Pure and Physics-encoded Spatiotemporal Deep Learning for Climate-Vegetation Dynamics

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NEURAL INFORMATION PROCESSING SYSTEMS

Introduction

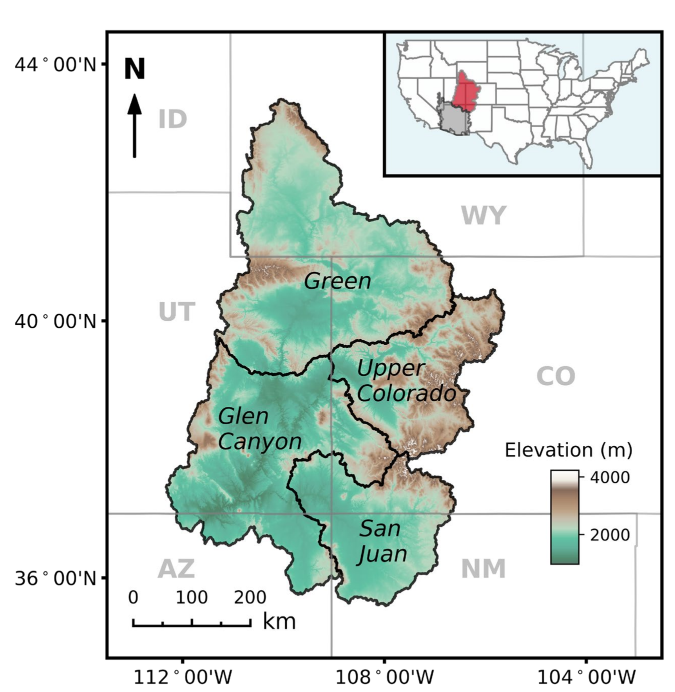
- Vegetation regulates land surface water and energy exchanges
- Accurate representation of climate-vegetation feedback is crucial for reliable climate projections and water resource management
- Limitations of current approaches exist.

Traditional Process-Based Vegetation Models	Existing Deep Learning (DL) Applications
Oversimplified parameterizations - monthly climatology fails to capture extremes and trends; fixed plant functional types insufficiently represent real diversity	**Black-box limitations** - lacks interpretability and physical consistency for scientific understanding
Structural errors - rules derived from point-scale observations do not scale well	**Forecast-focused instead of projection-focused** - incorporates prior vegetation states, unsuitable for climate impact studies
Limited spatiotemporal interactions - prioritize vertical atmospheric feedbacks while neglecting horizontal processes	**Limited spatially distributed applications** - point-scale or flattened inputs overlook heterogeneity and risk overfitting

- We aim to develop a climate-driven, spatially distributed deep learning framework for daily-scale vegetation dynamics.

Study Area and Dataset

- Upper Colorado River Basin (UCRB) is a critical water source region with diverse hydroclimatic gradients and complex vegetation dynamics

