

Data and Model Synthesis for Process-Level Understanding of Terrestrial Ecosystems

Anthony Walker

Martin De Kauwe, Belinda Medlyn, Sönke Zaehle,
Alistair Rogers, Shawn Serbin,
Dan Lu, Ming Ye

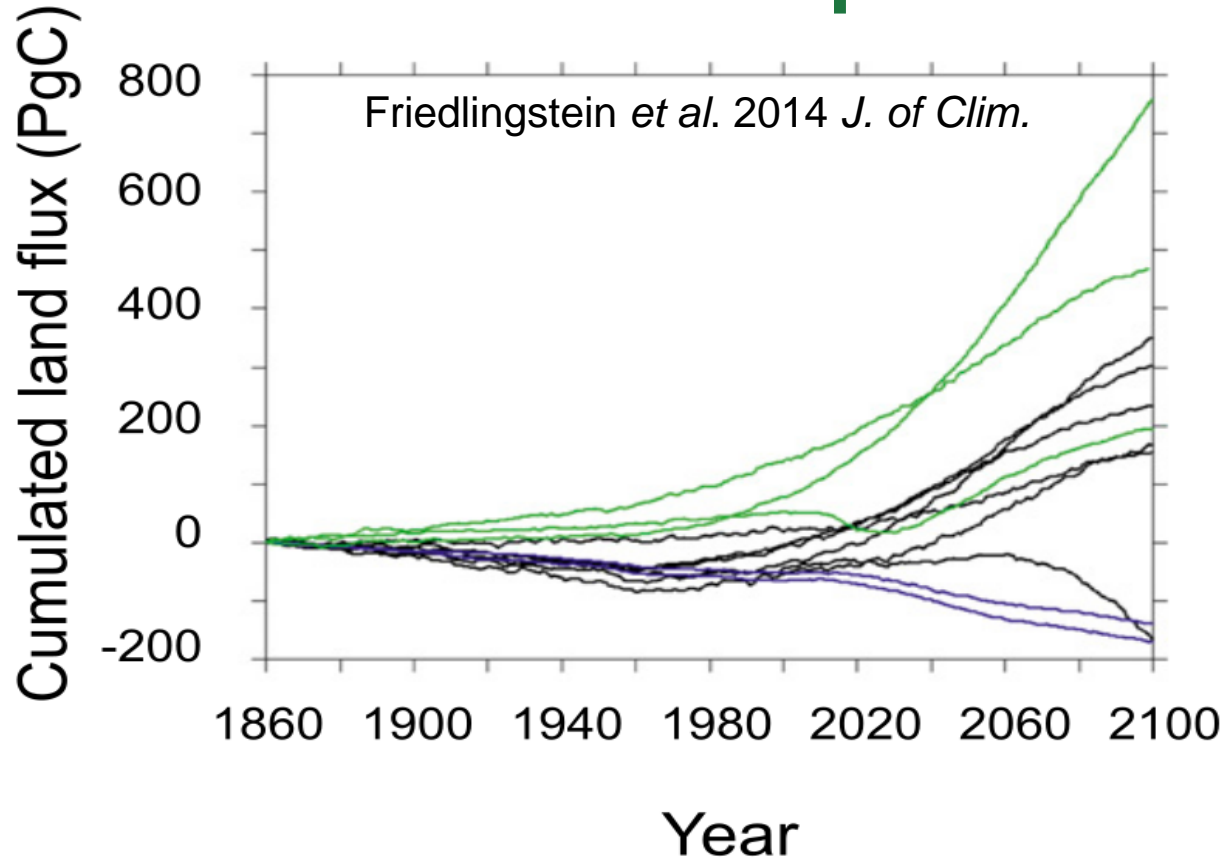


Talk Outline

- Intro
- FACE Model Data Synthesis – 10 yr forest biomass responses to elevated CO₂
- Multi-assumption modelling (MAAT)
- Model GPP evaluation against GPP proxies using PCA

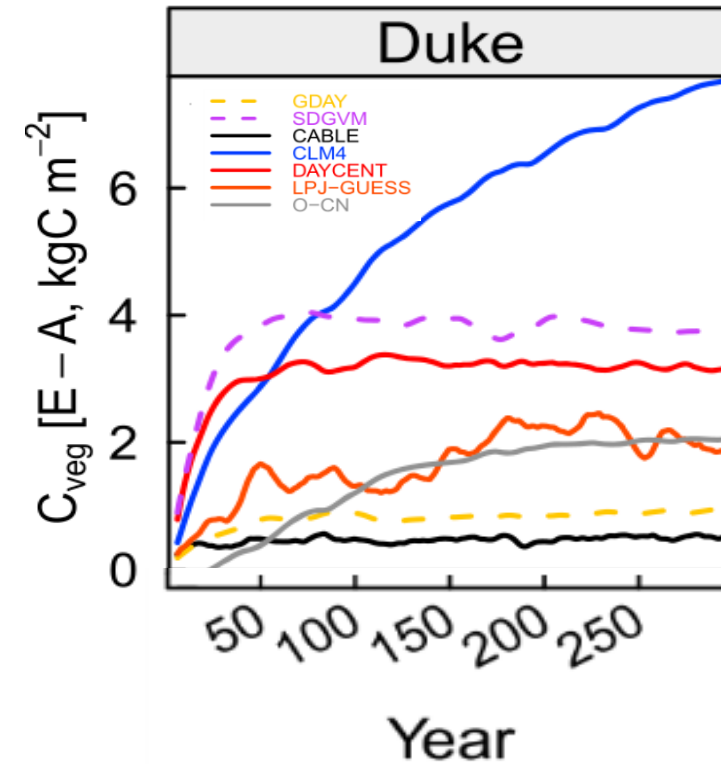
Inherent uncertainty in ecosystem models precludes predictive understanding

Global scale C uptake



Forest stand scale C uptake

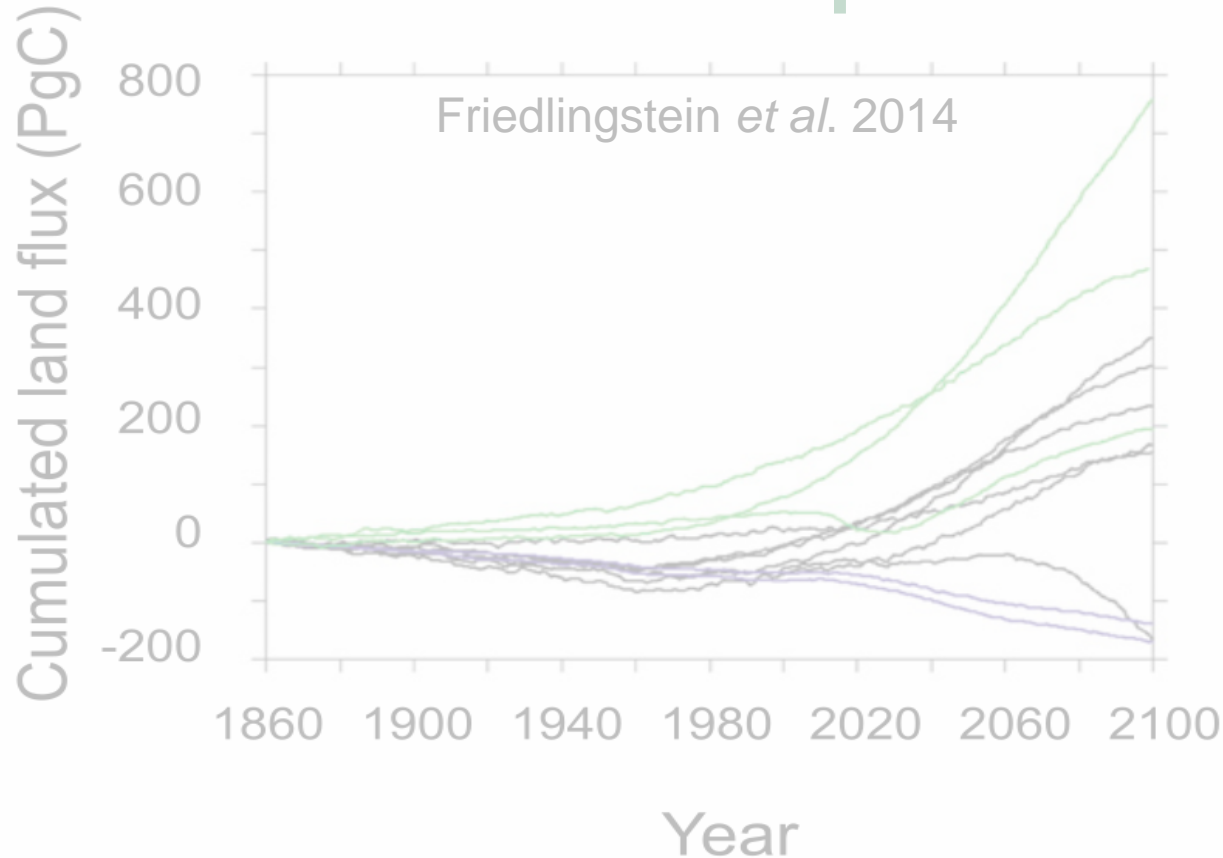
Walker et al. 2015 *Biogeochem. Cycles*



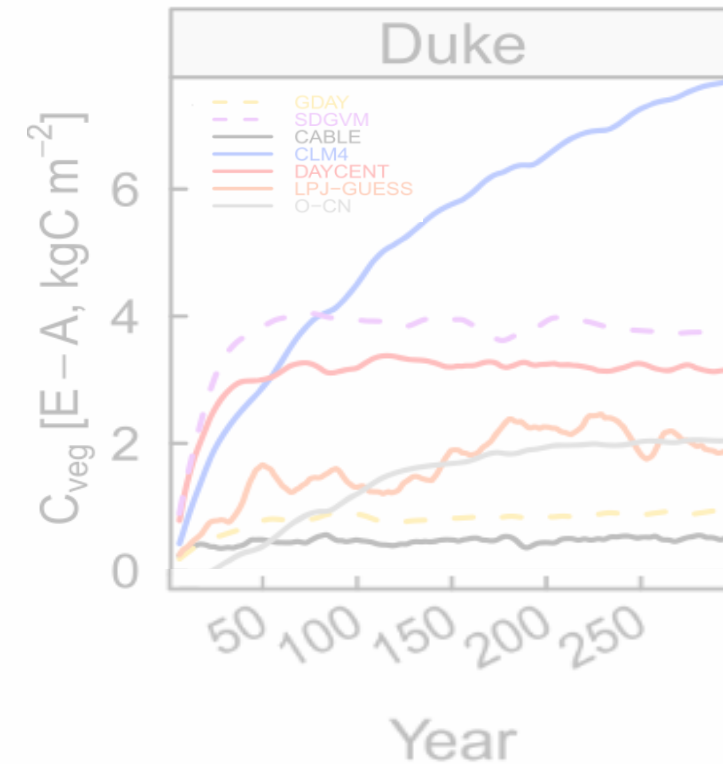
The first step towards predictive understanding is to properly characterise uncertainty and identify its sources

Forest stand scale C uptake

Global scale C uptake

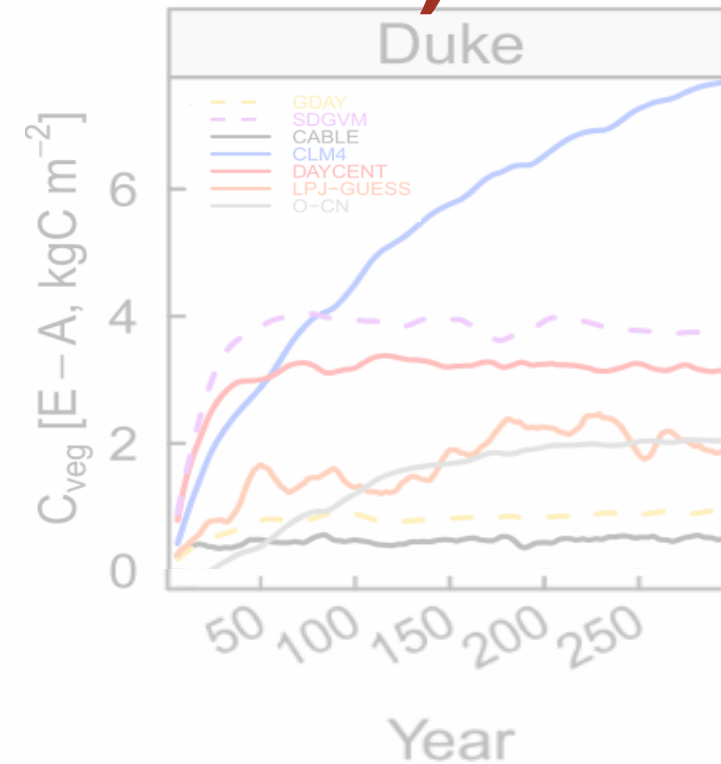
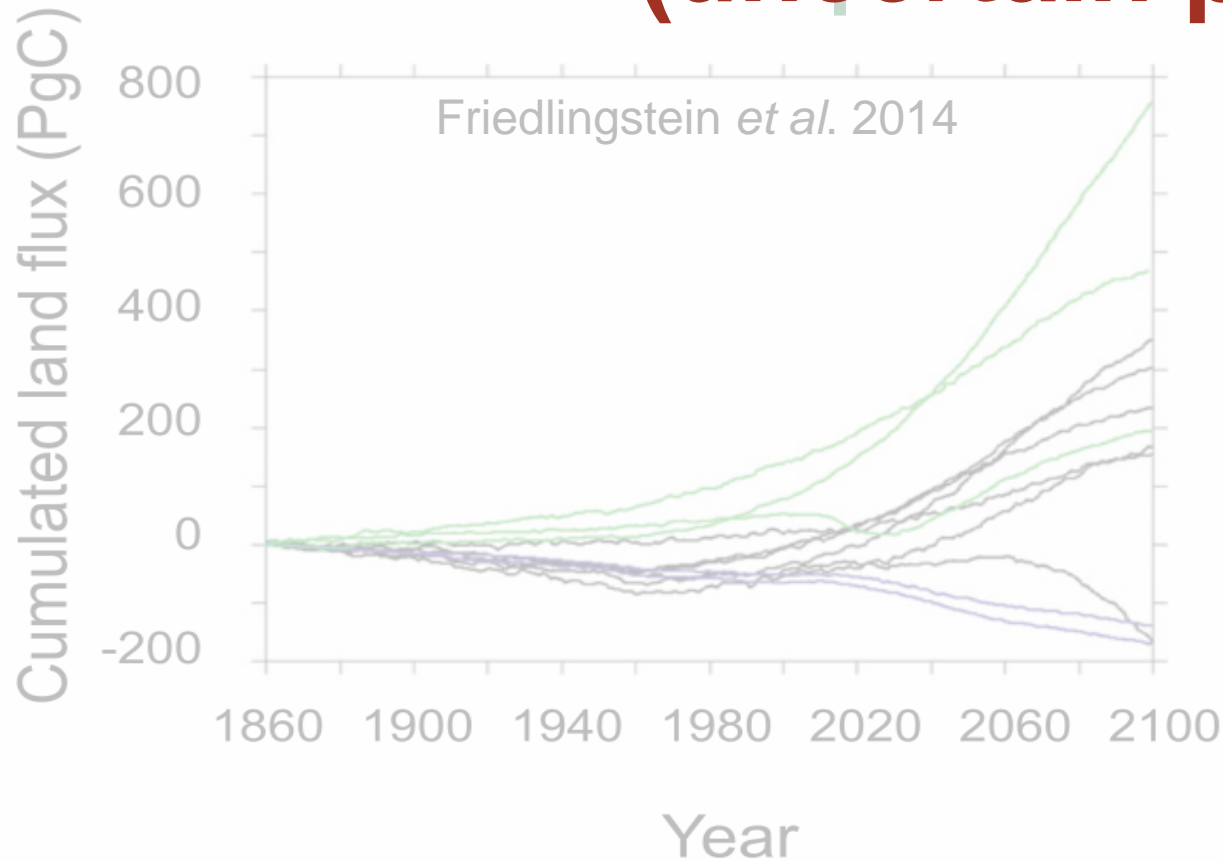


Walker *et al.* 2015



The first step towards predictive understanding is to properly characterise uncertainty and identify its sources

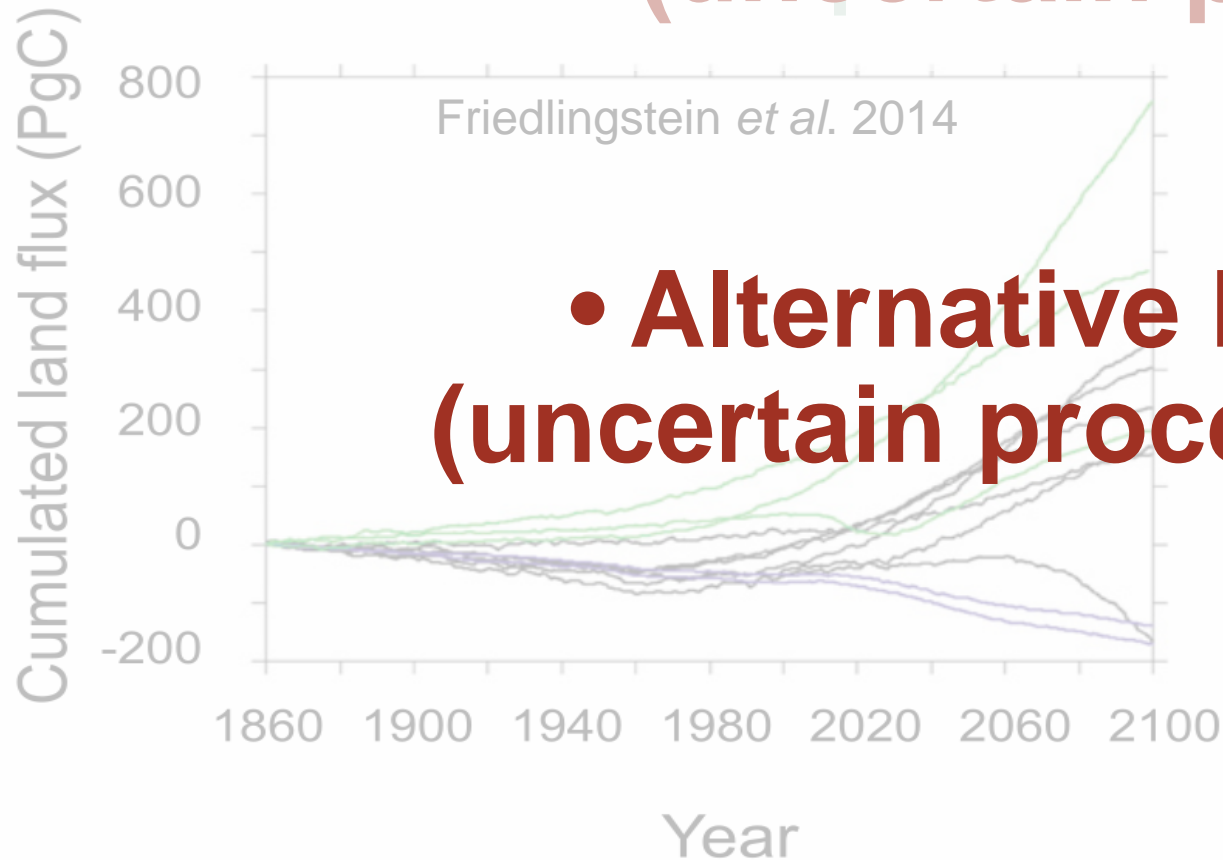
- **Alternative trait values (uncertain parameters)**



The first step towards predictive understanding is to properly characterise uncertainty and identify its sources

- **Alternative trait values**

Global scale C uptake (uncertain parameters) *Wickett et al. 2015*



- **Alternative hypotheses**
(uncertain process knowledge)



