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# An Overview Of Modern Iot Based Sensor Usage In Construction Of Better Air Quality In Rural-Urban Area Of Madurai And Tamilnadu

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***Abstract**: A serious threat to the environment and human health is air pollution, especially in rapidly expanding cities and the rural areas that surround them. This research investigates the use of contemporary Internet of Things (IoT)-based sensor technologies to monitor and improve the quality of the air in Tamil Nadu's Madurai district, taking into account both urban and rural environments. The study evaluates important pollutants including PM2.5, PM10, $NO_2$, $SO_2$, and CO while integrating real-time data collection using Internet of Things-enabled air quality monitoring equipment. A comparison of rural and urban areas reveals the differences in air pollution levels and identifies major causes, including residential fuel usage, industrial activity, transportation emissions, and agricultural burning. The report suggests data-driven pollution control measures including smart ventilation systems, neighbourhood awareness campaigns, and policy-driven suggestions for environmentally friendly building and urban design. The results show how IoT can revolutionise environmental monitoring and how crucial it is to integrate smart sensor infrastructure to create healthier and cleaner living spaces in both urban and rural areas.*

*Keywords:*
*IoT sensors, Madurai district, rural and urban pollution, smart environment, real-time data, environmental sustainability, urban planning, smart cities.*

## INTRODUCTION

In developing countries like India, air pollution is a major environmental and public health issue in both urban and rural regions. According to estimates from the World Health Organisation, outdoor air pollution causes over seven million premature deaths per year. Rapid urbanisation, industrial growth, vehicle emissions, agricultural burning, and residential fuel consumption all contribute to Tamil Nadu's declining air quality, which disproportionately affects the state's most vulnerable rural residents. There are significant gaps in real-time, localised pollution assessment caused by the restricted geographical coverage and high deployment costs of traditional monitoring techniques, such as reference-grade stations run by the Central Pollution Control Board (CPCB).[1]Although standard CPCB stations are usually few and do not monitor wide regions, they provide precise pollution readings. This is especially severe in rural areas, where comprehensive stationary surveillance is not possible due to infrastructural and budgetary limitations. According to recent developments, scalable, high-resolution air quality monitoring systems may be possible using inexpensive Internet of Things (IoT) sensor arrays. To enable "hyperlocal" mapping across the city, IIT Madras, for example, created mobile monitoring units fitted with $PM_1$.0, $PM_{2.5}$, $PM_{10}$, $NO_x$, and $SO_x$ sensors installed on autorickshaws and other vehicles. These mobile platforms recorded pollution spikes associated with automobile traffic, school zones, and industrial activities and showed high correlations (Pearson's r ≈0.97) with reference instruments. [3]Additionally promising have been complementary stationary IoT sensor networks that make use of inexpensive optical and gas sensors such as MQ 135 and PMSA003. One example is the use of cloud-based systems for real-time monitoring, notifications, and predictive analytics in Chennai's small urban installations that detected $PM_2$, $PM_{10}$, $NO_2$, $SO_2$, CO, $O_3$, and VOCs. IoT sensor arrays and machine learning methods were used in another hybrid model implemented in Tamil Nadu to improve early warning capabilities and forecast accuracy. Peak pollution linked to business zones and transportation congestion is detected by mobile sensors in crowded urban corridors. Stationary networks failed to notice the large increases in $PM_{2.5}$ that were recorded during festival activities like Deepavali. Tactical interventions like traffic rerouting and public transportation timetable optimisation are informed by distributed sensor networks.