The response of the NCAR CAM3 and CCCma GCM to the McICA radiative transfer methodology

Howard Barker and Jason Cole, Meteorological Service of Canada   Jiangnan Li, Canadian Centre for Climate Modelling and Analysis

Introduction

The Monte Carlo Independent Column Approximation (McICA) introduces a new approach for parametrizing radiative transfer within global climate models (GCMs). The McICA computes domain-averaged, spectrally-integrated radiative fluxes by randomly sampling stochastically-generated subgrid-scale columns during spectral integration. The McICA is unbiased with respect to the full ICA, and because it removes the description of cloud structure from the radiative transfer code, it is flexible and computationally efficient. However, since the McICA is a Monte Carlo procedure, it generates conditional (unbiased) random noise. Given the range of nonlinear parametrizations in GCMs and their interactions with radiation, the impact of McICA noise may be model dependent. The success of McICA depends on these impacts being 'negligible'. Therefore, we are testing for the impact of McICA's noise in several GCM's and present here results from two of these GCMs: the NCAR CAM3 and the CCCma GCM15c.

Monte Carlo Independent Column Approximation

Within each GCM, various renditions of the McICA were used. These renditions are explained below and listed so that McICA noise decreases down the list. Each rendition of the McICA generates unbiased estimates of domain-mean broadband fluxes and heating rates relative to the full ICA.

Independent Column Approximation (ICA)

Using the ICA in conjunction with a correlated *k*-distribution (CKD) with K integration points and a cloud field consisting of N clear and cloudy columns, domain-mean broadband flux can be computed as

$$F = \frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K} F(i,k)$$

"1COL" McICA

This approach integrates over a CKD using a *single* column, indexed α, selected at random (i.e., the column is either clear or overcast). This approach (almost) maximizes McICA noise and approximates F as

$$F = \sum_{k=1}^{K} F(\alpha, k)$$

"BASIC" McICA

The most straightforward version of McICA randomly samples a clear or cloudy column, α_k, for each CKD point and approximates F as

$$F = \sum_{k=1}^{K} F(\alpha_k, k)$$

"CLDS" McICA

Since clear-sky fluxes are computed by default for diagnostic purposes, limiting random samples to cloudy columns only, $\alpha_{cld,k}$, reduces sampling noise and approximates F as

$$F = A_c \sum_{k=1}^{K} F_{cld}(\alpha_{cld,k}, k) + \sum_{k=1}^{K} (1 - A_c)\, F(k)$$

"SPEC" McICA

Monte Carlo noise can be reduced further by using $N_k > 1$ samples for CKD points that are associated with the production of noise (see Räisänen and Barker 2004). Hence, F can be approximated as

$$F = A_c \sum_{k=1}^{K} \left(\frac{1}{N_k} \sum_{i=1}^{N_k} F(\alpha_{cld,k}, k) \right) + \sum_{k=1}^{K} (1 - A_c)\, F(k)$$

For the experiments proposed here, the sum of N_k equals $1.5K$ and they are distributed in k so as to minimize flux and heating rate noise.

