Reverse engineering* convection
Digesting fast-process observations for climate models

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Here needed a term for:

- using large data sets to infer input-output relationships
- but physical-hypothesis driven; distinguishing from unsupervised learning;
- human-very-much-in-the-loop but systematic

*Reverse engineering: analyzing subject system to identify components & interrelationships and create representations... (after IEEE);

Original title had: “and stochastic hierarchies” — truncated in interest of time

Components:
(based on physical hypotheses)

- Buoyancy *B* typifying updrafts (& seek integral measure)
- conserved variable (equiv. potential temperature θ_e)
- Influence function I

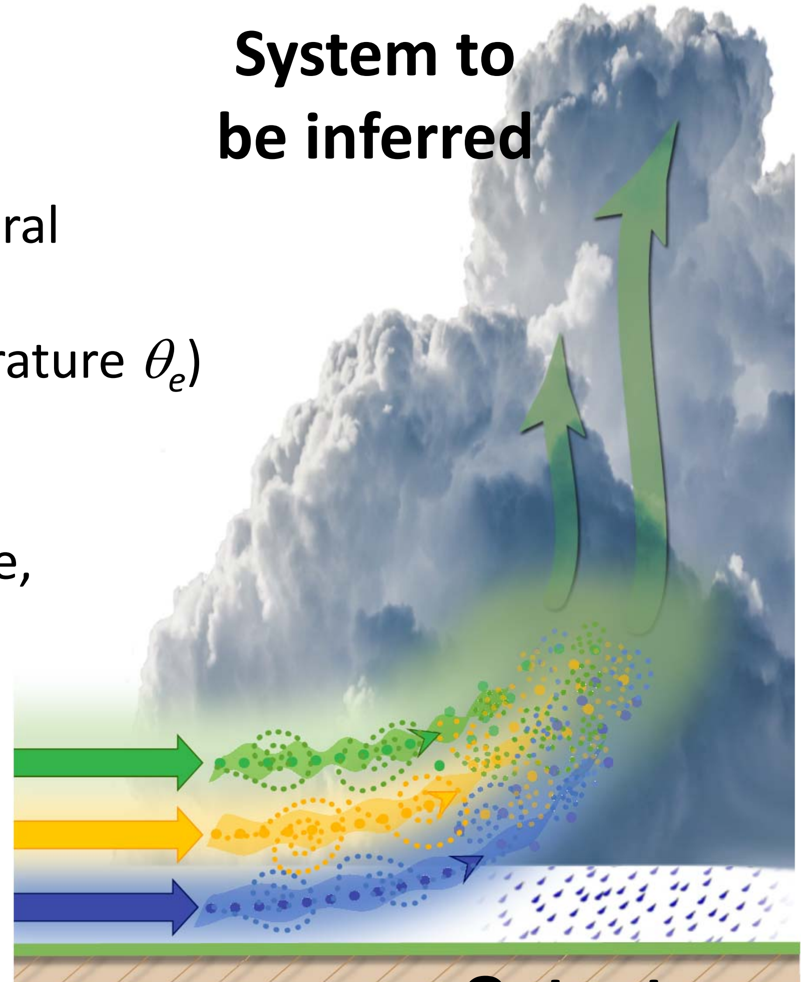
constrained by mass flux m framework

agnostic w.r.t mixing mechanism (turbulence, coherent inflow, nonlocal entrainment)

$$r(z) = \int_{z_0}^{z_B} I(z_B, z)\, \tilde{r}\, dz$$
$$= \frac{1}{m(z_B)} \int_{z_0}^{z_B} \tilde{r} \frac{\partial m}{\partial z} dz$$

r is a conserved variable in the updraft, e.g., θ_e
$\tilde{r}$ is the environmental value
z_B is the height at which buoyancy is evaluated
m mass flux

Input:
T, q of the environment



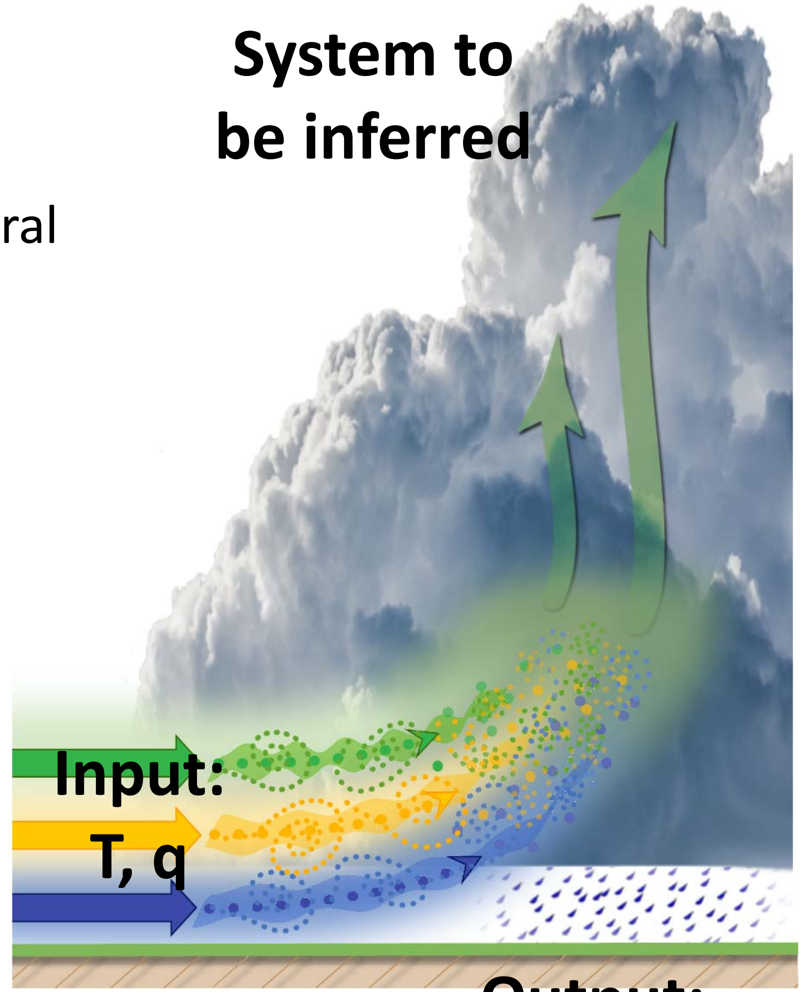
Output:
Precipitation

Schiro, Ahmed, Neelin, and Giangrande 2018 (PNAS)
Ahmed and Neelin 2018 (JAS)

(cf. Stull 1984; Larson 1999; Kuang 2010, Romps & Kuang, 2011; Holloway & Neelin 2009)

Components:
(based on physical hypotheses)

- Buoyancy B typifying updrafts (& seek integral measure)
- conserved variables ($T, q \Rightarrow \theta_{e,\ldots}$)
- Influence function I
  constrained by mass flux m framework



Schiro, Ahmed, Neelin, and Giangrande 2018 (PNAS)
Ahmed and Neelin 2018 (JAS)

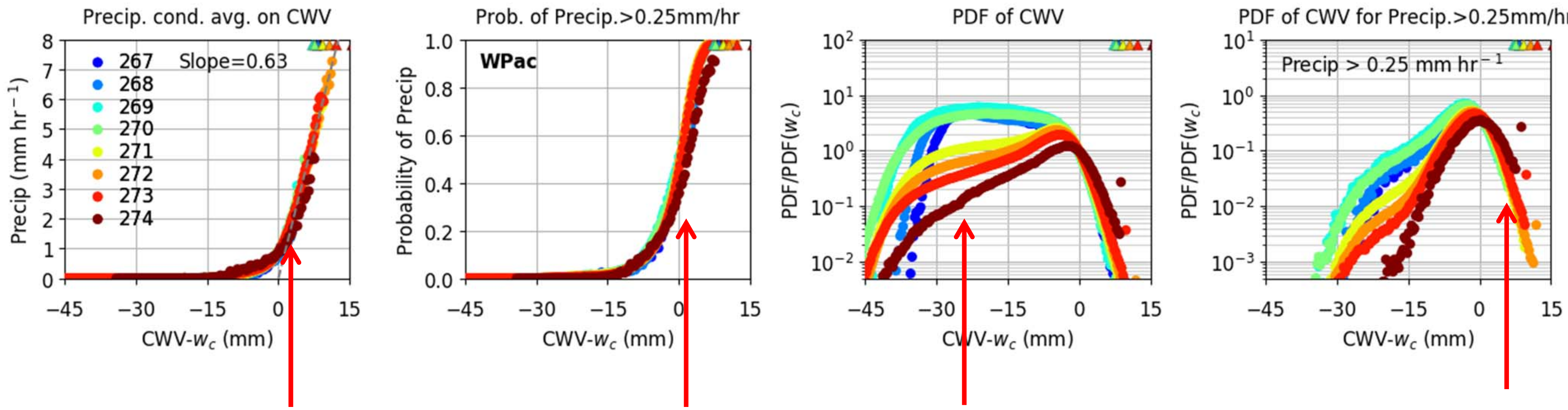
Outline:

- **Do it forward:**
  radar $\Rightarrow m \Rightarrow I$; $I(\theta_e) \Rightarrow B$: Check $\boldsymbol{P}(B)$
- **Do it backward (reverse engineer):**
  Find $\boldsymbol{P}(\theta_{e,}$ coeffs by layer$)$
  Collapse to $\boldsymbol{P}(B) \Rightarrow I(\theta_{e,}$ coeffs by layer$) \Rightarrow m$
- check on other regions

But first some background:
Deep Convective Transition statistics

A set of related precipitation statistics collapse to the same function of thermodynamic variables (column water vapor CWV) & tropospheric-av. temp.

Precip binned by column water vapor | **Probability of precipitation** | **Probability distribution all points vs. precipitating points**



Transition to strong precipitation & high probability—rapid increase above threshold w_c

Dynamics in the non-precipitating regime controlled by factors incl. mean descent

Fluctuations across threshold into strong precip regime

Kuo et al. (2018); see also Bretherton et al. 2004, daily; Neelin et al. (2009) instantaneous,...

