

Uncertainty Quantification and Calibration of E3SM Land Model



Khachik Sargsyan (SNL), Daniel Ricciuto (ORNL)

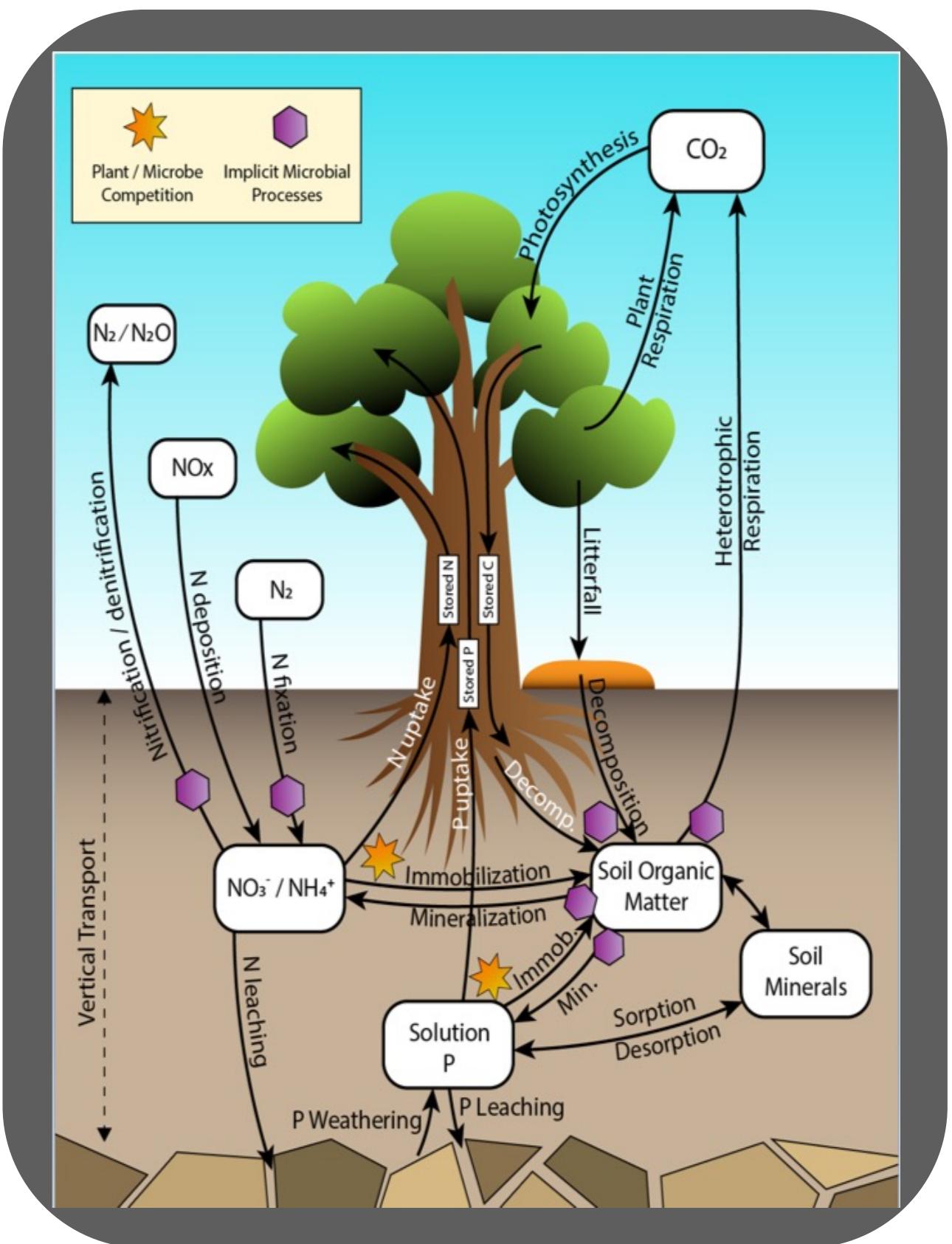


Objective

