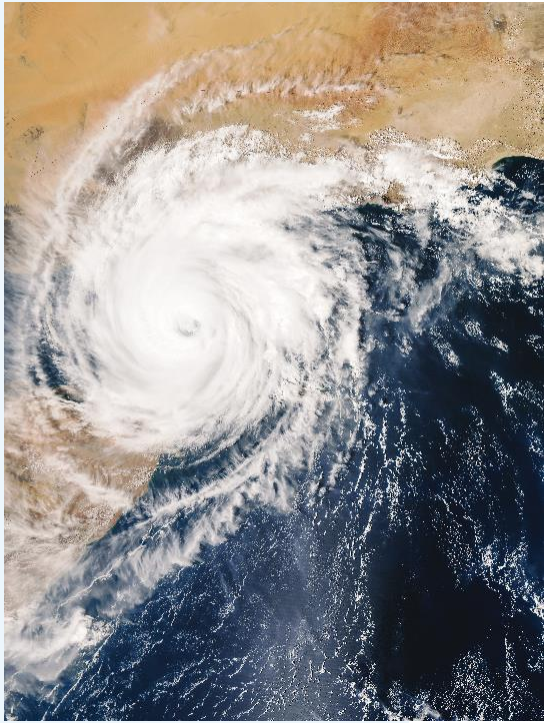


VULCAN CLIMATE MODELING

Are Global Storm-Resolving Models a Path to Reduce Precipitation Biases in Climate Projections?

Chris Bretherton, University of Washington and Vulcan Inc.

GFDL collaborator: Lucas Harris

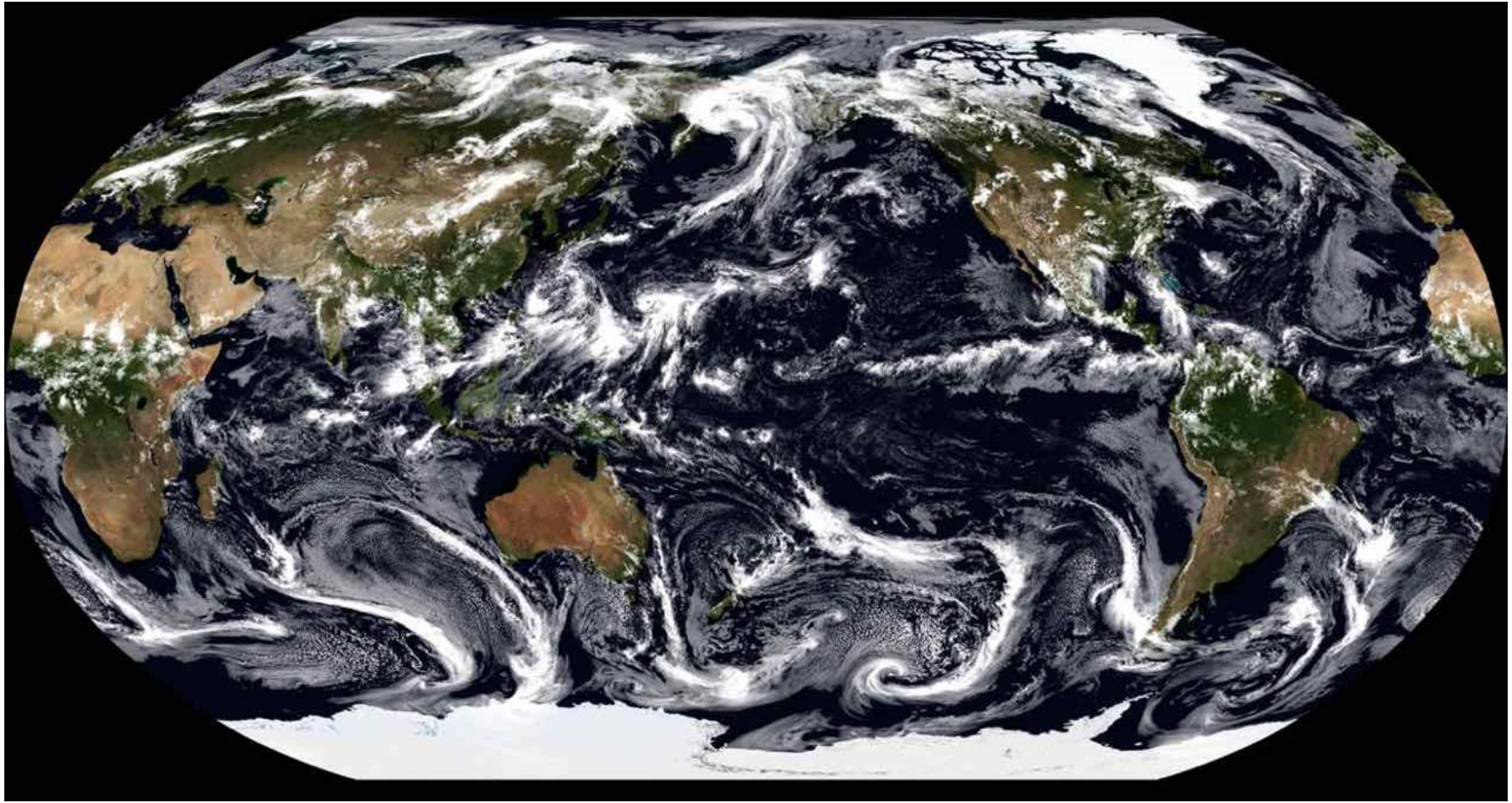
Vulcan Climate Modeling team, esp. Spencer Clark

