RGCM

Diagnosing the Sensitivity of CAM5's MJO to Physical Parameters

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ASR Atmospheric System Research

CAPT Cloud-Associated Parameterizations Testbed

Motivation and Approach

- **Modelers would like to understand how their climate models could better simulate an MJO**
- **We systematically explore the dependencies of CAM5's MJO simulation on uncertain parameters, with a "perturbed-parameter ensemble" technique**
  - To what extent, do the parameters control the interactions of the parameterized processes and influence the MJO?
  - *Are better MJOs within tuning ranges? Or are new parameterizations needed?*
- **We more fully explore the range of model MJO behaviors by perturbing uncertain parameters in CAM5 physics**

Perturbed Parameter Ensemble (PPE)

- CAM5.1 @ 2° resolution
- 5-year prescribed SST simulations (2000-05)
- Simultaneously perturb 22 parameters using Latin Hypercube Sampling ("LHS")
- # of simulations = 1100
- Simulations were performed for DOE's Climate Science for a Sustainable Energy Future project

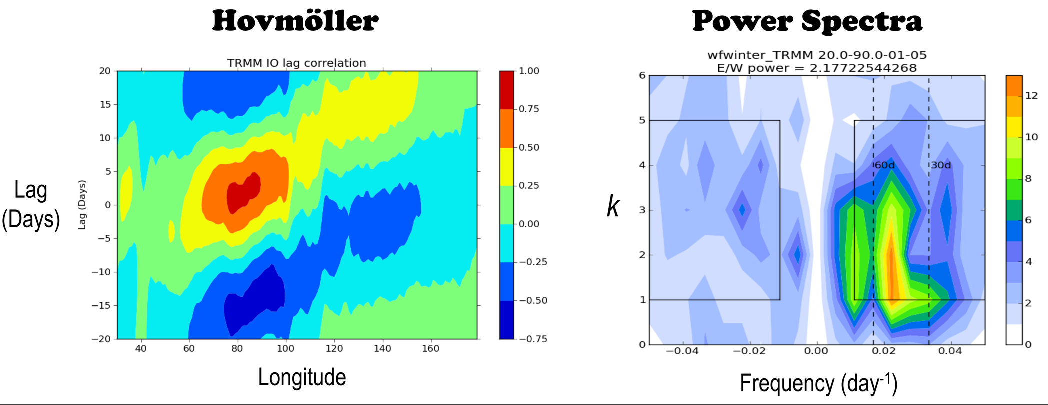
Parameters Perturbed

Group	modelSection_modelVariable	variable description	low value	default	high value
Large-Scale Cloud	cldfrc_rhminh	Threshold RH for fraction high stable clouds	0.65	0.8	0.85
	cldfrc_rhminl	Threshold RH for fraction low stable clouds	0.8	0.8875	0.99
	cldwatmi_ai	Fall speed parameter for cloud ice	350	700	1400
	cldwatmi_as	Fall speed parameter for snow	5.86	11.72	23.44
	cldwatmi_cdnl	Cloud droplet number limiter	0	0	1e+06
	cldwatmi_dcs	Autoconversion size threshold for ice to snow	0.0001	0.0004	0.0005
	cldwatmi_eii	Collection efficiency aggregation of ice	0.001	0.1	1
	cldwatmi_qcvar	Inverse relative variance of sub-grid cloud water	0.5	2	5
Aerosol	dust_emis_fact	Dust emission tuning factor	0.21	0.35	0.86
PBL Turb.	eddydiff_a2l	Moist entrainment enhancement parameter	10	30	50
Large-Scale Cloud	micropa_wsubimax	Maximum sub-grid vertical velocity for ice nucleation	0.1	0.2	1
	micropa_wsubmin	Minimum sub-grid vertical velocity for liquid nucleation	0	0.2	1
Shallow Conv.	uwshcu_criqc	Maximum updraft condensate	0.0005	0.0007	0.0015
	uwshcu_kevp	Evaporative efficiency	1e-06	2e-06	2e-05
	uwshcu_rkm	Fractional updraft mixing efficiency	8	14	16
	uwshcu_rpen	Penetrative updraft entrainment efficiency	1	5	10
Deep Conv.	zmconv_alfa	Initial cloud downdraft mass flux	0.05	0.1	0.6
	zmconv_c0_lnd	Deep convection precipitation efficiency over land	0.001	0.0059	0.01
	zmconv_c0_ocn	Deep convection precipitation efficiency over ocean	0.001	0.045	0.1
	zmconv_dmpdz	Parcel fractional mass entrainment rate	0.0002	0.001	0.002
	zmconv_ke	Evaporation efficiency parameter	5e-07	1e-06	1e-05
	zmconv_tau	Convective time scale	1800	3600	28800

