 to capture seasonal variations in air quality. Volunteers received United Nations Volunteering Service Certificates, proportional to the volume of data points they collected, as a token of appreciation for their efforts.

Step 5: Provision of IoT Devices and Mobile Application

Citizen scientists were equipped with IoT devices and a mobile application developed by UNDP to enhance their data collection capabilities. These tools enabled the collection of air quality data, geo-coordinates, and relevant field information.

Step 6: Capacity Building

A comprehensive capacity-building program was implemented to train volunteers and transform them into proficient citizen scientists. The training covered the following key modules:

a) Fundamentals of Air Pollution and Climate Change
b) Types of Emissions, Measurement Techniques, and Error Mitigation
c) Usage of Mobile Application and Air Quality Sensors, including Ethical Considerations
d) Utilization of Secondary Data Sources on Emissions
e) Data Labelling and Modelling Techniques
f) Understanding the Impact Pathways from Data Collection to Mitigation
g) Personal Data Protection and Data Privacy Guidelines

Step 7: Refresher Training

To ensure data quality and maintain consistency, online and offline refresher training sessions were conducted in both the cities as needed. These sessions helped citizen scientists refine their skills and uphold the accuracy of data collection.

Step 8: Submission of Training Modules and Reports

DA developed and submitted detailed training modules outlining the curriculum and content covered during the capacity-building sessions. A detailed report on the project was also submitted to the relevant stakeholders.

4. **Data Collection:** The data collection methodology was designed to ensure comprehensive and accurate acquisition of air pollution data. This was discussed in detail with the GMDA before finalization to attain the best results. This approach incorporated IoT-based low-cost air quality sensors and a dedicated mobile application, *VAYU BY UNDP,* enabling precise monitoring and documentation of pollution sources. To provide a holistic overview of air pollution sources, data collection was categorized into the following key segments:
    a) **Industrial Pollution:** Geo-coordinates of polluting industries were recorded, accompanied by photographs and sensor data reflecting ambient air pollution. Additional details, including the industry's name and type, were also documented.
    b) **Vehicular Pollution:** Photographs of number plates from highly polluting vehicles were captured for analysis.
    c) **Solid Waste Burning:** Geo-coordinates of waste dump sites were collected, along with photographs and sensor data depicting ambient air pollution levels. Satellite data was used to enhance accuracy. Additionally, waste dump classification, legal status, and size estimates were documented.
    d) **Brick Kilns:** UNDP's GeoAI platform's existing mapping of brick kilns was utilized for validation and supplementary documentation.
    e) **Construction & Demolition (C&D) Activities:** Geo-coordinates and photographs of major C&D hotspots were gathered to assess their impact on ambient air pollution.
    f) **Continuous ambient air pollution:** Monitoring of ambient air pollution across various parts of the cities was conducted.

4. Low-Cost Sensors

Air pollution in urban centers poses an increasing risk to both public health and environmental sustainability. In response to this pressing issue, a pioneering hyperlocal air quality monitoring project was launched in Gurugram, utilizing low-cost, IoT-enabled air pollution sensors. These advanced devices delivered real-time, high-resolution data, allowing for detailed analysis of pollution trends across various city areas. Unlike conventional monitoring stations, which were limited in number and coverage, the low-cost sensors offered a scalable, economical solution for comprehensive air quality evaluation.

As part of the initiative, fifty sensors were acquired, with forty-eight strategically installed to maximize spatial coverage and effectively capture pollution dynamics. By linking these sensors to mobile applications, the initiative empowered citizen scientists to contribute to data collection, creating a more inclusive and resilient monitoring network. The sensors tracked critical pollutants such as carbon monoxide (CO), nitrogen oxides (NOx), methane (CH4), and particulate matter (PM2.5 and PM10), equipping policymakers and urban planners with actionable insights. This data-driven strategy enabled more precise interventions and proactive measures to improve air quality. By combining technological innovation with community engagement, the project marked a significant step toward healthier, more sustainable urban living.

4.1 Technical specifications

The air quality sensors used in this project were based on Internet of Things (IoT) technology and engineered to deliver precise, real-time measurements of key air pollutants. Each unit featured a dedicated power supply, pollutant detection modules, and electronic components to transmit data via cellular networks.

A built-in microprocessor controlled the sensor's operations, while an integrated battery supported continuous functionality. To ensure accurate spatial tracking of pollution data, each sensor was also equipped with a GPS module. The collected data was sent to cloud servers, where it was processed, stored, and made available for further analysis.

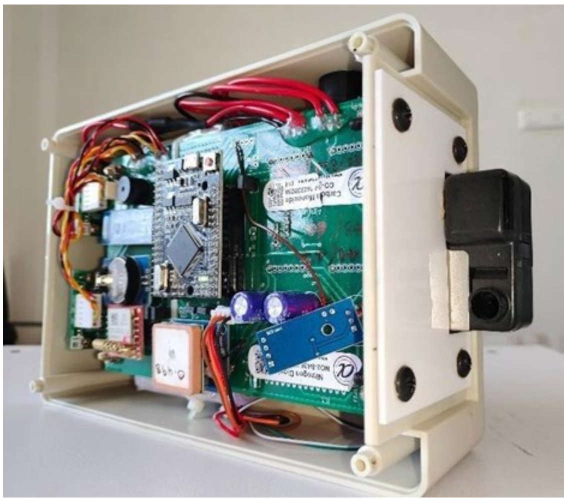


Figure 7: *Various components of a Sensor*

Sourced from Airshed Planning Professionals Private Limited, the sensors could monitor a range of environmental variables, including temperature, relative humidity, and critical air pollutants such as carbon monoxide (CO), carbon dioxide (CO2), nitrogen dioxide (NO2), methane (CH_4), and particulate matter (PM2.5 and PM10). The sensors' measurement ranges are detailed in Table 2:

Table 2 : Permissible Limits of Pollutants

Parameters	Range
Carbon monoxide (CO)	0–1000 ppm
Carbon dioxide (CO_2)	0–40,000 ppm
Nitrogen dioxide (NO_2)	0–20,000 ppb
Methane (CH_4)	0–100 ppm
Particulate matter (PM2.5, PM10)	0–2000 µg/m³

Each sensor was equipped with a SIM card, enabling seamless data transmission to cloud-based servers. This connectivity ensured that air quality readings were continuously updated and readily available for analysis.

The working principles (e.g., electrochemical, optical, or other methods) of the Sensors are shown in Table 3 below:

Table 3 : Range, Relative Error and Sensitivity Threshold of Sensors

Pollutant	***Technology***	***Range***	***Relative Error***	***Sensitivity Threshold***
PM10	*Optical laser light scattering*	*0-1999µg/m3*	*Less than 5%*	*1 µg/m³*
PM2.5	*Optical laser light scattering*	*0-999µg/m3*	*Less than 5%*	*1 µg/m³*
CO2	*Photoacoustic NDIR*	*400–5000 ppm*	*±3% of the reading*	*10–50 ppm*
CO	*Electrochemical*	*0–2000 ppm*	*±2% of the reading*	*0.1–0.2 ppm*
CH4	*Micro Electromechanical*	*0–10000 ppm*	*±5% of the reading*	*>1 ppm*
NO2	*Electrochemical*	*0–20 ppm*	*±10% of the reading*	*0.02–0.05 ppm*

Two distinct categories of sensors were employed for air monitoring: ***static sensors*** and ***dynamic sensors***, each serving a unique purpose in data collection.

Static Sensors: These stationary sensors were installed at predetermined locations, selected through hotspot analysis conducted by the TARA team. The placement strategy was guided by.

Land Use and Land Cover (LULC) classifications and identified air pollution hotspots. Additionally, site selection was conducted in collaboration with the Gurugram Metropolitan Development Authority (GMDA) for Gurugram. To ensure optimal performance, each static sensor was securely positioned with access to a reliable power source, allowing for continuous air quality monitoring.

Figure 8: *Image of a Dynamic Sensor(left) and a Static Sensor(right)*

A. Dynamic Sensor ***B. Static Sensor***

Dynamic Sensors: These portable sensors were distributed among trained volunteers, known as Citizen Scientists, in both cities. The Citizen Scientists carried the sensors along their daily routes, enabling the collection of real-time air quality data across various locations. This approach provided a comprehensive understanding of pollution variations throughout the day, capturing exposure levels in diverse environments such as residential areas, commercial zones, and high-traffic corridors.

The study effectively mapped air pollution patterns by combining static and dynamic sensors, producing hyperlocal insights that are essential for focused air quality control operations.

As part of the initiative, UNDP developed ***VAYU***, an Android-based mobile application designed to enhance citizen-led air quality monitoring. This user-friendly platform empowered Citizen Scientists by providing real-time data visualization, intuitive navigation, and optimized route guidance for efficient data collection. VAYU facilitated seamless integration with IoT sensors, enabling the collection of air quality data alongside geo-coordinates, field observations, and photographic evidence. The application allowed users to categorize pollution sources into five distinct categories - **Industrial Pollution, Waste Burning, Vehicular Emissions, Construction and Demolition Waste, and Brick Kilns** - ensuring comprehensive documentation of air pollution hotspots. By streamlining data collection and visualization, VAYU played a crucial role in generating high-resolution, hyperlocal air quality insights, supporting informed decision-making for targeted pollution mitigation strategies.

4.2 Sensor Selection

The selection of Low-Cost Air Quality Monitoring Sensors (LCAQMS) was based on specific technical and operational benchmarks to ensure accuracy, efficiency, and ease of deployment. The key factors considered were:

a) *Pollutant Detection Capabilities* - The sensors needed to precisely measure CO, CO2, NO2, CH4, PM2.5, and PM10 within defined concentration limits to capture a comprehensive pollution profile.
b) *Data Transmission & Storage* - The ability to transmit data in real-time via Wi-Fi, Bluetooth, or GSM was essential, along with onboard storage to prevent data loss in case of network disruptions.
c) *Refresh Rate & Accuracy* - A refresh rate of at least 15 minutes was required to maintain up-to-date readings, with an acceptable accuracy range of 5-10% to ensure data reliability.
d) *Display & Power Supply* - A built-in display was recommended for instant local data access, and sensors needed to operate on a durable power source, either via a rechargeable battery or direct DC supply.
e) *Portability & Design* - Compactness was a priority, with a maximum size of 20cm × 20cm × 10cm to facilitate easy installation across various monitoring locations.

By adhering to these selection specifications, the project ensured the deployment of efficient, high-precision sensors capable of providing detailed hyperlocal air pollution insights.

4.3 Strengths and Limitations of Low-Cost Sensors

Advantages:

a) Cost-Effective Deployment - These sensors offer a budget-friendly alternative to high-end monitoring systems, allowing for large-scale installation without excessive financial burden.
b) Expanded Monitoring Network - Their affordability enables a denser network of sensors, improving air pollution tracking at a granular level.
c) Real-Time Air Quality Insights - With continuous data updates, these sensors facilitate timely identification of pollution trends and hotspots.
d) Easy Installation and Portability - Their compact design makes them easy to install in multiple locations, and mobile versions enable on-the-go monitoring by citizen scientists.

e) Public Engagement and Awareness - By making air quality data accessible, these sensors empower communities to take informed actions toward pollution mitigation.

