Implementing a Neural Network scheme for deep convection in CAM6 and testing it in a hierarchy of idealized configurations

Xavier J. Levine
Columbia University - Earth & Environmental Engineering

Contributors: Judith Berner, Paul O’Gorman, Jack Atkinson, William Chapman, Janni Yuval, Griffin Mooers

30th Annual CESM Workshop 2025
June 11th, 2025

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 a data-driven scheme that captures key processes in cumulus convection

(2) port it to CESM with minimal tuning or alteration

(3) show that it reduces known biases in climatology and climate variability, in a hierarchy of model configurations

Training of a NN convection scheme in SAM

NN architecture and training are described in details in Yuval, O'Gorman, Hill, 2021 (Geophys. Res. Lett.)

A neural network (5 layers × 128 nodes), “YOG”, is trained to predict vertical subgrid fluxes of dry energy and moisture, as well as microphysical tendencies, from local profiles of temperature (T) and humidity (q_T).

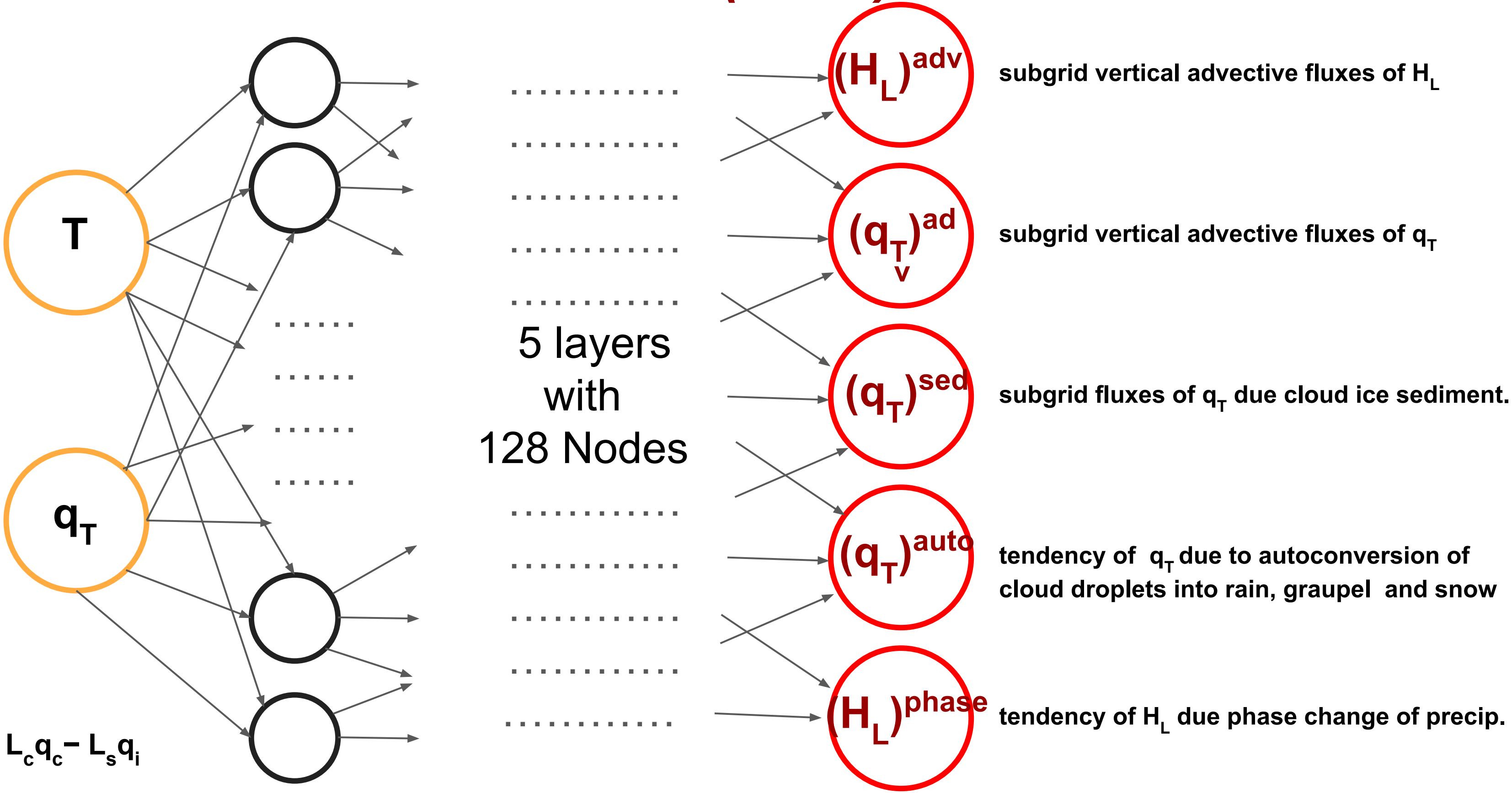
Training data is a high-resolution aquaplanet simulation with SAM v6.3, forced by Qobs SSTs and prescribed radiative forcing.

