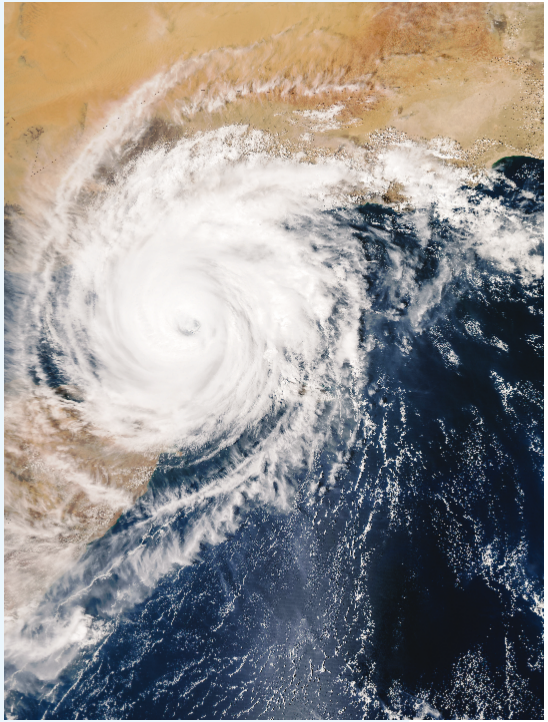


VULCAN CLIMATE MODELING

Machine Learning Climate Model Dynamics: Offline versus Online Performance

Noah Brenowitz, Brian Henn, Jeremy McGibbon, Spencer Clark, Anna Kwa, Andre Perkins, Oli Watt-Meyer, Chris Bretherton

Climate models help predict future changes

- Numerically solves fluid mechanics equations
- A longer weather simulation (w/ coupling to ocean/ice)
- Many parametrizations
- Discretized:
  - Large grid size (50 – 100 km)

