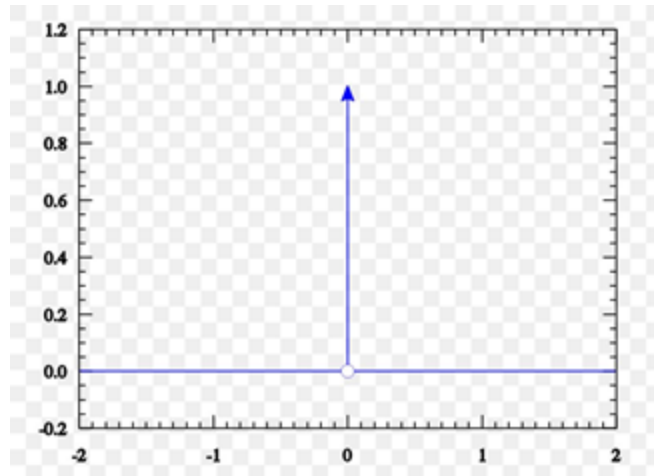



# Reanalysis-based Global Radiative Response to Sea Surface Temperature Patterns: Evaluating the Ai2 Climate Emulator



 **ACE**

## Ai2 Climate Emulator

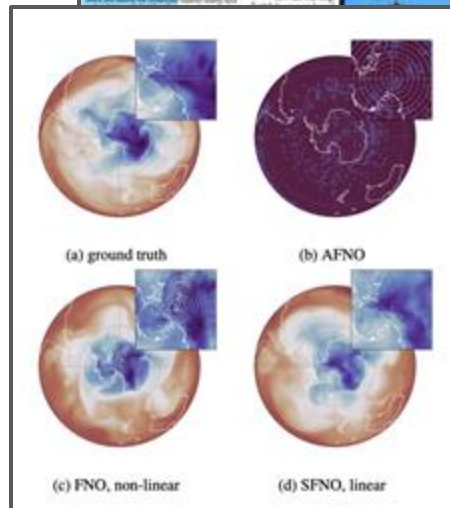
Ai2 Climate Emulator (ACE) is a fast machine learning model that simulates global atmospheric variability in a changing climate over time scales ranging from hours to centuries.

This repo contains code accompanying four papers describing ACE models:

- "ACE: A fast, skillful learned global atmospheric model for climate prediction" ([link](#))
- "Application of the Ai2 Climate Emulator to E3SMv2's global atmosphere model, with a focus on precipitation fidelity" ([link](#))
- "ACE2: Accurately learning subseasonal to decadal atmospheric variability and forced responses" ([link](#))
- "ACE2-SOM: Coupling to a slab ocean and learning the sensitivity of climate to changes in CO2" ([link](#))

# Overview

- ACE
  - 3 versions
  - SFNO
- Green's Function Experiment
  - Response on perturbations
  - ~~Well, let's guess everything is linear~~
- GFMIP setups
  - Emulator testing framework



Function

# Motivation (Section 1.1)

- Understanding Climate Feedback → GCMs
  - But..... Lots of parametrizations
  - And..... Slow
  - So..... Machine learning → Emulators!!
  - Emmm..... Are they good?
  - $\neg\_(\text{ツ})\_/\_...$  I don't know..... but they are definitely fast...
  - ..... ...
  - Emmmmmm... I mean, they parametrized EVERYTHING. What do you expect...
  - $(\mu^\circ \square^\circ) \mu \frown \text{—} \text{—} \text{—}$
- What if we want to analyze climate emulators like GCMs?

