

Probabilistic Machine Learning for Stochastic Parameterization of Deep Convection Triggering

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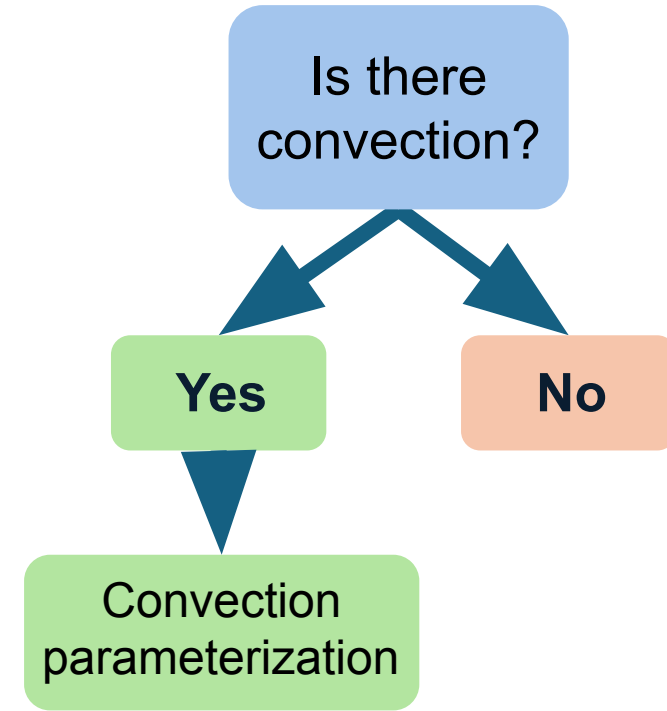
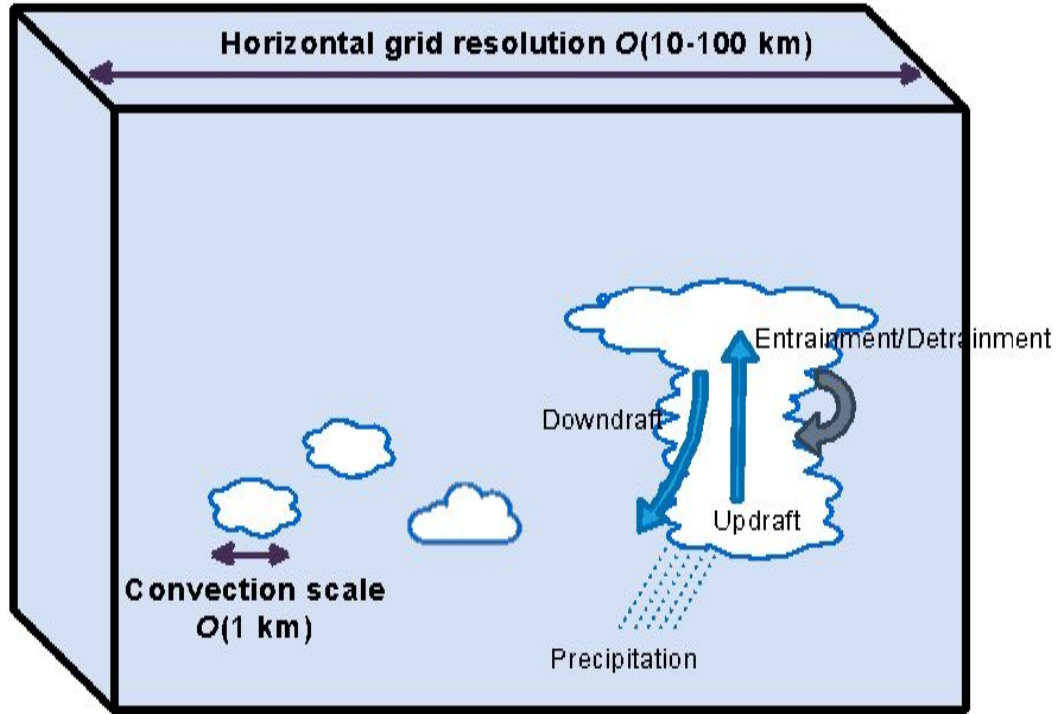


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Convection trigger: where and when deep convection occurs in models

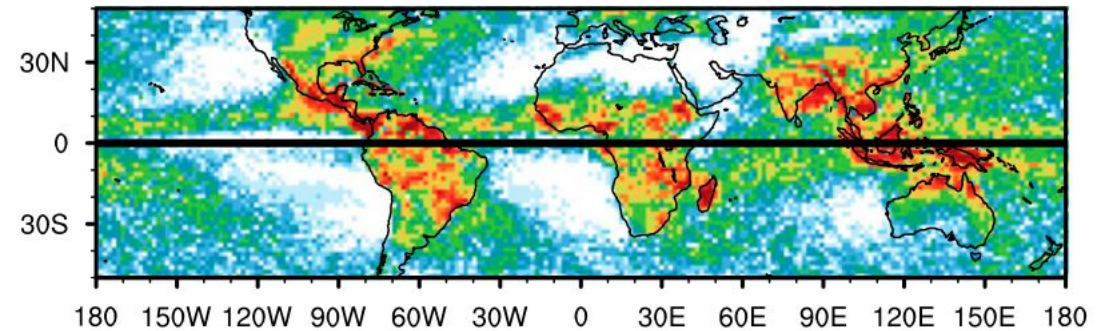


Parameterization of convection □ issues in model simulations

- Poor simulations of precipitation frequency and intensity (“drizzle problem”), diurnal cycle, ITCZ, etc.
- Most convection triggers in models are deterministic, without considering the uncertainty in the convective state as a stochastic process

Diurnal peak amplitude of

Observations (TRMM)



CAM with optimized dCAPE trigger

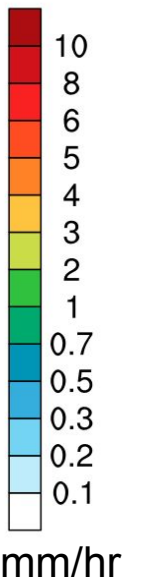
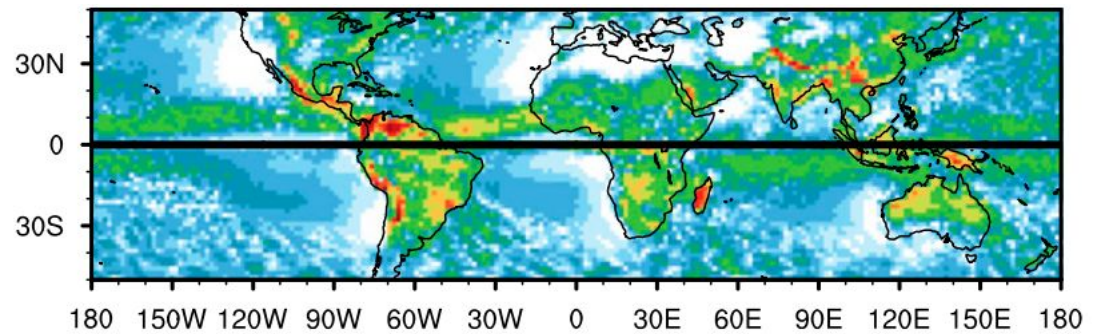


Figure from Cui et al. (2021)

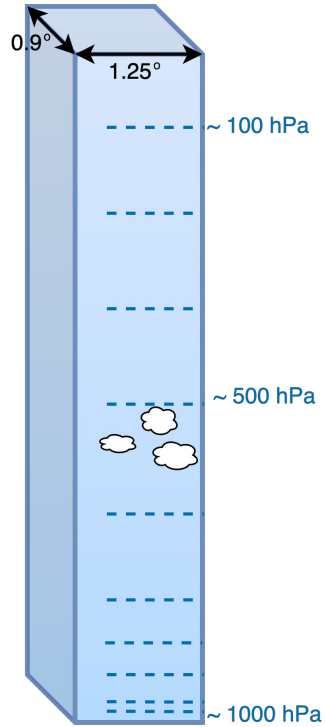
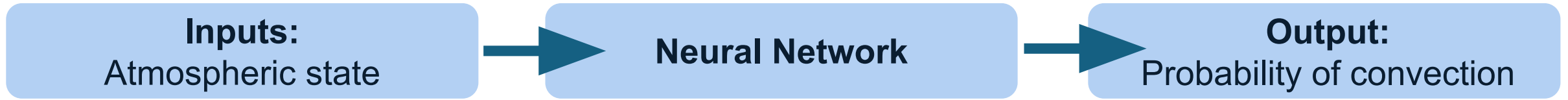
How can we improve the representation of convection in climate models?

