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How Much Do Different Land Models Matter for Climate Simulation?

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1. Introduction

One of the largest uncertainties in climate simulations is from the representation of land processes, because there are few observations to calibrate or constrain it. Different land surface schemes (LSSs) use quite different parameterizations to describe the complex hydrological, biogeophysical, and biogeochemical processes. Even when forced by the same atmospheric forcing and provided the same parameter settings, different LSSs can still give significantly different surface fluxes. When these LSSs are coupled to the Atmospheric General Circulation Models (AGCMs), their different behaviors will bring uncertainties into the simulated climate. As the land-atmosphere system is nonlinear, uncertainties from LSSs can be amplified or reduced during land-atmosphere interaction. This problem is systemically addressed in this study. In addition to the climatology and variability, different LSSs can lead to different coupling strength between land and atmosphere (i.e., contribution of land to prediction of atmosphere). Within the framework of Global Land-Atmosphere Coupling Experiment (GLACE), we perform GLACE-type experiments to investigate this problem.

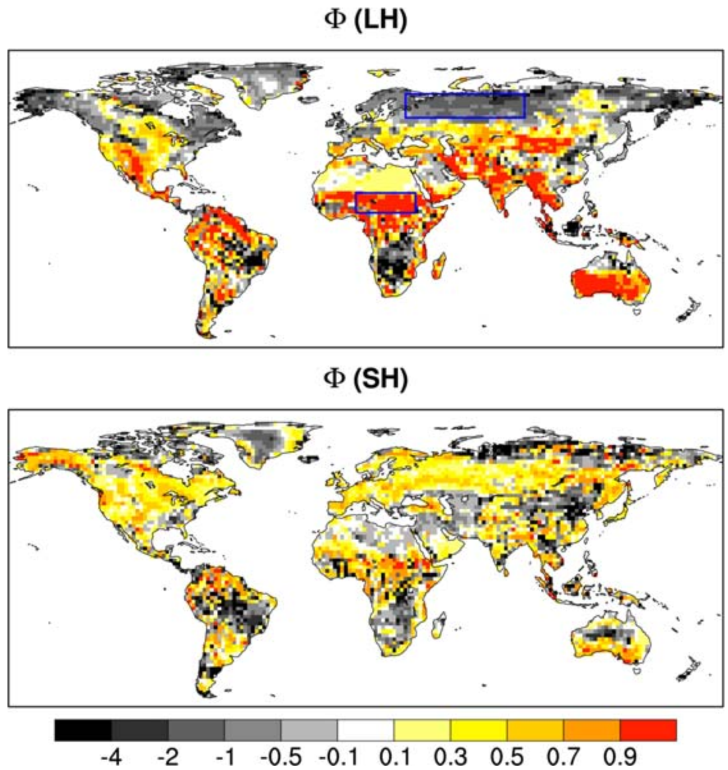

Fig. 1 The ratio Φ (see equation 1) for 1987-2004 average JJA latent (LH; upper panel) and sensible (SH; bottom panel) heat fluxes. The regions enclosed by blue boxes are for further analysis in Figure 2.

In this study, we show results from COLA AGCM coupled to three state-of-the-art LSSs: SSiB, CLM3.5, and Noah. Two experiments are performed. In the first experiment (I), three LSSs are coupled to the AGCM individually. In the second experiment (C), the three LSSs are coupled to the AGCM in combination, i.e. the LSSs receive the same atmospheric forcing from the AGCM and the average surface fluxes from the LSSs are passed back to the AGCM at each grid point and at every time step. Experiment C is similar to three land model offline experiments with a same atmospheric forcing, but this forcing is affected by the average feedback from the LSSs.

We try to investigate the uncertainties of the three LSSs and their influence on climate simulation. We also explore the influence of land-atmosphere coupling on the simulation uncertainties. In addition, GLACE-type experiments with the COLA AGCM coupled to three land models are performed. By comparing the coupling strength of the three coupled models, we can know the impact of different land models on the coupling strength. In summary, the purpose of this study is threefold: firstly, to investigate current uncertainties in the behavior of LSSs; secondly, to investigate how much these uncertainties can influence

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atmospheric simulation through land-atmosphere interaction; thirdly and most importantly, to have a better understanding of the mechanisms of land-atmosphere coupling.

2. Climatology

The three LSSs produce significantly different surface fluxes over most of the land, no matter whether they are coupled individually (different forcing to land) or in combination (same forcing to land). See Wei et al. (2009a) for a detailed discussion. A question is whether land-atmosphere interaction can amplify the uncertainties from LSSs if they are coupled to an AGCM.

Let *Var*(I) and *Var*(C) be the inter-model (3 cases) variances of fluxes from land to atmosphere in experiments I and C, respectively. Intuitively, *Var*(I) should be larger than *Var*(C) because the LSSs receive the same atmospheric forcing in C but not in I. Thus *Var*(I) is the inter-model variance caused by LSS differences and land-atmosphere feedback, while *Var*(C) is the variance caused by LSS differences only. Then the ratio

$$\Phi = \frac{Var(I) - Var(C)}{Var(I)}$$

is the percentage of inter-model variance caused by land-atmosphere feedback. If $Var(I) \geq Var(C)$, $0 \leq \Phi \leq 1$. However, if $Var(I) < Var(C)$ ($\Phi < 0$), a negative feedback between land and atmosphere is implied and we cannot estimate the relative contributions of LSS differences and land-atmosphere interactions to the variance.

