Effect of land model ensemble versus coupled model ensemble on the simulation of precipitation climatology and variability

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Received: 15 August 2017 / Accepted: 20 October 2017 / Published online: 31 October 2017
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Abstract Through a series of model simulations with an atmospheric general circulation model coupled to three different land surface models, this study investigates the impacts of land model ensembles and coupled model ensemble on precipitation simulation. It is found that coupling an ensemble of land models to an atmospheric model has a very minor impact on the improvement of precipitation climatology and variability, but a simple ensemble average of the precipitation from three individually coupled land-atmosphere models produces better results, especially for precipitation variability. The generally weak impact of land processes on precipitation should be the main reason that the land model ensembles do not improve precipitation simulation. However, if there are big biases in the land surface model or land surface data set, correcting them could improve the simulated climate, especially for well-constrained regional climate simulations.

Electronic supplementary material The online version of this article (<https://doi.org/10.1007/s00704-017-2310-7>) contains supplementary material, which is available to authorized users.

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1 Introduction

Land surface processes include complex interactions of various hydrological, biogeophysical, and biogeochemical processes, and it is a challenge to describe them with numerical models. Land surface models (LSMs) have evolved from the first-generation bucket-type schemes in the 1960s, the second-generation schemes with biophysics in the 1980s, to the third-generation schemes with carbon cycle and dynamic vegetation (Sellers et al. 1997; Pitman 2003). However, due to the complexity of the land surface processes and the scarcity of large-scale land surface observations, current LSMs still have large uncertainties in simulating the surface processes (e.g., Dirmeyer et al. 2006a; Dirmeyer et al. 2006b; Jimenez et al. 2011). When driven by the same atmospheric forcing, different LSMs may give significantly different surface fluxes (Henderson-Sellers et al. 1995; Henderson-Sellers et al. 1996; Pitman et al. 1999).

As land surface is an important component of the climate system, the discrepancies among LSMs can impact the simulations with the coupled climate models through surface fluxes. Wei et al. (2010a) coupled one atmospheric general circulation model (AGCM) with three different LSMs and investigated the impact of different LSMs and land-atmosphere coupling on climate simulation. It was found that for surface variables, like latent and sensible heat fluxes and surface air temperature, atmospheric feedback may amplify or reduce the discrepancies caused by different LSMs, depending on the different local climate and feedback processes. Further studies showed that in the land-atmosphere coupled model simulations, the precipitation variability, predictability, and land-atmosphere coupling strength are mainly determined by the AGCM, rather than the LSM (Wei and Dirmeyer 2010; Wei et al. 2010b).

Due to limitations in understanding and representing various physical processes in models, every model has biases. The multi-model ensemble (MME) is a common method to counteract the biases from different models and to get better simulation and prediction results (e.g., Reichler and Kim 2008). This approach is based on the fact that the biases of the models are more or less independent. In addition, due to the chaotic nature of atmospheric and oceanic evolutions, the model simulations are also sensitive to initial conditions. Perturbing initial conditions is a way to consider the effect of their uncertainties (e.g., Stensrud et al. 2000; Zhu et al. 2012; Zhu et al. 2013). In this study, we mainly consider the effect of model biases and how MME may improve the simulations. MME has been applied to both coupled earth system models (Krishnamurti et al. 2000; Barnston et al. 2003; Palmer et al. 2004; Kirtman et al. 2014) and offline LSMs (Guo et al. 2007), and it was found that results from MME are generally better than those from most individual models. An unexplored problem is whether a land model ensemble can improve climate simulations in coupled land-atmosphere models and how effective the land model ensemble is compared to the traditional MME across the coupled models. Land strongly

responds to the forcings from atmosphere, but is less chaotic as the dynamical fluid systems like atmosphere and ocean. In this study, we expand the work of Wei et al. (2010a) with additional experiments and analyses, with a focus on the impacts of model ensembles on the simulated climatology and variability of precipitation.

2 Model and experiments

One AGCM and three LSMs are used for the experiments (same as in Wei et al. (2010a)). The AGCM used is version 3.2 of the Center for Ocean-Land-Atmosphere Studies (COLA) AGCM (Misra et al. 2007). It has 28 vertical sigma levels, and the horizontal is at T62 spectral resolution ($\sim 1.9^\circ \times 1.9^\circ$). Three LSMs are coupled to the AGCM in this study: the simplified simple biosphere model (SSiB) (based on Xue et al. (1991); Dirmeyer and Zeng (1999)), the Community Land Model (CLM) version 3.5 (Oleson et al. 2008), and version 2.7 of the Noah land model (Ek et al. 2003). These LSMs have been widely used in weather and climate research. They have different numbers of soil layers

Fig. 1 The three types of experiments. **a** Individually coupled. **b** Combined. **c** Selected

(a) Individually coupled experiment

(b) Combined experiment

(c) Selected experiment

and soil depths, and each uses its own soil and vegetation data sets. There are many differences among these LSMs in the parameterization of specific processes—please refer to the references above for more details. The coupling between LSMs and the AGCM and model simulations is all conducted at T62 resolution. The integration time step is the same for the LSMs and the AGCM (12 min). There has been no tuning or nudging in the coupling for all the model combinations.