Limitations:

a) Lower Sensitivity to Certain Pollutants - Due to cost constraints, these sensors were less sensitive to methane (CH_4) emissions, requiring substantial concentrations before detection.
b) Lower Accuracy Levels - Compared to regulatory-grade monitors, these sensors have a higher margin of error, affecting the reliability of certain pollutant measurements.
c) Influence of Environmental Conditions - Variations in temperature, humidity, and sensor aging impact data accuracy, necessitating periodic calibration.
d) Dependence on Connectivity - Since these sensors rely on GSM networks, they experience transmission issues in low-connectivity areas, impacting real-time data availability.
e) Limited Lifespan and Maintenance Needs - Frequent recalibration and maintenance are essential due to sensor degradation over time.

5. An Innovative Approach - Citizen Science

Citizen Science is a process that involves public engagement and collaboration in scientific research to further scientific understanding. Citizen science allows any individual to engage in data collection and contribute to data monitoring and tracking initiatives.

The contemporary landscape of data generation and analysis is increasingly characterized by the meeting of public participation and high-resolution spatial information technologies (Wiggins & Crowston, 2023). Citizen science (CS), involving the public in scientific endeavors, and hyperlocal mapping, focusing on extremely detailed local-level geographic data, are converging in powerful ways (Sitthi et al., 2022). This convergence is fueled by advancements in Web 2.0, ubiquitous sensing technologies, mobile devices, and the growing availability of geospatial tools (Middel et al., 2022). The potential to harness collective public effort for fine-grained spatial analysis offers new avenues for addressing complex environmental and societal challenges, ranging from urban sustainability to public health and disaster resilience (Environmental Defense Fund [EDF], 2022).

Traditional methods for collecting localized data often face significant limitations in terms of cost, spatial coverage, or temporal frequency(EDF, 2022). Monitoring dynamic urban phenomena like air quality variations or the urban heat island effect at a neighborhood or street level, for instance, typically requires dense sensor networks or frequent surveys that are expensive to deploy and maintain Peng et al., 2021). Similarly, mapping resources, infrastructure, or environmental conditions in remote or rapidly changing areas can be challenging for official agencies (Gunnell et al., 2023). Citizen science hyperlocal mapping emerges as a compelling alternative or complementary approach, leveraging distributed public participation to generate granular spatial data that might otherwise be unattainable(Peng et al., 2021).

5.1 Approach

The intersection of citizen science and hyperlocal mapping occurs when participatory methods are employed to generate the high-resolution spatial data required for detailed, localized maps. Citizen science provides the framework for engaging the public (the *participatory mechanism*), while hyperlocal mapping defines the *spatial scale and detail* of the endeavor. In this context, citizens effectively function as a distributed network of "human sensors," collecting the fine-grained observations or interpretations needed to populate hyperlocal datasets (Peng et al., 2021).

Volunteered Geographic Information (VGI) is central to this intersection. Defined by Michael Goodchild as geo-referenced data created by citizen volunteers, often non-professionals using readily available tools , VGI represents the *data product* generated through many citizens science hyperlocal mapping activities(Patel et al., 2023). VGI is an umbrella term encompassing geographic data from various participatory sources, including formal citizen science projects, crowdsourcing platforms, participatory mapping initiatives, neogeography efforts, and even implicitly spatial data from social media.

Prominent examples include the road networks compiled by OpenStreetMap (OSM) contributors or species occurrence records submitted via platforms like eBird. The term "volunteered" itself can sometimes be ambiguous, as data might be generated passively (e.g., through location tracking) rather than explicitly contributed; in such cases, the emphasis shifts to the non-expert origin of the data (Goodchild, 2022).

While closely related, VGI and Citizen Science are distinct concepts(Liu et al., 2023). VGI refers specifically to the *geospatial data* contributed by volunteers, whereas Citizen Science describes the broader *process* of public participation in research (Fast & Rinner, 2014). Not all citizen science generates VGI (e.g., projects without a spatial component), and not all VGI originates from structured citizen science projects (e.g., geotagged photos on Flickr) (Liu et al., 2023). However, in the context of hyperlocal mapping, the synergy is strong: citizen science methodologies, particularly contributory and co-created approaches, often utilize VGI platforms and tools (like OSM, MapSwipe, or mobile data collection apps) to collaboratively produce detailed hyperlocal maps, thereby addressing critical data gaps at fine spatial and temporal scales(Peng et al., 2021).

The very nature of "hyperlocal" mapping, demanding high spatial and often temporal resolution, frequently pushes beyond the capacities of traditional, centralized data collection methods, particularly in complex and dynamic urban environments. This makes citizen participation, facilitated by VGI tools and platforms, a prerequisite rather than merely an alternative for achieving hyperlocal coverage cost-effectively (Peng et al., 2021).

However, this reliance creates a critical dependency: the inherent limitations of VGI, such as potential biases in participation and data quality concerns(Goodchild, 2022), directly translate into uncertainties and potential inaccuracies in the resulting hyperlocal maps. This feedback loop, where the enabling methodology simultaneously introduces limitations, underscores the need for careful project design, robust validation protocols, and potentially hybrid approaches that integrate VGI with other data sources to ensure the reliability and responsible use of citizen-generated hyperlocal information.

5.2 Citizen Scientist Profiles

To fulfil the project objective of generating hyperlocal data sets from the entire spectrum of pollution sources and hotspots in Gurugram, citizen scientists from different walks of life were chosen. These were typically graduate or post-graduate students with an interest in environment-friendly causes.

The allocation of territories to citizen scientists was guided by the identified air pollution hotspots and the individuals' residential locations or places they regularly visited, such as colleges or workplaces. Exceptional care was taken to avoid redundancy in data collection. For instance, when multiple participants from the same hostel were assigned dynamic sensors, they were directed to cover distinct routes or locations, such as their respective colleges, offices, or NGOs to ensure a diverse and representative dataset from different areas.

Citizen scientists were expected to operate their sensors for 8 - 10 hours daily in their regular environments. Additionally, they were instructed to actively move with the sensor for at least 2- 3 hours each day to capture data from surrounding areas, especially in relation to industrial zones, air pollution hotspots, brick kilns and the traffic prone areas. They were also required to document visibly high pollution areas by taking photographs and uploading them to the VAYU portal.

At the end of each month, they submitted a detailed report summarizing the key locations monitored, along with the maximum and minimum values recorded for parameters such as PM2.5, PM10, CO, CO2, and NO2.

The citizen scientists faced certain challenges due to the ongoing metro construction in Gurugram as heavy traffic made it difficult to stop in one place, capture data, and take photographs safely. During winter months, dense fog, and haze reduced visibility, making it hard to capture clear images for uploading to the Vayu portal. In and around industrial areas and brick kilns, citizen scientists were often denied access or met with resistance, limiting their ability to collect data from key pollution sources.

There were also challenges posed by improper maintenance of the sensors caused by the infrequent cleaning of the PM inlets and outlets led to the occasionally inaccurate, and high readings of PM2.5 and PM10.The sensor could not record location data indoors or when surrounded by walls, requiring it to be moved outdoors for proper GPS calibration. As the sensors were battery-powered, users had to carry chargers and ensure timely charging to prevent data interruptions in collection. The sensor relied on SIM-based network access, which occasionally failed, preventing real-time data upload to the Vayu portal which was an issue beyond the citizen scientist's control.

Some participants failed to switch on their sensors for extended periods, resulting in occasional data gaps. Issues also arose due to improper/ overuse of sensor chargers, leading to malfunctions. Citizen scientists occasionally left the city without prior intimation, again contributing to data collection gaps. The images uploaded to the VAYU Portal were often blurry, irrelevant, or did not accurately represent the pollution category, requiring follow-up corrections. Many participants did not regularly check the Vayu portal to verify if their sensors were functioning or uploading data, which led to delays in identifying and resolving sensor malfunctions, sometimes noticed only after 3-4 days.

To manage the network of citizen scientists to avoid data collection gaps, TARA evolved a daily process of monitoring and reviewing the data generation from all the static and dynamic sensors. It also trained a team of electricians that would follow through with site visits on the same day, based on the daily morning review. This was found to be the best solution to keeping sensor downtime low.

5.3 Engagement

The project was able to generate a high level of engagement as participants with a genuine interest in protecting the environment saw value being generated through their work. Citizen scientists learnt about air pollution issues in their vicinity and were able to advise their family and friends about safety measures during peak pollution periods. During the project period, online and offline refresher training, as well as sensor checks were conducted to equip the citizen scientists to effectively perform their responsibilities. Finally, they were provided constant support through quick resolution of the issues that they faced at any time. The fact that citizen scientists were associated with a project backed by GMDA brought a high degree of seriousness in their efforts.

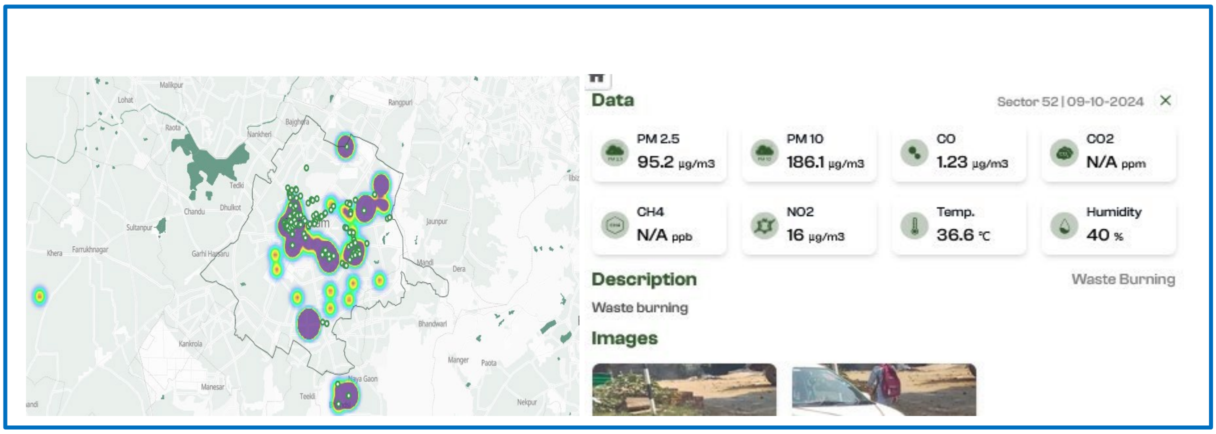
Figure 9 :*Initial Training of Citizen Scientists during project launch in Gurugram, Haryana*

Figure 10 :*A Refresher Training Program for Citizen Scientists in DA World HQ in January 2025*

5.4 Output and Expectations

5.4.1 The VAYU Platform: Transforming Data into Action

The collected data is aggregated and visualized on the **VAYU digital platform** (vayu.undp.org), developed by MistEO, where it is analyzed using artificial intelligence and machine learning. This platform offers real-time tracking of air quality trends, identifies pollution hotspots, and aims to provide policymakers with customizable solutions to address these issues effectively. The use of AI/ML enhances the precision and usability of



the data, enabling targeted interventions that are both cost-effective and impactful.

