Evaluating a Neural-Network Approach to Deep Convection in CAM6: Improvements and Remaining Challenges

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NCAR AMWG Meeting, February 4th, 2026

M2LInES

Motivation for the development of a new convection scheme

- Convection is central to vertical transport but unresolved at typical grid scales in global climate models. Most atmospheric models use finely tuned schemes to represent subgrid-scale convection, yet these schemes remain a major source of model uncertainty (e.g. Arakawa 2004; Randall et al., 2003).

- Physically-based parameterizations struggle to capture the complexity of convection, due to the wide range of interacting scales and large number of physical processes involved (e.g. Slingo and Palmer, 2011; Yano and Plant, 2012; Bony et al., 2015).

- Recent advances in computing power, algorithm performance, and data availability makes learning subgrid convection from data directly more feasible and promising than ever (e.g. Gentine et al., 2018; Rasp et al.; 2018).

Challenges in the development of convection scheme

- ML approaches typically seek to either create a new scheme using a fully empirical learning model (e.g. O'Gorman and Dwyer, 2018; Yuval et al., 2022), or to use an existing scheme and tune its parameter (e.g. Kumar et al., 2024); each approach comes with distinct advantages and limitations (e.g. Eyring et al., 2024).

- Training and assessing success of any new scheme is complicated due to overlapping and interdependent processes from multiple schemes (e.g., cloudiness is influenced by deep convection, microphysics, shallow convection, boundary layer mixing); this can easily obfuscate efficient learning or performance assessment.

What we want to achieve

(1) produce NN, a data-driven scheme that captures key processes in cumulus convection

(2) port NN to CAM6,

(3) evaluate sensitivity of CAM6 to various parameter changes in NN,

(4) show that NN reduces known biases in climatology in CAM6, on a range of spatial and temporal scales (seasonal-mean, subseasonal, synoptic).

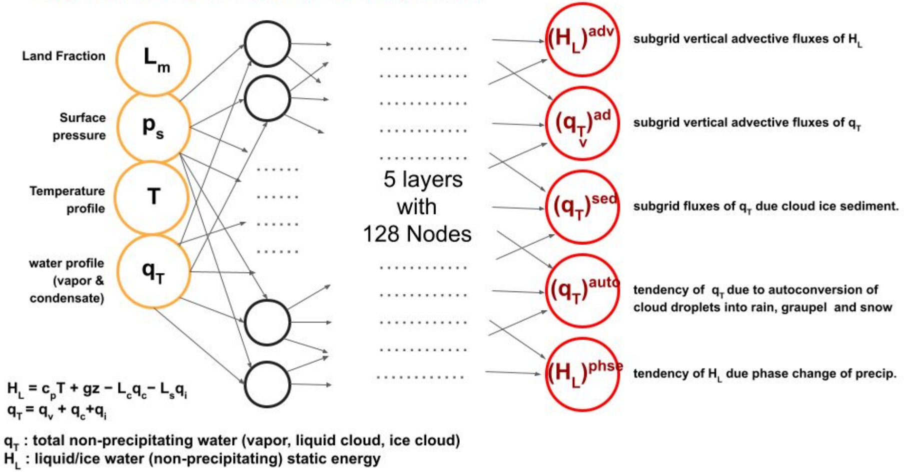
Architecture of a NN convection scheme

The NN architecture and training follow broadly in Yuval, O'Gorman, Hill, 2021 (Geophys. Res. Lett.) <u>but has been updated to be active over both land and ocean</u>.

A Feedforward Neural Network is trained to predict vertical subgrid fluxes of dry energy and moisture, as well as microphysical tendencies, from 4 inputs (2 profiles, 2 scalars):

temperature (T), non-prec. water mixing ratio (q_T), surface pressure (p_s), land fraction (L_m)

Schematic of the NN network



where,

$H_L = c_pT + gz - (L_cq_c + L_sq_i)$ is the non-precipitating ice/liquid static energy

$q_T = q_v + q_c + q_i$ is the non-precipitating water mixing ratio (water vapor + cloud water + cloud ice)

Physical properties of the NN scheme

Inputs (2 vertical profiles, 2 surface scalars): temperature (T), total non-precipitating water mixing ratio (q_T), surface pressure (p_s), land fraction (L_M).

