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EcoEdge-AI: A Carbon-Aware Lightweight Edge AI Frameworkfor Sustainable Environmental Monitoring

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Abstract
Artificial intelligence is increasingly being used to support environmental monitoring, but the computing required to train and deploy AI models can itself consume energy and create environmental costs. This paper proposes EcoEdge-AI, a lightweight and carbon-aware edge computing framework for environmental monitoring. The framework is designed around a simple principle: perform time-critical inference close to the sensor, keep raw data local whenever possibleand transmit only meaningful information, and treat energy, latency and prediction quality as joint design objectives. The proposed framework combines Internet of Things (IoT) sensing, lightweight machine learning, edge inference, selective cloud synchronization and an explicit sustainability score. The research uses the publicly documented UCI Air Quality dataset as a reproducible evaluation basis. The dataset contains 9,358 hourly observations and 15 attributes related to air-quality sensor responses, pollutant concentrations and meteorological variables. The proposed evaluation protocol compares predictive quality with computational cost, latency and data-transfer requirements rather than reporting accuracy alone. A mathematical objective function is introduced to select a model under a predefined sustainability budget. The framework is aligned with the conference themes of computer-based environmental protection and ethical, responsible computing. Recent research indicates that Green AI methods such as model compression, quantization and efficient architectures can reduce computational demand, while sustainable edge computing research emphasizes energy-aware task placement and carbon-aware operation. The proposed framework brings these ideas together at the application level and provides a practical blueprint for low-resource environmental intelligence. The work is intended as a reproducible research framework; measured hardware-energy results should be added only after execution on the selected edge device.
***Keywords**: Green AI; Edge AI; Sustainable Computing; IoT; Environmental Monitoring; Carbon-Aware Computing; Air Quality; Responsible AI; Energy Efficiency.*

1. Introduction

Environmental protection is increasingly dependent on digital systems. Sensors continuously collect information about air quality, temperature, humidity, water quality, traffic, industrial activity and other environmental conditions. Artificial intelligence can convert these observations into predictions and alerts, making environmental monitoring more responsive. However, the environmental cost of computing should also be considered. Modern AI workloads may require substantial electricity, cooling and network infrastructure, especially when large models are repeatedly executed in centralized data centers.

This creates an important research question for computer science: how can useful AI-based environmental monitoring be delivered with less computational and communication overhead? One answer is to move suitable computation from centralized cloud systems to edge devices. Edge AI places processing closer to the sensor or gateway. This can reduce latency, reduce repeated data transmission and improve privacy. At the same time, edge devices have limited CPU, memory, storage and energy resources. Therefore, simply moving an AI model to the edge does not automatically make a system sustainable.

Recent literature has begun to treat sustainability as a property of the entire AI lifecycle rather than as a secondary concern. A 2026 systematic review of Green and Sustainable AI identifies model-level efficiency, hardware and system optimization, lifecycle-aware methods, and operational or policy-level sustainability as major categories. Another recent review of Green AI reports that model compression, quantization, efficient architectures and infrastructure measures are important routes for lowering AI energy requirements. Research on sustainable edge computing also highlights carbon-aware task placement, energy-aware offloading and measurement of energy and carbon footprints.

The present paper proposes EcoEdge-AI as an application-oriented framework for environmental monitoring. The focus is not on building a very large AI model. Instead, the contribution is a structured method for selecting a sufficiently accurate and computationally efficient model for environmental sensing. The framework connects four components: IoT sensing, lightweight AI, edge decision-making and carbon-aware resource management.

The conference theme explicitly includes Computer Vision, Robotics and Internet of Things for Environmental Protection and Ethical AI and Responsible Computing for Environmental Sustainability. EcoEdge-AI is designed at this intersection. It treats sustainability as an engineering constraint and responsibility rather than simply as a claim about the final application.

