Parameter Tuning and Calibration of RegCM3 with MIT–Emanuel Cumulus Parameterization Scheme over CORDEX East Asia Domain

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ABSTRACT
In this study, the authors calibrated the performance of the Regional Climate Model, version 3 (RegCM3), with the Massachusetts Institute of Technology (MIT)–Emanuel cumulus parameterization scheme over the Coordinated Regional Climate Downscaling Experiment (CORDEX) East Asia domain by tuning seven selected parameters based on the multiple very fast simulated annealing (MVFSA) approach. The seven parameters were selected based on previous studies using RegCM3 with the MIT–Emanuel convection scheme. The results show the simulated spatial pattern of rainfall, and the probability density function distribution of daily rainfall rates is significantly improved in the optimal simulation. Sensitivity analysis suggests that the parameter relative humidity criteria (RHC) has the largest effect on the model results. Followed by an increase of RHC, an increase of total rainfall is found over the northern equatorial western Pacific, mainly contributed by the increase of explicit rainfall. The increases of the convergence of low-level water vapor transport and the associated increases in cloud water favor the increase of explicit rainfall. The identified optimal parameters constrained by total rainfall have positive effects on the low-level circulation and surface air temperature. Furthermore, the optimized parameters based on the chosen extreme case are transferable to a normal case and the model's new version with a mixed convection scheme.

1. Introduction
With their better-resolved regional terrain and surface characteristics, regional climate models (RCMs) have been widely used as a downscaling tool in regional climate research and future climate projection (Giorgi and Mearns 1999; Leung et al. 2003; Y. Wang et al. 2004; Christensen et al. 2007). Many coordinated projects have been carried out, with the focus on different regions of the world, such as North America (Mearns et al. 2009), Europe (Christensen and Christensen 2007; Van der Linden and Mitchell 2009), and East Asia (Fu et al. 2005). Recently, the Coordinated Regional Climate Downscaling Experiment (CORDEX) was established (Giorgi et al. 2009; Jones et al. 2011). The aim of CORDEX is to develop high-resolution regional climate change projections for all land regions of the globe based on phase 5 of the Coupled Model Intercomparison Project (CMIP5) multimodel, multiple representative concentration pathway (RCP) centennial projections using multiple regional climate downscaling (RCD) methods. The application of different RCMs over different regions has enriched our understanding of the
The Regional Climate Model (RegCM) system is a community model developed at the Abdus Salam International Centre for Theoretical Physics (ICTP) and has been used in numerous regional model intercomparison projects (Pal et al. 2007). Since it has been mainly developed and tested in the midlatitudes, customizations or calibrations of RegCM are usually required, in particular when applying it to other regions where the climate regime differs from that of the midlatitudes. Currently, these customizations of RegCM are generally carried out via sensitivity experiments by varying the physics scheme or key parameters one at a time (e.g., Giorgi et al. 1993a,b; Chow et al. 2006; Davis et al. 2009; Segele et al. 2009; Zou and Zhou 2011).

Previous studies have attempted to customize RegCM, version 3 (RegCM3), with the Massachusetts Institute of Technology (MIT)–Emanuel cumulus parameterization scheme by designing sensitivity experiments through three different approaches. The first approach is to apply some convection suppression criteria to the MIT–Emanuel cumulus parameterization scheme (Chow et al. 2006). The physical basis is that the cumulus parameterization schemes mainly driven by buoyancy, such as the MIT–Emanuel scheme, generally overestimate the occurrence of convection, since some unfavorable large-scale conditions may inhibit its formation (Markowski et al. 2006). Results indicate that combining the relative vorticity and relative humidity criteria significantly improves the simulated Asian summer monsoon precipitation (Chow et al. 2006). The second approach is to vary the key parameters in the MIT–Emanuel scheme that control the rate of convective mass flux and the fraction of condensed water converted to precipitation (Segele et al. 2009). Results show that the amount of condensed water that ultimately generates as rain crucially affects the simulated rainfall amount over the Horn of Africa. The third approach is to adjust the gridbox relative humidity threshold for cloudiness and the autoconversion scale factor in the subgrid explicit moisture (SUBEX) scheme. Based on the sensitivity simulations performed, the simulated convective partition and total rainfall are significantly improved over the tropical regions of eastern Africa and the Indian Ocean (Davis et al. 2009). This type of sensitivity experiment is computationally economic and effective for model physics selection, but the disadvantage is it is difficult to identify the optimal parameter sets in the model physics and quantify the interaction among multiple parameters, because each time only one parameter is perturbed.

