

# Linking Plant Functional Traits and Carbon Processes to Evaluate Terrestrial Biosphere Models Based on A Traceability Framework

**Jiayang Xia**<sup>1</sup>, Erqian Cui<sup>1</sup>, Jian Zhou<sup>1</sup>, Chengyu Bian<sup>1</sup>, Ning Wei<sup>1</sup>, Ying-ping Wang<sup>2</sup>, Yiqi Luo<sup>3</sup>,  
MsTMIP & CMIP modelers

<sup>1</sup> School of Ecological and Environmental Sciences, East China Normal University (Shanghai, CN)

<sup>2</sup> CSIRO Oceans and Atmosphere (Victoria, AU)

<sup>3</sup> Center for Ecosystem Science and Society, Northern Arizona University (Flagstaff, US)

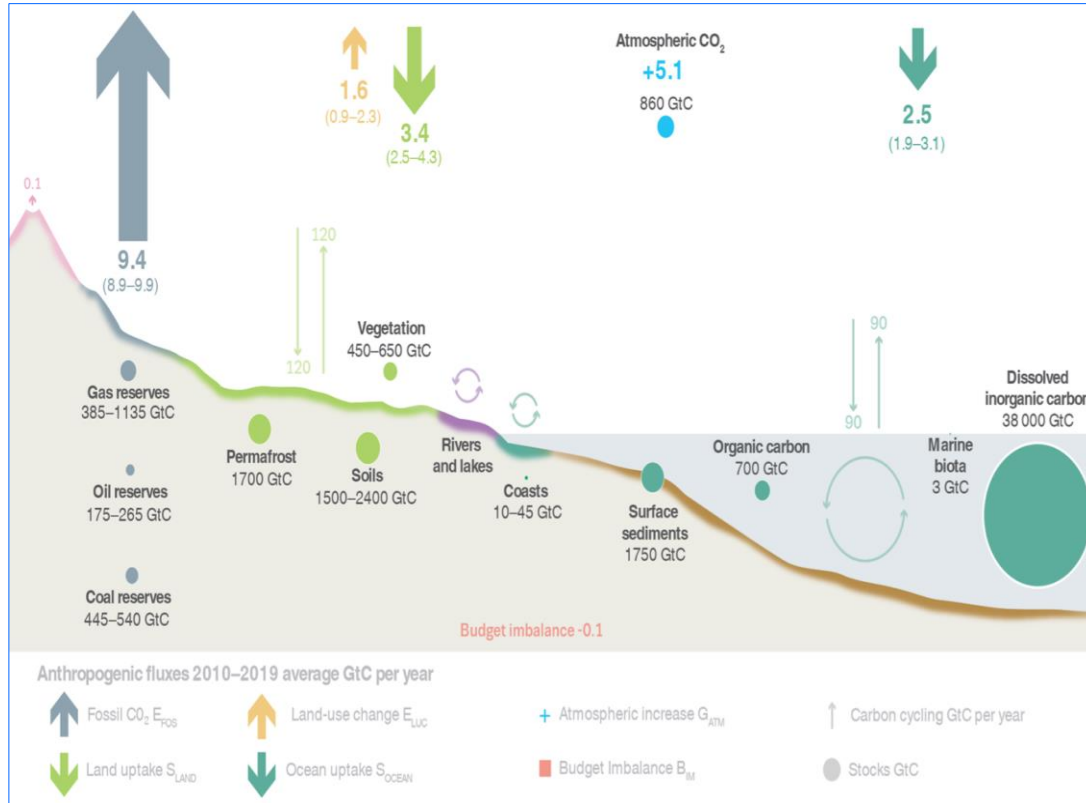


August 20, 2021

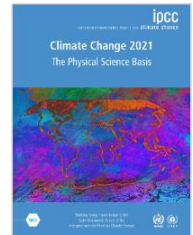
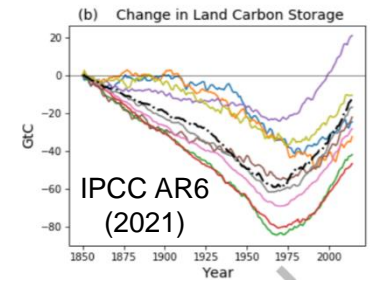
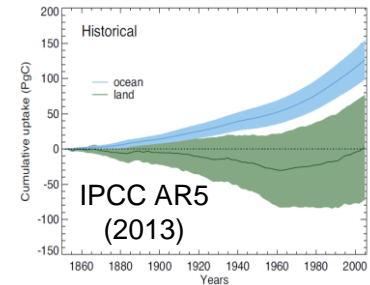
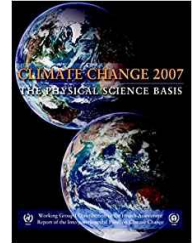
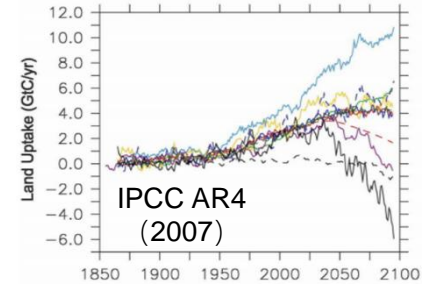


# Challenge:

## Large uncertainty of land C cycle in Earth system models



Friedlingstein *et al.*, 2020 *ESD*



# ILAMB in IPCC AR6:

## Improved model performance on land C cycle from CMIP5 to CMIP6



(a) Land Benchmarking Results

	CMIP5 ESMs										CMIP6 ESMs										Mean CMIP5	Mean CMIP6
	bcc-csm1-1	CanESM2	CESM1-BGC	GFDL-ESM2G	IPSL-CM5A-LR	MIROC-ESM	MPI-ESM-LR	NorESM1-ME	HadGEM2-ES	BCC-CSM2-MR	CanESM5	CESM2	GFDL-ESM4	IPSL-CM6A-LR	MIROC-ES2L	MPI-ESM1.2-LR	NorESM2-LM	UKESM1-0-LL				
<b>Land Ecosystem &amp; Carbon Cycle</b>	-0.72	-0.93	-1.55	-1.51	-0.13	0.60	-0.43	-1.31	0.19	-0.43	0.66	0.48	-1.09	0.22	0.60	-0.07	1.00	0.49	1.63	2.30		
Biomass	0.20	-0.45	-1.52	-0.40	-1.26	-0.26	-1.07	-1.77	0.92	1.39	0.74	-0.20	-0.54	0.16	0.93	-0.96	-0.01	1.04	1.23	1.82		
Burned Area			-0.87				0.10	-0.83				1.60										
Leaf Area Index	-0.20	-0.64	-1.30	-2.53	-0.01	0.30	0.01	-1.85	-0.16	0.27	0.08	0.34	-0.70	1.19	0.82	0.46	0.37	0.69	1.04	1.81		
Soil Carbon	0.27	1.26	-1.46	0.07	0.75	0.47	-0.03	-1.14	0.07	0.23	1.35	-0.99	-2.04	-1.55	0.90	-0.75	-0.17	0.24	1.01	1.48		
Gross Primary Productivity	0.59	-1.23	0.01	-1.81	-1.40	0.29	-0.53	-0.24	-1.04	0.77	0.04	0.59	-0.38	1.17	-1.02	-0.37	0.73	0.09	1.51	2.22		
Net Ecosystem Exchange	-0.42	-1.81	-0.21	-0.65	1.10	-0.24	0.80	0.02	-1.03	-1.02	-1.19	0.59	1.69	-0.42	0.63	-0.21	1.08	-1.43	1.28	1.43		
Ecosystem Respiration	0.90	-0.56	-0.86	-0.24	-1.35	0.99	-0.01	-0.94	-1.54	0.81	0.59	0.51	-0.79	0.90	-0.21	-1.24	0.43	-0.94	1.34	2.21		
Carbon Dioxide		-1.54	-0.36	-2.92	-0.74	1.53	-0.00	0.37	0.85	0.42	0.26	0.39	0.59	1.10	-0.87	0.21	0.69		0.09	-0.07		
Global Net Carbon Balance		-1.64	-0.88	-1.13	0.17	-0.31	-0.38	-0.50	0.24	-0.23	1.34	-1.70	0.17	-0.74	1.45	1.56	0.26		0.92	1.40		

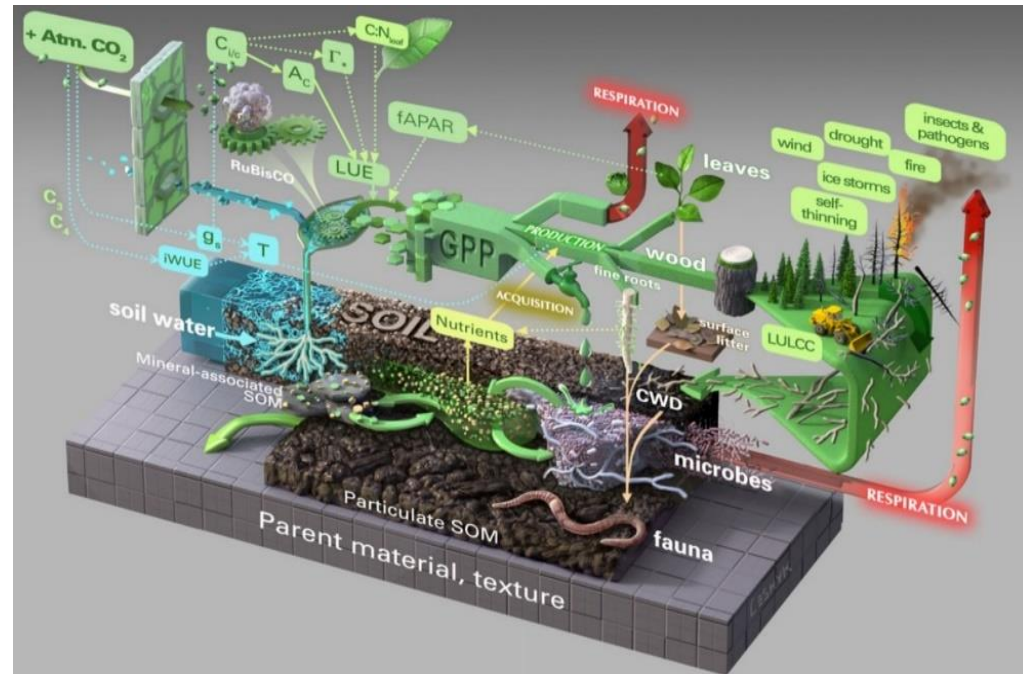
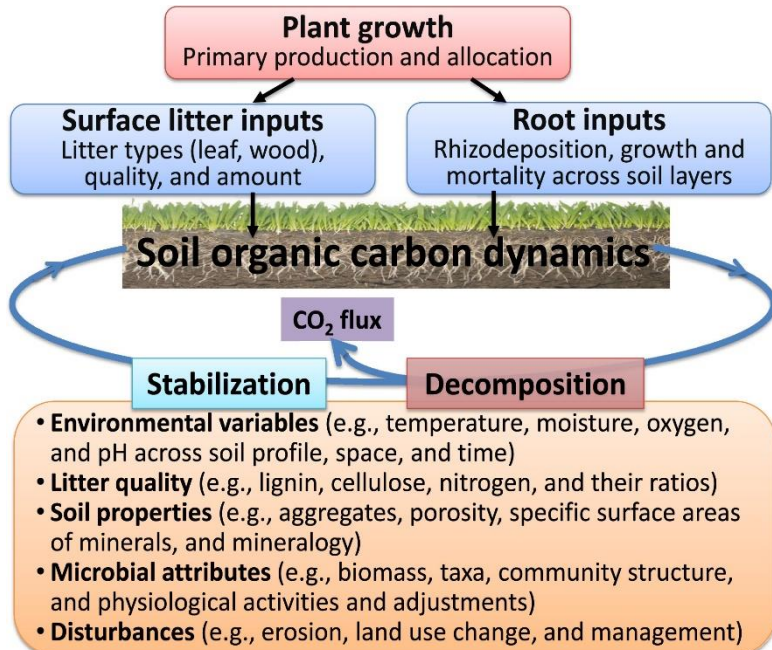
**Model-Data difference:**  
Small improvements in net land C exchange

