

# The Equilibrium Response of Atmospheric Machine-Learning Models to Uniform Sea Surface Temperature Warming

Zhang and Merlis, 2025

# ML for climate-timescale atmospheric modeling

Potential benefits of ML climate modeling:

- Significantly reduced computational cost → large ensembles
- Capturing processes that traditional models can't
- Make better use of existing observations

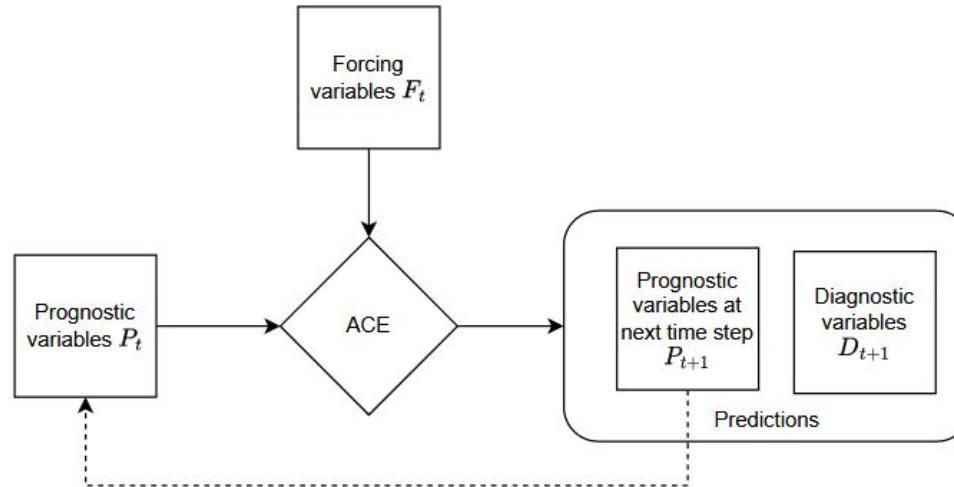
Two large challenges compared to weather modeling:

- Decadal to centennial stability
- **Generalizing to unseen climate states**

# Types of ML climate models - pure ML

Examples - ACE, DLESyM

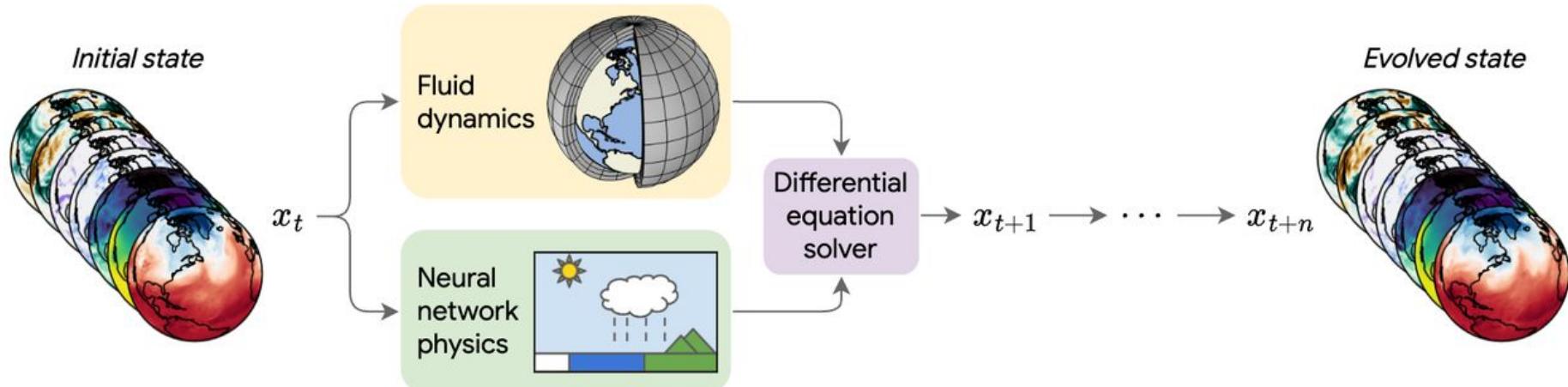
Key feature: autoregressive prediction



# Types of ML climate models - hybrid physics/ML

Example - NeuralGCM

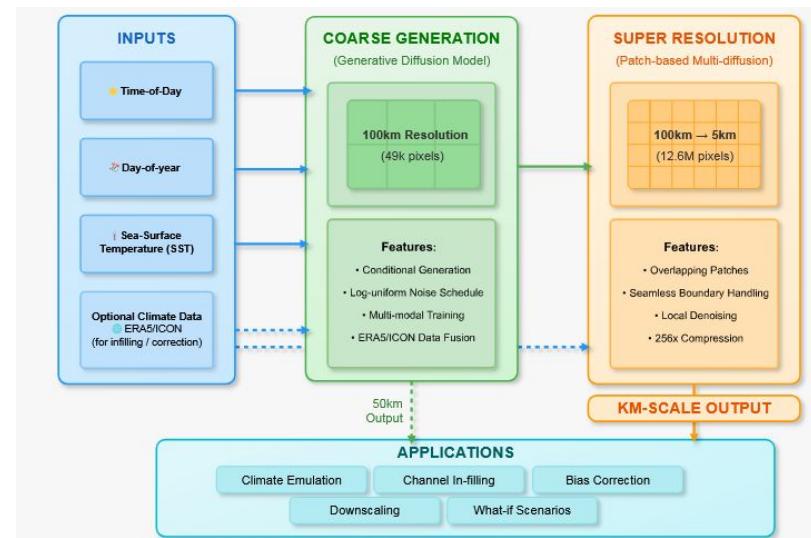
Key feature: retaining dry dynamical core



# Types of ML climate models - generative

## Example - cBottle

Key feature: no autoregression, directly predicts outputs from boundary conditions (SST, time of year, etc.)



# Uniform SST warming experiments

- Standard benchmark for climate models
- Evaluates a model's climate sensitivity and response to warming
- Easy to set up, rapid equilibration

# Experimental setup

ML models tested: ACE, NeuralGCM, cBottle

Traditional reference model: AM4 (GFDL)

Control simulation: forced with monthly climatological SST and SIC from 1981-2014

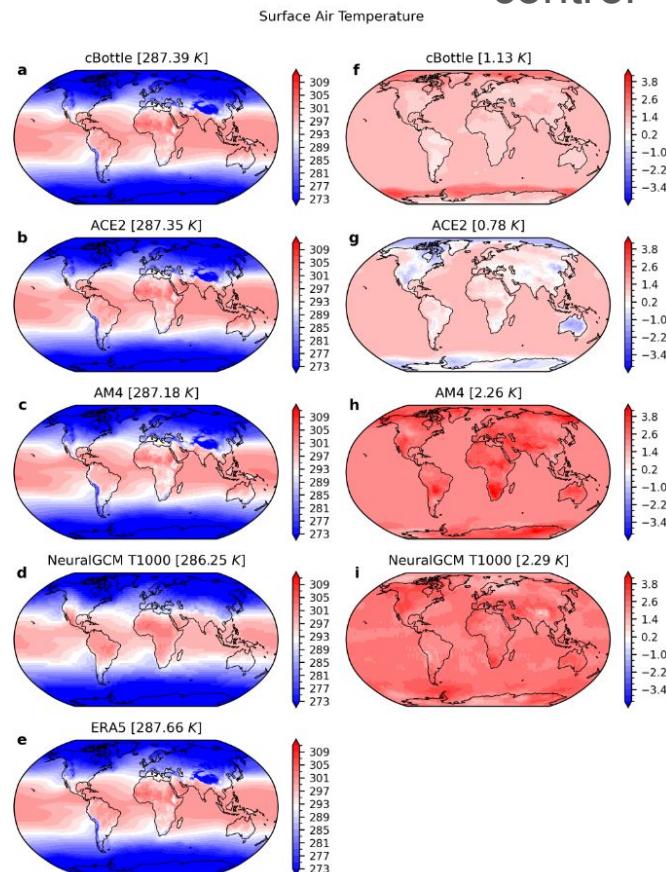
Warming simulation: +2 K SST applied at every grid point

