Emergent Constraints

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Outline of the Lecture

1. What are **Emergent Constraints** (good for)?
2. The **Concept and Ingredients** of Emergent Constraints
3. Illustrative and In-depth **Examples**
4. **Different Types** of Emergent Constraints
    1. EC in **Space**
    2. EC in **Time**
    3. EC across **Variables**
5. **Uncertainties, Pitfalls, and Limitations** of Emergent Constraints

Motivation

- A major research discipline in climate science is looking back (paleoclimatology) or forward (future climate change research) in time.
- Model Intercomparison Projects as tool (e.g. CMIPs): focus on scenarios and future projections of how the Earth system changes under the human influence.
- Key remarkable aspect of MIP-style modeling: **huge uncertainty in key entities of the climate / Earth system**, e.g. climate sensitivity (global T increase for $2xCO_2$), land carbon sink of CO_2 emissions.
- Emergent Constraints is a method to reduce uncertainty in important **unknown entities** of the climate system using **observations.**

Predictand

Predictor

The Predictand - the variable we want to know

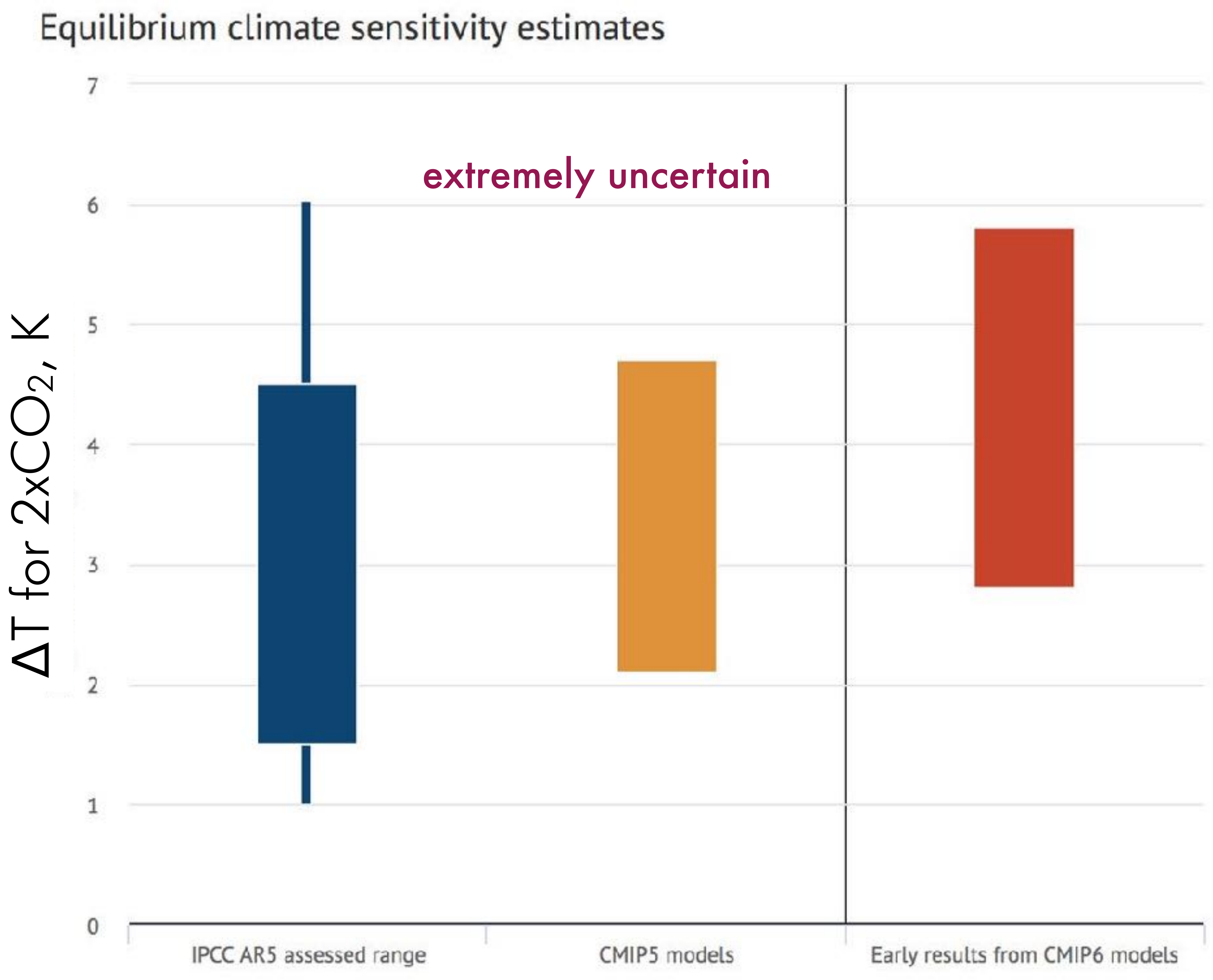
- Unknown entity of the system (high uncertainty):

  1. Not observable or difficult to measure (e.g. only measurable at local scale but not on large scale)

  2. System at different state (e.g. at potential future CO_2 concentration)

  3. Combination of 1. and 2.

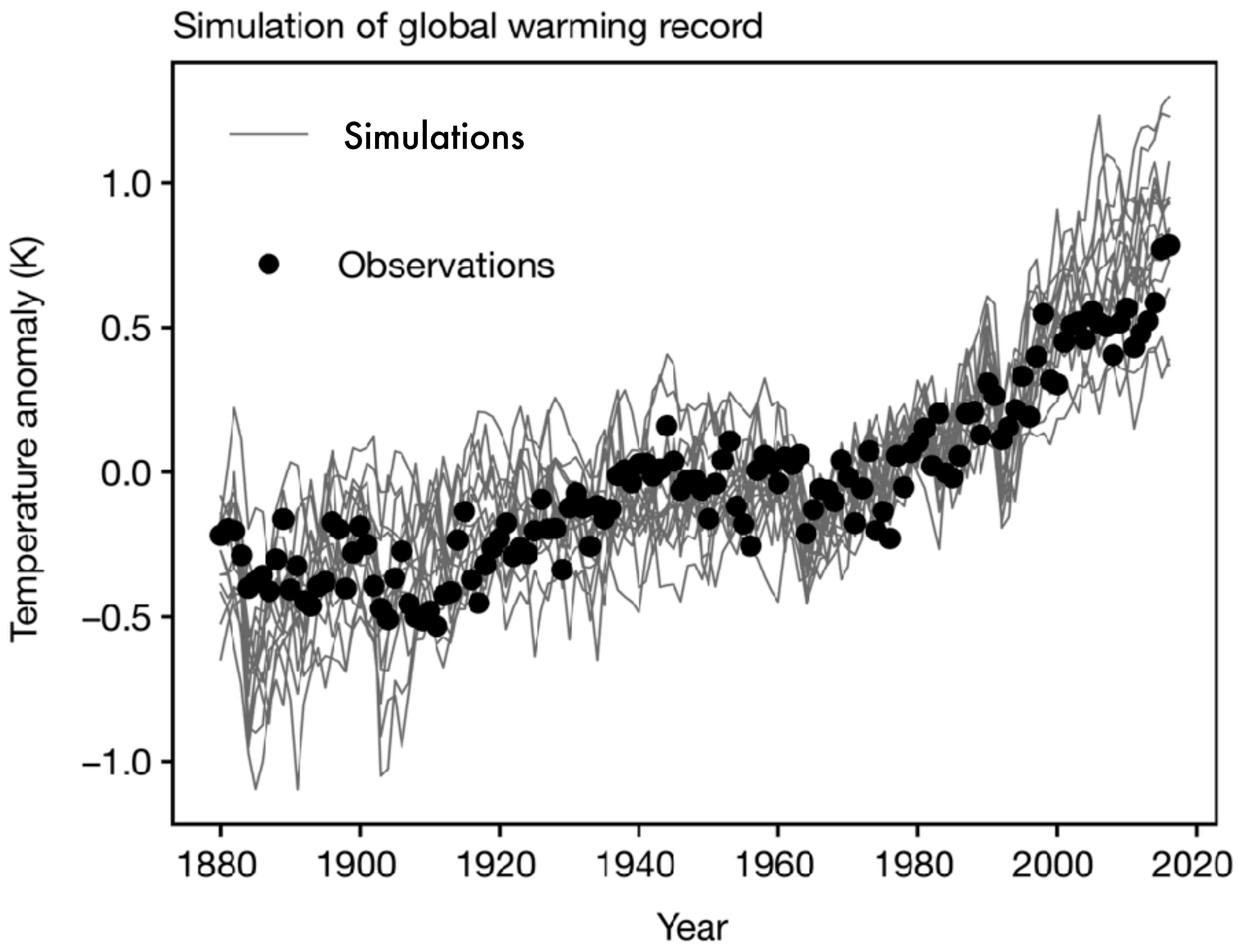
- Example: **Equilibrium climate sensitivity** (not observable and at a different state of the system)



Source: https://www.carbonbrief.org/guest-post-why-results-from-the-next-generation-of-climate-models-matter

The Predictor - the variable we can observe

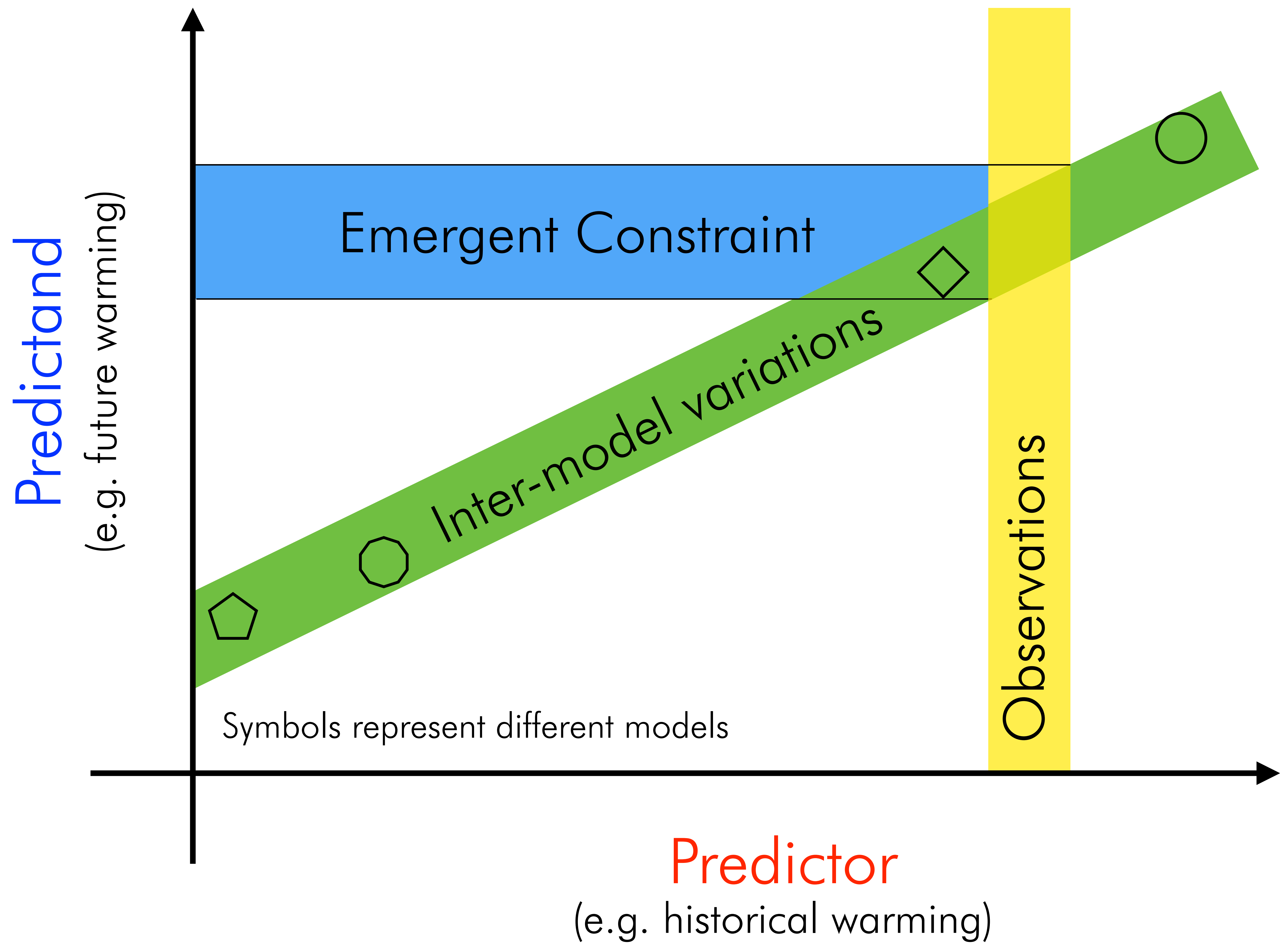
- **Observable entity of the system**:
  - diagnostic variable of the predictand via causal relationship
  - representable for the state of the system
- **Predictor can be estimated** using
  - the long-term change of the system (i.e. sensitivity to a forcing)
  - mean state of the system
  - inter-annual variations
  - seasonality
  - spatial gradients (space for time)
- Example: Observations and simulations of historical warming



Cox et al., *Nature,* (2018)

At on glance: The Concept of *Emergent Constraints*

- **Forcing** of the system (i.e. increasing CO_2 concentration)
- **Predictand:**
  - predicted response to forcing
  - not observable
  - at different state of the system
- **Predictor:**
  - diagnostic variable of **Predictand**
  - observable entity of the system
  - representative historical period

