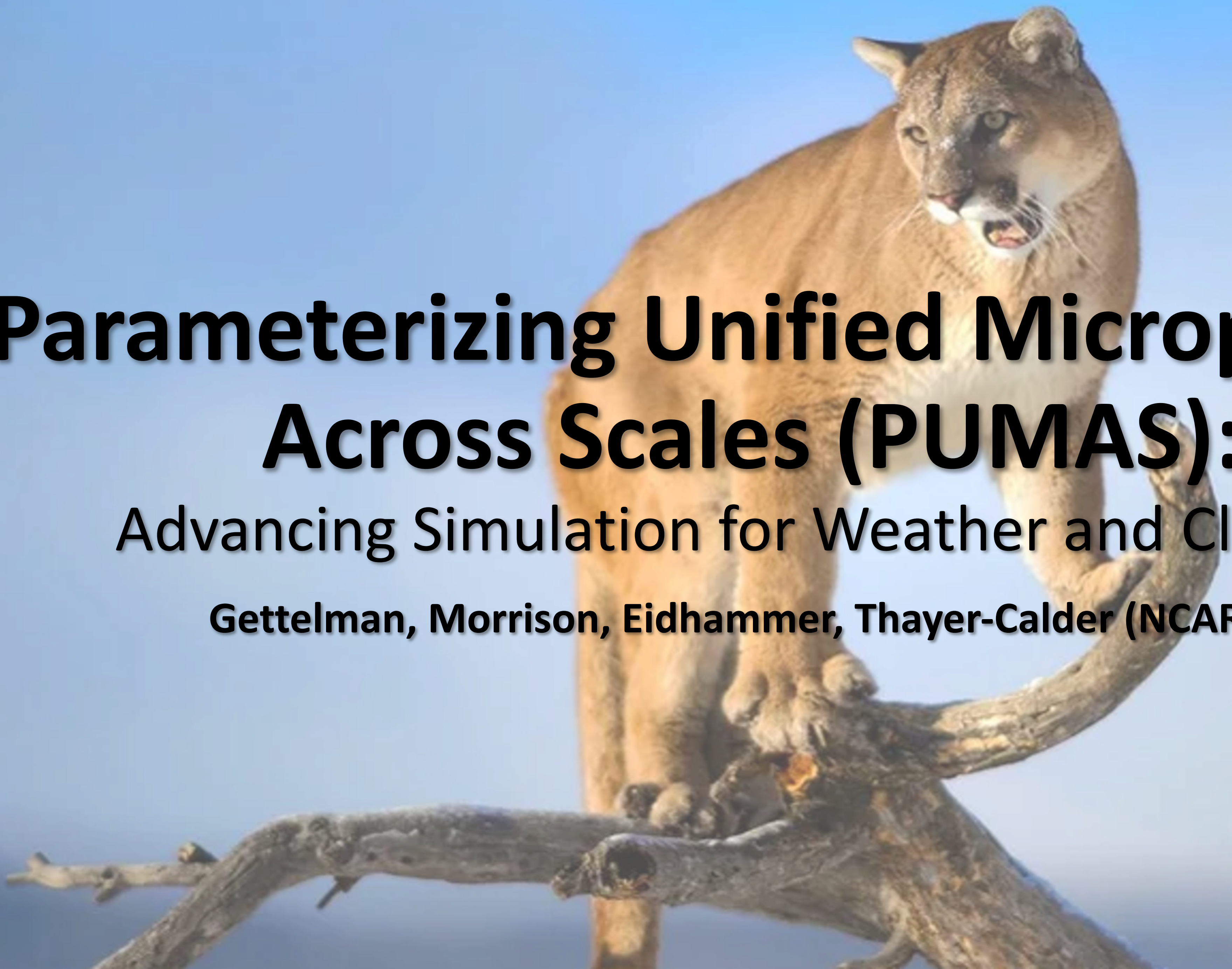


Parameterizing Unified Microphysics Across Scales (PUMAS):

Advancing Simulation for Weather and Climate

Gettelman, Morrison, Eidhammer, Thayer-Calder (NCAR)

Cloud Microphysics Critical for Weather & Climate

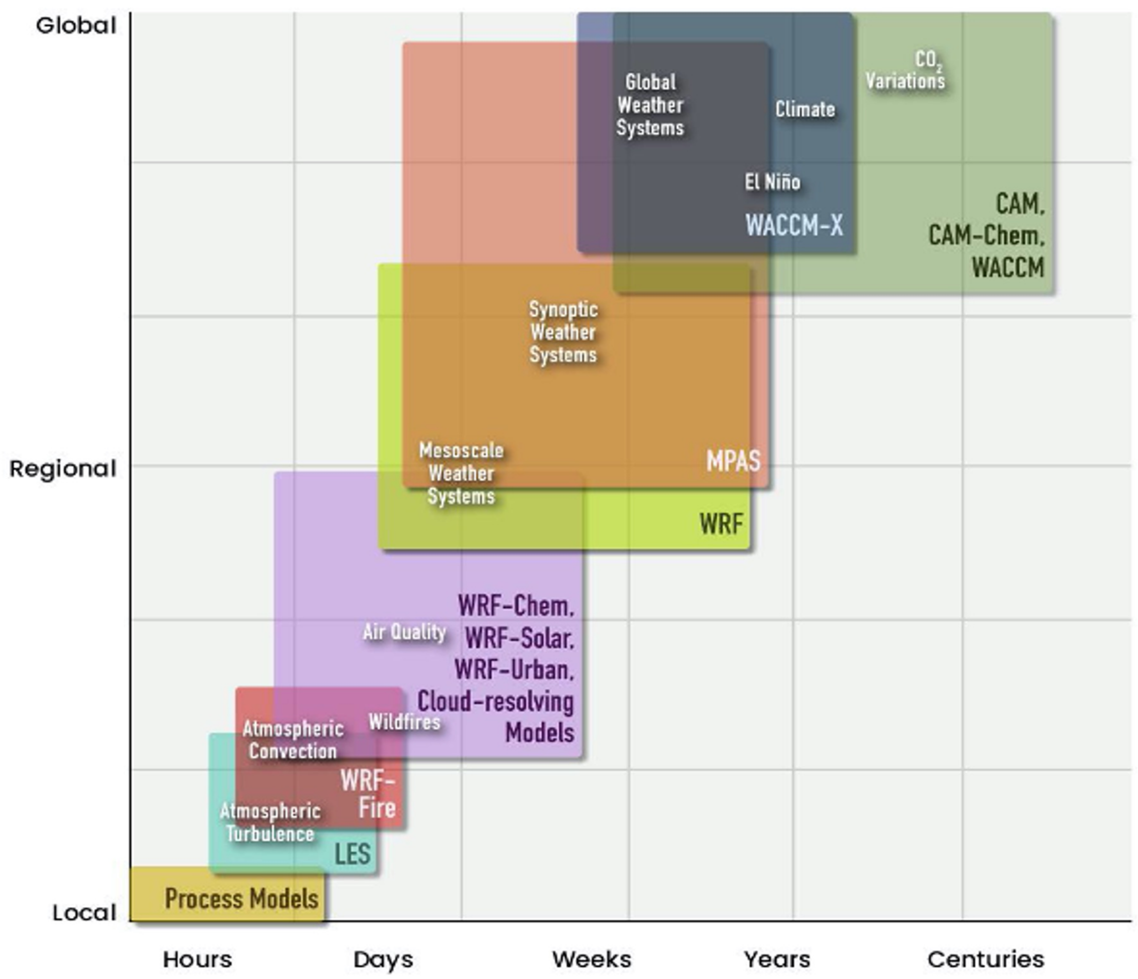
Major Issues for Clouds, Precipitation and Aerosols