Outputs (5 vertical profiles): fluxes and tendencies for budgets of non-precipitating liquid/ice static energy (H_L), and q_T.

$$\partial_t(H_L) = \partial_z(H_L)^{adv} - L_p(q_T)^{auto} - L_f\,\partial_z(q_T)^{sed} + (H_L)^{phse}$$

$$\partial_t(q_T) = \partial_z(q_T)^{adv} + (q_T)^{auto} + \partial_z(q_T)^{sed}$$

L_c is the latent heat of condensation; L_s is the latent heat of sublimation; L_f is the latent heat of fusion;

$L_p = L_c + L_f(1-\omega_p)$ is the effective latent heat associated with precipitation, where ω_p is ratio between precipitating ice and liquid phases.

Note: vertically integrated H_L and q_T are conserved conserved during reversible adiabatic convection, i.e., non-conservation may only come from diabatic effects $\mathbf{(q_T)^{auto}}$ and $\mathbf{(H_L)^{phse}}$.

Predicting fluxes for conservative subgrid-scale processes ensures basic conservation.

Training of a NN convection scheme

Training on gSAM (with selection of new set of NN inputs) was done by G. Mooers.

Training is done from a high-resolution simulation with gSAM, forced by Qobs SSTs and prescribed radiative forcing.

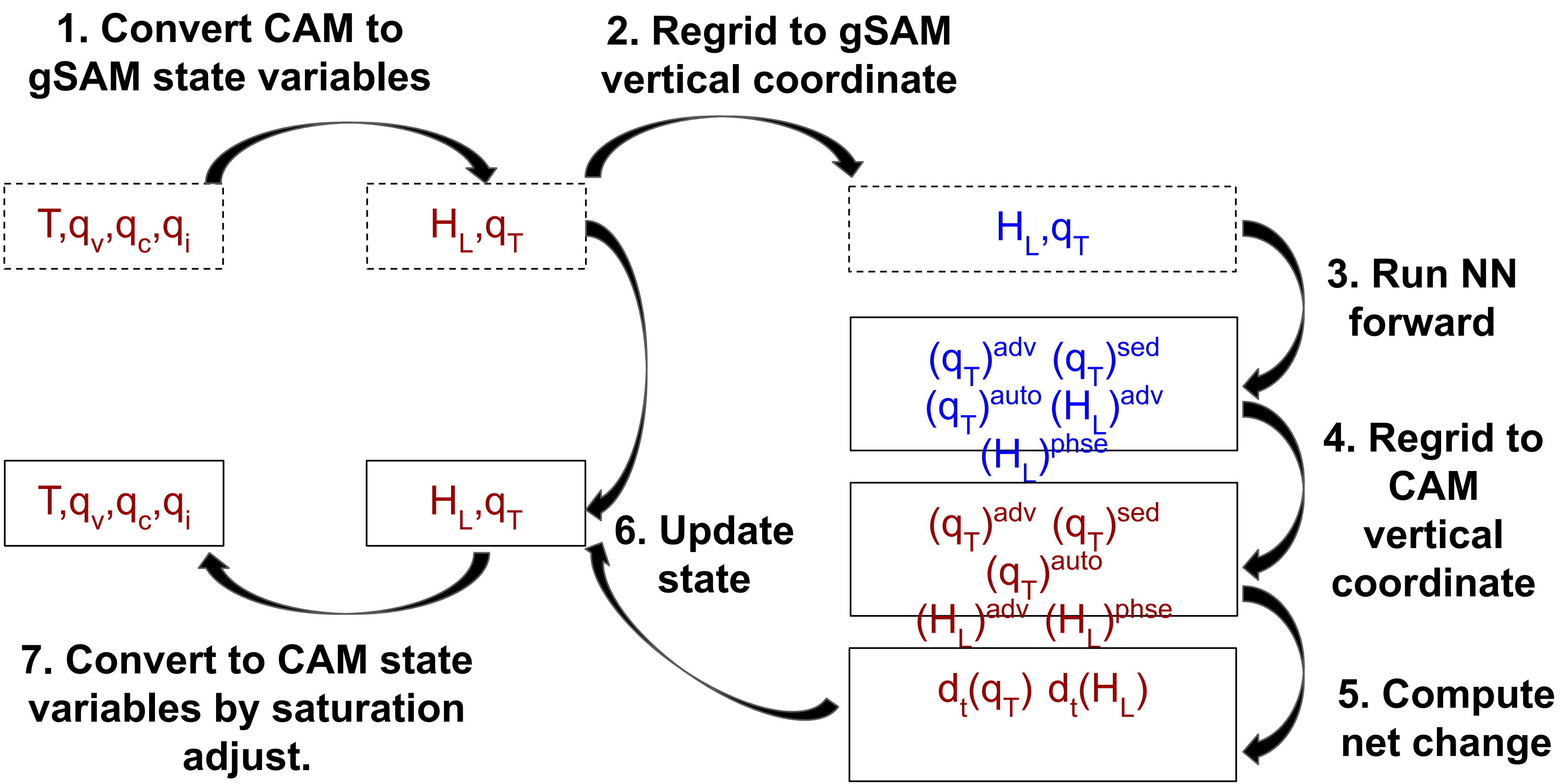
gSAM: Global System for Atmospheric Modeling (Khairoutdinov, M.F et al., 2022, JAMES) is a state-of-the-art model that is optimized for studying convection at very high resolution (~4km effective horizontal resolution).

