

Cutting out the middleman: Calibrating and validating an ecosystem model using remotely sensed surface reflectance

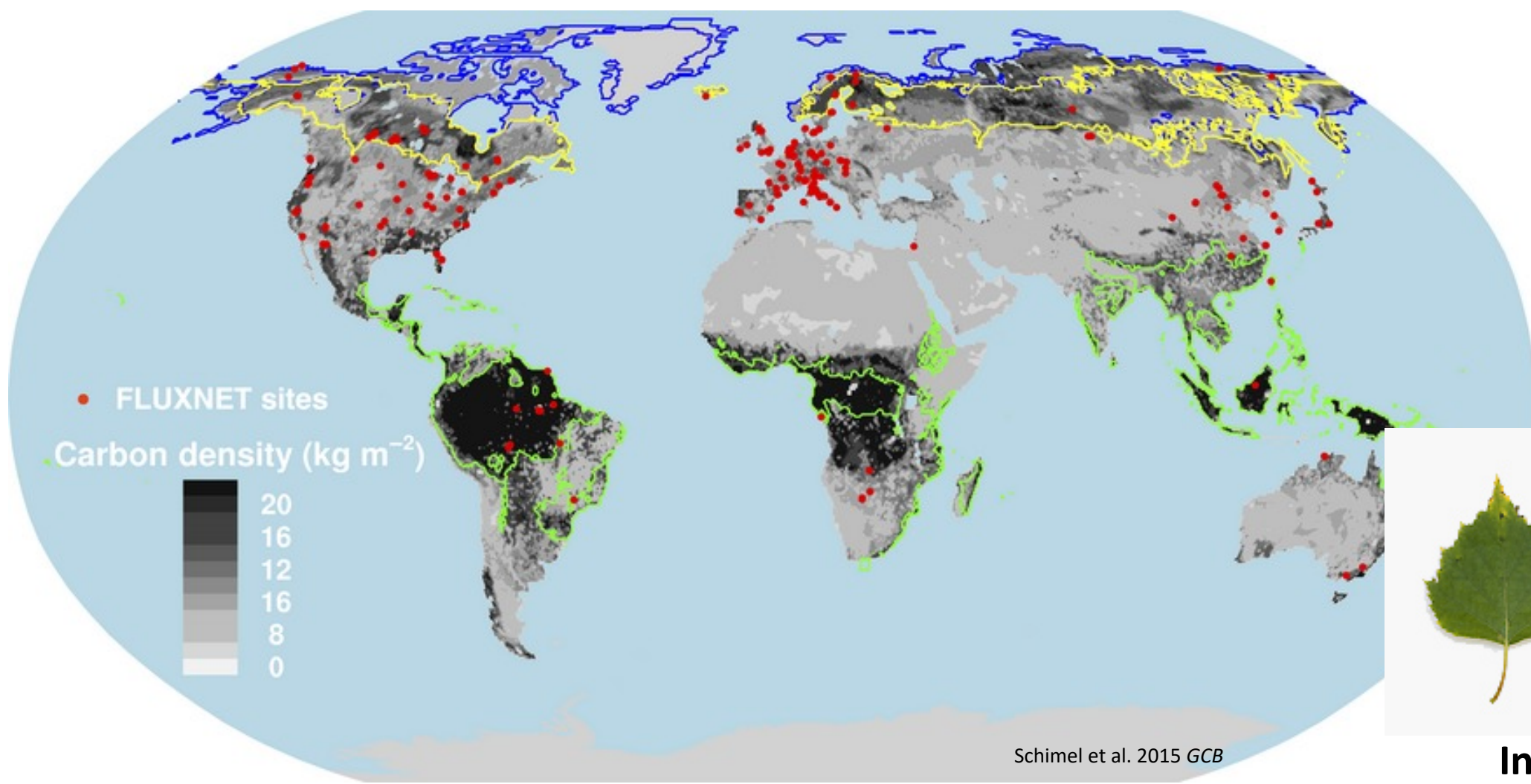
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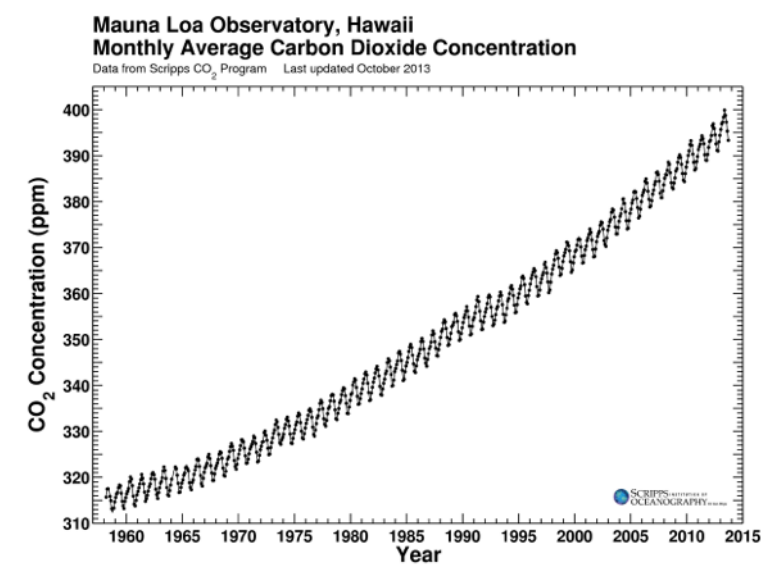
⁴ Brookhaven National Laboratory



Remote sensing is an exceptional data source for constraining ecosystem models...



Interannual variability



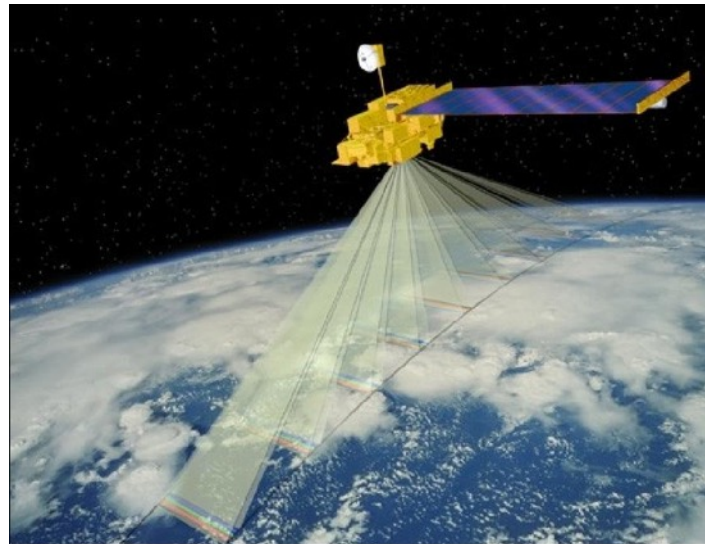
Intra-annual (e.g. seasonal) variability

Comprehensive spatial coverage...

