Machine Learning Rain Formation and the Impacts on Clouds, Precipitation and Radiation

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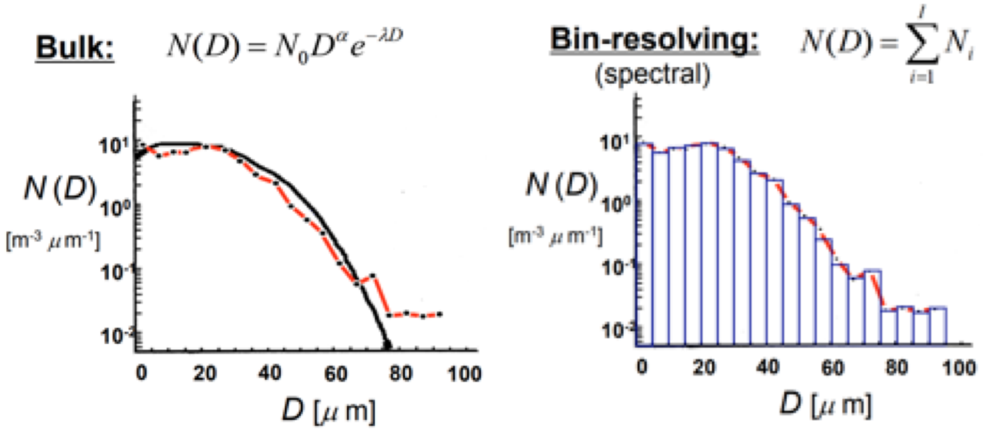
Introduction

- The warm rain formation process is critical for weather and climate prediction
- Warm rain is simply parameterized in large scale models with bulk microphysics. Often models use empirical fits to a detailed ('reference') model
- More detailed 'reference' treatments computationally expensive
- Machine learning (neural networks) can perhaps provide more flexibility and a better solution than current methods
- Goal of this study (in preparation) is to test two hypotheses…

Hypotheses (and preliminary answers):

1. Can we simulate warm rain using alternative methods, what does it do to ‘cloud susceptibility’ (to aerosols) and cloud feedback (to climate change)?
    - Short Answer: ‘Yes’, but: very slow (Factor of 5 slower). Emulator is better
    - Not surprisingly: different results….trying to understand why
    - Same results for aerosol cloud interactions, different S. Ocean cloud feedback
2. Can we use Neural Network emulators (NN) to then speed up this process and reproduce these changes….
    - Yes, emulator works well to reproduce new kernel results
    - But current version has mass fixer: invoked in regions where we see differences
    - Emulator speeds up the code, but is slower than control. Working on this.

Methodology



- Use a neural network to emulate a detailed process model in a global General Circulation Model (GCM)
- GCM = Community Atmosphere Model version 6
- Method: Replace existing CAM6 microphysics BULK warm rain formation process (Khairoutdinov & Kogan or KK2000: Extra Slide 1) with a more explicit treatment: The stochastic collection kernel from the Tel Aviv University (TAU) Bin microphysics scheme [Details: extra slide 2]
- Then: Build a Neural network emulator of the TAU Bin code and put back into CAM [Details: Extra slide 3]

Simulations

- CAM6: Control
- TAU or TAU-bin: Stochastic Collection Kernel
- TAU-ML: Machine learning Emulator for TAU code

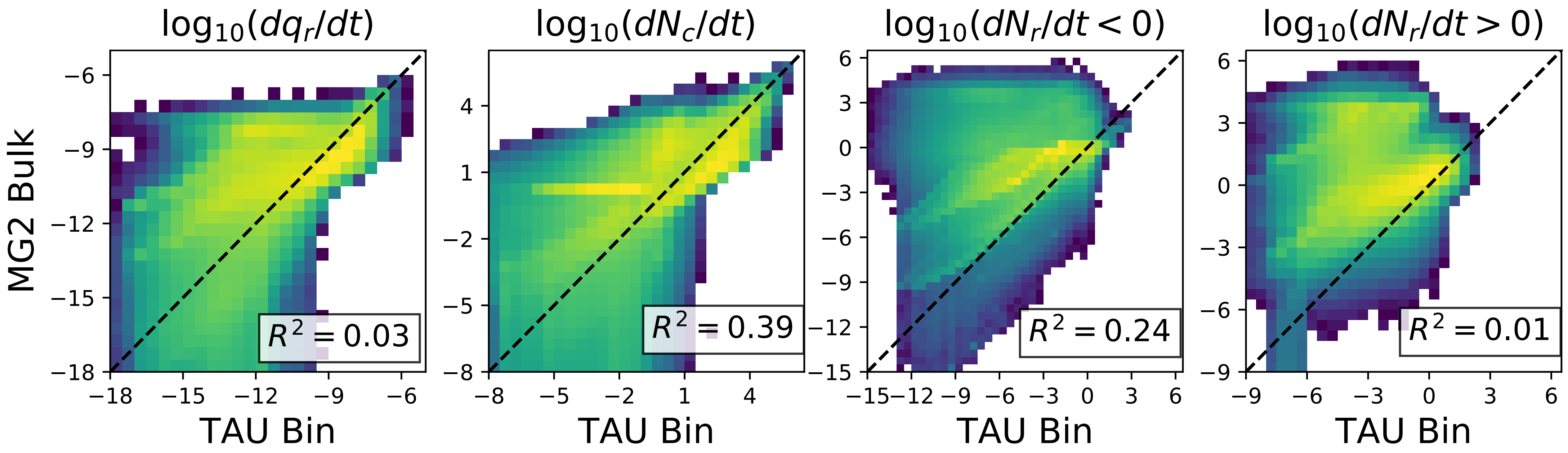
- For each, global 0.9˚x1.25˚ simulation, 9 years, 1st year high frequency instantaneous output
  - Base (2000 Climatology)
  - Pre-Industrial (1850) aerosols. (For aerosol cloud interactions)
  - SST+4K (For Cloud Feedbacks)

MG2 v. TAU Individual process rate statistics

Note that dq_r/dt = $-dq_c/dt$

Negative Nr Tendencies

Positive Nr Tendencies



Large q_r dq_r/dt TAU > MG2
Small q_r, other way around

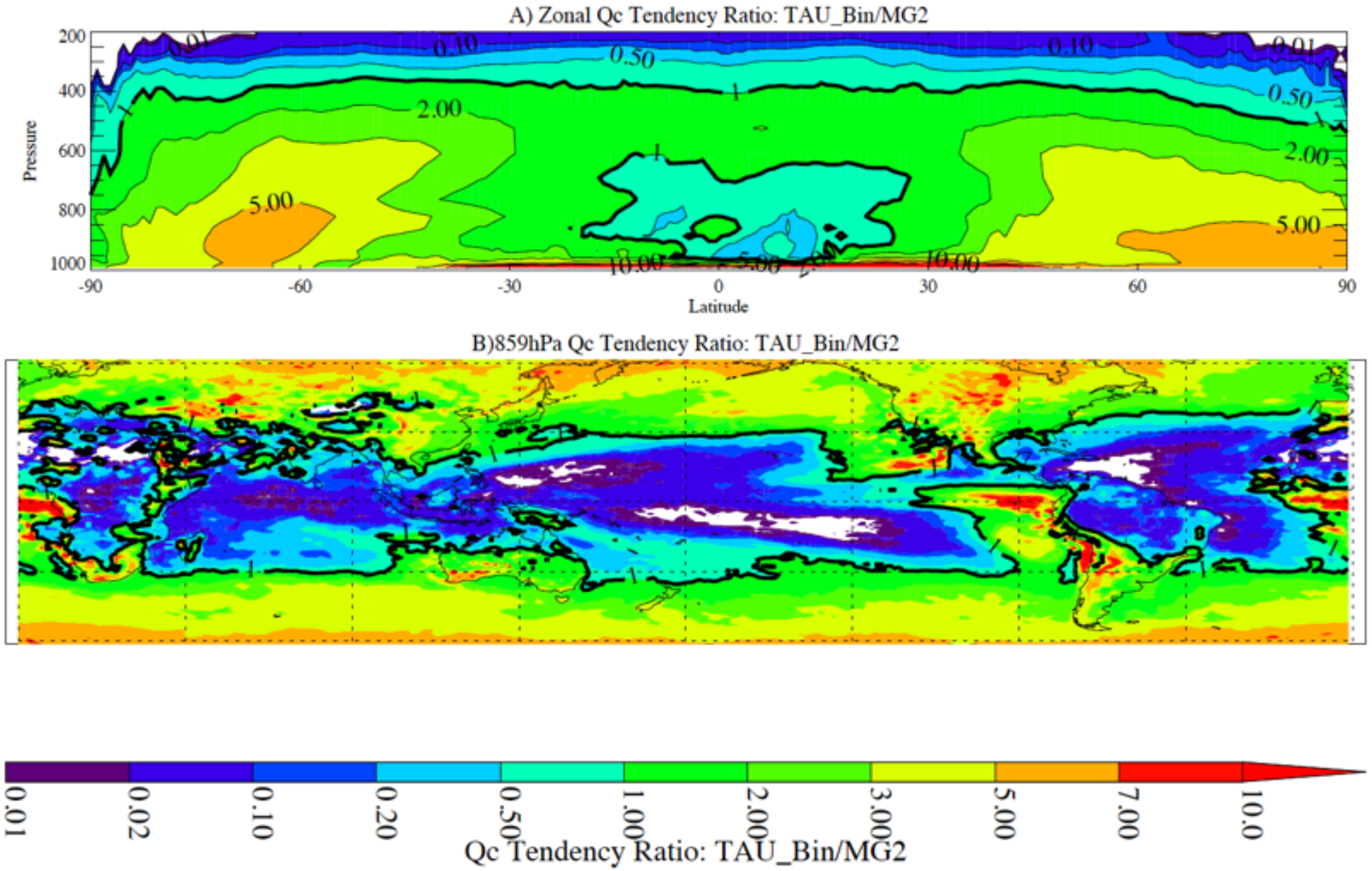
MG2 flatlines at a threshold (1/cm-3)