Training data is made of 30 days of hourly data.

Training is done by

(a) coarse-graining high-resolution (2~km) convective output onto a 100 km grid,
(b) defining grid and subgrid convective output on the 100 km grid,
(c) optimizing NN to predict subgrid convective output from grid-scale input profiles.

Schematic of NN implementation in CAM6



Changing moist physics scheme to be a deep convection scheme

- **NN** is added to CAM6 source code and replaces the **ZM** deep convection scheme (Zhang & McFarlane 1995 - Atmos. Ocean). **Other CAM6 schemes are active** (e.g. CLUBB for boundary layer turbulence and shallow convection, MG for cloud microphysics, etc.).

- Compared to Yuval et al., 2021, weights were trained to output **subgrid-scale microphysical conversion** of condensate while grid-scale conversion is handled by the MG (cloud microphysics) scheme.

- **NN** is activated only during deep convective events. It is turned off wherever no net precipitation is diagnosed, and above highest level reached by the subgrid scale vertical energy flux.

Which metrics to evaluate NN scheme performance?

Some key metrics biased by traditional convection schemes, which we seek to improve with NN:

- Climatological bias (e.g. relative humidity, cloud fraction).
- Precipitation intensity distribution (e.g. drizzle vs. extremes) and diurnal cycle
- Dynamical variability on synoptic to subseasonal timescales (e.g. tropical waves).

Ideally, **NN** should represent above features better than **ZM**, when compared to observations, and at a similar computational cost or less.

Experimental setup

CAM6 (Community Atmosphere Model, version 6), with prescribed daily SST and SIC for period 01/01/2010-12/31/2014 (**FHIST** compset).

