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Dolna 17, Warsaw,
Poland 00-773
+48 226 0 227 03
editorial_office@rsglobal.pl

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# APPLYING GEOGRAPHIC INFORMATION SYSTEMS (GIS) AND IOT SENSOR DATA TO MODEL THE IMPACT OF AIR POLLUTION ON THE INCIDENCE OF RESPIRATORY DISEASES

***Filip Kowal*** *(Corresponding Author, Email: fkowal55@gmail.com)*
*Medical University of Silesia, Katowice, Poland*
*ORCID ID: 0009-0004-2775-4264*

***Kamila Krzyżanowska***
*Medical University of Silesia, Katowice, Poland*
*ORCID ID: 0009-0002-4875-244X*

***Michał Pietrucha***
*Medical University of Silesia, Katowice, Poland*
*ORCID ID: 0009-0001-0637-1270*

***Karol Demel***
*University Clinical Hospital in Katowice, Katowice, Poland*
*ORCID ID: 0009-0005-5485-7987*

***Justyna Talaska***
*Independent Public Healthcare Institution of the Ministry of the Interior and Administration in Katowice, Katowice, Poland*
*ORCID ID: 0009-0005-4723-9777*

***Adrian Dyląg***
*District Railway Hospital in Katowice, Katowice, Poland*
*ORCID ID: 0009-0000-1599-0383*

***Jakub Król***
*Provincial Specialist Hospital No. 4 in Bytom, Bytom, Poland*
*ORCID ID: 0009-0006-0696-1904*

***Maciej Łydka***
*LUX MED St. Elizabeth Hospital, Warsaw, Poland*
*ORCID ID: 0000-0002-3024-2524*

***Justyna Lewandowska***
*Warsaw Southern Hospital, Warsaw, Poland*
*ORCID ID: 0000-0001-7570-3374*

***Monika Dziedzic***
*Complex of Municipal Hospitals in Chorzów, Chorzów, Poland*
*ORCID ID: 0009-0002-4482-0898*

**ABSTRACT**

Ambient air pollution is a major global health threat, yet modeling its localized impact on respiratory diseases is hindered by sparse monitoring networks, leading to exposure misclassification. This paper outlines a high-resolution framework integrating Geographic Information Systems (GIS) and Internet of Things (IoT) sensor data to overcome these limitations. The methodology involves using calibrated, dense IoT networks to capture real-time (PM2.5) data, which is then integrated with health records. GIS techniques, including Kriging and Geographically Weighted Regression (GWR), are used to create continuous exposure surfaces and analyze spatially varying health relationships. The anticipated results include the identification of pollution hotspots and disease clusters, with the key finding being the quantification of spatial heterogeneity. This synergistic approach provides a powerful evidence base for targeted public health interventions and addressing environmental inequities.

**Background:** Air pollution, particularly (PM2.5), (NO2), and (O3), is a leading cause of global morbidity and mortality, strongly linked to respiratory diseases like asthma and COPD. Accurately assessing population exposure is a significant challenge. Traditional air quality monitoring relies on sparse, fixed regulatory stations. This method fails to capture the complex, micro-environmental variations in pollutant concentrations, leading to a "spatial data gap." This gap results in exposure misclassification in epidemiological studies, potentially underestimating the true health risks for vulnerable populations living in localized "hotspots."

**Purpose of Research:** The primary aim of this paper is to outline and propose a high-resolution geospatial modeling framework. This framework integrates real-time, high-granularity data from dense, low-cost Internet of Things (IoT) sensor networks with advanced Geographic Information Systems (GIS) analysis. The goal is to more accurately quantify the localized, spatially varying relationship between air pollution exposure and the incidence of respiratory diseases, moving beyond traditional, spatially-uniform risk assessments.



**KEYWORDS**

Air Pollution, GIS, IoT Sensors, Respiratory Diseases, Spatial Analysis, Public Health, Geographically Weighted Regression (GWR)

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## Introduction

Air pollution remains one of the most significant environmental threats to public health globally, contributing to a substantial burden of disease and premature mortality worldwide [1]. The pervasive nature of airborne contaminants, particularly fine particulate matter (PM2.5), nitrogen dioxide (NO2), and ground-level ozone (O3), has been unequivocally linked to a wide range of adverse health outcomes. Among these, respiratory diseases, including asthma, chronic obstructive pulmonary disease (COPD), and acute lower respiratory infections, are profoundly impacted by the quality of the air we breathe [2, 3]. The World Health Organization (WHO) estimates that ambient air pollution is responsible for millions of deaths annually [4]. The respiratory system is a primary target for pollutants, leading to inflammation, oxidative stress, and impaired lung function [5, 6].

Despite a clear understanding of the causal link between air pollution and respiratory illness, accurately quantifying population exposure and its direct impact at a local level remains a significant challenge. Traditional air quality monitoring relies on a sparse network of fixed, regulatory-grade monitoring stations. While these stations provide highly accurate data, their limited spatial coverage often fails to capture the complex micro-environmental variations in pollutant concentrations across a city or region [7, 8]. This spatial data gap can lead to exposure misclassification in epidemiological studies, potentially underestimating the true health risks, especially for vulnerable populations living in close proximity to pollution "hotspots" that are not captured by the official network [9, 10].