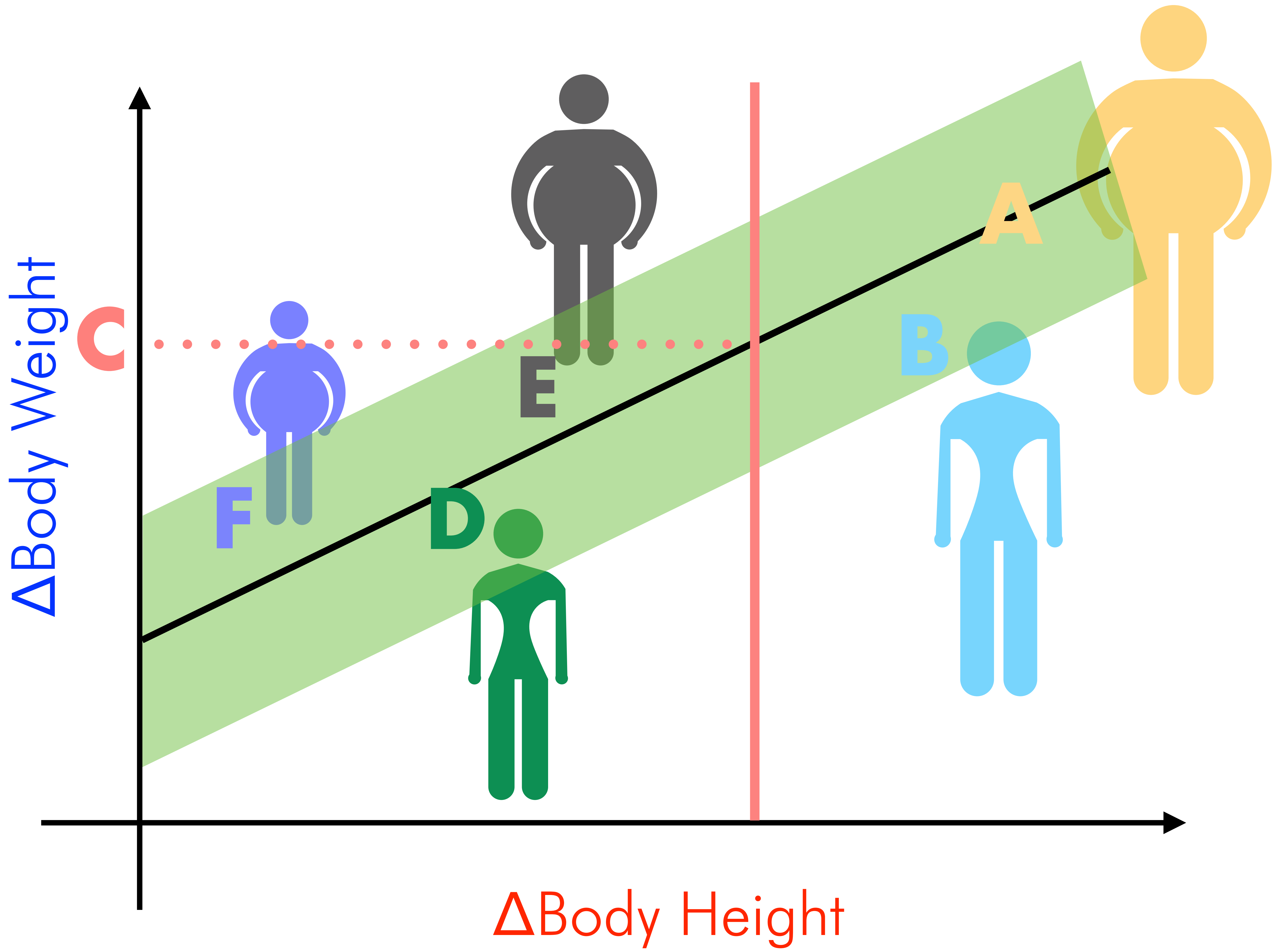


Essential ingredients of Emergent Constraints

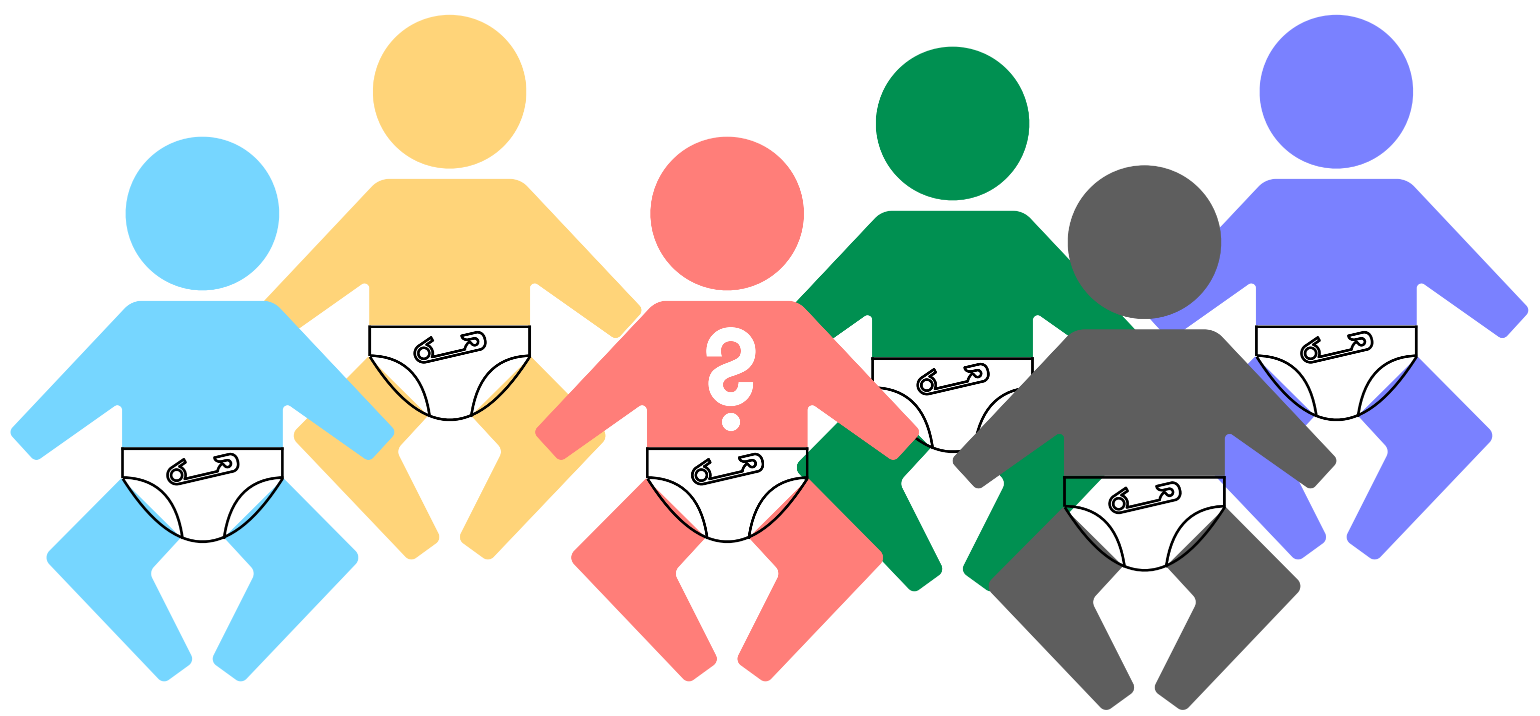
1. Multi-model ensemble of **historical simulations** and **predictive simulations** (e.g. climate projections)
2. **Causal relationship** between the entity of interest (predictand) and an observable variable (predictor).
3. Linear* **emergent relationship** between the two variables arising from the collective model behavior in an ensemble.
4. Observational predictor estimate for imposing a constraint on the predictand.

*non-linear predictor-predictand relationships are under debate

Non-Climate Science example



„Multi-Baby" Ensemble



- **Predictand:** increase in body weight
- **Forcing:** all babies receive the same nutrition (analog to CO_2 forcing)
- **Predictor:** increase in body height
- **Causal relationship:** human body height and weight are correlated
- Individual human metabolism analog to specific process implementation of different models.
- We know the height of Person C, what is his*her body weight?

Disclaimer: This example is only partially transmissive to Emergent Constraints in Climate Science.

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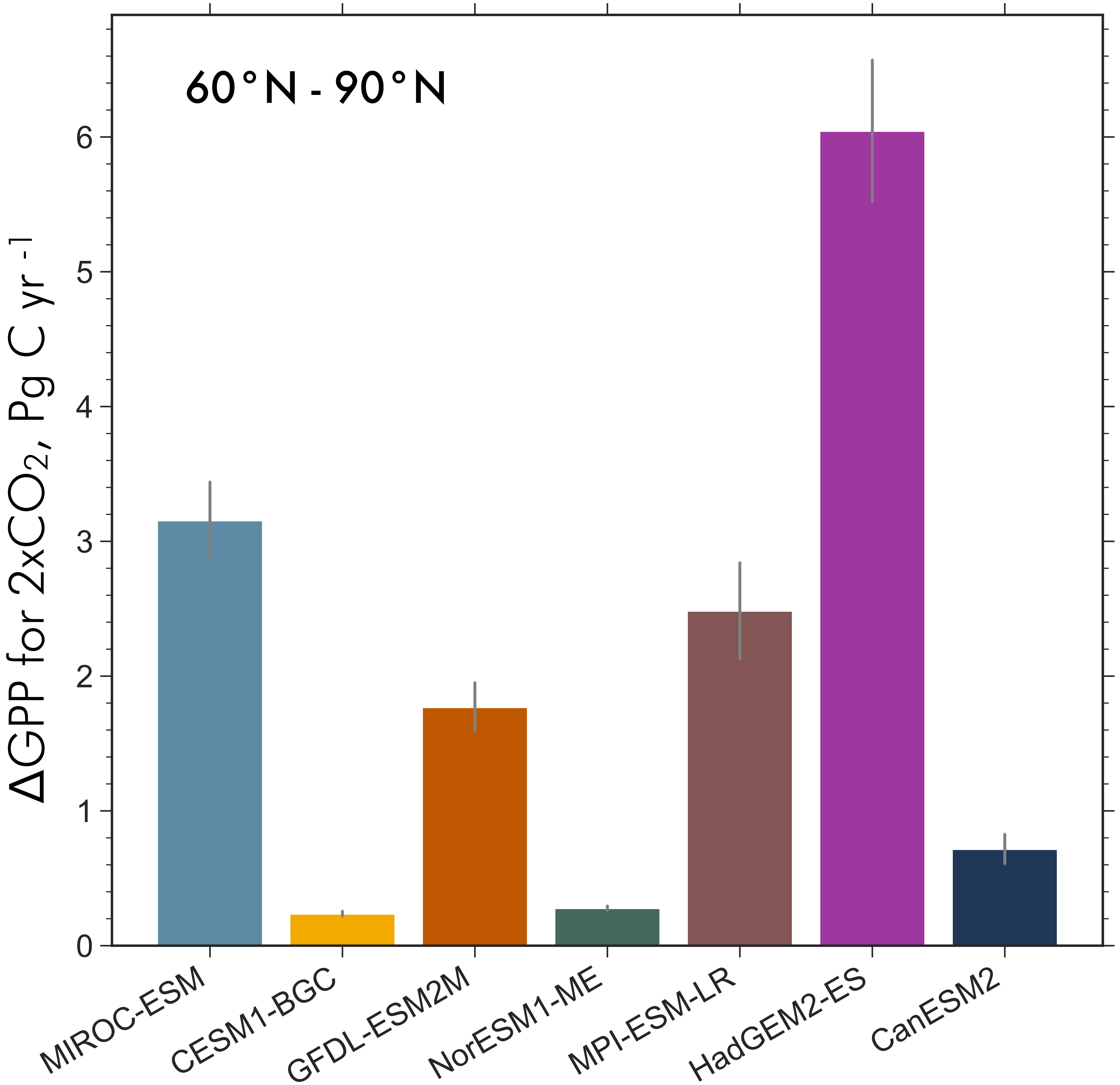
Uncertainty in Climate Change Projections

- CMIP5 **models largely disagree on the gross primary production (GPP) response** to rising CO_2.
- Conventional approach of handling these multi-model ensembles is to use **unweighted ensemble averages**.
- Can we apply the **observed greening response to reduce the uncertainty in GPP projections?**

CMIP5 1pctCO2



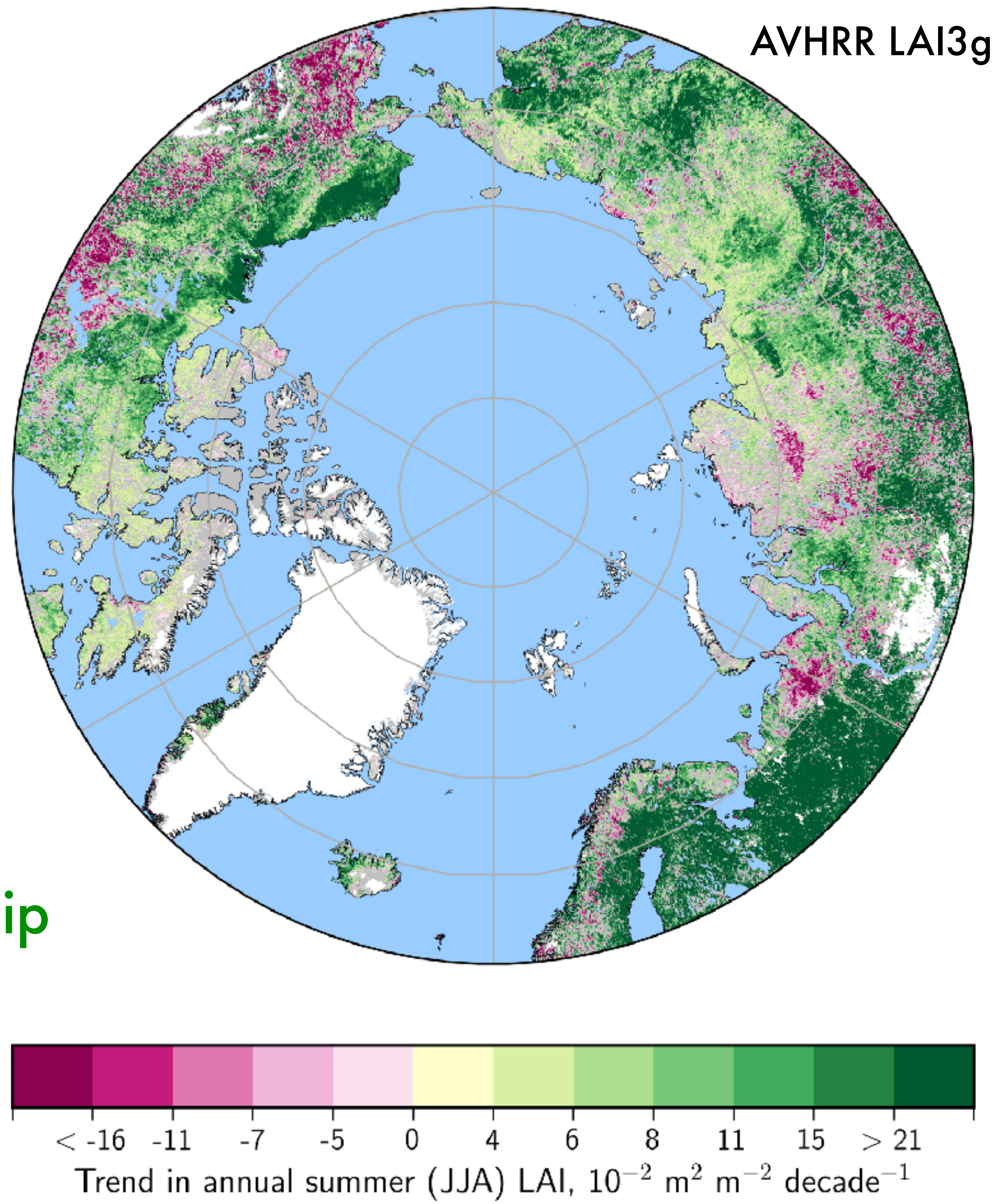
Predictand

Greening of Northern Lands

- **Widespread increase in summer time Leaf Area Index** (LAI) for the observational period (1982-2016).
- **52% of vegetated land** show **significant greening trends** (12% browning trends likely due to disturbances).
- Link between greening and enhanced photosynthetic activity (GPP):
  - carbon allocation to leaves
  - more leaves → higher carbon assimilation

