A14C-08: Correcting Coarse-Resolution Weather and Climate Models by Machine Learning from Global Storm-Resolving Simulations

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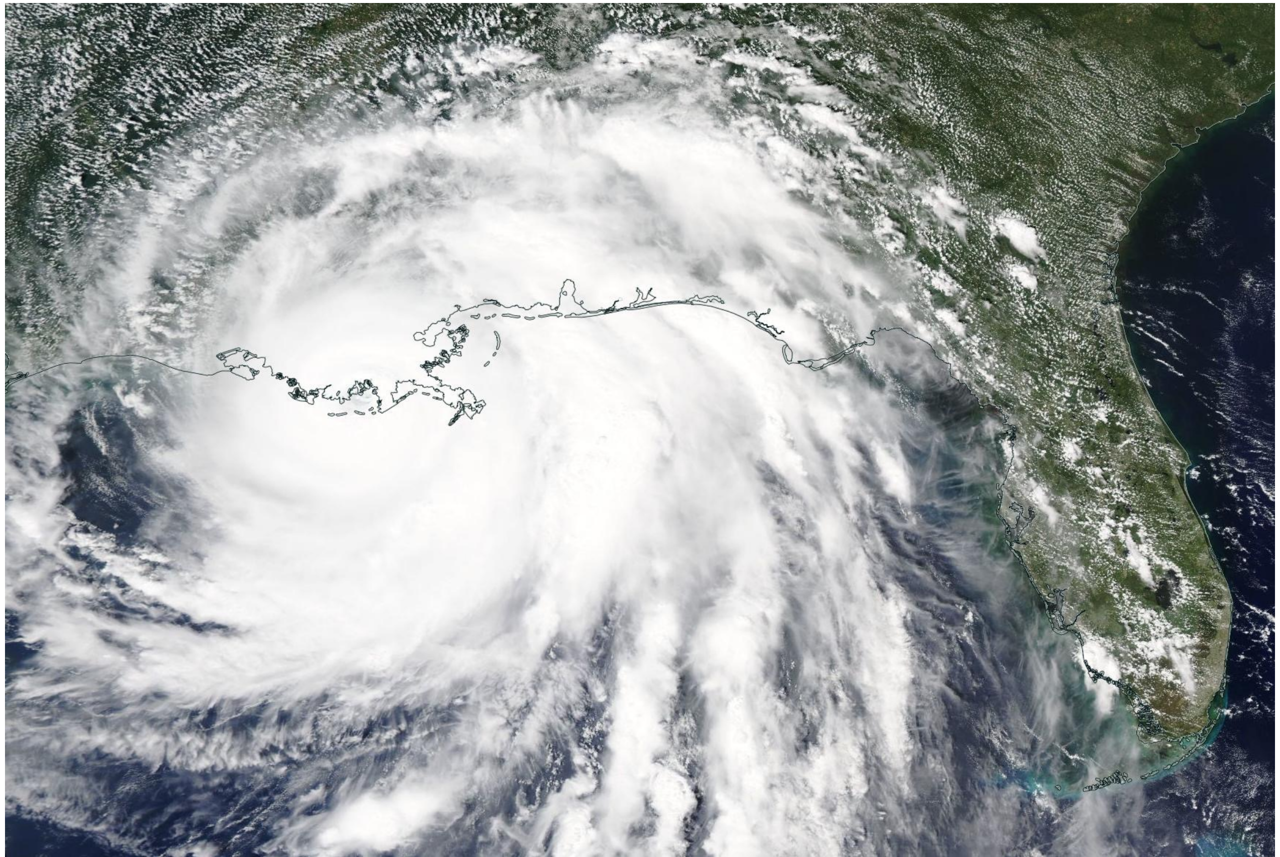

