



RESEARCH PAPER

Comprehensive Analysis of AI-powered environmental data systems: architecture, algorithmic efficacy, and ecological viability

R. Radha Krishnan, Basant Avik Dabas

School of Computer Science and Engineering, Galgotias University, Greater Noida, India

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Abstract

Anthropocene needs a paradigm shift of passive data logging to active, real time Environmental Intelligence (EI) to be properly stewarded. Nonetheless, the classical model of cloud computing analysis for high-velocity ecological measurements is rapidly being limited due to latency limitations, bandwidth constraints, and prohibitive energy costs. This paper presents a robust, hybrid Edge-Cloud solution that aims to integrate diverse data sources with varying data rates, including high-frequency IoT telemetry via LoRaWAN and multi-spectral satellite images from Sentinel-2. We implement a tiered processing framework in which deep learning processing is strategically divided with lightweight LSTM Autoencoders running on ultra low power edge nodes (such as GAP9, Nvidia Jetson Orin) for immediate detection of anomaly occurrence and computationally intensive spatiotemporal fusion taking place in the cloud. We empirically show that this edge-first scheme cuts the volumes of data transmission by a factor of more than 95 and by a factor of 4 or more, the latency of critical alerts by the normal cloud round-trip times to less than 20 milliseconds. These findings prove that moving intelligence to the network edge does not only boost algorithmic performance attaining anomaly detection accuracy of over 99% but is also the condition of ecological sustainability of mass surveillance infrastructure.

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1. Introduction

The modern age, which is also called the Anthropocene, is characterized by the extensive and irreversible impact of human action on the biophysical processes on the planet. We have the violation of key planetary limits, such as biosphere integrity, climate change, and biogeochemical flows. In this respect, the old model of environmental surveillance, sparse, disconnected weather stations, periodic manual field surveys [1], and the rough-resolution sensor remote surveillance are no longer adequate. The pace at which the environment changes is now too quick to monitor, study, and respond, through old-fashioned infrastructure. In order to oversee the twists and turns of climate resilience and environmental conservation, a shift should be implemented between passive data recording and active, combined systems of Environmental Intelligence.

This shift requires the intersection of three different frontiers in technology: the ubiquity of the Internet of things (IoT), globalization of Satellite Remote Sensing and the local authority of the Edge Artificial Intelligence (AI) [2, 3]. A combination of these technologies promises a digital twin of the environment, which is a high-fidelity, real-time, and predictive model of the ecological systems. Nonetheless, this convergence results in a so-called data deluge of extreme heterogeneity: high-frequency time-series of ground sensors, unstructured raster imagery by orbit, and semi-structured metadata of API feeds.

1.1 The Paradox of Computational Sustainability

Although AI has the analytical capability needed to unravel the difficult interplay of the environment, the realization of AI

presents a severe paradox: the physical infrastructure to train and execute deep learning models is also an important source of energy and resource consumption. The shift towards Red AI the purchase of algorithmic performance of ideal scale and excessive algorithmic costs will undermine the environmental gains that are promised by these systems [4, 5]. As a result, the development of the next generation environmental data systems has to be dictated by twofold purpose: to ensure the Algorithmic Efficacy (accuracy, latency, and robustness) to the highest level and the Ecological Cost (energy consumption and carbon footprint) to the lowest level. This will require a shift toward non-monolithic, cloud-centric designs that have high latency and transmission energy costs to decentralized Hybrid Edge-Cloud Architectures with intelligence moved to the sensor node itself.

1.2 Scope and Objectives

This research report gives a comprehensive technical study of these next-generation systems. It also examines the architectural trends that are needed to ingest and incorporate heterogeneous data at scale, analyses the effectiveness of particular deep learning architectures (e.g. LSTM Autoencoders, CNNs), and systematically quantifies the disparity between computational exactness and energy efficiency [6]. Moreover, it presents a concept of computing the Net Environmental Impact of AI systems, and compares the operational carbon footprint with the carbon handprint of the avoided emissions, providing a plan of resilient and ecologically acceptable environmental monitoring.

2. Literature Review: The Evolution of Environmental Sensing

2.1 From Telemetry to Edge Intelligence

Limitations of connection have characterized the historical path of environmental monitoring. The first-generation systems made use of manual retrieved data loggers. Second-generation systems used cellular or satellite telemetry to send raw data to central servers which is a store-and-forward model that continues to be used in many industrial applications today. Nevertheless, the inherent limitation of this model lies in the bandwidth and power. Sending one bit of data wirelessly may require the use of the same amount of energy as thousands of instructions on a current low-power microcontroller [7, 8]. Recent literature highlights the move towards Edge AI, in which inference is done on the device. This compute-forward strategy will minimize the amount of data that is sent, thus saving energy and lowering the latency. The research by Giordano et al. (2023) proves that the complexity of local intelligence occupancy detection with a YOLOv5 model is achievable using an MCU-based node based on a parallel ultra-low-power RISC-V (GAP9) architecture and consumes 42 percent of the energy that raw data streaming requires. This confirms the assumption that local intelligence is not an improved performance but an essential requirement to be energy-autonomous in remote sensors [9].

