



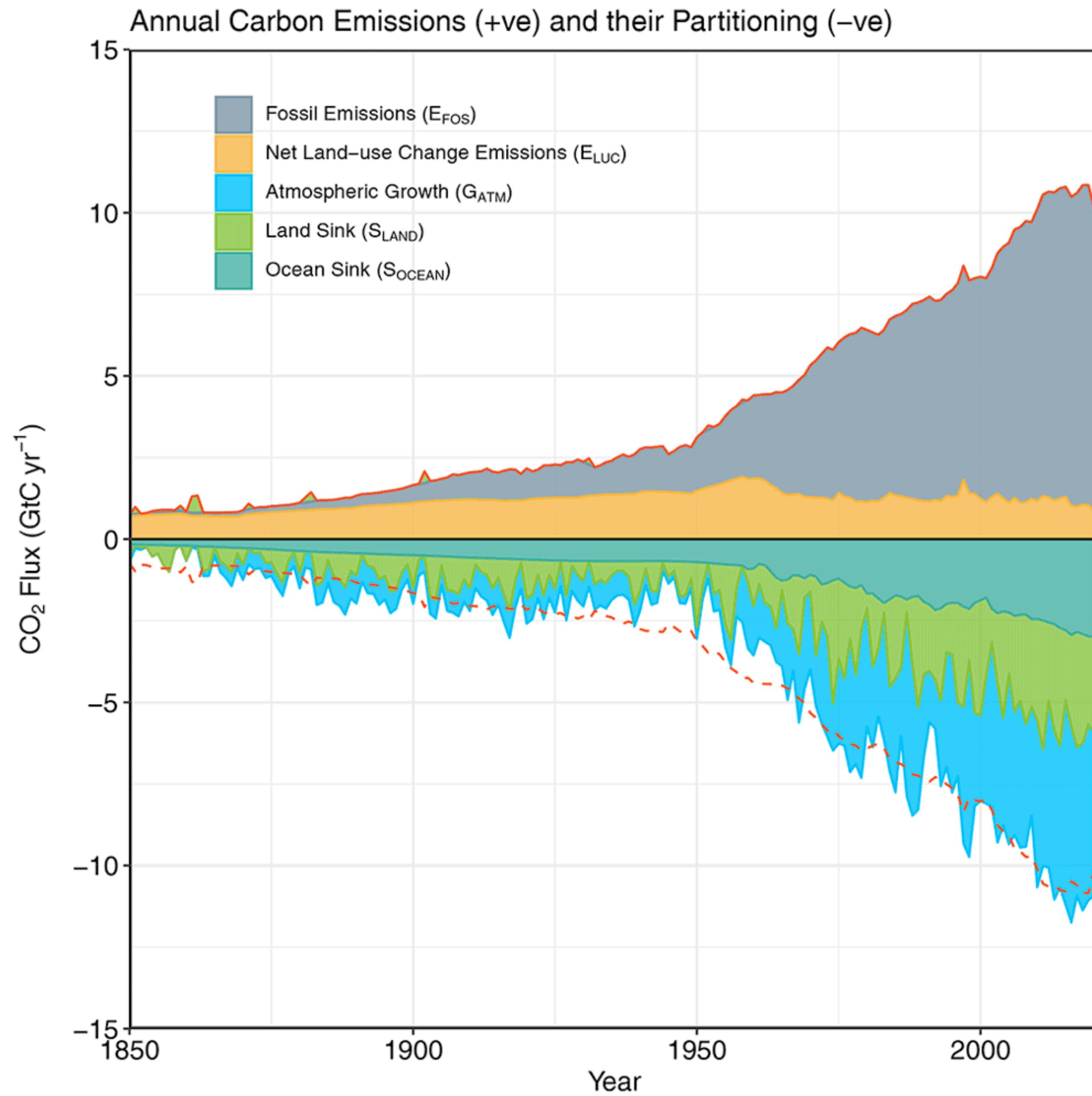
Moving toward the next-generation land surface modeling

Yujie Wang
Research Scientist, Caltech



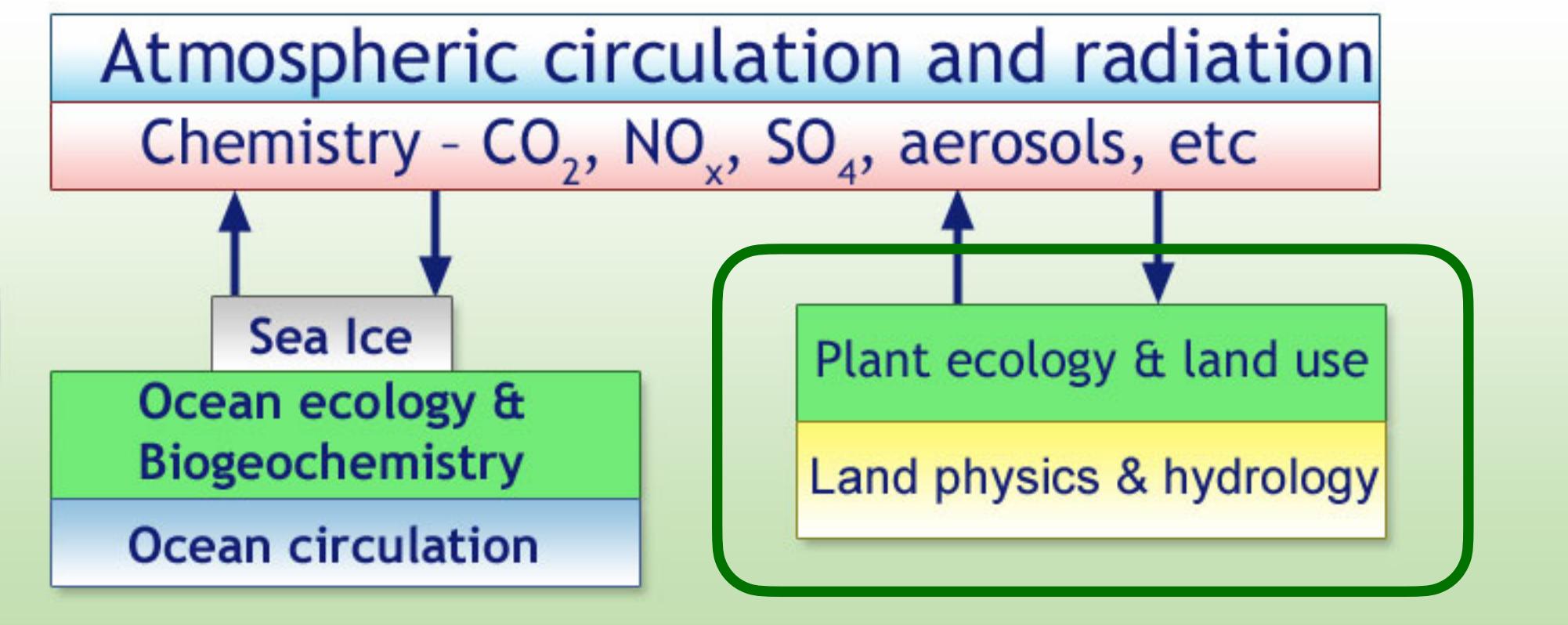


Land takes up
25% of emitted
CO₂, but we do
not know how
much nature
can help in the
future





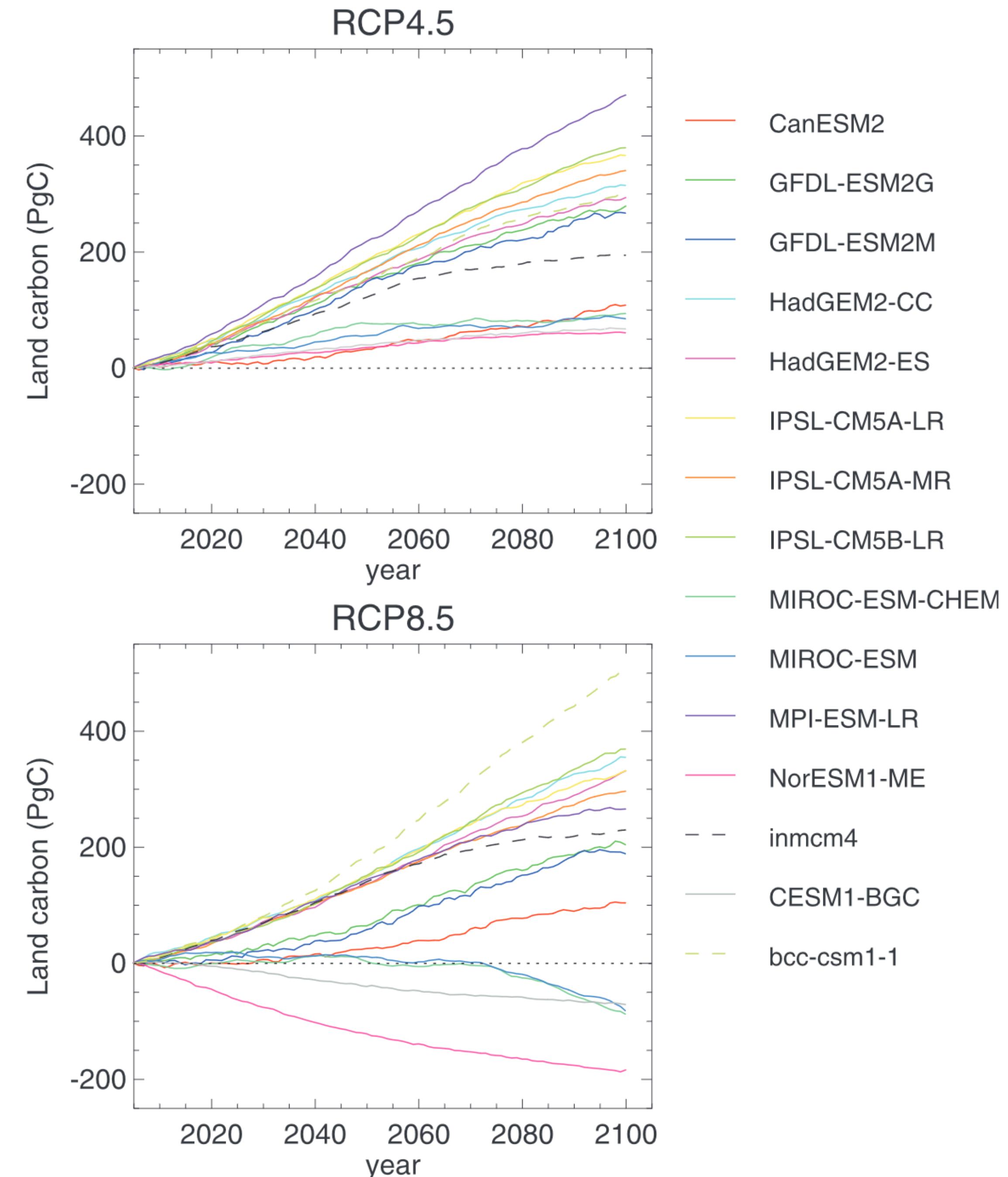
Climate Model Earth System Model



Land Surface Model

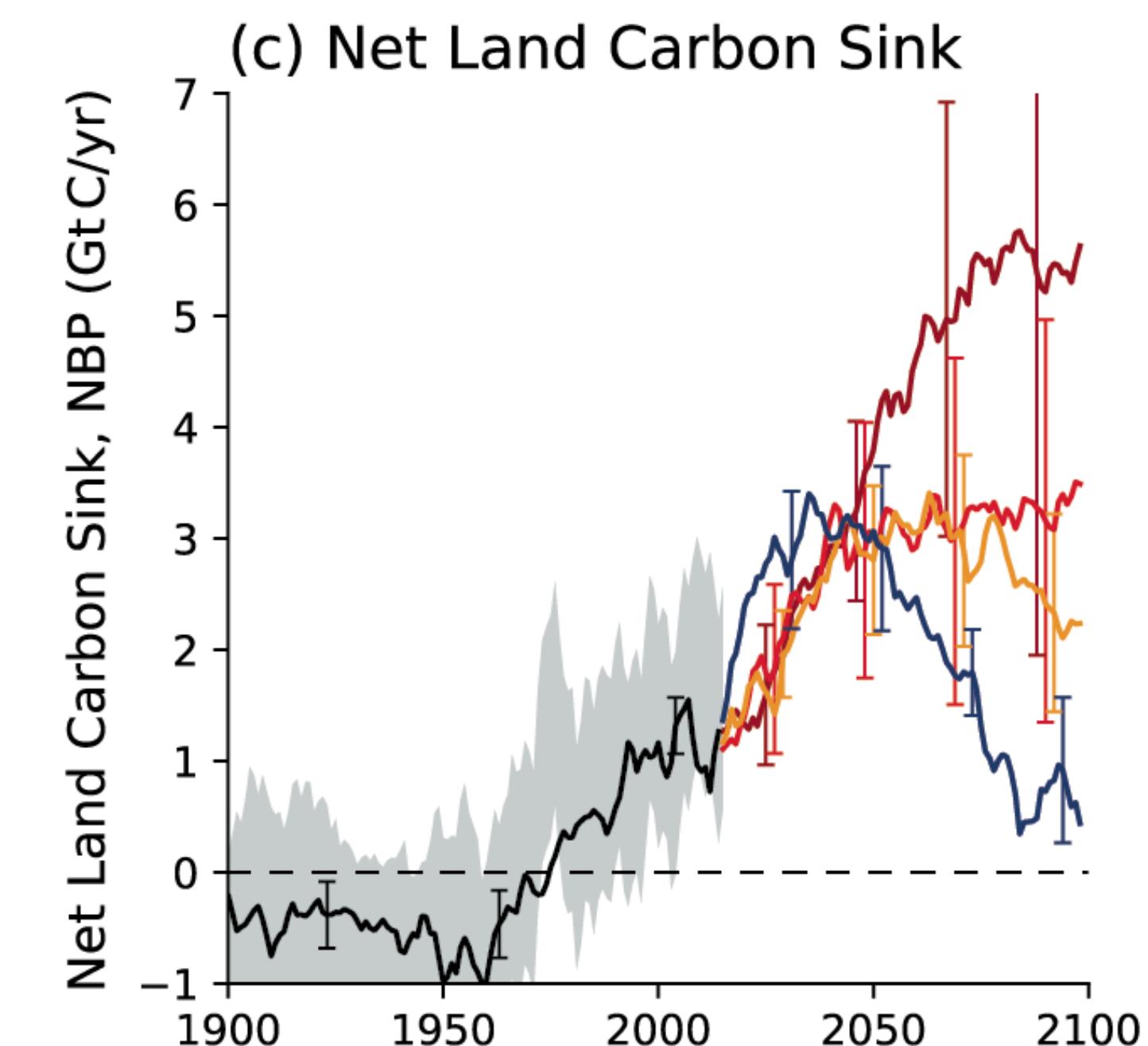
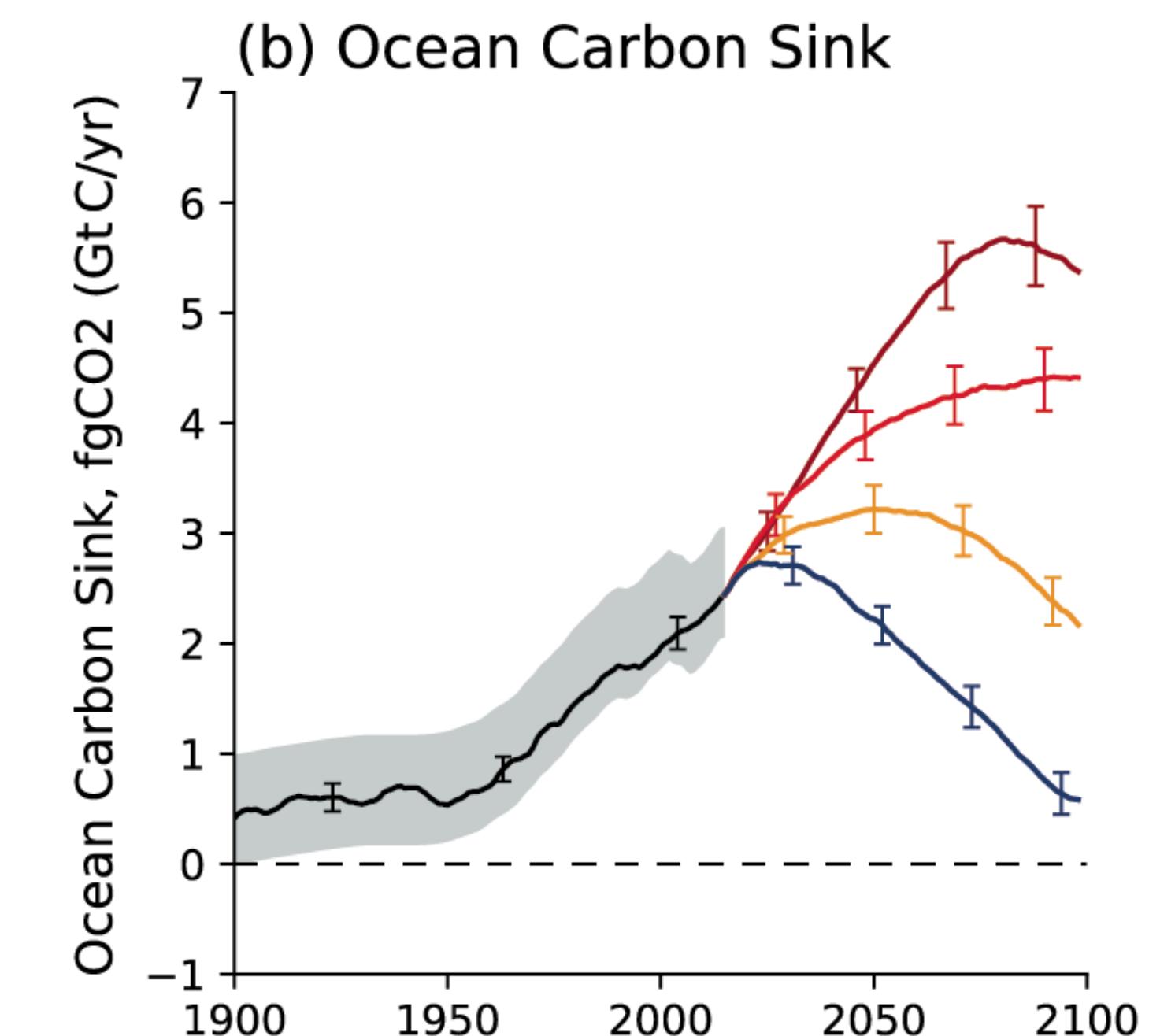


Climate models differ in their projections of land carbon sink strength, even in the directions



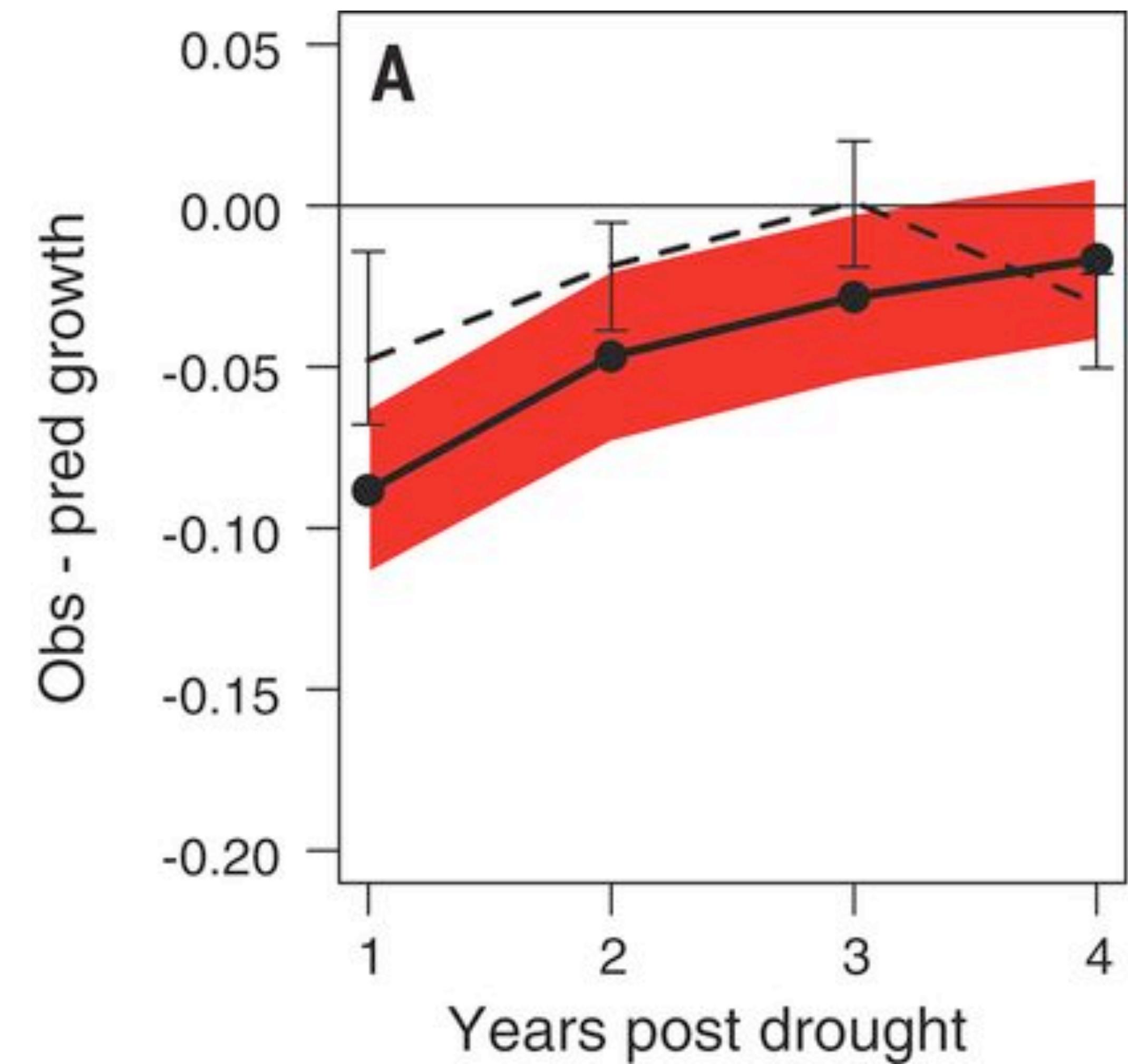


Climate models **differ** in their projections of land carbon sink strength, even in the **directions**

