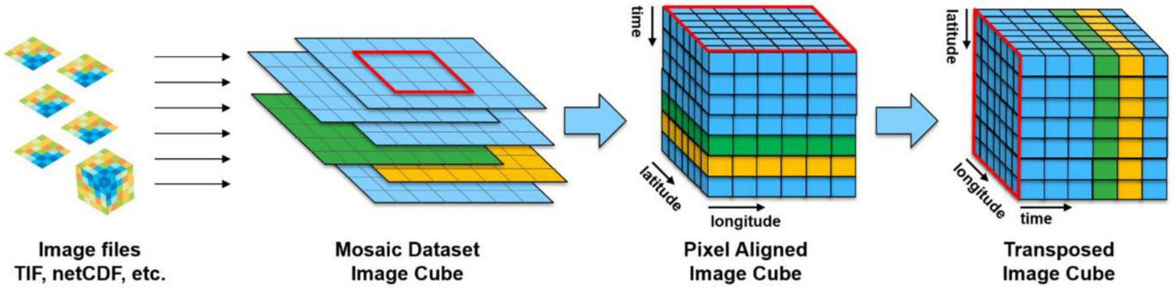
Modeling Geospatial Machine Learning Problems

Amini Geospatial AI Series

Key Challenges of Geospatial Data

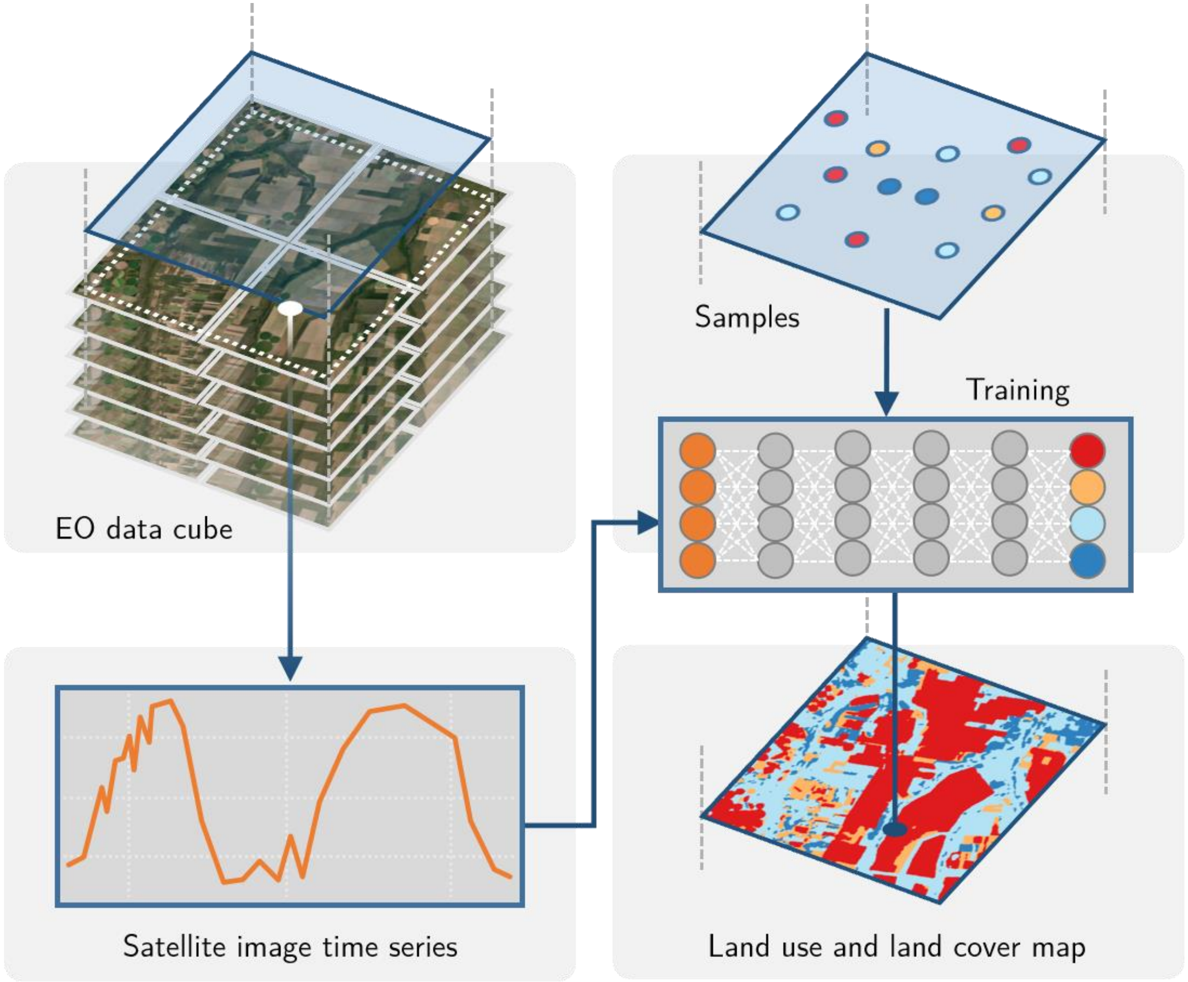
1. **Data Volume**
    - High-resolution imagery, frequent acquisitions → big data storage & compute.
2. **Complexity**
    - Spatial, temporal, and spectral dimensions.
3. **Domain-Specific Knowledge**
    - GIS expertise, remote sensing fundamentals, coordinate systems.