- Cloud Phase
  - Critical for radiative effects at high latitudes AND for cloud feedbacks. Also weather impacts
- Cloud Microphysics: size distributions govern process rates
- Dynamics-Microphysics coupling
  - Vertical structure of clouds: cloud base, freezing, entrainment at top
- Aerosol activation (cloud-aerosol interactions)
  - Vertical velocity critical
- Precipitation Formation: Frequency & Intensity

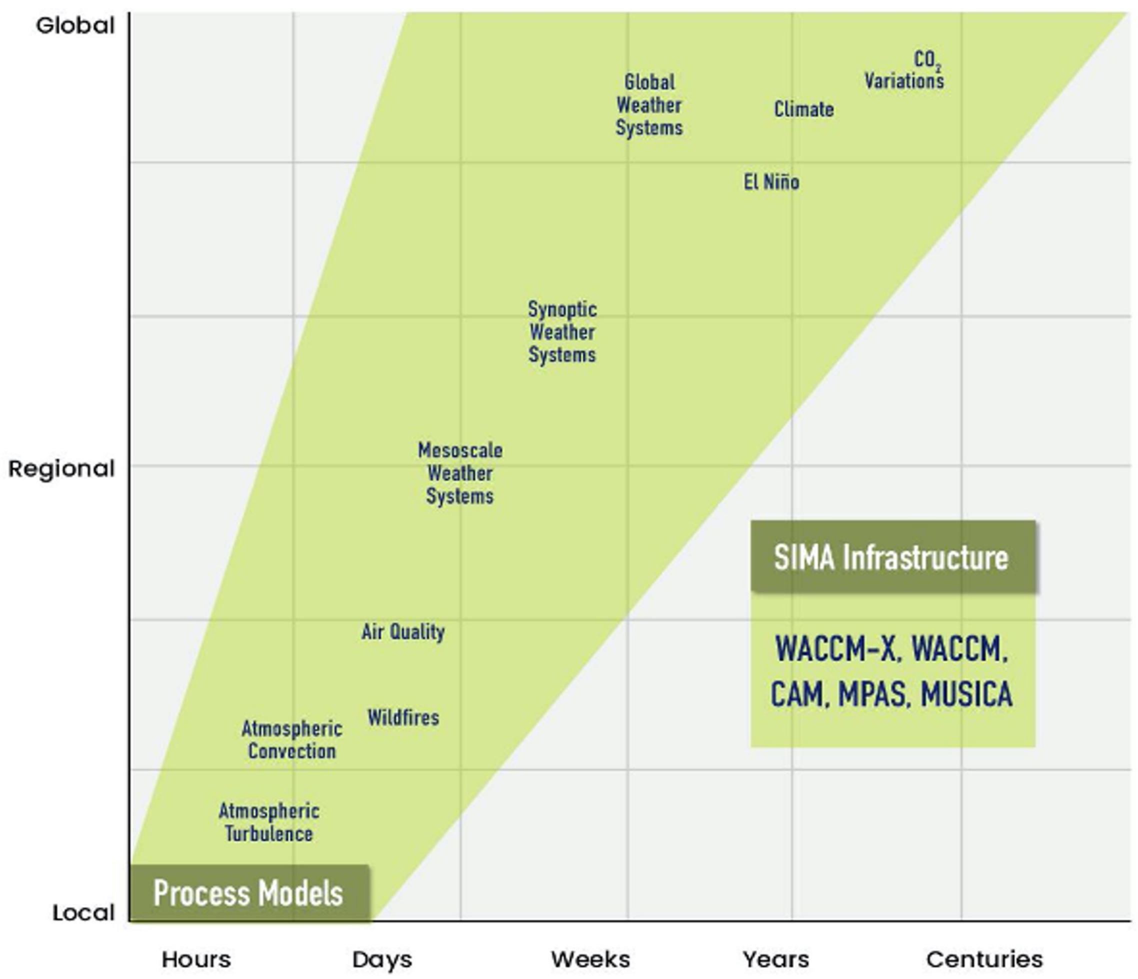
A (not so unique) vision: Seamless Prediction

System for Integrated Modeling of the Atmosphere (SIMA)

Atmospheric Modeling Ecosystem in Mid-2010s

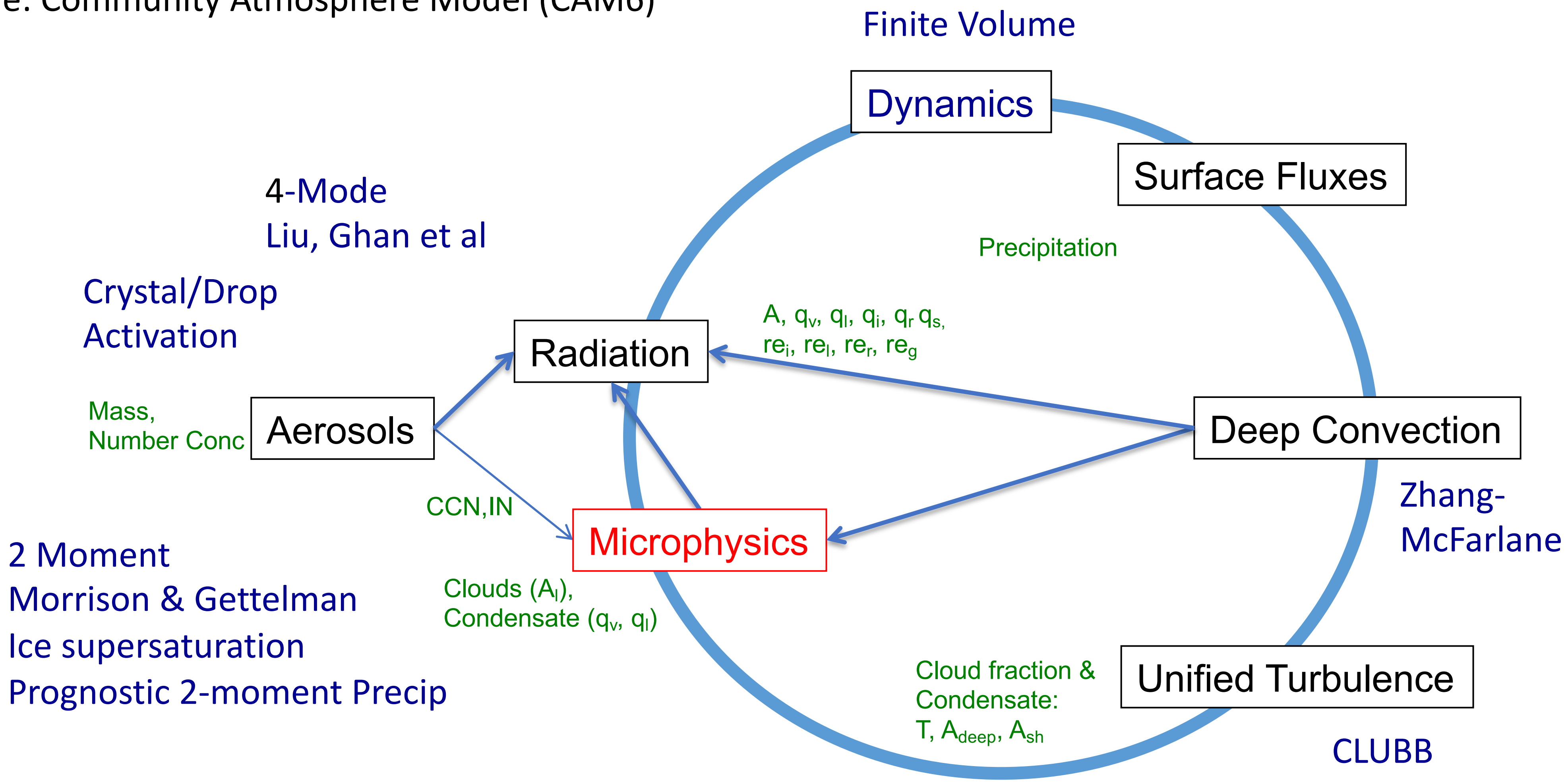


SIMA-based Atmospheric Modeling System in Mid-2020s



What is Cloud Microphysics?

