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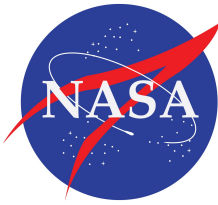
U.S. DEPARTMENT OF  
**ENERGY**

Office of  
Science



**RUBISCO**

REDUCING UNCERTAINTIES IN BIOGEOCHEMICAL  
INTERACTIONS THROUGH SYNTHESIS AND COMPUTATION



# CO<sub>2</sub> fertilization of terrestrial photosynthesis inferred from site to global scales

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**RUBISCO Biogeochemistry Science Seminar  
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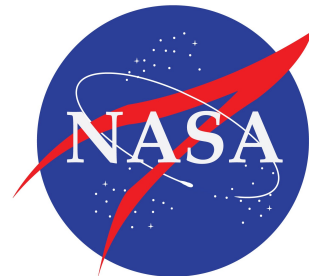
# The research questions

1. **When** and **how** can we detect a signal of **CO<sub>2</sub> fertilization effect** (CFE) emerge in long-term measurement of carbon flux from globally distributed networks?



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2. Can we accurately **constrain** CFE using satellite observations / meteorological reanalysis data?



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# First-order CO<sub>2</sub> fertilization effect

- Terrestrial photosynthesis is quantified by terrestrial Gross Primary Productivity (GPP).
- Exchange of CO<sub>2</sub> and water vapor fluxes between the land and the atmosphere.
- Both fluxes can be described by the Fickian gas diffusion.

Stomatal conductance      leaf intercellular CO<sub>2</sub> mole fraction

e.g.:  $f_c = g(c_a - c_i)$

CO<sub>2</sub> flux      Atm. CO<sub>2</sub> mole fraction

The diagram illustrates the equation  $f_c = g(c_a - c_i)$  with arrows indicating the variables:  $f_c$  is labeled as CO<sub>2</sub> flux;  $g$  is labeled as Stomatal conductance;  $c_a$  is labeled as Atm. CO<sub>2</sub> mole fraction; and  $c_i$  is labeled as leaf intercellular CO<sub>2</sub> mole fraction.

- **Fertilization:  $c_a$  is increasing @2.1 ppm yr<sup>-1</sup>**

# Optimization: carbon-water economy

Plants adjust  $g$  and  $c_i$  to optimize the gas exchange problem!

Loss: Water flux

$$f_e = 1.6g(e_i - e_a) \approx 1.6gD$$

Stomatal  
conductance

leaf intercellular  $\text{CO}_2$   
mole fraction

$$f_c = g(c_a - c_i)$$

Gain:  $\text{CO}_2$  flux

Atm.  $\text{CO}_2$   
mole fraction

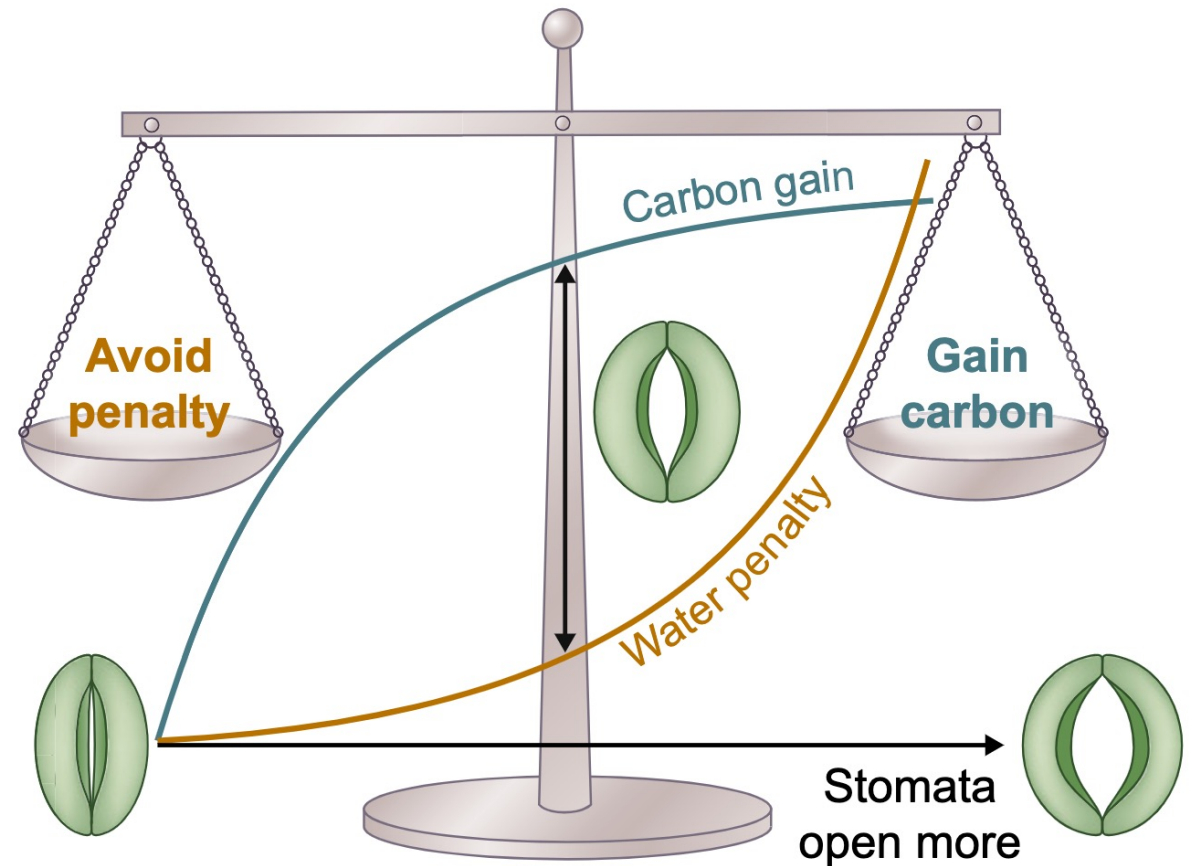


Figure credit: Wang et al. (2020)

# Major challenges

The magnitude of the  $\text{CO}_2$  fertilization effect (CFE) on terrestrial GPP is **not directly observed** and is subject to **confounding effects of (1) climate variability & (2) model representations.**

