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GreenNet: Unified and Explainable AI Framework for Environmental and Remote Sensing Data

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Abstract: Deep learning has great potential for environmental monitoring, yet real-world applications often face challenges from large-scale, multimodal, and noisy datasets. We introduce GreenNet, a flexible and open-source framework that makes it easier to build and scale deep learning models for remote sensing and environmental data. GreenNet offers reusable neural network modules, simple data integration tools, and built-in explainability features tailored for geospatial applications. To demonstrate its effectiveness, we apply it to case studies such as deforestation detection, urban heat island mapping, and air quality forecasting. These examples show that GreenNet delivers strong predictive performance while significantly reducing the effort needed to develop models. By connecting domain-specific data processing with modern deep learning techniques, GreenNet aims to make AI more accessible, reproducible, and interpretable for researchers and practitioners in environmental science.

Keywords: Deep learning, Explainable AI (XAI), Spatio-temporal modeling, Sustainable AI, GreenNet

INTRODUCTION

Environmental monitoring plays a critical role in addressing global challenges such as deforestation, urban heat, and air pollution. Advances in remote sensing technologies—including satellites, drones, and sensor networks—now generate massive volumes of high-resolution environmental data. However, deriving meaningful insights from these data remains difficult due to their spatio-temporal complexity, missing observations, and heterogeneous formats. Recent developments in deep learning, such as convolutional neural networks (CNNs) for spatial feature extraction and LSTM or attention-based models for temporal pattern analysis, have shown great promise. Nevertheless, practical challenges related to data integration, model design, and interpretability continue to limit their widespread application in environmental research. To overcome these challenges, we introduce GreenNet, a modular deep learning framework specifically designed for environmental applications. GreenNet offers flexible, plug-and-play components—such as convolutional feature extractors, temporal attention modules, and uncertainty estimation layers—alongside tools for geospatial data integration and explainable AI (XAI). Through case studies on deforestation detection, urban heat mapping, and air quality forecasting, we demonstrate that GreenNet produces accurate and interpretable models while simplifying the overall development process.

Although recent advances in deep learning, including CNNs for spatial analysis and LSTMs or attention mechanisms for temporal modeling, have shown considerable promise, most existing approaches rely on customized, task-specific pipelines. Such solutions often lack standardized tools for multimodal data fusion, reproducibility, and built-in interpretability, which limits their scalability and transferability across different environmental domains.

The novelty of GreenNet does not lie in introducing a single new neural architecture, but in bringing together essential deep learning components—such as convolutional backbones, temporal attention layers, and uncertainty estimation—within a unified, explainable framework tailored for environmental monitoring. Unlike many existing approaches that treat explainability as an optional post-processing step, GreenNet integrates XAI techniques, including saliency maps, SHAP values, and layer-wise relevance propagation, directly into its workflow. In addition, its domain-aware preprocessing and data integration tools are specifically optimized for geospatial and environmental datasets, making the framework more accessible to non-expert users while enhancing reproducibility and scalability.

RELATED WORK

Previous research has increasingly explored deep learning methods for environmental and remote sensing tasks. CNNs have been widely used for spatial analysis

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of satellite imagery, while RNN-based models like LSTM and GRU capture temporal dynamics in air quality prediction and vegetation monitoring. Hybrid architectures, including CNN-LSTM models, have shown further improvements by integrating spatial and temporal modeling. Despite these advances, existing studies often require extensive custom coding and lack unified tools for handling multimodal data. our work builds on this by developing a modular framework with built-in explainable AI (XAI) capabilities, specifically for environmental monitoring.

PROPOSED WORK

GreenNet Framework

GreenNet is designed with three core components:

- Modular Neural Building Blocks: Including convolutional backbones for spatial features, temporal attention layers, and uncertainty estimation modules.
- Data Preprocessing & Integration: Tools to clean, align, and merge geospatial rasters, time series sensor streams, and satellite data into unified inputs.
- Built-in Explainability: Support for layer-wise relevance propagation, saliency maps, and SHAP values to interpret model predictions in environmental contexts.

