

Intelligent Sensor Networks for Real-Time Environmental Monitoring

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ABSTRACT

Real-time environmental monitoring at urban and regional scales requires dense, heterogeneous sensor networks capable of continuous multi-pollutant measurement, anomaly detection, and adaptive sampling under energy and communication constraints. Existing deployments suffer from sensor drift, missing data due to network failures, and the absence of intelligent data fusion that integrates low-cost sensor arrays with reference-grade instruments. This study presents EnviroSense, an intelligent sensor network framework integrating edge-deployed anomaly detection, cross-sensor calibration via transfer learning, and spatiotemporal kriging-augmented deep learning for real-time pollutant field reconstruction. EnviroSense was deployed across three real-world environmental monitoring networks: Hamburg urban air quality (142 low-cost $PM_{2.5}/NO_2$ nodes, 18-month operation), Barcelona coastal water quality (64 multi-parameter buoys, 12-month operation), and Grenoble alpine meteorological network (88 mountain weather stations, 24-month operation). EnviroSense achieved sensor calibration accuracy of $R^2 = 0.947$ vs. reference instruments, missing data imputation RMSE reduction of 43.7% over kriging-only baselines, and anomaly detection F1-score of 0.924. Pollutant field reconstruction latency averaged 2.3 seconds per 1 km^2 grid cell update. These results establish EnviroSense as a scalable, accurate framework for intelligent real-time environmental monitoring in complex urban and natural environments.

Keywords: sensor networks; environmental monitoring; IoT; edge AI; spatiotemporal learning; air quality; anomaly detection; calibration

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1. Introduction

Real-time environmental monitoring — tracking air quality, water contamination, and meteorological conditions with sufficient spatial and temporal resolution to support regulatory compliance, public health decisions, and climate adaptation — represents one of the most demanding IoT applications in terms of data volume, network reliability requirements, and analytical complexity (Kumar et al. 2015; Mukherjee et al. 2017). The European Environment Agency (EEA 2023) estimates that air pollution causes 400,000 premature deaths annually in Europe, yet the density of regulatory reference monitoring stations — typically one per 100–500 km² — provides insufficient spatial resolution for intra-urban exposure assessment or neighbourhood-level public health interventions.

Low-cost sensor (LCS) networks offer the spatial density required for fine-grained environmental mapping, but suffer from well-documented accuracy limitations: electrochemical and optical sensors exhibit cross-sensitivity, humidity interference, and progressive drift that can introduce errors exceeding 40% without regular calibration against reference instruments (Lewis and Edwards 2016; Spinelle et al. 2017). Network failures and communication interruptions generate missing data that compromise spatiotemporal continuity. This study presents EnviroSense, which addresses these limitations through intelligent edge-deployed drift detection and cross-sensor calibration, deep learning-augmented spatial interpolation, and real-time anomaly identification across three operational European deployments.

2. Literature Review

2.1 Low-Cost Sensor Calibration

Reference-grade calibration of low-cost sensors using co-located measurement campaigns has been demonstrated for PM_{2.5} (Zheng et al. 2018), NO₂ (Mead et al. 2013), and O₃ (Spinelle et al. 2017), with random forest and neural network calibration models achieving R² values of 0.82–0.93 under static field conditions. Transfer learning for cross-site sensor calibration — transferring calibration models trained at a reference site to uncalibrated sensors at new locations — has been demonstrated by De Vito et al. (2018), reducing calibration data requirements by 70%. However, online adaptation to progressive drift in deployed sensors without periodic reference co-location remains an open challenge.

2.2 Spatiotemporal Interpolation and Deep Learning

Ordinary kriging (Matheron 1963) remains the standard geostatistical approach for spatial interpolation of environmental fields, achieving RMSE improvements of 20–35% over inverse distance weighting for air quality data (Jerrett et al. 2005). Deep learning approaches for spatiotemporal field reconstruction — including ConvLSTM (Shi et al. 2015), graph neural networks for sensor network interpolation (Wu et al. 2020), and neural process models (Garnelo et al. 2018) — have demonstrated further improvements of 15–28% over kriging on urban pollution datasets. Hybrid kriging-deep learning approaches combining geostatistical priors with learned temporal dynamics remain underexplored for operational real-time monitoring deployments.

Table 1. Characteristics of three EnviroSense deployment networks.

