

please ping me with questions:
@realaaronspring
aaron.spring@mpimet.mpg.de

Inherent Uncertainty Disguises Attribution of Reduced Atmospheric CO₂ Growth to Emission Reductions for up to a Decade

Aaron Spring, Tatiana Ilyina and Jochem Marotzke

Max Planck Institute for Meteorology

This talk will also be delivered by videoconferencing Friday May 8th 17:45 via zoom.
You can find the agenda [here](#) and you can sign up [here](#).



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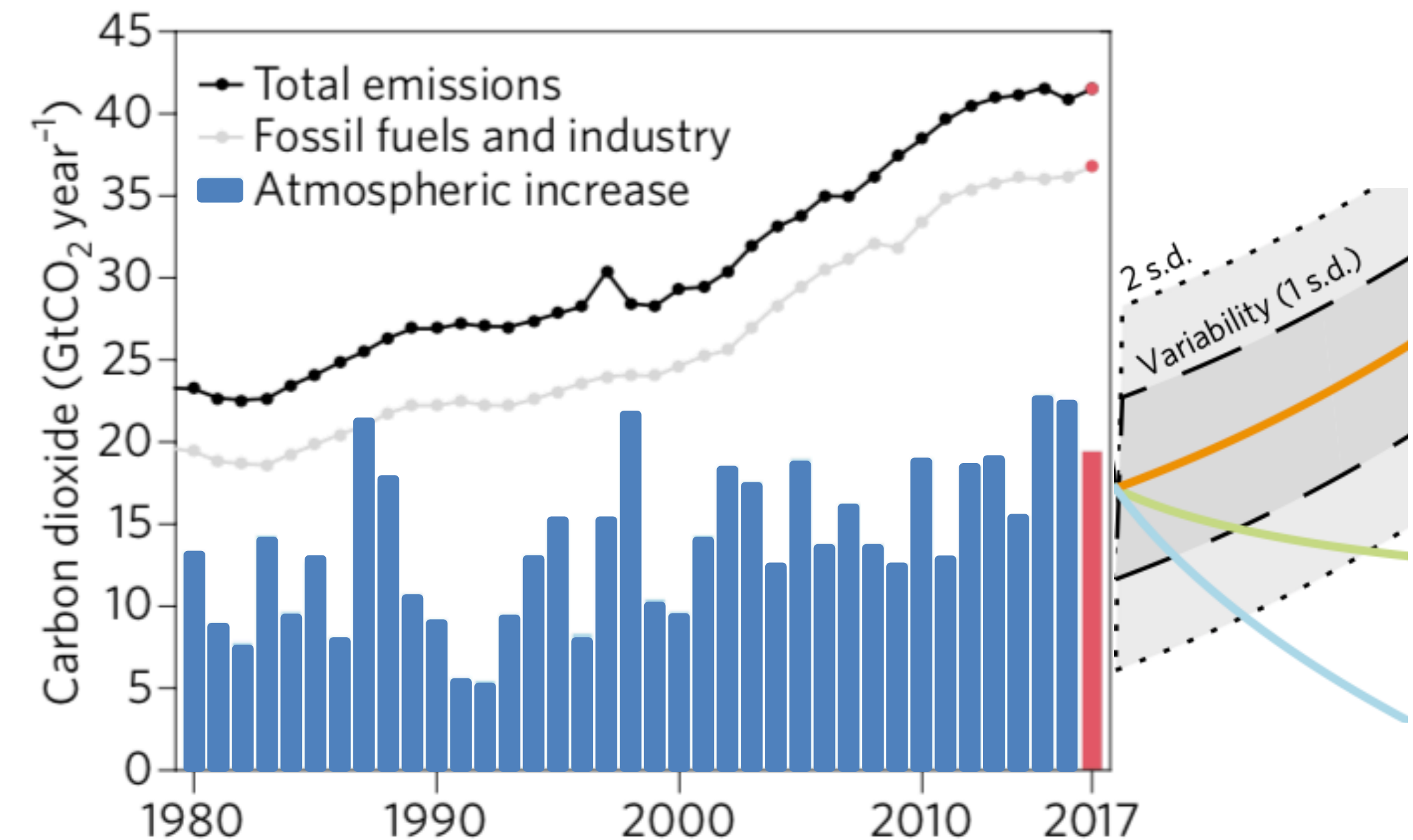
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The global carbon cycle is sensitive towards climate-driven internal variability, which might obscure the identification of changes in anthropogenic emissions.

- ▶ Long-term dominance of the forced signal undisputed
- ▶ When are emission reductions detectable in atmospheric CO₂ measurements?
 - ➔ COVID19 signal not yet detectable at Mauna Loa [PFriedling]
 - ➔ Policy-relevant when emission reduction efficacy is assessed by global stocktake.
- ▶ On which time-scales does internal variability in atmospheric CO₂ dominate over changes in the forced signal?



[Peters et al. 2017 Figs. 1&2]

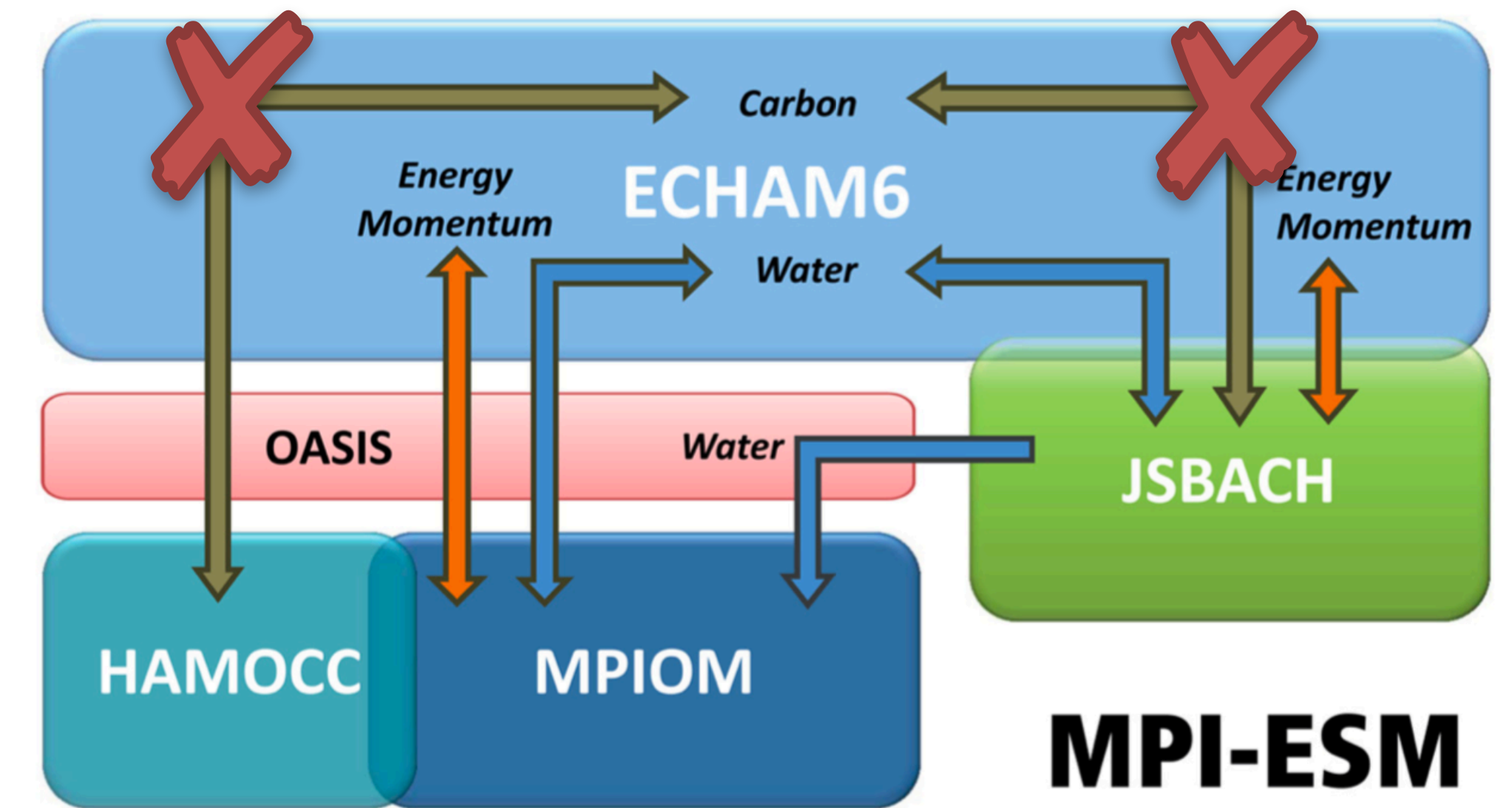
Research questions: Inherent uncertainty in atmospheric CO₂ projections and attribution of emission reductions