MJO Metrics

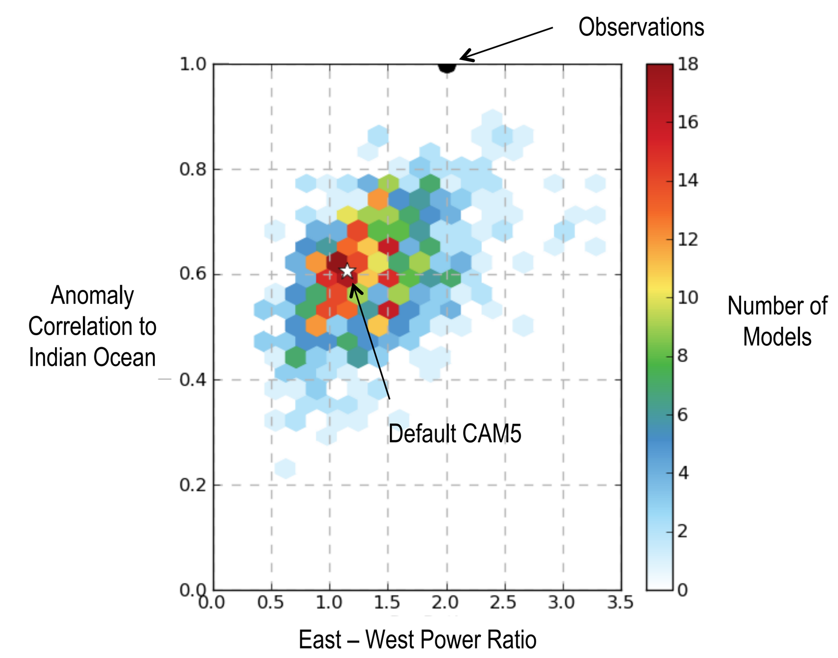
From the CLIVAR MJO Task Force (2009):

1. **Hovmöller:** Correlation coefficient of model with observations for the pattern of lead-lag correlation coefficients of band-passed filtered 5°N-5°S averaged precipitation with that in the Indian Ocean (70°-90°E)
2. **Power Spectra:** East-west power ratio of precipitation variance in wavenumbers 1-5 and periods 20 – 90 days