## Different GPP magnitudes

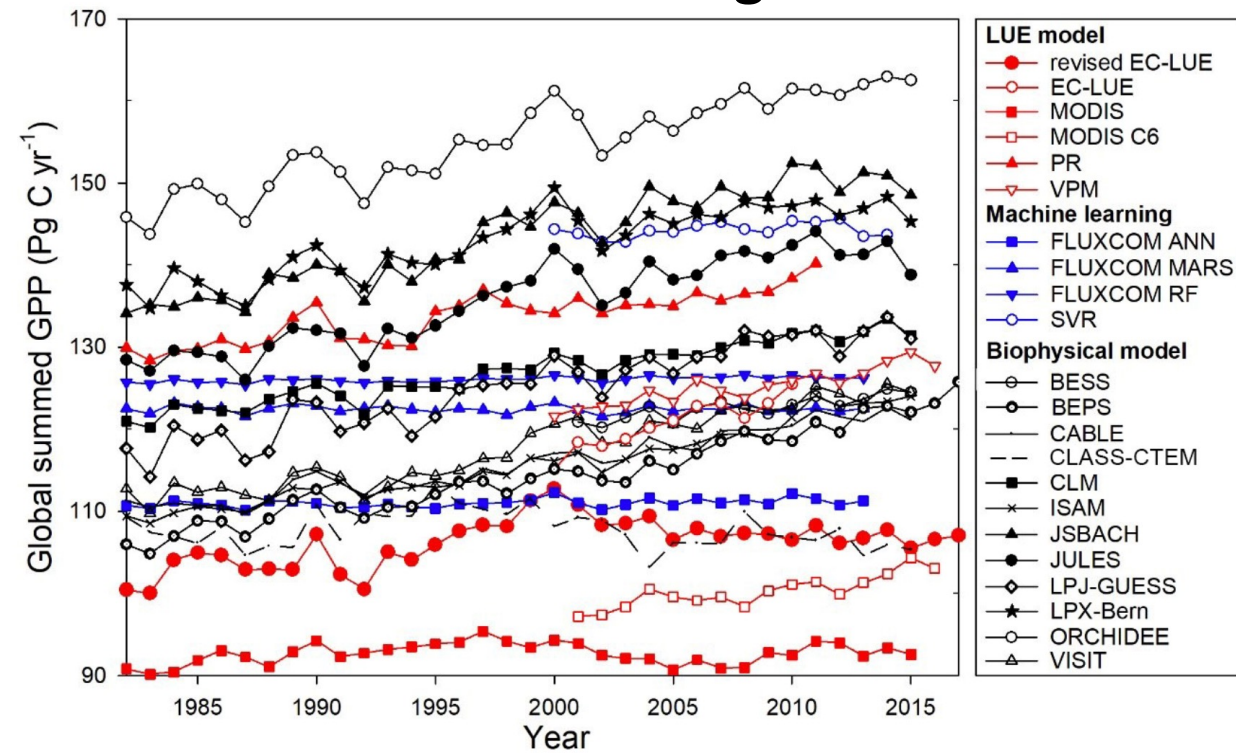


Figure credit: Zheng et al. (2020)

