Correcting weather and climate models with machine learned nudging tendencies

Oliver Watt-Meyer, Lead Research Scientist, Climate Modeling
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Ai2

Allen Institute for AI (Ai2)

"Breakthrough AI to solve the world's biggest problems"

Ai2 is a **non-profit** research institute in Seattle, WA funded primarily by the Paul G. Allen Family Foundation with some auxiliary support from federal agencies (e.g. NSF, DOE)

Primary focus is on core AI topics and applications

- E.g. natural language processing, computer vision, robotics
- **Strong commitment to open source and open data**
    - e.g. "OLMo" a fully end-to-end open source LLM: https://allenai.org/olmo

Climate Modeling team sits within a more applied "AI for the Environment" section

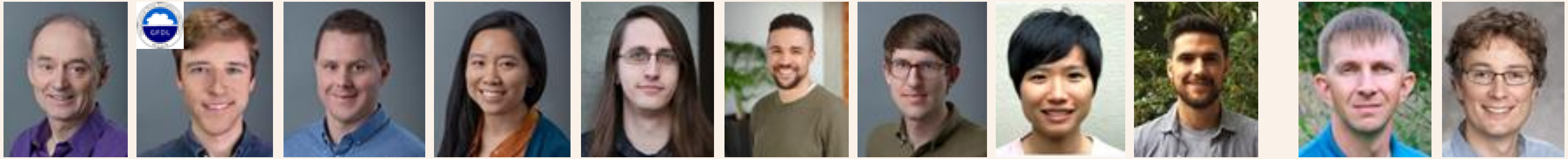
Ai2 Climate Modeling

- Goal: Reduce uncertainty about 21st century local precipitation trends/extremes
- Strategy: Make better coarse-grid climate models using fine-grid models as reference

We closely partner with NOAA/GFDL, developers of a 3-km version of FV3GFS global weather model.

Also have ongoing collaborations with other R&D groups (Lawrence Livermore National Lab, NVIDIA) and summer interns.

External partners



Chris Bretherton | Spencer Clark | Brian Henn | Anna Kwa | Jeremy McGibbon | Andre Perkins | Oli Watt-Meyer | Elynn Wu | James Duncan | Lucas Harris | Peter Caldwell

How can ML help weather/climate models?

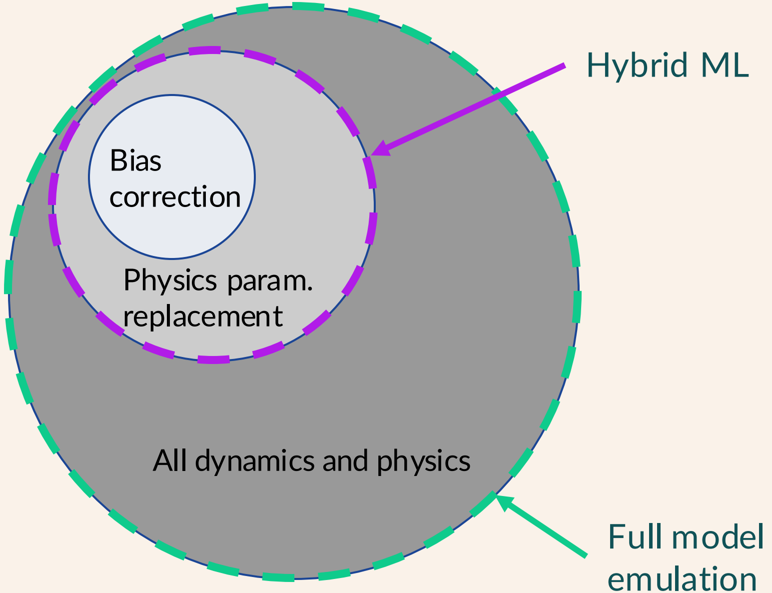
Make global weather and climate models:

- more accurate
- faster
- more affordable/accessible

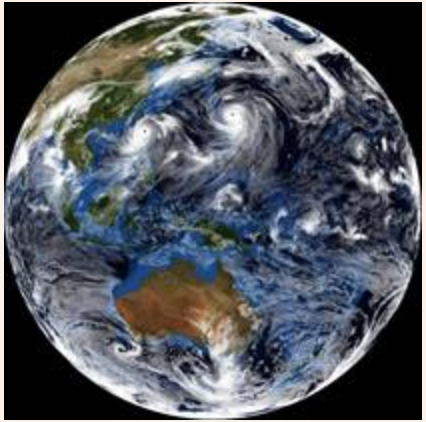
Three common strategies (atmospheric focus):

- **ML replaces or corrects parts of the atmospheric model (“hybrid”)**
- ML for post-processing bias correction and/or downscaling
- Full model emulation: machine learning of entire global atmospheric evolution

What is the ML responsible for?

