Model precipitation uncertainties and constraints on entrainment from convective onset

J. David Neelin[1]

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- Examples of issues with precipitation simulation
- The transition to strong, deep convection: constraining climate model representations
- [Farewell to the moist adiabat?]

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Examples and issues with precipitation simulation: global warming, El Niño…

- **Severe problems with model disagreement on precipitation change at regional/seasonal scales, markedly so in tropics**
- **some agreement on large-scale or amplitude**
- **Poor simulation of El Niño remote precipitation anomalies**
- **Sensitivity to differences in model parameterizations**
- **Teleconnections of errors in other parts of the climate system to influence edges of convection zones/storm tracks**

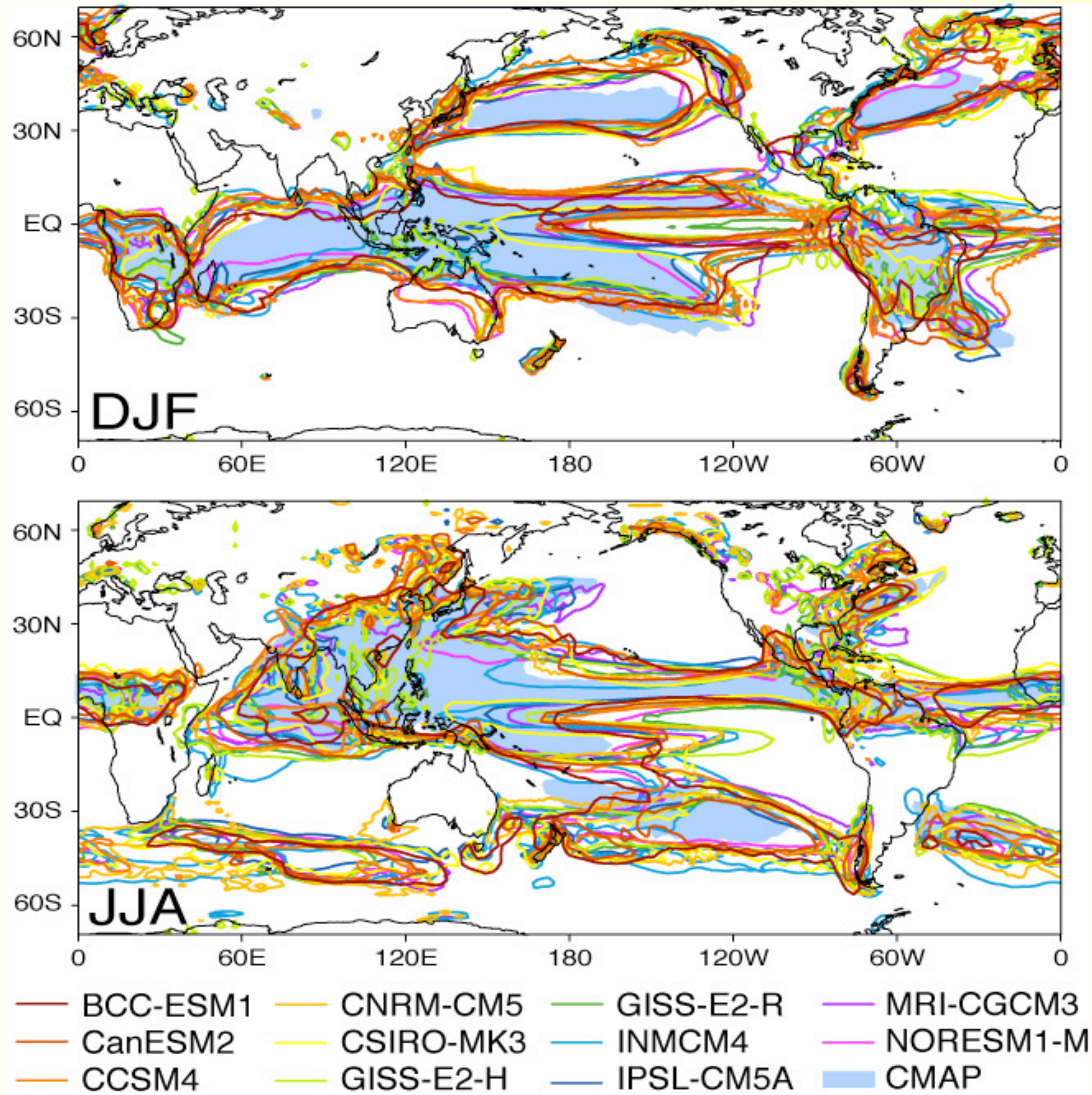
e.g., IPCC 2001, 2007; Wetherald & Manabe 2002; Trenberth et al 2003; Neelin et al. 2003; Maloney and Hartmann 2001; Joseph and Nigam 2006; Biasutti et al. 2006; Dai 2006; Tost et al. 2006; Bretherton 2007, Frierson, ...

Observed (CMAP) and CMIP5 coupled models
4 mm/day precip. contour

Coupled simulation climatology (20th century run, 1979-2005)

December-February precipitation climatology

June - August precipitation climatology



Coupled Model Intercomparison Project (CMIP5)

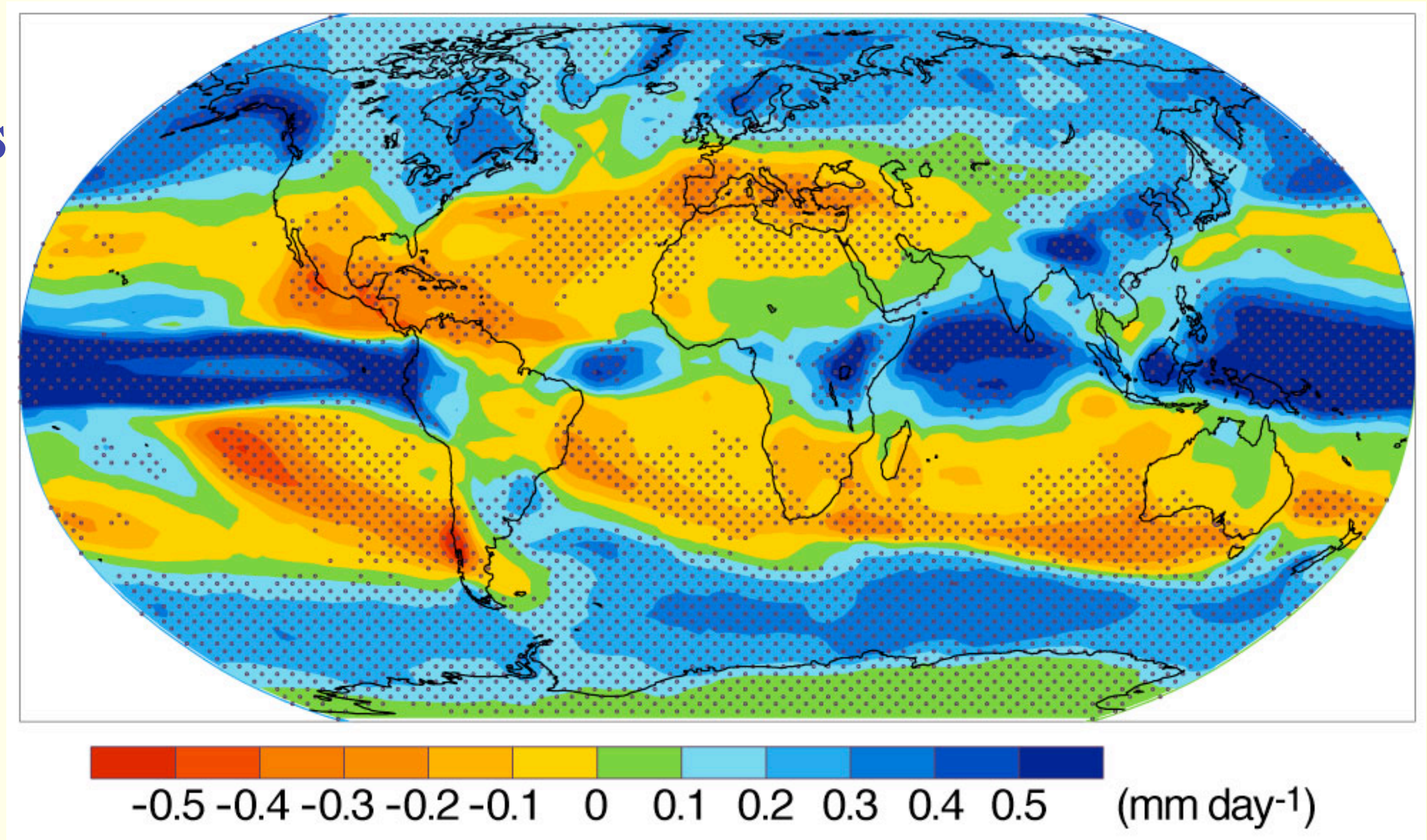
Analysis: J. Meyerson

IPCC 2007 multi-model, annual mean precipitation change (2080-2099 relative to 1980-1999)

High latitudes wetter

Subtropics dryer/expand

Deep tropics wetter



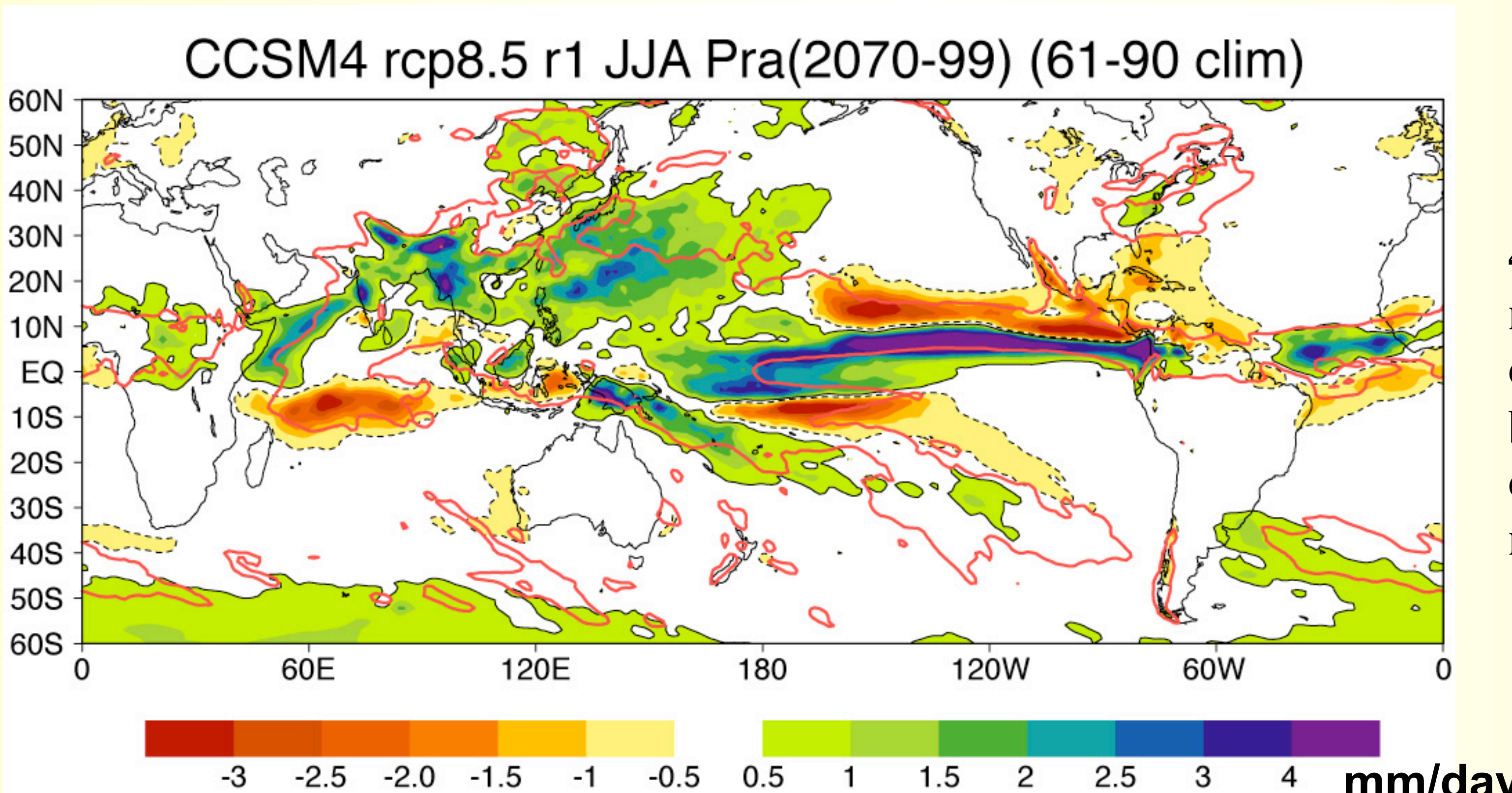
Stippled where 80% of the models agree on sign of the mean change. Note typical magnitudes <0.5mm/d.

IPCC 4th Assessment Report (WG1 2007, chpt 10; A1B Scenario)

CMIP5/IPCC 5th Assessment report models

- **Representative Concentration Pathway RCP 8.5 (akin to CMIP3 A2 scenario) for greenhouse gases, aerosol forcing**

Precipitation change: HadCM3, Dec.-Feb., 2070-2099 avg minus 1961-90 avg.



4 mm/day model climatology black contour for reference

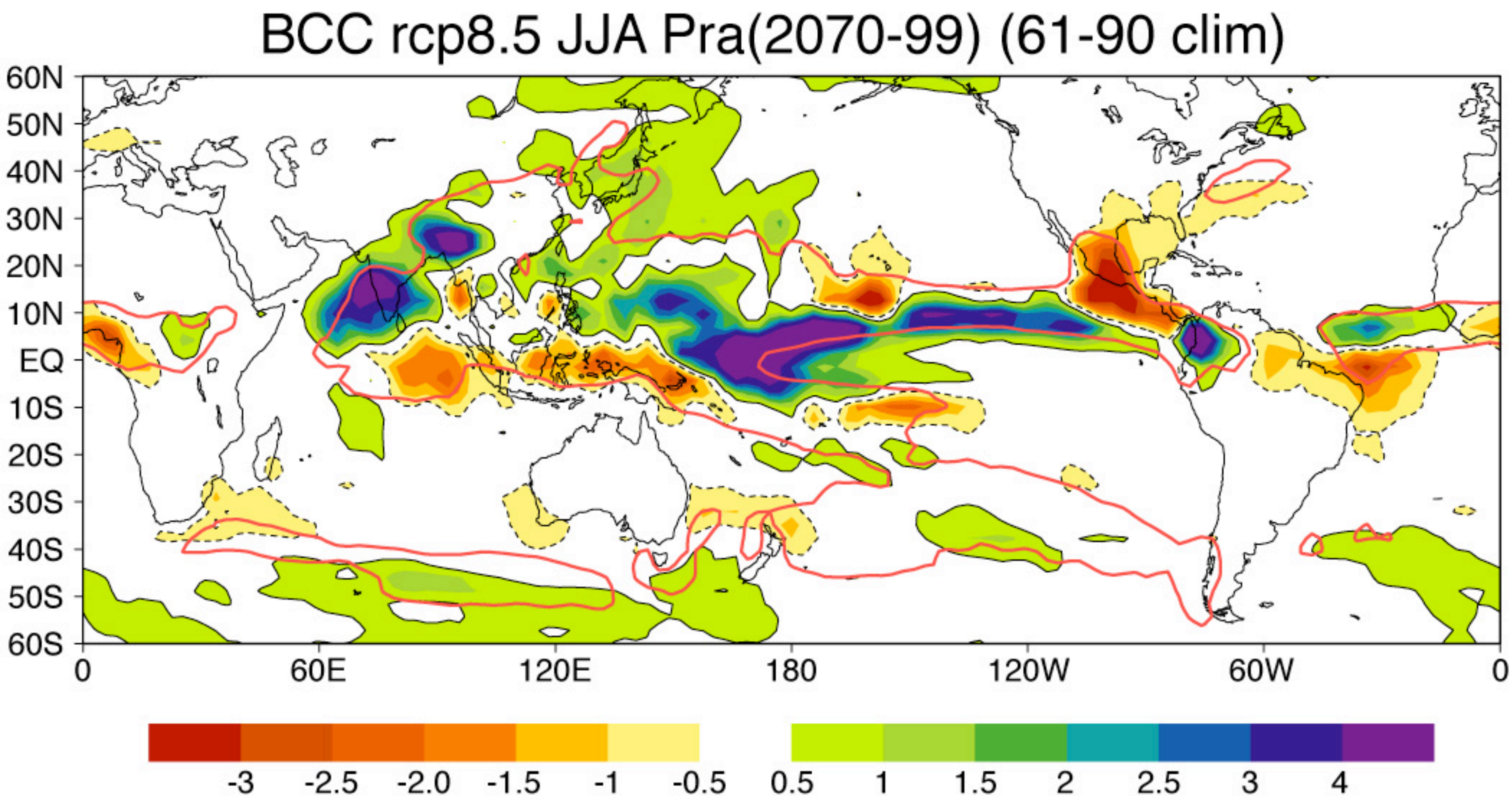
Analysis: J. Meyerson

NCAR Community Climate System Model

CMIP5

BCC-ESM1-1

JJA Prec. Anom.

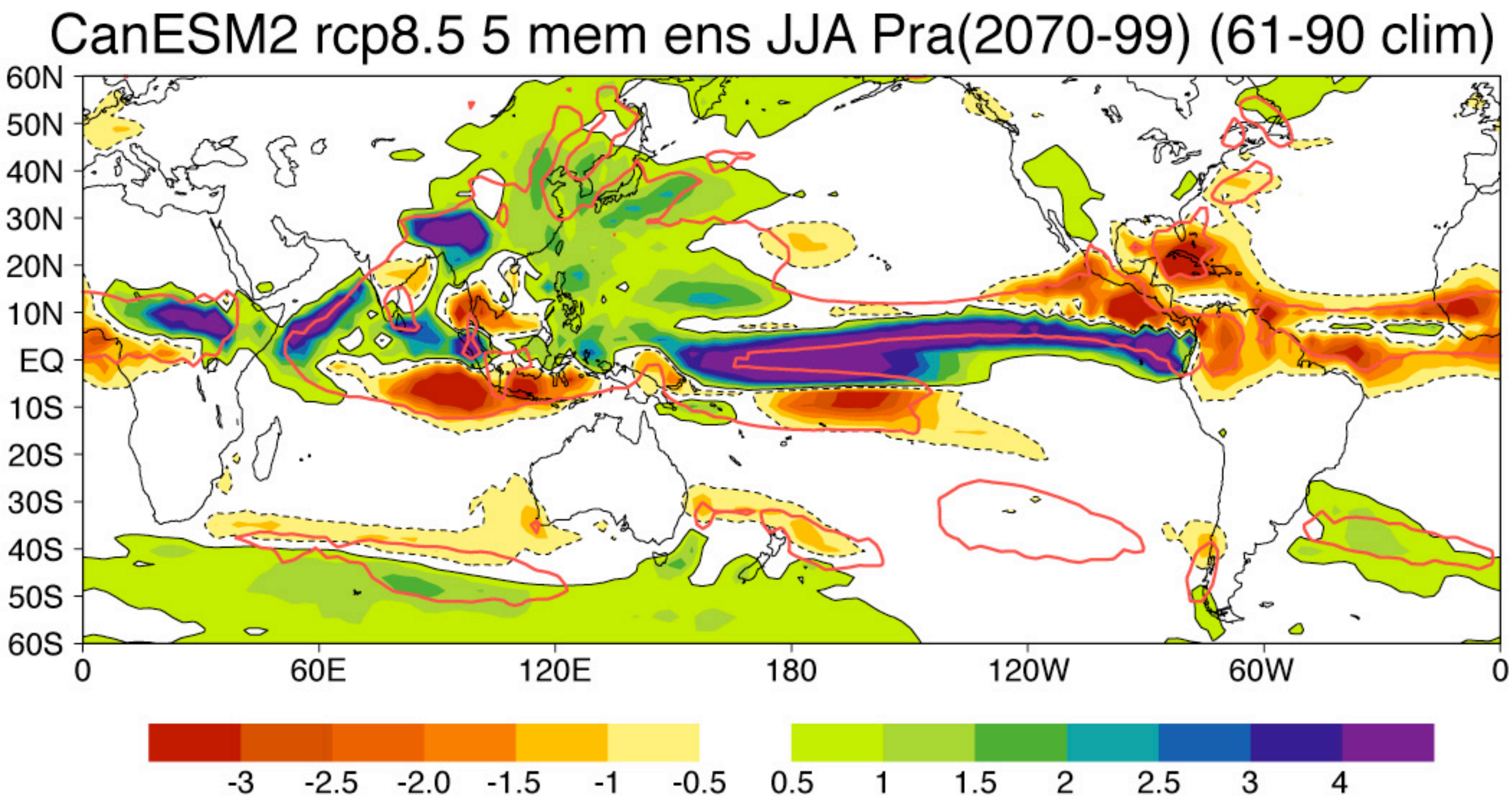


Beijing Climate Center, China

CMIP5

CanESM2

JJA Prec. Anom.

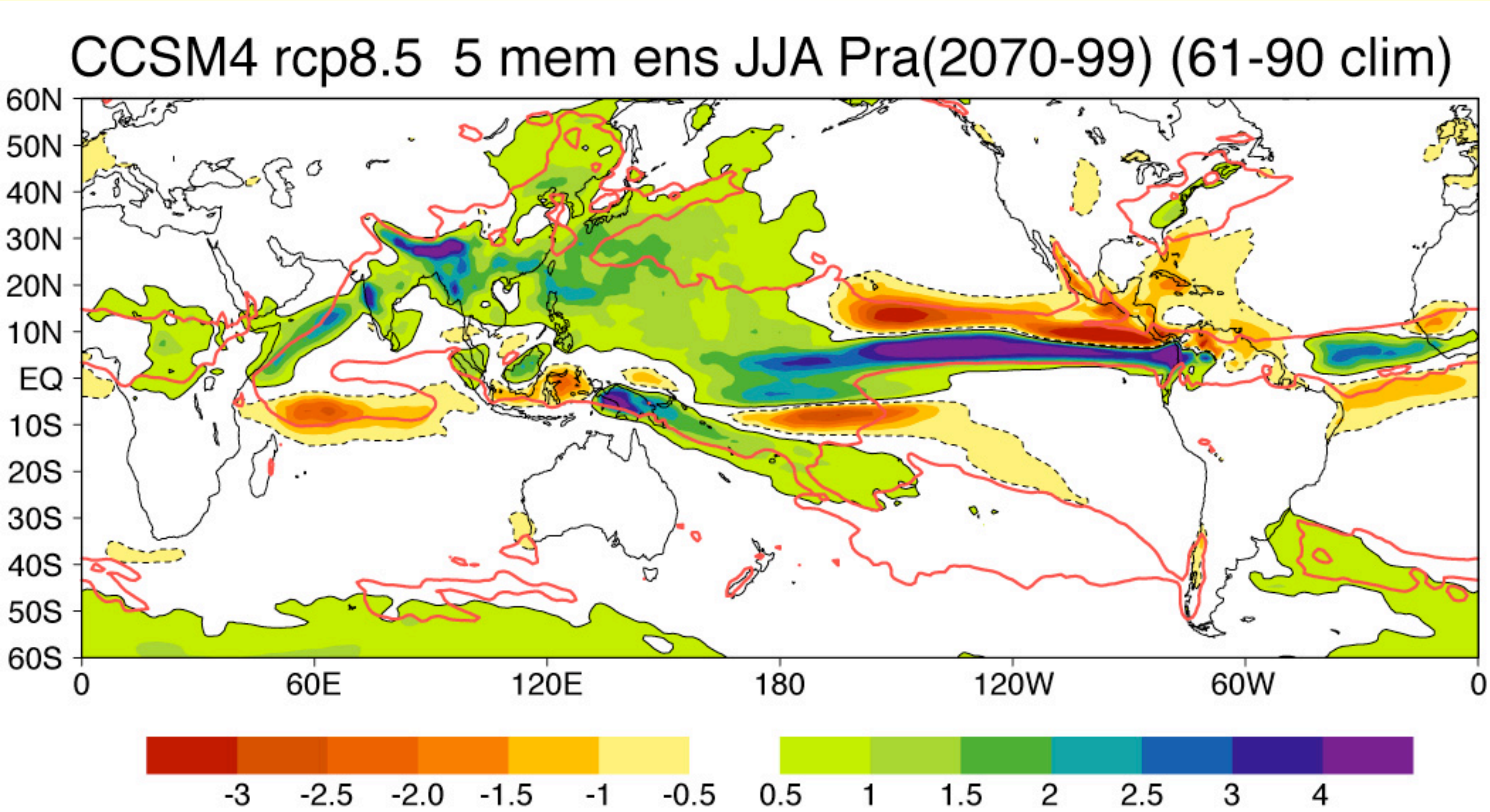


Canadian Center for Climate Modelling and Analysis, Canada.

CMIP5

CCSM4

JJA Prec. Anom.

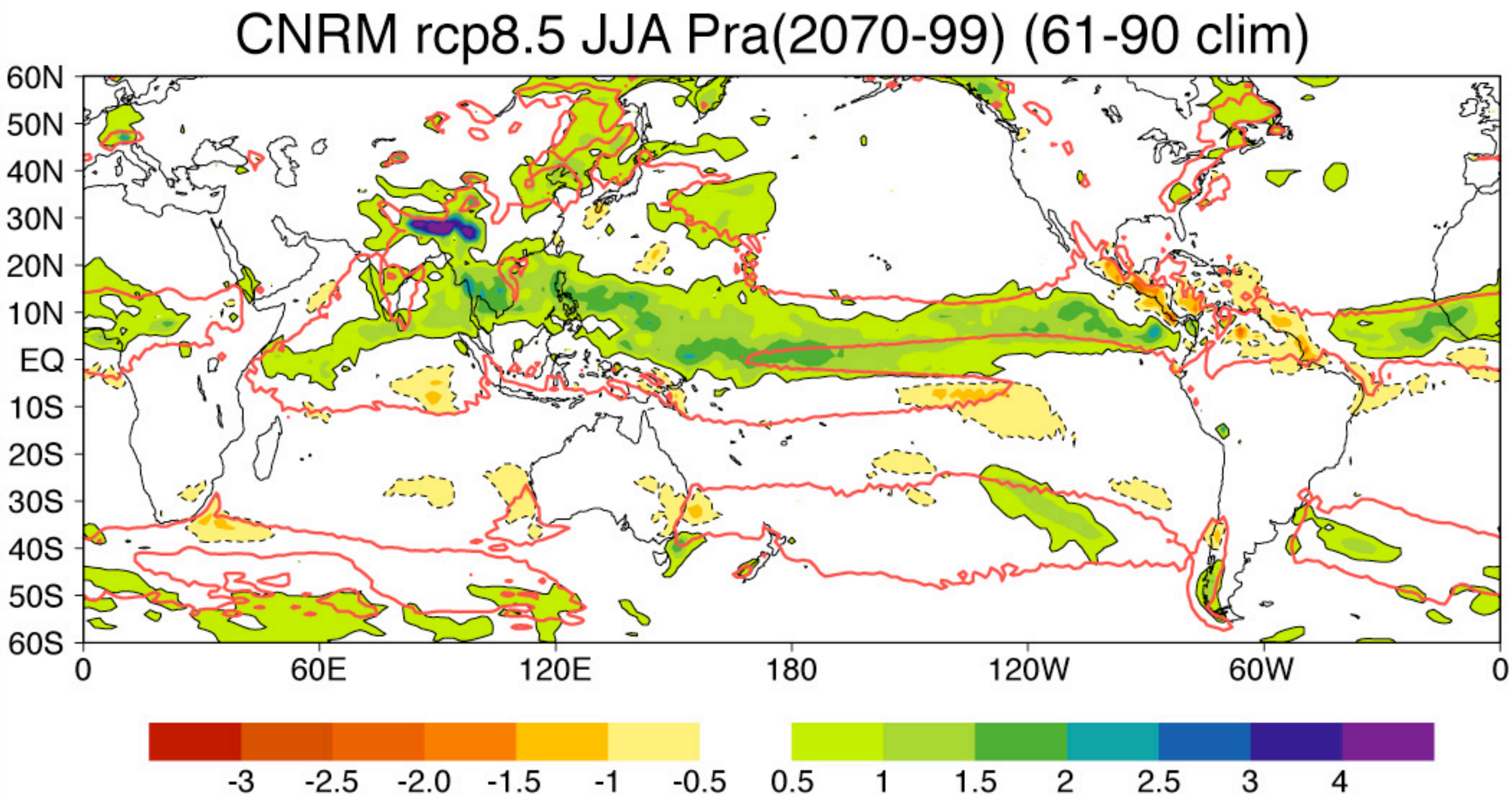


NCAR Community Climate System Model

CMIP5

CNRM-CM5

JJA Prec. Anom.

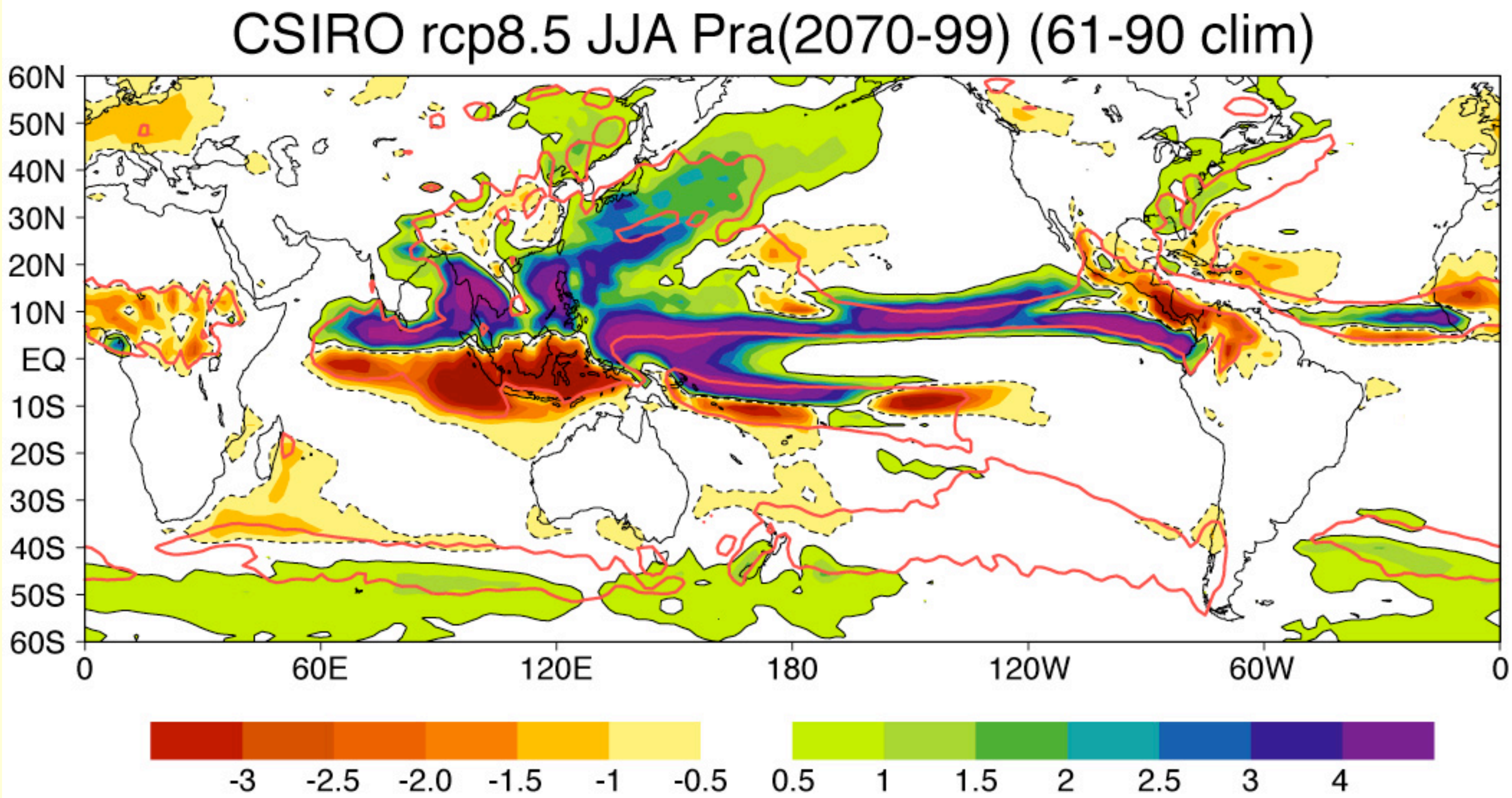


Centre National de Recherches Mereorologiques/ Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique, France.

CMIP5

CSIRO-MK3

JJA Prec. Anom.

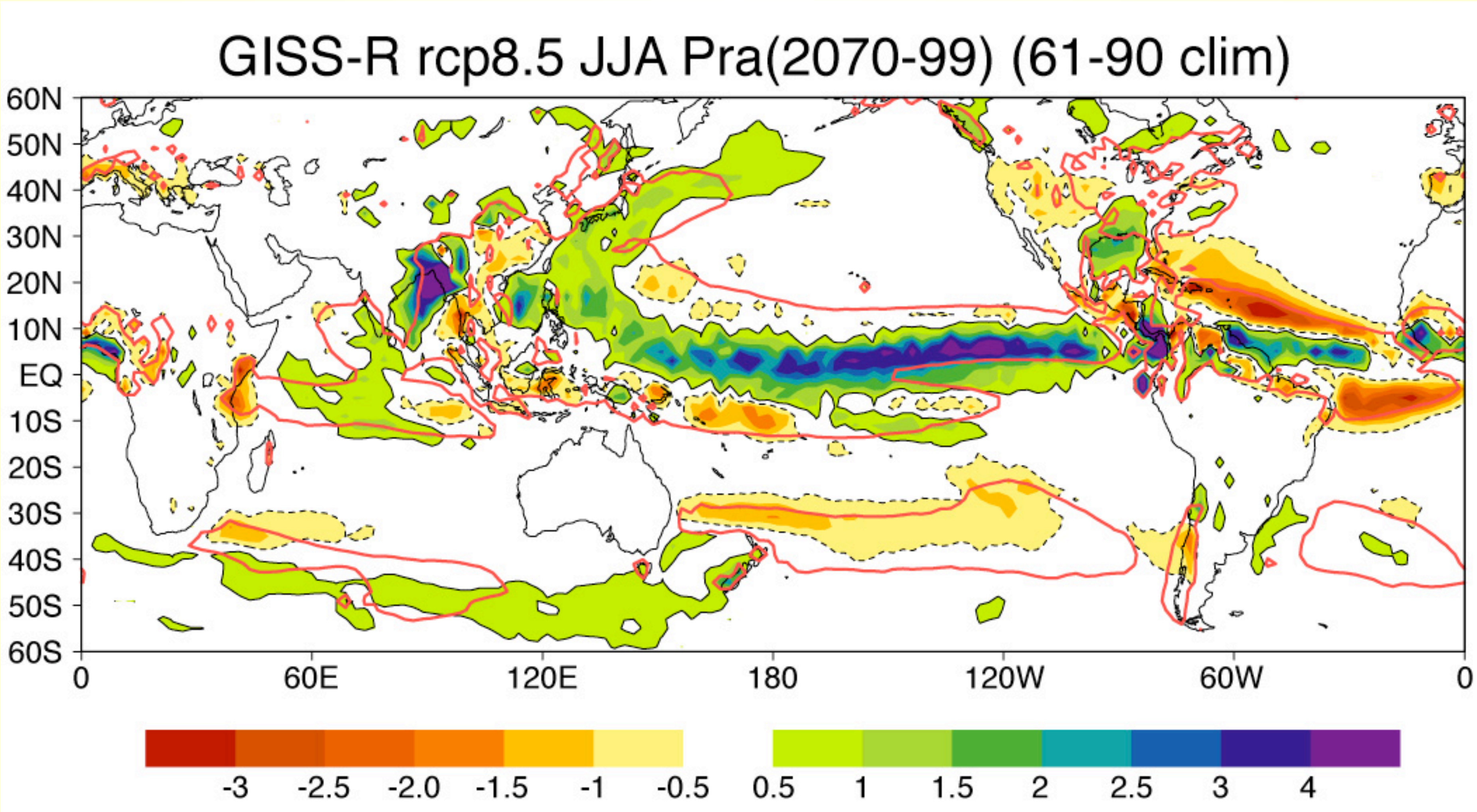


Commonwealth Scientific and Industrial Research Organization, Aus.