2. Problem Statement and Research Gap

Conventional environmental monitoring architectures commonly transmit large amounts of sensor data to a cloud server for processing. This architecture is convenient, but it can create repeated network traffic and delay decisions that could be made locally. At the opposite extreme, a fully local system may use a model that is too computationally expensive for a low-power gateway. The practical gap is therefore the absence of a simple deployment rule that jointly considers prediction quality, energy cost, latency and data transfer.

Existing Green AI studies often evaluate individual techniques such as quantization or model compression, while edge-computing studies frequently focus on latency, offloading or resource allocation. EcoEdge-AI combines these concerns into one environmental-monitoring workflow. The research gap addressed here is therefore methodological: a lightweight, interpretable framework is needed for choosing an environmental AI model under an explicit sustainability budget.

3. Objectives

• Design a lightweight Edge AI architecture for real-time environmental monitoring.

• Define a multi-objective model-selection score that includes prediction quality, energy, latency and communication cost.

• Use a public air-quality dataset to create a reproducible evaluation protocol.

• Show how ethical and responsible computing principles can be incorporated into environmental AI.

• Provide a deployment pathway suitable for low-resource IoT gateways and future smart environmental systems.

4. Literature Review

The UCI Air Quality dataset is a well-documented multivariate time-series dataset in the Computer Science subject area. It contains 9,358 hourly observations from an air-quality chemical multisensor device deployed in an Italian city and includes 15 attributes. The dataset provides reference measurements for CO, non-methane hydrocarbons, benzene, NOx and NO_2 together with sensor responses, temperature, relative humidity and absolute humidity. Missing values are encoded as −200. The dataset is suitable for regression-oriented experiments and is available under a CC BY 4.0 license.

Recent Green AI literature has moved beyond the question of accuracy alone. A 2026 review reports that model compression, knowledge distillation, low-precision computation and efficient architectures can reduce computational requirements, while also noting that energy reporting is not yet standardized across studies. This supports the need to include resource metrics directly in the experimental design.

Research on AI-driven data-centre energy management emphasizes workload scheduling, power management, cooling and renewable integration. Sustainable edge-AI research similarly identifies carbon-aware task offloading, energy-efficient hardware/software co-design and measurement of energy consumption as important directions. These findings motivate the EcoEdge-AI design, in which the model and the placement of computation are considered together.

The ethical dimension is equally important. Environmental AI systems can influence alerts, public communication and operational decisions. A responsible system should therefore retain an auditable record of model version, input quality, confidence or uncertainty, and the conditions under which an alert was generated. Privacy is also relevant because sensor networks may indirectly reveal information about traffic, industrial activity or human movement. Keeping raw data local where possible reduces unnecessary exposure.

