Emulators of Climate Models

12.S992 AI for Climate Action

Spring 2026

Speaker: Abigail Bodner

Reminder: Super-resolution

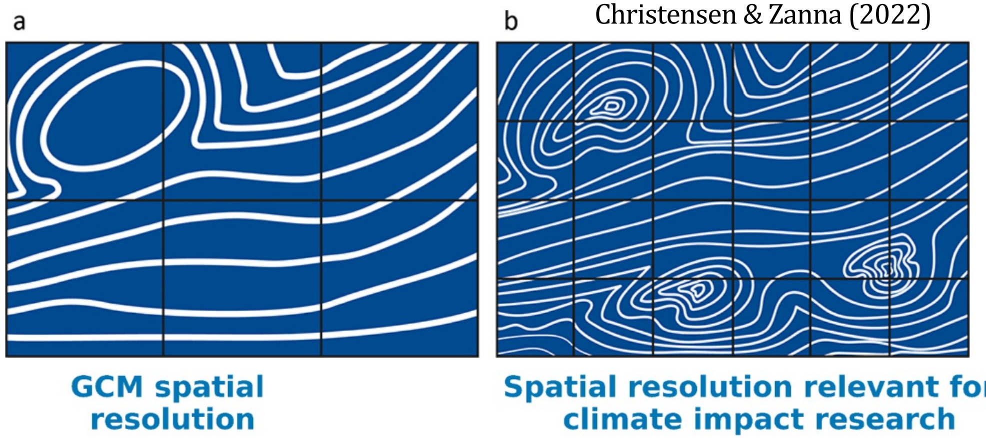
Also known as “upsampling” or ”downscaling”

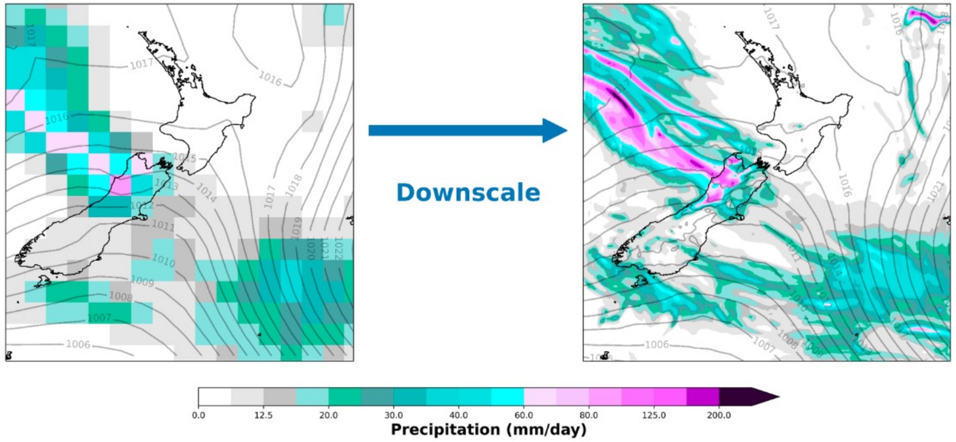
The process of going from a low-resolution (LR) field to a fine-resolution (FR) equivalent

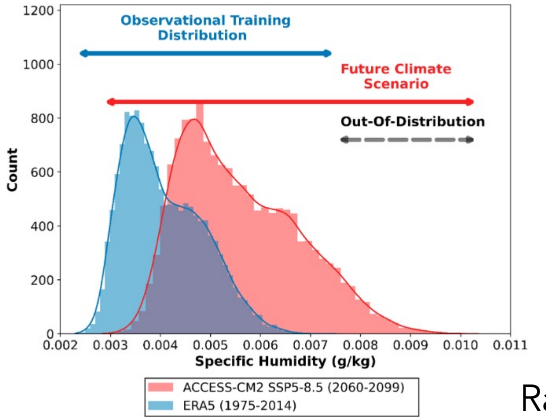
Challenges

- No feedback of FR back onto low resolution evolution (recall parameterizations)
- Requires that predicted FR remains physically consistent
- Desired that captures extremes in FR
- Preforms well out of distribution

Christensen & Zanna (2022)

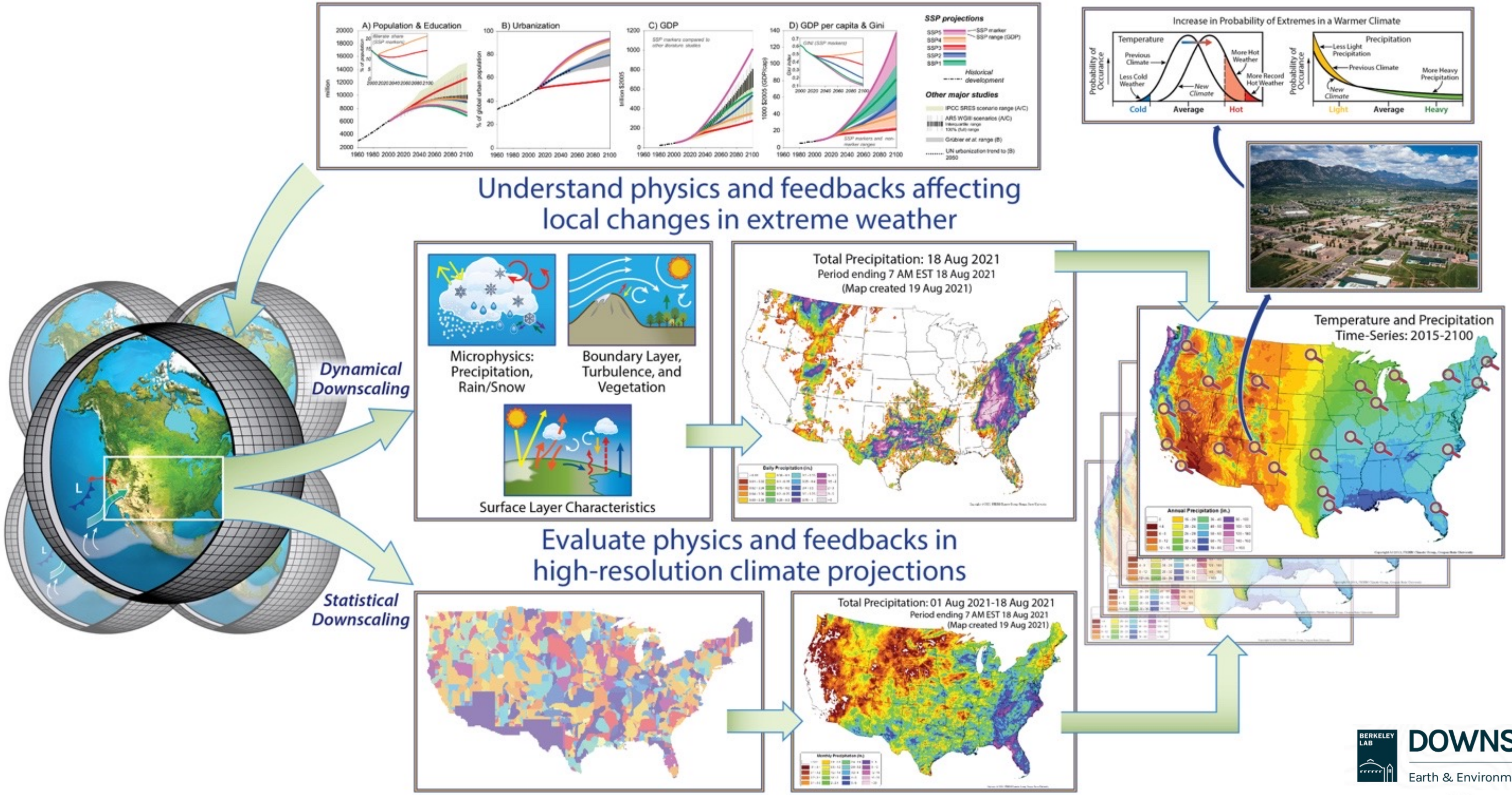






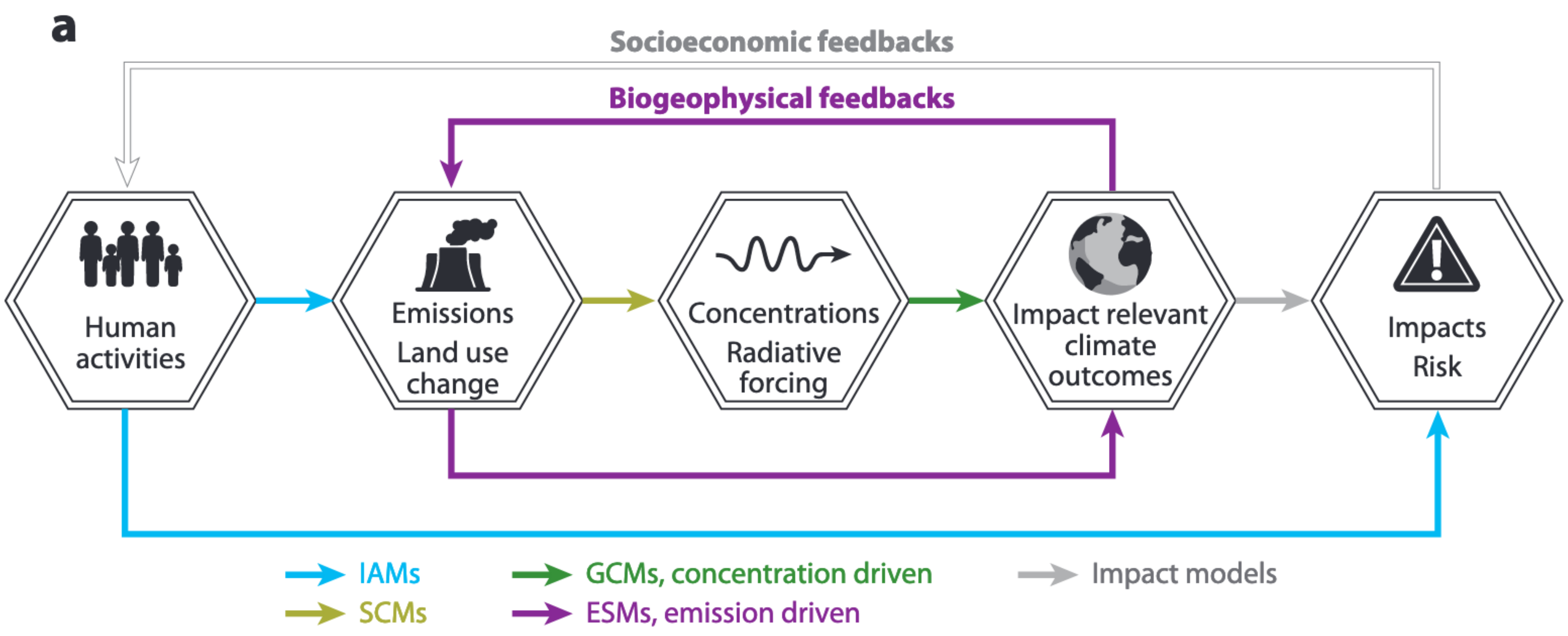
Rampal et al (2024)

Dynamical vs statistical downscaling



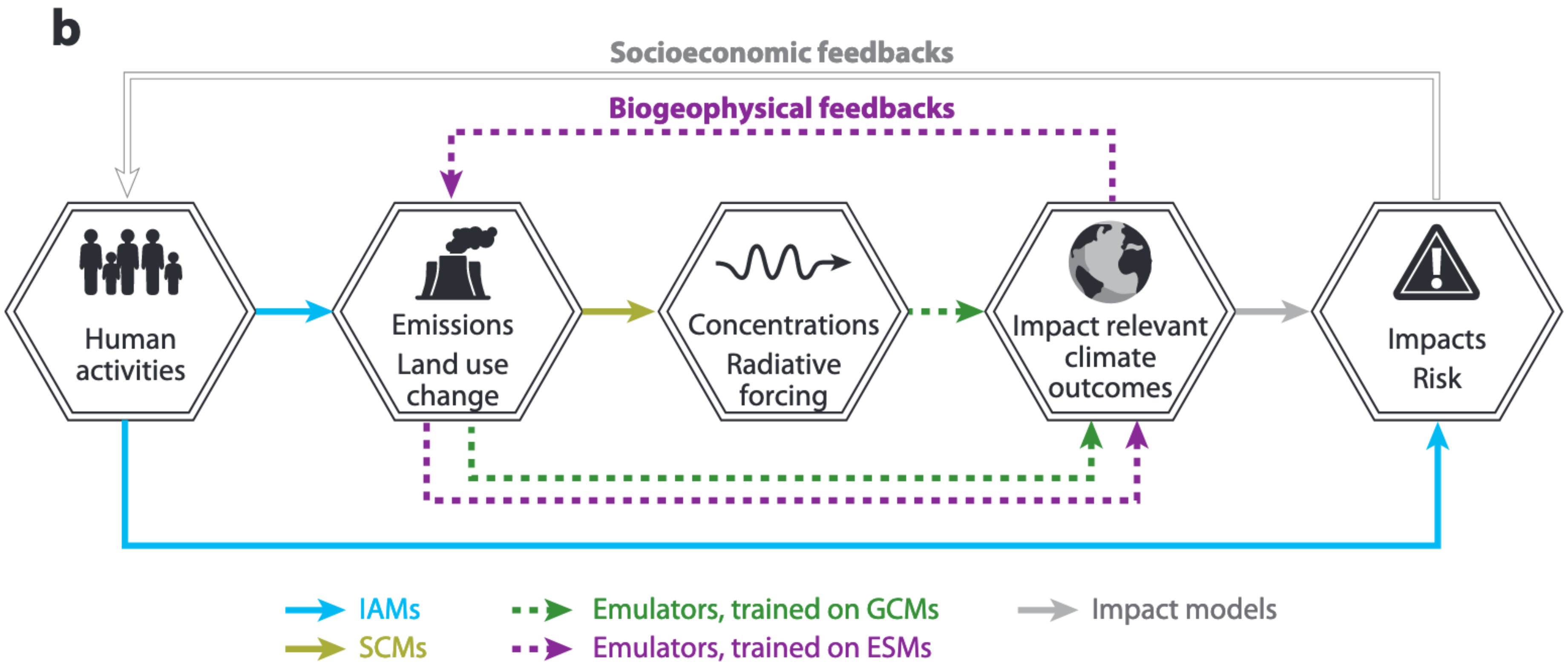
BERKELEY LAB DOWNSCALING
Earth & Environmental Sciences Area
EESA21-045

Emulators



Tebaldi et. al. (2025)

Emulators



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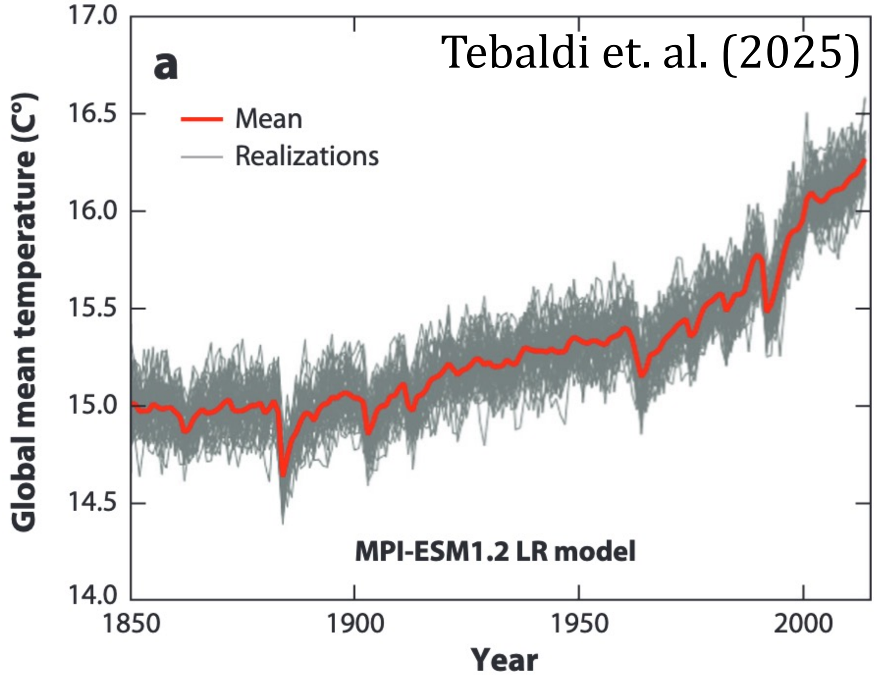
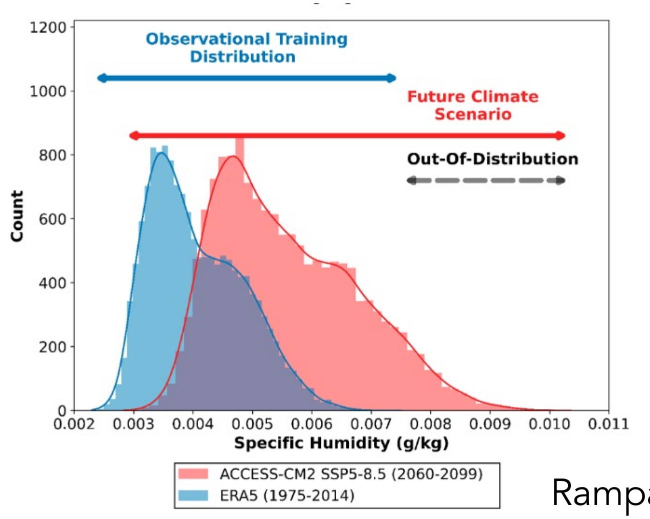
Emulators

