Implementation of a neural-network convection scheme in the Community Atmosphere Model

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Part of the M^{2}LInES project

Use of machine learning to create subgrid parameterization for climate models

Climate model

Laws of physics for resolved motions
(e.g. fluid dynamics)

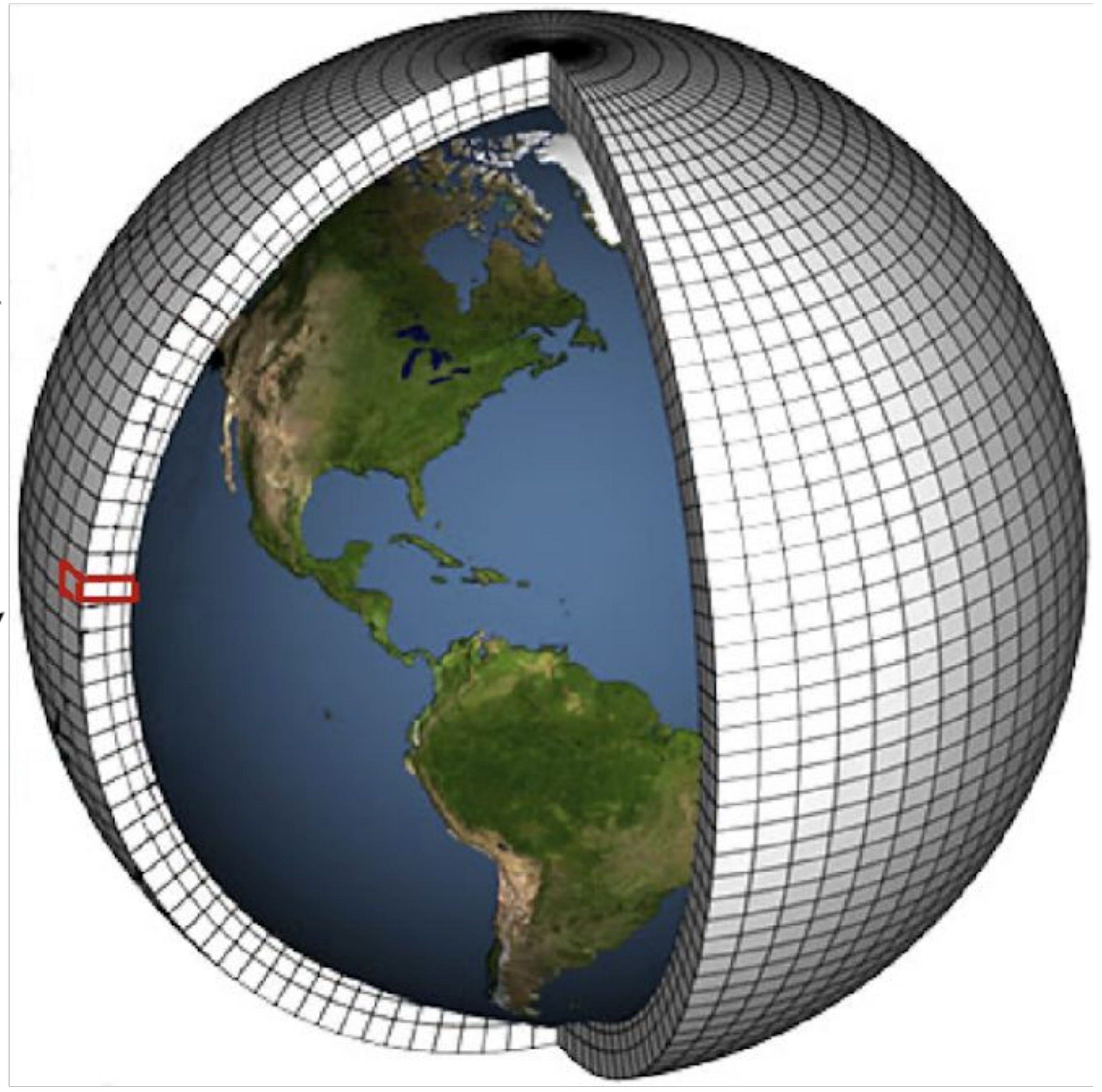
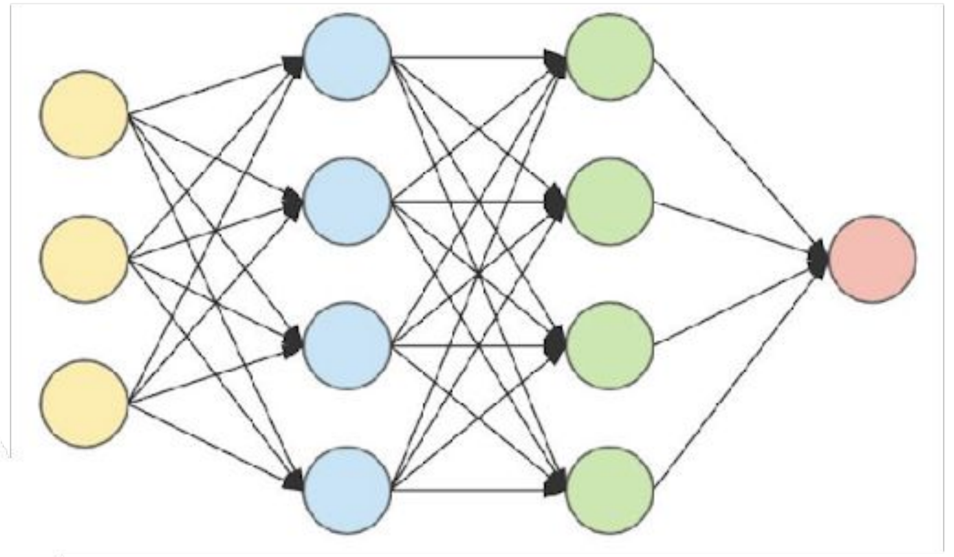


Image credit: NOAA

Machine learning
parameterization
for subgrid processes



High-resolution model

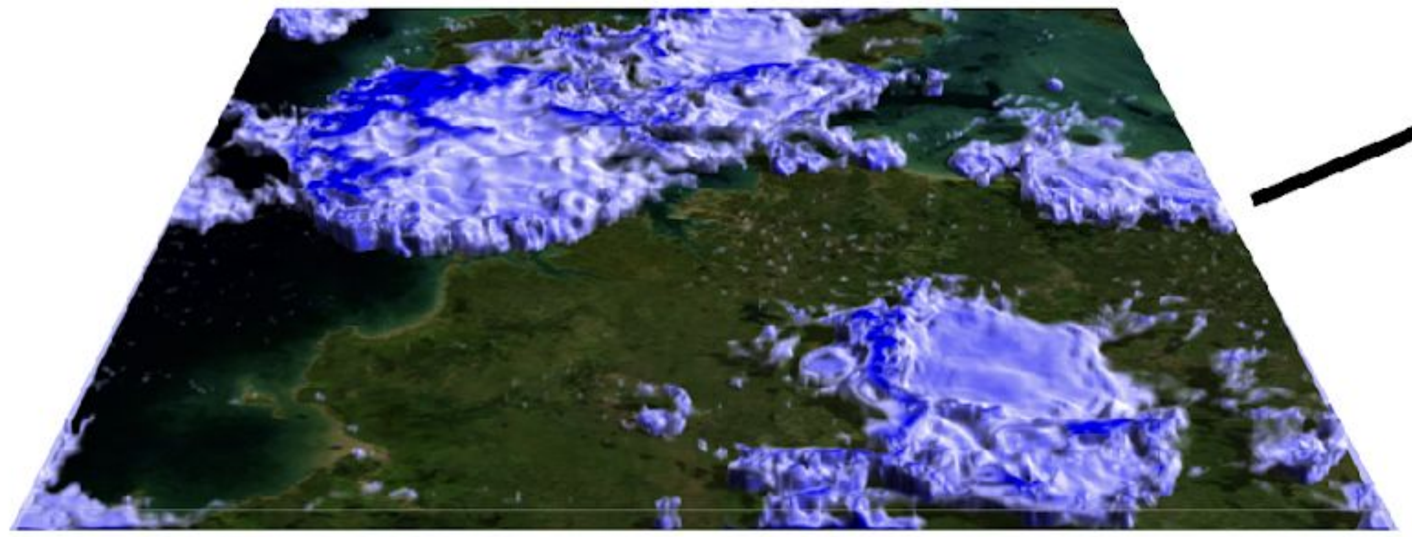
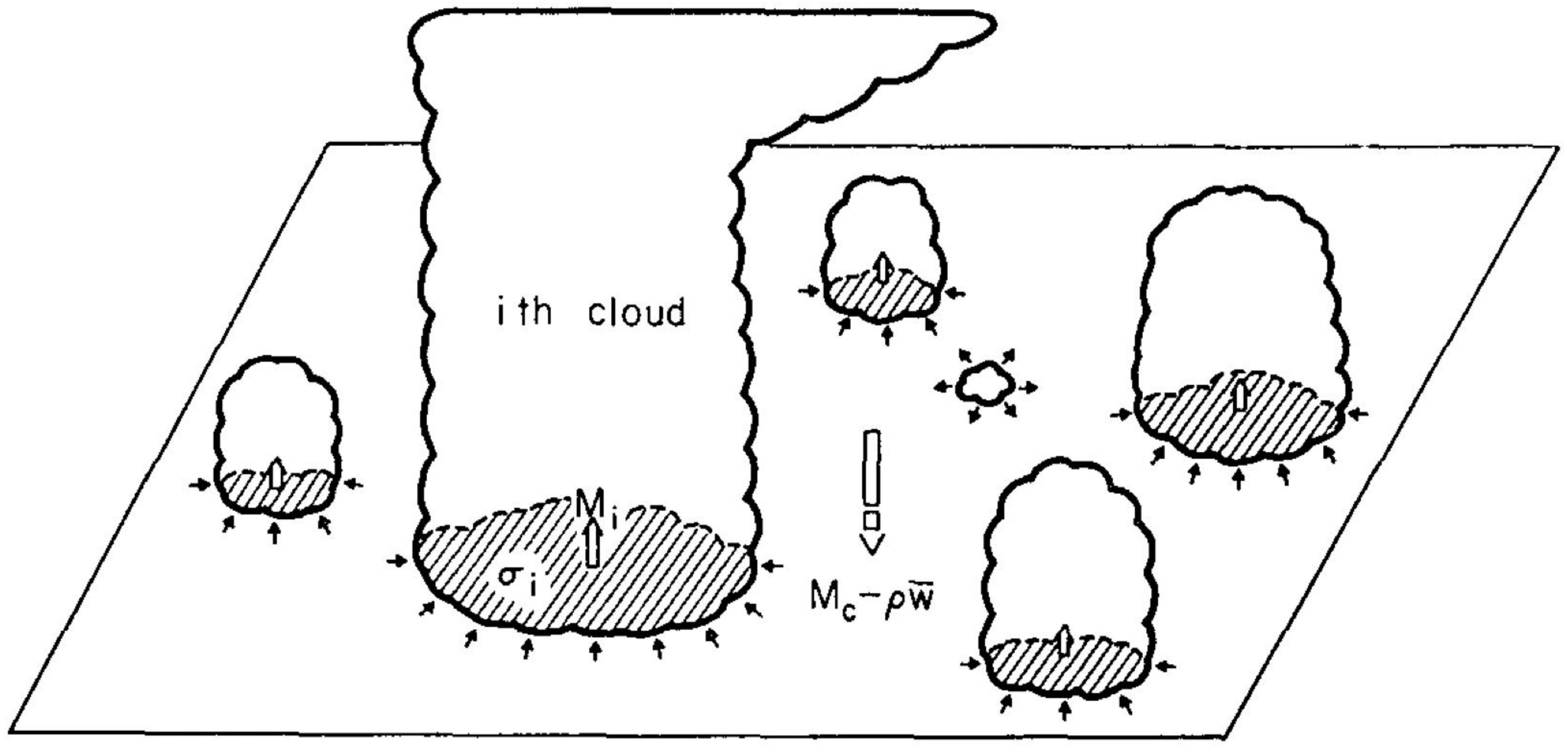


