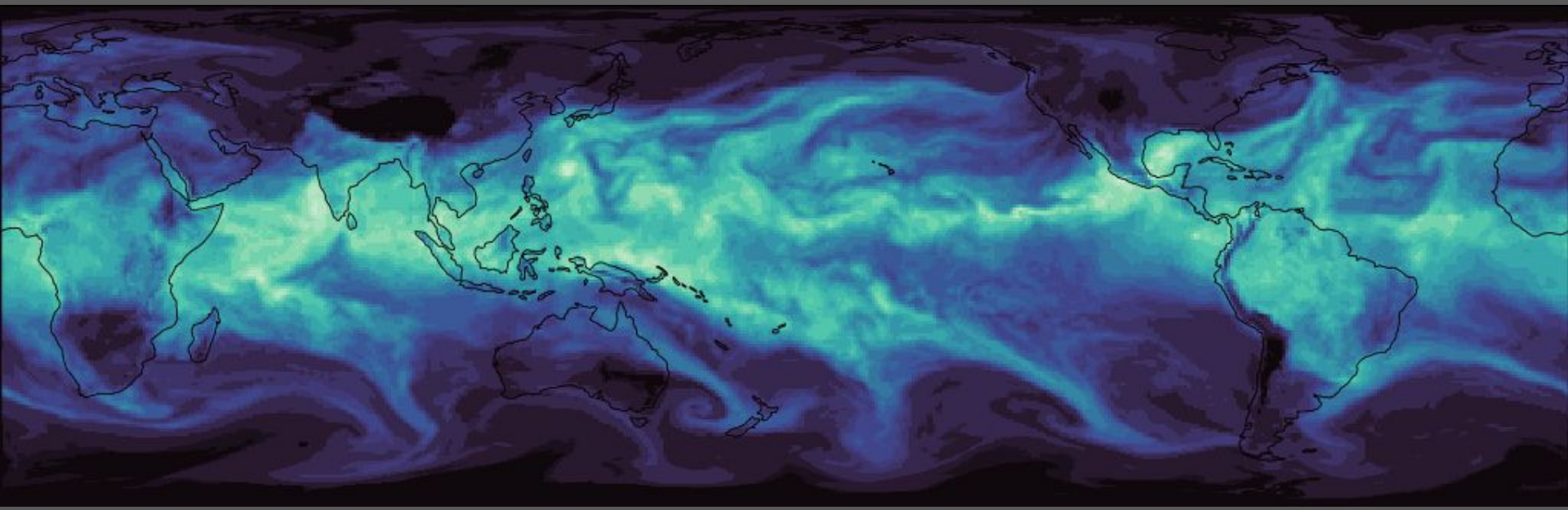
AI-based climate modeling with NeuralGCM



Stephan Hoyer
Google Research

NCAR CESM Workshop
June 11, 2024
Boulder, CO

Acknowledgments: the Neural GCM team

Google Research


Dmitrii Kochkov


Janni Yuval

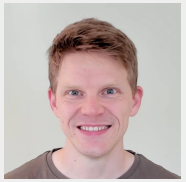

Ian Langmore


Peter Norgaard


Jamie Smith


Griffin Mooers


James Lottes


Stephan Rasp


Michael Brenner


Stephan Hoyer

ECMWF


Sam Hatfield


Peter Düben


Milan Klöwer

Google DeepMind


Peter Battaglia


Alvaro Sanchez-Gonzalez


Matthew Willson

The AI revolution has arrived for weather prediction

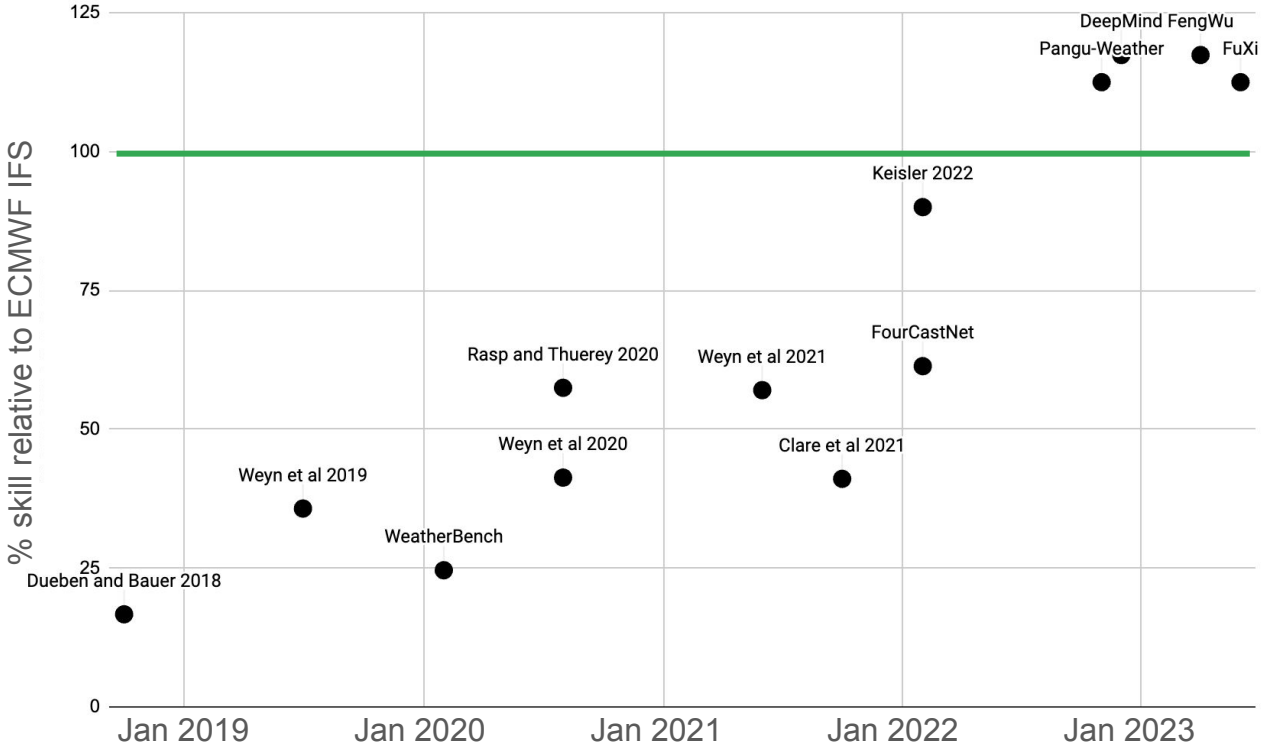
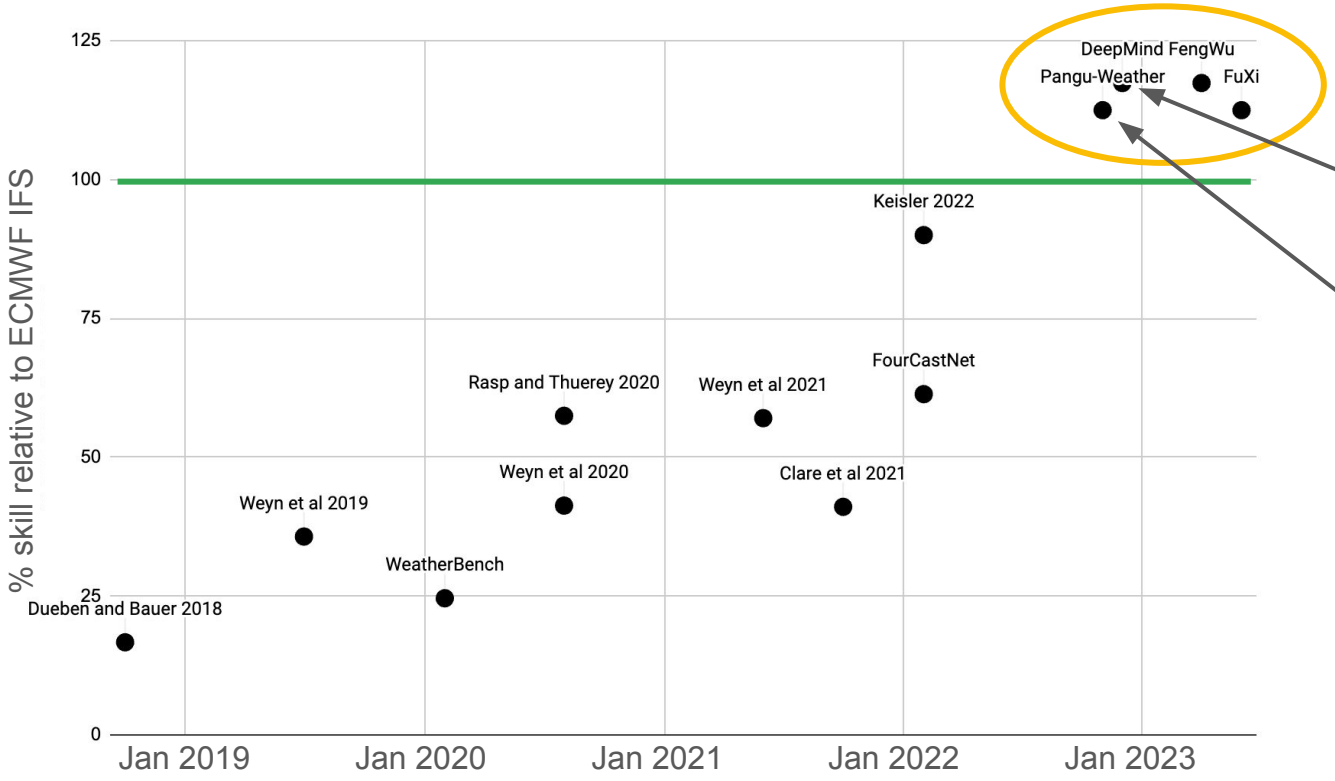