Emulators can substitute for earth system models, and help fill the gap between simulating the physical conditions and the societal need for impact risk





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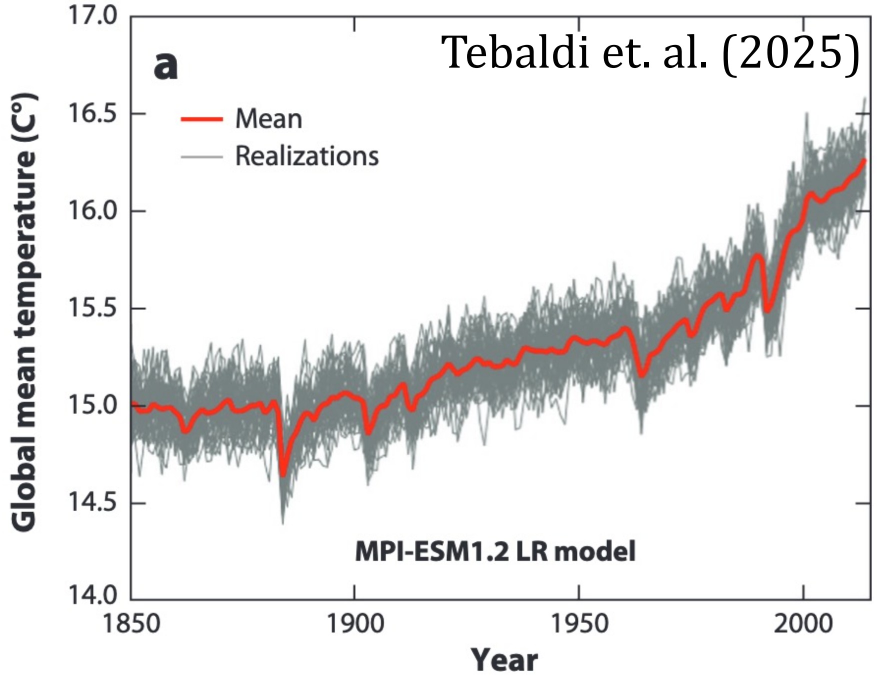

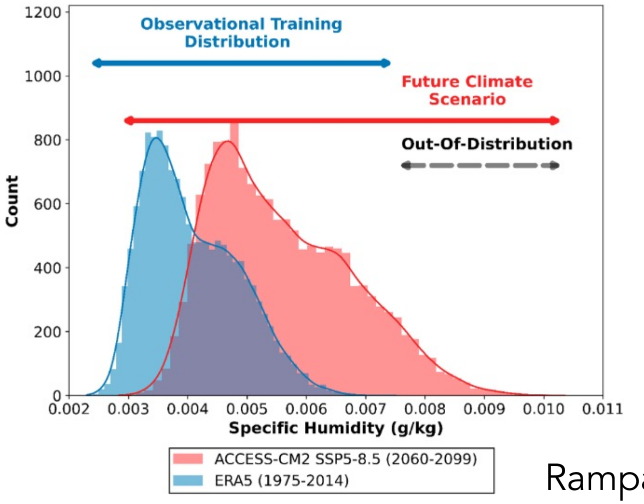

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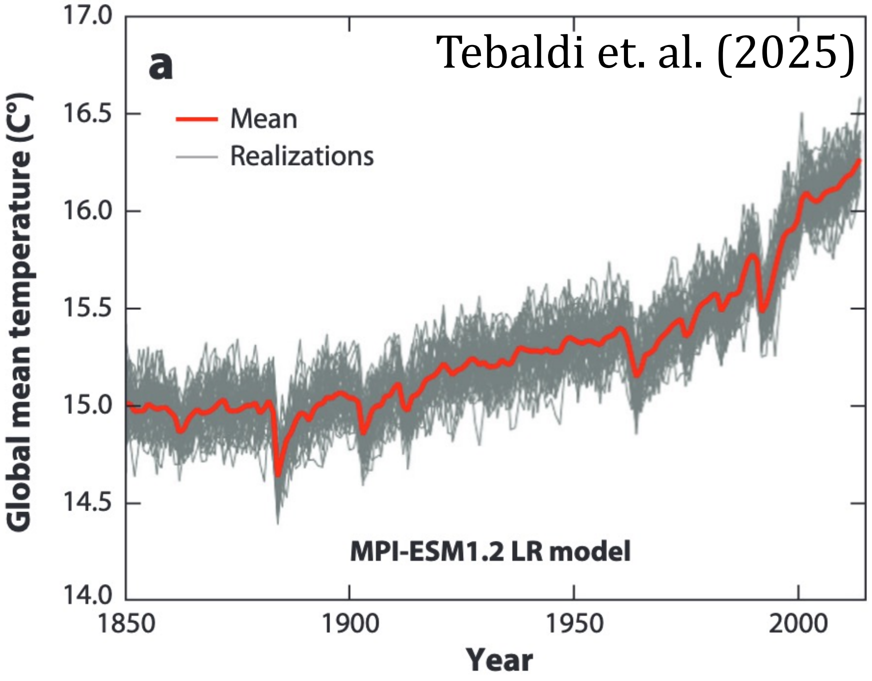
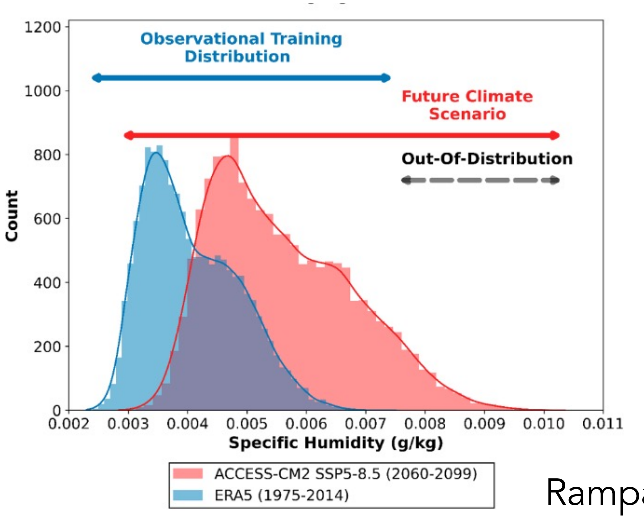
Emulators

Emulators can substitute for earth system models, and help fill the gap between simulating the physical conditions and the societal need for impact risk

Challenges

- Requires data from trusted model output
- Needs to be stable over the relevant time period
- Extremes and general circulation patterns should remain physical and realistic





Rampal et al (2024)

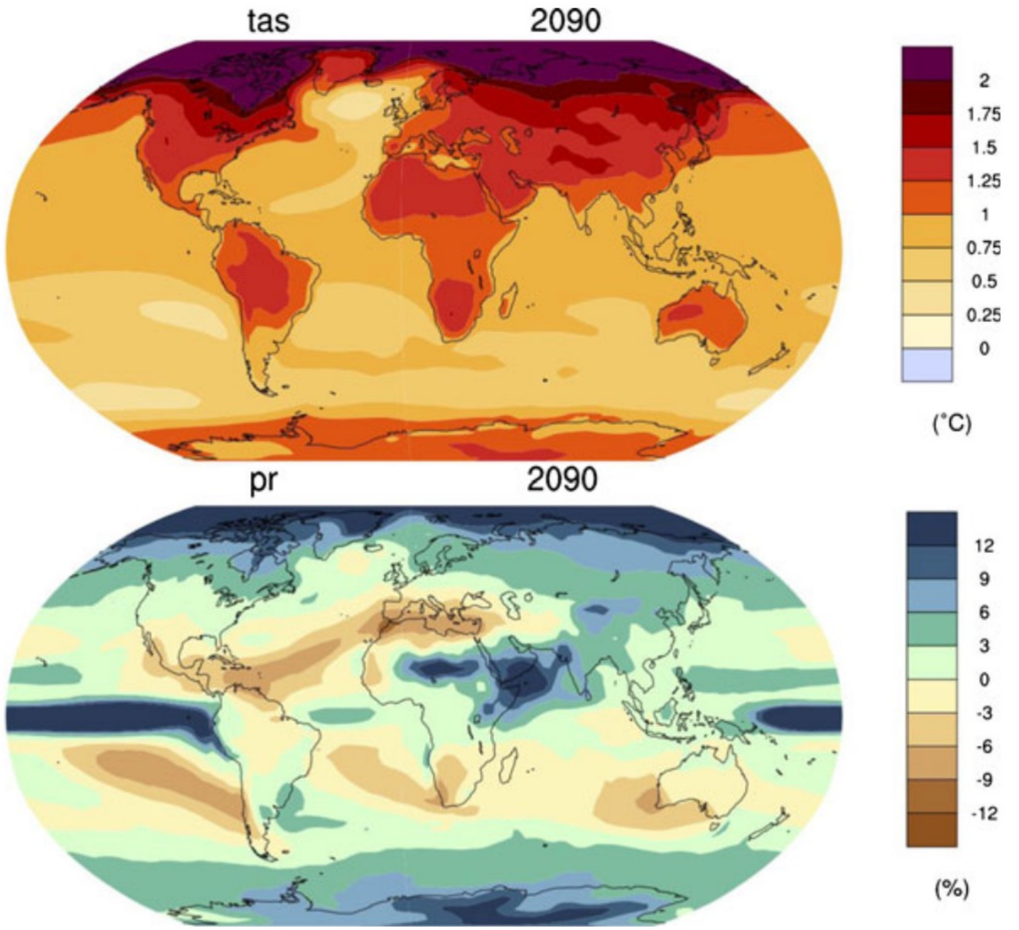
Pattern Scaling

- Changes at each model grid location are a function of change in global temperature.

- Location-specific linear coefficients form scenario- and time-invariant patterns, which are multiplied by a scenario's global temperature outcome.

- Represents only forced change.

$$\mathbf{P}(\mathbf{t},\mathbf{x},\mathbf{y},\mathbf{s}) = \mathbf{T}(\mathbf{t})\,\mathbf{p}(\mathbf{x},\mathbf{y},\mathbf{s})$$



Tebaldi & Arblaster (2015)

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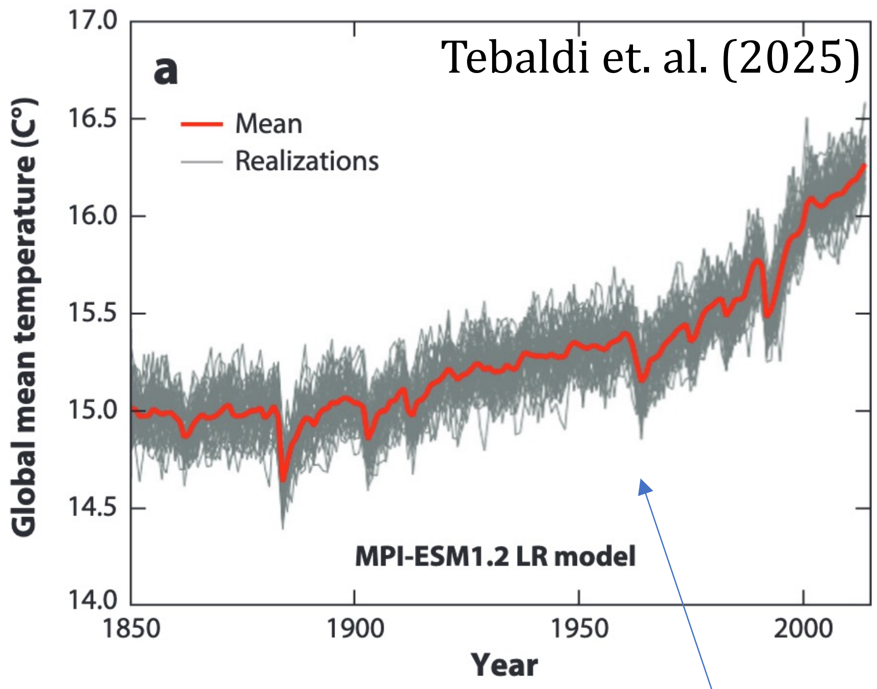


Will only capture the mean with no internal variability

Tebaldi & Arblaster (2015)

Tebaldi et. al. (2025)

Pattern Scaling

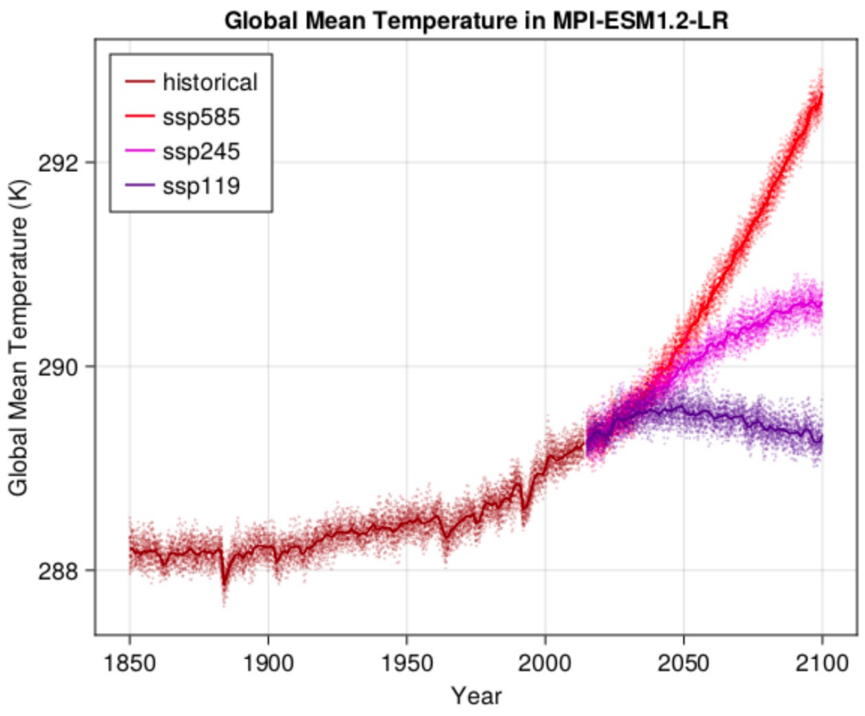
- Extensions add patterns representing additional forcers, timescales, drivers, or simple estimates of internal variability to the forced component.
- Other extensions include noise to account for internal variability, or use nonlinear scaling.