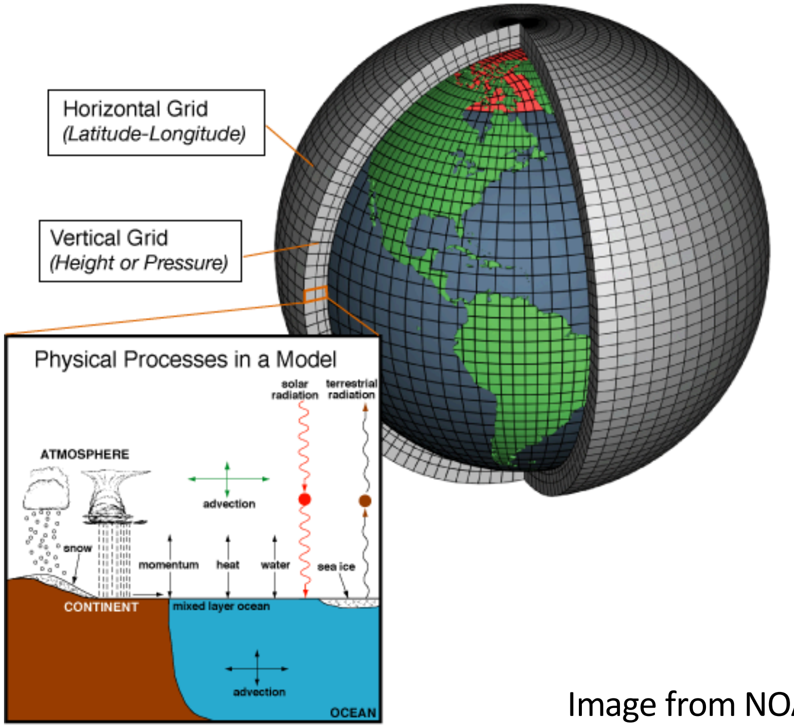
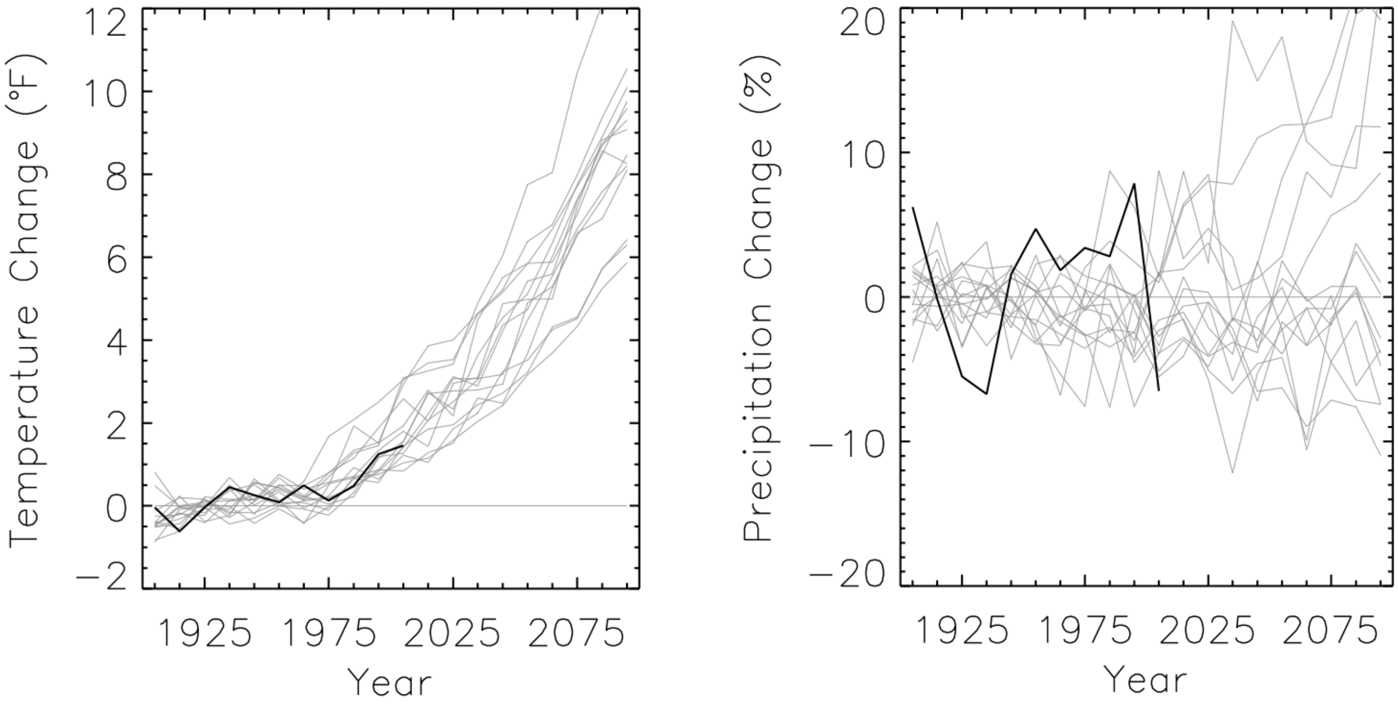


Image from NOAA

Climate models find local precipitation trends harder to predict than temperature

WA/OR/ID average



VCM pioneers novel software to improve weather and climate models

VCM = Vulcan Climate Modeling, a philanthropic, open-source project of Vulcan Inc. in Seattle (Paul Allen)

https://www.vulcan.com/Our-Work/Climate/Advancing-Climate-Science.aspx

Two interlocking groups, partnering with NOAA's Geophysical Fluid Dynamics Lab, using next-gen version of US global weather forecast model

- **"Faster"** (led by Oli Fuhrer): Use a domain-specific language (DSL) to rewrite the model to run faster on modern supercomputers (CPU or GPU), enabling multiyear climate simulations with 1-3 km grids
- **"Better"** (led by Chris Bretherton): Train machine learning (ML) on these simulations to increase accuracy of rainfall predictions by an affordable 25 km-grid GCM

These projects are mutually beneficial:

- **"Faster" gives training data for "Better":** We need fast high-resolution models to provide ML training data
- **"Better" gives code that runs on the GPU "Faster":** ML runs on GPUs very efficiently

We are 1 year into a 2-year pilot phase, focused on the atmospheric model component, FV3GFS

Parameterizations as a machine learning problem

- Inputs
  - Weather variables: Humidity, temperature, sunlight, elevation
- Outputs:
  - Heating and moistening rates due to unresolved storms

