

A Comparative Analysis of Conventional Methods for Sensor-Driven Spatial Interpolation for Air Quality Monitoring

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Abstract: Accurate air quality mapping in regions with sparse sensor deployment remains a challenge due to high infrastructure costs. While modern literature increasingly favors heavy, cloud-based Artificial Intelligence frameworks that assume dense input networks, the operational boundaries and mathematical fidelity of lean, edge-computed spatial interpolation models in ultra-sparse (e.g., 5-node) live frameworks remain poorly defined. This work presents a case-study comparative evaluation of conventional spatial interpolation techniques for estimating pollutant concentrations in sensor-limited environments. Eight interpolation methods, namely Inverse Distance Weighting (IDW), Kriging, Empirical Bayesian Kriging (EBK), Radial Basis Function (RBF), Nearest Neighbor (NN), Akima, Piecewise Cubic Hermite Interpolation (PCHIP), and Cubic Spline (CS), were analyzed using real-time environmental data collected from five locations in Kalady, Kerala, India. The interpolation performance was evaluated using RMSE and MAE metrics through leave-one-out validation. Results indicate that, within this deployment, Kriging and IDW achieved the best estimation accuracy for PM_{2.5}, PM₁₀, humidity, and temperature compared to the other methods evaluated. A LoRa-based sensing framework was also integrated to support low-power real-time environmental monitoring. As a single-region case study based on five monitoring nodes, the findings are specific to this deployment, and broader validation across additional stations and regions is identified as future work. The proposed approach demonstrates the feasibility of resource-efficient air quality estimation in regions with limited monitoring infrastructure.

Index Terms: Air quality monitoring, spatial interpolation techniques, real-time LoRa-Based sensor system

1. Introduction

Air quality monitoring is essential because of its important impact on public health and environmental sustainability. The Air Quality Index (AQI) offers a tool to indicate pollution levels, which helps individuals examine the safety of different locations. However, acquiring accurate AQI across different areas needs a large array of sensors, which can be logistically and economically challenging. This issue is particularly obvious in regions where pollution is affected by various elements such as traffic, industrial emissions and operations, and geographical characteristics which make the air difficult to breathe. Air pollutants such as PM_{2.5}, PM₁₀, ozone, NO₂, SO₂, CO, and others can contaminate the water sources and environment which results in various health problems like coughing and itchy eyes. They can also lead to worse and more serious respiratory illnesses, increasing the chances of hospital visits, cancer, and premature death. Many residents, especially those residing near the hotspots and industrial zones are unaware of the severity of these air quality issues.

Although several studies have explored spatial interpolation methods for air quality mapping, a critical review of the state-of-the-art reveals three highly specific research gaps that transcend general sensor scarcity:

- 1) **Computational and Architectural Asymmetry:** Contemporary literature predominantly targets high-resource AI frameworks, Spatio-temporal Graph Neural Networks (e.g., RelMap), or multi-modal satellite fusions. These assume extensive data pipelines and high back-end processing, rendering them incompatible with lightweight, real-time edge computing on low-power architectures.
- 2) **Micro-Scale Meteorological and Spatial Volatility:** Existing regional interpolation designs assume macro-scale spatial smoothness. However, semi-urban environments (such as Kalady, Kerala) undergo severe micro-scale variations induced by sudden transitions between localized traffic bottlenecks, micro-industrial pockets, and tropical microclimatic features (such as heavy monsoon deposition versus dry-period stagnation).
- 3) **The Sparse Edge-Integration Validation Gap:** There is a lack of empirical hardware-linked literature mapping how classical deterministic and geostatistical equations scale dynamically when bound to a live, low-power, long-range wireless infrastructure (LoRaWAN) constrained to an ultra-sparse 5-node topology.

To bridge these explicit gaps, this study intentionally forces extreme hardware resource boundaries to evaluate which classical interpolation formulations maintain mathematical stability and actionable precision under micro-scale urban fluctuations.

Existing literature also provides insufficient discussion regarding computational feasibility, scalability, and region-specific suitability of interpolation methods under limited sensor availability.

The initial difficulty is the interaction of diverse environmental, meteorological, and geographical factors that shape air pollution patterns [1]. Pollutants like PM_{2.5}, PM₁₀, SO₂, CO, and O₃, released from both industrial activities and vehicle emissions disperse in many different ways influenced by local geography, climate conditions, and urban infrastructure. The absence of advanced monitoring systems that consider these variables makes it challenging to accurately calculate and evaluate pollution patterns. This research compares various spatial interpolation techniques such as Kriging, IDW and Nearest Neighbor (NN) [2], Akima interpolation [3], Cubic Spline (CS) [4], Piecewise Cubic Hermite Interpolation (PCHIP) [5], Radial Basis Function (RBF) [6], and Empirical Bayesian Kriging (EBK) [7]—to identify the most accurate method for calculating. The equations of the different methods are illustrated in the proposed system section. These methods use available sensor data to predict pollution levels at unsampled sites, considering the geographic and meteorological parameters that affect air quality. The geographical characteristics such as its landscape, high population density, and industrial zones, lead to wide range patterns of pollution distribution. By examining satellite images and conducting resident surveys, we can collect pollution prone areas and determine optimal sensor deployment. There is an additional methodological improvement has been incorporated in the above methods. Additionally, the local climate factors which include monsoon winds, temperature inversions, and changes in atmospheric pressure play a significant role in the spread and building up of pollutants. While the monsoon rain helps purify the air in which the dry periods result in the accumulation of pollutants, such as particulate matter and gas emissions, which reduce the air quality. Understanding these meteorological influences is essential for estimating accurate air quality index (AQI) forecasting models through spatial interpolation.

This research proposes a conceptual health assessment support framework that utilizes localized air quality information for future personalized environmental risk assessment applications. that make use of localized air quality information with health score after a questionnaire through Web application, ensuring residents, particularly those exposed to the areas like schools and healthcare facilities, receive real time updates to protect their well-being. The LoRa Technology implementation has enabled effective sparse sensor coverage in which it serves as a gateway technology that helps in integration of multiple sensor nodes within its range of communication. Its low-power and long-range capabilities make it highly feasible especially in conventional infrastructure environments, hence expanding sensor networks.

It is important to clarify the evidentiary status of this component: the health-assessment framework and the questionnaire-based scoring described above are presented as a conceptual design integrated with the LoRa sensing pipeline, not as an experimentally validated clinical or epidemiological outcome. Only the spatial-interpolation

performance (RMSE/MAE under leave-one-out cross-validation) reported in Section 4 has been empirically evaluated in this work; the health-scoring application has not yet been tested against real user outcomes or ground-truth exposure-health data, and its empirical validation is left as future work, consistent with the Conclusion.

In conclusion, this study proposes spatial interpolation techniques to estimate air quality levels that consider both the difficulties of sensor coverage and the area's different environmental factors. By minimizing the number of sensors and utilizing interpolation to avoid data gaps, we can deliver more precise, localized air quality assessments that assist both community members and policymakers of the area. This method not only enhances the analysis of pollution patterns but also helps in the advancement of air quality management and the safeguarding of public health.