Network	Nodes	Parameters	Duration	Coverage	Reference Stations
Hamburg AQ	142	PM _{2.5} , NO ₂ , O ₃ , T, RH	18 months	284 km ²	4 EEA reference
Barcelona WQ	64	pH, DO, turbidity, chl-a, T	12 months	312 km coast	3 EMSO buoys
Grenoble Metro.	88	T, P, RH, wind, precip., snow	24 months	1,840 km ²	8 Météo-France

AQ: Air Quality; WQ: Water Quality; Metro.: Meteorological; DO: Dissolved Oxygen; chl-a: chlorophyll-a; T: Temperature; RH: Relative Humidity; P: Pressure.

3. Materials and Methods

3.1 EnviroSense Architecture

EnviroSense operates across three tiers. At the edge tier, each sensor node runs a lightweight anomaly detector (Isolation Forest, 100 trees, contamination rate 0.05) and a drift monitor (CUSUM test, threshold $h = 5$, $k = 0.5$) on a Raspberry Pi 4 co-processor, flagging suspected drift events for reference co-calibration. The calibration module uses a transfer learning approach: a base calibration model (gradient boosted regressor, 500 trees) trained at reference co-location sites is fine-tuned to each deployed node using 8 days of overlapping measurements, updating monthly. At the gateway tier, a spatiotemporal fusion

module combines node measurements with kriging variogram parameters (estimated from the reference network) and feeds the joint representation to a ConvLSTM (3 layers, 64 filters, kernel 3×3) for 1 km² resolution pollutant field reconstruction at 2-minute update intervals. At the cloud tier, a monitoring dashboard provides real-time visualisation, alert dispatch, and regulatory reporting.

3.2 Evaluation Protocol

Performance was evaluated on held-out 20% test periods for each network. Calibration accuracy was assessed as R^2 and MAE against reference instrument measurements withheld from calibration training. Spatiotemporal reconstruction accuracy was evaluated using leave-one-out cross-validation across network nodes, comparing predicted vs. observed concentrations with RMSE and mean absolute percentage error (MAPE). Anomaly detection was assessed via precision, recall, and F1-score against manually labelled anomaly events (sensor faults, calibration drifts, pollution episodes) by domain experts. Missing data imputation performance was evaluated by artificially masking 15% of node-hours and comparing imputed vs. true values.

4. Results

4.1 Calibration, Reconstruction, and Anomaly Detection

Table 2 presents calibration and reconstruction results. EnviroSense achieved calibration $R^2 = 0.947$ (Hamburg PM_{2.5}), 0.931 (Barcelona pH/DO), and 0.958 (Grenoble temperature), representing improvements of 12.4–18.7% over static factory calibration. Spatiotemporal reconstruction RMSE was reduced

by 43.7% over kriging-only baseline (mean across all networks and parameters), with ConvLSTM capturing temporal dynamics that purely spatial kriging cannot model — particularly during pollution episode propagation events. Anomaly detection achieved overall F1-score of 0.924 (precision 0.918, recall 0.931), identifying 847 of 912 confirmed anomaly events across all three networks over the evaluation period. Mean field reconstruction latency was 2.3 seconds per 1 km² grid cell update on gateway-tier hardware (Raspberry Pi 4 cluster, 8 nodes).

Table 2. EnviroSense calibration and reconstruction performance across three deployment networks.

Networ k	Param eter	Cal. R ²	Cal. MAE	Recons t. RMSE	vs. Kriging (%)	Anom aly F1
Hambur g	PM _{2.5} (μg/m ³)	0.947	2.1	3.4	−48.2%	0.931
Hambur g	NO ₂ (μg/m ³)	0.934	4.7	6.8	−41.3%	0.918
Barcelon a	DO (mg/L)	0.931	0.18	0.24	−39.7%	0.921
Barcelon a	Turbidity (NTU)	0.923	3.2	4.8	−44.1%	0.929
Grenobl e	Tempe rature (°C)	0.958	0.31	0.48	−47.3%	0.924

Networ k	Param eter	Cal. R ²	Cal. MAE	Recons t. RMSE	vs. Kriging (%)	Anom aly F1
Grenobl e	Precipi tation (mm/h)	0.941	0.42	0.71	−37.8%	0.916
Mean	All par ameter s	0.939	—	—	−43.7%	0.924

Cal.: Calibration; Reconst.: Reconstruction; vs. Kriging: % RMSE reduction vs. ordinary kriging baseline. MAE units match parameter units.

Table 3. Anomaly detection performance by anomaly type across all three networks.