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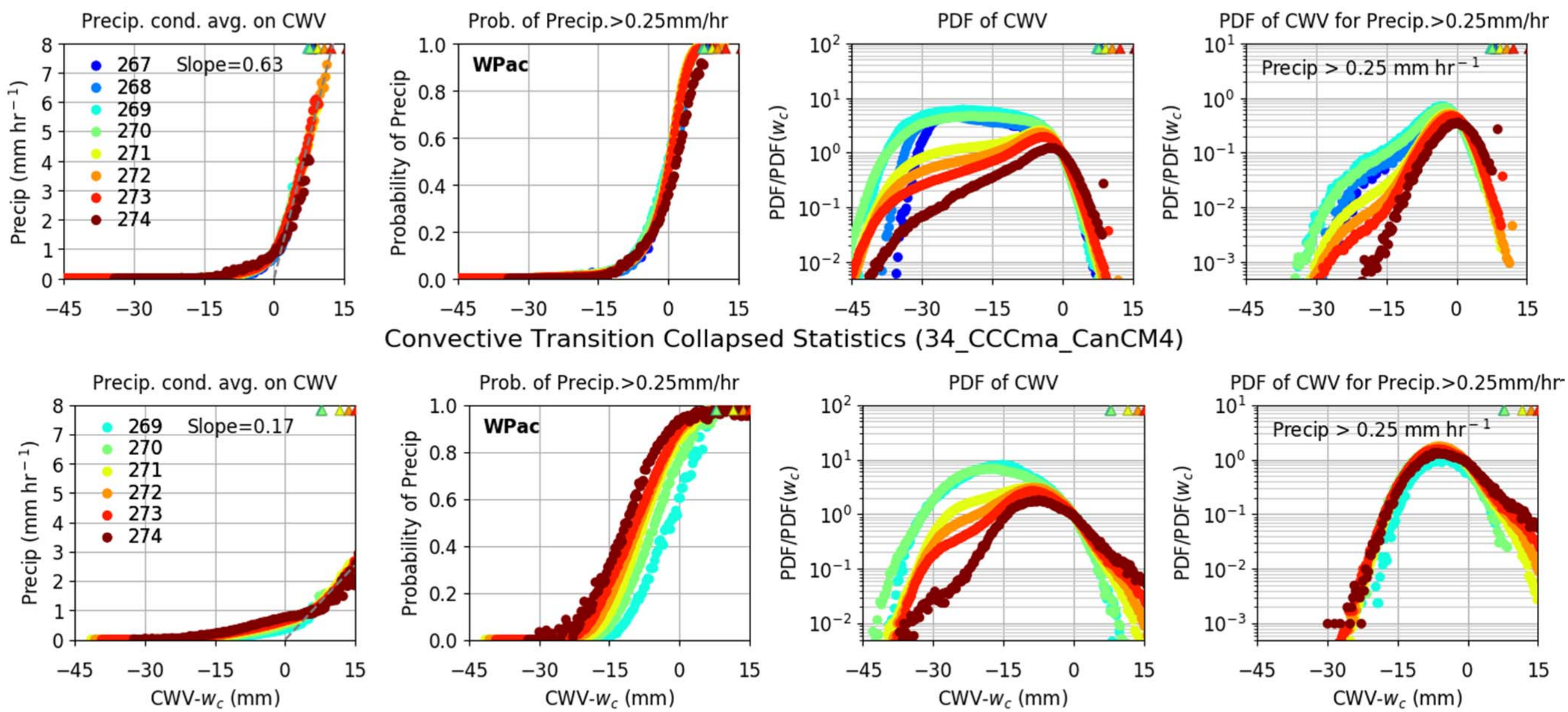
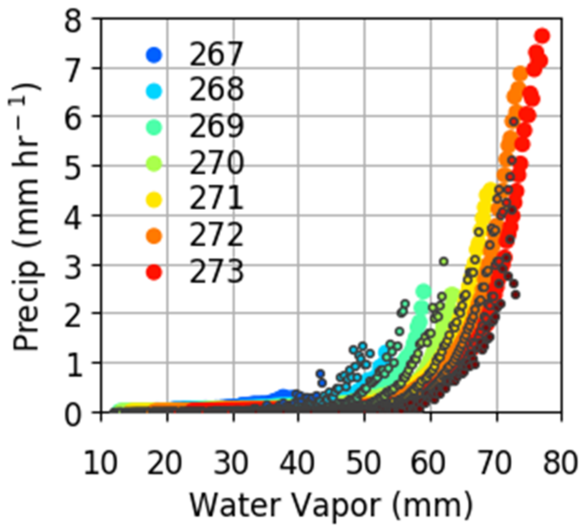
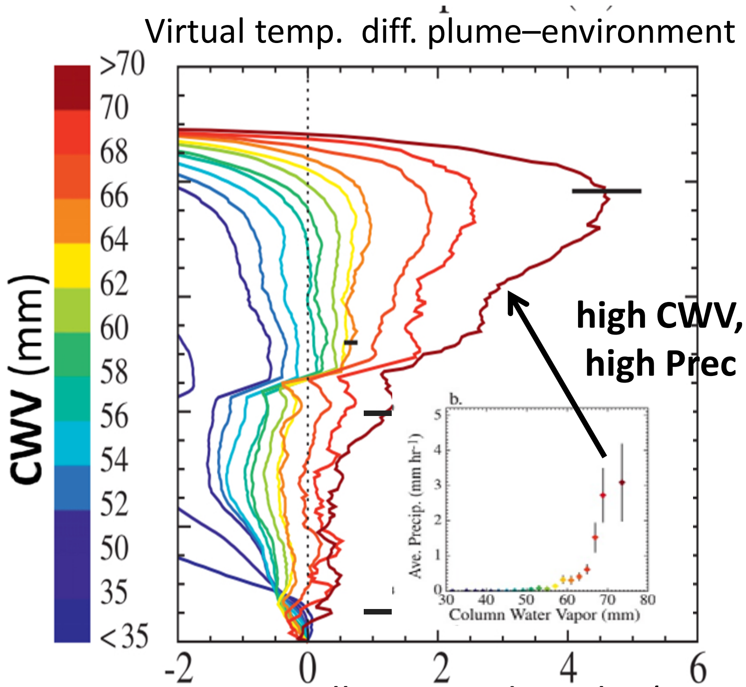


Models can do well or badly at these fast-process diagnostics e.g., CanCM4: 2-step pickup, broad PDFs

Background cont'd: convective transition dependence on buoyancy, mixing



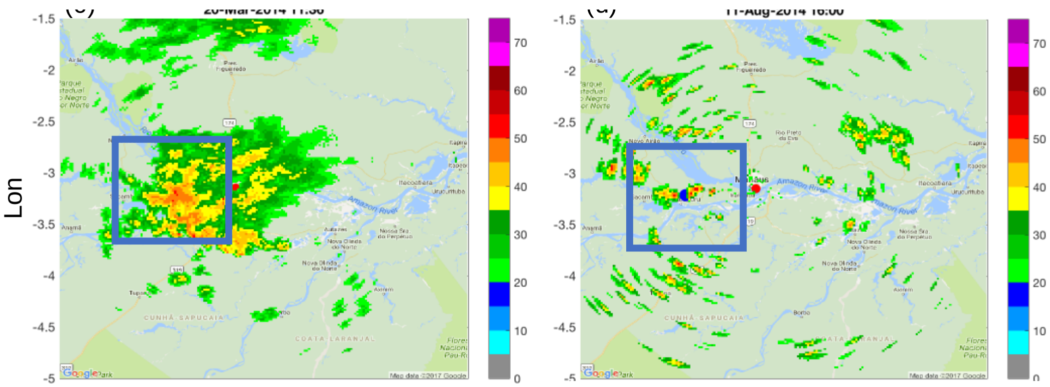


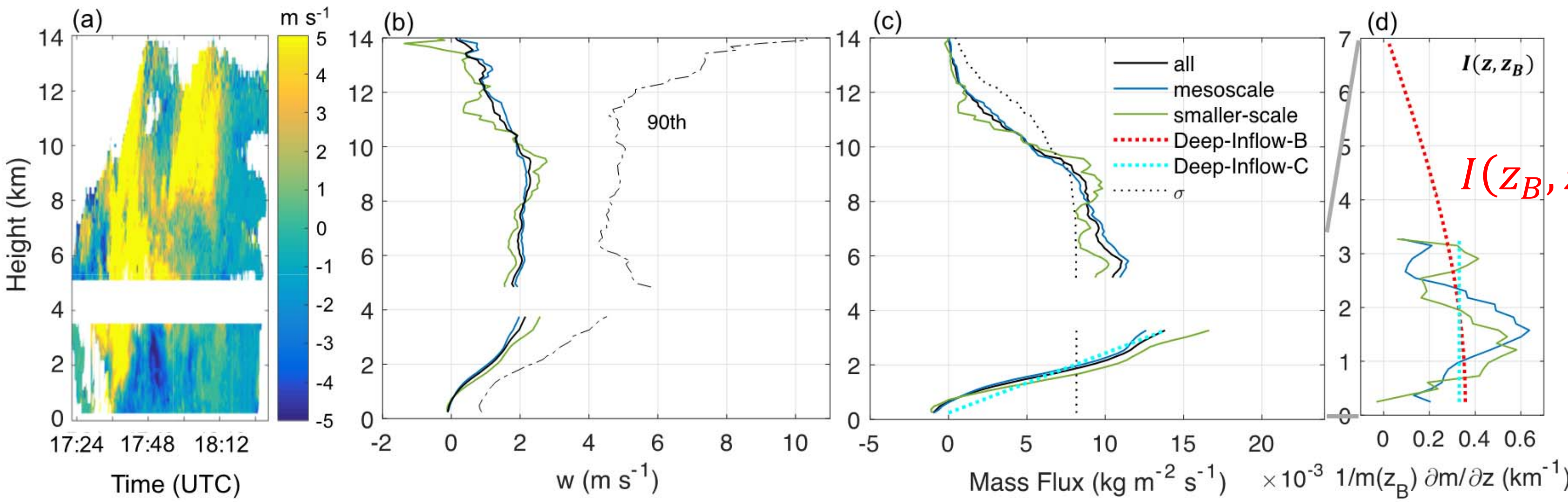
Holloway and Neelin (2009), see also Sahany et al. (2012), Kuo et al. (2017)