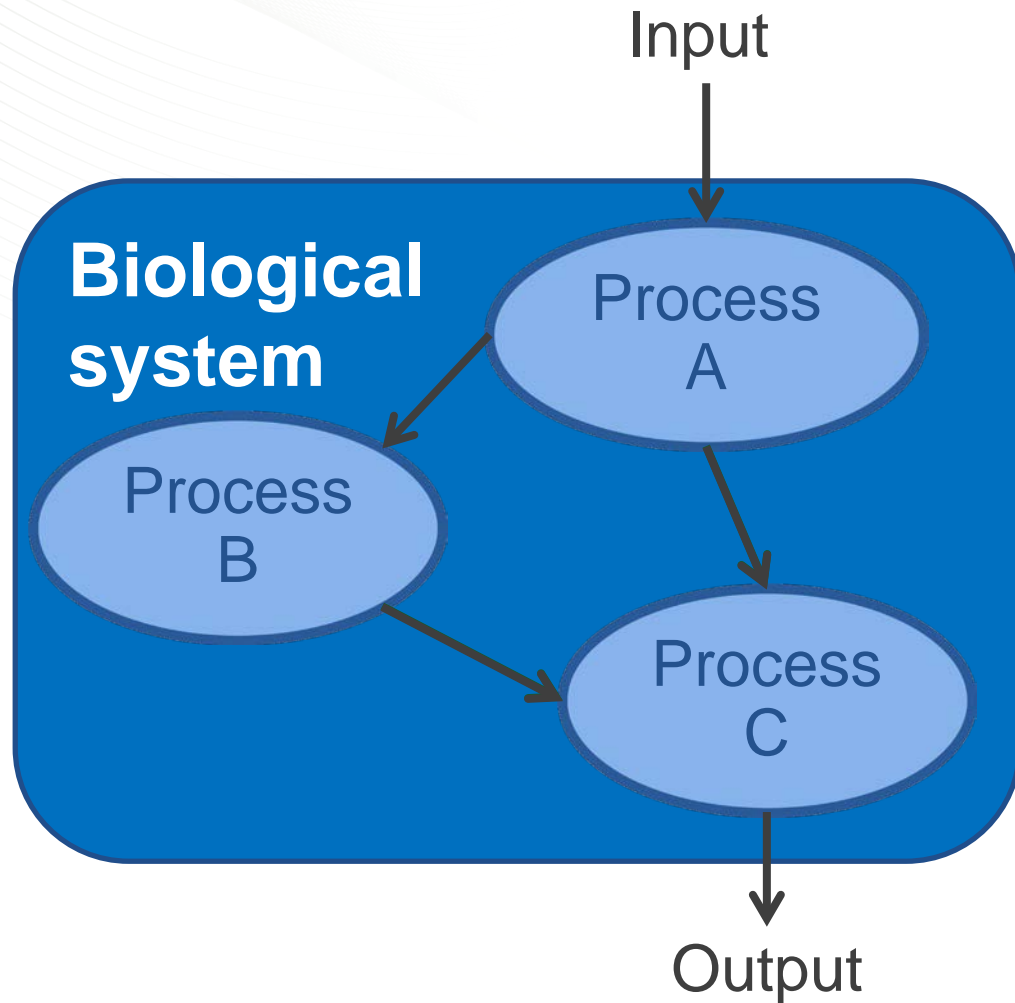
Hypothesis

A mechanistic description of how a process works.

synonyms:

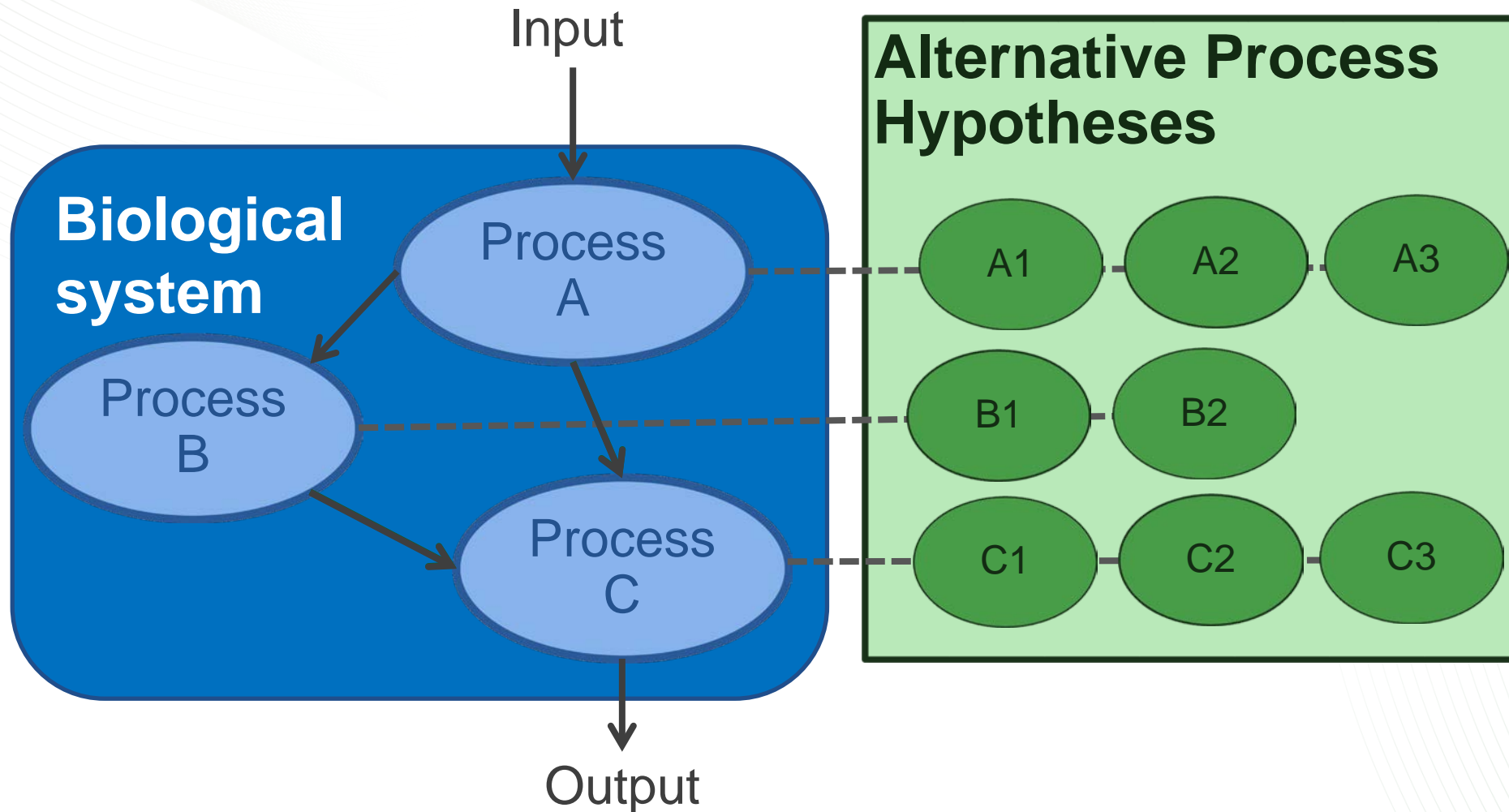
- process representation
- model structure
- assumption (not exactly)

Systems are composed of multiple processes



Systems are composed of multiple processes

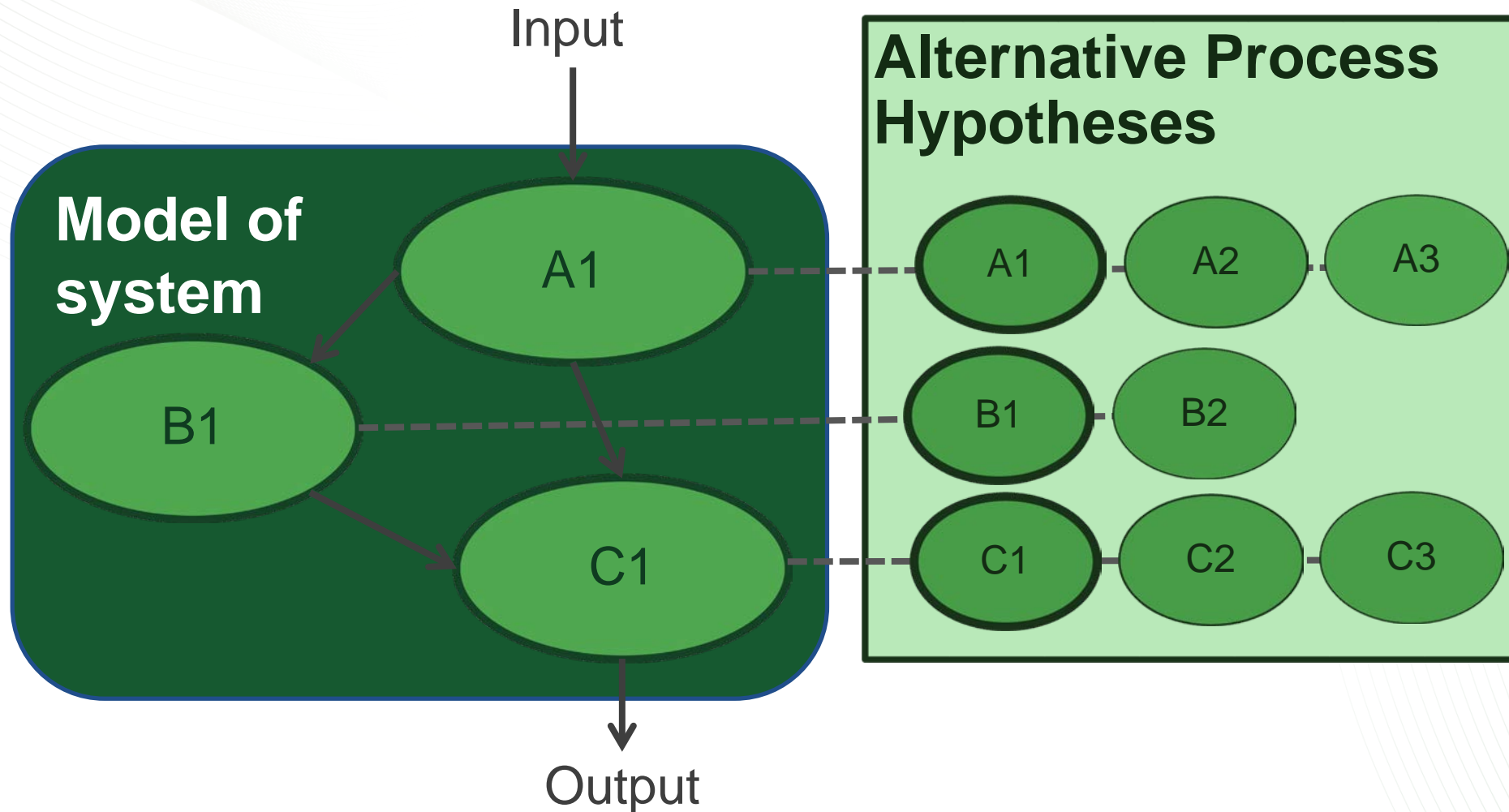
Competing hypotheses can exist for each process



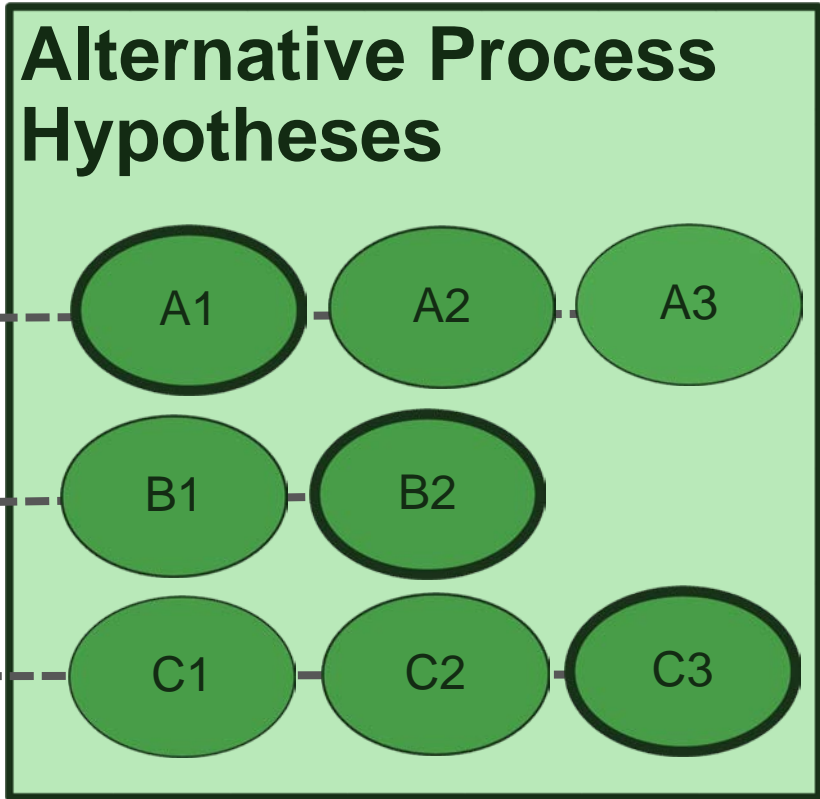
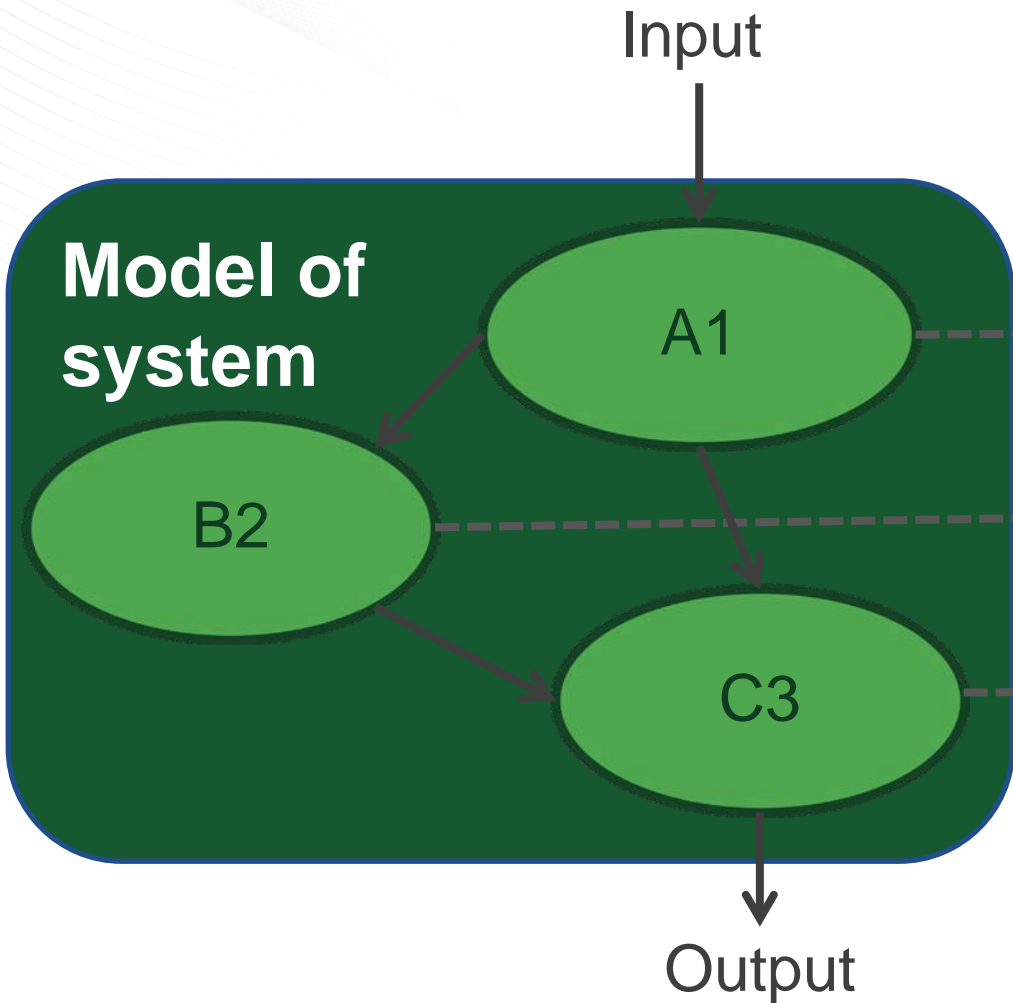
Systems are composed of multiple processes

Competing hypotheses can exist for each process

Resulting in multiple possible models of the system



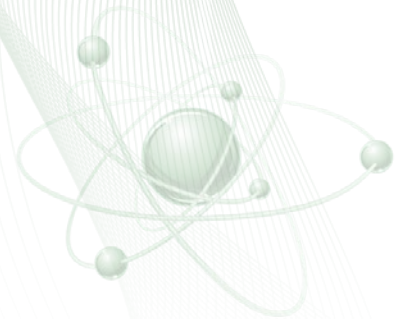
Systems are composed of multiple processes
Competing hypotheses can exist for each process
... but alternative models are possible



18 possible system models
in this simple example

FACE Model Data Synthesis

A model inter-comparison evaluated
against FACE data



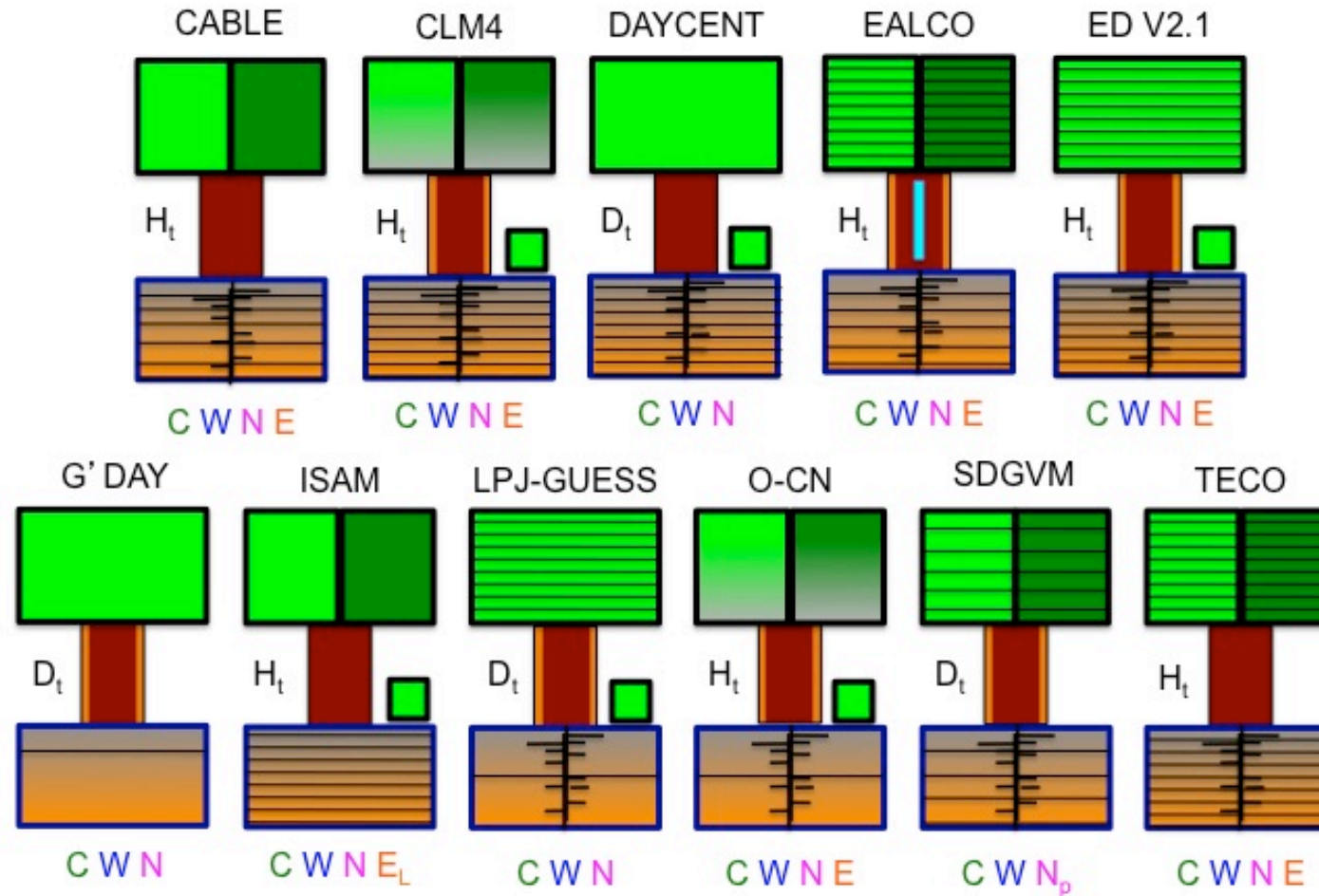
Biomass responses to eCO₂



	Rhineland	ORNL	Duke	KSC
MAT [°C]	6.0 (0.8)	14.8 (0.9)	14.8 (0.6)	22.1 (0.4)
MAP [mm]	662 (122)	1221 (218)	1081 (168)	1094 (207)
MAPET [mm]	1187 (178)	1483 (78)	1494 (53)	2391 (156)
MI	0.57 (0.15)	0.74 (0.17)	0.65 (0.14)	0.46 (0.10)

