

Background

Land Use (LU), Land Cover (LC), and Leaf Area Index (LAI) act as boundary conditions for the atmosphere aloft, and are crucial for the modulation of local and regional climate, regulating energy, water, and carbon exchanges, and playing a key role in the terrestrial carbon cycle.

- **Improved representation of land-atmosphere interactions** ensures more realistic fluxes of water, energy, and carbon towards the atmosphere.
- **Enhanced forecasts and projections** improve near-surface weather and climate predictions for better risk management, adaptation, and mitigation.

Earth Observation (EO) provides global coverage for Land Surface Boundary Conditions (LSBC), but for historical data and future projections, we lack consistent high-resolution datasets. In this project, we try to tackle this challenge in two phases. Phase one: producing annually varying LU and LC. Phase two: expanding to weekly varying LAI.

Spatiotemporal Super Resolution

We have created a super-resolution framework that will allow us to consistently generate LU datasets from as far back as 1850 (the start of industrialization) to future projections up to the year 2100. Figure 1 shows the temporal coverage of the dynamic predictors (LU), static predictors (topography, soil texture, and climatic zones), target LU, and inference period.

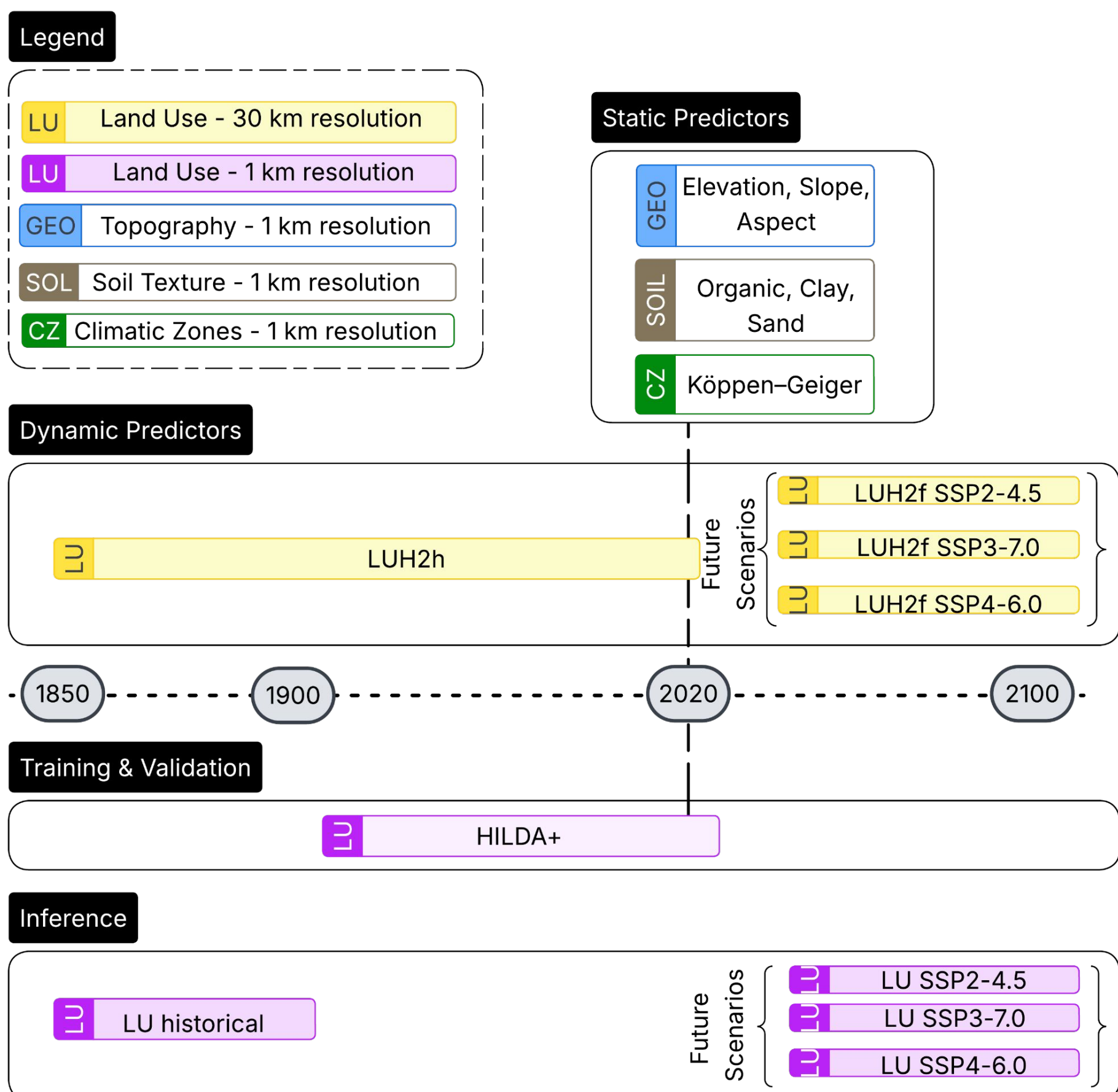


Figure 1: Temporal coverage of the framework's data. This includes the dynamic predictors (coarse 30 km LUH2h), static predictors (1 km topography, soil, and climate), the high-resolution training target (1 km HILDA+), and the final inferred 1 km LU output for 1850-2100.

