Multi-model comparison of carbon cycle predictability in initialized perfect-model simulations

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Overview: Potential predictability of carbon sinks

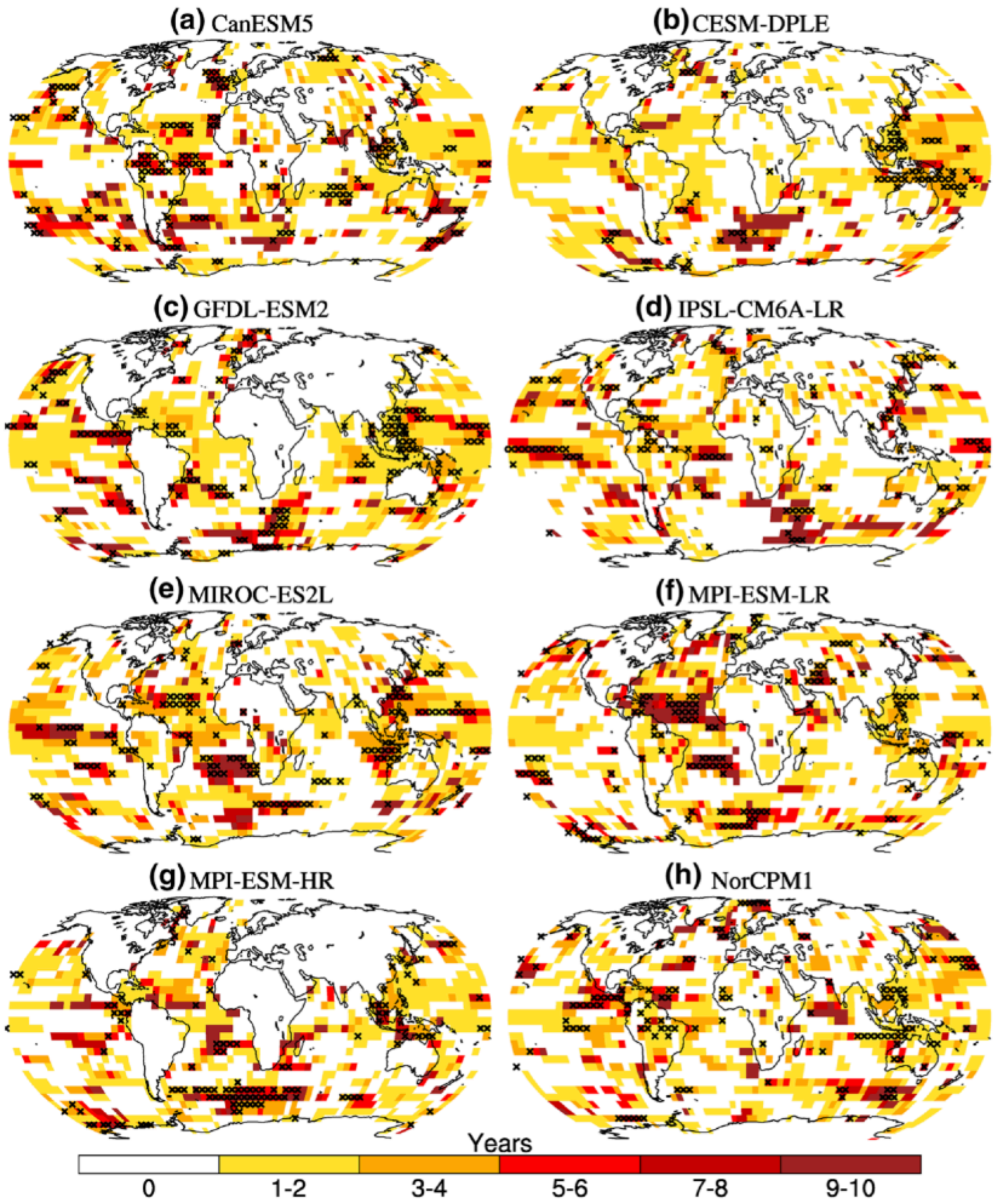
- Retrospective forecasts predict global annual
  - air-sea CO_2 fluxes up to lead year 6
  - air-land CO_2 fluxes up to lead year 2
  - atm. CO_2 growth rate up to lead year 2 [Ilyina et al., 2021]
  - Large spatial differences in predictability across models

- Predictability = "ability to predict itself" [Boer et al., 2004]
- Use idealised perfect model framework to understand limits and drivers of predictability independent of initialization (in MPI-ESM-LR):
  - Atm. CO_2 is predictable for 3 years [Spring and Ilyina, 2020]
  - Air-land and air-sea CO_2 flux predictable for 2 years

➡ multi-model comparison in a perfect-model framework

How does carbon cycle predictability vary across models (independent of assimilation/initialization)?
➡ air-land and air-sea CO_2 flux and atm. CO_2

Ilyina et al. [2021] CO_2 flux Predictability horizon



Multi-model perfect-model framework

Initial conditions are not aligned by design and therefore not directly comparable.

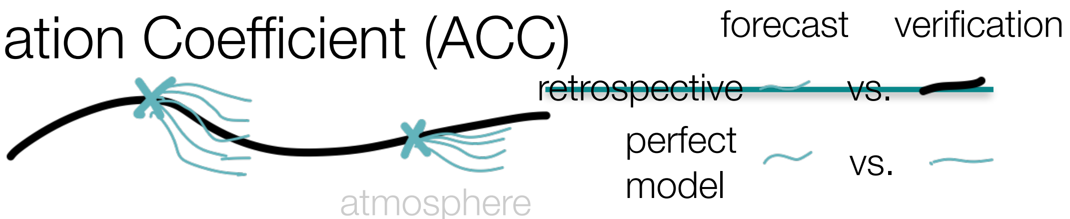
Model	# initial-isations	# mem-bers	# lead years	Initialization technique	Reference paper	Comment
MPI-ESM-LR	12	10	10	Tiny atmospheric perturbations	Spring and Ilyina 2020	
EC-Earth3	20	10	6	?	Sanchez-Gomez et al. 2016	Initialized Nov 1st instead of Jan 1st
IPSL-CM6A-LR	10	10	10	Tiny atmospheric perturbations	Boucher et al. 2020	Large scale variability from control sampled
GFDL_ESM2M	6	40	10	Tiny ocean perturbations	Frölicher et al. 2020	missing cLand
CanESM5	10	10	7	Tiny atmospheric perturbations	Sospedra-Alfonso et al. 2021	
NorESM1	22	10	10	Tiny ocean perturbations	Fransner et al. 2020	Transient forcing: CO_2, aerosols and volcanoes, missing lai, intpp
MIROC-ES2L	30	10	10	Tiny ocean perturbations	Hajima et al. 2020	missing nep