Example: Community Atmosphere Model (CAM6)

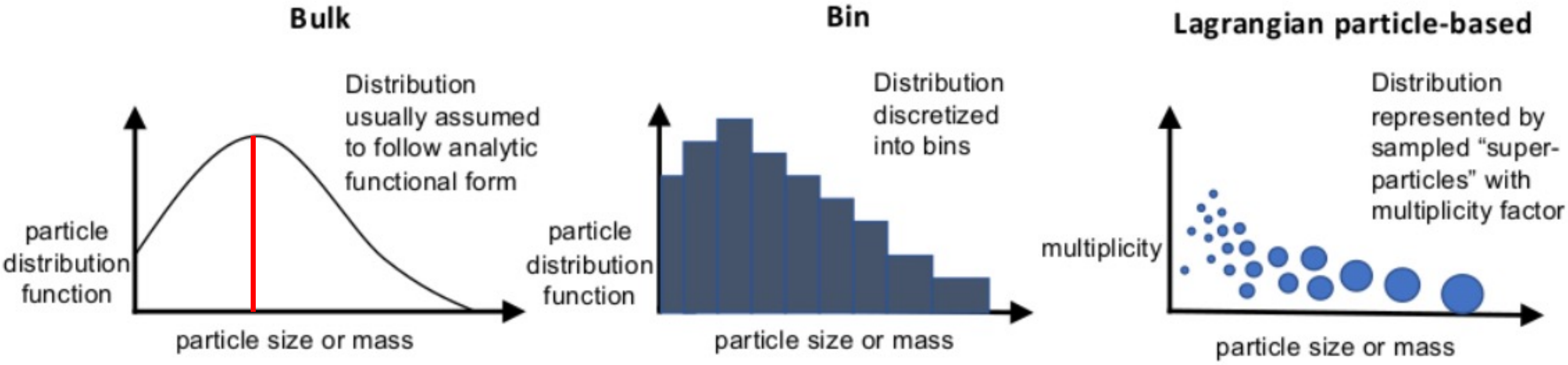


A = cloud fraction, q=H_2O, re=effective radius (size), T=temperature
(i)ce, (l)iquid, (v)apor, (r)ain, (s)now

Types of Microphysical Schemes

Used in models at scales:

Global & Mesoscale models | Mesoscale /Large Eddy Simulations/Parcel | LES/Parcel



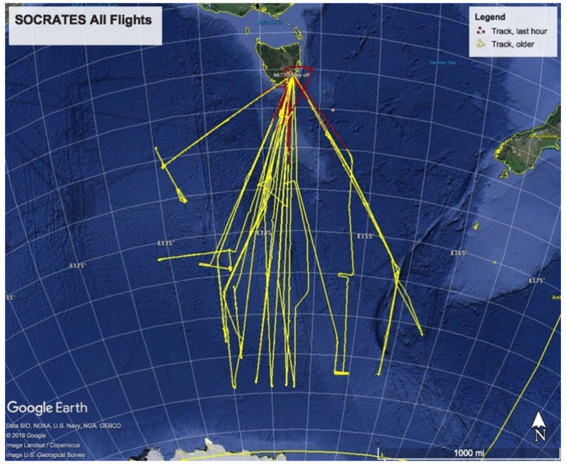
Two Moment = Prognostic Mass and Number

One Moment = Prognostic Mass, Diagnostic Number/Size

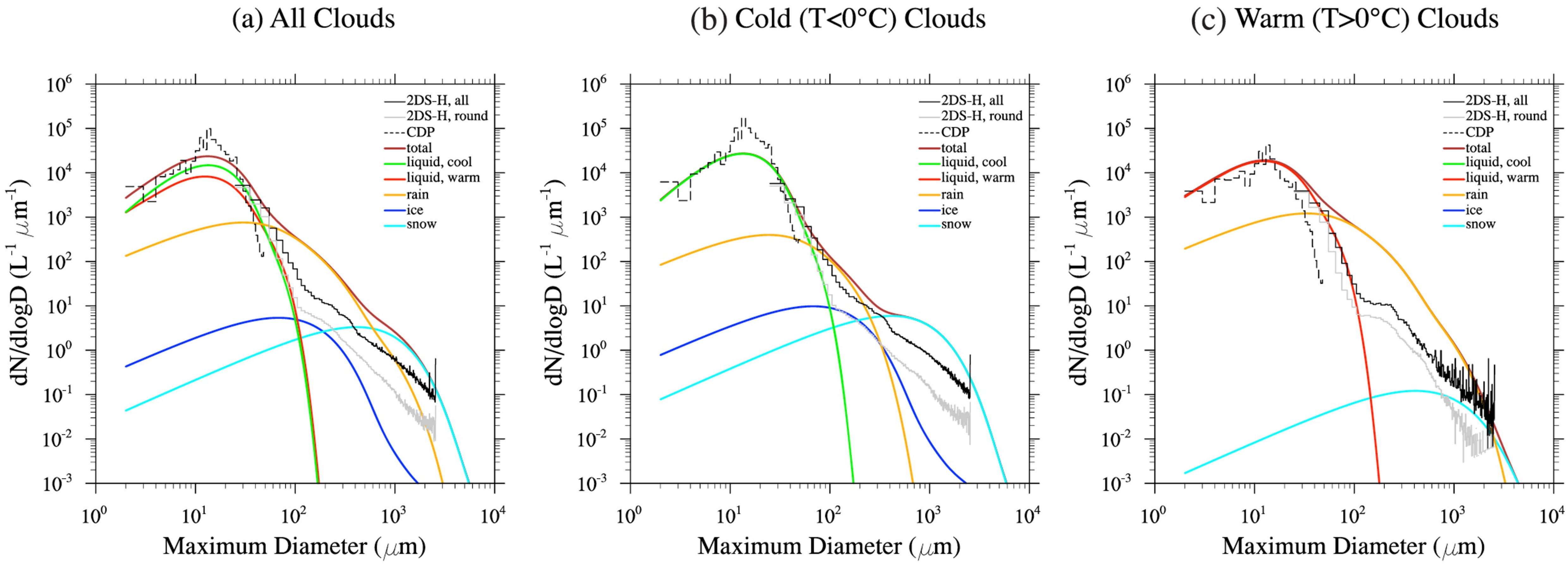
Figure: Morrison et al 2020, JAMES

Microphysics, Size distributions

Advanced GCMs/GSRMs can be compared directly to cloud microphysical size distributions (here from SOCRATES).