Hurricane Ida
29 Aug. 2021
NASA Worldview

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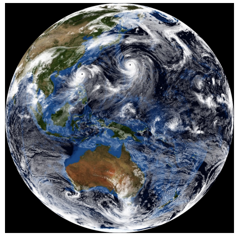
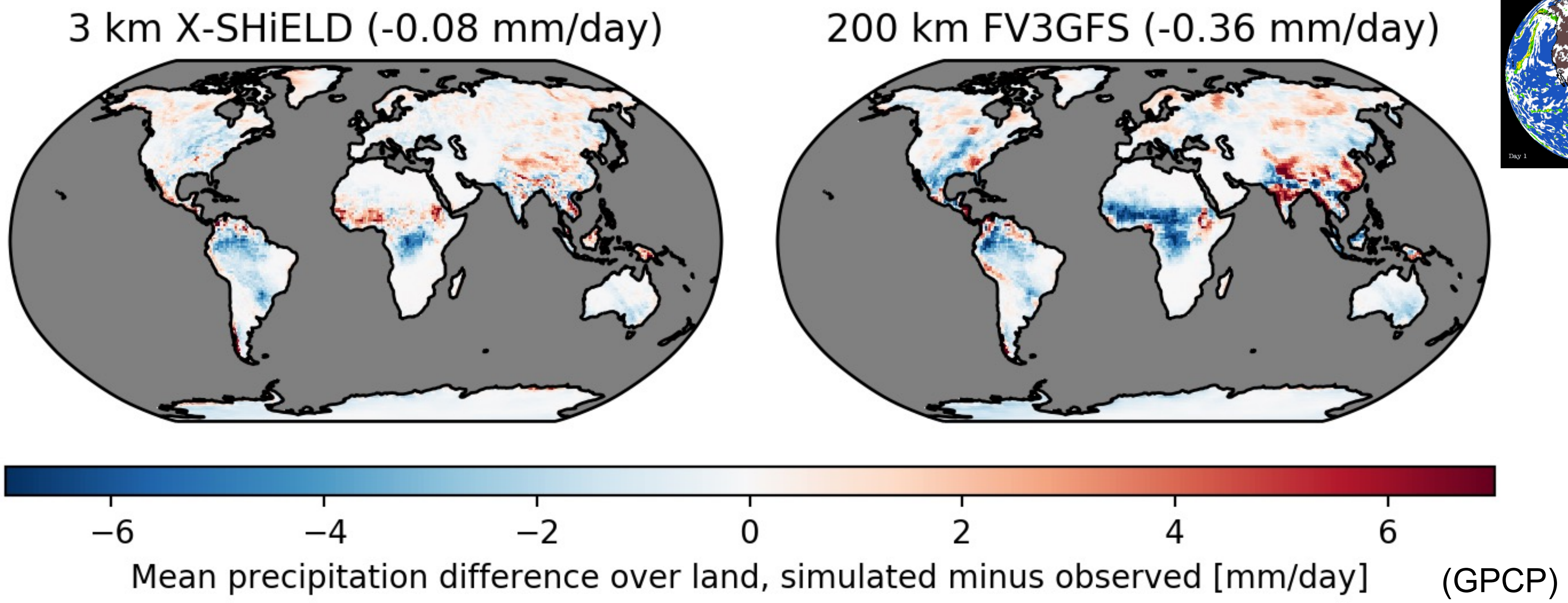
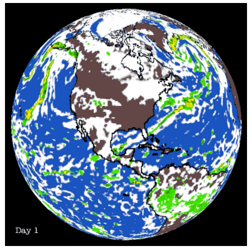
Climate models are our window into our warming world

- Regional hydrological trends and extremes remain an important modeling uncertainty
- Global storm-resolving models (GSRMs, Δx = 2-5 km, 50-150 levels) give more realistic-looking simulations than CMIP6 GCMs with less subgrid modeling assumptions, but are computationally expensive.
- Could GSRMs + machine learning (ML) improve or replace the physical parameterization suites used in conventional GCMs?
- Could this enable more trustworthy projection of hydrological cycle?