- Sharp Precip pickup associated with conditional instability yielding deep convection
- as seen in soundings with estimates of plume buoyancy with entrainment
- Move beyond bulk thermodynamic measures such as CWV, <T> to vertical thermodynamic structure and mixing processes
- Quantities, (e.g. **buoyancy**) closer to that used in cumulus parameterization schemes
- But *which* buoyancy? Depends on levels where air enters the plume
- models that get this wrong capture onset poorly

<u>Forward procedure</u> to estimate influence function

for interaction between updraft and environment using mass flux from GoAmazon2014/5 data





- Radar wind profiler vertical velocity $\Rightarrow m \Rightarrow$ *I: empirical & approx.*
- S-Band radar to identify mesoscale and smaller-scale convection

$$r(z) = \frac{1}{m(z_B)} \int_{z_0}^{z_B} \tilde{r} \frac{\partial m}{\partial z} dz = \int_{z_0}^{z_B} I(z_B, z)\, \tilde{r}\, dz$$

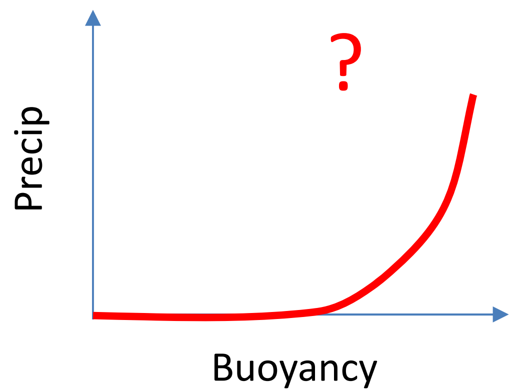
r is the conserved variable in the updraft
$\tilde{r}$ is the environmental value
z_B is the height at which buoyancy is evaluated

If m linear in z ($m = cz$), $\frac{\partial m}{\partial z}$ constant, the above reduces to layer mean, and $\frac{1}{m}\frac{\partial m}{\partial z} = \epsilon$ (detrainment neglected) reduces to $\frac{c}{cz} = \epsilon = \frac{1}{z}$

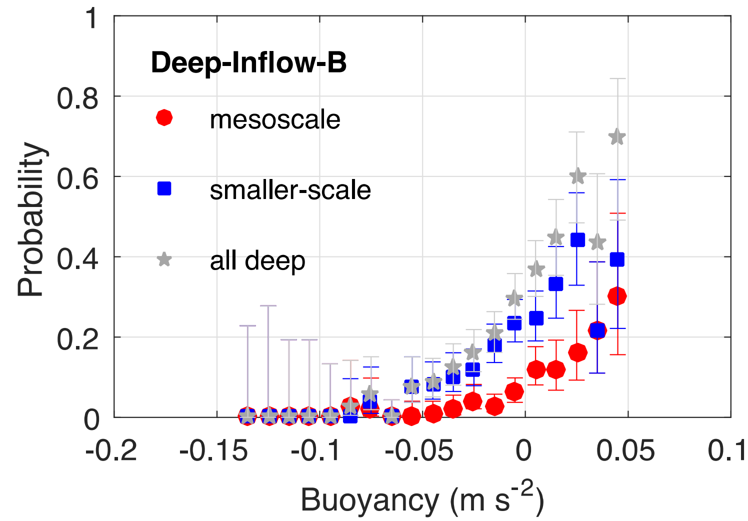
<u>Robust formulation without tunable coefficients</u>

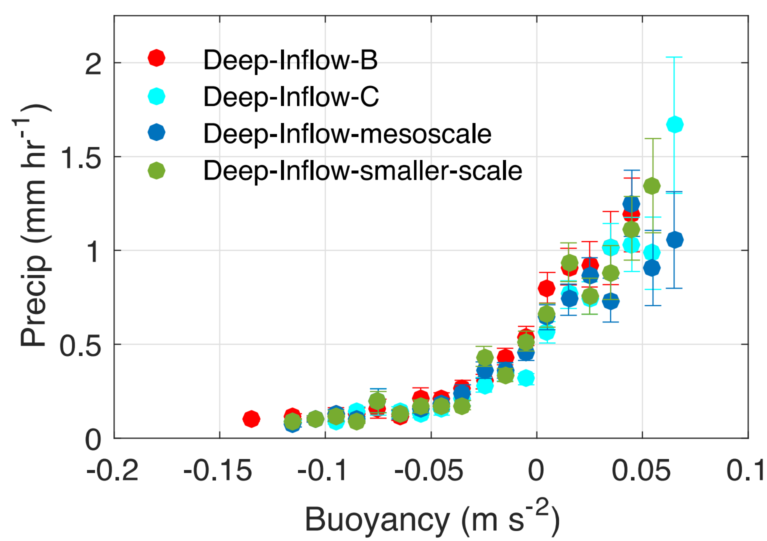
<u>Forward procedure</u> testing empirically estimated influence function

evaluate success and robustness of assumption in representing convective onset



[Computed with empirical influence function]





- Works well for mesoscale and smaller-scale convection alike
- Convective onset stats insensitive to exact deep-inflow formulation

Schiro, Ahmed, Neelin, and Giangrande 2018 (PNAS)

Reverse-engineering approach to estimate influence function

θ_e-based variables

Consider thermodynamic variables below freezing level in three separate layers.

Boundary Layer variations: $<\theta_e>_{BL}$

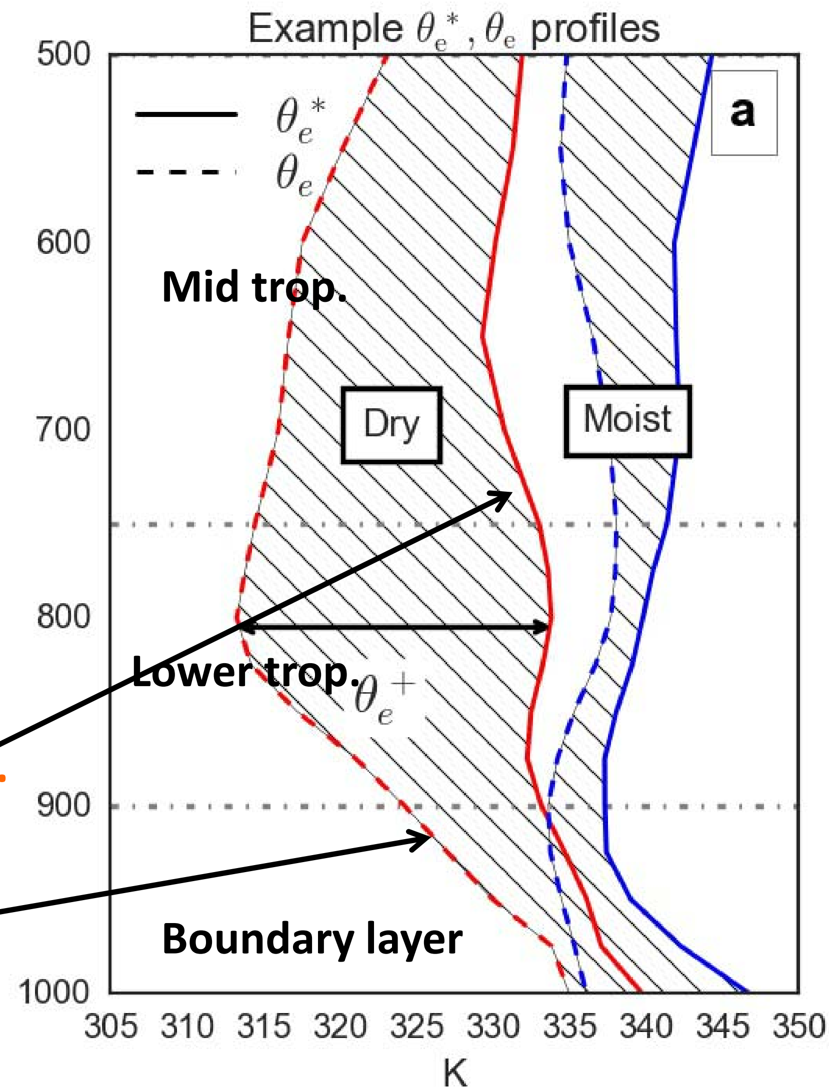
$$<T> \;\rightarrow\; <\theta_e^*>_{deep}$$