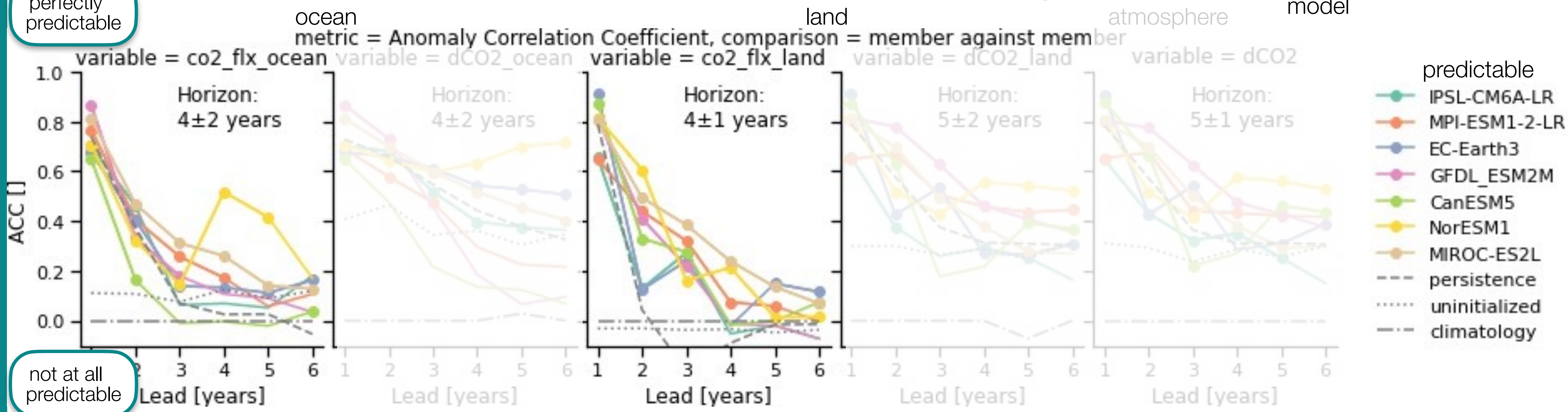
Variables:
- Ocean BGC: fgco2, spco2, intpp
- Ocean: tos, sos, mlotst
- Land: nbp, nep, cLand
- Atmosphere: tas, pr, uas, vas

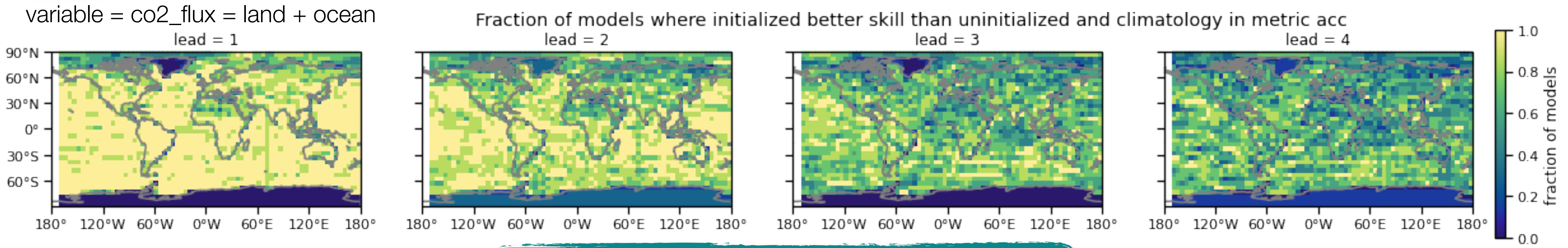
Perfect initialization: no more that the butterfly effect!

Results: Long predictability based on Anomaly Correlation Coefficient (ACC)

- ACC: predict the wiggles, no the amplitude







Global summation aggregates the noise.

