



U.S. DEPARTMENT OF
ENERGY

Office of Science



**Pacific
Northwest**
NATIONAL LABORATORY

Simulating Cloud Microphysics Across Scales for Predicting Climate Extremes

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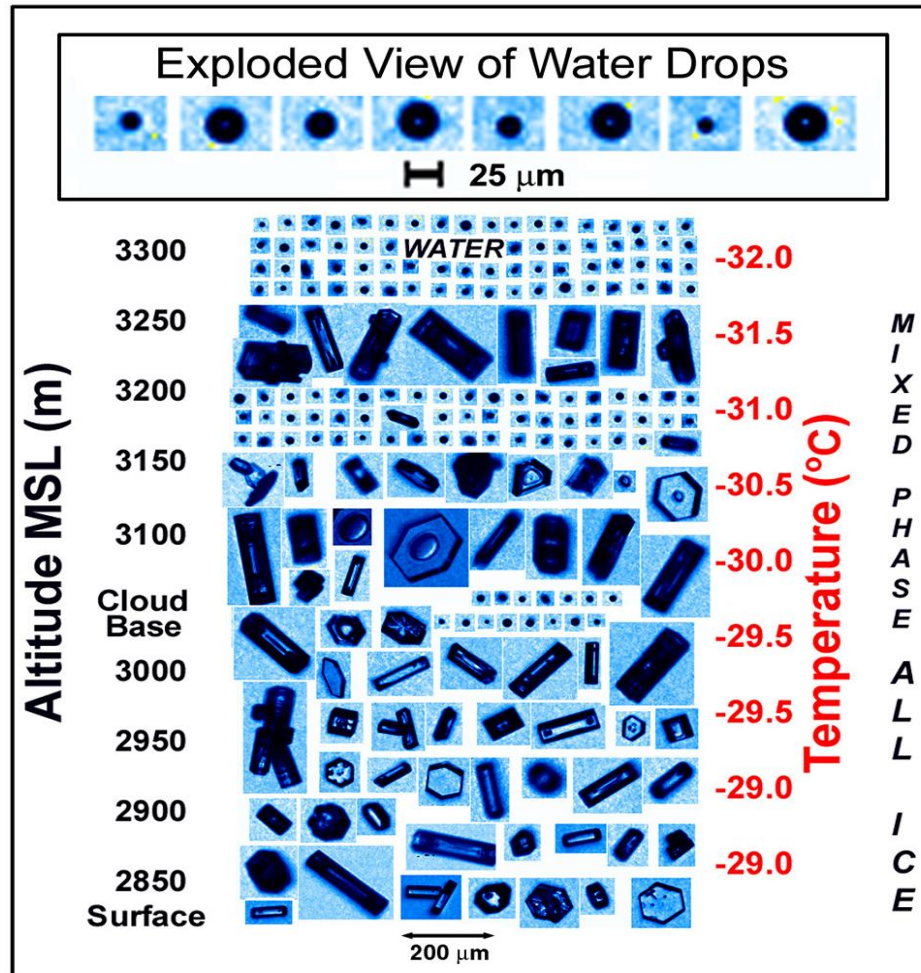
BATTELLE

What do we do next?

Outline

- Motivation (Forcing and Feedback)
- Models and Observations
- Uncertainty and interactions between forcing, feedback, processes (PPEs)
- ‘What’s wrong’ and ways forward: machine learning (one example)
- Not your academic grandfather’s climate model (extremes & crossing scales)
- Some ideas for next steps

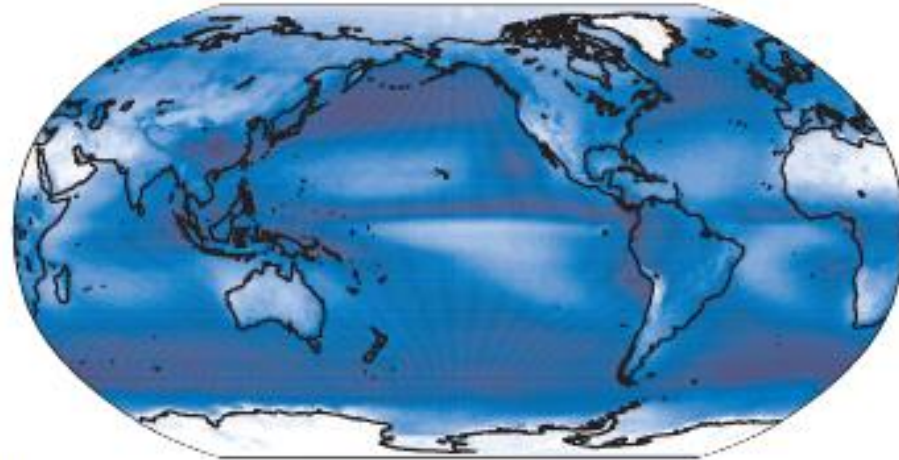
Spanning Scales $10^{-6}\text{m} \rightarrow 10^6\text{m}$



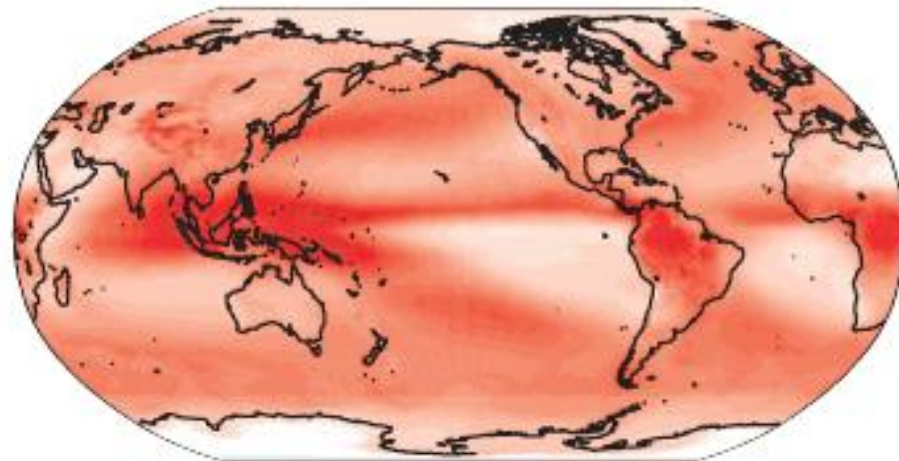
$\longleftrightarrow 1.2 \times 10^7 \text{m} \longleftrightarrow$

Cloud Radiative Effects are Large

(a) Shortwave (global mean = -47.3 W m^{-2})

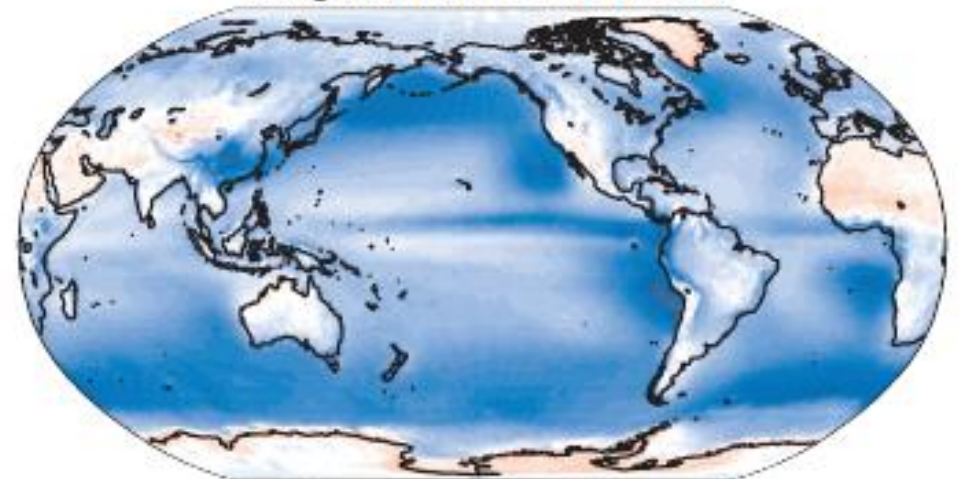


(b) Longwave (global mean = 26.2 W m^{-2})

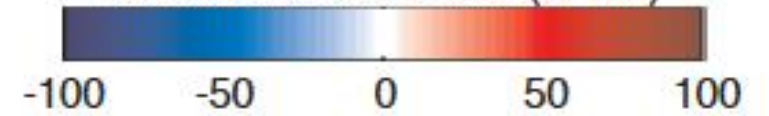


$$R_{\text{cloudy}} - R_{\text{clear}}$$

Net (global mean = -21.1 W m^{-2})