## Green's Function Experiment

Before that, Let's quickly cover the ML basics →

# AI2 Climate Emulator (ACE) (Section 2.1)

- Based on Spherical Fourier Neural Operators

- (Bonev et al., 2023; Yik 2025, UW Atmos MLJC)

- Autoregressive

- input T, output T+6hr

- 3 Versions

- ACE-VF3  $\leftarrow$  GFS
- ACE-EAM  $\leftarrow$  E3SM
- ACE2-ERA5  $\leftarrow$  ERA5
  - Also forced by CO2

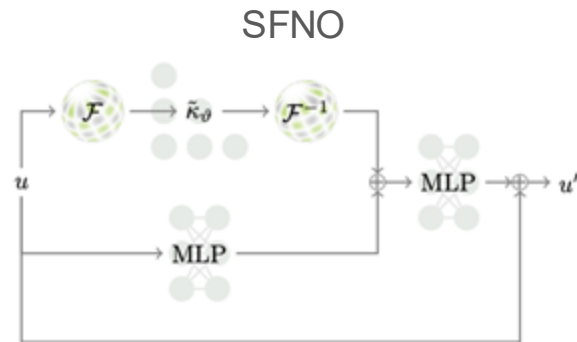


Figure 2 from Bonev et al., 2023

a Input-output diagram of ACE

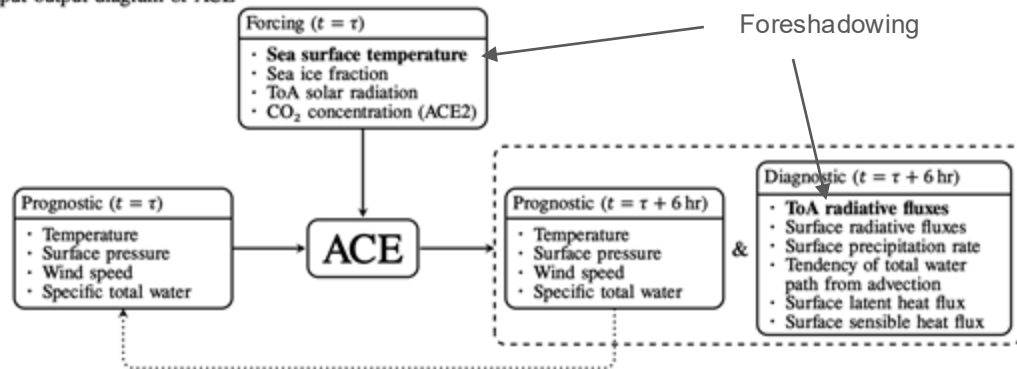


Figure 1a

Thank you.

That's all I am going to say about Machine Learning in this meeting.

Thanks for listening, and enjoy your pizza...

( ^\_^ ) o自自o ( ^\_^ )

Now, back to Green's function→

# Green's Function (Section 1.2)

- How the dynamical systems behave under point-perturbation
  - Idealized situation
- Response to local perturbation
  - Note: No time-dependence. We are more interested in long-term response, i.e. the new equilibrium. We don't need the transient response.
  - Perturbation is like a constant source, and the sink is the ambient whatever
- Representing the causal response
  - Because we literally poke the system, observe its response, and compare against control.

$-\log($



)

# Green's Function Experiment (Section 2.2)

**Main Quest:** (Finish all side quests to unlock this one)

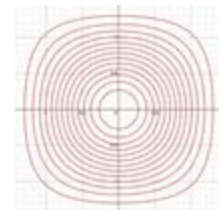
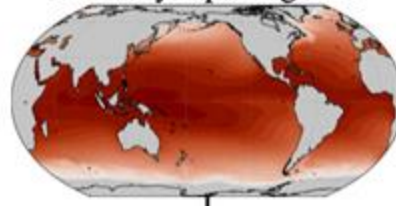
 **Find the TOA response R given local perturbation in SST**

**Side Quest:**

1. Control Run, 20 years
2. Apply the SST perturbation
3. Run the new system for 2 + 10 year
4. REPEAT 3 for each patch
5. Calculate feedback using this equation
6. HAHA, Repeat 1-5 for each ACE