- ▶ On what time-scales are trend reductions in atmospheric CO₂ attributable to emission reduction?
 - What is the probability that even if emissions are reduced, the trend in atmospheric CO₂ keeps rising even stronger?
 - How many years after reduced emissions can we be certain that these reduced emissions caused a reduction in atm. CO₂ trend?

MPI-ESM Grand Ensemble provides a 1% resolution in climate event attribution [Marotzke, 2019].

- Uninitialised ensemble to separate internal variability from forced signal [Maher et al., 2019]:
 - 100 ensemble members from piControl
 - 3 scenarios

- Causal Theory [Pearl 2020, Hannart et al. 2016]
 - Factual world
 - Counter-factual world
 - Necessary and sufficient causality

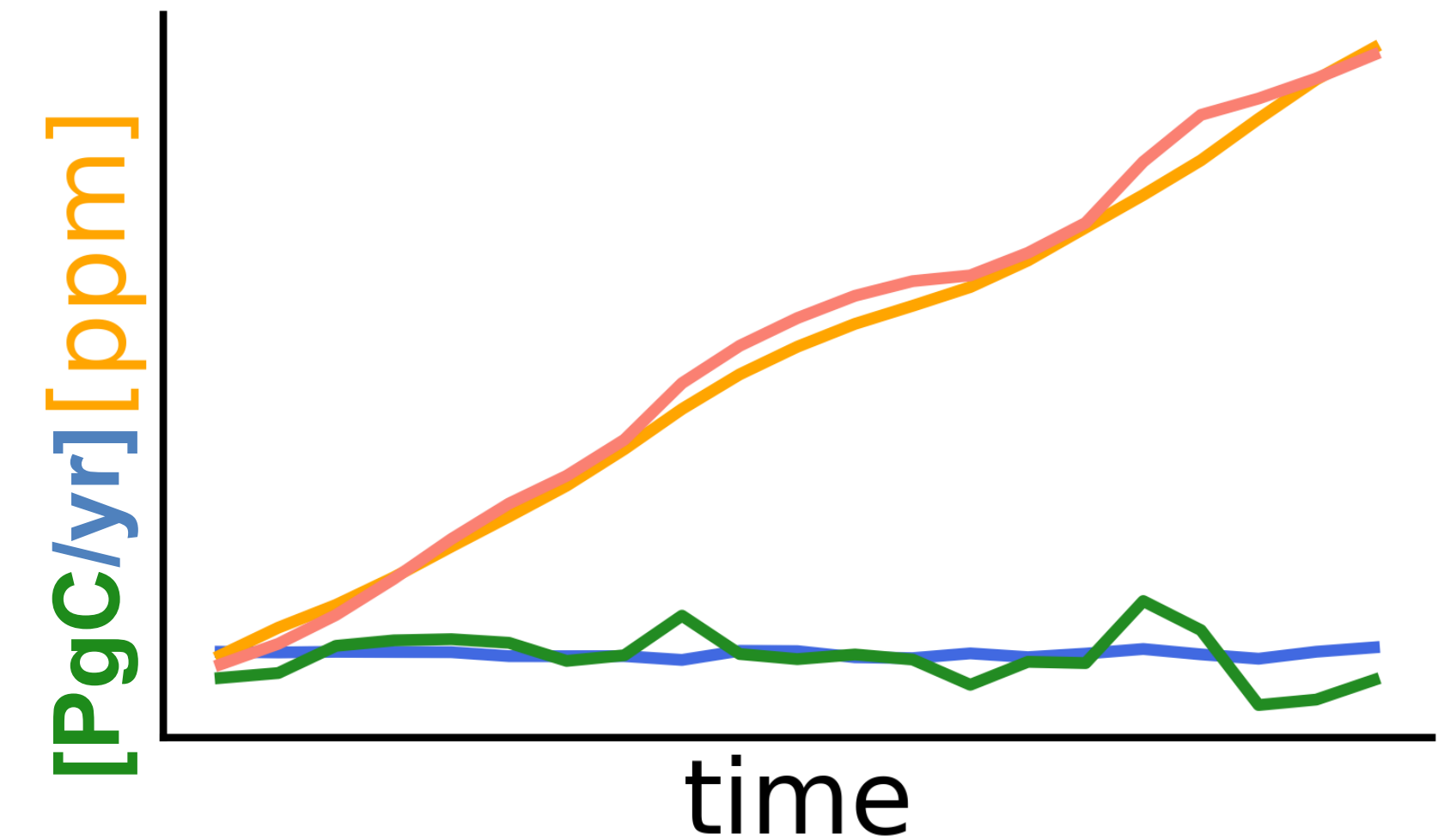


MPI-ESM
Giorgetta et al. 2013

- MPI-ESM1.1-LR historical + RCPs
 - Atmosphere & Land: T63 (1.8°)
 - Ocean: GR15 (1.5°)
 - prescribed atmospheric CO₂ forcing

Diagnosing global atmospheric CO₂ variations from the prescribed CO₂ signal and the global carbon sinks ensemble mean residuals.