Training is done by

(a) coarse-graining high-resolution (~4 km) output onto a 96 km grid,
(b) defining convective fluxes and tendencies,
(c) optimizing NN to predict convective fluxes and tendencies from T and q_T profiles.

NN scheme is only applied/applicable to ocean areas.

Schematic of the NN network (SAM)



$H_L = c_pT + gz - L_cq_c - L_sq_i$
$q_T = q_v + q_c + q_i$

q_T : total non-precipitating water (vapor, liquid cloud, ice cloud)
H_L : liquid/ice water (non-precipitating) static energy

Schematic of NN implementation in CAM6

1/ **Convert CAM input variables to SAM variables & grid**

- Convert dry mixing ratios (q_v,q_c,q_i) from moist mixing ratios (r_v,r_c,r_i)
- Compute static energy (H_L) from temperature (T) and mixing ratios (q_c,q_i)
- Regrid temperature (T), dry mixing ratios (q_T), and static energy (H_L) from CAM to SAM vertical grid

2/ **Run Neural Network (NN) forward (on SAM grid)**

- Compute tendencies $F(T,q_T) \Rightarrow (H_L)^{adv}, (q_T)^{adv}, (q_T)^{sed}, (q_T)^{mic}, (q_T)^{phase}$
- Update (H_L, q_T) from initial values and above tendencies
- Diagnose precipitation from moisture tendencies $(q_T)^{mic}$.

3/ **Convert NN output to CAM output variables & grid**

Convert (H_L, q_T) back to (T, r_v, r_c, r_i) using CAM thermodynamic functions

4/ **Compute convective tendencies**(*) (δT, δr_v, δr_c, δr_i) from initial / updated values

(*): same tendencies as output by other convective schemes like ZM

Changing YOG moist physics scheme to be a deep convection scheme

- **YOG** 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.

- YOG is activated within convecting air columns, as identified by the vertical extent of the subgrid scale vertical energy flux, and is turned off elsewhere.

Assessing YOG in hierarchy of CAM6 configuration

A. Single column CAM (TOGA-COARE forcings)
   - compare directly with observation 👍
   - large-scale fields are forced and not adjusting 👎
   - only one location and time period is tested 👎

B. Aquaplanet CAM (fixed annual-mean 'Qobs' SST)
   - test YOG over all climate regions 👍
   - unable to compare directly with observation 👎
   - no land feedback 👎

C. Full CAM (time-varying historical SST)
   - compare with global observations 👍
   - harder to understand source of bias 👎
   - need to turn-off YOG over land 👎

Which metrics to evaluate YOG scheme performance?