ACE-VF3    ACE-EAM    ACE2-ERA5

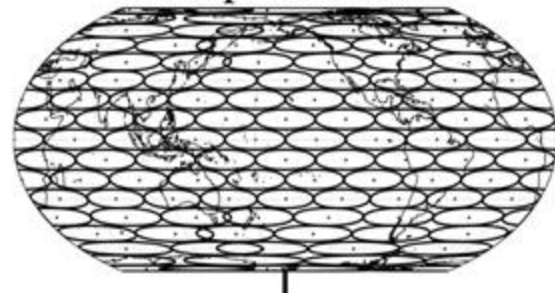
Annually repeating SST



$$f(x, y) = (\cos(x))^2 (\cos(y))^2$$

$$T_p(\varphi, \vartheta) = \begin{cases} A \cos^2 \left( \pi \frac{\varphi - \varphi_p}{\delta \varphi_p} \right) \cos^2 \left( \pi \frac{\vartheta - \vartheta_p}{\delta \vartheta_p} \right) & \begin{cases} \varphi - \varphi_p \in [-\delta \varphi_p, \delta \varphi_p] \\ \vartheta - \vartheta_p \in [-\delta \vartheta_p, \delta \vartheta_p] \end{cases} \\ 0 & \text{elsewhere} \end{cases} \quad (1)$$

Patch perturbations



$$\frac{\partial R}{\partial T_j} = \frac{1}{\sum_p T_{p,j}} \sum_p \frac{T_{p,j}}{\langle T_p \rangle} \Delta_p R \quad (2)$$

\* Please don't ask me any questions about this equation. It broke me

# Green's Function Experiment



- Previous procedure is from
  - Green's Function Model Intercomparison Project (GFIMP; Bloch-Johnson et al. 2023)
  - Protocol for GCMs
  - How models response to pattern effect.
  - GCM doesn't respond consistently
    - No "Ground Truth"

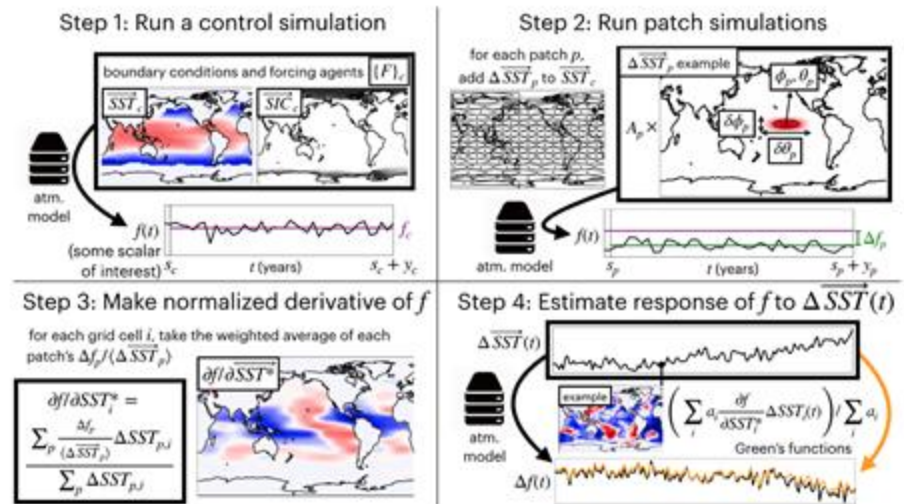
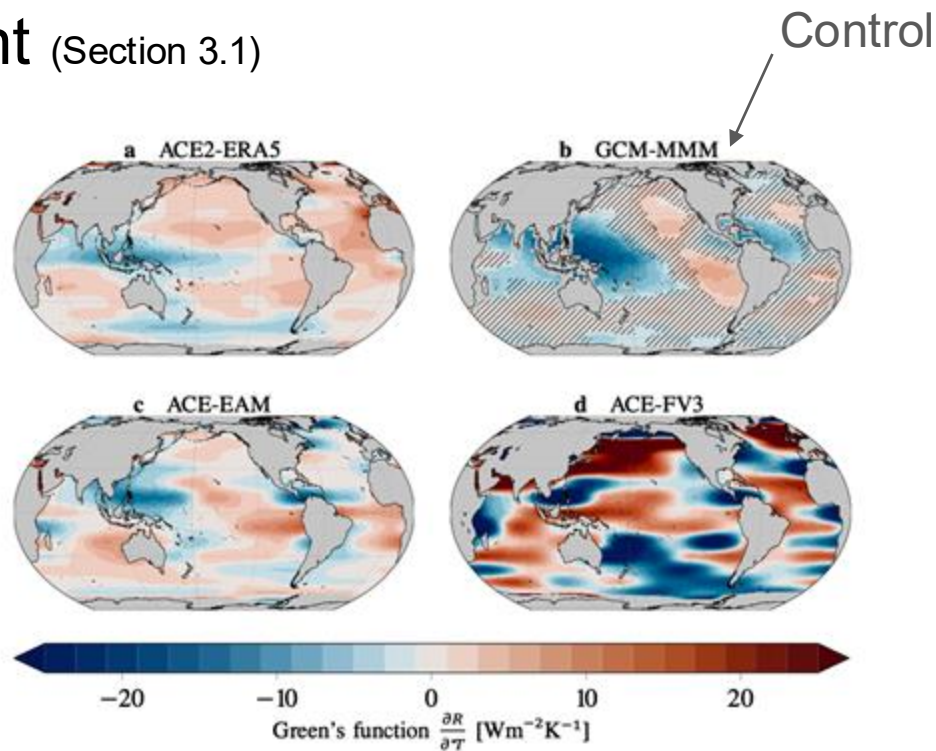