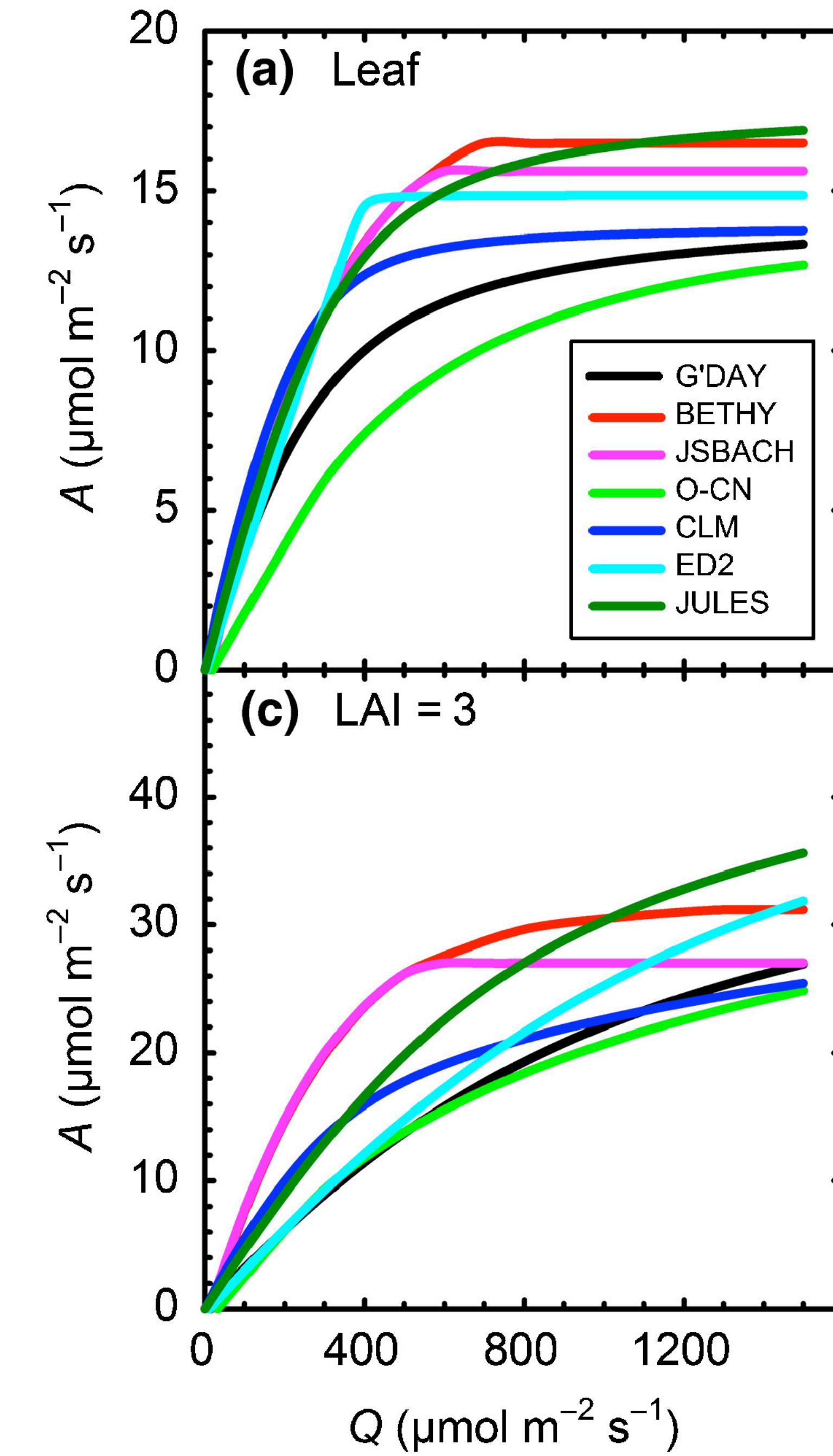


Potential Reasons

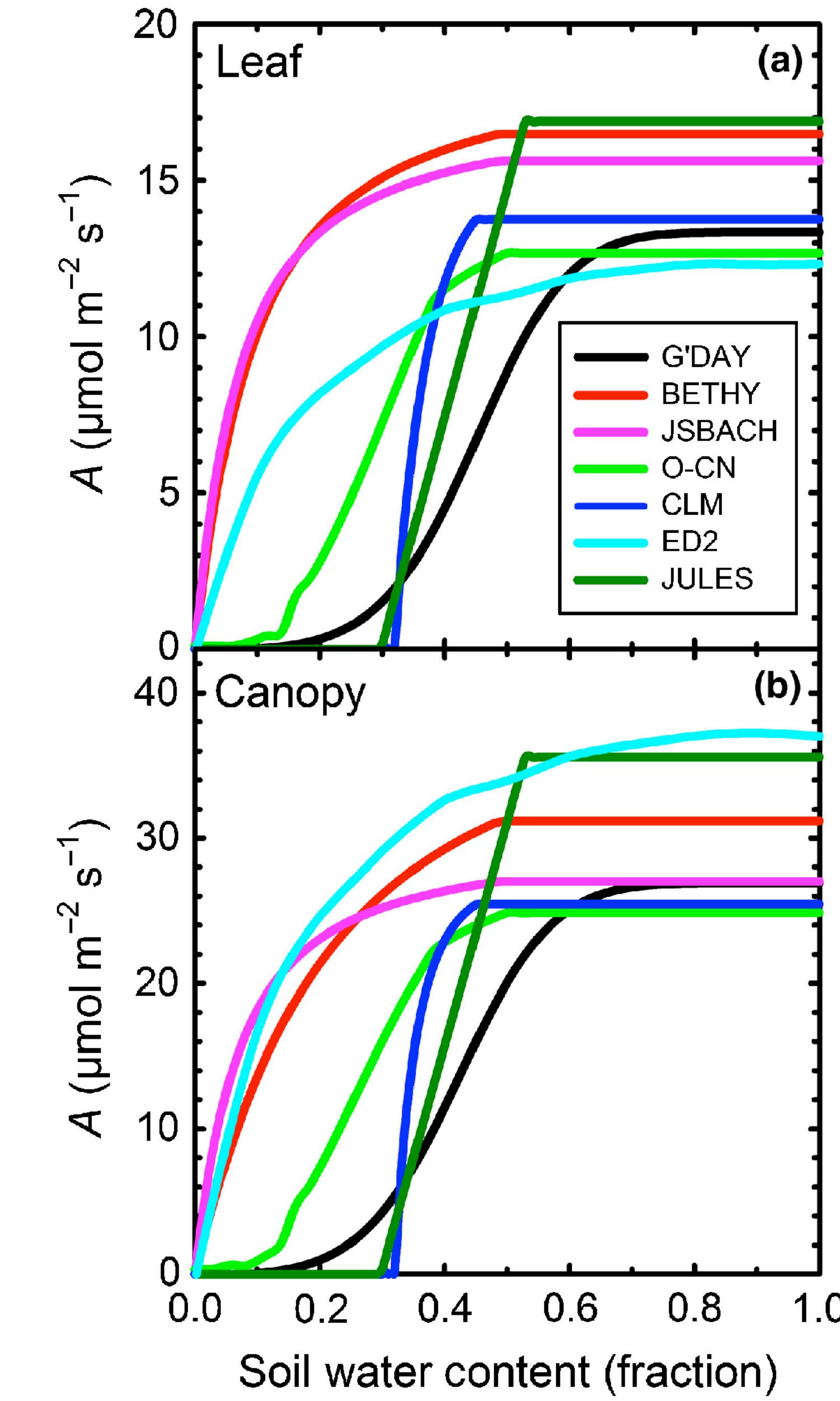
1. Lack physiological representations



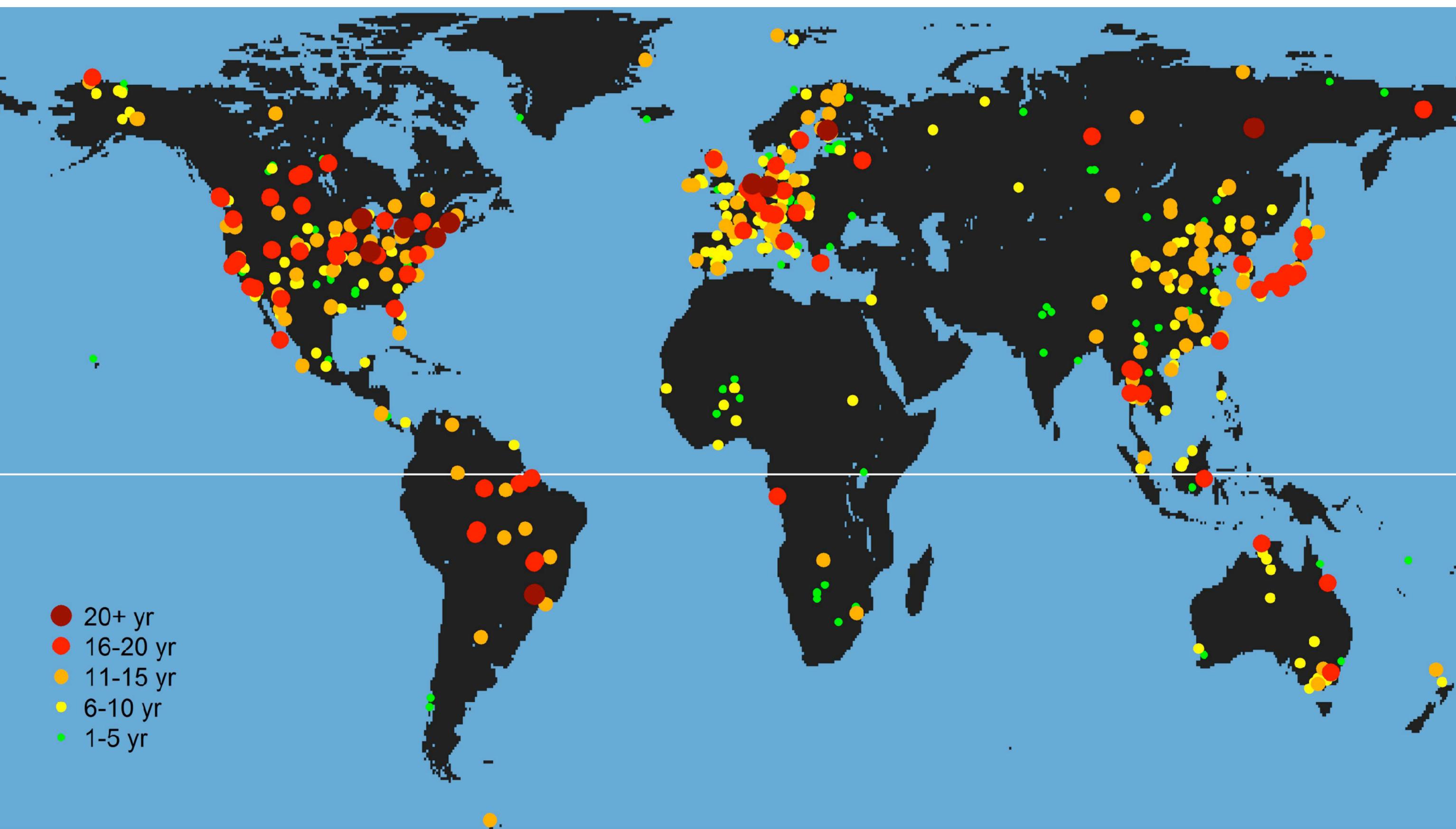
2. Contrasting model parameterization



2. Contrasting model parameterization



3. Limited data to calibrate the model



3. Limited data to calibrate the model





3. Limited data to calibrate the model





	Site ID	Policy <small>i</small>	Data Product <small>i</small> (Variables) <small>i</small>	1990	1995	2000	2005	2010	2015	2020
	<input checked="" type="checkbox"/> BR-CST	C	AmeriFlux BASE (32) AmeriFlux FLUXNET						✓ ✓	✓ ✓
	<input checked="" type="checkbox"/> BR-Sa1	C	AmeriFlux BASE (17)				✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓			
	<input checked="" type="checkbox"/> BR-Sa3	L	AmeriFlux BASE (26)				✓ ✓ ✓ ✓ ✓			
	<input checked="" type="checkbox"/> CA-Ca1	C	AmeriFlux BASE (33)			✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓				
	<input checked="" type="checkbox"/> CA-Ca2	C	AmeriFlux BASE (28)			✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓				
	<input checked="" type="checkbox"/> CA-Ca3	C	AmeriFlux BASE (39)			✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓				

Challenges



Caltech



1. Schemes

Improve model representation of soil-plant-air continuum

2. Setups

Advance model parameters configuration

3. Calibration

Use more data to calibrate the models

Caltech



Next-Generation Land Surface Model

CLiMA Land





Next generation

What make a
next generation
model?

Learn from data

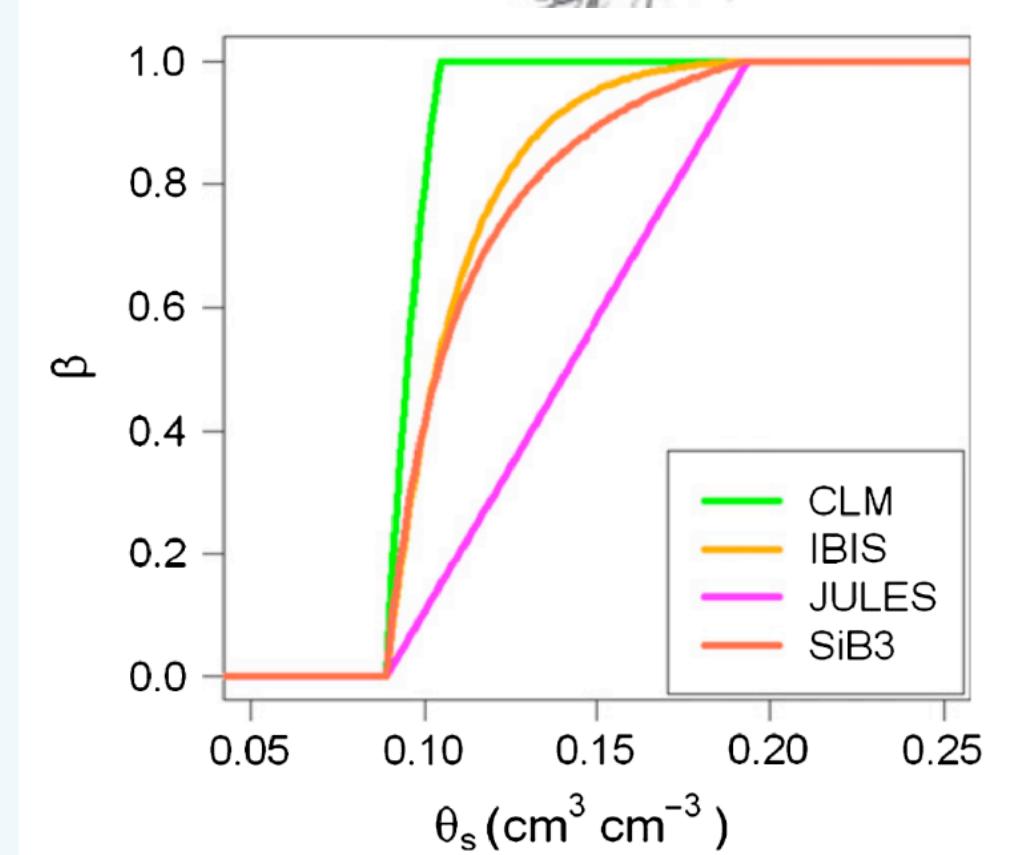
- **What to learn?**
- **How to learn?**
- **Whom to learn?**

Model framework

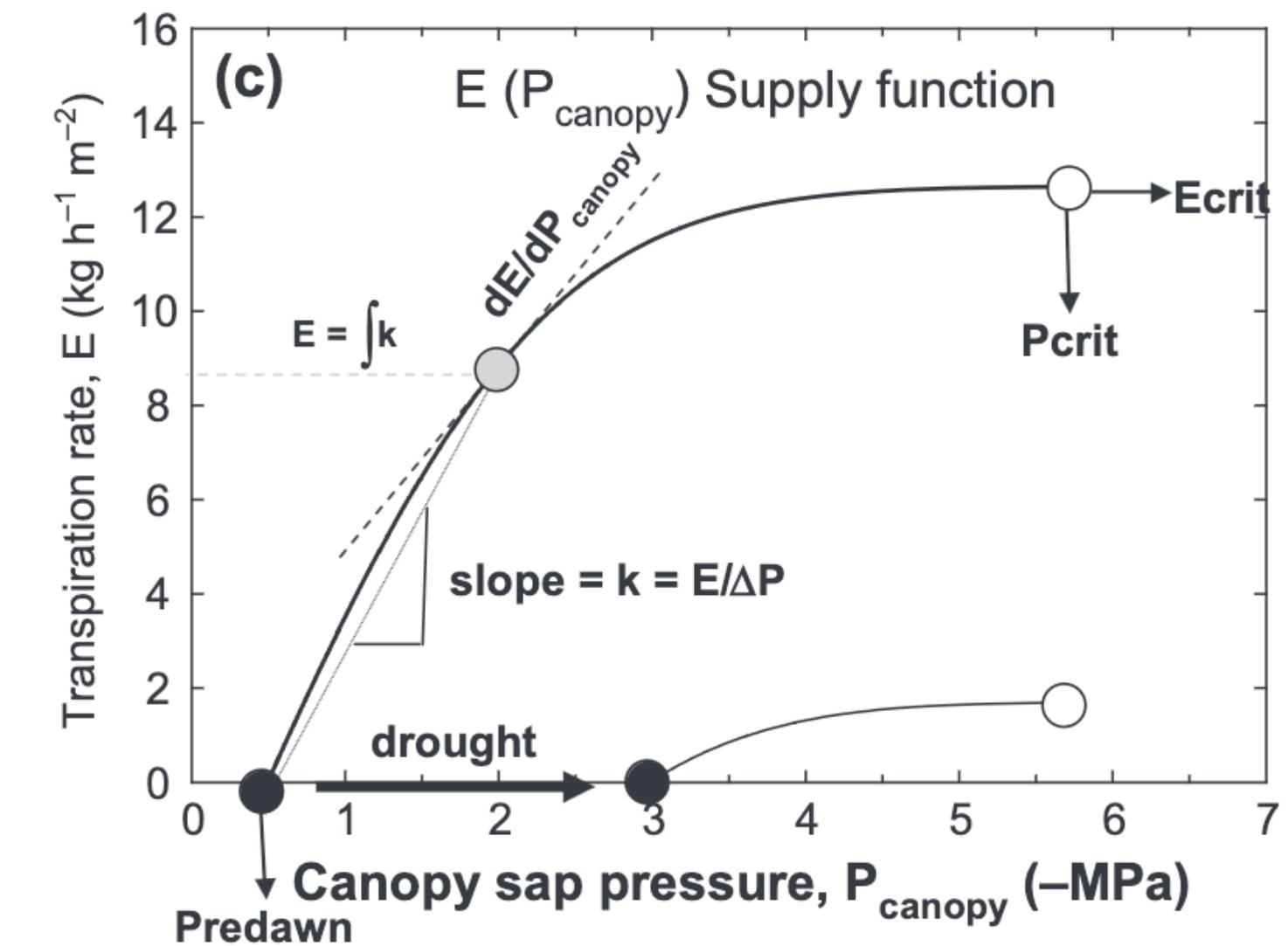
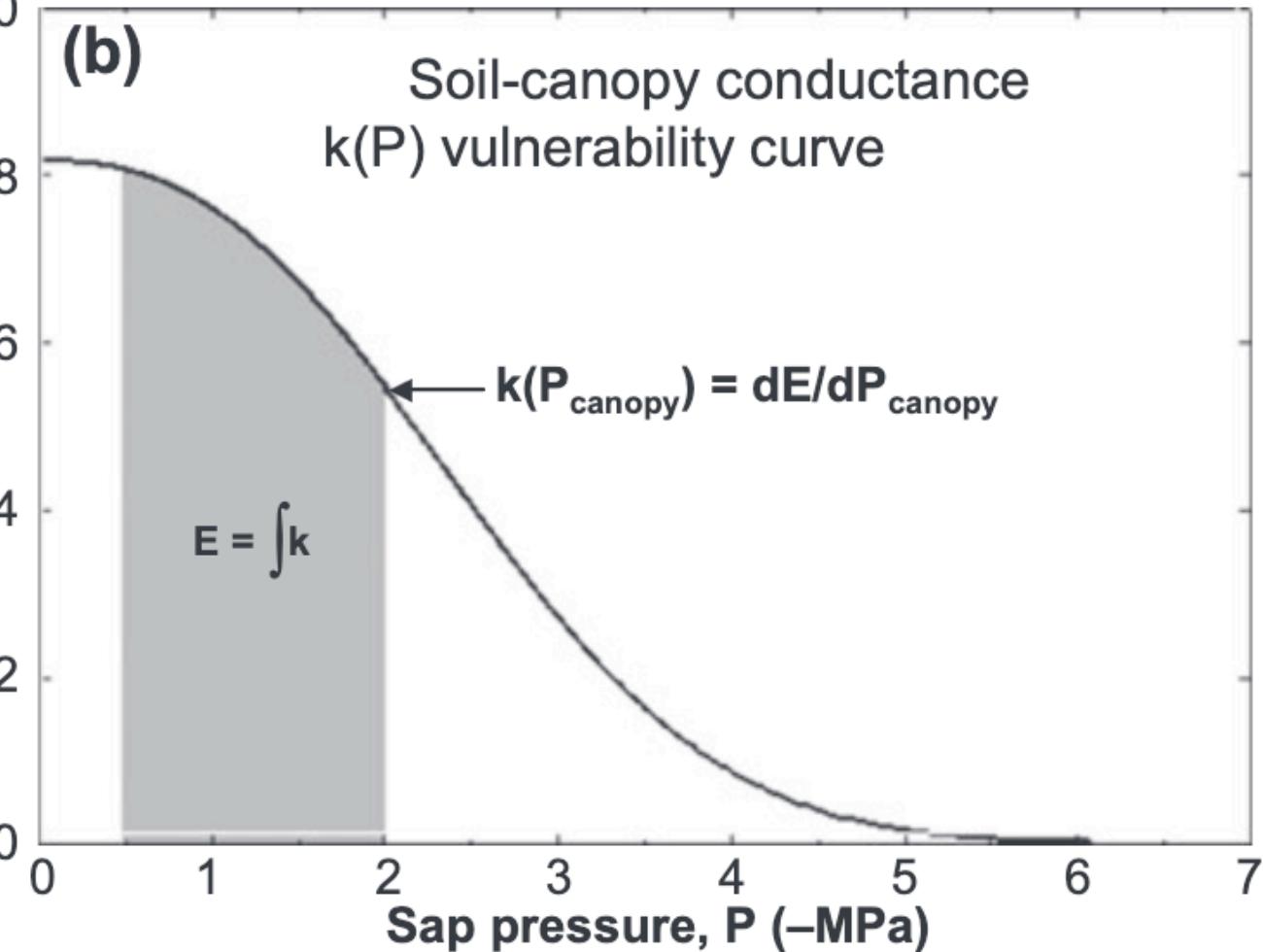
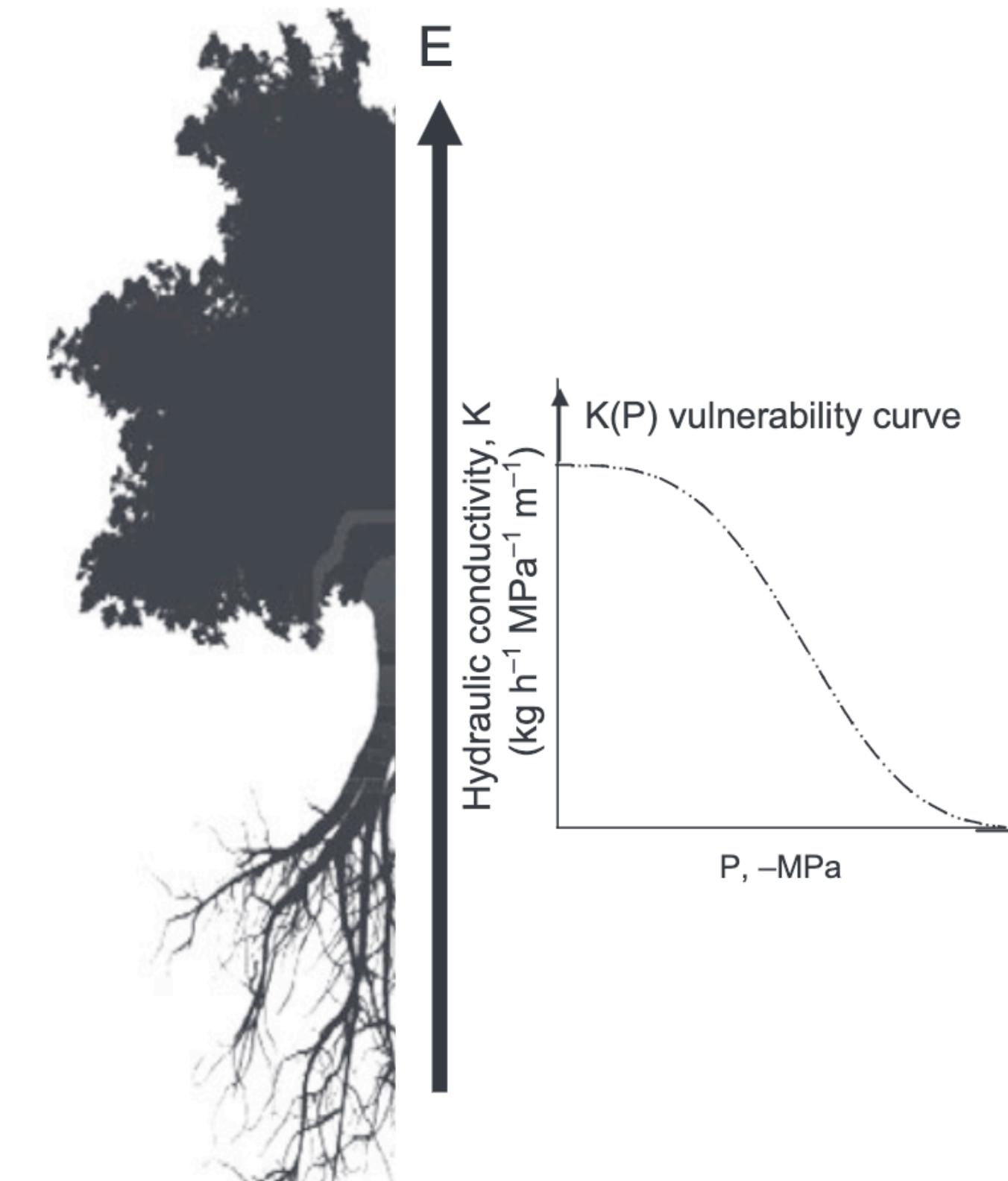
- **Modularity**
- **Scalability**
- **Architecture**
- **User friendly**

1. Schemes

Improve model representation of plant water relations



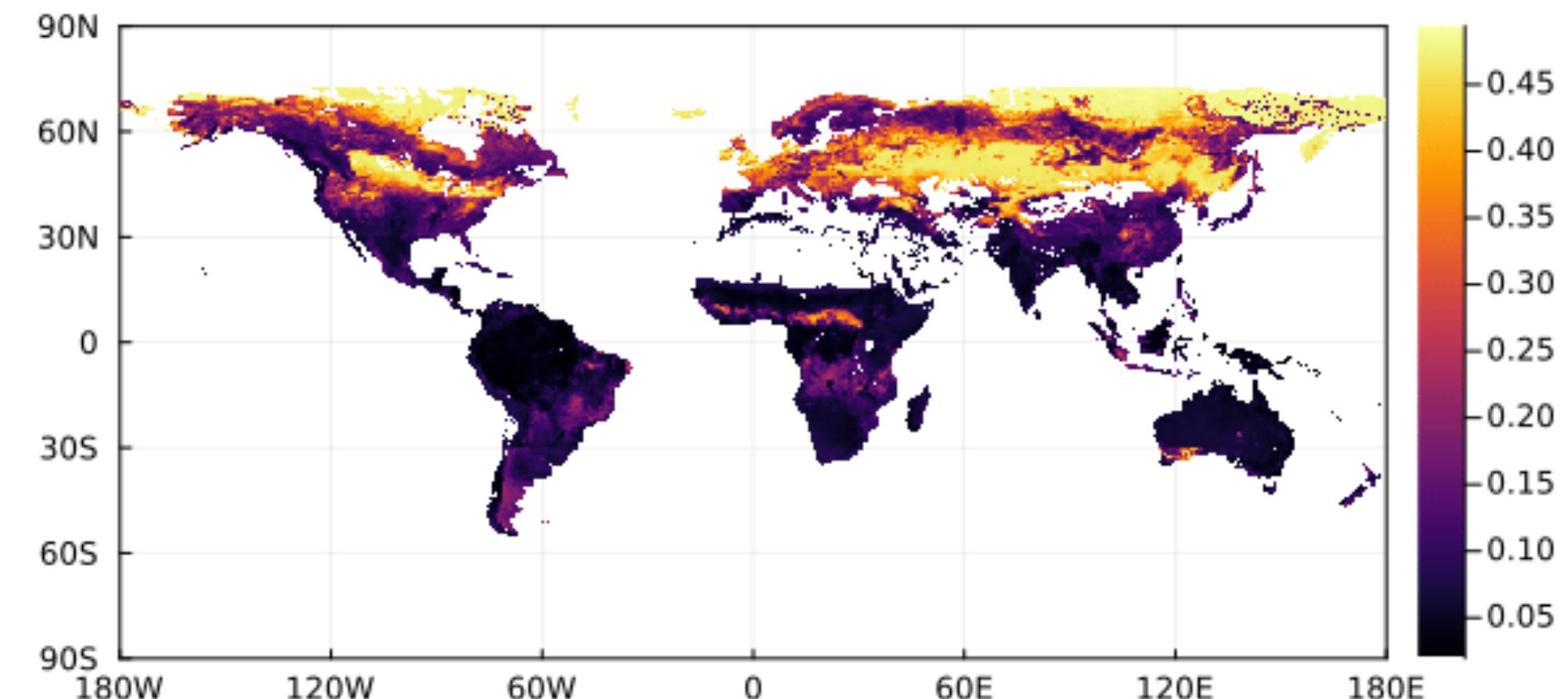
(a) Single element continuum with one conductivity $K(P)$ vulnerability curve



