© February 2026 | IJIRT | Volume 12 Issue 9 | ISSN: 2349-6002

Development of Innovative Technique for Air Quality Monitoring

Shahejama Fatima[1], Dr. Nitin Y. Patil[2]
[1]*Research Scholar, Department of Civil Engineering, Mansarovar Global University, Sehore (M.P.), India*
[2]*Supervisor, Department of Civil Engineering, Mansarovar Global University, Sehore (M.P.), India*

Abstract—**Air contamination poses a significant threat to environmental sustainability and public health, particularly in rapidly urbanizing and industrializing regions of India. While extensive research has been conducted in major metropolitan cities, smaller urban-industrial and semi-urban areas remain underrepresented in scientific air quality assessments. This study addresses that gap through a comprehensive, interdisciplinary approach integrating ground-based air sampling, elemental and ionic characterization, satellite remote sensing, meteorological analysis, and artificial intelligence (AI)-based modeling. The investigation was carried out across three contrasting zones in Madhya Pradesh: Bhopal (urban), Mandideep (industrial), and Sehore (semi-urban). Airborne concentrations of particulate matter ($PM_{2.5}$ and PM_{10}), volatile organic compounds (VOCs), and heavy metals (Pb, Zn, Cr, Cu) were measured using active and passive sampling techniques. Advanced instrumentation including Gas Chromatography-Mass Spectrometry (GC-MS), X-Ray Fluorescence (XRF), and Ion Chromatography was used to determine contamination sources and composition. Remote sensing data from MODIS and Sentinel-5P were analyzed for Aerosol Optical Depth (AOD) and NO_2 distribution, validated against ground observations. The results revealed Mandideep as the most polluted site, driven by high industrial emissions, followed by Bhopal and Sehore. Seasonal variations showed significant winter peaks due to atmospheric inversion and secondary aerosol formation. High correlations ($R^2 > 0.85$) between satellite and ground measurements confirmed the reliability of remote sensing for regional air quality monitoring. AI-based models developed using machine learning algorithms (Random Forest, Neural Networks) forecasted contamination trends with high accuracy (R^2 up to 0.88). The study's findings underscore the need for a data-driven, technology-enabled, and regionally adaptive air quality management framework that combines traditional monitoring with emerging digital tools.**

Index Terms—**Air contamination, $PM_{2.5}$, Remote sensing, Machine learning, Industrial emissions, Air Quality Index**

I. INTRODUCTION

Air quality is an essential aspect of environmental health that profoundly influences human welfare and ecosystem vitality. It pertains to the concentration of airborne contaminants, which can adversely affect both human and environmental health. Optimal air quality signifies the absence of dangerous contaminations, whereas suboptimal air quality arises when deleterious elements, including particulate matter (PM), gases, and chemicals, exceed acceptable limits.

In India, air contamination primarily originates from three sources: vehicular emissions, industrial activities, and household sources. Major cities face significant air quality challenges, with vehicular contributions increasing from 23% in 1970-71 to a projected 72% by 2000-01. Additionally, 24 critically polluted areas have been identified across India where industrial concentrations create severe contamination problems.

Traditional air quality monitoring techniques face limitations in terms of cost, geographical coverage, and real-time data availability. These methods are typically concentrated in urban areas, leaving vast rural and remote regions under-monitored. This study addresses these gaps by exploring innovative monitoring techniques integrating emerging technologies such as low-cost sensors, satellite-based measurements, Internet of Things (IoT) integration, and artificial intelligence (AI) for enhanced air quality assessment.

1.1 Objectives of the Study

- To evaluate potential health risks and property damage caused by air contamination.
- To establish baseline contamination levels for use in industrial zoning, urban planning, and site selection.
- To determine the extent of air contamination control measures needed for existing industrial operations.
- To identify and characterize industrial and other significant sources of air contamination.

II. STUDY AREA AND METHODOLOGY

2.1 Selection of Study Areas

The study was conducted across three distinct environmental settings in Madhya Pradesh, India, as detailed in Table 1.