Geospatial data cube

Modelling Approaches

- **Geostatistical**
  - Kriging, variogram-based interpolation.
- **Machine Learning – Classical**
  - Random Forest, XGBoost
- **Deep Learning**
  - CNN, RNN , 3D CNNs, Transformers, Diffusion Models



LULC Data Cube

Classical ML on “Flattened” Data Cubes

Treat each pixel (or grid cell) in the data cube as an independent sample, with each band/time step as a separate feature/column.

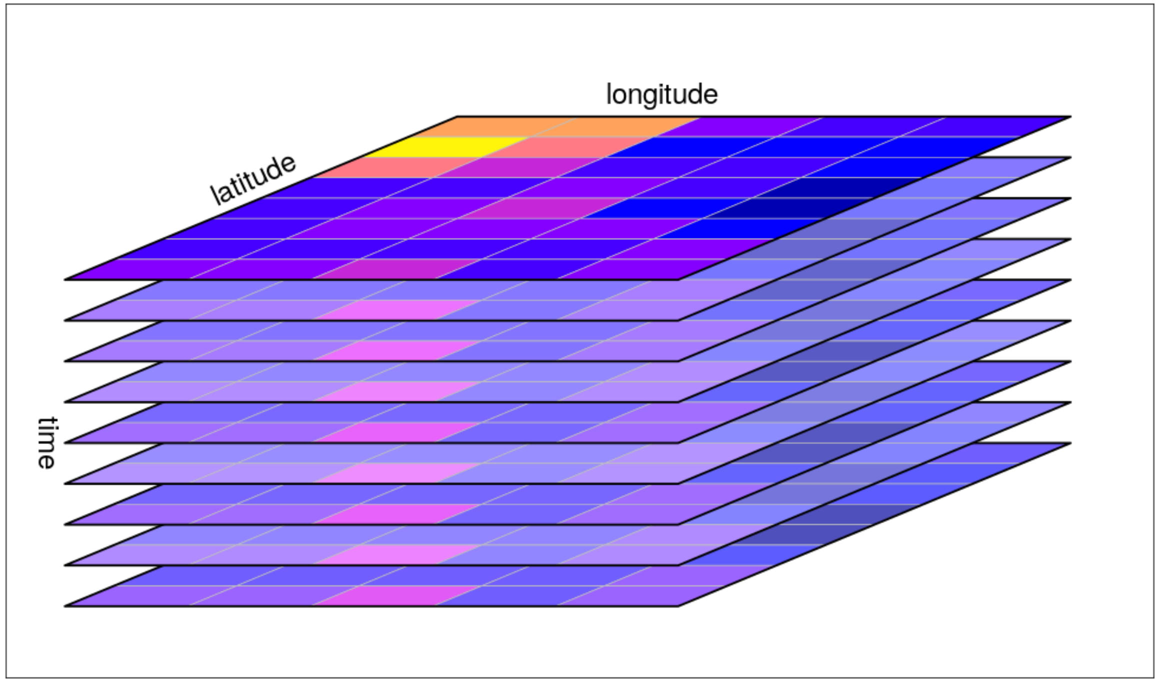
- Straightforward pipeline (raster → flatten → ML); easy to implement.
- Neglects spatial/contextual information and often temporal dependencies

