Precipitation relation to its thermodynamic environment in CMIP6 models

+ connections between the NOAA Model Diagnostic Task Force and DOE programs

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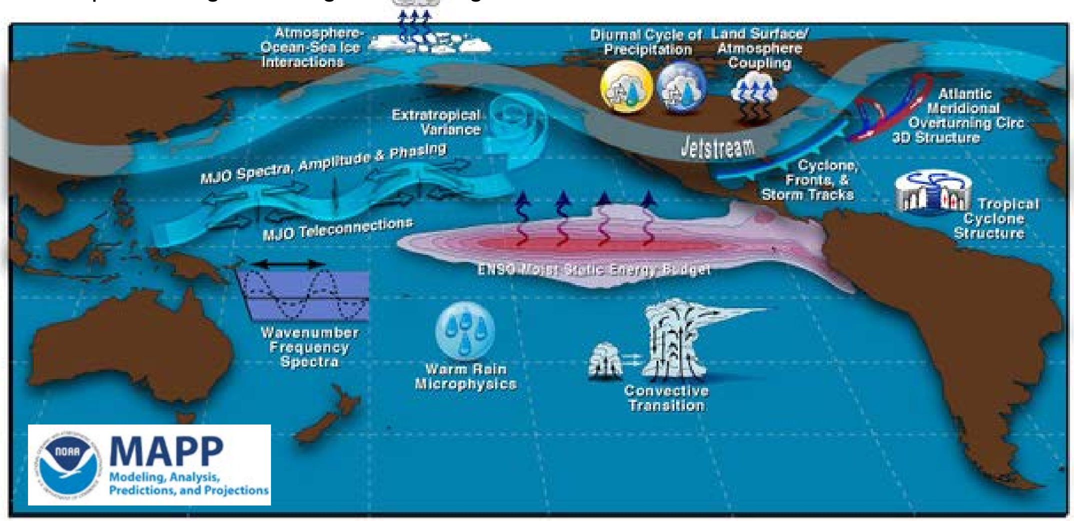
NOAA Model Diagnostics Task Force

Leads team: D. Neelin (UCLA), J. Krasting & Y. Ming (GFDL), A. Gettelman (NCAR), E. Maloney (CSU), Peter Gleckler (LLNL), A. Wing (FSU) with D. Barrie (NOAA)

- Open framework to entrain process-oriented diagnostics (PODs) into development stream of modeling centers (GFDL & NCAR) + coordination of multiple PI teams

- Coordination with PCMDI (P. Gleckler), CMEC (Common Model Evaluation Capabilities; P. Ullrich) on common standards for metrics & diagnostics
- E.g. of adaptation of POD to ARM diagnostics package (UCLA-LLNL with S. Xie)
- Coord with Precip. Metrics (R. Leung, A. Pendergrass,…)

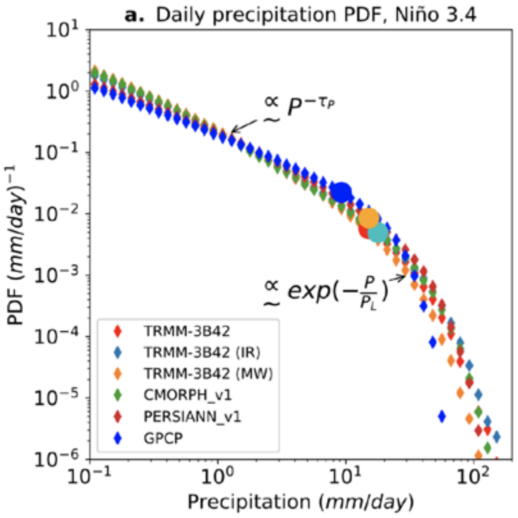
https://www.gfdl.noaa.gov/mdtf-diagnostics/