CMIP5

GISS-E2-R

JJA Prec. Anom.

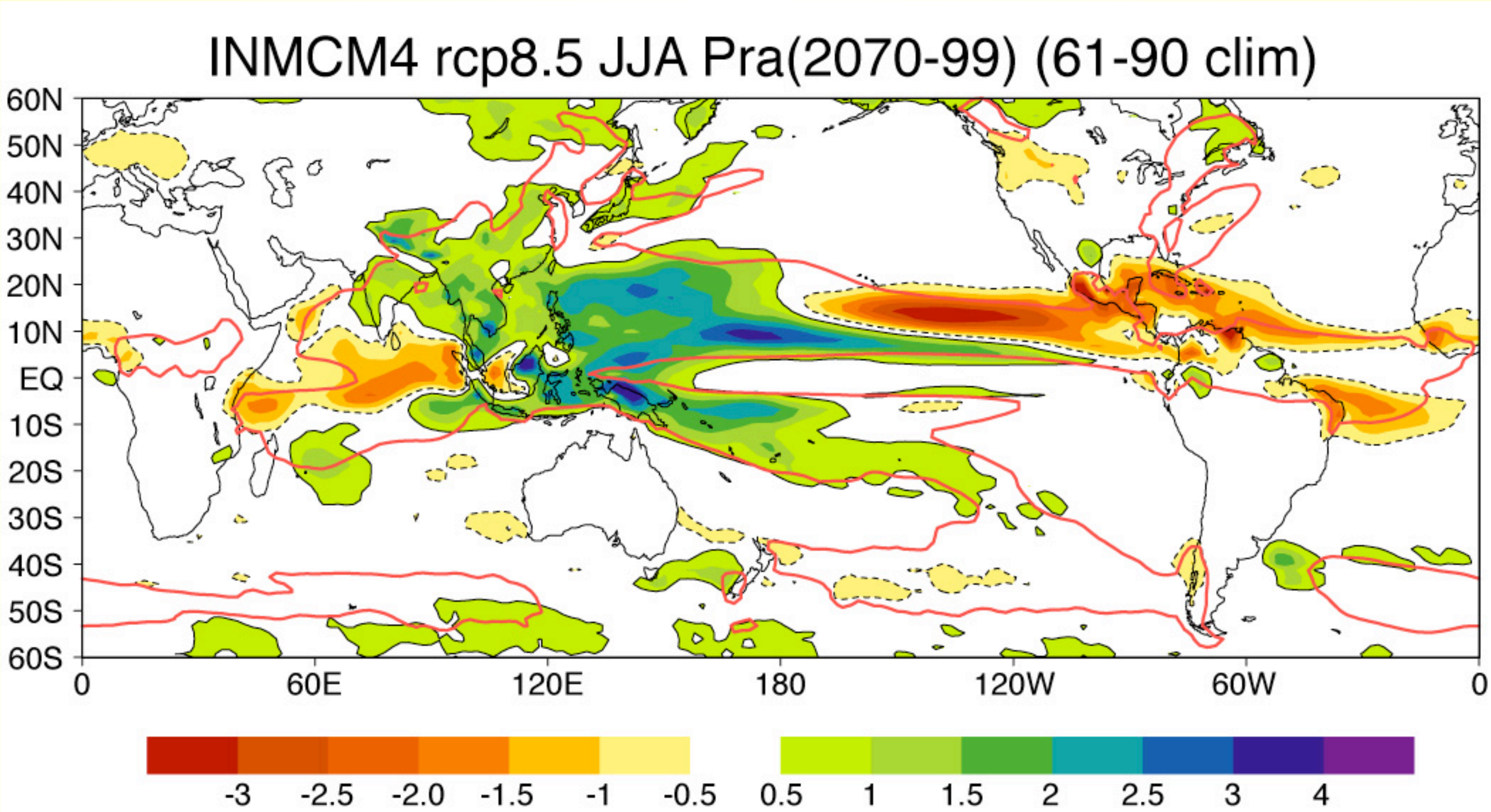


Goddard Institute for Space Studies

CMIP5

INNMCM4

JJA Prec. Anom.

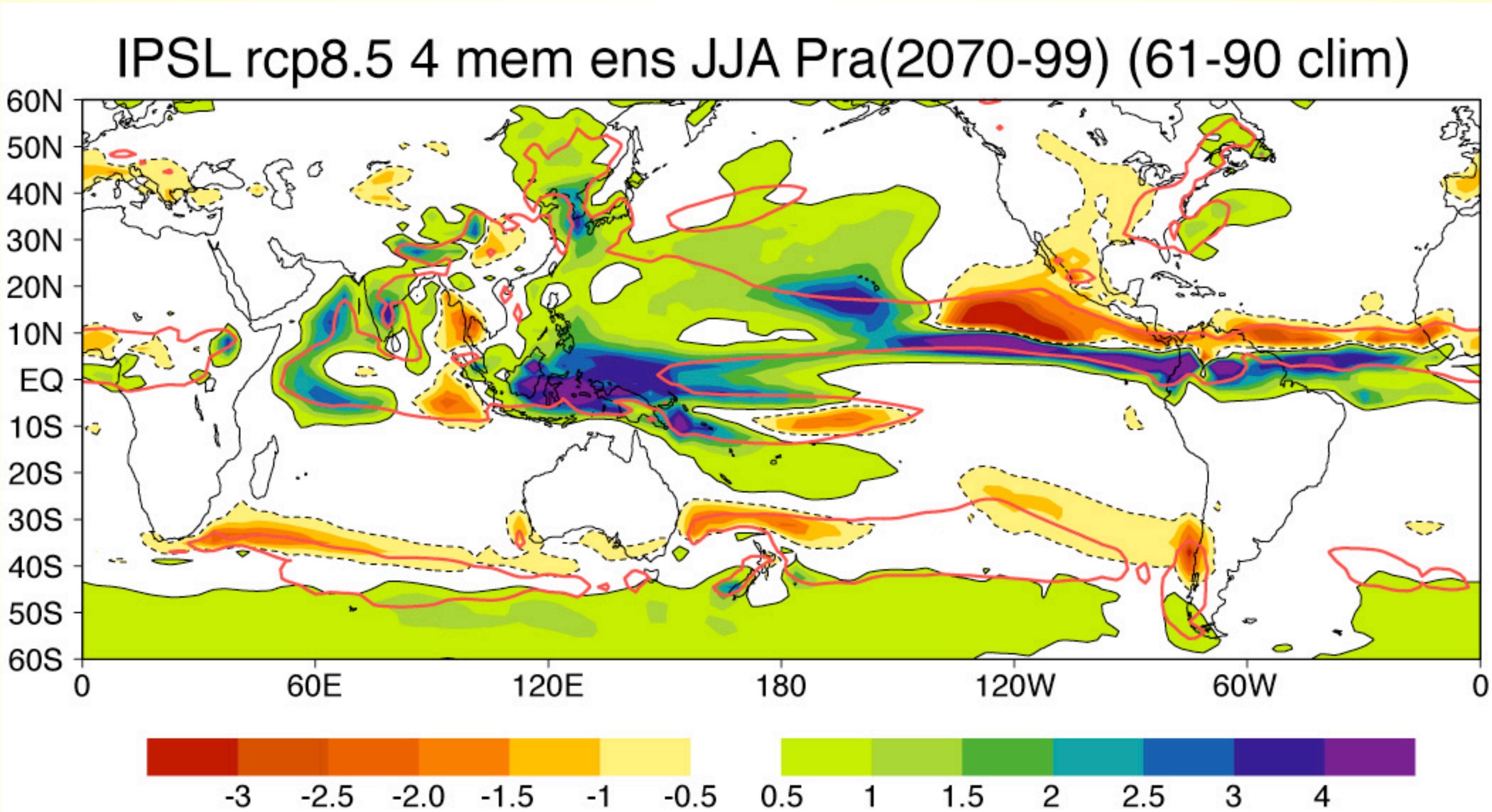


Institute for Numerical Mathematics, Russia.

CMIP5

IPSL-CM5A

JJA Prec. Anom.

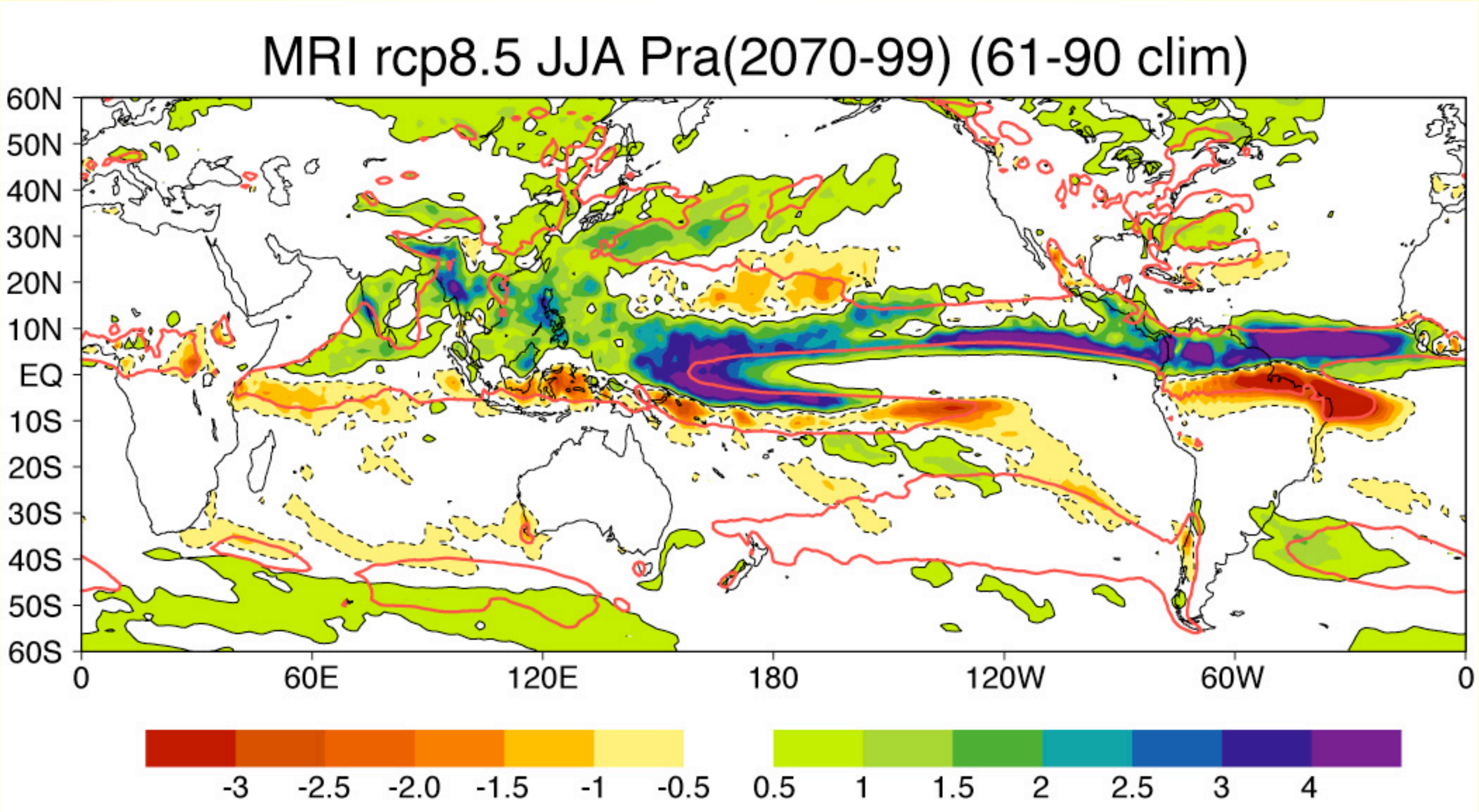


Institut Pierre Simon Laplace, France.

CMIP5

MRI-CGCM3

JJA Prec. Anom.

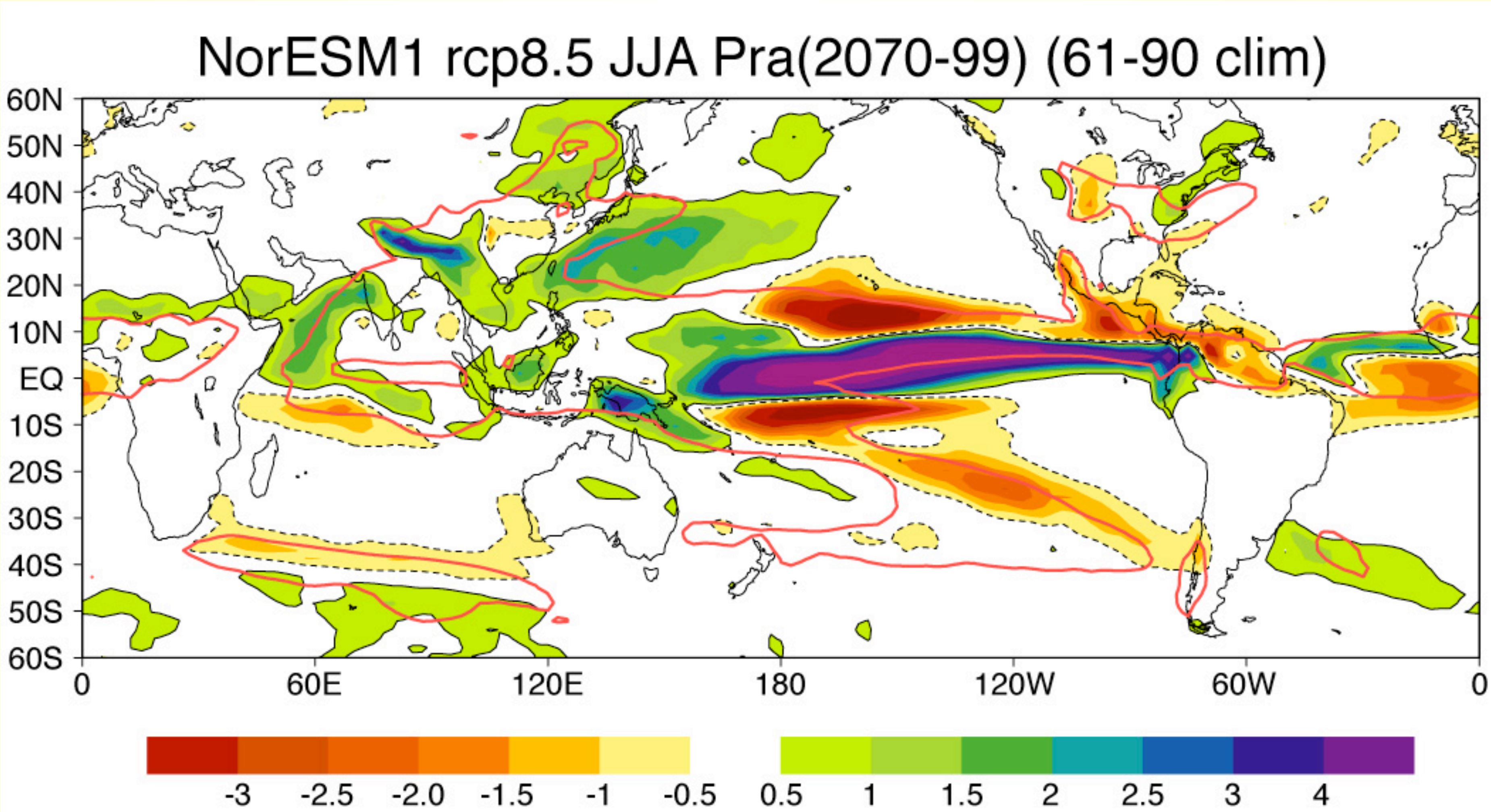


Meteorological Research Institute, Japan

CMIP5

NORESM1-M

JJA Prec. Anom.

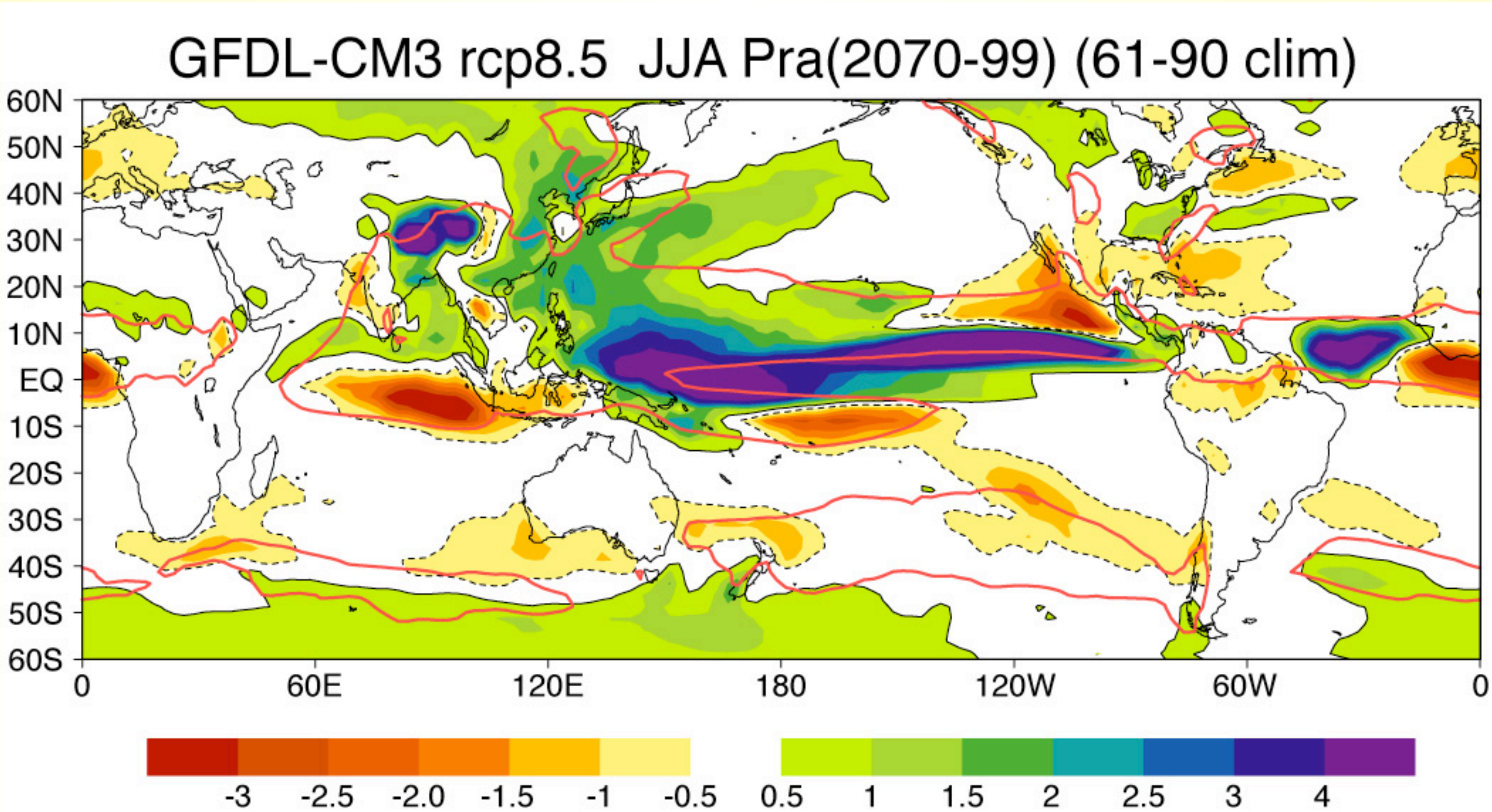


Norwegian Climate Center, Norway

CMIP5

GFDL-CM3

JJA Prec. Anom.

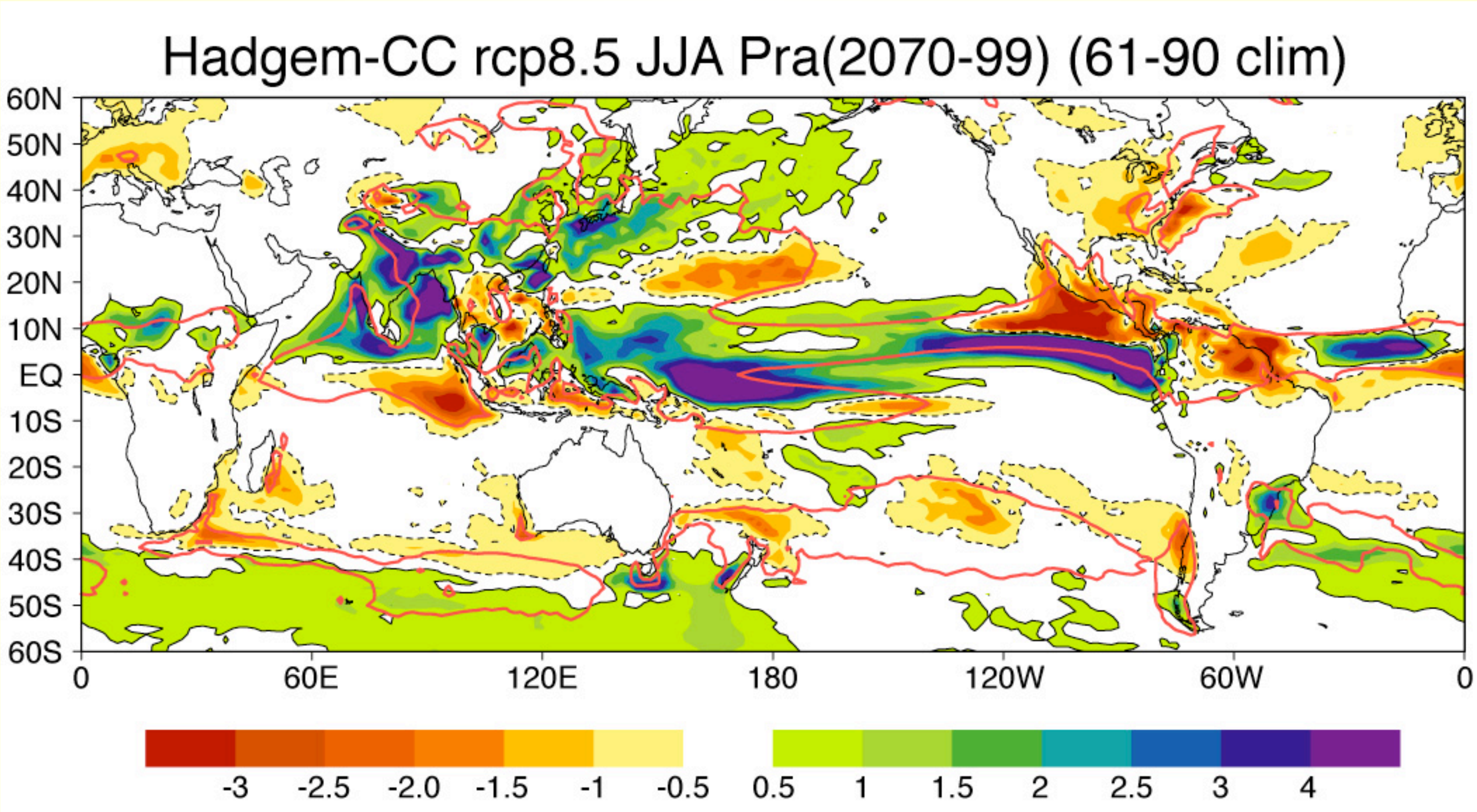


NOAA Geophysical Fluid Dynamics Laboratory

CMIP5

HADGEM-CC

JJA Prec. Anom.

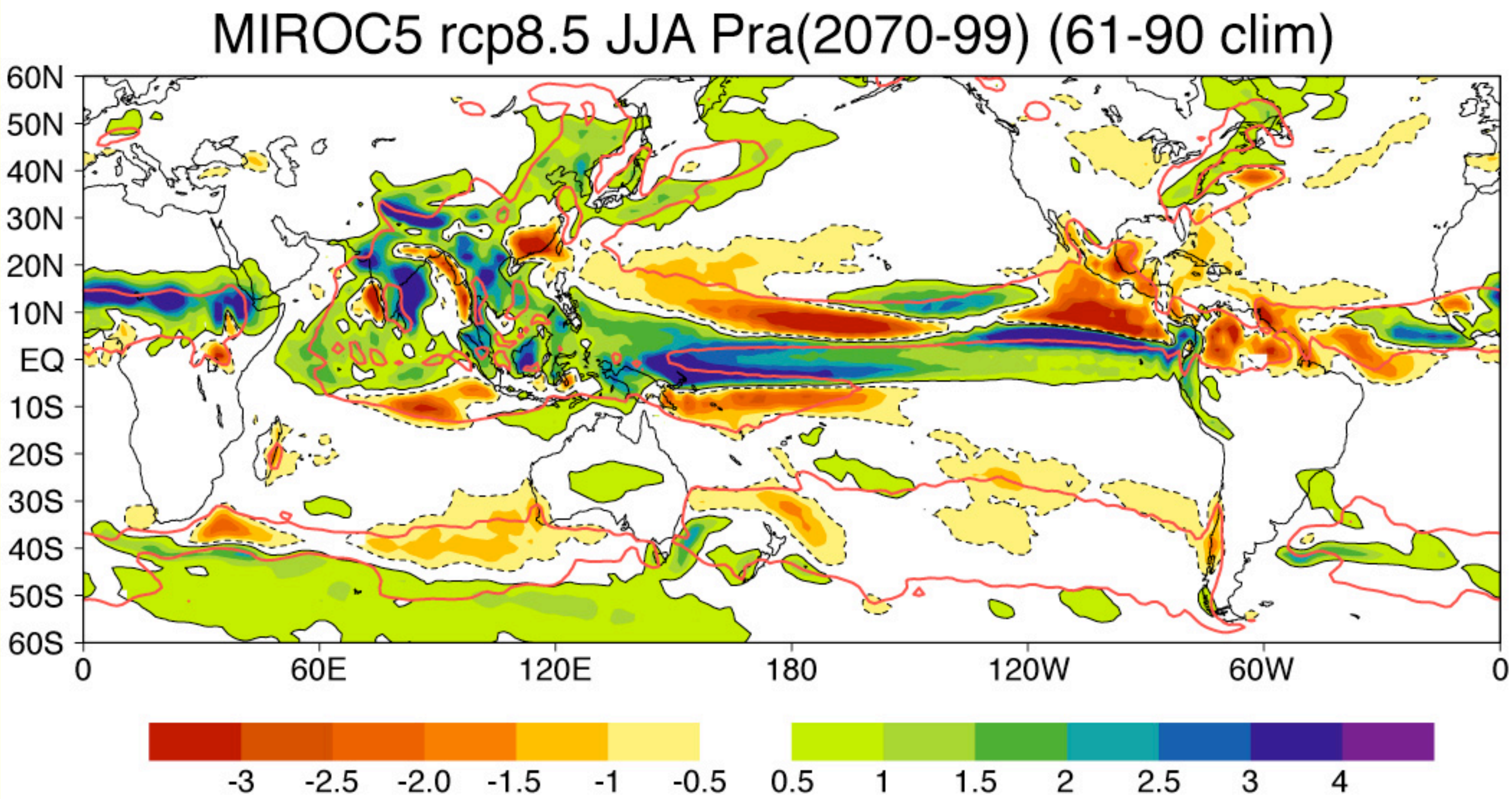


Met Office Hadley Centre, UK

CMIP5

MIROC5

JJA Prec. Anom.

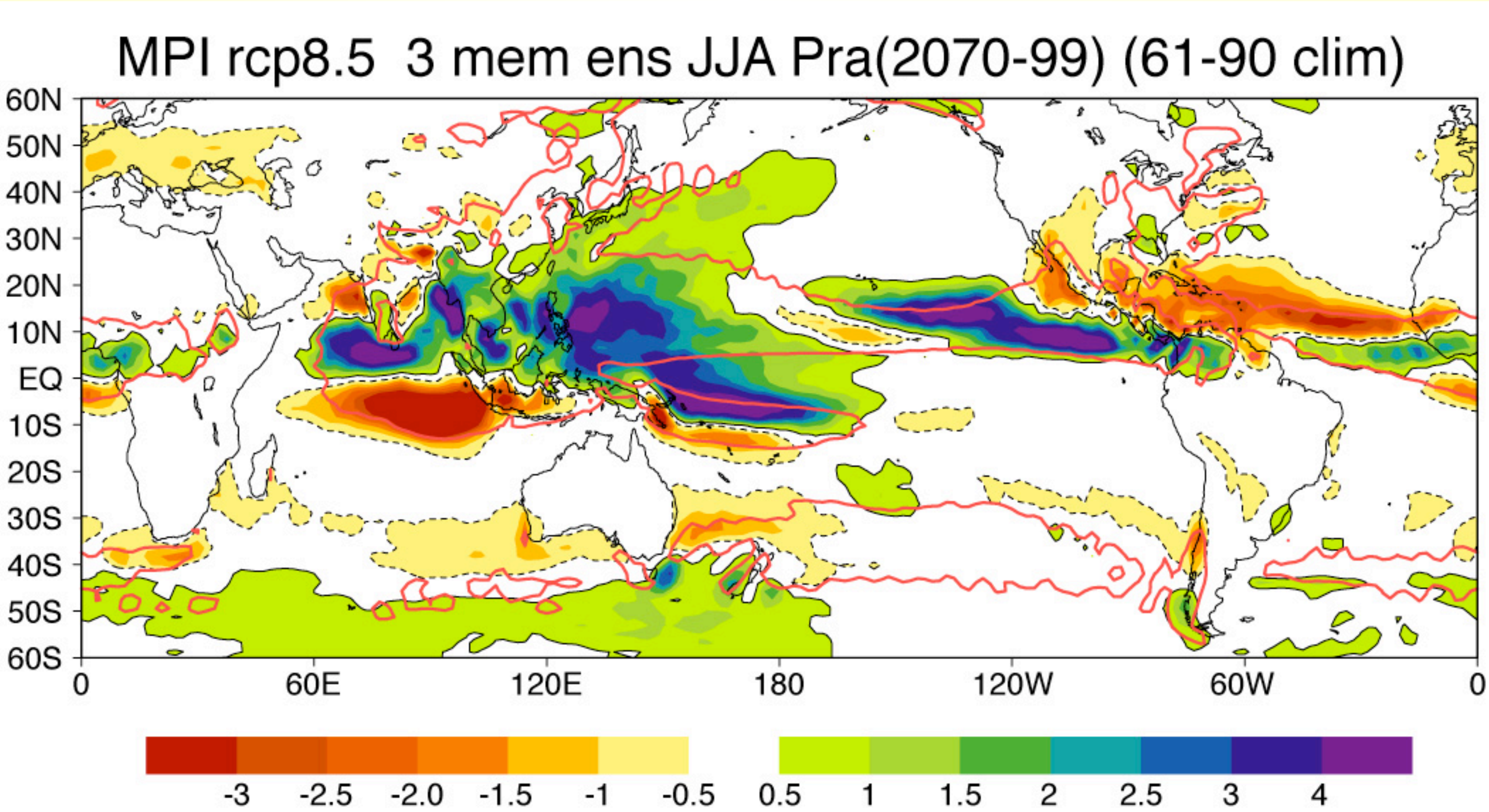


Model for Interdisciplinary Research on Climate - AOEI, NIES, JAMSTEC, Japan

CMIP5

MPI-ESM-LR

JJA Prec. Anom.

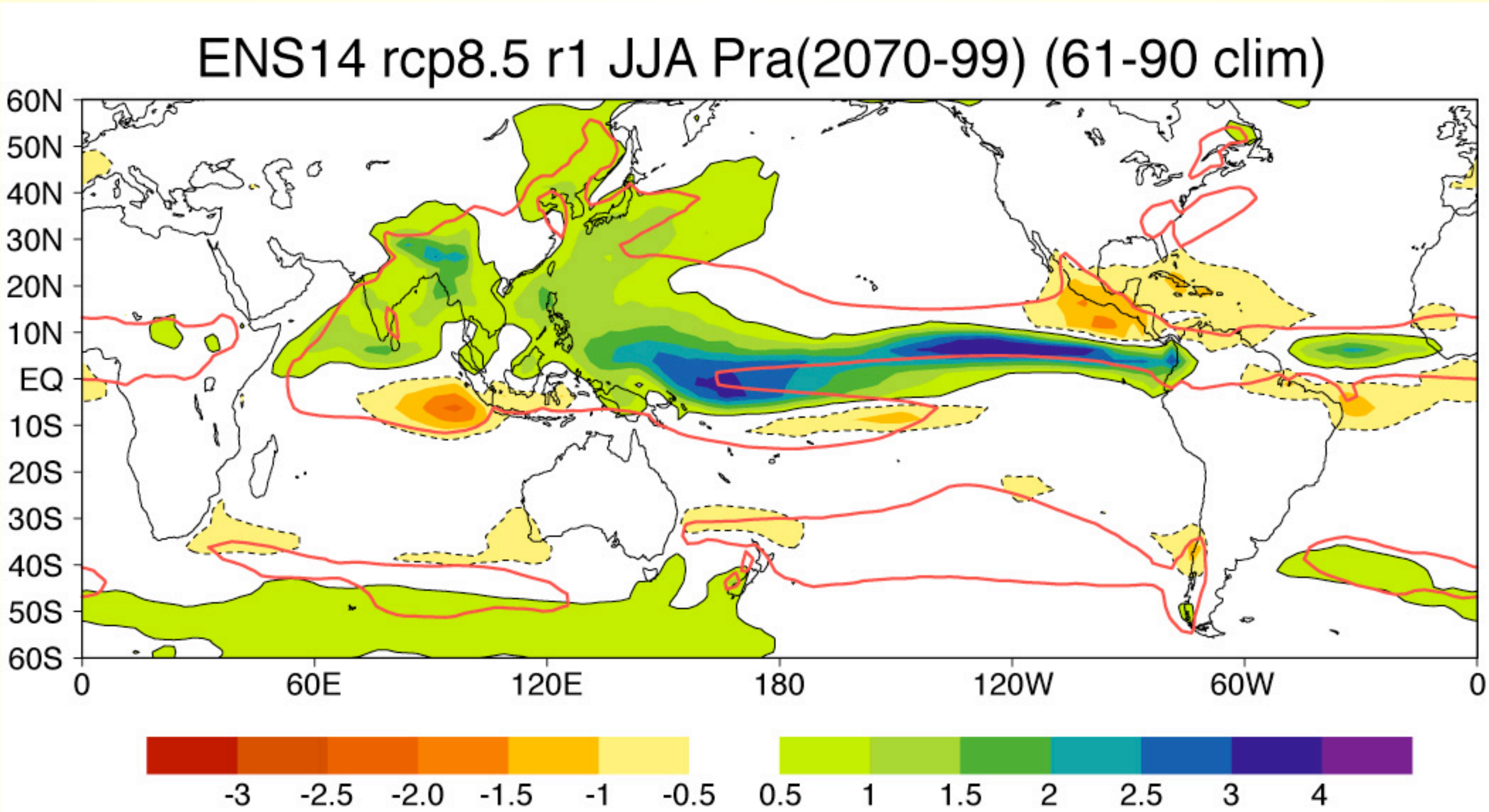


Max Planck Institute for Meteorology, Germany

CMIP5

Multi-model Ensemble Mean (14 model)

JJA Prec. Anom.