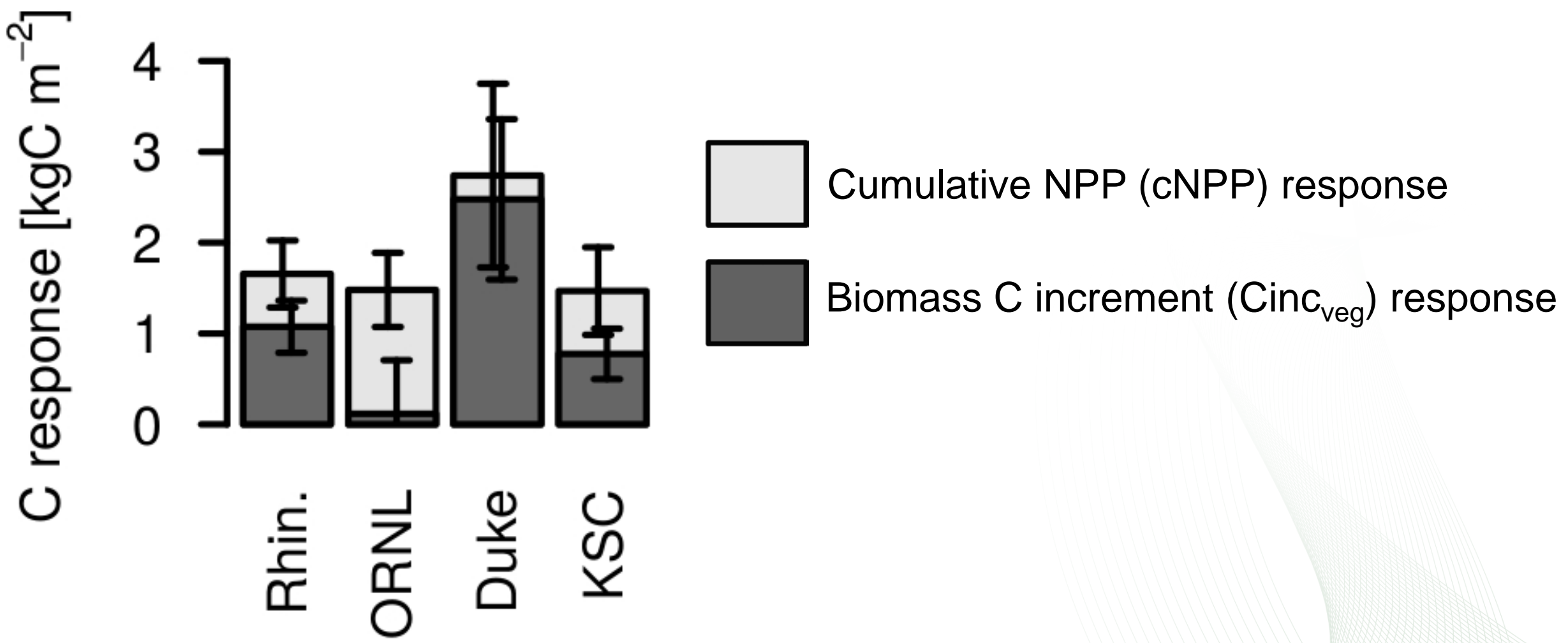
MAT – mean annual temperature, MAP – mean annual precipitation, MAPET – mean annual potential evapotranspiration calculated using the Penman-Monteith equation assuming zero canopy resistance. MI – Moisture index (MAP/MAPET). Standard deviation in parentheses.

Models



Schematic of the 11 models of the first phase of the FACE Model Data Synthesis project showing common processes but different ways in which those processes are represented

10 year response of NPP and Biomass C increment to eCO₂



Meta-analysis using mixed-effects regression models

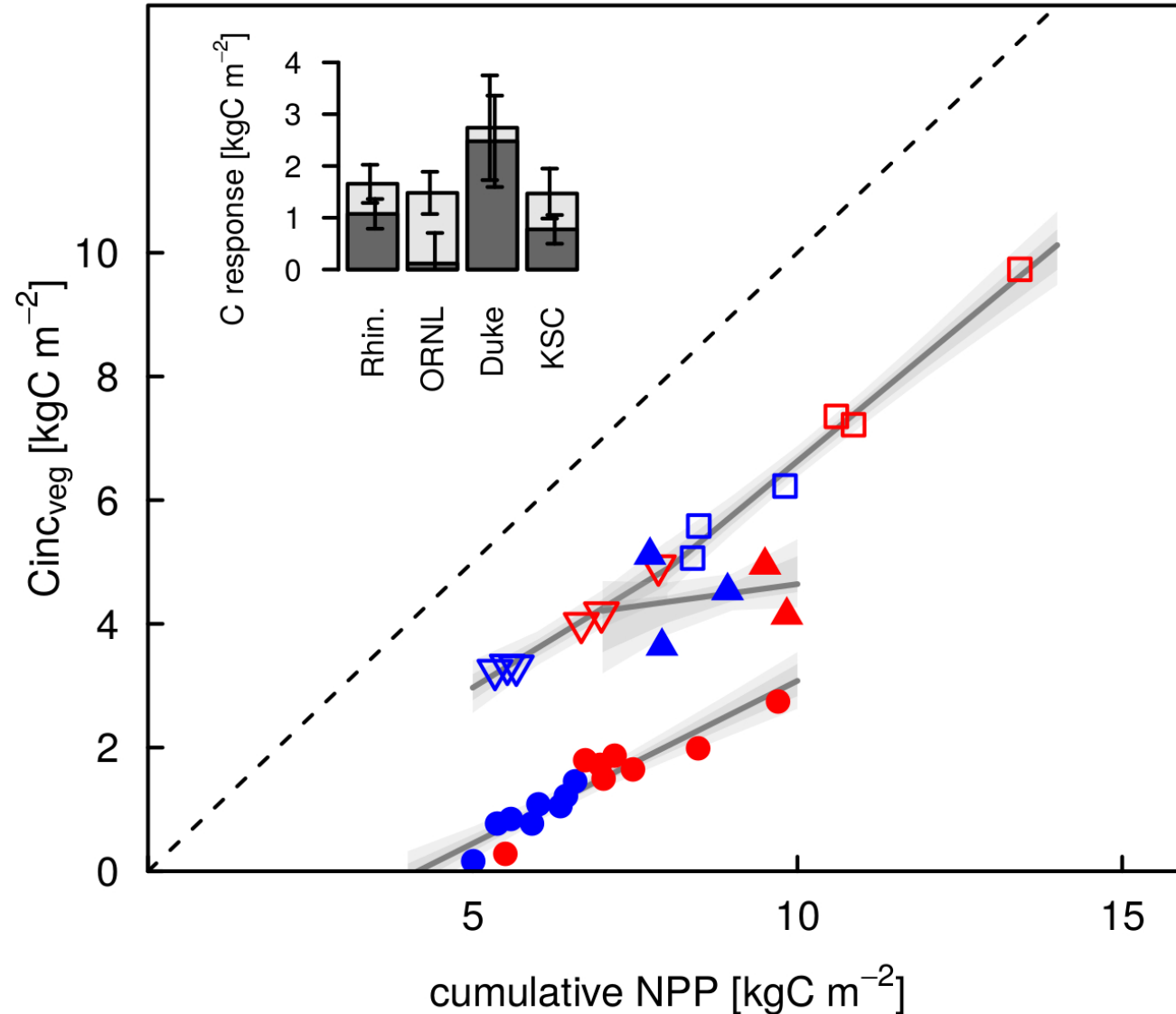
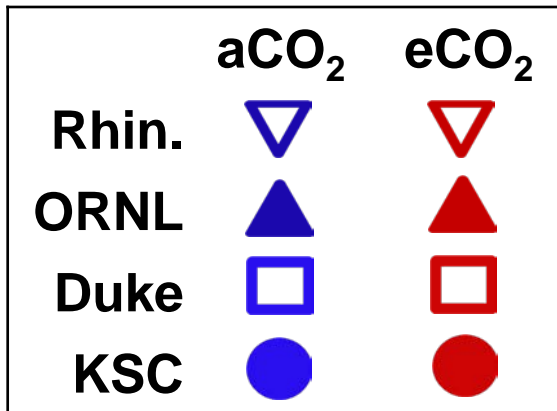
model	response	Fixed effect	parameter	SEM	Random effects		
					re.site	re.Intercept	re.slope
1	NPP	Intercept	0.723	0.133	Rhin.	0.516 (0.481–0.556)	-
		eCO ₂	0.164	0.031	ORNL	0.814 (0.773–0.849)	-
					Duke	1.050 (1.003–1.086)	-
					KSC	0.511 (0.486–0.540)	-
2	Cinc _{veg}	Intercept	3.616	1.156	Rhin.	3.320 (2.995–3.652)	-
		eCO ₂	1.045	0.258	ORNL	4.047 (3.698–4.376)	-
					Duke	6.294 (5.913–6.585)	-
					KSC	0.801 (0.825–0.614)	-

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					KSC	0.801 (0.825–0.614)	-
3	Cinc _{veg}	Intercept	-0.332	1.422	Rhin.	-0.245 (-1.055–0.627)	0.642 [†] (0.504–0.764)
			0.546 [†]	0.173	ORNL	3.205 (-0.436–3.849)	0.144 [†] (0.070–0.553)
					Duke	-2.103 (-2.704– -0.985)	0.873 [†] (0.767–0.933)
					KSC	-2.183 (-2.640– -1.720)	0.526 [†] (0.460–0.594)

[†] Indicates the biomass production rate, i.e. the slope of the assumed linear relationship between Cinc_{veg} and cNPP.

Plot level relationship of Cinc_{veg} to cNPP



Meta-analysis using mixed-effects regression models









model	response	Fixed effect	parameter	SEM	Random effects		
					re.site	re.Intercept	re.slope
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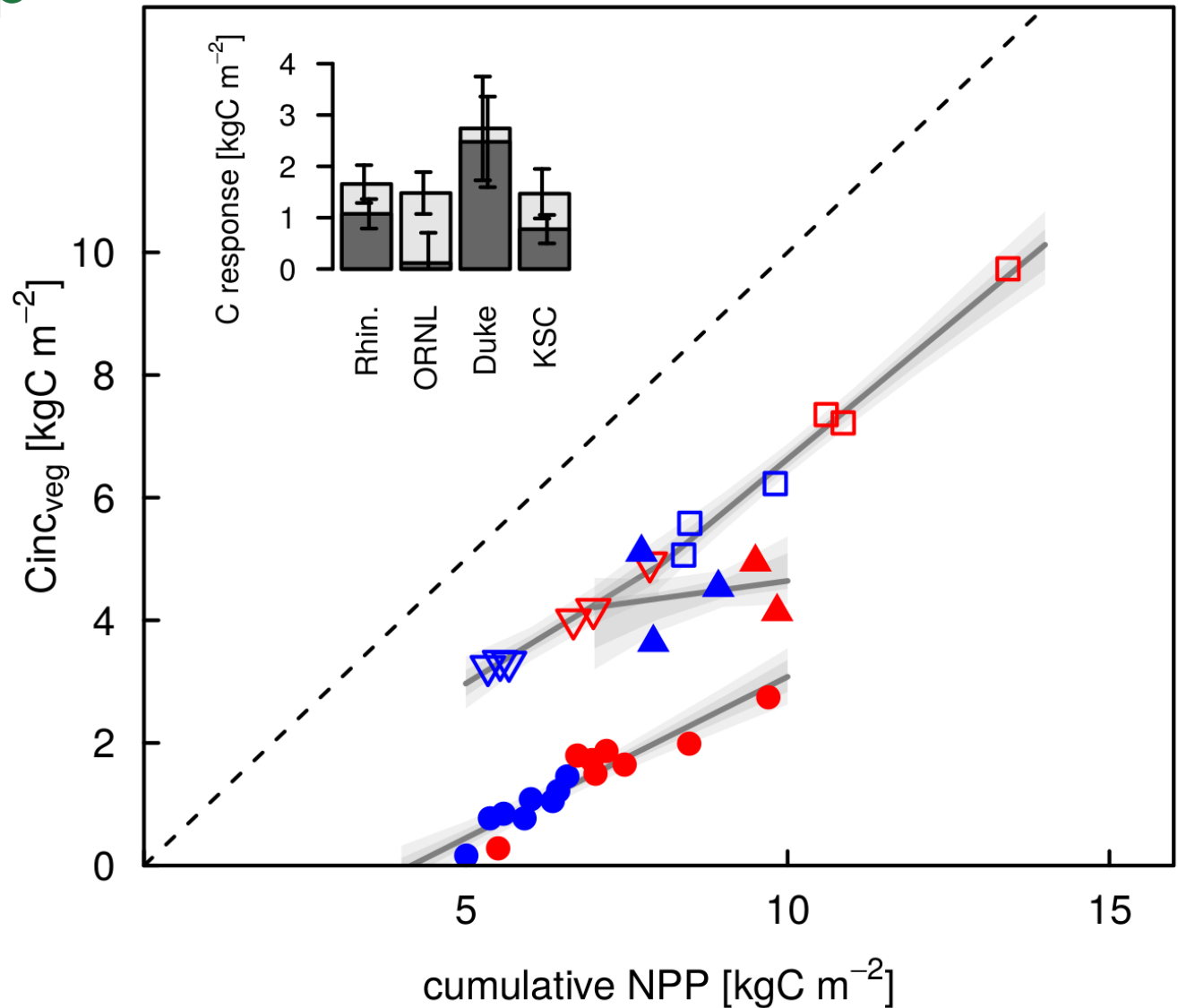
No direct CO₂ effect on Cinc_{veg}!

[†] Indicates the biomass production rate, i.e. the slope of the assumed linear relationship between Cinc_{veg} and cNPP.

$Cinc_{veg}$ response can be predicted by cNPP response and slope of the relationship

$$Cinc_{veg} = \Delta cNPP \cdot \frac{dCinc_{veg}}{dcNPP}$$

	aCO ₂	eCO ₂
Rhin.		
ORNL		
Duke		
KSC		



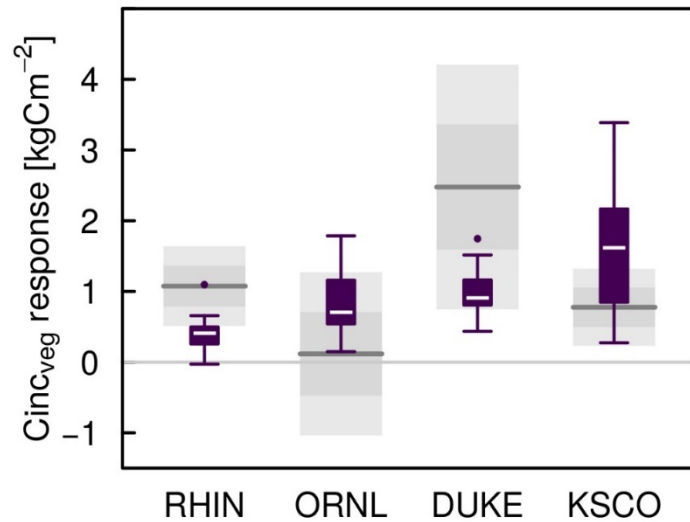
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					KSC	-2.183 (-2.640– -1.720)	0.526 [†] (0.460–0.594)
4	fW	Intercept cNPP	0.365	0.121	Rhin.	0.476 (0.435–0.507)	-
			0.020	0.005	Duke	0.480 (0.417–0.529)	-
					KSC	0.139 (0.101–0.172)	-

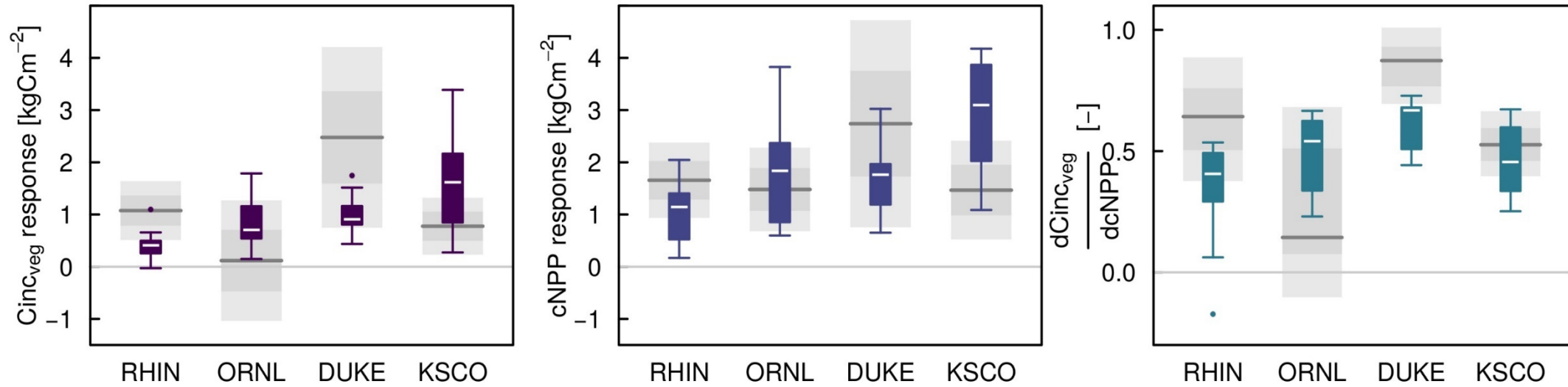
**Assuming wood allocation dominates veg turnover,
biomass production rate can be calculated:**

$$\frac{dCinc_{veg}}{dcNPP} = fW_a + 2 \frac{dfW}{dcNPP} cNPP$$

Model ensemble Cinc_{veg} response



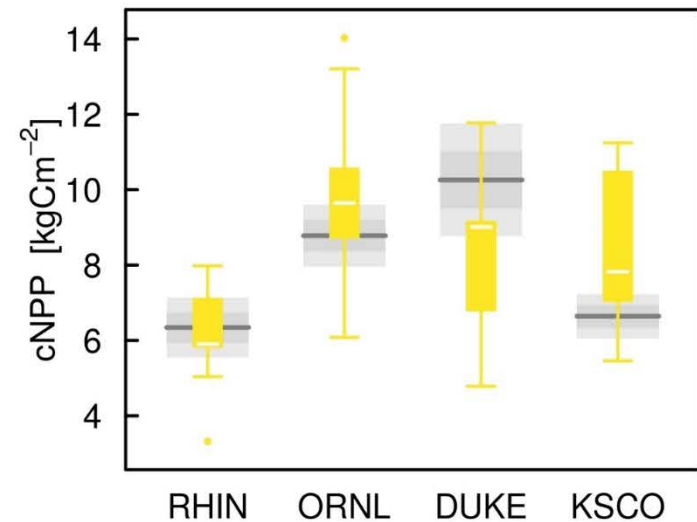
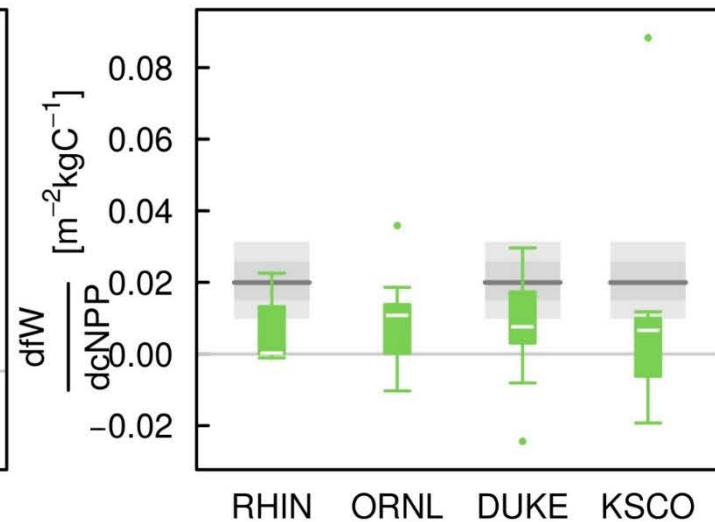
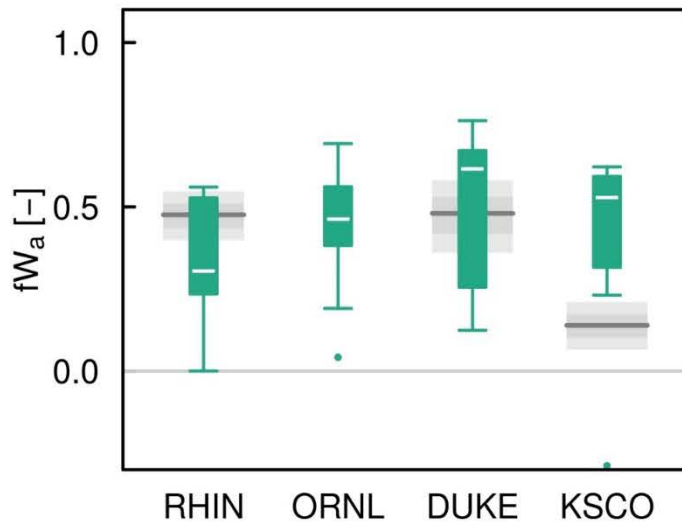
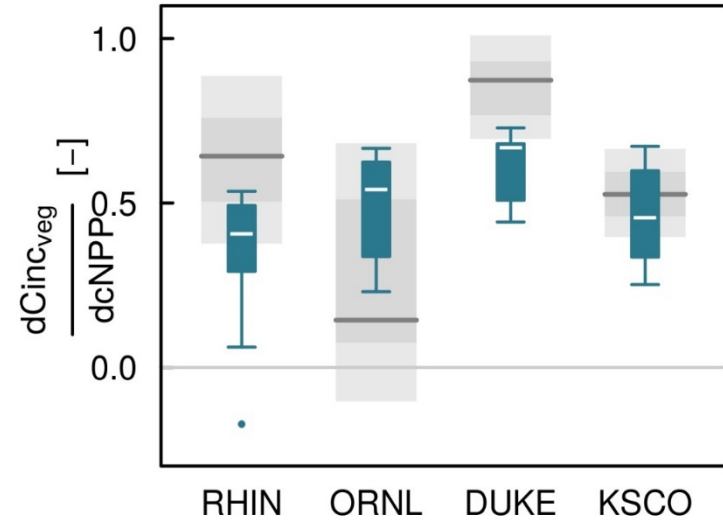
Model ensemble Cinc_{veg} response