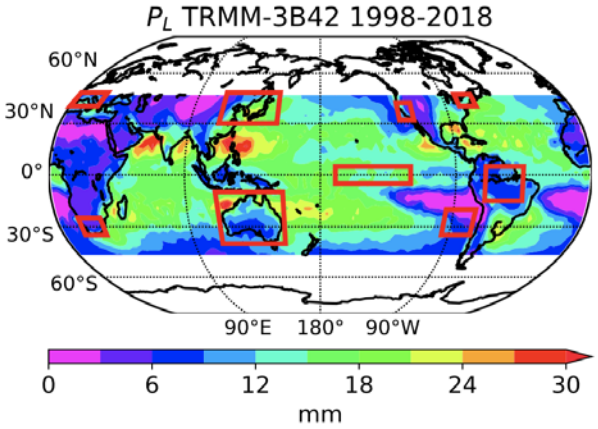


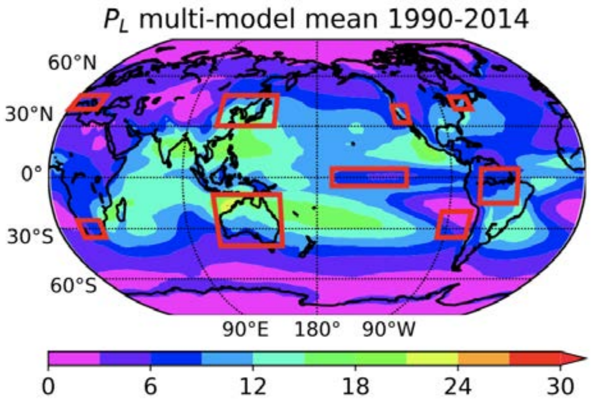
https://mdtf-diagnostics.readthedocs.io/_/downloads/en/latest/pdf/

Daily precipitation probability distributions in CMIP6

- Daily precipitation PDFs are characterized by a power law range and a cutoff-scale P_L
- The cutoff-scale controls the large event range probability.





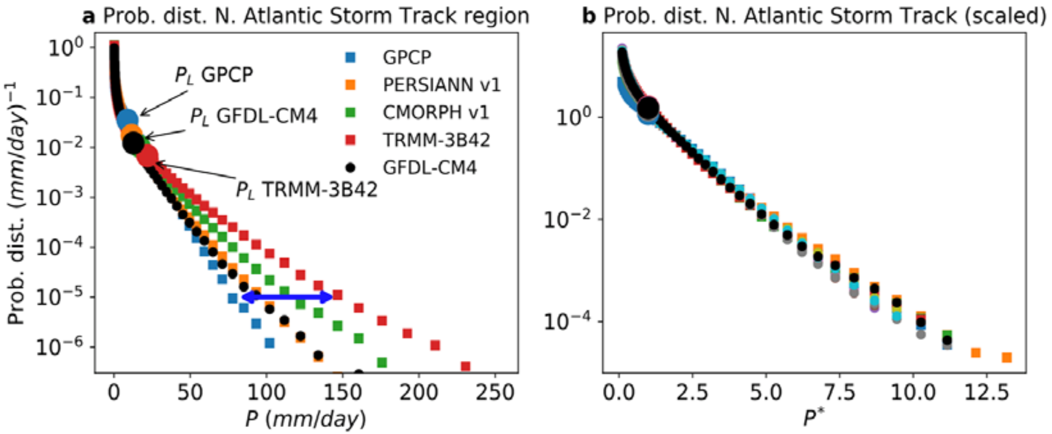


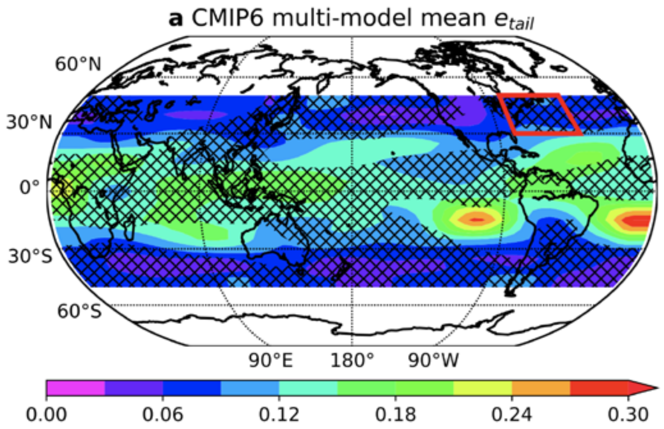
Martinez-Villalobos, Neelin and Pendergrass. In prep.

Physics of the cutoff scale: Neelin et al. 2017; Martinez-Villalobos & Neelin 2019

Daily precipitation probability distributions in CMIP6

- Probability distributions can be rescaled to evaluate the shape of the tail.
- Most models simulate *shape* of large-event tail closer to TRMM-3B42 than the difference between common obs. datasets (GPCP and TRMM-3B42).

