Perturbed-parameter Simulations of the MJO with CAM5

James Boyle, Stephen Klein, Don Lucas, John Tannahill, Shaocheng Xie, Ken Sperber
Program for Climate Model Diagnosis and Intercomparison / Lawrence Livermore National Laboratory

Rich Neale
National Center for Atmospheric Research

Motivation and Approach

- Modelers would like to understand how their climate models could better simulate an MJO
  - CAM5 is noticeably worse than CAM4 which was quite good (Subramanian et al. 2012). *Why?*
- 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 wish to more fully explore the range of model MJO behaviors as a function of parameters

Perturbed Parameter Simulations

"Climate":

- CAM5.1 @ 2° resolution
- 5-year "AMIP" simulations (i.e. prescribed SSTs for 2000-05)
- Two ensembles:
  - Perturbed each of 22 parameters in CAM's physical parameterizations ONE-AT-A-TIME ("OAT") (# of simulations = 2*22 + 1 = 45)
  - Simultaneously perturb 22 parameters using Latin Hypercube Sampling ("LHS") (# of simulations = 1100)
- These simulations were performed for another project → Only hourly (total) precipitation is available for our analysis

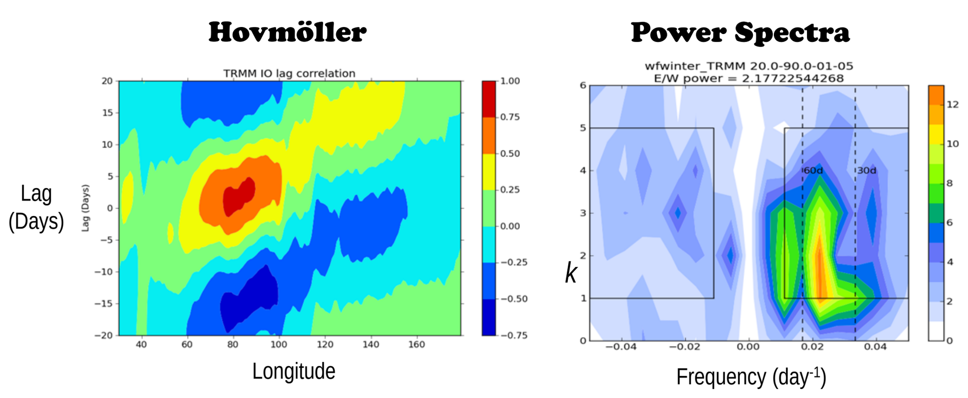
Parameters Varied

	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

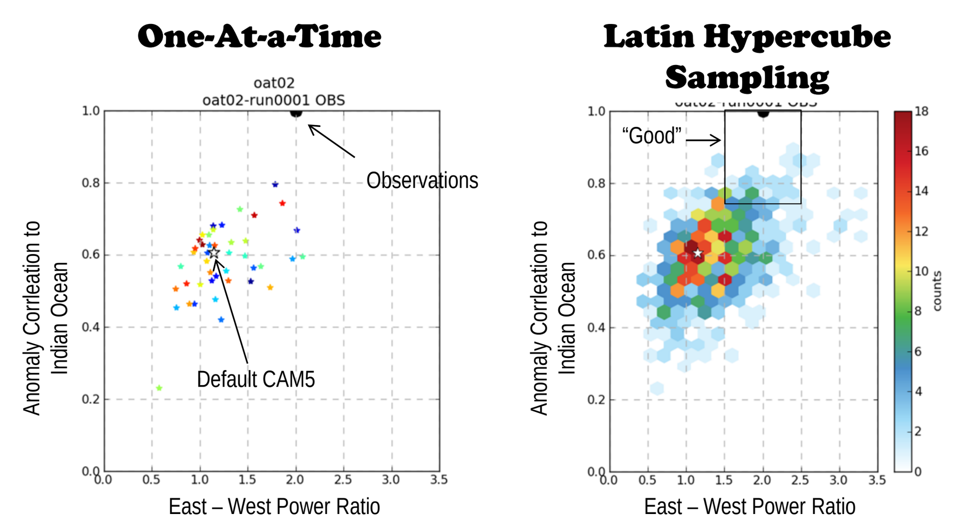
MJO Metrics

a) Correlation coefficient with 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)