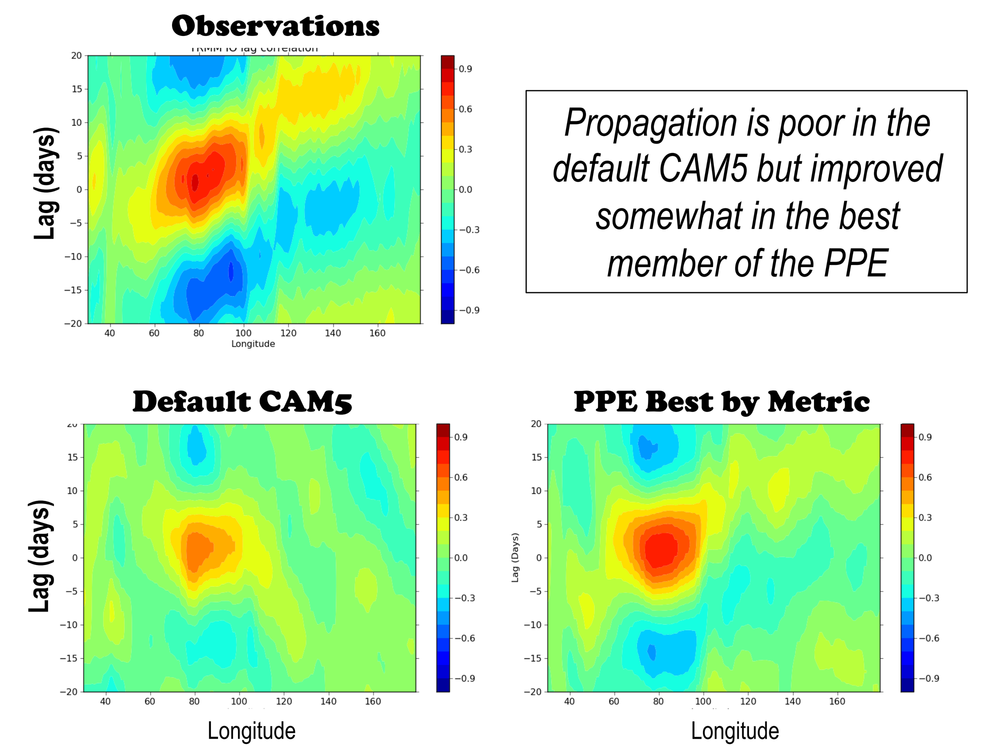
MJO Behavior in the PPE

Density Plot of Metrics from the PPE Ensemble



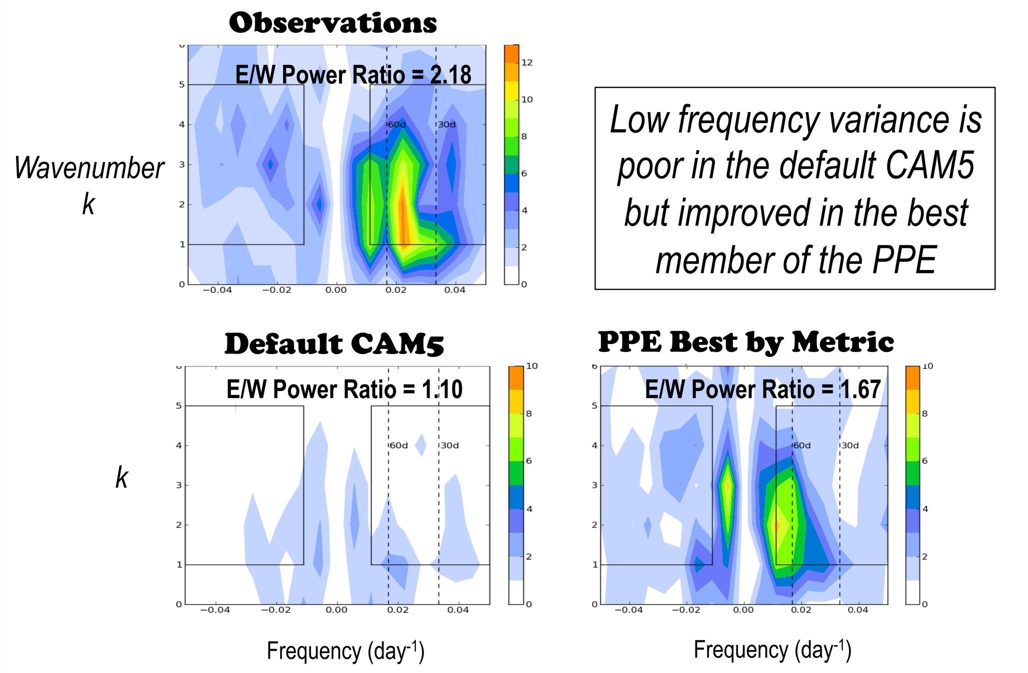
While most models have a poor MJO, the ensemble displays a wide range of performance in these MJO metrics

Precipitation Hovmöller



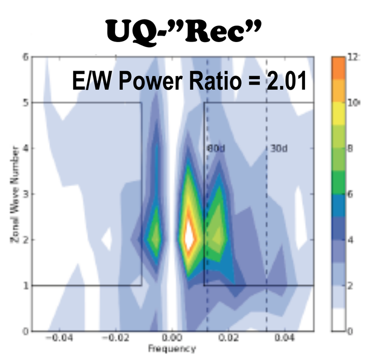
Propagation is poor in the default CAM5 but improved somewhat in the best member of the PPE

Power-Spectra



Low frequency variance is poor in the default CAM5 but improved in the best member of the PPE

MJO in "UQ-Rec"



Altering only the 4 parameters that influence the MJO yields the best MJO simulation

Which parameters affect CAM5's MJO? What parameter values would improve CAM5's MJO?