Figure 11 : *Snapshot of the VAYU by UNDP Website showing data captured by Citizen Scientists in Gurugram*

(a) Mobile app for data collection

The Vayu Mobile App serves as the primary tool for citizen scientists and volunteers participating in the Hyperlocal Mapping of Air Pollution project. It is an Android-based application designed to empower users to easily collect and submit crucial on-the-ground data regarding air quality and pollution sources. Users begin by downloading the app, either from the Google Play Store (as **'Vayu by UNDP'**) or via a shared APK file, and then proceed through a straightforward sign-up process, providing necessary details to create a volunteer account. This initial registration is followed by an admin approval step, ensuring that data contributors are vetted before they can fully access the app's features.

Once approved, the Vayu app enables volunteers to actively engage in data collection. The app features a home screen that provides an overview of the user's activity, including the number of records collected and any tasks assigned to them. A core functionality is the ability to record new pollution data. This involves confirming the precise location (often using device GPS and an interactive map), selecting a relevant pollution category (e.g., industrial pollution), uploading photographic evidence of the observation, and adding a descriptive note. Volunteers can also be assigned specific tasks, viewable within the app, which might direct them to areas or types of pollution to investigate. All submitted data, including images and descriptions, is then accessible for review, contributing to the broader project's goal of creating a detailed, hyperlocal map of air pollution.

(b) Public Web Portal

The Vayu public web portal, accessible at vayu.undp.org.in, functions as the central, publicly accessible platform for visualizing and disseminating the hyperlocal air quality data collected through the "Hyperlocal Mapping of Air Pollution" project. It is the "citizen portal" component of the VAYU digital stack, designed for broad data outreach. The portal's key feature is an interactive map that displays air quality information, such as levels of PM2.5, PM10, and other relevant pollutants, from the network of IoT-based low-cost sensors and data submitted by citizen scientists via the mobile app. This allows users to see near real-time air quality readings at specific, localized points within the monitored areas.

Beyond just displaying current data, the Vayu portal aims to empower various stakeholders. Citizens can use it to understand the air quality in their immediate surroundings, identify pollution hotspots, and track changes over time. For researchers, it provides a valuable dataset for environmental studies. Crucially, for regulatory authorities and policymakers, the portal offers a clear overview of pollution distribution, supporting the identification of risk zones and facilitating targeted interventions to mitigate air pollution. By making complex environmental data transparent and easily digestible, the portal plays a vital role in fostering public awareness, promoting community engagement, and informing evidence-based environmental management strategies.

(c) Democratization of Open Data

The Vayu project strongly champions an open data approach, a critical element for fostering transparency, collaboration, and innovation in tackling air pollution. A cornerstone of this philosophy is the provision for users, including researchers, data scientists, policymakers, and the public, to download the entire sensor dataset collected through its network of IoT devices. This means that the raw, granular air quality measurements (such as PM2.5, PM10, and other relevant parameters captured over time from various locations) are not just visualized on the portal but are made directly and freely accessible for wider use and scrutiny.

By making this comprehensive dataset openly available, the Vayu initiative significantly magnifies its potential impact beyond its immediate project goals. It allows independent researchers to conduct in-depth analyses, validate findings, and explore new correlations or patterns that might not have been initially apparent. Developers and civic tech communities can leverage this data to build novel applications, create custom visualizations, or integrate it into existing platforms for broader public benefit. This commitment to open data democratizes access to vital environmental information, empowering a wider community to contribute to understanding and addressing hyperlocal air pollution, fostering a more informed, participatory approach to environmental management, and potentially accelerating the development of sophisticated AI/ML-driven solutions by diverse actors.

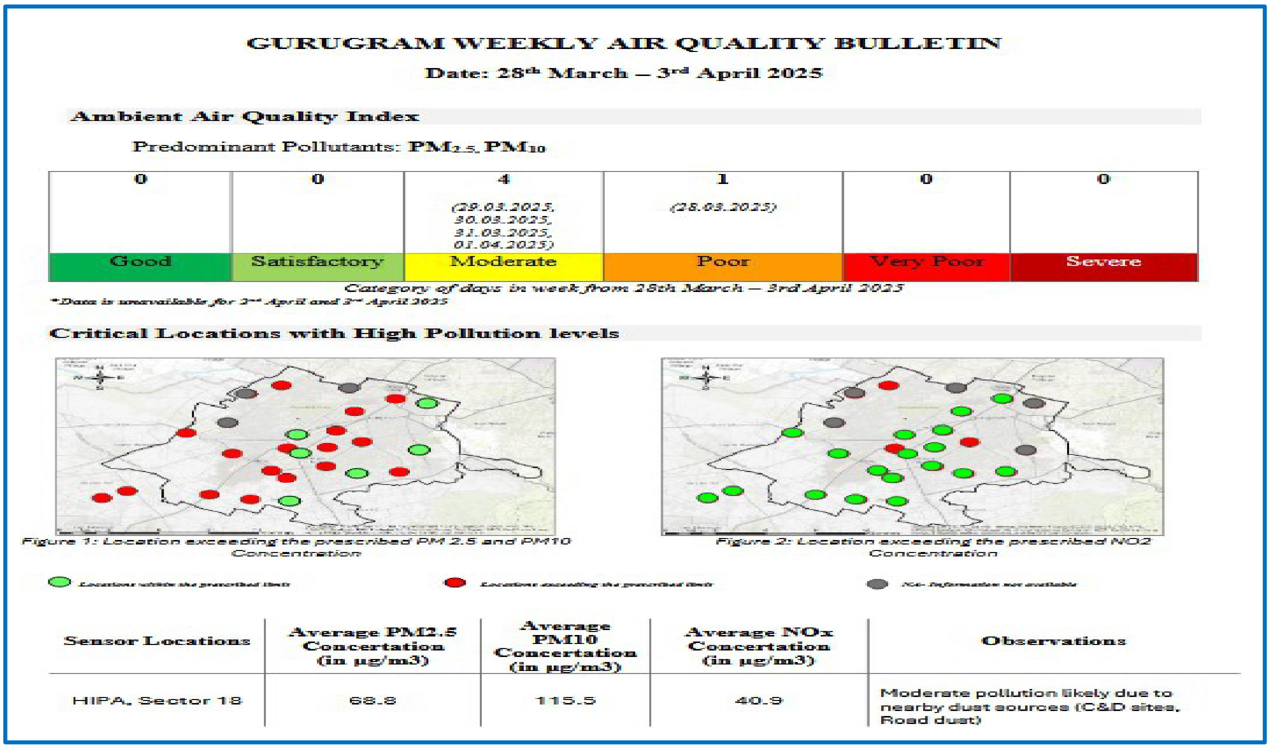
This user-friendly platform empowered Citizen Scientists by providing real-time data visualization, intuitive navigation, and optimized route guidance for efficient data collection.

VAYU facilitated seamless integration with IoT sensors, enabling the collection of air quality data alongside geo-coordinates, field observations, and photographic evidence. The application allowed users to categorize pollution sources into five distinct categories - **Industrial Pollution, Waste Burning, Vehicular Emissions, Construction and Demolition Waste, and Brick Kilns** - ensuring comprehensive documentation of air pollution hotspots. By streamlining data collection and visualization, VAYU played a crucial role in generating high-resolution, hyperlocal air quality insights, supporting informed decision-making for targeted pollution mitigation strategies.

5.4.2 A Transformative Approach

By involving twenty trained citizen scientists across Gurugram, the initiative has fostered a sense of ownership and awareness that traditional top-down monitoring methods often lack. The hyperlocal data collected ensures that solutions are tailored to the specific needs of neighborhoods, addressing root causes rather than surface symptoms.

Using data from the VAYU digital platform, a partner agency, SEEDs, using appropriate statistical techniques, enabled generation of Weekly Bulletins for action by the Gurugram Municipal Development Authority (GMDA) as shown in Figure 12 below :



GURUGRAM WEEKLY AIR QUALITY BULLETIN

Date: 28th March – 3rd April 2025

Ambient Air Quality Index

Predominant Pollutants: $PM_{2.5}$, PM_{10}

Good	Satisfactory	Moderate	Poor	Very Poor	Severe
0	0	4 (29.03.2025, 30.03.2025, 31.03.2025, 01.04.2025)	1 (28.03.2025)	0	0

Category of days in week from 28th March – 3rd April 2025

**Data is unavailable for 2nd April and 3rd April 2025*

Critical Locations with High Pollution levels

Figure 1: Location exceeding the prescribed PM 2.5 and PM10 Concentration

Figure 2: Location exceeding the prescribed NO2 Concentration

Sensor Locations	Average PM2.5 Concentration (in µg/m3)	Average PM10 Concentration (in µg/m3)	Average NOx Concentration (in µg/m3)	Observations
HIPA, Sector 18	68.8	115.5	40.9	Moderate pollution likely due to nearby dust sources (C&D sites, Road dust)

Figure 12 : *Weekly Bulletin for Gurugram*

GMDA was able to act on these insights on a daily and weekly basis, leading to a respite for the local population.

6. Comprehensive Risk Assessment - Identification of Air Pollution Risk Hotspots

An *air pollution risk hotspot* is a specific urban location where pollution levels consistently exceed national air quality standards, posing significant health risks to residents. These hotspots are the priority areas for air quality management (such as traffic intersection, congested roads, landfill sites, parking areas, high polluting industrial clusters etc.) that fail to meet or likely to fail to meet the specified standards (**USEPA, 2010; Gulia et al., 2016, 2018**) (Sahu et al., 2018).

Urban land-use diversity leads to complex pollution patterns that fluctuate temporally (hourly to seasonally) and spatially as well, complicating the mitigation efforts.

The heterogeneity in sources contributing to air pollution due to the varying land-use patterns creates complex spatio-temporal distributions which lead to the formation of air pollution risk hotspots within a city. Further, the intensity of pollution level at these hotspots could vary hourly, daily, monthly, or even seasonally depending on the location of the monitoring stations, diurnal/seasonal variations in source activities, distribution of types of sources and the influencing atmospheric dynamics.

These complexities create challenges for air quality regulators in optimizing the best mitigation strategies for such risk hotspots where city-level control measures do not comply (based on the average pollution level of the city).

6.1 Methodology for Risk Hotspot Identification

There is no universally accepted methodology for defining and delineating the Air Pollution Risk Hotspot. Researchers have adopted numerous methods for identifying these locations for local air quality concerns. The methods adopted are pollution data from low-cost sensors, modelling simulations for build and no-build scenarios (with or without human activities), and comparison with specified standards using statistical tool (Querol et al., 2006; Goyal et al., 2019), fast track process involving like livelihood/risk of exceedance and/or local intelligence (Dea, 2018; USEPA, 2010; DEAT, 2008; Báthory and Palotas, 2019; Taleb, 2019). Moreover, researchers have also named the areas as air pollution hotspots based on the source activity levels i.e., high traffic density areas (Gokhale and Khare, 2007; Pant et al., 2015; Gulia et al., 2018).