Predictor

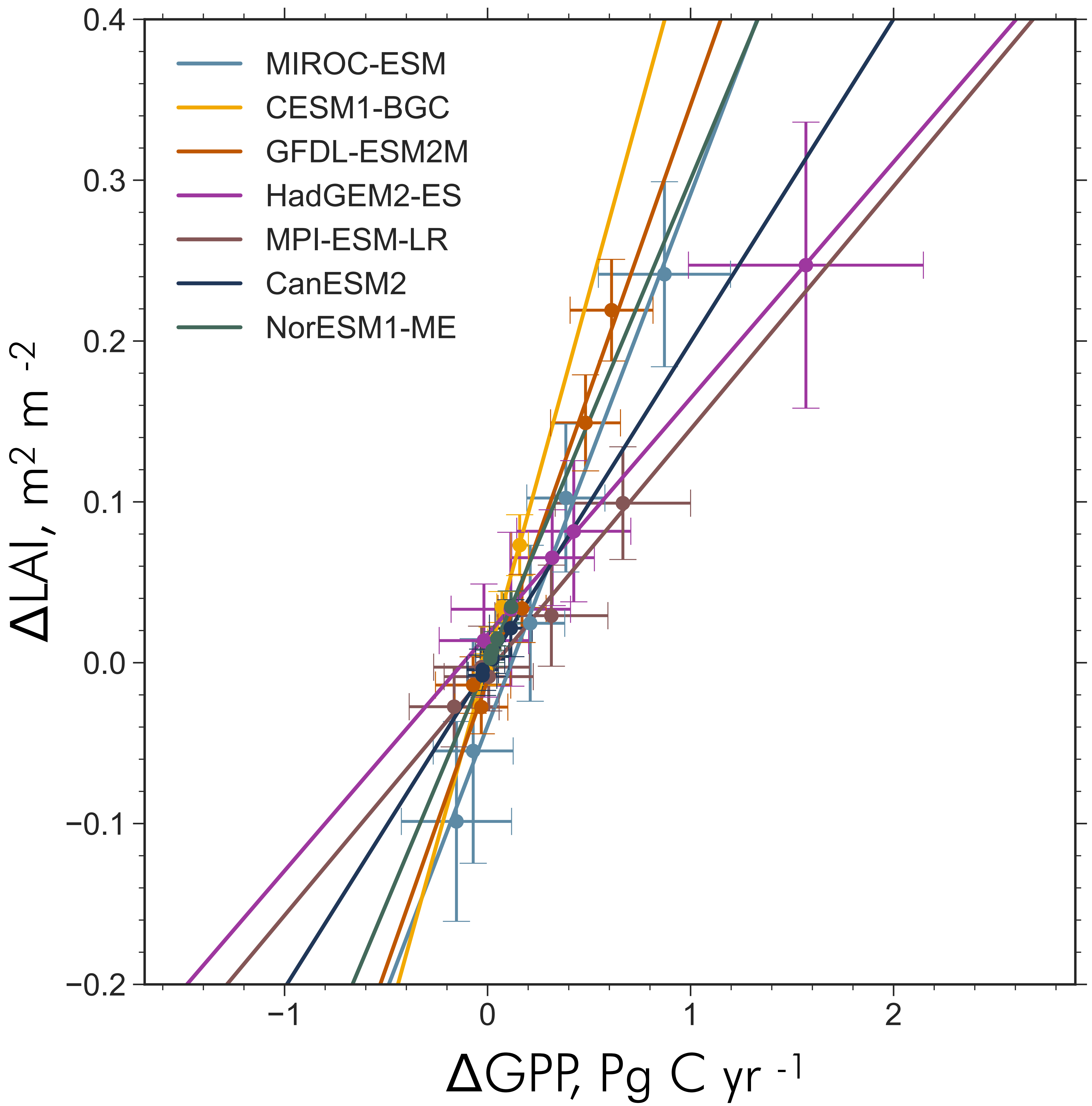
Causal relationship



Tight Coupling of Changes in LAI and GPP

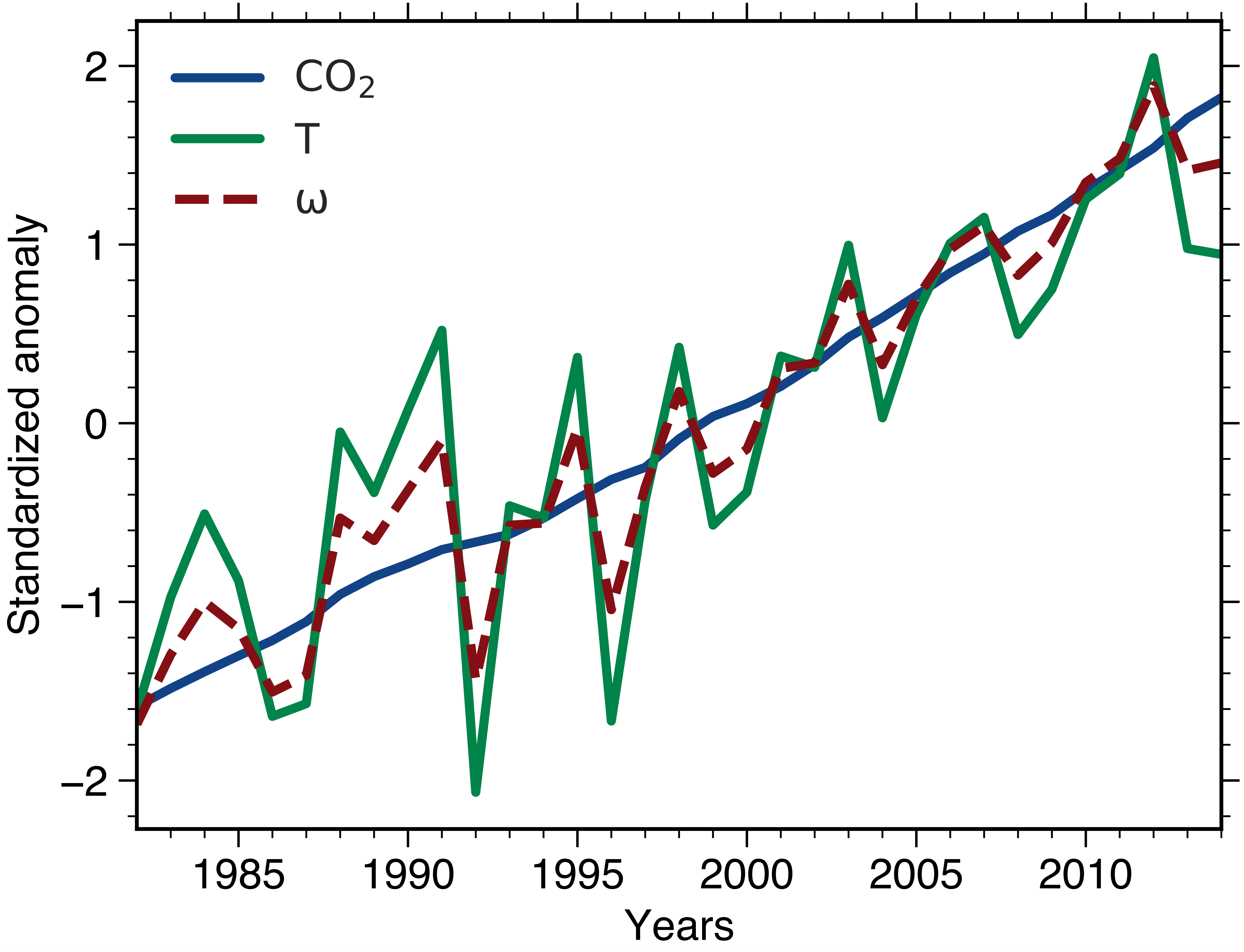
CMIP5 esmHistorical

- **Predictor-Predictand relationship** in historical simulations (1850 – 2005, 30-years averages).
- **Linear relationship** between concurrent changes in LAI and annual mean GPP across all models.