## Different GPP trends

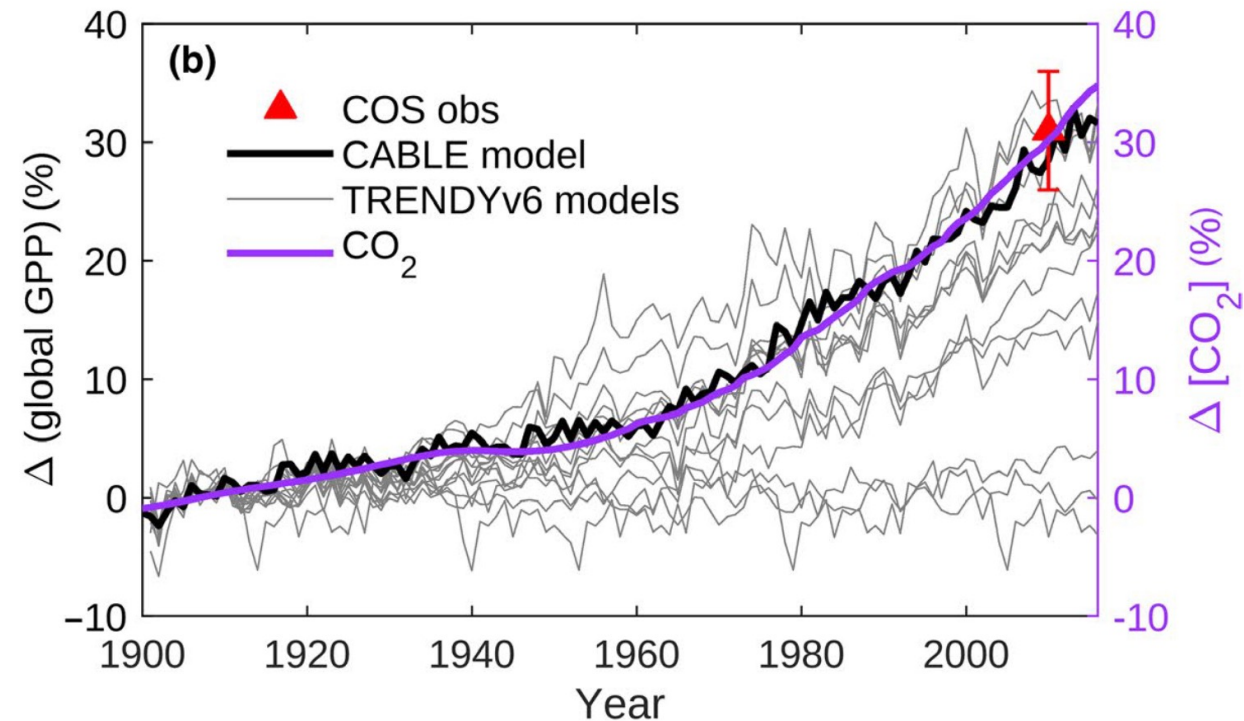


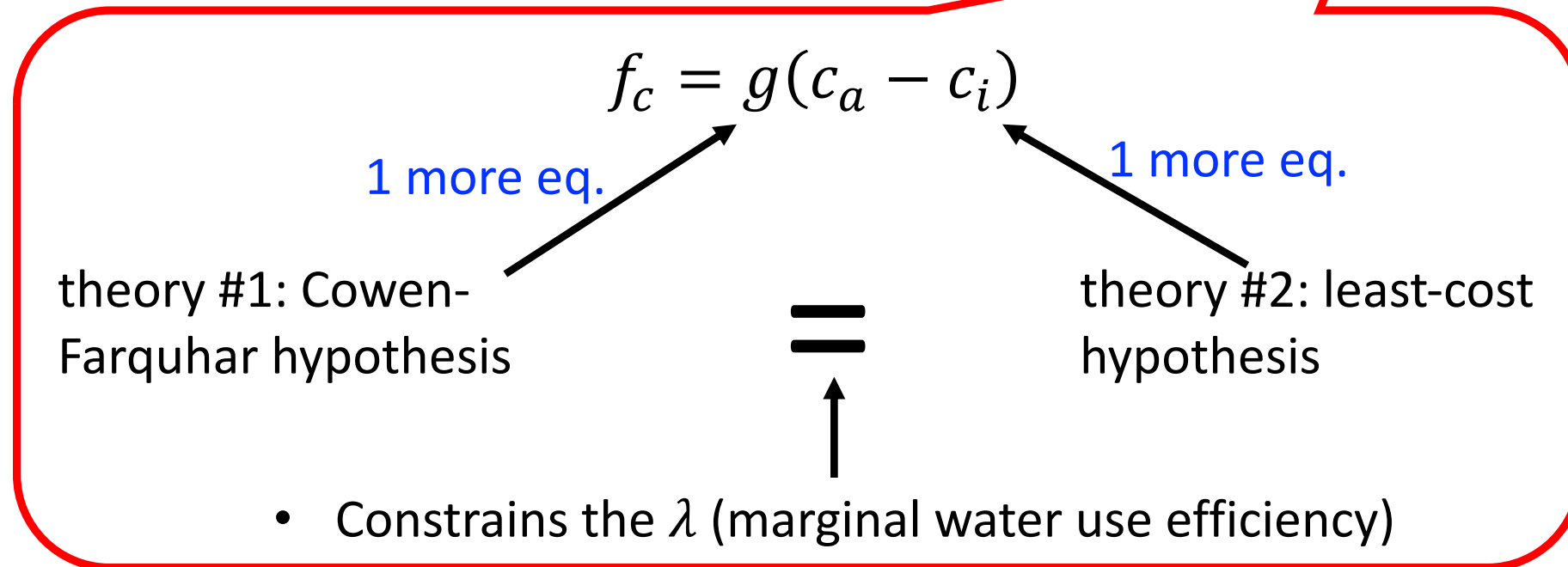
Figure credit: Harverd et al. (2020) 5

# Constrain the CFE at the leaf level

Eco-Evolutionary Optimality (EEO) model to constrain the **partial differential** GPP sensitivity to  $\text{CO}_2$ .

$$\beta_{\text{CO}_2} = \frac{\partial \text{GPP}}{\partial c_a}$$

Also need the Farquhar photosynthesis model



# Constrain the photosynthetic capacity

The Farquhar photosynthesis model

- Light-saturated:  $A_c = \frac{V_{cmax}(c_i - \Gamma^*)}{K + c_i} - R_d$
- Light-limited :  $A_j = \frac{J(c_i - \Gamma^*)}{4(c_i + 2\Gamma^*)} - R_d$
- $f_c = \min(A_c, A_j)$

Balancing the nutrient allocation: apply the coordination hypothesis to constrain reference  $V_{cmax}$  and  $J_{max}$

$$\overline{A_{c,peak}} = \overline{A_{j,peak}}$$

**Climatological mean environment of the peak LAI month**

**No need about the biome type information!**

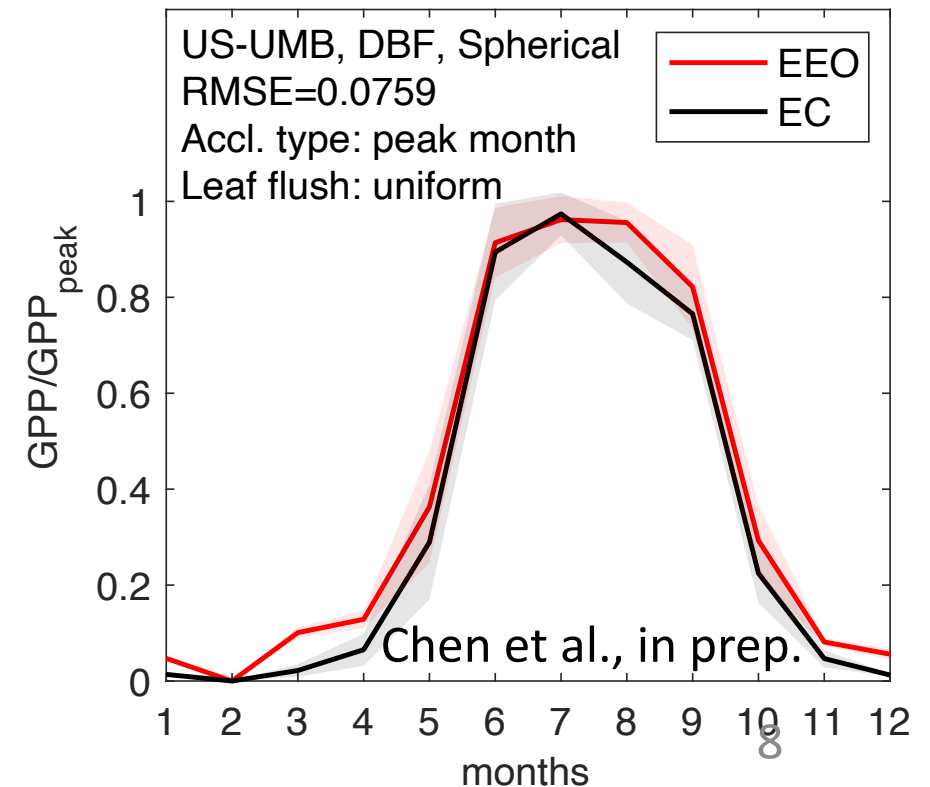
# The canopy upscaling factor: $\left| \frac{G(\mu)}{\mu} \right|$

- Big leaf
- Least square with FLUXNET
- **No interannual variation**

GPP and CFE are constrained by 7 variables:

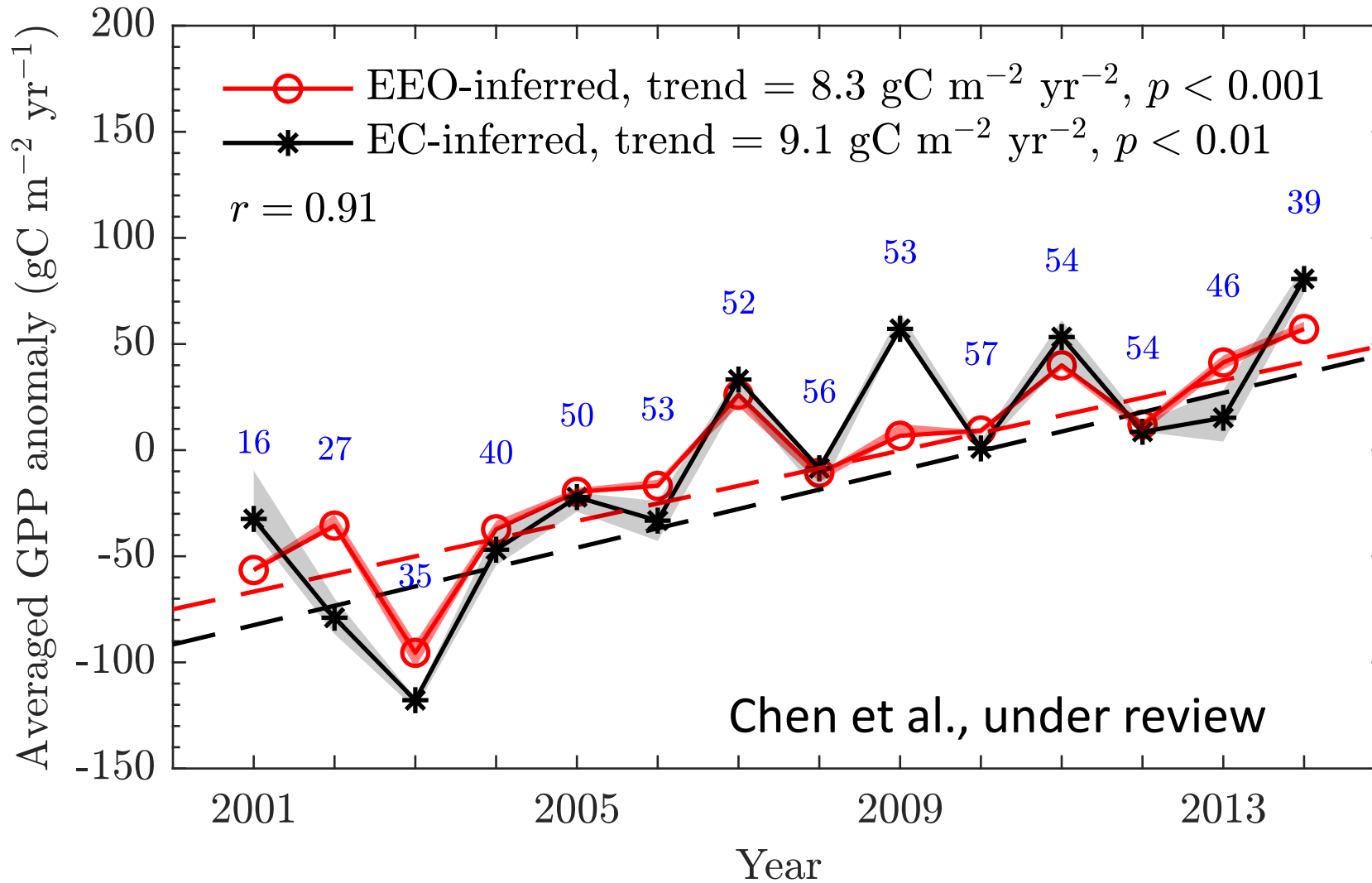
- $C_a$
- Satellite LAI
- $T_a$
- SWC
- $q_a$
- $SW_{in}$
- $P$