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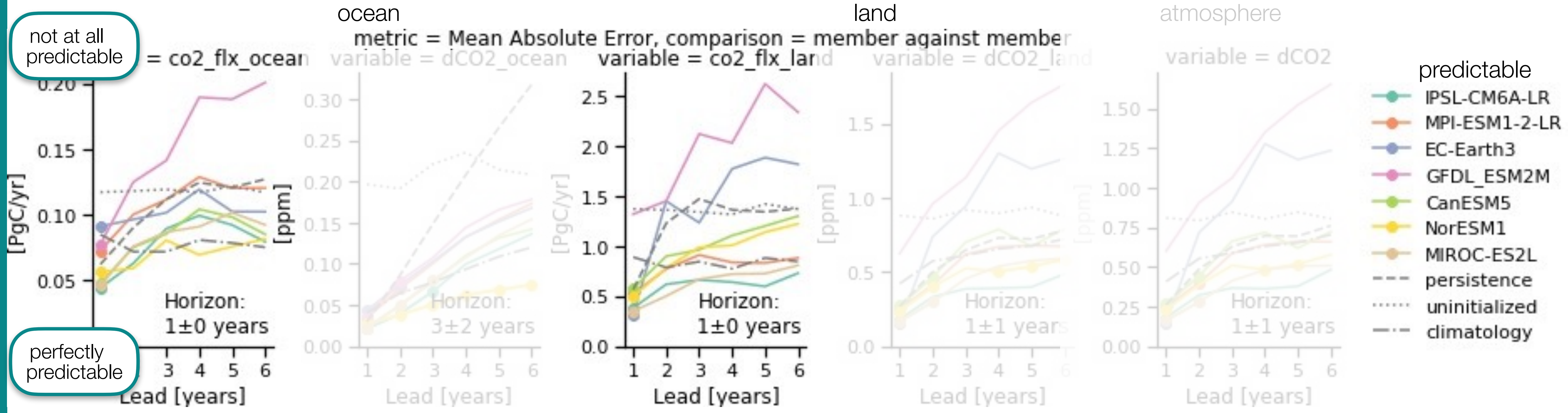
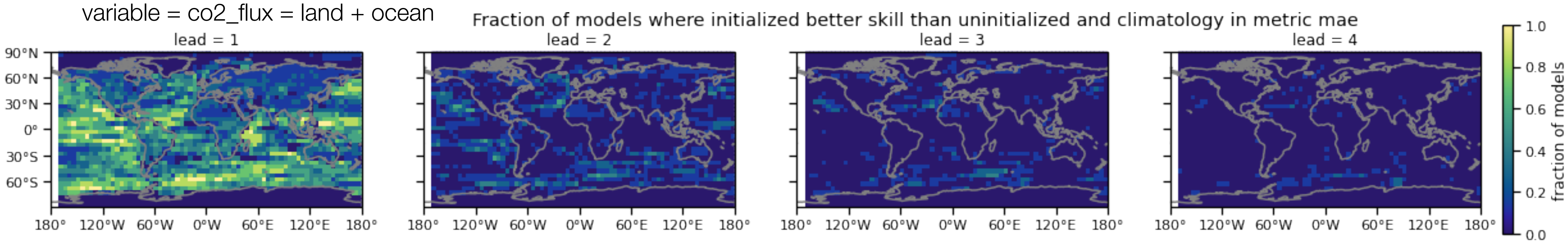
Results: Predictability based on mean absolute error (MAE) much shorter

- Error/distance much more useful to make forecasts of extensive quantities like CO_2 flux and atm. CO_2



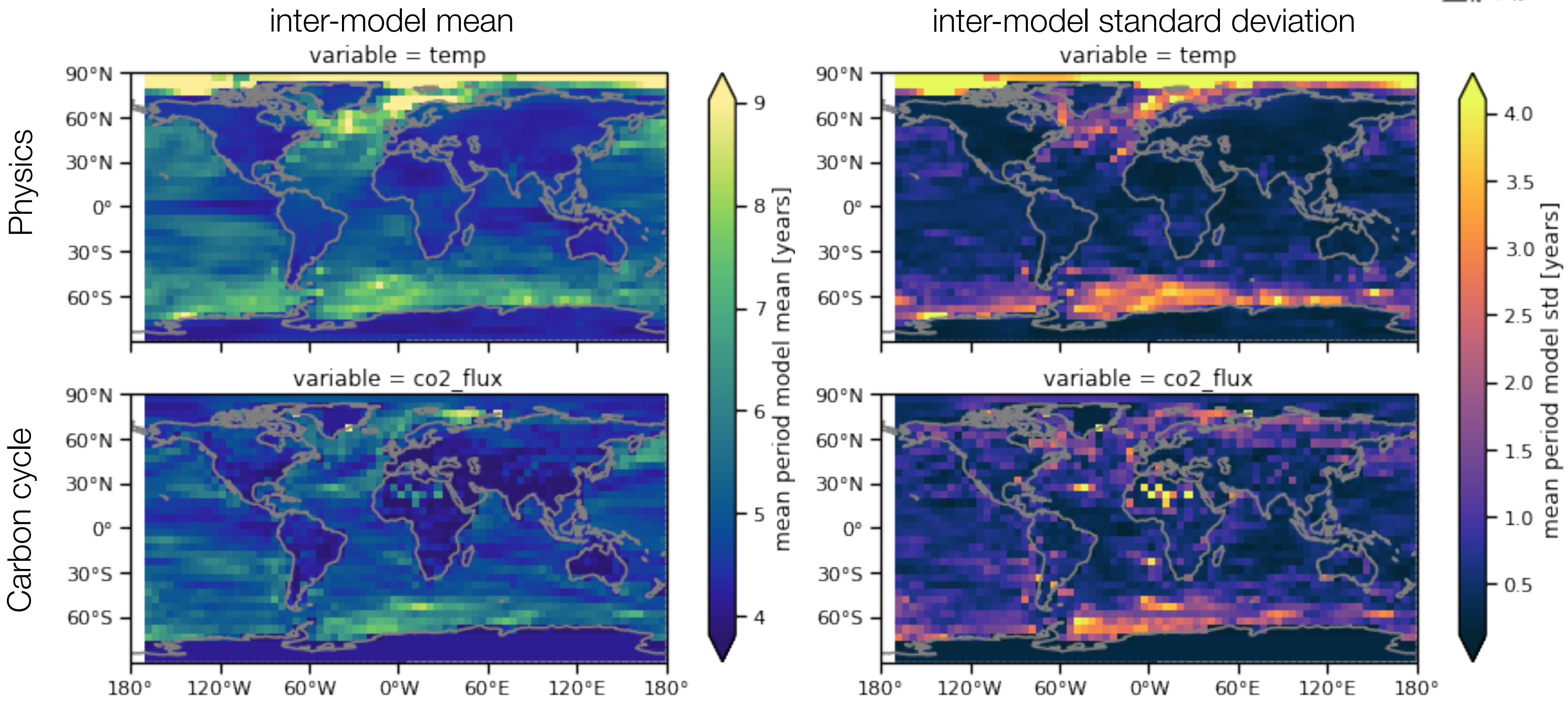


Large inter-model spatial differences in predictability, while globally similar.