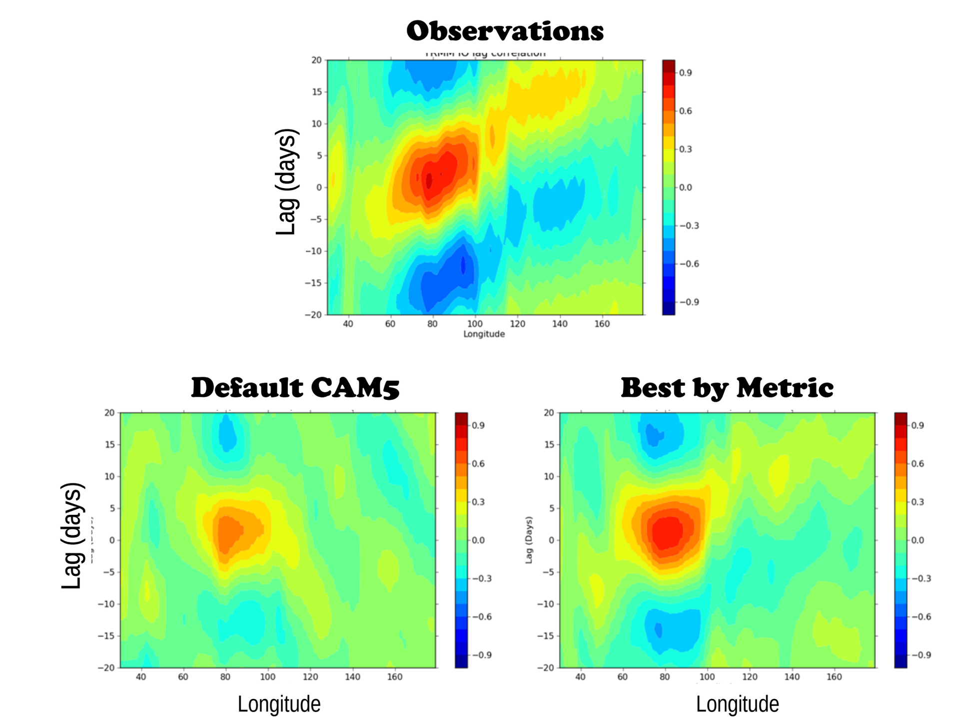
b) East-west power ratio of precipitation variance in wavenumbers 1-5 and periods 20 – 90 days



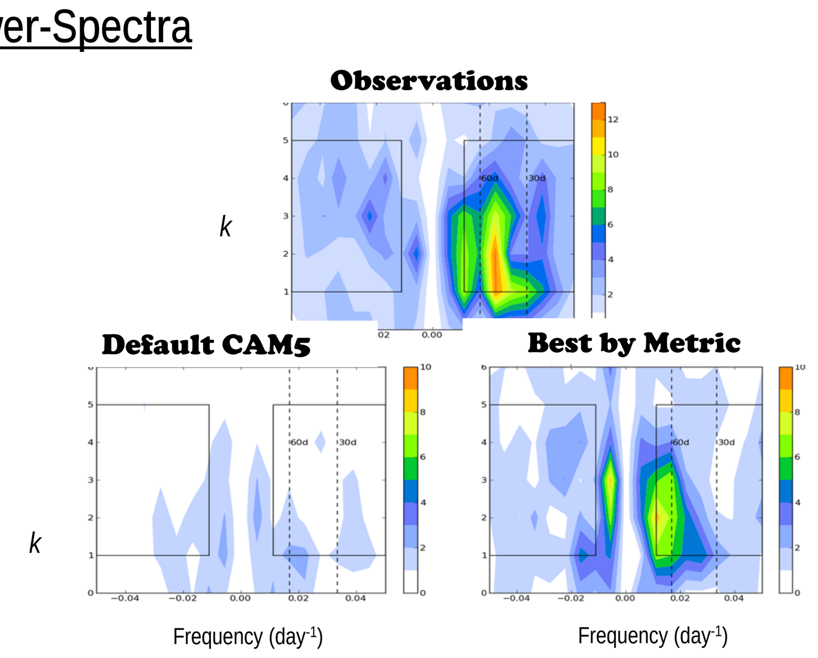
Variability in Metrics



Lead-Lag Correlations Patterns



Power-Spectra



Surrogate Model

What Parameters Matter? What values improve the simulations?