Identifying a set of optimal values from the tunable input parameter space can be regarded as a problem of global optimization. Many sampling approaches have been developed to efficiently sample parameters in multidimensional parameter spaces. The multiple very fast simulated annealing (MVFSA) algorithm (see the method description in section 2b) has been shown to be a practical method that can progressively and efficiently move toward regions of the parameter space that minimize model–observation differences (Ingber 1989; Jackson et al. 2004). Jackson et al. (2003) used the MVFSA algorithm to identify the optimal parameter set of a land surface model. The results showed that the MVFSA algorithm is much more efficient than the Gibbs’ sampler. Jackson et al. (2008) applied this method to optimize six parameters related to cloud and convection processes in the Community Atmospheric Model, version 3.1 (CAM3.1). Constrained by different sets of observations, their results indicated that the model’s skill is improved by 7%–10%. Using the same method, Yang et al. (2012) optimized the five parameters of the Kain–Fritsch (KF) convective parameterization scheme in the Weather Research and Forecasting (WRF) model based on the constraint of high-resolution observed precipitation over the southern Great Plains. The results showed the simulated precipitation to be significantly improved when five optimized parameters were used. Yan et al. (2014) found that optimized parameters and their sensitivities are to some extent transferable across physical processes, spatial scales, and climate regimes.

In this study, focusing on precipitation, we apply the MVFSA technique to calibrate RegCM3 with the MIT–Emanuel cumulus parameterization scheme over the CORDEX East Asia domain. Our objectives are to 1) identify a set of optimal values of the key parameters tuned in previous sensitivity studies and 2) investigate the sensitivity of precipitation to those key parameters. The East Asian summer monsoon in the year 1998 is chosen because of the unprecedented 1997/98 El Niño event and because this case has been previously selected for the evaluation of global atmospheric general circulation models (B. Wang et al. 2004), RCMs (Wang et al. 2003; Chow et al. 2006; Zou and Zhou 2013a), and regional atmosphere–ocean coupled models (Zou and Zhou 2011, 2012).

The remainder of the paper is organized as follows. The model configuration, selected parameters, optimization approach, and experimental design are described in section 2. Section 3 presents the results, including the responses of the model to the perturbed parameters and
the transferability of the optimized parameters to another case and the new version of the model. Section 4 is the summary and concluding remarks.

2. Model, methodology, and experimental design

a. Model and the selected parameters

To facilitate comparison between previous customizations of RegCM3 and those with the MIT–Emanuel cumulus parameterization scheme, the model used in this study is also RegCM3, instead of the newly developed RegCM4 (Giorgi et al. 2012). RegCM3 (Pal et al. 2007) is the advanced version of RegCM2 (Giorgi et al. 1993a,b; Qian and Giorgi 1999). It is a hydrostatic, compressible model with a terrain-following sigma vertical coordinate system. The following physics schemes are employed in our study: the cumulus parameterization scheme of MIT–Emanuel (Emanuel 1991; Emanuel and Zivković-Rothman 1999); SUBEX scheme (Pal et al. 2000); the radiation package of the National Center for Atmospheric Research (NCAR) Community Climate Model, version 3 (CCM3) (Kiehl et al. 1996); the nonlocal planetary boundary layer (Holtslag et al. 1990); the Biosphere–Atmosphere Transfer Scheme of Dickinson et al. (1993); and the ocean–atmosphere flux algorithm proposed by Zeng et al. (1998).

There are a number of tunable input parameters in the model’s configuration. Here, we only select seven parameters, which have been tuned in previous sensitivity studies, for customization of RegCM3 with the MIT–Emanuel cumulus parameterization scheme (Chow et al. 2006; Davis et al. 2009; Segele et al. 2009). These seven parameters can be divided into three categories:

1) Convection suppression criteria. We choose relative humidity criteria (RHC) in this study. The convection is activated when the RH averaged from the cloud top to the cloud base is larger than a critical value (RHC). In the default setting, the convection is driven by the buoyancy, and effects of the large-scale environment are not considered.

2) Based on the study of Segele et al. (2009), another two parameters in the MIT–Emanuel cumulus parameterization scheme are selected: i) the relaxation rate, \( \alpha \), determining the rate at which the cloud-base upward mass flux is relaxed to steady state and ii) the warm cloud autoconversion threshold \( l_0 \) that quantifies the amount of cloud water available for precipitation conversion. We set a range from 0.0002 to 0.8 for \( \alpha \), and from 0.0001 to 0.05 for \( l_0 \).

