

# **A Review on the Geospatial Modeling of Air Pollution around Major Dumpsites in Lagos**

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## **Abstract**

Air pollution from unmanaged dumpsites is an escalating environmental and health concern in rapidly urbanizing cities, particularly across sub-Saharan Africa. This review critically synthesizes geospatial methods used in modeling dumpsite-related air pollution, including interpolation techniques (Kriging, Inverse Distance Weighting, Natural Neighbor), predictive tools (LandGEM, AERMOD), and satellite-based products such as MODIS aerosol optical depth. Emerging hybrid frameworks that integrate regression, GIS, and socio-environmental drivers are also discussed. Compared to localized ground measurements, these geospatial models enable more comprehensive spatial and temporal assessment of pollutant emissions. Findings from the reviewed studies consistently indicate elevated concentrations of particulate matter, nitrogen dioxide, and landfill gases, with serious implications for respiratory, cardiovascular, and long-term health outcomes in nearby populations. Policy-oriented applications are emphasized, including enforcing buffer zones, modern landfill management, and integrated monitoring strategies. This review highlights both the progress and gaps in geospatial approaches for air pollution assessment, offering a foundation for improved environmental planning and public health protection.

*Keywords: Geospatial modeling; Dumpsites; Air pollution; Landfill emissions; Remote Sensing*

## **1.0 INTRODUCTION**

**A**ir pollution remains one of the world's most serious environmental and public health challenges. According to the World Health Organization (WHO, 2023), over 7 million premature deaths are attributed annually to exposure to polluted air, with the greatest burden falling on low- and middle-income countries. Rapid urbanization, population growth, and poor waste management systems exacerbate this crisis, particularly in developing nations where open dumping remains the most common form of waste disposal. In such environments, solid waste degradation produces large volumes of particulate matter, greenhouse gases, and toxic emissions that degrade air quality and contribute to climate change.

Open dumpsites are recognized as significant yet under-monitored sources of air pollution. They release a complex mixture of pollutants, including methane (CH<sub>4</sub>), carbon dioxide (CO<sub>2</sub>), nitrogen dioxide (NO<sub>2</sub>), sulfur dioxide (SO<sub>2</sub>), particulate matter (PM<sub>2.5</sub> and PM<sub>10</sub>), and volatile organic compounds (VOCs). These gases not only affect local air quality but also contribute to global greenhouse gas accumulation. Moreover, in many developing cities—such as Lagos, Nigeria—dumpsites are often situated near residential neighborhoods, exposing thousands of people to continuous emissions and odors. Despite the magnitude of this issue, research attention has historically focused more on vehicular and industrial pollution, leaving dumpsite-related air contamination comparatively understudied.

Air pollution is therefore a persistent global health and environmental challenge, with particular intensity in developing countries where waste management remains largely uncontrolled. Unmanaged dumpsites release a complex mix of particulate matter, landfill gases, and secondary pollutants into the atmosphere. These emissions pose significant risks for populations residing nearby, often in densely populated settlements. While numerous site-specific studies exist, there remains a lack of comprehensive synthesis that evaluates and compares the geospatial methods used to model dumpsite air pollution.

Geospatial modeling approaches provide the opportunity to move beyond point-based monitoring to integrated spatial and temporal analyses. Interpolation methods such as Kriging, Inverse Distance Weighting (IDW), and Natural Neighbor allow for spatial estimation of pollutants from limited ground-based data. Predictive models such as the Landfill Gas Emissions Model (LandGEM) and the AERMOD dispersion model extend analysis to landfill-specific gases and atmospheric dispersion dynamics. Remote sensing products, including the MODIS aerosol optical depth dataset, provide cost-effective coverage at broad spatial scales. Newer hybrid frameworks, such as regression–GIS models, integrate both environmental and socio-economic drivers of pollution, enhancing predictive accuracy.

