Impacts of Systematic Error Reduction on CAM3.1 Sensitivity to CO2 Forcing

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Summary: The current disparity that exists among models of the climate system in their response to projected increases in greenhouse gases provides a measure of uncertainty in the model development process. A large part of this uncertainty is likely related to specification of model parameters. We estimate a lower bound to this part of the uncertainty as may be inferred from an ensemble of model configurations made from a single model (the NCAR CAM3.1 atmospheric GCM). The choice of ensemble members is constrained by a stochastic, Bayesian based, importance sampling strategy whose likelihood function includes a normalized, multivariate measure of model skill that quantifies the distance among seasonal climatologies of model predictions and fifteen observational/reanalysis data products. We consider the effects of six parameters important to clouds and convection. The top six performing parameter sets improved model skill by 7% with nearly identical skill scores, but for different reasons related to the wide range of selected parameter values. These model configurations were chosen for estimating the effect of parametric uncertainties on the predicted global warming response to 2xCO2. Five of the six model configurations had a 2xCO2 near surface air temperature sensitivity of 3 or 3.1 degrees with the final member having a sensitivity of 3.4 as compared to the 2.4 degree sensitivity of the default model configuration. Although the range in sensitivities was quite narrow after parameter values have been systematically constrained by observations, the regional climate predictions exhibited significant uncertainties up to 25% of the climate change signal for predictions of surface air temperature and up to 160% of the signal for precipitation. This calculation demonstrates the potential of using observations to substantially reduce climate model prediction uncertainties with a more formal method of multivariate model tuning. It also provides an estimate of the upper bound for single-model prediction skill, particularly for regional climates.

Motivation

- The uncertainty demonstrated by climate model projections of future climate is equal to 100% of the signal (i.e. ~3 degree warming with a 95% likelihood between 2 and 6 degrees when CO2 is doubled). The size of this uncertainty has remained virtuly unchanged over the many generations of model evaluation and improvement.
- This reality raises important questions about 1) whether this uncertainty is fundamental to the problem and 2) the nature of the processes is responsible for this uncertainty. The multiple differences among models preclude an easy analysis of these questions.

Science Objectives

- Quantify uncertainties in the climate model development process by testing choices in CAM3.1 model parameter values that may only be indirectly constrained by observations.
- Identify an ensemble of climate model configurations that represent these uncertainties and the constraints provided by observations of climate over the past decade.

Methods

The choice of ensemble members is constrained by a stochastic, Bayesian based, importance sampling strategy whose likelihood function includes a normalized, multivariate measure of model skill that quantifies the distance among seasonal climatologies of model predictions and fifteen observational/reanalysis data products. We consider the effects of six parameters important to clouds and convection:

- Use of stochastic sampling is only required when effects of model parameters are non-linearly related to one another. We have confirmed this non-linearity exists and likely includes multiple minima in skill scores, indicating observations provide non-unique constraints for climate model development.
- We use Multiple Very Fast Simulated Annealing as an efficient approximation to more general Monte-Carlo Markov Chain type sampling strategies. This sampling strategy is several orders of magnitude more efficient and is essential to making this problem tractable given the computational expense of a typical climate model.
- Sampling strategy includes a search for an appropriate normalization of the skill score which is required when correlations exist among the multiple observational constraints of model performance.

Model

NCAR CAM3.1 is used to make an 11-year control simulation of the present-day-climate. The model is forced with observed monthly sea surface temperature (SST) and sea ice extent from 03/1990 to 02/2001. The model uses standard T42 horizontal resolution (roughly 2.8° x 2.8°) and 26 vertical levels. For global warming experiments, CAM3.1 is coupled to a slab-ocean to approximate the thermodynamic response of the upper ocean to increased radiative forcing.