DYAMOND intercomparison, esp. Falko Judt, Marat Khairoutdinov and Bjorn Stevens

UW PIRE-Cirrus group, esp. Jacqueline Nugent, Rachel Atlas and Peter Blossey

Dec. 1, 2020

NOAA's fine-resolution GSRM: FV3GFS/X-SHiELD

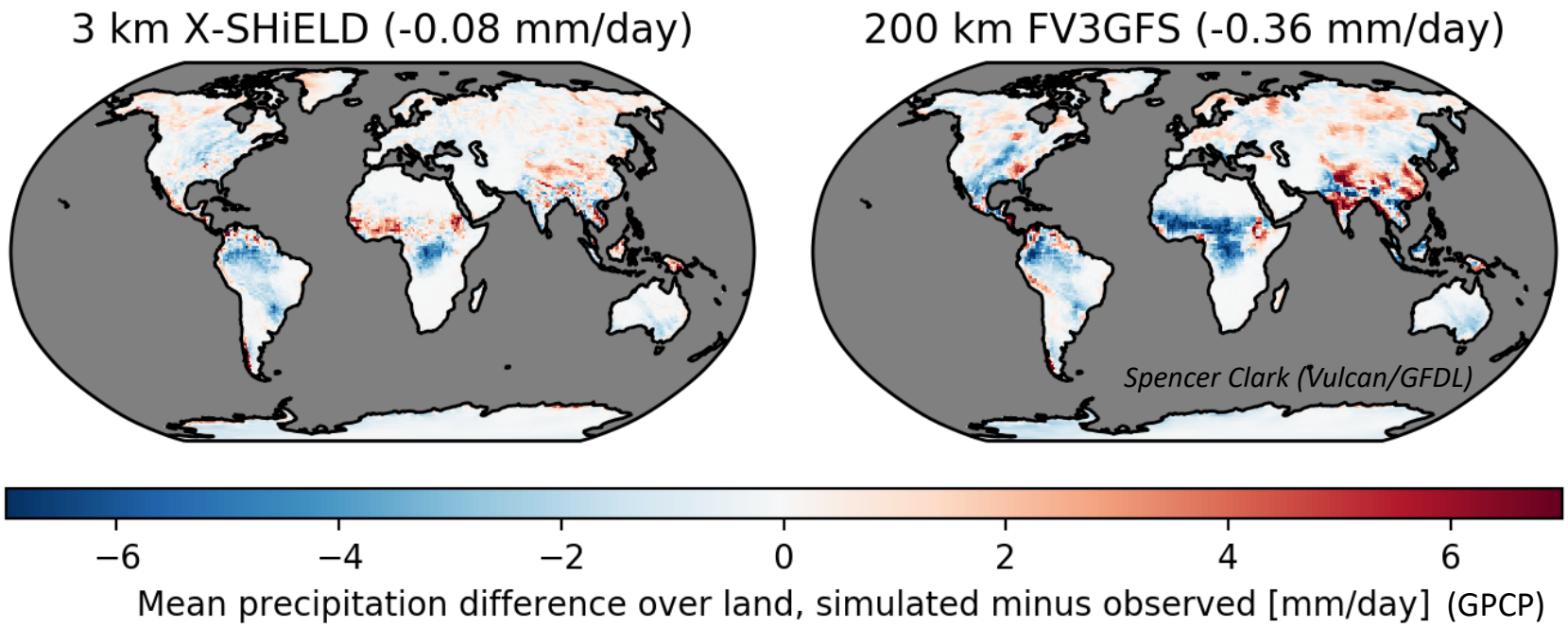


SHiELD 40-day DYAMOND run, S.-J. Lin and Xi Chen, GFDL

Outline

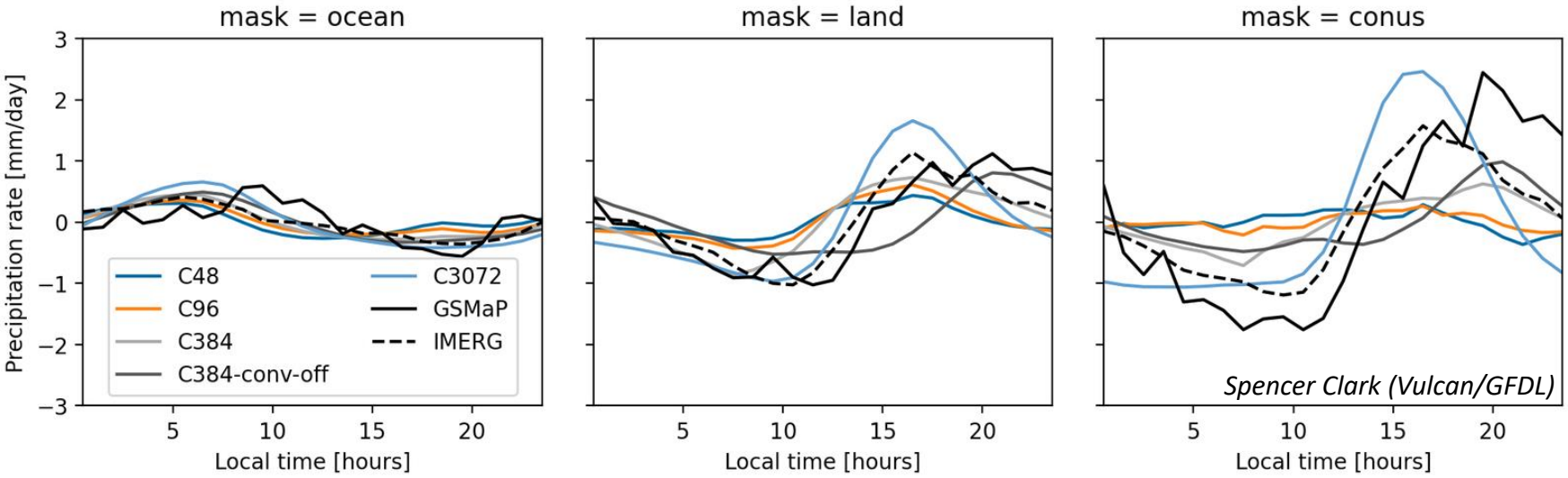
- Can GSRMs (global, dx = 2-5 km, dz ~200-500 m) do precipitation better than GCMs?
- GSRMs, like GCMs, have biases (and therefore need tuning)
- GSRMs are sensitive to their microphysics parameterizations
- How better GSRM rainfall simulations could lead to better GCM rainfall simulations