The suggested methodology for identification of Air Pollution Risk Hotspot is to exhibit higher $PM^{2.5}$ and PM^{10} concentrations separately based on both the annual average and the winter period average to capture seasonal variations and persistent pollution trends. Due to the initiation of data collection through Vayu portal from June 2024, the methodology adopted is to consider, the average PM2.5 and PM10 concentrations for the winter period from October 2024 – December 2024 on IoT Low-Cost Sensors to identify specific Air Pollution Risk Hotspot. The approach benefited from GMDA’s inputs during the finalization.

6.1.1 Methodological Approach

The methodology adopted combines geospatial analytics, temporal trend analysis, and pollution threshold exceedance to delineate high-risk zones across Gurugram. The assessment is grounded in the following elements:

a) **Sensor-based data acquisition**: Over 1.3 million validated data records were captured from static IoT-enabled low-cost sensors deployed across Gurugram. The data include PM2.5, PM10, CO, NO_2, CO_2, CH_4, temperature, and relative humidity at three-second intervals.

b) **Data preprocessing and validation**: Time-series standardization, outlier removal using the interquartile range (IQR), and min-max normalization were applied to ensure data integrity.

c) **Temporal aggregation**: Data were aggregated into hourly and daily averages to evaluate diurnal, seasonal, and episodic trends, particularly for the winter period (October to December 2024).

d) **Threshold-based risk classification**: National Ambient Air Quality Standards (NAAQS) for PM2.5 (60 µg/m³) and PM10 (100 µg/m³) were used to establish five exceedance categories, ranging from "Unhealthy" to "Hazardous".

e) **Spatial mapping**: Heatmaps were developed to visualize spatial distributions of PM2.5 and PM10 concentrations and to identify persistent exceedance zones.

6.1.2 Risk Categorization Framework

To enable actionable classification of exposure levels, a structured risk categorization framework was applied. Based on the degree of exceedance over daily NAAQS values, six discrete risk bands were defined. Areas with PM2.5 levels below 60 µg/m³ were classified as 'Good', while those exceeding 240 µg/m³ were categorized as 'Hazardous'. A large share of the identified hotspots fell within the 'Very Poor' and 'Severe' brackets, particularly during the peak winter months. This framework allows policymakers to prioritize interventions based on quantifiable risk exposure and population vulnerability, including proximity to schools, hospitals, and residential zones.

Table 4: Risk Categorization Framework

Exceeding limit	PM 2.5 (µg/m³)	PM 10 (µg/m³)	Risk Category
Under the Prescribed limit	0-60	0-100	Good
> 1X Exceedance	61-90	101-150	Unhealthy
> 1.5 X Exceedance	91-120	151-200	Poor
> 2 X Exceedance	121-180	201-300	Very Poor
> 3 X Exceedance	181-240	301-400	Severe
> 4 X Exceedance	>240	>400	Hazardous

6.1.3 Risk Assessment – Gurugram

Gurugram, a rapidly expanding economic and industrial hub within the National Capital Region (NCR), experiences persistently elevated levels of ambient air pollution. Despite its exclusion from the list of non-attainment cities under India's National Clean Air Program (NCAP), Gurugram consistently exceeds national permissible limits for particulate matter, particularly PM2.5 and PM10. The city's unique urban morphology—characterized by a dense built-up core, high vehicular traffic, and scattered construction activities—results in significant spatial heterogeneity in air pollution exposure.

The current risk assessment aims to identify and analyze hyperlocal air pollution hotspots in Gurugram using real-time data collected from a network of low-cost IoT-enabled air quality sensors. This analysis, part of a broader initiative on hyperlocal air quality mapping, is intended to support evidence-based air quality interventions by providing detailed insights into spatio-temporal pollution patterns, severity classifications, and location-specific exposure risks.

6.2 Temporal Trends and Seasonal Variation

The seasonal variation in PM2.5 and PM10 levels in Gurugram followed a trajectory consistent with meteorological expectations for north Indian cities. During the monsoon season in July and August, pollution levels remained low due to frequent rainfall, enhanced atmospheric cleansing, and higher wind speeds. However, from September onwards, a pronounced upward trend was observed, culminating in peak pollution levels during October and November.

The post-monsoon and winter months witnessed several contributing factors that led to severe deterioration in air quality. These included agricultural stubble burning in neighboring states, increased traffic congestion, construction dust, reduced dispersion conditions, and widespread use of firecrackers during Diwali festivities. The pollution load remained elevated through December, although a slight decline was observed owing to occasional western disturbances and shifts in wind direction.

Temporal analysis also revealed diurnal variation patterns, with peak pollution levels typically observed during early morning and late evening hours, coinciding with low atmospheric boundary-layer heights and peak traffic congestion periods.

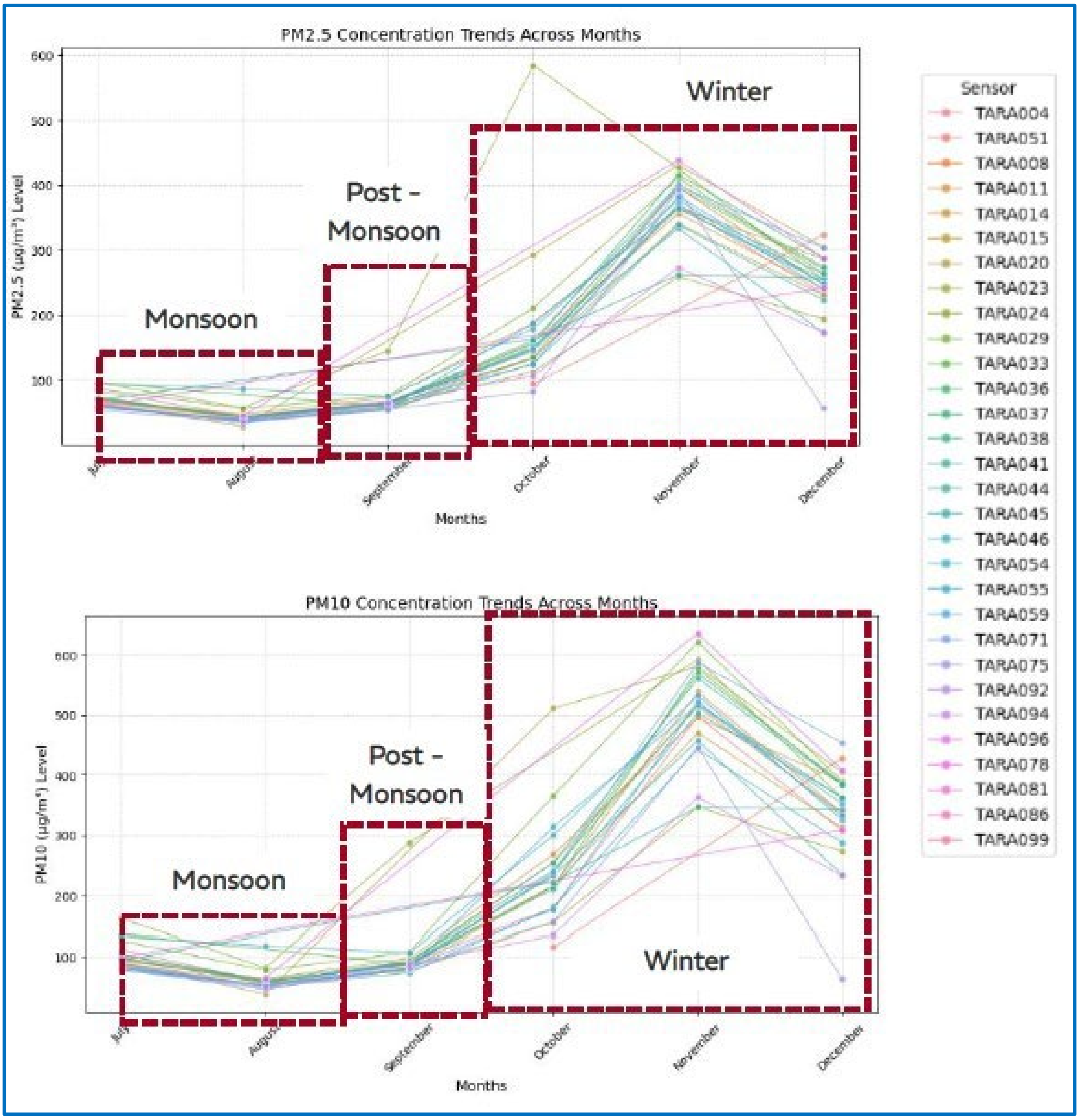


Figure 13: *Monthly Variation in PM2.5 and PM10 in Gurugram; Sharp rise in particulate matter concentrations from September, peaking in October and November due to seasonal and anthropogenic triggers.*

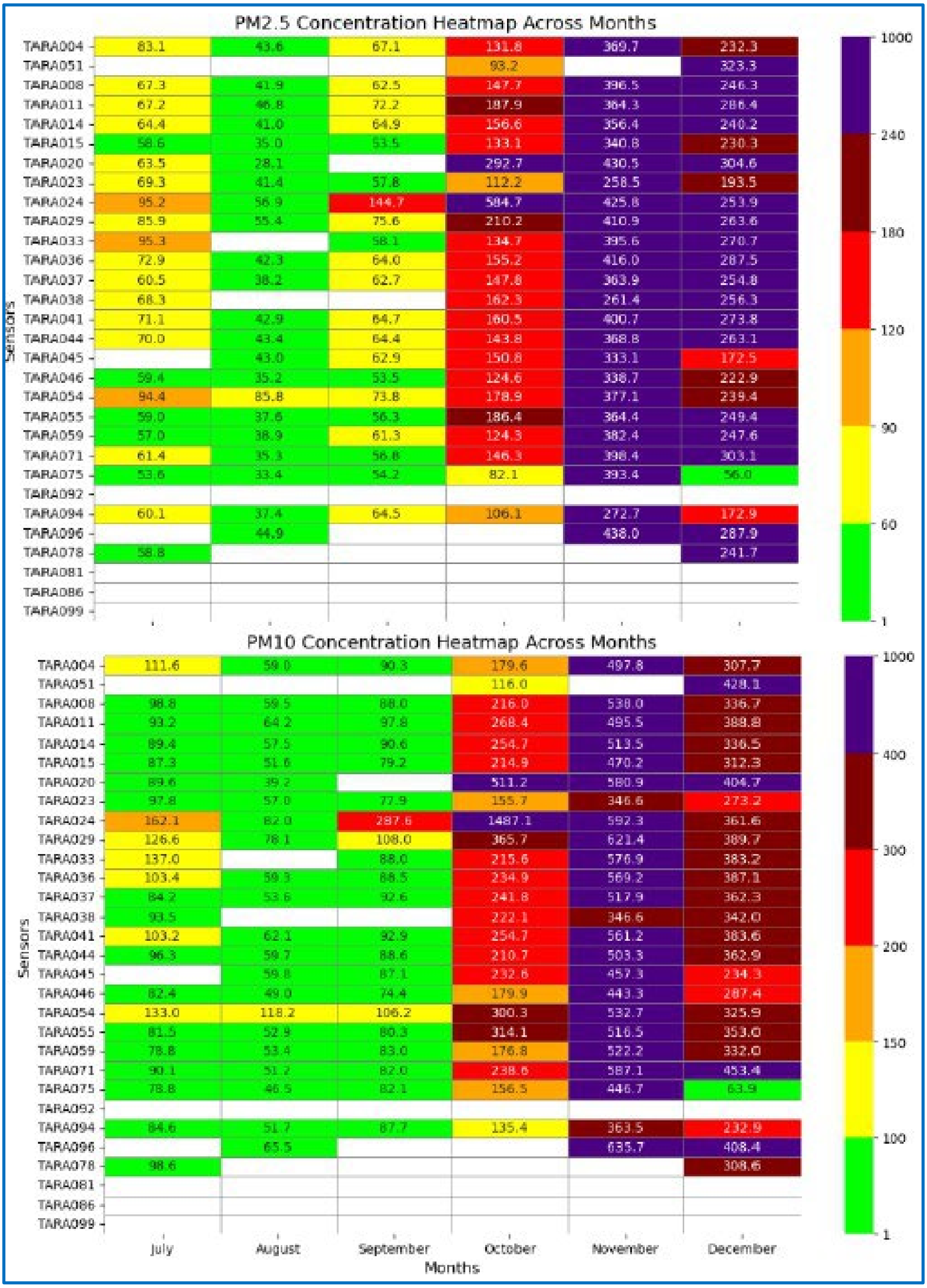


Figure 14: *Heatmap of Pollution Hotspots – Gurugram (Oct–Dec 2024); Spatial distribution of PM2.5 and PM10 values indicates elevated exposure risks in institutional, mixed-use, and residential nodes.*