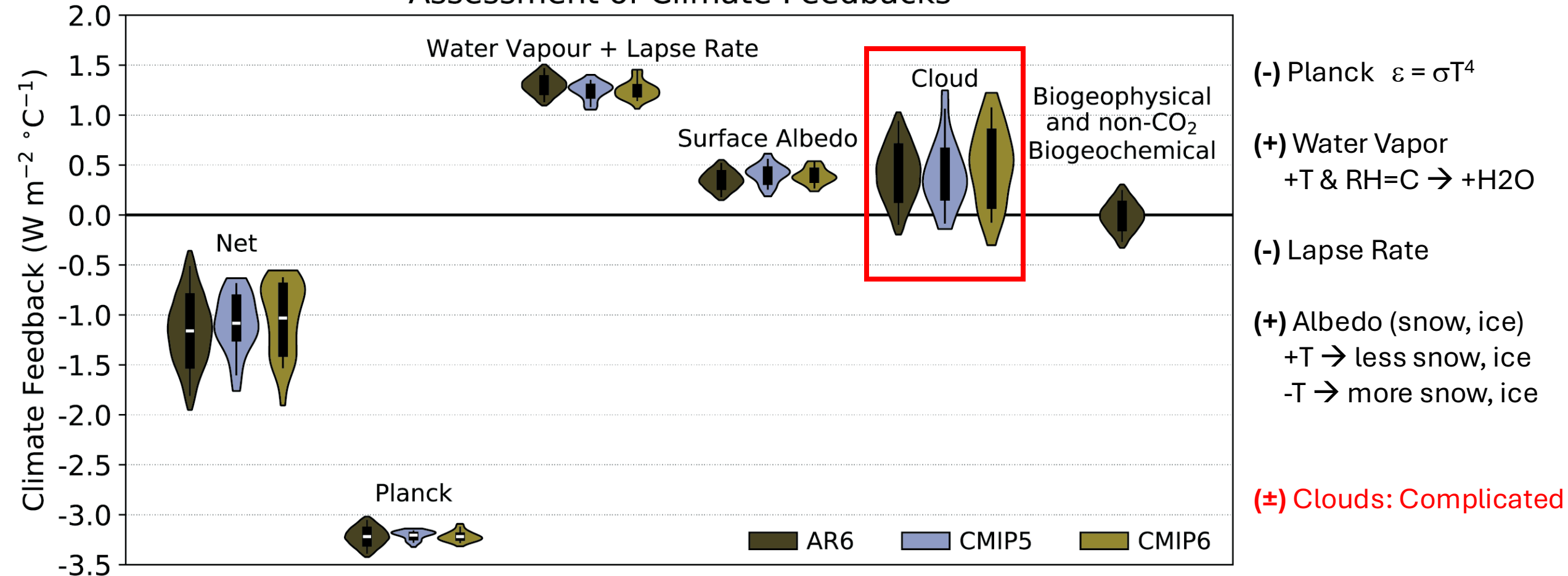


Cloud Radiative Effect (W m^{-2})



Clouds = Largest Uncertainty in Climate Feedbacks

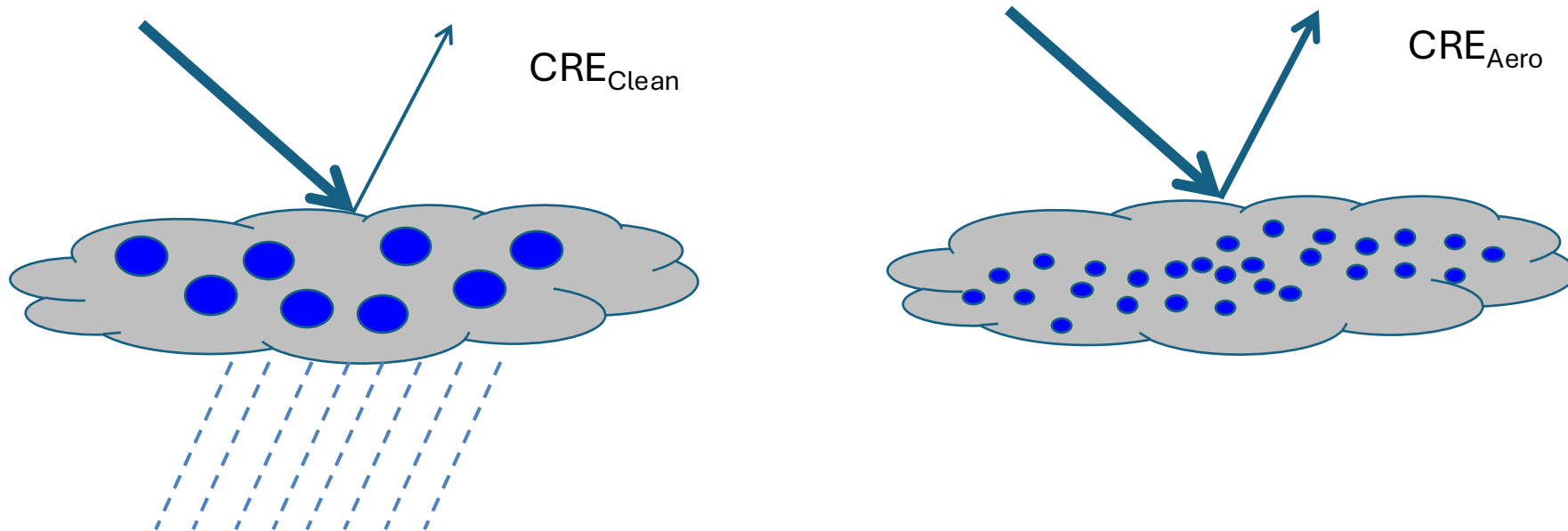
Assessment of Climate Feedbacks



Aerosol Effects on Clouds

- Scattering & Absorption = Direct effects
- Aerosol – Cloud – Interactions (ACI)

$$+\text{Aerosols} \rightarrow +\text{CCN} \rightarrow +N_c \rightarrow \Delta\text{CRE}$$

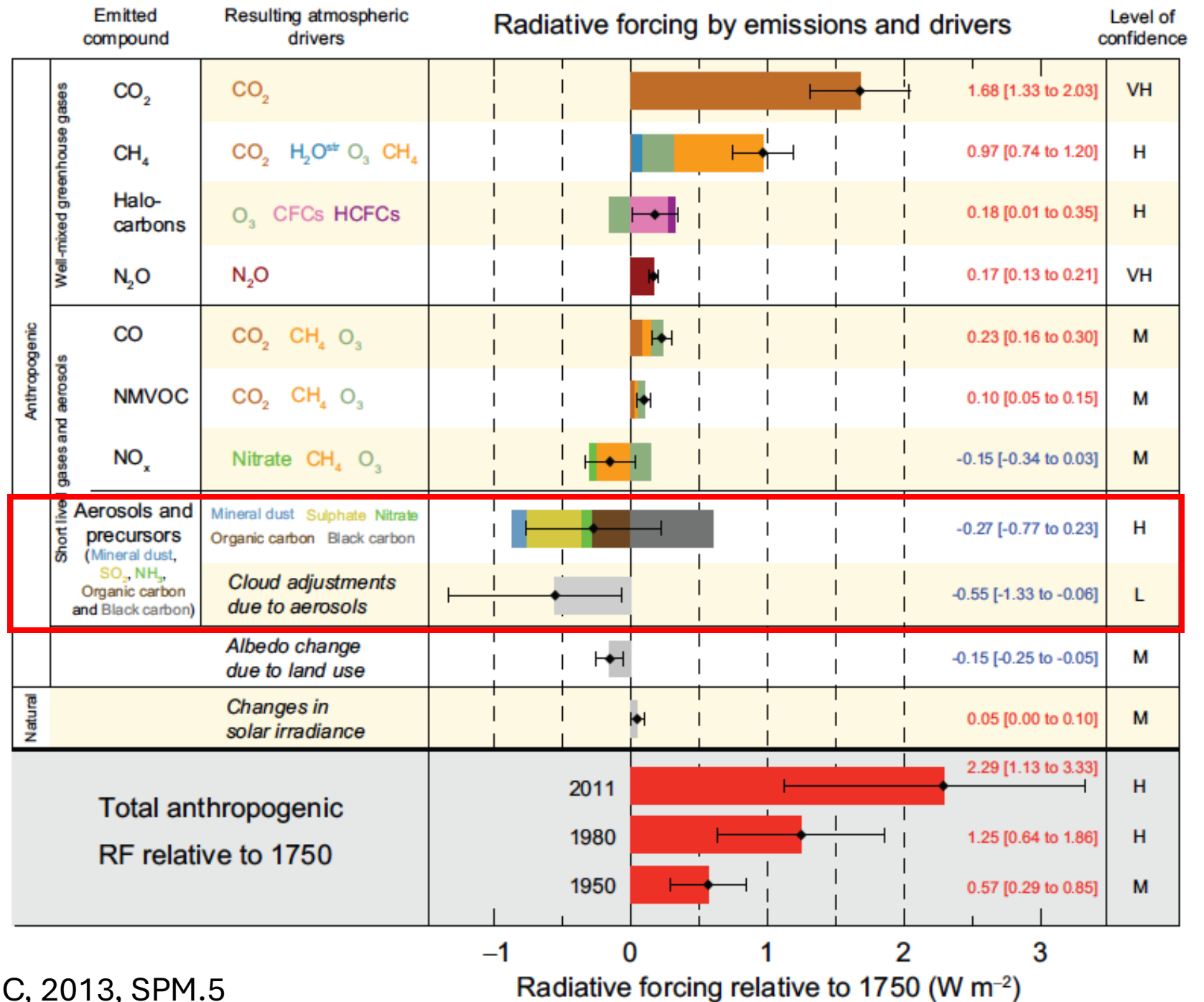


Net Cooling Effect: brighter clouds

Also: delay in precipitation. Longer lived Clouds?