Bulk temperature becomes bulk sat. θ_e (mid. + lower trop)

$$CWV \;\rightarrow\; <\theta_e^+>_{LT}, <\theta_e^+>_{MT}$$

Water vapor parsed out into lower and mid. trop. sub saturation variables

Subsaturation: $\theta_e^* - \theta_e$

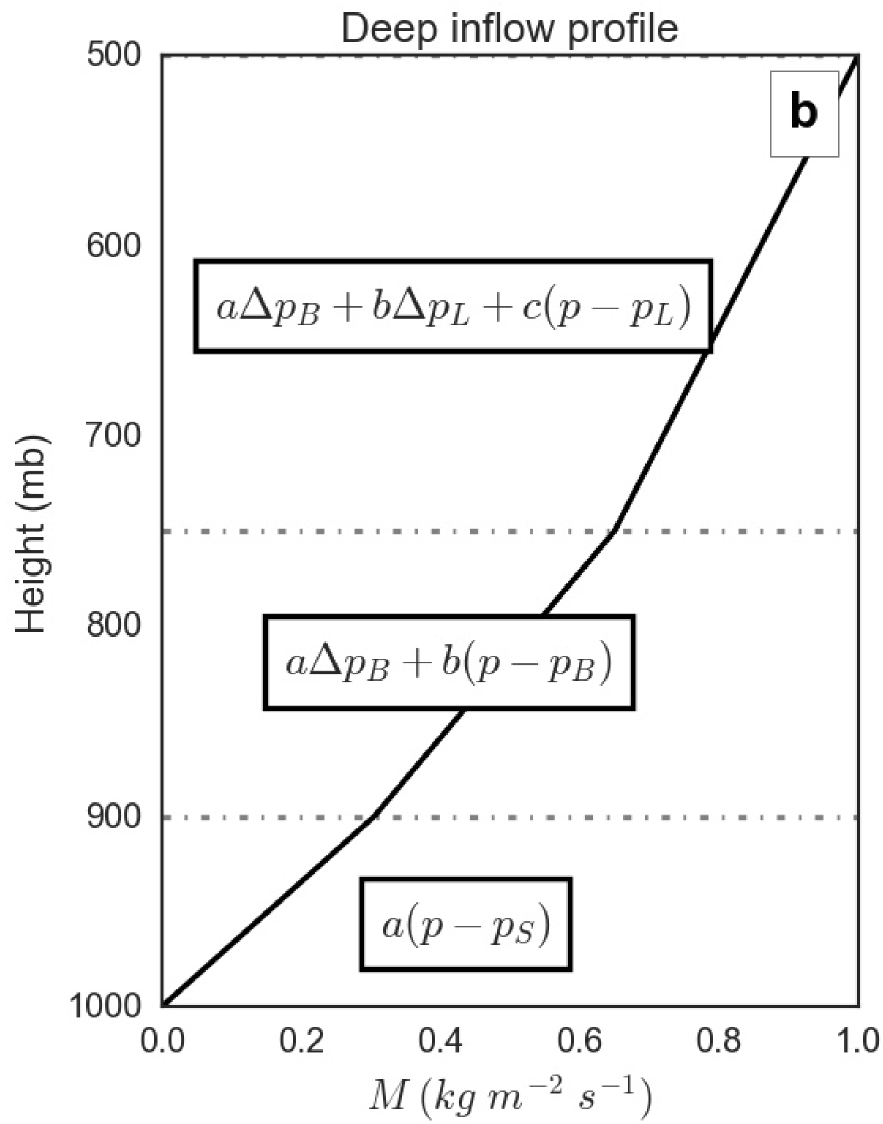


Ahmed and Neelin 2018 (JAS)

Reverse-engineering approach

Influence function set up

- 3 lower-tropospheric layers, each with a weighting coefficient TBD
- Corresponds to linear piecewise mass flux structure, **but slopes are free to vary**
- slope ⇔ **relative influence** of each layer on the convection
- If all slopes>0: represents lateral inflow of environmental air through a **deep layer** (500 mb thick).



Ahmed and Neelin 2018 (JAS)

Analytical expression for buoyancy

Plume Env.

$$B(z) = g\left(\frac{\theta_e(z) - \tilde{\theta}_e^*(z)}{\tilde{\theta}_e^*(z)}\right)$$

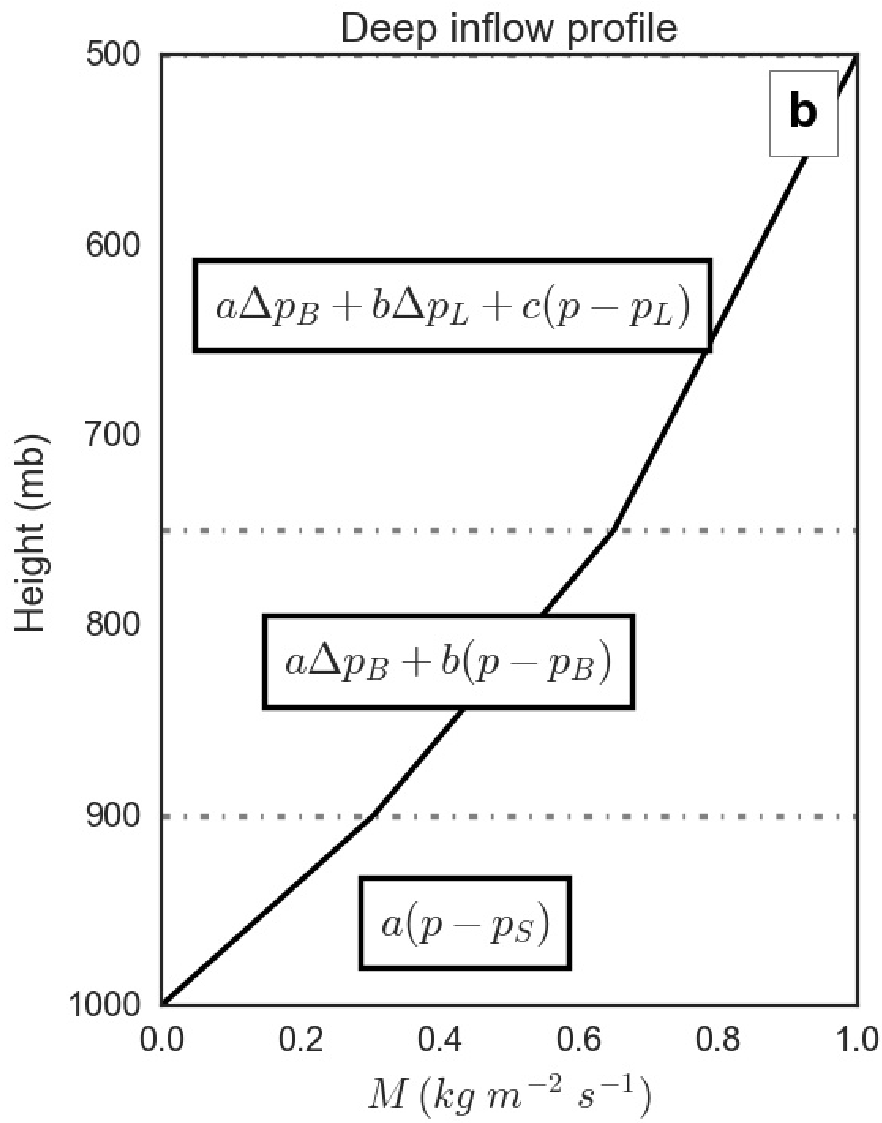
Buoyancy definition as plume-env. difference.

$$\theta_e(z) = \int_0^z I(z,z')\tilde{\theta}_e(z')\,dz'$$

***I(z,z')*: Captures influence of env. below z on plume $\theta_e(z)$.**

$$I(z,z') = \frac{1}{M(z)}\frac{\partial M(z')}{\partial z'}$$

This is where the relative layer influence comes in.



Ahmed and Neelin 2018 (JAS)

Analytical expression for buoyancy at freezing level

$$B_F \propto \left(A_{BL}\left\langle\tilde{\theta}_{eBL}\right\rangle - B_{LT}\left\langle\tilde{\theta}_{eL}^{\;+}\right\rangle - C_{MT}\left\langle\tilde{\theta}_{eM}^{\;+}\right\rangle + D\left\langle\tilde{\theta}_{e}^{\;*}\right\rangle_{Deep}\right)$$

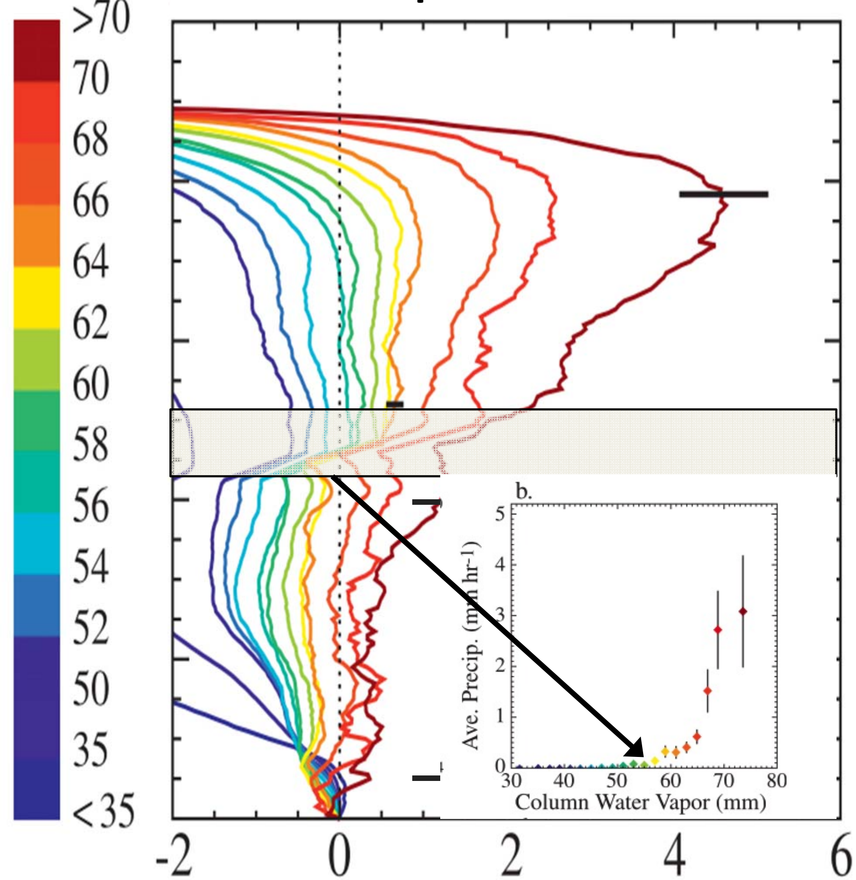
500-900 mb saturation θ_e^*

Boundary layer θ_e

750-900 & 500-750 Subsaturation θ_e^+

- B_F - a linear combination of four layer-averaged quantities
- A_{BL}, B_{LT}, C_{MT} yield information about:
  - i) **Relative layer influence**
  - ii) **A buoyancy measure**
- Conjecture: Convective onset is related to a **threshold B_F**

Virtual temp. diff.