We compare 3 set-ups:

- CAM6 with Zhang-MacFarlane convection (ZM)
- CAM6 with convection turned off (OFF)
- CAM6 with NN convection (NN)

We compare to observation or reanalysis:

RELHUM: fifth generation ECMWF atmospheric reanalysis ERA-5 (0.25° x 0.25°)

CLR: 3S-GEOPROF-COMB CloudSat Radar & CALIPSO Lidar (2.5° x 2.5°)

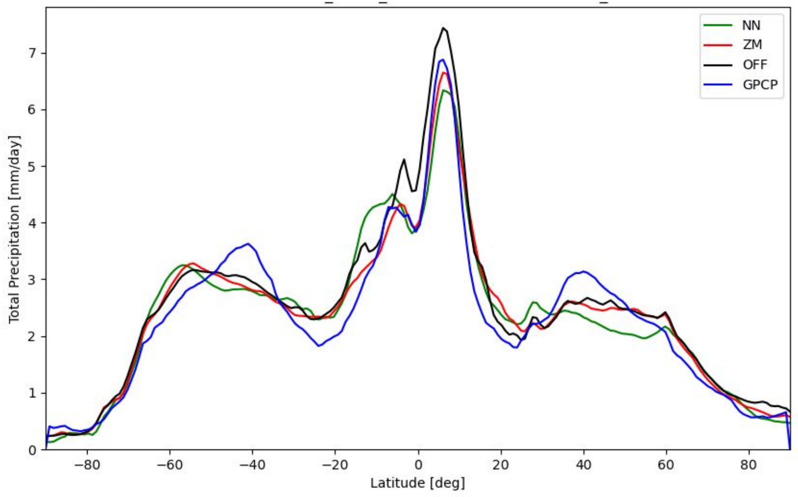
PREC: GPM IMERG Final Precipitation L3 Half Hourly V07 (0.1° x 0.1°)

GPCP Precipitation Monthly Analysis Product (2.5° x 2.5°)

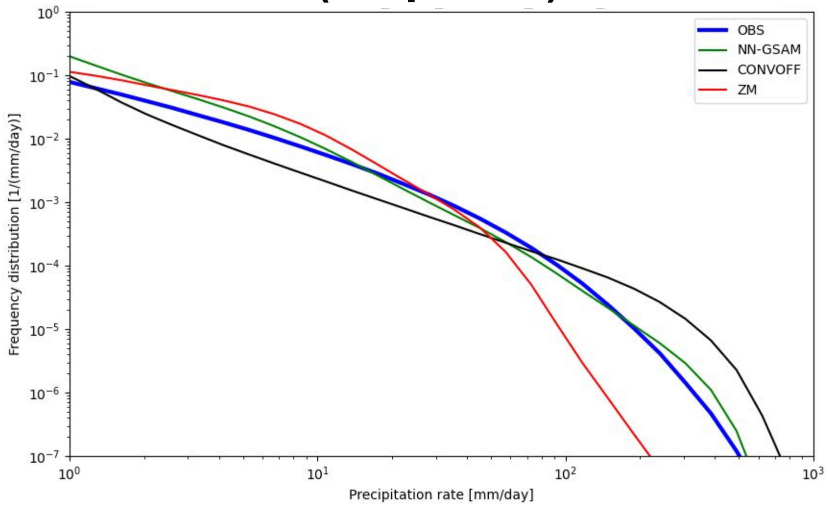
OLR: Outgoing Longwave Radiation (OLR) Climate Data Record (CDR) (1° x 1°)

Precipitation Climatology and Probability Distribution

Annual-mean, zonal-mean



Probability Distribution (Trop. Pac)



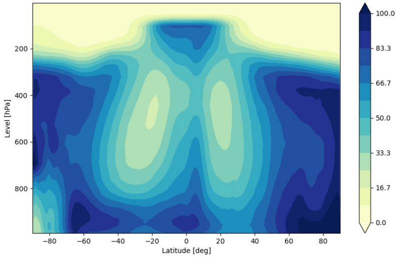
NN provides a reasonable annual-mean precipitation climatology

NN outperforms ZM in the frequency-intensity distribution of 3 hrly precipitation