"REF" McICA

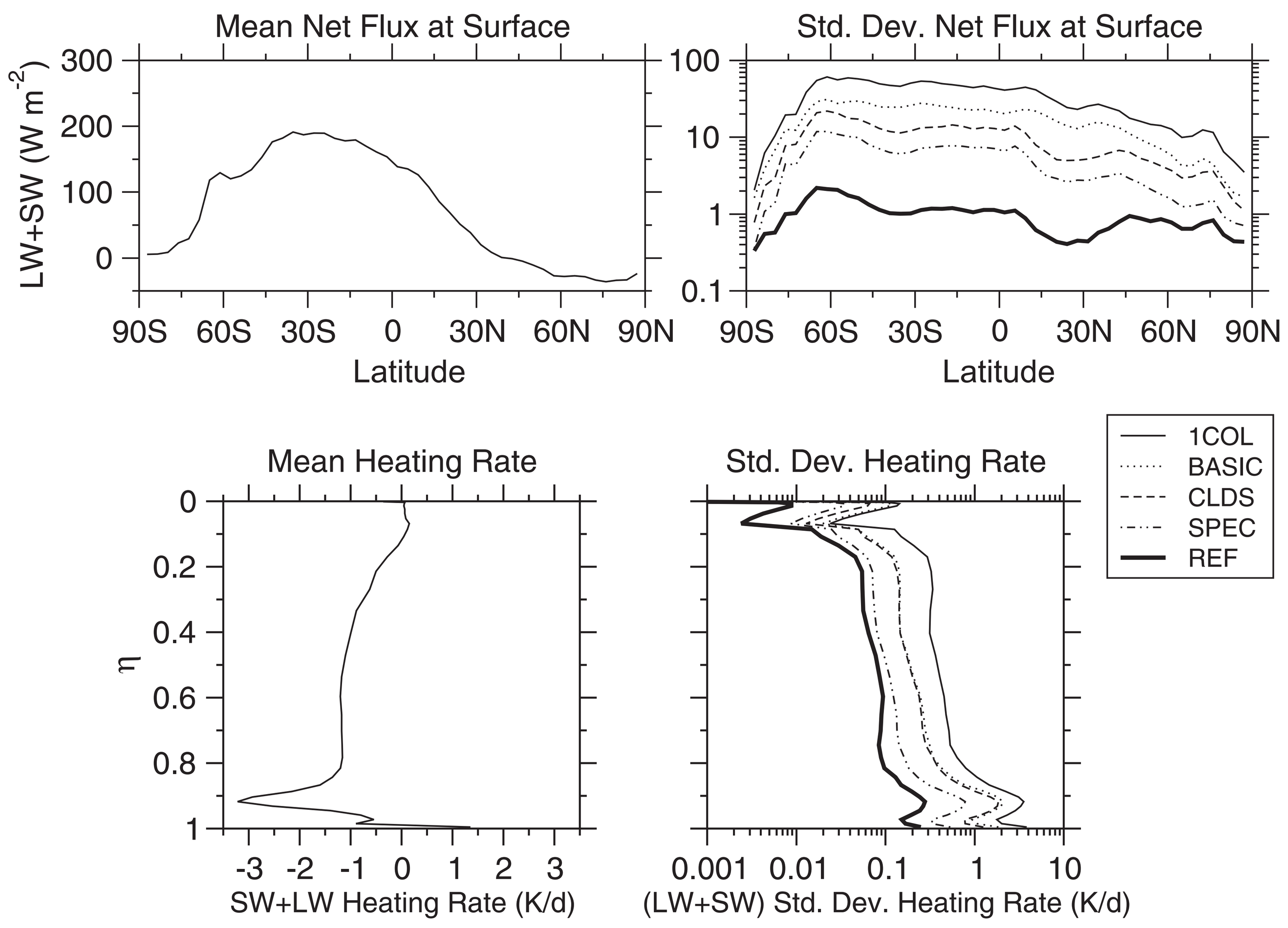
Increasing the number of samples for SPEC McICA by approximately 10 times causes the McICA noise to be reduced by approximately a factor of 5 relative to the standard SPEC McICA.

Description of Experiments

- Ensemble of 10, 14-day simulations were generated for each rendition of McICA
- Started a new simulation every 6 hours beginning on 00:00 Z on January 1.
  - Spun up the GCM for 1 year
- Assumed clouds to be maximum-random overlapped and horizontally homogeneous.
  - This may differ from standard assumptions in the GCMs.
- Performed paired t-test to determine significance of biases

Example of McICA Noise Reduction

- For one simulation from each of the McICA renditions, mean and standard deviation of radiative fluxes and heating were computed.
- At each radiation timestep the radiative transfer subroutine was called 10 times.
- Standard deviations are *not* for zonal/global mean but rather represent local instantaneous values (averaged zonally).