The major contributions of this work are summarized as follows:

- 1) Comparative evaluation of eight conventional spatial interpolation techniques for sparse air quality monitoring.
- 2) Integration of LoRa-based low-power sensor communication for real-time environmental monitoring.
- 3) Validation of interpolation performance using RMSE and MAE metrics under leave-one-out evaluation.
- 4) Analysis of region-specific interpolation suitability for semi-urban environmental conditions.

This paper is structured as follows: section 2 presents a review of the state of the art methods. Afterwards, section 3 presents the proposed approach. We then present our spatial techniques approaches leveraged for the experiment. We analyze the experimental results in section 4 and section 5 presents a conclusion of the paper. In final, section 6 provides the acknowledgments.

2. Related Works

In this section, we review the state-of-the-art spatial interpolation techniques. Air pollution monitoring and its environmental and public health effects have received considerable role in recent years, leading to the development of various innovative approaches for data collection, spatial analysis, and impact assessment. Research in this field highlights the incorporation of advanced technologies such as artificial intelligence (AI), geospatial analysis, and low-cost sensors to improve air quality monitoring and forecasting.

Furthermore, there is an increasing importance on understanding the relationship between socioeconomic factors and environmental conditions, that highlight the associative nature of modern air pollution studies. James J. Kulez and Ronald W. Lee [8] proposed a system that states the importance of accurate and dependable data collection systems in air quality assessments for monitoring the environmental conditions. Similarly, Hasakarn Thongzunhor and Nopparat Pochai [9] proposed numerical simulations to examine two-dimensional air pollution measurements in street canyons, providing valuable information into urban air quality dynamics shaped by different urban designs.

Expanding the research opportunities in urban air pollution, Jimena García-Burgos et al. [10] studied the spatial distribution of air pollution in Mexico City, merging pollutant levels with socioeconomic factors and thereby focusing on issues of environmental justice.

Moreover, advanced spatial analysis techniques have been studied, as demonstrated by Zhexu Ji et al. [11], who used spatial analysis methods to assess air pollution in Bogota, Colombia, finding region-specific pollution patterns. Similarly, H. L. Brantley et al. [12] examined mobile air monitoring strategies, focused on data processing methods to find spatial trends. Furthermore, Lauren E. Padilla et al. [13] showcase innovative techniques for finding street-scale air pollution patterns, while Dian Huang et al. [14] explored the impact of land cover variations on air pollution at diverse spatial scales.

Emerging technologies, like AI and IoT, are reframing in this field. Lu Liang et al. [15] combined low-cost sensor data with satellite mapping and geospatial AI for predicting urban air pollution, that shows the potential of integrated approaches to overcome the limitations of traditional monitoring.

En Xin Neo et al. [16] expanded this idea by expanding the use of AI for smart city air quality management, in which it emphasizes the scalability of these methods in urban planning. The Multi-Modal Attention-based Spatio-Temporal Network (MAST-Net) employs a combined framework of concurrent Convolutional Neural Networks and Bi-directional Long Short-Term Memory units to integrate spatial and temporal attributes from diverse data sources. This system combines high-resolution satellite images from Sentinel-5P, MODIS, and Landsat-8 with meteorological reanalysis, using a dynamic feature selection approach and uncertainty quantification to enhance forecast accuracy.

Experimental findings from various global metropolitan areas indicate that MAST-Net realizes noteworthy performance improvements, decreasing prediction error by 23-31% and reaching correlation coefficients (R^2) up to 0.94 for pollutants like NO_2 and $PM_{2.5}$ [17]. Deep Classifier Kriging (DCK) for probabilistic space prediction on the Air Quality Index (AQI), which combines sparsely observed ground monitoring data with densely simulated CMAQ model predictions.

Their method does not assume the Gaussian distribution, and it turns an AQI prediction task into a classification problem and uses deep neural networks to learn the nonlinear spatial correlations. The approach yields full predictive distributions and their uncertainty, and results in far lower predication error compared to traditional geostatistical methods. This study also confirms the increasing use of deep learning with spatial interpolation for large-scale environmental monitoring. [18]

State-of-the-art spatial interpolation recently has incorporated deep learning to supplement traditional geostatistical methods in sparsely monitored areas. Chen et al. (202) proposed RelMap, a robust spatial-temporal interpolation framework which enhances the heat maps generation using Graph Neural Network (GNN)-based data imputation in the interpolating procedure.

Firstly, the approach conducts adaptive sensor densification via inserting virtual sensors in few-nodes-covered region, and secondly, employs spatiotemporal GNN model that combines PNA (Principal Neighborhood Aggregation) and GPE (Geographical Positional Encoding) to capture complex spatial-temporal correlations. A combination of estimated values and original sensor data using Radial Basis Function (RBF) interpolation leads to enhanced interpolation accuracy and robustness. [19]

Spatial interpolation methods have been commonly used in air quality appraisal to predict pollutant levels at locations not covered by monitoring sites. Abdul Kareem et al. have reviewed widely used GIS-based interpolation methods and found IDW and Kriging are still the preferred approaches for mapping pollutants like PM_{2.5}, PM₁₀, NO₂, SO₂, and CO.

The investigation demonstrated that IDW can be computationally attractive (with potentially lower computing cost) for moderately dense monitoring networks, while Kriging generally yields better predictive performances owing to the consideration of spatial autocorrelation and reduction in estimation variance. Spline interpolation proved successful for continuous RAI variables but may generate unrealistic extremes in regions of sharp spatial variation. [20]

Conversely, the Nearest Neighbor approach was not suitable for air pollution mapping because it fails to consider spatial continuity. Additionally, the review underlined that cross-validation strategies were necessary, such as leave-one-out validation tests to assess model performance on statistical indicators e.g. RMSE and Mean Error. The results indicate that data distribution, spatial variability and study aim need to be taken into account when selecting an interpolation method in order to obtain a trustful predictive mapping of air quality.

Abdul Kareem et al. review conventional GIS interpolation methods (IDW, Kriging, Spline and Nearest Neighbor) and compares their fitness and accuracy for air quality mapping in order to provide an evaluation of traditional GIS interpolation techniques. In comparison, Chen et al. propose a deep learning enhanced spatiotemporal framework by combining graph neural networks with interpolation for enhancing the reliability and uncertainty estimation in unmonitored sensor networks.

There are real-time air quality monitoring systems that deploy sensors and utilize Lora WAN communication for long distance data transmission. There are various commercial solutions like Continuous Ambient Air Quality Monitoring Systems (CAAQMS) and Oizom's Polludrone, track pollutants such as SO₂, NO_x, and particulate matter (PM_{2.5}, PM₁₀) in real time. But these systems can be expensive, bulky, and difficult to implement in all pollution hotspots even after several progress. Table 1 illustrates the comparison of Air Quality Monitoring and Spatial Interpolation studies.