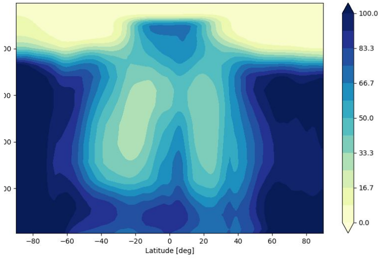
Annual zonal-mean climatology

Relative Humidity

ERA-5



ZM



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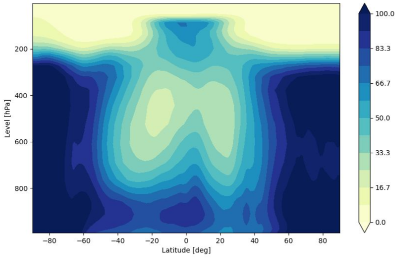
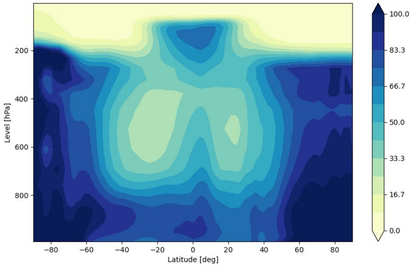
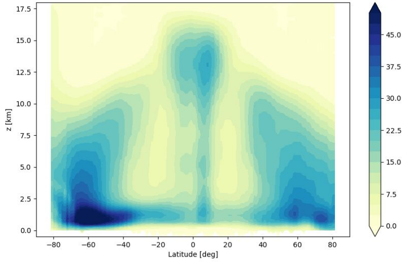


NN

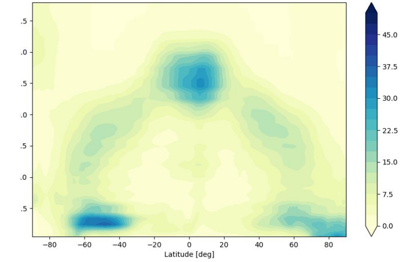


Cloud Cover

GEOPROF



ZM



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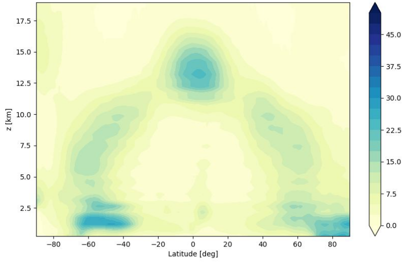
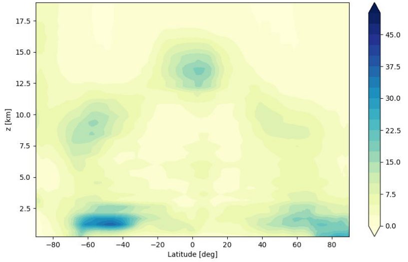
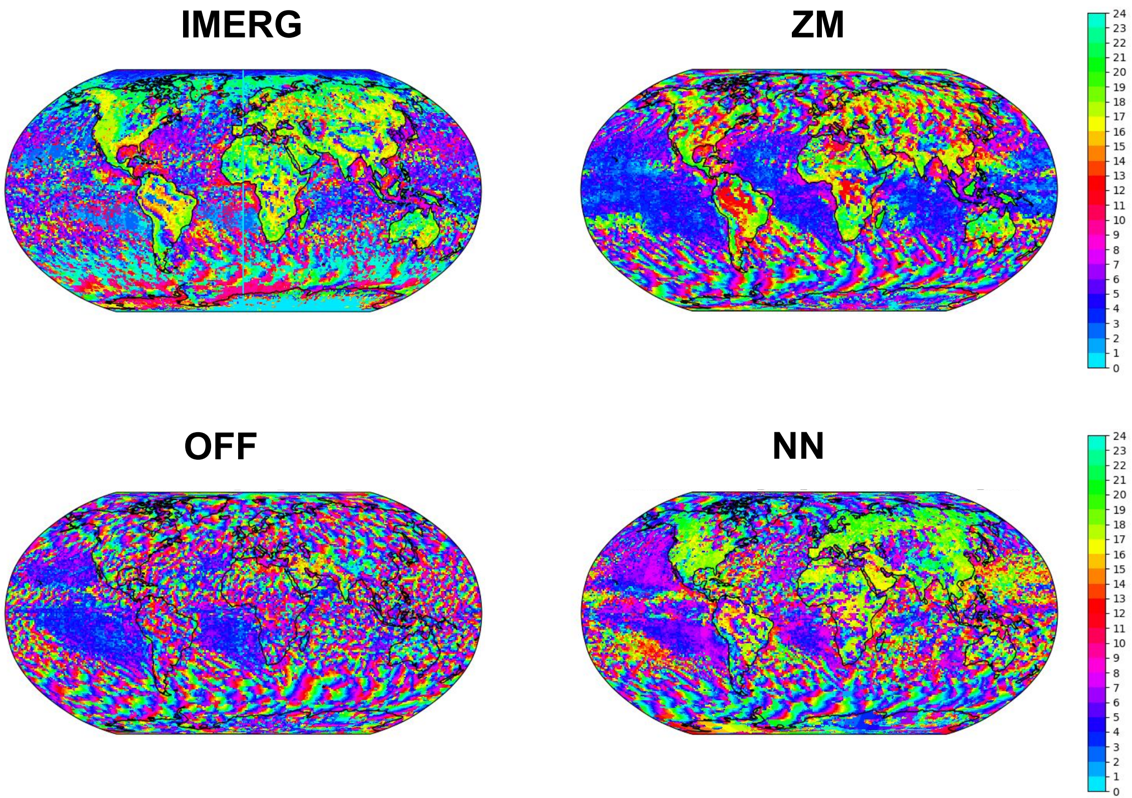