Climate Forcing

Aerosol Cloud interactions are the largest uncertainty in Climate forcing

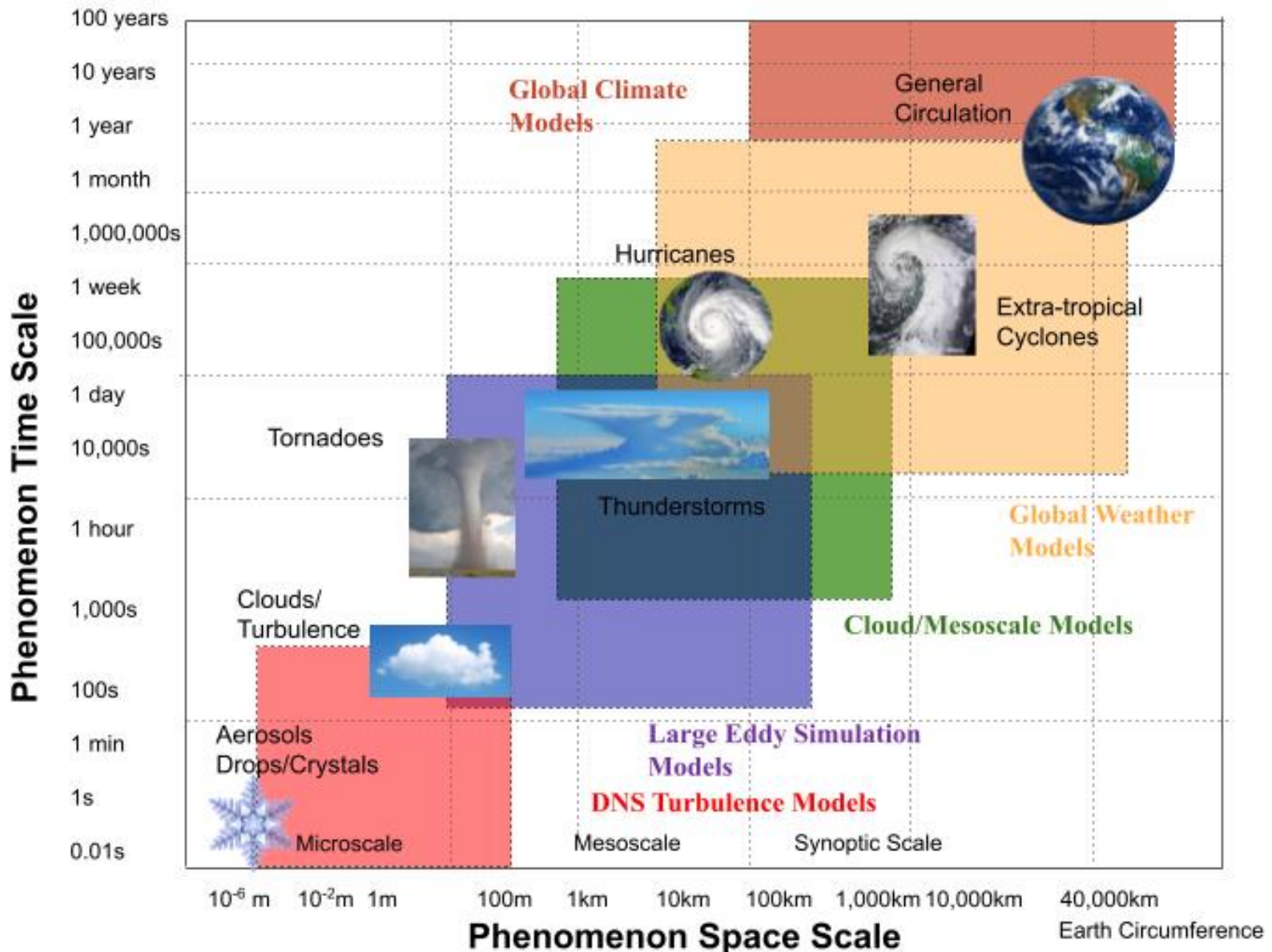


Cloud Microphysics Kills!

- Clouds are responsible for most severe weather
 - Tornadoes, Thunderstorms, Hail, Tropical Cyclones
- Critical cloud processes depend on microphysics (latent heat release, cold pools, freezing, electrification)



Scales of Atmospheric Processes



Types of Microphysical Schemes

How do we use them across scales?

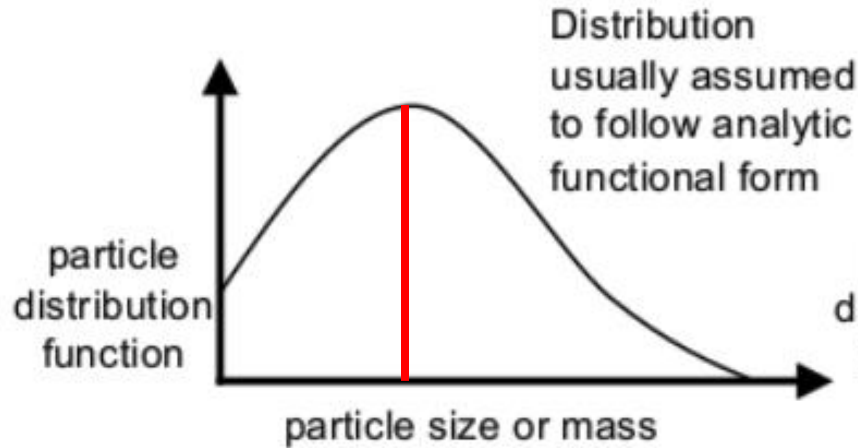
Used in models at scales:

Global & Mesoscale models

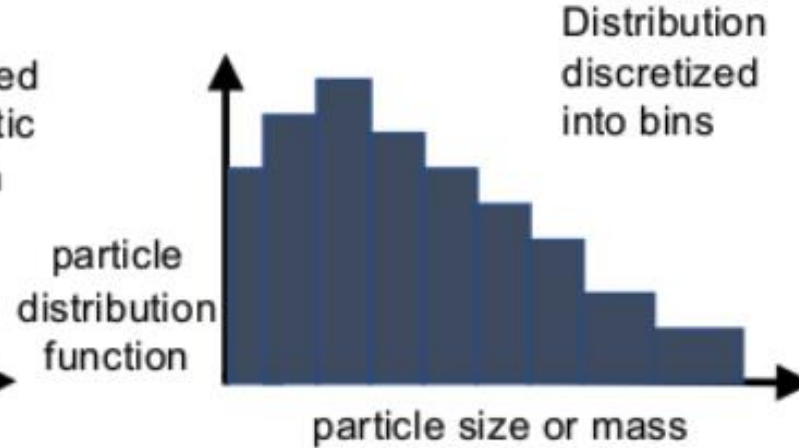
Mesoscale /Large Eddy Simulations/Parcel