3 km SHiELD simulates mean rainfall better than 200 km FV3GFS



- 3 km rainfall bias much smaller over sub-Saharan Africa and Himalayas
- Afternoon maximum of precipitation over land is also better simulated

3 km GSRM improves diurnal cycle of precip over land

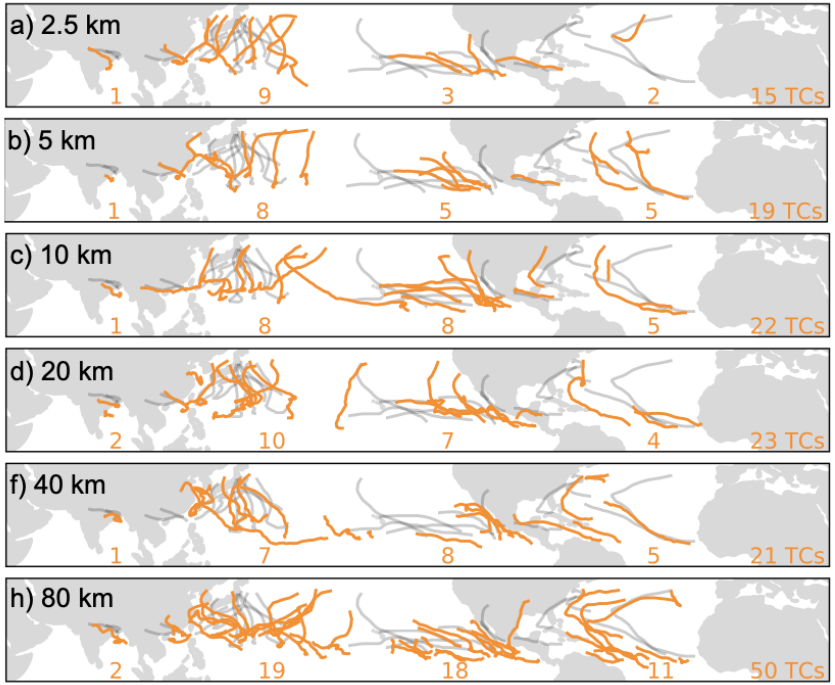


- In SHiELD, 25 km and coarser grids all make too weak a diurnal cycle over land
- 25 km with no deep convection stronger but has a 4 hr phase delay
- 3 km has too strong afternoon peak compared to IMERG

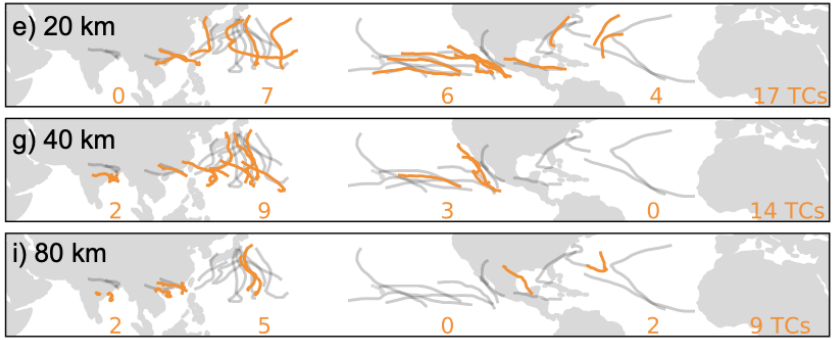
✓ Can GSRMs do precipitation better than GCMs? - yes, but not perfect