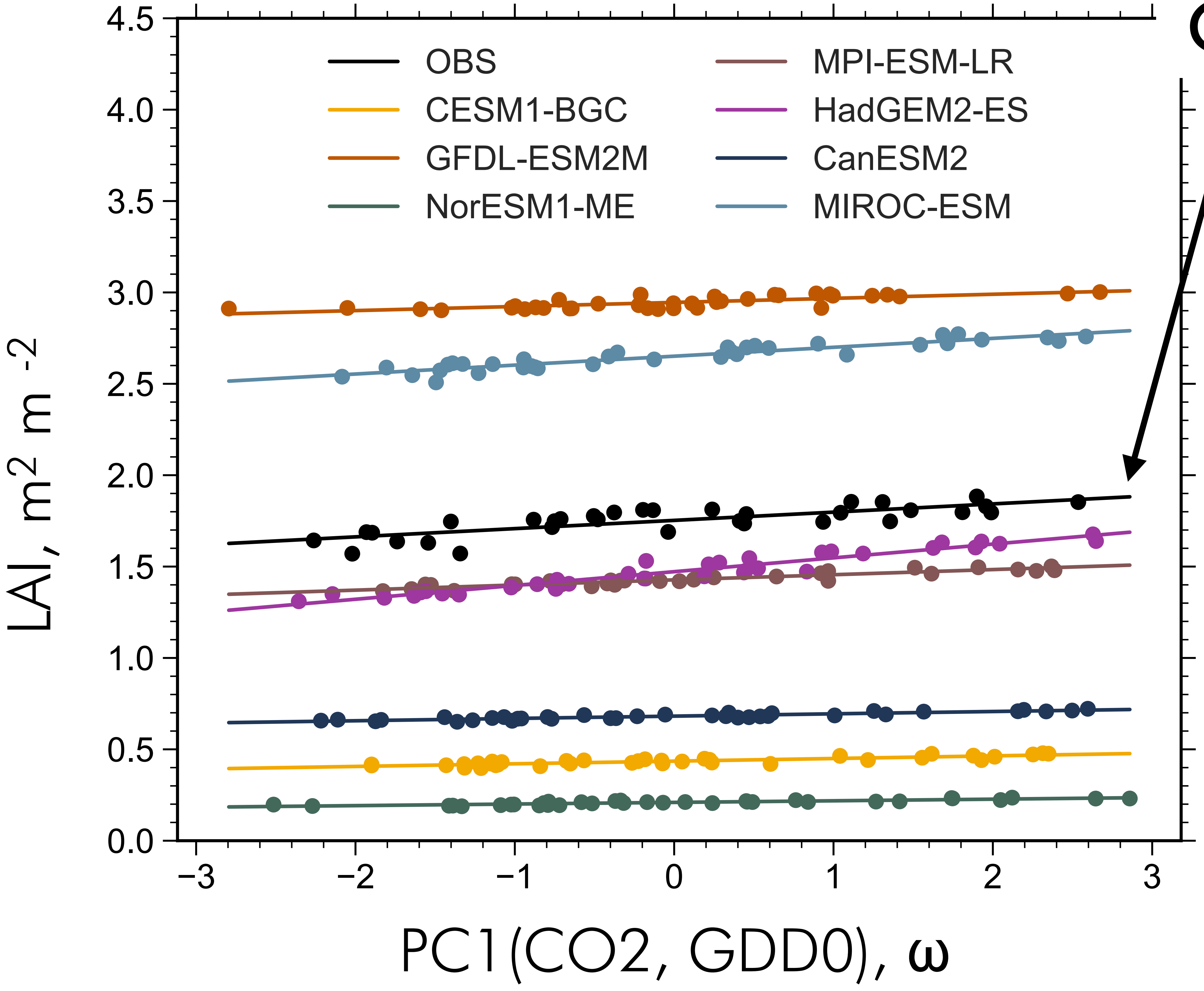


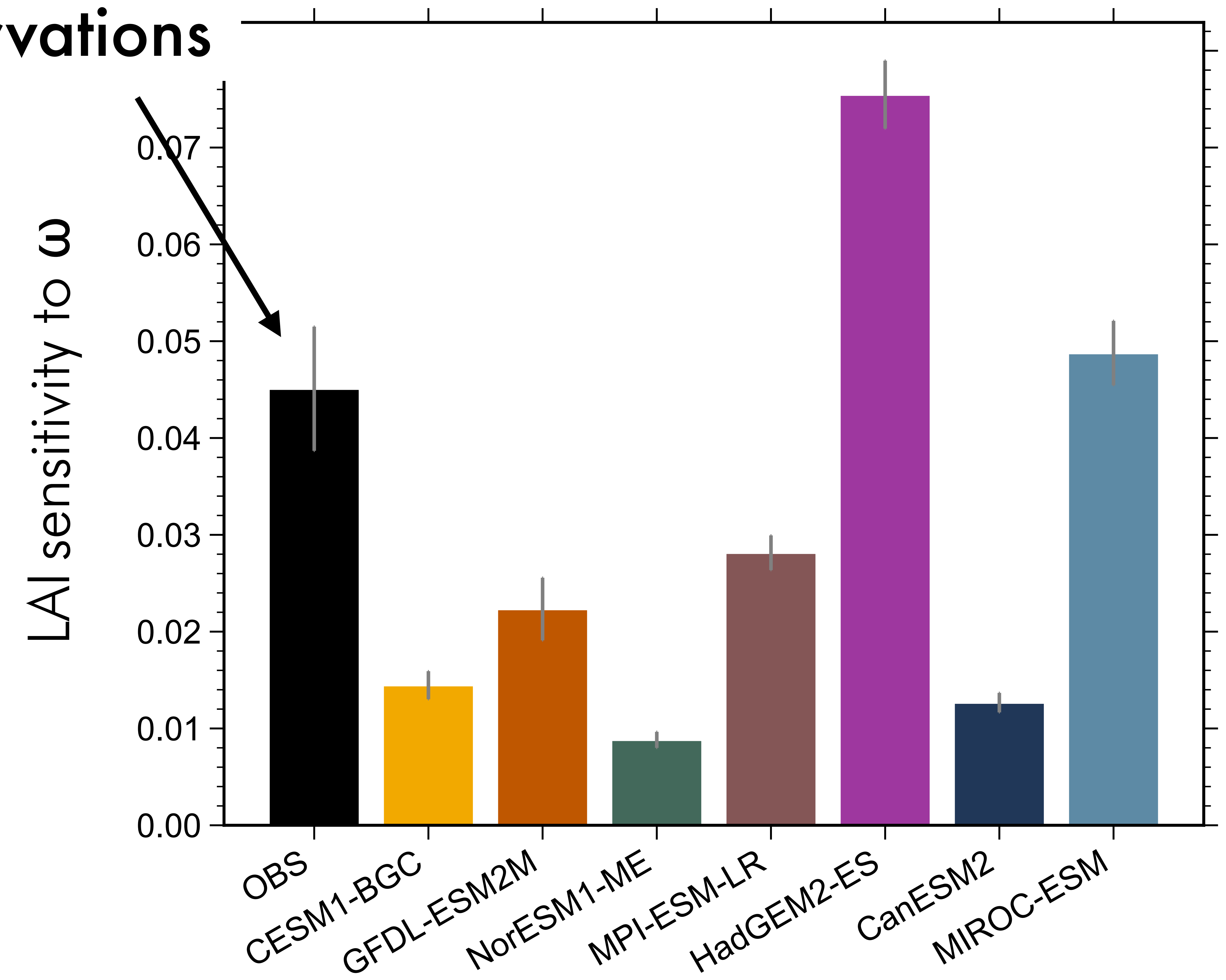
Dominant Forcing in Northern High Latitudes

- **CO_2 and temperature** are highly **correlated** for northern lands.
- **Overall forcing signal**: First Principal Component (**ω**) explains most of the variance.



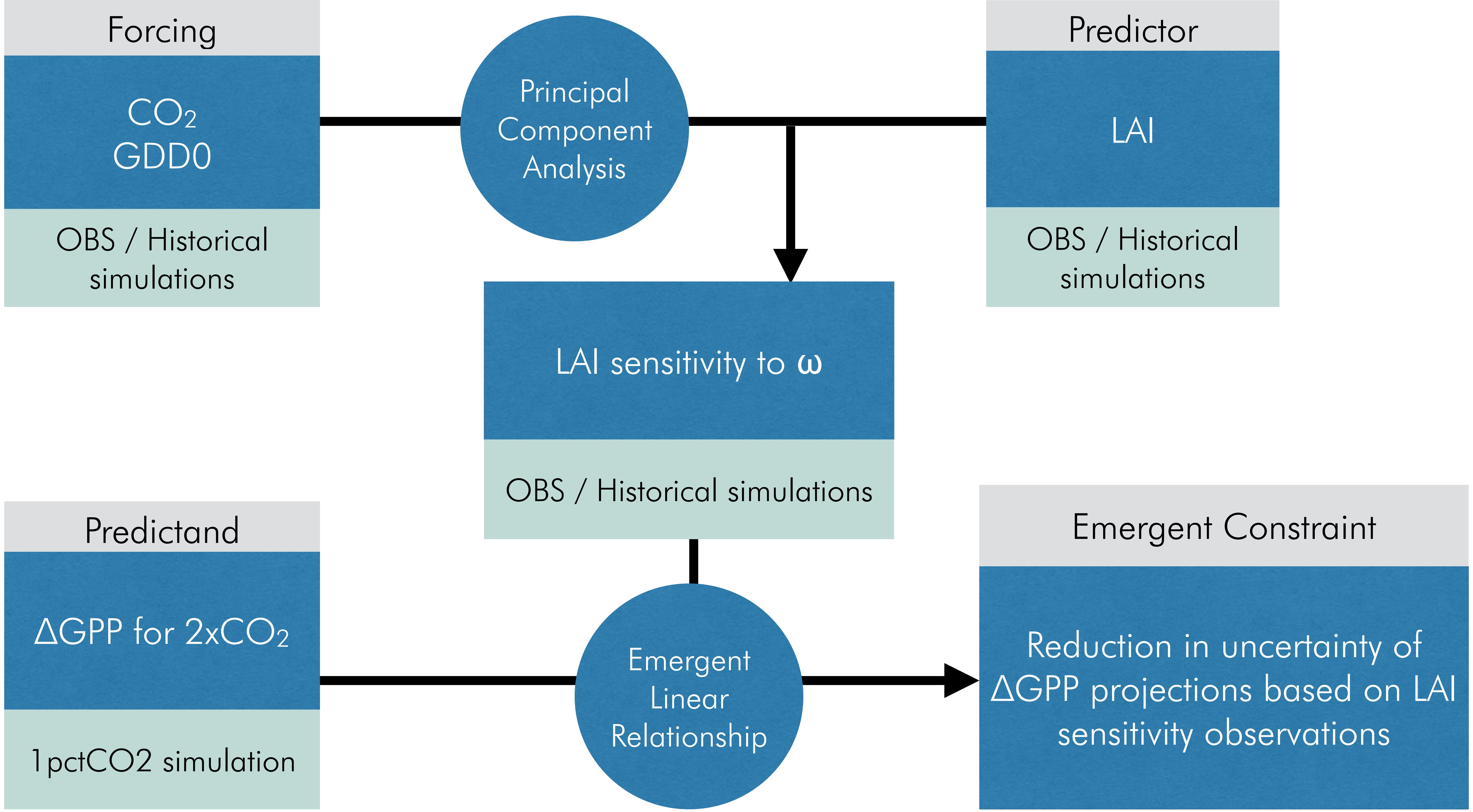
Observed and Modelled Sensitivities to Forcing



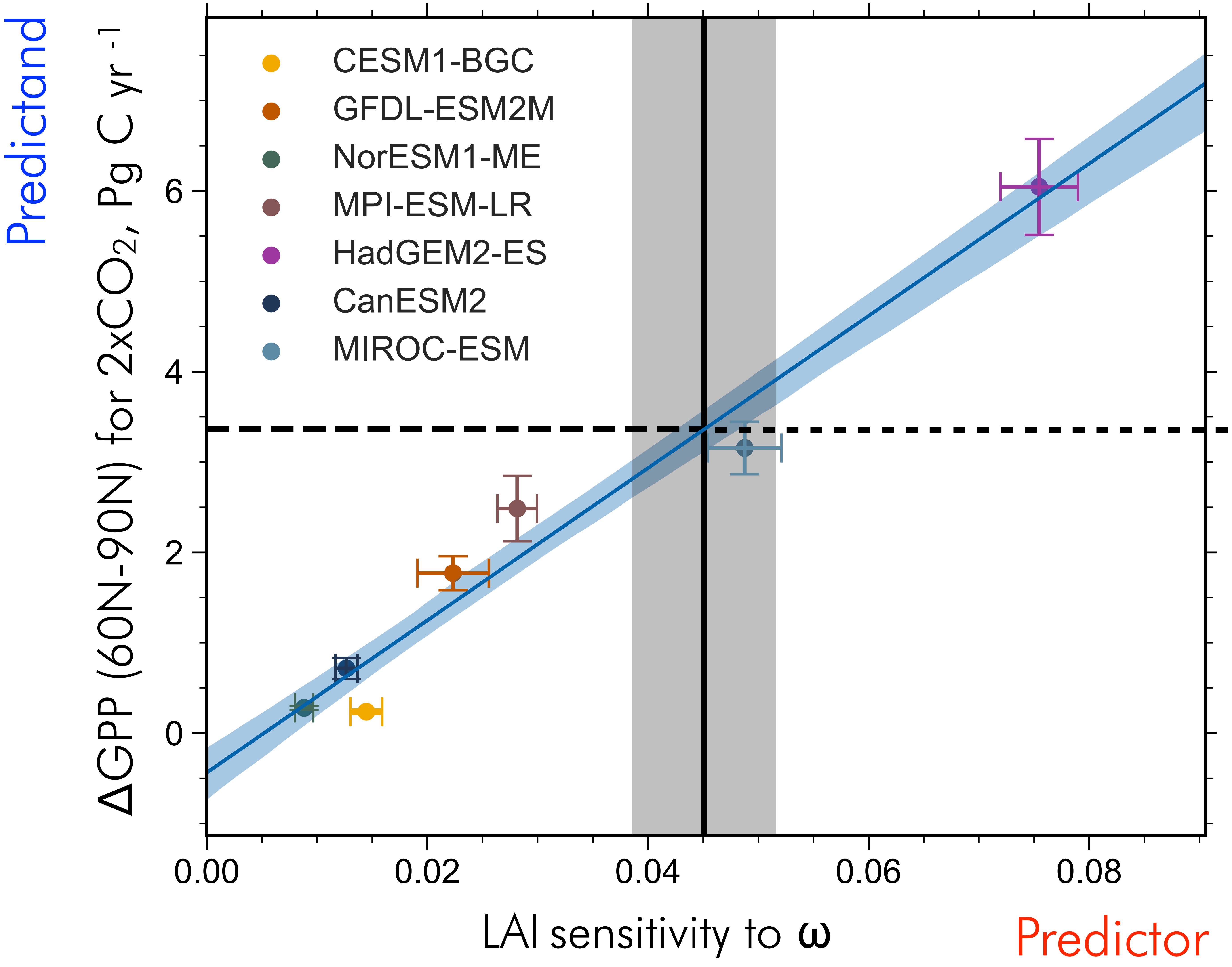


Winkler, *Nature Communications*, (2019)