Although recent studies increasingly employ AI, deep learning, satellite integration, and graph neural network approaches for air quality prediction, these techniques generally require high computational resources, large-scale datasets, and dense monitoring infrastructures. In contrast, conventional interpolation methods remain computationally efficient and practical for sparse sensor deployments. However, limited studies provide detailed comparative validation of multiple conventional interpolation methods under low-cost real-time IoT deployments. Therefore, this work focuses on evaluating classical interpolation techniques within a practical sparse sensing framework suitable for resource-constrained environments.

The validation and comparison of spatial interpolation techniques have been extensively studied across different environmental applications. Kebede et al. [21] conducted a comprehensive evaluation of spatial interpolation methods using ground-based gravity and elevation datasets in the central Main Ethiopian rift. Their study compared multiple techniques including IDW, Kriging variants, and Spline methods, demonstrating that the selection of appropriate interpolation methods significantly depends on data characteristics, spatial distribution patterns, and the physical properties of the variables being interpolated. The findings emphasized the importance of rigorous validation procedures in assessing interpolation accuracy.

Building on conventional interpolation approaches, Lotrecchiano et al. [22] specifically focused on comparing spatial interpolation techniques for innovative air quality monitoring systems. Their research evaluated the effectiveness of IDW, Kriging, and Spline methods for predicting concentrations of various air pollutants including SO₂, NO₂, CO, and PM_{2.5} in unmonitored regions. The study demonstrated that both IDW and Kriging methods effectively assess air quality in areas with limited monitoring infrastructure, providing valuable guidance for implementing cost-effective monitoring networks in urban environments. Their findings highlighted the trade-offs between computational efficiency and prediction accuracy across different interpolation techniques.

Recent studies have focused on practical applications in specific urban contexts. Nair et al. [23] investigated the selection of interpolation techniques for mapping the spatial distribution of prominent pollutants in traffic-induced polluted areas. Their study in Thiruvananthapuram corporation compared five interpolation techniques—Universal Kriging, Ordinary Kriging, IDW, Spline Regularised, and Spline Tension—to determine the most accurate method for PM₁₀ concentration mapping. The results identified Ordinary Kriging and IDW as the best methods for this specific urban environment, demonstrating the importance of context-specific validation in method selection.

Similarly, Yadav and Ganguly [24] assessed air quality in Kanpur city, India, a highly polluted industrial city, using

IDW and Kriging spatial interpolation techniques during the summer season. Their study generated spatial distribution maps of PM₁₀ concentrations, successfully identifying pollution hotspots in areas with heavy traffic and industrial activities. The research demonstrated that geospatial techniques provide crucial insights into spatial distribution and potential hotspots of air pollution, with significant implications for urban planning, environmental management, and public health interventions. The findings confirmed that PM₁₀ concentrations were significantly higher in industrial and commercial areas compared to residential zones.

Recent research has explored the integration of IoT sensors with classical interpolation methods for granular air quality monitoring. Garbagna et al. [25] conducted a UK case study analyzing spatial patterns of multiple air pollutants (PM_{2.5}, PM₁₀, and NO₂) using Aeroqual IoT devices for data collection. Their study compared three interpolation techniques—Inverse Distance Weighted (IDW), Ordinary Kriging, and Radial Basis Function—to predict pollution concentrations at unmeasured locations. The performance evaluation using Root Mean Squared Error (RMSE) and Mean Squared Error (MSE) demonstrated that IDW emerged as the best-performing interpolation technique for most pollutants, achieving the lowest error scores. This work highlights the practical applicability of combining low-cost IoT sensors with conventional interpolation methods for creating reliable, granular pollution concentration maps in urban environments.

The evolution of air quality monitoring has seen significant advancements in both sensing technologies and computational methods. Elbestar et al. [26] conducted a comprehensive review of 47 studies, systematically categorizing computational advancements in air quality monitoring into sensor-based and image-based techniques. Their analysis revealed that sensor-based algorithmic methods, representing 62% of the reviewed literature, are reliable but often lack flexibility and real-time monitoring capabilities. In contrast, image-based techniques, while innovative, face limitations related to dataset size and diversity, and primarily function only during daylight hours. To address these limitations, the authors proposed a hybrid approach that integrates both sensor-based and image-based methods, enhanced with an augmented reality layer for visualizing pollution levels. This hybrid model aims to provide mobile users with comprehensive air quality monitoring capabilities by establishing diverse image-based datasets that incorporate features not previously considered in existing systems. The review highlights the ongoing transition from fixed monitoring stations to mobile, flexible monitoring solutions that can provide real-time, spatially distributed air quality data.

Table 1. Comparison of Air Quality Monitoring and Spatial Interpolation Studies

Ref	Author(s)	Year	Approach Type	Method/Model	Main Contribution	Key Strength
[8]	Kulez & Lee	2010	Monitoring System	Data acquisition framework	Emphasized reliable data collection systems for air quality assessment	Improves monitoring accuracy
[9]	Thongzunhor & Pochai	2022	Numerical Modeling	2D simulation in street canyons	Studied urban design impact on pollution dynamics	Captures micro-scale urban effects
[10]	García-Burgos et al.	2022	Spatial-Socio economic Analysis	GIS + Socio economic integration	Linked pollution levels with environmental justice issues	Incorporates social dimension
[11]	Ji et al.	2022	Spatial Analysis	GIS-based spatial methods	Identified regional pollution patterns	Region-specific mapping
[12]	Brantley et al	2014	Mobile Monitoring	Mobile sensor mapping	Analyzed spatial trends using mobile data	High spatial resolution
[13]	Padilla et al.	2022	Street-Scale Monitoring	Fine-scale mapping	Detected street-level pollution variability	High local detail
[14]	Huang et al	2021	Land Cover Impact	Multi-scale spatial analysis	Studied land cover influence on pollution	Multi-scale assessment
[15]	Liang et al.	2023	AI + Geospatial	Low-cost sensors + Satellite + AI	Integrated AI and remote sensing for prediction	Hybrid data fusion
[16]	Neo et al.	2023	Smart City AI	AI-based management	Scalable smart-city air quality control	Urban scalability
[17]	MAST-Net	2025	Deep Learning	CNN + Bi-LSTM + Attention	Spatiotemporal fusion of satellite & meteorology data	23–31% RMSE reduction
[18]	Deep Classifier Kriging	2025	Deep Learning + Geostatistics	Classification-based kriging	Probabilistic AQI prediction with uncertainty	Non-Gaussian modeling
[19]	RelMap (Chen et al.)	2025	GNN-based Interpolation	GNN + RBF	Adaptive sensor densification + uncertainty visualization	Improved reliability in sparse areas
[20]	Abdul Kareem et al.	2025	GIS-Based Review	IDW, Kriging, Spline, NN	Comparative evaluation of classical interpolation methods	Practical GIS validation
[21]	Kebede et al.	2024	Geospatial Interpolation	IDW, Kriging, Spline	Evaluated interpolation methods for gravity and elevation datasets	Cross-domain validation
[22]	Lotrecchiano et al.	2023	GIS-Based Comparison	IDW, Kriging, Spline	Compared techniques for SO ₂ , NO ₂ , CO, PM _{2.5} prediction in unmonitored regions	Air quality-specific methodology