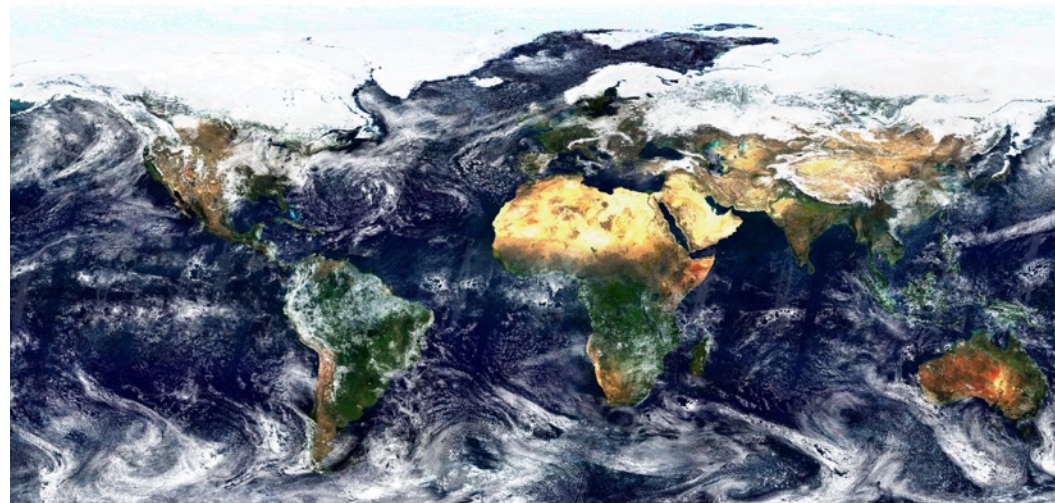
...and repeat observations through time

...but derived remote sensing data products can be tricky to use with models

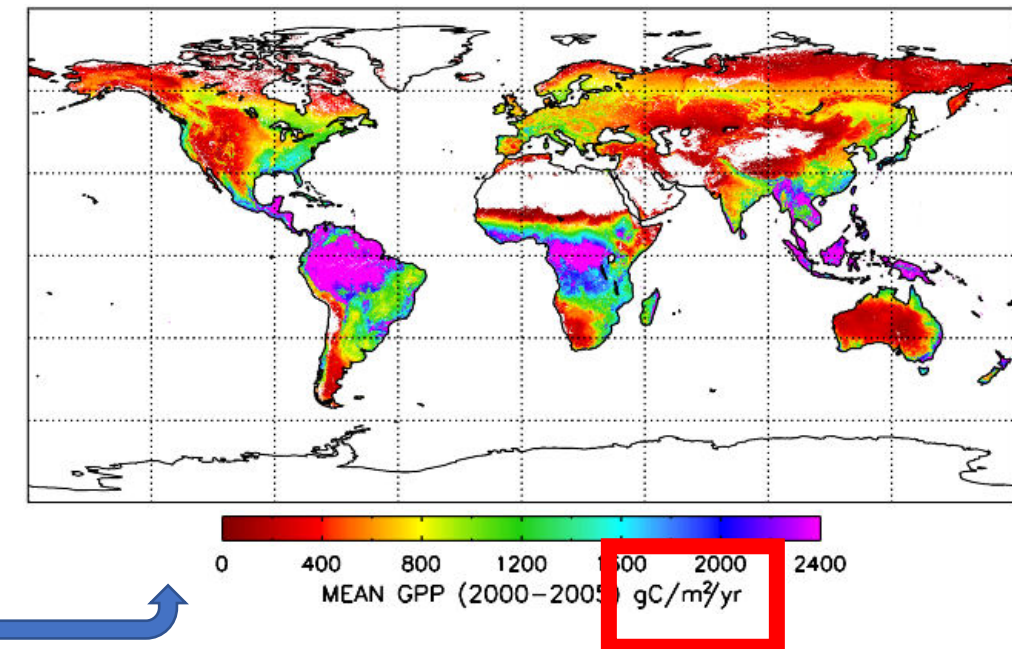
Raw observation



Surface reflectance

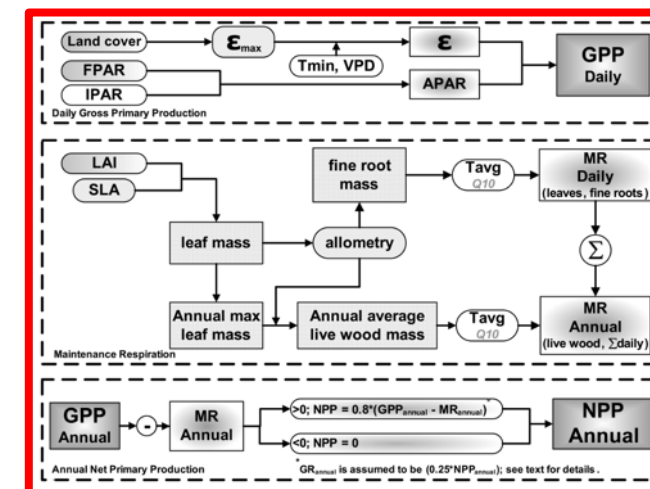


Gross primary productivity (GPP)



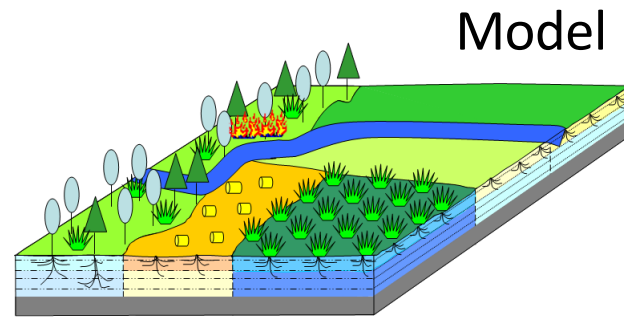
Atmospheric correction,
Orthorectification

High-level data products often use *models* whose assumptions may be inconsistent with those of your model

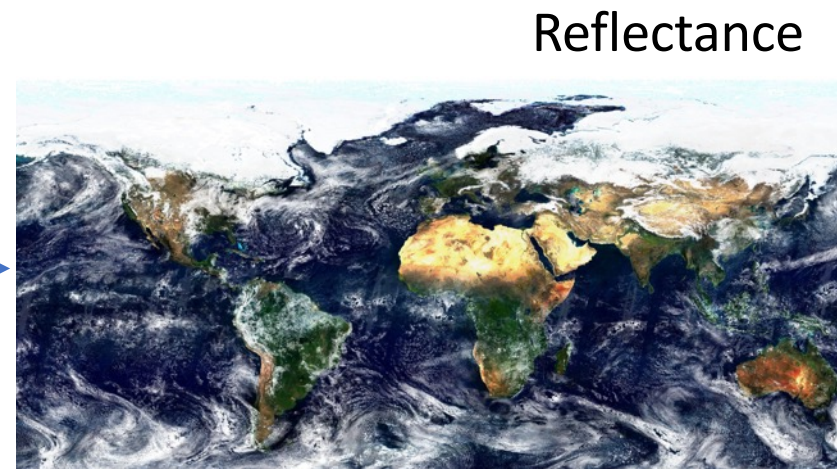
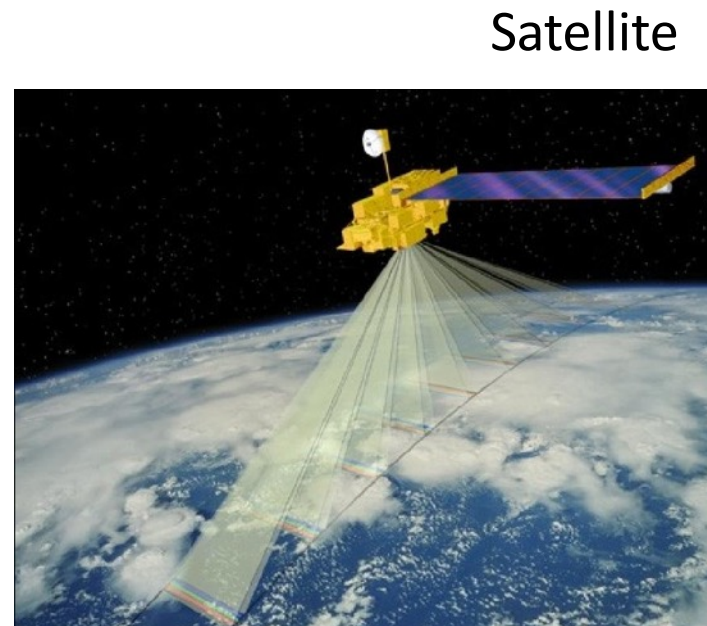
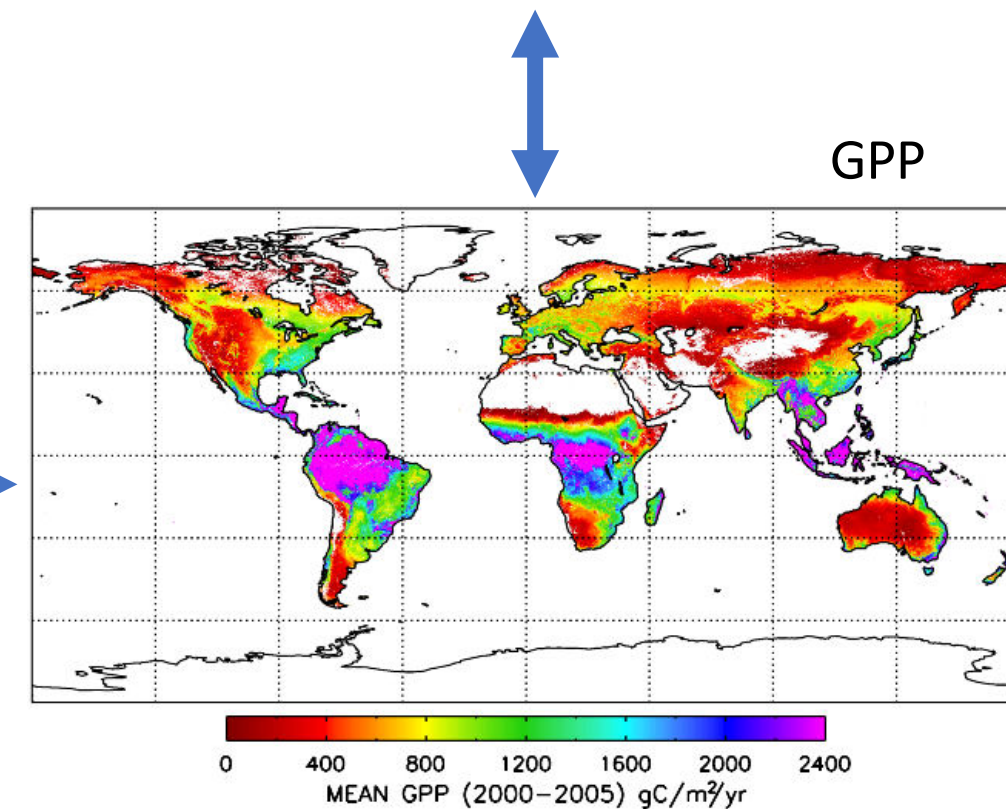
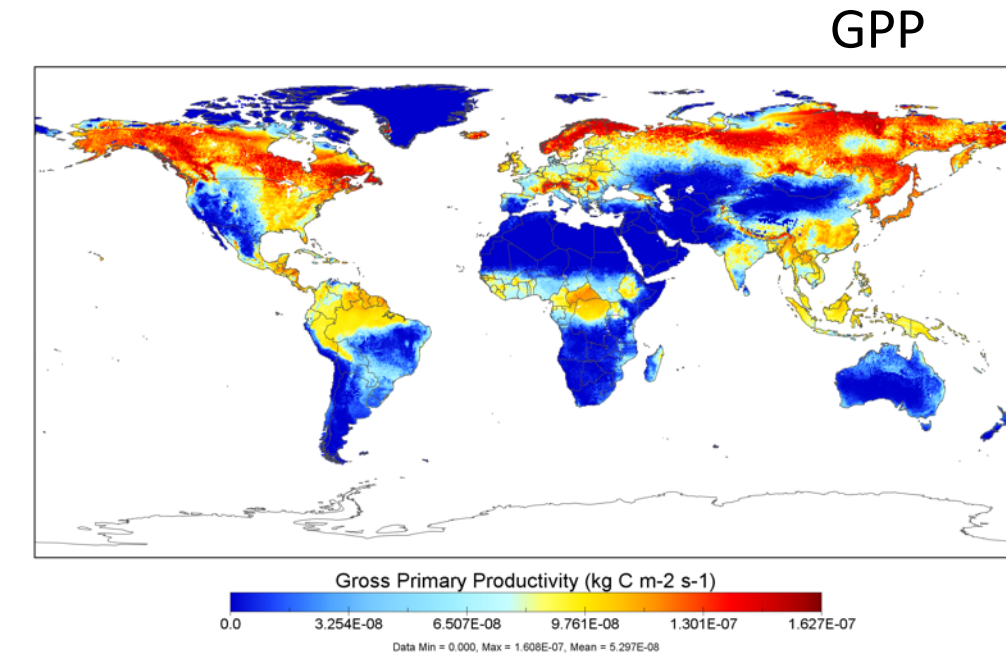