3 km grid gives a better rainfall simulation than 200 km







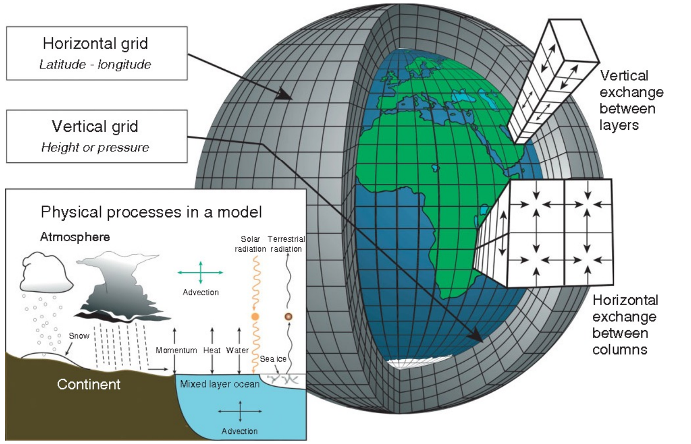
Enabled by explicit simulation of cumulonimbus cloud systems & well-resolved mountains

The 3 km model resolves variability that requires complex subgrid parameterization in GCMs

AI2-CM ML approach to climate modeling

- A global atmosphere model simulates weather and its interaction with land, ocean and ice surfaces for a long time
- Equations for temperature, moisture and winds on a 3D grid:

  Rate of change = grid-resolved air flow + other processes
- Usual approach: Expert-designed parameterizations represent other processes: clouds/rain, turbulence, radiation, etc.
- These processes are complex, but mostly work column-wise
- AI2-CM approach: Correct or replace parameterizations using column-wise ML trained on a reference data set.

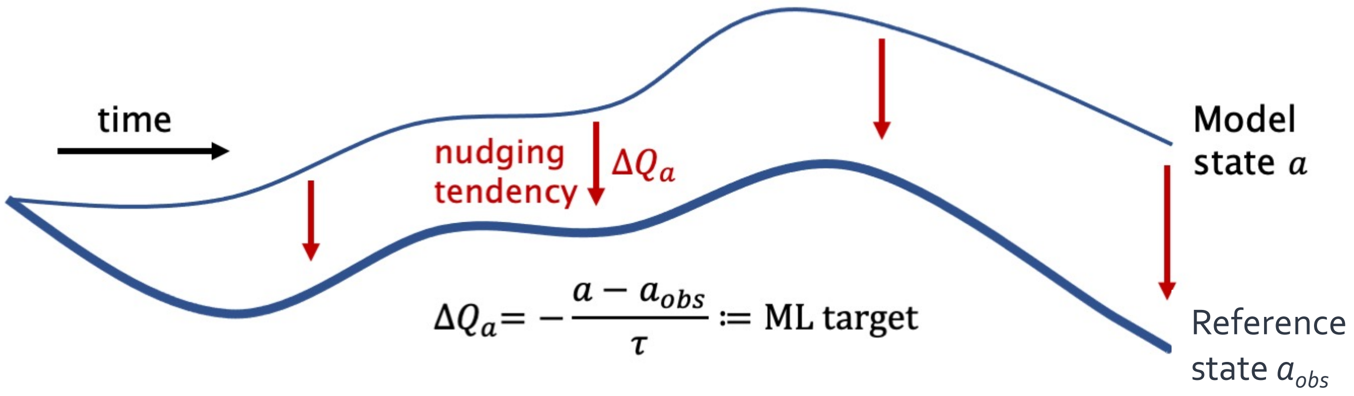


ML goal: Make coarse-grid model evolve like reference

Reference datasets:

- Reanalysis (present-day climate, data-based) - *Watt-Meyer et al. 2021, GRL, doi:10.1029/2021GL092555*
- **Fine-grid model** (range of climates, uncertain biases) – *Bretherton et al. 2021, JAMES, submitted (ESSOAr)*

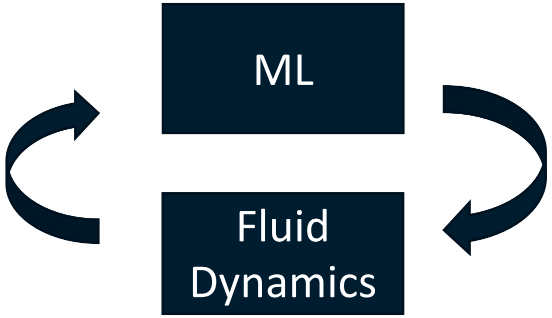
Corrective ML Method: 'Nudge' coarse model state to the reference state on a 3-6 hour timescale and machine-learn the 'nudging tendencies' that do this.



