Limitations of Machine Learning Approaches for Emulating Simplified Physical Parameterizations in CAM6

Garrett C. Limon

University of Michigan

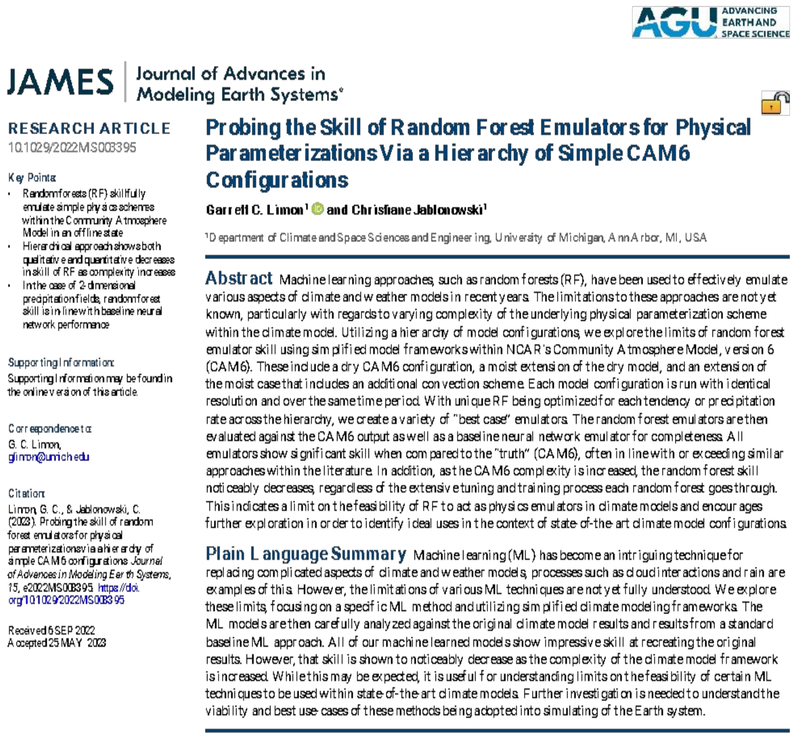
Department of Climate and Space Sciences and Engineering

2023 CESM Workshop

Tuesday, June 13th, 2023

Overarching Questions

- Can Machine Learning (ML) methods reproduce physical parameterizations in CAM6?
- How does the ML performance depend on the complexity of the parameterization scheme?
- Can domain knowledge improve our use of ML?
- Complete discussion in recently published manuscript



AGU ADVANCING EARTH AND SPACE SCIENCE

JAMES | Journal of Advances in Modeling Earth Systems®

RESEARCH ARTICLE
10.1029/2022MS003395

Key Points:
- Random forests (RF) skillfully emulate simple physics schemes within the Community Atmosphere Model in an offline state
- Hierarchical approach shows both qualitative and quantitative decreases in skill of RF as complexity increases
- In the case of 2-dimensional precipitation fields, random forest skill is in line with baseline neural network performance

Supporting Information:
Supporting Information may be found in the online version of this article.

Correspondence to:
G. C. Limon,
glimon@umich.edu

Citation:
Limon, G. C., & Jablonowski, C. (2023). Probing the skill of random forest emulators for physical parameterizations via a hierarchy of simple CAM6 configurations. *Journal of Advances in Modeling Earth Systems*, 15, e2022MS003395. https://doi.org/10.1029/2022MS003395

Received 6 SEP 2022
Accepted 25 MAY 2023

Probing the Skill of Random Forest Emulators for Physical Parameterizations Via a Hierarchy of Simple CAM6 Configurations

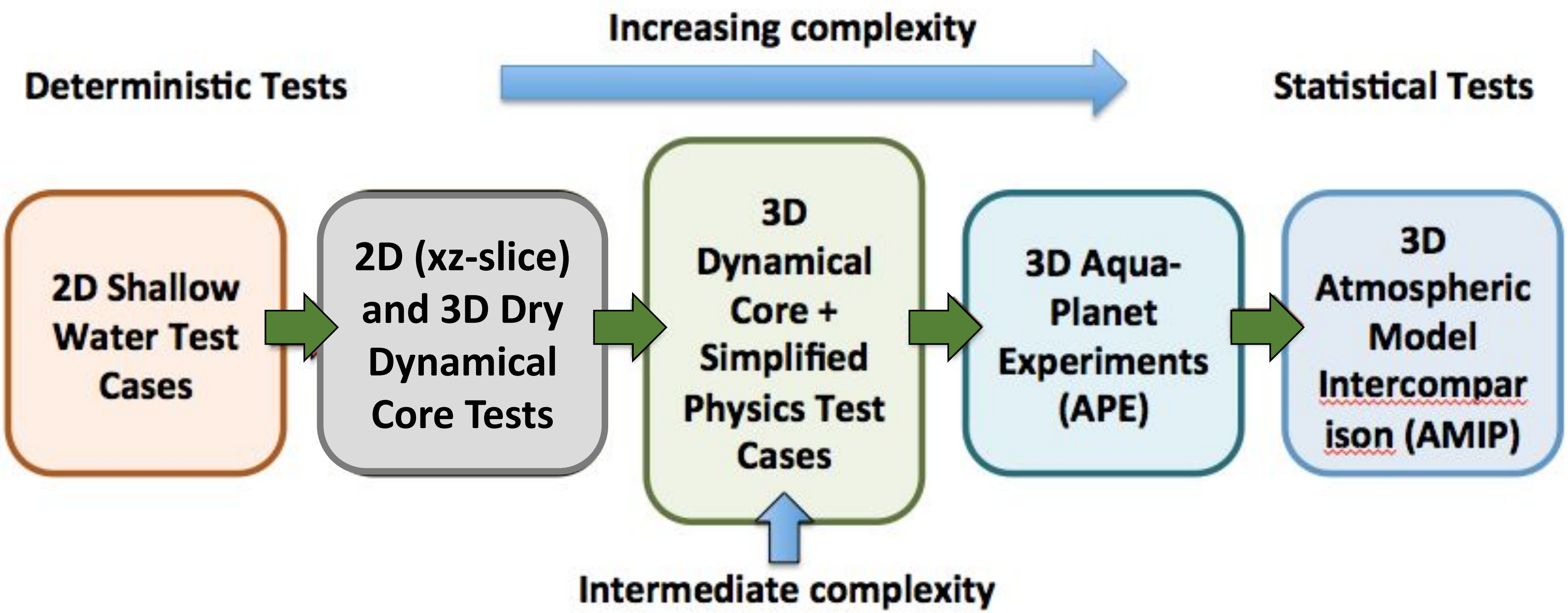
Garrett C. Limon[1] and Christiane Jablonowski[1]

[1]Department of Climate and Space Sciences and Engineering, University of Michigan, Ann Arbor, MI, USA