Single Atmospheric Column

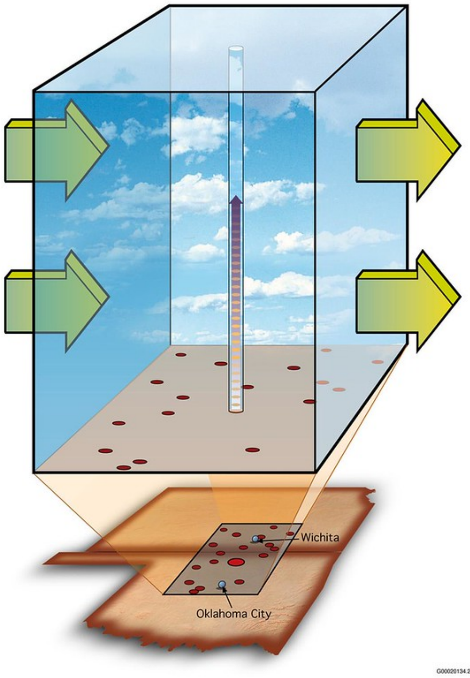


Image courtesy of the U.S. Department of Energy Atmospheric Radiation Measurement (ARM) user facility.

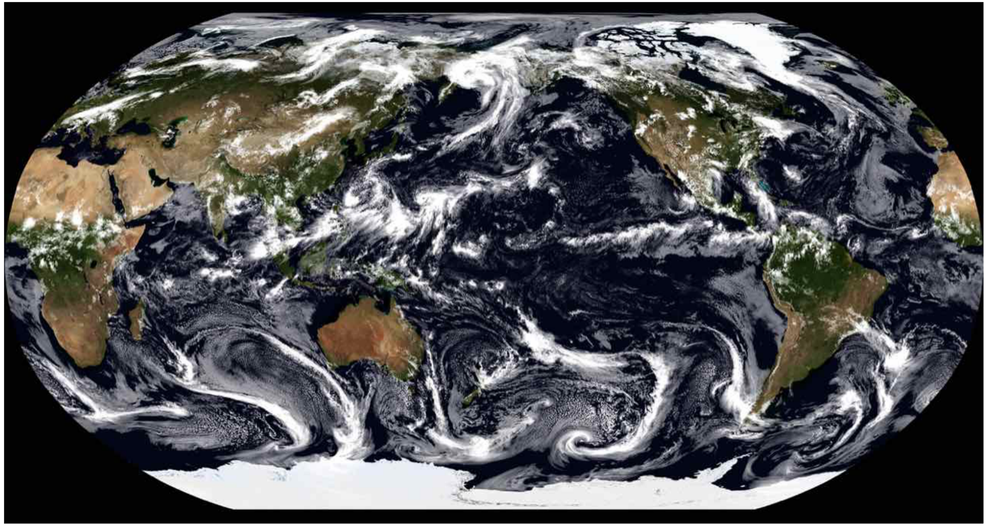
Literature overview

Authors	Training Data	Evaluation Technique	ML Model
Krasnopalsky, et. al. (2010, 2013)	Local Cloud Resolving Model	Offline	NN
Brenowitz and Bretherton 2018, 2019	Global Cloud Resolving Model (GCRM), Aquaplanet	offline (2018), single column model (2018), online (2019)	NN
Pritchard, Rasp, Gentine, and others	Super-parameterized (SP) aqua-planet	Offline (2018) and online (2019)	NN
Yuval and O’Gorman	GCRM, aqua-planet	Offline (2019) and online (2020)	RF(2019), NN(2020)
Han, et. al. (2020)	SP, realistic topography	Offline, single column model	NN
Mooers, et. al. (2020)	SP, realistic topography	Offline	NN
Brenowitz, et. al (2020)	GCRM, realistic topography	Offline, online	NN and RF

This presentation

Training Data

- NOAA's fine-resolution GSRM: FV3GFS/X-SHiELD
- C3072 Horizontal resolution (approximately 3 km)
  - Resolves large thunderstorms
- Nudged towards observations
- Initialized at midnight (UTC) on August 1, 2016
- 40 days, saved at C384 resolution (25 km) every 15 minutes