Chart by Stephan Rasp

The AI revolution has arrived for weather prediction

Chart by Stephan Rasp

The AI revolution has arrived for weather prediction



Science

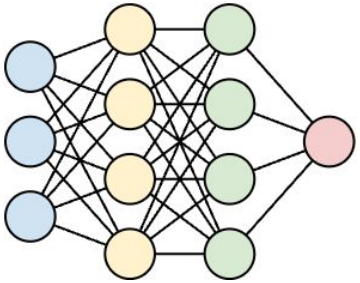
nature

ECMWF

NOAA

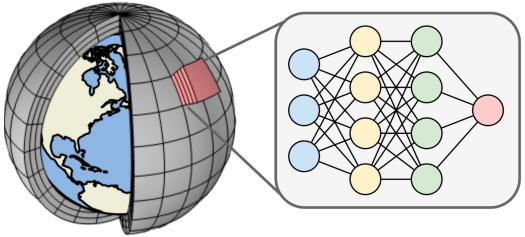
Can hybrid approaches bring AI to climate modeling?

Pure ML



GraphCast
Pangu-Weather

Hybrid models



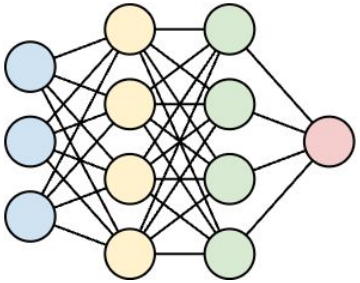
NeuralGCM

Physics-based

Traditional NWP
Climate models

Can hybrid approaches bring AI to climate modeling?

Pure ML



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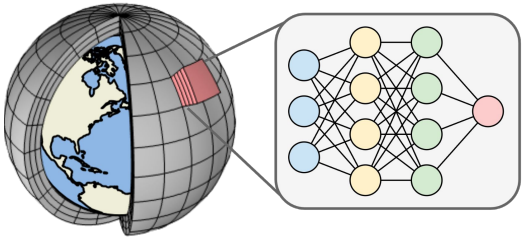


NeuralGCM

Physics-based

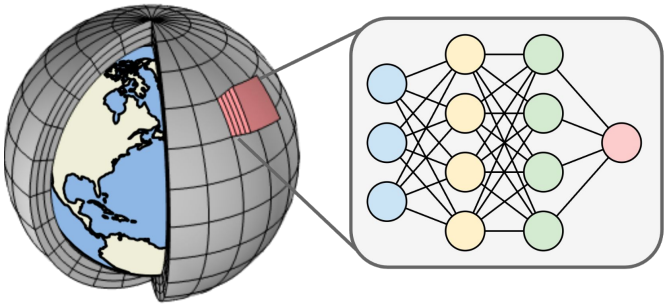
Traditional NWP
Climate models

Very little code
Based on data
Optimized for forecast accuracy

Complex, but interpretable
Based on physics
Designed to generalize

So far, hybrid models have had mixed success

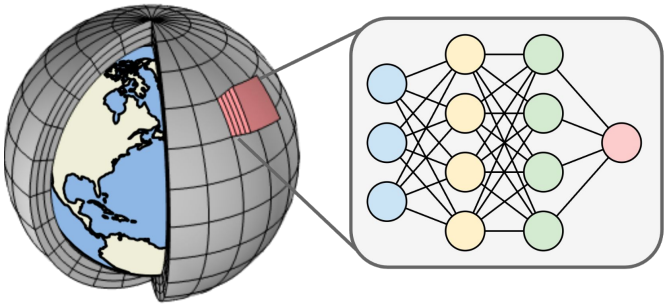
- Unstable simulations, climate drift
- Idealized setting/learning from idealized models
- Modest improvements in realistic settings



E.g., Rasp et al. 2018, Brenowitz & Bretherton (2019), Yuval and O'Gorman (2021), Kwa at al. (2023)

So far, hybrid models have had mixed success

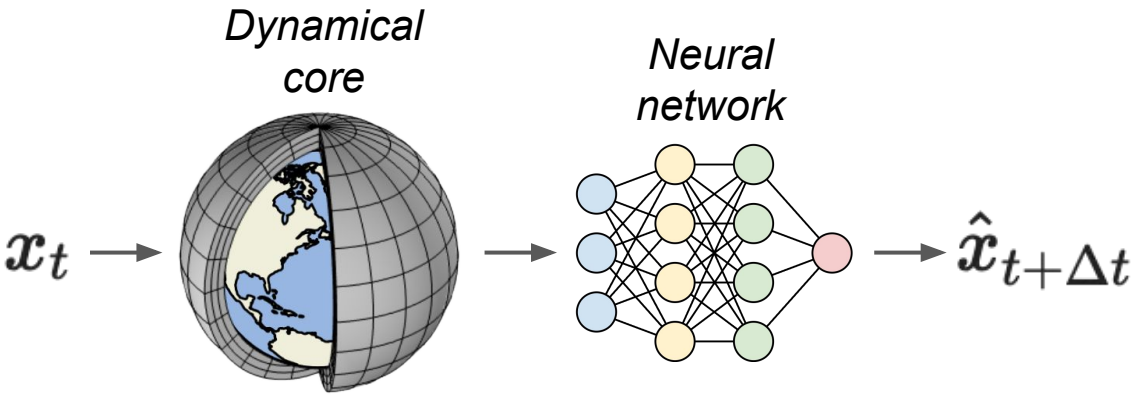
- Unstable simulations, climate drift
- Idealized setting/learning from idealized models
- Modest improvements in realistic settings



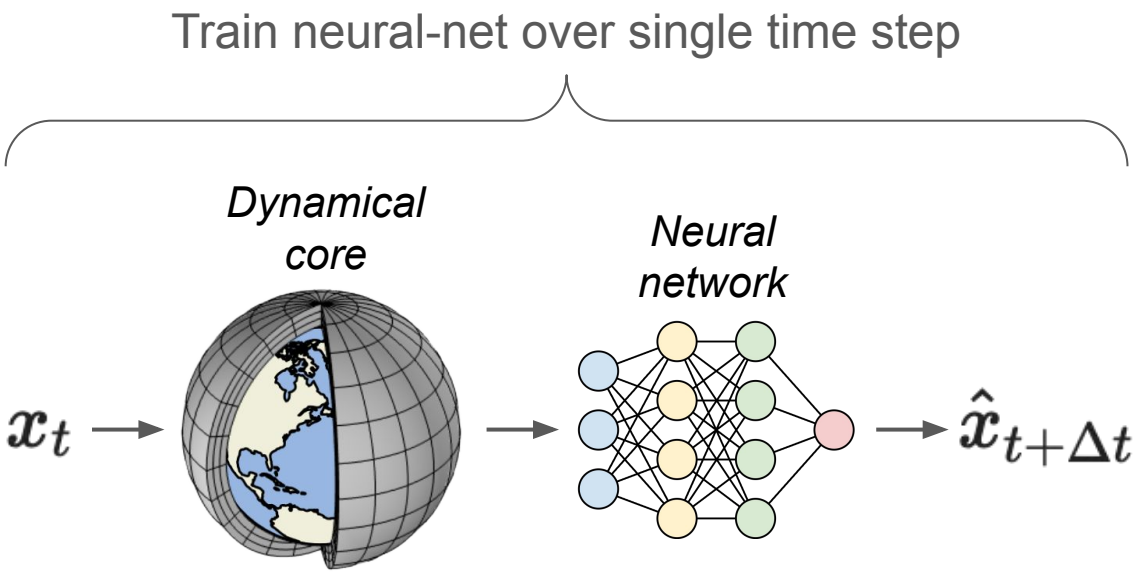
Why? Hybrid models typically optimize the "wrong" metric (offline learning)

