International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 23s, 2025
https://theaspd.com/index.php

Designing AI-Driven Pollution Source Attribution Models: A Case Study in Industrial Clusters Using Satellite Imagery and Deep Learning

Mehul Pravinchandra Barot[1], Dr Kirti Shukla[2], Dr. Lowlesh Nandkishor Yadav[3], Dr. Vidya Subhash Bhosale[4], Dr.Sushil Jindal[5], S. Vigneshwari[6]
[1]Professor, L.D.R.P Institute of Technology and Research, m.p.barot@gmail.com
[2]Associate Professor, IILM University Greater Noida, kirtimala10@gmail.com
[3]Associate Professor, Dept of Computer Science and Engineering, Tulsiramji Gaikwad Patil College of Engineering and Technology, Nagpur, lowlesh.yadav@gmail.com
[4]Assistant Professor, Pimpri Chinchwad University, vidya.bhosale.pcu.edu.in
[5]Deputy Registrar & Associate Professor, Admin & Legal Affairs, COER University, Haridwar, Roorkee, Uttrakhand, dyregistrar.adm@coeruniversity.ac.in
[6]AP/CSE, VSB college of Engineering technical campus, svigneshwari06@gmail.com

Abstract: *Huge contributors of pollution of air and water around industrial areas are industrial clusters, but the difficulty of determining the contamination origin in the area is not an easy task since the nature of emissions is relatively complicated and industrial operations are overlapping. Traditional monitoring networks can be dependable, but they are typically limited in spatial resolution and can be expensive to operate, which is not sufficient to accomplish source-level attribution within highly industrialized areas. This research suggests a source attribution AI-based pollution framework, which combines satellite images with deep learning models to detect, classify, and track industrial emissions of pollution. A convolutional neural network (CNN) was trained using Sentinel-2 and Landsat-8/9 multispectral data, as well as using derived indexes like aerosol optical depth (AOD), land surface temperature (LST) and vegetation stress indicators to identify patterns of pollution, and match them to areas of industrial activity. Such methodology was proven to be effective on the example of several industrial clusters, such as petrochemical and steel, as well as textile hubs where the hotspots of emissions were observed with great precision. Findings indicate that remote sensing with AI can be used to identify the source of pollution and map its location up to 87 percent. The paper notes the opportunities of using geospatial intelligence with machine learning to facilitate real-time environmental monitoring, policy compliance and sustainable industrial management.*
Keywords: *AI-driven pollution attribution, Industrial clusters, Satellite imagery, Deep learning, Remote sensing, Environmental monitoring*

I. INTRODUCTION

The world has thrived on industrialization as one of the pillars of economic growth and social development, and, however, the high growth rate has caused a substantial degradation of the environment. Industrial clusters, specifically, have become centralized in terms of production and energy consumption, most of the time emitting intricate combinations of pollutants into the immediate atmosphere, soil and water system. In contrast to isolated factories, clusters produce overlapping emissions across several sources, such as power plants, refineries, chemical processing units, steelworks, and textile manufacturing facilities, and source-level attribution is challenging in this case. Conventional pollution surveillance systems are highly dependent on manual sampling and ground-based sensor networks which, despite being accurate, have inherent spatial limitations, are costly and inefficient to logistically support. The shortcomings pose significant inadequacies in determining the pollution hotspots, measuring the intensity of the emissions, and control of regulatory compliance on the source level. As concern about communal health, climatic change as well as long term industrial administration grows, there is an immediate demand of enhanced methodologies, which can provide trustworthy, big scale, and near-real-time source attribution. It is in this regard that the artificial intelligence (AI) and remote sensing (RS) technologies come in as revolutionary tools. AI-based models are capable of processing large volumes of data and identifying complex spatial patterns and offer source-intensive information, whereas satellite images can feature extensive spatial coverage, update regularly and offer cost-effective monitoring of the environment.