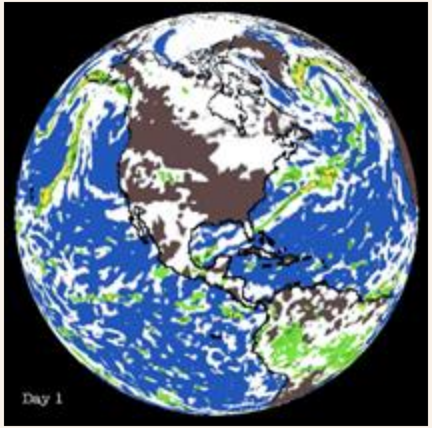


Corrective machine learning approach



High fidelity reference:
Observational reanalysis or
fine-grid (3 km) simulation

Use machine learning to
make coarse model behave
more like reference

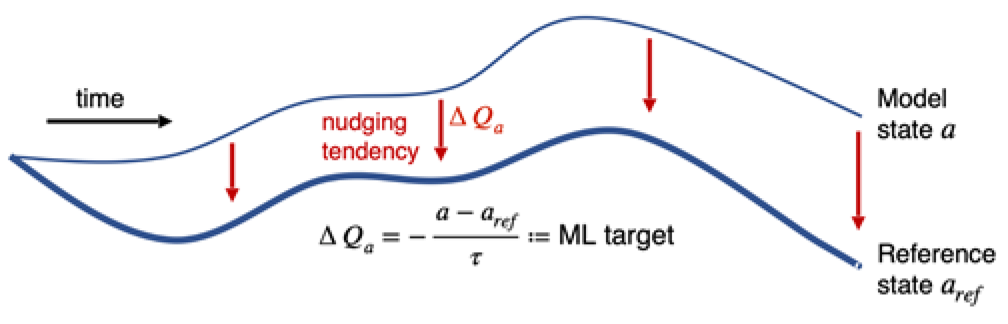


Climate model (25-200 km)

Corrective machine learning approach

- Online bias correction has a history! (e.g. Leith 1978, DelSole et al. 2008)
- Most past strategies used simple (e.g. constant or linear) estimates of state-dependent bias

- Our approach:
  a. Nudge coarse-resolution dataset towards some reference dataset
  b. Train ML to predict nudging tendencies using coarse-res model state as input
  c. Now for free-running predictions, run coarse-res model again with ML prediction corrective tendency at each time step

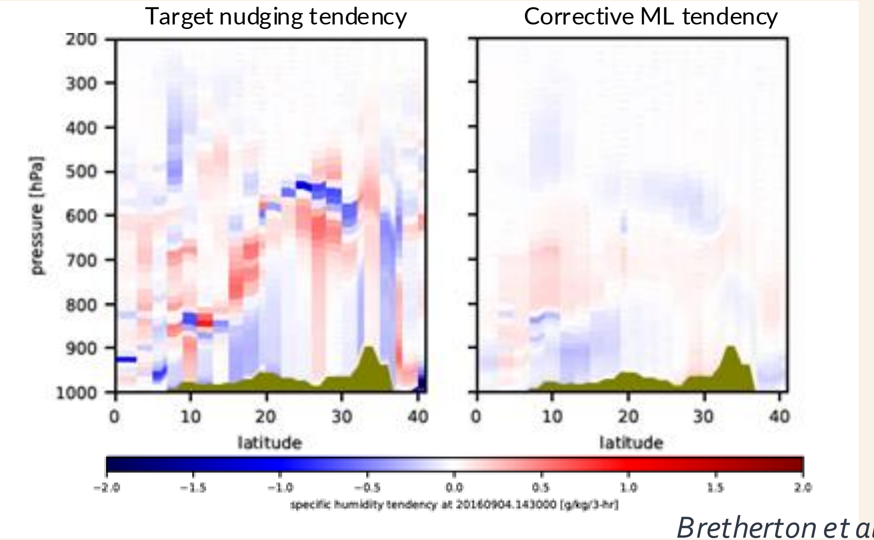


Training setup

- Training data comes from 200km simulations nudged towards either reanalysis or a coarsened high-res simulation (3km or 25km)
- Depending on case, we use random forest or simple MLP neural network as ML architecture
- Single column assumption
  - ML inputs: vertical profile of temperature, humidity, winds, plus surface type, topography, cos(zenith angle)
  - ML outputs: vertical profile of tendencies of temperature, humidity and winds