6.3 Spatial Distribution and Identified Risk Hotspots

Spatial analysis was conducted using the aggregated pollution data from the fixed sensor network for October to December 2024. This analysis revealed distinct clusters of high pollution exposure, many of which were located near arterial roads, institutional campuses, residential complexes, and commercial corridors. The locations identified as PM2.5 and PM10 Air Pollution Risk Hotspot **during episodic winter event are :**

- **a) Gurugram University,**
- **b) Sector 87,**
- **c) Govt. School, Sector 84,**
- **d) DPG College,**
- **e) Fire Station, Sector 37,**
- **f) Mini Secretariat,**
- **g) Boosting Station, HSIIDC Apartments,**
- **h) HIPA, Sector 18,**
- **i) Sector 42, and**
- **j) Mahindra Aura Society.**

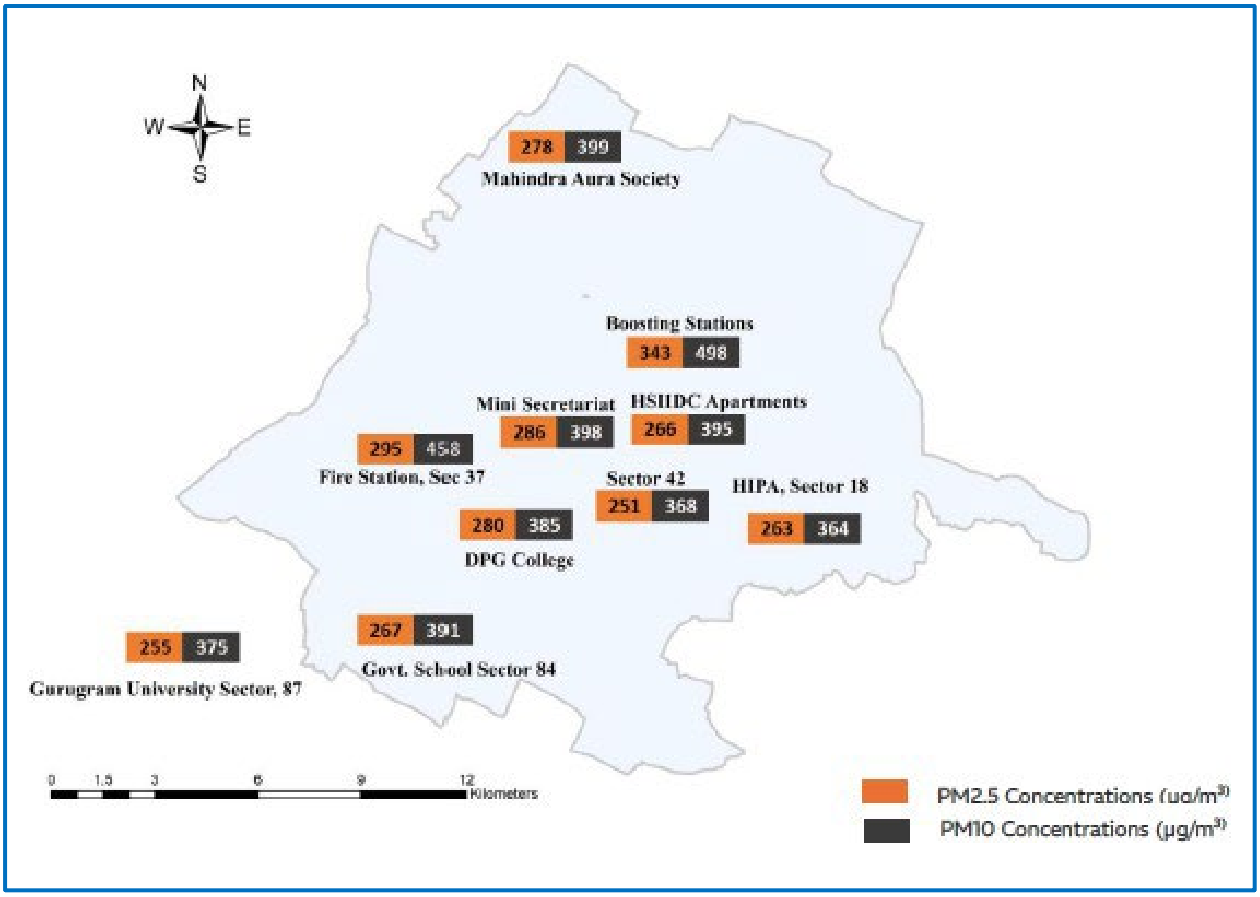


Figure 15: *Identified Risk Hotspots in Gurugram*

GMDA team was able to act on this input and was able to set actions in place for the reduction in particulate matter emissions.

6.4 ClearSky Hackathon 2025

The ClearSky Hackathon 2025, held from February 24 to March 26, brought together multidisciplinary teams to create impactful, data-driven solutions for hyperlocal air quality challenges in Gurugram and Gurugram. Organized by UNDP India, the hackathon leveraged real-time sensor data, citizen science, and open-source datasets to encourage innovative and actionable tools that support climate resilience and clean air policymaking.

Datasets shared included hyperlocal air quality data from 50 Sensors in Gurugram, emission hotspot data, GPS-tagged sensor readings, and static/dynamic pollution metrics. Additional open datasets included:

a) WorldPop population density,
b) OpenStreetMap spatial data,
c) Urban Emissions India,
d) NASA Earth observation data,
e) Traffic, weather, and land use data.

API and documentation were provided through the VAYU Data Portal and three thematic areas were identified as shown in Figure __ below:

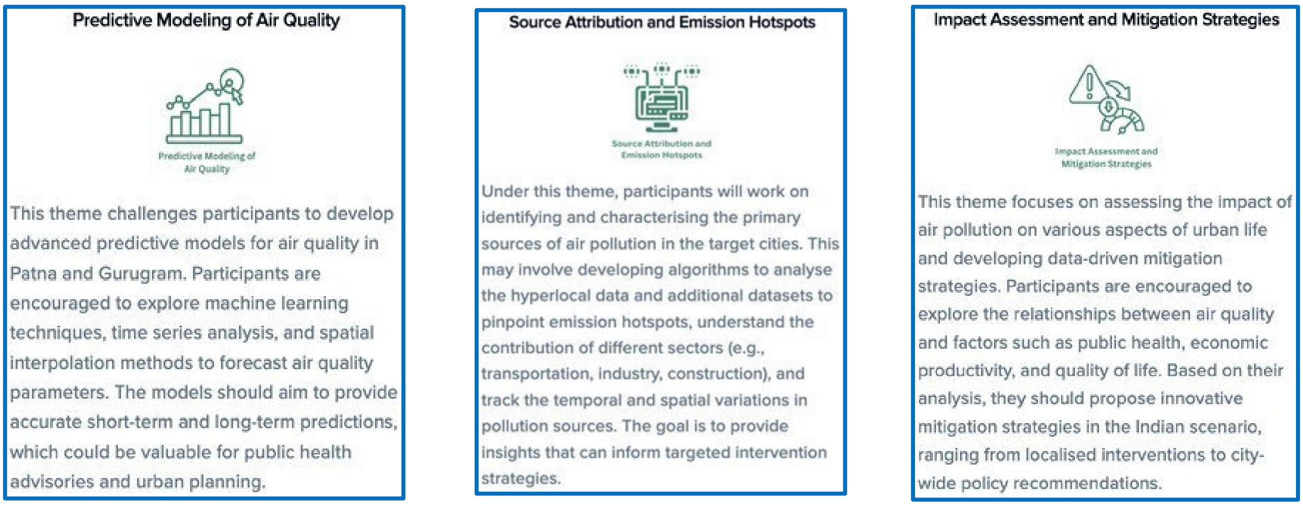


Figure 16: *Three Hackathon Themes*

The hackathon was held in two phases:

a) Phase 1 (Open Submission): Participants submitted their initial concepts without code.
b) Phase 2 (Finalist Selection & Mentorship): The top five teams were selected for mentorship from UNDP and domain experts.

Finalists built complete solutions with code, documentation, and demos, culminating in a live virtual pitch on March 26, 2025.

6.5 ClearSky Hackathon – Proposed solutions

The winning solutions were proposed by EconAI and Team VayuDevs. They are briefly described below:

EconAI developed a hyperlocal forecasting system using Graph Neural Networks (GNNs) to predict PM2.5 levels up to 8 hours in advance. Their pipeline integrates:

a) Meteorological data via Open Meteo API
b) Human settlement data (building density, road proximity)
c) Hyperlocal VAYU sensor readings. They built a spatial-temporal graph model to learn relationships between sensors and external predictors, delivering accurate, explainable forecasts tailored for city planners and health advisors.

Team VayuDevs Built VayuAssist, a RAG-based AI chatbot and interactive AQI dashboard. Key features of the solution are:

a) Ward-level hotspot detection using dynamic/static sensors,
b) Exposure estimation using population-weighted models,
c) AI chatbot for real-time insights and mitigation strategies
d) Backend using FastAPI, OpenAI GPT-3.5, Pathway RAG, EasyOCR. Their solution helps policymakers identify vulnerable zones and access contextual data and documents interactively.

7. Challenges and Limitations

Despite the growing applications and demonstrated potential, citizen science hyperlocal mapping initiatives face significant challenges and limitations that must be carefully navigated. These can be broadly categorized into data collection issues, technical limitations, and operational challenges.