The EC Approach at one Glance



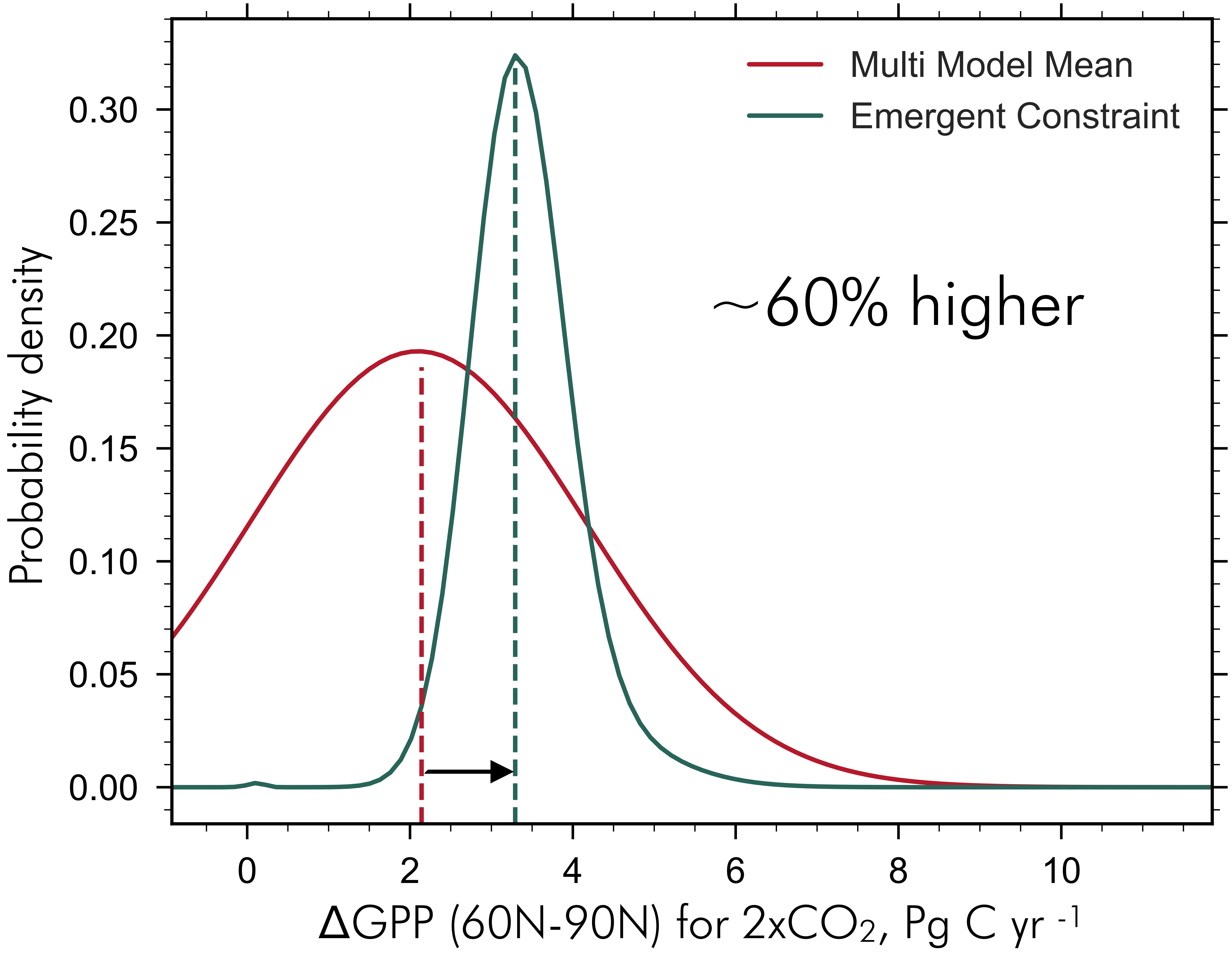
Emerging Linear Relationship



Emergent Constraint

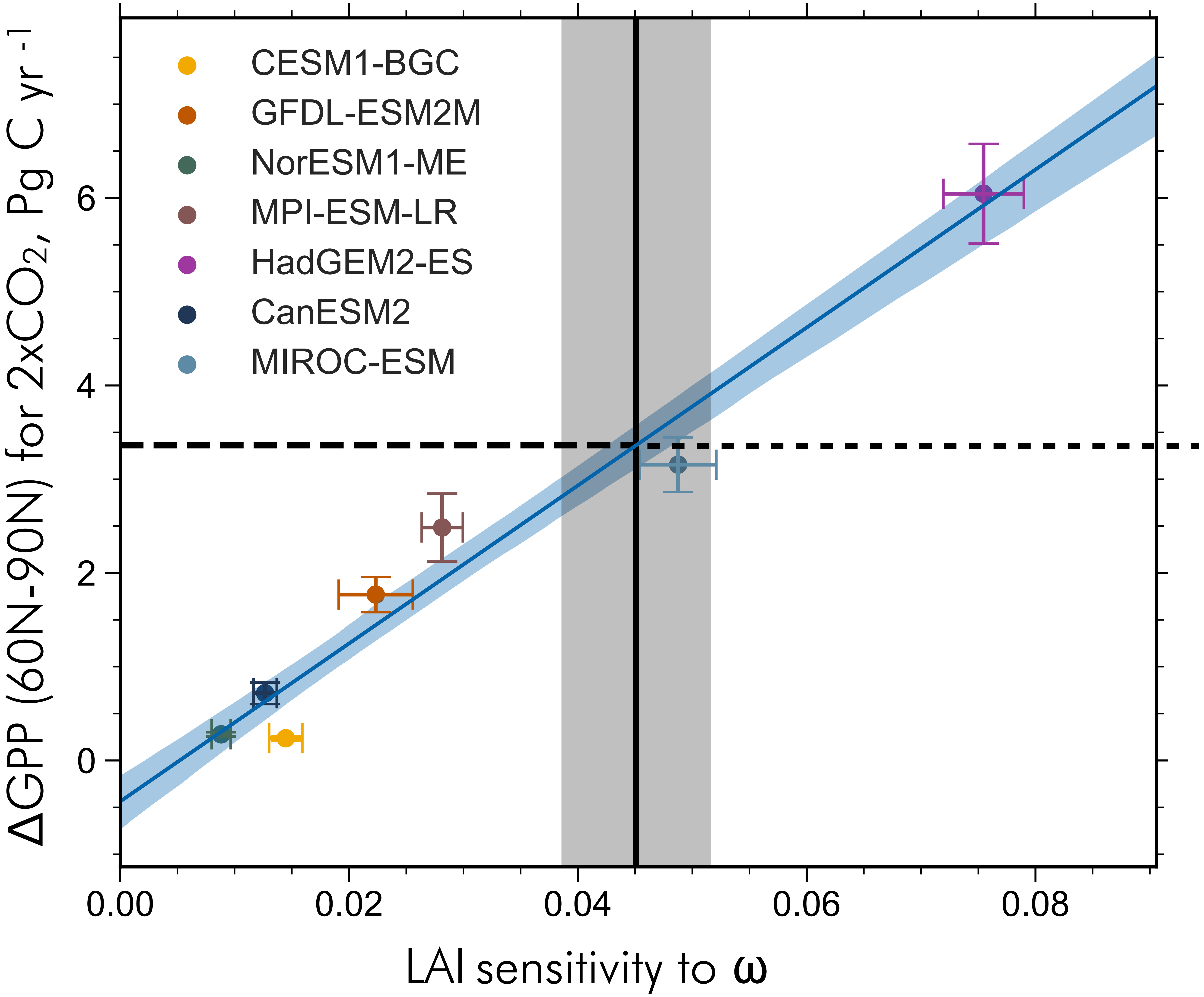
3.4 ± 0.2 Pg C yr^{-1}

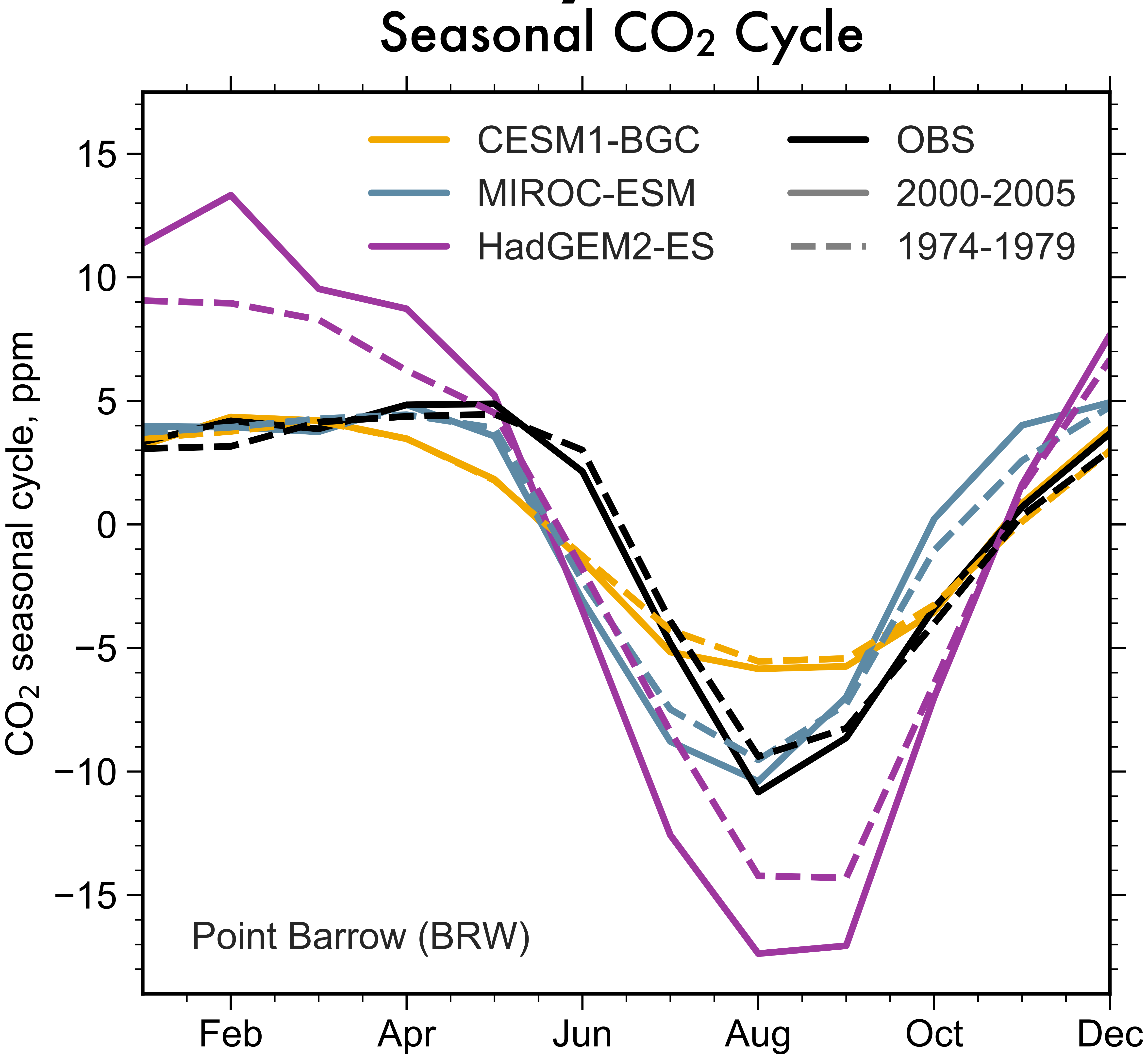
Emergent Constraints: Reducing Uncertainty of ΔGPP



Winkler, *Nature Communications*, (2019)

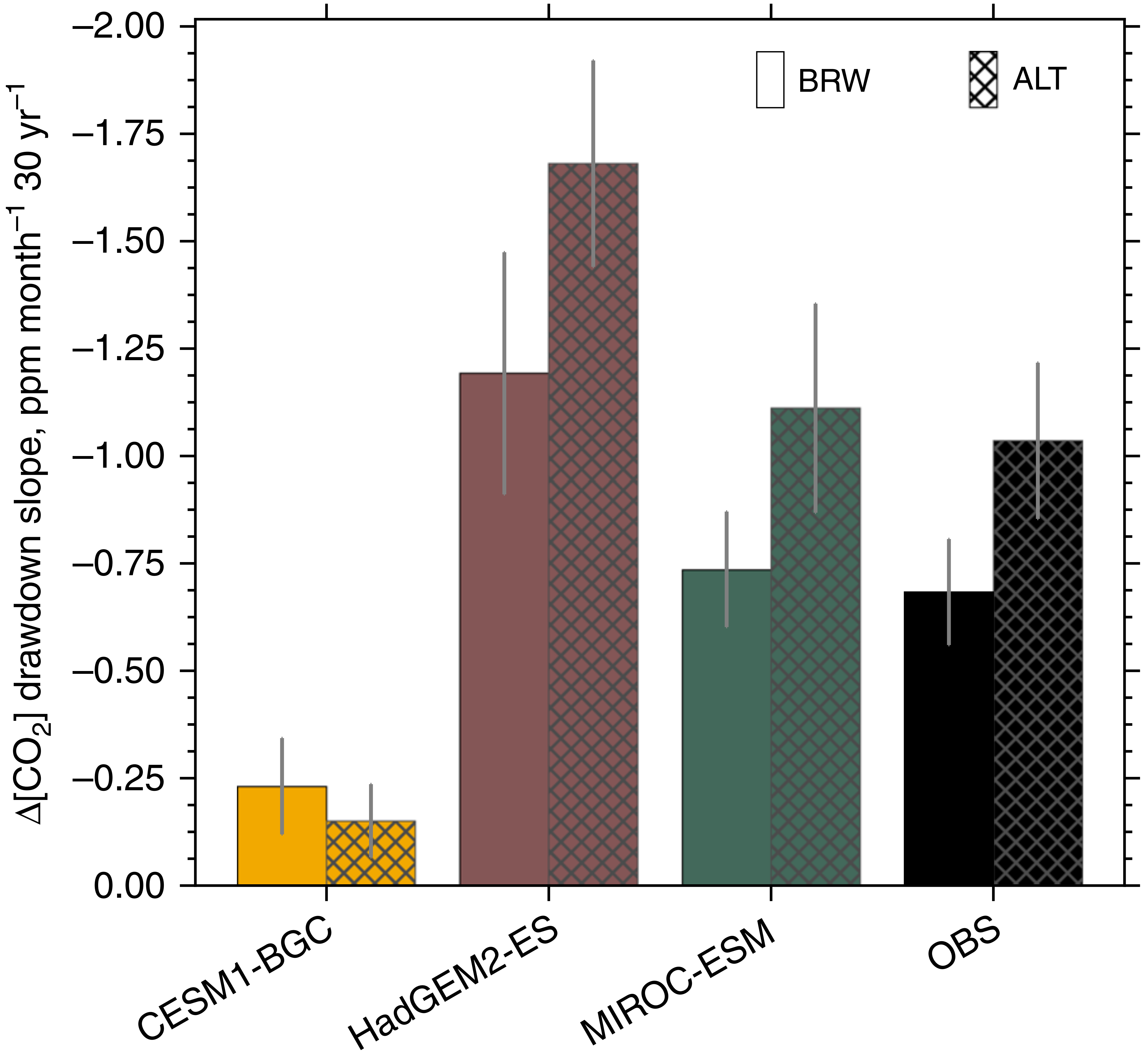
Lines of Evidence for EC: Seasonal CO_2 Cycle