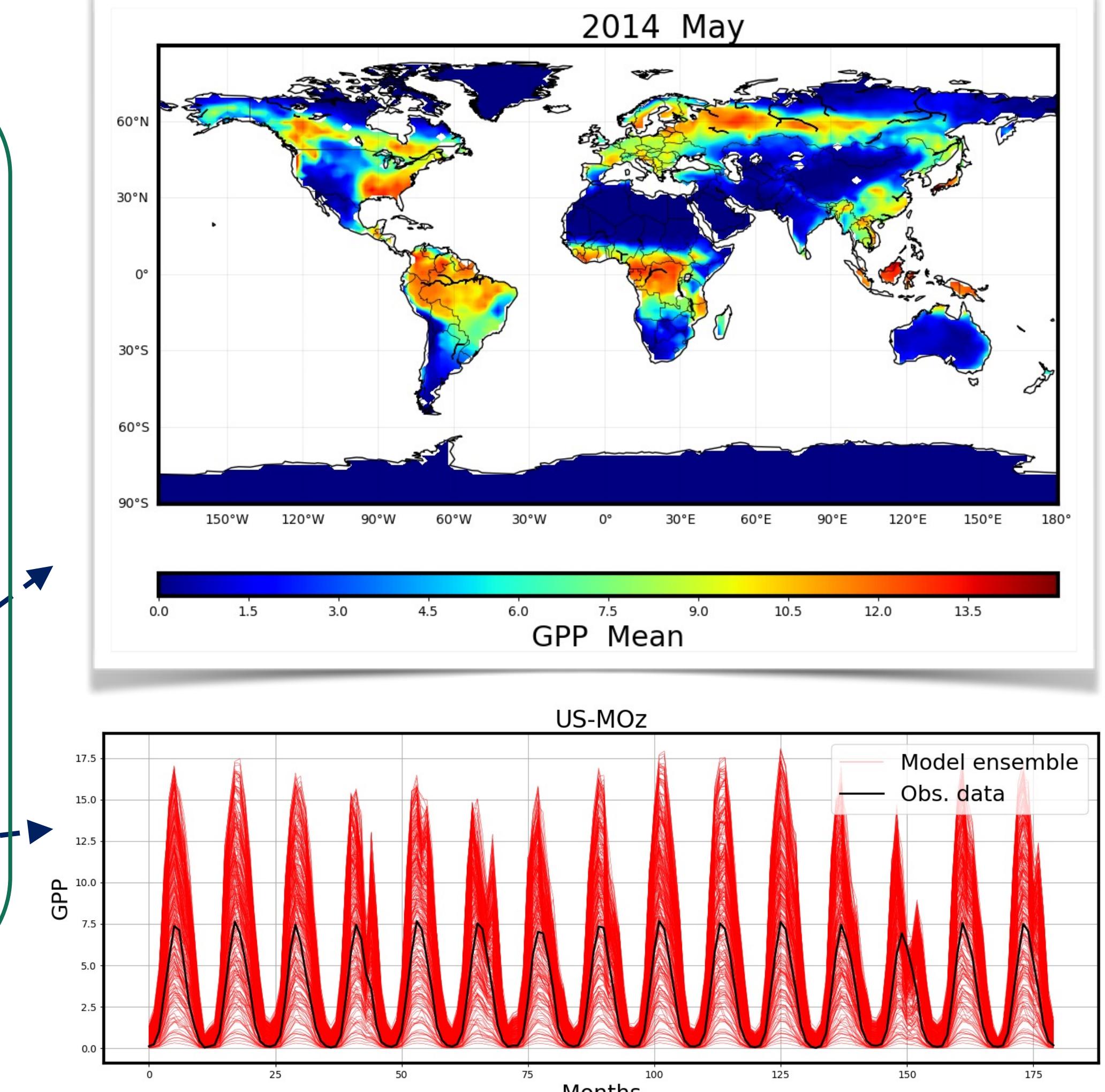
Develop workflows of surrogate construction for outputs of earth system models (ESM) to enable uncertainty quantification (UQ)