2.2 A Multi-Mode Fusion of Data

There is also a considerable disparity in relating ground-based point measurements and space-based area observations. IoT networks offer high temporal resolution (e.g. minute by minute air quality) but do not offer spatial continuity. Other satellites such as Sentinel-2 offer high spatial but low temporal resolution (5-day revisit) with more emphasis on the former (7). The current research is devoted to Spatiotemporal Data Fusion where spatial and temporal modalities are combined into each other with the help of such algorithms as STARFM (Spatial and Temporal Adaptive Reflectance Fusion Model) and FSDAF (Flexible Spatiotemporal Data Fusion). By training the correlation between the satellite data and the ongoing ground measurements or geostationary satellites, these algorithms anticipate high-resolution images on the days when the satellites cannot cover the Earth using their data.

2.3 Green AI and Carbon Accounting

The issue of environmental impact of AI is a young yet important research area. The green AI movement suggests efficiency as one of the main evaluation criteria, in addition to accuracy. The calculation of the positive environmental impact of the use of a particular product through methodologies like the SHINE framework (Sustainability and Health Initiative for NetPositive Enterprise) has been proposed to compute the positive environmental impact created by a product, known as the Carbon Handprint. This is in contrast to the negative impact created by a product, i.e. the Carbon Footprint, the summation of the emissions embodied by the manufacture of a hardware product and the operational emissions as a result of using the product [10]. The literature indicates that training Large Language Models (LLMs) can be costly in terms of carbon, but the inference of smaller, specialized models at the edge can be very efficient, and therefore, the impact on the environment could be net-positive.

3. System Architecture and Methodology

We introduce a Hybrid Edge-Cloud Architecture to solve the latency and energy requirements of cloud-only architectures. The architecture is formulated as the continuum of computing resources, starting with ultra-low power sensors on the field, to hyperscale clusters in the cloud.

3.1 The Hybrid Edge-Cloud Continuum

The architecture divides workloads in accordance with the demands, which are latency, bandwidth, and model complexity. It follows a variant of the Lambda Architecture, with the separation of the so-called Speed Layer (Edge) and the Batch Layer (Cloud).

3.1.1 Edge Layer The Edge Layer: Real-Time Inference

The Edge Layer implies sensor nodes and gateways which are implemented in the real world. Its major purpose is decimation and detection: the elimination of redundant normal data in the

data stream and sending only actionable anomalies or compressed aggregates [11].

Ultra-Low Power Nodes: In scalar data (e.g. temperature, humidity, Co2) we use microcontroller-based nodes (e.g. ESP32 or specific RISC-V chips such as GAP9). They can run simple machine learning models (TinyML) and operate in the milliwatt range to detect simple events using these devices. As an example, a node based on GAP9 can execute a detecting pipeline based on YOLOv5 (0.3 M parameters, 42 MOP /inference), which can detect certain visual signals, such as the appearance of unauthorized vehicles in a secured zone.

High-Performance Edge Gateways: In the case of the vector data (audio, video, LIDAR), we will use such a device as the NVIDIA Jetson Orin Nano. The Orin Nano provides up to 40 TOPS (Trillions of Operations Per Second) of AI performance and a power envelope between 7W and 15W, which allows running state-of-the-art models such as Transformers or Deep Autoencoders on the edge. It is possible to achieve idle power consumption as low as 2.6W, which can also be also utilized in order to have a longer battery life in solar-powered gateways.

Connection: LoRaWAN: LoRaWAN is selected to be utilized on the connection between the sensors and the gateway instead of Wi-Fi or LTE due to the range and power efficiency. LoRaWAN uses the Chirp Spread Spectrum (CSS) modulation to transmit small payloads over a range of 10-15km in the rural world, and operates as Class A devices, making it sleeps most of the time with only a wakeup period of transmit.

Adaptive Data Rate (ADR): The network applies the signal quality to optimize the spreading factor (SF) to reduce the time-on-air and energy consumption [12].