Probabilistic
machine learning

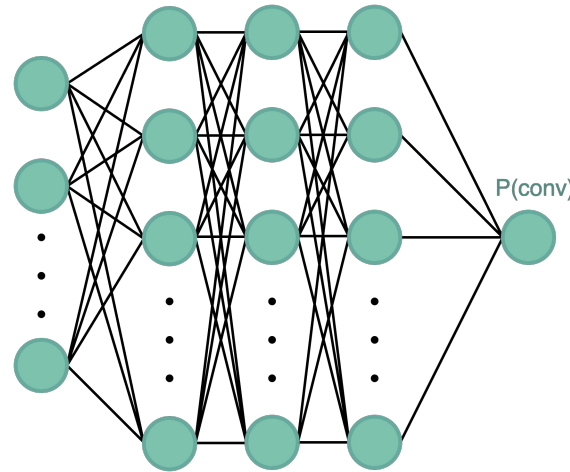
Stochastic
parameterization

- Develop a machine learning model that predicts the probability of deep convection occurrence
 - Characterize sources of uncertainty for convection
 - Implement as stochastic parameterization in operational climate model

Methods



- Total column water vapor
- Pressure (surface)
- Temperature (levels)
- Specific humidity (levels)
- Vertical velocity (levels)

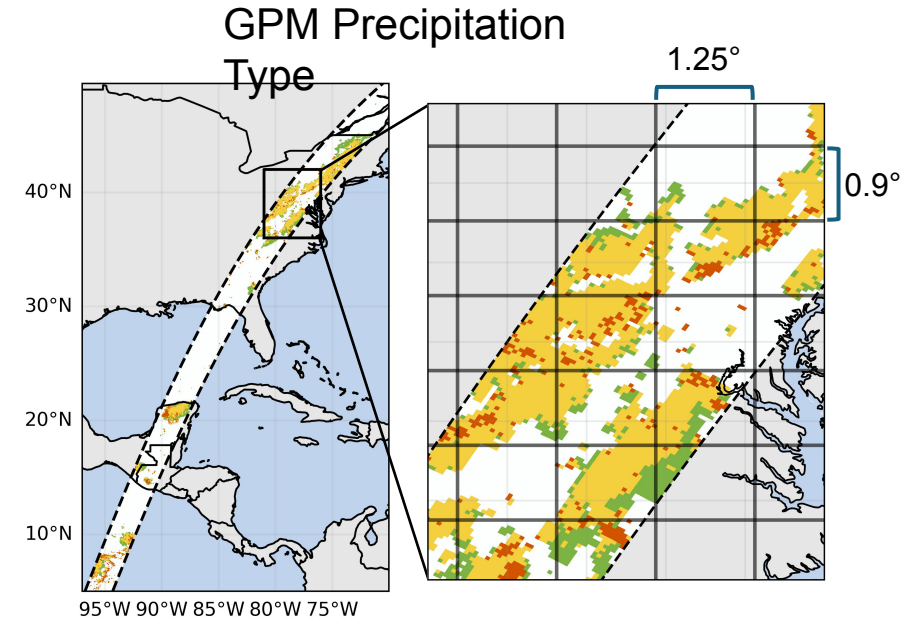


- ECMWF ERA5 reanalysis
- Hourly
- Re-gridded to CAM6 resolution:

0.9° lat x 1.25° lon

10/22 vertical model levels

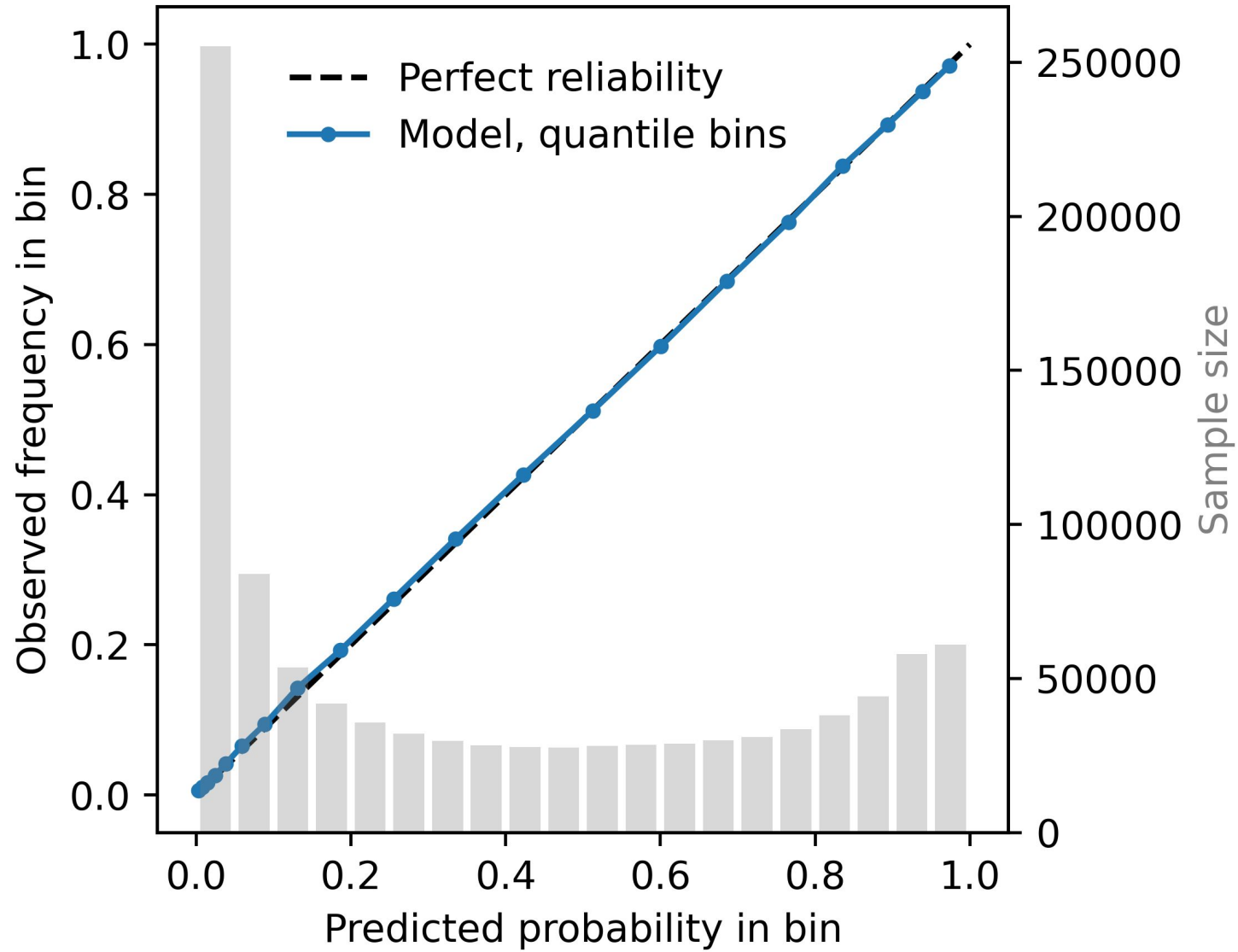
- Train on 2018 and 2020, test on 2019 and 2021
- Loss function: binary cross-entropy



- Convective
- Stratiform
- Other

- Convective precipitation from Global Precipitation Measurement (GPM) dual-frequency precipitation radar
- 65°S to 65°N

