Improving climate models using corrective machine learning

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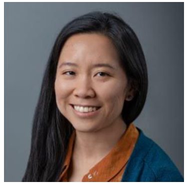

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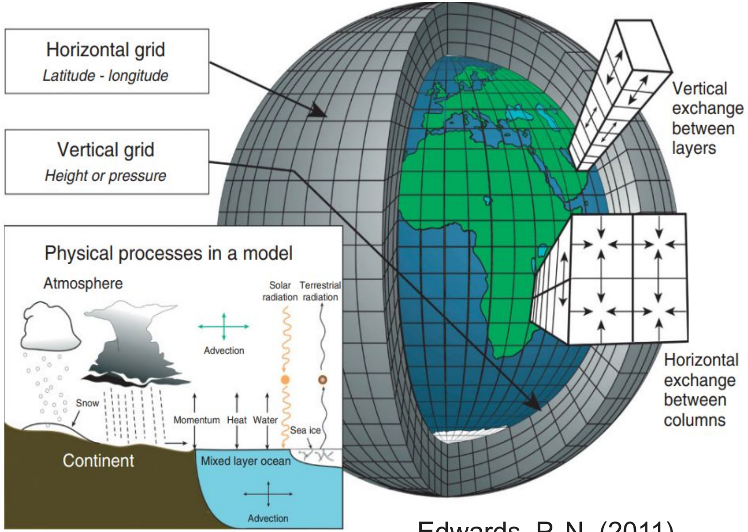
Webpage: https://allenai.org/climate-modeling
Code: https://github.com/ai2cm/index

AGCM parameterizations are human-designed, column-local

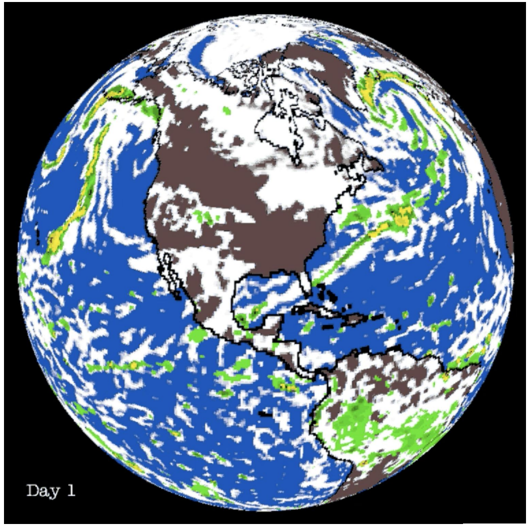
- Representing subgrid variability is uncertain.
- Common inputs
  - Profiles of humidity, temperature, winds
  - Sunlight, elevation, surface fluxes, land heterogeneity
- Outputs:
  - Profiles of diabatic heating, moistening rates, drag

→ Improving 'column physics' is naturally framed as a machine learning (ML) problem being actively explored by several groups.



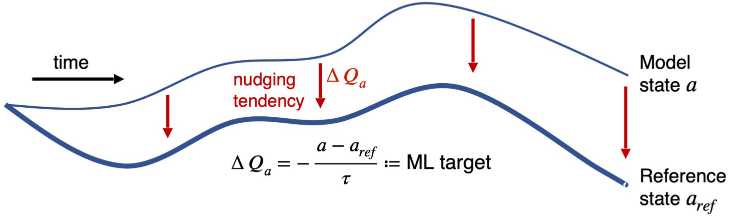
Edwards, P. N. (2011)

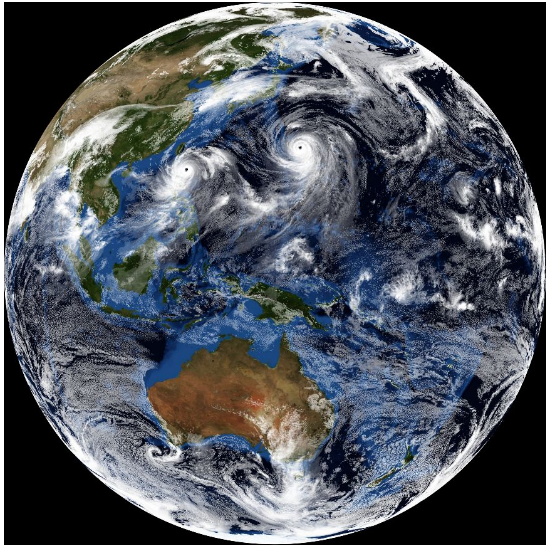
ML Goal: Improve coarse-model simulations



Climate model (25-200 km)

Train ML to correct parameterized column physics to make temperature and humidity of the coarse model track reference data.