Ref	Author(s)	Year	Approach Type	Method/Model	Main Contribution	Key Strength
[23]	Nair et al.	2025	Traffic Pollution Mapping	Universal Kriging, Ordinary Kriging, IDW, Spline	Identified PM ₁₀ as prominent pollutant; validated five interpolation methods	Traffic-induced pollution focus
[24]	Yadav & Ganguly	2024	Urban Air Quality Assessment	IDW, Kriging	PM ₁₀ spatial distribution mapping in industrial city; identified hotspots	Practical industrial city application
[25]	Garbagna et al	2024	IoT Interpolation +	IDW, Ordinary Kriging, RBF	UK case study with Aeroqual IoT devices; compared three interpolation methods for PM _{2.5} , PM ₁₀ , NO ₂	IDW best performance with lowest RMSE/MSE
[26]	Elbestar et al.	2024	Comprehensive Review	Sensor-based + Image-based	Reviewed 47 studies; categorized methods (62% sensor-based); proposed hybrid approach with AR visualization	Systematic categorization and hybrid integration framework

As summarized in Table 1, the overarching trend in modern research focuses on resolving data limitations through heavy deep learning frameworks (e.g., MAST-Net, Deep Classifier Kriging) or mobile sensor maps. While effective, this creates an unaddressed literature gap regarding low-resource edge infrastructure: the field lacks rigorous empirical boundaries mapping how classical equations respond under severe, multi-pollutant spatial constraints (PM_{2.5}, PM₁₀, and meteorology) using an integrated low-power LoRa network. Consequently, this paper establishes a specific baseline by determining whether classical frameworks can sustain spatial accuracy under localized structural constraints without triggering the computational overhead of AI engines.

Table 1 is used analytically, not only descriptively, to justify method selection for this study: rows 8–14 and 17–19 (AI-, GNN-, and deep-learning-based approaches) are computationally intensive and depend on dense sensor networks or satellite fusion, which are unavailable in a 5-node deployment, and are therefore excluded from this comparison. Rows 20–26, which evaluate conventional GIS-based methods (IDW, Kriging, Spline, RBF, Nearest Neighbor) under sparse or resource-constrained conditions comparable to this study, motivate the eight classical interpolators selected here. In this respect, the specific research gap addressed is narrower than general “limited sensor coverage”: no prior study jointly (i) benchmarks eight classical interpolators, (ii) under an ultra-sparse 5-node topology, (iii) bound to a live LoRa-based acquisition pipeline, with (iv) formal statistical validation (Friedman/Wilcoxon testing) of the ranking rather than point-estimate comparison alone. The method-selection procedure itself is formalized rather than left to qualitative judgement: for each parameter (PM_{2.5}, PM₁₀, temperature, humidity), the selected method m^* is the one minimizing the mean leave-one-out RMSE across all five stations, $m^* = \operatorname{argmin}_m (1/n) \sum \operatorname{RMSE}_m(i)$, with ties broken using the paired Wilcoxon signed-rank test reported in Fig. 5; a method is retained as “best” only when its RMSE is not statistically distinguishable from the minimum at $\alpha = 0.05$ after Holm correction.

3. Proposed Approach

The system consists of sensor nodes equipped with LoRa technology to collect essential environmental data (concentrations of pollutants, temperature, humidity, and pressure). These sensor nodes send their readings to a central LoRaWAN gateway that converts the incoming signals into structured data formats like Excel files or database records. It is necessary to establish a dependable connection to the LoRaWAN gateway and connecting it to the ThingStack server for improved system's efficiency. The backend structure ensures smooth data flow from the LoRa readings to the web application via an API and it is depicted in Fig.1. The optimal interpolation method was selected using quantitative validation based on RMSE and MAE performance metrics obtained through leave-one-out cross-validation. The interpolation technique producing the minimum average prediction error across environmental parameters was considered the most suitable method for the Kalady region.⁸ different methods which are finely tuned to make sure to get accurate interpolated data from the unsampled locations even with a limited number sensor by considering elements such as location of sensor, distance between sensors and sensor count. This is beneficial for the public, as it provides real time air quality updates thereby improving environmental awareness and decision-making. A user interface has been integrated, consisting of a registration system to collect user data for sending personalized notifications and messages based on changes in pollutant levels. The system is backed by a wide dataset from the deployed sensors, that includes environmental factors such as temperature, pressure, and humidity, as well as demographic information like age and health condition through questionnaire for assessing health risks and can support future alert generation mechanisms.

The proposed architecture demonstrates low communication latency due to lightweight LoRa packet transmission and localized interpolation computation. LoRa communication ensures reliable long-range data transmission with low power consumption. Furthermore, the modular system architecture enables future scalability through the addition of multiple sensing nodes without significant infrastructure modification.

To provide a deeper analysis of the system architecture rather than a purely descriptive block diagram, the following

characteristics of the pipeline in Fig. 1. are quantified. Data-flow latency: each LoRa uplink packet (payload ≤ 51 bytes at SF7/BW125kHz) is transmitted at a duty-cycle-limited interval of one reading per minute per node, so end-to-end latency from sensor sampling to gateway ingestion is dominated by the LoRa air-time (typically well under 1 s) rather than by processing, and the subsequent interpolation step (IDW/Kriging over five stations) executes in milliseconds on the backend, keeping the sensor-to-dashboard delay in the sub-second-to-few-second range and compatible with near-real-time updates. Communication reliability: LoRaWAN's use of spread-spectrum chirp modulation and forward error correction provides robustness to multipath fading and interference over the sub-1 km links used in this deployment, and the star-of-stars gateway topology means the loss of a single node does not affect data collection from the remaining stations. Scalability: because each additional sensor node only adds a small, fixed uplink payload rather than new backend logic, the architecture scales near-linearly in the number of nodes until the LoRaWAN gateway's channel capacity becomes the limiting factor; a formal capacity/latency analysis under a larger node count is identified as future work. Computational complexity and real-time feasibility: IDW and Nearest Neighbor scale as $O(n)$ per query station and EBK/Kriging as $O(n^3)$ due to covariance-matrix inversion, where n is the number of stations ($n = 5$ in this study); running all eight methods simultaneously for four parameters therefore completes in well under a second on standard hardware at this sensor count, though the $O(n^3)$ terms for Kriging/EBK would need to be revisited (e.g., via local/windowed Kriging) before scaling to networks with tens of nodes.