Models

- Random Forest, Gradient Boosting, SVM, Logistic Regression, etc.

Use Cases

- Land cover classification, pixel-wise anomaly detection, basic regression tasks (e.g., yield prediction at the pixel level).



Geospatial Raster Stack

Spatiotemporal Modeling

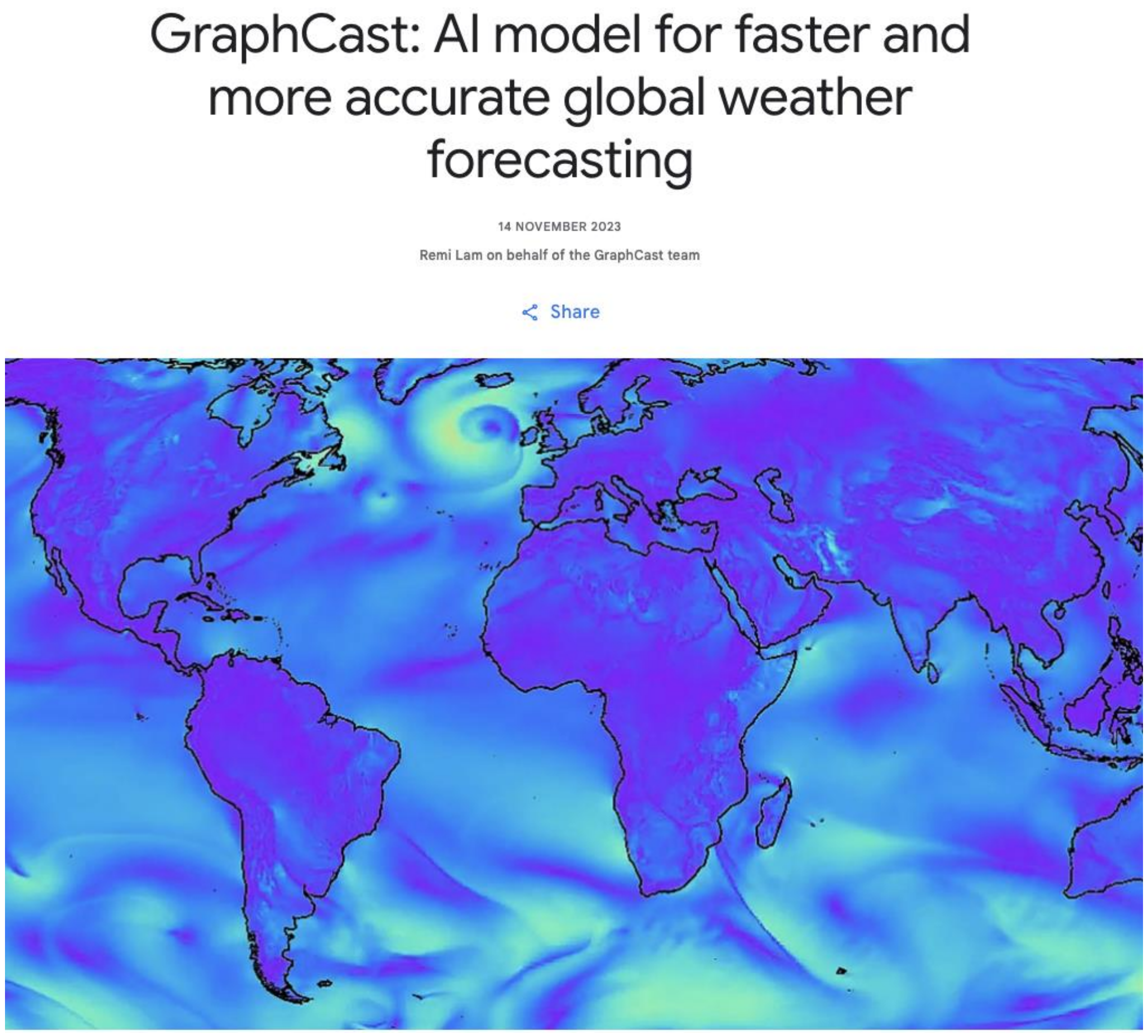
- Models both spatial and temporal dependencies (e.g., changes over time at each location).