Model Design

Our data pipeline processes static and dynamic channels at flexible spatial resolutions, using multiple prior time steps to generate multiple prediction steps. This framework enables both forward (forecasting) and backward (hindcasting) predictions. We tested CNN, XGBoost, and U-Net models, with U-Net outperforming the others in both accuracy and computational efficiency. In our U-Net model, prior steps are masked to ensure the model learns to predict, not just copy prior states.

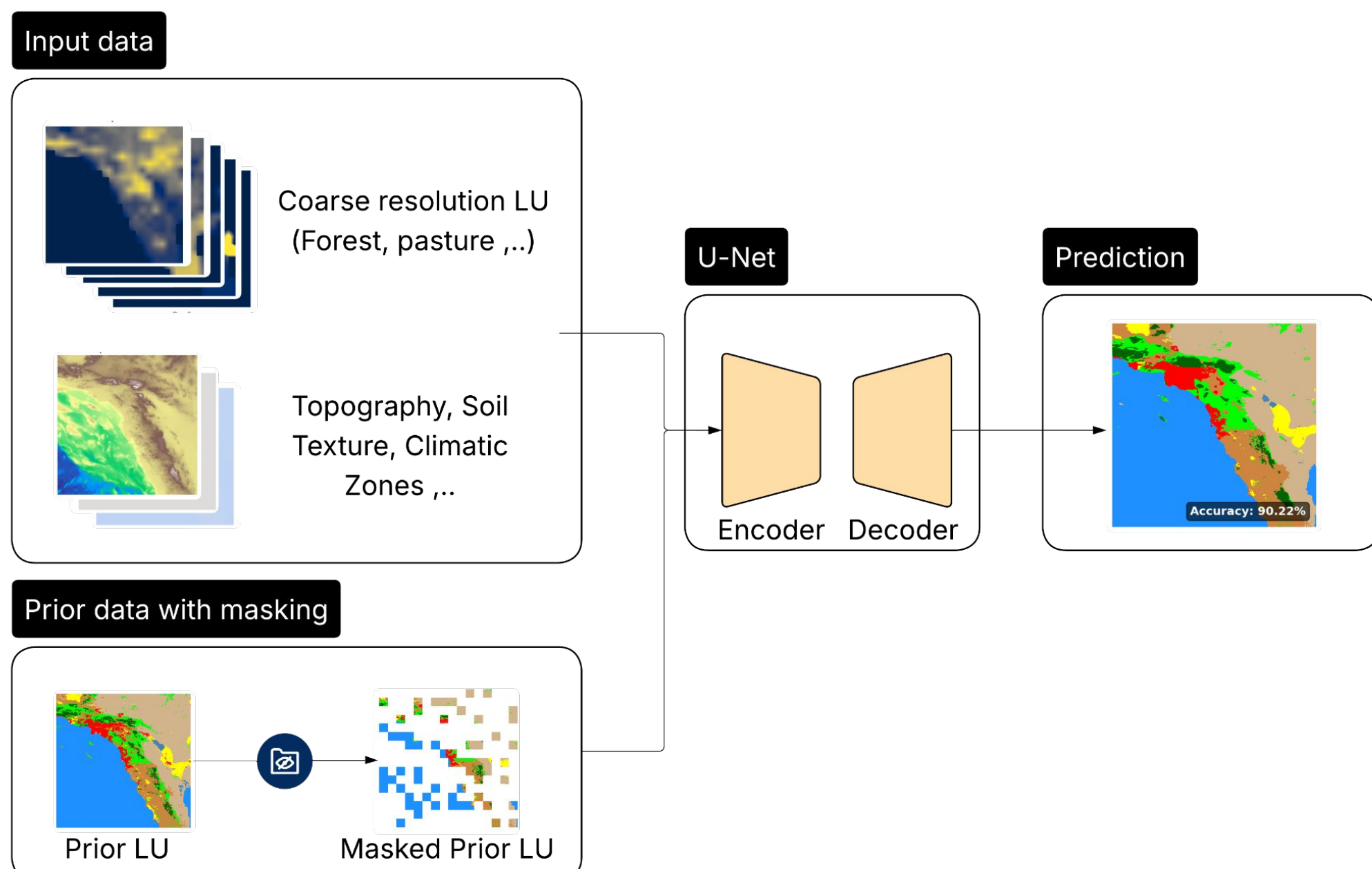


Figure 2: Overview of the LU reconstruction pipeline. The U-Net model combines coarse-resolution LU, static data (elevation, soil, climate), and a masked prior LU map to predict the final high-resolution LU output.

Results

Trained on 30k samples, our U-Net achieved a 0.626 mIoU (90% accuracy w/ 75% masking). Analysis of the mIoU score shows robust detection of dominant classes but confusion between similar vegetation types. This problem was amplified for underrepresented LU types, where mIoU dropped to ~0.42. Figure 3 provides a qualitative example of this task, illustrating the input channels, masked prior, and the resulting model predictions for the years 2004 and 2005.

