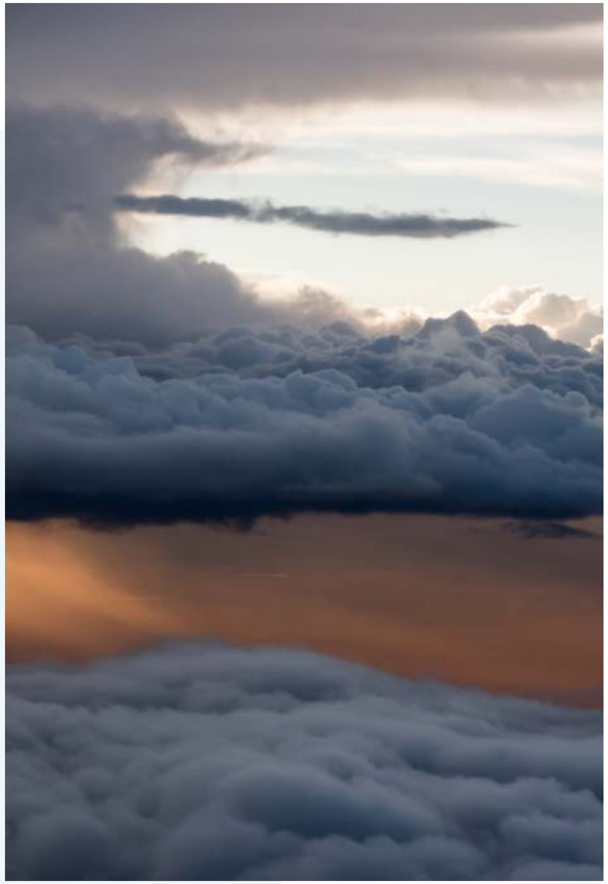
VULCAN CLIMATE MODELING

Machine-learning Climate Model Parameterizations From Global Cloud-resolving Model Outputs



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Goal: Improving a climate model to improve rainfall predictions using machine learning (ML)

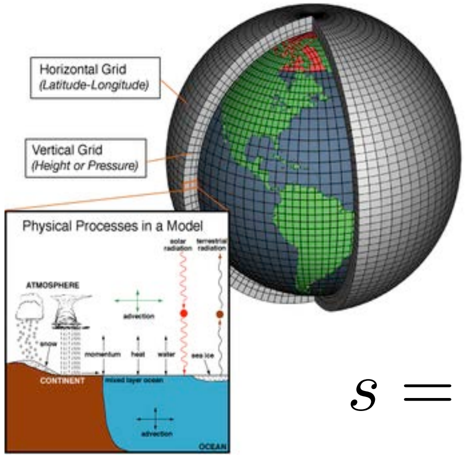
A global cloud-resolving model (GCRM) with a finer grid of 1-3 km may (with work) better simulate individual storm clouds and mountains than a conventional 25-200 km grid GCM

….but is too computationally intense for ensembles of multidecadal integrations.

Goal:

Use a realistic GCRM for training a skillful machine-learning based parameterization of subgrid clouds and precipitation for a coarser-grid global climate model.

Coarse-resolution dynamics and parameterized physics



$$s = T + \frac{g}{c_p} z \qquad\qquad q = \frac{\text{Mass water vapor}}{\text{Mass dry air}}$$

$$\frac{\partial \overline{s}}{\partial t} + \overline{\mathbf{v}} \cdot \overline{\nabla} \overline{s} = Q_1$$

Apparent heating (K/day)

SW+ LW radiation, latent heating, etc

$$\frac{\partial \overline{q}}{\partial t} + \overline{\mathbf{v}} \cdot \overline{\nabla} \overline{q} = Q_2$$

Apparent moistening (g/kg/day)

$$\frac{\partial \overline{\mathbf{u}}}{\partial t} + \overline{\mathbf{v}} \cdot \overline{\nabla} \overline{\mathbf{u}} + \mathbf{f} \times \overline{\mathbf{u}} - \frac{1}{\rho} \nabla \overline{p} = Q_{u,v}$$

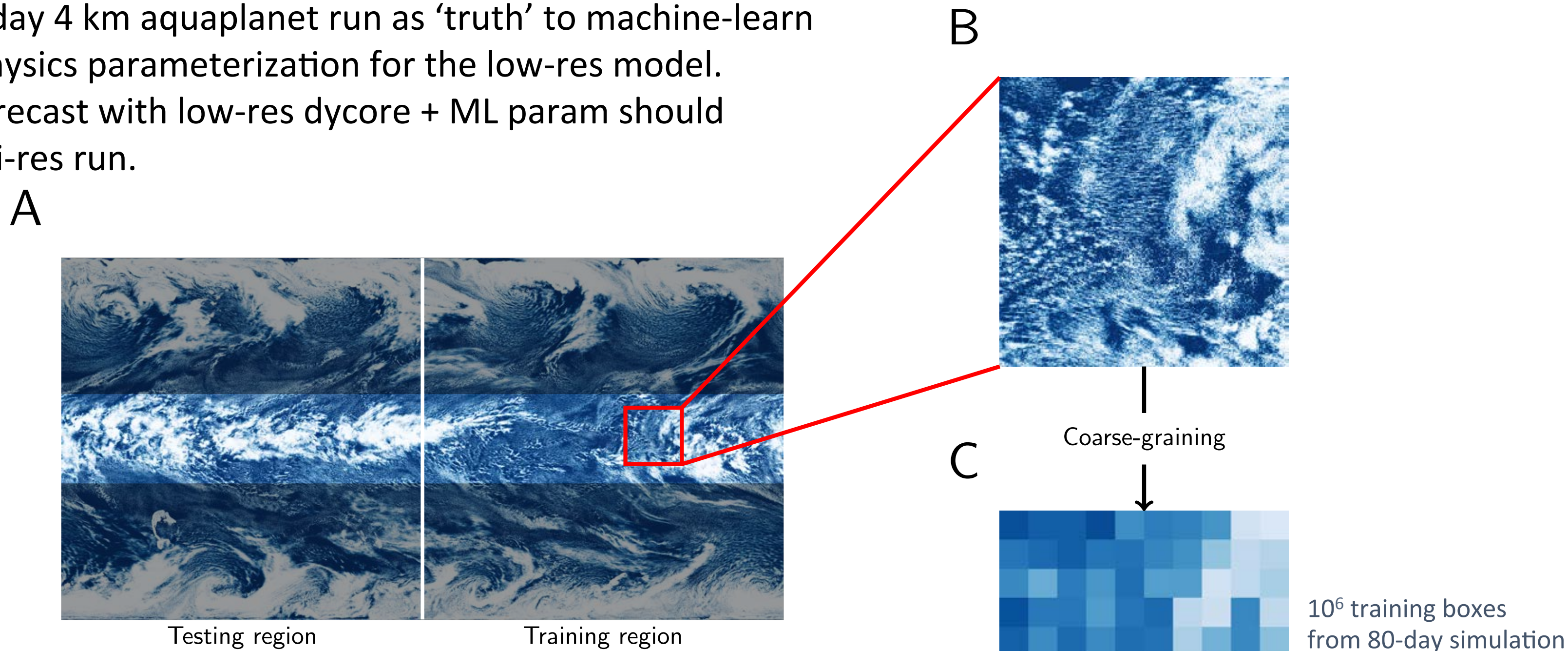
Apparent momentum source
(for now rely on coarse model parameterizations of PBL, GWD, etc.)