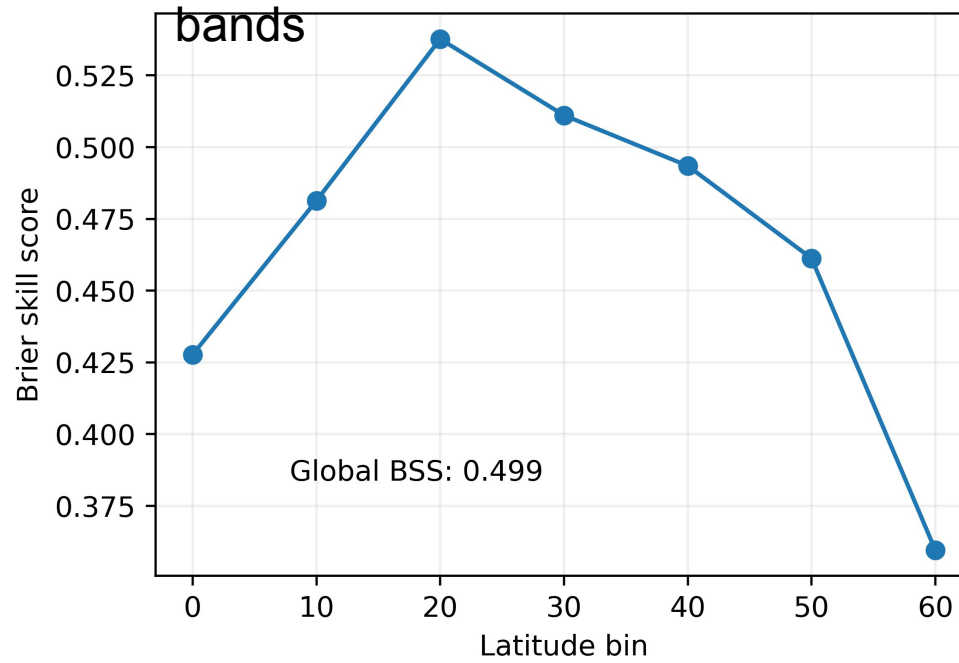
Model performance



Model performance



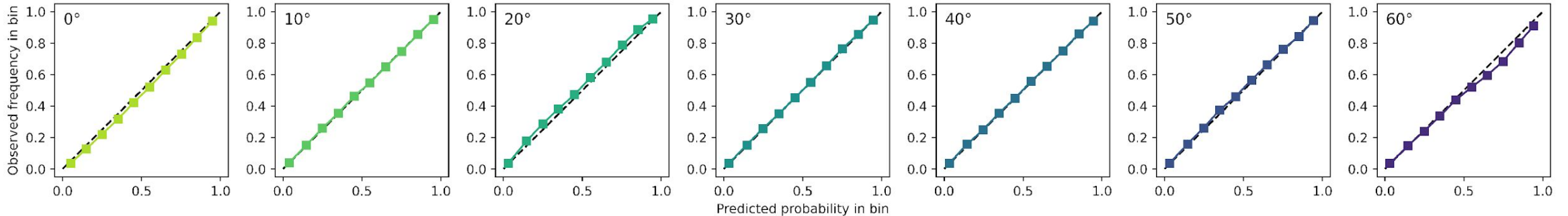
BSS shows skill across latitude



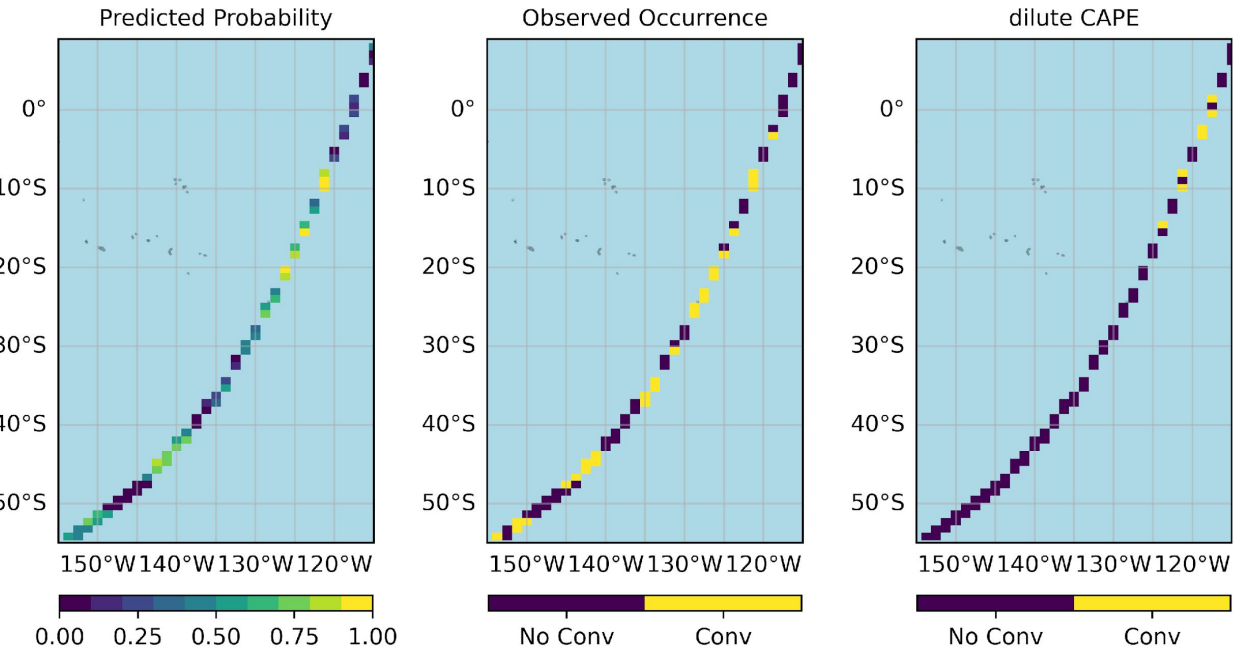
$$BSS = 1 - \frac{BS}{BS_{climatology}}$$

$$BS = \frac{1}{n} \sum_{i=1}^n (p_i - o_i)^2$$

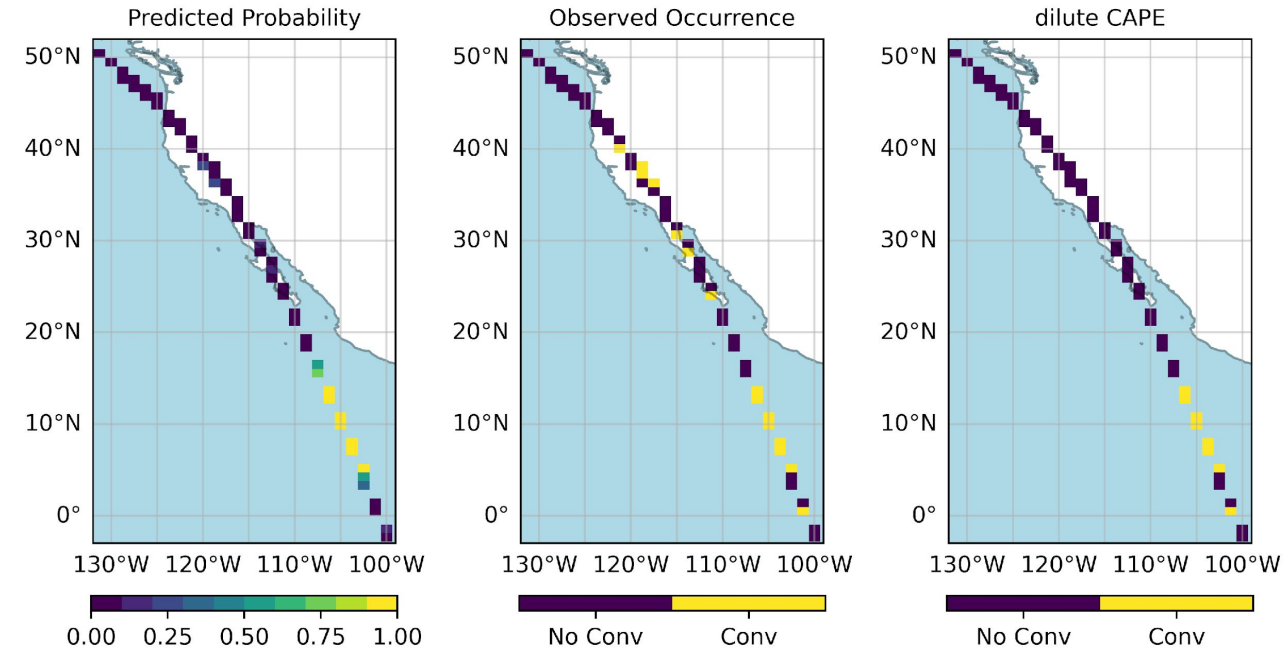
Consistent reliability across latitude bands