(Holloway and Neelin, 2009)

Reverse-engineering the layer weights

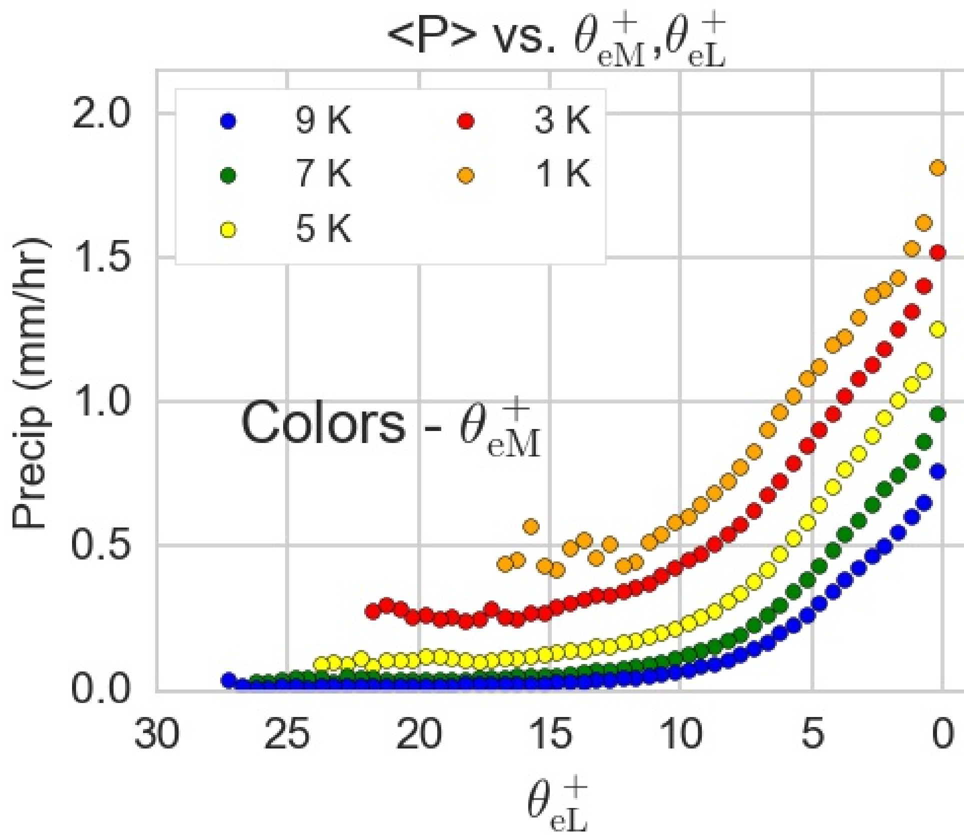
$$B_F \propto \left(A_{BL} \left\langle \tilde{\theta}_{eBL} \right\rangle - B_{LT} \left\langle \tilde{\theta}_{eL}{}^{+} \right\rangle - C_{MT} \left\langle \tilde{\theta}_{eM}{}^{+} \right\rangle + D \left\langle \tilde{\theta}_{e}{}^{*} \right\rangle_{Deep} \right)$$

- Extract layer weights from data: ERA-I thermodynamic structure and TRMM 3B42 precip @ .25 deg, 6 hrly resolution
- Pool all tropical ocean data together: improve sampling
- Bin precip. by four layer-averaged variables

Reverse-engineering the layer weights

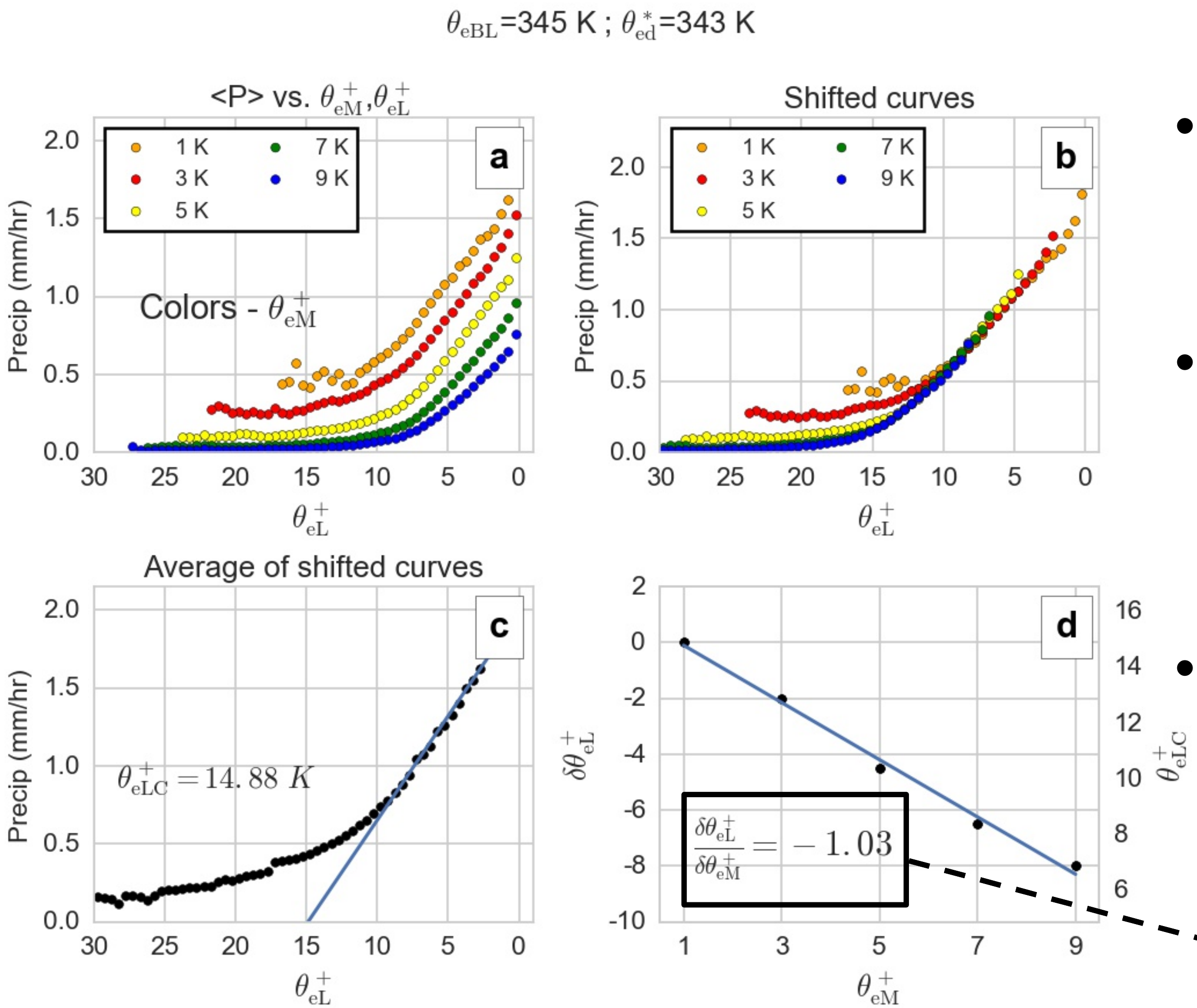
$$B_F \propto \left(\boxed{A_{BL} \left\langle \tilde{\theta}_{eBL} \right\rangle} - B_{LT} \left\langle \tilde{\theta}_{eL}{}^{+} \right\rangle - C_{MT} \left\langle \tilde{\theta}_{eM}{}^{+} \right\rangle + \boxed{D \left\langle \tilde{\theta}_{e}{}^{*} \right\rangle_{Deep}} \right)$$

Holding two variables fixed



- ERA-I thermodynamic structure and TRMM 3B42 precip @ .25 deg, 6 hrly
- Bin precip. by four layer-averaged variables (tropical oceans)

Reverse-engineering the layer weights



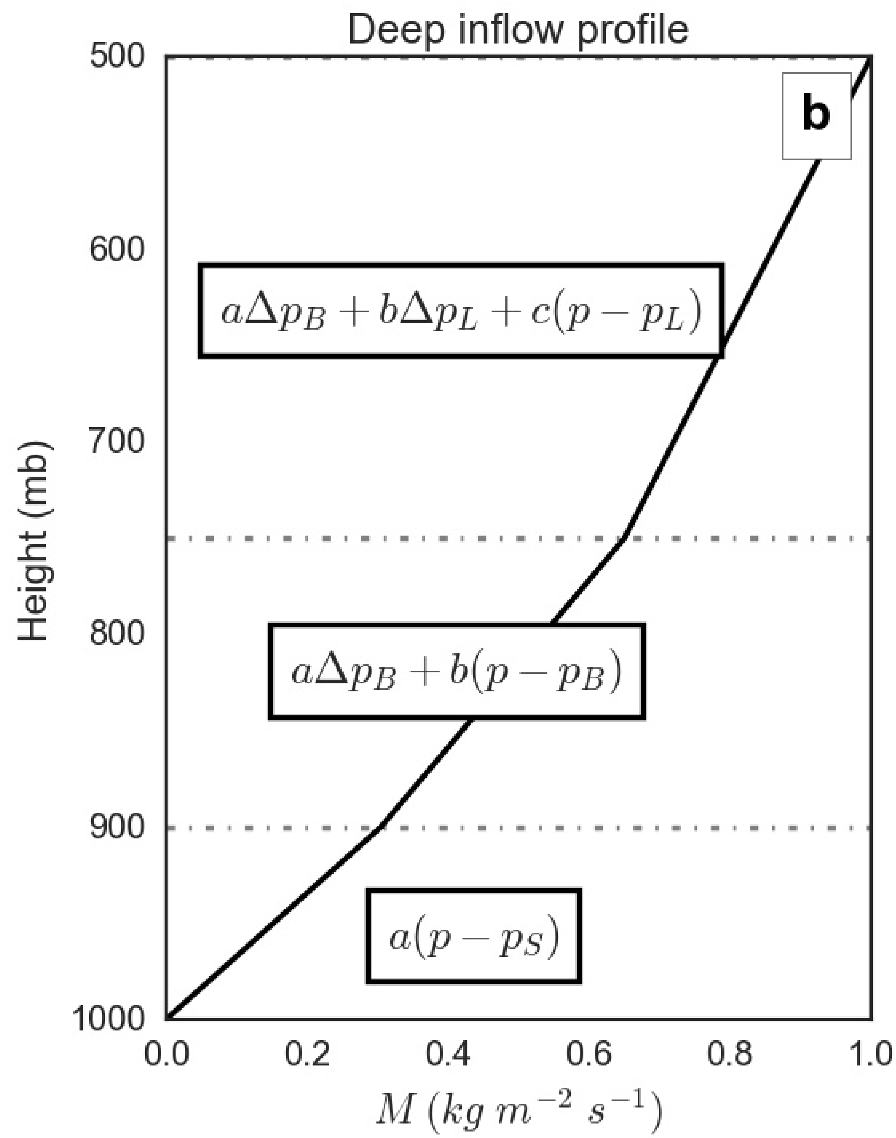
- i) Shift to match precipitation onset
- ii) Degree of shift gives relative layer influences
- iii) Similar exercise for boundary layer influence

$$\frac{B_{LT}}{C_{MT}}$$

Ahmed and Neelin 2018 (JAS)