Aqua-planet prototype

Past work: Training ML using a coarse-grained 4 km tropical channel simulation

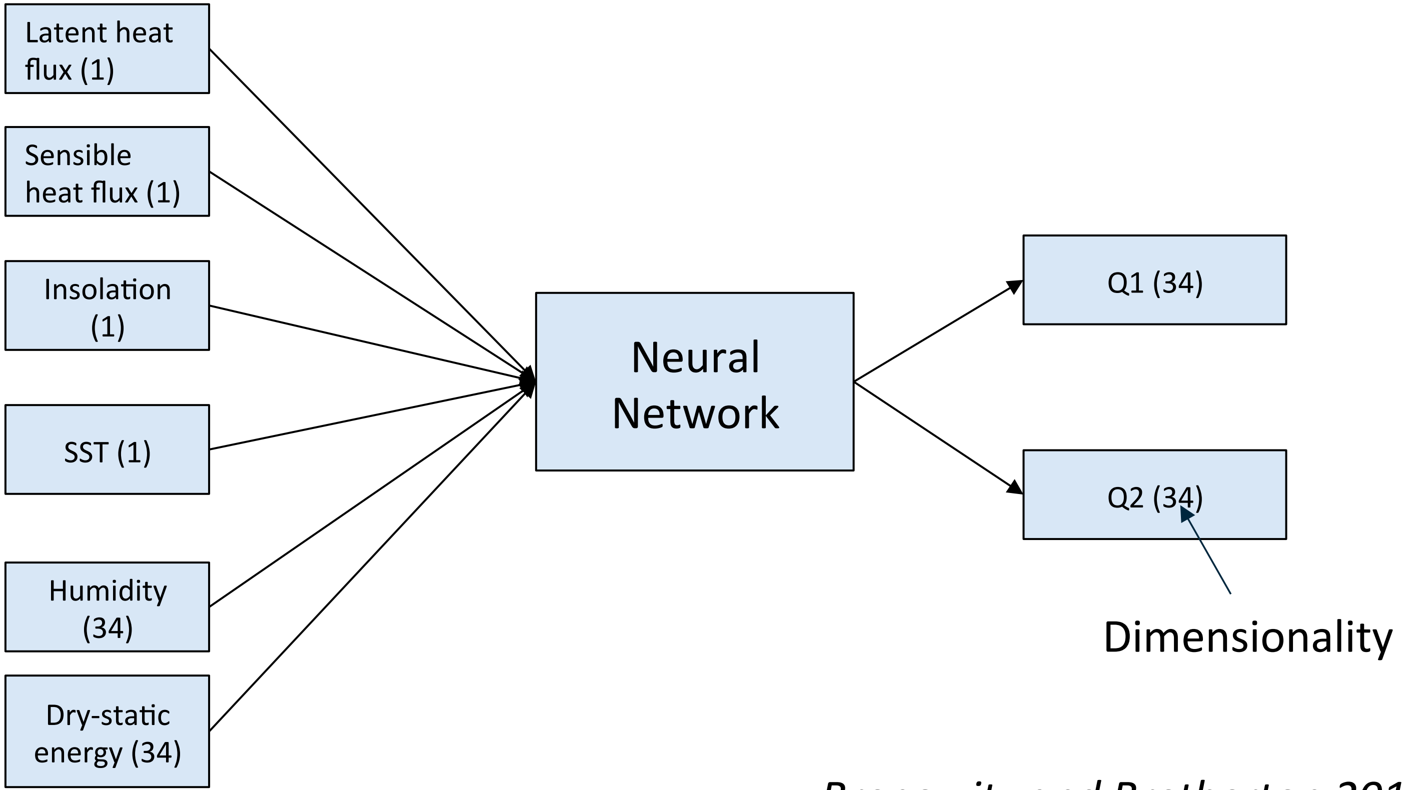
Brenowitz and Bretherton 2018, 2019; Rasp et al. 2018; O'Gorman and Yuval 2020

- Use 80-day 4 km aquaplanet run as 'truth' to machine-learn moist physics parameterization for the low-res model.
- Goal: forecast with low-res dycore + ML param should match hi-res run.



- 160 km coarse (low-res) grid
- Calculate $Q_{1,2}(\mathbf{r}, t)$ (coarse-grid 'moist physics' tendencies including radiation) as residuals of dynamical equations.
- Unified moist physics, turbulence and radiation parameterization: Learn $Q_{1,2}$ as functions of local column conditions using a neural net.