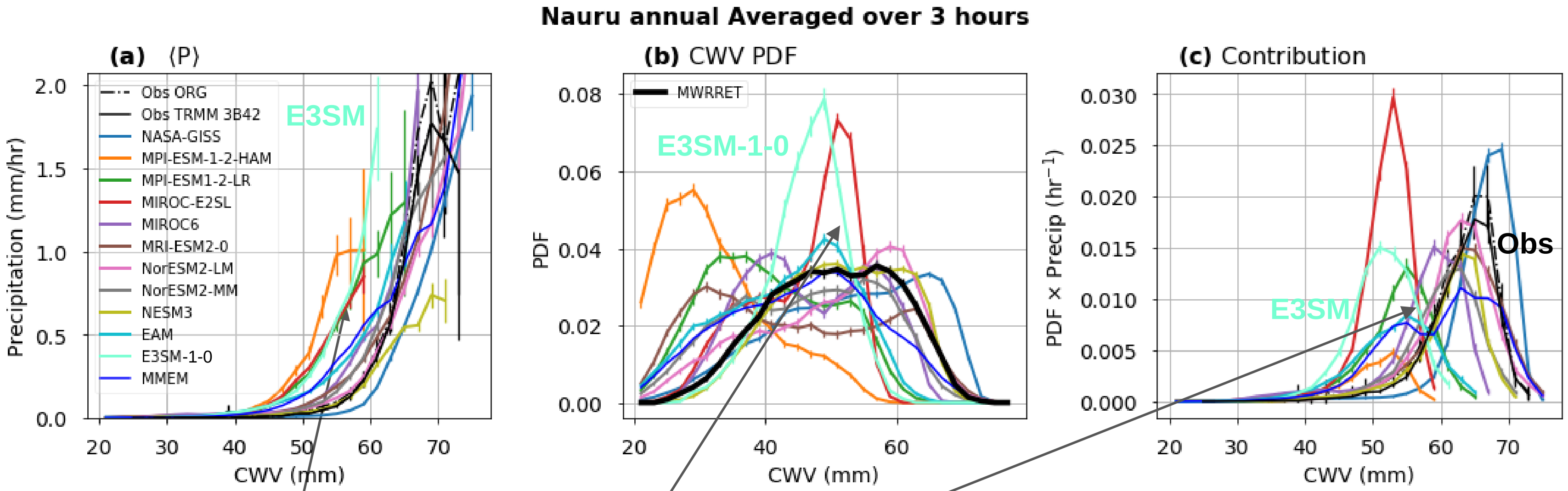




Martinez-Villalobos and Neelin. In review

CMIP6 Convective transition statistics in ARM-DIAGN

A collaboration of UCLA group with Shaocheng Xie, Jill Zhang, Cheng Tao, Wuyin Lin to bring convective transition diagnostics into ARM Diagnostics package



(a) CWV conditional-av. precip. <P>

(b) CWV PDF

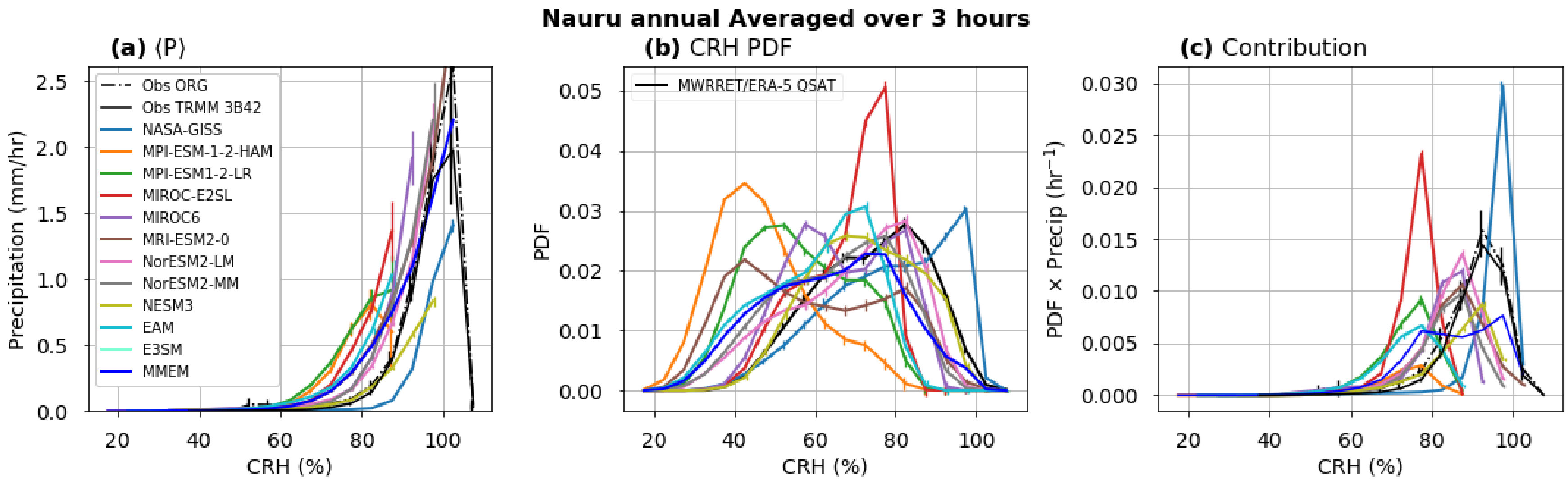
(c) precipitation contribution, I.e., <P>-weighted PDF combines a-b, shows range producing most Precip