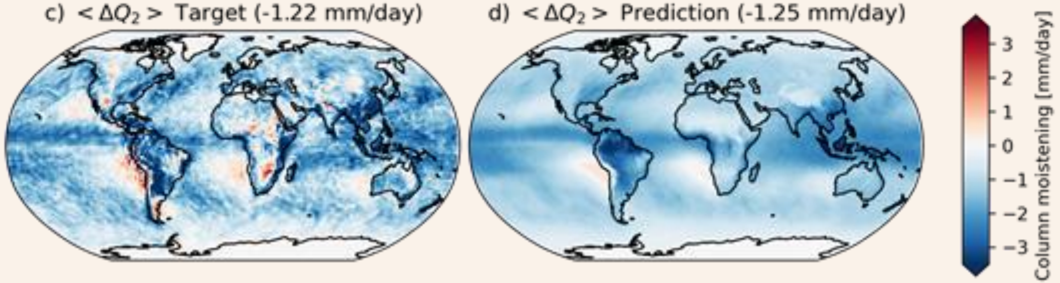
Offline ML evaluation

Snapshot



Bretherton et al. 2022

Mean tendency



Watt-Meyer et al. 2021

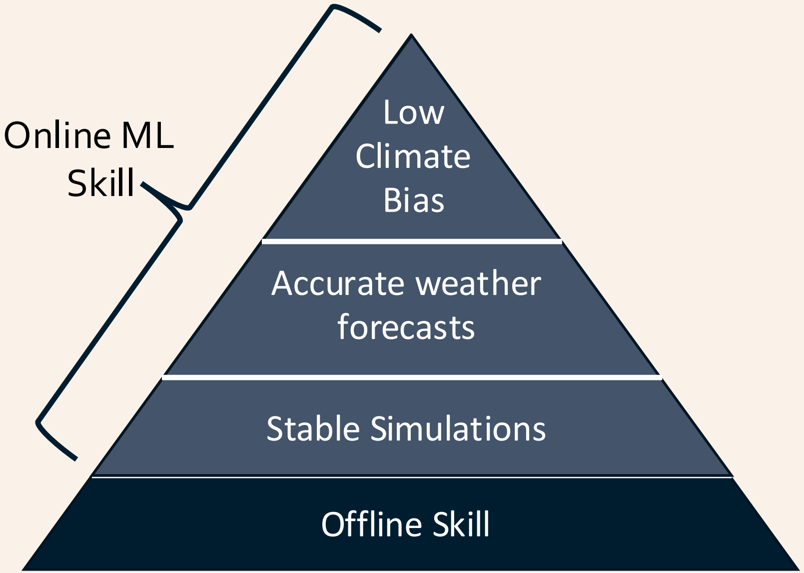
Nudging tendencies demonstrate systematic errors of coarse model vs. reference.

The ML schemes produce a smoothed, lower-amplitude, unbiased version of the noisy nudging tendencies

Challenge of hybrid ML

Coupling to fluid dynamics and parameterized physics

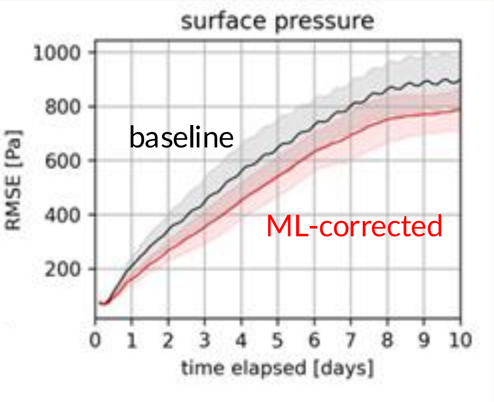
Training ≠ Testing
(offline) (online)