Reverse-engineered layer weights

- Nearly **equal weighting** for each layer (slopes shown are the actual estimate)
- Implies a “deep-inflow” mass-flux profile
- Allows buoyancy computation: B_F and B_{int} (averaged between 500 mb – 900 mb)
- B_{int} takes $<\theta_e^*>_{deep}$ into account, a **more complete** buoyancy measure

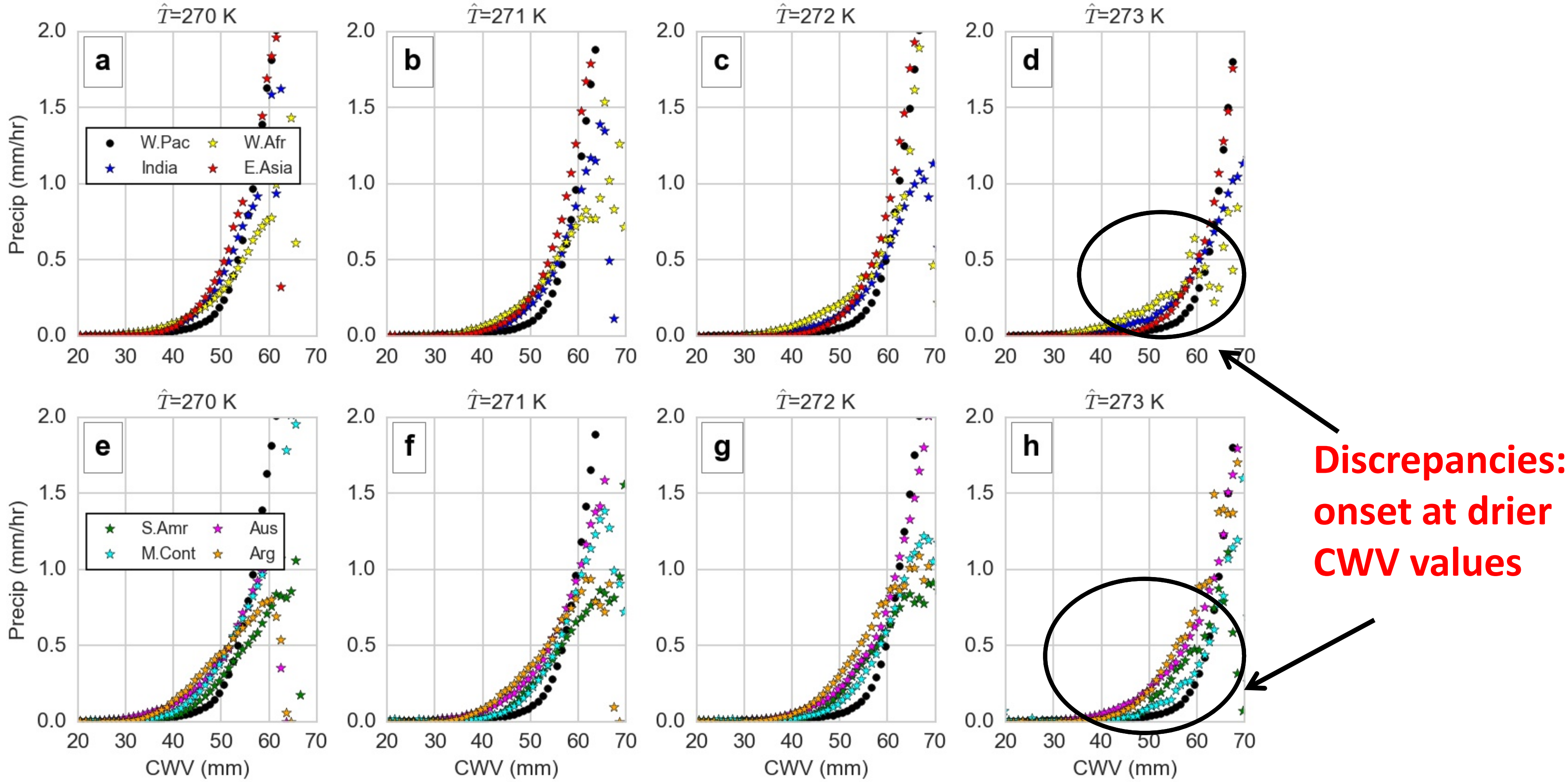


Ahmed and Neelin 2018 (JAS)

Convective transition in bulk thermo. variables

CWV, <T> capture leading-order behavior, for comparison

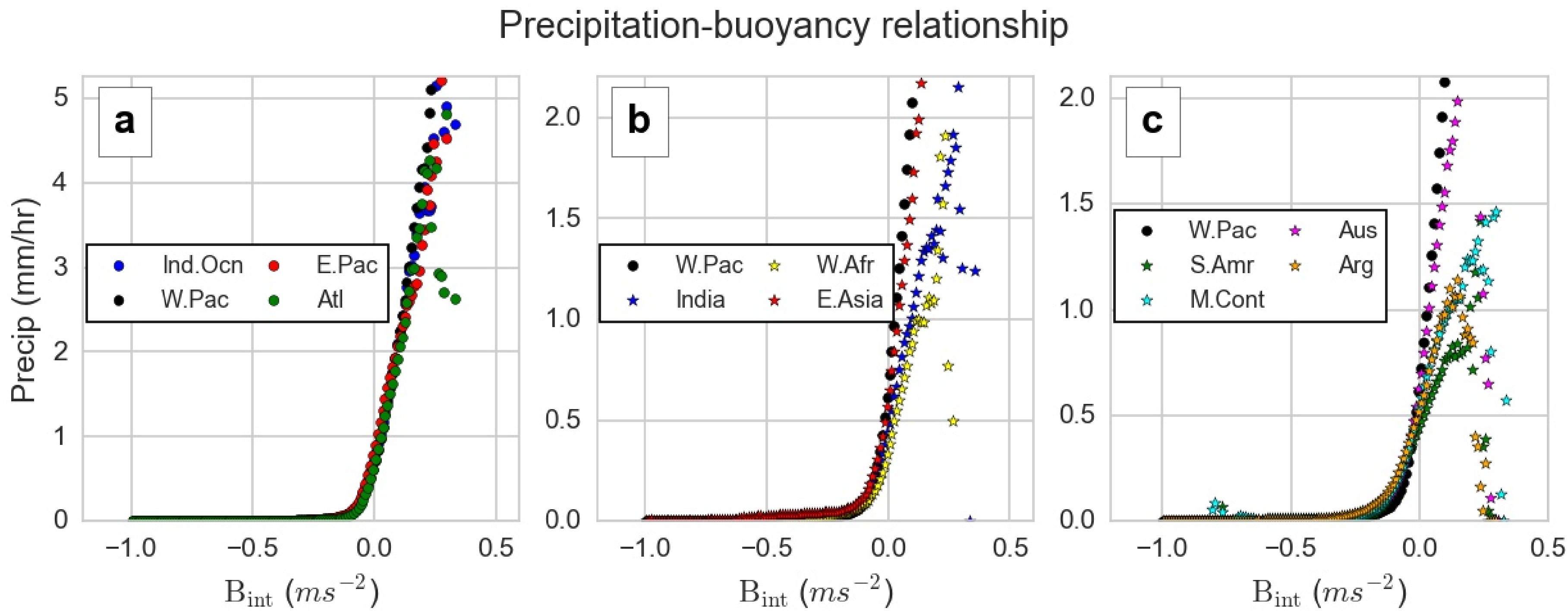
black-Tropical WPac. **color-tropical land regions**



Discrepancies: onset at drier CWV values

Ahmed and Neelin 2018 (JAS)