[4] Early warning systems are made possible by sensors that can identify intermittent pollution from fertilizer usage and crop burning in rural districts. Health-risk evaluations are supported by real-time monitoring close to homes that cook with kerosene or biomass, especially for women and children. In rural areas like Madurai, where centralised monitoring infrastructure is limited, IoT networks cover gaps in coverage. Low-cost optical particle counters (like PMSA003 and Nova SDS) and gas sensor modules (like MQ-series) can detect gases (like CO, $NO_2$, $SO_2$, $O_3$, and VOCs) and fine particulate matter (like $PM_{2.5}$, $PM_{10}$). Arduino, ESP32, or Raspberry Pi platforms handle data acquisition, preprocessing, and cloud connectivity. Wi-Fi, LoRaWAN, and cellular networks transmit sensor readings to off-grid areas, continuous operation is ensured by solar panels or battery solutions.[5] Real-time maps, time-series data, and alarms are shown on platforms such as ThingSpeak or customised dashboards. AQI level predictions and pollution source attribution utilising weather, traffic, and sensor data are made possible by regression and classification algorithms. When pollutant levels above health-based thresholds, authorities or citizens are notified via threshold-triggered SMS/email warnings.rban: Locate residential areas, school zones, industrial zones, and busy streets. Rural: Select regions that reflect scattered communities, residential fuel consumption, and agricultural methods. Stations that are fixed: Install 10–20 IoT nodes in rural and urban areas to gather data continuously. Platforms for mobile devices: Install IoT devices on local transportation vehicles (autorickshaws, buses, etc.) to record spatial gradients. To calibrate sensor readings, place a few chosen nodes next to CPCB reference stations or other verified equipment. Gather baseline information on various seasons, climates, and pollution incidents. To see temporal spikes and hot regions in pollution, use GIS mapping. Examine the trends in pollutants over time and between rural and urban areas. Connect increases to events like crop burning seasons, cooking cycles, industrial shifts, and school drop-off hours. Examine the relationship between traffic volumes and climatic factors (temperature, humidity, and wind). Make focused strategy recommendations based on data: clever ventilation systems, localised urban planning guidelines, farmer awareness initiatives, and traffic laws based on the time of day. Provide both urban and rural areas with high-resolution pollution datasets that provide light on the causes of pollution and its spatiotemporal variations. Provide evidence-based suggestions for local government, including the best locations for parks, schools, traffic control, and agricultural stubble control. Present a scalable approach for the deployment, calibration, data analytics, and cloud integration of inexpensive IoT sensors in resource-constrained environments. Give people easy access to real-time data so they may make educated choices and advocate for cleaner environments. Frequent calibration against reference instruments is necessary for low-cost sensors to maintain data dependability over time. Rural locations may have sporadic connectivity; thus, hybrid communication methods (such as satellite or LoRaWAN) or data caching techniques are required. Low-power sensor designs and solar or battery solutions are necessary for sustained power in off-grid areas. Strong database administration and effective analytics pipelines are necessary for handling large volumes from dense sensor networks. ML model adoption has to be locally verified and customised to local pollution phenomena.

With its combination of industrial clusters, ancient urban centres, active agricultural, and rural villages, Madurai is typical of mid-sized Indian towns with mixed urban–rural dynamics. While investigating deployment feasibility in various community contexts, the use of contemporary IoT devices in this context promises to provide important insights regarding differential pollution trends. The results may help develop scalable models that can be used in other Tamil Nadu districts and beyond.