# Surface temp. response

We expect

1. Polar amplification
2. Enhanced land warming

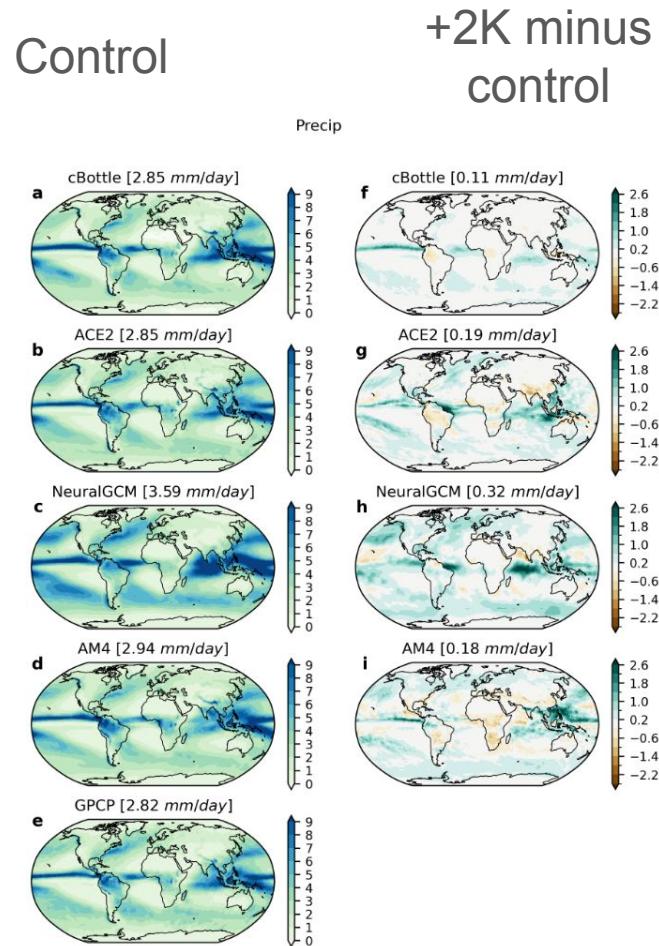
Control                            +2K minus control



# Precipitation

## We expect

1. ~3%/K increase in precip
  2. Strongest changes at tropics

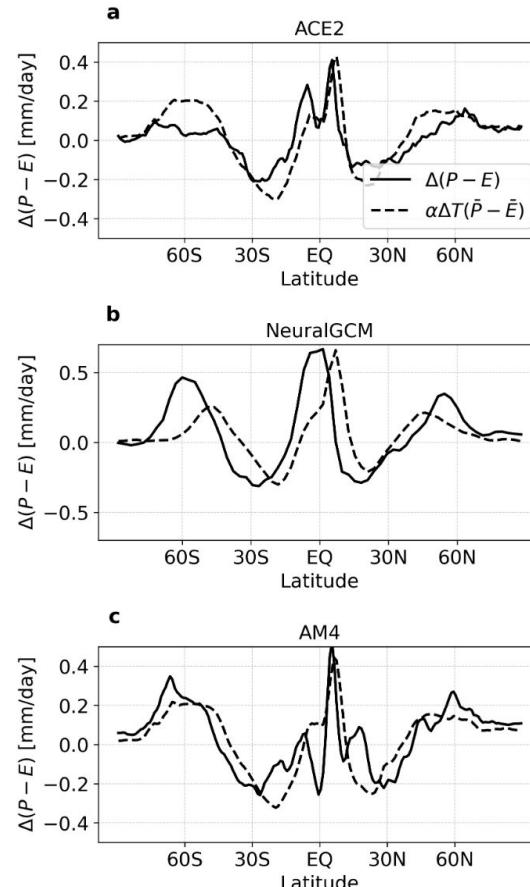


# Precipitation

We expect

- “Wet-gets-wetter, dry-gets-drier”

+2K minus  
control



# Upper level temp. response

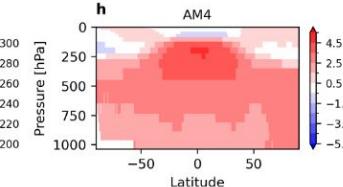
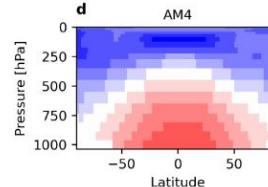
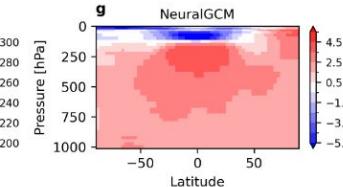
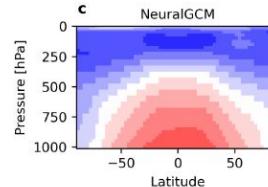
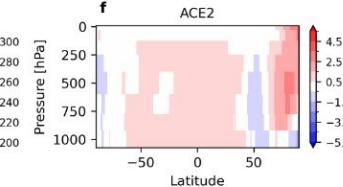
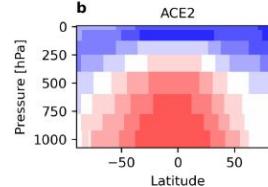
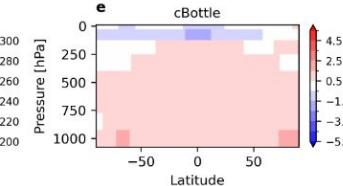
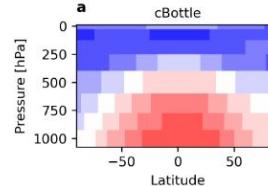
We expect