Three sets of experiments are performed for this study, and they are shown schematically in Fig. 1. In the first experiment, the three LSMs are coupled to the AGCM individually (Fig. 1a). In the second experiment, called “combined,” an innovative coupling method is used to couple the three LSMs to the AGCM in combination with a shared atmosphere. Over each grid point and at every time step, the LSMs receive the same atmospheric forcing from the AGCM, calculate their state variables and surface fluxes separately, and the average surface fluxes from the three LSMs are passed back to the AGCM (Fig. 1b). In the third experiment, called “selected,” we first compared the simulated monthly precipitation climatology from the individually coupled runs in the first experiment with the observation-based Global Precipitation Climatology Project (GPCP) v3.2 precipitation (2.5° grid interpolated to the model grid; Adler et al. (2003)), and in each of the 12 months and over each grid point we select one of the three runs that the simulated mean precipitation is closest to that of GPCP (Fig. 2). The new simulation is similar to that in the second experiment, but in each month and over each grid point, only the surface fluxes from one selected LSM are passed back to the AGCM (Fig. 1c).

Actually, the same code is run for all three experiments; the difference is effectively in the weights applied to the fluxes calculated by each LSM. Running with any single LSM is equivalent to assigning the fluxes (including sensible, latent, momentum, surface reflected shortwave, and upward longwave fluxes) from that scheme a weight of 1.0 and 0.0 for the other two. In the second experiment (combined run), each LSM receives identical 1/3 weight, so each LSM has equal opportunity to impact the atmosphere. In the third experiment (selected run), a weight of 1.0 is given to one of the LSMs, which varies monthly and over points. The purpose of the second experiment is to investigate whether the land model ensemble results in a better precipitation simulation, and the purpose of the third experiments is to examine whether using the “best” land model at each grid point can produce an overall better simulation for the globe.

All the simulations start from April 1, 1982 and end on January 1, 2005 (nearly 23 years) and are forced by the weekly sea surface temperature from observations (Reynolds et al. 2002). After spin-up, the last 18 years of data are used for analysis. In addition to the three experiments, we also calculate the monthly ensemble mean precipitation of the three individually coupled simulations; it is called “3-model

Fig. 2 Models that are selected for coupling over each grid point for the selected run. Each of the 12 months has a different pattern, but only June, July, and August are shown here

average” in the analysis. As observationally based precipitation data still have substantial uncertainties (e.g., Fekete et al. 2004), we used both GPCP data (based on both gauge observations and satellite estimates) at 2.5° resolution and the Climate Prediction Center (CPC) Unified Gauge-Based Analysis of precipitation (Xie et al. 2007; Chen et al. 2008) at 0.5° resolution for model evaluation. The results based on two precipitation data sets are similar and we only show evaluations based on GPCP data in the paper, and please check the supplementary material for evaluations based on CPC data.

3 Results

We first compare the simulated precipitation climatology from different experiments with the observations from GPCP (Fig. 3). The climatologies of the different simulations show similar spatial correlations with GPCP. The global mean precipitation from GPCP is in the range of the three individually

Fig. 3 The annual mean land precipitation of 1987–2004 **a** from the observational data of GPCP and **b–g** the spatial patterns of experiments minus GPCP. Unit: mm/day. The first number in the corner of each panel is the global average of the mean precipitation (not difference), and the second number in the parentheses is the spatial correlation (uncentered) of the mean precipitation between model experiments and GPCP

coupled simulations, and the combined and selected simulations are also in this range. Except over parts of Africa, the different model simulations show similar spatial patterns in biases, which indicates that most biases in these experiments are probably not related to the LSMs, although there is a chance that all of the three LSMs are biased in the same way. The divergence of biases over Africa could be a sign that the land processes here are more important than those in other regions, consistent with the study of Wei et al. (2016).

Next, we focus on examining whether the combined and selected ensemble experiments and the 3-model average (hereafter we call all of them ensemble experiments) produce more accurate precipitation than the individually coupled simulations. Figure 4 shows the total number of individually coupled runs that produces a less accurate precipitation climatology than the ensemble experiments. A number of 3 denotes that the results of the ensemble experiments are more accurate than all of the three individually coupled runs.

Note that there are only four possible values in Fig. 4 (0, 1, 2, and 3), and for a random uniform distribution each value

will be for 25% of the grid points. If the percentage of grid points with a value (two values) is not much larger than 25% (50%), the impact associated with the value (two values) is not globally significant.