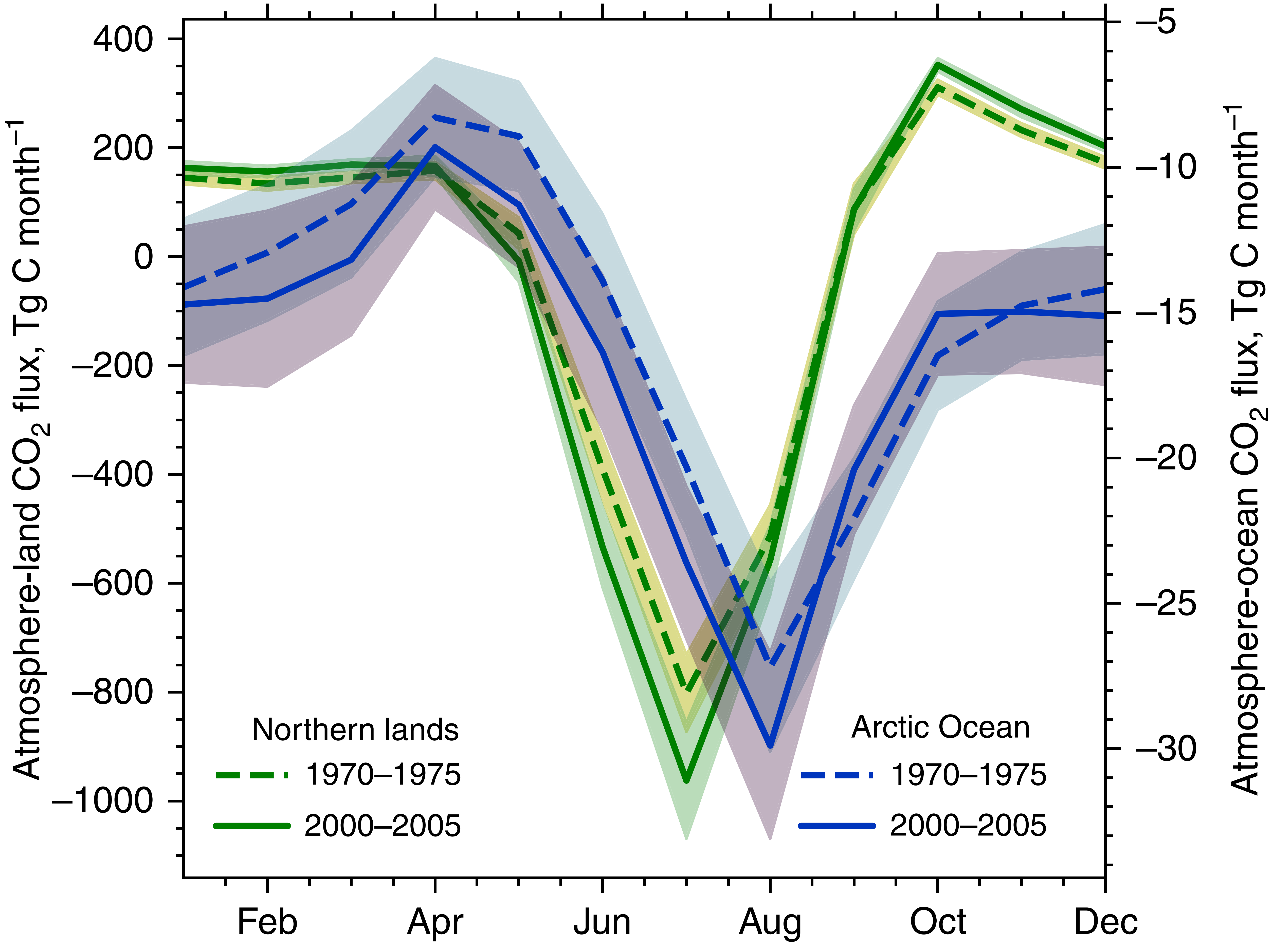




Winkler et al., *Nature Communications*, (2019)

Lines of Evidence for EC: CO_2 Drawdown Slope

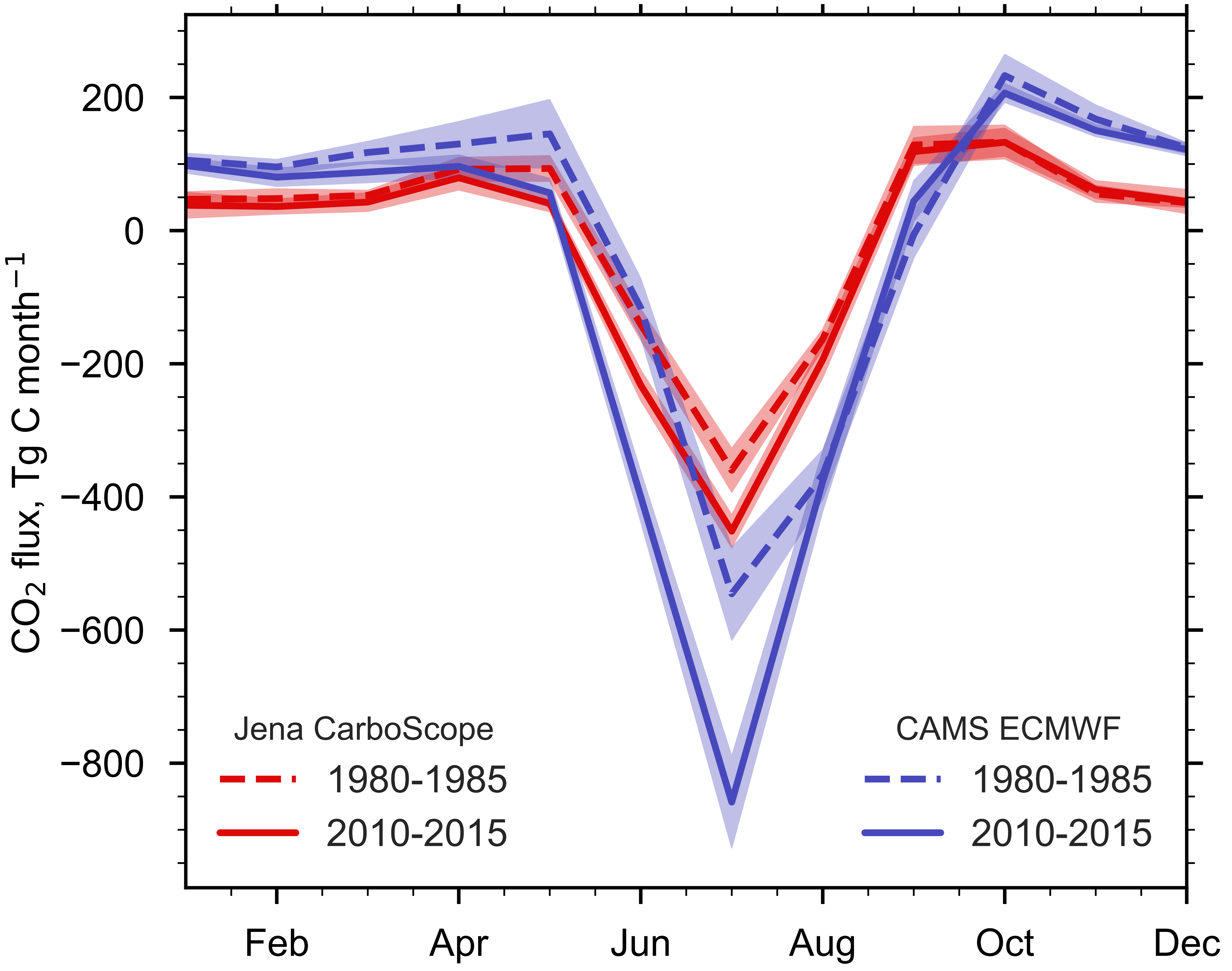




Lines of Evidence for EC: Atmospheric CO_2 Inversions

- Analysis of two state-of-the-art inversion products (Jena Carboscope, CAMS ECMWF).
- Both products agree on increasing carbon sink of high latitudes ecosystems in the last 30 years:
  - JENA: ~**0.45 Pg C yr^{-1}**
  - CAMS: ~**1.13 Pg C yr^{-1}**
- In line with *Emerging Constraint* estimate of ~**0.46 Pg C yr^{-1}***

*converted to NPP and adjusted to CO_2 increase in the last three decades



Different Types of Emergent Constraints

1. EC in **Time** (e.g. historical increase in T to constrain increase in T at 2xCO_2)

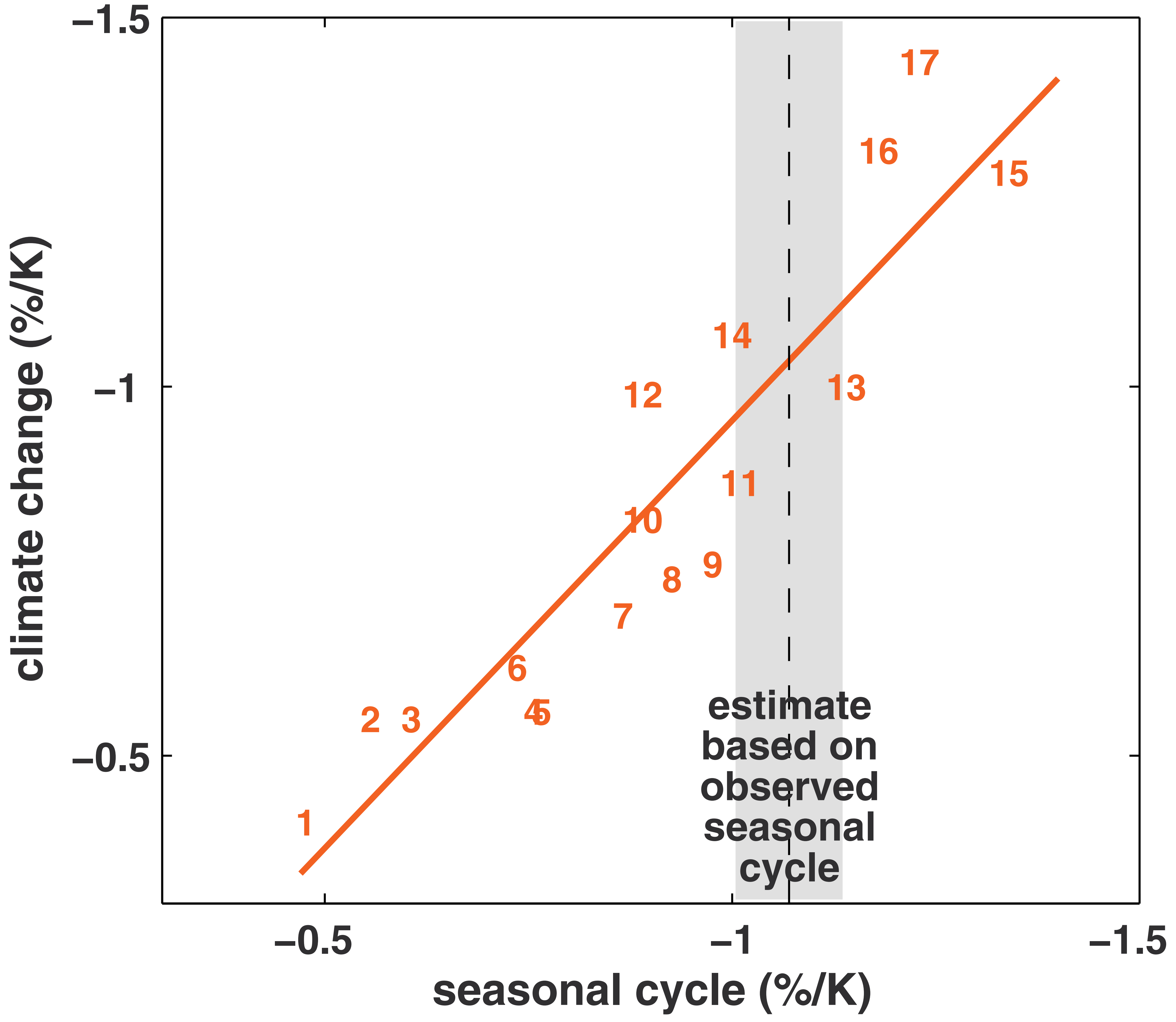
2. EC in **Space** (e.g. local measurements to constraint large scale process)

3. EC across different **Variables** (observable variable, e.g. LAI, to constrain difficult-to-measure variable, e.g. GPP)

4. **Mixed types** of EC

Emergent Constraints in Time

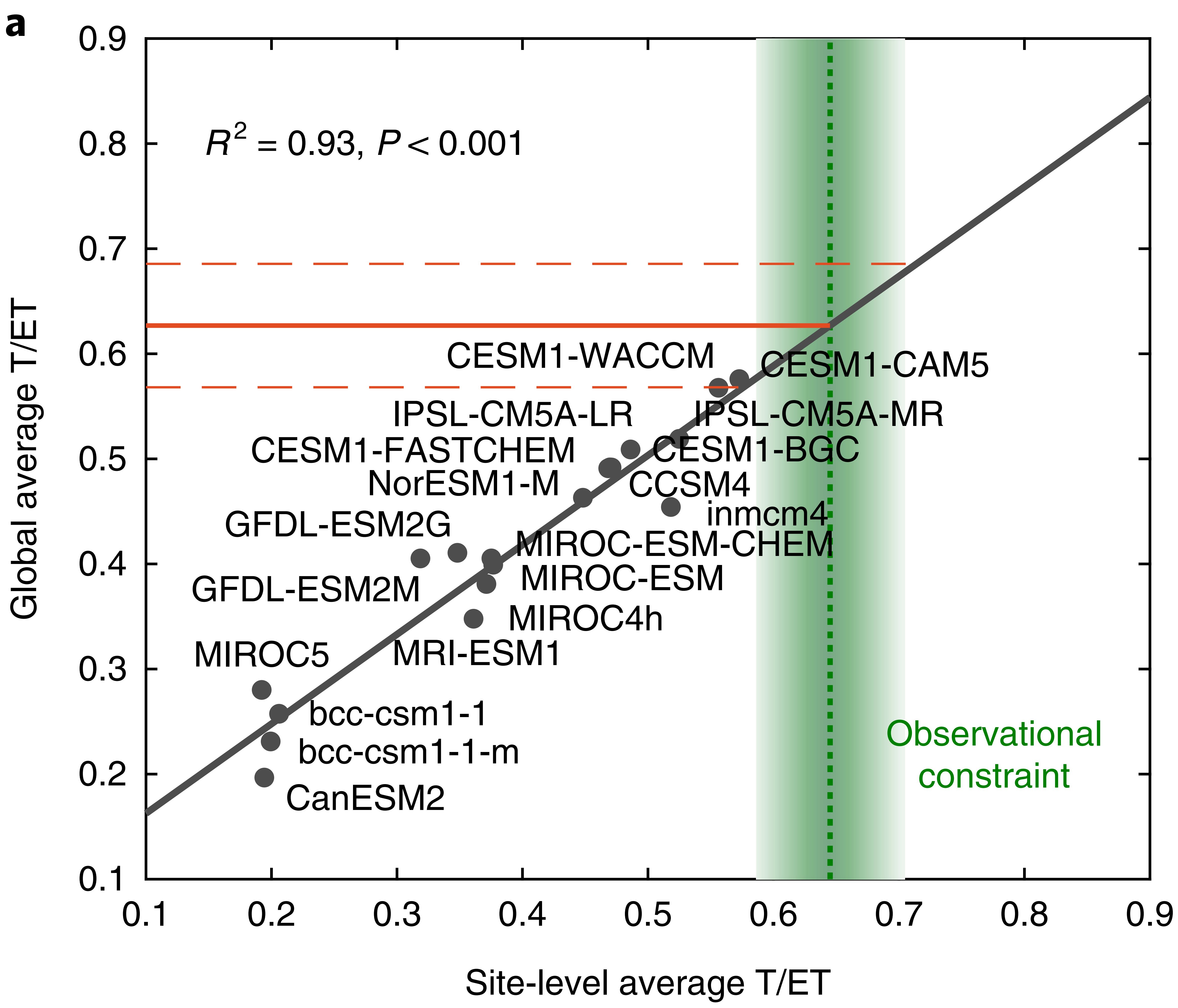
- **Concept:** Use observations of the contemporary/past climate to constrain the future/different state of the system
- Example: **Hall & Qu** (2006)
  - Predictand: future snow albedo feedback under climate change
  - Predictor: snow albedo feedback of the current seasonal cycle