E.g., Rasp et al. 2018, Brenowitz & Bretherton (2019), Yuval and O'Gorman (2021), Kwa at al. (2023)

Conventional hybrid models train an ML model “offline”



Conventional hybrid models train an ML model “offline”



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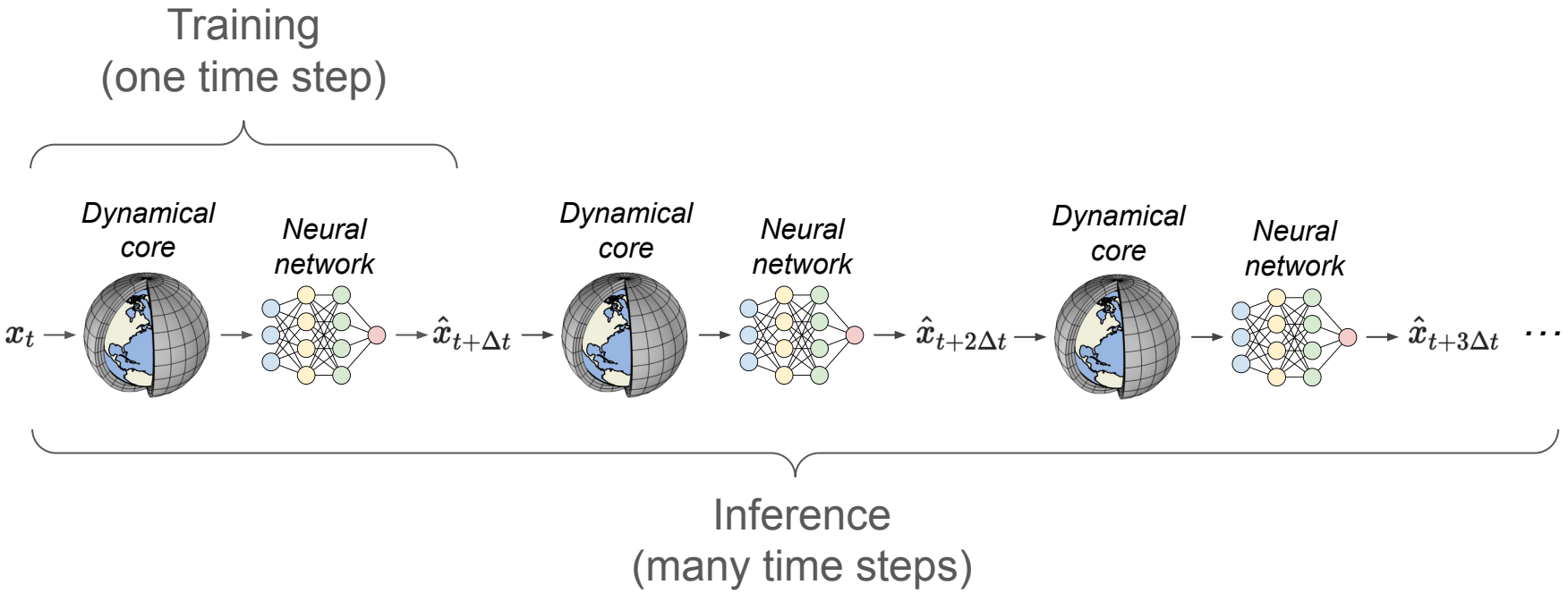
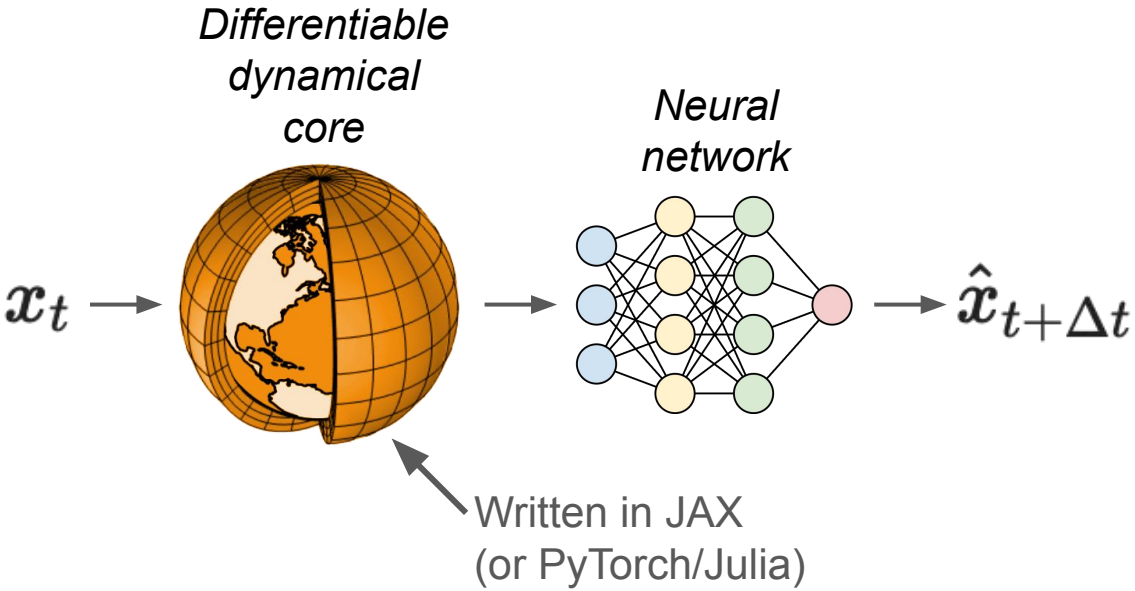
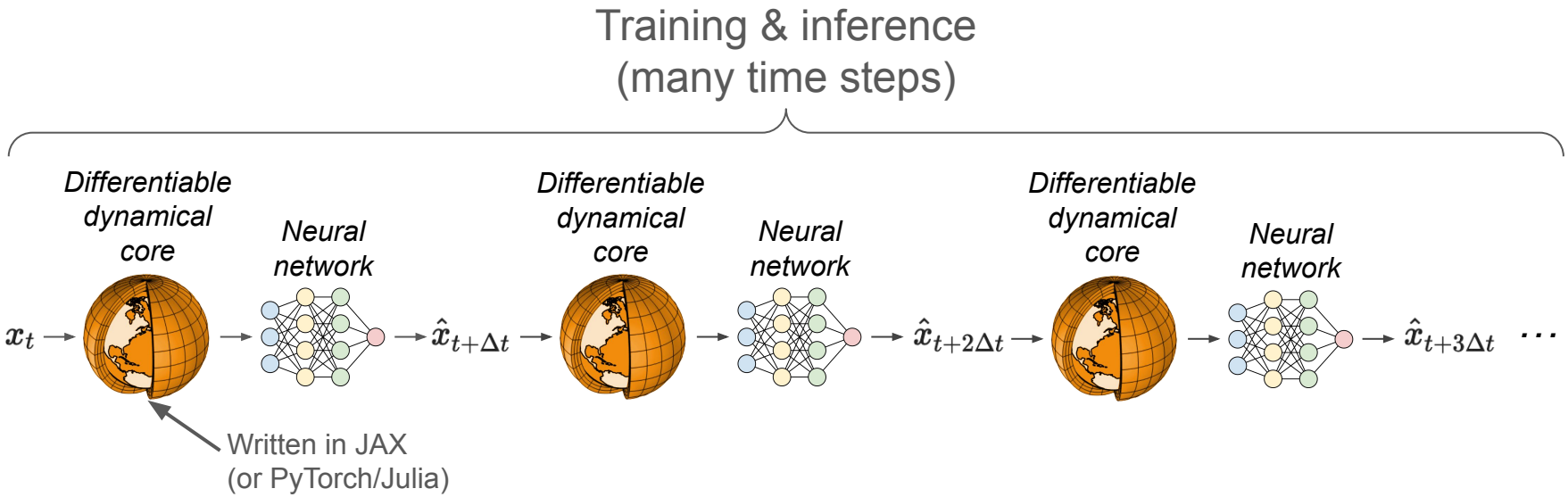