- Upper tropospheric warming amplification

+2K minus  
control

Control

Temperature



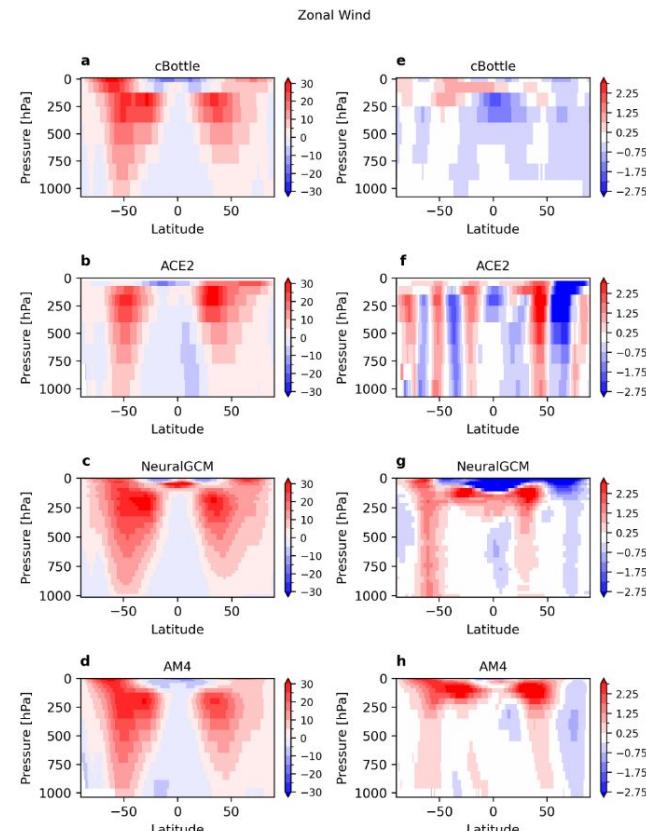
# Upper level temp. response

We expect

- Amplified upper tropospheric westerlies (matching upper tropospheric warming)
- Poleward shift of surface easterlies

+2K minus control

Control



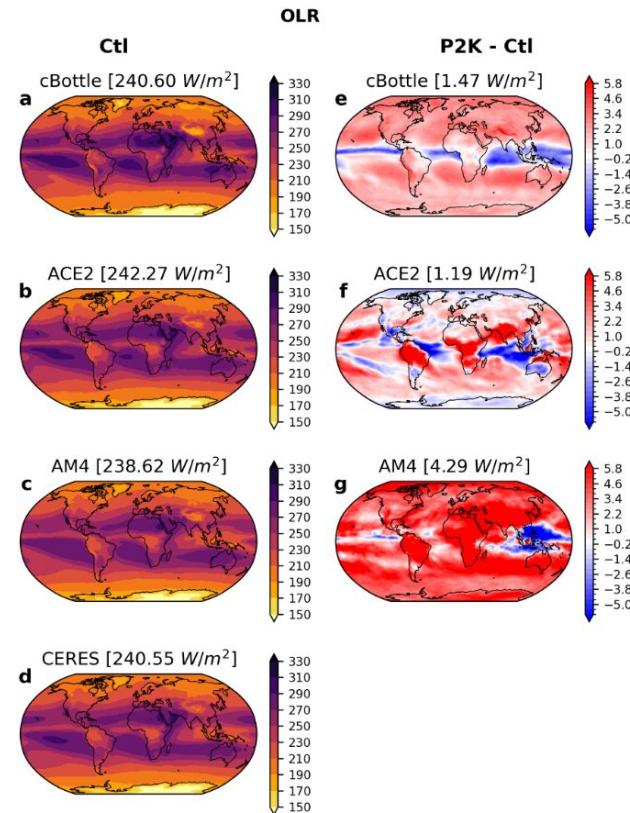
# Radiation

We expect

- Global mean increase in outgoing longwave radiation (OLR), indicating enhanced longwave cooling

+2K minus control

Control



# Conclusion and takeaways

- Uniform SST experiments remain a tractable benchmark for ML and traditional GCMs alike
- ML models reproduce some key physical responses, particularly in precip., but struggle with others like land warming and radiative response

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**Big question for the field: Can we train a generalizable ML climate model from exclusively historical data?**

- Distilling physical laws from historical data
- In distribution vs. out of distribution

# How should we test our ML models?

Group discussion