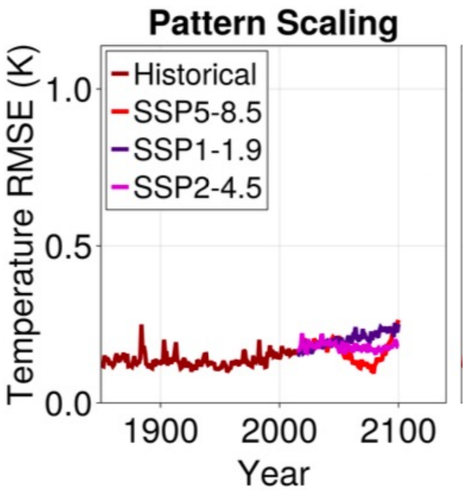
Tebaldi & Arblaster (2015)

Tebaldi et. al. (2025)

Pattern Scaling

- Example: pattern scaling extension
- Train emulator that predicts distributions of coarse-grained monthly averaged variables as a multivariate Gaussian distribution

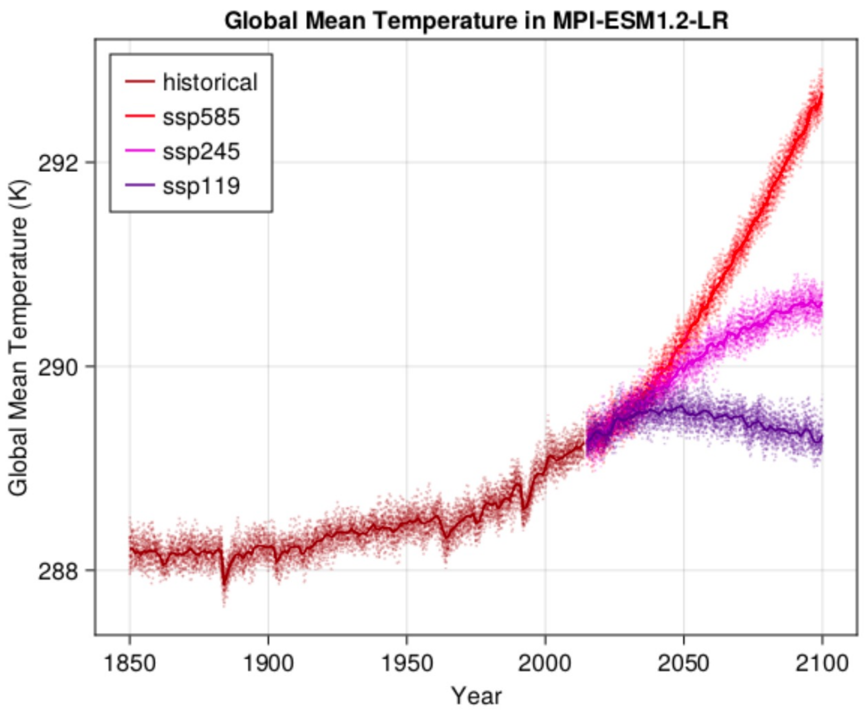


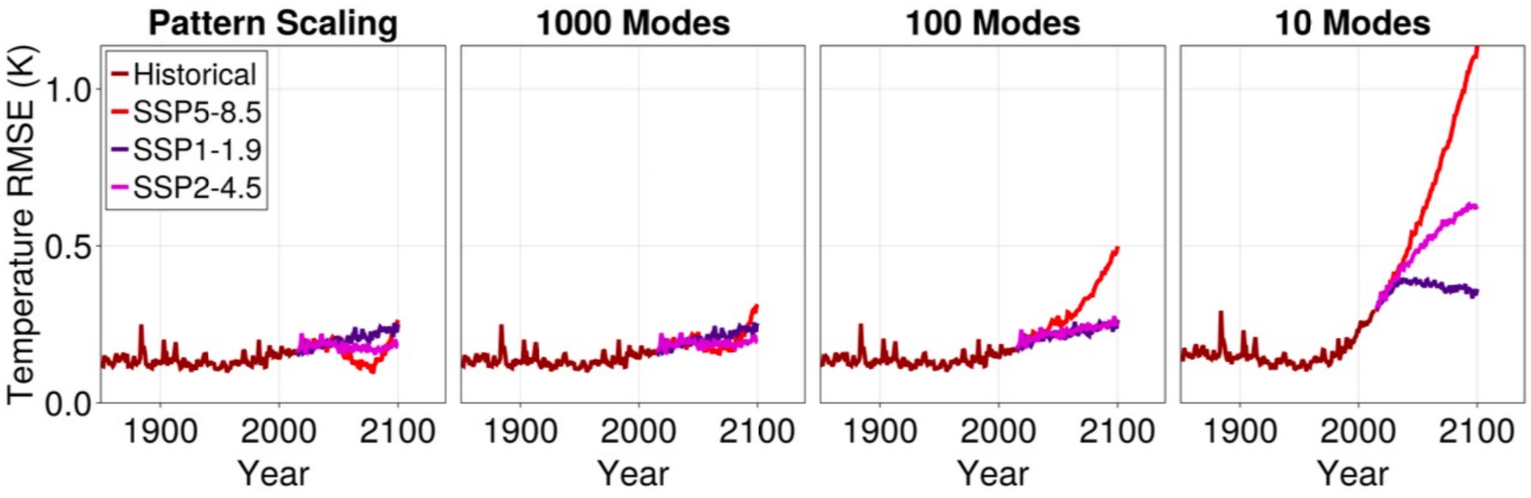


Souza et al (2024)

Pattern Scaling

- Example: pattern scaling extension
- Train emulator that predicts distributions of coarse-grained monthly averaged variables as a multivariate Gaussian distribution
- captures regional monthly temperature and relative humidity fields and internal variability

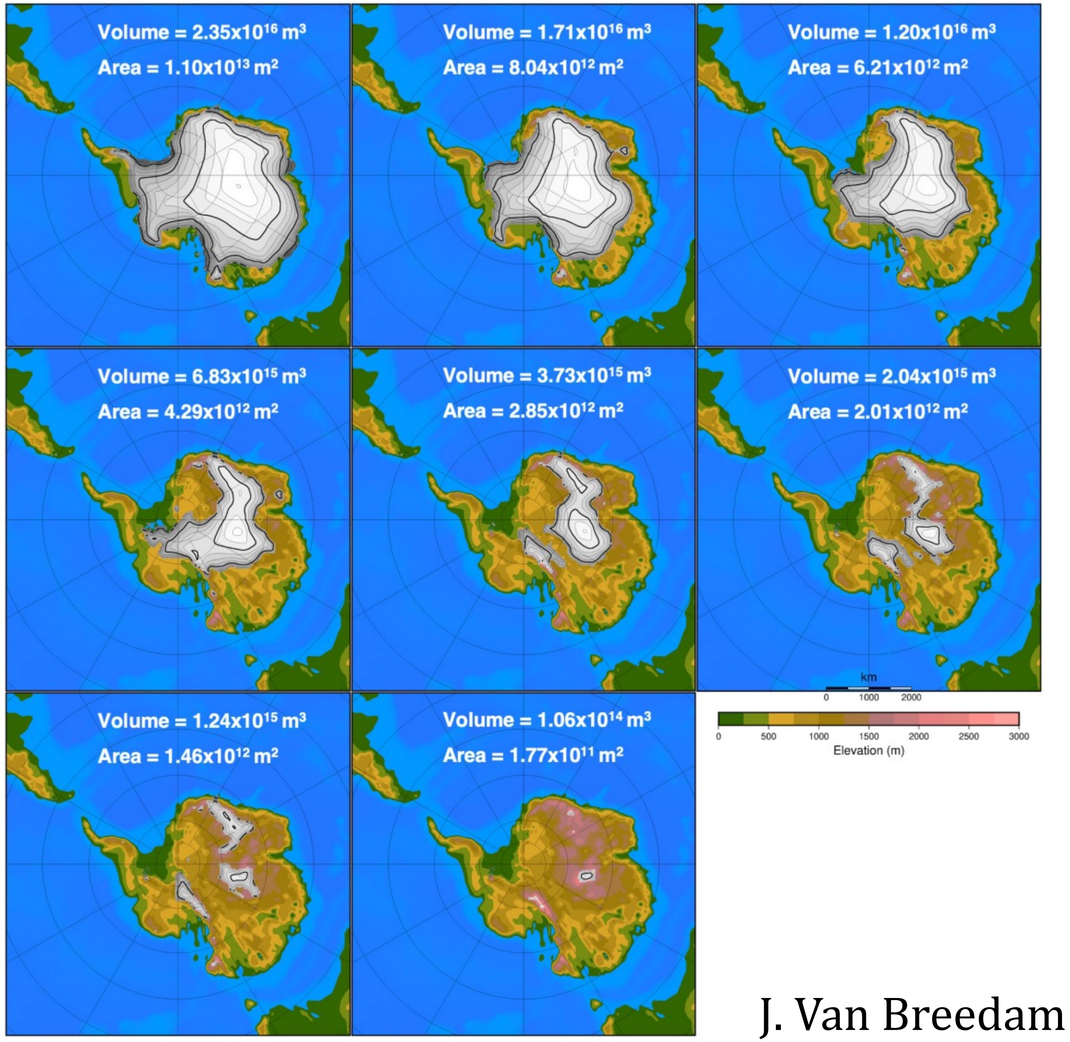




Souza et al (2024)

"Light" machine learning applications

- Interested in climate evolution over Antarctica
- Apply Gaussian Process + PCA which considers the response of an ice sheet to changing conditions
- Inputs for GP are ice sheet parameters (thickness, area)
- Outputs are PCAs of climate variables, i.e., maps of temperature, precipitation



J. Van Breedam et al (2021)

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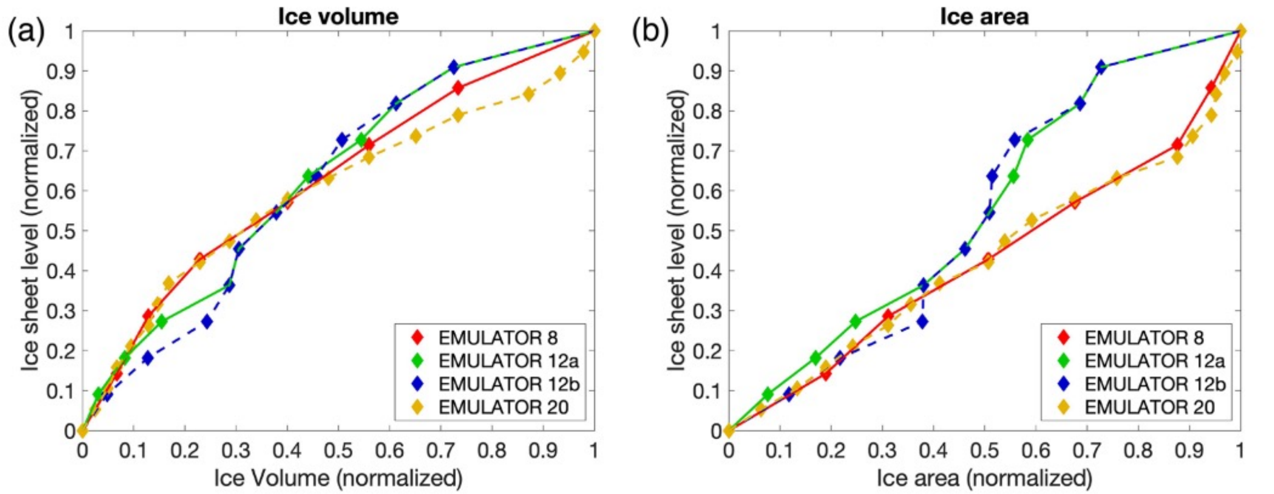

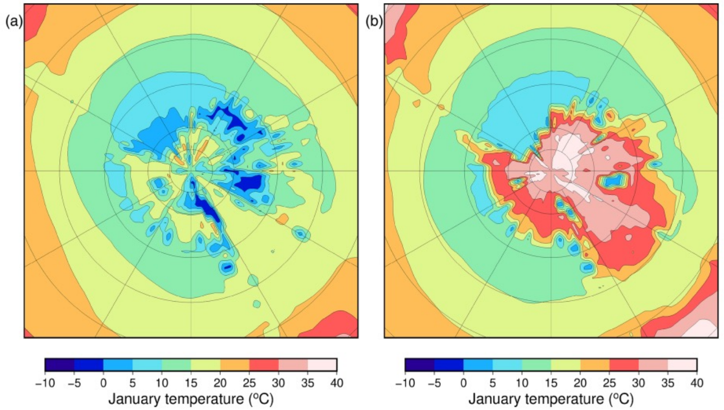

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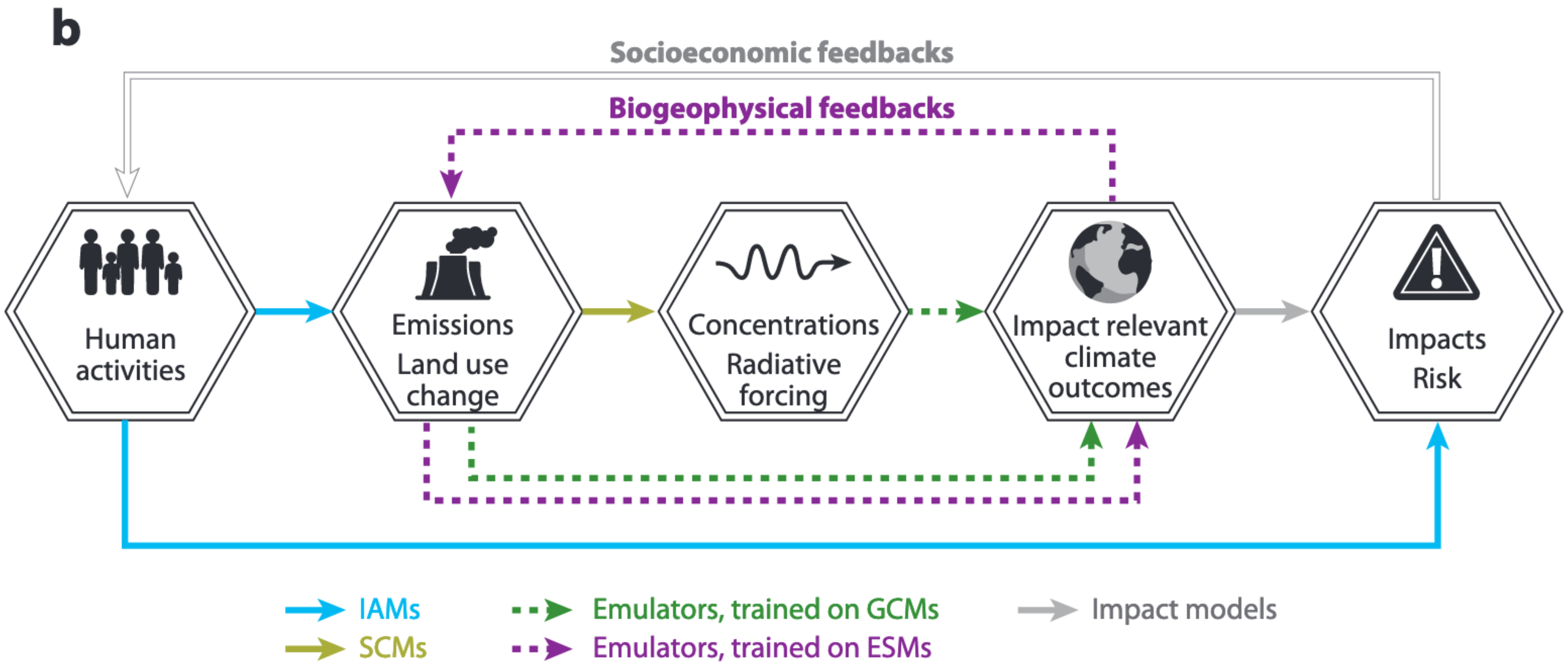
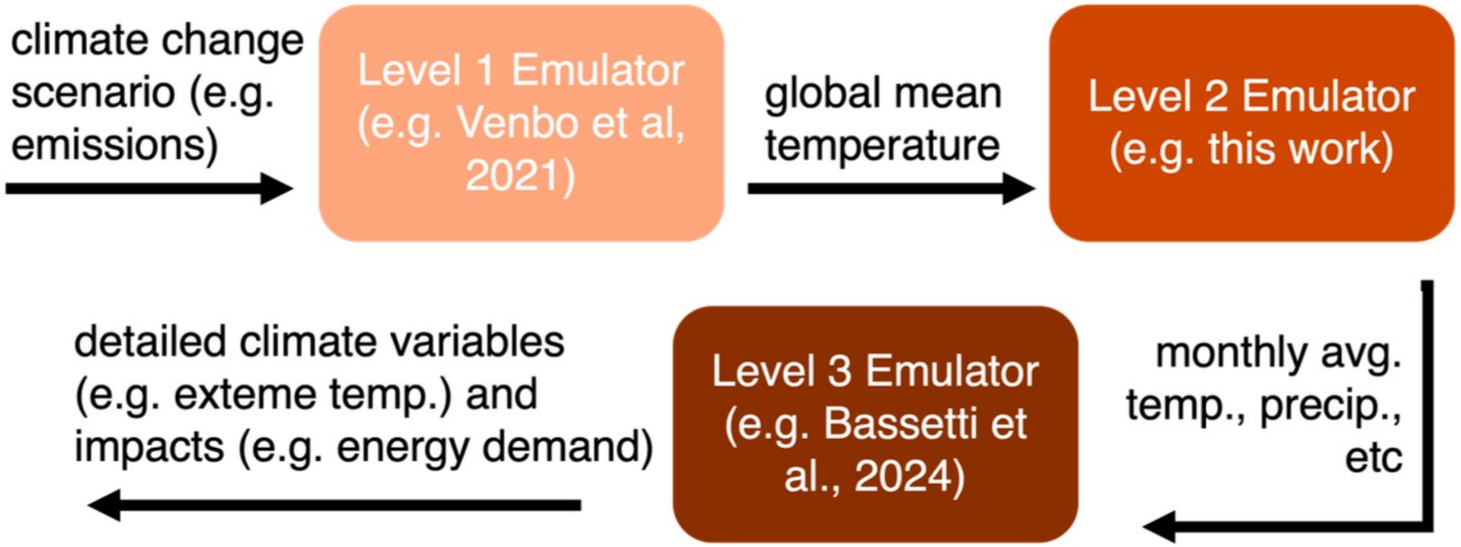
AI Emulators