Convective transition in reverse-engineered buoyancy

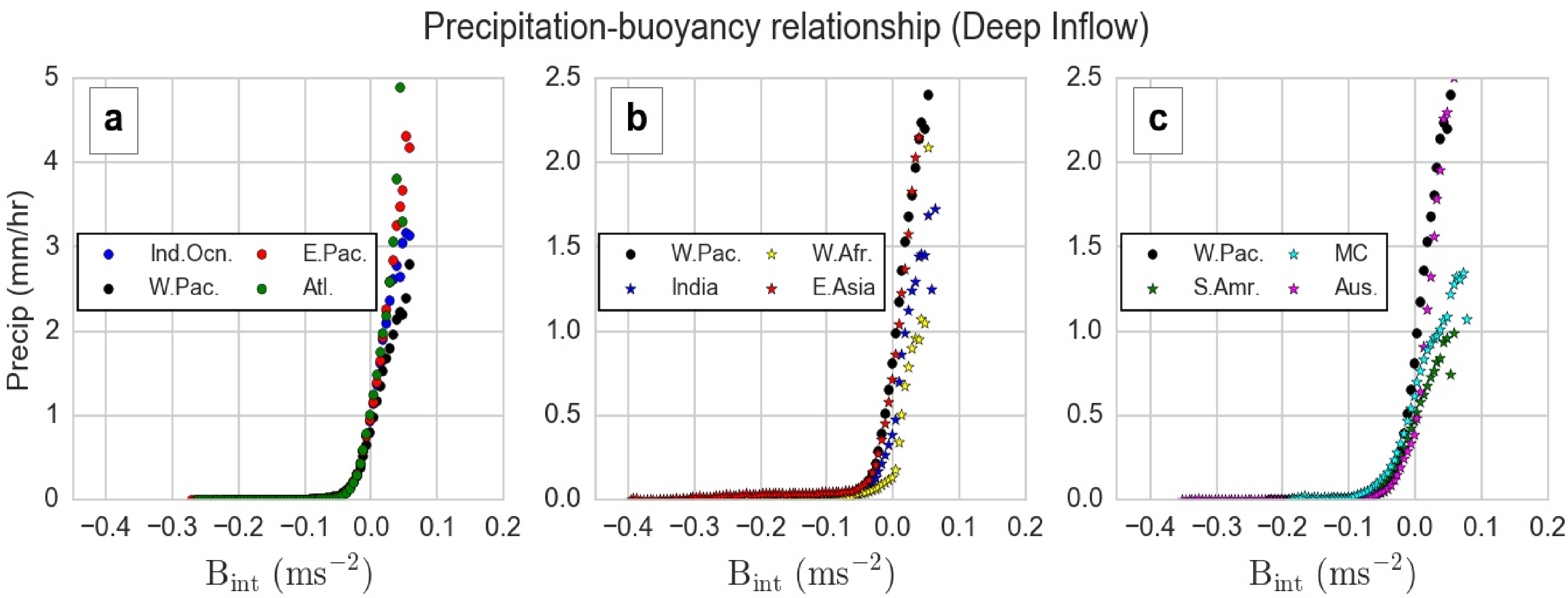


B_{int} is a stronger predictor of convective onset over both tropical land and ocean.

B_{int} is a bulk measure that accounts for vertical structure and mixing assumptions. Similar to variables of conv. parameterization: e.g. **cloud work function** (Arakawa and Schubert 1974) but with mixing empirically determined to capture strong precip systems

Ahmed and Neelin 2018 (JAS)

Convective transition in forward procedure buoyancy

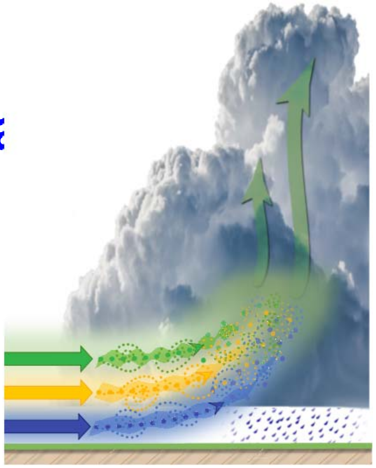


B_{int} with **forward estimate** of the inflow influence function gives very similar results — reproduces convective onset over both tropical land and ocean.

Schiro et al. 2018 (PNAS)

Reverse engineering convection— summary

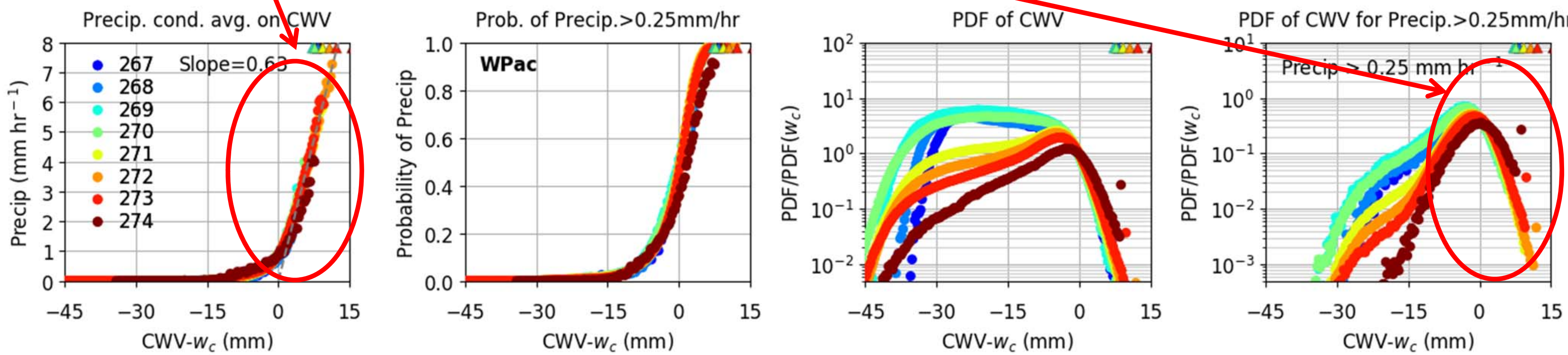
- **Precip vs. integrated buoyancy relationship** and the **influence function** that produces this are **robust** between **two complementary** approaches
- Interpretable as inflow of mass through a deep lower tropospheric layer, giving roughly equal weighting to the entire lower troposphere
- Works for mesoscale and smaller-scale systems— surprising but useful — suggests rethinking entrainment paradigms
- Can be used as a more refined comparison statistic for model parameterization
- also a **step towards a (semi-)empirical parameteriz** constraint on closure or with vertical structure from mass flux constraints, or empirically



Set up for stochastic hierarchical modeling: recall Deep Convective Transition statistics

Ingredients here allow simple but quantitative process model of precip. regimes

Precip binned by column water vapor | Probability of precipitation | Probability distribution all points vs. precipitating points



- Critical value w_c for the onset as a function of temp. carries information about fast timescale processes useful for testing convective parameterizations
- Collapsed form similar under global warming (Sahany et al. 2014)

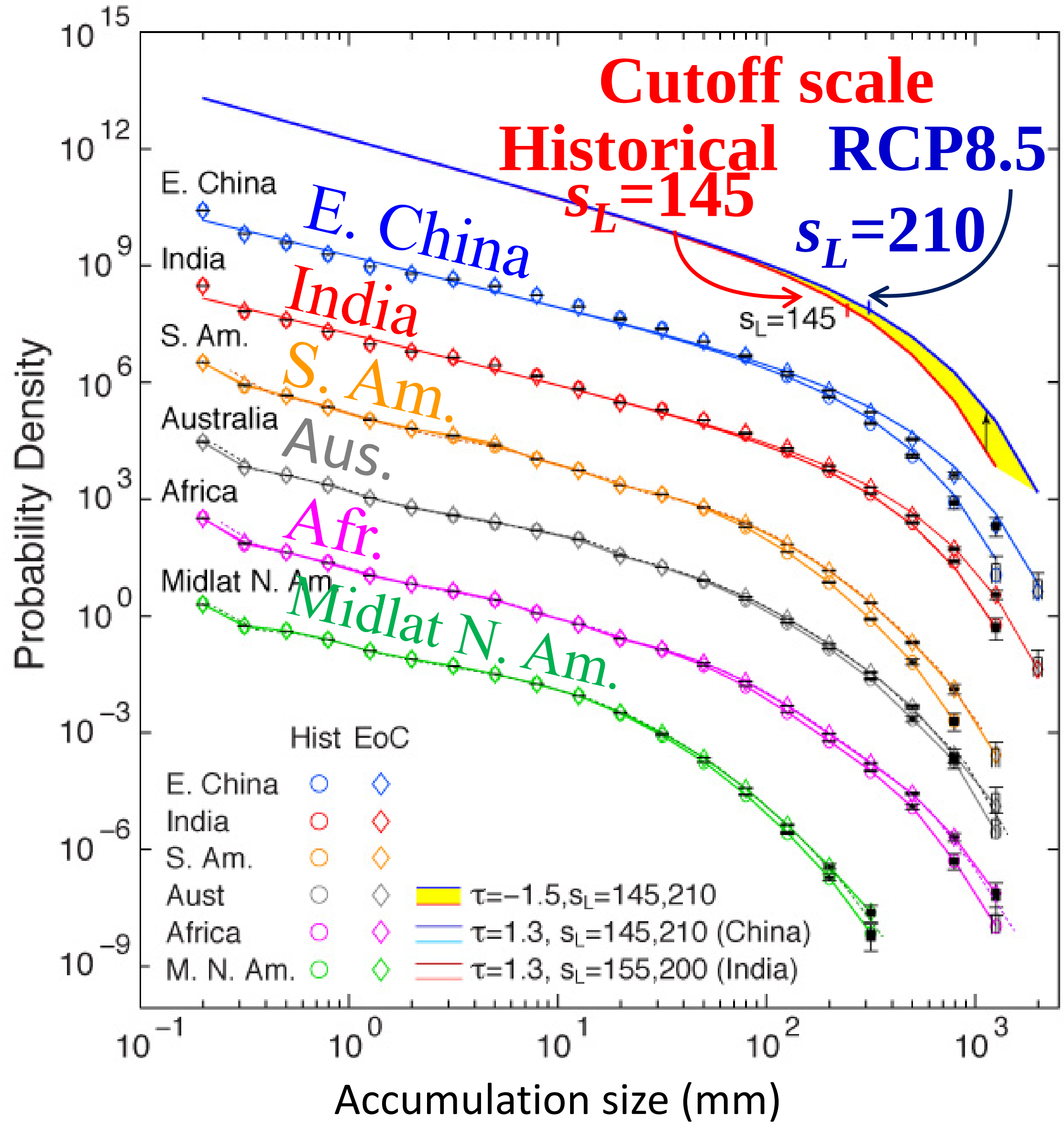
Provides ways of quantifying rich-get-richer (Chou & Neelin 2004, Trenberth 2011) aka wet-get-wetter (Held and Soden 2006) mechanism for variability