Location	Zone Type	Characteristics
Bhopal	Urban	Capital city, population >2.5 million, dense traffic, mixed land-use
Mandideep	Industrial	Industrial belt, chemical manufacturing, pharmaceutical units, heavy engineering
Sehore	Semi-Urban	Transitional zone, agricultural activities, biomass burning, rural industries

Table 1: Description of Study Locations

2.2 Sampling Techniques

- Passive Sampling: Passive diffusion tubes and badge-type samplers were deployed for 7-30 days to monitor NO_2, SO_2, and O_3. High recovery rates were achieved: NO_2 (96.4%), SO_2 (94.8%), and O_3 (92.1%).
- Active Sampling: High-volume and low-volume air samplers were used for real-time monitoring of Particulate Matter ($PM_{2.5}$ and PM_{10}), Carbon Monoxide (CO), Volatile Organic Compounds (VOCs), Oxides of Nitrogen (NO_x), and Sulfur Compounds (H_2S, SO_2).

2.3 Instrumentation and Analytical Techniques

The analytical instruments used for sample analysis, along with their purposes and detection limits, are summarized in Table 2.

Instrument	Purpose	Detection Limit
GC-FID	VOC Analysis	1 ppb
GC-ECD	Halogen Detection	0.5 ppb
XRF	Heavy Metal Analysis	1 ng/cm²
Ion Chromatography	Ionic Species Analysis	0.01 mg/L
Lidar	Aerosol Profiling	0.1 µg/m³
UAV Drone	3D Air Quality Mapping	1 µg/m³

Table 2: Instrumentation for Chemical Analysis

2.4 Remote Sensing Integration

- Satellite Platforms: MODIS (Aerosol Optical Depth), Sentinel-5P (NO_2 column density, trace gases), Landsat-8 (Land-use/land-cover classification).
- Tools: Google Earth Engine, QGIS, ArcGIS, Python, SNAP Toolbox.

2.5 AI-Based Modeling

- Machine Learning Algorithms Implemented: Decision Trees (DT), Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random Forest Regression (RFR).
- Performance Metrics: R^2, Mean Absolute Error (MAE), Root Mean Square Error (RMSE).

III. RESULTS AND DISCUSSION

3.1 Contamination Profiles Across Study Locations

The average concentrations of key air pollutants varied significantly across the three study locations, as shown in Table 3.

Location	Zone Type	PM10 (µg/m³)	PM2.5 (µg/m³)	SO_2 (ppb)	NO_2 (ppb)	O_3 (ppb)
Bhopal	Urban	112	72	12	34	22
Mandideep	Industrial	148	95	28	49	18
Sehore	Semi-Urban	86	54	8	20	27

Table 3: Average Contamination Levels Across Study Locations

3.2 Seasonal Variation in Particulate Matter

Winter months consistently exhibited higher particulate concentrations across all locations (Table 4). This is due to thermal inversion conditions trapping contaminants near the surface, increased biomass burning for heating, and reduced atmospheric mixing. Mandideep showed the most dramatic increase ($PM_{2.5}$: 80→110 µg/m³), highlighting the compounding effect of industrial emissions under unfavorable meteorological conditions.

Location	PM2.5 Summer (µg/m³)	PM2.5 Winter (µg/m³)	PM10 Summer (µg/m³)	PM10 Winter (µg/m³)
Bhopal	65	82	104	120
Mandideep	80	110	135	165
Sehore	45	63	70	90

Table 4: Seasonal Variation in PM Concentrations

3.3 VOC Distribution and Industrial Footprint

Mandideep recorded the highest VOC concentrations (Table 5), particularly toluene (4.5 ppb) and xylene (5.0 ppb), reflecting industrial processes such as solvent evaporation, degreasing, and chemical manufacturing. Benzene, a Group 1 human carcinogen, was detected at 2.4 ppb in Mandideep, exceeding international health-based reference values and necessitating urgent emission control measures.