Image credit: NASA

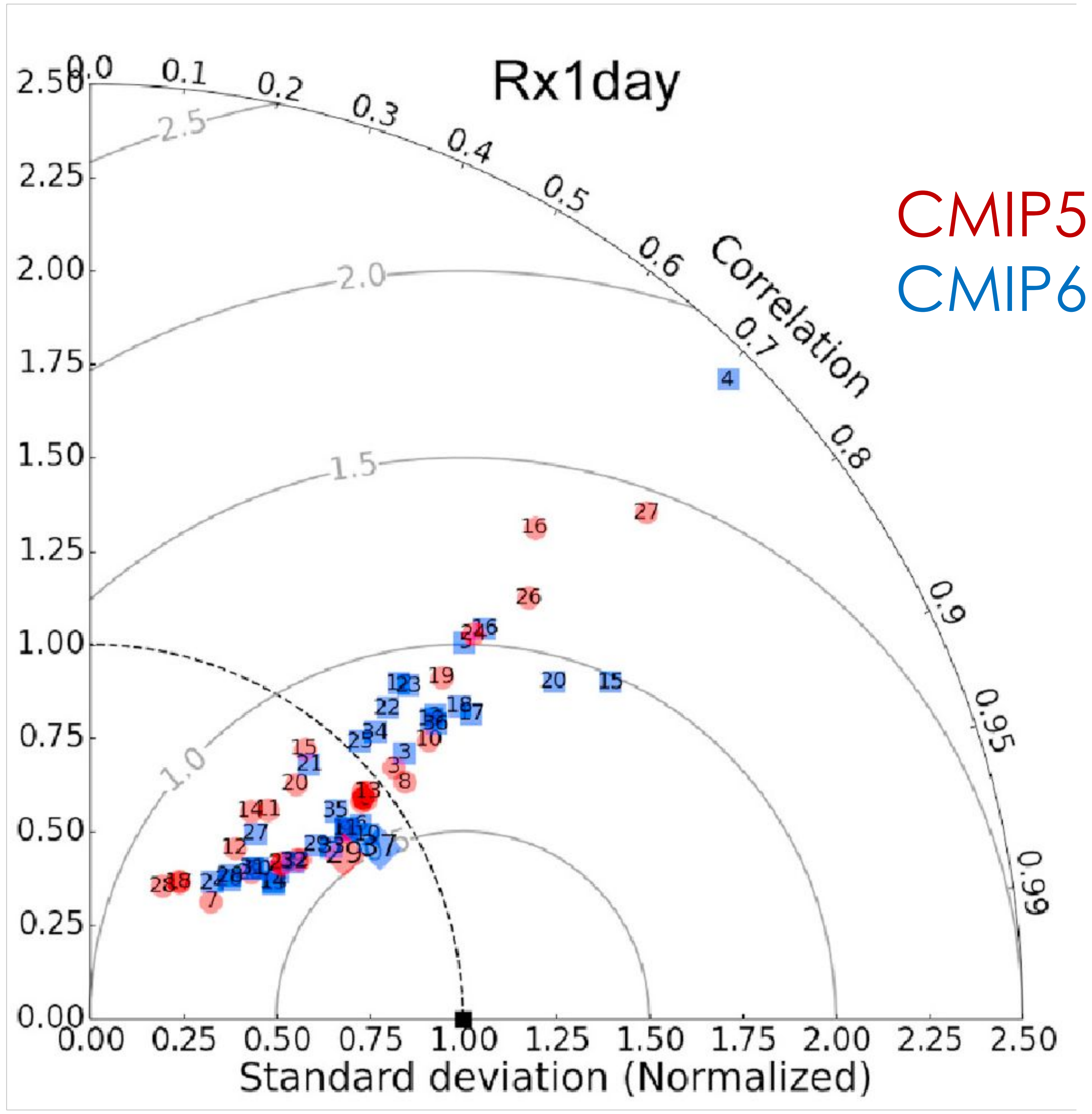
Krasnapolsky et al, 2013
O'Gorman and Dywer, 2018
Rasp et al, 2018
Brenowitz and Bretherton, 2019
Yuval and O'Gorman, 2020
Zanna et al, 2020
Han et al 2023

Motivation to develop machine learning parameterizations of moist convection



Arakawa and Schubert, JAS, 1974

Conventional convection parameterizations have some success but face a very challenging problem (e.g. precipitation-driven cold pools, multiscale organization, ice processes)

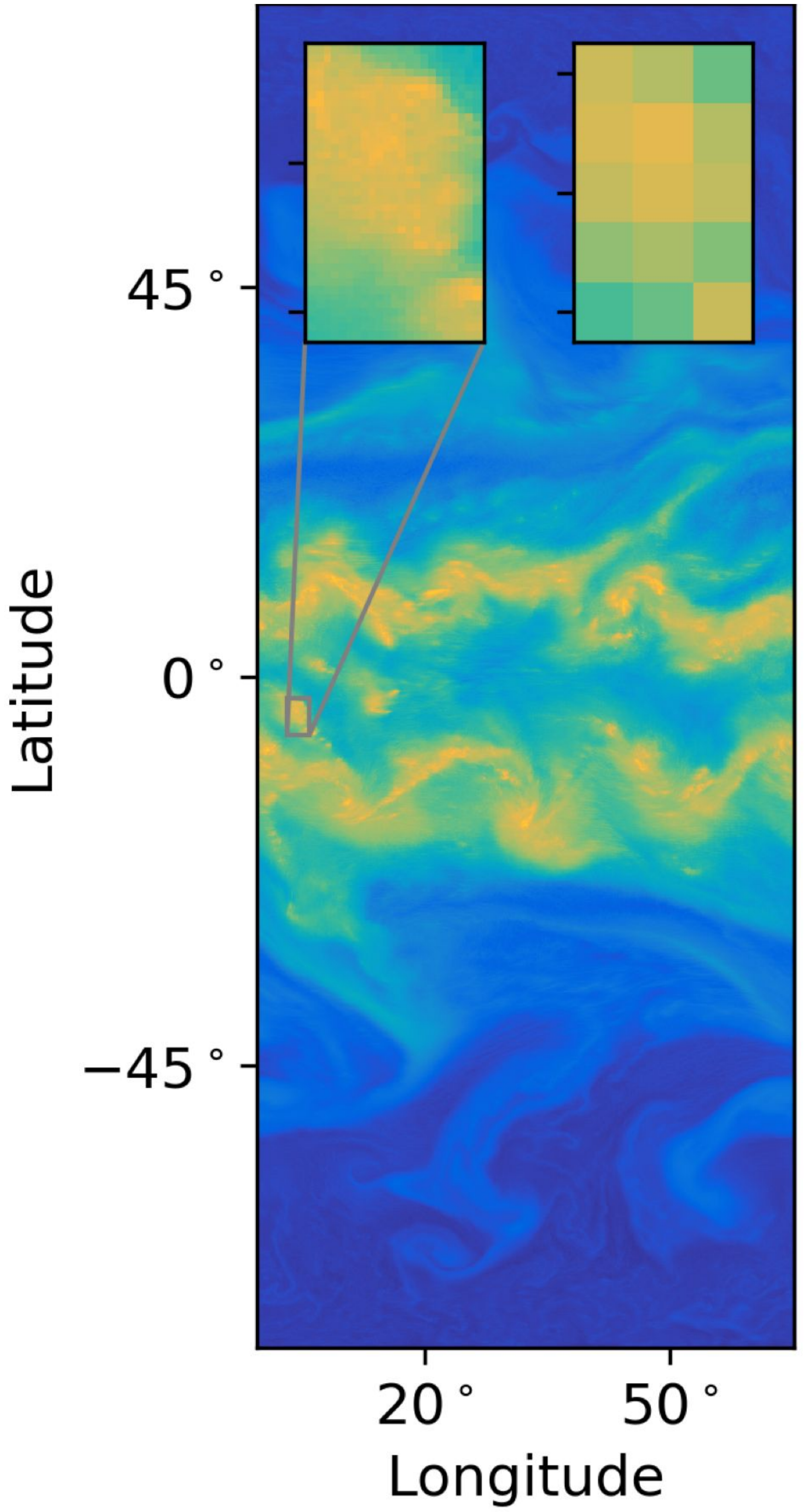


CMIP5 models
CMIP6 models

Wehner et al 2020

Convection parameterizations contribute to stubborn biases in precipitation intensity, and also winds, humidity