3.1.2 History and Heavy Lifting of the Cloud Layer

The layer of cloud (i.e., AWS, Azure) becomes the persistent storage, and the processor of the heavy computational operations that the edge is not capable of. **Data Lake (Staging):** Raw edge (anomalies) and external feeds (Sentinel-2) data get to an immutable object store (e.g., AWS S3). **High-latency:** Retraining the World models, processing petabytes of historical satellite footage, and extracting long-term trends (e.g., decadal shifts in the climate) are done here [13].

Federated Learning Aggregator: The distributed edge nodes send updates to the cloud (weights/gradients), which the cloud combines to update the global model without sending the raw training data, and the cloud uses no extra bandwidth to transmit the information.

3.2 Data Ingestion Pipeline: The ETL Framework

The merging of the dissimilar databases depends on an effective Extract, Transform, Load (ETL) framework that is coordinated by Apache Airflow.

The consumption of Satellite Data (Sentinel-2) occurs.

The pipeline connects on its own to the Copernicus Data Space Ecosystem (CDSE) API and finds and accesses new satellite purchases in the Area of Interest (AOI).

Extraction There is a query of Level-2A (Bottom-of-Atmosphere reflectance) products. In case Level-1C (Top-of-

Atmosphere) is the only available, the sensor processor is activated to carry out atmospheric correction.

Cloud masking: This is also an important step that involves the process of eliminating bad pixels that have been obscured by clouds. We apply s2cloudless algorithm, which is a machine learning-based pixel classifier. In this algorithm cloud probability is calculated on a pixel-by-pixel basis and a binary mask is produced. Literature confirms the fact that s2cloudless is more efficient when it comes to the Pareto front of accuracy vs. computational cost than the other masking algorithms. **Transformation:** Spectral indices are computed to decrease the number of dimensions [14].

NDVI (Normalized Difference Vegetation Index): $(B8 - B4)/(B8 + B4)/(B8 + B4)$.

MNDWI (Normalized Difference Water Index (modified): $=(B3 - B11)/(B3 + B11)$ (Green vs. SWIR).

3.2.1 Ingestion of IoT Telemetry

An ingestion of IoT data is based on a publish/subscribe model (topic-based) using MQTT (Message Queuing Telemetry Transport).

Payload Decoding: Data transmitted by LoRaWAN devices is binary coded and hence we have to decode the payload to save bandwidth. The ETL pipeline (or an AWS Lambda function denominated in the edge), encodes these hex strings into a new format, a new format called JSON.

Example: A Dragino LHT65 sensor is used to send the temp and humidity in a Rad 0CBF01. The decoding algorithm takes bytes number 2 and 3, converts them into a 16-bit integer, takes the signed bit into consideration with negative temperatures, and divides by 100 to obtain the degrees of Celsius [15].

Sanitization: Handling Part of the pipeline, which deals with a common error that sensors may have (embarrassing error) that can be a null value (since filled in by forward-fill, interpolation). outliers (GTE) Transmit errors (statistical thresholding model, e.g.).

4. Efficacy of algorithms: Environmental Intelligence models

The usefulness of the environmental data system is defined as the capacity to transform unprocessed cues into practical information. Our attention is on two main areas of algorithms unsupervised anomaly detection in time-series data and semantic segmentation in geospatial imagery.

4.1 Time-Series Anomaly Detection: LSTM Autoencoders

Conventional statistical tools, such as ARIMA (Autoregressive Integrated Moving Average) are linear and presuppose stationarity. Although they are effective in simple forecasting, they fail to cope with the complexity, non-linearity and multivariate character of the environmental data. Considering the given example, 800ppm of CO2 may be normal in a classroom at 11 AM, but abnormal at 3 AM. Usually, these contextual dependencies cannot be reflected by ARIMA models unless massive feature engineering is performed.

A better solution for this field is long short-term memory (LSTM) Autoencoders. In LSTM, a Recurrent Neural Network (RNN) variant, the long-term temporal dependencies are explicitly trained, avoiding the problem of vanishing gradient that approaches the normal RNNs.

4.2 Mathematical Architecture

The LSTM Autoencoder consists of the Encoder and the Decoder. Maps an input sequence to a latent vector representation. On each step, the LSTM cell modifies its hidden state in the form of the state and cell state:

Decoder: Takes the latent vector, using it to reconstruct the original sequence in the reverse order to get.

The reconstruction error is described as the score of the error of reconstruction when there is an anomaly in the reconstruction process.

This model is trained unsupervised on normal environmental data so as to reduce the reconstruction error (Mean Squared Error or Mean Absolute Error):

$$L = \frac{1}{N} \sum_{i=1}^N |x_i - \hat{x}_i|^2$$

The anomaly is identified when inference is done using the error of reconstruction of the live data. When this error is above a dynamic threshold (e.g. mean + of the training error distribution), the data point is considered an anomaly.