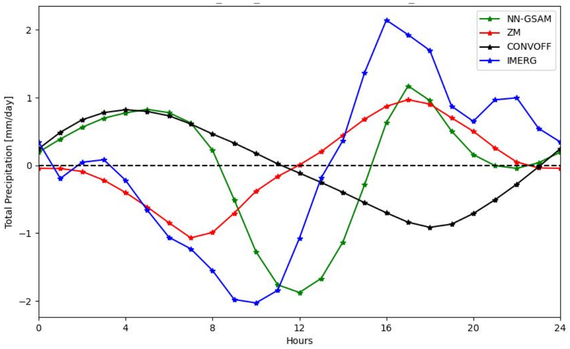
NN

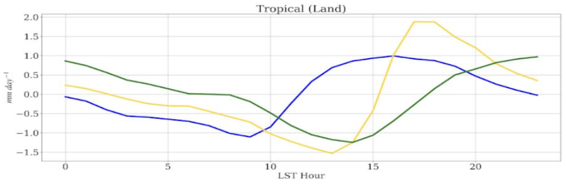


Diurnal cycle: Precipitation

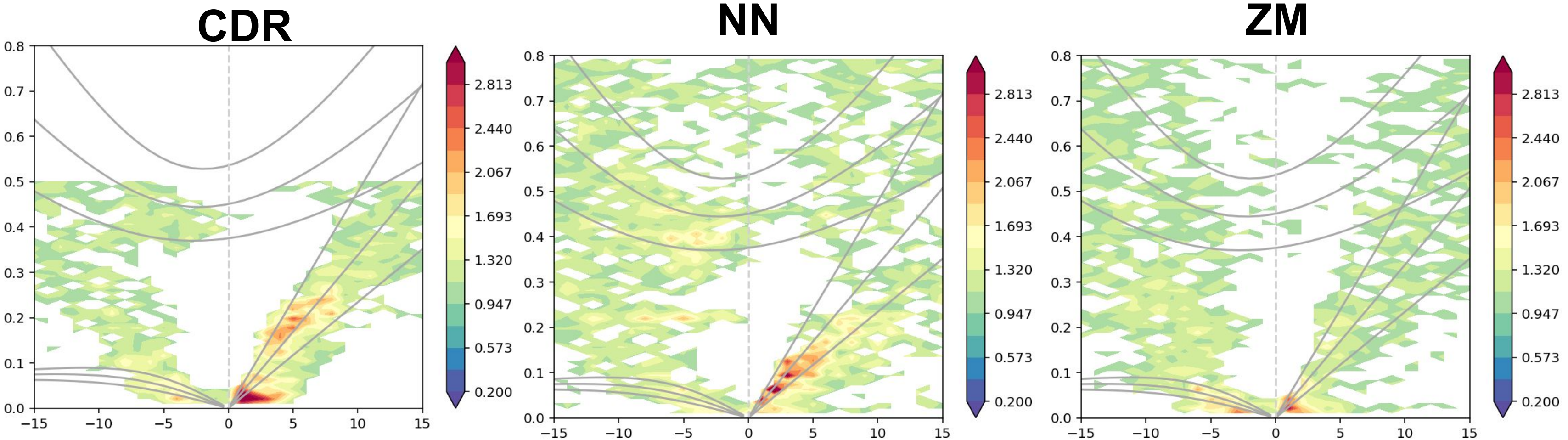


Trop. Land diurnal cycle

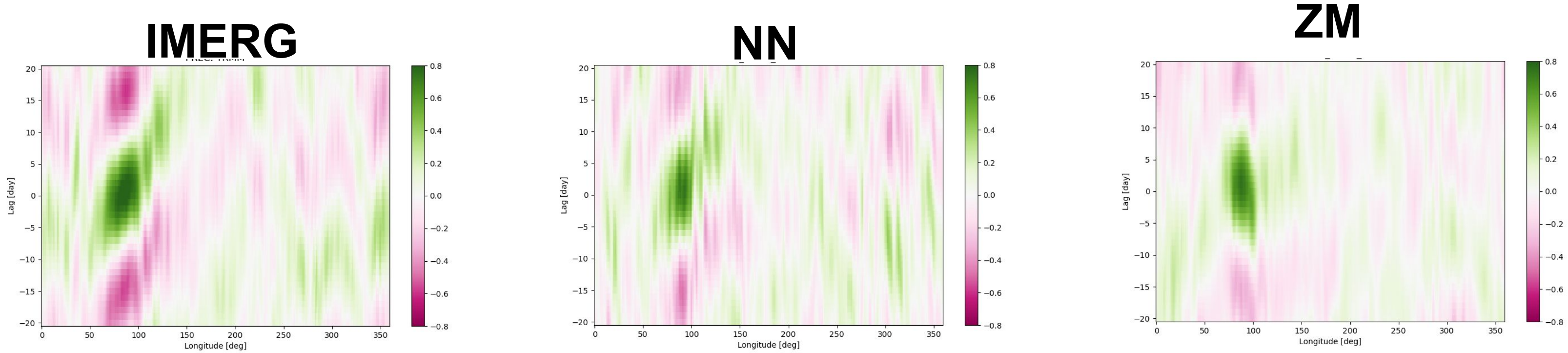




Tropical waves Spectrum (OLR)



And MJO propagation (Precipitation)



Summary

We build a Feed Forward Neural Network to represent deep moist convection, and train this scheme on a high-resolution (2km) gSAM simulation.

Replacing the current deep convection scheme in CAM6 by this new NN scheme, we obtain stable simulations that respect basic conservation of energy and moisture.

We find that a NN scheme can simulate deep convection reasonably well in a realistic CAM6 configuration with fixed SST/SIC for a range of statistics.

We’re aiming to improve some of the more difficult of convection to ‘get right’, such as: cloud-radiative feedback, diurnal cycles, or tropical waves.

We’re working to complete implementation of NN in CAM6 with tunable parameters, to ease calibration.

Thank you!

This project was supported by **Schmidt Sciences**, LLC. All simulations were carried out on the **Derecho** high-performance computing system. We gratefully acknowledge the **NCAR staff** for helping us run our CAM6 experiments.

Addisu Semie is implementing of our scheme in **FTorch**, to be released soon with **CESM3**.