Neural network compared to spatial observations

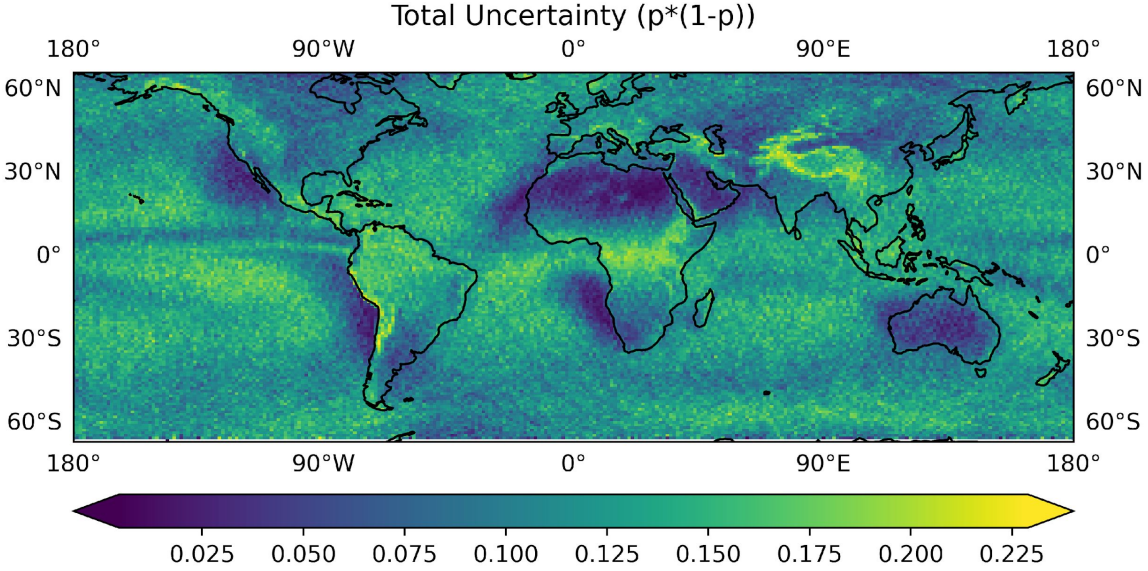
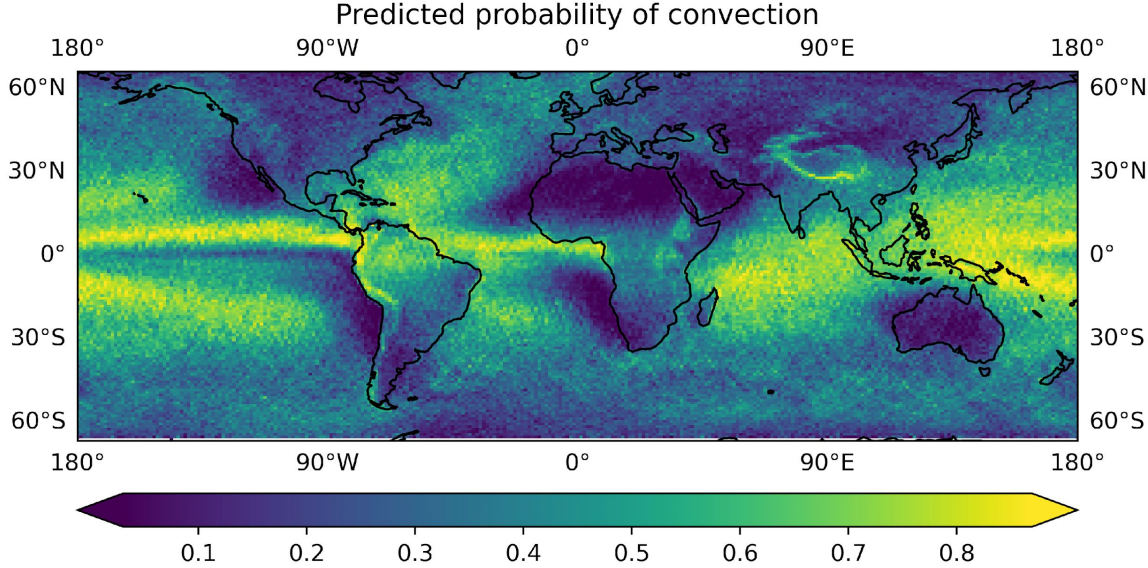
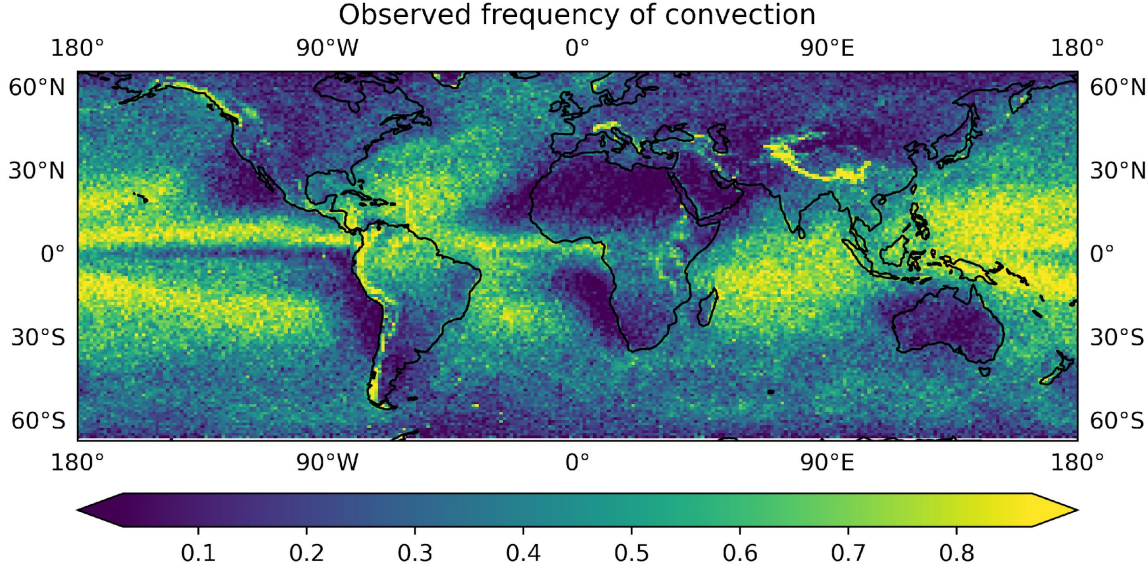


2019/07/07 5:00
UTC

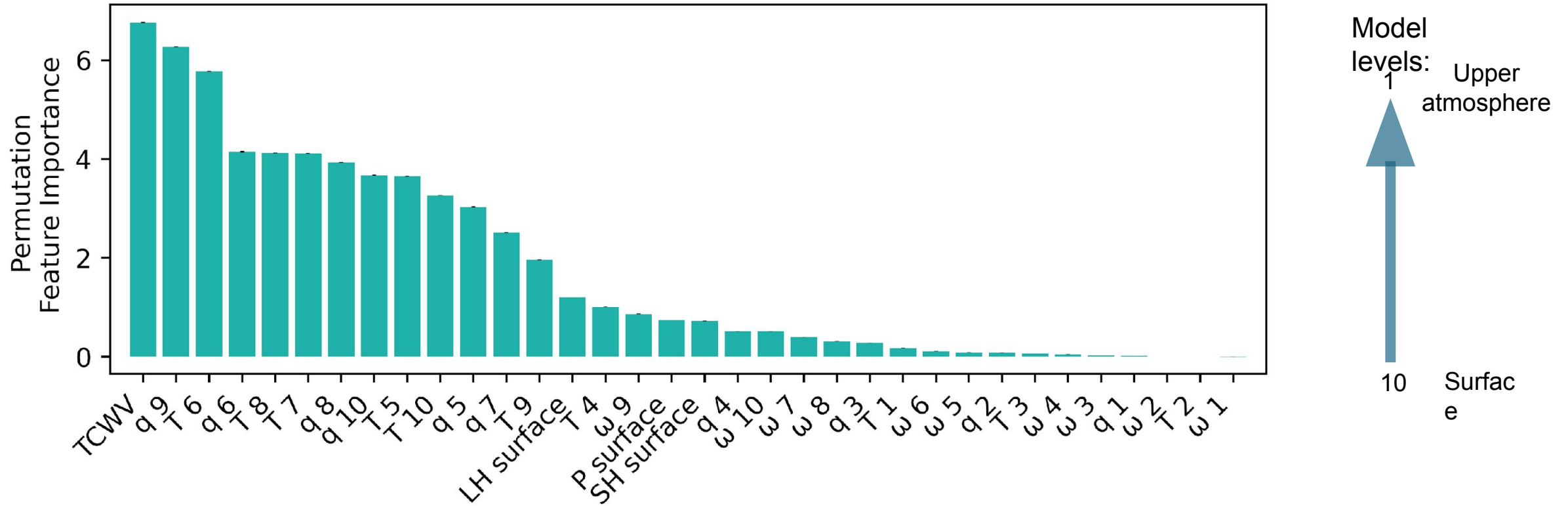


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UTC

Global annually averaged maps of neural net vs observations



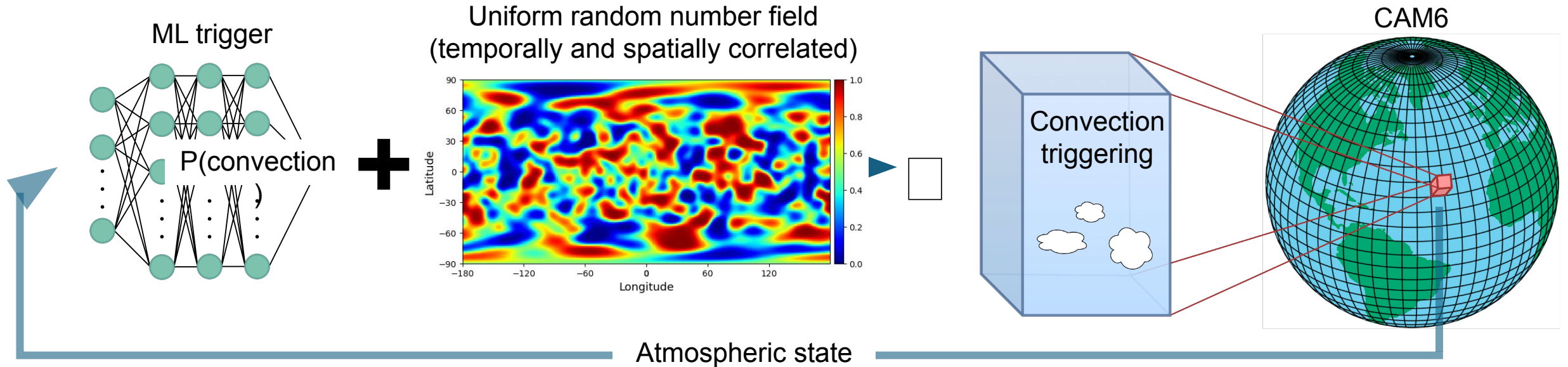
Neural network feature importance



Part 2:

Implement the probabilistic ML model as a stochastic parameterization for the convection trigger in the Community Atmosphere Model (CAM6)

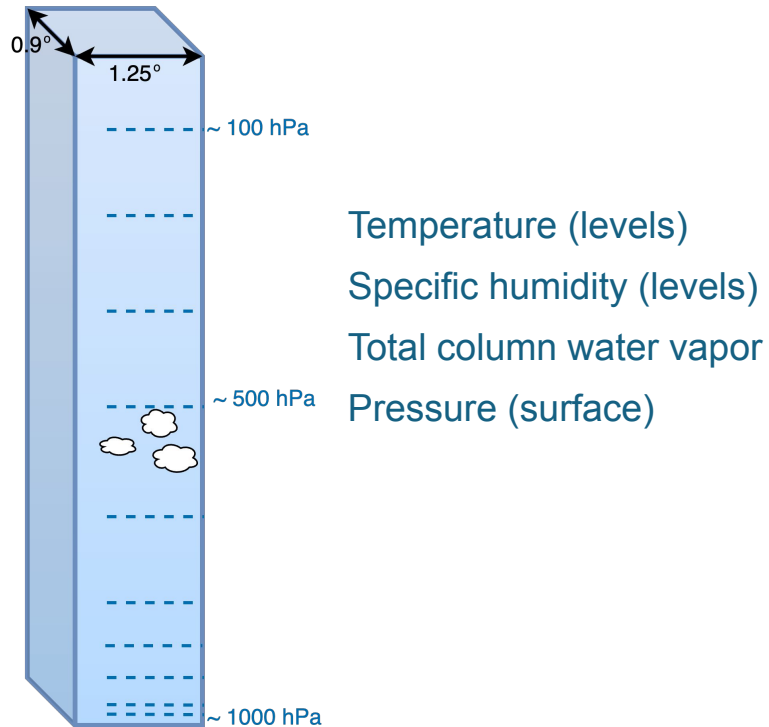
Implementing ML stochastic convection trigger in CAM6



- Quantifies uncertainty directly from observations
- Mass and energy conservation
- Generalization to warmer climates?

First implementation in CAM: simplified NN

Inputs

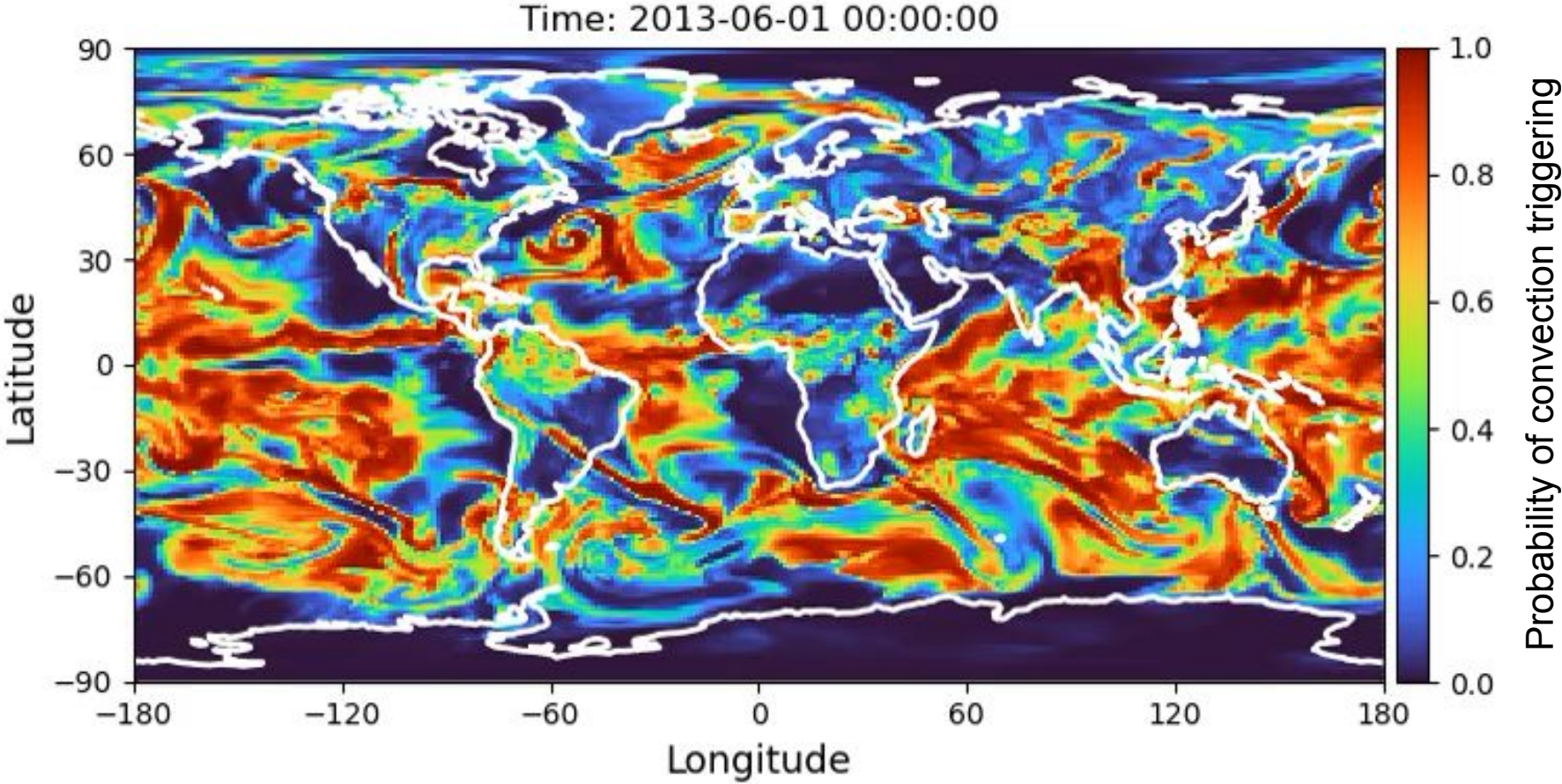


- Replace Zhang McFarlane (ZM) deep convection trigger: dilute CAPE > 70 J/kg
- ML implementation in CAM: FTorch (Cambridge ICCS)
- Compare CAM 3-year (2011-2013) runs:
 1. Original CAPE trigger
 2. Deterministic ML trigger (P=0.5 threshold)
 3. Stochastic ML trigger (random number field)

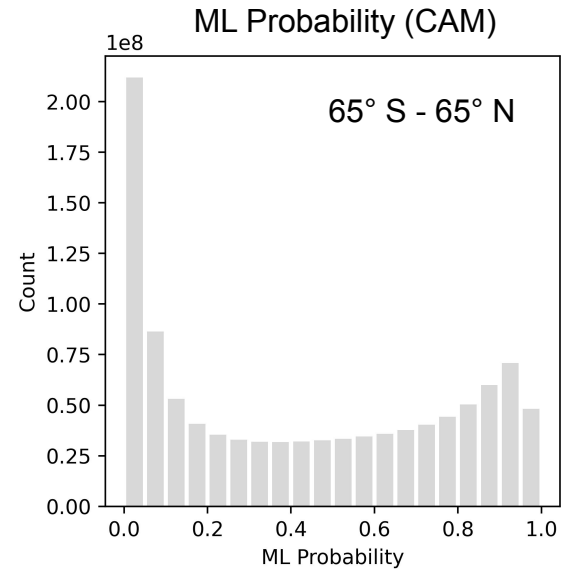
Part 3:

Preliminary results: ML probability of convection as a diagnostic output (not implemented as trigger)

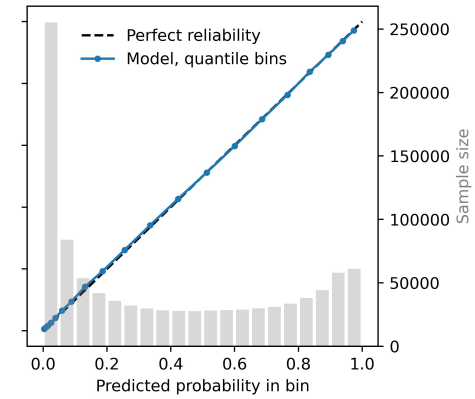
Preliminary Results: ML probability (diagnostic)