TC dependence on grid resolution in ICON GSRM

ICON no-conv



ICON conv



With conv param, coarse GCM ⟶ few TCs

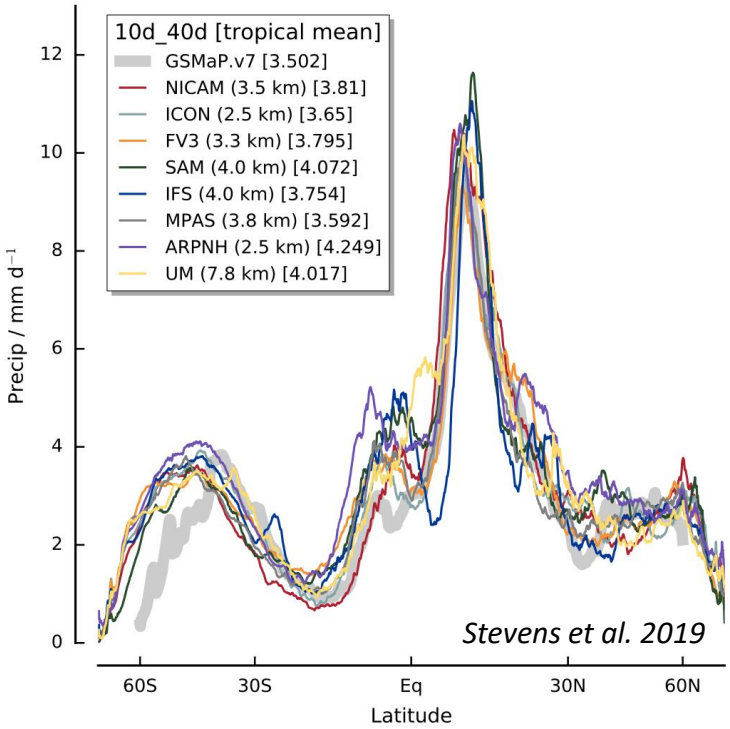
W/o conv param, coarse GCM ⟶ excess TCs

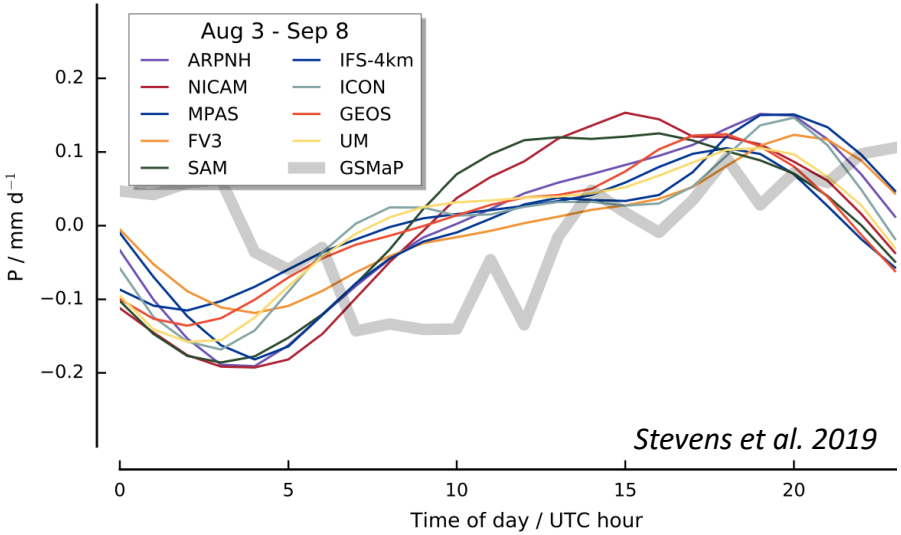
✓ TC rainfall better in GSRM than coarse GCM

Judt et al. 2020

Do GSRMs simulate organized precipitating convection similarly?

DYAMOND intercomparison: 40 day free run starting 1 Aug 2016, specified SST (Stevens et al. 2019); 4 US + 4 European + 1 Japanese GSRMs, 3-20x real time

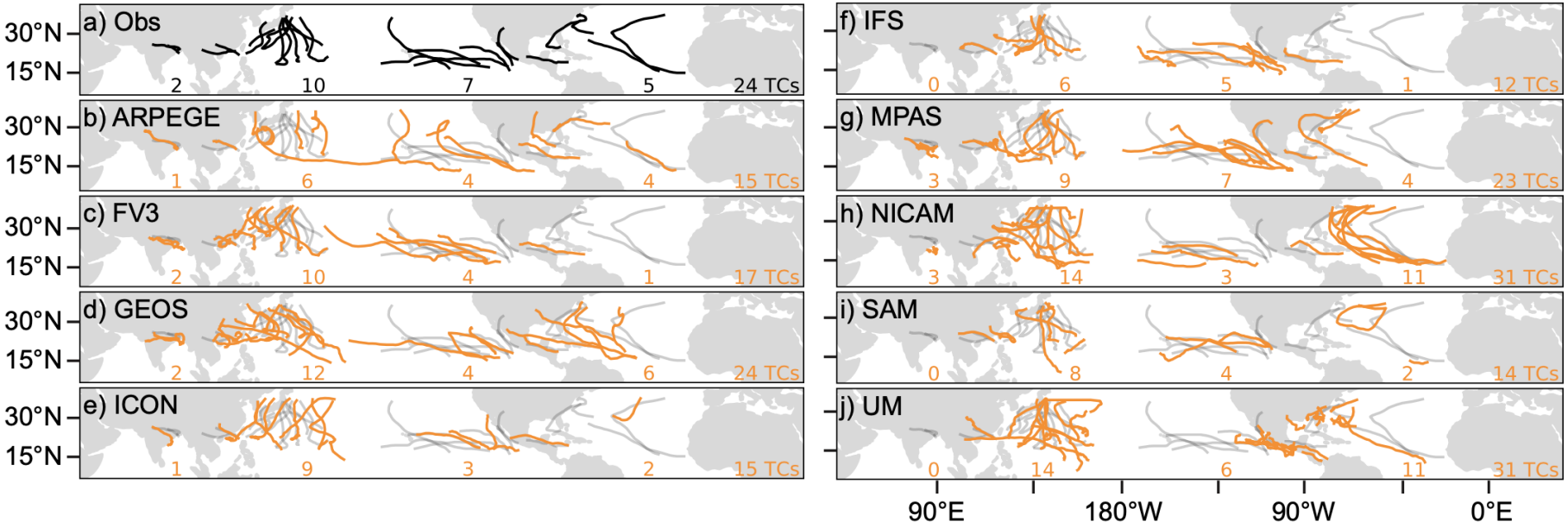




✓ Zonal mean and diurnal cycle are a bit more similar than a comparable sample of GCMs.