MG2 has larger rain# tendency

MG2 less frequent small dq_r, dNr, compensated by more frequent higher values
Nr, qr tendencies larger for MG2 than TAU (Extra Slide 4)

Ratio of q_c/dt between TAU Bin and MG2

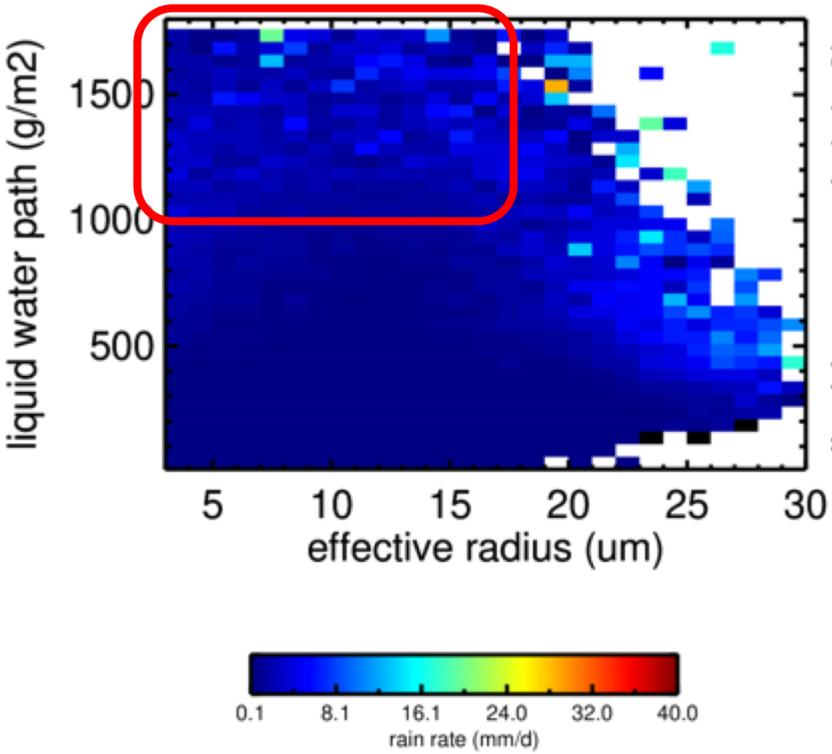
- TAU-bin = more rain formation at higher latitudes, where LWP larger (Ratio > 1)
- TAU-bin = less in dry regions with little precip). (Ratio < 1)
- 30N/S is changeover latitude (Ratio =1) near surface



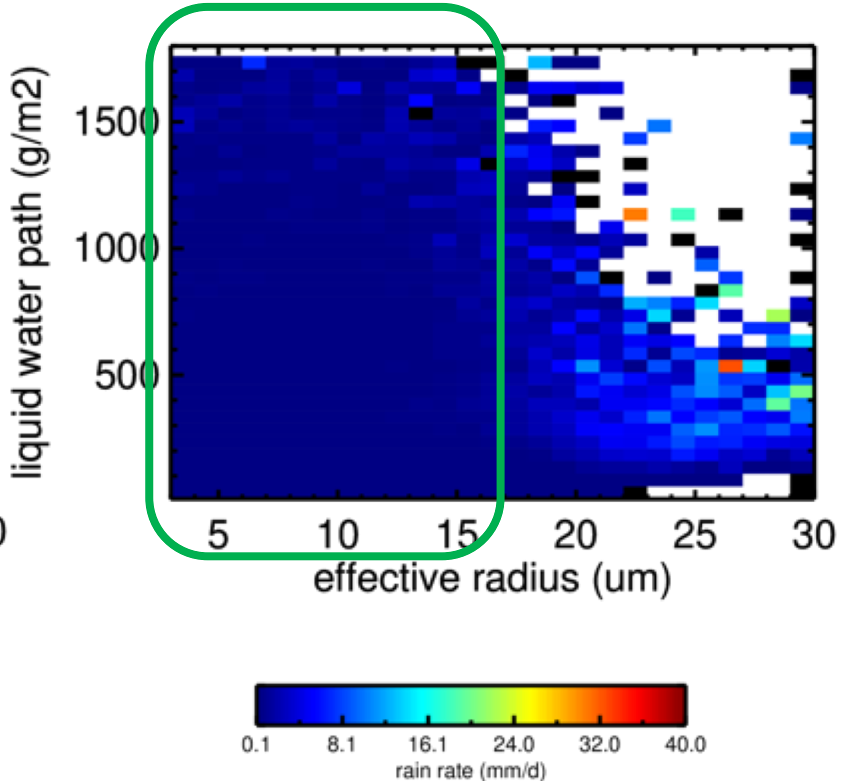
Rain formation and Drop size

Rain rate (Color) as a function of Re and LWP. Note that CAM6-Control has higher rain rates for high LWP and small Re
TAU-Bin and TAU-ML have much lower frequency of rain occurrence for Re<15um: this matches LES (Rosenfeld Ref)

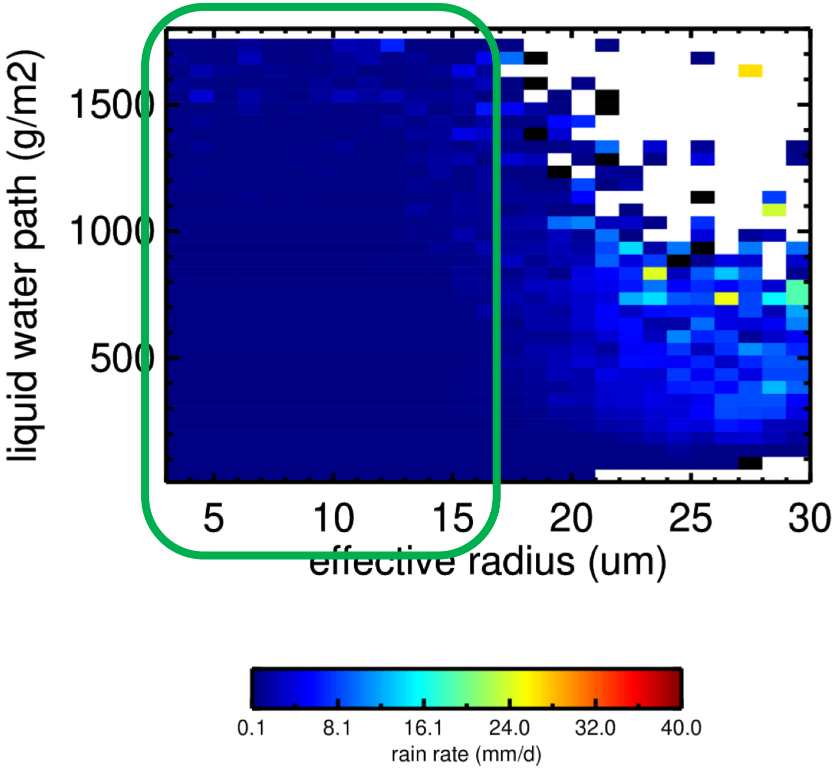
CAM6: Control



TAU-Bin



Tau ML



Climate Impact of Stochastic Collection

Zonal means of Control, TAU (Stochastic Collection) and Observations (CERES EBAF4.1). Also shown is the Emulator for the TAU code (TAU-ML). Return to that later.