Compound	Bhopal (ppb)	Mandideep (ppb)	Sehore (ppb)
Benzene	1.2	2.4	0.8
Toluene	2.8	4.5	1.6
Xylene	3.1	5	1.9
Ethylbenzene	1	2.2	0.7

Table 5: VOC Concentrations Measured by GC-FID

3.4 Heavy Metal Enrichment

Heavy metal concentrations followed the hierarchy Mandideep > Bhopal > Sehore, confirming industrial clusters as localized hotspots (Table 6). Lead (195 ng/m³) and chromium (89 ng/m³) in Mandideep are particularly concerning due to their neurotoxic and carcinogenic properties. Zinc (420 ng/m³) indicates galvanizing operations and tire wear, while elevated chromium suggests electroplating and metallurgical activities requiring stringent emission controls.

Element	Bhopal (ng/m³)	Mandideep (ng/m³)	Sehore (ng/m³)
Lead (Pb)	110	195	88
Zinc (Zn)	290	420	170
Copper (Cu)	75	110	60
Chromium (Cr)	48	89	37

Table 6: Elemental Analysis of Heavy Metals via XRF

3.5 Ionic Composition of $PM_{2.5}$

High sulfate and nitrate concentrations confirm that secondary inorganic aerosols are major $PM_{2.5}$ components, formed from SO_2 and NO_x emissions through atmospheric oxidation (Table 7). The presence of ammonium indicates acid-base neutralization reactions, likely involving ammonia from agricultural or industrial sources.

Ion	Bhopal (µg/m³)	Mandideep (µg/m³)	Sehore (µg/m³)
Sulfate (SO_4^{2-})	6.2	9.8	4.5
Nitrate (NO_3^-)	5.5	8.1	3.9

Ammonium (NH_4^+)	3.1	4.7	2.6
Chloride (Cl^-)	2.4	3.9	2.1

Table 7: Ionic Species Concentration in $PM_{2.5}$ from Ion Chromatography

3.6 Remote Sensing Observations

Mandideep exhibited the highest Aerosol Optical Depth (AOD) values throughout the year (peak 0.57 in July), indicating persistent aerosol loading from industrial emissions (Table 8). Monsoon peaks suggest aerosol hygroscopic growth and secondary formation under humid conditions. Sehore's lower but noticeable AOD values confirm regional contamination transport from nearby industrial-urban areas.

Month	Bhopal AOD	Mandideep AOD	Sehore AOD
January	0.43	0.47	0.32
July	0.5	0.57	0.46
November	0.46	0.53	0.43

Table 8: Monthly Aerosol Optical Depth (AOD) Values from MODIS

Mandideep's elevated NO_2 column density (annual average 0.000024 mol/m²) reflects continuous industrial combustion and transportation emissions (Table 9). Bhopal's moderate levels (0.000019 mol/m²) indicate urban vehicular sources, while Sehore's lowest values (0.000015 mol/m²) confirm minimal local emissions.

Location	Min (mol/m²)	Max (mol/m²)	Annual Avg (mol/m²)
Bhopal	0.000011	0.000031	0.000019
Mandideep	0.000015	0.000038	0.000024
Sehore	0.000009	0.000027	0.000015

Table 9: NO_2 Column Density from Sentinel-5P

3.7 Validation: Satellite vs. Ground Measurements

High correlation coefficients ($R^2 > 0.86$) across all sites validate satellite-derived AOD as a reliable proxy for ground-level aerosol concentrations (Table 10). Mandideep's strongest correlation (0.91) confirms satellite capability in capturing complex industrial emission patterns.

site	AOD Ground Avg	AOD Satellite Avg	Correlation (R^2)
Bhopal	0.44	0.43	0.89
Mandideep	0.49	0.5	0.91
Sehore	0.38	0.37	0.86

Table 10: Correlation Between Satellite and Ground AOD Measurements

Error percentages below 5% across diverse contamination contexts (Table 11) demonstrate the efficacy of satellite remote sensing as a complementary tool to ground-based monitoring, particularly valuable for regional assessments in areas with sparse monitoring infrastructure.