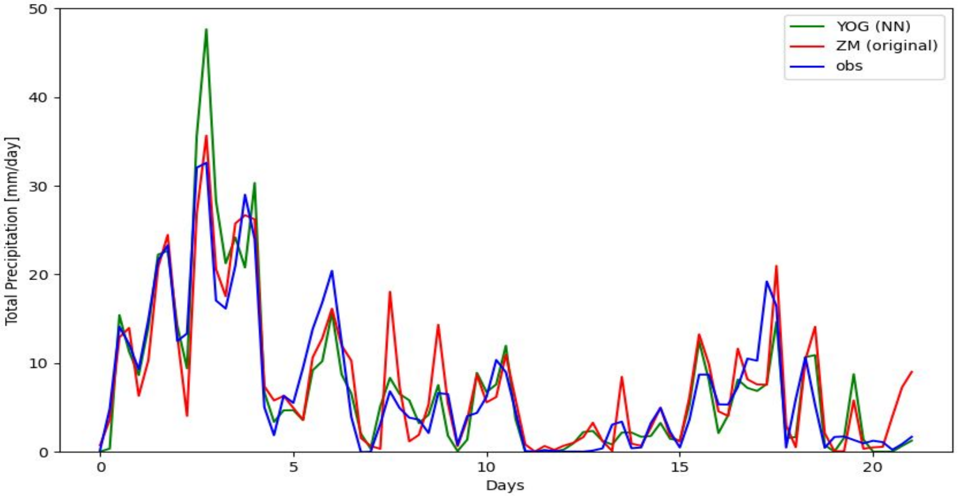
Some key metrics biased by traditional convection schemes, which we seek to improve with YOG:

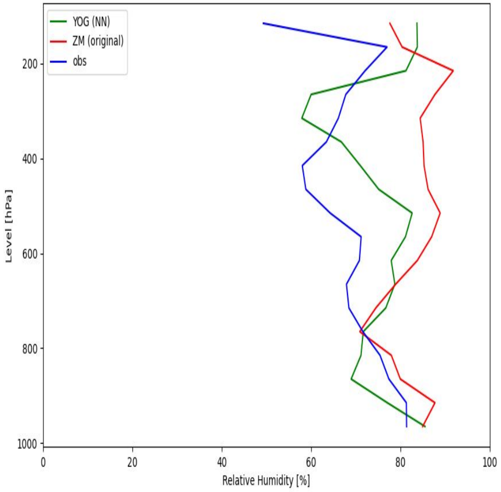
- Climatological bias (e.g. lapse rate, relative humidity, cloud fraction, radiative forcing).
- Precipitation intensity distribution (e.g. drizzle vs. extremes) and diurnal cycle
- Dynamical variability on synoptic to subseasonal timescales (e.g. tropical waves).

Ideally, **YOG** should represent above features better than **ZM**, <u>when compared to observations</u>, and at a <u>similar computational cost</u> or less.

A. Single Column CAM6 (TOGA-COARE forcing)

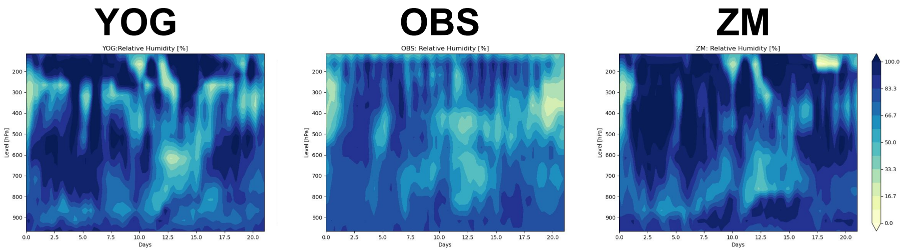
Precipitation bias are comparable in YOG and ZM