We learn from a high-resolution simulation of the atmosphere in a quasi-global domain

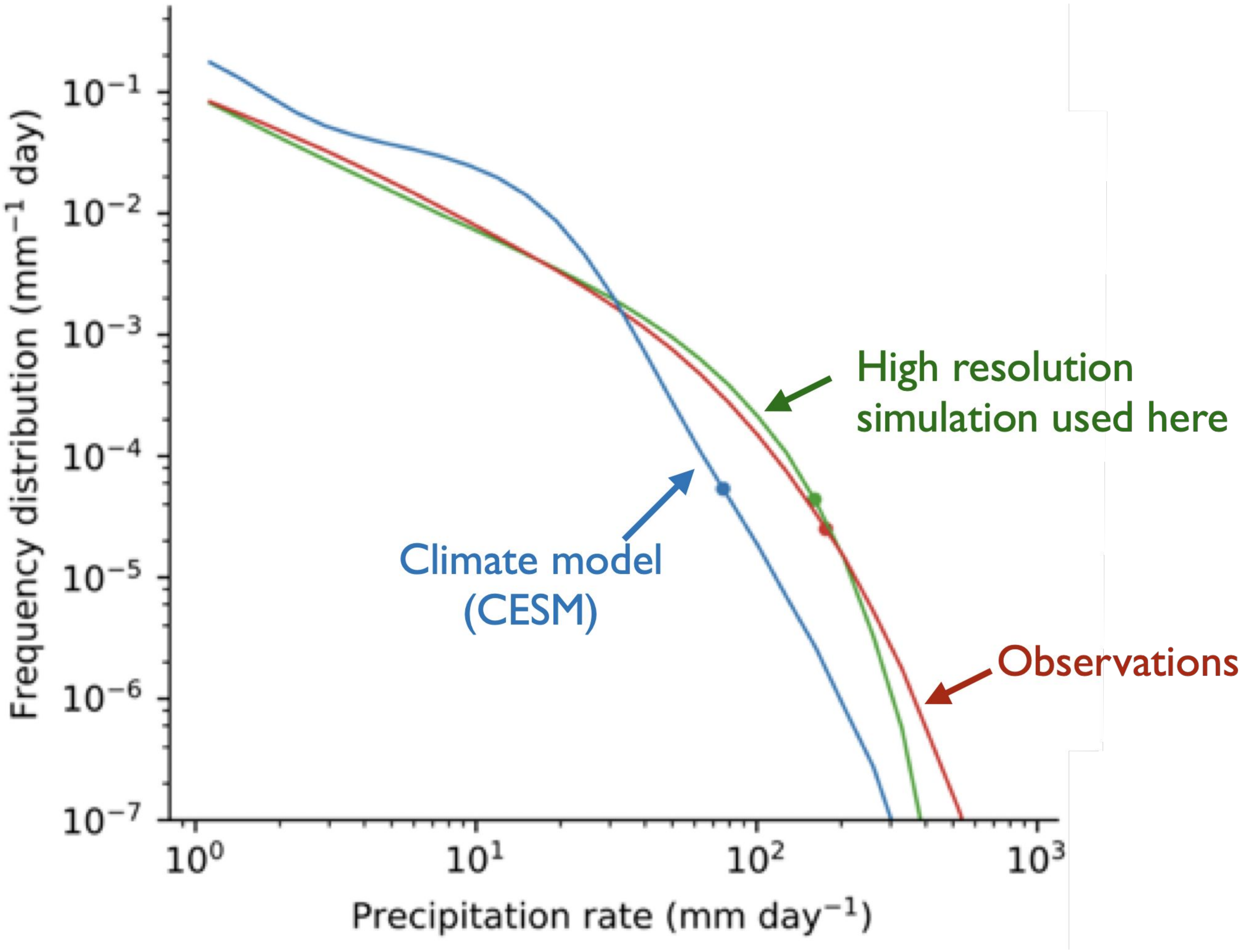


- SAM model with hypohydrostatic rescaling (grid spacing 12km with rescaling by factor 4)
- Prescribed sea-surface temperature distribution that is symmetric about the equator
- Coarse-grain the output of the high-resolution simulation over blocks of 8x8 gridcells (96km)

Yuval & O'Gorman, Nature Comm., 2020
Yuval, O'Gorman & Hill, GRL, 2021

SAM model: Khairoutdinov et al 2003
Original simulations thanks to Bill Boos and Alexey Federov

High resolution simulation has good representation of precipitation



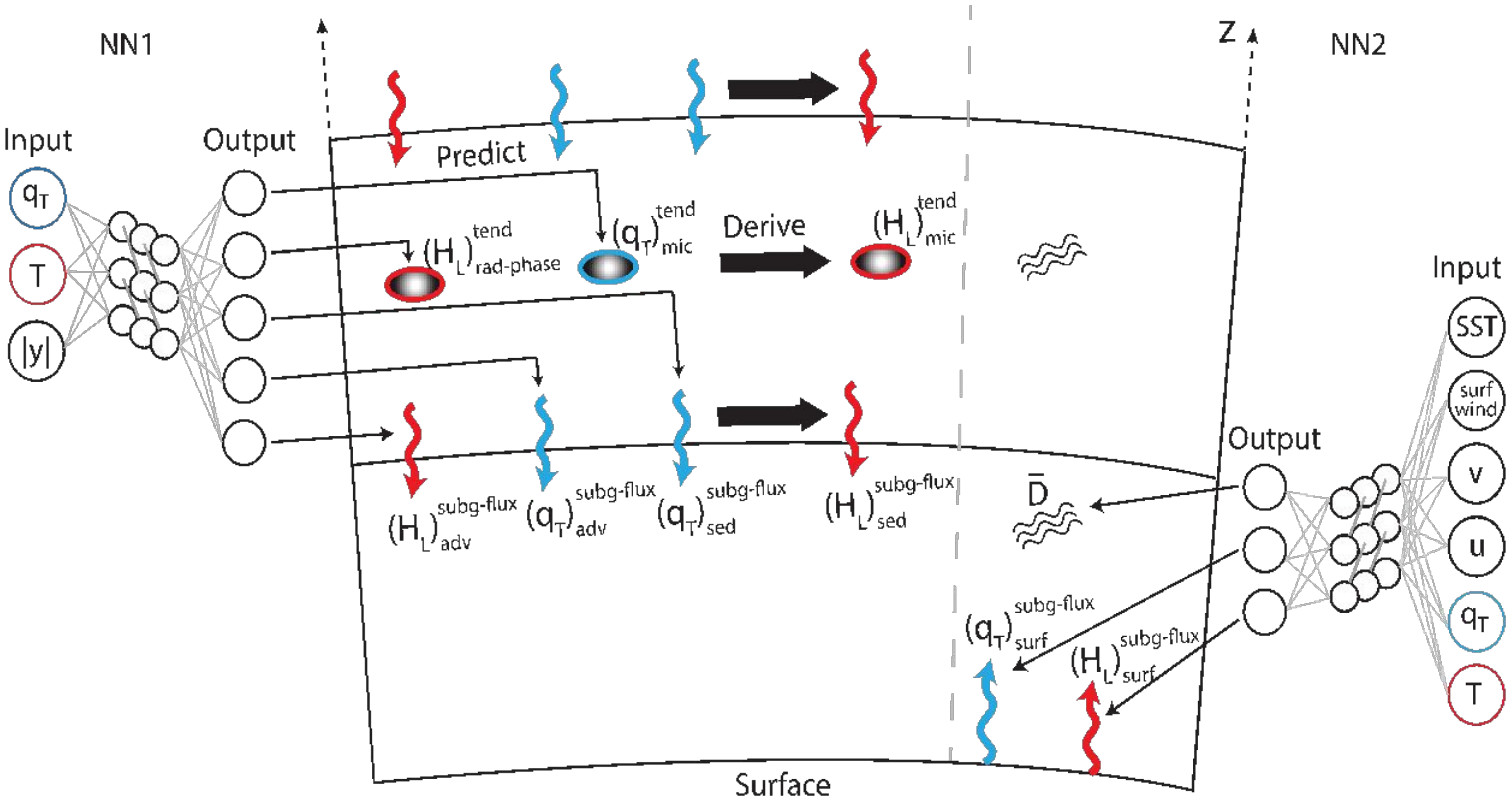
O'Gorman et al, Philiosophical Transactions A, 2021

6-hourly precipitation compared to TRMM 3B42 in tropical Pacific at consistent grid spacing

Aim to calculate subgrid terms accurately and satisfy conservation laws

1. *Accuracy:* calculate the subgrid terms exactly by coarse-graining the equations of the model process by process

2. *Ensure conservation of water and energy:* predict fluxes and sources/sinks (rather than net tendencies)