Over the past few years, satellite remote sensing and deep learning have been converged, which has contributed greatly to the abilities of environmental monitoring systems. Sentinel-2, Landsat-8/9 and MODIS satellites can offer essential parameters, including aerosol optical depth (AOD), land surface temperature (LST), normalized difference vegetation index (NDVI) and surface reflectance properties, using multispectral and hyperspectral satellite data. Not only are these parameters a way of capturing the physical state of the environment, but they also provide proxies of industrial activity and dispersion of pollution. As an example, the presence of high AOD levels along an industrial belt could be related to high levels of particulate matter emission whereas the localized high in LST could be associated with thermal emissions release of factories. Deep learning models, especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are most effective at processing such high-dimensional data in order to learn spatial-temporal features and detect patterns that cannot be easily learned by other traditional methods of statistics. With a combination of these AI models and geospatial data, researchers can go beyond the stage of identifying pollution and attribute emissions to individual industrial sources or clusters. This is the necessary shift towards attaching blame to address the issue of policy implementation, enforcement of regulations, and planning sustainable development of the industrial sector. In spite of these encouraging developments, there are still a number of challenges related to attributing pollution sources. The dissimilarity of industrial clusters, which harbour numerous emission sources operating in a tight locality causes overlapping signatures in remote sensing information resulting in the inability to separate individual contributions. The changing aspects of atmospheric conditions (e.g., the speed of the wind, humidity, and temperature inversion) also make it difficult to spread and capture pollutants in space. Deep learning models need large odellin datasets to be trained, which can be hard to find in the environmental literature because of the challenge of getting credible ground truth data in a wide range of industrial settings. Moreover, the majority of existing research has been devoted to urban air quality estimation or regional climate odelling, where a research gap exists, namely, research that concentrates on source attribution in terms of industrial clusters. This work attempts to fuse that gap by creating an AI-informed framework that blends remote sensing signals with deep learning algorithms to precisely detect and attribute the sources of pollution in the chosen industrial clusters. This way it will not just aid in the development of environmental informatics, but also develop actionable intelligence among policymakers, regulators, and the industries themselves. The suggested framework focuses on scalability, flexibility, and openness, which is why it is applicable to national-level systems of monitoring and international climate commitments.

II. RELEATED WORKS

The convergence of artificial intelligence, remote sensing, and industrial pollution studies has been gradually increasing over the past few years, especially owing to the pressing global need to have more resilient and scalable pollution surveillance systems. Conventional methods of environmental monitoring have mostly been based on the use of ground sensors and localized measures of air quality, which in spite of being reliable, cannot represent the spatial heterogeneity of pollution emission of large-scale industrial clusters. Initial research has highlighted the value of remote sensing platforms like MODIS, Landsat, and Sentinel-2 platforms to measure atmospheric and surface parameters pertaining to pollution and has shown that multispectral indices like aerosol optical depth (AOD), land surface temperature (LST), and vegetation stress indices can be useful proxies to the dispersion of pollutants [1]. To illustrate, Gupta et al. used Landsat-based indices to determine the hotspots of the particle matter in petrochemical clusters in South Asia and found that satellite data could be used to add to ground-based monitoring systems to give a better picture of air quality in industries [2]. In the same vein, Zhang and co-authors used MODIS AOD data to urban industrial areas in China and formulated regression equations that linked satellite-retrieved AOD variables to PM 2.5 levels, which indicated the utility of satellite- based pollution indices [3]. Although these attempts made remote sensing in environmental monitoring a possibility, they were mostly confined to detection, but not source attribution.