3) Based on the study of Davis et al. (2009), two other parameters are also selected: i) the gridbox relative humidity threshold for cloudiness \( \text{RH}_{\text{min}} \) and ii) the autoconversion scale factor \( C_{\text{asc}} \) in the SUBEX scheme. The quantities \( \text{RH}_{\text{min}} \) and \( C_{\text{asc}} \) can be defined separately for land and ocean, so there are four parameters in total \( (C_{\text{asc,land}}, C_{\text{asc,ocean}}, \text{RH}_{\text{min,land}}, \text{RH}_{\text{min,ocean}}) \). The range for \( \text{RH}_{\text{min}} \) is set from 0.6 to 1.0, and \( C_{\text{asc}} \) is set from \( \frac{1}{2} \) to 2 times the original values.

Table 1 summarizes the default value and the range of values for the selected seven parameters.

b. Optimization approach

We apply the MVFSA technique to optimize these seven selected parameters. The MVFSA sampling algorithm operates by taking random steps in the parameter space, and at each step running the model, quantifying the model–observation differences in terms of a scalar skill score or “cost,” and reselecting parameter values based on the skill score such that the algorithm progressively moves toward regions of the parameter space that minimize modeling bias. Candidate parameter values are initially chosen from a uniform prior and perturbed randomly following a Cauchy distribution. The perturbed parameter set will be accepted or rejected with a probability based on the skill.

### Table 1. Short names, default, minimum and maximum values, and descriptions of the seven parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Default</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>RHC</td>
<td>—</td>
<td>0.4</td>
<td>0.9</td>
<td>Convection is activated when the RH averaged from the cloud top to the cloud base is larger than a critical value (RHC). In the default setting, the convection is driven by the buoyancy, and effects of the large-scale environment are not considered.</td>
</tr>
<tr>
<td>( C_{\text{asc,land}} )</td>
<td>0.4</td>
<td>0.2</td>
<td>0.8</td>
<td>Autoconversion scale factor over ocean</td>
</tr>
<tr>
<td>( C_{\text{asc,ocean}} )</td>
<td>0.4</td>
<td>0.2</td>
<td>0.8</td>
<td>Autoconversion scale factor over ocean</td>
</tr>
<tr>
<td>( \text{RH}_{\text{min,land}} )</td>
<td>0.8</td>
<td>0.6</td>
<td>1.0</td>
<td>Gridbox RH threshold for cloudiness over land</td>
</tr>
<tr>
<td>( \text{RH}_{\text{min,ocean}} )</td>
<td>0.9</td>
<td>0.6</td>
<td>1.0</td>
<td>Gridbox RH threshold for cloudiness over ocean</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>0.2</td>
<td>0.0002</td>
<td>0.8</td>
<td>Rate at which the cloud base upward mass flux is relaxed to steady state</td>
</tr>
<tr>
<td>( l_0 )</td>
<td>0.0011</td>
<td>0.0001</td>
<td>0.05</td>
<td>Amount of cloud water available for precipitation conversion</td>
</tr>
</tbody>
</table>
score. As sampling progresses, the Cauchy distribution width becomes increasingly focused on the last accepted parameter set so as to accelerate the convergence process (Ingber 1989). This convergence chain is usually repeated several times starting from randomly chosen points in the parameter space to reduce the probability of being trapped into a local minimum. For more details about the MVFSA algorithm, readers are referred to Jackson et al. (2004, 2008) and Yang et al. (2012).

**c. Experimental design**

The model domain of RegCM3 covers the CORDEX East Asia domain (Giorgi et al. 2009; Jones et al. 2011) with a uniform horizontal resolution of 50 km (Fig. 1). The model has a standard vertical configuration of 18 sigma layers, with the model top at 10 hPa. The buffer zone of RegCM3 is 15 grid layers. The initial and lateral boundary conditions are derived from the National Centers for Environmental Prediction–U.S. Department of Energy (NCEP–DOE) reanalysis 2 (NCEP2) (Kanamitsu et al. 2002), which is updated every 6 h. The SST forcing is from the weekly optimal interpolation sea surface temperature (OISST) data (Reynolds et al. 2002).