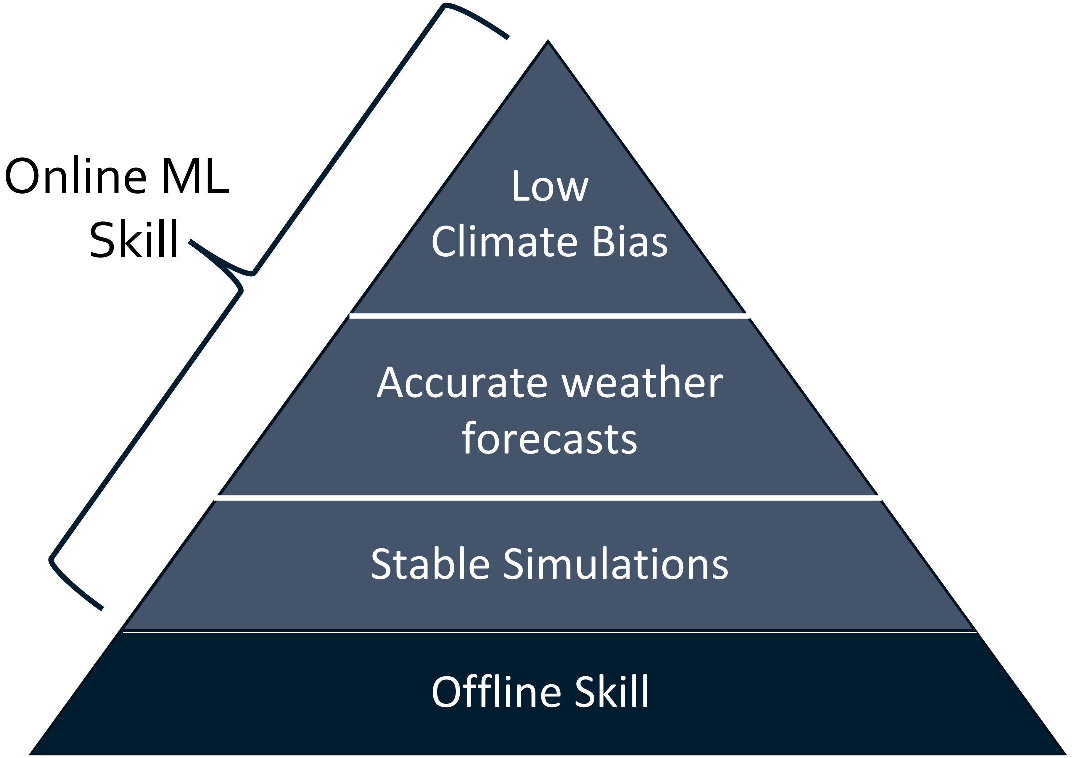
- This methodology can naturally transfer to any coarse-grid target model and fine-grid reference

