A Hybrid Differentiable Land Surface Model for Improved Land-Atmosphere Flux Predictions

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We are developing a novel JAX-based hybrid framework that combines physics-based LSM with deep learning to model land-atmosphere fluxes

- Novel integration of differentiable physics-based LSM with LSTM for latent and sensible heat prediction
- Leverages global FLUXNET data to target broad applicability across diverse ecosystems
- JAX implementation provides end-to-end differentiability with state-of-the-art numerical solvers

Problem Statement

- Latent/sensible heat flux accuracy is critical in climate feedback mechanisms, drought prediction, and cloud formation processes
- Traditional LSMs have rigid parameterizations causing ecosystem-specific overfitting and poor generalization
- Machine learning approaches show promise but often lack physical/causal constraints
- Need for architectures that preserve process equations while enabling global calibration

Our Approach

- Developed a coupled energy-mass balance land surface model (LSM)
- A Long Short-Term Memory (LSTM) network used to dynamically parameterize LSM
- Unified LSM-LSTM model implemented in a differentiable Python framework called JAX
- Potential advantages: global calibration and skill transfer to untrained variables (runoff)
- Preliminary analysis conducted on a single FLUXNET site which will be scaled to all sites in the future

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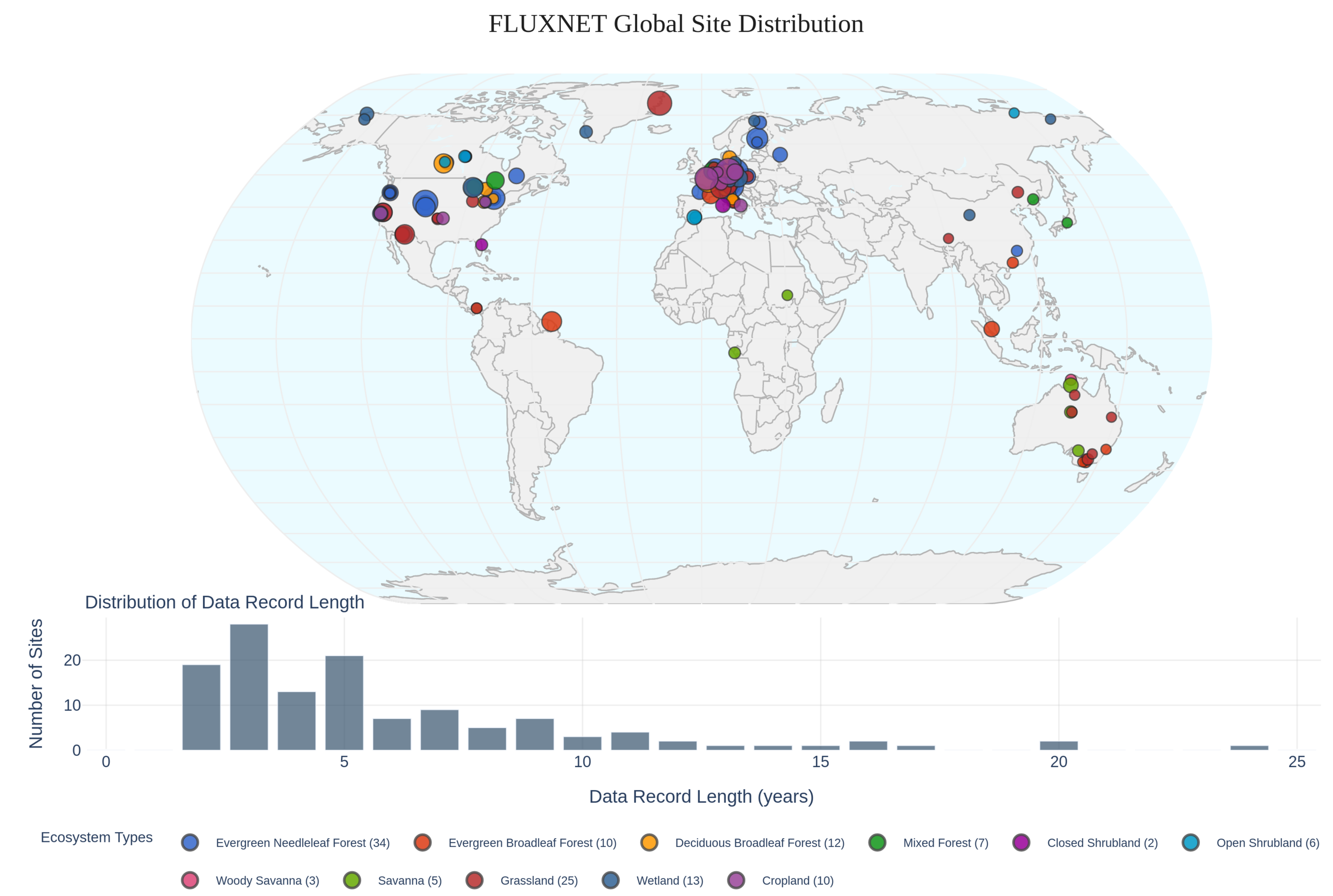
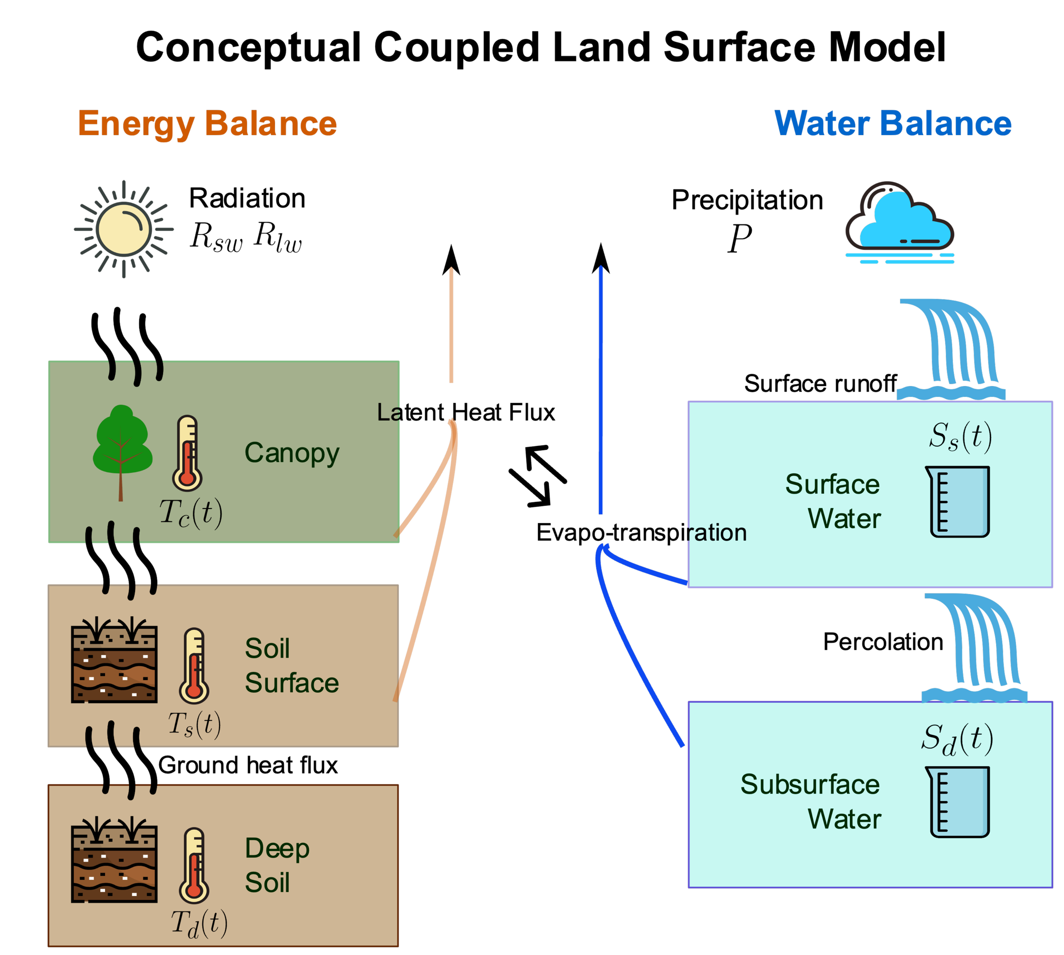
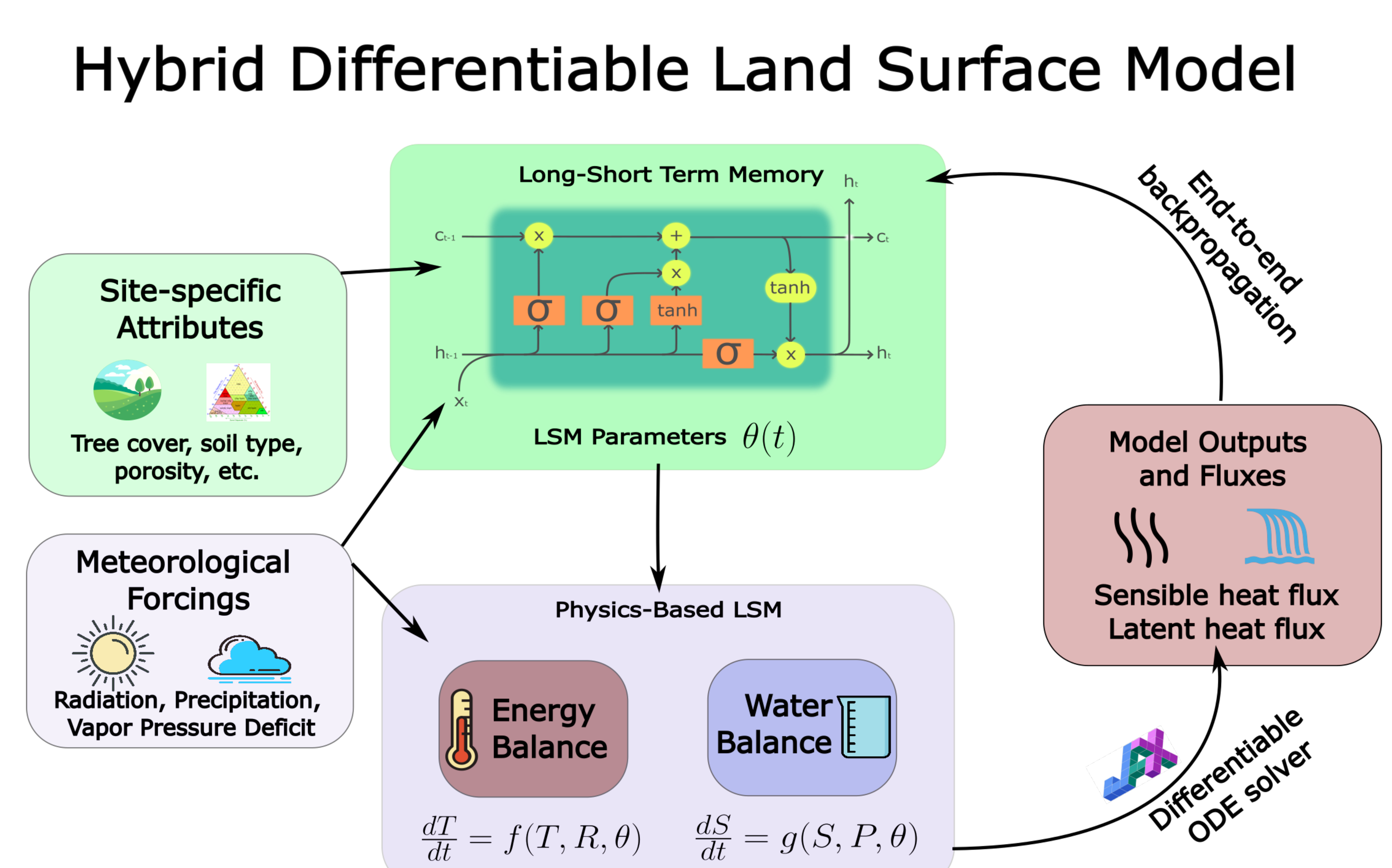
1 Global distribution of 212 FLUXNET sites provides diverse training data across biomes and climate zones



2 Our LSM captures key water and energy interactions through coupled mass and energy balance equations



3 Differentiable programming in JAX enables end-to-end training of LSTM-LSM hybrid model



4 Preliminary analysis at Metolius Mature Pine, Oregon identifies potential strengths and areas for improvement