TAU code

A. Lower LWP than Control

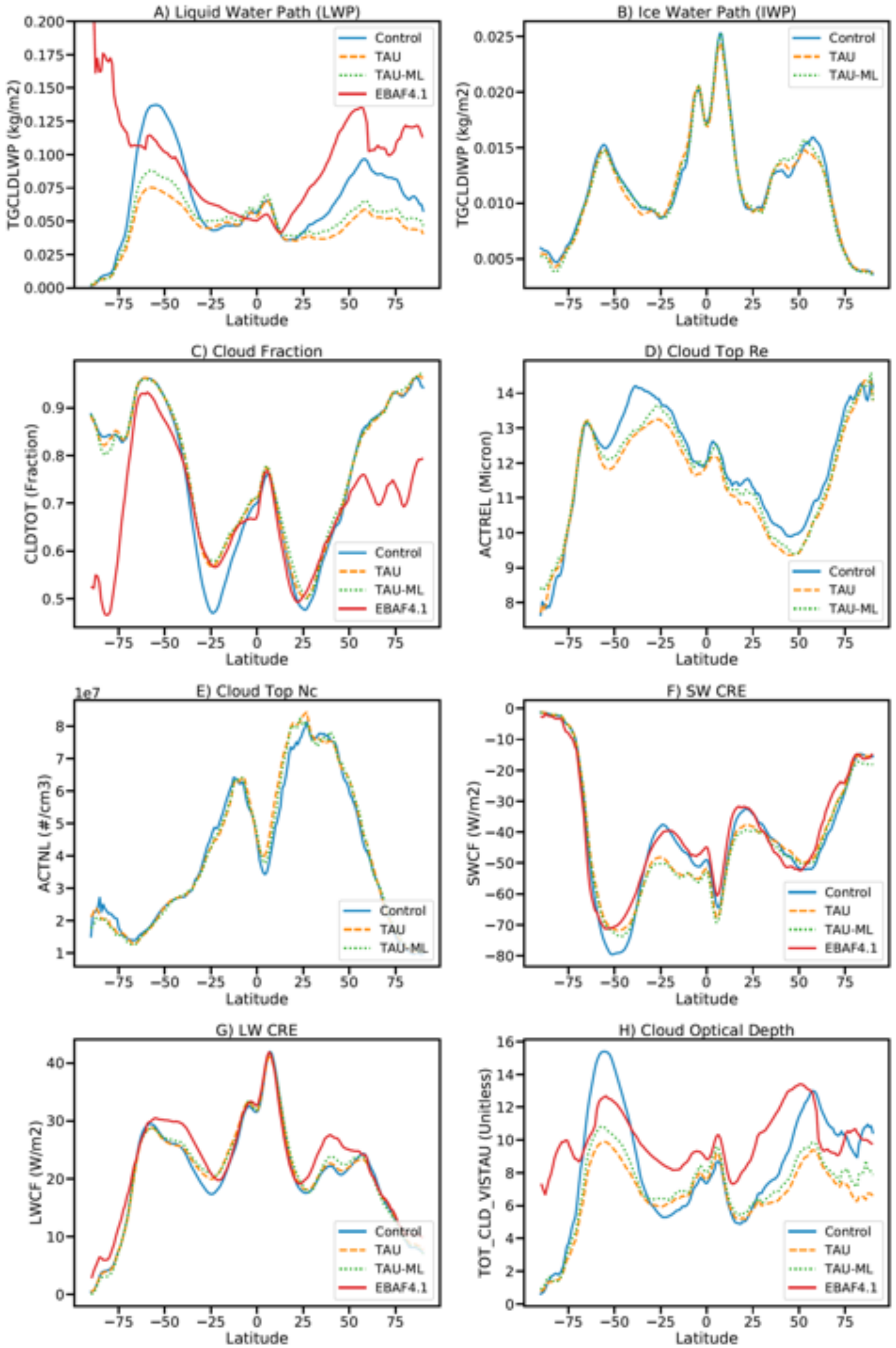
C. Higher cloud fraction in SH Subtropics (Better)

D. Slightly smaller drop number (esp -50 to -25 S), but similar Nc

F. SW Cloud Radiative Effect (CRE) reduced in SH storm track (good), larger in subtropics (bigger bias)

G. LW Cloud Radiative Effect (CRE) similar

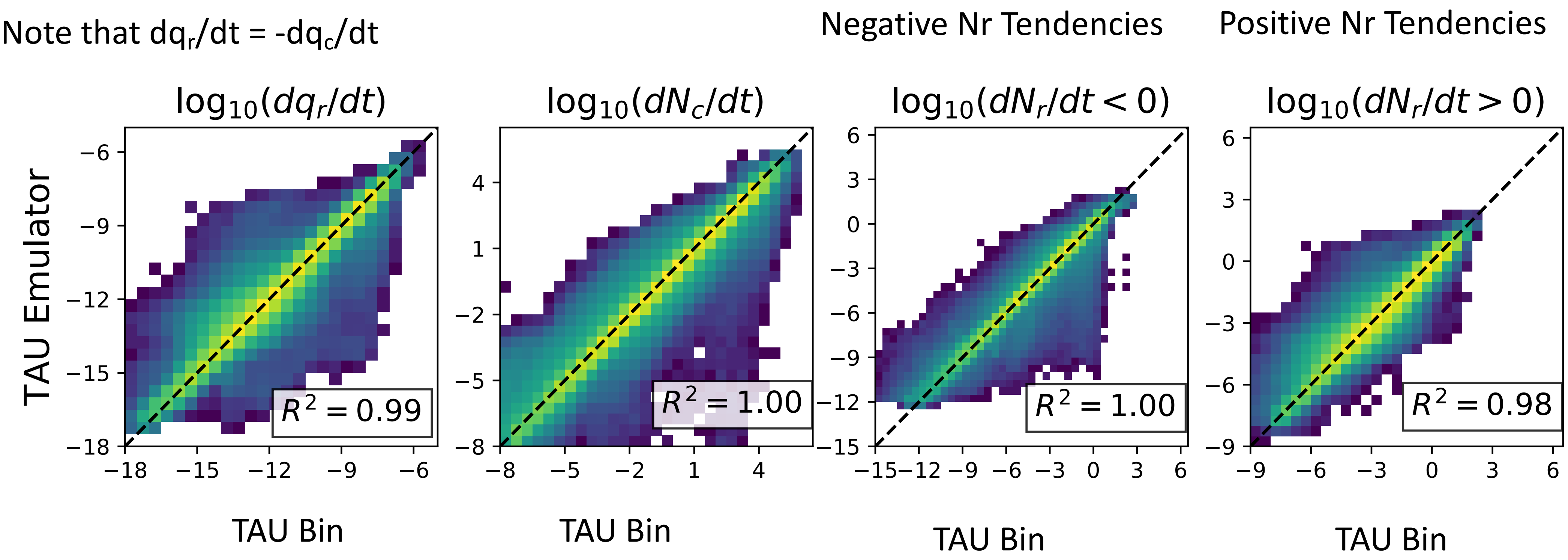
H. Cloud Optical depth lower in SH storm track and NH high lats



Now apply the Neural Network Emulator

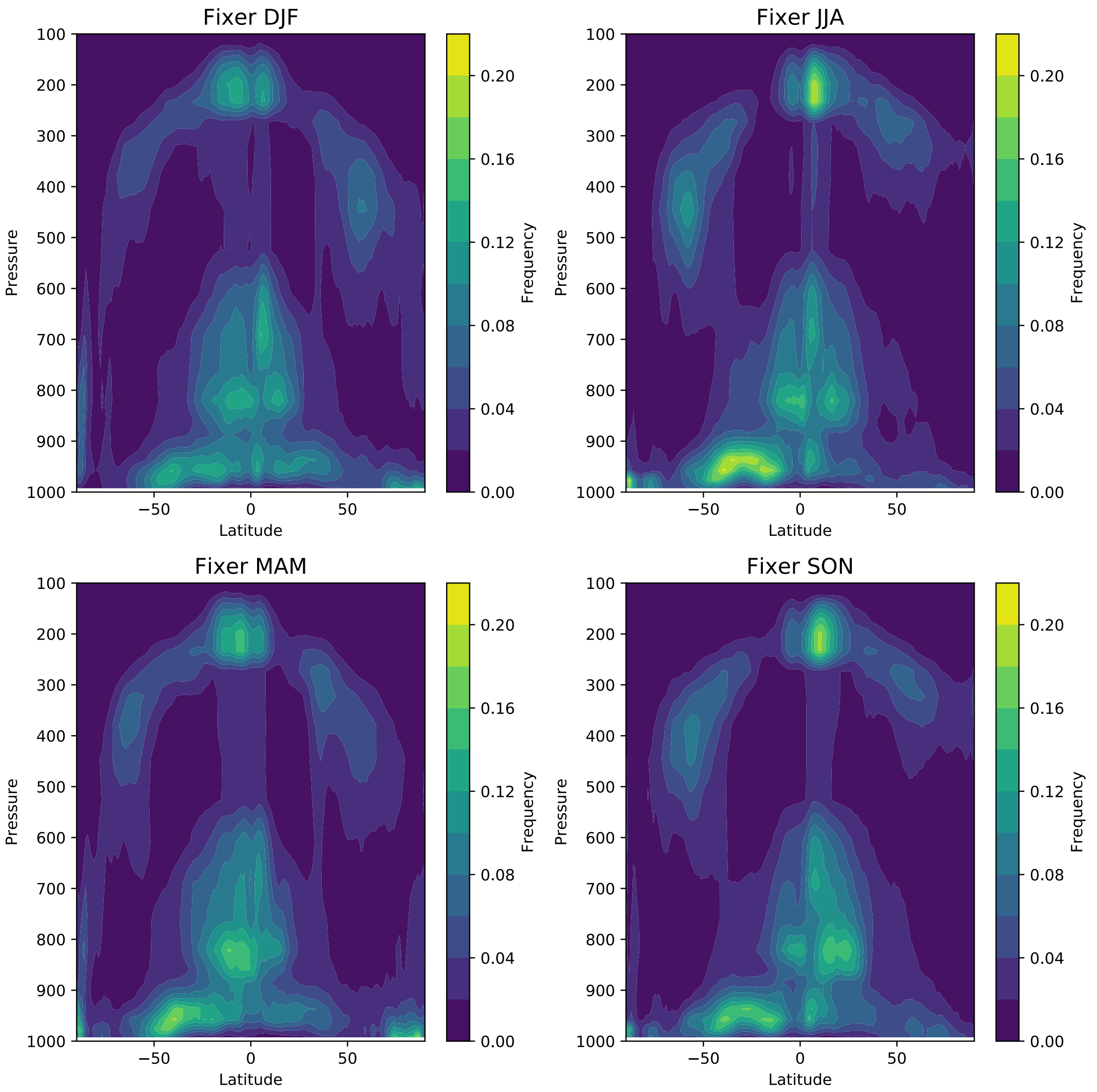
Individual process rate statistics
Emulator is working at the process level: most tendencies on the 1:1 line