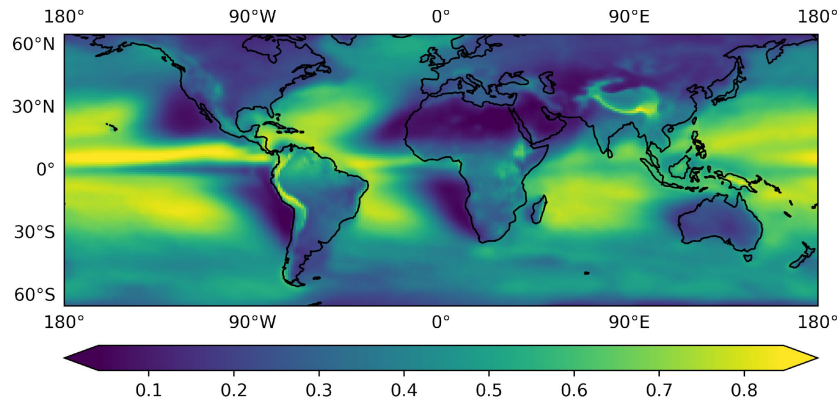
Preliminary results: ML probability (diagnostic) vs Observations



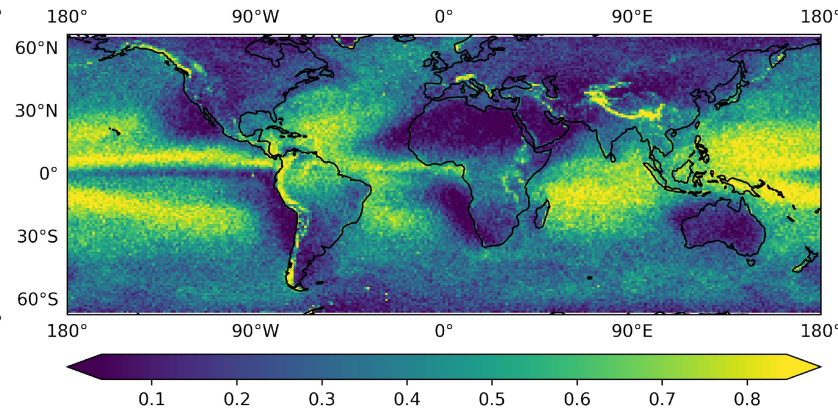
Previous ML trigger (ERA5)



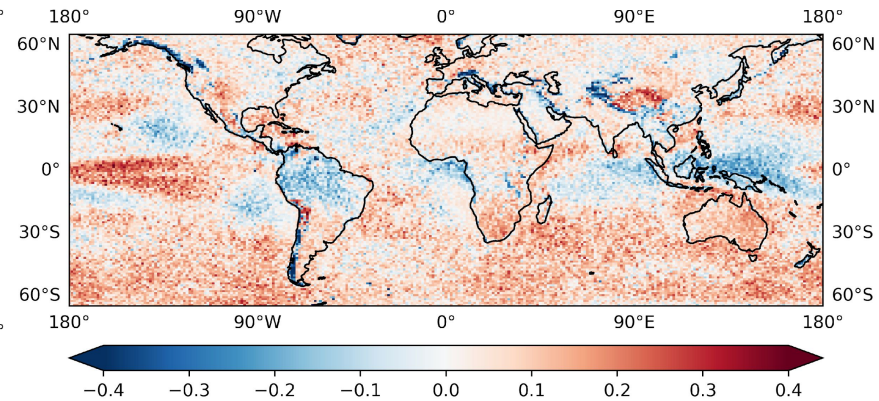
ML Probability (CAM)



Observed frequency of convection (GPM)



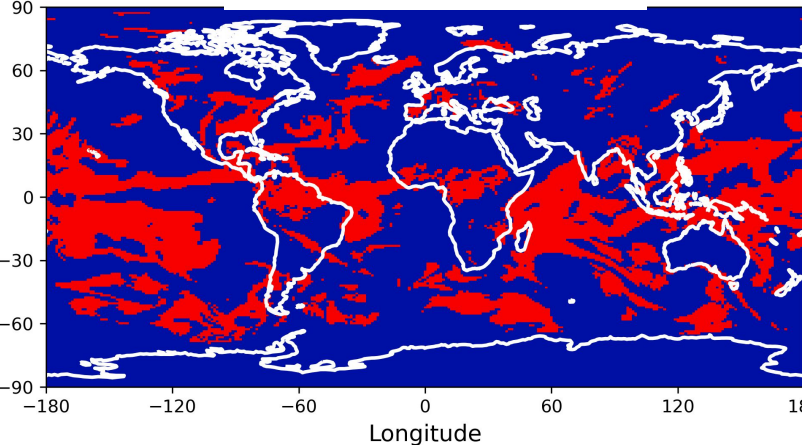
Difference (ML Probability-GPM)



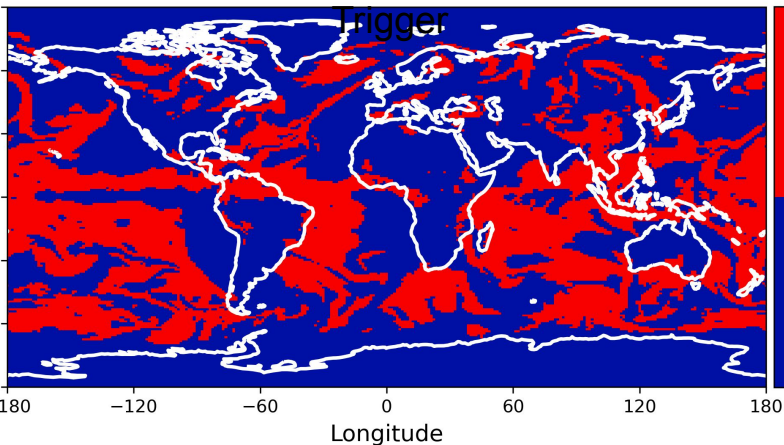
How does the ML trigger (diagnostic) compare to the CAPE trigger?

For one timestep:

Dilute CAPE Trigger

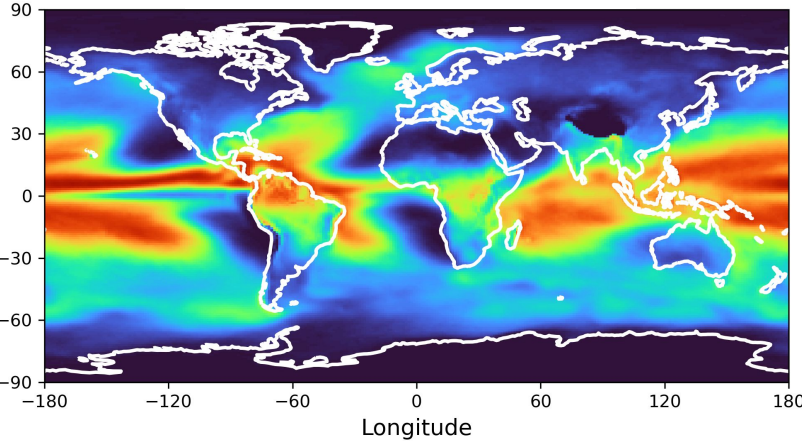


Deterministic ML Trigger

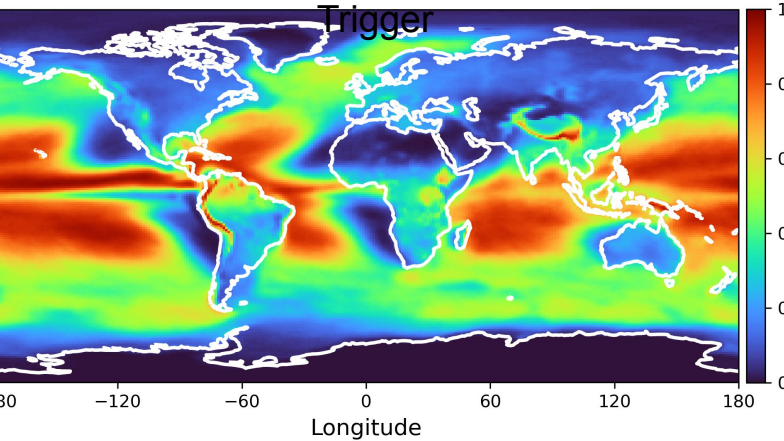


Average 2011-2014

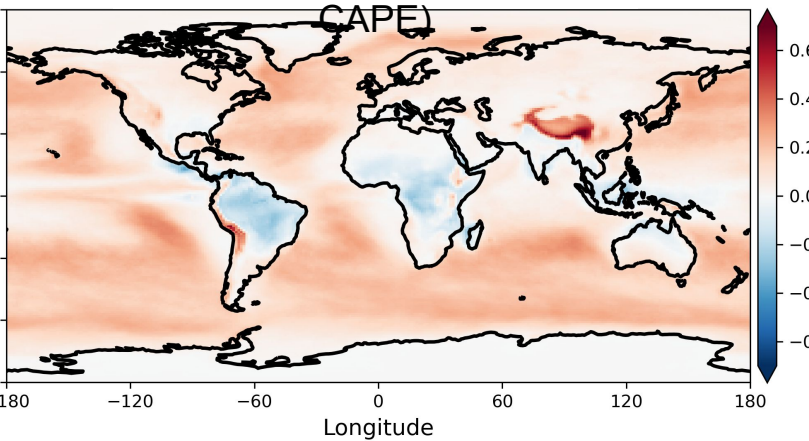
Dilute CAPE Trigger



Deterministic ML Trigger



Difference (ML Trigger - CAPE)