**Inter-model difference:**  
Still large

# Further model improvements:

## A better parameterization of carbon cycle processes

**Plant functional traits** are fundamental parameters in current global carbon-cycle models



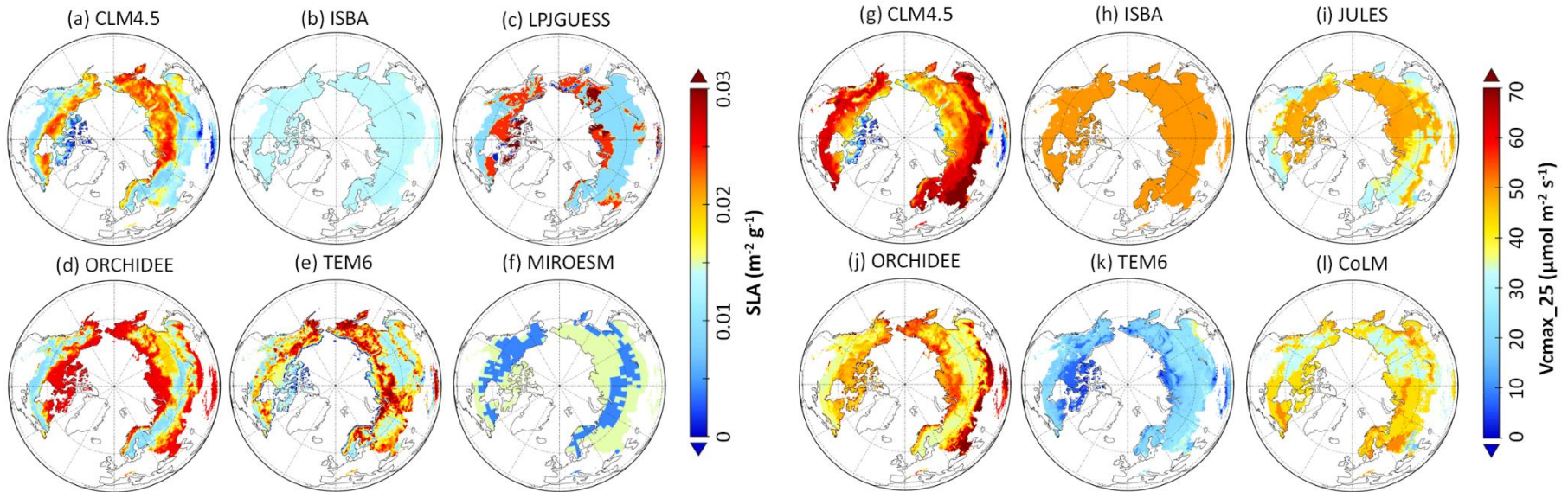


# Further model improvements:

## A better parameterization of carbon cycle processes



**Key Question:** Can we reduce the model uncertainty on land C cycle by an improved parameterization of plant functional traits?



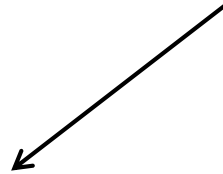
Xia et al. 2017 JGR Biogeosciences

## Further model improvements:

### A better parameterization of carbon cycle processes

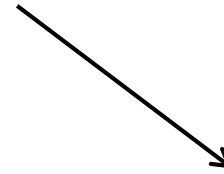


**Key Question:** Can we reduce the model uncertainty on land C cycle by an improved parameterization of plant functional traits?



#### Question 1

Can we link plant functional traits and land carbon cycle for model evaluation?



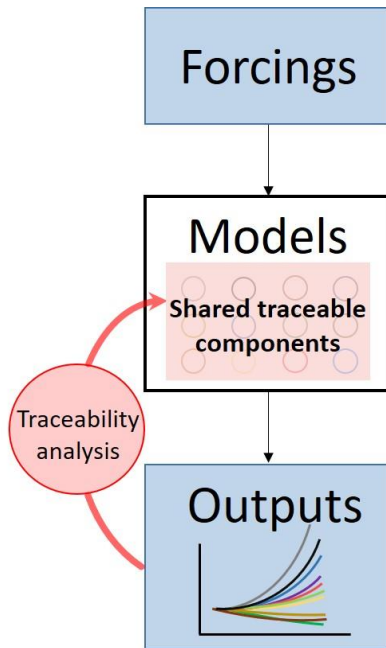
#### Question 2

How to improve model parameterization of plant functional traits based on data?

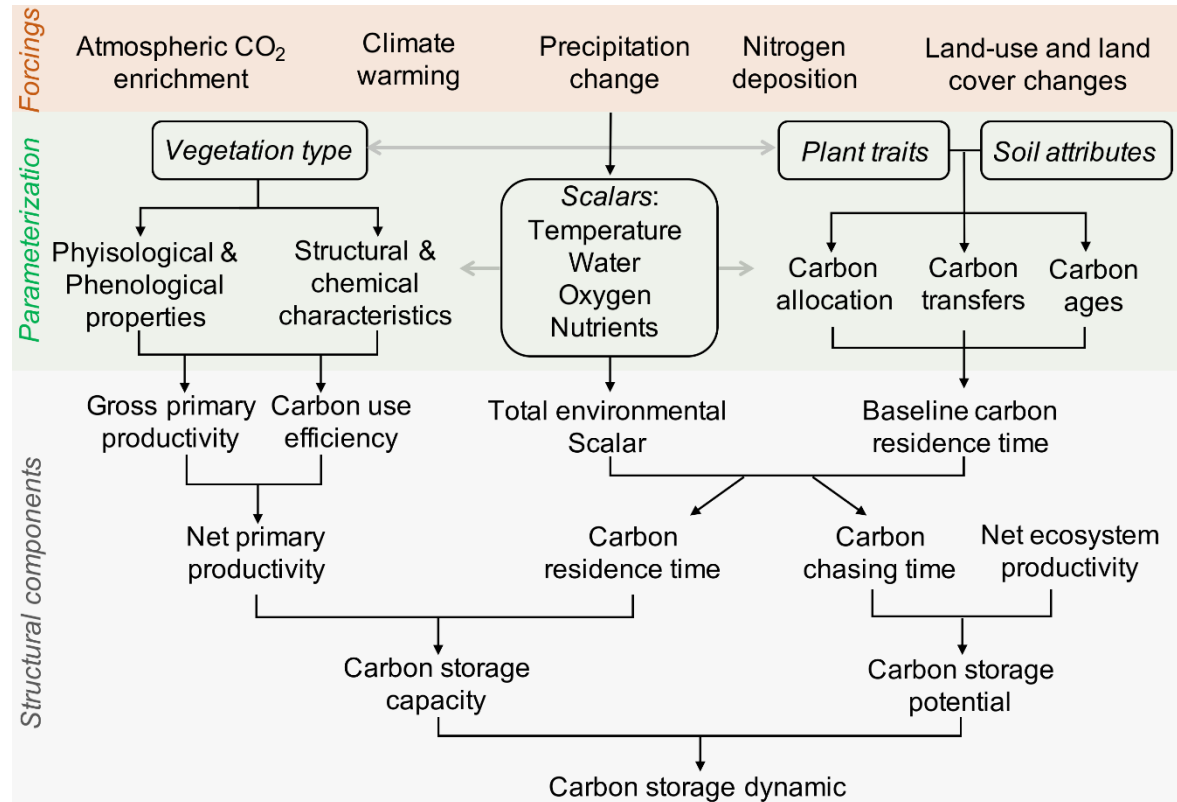
# Question 1: Can we link the key plant functional traits to land carbon processes?

## Tool: Traceability Analysis for Model Evaluation (TraceME)

$$\frac{d\mathbf{X}(t)}{dt} = u(t)\mathbf{B} - \xi(t)\mathbf{A}\mathbf{C}\mathbf{X}(t)$$



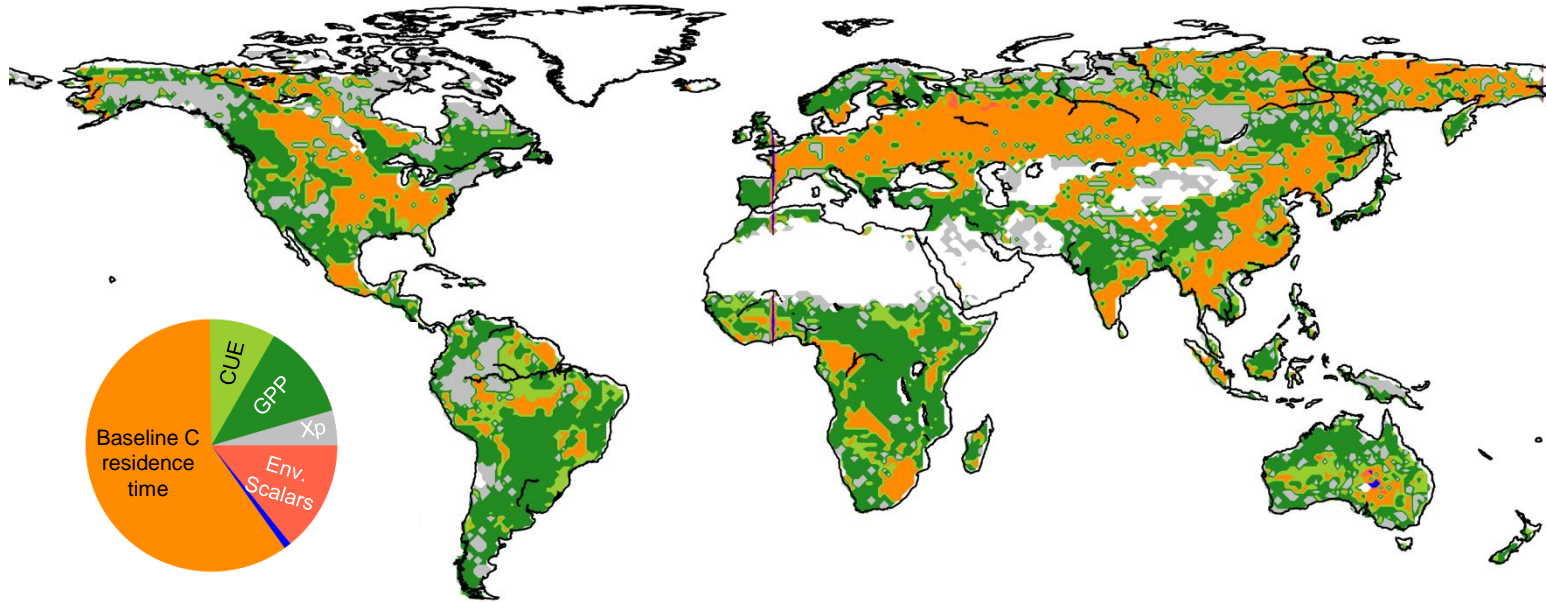
Luo & Weng, 2011 TREE  
 Xia *et al.*, 2013 GCB  
 Luo *et al.*, 2017 BG  
 Xia *et al.* 2020 GCB