Approaches:

- CNN + RNN or CNN + LSTM pipeline: A CNN extracts spatial features, then an RNN (or LSTM, GRU) handles time series.
- Graph Neural Networks: If you think of pixels/regions as nodes with spatial adjacency, can be used for traffic or weather forecasting.

Use Cases:

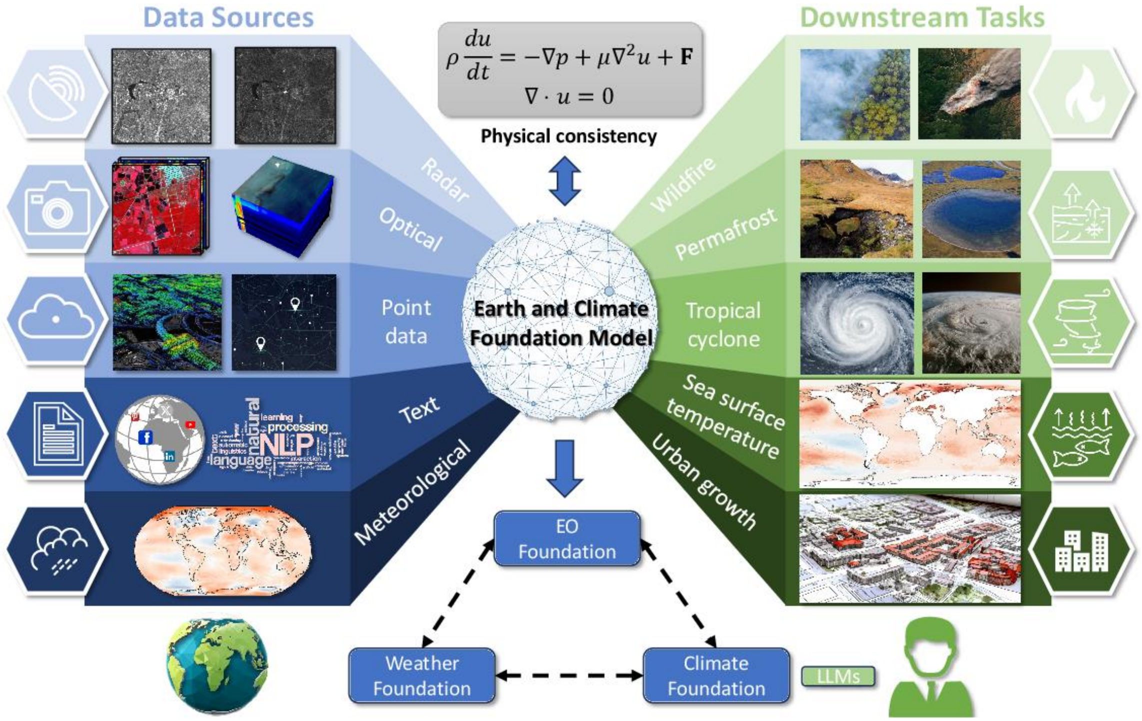
- Weather prediction (e.g., Google's GraphCast), traffic flow/ETA, crop phenology monitoring through time-series imagery.
- Better captures the "when" as well as the "where" which is crucial for forecasting or event detection.



