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Uncertainty Quantification and Parameter Tuning in the Cam5 Zhang-McFarlane Convection Scheme and Impact of Improved Convection on the Global Circulation and Climate

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Uncertainty quantification and parameter tuning in the CAM5 Zhang-McFarlane convection scheme and impact of improved convection on the global circulation and climate

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[1] In this study, we applied an uncertainty quantification (UQ) technique to improve convective precipitation in the global climate model, the Community Atmosphere Model version 5 (CAM5), in which the convective and stratiform precipitation partitioning is very different from observational estimates. We examined the sensitivity of precipitation and circulation to several key parameters in the Zhang-McFarlane deep convection scheme in CAM5, using a stochastic importance-sampling algorithm that can progressively converge to optimal parameter values. The impact of improved deep convection on the global circulation and climate was subsequently evaluated. Our results show that the simulated convective precipitation is most sensitive to the parameters of the convective available potential energy consumption time scale, parcel fractional mass entrainment rate, and maximum downdraft mass flux fraction. Using the optimal parameters constrained by the observed Tropical Rainfall Measuring Mission, convective precipitation improves the simulation of convective to stratiform precipitation ratio and rain-rate spectrum remarkably. When convection is suppressed, precipitation tends to be more confined to the regions with strong atmospheric convergence. As the optimal parameters are used, positive impacts on some aspects of the atmospheric circulation and climate, including reduction of the double Intertropical Convergence Zone, improved East Asian monsoon precipitation, and improved annual cycles of the cross-equatorial jets, are found as a result of the vertical and horizontal redistribution of latent heat release from the revised parameterization. Positive impacts of the optimal parameters derived from the $2^s/C_14$ simulations are found to transfer to the $1^s/C_14$ simulations to some extent.


1. Introduction

[2] Global circulation models (GCMs) have been employed as a useful tool in climate simulations and predictions. Although GCMs can reproduce important salient features of the current climate, projections of future climate produced by different climate models can vary substantially at the regional scale [Cubasch et al., 2001]. The latter may result because some physical assumptions suitable for the current situations may break down as the climate evolves or because compensating errors that exist among the parameterization schemes for different physical processes no longer cancel out in the future [Gilmore et al., 2004; Molders, 2005; Golaz et al., 2007; Min et al., 2007; Murphy et al., 2007]. Ensemble simulations with multiple models or parameterizations have been applied as effective approaches to characterize uncertainties associated with dynamical or physical processes in the model [Allen et al., 2000; Giorgi and Mearns, 2002; Stainforth et al., 2005; Lopez et al., 2006].

[3] Tunable parameters are often used in the climate model parameterization schemes. Determination of parameter values is typically based on limited measurements or theoretical calculations. Adjustments of parameter values are often needed to better match model simulations with observations, but improved model skill associated with the given parameter values may have been accomplished through compensating errors among different local or even nonlocal physical processes. Calibration of model parameters is important not only for the reduction of model uncertainties, but...
also for better understanding of the dynamical and physical processes within the climate system. As perturbed parameter ensembles (PPEs) with the same climate model, but different parameter combinations, have been applied to estimate the uncertainty of future climate projections [Jackson et al., 2003, 2008; Murphy et al., 2004; Collins et al., 2011], more reliable future projections from multimodel or parameterization ensembles are also expected if more reliable parameters are applied in each individual model.

[4] Various sampling approaches exist for parameter optimization or probability density function (PDF) estimation in multidimensional spaces. Some algorithms, such as Monte Carlo or quasi-Monte Carlo and Latin hypercube selection [Stein, 1987], are able to sample the parameter space at low density while still representing the entire parameter space. Another class of approaches, including multiple very fast simulated annealing (MVDSA) [Ingber, 1989; Jackson et al., 2004], annealing evolutionary stochastic approximation Monte Carlo [Liang, 2011], simulated stochastic approximation annealing (SSAA) (F. Liang et al., Simulated stochastic approximation annealing for global optimization with a square-root cooling schedule, manuscript in review, 2012), and others [Tierney and Mira, 1999; Haario et al., 2001], uses an importance-sampling technique that can sample points progressively to converge to the optimal values.

[5] Cumulus convection is a key process for producing precipitation and redistributing atmospheric heat and moisture [Arakawa, 1975, 2004]. Precipitation and the associated latent heat release drive the Earth’s hydrological cycle and atmospheric circulations. Cumulus convection can also affect the distribution of clouds and, consequently, the global radiative budget. Since GCMs are unable to resolve the convective processes, various convection parameterization schemes (CPSs) have been developed based on different types of assumptions [Arakawa and Schubert, 1974; Kain and Fritsch, 1990; Janjic, 1994; Zhang and McFarlane, 1995; Emanuel and Zivkovic-Rothman, 1999; Gregory et al., 2000; Grell and Devenyi, 2002]. CPS usually includes multiple tunable parameters, which are related to the subscale internal physics and are thought to have wide ranges of possible values [Jackson et al., 2008; YANG ET AL., 2011]. The dependence of CPS parameters on model grid size and climate regime is an important issue for weather and climate simulations [Arakawa et al., 2011]. It has been a challenge to calibrate the CPS parameters given the large number of parameters and the wide ranges of possible values. Jackson et al. [2008] applied the MVDSA approach to optimize six cloud-related parameters in the Community Atmosphere Model (CAM) and derived six member-optimized model configurations that significantly improved the model skill. With the same algorithm, Yang et al. [2012] studied some issues of uncertainty quantification (UQ) and parameter tuning in CPS in the weather research and forecasting (WRF) model. Their results indicated that model performance could be improved significantly with optimized parameters and that such improvements were transferable across physical processes, spatial scales, and climate regimes, to some extent.

[6] The CPSs are generally developed with the assumption that the scale of a convective cloud is much smaller than the grid scale, which allows one to formulate the statistical effects of cloud ensembles. When a locally unstable condition exists, precipitation will be generated if the convective updrafts can penetrate the unstable layers to some height [Zhang and McFarlane, 1995; Kain, 2004]. With these constraints, the CPS parameterizations tend to simulate the unresolved component of the moist convective process, assuming that all the clouds are of convective type [Arakawa, 2004]. In addition to the CPS that simulates the convective precipitation, GCMs also include parameterizations of macrophysics, microphysics, and subgrid vertical velocity and cloud variability to simulate the subgrid stratiform precipitation. Representing the interactions between convective and stratiform processes, at grid or subgrid scale, is one of the major challenges in the current model physics [Arakawa, 2004], as latent heat release, moisture transport, cloud/radiative properties, and other climate aspects are highly affected by how convective and stratiform processes interact and how precipitation is partitioned between the convective and large scale in the models. Dai [2006] found that most of the GCMs examined still had problems producing the right magnitude of stratiform precipitation, compared with the Tropical Rainfall Measuring Mission (TRMM) precipitation radar (PR) data, which showed that around 40% of the tropical total precipitation was contributed by the stratiform precipitation [Schumacher and Houze, 2003].

[7] The Community Atmosphere Model version 5 (CAM5) [Neale et al., 2010] is a state-of-the-art community GCM being broadly applied for climate simulations and predictions. While total precipitation is reasonably simulated in the standard CAM5, the partitioning between the simulated convective and stratiform precipitation is very different from the TRMM observations when the model resolution is coarser than 1°, that is, too much (little) convective (stratiform) rain in the model (see section 3). Many model processes, including deep convection and stratiform cloud micro- and macrophysics, are responsible for the partitioning of precipitation through competition for moisture and cooperation for precipitation generation. Song and Zhang [2011] showed that detrainment of convective cloud hydrometeors could significantly affect stratiform cloud and precipitation. They adopted a microphysics parameterization scheme for convective clouds in CAM that substantially increased the simulated stratiform precipitation.