Tebaldi et. al. (2025)

Example: DiffESM

- Takes monthly climate data of temperature, precipitation
- Generates realistic daily sequences using diffusion models



Souza et al (2024)
Bassetti et al (2024)

Example: DiffESM

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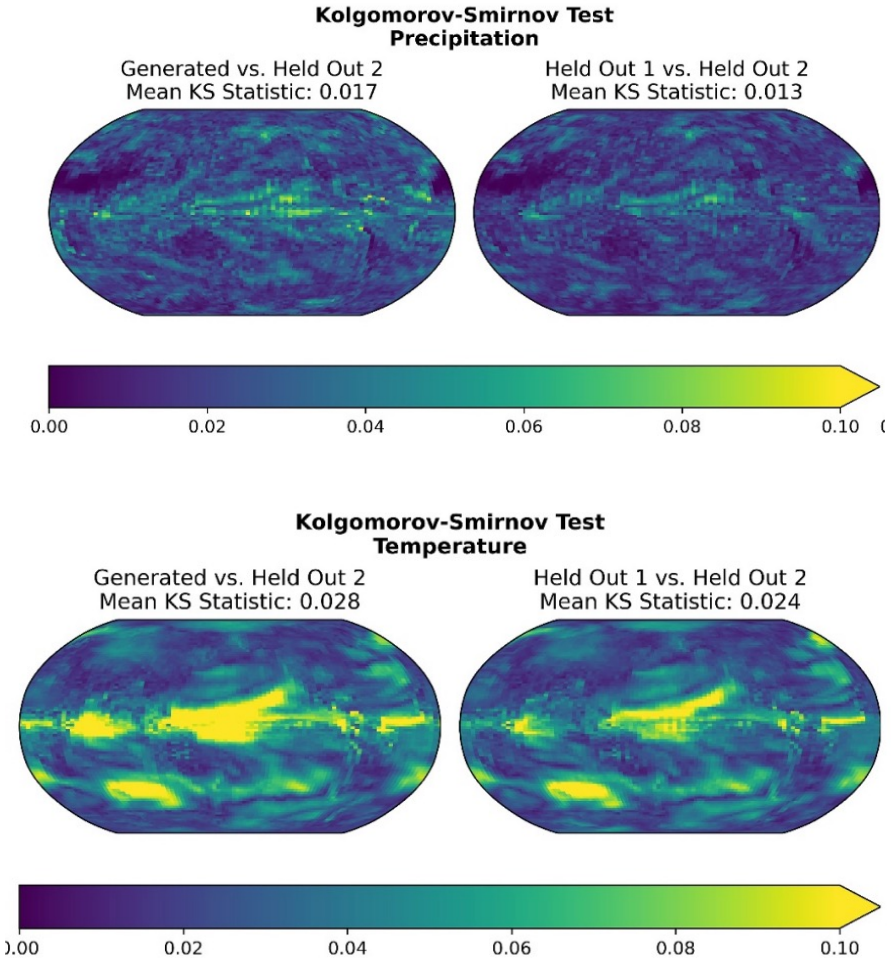
- The diffusion model is able to preserve the overall statistics of daily temperature and precipitation



Bassetti et al (2024)

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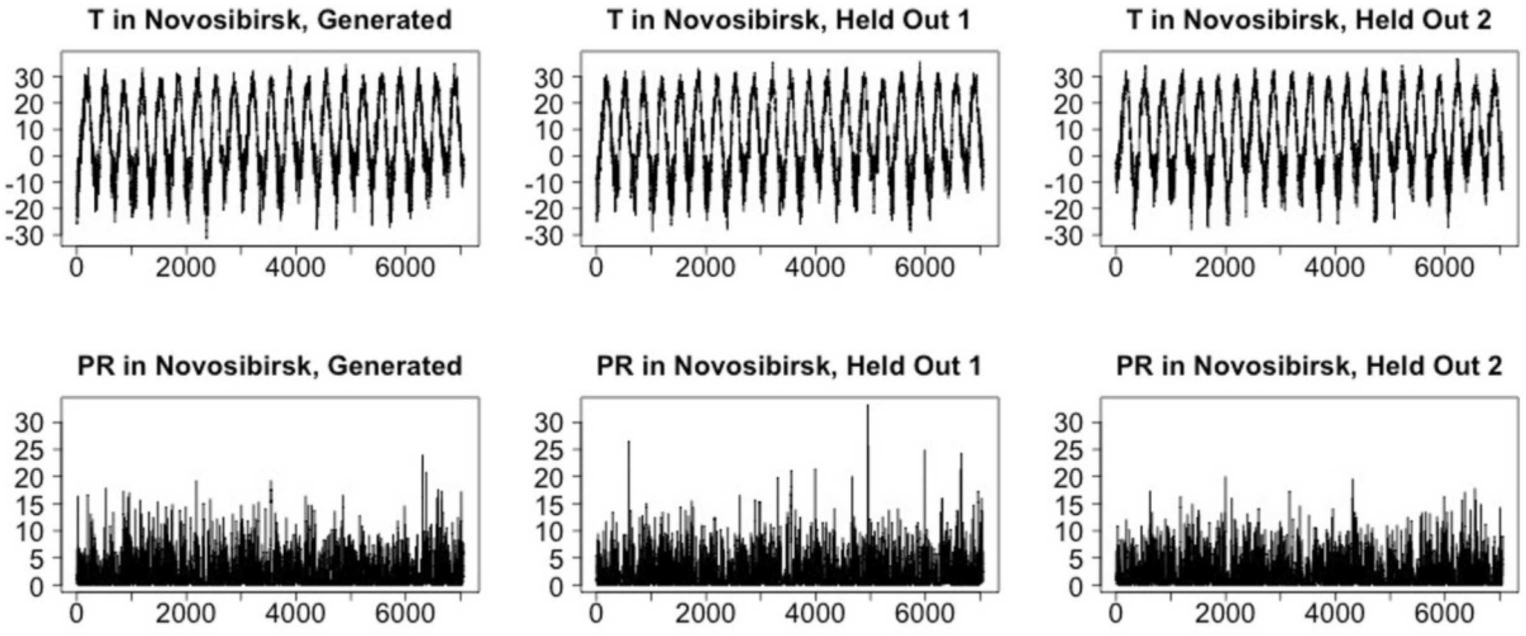
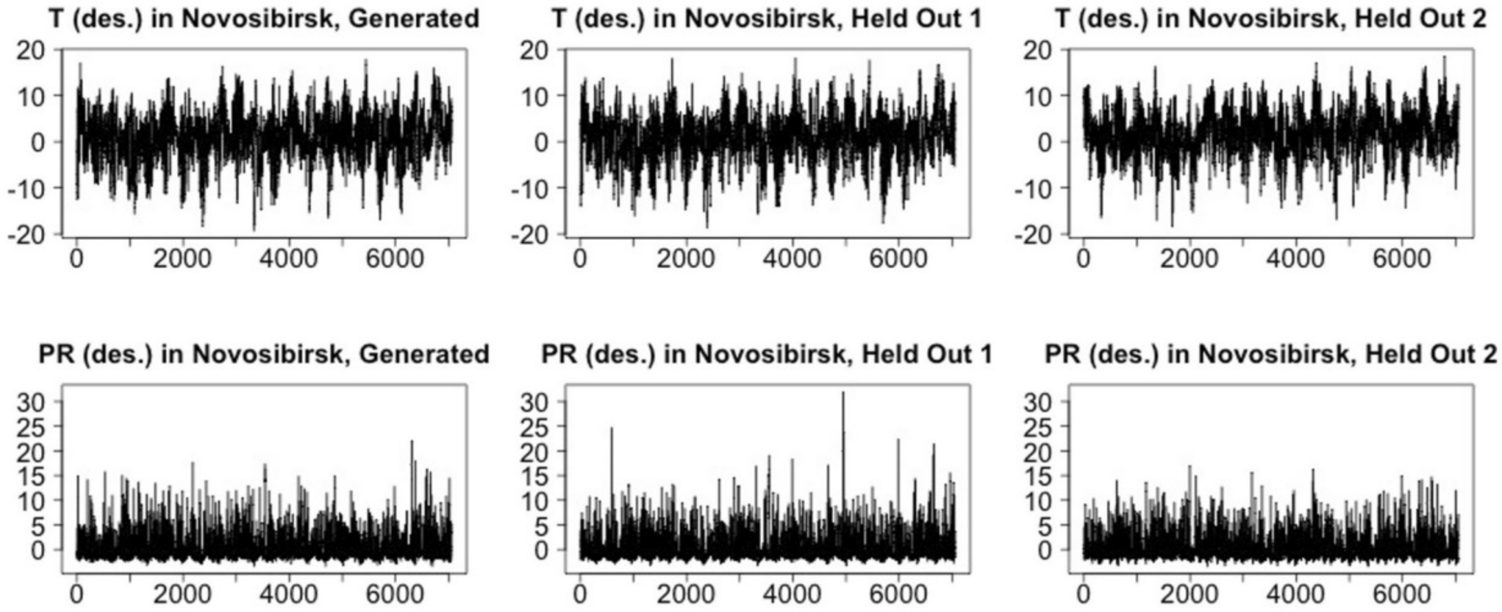


Bassetti et al (2024)

Example: DiffESM

- Takes monthly climate data of temperature, precipitation
- Generates realistic daily sequences using diffusion models
- The model is able to preserve the overall statistics of daily temperature and precipitation
- The model is not sensitive to the seasonal cycle



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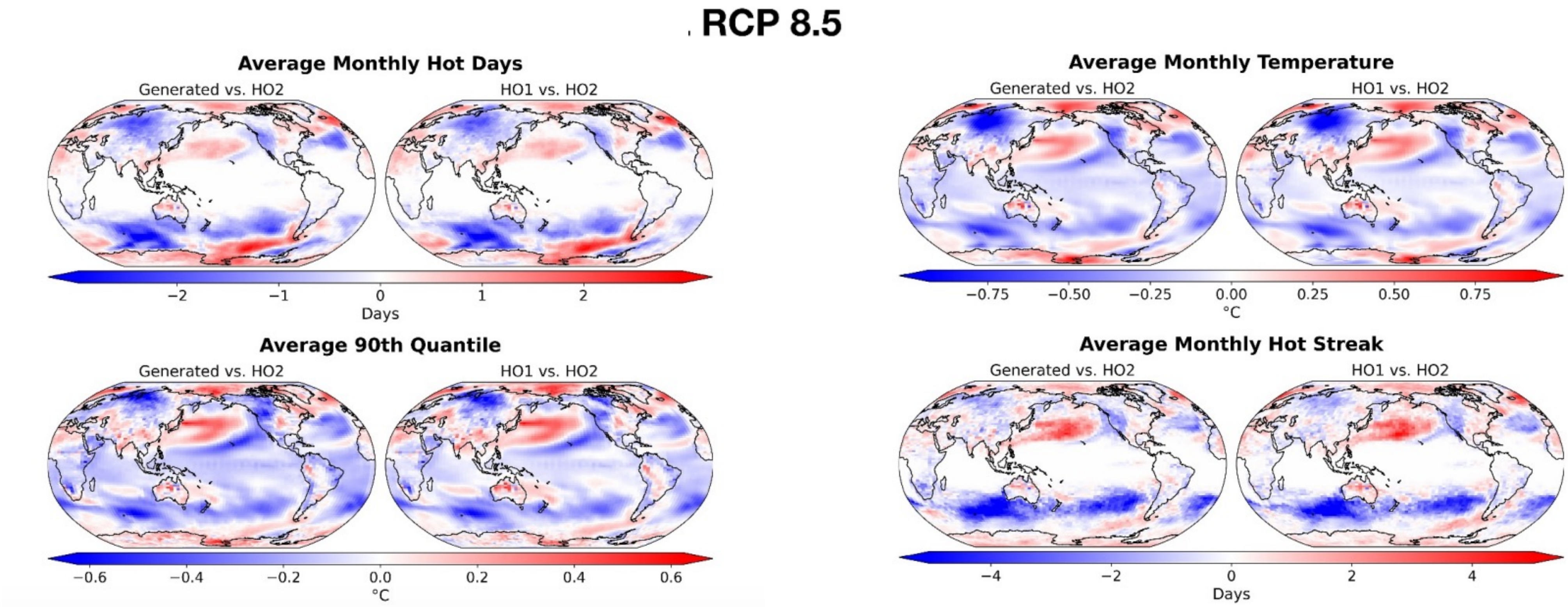

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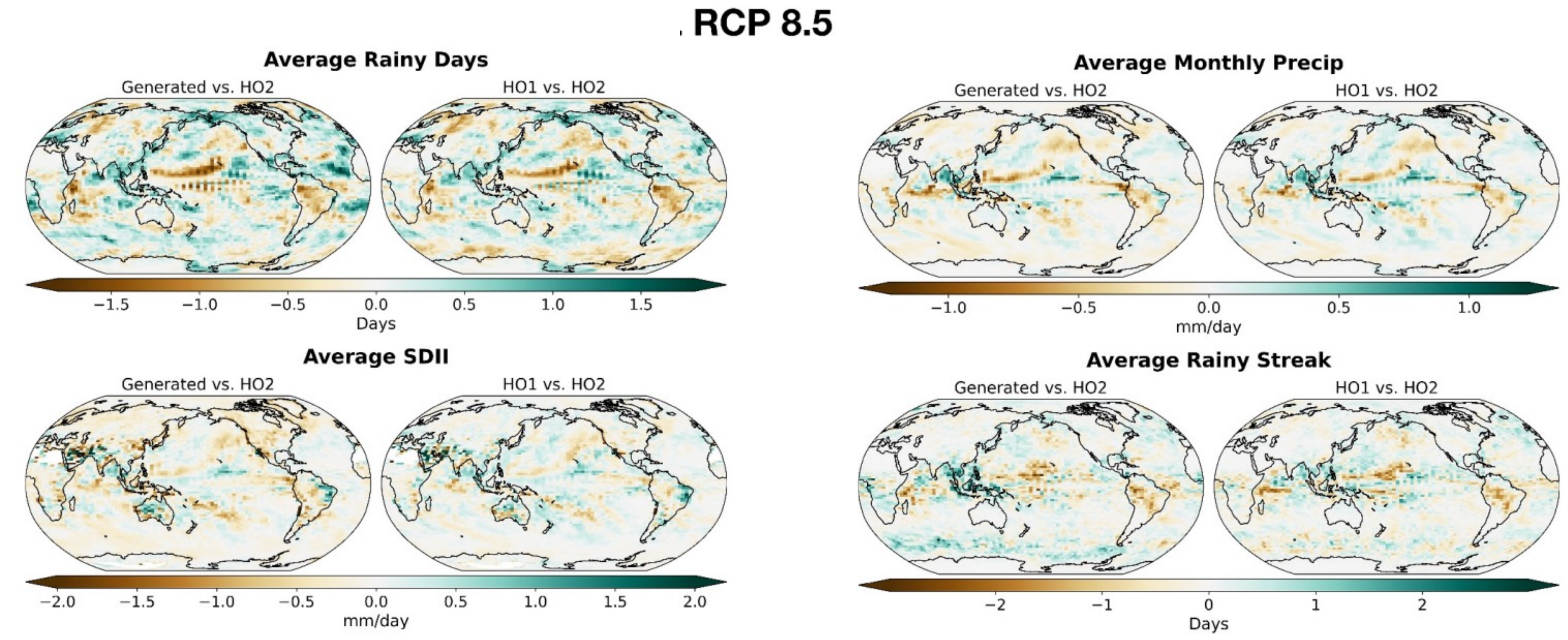