R^2(OBS, YOG) = 0.78

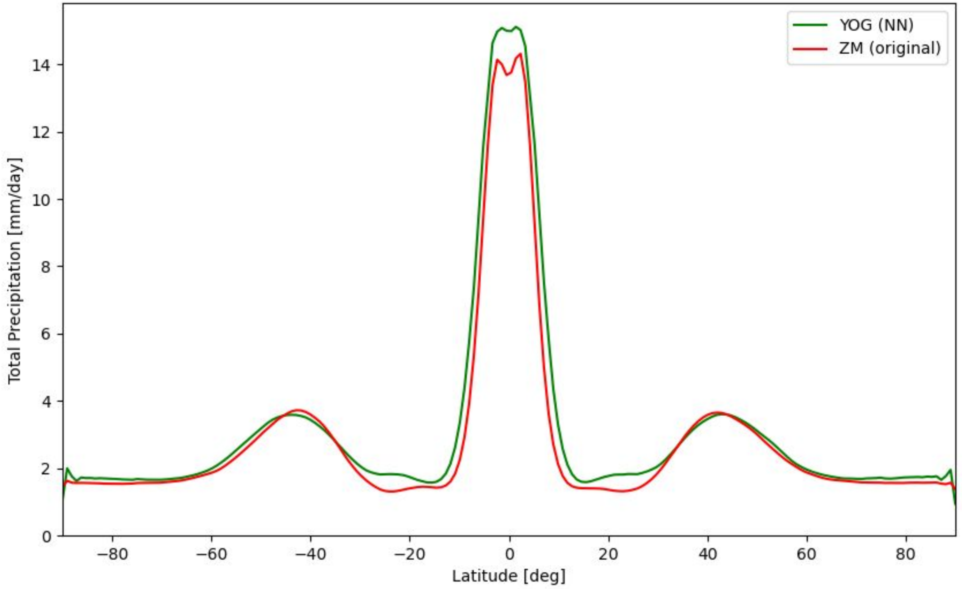
R^2(OBS, ZM) = 0.77



B. Aquaplanet CAM6 (fixed annual-mean ‘Qobs’ SST)

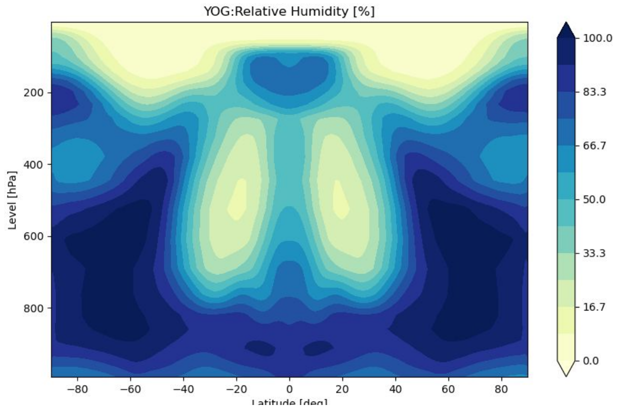
YOG reproduces mean hydrology

Time and zonal-mean precipitation