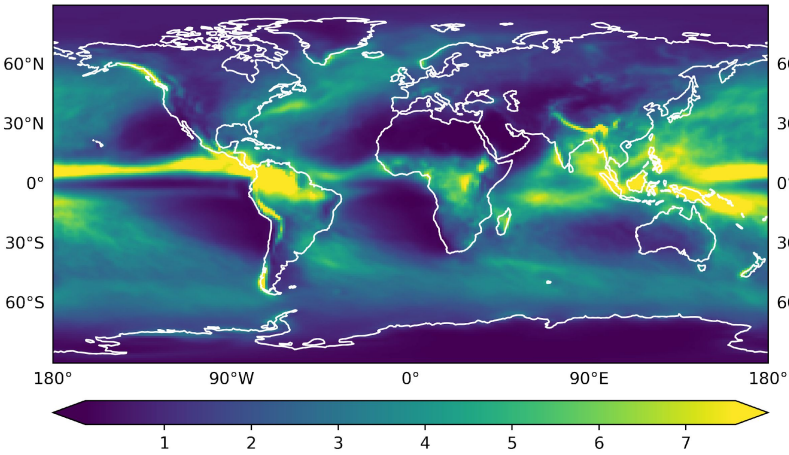


Part 4:

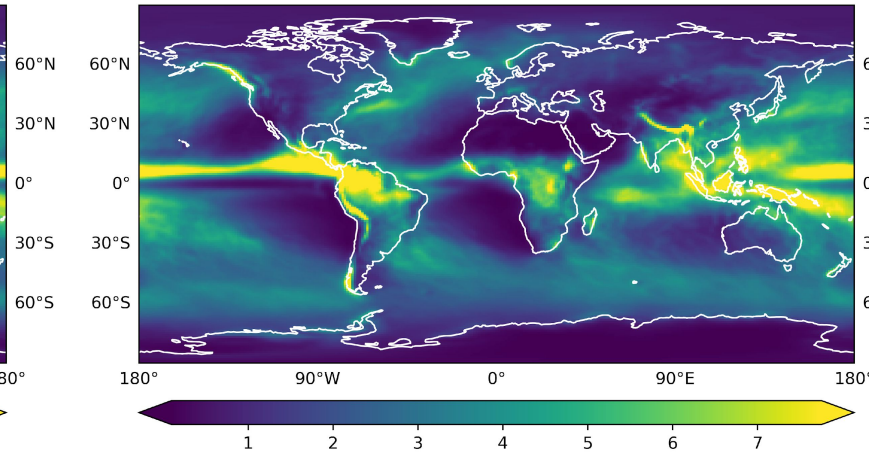
Preliminary results: ML trigger feedbacks in CAM

Preliminary Results: Global Average Precipitation

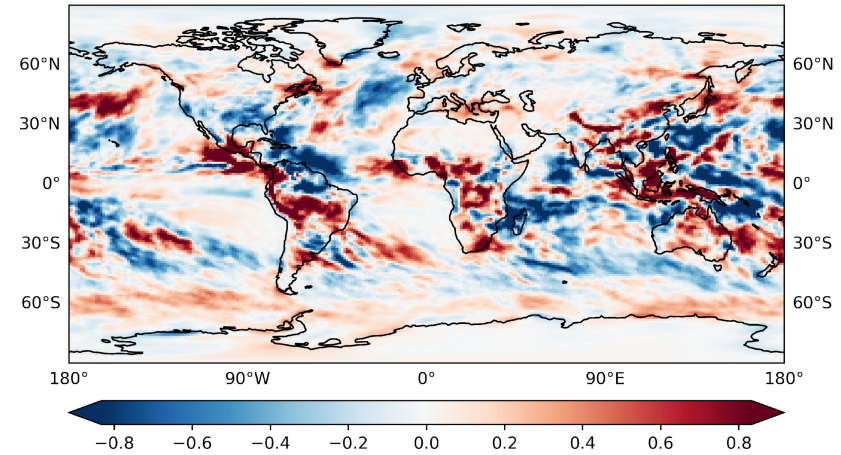
Control Precip (mm/day)



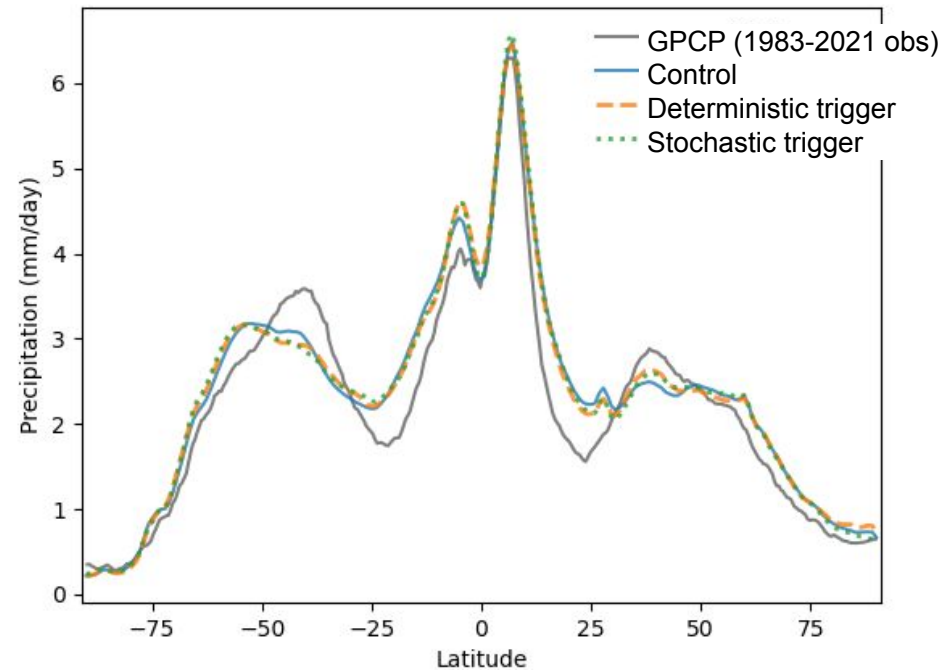
Stochastic ML Trigger Precip (mm/day)



Stochastic - Control (mm/day)



Zonal Average Precipitation

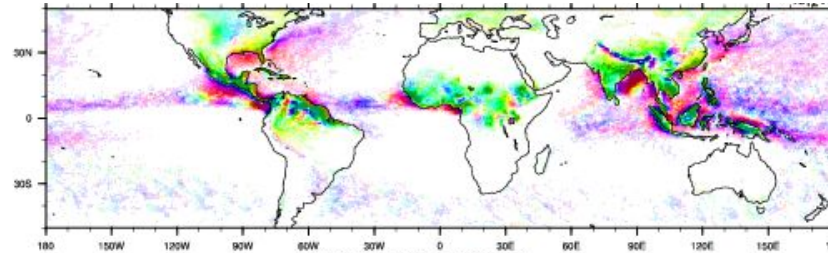


2011-2013

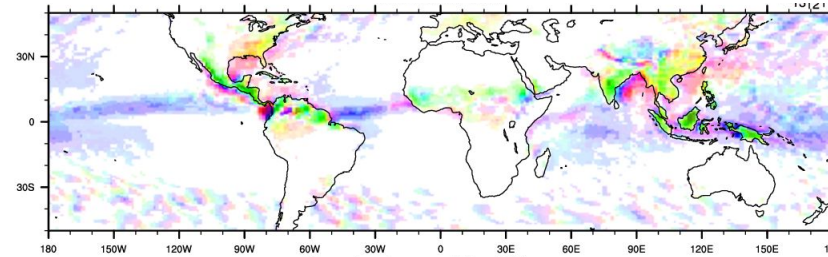
Preliminary Results: Diurnal Cycle (JJA)

Diurnal cycle

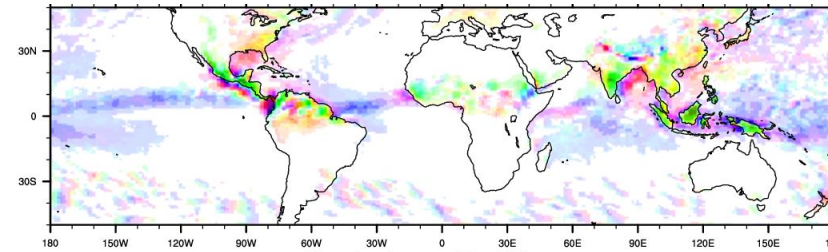
TRMM
Observations
(1988-2013)