The RegCM3 experiments are performed one by one with a set of simultaneously perturbed parameters sampled by the MVFSA technique. To obtain the global optimal values, we repeat the MVFSA procedure three times with different starting parameter sets (three chains). There are 80 experiments in each chain. Each simulation is integrated starting from 1 May through 31 August 1998. The first month is regarded as the spin-up time of the simulation, and the results of June–August (JJA) are analyzed.

The three monthly means of precipitation are used to constrain the RegCM3 simulation. For each simulation with a given set of parameters \( m \), the cost function \( E(m) \) is used to quantify the model skill. The \( E(m) \) is defined as

\[
E(m) = \log \left( \frac{4\sigma_{\text{obs}}(\sigma_{\text{mod}} + \sigma_{\text{mod}}(\sigma_{\text{obs}})^2)}{(1 + R)^4} \right),
\]

where \( \sigma \) is the spatial standard deviation and \( R \) is the spatial correlation coefficient between the simulation and observation. The subscripts obs and mod denote observation and simulation, respectively. Variables \( x \) and \( y \) with \( N \) grid points are assumed to derive from observation and simulation, respectively. The standard deviation is defined as

\[
\sigma_{\text{obs}} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (x_n - \bar{x})^2}
\]

and

\[
\sigma_{\text{mod}} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (y_n - \bar{y})^2}.
\]

The spatial correlation coefficient \( R \) is defined as

\[
R = \frac{\frac{1}{N} \sum_{n=1}^{N} (x_n - \bar{x})(y_n - \bar{y})}{\sigma_{\text{obs}}\sigma_{\text{mod}}}
\]

This metric follows Taylor (2001), was used in Yang et al. (2013), and has been demonstrated to be an effective constraint for optimization.

**d. Observational datasets**

Since the CORDEX East Asia domain covers a large portion of the eastern Indian Ocean and western North Pacific (WNP), the high-resolution satellite-retrieved precipitation dataset of the Tropical Rainfall Measuring Mission (TRMM) 3B42 (Huffman et al. 2007) is used as the observational evidence to evaluate the model performance. Because of the limited spatial data coverage of the TRMM 3B42 data, the precipitation covering \((-10^\circ S–40^\circ N, 65^\circ–170^\circ E)\) is used for the calibration of the model.

In addition, the following datasets are also used to evaluate the performance of the optimal simulation: 1) monthly mean circulation fields (e.g., \( u \), \( v \), and \( q \)) derived from NCEP2; 2) daily mean gridded surface air temperature of monsoonal Asia with a \( 0.5^\circ \times 0.5^\circ \) grid, compiled by the Asian Precipitation Highly Resolved Observational Data Integration Toward the Evaluation of Water Resources [APHRODITE (APHRO)] project.
(Yasutomi et al. 2011). For simplicity, the satellite-retrieved rainfall dataset and the reanalysis-derived circulation dataset are referred to as “observation” in the following discussion.

3. Results

a. Rainfall in the simulation with default and optimal parameters

Before we evaluate the rainfall performance, Table 2 gives the identified optimal parameters. The optimal value of RH is 0.73, which is larger than the value (0.55) set in Chow et al. (2006). The identified optimal value of \( l_0 \) is 0.0447, which is much larger than the default value (0.0011). It seems that this is reasonable, since a previous study also found that the larger-than-default \( l_0 \) may induce better model performance in simulating the precipitation over the Horn of Africa (Segele et al. 2009).

Figure 2 shows the spatial distribution of precipitation averaged for JJA 1998 from observation and simulations with default and optimal parameters separately. The observed precipitation is characterized by a major rainband over the tropics, the Bay of Bengal, and the mei-yu front region. The above-normal mei-yu rainfall causes severe flooding over East Asia (Ding and Liu 2001). In the simulation with default parameters, however, the simulated precipitation over the Bay of Bengal, the northern South China Sea, and the WNP is largely overestimated, but over the northern equatorial western Pacific, it is significantly underestimated. A similar bias pattern was also found by Chow et al. (2006), in which the domain was smaller than the CORDEX East Asia domain. The spatial correlation coefficient (SCC) is 0.29, and the model skill with default parameters is 2.02. The simulation with optimal parameters significantly improves the model performance, with the model skill \( E \) (lower \( E \) means better performance) decreasing from 2.02 to 1.60 (Table 2). In particular, the overestimated rainfall is reduced over the Bay of Bengal, the northern South China Sea, and the WNP, while the dry bias over the northern equatorial western Pacific decreases. The SCC is increased to 0.50 in the simulation with optimal parameters. Unfortunately, the simulation with optimal parameters does not show any evident improvement in the simulation of the northward propagation of the mei-yu rainband (figure not shown).