# Application of TraceME to CMIP6 models:

Baseline C residence time is a major uncertainty source in CMIP6 models

(Historical runs: 1850-2014)

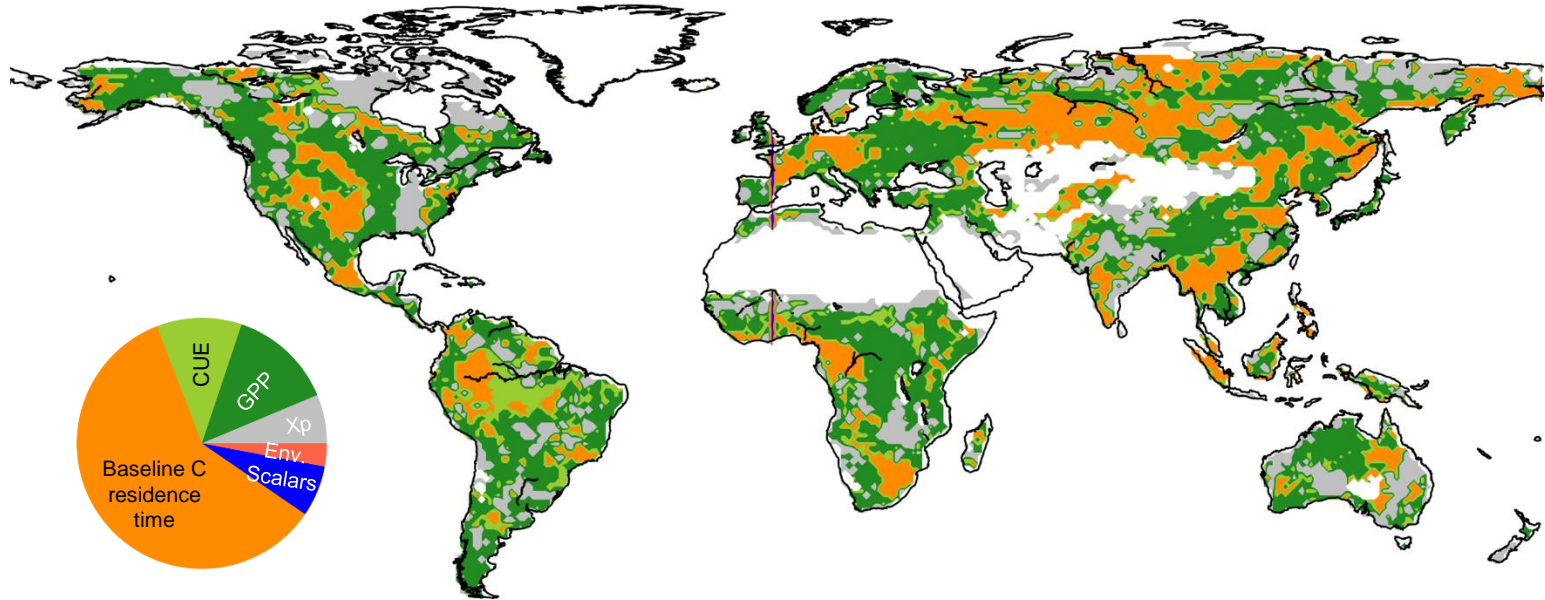




# Application of TraceME to CMIP6 models:

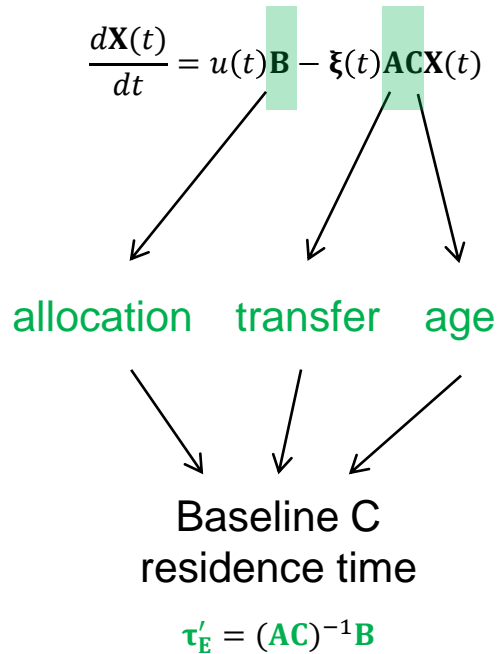
Baseline C residence time is a major uncertainty source in CMIP6 models

(Initial state: 1850)

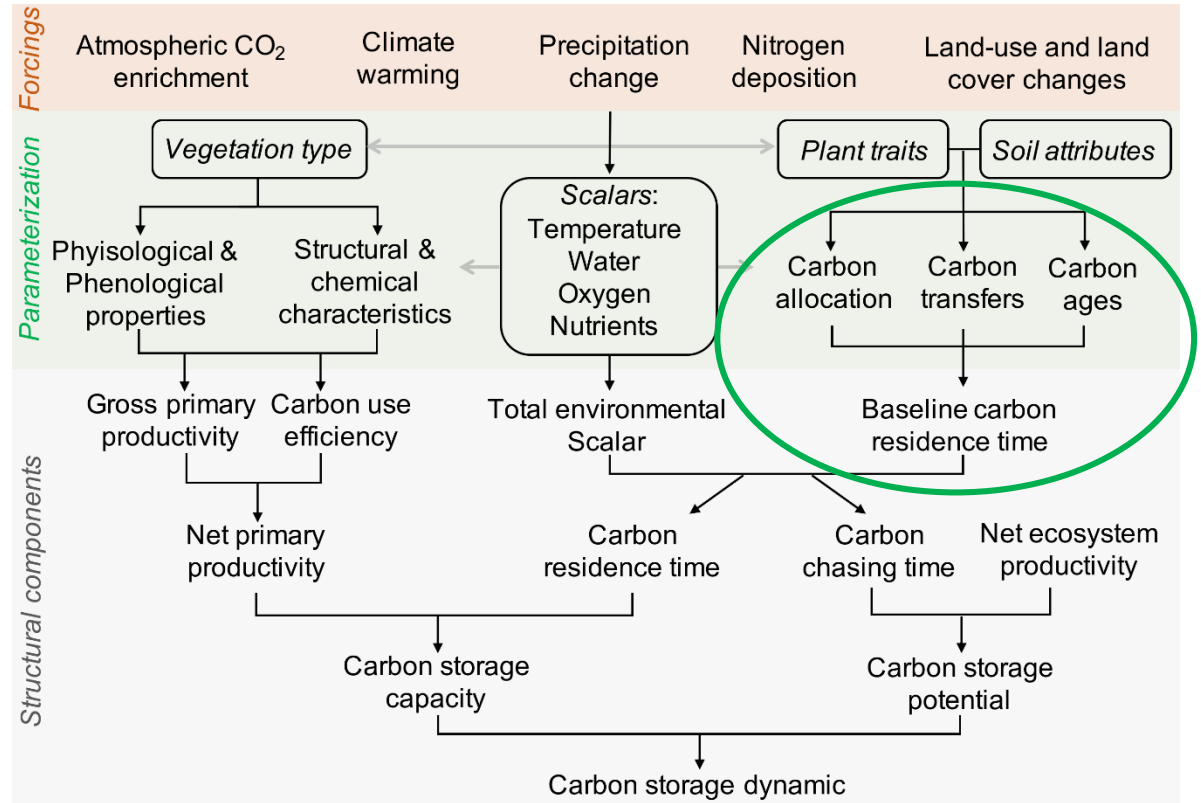


- More parameter information of plant functional traits is useful for evaluating and understanding land C cycle uncertainty in CMIP6 models.