Uncertainties in data products are typically not well quantified

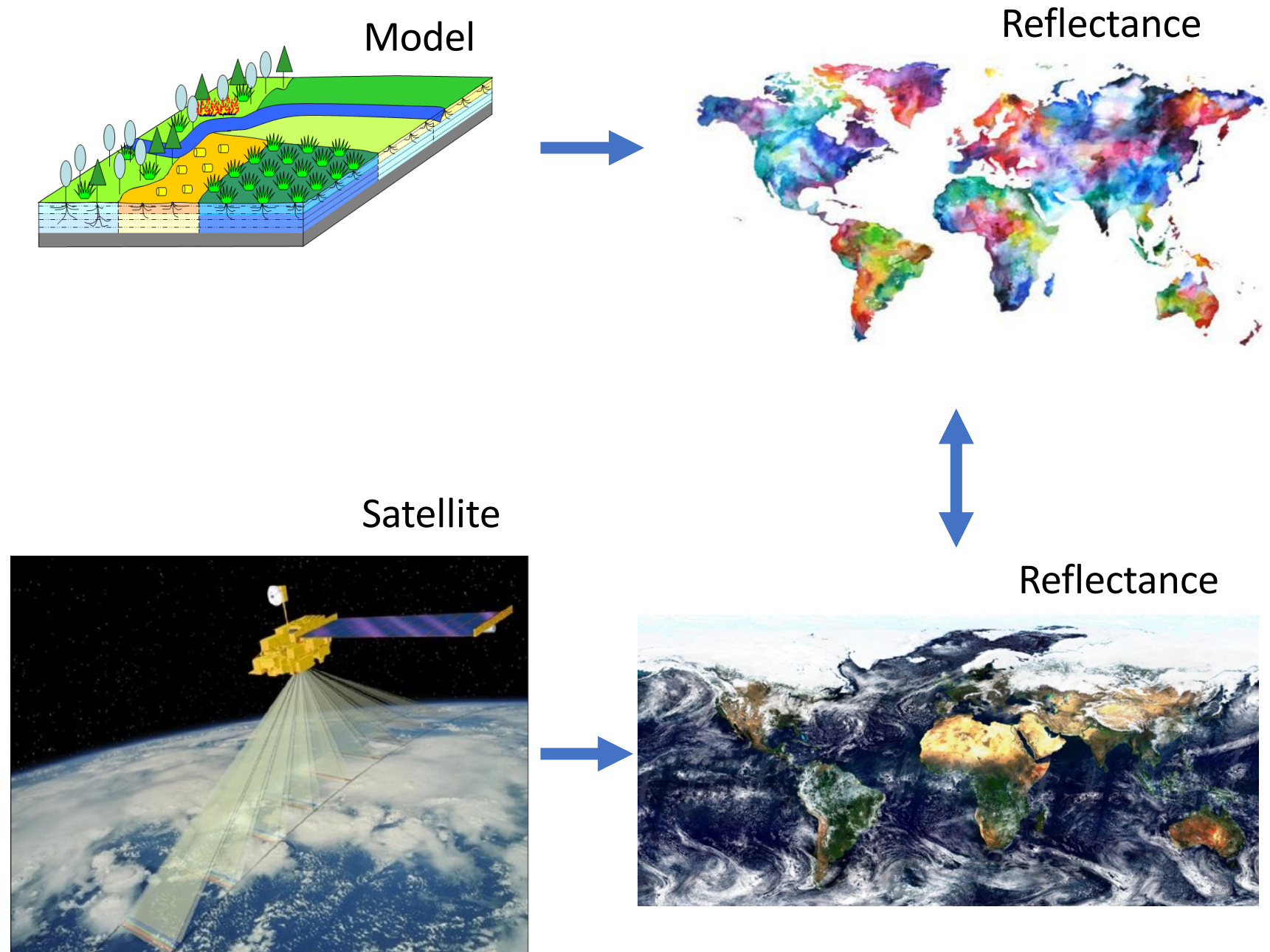
Typical approach: Compare model output to satellite data product (e.g. GPP)



This is problematic for the reasons discussed in the previous slide.



Alternate approach: Compare model *reflectance* vs. satellite *reflectance*

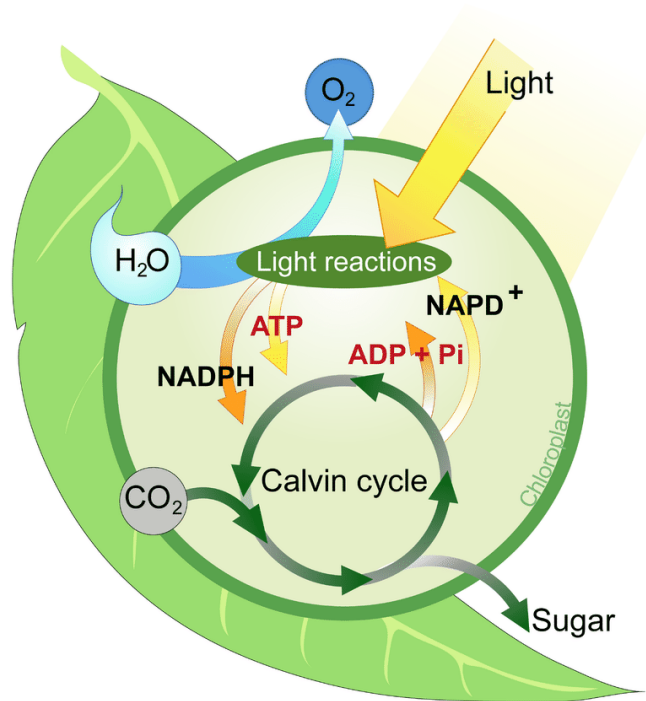


We now compare model output to a quantity **much closer to what remote sensing is actually measuring**.