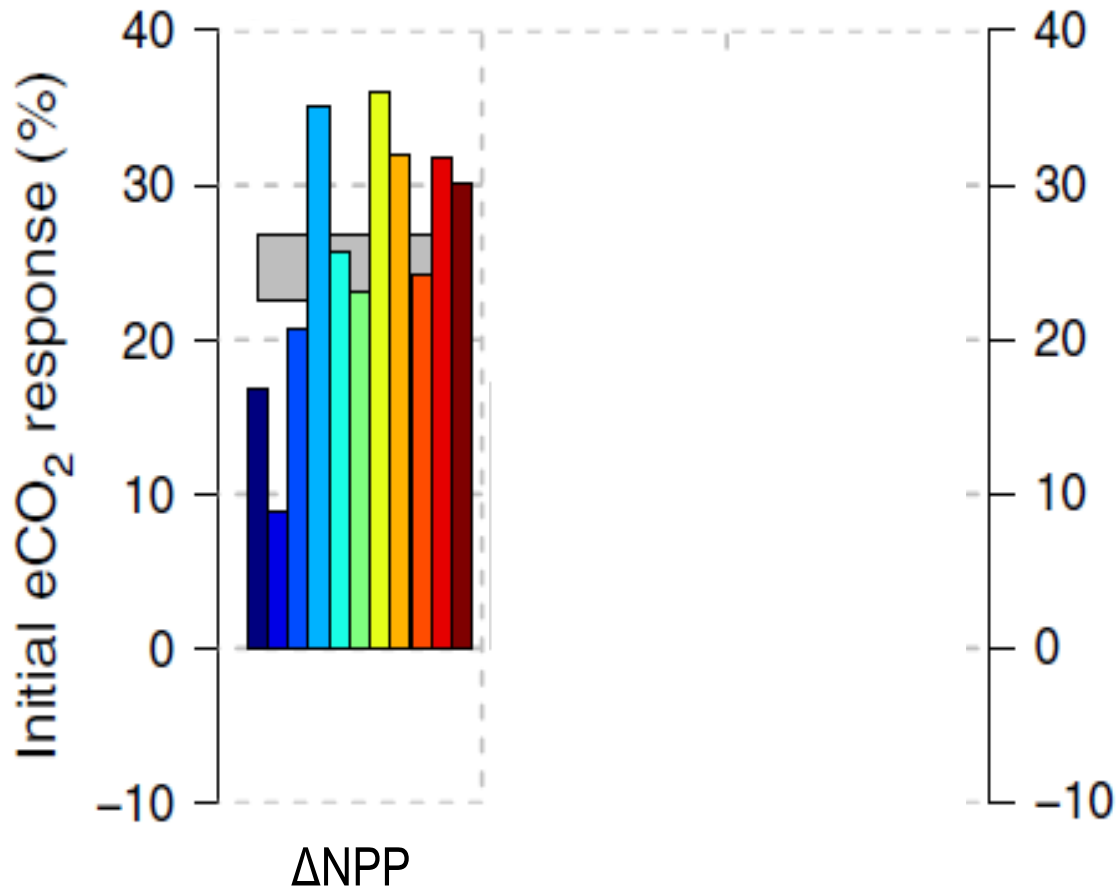
$$Cinc_{veg} = \Delta cNPP \cdot \frac{dCinc_{veg}}{dcNPP}$$

Model ensemble Cinc_{veg} response

$$\frac{dCinc_{veg}}{dcNPP} = fW_a + 2 \frac{dfW}{dcNPP} cNPP$$

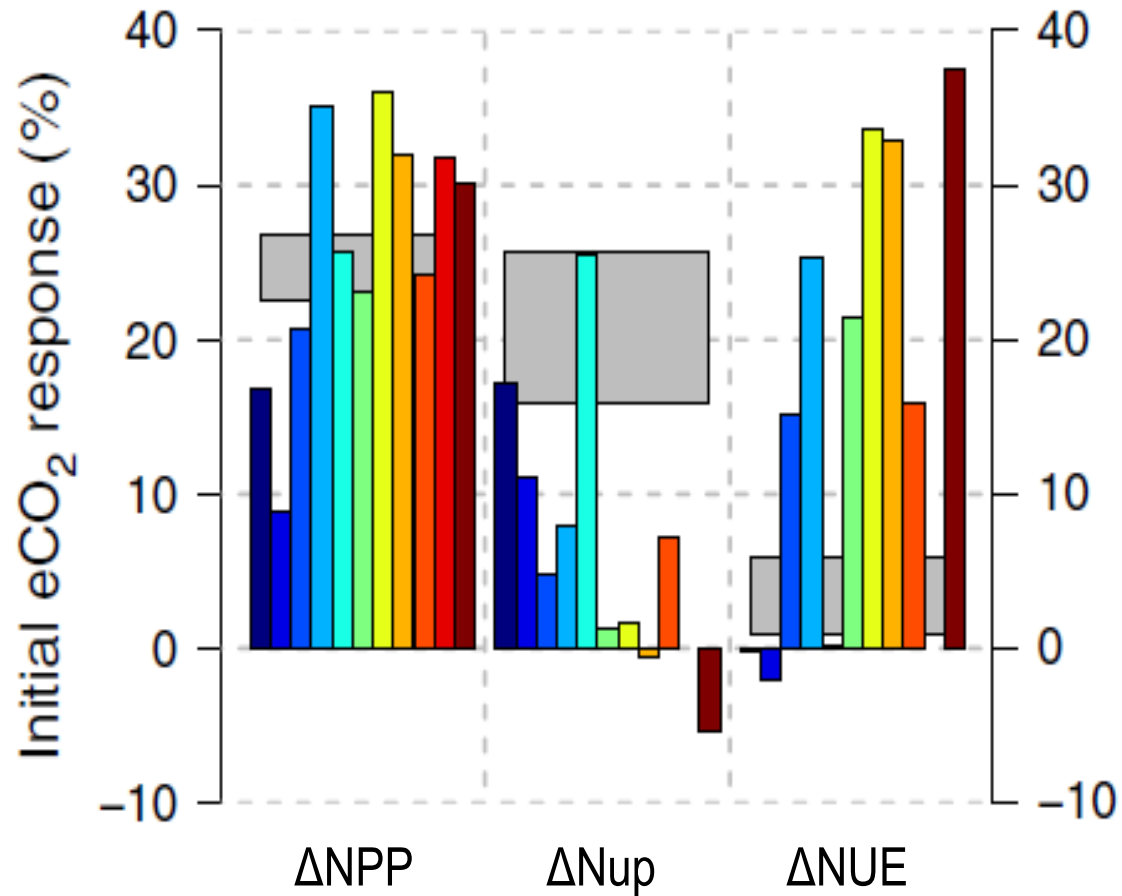


NPP & N response to eCO₂, Duke



$$NPP = N_{up} \times NUE$$
$$\Delta NPP = \Delta N_{up} \times \Delta NUE$$

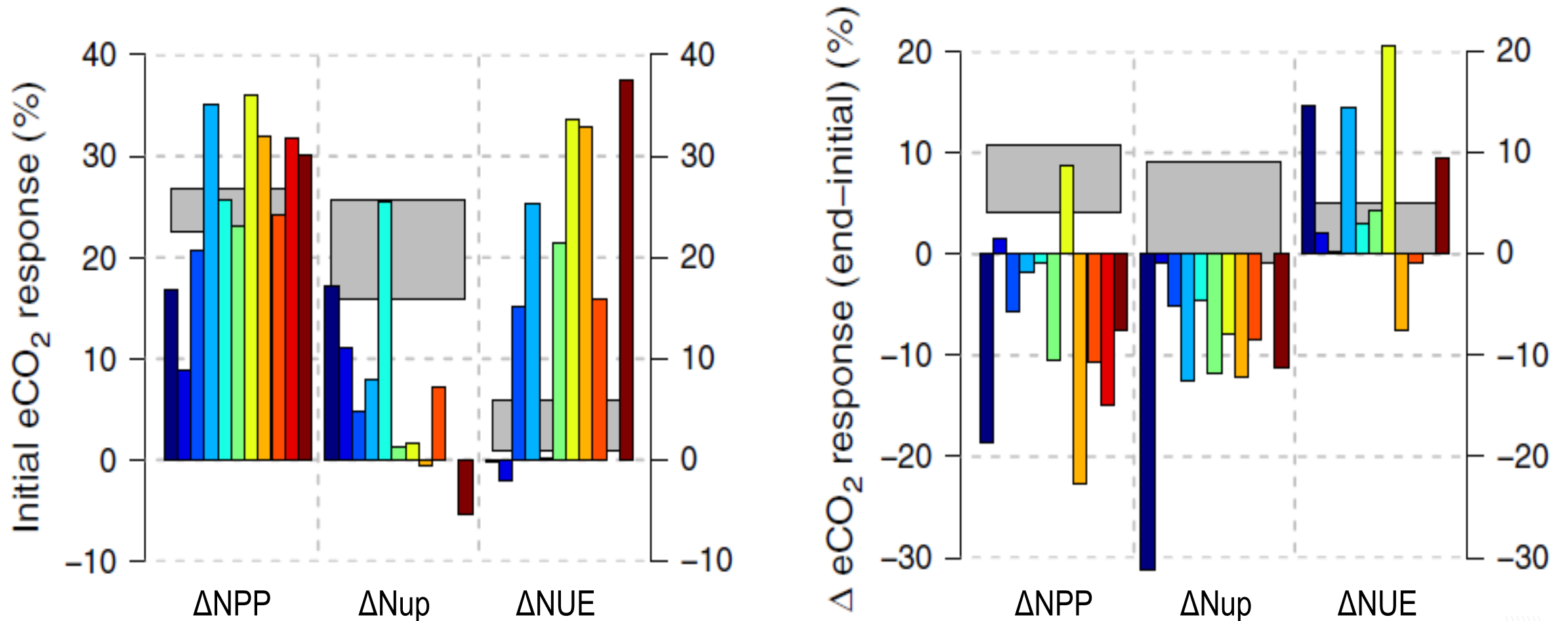
NPP & N response to eCO₂, Duke



$$NPP = N_{up} \times NUE$$

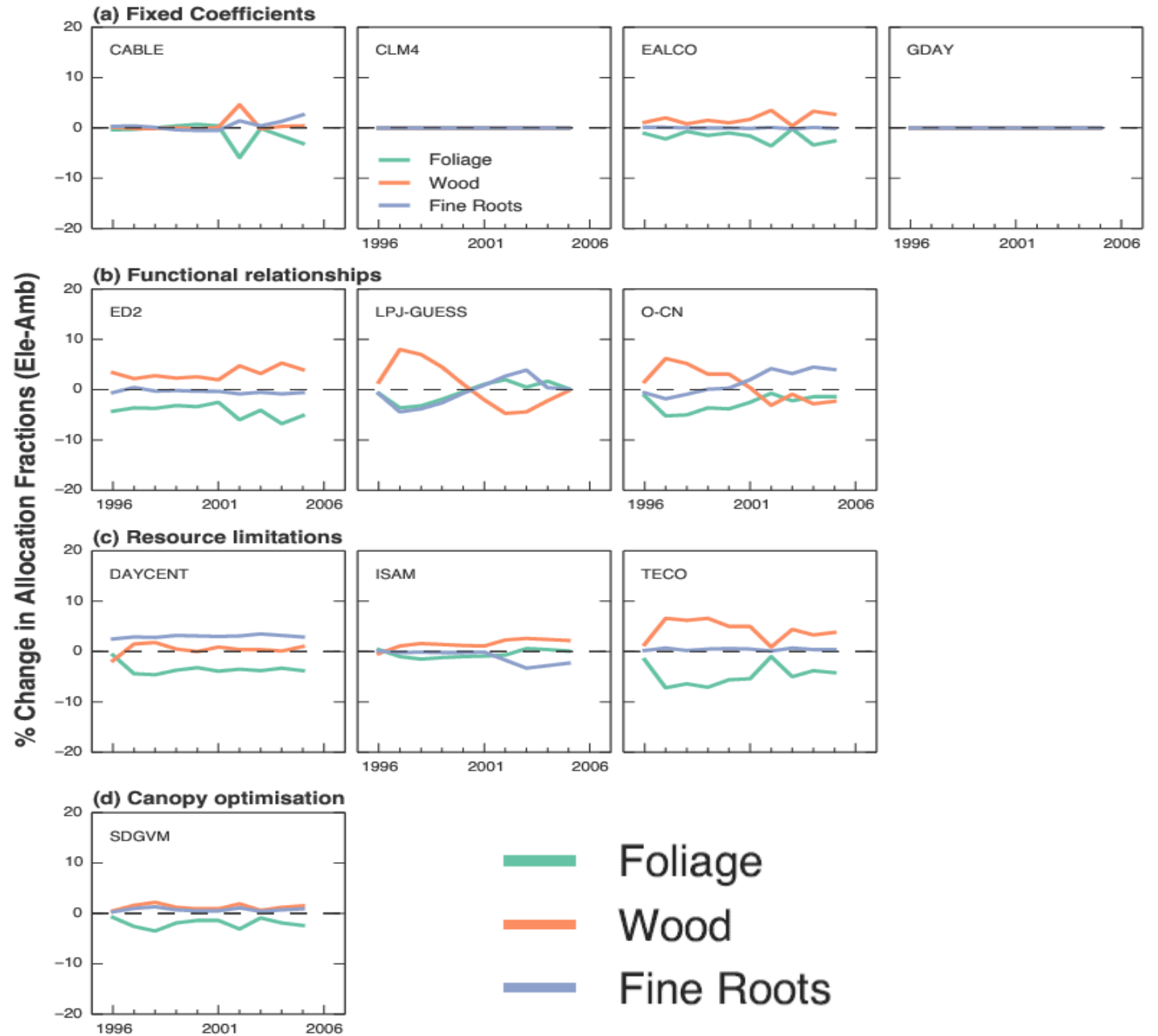
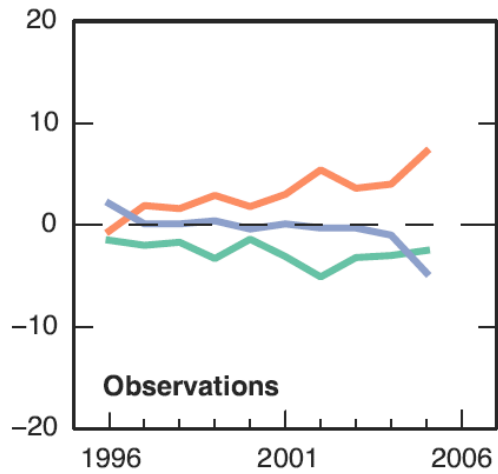
Models generally captured the initial NPP response but confounded the N_{up} response with the NUE response.

NPP & N response to eCO₂, Duke

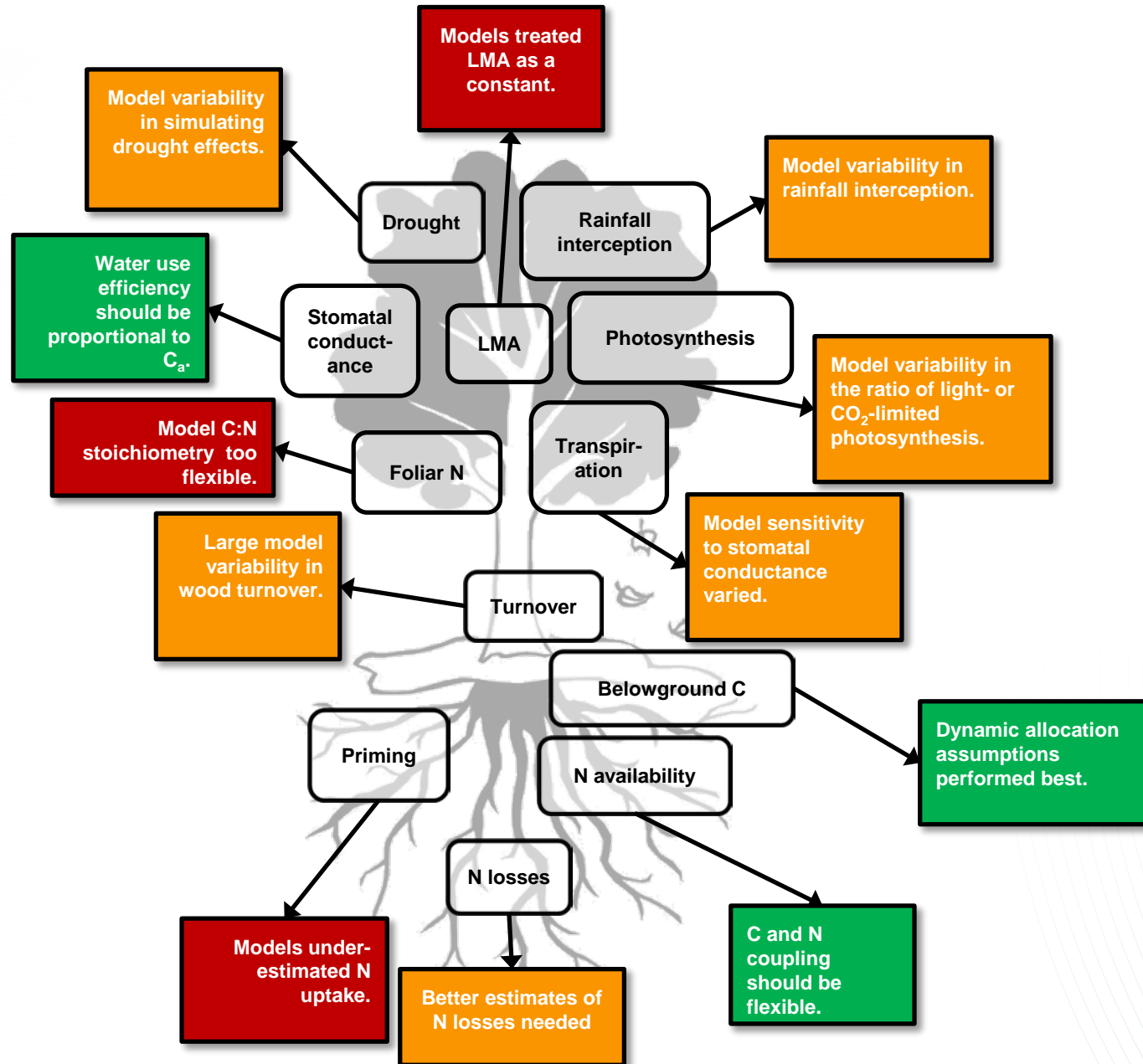


NPP increased by the end of the experiment, all but one model predicted a decrease. Increased Nup was not sustained by the models