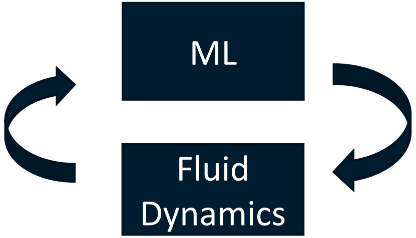




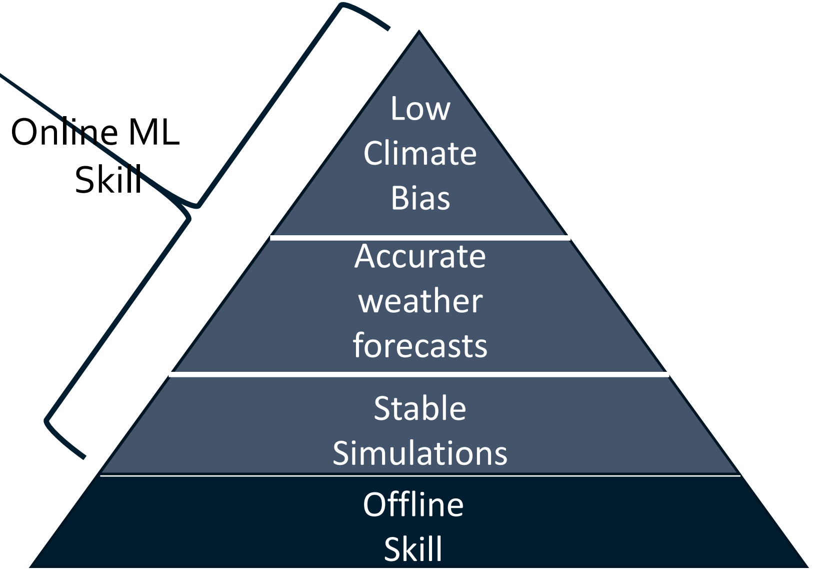
High fidelity reference: observations or fine-grid (3 km) simulation

Challenge of ML coupled to other components

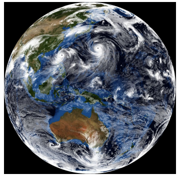
Coupled to fluid dynamics and parameterized physics

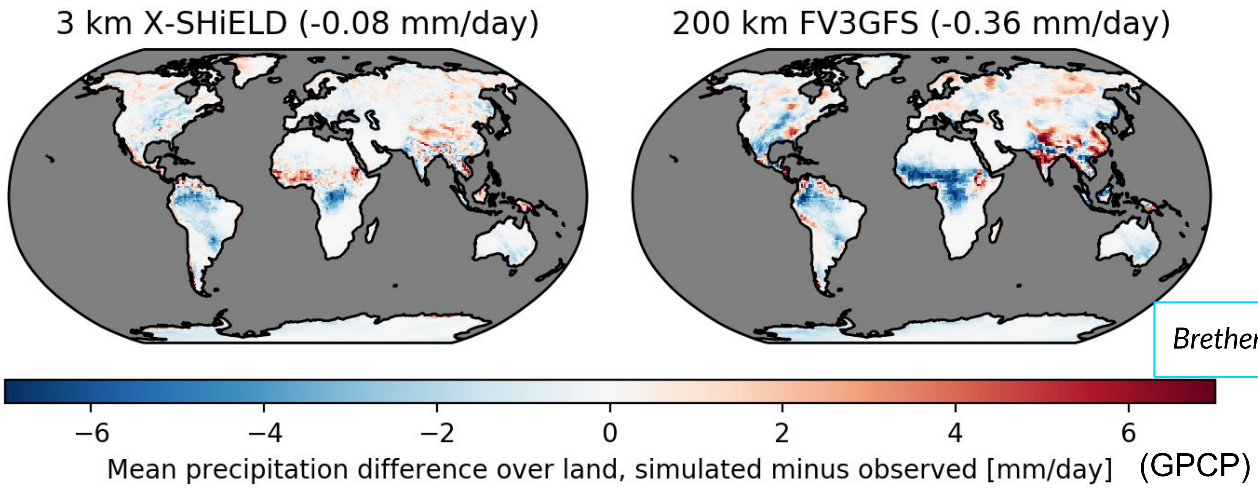


Training ≠ Testing
(offline) (online)