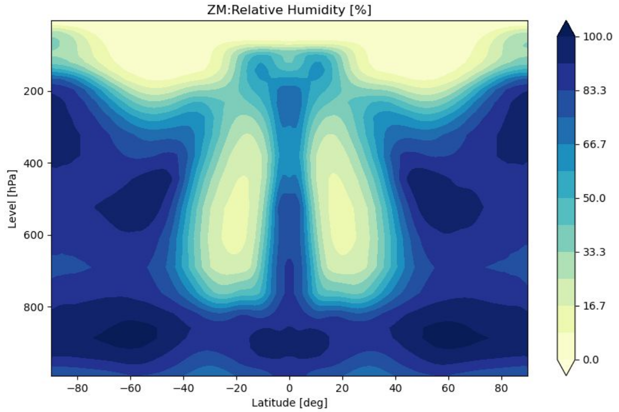


Relative Humidity

YOG

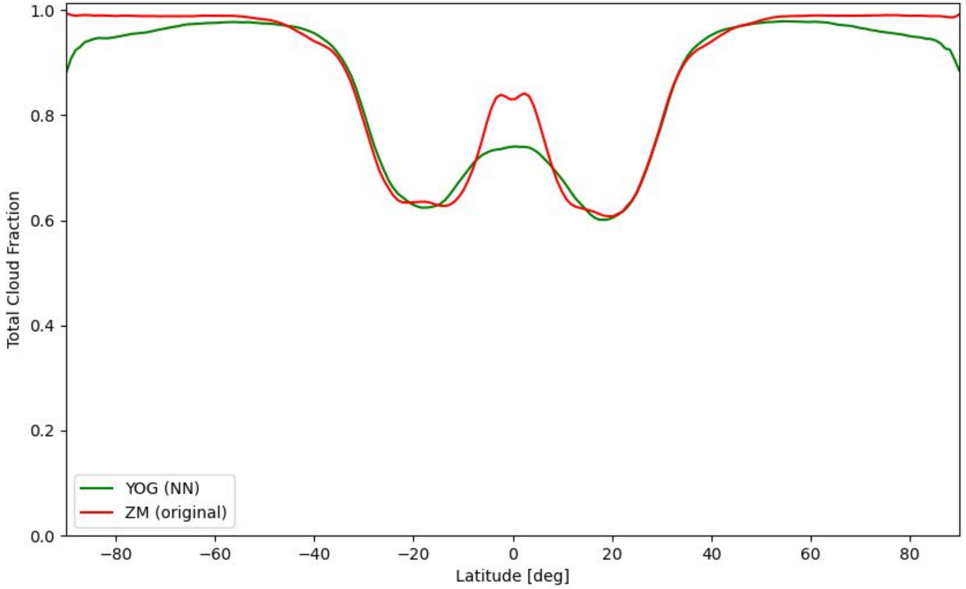


ZM



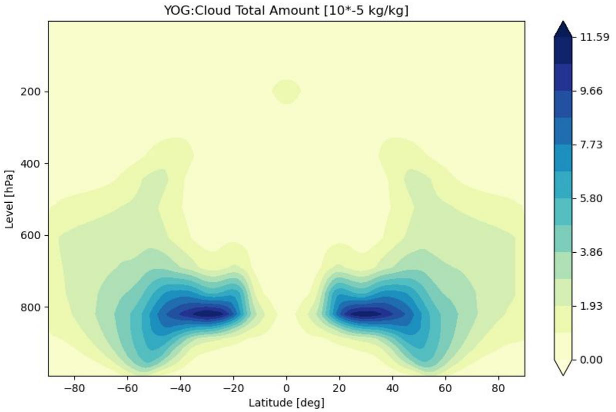
YOG reproduces cloud climatology

Total Cloud Cover

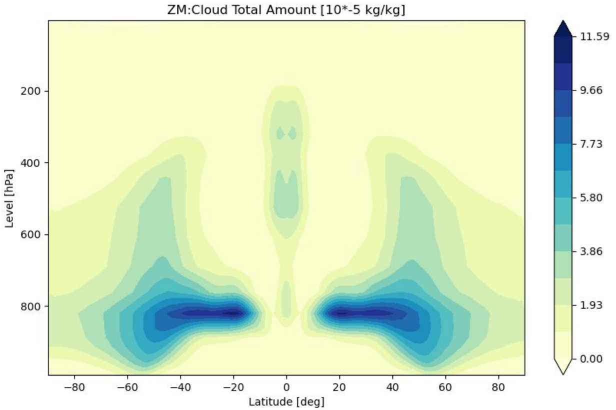


Cloud Condensate (Liquid + Ice)