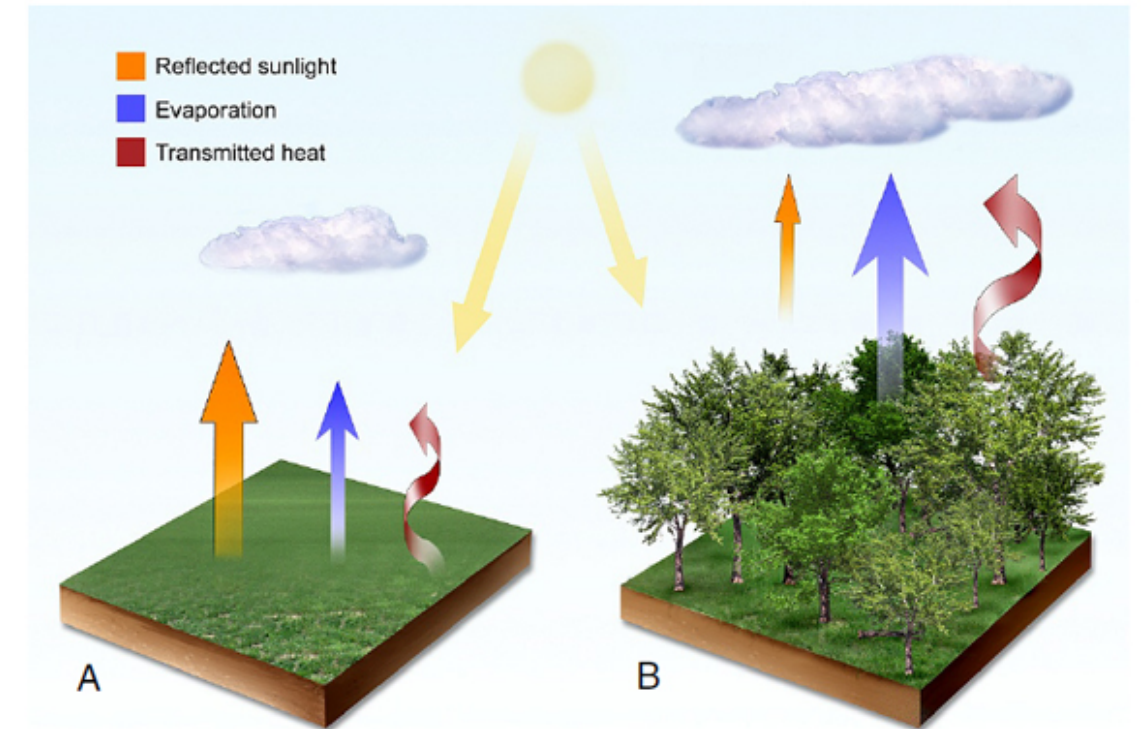
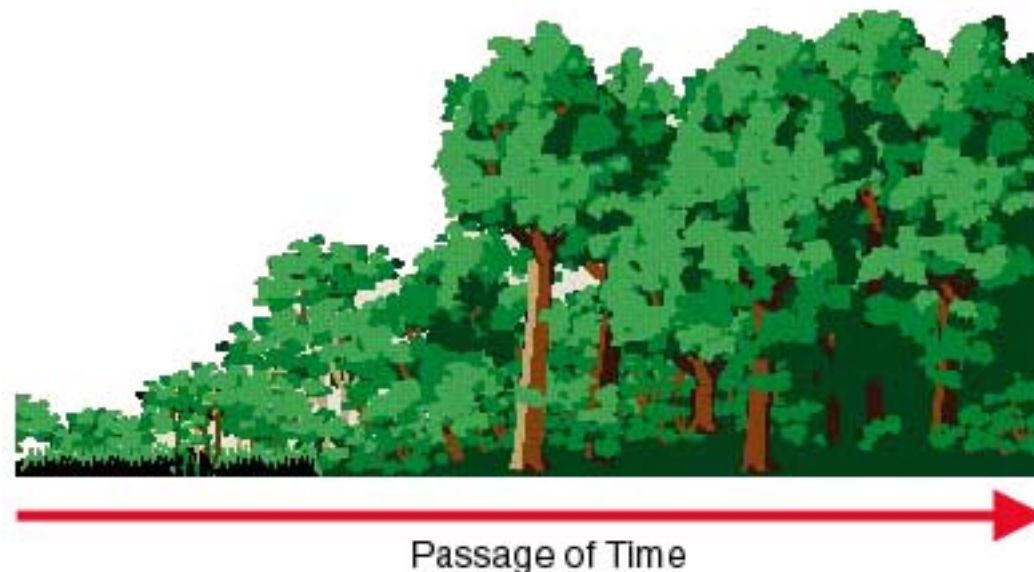
Therefore, we can be **more certain that differences between the model and the observations are errors in the model** (rather than errors in the derivation of the data product).

Getting surface reflectance right in models is important because reflectance is related to all of the following:

Physiological processes, such as photosynthesis



Ecological processes, such as competition and succession



Jackson et al. 2008 *ERL*

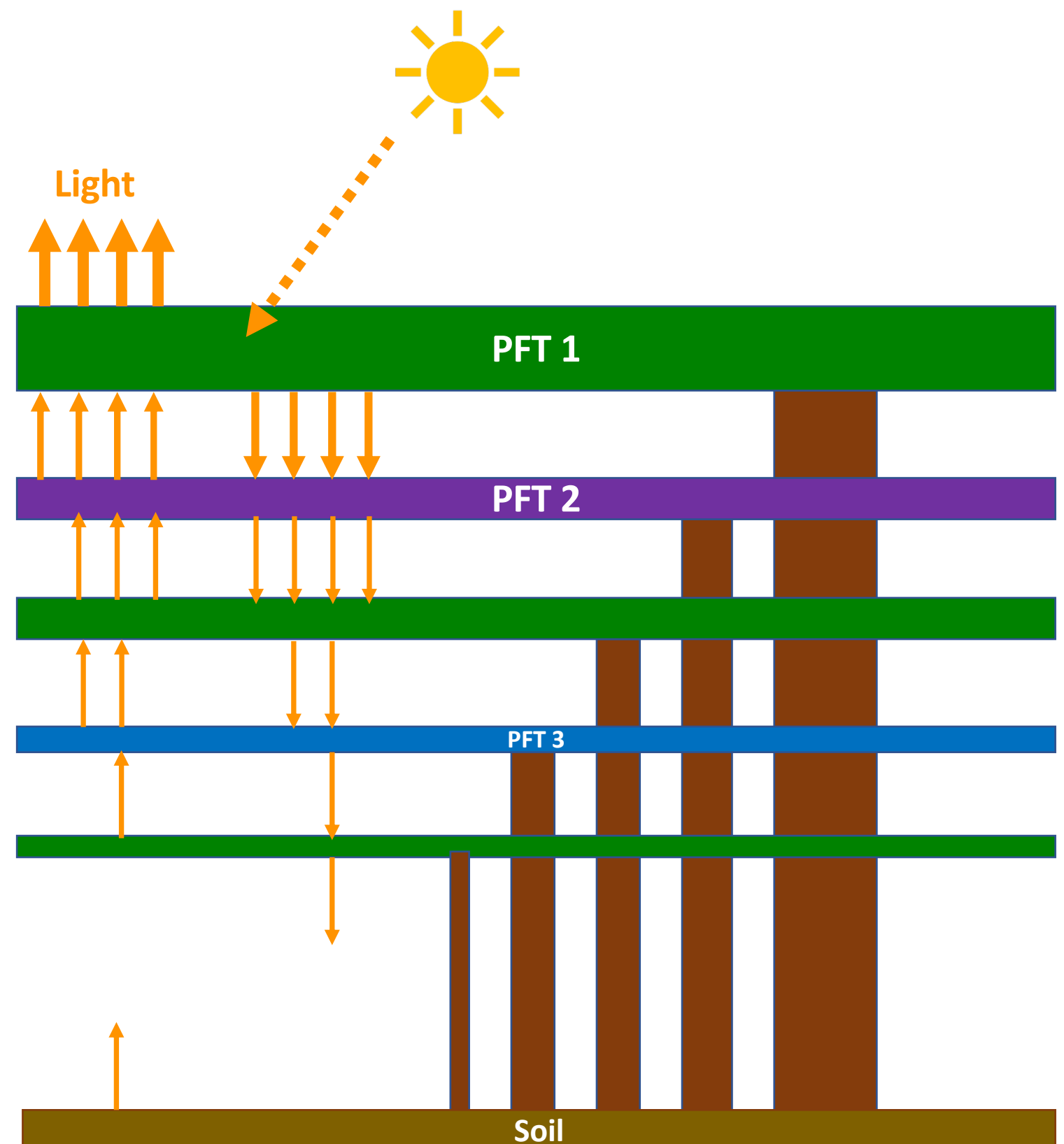
Biophysical processes, such as energy balance and climate feedbacks

Objectives

- **Teach** an ecosystem model (ED2) to predict **surface reflectance**
- **Calibrate** this model against airborne spectroscopy (AVIRIS) data
- Use the model to **predict** a time series of surface reflectance, and **validate** the prediction against Landsat observations

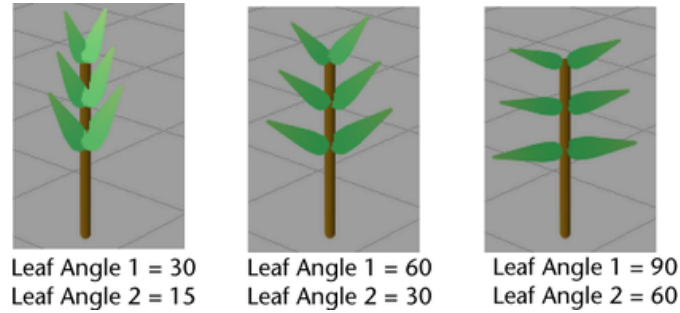
Ecosystem Demography Model (ED2)

- Cohort-based, dynamic vegetation model. Within a single location, multiple cohorts of different plant functional types (PFTs) co-exist and compete for the same resources.
- Includes a two-stream, multi-layer canopy radiative transfer model (RTM) that calculates the full vertical profile of light as a function of canopy composition and structure and soil properties.
- By default, the model does these calculations in **two wide bands** – “visible” and “near-infrared” – and uses **directly prescribed leaf optical properties** (reflectance and transmittance) for each PFT.



We coupled the ED2 canopy RTM to a leaf RTM (PROSPECT 5) and simple soil RTM to predict **full-range hyperspectral reflectance** as a function of leaf structure and biochemistry, canopy structure (mean leaf orientation; canopy clumping), and soil moisture.