5. Proposed EcoEdge-AI Framework

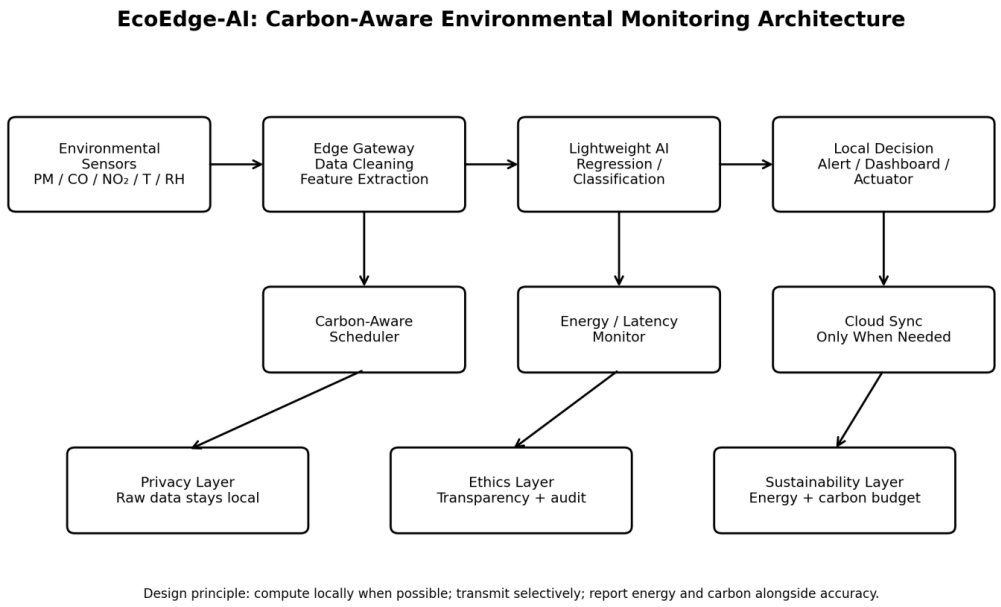


Figure 1.Proposed architecture of EcoEdge-AI.

The architecture has six logical layers. The first layer contains environmental sensors. The second layer performs cleaning and feature extraction at the edge gateway. The third layer executes a lightweight model. The fourth layer converts predictions into local alerts or control actions. The fifth layer contains energy and carbon-aware scheduling. The sixth layer provides governance functions such as privacy, transparency and auditability.

• Local-first inference: time-sensitive predictions should be computed locally when the gateway has sufficient resources.

• Selective synchronization: cloud transmission should be limited to summaries, anomalies, model updates or records required for audit.

• Model efficiency: smaller models should be considered before deploying computationally heavy models.

• Energy-aware scheduling: non-urgent retraining or batch processing can be scheduled when the energy/carbon budget is more favorable.

• Auditability: each decision should be traceable to a model version, timestamp, input-quality status and confidence measure.

6. Dataset and Experimental Design

Item	Specification	Purpose
Dataset	UCI Air Quality	Reproducible environmental data
Observations	9,358 hourly records	Time-series evaluation
Attributes	15	Sensor, pollutant and weather variables
Task	Regression	Predict a selected pollutant
Missing-value code	−200	Replace/handle during preprocessing
Candidate target	NO_2(GT) or CO(GT)	Environmental prediction
Models	Linear / shallow tree / compact ensemble	Accuracy-efficiency comparison
Metrics	MAE, RMSE, R^2, latency, memory, energy	Multi-objective evaluation

The UCI repository documents the dataset as a multivariate time series with 9,358 instances and 15 features. The dataset contains missing values represented by −200, so the preprocessing stage must identify these entries rather than treating them as real pollutant measurements. A time-

aware train/validation/test split is preferable to random shuffling because random splitting can allow information from later observations to influence model training.

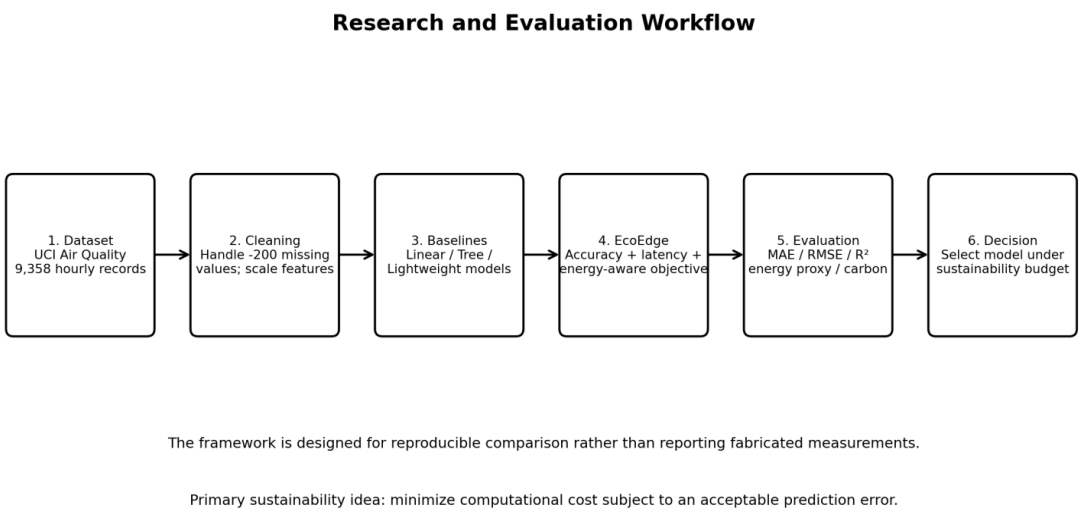


Figure 2.Reproducible research and evaluation workflow.