# Plant functional traits and baseline C residence time

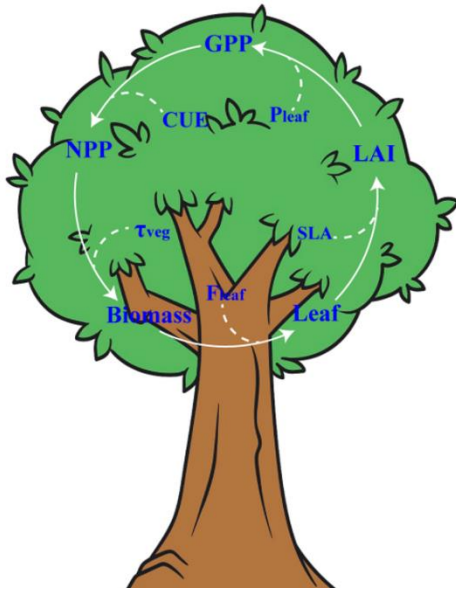


Luo & Weng, 2011 TREE  
 Xia *et al.*, 2013 GCB  
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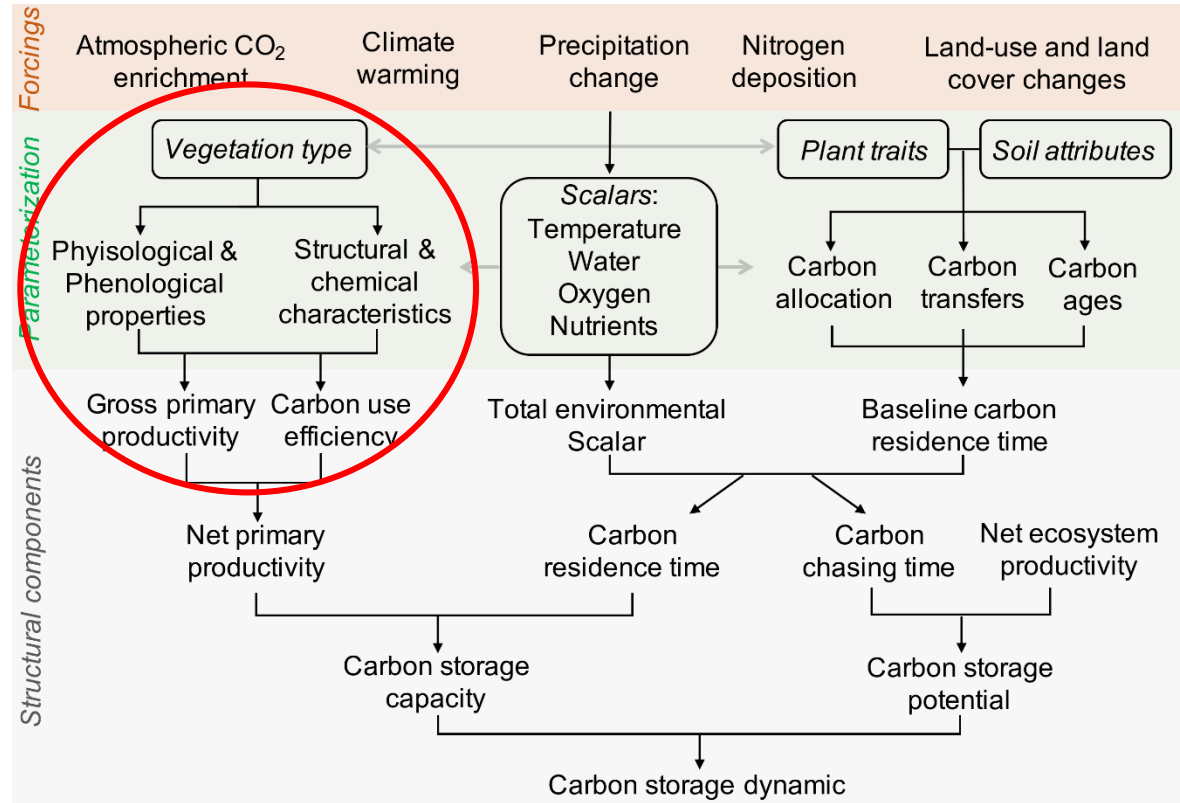


# Do plant functional traits contribute to the model uncertainty on ecosystem C uptake?

$$\frac{d\mathbf{X}(t)}{dt} = \mathbf{u}(t)\mathbf{B} - \xi(t)\mathbf{A}\mathbf{C}\mathbf{X}(t)$$



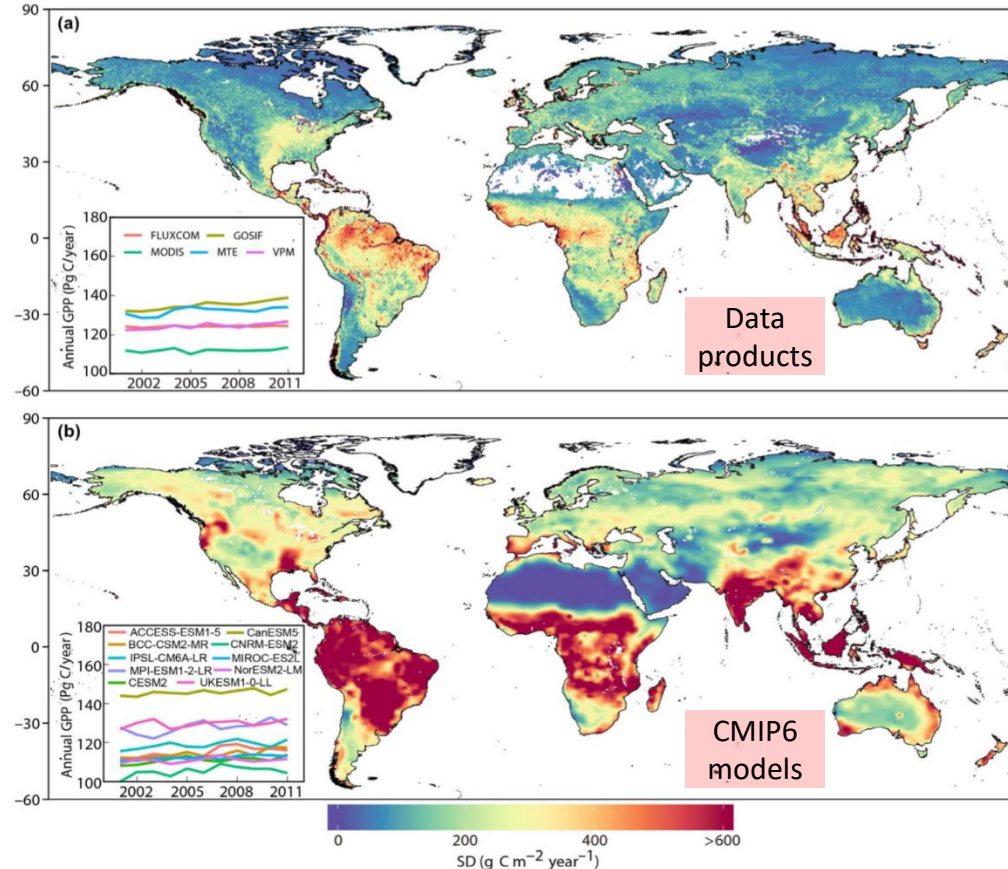
- Uncertainty propagates between plant traits and ecosystem C processes



# Do plant functional traits contribute to the model uncertainty on ecosystem C uptake?

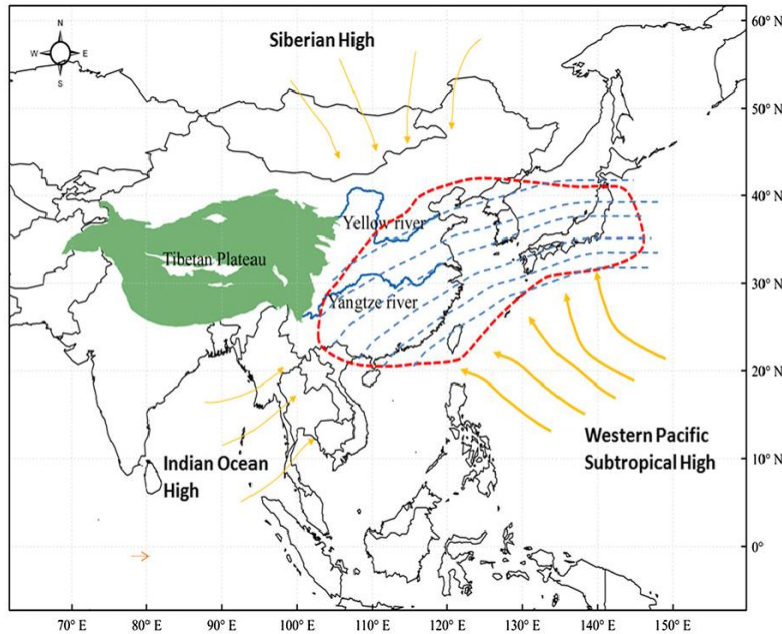
$$\frac{d\mathbf{X}(t)}{dt} = \mathbf{u}(t)\mathbf{B} - \xi(t)\mathbf{A}\mathbf{C}\mathbf{X}(t)$$

- Both data products and CMIP6 models have large uncertainty on terrestrial gross primary productivity (GPP).
- It is important to understand why GPP is differently simulated among the models.

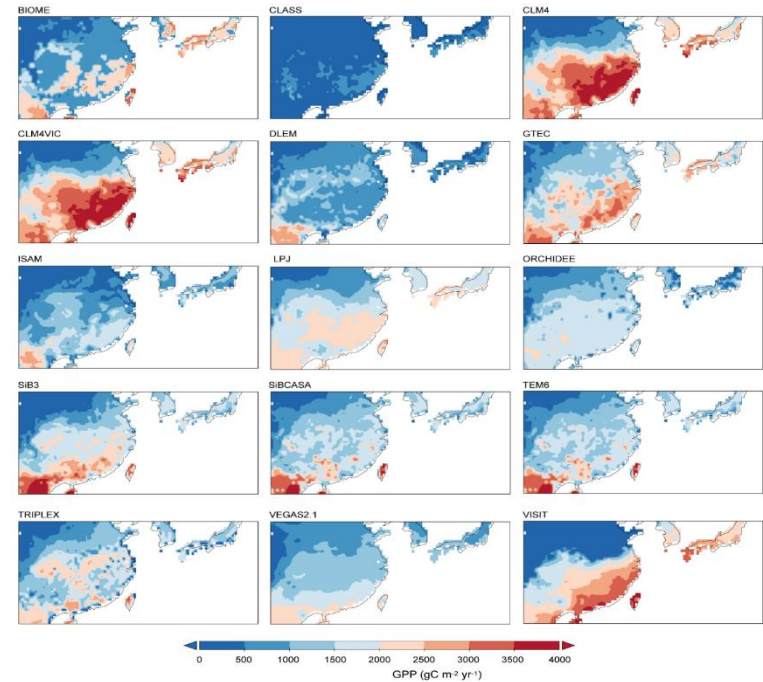


# Modeling results: MsTMIP project

- East Asian Monsoon (EAM) region is a large C sink at middle to low latitudes .
- GPP uncertainty is large in current terrestrial biosphere models.



Yu *et al.* 2014 PNAS



Cui *et al.* 2019 GBC



# MsTMIP project: experimental design

① **Baseline simulations** → constant environmental drivers


Order	Domain	Scenario	Climate	LULUC	Atm. CO <sub>2</sub>	Nitrogen
1		RG1	Constant	Constant	Constant	Constant
2		SG1	Time-varying (CRU+NCEP)			
3		SG2		Time-varying (Hurtt)		
4		SG3			Time-varying	
5		BG1				Time-varying

Diagram description: A table with 7 columns: Order, Domain, Scenario, Climate, LULUC, Atm. CO<sub>2</sub>, and Nitrogen. The 'Domain' column contains a world map icon. The 'Scenario' column is highlighted with a red box. Blue arrows point from a single source to the 'Scenario' cells for rows 1 through 5. The table shows a factorial design where different environmental drivers (Climate, LULUC, Atm. CO<sub>2</sub>, Nitrogen) are held constant or varied across different scenarios (RG1, SG1, SG2, SG3, BG1).