Challenge of 'hybrid' ML coupled to other components

Coupled to fluid dynamics and parameterized physics

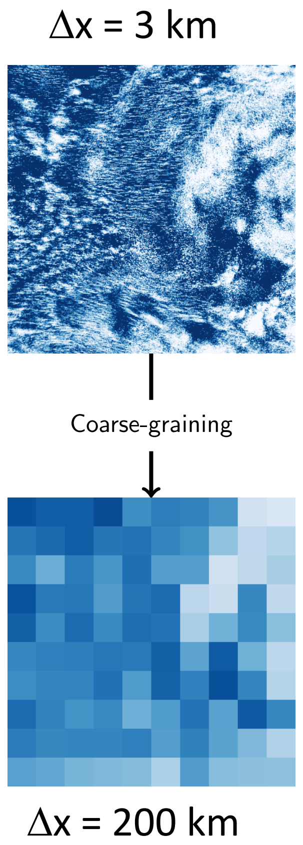


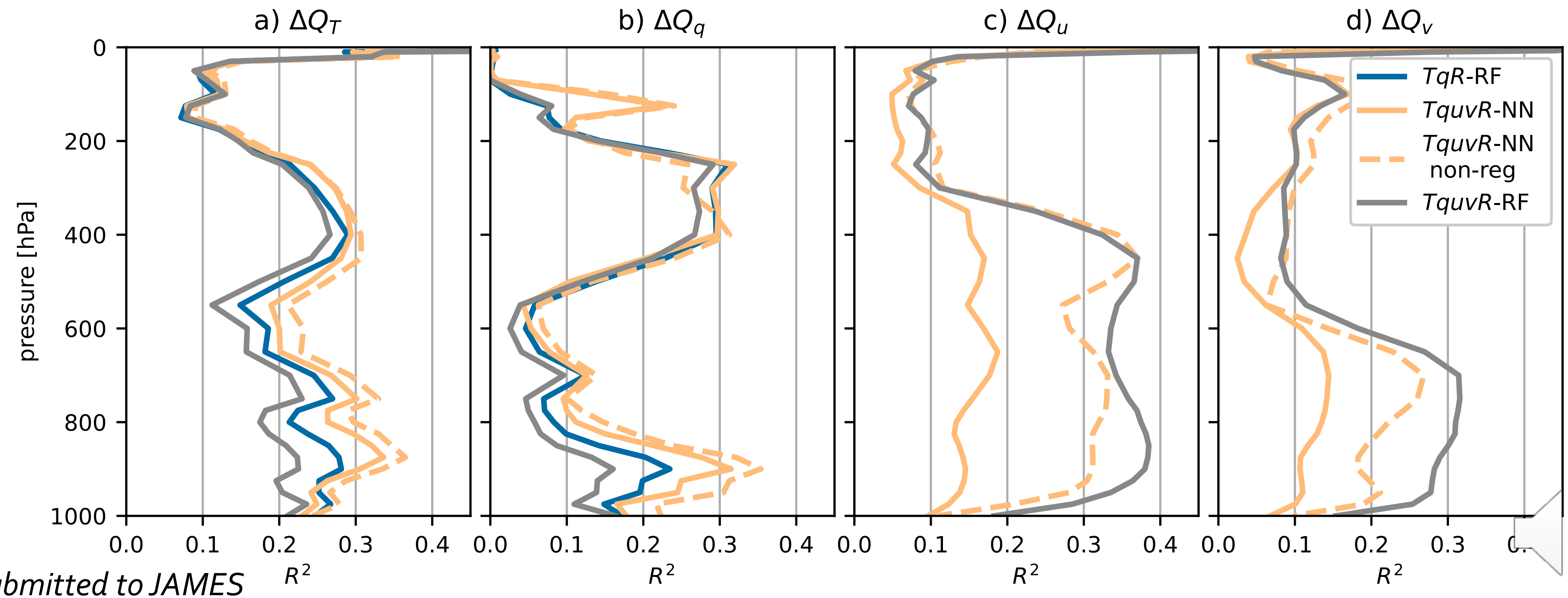
Training ≠ Testing
(offline) (online)



Corrective ML skill: Good on time-mean, modest on variability

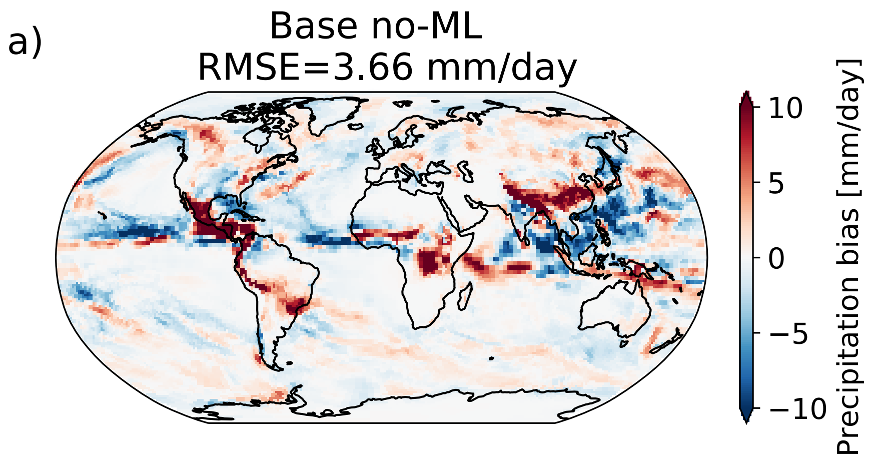
- Training run nudged to coarsened 3 km X-SHiELD, 40 days
- ML for nudging tendencies of *T*, *q*, and optionally *u*, v, and surface downwelling radiation *R*;
- ML inputs: column *T*, *q*, *u*, *v*, cos(*zenith*), z_{sfc}
- Google Cloud workflow with custom Python wrapper for FV3GFS (*McGibbon et al. 2021, GMD*)