2. Setups

Advance model parameter configuration for leaf traits

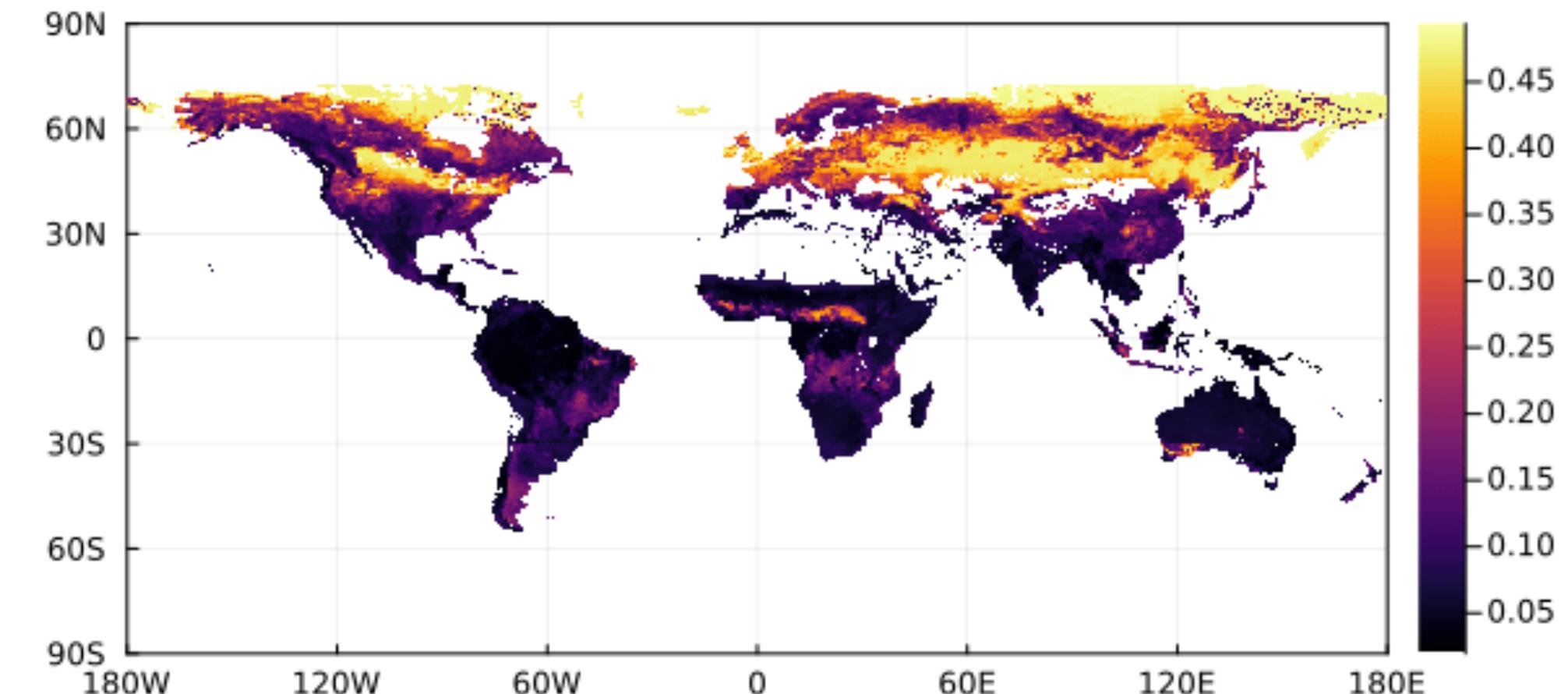
Plant Functional Type	χ_L	α_{vis}^{leaf}	α_{nir}^{leaf}	α_{vis}^{stem}	α_{nir}^{stem}	τ_{vis}^{leaf}	τ_{nir}^{leaf}
NET Temperate	0.01	0.07	0.35	0.16	0.39	0.05	0.10
NET Boreal	0.01	0.07	0.35	0.16	0.39	0.05	0.10
NDT Boreal	0.01	0.07	0.35	0.16	0.39	0.05	0.10
BET Tropical	0.10	0.10	0.45	0.16	0.39	0.05	0.25
BET temperate	0.10	0.10	0.45	0.16	0.39	0.05	0.25
BDT tropical	0.01	0.10	0.45	0.16	0.39	0.05	0.25
BDT temperate	0.25	0.10	0.45	0.16	0.39	0.05	0.25
BDT boreal	0.25	0.10	0.45	0.16	0.39	0.05	0.25



2. Setups

Advance model parameter configuration for leaf traits

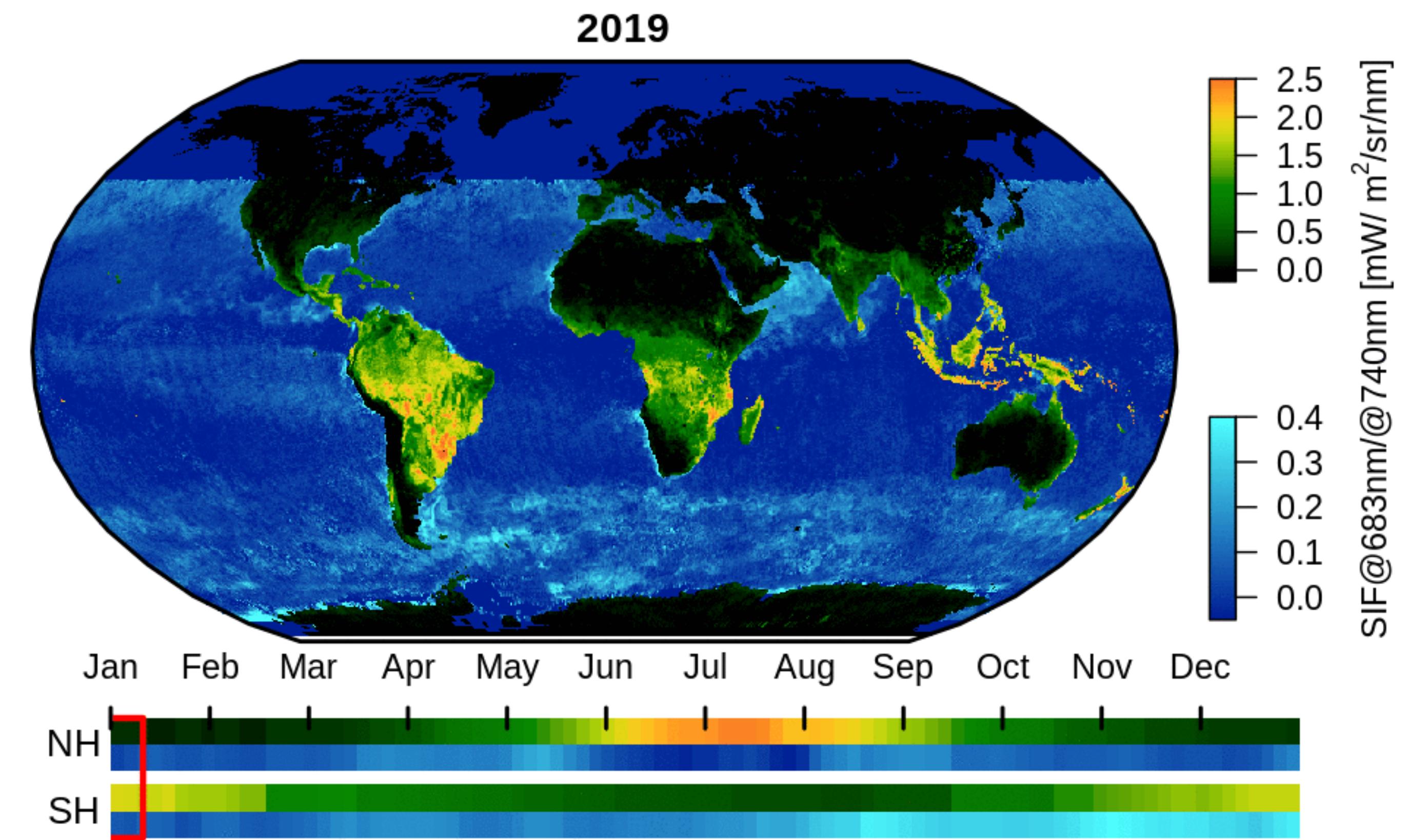
Plant Functional Type	χ_L	α_{vis}^{leaf}	α_{nir}^{leaf}	α_{vis}^{stem}	α_{nir}^{stem}	τ_{vis}^{leaf}	τ_{nir}^{leaf}
NET Temperate	0.01	0.07	0.35	0.16	0.39	0.05	0.10
NET Boreal	0.01	0.07	0.35	0.16	0.39	0.05	0.10
NDT Boreal	0.01	0.07	0.35	0.16	0.39	0.05	0.10
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BET temperate	0.10	0.10	0.45	0.16	0.39	0.05	0.25
BDT tropical	0.01	0.10	0.45	0.16	0.39	0.05	0.25
BDT temperate	0.25	0.10	0.45	0.16	0.39	0.05	0.25
BDT boreal	0.25	0.10	0.45	0.16	0.39	0.05	0.25





3. Calibration

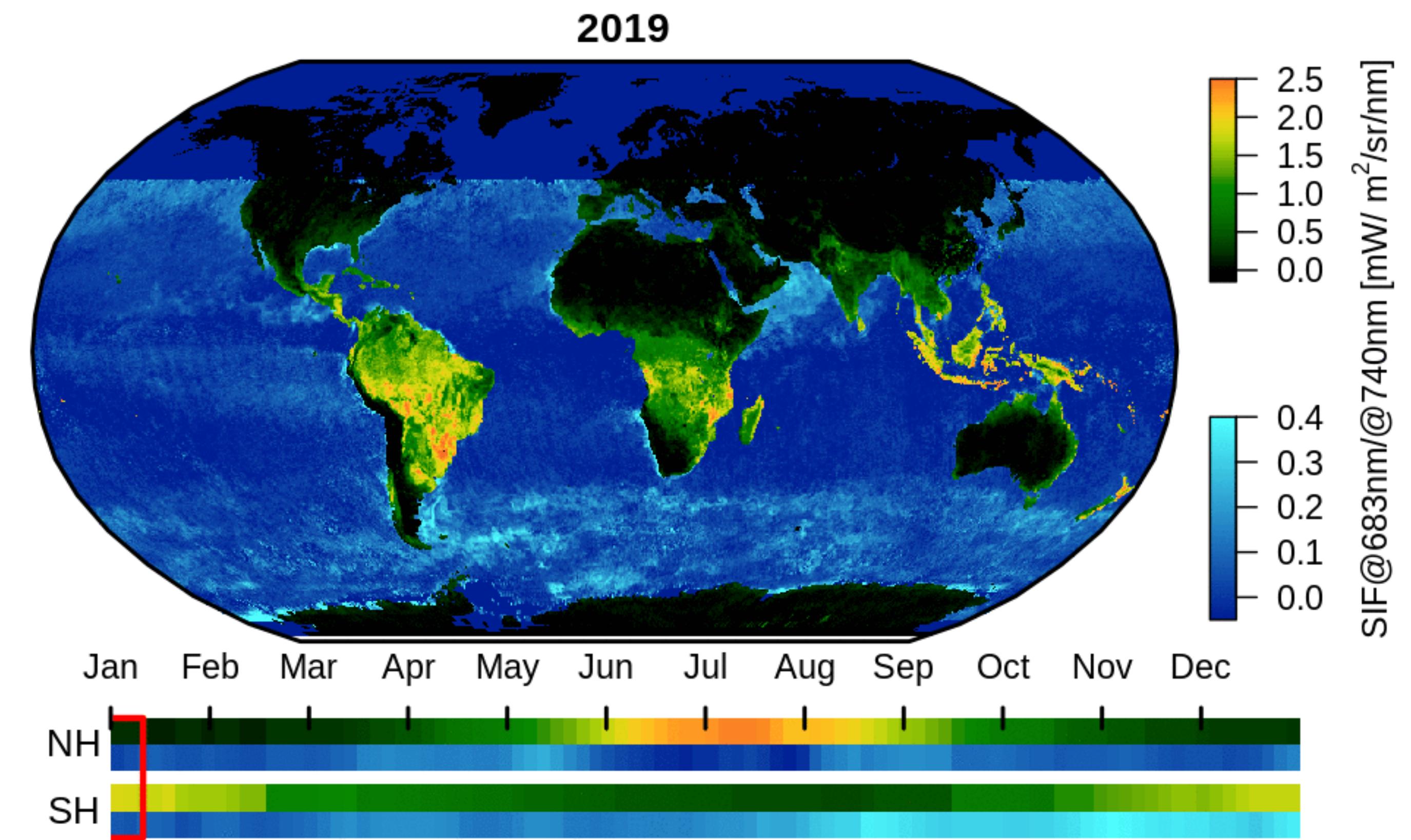
Use remote sensing data to calibrate the models





3. Calibration

Use remote sensing data to calibrate the models



Towards a more physiology-based representation of daytime stomatal conductance



1. Schemes

Improve model representation of soil-plant-air continuum

2. Setups

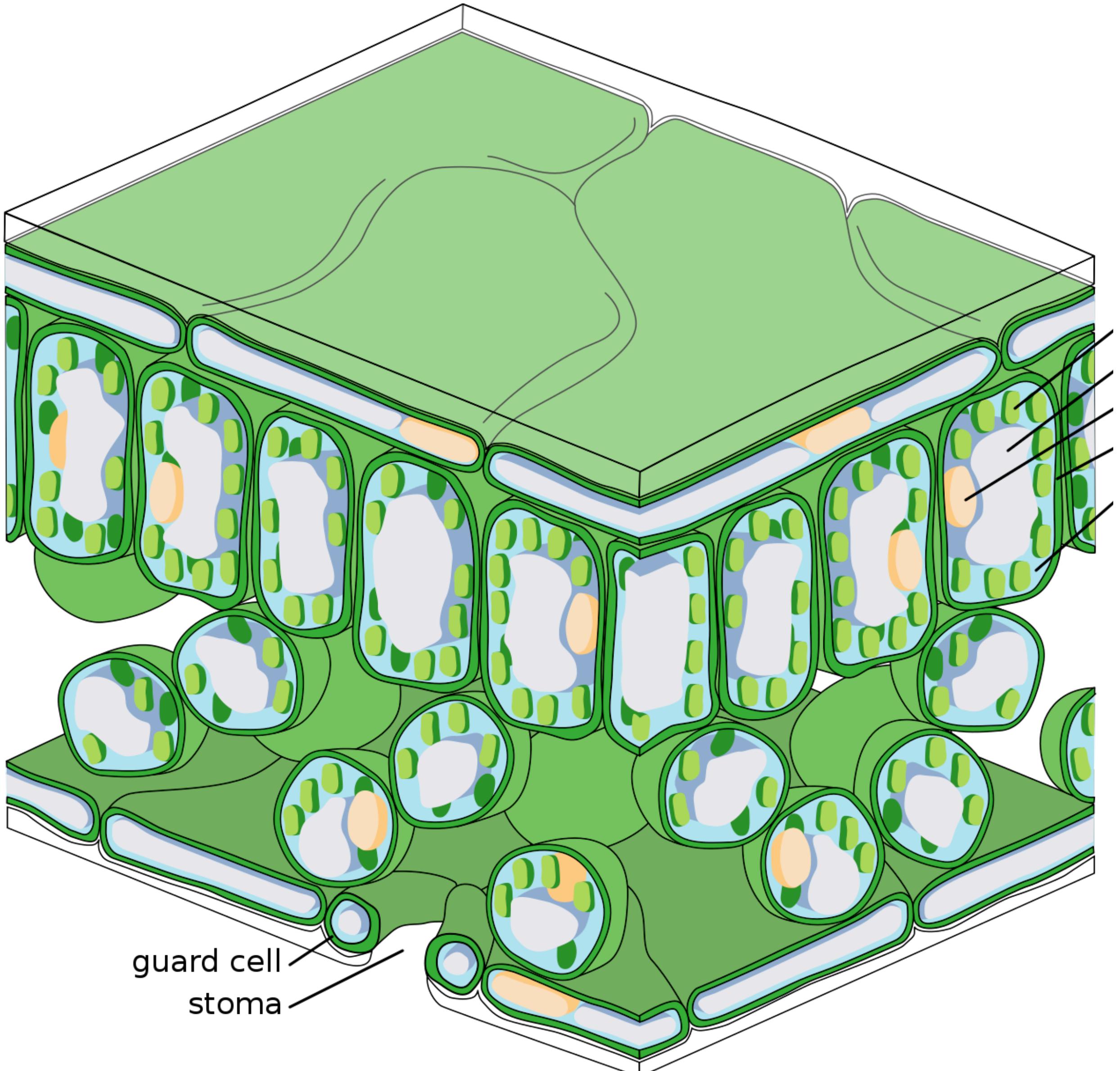
Advance model parameters configuration

3. Calibration

Use more data to calibrate the models

**~30% of
precipitation
back to air**

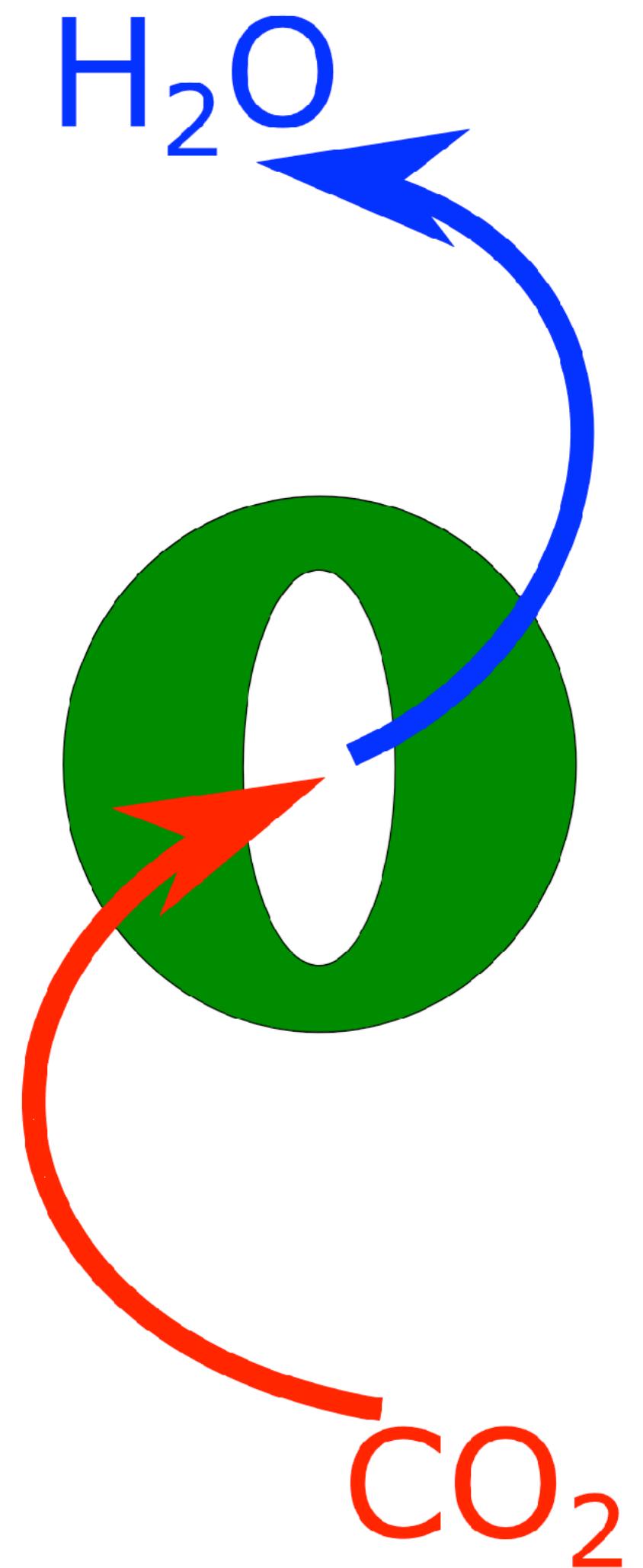
**almost all of
land CO₂
fixation**





Physiology

- ABA
- Leaf turgor
- Hydraulic conductance
- Photosynthetic capacity
- Mesophyll conductance

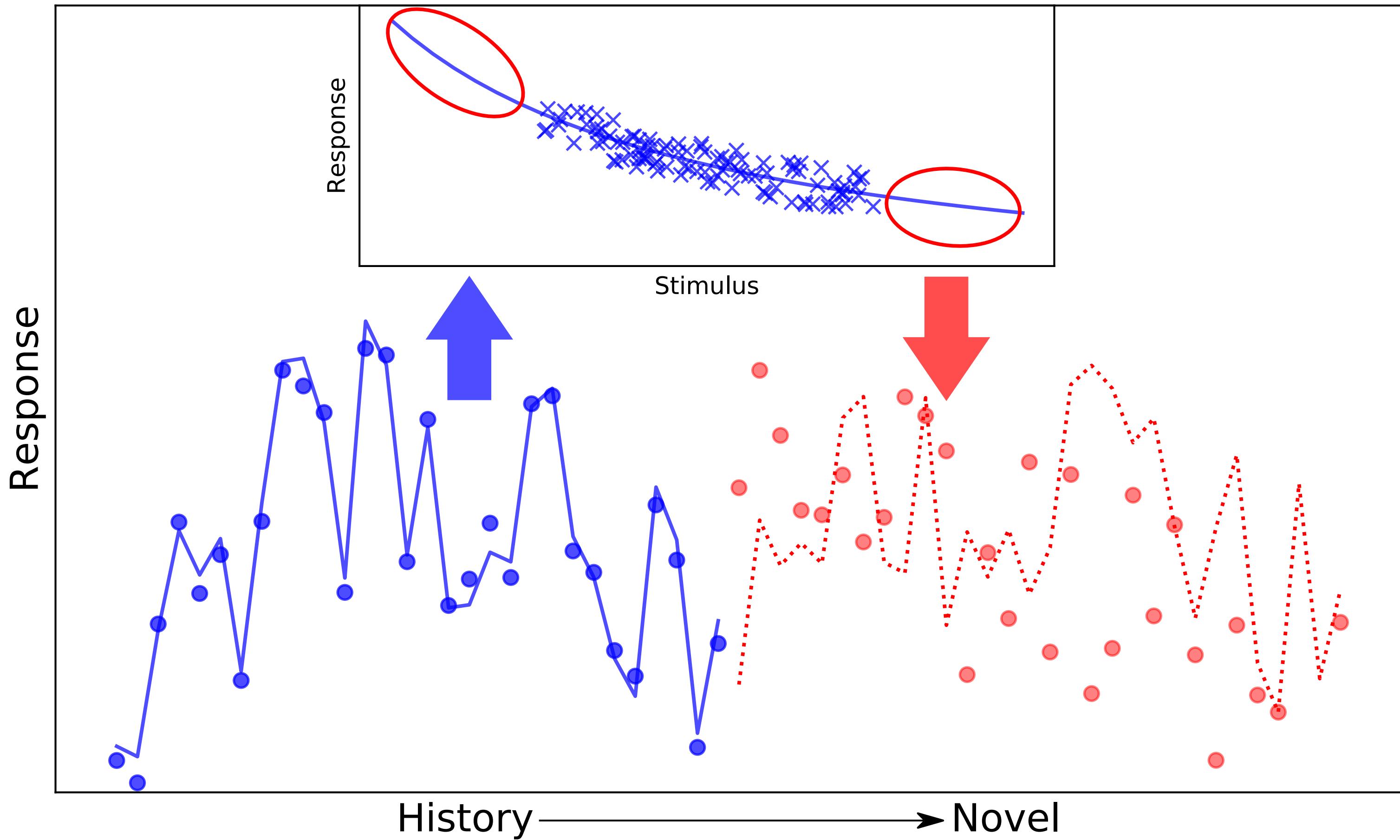


Environment

- Atmospheric CO₂
- Air humidity
- Air temperature
- Radiation
- Wind speed
- Soil moisture

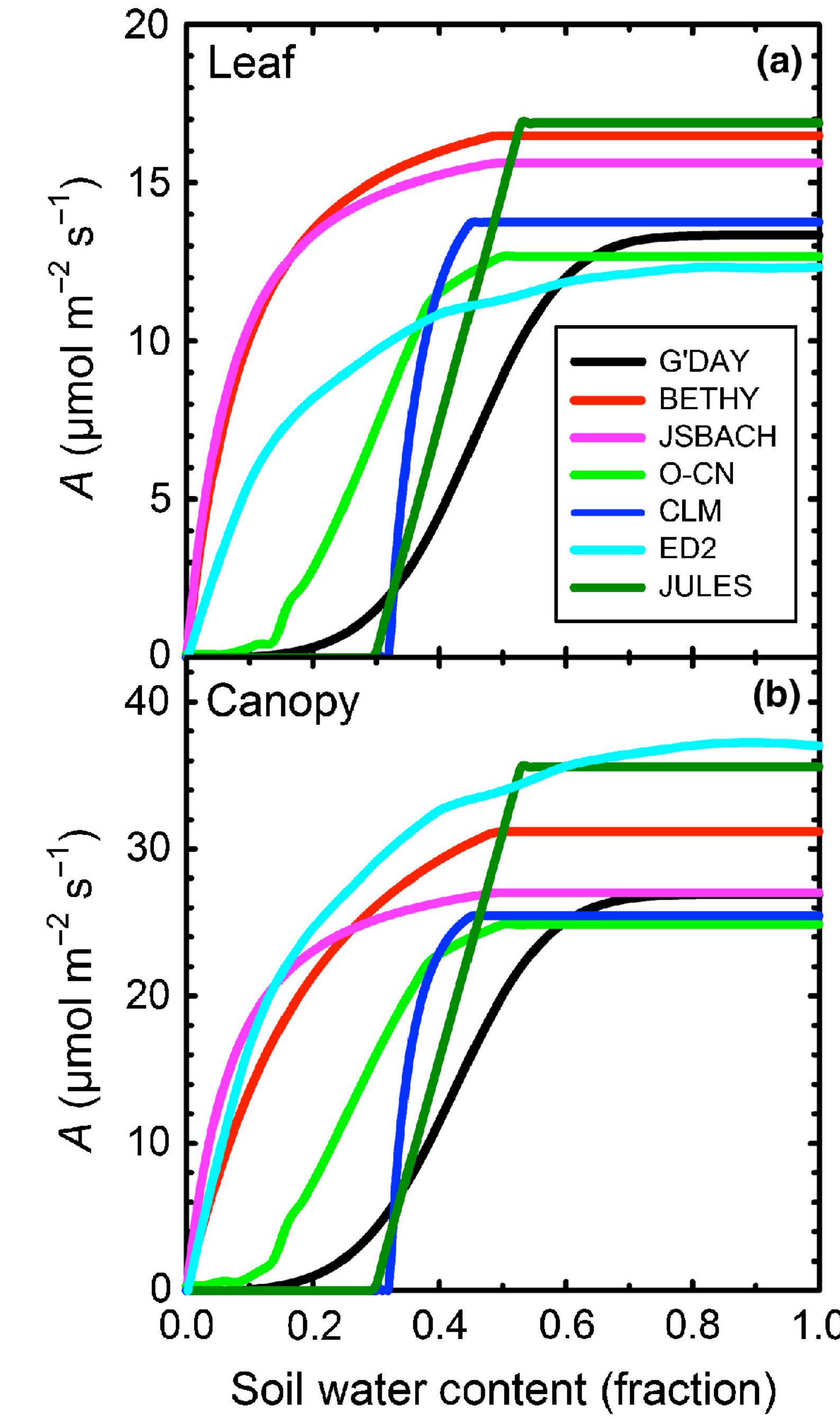


Statistical models are efficient, but cannot well capture the responses to novel environment