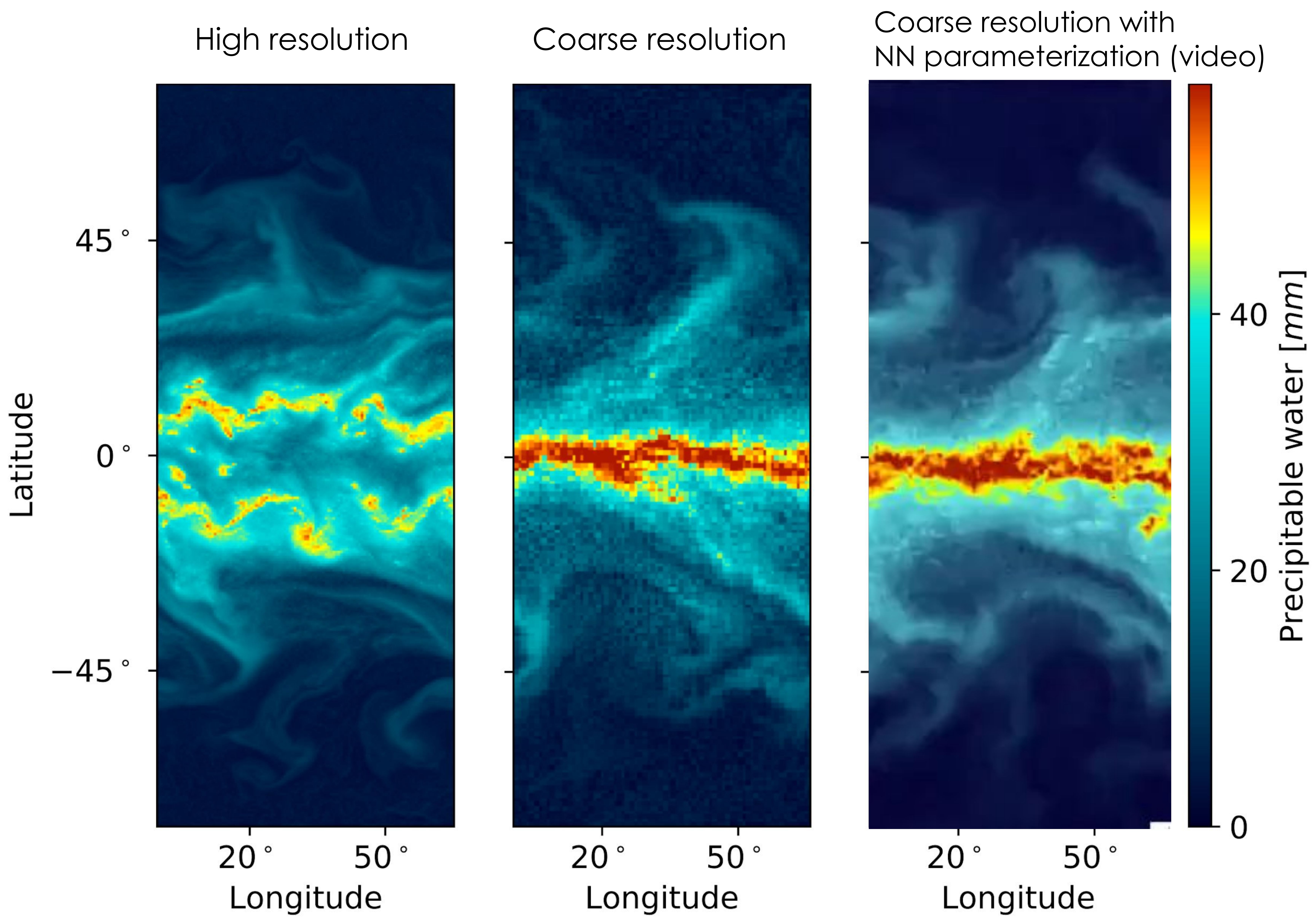


Outputs:

- Subgrid fluxes and conversions of energy and water
- Corrections to surface fluxes
- Turbulent diffusivity
- Radiative cooling

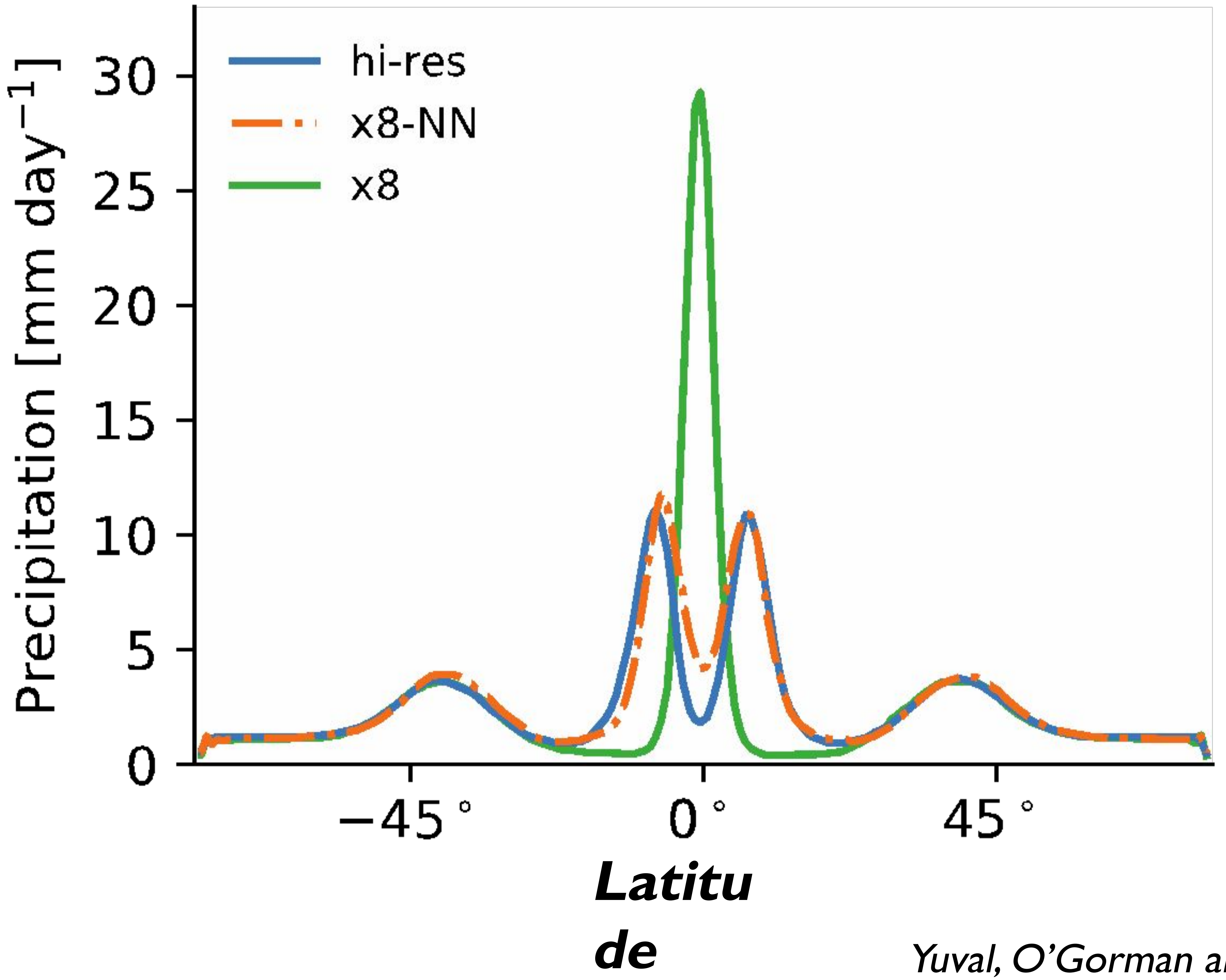
Yuval & O'Gorman, Nature Comm., 2020
Yuval, O'Gorman & Hill, GRL, 2021

Coarse-resolution simulation with NN parameterization matches high-resolution simulation



Machine learning gives stable simulations with accurate mean and extreme precipitation

Mean precipitation



Yuval, O'Gorman and Hill, GRL 2021

Implementation in CAM6 as a convection scheme

Implementation in CAM6 as a convection scheme

Overall approach:

Replace Zhang and McFarlane deep convection scheme, while keeping CLUBB scheme (turbulence, cloud macrophysics) and MG2 microphysics scheme

Changes from SAM implementation:

- Don't predict momentum fluxes, turbulence diffusivities, radiative cooling, or surface flux corrections
- Microphysical conversion of condensate to precipitation now only includes subgrid component
- Don't include distance from equator as input (used in SAM parameterization as proxy for radiative properties like surface albedo)

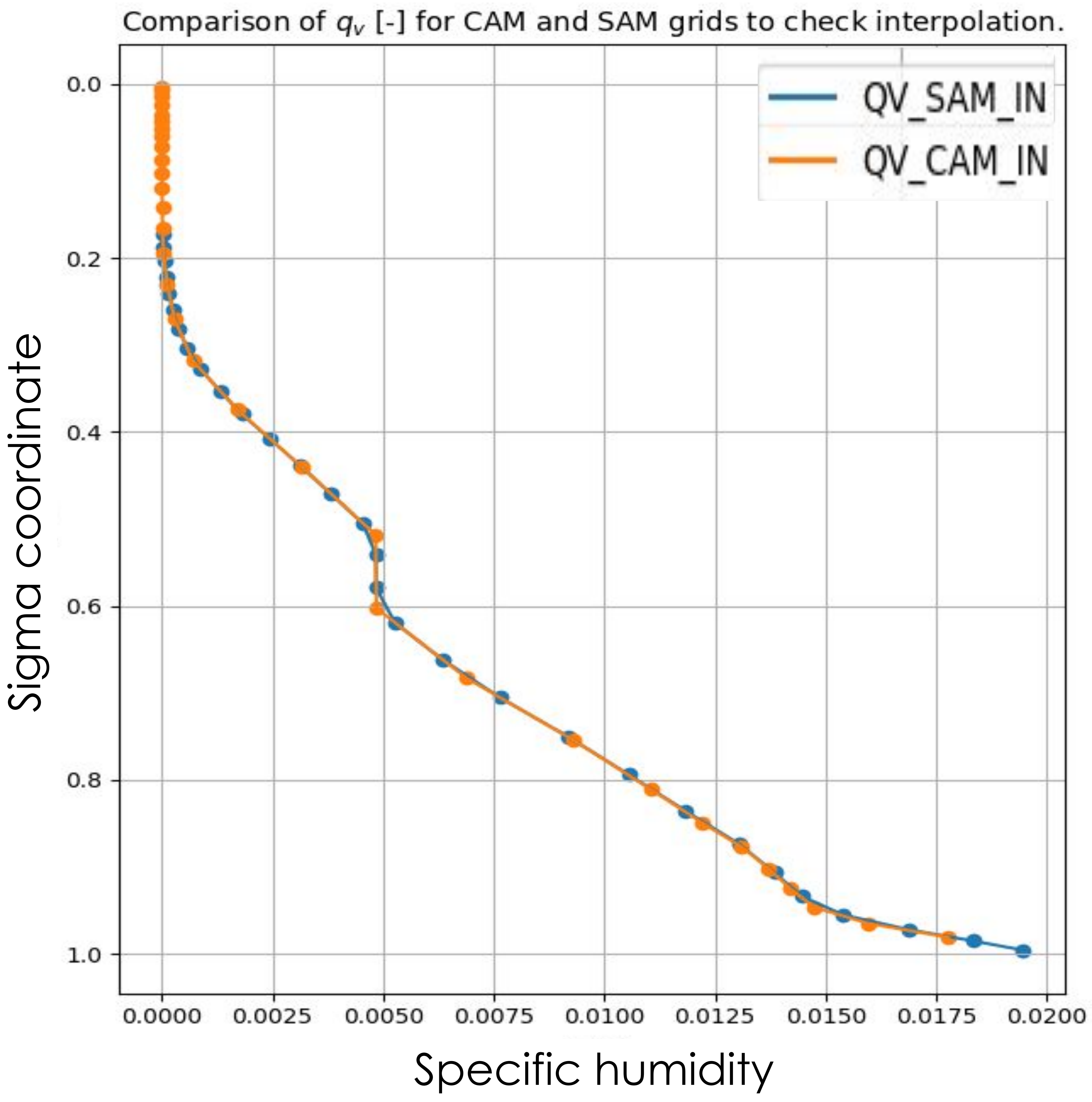
Conversion between SAM and CAM: vertical grids and variables