- Early pickup in models leads to early dropoff in column water vapor (CWV) PDF and Precip Contribution;
- Some models spend too much time in low-q nonprecipitating range

Emmenegger et al., 2020, subm.; Zhang et al., 2020, *BAMS*

CMIP6 Convective transition statistics in ARM-DIAGN

Column relative humidity (CRH) $=CWV/q_{sat}$



(a) CWV conditional-av. precip. <P>, CRH

(b) CWV PDF in

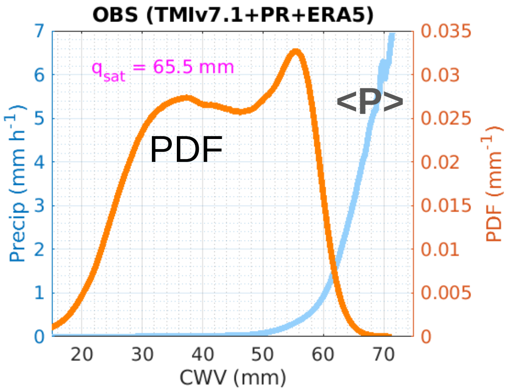
(c) precipitation contribution, I.e., <P>-weighted PDF combines a-b, shows range producing most Precip

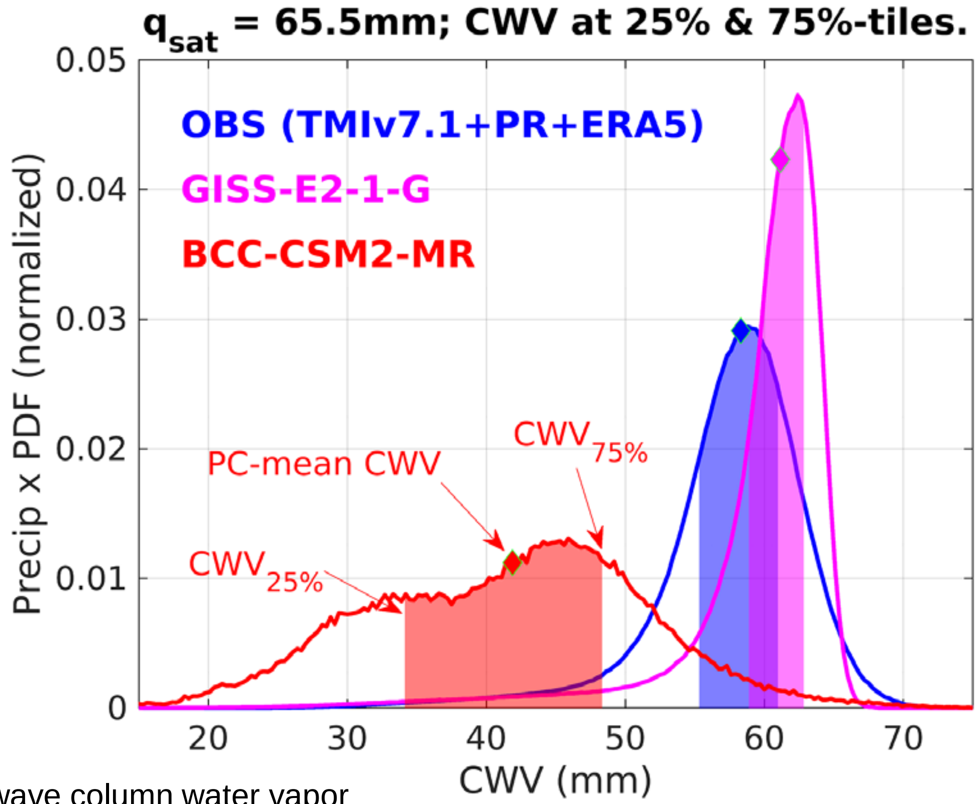
- CRH can compensate for biases in temperature, but does not resolve the early pickup problem:
- Models that pickup early in CWV, still pickup early in CRH;
- Likely suspects: insufficient dependence on lower-free troposphere q.