Sample-intensive studies, such as UQ and parameter calibration, for earth system models require a construction of a **surrogate model** that approximates the ESM behavior across a range of conditions and input parameters.

$$\begin{array}{ccc} \text{Model output} & M(\lambda; x) & \approx M_s(\lambda; x) \\ \text{Quantity of Interest (QoI)} & \text{Uncertain input parameters} & \text{Conditions, e.g.} \\ & & (\text{Longitude, Latitude, Altitude, Pressure, Time}) \end{array}$$



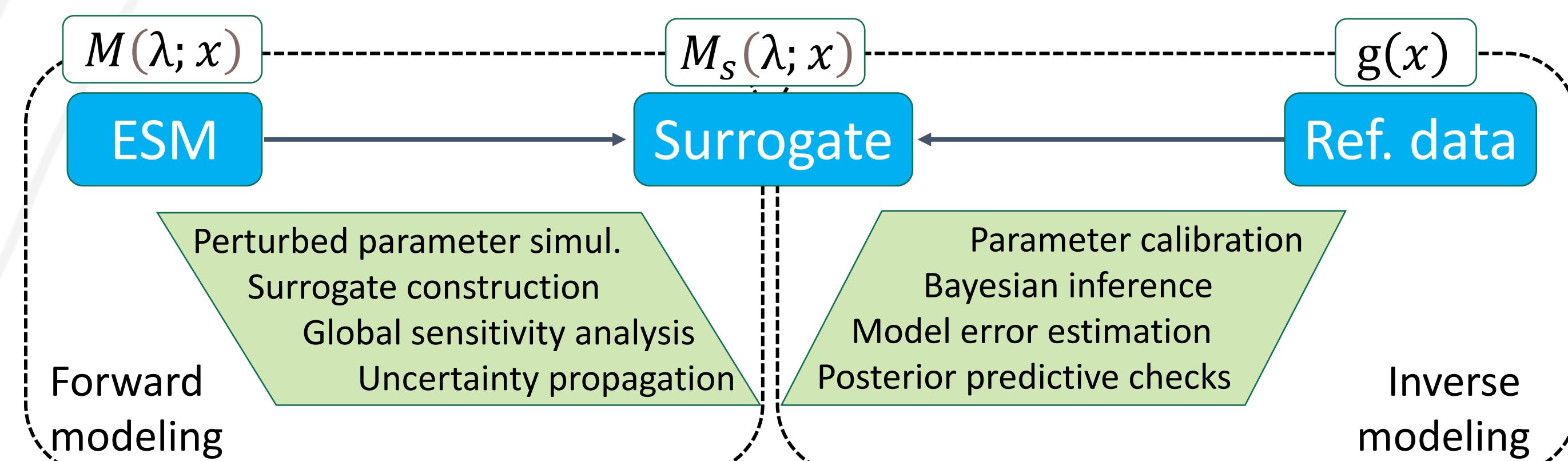
E3SM Land Model



Satellite Phenology version used for this study

Quantity of Interest:
Gross primary productivity (GPP)...
resolved in space ...
... and time.

UQ Workflow



Major challenges:

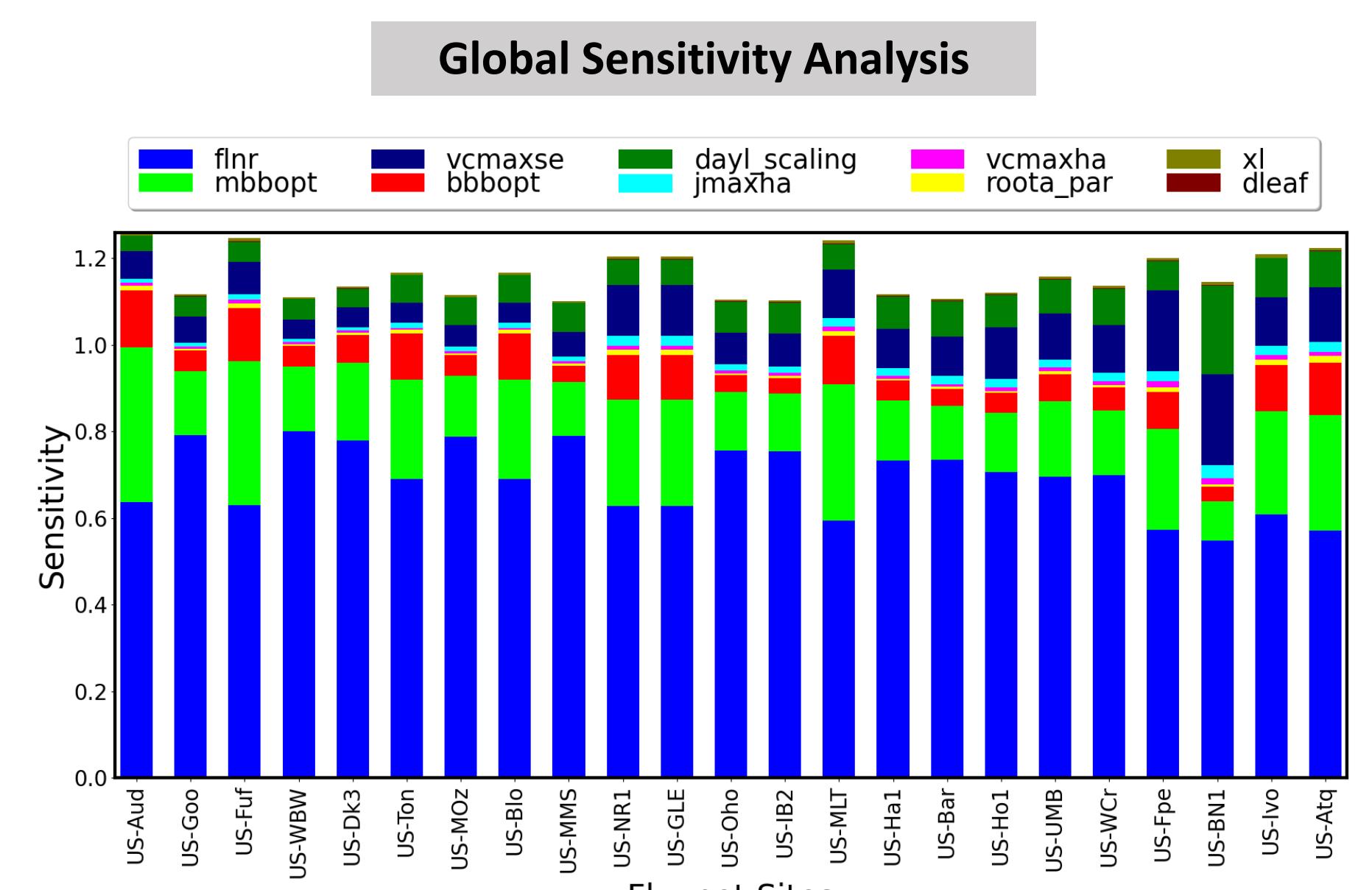
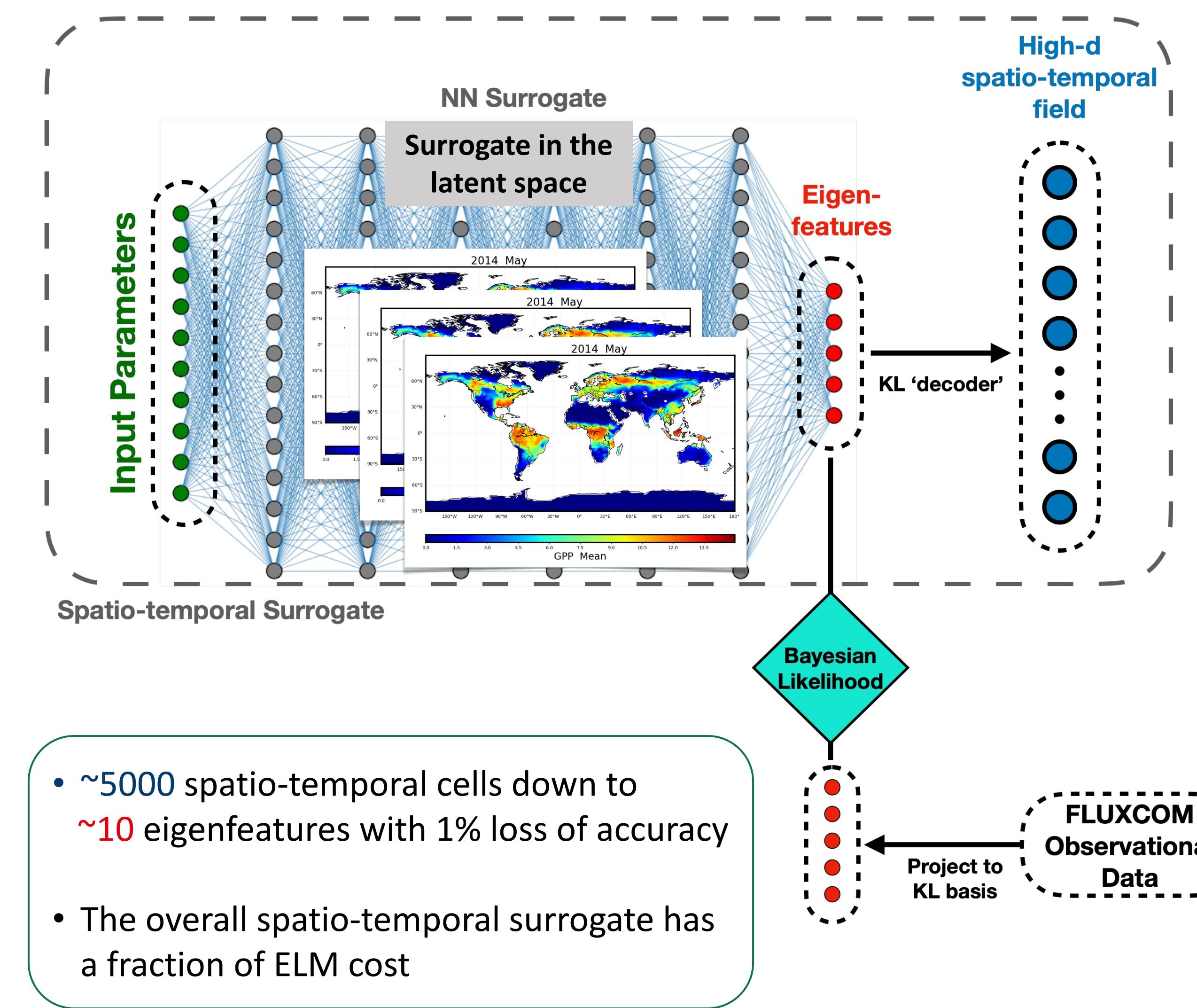
- Large number of conditions / high-dimensional output fields
 - Employ Karhunen-Loève decomposition to reduce dimensionality

$$M(\lambda; x) \approx \bar{M}(\lambda; x) + \sum_{j=1}^J \xi_j(\lambda) \sqrt{\mu_j} \phi_j(x)$$
 - Construct surrogate in the latent eigen-space

$$\xi(\lambda) \approx \xi_s(\lambda)$$
- Large number of uncertain inputs / high-dimensional stochastic space
 - Employ polynomial surrogates with compressed sensing to pick only relevant parameter combinations

$$\xi_s(\lambda) = \sum_{k=1}^K c_k \Psi_k(\lambda)$$
- Expense of ESM / low number of training simulations
 - No real remedy but cross-validation and hyperparameter optimization help.

Land Model Calibration enabled by Spatio-Temporal Neural Network Surrogate



Model calibration via Bayesian inference