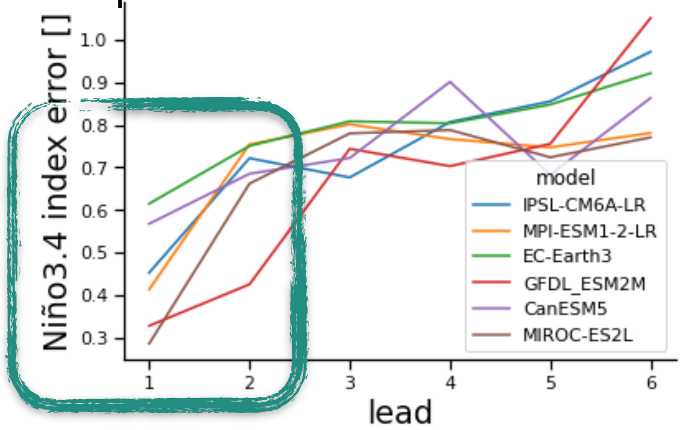
Explanation: Large inter-model (carbon cycle) variability differences among models

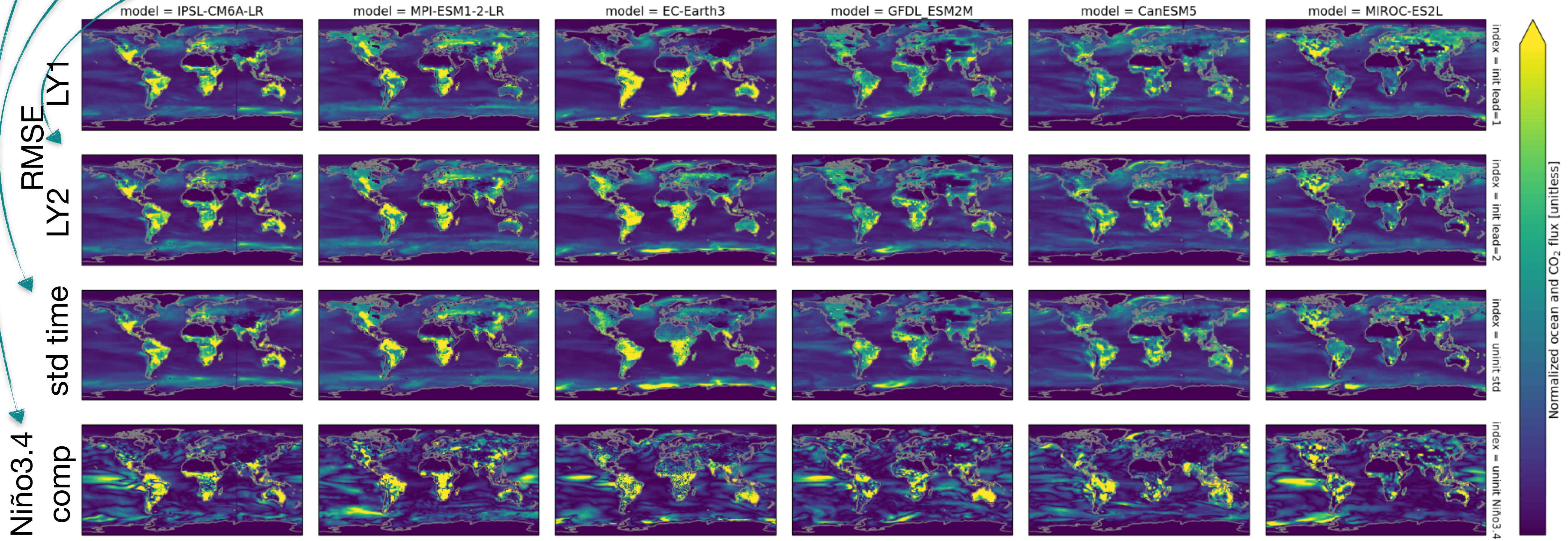
- Diagnose potential predictability on a control run [Boer et al. 2004, Resplandy et al. 2015, Seferian et al., 2018]
- Use variance-weighted mean period P_x [Branstator and Teng, 2010].

$$P_x = \frac{\sum_k V(f_k, x)}{\sum_k f_k \cdot V(f_k, x)}$$



Explanation: ENSO is strongest driver of CO_2 flux variability & initialized prediction error