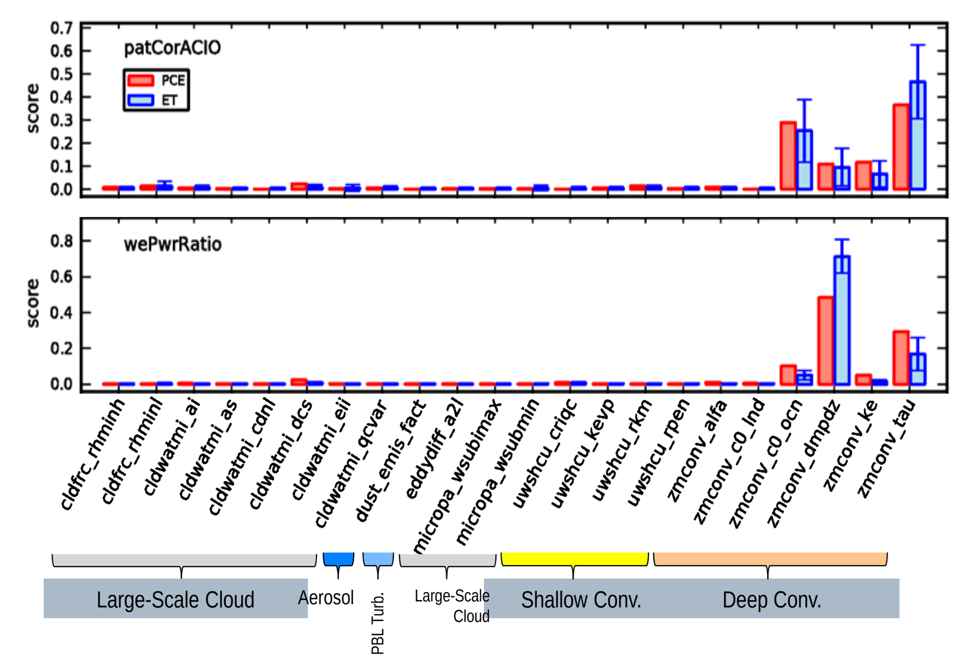
General approach

- 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 methods used

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

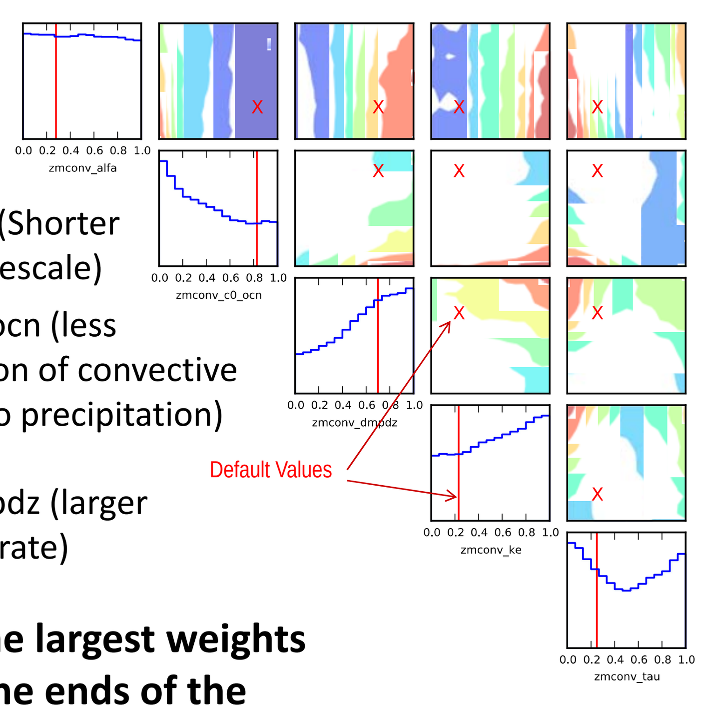
Deep convection parameters matter



Deep convection parameters matter

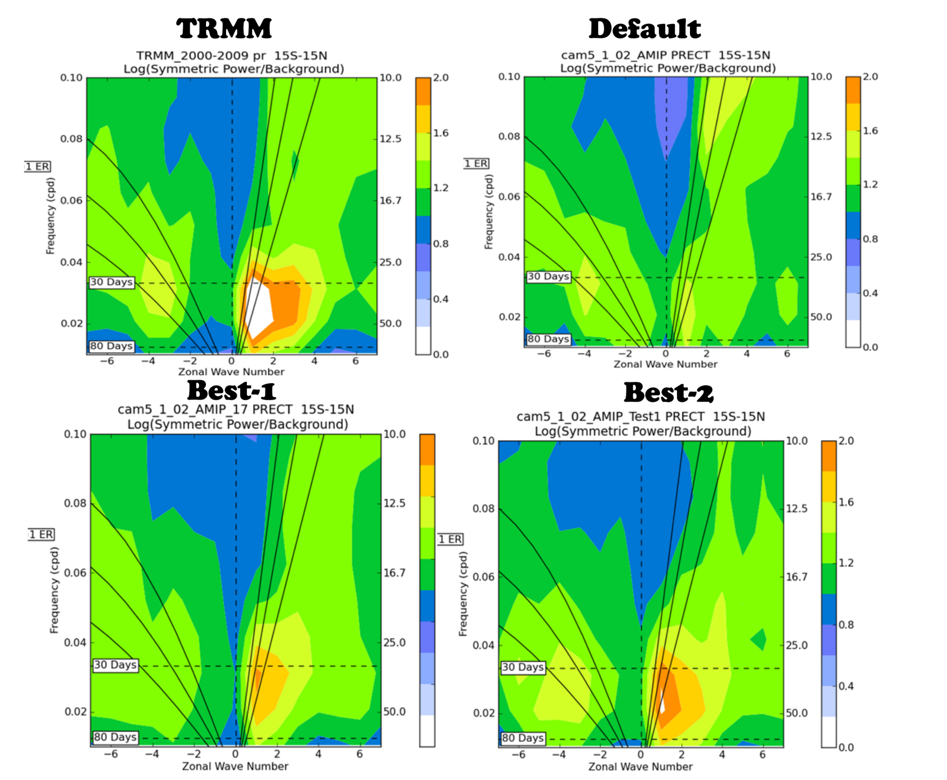
Parameter Likelihoods

- **Suggested parameter improvements**
  - Zmconv_tau (Shorter & Longer timescale)
  - Zmconv_c0_ocn (less autoconversion of convective condensate to precipitation)
  - Zmconv_dmpdz (larger entrainment rate)



- **Note that the largest weights happen at the ends of the parameter ranges**
  - This suggests that improvement performance would result if one allowed the parameters to go outside of the pre-specified ranges

Improved MJO



Best-1: best setting based on initial creteria

Best-2: guidance from UQ Minimum values of c0_ocn, tau, and conv_ke. dmpdz used the default, alfa used default. UQ indicated the dmpdz was about right and alfa had low sensitivity

Preliminary Conclusions

- Perturbed-parameter technique allows a more thorough exploration of model sensitivities than normally done
- Improved simulations result from making it harder for deep convection to occur but when it occurs reducing the drying tendency of convection while trying get the convection over faster
- Issues:
  - 5 years is a bit short and introduces noise
  - 1100 simulations is insufficient for a 22 dimensional space

Future Work

- Next steps
  - More diagnostics from longer simulations for selected runs
  - Would an improved simulation result if we just change the parameters that are important, rather than all 22 simultaneously
  - Would we get a different impression from coupled-ocean atmosphere modeling?
- Comparison with hindcasts results (not shown today):
  - Difference: c0_ocn is unimportant for precip in hindcasts (it matters for OLR/WVP)
  - Similarity: shorter tau is a better solution

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