Results I

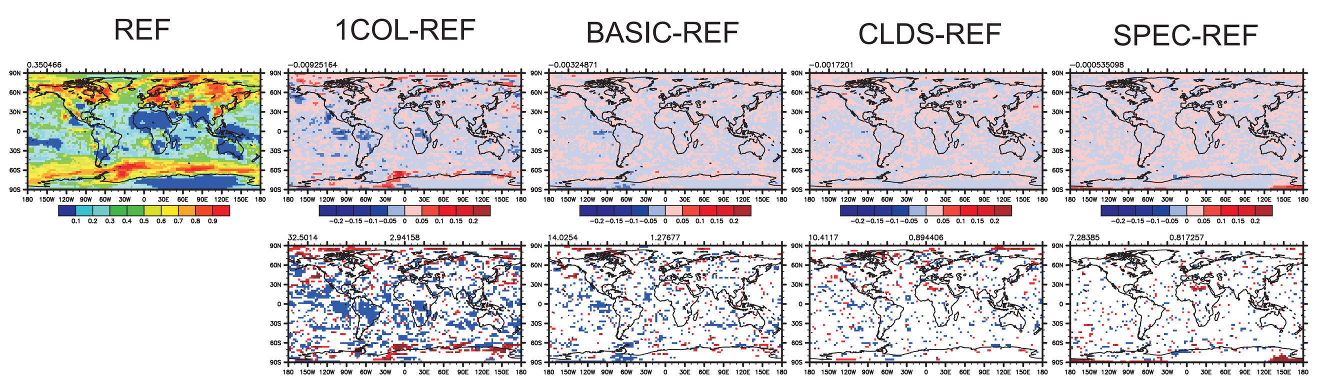
- The table below summarizes the ensemble global mean biases for each rendition of the McICA relative to "REF".
- Differences in *italics* and ***bold*** are statistically significant at the 95% and 99.9% confidence level, respectively**.**
- For each model variable, the upper row corresponds to the NCAR CAM3 and the lower row corresponds to the CCCma GCM.

Model Variable (Units)	REF	Δ 1COL	Δ BASIC	Δ CLDS	Δ SPEC
SW CRE TOA (W m^{-2})	-61.394 -68.509	**1.4551** *-0.2119*	**0.4395** *-0.3352*	*0.2261* -0.0740	*0.1318* 0.0053
LW CRE TOA (W m^{-2})	25.972 27.619	**-0.1421** -0.0098	*-0.0497* 0.0311	0.0297 -0.0312	-0.0270 0.0331
Low Cloud	0.3505 0.4993	**-0.0093** 0.0006	**-0.0032** 0.0015	**-0.0017** -0.0003	-0.0005 0.0012
Middle Cloud	0.1752 0.1154	**-0.0020** 0.0001	*-0.0008* 0.0003	-0.0002 -0.0001	-0.0003 0.0003
High Cloud	0.3936 0.2590	-0.0003 -0.0006	-0.0000 -0.0007	*-0.0010* -0.0009	0.0004 0.0005
Total Cloud	0.6412 0.6554	**-0.0057** 0.0008	**-0.0025** *0.0016*	-0.0007 -0.0001	*-0.0009* 0.0011
LWP (g m^{-2})	129.591 54.588	**-1.3558** -0.0460	*-0.3510* 0.1258	-0.0090 -0.0233	-0.0289 0.0249
IWP (g m^{-2})	18.200 6.441	-0.0117 -0.0176	-0.00154 0.0023	0.0409 -0.0069	-0.0009 0.0187
Net SW Rad. Flux SFC (W m^{-2})	170.629 154.074	**1.6661** *-0.2334*	**0.5105** *-0.3874*	**0.2628** -0.0667	**0.1500** -0.0099
Net LW Rad. Flux SFC (W m^{-2})	-55.6584 -51.719	**-0.5167** 0.0727	**-0.2070** *0.1380*	**-0.1045** 0.01812	**-0.0532** 0.0852
T_{2m} (K)	285.46 284.88	-0.0013 -0.0066	0.0011 -0.0035	0.0056 -0.0064	-0.0014 -0.0021
PW (kg m^{-2})	22.605 22.751	-0.0223 0.0078	-0.0094 0.0046	-0.0016 -0.0008	-0.0028 0.0154
Precip (mm d^{-1})	3.006 2.836	0.0014 -0.0008	0.0014 -0.0047	-0.0015 0.0022	0.0008 0.0026
$z_{500\ hPa}$ (m)	5646.64 5611.80	**0.5082** -0.1186	*0.1565* -0.1070	*0.1282* -0.0333	-0.0039 -0.1374