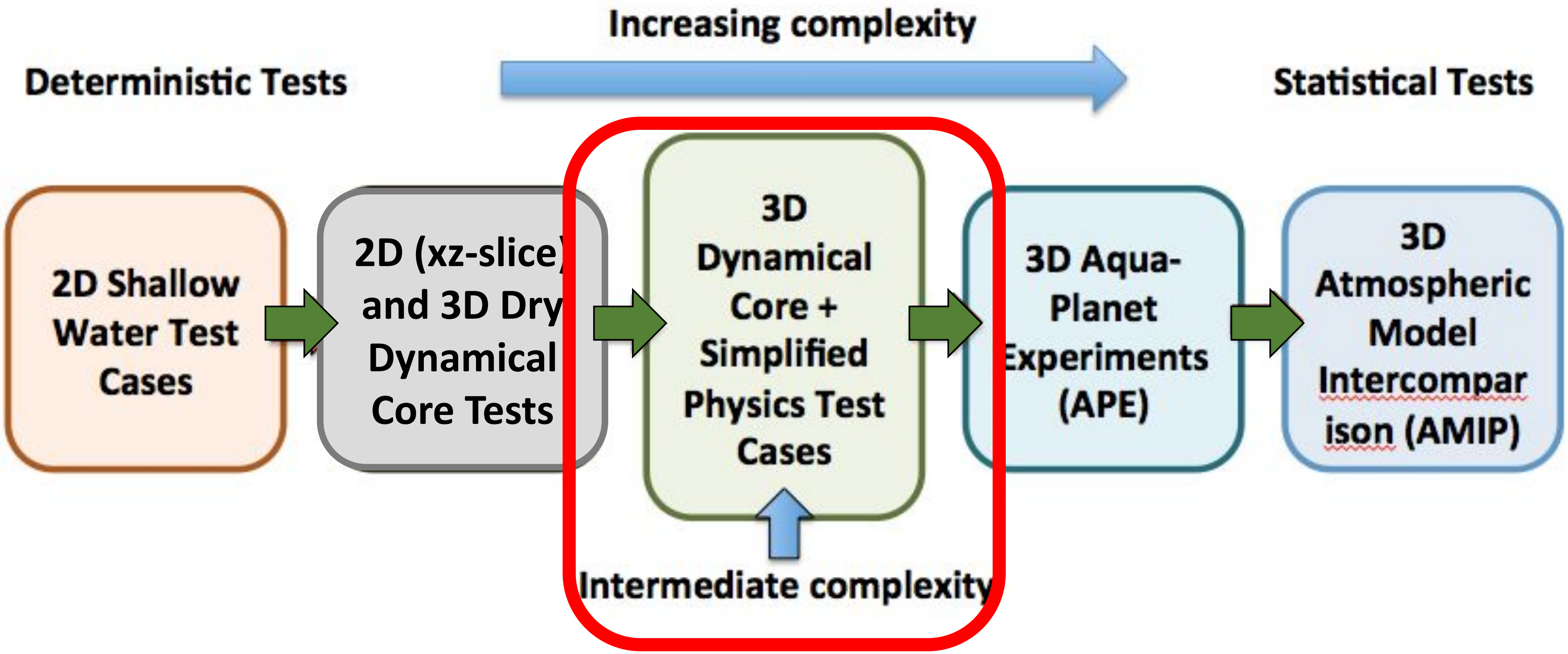
Abstract Machine learning approaches, such as random forests (RF), have been used to effectively emulate various aspects of climate and weather models in recent years. The limitations to these approaches are not yet known, particularly with regards to varying complexity of the underlying physical parameterization scheme within the climate model. Utilizing a hierarchy of model configurations, we explore the limits of random forest emulator skill using simplified model frameworks within NCAR's Community Atmosphere Model, version 6 (CAM6). These include a dry CAM6 configuration, a moist extension of the dry model, and an extension of the moist case that includes an additional convection scheme. Each model configuration is run with identical resolution and over the same time period. With unique RF being optimized for each tendency or precipitation rate across the hierarchy, we create a variety of "best case" emulators. The random forest emulators are then evaluated against the CAM6 output as well as a baseline neural network emulator for completeness. All emulators show significant skill when compared to the "truth" (CAM6), often in line with or exceeding similar approaches within the literature. In addition, as the CAM6 complexity is increased, the random forest skill noticeably decreases, regardless of the extensive tuning and training process each random forest goes through. This indicates a limit on the feasibility of RF to act as physics emulators in climate models and encourages further exploration in order to identify ideal uses in the context of state-of-the-art climate model configurations.

Plain Language Summary Machine learning (ML) has become an intriguing technique for replacing complicated aspects of climate and weather models, processes such as cloud interactions and rain are examples of this. However, the limitations of various ML techniques are not yet fully understood. We explore these limits, focusing on a specific ML method and utilizing simplified climate modeling frameworks. The ML models are then carefully analyzed against the original climate model results and results from a standard baseline ML approach. All of our machine learned models show impressive skill at recreating the original results. However, that skill is shown to noticeably decrease as the complexity of the climate model framework is increased. While this may be expected, it is useful for understanding limits on the feasibility of certain ML techniques to be used within state-of-the-art climate models. Further investigation is needed to understand the viability and best use-cases of these methods being adopted into simulating of the Earth system.

Bridging the Gap:
Model Hierarchy with Increasing Complexity



Bridging the Gap:
Model Hierarchy with Increasing Complexity



- Moist version of the Held-Suarez test (Thatcher & Jablonowski, 2016)
- Coupled Moist Version with convection scheme (Betts & Miller, 1986)

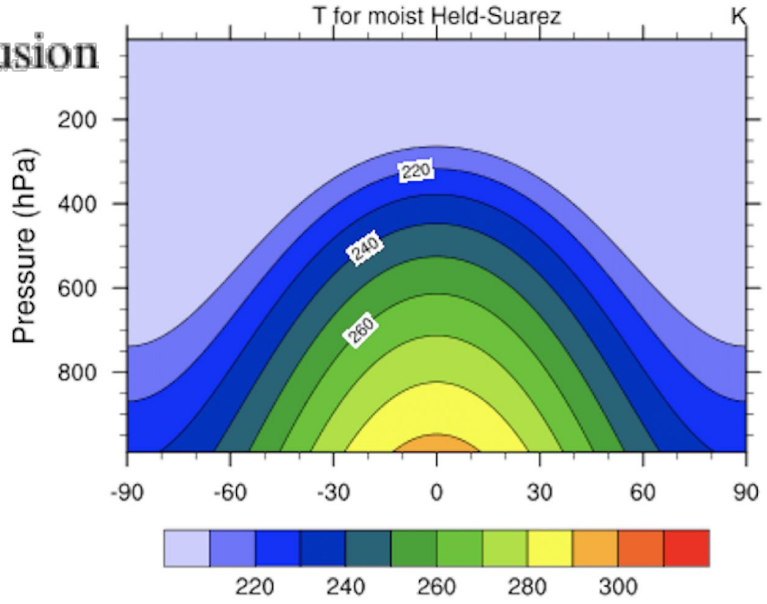
Moist Held-Suarez (TJ)

$$\left(\frac{\partial q}{\partial t}\right)_{\mathrm{TJ}} = -C + \frac{C_E|\vec{v}_a|(q_{\mathrm{sat},s} - q_a)}{z_a} + \mathrm{PBL\,diffusion}$$

$$\left(\frac{\partial T}{\partial t}\right)_{\mathrm{TJ}} = -k_T(\phi,p)\left[T - \tilde{T}_{\mathrm{eq}}(\phi,p)\right] + \frac{L}{c_p}C + \frac{C_H|\vec{v}_a|(T_s - T_a)}{z_a} + \mathrm{PBL\,Diffusion}$$

$$P_{\mathrm{ls}} = \frac{1}{\rho_{\mathrm{water}}g}\int_{p_{top}}^{p_s} C\,dp$$

L: Latent heat of vaporization
C: Condensation rate



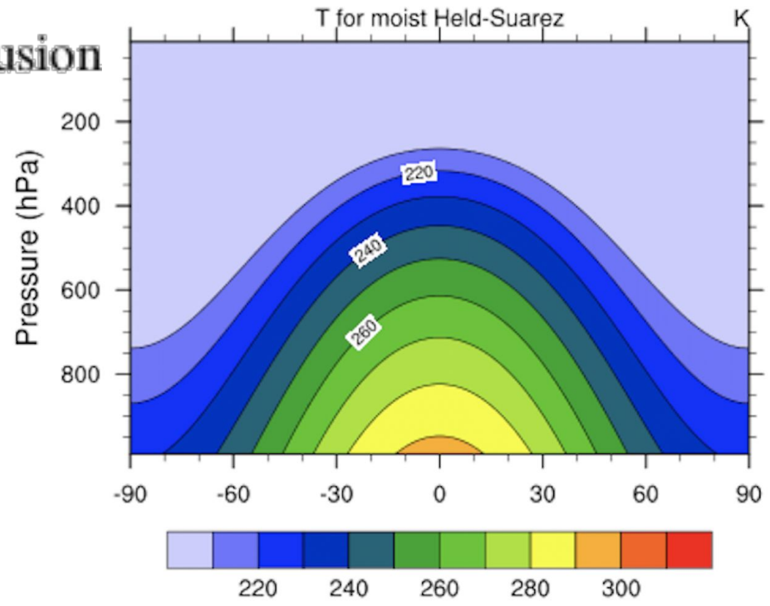
Moist Held-Suarez (TJ)

$$\left(\frac{\partial q}{\partial t}\right)_{\text{TJ}} = -C + \frac{C_E|\vec{v}_a|(q_{\text{sat},s} - q_a)}{z_a} + \text{PBL diffusion}$$

$$\left(\frac{\partial T}{\partial t}\right)_{\text{TJ}} = -k_T(\phi,p)\left[T - \tilde{T}_{\text{eq}}(\phi,p)\right] + \frac{L}{c_p}C + \frac{C_H|\vec{v}_a|(T_s - T_a)}{z_a} + \text{PBL Diffusion}$$

$$P_{\text{ls}} = \frac{1}{\rho_{\text{water}} g}\int_{p_{top}}^{p_s} C\,dp$$

L: Latent heat of vaporization
C: Condensation rate



w/ Betts-Miller Convection (TJBM)

$$\left(\frac{\partial q}{\partial t}\right)_{\text{BM}} = -\frac{q - q_{\text{ref}}}{\tau} + \left(\frac{\partial q}{\partial t}\right)_{\text{TJ}}$$

$$\left(\frac{\partial T}{\partial t}\right)_{\text{BM}} = -\frac{T - T_{\text{ref}}}{\tau} + \left(\frac{\partial T}{\partial t}\right)_{\text{TJ}}$$