Note that $dq_r/dt = -dq_c/dt$



Emulator yields slightly narrower range of values than full bin calculation: Extra Slide 5

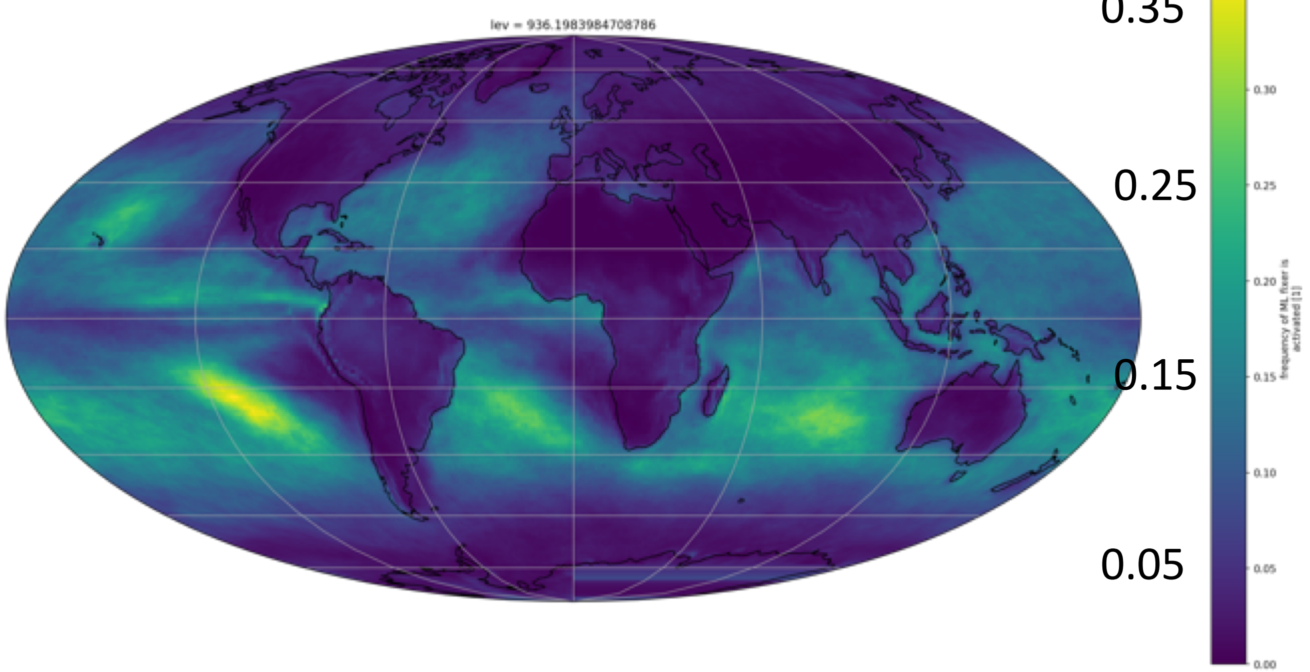
Mass Fixer for Emulator code



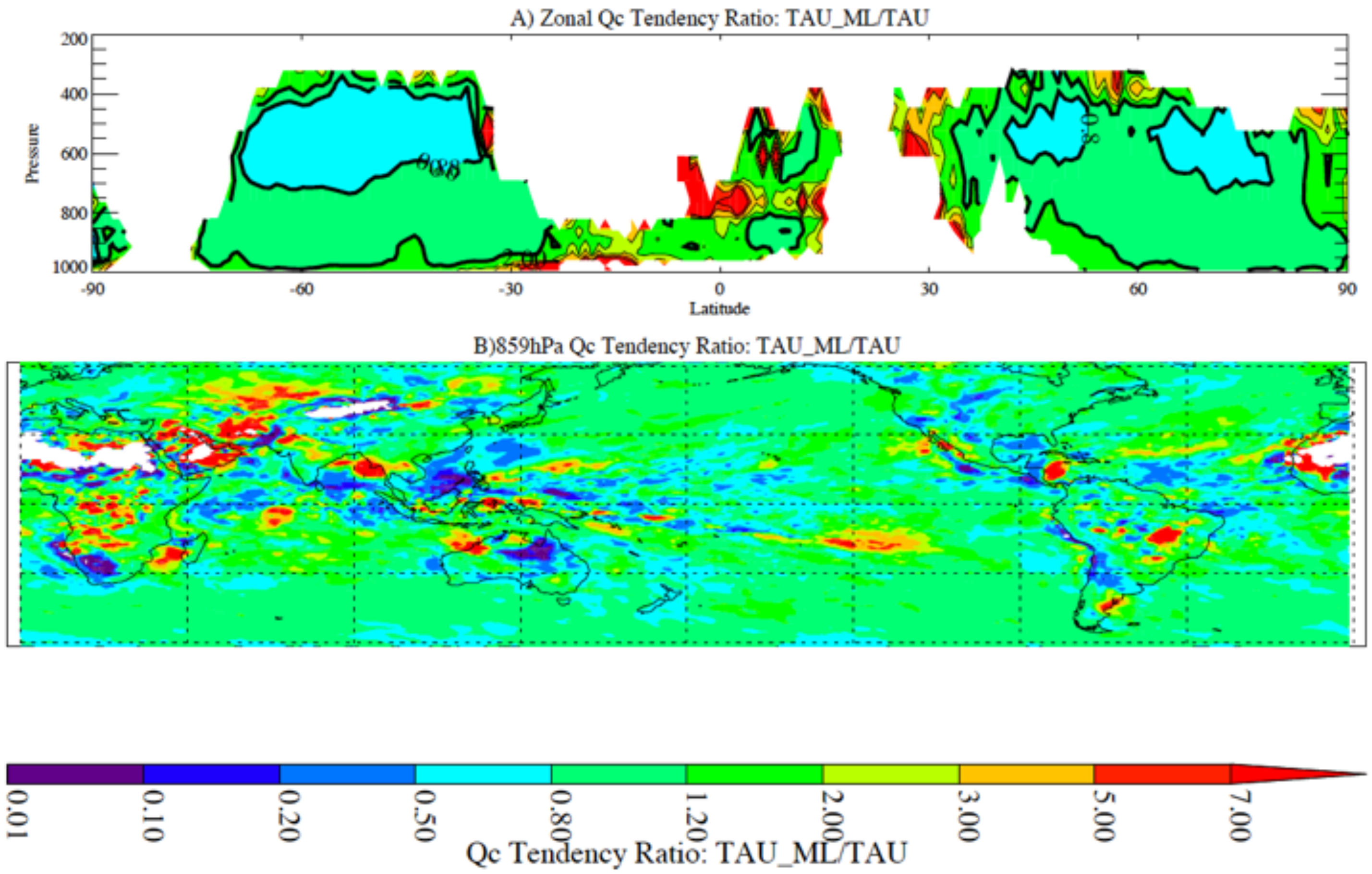
Emulator needs a mass fixer or tendencies can crash the model
How often does mass fixer kick in and where?