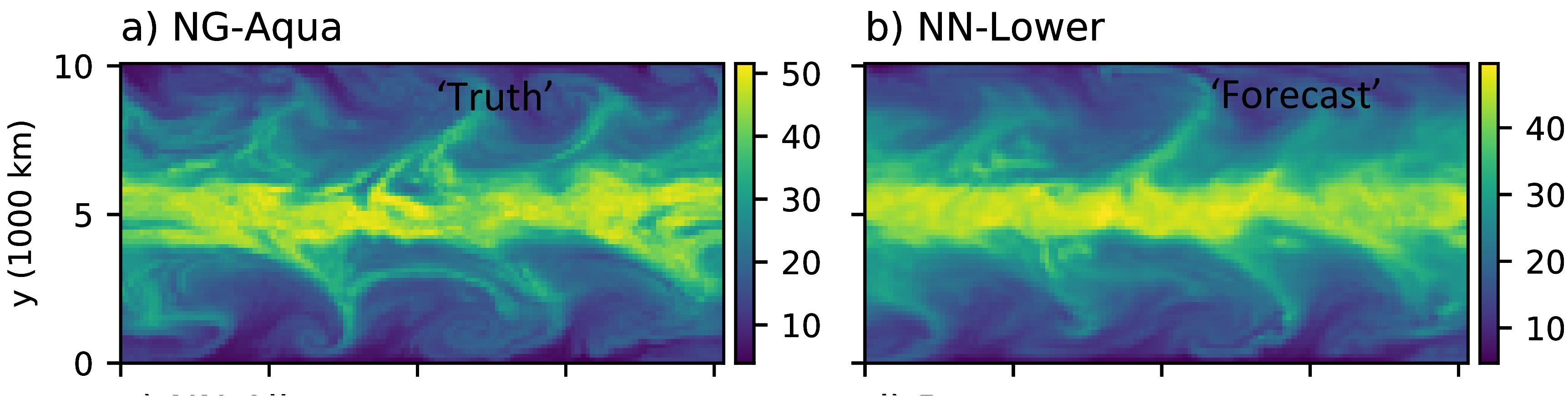
Column Moist Physics Parameterization



Brenowitz and Bretherton 2018, 2019

Couple the ANN to the flow solver on 160 km grid

If inputs and error metric are carefully designed to prevent rapid model blow-up, hi-res model is skillfully forecast by low-res model with NN parameterization



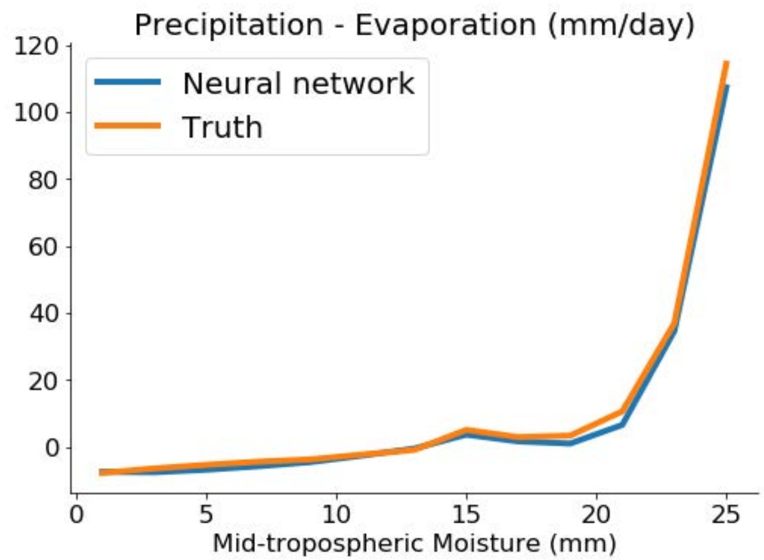
Brenowitz and Bretherton (2019)

Precipitable water after 5 days

…but the 'climate' slowly drifts after 10 days toward a weaker ITCZ
See Rasp et al. (2018, GRL) and O'Gorman and Yuval (2020, arXiv) for other aquaplanet successes with similar methods applied to related models.

Does our network behave realistically?

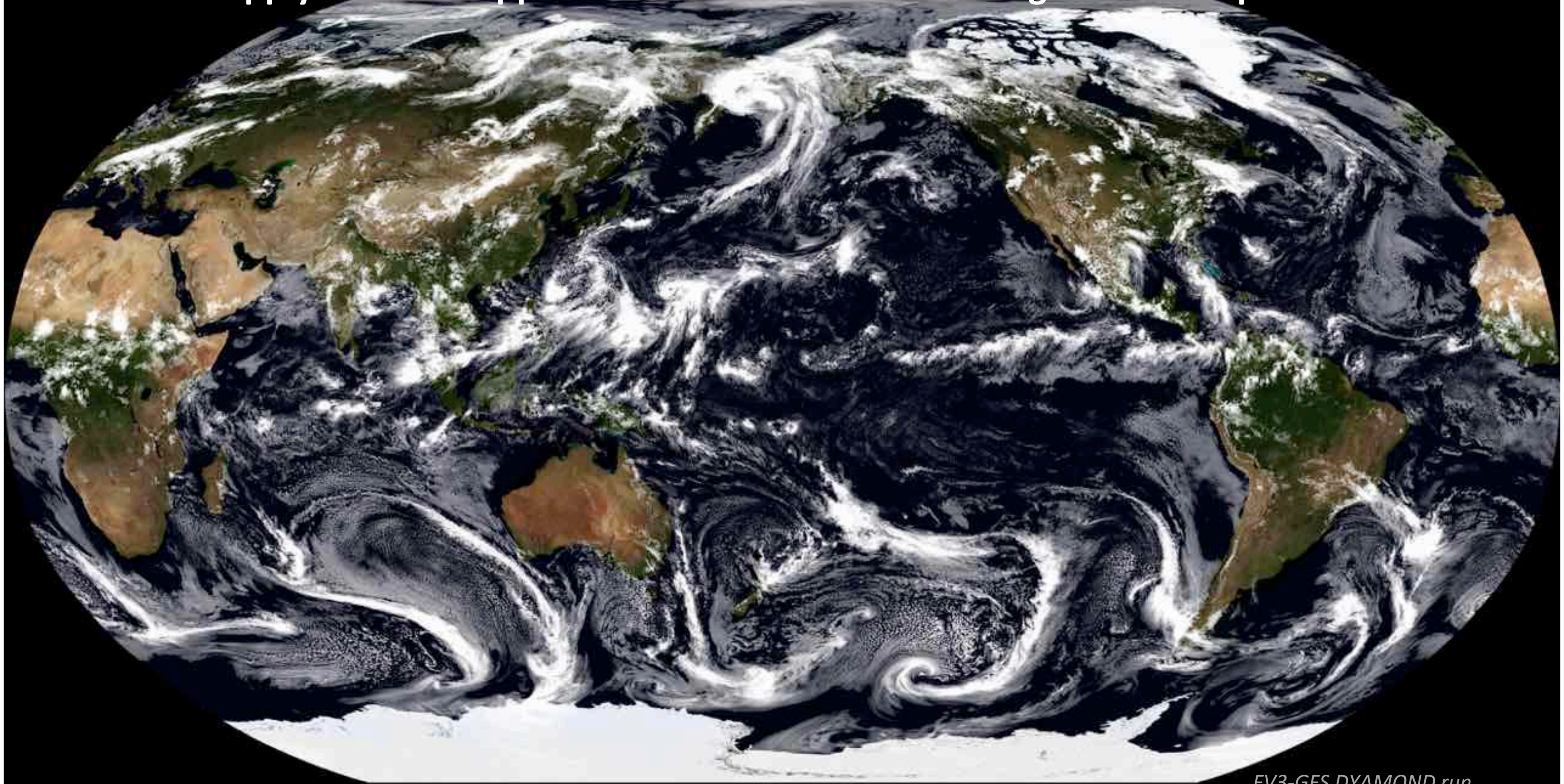
- Observed precipitation increases exponentially with humidity
- Neural networks behave the same
  - Average inputs over bins of moisture
  - Predict with averaged inputs