*Mathematical description of convective precipitation can be found in Frierson (2007)

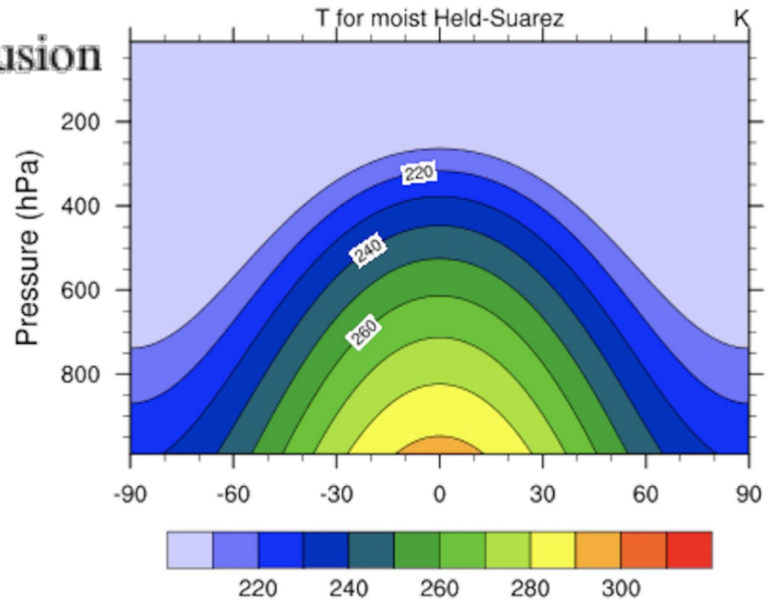
Moist Held-Suarez (TJ)

$$\boxed{\left(\frac{\partial q}{\partial t}\right)_{\mathrm{TJ}}} = -C + \frac{C_E|\vec{v}_a|(q_{\mathrm{sat},s} - q_a)}{z_a} + \mathrm{PBL\,diffusion}$$

$$\boxed{\left(\frac{\partial T}{\partial t}\right)_{\mathrm{TJ}}} = -k_T(\phi,p)\left[T - \tilde{T}_{\mathrm{eq}}(\phi,p)\right] + \frac{L}{c_p}C + \frac{C_H|\vec{v}_a|(T_s - T_a)}{z_a} + \mathrm{PBL\,Diffusion}$$

$$P_{\mathrm{ls}} = \frac{1}{\rho_{\mathrm{water}}g}\int_{p_{top}}^{p_s} C\,dp$$

L: Latent heat of vaporization
C: Condensation rate



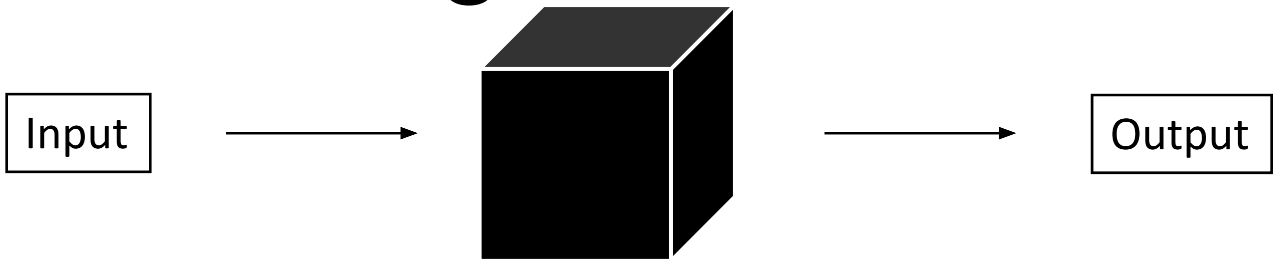
w/ Betts-Miller Convection (TJBM)

$$\left(\frac{\partial q}{\partial t}\right)_{\mathrm{BM}} = -\frac{q - q_{\mathrm{ref}}}{\tau} + \boxed{\left(\frac{\partial q}{\partial t}\right)_{\mathrm{TJ}}}$$

$$\left(\frac{\partial T}{\partial t}\right)_{\mathrm{BM}} = -\frac{T - T_{\mathrm{ref}}}{\tau} + \boxed{\left(\frac{\partial T}{\partial t}\right)_{\mathrm{TJ}}}$$

*Mathematical description of convective precipitation can be found in Frierson (2007)

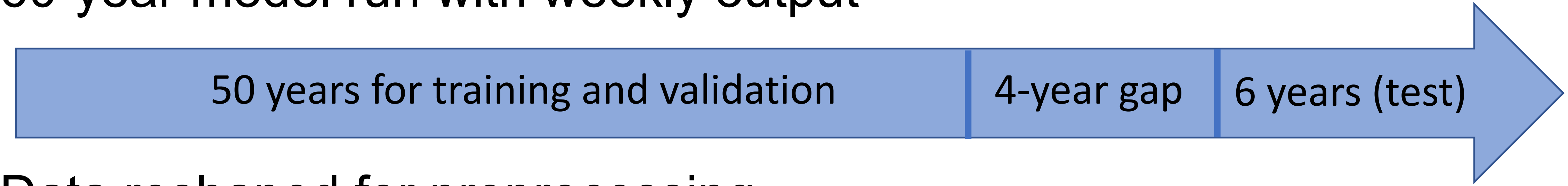
Machine Learning



- Determines a functional relationship between data
- Our focus: Random Forests (RF)
  - Include baseline Neural Network (NN) comparison
- Built using Scikit-Learn & Keras (TensorFlow)
  - Tuned with SHERPA
- Uniquely trained *and* <u>tuned</u> RFs
  - Can be considered our 'best possible case'

GCM Configuration

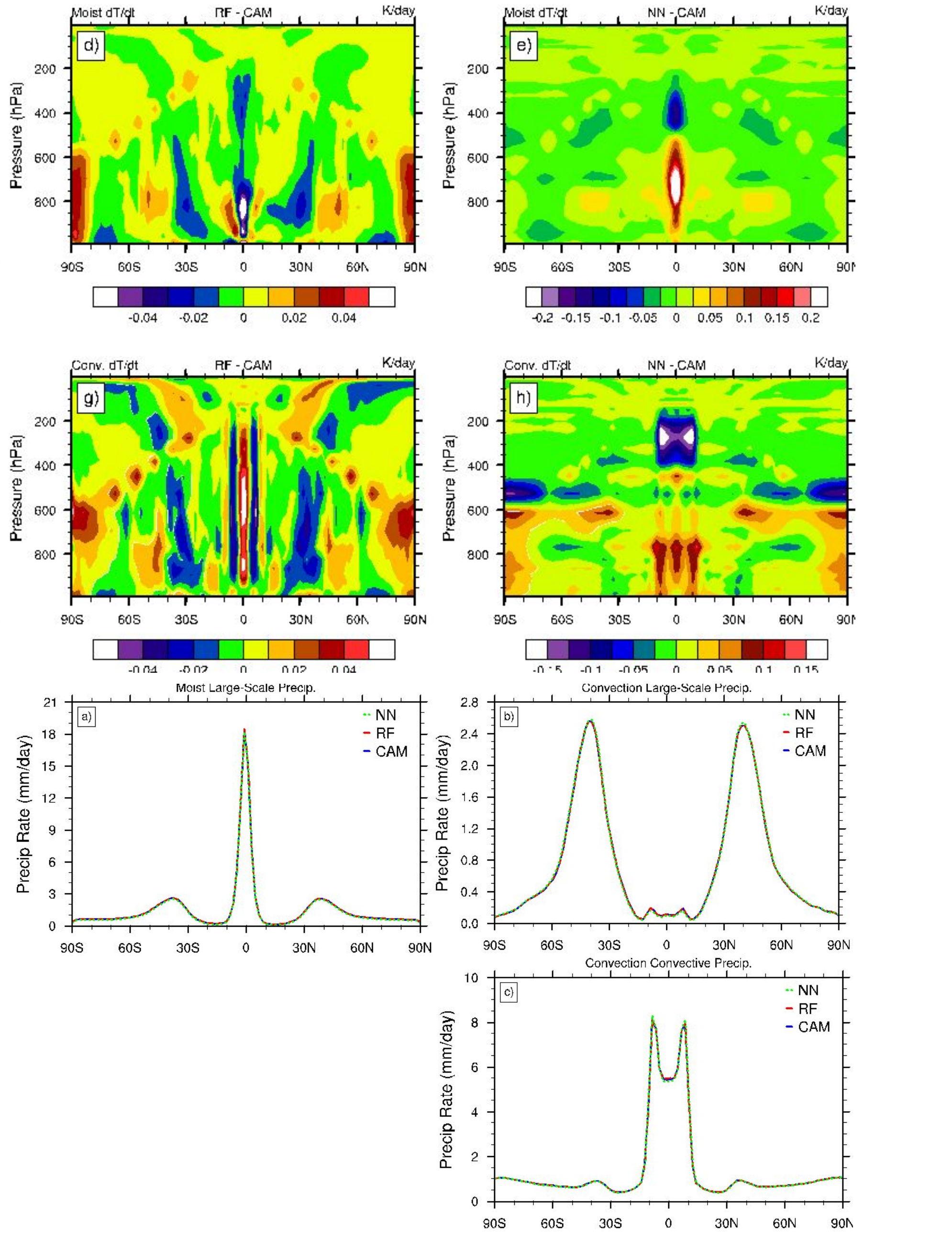
- NCAR’s Community Earth System Model (CESM) version 2.1
- Finite-Volume (FV) CAM6 run at 1.9 x 2.5 horizontal resolution with 30 vertical levels
- 60-year model run with weekly output