The simulation with identified optimal parameters also improves the simulation of the probability density function (PDF) distribution of daily rainfall rates over the selected regions during JJA 1998. Figure 3 shows

![Figure 2](image-url)

**Table 2.** Values of seven parameters in the default and optimal simulation and the corresponding model skill.

<table>
<thead>
<tr>
<th>RHC</th>
<th>( C_{asc_land} )</th>
<th>( C_{asc_ocean} )</th>
<th>( RH_{min_land} )</th>
<th>( RH_{min_ocean} )</th>
<th>( \alpha )</th>
<th>( l_0 )</th>
<th>( E )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Default</td>
<td>—</td>
<td>0.4</td>
<td>0.4</td>
<td>0.8</td>
<td>0.9</td>
<td>0.2</td>
<td>0.0011</td>
</tr>
<tr>
<td>Optimal</td>
<td>0.73</td>
<td>0.27</td>
<td>0.27</td>
<td>0.85</td>
<td>0.82</td>
<td>0.78</td>
<td>0.0447</td>
</tr>
</tbody>
</table>

**FIG. 2.** Spatial distributions of precipitation (mm day\(^{-1}\)) averaged from June to August 1998 derived from (a) TRMM 3B42, (b) the simulation with default parameters, and (c) the simulation with the identified optimal parameters. Boxes in (a) illustrate the seven subregions of the simulated domain: tropical Indian Ocean (TIO; 10°S–0°, 70°–100°E); southern South China Sea (SSCS; 5°–10°N, 105°–120°E); northern equatorial western Pacific (0°–10°N, 130°–165°E); Bay of Bengal (BOB; 10°–20°N, 80°–95°E); southern China (SC; 16°–26°N, 105°–125°E); Yangtze River (YR; 26°–33°N, 105°–125°E); and western North Pacific (13°–25°N, 125°–160°E).
the observed and simulated PDF distributions of daily rain rate. The simulation with default parameters overestimates the frequencies of rain rates below 12 mm day$^{-1}$, while for higher rain rates, different regions exhibit different biases. For example, the frequencies of occurrence are overestimated across all the rain rates over the WNP, while the frequencies of rain rates larger than 14 mm day$^{-1}$ are significantly underestimated over the northern equatorial western Pacific. With optimal parameters, the simulated PDF distributions of daily rain rates are improved over all regions.

b. Sensitivity of model performance to the seven parameters

Among the total 240 simulations, the $a$ parameter has the largest impact on decreasing the $E$ score. Followed by an increase of $a$, the $E$ score is decreased significantly (figure not shown). In the total 240 simulations, there are 151 simulations that have lower $E$ than the simulation with default parameters (the $E$ of the default simulation is 2.02). These simulations are termed as good simulations. Figure 4 shows the frequency distributions of the good simulations for the seven parameters.
The parameter RHC has significant effects on the model results. Around 75% of the good simulations are obtained when the RHC is from 0.65 to 0.85. The highest probability for obtaining a good simulation is when the RHC is around 0.75. The second most important parameter is the $l_0$. The frequency of good simulations is about 30% when the $l_0$ is around 0.040. The remaining parameters have weaker effects on the model results, especially RH$_{min_land}$, RH$_{min_ocean}$, and the relaxation rate $\alpha$, whose frequency distributions are rather uniform.

Figure 5 shows the responses of rainfall over different regions to the seven parameters. We select seven regions in terms of the observed major rainband, except the WNP, where evident differences are found between the simulation with default parameters and that with optimal parameters. Following those employed in Yang et al. (2012, 2013), the sensitivity responses are shown as
the correlation coefficients between the regional rainfall averaged over the seven regions and the perturbed seven parameters from the total 240 simulations. Among the seven parameters, overall, the parameter RHC is the most sensitive parameter, with high influence on the rainfall over all the regions except that over the Yangtze River valley and over the tropical Indian Ocean. The parameter RHmin_land (RHmin_ocean) has more effects on the rainfall over the Yangtze River valley (tropical Indian Ocean). In the following discussions, we focus mainly on the sensitivity of model results to the most sensitive parameter, RHC.