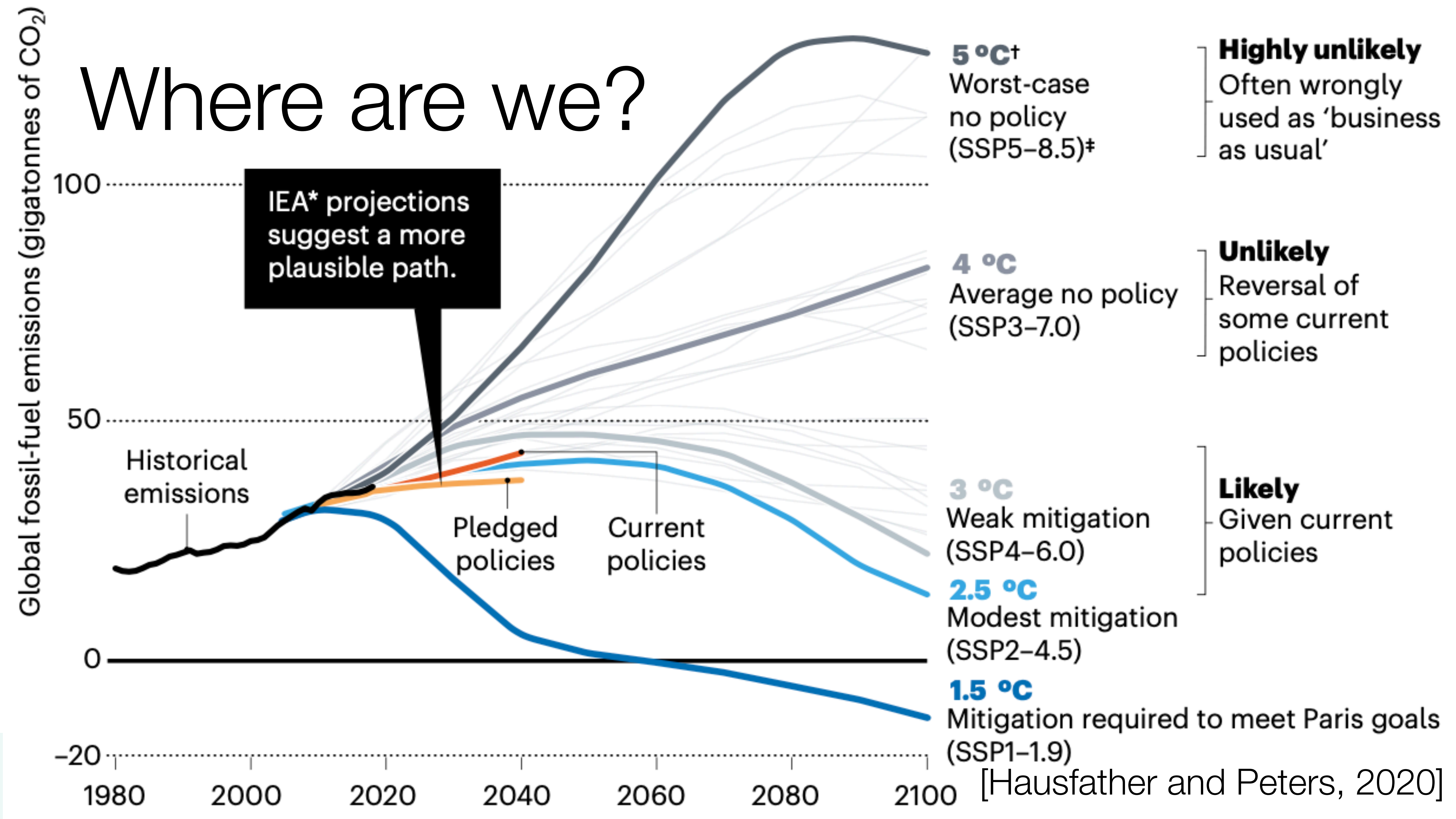
$$\text{XCO}_2(t) = \sum_{t'=t_{\text{start}}}^t (\underbrace{\text{CO}_2\text{flux}'(t')}_{\substack{=\text{time mean control} \\ =\text{member mean}}}) \frac{\text{ppm}}{2.12 \text{ PgC}} + \underbrace{\text{forcing}(t)}_{=\text{CO}_{2,\text{atm}} \text{ forcing (IAM)}}$$



► Assumptions:

- Instantaneous global atmospheric mixing [Ballantyne et al. 2012]
- Internal variability of carbon cycle driven by climate variability
- Disregards short-term influence of atm. CO₂ variability on carbon cycle

Where are we?



The MPI-ESM Grand Ensemble provides a **Paris targets (RCP2.6)** and **current pledges pathway (RCP4.5)** scenario with diverging CO₂ forcing after 2020.

► Expected climate response to emission cuts: decrease in atm. CO₂ trend

► Uninitialised large ensemble simulations:

- 100 ensemble members

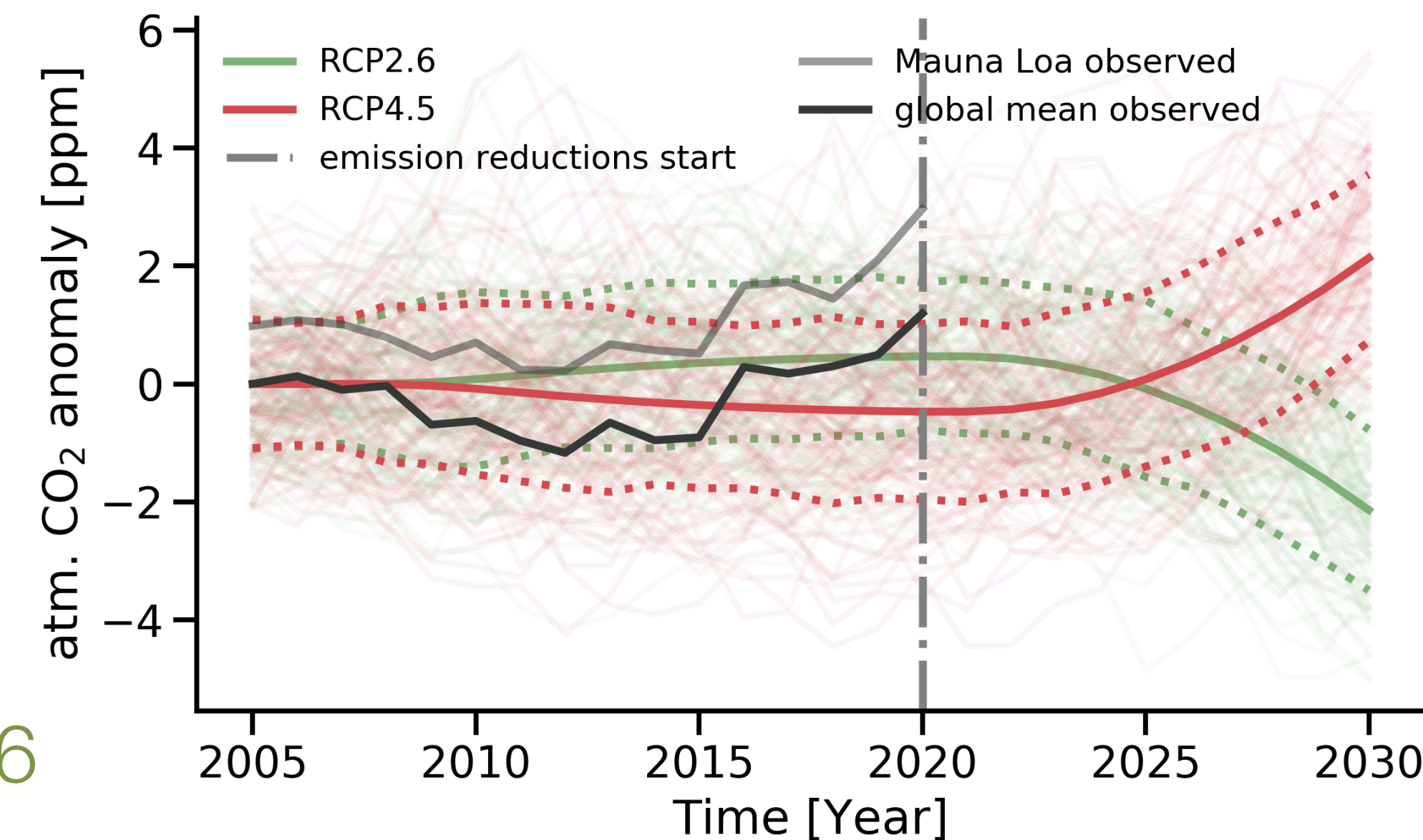
- 2 scenarios:

- **RCP2.6: emission reduction to reach Paris goals**
- **RCP4.5: current, no emis. reductions before 2040**
- Emission cuts as policy change from **RCP4.5** to **RCP2.6**

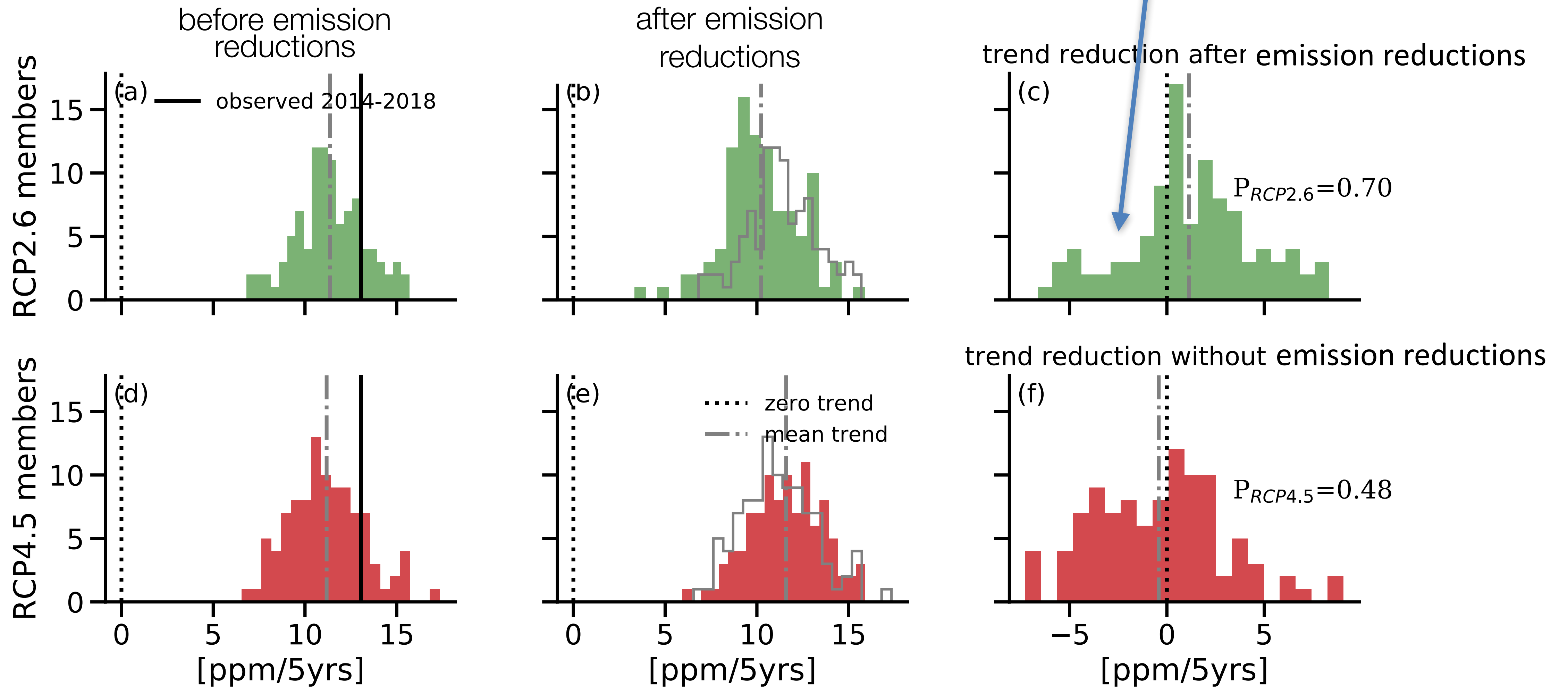
► Probabilities of reduction in 5-year trends

$$P_{RCP_x} = \sum_{ens=1}^{100} (trend_{ens}^{2016-2020} > trend_{ens}^{2021-2025}) \%$$

[adopted from Marotzke, 2019]



Atmospheric CO₂ 5-year trends might even increase despite of implemented emission reductions policy due to internal variability.



Three facets of causation

Switch C_1 = policy change from RCP4.5 to RCP2.6
Switch C_2 = internal variability (no strong natural C outgassing)
Light bulb E = reduced atm. CO₂ trends

Does policy change cause reduced atm. CO₂ trends?

► necessary causation

- Without switch C_1 , bulb E is off. Yet C_1 not always turns on E , as C_2 is also required
- ask retrospectively whether policy change was **necessary**

► sufficient causation

- Bulb E is lit every time C_1 is turned on. Yet if C_1 is off, E might still be lit by C_2
- ask in advance whether a policy change would be **sufficient** to cause a trend reduction

► necessary and sufficient causation

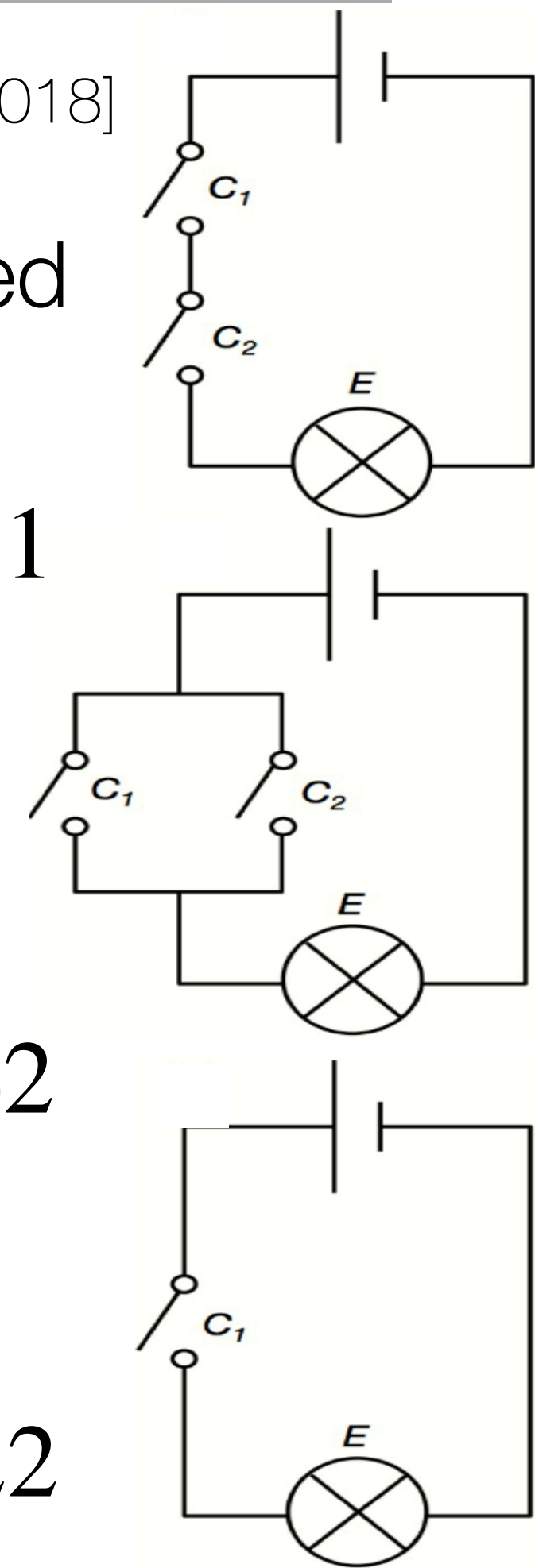
- Turning on C_1 always lights E , and E may not be lighted unless C_1 is on.
- policy change is both **necessary and sufficient**