Changes in C allocation in response to eCO₂, Duke



FACE-MDS Phase-1 Summary



FACE-MDS 10 yr Biomass Summary

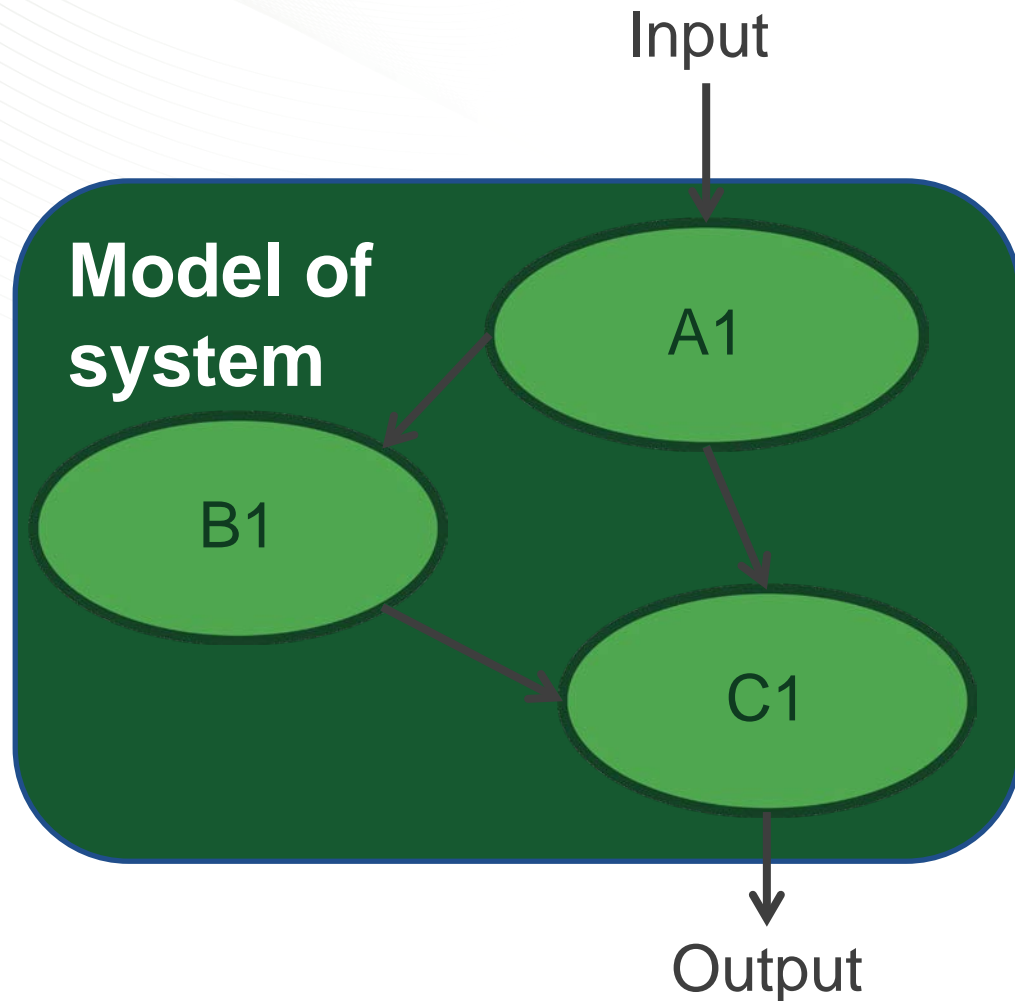
- A sustained long-term stimulation of forest biomass in response to CO₂ concentrations predicted for the middle of the century was clearly demonstrated.
- Modelling this is site specific:
 - At ORNL uncertainty was too high in 10 year biomass response
 - At KSC the temperature by CO₂ interaction was not observed
 - At Rhin and Duke NPP was under-predicted due to inability to increase N uptake AND allocation response to CO₂ was too low

MAAT & multi-hypothesis modeling

Systems are composed of multiple processes

Competing hypotheses can exist for each process

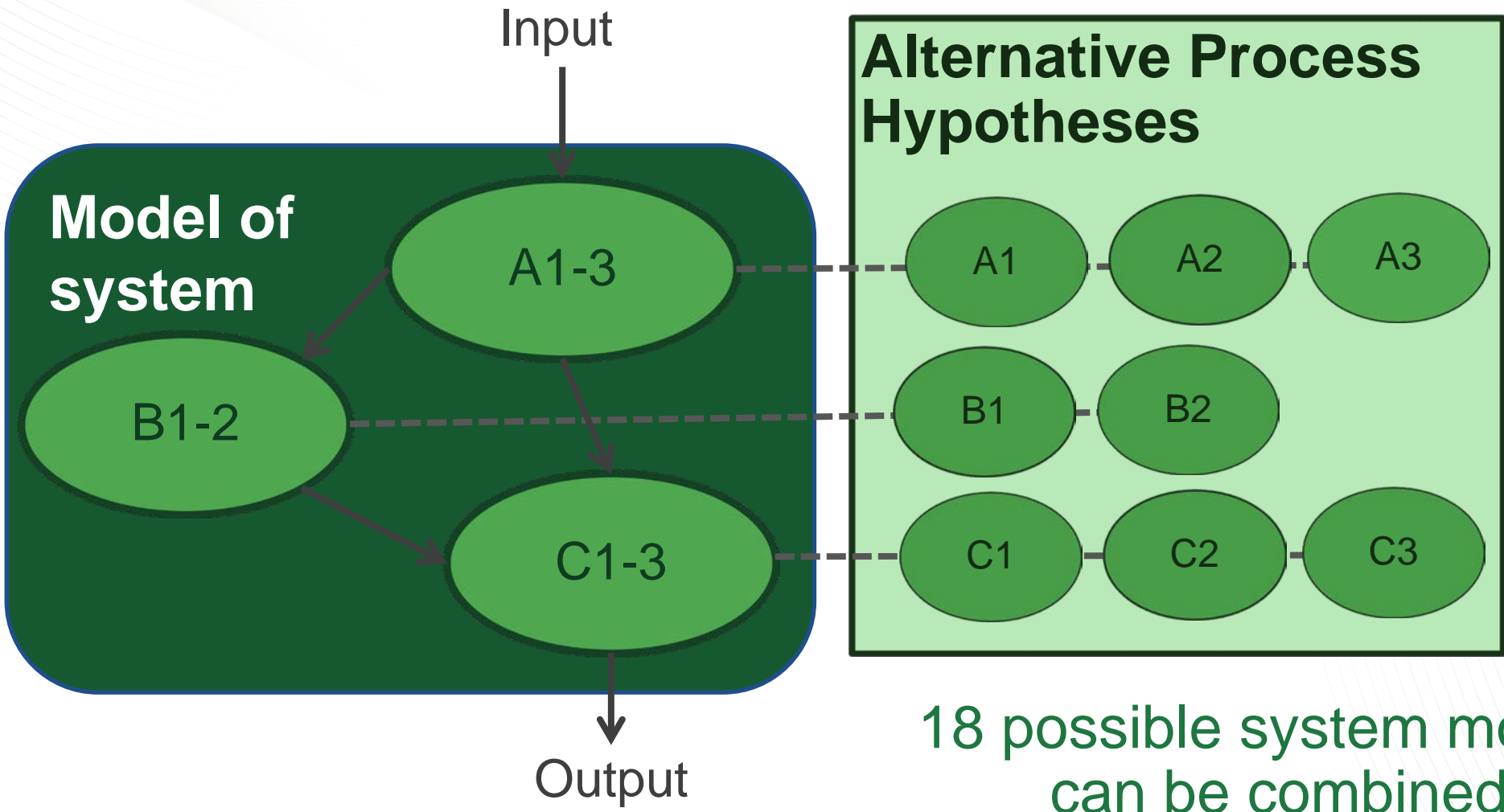
Traditional models use only single hypotheses



Systems are composed of multiple processes

Competing hypotheses can exist for each process

Multi-hypothesis modeling

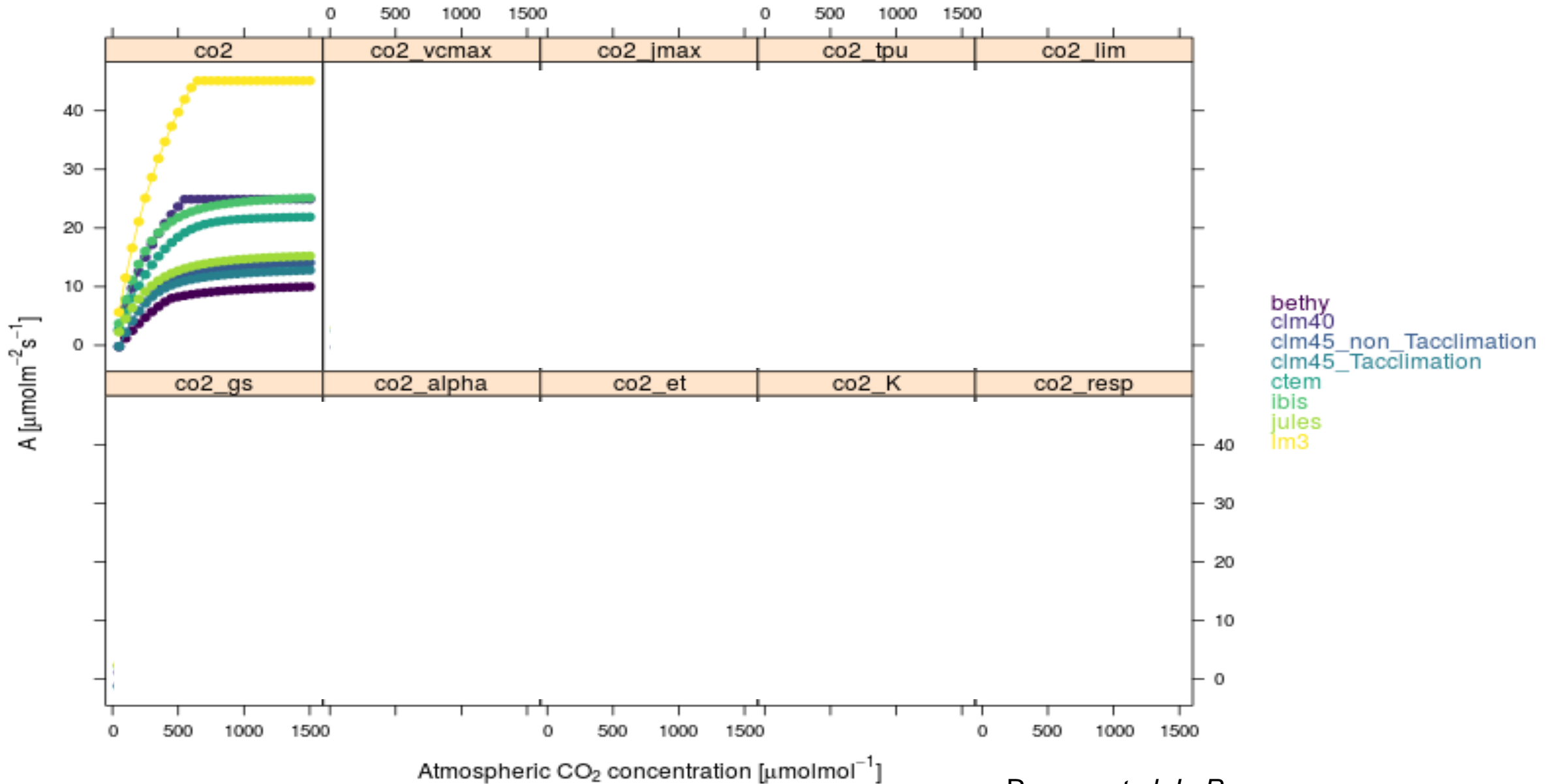


18 possible system models can be combined

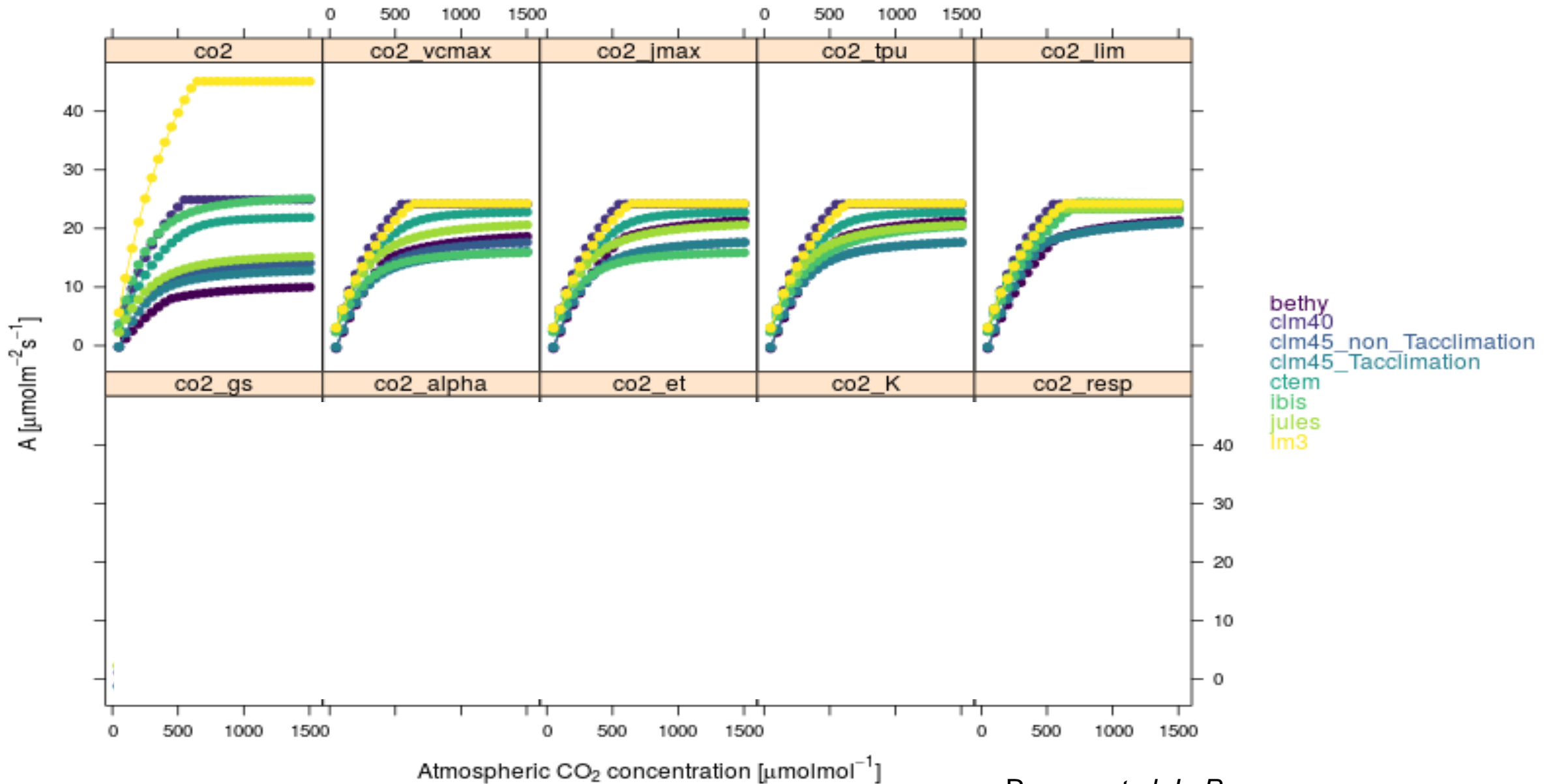
Multi-Assumption Architecture & Testbed (MAAT)

- A multi-hypothesis software framework developed to allow system model configuration with process hypotheses, parameters (traits), and boundary conditions on-the-fly during runtime
- Designed to analyze the variation in system model outputs caused when multiple competing hypotheses exist for multiple processes (considers parameter variability)
- Framework is general and not system specific
- Currently applied to modelling leaf-scale photosynthesis
- Can mimic ALM, CLM, LM3, JULES, BETHY, + others ... or can create and run all possible model combinations
- Employs a novel algorithm for process-level global sensitivity analysis (Dai, *et al.* 2017 *WRR*), as well as for global parameter sensitivity analysis (Saltelli *et al.*, 2010)

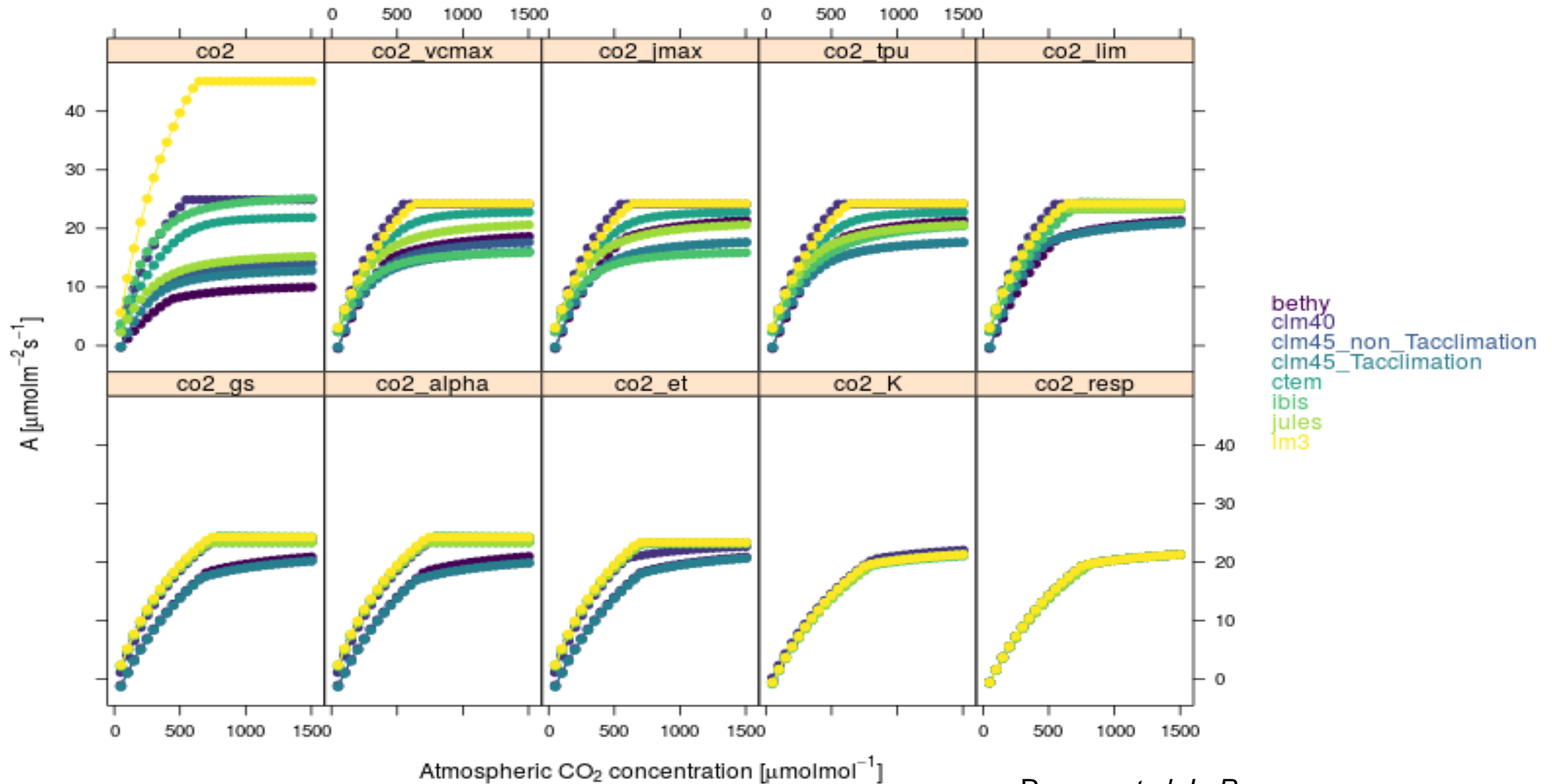
Mimicking & unifying CMIP5 models



Mimicking & unifying CMIP5 models



Mimicking & unifying CMIP5 models






The first step towards predictive understanding is to properly characterise uncertainty and identify its sources