Brenowitz, et. al. (2020). *Arxiv*

Realistic GCM

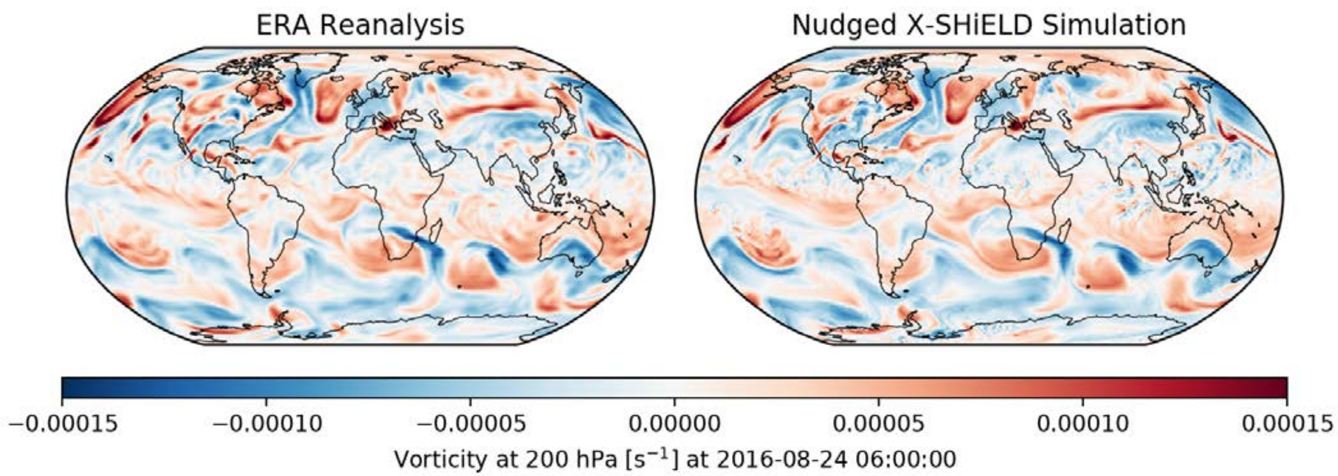
Can we apply same ML approach to GFDL's 3 km FV3-GFS global atmospheric model?



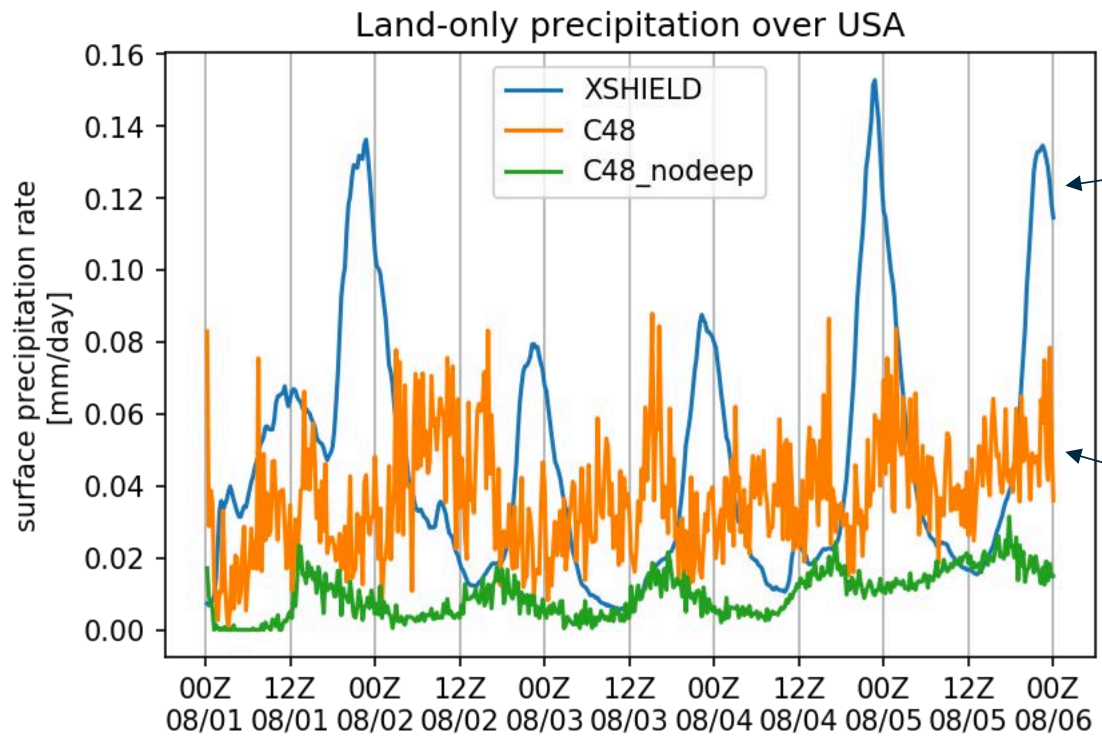
FV3-GFS DYAMOND run
S.-J. Lin and Xi Chen, GFDL

Training dataset: nudged 3 km SHiELD (modified FV3-GFS)

- Training dataset: 40 d 'nudged DYAMOND' simulation on GAEA (1 Aug to 9 Sep 2016):
- Observed SSTs
- Light nudging (τ = 1 day) of 3 km T/u/v/ps to ERA5 reanalysis keeps meteorology 'data-aware'. Nudging tendencies are considered to be part of the learned physics
- Store atmospheric and land-surface restart fields coarse-grained to 25 km every 15 min



Improved diurnal cycle of precipitation over land



3 km SHiELD

200 km resolution GCM

Correcting model errors with machine learning

- Uncorrected coarse model:

$$\left(\frac{\partial a_c}{\partial t}\right)_0 = A_c + Q_a^p, \qquad A_c = -\mathbf{u}_c \cdot \nabla a_c$$

- Coarse model can include no physics (Q_a^p = 0) or a subset of parameterized physical processes that help track the fine-grid model (e. g. turbulence, radiation, clouds, Cu parameterization).