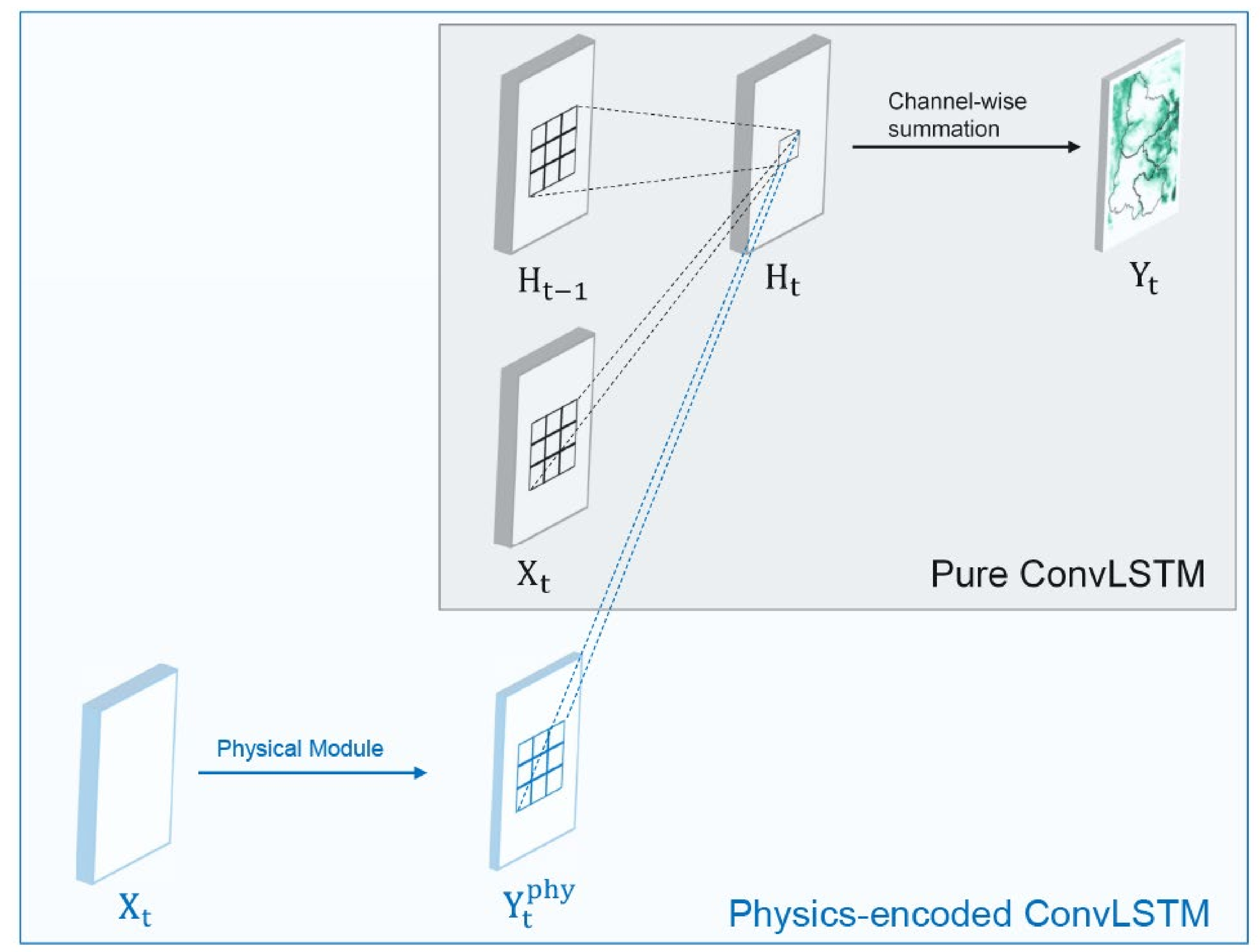


Location of Upper Colorado River Basin (UCRB) and subbasins

- **Climate data**: daily precipitation, temperature, radiation, and humidity from NLDAS-2 at 1/8° resolution, providing consistent forcing inputs across CONUS
- **Vegetation data**: GLOBMAP Leaf Area Index (LAI) at 0.073° resolution, with global coverage from 1981 onward at half-monthly to 8-day intervals
- **Data split**: temporal split, training (1981-2001), validation (200-2008), testing (2009-2016)