Summarizing the thermodynamic environment of Precip in CMIP6

Recall: precipitation contribution, i.e., <P>-weighted PDF

Use percentiles of precip contribution to characterize thermodynamic range producing most Precip





Here over tropical oceans 20°S-20°N, TRMM microwave column water vapor (CWV), precipitation radar; ERA5 reanalysis vertically integrated q_{sat}

Kuo et al., 2018, 2020

Analysis: Yi-Hung Kuo

Summarizing the thermodynamic environment of Precip in CMIP6:
Column rel. humidity (CRH) and vertically integrated saturation value q_{sat}

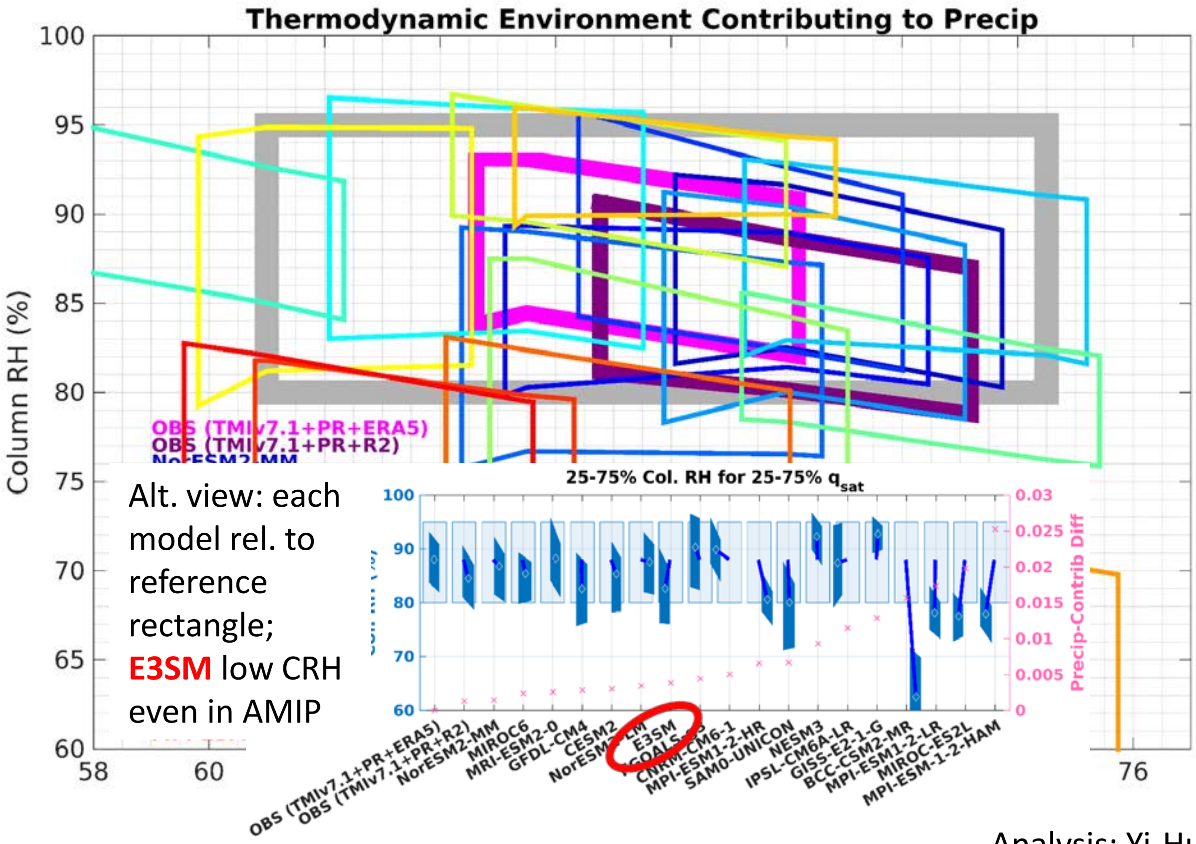
Contribution to precip. as a function of CRH at each qsat