- Low altitudes and tropical high altitudes (cirrus)
- Low altitude (below is 936hPa), mostly in sub-tropical strato-cumulus regions, edge of stratus regions. Mostly SH.
- Also a tropical peak at 800hPa

Annual Frequency of Mass Fixer, 936hPa



Process rate Ratio: TAU-ML/TAU code



Solid lines in upper panel are 0.8 and 1.2 ratio: most of the atmosphere within 20% for TAU-ML code compared to the TAU code it is trained on.

Lower level slice shows the same (bottom panel). Emulator is doing it's job.

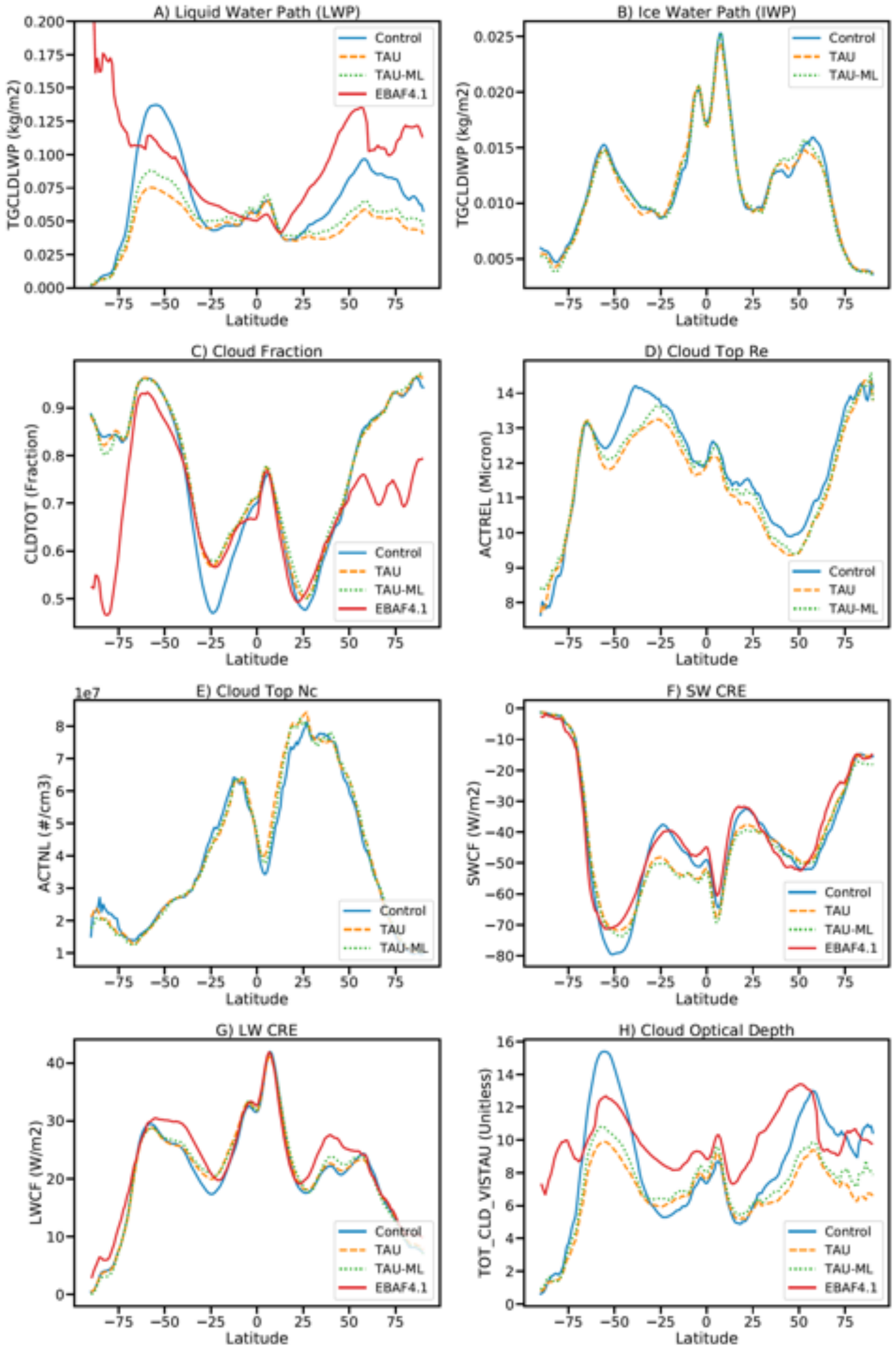
Climatology results (earlier zonal mean figure)

Zonal means of Control, TAU (Stochastic Collection) and Observations (CERES EBAF4.1). Also shown is the Emulator for the TAU code (TAU-ML).

Emulator is basically same climate for Emulator as TAU bin code

A) Emulator has a bit more LWP than TAU, especially S. Ocean Storm track

D-E) Similar drop number and size. CRE not too different, but translates into a bit larger (H) optical depth