Leaf orientation



c = clumping

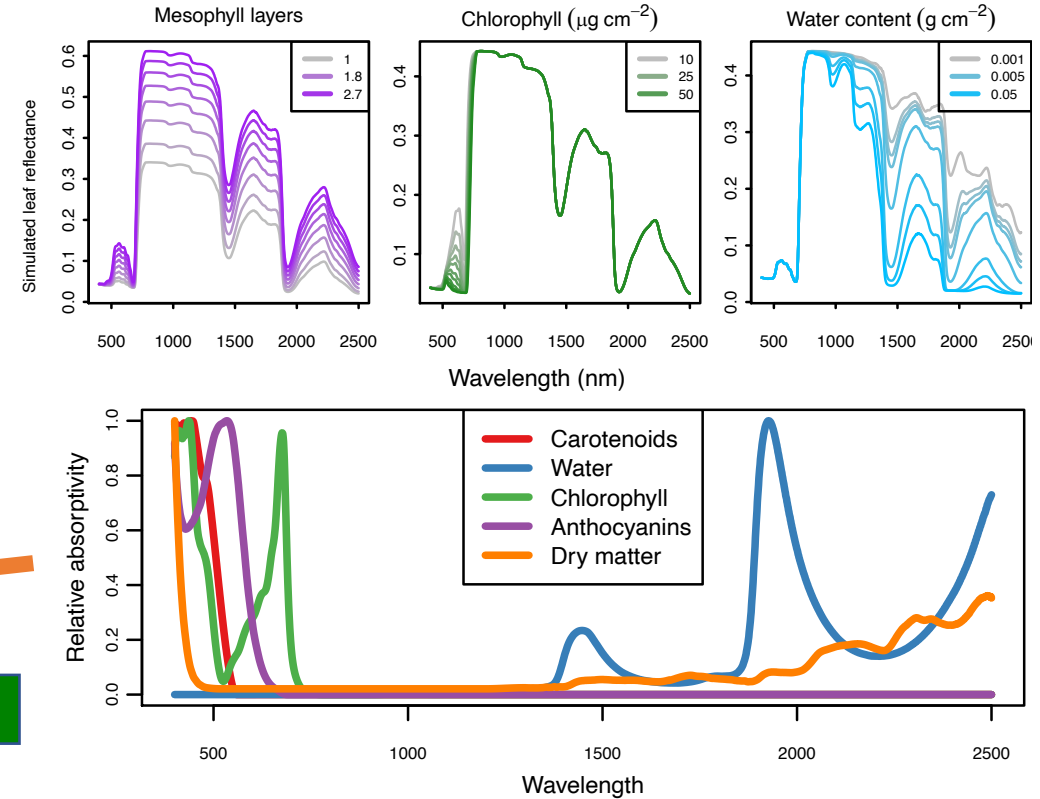


low



high

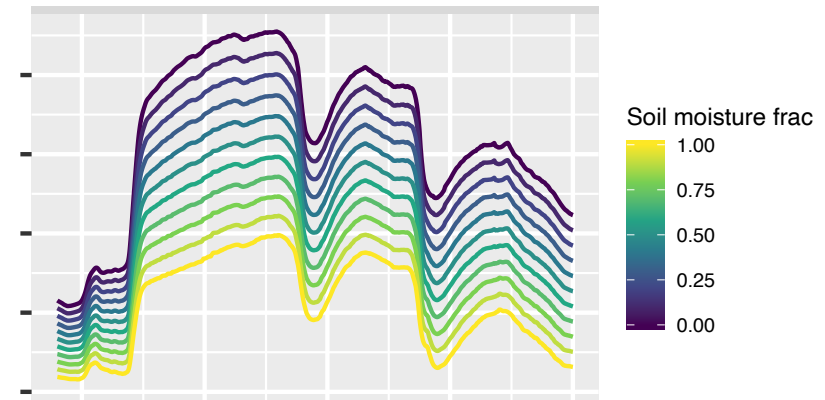
$$\text{eLAI} = f(\text{DBH} \mid \alpha, \beta) \times c$$



PROSPECT 5

Leaf reflectance as
function of:

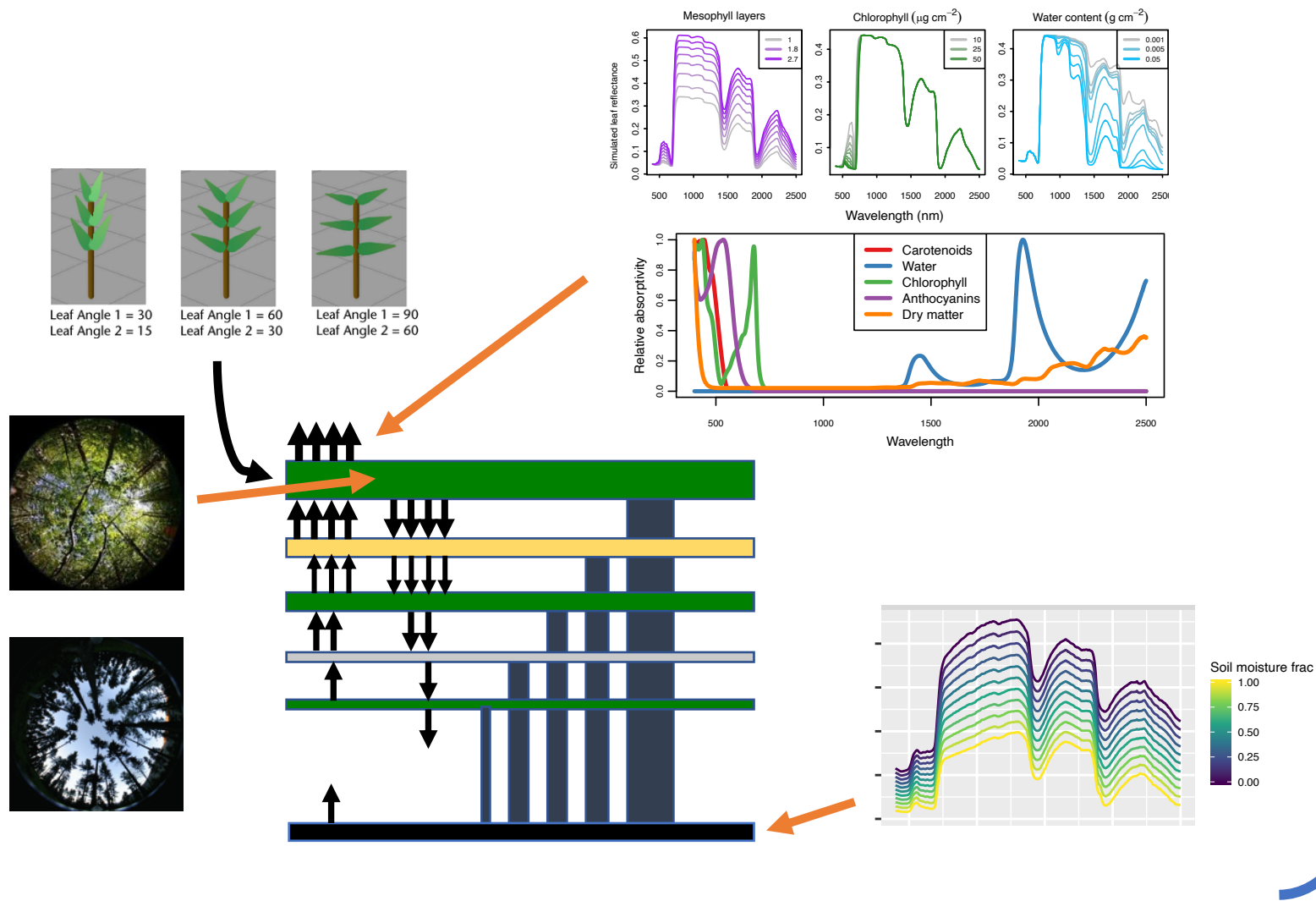
- Mesophyll structure
- Chlorophyll
- Carotenoids
- Water
- Dry matter