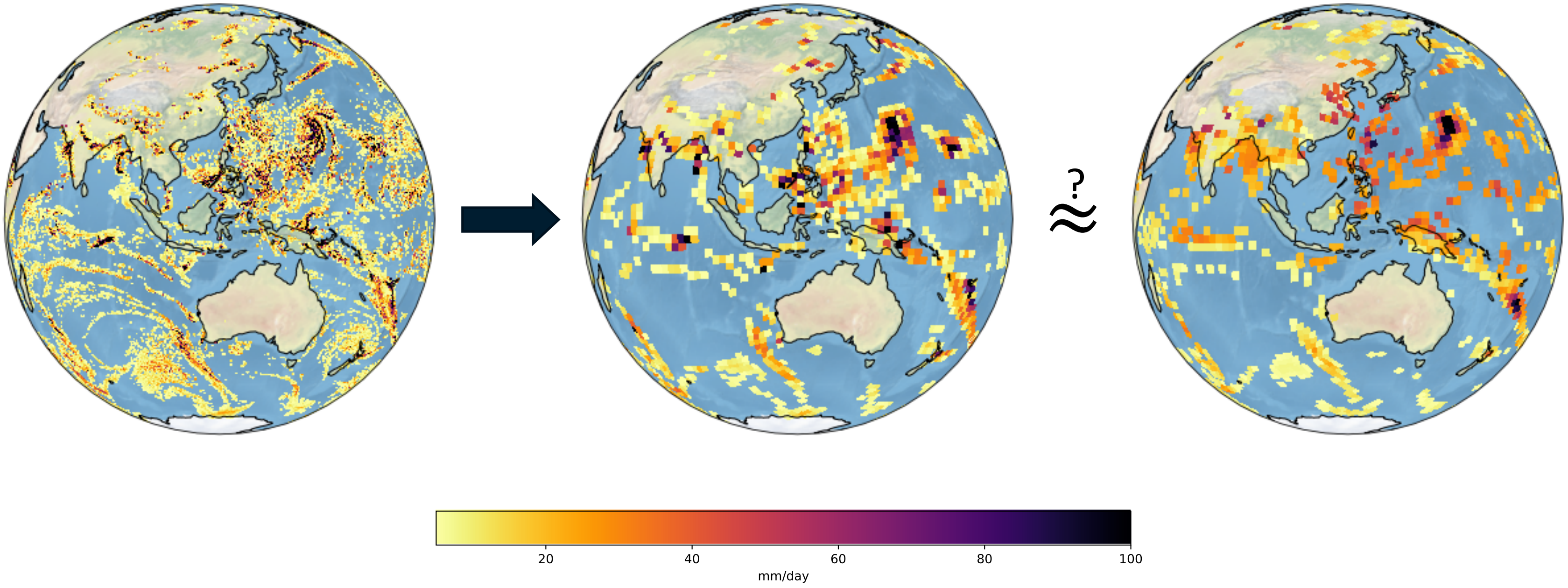
SHiELD 40-day DYAMOND run, S.-J. Lin and Xi Chen, GFDL

ML parameterizations via coarse graining

Fine-resolution Reference model

Coarsened Reference Model

Baseline Parameterization



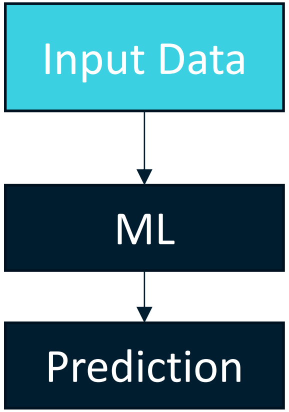
Precipitation

ML Models

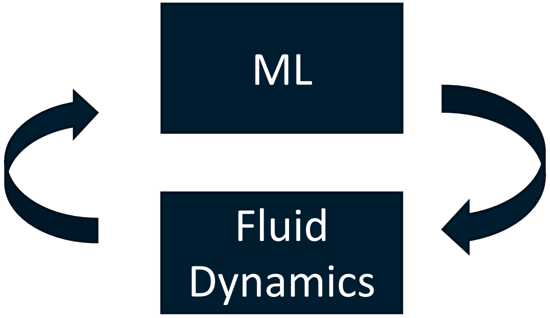
- Random Forest
  - Max depth: 13
  - Ensemble size: 13
- Neural Network
  - Multilayer perceptron
  - 2 layers, 128 nodes per layer
  - ReLU activation

Evaluation: Online ≠ Offline

Offline Skill = “Traditional ML”