Differentiable hybrid models can be trained end-to-end for “online” performance



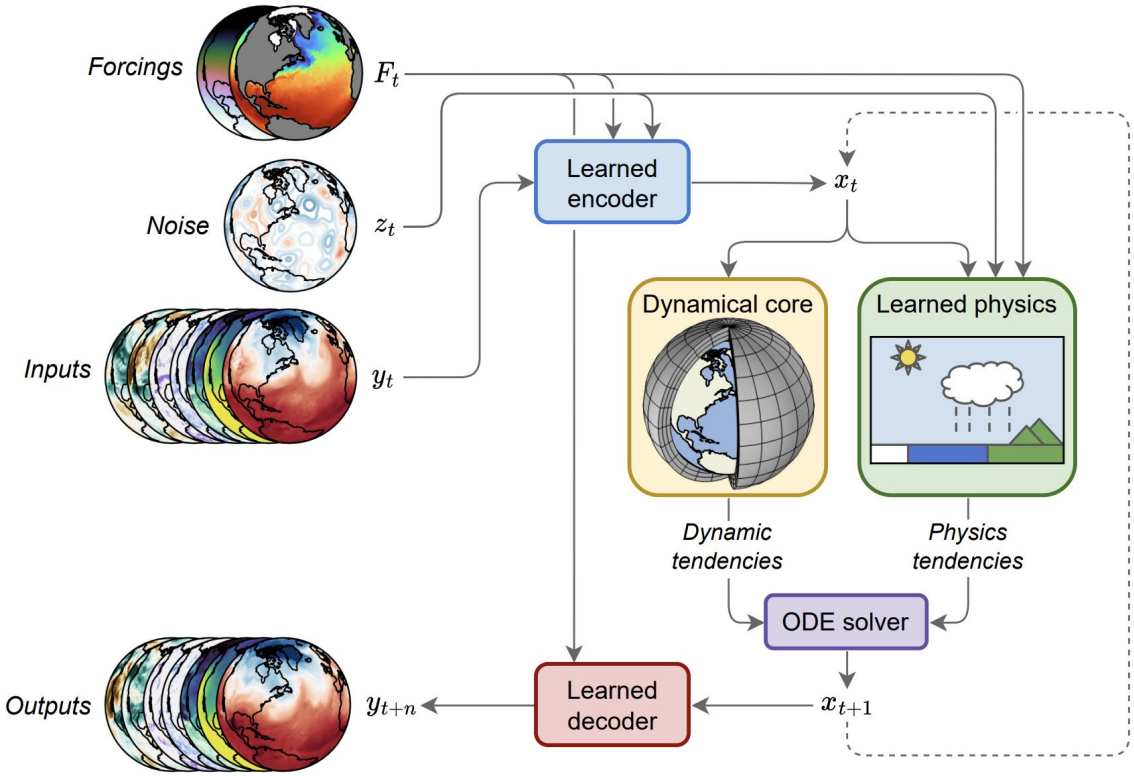
Differentiable hybrid models can be trained end-to-end for “online” performance



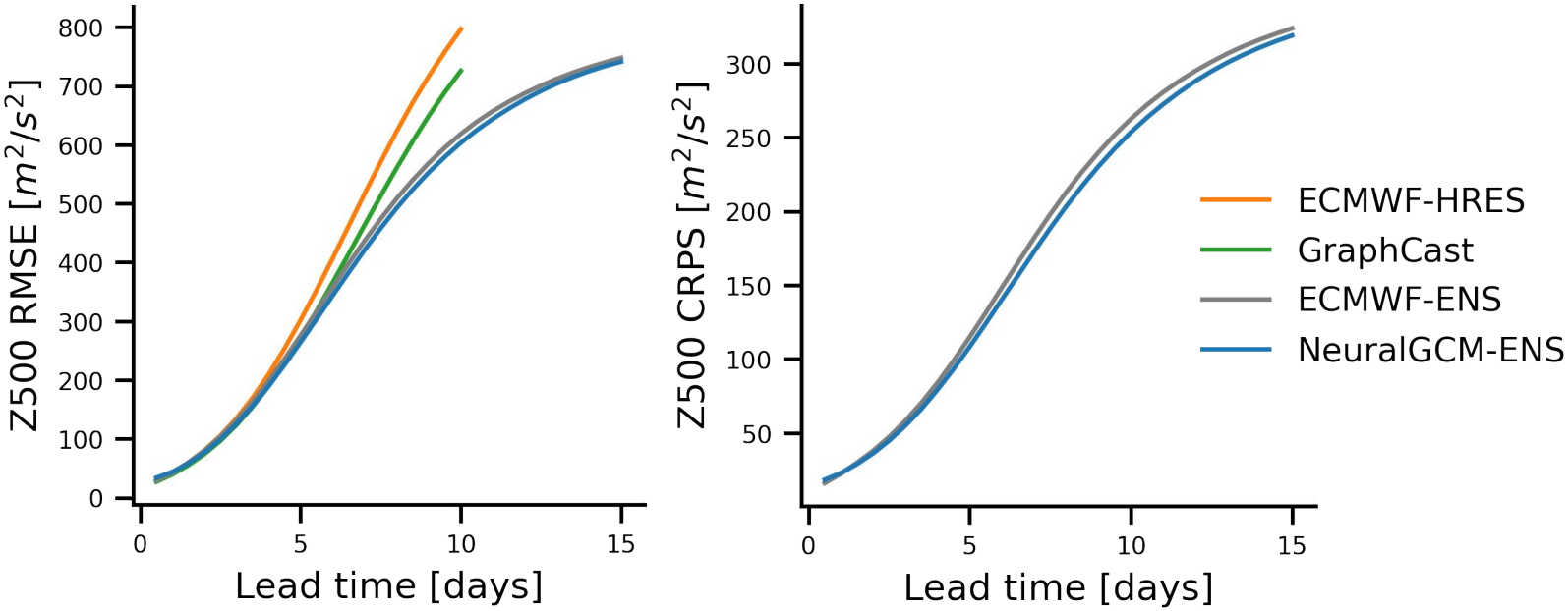
NeuralGCM is a differentiable hybrid model for the Earth's atmosphere

NeuralGCM combines a spectral **dynamical core** (written in JAX) with **neural network "learned physics**."

Models are trained on 3-5 day weather forecasts of the ERA5 reanalysis.

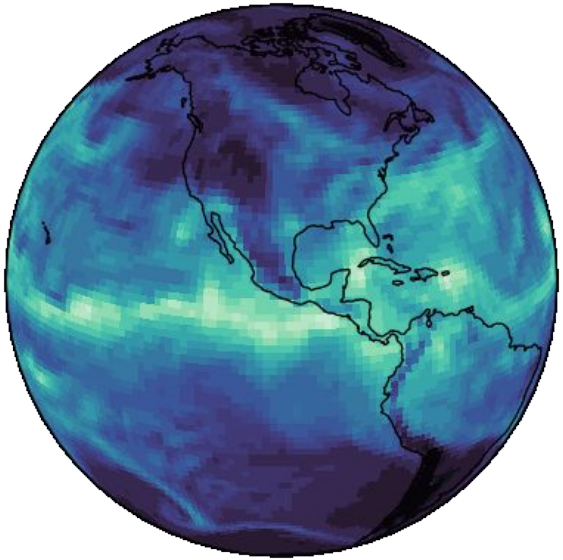


NeuralGCM is the first ML model to beat ECMWF's ensemble weather forecast on most metrics

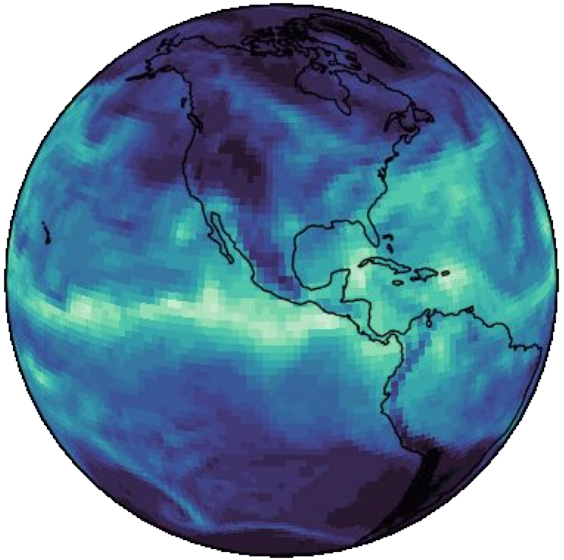


Audience quiz: Which of these forecasts is ERA5?