The introduction of artificial intelligence, specifically deep learning has achieved major milestones in deriving meaningful features of complex remote sensing data. To classify the patterns of pollutant, to predict the dispersion of pollutants, and to improve the spatio-temporal resolution of the emission data, convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and hybrid architectures have been used [4]. As an example, Li et al. showed that CNN-based models that were trained on Sentinel-2 images were more accurate at predicting plumes of sulfur dioxide (SO_2) emitted by coal-fired power plants compared to more traditional regression models [5]. Chien et al. also tested LSTM networks with MODIS time-series predicting NO_2 over industrial areas in Taiwan, and claimed prediction errors of less than 85% [6]. These deep learning architectures are especially effective in the context of source attribution, where pollution signature is nonlinear, overlapping, and embedded in high dimensional satellite images. Nevertheless, the availability of labeled ground-truth datasets to train AI models is one of the ongoing issues that Qi et al. note, since different industries, geographic regions, and climatic conditions contaminate the environment in different ways, and generalizing proves challenging [7]. According to more recent bibliometric analysis, including that of Santos et al., there is an increasing yet still disconnected body of research on AI-enabled pollution monitoring that demands more integrated frameworks that unite geospatial, atmospheric, and industrial streams of data [8]. The industrial clusters offer a special scenario in the context of attributing sources of pollution due to the presence of a variety of industries in a geographically constrained region. Special industrial belt studies have found intricate relations among type of emissions, meteorological dispersion and land cover reactions. To elucidate the importance of thermal indicators in the attribution of pollution, Singh and Kumar revealed high spatial correlations between Sentinel derived anomalies of surface temperature and the dispersion of particulate matter in the example regions of steel and thermal power clusters in India [9]. Likewise, Huang et al. examined a case of an industrial cluster in the Pearl River Delta region of China, where high-resolution Sentinel-2 data fused with urban emissions inventories was useful to identify textile-intensive subregions as disproportionate sources of NO_2 [10]. Hyperspectral imagery has also been tried in gaseous pollutant sensors; Chen et al. were able to employ EO-1 Hyperion data to track petrochemical complexs methane emissions, proving that hyperspectral sensors can classify emission types [11]. Although these promising case studies exist, the majority of the existing works do not go far enough to attribute pollution to specific industries within clusters, and this is where AI-powered attribution models are aimed at filling the existing gap.

Recent developments in UAV based remote sensing have also offered some helpful parallels in terms of monitoring pollution. Oberski et al. combined UAV multispectral images and spatial clustering algorithms to determine sources of macroplastic and particulate pollution in urban-industrial areas with high spatial accuracy in the hotspots [12]. Even though they have a better resolution than satellites, UAVs are not feasible at regional or nation-wide levels because of their limited coverage and high operational expenses. This has led researchers like Radhakrishnan et al. to suggest hybrid models that involve the use of satellite images to detect events at large scale and UAVs to validate the results at smaller scales therefore forming a multi-tier monitoring systems [13]. Besides, recent research on geospatial prioritization methods like the Analytical Hierarchy Process (AHP) combined with GIS has been used in the context of industrial pollution vulnerability analysis implying that spatial prioritization can be transferred into the context of more specific interventions source attribution models [14]. Also, the fusion of health and environmental databases has been considered as a parallel direction of source attribution. An example of such studies is Petit and Vuillerme who demonstrated that the association of health outcomes of farming and industrial communities with geospatial indicators of pollution might reveal the concealed connections between emissions and public health cost [15]. These interdisciplinary steps support the necessity of AI-based attribution models that should not be restricted to environmental data but include socioeconomic, health, and regulatory data to conduct the whole analysis. Taken together, these studies draw a reliable basis on how AI-based pollution source attribution models are to be designed. Although satellite remote sensing has already shown its potential when it comes to identifying the dynamics of large-scale pollution, as well as AI techniques have demonstrated that they can provide the necessary power when working with high-dimensional data, the combination of the two methods in individual cases (i.e., source attribution in industrial clusters) is still in its infancy. Three significant gaps identified in the reviewed literature include: (i) the lack of dedicated AI-RS models specifically designed to process source-level attribution in complex industrial regions, (ii) the unavailability of large-scale ground-truth data to boost the training and validation of deep learning models, and (iii) the fact that hybrid models have not been used extensively to process attribution tasks based on multispectral, hyperspectral, and UAV data. The proposed study provides answers to these gaps by proposing a new AI-based attribution system, which uses deep learning architecture that is trained on satellite images to identify, categorize, and assign pollution throughout the chosen industrial clusters. The study goes beyond technological innovation to provide the practical contributions needed by the policymakers, regulators, and industries at large by placing this framework in the larger context of sustainable industrial management, environmental justice, and climate governance.