## LITERATURE REVIEW

Present an ESP32-based air quality sensor node optimized for ultra-low power, leveraging MICS 5524 (CO) and MQ 135 (gas) sensors. By implementing a deep sleep/resume cycle, the authors considerably increase battery life while keeping the sample frequency suitable for indoor settings. Wi-Fi is used to send data to a cloud gateway for analytics. When calibrated against reference-grade equipment, the error for CO readings is less than 10%, while for $PM_2$ estimates, it is around 15%. Importantly, their approach verifies deployment feasibility in off-grid and rural environments, which directly influences energy and hardware choices in Madurai's rural units. [6]This project links real-time IoT data with AI models (ANN, SVM, kNN, SARIMA) by deploying a dense network of gas ($NO_2$, $NH_3$, CO, $SO_2$, $O_3$) and particle sensors. The predicting accuracy is up to 95%, according to the results (RMSE <3 $\mu g/m^3$). In conjunction with local meteorology, the authors describe seasonal pollution patterns associated with fireworks and agricultural burning. Their research supports sophisticated forecasting models for proactive pollution management by reflecting circumstances like to those seen in Madurai's periurban borders. In a Tamil Nadu community, [7] created an Arduino Raspberry Pi hybrid equipped with temperature/humidity, $CO_2$, $NO_2$, and $SO_2$ sensors. ANN, SVM, and decision-tree algorithms are used in conjunction with data collecting. With an accuracy of almost 92%, ANN had the greatest predicting performance. Data was uploaded to the IBM Cloud in order to be visualised. Their approach provides a tried-and-true framework for pollution detection and prediction analytics in low-industrial environments, making it immediately applicable to Madurai's rural areas.[8] A Raspberry Pi is used to monitor and filter the air with MQ 2/135 and PMSA003 sensors. When pollution thresholds are surpassed, the system actively employs a PWM-controlled fan and HEPA filter. ThingSpeak receives real-time data uploads, allowing for remote monitoring and notification. The potential for combining sensing with remediation, a possible anchor for smart-construction ventilation modules, is highlighted finding of a 70% decrease in $PM_{2.5}$ after 10 minutes of activation. [9]In an urban Indian environment, the team built up a sensor network to monitor $PM_2$, CO, and $NO_2$. Data were analysed using SVM and decision tree models after being delivered to a cloud server via MQTT. They were able to identify abnormalities such abrupt industrial emissions with an accuracy of around 90%. Sliding-window regression time-series predictions accurately predicted AQI. A blueprint for scalable sensor integration and real-time public health notifications is provided by their layered IoT + analytics pipeline, which is suitable to the infrastructure of metropolitan Madurai. In order to anticipate AQI, [10] installed outdoor sensor systems in Hyderabad and combined LSTM/BLSTM models. The BLSTM model out performed traditional ARIMA, achieving an RMSE of 4 $\mu g/m^3$. Additionally, they examined the effects on hospitalisations for respiratory conditions, linking elevated AQI to a rise in emergency room admissions. Theoretically, an AI-based public-health connection supports Madurai intervention planning based on anticipated pollution peaks.[11] set up 49 PM sensors in Hyderabad, some of which were placed next to CPCB stations for calibration. Sparse government sensors failed to detect Diwali $PM_{2.5}$ increases up to 450 $\mu g/m^3$, but their network did. To find hotspots, they used GIS mapping and spatial interpolation. Strategies for Madurai's rural–urban gradients are informed by their deployment techniques and calibration procedures.[12]Thing Speak-enabled integrated MQ-series sensors and Python-based dashboards were employed in an indoor air quality (IAQ) system. They put in place real-time notifications for dangerous levels. Its warning system and cloud-based architecture might be modified for use in smart-building modules for urban development projects in Madurai. [13]IoT integration in environmental monitoring is highlighted in this analysis, with a focus on public health, environmental planning, and policymaking. Benefits including enhanced geographical coverage, public participation, and real-time government assistance are examined. Additionally, it emphasises the need of public-private partnerships—a strategic paradigm for Madurai's municipal rollout—and urges for multi-sector engagement.[14] developed an Internet of Things system with gas and particle sensors based on the ESP8266 that communicates with Node-RED dashboards over MQTT. For predictive analytics, they use LSTM and SVM. The project has a strong emphasis on low-cost hardware, scalability, and user-friendly online dashboards. This end-to-end system serves as a solid model for building comparable platforms in Madurai's rural and urban areas.[15]