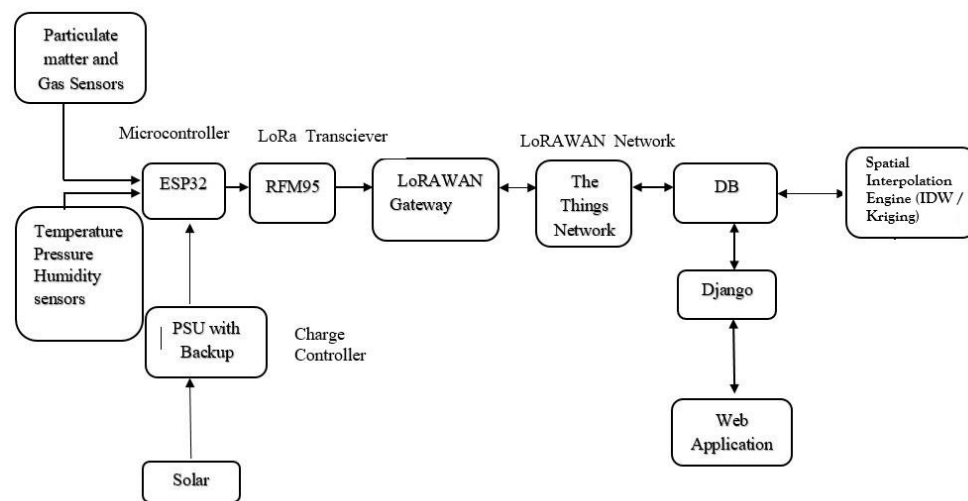


Fig. 1. Block diagram of the complete system

The proposed LoRa-based architecture supports low-power long-range communication suitable for sparse environmental monitoring deployments. The communication framework enables scalable integration of multiple sensor nodes with minimal infrastructure requirements. Due to the lightweight nature of LoRa communication, the system supports near real-time environmental monitoring with low transmission overhead. Furthermore, the architecture can be expanded for larger monitoring areas by incorporating additional gateway nodes.

The present study primarily focuses on validating interpolation performance using sensor measurements collected through the LoRa-based sensing framework. Detailed large-scale communication reliability analysis and long-term network performance evaluation are considered as part of future work.

A comparative analysis of multiple spatial interpolation techniques was conducted and optimized their parameters to estimate the values at unsampled locations using surrounding sampled point. The optimal interpolation method was selected using quantitative validation based on Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) between interpolated values and actual sensor observations. Leave-one-out validation was performed by treating one sensor node as an unknown location while using the remaining sensor measurements for interpolation. For each interpolation method, one sensor node was iteratively excluded and treated as an unknown location, while the remaining sensor observations were used for interpolation. This process was repeated for all monitoring locations and environmental parameters. The final RMSE and MAE values were obtained by averaging the prediction errors across all validation iterations. From a computational perspective, IDW and Nearest Neighbor methods exhibited lower processing complexity and faster execution due to their deterministic nature. Kriging and EBK required higher computational overhead because of covariance matrix estimation and semivariogram modeling. However, since the study involves sparse sensor deployment with only five monitoring nodes, the computational latency remained sufficiently low for near real-time implementation within the proposed LoRa-based framework. The process was repeated across multiple pollutants and meteorological parameters. The interpolation method yielding the minimum average RMSE and MAE was selected as the most suitable method for the Kalady region.

The mathematical formulations for each technique are as follows:

A) Inverse Distance Weighting (IDW)

IDW is a deterministic spatial method that assumes influences of nearby sampled locations are stronger for an unsampled location than distant sampled locations. The interpolated value is estimated by weighted sum of the sampled points around, where the weights are determined by the distance and a power parameter. Power controls the rate at which influence drops off with distance; it is higher for closer sites. IDW is intuitive and easily implemented with low computational cost and has been applied in environmental monitoring extensively.

Here the pollutant concentrations are estimated based on the inverse distances from known data points:

$$w_i = \frac{1}{d_i^p} \quad (1)$$

$$V(x_0) = \frac{\sum_{i=1}^n w_i V(x_i)}{\sum_{i=1}^n w_i} \quad (2)$$

where distance is:

$$d = \sqrt{(x - x_i)^2 + (y - y_i)^2} \quad (3)$$

where w_i represents the interpolation weight assigned to the i^{th} sampled location, d_i denotes the distance between the target point and sampled point, and p represents the distance decay power parameter, typically ranging from 1.5 to 3.0.

Improved Inverse Distance Weighting (IDW)

$$V(x_0) = \frac{\sum_{i=1}^n (\varphi_i V(x_i))}{\sum_{i=1}^n \varphi_i} \quad (4)$$

Where $V(x_0)$ represents the interpolated value at target location x_0 . $V(x_i)$ represents known values at sampling locations x_i .

$$\varphi_i = \frac{1}{[d(x_0, x_i)]^\alpha} \quad (5)$$

$$d(x_0, x_i) = \sqrt{(lat_0 - lat_i)^2 + (lon_0 - lon_i)^2} \quad (6)$$

$\alpha(r)$ is the adaptive power parameter

$$\alpha(r) = \alpha_0(1 + \beta r) \quad (7)$$

$$r = \frac{(d - d_{min})}{d_{max} - d_{min}} \quad (8)$$

B) Kriging

Kriging is a geostatistical interpolation method that predicts values using weighted averages:

$$Z(s) = \mu(s) + \varepsilon(s) \quad (9)$$

Where $Z(s)$ is the predicted value at location s . $\mu(s)$ is the deterministic trend. $\varepsilon(s)$ is the spatially correlated random error.

Modified Kriging with Local Variance

$$V(x_0) = \sum_{i=1}^n [\omega_i(x_0) V(x_i)] \quad (10)$$

Subject to the constraints:

$$\sum_{i=1}^n \omega_i(x_0) = 1 \quad (11)$$

$$E[V * (x_0) - V(x_0)] = 0 \quad (12)$$

Where $\omega_i(x_0)$ are the location-specific weights. The weights are determined by solving

$$\begin{bmatrix} C_{21} & C_{12} & \cdots & C_{1n} & 1 \\ C_{21} & C_{22} & \cdots & C_{2n} & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ C_{n-1} & C_{n2} & \cdots & C_{nn} & 1 \\ 1 & 1 & \cdots & 1 & 0 \end{bmatrix} \begin{bmatrix} \omega_1 \\ \omega_2 \\ \vdots \\ \omega_n \\ \lambda \end{bmatrix} = \begin{bmatrix} C_{10} \\ C_{20} \\ \vdots \\ C_{no} \\ 1 \end{bmatrix} \quad (13)$$

$$\text{With } C_{ij} = \sigma^2 \times \rho(\|x_i - x_j\|/\theta)$$

C) Radial Basis Function (RBF)

RBF interpolation employs radial functions to estimate unknown values. Smooth interpolation with radial basis functions is smooth interpolator with the positive definite radial function centered at sampled points. The estimate is obtained using a linear combination of radial basis functions, whose effect varies according to the distance from the points with available information. The parameter is the shape of the interpolated surface. RBF has the advantage of generating smooth continuous surfaces and is effective when input environmental data vary smoothly.