Model Evaluation

- Model-data biases are projected onto orthogonal modes of variability (EOFs) in six 30 degree latitude bands in each of the 4 seasons. Model-data biases are normalized within each band by the amount of variability of each mode.
- The EOF-based measure of model performance weighs more strongly modeled-observational differences that occur over regions where these differences are large and natural variability is well defined.
- Comment: The definition of the skill score should include scientific value judements concerning the balance of processes that are required to simulate climate and its sensitivity to change. The current effort only specifies an equal weighting among climatologies (long term averages) of many fields a model predicts for which there exists observations or reanalysis "data".

Results 1: The top six performing parameter sets improved model skill by 7% with nearly identical skill scores, but for different reasons related to the wide range of selected parameter values.

Discussion: We were encouraged to see that the top six model configurations were representative of the uncertainties in estimates of the posterior distribution (figure 1). We are only about a quarter of the way through sampling. Details of distributions may change substantially. However top six models likely representative of the uncertainties.

Table 1. Breakdown of field components contributing to cost function. All components are weighted equally except for the three cloud fields which are each weighted by a third. Color indicates fields that are at least 5% less (green) or 5% more (red) than the default configuration.

	Default	Line 1, gen 48	Line 2, gen 31	Line 3, gen 34	Line 4, gen 43	Line 5, gen 31	Line 6, gen 35
Total	~85	81.51	78.84	79.62	79.84	80.69	81.07
CLDLOW	84.46	82.01	81.58	82.82	80.72	84.82	80.76
CLDMED	36.02	35.91	41.18	38.34	40.17	45.45	37.27
CLDHGH	64.56	66.34	69.64	66.90	68.14	72.03	67.26
FSDS	64.04	53.41	55.65	52.57	54.83	59.13	53.21
FSNT	134.30	148.30	142.8	149.7	141.5	132.90	144.4
FLNT	28.90	29.20	29.42	29.01	28.85	31.81	29.33
BALANCE	202.00	121.20	140.3	122.7	142.70	155.70	126.90
TREFHT	43.13	41.60	42.58	42.88	43.12	41.69	42.40
SHFLX	55.62	54.70	55.81	56.02	55.11	54.37	54.64
LHFLX	41.15	39.01	39.49	40.57	39.53	40.27	38.89
RELHUM	236.6	265.20	212.00	225.0	227.70	220.80	258.4
T	171.2	165.70	161.50	170.2	160.00	163.50	163.4
U	37.52	33.40	36.00	35.56	35.63	35.39	35.27
PSL	26.25	24.48	25.06	25.51	25.27	25.29	24.00
PRECT	24.20	21.99	20.21	22.65	20.55	20.78	21.23

Table 2. Names and descriptions of parameters important to clouds and convection in CAM3.1

Parameter	*Description*
RHMINL	critical relative humidity for low cloud formation
RHMINH	critical relative humidity for high cloud formation
ALFA	initial cloud downdraft mass flux
TAU	rate at which convective clouds consume available potential energy
ke	environmental air to cloud entrainment rate coefficient
c0	deep convection precipitation production efficiency parameter