7.1 Data Collection Issues

Concerns about the quality of data generated by non-expert volunteers can become a barrier to wider acceptance and use, particularly in scientific research and formal decision-making (Goodchild, 2022).

a) **Accuracy:** Issues can arise with positional accuracy (e.g., GPS errors, incorrect geotagging), thematic accuracy (e.g., misidentification of species, incorrect classification of land cover), and temporal accuracy (e.g., delays in reporting) (Peng et al., 2021).The heterogeneity of contributors, equipment, and methods contributes to variable data quality (Antoniou, 2010).
b) **Bias and Representativeness:** Citizen-generated data is often not a random or representative sample of the phenomenon of interest Goodchild, 2022). *Spatial bias* occurs as contributions tend to cluster in easily accessible locations, populated areas, or places of particular interest to volunteers, leaving other areas under-sampled(Antoniou, 2010).*Temporal bias* results from data collection often being opportunistic rather than systematic. *Demographic bias* arises from unequal participation across different social groups, influenced by factors like access to technology (the digital divide), available time, education levels, or specific interests (Haworth & Bruce, 2015). *Thematic bias* can occur if participants focus on reporting certain types of features while ignoring others. These biases mean that VGI may not accurately reflect the true distribution or characteristics of the phenomena being mapped, potentially leading to skewed analyses or conclusions if not properly accounted for.
c) **Completeness:** Assessing whether the data captures all relevant features within an area is challenging, especially in the absence of comprehensive ground truth.[61] Participatory mapping exercises, for instance, have been shown to sometimes omit certain water sources or landscape-scale hazards.

The solution to these issues lies in managing the citizen scientist network with rigorous data processes, standard operating procedures, and periodic training. Unless sensor performance and data quality are monitored daily, or at more frequent intervals, there is a strong likelihood of error at this interface. The network design must factor in automation, appropriate processes, technology, and operating procedures to manage the human interface.

7.2 Technical Limitations

The tools and technologies employed in citizen science hyperlocal mapping, while enabling, also present technical limitations.

a) **Sensor Performance:** Low-cost sensors, while increasingly used, often have technical limitations in sensing capacity, making them less reliable than regulatory-grade monitors. Issues include accuracy, calibration needs (especially considering environmental influences like humidity and temperature), sensitivity, robustness, and operational lifespan. Ensuring data quality from these sensors is demanding.

b) **Validation Challenges:** Implementing robust Quality Assurance/Quality Control (QA/QC) procedures is essential but can be difficult and resource-intensive(Peng et al., 2021). Comparing VGI with authoritative data is common, but reference data may be outdated, inaccurate, unavailable, or at a different scale (Keßler & Lemmens, 2013). Crowdsourced validation methods (e.g., peer review, consensus) require sufficient participant numbers and engagement(Keßler & Lemmens, 2013). Developing and applying sophisticated validation algorithms requires technical expertise(Goodchild, 2022).

In the current project, the sensors were calibrated twice within a nine-month period to ensure integrity of data. Also, data being received on the VAYU portal was checked by our partners , SEEDs, to remove anomalies quickly.

c) **Integration and Interoperability:** Bridging the gap between citizen-generated VGI and official datasets or workflows is often challenging. (Müller et al., 2023). Differences in data standards, formats, accuracy requirements, metadata documentation, and institutional cultures hinder integration. The variety of sensors and platforms leads to a lack of standardization and interoperability.

Our partner, MistEO, who designed the VAYU portal were able to address this early in the project, so that the data analysis phase did not suffer from lack of integration and interoperability.

d) **Metadata Management:** Ensuring comprehensive and up-to-date metadata for sensor data is crucial for understanding quality and uncertainty, but standardization methods are lacking.
e) **Scalability:** Scaling up successful pilot projects often presents technical challenges related to maintaining data quality and managing larger infrastructure(Sitthi et al., 2022).
f) **Platform Usability:** Ensuring tools and platforms are user-friendly, reliable, and accessible across different devices is crucial for participation. Robust data management systems are needed for large, heterogeneous datasets(MapLibrary.org, n.d.).

7.3 Operational Challenges

Beyond data and technology, operationalizing and sustaining these projects involves significant hurdles.

a) **Participant Engagement and Sustainability:** Attracting and retaining a sufficient and diverse number of participants is difficult, especially for long-term monitoring. Volunteer fatigue, changing interests, or lack of perceived impact can lead to drop-off(Scientific and Technical Advisory Panel [STAP], 2024). Projects need to balance data needs with participant burden, ensuring a rewarding experience with benefits like learning or seeing tangible outcomes(KrakenSense Team, 2023).

Realizing these challenges early in the project helped us to take proactive action. Beginning with careful recruitment, constant monitoring, training, and incentivizing played a key role in ensuring an important level of participant engagement.

b) **Project Sustainability:** Securing ongoing funding for platform maintenance, data management, coordination, sensor calibration, and outreach is a major hurdle(Geekiyanage et al., 2021). Reliance on short-term grants hinders long-term goals(STAP, 2024). UNDP, as the donor, managed the flow of financial resources well by making a tranche of funds available every quarter thus avoiding resource constraints,

c) **Institutional Capacity:** Host organizations may lack funding, staff time, technical expertise, or established protocols to effectively manage projects, ensure data quality, or utilize the data(STAP, 2024). A lack of participatory culture can also be a barrier(Geekiyanage et al., 2021). As the host organization, UNDP structured the project delivery into a few formal roles for which capable partners were chosen. Further, during the project period weekly reviews were held to plan project delivery and resolve issues, if any. This allowed the project to progress smoothly without facing major barriers,

d) **Ethical Issues:** A range of ethical considerations must be addressed:

i. *Data Ownership and IP:* Clear agreements on data ownership, licensing, sharing, and use are needed, respecting local/Indigenous knowledge(Environmental Defense Fund [EDF], 2022) .

ii. *Privacy and Security:* Location data collection poses privacy risks; participants need informed consent regarding data use and protection (Seto Lab, n.d.). Security measures against misuse are necessary(Goodchild, 2022).

iii. *Informed Consent and Transparency:* Participants need clear information on project goals, methods, data use, risks, and benefits. Transparency about funding and affiliations is important(Wiggins & Crowston, 2023).

iv. *Equity and Inclusion:* Projects should strive for diverse participation, actively overcoming barriers (digital divide, gender, socioeconomic status) and ensuring the process does not marginalize groups or exacerbate conflicts(STAP, 2024).

v. *Extractive Practices:* Projects must avoid relationships where researchers benefit without reciprocal value for participants/communities (e.g., sharing results, co-authorship) (Motedayyen et al., 2024). "Dark Citizen Science" highlights potential negative divergences regarding power and public effect(Claerhout et al., 2024).

These challenges are often interconnected, requiring a holistic perspective considering technical, social, and ethical dimensions simultaneously(Goodchild,2022). A fundamental tension exists between openness/participation and the control/standardization needed for data quality and ethical risk management(Wiggins & Crowston, 2023).

8. Impact and Implications

Citizen science hyperlocal mapping initiatives generate significant impacts that extend beyond data collection, influencing policy, empowering communities, and advancing scientific understanding. However, realizing the full potential requires careful consideration of policy integration and effective community and stakeholder engagement.

8.1 Use Case Development

Effective air quality management begins with the ability to collect, analyze, and communicate pollution data in a way that is accurate, actionable, and accessible to stakeholders. With the increasing availability of low-cost air quality sensors and the rise of AI-driven analytics, there is a growing opportunity to transform environmental data into meaningful insights that drive public health protection and policy interventions.

To leverage this potential in Gurugram, a comprehensive technological framework has been developed to support the implementation of various air quality use cases. At its core, interactive dashboards that visualize real-time pollution trends with integrated predictive models and with other key features (calculated AQI, traffic score, hotspot disclaimer, and many other) to anticipate future pollution scenarios. This serves as the operational backbone for both public engagement and institutional decision-making.

These systems are built primarily using Python, leveraging its powerful ecosystem of libraries for data ingestion, statistical analysis, and machine learning.

For time-series forecasting, models such as LSTM (Long Short-Term Memory) and Prophet are employed to predict short-term pollution levels with temporal precision, factoring in seasonal trends and special event markers.

For source attribution and scenario modelling, Random Forest and XGBoost algorithms are used. These models help identify the contribution of specific pollution sources—such as traffic congestion scoring, brick kiln activity, or large-scale events—to observe pollutant concentrations. The models are trained on multi-layered datasets combining historical air quality data, meteorological inputs, traffic intensity, and event metadata.

To support spatial intelligence, geospatial tools were utilized to correlate pollution levels with sensor location and to visualize pollution dispersion across urban zones.

Air quality data inputs come from a mix of static and dynamic low-cost sensor networks, open weather APIs and Google distance matrix API. These data streams are managed via efficient real-time pipelines, ensuring minimal latency in system updates and alert delivery.

Together, these technologies form an integrated and intelligent infrastructure, capable of enabling real-time monitoring, forecasting, and targeted responses to air pollution challenges in Gurugram. The following selected use cases are strategically designed for high impact, operational feasibility, and alignment with ongoing national and city-level clean air initiatives, ensuring their sustainability and relevance within the respective city governance framework.

Use Cases developed in Gurugram

Use Case 1: Real-Time Air Quality Intelligence for citizen empowerment in Gurugram

Gurugram, often ranked among India's one of the most polluted urban centers, experiences severe air quality fluctuations due to traffic emissions, industrial activity, construction dust, and seasonal stubble burning from neighboring states. To enable timely awareness and community response, a real-time air quality dashboard tailored for Gurugram has been developed. This platform continuously monitors critical pollutants such as PM2.5, PM10, NOx, CO, and CO_2 across key locations—residential areas like Sector 56, industrial hubs such as Udyog Vihar, commercial zones like Cyber Hub phase-3, Mini Secretariat and major traffic corridors.