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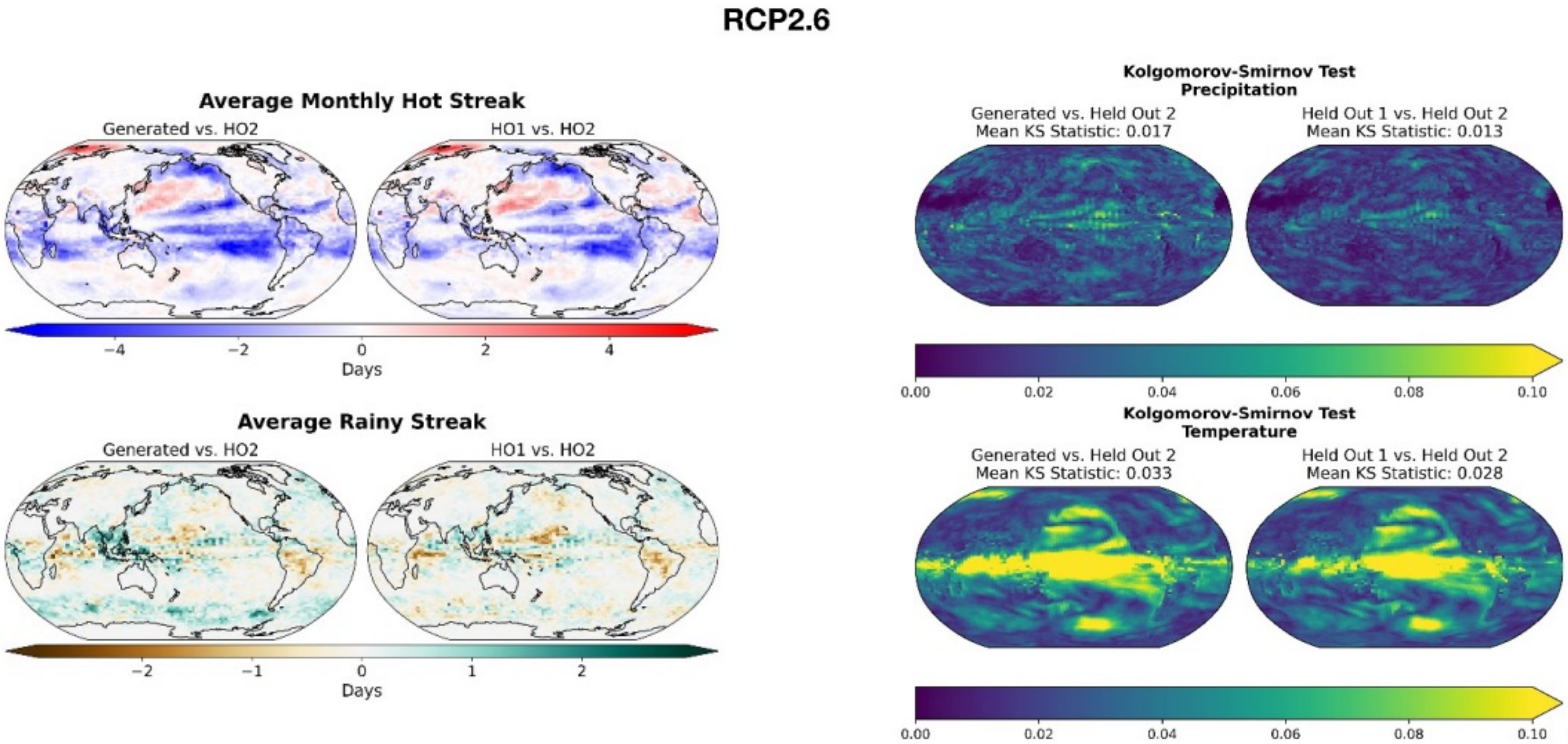
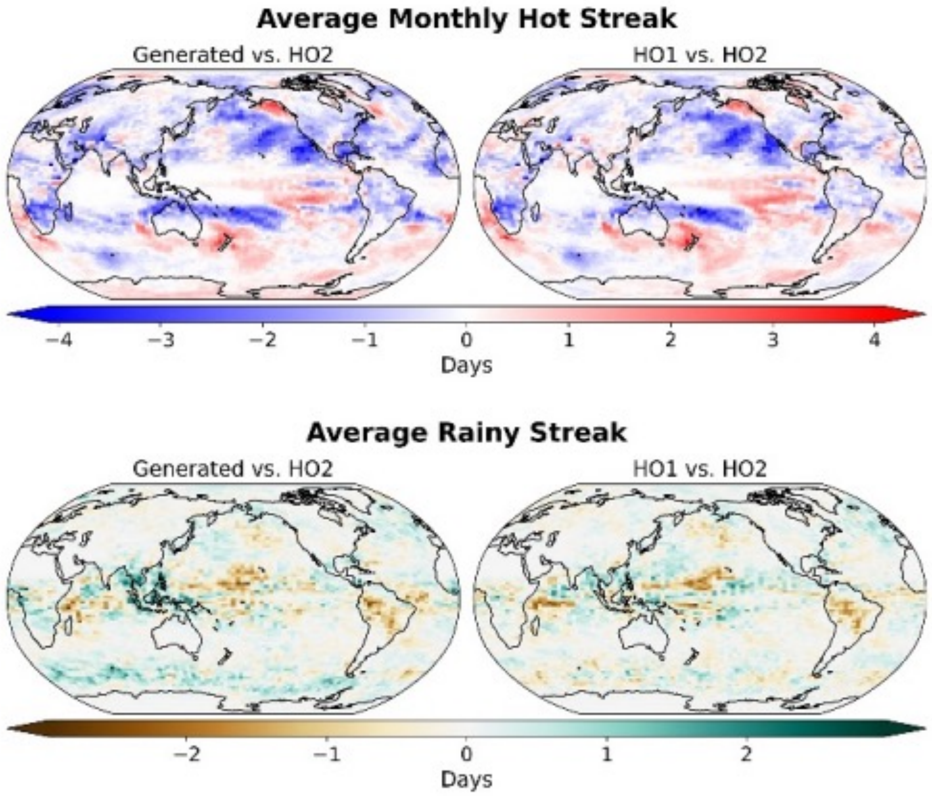


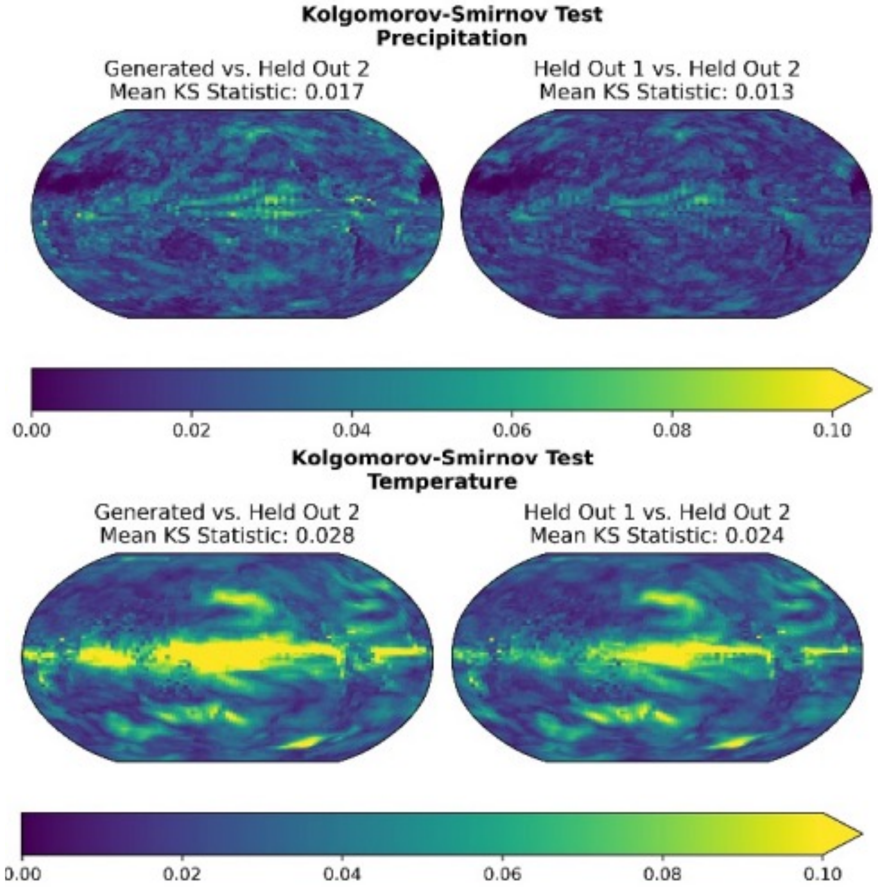
The model is able to generalize
onto other RCP scenarios

Bassetti et al (2024)

Example: DiffESM

RCP4.5



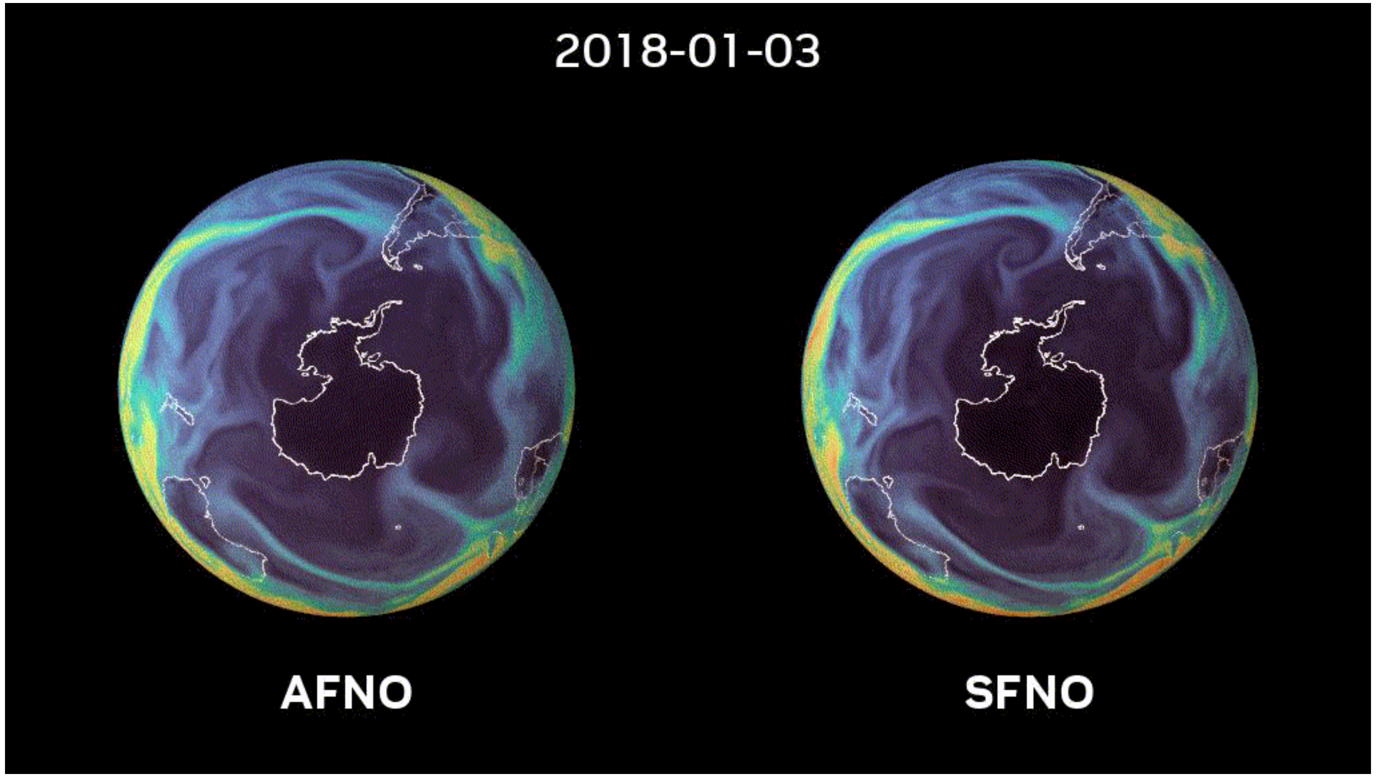


The model is able to generalize onto other RCP scenarios

Bassetti et al (2024)

ACE: AI2 Climate Emulator

- Adapted Nvidia's spherical Fourier neural operators approach for long climate rollouts



Watt-Meyer et al (2023)

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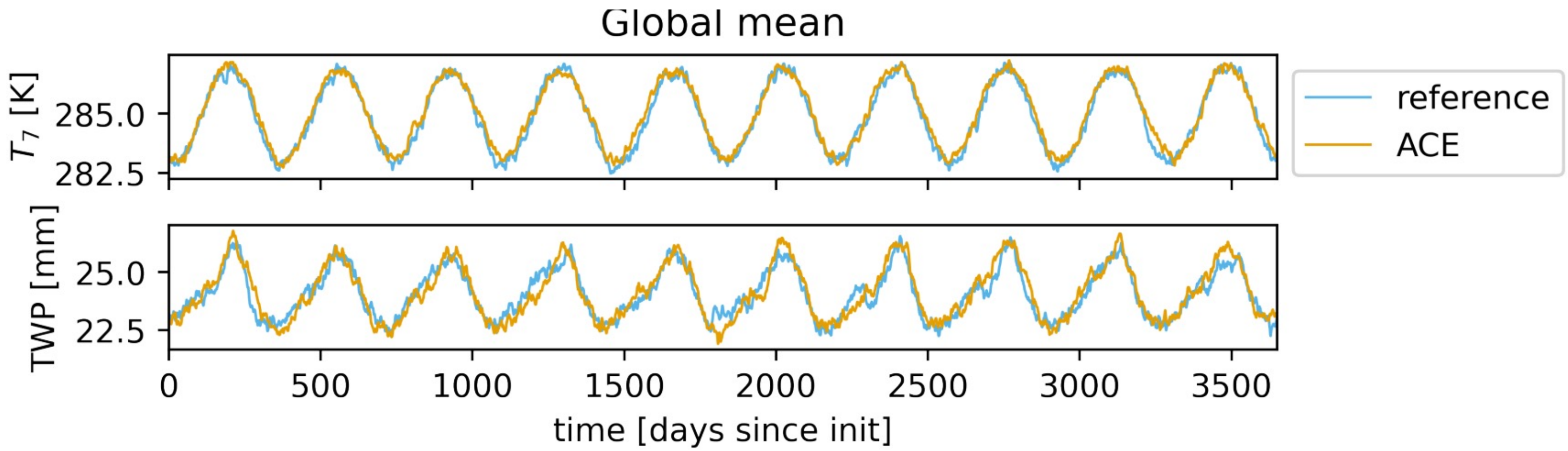
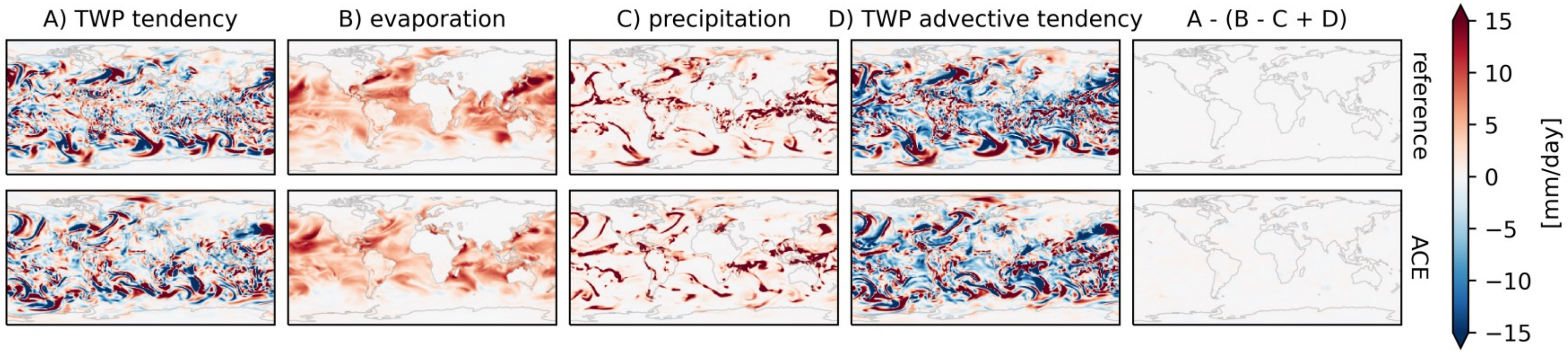
- Trained on 10 years of global atmospheric model output (not ERA5 like most data assimilation / weather prediction tools)