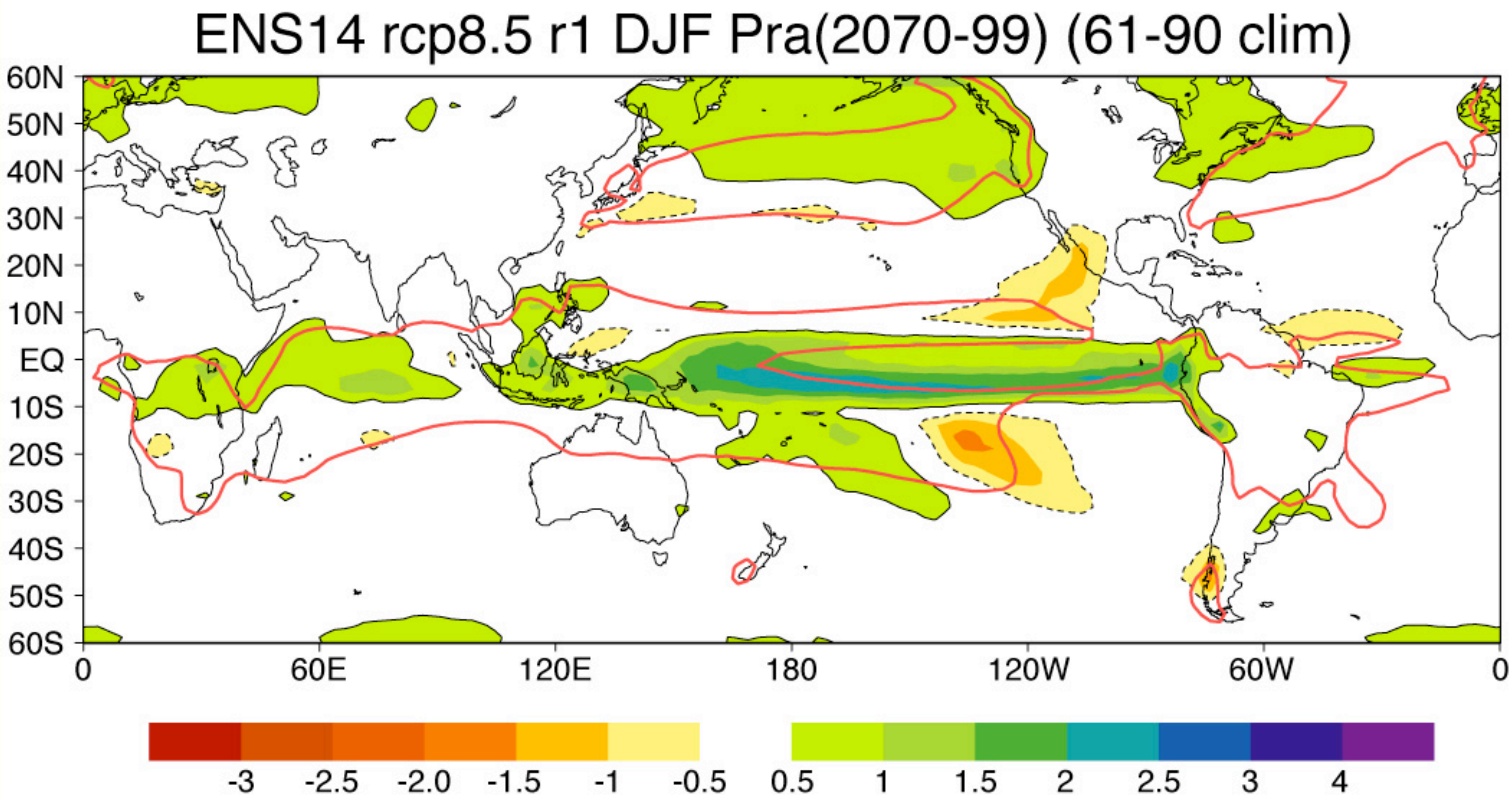


Max Planck Institute for Meteorology, Germany

CMIP5

Multi-model Ensemble Mean (14 model)

DJF Prec. Anom.



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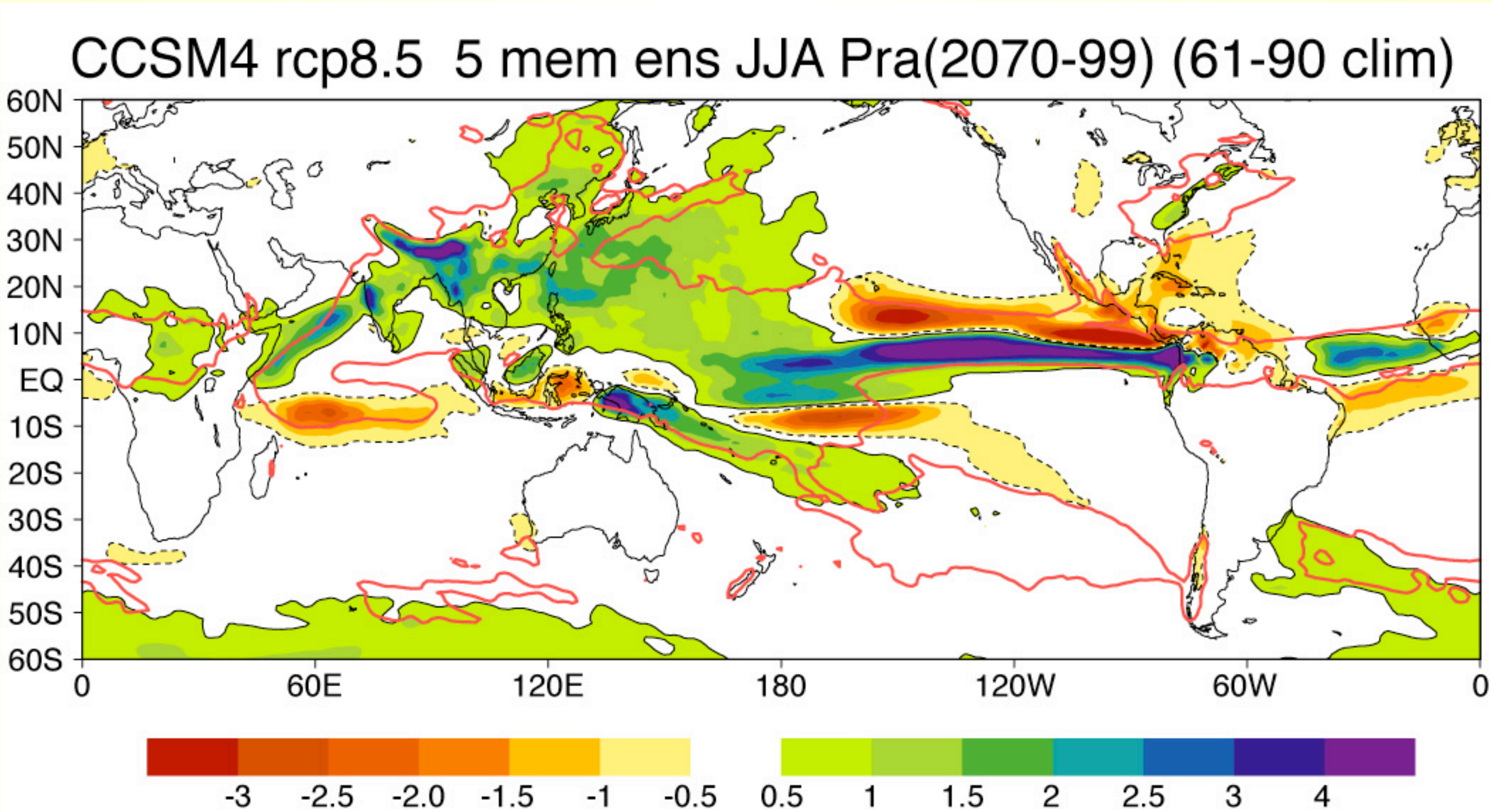
CMIP5

CCSM4 5 member ensemble

JJA Prec. Anom.



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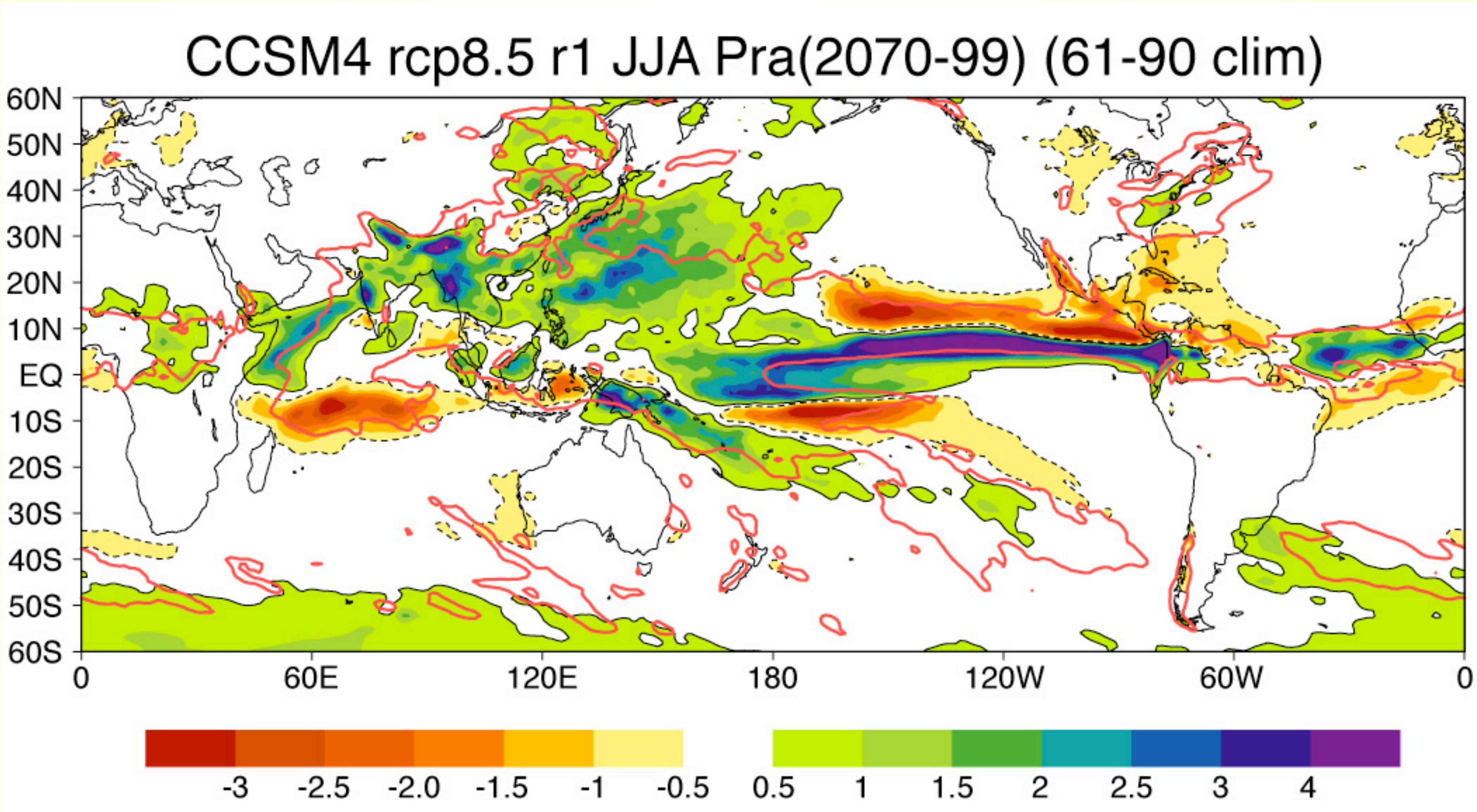
CMIP5

CCSM4 r1

JJA Prec. Anom.

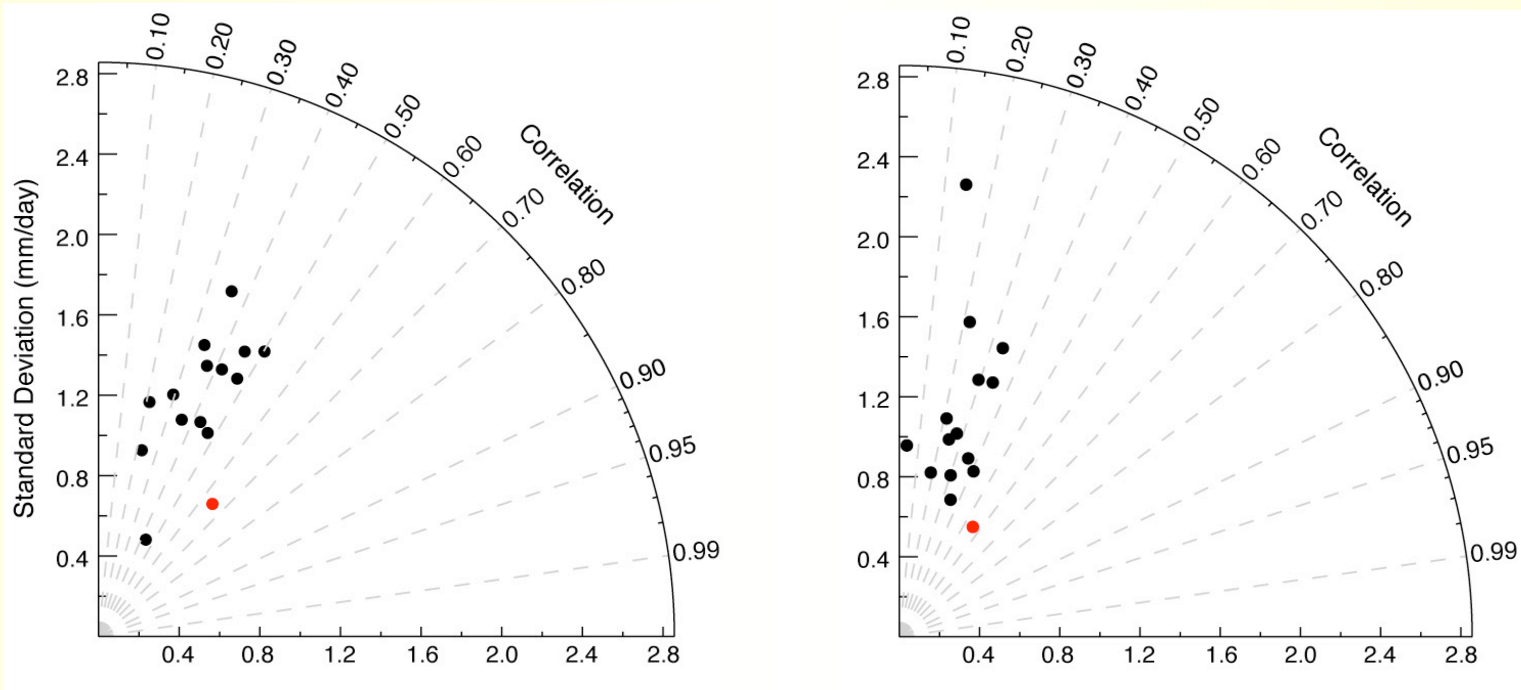


NCAR Community Climate System Model

CMIP5

CMIP5 Intermodel disagreement on regional precip. change

Taylor plots of the precipitation change pattern for RCP8.5 2081-2100*.
Angular direction: Average of the spatial correlation of a given model precipitation change pattern to each of the other members of the ensemble.
Radial direction RMS amplitude (for the tropics, 25S-25N).
Amplitude of ensemble mean & correlation to each member shown in red.



Multi-model ensemble mean substantially lower amplitude than the mean of each model's amplitude

Analysis: B. Langenbrunner; *relative to 1961-1990; for tropics

CMIP5

Mechanisms & constraints from moisture/energy budgets

Moisture budget for perturbations

$$P' \;=\; -\langle q' \nabla \cdot \boxtimes v \rangle - \langle \boxtimes v \cdot \nabla q' \rangle - \langle \boxtimes q \, \nabla \cdot v' \rangle \;+ E' + \ldots$$

Precip — Rich-get-Richer — Upped-ante — Convergence Fb — Evap

0. At global scale neglect transport $P' \approx E'$, set by surface energy balance ⇒ small increase (e.g., Allen & Ingram 2002,…)

0.1 Warmer temperatures & Clausius-Clapeyron ⇒ q' tends to increase [Interplay with convection and dynamics ⇒ $\nabla q'$]

$\langle\ \rangle$ = vertical average; q' specific humidity; $'$ denotes changes

–

Mechanisms & constraints from moisture/energy budgets

Moisture budget for perturbations

$$P' \quad = \quad -\langle q' \nabla \cdot \square\, v \rangle - \langle \square\, v \cdot \nabla q' \rangle - \langle \square\, q \nabla \cdot v' \rangle \quad + E' + \ldots$$

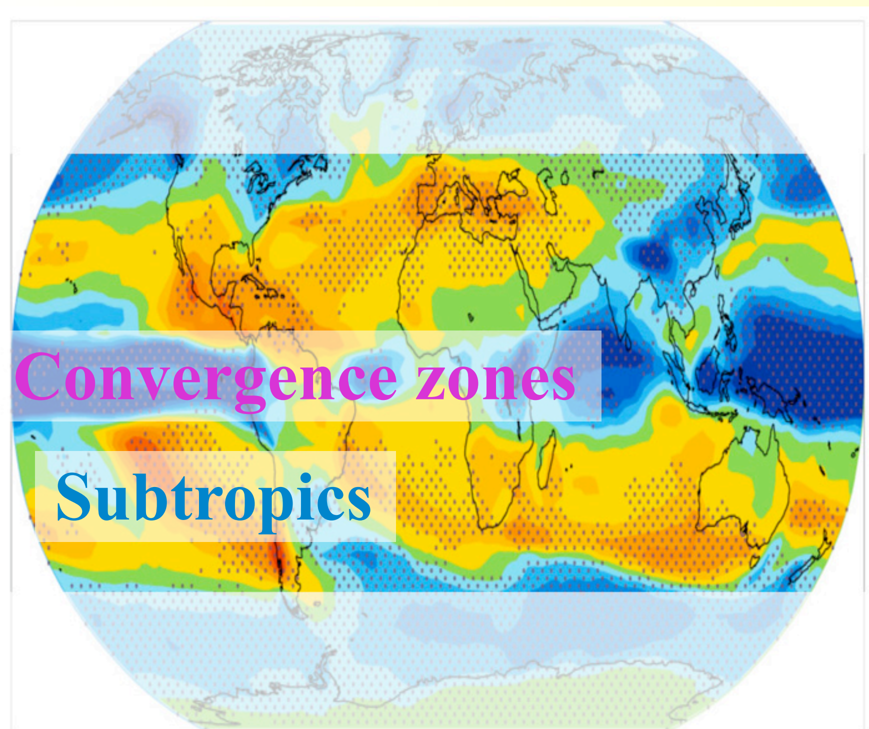
Precip | Rich-get-Richer | Upped-ante | Convergence Fb | Evap

"Rich-get-richer mechanism*"

Subtropics: low-level divergence

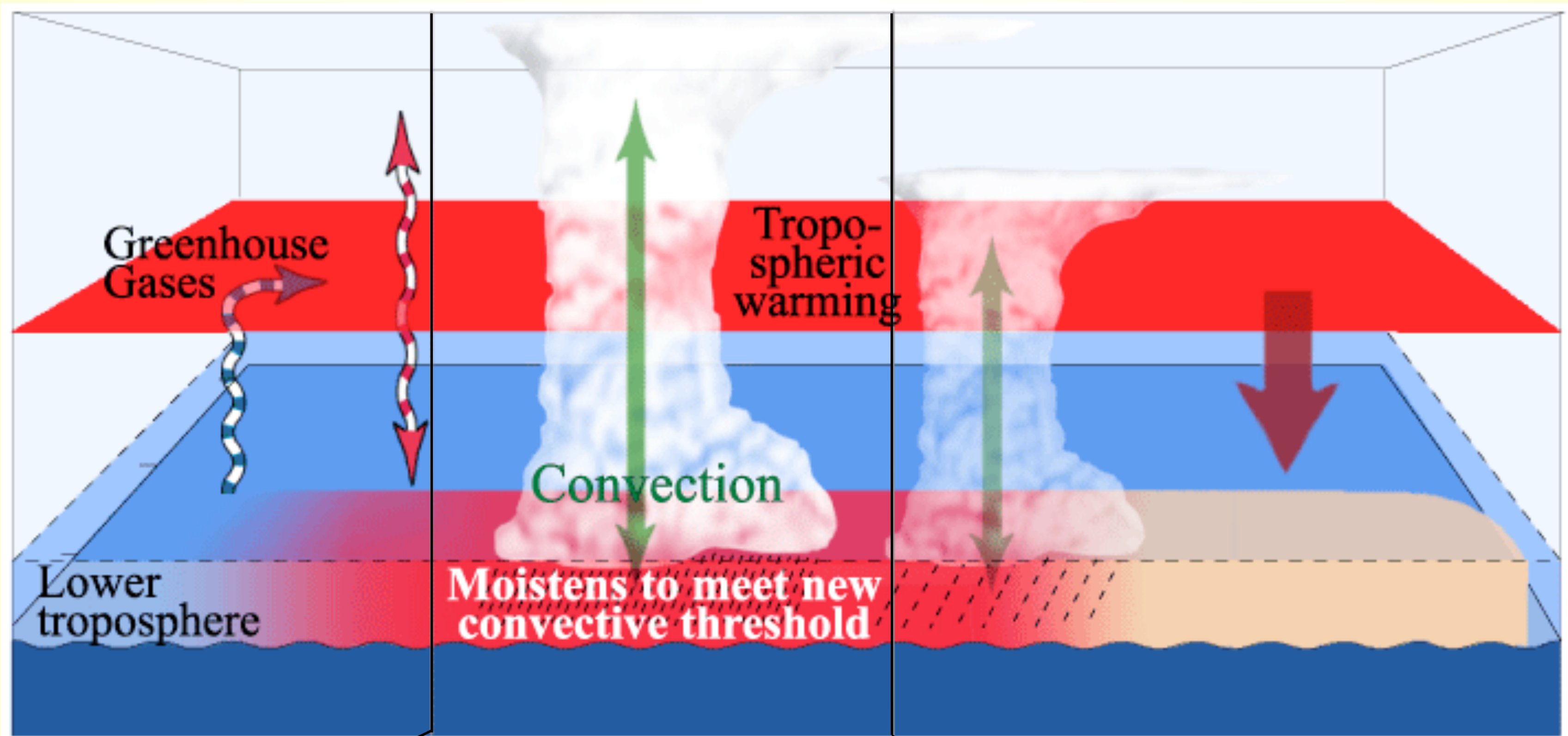
so q' increase ⇒ Precip decrease

Convergence zones: vice versa



*(a.k.a. thermodynamic component):

The Rich-get-richer or wet-get-wetter mechanism



Center of convergence zone: incr. moisture convergence ⇒ incr. precip

Descent region: incr. moisture divergence; less often meets conv. threshold

Chou & Neelin, 2004, Held & Soden 2006, Chou et al 2008

Mechanisms & constraints from moisture/energy budgets

Moisture budget for perturbations

$$P' = -\langle q' \nabla\cdot \bar{v} \rangle - \langle \bar{v} \cdot \nabla q' \rangle - \langle \bar{q}\, \nabla\cdot v' \rangle + E' + \ldots$$

Precip   Rich-get-Richer   Upped-ante   Convergence Fb   Evap

[Regional differences]

a. energy budget & convective threshold feedbacks, esp. $q\nabla\cdot v'$

$\& \; v \cdot \nabla q'$ in particular regions (Chou & Neelin 2004)

b. Neglect $\nabla\cdot v'$, (Held and Soden 2006; plausible for large scales)

$\nabla\cdot v'$ large at regional scales! $\Rightarrow$ a major factor in uncertainty

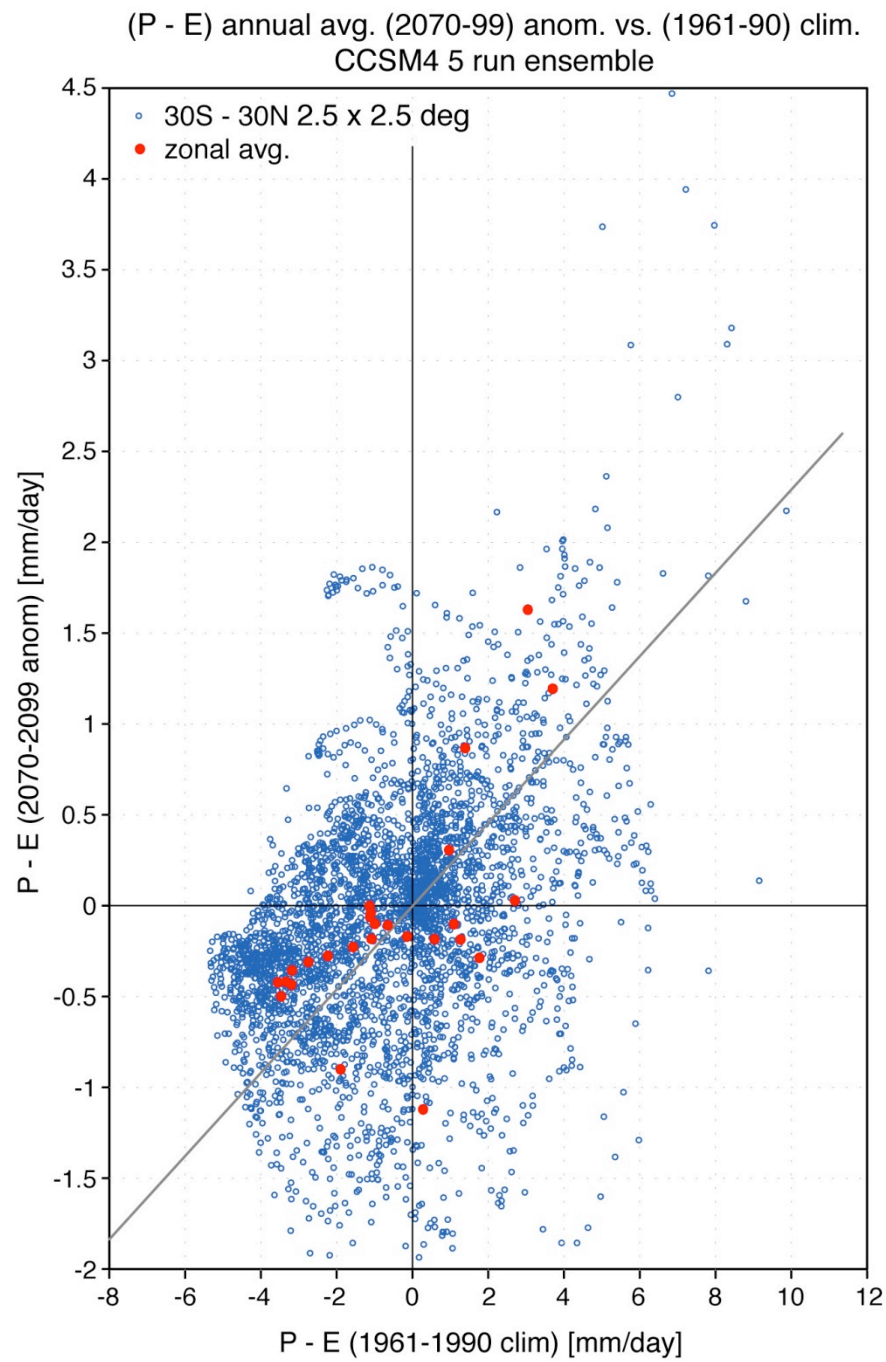
Averaging over larger scales, e.g., latitude bands; or multi-model ensemble can reduce visibility of convergence feedback terms---

but simplest “wet-get-wetter” statement is poor local predictor

“Rich-get-richer” or “wet-get-wetter” mechanism---caution on simplest version

Ann. avg. precip minus evaporation (P-E) change for RCP8.5 2070-2099 relative to 1961-90
vs. climatology of P-E (5-run ensemble avgs from CCSM4).

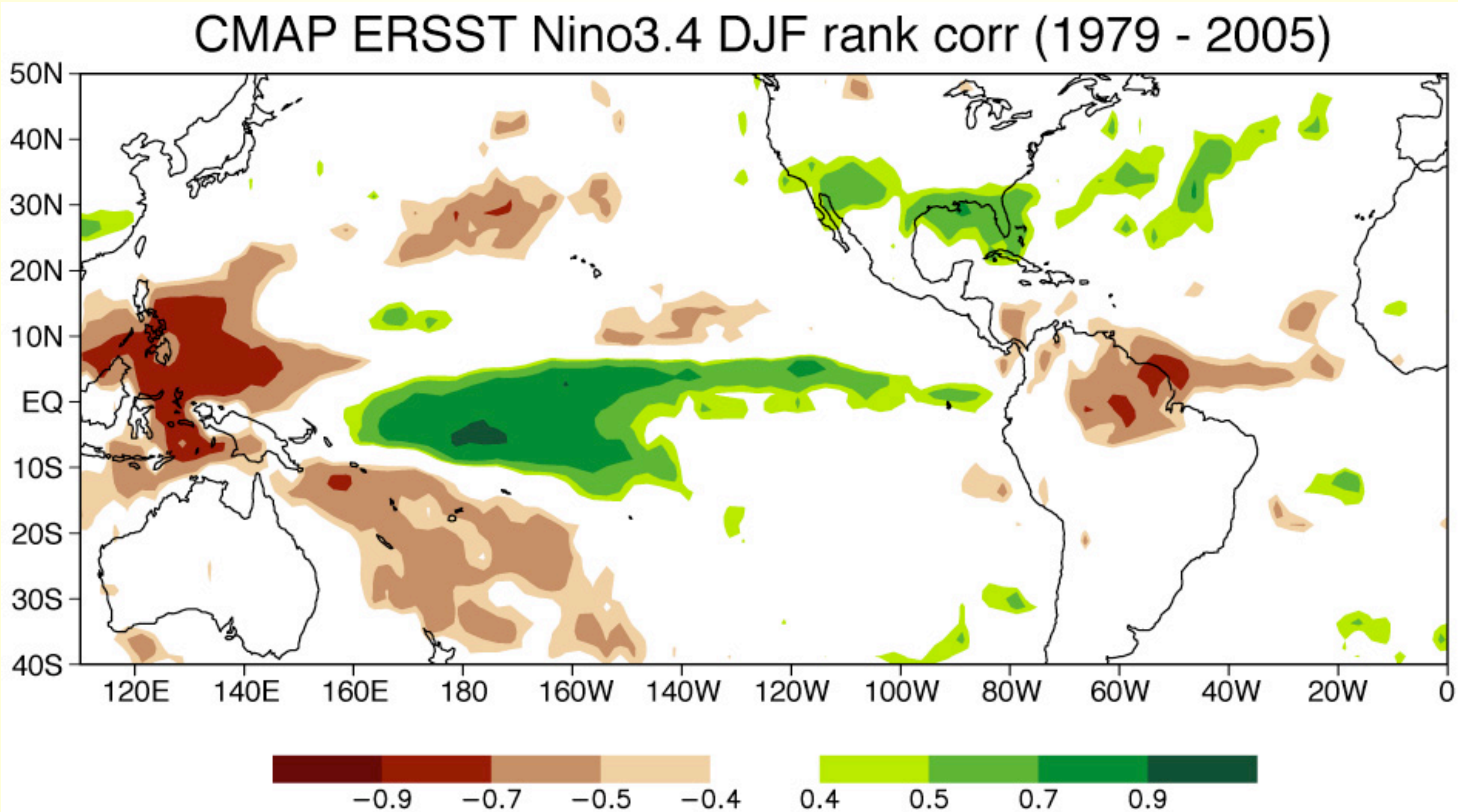
Red dots: zonal averages.
Blue dots: 2.5 ° boxes.
Reference line: climatological P-E fractional increase of 7% x tropical avg. temperature change.



How do the models do for El Niño/Southern Oscillation (ENSO)?

- A phenomenon we can observe
- Important for interannual prediction
- Satellite precipitation retrievals since 1979
- Atmospheric model component runs with observed sea surface temperature (SST) or ocean atmosphere models
- Rank correlation/Regression/compositing of events based on an equatorial Eastern Pacific SST index “Nino3.4”

Observed Nino3.4 rank correlations (Dec.-Feb.)
CMAP



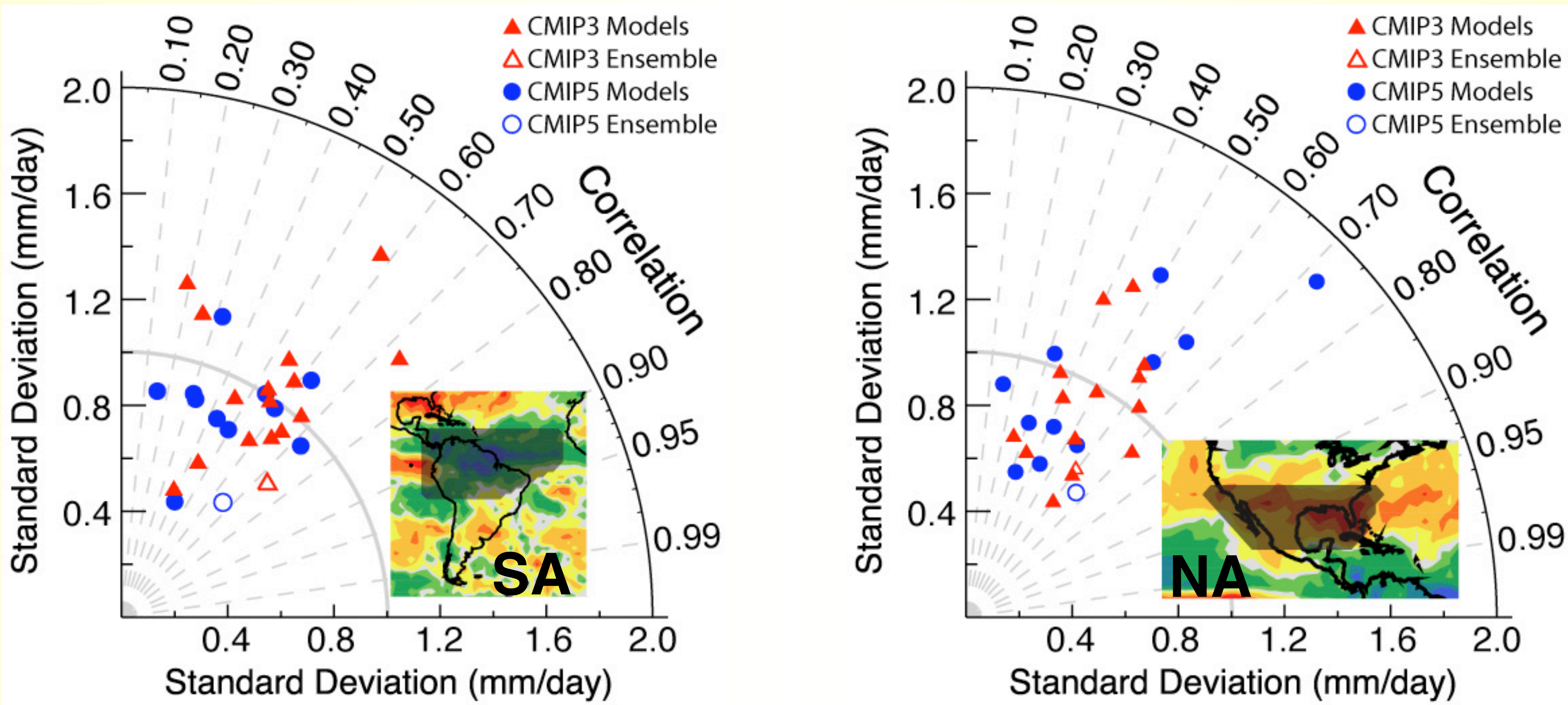
CPC Merged Analysis of Precipitation

Compare to CMIP5 atm. models with obs. SST

Analysis: B. Langenbrunner

Regional scale disagreement on ENSO teleconnections: poor model performance by some measures but some hope

Taylor plot of CMIP5 AMIP*-run ampl. & spatial correlation with observed ENSO teleconnection pattern (regression on Niño 3.4 index); unimpressive---despite observed SST!