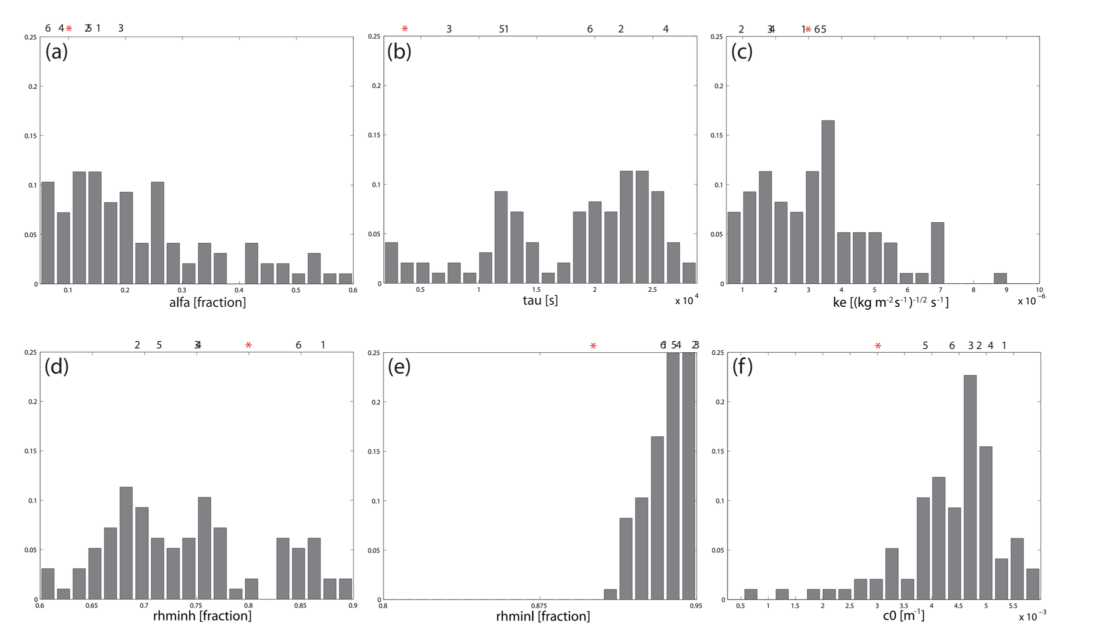

Figure 1. Estimates of the PPD for 6 parameters of CAM3.1 important to clouds and convection (see table 2). The histograms include 95 of the 250 experiments whose cost values showed an improvement of over the default model configuration. The parameter values of the default model are given by a red asterisk (*). The values of the top performing six parameter sets are labeled by the particular line number that produced them.

Results 2: An ensemble of 6 model configurations representative of the uncertainty in defining six model parameters show nearly identical sensitivity to a doubling of atmospheric carbon dioxide.

Discussion: These results suggest one of two things: 1) That the spread among climate models is not fundamental to the climate model development process. With an objective analysis, one could make better use of observations to constrain modeling uncertainties. Or 2), we have not identified the primary sources of modeling uncertainty. 6 parameters down, many other suspects to go.