Graphcast

Representation Learning

- Learning robust, reusable representations (embeddings) of data, often in an unsupervised or self-supervised way, before fine-tuning for a specific downstream task.
- Geospatial Foundation Models: Large-scale models trained on huge amounts of satellite imagery that can be fine-tuned for tasks like segmentation, classification, or object detection.
- Can drastically reduce labeled data requirements; the model “knows” a lot about generic geospatial features from large pretraining sets



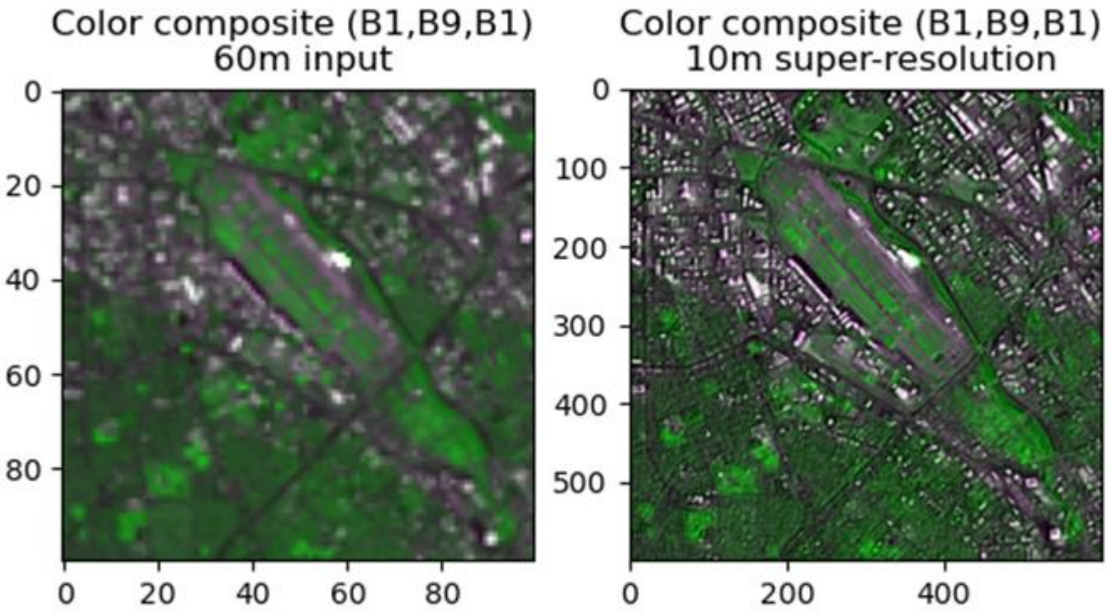
Earth Foundation Models

Downscaling & Super-Resolution

Enhances resolution or translate coarse data into finer resolution imagery.

- Diffusion Models
- GANs (Generative Adversarial Networks)