[8] In this study, we applied techniques in parameter estimation to evaluate the Zhang-McFarlane (ZM) deep convection scheme within CAM5. Our objectives were to (1) investigate the sensitivity of precipitation and internal physical and dynamical processes of the climate system to the key parameters in the ZM scheme, (2) use the observed deep convective precipitation obtained from TRMM and the Global Precipitation Climatology Project (GPCP) [Huffman et al., 2001] to reduce uncertainties in the parameters in the ZM scheme, and (3) investigate the impact of improved convection on the global circulation and climate.

[9] The paper is organized as follows. Section 2 describes the CAM5 model configurations, input parameters of the ZM deep convection scheme, the optimization approach, and the observational data. The results of sensitivity and optimization, as well as the impact of improved convection on the global circulation and climate, are analyzed in section 3. Conclusions are summarized in section 4 along with discussion.

2. Model and Approach

2.1. CAM5 Model

[10] The CAM5 is used with the finite volume (FV) dynamical core. The stratiform microphysics processes are
represented by the two-member bulk microphysics parameterization of Morrison and Gettelman [2008]. The cloud microphysics scheme, which provides a subgrid environment for the microphysics processes [Smith, 1990; Rasch and Kristjansson, 1998; Zhang et al., 2003] and includes a suite of physical processes related to the calculations of cloud fraction, overlapping structures, and partial condensation, is described by Neale et al. [2010]. Shallow and deep convective processes are parameterized using the methods described by Park and Bretherton [2009] and Zhang and McFarlane [1995], respectively.

The CAM5 experiments are conducted one by one with different parameter combinations in the optimization procedure. Each CAM simulation is performed at 2.5° (longitude) by 1.9° (latitude) spatial resolution for 18 months forced by observed sea-surface temperature (SST) and sea ice from 1 July 2002 to 31 December 2003, with the first 6 months discarding for model spin-up. The simulated monthly mean convective precipitation in 2003 is compared to observations based on a model skill score (see section 2.3.2). The SST and sea ice conditions are prescribed during the simulation time.

Two additional 10 year simulations are performed starting from 2000 to 2010 (first year as model spin-up), with the default and optimized parameters identified from the 18 month simulations for further verification of the results and analysis of the climate impacts of the optimized parameters. Another set of two 10 year simulations at higher resolution (i.e., 1°) are also conducted to explore whether the optimal parameters derived from the 2° simulations are transferable to the 1° simulations.

### 2.2. Selected Parameters in ZM Deep Convective Scheme

In CAM5, the deep convective process is parameterized by the ZM deep convection scheme, which was originally developed by Zhang and McFarlane [1995], with additional modifications [Gregory et al., 1997; Neale et al., 2008; Richter and Rasch, 2008; Neale et al., 2010] (see more details in Appendix A). Some convection parameterizations [e.g., Emanuel and Zivkovic-Rothman, 1999; Donner et al., 2001] explicitly include contributions to precipitation from cloud elements usually labeled as stratiform clouds, including components that are not explicitly associated with precipitation in vigorous up and downdrafts. However, this is not the case for the ZM scheme in CAM5, which only represents convective precipitation associated with up and saturated downdrafts.

Several key parameters related to the processes of updrafts, downdrafts, cloud-rain conversion, and convective available potential energy (CAPE) are important in the ZM deep convection scheme, but the ranges of the values of those parameters are uncertain [Jackson et al., 2008]. In this study, we focus on the following selected parameters: the cloud to rain conversion coefficient, \( C_0 \), in equation (A1); the maximum cloud downdraft mass flux fraction, \( z_0 \) (hereafter \( z \)), in equation (A2); the CAPE threshold value and CAPE consumption time, that is, \( \text{CAPE}_0 \) and \( \tau \), in equation (A3); the evaporation efficiency \( K_e \) in equation (A4); and the parcel fractional mass entrainment rate for the CAPE calculation (referred to as PE). We also tune the parameters of the sizes of detrained cloud ice, referred to as \( D_{\text{ice}} \), and allow two parameters, \( C_0 \) and PE, to have different values for convective clouds over land and ocean. Therefore, nine parameters overall are selected for evaluation and optimization, and the default value and range for each parameter are summarized in Table 1.

### 2.3. Optimization Approach

#### 2.3.1. Approach

The SSAA method is applied in this study. The SSAA is a method for global optimization that takes advantage of both the annealing [Ingber, 1989; Jackson et al., 2004] and SAMC (i.e., stochastic approximation Monte Carlo) [Liang, 2011] techniques, which enable the algorithm to converge to the optimal results (based on a model skill score in section 2.3.2) more efficiently with a low probability of a local minimum trap (see more details in Appendix B). Jackson et al. [2004] suggested that an average cost of 199 forward-model evaluations are needed for very fast simulated annealing algorithm to converge for a nine-parameter problem. Here a total of 200 forward-model evaluations (i.e., CAM simulations) are conducted in the SSAA optimization procedure.

#### 2.3.2. Evaluation Metric

In this study, we adopt a skill function metric, following Taylor [2001], to quantitatively evaluate the spatial standard deviation (SD) and spatial correlation of a model output variable (e.g., precipitation rate) against the observations.

Consider two variables \( x \) and \( y \) at \( N \) grid points in space. The SD \( \sigma_x \) of \( x \) is defined as equation (1):

\[
\sigma_x = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \bar{x})^2},
\]
and the correlation coefficient \( R \) between \( x \) and \( y \) is defined as equation (2):

\[
R = \frac{1}{N} \sum_{n=1}^{N} \frac{(x_n - \bar{x})(y_n - \bar{y})}{\sigma_x \sigma_y}.
\]

[19] The cost function, \( E(m) \), of the simulation with the parameter set, \( m \) (which is inversely proportional to a skill score), is written as equation (3):

\[
E(m) = \log \left[ \frac{(\sigma_{obs}/\sigma_{mod} + \sigma_{mod}/\sigma_{obs})(1 + R_0)^k}{4(1+R)^k} \right],
\]

where the observed and simulated results are denoted by the subscripts, “obs” and “mod,” respectively. \( R \) is the spatial correlation coefficient between the simulation and observation. \( R_0 \) is the maximum possible spatial correlation coefficient (set to 1 here), \( k \) is a specified value used to control the relative weight of the spatial correlation, compared to the SD penalty term. We set \( k=4 \) to give a larger weight to the spatial pattern, as indicated by the spatial correlation, given that, for some observations (e.g., satellite-retrieved precipitation), spatial patterns are more reliable than exact magnitude. A lower value of \( E(m) \) indicates a better model performance, and \( E(m) \) becomes 0 when the simulation and observation are identical.

[20] We performed some test simulations (with a 4 month period for each run) and found that the mean biases were proportional to the biases of the SD. Therefore, the Taylor diagram-based metric used in this study is an effective constraint for optimization, including all the bias sources of the mean, SD, and spatial pattern. In fact, we did several tests of short-term simulations using different skill metrics and found the dependency of optimization for convective precipitation on the choice of skill metric is very weak.

[21] Only the observed convective precipitation is used to constrain the CAM5 simulation for three reasons: (1) the parameters selected from the ZM deep convection scheme are most directly related to convective precipitation; (2) the magnitude of total precipitation simulated by CAM5 shows only a weak sensitivity to the parameters we selected, indicating that changes in convective and stratiform precipitation tend to be complementary; and (3) the spatial patterns are strongly correlated among convective, stratiform, and total precipitation in the model.