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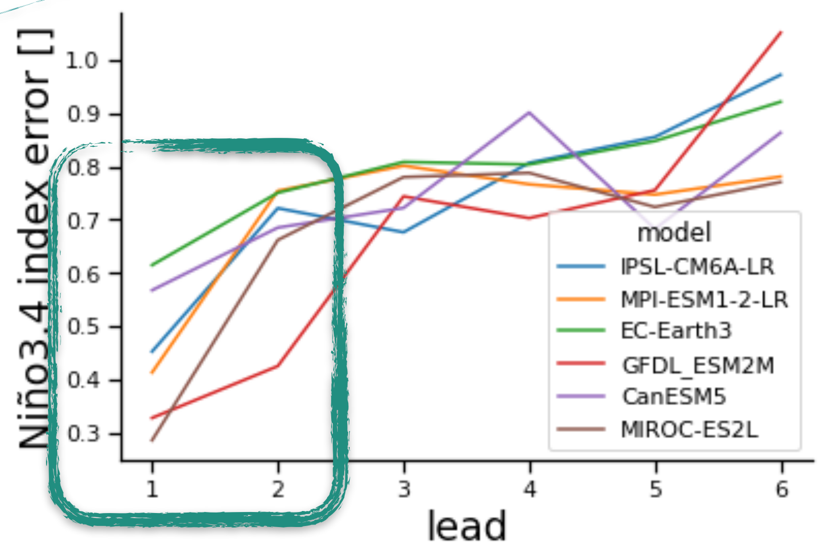
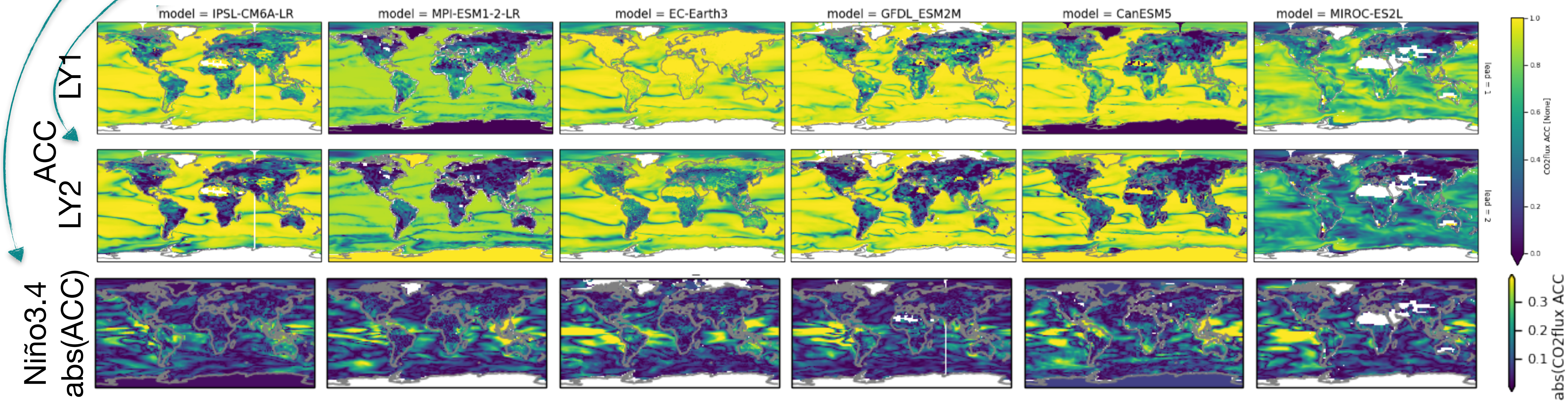
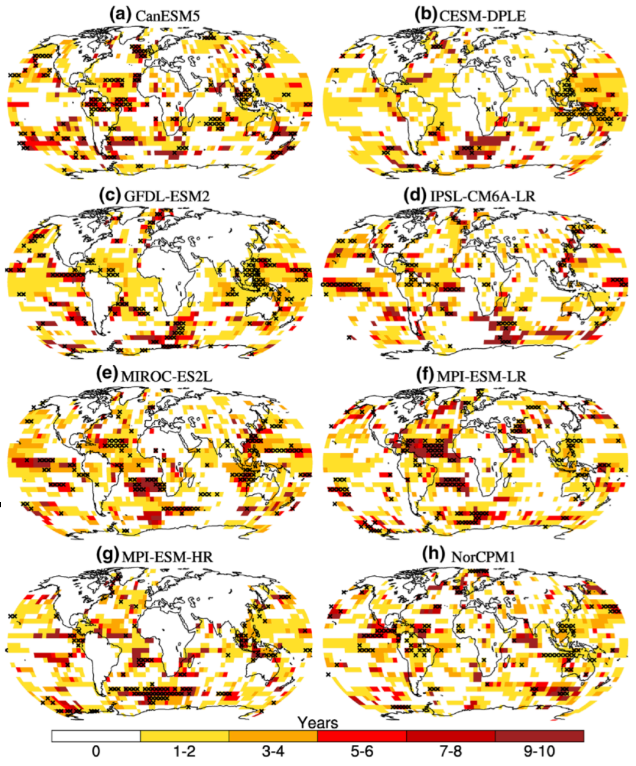




Summary and Conclusions



- Single model perfect-model framework global annual predictability limits of the carbon cycle [Seferian et al. 2018, Spring et al. 2020] confirmed by 6 other models.
- Predictability horizon heavily depends on metric and comparison used.
- Models don't agree on predictable patterns.
- Carbon cycle low-freq variability patterns vary a lot across models - also in physics.

➡ Large inter-model spatial differences in retrospective forecasts [Ilyina et al. 2021] likely due to model variability and not initialization technique.

➡ Use ESMs to predict **global** carbon uptake or atm. CO_2 growth rate, but not regionally.

➡ Manuscript in prep.

➡ Repository with 5°x5° regridded data and demo notebooks for review and future analysis in prep.

tl;dr Perfect-model CO_2 flux predictability: "same global scales, but diverse spatial patterns across models"

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Public reports of the project will be available for download on the 4C website: https://4c-carbon.eu/
Project coordinator: Professor Pierre Friedlingstein (UNEXE)
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Weird stuff going on:

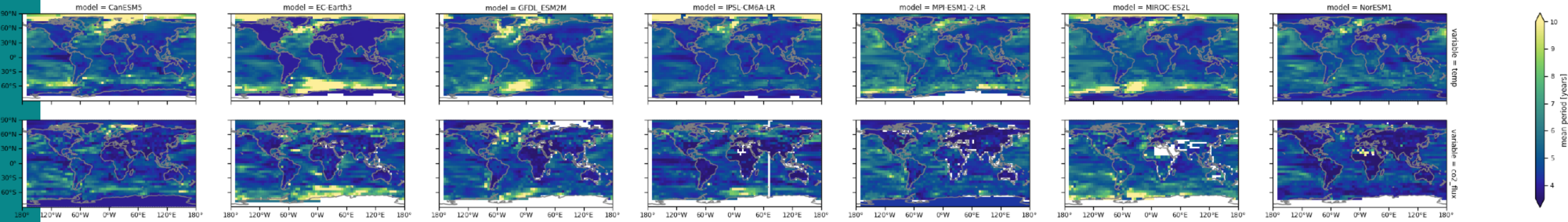
- NorESM1: lead 4 more predictable than lead 3, impossible to fettend without introducing artificial skill in fgco2 and spco2, also volcanoes