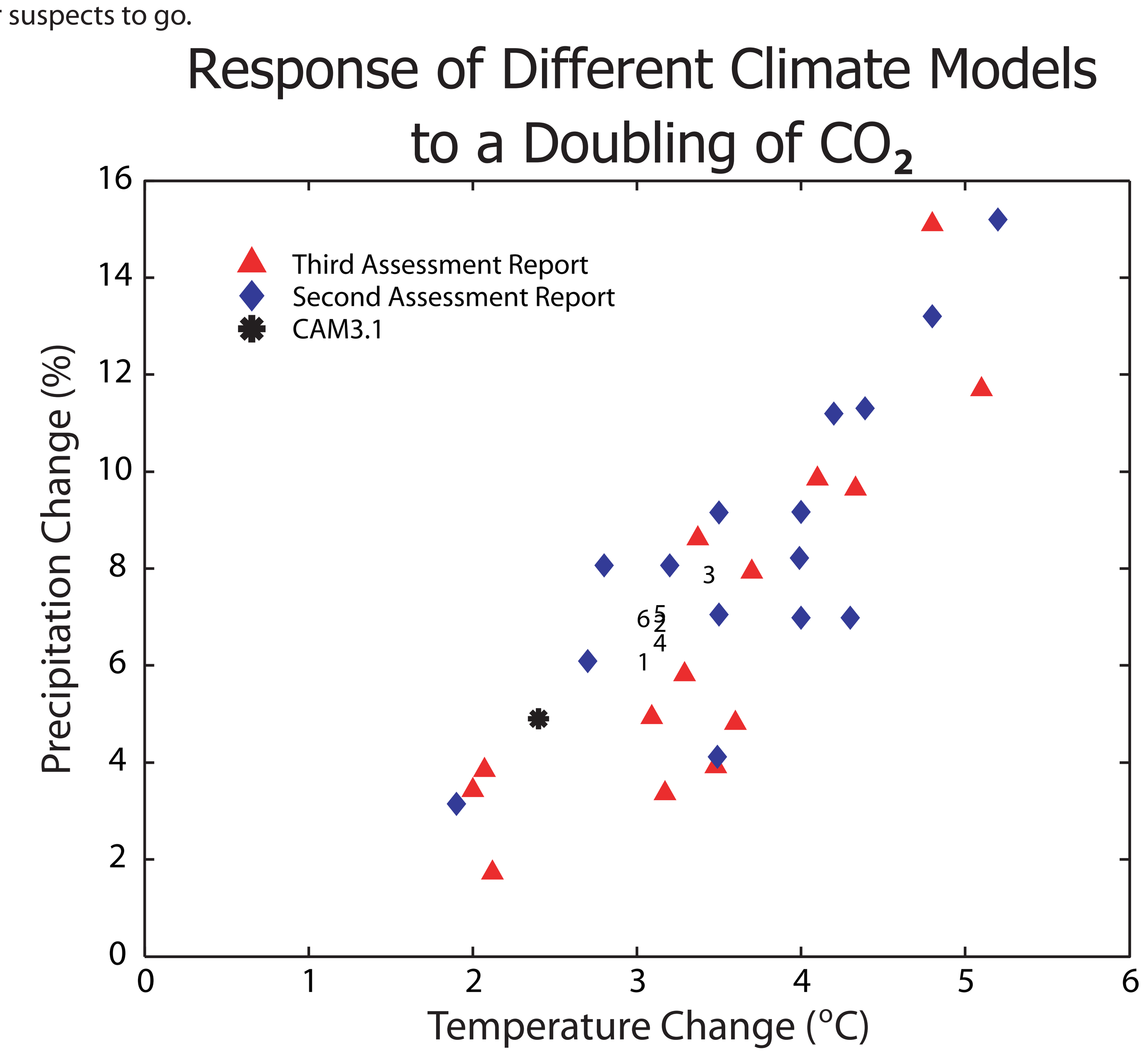

Figure 2. Response of global mean annual mean surface air temperature and precipitation within different climate models to a doubling of atmospheric CO2 concentration. Second and Third Assessment Reports refer to results presented in the Intergovernmental Panel on Climate Change (IPCC 1995 and 2001).

Results 3: Although the range in sensitivities was quite narrow after parameter values have been systematically constrained by observations, the regional climate predictions exhibited significant uncertainties up to 25% of the climate change signal for predictions of surface air temperature and up to 160% of the signal for precipitation.

Discussion: This result underscores the challenge in predicting regional climates. It has been previously assumed that these uncertainties are related to uncertainties that are manifested at the global scales, however we show that this is not true.