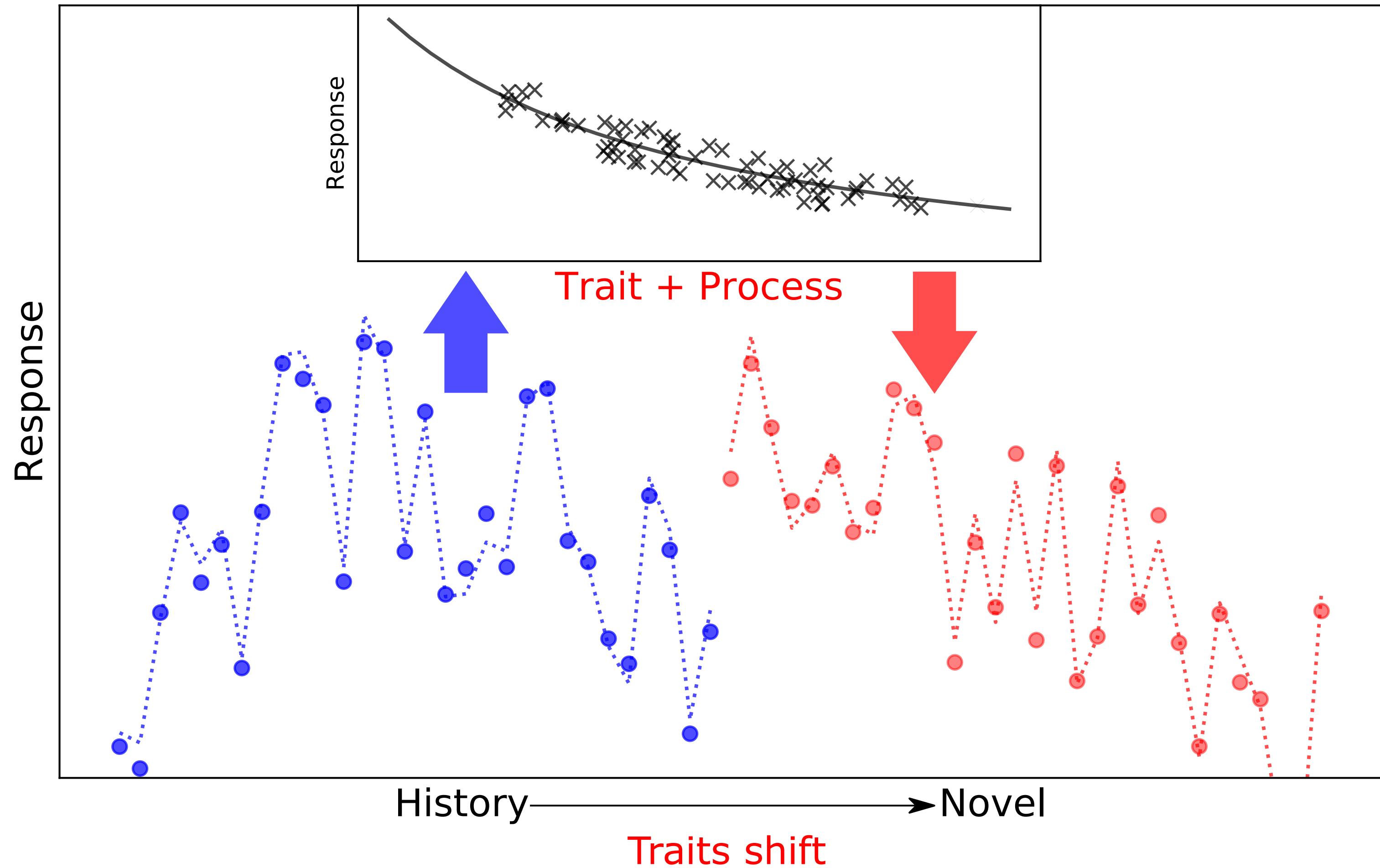


Statistical models are
efficient, but cannot
well capture the
responses to novel
environment





Mechanistic models
are less efficient, but
can capture the
responses to novel
environment due to
the use of **traits** and
processes

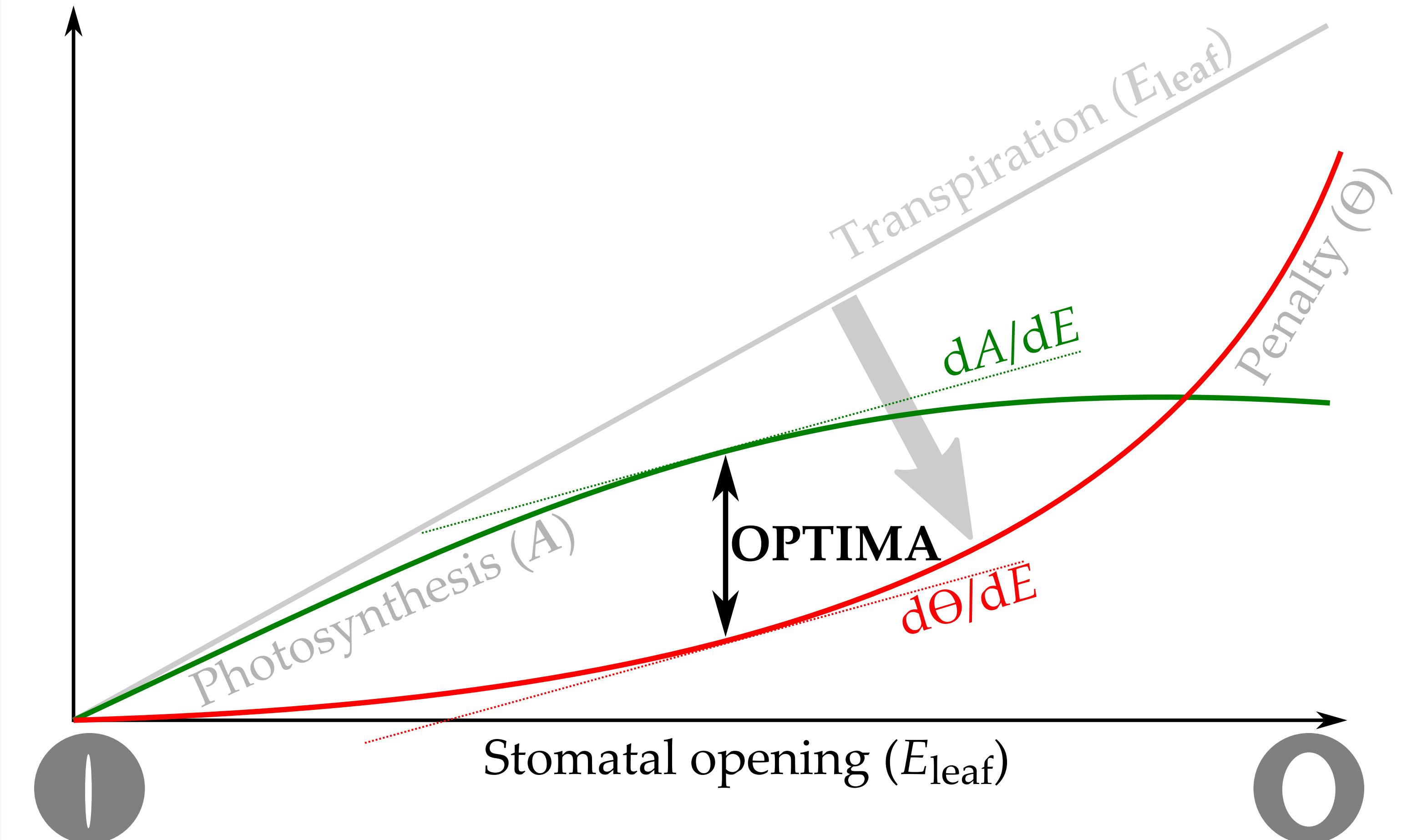


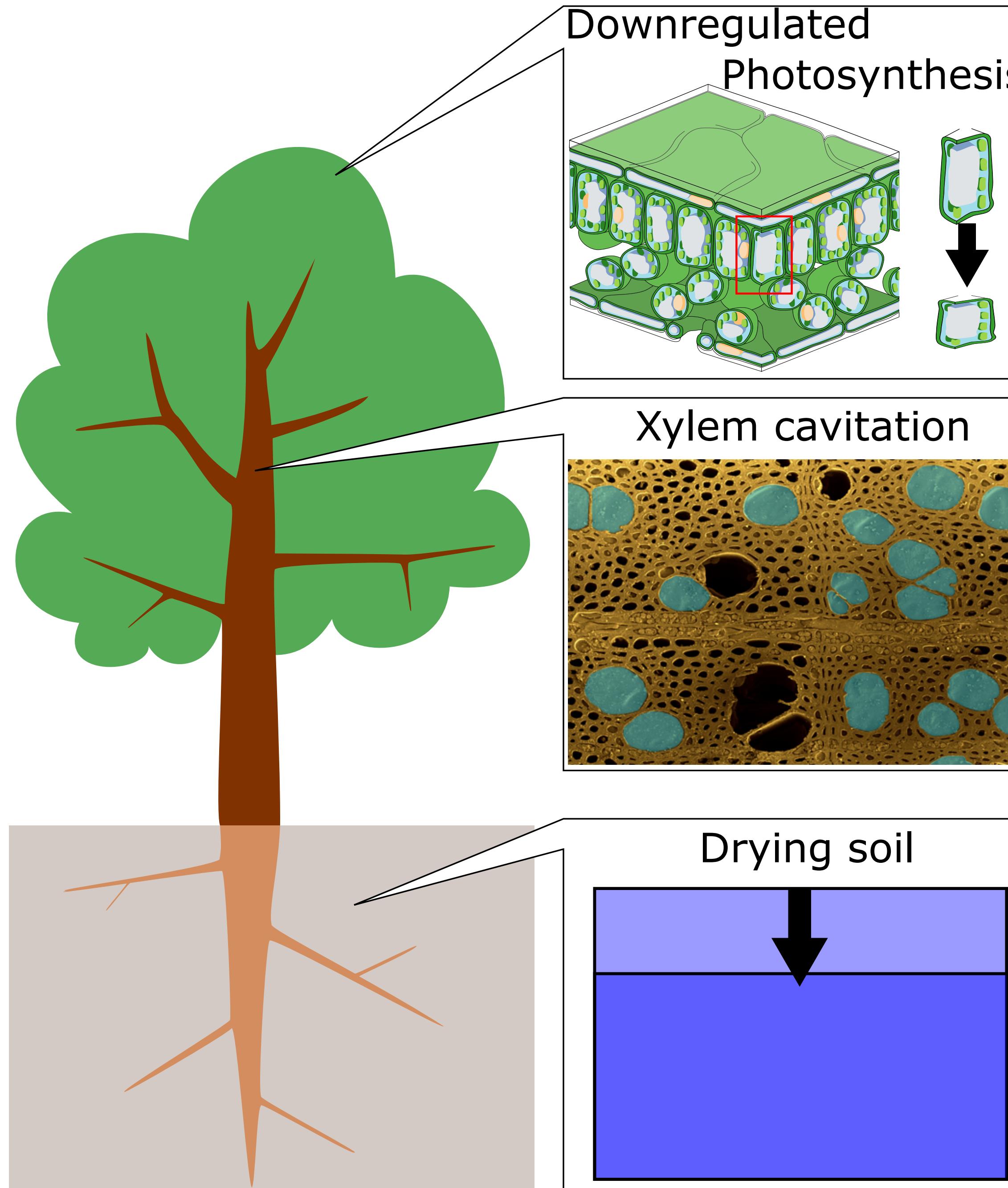


Optimality

Maximize the difference between gain and cost **when**

$$\frac{dA}{dE_{leaf}} = \frac{d\Theta}{dE_{leaf}}$$





Holtta *et al.* (2017)

Dewar *et al.* (2018)

Huang *et al.* (2018)

... ...

Wolf *et al.* (2016)

Sperry *et al.* (2017)

Anderegg *et al.* (2018)

Eller *et al.* (2019)

... ...

Cowan & Farquhar (1977)

... ...

Manzoni *et al.* (2013)

Prentice *et al.* (2014)

Lu *et al.* (2016)

... ...



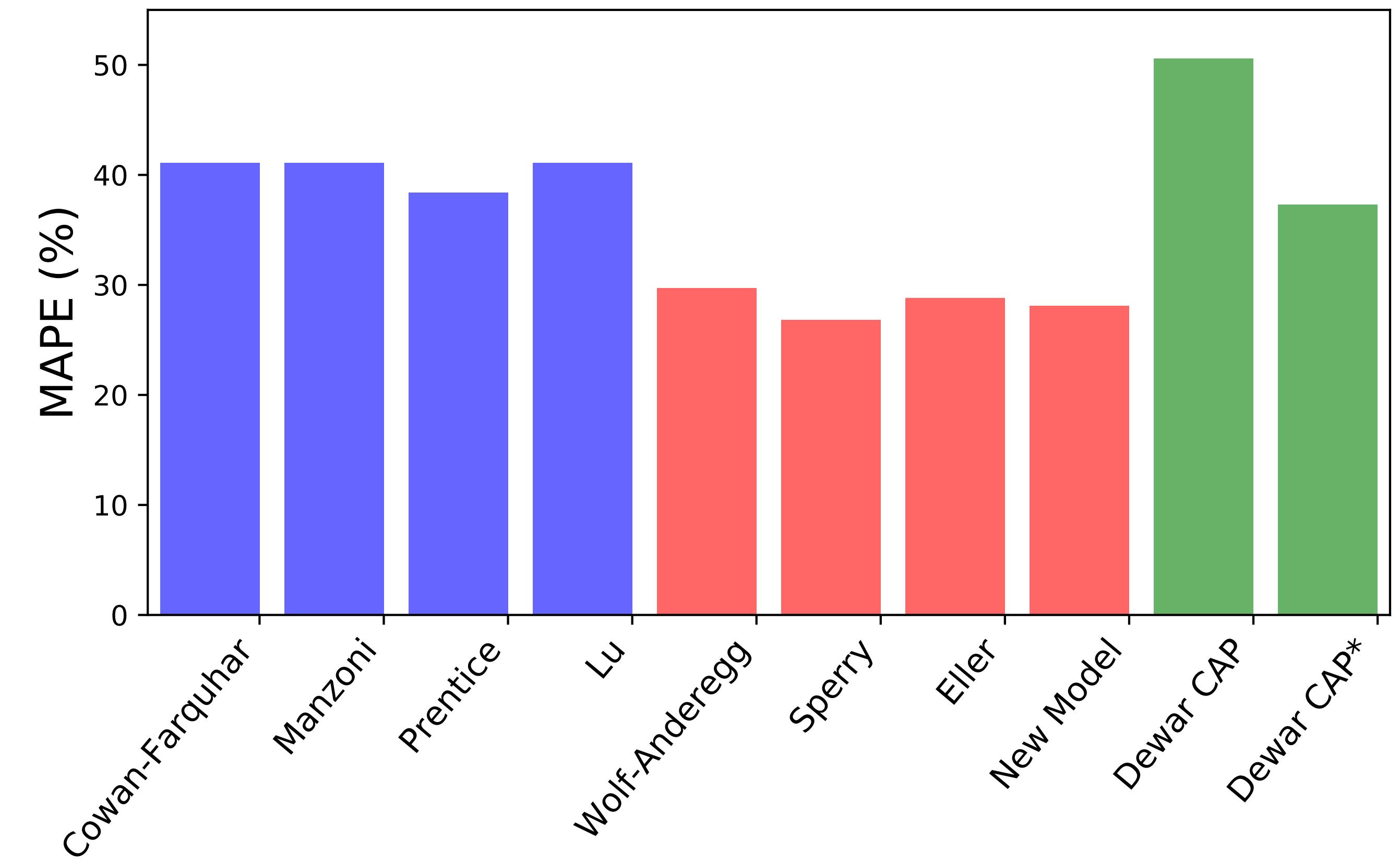
Model	Reference	Water Penalty (Θ or Θ')	Marginal Penalty ($d\Theta/dE$ or $d\Theta'/dE$)	Response	
				Criteria I–III	Criteria IV–VII DCPK
Cowan-Farquhar	(Cowan and Farquhar, 1977)	$\Theta = \frac{E_{\text{leaf}}}{\lambda}$	$\frac{d\Theta}{dE} = \frac{1}{\lambda}$	YNN	NNNN
Manzoni	(Manzoni et al., 2013)	$\Theta = \frac{E_{\text{leaf}}}{\Lambda}$	$\frac{d\Theta}{dE} = \frac{1}{\Lambda}$	YNN	NNNN
Prentice	(Prentice et al., 2014)	$\Theta = A \cdot \left(1 - \frac{1}{c_E E_{\text{leaf}} + c_V V_{\text{cmax}}} \right)$	$\frac{d\Theta}{dE} = \frac{A}{E_{\text{leaf}} + \frac{c_V}{c_E} V_{\text{cmax}}}$	YNY	YYNN
Lu	(Lu et al., 2016)	$\Theta = \frac{E_{\text{leaf}}}{\lambda}$	$\frac{d\Theta}{dE} = \frac{1}{\lambda}$	YNN	NNNN
Wolf-Anderegg	(Wolf et al., 2016) (Anderegg et al., 2018)	$\Theta = aP^2 + bP + c$	$\frac{d\Theta}{dE} = \frac{2aP + b}{K}$	YYN	NNYY
Sperry	(Sperry et al., 2017)	$\Theta = A_{\text{max}} \cdot \left(1 - \frac{K}{K_{\text{max}}} \right)$	$\frac{d\Theta}{dE} = -\frac{dK}{dE} \cdot \frac{A_{\text{max}}}{K_{\text{max}}}$	YYY	YYYY
Eller	(Eller et al., 2018)	$\Theta = A \cdot \left(1 - \frac{K}{K_{\text{max},0}} \right)$	$\frac{d\Theta}{dE} = -\frac{dK}{dE} \cdot \frac{A}{K}$	YYY	YYYN
New Model		$\Theta = A \cdot \frac{E_{\text{leaf}}}{E_{\text{crit}}}$	$\frac{d\Theta}{dE} = \frac{A}{E_{\text{crit}} - E_{\text{leaf}}}$	YYY	YYYY
Hölttä	(Hölttä et al., 2017)	$\Theta' = A_{\text{ww}} \cdot \frac{\text{SC}}{\text{SC}_{\text{max}}}$	$\frac{d\Theta'}{dE} = \frac{A}{\text{SC}_{\text{max}} - \text{SC}} \cdot \frac{d\text{SC}}{dE}$	YYY	YYYY
Dewar CAP	(Dewar et al., 2018)	$\Theta' = A_{\text{ww}} \cdot \frac{P}{P_{\text{crit}}}$	$\frac{d\Theta'}{dE} = \frac{A}{K \cdot (P_{\text{crit}} - P)}$	YYY	YYYY



Birch dataset

Growth chamber

- CO₂
- Air humidity
- Soil moisture

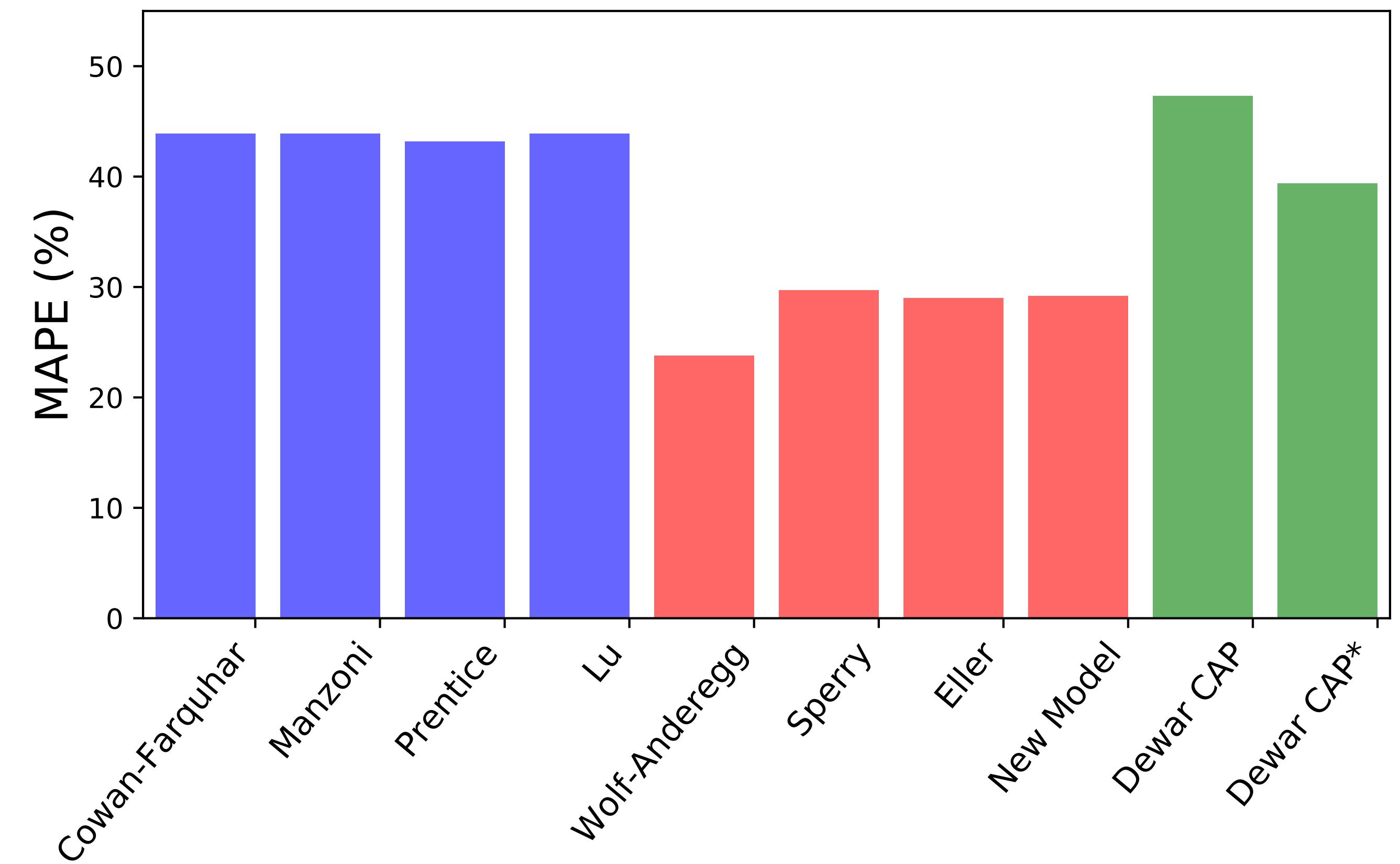




Aspen dataset

Research garden

- Soil moisture
- Air humidity*

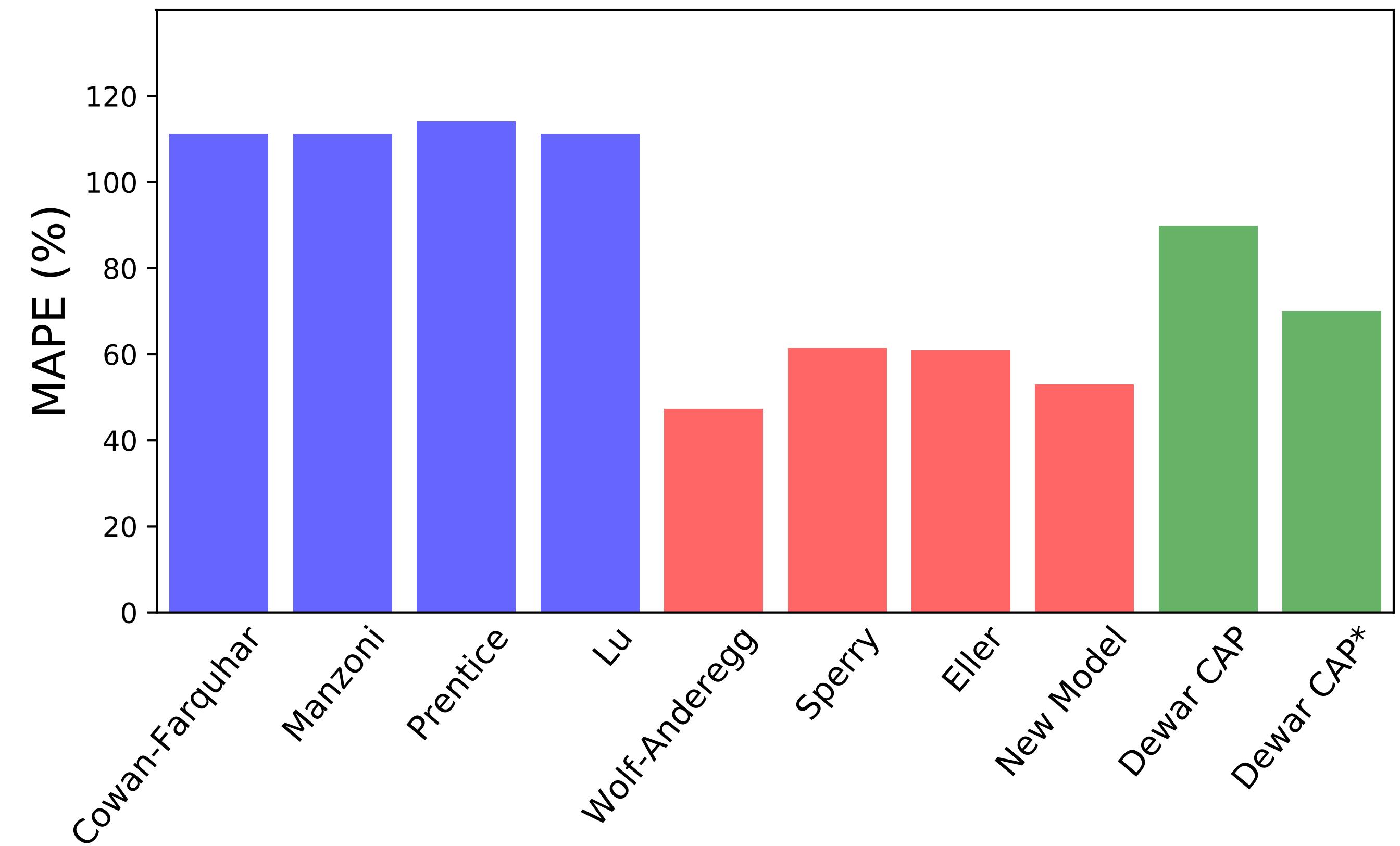
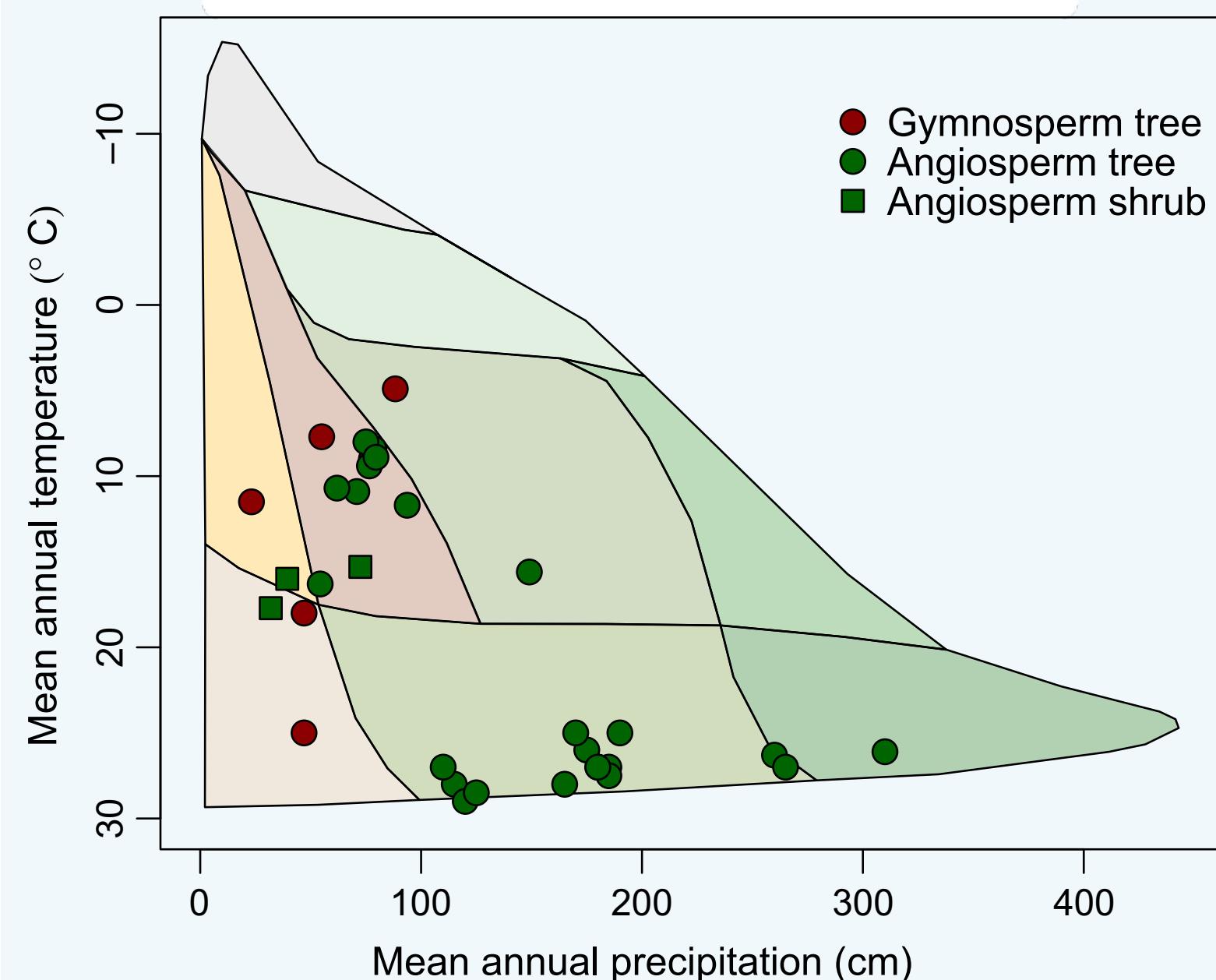