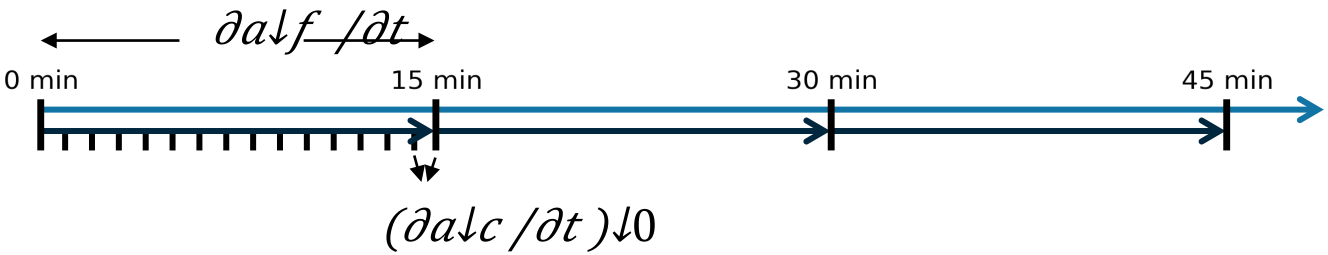
- Machine-learn a state-dependent corrective source ΔQ_a for the coarse model:

$$\left(\frac{\partial a}{\partial t}\right)_c = \left(\frac{\partial a_c}{\partial t}\right)_0 + \Delta Q_a = A_c + Q_a^p + \Delta Q_a$$

- Apparent moistening: $Q_2 = Q_{q_v}^p + \Delta Q_{q_v}$

Tendency difference method for computing correcting source

Coarsened state of fine-resolution model saved every 15 minutes.
Fine-res tendencies computed from these snapshots.



Coarse-resolution model initialized from each coarsened high-resolution snapshot and run forward for 15 minutes, with a 1-minute timestep.

Low-res tendencies computed from final minute.

Correcting source:

$$\Delta Q_a = \partial a_f/\partial t - (\partial a_c/\partial t)$$

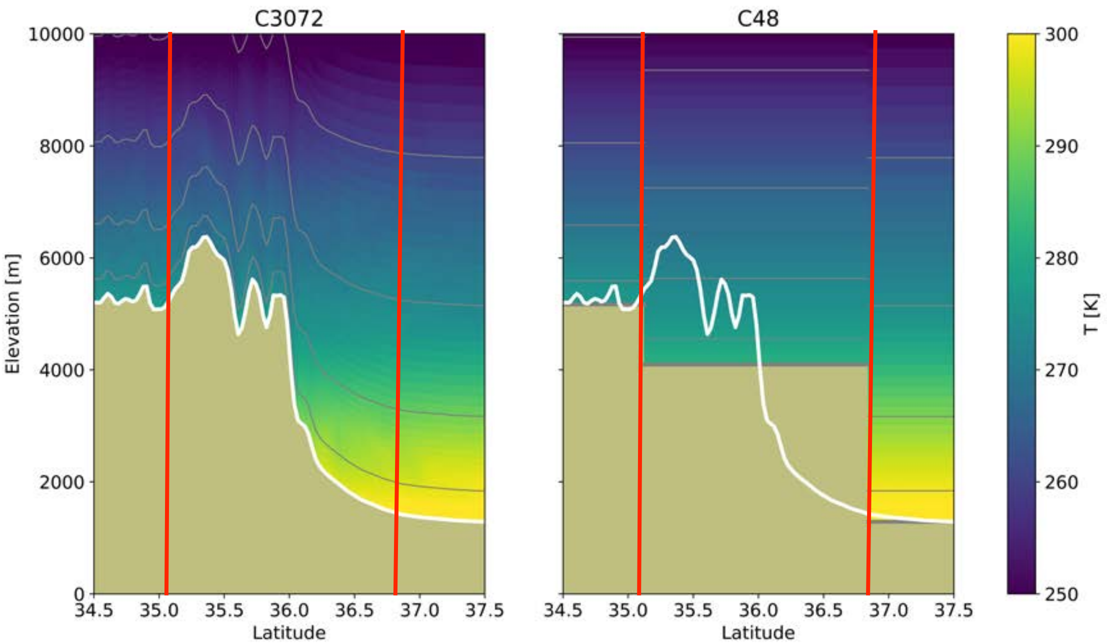
Baseline model physics

We run ML on top of several configurations of the coarse-resolution model:

1. **physics-on**
   - All physical parameterizations on
     (land surface, boundary layer, convection, radiation, microphysics, gravity wave drag)
2. **clouds-off**
   - Deep and shallow convection schemes off
   - No microphysics
   - Use clear-sky radiation only
3. **physics-off**
   - Run only dynamical core

Conceptual issues over topography

Consider 3 km -> 200 km coarse-graining over the Himalayas



- We coarse-grain to obtain vertical **profiles** and **apparent sources** of T, q, etc.
- 5 km relief within a coarse cell
- Most fields are much more constant along a pressure surface than along a terrain-following model surface

→ Coarse-grain on pressure levels, not model levels

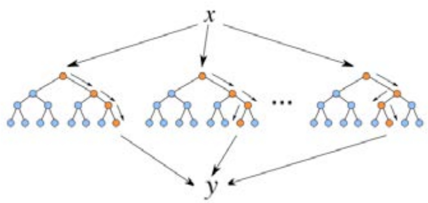
Machine learning: model training

Training set = 1.7M samples (130 initializations x 13824 grid points)
Test set = 660K samples (48 initializations x 13824 grid points)
Train/test data separated by split date to minimize correlated data across sets

Features

- air temp vertical profile
- specific humidity vertical profile
- additional potential features, ex. insolation, surface temp, surface geopotential, ...