Despite these advancements, reviews that systematically compare these approaches remain scarce, especially with respect to dumpsites in African megacities such as Lagos, Nigeria. This review therefore synthesizes existing methods and applications, critically evaluates their strengths and limitations, and draws connections to public health risks and policy interventions.

### **1.1 Literature synthesis**

Representative studies across different regions indicate a clear trajectory in methods. Early GIS regression and mapping approaches (Briggs *et al.*, 1997; Bozyazi *et al.*, 2000) established the value of combining monitoring data with land-use and traffic information. The integration of satellite aerosol products (MODIS) with ground observations expanded spatial coverage and allowed long-term trend analyses (Mohammad *et al.*, 2007; Silas *et al.*, 2017). Geostatistical interpolation methods (Kriging, IDW, Natural Neighbor) remain widely used for urban-scale mapping where monitoring data exists, while models such as LandGEM have been applied to estimate landfill gas emissions and timelines (Ghasemzade *et al.*, 2017; Saed *et al.*, 2019). Recent hybrid approaches combining regression–GIS and remote sensing provide socio-environmental insights by linking pollution patterns with population density, land use, and waste generation (Zhang *et al.*, 2016; Cheng *et al.*, 2019).

This review does not reproduce individual monitoring datasets; instead, it synthesizes methodological strengths, limitations, and suitability across contexts, with Lagos used as an illustrative case where appropriate.

#### **1.1.1 Literature Search and Selection**

To ensure a comprehensive and objective review, a systematic literature search was conducted following the PRISMA 2020 guidelines (Page *et al.*, 2021). The search focused on identifying studies that applied *geospatial modeling* to assess *air pollution* associated with *dumpsites* or *landfill emissions*.

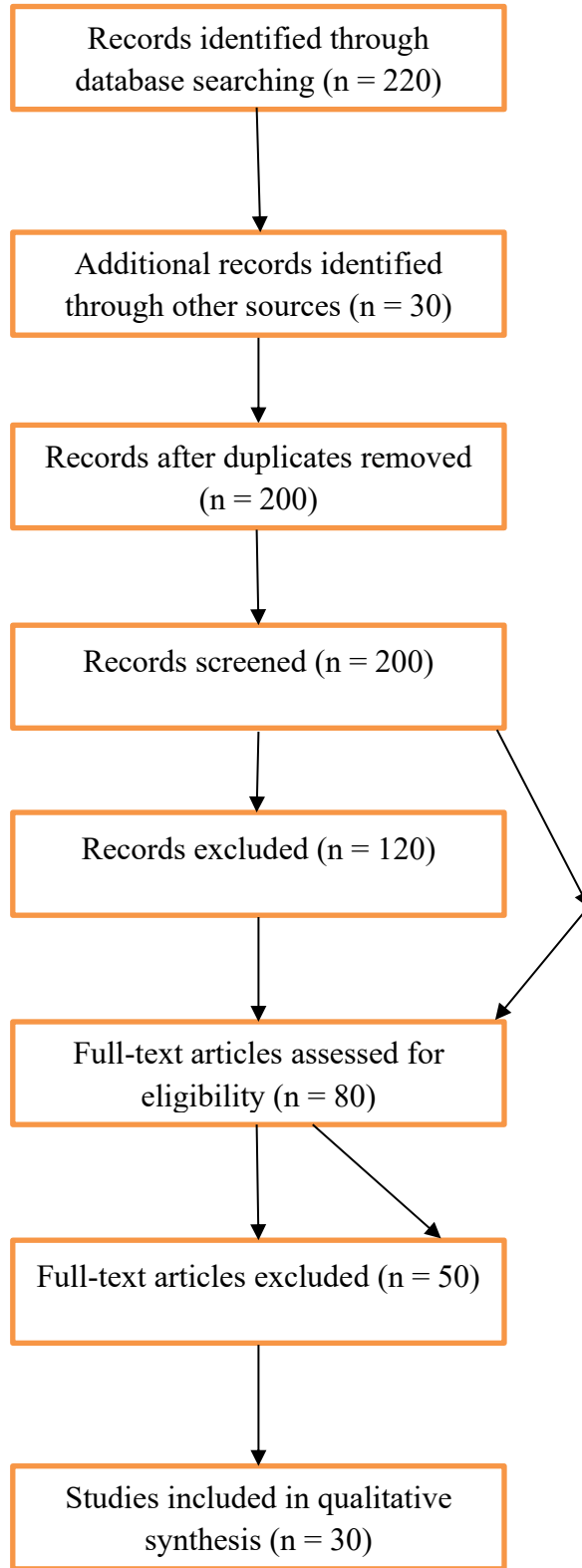
The databases consulted included Scopus, Web of Science, ScienceDirect, PubMed, and Google Scholar. The search terms combined keywords such as “*geospatial modeling*”, “*air pollution*”, “*dumpsites*”, “*landfill gas emissions*”, “*remote sensing*”, “*LandGEM*”, “*AERMOD*”, and “*particulate matter*”. Searches were limited to peer-reviewed journal articles and conference papers published between 2000 and 2025. After removing duplicates, 200 records remained for screening by title and abstract. Studies were excluded if they:

- a) did not apply geospatial or GIS-based methods;
- b) addressed pollutants unrelated to waste management;
- c) lacked quantitative or spatial results; or
- d) were purely conceptual without methodological implementation.

A total of 80 studies were reviewed in full text, of which 30 met the inclusion criteria and were incorporated into this review. The selected studies span Africa, Asia, Europe, and North America, highlighting diverse data environments and modeling strategies. They collectively demonstrate the growing integration of GIS, remote sensing, and predictive modeling in assessing landfill-related air pollution.

Representative studies meeting the inclusion criteria are summarized in Table 1, which highlights their study areas, geospatial approaches, pollutants analyzed, and major findings. The methodological families identified from these studies are further compared conceptually in Table 2 (see Section 3).

Figure 1 below illustrates the PRISMA flow diagram summarizing the search and screening process.



**Figure 1. PRISMA 2020 flow diagram illustrating the literature selection process for this review.**

Table 1. Representative studies on geospatial modeling of air pollution around dumpsites

Author (Year)	Study Area	Geospatial Method	Pollutants Modeled	Key Findings
Briggs <i>et al.</i> (1997)	Europe	Regression-based GIS modeling	NO <sub>2</sub> , PM <sub>10</sub>	Demonstrated high spatial variability of urban pollutants using GIS interpolation.
Ghasemzade & Pazoki (2017)	Iran	LandGEM modeling	CH <sub>4</sub> , CO <sub>2</sub>	Estimated landfill gas generation potential; validated with measured data.
Carmona <i>et al.</i> (2021)	Spain	MODIS AOD analysis	PM <sub>2.5</sub>	Correlated satellite-derived AOD with ground PM <sub>2.5</sub> concentrations.
He <i>et al.</i> (2021)	China	MAIAC satellite-based modeling	PM <sub>2.5</sub> , Aerosols	Improved PM <sub>2.5</sub> estimation accuracy using high-resolution remote-sensing data.
Daramola & Makinde (2024)	Nigeria	Kriging + LandGEM integration	NO <sub>2</sub> , PM, CH <sub>4</sub>	Modeled major pollutant concentrations at Lagos dumpsites; recommended 15 km buffer.
Okafor (2024)	Nigeria	IDW interpolation	PM <sub>10</sub> , CO, SO <sub>2</sub>	Showed elevated pollutant levels near open dumps; proposed better waste segregation.
Ramprasad <i>et al.</i> (2022)	India	LandGEM + energy potential modeling	CH <sub>4</sub> , CO <sub>2</sub>	Quantified landfill gas emissions and renewable energy prospects.
Sonibare <i>et al.</i> (2020)	Nigeria	GIS spatial mapping	VOCs, PM	Found direct link between waste burning and ambient pollutant rise.