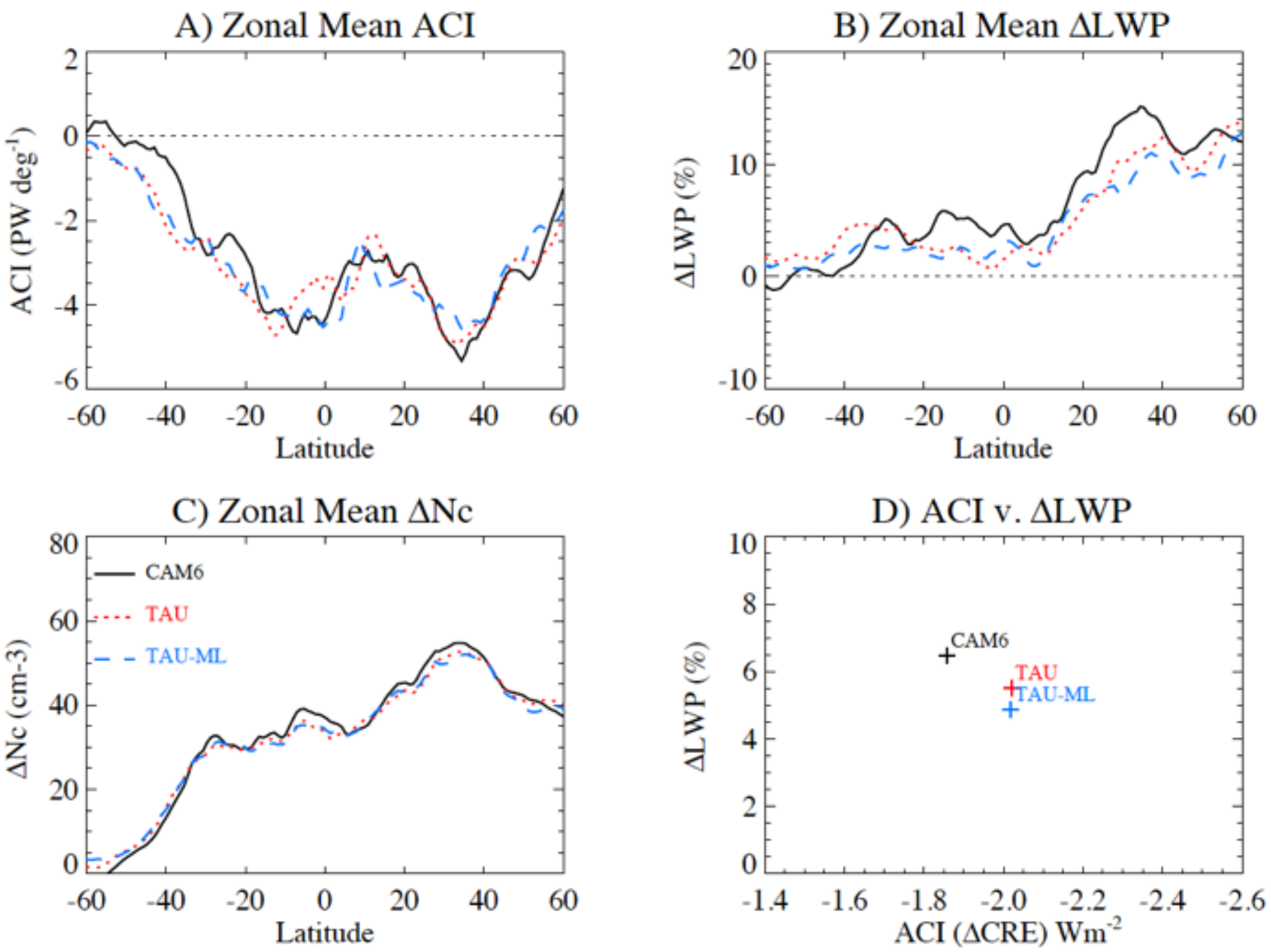


Emergent properties: Forcing and Feedback

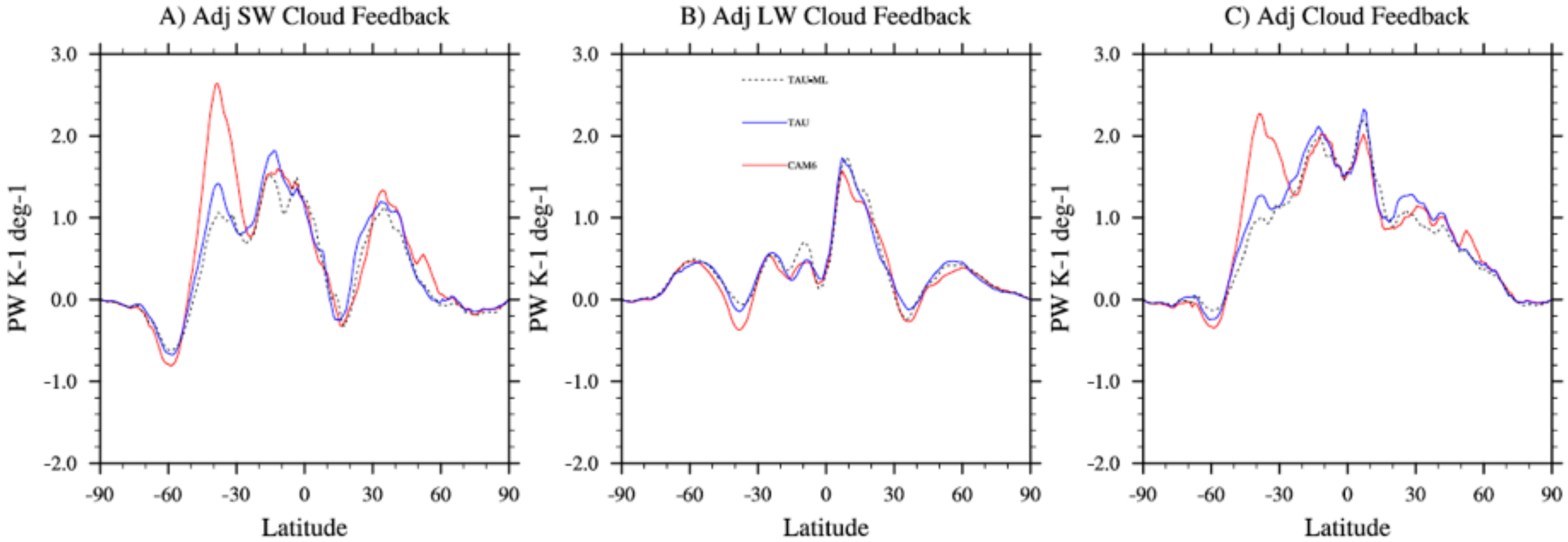
- Aerosol-Cloud Interactions (ACI)
  - Higher aerosols leads to higher Cloud Condensation Nuclei and thus higher cloud drop number (Twomey 1977). Affects microphysics of clouds and warm rain. May delay rain (Albrecht 1989)
- Cloud Feedback
  - Largest uncertainty in estimates of total sensitivity of climate to greenhouse gases.
  - Cloud phase at higher latitudes is important (Tsushima et al 2006, Gettelman 2019), and shallow subtropical clouds are important (Bretherton, Sherwood, Etc).

Aerosol Cloud Interactions (Forcing)

- ACI are similar between control and TAU code.
- Slightly lower LWP change, but forcing is similar, a bit higher in S. Hemisphere.
- Emulator reproduces TAU results.



Cloud Feedback



There are different SW cloud feedbacks in the S. Hemisphere mid-latitudes.
Significantly lower than control (CAM6) simulation

Why? Different cloud fraction change and different ice fraction in base state: emulator for warm rain affects mixed phase clouds. Extra Slides 6-8

Summary

- TAU Bin collection kernel can reproduce the warm rain formation process (Autoconversion + Accretion) in a global model (GCM).
- Bin code yields better thresholding of rain formation with cloud Re (large drops necessary): good
- ML Emulator is able to reproduce climatology of TAU code, and also higher order emergent properties of cloud feedbacks and aerosol forcing
- Not much difference in ACI between control and TAU or TAU-ML: overall TAU and emulator also yield strong negative ACI
- Differences in cloud feedbacks in S. Ocean sub-tropics! TAU bin code lower.
  - Less cloud fraction change than Control run (might be ice fraction)
- There are still large frequencies of Mass fixer being invoked in key regions

Extra and Background

Extra 1: Auto-conversion (Ac) & Accretion (Kc)

Khairoutdinov & Kogan 2000: regressions from LES experiments with explicit bin model

Ac = $$\left(\frac{\partial q_r}{\partial t}\right)_{\text{auto}} = 1350 q_c^{2.47} N_c^{-1.79}, \qquad (29)$$

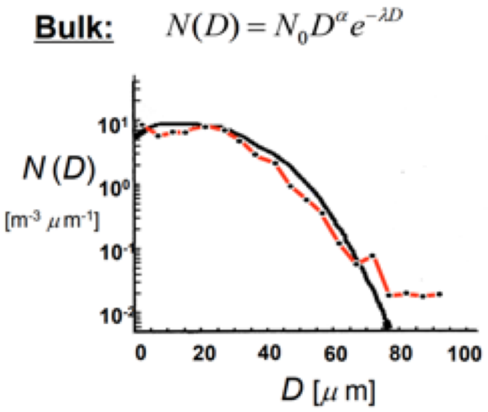
Kc= $$\left(\frac{\partial q_r}{\partial t}\right)_{\text{accr}} = 67 (q_c q_r)^{1.15}. \qquad (33)$$

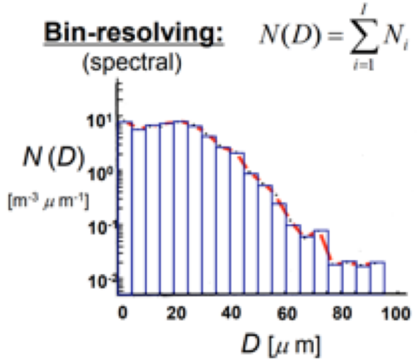
- Auto-conversion an inverse function of drop number
- Accretion is a mass only function

Balance of these processes (sinks) controls mass and size of cloud drops

The LES experiments with an explicit bin model use a stochastic collection kernel to describe how individual drop bins interact (collect and coalesce) with other bins. Let's just use this directly.

Extra 2: Detailed Steps



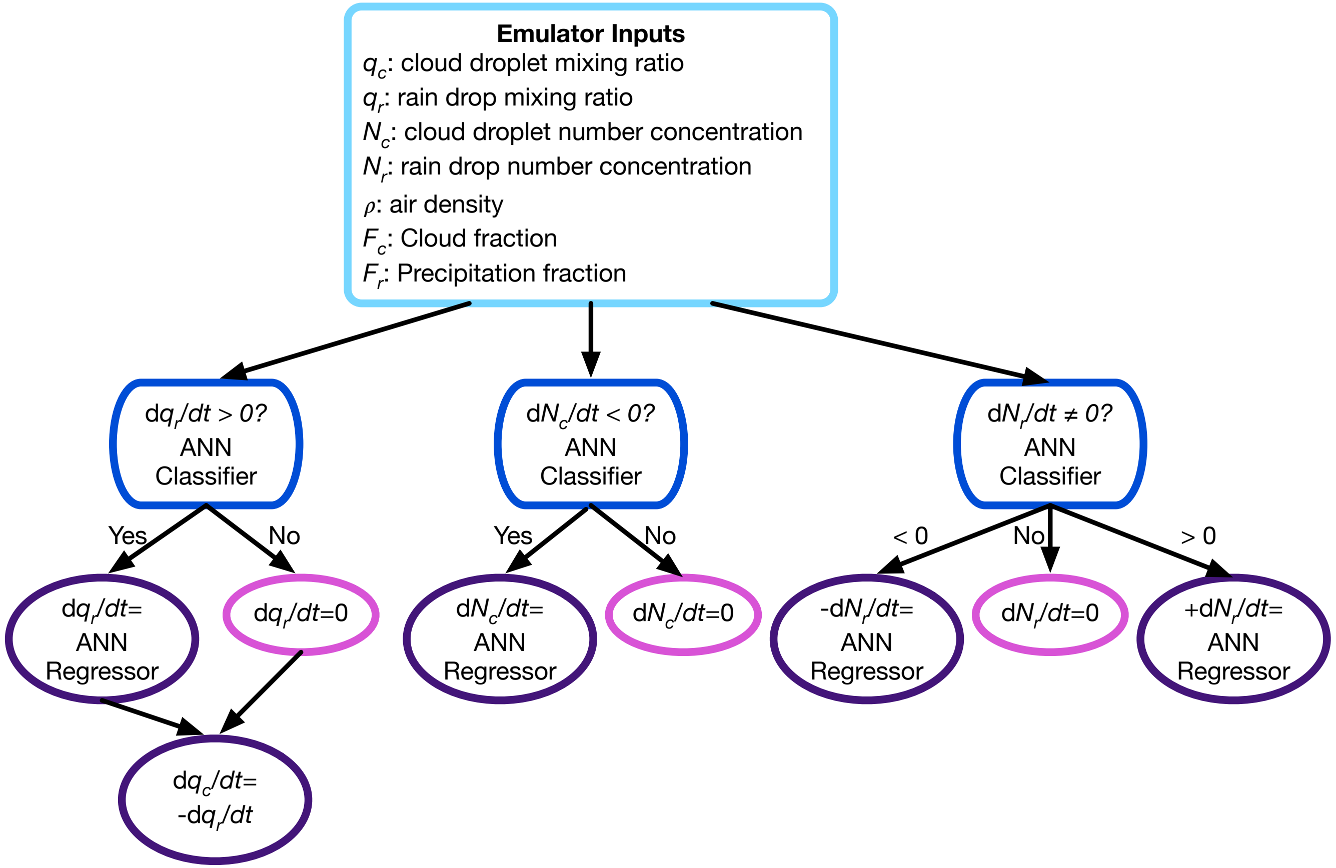


Qx = Mass Mixing ratio of [X] where X = liquid or rain
Nx = Number concentration of [X]