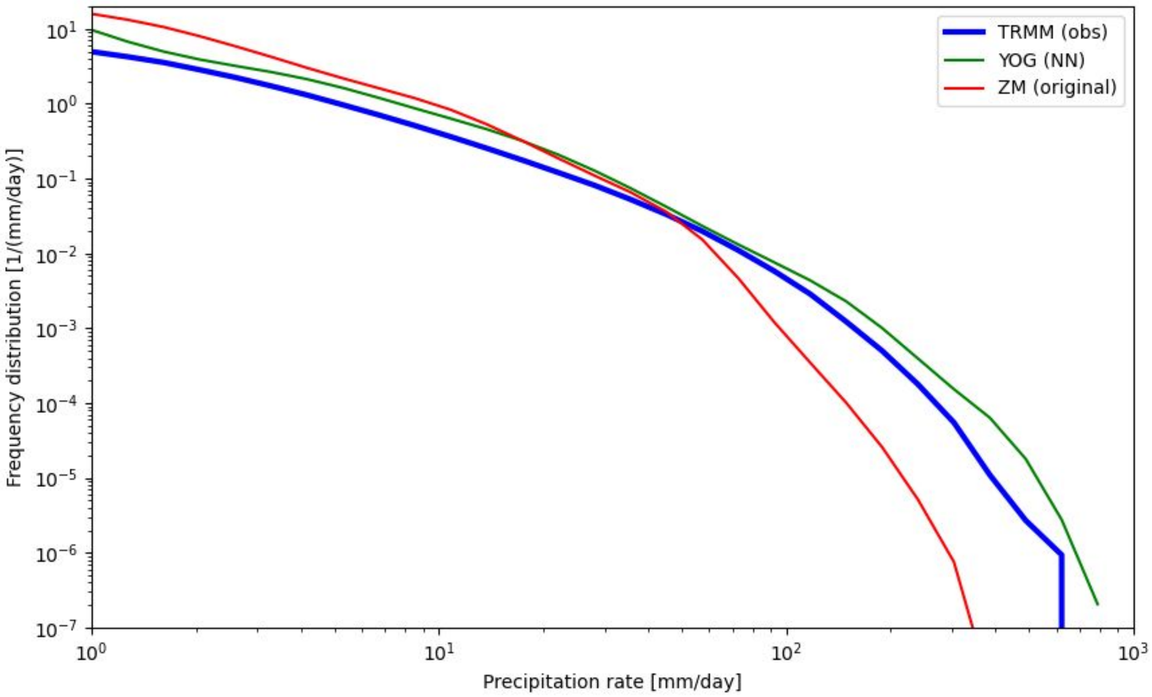
YOG



ZM



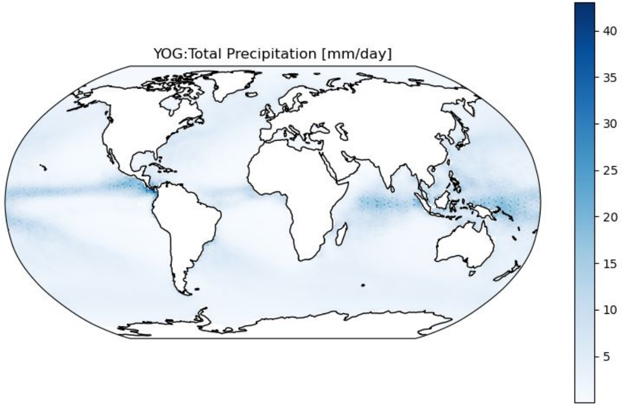
YOG improves drizzle/extreme biases

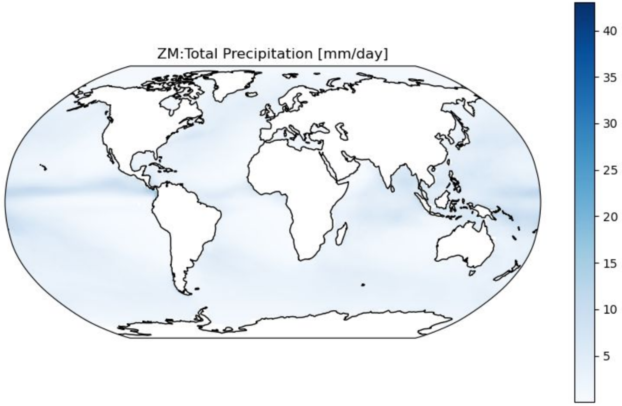


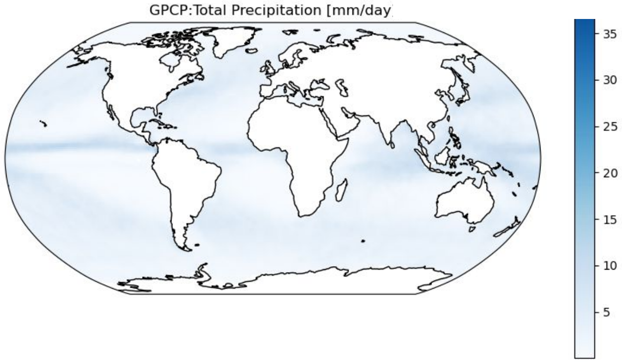
C. Full CAM6 (time-varying historical SST)