Figure 2 from B-J et al. 2023



# Green's Function Experiment (Section 3.1)

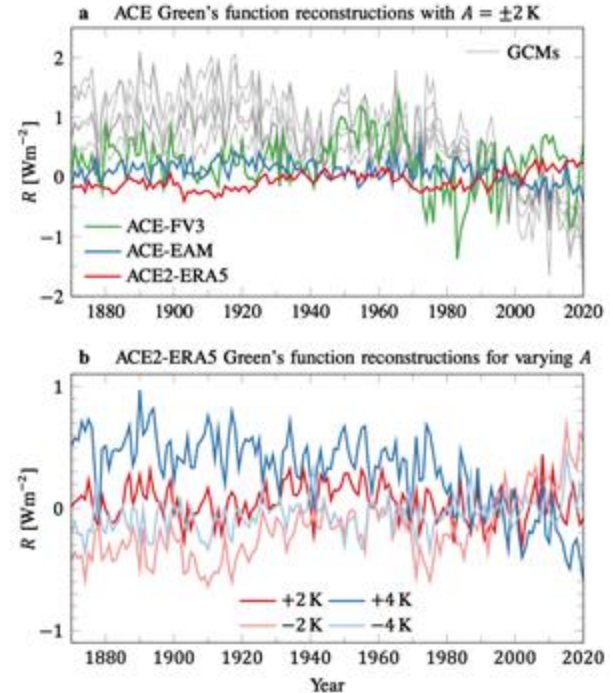
- ACE2-ERA5
  - Reproduce some features
  - Amplitude is low
- ACE-EAM
  - Good!
- ACE-FV3
  - Bad
  - (possible reason) Numerical Weather Prediction model is not energetically closed



**Figure 2.** Green's functions of (a) ACE2-ERA5, (b) Multi-model mean (MMM) of 5 GCMs (Bloch-Johnson et al., 2024), (c) ACE-EAM, and (d) ACE-FV3. Note that the resolution of ACE is  $1^\circ \times 1^\circ$ , while the GCMs are on a  $3.75^\circ \times 2.5^\circ$  grid. Hatching in b indicates regions where at least one GCM disagrees on the sign of the Green's function.

# Green's Function Experiment (Section 3.2)

- Historical Reconstruction using ACE Green's Function
- The reconstruction is not linear.



**Figure 3.** Historical reconstruction of the net ToA radiation  $R$ , formed by convolving the Green's functions with AMIP sea surface temperature anomalies with respect to 1971-2020.

# Discussion (Section 4)

- **[Potential Problem]** Observation is too short to see response. We have to rely on GCMs currently.
- ACE2-ERA5 have fixed CO2 during the Green's function experiment.
- **[Problem]** ACE2-ERA5 biased toward the observation, and have hard time extrapolate prediction
- **[Potential Fix]** physical constrain the ACE2 model
- **[Benefit]** Investigate nonlinear feedback using emulator.
- Emulator is doing poorly in green's function experiment.
  - Turn the bug into feature: green's function experiment is a good benchmark for emulator!