The advent of two transformative technologies, the Internet of Things (IoT) and Geographic Information Systems (GIS), offers a powerful new paradigm for environmental health research. Low-cost IoT sensors enable the deployment of dense air quality monitoring networks, providing data with unprecedented spatial and temporal resolution [11, 12]. This high-resolution data stream can reveal the dynamic nature of air pollution within urban landscapes. In parallel, GIS provides the essential framework for integrating, analyzing, and visualizing this complex spatial data. By combining sensor readings with other geospatial datasets—such as land use, traffic density, and population distribution—GIS allows for the creation of sophisticated exposure models.

The primary aim of this study is to develop and validate a high-resolution geospatial model by integrating real-time air quality data from a network of IoT sensors with localized health data on respiratory disease incidence. Using advanced GIS-based spatial analysis techniques, we seek to quantify the relationship between exposure to key air pollutants and respiratory morbidity in the study area. This paper begins with a comprehensive review of the existing literature on the application of GIS and IoT in public health. This is followed by a detailed description of the methodology, including the study area, data sources, and the analytical framework. Subsequently, the results of the spatial and statistical analyses are presented, which are then interpreted in the discussion section in the context of their implications for public health policy. The paper concludes with a summary of the key findings and provides recommendations for future research directions.

**Literature review**

A substantial body of evidence confirms the strong link between exposure to ambient air pollutants and the incidence of respiratory diseases. Key contaminants, particularly fine particulate matter (PM2.5), nitrogen dioxide (NO2), and ozone (O3), can penetrate deep into the lungs, triggering oxidative stress and inflammation. These mechanisms are fundamental to the exacerbation of chronic conditions like asthma and COPD [3, 13]. They also contribute to the overall decline in lung function with long-term exposure. The health risks are not uniform, varying with the type of pollutant and the duration of exposure [14, 15].

Geographic Information Systems (GIS) have become an essential tool in spatial epidemiology, enabling researchers to analyze the geographic context of disease by integrating health data with various environmental layers to identify "hotspots." The traditional method of air quality assessment, relying on sparse regulatory monitoring stations [7], is being revolutionized by the rise of low-cost Internet of Things (IoT) sensors. These sensors facilitate the creation of dense monitoring networks capable of capturing air quality data with high spatial and temporal resolution [8], offering a far more accurate picture of personal exposure [5].

However, the utility of these low-cost sensors is contingent upon addressing significant challenges related to their data accuracy and reliability. The performance of these devices can be influenced by environmental conditions, and they require rigorous calibration against reference-grade instruments to ensure the data is robust enough for health-related research [11]. The synthesis of calibrated, high-resolution IoT sensor data with GIS modeling represents the new frontier in environmental health science. This integration allows for the creation of dynamic, near real-time air quality maps, paving the way for more precise and effective public health strategies [16].

**Methodology**

The methodological framework for modeling the health impacts of air pollution using GIS and IoT data follows a structured, multi-stage geospatial workflow. The process begins with the acquisition of three key datasets: high-temporal-resolution air quality measurements (particularly PM2.5 ) from a dense network of low-cost IoT sensors; anonymized public health data on respiratory disease incidence, aggregated to administrative units like census tracts; and fundamental GIS layers (e.g., boundaries, road networks). A critical initial step involves the calibration of sensor data against official reference stations to ensure its accuracy and reliability [11, 17]. Subsequently, geostatistical methods, most notably Kriging, are employed to interpolate the point-based sensor readings into a continuous pollution surface, which allows for the estimation of exposure across the entire study area [16]. The final analytical stage utilizes advanced spatial statistical models, with Geographically Weighted Regression (GWR) being a primary example, to analyze the relationship between pollution levels and health outcomes. This approach is superior to global models as it allows researchers to identify local "hotspots" where the impact of air pollution on respiratory health is significantly more pronounced [13,20].

**Results**

The application of the integrated GIS and IoT sensor-based methodology is expected to yield a series of clear, spatially explicit results that provide deep insights into the environment-health nexus. The findings are typically presented as a combination of high-resolution maps and statistical outputs that visualize and quantify the relationship between air pollution and respiratory disease [5, 7].

**High-Resolution Air Pollution Surfaces**

A primary outcome of the spatial interpolation (Kriging) of the calibrated IoT sensor data would be a continuous raster surface representing the average PM2.5 concentrations. This map would reveal significant intra-urban variability, clearly delineating pollution "hotspots" concentrated along major traffic corridors and in industrial zones. Conversely, it would also identify areas with relatively better air quality, such as large green spaces, providing crucial visual evidence of localized population exposure [13, 15].

**Spatial Distribution of Respiratory Diseases**

The second set of visual results would consist of choropleth maps displaying the incidence rates of respiratory diseases aggregated at the census tract level. These maps would typically show a non-uniform pattern, with distinct clusters of high incidence often appearing in specific neighborhoods. A preliminary visual comparison would likely suggest a spatial correspondence between the disease clusters and the pollution hotspots [7, 5].