Comparison is GCM cloud microphysics along aircraft flight tracks with in-situ data

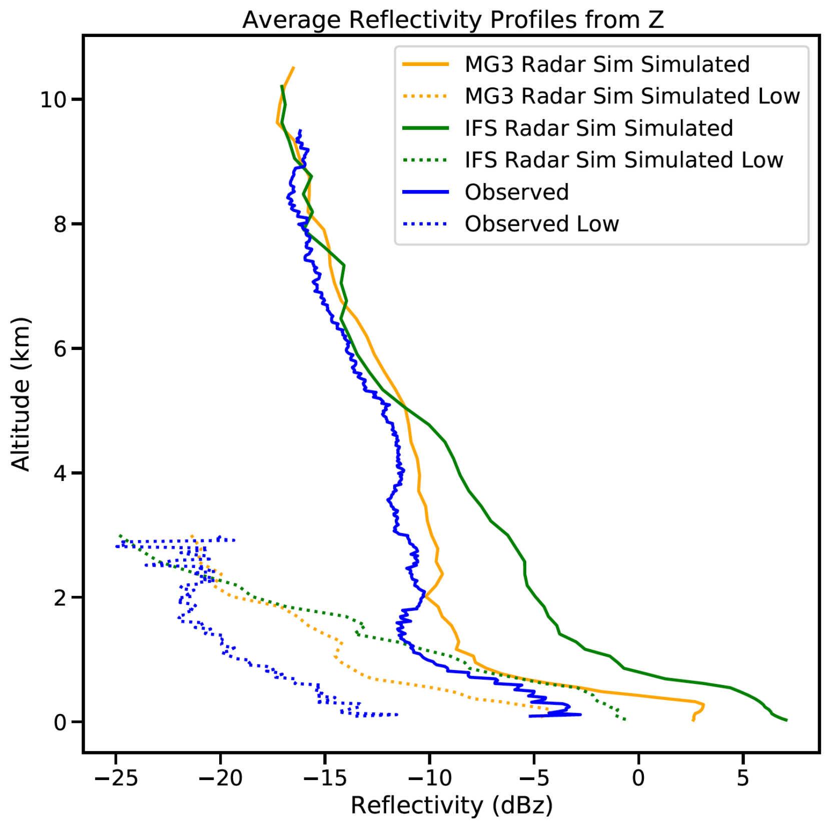


Note potential issue with too large rain sizes

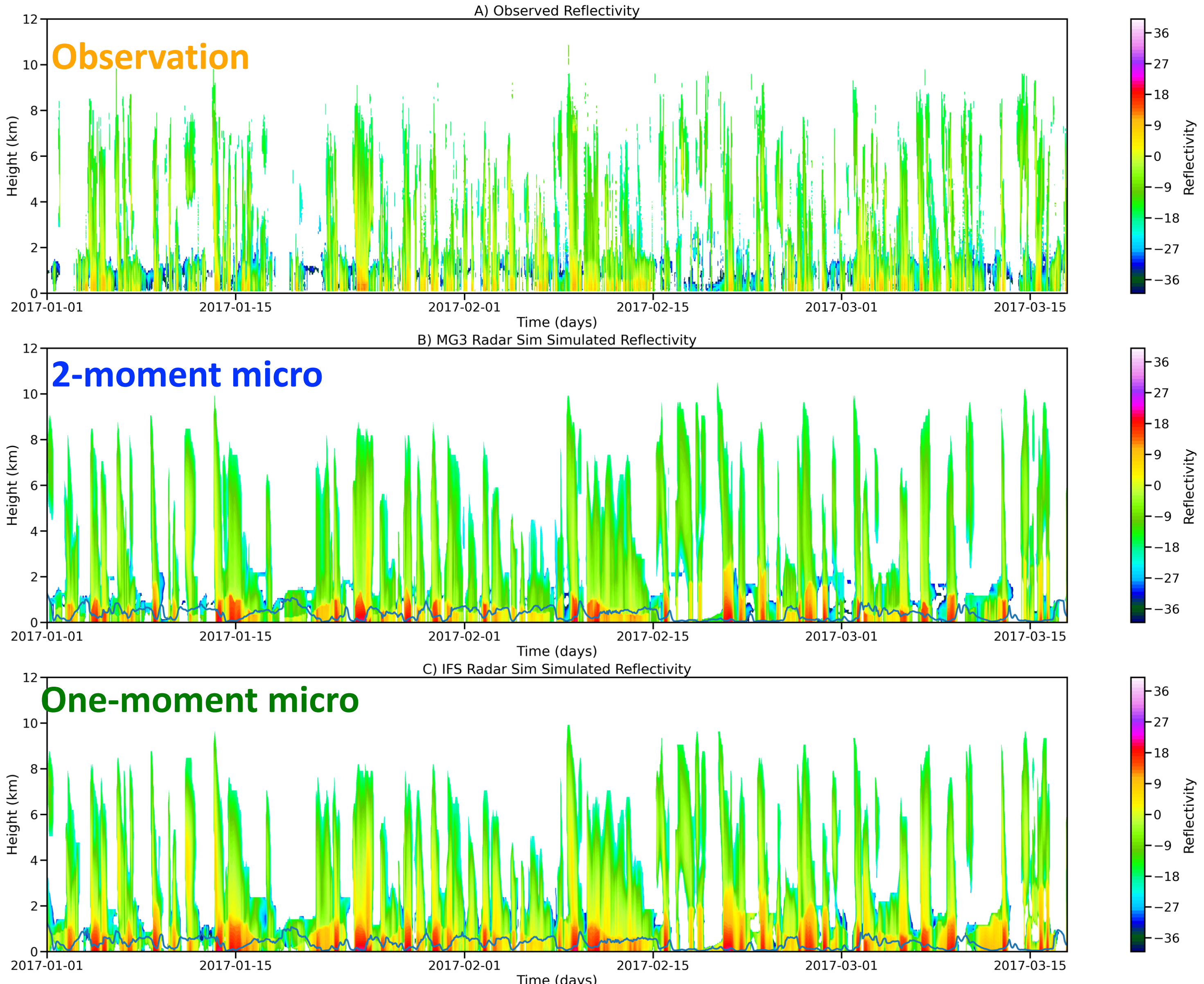
Gettelman et al 2020

Microphysics: Comparing to Reflectivity

Comparisons over Macquarie Island in S. Ocean between a **precipitation radar** and single column simulations with **one-moment** and **2-moment** microphysics in the ECMWF-IFS SCM.