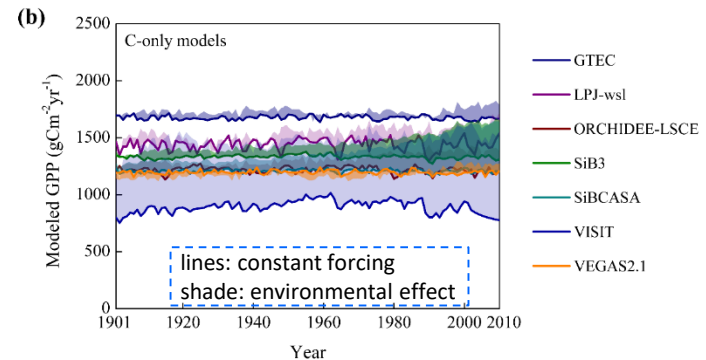
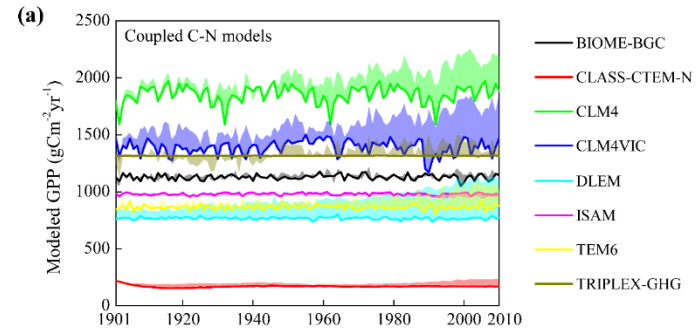
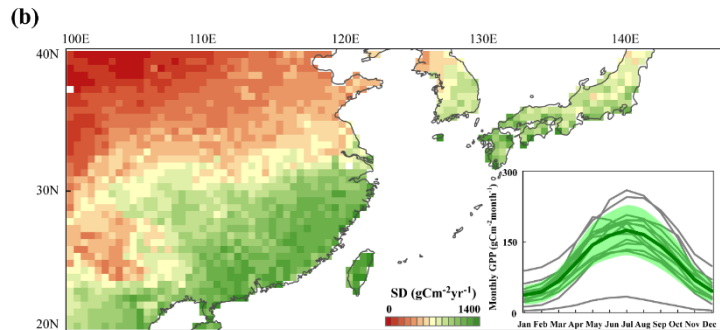
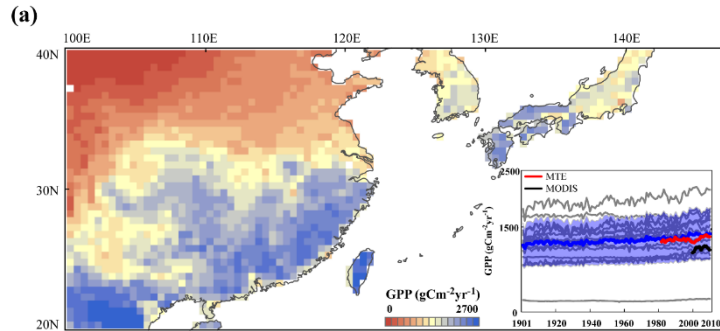
② **Environmental impacts** → turn one environmental driver on at a time

**Factorial analyses on impacts of environmental drivers:**

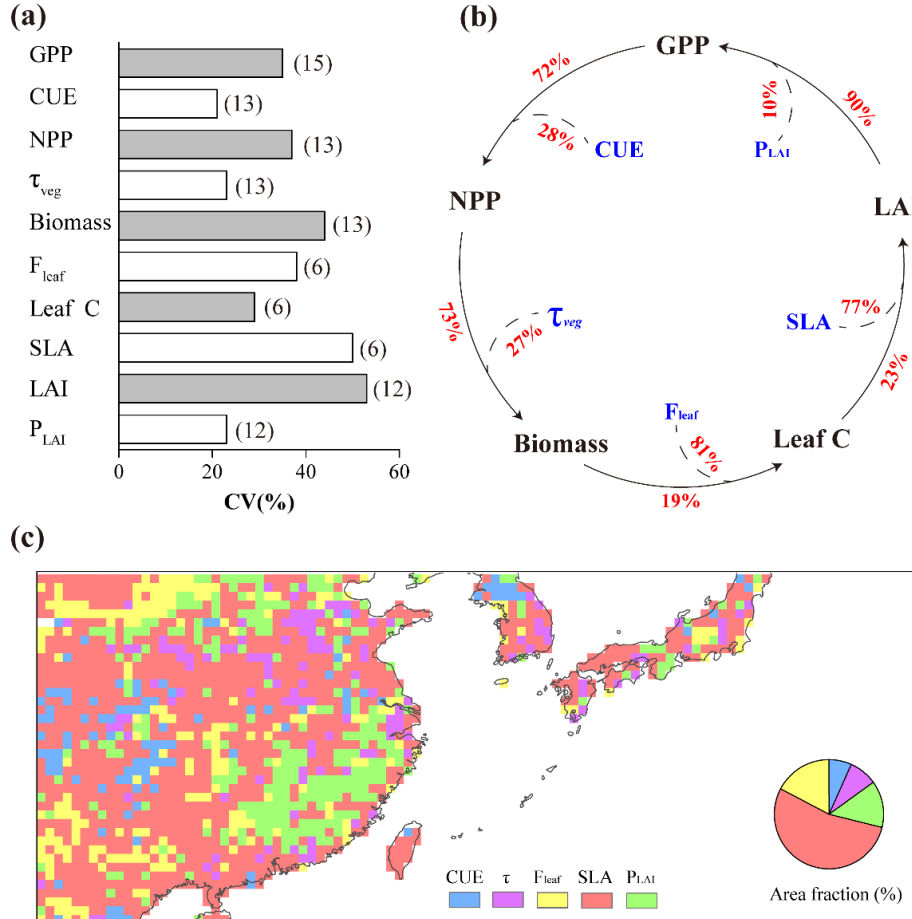
- Climate (SG1 - RG1)      Land-use land-cover change (SG2 - SG1)
- Atmospheric CO<sub>2</sub> concentrations (SG3 - SG2)      Nitrogen deposition (BG1 - SG3)

# Modeling uncertainty in the East Asian Monsoon region

- The inter-model variation in GPP across the EAM region stems from the initial states.
- Model structure and parameterization of plant traits are important uncertainty sources



# Plant functional traits are important model uncertainty sources



- Specific leaf area has a large contribution to GPP uncertainty in most area of the EAM region .
- It is important to use data to constrain plant trait parameters in the models.

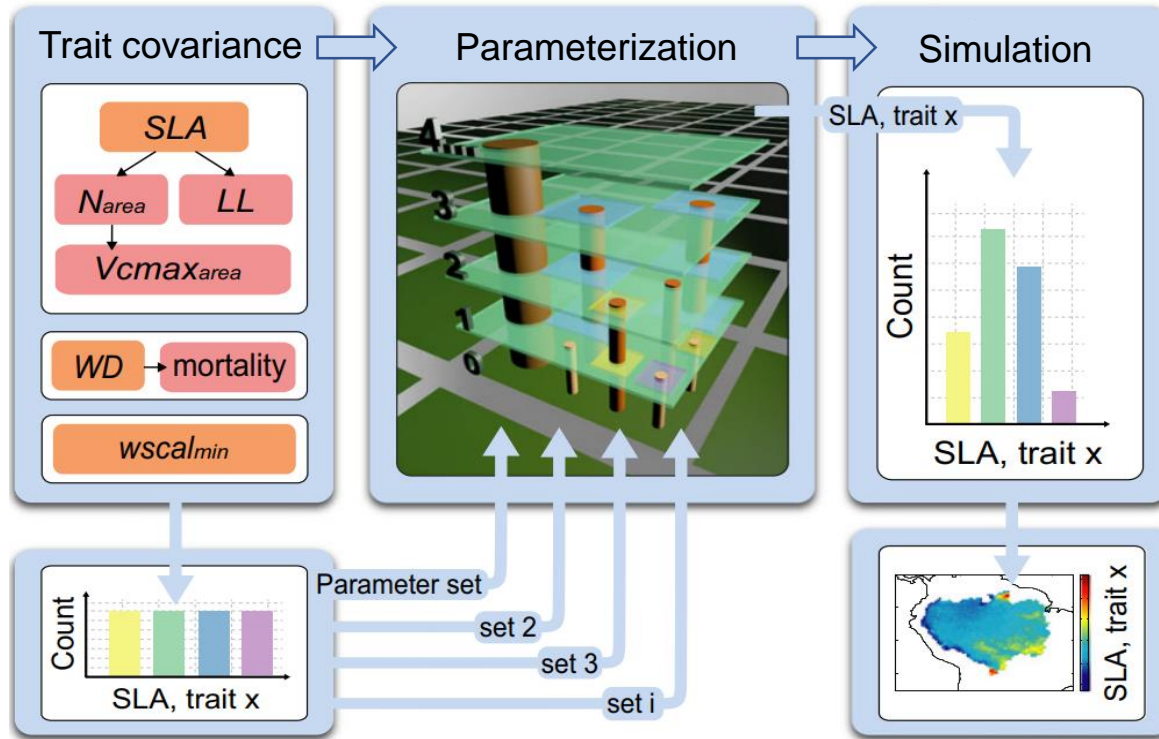
SLA: Specific leaf area

$F_{leaf}$ : Fraction of leaf in vegetation biomass

$P_{LAI}$ : Gross primary productivity per leaf area

## Question 2: How to improve model parameterization of plant traits based on data?

Incorporation of trait acclimation and covariance to improve modeling of C processes



Two important types of plant traits for C cycle:

### ■ Photosynthesis

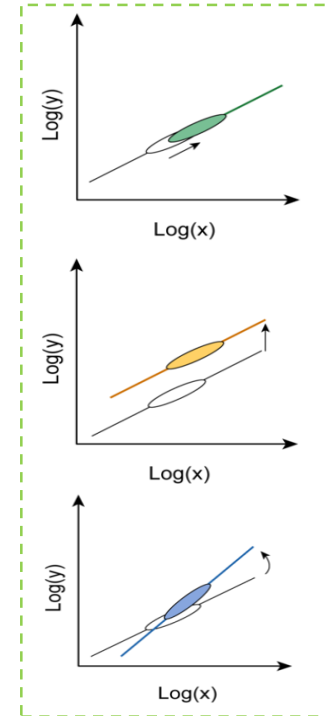
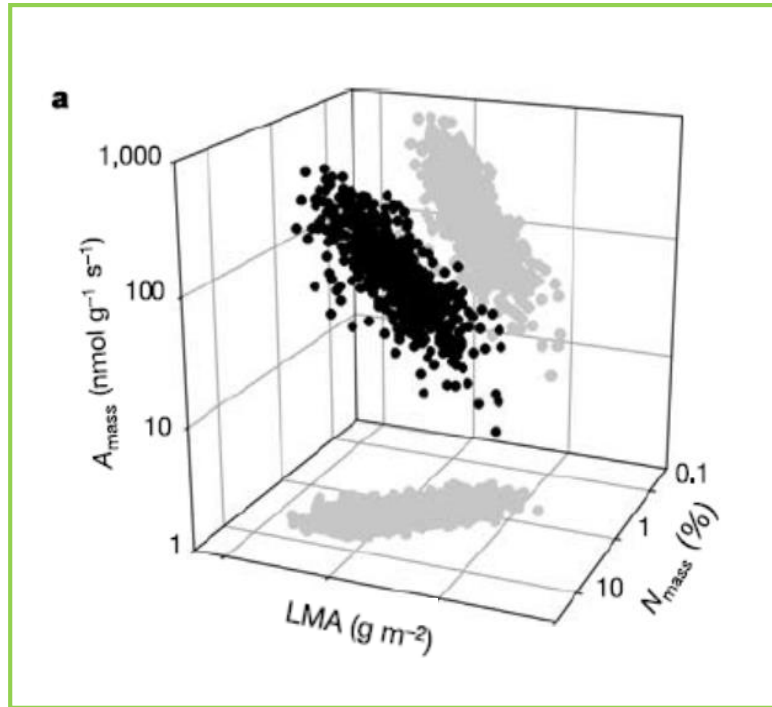
- Photosynthetic capacity
- Leaf area
- Leaf nitrogen content
- Leaf life span
- ...