*AMIP= Atmospheric Model Intercomparison Project style runs with observed sea surface temperatures

Langenbrunner et al., 2012

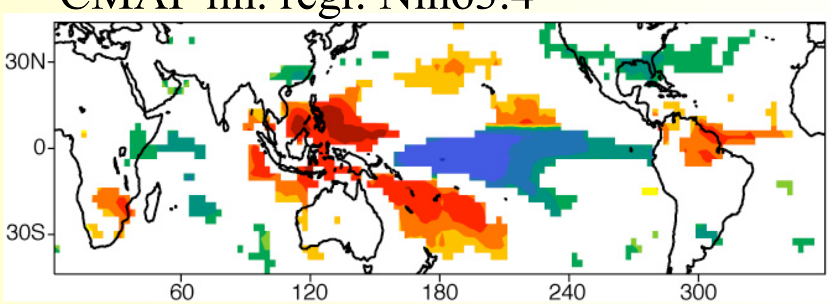
CMIP5

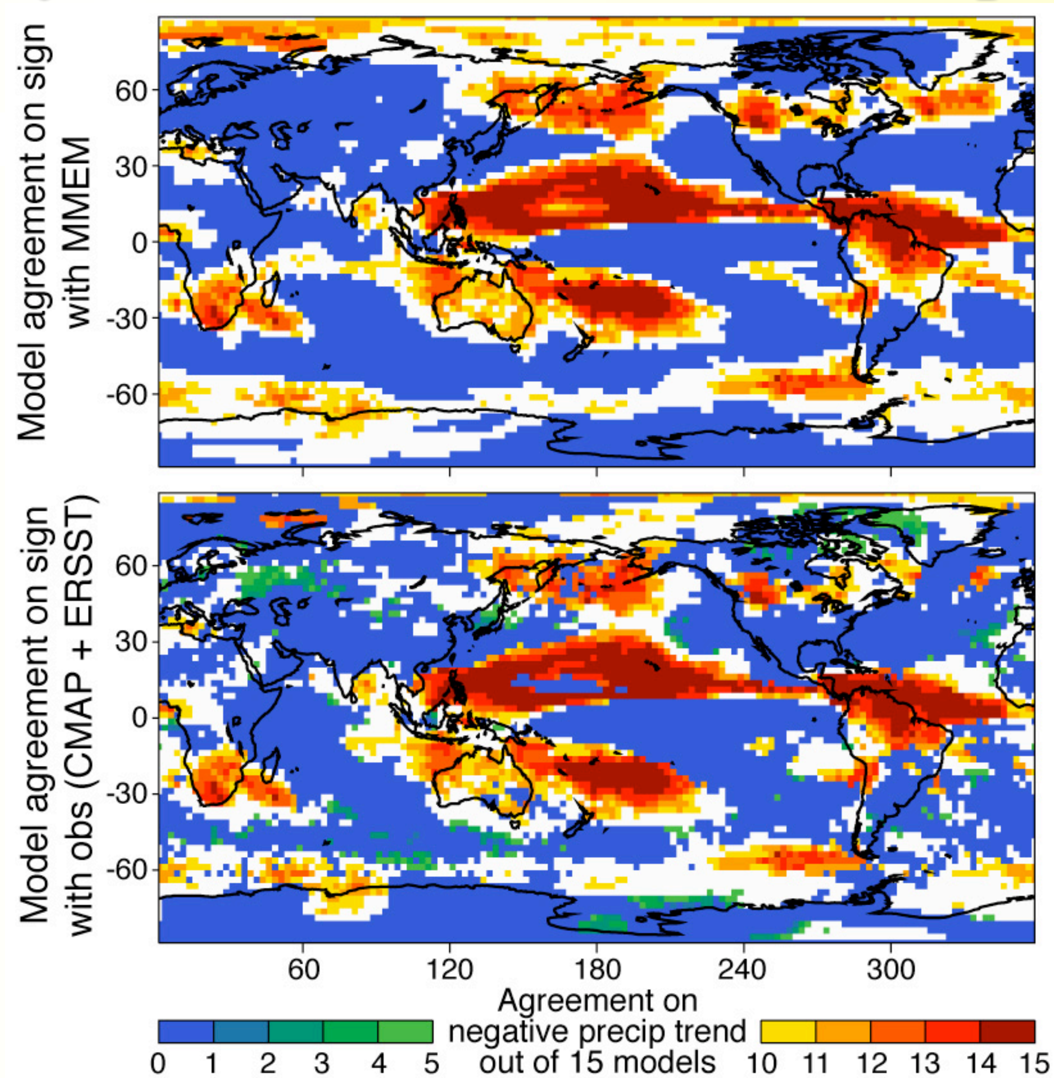
Regional scale disagreement on ENSO teleconnections: poor model performance by some measures but some hope

Number of models that agree on drying signal with:
Top: multi-model ensemble mean
Bottom : observed

Top does reasonable job predicting agreement with observed
(even where regr. not at 95%)

CMAP lin. regr. Nino3.4





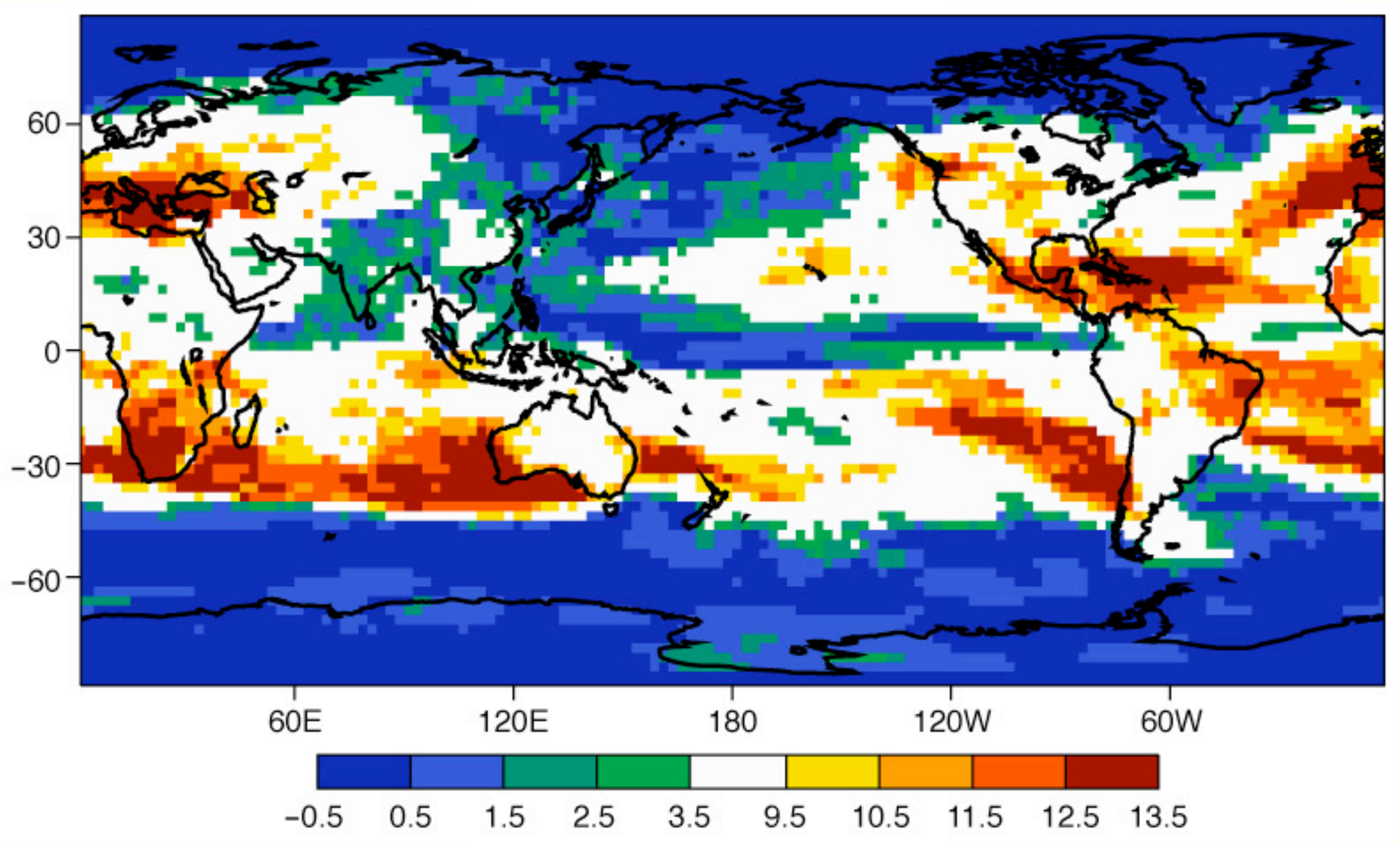
High numbers = agreement on negative precip change; Low numbers = agreement on positive precip change

Langenbrunner et al., 2012

CMIP5

Statements of regions where models agree on the sign of the trend: weak? ENSO case supports usefulness.

CMIP5 Number of models with negative JJA precipitation change for RCP8.5 2081-2100 (relative to 1961-1990). Similar to CMIP3.



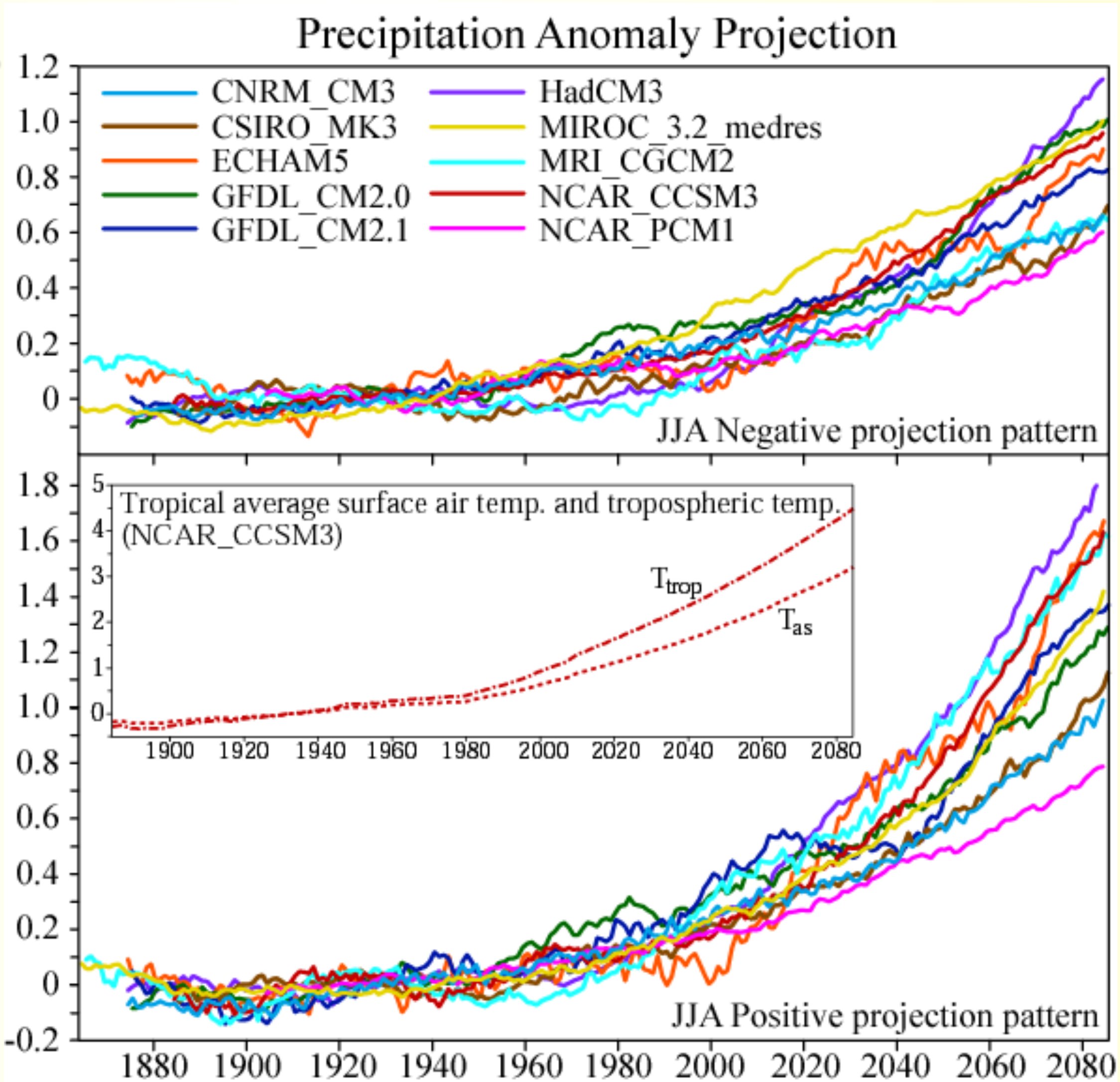
CMIP5

Analysis: B. Langenbrunner ; Small numbers indicate agreement on positive precipitation change

Despite disagreement on precise location, seek measures of extent of precip change that are more predictable

E.g., amplitude of precip incr/decr pattern shows better agreement

Projection of Jun-Aug (30yr running mean) precip pattern onto normalized positive & negative late-century pattern for each model

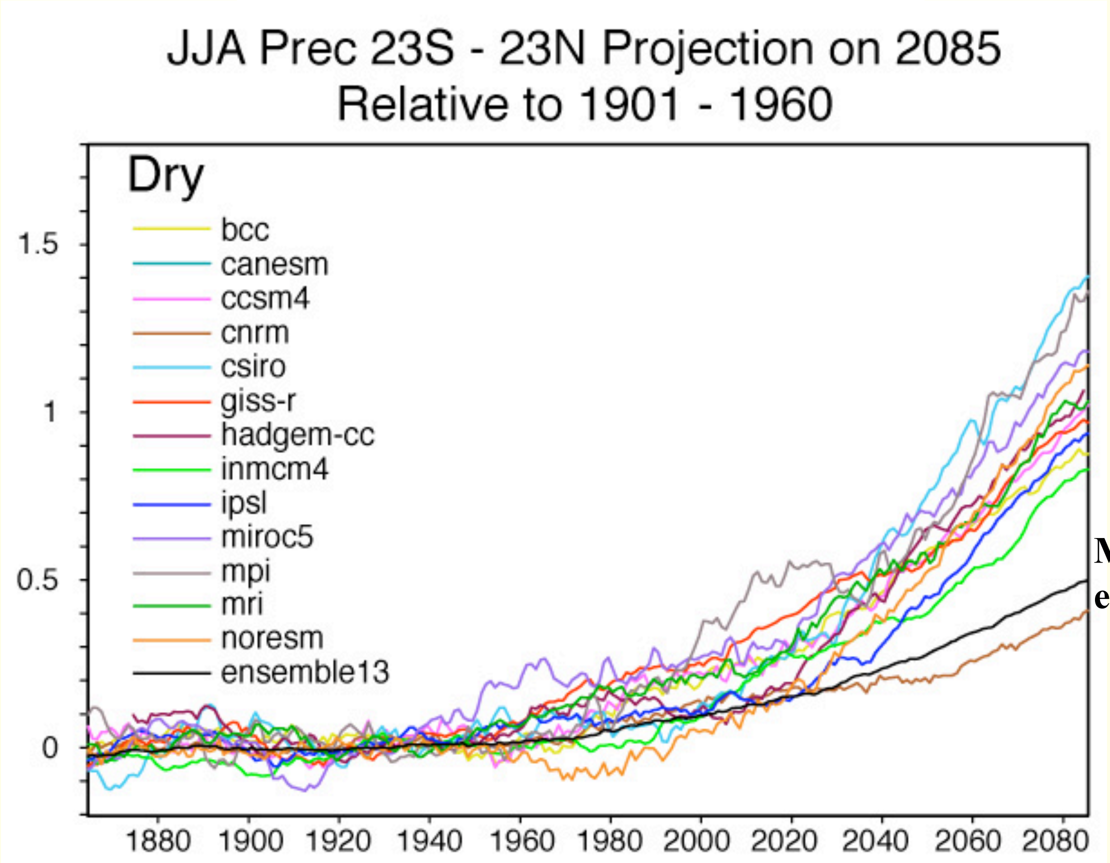


Neelin, Munnich, Su, Meyerson and Holloway , 2006, *PNAS*

CMIP3

Integrated measures of regional precip. change

Projection of the precipitation change pattern (relative to 1961-1990) on end of century negative precipitation change pattern for each model



Multi-model ensemble mean

Multi-model ensemble mean substantially lower amplitude than the mean of each model's amplitude

CMIP5

Analysis: J Meyerson; 30-year running mean shown; for CMIP3 see Neelin et al. 2006, *PNAS*

What is being done across the field?

- Higher-resolution models… (no guarantee)
- Regional models (boundary conditions from global models)
- Multimodel ensemble means and general (vs. regional) statements
- Large satellite data sets, field campaigns, monitoring at Atmospheric Radiation Measurement sites….
- Need to digest in ways that better constrain parameterizations* of moist convection at short time scales
- Understanding of parameter sensitivity/uncertainty quantification; practical means of optimizing models with available data
- Alternatives to point by point multi-model ensemble mean

*Parameterization: representation of bulk effects of small-scale phenomenon as a function of grid-scale variables

Reduction of model uncertainty on precipitation change over large regions: slow

- Work by Cloud, Convection, Precipitation and Radiation community to find new constraints for climate model parameterizations remains urgent

- One target: The onset of strong convection; Observational statistics versus model

Background: Departures from convective quasi equilibrium (QE) and stochastic parameterization

- QE: Above onset threshold, convection increases rapidly to keep system close to onset (assumed) Arakawa & Schubert 1974
- But: prototype many-element systems suggest interesting properties (power law size distns,…) near such a transition
- ensemble size of deep convective elements in O(200km)^2 grid box is not large: Expect variance about ensemble mean
- stochastic parameterization [Yu & N 1994; Buizza et al 1999; Lin and Neelin 2000, '02,'03; Majda et al (1999 PNAS, 2003 JAS); Majda and Khouider (2002 PNAS), Khouider et al. (2003 PNAS), …., Craig and Cohen 2006; Teixeira et al 2007, Tompkins & Berner 2009, Mueller et al 2009, Bengtsson-Sedlar 2012]
- Or super-parameterization (embedded cloud model for small fraction of domain; Grabowski et al 2000; Khairoutdinov & Randall 2001; Randall et al 2003,…)

Representing small-scale convection in climate models: Convective Quasi-equilibrium closures

- Slow driving by large scales, fast removal of buoyancy by moist convection
- Above onset threshold, strong convection/precip. increase to keep system close to onset (assumed) Arakawa & Schubert 1974
- Postulate dependence of convective statistics on buoyancy-related fields – temperature *T* & moisture
- Adjustment timescale τ_c (e.g. linear pick-up of convective heating with buoyancy) makes a difference Betts & Miller 1986; Moorthi & Suarez 1992; Randall & Pan 1993; Zhang & McFarlane 1995; Emanuel 1993;
- Constrains large-scale (Emanuel et al 1994; Yu and Neelin 1994; …)
- Missing variance? Stochastic or super parameterization
- Need to characterize this transition

Departures from QE and stochastic parameterization

- **In practice, ensemble size of deep convective elements in O(200km)^2 grid box x 10minute time increment is not large**
- **Expect variance in such an avg about ensemble mean**
- **This can drive large-scale variability**
  - (even more so in presence of mesoscale organization)
- **Have to resolve convection?! (costs *10^9) or**
  - **stochastic parameterization? [Buizza et al 1999; Lin and Neelin 2000, 2002; Craig and Cohen 2006; Teixeira et al 2007]**
  - **super-parameterization?** with embedded cloud model for small fraction of domain **(Grabowski et al 2000; Khairoutdinov & Randall 2001; Randall et al 2003)**

Transition to strong, deep convection: Background

- **Precip increases with column water vapor at monthly, daily time scales (e.g., Bretherton et al 2004). What happens at shorter time scales needed for stochastic convective parameterization, and for strong precip/mesoscale events?**

- **Simple e.g. of convective closure (Betts-Miller 1996)** shown for vertical integral**:**

$$Precip = (w - w_c(T))/\tau_c \qquad \text{(if positive, zero otherwise)}$$

w vertical integrated column water vapor

w_c convective threshold, dependent on temperature T

τ_c time scale of convective adjustment

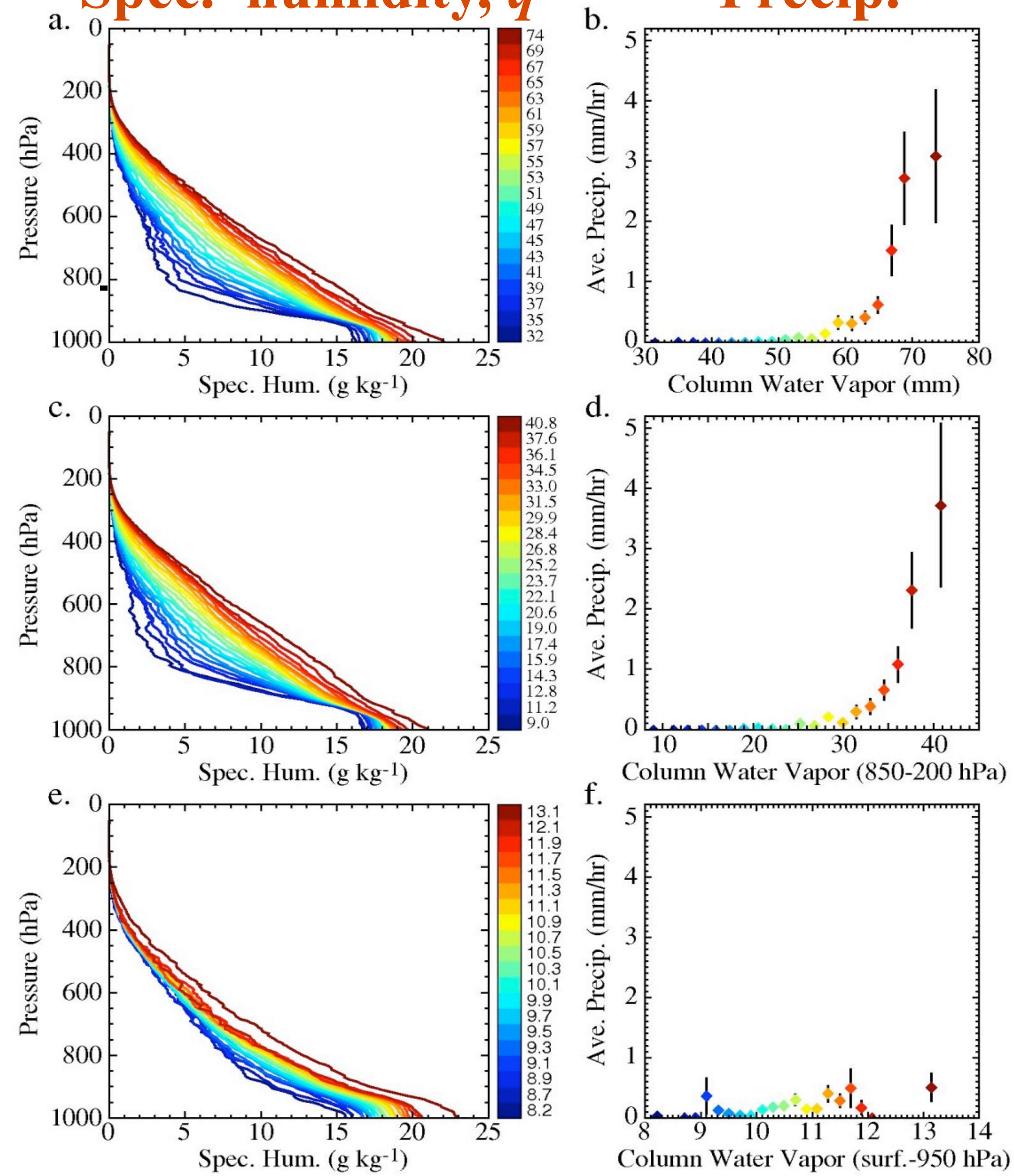
An example of quantifying convective onset

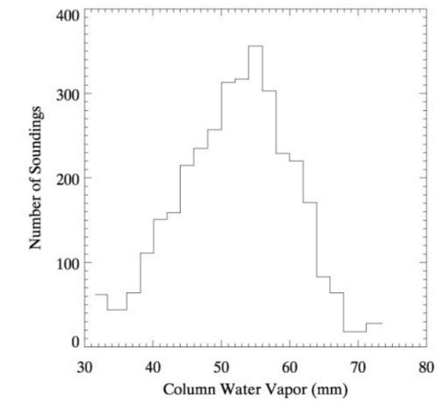
Binned by:
Column water vapor

850-200 mb

Surface-950mb

Spec. humidity, *q* **Precip.**





[Note fewer soundings in high bins]

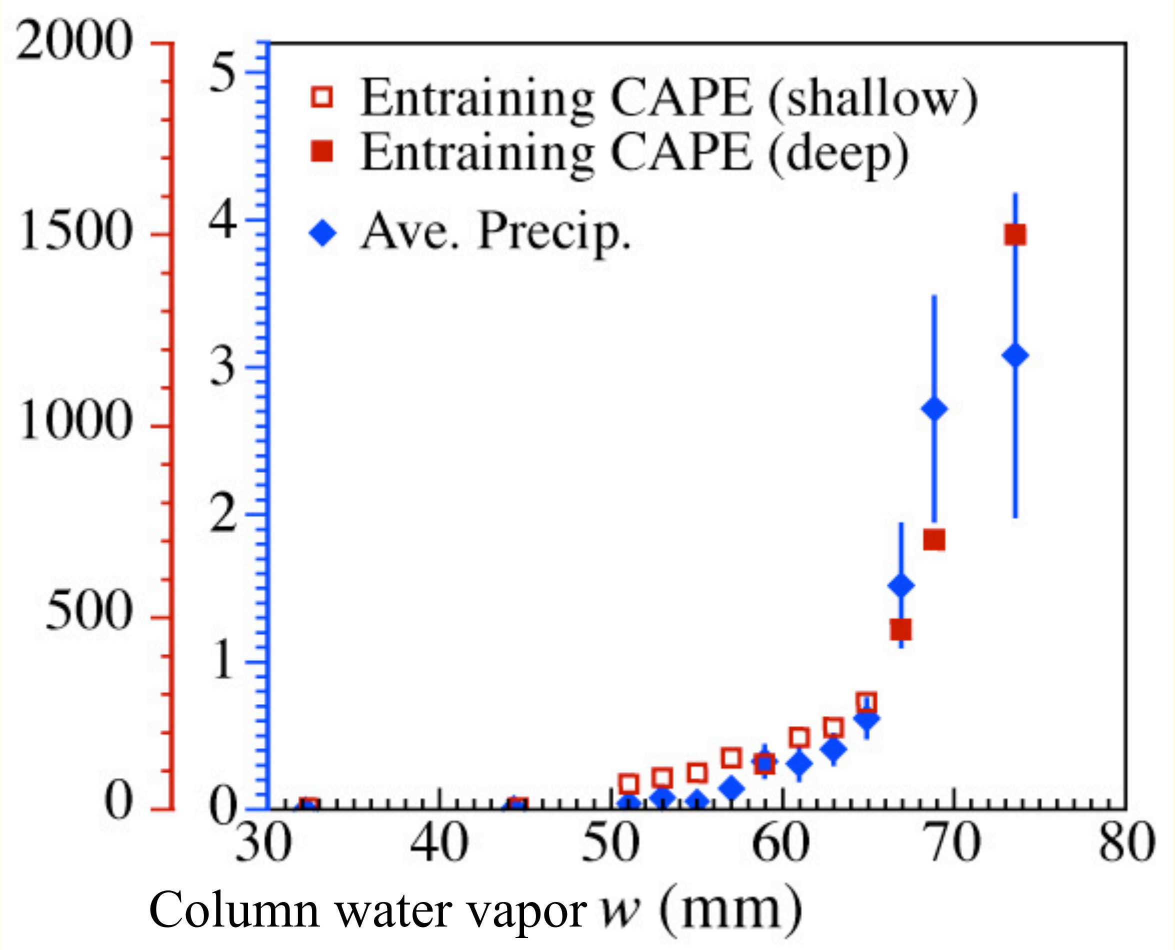
Nauru ARM site data

Holloway & Neelin, *JAS*, 2009

An example of quantifying convective onset:

Precipitation binned by column water vapor (CWV), *w*

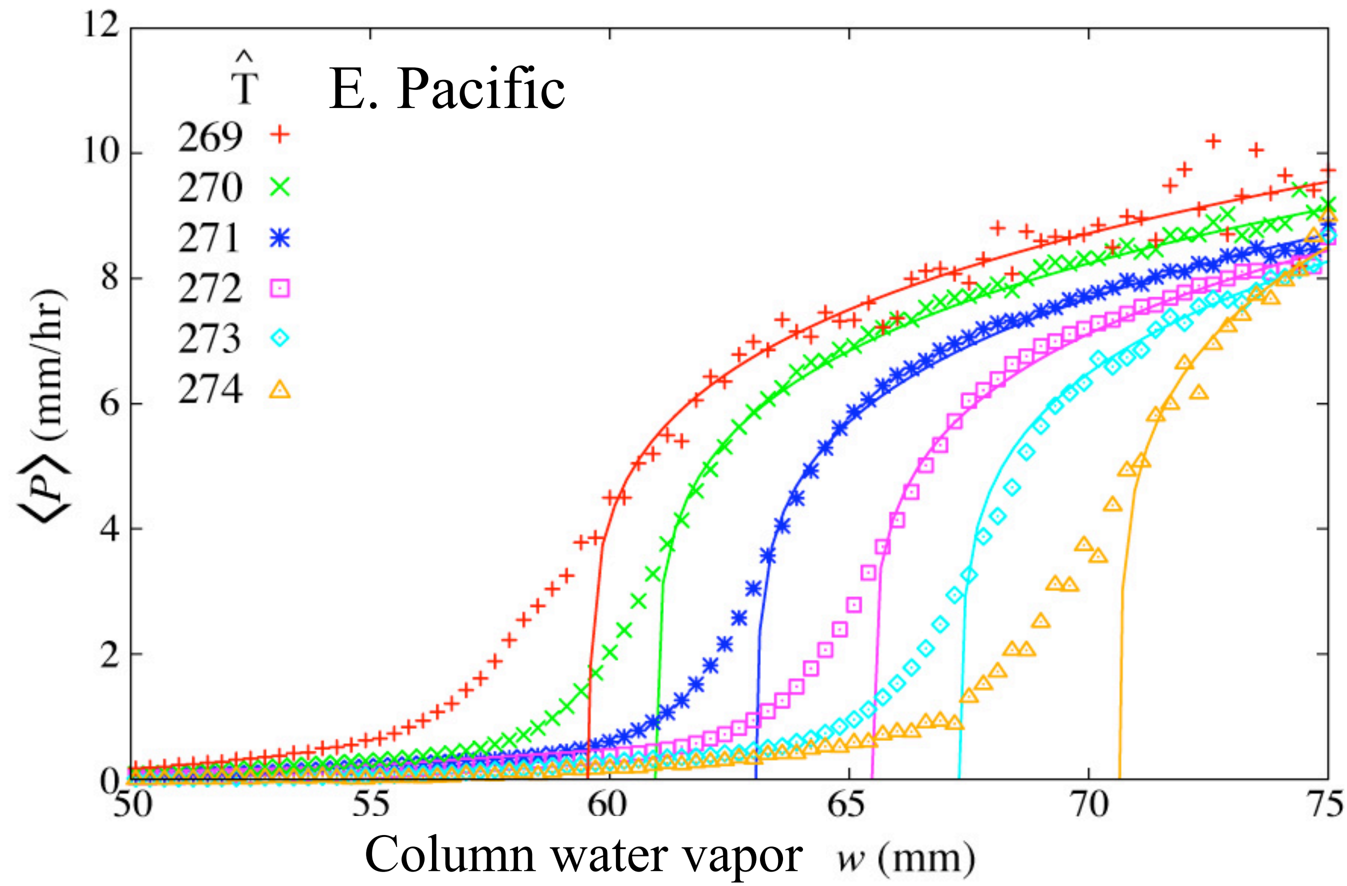
- **buoyancy & precip. pickup at high CWV**
- **Entraining convective available potential energy (CAPE) can match onset---if include enough turbulent entrainment into convecting parcel**
- **CWV useful because large microwave data sets available…**



Neelin, Peters, Lin, Holloway & Hales, 2008, *Phil Trans. Roy. Soc. A*

Transition to strong convection: Precip. dependence on tropospheric temperature & column water vapor

- Averages conditioned on vert. avg. temp. $\hat{T}$, as well as w (T 200-1000mb from ERA40 reanalysis)
- Power law fits above critical: w_c changes, same β
- [note more data points at 270, 271]

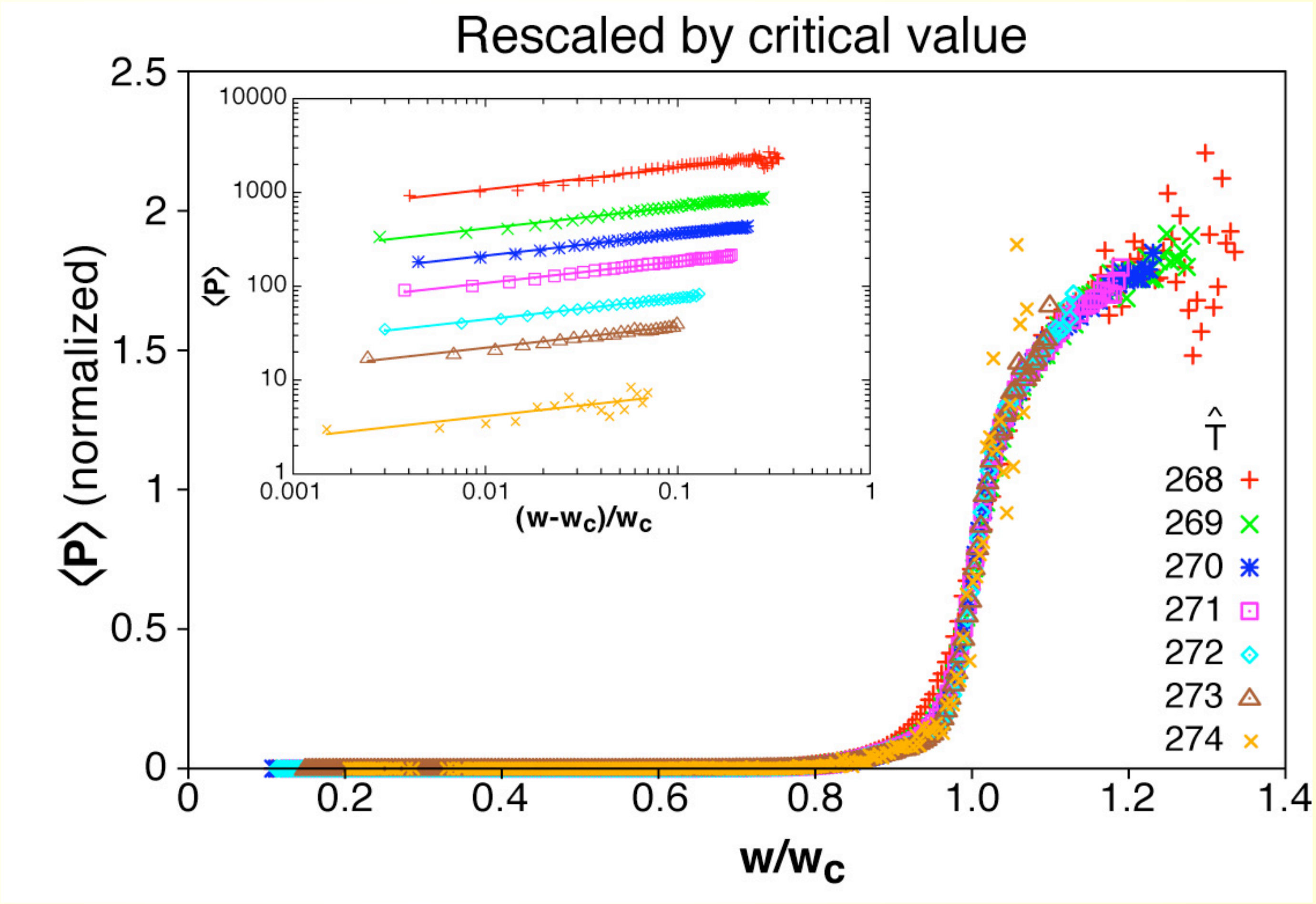


Neelin, Peters & Hales, 2009 *JAS*

- Analysed in tropics 20N-20S
- Hilburn & Wentz 2008 retrievals; background: Bretherton et al. 2004 daily