$$\varphi(r) = \sqrt{(r^2 + c^2)} \quad (14)$$

where r is the Euclidean distance. c is a shape parameter

Generalized Radial Basis Function (RBF)

$$V(x_0) = \sum_{i=1}^n [\beta_i \times \Phi(\|x_0 - x_i\|)] \quad (15)$$

Where

$$\Phi(r) = \sqrt{(r^2 + \gamma^2)} \times \exp(-r^2/2\sigma^2) \quad (16)$$

$$\Phi(r) = \sqrt{(r^2 + \gamma^2)} \exp\left(-\frac{r^2}{2\sigma^2}\right)$$

γ is the shape parameter. σ is the scale parameter. β_i are coefficients determined by solving:

$$\Phi B = V \quad (17)$$

$$\Phi_{ij} = \Phi(\|x_i - x_j\|) \quad (18)$$

D) Empirical Bayesian Kriging (EBK)

EBK extends traditional Kriging by incorporating Bayesian inference:

$$K(x, x') = \sigma^2 \exp\left(-\frac{\|x - x'\|^2}{2l^2}\right) \quad (19)$$

Where σ^2 - variance (controls magnitude), l - length scale (controls smoothness) and $\|x - x'\|$ - distance between two locations

$$K(x, x') = \sigma^2 \left(1 + \frac{\sqrt{5}r}{l} + \frac{5r^2}{3l^2}\right) \exp\left(-\frac{\sqrt{5}r}{l}\right) \text{ [Matern kernel]} \quad (20)$$

Where $r = \|x - x'\|$

The Matern kernel is more flexible than Gaussian and allows different smoothness levels. EBK is a better model for environmental data (which are not perfectly smooth). It is widely used in geostatistics.

The final prediction is a weighted average:

$$\text{prediction} = \Sigma (\text{likelihood}_i * \text{prediction}_i) / \Sigma (\text{likelihood}_i) \quad (21)$$

E) Nearest Neighbor (NN) Interpolation

NN interpolation assigns the value of the nearest measured data point to the target location:

$$\text{distance} = \sqrt{(x - x_{\text{target}})^2 + (y - y_{\text{target}})^2} \quad (22)$$

This is the Euclidean distance formula. It calculates the straight-line distance between:

A sampled point (x, y), The target (unsampled) location (x_{target} , y_{target}). It comes from the Pythagorean theorem. Because Nearest Neighbor interpolation needs to find which sampled point is closest to the target location.

$$\text{value} = \text{values}[\arg \min(\text{distances})] \quad (23)$$

distances = list of distances from target to all sampled points

min(distances) = smallest distance

arg min(distances) = index (position) of the smallest distance

F) Akima Interpolation

Akima interpolation uses piecewise polynomials to estimate values:

Slope Estimation:

$$m_i = w_1 t_i + w_2 t_{i+1} \quad (24)$$

where t_i are divided differences. w_1 , w_2 are weights based on $|t_{i+1} - t_i|$ and $|t_i - t_{i-1}|$. If slopes change suddenly (large difference), Akima reduces influence to prevent oscillations. So it adapts based on local gradient variation.

G) PCHIP (Piecewise Cubic Hermite Interpolation)

PCHIP maintains monotonicity and preserves shape during interpolation:

$$p(x) = h_{00}(t)p_k + h_{10}(t)h_k\delta_k + h_{01}(t)p_{k+1} + h_{11}(t)h_k\delta_{k+1} \quad (25)$$

where t is the normalized distance. h_{ij} are Hermite basis functions. δ_k , δ_{k+1} are slopes, p_k - value at left point, p_{k+1} value at right point.

H) Cubic Spline (CS) Interpolation

Cubic spline fits a series of cubic polynomials between each pair of data points. Instead of one global polynomial, it builds small cubic functions for each interval.

$$f(x) = a_i(x - x_i)^3 + b_i(x - x_i)^2 + c_i(x - x_i) + d_i \quad (26)$$

a_i , b_i , c_i , d_i -coefficients for interval $[x_i, x_{i+1}]$, where coefficients ensure C^2 continuity and ensuring smooth transitions between intervals.

4. Results

The findings from the spatial interpolation analysis over a one-year period in estimating air quality parameters; PM2.5, PM10 and meteorological factors like Temperature, Humidity, Pressure is in the Figure 2-3. The dataset was collected from five locations in Kalady, in Ernakulam District, Kerala, India: A-Mattoor (10°10'15"N 76°25'46"E), B-Marottichodu (10°10'18"N 76°25'17"E), C-Kaipattoor (10°10'27"N 76°26'46"E), D-Kalady Junction (10°09'57"N 76°26'20"E), E-Chengal (10°09'35"N 76°25'44"E).

These locations are selected based on high population density, traffic congestion, residential and industrial zones, educational institutions, frequent pollution complaints and surveys. A is interpolated using locations B, C, D, E. The interpolated values were compared against the actual sensor measurements, with their performance are computed using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics.

Five-fold cross-validation was employed to improve statistical reliability and reduce model overfitting during interpolation model evaluation.

Among the eight interpolation methods analyzed (Akima, CS, IDW, Kriging, NN, PCHIP, EBK, and RBF), Kriging and IDW consistently demonstrated the best performance, especially in assessments of humidity, PM2.5, and PM10. Based on the results, the Kriging interpolation and Inverse Distance Weighting Interpolation method is selected for "Kalady" region. Table 3 depicts the sample dataset of the work.

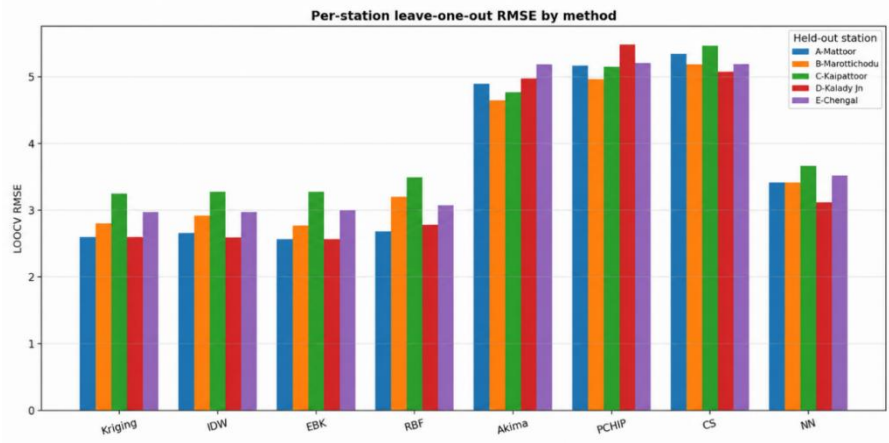


Fig. 2. Station-wise LOOCV RMSE comparison of spatial interpolation methods.