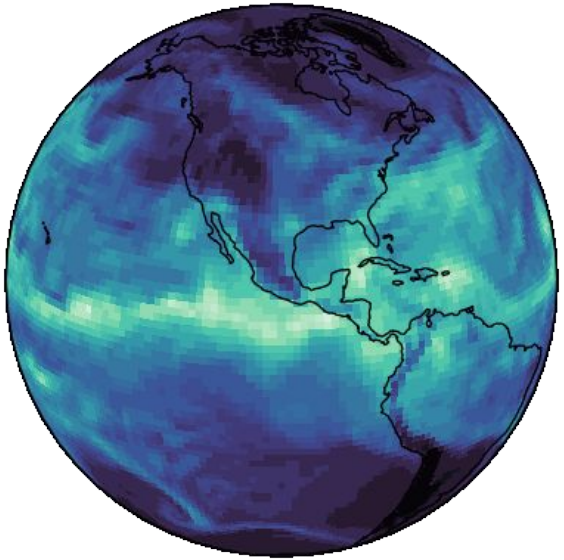
The other two are NeuralGCM ensemble members



Option A



Option B

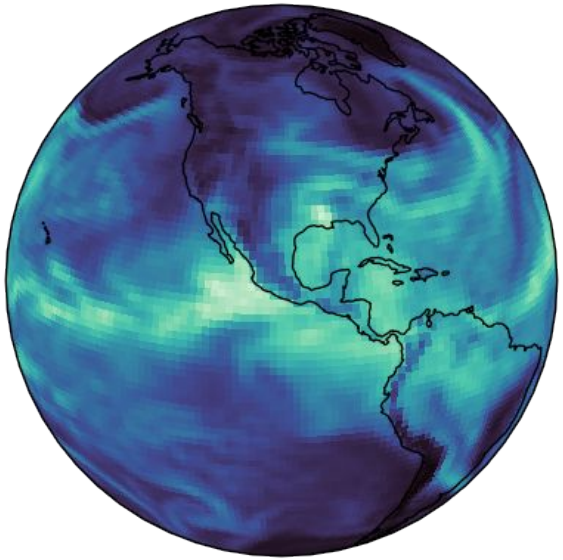


Option C

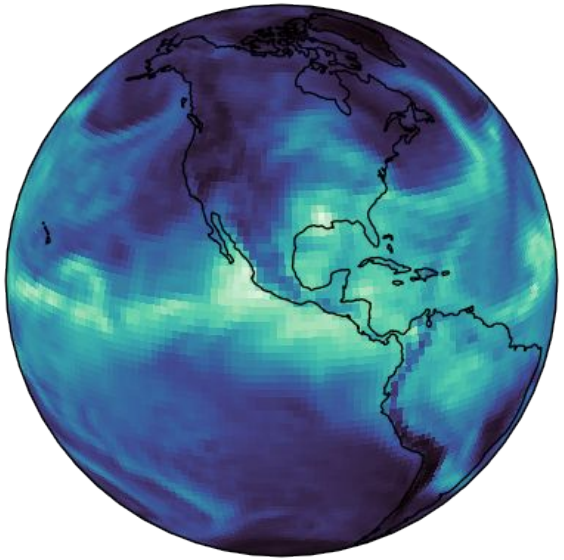
Total column water, 0-15 days

Audience quiz: Which of these forecasts is ERA5?

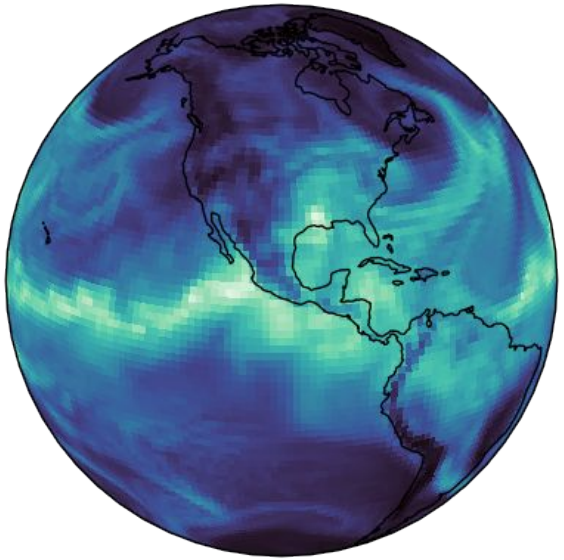
The other two are NeuralGCM ensemble members



Option A



Option B

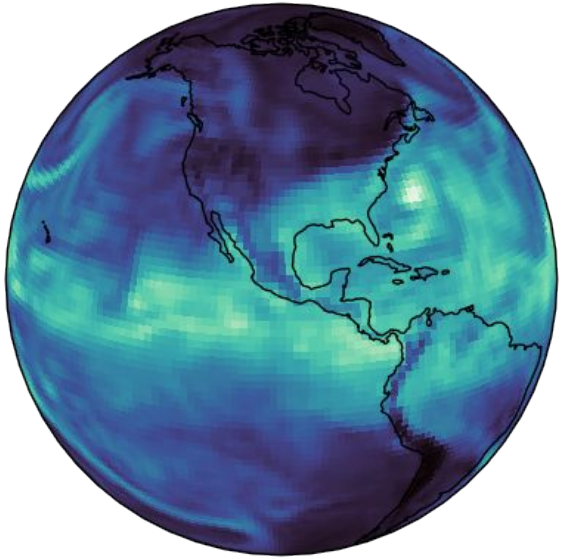


Option C

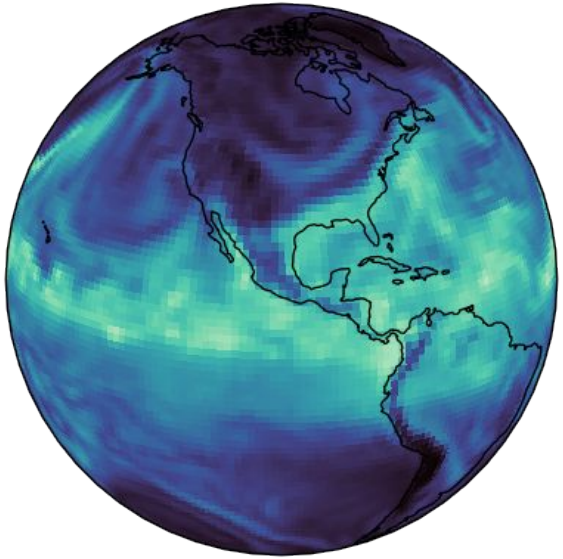
Total column water, +5 days

Audience quiz: Which of these forecasts is ERA5?

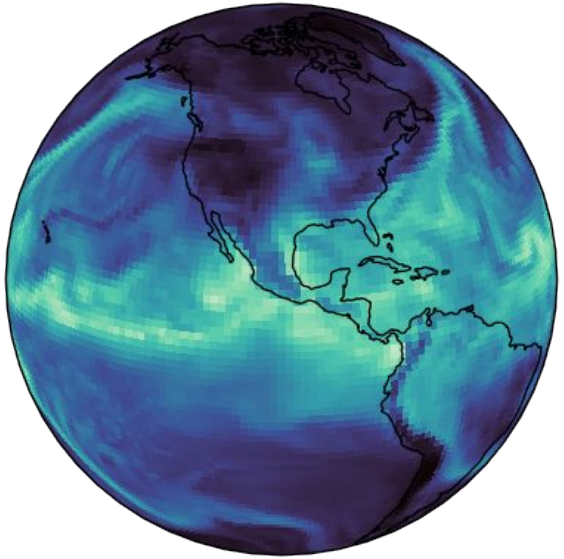
The other two are NeuralGCM ensemble members



Option A



Option B

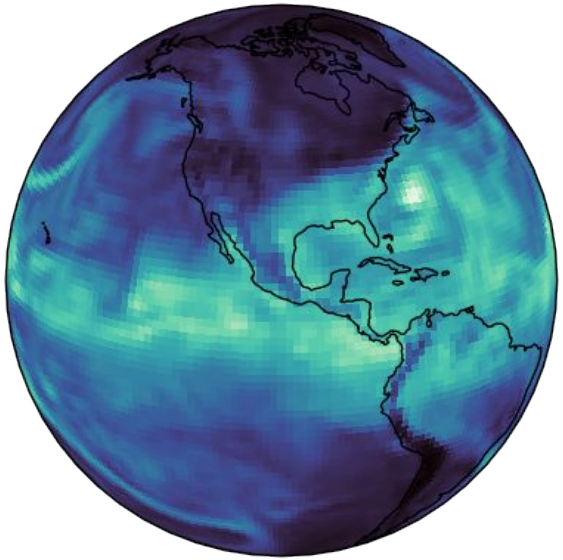


Option C

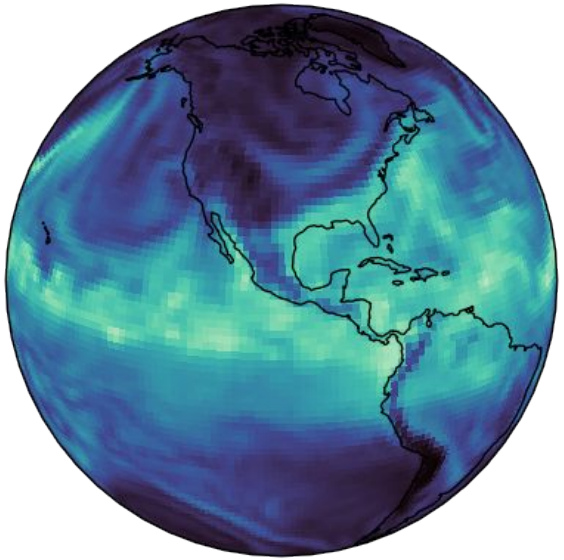
Total column water, +15 days

Audience quiz: Which of these forecasts is ERA5?