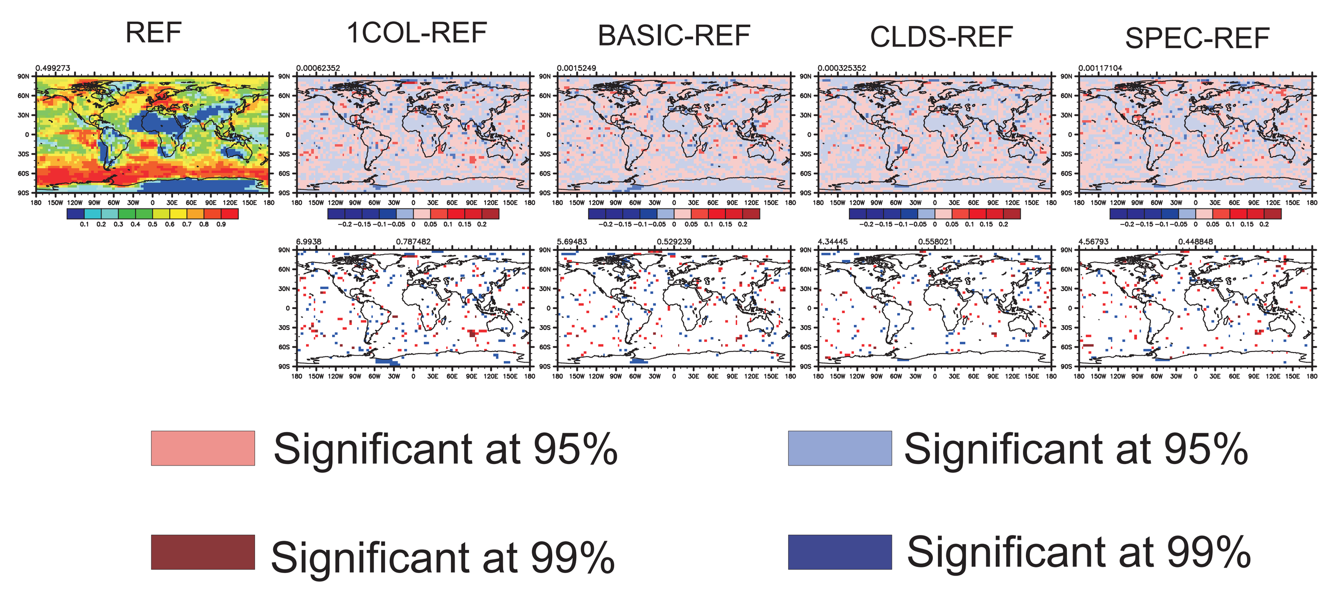
Results II

- In addition to global mean biases, distributions of biases are examined too.
- For example, as shown below, the NCAR CAM3 exhibits a significant bias in low cloud amount, especially for 1COL. It also shows a strong dependance on noise level.
  - On the other hand, the CCCma GCM shows little response.