A follow-up work: EEO model + a full canopy radiative transfer





# Reproducing GPP trend and interannual variability (IAV)



Annual summed GPP  
for each site



GPP annual anomaly  
for each site



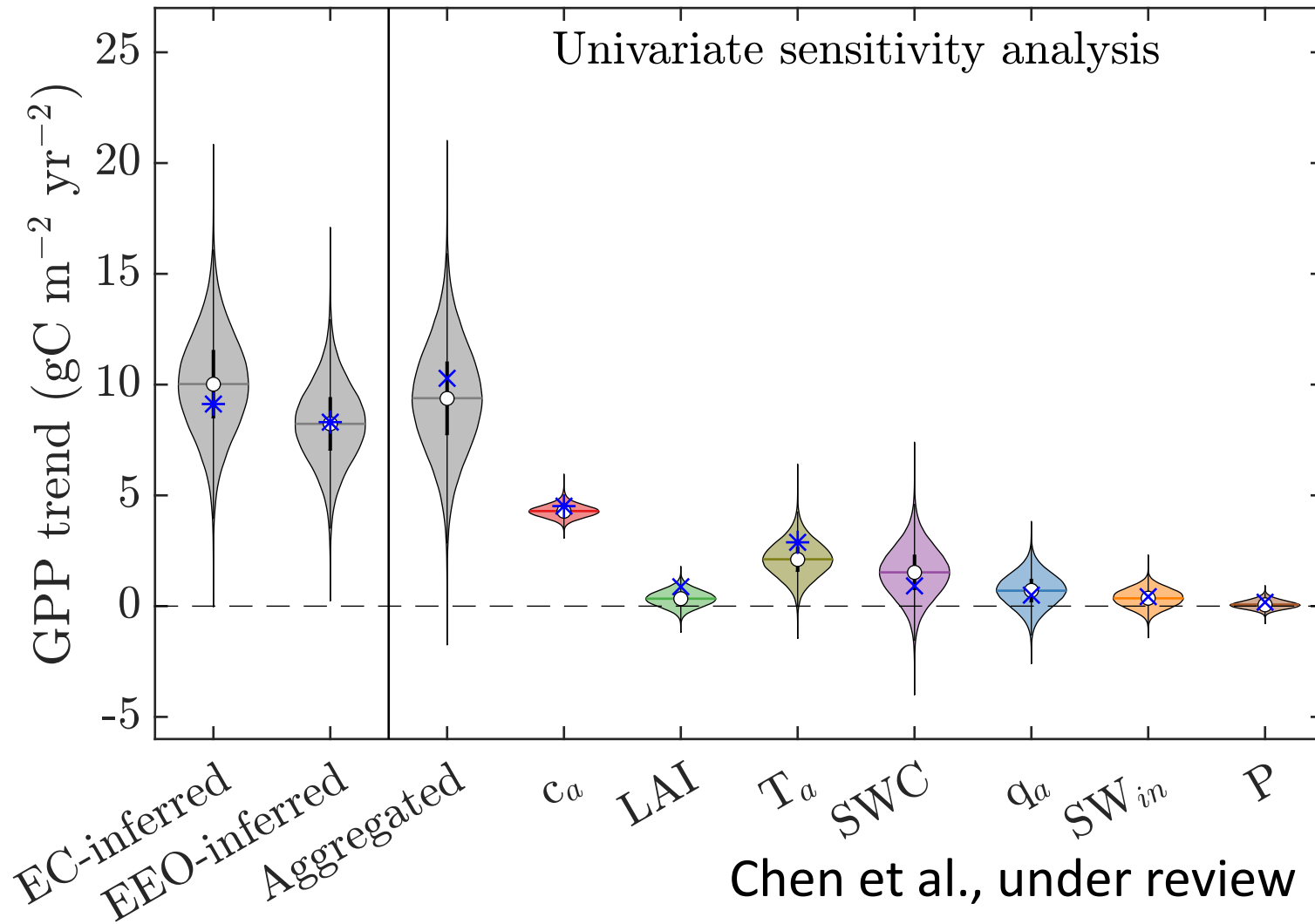
Average the anomaly  
across sites



Test the trend

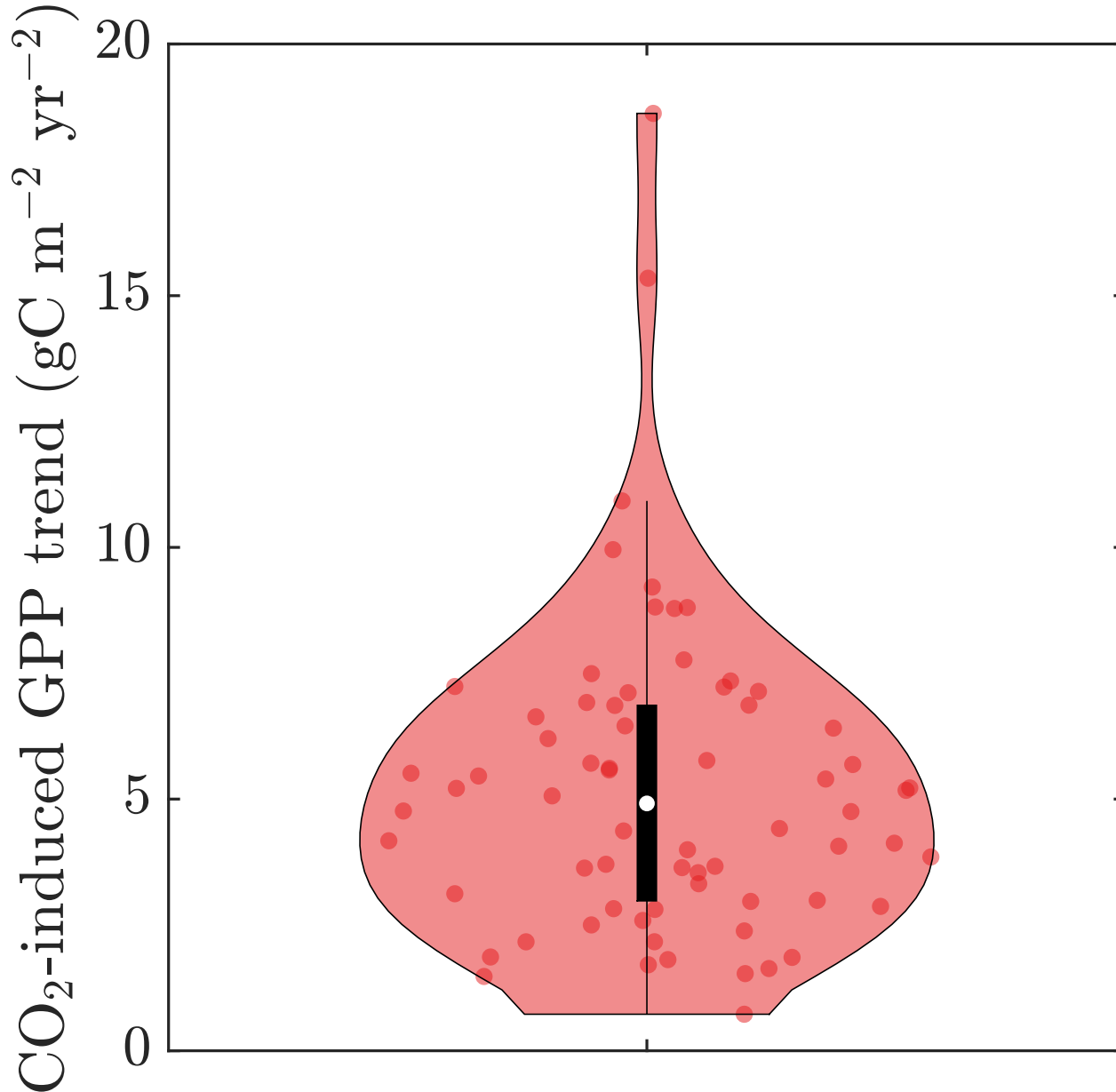
- EEO-inferred: Evo-Evolutionary Optimality model
- EC-inferred: FLUXNET2015

# Overall trend attribution



- >40% of the overall GPP trend across the sites is due to  $\text{CO}_2$
- $4.5 \text{ gC m}^{-2} \text{ yr}^{-2}$