Gettelman, Forbes, Fielding, in Prep



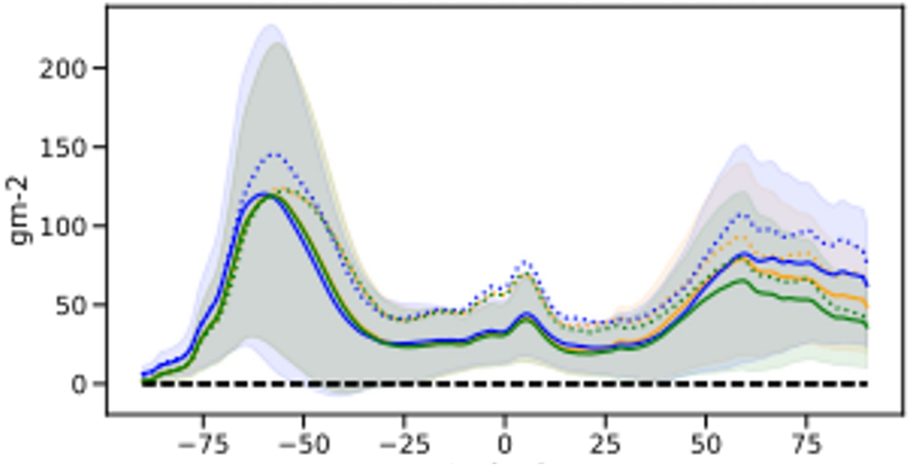
Robustness: Parameter Uncertainty

Perturbed Parameter Ensemble (PPE)

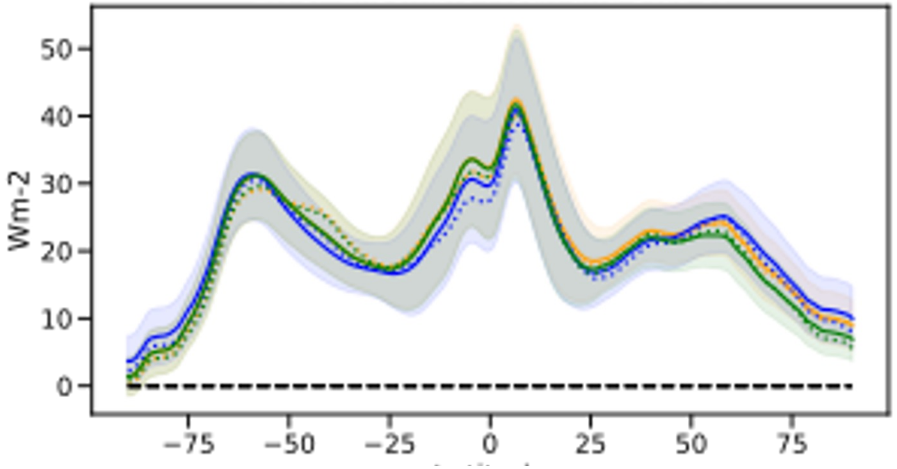
Eidhammer, Gettelman, Thayer-Calder, Duffy

· · · · · · Control run (Baseline CAM6 parameters)
—— Mean over all 250 simulations

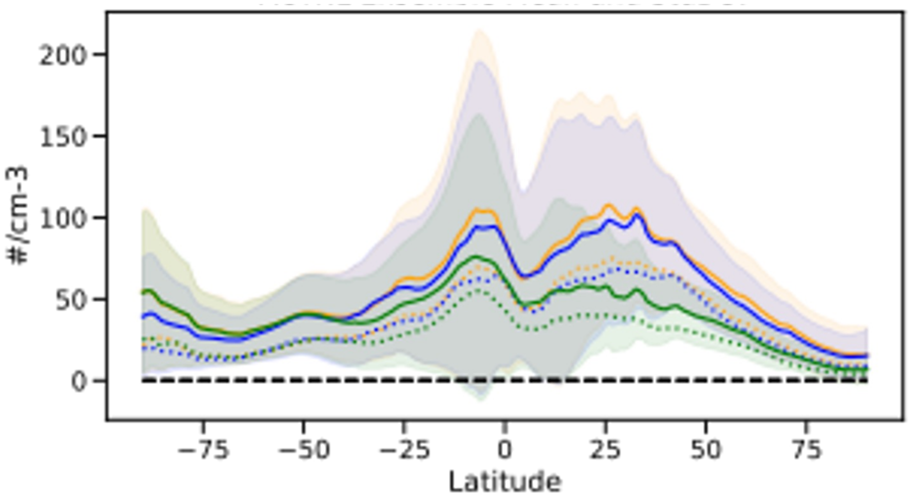
Liquid water path



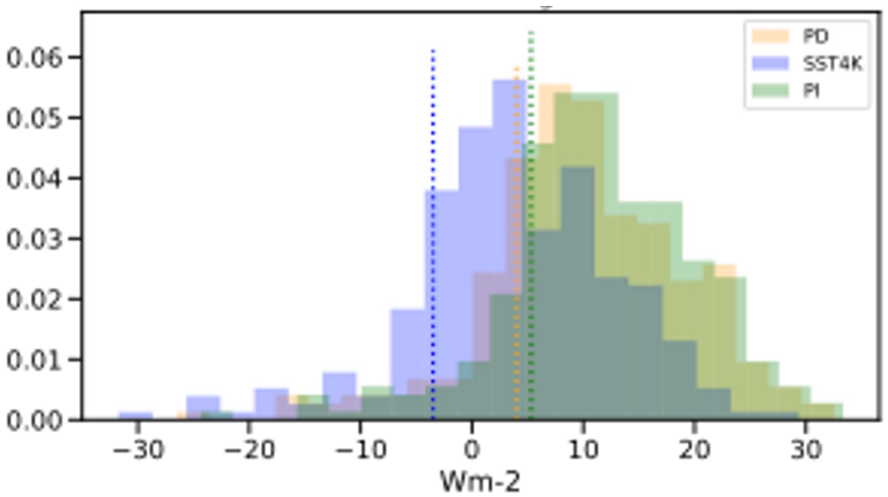
Longwave cloud forcing



Average cloud top liquid number



Net solar flux at top of model

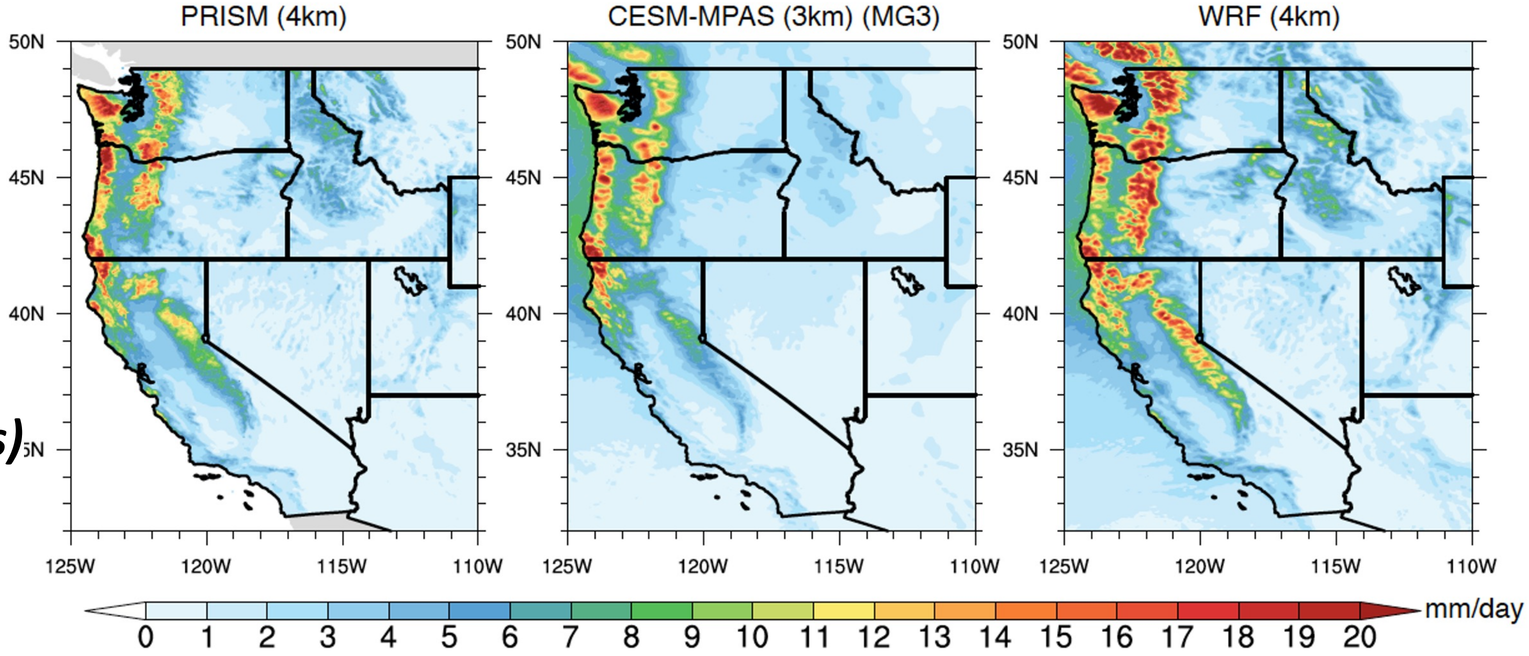


Climate Extremes: Variable-Resolution (60→3 km)