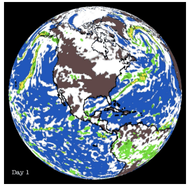


Fine-grid reference model: X-SHiELD





Bretherton et al. 2022, JAMES



3 km grid gives a better rainfall simulation over land than 200 km:

- Enabled by explicit simulation of cumulonimbus clouds & well-resolved mountains

3 km model is expensive & imperfect but enables 1+ yr simulations in multiple climates

ML for correcting model physics: ‘Nudge to fine’

Corrective ML Method:

- ‘Nudge’ coarse model state to the fine-grid reference state (3 hr timescale)
- Machine-learn the ‘nudging tendencies’ that do this as a function of coarse model column T, q, [u, v]

Bretherton et al. 2022, JAMES

Our published example:

Fine-grid reference (NOAA GAEA supercomputer):

- 40-day GFDL X-SHiELD 3-km global storm resolving run (DYAMOND project)
- Petabytes of model output coarsened online each 15 min and stored to Google Cloud.

Nudged training run and ML on Google Cloud

‘Nudge to fine’: ML methodology

From nudging tendencies every 3 hrs for 40 d, subset to:

Training set = 1.8M samples (130 times x 13824 grid columns)

Test set = 700K samples (50 times x 13824 grid columns)

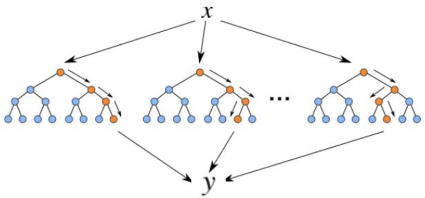
Features

- air temp vertical profile
- specific humidity vertical profile

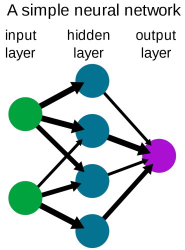
additional potential features, ex.

insolation
land/sea mask
surface elevation

Random forests
(13 trees, max depth 13)



Neural network ensembles
(fully connected, 3 layers, 128 neuron width)