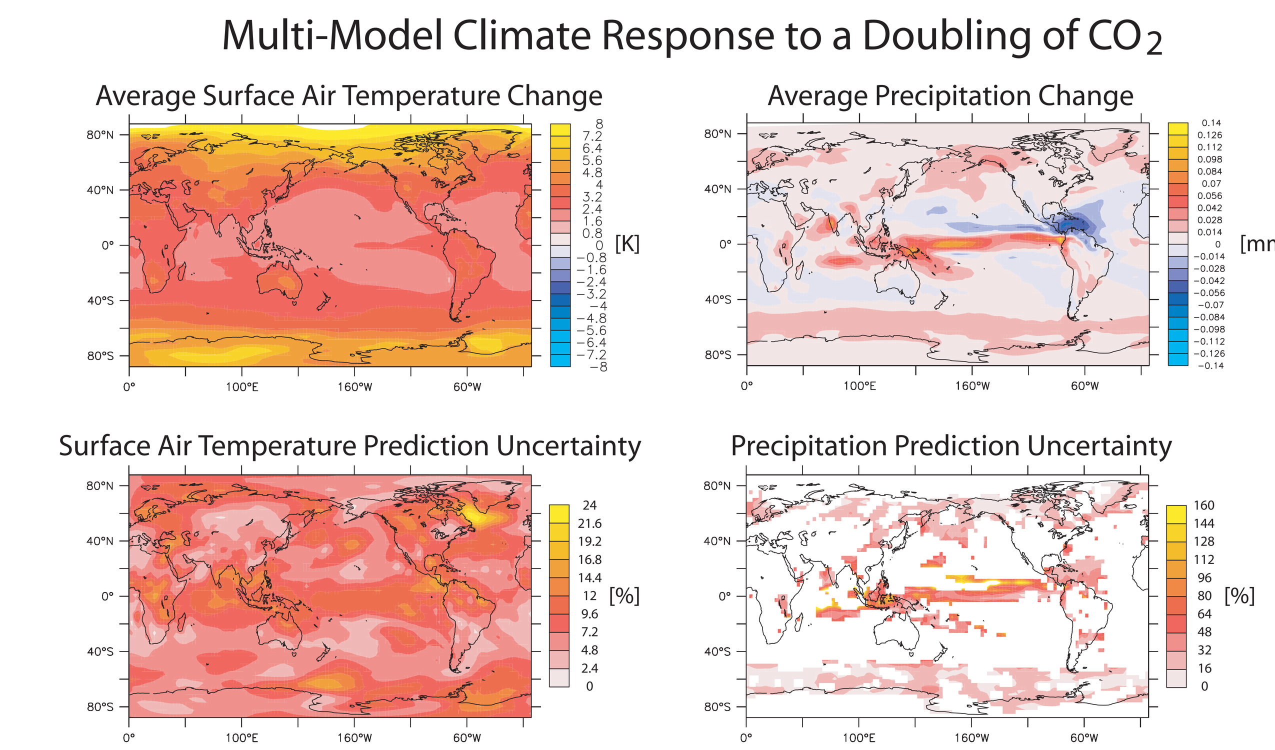

Figure 3. Top panels: Average response among 6 model configurations identified in Figure 1 to a doubling of atmospheric CO2 concentrations for surface air temperature (left) and precipitation (right). Bottom panels: Percent deviation among ensemble members as a fraction of the local signal. Masked areas in precipitation indicate regions where precipitation change was not significantly different from natural variability.

Results 4: Although we only targeted reducing biases in time-averaged quantities, there were tremendous gains in predicting precipitation extremes.

Discussion: Although climate models get the right total amount of rainfall, model's rain too lightly too frequently. The dramatic improvements we found still miss the heavy rainfall events typical of continental thunderstorms (particularly over the continental US and South America.). Thus our results point to missing physics in the current generation parameterizations for getting small scale deep convection. The predictions from models that miss these tails, seriously underestimate how global warming will affect precipitation extremes.