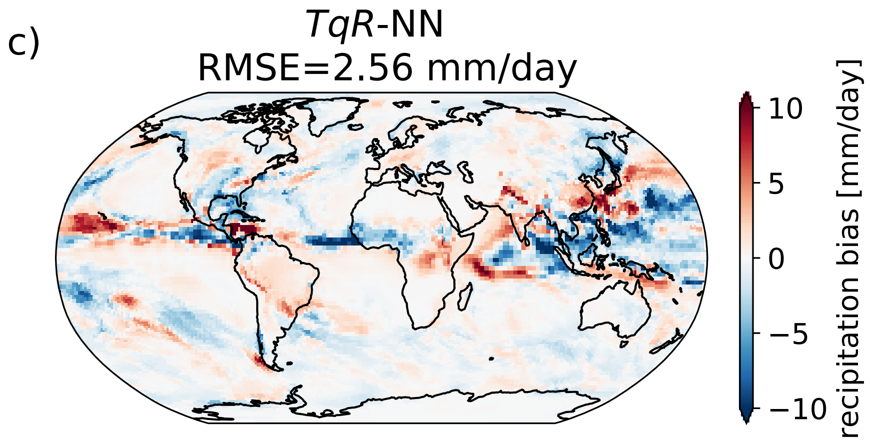


Bretherton et al. 2021, submitted to JAMES

‘Nudge-to-fine’ ML reduces climate bias vs. reference



- Reference for prognostic runs (like training): 3 km X-SHiELD, 40 days
- RF or 3-layer neural net reduces time-mean precipitation error vs. reference by 30%.
- ML for surface radiation removes land precip bias