2.3.3. Observational Data Set

[22] Observed precipitation rates and precipitation types derived from the GPCP and TRMM data are used in this study. Based on the vertical extent, maximum values, and horizontal variability of the observed radar reflectivity, the TRMM data can be categorized into different types of precipitation, for example, convective and stratiform precipitation [Kozu et al., 2001]. The TRMM version 3A25 data set provides the statistical information about monthly convective and stratiform precipitation at 0.5° spatial resolution.

[23] However, the monthly TRMM data are somewhat noisy due to sampling issues. Therefore, we also use monthly mean GPCP precipitation (1°, daily), which is a product derived from observations by multiple satellites that has been verified by surface rain-gauge observations [Huffman et al., 2001]. The total precipitation from GPCP is partitioned into deep convective, shallow convective, and stratiform precipitation using the ratio information obtained from TRMM. Due to the limitation of data coverage of TRMM 3A25, only tropical (37°S–37°N) precipitation is used for constraining the model in this study.

[24] The monthly mean European Center for Medium range Weather Forecasting (ECMWF) Re-Analysis (ERA)-Interim reanalysis [Dee et al., 2011] for selected variables (i.e., \( T, Q, U, V, \) and \( \omega \)) at grid spacing of 1.5° from years 2001 to 2010 is also used for later evaluation of other model aspects. ERA-Interim global atmospheric reanalyses are produced by the ECMWF, covering the period from 1 January 1989 to the near-real time.

3. Results

[25] In this section, we first analyze the sensitivity of the model performance and simulated climate system to the choice of parameters. Next, results from a 10 year simulation with optimized parameters are evaluated against observations of precipitation and other precipitation-related variables. Last, we investigate the response of the global circulation to the simulated convective precipitation to determine whether the improved convection has a positive impact on the global circulation and climate.

3.1. Model Sensitivity to Parameters in the ZM Scheme

[26] Overall, 200 simulations were conducted, each with a different parameter set generated by the SSAA process. Figure 2 shows the frequency distributions of “good” experiments defined as simulations that produced a higher skill score, compared to the simulation that used the default values for individual parameters. Except for a few ranges of parameter values with insufficient numbers of samples, these results show the sensitivity of the model performance to some important parameters. For example, the CAPE consumption time \( \tau \) has significant effects on the model results. When \( \tau \) is larger than 12,000 s, the frequency of good experiments is always below 25%, but when \( \tau \) is smaller than 12,000 s, the chance of obtaining a good experiment is much higher. When the precipitation evaporation efficiency \( K_e \) and parcel fractional mass entrainment rate over land \( (PE_{land}) \) are around \( 5 \times 10^{-6} (kg m^{-2} s^{-1})^{-1/2} s^{-1} \) and \(-0.6 \times 10^{-3} m^{-1} \), respectively, there is also a higher probability of good experiments. The number of good experiments in each bin for a certain parameter might also depend on the rest of parameters in the same set. There are more chances to get good experiments with \( D_{sec} \) smaller than 20 \( \mu m \), but almost no good experiments with \( D_{sec} \) around 30 \( \mu m \). For other parameters, the frequency distributions are either more uniform or irregular, suggesting larger uncertainties in those
Figure 1. Spatial distributions of ANN (a and b) deep convective, (c and d) stratiform, and (e and f) total precipitation for 2001–2010, observed (left column) and simulated (right column) by the standard CAM5 (2°C). The observation is combined from TRMM and GPCP precipitation data set. The observed global means and the simulated mean bias, root mean square error (rmse), and spatial correlation (r) relative to observation are also presented. Units are in millimeters per day.

Figure 2. Frequency (%) distributions of good experiments as a function of values of each parameter. Good experiments are defined as simulations that produced higher skill score, compared to the simulation that used the default for individual parameters in ZM scheme. Frequency is calculated as the ratio of the number of good experiments to the total number in each bin.
parameters based on skill measures of convective precipitation alone.

[28] The responses of several important tropical mean variables (see Table 2) to the nine convective parameters are summarized in the top panel of Figure 3. Only boreal summer (June/July/August; JJA) results are shown as an example. The CAPE consumption time ($\tau$) is the most important parameter [Scinocca and McFarlane, 2004], with a strong influence on all selected response variables except for liquid water path (LWP). The maximum downdraft mass flux fraction ($\zeta$) can influence the convective precipitation (Cu_Precp), but it has less impact on other response variables. The deep convective precipitation efficiencies ($C_p$, especially over oceans) are very important for the ice water path (IWP)/LWP and cloud/radiation properties. The size of detrained ice ($IWP/LWP$ and cloud/radiation properties) is especially over oceans) are very important for the ice water path (IWP). The CAPE consumption time ($\tau$) and parcel entrainment rate over oceans (PE_ocn) are still the most important parameters across the different regions. The precipitation evaporation efficiency ($K_s$) has a strong impact on some regional fields, such as precipitation over East Asia (EA), the northwestern Pacific (NWP), and southern Pacific (SP), as well as the zonal wind over the tropical eastern Pacific (TEP), but it has a weaker effect on the tropical mean precipitation and cloud/radiation-related properties. Total precipitation over the Intertropical Convergence Zone (ITCZ) increases with the increase of the maximum downdraft mass flux fraction, CAPE threshold value, and CAPE consumption time or the decrease of PE_ocn, all of which correspond to a reduction of the tropical mean convective precipitation. Precipitation over EA and the NWP shows the same response to the precipitation evaporation efficiency and CAPE threshold, but opposite responses to the maximum downdraft flux fraction, PE, and CAPE consumption time, while the latter ones are the most important parameters for tropical mean convective precipitation, as shown in the top panel of Figure 3. The cross-equatorial jets show almost the same response over different regions to the parameters, especially to those with large impacts on convective precipitation. Significant impacts of the parameters over land can be seen on precipitation over the Maritime Continent (MC) and zonal wind over the tropical western Pacific (TEP) and TEP probably due to a modification of land-ocean contrast by the perturbed parameters. It should be noted that most of the output variables in Figure 3 are calculated over the tropics and ocean, so they are less sensitive to parameters such as the PE_lnd.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Subregions</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cu_Precp</td>
<td>0°–360°E, 30°S–30°N</td>
<td>Deep convective precipitation</td>
</tr>
<tr>
<td>Tot_Precp</td>
<td>0°–360°E, 30°S–30°N</td>
<td>Total precipitation</td>
</tr>
<tr>
<td>LH</td>
<td>0°–360°E, 30°S–30°N</td>
<td>Latent heat flux at surface</td>
</tr>
<tr>
<td>LWP</td>
<td>0°–360°E, 30°S–30°N</td>
<td>Liquid cloud water path</td>
</tr>
<tr>
<td>IWP</td>
<td>0°–360°E, 30°S–30°N</td>
<td>Ice cloud water path</td>
</tr>
<tr>
<td>CLD_FRA</td>
<td>0°–360°E, 30°S–30°N</td>
<td>Total cloud fraction</td>
</tr>
<tr>
<td>OLR_TOA</td>
<td>0°–360°E, 30°S–30°N</td>
<td>Outgoing longwave radiation at top of atmosphere</td>
</tr>
<tr>
<td>FSNT_TOA</td>
<td>0°–360°E, 30°S–30°N</td>
<td>Net shortwave radiation at top of atmosphere</td>
</tr>
<tr>
<td>SWD_SF</td>
<td>0°–360°E, 30°S–30°N</td>
<td>Downward solar radiation at surface</td>
</tr>
<tr>
<td>SWCF</td>
<td>0°–360°E, 30°S–30°N</td>
<td>Shortwave cloud forcing (absolute value)</td>
</tr>
<tr>
<td>LWCF</td>
<td>0°–360°E, 30°S–30°N</td>
<td>Longwave cloud forcing</td>
</tr>
<tr>
<td>P_NIO</td>
<td>75°E–100°E, 0°–15°N</td>
<td>Total precipitation over northern Indian Ocean</td>
</tr>
<tr>
<td>P_MC</td>
<td>100°E–150°E, 10°S–10°N</td>
<td>Total precipitation over Maritime Continent</td>
</tr>
<tr>
<td>P EA</td>
<td>105°E–140°E, 15°N–40°N</td>
<td>Total precipitation over EA</td>
</tr>
<tr>
<td>P_NWP</td>
<td>150°E–200°E, 15°N–40°N</td>
<td>Total precipitation over NWP</td>
</tr>
<tr>
<td>P SP</td>
<td>160°E–210°E, 15°S–0°</td>
<td>Total precipitation over SP</td>
</tr>
<tr>
<td>P ITCZ</td>
<td>210°E–270°E, 6°N–12°N</td>
<td>Total precipitation over ITCZ</td>
</tr>
<tr>
<td>V IO</td>
<td>75°E–100°E, 5°S–5°N</td>
<td>Cross-equatorial jet over Indian Ocean</td>
</tr>
<tr>
<td>V MC</td>
<td>105°E–140°E, 5°S–3°N</td>
<td>Cross-equatorial jet over Maritime Continent</td>
</tr>
<tr>
<td>V EP</td>
<td>210°E–270°E, 5°S–5°N</td>
<td>Cross-equatorial jet over eastern Pacific</td>
</tr>
<tr>
<td>U SA</td>
<td>75°E–120°E, 0°–10°N</td>
<td>Zonal wind over South Asia</td>
</tr>
<tr>
<td>U TWP</td>
<td>120°E–180°E, 0°–10°N</td>
<td>Zonal wind over TWP</td>
</tr>
<tr>
<td>U TEP</td>
<td>210°E–270°E, 5°S–5°N</td>
<td>Zonal wind over TEP</td>
</tr>
</tbody>
</table>