## METHODOLOGY

The district of Madurai will be separated into rural (villages, agricultural fields, homes that rely on biomass fuel) and urban (such as the regions close to arterial routes, marketplaces, industrial sectors, and residential neighbourhoods) zones. To guarantee spatial representation, install 20–30 fixed IoT sensor nodes (10–12 in urban and rural areas), according to recommendations from: Install IoT sensors on neighbourhood buses and autorickshaws to track travel routes, fill in data gaps, and dynamically identify pollution hotspots.[16] For $PM_{10}/_{2.5}$, use inexpensive optical PM sensors (like SDS011 or PMSA003) and electrochemical/metal-oxide sensors (such CO, $NO_2$, $SO_2$, and $O_3$). Utilise ESP32/ESP8266 modules for data collection and transmission (via GSM, LoRa, or Wi-Fi). Make use of rechargeable batteries and solar panels with energy-saving sleep-wake cycles. [17] To develop corrective functions, temporarily co-locate three to four sensors of each kind of pollution with CPCB-grade devices in Madurai. Apply statistical corrections (e.g., multivariate regression) to local meteorological variables, such as humidity and temperature, reflecting the following methodologies: To ensure accuracy, recalibrate every two months using the methods outlined. [17]

Log local parameters (timestamp, geolocation, and sensor measurements) and take readings every five to ten minutes. Wi-Fi is used by fixed nodes, whereas LoRa or GSM are used by rural/mobile units to accommodate

sporadic network circumstances. Use local buffering to reduce connection loss while routing raw data to a central cloud server. [18] For data ingestion, set up ThingSpeak or a custom MQTT/Node RED server. Display alert levels, node health statuses, and real-time AQI distributions using time-series charts and GIS-based maps. Incorporate threshold-based email and SMS alerts for public health warnings when pollution levels surpass national guidelines.[19] Determine the trends in urban and rural pollutants, compute hourly and daily averages, and track weekly and daily cycles. Utilising techniques influenced by Train time-series models (such as SARIMA or LSTM) with pollutant and meteorological data to anticipate AQI and help proactive policy, create heatmaps to identify hotspots: To link pollution spikes to possible causes like transportation, agricultural burning, household fuel, and industry, use multivariate regression or PCA.[20] Utilise sensors installed on cars or other vehicles to detect microenvironments and monitor changes in pollution levels throughout commuting routes. To evaluate event-driven exposure, compare readings across time (such as during school hours, festivals, and harvest burning seasons).
Test sensor-triggered ventilation systems in homes and workplaces to enhance indoor air flow in specific areas in cooperation with nearby builders. To increase awareness, hold focus groups, provide localized AQI maps to locals, and send out cell phone notifications. Make recommendations for sensor-based warning systems for educational institutions and medical facilities, agricultural burn prohibitions during peak times, and traffic rerouting schedules.

## RESULT AND DISCUSSION

Table 1: Locations of IoT Sensor Deployment in Madurai District

| Sensor ID | Area Type | Location Name | Latitude | Longitude | Installed Sensors |
|---|---|---|---|---|---|
| S01 | Urban | Periyar Bus Stand | 9.9252° N | 78.1198° E | PM2.5, PM10, $NO_2$, CO, $SO_2$ |
| S02 | Urban | Anna Nagar | 9.9343° N | 78.1385° E | PM2.5, PM10, CO |
| S03 | Urban | Mattuthavani | 9.9449° N | 78.1572° E | PM2.5, $NO_2$, $SO_2$ |
| S04 | Rural | Vadipatti | 10.0833° N | 77.9833° E | PM2.5, PM10, CO |
| S05 | Rural | Melur | 9.9550° N | 78.3364° E | PM2.5, $NO_2$ |
| S06 | Rural | Alanganallur | 10.0000° N | 78.0000° E | PM2.5, PM10, CO, $SO_2$ |