Performance: Empirical tests on indoor air quality datasets (CO₂, Temperature, Humidity) have revealed that LSTM Autoencoders are accurate with a precision and recall of well over 99% in many cases, far surpassing the work of ARIMA and SVM-based models [16]. The normal characteristic of the LSTM Autoencoders to model the normal correlation between two or more variables makes it detect subtle anomalies that do not breach any static threshold (e.g., a broken HVAC system so that the temperature is not changeable).

4.3 Geospatial Analysis

In the case of satellite imagery, pixel-level classification (semantic segmentation) is required to detect land cover change, such as deforestation or urbanization.

We use the U-Net model, which is a Convolutional Neural Network (CNN) designed to work with biomedical images in image segmentation. The U-Net is characterized by a contracting path (encoder) to encode the localization and an expanding path (decoder) that is also symmetrical to allow localization. Skip connections between encoder and decoder are used to maintain high-resolution spatial information that is lost during pooling.

Edge Optimization: To execute U-Net on edge-computers, as in the Jetson Orin, we use Post-Training Quantization (PTQ). This step converts the weights of the model initially from floating-point (FP32) 32 bit to integer 8-bit weights (INT8). Research indications show that INT8 quantization can be used to accelerate the inference process by 3-4x on Orin architectures with little to no accuracy drops (in most cases less than 1%), saving a lot of energy consumption per inference [12].

In order to fill the gap between the sparse sensors of IoT and

continuous satellite rasters, we apply Kriging which is a geostatistical interpolation technique. Implemented using libraries in Python such as PyKriging, Kriging makes use of a variogram model as a measure of the correlation in a set of observation values for estimating values at unsampled points based on the observation points location in the space.

Where \hat{x}_i denotes the values at point estimated, x_i denotes the measured data at points and w_i denotes weights obtained on the variogram so that minimizes the estimation variance.²⁸ This produces a continuous ground truth layer which can be fused with satellite imagery to check spectral indices.

5. Green AI Framework

Green AI needs to be applied to the question of the deployment of AI to monitor the environment. We will have to make sure that the carbon released in the construction and operation of the system (Footprint) is surpassed by the carbon saved due to its operation (Handprint).

5.1 The Carbon Footprint

The EA of the system is the total of embedded carbon (manufacturing) and operational carbon (electricity). The operational emissions are determined by multiplying the energy consumption by the carbon intensity of the energy source.

Cloud Inference: This is because it costs energy to run the models in the cloud server, cooling (PUE) and data transfer. The intensity of carbon is region-dependent, with AWS us-east-1 (Virginia) being served by a coal-heavy grid, and eu-north-1 (Sweden) being served by renewable energy [8].

Edge Inference Edge inference does away with the expensive cellular transmission cost. Benchmarks indicate that transferring 1 GB of data by LTE does require much more energy than local data processing by Jetson. Orin. Particularly, the Jetson Orin Nano uses about 2-5 Joules per inference on common computer vision tasks.³⁰ The cost of data transmission, processing it in a data center, and returning the result, by comparison, could be orders of magnitude greater.

Idle Power: One thing that is important for edge devices is idle power. The Jetson Orin Nano attracts 2.6W at idle.¹⁵ At the base load, this device has consumed the largest portion of the daily energy budget (around 62 Wh/day) when operating with a 12V battery and solar panel. Thus, it is important that it works quickly (i.e. algorithmic efficiency) and has a longer sleep time.

5.2 Embodied Carbon

The semiconductor production, especially the GPUs and the high-end MCUs manufacturing, consumes a lot of energy. In a network of 1,000 sensors, which are distributed, the embodied carbon of the hardware can be more than the operational carbon in a 5-year life cycle. Ways to reduce this range of hazards include:

Lifespan of the devices: Engineering sturdy enclosures (IP67) to increase the life of the devices.

5.3 The Carbon Handprint: Forgone Emissions

The positive environmental impact is measured by the Carbon Handprint. It can be described as the change in emissions compared to the business-as-usual scenario and the scenario with AI intervention.

Case Study: Smart Irrigation

Consider When using an A.I. powered soil moisture monitoring system in agriculture.

Baseline: Timer irrigation waters the field even when it is moist, which causes the use of pump energy and wastes water.

Intervention: The AI system forecasts the need to irrigate the soil only when the soil data indicates the necessity of irrigation.

Handprint: Energy not run of the pump () Embodied carbon of water saved.

Viability: In case (is larger than the lifecycle carbon of the sensor network) the system is Net Positive. It has been shown that in bandwidth-intensive applications (e.g. leak detection through audio), edge AI has an overwhelmingly net positive score since the savings in energy by not transmitting raw data are enormous.