Hall & Qu, *Geophys. Res. Lett.*, (2006)

Emergent Constraints in Space

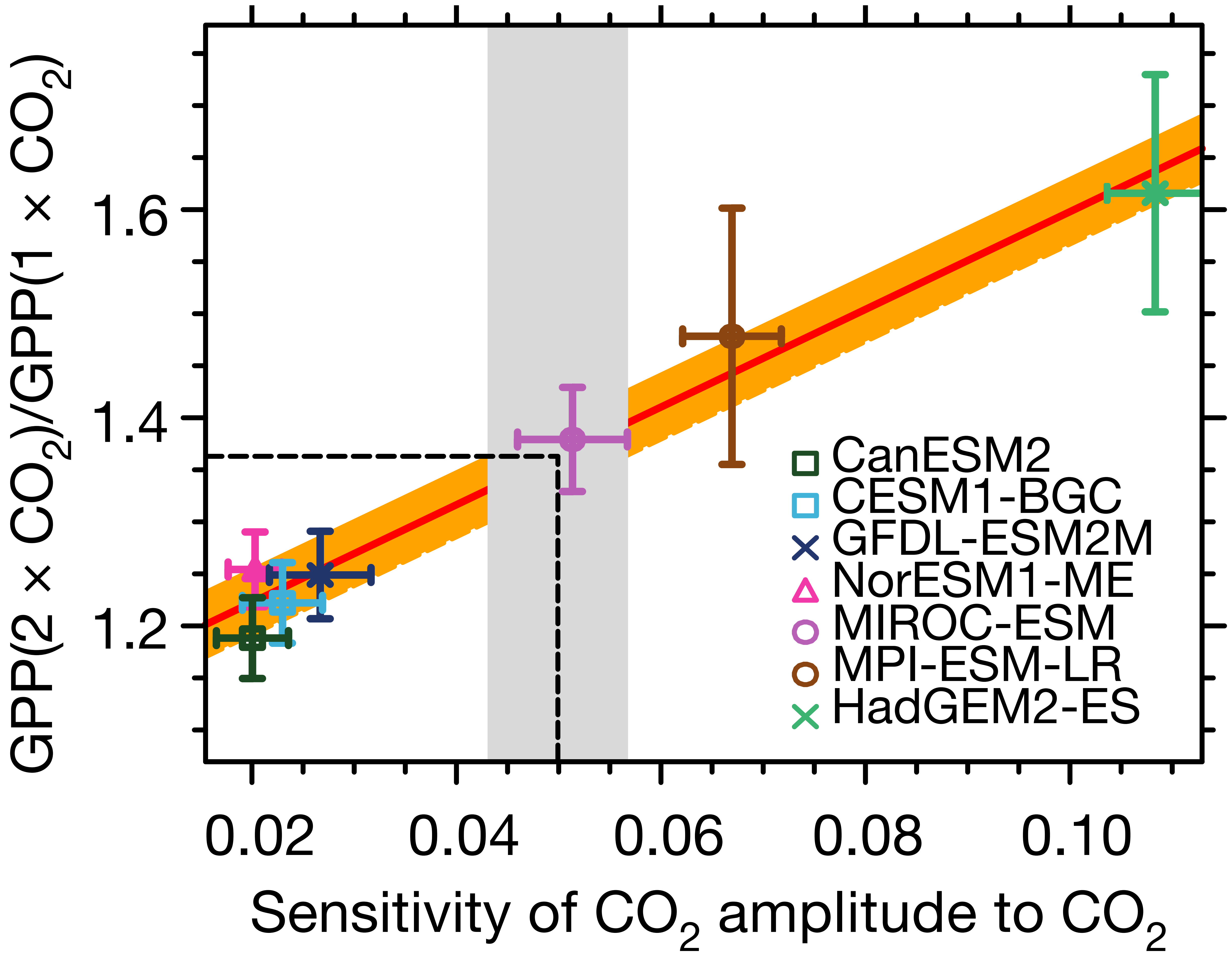
- **Concept:** Use local measurements to constrain large-scale/global estimates
- Example: **Lian et al.** (2018)
  - Predictand: global average ratio of transpiration to evapotranspiration
  - Predictor: site-level average ratio of transpiration to evapotranspiration



Lian et al., *Nature Climate Change,* (2018)

Emergent Constraints across variables

- **Concept:** Use observable variable to constrain non-observable variable
- Example: **Wenzel et al.** (2016)
  - **Predictand:** relative change in GPP for a doubling of atmospheric CO_2
  - **Predictor:** historical sensitivity of CO_2 amplitude to rising CO_2
  - **Causal relationship**: In the high northern ecosystems, changes in plant productivity lead to changes in CO_2 amplitude
  - This example is actually a mixed type: EC across variables (CO2 amplitude vs. GPP) and in time (historical vs. $2xCO_2$)



Wenzel et al., *Nature*, (2016)

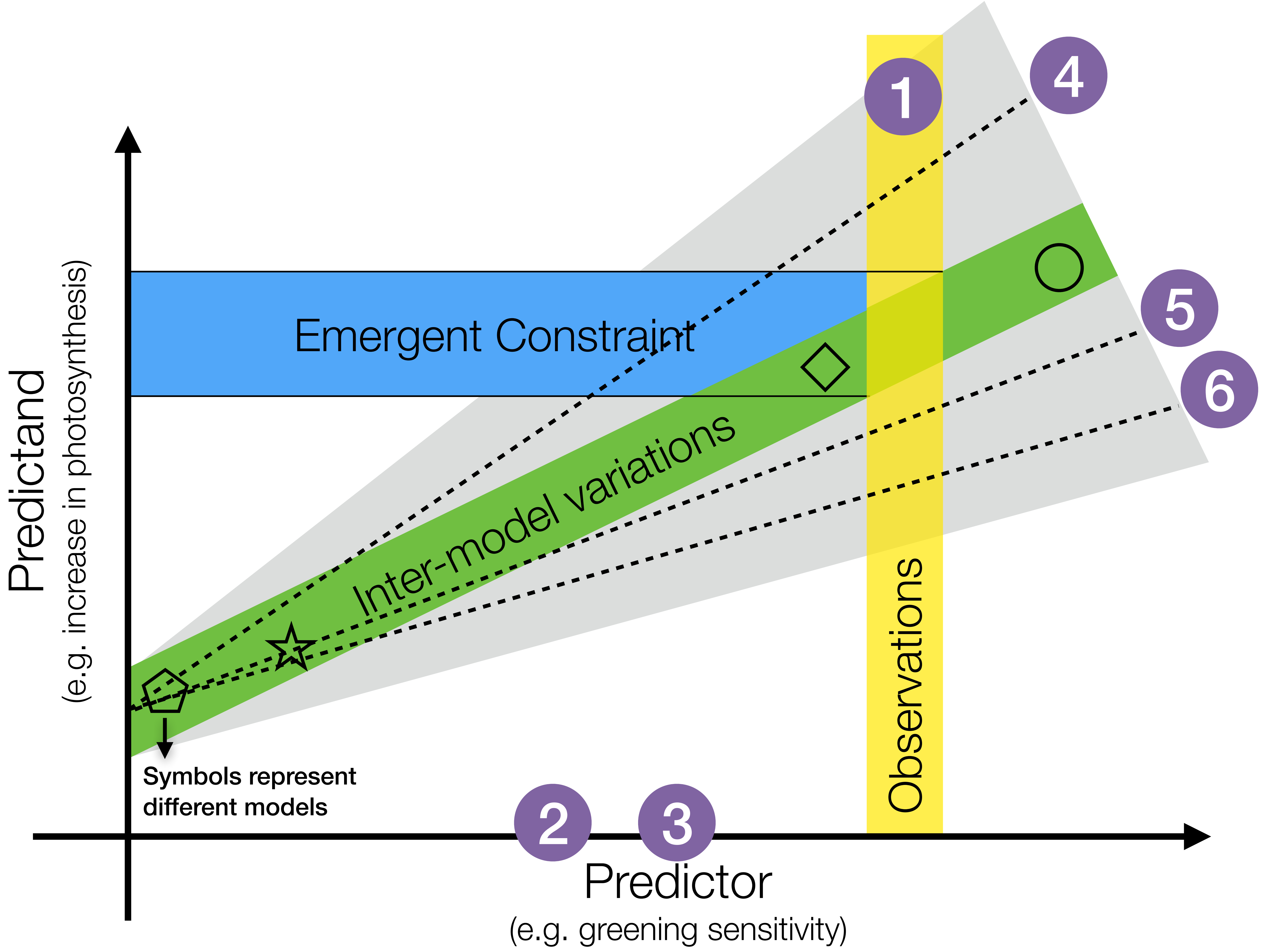
General Uncertainties in the Multi-Model Ensemble

- **Common systematic errors in a multi-model ensemble** (i.e., the entire ensemble misses an unknown process that plays a key role in a high CO_2 world): general overestimation or underestimation of the constrained value
- **Set of forcing variables** for historical simulations may be **incomplete** (i.e., not yet identified drivers of observed changes): comparability of observations and model simulations could be limited
- EC method can be **overly sensitive to individual models** of the ensemble: test ensemble for influential models (see Bracegirdle and Stephenson, 2012)

Applicability of the EC method

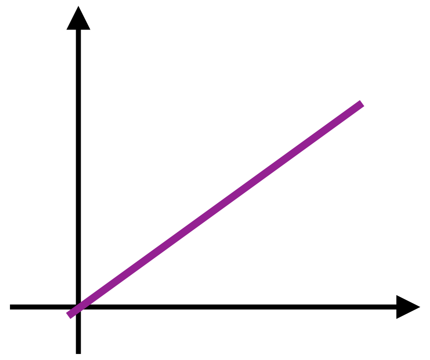
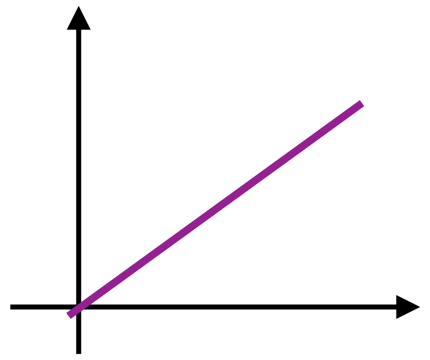
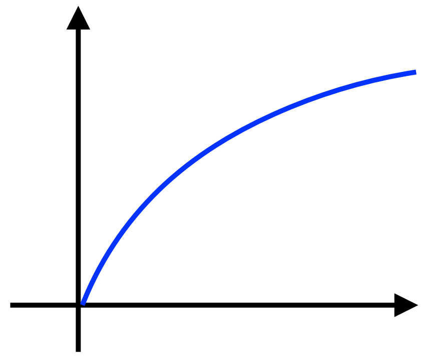
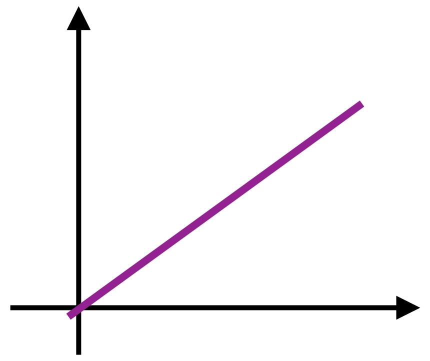
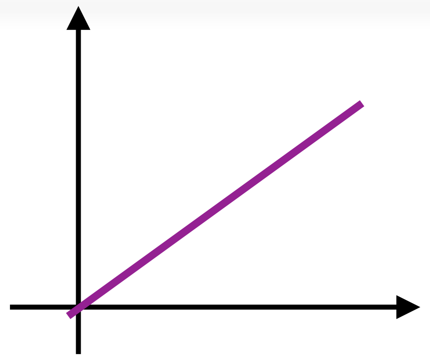
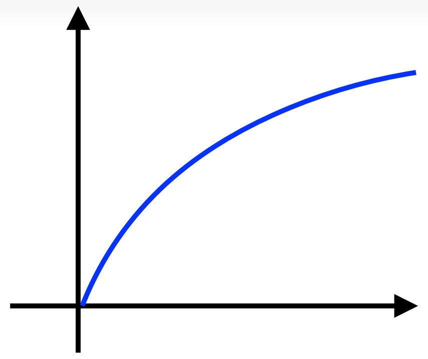
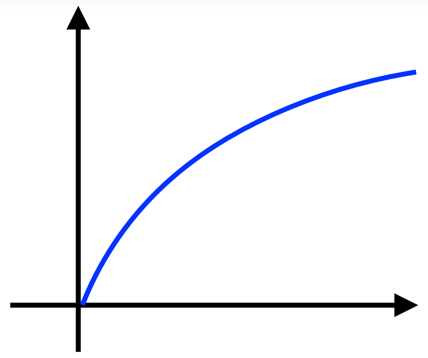
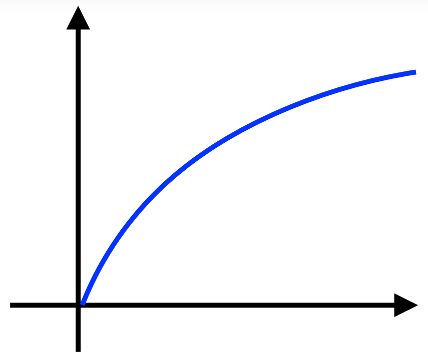
Key issues concerning the applicability of the EC method:

1. Uncertainty in data source of **observed predictor**
2. Uncertainty due to **spatial aggregation**
3. Uncertainty due to **temporal variations of the predictor**
4. Level of CO_2 forcing
5. Time rate of CO_2 forcing
6. Different effects of CO_2 forcing



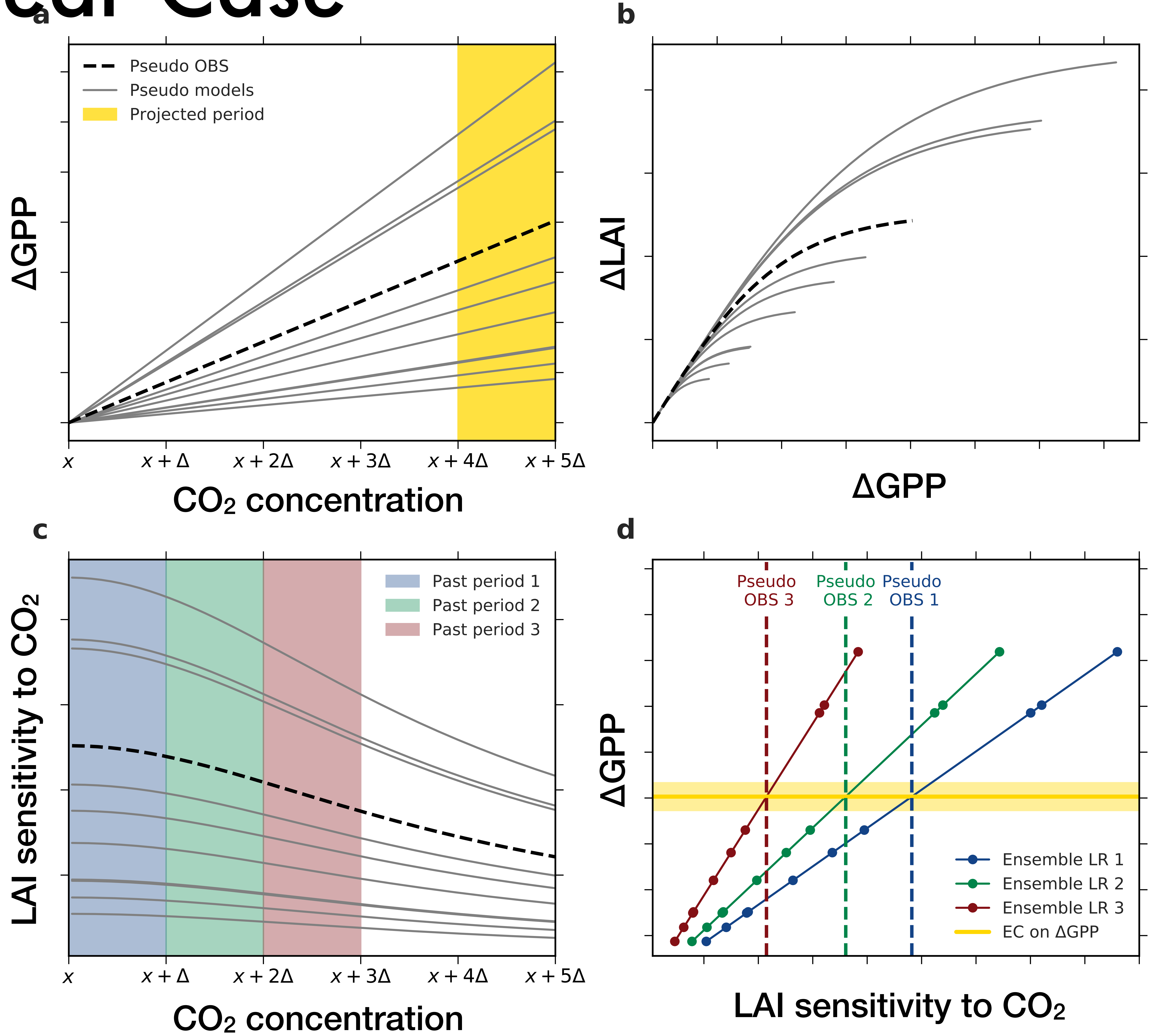
Thought Experiment

- Does EC implicitly assume that the mechanism underpinning the **relation remains unchanged** because the future state of the system is being predicted based on its past behavior?
- Understanding the relationship and interplay between **forcing** (CO_2), **predictor** (LAI), and the **predictand** (GPP) is key to evaluating the EC method.
- Thought experiment of four possible scenarios under increasing forcing: All linear, all nonlinear (saturation), and two mixed linear / nonlinear cases.

Different assumptions	$\frac{\text{d[Predictand]}}{\text{d[Forcing]}}$	e.g. $\frac{\mathrm{d[GPP]}}{\mathrm{d[CO_2]}}$	$\frac{\text{d[Predictor]}}{\text{d[Predictand]}}$	e.g. $\frac{\mathrm{d[LAI]}}{\mathrm{d[GPP]}}$
1	linear		linear	
2	nonlinear		linear	
3	linear		nonlinear	
4	nonlinear		nonlinear	

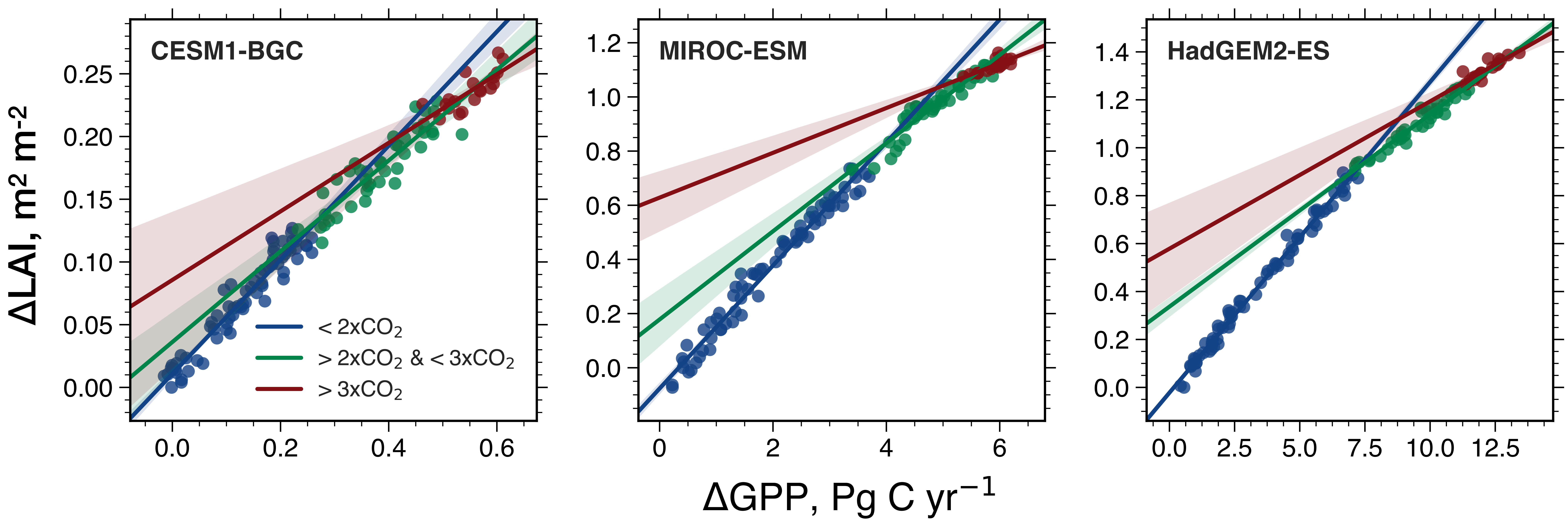
Example: Linear / Nonlinear Case

- **Multi-model ensemble emulated** using different random parameterizations for linear and saturation (hyperbolic tangent function) responses.
- Constrained GPP estimate in theory **independent of the past periods** from when the observational sensitivities are derived.
- Relationship between predictor and predictand remains linear within the model ensemble, although their **relationship becomes non-linear within each model** and reality.



Saturation at high CO_2 levels

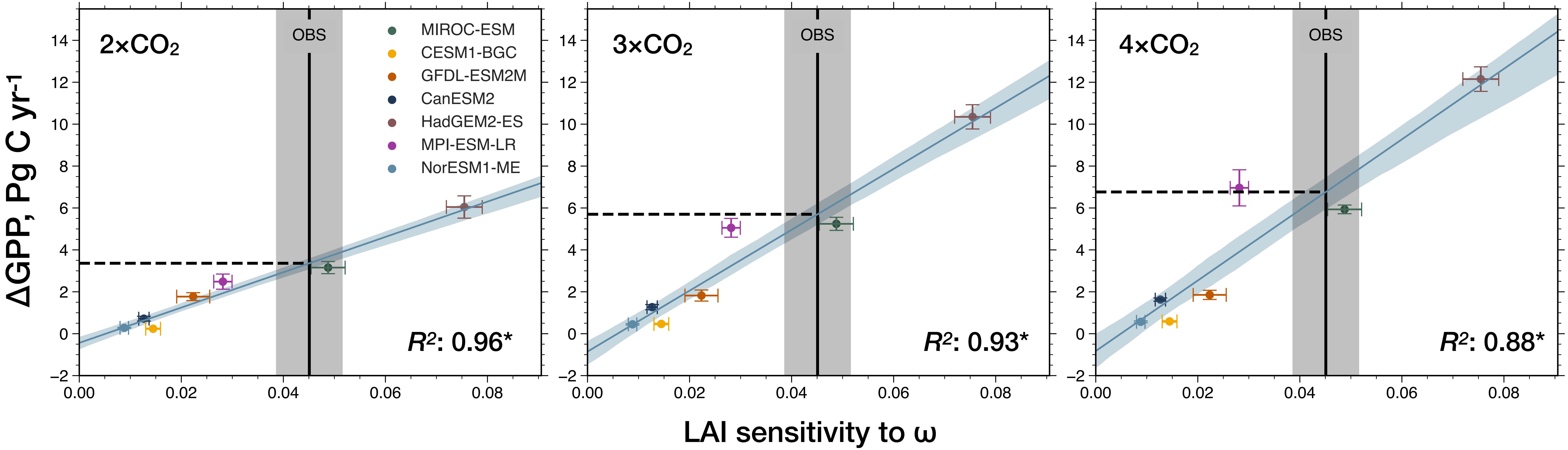
CMIP5 1pctCO2
60°N - 90°N



- Changes in GPP and LAI **relate linearly** in all CMIP5 models until $2 \times CO_2$.
- Beyond $2 \times CO_2$, all models show **weakening linearity** (saturating rate of allocation of additional GPP to new leaves).
- How does the **weakening relationship between predictor and predictand** at higher CO_2 concentration affect the EC analysis?

Constraints at different CO_2 levels

* $p < 0.05$



- **Linear relationship** between predictor and predictand within the CMIP5 ensemble **breaks up** with rising CO_2 concentration.
- **Saturation effect** manifests in **decreasing increments in constrained GPP** estimates for successive equal increments of CO_2.
- All CMIP5 models **agree on saturation**, but **disagree on the timing and magnitude** of saturation.

Summary

- Emergent Constraints are a tool to **reduce uncertainties** of unknown entities in the Earth system using observations.
- Understanding the relationship and interplay between **forcing**, **predictor**, and the **predictand** is key to evaluating the Emergent Constraints method.
- Three different types of Emergent Constraints have been identified: in **time**, in **space** and across **variables** - most studies apply **mixed types**.
- Emergent Constraints are subject to several sources of uncertainty, pitfalls and limitations.
- Emergent Constraints should not be ‚sold' as the ‚true' value, but rather as an improvement compared to the unweighted average value of the multi-model ensemble.

Further Reading

Overview of Emergent Constraint Method and Examples

- Brient, F. (2020). Reducing Uncertainties in Climate Projections with Emergent Constraints: Concepts, Examples and Prospects. *Advances in Atmospheric Sciences*, *37*(1), 1–15. https://doi.org/10.1007/s00376-019-9140-8

- Winkler, A. J., Myneni, R. B., & Brovkin, V. (2019). Investigating the applicability of emergent constraints. *Earth System Dynamics*, *10*(3), 501–523. https://doi.org/10.5194/esd-10-501-2019

- Hall, A., Cox, P., Huntingford, C., & Klein, S. (2019). Progressing emergent constraints on future climate change. *Nature Climate Change*, *9*(4), 269–278. https://doi.org/10.1038/s41558-019-0436-6

- Cox, P. M. (2019). Emergent Constraints on Climate-Carbon Cycle Feedbacks. *Current Climate Change Reports*. https://doi.org/10.1007/s40641-019-00141-y

Details on Methods:

- Winkler, A. J., Myneni, R. B., Alexandrov, G. A., & Brovkin, V. (2019). Earth system models underestimate carbon fixation by plants in the high latitudes. *Nature Communications*, *10*(1), 885. https://doi.org/10.1038/S41467-019-08633-Z

- Cox, P. M., Pearson, D., Booth, B. B., Friedlingstein, P., Huntingford, C., Jones, C. D., & Luke, C. M. (2013). Sensitivity of tropical carbon to climate change constrained by carbon dioxide variability. *Nature*, *494*(7437), 341–344. https://doi.org/10.1038/nature11882

Question 1:

Can you think of at least three interesting **Predictands** in the Earth system?

Question 2:

Can you specify adequate Predictors of the Predictands
you determined in Question 1?

Question 3:

What do you think are potential uncertainties or limitations of the Emergent Constraint method?