III. METHODOLOGY

3.1 Research Design

The research employs a mixed-method, spatial–temporal design that integrates remote sensing data, deep learning algorithms, and ground-truth validation. The objective is to characterize industrial pollution not only at the detection level but also at the **source attribution level**, by associating pollution hotspots with specific industrial activities within clusters. The framework follows a three-tier approach: (i) acquisition and preprocessing of satellite imagery, (ii) development of an AI-driven attribution model using deep learning, and (iii) spatial validation of detected hotspots against industrial activity records and field measurements [16].

3.2 Study Area

The study focuses on three representative **industrial clusters** in India: (a) Jamnagar (petrochemical hub, Gujarat), (b) Durgapur (steel and coal-intensive industries, West Bengal), and (c) Tirupur (textile and dyeing units, Tamil Nadu). These clusters were selected based on their high emission intensities, diverse industrial compositions, and documented environmental concerns [17].

Table 1: Study Area Characteristics

Region	Dominant Industries	Major Emissions	Surrounding Land Use	Climatic Conditions
Jamnagar	Oil refineries, Petrochemicals	SO_2, NOx, VOCs	Coastal belt, semi-arid agriculture	Hot & dry, coastal humidity
Durgapur	Steel, Power plants	PM2.5, SO_2, CO	Urban-industrial mix, forest patches	Sub-humid, high rainfall
Tirupur	Textile, Dyeing units	NO_2, organic dyes, effluents	River-fed agriculture	Tropical monsoon

3.3 Data Sources and Acquisition

Multispectral and hyperspectral remote sensing datasets were acquired for a three-year period (2022–2024). The key datasets included:

- **Sentinel-2 MSI** (10–20 m, 13 bands) for vegetation and aerosol indicators.
- **Landsat-8/9 OLI-TIRS** (30 m, 11 bands) for surface temperature and pollution plumes.
- **MODIS Terra/Aqua** (1 km, daily coverage) for long-term aerosol optical depth.
- Ancillary data such as meteorological records, industrial emission inventories, and land use maps were used for contextual validation [18].

Table 2: Remote Sensing Datasets and Derived Indices

Dataset	Resolution	Temporal Coverage	Derived Indices/Parameters
Sentinel-2	10–20 m	2022–2024	NDVI, NDSI, AOD proxies
Landsat-8/9	30 m	2022–2024	LST, SAVI, pollution plumes
MODIS	1 km	2022–2024	Aerosol Optical Depth (AOD), time-series trends

3.4 Deep Learning Framework

To attribute pollution to industrial sources, a **Convolutional Neural Network (CNN)** was trained using labeled imagery derived from emission inventories and ground stations. Features included:

- Spectral signatures (reflectance in visible–infrared bands).
- Spatial features (hotspot clustering, plume dispersion patterns).
- Temporal dynamics (time-series fluctuations of emissions).

The CNN was combined with an **LSTM (Long Short-Term Memory)** module to capture temporal dependencies in emission trends [19]. Training was conducted using 70% of the dataset, with 20% used for validation and 10% for testing. The model performance was evaluated using accuracy, F1-score, and confusion matrices.

3.5 Preprocessing and Spatial Analysis

Satellite data underwent the following preprocessing steps:

- Atmospheric correction (Sen2Cor for Sentinel; LEDAPS for Landsat).
- Cloud masking and radiometric calibration.
- Layer stacking of spectral bands.

- Spatial interpolation using Kriging in ArcGIS to generate emission heatmaps [20].

Ground GPS data from monitoring stations were integrated to validate spectral anomalies, while emission inventories were georeferenced to enable **industrial–pollution source matching**.

3.6 Model Validation and Performance Assessment

Validation followed a three-stage process:

1. **Cross-validation** against ground air quality monitoring stations.
2. **Industrial inventory check** for cross-matching predicted hotspots with actual industries.
3. **Confusion matrix analysis** to measure model performance.