[30] The CAPE consumption time ($\tau$) and parcel entrainment rate over oceans (PE_ocn) are still the most important parameters across the different regions. The precipitation evaporation efficiency ($K_s$) has a strong impact on some regional fields, such as precipitation over East Asia (EA), the northwestern Pacific (NWP), and southern Pacific (SP), as well as the zonal wind over the tropical eastern Pacific (TEP), but it has a weaker effect on the tropical mean precipitation and cloud/radiation-related properties. Total precipitation over the Intertropical Convergence Zone (ITCZ) increases with the increase of the maximum downdraft mass flux fraction, CAPE threshold value, and CAPE consumption time or the decrease of PE_ocn, all of which correspond to a reduction of the tropical mean convective precipitation. Precipitation over EA and the NWP shows the same response to the precipitation evaporation efficiency and CAPE threshold, but opposite responses to the maximum downdraft flux fraction, PE, and CAPE consumption time, while the latter ones are the most important parameters for tropical mean convective precipitation, as shown in the top panel of Figure 3. The cross-equatorial jets show almost the same response over different regions to the parameters, especially to those with large impacts on convective precipitation. Significant impacts of the parameters over land can be seen on precipitation over the Maritime Continent (MC) and zonal wind over the tropical western Pacific (TEP) and TEP probably due to a modification of land-ocean contrast by the perturbed parameters. It should be noted that most of the output variables in Figure 3 are calculated over the tropics and ocean, so they are less sensitive to parameters such as the PE_lnd.

3.2. Impacts of Optimization on Precipitation
(Based on Two 10 Year Simulations)

[31] Within the 200 experiments, we identify three sets of optimized parameters, based on their skill scores for the
simulated deep convective precipitation in the boreal summer (JJA), boreal winter (December/January/February; DJF), and annual mean (ANN). Table 3 shows the values of the nine ZM parameters used in the three simulations with best performance in ANN, JJA, and DJF deep convective precipitation, and Table 4 shows the corresponding skill scores (along with the default skill scores) for both convective and total precipitation. The differences in model skill for convective precipitation are relatively small among the three sets of parameters, but the parameter set optimized for JJA produces better total precipitation than the other two sets of parameters, except for DJF. Therefore, the optimal parameter set for JJA is applied in the following analysis for a 10 year simulation from 2000 to 2010.

Figure 4 shows the annual mean (for 2001–2010) deep convective, stratiform, and total precipitation from the 10 year simulation with the optimal parameters. The partitioning of total precipitation between convective and stratiform types is substantially improved from the standard CAM5, when compared to the TRMM observation shown in Figure 1. The overestimation of convective precipitation by the standard CAM5 is significantly reduced with the optimal parameters. The global mean bias and root mean square error are also remarkably reduced for deep convective and stratiform precipitation in the simulation with the optimal parameters. The simulated meridional distributions of the ratio between deep convective and total precipitation (hereafter RDT) over southern Asia, eastern Asia, and the eastern Pacific with the default and optimal parameters are compared to the observed distributions in Figure 5, along with the zonal distribution over the tropical region. The observed RDT varies from 0.2 to 0.6, with higher ratios at lower latitudes than at higher latitudes, except over the eastern Pacific region, and higher values over land than over ocean (as seen in Figure 5d). With the standard ZM deep convective parameters, the total precipitation is mainly from deep convection, with RDT around 0.8 at low latitudes and around 0.3 beyond 30°C or 30°N. When the optimal parameters are used, the convective precipitation ratios are closer to the observation. The overall zonal and meridional distributions of the convective precipitation ratios are also improved over most areas. The tropical zonal distribution shows that the RDTs are higher than observation in both simulations with the default and optimal parameters over tropical Africa (around 20°E) and South America (around 60°W). This is due to an overprediction of convective precipitation and an underprediction of stratiform precipitation over land at relatively coarse resolution (see Figures 1 and 4).

Table 3. Values of Nine ZM Parameters Used in the Three Simulations With Best Performance on ANN, JJA, and DJF Deep Convective Precipitation, Respectively

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Default</th>
<th>Optimal ANN</th>
<th>Optimal JJA</th>
<th>Optimal DJF</th>
</tr>
</thead>
<tbody>
<tr>
<td>C₀_lnd</td>
<td>0.0059</td>
<td>0.0440</td>
<td>0.0060</td>
<td>0.0240</td>
</tr>
<tr>
<td>C₀_ocn</td>
<td>0.045</td>
<td>0.034</td>
<td>0.012</td>
<td>0.034</td>
</tr>
<tr>
<td>Kₑ</td>
<td>1.0E-06</td>
<td>4.9E-06</td>
<td>7.0E-07</td>
<td>4.8E-06</td>
</tr>
<tr>
<td>α</td>
<td>0.10</td>
<td>0.25</td>
<td>0.11</td>
<td>0.36</td>
</tr>
<tr>
<td>CAPE₀</td>
<td>70.0</td>
<td>103.6</td>
<td>74.8</td>
<td>97.2</td>
</tr>
<tr>
<td>PE_lnd</td>
<td>1.0E-03</td>
<td>7.0E-04</td>
<td>3.0E-04</td>
<td>8.0E-04</td>
</tr>
<tr>
<td>PE_ocn</td>
<td>1.0E-03</td>
<td>1.2E-03</td>
<td>1.8E-03</td>
<td>1.8E-03</td>
</tr>
<tr>
<td>τ</td>
<td>3600</td>
<td>5925</td>
<td>8903</td>
<td>4971</td>
</tr>
<tr>
<td>Dₑ</td>
<td>25.0</td>
<td>18.8</td>
<td>12.9</td>
<td>24.9</td>
</tr>
</tbody>
</table>

Figure 3. Relative sensitivities (response) of several important CAM5 output variables (see Table 2) at both tropical (top) and regional scale (bottom; see Table 2) to the nine ZM convective parameters (see Table 1) in JJA. Sensitivity ranking is calculated based on the regression coefficients between output variables and input parameters from the 200 experiments. Positive and negative correlations are denoted by plus and minus symbols, respectively.
applied, even though only the parameters related to deep convective precipitation are perturbed and the same SSTs are prescribed in all the simulations. From Figures 1 and 4, we see a reduction of the double ITCZ bias and a slight improvement in the simulated precipitation over the EA/NWP region when using the optimal parameters. Although the northern ITCZ is further enhanced, the zonal distribution of precipitation along the ITCZ agrees better with the observation.