Regridding in vertical:

- Regrid using sigma coordinate
- Linear interpolation for inputs
- Conservative regridding for outputs (so that conserve water and energy)

Variables:

- Convert from liquid-ice static energy in SAM to dry static energy in CAM
- Convert from total non-precipitating water in SAM to moist mixing ratios in CAM



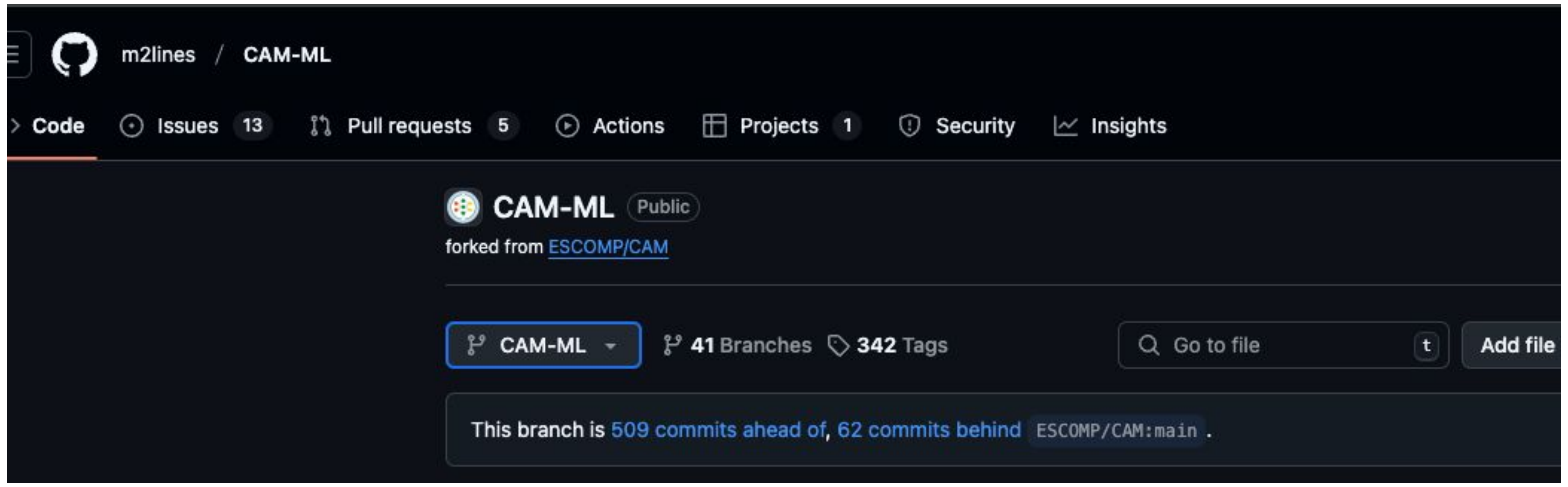
Software implementation

Set up as a fork of ESCOMP/CAM at github.com/m2lines/CAM-ML

Neural network (5 layers) is coded in fortran90 and weights are read in as a netcdf file

Parameterization called from physpkg.F90 since it could replace more than just the deep convection scheme

Uses physics timestep and computational cost is similar to Zhang and McFarlane

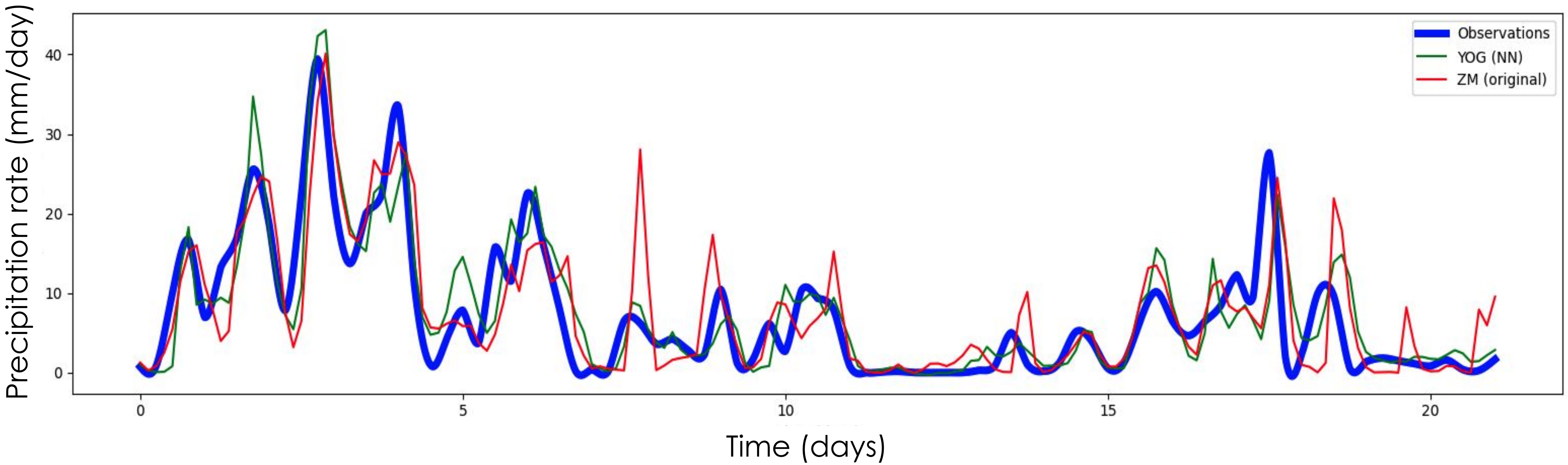


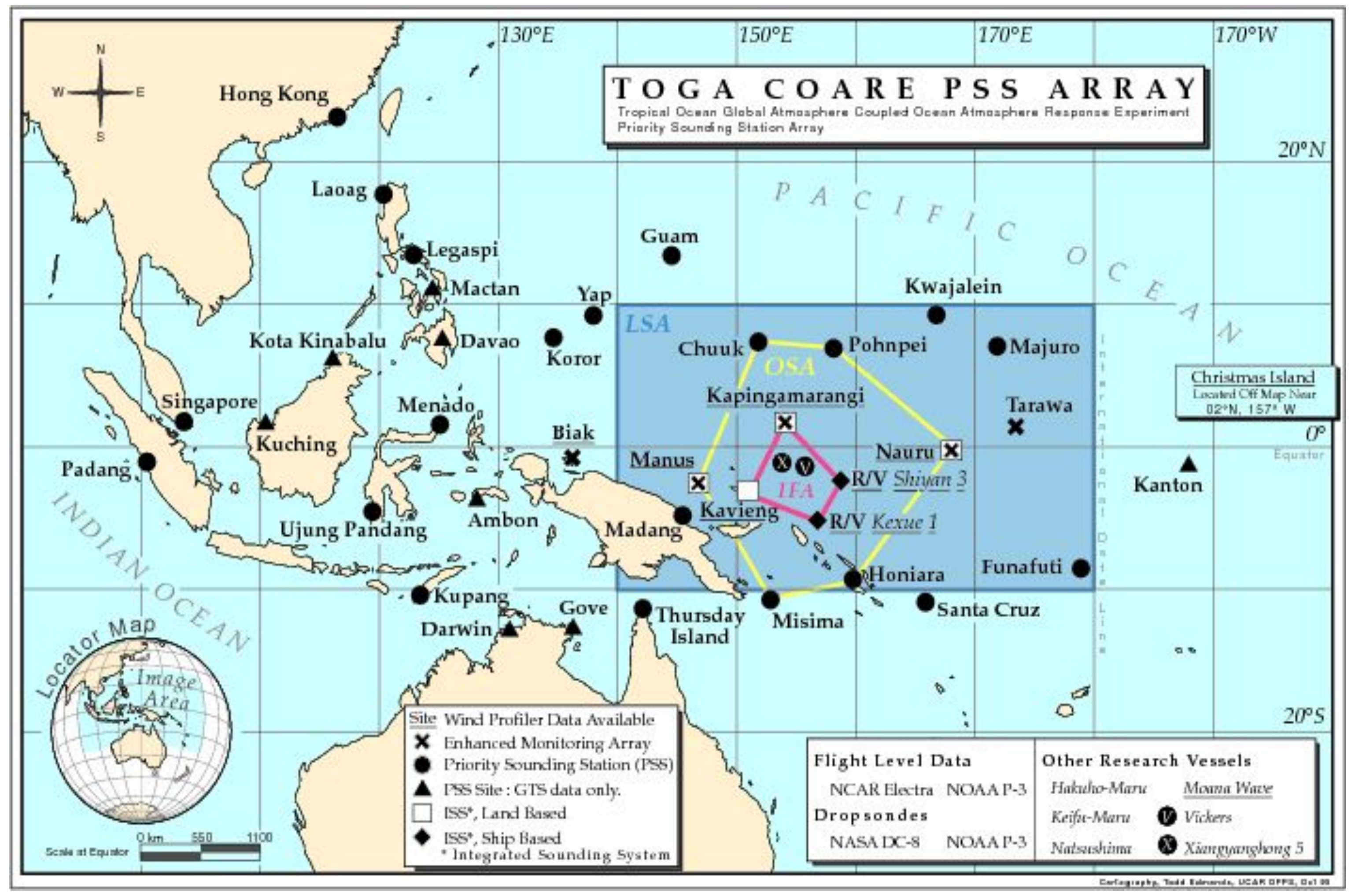
Institute of Computing for Climate Science