Methods

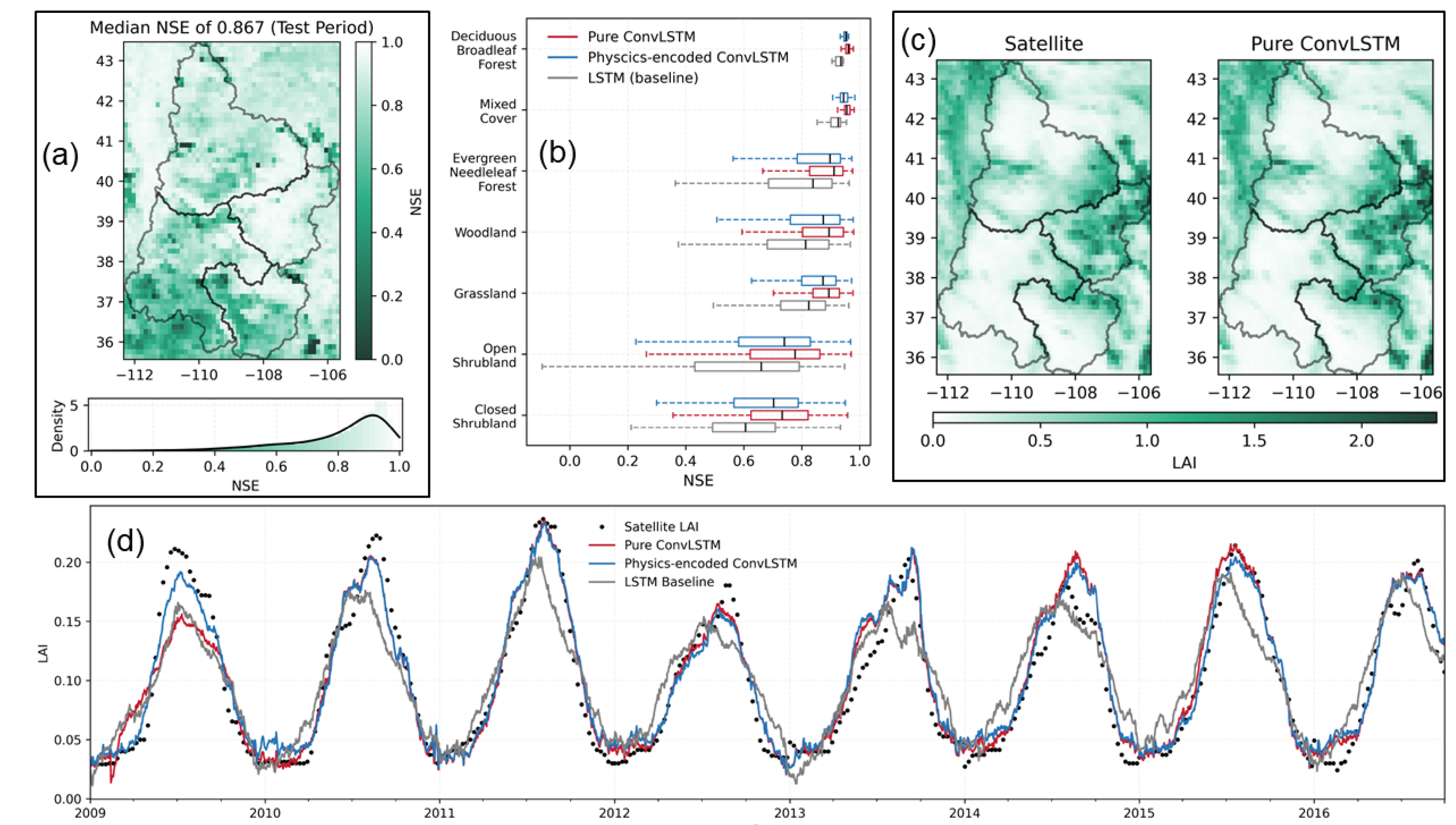
- A one-layer ConvLSTM model with 16 filters is employed, framing LAI prediction as a spatiotemporal sequence-to-sequence problem to process 2D climate inputs and output LAI maps



- Two variants are implemented: (1) Pure ConvLSTM using only climate forcings; (2) Physics-Encoded ConvLSTM that integrates process-based LAI simulation as an additional input, acting as a bias-corrector
- Models are trained on 63×54 spatial grids using the AdamW optimizer with early stopping to ensure robust learning and prevent overfitting