[Pearl 2020, Hannart et al. 2018]

$$P_N = 1 - \frac{P_{RCP4.5}}{P_{RCP2.6}} = 0.31$$

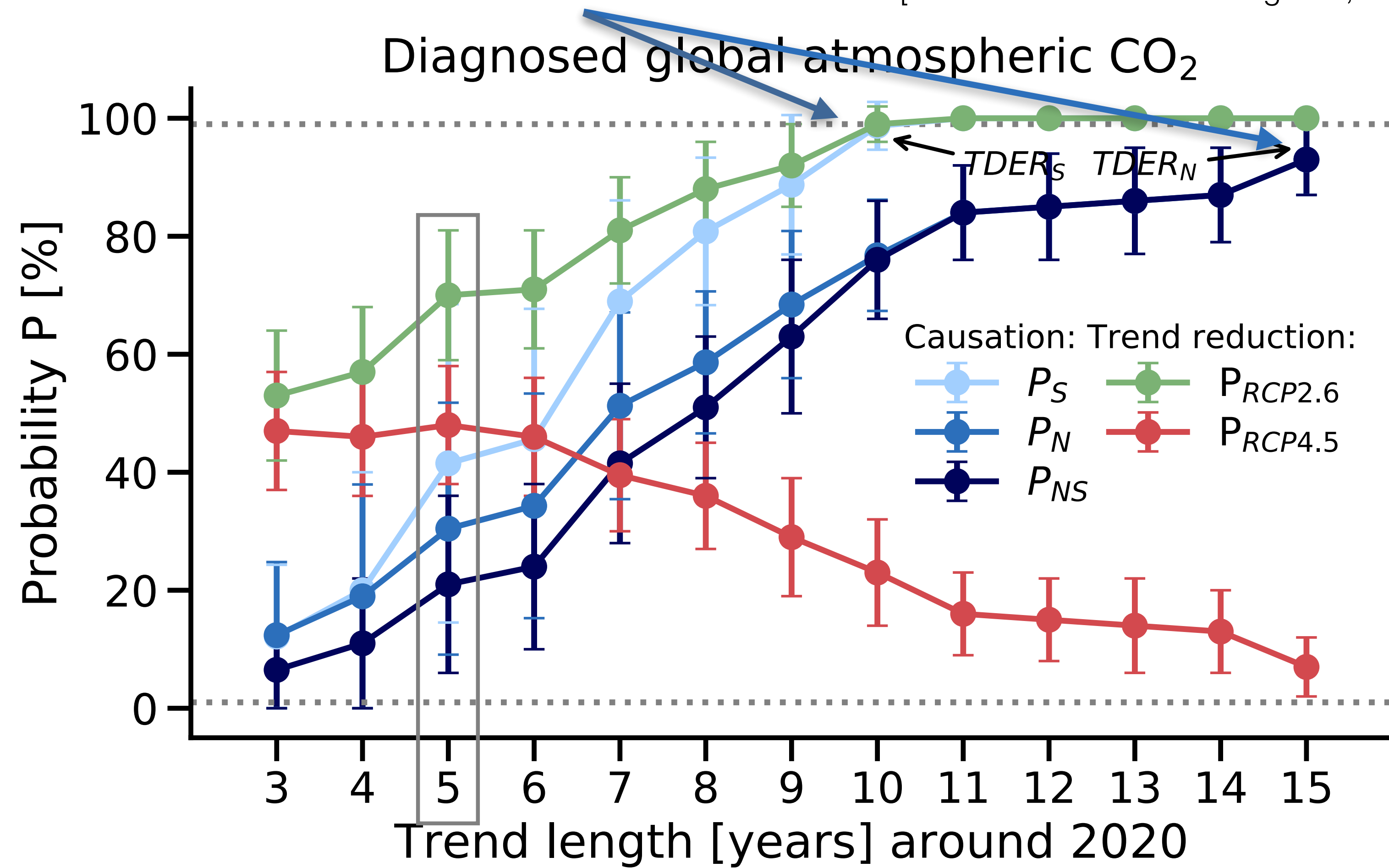
$$P_S = \frac{P_{RCP2.6} - P_{RCP4.5}}{1 - P_{RCP4.5}} = 0.42$$

$$P_{NS} = P_{RCP2.6} - P_{RCP4.5} = 0.22$$



Reduced emissions are certain to cause reduced trends in atmospheric CO₂ in a sufficient causation sense when considering 10-year trends.

time of detection of emission reduction [similar Tebaldi and Friedlingstein, 2013]



- Ask in advance whether a policy change would be **sufficient** to cause a trend reduction:

[Hannart et al. 2016]

$$P_S = \frac{P_{RCP2.6} - P_{RCP4.5}}{1 - P_{RCP4.5}}$$

- Ask retrospectively whether policy change was **necessary**:

$$P_N = 1 - \frac{P_{RCP4.5}}{P_{RCP2.6}}$$

- Policy change from RCP4.5 to RCP2.6 is both **necessary and sufficient**:

$$P_{NS} = P_{RCP2.6} - P_{RCP4.5}$$

Take home messages: Inherent uncertainty in atmospheric CO₂ projections might disguise emission reduction effects up to a decade.