Compiled dataset

Natural forests

- Soil moisture*
- Air humidity*





Model	Reference	Water Penalty (Θ or Θ')	Marginal Penalty ($d\Theta/dE$ or $d\Theta'/dE$)	Response	
				I-III	IV-VII DCPK
Cowan-Farquhar	(Cowan and Farquhar, 1977)	$\Theta = \frac{E_{\text{leaf}}}{\lambda}$	$\frac{d\Theta}{dE} = \frac{1}{\lambda}$	YNN	NNNN
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Sperry	(Sperry et al., 2017)	$\Theta = A_{\text{max}} \cdot \left(1 - \frac{K}{K_{\text{max}}} \right)$	$\frac{d\Theta}{dE} = -\frac{dK}{dE} \cdot \frac{A_{\text{max}}}{K_{\text{max}}}$	YYY	YYYY
Eller	(Eller et al., 2018)	$\Theta = A \cdot \left(1 - \frac{K}{K_{\text{max},0}} \right)$	$\frac{d\Theta}{dE} = -\frac{dK}{dE} \cdot \frac{A}{K}$	YYY	YYYN
New Model		$\Theta = A \cdot \frac{E_{\text{leaf}}}{E_{\text{crit}}}$	$\frac{d\Theta}{dE} = \frac{A}{E_{\text{crit}} - E_{\text{leaf}}}$	YYY	YYYY
Hölttä	(Hölttä et al., 2017)	$\Theta' = A_{\text{ww}} \cdot \frac{\text{SC}}{\text{SC}_{\text{max}}}$	$\frac{d\Theta'}{dE} = \frac{A}{\text{SC}_{\text{max}} - \text{SC}} \cdot \frac{d\text{SC}}{dE}$	YYY	YYYY
Dewar CAP	(Dewar et al., 2018)	$\Theta' = A_{\text{ww}} \cdot \frac{P}{P_{\text{crit}}}$	$\frac{d\Theta'}{dE} = \frac{A}{K \cdot (P_{\text{crit}} - P)}$	YYY	YYYY

Towards a more physiology-based representation of nighttime stomatal conductance

1. Schemes

Improve model representation of soil-plant-air continuum

2. Setups

Advance model parameters configuration

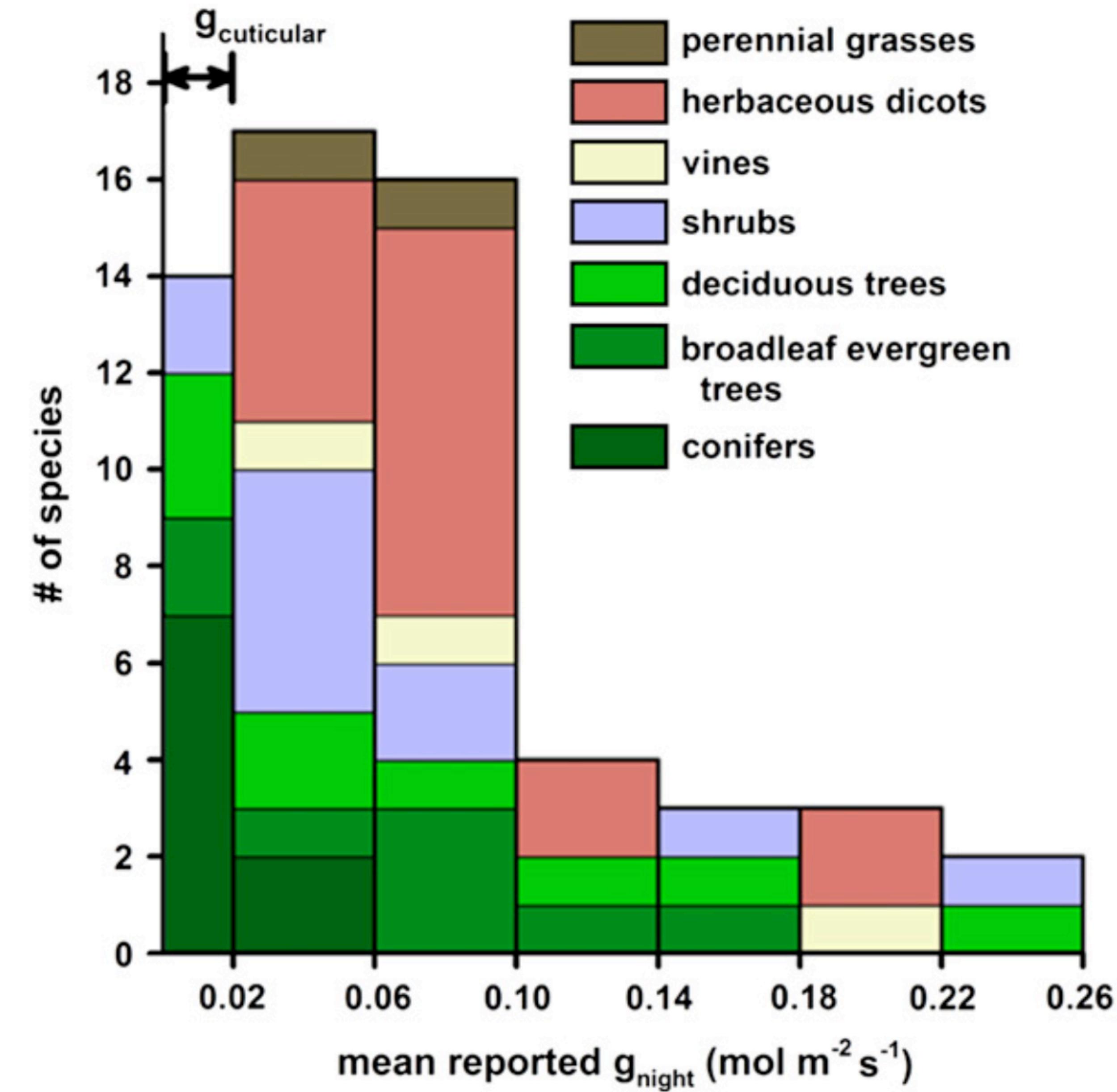
3. Calibration

Use more data to calibrate the models





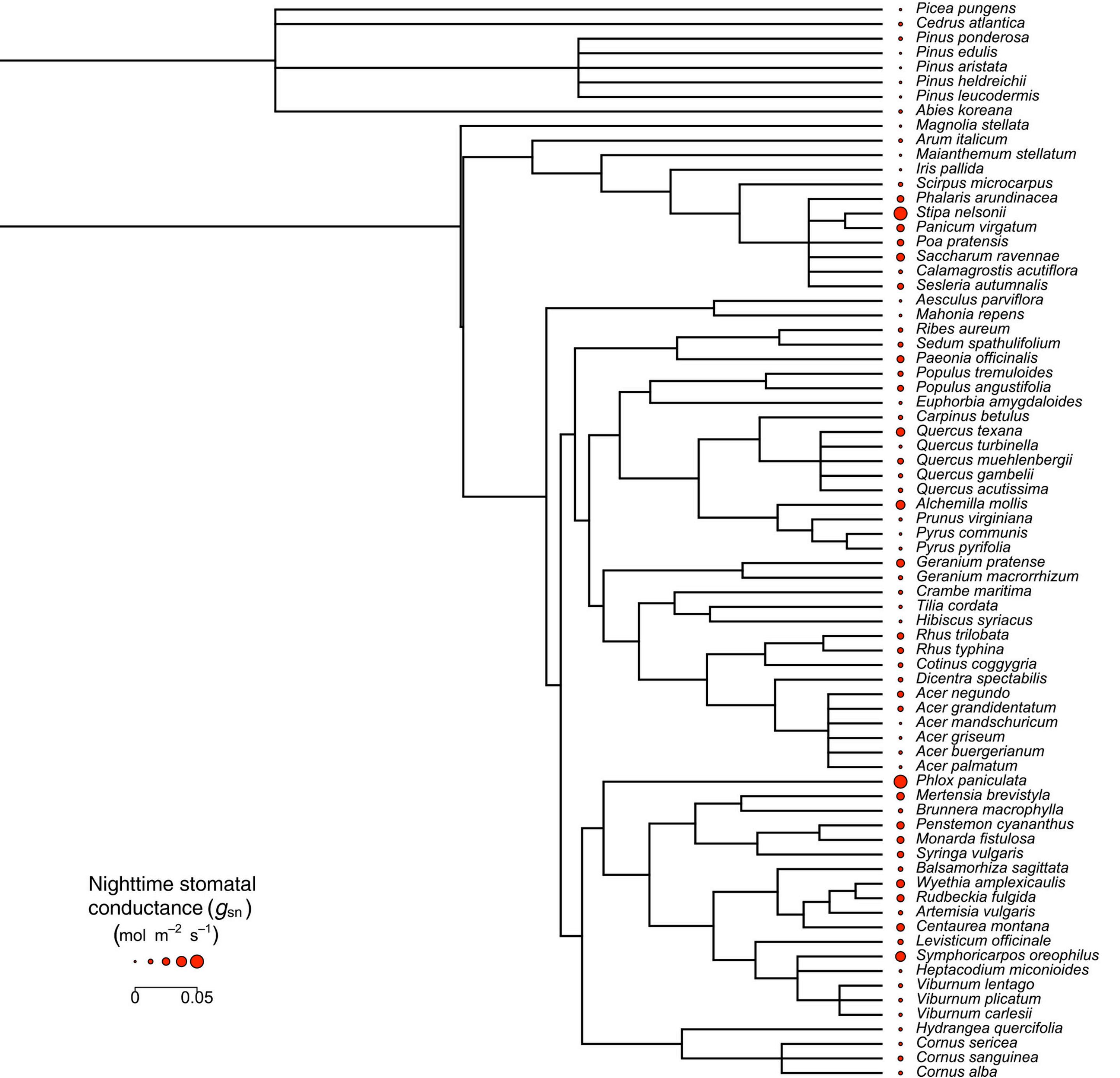
Nighttime E
About 10% to
15% of the
daytime E



Nighttime E

Found in various species

Nighttime stomatal conductance (g_{sn})
 $(\text{mol m}^{-2} \text{s}^{-1})$





Major drivers?

- **Leaky stomata**
- **Nutrient uptake**
- **Oxygen uptake**
- **Competition**
- **Evaporative cooling**
- **Circadian rhythm**

Responses to

- **Air humidity**
- **CO₂**
- **Soil moisture**
- **Leaf temperature**
- **Leaf respiration**



Optimality

Maximize the difference between gain and cost

Gain

- All benefits

Risk

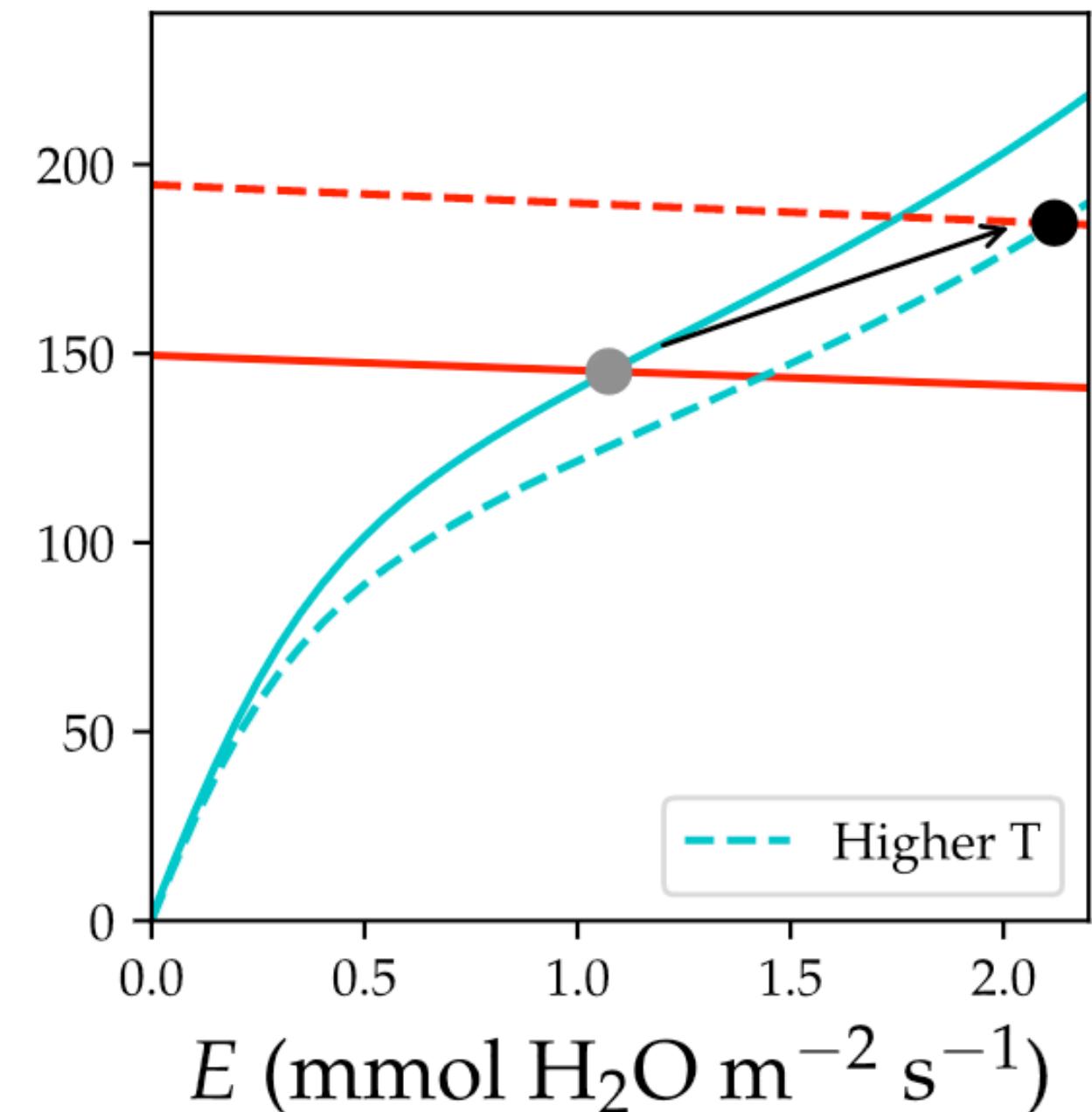
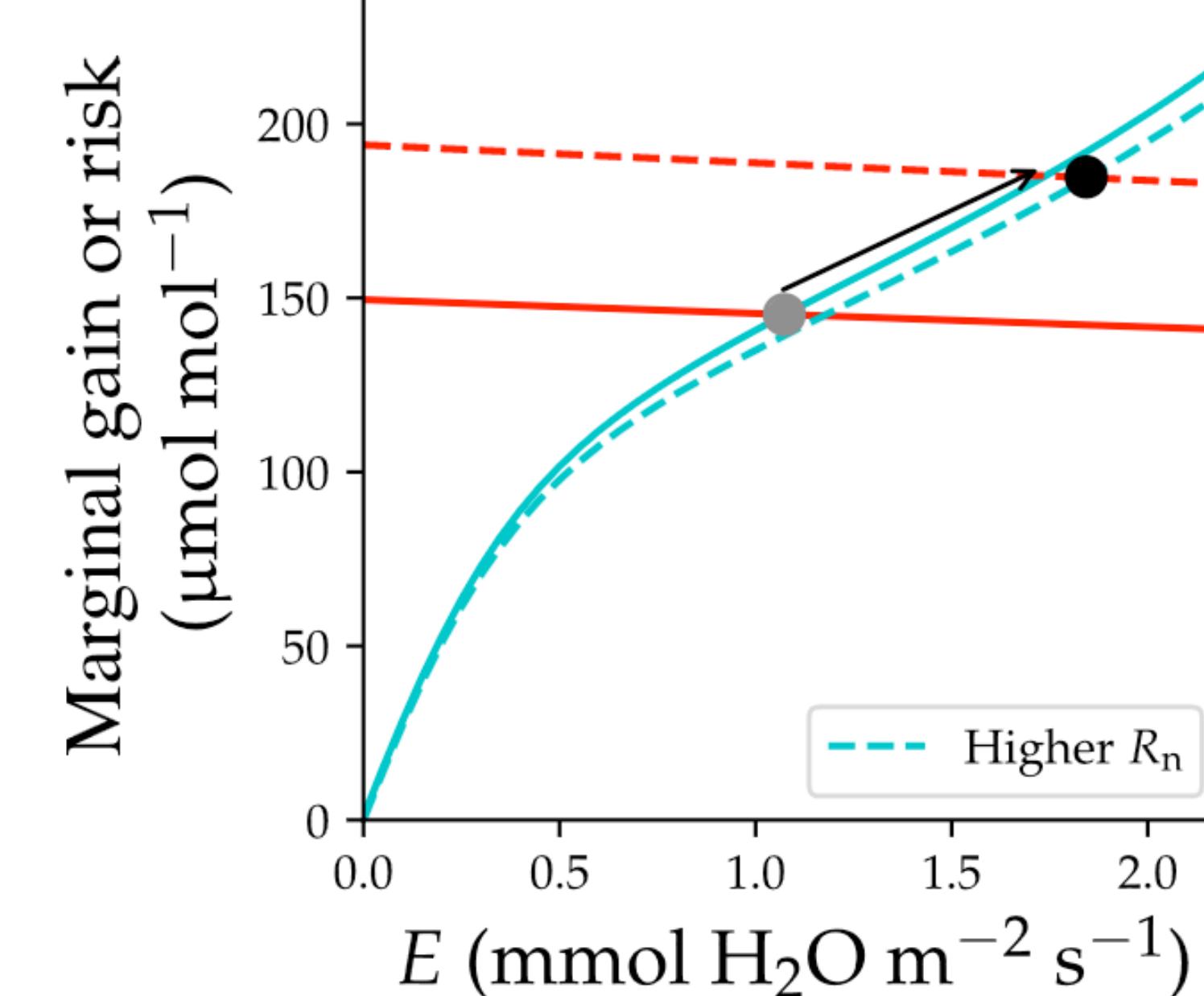
- Daytime photosynthesis



Optimality

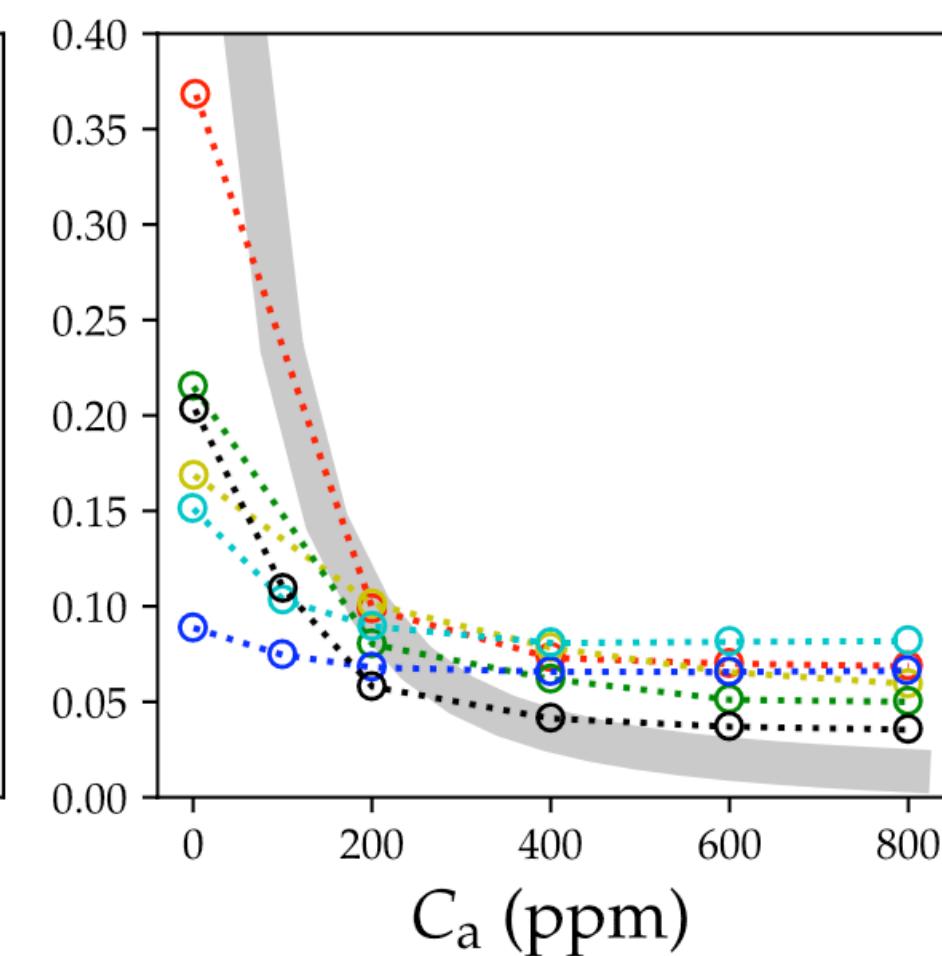
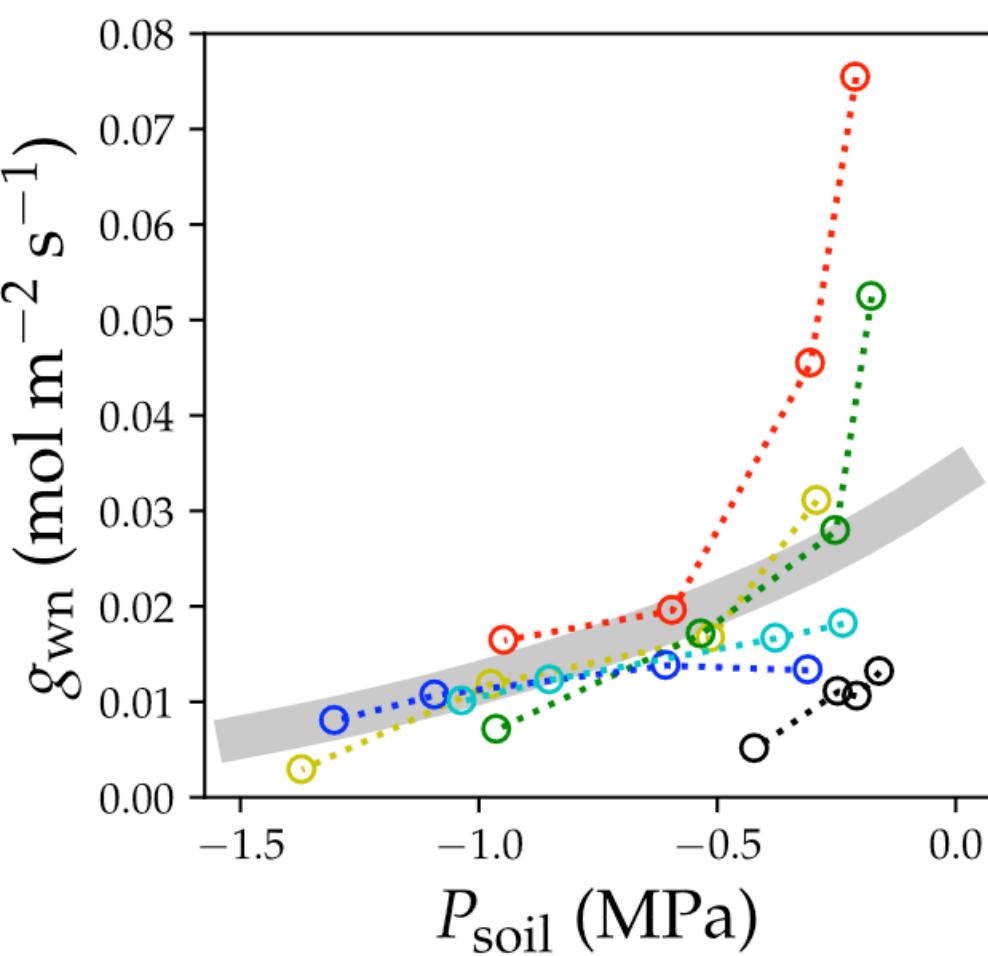
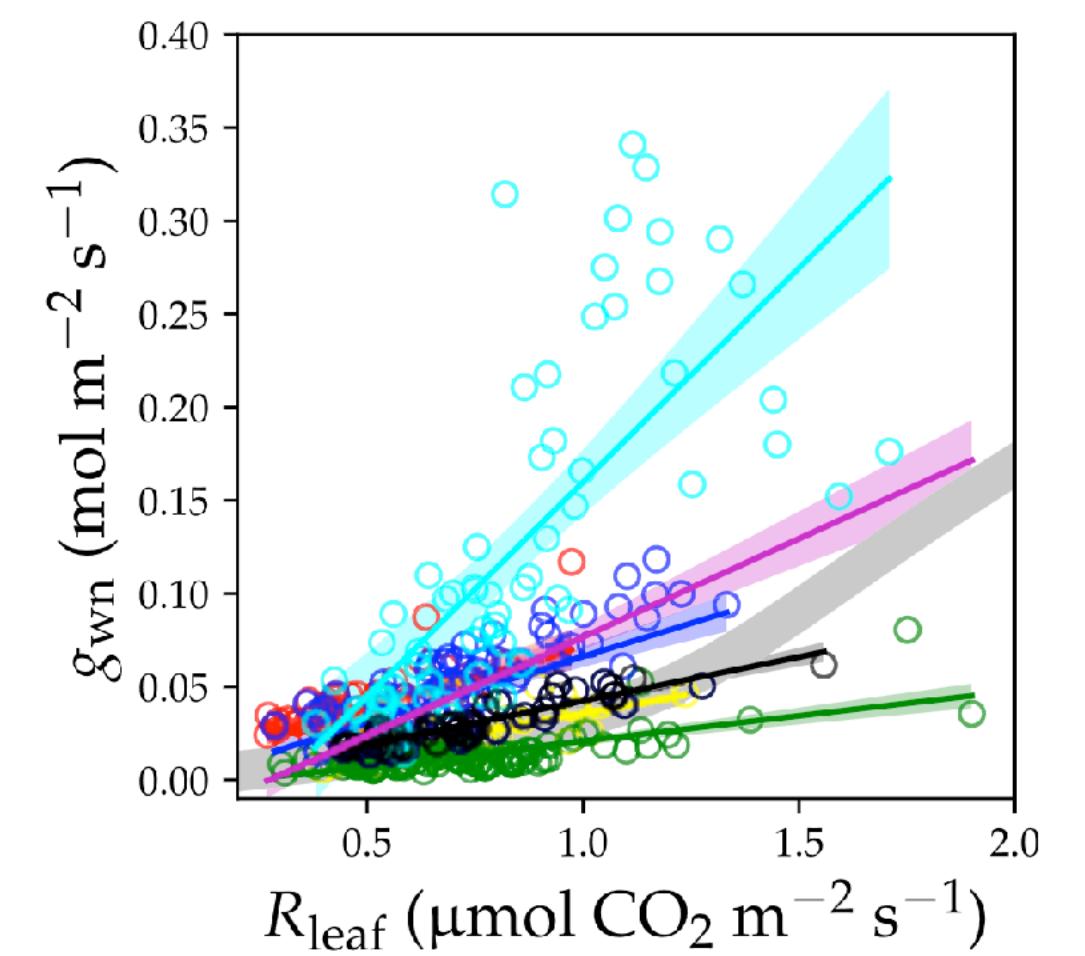
Maximize the difference between gain and cost

$$-\frac{\partial R_{\text{leaf}}}{\partial E_n} - f_f \cdot \frac{A_d(E_n)}{E_{\text{crit}} - E_n} = 0$$