- Data reshaped for preprocessing
  - Ex: diagnostic vars(time, lev, lat, lon) -> features(time*lat*lon,lev*vars)
  - NNs have normalization input layer

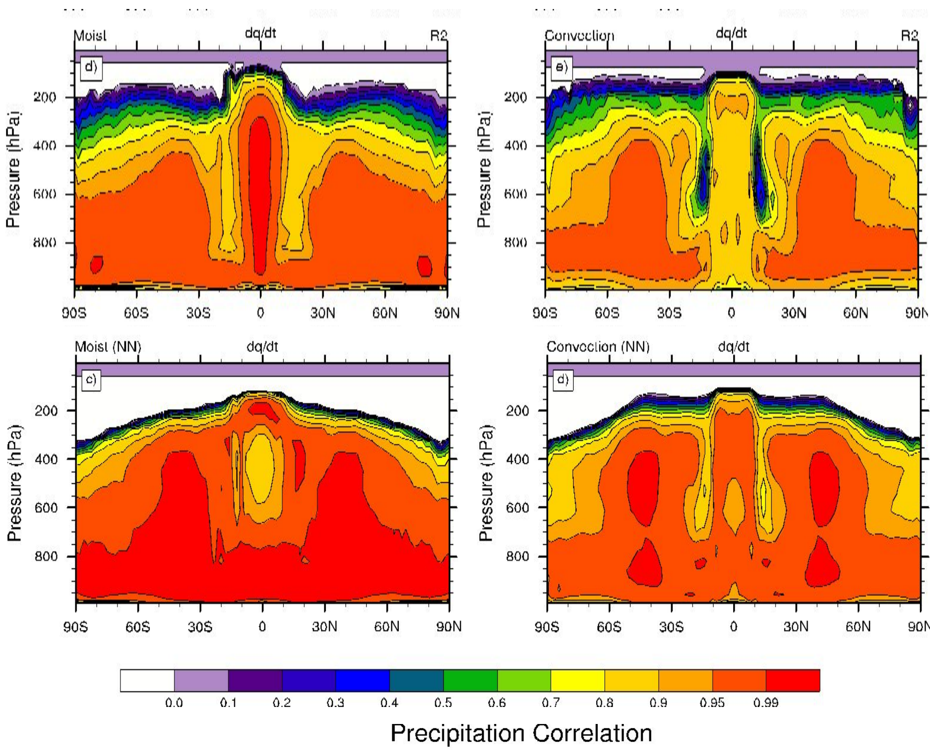
Zonal-Mean Time-Mean

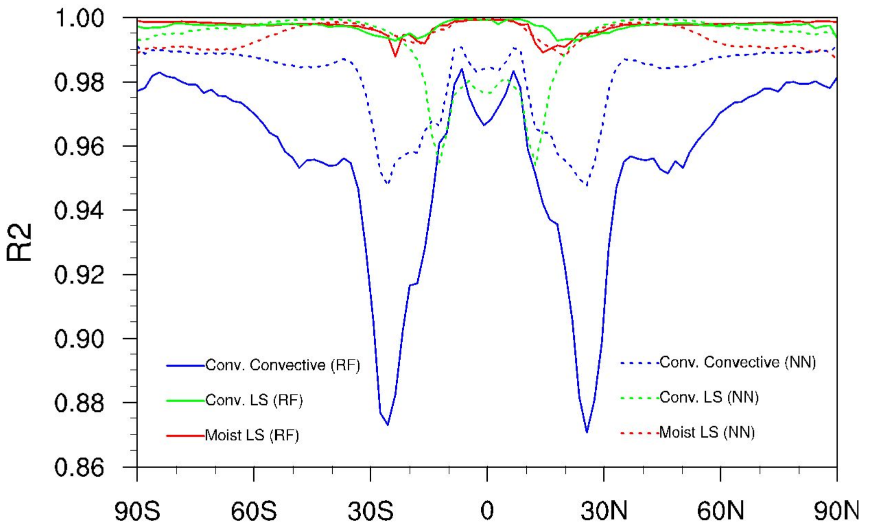
- ML reproduces dT/dt effectively
- Increase in regions of significant ML anomaly in dT/dt convection case for
- Precipitation is almost indistinguishable



R^2 Investigation

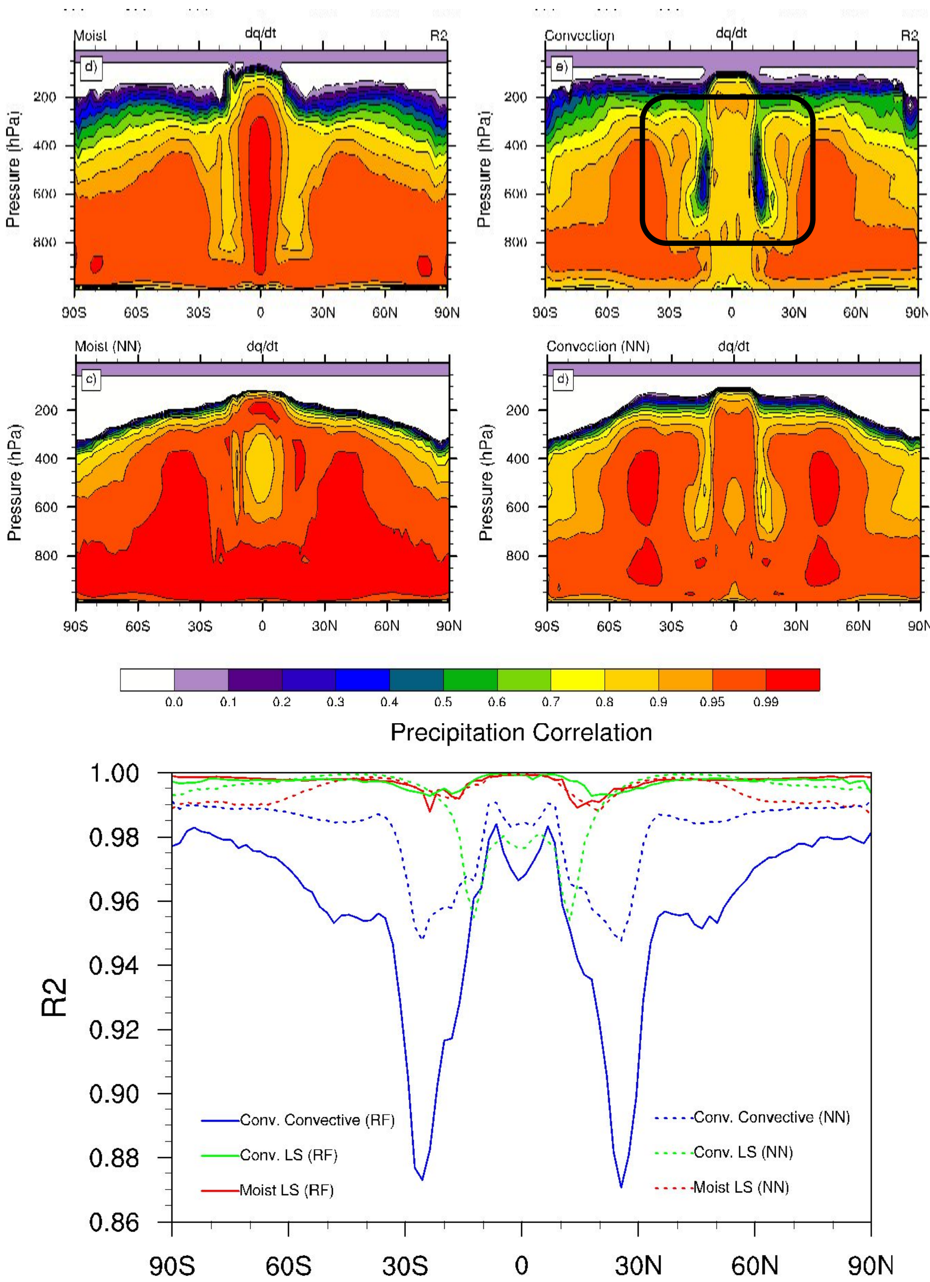
- Correlation coefficient:
  - Ratio of error to the variance
  - Closer to 1.0: `learned' better
- R2 decreases when complexity increases
  - More significantly for RFs