[34] Figure 6 compares the observed (ERA-Interim reanalysis) and simulated (with the default and optimal parameters) pressure-longitude distributions of circulation and the total diabatic heating rate (TDH) along the ITCZ (6°N–12°N) in JJA and DJF. The TDH is calculated as the residual of the thermodynamic equation in pressure layers [Nigam et al., 2000; Hagos et al., 2010], as shown by equation (4):

$$TDH = \frac{C_p T}{\theta} \left( \frac{\partial \theta}{\partial t} + u \frac{\partial \theta}{\partial x} + v \frac{\partial \theta}{\partial y} + \omega \frac{\partial \theta}{\partial p} \right),$$  (4)

where $C_p$ is the specific heat capacity of dry air, $T(\theta)$ is the air temperature (potential temperature), and $u$, $v$, and $\omega$ are the velocities at the directions of $x$, $y$, and $p$, respectively.

[35] In JJA, although the TDH is overestimated when using the optimal parameters associated with the stronger ITCZ precipitation (Figure 4), its zonal gradient is much closer to the observations than that simulated by the standard CAM5, which produces precipitation nearly uniformly along the ITCZ. The improvements with the optimal parameters in DJF are more significant than in JJA, with reduced biases over both western and eastern regions and better simulated circulation and TDH patterns.

[36] Precipitation over the EA and NWP regions is also improved by applying the optimal parameters. Figure 7 presents the observed zonal distribution of 500 hPa vertical velocity in JJA and DJF, along with the simulated distributions with the default and optimal parameters, respectively. In JJA, positive and negative biases of 500 hPa vertical velocity over the northwestern Pacific (east of 135°E) and eastern Asia (west of 135°E) are seen in the simulation with the default parameters. Using the optimal parameters, both the

---

**Figure 4.** Spatial distributions of ANN (a) deep convective, (b) stratiform, and (c) total precipitation for 2001–2010 simulated by CAM5 at 2° resolution with the optimized parameters. The simulated global-mean bias, root mean square error (rmse), and spatial correlation ($r$) relative to observation (TRMM/GPCP) are also presented.

**Figure 5.** Meridional distributions of the ratios of deep convective versus total precipitation (RDT) from the TRMM/GPCP observation and two model simulations over (a) South Asia, (b) East Asia, and (c) Eastern Pacific, respectively, along with (d) the zonal distribution over the tropical region.
Figure 6. Pressure-longitude distributions of circulation (vectors) and TDH rate (shade), observed (ERA-Interim reanalysis; top row) and simulated with the default (middle row) and optimized (bottom row) parameters, along the ITCZ (6°N–12°N average) in JJA (left column) and DJF (right column), respectively.

Figure 7. Zonal (averaged over 12°N–35°N zone) distributions of 500 hPa vertical velocity over EA and NWP region in JJA (left) and DJF (right), observed (ERA-Interim reanalysis) and simulated with the default and optimized parameters, respectively.
positive bias over the northwestern Pacific and the negative bias over eastern Asia are reduced as a result of the improved precipitation pattern. Improvement of the 500 hPa vertical velocity is also seen in DJF.

The cross-equatorial jets play important roles in atmospheric moisture transport and global distribution of precipitation [Wang et al., 2003; Zhou and Yu, 2005]. The annual cycles of the cross-equatorial jets at 850 hPa over southern Asia, eastern Asia, and the eastern Pacific are shown in Figure 8. It is evident that the standard CAM5 underestimates the intensity of the cross-equatorial jets over all three regions throughout the year. When the optimal parameters are applied, the model results show more reasonable annual variations, compared to the observations.

Since convective precipitation is suppressed with the optimal parameters (relative to the default simulation), more water vapor and atmospheric instability are built up, which possibly results in heavier precipitation and affects the frequency distribution of precipitation intensity. The PDF of observed and simulated rain rate with the standard and optimal parameters, together with the 95th percentile rain rate, over four regions (the ITCZ, Indian Ocean, Maritime Continent, and eastern Asia) are shown in Figure 9. The standard CAM5 overestimates the frequencies of rain rate below 20 mm day$^{-1}$, but underestimates the frequencies of higher rain rates over all regions. When using the optimal parameters, the frequencies of light and moderate precipitation (i.e., $<20$ mm day$^{-1}$) are reduced, while heavy precipitation occurs more frequently, leading to higher 95th percentile rain rates that are much closer to observations in all four regions. However, significant biases still exist between the optimized results and observations, especially for light precipitation.

As cloud properties are sensitive to the perturbed convective parameters, changes in these parameters can induce large impacts on the other model fields (Figure 3, top panel). Since the optimization focused only on precipitation, these impacts can be either positive or negative. Annual global mean cloud amount and cloud-radiative forcing variables (see Table 2) from the CAM5 simulations and observations are shown in Table 5. The standard CAM5 clearly underestimates the magnitude of LWP, when compared with observations. This bias is reduced with the optimal parameters. Total cloud fraction as well as shortwave and longwave cloud forcing (absolute value) all increase with the optimal parameters, and the net shortwave and longwave radiative fluxes at the top of atmosphere (TOA) are reduced correspondingly. Figure 10 shows the global distributions of ANN net shortwave and outgoing longwave radiative fluxes at the TOA for the observation and two simulations. The spatial patterns of net shortwave and outgoing longwave radiative fluxes between the two CAM5 simulations with the default and optimal parameters are very similar, both reasonably reproducing the observed global patterns of the TOA radiative fluxes. On global average, the default simulation shows a positive bias (3.6 W m$^{-2}$) and the optimal simulation shows a negative bias ($-3.2$ W m$^{-2}$) for net shortwave radiation. For outgoing longwave radiation, both simulations show a negative bias. The root mean square errors are lower in the default simulation for both shortwave and longwave fluxes because tuning for radiation balance is an important consideration that yielded the parameters used in the default simulation, while the optimal simulation was only optimized for the convective precipitation based on observations. Nevertheless, the differences in TOA radiative budgets (shortwave plus longwave) between the CAM5 simulations are small, since SST is prescribed in these simulations. Because of prescribed SST, the full range of cloud-radiative feedbacks cannot be totally reflected in the optimization process. Compensating errors in the simulation of cloud-radiative features are also expected among different physical schemes, which is beyond the scope of this study.

3.3. Impacts of the Optimized Convection on the Global Circulation and Climate (Based on Ensemble Simulations)

As shown in the bottom panel of Figure 3, optimizing parameters of the convective scheme influences not only convective precipitation, but also global circulation and climatic features, as changes in the partitioning between convective and stratiform precipitation can alter the diabatic heating profiles. To assess the impacts of model parameters
on global circulation, we divide the 200 experiments into six groups based on the global-average convective precipitation. The global-average convective precipitation of each simulation is normalized by subtracting the mean of the 200 simulations and then scaling by the variance of the 200 simulations. Simulations with normalized global convective precipitation smaller (larger) than $1/C_0$ are categorized in the low-ratio (high-ratio) group, which represents the lower (higher) side of the precipitation spectrum, and convection is greatly suppressed (favored) in the model. By analyzing the difference between the two groups of simulations, we can study the response of global circulation and climate to changes in convective rain ratio in the CAM5.