Watt-Meyer et al (2023)

ACE: AI2 Climate Emulator

- Adapted Nvidia's spherical Fourier neural operators approach for long climate rollouts
- Trained on 10 years of global atmospheric model output (not ERA5 like most data assimilation / weather prediction tools)
- Runs stably for 100 years
- Water budget terms remain close to ensemble mean from 11 members of global atmospheric models



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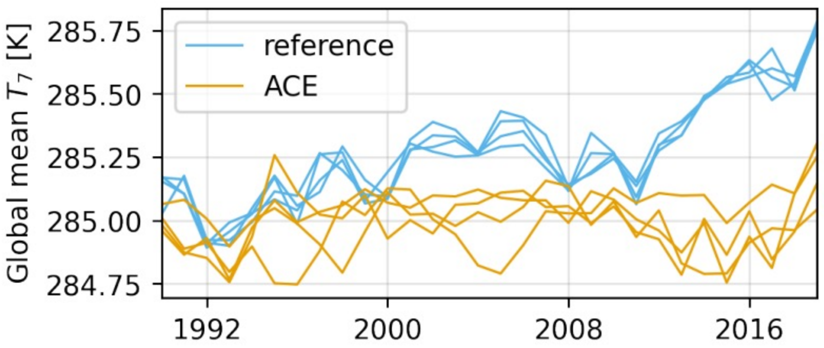
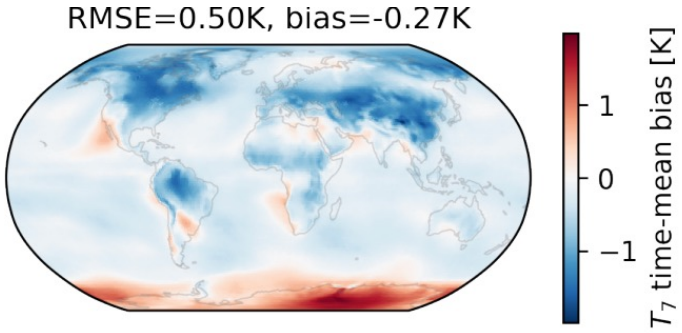
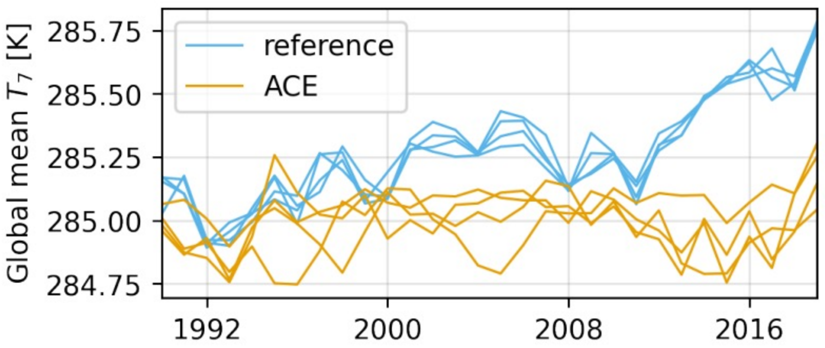


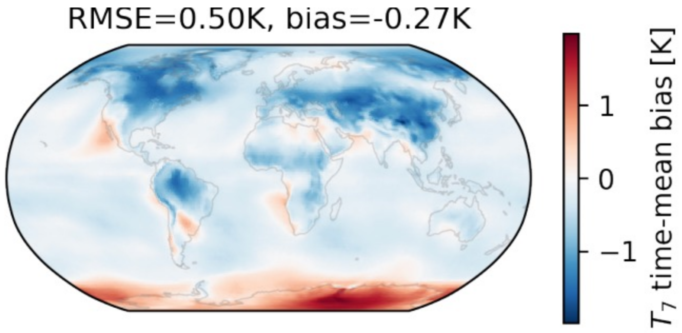


- However, is not able to capture trends in temperature changes

Clark et al (2025)
Watt-Meyer et al (2023)

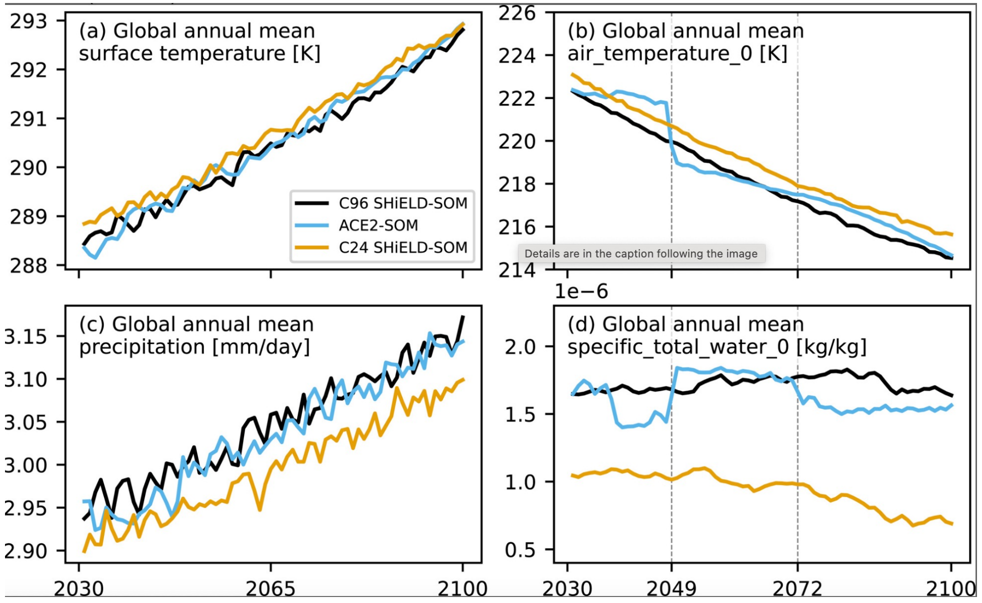
ACE-SOM (slab ocean model)





- However, is not able to capture trends in temperature changes

- A follow-up study with ocean forcing is able to correct for the trend



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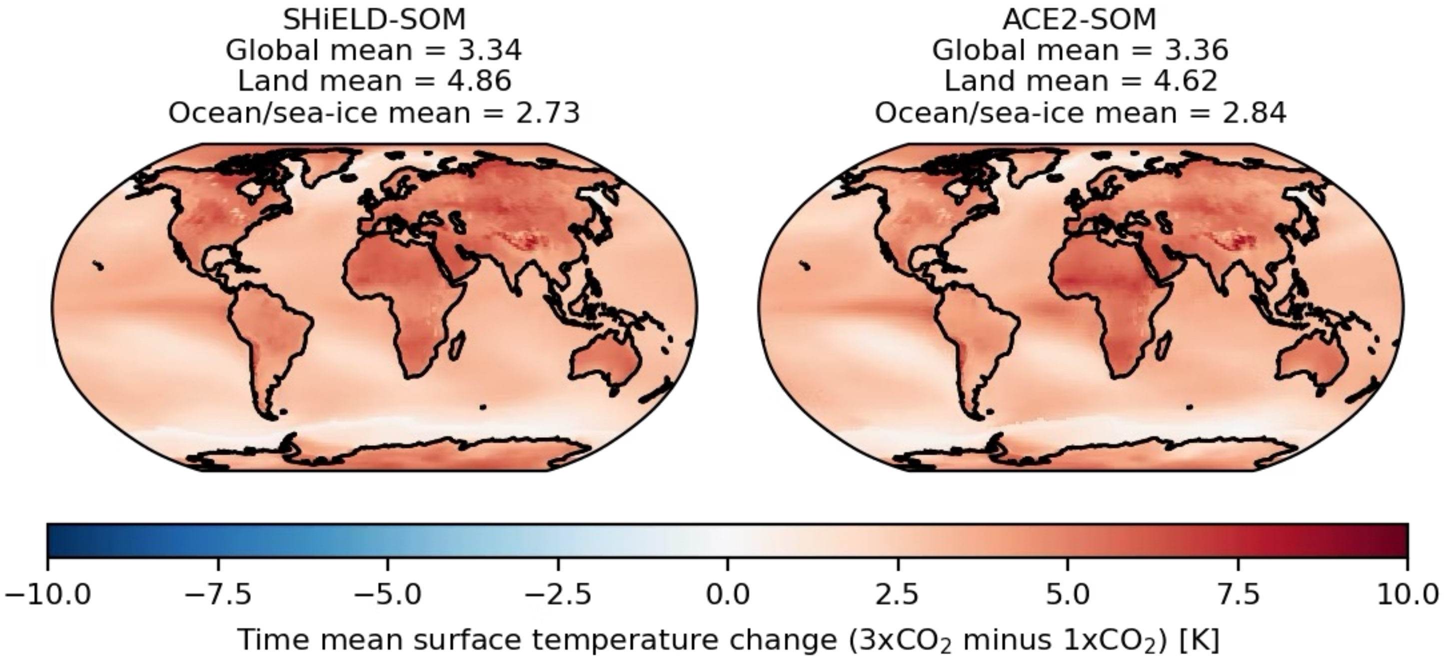
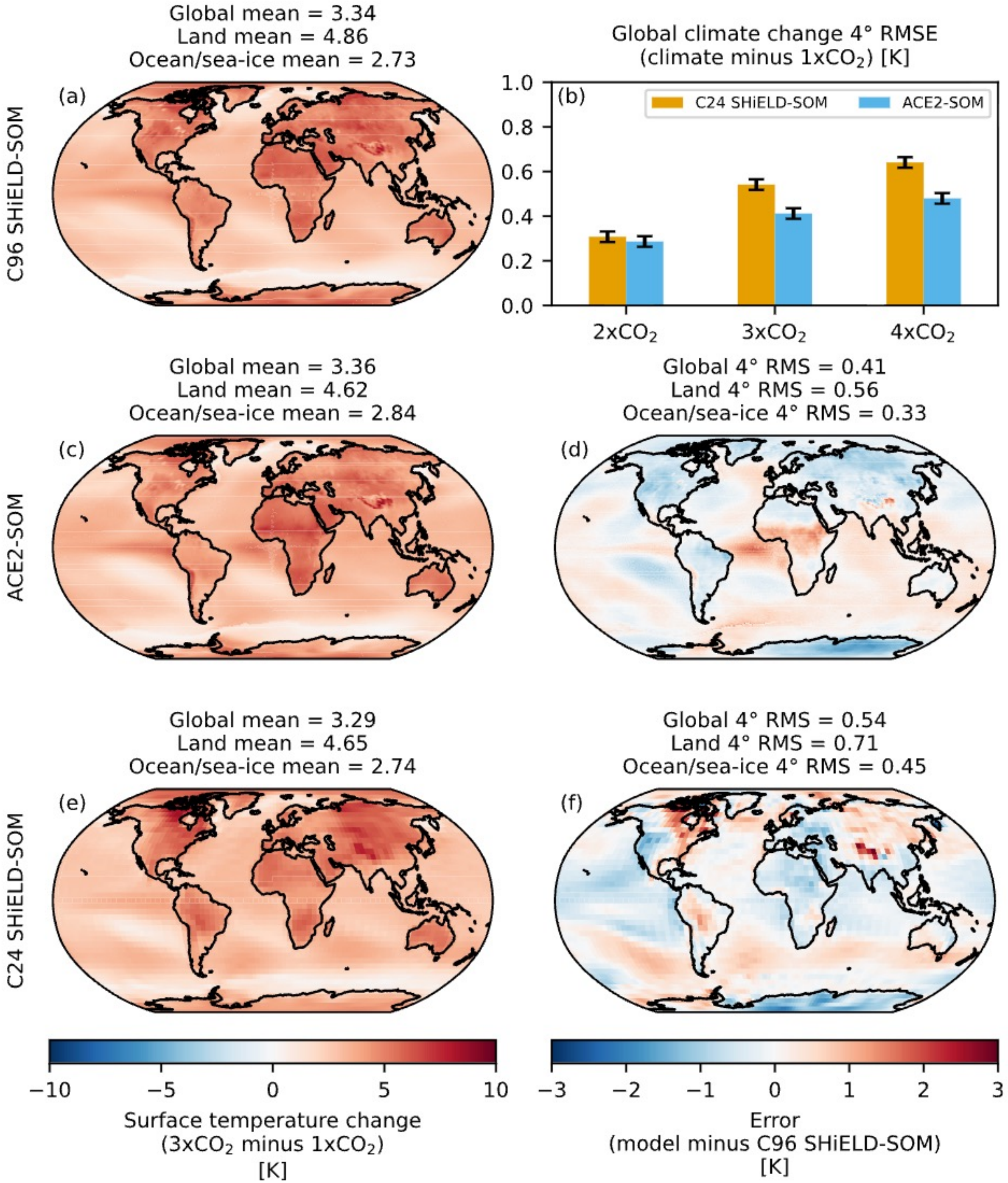


Clark et al (2025)
Watt-Meyer et al (2023)

ACE-SOM (slab ocean model)

- ACE-SOM has skill over different climate change scenarios.