AGU PUBLICATIONS

Water Resources Research

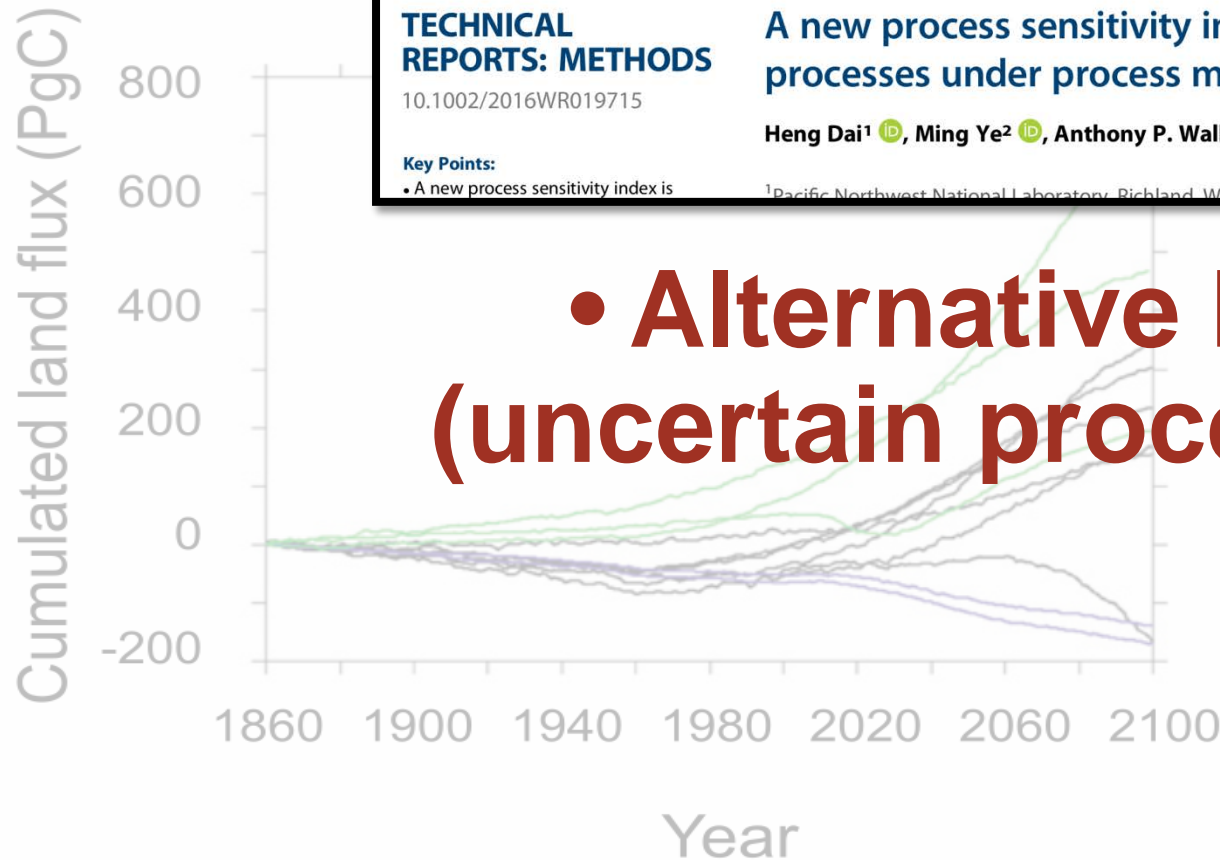
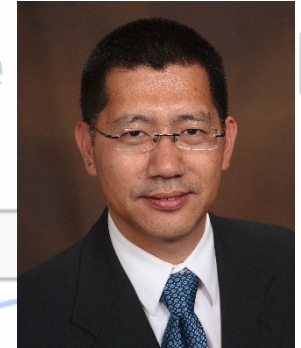
TECHNICAL REPORTS: METHODS
10.1002/2016WR019715

A new process sensitivity index to identify important system processes under process model and parametric uncertainty

Heng Dai¹ , Ming Ye² , Anthony P. Walker³ , and Xingyuan Chen¹ 

Key Points:
• A new process sensitivity index is

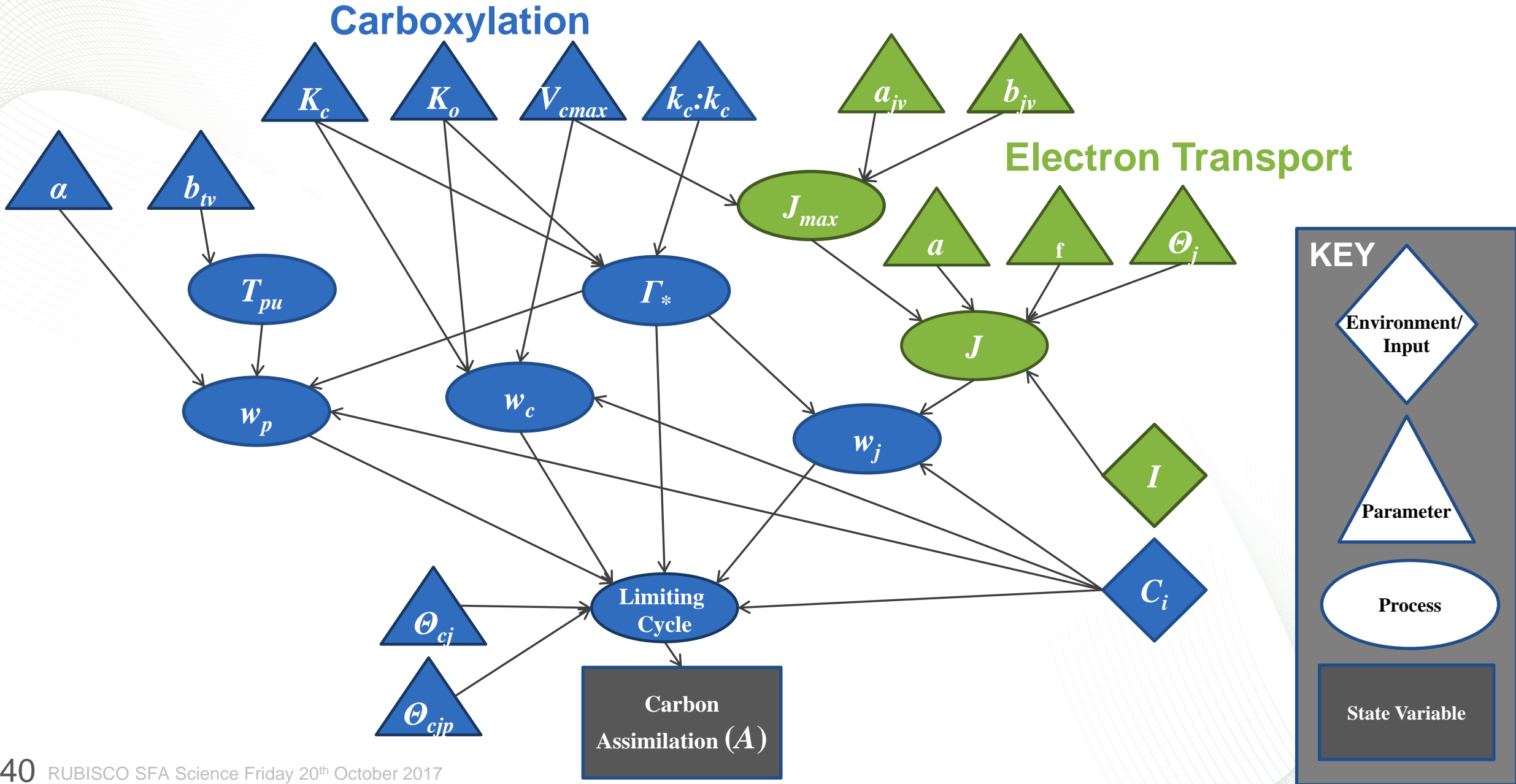
¹Pacific Northwest National Laboratory, Richland, Washington, USA. ²Department of Scientific Computing, Florida State



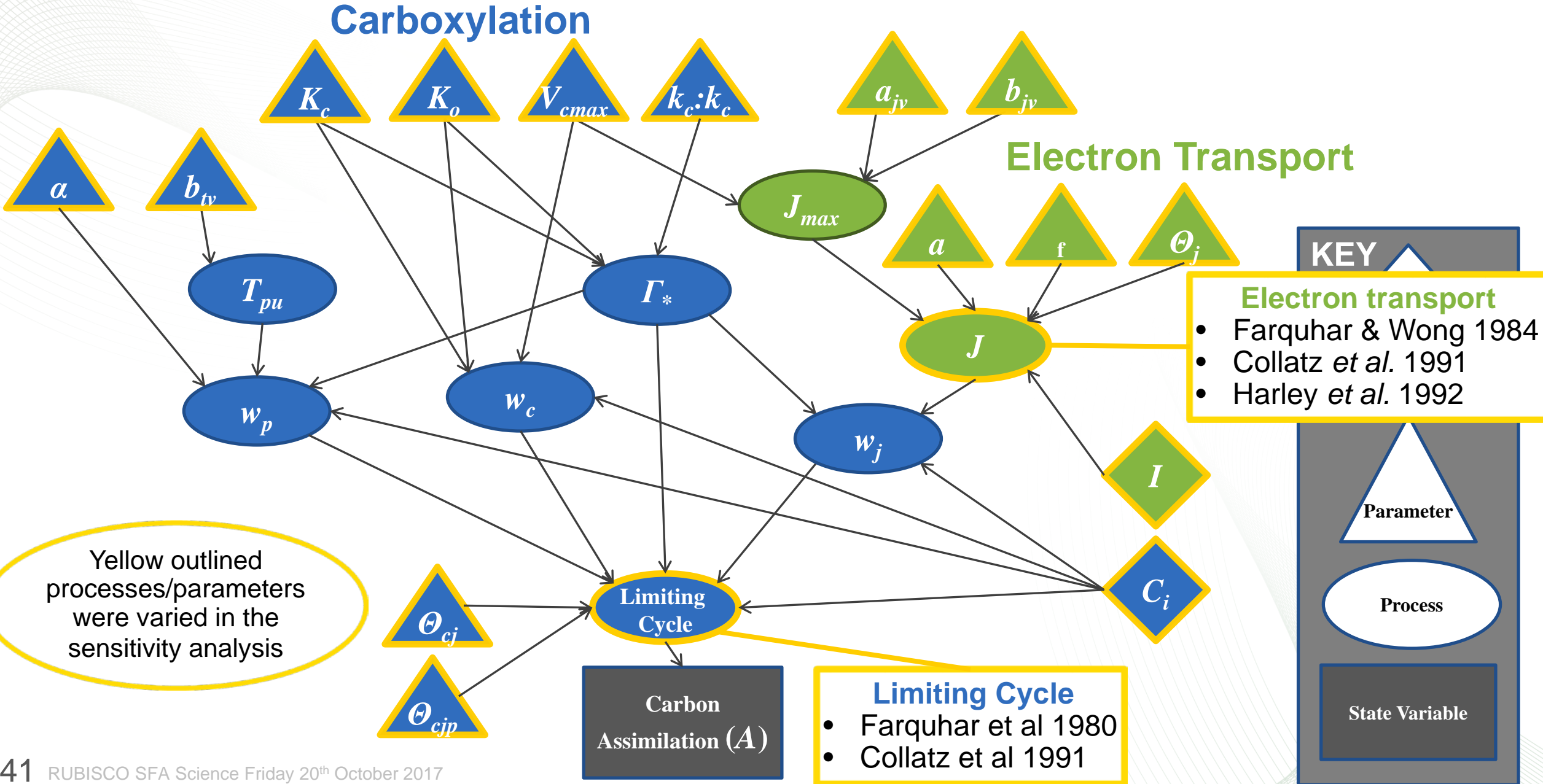
- **Alternative hypotheses (uncertain process knowledge)**



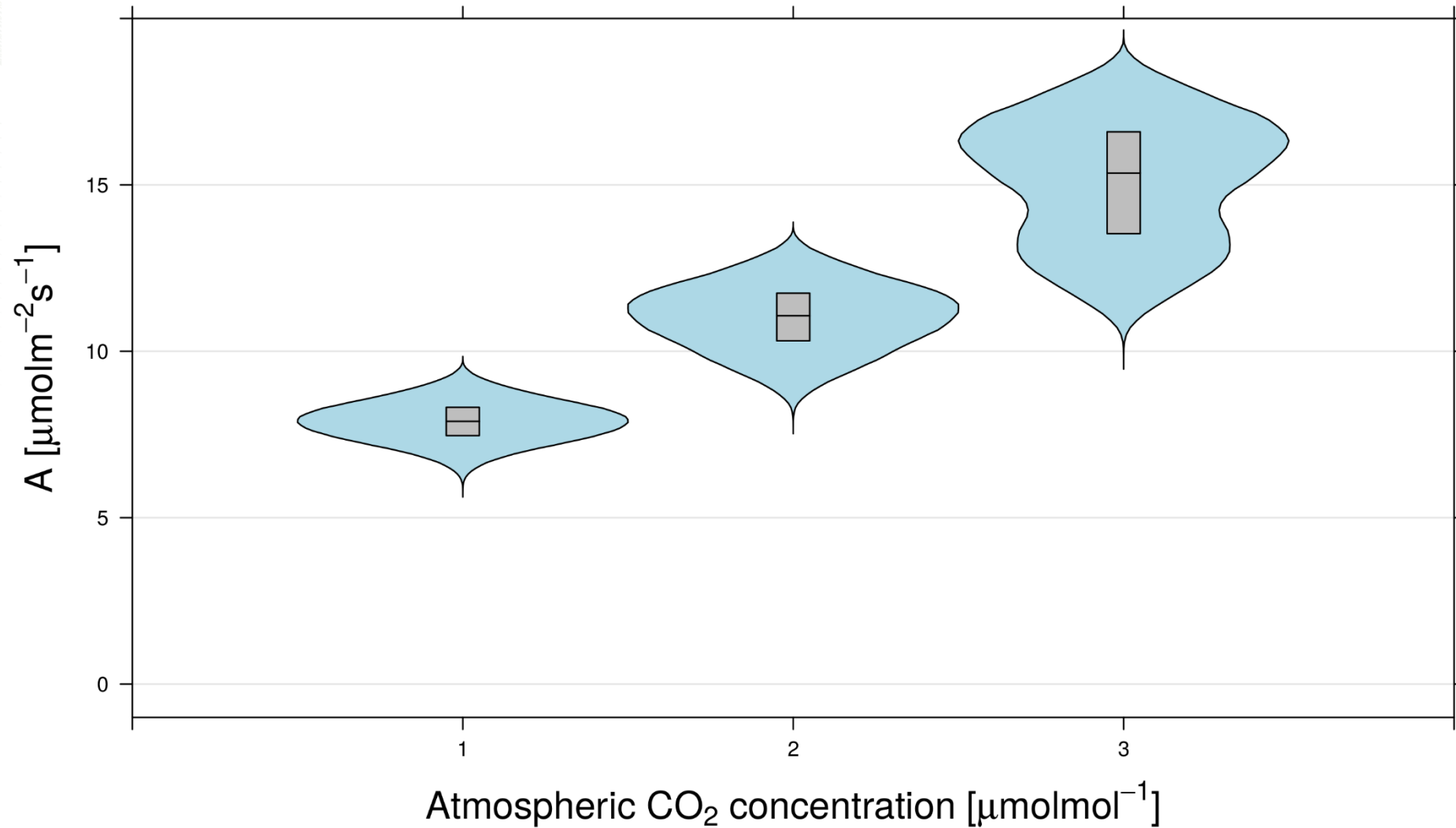
Graph of the enzyme kinetic model of C3 photosynthesis:



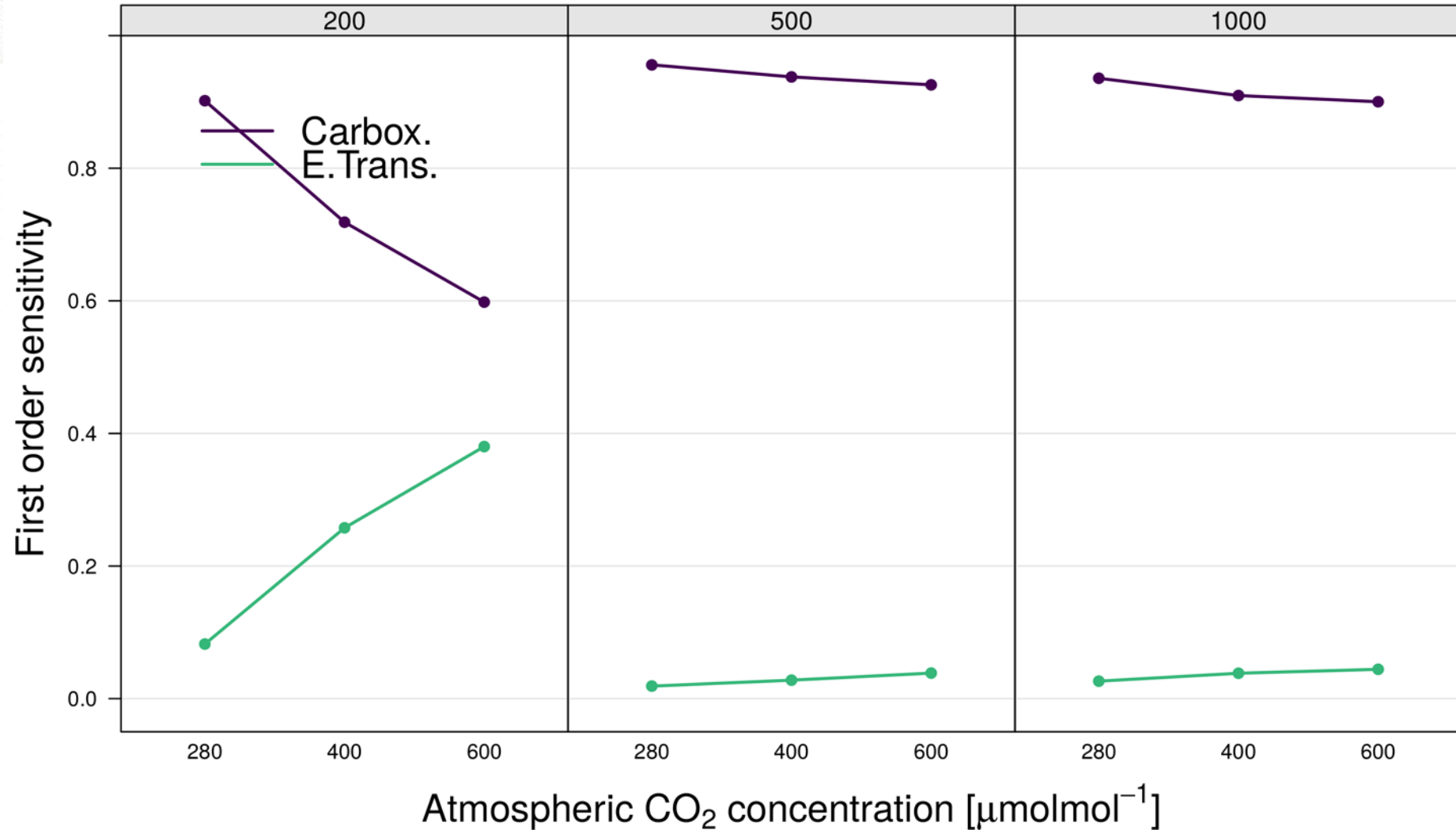
Graph of the enzyme kinetic model of C3 photosynthesis:



Variability in carbon assimilation

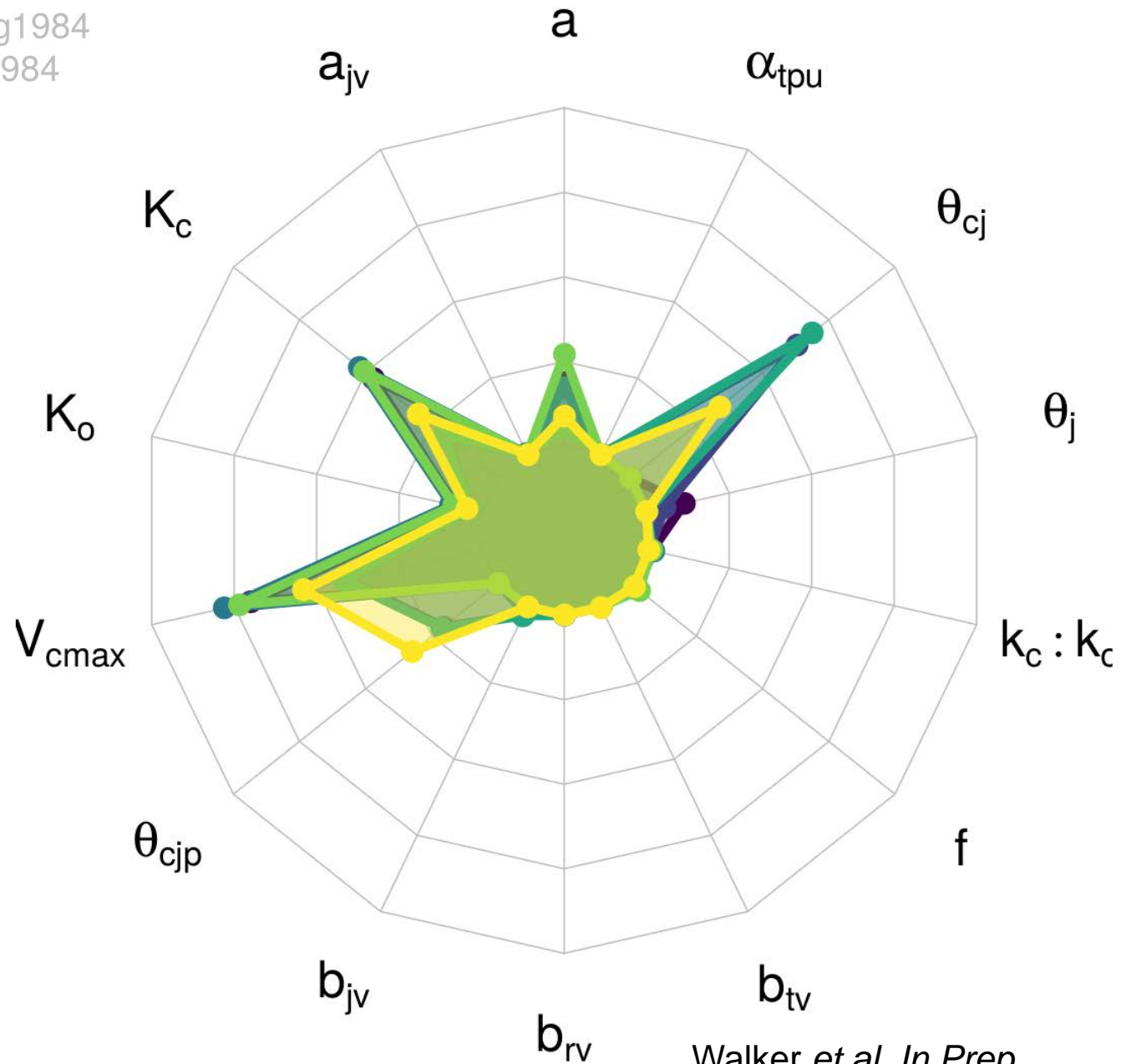


Process Sensitivity Index against CO₂

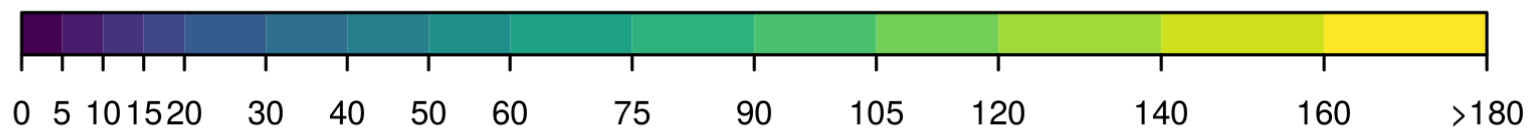
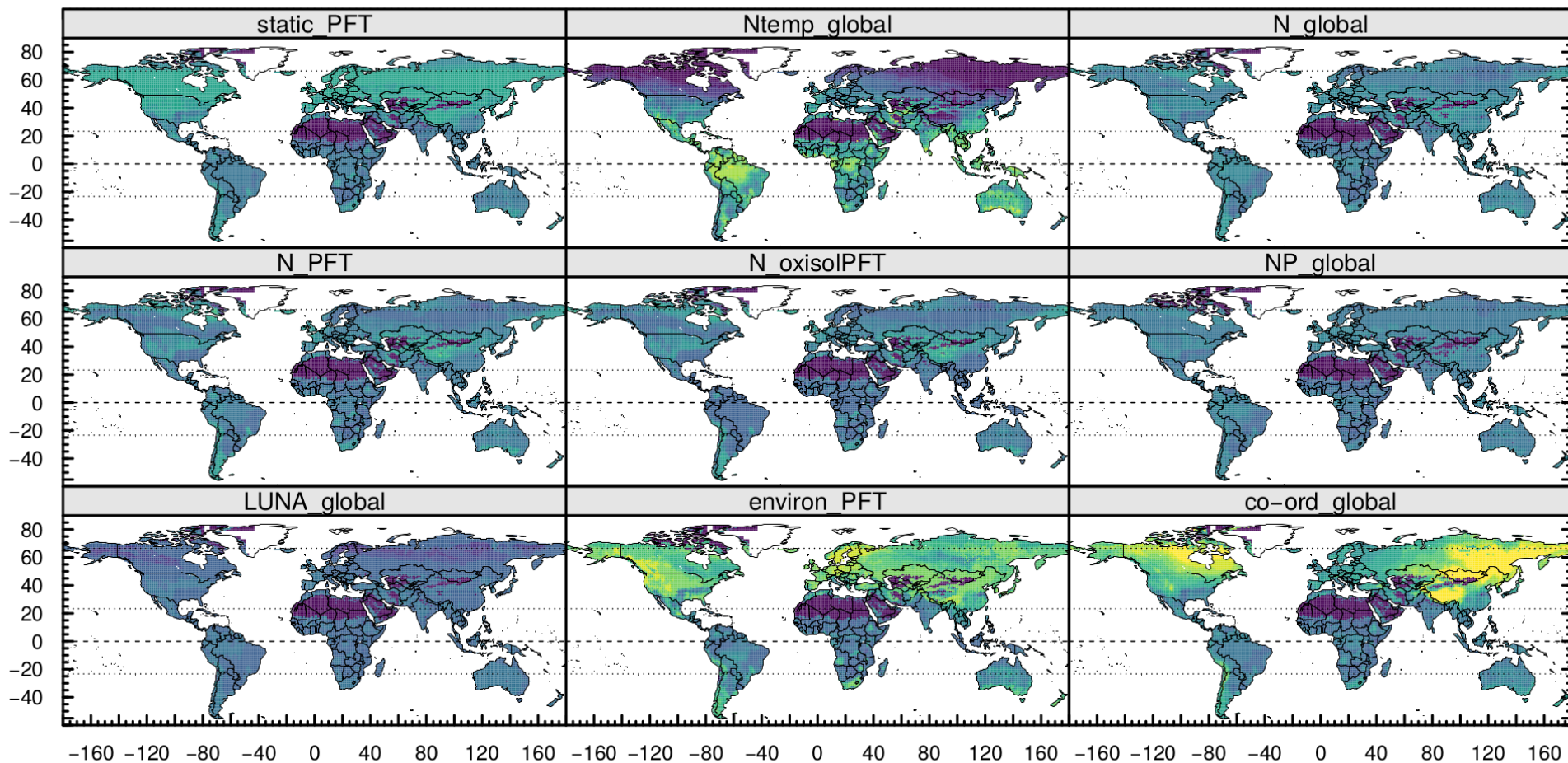


Parameter Sensitivity Index

- f_lim_farquhar1980 f_j_farquharwong1984
- f_lim_collatz1991 f_j_farquharwong1984
- f_lim_farquhar1980 f_j_harley1992
- f_lim_collatz1991 f_j_harley1992
- f_lim_farquhar1980 f_j_collatz1991
- f_lim_collatz1991 f_j_collatz1991

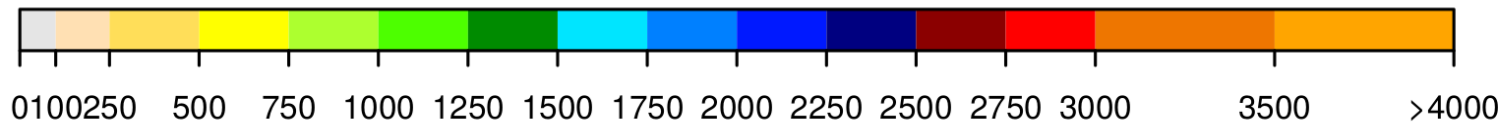
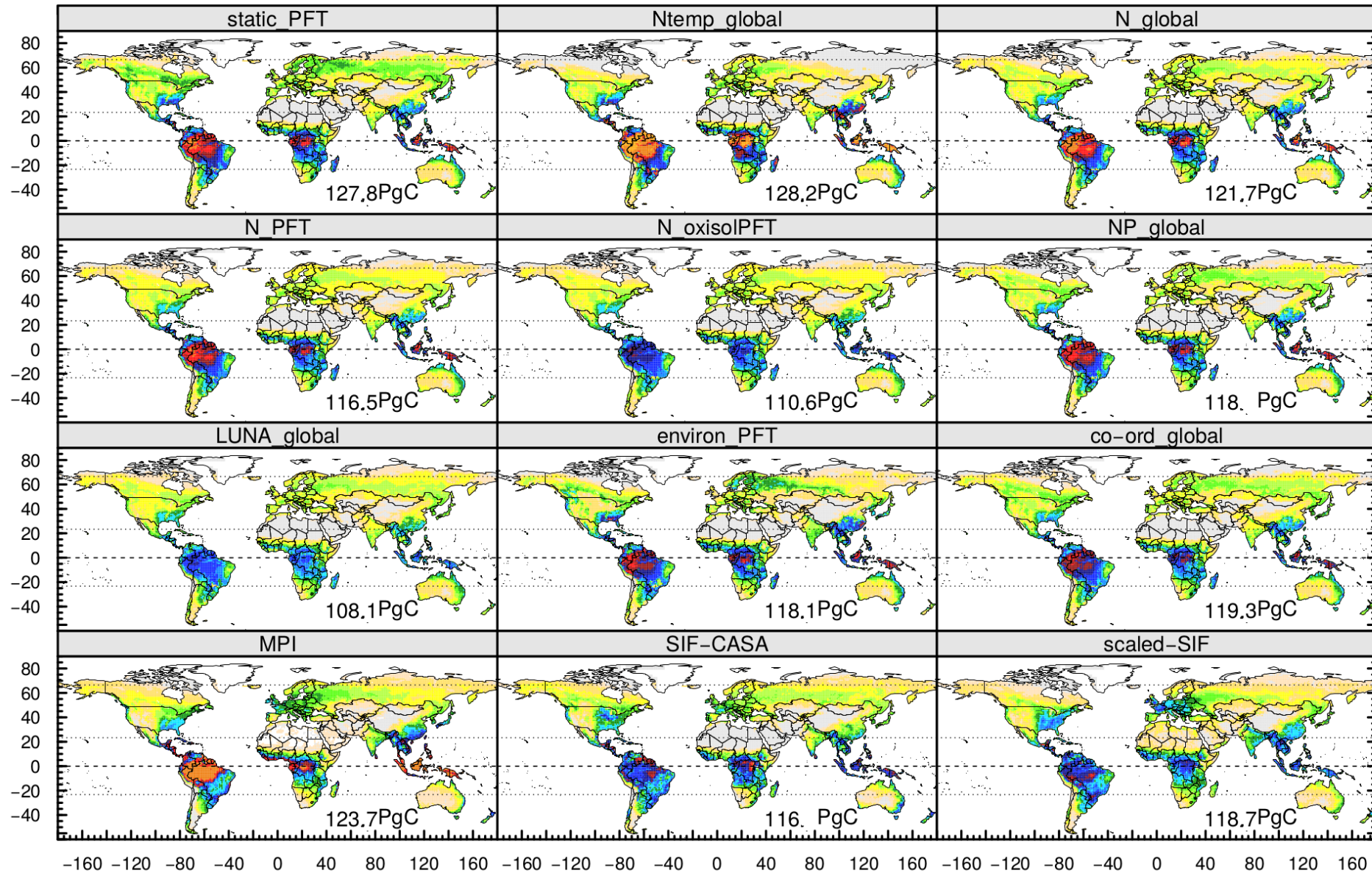


Evaluation of global GPP

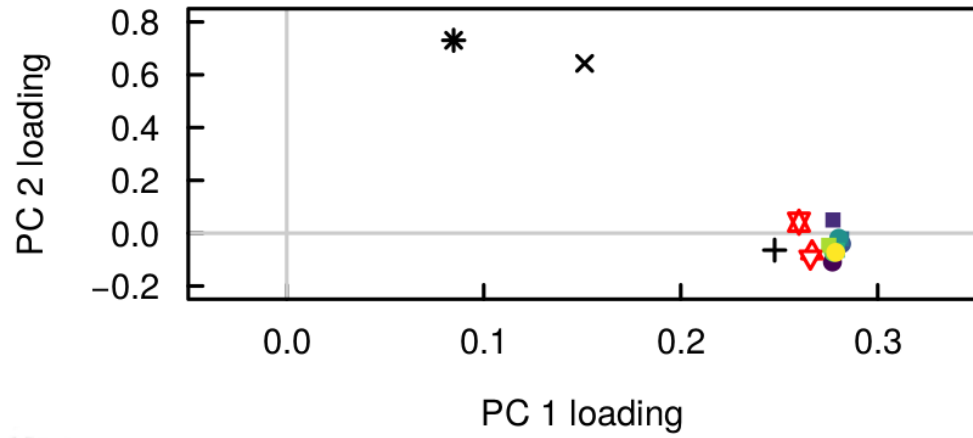


$V_{cmax} (\mu\text{mol m}^{-2} \text{s}^{-1})$

GPP

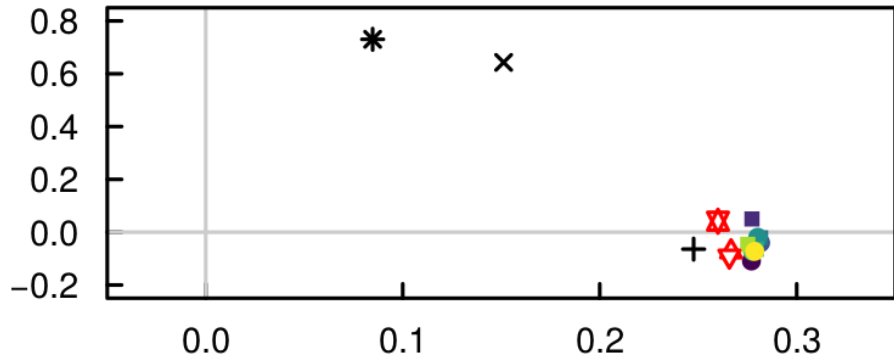


PCA as a model evaluation tool

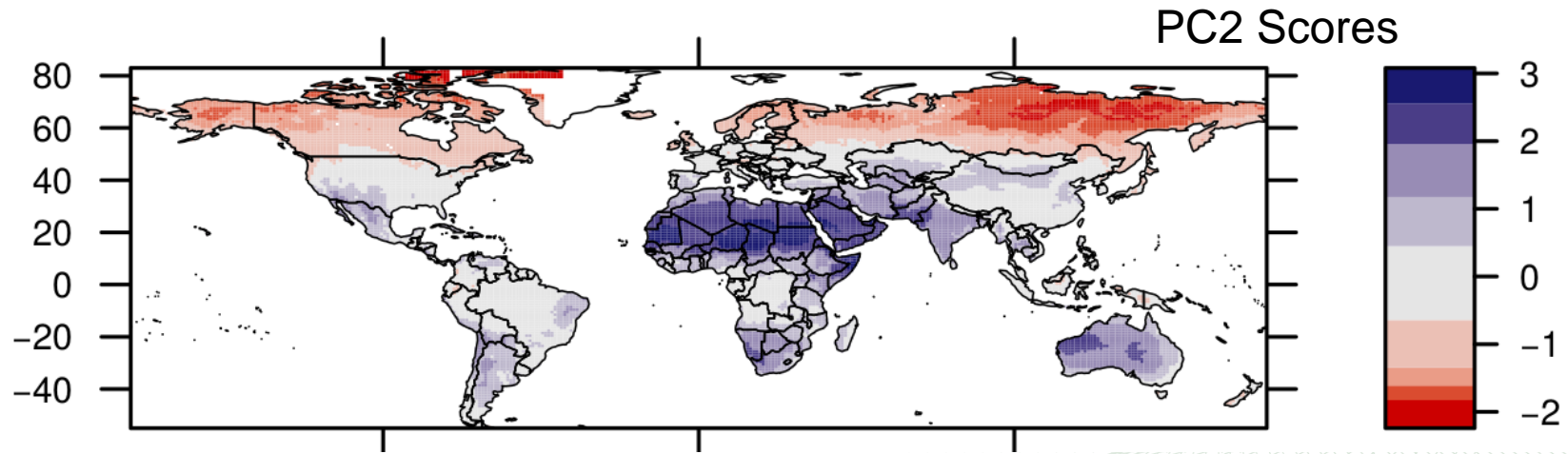
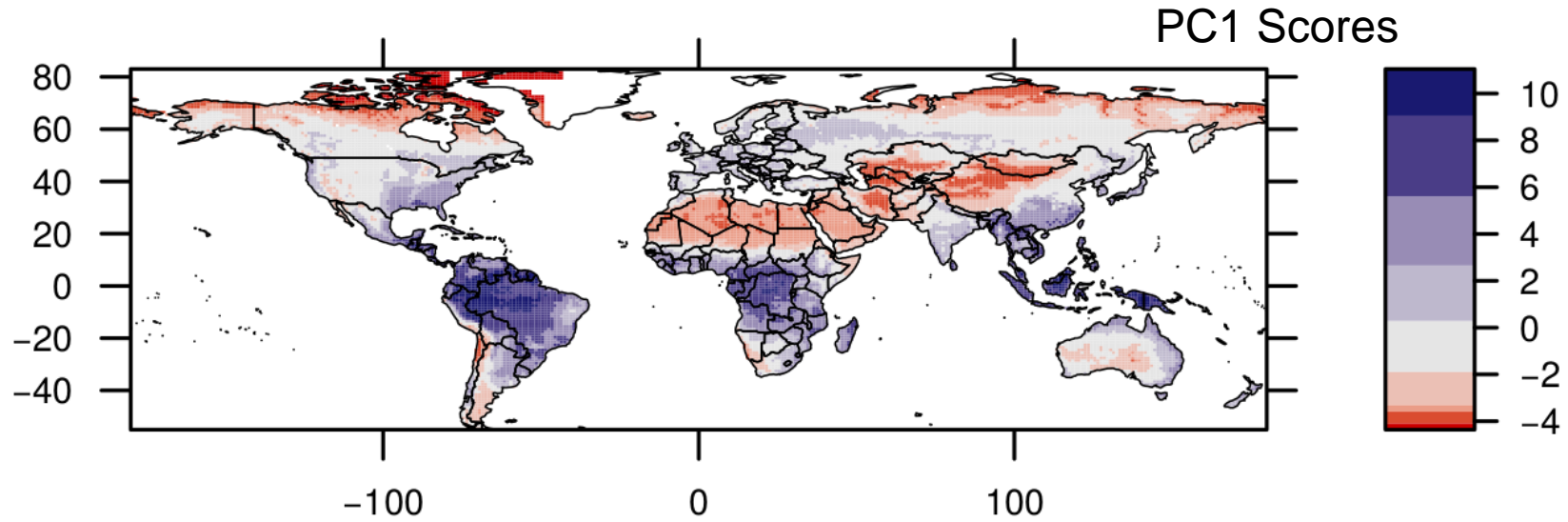


- | | | | |
|--------------|---|---------------|---|
| static_PFT | ● | co-ord_global | ● |
| Ntemp_global | ■ | MPI | △ |
| N_global | ● | scaled-SIF | ⊠ |
| N_PFT | ■ | SIF-CASA | ▽ |
| N_oxisolPFT | ● | prc | + |
| NP_global | ■ | tmp | × |
| LUNA_global | ● | swr | * |
| environ_PFT | ■ | | |