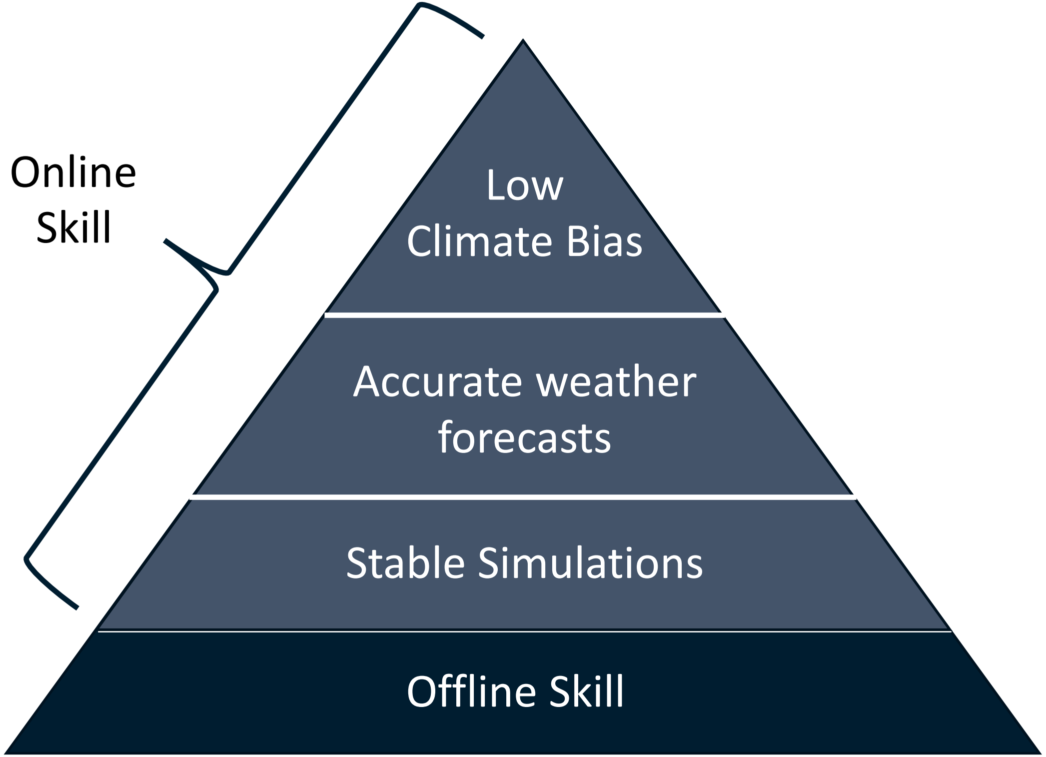


Online = Coupled to Fluid Dynamics



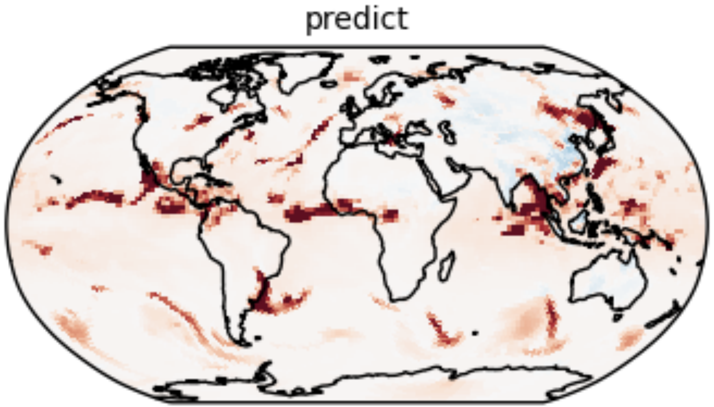
Many iterations

ML Parameterization “Hierarchy of Needs” for Climate Modeling

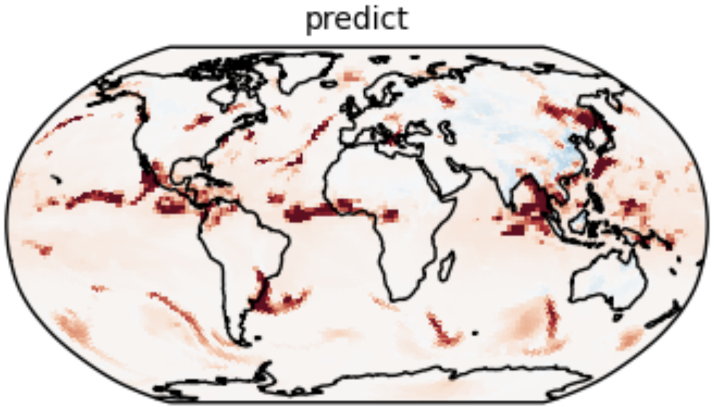


RF and NN make similar predictions “offline”