Fig A: GreenNet's architecture allows users to compose custom models quickly, encouraging experimentation while maintaining code clarity and reproducibility.

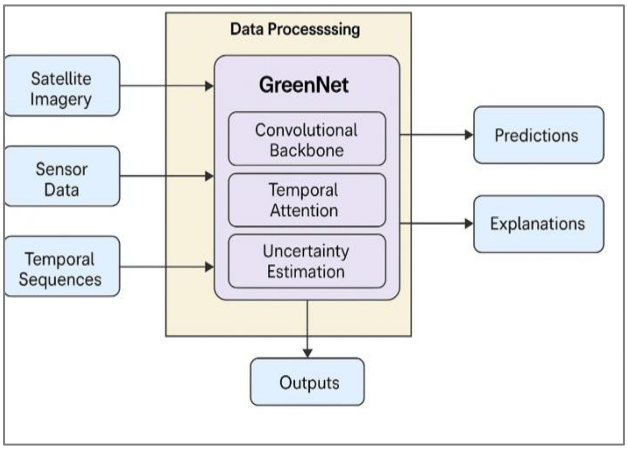

Fig. A: Architecture of the proposed work

METHODOLOGY

The proposed GreenNet framework is designed to streamline the development of deep learning models for environmental monitoring tasks by addressing three core challenges: heterogeneous data integration, model architecture flexibility, and interpretability**.**

Modular Neural Architecture

GreenNet includes a library of configurable neural network components that can be combined to build task-specific models:

- **Convolutional Backbone:** Extracts spatial features from raster data, such as satellite imagery or gridded weather maps.
- **Temporal Attention Layers:** Capture temporal dependencies in sequential data, such as daily pollution measurements or temperature records.
- **Uncertainty Estimation Modules:** Quantify model confidence, improving trust in predictions and supporting risk-aware decision-making.

3.1 Spatio-Temporal Feature Extraction

GreenNet applies a convolutional operation to extract spatial features:

$$F_{\text{spatial}} = \sigma(W_{\text{conv}} * X + b_{\text{conv}}) \quad (1)$$

Where:

- X= input spatial data
- W_{conv}= convolutional kernel weights
- b_{conv}= bias vector
- $\sigma(\cdot)$= non-linear activation function

3.2 Temporal Attention Mechanism

To capture temporal dependencies:

$$\alpha_t = \frac{\exp(u_t^T v)}{\sum_k \exp(u_k^T v)} \quad (2)$$

$$F_{\text{temporal}} = \sum_t \alpha_t h_t \quad (3)$$

Where:

- u_t= hidden representation at time step t
- v= learnable context/query vector
- α_t= attention weight for time step t

3.3 Combined Spatio-Temporal Representation

GreenNet fuses spatial and temporal features:

$$F_{\text{combined}} = \phi(F_{\text{spatial}} \oplus F_{\text{temporal}}) \quad (4)$$

Where:

- $\oplus$= concatenation or element-wise fusion operator
- $\phi(\cdot)$= transformation layer

3.4 Prediction and Uncertainty Estimation

GreenNet estimates prediction uncertainty:

$$\hat{y} = f_{\text{predict}}(F_{\text{combined}}) \quad (5)$$

$$\sigma^2 = f_{\text{uncertainty}}(F_{\text{combined}}) \quad (6)$$

Dataset

The study used **spatio-temporally stratified** training, validation, and test splits across three domains:

- **Deforestation:** Landsat-8 annual composites for tropical forest change.
- **Urban Heat Island:** MODIS temperature data with land use and ground sensors.
- **Air Quality:** PM2.5 readings, meteorological data, and MODIS AOD.