Fig. Kuo et al. (2018.); Dynamics Stechmann and Neelin (2014); Neelin et al. (2017)

Precip. accumulation* distribution – theory & CESM1

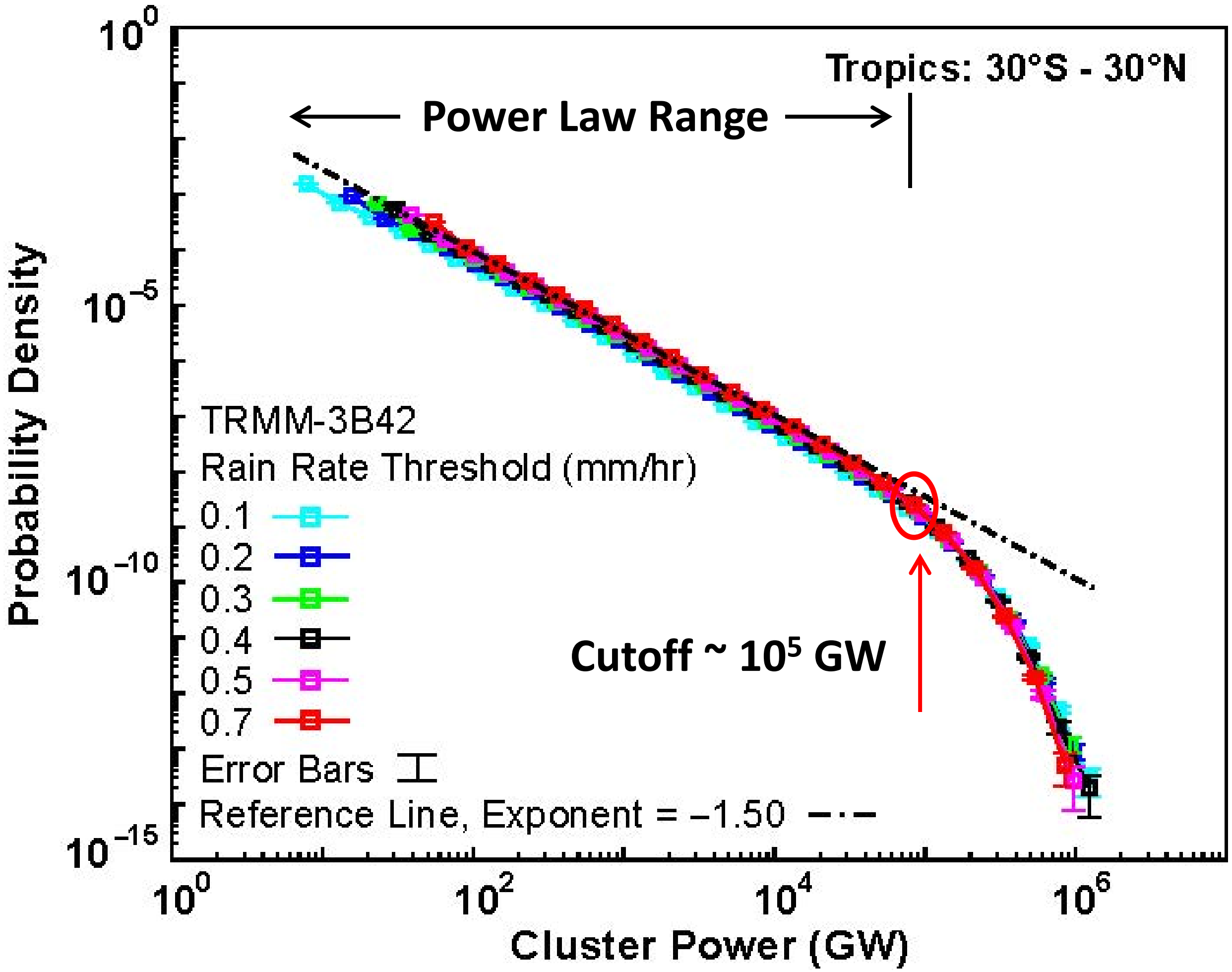
- Historical 1976-2005+ end-of-century (EoC) from 15 CESM1 RCP8.5 runs 2071-2100
- Simple stochastic model based on moisture equation yields theoretical distribution for power law range and large-event cutoff s_L
- predicts s_L increases
- Modest increase in $s_L \Rightarrow$ large probability increase above cutoff

- *event size=integrated precip over event P>0.4 mm/hr



Neelin, Sahany, Stechmann and Bernstein (2017)

Observed Precipitation Cluster Power PDFs

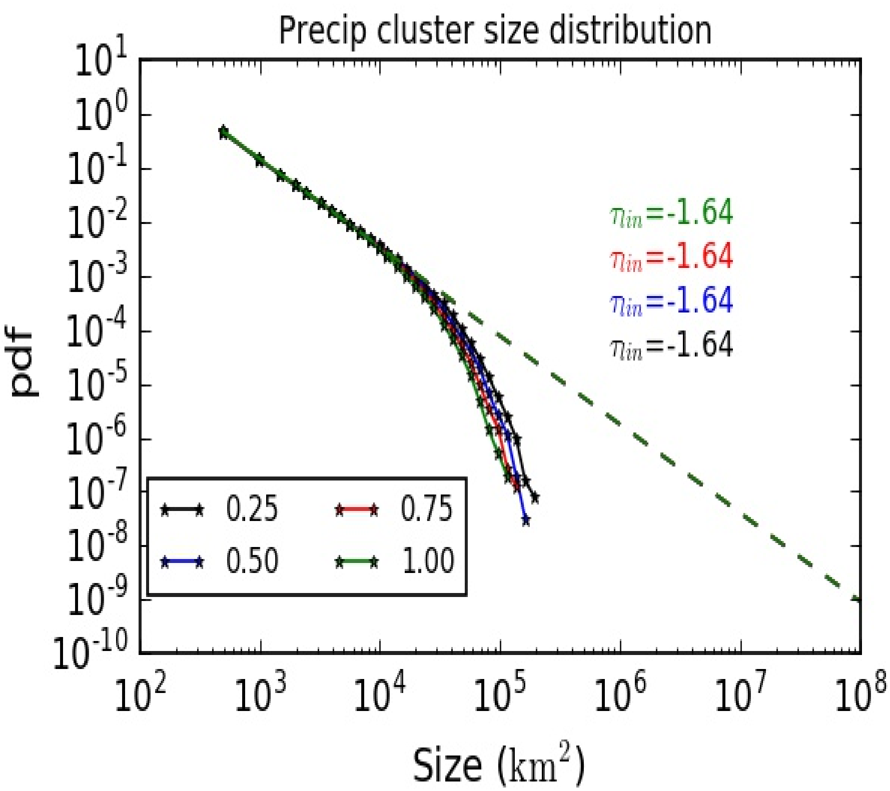


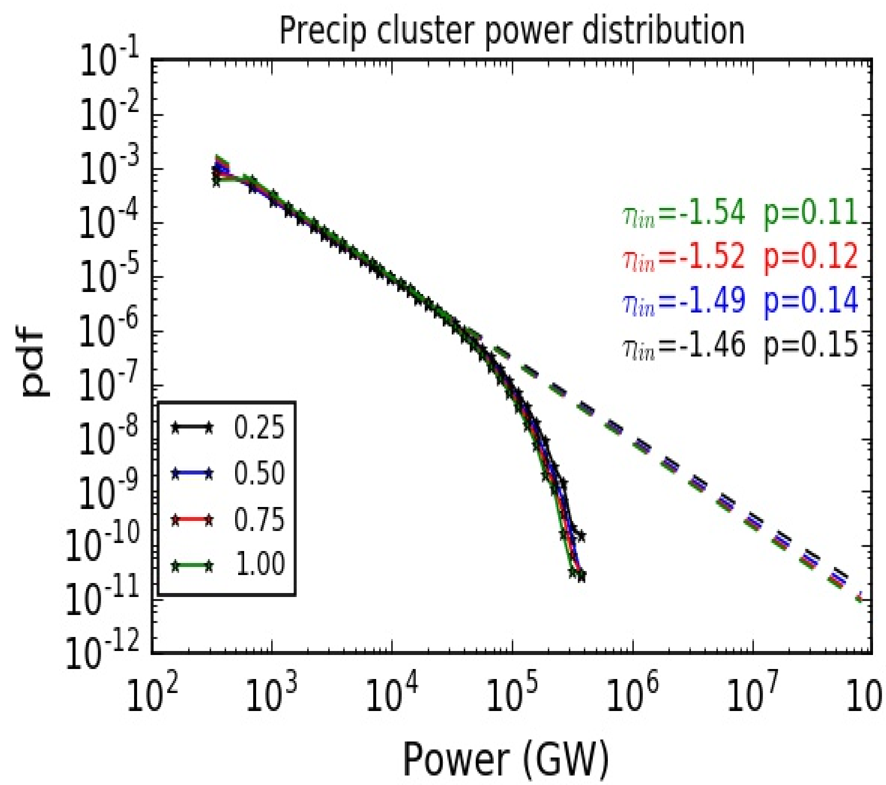
- Long, approximately power law range followed by a cutoff
- Little sensitivity to rain rate threshold used to define cluster
- Analogy to theory for time-dependent case suggests cutoff contains important physics; susceptible to change under global warming

Quinn and Neelin 2017

Cluster power distros for 1 May-30 Sep 1998-2008, retrieved at 00/12 UTC daily

Cluster distributions from stochastic model: column moisture eq. + WTG





Ahmed & Neelin
2018 in prep

WishList

- Tighter cycles between observational analysis, theory, model constraints
- With sufficient data, comparison statistics for model parameterization could become empirical parameterizations — but with physically based hypotheses
- Emergent properties of convection, including distributions of extreme events, are amenable to understanding from fairly simple hierarchical models — extend these so they become model development partners