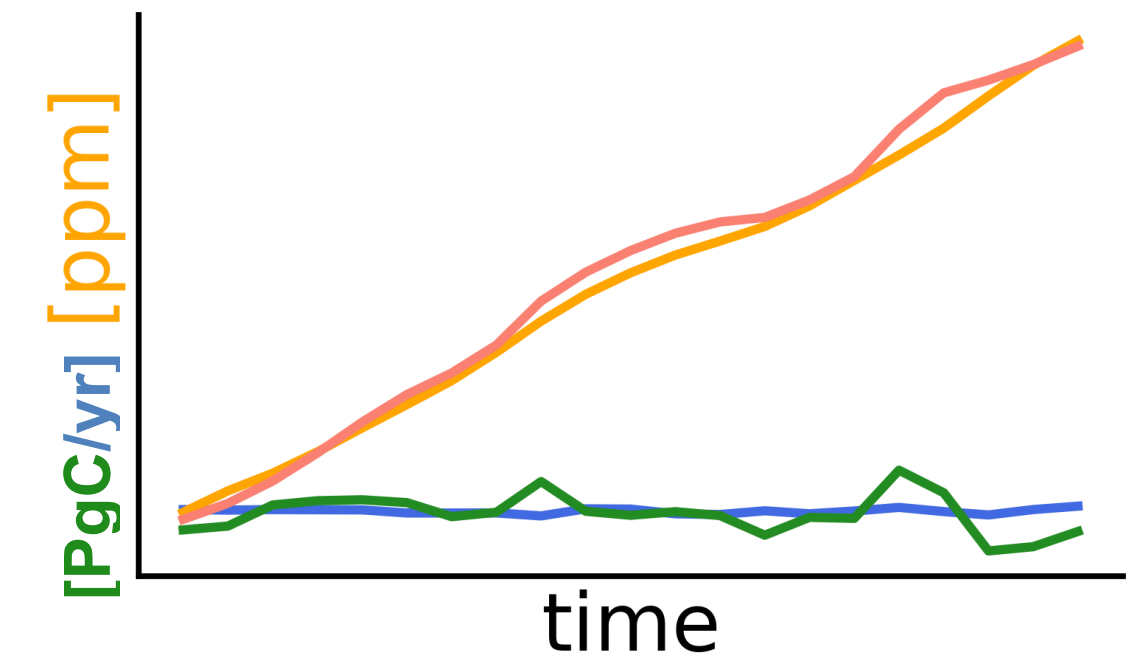
- ▶ Policy change from RCP4.5 to RCP2.6 is *sufficient* to cause 5-year CO₂ trend reduction with P=42% and *necessary* with P=31% and *necessary and sufficient* with P=22%.
- ▶ These probabilities, when covering the time-scales of the Global Stocktake, are **far from certain**.
- ▶ Certainty is reached after 10 (*sufficient* causation) and 15 (*necessary*) years.
- ▶ Results are based on one model. All models have internal variability.
- ▶ Policy-makers should be informed by initialized predictions about near-term internal variability in atmospheric CO₂ evolution [Spring and Ilyina, 2020].
- ▶ This influence of internal variability in atm. CO₂ on sub-decadal time-scales in emission reduction attribution is challenging to communicate to the public.

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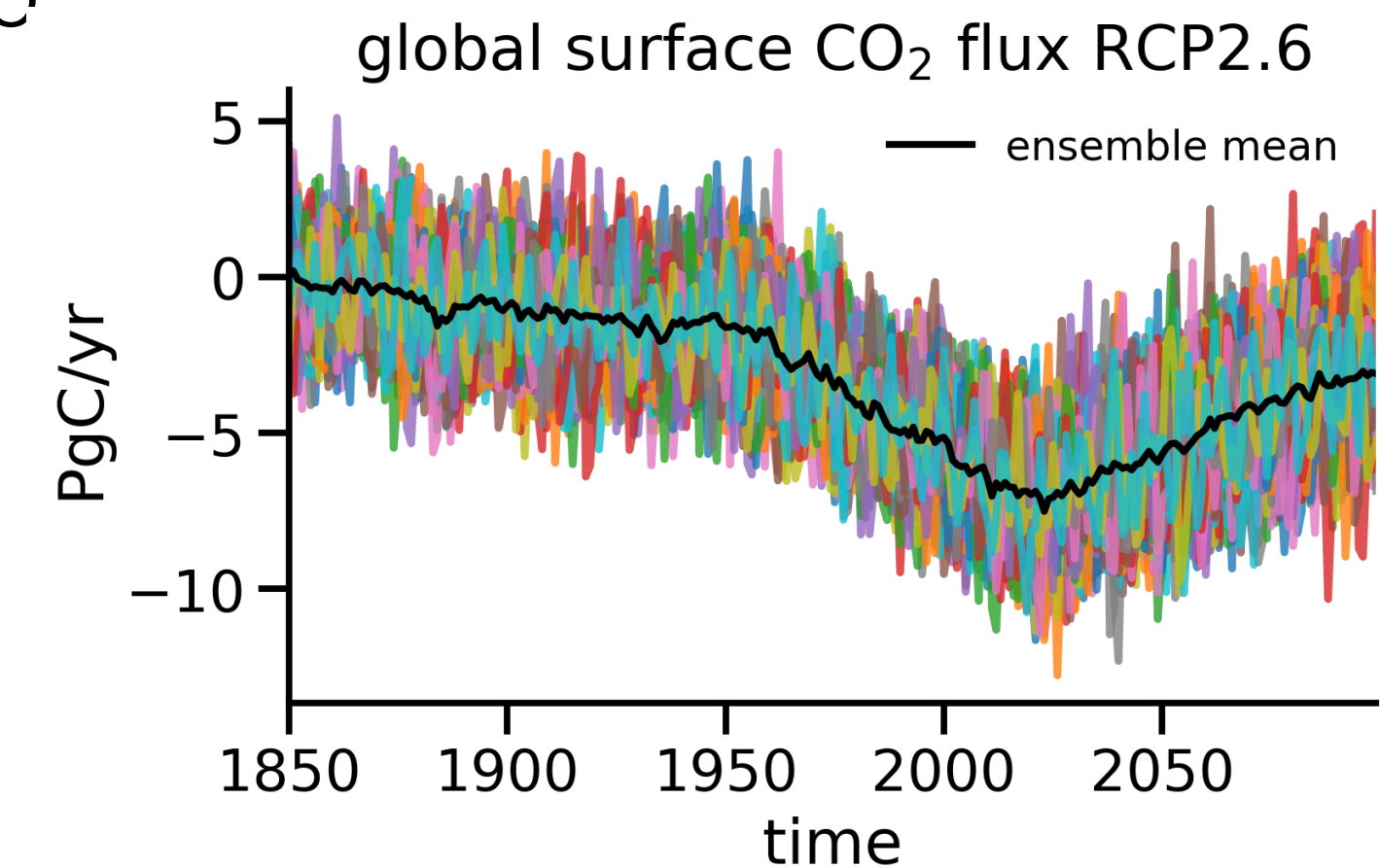
Assumptions about diagnosed atmospheric CO₂

$$XCO_{2,atm}(t) = \sum_{t'=t_{start}}^t \underbrace{(CO_2flux'(t'))}_{\substack{= \text{time mean control} \\ = \text{member mean}}} \frac{\text{ppm}}{2.12 \text{ PgC}} + \underbrace{forcing(t)}_{\substack{= \text{Historical: } CO_{2,atm} \text{ forcing (IAM)} \\ \text{esmHistorical: member mean } CO_2}}$$



► Assumptions:

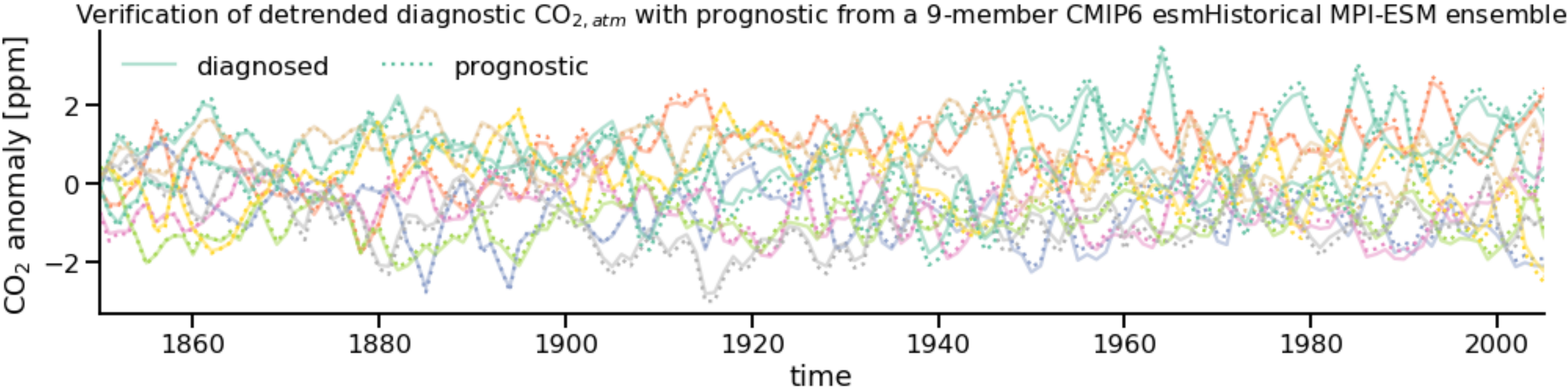
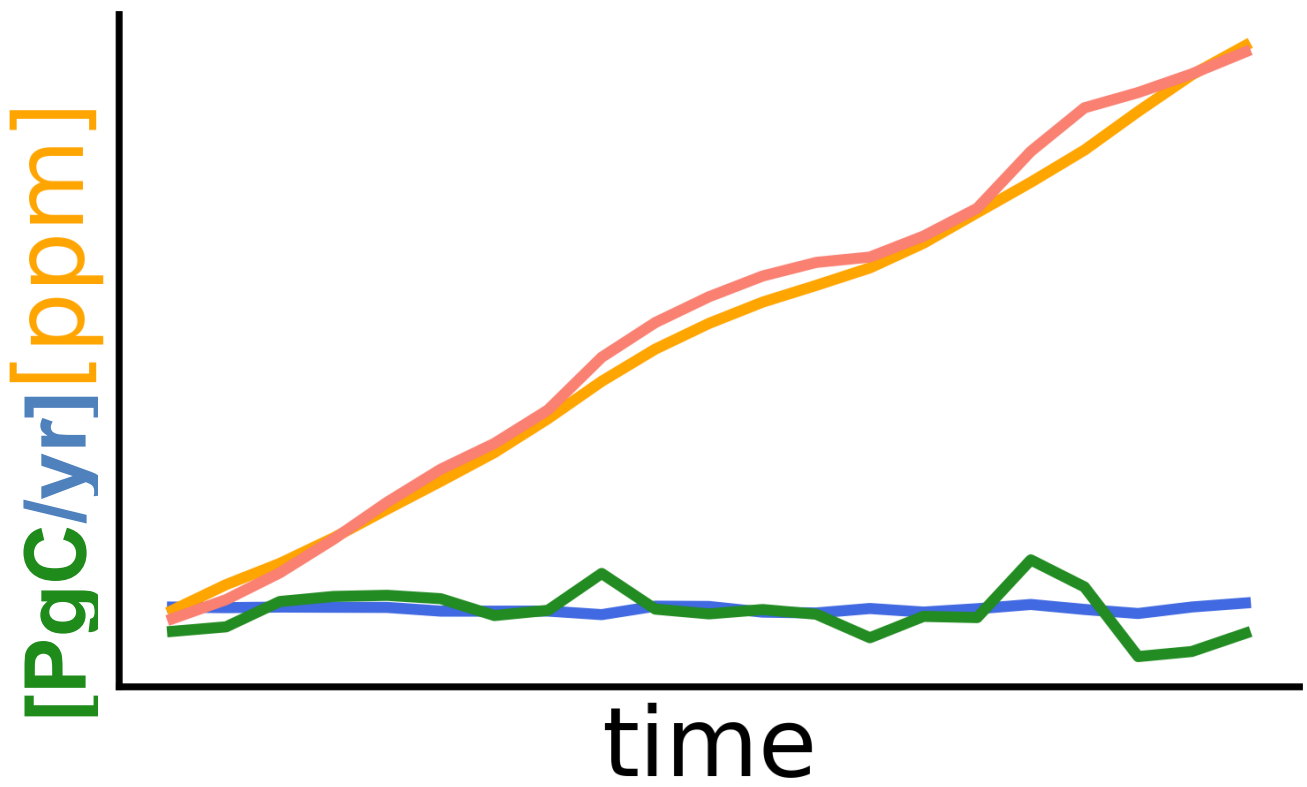
- Instantaneous global atmospheric mixing: conversion factor 2.12 PgC to 1 ppm [Ballantyne et al. 2012]
- Internal variability driven by climate-induced variability (temperature effect on biogeochemistry, circulation changes, ...)
- ignores short-term terrestrial CO₂ fertilisation effect and oceanic sensitivity to variability in CO₂ (as all concentration-driven experiments)
- Same approach as diagnosing compatible emissions from concentration-driven simulations [Jones, 2013] but “backwards”



Verification: Diagnosing global atmospheric CO₂ variations tracks actual global atm. CO₂ concentrations in emission-driven simulations.