Methods

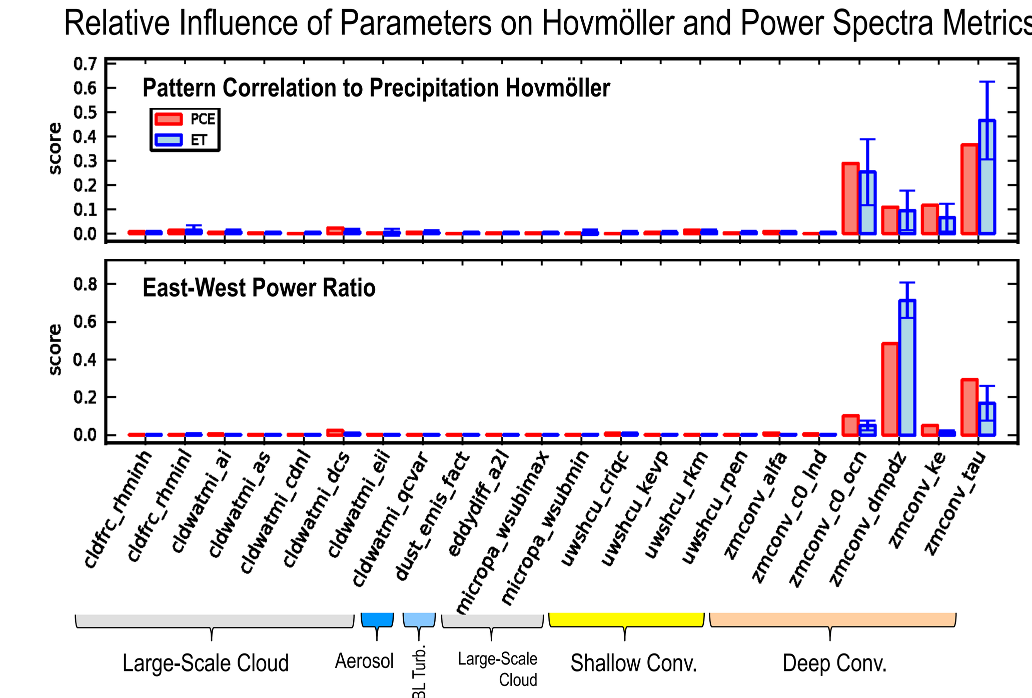
- Fit a mathematical "surrogate" model that relates the predictands (metrics of MJO simulation) to the predictors (physics parameters perturbed)
- Use "surrogate" model to tell you which predictors have influence and which are immaterial
- Create a new "surrogate" model with only the important predictors
- Use the new "surrogate" model and the observed predictand values to create likelihood estimates of the predictors

Specific techniques used

- Sparse Polynomial Chaos Expansion (3rd order) (PCE)
- Random Forest Regression (ET) *(Breiman 2001)*

Deep convection parameters matter

Relative Influence of Parameters on Hovmöller and Power Spectra Metrics



Suggested Parameter Changes

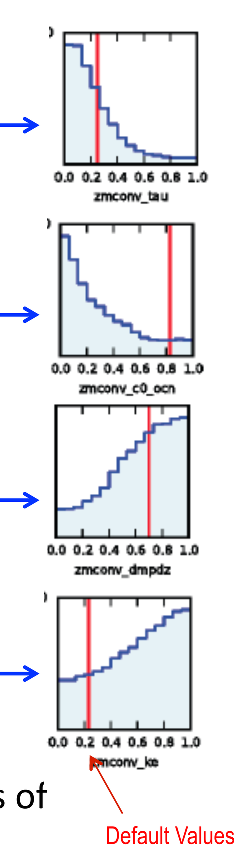
Parameter Likelihoods

zmconv_tau: shorten convective time-scale

zmconv_c0_ocn: less autoconversion of convective condensate to precipitation

zmconv_dmpdz: increase entrainment rate

zmconv_ke: increased evaporation of convective precipitation



Note that the largest weights happen at the ends of the parameter ranges, suggesting that improved performance would result if one allowed the parameters to go outside of the pre-specified ranges

"UQ-Rec"