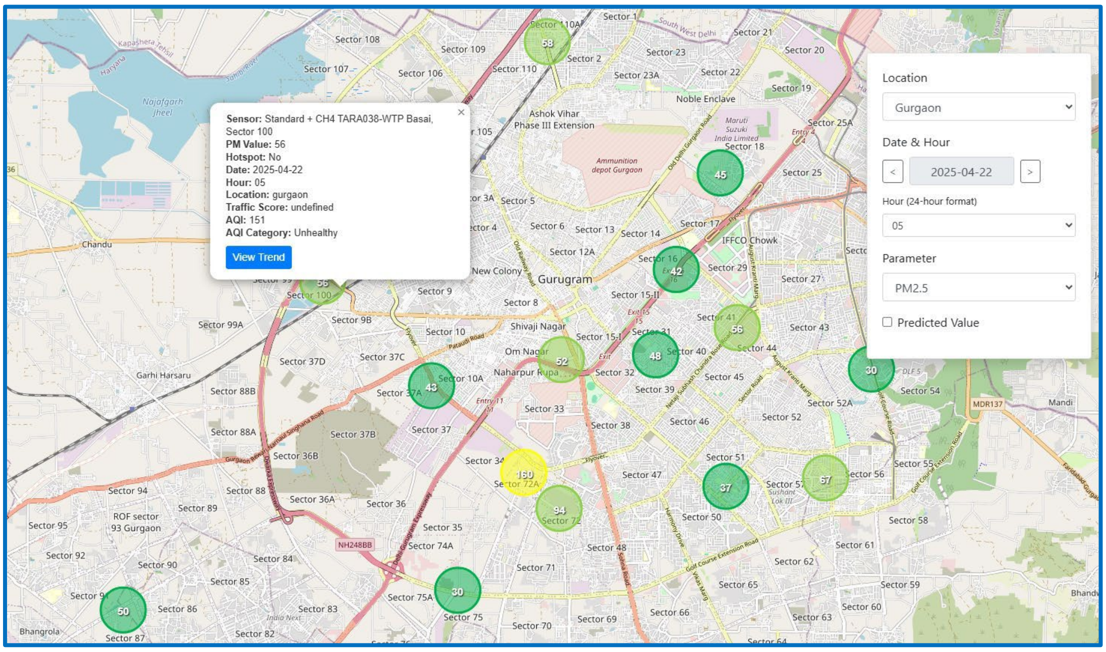


Figure 17: *Analysis Dashboard*

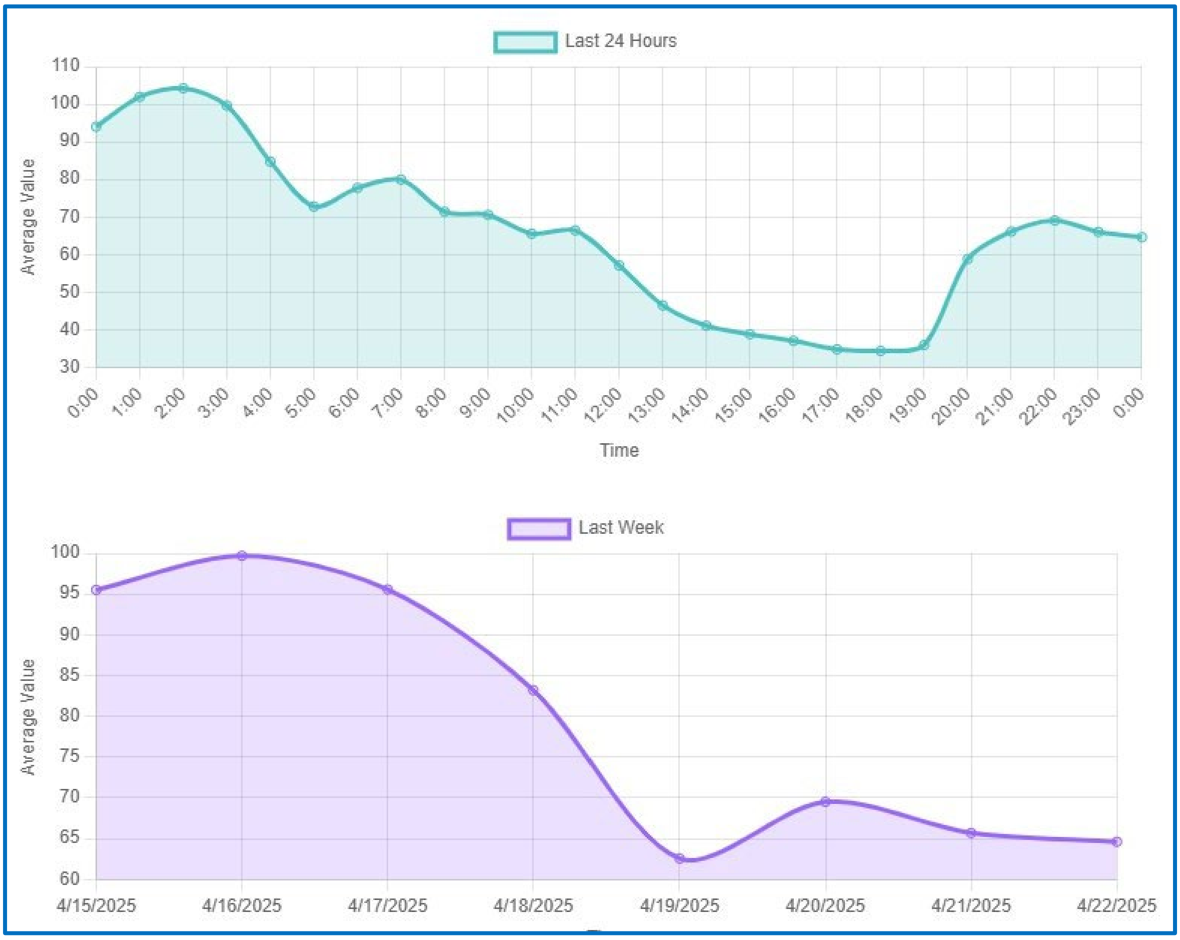


Figure 18: *Trend Analysis of TARA038 sensor*

Users can view air quality trends by selecting specific dates and times, and access predictive data using an AI-powered model that factors in seasonal patterns. The dashboard visually highlights pollutant spikes through animated sensor indicators ("pumping" effect) to depict real-time anomalies. When pollutant levels breach safety thresholds, an automated alert system is triggered. These alerts—delivered via SMS, email, and push notifications—reach city authorities, school administrators, environmental agencies, and housing societies. They include severity classification, geospatial coordinates, sources (e.g., heavy traffic or construction), and recommended interventions such as school closures, work-from-home advisories, or temporary factory shutdowns.

To view the prediction model, select a future date (the dashboard may initially appear empty), and click on **"Predict Values"** to see the predictions.

The prediction model is currently in Beta Mode. While it considers several parameters—including Month and Day—the accuracy is still a work in progress. Additionally, we are in the process of incorporating **traffic data** and other relevant factors to further improve the model's performance.

Further, there is an additional feature to the model, that whenever the pollutant concentration of any sensor exceeds the prescribed limit – the sensor representing circle will start "pumping" - more intense, frequent pumping will be depicted as the anomaly spike.

Citizen Scientist Integration

In parallel, a similar alert is dispatched to the nearest registered citizen scientist. These are trained volunteers equipped with portable sensing devices, enabling them to verify the pollution event on the ground. This community-driven verification layer adds credibility and precision to the monitoring process, ensuring data accuracy and fostering public involvement.

Impact on air pollution control

Timely dissemination of verified information empowers both stakeholder departments and the public to make informed decisions. Local governments can deploy mitigation measures faster, and citizens can take personal precautions, such as wearing masks or avoiding outdoor activity during peak pollution hours.

Access to real-time data can also empower communities to advocate for policy changes and hold polluters accountable. By translating complex pollutant data into a simple, understandable format, the interactive dashboard serves as a vital tool for public empowerment and improved health outcomes in Gurugram.

Use Case 2: Data-Driven Optimization of Urban Mobility for Pollution Mitigation Vehicular emissions remain one of the top contributors to air pollution in Gurugram. The city's reliance on private vehicles, limited public transport, and daily traffic bottlenecks at nodes like Sohna Road necessitate a smarter, pollution-conscious mobility system. To address this, a dynamic urban mobility dashboard has been created that integrates real-time air quality data with live traffic analytics, powered by tools such as the Google Distance Matrix API. It correlates pollution levels—specifically PM2.5, NOx, and CO—with traffic congestion and speed, identifying pollution hotspots in real time.

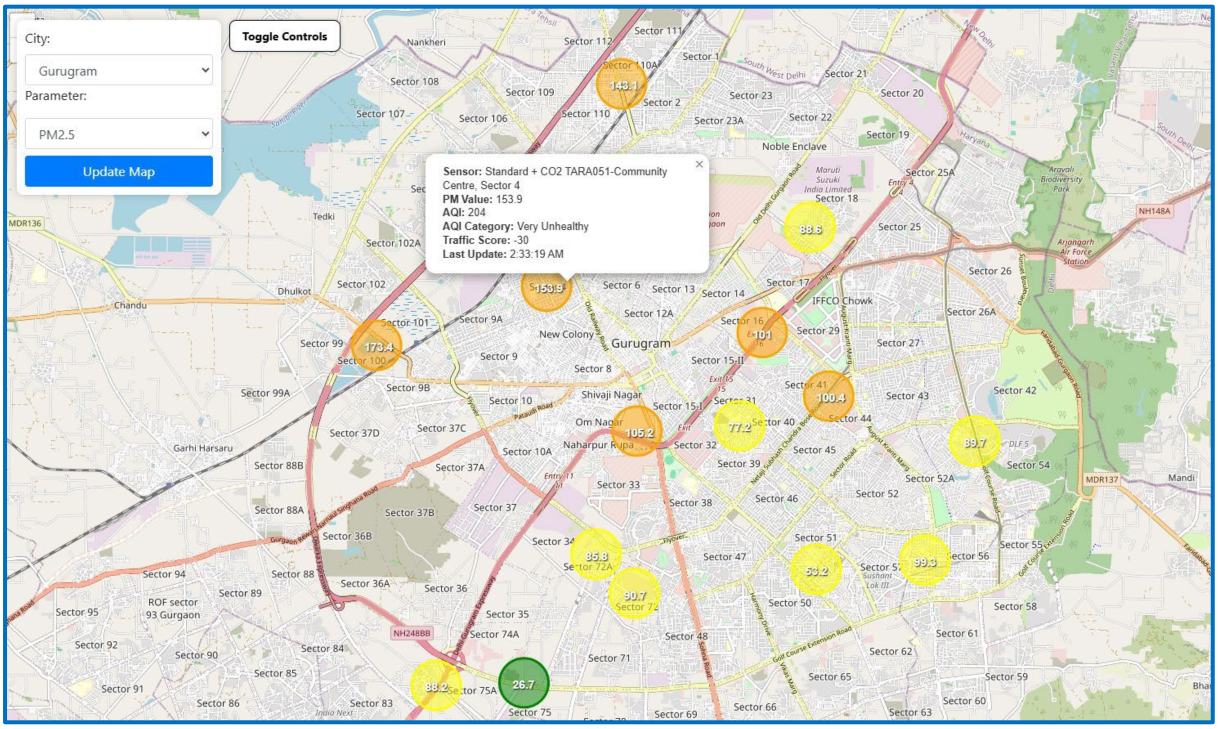


Figure 19: *Live Dashboard with Traffic Scoring*

Whenever pollution levels exceed permissible limits, alerts are automatically sent to transport department and Gurugram traffic police, complete with pollutant readings, traffic scores, and location-specific recommendations. These may include signal timing adjustments, temporary vehicle restrictions, or rerouting of vehicles. The system's core feature is its ability to suggest "cleaner corridors" by analyzing current traffic and pollution data to identify routes with lower emissions exposure. These routes can be leveraged by emergency services, school buses, and public transport operators to minimize exposure and improve travel efficiency.

Traffic Score Calculation

The system calculates a **composite traffic score** for each road segment by combining:

- **Travel Time Estimates** from the **Google Distance Matrix API**, which factors in real-time traffic congestion, road closures, and historical data.
- **Vehicle Flow Density**, estimated through sensor data and third-party traffic feeds

Heavy-duty commercial vehicles, such as freight trucks entering via Kherki Daula toll, can be dynamically redirected to bypass inner-city roads during peak pollution hours. Furthermore, this system is integrated with smart signage in key sectors, allowing real-time updates to be displayed for commuters. This dual-purpose platform improves both air quality management and traffic flow, contributing to healthier urban living.