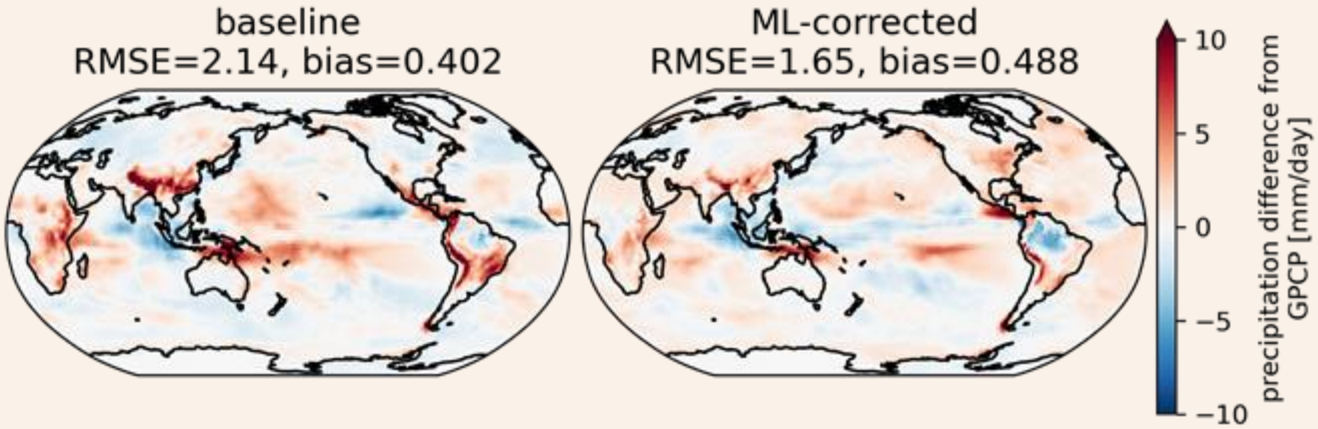


Training the ML in concert with dynamics and everything else might help (e.g. NeuralGCM)
but can require full rewrite of dycore to allow differentiability!

ML-predicted correction improves weather and climate

- Adds a full day to medium-range weather forecast skill (but note the baseline is a 200km model!)
- Annual-mean precipitation error reduced 23% vs. no-ML baseline 200 km model, even though precipitation is not ML target

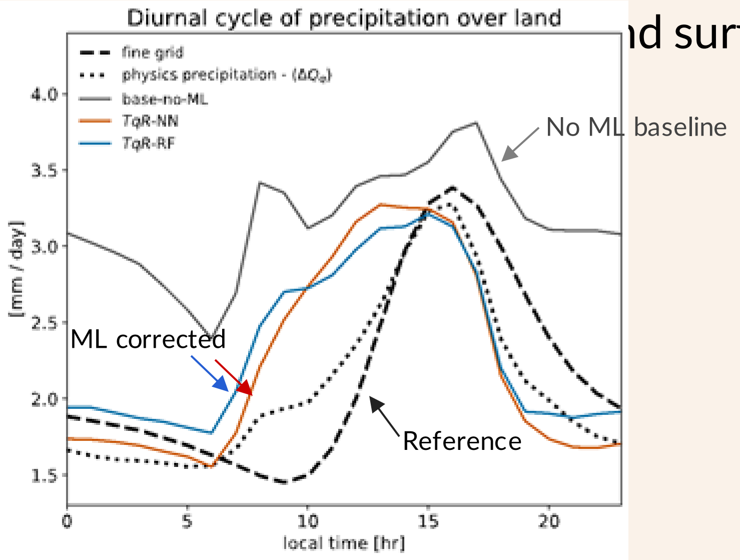




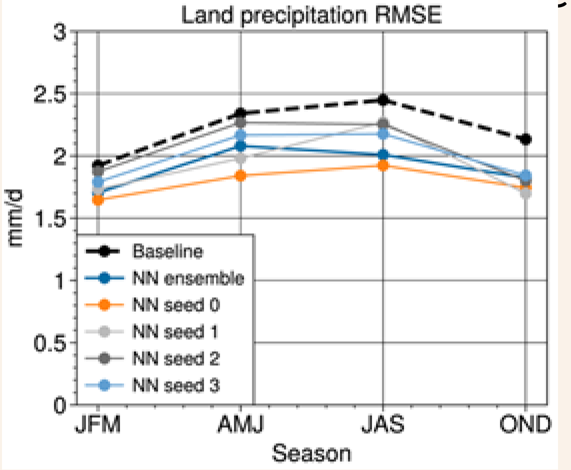
Watt-Meyer et al. 2021, GRL

Works across the diurnal+seasonal cycle...