For the parameter RHC, larger RHC means that convection is more likely suppressed. In most cases, the total rainfall is correspondingly reduced. This is indeed the case seen in most regions (Fig. 5), except for the northern equatorial western Pacific, where larger RHC is accompanied by increased total rainfall. To examine the causes of this difference, we compare the response to RHC over two regions (i.e., the Bay of Bengal and the northern equatorial western Pacific) where total rainfall exhibits negative and positive responses to RHC, respectively. Figure 6 shows the responses of total, convective, and explicit rainfall to the parameter RHC for the two regions. As in those shown in Fig. 5, the increased RHC is followed by increased (decreased) total rainfall over the northern equatorial western Pacific (Bay of Bengal) (Figs. 6a,d). The responses of convective rainfall to RHC are similar for both regions [i.e., the convective rainfall is reduced especially when the RHC is larger than 0.70 (Figs. 6b,e)]. However, the responses of explicit rainfall to RHC are quite different for the two regions. The simulations with larger RHC produce more explicit rainfall over the northern equatorial western Pacific but reduce the explicit rainfall over the Bay of Bengal.

Why are the responses of explicit rainfall to the RHC different for the two regions? A previous study suggested that in convection suppression experiments using RegCM3, the changes in large-scale rainfall are mainly contributed to by the variations of cloud water (Zou and Zhou 2011). Figures 7a and 7c show the responses of the column-averaged cloud water mixing ratio (no ice cloud included) mixing ratio to RHC for the two regions, respectively. As expected, followed by an increase of

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**Figure 6**: As in Fig. 6, but for the column-averaged cloud water mixing ratio ($10^{-5}$ g g$^{-1}$) and the convergence of 850-hPa water vapor transport ($10^{-8}$ kg m$^{-2}$ s$^{-1}$).
RHC, the increased (decreased) explicit rainfall over the northern equatorial western Pacific (Bay of Bengal) corresponds to an increase (reduction) of cloud water. More cloud water favors more large-scale rainfall to be condensed, and vice versa.

The changes of cloud water are partly related to the changes of water vapor transport. Since the atmospheric moisture is concentrated mainly in the lower troposphere and the vertically integrated water vapor transport is dominated by the low-level atmosphere (Zhou and Yu 2005), an analysis of water vapor at 850 hPa is reasonable. Figures 7b and 7d show the responses of the convergence of 850-hPa water vapor transport to RHC for the two regions, respectively. Followed by an increase of RHC, the increase of convergence (divergence) of low-level water vapor transport is found over the northern equatorial western Pacific (Bay of Bengal) (Figs. 7b, d), favoring the increase (reduction) of cloud water, which contributes to the changes of explicit rainfall. The increase of convergence of low-level water vapor transport over the northern equatorial western Pacific is in fact a result of the reduction of convective rainfall over the Indian Ocean. Decreased rainfall in the Bay of Bengal leads to more water vapor transport to the northern equatorial western Pacific (NEWP) region (since less vapor is consumed in the Bay of Bengal) and so may increase the available water vapor for precipitation in the NEWP region.

c. Impacts of optimization on circulation and temperature

Note the optimization process is solely constrained by the total precipitation, and so it is interesting to examine whether the simulation with optimal parameters has positive effects on other variables. Figure 8 shows the spatial distribution of observed and simulated 850-hPa low-level wind and associated wind speed averaged from June to August 1998. Compared with the observation, the low-level westerly associated with the Indian summer monsoon is too strong and extends too far eastward to the WNP in the simulation with default parameters (Fig. 8b). The simulated WNP subtropical high (WNPSH; anticyclonic circulation over the WNP) is too weak and presents too far southward compared with the observation. When the optimal parameters are applied, the simulated low-level wind speeds are close to the observation (Fig. 8c). The biases of simulated low-level wind in the simulation with default parameters are significantly reduced. The simulated shape and strength of the WNPSH is improved as well.

The improved simulation of the low-level wind over the WNP is closely linked to the reduced convective rainfall. The suppressed convective heating over the WNP forces a low-level anomalous anticyclone to its north as a baroclinic Rossby wave response. The low-level southwesterly flow is then weakened (as seen in Fig. 8c), favoring a decrease of evaporation from the sea surface, which will in turn reduce the convective rainfall. This positive feedback between convective precipitation, low-level southwesterly flow, and surface evaporation over the WNP has been discussed previously in Zou and Zhou (2013a).