7. EcoEdge Mathematical Objective

The central mathematical contribution is a normalized multi-objective score. Let E be prediction error, L be latency, P be energy consumption per inference, and B be the amount of data transmitted per inference. After normalization to the interval [0,1], define the EcoEdge Cost as:

$C_Eco = w_1E + w_2P + w_3L + w_4B$

where $w_1 + w_2 + w_3 + w_4 = 1$. A model is eligible for deployment only when its error is below a predefined application threshold. Among eligible models, the system selects the model with the lowest EcoEdge Cost. This formulation makes the trade-off explicit rather than assuming that the model with the highest predictive score is automatically the best deployment choice.

For an environmental monitoring application, a possible initial weighting is $w_1 = 0.40$, $w_2 = 0.25$, $w_3 = 0.20$ and $w_4 = 0.15$. These values are not universal recommendations; they are a starting configuration that should be changed according to the application. For example, an emergency pollution-warning system may assign a larger weight to latency, while a battery-powered remote sensor may assign greater weight to energy.

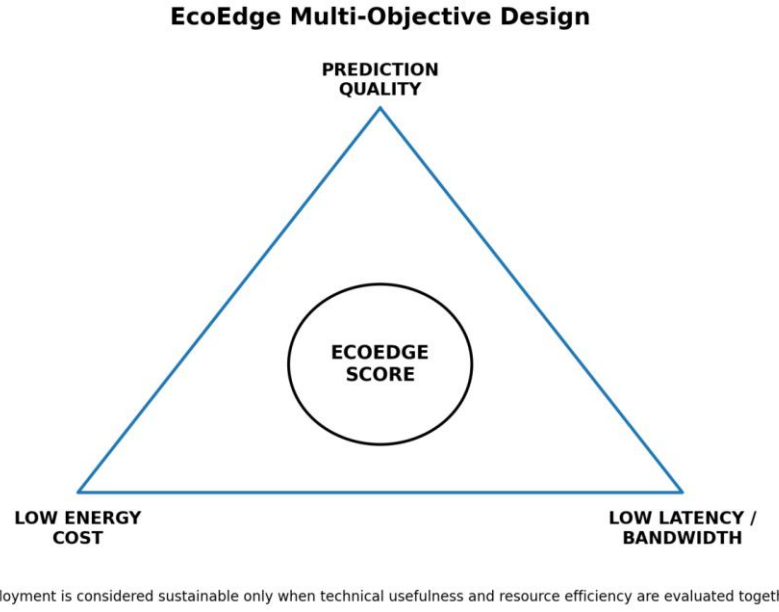


Figure 3.Conceptual relationship among prediction quality, energy and latency.

8. Ethical and Responsible Computing Layer

The framework includes ethics as an engineering layer. First, data minimization is encouraged: the system should collect and transmit only information necessary for the environmental task. Second, local processing can reduce exposure of raw sensor streams. Third, model decisions should be logged so that alerts can be reviewed after deployment. Fourth, uncertainty should be visible to the operator; a prediction should not be presented as a measurement when it is actually a model estimate. Finally, sustainability claims should be supported by measured energy data whenever possible.

• Transparency: document dataset, preprocessing, model version and decision thresholds.
• Human oversight: environmental alerts should support, not silently replace, responsible human decision-making.
• Privacy: avoid unnecessary transmission of raw data.
• Reliability: monitor sensor drift and data-quality failures.
• Sustainability reporting: record energy and communication metrics alongside accuracy.

