Barcelona Supercomputing Center
Centro Nacional de Supercomputación

NEURAL INFORMATION PROCESSING SYSTEMS

Climate Change AI

Historical Reconstruction and Future Projection of Land Surface Boundary Conditions

Amirpasha Mozaffari[1], Marina Castaño[1], Stefano Materia[1], **Amanda Duarte**[1]

[1] Barcelona Supercomputing Center

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Motivation

Why this matters: Land Surface Boundary Conditions (LSBCs) like Land Use (LU) and Land Cover (LC) are crucial for modulating regional climate.

What they do: They regulate the exchange of energy, water, and carbon between the land and atmosphere.

The Benefit: Better representation leads to more realistic climate models and improved near-surface weather predictions.

The Problem: We lack consistent, high-resolution datasets for *historical periods* (pre-EO) and *future projections*.

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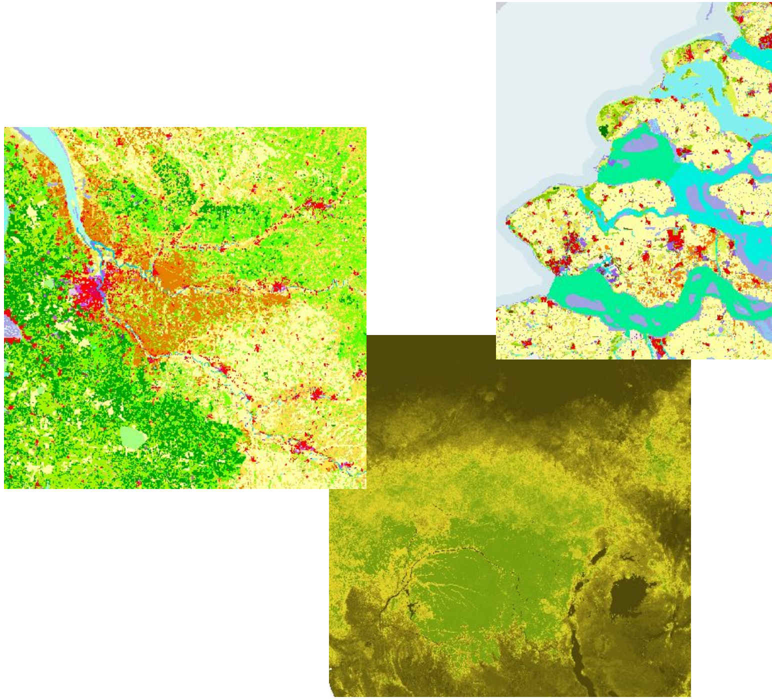
Objective & approach

Goal: Create a spatiotemporal super-resolution framework to generate consistent, high-resolution Land Surface Boundary Conditions.

Phased Plan:

- **Phase 1:** Produce annually varying Land Use (LU) and Land Cover (LC).
- **Phase 2:** Expand to predict high-frequency (weekly/monthly) Leaf Area Index (LAI).



Land use

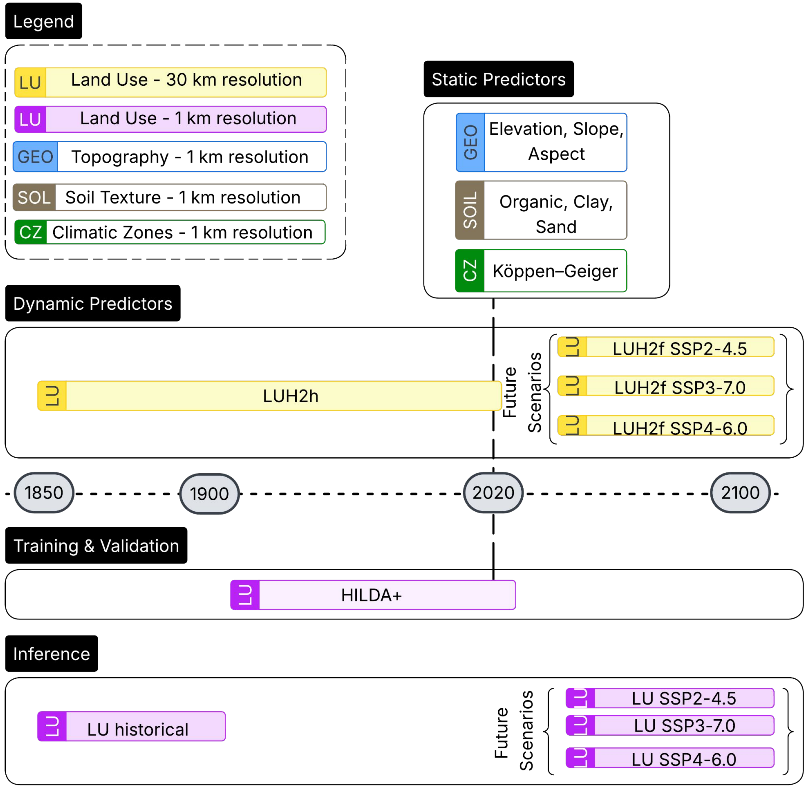
This figure illustrates the timeline and data sources for our framework.