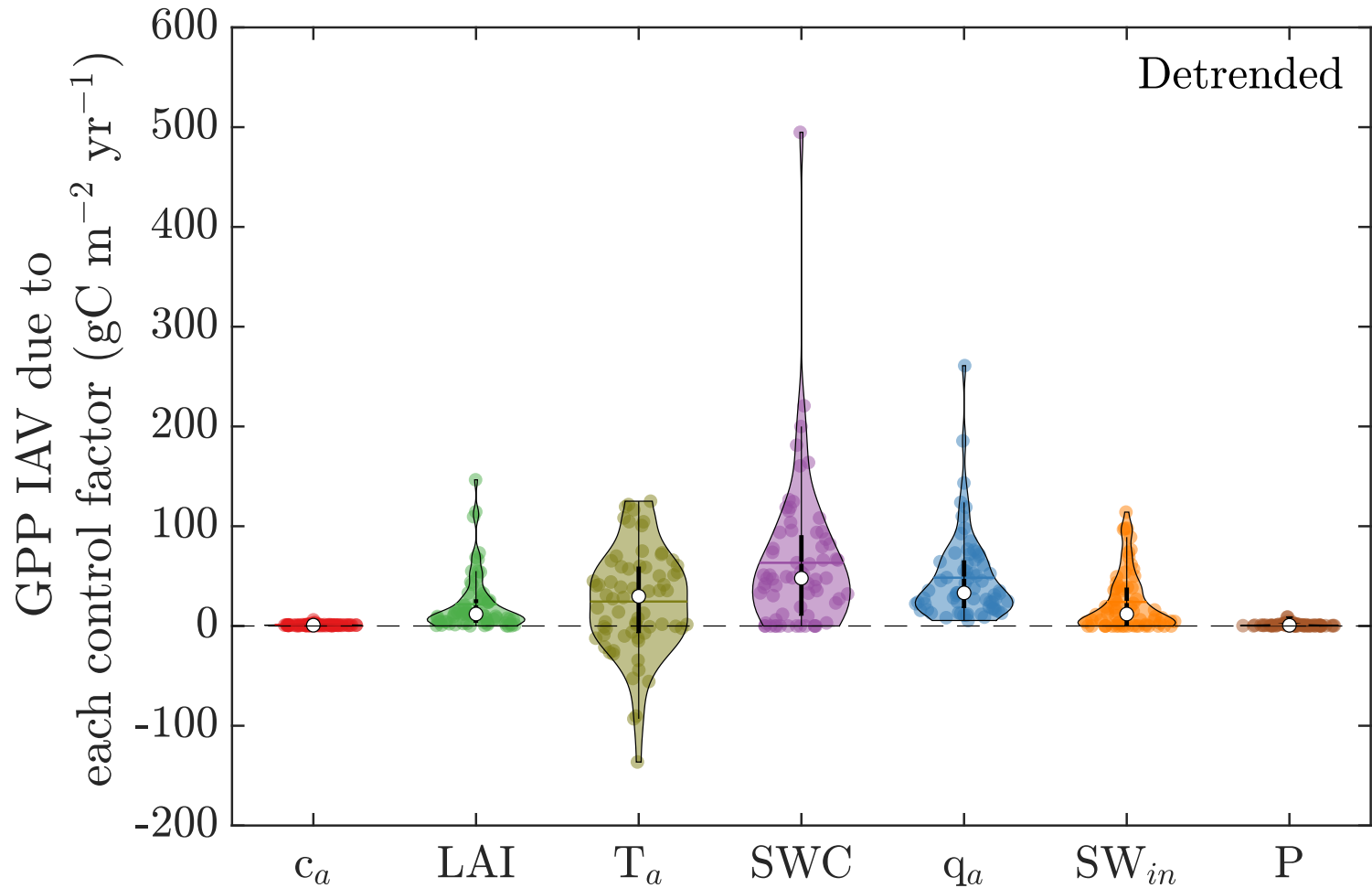
# Diagnosed CFE for each site



Analytical constraints for **individual sites**

- $CFE = \frac{\partial GPP}{\partial c_a} \times \Delta c_a$
- $\Delta$  represents the trend
- Median CFE = 4.9 gC m<sup>-2</sup> yr<sup>-2</sup>
- CFE from the univariate analysis = 4.5 gC m<sup>-2</sup> yr<sup>-2</sup>