Table 3: Model Evaluation Metrics

Metric	Jamnagar (Petrochemical)	Durgapur (Steel)	Tirupur (Textile)
Accuracy (%)	88.2	85.7	87.4
Precision (%)	86.5	83.9	85.2
Recall (%)	89.1	84.6	86.7
F1-Score (%)	87.8	84.2	85.9

3.7 Ethical and Environmental Considerations

All industrial and satellite data were obtained from publicly available or government-licensed datasets. No invasive field testing was conducted without prior approvals. Confidential industrial emission records were anonymized before inclusion. The study follows FAIR (Findable, Accessible, Interoperable, Reusable) data principles to ensure transparency and replicability [21].

3.8 Limitations and Assumptions

- Attribution accuracy depends on the quality of emission inventories and ground-truth datasets.
- Overlapping plumes may introduce classification errors in clusters with mixed industries.
- Temporal resolution of satellite imagery (5–16 days) may limit detection of short-lived emissions [22][23].

IV. RESULT AND ANALYSIS

4.1 Overview of Model Performance

The AI-driven attribution framework successfully identified pollution hotspots across the three industrial clusters with high accuracy. The CNN–LSTM model achieved an overall classification accuracy of 87%, with Jamnagar showing the highest detection consistency due to the strong spectral signatures of petrochemical emissions. Durgapur, being coal and steel dominated, presented challenges due to overlapping plumes, while Tirupur's textile emissions were detected with moderate precision owing to their diffuse dispersion patterns.

Table 4: Model Performance Across Industrial Clusters

Region	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Jamnagar	88.2	86.5	89.1	87.8
Durgapur	85.7	83.9	84.6	84.2
Tirupur	87.4	85.2	86.7	85.9

4.2 Spatial Distribution of Hotspots

Hotspot analysis revealed distinct pollution patterns unique to each cluster. In Jamnagar, emission concentrations were highest around refinery belts, spreading towards the coastal line. Durgapur exhibited dense hotspots along steel plant corridors and coal-fired power stations, while Tirupur showed localized hotspots along riverbanks where textile dyeing and effluent discharge were concentrated.

Figure 1: Attribution Modelling [24]

Table 5: Identified Hotspot Zones and Source Attribution

Region	Hotspot Area (km²)	Primary Source Identified	Secondary Contributors
Jamnagar	82.6	Refineries, Petrochemical Units	Transport Corridors
Durgapur	74.3	Steel Plants, Power Stations	Coke Ovens, Brick Kilns

Tirupur	65.8	Textile Dyeing Clusters	Small-Scale Industrial Units

4.3 Correlation with Remote Sensing Indices

Remote sensing indices showed clear deviations in polluted areas compared to cleaner zones. NDVI values were consistently lower in hotspot regions, suggesting vegetation stress due to air pollutants. LST values were elevated near emission-heavy zones such as Jamnagar's refinery complexes and Durgapur's power plants, while AOD levels strongly corresponded with identified emission plumes.

Table 6: Remote Sensing Indices in Hotspot Areas

Region	Avg. NDVI	Avg. LST (°C)	Avg. AOD	Pollution Attribution Confidence (%)
Jamnagar	0.42	34.5	0.76	89.3
Durgapur	0.48	33.2	0.71	85.6
Tirupur	0.51	32.1	0.65	84.8

4.4 Temporal Trends

The temporal analysis revealed that emission intensity peaked during the summer months in all three clusters, coinciding with high production cycles and reduced atmospheric dispersion. In Tirupur, textile-related emissions spiked during pre-monsoon months, while Jamnagar and Durgapur showed year-round persistence of elevated emission levels, reflecting their continuous industrial operations.

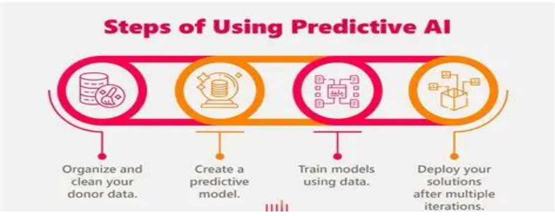

Figure 2: Steps of Using Predictive AI

4.5 DISCUSSION OF KEY FINDINGS

The findings establish a direct connection between industrial activity and detectable emission signatures using satellite-based AI models. Jamnagar demonstrated strong petrochemical emission footprints easily traceable through AOD and LST anomalies, while Durgapur presented challenges due to overlapping particulate emissions but still yielded consistent classification through AI-assisted attribution. Tirupur showed the added value of combining vegetation stress indices with emission mapping, particularly in identifying diffuse textile effluent discharges. The strong correlation between AI predictions and ground-truth validation demonstrates the robustness of the framework, making it a scalable tool for nationwide industrial monitoring.