Random Forest



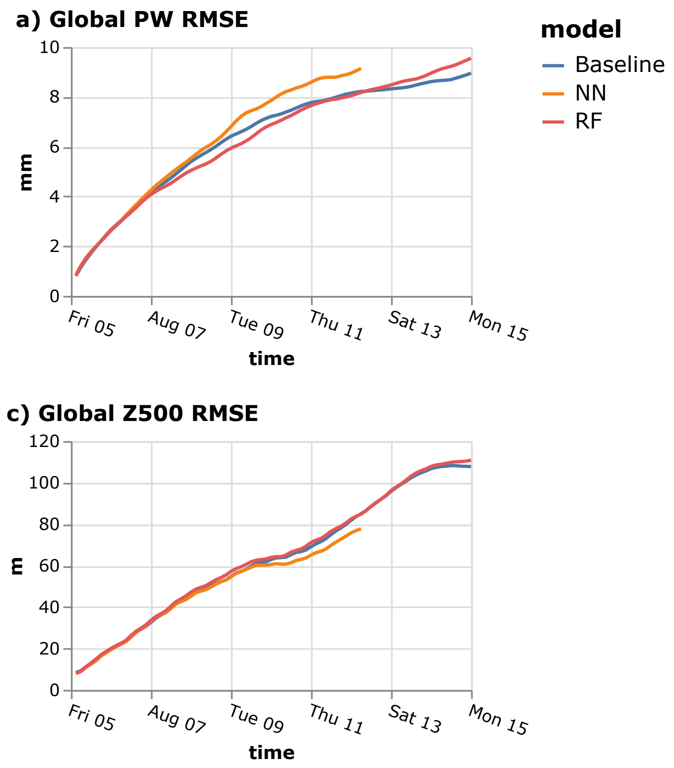
Neural Network



Net “drying” = - precipitation

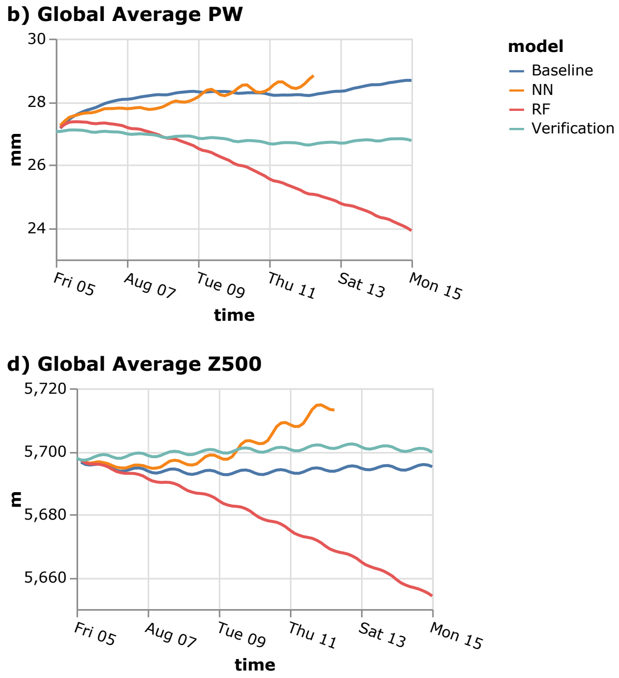
Forecast Skill (online)

- Weather simulations initialized on Aug. 8, 2016 at 0 UTC
- Root-mean squared error of
  - Moisture (PW)
  - PWSE
- Random forest outperforms baseline
- Neural network is unstable and crashes



Climate drifts in RF and NN

- Global average precipitable water (PW) decreases in RF
  - Too much rain!
- Global average 500 mb height decreases in RF
  - Changes in circulation
- NN is more sensitive to drifts and crashes



Thanks!

https://arxiv.org/abs/2011.03081