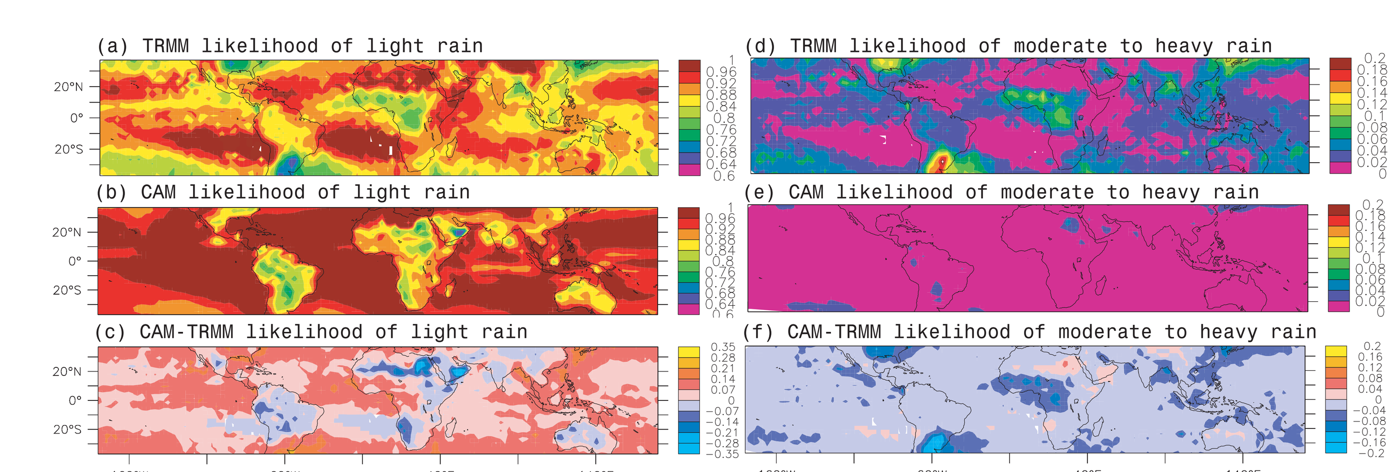

Figure 4. Ratio of the number of rainfall events with a rain rate in the range 0.1-1 mm/hr to the total number of rainfall events in (a) TRMM, (b) CAM and (c) CAM-TRMM. Ratio of the number of rainfall events with a rain rate in the range 2-5 mm/hr to the total number of rainfall events in (d) TRMM, (e) CAM) and (f) CAM-TRMM.

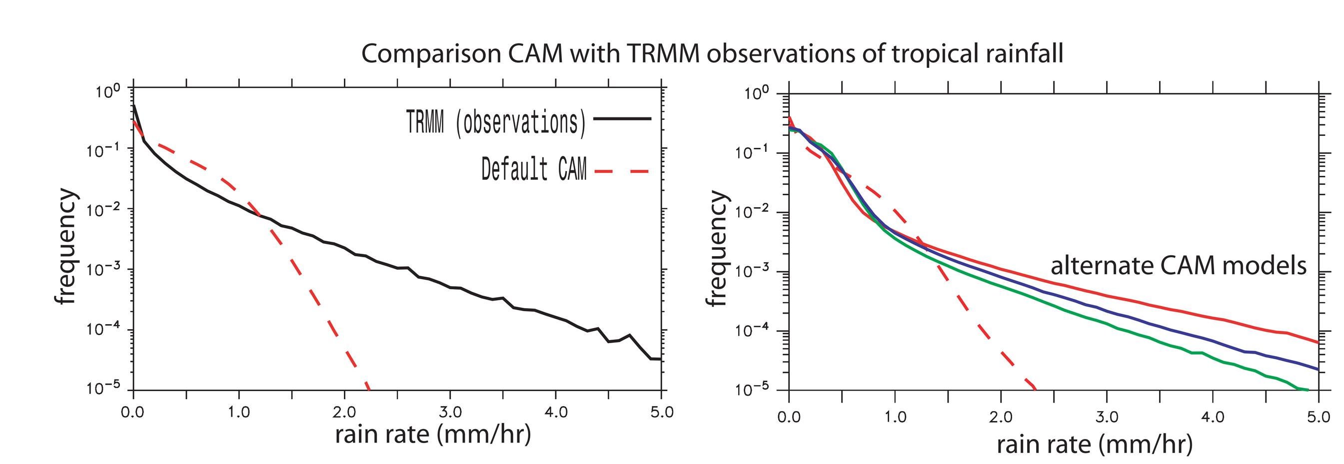

Figure 5. Regionally aggregated PDF of rain rate for ITCZ in TRMM (black line) and deault CAM and alternate configurations 4, 5, and 6 (color lines).

Conclusion: This calculation demonstrates the potential of using observations to substantially reduce climate model prediction uncertainties with a more formal method of multivariate model tuning. It also provides an estimate of the upper bound for single-model prediction skill, particularly for regional climates.

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