Figure 11 compares the mean total precipitation in the high-ratio and low-ratio simulation group, as well as their difference, in JJA and DJF, respectively. The difference between the low-ratio and high-ratio group is generally consistent with the difference between simulations with the optimal and default parameters because the optimal parameters reduce the ratio of convective versus total precipitation in the default CAM5 simulation.

The difference in total precipitation between the standard CAM simulation and the observations is also shown in Figures 11d1 (JJA) and 11d2 (DJF). If the signs of the low-ratio minus high-ratio difference and of the CAM5 minus observation difference are opposite to each other, lowering the RDT simulated by the standard configuration improves the model performance on the total precipitation in that region. It should be noted that the high-/low-ratio results are based on a 1 year model output from about 35 simulations, while the default CAM5/observation differences are based on a single 10 year continuous simulation. To better illustrate the impact of model parameters, grid points with the same or opposite signs are indicated by red or blue colors, respectively, in Figures 11e1 and 11e2.

Table 5. Global ANN Cloud Properties, Radiative Forcing, and Net Shortwave and Outgoing Longwave Radiation Flux at TOA From CAM5 Simulations and Observation

<table>
<thead>
<tr>
<th>Property</th>
<th>Default</th>
<th>Optimized</th>
<th>Observation</th>
</tr>
</thead>
<tbody>
<tr>
<td>LWP (g m$^{-2}$)</td>
<td>47.07</td>
<td>62.69</td>
<td>80–97$a$</td>
</tr>
<tr>
<td>IWP (g m$^{-2}$)</td>
<td>16.89</td>
<td>37.3</td>
<td></td>
</tr>
<tr>
<td>CLD_FRA (%)</td>
<td>61.63</td>
<td>62.77</td>
<td>65–75$b$</td>
</tr>
<tr>
<td>OLR TOA (W m$^{-2}$)</td>
<td>236.59</td>
<td>232.3</td>
<td>233.95–239.57$c$</td>
</tr>
<tr>
<td>FSNT TOA (W m$^{-2}$)</td>
<td>244.13</td>
<td>237.31</td>
<td>234–244.7$^c$</td>
</tr>
<tr>
<td>SWCF (W m$^{-2}$)</td>
<td>47.36</td>
<td>53.7</td>
<td>47.07–54.16$^c$</td>
</tr>
<tr>
<td>LWCF (W m$^{-2}$)</td>
<td>23.3</td>
<td>27.34</td>
<td>26.48–30.36$^c$</td>
</tr>
</tbody>
</table>

$a$Observed LWP is derived from SSM/I for the years 1987–2000 [Greenwald et al., 1993; Weng and Grody, 1994; Ferraro et al., 1996] and NVAP for the years 1988–1999 [Engelen and Stephens, 1999]. Both data are restricted to oceans.

$b$Observed CLD_FRA are obtained from ISCCP for the years 1983–2001 [Rossow and Schiffer, 1999], MODIS data for the years 2001–2004 [Platnick et al., 2003], and HIRS data for the years 1979–2001 [Wylie et al., 2005].

$c$OLR TOA, FSNT TOA, SWCF, and LWCF observations are taken from ERBE for the years 1985–1989 [Kiehl and Trenberth, 1997], CERES for the years 2000–2003, and CERES-EBAF for the years 2000–2010 [Wielicki et al., 1996; Young et al., 1998].
In JJA, the total precipitation is overestimated in the standard CAM simulation over the NWP and underestimated in the coastal area of eastern Asia. The difference between the low-ratio and high-ratio simulations shows a reduction of northwestern Pacific precipitation, but an increase of precipitation over the eastern Asia coastal area, indicating a shift of precipitation toward the coastal area of China and Japan. In general, the simulated total precipitation over the northwestern Pacific and eastern Asia regions is improved by lowering the RDT. Precipitation over Arabia, India, the northern Indian Ocean, Maritime Continent, and the southern Pacific is also improved, as indicated by the opposite signs between the low-/high-ratio difference and standard CAM/observation difference. The significant positive bias in the southern ITCZ in the standard CAM simulation (known as the double ITCZ) is slightly reduced by lowering the RDT in JJA. Some negative impacts are produced by lowering the RDT (e.g., in precipitation over the

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**Figure 10.** Spatial distributions of ANN net shortwave radiative flux (left column) and outgoing longwave radiative flux (right column) at the TOA (unit: W m\(^{-2}\)), observed (CERES_EBAF, 2000–2010, first row) and simulated (2001–2010) with default (second row) and optimal (third row) parameters, as well as the simulation-observation differences (fourth and fifth rows). Observed global means and simulated mean biases, root mean square errors (rmse), and spatial correlation (r) relative to observations are also given on the figure.
southern Indian Ocean and over the ITCZ region). In DJF, the biases of simulated total precipitation over Africa, the northern Indian Ocean, and western and northwestern Pacific are reduced by lowering the RDT, and the double ITCZ is also significantly reduced when convective precipitation is reduced. Positive effects are also found over west Australia and the Atlantic, especially over the southern Atlantic. Negative impacts are mainly located over the southwestern Indian Ocean, southwestern Pacific, and northeastern Pacific region. Overall, from the global-scale point of view, the total precipitation in JJA and DJF is not significantly improved in the simulation with optimal parameters, but the ratio of convective to total precipitation is improved.

Circulation plays the most important role in determining the spatial distribution of precipitation, which can, in turn, affect the circulation through latent heat release [Emanuel et al., 1994]. Figure 12 shows the atmospheric circulation at 850 hPa from the ensemble average of the high- and low-ratio simulations in JJA and DJF. The differences between the low- and high-ratio groups, as well as the differences between the results from the standard CAM and observation, are also presented for comparison. In boreal summer (i.e., JJA), atmospheric circulation at 850 hPa mainly consists of the southerly cross-equatorial jets over the Indian Ocean and the India summer monsoon (ISM), the western Pacific subtropical high (WPSH) and the east Asian summer monsoon (EASM), and the strong easterlies over the tropical Pacific. From the default CAM/observation difference, we see a significant easterly bias over the tropical Pacific region and a divergence from the ITCZ toward the higher latitudes in the standard CAM simulations. The difference between low- and high-ratio simulations shows an opposite pattern, indicating a positive impact on circulation by lowering the RDT over this region. The response of the tropical Pacific low-level winds plays an essential role in the spatial distribution of precipitation over this region. The

Figure 11. Spatial distributions of ensemble mean total precipitation from (a1 and a2) high-ratio and (b1 and b2) low-ratio simulation group, as well as (c1 and c2) their differences, in JJA (left column) and DJF (right column), respectively. The difference between the simulated (with the default parameters) and observed (TRMM/GPCP) total precipitation is also shown in Figures 11d1 and 11d2. Figures 11e1 and 11e2 present the relationship between the low-/high-ratio difference and default-observation difference, where red/blue color represents a same/opposite sign at each grid (blank are shown for grids with weak sensitivity, i.e., low-/high-ratio difference <0.25 mm d$^{-1}$).
cross-equatorial jets are significantly underestimated in the standard CAM simulation, compared to the observation (also seen in Figure 8). This is improved when lowering the RDT. Positive impacts are also seen in the mid-latitudes. For example, a weak cyclonic circulation bias exists over the northwestern Pacific (10°N–30°N) region in the standard CAM; reducing the convection reverses the bias to shift precipitation closer to the eastern Asia coastal area. Significant opposite wind patterns can be seen over the southern Indian Ocean between 30°S and 60°S. Similar positive effects on circulations by lowering the RDT are also seen at 500 hPa (figure not shown). In DJF, some aspects of the 850 hPa circulation, including the north-to-south cross-equatorial jets and winds along the equator over the Pacific are also better simulated by lowering the RDT. However, some negative impacts are induced by lowering the RDT, which may point to structural limitation of the convective parameterization or limitations imposed by other physics parameterizations used in the model.