# Diagnosed the IAV for each site

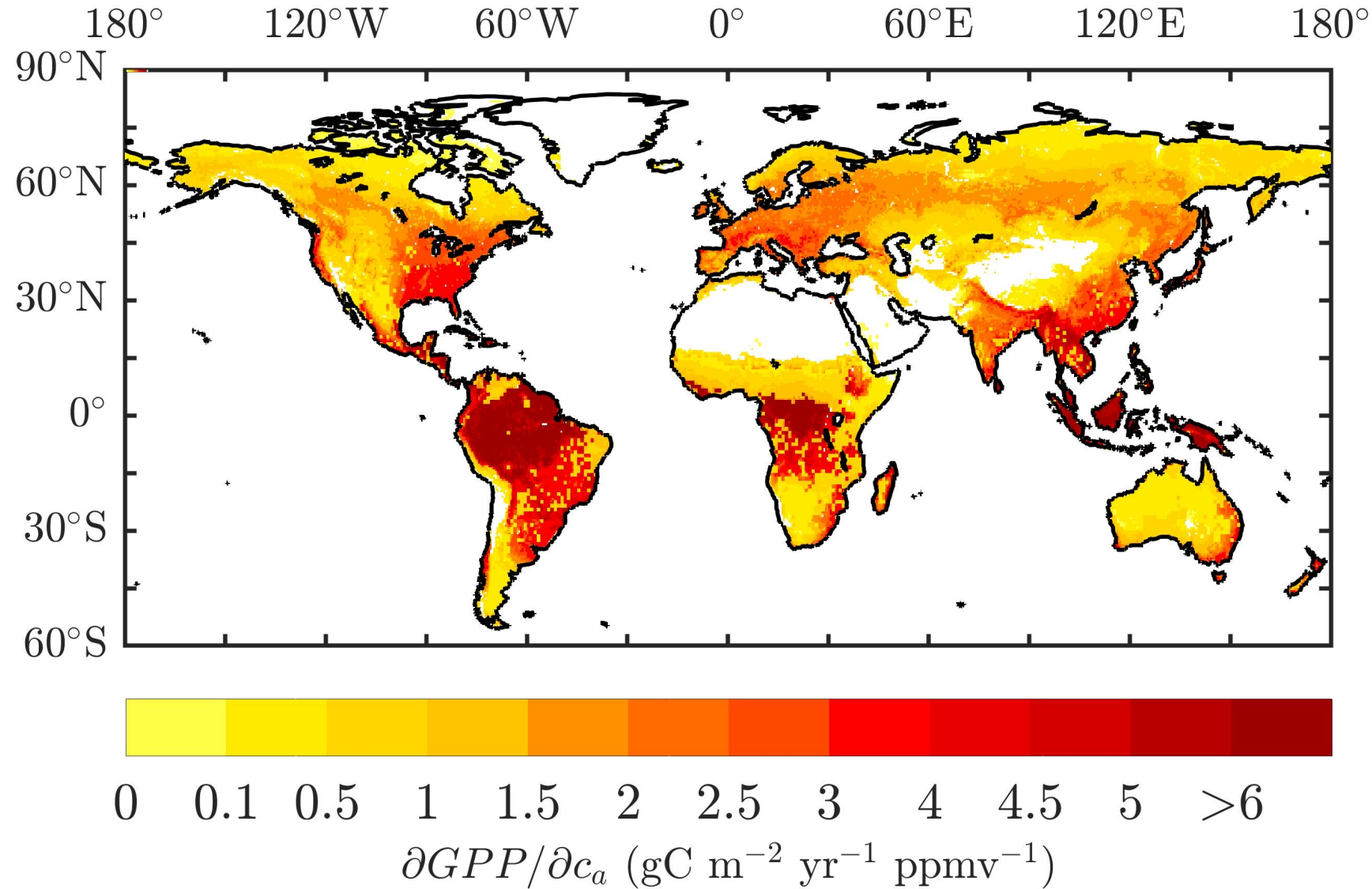


Chen et al., under review

Ability of each factor to cause GPP IAV

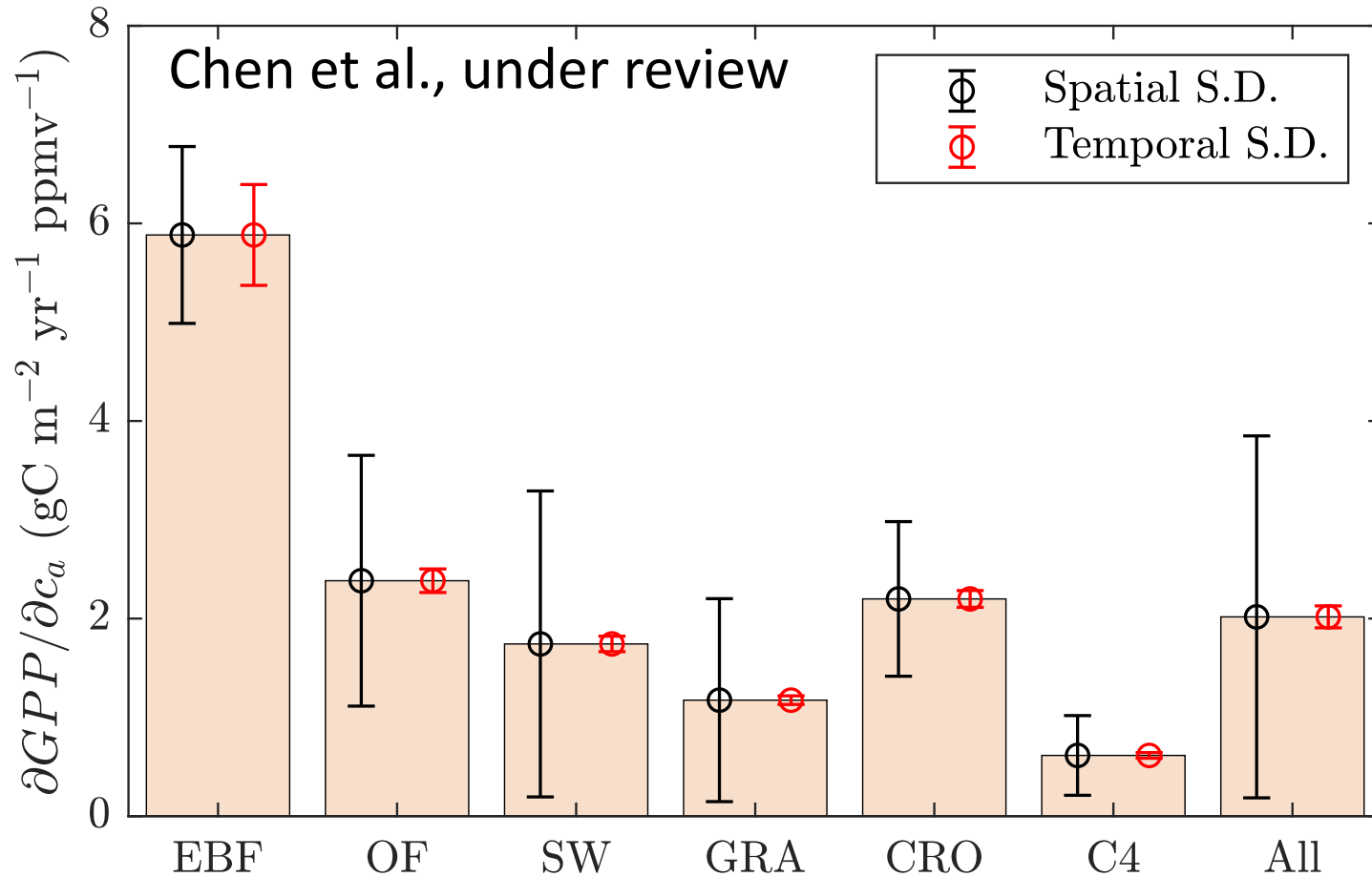
- $\frac{\partial GPP}{\partial X} \times Std_X$
- $SWC > q_a > T_a$
- $c_a$  negligible

# $\beta_{CO_2}$ at the global scale



- Inputs: ERA5 + MODIS LAI
- Canopy upscaling calibration: multiple satellite GPP products
- CO<sub>2</sub> trend @  $\sim 2.1 \text{ ppm yr}^{-1}$
- Global average =  $4.4 \text{ gC m}^{-2} \text{yr}^{-1} \text{ppmv}^{-1}$

# Within biome $\beta_{CO_2}$ variation driven by climate



**Bars:** mean  $\beta_{CO_2}$  for each biome type

- $\beta_{CO_2}$  is a function of climate and  $CO_2$ , but  $CO_2$  are prescribed without spatial variations
- No sig. temporal fluctuations due to climate variability

# Relative CFE is conserved

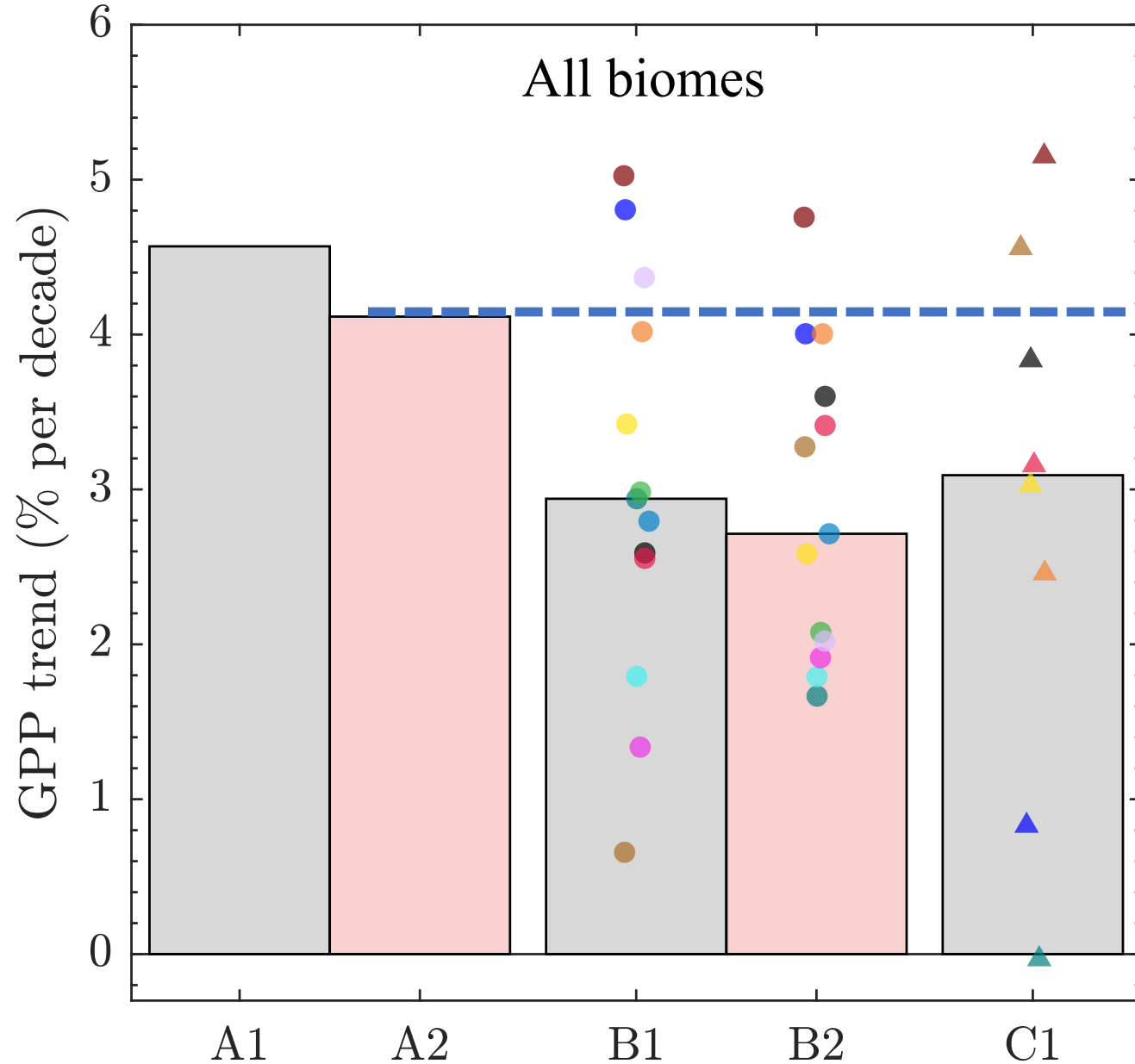
GPP source used to calibrate the EEO framework	EBF	OF	SW	GRA	CRO	C4	All biomes
Ensemble mean of 8 satellite-derived GPP	4.76	4.27	4.75	5.02	5.06	1.35	4.12
BEPS	4.89	4.50	4.85	5.18	5.35	1.41	4.36
BESS	4.85	4.29	4.76	5.16	5.14	1.38	4.24
FluxCom	4.81	4.35	4.77	4.85	4.91	1.28	4.07
MOD-C55	4.76	4.37	4.88	5.19	5.12	1.37	4.20
MOD-C6	4.69	4.36	4.89	5.22	5.11	1.38	4.17
Pmodel-s0	4.71	4.06	4.52	4.66	4.71	1.25	3.91
PR-model	4.96	4.07	4.60	4.76	4.95	1.34	4.08
VPM	4.67	4.31	4.88	5.23	5.08	1.34	4.03