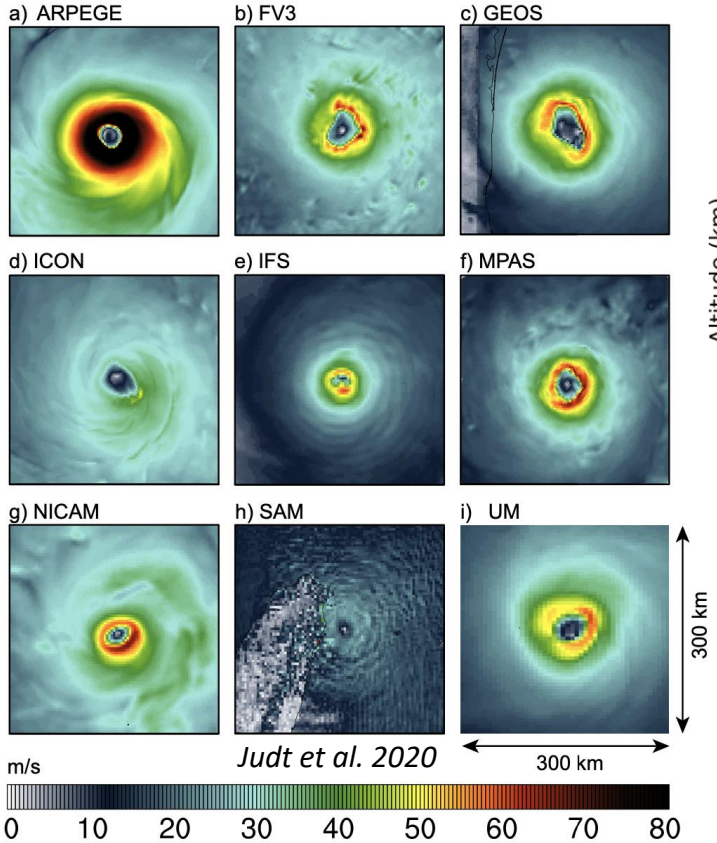
TC track statistics are qualitatively similar between DYAMOND GSRMs

Judt et al. 2020



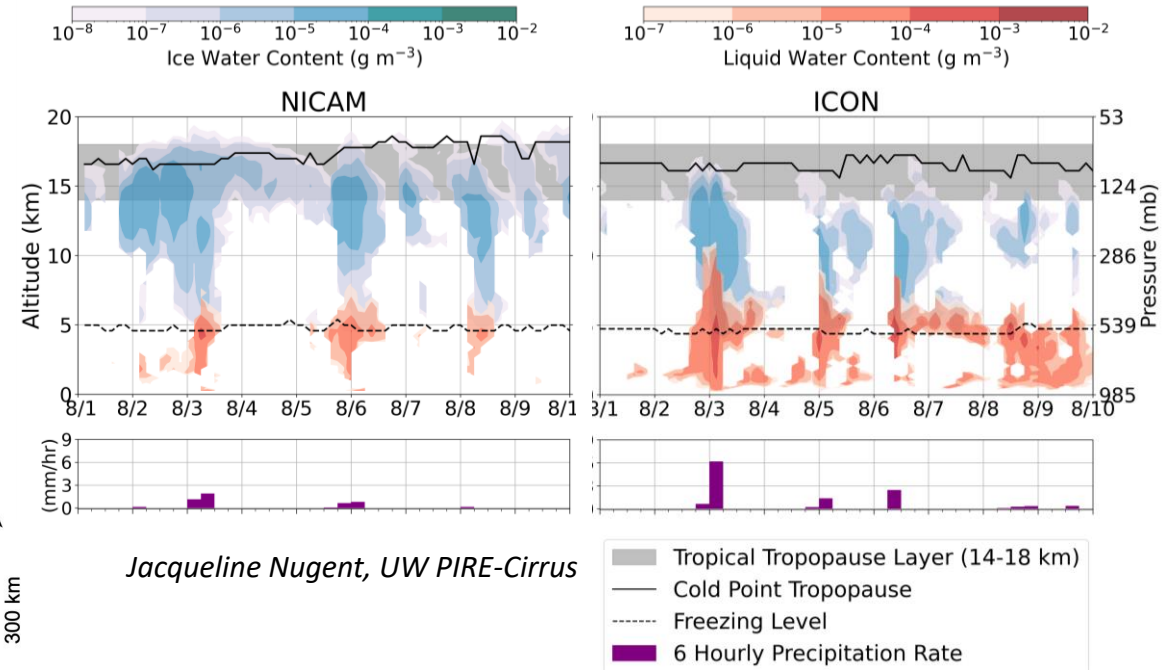
But deep convective structures and related clouds vary between GSRMs