Optimality
Maximize the difference between gain and cost





A highly modularized next generation land surface model—CliMA Land

1. Schemes

Improve model representation of soil-plant-air continuum

2. Setups

Advance model parameters configuration

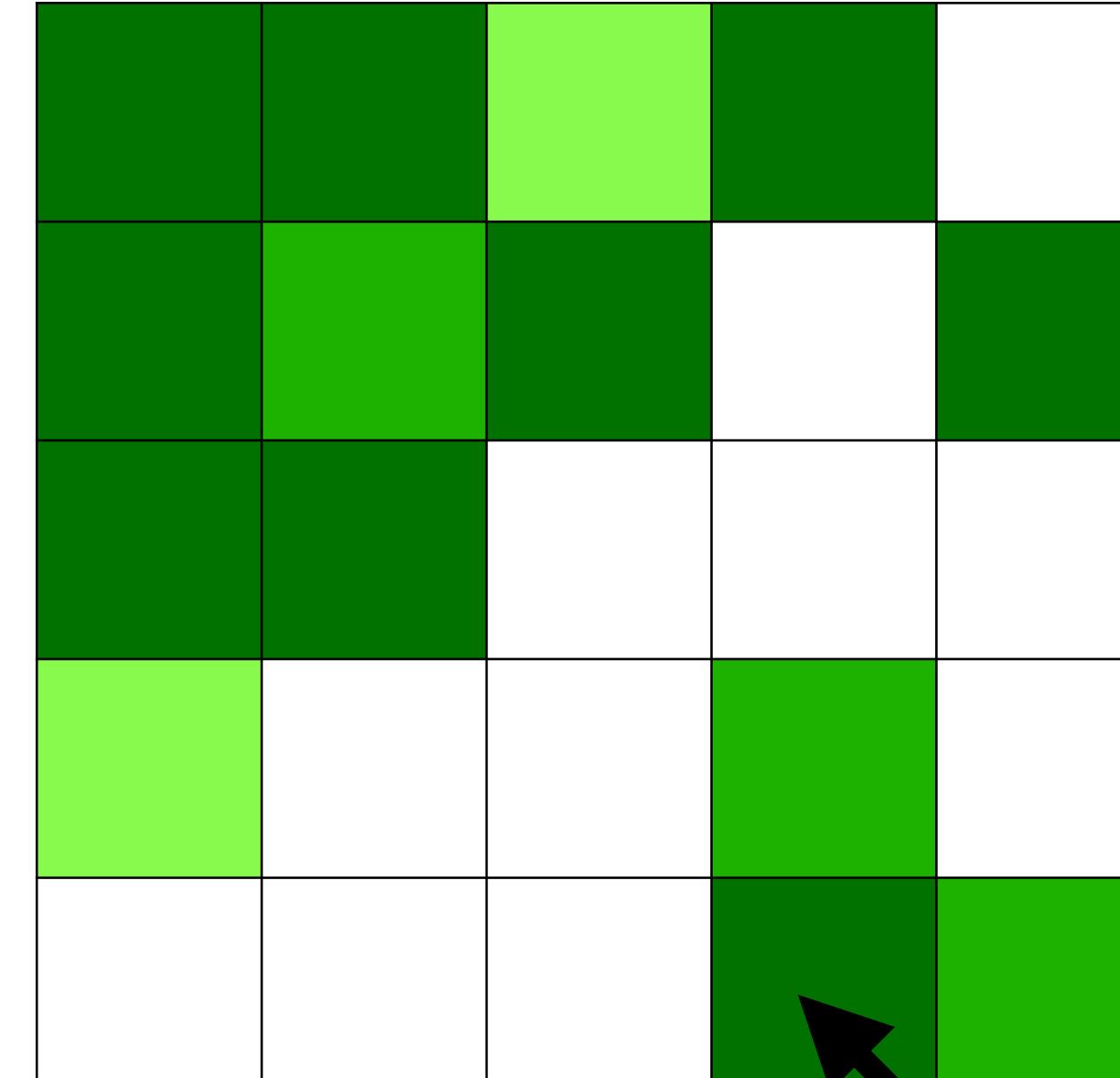
3. Calibration

Use more data to calibrate the models

Tradeoffs

- Complexity
- Accuracy
- Delivery
- Efficiency

Traits are what
we need to learn

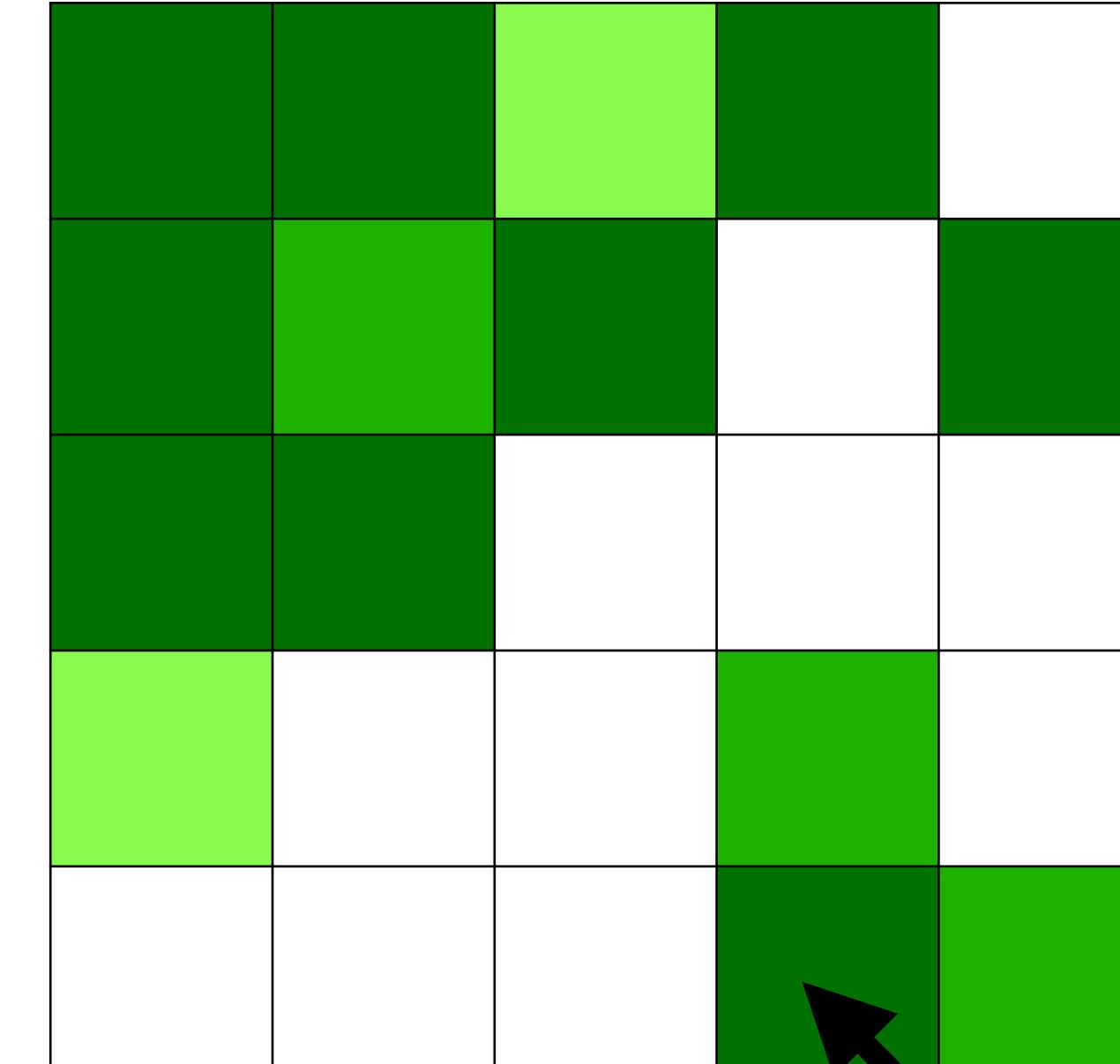


Minimum Element
Soil-plant-air continuum

Tradeoffs

- Complexity
- Accuracy
- Delivery
- Efficiency

Traits are what
we need to learn



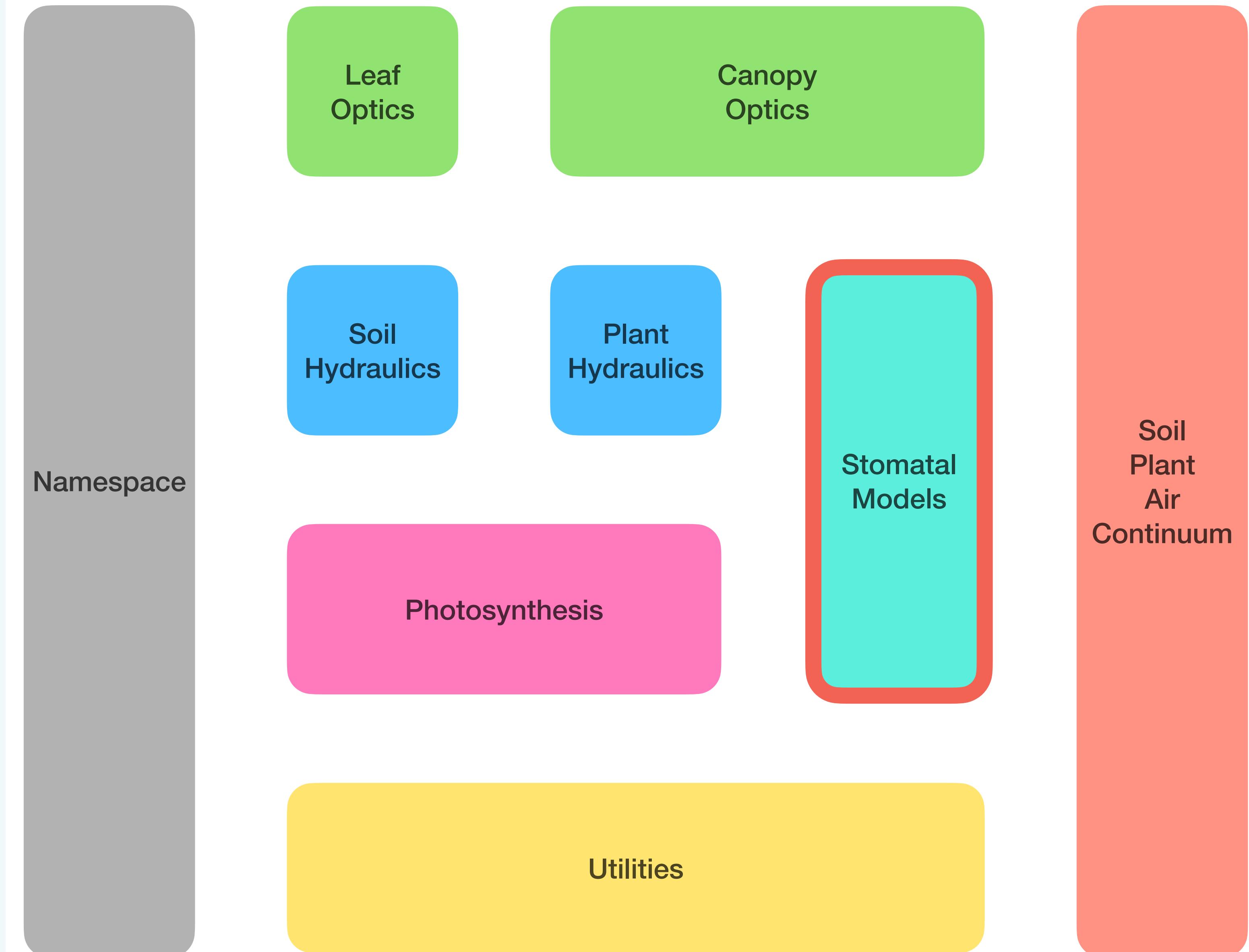
Minimum Element
Soil-plant-air continuum





1. Modularity

**Each module
can be used as
a **standalone**
package**





1. Modularity

Each module
can be used as
a **standalone**
package

```
config = EmeraldLand.Namespace.SPACConfiguration{FT}();  
bio = EmeraldLand.Namespace.LeafBio(config);  
EmeraldLand.LeafOptics.leaf_spectra!(config, bio, FT(5));
```



2. User friendly

**Convenient
functions to
begin with**

**GUI on the way
for teaching
purpose**

```
config = EmeraldLand.Namespace.SPACConfiguration{FT}();
spac = EmeraldLand.Namespace.BulkSPAC(config);
EmeraldLand.SPAC.initialize!(config, spac);
EmeraldLand.SPAC.spac!(config, spac, FT(1));
```



3. Freedom Various model schemes to choose from

Namespace
Free combinations

Leaf Optics

Broadband
Hyper-spectral

Canopy Optics

Broadband / hyper-spectral
Single to multiple layers

Soil Hydraulics

Van Genuchten
Brooks Corey

Plant Hydraulics

Multiple VC forms
Custom structure
SS or NSS

Stomatal Models

(Empirical)
Ball Berry
Leuning
Medlyn
Gentine

(Optimality)
Wolf-Anderegg
Pacala
Sperry
Eller
Wang

Soil
Plant
Air
Continuum

Single elements
Complex SPAC

Photosynthesis

Classic C3 model
Classic C4 model
New Cytochrome C3 model

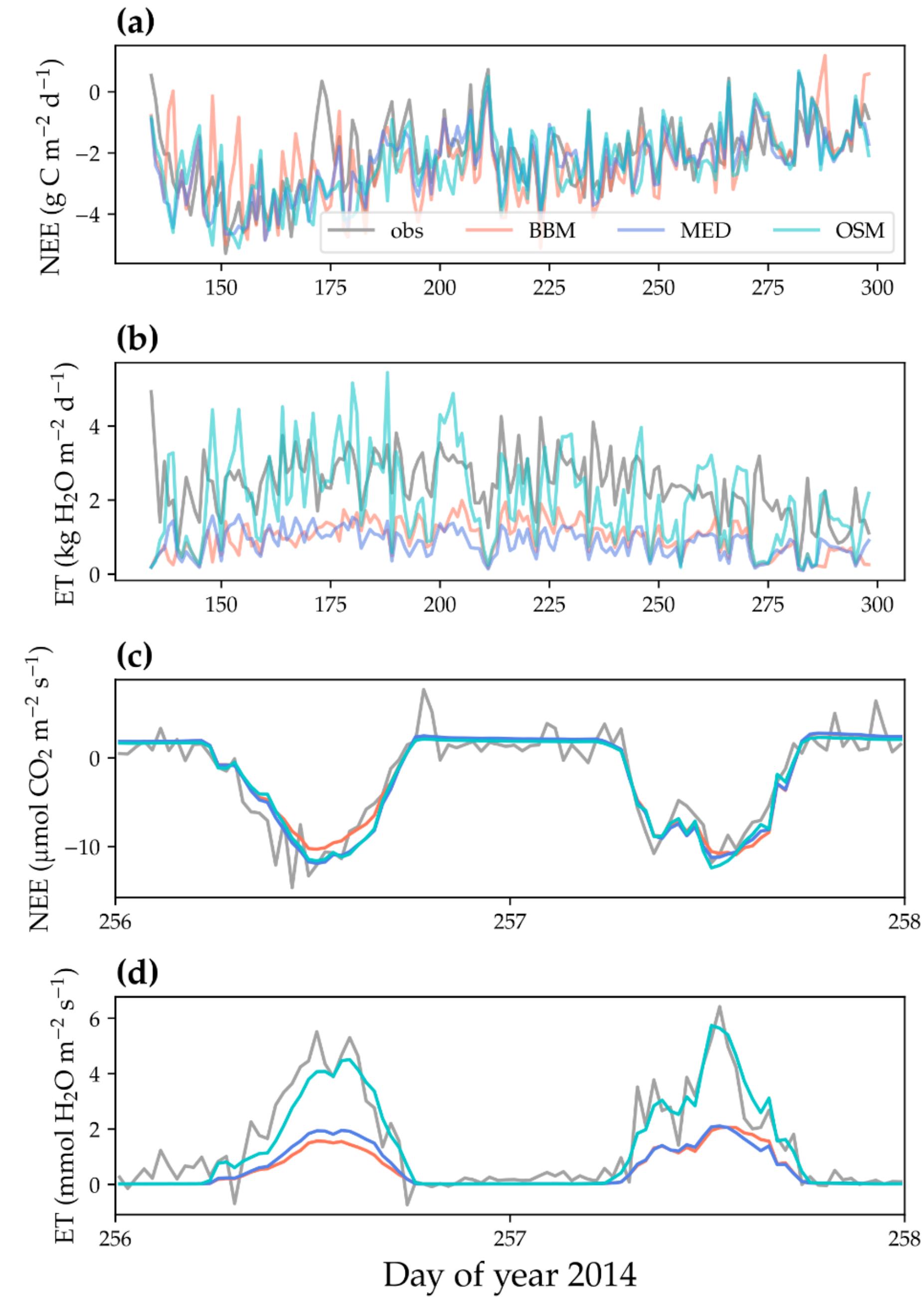
Utilities

Shared constants
Solvers
IO Tools



3. Freedom

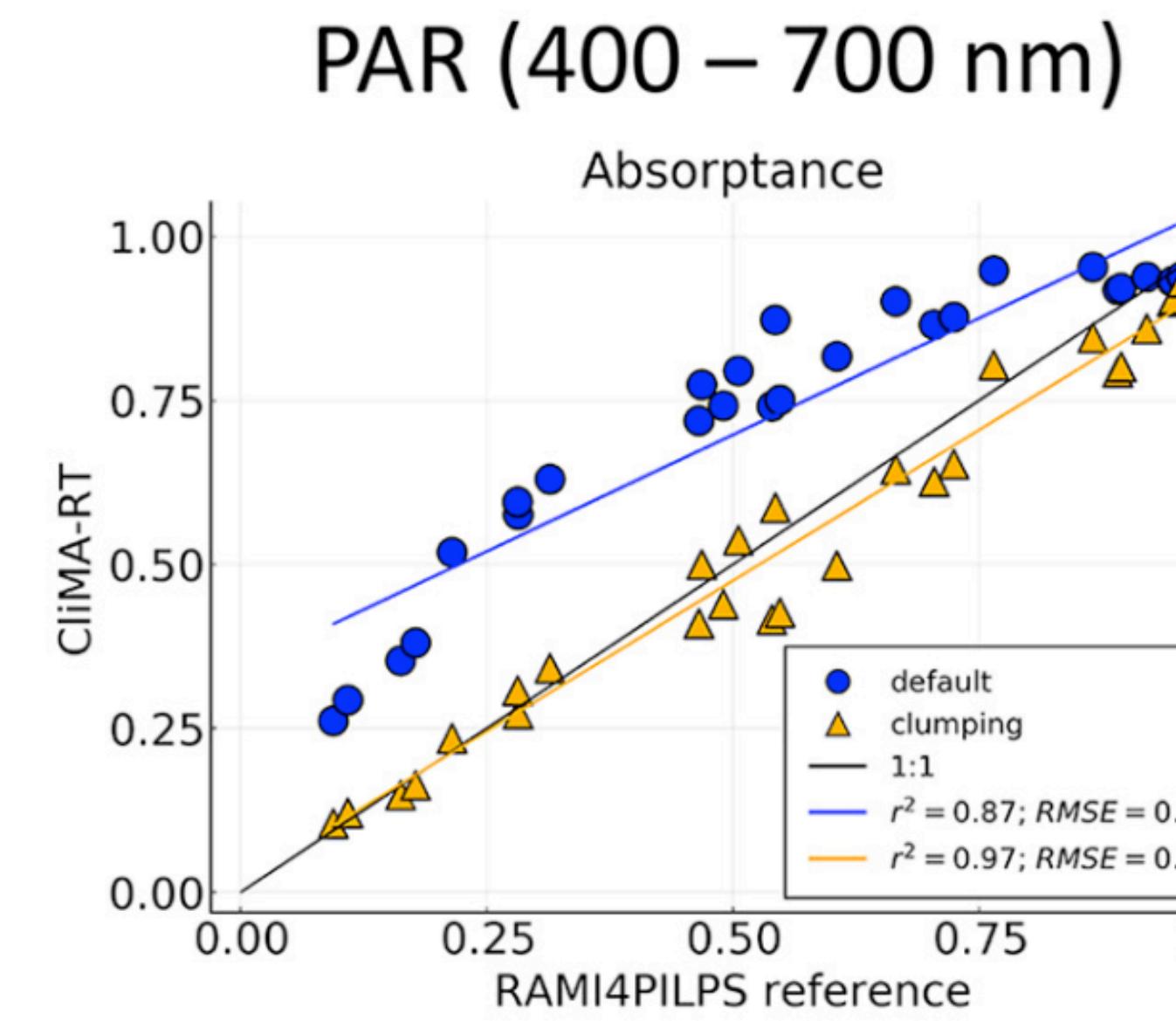
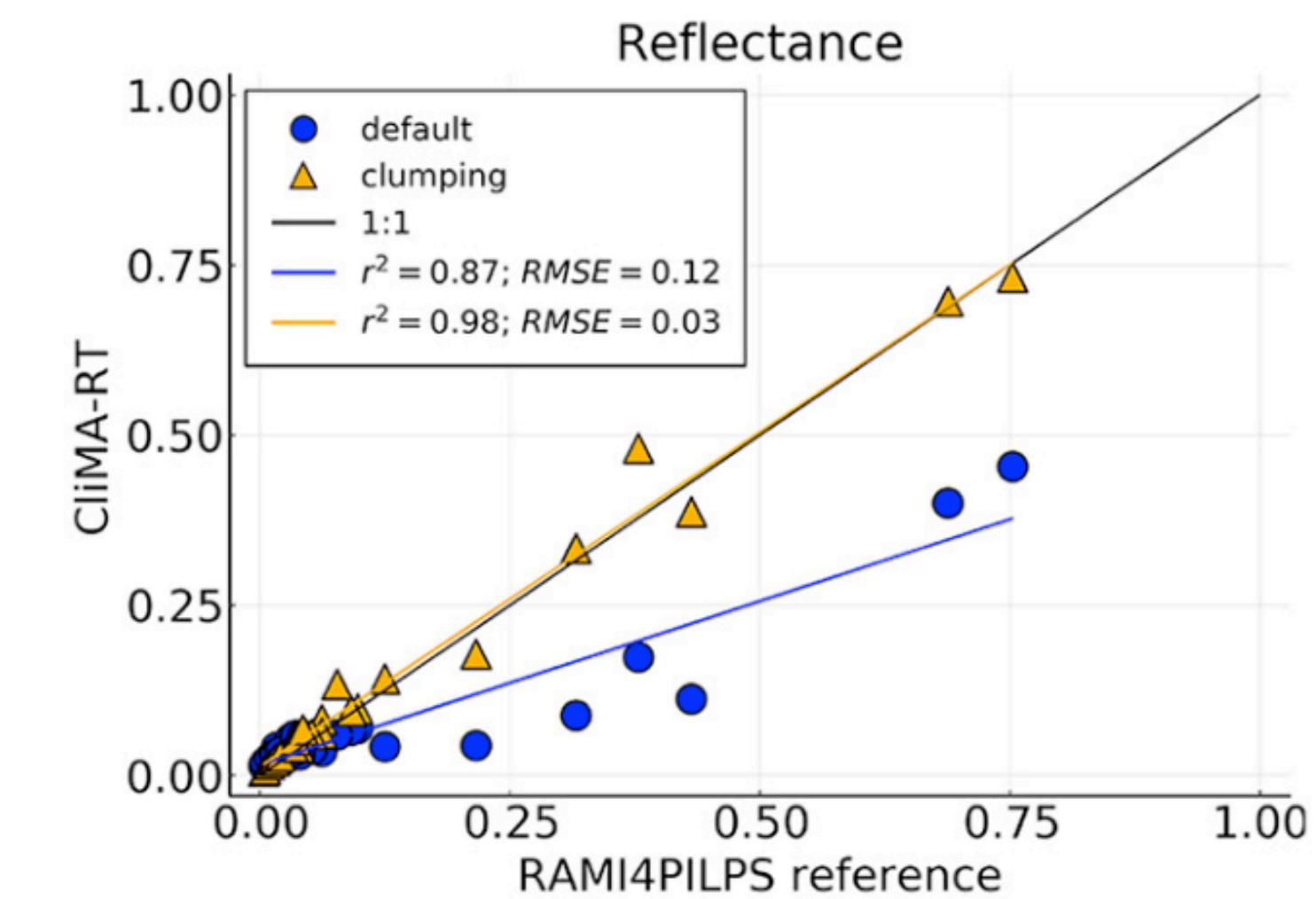
Example 1:
Comparison of
three stomatal
models