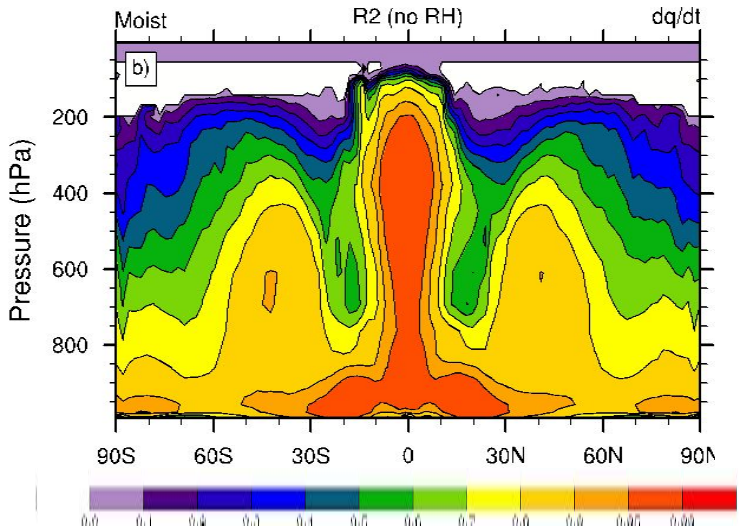
R^2 Investigation

- Correlation coefficient:
  - Ratio of error to the variance
  - Closer to 1.0: `learned' better
- R2 decreases when complexity increases
  - More significantly for RFs
- Low skill region in (e) associated with peaks in convective precip
  - Less apparent in NN



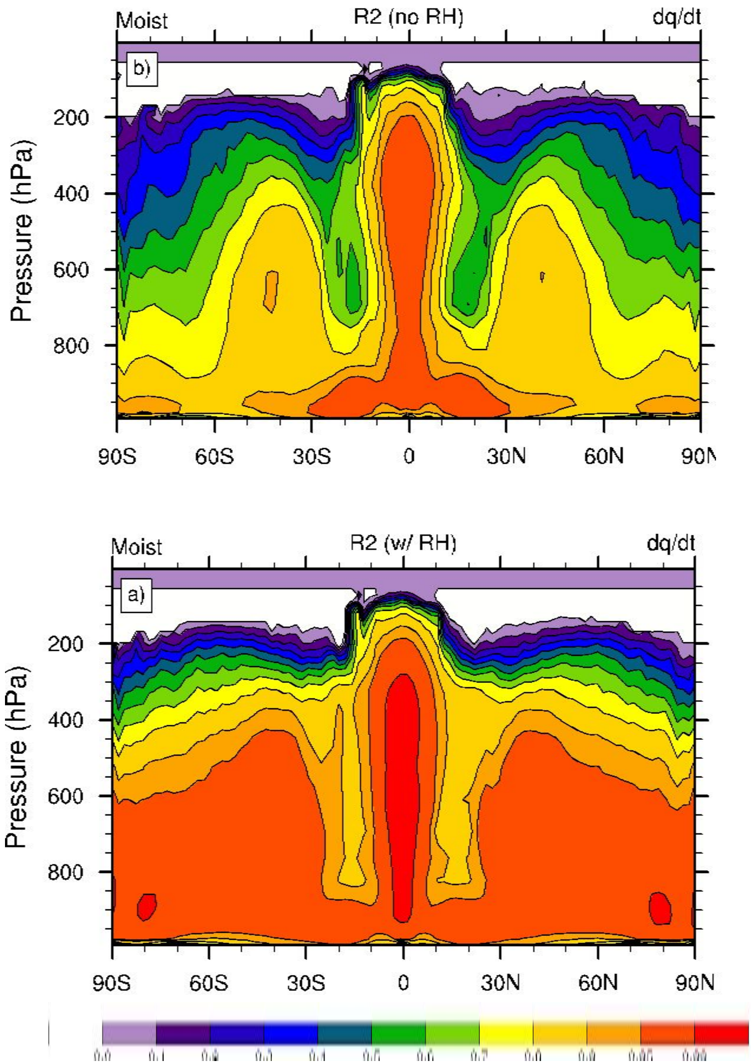
Domain Knowledge

- Tendencies don't utilize RH internally
- We are aware of connections between RH and the internal processes.



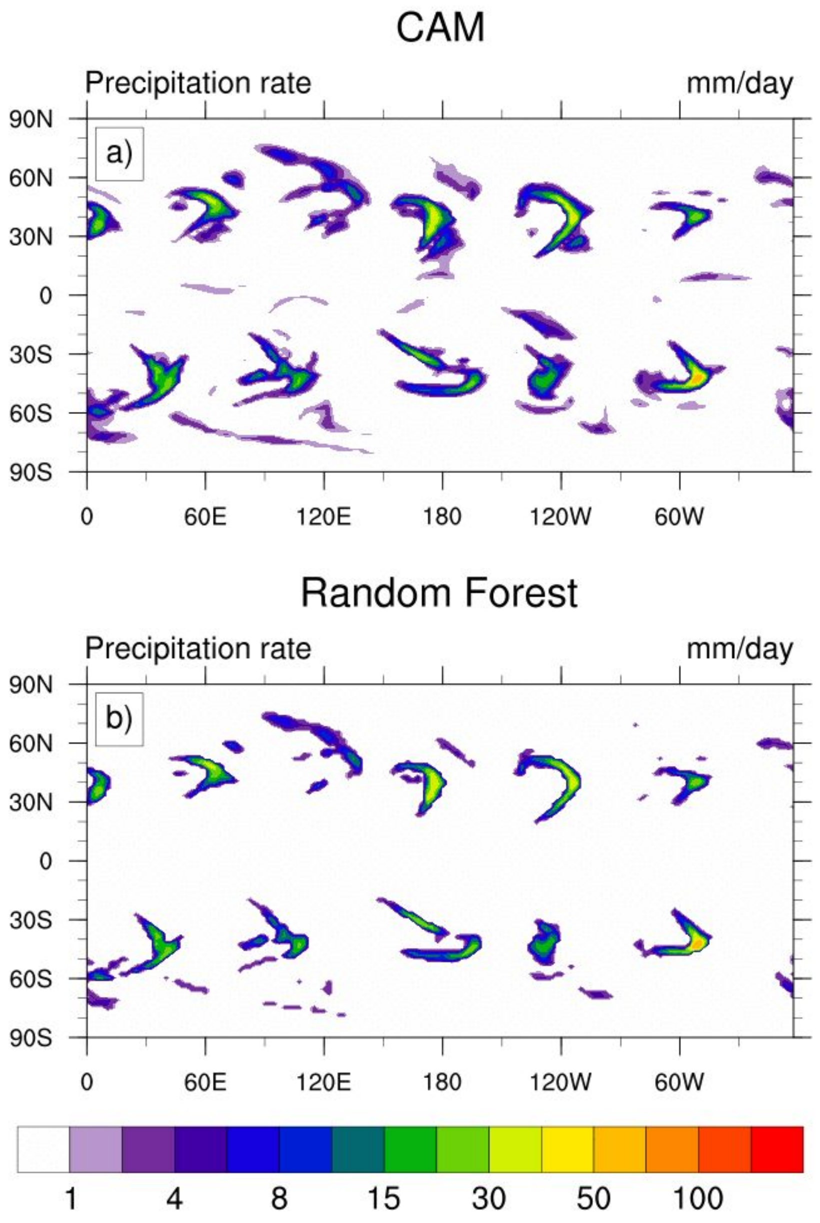
Domain Knowledge

- Tendencies don’t utilize RH internally
- We are aware of connections between RH and the internal processes.
- ML improved *significantly* when included.
- Unexpected from data science perspective, but unsurprising from atmospheric science perspective



Application to 2-Hourly Data

- Simple example of 'transfer learning'
- Regions of minimal precipitation appear to be missing (1-4mm/day)
- Unsure why (still preliminary)
  - Bug? Not an issue in weekly-dataset
  - Prioritizing large-scale features? (Chattopadhyay, 2023 arXiv:2304.07029)
  - Could impact online performance



Ongoing & Future Work

- Coupling these to CAM
  - We are close – hit a few ”known unknowns” in recent weeks
  - RF size/feasibility for online runs
  - ‘MaxDepth’ parameter *significantly* impacts both skill and size

- Offline transfer learning

- Adding steps to the hierarchy
  - Repeatable ‘Simple Physics’ CAM-ML workflow?