LES/Parcel

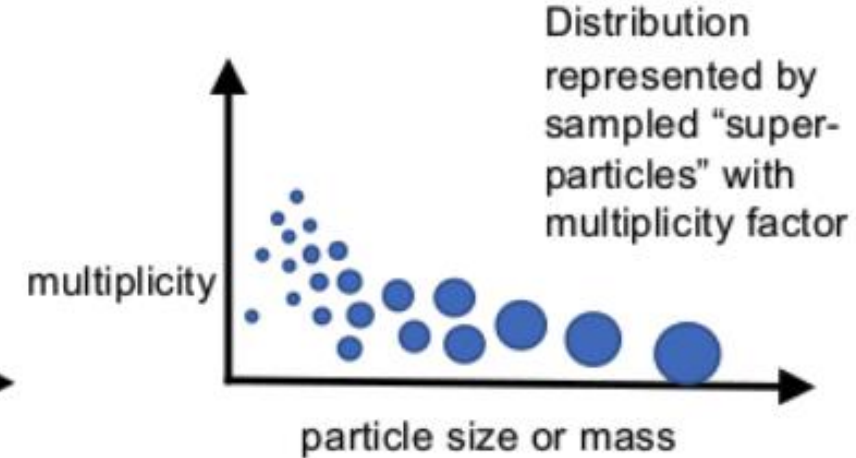
Bulk



Bin



Lagrangian particle-based



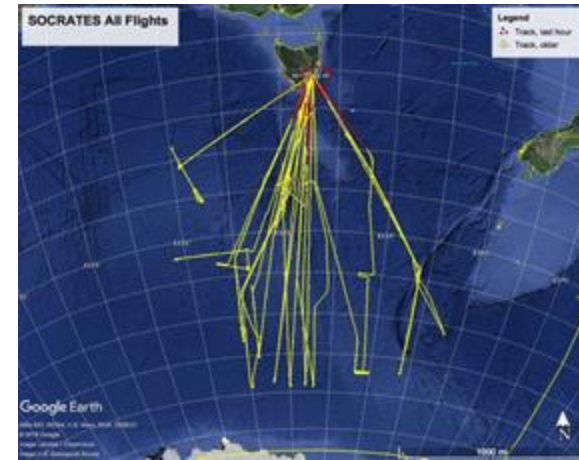
Two Moment = Prognostic Mass and Number

One Moment = Prognostic Mass, Diagnostic Number/Size

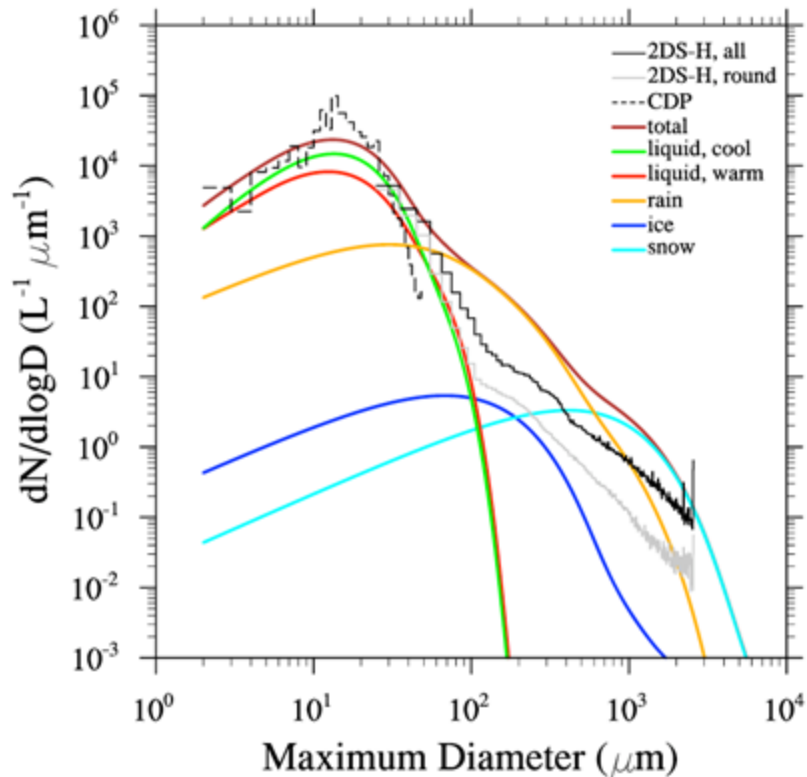
Microphysics, Size distributions

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

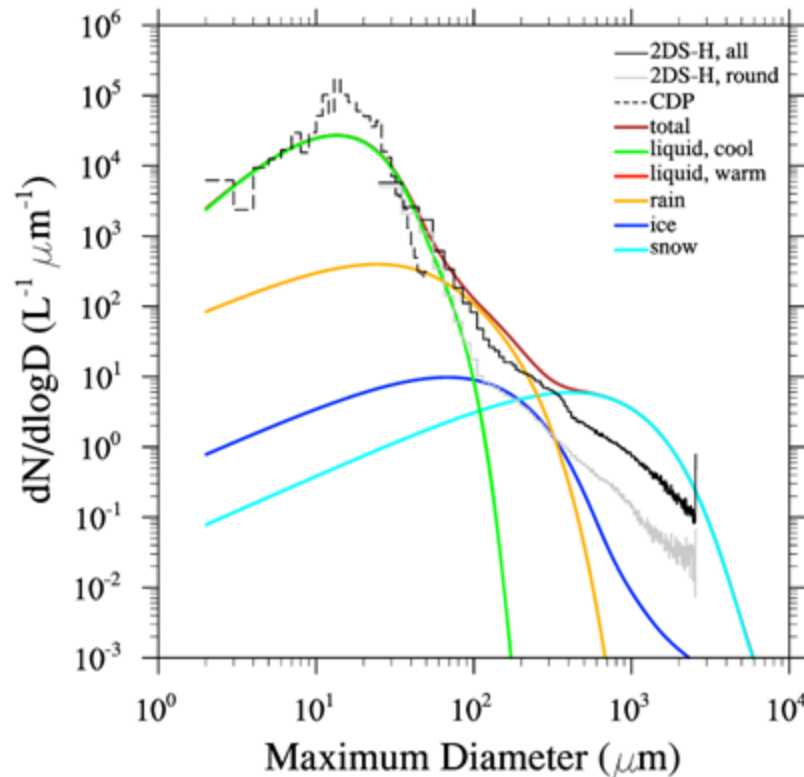
Comparison is GCM cloud microphysics along aircraft flight tracks with in-situ data



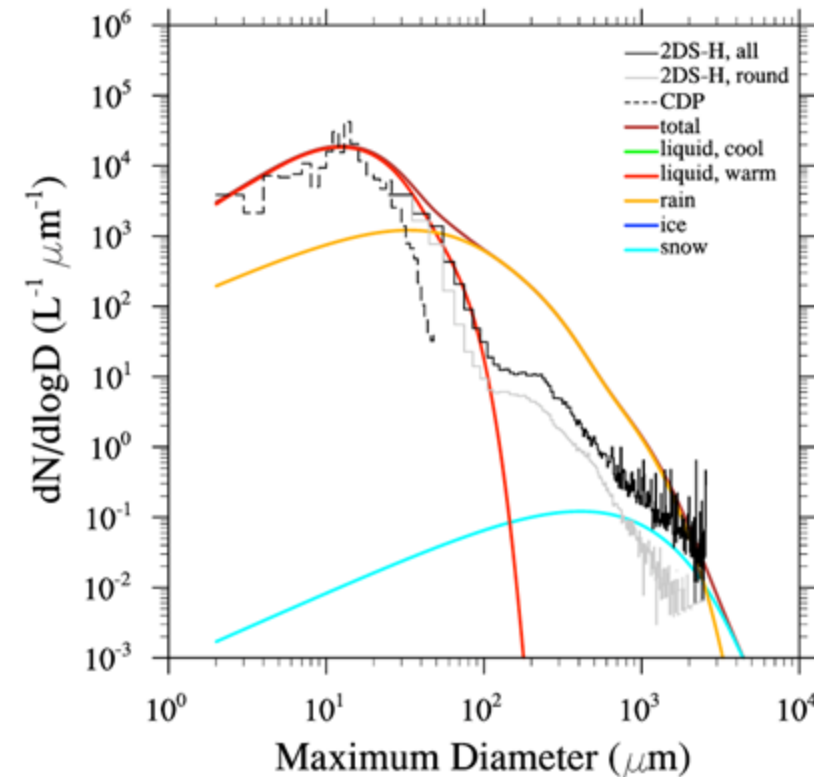
(a) All Clouds



(b) Cold ($T < 0^\circ C$) Clouds



(c) Warm ($T > 0^\circ C$) Clouds



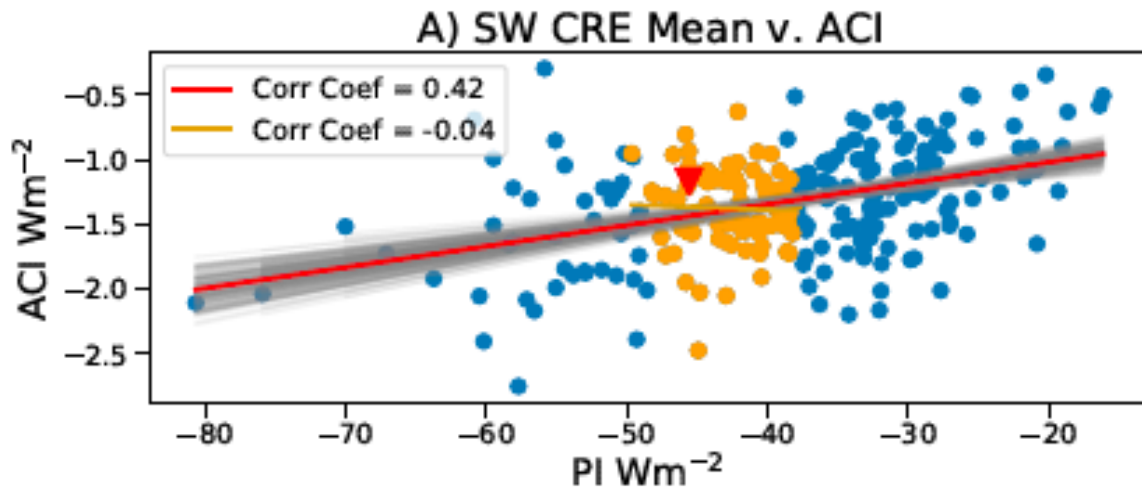
Issues: too much rain, narrowness of peak of DSD