- Global Model: CESM-MPAS: 3km regional, no hydrostatic dynamics.
- Regional climate model: WRF (CONUS) 4km (Rasmussen et al., 2021)

W. USA Wet-season (Nov-Mar) precip (5yrs)

- CESM-MPAS results compare well to obs
- Smaller biases than WRF mesoscale model



Wet-season (Nov-March) mean precipitation over western US (1999-2000)

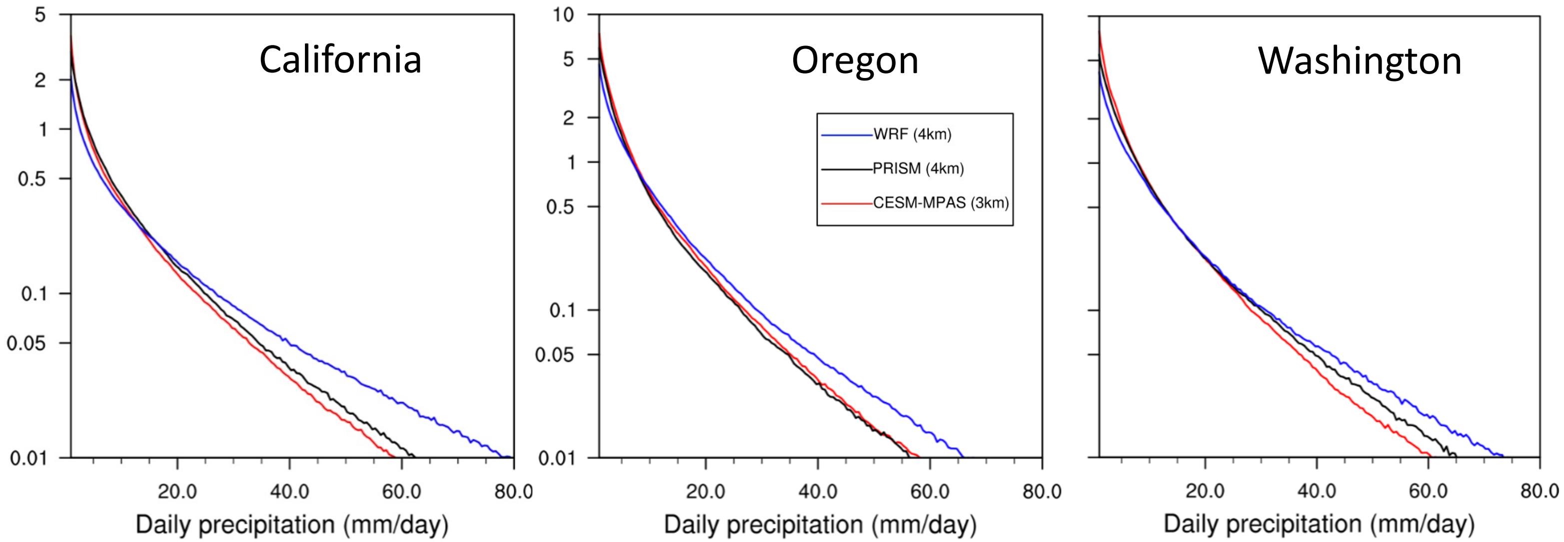
Daily precipitation Intensity PDF

4km Mesoscale Model (WRF)

3km Global Model (CESM)

4km Observations

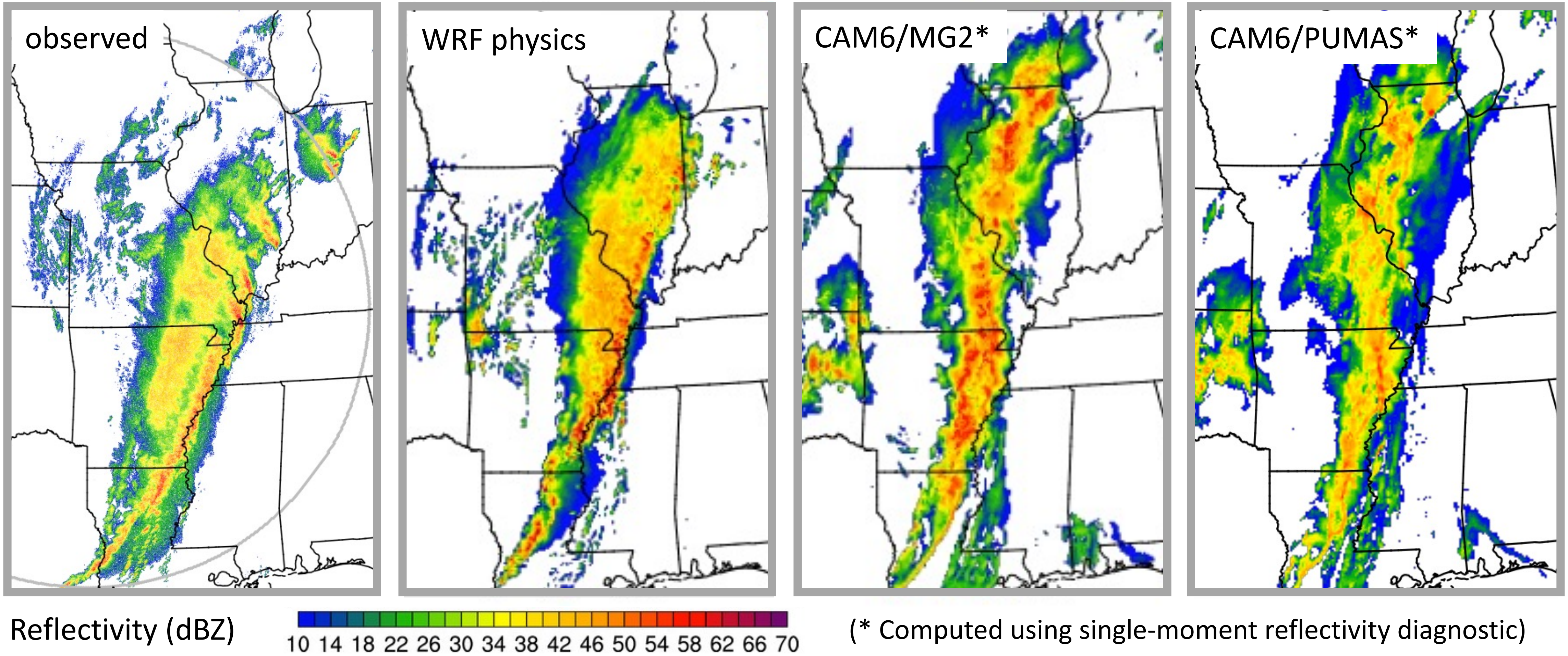
CESM captures **observed PDF** better than **WRF**, especially for extreme precipitation