Tropical cyclones



Judt et al. 2020

Sahel deep convective squall lines



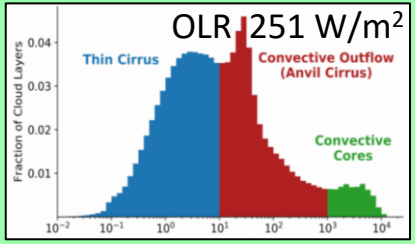
Jacqueline Nugent, UW PIRE-Cirrus

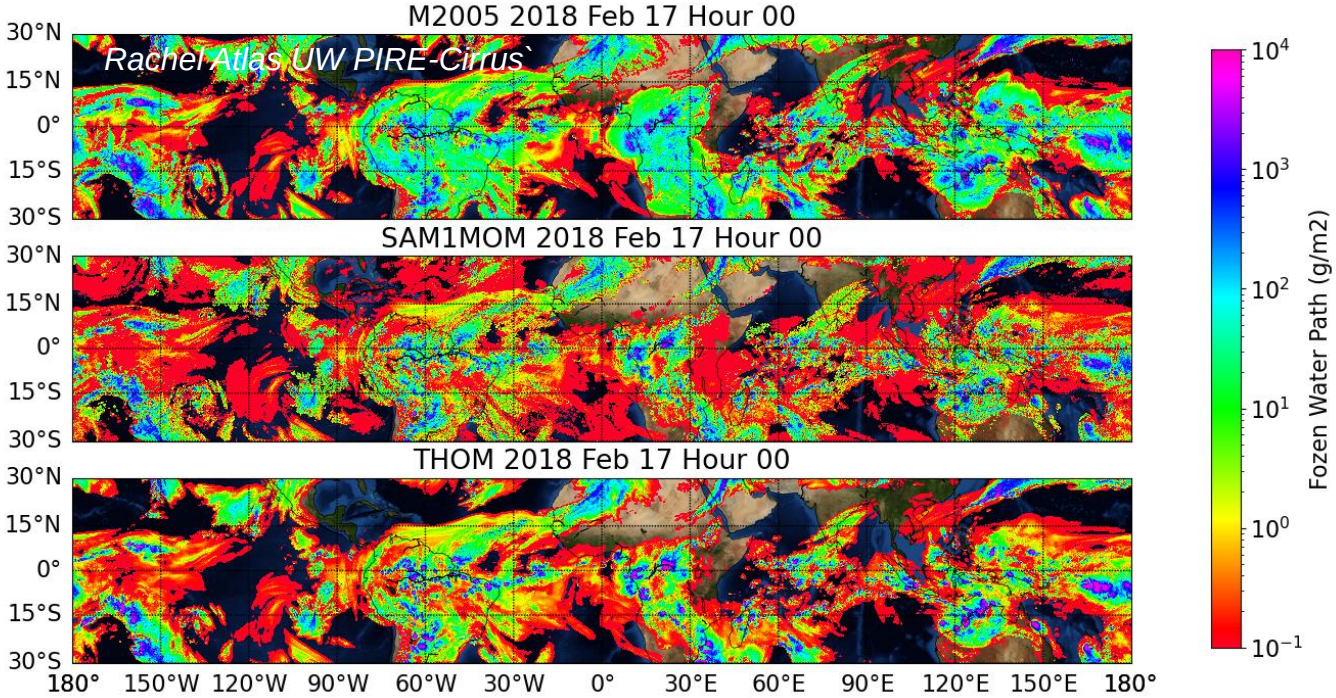
PBL, microphysics, land params + dycore
all cause differences between GSRMs

Ice microphysics matters in GCRMs

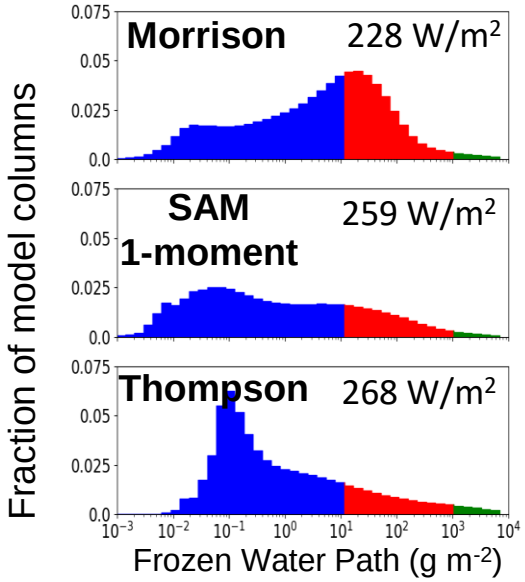
- Global SAM, dx ~ 4 km, 75 layers, 5-day nudged hindcasts
- Morrison microphysics has too much thick anvil cirrus
- Thompson microphysics has mostly thin cirrus
- This explains their large tropical OLR biases

DARDAR analysis
Sokol and Hartmann 2020





Forecast day 2-5, 15 S-15 N



Use machine learning to bias-correct a GCM to evolve like a GSRM

Goal: Train an ML correction to supplement the physical parameterizations of a coarse-grid climate model with a 25-200 km grid so it evolves like a 'reference' fine-grid GSRM

- Aquaplanet: Brenowitz and Bretherton (2018, 2019), Yuval and O'Gorman (2020)
- Real geography is more challenging.
- A small ML team at Vulcan Climate Modeling, in partnership with GFDL, has adapted FV3GFS to this task using 'pressure-level coarsening' to horizontally average fine-grid outputs to coarse grid.

Nudge coarse model to fine for ML training

$a(t,x,y,p)$: advected scalar (e.g. humidity).

Coarsened fine-res scalar (known) $\overline{a_f}(t,x,y,p)$

Nudged coarse-resolution scalar $a_n(t,x,y,p)$ which tracks $\overline{a_f}(t,x,y,p)$:

$$\frac{\partial a_n}{\partial t} = -\mathbf{v}_n \cdot \nabla a_n + Q_a^p + \Delta Q_a^N \cong \frac{\partial \overline{a_f}}{\partial t}$$

$\longrightarrow$ Nudging tendency $\Delta Q_a^N = \frac{\overline{a_f} - a_n}{\tau}$

Nudging time scale $\boldsymbol{\tau}$ = 3 hours used for 200 km coarse & 3 km fine scales

- Slow enough to keep a_n near its 'slow manifold'
- Fast enough to keep a_n near the coarsened fine model $\bar{a}_f$

Machine learn the nudging tendency as function of nudged model column state and use the resulting ΔQ_a^{ML} as a forecast correction to the coarse model:

$$\frac{\partial a_c}{\partial t} = -\mathbf{v}_c \cdot \nabla a_c + Q_a^p + \Delta Q_a^{ML}$$