9. Evaluation Protocol and Research Outcomes

The experimental comparison should report two groups of results. The first group contains conventional predictive measures such as MAE, RMSE and R^2. The second group contains system measures such as inference latency, memory use, energy per inference and transmitted bytes. Reporting both groups is important because an environmentally useful model should be accurate enough for the task without imposing unnecessary computational cost.

A useful result table should therefore contain one row per candidate model and columns for MAE, RMSE, R^2, latency, memory, energy and EcoEdge Cost. The final deployment decision should be based on the predefined error constraint and the lowest sustainable cost among eligible models. This procedure prevents a high-accuracy but resource-intensive model from being selected solely because of a small accuracy improvement.

No hardware-energy value is invented in this paper. Actual energy measurements should be collected on the intended edge device using a reproducible measurement method. This distinction is important for scientific credibility. Literature-reported energy reductions may be used as background evidence, but they should not be presented as experimental results from this study.

10. Discussion

EcoEdge-AI offers a practical way to connect current Green AI research with environmental IoT. The framework is intentionally model-agnostic. It can be implemented with linear regression when interpretability and very low computation are priorities, or with a compact tree-based model when nonlinear relationships are important. Quantization or pruning can be added after a suitable baseline has been established. The same framework can also support anomaly detection rather than only regression.

A major advantage of edge intelligence is that environmental decisions can be made without waiting for a remote cloud response. This is useful for applications such as local pollution alerts, industrial threshold monitoring, agricultural sensing and smart-city systems. However, edge deployment introduces its own limitations, including hardware constraints, sensor maintenance, model updates and energy availability. The proposed multi-objective score is intended to make these trades-offs explicit.

The framework also supports a more balanced definition of sustainable computing. Sustainability is not simply the reduction of CPU usage. Network traffic, memory, device lifetime, hardware replacement and data-centre dependence can all influence environmental impact. A responsible environmental AI system should therefore measure what it can and avoid unsupported claims about total carbon reduction.

11. Limitations

• The UCI dataset represents one historical monitoring deployment and should not be treated as a universal representation of present-day air quality.
• The proposed framework is a research design; hardware-energy results require execution on a specified edge device.
• Carbon intensity depends on the electricity source and location, so a single universal carbon factor is inappropriate.

• Sensor drift and missing data can affect model performance and require continuous monitoring.
• The proposed weights in the EcoEdge Cost function are configurable and should be validated for each application.

12. Future Scope

Future work will implement EcoEdge-AI on a low-power gateway connected to real environmental sensors and measure energy per inference directly. The study can then compare quantized and non-quantized models, evaluate different hardware platforms, and test adaptive cloud-edge task allocation. A further extension is a carbon-aware scheduler that uses electricity carbon intensity and renewable availability when deciding whether non-urgent model training should run locally or in the cloud. Digital twins, federated learning and privacy-preserving distributed training are also promising extensions for multi-site environmental monitoring.

For a regional deployment, the framework could be adapted to monitoring locations in Maharashtra by combining air-quality measurements with weather, traffic and industrial activity data. Such a study would create a stronger local research contribution, provided that consistent and verifiable data are available.

13. Conclusion

This paper proposed EcoEdge-AI, a carbon-aware lightweight Edge AI framework for sustainable environmental monitoring. The central idea is straightforward but important: environmental intelligence should be evaluated not only by what it predicts, but also by the computational and communication resources required to produce that prediction. The framework integrates IoT sensing, local inference, selective cloud synchronization, energy-aware scheduling and responsible-AI governance. A mathematical multi-objective score was introduced to formalize the trade-off among prediction error, energy, latency and data transfer.

The use of the UCI Air Quality dataset provides a reproducible foundation for future implementation and testing. The paper deliberately avoids inventing hardware-energy results; instead, it specifies a protocol through which those measurements can be collected and reported. This approach keeps the research transparent and makes the framework extensible to real environmental deployments. EcoEdge-AI therefore provides a practical computer-science pathway for connecting Edge AI, IoT, Green Computing and environmental responsibility within a single research design.

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