The other two are NeuralGCM ensemble members



NeuralGCM



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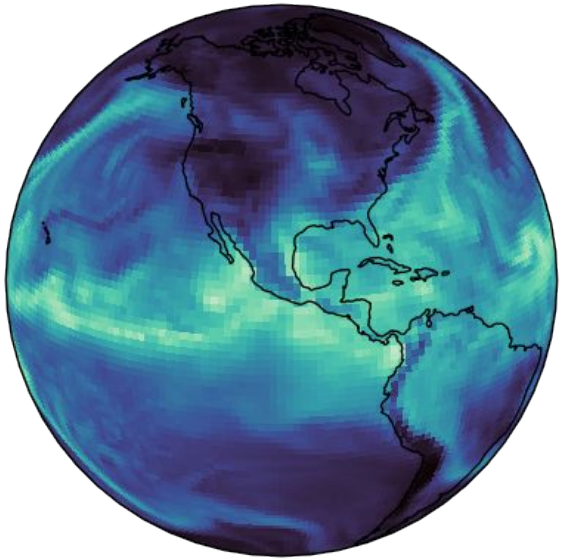
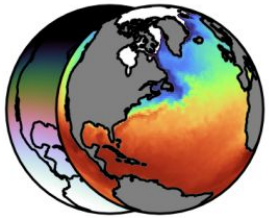


ERA5

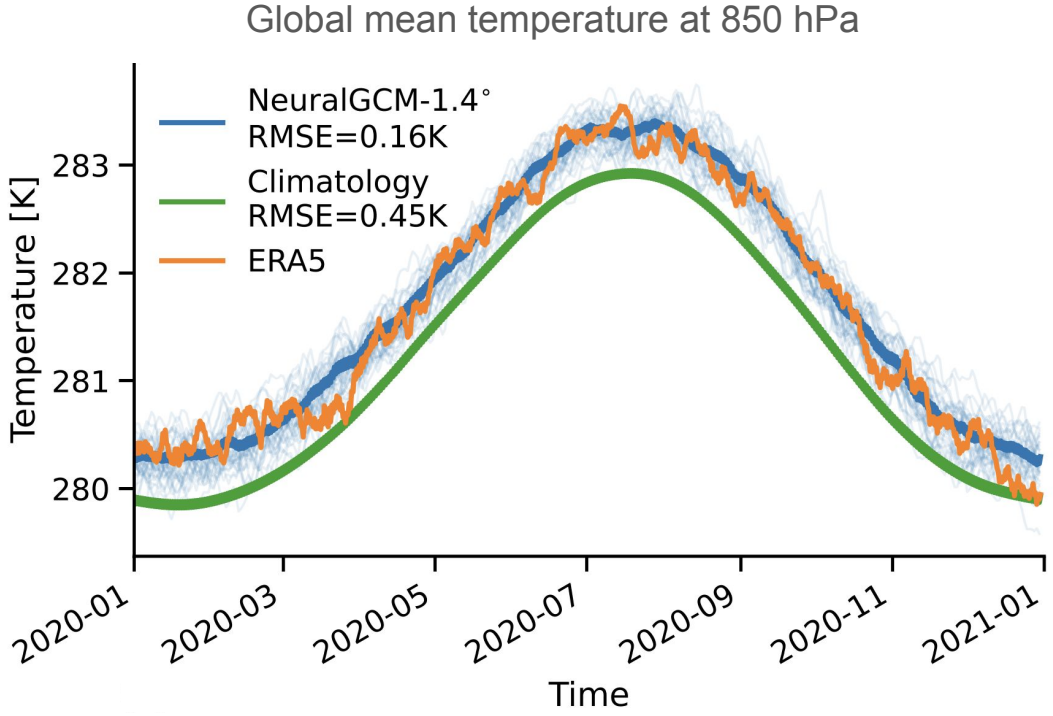
Total column water, +15 days

NeuralGCM trained on weather can also make climate forecasts (with prescribed sea surface temperature)

Boundary conditions



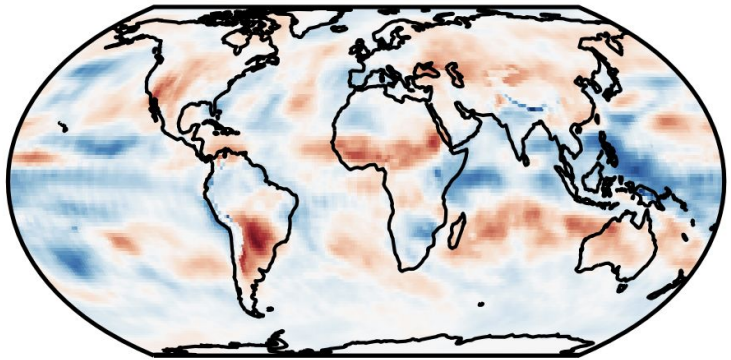
Total incident solar radiation
Sea surface temperature
Sea ice concentration



NeuralGCM near-term climate forecasts have less bias than a global storm resolving model

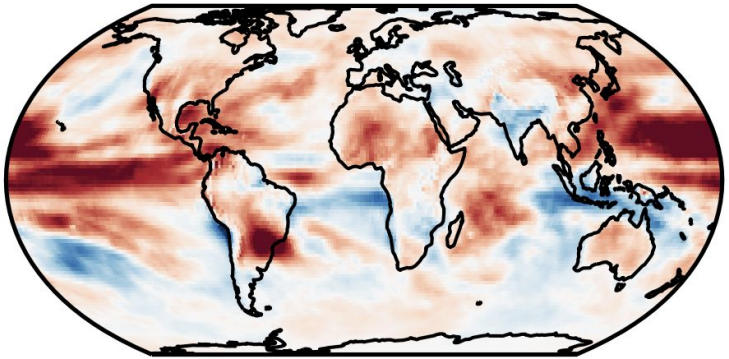
140 km Neural GCM

RMSE = 1.09 mm

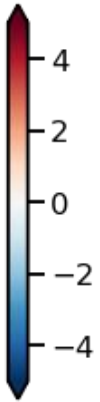


3 km GFDL X-SHiELD

RMSE = 1.74 mm



Precipitable water bias for 2020 [mm]



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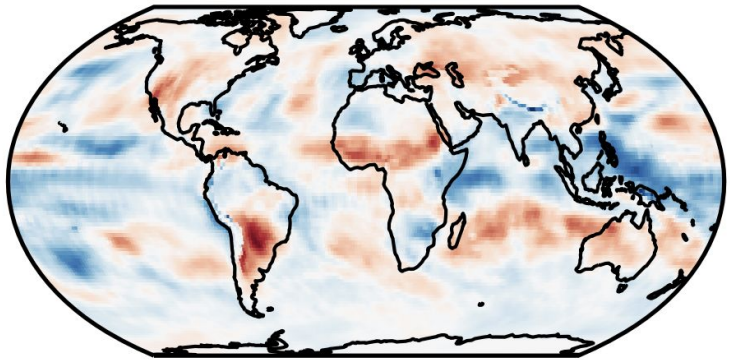
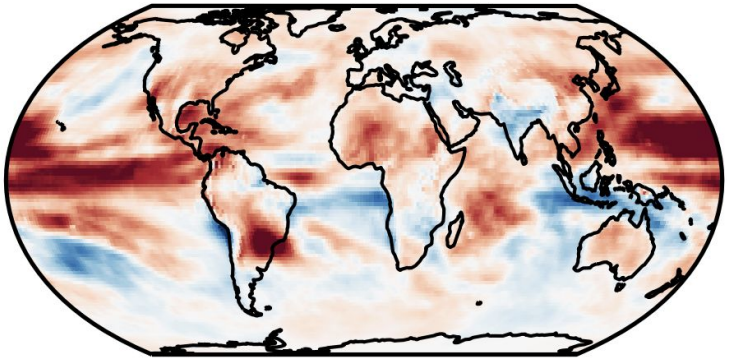