### ■ Mortality

- Tree mortality rate
- Stem size
- Wood density
- ...

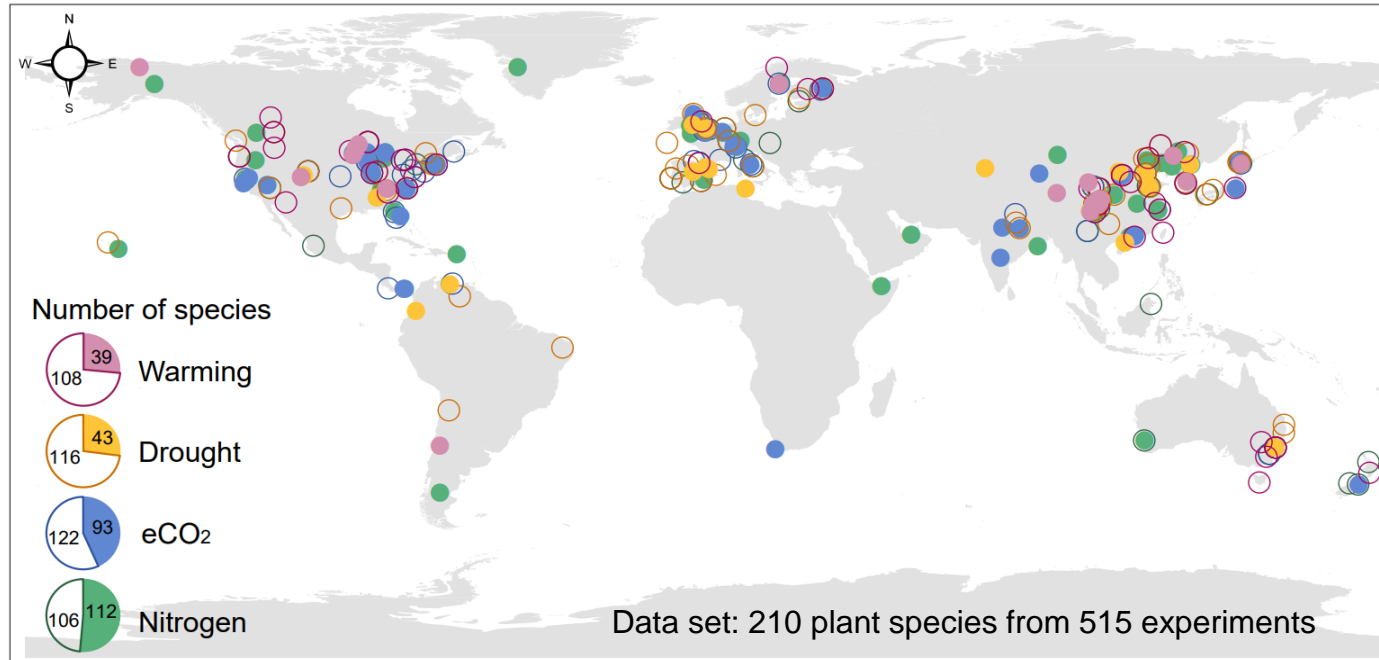
# Leaf photosynthetic traits

Whether and how global environmental changes affect plant traits and their covariance?

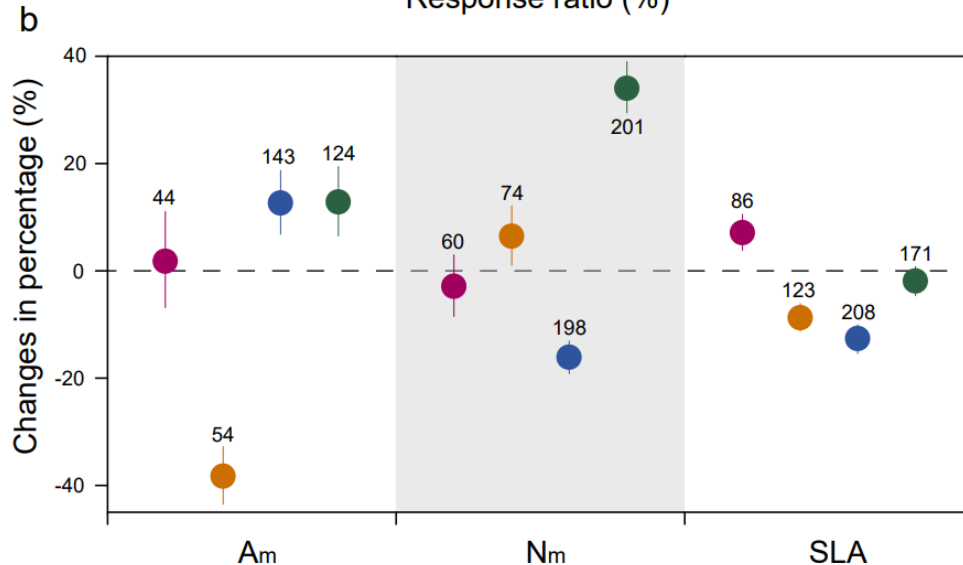
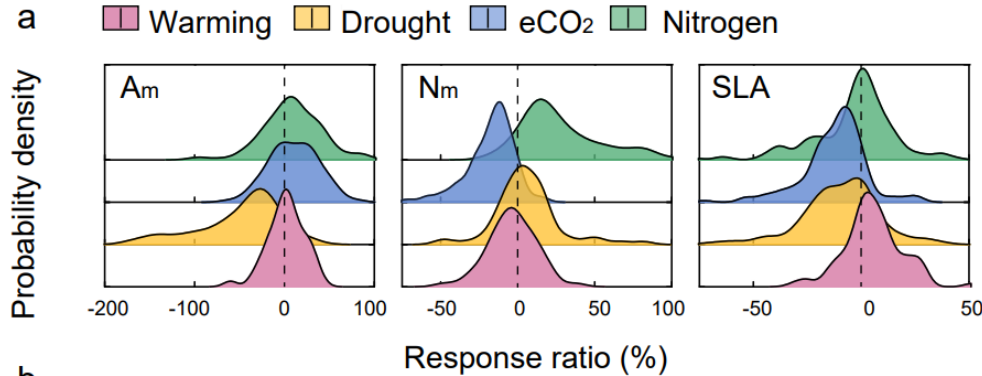