- General comment: Community is not consistent on how global (aggregated) skill is calculated:
    - First Global aggregates, then prediction skill on these global aggregates [Seferian et al. 2018, Li et al. 2019, Lovenduski et al. 2019, Spring and Ilyina 2020]: calc prediction skill for a global timeseries (thats the application IMO)
    - First prediction skill on each grid point, then global aggregates [Frölicher 2020]: calc predictable fraction
    - Prediction skill calculated over each grid point, member and initialization at once [Fransner et al. 2021]: calc prediction of the spatial pattern
    - Coding example: https://climpred.readthedocs.io/en/latest/examples/decadal/verify_dim_implications.html
    - The problem is that we are incentivised to take the method with the most predictable results because null results aren't publishable - we should take the hardest baseline/reference forecasts and focus on metrics, comparisons and methods as used in applications

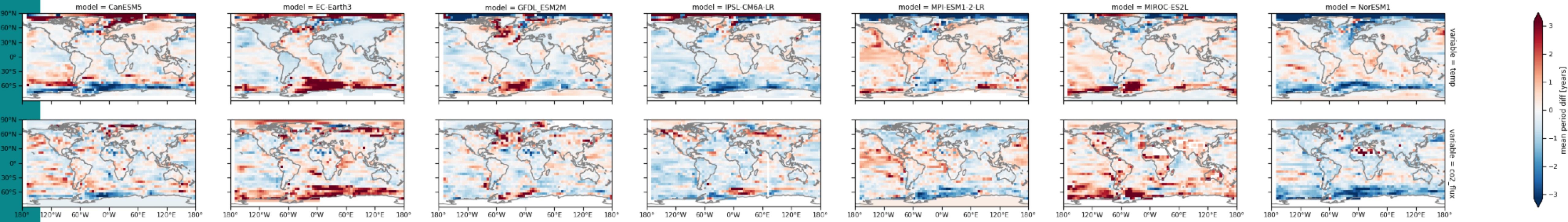
Variance-weighted mean period by model

$$P_x = \frac{\sum_k V(f_k,x)}{\sum_k f_k \cdot V(f_k,x)}$$

Px



Px deviations to model mean



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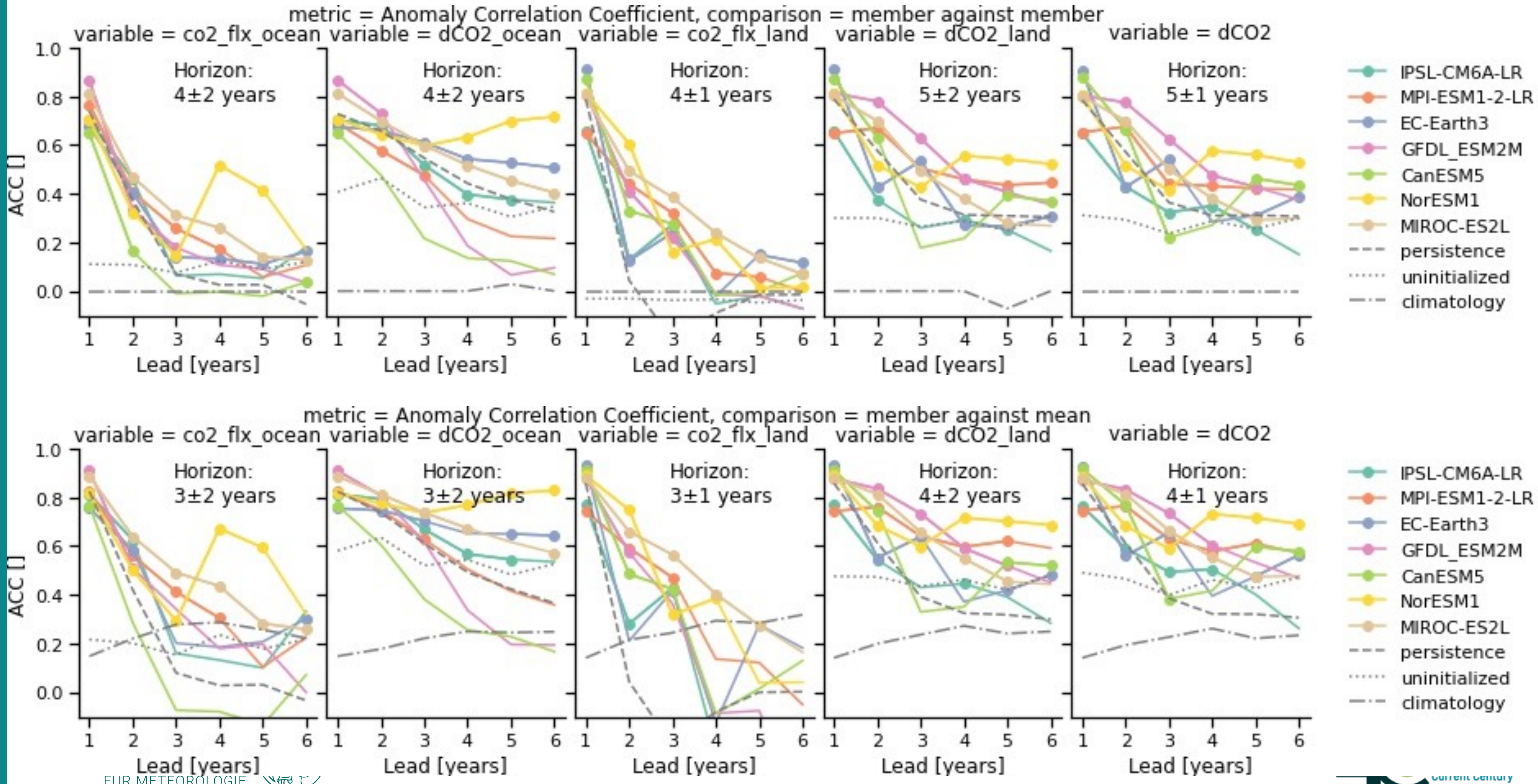
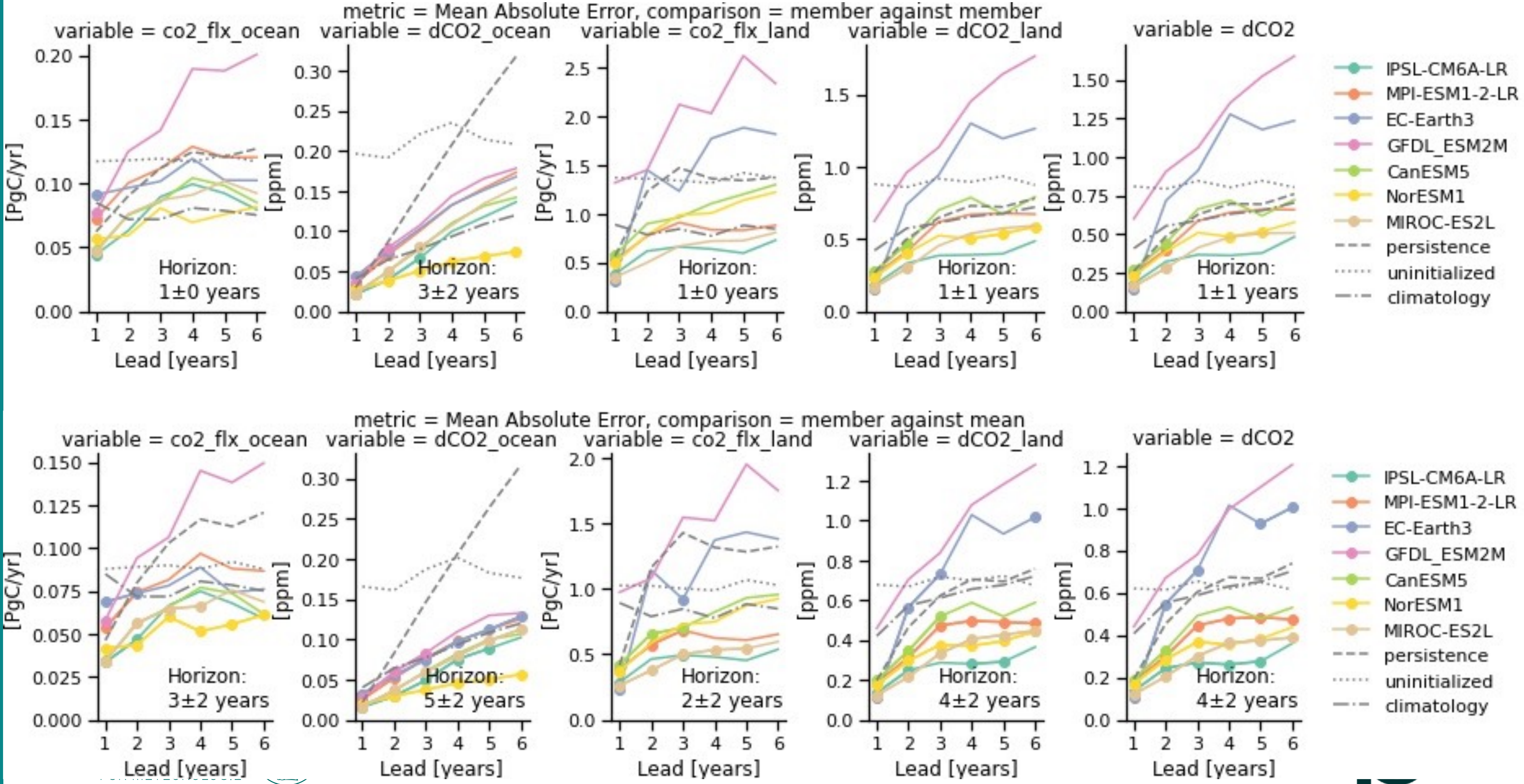
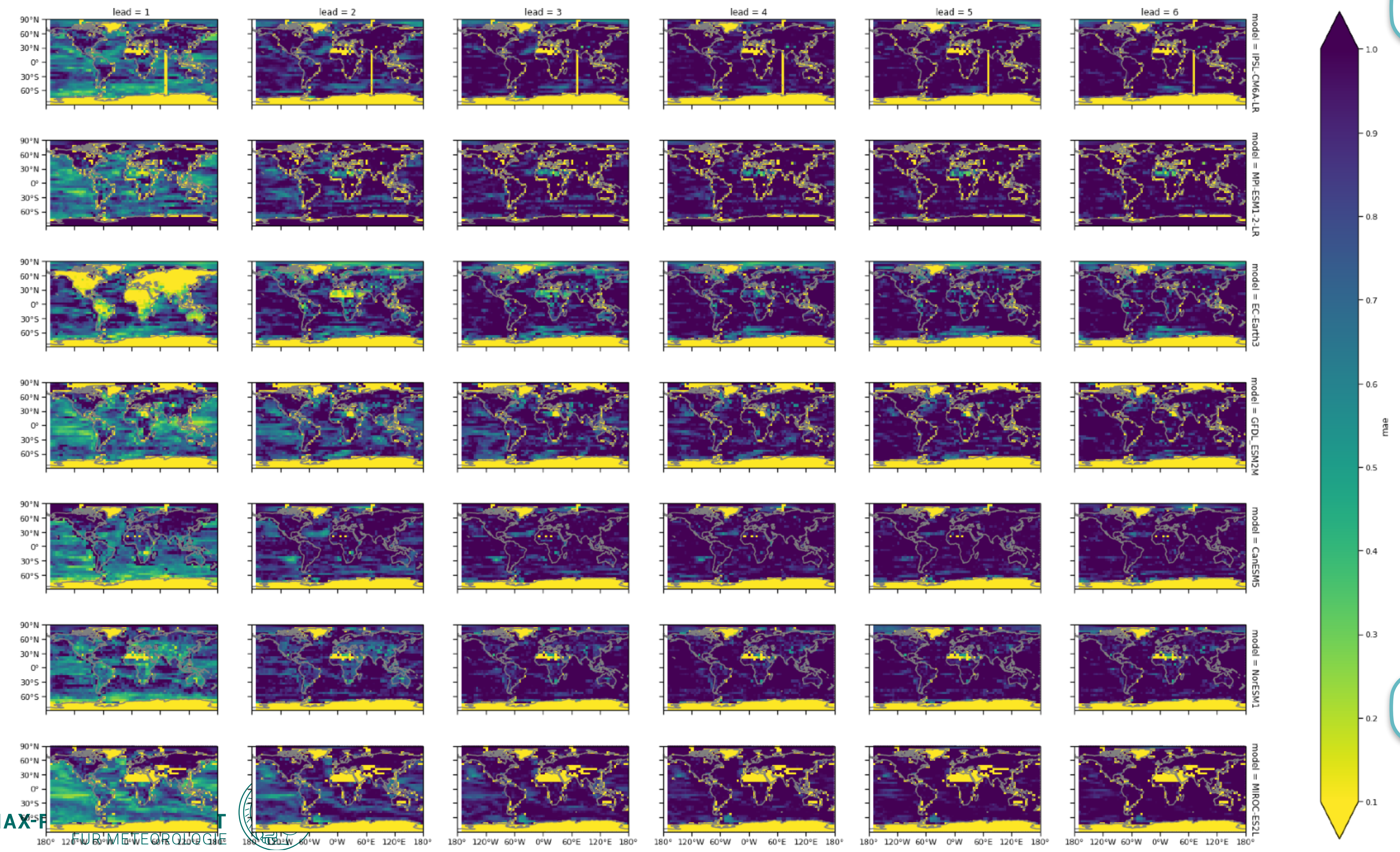
Comparison ACC