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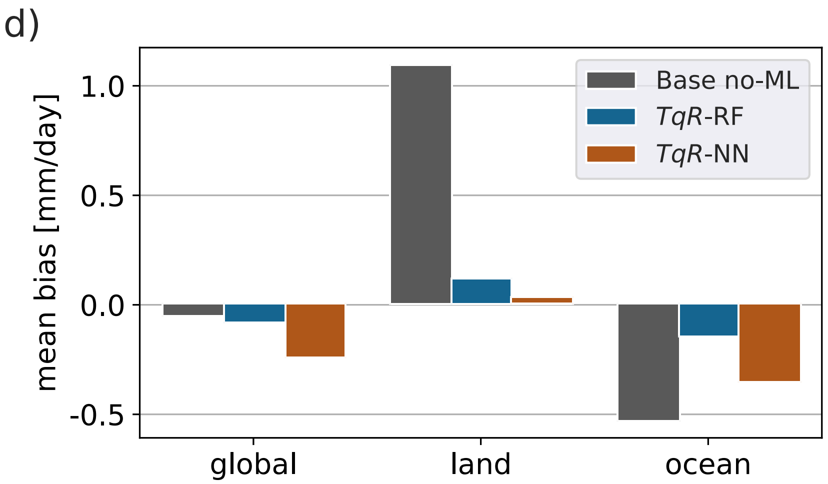
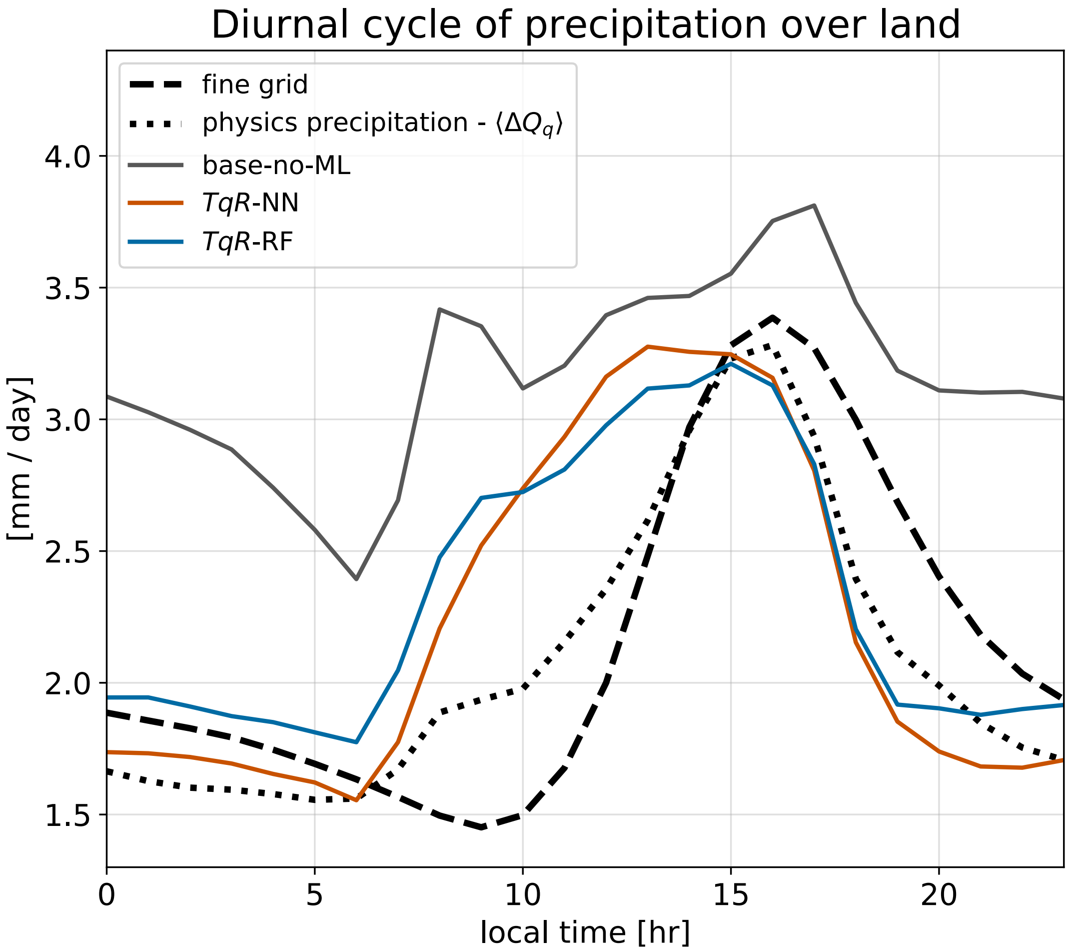