Jack Atkinson and ICCS team
with help from Judith Berner and others at NCAR

Test in single column mode using TOGA field data

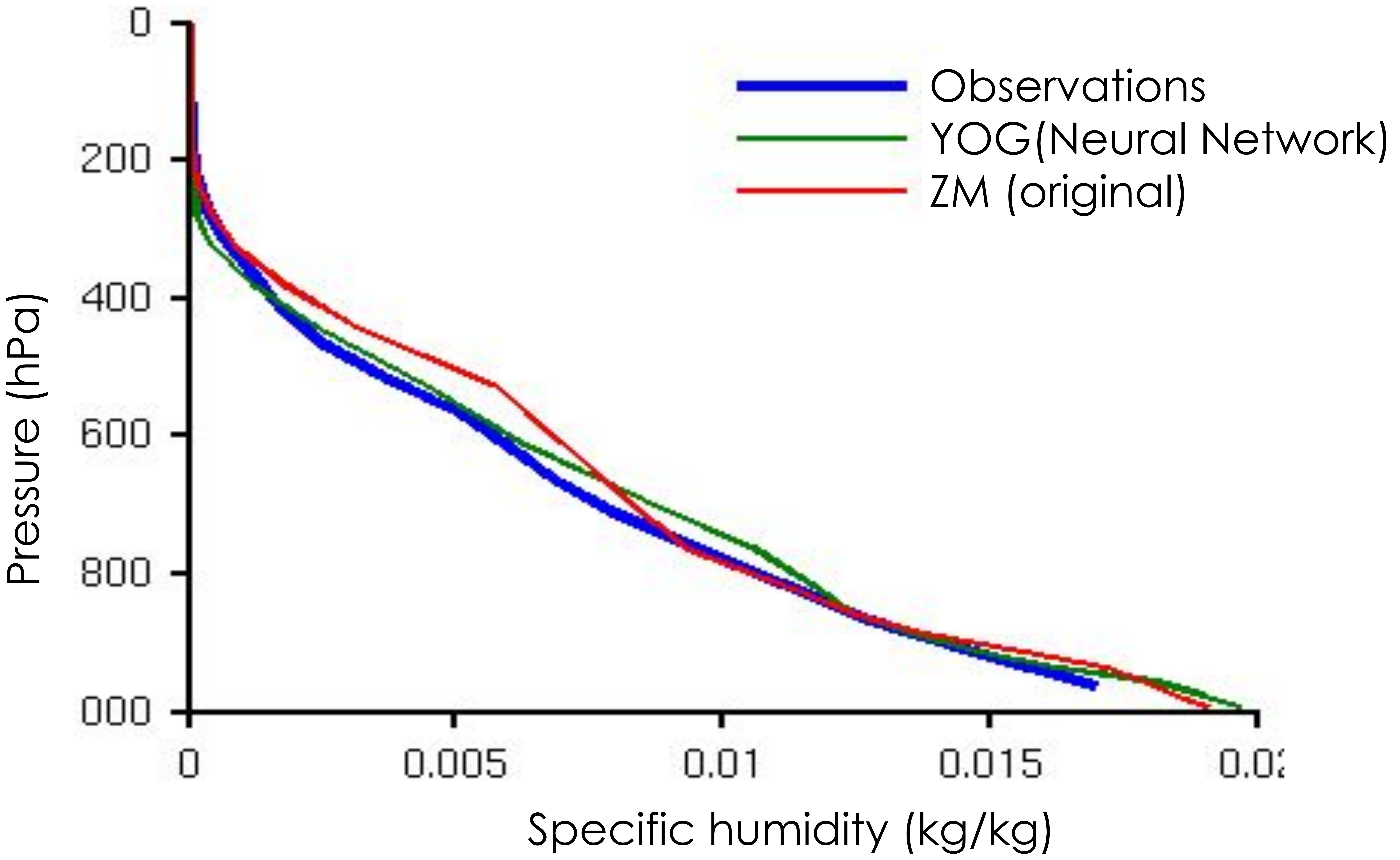
Precipitation is well captured and sometimes improves on original scheme





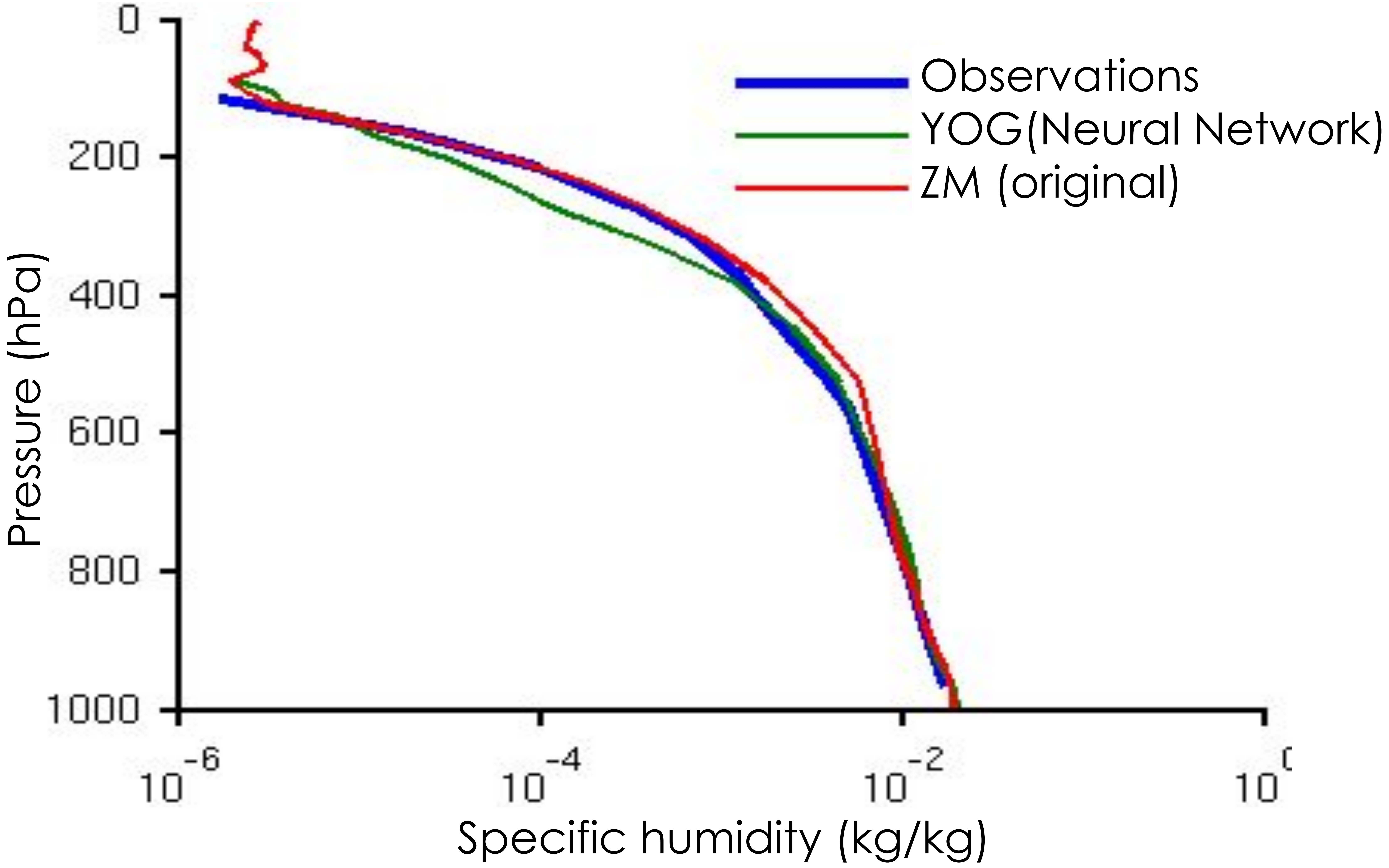
Single column test using SCAM6 *(Gettelman et al, JAMES, 2019)* and TOGA COARE field data *(Webster and Lukas, BAMS, 1992)*