- Moving on from RFs?

Thank You!

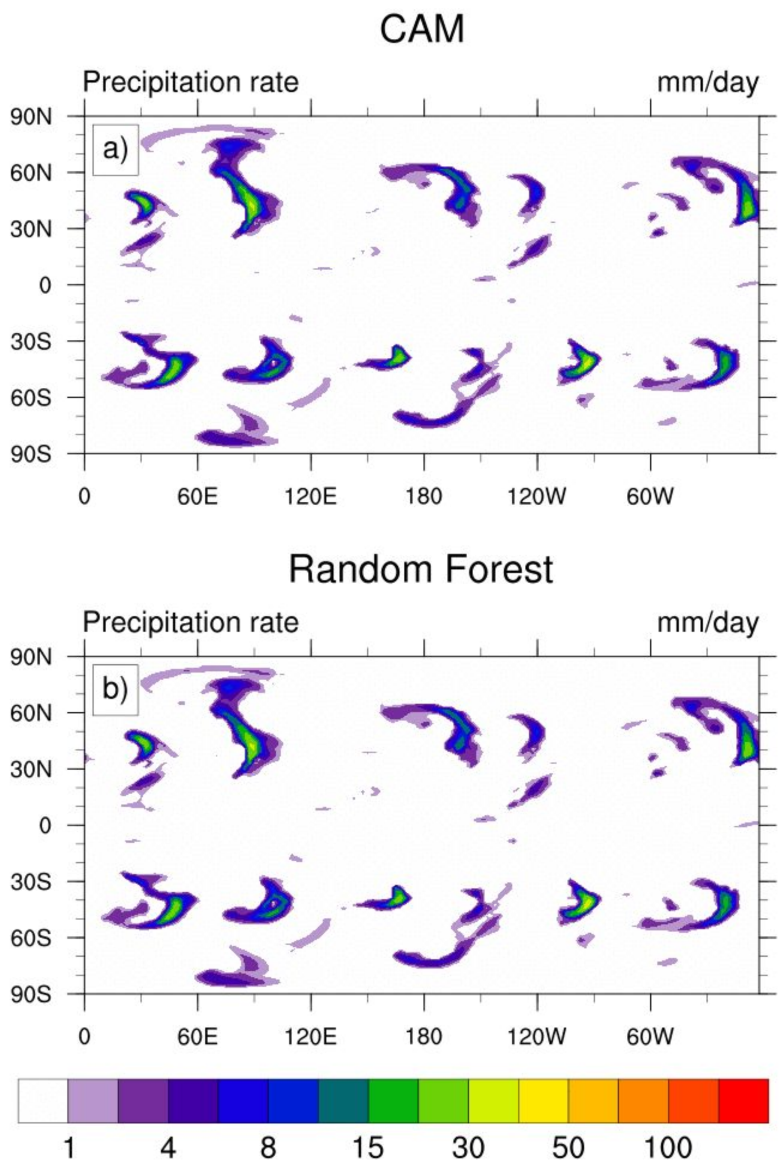
Contact

glimon@umich.edu

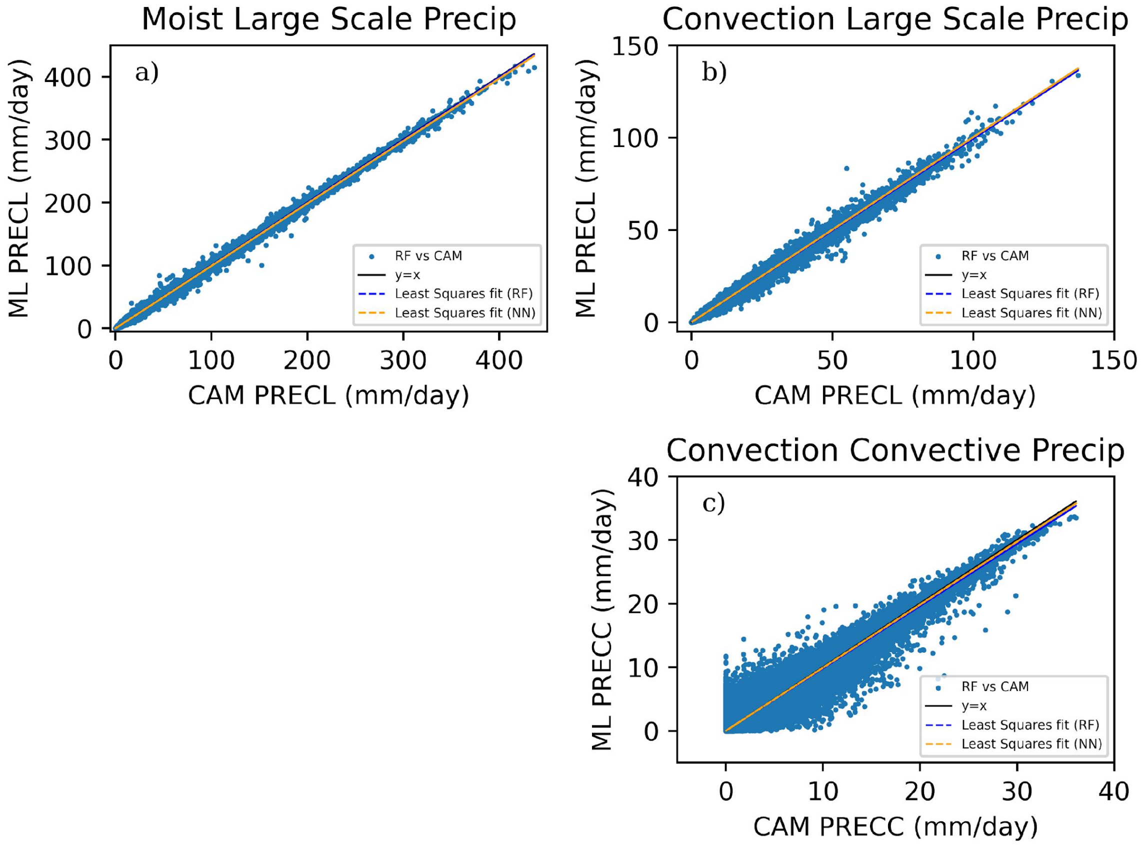
Paper

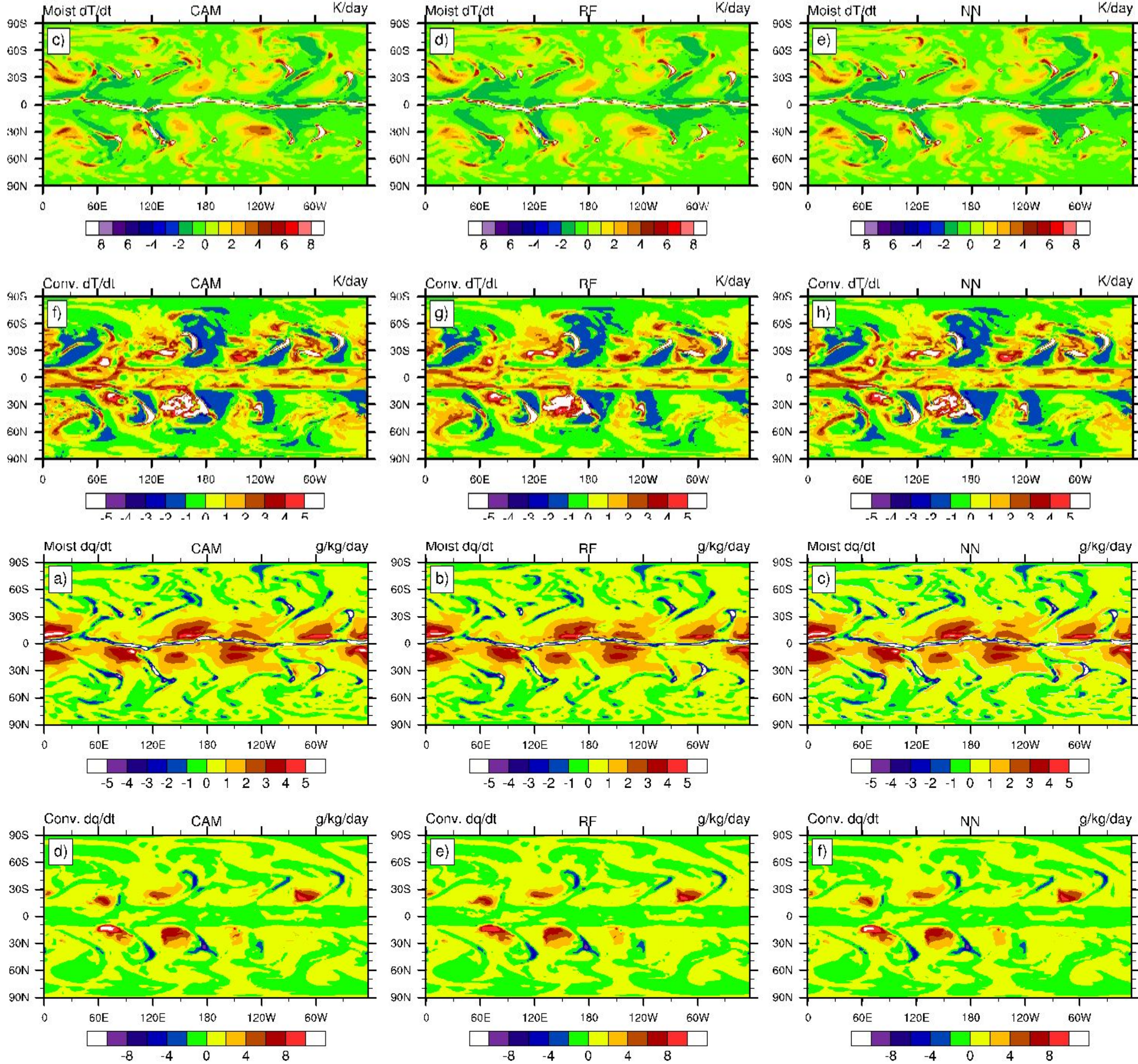
On Original data

- Weekly output, 20 weeks (very choppy)
- Captures the 1-4mm/day

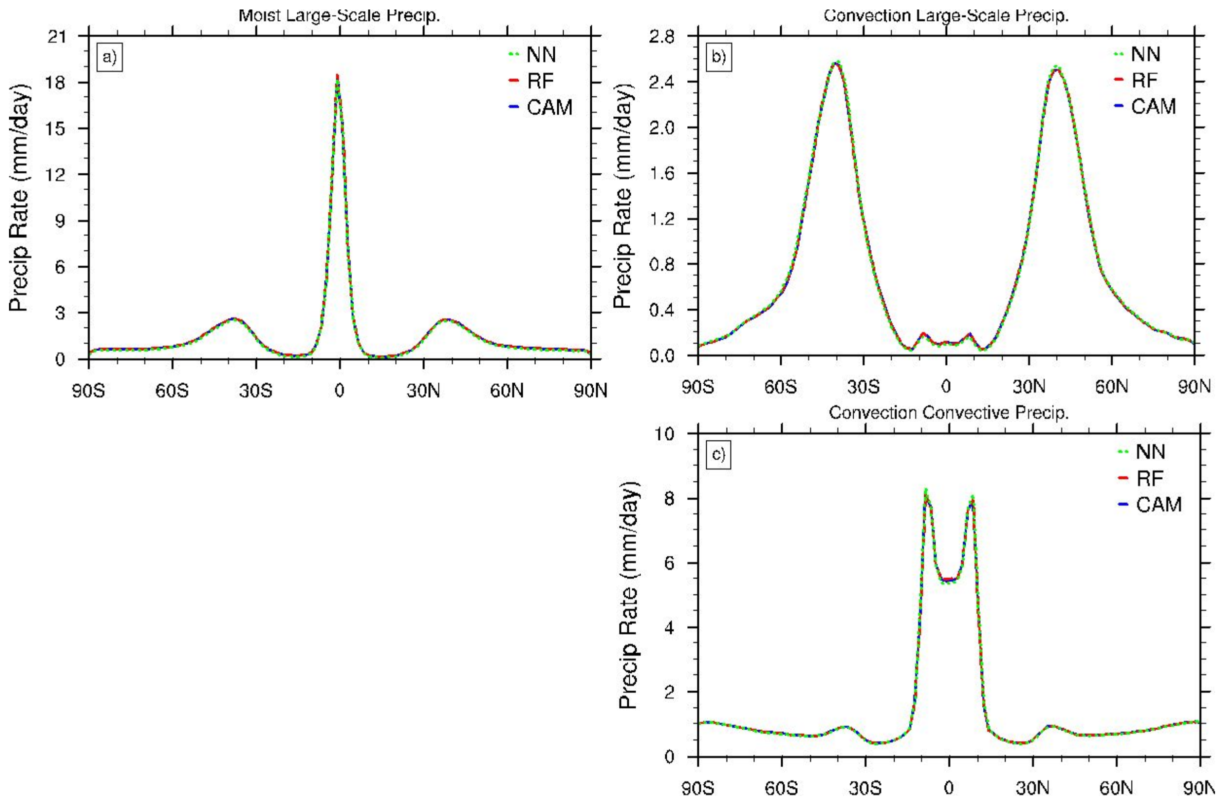


Snapshots

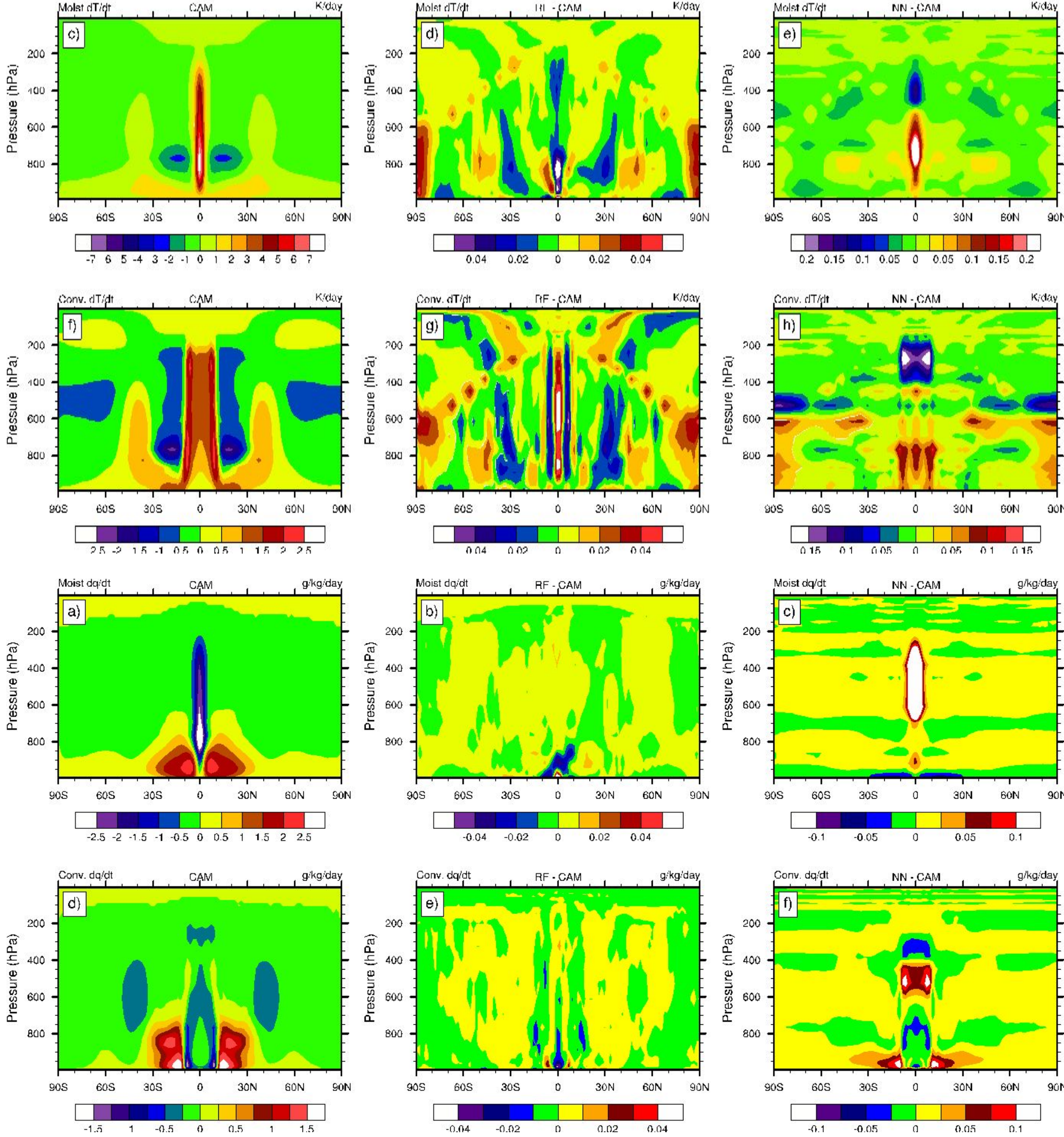

Moist Large Scale Precip
a)
ML PRECL (mm/day)
CAM PRECL (mm/day)
RF vs CAM
y=x