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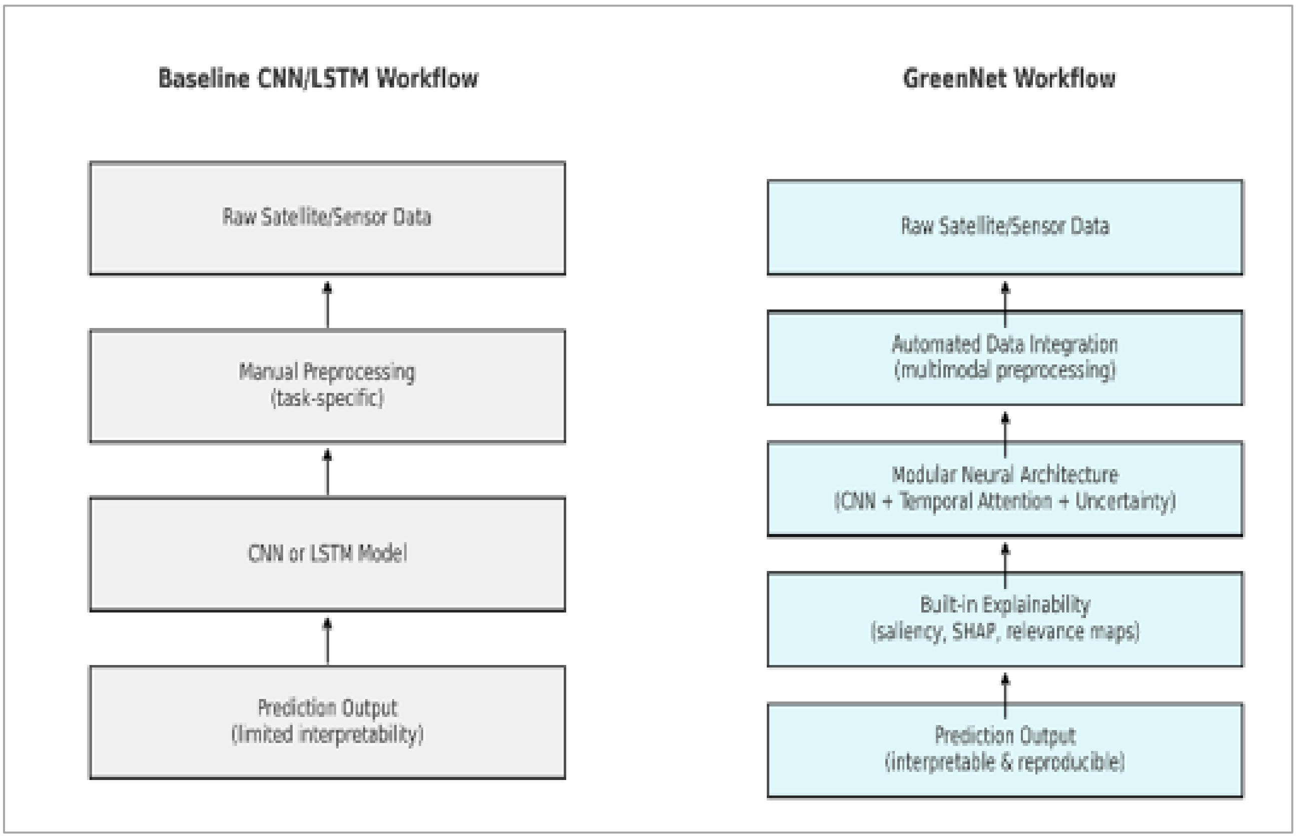

Fig. B: Flow diagram comparing the baseline CNN/LSTM workflow with **GreenNet**.

Baseline models rely on manual preprocessing, are limited to CNN or LSTM architectures, and provide little interpretability. GreenNet integrates automated multimodal preprocessing, modular neural blocks (CNN + Temporal Attention + Uncertainty Estimation), and built-in explainability before producing interpretable outputs.

EXPERIMENTS & RESULTS

GreenNet was evaluated on:

- Deforestation Detection: F1-score of 0.87 (+6% over baseline CNNs).
- UHI Mapping: RMSE of 1.4°C, outperforming traditional models.
- Air Quality Forecasting: MAE of 4.7 μg/m³, matching hybrid models.