Location	Ground PM2.5 (µg/m³)	Satellite AOD-Predicted (µg/m³)	Error (%)
Bhopal	82	79	3.66
Mandideep	110	106	3.63
Sehore	63	60	4.76

Table 11: Validation of Satellite-Derived PM2.5 Against Ground Measurements

3.8 Vertical Aerosol Profiling

A clear vertical gradient shows highest concentrations near ground level (0-100 m) from surface emissions, decreasing progressively with altitude (Table 12). Mandideep's elevated profile throughout all heights indicates stronger emission sources and vertical mixing. This data is crucial for understanding contaminant dispersion and exposure assessment.

Height (m)	Bhopal (µg/m³)	Mandideep (µg/m³)	Sehore (µg/m³)
0-100	68	95	50
100-500	42	60	38
500-1000	30	45	28
>1000	15	20	12

Table 12: Lidar-Based Vertical Profile of Aerosol Concentrations

Drone-based monitoring revealed decreasing contamination with altitude, confirming surface-level emission dominance (Table 13). This fine-scale vertical data complements satellite and ground measurements, enabling comprehensive 3D air quality assessment.

Flight ID	Altitude (m)	PM2.5(μg/m³)	NO_2 (ppb)	Coordinates
DR001	50	78	25	23.254N, 77.402E
DR002	100	68	21	23.259N, 77.410E
DR003	150	60	19	23.261N, 77.399E

Table 13: Drone Flight Details and Vertical Pollutant Profile

3.9 Machine Learning Model Performance

Random Forest outperformed all models with the highest R^2 (0.88) and lowest errors (MAE=4.9, RMSE=6.5), demonstrating a superior capability in handling complex, nonlinear relationships in air quality data (Table 14). Neural Networks also showed strong performance (R^2=0.85), validating deep learning approaches for contamination prediction.

Model	R^2	MAE	RMSE
Decision Tree	0.72	7.2	9.4
SVM	0.8	6.1	8.2
Neural Network	0.85	5.3	7
Random Forest	0.88	4.9	6.5

Table 14: Performance Comparison of Machine Learning Models

PM2.5 emerged as the most significant predictor (0.31), followed by meteorological parameters (Table 15), confirming that both contaminant concentrations and atmospheric conditions collectively influence air quality dynamics.

Feature	Importance Score
PM2.5	0.31
Temperature	0.24
Wind Speed	0.18
AOD	0.14
NO_2	0.13

Table 15: Feature Importance Scores from the Random Forest Model

3.10 Air Quality Index and Health Risk Assessment

Mandideep's "Very Poor" AQI classification indicates severe health hazards requiring immediate intervention (Table 16). Bhopal's "Poor" category signals considerable risk, while Sehore's "Moderate" classification still warrants attention, particularly for sensitive populations.

Location	PM2.5 AQI	PM10 AQI	Overall AQI Category
Bhopal	189	210	Poor
Mandideep	240	280	Very Poor
Sehore	130	160	Moderate

Table 16: Comparative Air Quality Index (Winter Average)

All three locations exceeded safe limits, with Mandideep's winter average (110 μg/m³) falling in the "Very Poor" category, posing serious health risks to the entire population (Table 17). Even Sehore's levels (63 μg/m³) reached the "Moderate" category, affecting sensitive groups.

PM2.5Range (μg/m³)	AQI Category	Health Impact
0-30	Good	Minimal risk
31-60	Satisfactory	Minor breathing discomfort
61-90	Moderate	Possible risk to sensitive groups
91-120	Poor	Increased likelihood of respiratory effects
>120	Very Poor	Serious risk, avoid outdoor activity

Table 17: Health Risk Categories Based on PM2.5 Exposure

3.11 Source Apportionment

Chemical fingerprinting successfully identified distinct contamination sources for each location, as detailed in Table 18.

Site	Dominant Elements	Likely Source
Bhopal	Zn, Pb, S	Traffic emissions
Mandideep	Cr, Ni, Fe	Industrial exhaust
Sehore	Ca, K, NH_4^+	Biomass burning

Table 18: Source Apportionment by Chemical Fingerprinting.

3.12 Sensor Calibration

High R^2 values (0.88-0.92) confirm excellent calibration performance for the low-cost sensors used in this study (Table 19). The PM2.5 optical sensor showed near-perfect linearity (slope=1.05), while the CO electrochemical sensor requires periodic recalibration for nonlinear responses. These calibrations ensure reliable conversion of raw sensor signals into accurate contamination concentrations.