# Meta-analysis: Data of trait acclimation and covariance in experiments

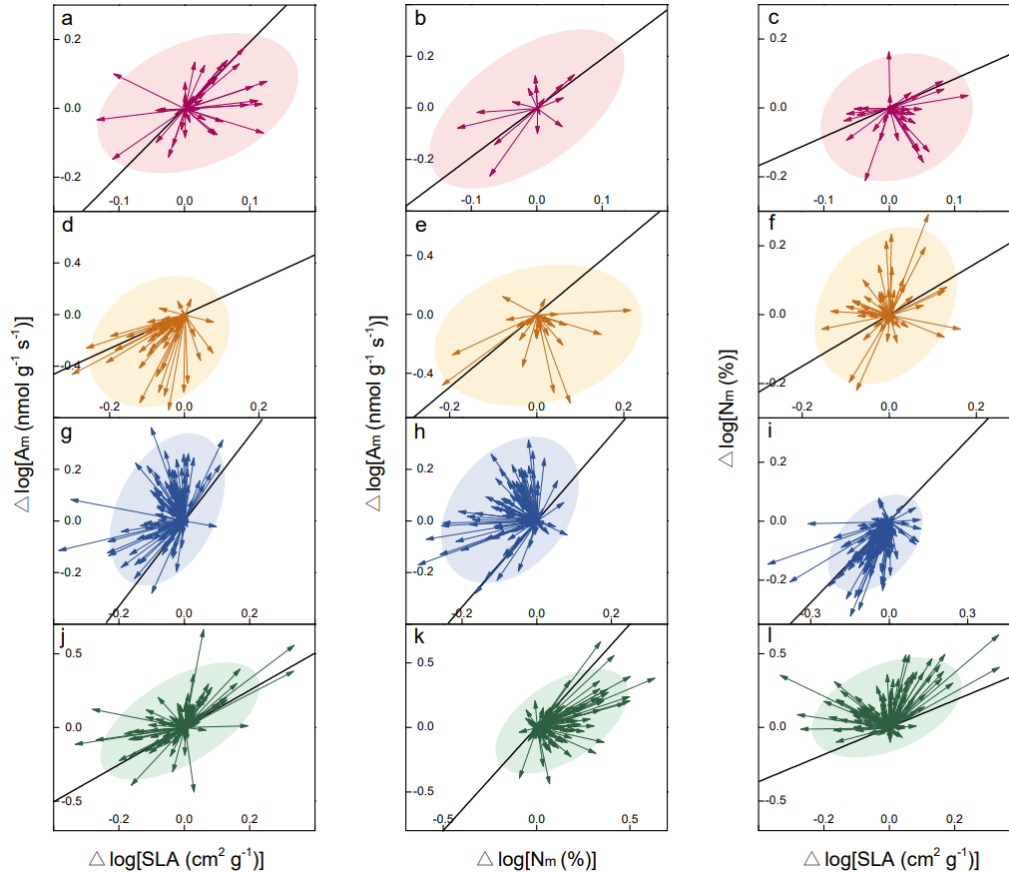


# Trait acclimation under global changes



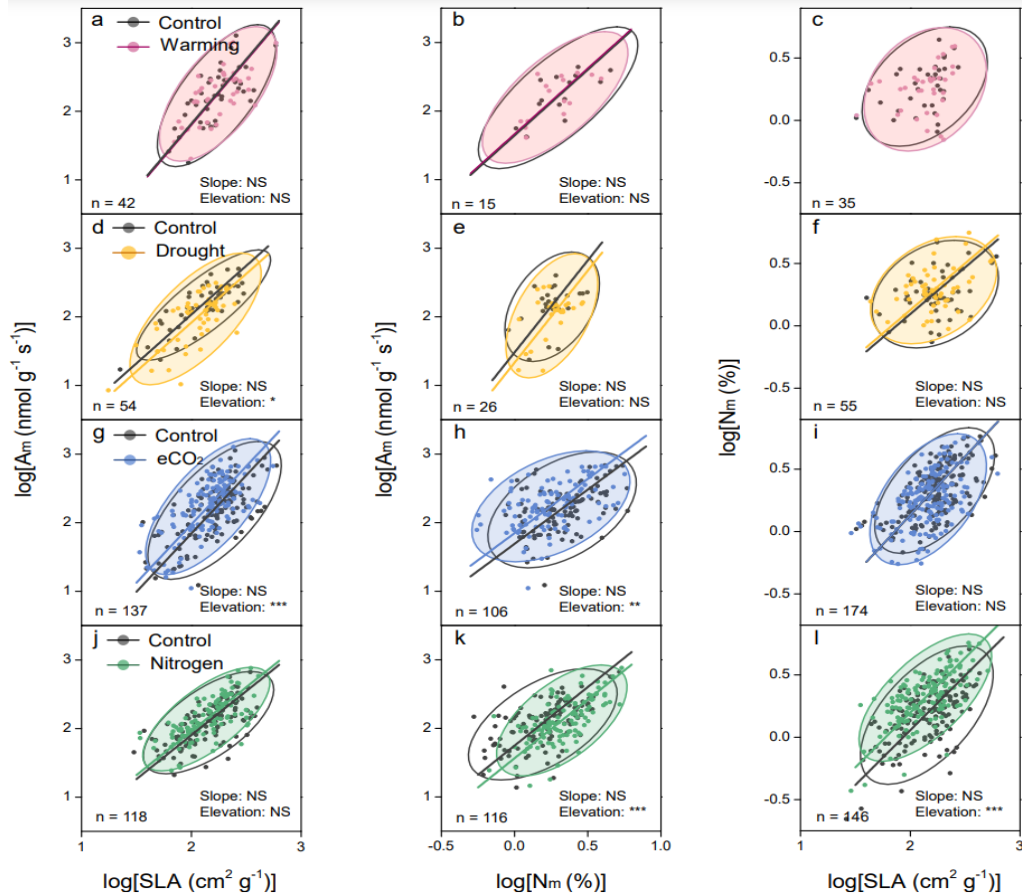
- Plant functional traits are sensitive to global changes
- Trait acclimation could be represented as probability distributions
- Different acclimation directions of plant trait among global change factors

# Various trait acclimation on the species level



- Plant functional traits are sensitive to global changes
- Trait acclimation could be represented as probability distributions
- Different acclimation directions of plant trait among global change factors
- **Diverse directions of trait acclimation between species**

# Robust trait covariance over space under environmental changes

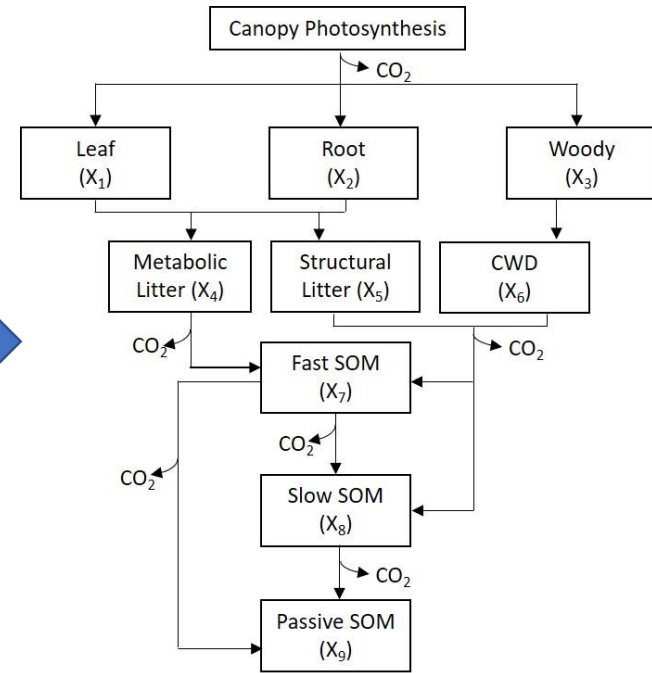
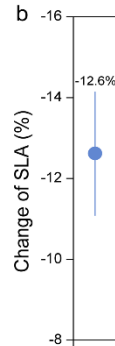
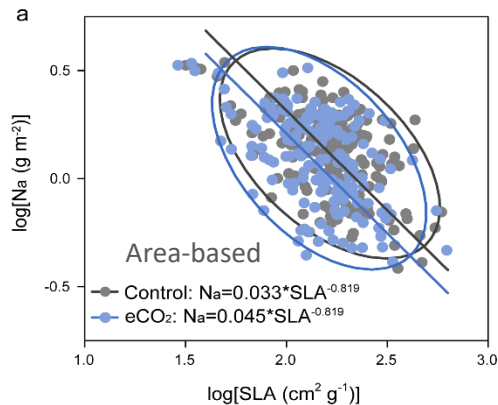


- Plant functional traits are sensitive to global changes
- Trait acclimation could be represented as probability distributions
- Different acclimation directions of plant trait among global change factors
- Diverse directions of trait acclimation between species
- A small change in trait covariance across species

# A modelling experiment:

Incorporating trait acclimation and covariance into a global process-based model

Simulation	[CO <sub>2</sub> ]	Δ SLA	SLA-N <sub>a</sub> covariance	Description
Control	1×CO <sub>2</sub>	/	$N_a=0.033*SLA^{-0.819}$	control
+CO <sub>2</sub>	2×CO <sub>2</sub>	/	$N_a=0.033*SLA^{-0.819}$	elevated CO <sub>2</sub>
+CO <sub>2</sub> +Acclimation	2×CO <sub>2</sub>	-12.6%	$N_a=0.033*SLA^{-0.819}$	elevated CO <sub>2</sub> + SLA acclimation
+CO <sub>2</sub> +Acclimation +Covariance	2×CO <sub>2</sub>	-12.6%	$N_a=0.045*SLA^{-0.819}$	elevated CO <sub>2</sub> + SLA acclimation + N <sub>a</sub> -SLA relationship acclimation

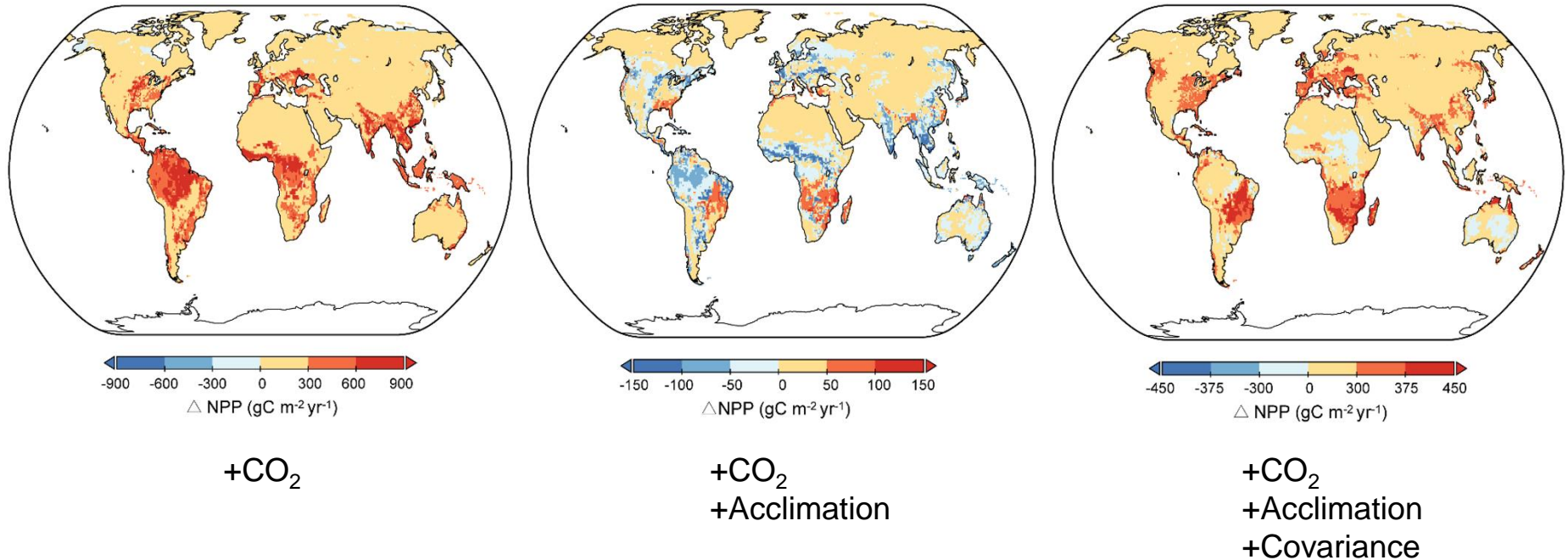


CABLE model



# A modelling experiment:

Incorporating trait acclimation and covariance can greatly change the modeled response of net primary productivity to CO<sub>2</sub> enrichment





# Mortality traits

Covariance between stem size and tree mortality rate in a 20-ha subtropical monsoon evergreen forest