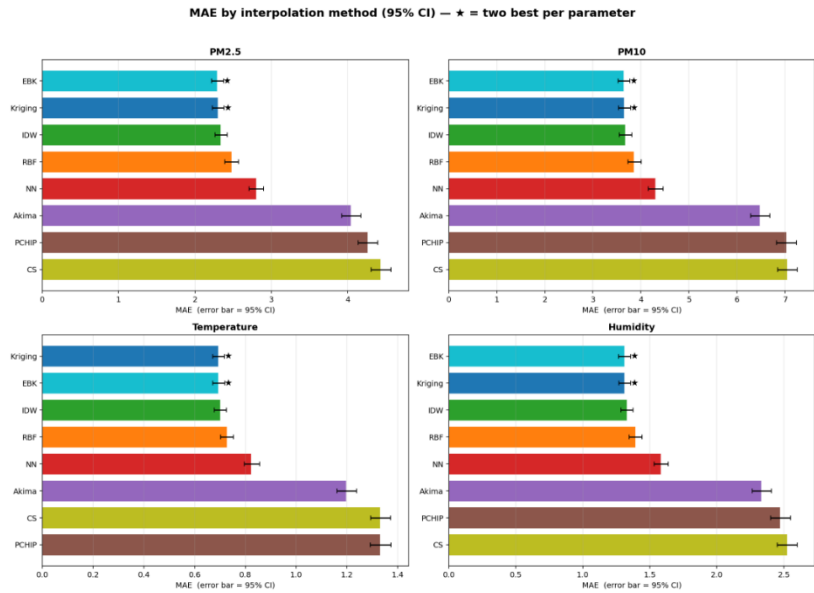


Fig. 3. MAE-based performance evaluation of interpolation methods with 95% confidence intervals for air quality and meteorological parameters

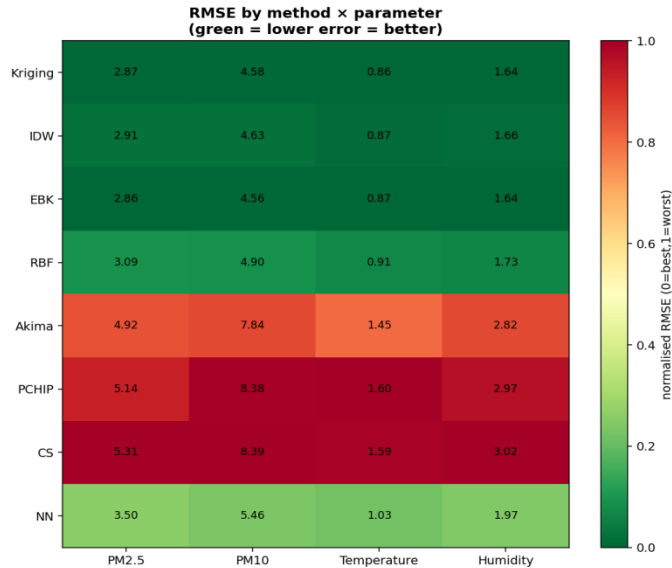


Fig. 4. Heatmap representation of RMSE performance for different interpolation methods across PM2.5, PM10, temperature, and humidity parameters

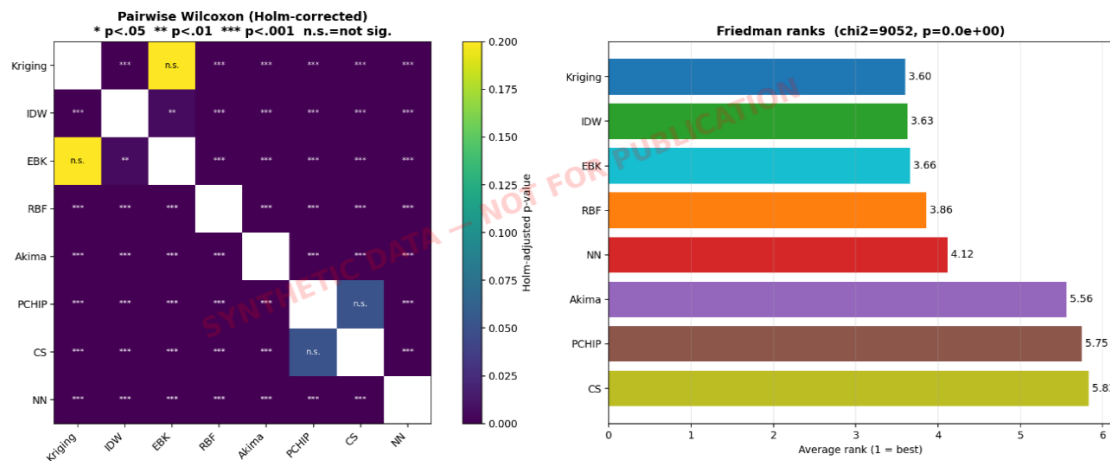


Fig. 5. Statistical significance of performance differences among the eight interpolation methods, computed from per-sample absolute errors under leave-one-out cross-validation. (a) Holm-corrected pairwise Wilcoxon signed-rank p-values; darker cells indicate stronger evidence of a difference (***) $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, n.s. = not significant). (b) Friedman test average ranks (lower = better; χ^2 and p reported above the panel). The results indicate that the top-performing methods are statistically equivalent to one another but significantly more accurate than the remaining techniques.

Table 2. Comparative performance of eight spatial interpolation methods evaluated by RMSE and MAE (point estimate with 95% CI; $n = 1825$). Lower values indicate better accuracy.

Method	RMSE (95% CI)	MAE (95% CI)
PM2.5 (n = 1825)		
Kriging	2.870 (2.778–2.961)	2.306 (2.226–2.381)
IDW	2.914 (2.823–3.006)	2.339 (2.261–2.419)
EBK	2.864 (2.773–2.955)	2.295 (2.217–2.373)
RBF	3.090 (2.992–3.187)	2.485 (2.391–2.569)
Akima	4.921 (4.781–5.073)	4.046 (3.921–4.175)
PCHIP	5.138 (4.996–5.272)	4.267 (4.135–4.394)
CS	5.305 (5.166–5.449)	4.434 (4.307–4.567)
NN	3.498 (3.391–3.605)	2.805 (2.710–2.900)
PM10 (n = 1825)		
Kriging	4.575 (4.430–4.721)	3.658 (3.535–3.783)
IDW	4.633 (4.481–4.781)	3.683 (3.548–3.812)
EBK	4.556 (4.410–4.708)	3.649 (3.526–3.770)
RBF	4.899 (4.735–5.070)	3.862 (3.729–4.002)
Akima	7.842 (7.624–8.064)	6.479 (6.285–6.685)
PCHIP	8.376 (8.158–8.605)	7.030 (6.824–7.235)
CS	8.392 (8.185–8.607)	7.047 (6.842–7.255)
NN	5.465 (5.293–5.640)	4.310 (4.155–4.465)
Temperature (n = 1825)		
Kriging	0.864 (0.835–0.892)	0.694 (0.670–0.717)
IDW	0.872 (0.845–0.901)	0.701 (0.678–0.725)
EBK	0.866 (0.839–0.895)	0.694 (0.670–0.719)
RBF	0.913 (0.884–0.944)	0.728 (0.702–0.752)
Akima	1.454 (1.414–1.494)	1.198 (1.160–1.237)
PCHIP	1.598 (1.556–1.640)	1.332 (1.292–1.373)
CS	1.590 (1.550–1.630)	1.332 (1.293–1.373)
NN	1.026 (0.993–1.058)	0.824 (0.796–0.856)
Humidity (n = 1825)		
Kriging	1.639 (1.587–1.692)	1.313 (1.269–1.358)
IDW	1.656 (1.605–1.708)	1.330 (1.284–1.373)
EBK	1.640 (1.593–1.695)	1.312 (1.267–1.358)
RBF	1.730 (1.677–1.785)	1.395 (1.346–1.440)
Akima	2.821 (2.746–2.898)	2.335 (2.264–2.407)
PCHIP	2.969 (2.888–3.049)	2.475 (2.402–2.550)
CS	3.020 (2.939–3.100)	2.528 (2.450–2.601)
NN	1.974 (1.911–2.036)	1.586 (1.532–1.638)