Gettelman et al 2020

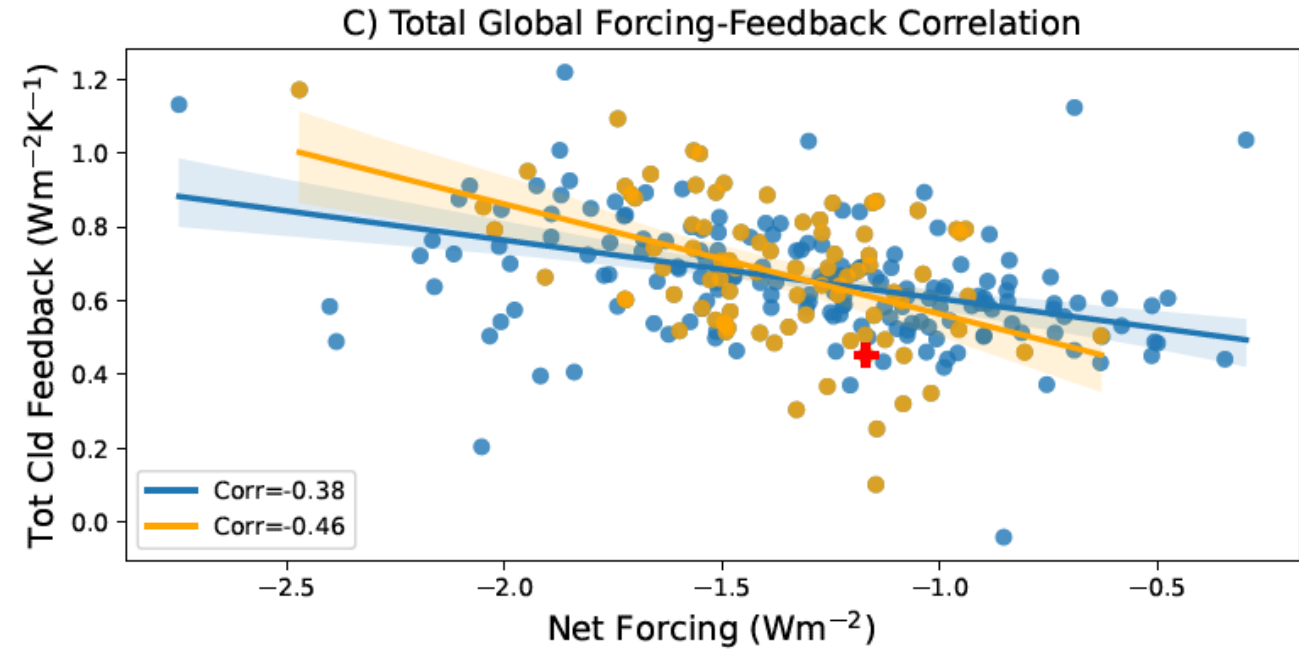
Defining Uncertainty

Using PPEs

CAM6 PPE Spread and a Constraint



Relationships



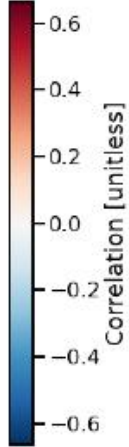
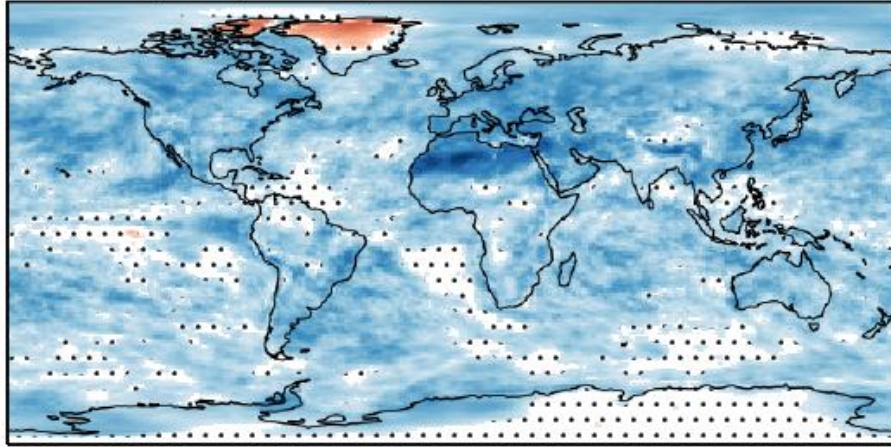
New PPEs:

- Multi-model
- Multi-scale (e.g. process model PPEs, LES, SCMs, etc.)

Gettelman 2024, JGR in press, Duffy et al 2023, Eidhammer et al 2024
Thanks to Lee et al 2011, Carslaw et al 2013, Regayre et al 2018, 2023

Forcing & Feedback Related through Microphysics

C) Net (LW+SW) ACI v. Total Cloud Feedback



Negative correlation between Forcing and Feedback. Stronger (more neg) forcing associated with stronger (more pos) feedback

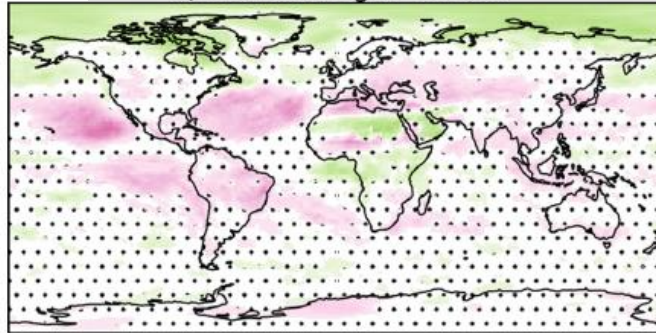
Why a negative correlation?
Related to 'mean state':
total cloud fraction and LWP
(Nc similar to LWP)

ACI
Forcing

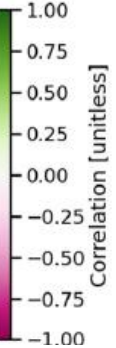
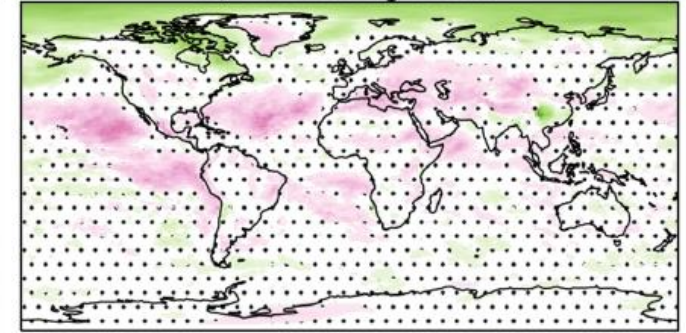
Note patterns. Global
correlations can give the
wrong answer.

Cloud
Feedback

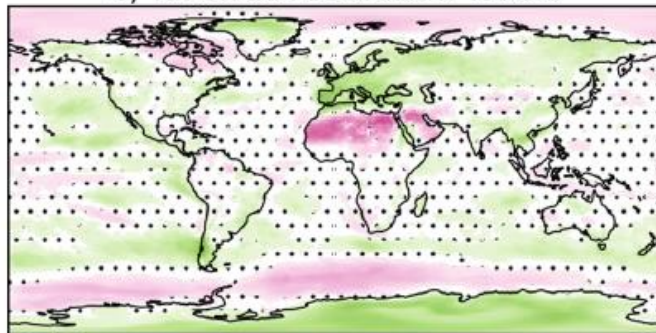
C) Net Forcing v. Tot Cld



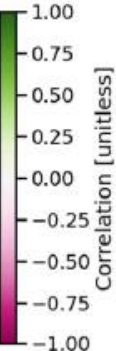
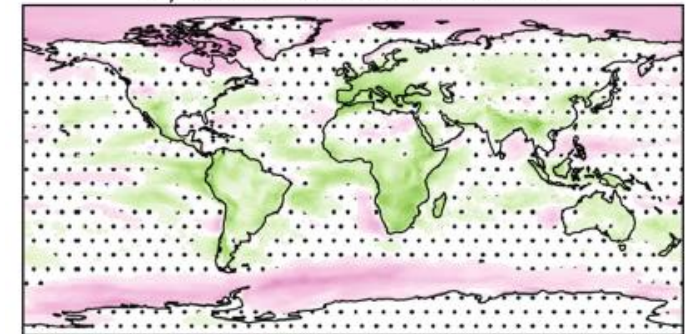
D) Net Forcing v. LWP



C) Tot Cloud Feedback v. Tot Cld

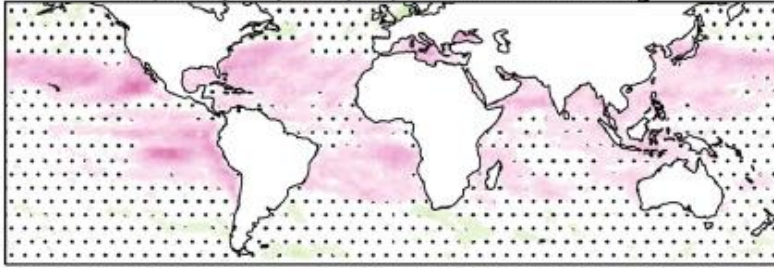


D) Tot Cloud Feedback v. LWP

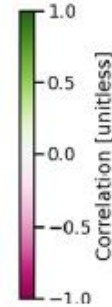
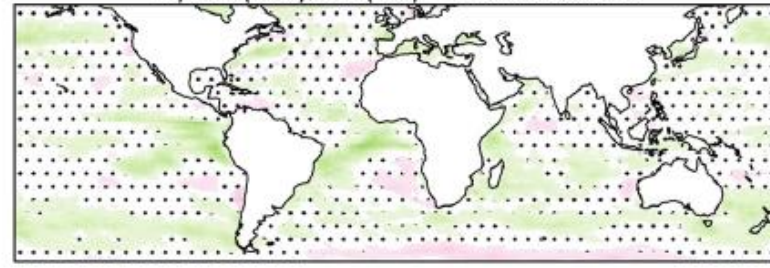


Forcing & Feedback Related through Microphysics

A) $d\ln(\text{Alb})/d\ln(\text{Nc})$ - Net ACI Forcing



B) $d\ln(\text{Alb})/d\ln(\text{Nc})$ - Tot Feedback



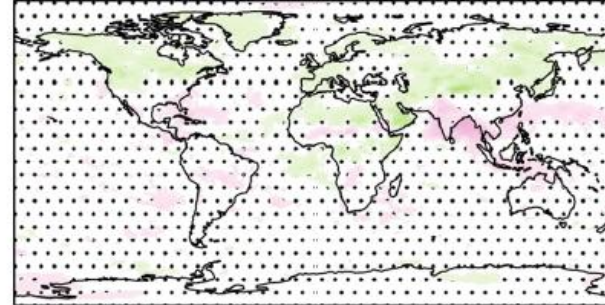
Aside: Albedo susceptibility strongly related to forcing, some relation to feedbacks...