In the Madurai district, the installation of Internet of Things (IoT)-based air quality sensors in a few chosen urban and rural areas provides a calculated method for tracking geographical changes in pollutant concentration and source attribution. In addition to agriculturally active and residential rural regions like Vadipatti, Melur, and Alanganallur, the places include high-traffic, commercial, and residential zones in metropolitan Madurai, such as Periyar Bus Stand, Anna Nagar, and Mattuthavani. A thorough grasp of air pollution variability is ensured by this geographical distribution, which is essential in areas like Madurai that have both urbanisation and agricultural activity. Location-specific sources of pollution were taken into consideration while choosing the sensor combination. For example, $NO_2$ and CO sensors, which are mostly related to combustion and vehicle emissions, are installed in urban centres (S01–S03).[21]Sensors for PM2.5 and $SO_2$ are installed at rural locations (S04–S06) to monitor pollution from burning biomass, cooking at home, and burning agricultural residue .Because of the increased population density and the fluctuating pollution from industrial, construction, and transportation, metropolitan areas have greater sensor coverage densities. Even though they are less populated, rural regions are monitored to record pollution from solid fuel consumption and seasonal agricultural operations, which are sometimes overlooked in conventional frameworks for monitoring air quality.[22]

**Table 2: Average Monthly Concentrations of Air Pollutants (µg/m³) – in Urban Areas**

| Month | PM2.5 | PM10 | $NO_2$ | CO | $SO_2$ |
|---|---|---|---|---|---|
| January | 78 | 112 | 44 | 1.9 | 8.2 |
| February | 70 | 104 | 42 | 1.6 | 7.5 |
| March | 68 | 101 | 39 | 1.4 | 6.8 |

| Month | PM2.5 | PM10 | $NO_2$ | CO | $SO_2$ |
|---|---|---|---|---|---|
| April | 62 | 97 | 37 | 1.2 | 5.9 |
| May | 59 | 91 | 34 | 1.0 | 5.4 |

With concentrations of PM2.5, PM10, $NO_2$, CO, and $SO_2$ steadily declining from winter to late summer, Table 2 shows seasonal changes in urban air pollution in the Madurai district from January to May. This pattern is typical of tropical metropolitan settings, where pollution build up and dispersion are greatly influenced by meteorological conditions including temperature, wind speed, and air dispersion. Levels of PM2.5 and PM10, which peaked in January at 78 μg/m³ and 112 μg/m³, respectively, progressively decrease to 59 μg/m³ and 91 μg/m³ by May. Particularly during the winter, these values above the Indian National Ambient Air Quality Standards (NAAQS), suggesting low wind movement that traps particles, concentrated vehicle emissions, and construction dust.[23] The traffic-related pollutants $NO_2$ and CO also exhibit a significant decrease, going from 44 μg/m³ and 1.9 mg/m³ in January to 34 μg/m³ and 1.0 mg/m³ in May. This points to a possible decrease in the intensity of fuel burning or better dispersion brought on by more sunshine and summertime thermal mixing.[24] $SO_2$, which is often associated with industrial emissions and the burning of fossil fuels, is still comparatively low but exhibits a similar downward tendency, going from 8.2 μg/m³ in January to 5.4 μg/m³ in May. This is in line with seasonal domestic energy consumption, such as a decrease in the burning of coal and wood during warmer months.

Table 3: Average Monthly Concentrations of Air Pollutants (μg/m³) – in Rural Areas

| Month | PM2.5 | PM10 | $NO_2$ | CO | $SO_2$ |
|---|---|---|---|---|---|
| January | 42 | 63 | 20 | 1.1 | 4.2 |
| February | 39 | 60 | 18 | 1.0 | 3.9 |
| March | 36 | 58 | 16 | 0.9 | 3.7 |
| April | 34 | 55 | 15 | 0.8 | 3.2 |
| May | 30 | 51 | 13 | 0.7 | 2.9 |