- Break bulk size distributions for Qc, Nc (liquid) and Qr, Nr (rain) into bins
- Run stochastic collection kernel
- Find minimum between peaks of distributions to separate Qc and Qr
- Recompose Qc, Nc and Qr, Nr distributions
- Difference before and after distributions are tendencies for Qc, Nc, Qr, Nr
  - Note that Qc = -Qr
- Apply a mass fixer to ensure no loss of mass or negative mass (TAU)
- Then: build a neural network emulator (TAU-ML)

Extra 3: Machine learning emulation of bin microphys

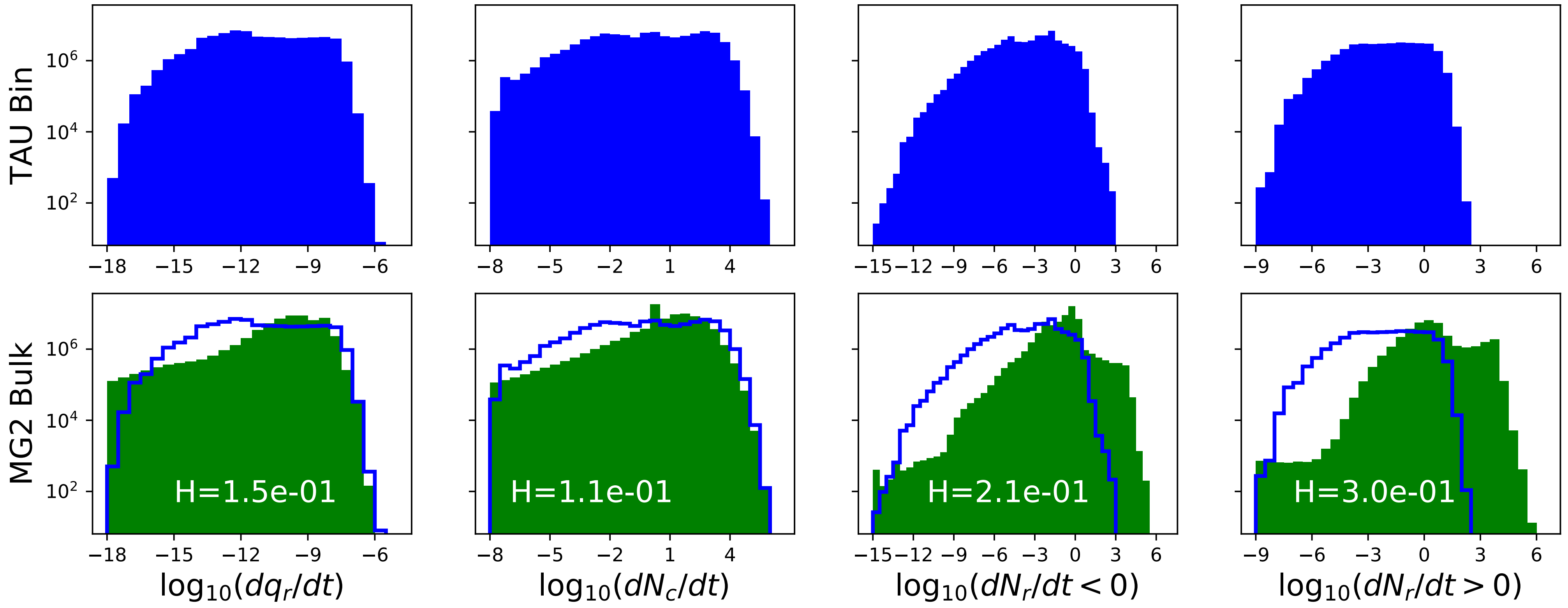
1. Run CESM2/CAM6 for two years and obtain instantaneous hourly output
2. Filter and subsample data to find grid points with realistic amount of cloud water
3. Transform and normalize inputs and outputs
4. Train classifier deep neural networks to classify zero and non-zero
5. Train regression deep neural networks to predict non-zero values
6. Evaluate and interpret neural network predictions