FIG. 8. Spatial distributions of 850-hPa low-level wind and associated wind speed (m s$^{-1}$) derived from (a) NCEP2, (b) the simulation with default, and (c) optimal parameters, averaged from June to August 1998.
The cold biases are found over most of the land area in the CORDEX East Asia domain. The regional averaged cold biases over eastern China (20°–40°N, 105°–125°E) are −0.58°C. These cold biases have also been found in previous simulations in RegCM3. The differences of surface air temperature between the simulations with optimized and default parameters (Fig. 9c) show that the biases are reduced in most regions when the optimal parameters are applied. The positive (negative) differences alleviate the cold (warm) biases by using the default parameters, except those over the Tibetan Plateau, where cold biases are enhanced. The regional averaged cold biases over eastern China are reduced to −0.42°C by using the optimal parameters.

### d. Case study of 2005: Effects of optimized parameters

The summer of 1998 is an extreme case with a very weak WNP summer monsoon (WNPSM). To examine whether the optimized parameters based on an extreme case are suitable in another normal monsoon case, we conduct another two simulations for the year 2005 with the default parameters and the optimized parameters. The year 2005 is selected because the WNPSM is normal in that year (see Fig. 6 in Wang et al. 2008).

Figure 10 shows the spatial distributions of 850-hPa low-level wind and rainfall averaged over JJA 2005 derived from observation and the simulations with default and optimal parameters, separately. The observed rainfall over the monsoon trough located east of the Philippines is much stronger than that in 1998 (Fig. 10a). The simulation with default parameters overestimates the rainfall over the Bay of Bengal and WNP but underestimates the rainfall over the monsoon trough, with an SCC of 0.22 (Fig. 10b). As in the 1998 case, the westerly associated Indian summer monsoon is too strong and extends too far eastward to the WNP, resulting in a suppressed WNPSH. In the simulation with the optimal parameters based on the 1998 case, the overestimated rainfall over the Bay of Bengal and especially the WNP is greatly suppressed, while the rainfall over the monsoon trough is slightly increased (Fig. 10c). The SCC of the improved simulation with the observation is 0.32. The corresponding low-level wind field is also much improved, resulting from the improved WNPSH. These results imply that the identified optimal parameters may help improve the Asian summer monsoon simulation, which is case independent.

### e. Case study of 1998 in RegCM4: Effects of optimized parameters

An updated version of RegCM, RegCM4, has been recently developed and released for public use (Giorgi et al. 2012). Although the current study mainly focuses on RegCM3, we ask whether the identified optimal parameters based on RegCM3 are also suitable for the new version model. To answer this question, we conduct two simulations employing RegCM4.4 for the 1998 case. The selected physics schemes are the same as those in RegCM3, but the mixed convection configuration is used. In the mixed convection scheme, the Grell scheme (Grell 1993) is applied over land while the Emanuel scheme is applied over ocean. This mixed convection configuration has been introduced for the first time in RegCM4, having been recommended in many CORDEX domains (Giorgi et al. 2012) and tropical band experiments (Coppola et al. 2012).
Figure 11 shows the spatial distributions of 850-hPa low-level wind and rainfall averaged over JJA 1998 derived from observation and the RegCM4 simulation with default and optimal parameters based on RegCM3. RegCM4 indeed exhibits better model skill than RegCM3 in simulating the rainfall (Fig. 11a) when default parameters are applied. The cost function score in RegCM4 is 1.80, which is lower than the 2.02 in the previous model version. Compared with the observation, although the rainfall over the Bay of Bengal and WNP is still overestimated, the wet biases are much reduced. The SCC of the rainfall is 0.36. The simulated WNPSH is also, to some extent, improved in terms of the shape of the low-level anticyclone over the WNP.

The simulation with optimal parameters shows encouraging results. As optimal parameters are applied, the simulated rainfall pattern is much improved (Fig. 11c), with an SCC of 0.44. The overestimated rainfall over the Bay of Bengal, especially over the WNP, is significantly reduced. As in RegCM3, the underestimated rainfall over the northern equatorial western Pacific in the default simulation increases in the optimal simulation. Meanwhile, the simulated low-level wind field associated with the Asian monsoon and the shape of the WNPSH are also improved in the simulation with optimal parameters. These results suggest that the identified optimal parameters based on RegCM3 are also suitable for the updated model version.