Sensor Type	Slope (m)	Intercept (c)	R^2
PM2.5 Optical	1.05	-2.3	0.92
CO Electrochemical	0.89	0.7	0.88
NO_2 Optical	0.93	-1.1	0.9

Table 19: Calibration Coefficients for Low-Cost Sensors

3.13 Air Quality Classification

The decision tree model successfully classified air quality categories based on PM2.5 and NO_2 thresholds (Table 20), demonstrating practical utility for automated monitoring systems and early warning applications.

Sample ID	PM2.5 (µg/m³)	NO_2 (ppb)	AQI Class
S001	65	22	Moderate
S002	120	38	Poor
S003	160	42	Very Poor
S004	50	16	Satisfactory

Table 20: Air Quality Classification Using Decision Trees

IV. CONCLUSIONS

This comprehensive study on innovative air quality monitoring techniques across three contrasting zones in Madhya Pradesh yields the following key conclusions:

- Spatial Contamination Gradient: Mandideep (industrial zone) exhibited the highest contamination levels across all parameters, followed by Bhopal (urban) and Sehore (semi-urban), confirming industrial activities as dominant emission sources.
- Seasonal Variability: Winter months showed significantly elevated particulate concentrations due to thermal inversion, reduced mixing height, and increased biomass burning.
- Chemical Characterization: Heavy metal enrichment (Pb, Cr, Ni) in Mandideep confirmed industrial sources, while ionic species (SO_4^{2-}, NO_3^-) revealed secondary aerosol formation as a major PM component.
- Remote Sensing Validation: Strong correlations ($R^2 > 0.85$) between satellite-derived data and ground measurements validated remote sensing as a reliable tool for regional air quality monitoring.
- AI Model Performance: Machine learning models, particularly Random Forest (R^2=0.88), demonstrated high accuracy in contamination prediction, with PM2.5 and temperature identified as the most influential features.
- Health Risk Assessment: All locations exceeded safe PM2.5 limits, with Mandideep's "Very Poor" AQI classification indicating severe health hazards requiring urgent intervention.
- Source Apportionment: Chemical fingerprinting successfully identified distinct sources—traffic emissions (Bhopal), industrial exhaust (Mandideep), and biomass burning (Sehore)—enabling targeted mitigation strategies.

V. RECOMMENDATIONS

Based on the findings, the following recommendations are proposed:

5.1 Policy and Regulatory Measures

- Industrial Emission Controls: Mandate continuous emission monitoring systems (CEMS) in Mandideep industries, enforce stricter emission standards, and promote cleaner production technologies.

- Urban Traffic Management: Implement low-emission zones, promote public transportation, and enforce vehicle emission standards in Bhopal.
- Biomass Burning Regulations: Develop alternative agricultural waste management practices and promote clean cooking fuels in Sehore and similar semi-urban areas.

5.2 Monitoring Infrastructure

- Expand Monitoring Networks: Establish additional ground monitoring stations in under-represented semi-urban and rural areas.
- Integrate Remote Sensing: Routinely use satellite products (MODIS, Sentinel-5P) alongside ground measurements for comprehensive regional assessment.
- Deploy Low-Cost Sensors: Implement IoT-based sensor networks for real-time, high-spatial-resolution monitoring in data-poor regions.

5.3 Technological Integration

- AI-Based Early Warning Systems: Deploy machine learning models for contamination forecasting and public health advisories.
- Drone-Based Monitoring: Utilize UAVs for vertical profiling and hotspot identification, particularly in industrial zones.
- Data Platforms: Develop centralized, open-access air quality data platforms integrating ground, satellite, and model outputs.

5.4 Public Health Interventions

- Health Risk Communication: Implement public awareness campaigns about air quality health impacts and protective measures.
- Vulnerable Population Protection: Develop targeted interventions for schools, hospitals, and elderly care facilities in high-pollution zones.
- Seasonal Action Plans: Implement winter-specific measures including emergency response protocols during severe pollution episodes.