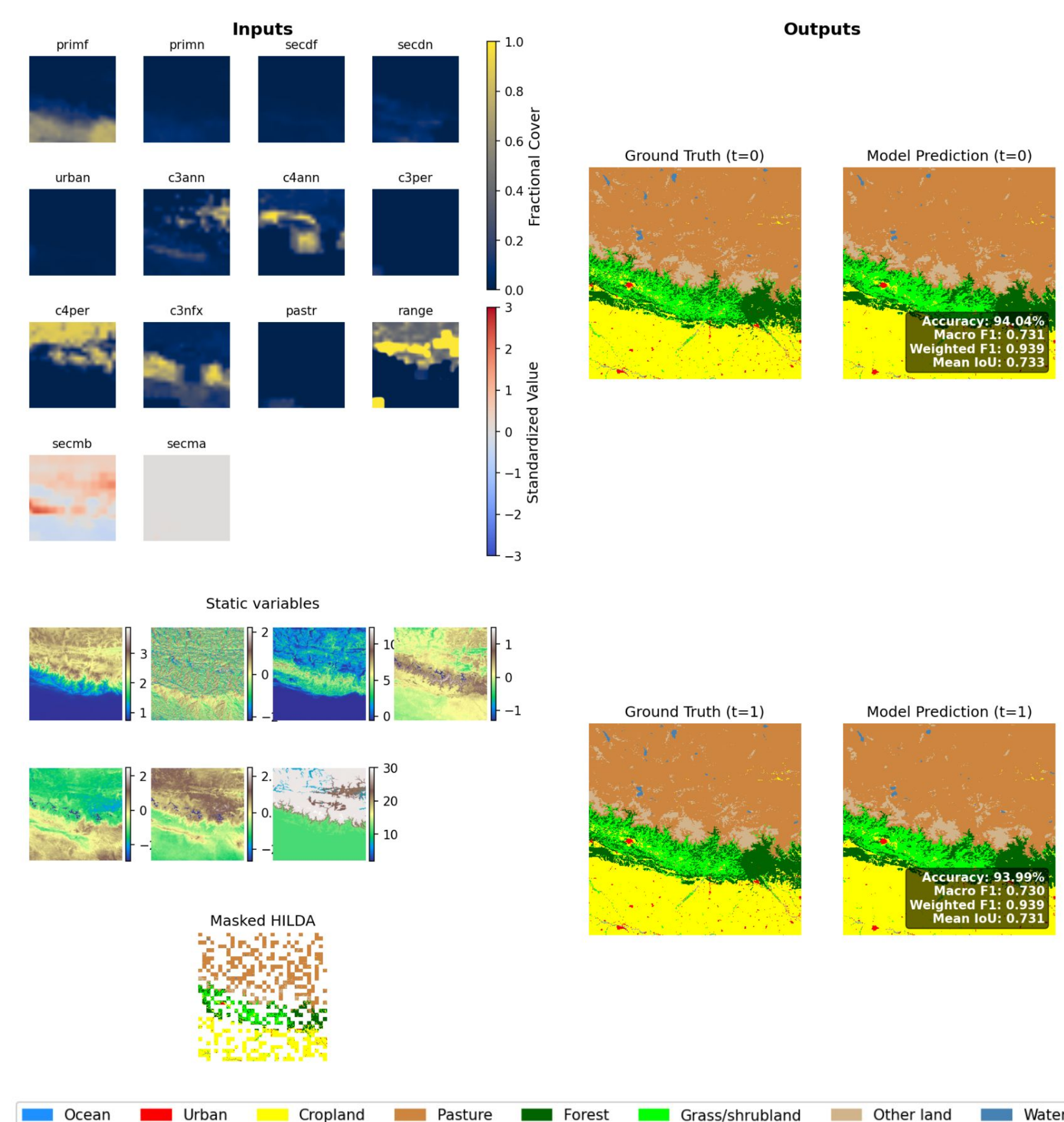


Figure 3: Qualitative results for the Himalayas region (Year 2003). The figure displays the full stack of input channels, including 12 coarse fractional LU inputs (top-left), 6 high-resolution static variables (middle-left), and the masked HILDA prior (bottom-left). The model's multi-step predictions (right) for two time steps (t=0, t=1) show strong agreement with the ground truth, achieving ~94% accuracy and a Mean IoU of ~0.73.

Future Work & Outlook

- **Complete LU/LC Reconstruction (Phase 1):** Build a global inference pipeline for merging tiles to produce seamless LU datasets, and extend the model to predict high-resolution LC.
- **Implement Dynamic Modeling (Phase 2):** Extend the framework to predict high-frequency variables, specifically weekly or monthly Leaf LAI, and to explore sequential and multi-task architectures.
- **Integrate Models as Emulators:** Couple the validated LU, LC, and LAI models into weather-climate frameworks to serve as real-time land surface parameters emulators for Digital Twins.