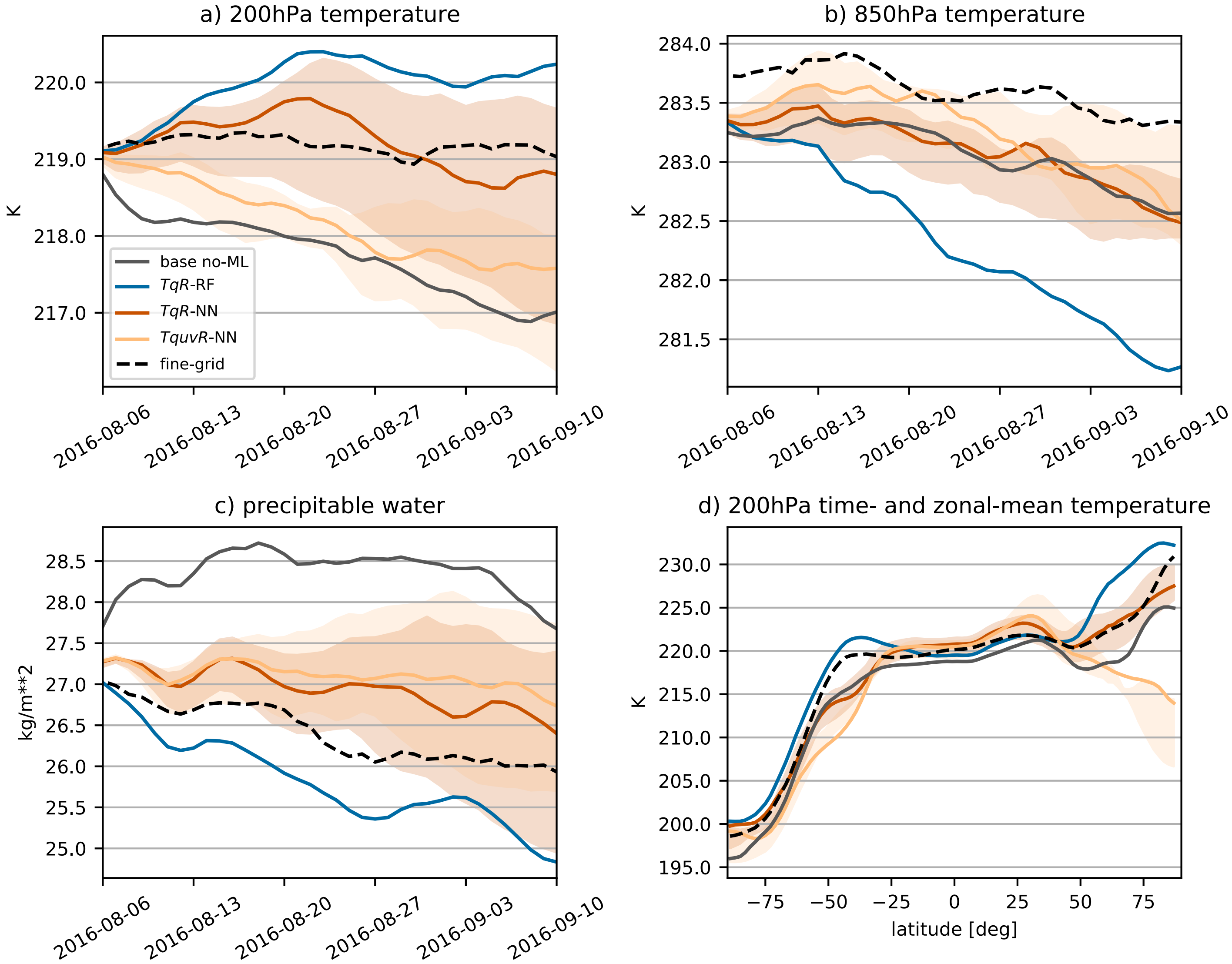
ML improves land precipitation diurnal cycle amplitude



Bretherton et al. 2021, submitted to JAMES

- Baseline simulation: too weak
- ML-corrected amplitude is good but phase is 3 hrs early.
- Diurnal cycle error is:
  - Half from nudging-based training
  - Half from ML

Mean-state drifts



- Drifts of *TqR*-NN are less than for baseline model, esp. in lower troposphere (T850, PW).
- Drifts are sensitive to initial random seed for NN (range of dark brown shading)
- Wind nudging (*TquvR*-NN) induces upper-tropospheric temperature drift

Bretherton et al. 2021, submitted to JAMES

Ongoing work

- Corrective ML trained and run for multiple climates (ΔSST = -4K, 0, 4K, 8K)
  - Reference fine-grid model: 25 km FV3GFS (runs fast), same physics as 200 km target
  - ML-corrected 5-year run reduces land surface T and precip biases vs. 200 km baseline across all climates, but stability and performance sensitive to random seed
  - See our poster A15E-1683 by Clark et al. for details

- Corrective ML trained on a year-long X-SHiELD 3 km training run from GFDL.
  - Prognostic 200 km runs corrected with some ML configurations can run for 2 years
  - Double-ITCZ bias and upper-tropospheric temperature drifts are still problem areas

- Prognostic simulations with ‘fine-only’ ML of full fine-grid physics: Fast PW drifts

Conclusions

- ‘Nudge-to-fine’ corrective ML trained with nudging of a coarse-resolution global atmosphere model to a fine-grid reference can improve its weather and climate skill
- In our example, time-mean precipitation distribution was improved 30%.
- The nudge-to-fine method generalizes easily to any global model.
- Two keys to its success:
    1. The coarse model physical parameterizations help maintain out-of-sample stability of the ML-corrected model
    2. The nudging framework avoids jolting the coarse model during training
- Controlling prognostic stability and climate drift remain challenging.