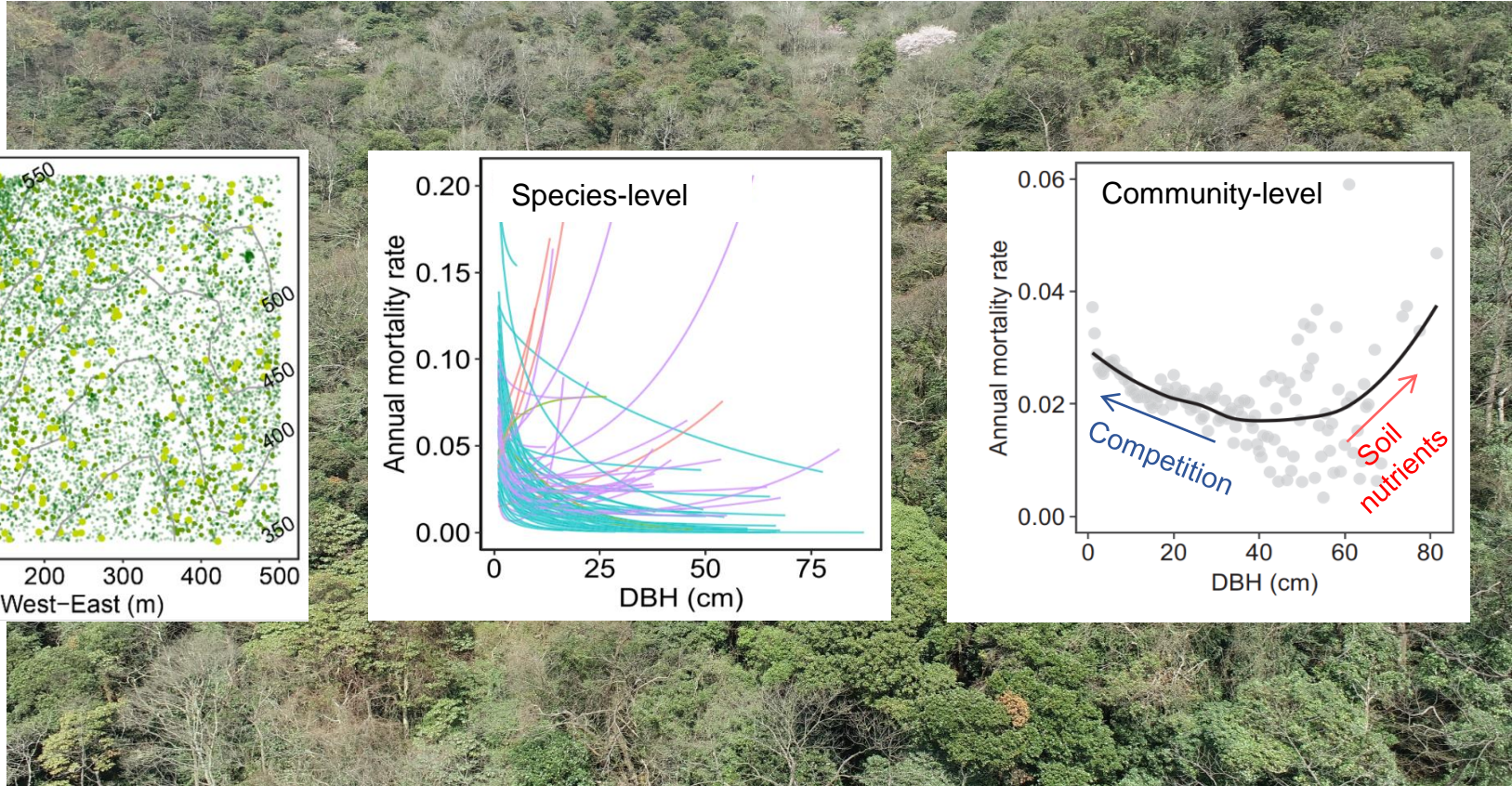
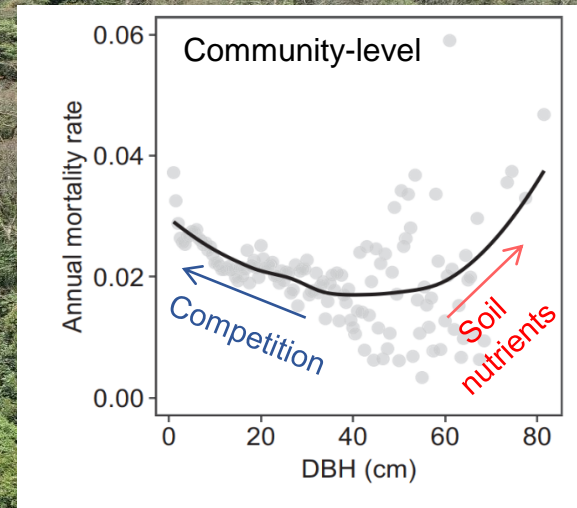
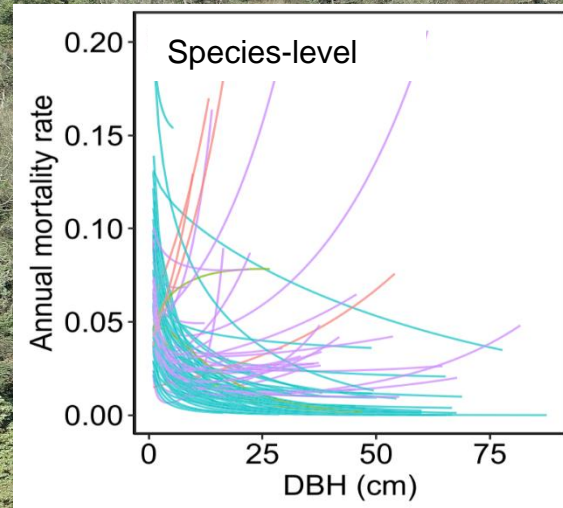
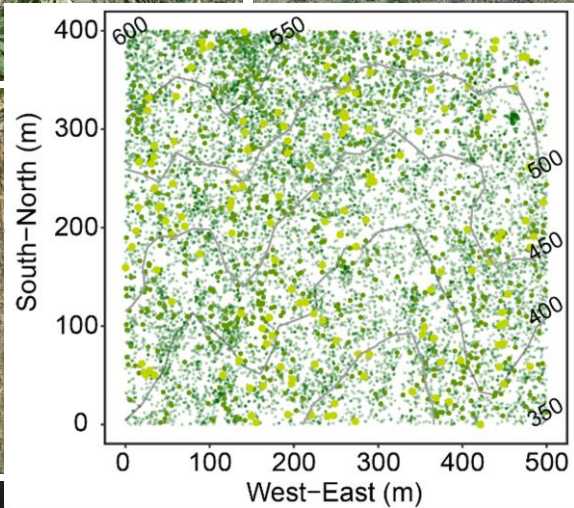


- ✓ 117 species
- ✓ Totally >150,000 individuals
- ✓ 14,678 trees died over 2010-2015



# Mortality traits

A U-shaped size-dependent mortality pattern in the species-rich forest



# Dynamic vegetation models use different traits to simulate mortality rate

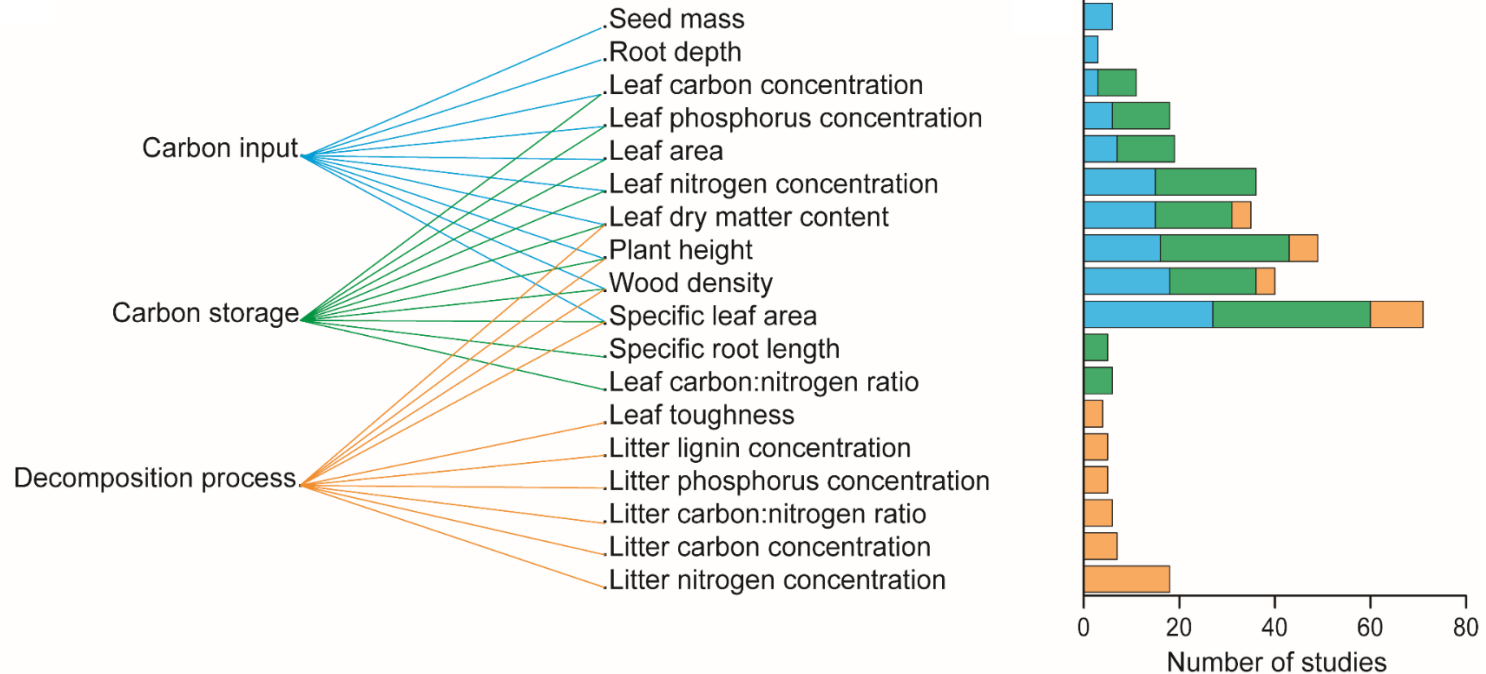
## Plant mortality algorithms in models

Mortality algorithms	Description	Model acronym
Productivity dependence	No explicit concept of mortality; biomass reduced via declining productivity	TRIFFID
Background rate	Mortality is set at a constant rate (approximately 1-2% yr <sup>-1</sup> ).	ORCHIDEE, BIOME-BGC, CLM, ED
	Mortality increases as wood density declines	ED
Age dependence	Death increases with age approaches the PFT-specific maximum	ForClim, CTEM, SDGVM
Size dependence	U-shaped mortality pattern for canopy trees	LM3-PPA
Growth efficiency threshold	Mortality occurs when biomass increment per unit leaf area falls below a quantitative threshold that varies between models.	SDGVM, LPJ-GUESS, CLM-DGVM, SEIB, ORCHIDEE, SDGVM, CLM 3.0
Shading/competition	Mortality increases as a function of canopy cover	ED, ED2, LPJ-GUESS, CLM-DGVM, SEIB, ORCHIDEE
Negative productivity	Death occurs if annual net productivity < 0.0 g	LPJ-GUESS, CLM-DGVM, SEIB, ORCHIDEE, CTEM
Carbon starvation	Mortality is a function of carbohydrate storage per unit leaf biomass	ED, CLM(ED), LM3-PPA
Climate tolerance	Death occurs if the average climate exceeds predefined monthly climatic tolerances	LPJ-GUESS, CLM-DGVM, SEIB, ORCHIDEE, CTEM
Heat stress threshold	Mortality is a function of the number of days per year in which the average temperature exceeds a threshold temperature, and the number of degrees by which this threshold is exceeded.	LPJ-GUESS, CLM-DGVM, SEIB, ORCHIDEE, CTEM, ED
Hydraulic failure	Mortality is a function of carbohydrate storage per unit leaf biomass	CLM(ED), LM3-PPA
Fire disturbance	Mortality is a function of fuel load, litter moisture	ED, SEIB, LPJ-GUESS, CLM(ED), LM3-PPA

# A literature survey on empirical trait-based studies

More studies are focusing on C uptake than decomposition processes

$$\frac{d\mathbf{X}(t)}{dt} = u(t)\mathbf{B} - \xi(t)\mathbf{A}\mathbf{C}\mathbf{X}(t)$$



# Summary

The model uncertainty on land C cycle can be further reduced by an improved parameterization of plant functional traits.

- ✓ Can we link plant functional traits and land carbon cycle for model evaluation?
  - Yes, we can trace baseline C residence time and GPP to some key plant traits.
  - Parameterization uncertainty can propagate between traits and to C processes.
  - It is still challenging to evaluate CMIP models without details of trait parameters.
- ✓ How to improve model parameterization of plant functional traits based on data?
  - Explore probability distributions of trait acclimations to environmental factors
  - More data of community-level trait covariance on both of spatial and temporal scales
  - Model outputs of plant functional traits associated with ecosystem processes



**Thanks for your listening!**