Random forest model



- Ensemble of 13 decision tree estimators, each with max depth of 13
- Easier to run with stability in prognostic simulations (relative to neural nets)

Predictions

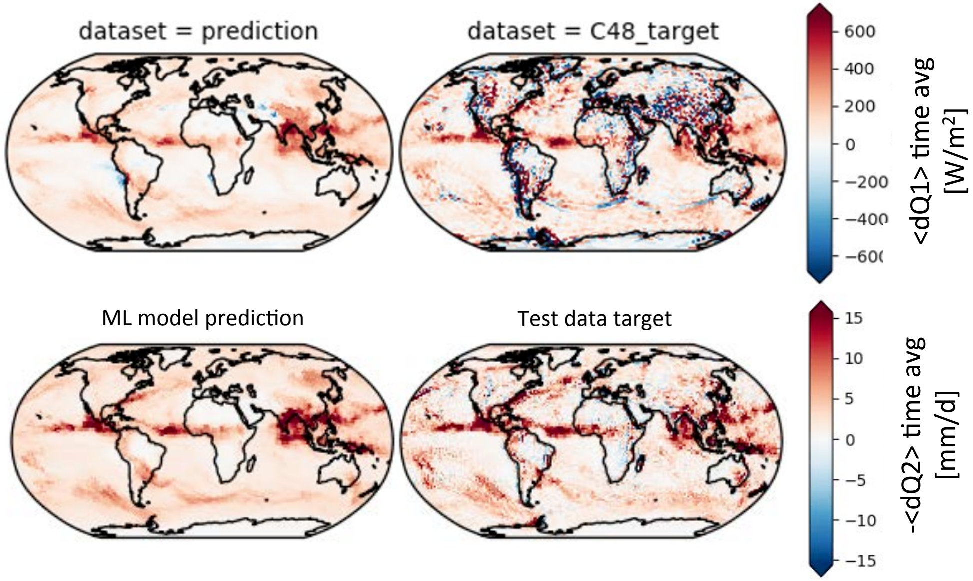
- dQ1 vertical profile
- dQ2 vertical profile

Machine learning: diagnostic skill

Column integrals of the ML-predicted vertical profiles reproduce spatial features of net heating and precipitation, while also smoothing out noise from coarse-graining and initialization.