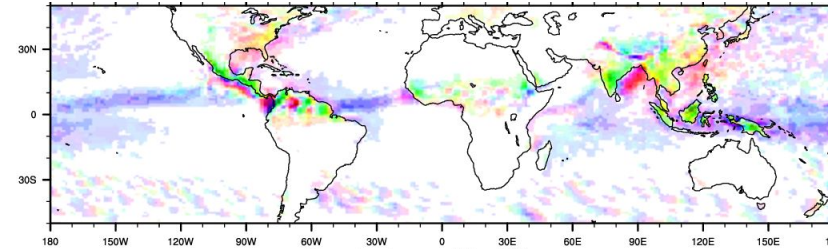
Control



Deterministic ML
Trigger



Stochastic ML
Trigger

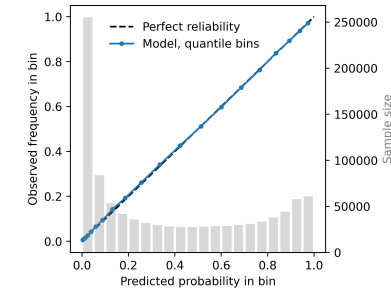


Next Steps

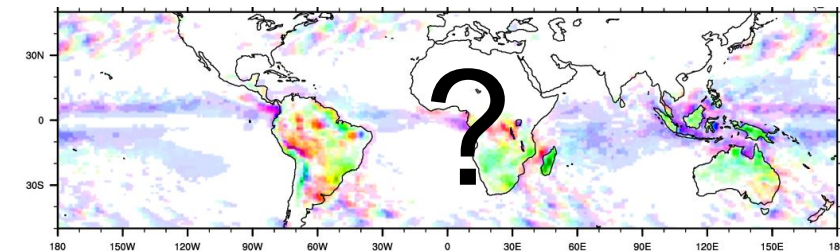
- Refine and test machine learning convection trigger
 - Add dynamics (~dCAPE), land-sea mask, topography
- Assess impact of deterministic vs stochastic model; test space and time correlation of stochastic field
- Assess impact on model mean climate, extremes, modes of variability, convection characteristics
 - Land vs ocean
 - Tropics vs extratropics
 - Summer vs winter hemisphere
- Validate convection in polar regions

Summary

The machine learning convection trigger predicts **reliable probabilities of convection occurrence** across latitudes.



Implementation in CAM will test how an **observation-based stochastic ML** trigger will impact precipitation biases (in progress).



References

Cui, Z., Zhang, G. J., Wang, Y., & Xie, S. (2021). Understanding the Roles of Convective Trigger Functions in the Diurnal Cycle of Precipitation in the NCAR CAM5. *Journal of Climate*, 34(15), 6473–6489. <https://doi.org/10.1175/JCLI-D-20-0699.1>

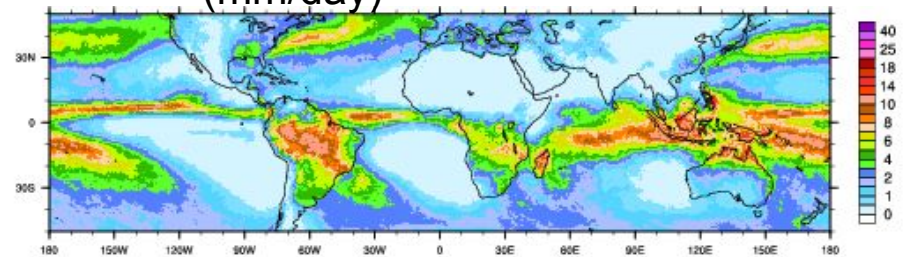
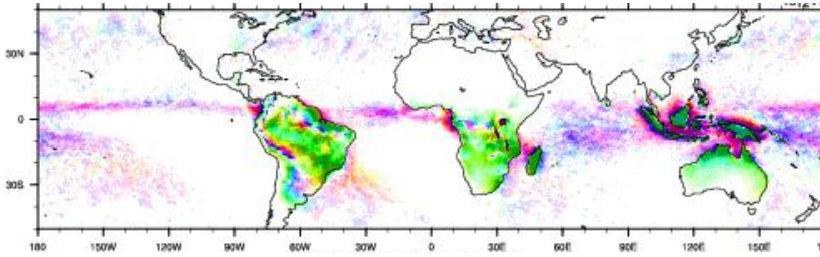
Preliminary Results: Diurnal Cycle (Dec/Jan/Feb)



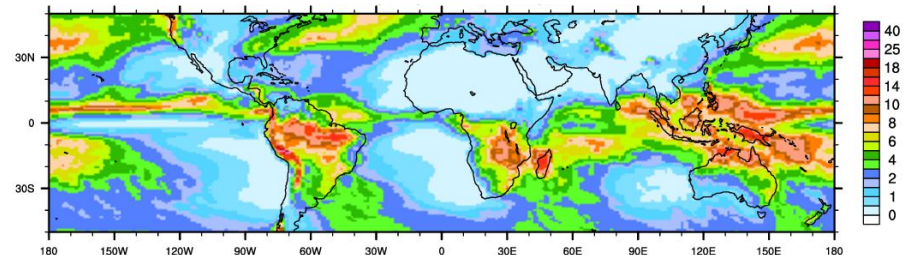
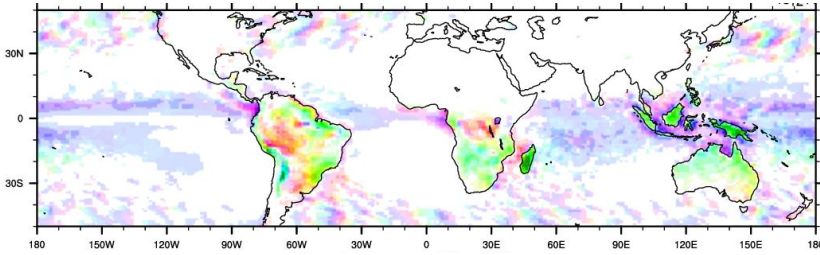
Diurnal cycle

Mean Precipitation (mm/day)

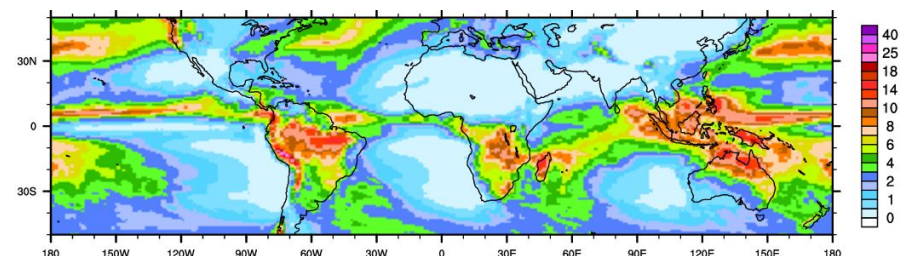
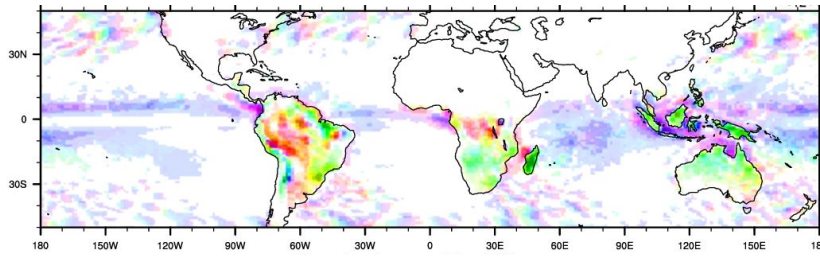
TRMM Observations (1988-2013)



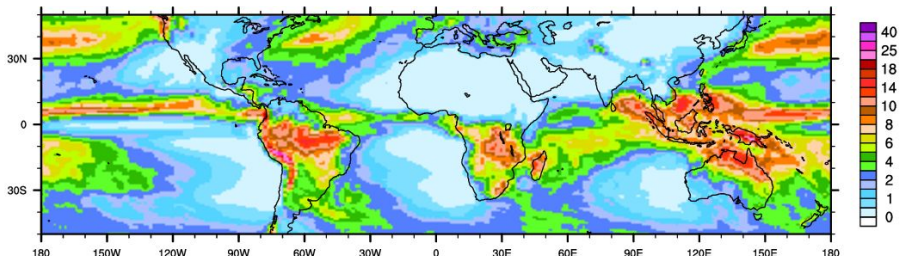
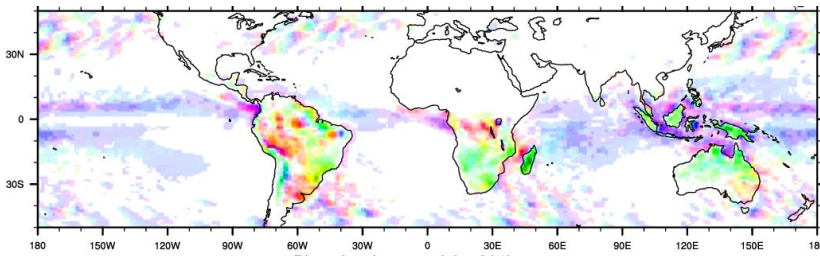
Control



Deterministic ML Trigger



Stochastic ML Trigger



Diurnal cycle