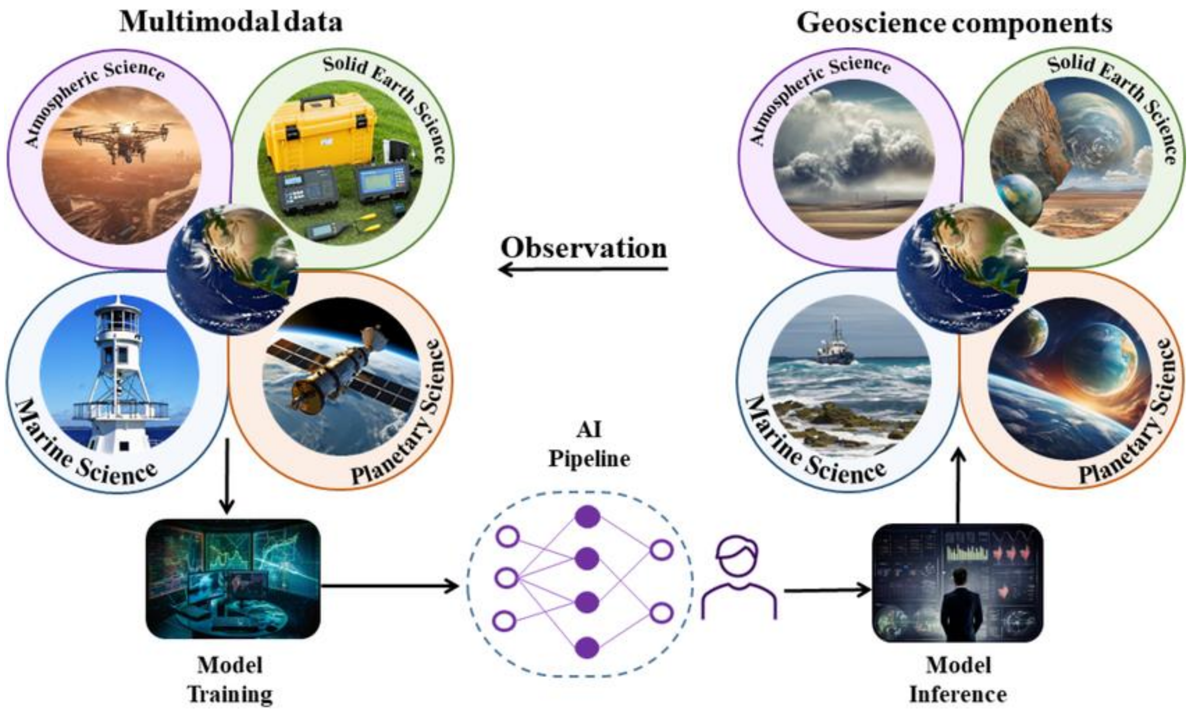
- **Use Cases**
  - Upgrading coarse imagery for detailed mapping, bridging data from different sensors/resolutions.



Super resolution

Data Fusion / Multi-Modal Approaches

- Combine different data modalities (optical, radar, LiDAR, IoT sensor data, meteorological data) within a single model or pipeline.
- Each source adds complementary information (e.g., radar can penetrate clouds, optical offers spectral info, LiDAR provides height).
- **Approaches**
    - Feature-level fusion: Concatenate or co-locate features from various sources.
    - Model-level fusion: Separate backbones for each data type, merged at some layer.



Evaluation & Explainability

Uncertainty Quantification

- Guides risk-sensitive decisions (e.g flood management, crop failures).

Sources of Uncertainty

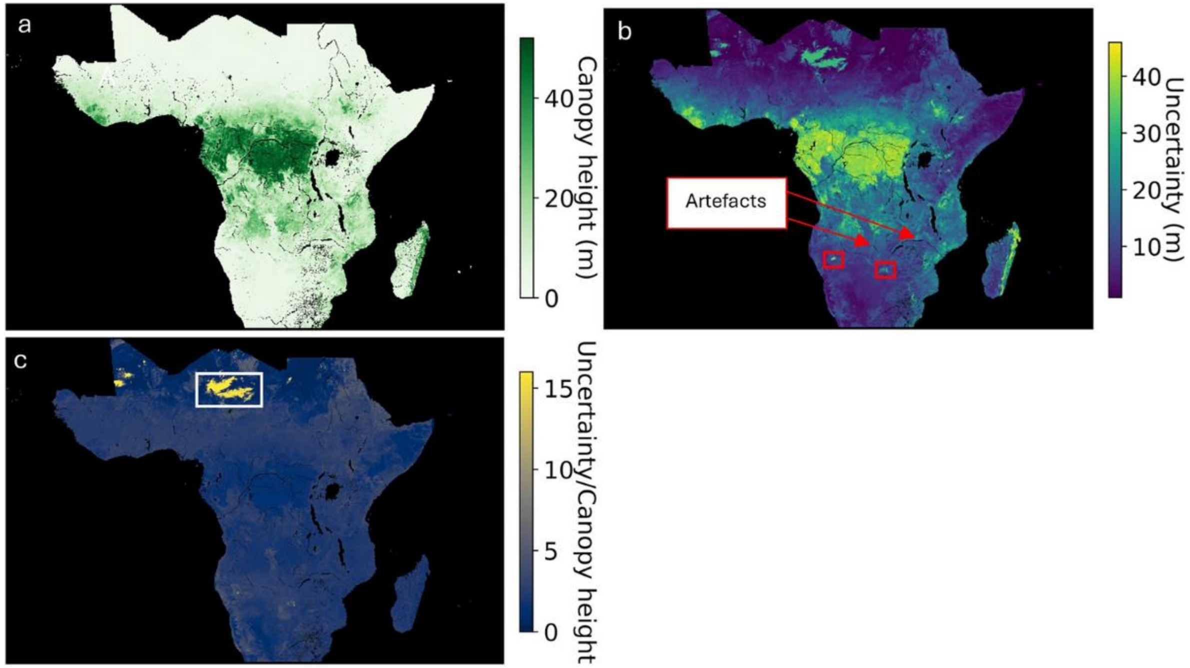
- Measurement noise (sensor, cloud), model assumptions, parameter variation.