The experimental evaluation indicates that, within this deployment, Kriging and IDW achieved the best interpolation performance, consistently producing lower RMSE and MAE values across PM2.5, PM10, temperature, and humidity, with Empirical Bayesian Kriging (EBK) performing comparably. Kriging showed reliable accuracy due to its ability to incorporate spatial autocorrelation and capture the underlying spatial variability of the measured parameters, while EBK provided similarly robust estimates by accounting for uncertainty in the spatial relationships. IDW also performed strongly

owing to its simple, effective distance-based weighting, although its accuracy depends on sensor distribution and spatial proximity. In contrast, Nearest Neighbor produced higher errors because it assumes abrupt spatial transitions and does not account for spatial continuity. The RBF, Akima, PCHIP, and Cubic Spline methods generated smoother surfaces but tended to over-smooth, reducing accuracy where pollutant concentrations changed rapidly. Statistical testing (Friedman test with Holm-corrected pairwise Wilcoxon comparisons) confirmed that the top-performing methods were statistically indistinguishable from one another while significantly outperforming the remaining techniques. Overall, the results identify Kriging and IDW as the most effective methods for spatial estimation in this sparse, single-region deployment, though broader validation is needed to generalize these findings.

Table 3. Sample Dataset (First 5 rows)

Date	Station	Latitude	Longitude	Parameter	Value
01-08-2022	A-Mattoor	10.1708	76.4294	PM2.5	23.66
01-08-2022	B-Marottichodu	10.1717	76.4214	PM2.5	26.36
01-08-2022	C-Kaipattoor	10.1742	76.4461	PM2.5	29.58
01-08-2022	D-Kalady Jn	10.1658	76.4389	PM2.5	23.27
01-08-2022	E-Chengal	10.1597	76.4289	PM2.5	21.50
02-08-2022	A-Mattoor	10.1708	76.4294	PM2.5	26.88
02-08-2022	B-Marottichodu	10.1717	76.4214	PM2.5	27.82
02-08-2022	C-Kaipattoor	10.1742	76.4461	PM2.5	30.70
02-08-2022	D-Kalady Jn	10.1658	76.4389	PM2.5	33.98
02-08-2022	E-Chengal	10.1597	76.4289	PM2.5	29.49

5. Conclusion

This work presents a case study evaluating spatial interpolation techniques for air-quality estimation under sparse, low-power sensing conditions. Using data from five LoRa-based monitoring nodes in the Kalady region, eight conventional interpolation methods were compared through leave-one-out cross-validation across multiple pollutant and meteorological parameters. Within this deployment, Kriging and IDW achieved the most consistent accuracy, although performance differed across stations and parameters — underscoring the strong influence of local topography, urban density, and atmospheric conditions on method selection.

The primary objective of this study is to comparatively evaluate interpolation performance under sparse sensing rather than to establish a large-scale regional pollution model. Accordingly, the findings are specific to this deployment and should not be generalized to larger or structurally different urban environments without further validation. The study is limited to five monitoring locations within a single semi-urban region, which restricts the generalizability of the results; interpolation accuracy and the best-performing method may vary with study area, sensor density, and microclimatic conditions.

Future work will focus on expanding the sensing infrastructure across additional stations and broader geographic regions, and on integrating larger and longer-duration datasets to enable more robust, generalizable evaluation. Further directions include incorporating additional pollutants and real-time meteorological data, and using the interpolated spatial fields as inputs to AI-based forecasting models — ultimately supporting a health-assessment application that advises users, based on their health status, whether a location is safe.

All the Declarations and Statements

Author Contributions Statement

Ajay Kumar (Department of Electronics and Communication Engineering) – Conceptualization, Methodology, and Supervision: Proposed the research idea and the interpolation-comparison framework, and supervised project execution and the LoRa-based sensor system design.

Albins Paul (Department of Electronics and Communication Engineering) – Hardware Design and Field Deployment: Designed the LoRa-based sensor hardware, carried out field deployment of the five monitoring stations, and validated sensor readings.

P V Rajaraman (Department of Artificial Intelligence & Data Science) – Data Curation and Algorithm Implementation: Handled data acquisition and preprocessing and implemented the eight spatial interpolation methods and the leave-one-out cross-validation pipeline.

Hasna Hameed (Department of Electronics and Communication Engineering / Centre for AI-IoT Innovation) – Formal and Statistical Analysis: Performed the RMSE/MAE analysis, prepared the performance charts and heatmaps, and

conducted the statistical significance testing (Friedman and Wilcoxon tests).

All authors contributed to writing, review and editing of the manuscript. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The authors declare no conflicts of interest.

Funding Declaration

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Data Availability Statement

This study analyzed data collected by the authors from five LoRa-based sensor nodes in Kalady, Kerala, India. The datasets are available from the corresponding author upon reasonable request.

Ethical Declarations

This study did not involve human subjects or animals beyond an anonymous, voluntary health-status questionnaire used solely to inform the conceptual health-assessment framework; no personally identifiable health data were collected or analyzed. Formal institutional ethical approval: Not applicable.

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Declaration of Generative AI in Scholarly Writing

During the preparation of this manuscript, the authors used Claude (Anthropic) to assist with sentence-level writing, grammar correction, and language translation, and to assist with generating and organizing portions of the code used for the interpolation analysis. All AI-assisted content was reviewed, verified, and edited by the authors, who take full responsibility for the accuracy, integrity, and originality of the final published work.

Abbreviations

The following abbreviations are used in this manuscript:

AI – Artificial Intelligence
IoT – Internet of Things
AQI – Air Quality Index
PM_{2.5} – Particulate Matter ($\leq 2.5 \mu\text{m}$)
PM₁₀ – Particulate Matter ($\leq 10 \mu\text{m}$)
IDW – Inverse Distance Weighting
EBK – Empirical Bayesian Kriging
RBF – Radial Basis Function
NN – Nearest Neighbor
PCHIP – Piecewise Cubic Hermite Interpolation Polynomial
CS – Cubic Spline
RMSE – Root Mean Square Error
MAE – Mean Absolute Error
LOOCV – Leave-One-Out Cross-Validation
LoRa/LoRaWAN – Long Range (Wide Area Network)

Appendix A/B/C..., with appendix title

Not applicable.

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