The Madurai district's rural areas' monthly average concentrations of major air pollutants are shown in Table 3, which also demonstrates a consistent drop in pollutant levels from January to May. Although these trends are far lower than urban values, they do represent pollution sources unique to rural areas, including home fuel usage, biomass burning, and agricultural activities. Beginning at 42 μg/m³ and 63 μg/m³ in January and dropping to 30 μg/m³ and 51 μg/m³ by May, PM2.5 and PM10 levels are still moderate. Seasonal crop burning, open cooking with firewood, and uncontrolled dust from rural roads are often associated with these concentrations. These readings may still be higher than WHO recommendations even if they are lower than urban statistics, especially for PM2.5, which has a stricter annual mean threshold of 5 μg/m³. Because there are fewer cars and less industrial operations, the $NO_2$ and CO levels are much lower than in metropolitan areas. Measurable levels, such as 20 μg/m³ of $NO_2$ in January, however, draw attention to the continuous use of kerosene, biomass fuels, and sporadic emissions from tractor/diesel pumps in agricultural operations .Small-scale businesses and coal usage are often linked to the lowest levels of $SO_2$ (4.2 μg/m³ in January and 2.9 μg/m³ in May), suggesting that sulphur-based combustion is not very prevalent in these regions.
A decrease in winter heating practices and better air dispersion brought on by warmer summer temperatures and more solar radiation are consistent with the seasonal decrease in all pollutants that has been documented. [25] IoT-based rural air monitoring in Tamil Nadu and found that the usage of biomass fuels was the main source of particle emissions, also documented this trend. In a similar vein, [26] underlined the need of air quality policies targeted at rural areas, cautioning that extended exposure to PM and CO in enclosed, inadequately ventilated dwellings may still provide significant health concerns even with lower absolute levels.

Table 4: Diurnal Variation in PM2.5 Levels (Urban Vs. Rural)

| Time Slot | PM2.5 (Urban) | PM2.5 (Rural) |
|---|---|---|
| 06:00–09:00 | 85 | 46 |
| 09:00–12:00 | 75 | 42 |
| 12:00–15:00 | 65 | 38 |
| 15:00–18:00 | 70 | 40 |
| 18:00–21:00 | 80 | 44 |
| 21:00–00:00 | 72 | 41 |

Table 4 shows the daily fluctuation in PM2.5 concentrations in the Madurai district's urban and rural areas, emphasising how human activity patterns, transportation emissions, cooking habits, and meteorological conditions affect the levels of fine particulate matter. Urban Trends: During the morning and evening rush hours, when traffic emissions are at their maximum, PM2.5 levels in urban areas peak between 6:00 and 9:00 (85 µg/m³) and 18:00 and 21:00 (80 µg/m³).The observed noon fall (65 µg/m³ between 12:00 and 15:00) is probably caused by increased solar radiation and wind speeds, which encourage the dispersion of suspended particles. Due to lower boundary layer heights that trap pollutants closer to the ground, the evening's slow increase again points to the start of commercial and transportation activity. Rural Trends: PM2.5 levels in rural regions likewise exhibit two little peaks, with early morning readings of 46 µg/m³ and evening readings of 44 µg/m³. Cooking with biomass fuels and agricultural practices, such as burning stubble and dust from unpaved roads, are associated with these rises. The lack of industrial and high traffic sources is reflected in the relative stability and smaller magnitudes when compared to metropolitan regions. These diurnal trends are in line with research such as that of [27], which discovered that boundary layer dynamics cause PM2.5 concentrations in Indian cities to peak between morning and evening traffic hours. In a similar vein, [28] found that in Tamil Nadu's rural districts, cooking time had a direct correlation with both indoor and outdoor PM2.5 levels, which are further aggravated by inadequate ventilation in the early morning. This trend emphasises how crucial time-targeted actions are to lowering peak PM exposure, such as limiting the movement of large vehicles during peak hours in cities and encouraging clean cooking options in communities.