Techniques

- Probabilistic models (Bayesian, Gaussian Processes), ensembles, MC Dropout in DL.

Visualization

- Uncertainty maps, confidence intervals, calibration plots.



Conopy height uncerteinity quantification

Evaluation & Validation

Metrics

- Classification: Accuracy, F1, IoU.
- Regression: RMSE, MAE, R^2.
- Spatially aware metrics for boundary or object detection.

Cross-Validation Strategies

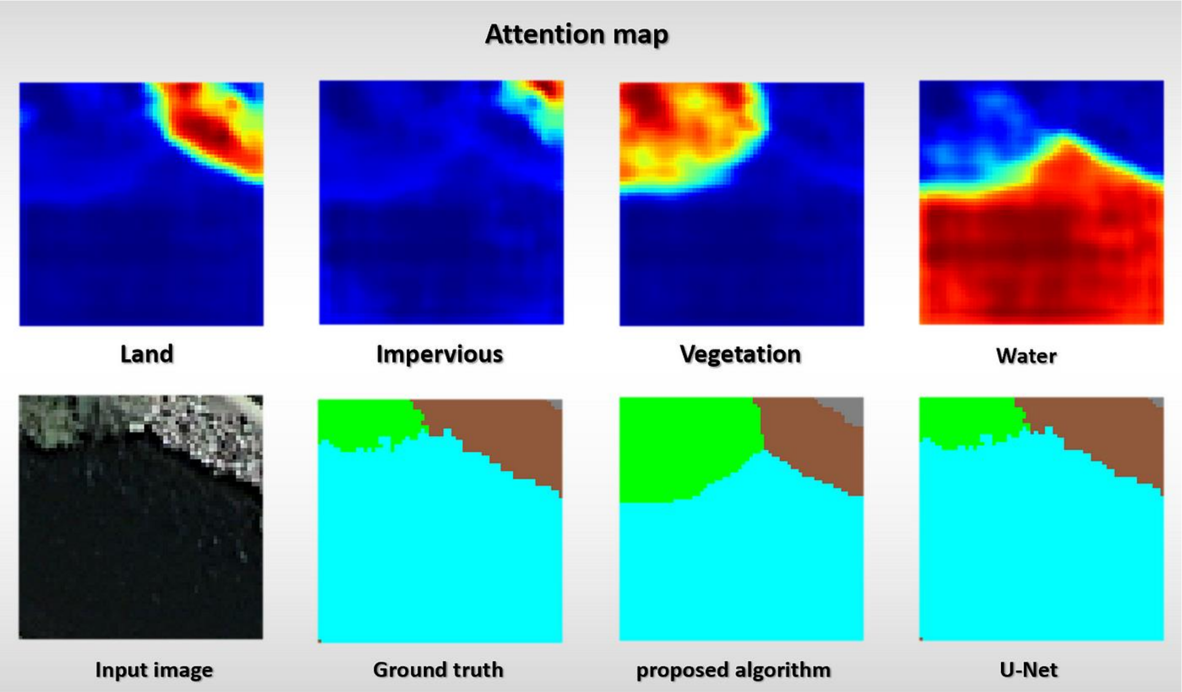
- Spatial cross-validation, time-based splits.

Error Analysis

- Residual maps, identifying systematic spatial or spectral biases.

Model Interpretability

- Feature importance (SHAP), attention maps, domain expert feedback loops.



Visualizing attention maps