Use 25th-75th percentile range in Precip. contribution at each qsat

and **25th-75th percentile range in qsat** to characterize where system produces a large fraction of precip. in this thermodynamic space

ERA5 and **NCEP2** reanalyses reasonably close, similar angle (CRH decrease w qsat)

CMIP6 models range from good to seriously off



Alt. view: each model rel. to reference rectangle; **E3SM** low CRH even in AMIP

Analysis: Yi-Hung Kuo

Precipitation-buoyancy relationships in CMIP6

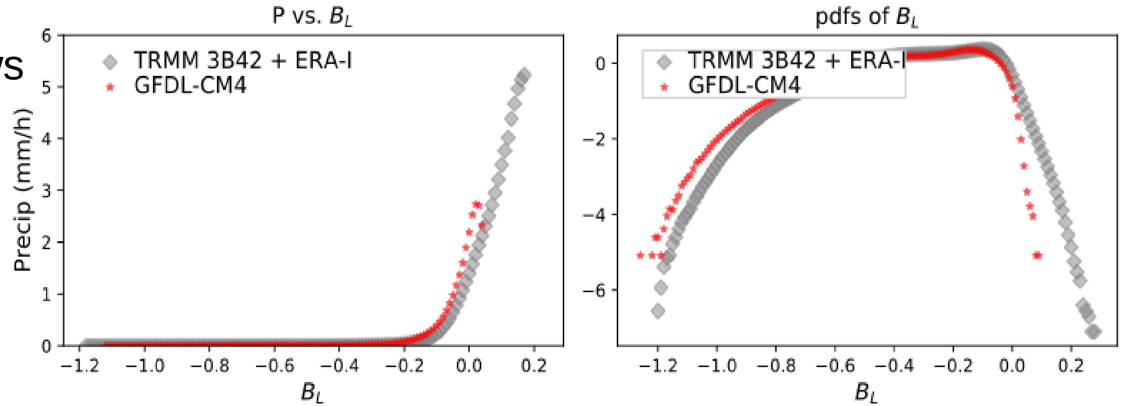
Precipitation-buoyancy relationship from ERA/TRMM data

Estimator of convective buoyancy B_L (with empirical weighting of boundary layer & lower free tropospheric inflow; Ahmed Neelin 2018, Schiro et al. 2018, Ahmed et al. 2020*).

Example model (GFDL-CM4) shows features similar to observed with pickup at slightly negative B_L

B_L components:

- CAPE-like stability relative to boundary layer moist static energy
- lower free tropospheric subsaturation.
- Are both components captured well?