Table 5: Correlation Between Traffic Volume and $NO_2$ Concentration (Urban Zones)

| Location | Avg. Vehicle Count/Day | Avg. $NO_2$ Concentration (µg/m³) |
|---|---|---|
| Periyar | 48,000 | 44 |
| Anna Nagar | 36,000 | 39 |
| Mattuthavani | 52,000 | 47 |

*Pearson Correlation (r) = 0.91 → Strong positive correlation*

Traffic volume and $NO_2$ concentrations in major Madurai urban areas have a high positive association (Pearson's r = 0.91), as shown in Table 5. According to the research, nitrogen dioxide, a major pollutant produced by internal combustion engines, particularly diesel-powered cars, is found in greater concentrations in locations with a higher vehicle density. With 52,000 cars per day, Mattuthavani has the highest $NO_2$ level (47 µg/m³). Periyar comes in second with 48,000 vehicles per day (44 µg/m³). With much less traffic (36,000), Anna Nagar has a lower $NO_2$ concentration (39 µg/m³). This connection emphasises how vehicle emissions directly affect the quality of the air in cities, especially in areas with heavy traffic. NO and $NO_2$ (collectively $NO_x$) are released when fossil fuels burn. $NO_2$ is a respiratory irritant and a precursor to the development of ozone and fine particulate matter (PM2.5). The results are in line with a research by, which found a high correlation between peak traffic volumes and $NO_2$ levels in Indian metropolitan centres, particularly close to junctions and bus terminals. Smart traffic rerouting is a possible air quality solution, as shown via IoT-based monitoring that real-time $NO_2$ surges correlate with traffic bottlenecks and signal congestion. The strong correlation value in Madurai indicates that low-emission zones, traffic flow optimisation, and EV promotion are examples of urban planning strategies that might dramatically lower $NO_2$ levels and enhance public health outcomes.

Table 6: Sources of Air Pollution Identified (Qualitative Survey)

| Source | Urban (%) | Rural (%) |
|---|---|---|
| Vehicle Emissions | 46 | 21 |
| Industrial Emissions | 24 | 5 |
| Biomass/Domestic Fuel Use | 12 | 41 |
| Agricultural Burning | 5 | 21 |
| Construction Activities | 13 | 12 |

Table 6 presents findings from a qualitative community survey that was carried out throughout Madurai district's urban and rural areas, indicating the main causes of air pollution that were thought to exist in each area. The findings emphasise the necessity for location-specific mitigation techniques by clearly illustrating source-specific disparities between urban and rural contexts. Urban Areas: Due to severe traffic congestion, especially in areas like Periyar and Mattuthavani, vehicle emissions (46%) were found to be the main cause. Two-wheelers and diesel-powered public transportation are major contributors to $NO_2$ and PM2.5 levels, yet they are essential to urban mobility. Another major urban issue was industrial emissions (24%), which came mostly from tanneries, textile processing plants, and small-scale manufacturing facilities in and around Madurai city.PM10 pollution is known to be caused by construction operations (13%), which include dust from building and road construction, particularly in expanding metropolitan areas. Rural Areas: Traditional cooking methods using firewood, cow dung, and agricultural leftovers are reflected in the primary issue of biomass and household fuel consumption (41%). This is a recognised cause of indoor air pollution, which disproportionately impacts women and children. Rural PM2.5 levels are greatly influenced by agricultural burning (21%), especially post-harvest stubble and field clearing, during certain seasons. It's interesting to note that building activities (12%) and car emissions (21%), which are also mentioned in rural regions, point to growing semi-urbanization, the expansion of road infrastructure, and the usage of private vehicles. These results are consistent with those of, who observed that the use of biomass fuel is a major source of home air pollution in rural Indian families, often exceeding WHO criteria. In a similar vein, highlighted that, mostly as a result of inadequate urban planning and inadequate emission management, emissions from construction and vehicles are increasing more quickly than those from industry in Indian cities. Clean fuel projects (like LPG, biogas) in rural houses and green mobility solutions (like EVs, public transport electrification) in metropolitan Madurai are thus crucial components of a distinct pollution management strategy.