[45] The zonal mean vertical circulations over three typical climate regimes (i.e., southern Asia, eastern Asia, and eastern Pacific) in JJA and DJF are shown in Figures 13 and 14, respectively. Similarly, ensemble means of the high- and low-ratio groups, as well as the low-/high-ratio difference and default/observation difference, are also presented. The associated TDHs are also indicated by the shaded colors in Figures 13 and 14. For observation and the standard CAM results, the TDHs are calculated as the residual of the thermodynamic equation, that is, equation (4). For the high-/low-ratio simulations, the TDHs are derived as the sum of temperature tendencies due to the latent heat release, vertical temperature diffusion, and shortwave and longwave radiative heating. The difference in TDHs calculated using the two different methods is very small.
From Figures 13 and 14, we can see that positive and negative TDHs are always associated with up and downward atmospheric motion, respectively. The upward motion region with positive TDH is more confined in simulations with lower RDT, especially in DJF (Figure 14). Therefore, the differences between the low- and high-ratio simulations are always positive within the regions with climatological upward motions, but negative over the regions surrounding the ascent center. In JJA, the upward motion and positive TDH are underestimated by the standard CAM near the equator and 30°N over the southern Asia region, while lowering the RDT slightly increases the TDH there, with the potential to reduce the bias of the standard CAM simulation. By lowering the RDT, the biases are reduced to some extent. At higher levels, the biases are more evident, indicating more improvement is needed in simulating the vertical structure of heating associated with convective and stratiform precipitation.

The opposite sign between the difference of low-/high-ratio and default CAM/observation are more obvious in DJF than JJA over the three regions (Figure 14). The low-/high-ratio difference and default CAM/observation difference are not perfectly correlated with each other either in DJF or JJA because many processes influence the climate system, so tuning parameters related to a specific process, while not adjusting parameters related to other processes,
cannot guarantee an improvement in climate simulations in all regions. It should also be noted that the double ITCZ is always associated with a lower layer positive biases of upward motion and TDH, which warrants further investigation in the future.

What mechanisms control the responses of the circulation and the heating distribution when only parameters related to the convective process in the model are tuned? Mapes and Neale [2011] found that precipitation from deep convective or stratiform clouds was always confined to the area with the most humid and unstable conditions when convection was suppressed by imposing a higher PE. The top panel of Figure 15 shows the correlation between the ensemble mean total precipitation and vertical velocity at 500 hPa for the high- and low-ratio groups, respectively. With a low ratio of convective precipitation, the total precipitation is more sensitive to vertical velocity. The responses of the correlation/regression coefficients between total precipitation and vertical velocity as a function of the RDT are also presented in the bottom panel of Figure 15, which shows that both correlation and sensitivity increase as the RDT decreases. Therefore, we conclude that when convection is suppressed by tuning the convective parameters in CAM5, the total precipitation tends to be more confined to the stratiform type over regions with strong atmospheric convergence and instability. The associated redistribution of diabatic heating can consequently induce an intensification of the circulation [Schumacher et al., 2004].

3.4. Dependence of Optimal Parameters on Model Grid Spacing

As shown in Figure 15, when convection is suppressed by tuning the convective parameters in CAM5, the total precipitation tends to be better correlated with the grid-scale vertical velocity, which, however, could be very sensitive to model resolution. Yang et al. [2012] showed that the benefits of tuning parameters could be transferable across different model resolutions to some extent. Here we explore whether the optimal parameters derived from the 2° resolution simulations are transferable to a higher resolution (e.g., 1°) in CAM5 for model improvement. Figure 16 shows the deep convective, stratiform, and total precipitation (2001–2010) simulated at 1° resolution with the default and optimal parameters obtained from the 2° resolution simulations. The partitioning between

![Figure 14. Same as Figure 13, but for DJF.](image)
parameters based on the 2° simulations than using the default parameters. Other positive impacts of the optimal parameters on circulation and climate are also transferable from 2° to 1°, to some extent. We realize that the change of model grid spacing from 2° to 1° is not dramatic. We plan to investigate the impact of parameter optimization on model performance with model grid spacing down to a higher resolution (e.g., 50 km or higher) in the future.

4. Summary and Discussion

Precipitation and the associated latent heat release play essential roles in driving the Earth’s hydrological cycle and atmospheric circulations. Although total precipitation is generally reasonably simulated in the standard CAM5, the partitioning between convective and stratiform precipitation in the model is very different from that seen in the TRMM PR data, namely, too much convective rain is simulated by the standard CAM5, compared with observations. Although many processes related to deep convection, cloud microphysics, and macrophysics parameterizations may be responsible for the misrepresented precipitation partitioning, as a first step, the deep convection process in the ZM deep convection scheme in CAM5 was investigated and the uncertainty related to input parameters was quantified in this study.

Our results show that the convective precipitation simulated by CAM5 is most sensitive to parameters such as parcel fractional mass entrainment rate, CAPE consumption time scale, and maximum downdraft mass flux fraction. Using the optimal parameters constrained by the observed convective precipitation, the model significantly improves the ratio of convective versus stratiform precipitation and the rain-rate frequency distribution. When convection is suppressed by the use of optimal parameters, precipitation tends to be more confined to the stratiform type over regions with strong atmospheric convergence and instability, which consequently affects atmospheric motion through redistribution of latent heat release by the modified convective system. As a result, simulations using the optimal parameters exhibit positive impacts on the global and regional circulation and hydrological cycle, including reduction of the double ITCZ bias, improved precipitation over the EA monsoon region, and more reasonable annual cycle of the cross-equatorial jets. The convective and stratiform ratio is also improved in the 1° simulations using the optimal parameters identified from the 2° simulations. Other positive impacts of the optimal parameters are also transferable from 2° to 1°, to some extent.

A number of limitations in this study deserve future research. Climate models represent climate processes in a self-consistent system, so perturbing model parameters related to one specific physical process may disturb the balance of the overall modeling system. For example, cloud properties exhibit large responses to the perturbed convective parameters in this study, which will induce large impacts on the radiation budgets. In this study, our primary goal was to understand the sensitivity of the climate systems to parameters in the ZM convection scheme. Because precipitation alone is constrained in the optimization and SST is prescribed, the TOA radiative budget (as shown in Figure 10) did not exhibit any improvements (and the outgoing longwave radiation flux bias actually
increases). If improving the overall climate simulation of CAM5 were the primary goal, it would be beneficial to add other quantities, particularly net global radiative balance, in the performance metric. As Jackson [2009] discussed, the errors among model fields are all physically linked with one another. With a similar sampling algorithm, but a multi-field constraint, they found that the model performance on the multiphysics climate can be significantly improved [Jackson et al., 2008]. However, the challenges of adding more quantities in the performance metric are (1) the need to identify many more free parameters (which means more simulations are needed), since many processes other than deep convection affect the radiation budget, and (2) assigning the relative weights in the performance metric for each quantity. Addressing these issues is especially important for optimizing coupled climate simulations in which TOA imbalance caused by overfitting a narrow set of variables has serious implications for long-term simulations or predictions.

Compensating errors are also expected among different physical schemes. The standard CAM has been tuned to produce reasonable radiative fluxes, but it fails to produce reasonable magnitude of liquid/ice-cloud water path, whereas the optimal parameters can produce cloud water paths closer to observations. Qian et al. [2012] suggested that the good agreement in solar radiative fluxes between GCMs and observations could result from compensating errors in the simulated cloud vertical structure, cloud fraction, overlap assumption, and cloud optical depth. Parameters optimized for a specific variable, such as precipitation, could potentially disrupt the balance of compensating errors, leading to unintended negative impacts on other aspects of the climate simulations.