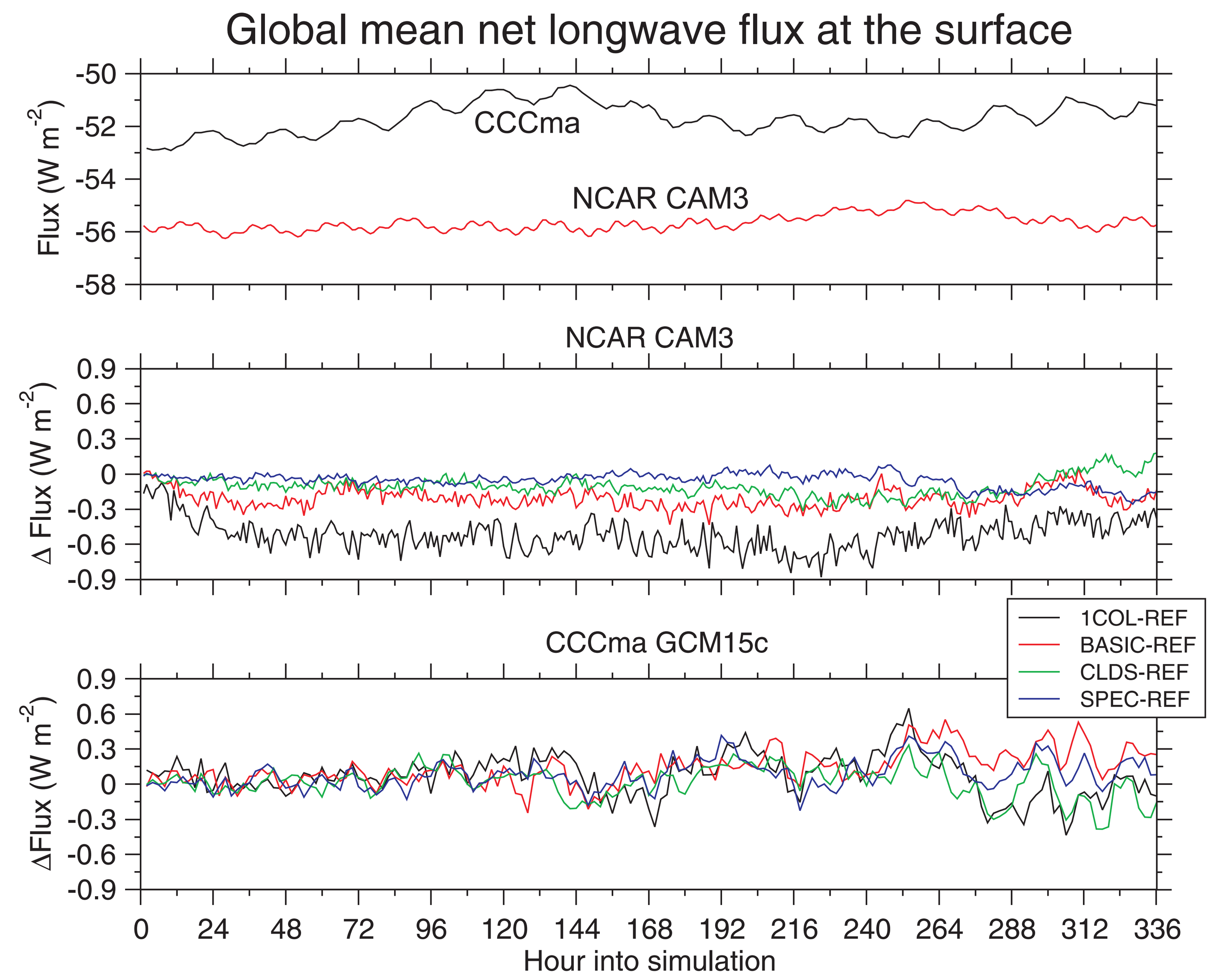
NCAR CAM3



CCCma GCM



- Time-series of global, ensemble means illustrate that biases develop and stablize quickly (< 48 hours) in the NCAR CAM3



Discussion

- The NCAR CAM3 reacts to levels of McICA noise similarly to the way CAM1.8 reacts (Räisänen et. al. 2005)
  - Likely due to interaction with a problematic boundary layer parameterization (per. comm., J. Hack, 2005)
- The fast-response of the CCCma GCM exhibits a very weak sensitivity to the level of McICA noise
  - Consistent with results found in Pincus et. al. (2003) for the ECMWF model using a proxy for McICA noise
- Similar experiments with McICA will be performed with other GCMs (ECMWF, GFDL, FMI, CMC) to examine the impact of McICA noise on a wide range of GCMs

References

Pincus, R., H. W. Barker, and J.-J. Morcrette (2003), A new radiative transfer model for use in GCMs. *J. Geophys. Res.*, **108(D13)**, 4376, doi:10.1029/2002JD003322.

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