70,000 sim days / day
1 Google TPU v4
$0.08 / simulated year

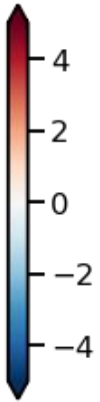
3 km GFDL X-SHiELD

RMSE = 1.74 mm

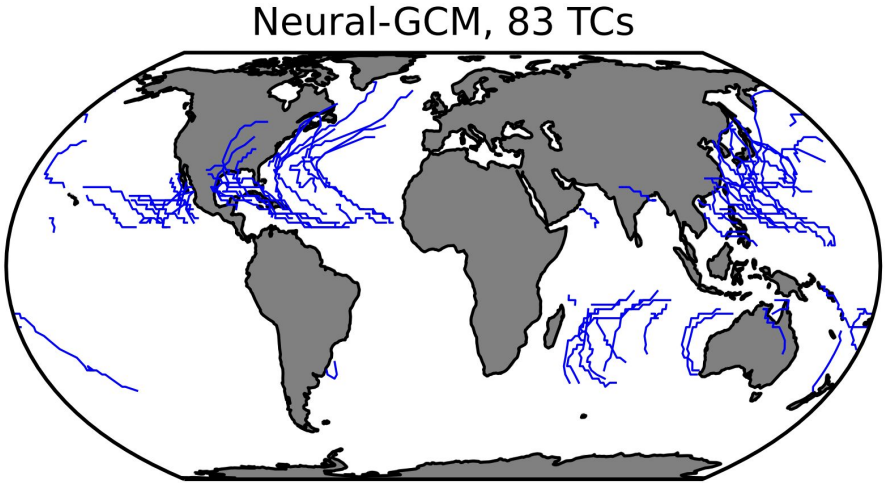


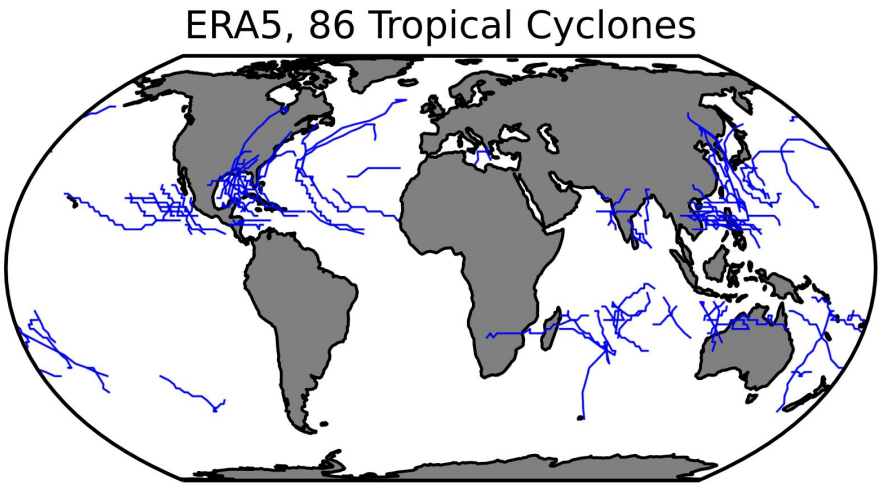
19 sim days / day
13,824 CPU cores
$80,000 / simulated year

Precipitable water bias for 2020 [mm]

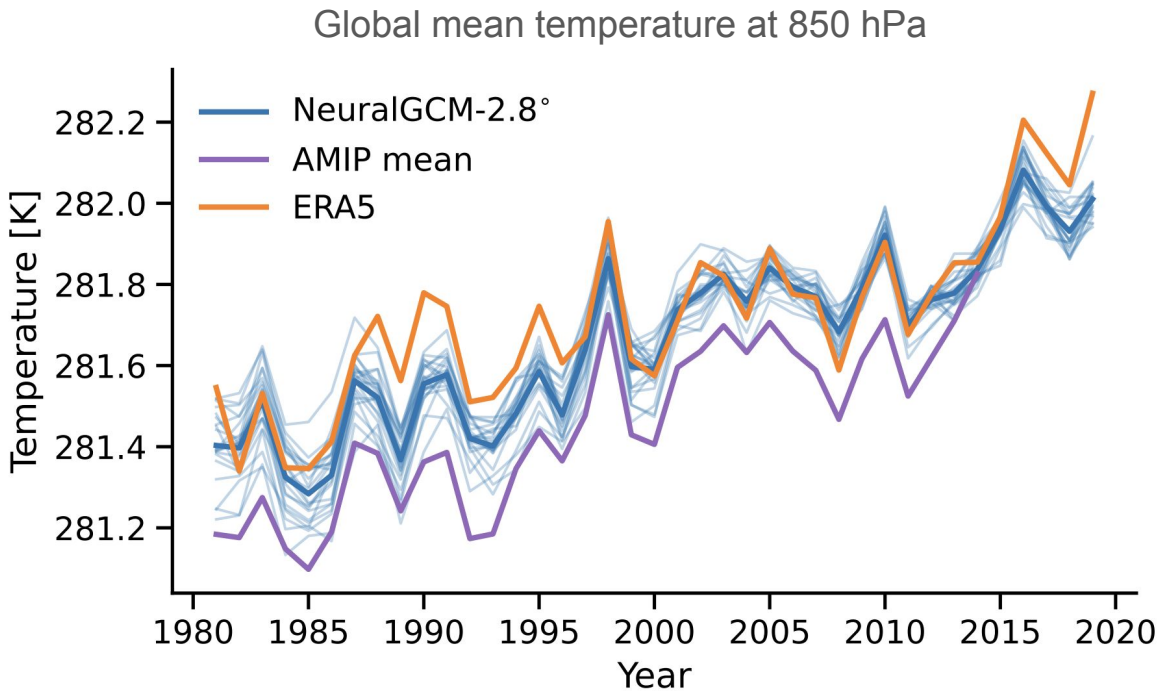


NeuralGCM near-term climate forecasts also have realistic distributions of tropical cyclones





NeuralGCM climate projections compare favorably to atmosphere only (AMIP) climate models

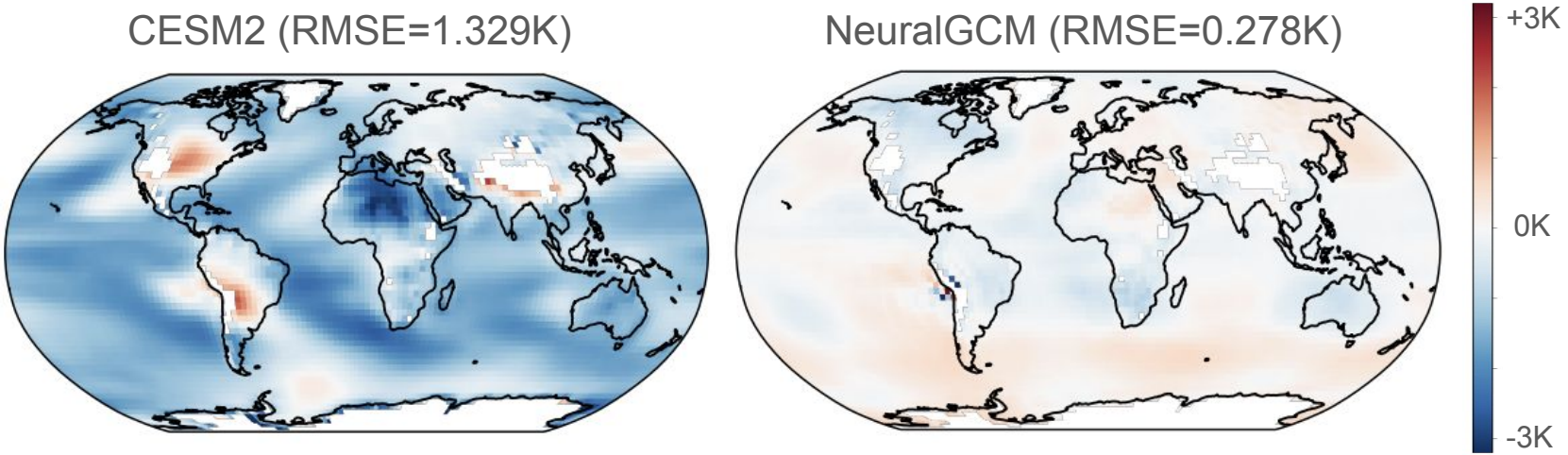


NeuralGCM climate projections compare favorably to atmosphere only (AMIP) climate models

850 hPa temperature bias vs ERA5 (1980-2017)