The reviewed studies demonstrate that while interpolation and predictive models have been widely used, their applicability varies with data availability, pollutant type, and site characteristics. A comparative evaluation of these methods is presented in the following section.

## 2.0 METHOD

This review adopts a methodological and comparative synthesis rather than presenting new monitoring data. It systematically analyzes the geospatial tools used across published studies and evaluates their applicability to dumpsite-related air pollution in Lagos and comparable urban contexts. Following the PRISMA 2020 framework for systematic

reviews (Page *et al.*, 2021), relevant publications were identified, screened, and categorized based on their analytical approach and data characteristics.

To critically evaluate these studies, geospatial methods were grouped into four broad categories widely recognized in the literature:

- a) Spatial interpolation techniques — including Kriging, Inverse Distance Weighting (IDW), and Natural Neighbor methods, which estimate pollution surfaces from point data (Briggs *et al.*, 1997; Daramola & Makinde, 2024; Okafor, 2024).
- b) Remote sensing products — such as the MODIS and MAIAC aerosol optical depth (AOD) datasets, used to infer particulate matter concentrations over broad regions (Carmona *et al.*, 2021; He *et al.*, 2021).
- c) Predictive and dispersion models — including the U.S. EPA’s Landfill Gas Emissions Model (LandGEM) and AERMOD, which simulate gas generation and atmospheric dispersion patterns (Ghasemzade & Pazoki, 2017; Ramprasad *et al.*, 2022; U.S. EPA, 2025).
- d) Hybrid regression–GIS frameworks — combining spatial modeling with statistical or machine-learning regression to incorporate environmental and socioeconomic variables (Zhang *et al.*, 2016; Sorek-Hamer *et al.*, 2020).

Each group was assessed in terms of data requirements, typical outputs, uncertainty characterization, computational complexity, and suitability for data-rich versus data-scarce settings. Emphasis was placed on how each approach contributes to spatial resolution, temporal consistency, and policy relevance in developing-country contexts. Table 2 presents a comparative summary of these methods, highlighting their operational characteristics, core assumptions, and representative applications from the reviewed literature.

**Table 2. Comparative summary of geospatial methods for modeling dumpsite-related air pollution**

Method category	Typical techniques / tools	Key data inputs	Major strengths	Main limitations / uncertainties	Representative studies
<b>Spatial interpolation techniques</b>	Kriging, Inverse Distance Weighting (IDW), Natural Neighbor	Ground-measured pollutant data (PM, NO <sub>2</sub> , SO <sub>2</sub> , etc.) and coordinates	Produces continuous spatial pollutant surfaces; identifies “hotspots”; suitable for local mapping	Accuracy depends on number/distribution of sampling points; limited predictive capability outside sampled areas	Briggs <i>et al.</i> (1997); Daramola & Makinde (2024); Okafor (2024)
<b>Remote sensing products</b>	MODIS AOD, MAIAC, Sentinel-5P	Satellite aerosol optical depth, land	Broad regional coverage; historical	Coarse spatial resolution; affected by clouds and	Carmona <i>et al.</i> (2021); He <i>et al.</i> (2021)

Method category	Typical techniques / tools	Key data inputs	Major strengths	Main limitations / uncertainties	Representative studies
	TROPOMI, Landsat imagery	cover, meteorological data	trend analysis; cost-effective in data-poor regions	surface reflectance; requires calibration with ground data	
<b>Predictive and dispersion models</b>	LandGEM, AERMOD, CALPUFF	Landfill gas composition, emission rates, meteorology, topography	Forecasts gas generation and dispersion; supports mitigation planning; allows scenario testing	Requires site-specific inputs often unavailable in developing countries; sensitive to input errors	Ghasemzade & Pazoki (2017); Ramprasad <i>et al.</i> (2022); U.S. EPA (2003, 2025)
<b>Hybrid regression–GIS frameworks</b>	Regression–Kriging, geographically weighted regression (GWR), ML-GIS hybrids	Combined environmental, land-use, and socioeconomic variables; sometimes satellite data	Integrates physical and socio-environmental drivers; adaptable to sparse data; increasing predictive power	Computationally intensive; limited adoption in low-income regions due to data and software	