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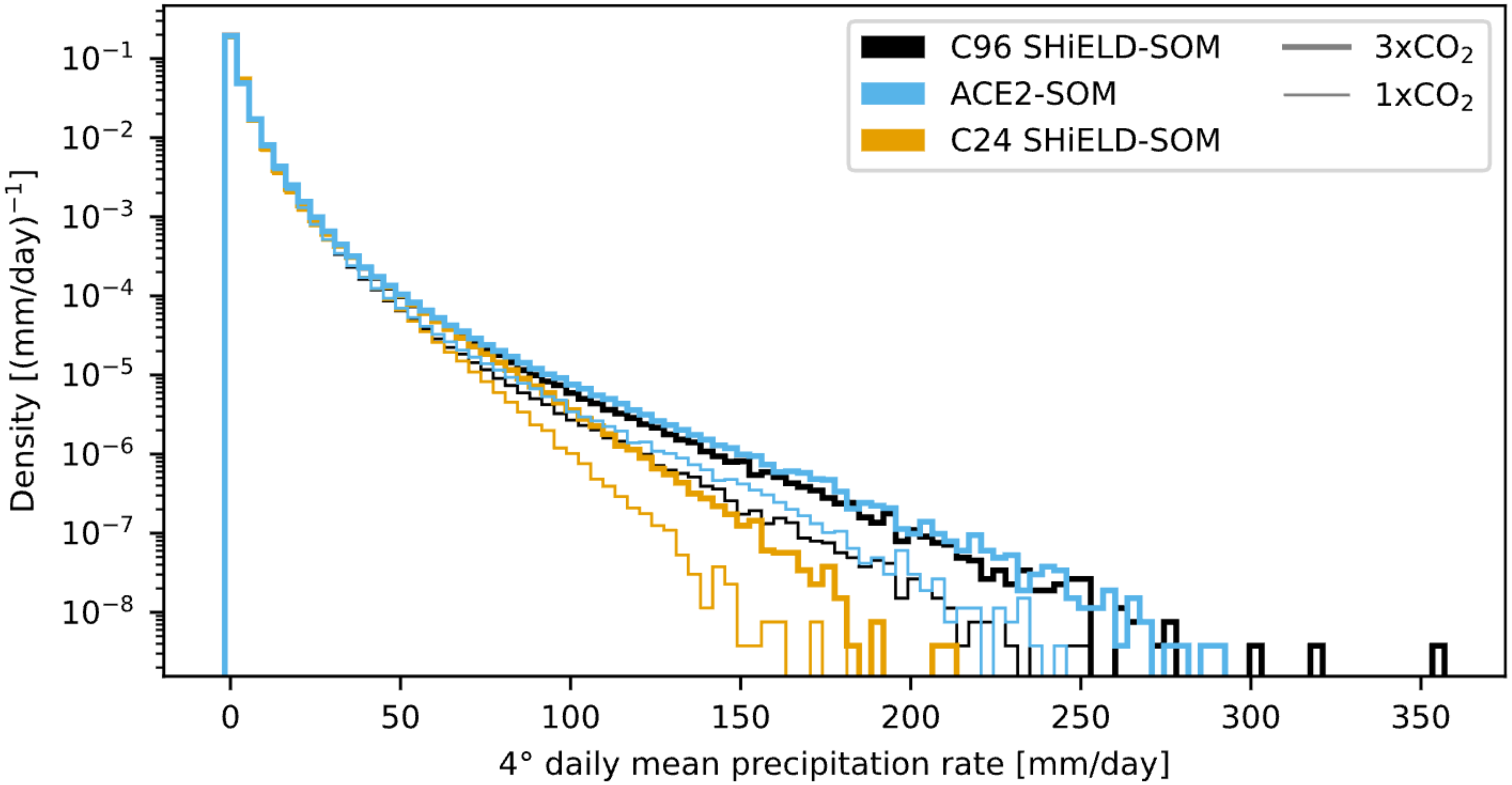

Clark et al (2025)
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Samudra:
Autoregressive AI ocean emulator

$$\widetilde{\mathbf{\Phi}}_{t+(n+1)\Delta t}, \widetilde{\mathbf{\Phi}}_{t+(n+2)\Delta t} = \mathcal{F}\left(\widetilde{\mathbf{\Phi}}_{t+(n-1)\Delta t}, \widetilde{\mathbf{\Phi}}_{t+n\Delta t}, \boldsymbol{\tau}_{t+n\Delta t}\right)$$

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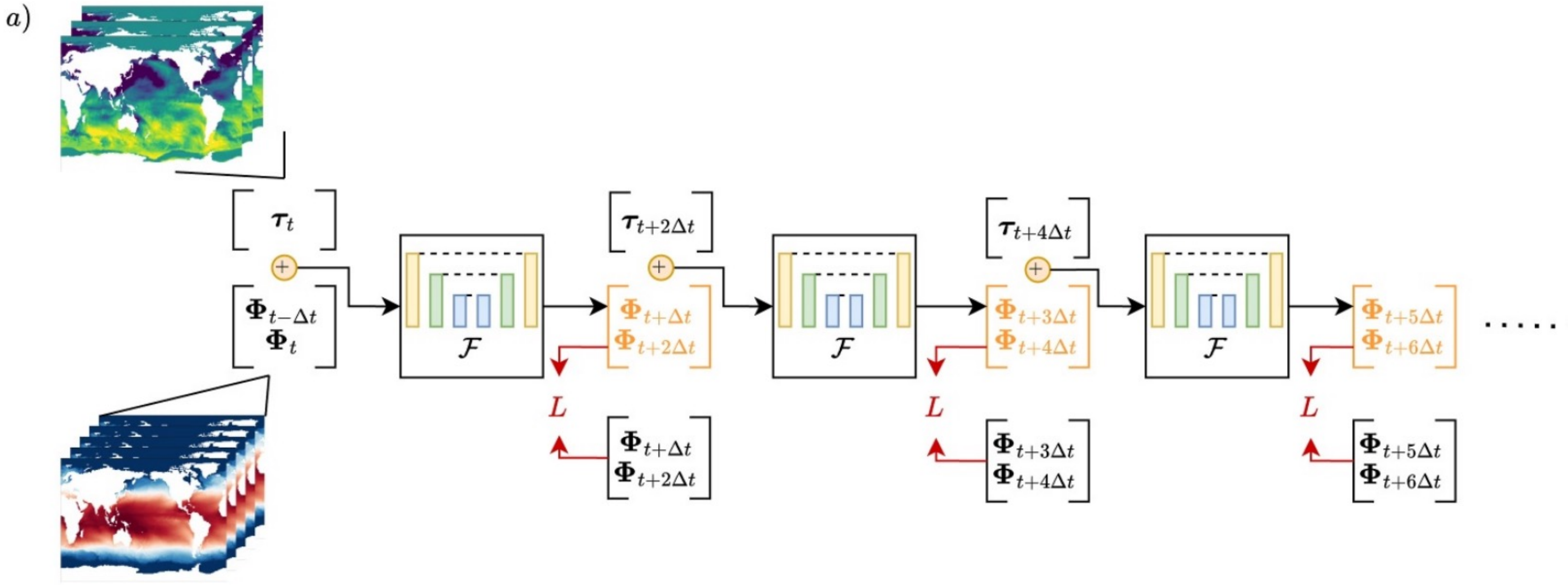

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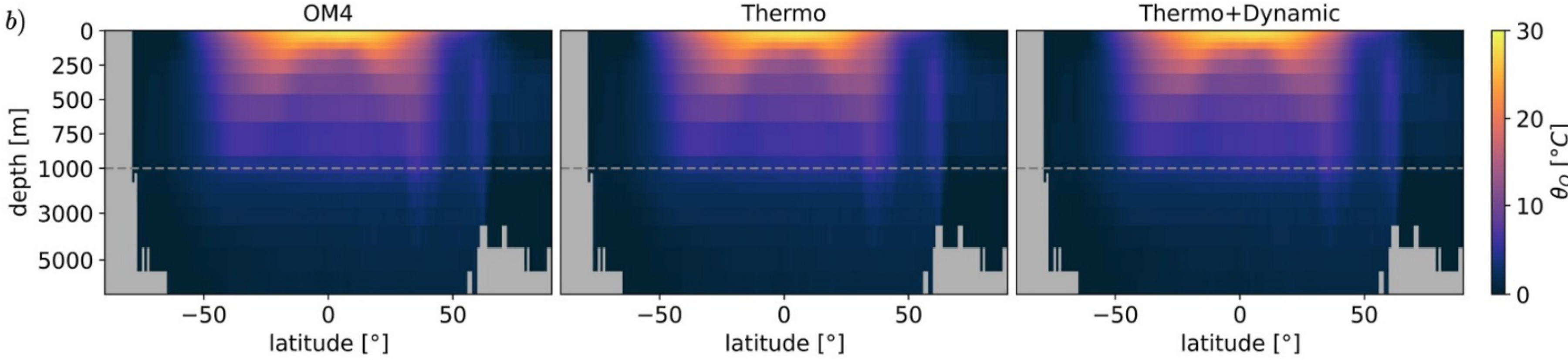

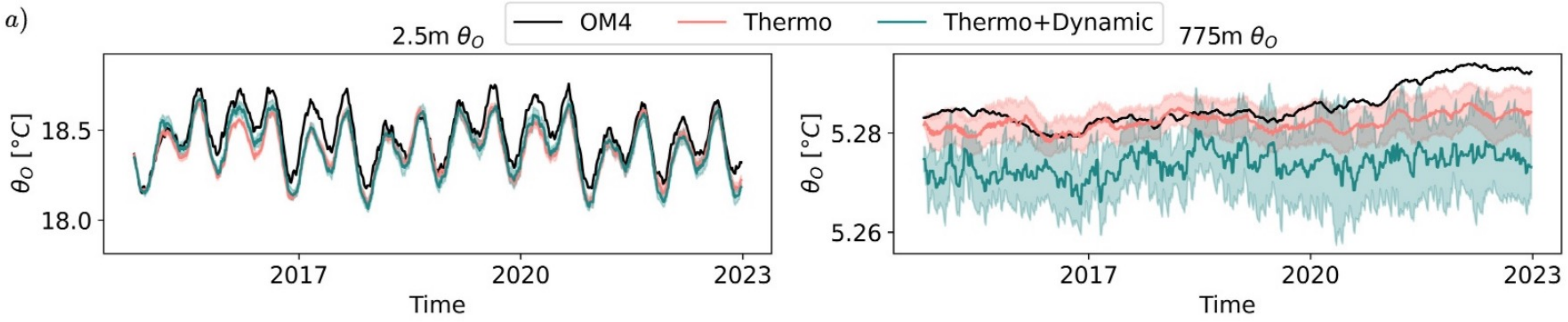

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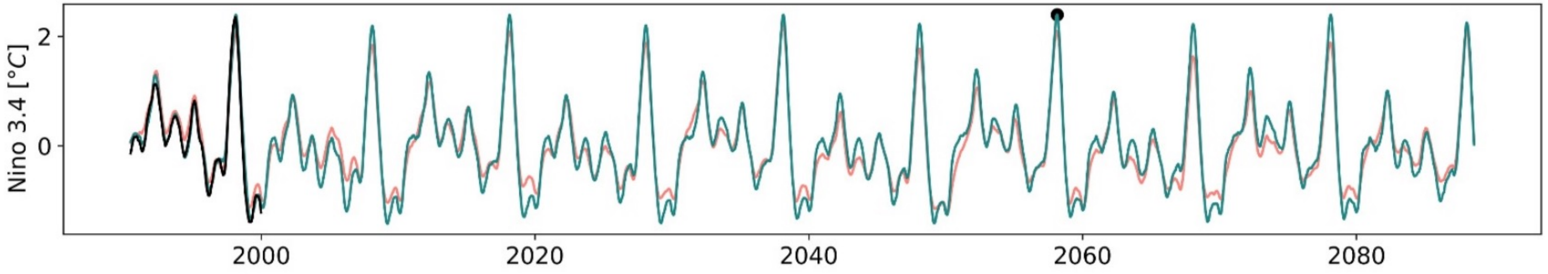
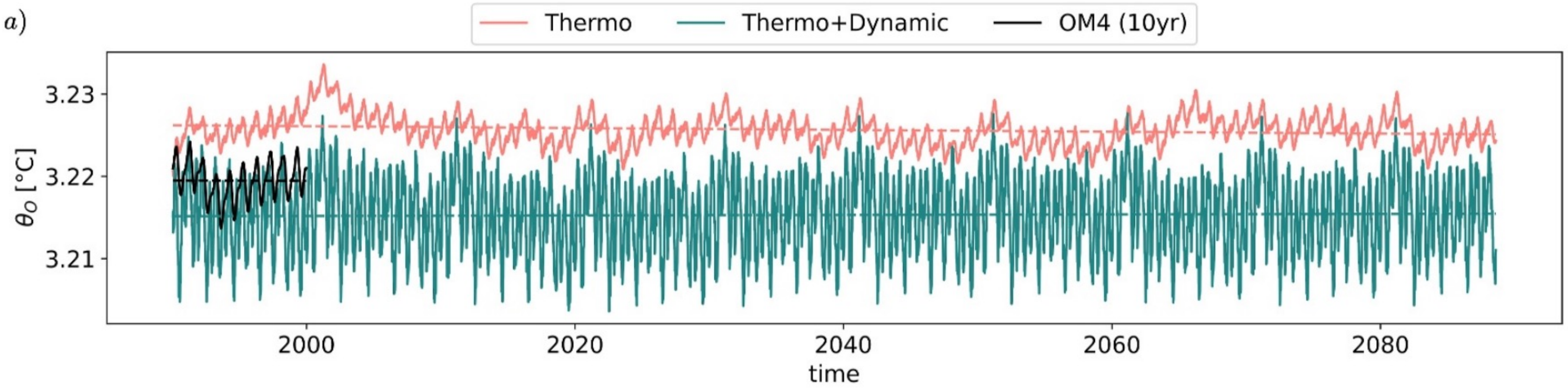
c)



a)



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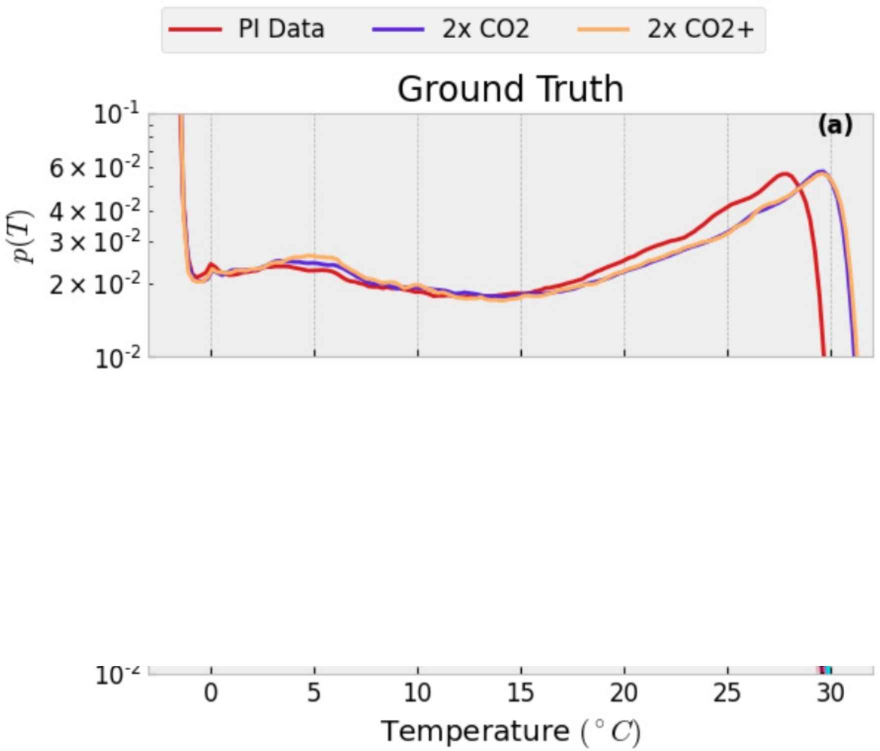

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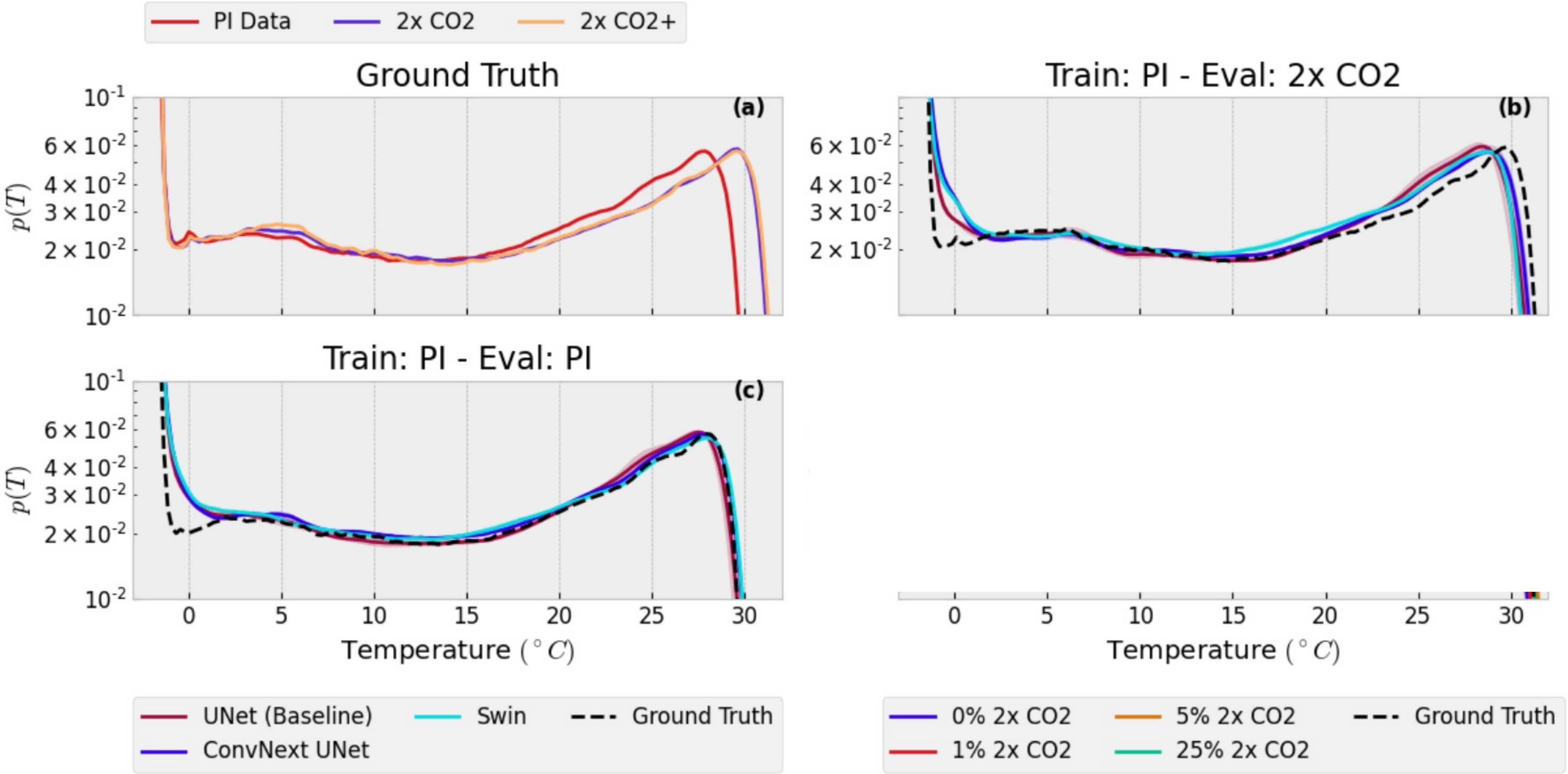