Comparison MAE



Initialized skill of CO_2 flux in metric normalised MAE



not at all predictable

perfectly predictable

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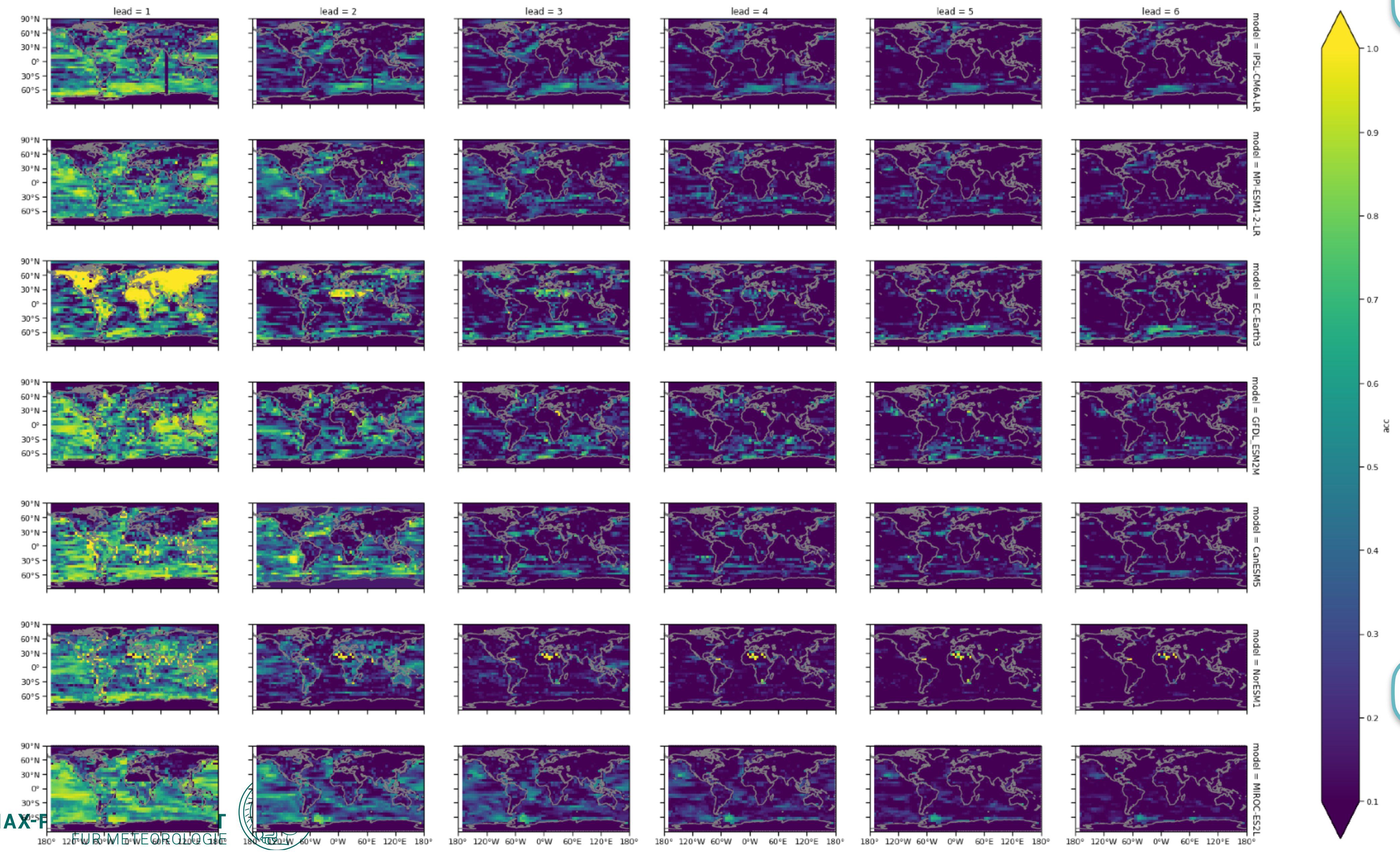
Initialized skill of CO_2 flux in metric ACC



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