Dynamic Predictors: We use coarse (30km) LUH2h data.

Static Predictors: We use high-resolution (1km) data for topography, soil, and climate zones*.

Training Target: The model is trained on high-resolution (1km) HILDA+ data.

Final Output: A consistent, 1km resolution LU dataset spanning 1850-2100.



** we are working on to incorporate climate zones as dynamic predictor.*

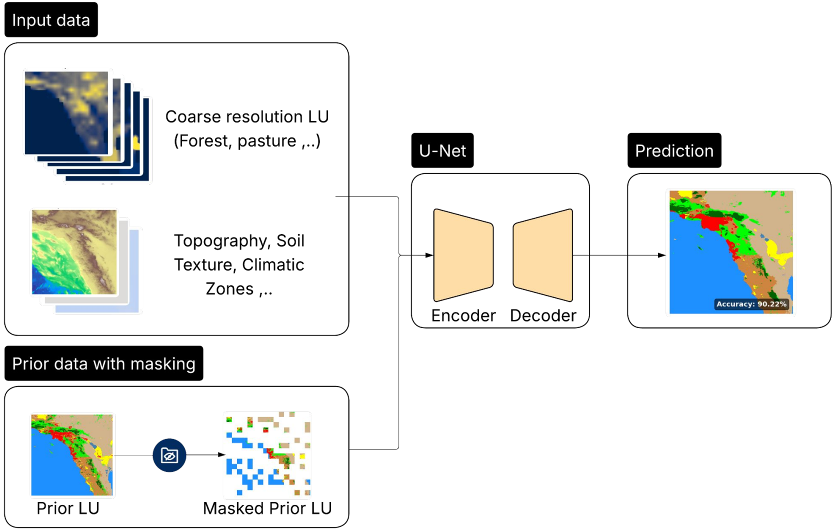
Model and training configuration

The core of our pipeline is a U-Net model.

Inputs: The model combines three key data streams:

- Coarse-resolution fractional LU maps.
- High-resolution static variable maps (Topography, soil texture, climatic zones).
- A masked, high-resolution LU map from a prior time step.

Output: The U-Net predicts the final, high-resolution Land Use map.