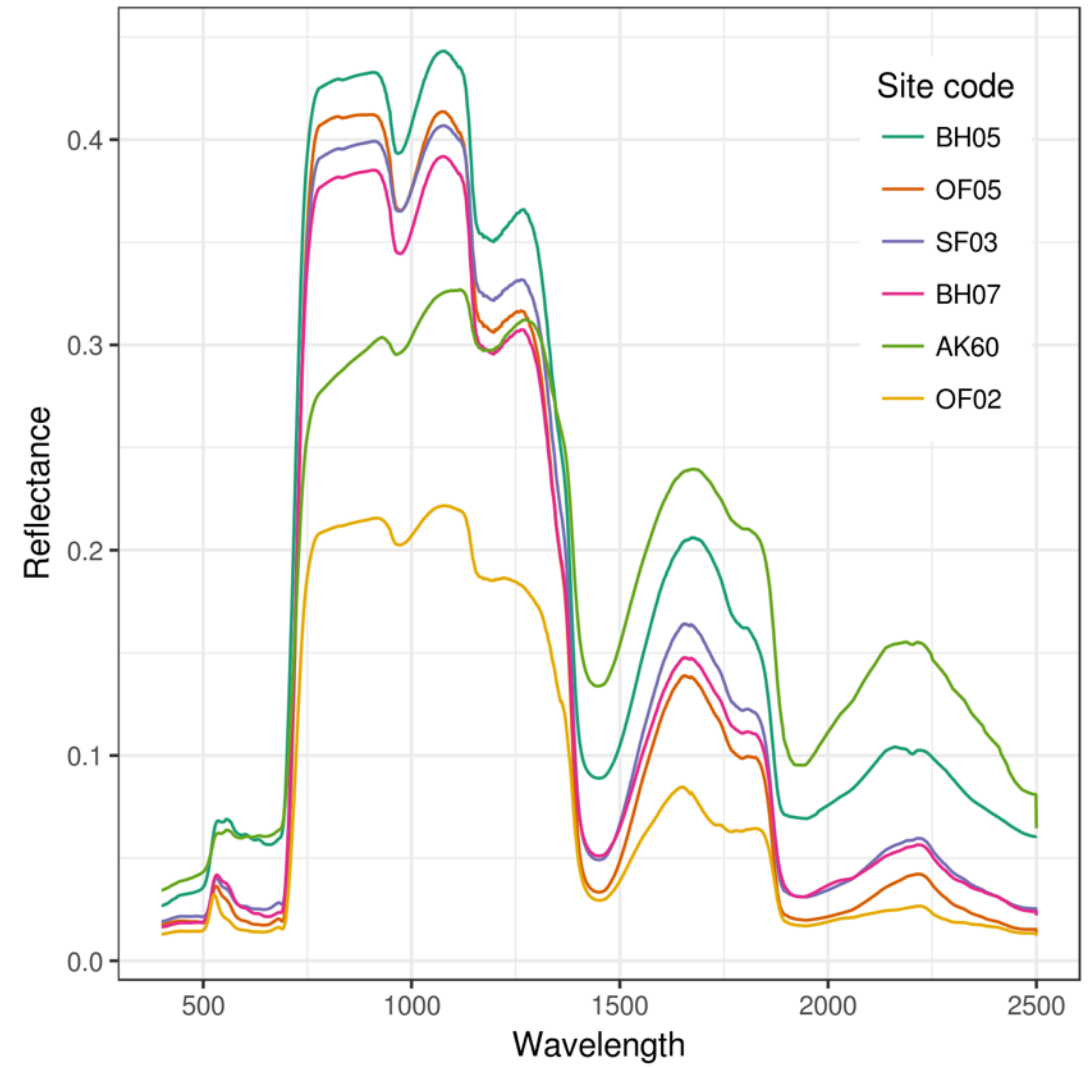
Hapke model

Soil reflectance as function of soil moisture

We coupled the ED2 canopy RTM to a leaf RTM (PROSPECT 5) and simple soil RTM to predict **full-range hyperspectral reflectance** as a function of leaf structure and biochemistry, canopy structure (mean leaf orientation; canopy clumping), and soil moisture. We'll call this model **EDR**.



ED2-predicted surface reflectance at six different sites



This predicted reflectance can be compared directly to, e.g., AVIRIS.

We grouped species at our sites into 5 PFTs, each with 10 parameters that must be calibrated. That makes 50 PFT-specific parameters total.

5 plant functional types (PFTs)



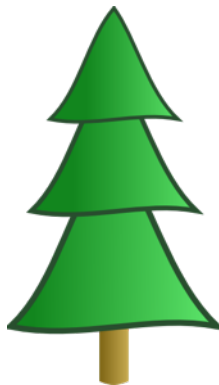
Early
Hardwood



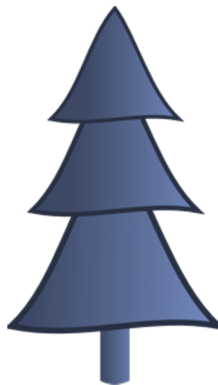
Mid
Hardwood



Late
Hardwood



Early
Conifer



Late
Conifer

PROSPECT 5
parameters



Mesophyll struct.
Chlorophyll
Carotenoids
Leaf water

Leaf dry matter
Canopy clumping
Leaf orientation
Specific leaf area

Leaf allometry
Wood allometry

Mesophyll struct.
Chlorophyll
Carotenoids
Leaf water

Leaf dry matter
Canopy clumping
Leaf orientation
Specific leaf area

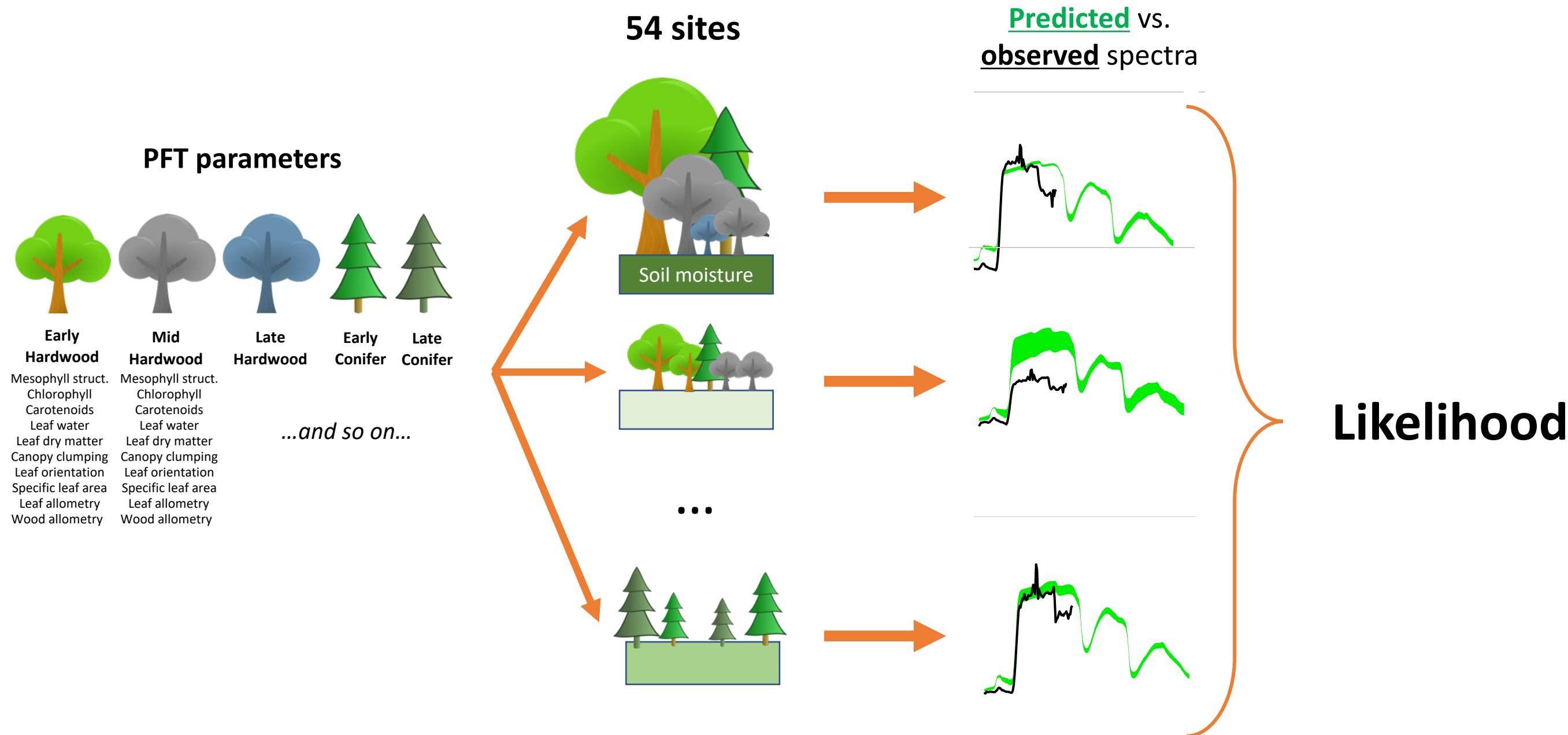
Leaf allometry
Wood allometry

...and so on...