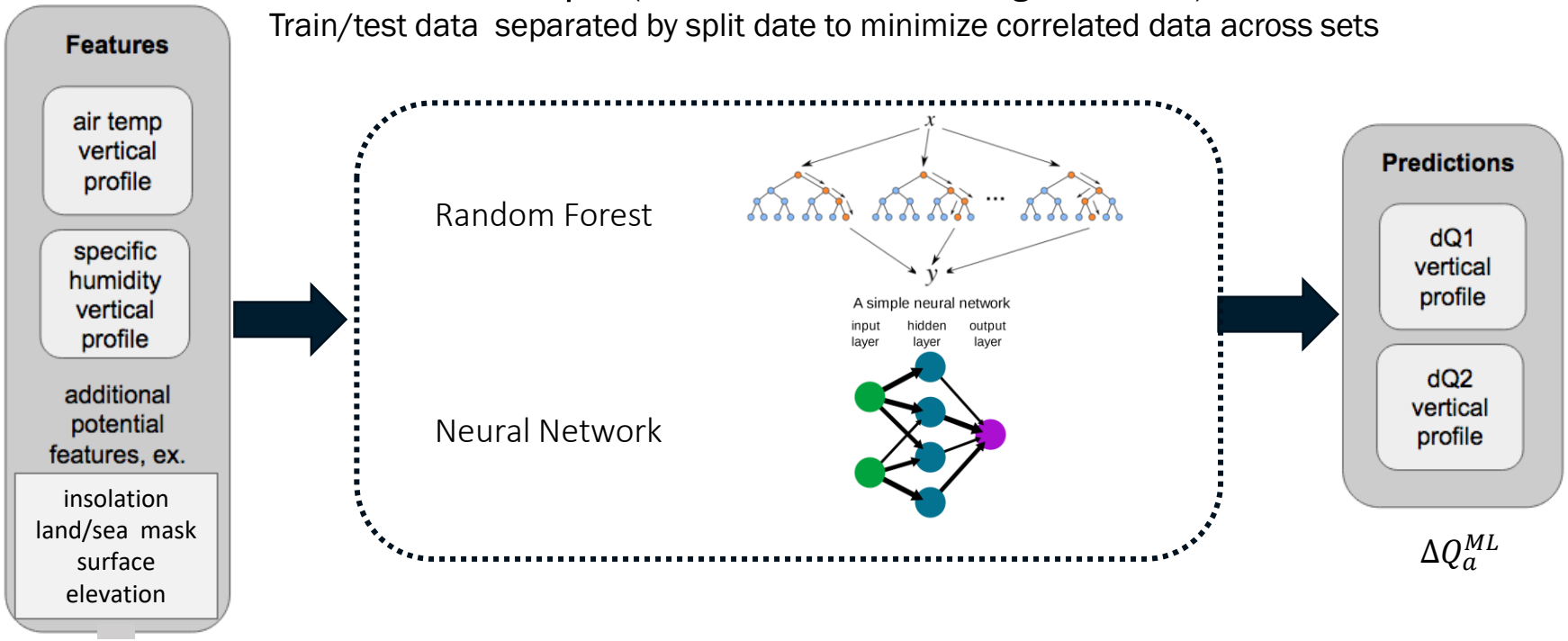
Machine learning: model training

From available training output (e. g. nudging tendencies every 15 min for 40 d), subset to:

Training set = 1.7M samples (130 initializations x 13824 grid columns)

Test set = 660K samples (48 initializations x 13824 grid columns)

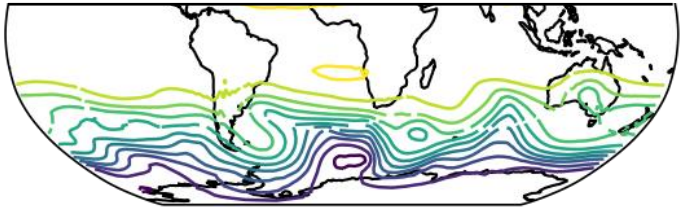
Train/test data separated by split date to minimize correlated data across sets