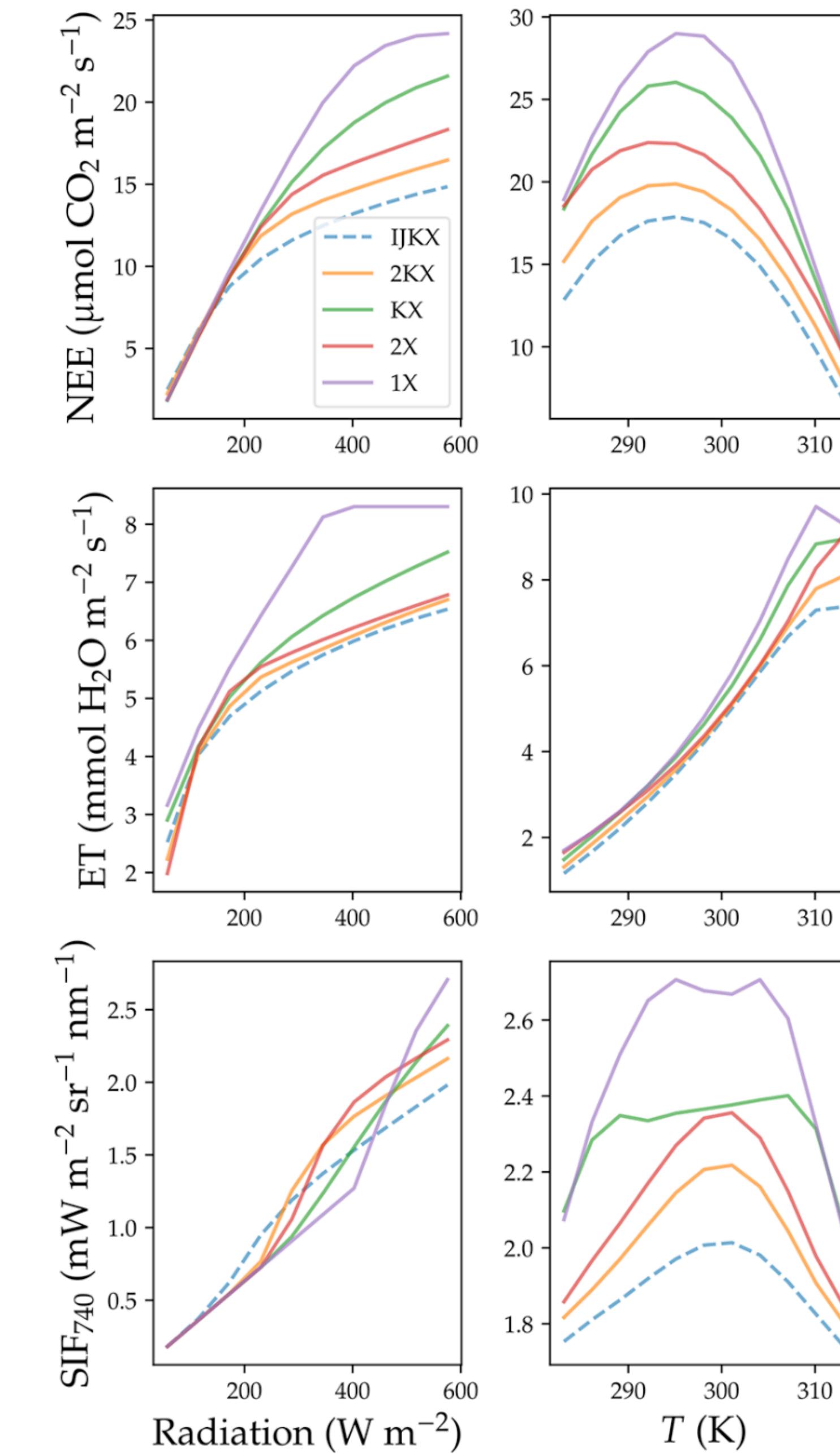
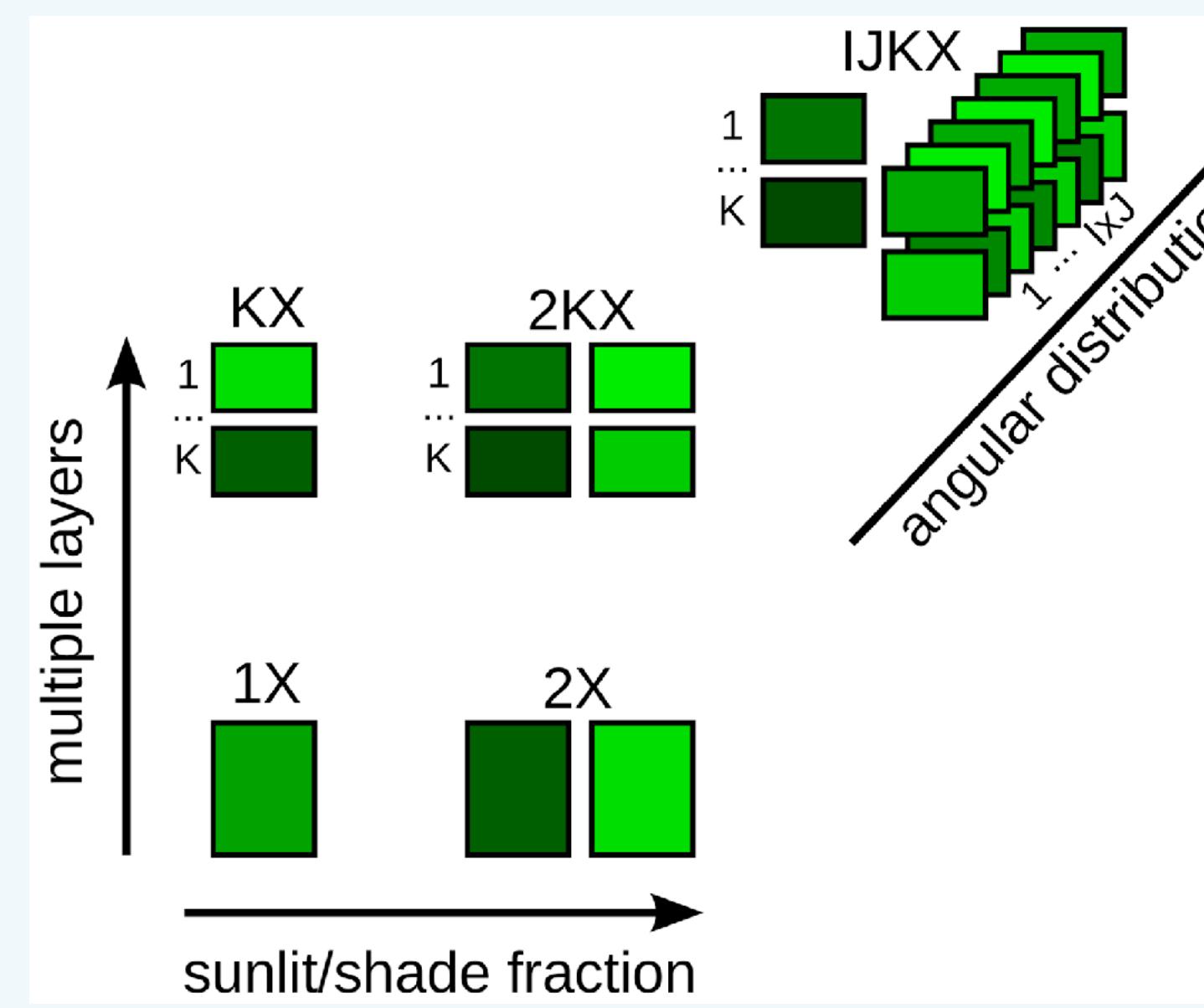
3. Freedom

Example 2:
Turn on/off
clumping index



3. Freedom

Example 3: Comparison of canopy complexity





Database and software for sharing global scale datasets—GriddingMachine

1. Schemes

Improve model representation of soil-plant-air continuum

2. Setups

Advance model parameters configuration

3. Calibration

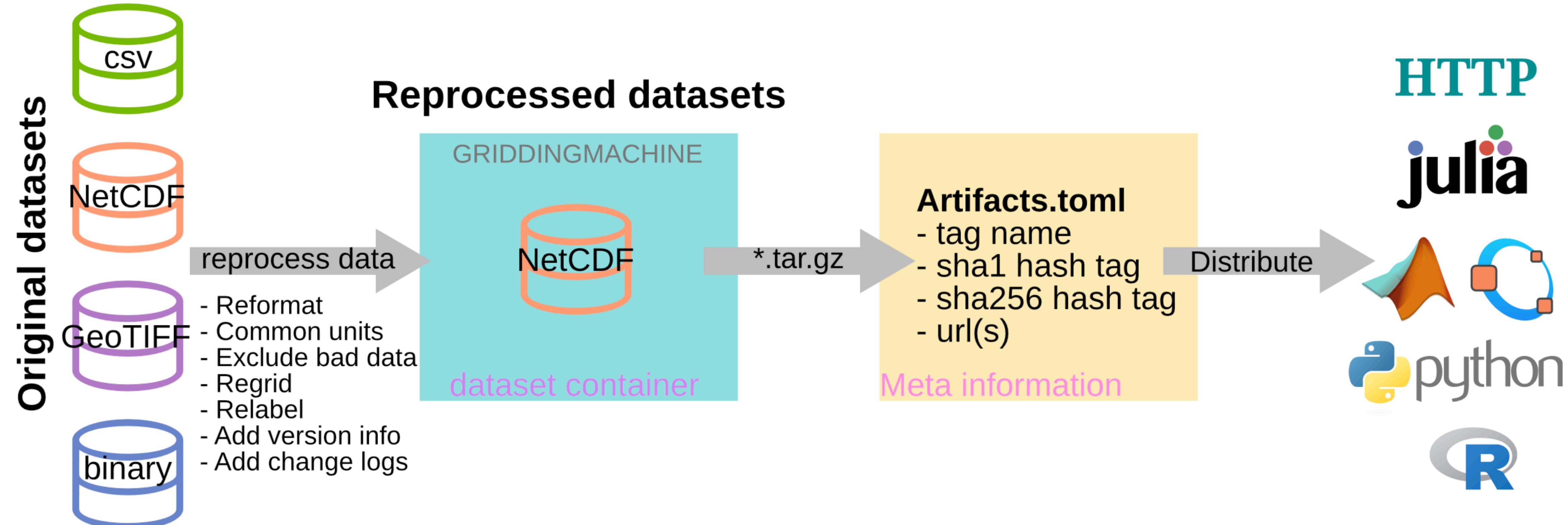
Use more data to calibrate the models

A byproduct

Need of traits at global scale to initialize CliMA Land

Challenges

- Hosted on different websites
- Different formats
- Not directly usable (scaling)
- Different orientations
- Different coverages
- Different projections
- Non-standard units
-
- One forget where the files are



GriddingMachine

Testing modules

- Blender
- Fetcher
- Partitioner

GriddingMachine.jl

Collector.jl

Tool to manage our collection of datasets locally

Indexer.jl

Tool to read the datasets locally

Requestor.jl

Tool to request data for a given latitude and longitude from the server

GriddedCollection

Data struct that contains information of the collection, such as supported data versions

query_collection

Function to locate the local dataset; if file does not exist, download it automatically

clean_collection!

Function to clean up the collection, such as out-of-dated collections

read_LUT

Function to read the data full or in part data from local files

request_LUT

Function to request data in part from a server, rather than from locally downloaded file



Convenient API

TAG is the only thing you need to know

```
using GriddingMachine.Collector: query_collection;
file_path = query_collection("VCMAX_2X_1Y_V1");

using GriddingMachine.Requestor: request_LUT;
dat,std = request_LUT("LAI_MODIS_20x_1M_2020_V1", 31.82, 117.23);
```

Dataset type	LABEL	EXTRALABEL	IX	JT	YEAR	VK	Reference	Change logs
Gross primary productivity	GPP	MPI_RS	2X	1M, 8D	2001-2019	V1	Tramontana et al. (2016)	4,9
	GPP	VPM	5X, 12X	8D	2000-2019	V2	Zhang et al. (2017)	1,4
Leaf area index	LAI	MODIS	2X, 10X, 20X	1M, 8D	2000-2020	V1	Yuan et al. (2011)	1,4,9
Latent heat flux	LE	MPI_RS	2X	1M, 8D	2001-2015	V1	Jung et al. (2019)	4,9
Solar induced chlorophyll	SIF	TROPOMI_683, TROPOMI_683DC	1X, 2X, 4X,	1M, 8D	2018-2020	V2	Köhler et al. (2020)	1,8



API

Query data within area of interest

- Partitioner

```
# new feature under testing
using GriddingMachine.Partitioner: query_data;
data = query_data("TROPOMI.json", polygon, 2020; months=[1,2]);
```



First global simulation of CliMA Land: Bridging vegetation processes with remote sensing

1. Schemes

Improve model representation of soil-plant-air continuum

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Use more data to calibrate the models

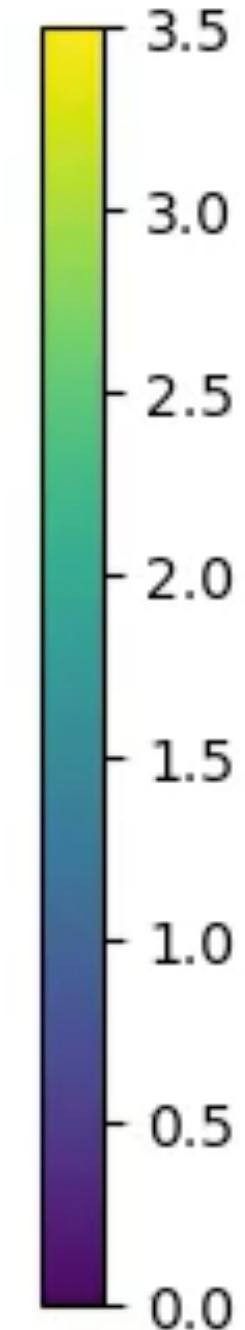
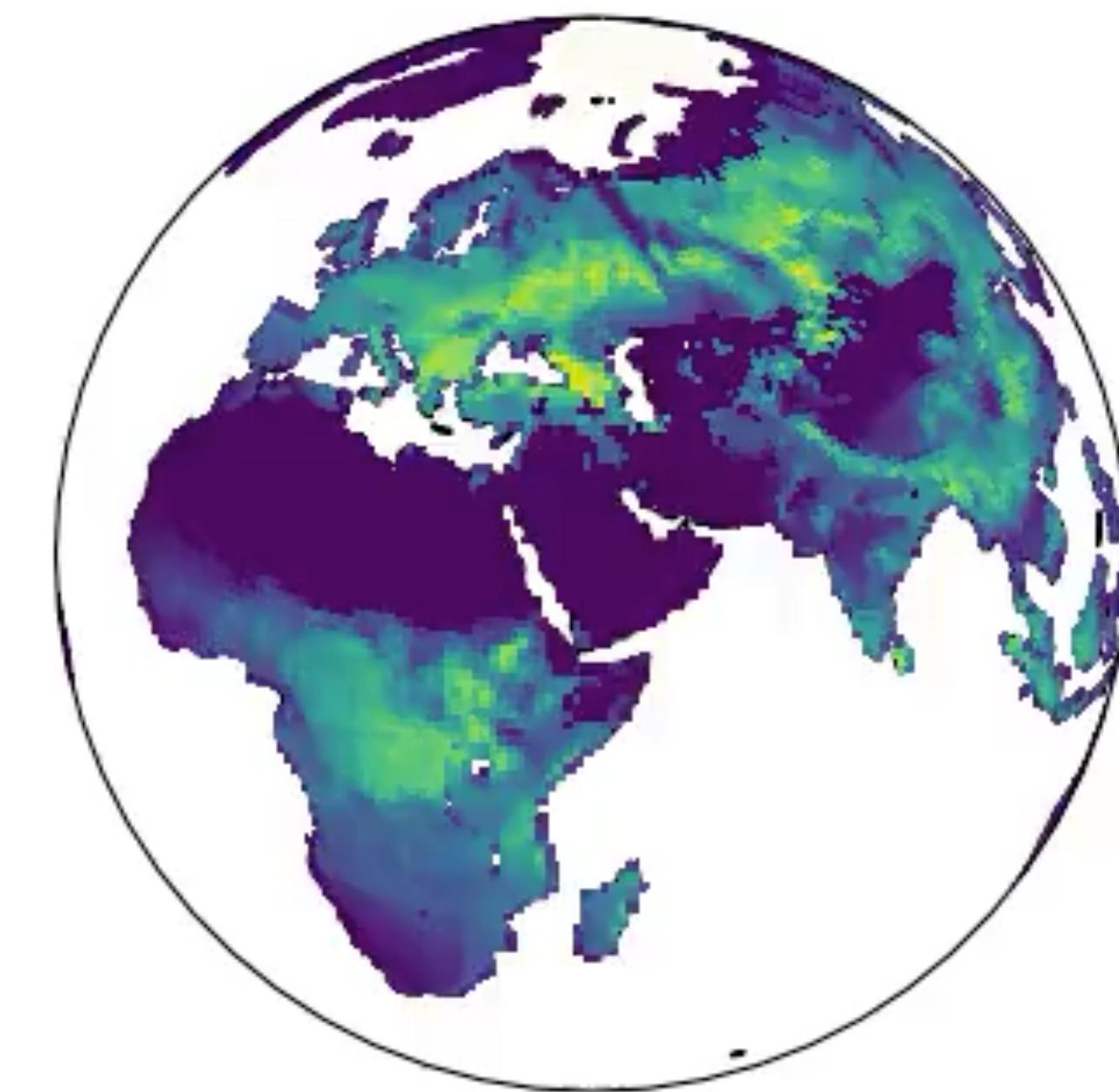
First global scale simulation of CliMA Land

Configurations

- Hyperspectral RT
- Empirical stomatal model
- Hourly ERA5 weather driver
- GriddingMachine inputs
-

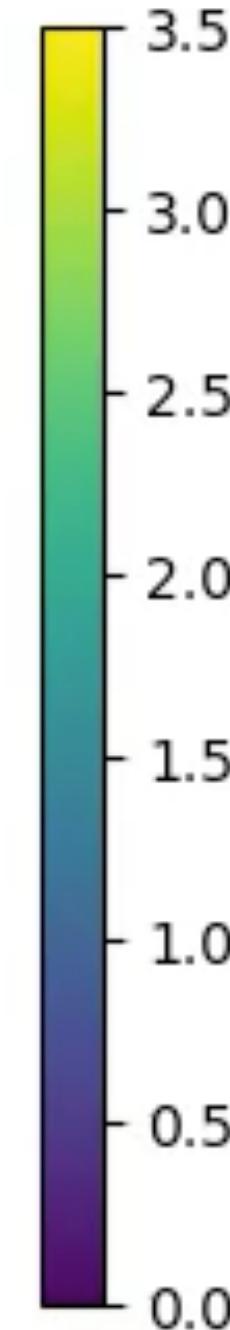
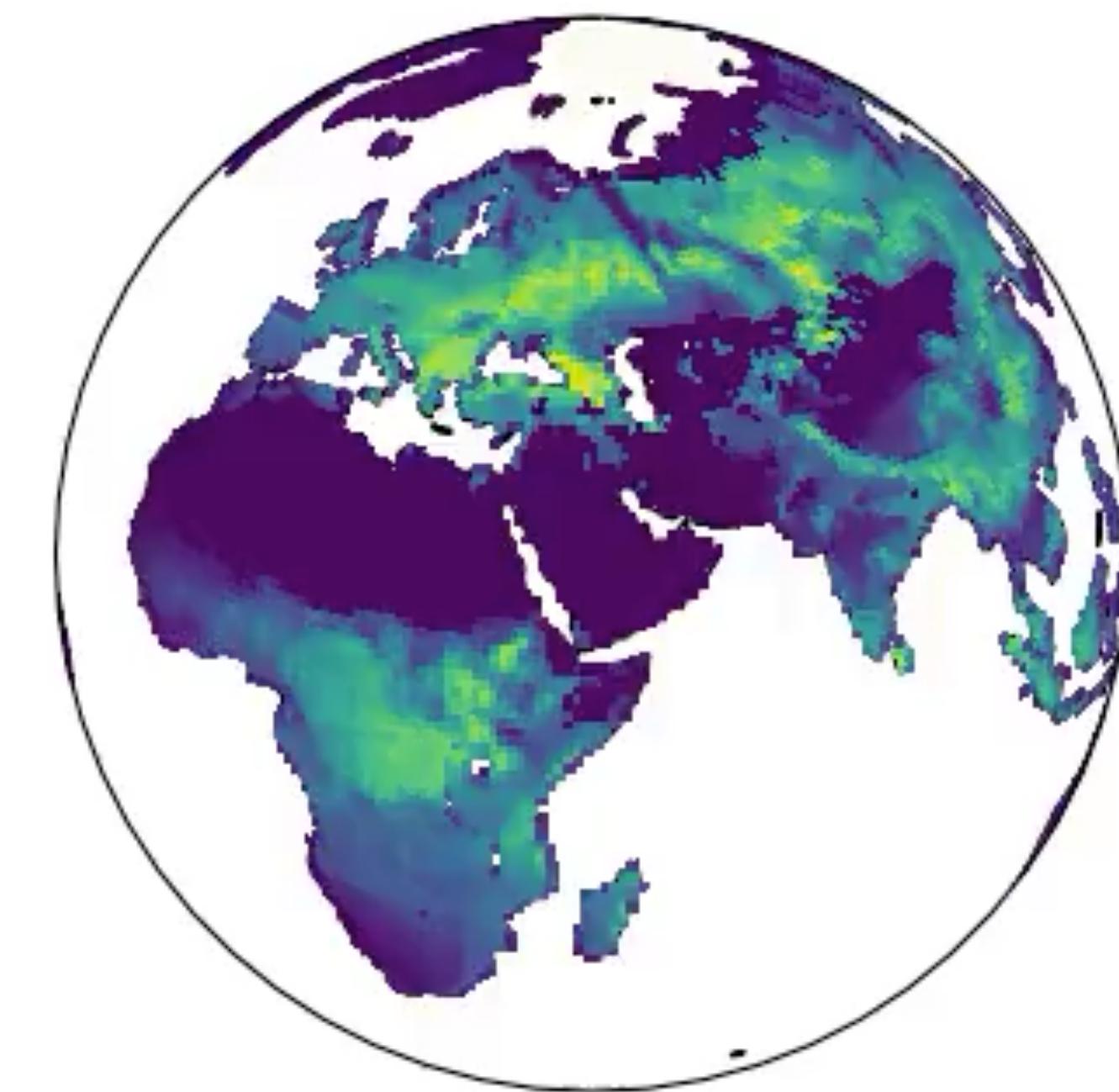
**~2 h for annual simulation on
hourly time step on 160 cores!**

**Global simulations of
canopy optical
properties that can be
seen from space**

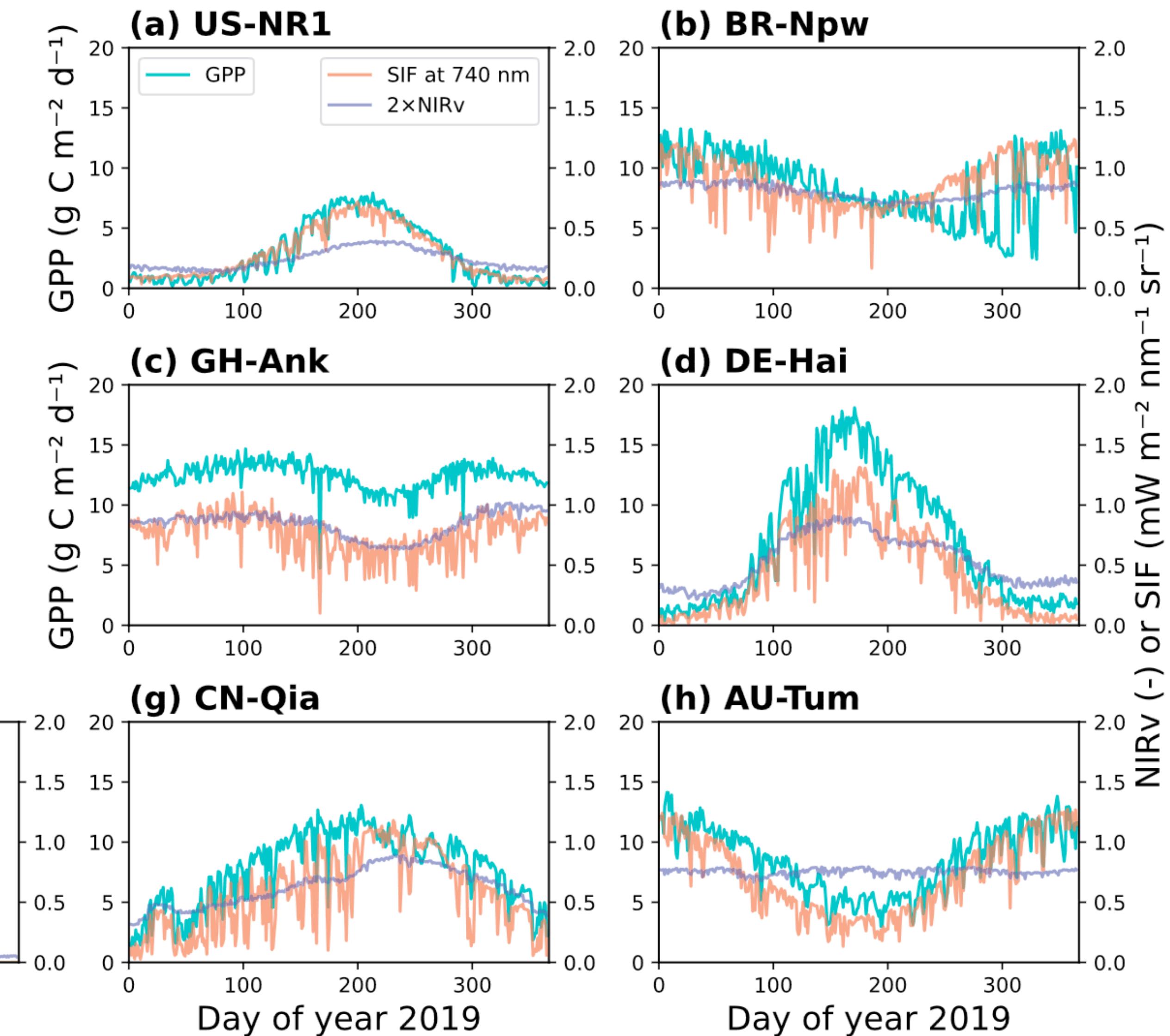
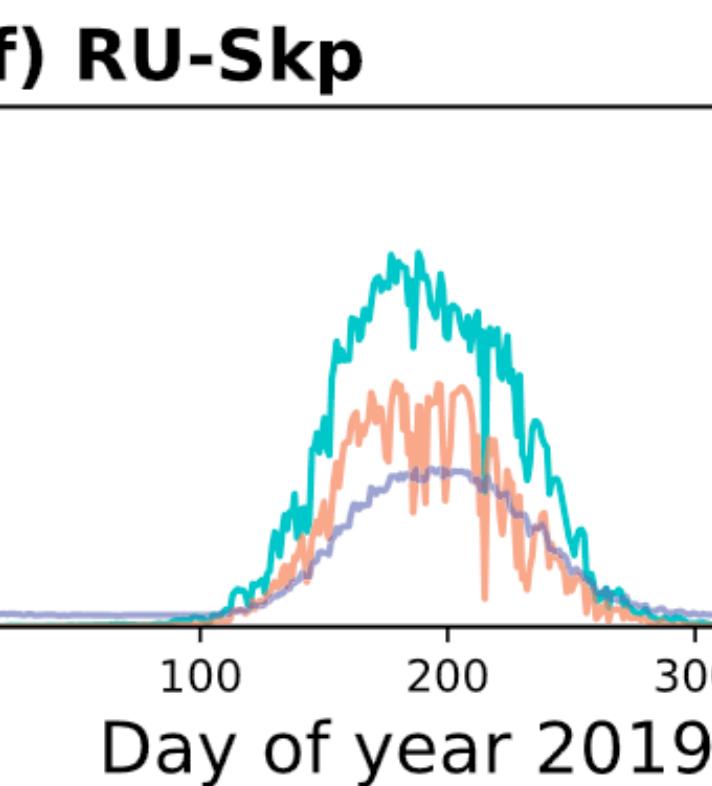
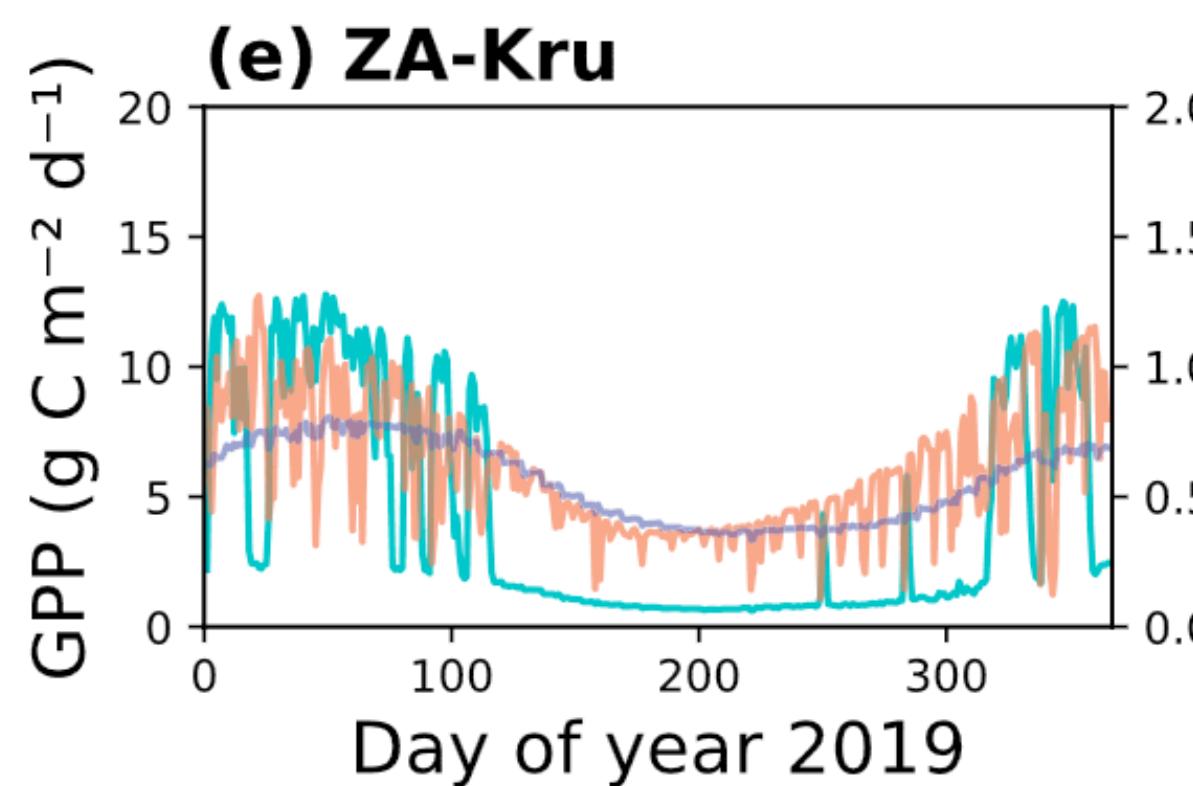