Use Case 3: Enhancing Resilience of Critical Infrastructure to Pollution Emergencies

Gurugram's schools, hospitals, and public offices need specialized protocols to manage pollution emergencies, which are common during the winter months and festival seasons. To support institutional preparedness, a forecasting dashboard has been introduced that uses AI and meteorological data to predict high-pollution days up to 72 hours in advance. This foresight allows critical infrastructure to shift from reactive to proactive management.

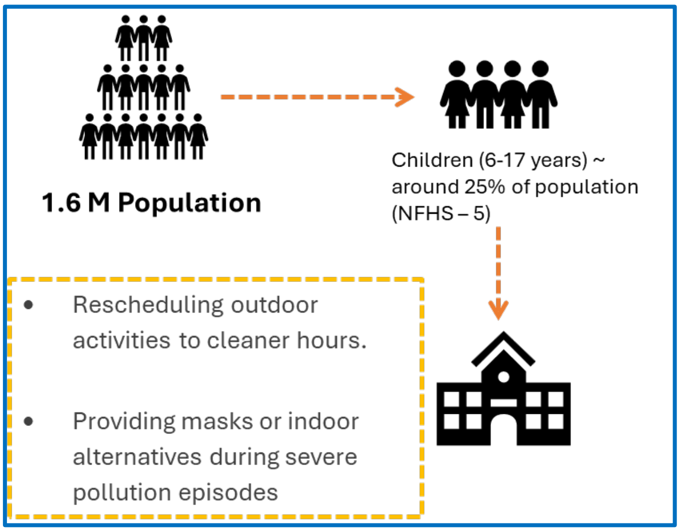


Figure 20: *Triggering recommendations for children*

For schools and sports authorities, these alerts can trigger specific recommendations aimed at reducing exposure time, particularly for children who are highly susceptible to the harmful effects of air pollution. Recommended actions could include rescheduling outdoor activities to times of the day with cleaner air, providing masks or indoor alternatives during severe pollution episodes, and adjusting ventilation systems to minimize the infiltration of polluted outdoor air.

Hospitals can prepare for an influx of respiratory patients, stock essential supplies, and improve indoor air filtration. Public offices may adopt flexible work arrangements or reschedule field operations. These predictive alerts are customized and geo-targeted, ensuring that relevant stakeholders receive actionable guidance in time.

Through this initiative, we will be able to create awareness in citizen to take proactive measure to minimize the exposure to air pollution promotes coordinated responses across departments, ensures operational continuity, and helps shield vulnerable populations— especially children, the elderly, and those with respiratory conditions—from harmful pollution exposure.

Use Case 4: Construction Dust Control and Compliance Enforcement

One of Gurugram's most prominent sources of air pollution is construction dust, driven by rapid urban expansion and inadequate on-site dust control practices. To address this issue, an AI-enabled monitoring system has been developed that integrates particulate sensors with video analytics at major construction sites. The geo-coordinates of Construction and Demolition (C&D) sites, sourced from the Dust Pollution Control Self-Assessment platform by HSPCB (developed under the direction of CAQM), will be integrated into this system.

Whenever a sudden increase in the $PM_{10}/PM_{2.5}$ ratio is detected, the system will send an alert to HSPCB to inspect nearby C&D sites. These alerts are backed by real-time data, facilitating prompt enforcement actions such as warnings, fines, or operational halts.

Additionally, the system includes a citizen engagement feature via a mobile application, enabling residents to report non-compliant construction sites. This enhances transparency and fosters community involvement in environmental monitoring.

By strengthening regulatory oversight and empowering public vigilance, Gurugram can more effectively tackle one of its most persistent air quality challenges.

8.2 Policy Implications and Recommended Actions

The identification of hyperlocal pollution hotspots in Gurugram offers a critical input into the design of spatially differentiated policy responses. While city-level strategies such as the Graded Response Action Plan (GRAP) have been activated periodically, they often fail to capture the intra-urban variability of exposure risks.

This study recommends the implementation of zone-specific interventions such as:

a) Deployment of mobile enforcement and dust suppression units in identified hotspots

b) Temporal restrictions on high-emission construction and transportation activities during peak hours
c) Installation of vegetative buffers and air filtration systems in and around sensitive locations such as schools and healthcare facilities
d) Enhanced public access to real-time air quality data through digital dashboards and SMS alerts.

Inclusion of citizen-generated data and community monitoring under the Vayu platform to augment municipal capacity

Citizen-generated hyperlocal data holds considerable potential to inform and influence policy, but bridging the gap between citizen science and formal decision-making requires strategic approaches.

e) **Acknowledge Policy Influence:** Citizen-generated data, maps and bulletins have already demonstrated impact by informing GMDA's action on a daily and weekly basis as discussed earlier in this report. These also have the potential of guiding environmental regulations, public health interventions, resource management, and disaster response protocols(Geekiyanage et al., 2021).
f) **Adopt Airshed Approaches:** For issues like air pollution that transcend administrative boundaries, regional or "airshed" level approaches are needed, requiring coordination across jurisdictions,
g) **Strengthen Integration Strategies:** Efforts are needed to build partnerships between citizen science groups, researchers, government agencies, and National Statistical Offices (NSOs) (Wueest et al., 2023). This involves establishing trust, developing data standards (including metadata), creating clear pathways for data incorporation into official monitoring and decision-making, and addressing legal/policy constraints. Defining the "fitness for purpose" of VGI for specific policy applications is crucial(Keßler & Lemmens, 2013).
h) **Promote Open Science and Data:** Aligning with Open Science principles by promoting transparency, open data access (where ethical), open-source tools, and collaborative knowledge creation can enhance policy relevance and trust(Datos.gob.es, 2023).
i) **Develop Context-Specific Guidance:** More nuanced ethical and quality guidelines tailored to specific contexts (e.g., AI use, passive sensing, diverse cultural settings) are needed to ensure responsible data use in policy(Goodchild,2022).
j) **Support Transboundary Cooperation:** For issues like transboundary air pollution, cooperative control mechanisms and potentially extending principles like "polluter-pays" across borders are needed, though political challenges exist. International environmental law and regional cooperative solutions are potential avenues. Regional bodies and frameworks can promote holistic management and knowledge exchange.

8.3 Community and Stakeholder Engagement

Effective engagement is crucial for the success, sustainability, and ethical conduct of citizen science hyperlocal mapping projects.

a) **Recognize Participant and Community Benefits:** Participation offers numerous benefits, including increased scientific literacy, environmental awareness, community engagement, empowerment, potential behavioral changes, and a stronger connection to place(Geekiyanage et al., 2021). Projects can improve local knowledge sharing, resource management, conflict resolution, community cohesion, and advocacy capacity(Gunnell et al., 2023).

b) **Prioritize Genuine Engagement:** Foster meaningful collaboration and communication, especially in co-created projects. Value local knowledge, provide training and support, ensure participants see benefits, and share results accessibly(Gunnell et al., 2023).Actively work to mitigate participation barriers like the digital divide(Middel et al., 2022).

c) **Embed Ethical Frameworks:** Proactively address ethics, including informed consent, privacy, data ownership, equity, inclusion, and avoiding extractive relationships(Geekiyanage et al., 2021). Adopt relational approaches valuing reciprocity and feedback(Motedayyen et al., 2024). Ensure transparency about goals and funding.

d) **Build Trust and Capacity:** Take time to build trust between researchers, communities, and authorities. Commit to long-term support and capacity building, enabling community ownership and control over the mapping process and data use.

e) **Address the Digital Divide:** Consciously work to overcome barriers related to technology access and digital literacy to ensure equitable participation(Haworth & Bruce, 2015).

f) **Improve Impact Assessment:** Develop systematic methods to assess the full range of impacts, including social, political, and educational outcomes, moving beyond anecdotal evidence(Ho et al., 2022).

g) **Manage Expectations:** Clearly communicate project goals and limitations to manage participant expectations, particularly regarding the potential for immediate policy change or environmental improvement.

Effective community and stakeholder engagement transforms projects from simple data collection exercises into collaborative efforts that build capacity, foster trust, and increase the likelihood of generating meaningful and sustainable change.

9. Way Forward

Citizen science hyperlocal mapping stands at a dynamic intersection of technology, public participation, and scientific inquiry. Its trajectory points towards increasing integration with advanced technologies and broader societal goals, while simultaneously demanding continued attention to fundamental challenges.

The future will see greater integration of **Artificial Intelligence (AI) and Machine Learning (ML)** for processing vast VGI datasets, enhancing data quality assessment, fusing diverse data sources (like VGI and remote sensing), and developing predictive models(Ho et al., 2022).

Advancements in **sensor technology** (cheaper, smaller, more efficient sensors, IoT integration, wearables) will expand opportunities for ubiquitous, passive data collection, enriching hyperlocal datasets(Peng et al., 2021). **Mobile and web platforms** will evolve towards greater interactivity and user-friendliness, potentially incorporating AR/VR , while **data fusion techniques** will become more sophisticated, combining VGI with remote sensing, IoT data, and official statistics for comprehensive hyperlocal representations(Sitthi et al., 2022).

Methodologically, a shift towards more **co-created citizen science models** is evident, prioritizing community needs, local knowledge, and empowerment alongside scientific goals(Gunnell et al., 2023). **Hybrid approaches**, strategically blending citizen science with expert validation, remote sensing, and modelling, will become more common to ensure robustness(Ho et al., 2020).

Integration with broader agendas, particularly the **Sustainable Development Goals (SDGs)**, will continue, leveraging citizen-generated data to monitor progress on goals related to health, climate, cities, water, and biodiversity(Sitthi et al., 2022). Strengthening connections with **formal policy-making processes** through partnerships, data standards, and established trust is a key future direction(Wueest et al., 2023). Alignment with **Open Science principles** will further enhance transparency and collaboration(Datos.gob.es, 2023).

However, realizing this potential requires addressing persistent challenges. **Evolving ethical frameworks** are needed for AI, passive sensing, data ownership, and equity(Goodchild,2022). Continued efforts towards **data quality standards** and accepted protocols for VGI assessment are necessary(Keßler & Lemmens, 2013). Critically, **bridging the digital divide** requires conscious strategies to ensure inclusivity(Haworth & Bruce, 2015).

The significance of citizen science hyperlocal mapping lies in its potential to democratize geographic knowledge production, foster inclusive environmental governance, and provide crucial local information for tackling complex challenges(Goodchild,2022). Moving forward, success depends not on a single pathway but on fostering adaptive, hybrid socio-technical systems. These systems must leverage the complementary strengths of citizen participation (local knowledge, distributed observation), technology (processing power, scalability, AI), and scientific rigor (validation, integration frameworks), grounded in ethical conduct, equity, and genuine collaboration between scientists, citizens, communities, and policymakers. In our experience, the close cooperation and support provided by the GMDA was instrumental in the project achieving its objectives. In any such study, the nodal government agency must be involved right from the design through the implementation and review phases to create the greatest impact.

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