EDR canopy
structure
parameters

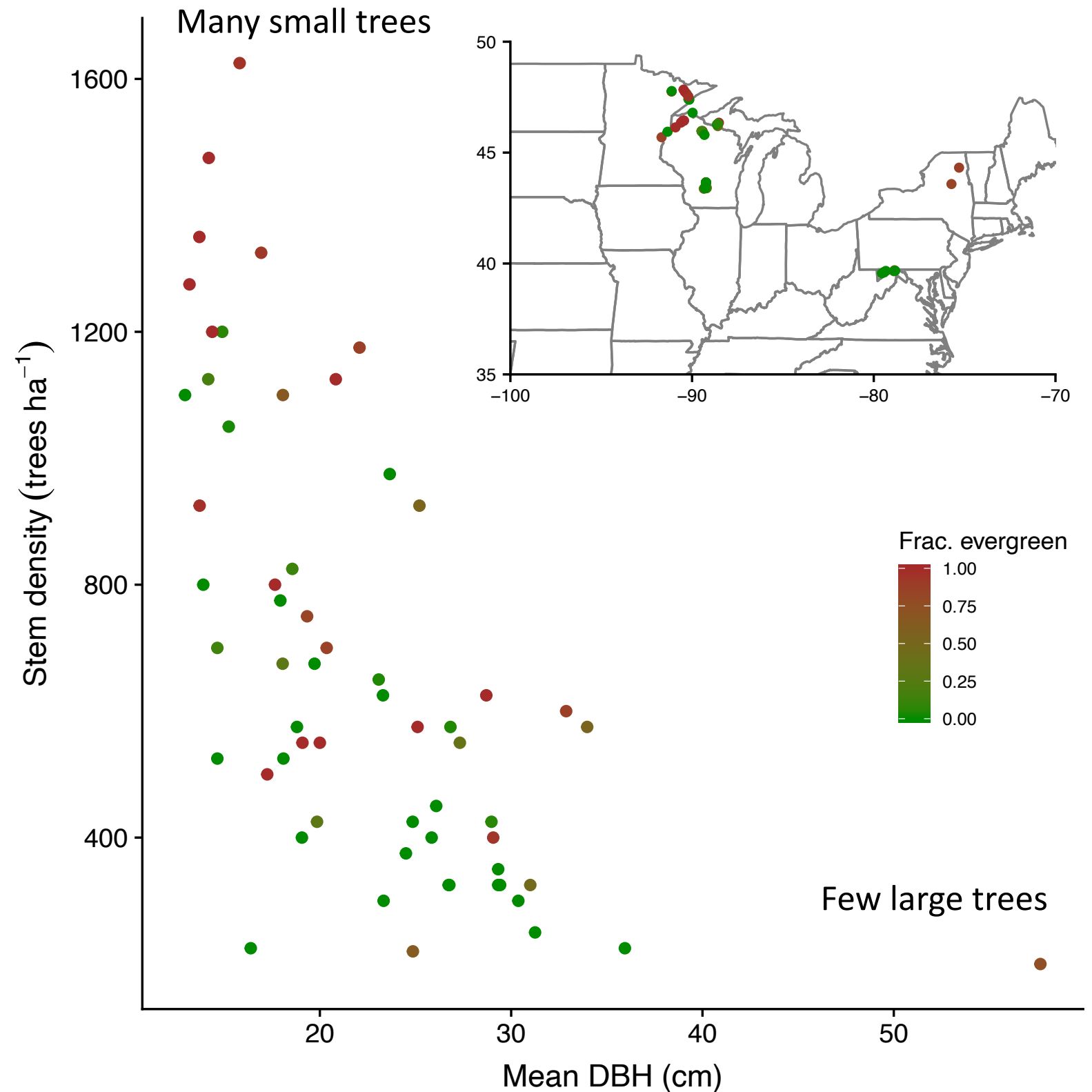


We performed the calibration *simultaneously* across 54 sites, each with known PFT composition. So, for a given set of parameters (50 PFT-specific parameters + 54 site-specific soil moisture coefficients, 1 for each site = 104 parameters total), we generate 54 predictions of surface reflectance—1 for each site—and then compare these predictions to AVIRIS observations. **The goal is to find the combination of PFT parameters and site-specific soil moisture coefficients that best matches observed spectra across all sites.**

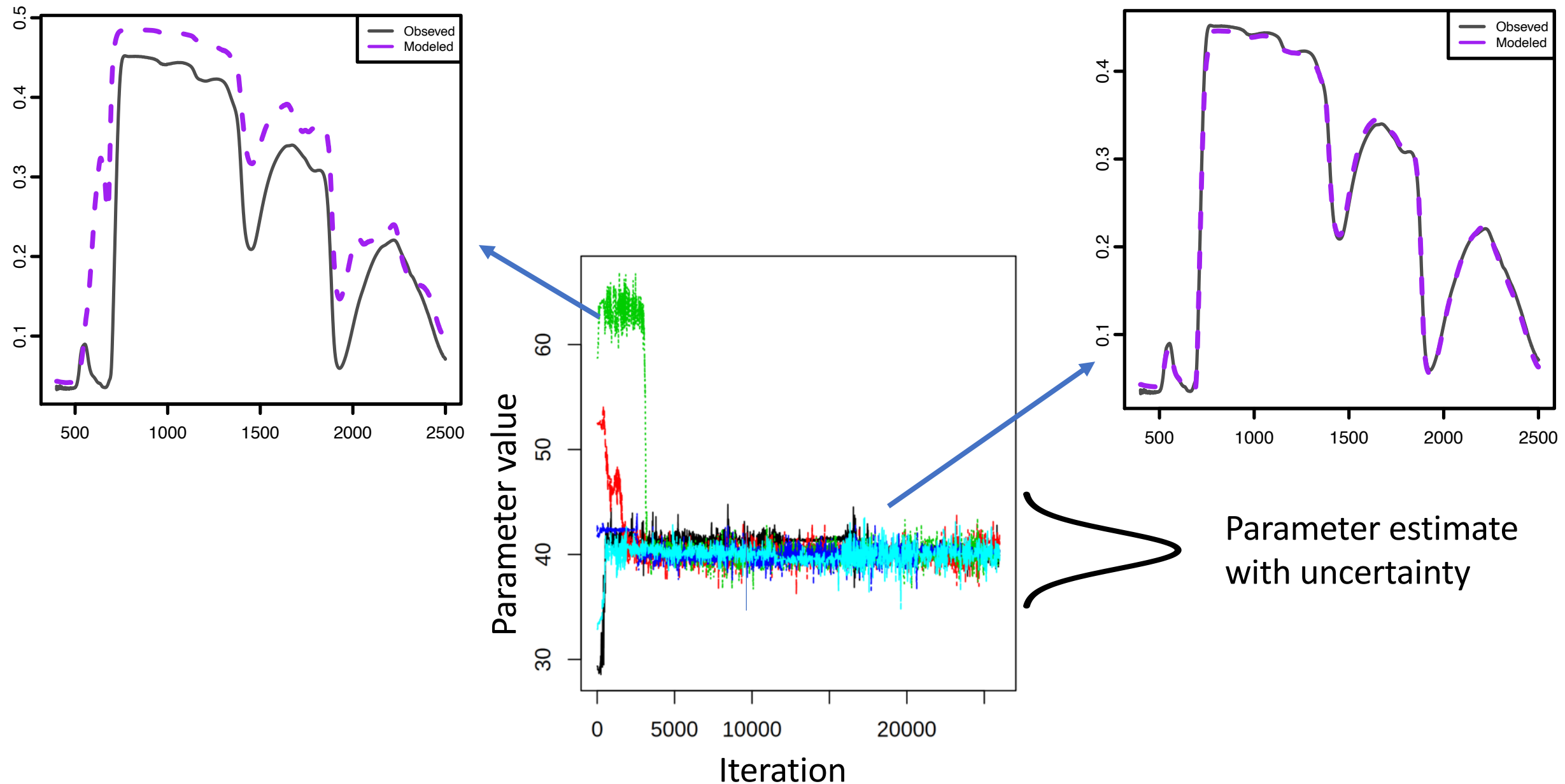


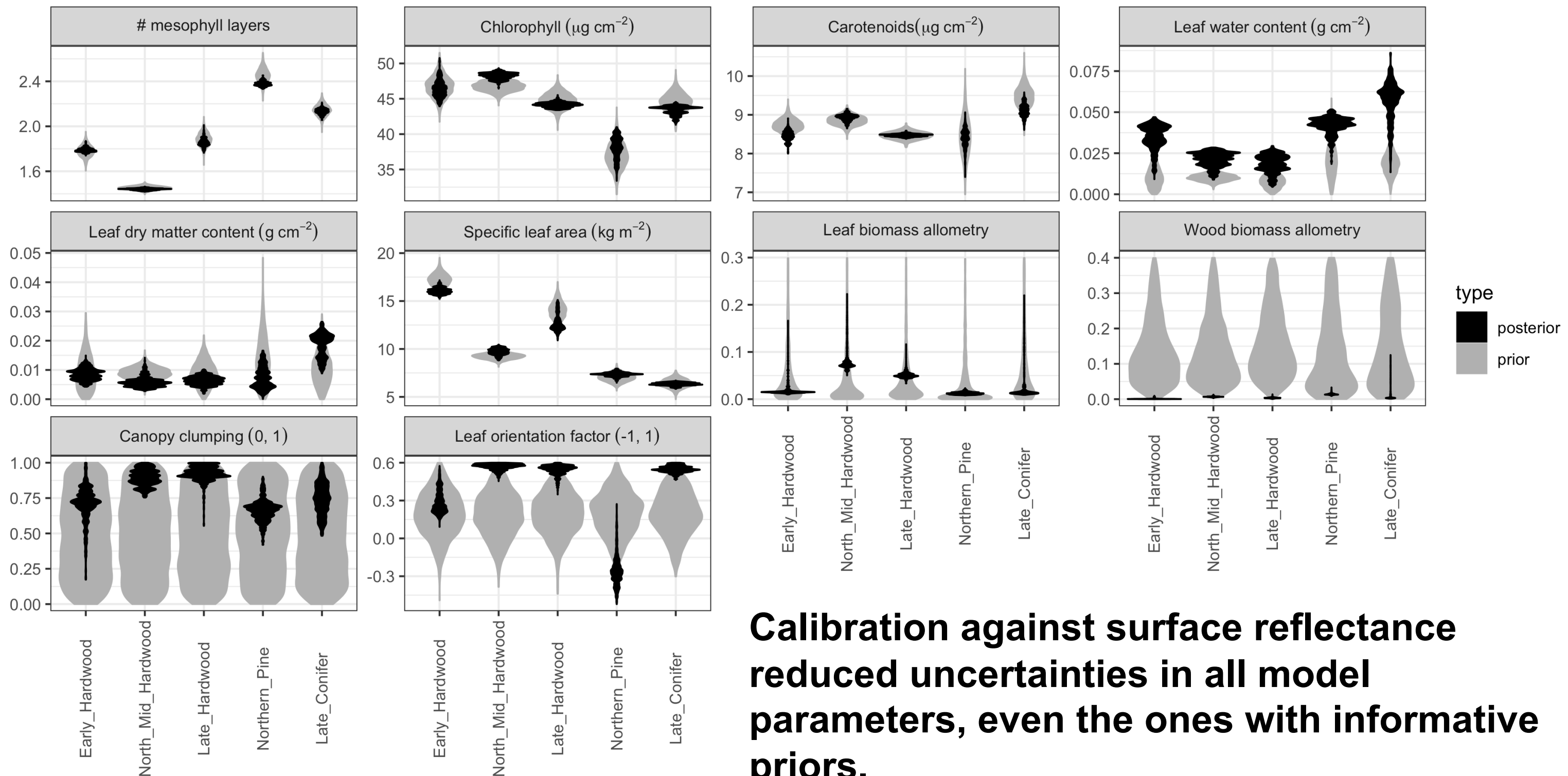
Study region: 54 sites across the US Midwest and Northeast