X. Huang, NCAR

Climate Extremes: Variable-Resolution (60→3 km)

- Central US Summertime squall line. 24 hour forecast valid 0 UTC 27 April 2017
- Mesoscale model v. Climate Model



(* Computed using single-moment reflectivity diagnostic)

M. Chen, W. Skamarock, X. Huang, NCAR

CAM6 = CMIP Model

CAM6+Graupel

Machine Learning the Warm Rain Process

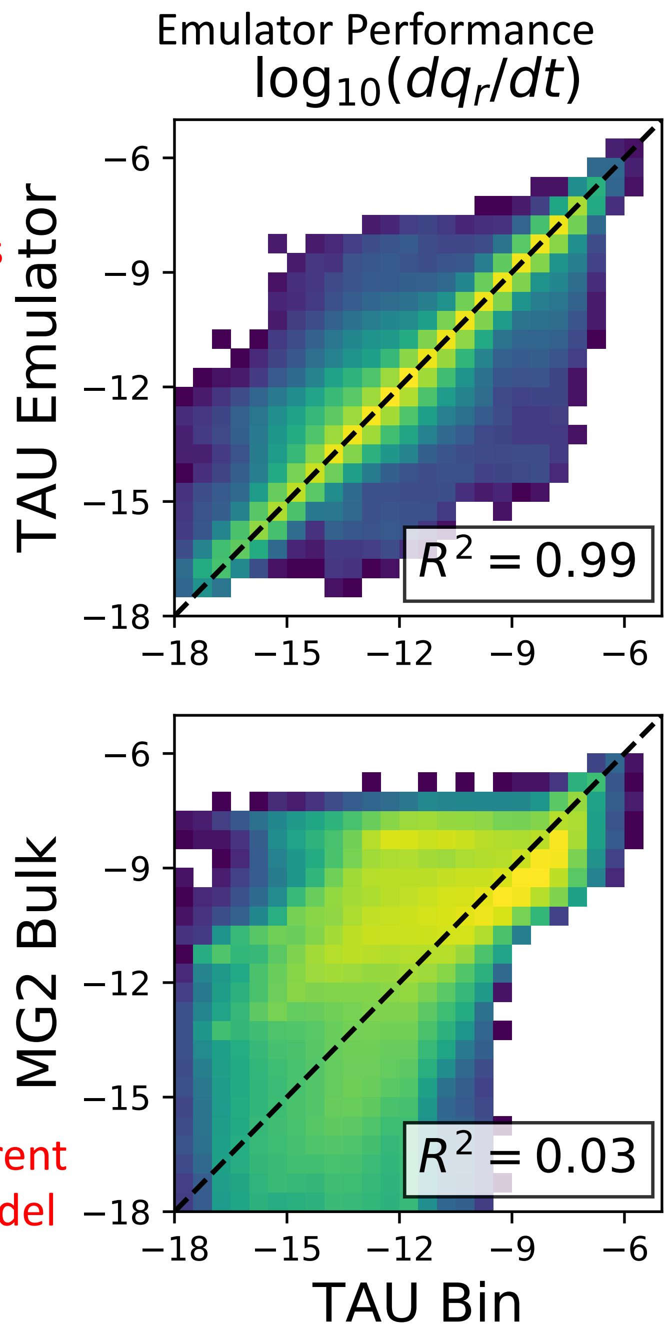
NN Emulator reproduces detailed code

Can we do the warm rain process better with Machine Learning?

Replace traditional GCM bulk rain formation with a bin model formulation for stochastic collection. This is too expensive for climate use. So emulate it with a neural network.

Results:

- We can change the answer in the model with the bin code.
- Very slow when using full treatment
- Recover speed and recover results with a neural network emulator (it works)
- Embedded NN in the microphysics: maintains conservation with series of checks