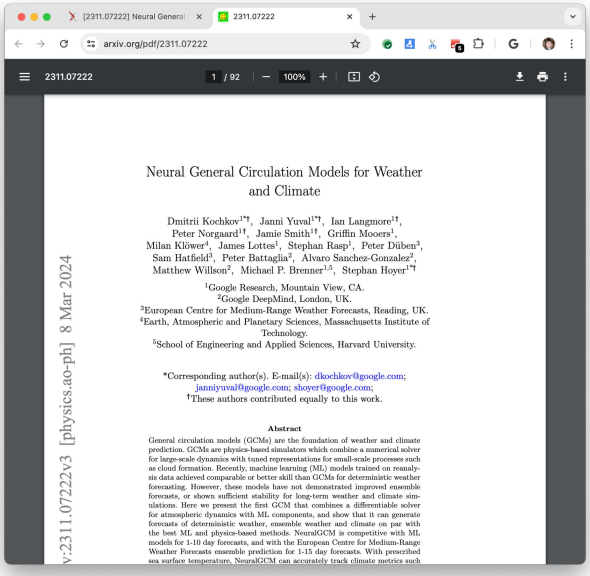
CESM2 (RMSE=1.329K)

NeuralGCM (RMSE=0.278K)



Learn more about NeuralGCM

Read the paper



Neural General Circulation Models for Weather and Climate

Dmitrii Kochkov[1*†], Janni Yuval[1*†], Ian Langmore[1†], Peter Norgaard[1†], Jamie Smith[1†], Griffin Mooers[1], Milan Klöwer[4], James Lottes[1], Stephan Rasp[1], Peter Düben[3], Sam Hatfield[3], Peter Battaglia[2], Alvaro Sanchez-Gonzalez[2], Matthew Willson[2], Michael P. Brenner[1,5], Stephan Hoyer[1*†]

[1]Google Research, Mountain View, CA.
[2]Google DeepMind, London, UK.
[3]European Centre for Medium-Range Weather Forecasts, Reading, UK.
[4]Earth, Atmospheric and Planetary Sciences, Massachusetts Institute of Technology.
[5]School of Engineering and Applied Sciences, Harvard University.

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†These authors contributed equally to this work.

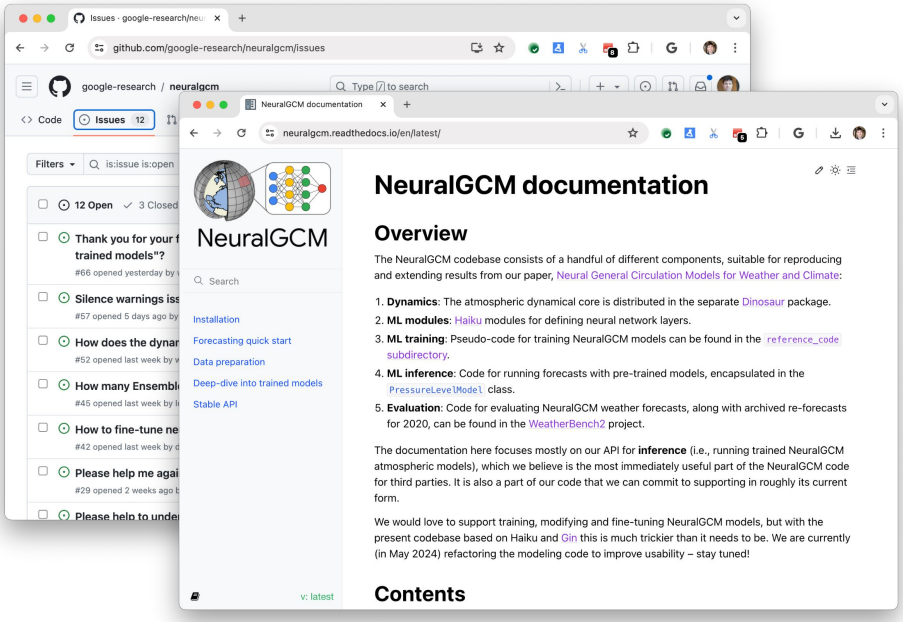
Abstract

General circulation models (GCMs) are the foundation of weather and climate prediction. GCMs are physics-based simulators which combine a numerical solver for large-scale dynamics with tuned representations for small-scale processes such as cloud formation. Recently, machine learning (ML) models trained on reanalysis data achieved comparable or better skill than GCMs for deterministic weather forecasting. However, these models have not demonstrated improved ensemble forecasts, or shown sufficient stability for long-term weather and climate simulations. Here we present the first GCM that combines a differentiable solver for atmospheric dynamics with ML components, and show that it can generate forecasts of deterministic weather, ensemble weather and climate on par with the best ML and physics-based methods. NeuralGCM is competitive with ML models for 1-10 day forecasts, and with the European Centre for Medium-Range Weather Forecasts ensemble prediction for 1-15 day forecasts. With prescribed sea surface temperature, NeuralGCM can accurately track climate metrics such

arXiv:2311.07222v3 [physics.ao-ph] 8 Mar 2024

arxiv.org/abs/2311.07222

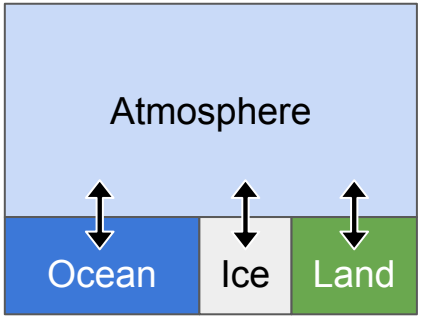
Run the open source code



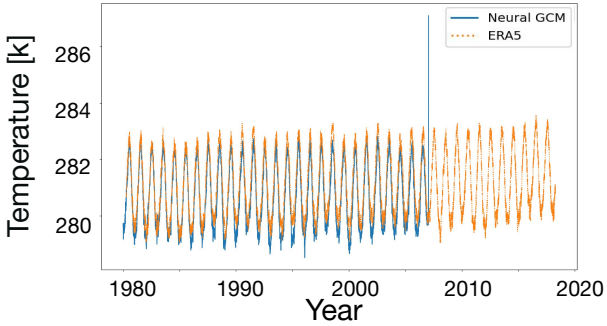
github.com/google-research/neuralgcm

NeuralGCM is not a complete climate model… yet

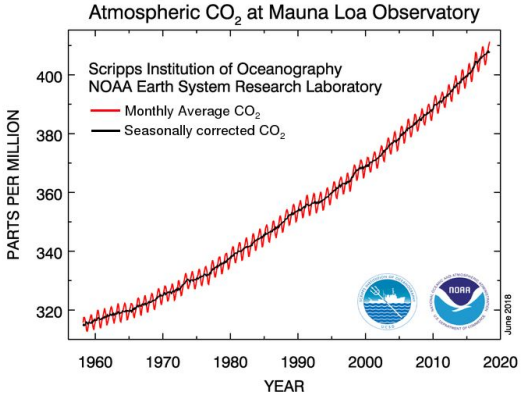
Needs to support coupled modeling (currently atmosphere only)



Differentiability helps, but climate instability & drift is still a challenge.

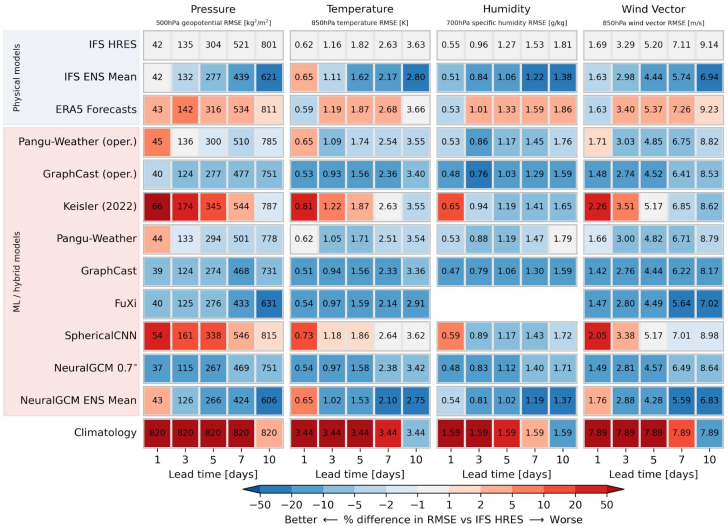


Needs to ensure generalization to unprecedented future climate



What the AI community needs from you: benchmarks!

Is there a WeatherBench for climate modeling?



Google Academic Research Awards for faculty:

- “Creating ML benchmarks for climate problems”
- Up to 300k in funding
- Applications due on July 17, 2024