Time-mean specific humidity is well captured



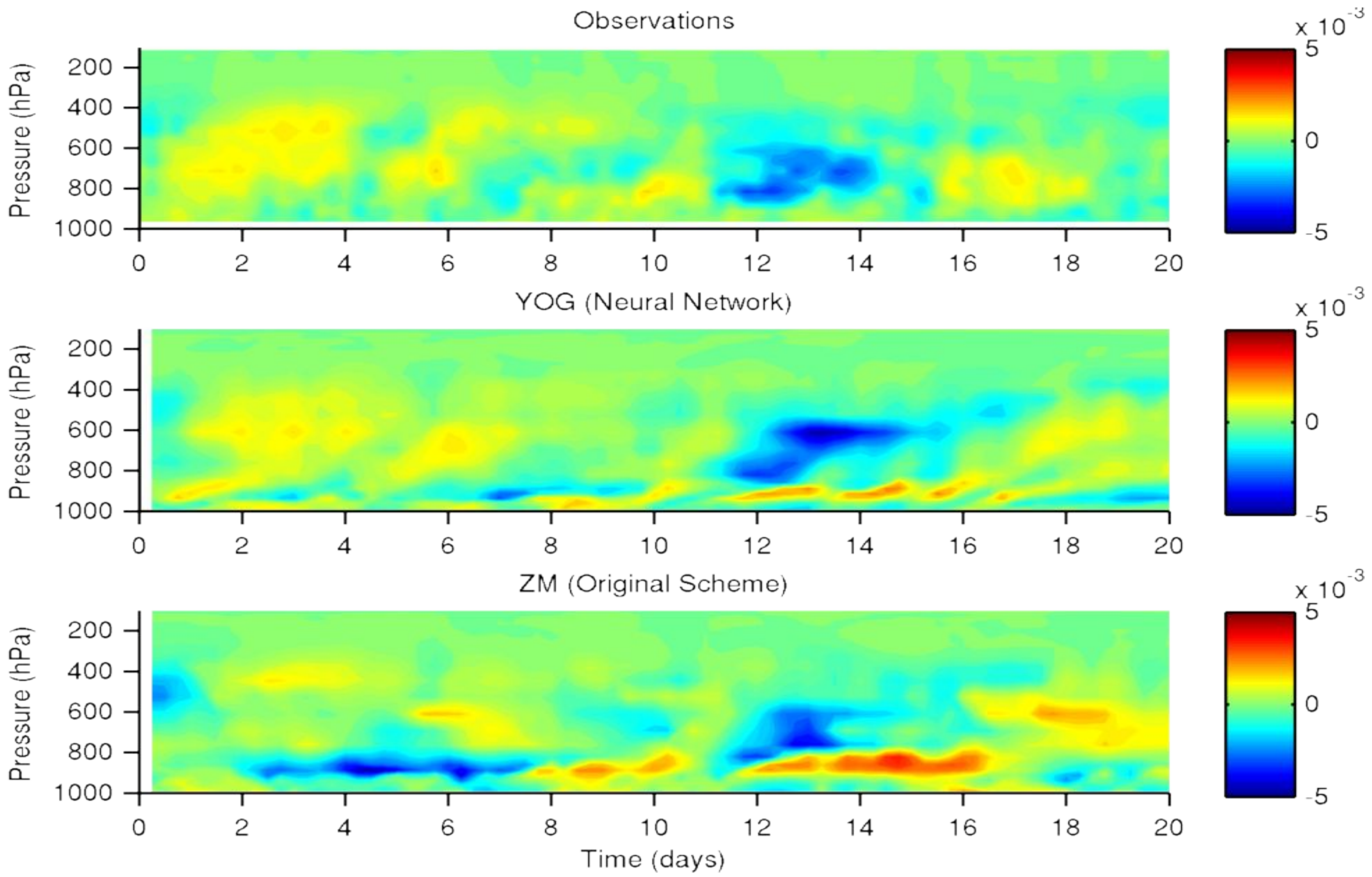
Single column test using SCAM6 and TOGA field campaign

When plotted on log scale, can see dry bias in upper troposphere (not clear if an issue)



Single column test using SCAM6 and TOGA field campaign

Specific humidity anomalies are improved

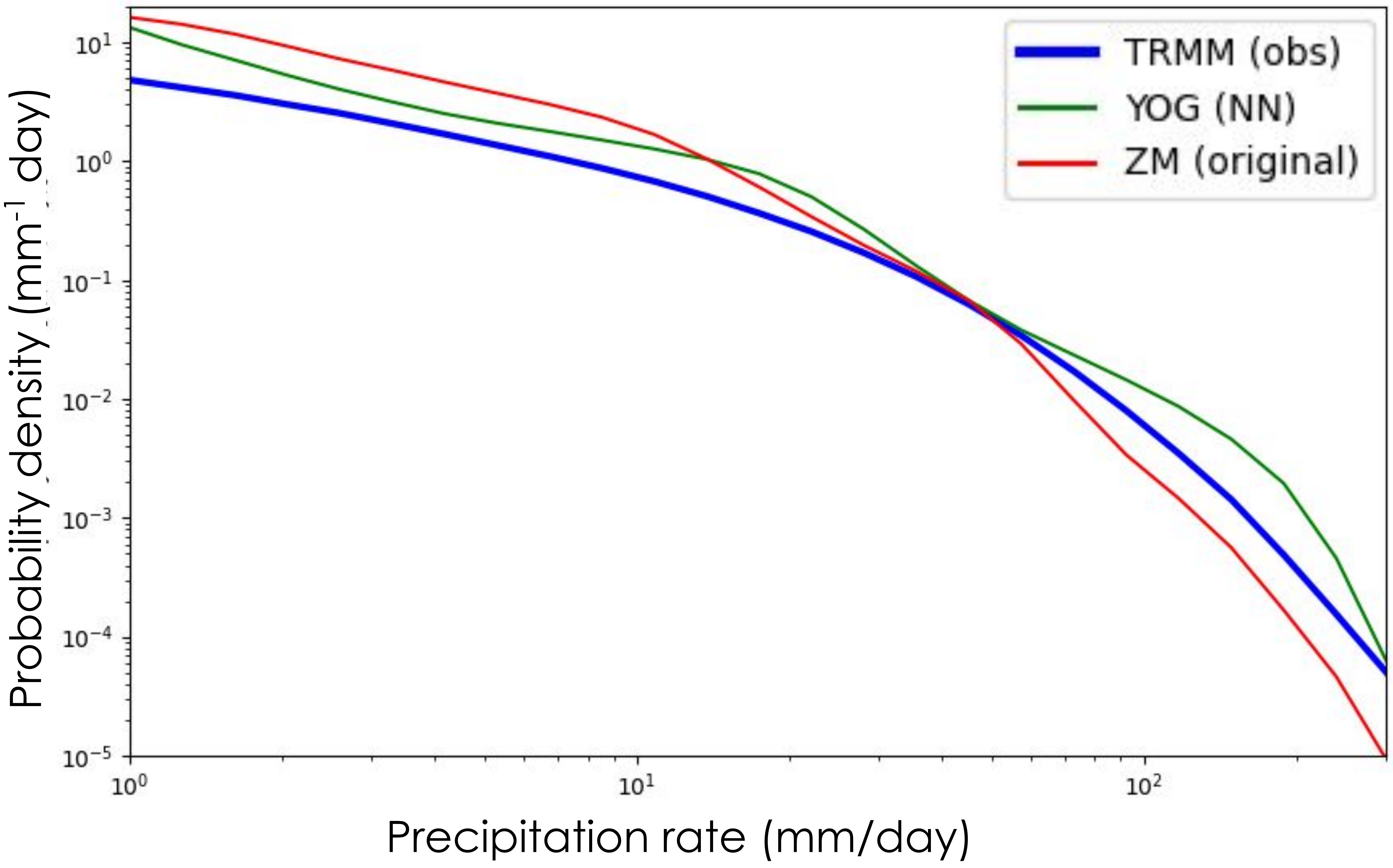


Anomalies defined as deviations from time mean

Single column test using SCAM6 and TOGA field campaign

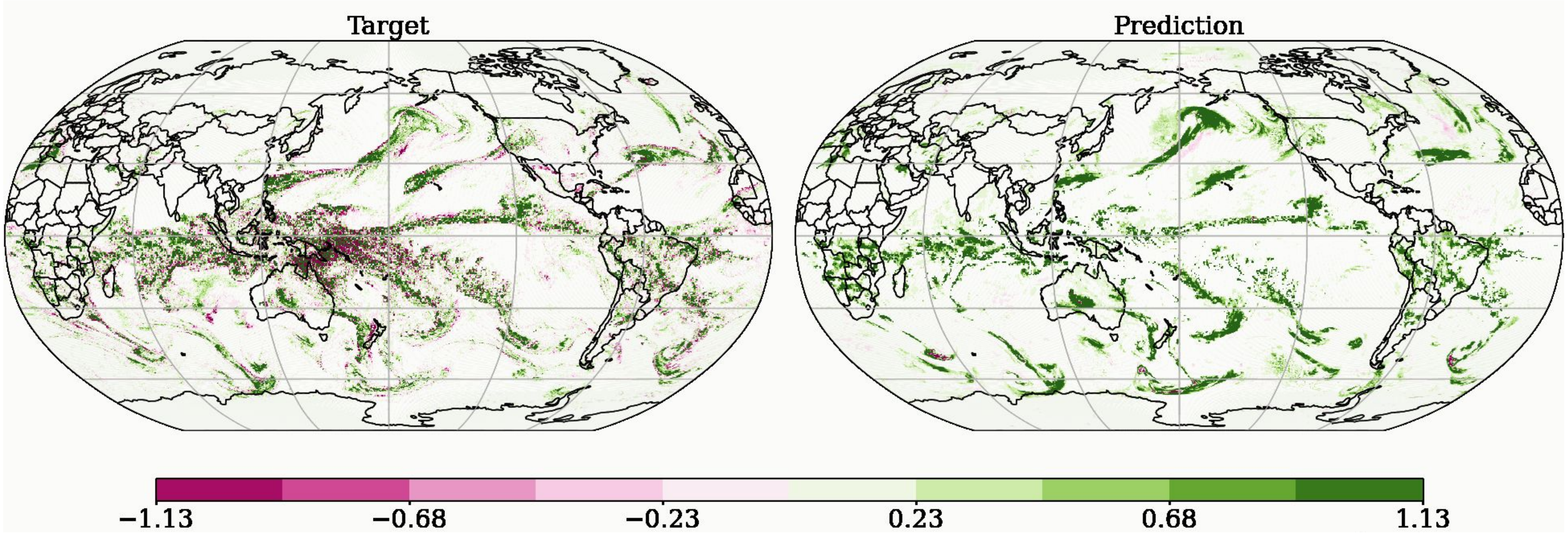
Ongoing work: Test in CAM6 aquaplanet simulation

Aquaplanet: Runs stably and shows improvements for shape of precipitation distribution



6-hourly precipitation compared to TRMM 3B42 in tropical Pacific at consistent grid spacing

Next will implement version of parameterization trained on DYAMOND2 simulation



Subgrid vertical flux of non-precipitating water at midtroposphere in 10^{-5} g m^{-2} s^{-1}
Credit: Griffin Mooers