Another issue that deserves further investigation is the interaction among the deep convective, shallow convective, and stratiform cloud macrophysics and microphysics processes in the model and their competition for moisture. Our results showed that the frequency of heavy precipitation is under and overestimated by CAM5 with the default and optimal parameters, respectively, which implies precipitation may be overly confined to the stratiform type spatially or temporally with the optimal parameters. Reducing the bias of total precipitation amount also needs more attention, but this is constrained, to some degree, by the surface latent flux, which is influenced by the prescribed SST. In spite of these issues, this study provides some useful insights on the sources of model biases among different physical processes and motivates further studies to assess the strategies for UQ and parameter optimization through improved understanding of the internal physical and dynamical processes of the atmospheric system.

Additionally, the extent of improvements by tuning parameters is limited by the incomplete representation of cloud and precipitation processes in the model. Song and Zhang [2011] adopted a microphysics parameterization for convective cloud in CAM, aiming to formulate a more realistic convective process and its interaction with aerosol and other processes. Houze and Betts [1981] suggested that besides the convective-scale cloud fluxes, models also need to account for the mesoscale up and downdrafts to simulate the tropical convection system. Further, Arakawa [2004] pointed out that artificial separation of processes and scales in the conventional approach of physical process is a major problem in current climate models and emphasized the importance of developing a conceptual framework for a “unified cloud parameterization” or “unified model physics” for climate models in the future.

Appendix A: ZM Deep Convective Parameterization Scheme in CAM5

In CAM5, the deep convective process is represented by the ZM deep convection scheme originally developed by Zhang and McFarlane [1995], with several additional
modifications [Gregory et al., 1997; Neale et al., 2008; Richter and Rasch, 2008; Neale et al., 2010]. Here we introduce several equations to provide a proper context for the important parameters being evaluated and optimized in this study. More details regarding the convective mass fluxes and the feedback to the grid-scale atmospheric properties can be found in the original work by Zhang and McFarlane [1995].

[58] The ZM deep convective scheme uses a bulk mass flux approximation on the basis of a plume ensemble concept first proposed by Arakawa and Schubert [1974]. An ensemble of convective-scale updrafts is assumed to exist when the lower troposphere is locally unstable. Liquid water is produced during the updraft condensation process. The conversion from cloud liquid water to rain water \( R_k \) is represented by the empirical formulation of Lord et al. [1982], as shown in equation (A1):

\[
R_k = C_0 M_a I,
\]

(A1)

where \( M_a \) is the updraft mass flux, \( C_0 \) is the conversion coefficient, and \( I \) is the cloud water content. Cloud condensates not converted to rain will detrain to the stratiform cloud area within the grid. The detrained condensates are partitioned to liquid and ice based on the environment temperature, with prescribed radius of 8 and 25 \( \mu \)m, respectively.

[59] Convective-scale downdrafts are induced and fueled by the rainwater evaporation when there is precipitation produced in the updrafts. The strength of the downdraft flux is controlled by a proportionality factor, \( x \) [Zhang and McFarlane, 1995], which is derived based on the precipitation produced in the updrafts (PCP) and the evaporation in downdrafts (EVP), as shown by equation (A2):

\[
x = x_0 \frac{PCP}{PCP + EVP}.
\]

(A2)

[60] Such a relationship indicates that there is no downdraft if no precipitation is produced. It also ensures that evaporation in the downdraft does not exceed a fraction \( x_0 = 0.1 \) of the total precipitation produced within the updrafts.

[61] The closure condition used in the ZM deep convection scheme is based on the concept that cumulus convection consumes the CAPE at a certain rate. The cloud-base upward mass flux \( M_b \) is calculated as shown by equation (A3):

\[
M_b = \frac{CAPE - CAPE_0}{\tau F},
\]

(A3)

where \( F \) is the CAPE consumption rate per unit updraft mass flux at the cloud base, \( CAPE_0 \) is the threshold for deep convection, and \( \tau \) is a prescribed time scale during which CAPE in excess of \( CAPE_0 \) is consumed by convection.

[62] In the original ZM convection scheme, CAPE is diagnosed by assuming an undiluted parcel ascent (i.e., there is no mixing between the parcel and the environment). A dilute CAPE with an entraining parcel has been introduced in the ZM convection scheme to bring more sensitivity of the CAPE calculation to tropospheric humidity [Neale et al., 2008].

[63] An evaporation formula, following Sundqvist [1988], has been employed to evaporate some precipitation directly to the grid-scale environment as it makes its ways to the surface, as shown in equation (A4):

\[
E_k = K_e (1 - RH_k) R_k,
\]

(A4)

where \( R \) is the total precipitation flux at model layer \( k \), \( RH \) is the relative humidity of the environment, \( K_e \) is the evaporation efficiency \( (1.0 - 0.6 (kg m^{-2} s^{-1})^{1/2} s^{-1}) \), and \( E \) is the corresponding evaporation in that layer.

### Appendix B: SSAA Optimization Approach

[64] The SSAA algorithm is a method for global optimization that takes advantages of both the annealing and SAMC techniques. The annealing technique helps to enhance the convergence efficiency by shrinking the desired sample space [Ingber, 1989; Jackson et al., 2004], while the SAMC technique favors more freely searching within the desired sample spaces so as to reduce the probability of local minimum/maximum trap [Liang, 2011].

[65] During the SSAA procedure for parameters optimization (in the ZM convection scheme in CAM5), the parameters are perturbed iteratively based on a skill score. For the first round, a parameter set \( (m) \) is randomly taken as \( m_0 \) from uniformly distributed values from the parameter spaces. Then, a CAM5 simulation is conducted with \( m_0 \) and the model performance is quantified based on a scalar skill score \( E(m) \) in section 2.3.2), commonly known as “cost” in statistics.

[66] Starting from the second round of the SSAA procedure, the parameters are perturbed to a new set \( (m_{new}) \) chosen from a Cauchy distribution with values centered at the parameter set of the previous step. The width of the Cauchy distribution is controlled by an annealing coefficient, \( T \). With lower \( T \), the distribution is more confined, so that the parameter set closer to the previous one will be sampled with higher probability.

[67] The acceptance or rejection of the new parameter set \( (m_{new}) \) is determined by applying the SAMC technique that divides the “cost” into different levels. Therefore, the parameter sets corresponding to the first/last level will have the best/worst model performance, respectively. The acceptance rate of the new parameter set \( (m_{new}) \) is calculated as shown in equation (B1):

\[
r = \exp\left(\theta_1 [E(m_0) - E(m_{new})]\right) \exp\left(\left[E(m_0) - E(m_{new})\right]/\theta_2\right).
\]

(B1)

[68] The acceptance rate, \( r \), is based on (1) the difference between the two cost functions for the new and old parameter sets (i.e., \( E \)) and (2) the difference between the acceptance frequencies (\( \theta \)) for the two cost levels of the new and old parameter sets, respectively, during the previous iterations (i.e., step 1 to \( k - 1 \)).

[69] The new set of parameters will be accepted with a higher probability if the new set shows an improvement over the old one, that is, \( E(m_{new}) - E(m_0) < 0 \), or the new set is of some cost level less than a previously accepted set, as long as the two levels are within some specified distance. If the new set is accepted, it will be used as the basis for the next iteration, that is, \( m_0 = m_{new} \).

[70] An annealing schedule (i.e., lowering \( T \) every step) is adopted, so that the Cauchy distribution will increasingly focus on the current accepted parameter set, which accelerates the convergence rate of the SSAA algorithm. At the same time, the SAMC technique helps to make the algorithm less prone to local trapping.
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References