Extra 4: PDFs

Note that $dq_r/dt = -dq_c/dt$

Negative Nr Tendencies   Positive Nr Tendencies



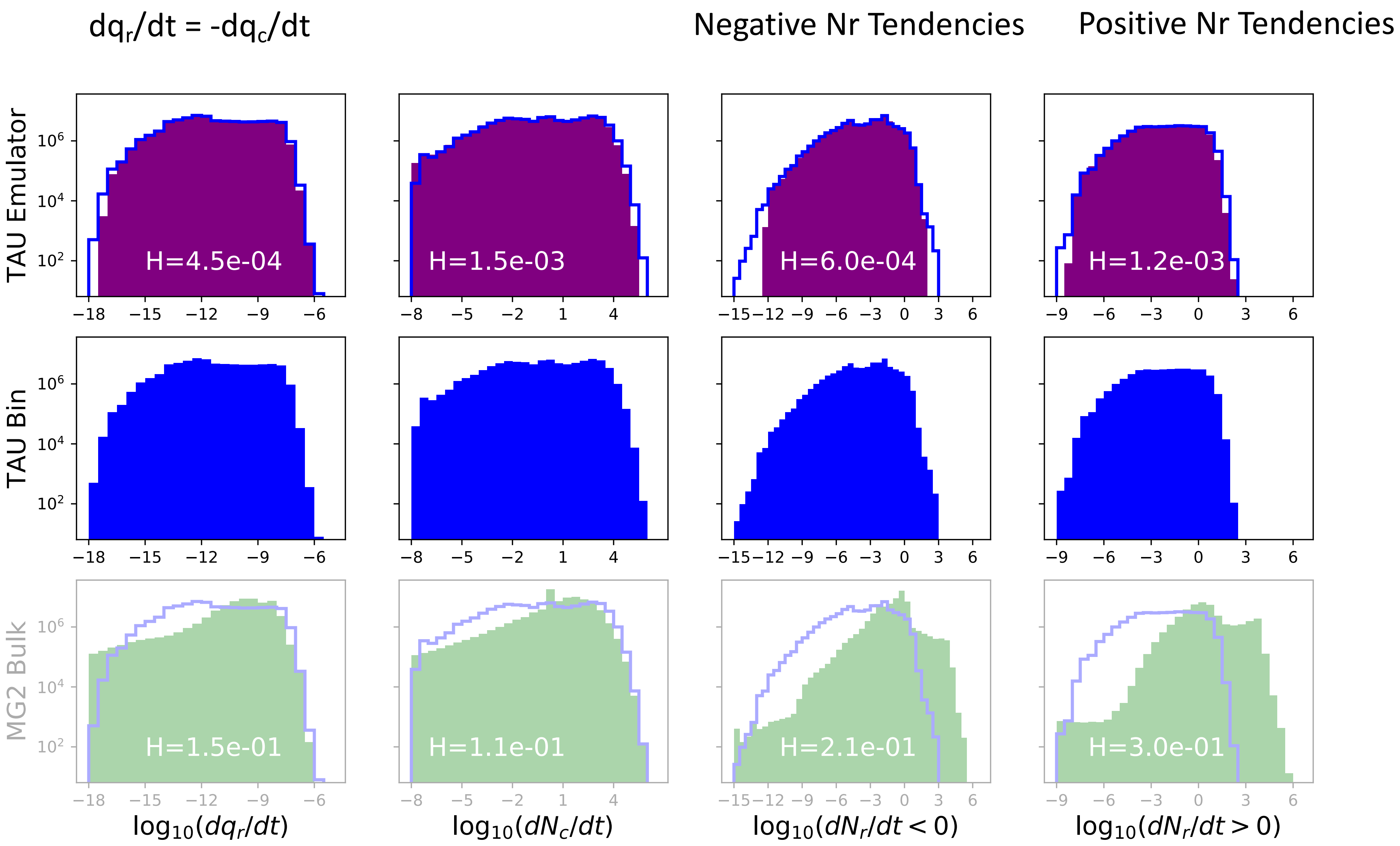
Larger →

MG2 less frequent small dq_r, dNr, compensated by more frequent higher values

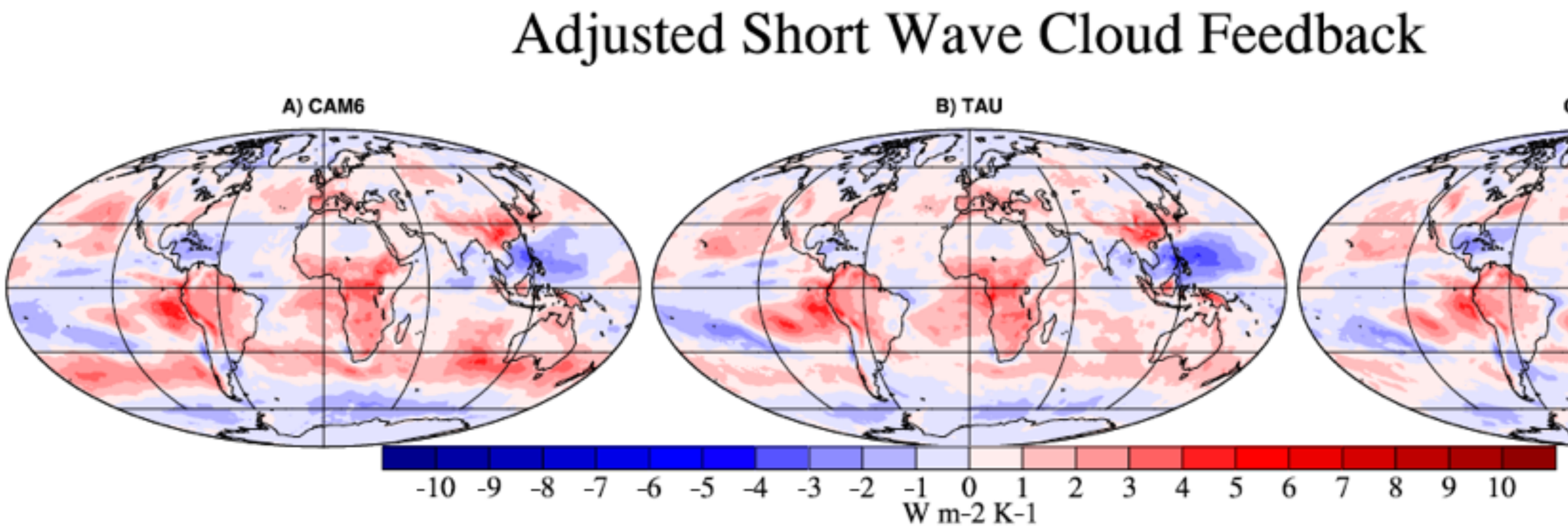
Nr, qr tendencies larger for MG2 than TAU

Extra 5: Emulator PDFs

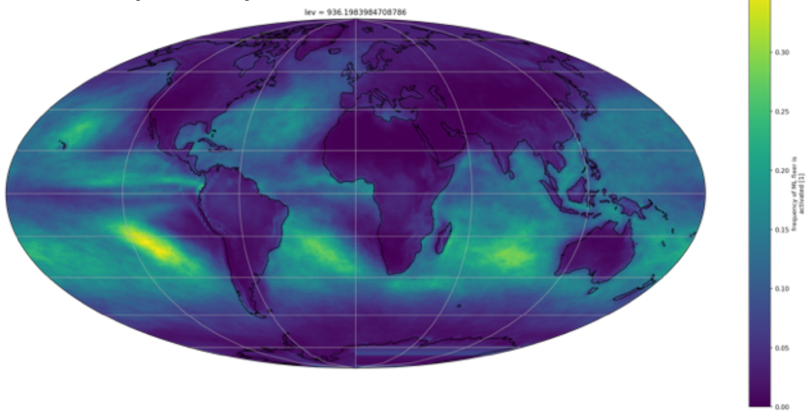
Emulator yields slightly narrower range of values than full bin calculation



Extra 6: Cloud Feedback: Map



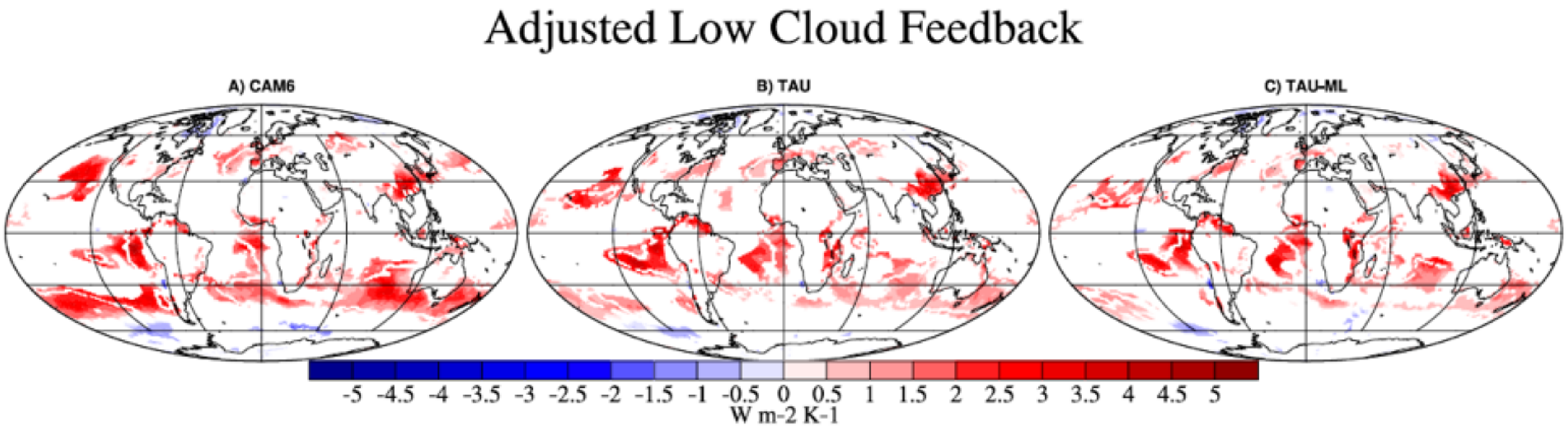
Annual Frequency of Mass Fixer, 936hPa



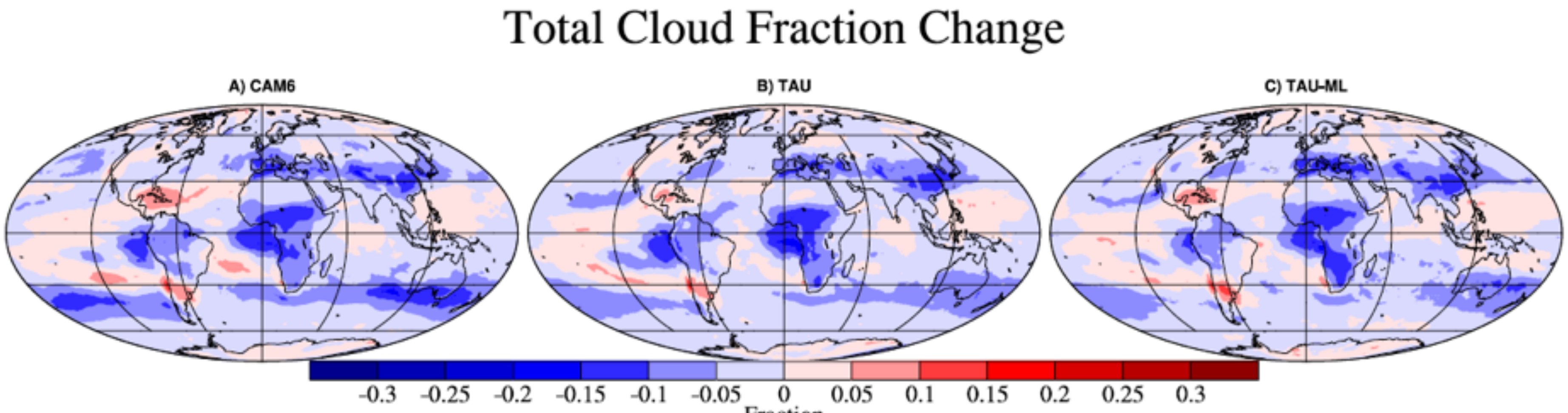
Difference in SW feedbacks is 30-60˚S
Poleward of where mass fixer is kicking in: in Storm Track region

Extra 7: Why Feedback Differences in SH?

- Feedback due to Shallow clouds…



- Likely a cloud fraction change… (less cloud fraction change in TAU runs)



Extra 8: A clue?

Higher Ice Fraction in the TAU and TAU-ML than control run
This might provide a bit of a cloud phase feedback (negative)