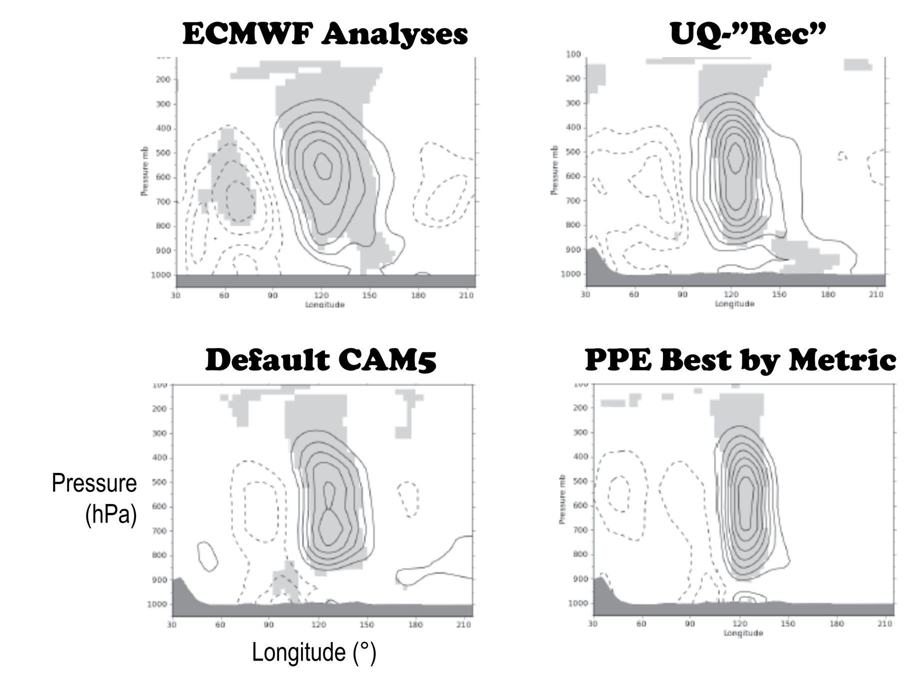
- We test whether the guidance from the PPE can yield a better MJO by doing a new simulation (called "UQ-Rec") which only changes the 4 parameters shown to have an impact on the MJO
  - Actually only three parameters need to be altered because zmconv_dmpdz is close to the optimal value

Is CAM5's MJO like the real MJO?

- Observational analyses have demonstrated that the MJO has a specific structure of moisture anomalies whereby the low-level moisture builds up to the east of the precipitation maximum. This is thought to be important for the eastward propagation of the MJO.

Moisture Anomalies in a Composite MJO

Zonal cross-section of moisture anomalies regressed onto band-passed filter precipitation at 120°E



The modified CAM simulation ("UQ Rec") shows the best agreement with ECMWF analyses – particularly for the shifted low level moisture anomalies in the lower troposphere

But is the mean climate improved?

Mean Climate Bias and Root-Mean-Square Errors

With respect to observations of 10-year DJF means

model	Precip. GPCP Bias	Precip. GPCP RMS	Shortwave Cloud Forcing CERES EBAF SWCF Bias	Shortwave Cloud Forcing CERES EBAF SWCF RMS	Cloud Liquid Water Path NVAP LWP Bias	Cloud Liquid Water Path NVAP LWP RMS	Outgoing Longwave Radiation CERES EBAF OLR Bias	Outgoing Longwave Radiation CERES EBAF OLR RMS
Default	0.301	1.284	-2.76	21.25	-35.32	39.71	-3.95	9.967
UQ-Rec	0.179	1.314	-20.82	36.17	216.54	355.20	-7.46	13.12
PPE-Best	0.252	1.501	-27.655	41.089	188.29	303. 08	-7.99	13.90

✔ UQ-Rec has lower precipitation bias and similar RMS to default

✗ UQ-Rec has a 21 W/m^2 bias in SWCF and a >200 g/m^2 in liquid water path

While the mean precipitation field has similar quality as the default CAM5, the radiation balance is unacceptably out-of-balance due to the build-up of highly reflective low-level cloud

Conclusions

- Through analysis of a large Perturbed-Parameter Ensemble, we determined which physical parameters had the greatest influence on CAM5's simulated MJO
- Altering the values of only the parameters that influence the MJO to their recommended values yielded the best simulation MJO simulation
- However, the simulation with the best MJO had significantly degraded radiation field, suggesting that other changes would be necessary to CAM5's physical parameterizations if this guidance were to used in the default model

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