Least Squares fit (RF)
Least Squares fit (NN)
Convection Large Scale Precip
b)
ML PRECL (mm/day)
CAM PRECL (mm/day)
Convection Convective Precip
c)
ML PRECC (mm/day)
CAM PRECC (mm/day)


Moist dT/dt
CAM
RF
NN
K/day
Conv. dT/dt
Moist dq/dt
g/kg/day
Conv. dq/dt

Mean Fields

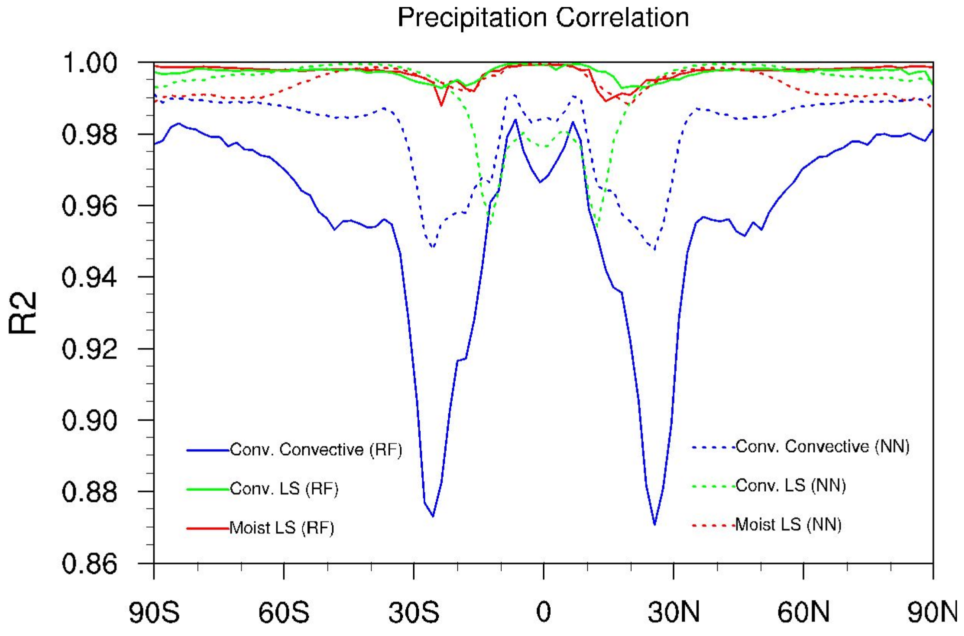


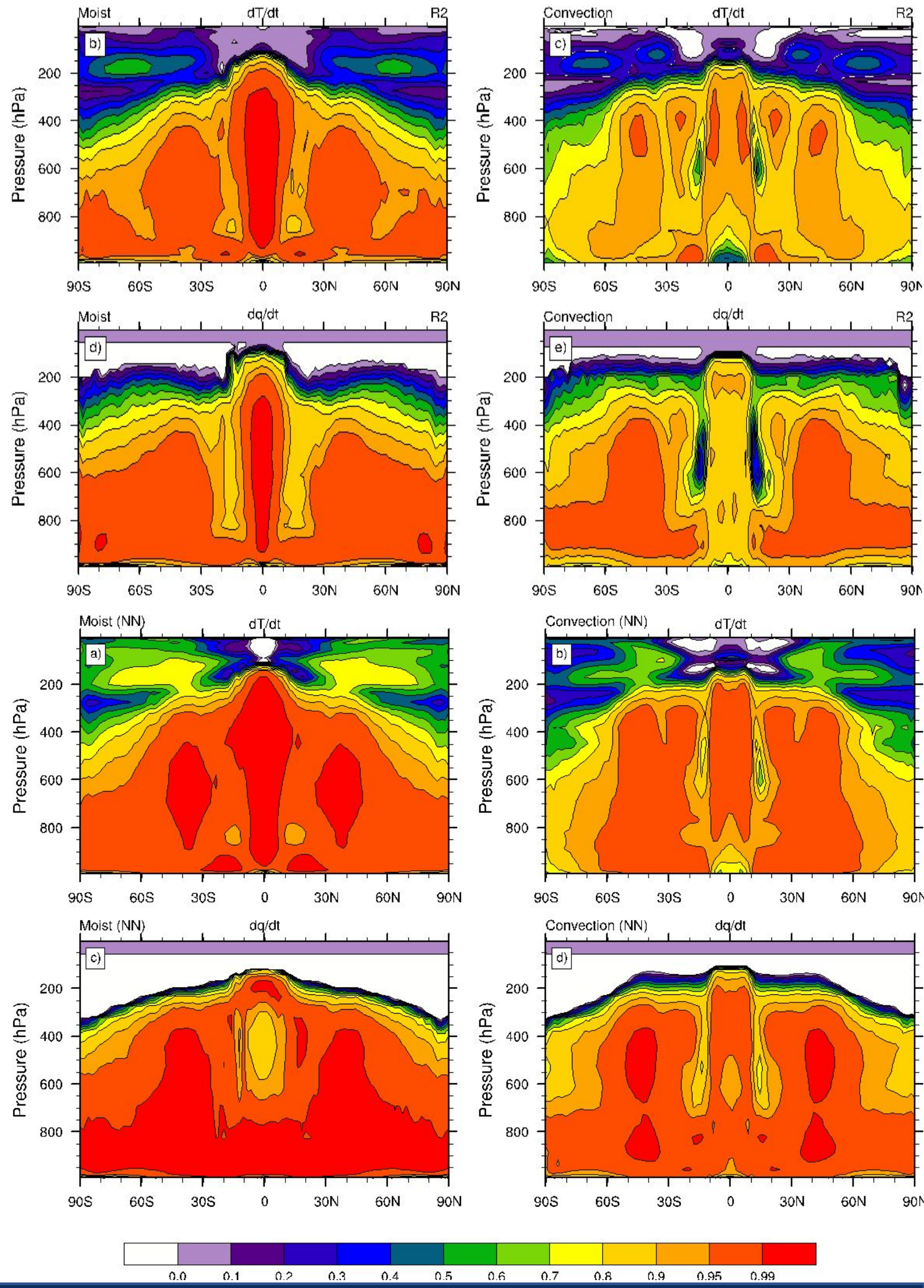
Moist Large-Scale Precip.
a)
NN
RF
CAM
Precip Rate (mm/day)
Convection Large-Scale Precip.
b)
Convection Convective Precip.
c)
90S 60S 30S 0 30N 60N 90N



Moist dT/dt CAM K/day
Moist dT/dt RF - CAM K/day
Moist dT/dt NN - CAM K/day
Conv. dT/dt CAM K/day
Conv. dT/dt RF - CAM K/day
Conv. dT/dt NN - CAM K/day
Moist dq/dt CAM g/kg/day
Moist dq/dt RF - CAM g/kg/day
Moist dq/dt NN - CAM g/kg/day
Conv. dq/dt CAM g/kg/day
Conv. dq/dt RF - CAM g/kg/day
Conv. dq/dt NN - CAM g/kg/day
Pressure (hPa)
90S 60S 30S 0 30N 60N 90N

R^2 Investigation





Skill Variation