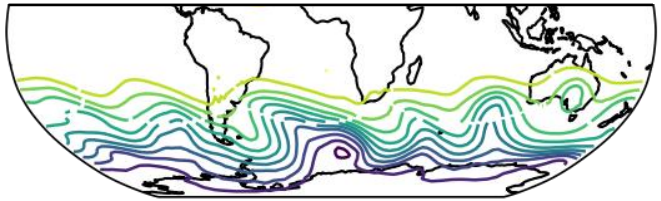
Improved weather forecast skill

Example: 500 hPa height

Simulation



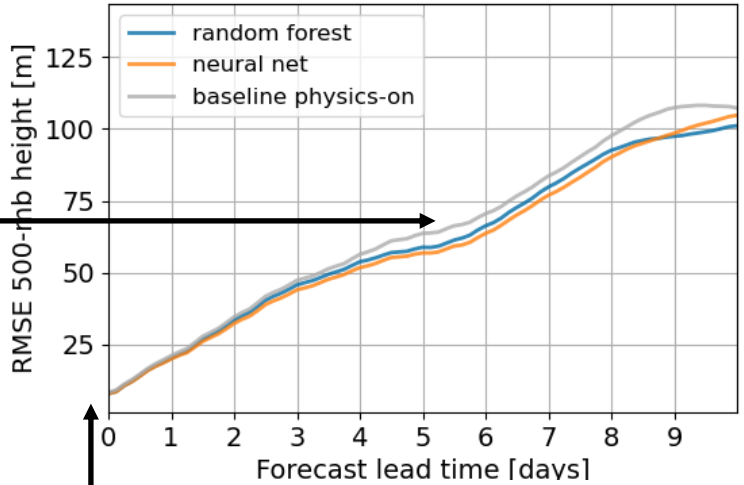
Reference



Vulcan Climate Modeling

$$\sqrt{\sum (x_{sim} - x_{obs})^2}$$

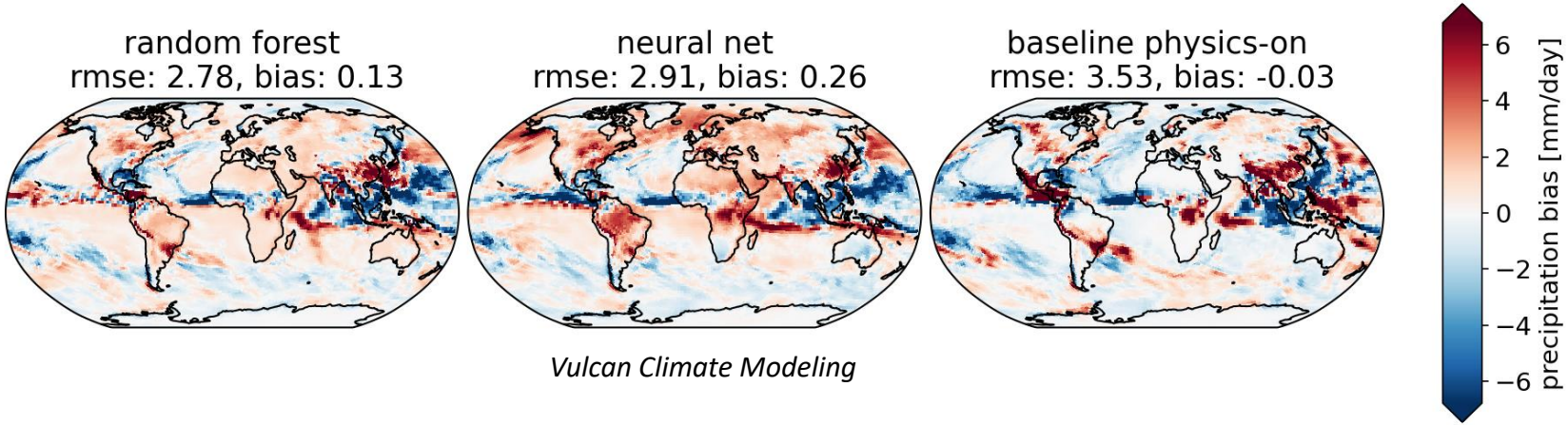
Error vs. forecast time
Lower is better



Two simulations initialized with state of atmosphere on August 5, 2016

Improvements in precipitation bias

- N2F improves 35-day mean precipitation bias pattern by 20% (RF)/15 % (NN)
- However, biases increase in dry subtropics, and both have overall wet biases

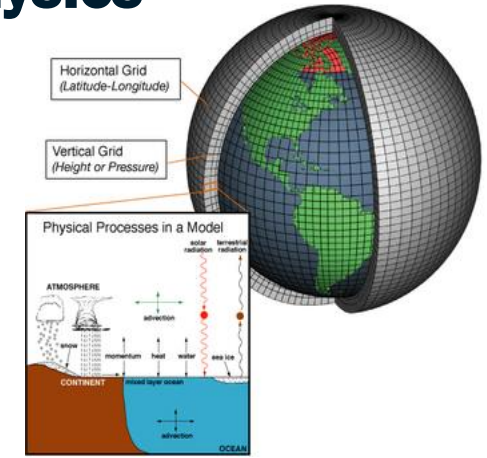


Vulcan Climate Modeling

Conclusions

- GSRMs can simulate precipitation better than GCMs over land and mountains
- GSRMs simulate convective structures such as TCs and squall lines but with intermodel differences due to their remaining parameterizations & dycore
- Uncertain ice microphysics parameterizations strongly affect radiative fluxes in GSRMs, which will feed back on large-scale circulations and precipitation patterns
- Machine learning shows promise in leveraging improved GSRM representation of physical processes to coarser-grid GCMs that we can run for decades to centuries
- A vital challenge is tuning GSRM cloud and land surface parameterizations to achieve their potential for weather and climate fidelity. Many processes can be tuned in a computationally affordable way on weather timescales using hindcasts.

Coarse-resolution dynamics and parameterized physics



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

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

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 (m/s/day)

Advection (numerical solver)

Column physics approximation

Physical parameterizations depend on the local atmospheric column conditions

- Typical parameterization inputs
  - Profiles of humidity, temperature, winds
  - sunlight, surface properties…
- Typical parameterization outputs:
  - Tendencies of humidity, temperature, winds
  - clouds, rain, snow….

This simplification is most appropriate when grid boxes are much wider than they are high.

Single Atmospheric Column

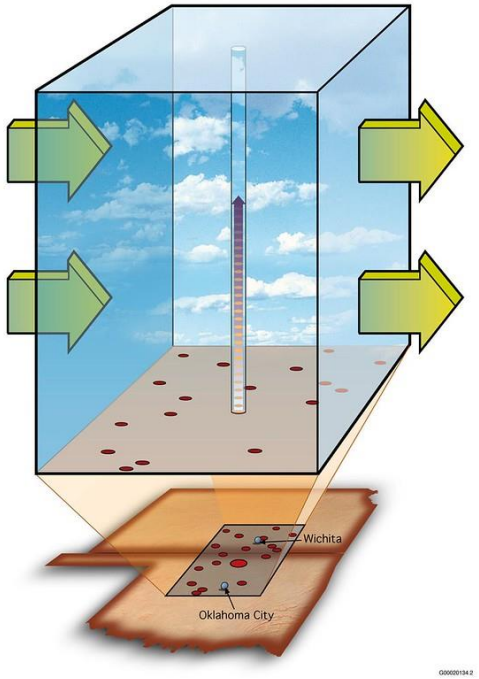


Image courtesy of the U.S. Department of Energy Atmospheric Radiation Measurement (ARM) user facility.

Conclusions

- At Vulcan, we have developed a sophisticated cloud-based workflow for applying Python-based machine learning to a full-complexity operational global numerical weather forecast model written in Fortran.
- We have developed machine learning schemes that improve the skill of global weather forecasts and their time-mean rainfall distribution.
- Our current ML schemes need to add physical constraints that keep them from excessively drifting from a reference climate.