Chen et al., under review

- $Relative\ CFE = \frac{\Delta GPP_{co2}}{GPP} \times 100\%$

- ~4.1% GPP per decade relative to corresponding GPP climatological mean

# Comparison to DGVMs and satellite GPP



- |              |             |
|--------------|-------------|
| ● CABLE      | ▲ BEPS      |
| ● CLASS-CTEM | ▲ BESS      |
| ● CLM4.5     | ▲ FluxCom   |
| ● DLEM       | ▲ MOD-C55   |
| ● ISAM       | ▲ MOD-C6    |
| ● JSBACH     | ▲ Pmodel-s0 |
| ● JULES      | ▲ PRmodel   |
| ● LPJ-GUESS  | ▲ VPM       |
| ● LPJ-wsl    |             |
| ● LPX-Bern   |             |
| ● ORCHIDEE   |             |
| ● VEGAS      |             |
| ● VISIT      |             |

A1: EEO-inferred, total GPP trend

A2: EEO-inferred, CO2-induced GPP trend

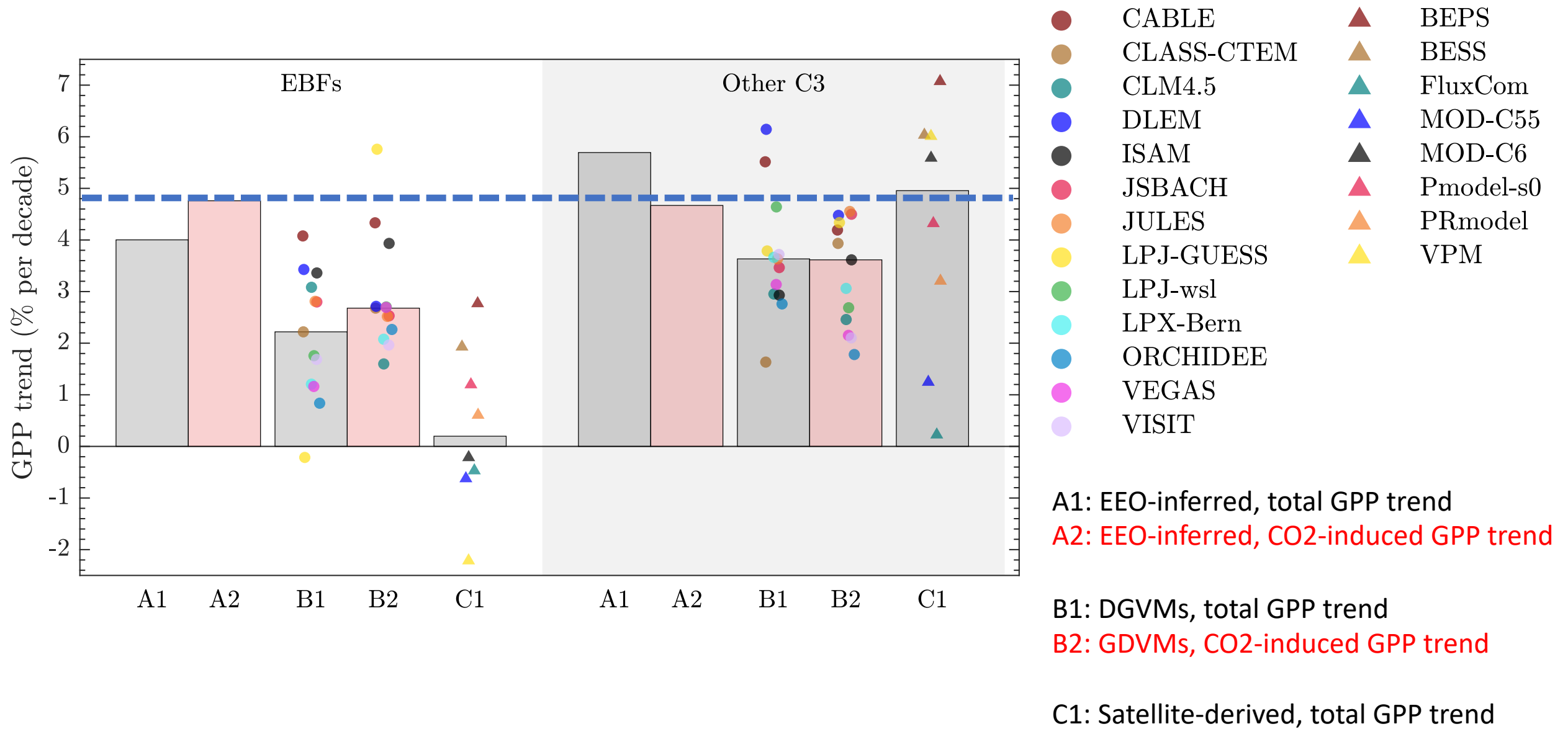
B1: DGVMs, total GPP trend

B2: GDVMs, CO2-induced GPP trend

C1: Satellite-derived, total GPP trend



# Comparison to DGVMs and satellite GPP



# Take home messages

- A strong CO<sub>2</sub> fertilization effect is detectable in the eddy covariance networks
- CO<sub>2</sub> fertilization effect can also be constrained at the global scale
- Our framework further provides the opportunity to diagnose the sensitivity of GPP to multiple factors

**Thank you!**

**Questions -> ([chenchi@lbl.gov](mailto:chenchi@lbl.gov))**