It can be seen in Fig. 4 that the percentage of grid points with a value of 3, i.e., the ensemble is more accurate than all of the individually coupled runs, is much less than 25%, and for values of both 2 and 3, i.e., the ensemble experiment is more accurate than at least two individually coupled runs, only the 3-model average has more than 50% points (64% for JJA and 58% for DJF). This suggests that the combined and selected experiments do not produce a significantly better precipitation climatology than the individually coupled runs, and a simple MME may produce better precipitation climatology than the individually coupled simulations and the ensemble simulations based on multiple LSMs. The selected run, although using an LSM that can simulate the best precipitation climatology at each grid point, does not show an overall better precipitation climatology

Fig. 4 The number of the individually coupled runs that are inferior (relative to GPCP) to **a, b** combined; **c, d** selected; and **e, f** 3-model average in the simulated annual average precipitation. JJA (left) and

DJF (right) of 1987–2004. Only the numbers greater than 1 are shown, and the percentages of land grid points that are in red are shown in each panel

compared to the individually coupled runs or the combined run.

Figure 5 shows the areas where the ensemble is more accurate than the individual runs in variance. It is evident that the 3-model average performs much better than the combined and selected runs, and the selected run performs slightly better than the combined run. The advantage of the 3-model average is even more evident in the simulated monthly variability of the precipitation time series evaluated with the Pearson correlation coefficient (Fig. 6). The monthly correlation with GPCP from the 3-model average is higher than all (at least two) of the individually coupled runs over 61% (90%) of the grid points. Note that the 3-model ensemble average can reduce the random noise/error of individual members, which leads to lower variance. However, this part of variance is much smaller than the month-to-month variance caused by seasonal cycle or other external forcings when seasonal cycle is removed (e.g., ENSO), so the impact of ensemble average on the

evaluation of monthly precipitation variability should be weak.

4 Discussion and concluding remarks

This study compares the impact of land model ensembles and coupled model ensemble on precipitation simulation. It is found that the land ensemble, including both combined and selected, have a very minor impact on the simulated precipitation climatology and variability, but a simple ensemble average of the precipitation from three individually coupled models produces better results, especially for precipitation variability.

The limited impact of local land processes on precipitation has been reported in some previous studies (e.g., Gao et al. 2008; Koster et al. 2011; Wei et al. 2016). Even if a land model ensemble can produce better land surface state and fluxes (Guo et al. 2007), their impacts on precipitation are often overshadowed by atmospheric

Fig. 5 Same as Fig. 4, but for the variance of month to month precipitation during 1987–2004. Original precipitation time series (left); seasonal cycles in the time series are removed (right)

processes, making the precipitation response weak and difficult to detect. By well-controlled model experiments and sophisticated statistical analysis, some hotspots of the impact of soil moisture on precipitation have been identified according to a designed coupling strength (Koster et al. 2004). However, as this coupling strength mathematically corresponds to the percentage of precipitation variance caused by prescribed soil moisture in the models (Koster et al. 2006; Yamada et al. 2007), it can be found that even in those hotspot regions the contributions of soil moisture to precipitation variability are still low (mostly < 10%). Similar coupling strengths are also found for the models used in this study (Wei et al. 2010b). The generally weak impact of land processes on precipitation should be the main reason that land model ensembles do not improve precipitation simulation. Another possible contributing factor is that land processes are less chaotic than the dynamic atmospheric processes and the variabilities of land surface fluxes are largely determined by the atmospheric forcing. With the same atmospheric forcing, less independent model

biases can be reduced by an ensemble average of LSMs.

This research suggests that if the model representation of atmospheric processes has strong biases, improvements in the LSM can rarely improve these biases. However, if the atmospheric processes are properly represented while the land surface processes have strong biases, a better LSM or more accurate land surface data set may help improve climate simulations in coupled models (e.g., Hagemann et al. 2016; Lin et al. 2016), especially in regional climate simulations where the atmosphere is constrained by boundary forcing so the signals from land surface stand out (e.g., Steiner et al. 2009; Lorenz et al. 2012).

We only show the simulation results of precipitation, but our preliminary analyses show that surface variables like ET and surface temperature have similar results. This may be because precipitation and the associated cloud cover have a strong impact on the surface water and energy balances, so their variabilities are similar. Although the ensemble size in this study is only three, the results are reasonable and consistent with our previous knowledge. The results from this

Fig. 6 Same as Fig. 4, but for the correlation of month to month precipitation with observations from GPCP during 1987–2004

study can provide guidance for the future design of model ensembles for climate simulation and prediction.

Acknowledgements This work was supported by a start-up grant to the first author from the Nanjing University of Information Science and Technology.

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