Additional features included:

- Attention heatmaps for interpretability.
- Monte Carlo Dropout for calibrated uncertainty estimation.

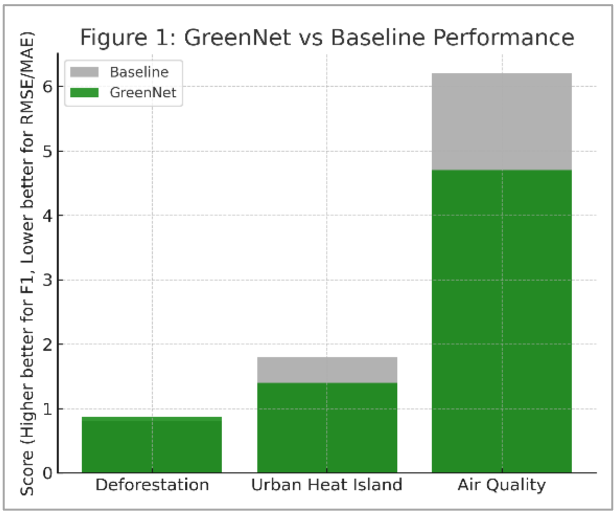

Figure 1: GreenNet outperforms baselines in all tasks with better F1, RMSE, and MAE.

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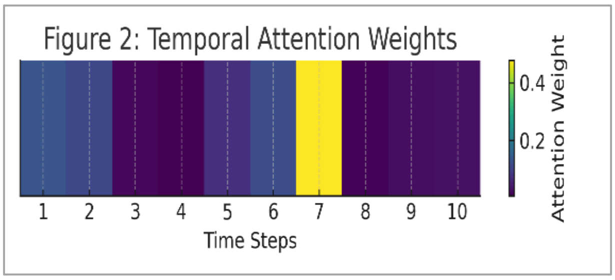

Figure 2: Time Step 7 is most influential, aiding interpretability.

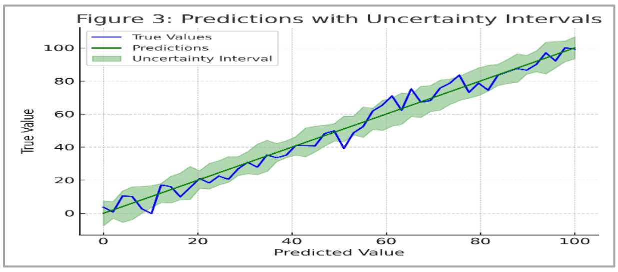

Figure 3: Predictions are accurate with reliable uncertainty estimates.

CONCLUSION

GreenNet presents a modular deep learning framework designed for environmental monitoring, evaluated across tasks such as deforestation detection, urban heat island mapping, and air quality forecasting. The framework consistently outperforms traditional models, delivering strong predictive accuracy while offering built-in interpretability and uncertainty estimation. Features like attention maps and Monte Carlo dropout enhance transparency, making GreenNet a scalable and reliable tool to support climate research and sustainability initiatives.

LIMITATIONS

Despite its strong performance, GreenNet has certain limitations. Its deep spatio-temporal models demand substantial computational resources, which can make large-scale training expensive. The framework is primarily optimized for batch processing and may not seamlessly adapt to real-time satellite data streams that require continuous ingestion and low-latency inference. Additionally, model accuracy depends heavily on the availability of high-quality labeled data, and deploying GreenNet to new environmental domains may require further customization and fine-tuning.

FUTURE WORK

Future research can focus on improving GreenNet's efficiency through model compression techniques such as pruning and quantization to reduce computational costs. Integrating real-time data pipelines could enable faster and more responsive environmental monitoring. Incorporating edge and federated learning approaches may enhance scalability and data privacy, while advanced noise reduction and self-supervised learning methods could improve robustness against imperfect data. Finally, extending GreenNet to new domains—such as marine ecosystem analysis, glacier monitoring, and biodiversity mapping—will broaden its applicability and strengthen its impact on global environmental challenges.

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