**Spatially Varying Relationships from GWR Model**

The key analytical results would be derived from the Geographically Weighted Regression (GWR) model. Instead of a single, global coefficient, GWR produces localized results, including:

- A map of local coefficients: This would visualize the strength of the relationship between PM2.5 and respiratory disease for each census tract, demonstrating spatial heterogeneity—proving that the impact of pollution is not uniform across the city.
- A map of local R-squared (R2) values: This would show how well the model explains the variation in respiratory disease in different parts of the study area.

Together, these outputs provide powerful, granular evidence for identifying specific communities that are most vulnerable to the health effects of air pollution [13, 18].

**Discussion**

The expected results from this methodological framework would provide a compelling, data-driven narrative about the localized public health crisis driven by air pollution. The key takeaway is not simply that air pollution is linked to respiratory disease, but that this relationship exhibits profound spatial heterogeneity. By moving beyond traditional, city-wide averages, the integrated GIS-IoT approach allows for a granular understanding of risk, revealing that where a person lives can drastically alter their environmental health burden.

**Interpretation of Key Findings**

The anticipated overlap between high-resolution PM2.5 "hotspots" and clusters of respiratory illness provides strong, visual evidence of environmental injustice. These findings would likely confirm that communities situated near major roadways or industrial facilities are disproportionately affected, a conclusion strongly supported by recent studies that use high-resolution mapping to examine pollution dynamics in disadvantaged communities [17, 19]. The results from the Geographically Weighted Regression (GWR) model would quantify this relationship, demonstrating a significantly stronger correlation between pollution and disease in these hotspots. The ability to map these local coefficients is the most powerful contribution of this methodology, transforming an abstract health risk into a tangible, geographically-defined problem.

**Implications for Public Health and Policy**

The practical implications of these findings are substantial. Instead of implementing broad, city-wide policies, public health officials could use these high-resolution risk maps to develop targeted interventions. For example, they could prioritize the placement of air filtration systems in schools and community centers within the most affected neighborhoods or launch localized public health campaigns.

For urban planners, these results would offer a clear evidence base for strategic decision-making. The maps could guide zoning regulations or inform the development of "green infrastructure." The rise of dense, low-cost sensor networks fundamentally changes how we can manage urban air quality, shifting from reactive monitoring to proactive, spatially-aware planning [7, 16].

**Limitations and Future Directions**

While powerful, this methodology is not without its limitations. The primary challenge remains the accuracy and long-term stability of low-cost IoT sensors. Although calibration methods can significantly improve data quality, they require continuous oversight to prevent measurement drift [6, 11]. Secondly, this model is susceptible to the ecological fallacy—making inferences about individuals based on aggregated data.

Furthermore, the model does not account for all potential confounding variables, such as socioeconomic status or indoor air quality. Future research should aim to integrate these additional datasets to build more comprehensive models.

**Conclusions**

This paper has outlined a powerful and increasingly vital methodological framework that integrates Geographic Information Systems (GIS) and Internet of Things (IoT) sensor data to model the impact of air pollution on respiratory diseases. The fusion of these technologies represents a paradigm shift, moving environmental health research from a reliance on sparse, fixed-site monitoring to a dynamic, high-resolution, and spatially-aware approach. By doing so, it addresses the critical shortcomings of traditional methods, which often fail to capture the true, localized nature of air pollution exposure and its subsequent health consequences.

The primary contribution of this integrated model is its ability to not only confirm the link between air quality and respiratory illness but to demonstrate its profound spatial variability. The capacity to identify specific "hotspots" where health risks are most severe provides an invaluable tool for public health officials and urban planners. It transforms abstract, city-wide statistics into actionable, neighborhood-level insights, enabling the development of targeted, evidence-based interventions that can protect the most vulnerable communities.

In summary, the synergy between GIS and IoT offers an unprecedented opportunity to understand and mitigate the public health crisis posed by air pollution. While challenges related to sensor accuracy and data complexity remain, the potential to create healthier, more equitable urban environments is immense. Future research must continue to refine these models by incorporating more comprehensive datasets and leveraging advancements in machine learning, further solidifying the role of geospatial technology as a cornerstone of modern public health.

**Disclosure**

**Author's contributions:**

**Conceptualization:** Filip Kowal
**Methodology:** Michał Pietrucha, Kamila Krzyżanowska
**Software:** Karol Demel, Adrian Dyląg, Jakub Król
**Check:** Maciej Łydka, Monika Dziedzic
**Formal analysis:** Michał Pietrucha, Justyna Lewandowska
**Investigation:** Justyna Talaska, Filip Kowal, Maciej Łydka
**Resources:** Karol Demel, Adrian Dyląg
**Data curation:** Jakub Król, Kamila Krzyżanowska
**Writing – rough preparation:** Justyna Lewandowska, Monika Dziedzic
**Writing – review and editing:** Karol Demel, Justyna Talaska
**Visualization: Michał Pietrucha,** Kamila Krzyżanowska, Adrian Dyląg
**Supervision:** Justyna Talaska, Filip Kowal, Maciej Łydka
**Project administration:** Jakub Król, Justyna Lewandowska

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