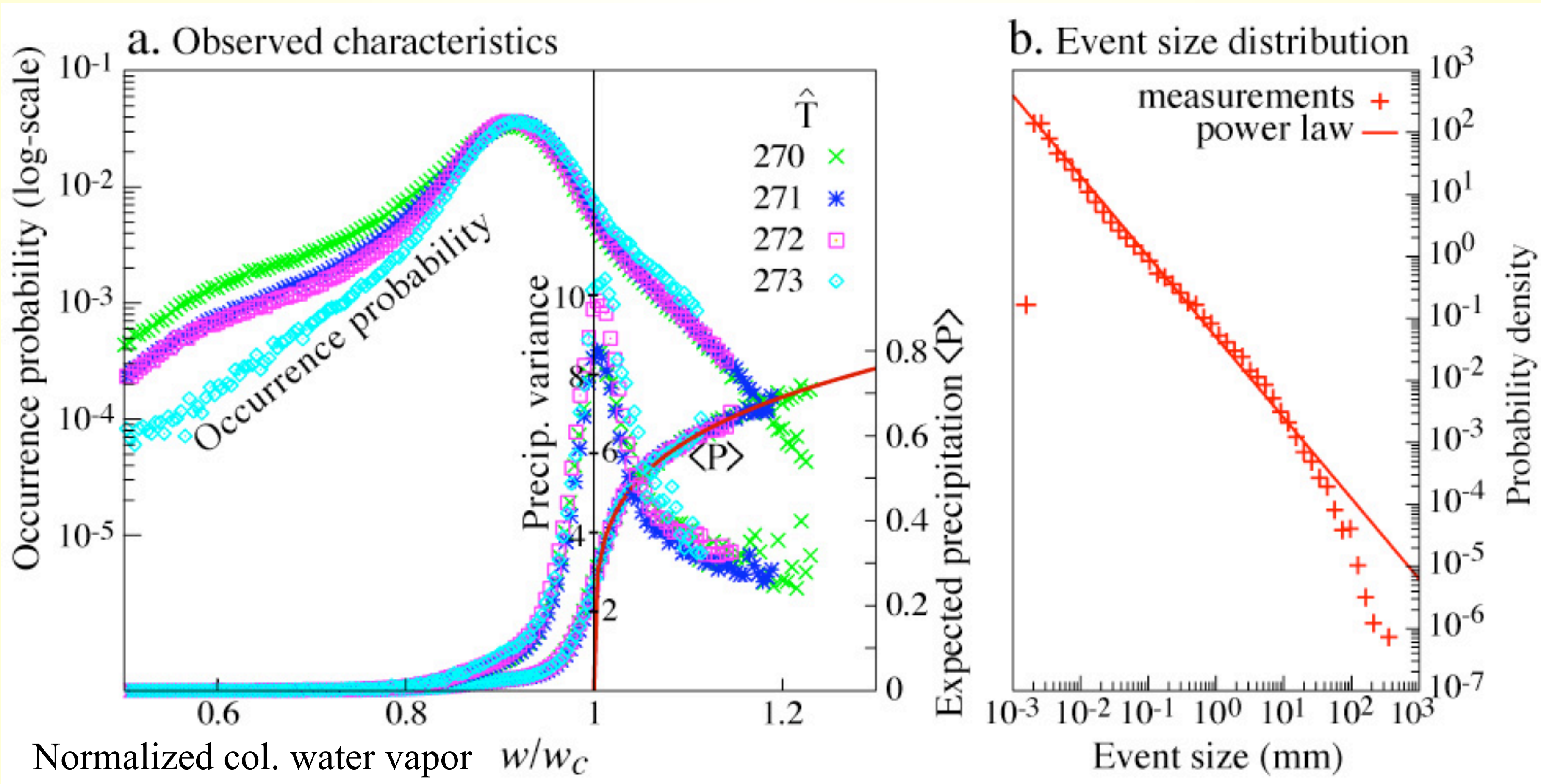
Precip. Collapse for various temperatures

- For various temp. $\hat{T}$, as function of w rescaled by critical value (E. Pacific)
- Quality of the collapse supports w_c fits
  - [note scatter at hi/lowest T assoc with fewer data]
- Inset: log-log above w_c



Behavior approaches $P(w)= a(w-w_c)^{\beta}$ above transition

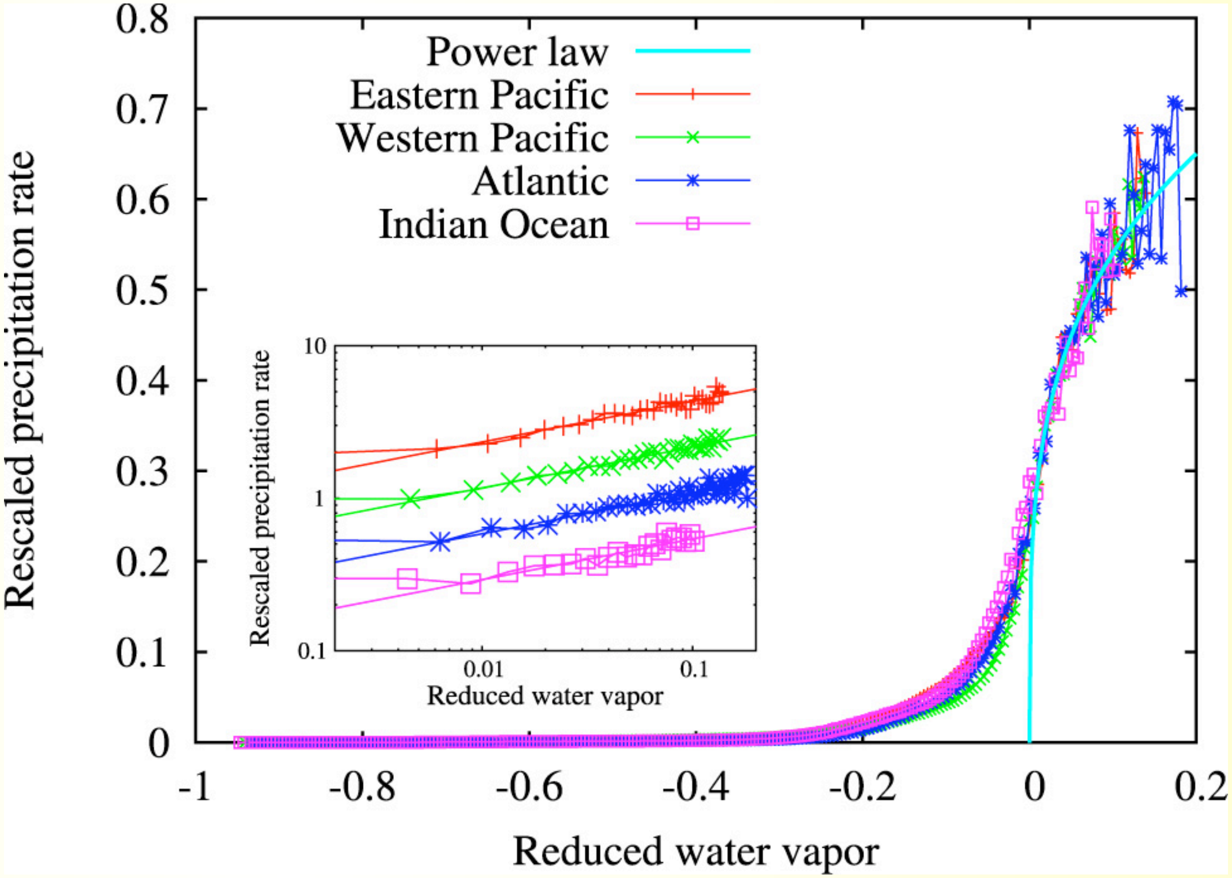
Collapsed statistics for observed precipitation



- **Precip. mean & variance dependence on *w* normalized by critical value w_c; occurrence probability for precipitating points (for 4 *T* values); Event size distribution at Nauru**

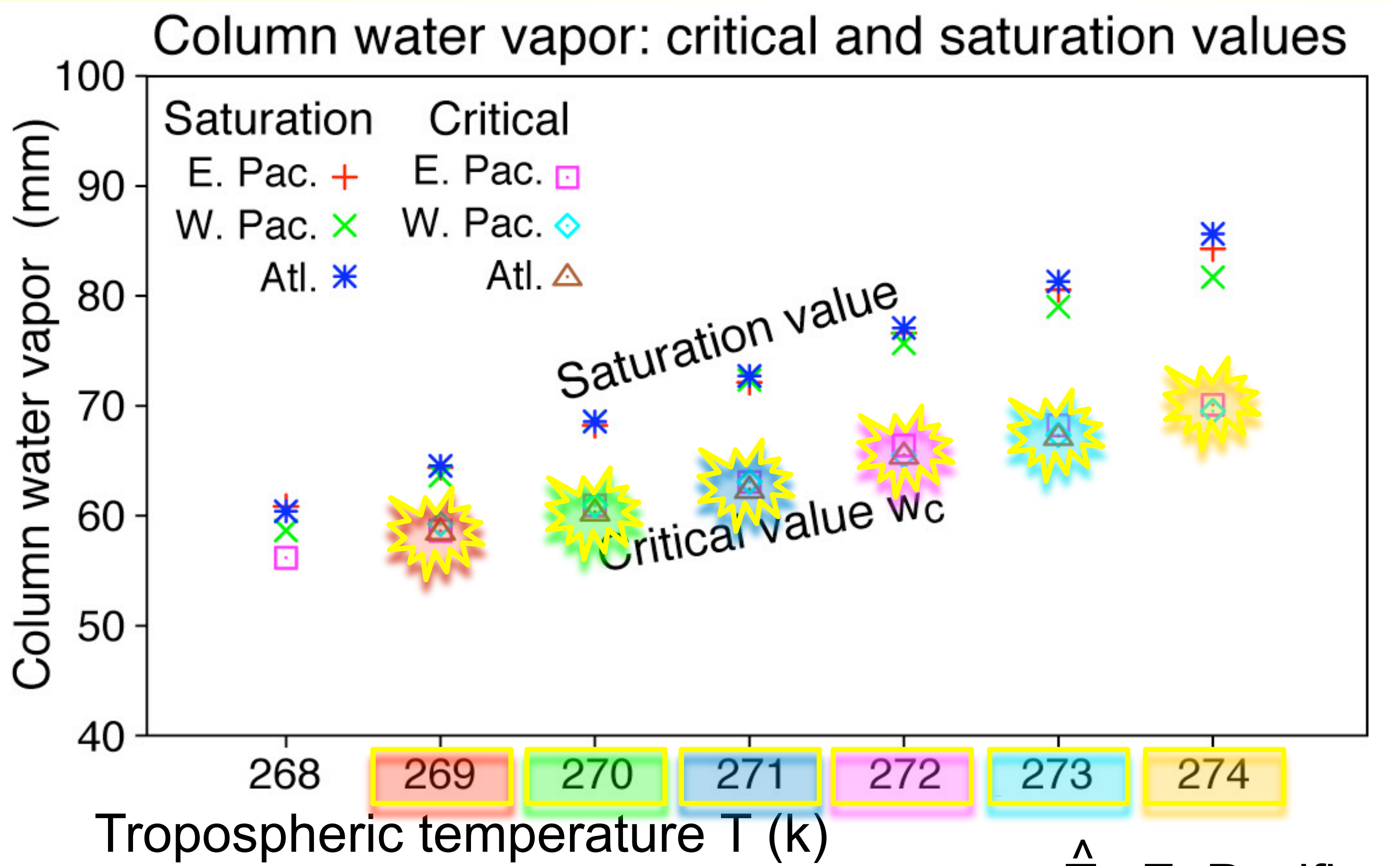
Check pick-up with radar precip data

- **TRMM radar data for precipitation**
- **4 Regions collapse again with w_c scaling**
- **Power law fit above critical even has roughly same exponent as from TMI microwave rain estimate**
- **(2A25 product, averaged to the TMI water vapor grid)**

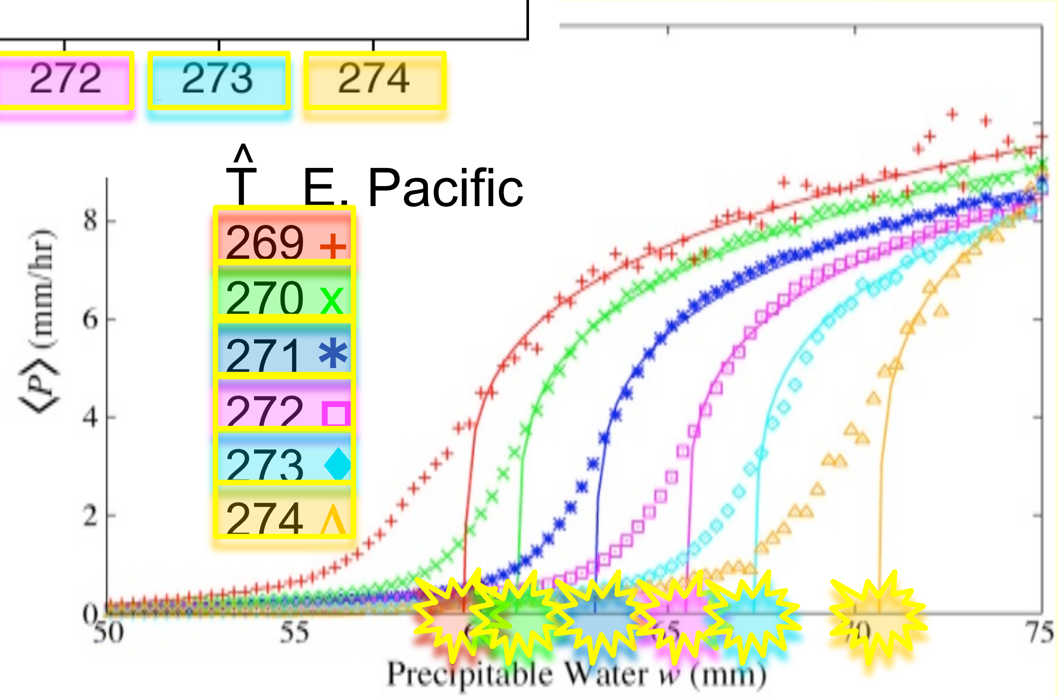


$(w-w_c)/w_c$

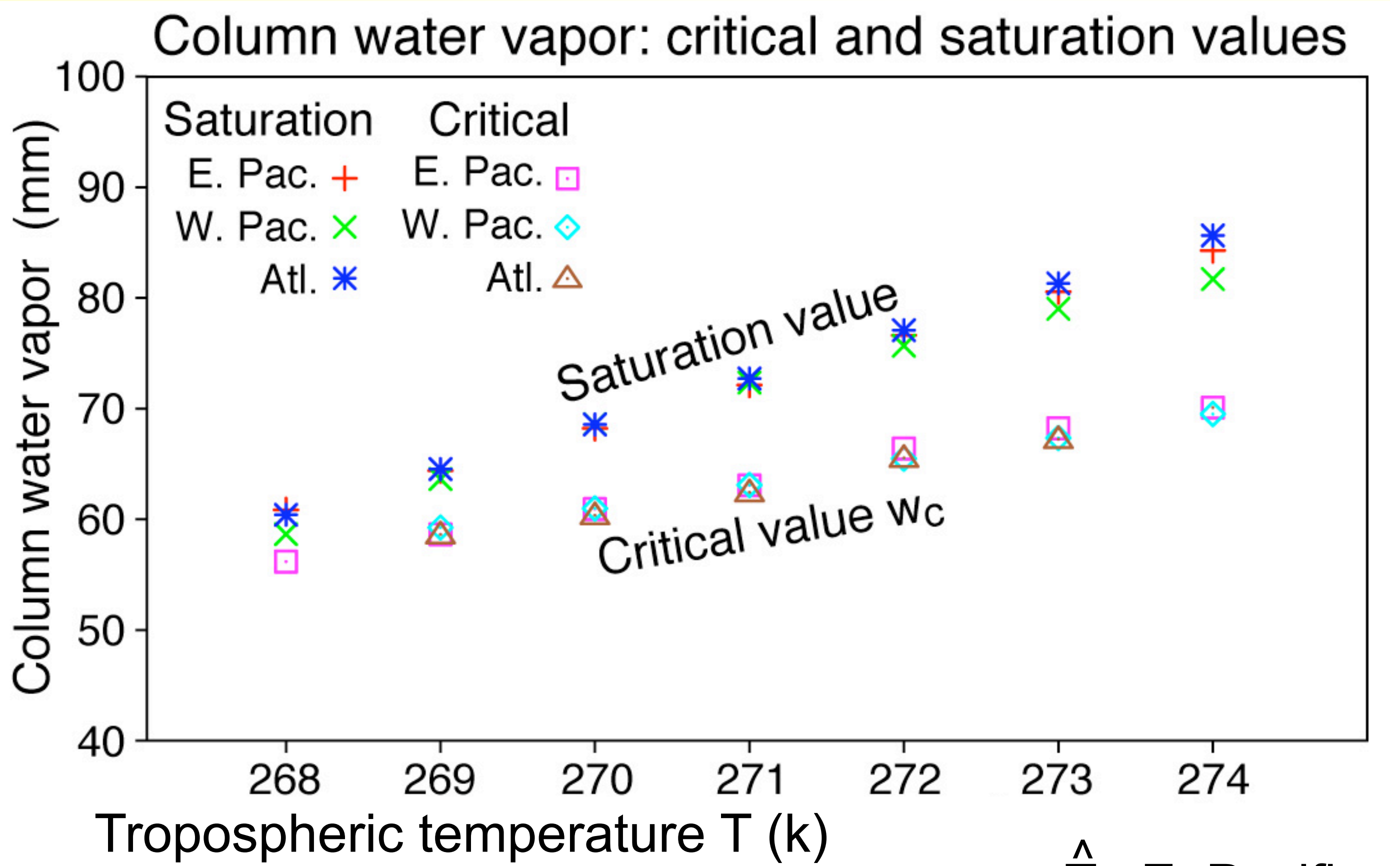
Peters, Neelin & Nesbitt, *JAS*, subm.



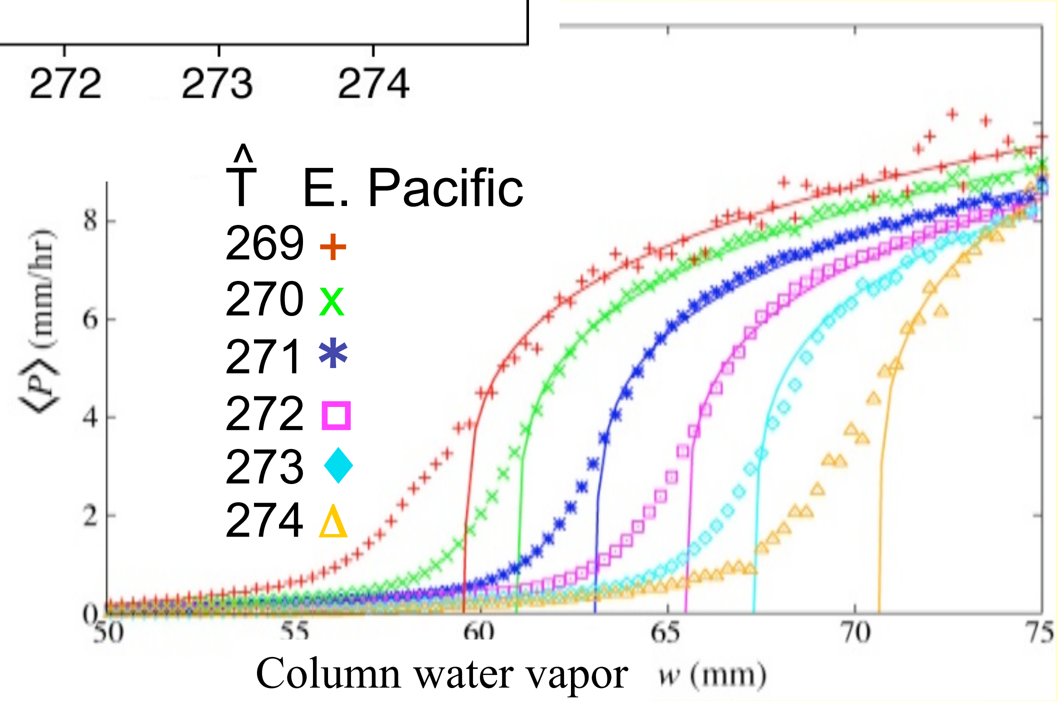
Column water vapor: critical and saturation values
Saturation
Critical
E. Pac.
W. Pac.
Atl.
Saturation value
Critical value wc
Column water vapor (mm)
100
90
80
70
60
50
40
268
269
270
271
272
273
274
Tropospheric temperature T (k)



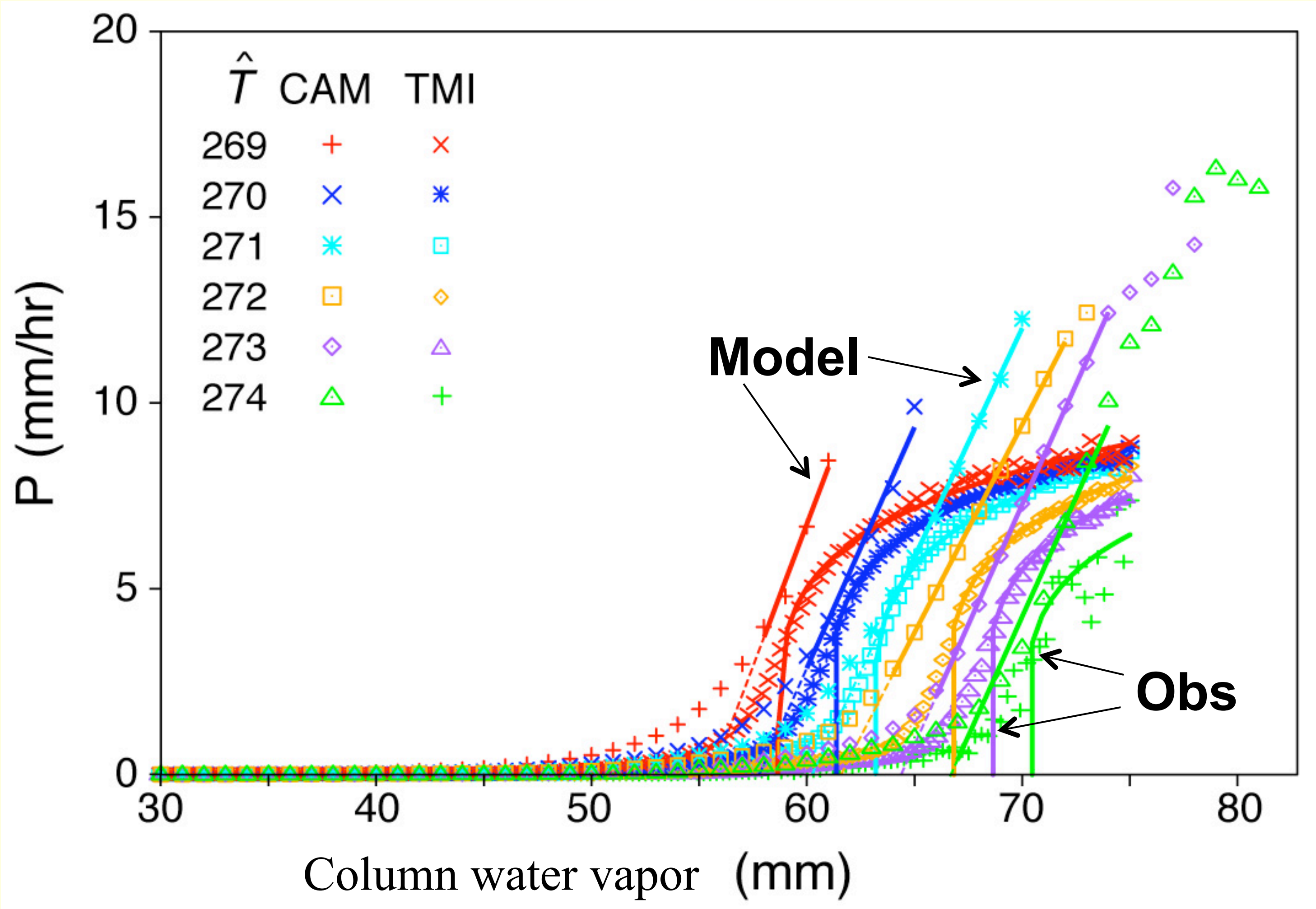
T̂ E. Pacific
269
270
271
272
273
274
⟨P⟩ (mm/hr)
8
6
4
2
0
50
55
75
Precipitable Water w (mm)



- **Defines an empirical thermodynamic surface for the onset of strong convection to test models**
- **Not a constant fraction of column saturation**



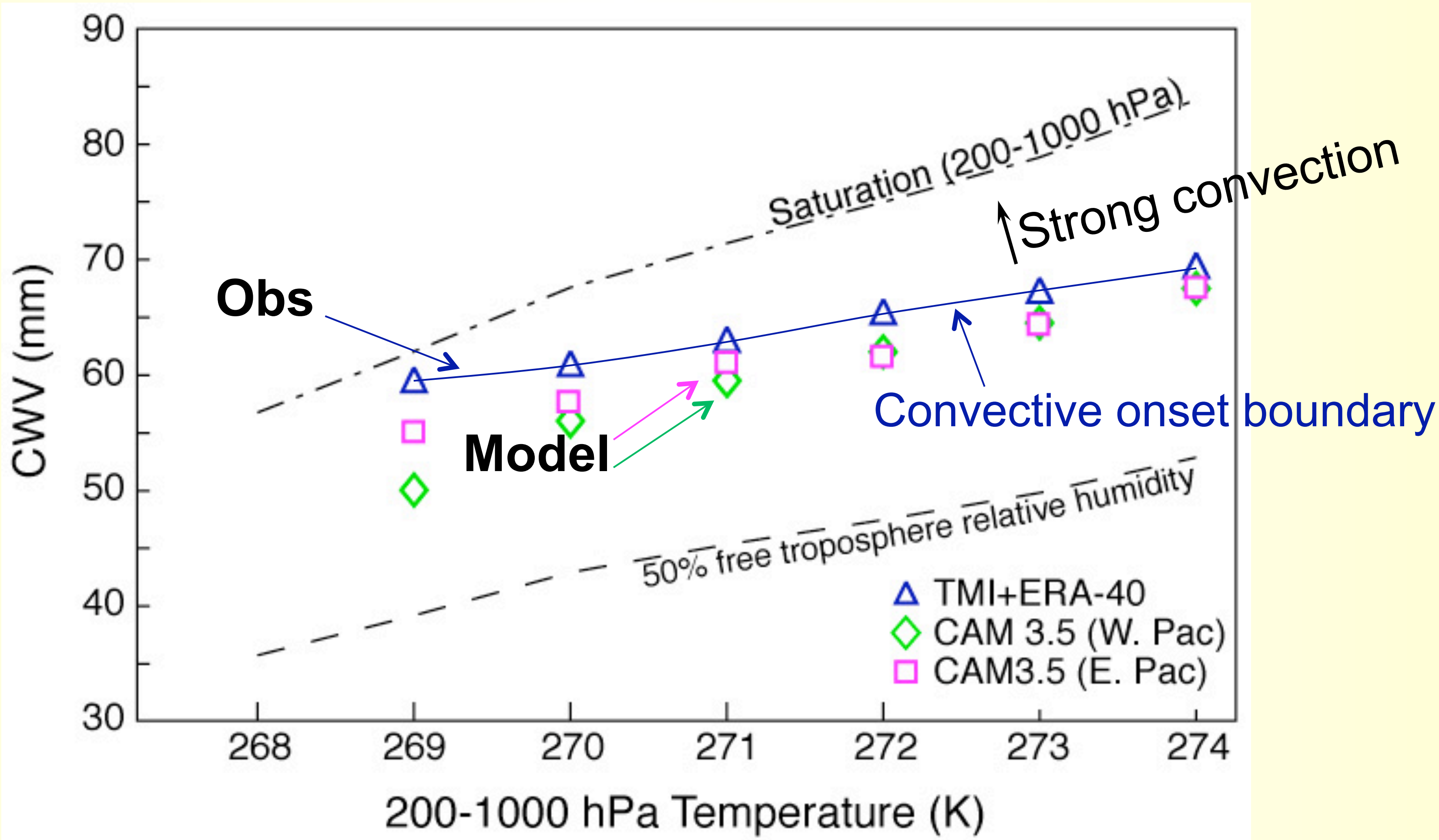
Transition to strong convection: High-resolution global model (CAM3.5, 0.5°) compared to observations (TMI)



Fit $P(w) = a(w-w_c)^{\beta}$ above w_c; CAM use β=1

Sahany et al. 2012, JAS

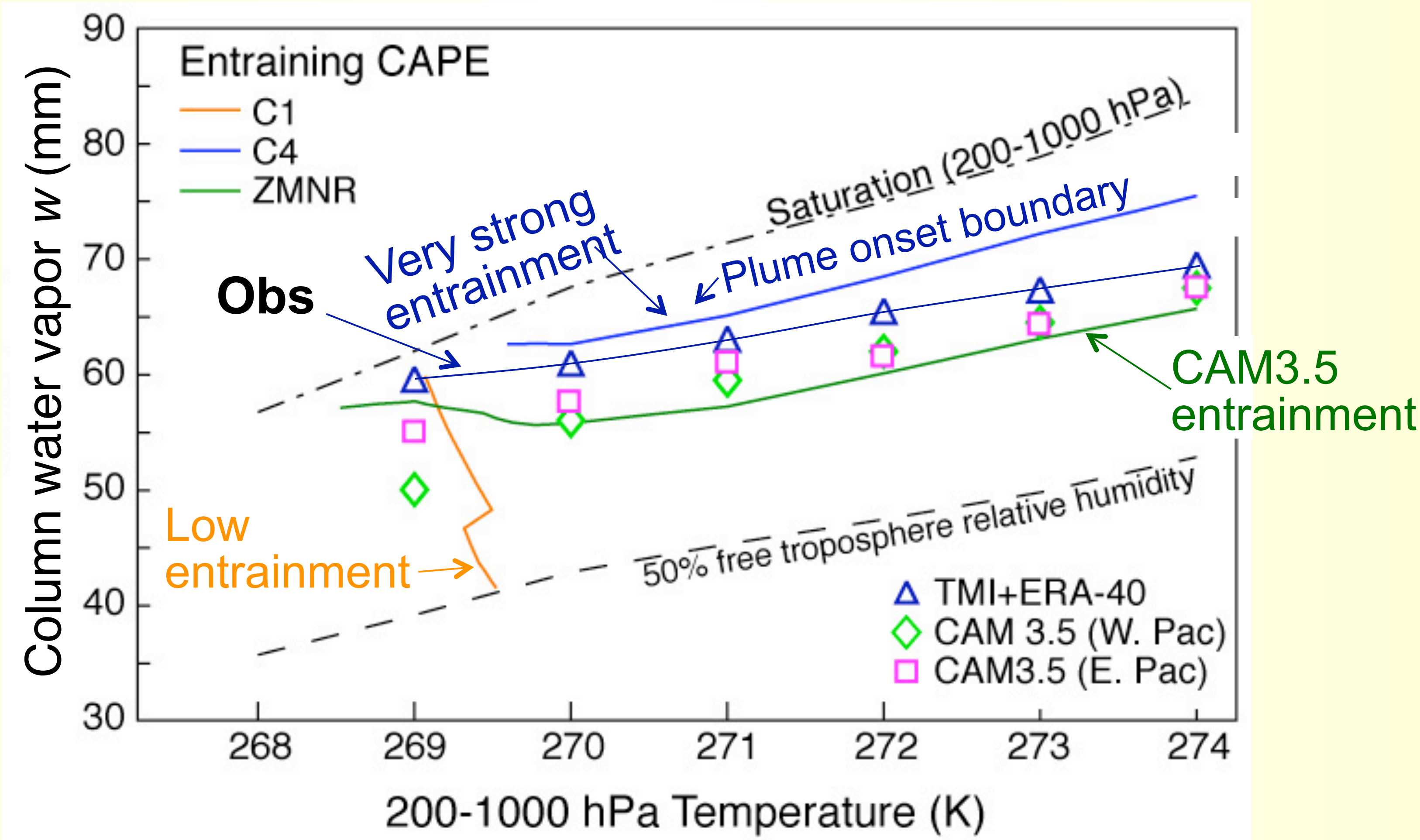
Transition to strong convection: **High-resolution global model (CAM3.5, 0.5°) compared to observations (TMI)**



Sahany et al. 2012, JAS

Transition to strong convection:

Obs. & model compared to simple convective plume instability calculation with different entrainment assumptions

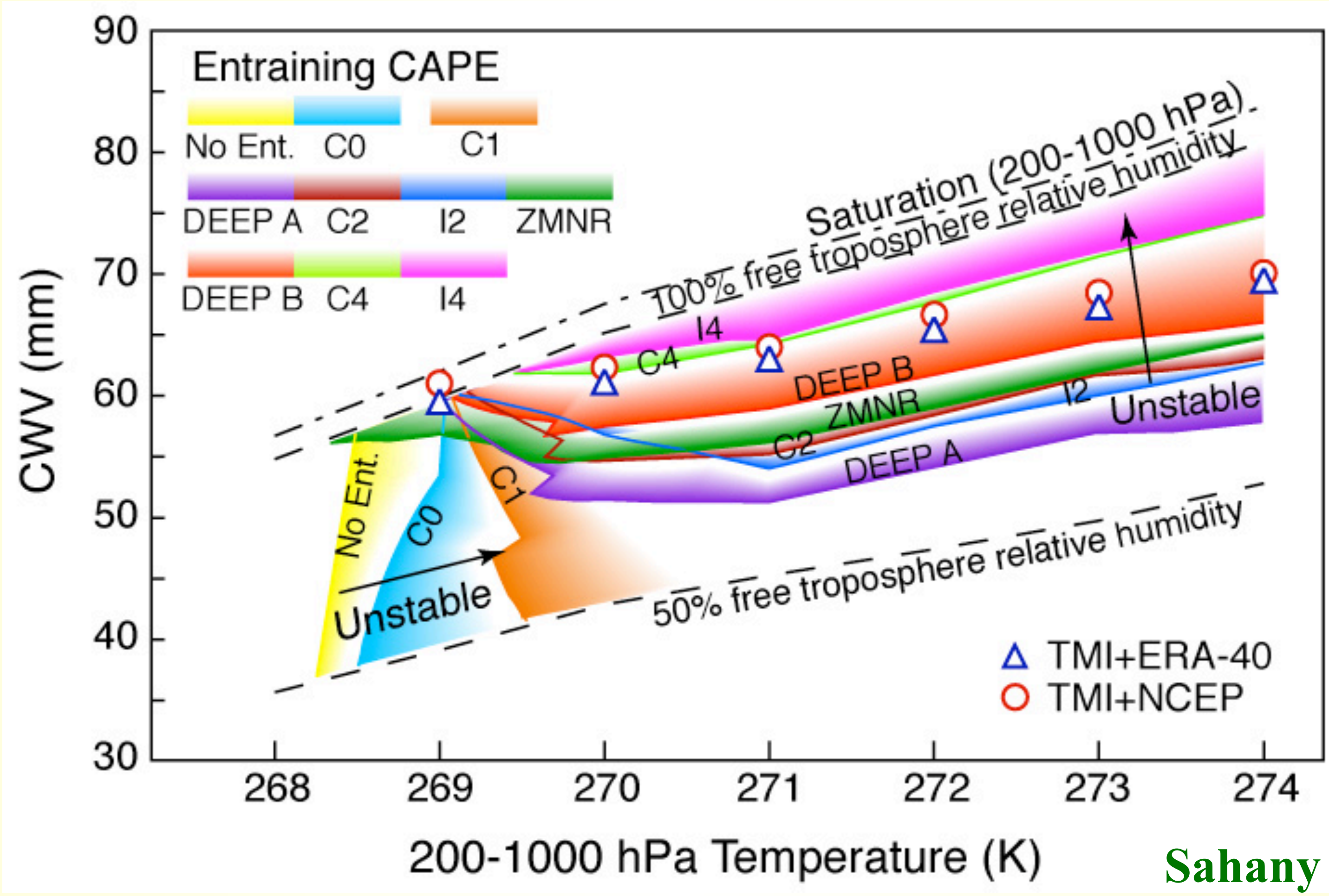


Low values of entrainment are inconsistent with observed onset

Sahany et al. 2012, *JAS* in press

Transition to strong convection: more detail

Obs. compared to simple convective plume instability calculation with various entrainment assumptions



Sahany et al. 2012

Deep A, B: 1/z vertical depc of entrainment (Siebesma et al, 2007)

I2, I4 includes dynamic entrainment contribution

C0, C1, C2, C4: 0, 1, 2, and 4 x 10^{-3} hPa^{-1} in free trop.