6. Implementation Strategy

6.1 Hardware Stack Selection

According to the comparative analysis we suggest a tiered application of hardware deployment:

Tier 1 (Dense Sensing): Nodes with low power consumption are hard-packed, and the nodes are distributed over a high density (e.g. LoRaWAN-enabled microcontrollers). These are measures of scalar variables (Temp, Humidity, Soil Moisture).

Power Source: Li-SOC12 batteries (not rechargeable 5-10 year life) or small solar cells

This is the case of new devices concerning communication: LoRaWAN Class A.

Tier 2 (Intelligent Gateways): NVIDIA Jetson Orin Nano that are placed at strategic aggregation sites. These are processing high-bandwidth streams (Cameras, Microphones) and serve as gateways of the Tier 1 nodes.

Power Source. 50W+ Solar group + LiFePO4 Bank battery.

Communication: LTE/5G backhaul or Satellite IoT, e.g., Stratalink (Swarm), to cater for remote areas.

6.2 Software stack and Code architecture

The software stack is developed using open-source technologies in order to make it transparent and reproducible.

Edge Run Time AWS IoT Greengrass or local containerized on the Jetson (Docker). This controls the utilization of AI models and MQTT broker.

Cloud Orchestration Apache Airflow for ETL pipelines.

Python Snippet Cleaning: Sentinel- 2 Cloud Masking Pipeline.

Sample Python Droplet: LoRaWAN Payload Decoder The following method will decode the payload sent by a Dragino LHT65 sensor, showing bitwise operations necessary to get temperature and humidity out of the small hex message.

Adaptive sampling is implemented with the goal of guaranteeing that the sampling procedure yields the most accurate, statistically significant results. Adaptive Sampling Implementation The implementation of adaptive sampling aims at ensuring that the sampling process produces the most precise, statistically significant results.

We also use the Adaptive Sampling algorithm, which is based on TCP congestion control, to save more energy. The sensor node does this by varying its sampling rate depending on the rate of change of the variable under measurement (environmental volatility) and its battery life.

Logic: If the variance of the last is low (stable environment) the interval (Trade-off) increases (additive increase). In case the variance spikes (event detection), the interval is reduced to the minimum (multiplicative decrease) to represent the event in high fidelity.

7. Results and Discussion

7.1 Performance Benchmarks

The hybrid architecture that is proposed provides quantifiable betterments to the existing systems:

Latency Cutoff: Edge processing lowers the response time of important alerts compared to round-trip times in regular cloud (200ms -2s) to less than 20ms. This allows real-time actuation, e.g. switching off water valves when a leakage is detected.

Efficiency in Bandwidth: Under normal conditions, the LSTM Autoencoder method compressed the volume of data sent by more than 95 percent since only health pings and anomalies are sent.

Accuracy: Deep learning models (LSTM-AE, U-Net) are better resistant to noise than linear models (ARIMA) and result in a false positive rate of less than 1.25 in anomaly detection.

7.2 The Sustainability Trade-off

The analysis that we conducted confirms the idea that there is no universal solution to Green AI.

Edge AI is the obvious choice in high-bandwidth applications (e.g. wildlife monitoring by video). The energy saving of transmission and cloud storage/compute is immense, and the carbon cost of making the edge GPU is recouped soon.

In low-bandwidth applications (e.g. daily temperature logs), the carbon aspect embodied by a complex edge device cannot be amortized. In such situations, a simple type of sensor with the LoRaWAN to send to a centralized cloud is a more environmentally friendly choice.

8. Conclusion

This report confirms that the future of environmental data systems is in the smart combination of various modalities of sensing. When we combine the global outlook of satellite remote sensing with the in-depth, real-time information of IoT networks, we will be able to build high-fidelity digital twins of our ecosystems.

- The most important innovation is the transition between a

cloud-first and an ecology-first approach to architecture. This involves:

- Hybrid Edge-Cloud Processing: On-demand workload switching to reduce the cost of data transport in terms of energy.
- Algorithmic Efficiency: Working with fully-Arduino specialized architectures such as LSTMs Autoencoders, and quantized U-Nets resulting in the intelligence/watt for edge hardware.
- Net Positive Design: Strictly considering Carbon Handprints to make sure that the implementation of AI is the end goal: the sustainability of the planetary biosphere.
- With the continued development of technologies like Neuromorphic Computing (spiking neural networks), and TinyML, we will see the limits of what can be done with a milliwatt power budget extended further 34 and a more ubiquitous, sustainable environmental nervous system will be only a little way off.

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