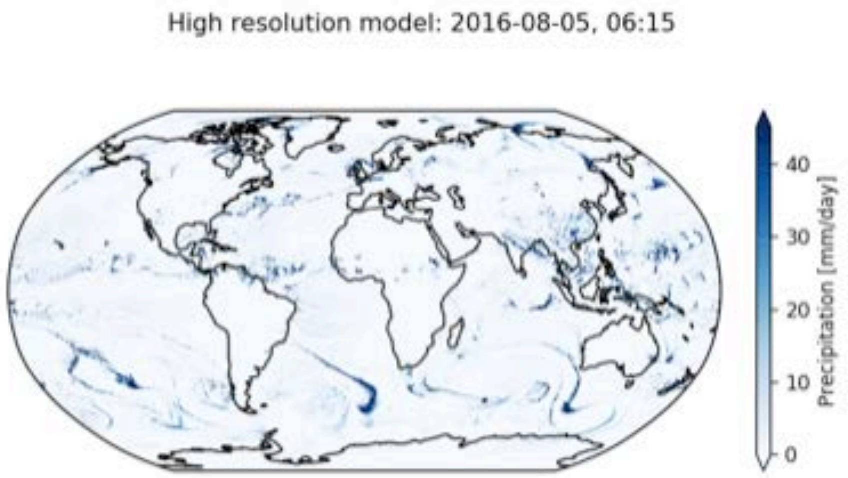
Net ML-implied heating

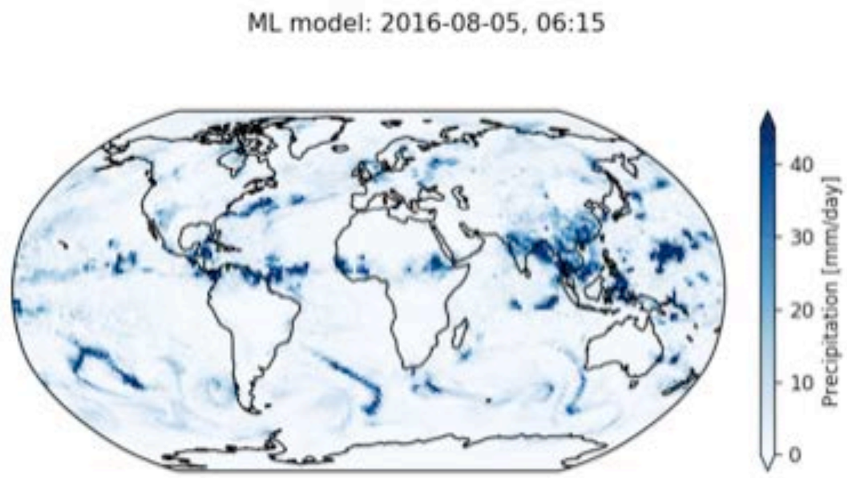
Net ML-implied precipitation



ML model trained with clouds-off configuration

2-day prognostic forecast of precipitation



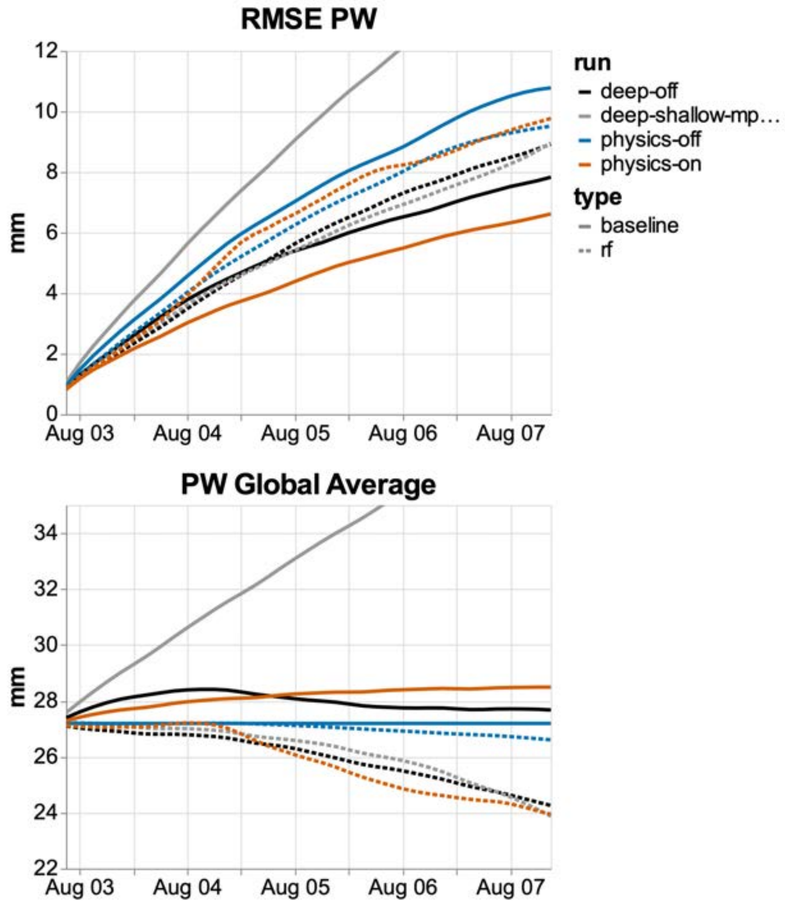


3 km simulation averaged to hourly 25 km

200 km FV3GFS with deep convection param replaced by ML

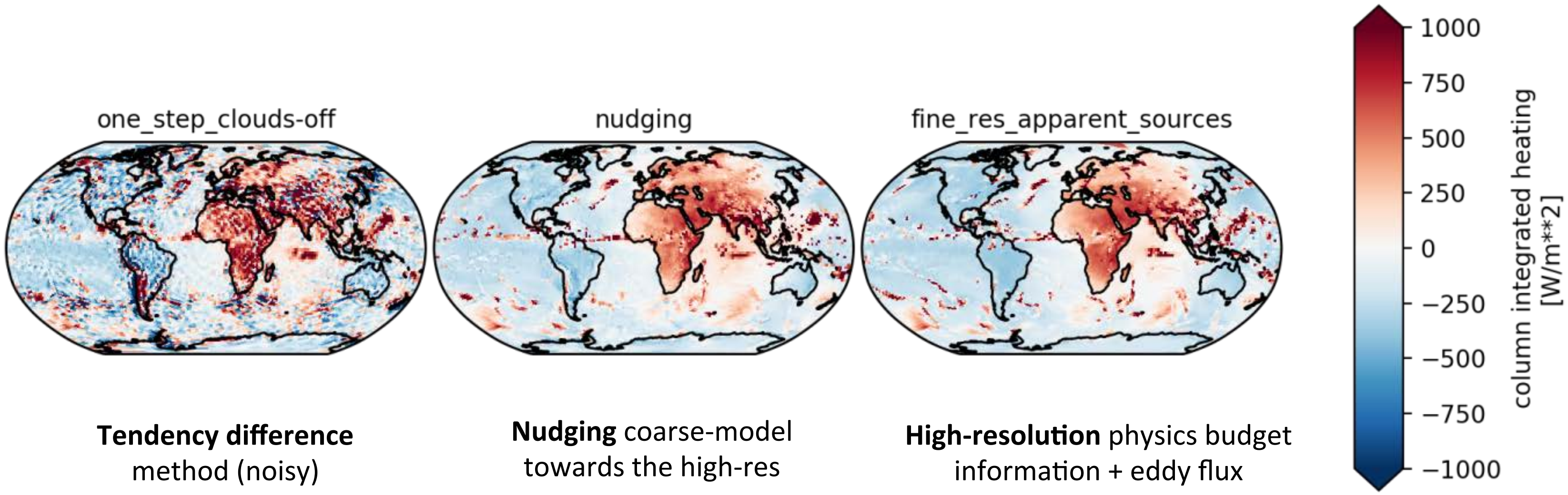
Weather forecast test

- 5-10 day 'weather forecasts' are an acknowledged test of global atmospheric model skill
- Goal is to match the evolution of the 3 km training model.
- Skill metric: root-mean-square error (RMSE) of map of column water vapor in 200 km model vs. coarsened 3 km model. Smaller is better.
- RMSE grows as coarse model diverges from training model.
- "Climate" skill metric: minimal global-mean drift over 5 days
- Currently, the best model configuration includes all conventional physics parameterizations and no ML.
- Most (not all) ML runs to date crash between 5 and 10 days
- ...but it's early days, and we are working to improve ML skill.



Alternative strategies for computing corrective sources

Snapshot of net column-heating in training dataset:



Tendency difference method (noisy)

Nudging coarse-model towards the high-res

High-resolution physics budget information + eddy flux convergence (like Yuval and O'Gorman 2020)

Testing these soon!

Conclusions and Outlook

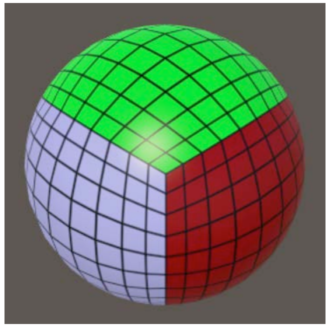
- VCM has developed a unique cloud-based workflow for training a ML correction to a coarse-resolution climate model based on fine-resolution GSRM simulations.
- We have trained stable ML schemes that can make skillful global rainfall forecasts over land and ocean for 10 days or longer given specified SST.
- Tendency-difference method is flexible but is degraded by vertical velocity transients
- Promising new approaches to improve training data quality

Thank You!