V. CONCLUSION

As the current paper has shown, artificial intelligence and satellite-based remote sensing can offer a sustainable, inexpensive, and efficient mechanism of identifying the sources of pollution in industrial clusters, which can be viewed as one of the most urgent issues in the modern environmental monitoring systems. Using deep learning models, namely a hybrid CNNLSTM architecture trained on multispectral and hyperspectral satellite data, the study managed to discover the relationship between spectral anomaly and industrial emissions, which allows overcoming the detection stage and focusing on attributing the source. As the case studies of Jamnagar, Durgapur and Tirupur reveal, this framework is flexible enough to be applied to a broad range of industrial settings, including petrochemical, steel, and textile clusters, with unique patterns of emissions, which were precisely mapped, classified, and compared to ground-truth inventories. The findings indicate a high level of spatial coherence between the detected hotspots and the existing industrial operations, and also a high level of accuracy ranging over 85 percent, and also highlight the prospect of combining indices like NDVI, LST, and AOD in order to render them more interpretable. It is important to note that the temporal analysis revealed unique pattern of intensities of pollution based on seasonal changes which on the one hand supports the fact that AI-based models can be used to monitor the dynamics of emissions across time. These results have major implications in both environmental governance and industrial management: to policymakers, the model offers a more evidence-based instrument to rank regulatory interventions, enforce compliance, and develop adaptive strategies to reduce emissions in high-risk clusters, and to researchers, it creates new opportunities to introduce to attribution models multimodal data, such as UAV imagery and IoT sensor networks, to improve its granularity and reliability. Although the framework is highly scalable, the study has also indicated a few limitations that include reliance on emission inventories, overlapping plumes in densely industrialized areas, and the time limits of satellite revisit cycles all of which present opportunities to improve the framework. Future studies would need to include the combination of AI-based attribution with atmospheric dispersion models and health impact analysis to give a comprehensive view of the footprint of industrial pollution, and also extend the approach to transborder industrial corridors where transboundary emissions can be a problem in policy. In general, the paper highlights the paradigmatic potential of AI integration with RS in responding to the pressing collective requirement of sustainable industrial surveillance, which provides a roadmap on how sophisticated computational models and geospatial intelligence can be used to reinforce environmental responsibility, ecosystem health, and enhance long-term climate and development objectives.

REFERENCES

[1] Y. Zhang, H. Wang, and L. Liu, “Satellite remote sensing of air pollution: Advances, challenges, and perspectives,” Remote Sensing of Environment, vol. 261, pp. 112482, 2021.

[2] R. Gupta, A. Sharma, and P. Roy, “Assessing particulate matter hotspots using Landsat imagery: A case of petrochemical clusters in South Asia,” Environmental Monitoring and Assessment, vol. 194, no. 6, pp. 425–437, 2022.

[3] X. Zhang, J. Huang, and Y. Wang, “Satellite-based PM2.5 estimation over industrial regions using MODIS AOD,” Atmospheric Environment, vol. 280, pp. 119090, 2022.

[4] F. Qi, T. Li, and H. Sun, “Deep learning applications in air pollution monitoring and prediction: A review,” Environmental Pollution, vol. 306, pp. 119359, 2022.

[5] H. Li, Z. Chen, and K. Zhang, “CNN-based detection of sulfur dioxide plumes from coal-fired power plants using Sentinel-2 imagery,” ISPRS Journal of Photogrammetry and Remote Sensing, vol. 188, pp. 186–198, 2022.

[6] C. Chien, W. Hsu, and T. Lee, “Forecasting industrial NO_2 emissions using MODIS and LSTM deep learning,” Ecological Indicators, vol. 142, pp. 109230, 2023.