Dheeshjith et al (2024)

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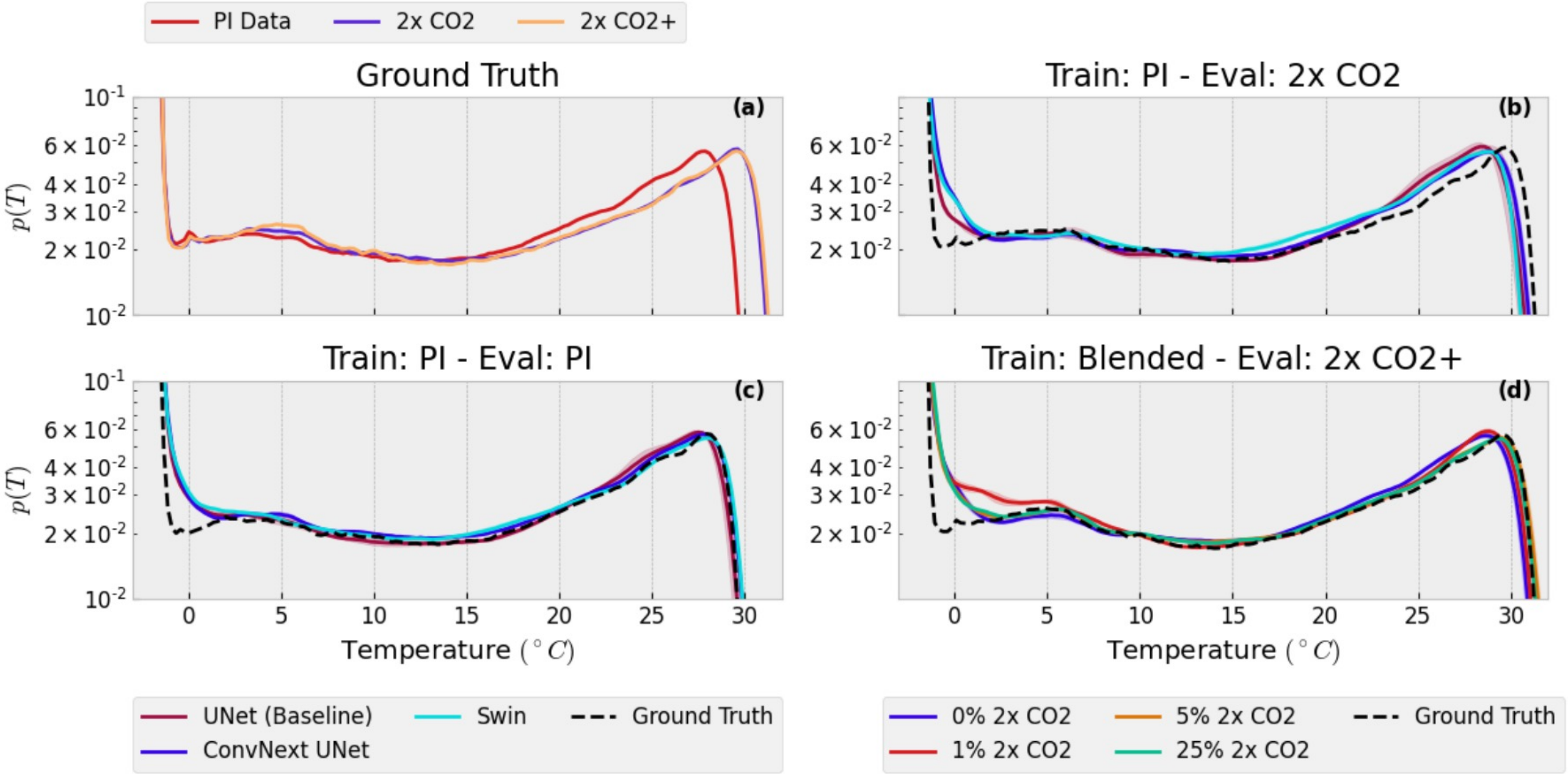

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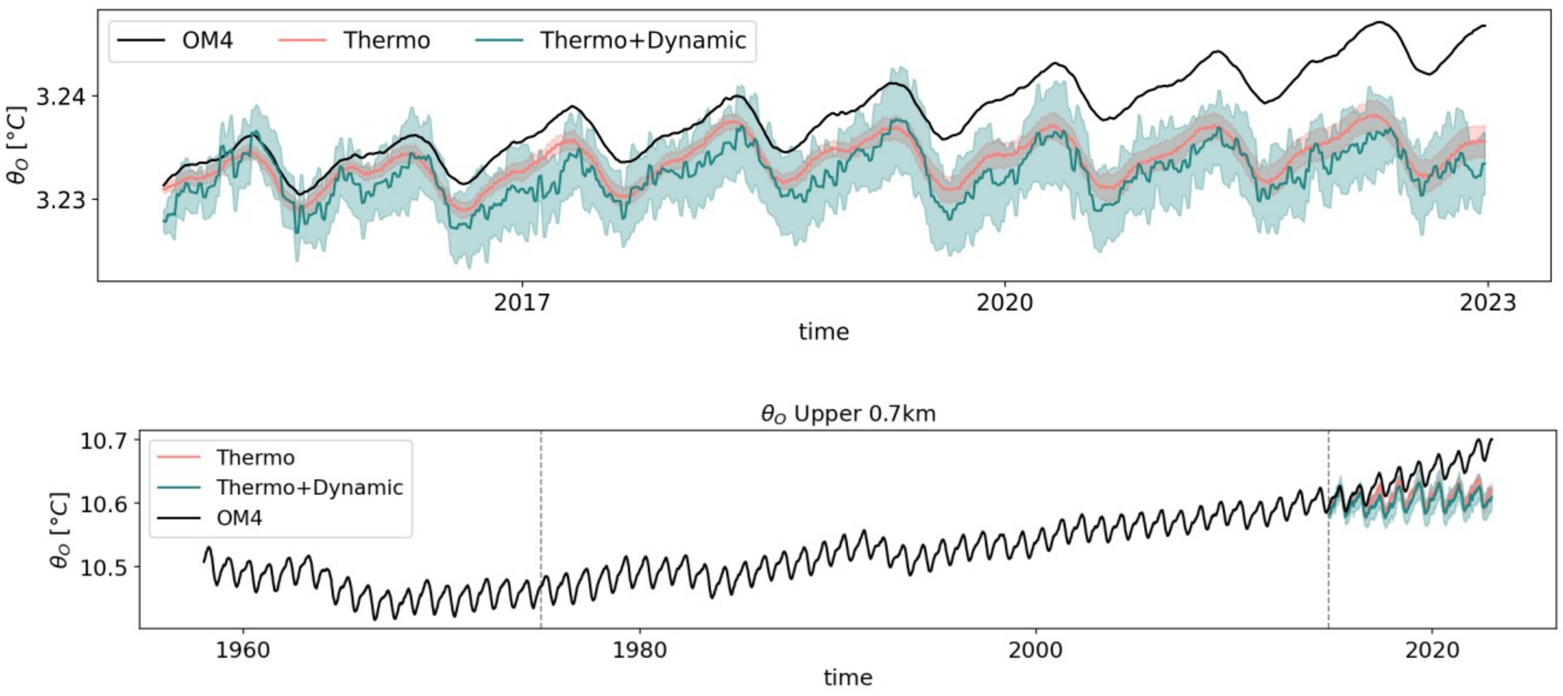

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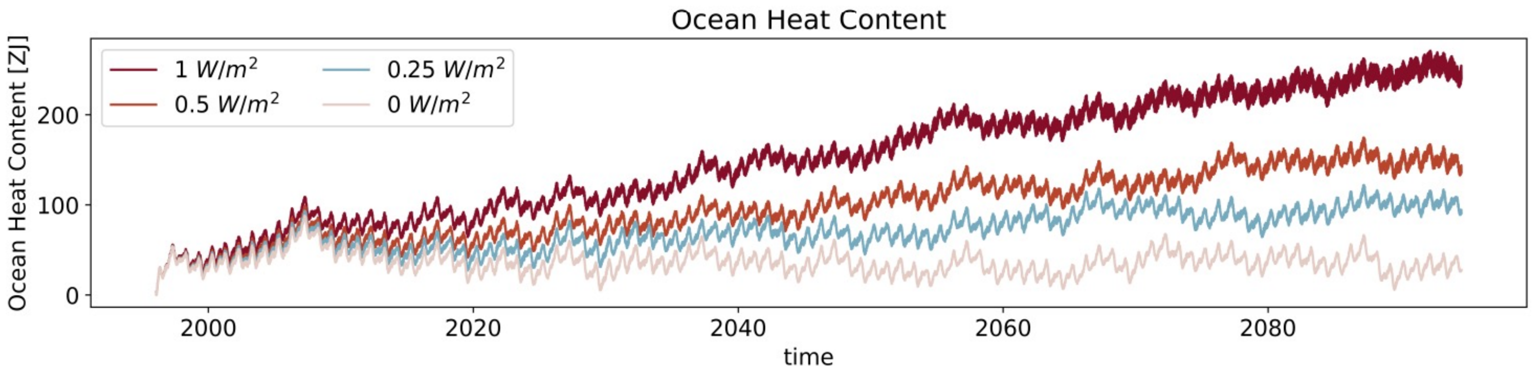
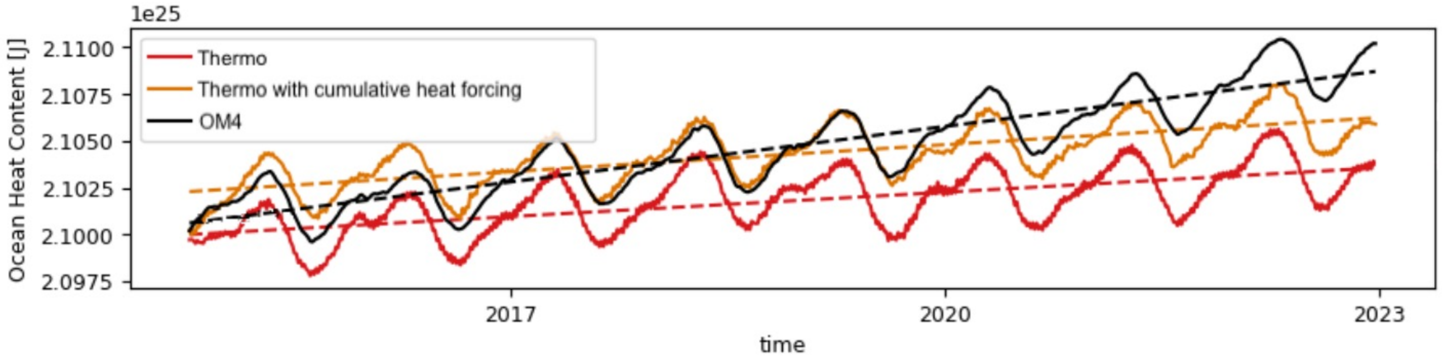
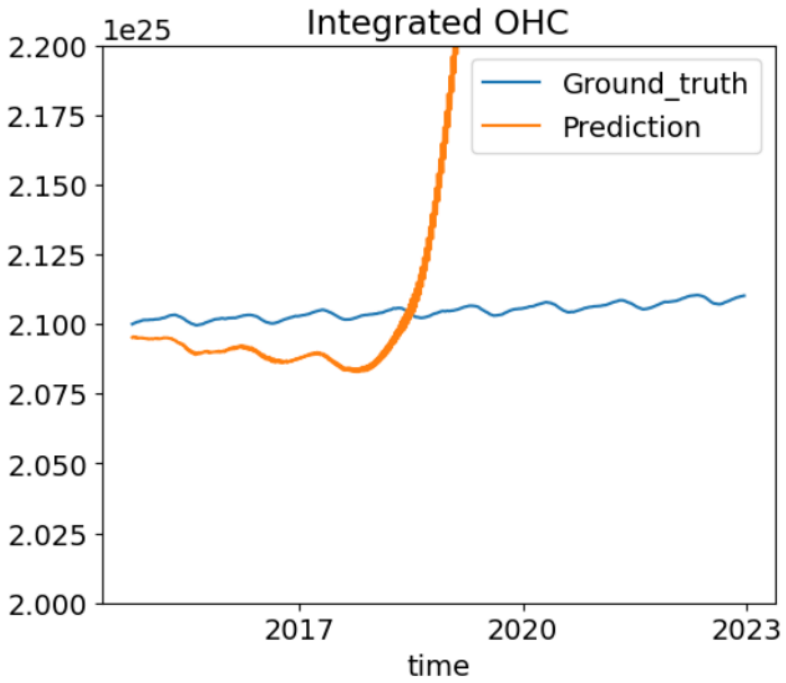


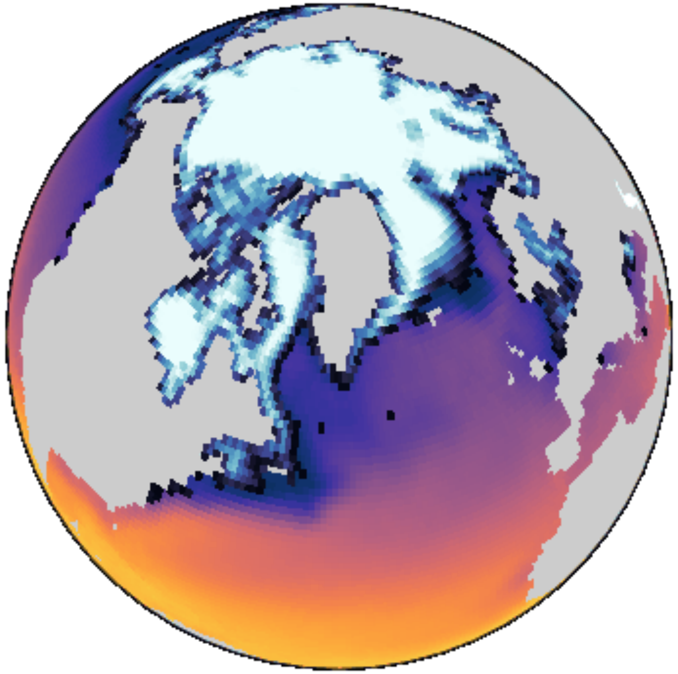




Dheeshjith et al (2025)

Example: SamudrACE (M2Lines & AI2)

- Coupling of climate-relevant physics
- 3D AI ocean-atmosphere-sea-ice climate emulator
- Enabling long-term projections at a fraction of the cost



Summary

- Climate emulators approximate complex Earth System Models to provide faster predictions and bridge physical simulations with societal impact needs
- They rely on high-quality training data and must remain stable, physically consistent, and realistic
- Pattern scaling is a simple emulator approach linking local changes to global temperature, but it captures mainly forced responses and lacks internal variability
- AI-based emulators (e.g., diffusion models, neural operators) can generate realistic high-resolution or temporal data and enable long, efficient climate simulations
- Key challenge: balancing speed with physical fidelity, especially for long-term trends, variability, and generalization across scenarios