NB: Convection scheme turned off over land

Precipitation is reasonably well-distributed spatially, although it is overestimated in specific areas.

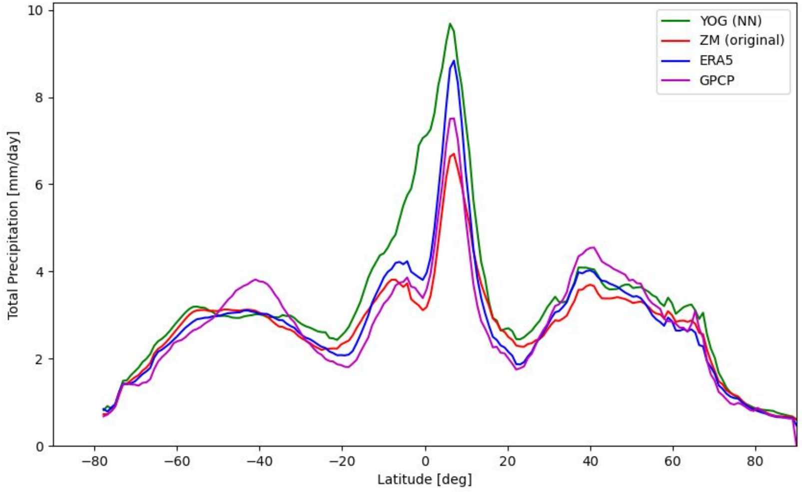




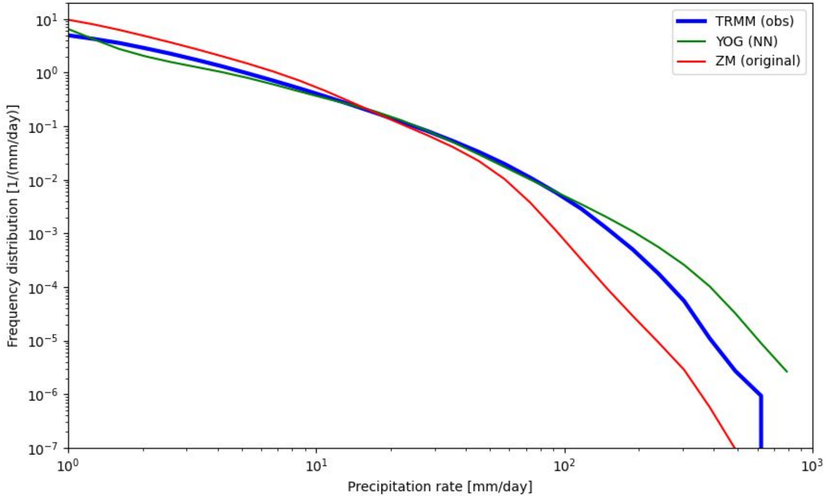


Promising results for precipitation, even if mean intensity is excessive

Time and zonal-mean precipitation



Probability distribution of precipitation



Summary

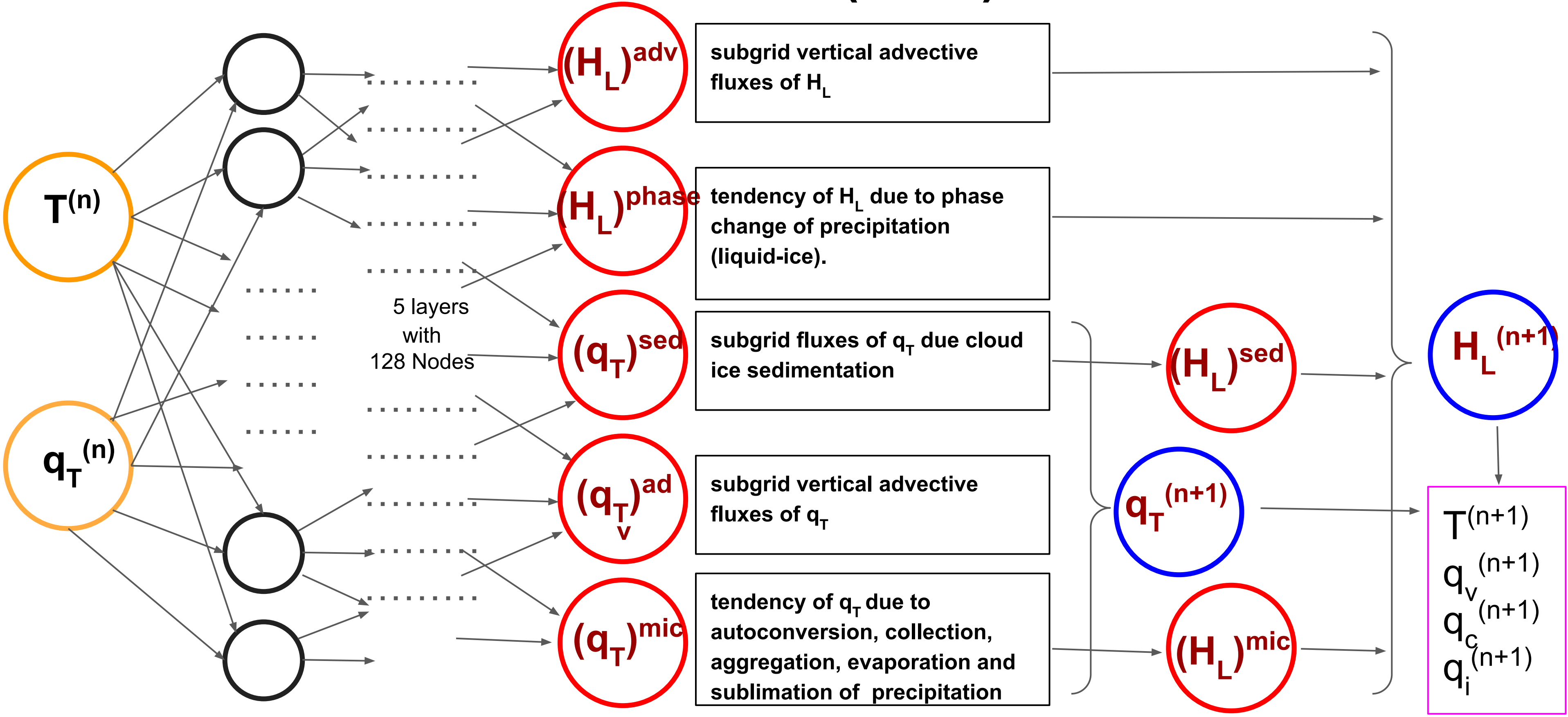
Using 3 idealized configuration in CAM6 (Single column with TOGA forcing, aquaplanet with Qobs SST, land-ocean with YOG off over land), we find that a NN scheme (YOG) can simulate deep convection reasonably well.

Pending work:

- Understand why the convective scheme is overly active in the tropics and address the resulting over-precipitation bias.
- Evaluate improvement of the hydrological cycle and cloudiness, on diurnal to seasonal timescales, and tropical waves.
- Modify scheme to be active over land (G. Mooers at MIT leads this effort).

Supplementary Material

Schematic of the NN network (SAM)



$H_L = c_pT + gz - L_cq_c - L_sq_i$
$q_T = q_v + q_c + q_i$

q_T : total non-precipitating water (vapor, liquid cloud, ice cloud)
H_L : liquid/ice water (non-precipitating) static energy

Still significant biases to resolve in cloud cover