Table 7: Effectiveness of Proposed Interventions (Pilot Study Results)

| Intervention Type | Pollutant | Reduction in (%) |
|---|---|---|
| Smart Ventilation (Indoor Test) | PM2.5 | 38 |
| Traffic Diversion Plan | $NO_2$ | 22 |
| Awareness Program (Rural) | CO | 17 |
| Air Purifier Installation | PM2.5 | 40 |
| Crop Burning Alert System | PM10 | 25 |

The assessed efficacy of five important treatments to reduce air pollution in both urban and rural settings that were piloted in the Madurai district is shown in Table 7. The findings demonstrate how behaviour-focused, technology-driven, and targeted approaches may greatly lower exposure to pollutants. As part of this intervention, IoT-based ventilation systems were installed in houses. These systems used sensors to monitor PM2.5 levels and automatically adjust airflow using window actuators or fans. This device was especially successful in rural families that burn biomass inside, reducing indoor particle concentrations by over 40%. Similar results were found by, who observed that smart ventilation improves interior air quality in semi-urban homes when paired with behaviour modification (leaving windows open after cooking).$NO_2$ concentrations decreased by 22% in high-traffic places like Periyar Bus Stand as a consequence of a dynamic rerouting technique. During crucial hours, the intervention diverted large cars from busy residential areas and school hallways. In rural regions, community-based education about the risks of burning biomass and the advantages of clean cooking resulted in a little but significant decrease in CO levels. This result confirms the effectiveness of non-technological approaches. In Bihar villages, organised rural awareness efforts combined with clean fuel availability decreased CO exposure by as much as 18%, The largest decrease in PM2.5 (40%) was seen with indoor air purifiers placed in senior care facilities and metropolitan government clinics. This demonstrates their effectiveness in confined, high-exposure settings, but cost still limits scalability. show comparable drops in the usage of HEPA-based purifiers in Delhi residences. Prior to expected fire seasons, a basic mobile-based alarm system was implemented in rural clusters. It provided incentives for sustainable activities, encouraged mulching, and issued warnings against open flames. This echoed experimental models in Punjab that were mentioned by lowering PM10 levels by 25% at seasonal peaks. The pilot projects show that a hybrid approach that combines community involvement (awareness campaigns, notifications) with Internet of Things technology (smart ventilation, traffic rerouting) may result in significant indoor and outdoor pollution reductions. Crucially, even inexpensive behavioural adjustments made a significant difference in air quality, particularly in rural areas.

## CONCLUSION

The research emphasises the vital role that smart technologies play in environmental monitoring and public health protection by examining how current IoT-based sensors are used to improve air quality in Madurai District, which spans both rural and urban areas. Real-time tracking of pollutants including PM2.5, PM10, $NO_2$, $SO_2$, and CO was made possible by the installation of IoT-enabled air quality sensors in specific places. This provided detailed information that conventional monitoring systems sometimes ignore, especially in semi-urban and rural areas. Key findings from the sensor data and comparative analysis show that while biomass burning, domestic fuel use, and seasonal agricultural practices have a major impact on rural areas, vehicle emissions, industrial output, and construction activities cause higher levels of air pollution in urban areas. Targeted mitigation measures were made possible by the IoT infrastructure's ability to record the temporal and diurnal fluctuation in pollutant levels. This data gave crucial insights into the key sources of pollution, geographic hot spots, and peak exposure hours. The feasibility of low-cost, scalable, and context-specific solutions was highlighted by the notable pollutant reductions shown by the pilot interventions tested in both urban and rural settings, including smart ventilation systems, traffic diversion plans, awareness campaigns, and crop burning alert mechanisms. Crucially, the research found that the strongest long-lasting effects on improving air quality come from a combination of technology-driven monitoring, community involvement, and governmental support. This study concludes that IoT-based air quality monitoring is a driver for proactive environmental stewardship rather than just a diagnostic tool. It facilitates the creation of intelligent, sustainable cities and villages, empowers local communities, and enables data-driven decision-making. Adopting such technology and policies will be crucial to creating communities across Tamil Nadu and beyond that are healthier, more resilient, and ecologically conscious as Madurai continues to urbanise and grow.

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