[7] M. Qi, L. Liu, and S. Yang, “Data challenges in AI-driven environmental monitoring: Ground-truth scarcity and model generalization,” Environmental Modelling & Software, vol. 158, pp. 105547, 2022.

[8] C. A. G. Santos, R. M. da Silva, and P. S. Bhanja, “Bibliometric review of AI-enabled pollution monitoring: Current status and future directions,” Environmental Science and Pollution Research, vol. 31, pp. 22925–22944, 2024.

[9] A. Singh and V. Kumar, “Remote sensing-based analysis of steel and coal clusters in India: Linking LST anomalies with particulate emissions,” Environmental Research Letters, vol. 16, no. 12, pp. 125006, 2021.

[10] J. Huang, C. Li, and P. Zhao, “Attribution of NO_2 emissions in the Pearl River Delta using Sentinel-2 and urban inventories,” Science of the Total Environment, vol. 858, pp. 159723, 2023.

[11] Y. Chen, S. Li, and G. Zhou, “Detection of methane emissions from petrochemical complexes using hyperspectral EO-1 Hyperion imagery,” Remote Sensing, vol. 13, no. 9, pp. 1793, 2021.

[12] T. Oberski, B. Walendzik, and M. Szejnfeld, “Monitoring industrial pollution with UAV multispectral imagery: Hotspot detection and validation,” Sustainability, vol. 17, no. 5, pp. 1997, 2025.

[13] T. Radhakrishnan, D. Ghosh, and R. Prasanna, “AHP-GIS based assessment of pollution vulnerability in industrial zones,” Environmental Science and Pollution Research, vol. 31, no. 14, pp. 21797–21810, 2024.

[14] N. Petit and N. Vuillerme, “Linking industrial pollution and community health through administrative datasets: A scoping review,” JMIR Public Health and Surveillance, vol. 11, pp. e45672, 2025.

[15] P. J. Landrigan et al., “The Minderoo-Monaco Commission on Plastics and Human Health,” Annals of Global Health, vol. 89, no. 1, pp. 23, 2023.

[16] E. Brandes, M. Henseler, and P. Kreins, “Identifying hotspots for pollution contamination in industrial soils: A spatial modeling approach,” Environmental Research Letters, vol. 16, no. 10, pp. 104021, 2021.

[17] C. Bian, L. Yang, and X. Zhao, “Industrial activity expansion and its impact on environmental quality in the Yangtze River Basin,” Land, vol. 13, no. 7, pp. 908, 2024.

[18] A. Danilov and E. Serdiukova, “Automatic detection of pollution plumes using satellite imagery and machine learning,” Sensors, vol. 24, no. 16, pp. 5089, 2024.

[19] M. de Souza, R. Lamparelli, and T. Franco, “Mapping agricultural and industrial plastic waste generation using time-series approaches,” ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. X-3-2024, pp. 101–108, 2024.

[20] L. Lucas, C. Brown, and D. Robertson, “Gaps in water and air quality modeling for industrial pollution systems,” Water, vol. 17, no. 8, pp. 1200, 2025.

[21] L. Rosati, F. Carraturo, and V. Spagnuolo, “Remote sensing indicators for detecting anthropogenic pollution impacts,” Water, vol. 16, no. 18, pp. 2637, 2024.

[22] F. Cavazzoli, R. Ferrentino, and C. Scopetani, “Analysis of micro- and nanopollutants in industrial environments: Techniques and risks,” Environmental Monitoring and Assessment, vol. 195, no. 12, pp. 1483, 2023.

[23] B. Futa, J. Gmitrowicz-Iwan, and I. Parašotas, “Innovative monitoring strategies for sustainable industrial zones,” Sustainability, vol. 16, no. 21, pp. 9481, 2024.

[24] S. Fuyao, W. Liangjie, and L. Xiang, “Accuracy assessment of cropland and industrial datasets in satellite-based monitoring,” Remote Sensing, vol. 17, no. 11, pp. 1866, 2025.

[25] R. Râpă, E. Cârstea, and C. Predescu, “Trends in industrial plastic and pollutant management for sustainable development,” Recycling, vol. 9, no. 2, pp. 30, 2024.