Parameter sensitivity in CAM4

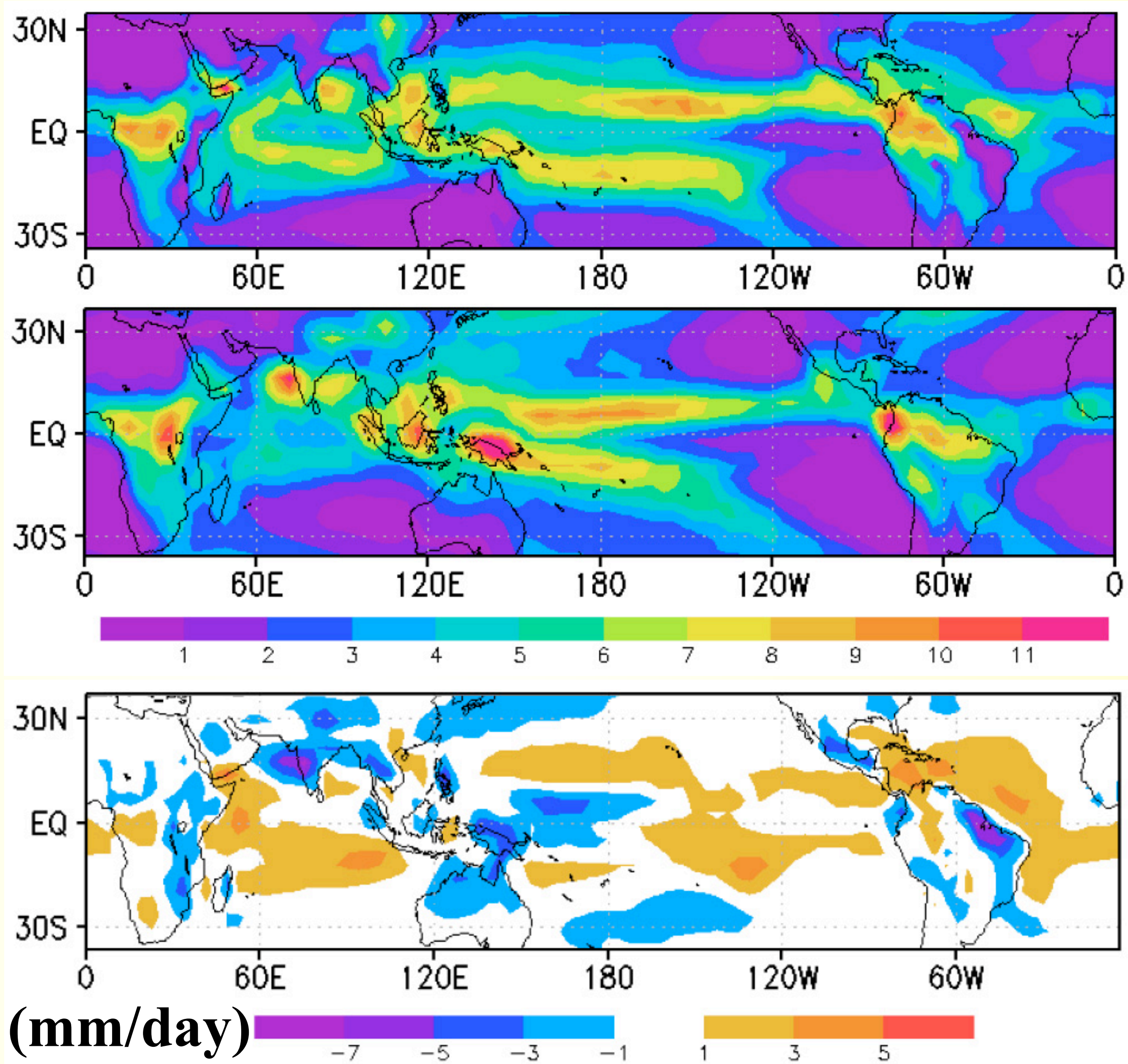
Precipitation (ann. avg.)

No entrainment

CAM4 standard

Precipitation difference (NoEnt-Stdrd)

Nonlinear: much less sensitive above standard

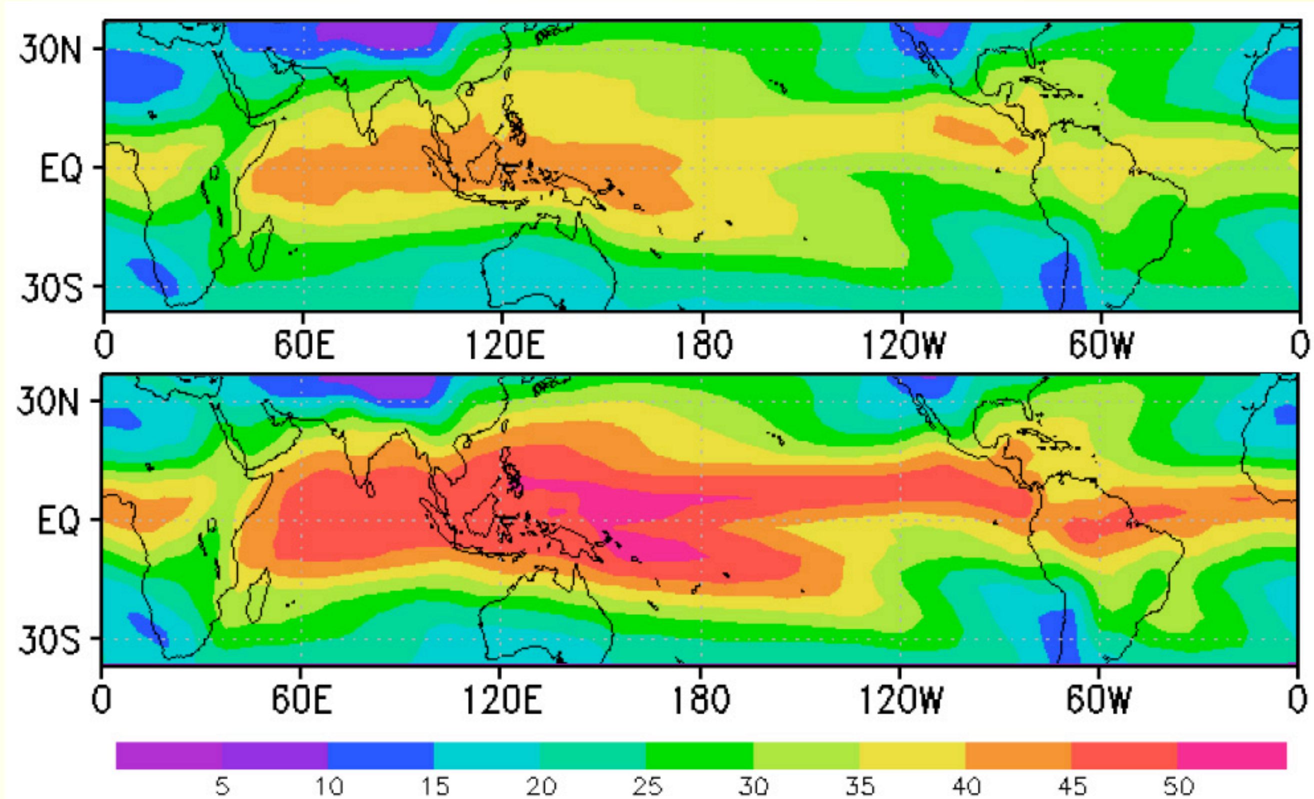


Parameter sensitivity in CAM4

Column water vapor (ann. avg.)

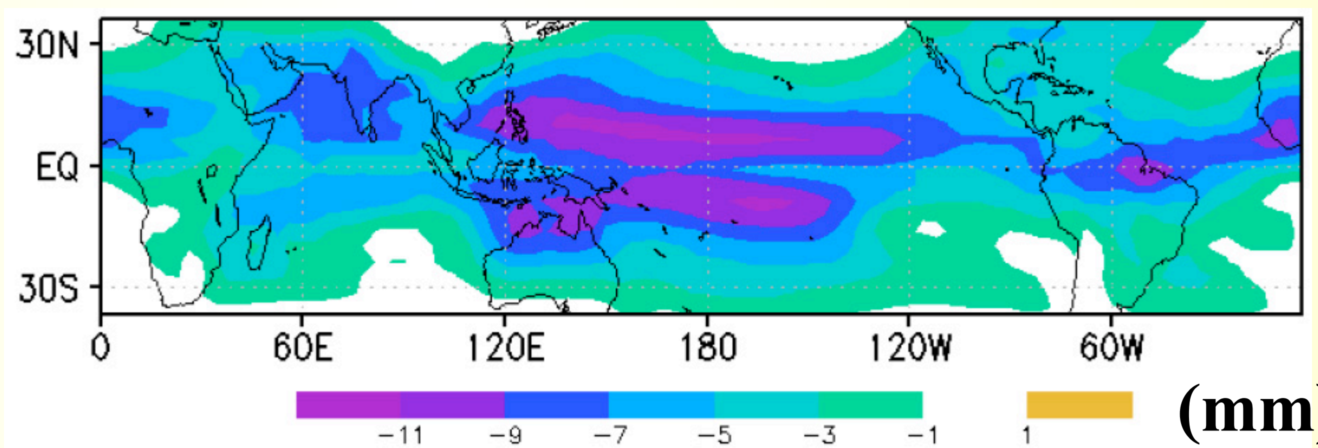
No entrainment

CAM4 standard



Difference (NoEnt-Stdrd)

(mm/day)

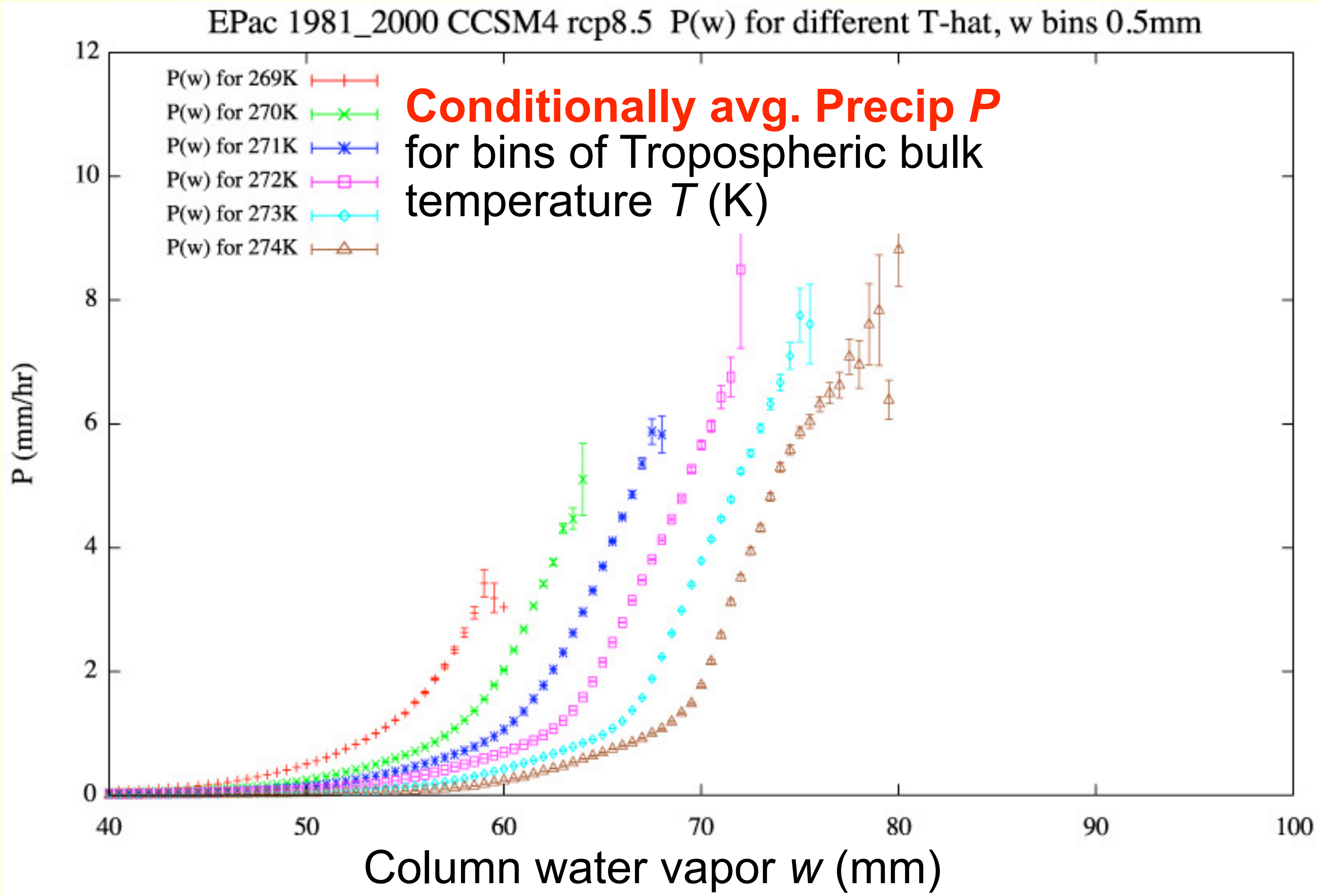


(mm)

Transition to strong convection: simulation of current conditions

Community Climate System Model 4 (CAM4, 1°)

Historical run 1981-2000

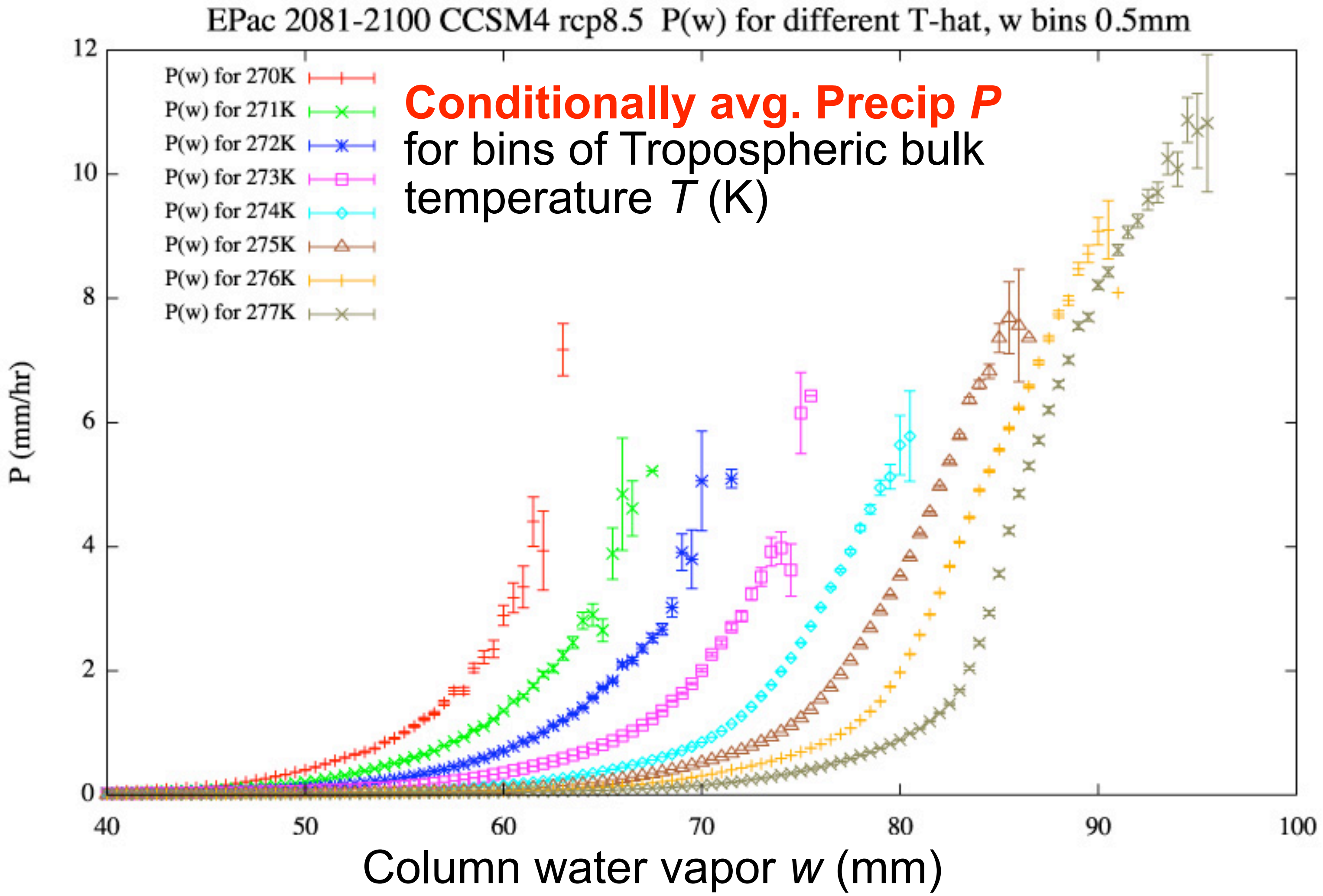


CAM4 Instantaneous precipitation data: R. Neale, Analysis K. Hales

Transition to strong convection: simulation under global warming

Community Climate System Model 4 (CAM4, 1°)

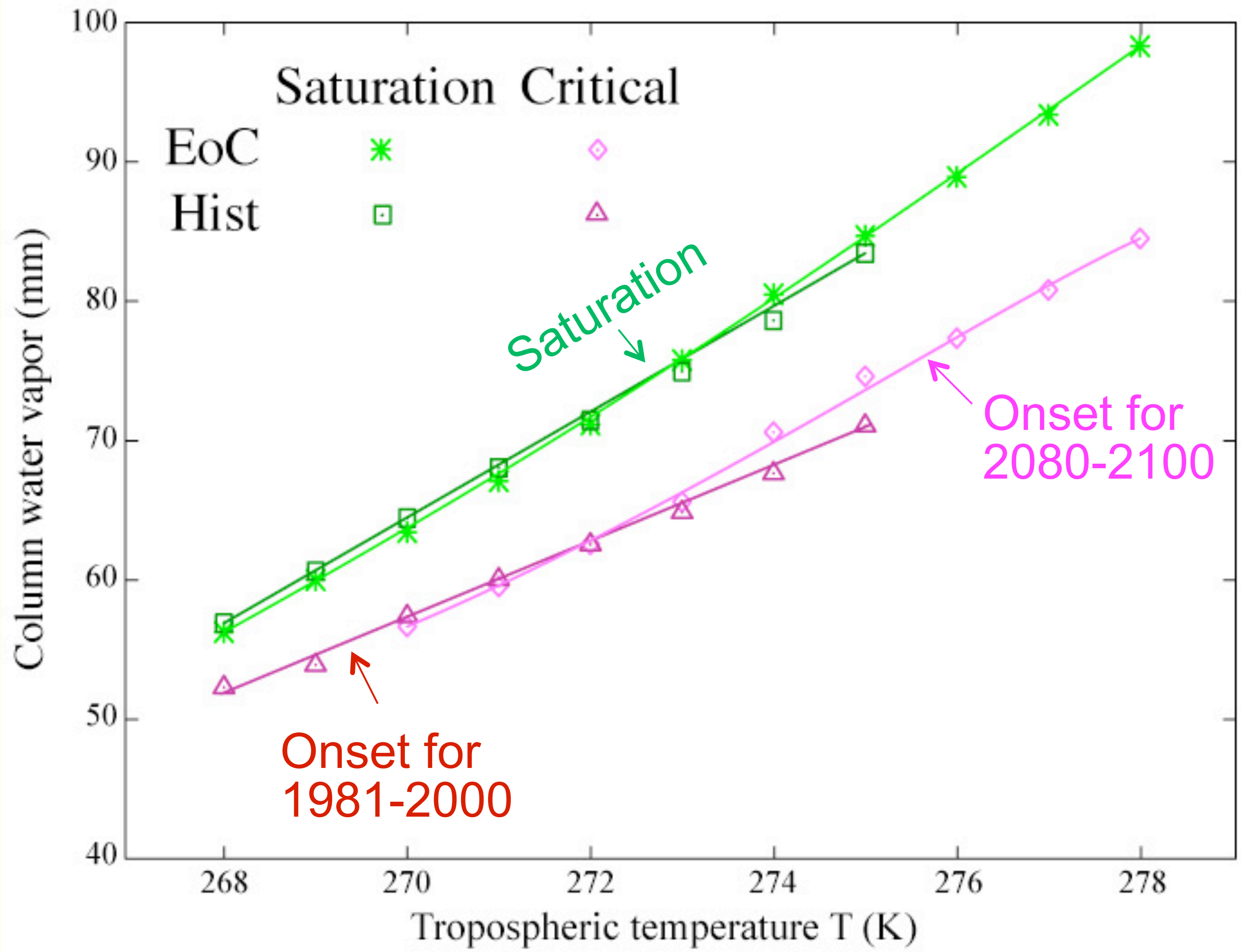
Representative Concentration Pathway run RCP8.5 2081-2100



CAM4 Instantaneous precipitation data: R. Neale, Analysis K. Hales

Transition to strong convection under global warming:

CCSM4 convective onset boundary estimates for current climate and end-of-century (EoC; 2081-2100) under RCP 8.5



Onset boundary under warming: modified angle to saturation

CCSM4 Instantaneous precipitation data: R. Neale, Analysis K. Hales

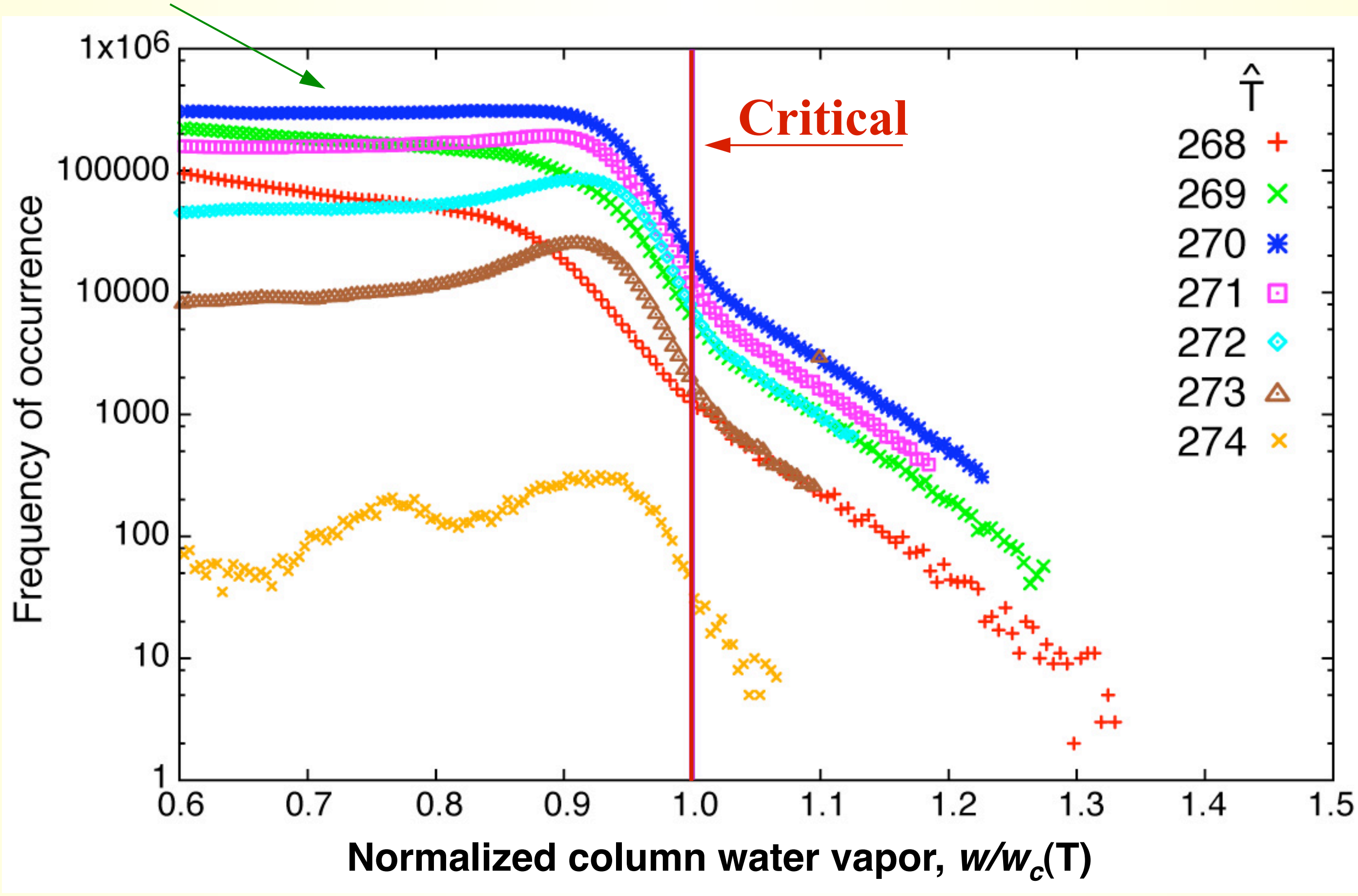
Water vapor probability density function

(*w* normalized by critical value for convective onset)

Eastern Pacific TMI obs for various tropospheric temperatures

Below critical, other effects set residence time

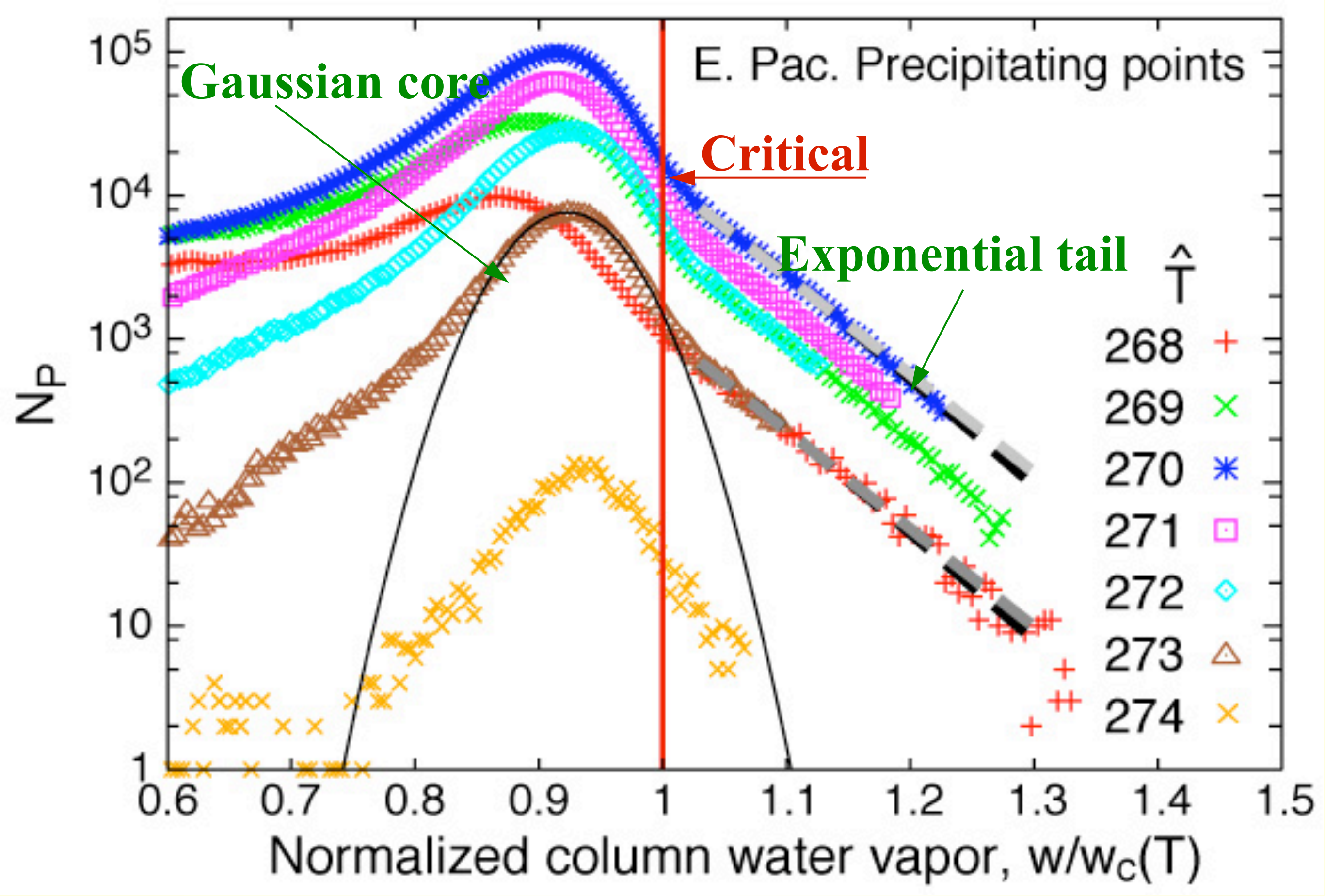
Drop across critical region and above, negative feedback of convection on water vapor



Obs.* probability density function of normalized water vapor w/w_c for precipitating points

Eastern Pacific for various tropospheric temperatures

- Peak just below critical pt. ⇒ self-organization toward w_c
- Exponential tail above critical pt. ⇒ *more extreme events*



Neelin et al. 2009, *JAS* ; *TRMM Microwave Instrument retrievals

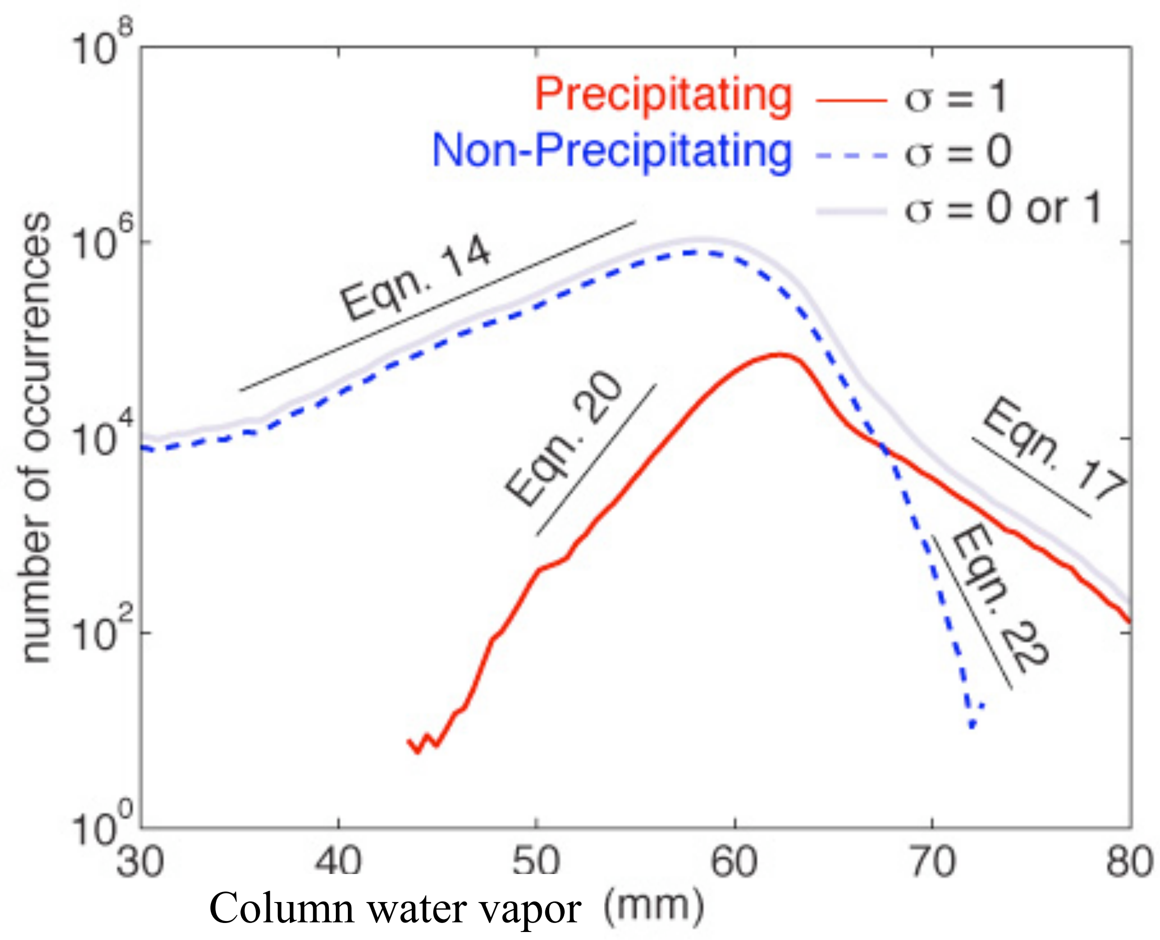
[Brief 1-slide advertisement]

Stochastic prototype for precipitation onset statistics can capture a number of these features

Gaussian core, exponential tail (i.e., large events are relatively frequent)

Fokker-Planck equation analytic solutions for various regimes to understand mechanisms

Frequency of occurrence for precipitating and nonprecipitating points

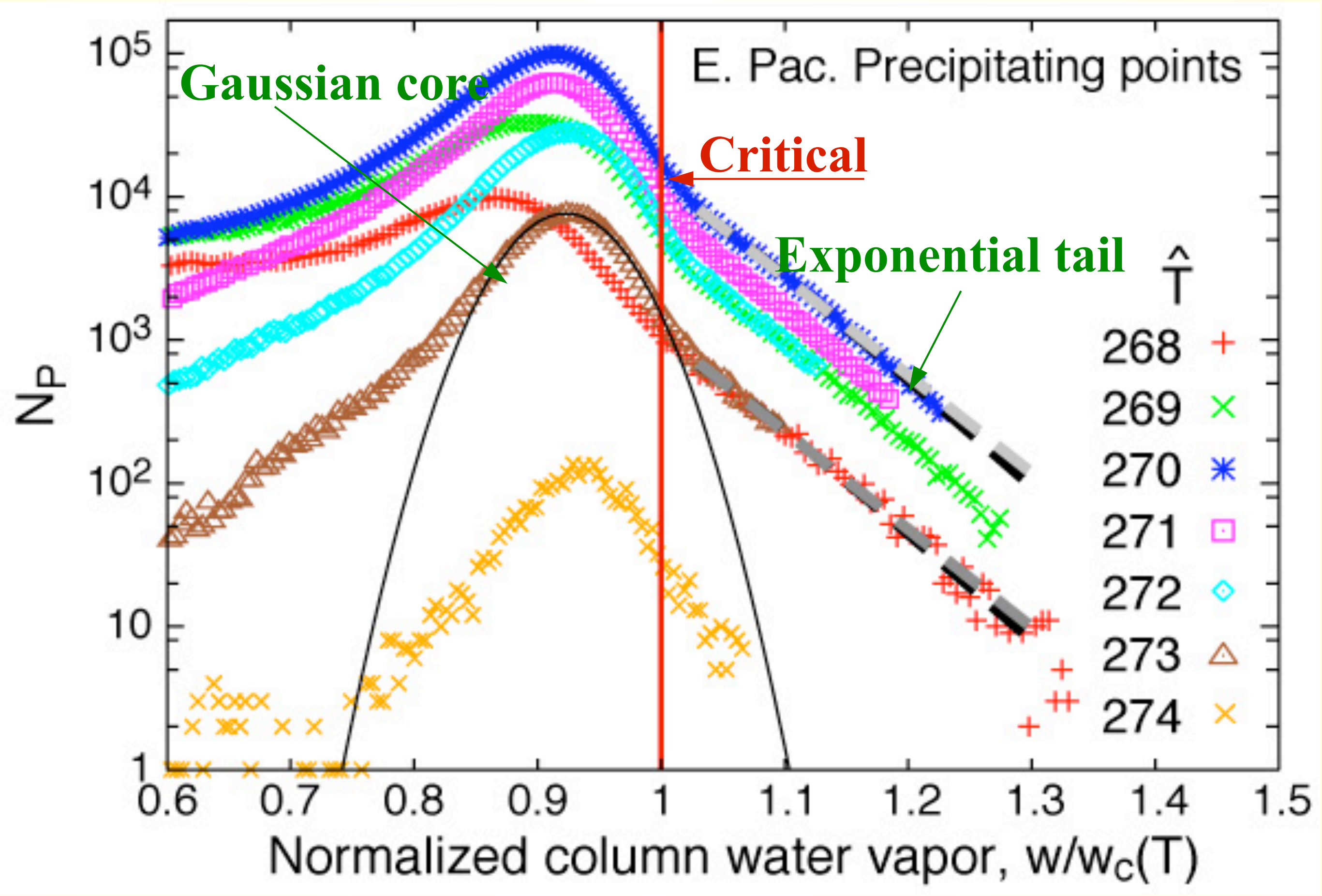


Stechmann & Neelin (2011; *JAS*)

Obs.* probability density function of normalized water vapor w/w_c for precipitating points

Eastern Pacific for various tropospheric temperatures

- Can a high-resolution global model capture this?