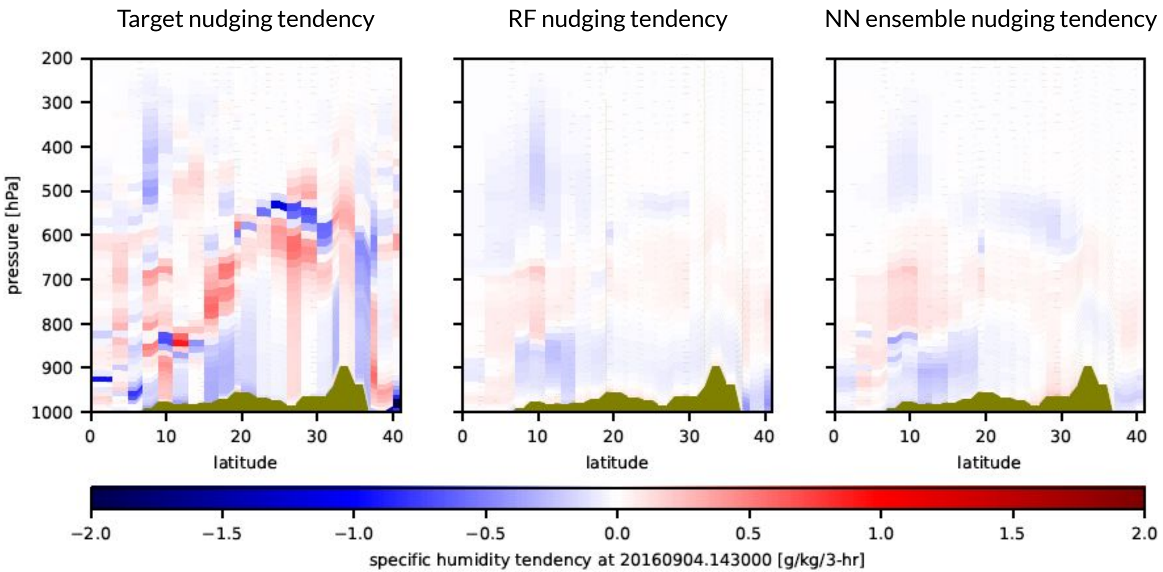
Predictions

- heating vertical profile
- moistening vertical profile

Surface downward radiation

‘Nudge to fine’: ML offline evaluation

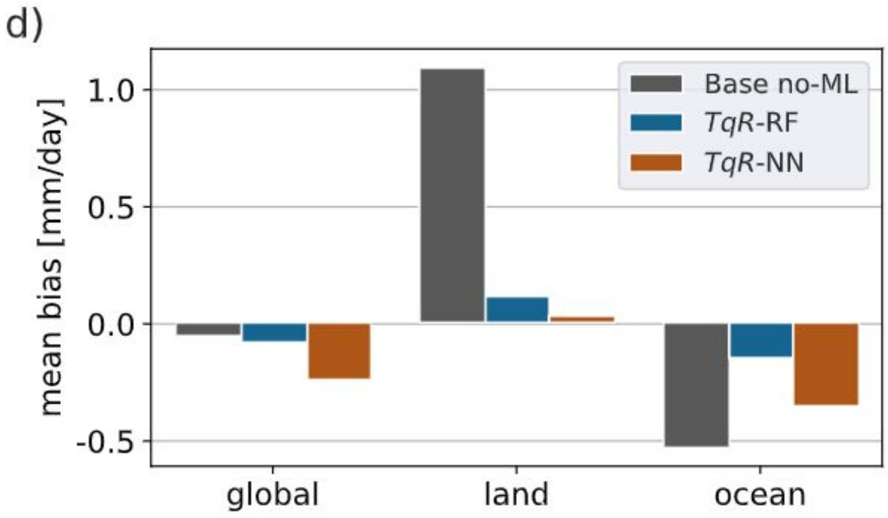
When evaluated out of sample but offline, the ML schemes produce a smoothed, lower-amplitude version of the noisy nudging tendencies

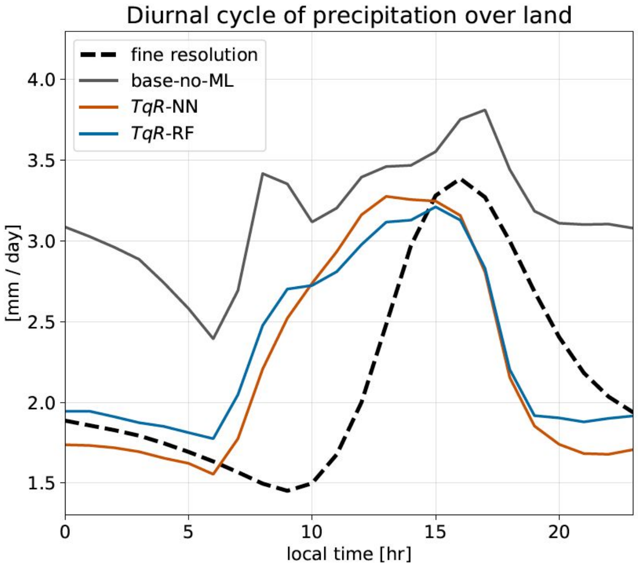


‘Nudge to fine’: Online performance

Compared to baseline, ML-corrected 40 d run has

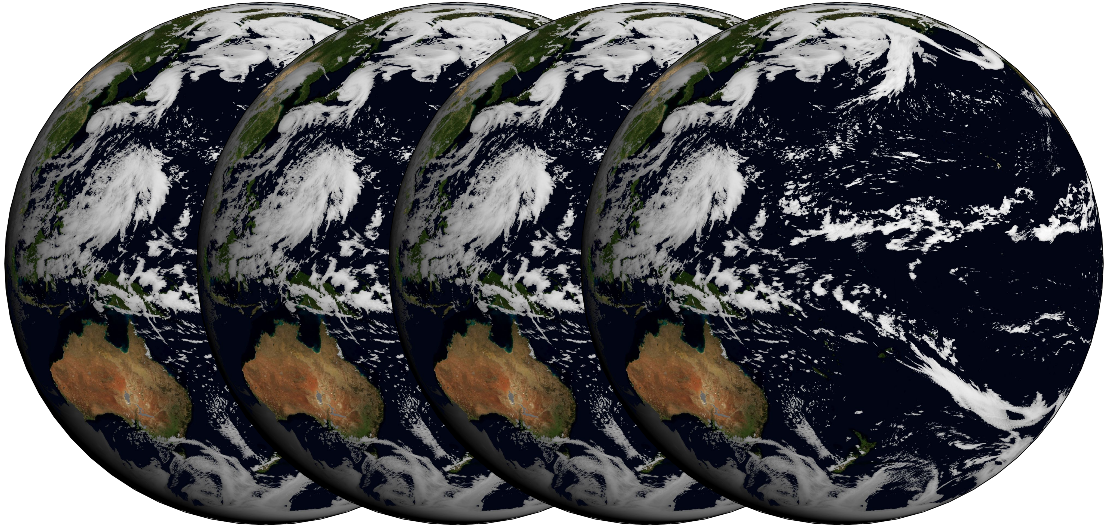
- Better land-mean and RMSE of precipitation
- Better land diurnal cycle of precipitation
- Better land surface temperature