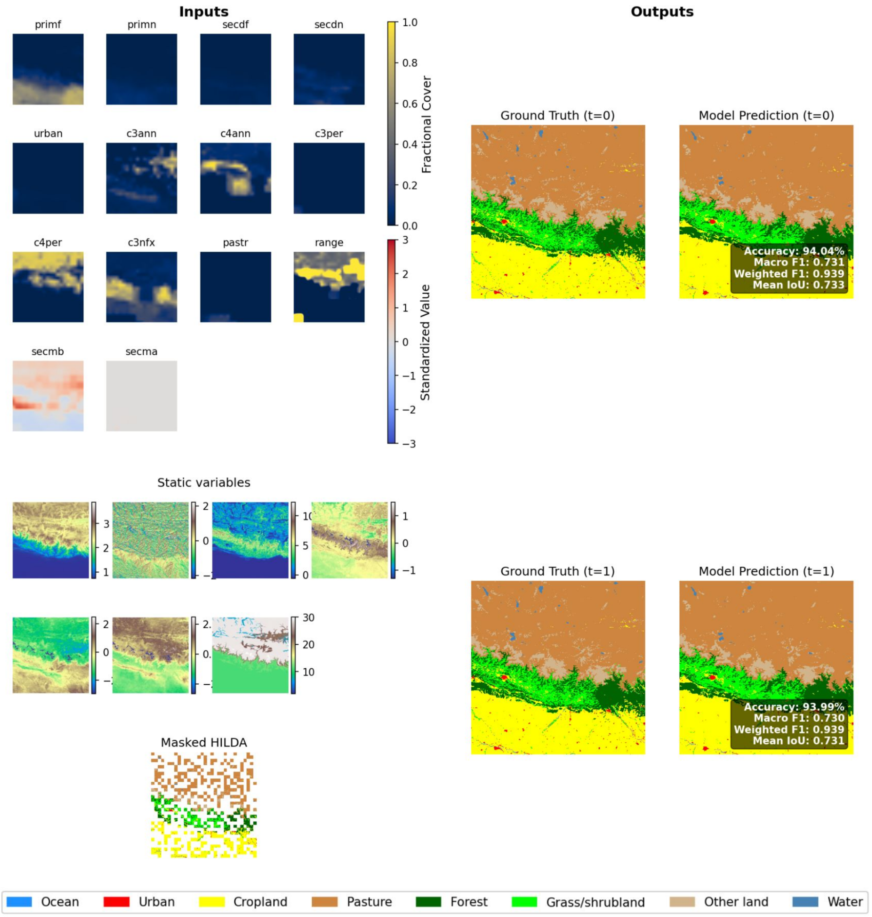


Preliminary results

Overall Performance: Trained on 30k samples, with 5-fold cross-validation, our U-Net achieved a 0.626 mean IoU (mIoU), with average 94% accuracy across classes.

Class	Accuracy	F1	IoU
Ocean	1.0000	0.9999	0.9999
Urban	0.5554	0.6656	0.4998
Cropland	0.9112	0.8978	0.8154
Pasture	0.9079	0.8996	0.8183
Forest	0.9415	0.9403	0.8878
Grass/shrubland	0.8046	0.8270	0.7064
Other land	0.9651	0.9669	0.9364
Water	0.7774	0.8404	0.7281

	Year 0	Year 1	Average
Accuracy	0.9462	0.9449	0.9455
Macro F1	0.8807	0.8787	0.8797
Weighted F1	0.9458	0.9445	0.9452
Mean IoU	0.8005	0.7976	0.7990



Next steps:

Phase 1 (Complete): Build a global inference pipeline to merge prediction tiles and produce seamless, high-resolution LU and LC datasets.

Phase 2 (Implement): Extend the framework to predict high-frequency variables, specifically weekly or monthly Leaf Area Index (LAI).

Future Goal: Explore more advanced sequential and multi-task architectures to improve dynamic modelling.

Integration: Couple the validated models into weather-climate frameworks to serve as real-time land surface emulators for Digital Twins of the Earth.

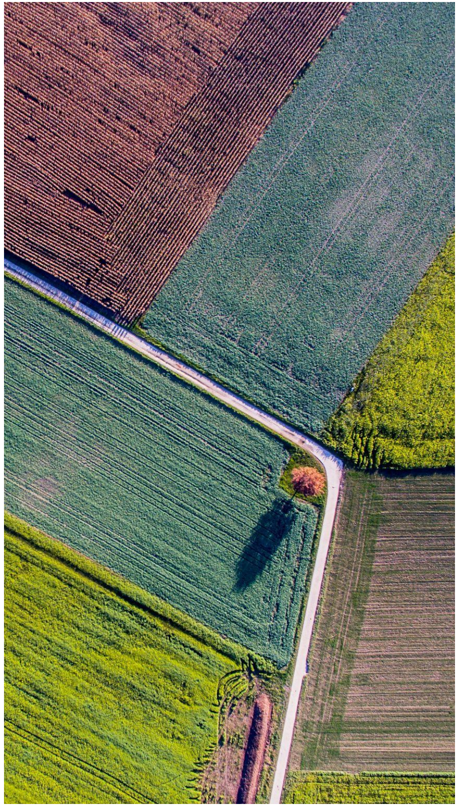


Photo by [jean wimmerlin](#) on [Unsplash](#)

Thank you

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