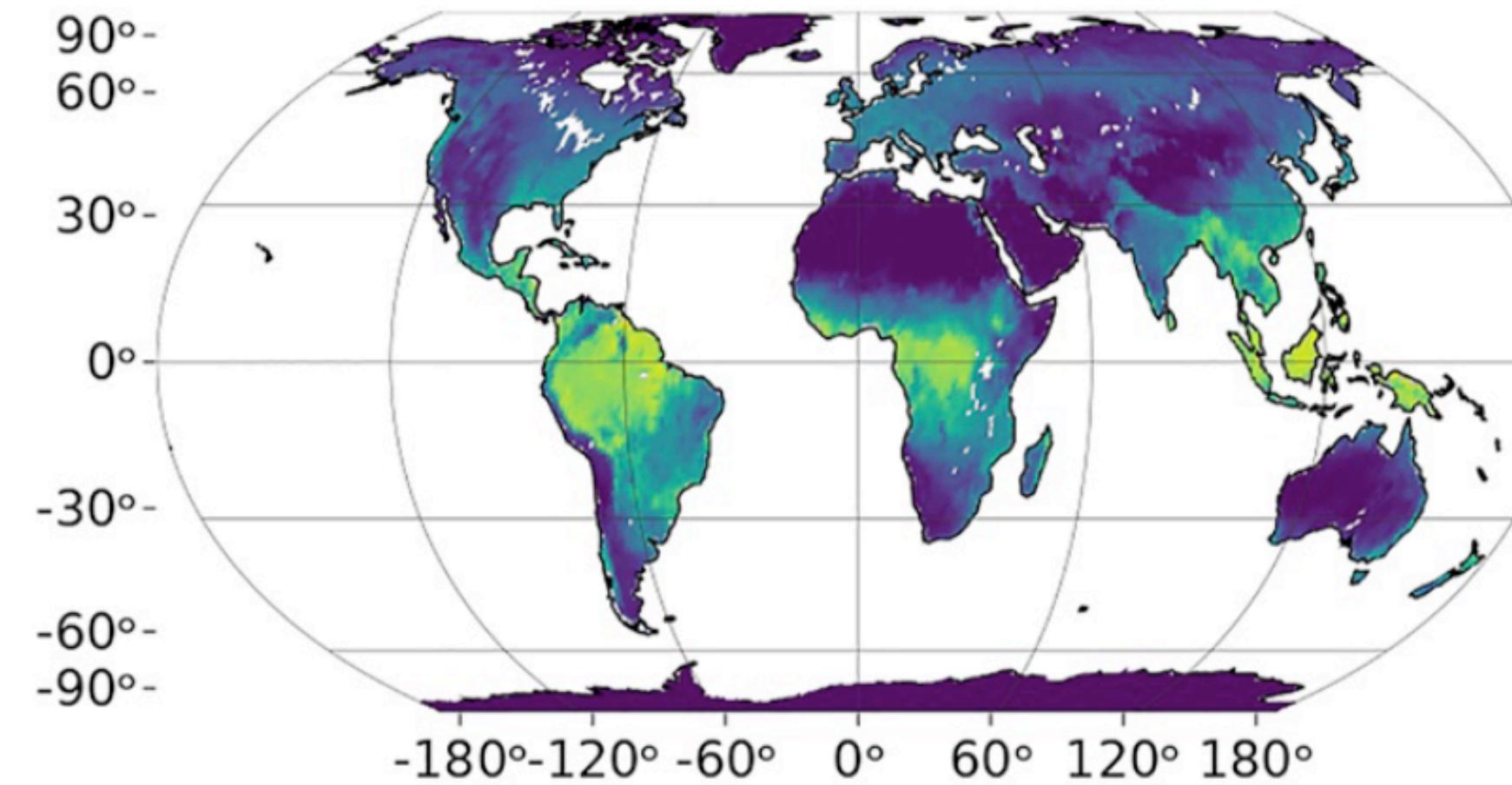
CliMA Land SIF @ 740 nm

**Global simulations of
canopy optical
properties that can be
seen from space**

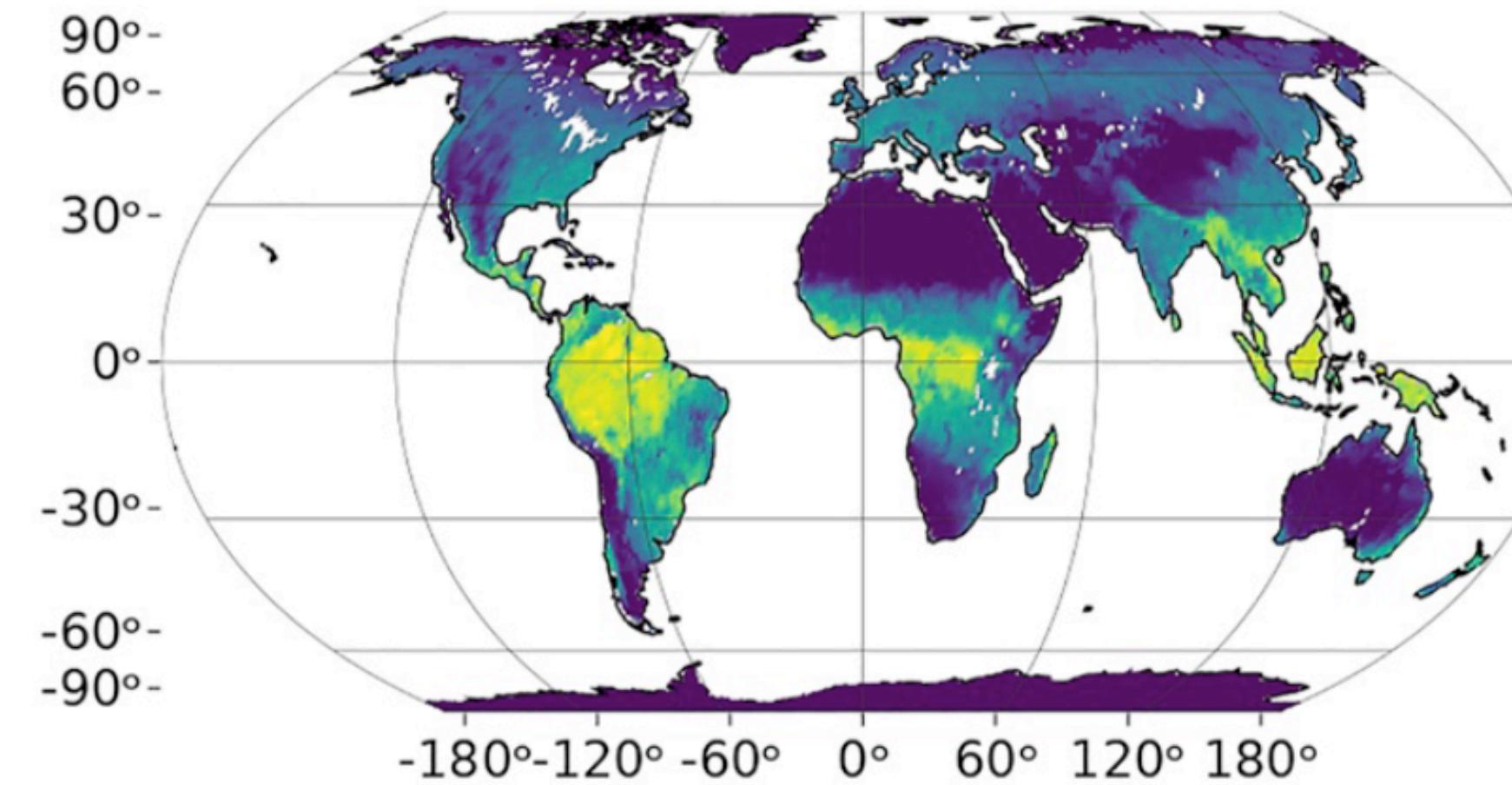


CliMA Land SIF @ 740 nm

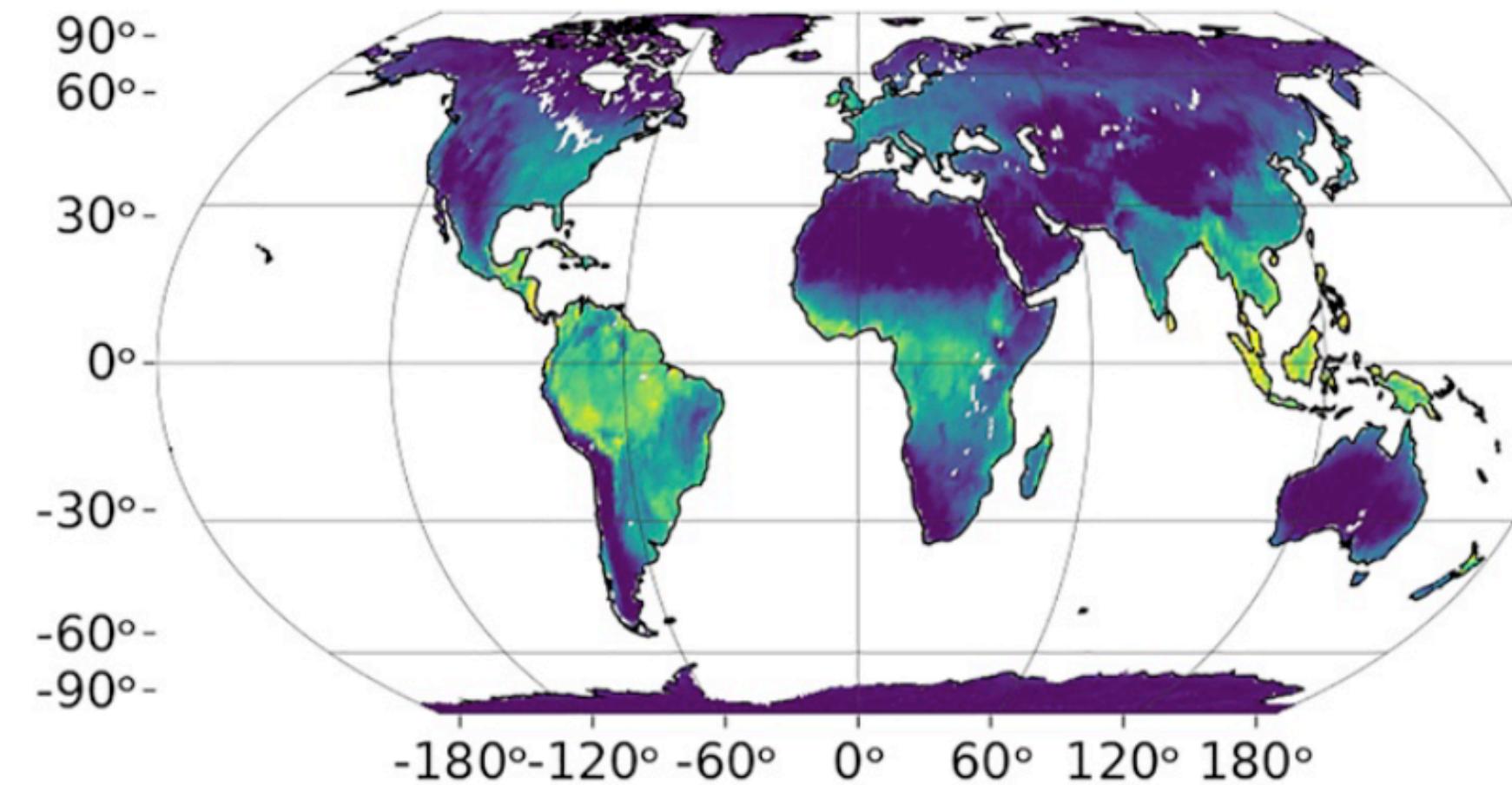




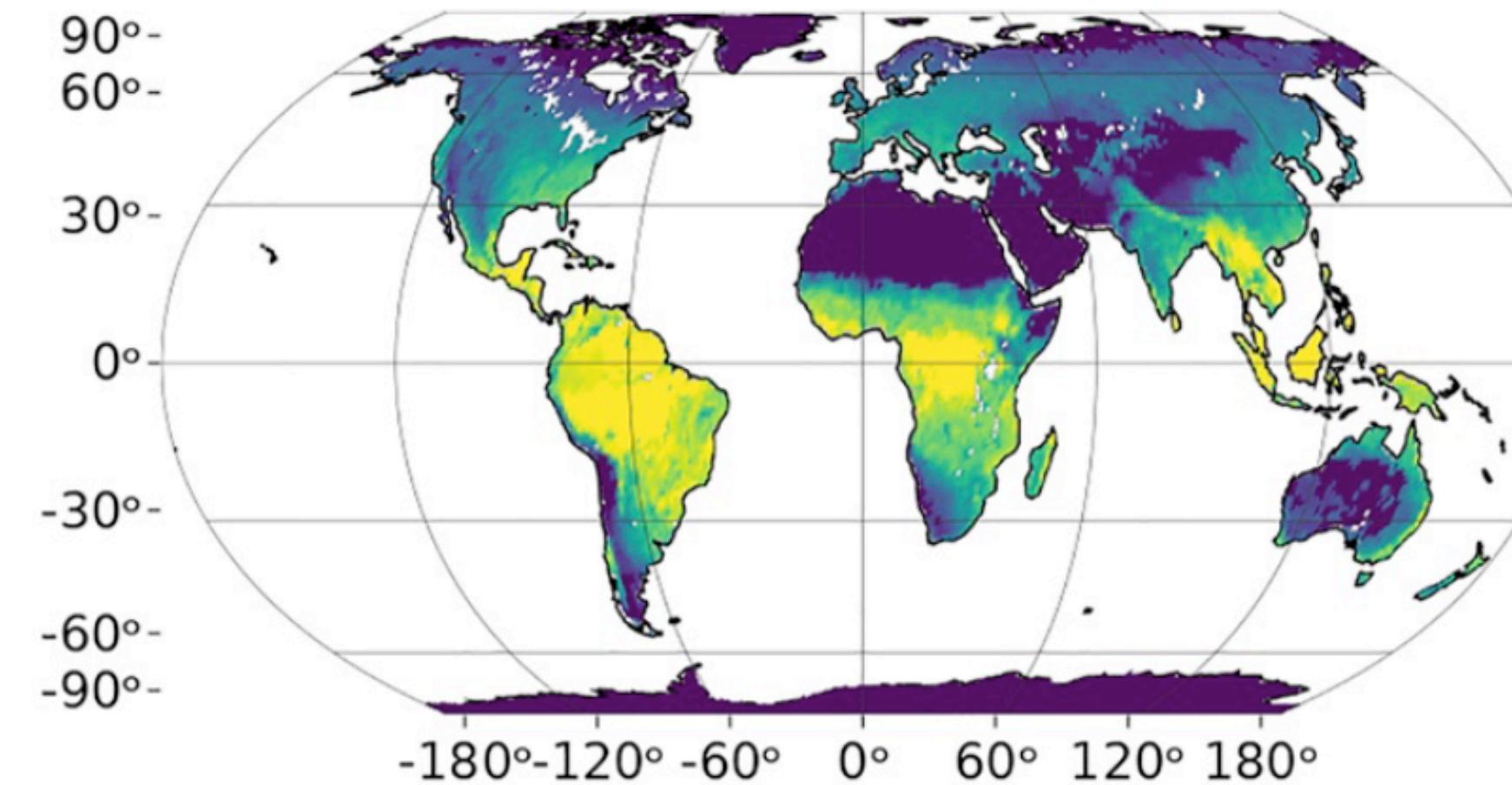
8
6
4
2
0
MPI RS GPP
($\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$)



15
10
5
0
CliMA GPP
($\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$)

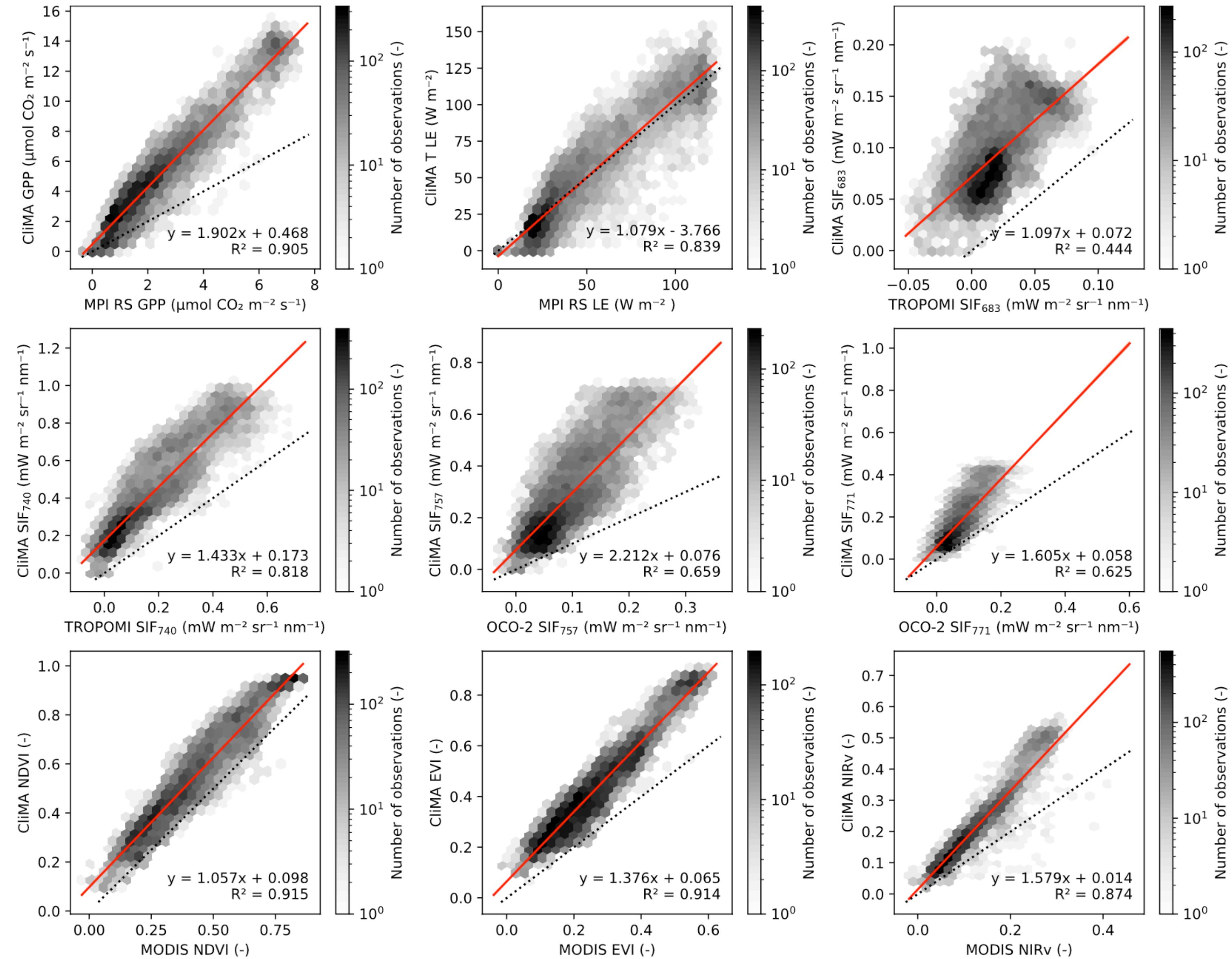


0.6
0.5
0.4
0.3
0.2
0.1
0.0
TROPOMI SIF₇₄₀
($\text{mW m}^{-2} \text{ sr}^{-1} \text{ nm}^{-1}$)

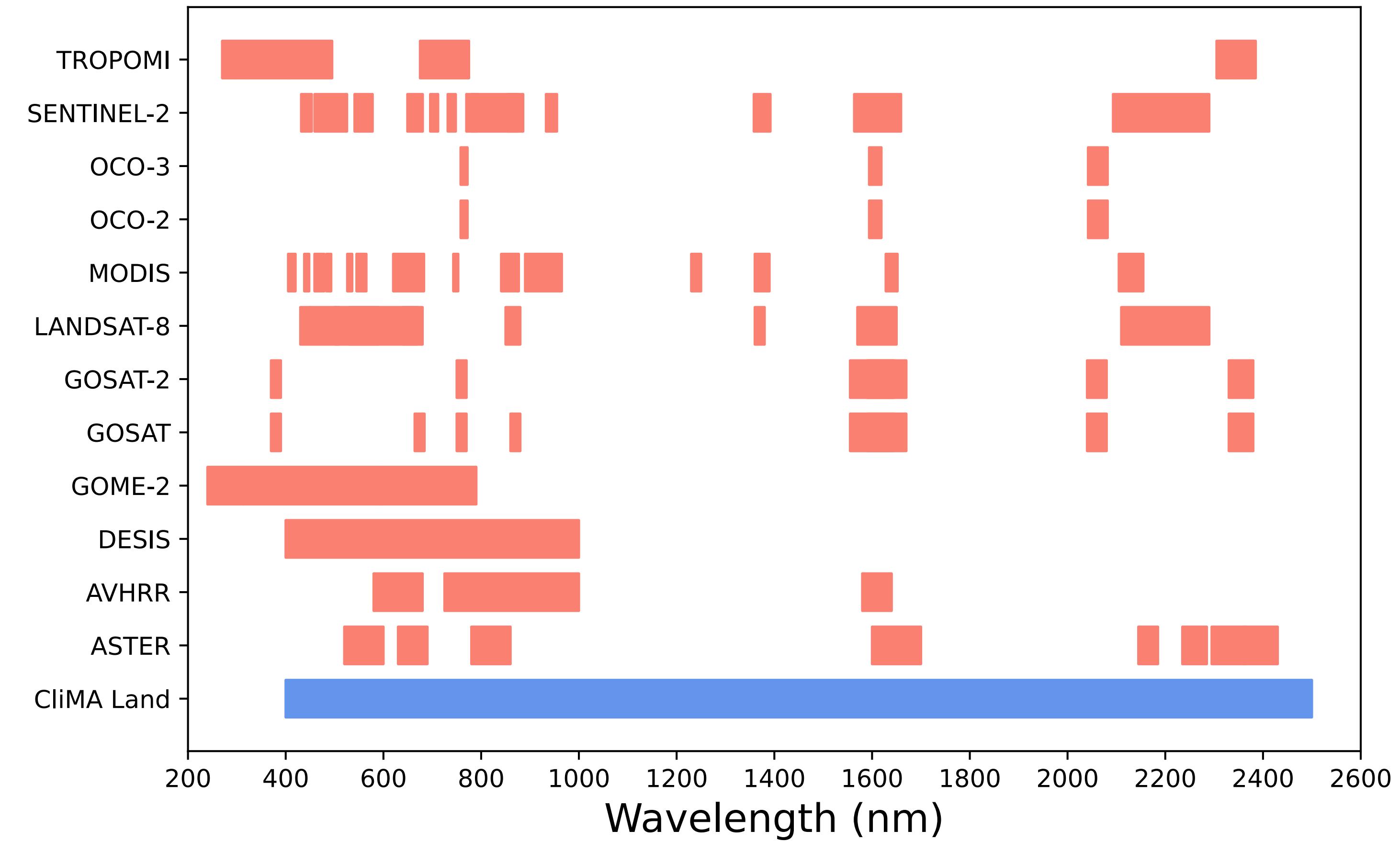


0.8
0.6
0.4
0.2
0.0
CliMA SIF₇₄₀
($\text{mW m}^{-2} \text{ sr}^{-1} \text{ nm}^{-1}$)

CiMA Land performs well for simulated quantities without any calibrations



Remote Sensing
CliMA Land is
capable of running
hyper-spectral
radiative transfer,
allowing for using
remote sensing
data directly



Future research plans

Caltech



CLIMA
CLIMATE MODELING ALLIANCE



1. Schemes

Improve model representation of soil-plant-air continuum

- Develop more physiology-based model schemes
- Dynamic growth based on optimality theory
- Close the energy balance for UV, IR
- Add more complex ecosystem
-

Future research plans

CliMA
CLIMATE MODELING ALLIANCE



Caltech



2. Setups **Advance model parameters configuration**

- Coupling to CliMA Atmosphere and Ocean models
- Test more existing model configurations
- Add more application scenarios, such as agriculture
- Better documentation and demos
-



Future plans

3. Calibration

Use more data to calibrate the models

- Add more features to GriddingMachine
- Run data assimilation to calibrate the traits
 - Leaf area index
 - Chlorophyll content
 - Canopy structure
 - Optimization framework
- Explore nature based solutions against climate change



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