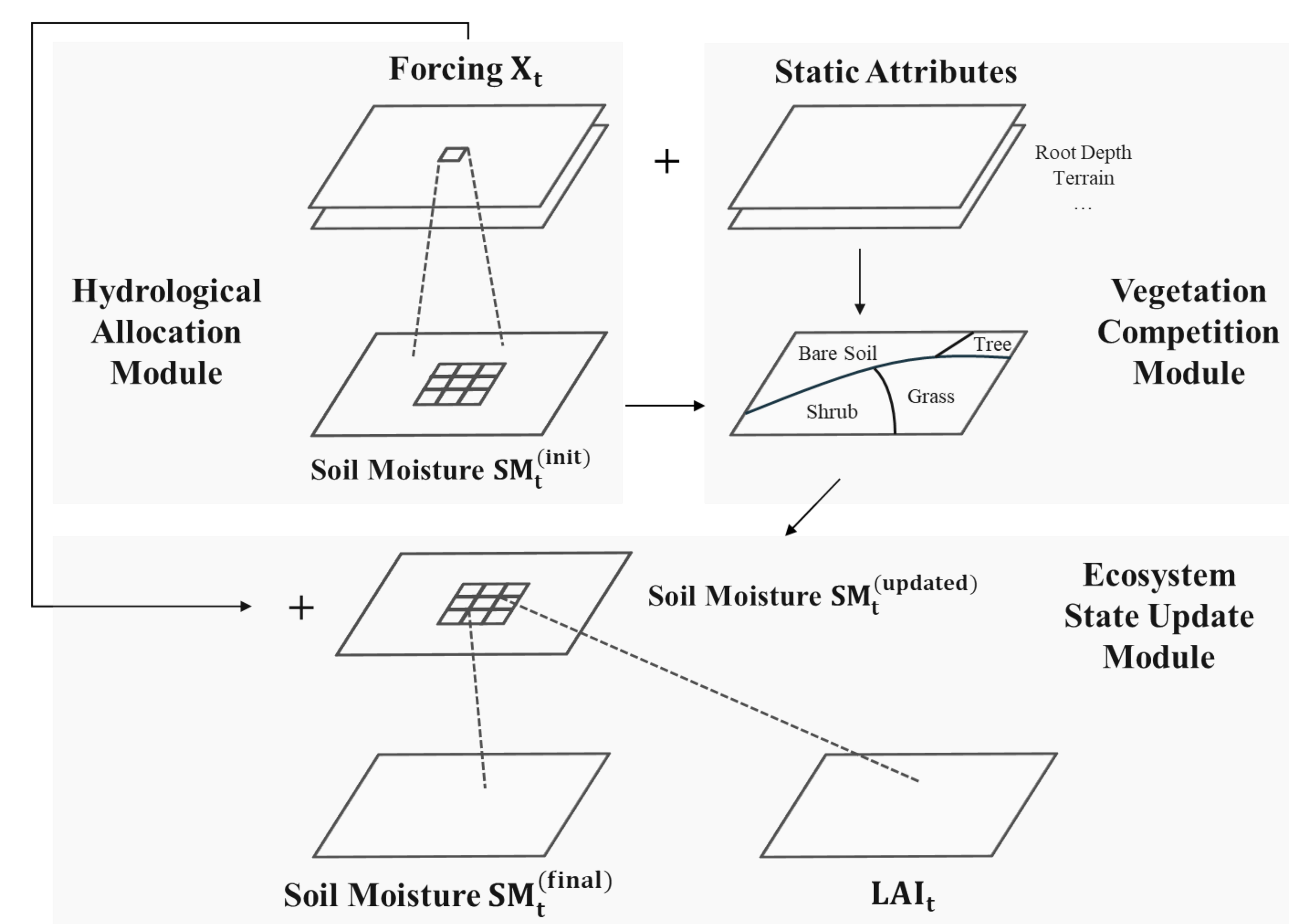
Results and Impact

- Pure ConvLSTM achieves the highest accuracy (median NSE: 0.867), followed by physics-encoded ConvLSTM (0.839), both substantially outperforming the LSTM baseline (0.787)
- Pure ConvLSTM excels at capturing both spatial patterns and temporal dynamics across diverse vegetation types, demonstrating its ability to learn complex ecohydrological interactions
- The physics-encoded variant shows enhanced stability in water-limited regions and reduces unrealistic fluctuations, proving valuable for reliable extrapolation in climate projection scenarios
- This spatially distributed deep learning framework enables more reliable vegetation and water resources projections under climate change, bridging AI and Earth science to support climate adaptation strategies



(a) Spatial distribution and probability density of NSE for the pure ConvLSTM over the study area during the test period (2009-2016); (b) Boxplots of NSE for the LSTM baseline, pure ConvLSTM, and physics-encoded ConvLSTM across dominant vegetation types; (c) Example spatial comparison between pure ConvLSTM-simulated LAI and satellite-derived LAI on May 9, 2014; (d) Example comparisons of simulated vegetation dynamics (Open Shrubland) from the LSTM baseline, pure ConvLSTM, and physics-encoded ConvLSTM during the test period.

Future Work: Knowledge-guided DL



Key References

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