4. Summary and concluding remarks
a. Summary
In this study, based on previous studies that customized RegCM3 with the MIT–Emanuel cumulus parameterization scheme, we applied the MVFSA sampling method to tune seven selected parameters of RegCM3 with the MIT–Emanuel scheme for optimization of
These selected seven parameters can be divided into three types: 1) relative humidity criteria of the large-scale environment, 2) two parameters related to the MIT–Emanuel convection scheme, and 3) four parameters related to the SUBEX resolvable precipitation scheme. The case we optimized was the extreme case in 1998 from May to August, and only the monthly mean precipitation was constrained. Sensitivity analyses were performed, and the transferability of the identified optimal parameters was also investigated.

Results indicated that when the identified optimal parameters are applied, the spatial pattern of simulated rainfall and the simulated PDF distribution of daily rainfall rates are significantly improved. Among these seven parameters, the RHC parameter has the largest effect on the model results. Most good simulations, which have better skill than the simulation with default parameters, were found when the RHC is around 0.75. The second most important parameter is the warm cloud autoconversion threshold parameter in the MIT–Emanuel scheme. The remaining parameters have little effect on the model skill.

Sensitivity analyses show that the total rainfall over most regions has a negative response to variations of RHC, while the northern equatorial western Pacific exhibits a positive response to RHC. Followed by an increase of RHC, the convective rainfall over the northern equatorial western Pacific is reduced to that over other regions; however, the explicit rainfall is prominently increased, which leads to the positive response of the total rainfall to RHC. The increased explicit rainfall is contributed to by the increase of cloud water, which is associated with the increase of the convergence of low-level water vapor transport.

The identified optimal parameters based on the optimization process constrained by rainfall have positive...
effects on the low-level circulation and surface air temperature. The simulated low-level wind is significantly improved in the simulation with the optimal parameters in terms of both the magnitude of wind speed and the shape of the WNPSH. The biases of surface air temperature caused by using the default parameters are reduced in the simulation with optimal parameters, except those over the Tibetan Plateau.

The optimized parameters based on the extreme case are suitable for a normal case and the model’s new version with the mixed convection scheme. The overestimated rainfall over the Bay of Bengal, and especially the WNP, are significantly reduced in the optimal simulations. The spatial pattern of the simulated mean rainfall and the associated low-level circulation are also significantly improved.

b. Concluding remarks

The limitations of the current study should be acknowledged. The simulation with the identified parameters is not perfect and still exhibits some biases. For example, the wet biases are still found over the Indian Ocean and WNP (Fig. 3c), and the rainband over the Yangtze River valley is still not well captured. These biases may be due to some model errors associated with other unperturbed parameters. These parameters could firstly be identified through sensitivity experiments and then optimized by applying the MVFSA approach.

The omission of local air–sea coupling may be another factor that contributes to the residual model biases in the simulation with optimal parameters. Previous studies have shown that the inclusion of local air–sea coupling in RCMs may improve the simulation of rainfall over the Indian Ocean (Ratnam et al. 2009), WNP (Zou and Zhou 2013b), and the Yangtze River valley (Yao and Zhang 2010). Whether or not the simulated rainfall could be further improved if the identified optimal parameters based on the stand-alone RegCM3 are applied in the corresponding regional air–sea coupled model deserves further investigation. Furthermore, whether or not the identified optimal parameters are different between the model with and without local air–sea coupling also remains an open question.

Another limitation of this study is that we constrained the model performance using total rainfall only (the main reason we adopted the rainfall variable was to facilitate comparison with previous studies). Rainfall is in fact the final outcome of many processes. The improved rainfall could be a result of compensating errors among different physical schemes. Future studies should be devoted to calibrating the physical processes (i.e., deep convection and cloud microphysics processes). Nevertheless, this current study still provides information that may be a useful reference for the future development of the RegCM model.

Acknowledgments. This work was jointly supported by the National Key Basic Research Program of China (2010CB951904, 2013CB956204), the National Natural Science Foundation of China (41205080, 41330423), the China R&D Special Fund for Public Welfare Industry (meteorology) (GYHY201306019), and the Strategic Priority Research Program of the Chinese Academy of Sciences (Grant XDA11010404). Part of this work was completed when the first author visited the Pacific Northwest National Laboratory (PNNL). The discussions with Ms. Huiping Yan at PNNL were greatly appreciated. The contribution of Yun Qian in this study was supported by the U.S. Department of Energy’s Office of Science as part of the Regional and Global Climate Modeling Program. The PNNL is operated for DOE by Battelle Memorial Institute under Contract DE-AC05-76RL01830.

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