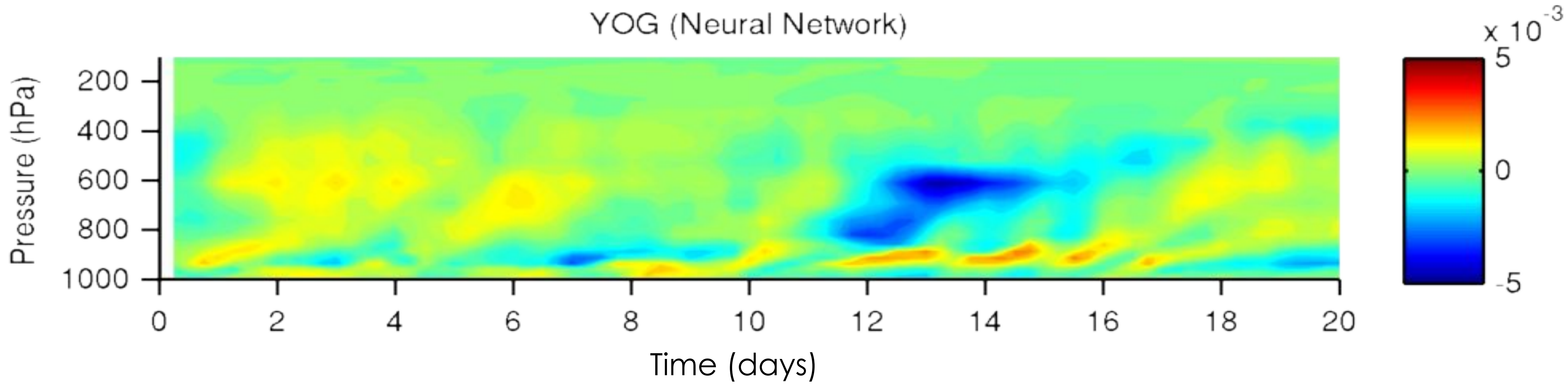
Global SAM simulation with horizontal grid spacing from 2km to 4km, includes land and topography
Parameterization trained using coarse-graining to CAM 1-degree grid
in collaboration with Janni Yuval and Marat Khairoutdinov: Khairoutdinov et al, JAMES, 2022

Conclusions: Neural-network convection scheme in CAM

1. Have developed moist physics parameterization using coarse-graining of 3D high-resolution atmospheric simulation and accurate calculation of subgrid terms for different processes

2. Implementation as convection scheme in CAM6 shows promising results for precipitation and humidity although more testing and development is needed

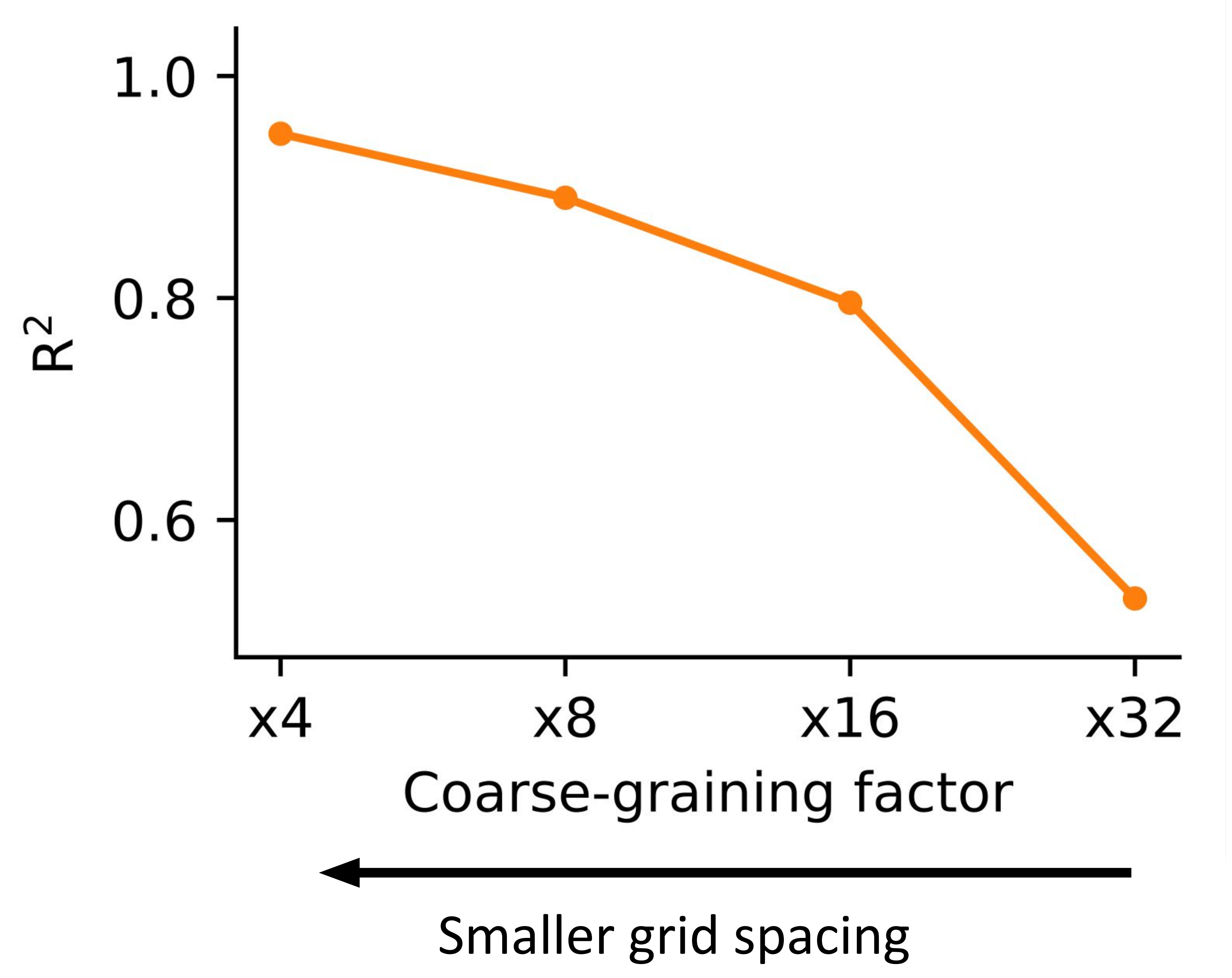
3. Computational cost is similar to conventional convection scheme



Research Scientist Xavier Levine will be regularly visiting NCAR and is working on the CAM implementation

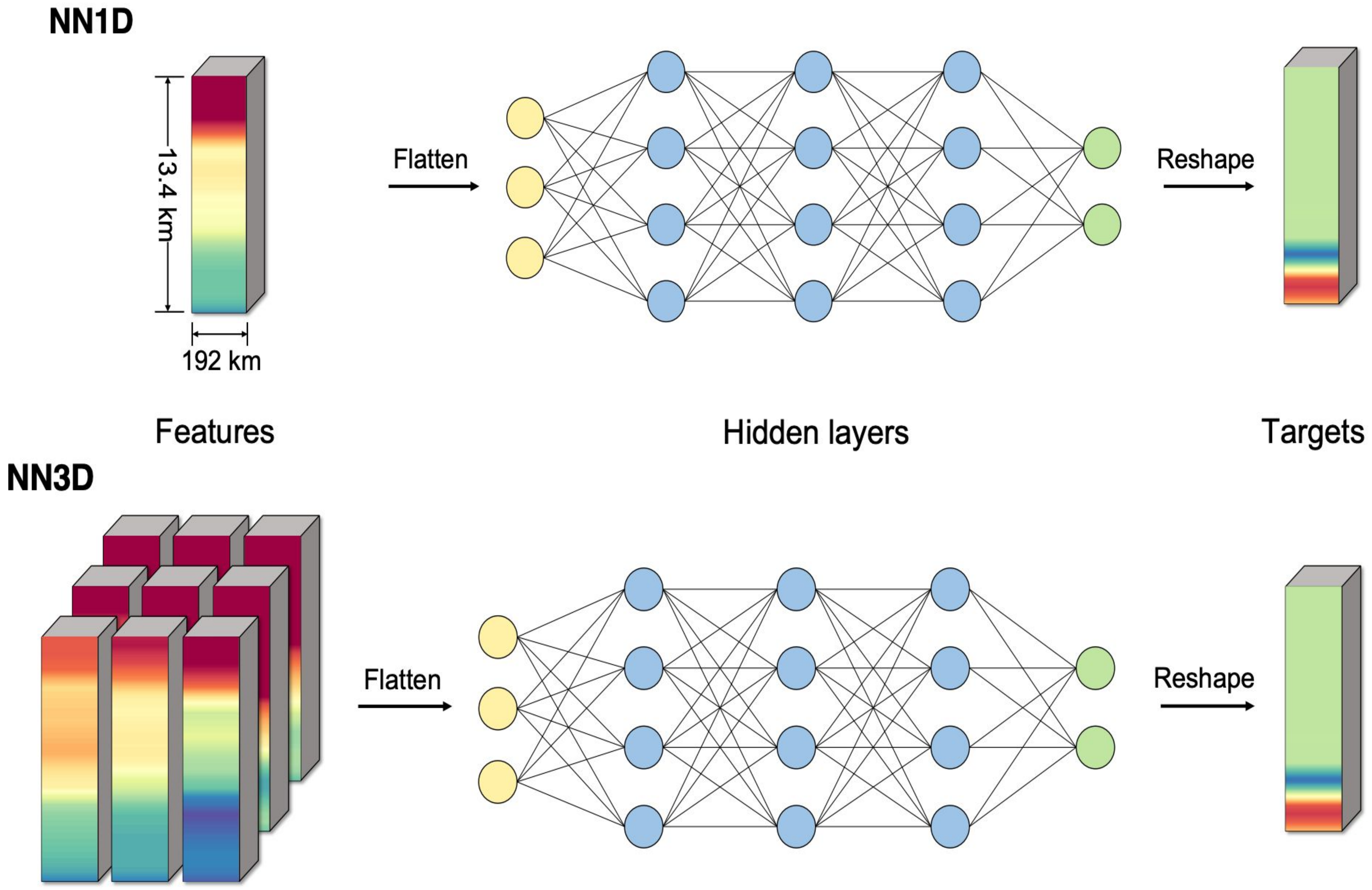
Future work: Use at higher resolution and inclusion of convective momentum transport

No problem with gray zone: Online skill is best for smaller coarse-graining factors



Yuval & O'Gorman, Nature Communications, 2020

Convective momentum transport works best when include neighboring columns as inputs



Yuval and O'Gorman, GRL, 2023
Wang, Yuval and O'Gorman, JAMES, 2022