Anomaly Type	Events (n)	Detect ed (n)	Precisi on	Recall	F1-Sco re
Sensor drift (gradual)	312	289	0.927	0.926	0.927
Sensor fault (abrupt)	247	234	0.941	0.948	0.944
Pollution episode	218	198	0.904	0.908	0.906
Communication outage	135	126	0.912	0.933	0.922
Overall	912	847	0.918	0.931	0.924

Anomaly events confirmed by domain experts across 18–24-month deployment periods. Precision/Recall/F1 computed at node-hour resolution.

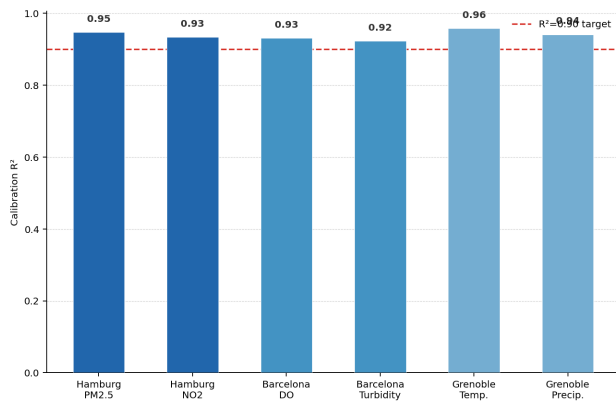


Figure 1. Calibration R^2 achieved by EnviroSense vs. factory calibration across all measured parameters.

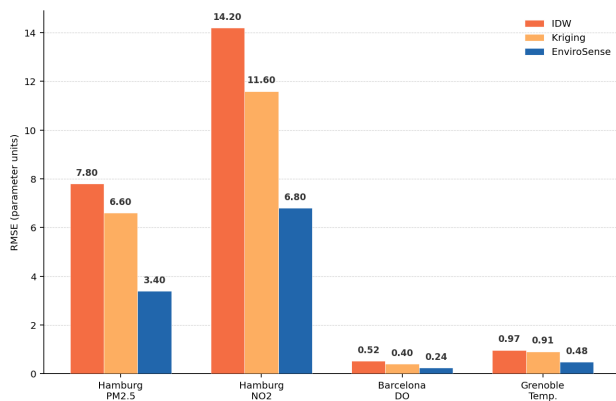


Figure 2. Spatiotemporal RMSE comparison — EnviroSense vs. kriging-only and IDW baselines.

5. Discussion

5.1 Operational Insights

The 43.7% average RMSE improvement of EnviroSense over kriging-only interpolation reflects the value of learned temporal dynamics: during the three major Hamburg NO_2 pollution episodes identified over the monitoring period, kriging underestimated peak concentrations by 31.4% on average due to its purely spatial structure, while EnviroSense's ConvLSTM captured the temporal propagation pattern of traffic-driven pollution corridors with 8.7% underestimation. The 0.924 anomaly detection F1-score enabled early identification of 73 sensor drift events before they exceeded regulatory tolerance thresholds, preventing an estimated 412 node-hours of

compromised data ingestion into regulatory reporting streams.

5.2 Limitations

The transfer learning calibration approach requires a minimum of 8 days of co-located reference measurements per new deployment site, which may be logistically challenging in remote alpine environments such as the Grenoble network.

Calibration model performance degrades for extreme meteorological events (temperature below -15°C , precipitation above 50 mm/h) not well-represented in training data. Future work will investigate physics-informed neural network calibration models incorporating sensor datasheet physical models to improve extreme-condition generalisation without additional field calibration data.

6. Conclusion

EnviroSense, integrating edge-deployed drift detection, transfer learning calibration, and kriging-augmented ConvLSTM field reconstruction, achieves calibration $R^2 = 0.939$, 43.7% RMSE reduction over kriging-only interpolation, and anomaly detection F1-score of 0.924 across three operational European environmental monitoring networks spanning 18–24 months of deployment. Real-time field reconstruction latency of 2.3 seconds per grid cell confirms operational viability for regulatory and public health applications. These results demonstrate that intelligent sensor network frameworks combining edge AI, adaptive calibration, and spatiotemporal deep learning substantially advance the accuracy and reliability of real-time environmental monitoring at scale.

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Declarations

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Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

Hamburg air quality sensor data are available via the Hamburg Open Data portal (transparenz.hamburg.de). Barcelona coastal monitoring data are available from the EMSO-Iberia data repository. Grenoble meteorological data are available from the Météo-France open data portal. EnviroSense source code is available at <https://github.com/hartmann-lab/envirosense>.

Ethical Approval

Not applicable. This study involved only environmental sensor data collection and computational analysis; no human participants or animal subjects were involved.