Bin code is Different than original model

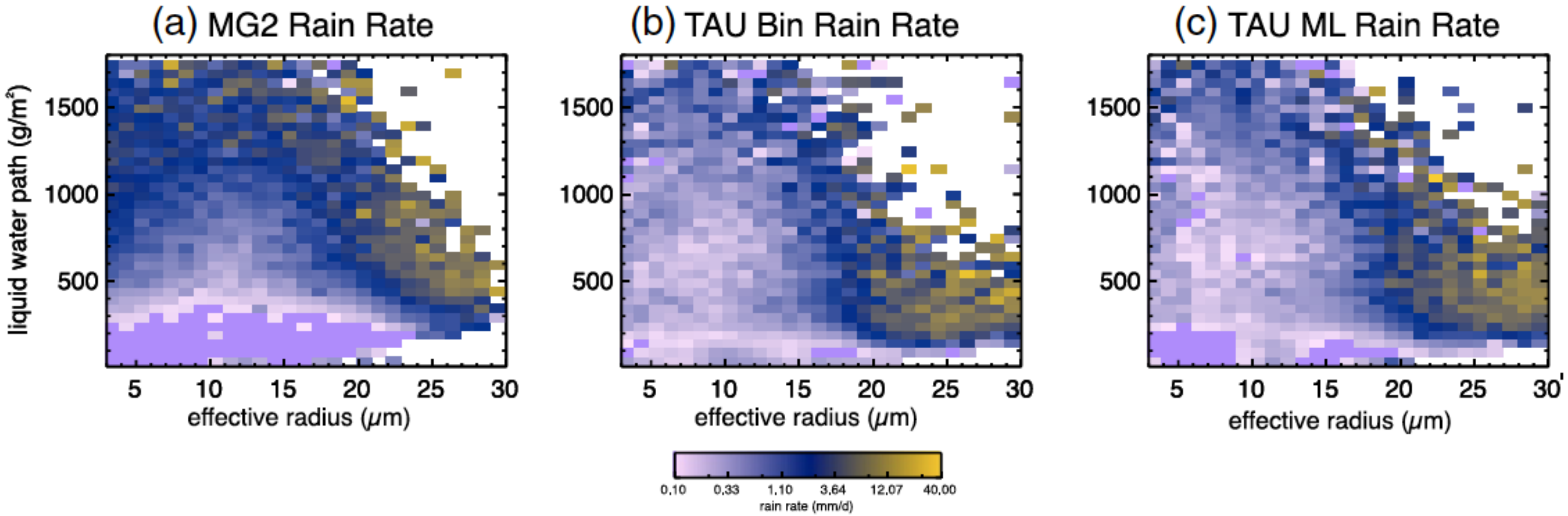
Gettelman et al 2021, JAMES

Improving results with Machine Learning

Stochastic collection equation for warm rain in a bulk scheme

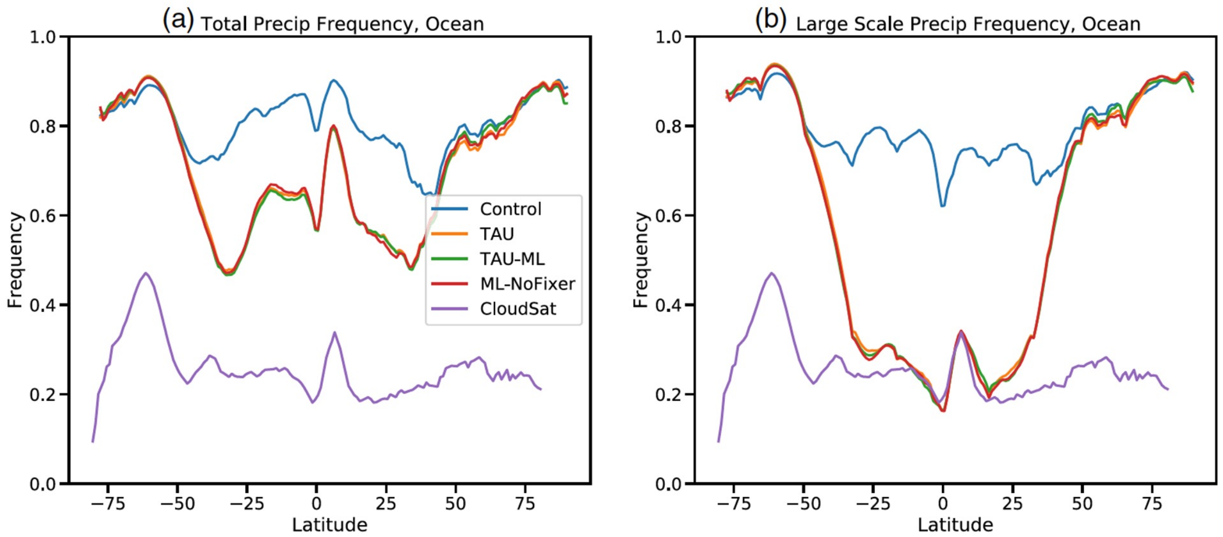
Reduces rain rate for small drop sizes but large LWP

Emulator reproduces this



Precipitation Frequency

Control v. **Observations** and
Bin precipitation and **ML Emulator.**
Using stochastic collection from a bin scheme improves large scale precipitation frequency in shallow clouds



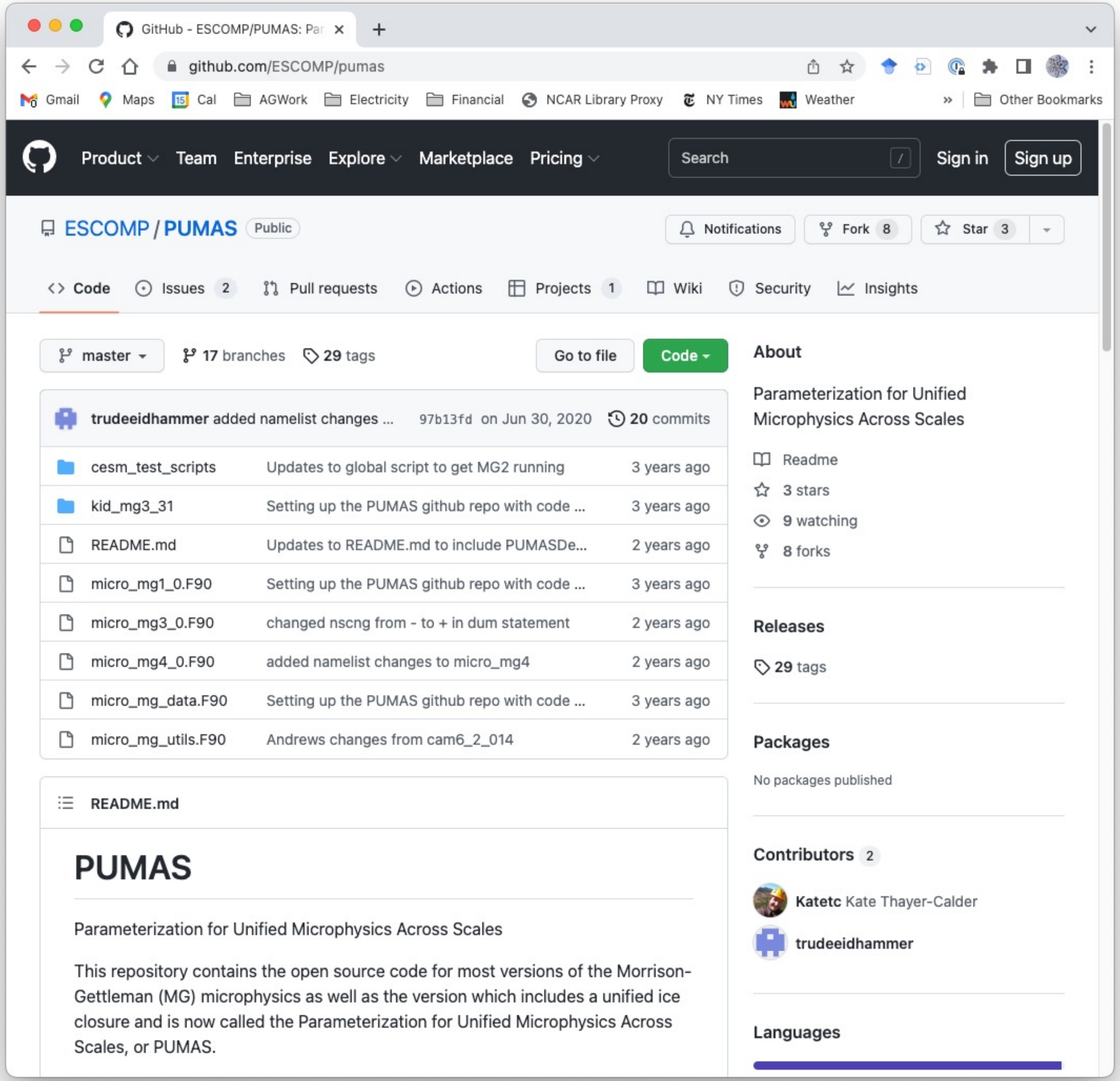
Gettelman et al 2021, JAMES

Latest developments

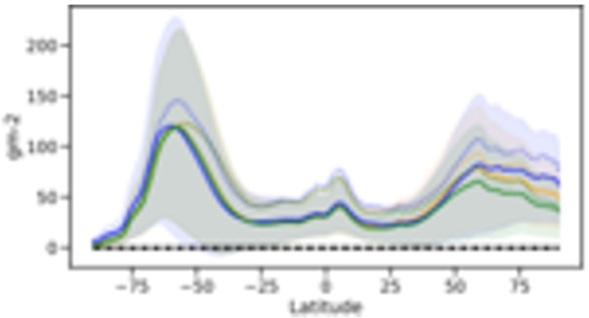
- Ice Nucleation: especially mixed phase
  - Evaluate CNT Treatment (Hoose et al 2010,) v. empirical from data (DeMott et al 2015, McCluskey et al 2018)
- Unified Ice/Snow: eliminate artificial separation
  - Predicted Particle Properties (P3)-like
  - Eidhammer et al 2016 (From Morrison and Milbrandt 2015)
- ‘Open up’ model structure: allow size distribution properties to vary, and learn them from data
  - Morrison et al (2020)

Open Source Code

- https://github.com/ESCOMP/pumas
- Used in different GCMs now
  - CESM1/2 (and derivatives)
  - GISS, DOE (E3SMv1), GFDL
  - Single column container version for development/tutorials
- Users contributing to development and evaluation



Future Work: Where does it all go?



- Better uncertainty quantification (parameters, processes)
- Machine learning/emulators
  - Parameterization replacement
  - Learning model structure (BOSS)
- Model-data fusion, using observations
- Crossing scales (LES--> Global)
- New modeling capabilities for global km scale models
- Scalable complexity
  - Complexity varies by scale (e.g. hail)
- Be careful not to get eaten!