‘Nudge to fine’: Multi-climate training / testing

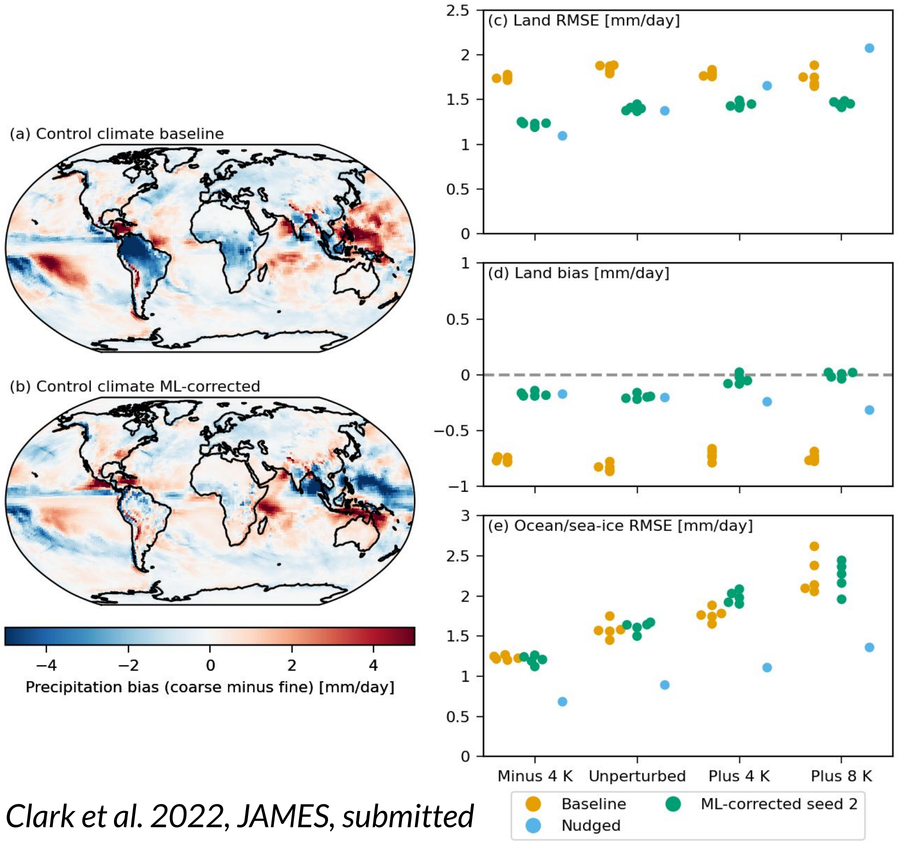
Train corrective ML from year-long 25 km ‘fine’ simulations in SST-perturbed climates to improve 200 km coarse-grid simulations in multiple climates.



Clark et al. 2022, JAMES, submitted

Land precipitation RMSE improved 15-30% across all climates

- ML inputs clipped above ~10 km for stability
- ML-corrected runs maintains stable climates over 5 years
- ML corrects dry bias over Amazonia and Africa.
- ML also reduces land-surface temperature biases.
- Ocean precipitation unimproved
- Shows potential of corrective ML for climate change modeling.



Clark et al. 2022, JAMES, submitted

Conclusions and outlook

- The ‘nudge-to-fine’ approaches improves forecast skill and land surface precipitation/temperature climatology of a coarse-grid global climate model, even across multiple climates.
- Climatological biases, appropriate inclusion of physical constraints, and out-of-sample ML behavior are persistent challenges.
- Ongoing enhancements:
  - Train using new 1 year global 3 km X-SHiELD simulations
  - Predict the entire physical parameterizations, not just a correction
  - ML architectures that actively enable reduction of climate bias