Which processes most important?

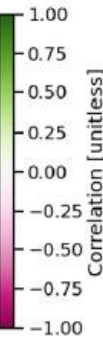
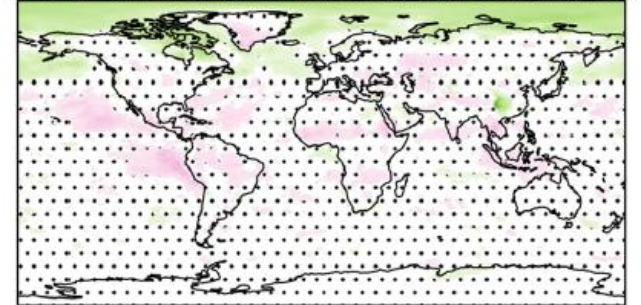
1. ice activation
2. liquid auto-conversion
3. accretion
4. ice auto-conversion
5. ice sedimentation
6. deep convective triggering

ACI
Forcing

A) Net ACI Forcing v. microp aero wsubi scale

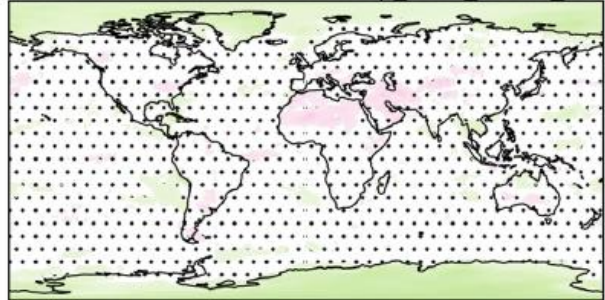


B) Net ACI Forcing v. micro mg autocon lwp exp

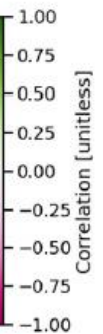
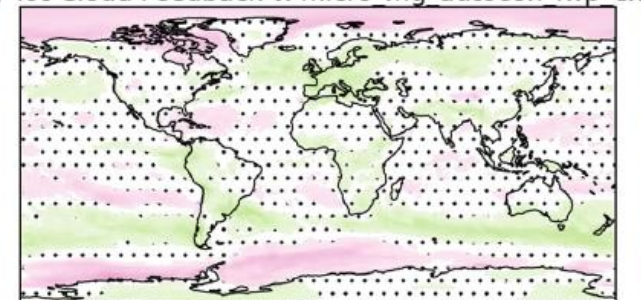


Cloud
Feedback

A) Tot Cloud Feedback v. microp aero wsubi scale



B) Tot Cloud Feedback v. micro mg autocon lwp exp



What is 'wrong' with microphysics

In climate models

- Ice: missing a framework to capture complexity
 - Ice nucleation (nucleation=number)
 - Shape habit = sedimentation, optical properties (secondary), growth (secondary)
- Mixed phase: inhomogeneity important (horizontal and vertical)
 - Ice nucleation
 - Some regimes: SIP
- Liquid: fundamentals at the right scale (e.g. rain formation)
- All phases: coupling to dynamics (turbulence/updrafts) and homogeneity
- Coupling with other parameterized processes is crude (e.g. turbulence and updrafts)

How to make progress?

- Learn from a hierarchy of models and observations
 - Microphysics AND microphysics-turbulence interactions
- One example: Emulation: More detailed treatments
- Other examples: modifying the structural form of microphysics (BOSS, Clima)

Where can we do better?

In climate models

- Ice: missing a framework to capture complexity
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Machine Learning the Warm Rain Process

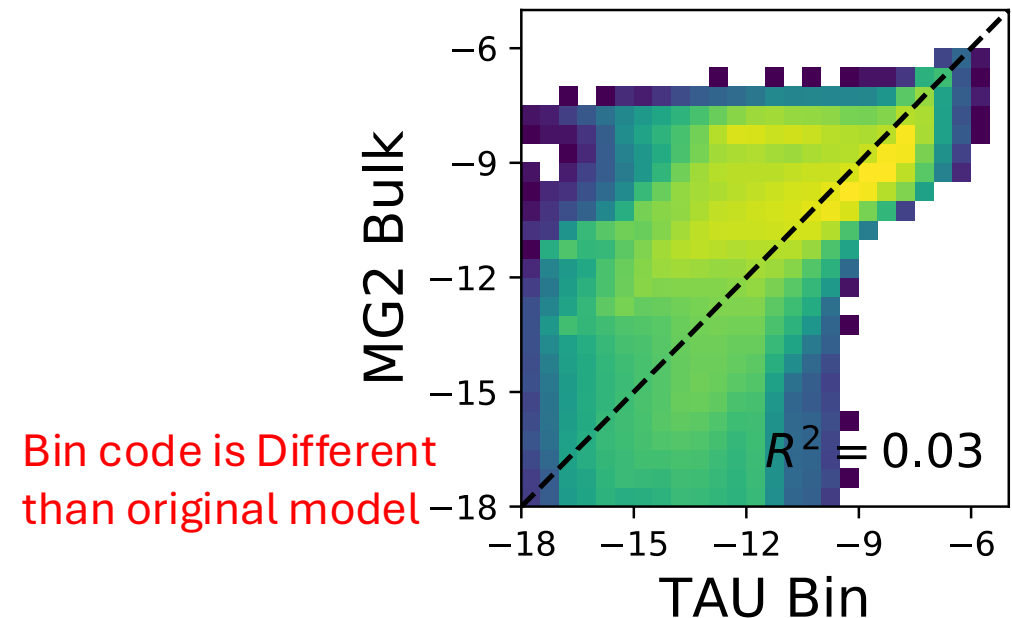
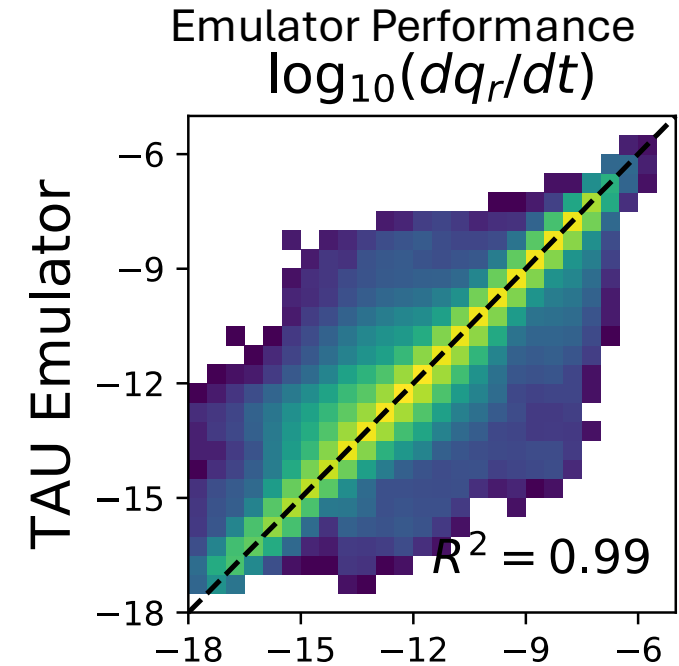
NN Emulator reproduces
detailed code

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

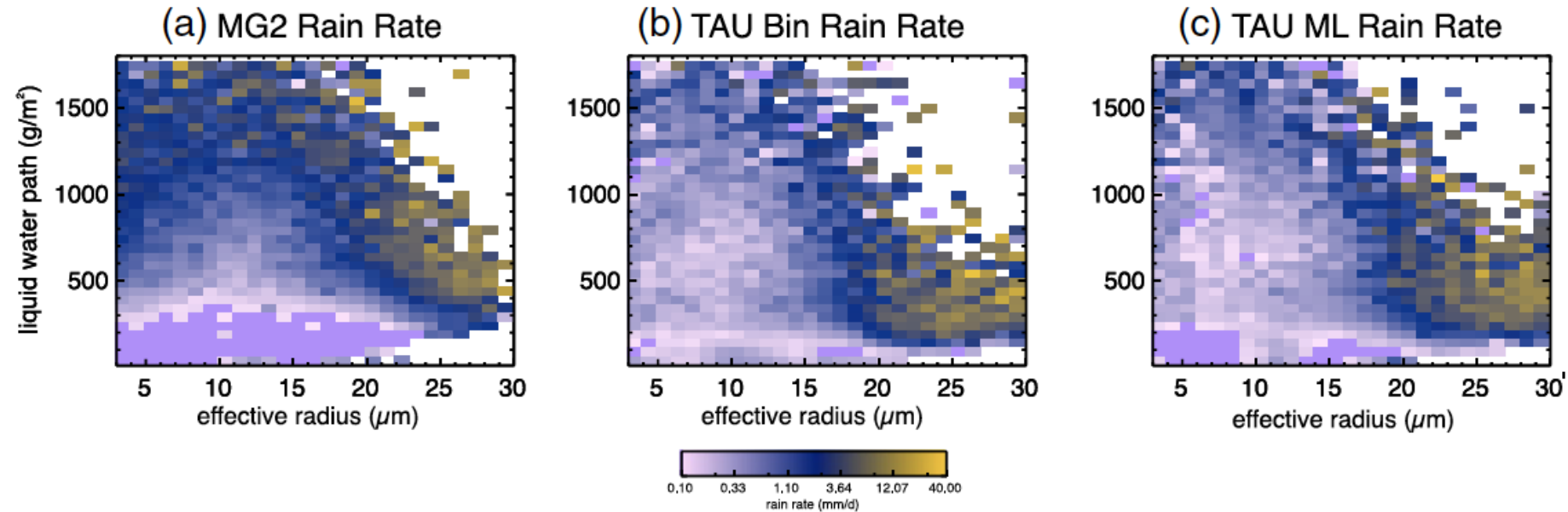


Bin code is Different
than original model

Improving results with Machine Learning

Replace autoconversion and accretion in a bulk scheme with stochastic collection with a bin scheme. Then emulate that with a neural network.