### **3.0 DISCUSSION**

The comparative evidence reviewed demonstrates that the choice of geospatial method strongly influences the interpretation of dumpsite-related air pollution. Interpolation approaches such as Kriging provide high-resolution spatial maps when dense monitoring data are available, enabling precise estimation of pollutant “hotspots” (Briggs *et al.*, 1997; Daramola & Makinde, 2024). In contrast, IDW and Natural Neighbor are more suited to contexts with sparse datasets, though their lack of error estimation reduces reliability and limits their use for predictive purposes (Okafor, 2024). Remote sensing products such as MODIS aerosol data offer valuable temporal coverage for trend detection and regional-scale analysis but cannot capture fine-scale variability in urban environments (Carmona *et al.*, 2021; He *et al.*, 2021). Predictive models, including LandGEM and AERMOD, extend analysis by forecasting landfill gas emissions and simulating pollutant dispersion (Ghasemzade & Pazoki, 2017; U.S. EPA, 2003; 2025). However, their outputs depend heavily on site-specific parameters such as waste composition, meteorology, and topography, which may not always be available in developing-country contexts. Hybrid and regression–GIS frameworks, though less commonly applied, provide added value by integrating socio-environmental drivers such as population density, land use, and waste generation patterns (Zhang *et al.*, 2016).

A major challenge in the reviewed studies is the uncertainty associated with input data and model assumptions. Many developing regions lack consistent monitoring networks, forcing researchers to rely on sparse or short-term datasets, which limits the accuracy of geostatistical interpolation and validation (Sonibare *et al.*, 2020). Similarly, emission models like LandGEM often assume idealized waste decomposition rates and gas generation parameters derived from temperate regions, which may not represent tropical or semi-arid conditions (Ramprasad *et al.*, 2022). The absence of standardized calibration protocols also contributes to variability across studies. Furthermore, differences in spatial resolution, data quality, and pollutant species modeled make it difficult to compare results directly or generalize findings across geographic contexts. Addressing these uncertainties through transparent reporting, sensitivity analysis, and model intercomparison will be critical for improving reliability and policy relevance (Page *et al.*, 2021).

In recent years, emerging innovations in geospatial data science have begun to reshape air pollution modeling. The integration of machine learning (ML) and artificial intelligence (AI) with GIS has enabled the extraction of nonlinear relationships between pollutant concentrations and environmental drivers such as meteorology, land use, and traffic density (Sorek-Hamer *et al.*, 2020). Coupled models that combine remote-sensing datasets (e.g., MODIS, MAIAC) with low-cost sensor data and in-situ measurements are improving spatial resolution and temporal coverage (He *et al.*, 2021). Similarly, Internet of Things (IoT)–based air-quality sensors offer real-time data streams that can feed directly into spatial models, enhancing both accuracy and responsiveness. These advancements promise to overcome some of the traditional data scarcity challenges that have limited geospatial modeling in Africa and other developing regions.

The health implications of the modeled pollutants remain substantial. Elevated concentrations of particulate matter (PM<sub>2.5</sub>, PM<sub>10</sub>) have been consistently associated with respiratory and cardiovascular illnesses, while nitrogen dioxide (NO<sub>2</sub>) exposure is linked to asthma, bronchitis, and impaired lung development in children (Briggs *et al.*, 1997). Landfill gases such as methane and volatile organic compounds (VOCs) contribute to smog formation and may increase long-term cancer risks (Ghasemzade & Pazoki, 2017). In Lagos, where densely populated settlements are located in close proximity to dumpsites such as Olusosun and Solous, the potential for chronic exposure is particularly high (Daramola & Makinde, 2024). By quantifying pollutant dispersion and identifying high-risk zones, geospatial models can play a critical role in supporting environmental health assessments and designing targeted interventions for vulnerable populations.