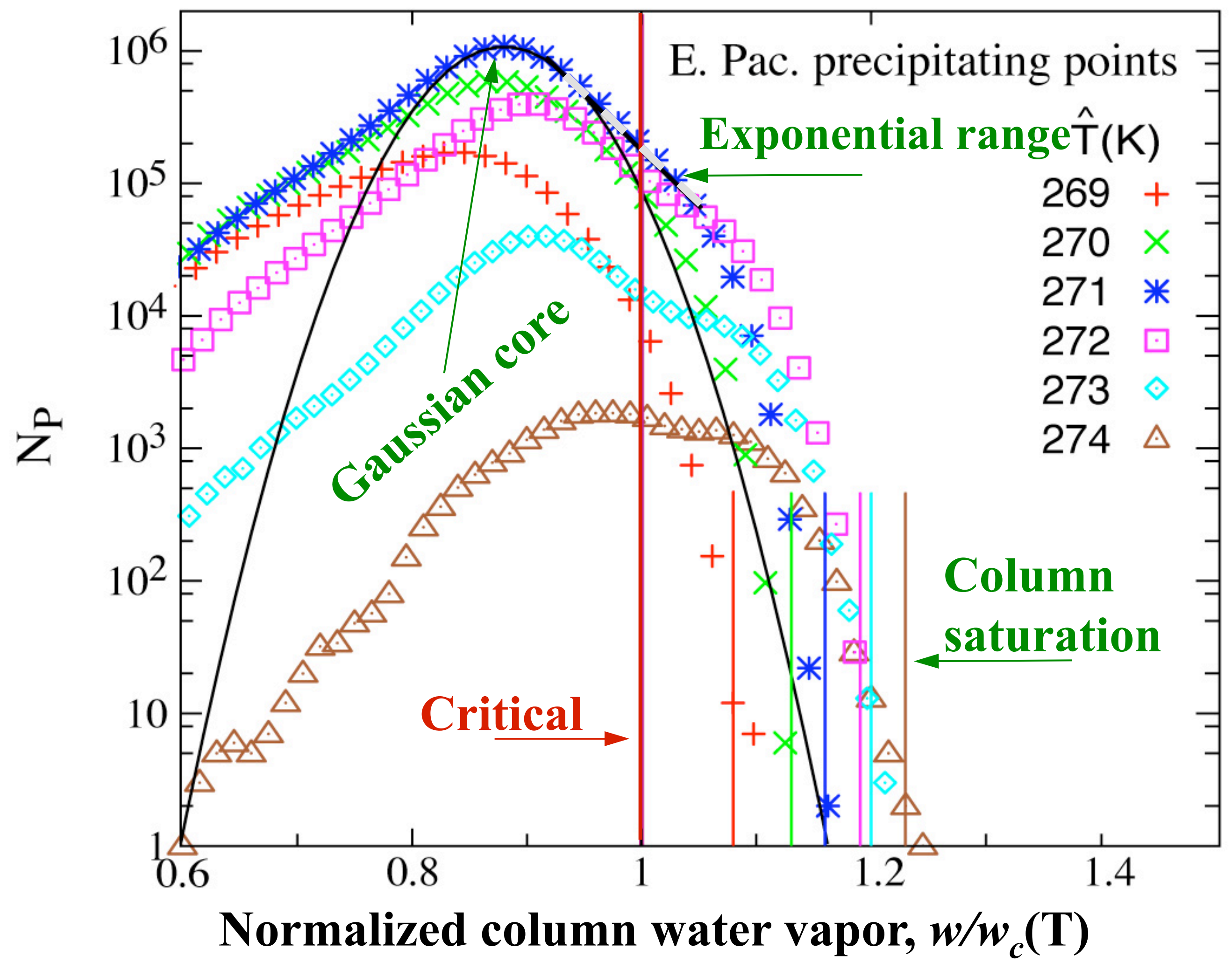


Neelin et al. 2009, *JAS* ; *TRMM Microwave Instrument retrievals

CAM3.5 at 0.5° resolution prob. density function of w/w_c for precipitating points

Eastern Pacific for various tropospheric temperatures

- Includes super-Gaussian ~exponential range above critical pt.

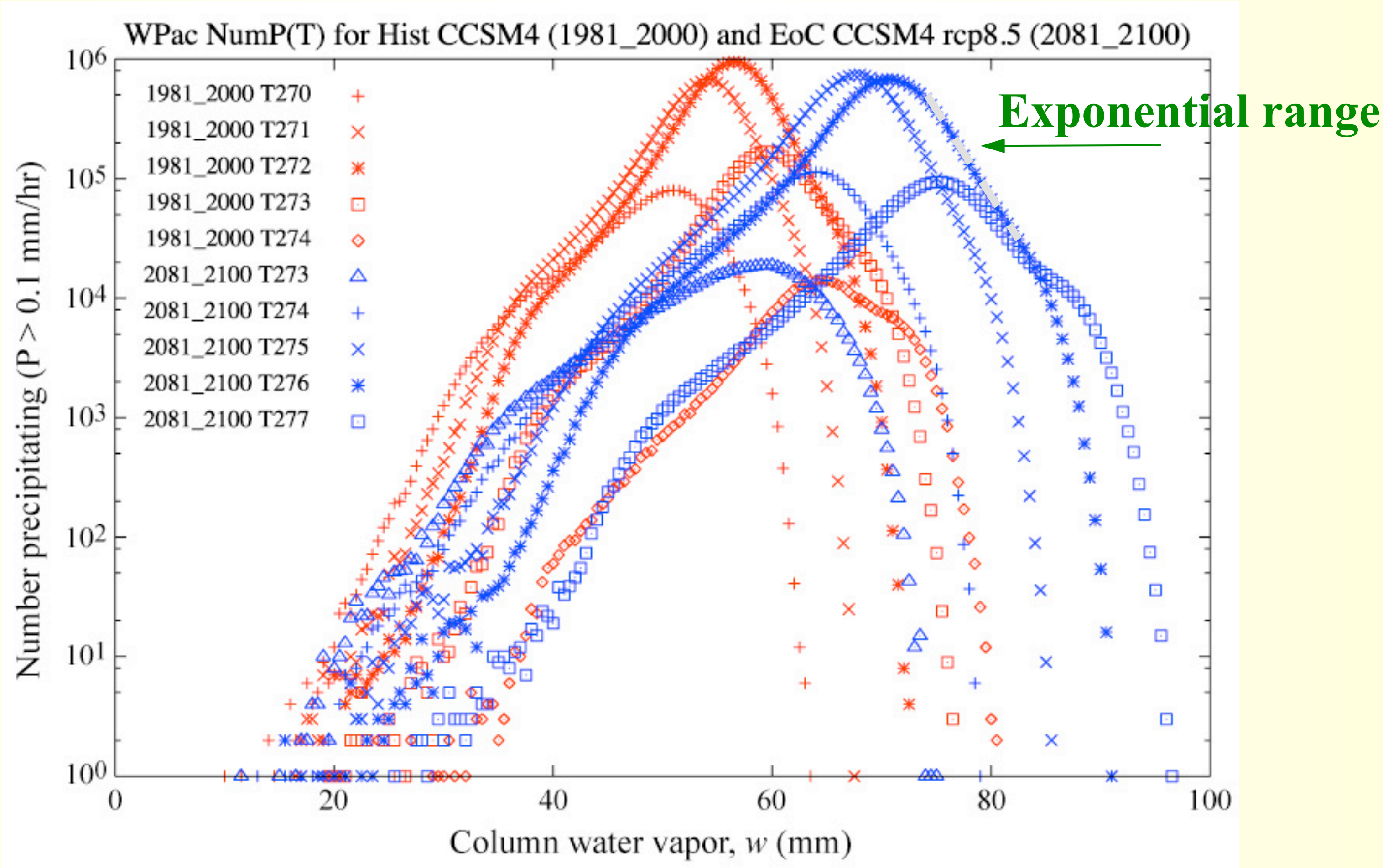


Runs R. Neale, analysis K. Hales

Can we make quantitative statements about the shift of this distribution with global warming?

Western Pacific for various tropospheric temperatures

•CCSM4 at 1° res. 1981-2000 and 2081-2100

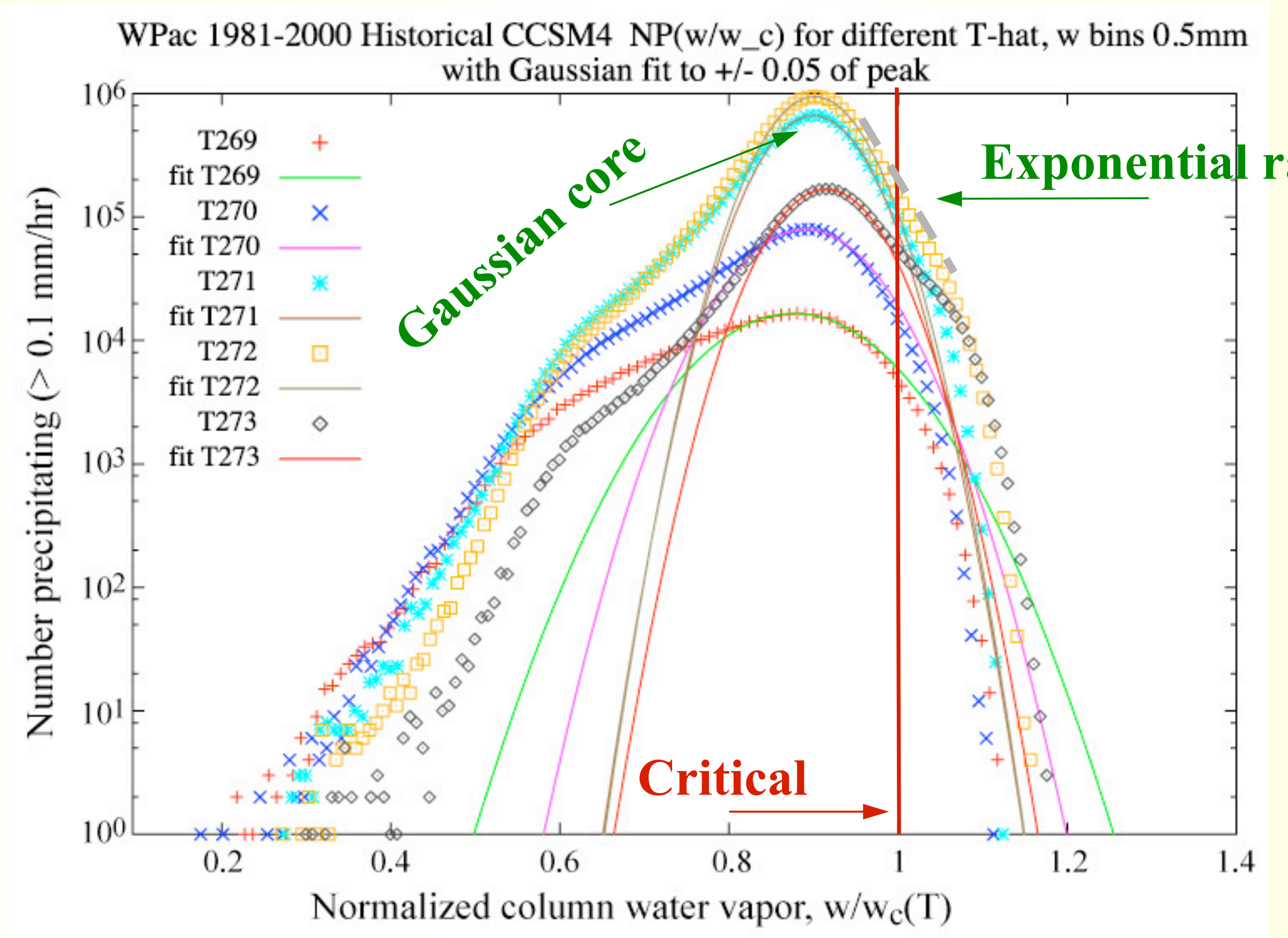


Instantaneous precip data R. Neale, analysis K. Hales

Precipitating freq. of occurrence vs. w/w_c

Western Pacific for various tropospheric temperatures

- CCSM4 1981-2000 base period
- Includes super-Gaussian ~exponential range above critical pt.



Instantaneous precip data R. Neale, analysis K. Hales

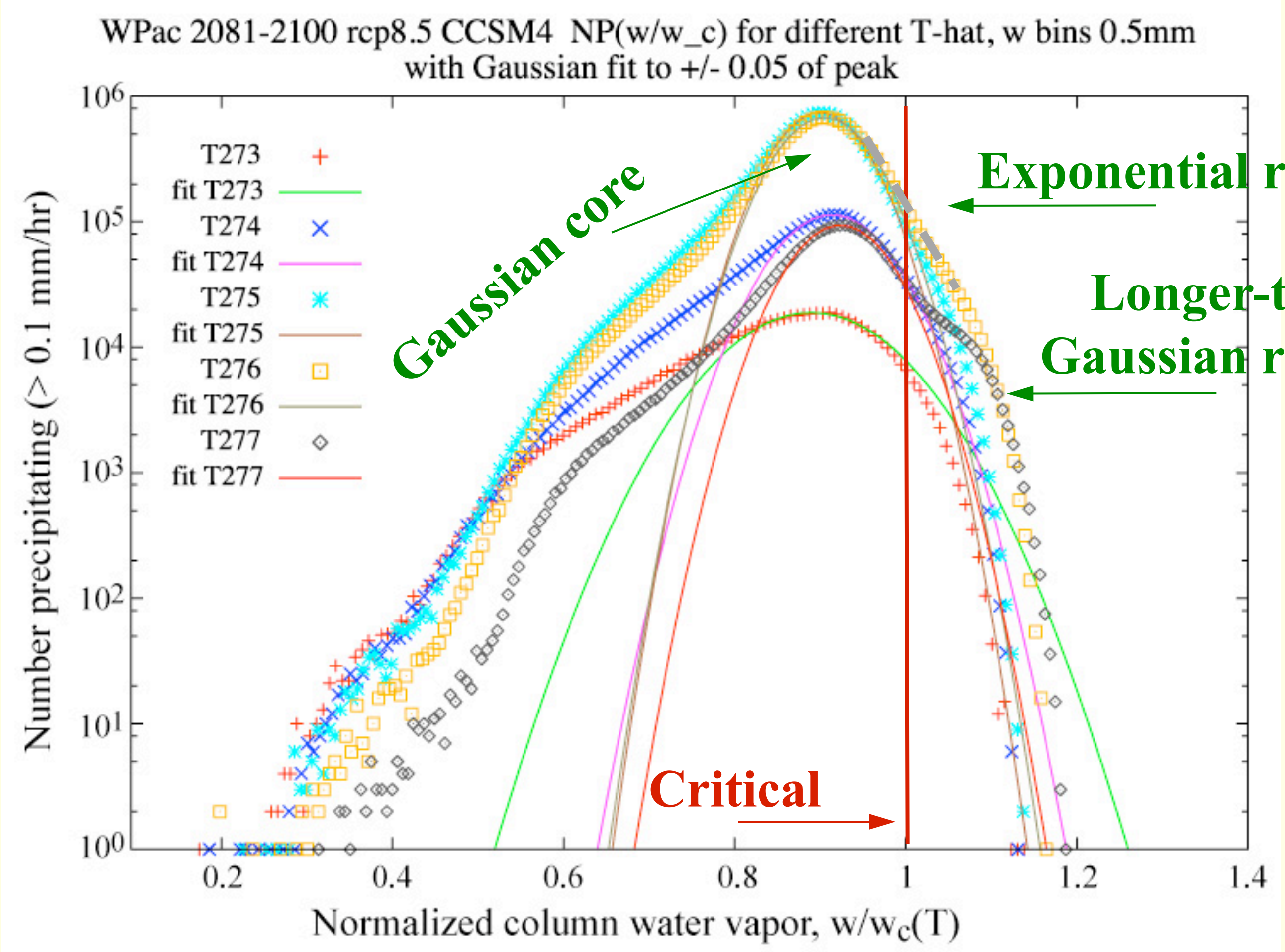
Precipitating freq. of occurrence vs. w/w_c

Western Pacific for various tropospheric temperatures

•CCSM4 2081-2100 base period

•To a first approximation distribution just shifts with critical pt.

• super-Gaussian range above critical pt enhanced with warming



Instantaneous precip data R. Neale, analysis K. Hales

Precipitating freq. of occurrence vs. w/w_c

Eastern Pacific for various tropospheric temperatures

•CCSM4 1981-2000 base period

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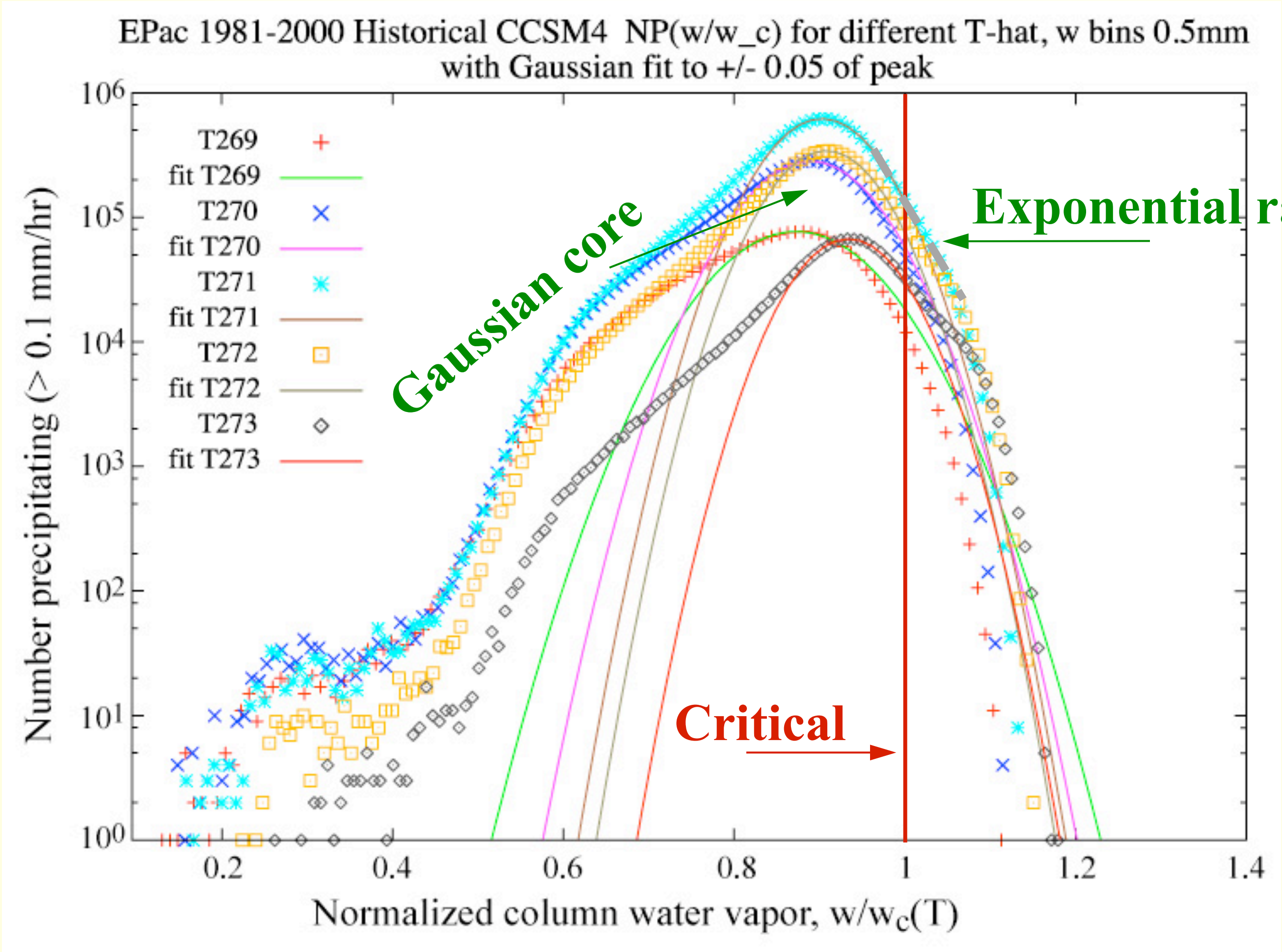

Instantaneous precip data R. Neale, analysis K. Hales

Precipitating freq. of occurrence vs. w/w_c

Eastern Pacific for various tropospheric temperatures

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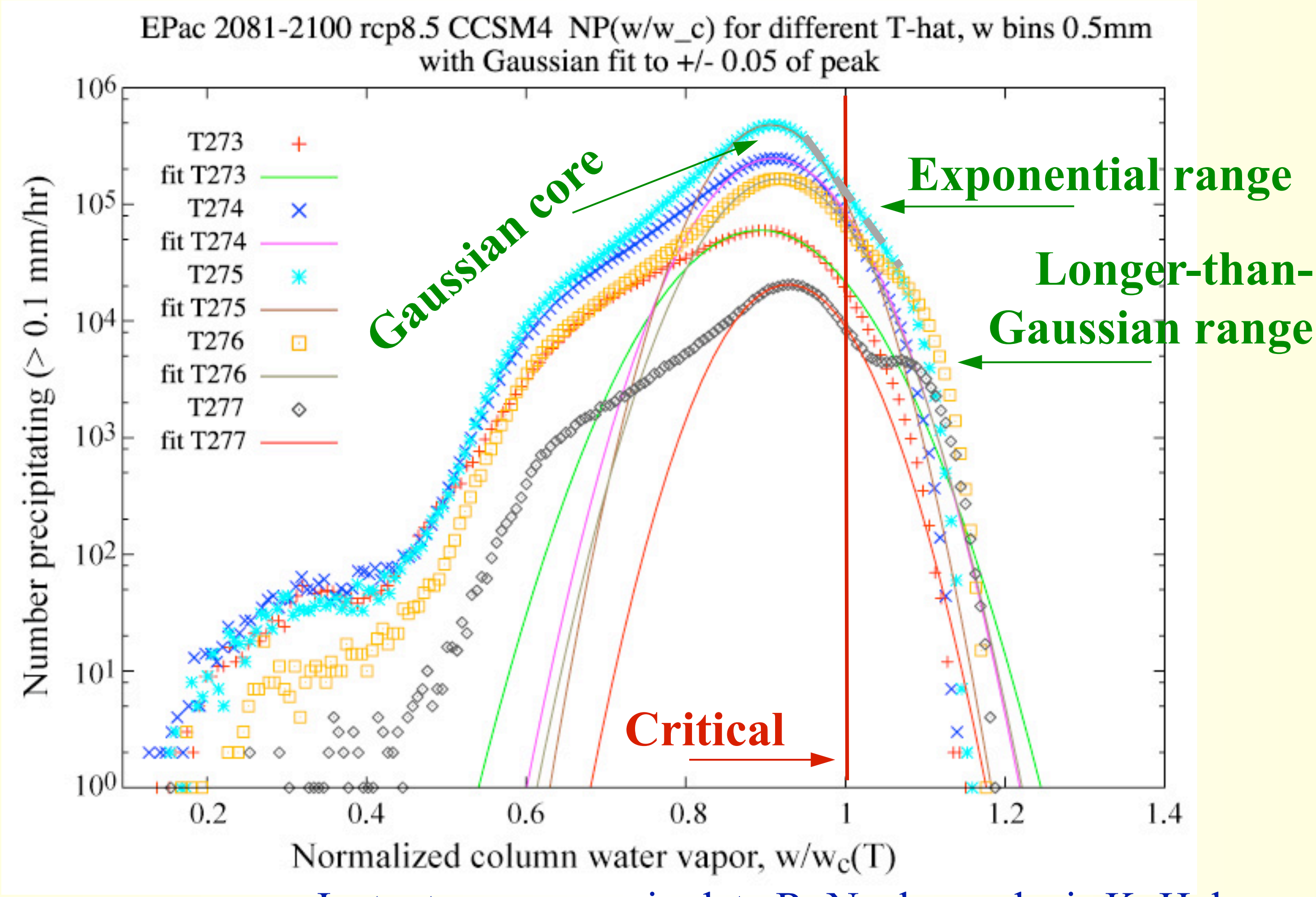


Instantaneous precip data R. Neale, analysis K. Hales

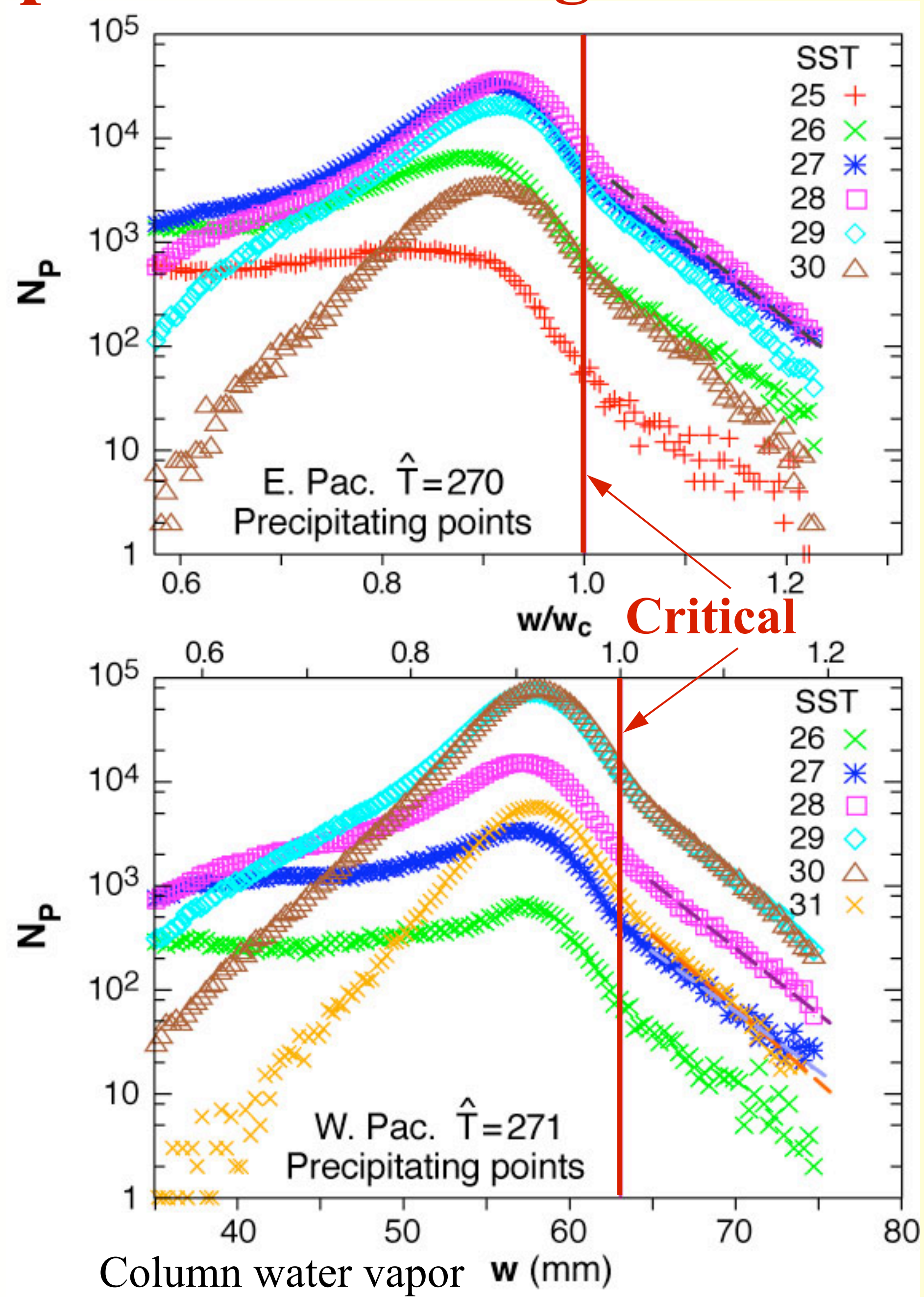
Variations with temp in super-Gaussian regime in obs?

Precipitating freq. of occurrence vs. *w/w$_c$*

Eastern & Western Pacific for various SST

- **Slope of exponential tail above critical varies ~10%**
- **Distribution near & above criticality reproducible over SST range spanning tropical large-scale conditions**

⇒Distribution quite robust to large-scale forcing in obs. strong precipitation regime



Column water vapor

Summary

- **Reduction of model uncertainty on precipitation change over large regions: slow (for global warming response, climatology, ENSO teleconnections,…)**
- **Leading issue in terms of decadal societal impact**
- **Fundamental questions on hydrological cycle sensitivity**
- **Work by Cloud, Convection, Precipitation and Radiation community to find new constraints for climate model parameterizations remains urgent**
- **The onset of strong convection: CCSM4 does fairly well vs. obs. statistics; Entrainment is key**
- **Changes in these statistics under global warming:**
- **1st approx. shift of distribution; Changes in distribution indicate more intense convection but occur in aspects that validate less well against current data**

[3-slide parenthesis: e.g. of simple modeling]

Stochastic prototype for precipitation onset statistics

$dq_t = E\,dt + D_0\,dW_t$, **if σ_t=0** (non-precipitating)

$\quad = -P\,dt + D_1\,dW_t$, **if σ_t=1** (precipitating)

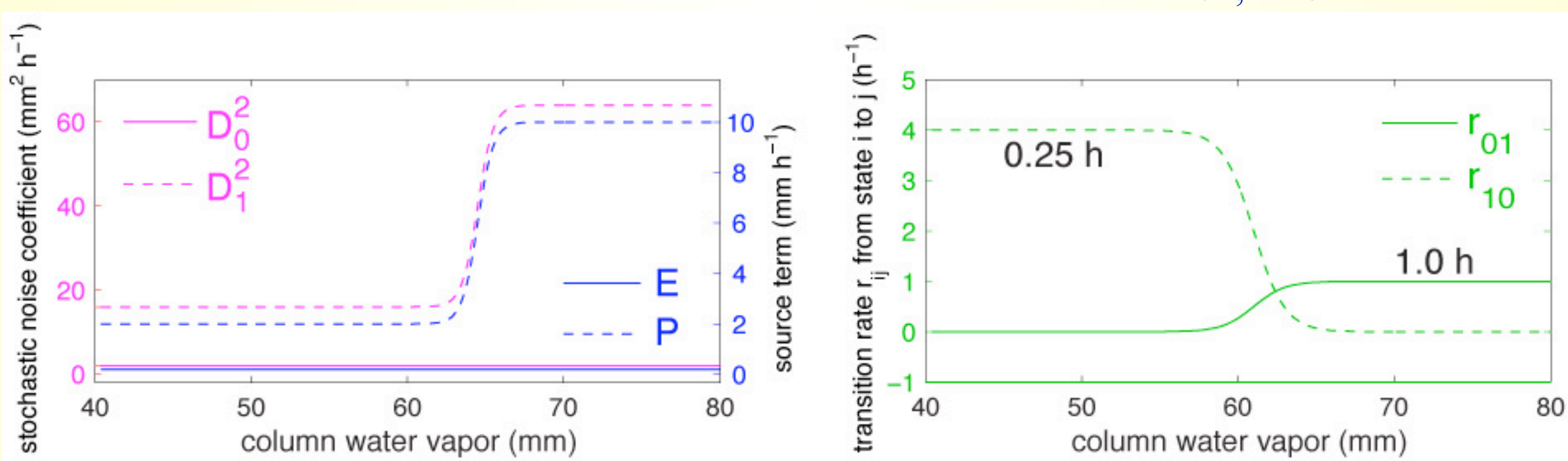
q Column water vapor

$P(q)$ Precipitation (deterministic contribution)

$D_1(q)\,dW_t$ Weiner proc. includes contributions by external dynamical forcing and precipitation variations

E, D_0 corresponding source, variations for no precip.