Reduces rain rate for small drop sizes but large LWP

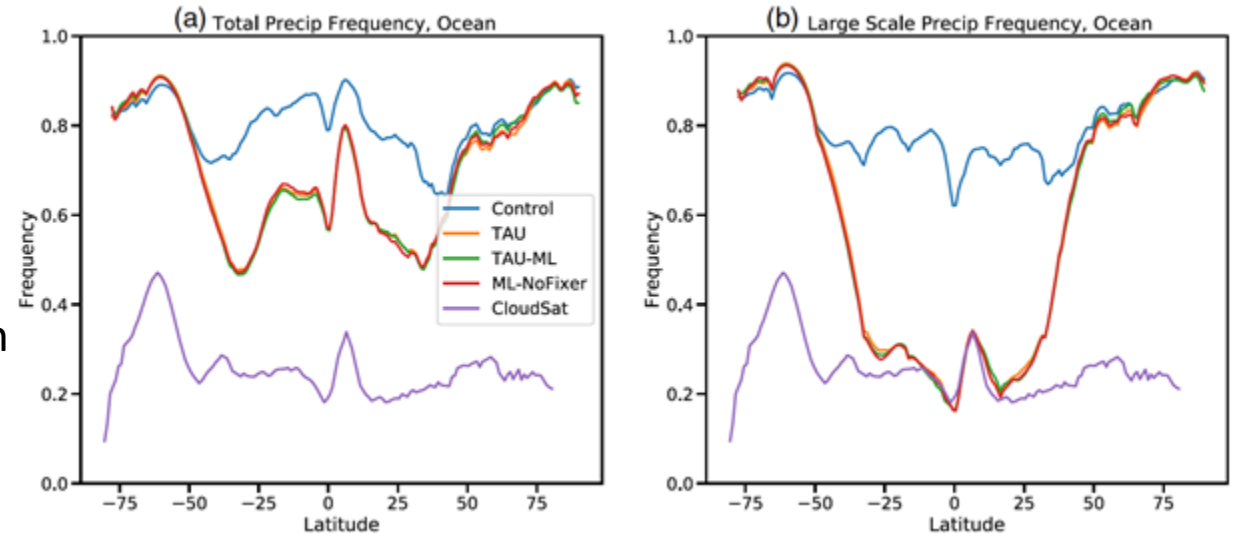


Precipitation Frequency

Control v. Observations and

Bin precipitation and ML Emulator.

Using stochastic collection from a bin scheme improves large scale precipitation frequency in shallow clouds



Cloud Microphysics Kills!

The global average mean temperature does not

- We might be asking some of the wrong questions with forcing and feedback
- One of the key areas for the future is NOT 100km climate models: it's weather extremes under climate change
 - Microphysics is critical for this
 - We need to be able to simulate weather extremes under climate change
 - So: can a climate model work at the mesoscale? Yes.
 - We have been simulating this scale for a generation, just not globally or for statistical averages

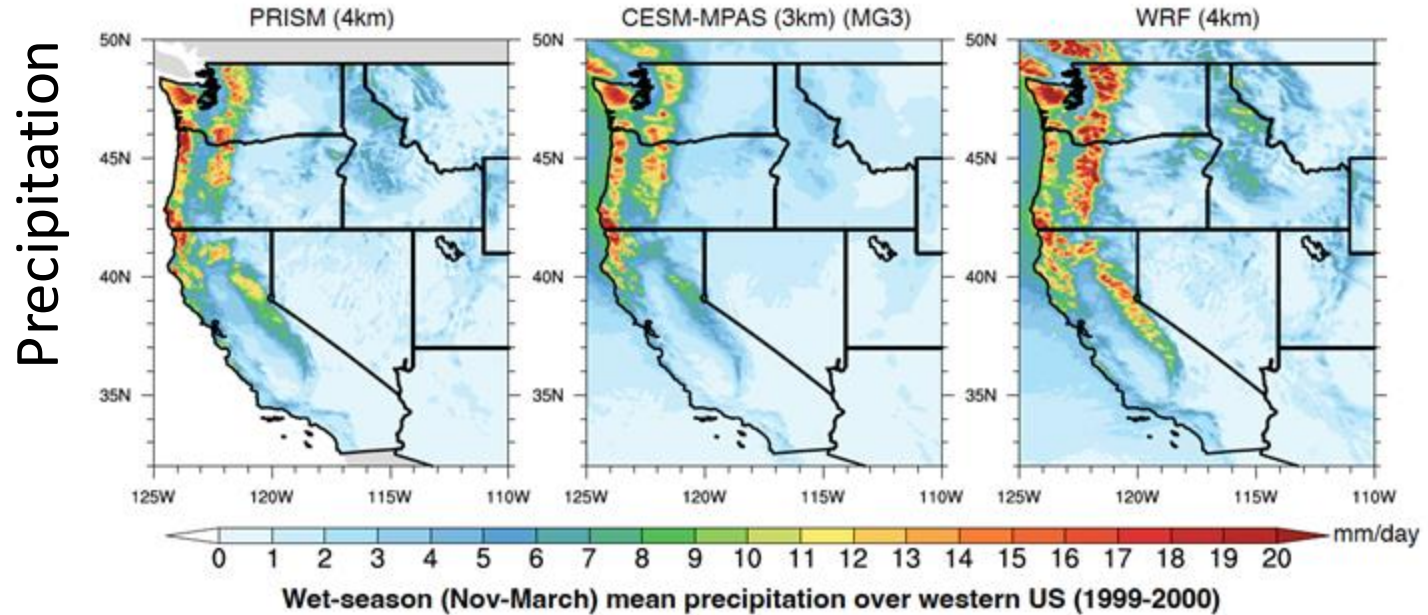


Climate Extremes: Variable-Resolution (60→3 km)

- Global Model: CESM-MPAS: 3km regional, non-hydrostatic dynamics. (Earthworks Prototype)
- 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



Daily precipitation Intensity PDF

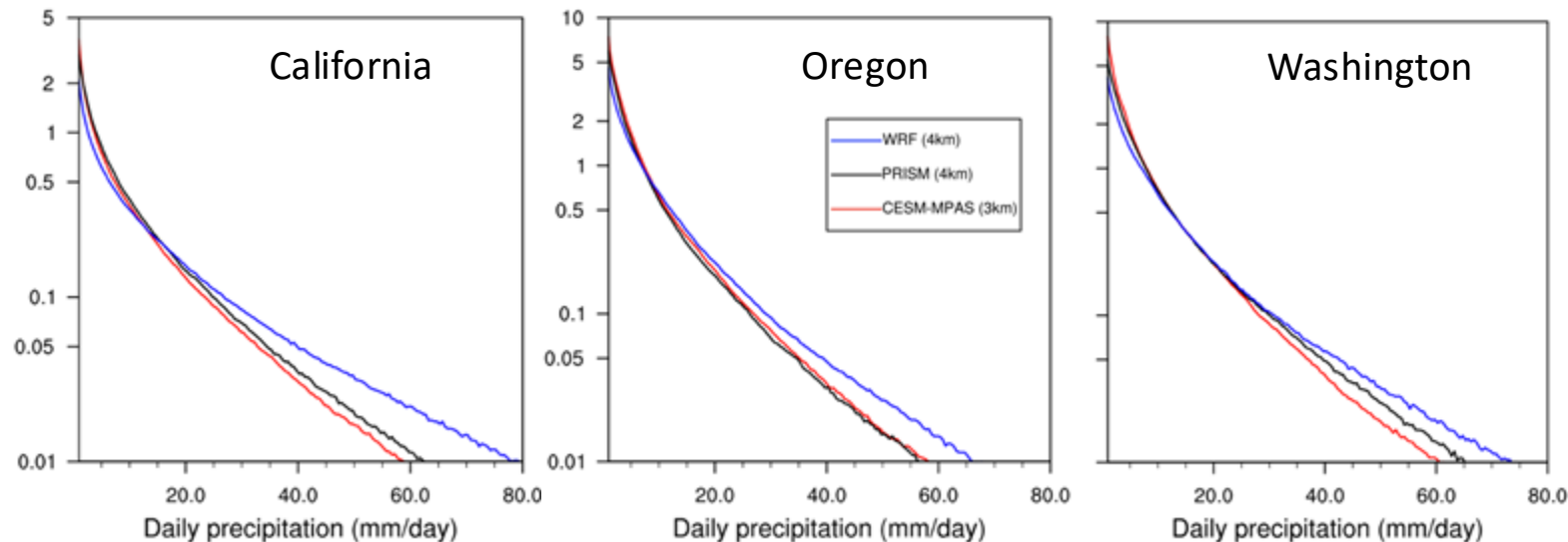
4km Mesoscale Model (WRF)