https://vulcan.com/Our-Work/Climate/Climate-Modeling-aspx

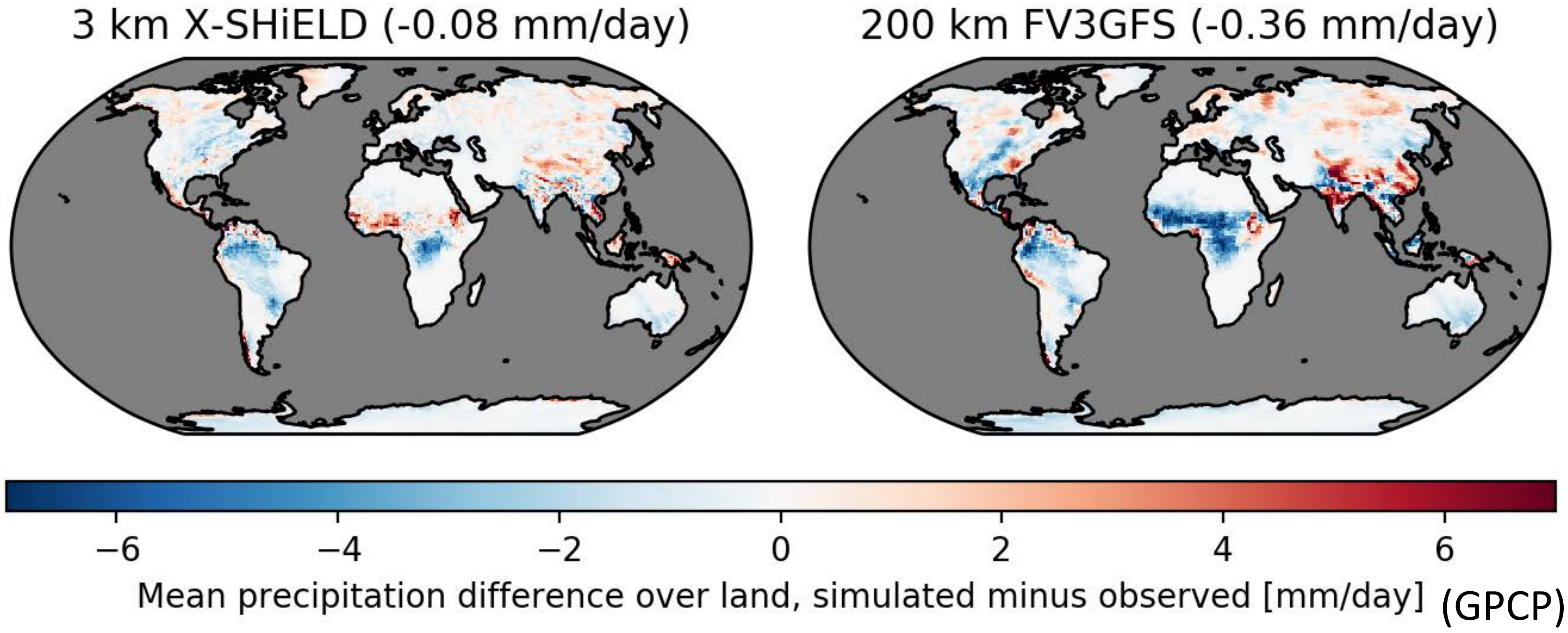
FV3GFS and SHiELD[1] global weather/climate models

- FV3GFS: Open-source global atmosphere model used by NOAA for operational weather forecasts
- FV3 dycore – Customized D-grid finite volume method on cubed sphere.
- Nonhydrostatic by default, 80 vertical levels used here.
- Specified time-varying sea-surface temperature used here
- **Horizontal grid resolutions:**
  - 3 km (C3072)   No deep cumulus parameterization or gravity-wave drag
  - 13 km   Used for NCEP's current operational global weather forecasts
  - 25 km   Finest grid currently practical for climate simulations of many decades
  - 200 km (C48)   Typical coarse climate model grid – good for prototyping or millennial runs.
- **Physical parameterizations:**
  - Land surface and surface fluxes (NOAH)
  - Radiation (RRTMG)
  - Gravity-wave drag
  - Boundary-layer (including shallow clouds) and shallow Cu (Han-Bretherton, Han-Pan)
  - Cloud microphysics and subgrid variability (GFDL one-moment)
  - Deep cumulus convection (SAS)



[1] GFDL's SHiELD is FV3GFS with modest changes to cloud physics and advection and is not open-source.

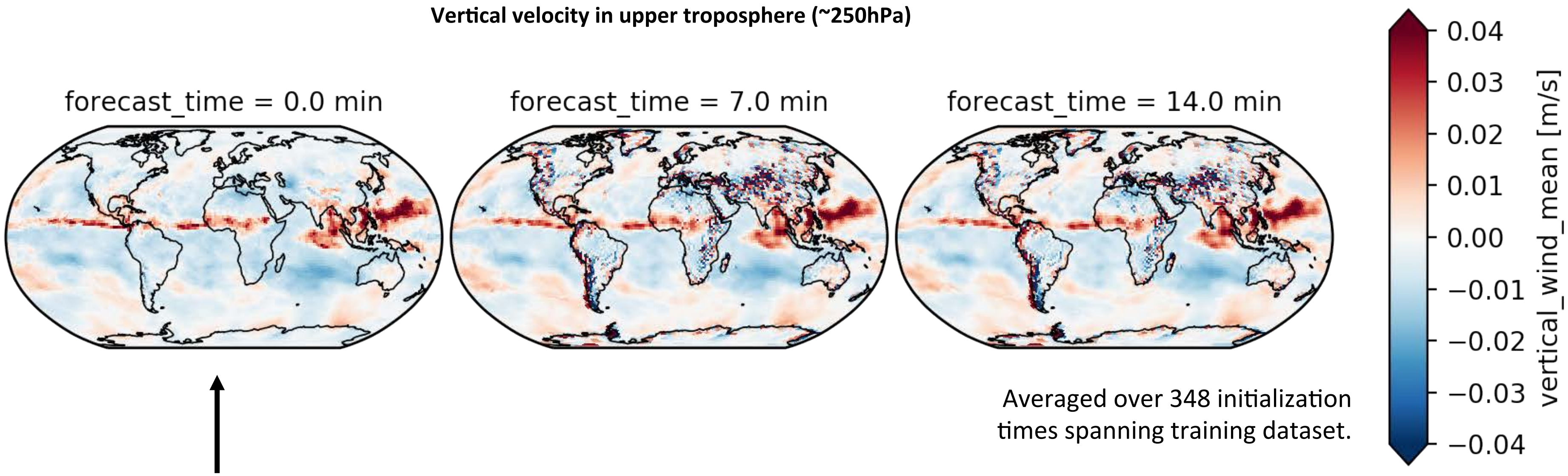
40 d mean precipitation bias over land: 3 km SHiELD vs. 200 km FV3GFS



3 km rainfall bias much smaller over sub-Saharan Africa and Himalayas

Diurnal cycle of precipitation over land is also greatly improved in SHiELD

Despite careful efforts of pressure-level coarse-graining, vertical velocity noise remains over topography



Fine resolution model coarsened to 200km resolution

These results are from clouds-off, but all physics configurations give comparable results