σ_t Stochastic jump process, transition rates $r_{01}, r_{10}(q)$

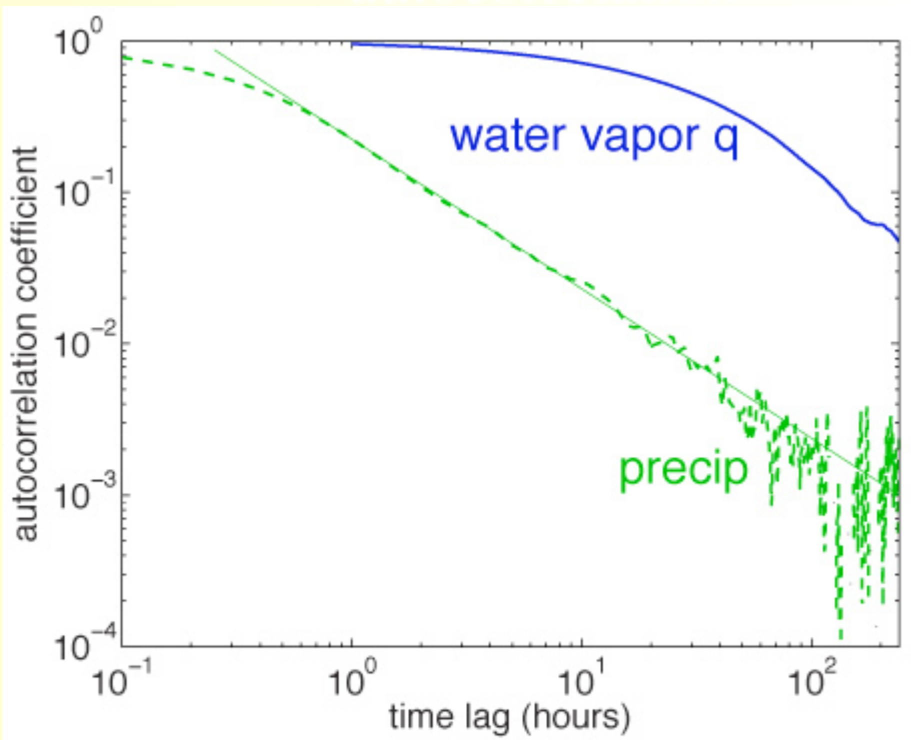


Stechmann & Neelin (2011; *JAS*)

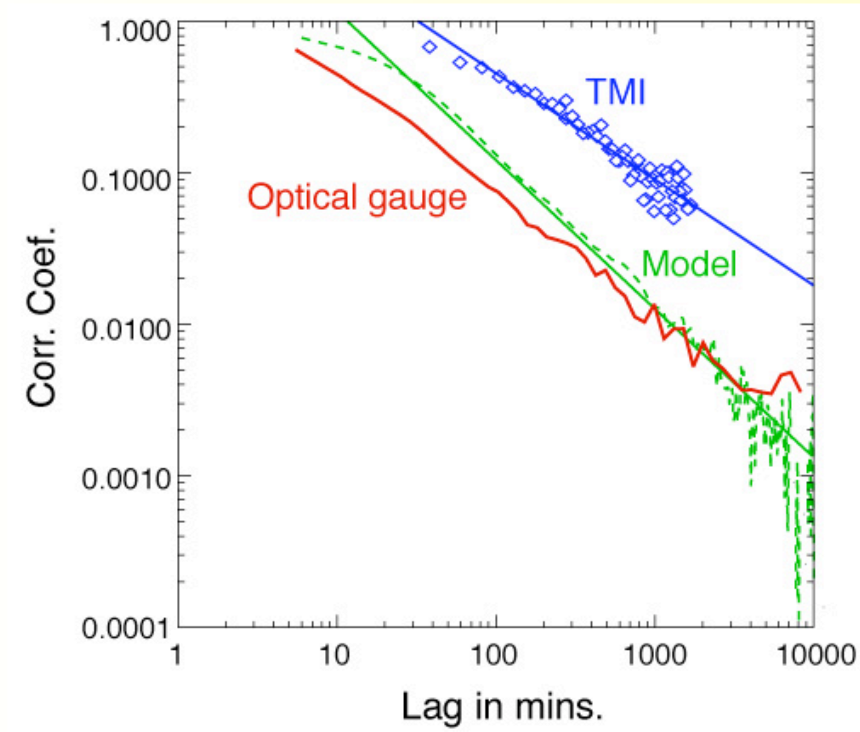
Note: Ito for simplicity, no difference from Stratonovich in limits of interest where D ~constant

Temporal autocorrelation

Model water vapor & Precip. autocorrelation



Precip. autocorr: model vs. obs*



•Water vapor decays slowly initially but ~exponentially

• Precipitation approx. power law decay akin to observed

•Key factor: stochastic forcing across the sharp onset

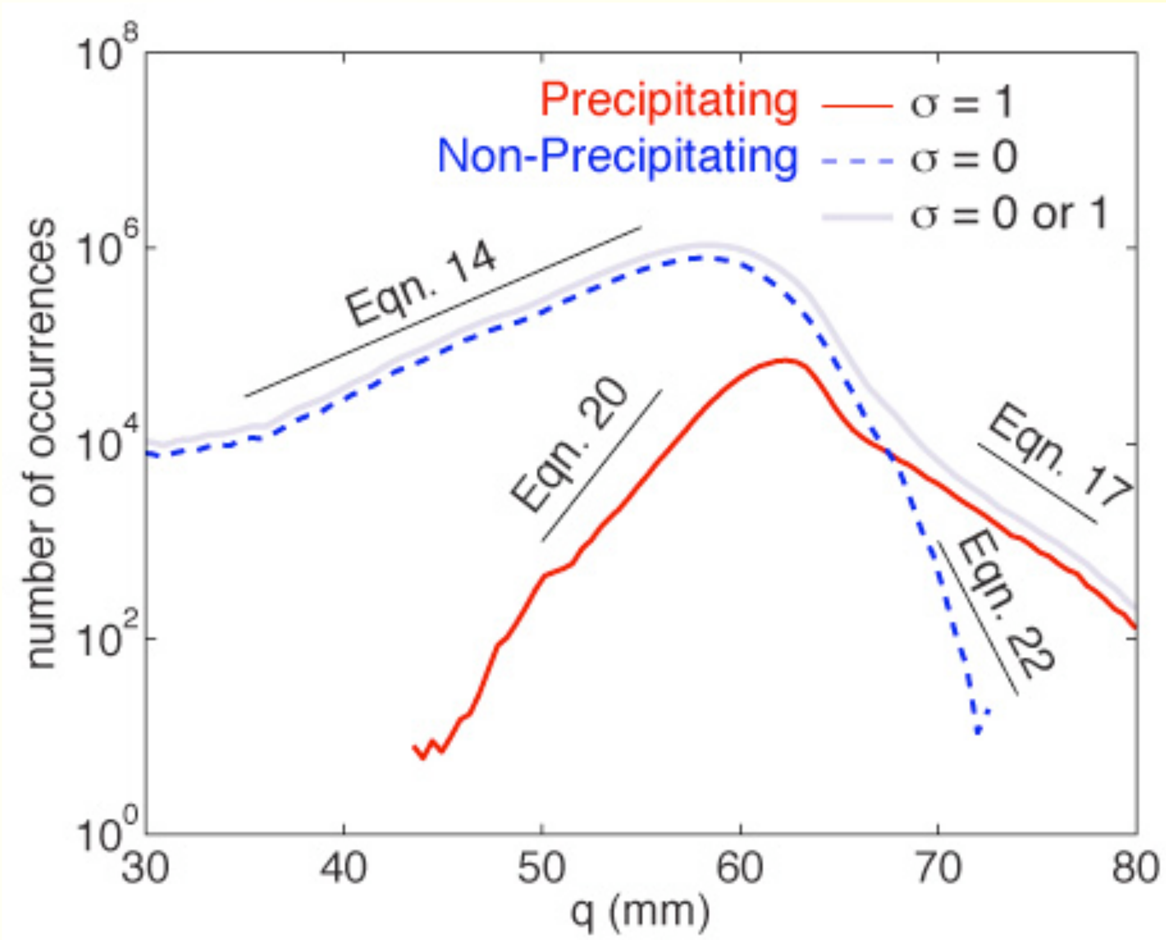
model: Stechmann & Neelin (2011; *JAS*)
Obs analysis: C. Holloway, B. Tian

Water vapor probability density function

Gaussian core, exponential tail (i.e., large events are relatively frequent)

Fokker-Planck equation analytic solutions for various regimes to understand mechanisms

Frequency of occurrence for precipitating and nonprecipitating points



Stechmann & Neelin (2011; *JAS*)

Fokker–Planck eqn. solutions in various regimes

Full Fokker-Planck + Master* equation (*term for jump process)

$$\partial_t \begin{pmatrix} p_0 \\ p_1 \end{pmatrix} + \partial_q \left[\begin{pmatrix} E & 0 \\ 0 & -P \end{pmatrix} \begin{pmatrix} p_0 \\ p_1 \end{pmatrix} \right] = \frac{1}{2}\partial_q^2 \left[\begin{pmatrix} D_0^2 & 0 \\ 0 & D_1^2 \end{pmatrix} \begin{pmatrix} p_0 \\ p_1 \end{pmatrix} \right] + \begin{pmatrix} -r_{01} & r_{10} \\ r_{01} & -r_{10} \end{pmatrix} \begin{pmatrix} p_0 \\ p_1 \end{pmatrix}$$

Approximate for various regimes, e.g.:

1. Precipitating low-CWV regime. $r_{01} \approx 0$ decouples the eqn. for p_1

$$-P\partial_q p_1 = \frac{D_1^2}{2}\partial_q^2 p_1 - r_{10} p_1$$

exponential solutions*

$$p_1(q) = A\exp(m_1 q), \quad m_1 = \frac{-P + \sqrt{P^2 + 2D_1^2 r_{10}}}{D_1^2} > 0$$

P* sink & jump vs. noise *D_1

2. Precipitating, high-CWV regime. $r_{10} \approx 0$ and $p_0 \approx 0$

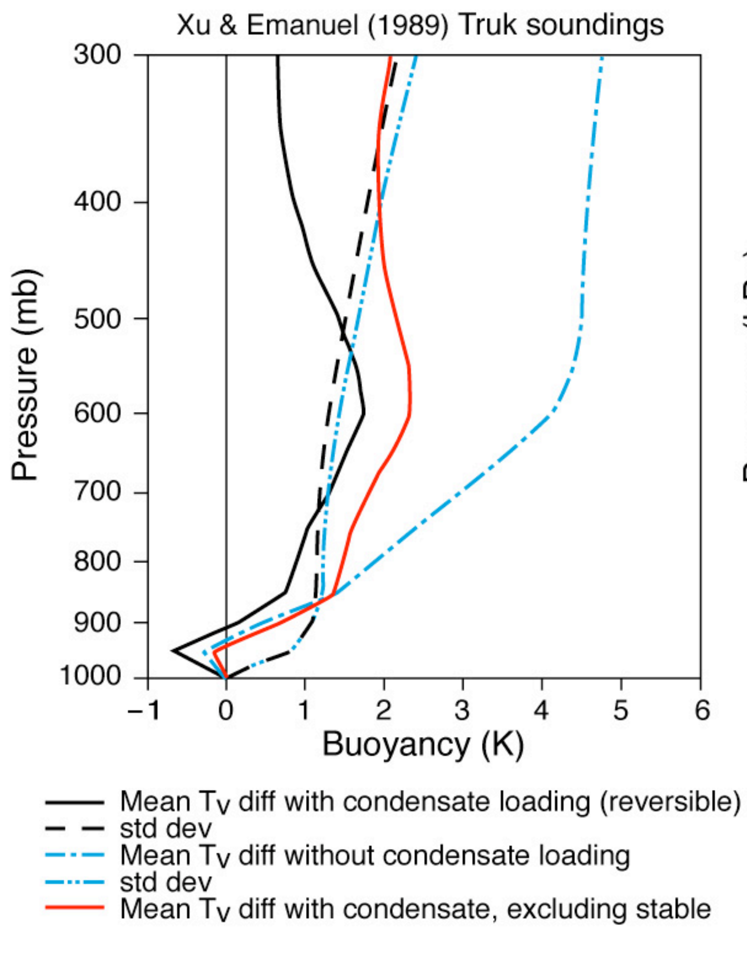
$$p_1(q) = A\exp\left(-\frac{2P}{D_1^2}q\right)$$

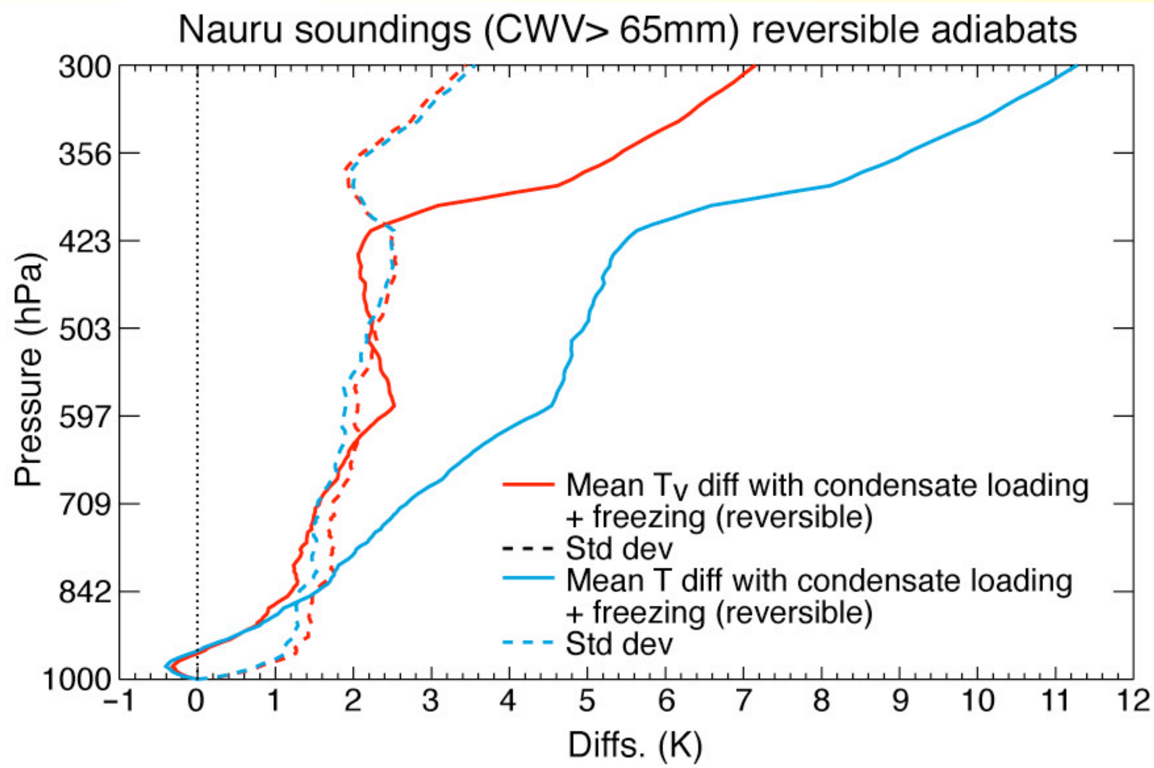
***P* sink vs. dynamical + conv. noise (precip.-on noise ampl. *D_1* is key)**

*within regime; match to neighboring regimes

Stechmann & Neelin (2011; *JAS*)

Farewell to the moist adiabat?



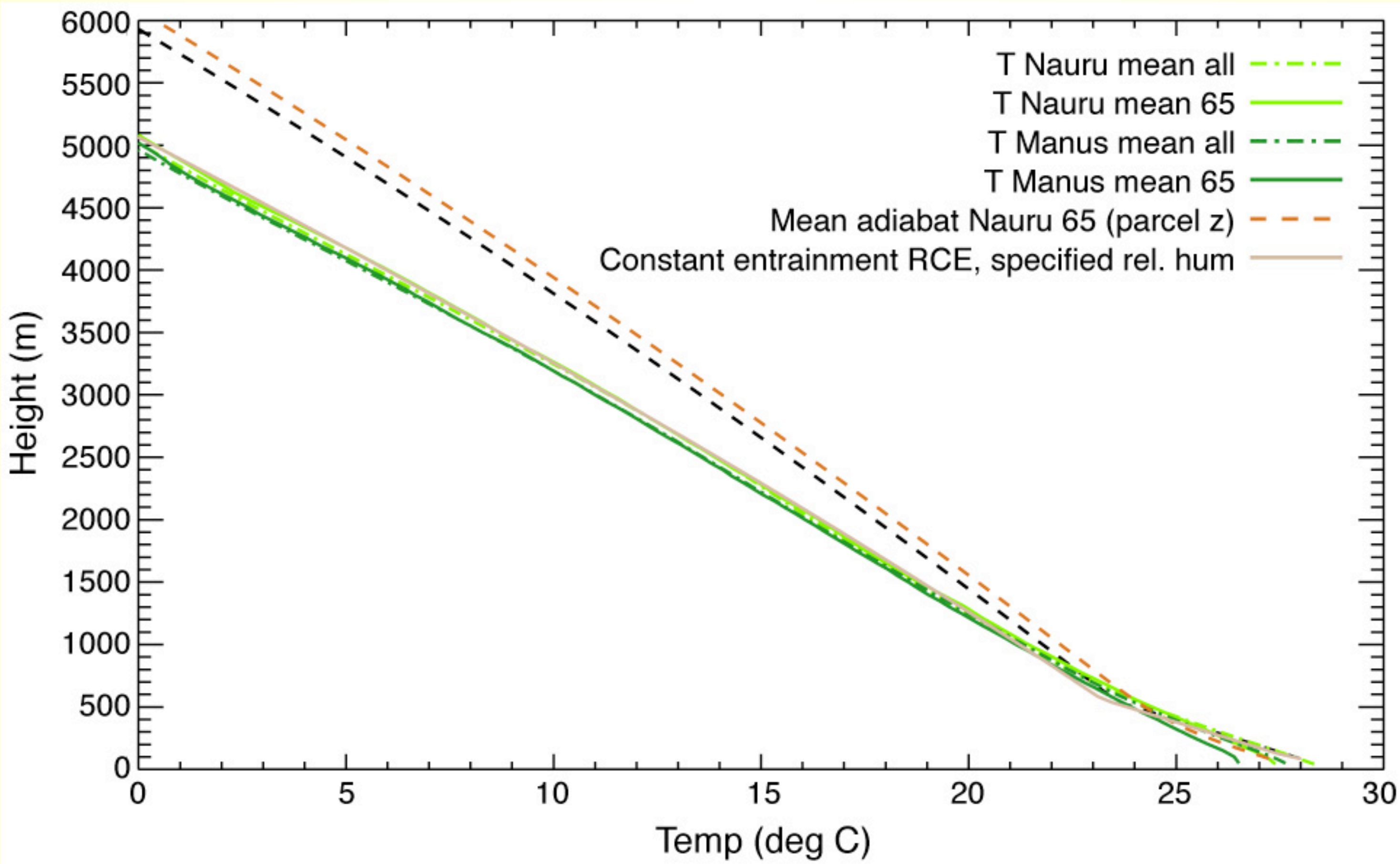


Xu &Emanuel 1989

Nauru arm site *T* & virtual temperature T_v difference from reversible adiabat (freezing at 0C)

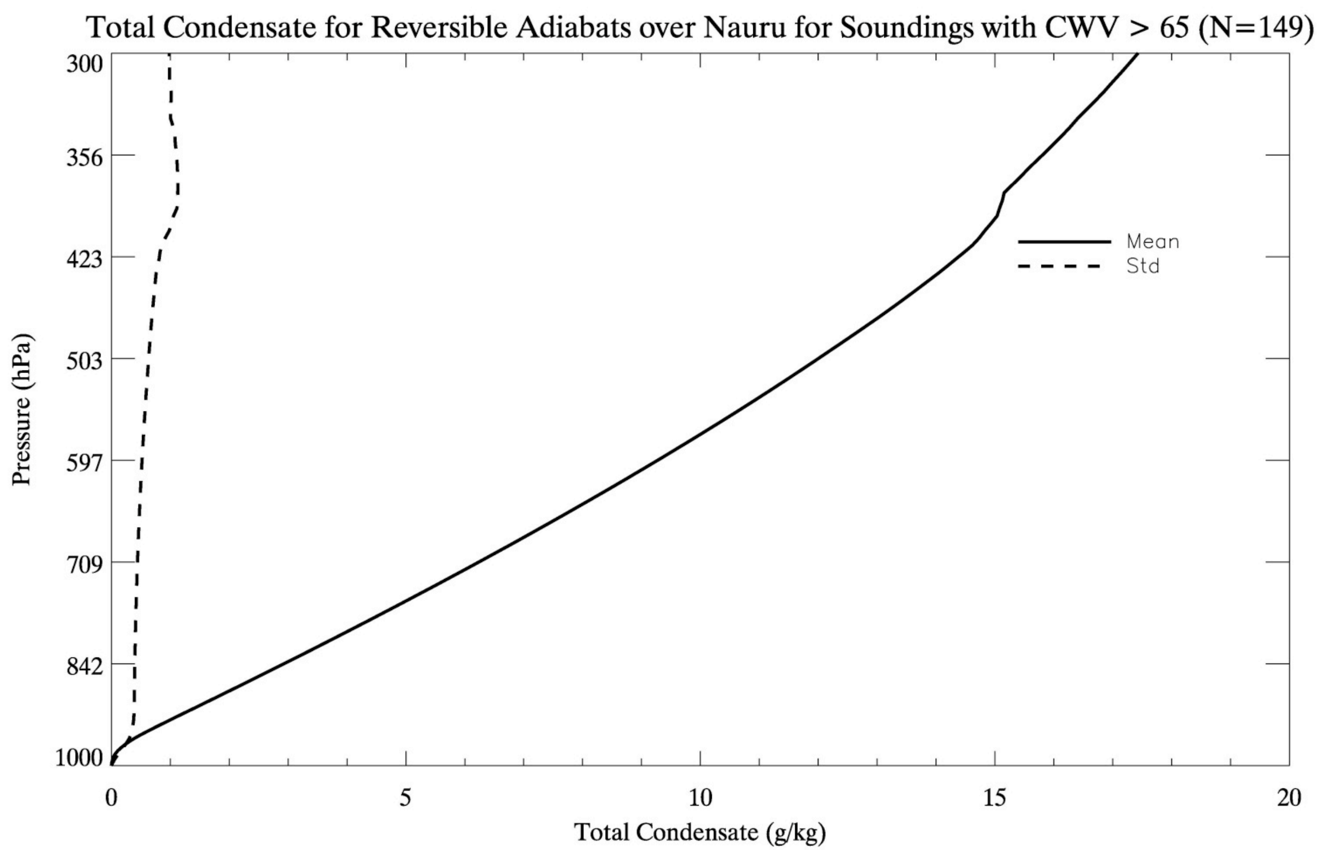
2C (T_v) to 4C (T) differences now matter. And reversible adiabat condensate reaches large values (~15g/kg at 400 mbar)

'Straightforward' to match observed T profile with an entraining plume (plausible analog for GCM tuning, while carefully acknowledging more complex processes possible!)



Simple radiative convective equilibrium with specified Nauru relative humidity profile; limit as cooling goes to 0 similar

[Application to Last Glacial Maximum in Western Pacific: Tripati et al. 2012, subm.]

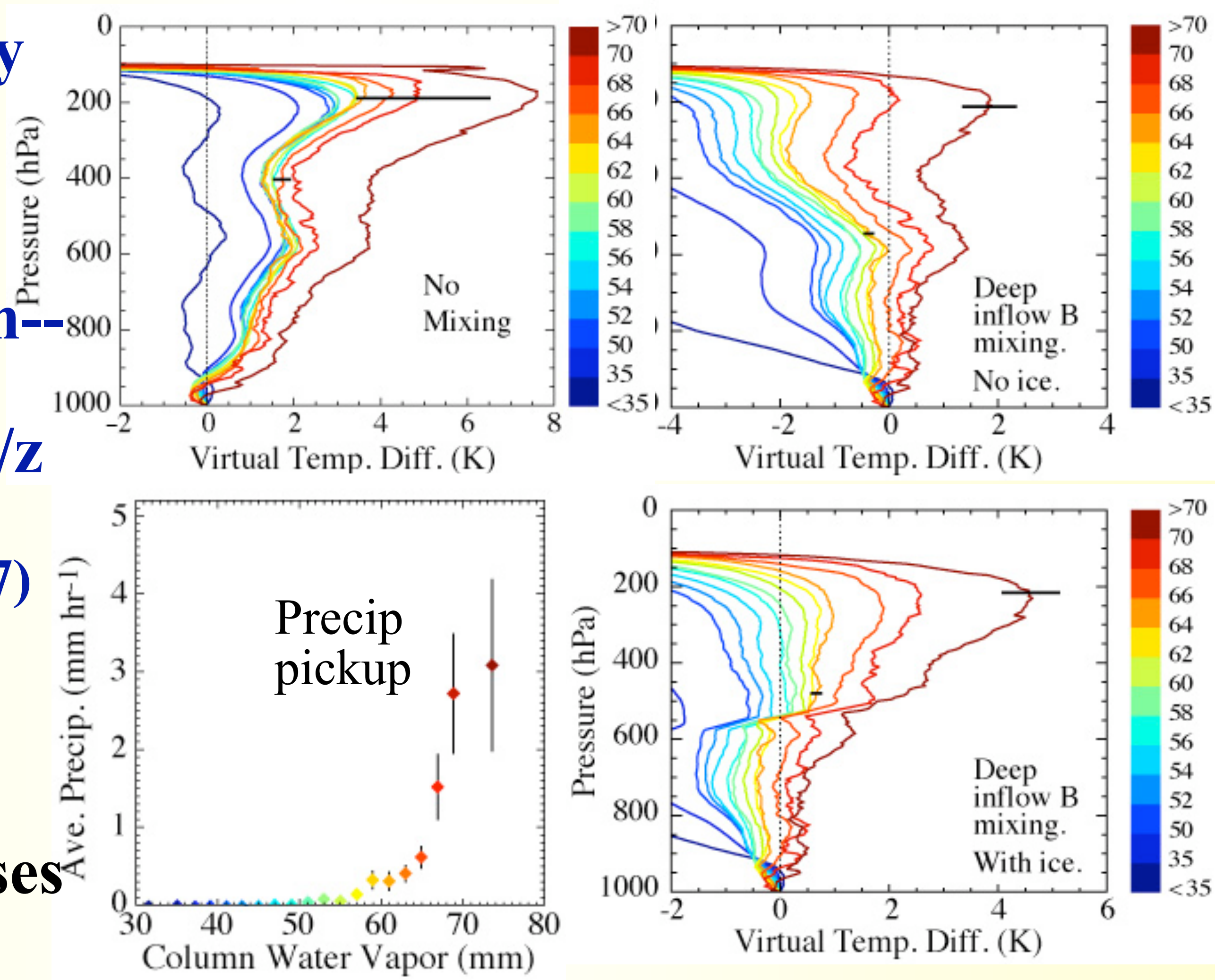

Total Condensate for Reversible Adiabats over Nauru for Soundings with CWV > 65 (N=149)
300
356
423
503
597
709
842
1000
Pressure (hPa)
0
5
10
15
20
Total Condensate (g/kg)
Mean
Std

Quantifying convective onset: not to forget microphysics!

Precip. & buoyancy binned by column water vapor (CWV)

- **precip. pickup: only top ~3 CWV bins**
- **Entraining plumes can match deep convective transition-- if include enough entrainment; here 1/z vertical dependence (eg, Siebesma et al, 2007)**

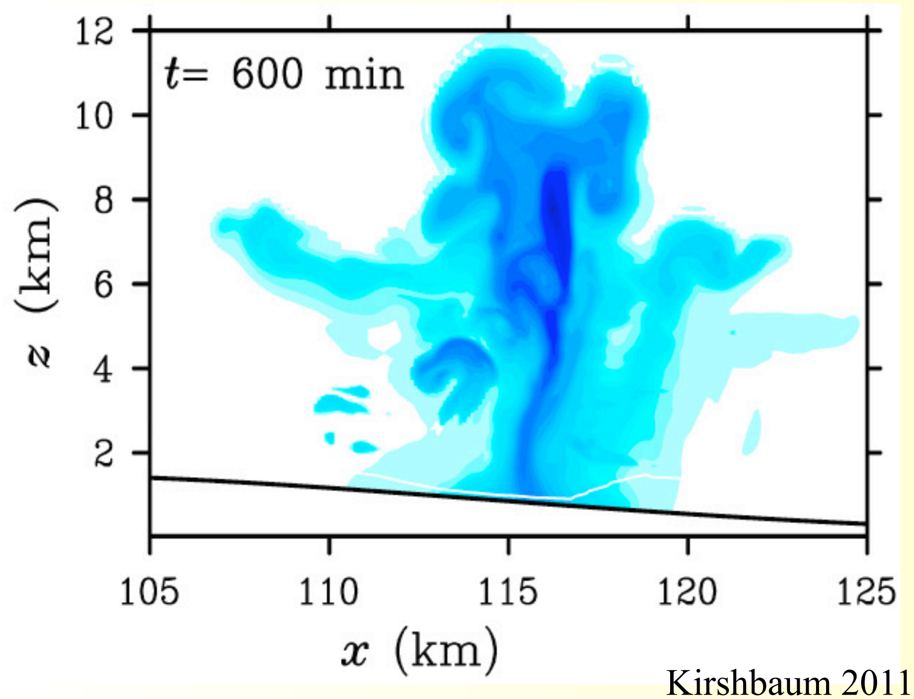
- **But there's also a dependence on condensate loading and freezing processes**



Holloway & Neelin, 2009, *JAS*

Importance of very small scales

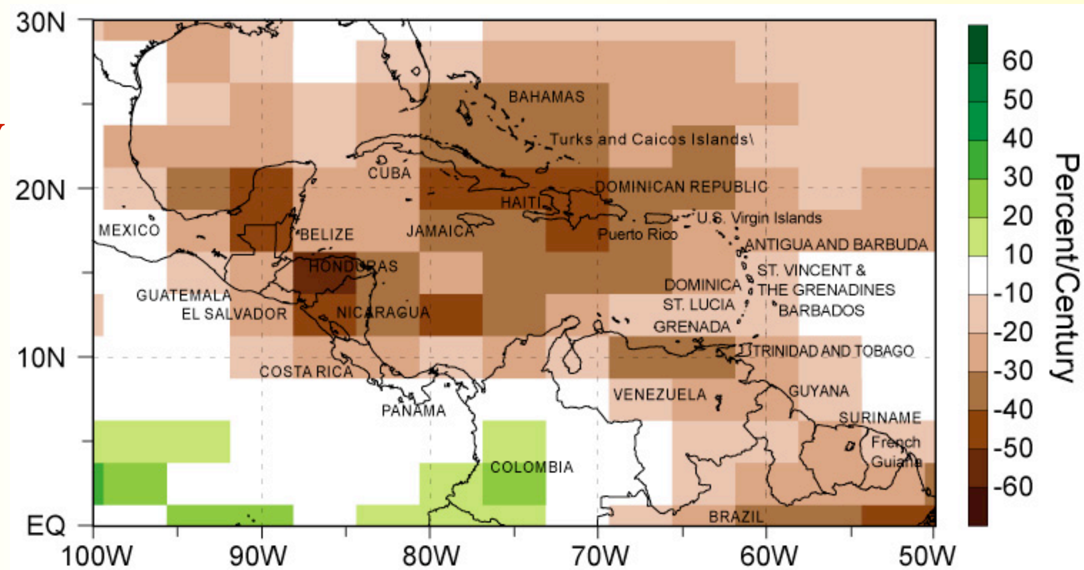
- Importance of entrainment to the onset of deep convection
- Explains sensitivity to free tropospheric water vapor
- can constrain using deep convective transition: but more precision involves joint constraints on microphysics
- what's the simplest acceptable replacement for a moist adiabat for describing a typical parcel lapse rate etc for those who can't run giga-LES?



Kirshbaum 2011

Outlook

- The regional scale changes in the hydrological cycle are arguably the most important aspect of climate sensitivity over the 21st century

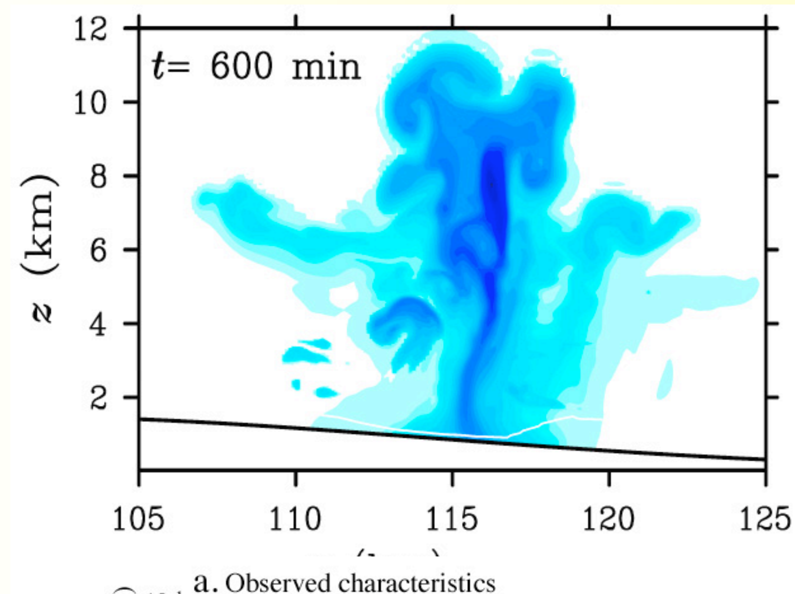


- Move from Uncertainty Quantification to Uncertainty Reduction: remains challenging in CMIP5 models

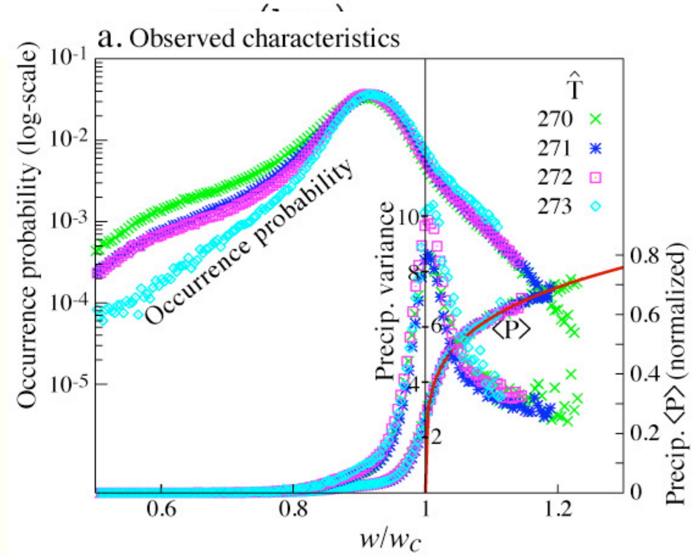
- Using climate model precipitation projections: Caution on simple statements; measure of uncertainty on multi-model ensemble mean; specific model validation for key phenomenon in the region of interest for each member of the ensemble

Outlook

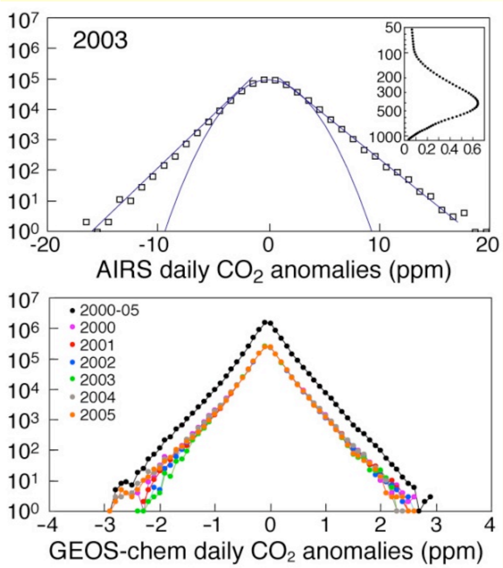
- The regional scale changes in the hydrological cycle are arguably the most important… Will we do any better at reducing uncertainty?



Current tackling of small scale processes, scale interactions, new observational constraints, systematic parameter estimation methods,… seem likely to yield progress--- although not high precision by July 2012



Some connections…



•**Long tails** seen in the probability distribution of water vapor also occur for **chemical tracers** including CO2: (B. Lintner, B. Tian, Q. Li, L. Zhang, P. Patra, M. Chahine)

•And **surface temperature** (T. Ruff)

•Simple stochastic model **Fokker-Planck** solutions indicate processes (S. Stechmann)

•**Nastier parameter dependence** can occur (M. Chekroun et al.)

•Do constraints on entrainment combine with new proxy data to resolve a surface temperature vs. glacial elevation conundrum at **last glacial maximum**? (A. Tripati, S. Sahany, D. Pittmann, R. Eagle, J. Eiler, J. Mitchell, L. Beaufort)

• theory for inflow air mass interacting with convective onset at the **margins of convection zones** can be tested in models (H.Y. Ma, C.R. Mechoso, X. Ji)

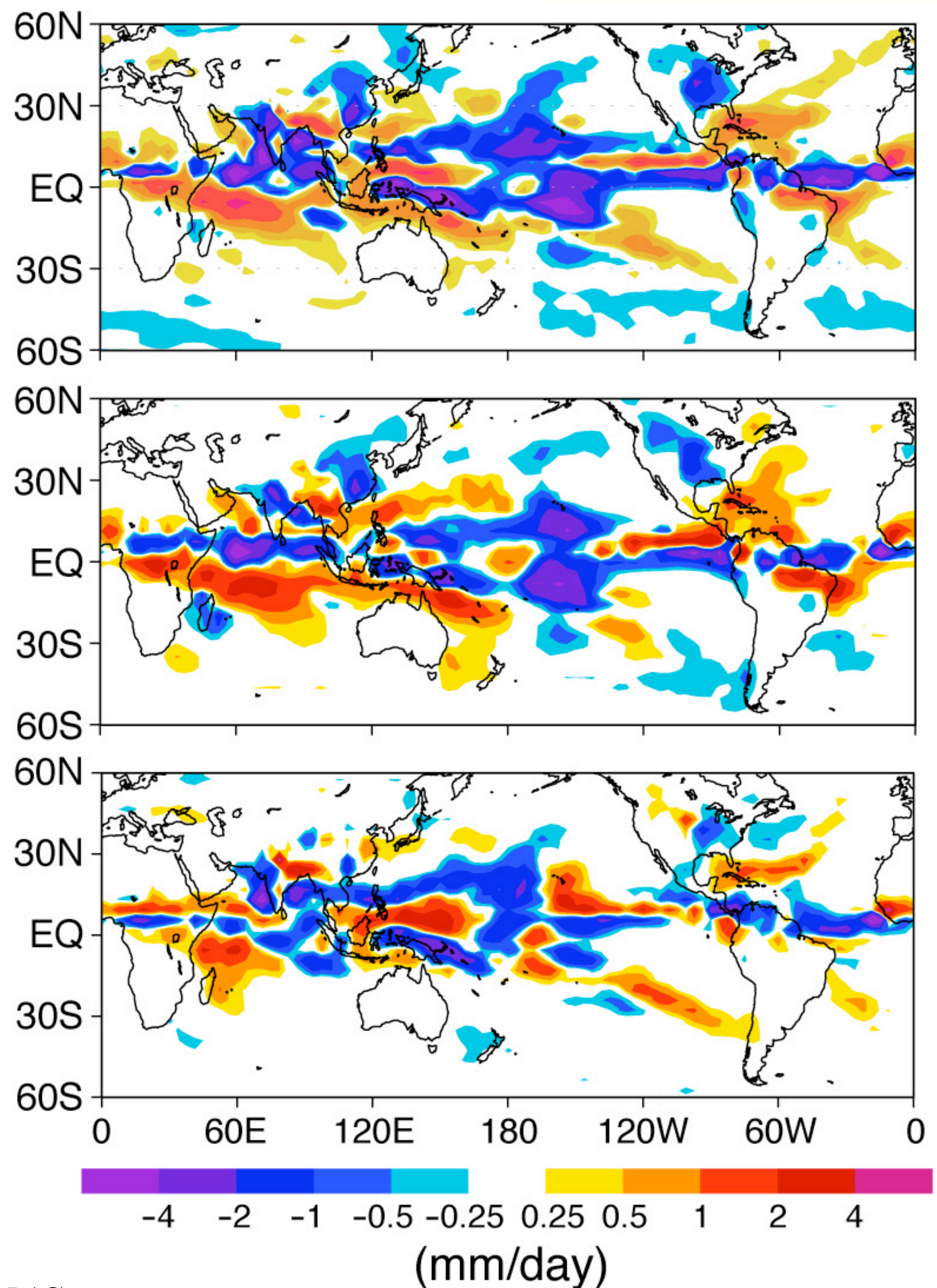
- **Extras after here**

Global warming precipitation change parameter sensitivity

Ensemble-mean JJA precipitation (as a departure from the annual mean) for Conv. rel. hum. param μ_{max} relative to the standard case for AGCM coupled to a mixed-layer ocean:
change for $2xCO_2$ minus pre-industrial.

Linear contribution

Nonlinear contribution



Neelin, Bracco, Luo, McWilliams, Meyerson 2010, *PNAS*.

Implications for multi-model ensemble average