3km Global Model (CESM)

4km Observations

CESM captures **observed PDF** better than

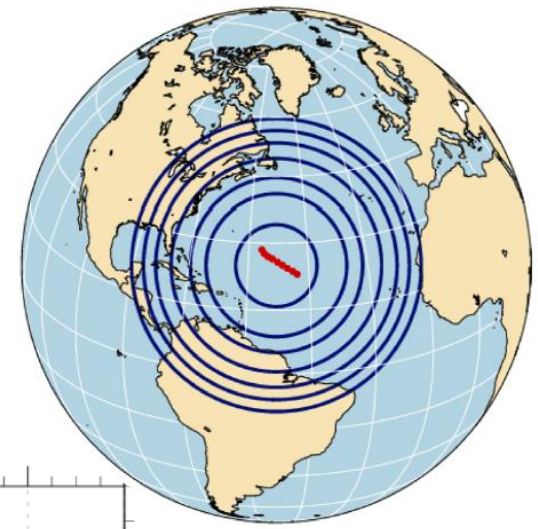
WRF, especially for extreme precipitation



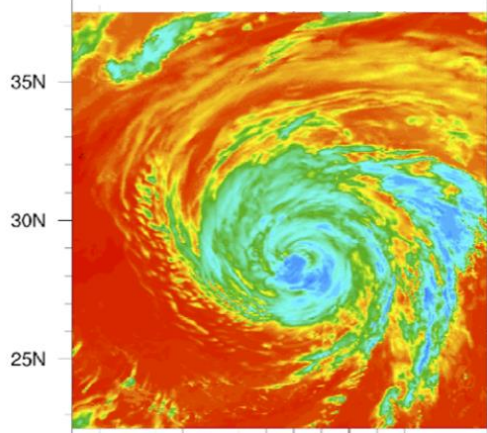
Tropical Cyclones: 3km

Tropical Cyclone Edouard (Sep 2017)

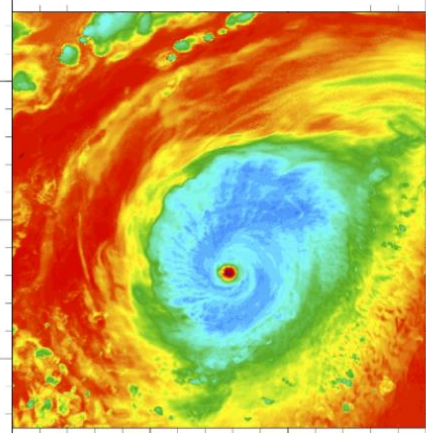
Skamarock, Chen, NCAR
Pers Comm



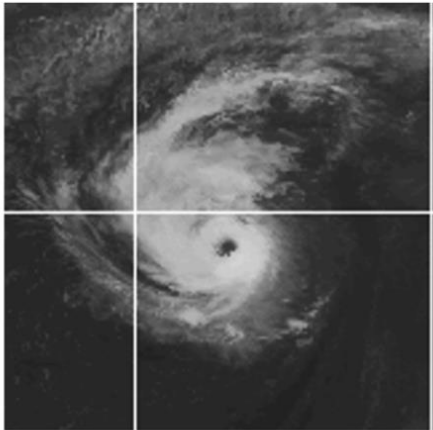
WRF Physics



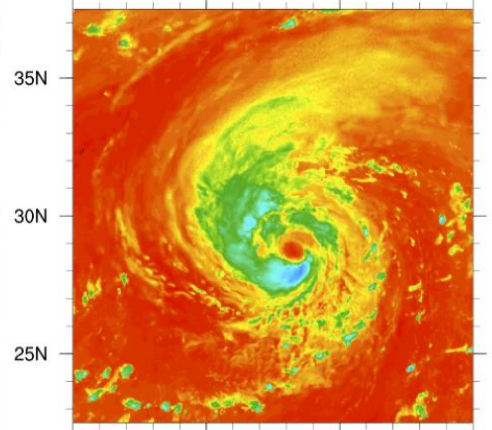
CAM Default



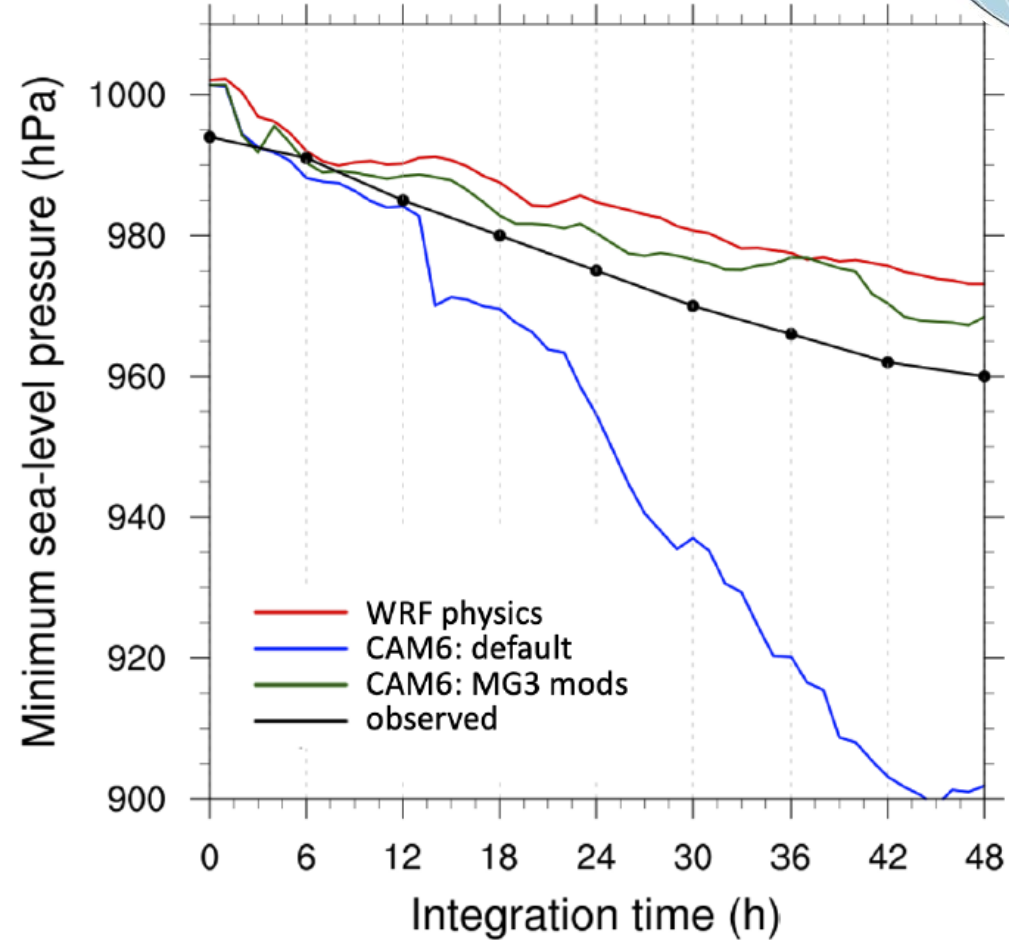
satellite



PUMAS Mods



Minimum Pressure



Summary

- Cloud microphysics is critical for weather and climate prediction
- Microphysics is structurally different across scales
 - But we can learn from different scales, model hierarchies, and detailed comparisons to observations
- We can represent microphysics statistics at the large scale
- Forcing and Feedback related through mean state and processes
 - Sensitive to cloud physics
 - In CAM: water amounts (also ice), and precipitation processes
- New methods for microphysics: emulation, evolving structure
- Missing interactions with ‘sub-grid’ scale: turbulence
- Resolving mesoscale motions enables us to do extremes

Where do we go next?

- Interactions with turbulence (unresolved dynamics)
 - Updrafts and entrainment drive clouds, don't represent them well
 - Interaction and scales of turbulence likely buffer ACI and cloud feedbacks
 - Ice too (cirrus cloud feedbacks)
- Ice and Mixed Phase: nucleation & secondary production
- Develop traceable cloud microphysics that works across scales
 - Choose the right set of tools.
 - Understand what we are missing when we go to larger or smaller scales.
 - Model hierarchies, traceable to obs at small and global scales

How do we get there? A 'new' paradigm?

Climate Process Teams for microphysics & climate

- Contrary to past, suggest specific topics (ice, liquid, turbulence)
- Make big teams (EU-like)
- Require each team span the community: multi-scale models (and multiple modeling centers), observations (satellite to in-situ to laboratory/chambers)
- Include field projects (or have a call for field projects after)
- Multi-agency, US CLIVAR 'steering group'
- Pick 2-3 teams, spread problems