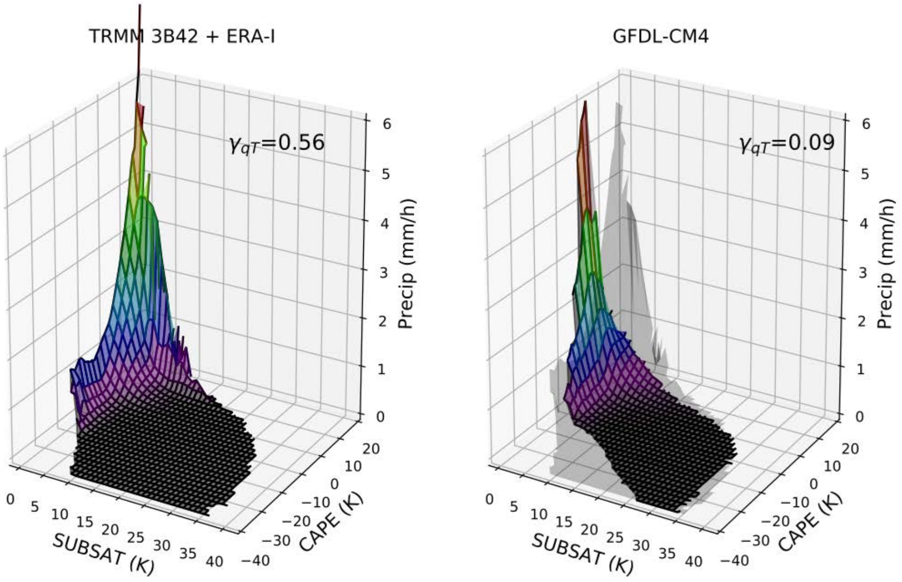


Analysis: Fiaz Ahmed

* + Budgets, theory: Adames et al. 2020, subm; Ahmed et al. 2020

Precipitation-buoyancy relationships in CMIP6

Split model precip. sensitivity Into components of B: CAPE-like stability (CAPE) and sub-saturation levels (SUBSAT)

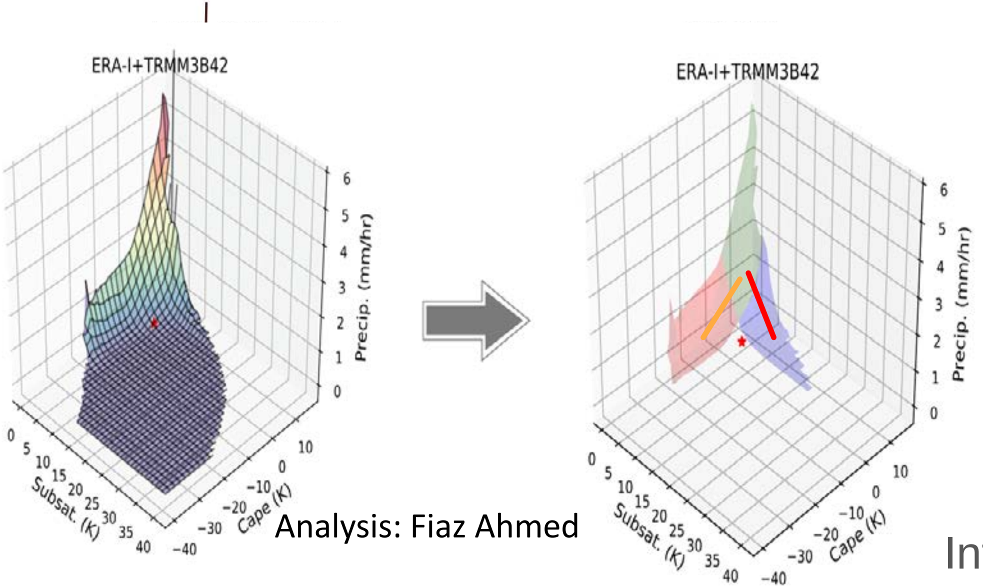


Example model has too little sensitivity to CAPE.

Analysis: Fiaz Ahmed

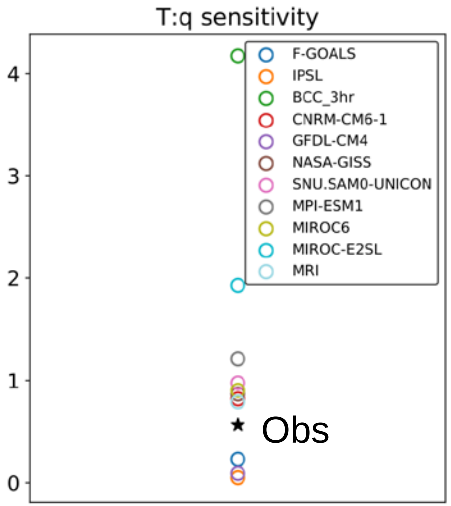
Precipitation-buoyancy relationships in CMIP6

Split model precip. sensitivity Into components of B: CAPE-like stability (CAPE) and sub-saturation levels (SUBSAT); Scalar metric for relative sensitivity



Analysis: Fiaz Ahmed

Ratio of the precip. gradient along CAPE direction vs. gradient along SUBSAT direction is T:q sensitivity.



Inter-model spread: Outliers, two groupings

Balancing Challenges: **0) More diagnostics;**
1) pushing diagnostics to further dissect processes;
2) dialogue with process models;
3) Condensing into scalar metrics without losing key information