REFERENCES

[1] Kumar, A., & Goyal, P. (2011). Forecasting of air quality in Delhi using principal component regression technique. Atmospheric Pollution Research, 2(4), 436-444.

[2] Liu, H., Li, Q., Yu, D., & Gu, Y. (2019). Air quality index and air pollutant concentration prediction based on machine learning algorithms. Applied Sciences, 9(19), 4069.

[3] Guan, Z., & Sinnott, R. O. (2018). Prediction of air pollution through machine learning on the cloud. *IEEE/ACM 5th International Conference on Big Data Computing Applications and Technologies*, 51-60.

[4] Maleki, H., Sorooshian, A., Goudarzi, G., et al. (2019). Air pollution prediction by using an artificial neural network model. Clean Technologies and Environmental Policy, 21, 1341-1352.

[5] Pant, P., Lal, R. M., Guttikunda, S. K., et al. (2018). Monitoring particulate matter in India: recent trends and future outlook. Air Quality, Atmosphere & Health, 12, 45-58.

[6] Chaloulakou, A., Grivas, G., & Spyrellis, N. (2012). Neural network and multiple regression models for PM10 prediction in Athens: A comparative assessment. Journal of Air & Waste Management Association, 53(10), 1183-1190.

[7] Naddafi, K., Hassanvand, M. S., Yunesian, M., et al. (2012). Health impact assessment of air pollution in megacity of Tehran, Iran. Iranian Journal of Environmental Health Science & Engineering, 9, 28.

[8] Sharma, N., Taneja, S., Sagar, V., & Bhatt, A. (2018). Forecasting air pollution load in Delhi using data analysis tools. ScienceDirect, 132, 1077-1085.

[9] Shakir, M., & Rakesh, N. (2018). Investigation on air pollution data sets using data mining tool. IEEE Xplore, CFP18OZV-ART.

[10] TikheShruti, S., Khare, K. C., & Londhe, S. N. (2013). Forecasting criteria air pollutants using data driven approaches: An Indian case study. International Journal of Soft Computing, 8(4), 305-312.

[11] Xayasouk, T., Lee, H., & Lee, G. (2020). Air pollution prediction using Long Short-Term Memory (LSTM) and Deep Auto Encoder (DAE) models. Sustainability, 12(6), 2570.

[12] Ma, J., Cheng, J. C. P., Lin, C., et al. (2019). Improving air quality prediction accuracy at larger temporal resolutions using deep learning and transfer learning techniques. Atmospheric Environment, 214, 116885.

[13] Wen, C., Liu, S., Yao, X., et al. (2019). A novel spatiotemporal convolutional long short-term neural network for air pollution prediction. Science of the Total Environment, 654, 1091-1099.
[14] Jo, J., Jo, B., Kim, J., et al. (2020). Development of an IoT-based indoor air quality monitoring platform. Journal of Sensors, 2020, 8749764.
[15] Zheng, K., Zhao, S., Yang, Z., et al. (2016). Design and implementation of LPWA-based air quality monitoring system. IEEE Access, 4, 3238-3245.
[16] Ghaemi, Z., Alimohammadi, A., & Farnaghi, M. (2018). LaSVM-based big data learning system for dynamic prediction of air pollution in Tehran. Environmental Monitoring and Assessment, 190(5), 300.
[17] Lai, X., Yang, T., Wang, Z., & Chen, P. (2019). IoT implementation of Kalman Filter to improve accuracy of air quality monitoring and prediction. Applied Sciences, 9(9), 1831.
[18] Mahajan, S., Liu, H. M., Tsai, T. C., & Chen, L. J. (2018). Improving the accuracy and efficiency of PM2.5 forecast service using cluster-based hybrid neural network model. IEEE Access, 6, 19193-19204.
[19] Khan, Y., & See, C. S. (2016). Predicting and analyzing water quality using Machine Learning: A comprehensive model. 2016 IEEE Long Island Systems, Applications and Technology Conference, 1-6.
[20] Balachandran, P. V. (2020). Adaptive machine learning for efficient materials design. MRS Bulletin, 45(7), 579-586.