- Inventory data (composition and DBH) from NASA Forest Functional Types (FFT) campaign (2008-2009)
- Sites cover a wide range of species compositions and structures



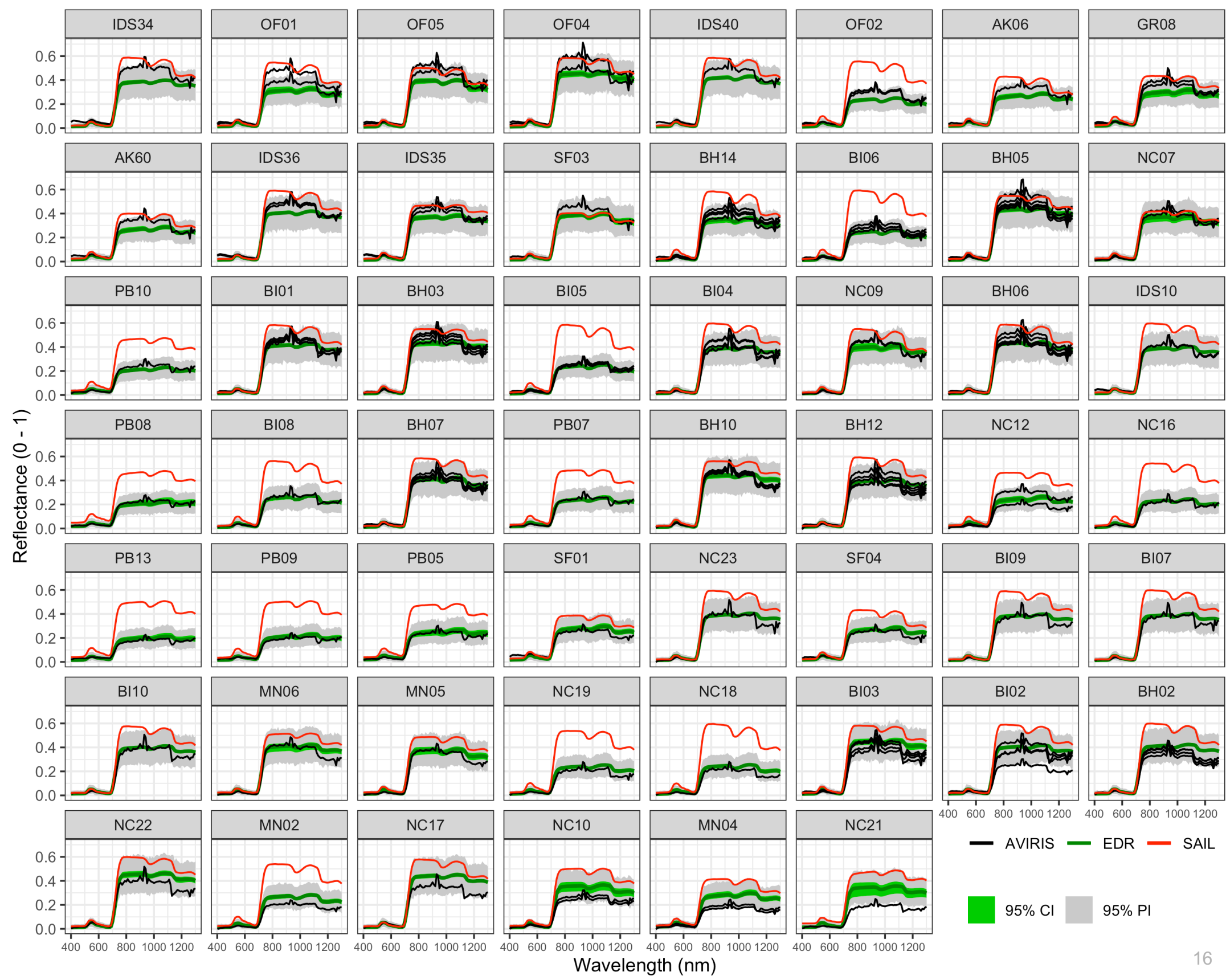
To fit the parameters, we use a **Bayesian MCMC approach**. At each iteration, we propose a parameter vector, simulate reflectance, and compare against observations. Parameter vectors with bad fits are rejected; parameter vectors with good fits are accepted. The samples of accepted parameters provide a **robust estimate of the joint posterior distribution**, with **fully quantified uncertainties** and parameter covariances.





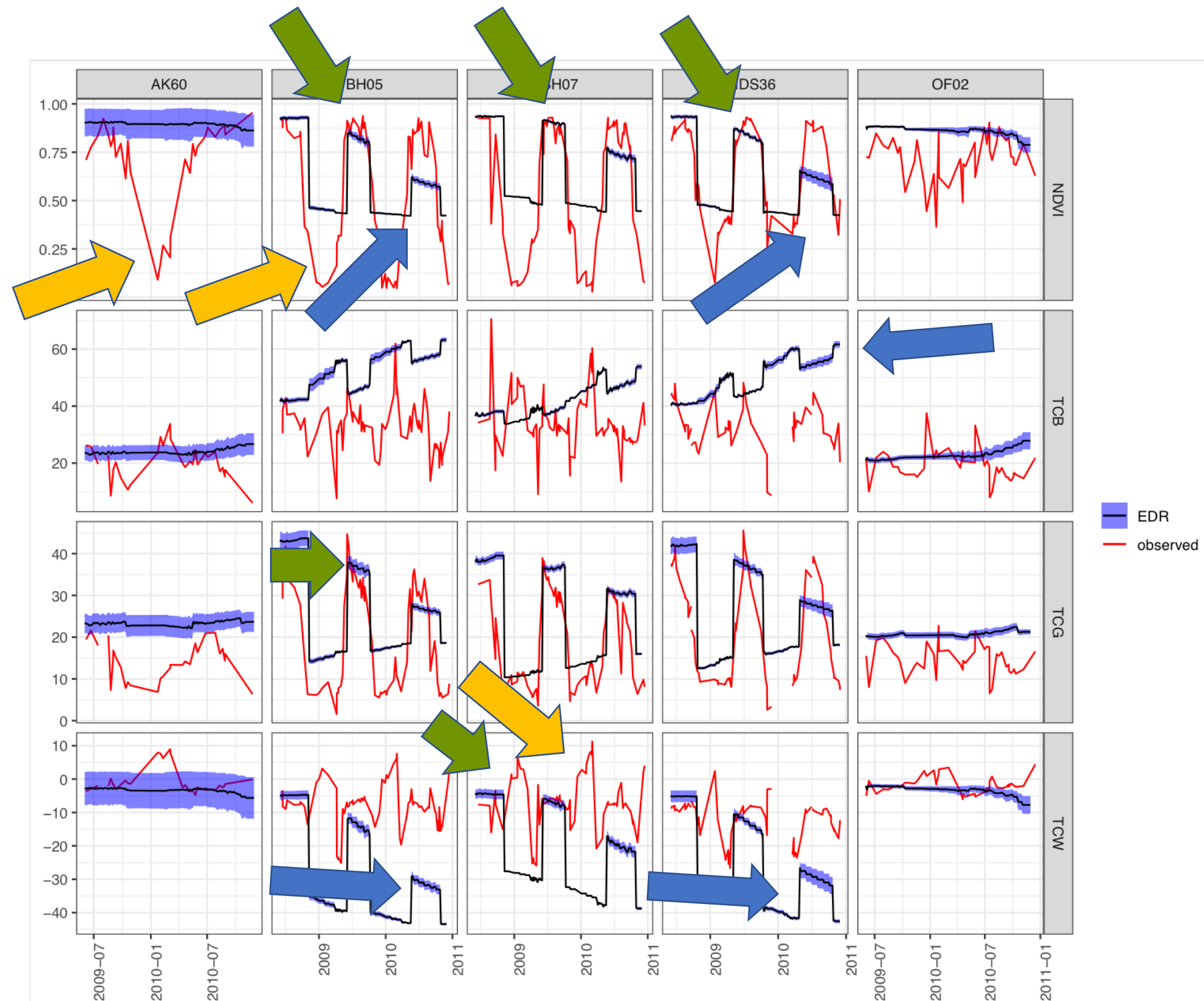
EDR accurately reproduces observed spectra across most sites

SAIL simulations here are forced by the same (effective) LAI, leaf orientation, and PROSPECT 5 parameters (posterior means for the top cohort at each site). This is not a perfect comparison, but it does show that EDR can hold its own against a similar two-stream-based model.



Does the model capture observed dynamics of surface reflectance?

- During first two growing seasons, yes
- Misses effects of snow on winter albedo
- Model forest start dying after first two years; real forests are fine



Summary

- **Radiative transfer equations** in ecosystem models provide a way to **tap into remote sensing data**, and are important for many **other processes**
- We modified an ecosystem model (ED2) to **predict remotely-sensed surface reflectance**, and **calibrated** the model against airborne spectroscopy (AVIRIS) data
 - Surface reflectance is effective for constraining parameters related to **leaf chemistry** and **canopy structure**
 - Model works well across many sites, except in sparse sites where model assumptions (closed canopy, turbid medium, no horizontal heterogeneity) are most violated
- Modeled reflectance **time series** can be compared against **Landsat** observations to evaluate model dynamics

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