- Trained/tested with 1 year 3 km 2020-SST simulation run by GFDL (Cheng et al. 2022)
- ML-corrected coarse AGCM maintains a stable climate with ~20% reduction in …nd surface temperature errors vs. fine-grid reference



Bretherton et al. 2022, JAMES

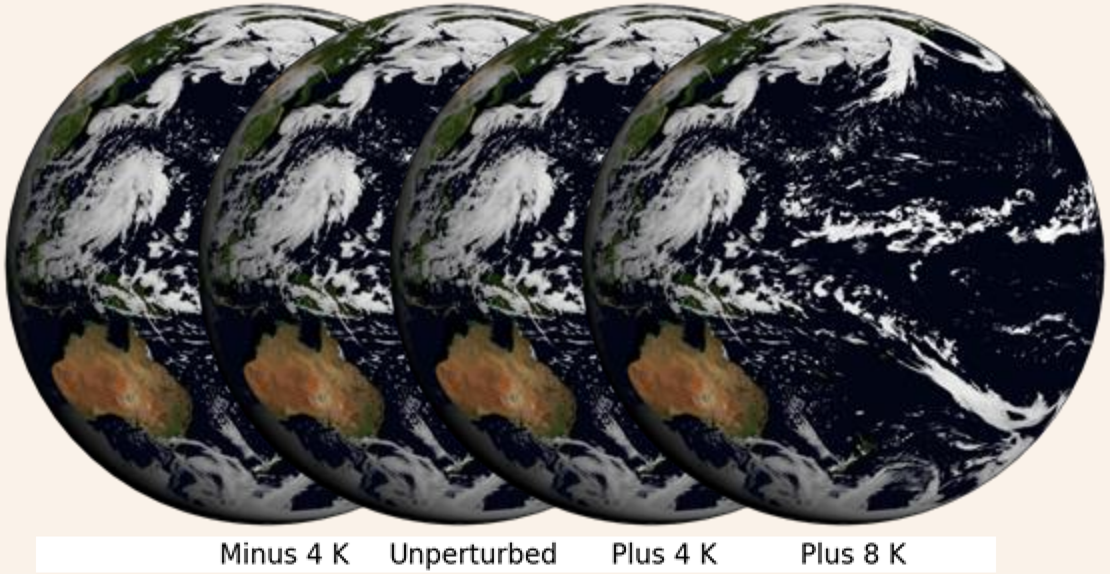


Up to 20% less error in seasonal land rainfall than baseline

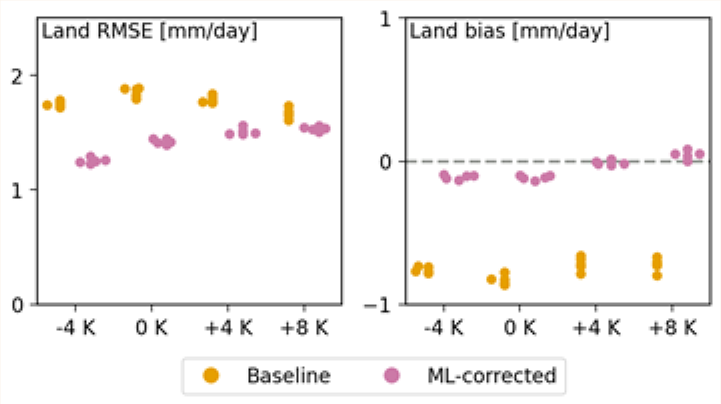
Kwa et al. 2023, JAMES

...and across climates

Train corrective ML from year-long 25 km 'fine' simulations in SST-perturbed climates to improve 200 km coarse-grid simulations in multiple climates.



Mean precip errors reduced in all climates



Clark et al. 2022, JAMES

Perspective

- Corrective ML trained on nudging tendencies allows a coarse-grid model to more closely follow fine-grid model evolution at much lesser computational cost
- It is (mostly) physically interpretable and works across seasonal cycle and climates
- But… we have struggled get beyond ~25% improvements in climate accuracy with this strategy
- Also, we have tried applying the method to a different atmospheric model (EAMv3) and had less encouraging results
- Our group has pivoted to focusing on “full model” machine learning emulation strategies (see talk on Ai2 Climate Emulator later today—short version for WGSIP and longer version for WGNE)