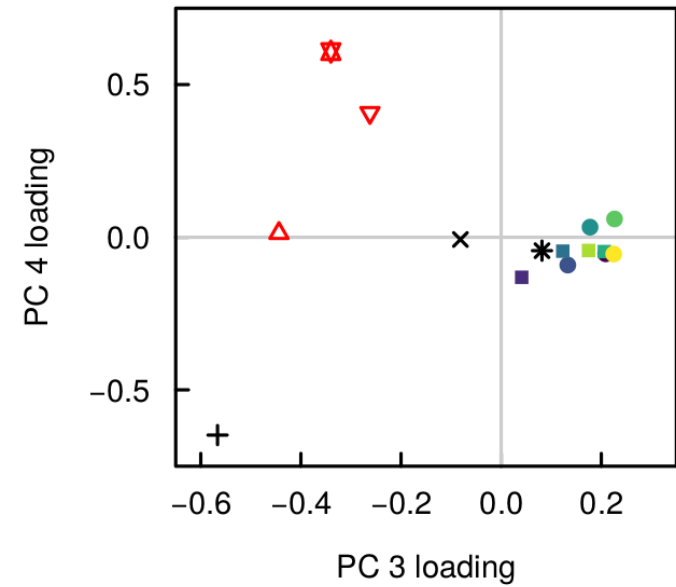
PCA suggests the first mode of spatial GPP variability is driven by precipitation



- | | | | |
|--------------|---|---------------|---|
| static_PFT | ● | co-ord_global | ● |
| Ntemp_global | ■ | MPI | △ |
| N_global | ● | scaled-SIF | ⊠ |
| N_PFT | ■ | SIF-CASA | ▽ |
| N_oxisolPFT | ● | prc | + |
| NP_global | ■ | tmp | × |
| LUNA_global | ● | swr | * |
| environ_PFT | ■ | | |

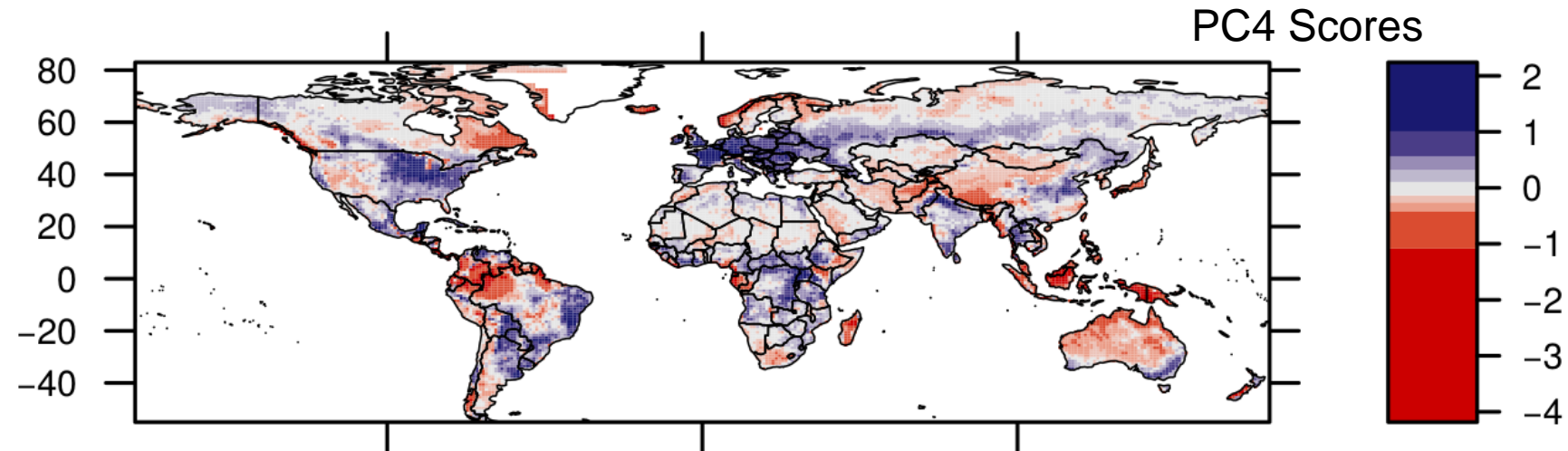
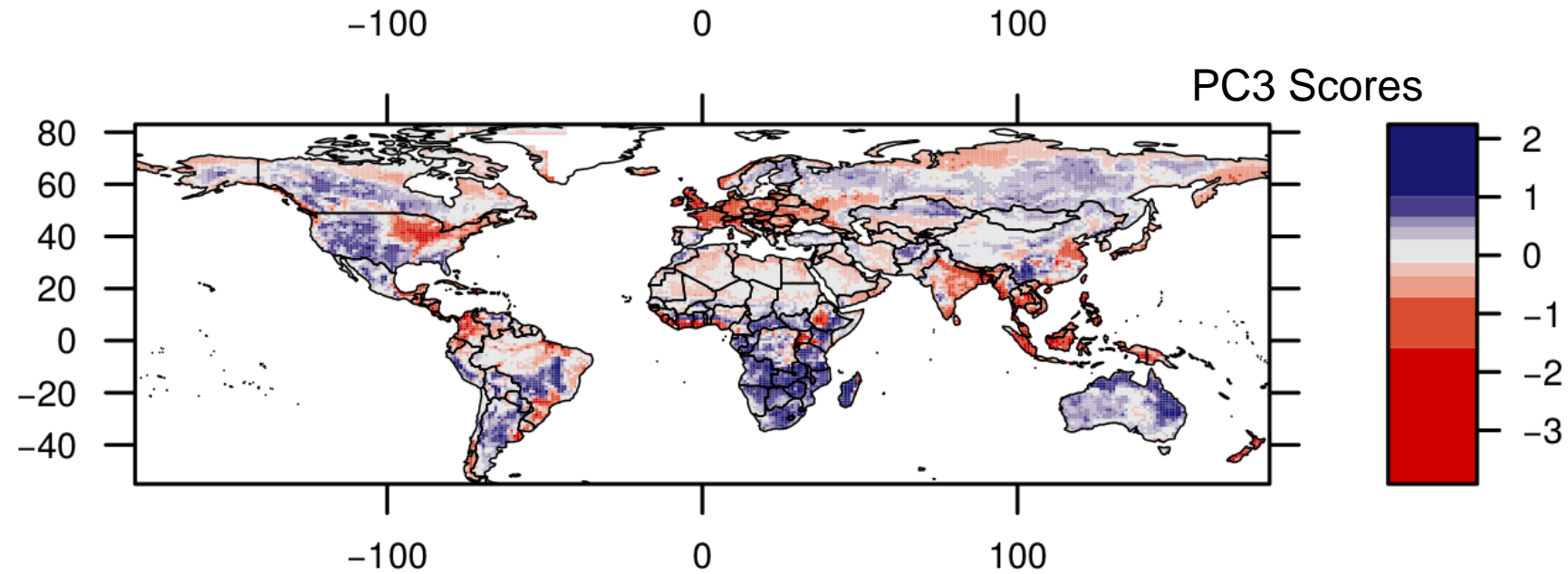
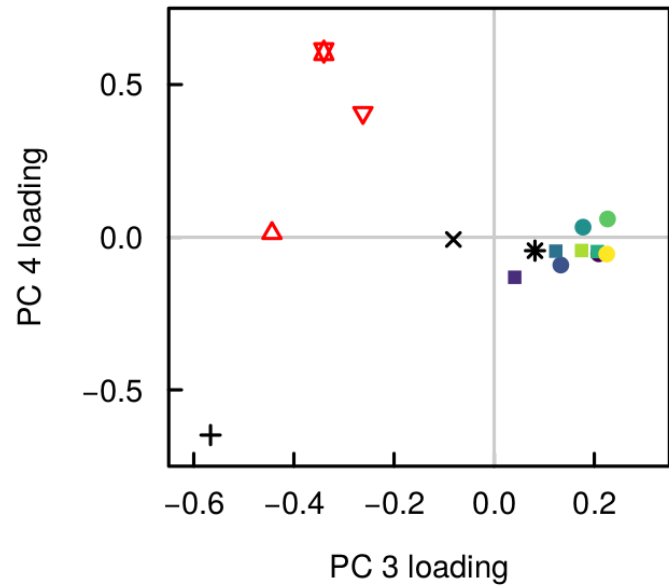


PC4 segregates SIF based GPP from precipitation



- | | | | |
|--------------|---|---------------|---|
| static_PFT | ● | co-ord_global | ● |
| Ntemp_global | ■ | MPI | △ |
| N_global | ● | scaled-SIF | ⊠ |
| N_PFT | ■ | SIF-CASA | ▽ |
| N_oxisoIPFT | ● | prc | + |
| NP_global | ■ | tmp | × |
| LUNA_global | ● | swr | * |
| environ_PFT | ■ | | |

PC4 segregates SIF based GPP from precipitation

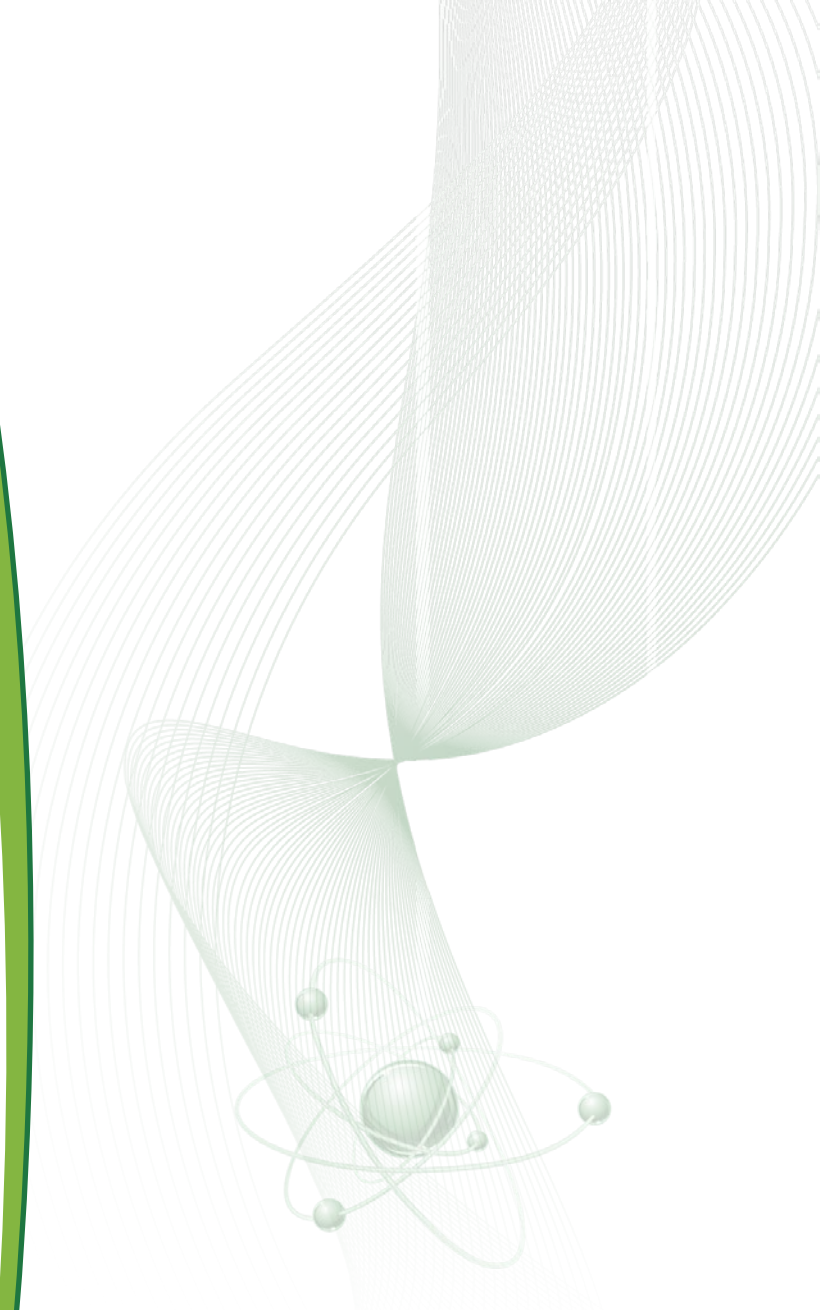


- | | | | |
|--------------|---|---------------|---|
| static_PFT | ● | co-ord_global | ● |
| Ntemp_global | ■ | MPI | △ |
| N_global | ● | scaled-SIF | ⊠ |
| N_PFT | ■ | SIF-CASA | ▽ |
| N_oxisoIPFT | ● | prc | + |
| NP_global | ■ | tmp | x |
| LUNA_global | ● | swr | * |
| environ_PFT | ■ | | |

Quick Summary

- Process based model analysis is useful and interesting
- A number of methods are out there including:
 - Variable decomposition
 - Comparison against simple models (not shown, but used in FACE-MDS)
 - Multi-assumption modelling
 - PCA (not strictly process based, but can be used to observed patterns and support process based hypotheses)

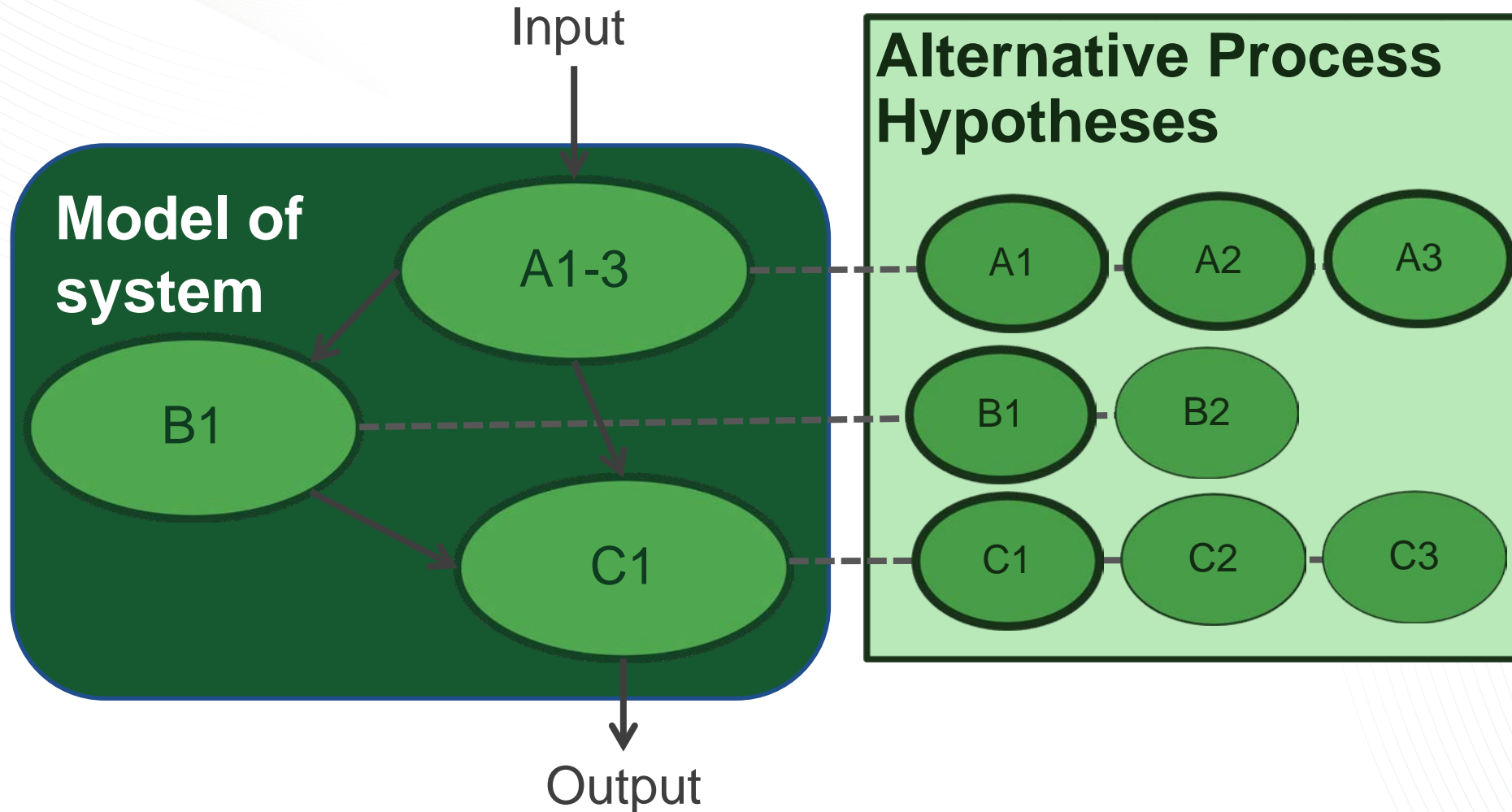
Thanks to you, collaborators, and sponsors



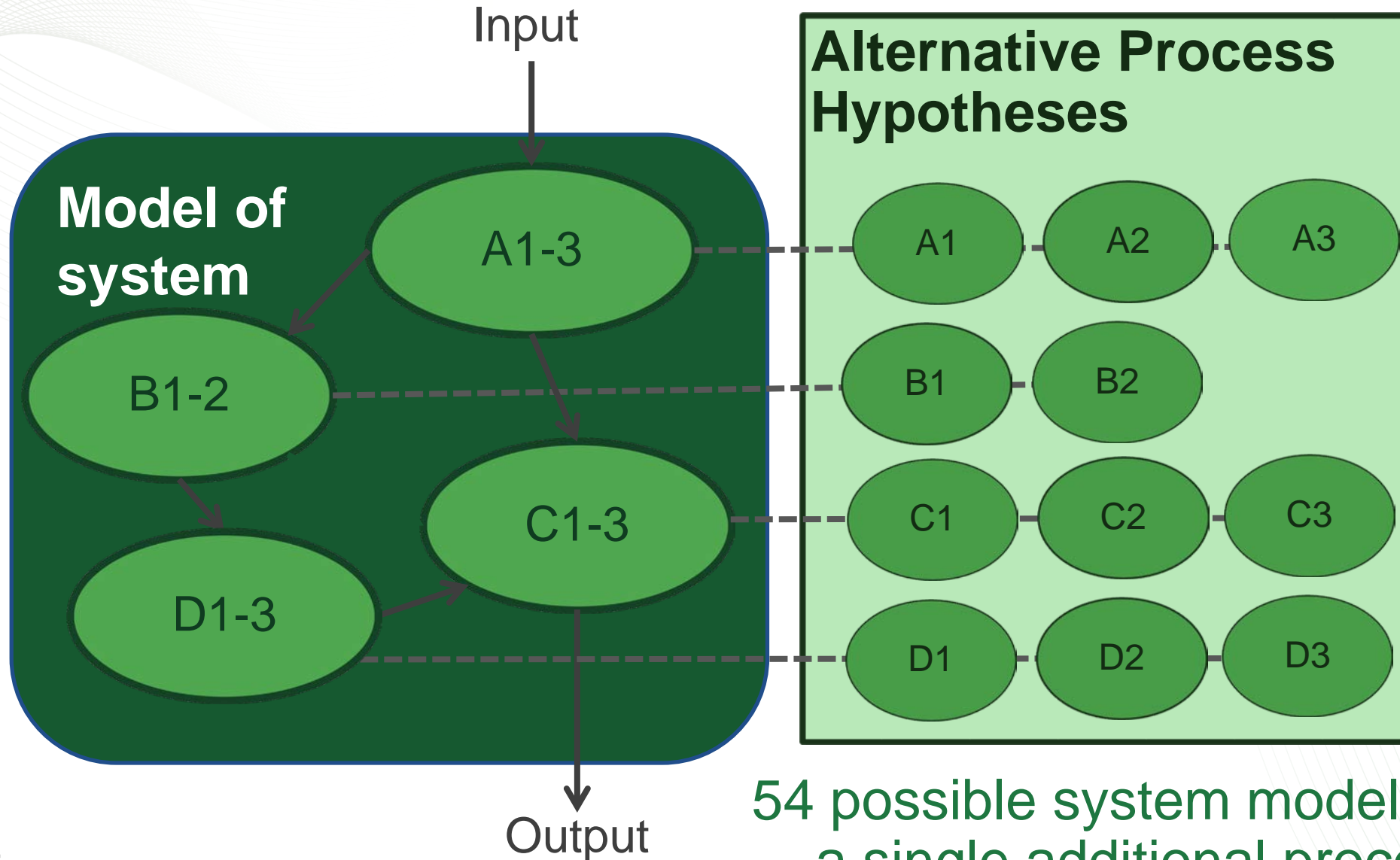
Systems are composed of multiple processes

Competing hypotheses can exist for each process

Single process multi-hypothesis modeling



... but additional processes come with the cost of additional uncertainty & model complexity



54 possible system models with a single additional process