From a policy perspective, geospatial modeling offers actionable insights that can guide waste management and urban planning. For Lagos, the evidence reviewed supports the need to establish and enforce buffer zones of at least 15 km around major dumpsites to reduce human exposure (Okafor, 2024; Daramola & Makinde, 2024). Additionally, the adoption of modern landfill management practices—including waste segregation, controlled incineration, and regular monitoring of landfill-gas emissions—can substantially reduce pollutant release (Ramprasad *et al.*, 2022). At a broader level, integrating ground-based monitoring with satellite observations and predictive models can form cost-effective air-quality surveillance systems in resource-constrained settings (Carmona *et al.*, 2021; He *et al.*, 2021). Such integrated frameworks not only improve local decision-making but also contribute to global agendas, particularly Sustainable Development Goals (SDG 11) and SDG 13.

Looking forward, there is a clear need for standardized modeling frameworks, open-access data sharing, and regional capacity building in geospatial analytics. Future studies should prioritize cross-validation of models, integration of socioeconomic factors, and community exposure assessments (Sorek-Hamer *et al.*, 2020). Collaborative efforts among researchers, policymakers, and environmental agencies can enhance the consistency and usability of geospatial pollution maps for both health-risk assessment and strategic waste-management planning. Establishing regional data repositories and harmonized metadata standards will ensure comparability and support evidence-based policymaking.

Overall, this discussion underscores that while no single modeling approach is universally superior, combining multiple geospatial methods provides the most robust foundation for assessing dumpsite-related air pollution. By linking methodological insights to human health outcomes and policy needs, this review highlights both the progress achieved and the critical gaps that remain in developing effective strategies to protect urban populations from the hazards of uncontrolled waste disposal.

#### **4.0 CONCLUSION**

This review has examined geospatial modeling approaches used to assess air pollution around major dumpsites, with particular attention to their relevance in Lagos and comparable urban environments. The analysis shows that while methods such as Kriging, IDW, and Natural Neighbor interpolation provide valuable spatial estimates, their accuracy is highly dependent on the density and distribution of monitoring data. Remote

sensing products, including MODIS, extend spatial coverage but are limited by resolution and retrieval uncertainties. Predictive models such as LandGEM remain essential for landfill gas estimation, especially when combined with ground-based and satellite observations. Evidence from Lagos and other regions indicates that integrated approaches, drawing on multiple models and data sources, provide the most reliable basis for assessing human exposure risks.

Importantly, this review highlights the policy implications of geospatial modeling for waste management and urban planning. For Lagos, the findings support the need for continuous geospatial monitoring, the enforcement of buffer zones of at least 15 km around major dumpsites, and the adoption of improved waste incineration and treatment methods. More broadly, geospatial methods can guide decision-makers in designing low-cost, scalable strategies to protect vulnerable communities. By synthesizing current knowledge and identifying methodological strengths and gaps, this review provides a framework for future research and policy actions aimed at mitigating the health and environmental risks of dumpsite-related air pollution.

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#### **AUTHORS' CONTRIBUTIONS STATEMENT**

EOM: Conceptualisation, Investigation, Methodology, Research supervision. SOD: Data collection, Formal analysis, Software, Review & editing of initial write-up. All authors read and approved the final *manuscript*.

#### **DATA AVAILABILITY**

Datasets generated or analysed during the current study will be made available on request.

#### **STATEMENTS AND DECLARATIONS**

##### **ETHICAL**

The current study did not include any human or animal subjects. Thus, this study is not subject to an ethics review committee and does not require any informed consent.

##### **COMPETING INTERESTS**

The authors declare that they have no known competing financial or non-financial interests or personal relationships that could have appeared to influence the work reported in this paper". Authors can revise/customise the sample statements according to their needs.

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