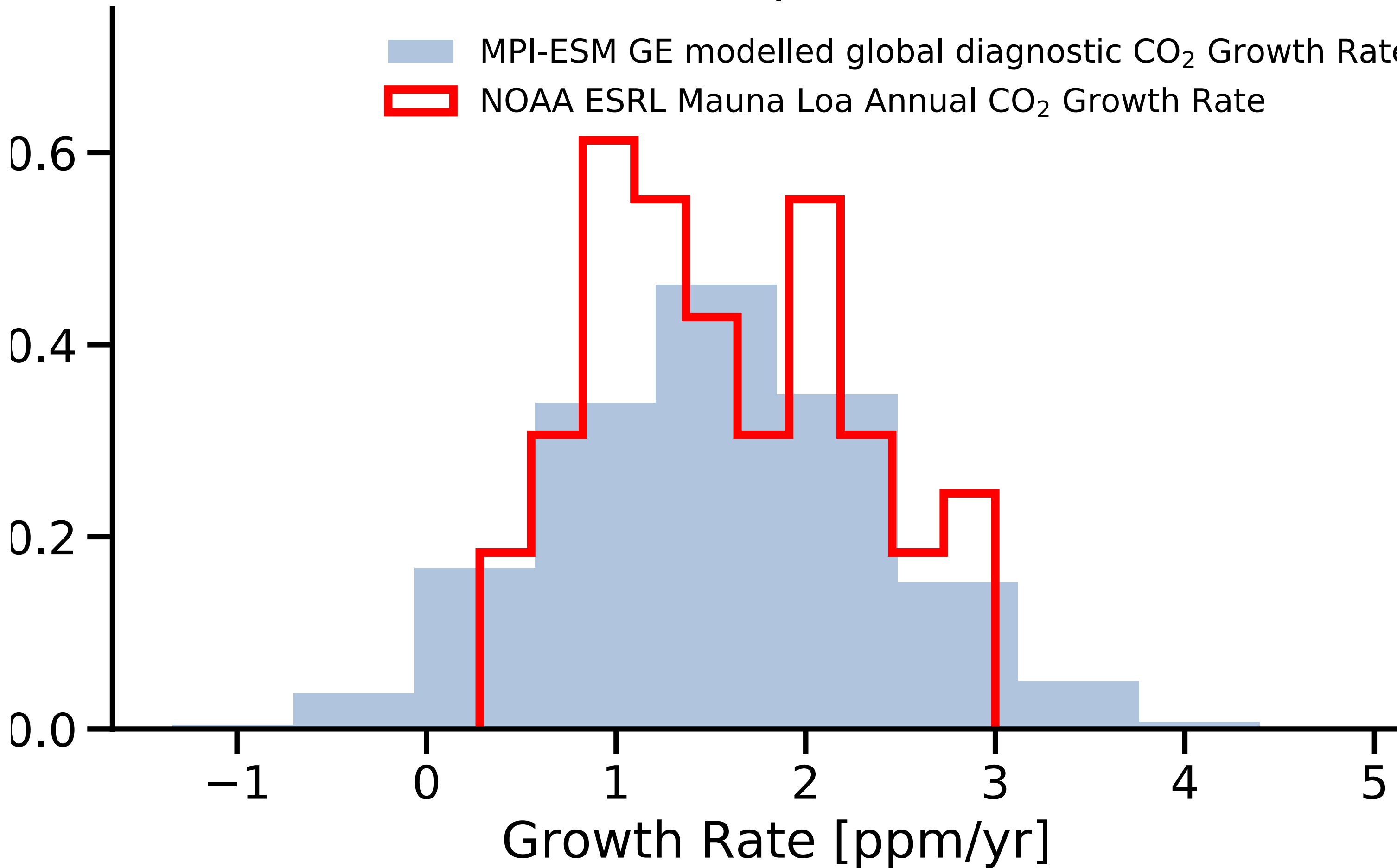
$$XCO_{2,atm}(t) = \sum_{t'=t_{start}}^t \underbrace{(\underbrace{CO_2flux'(t')}_{\text{time mean control}}))}_{\text{member mean}} \frac{\text{ppm}}{2.12 \text{ PgC}} + \underbrace{forcing(t)}_{\text{Historical: } CO_{2,atm} \text{ forcing (IAM)}}$$

- = time mean control = Historical: CO_{2,atm} forcing (IAM)
 - = member mean esmHistorical: member mean CO_{2,atm}

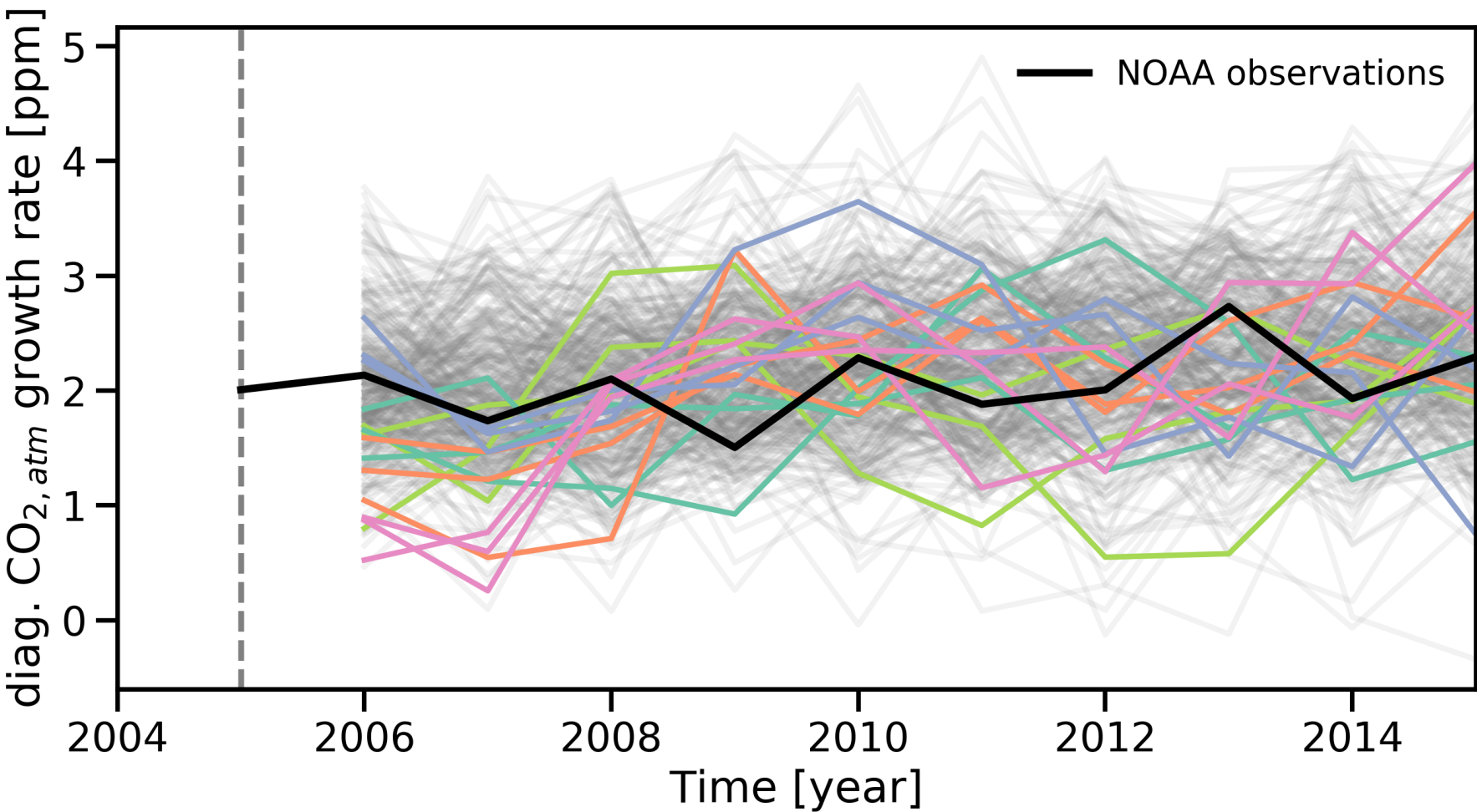


MPIESM Grand Ensemble simulates a realistic range of the atmospheric CO₂ annual growth rate.

Growth Rate of atmospheric CO₂ 1958-2018



	modelled	observed
count	6000.00	60.00
mean	1.54	1.58
std	0.85	0.67
min	-1.34	0.28
25%	0.95	1.04
50%	1.54	1.52
75%	2.12	2.04
max	4.50	3.01



emissions over time in RCP scenarios