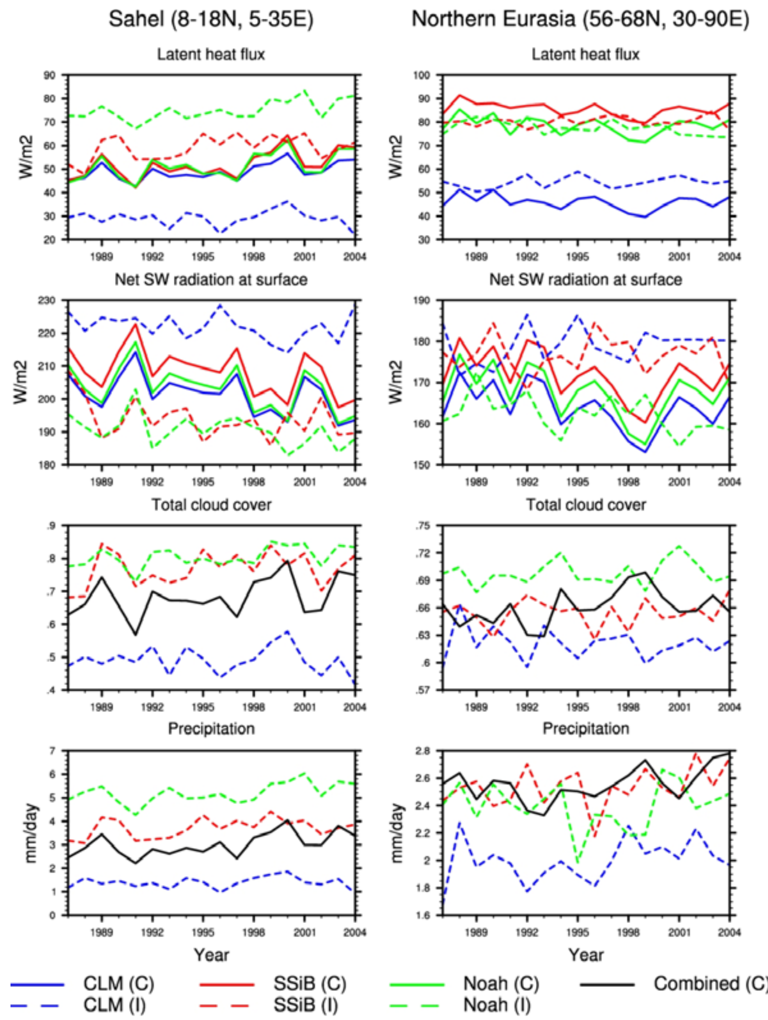

Fig. 2 The simulated 1987-2004 JJA average LH, SWnet, total cloud cover, and precipitation for northern Eurasia (left column) and Sahel (right column). The areas of the two regions are marked by blue boxes in Figure 1.

Figure 1 shows Φ averaged over JJA for sensible heat (SH) and latent heat (LH) fluxes. Over most land area, $0 \leq \Phi \leq 1$. However, there are still some areas with $\Phi < 0$. SH should have the same inter-model variance as LH if Rnet and the relatively small ground heat flux are the same for the LSSs. However, Rnet differs a lot among the models over some high latitude regions and dry regions. This is why the Φ values of SH and LH differ most over these regions (Figure 1). In order to investigate the cause of the different spread changes (positive and negative Φ), we selected the northern Eurasia and Sahel as two regions with contrasting values of Φ (blue boxes in Figure 1). Figure 2 shows the time series of LH, net shortwave radiation at surface (SW_{net}), total cloud cover, and precipitation over these two regions. It is evident that, compared to experiment I, the LH in experiment C strongly converge in Sahel but diverge in northern Eurasia, consistent with the value of Φ. In Sahel, the interannual time series of LH are negatively correlated with those of SW_{net} but are positively correlated with those of cloud cover and precipitation. This is a semi-arid, moisture-limited area, where evapotranspiration (ET) is nominally below the potential rate, so LH is strongly controlled by the land surface states, especially soil wetness, which is largely determined by rainfall. In experiment C, each LSS experiences the same rainfall, which leads to similar soil wetness and LH. In northern Eurasia, however, the correlation between SW_{net} and LH is positive for most of the time series. The soil moisture is plentiful in this region and the control on LH is mainly the radiation at surface.

3. Variability

The memories inherent in the surface heat fluxes differ greatly among the LSSs (see Wei et al. (2009a) for a detailed discussion). It would be interesting to examine how the different memories of land surface fluxes can influence precipitation variability. Figure 3 shows the lag-2-pentad precipitation autocorrelation in JJA. This method has been used in previous studies and is based on the assumption that a wetter soil caused by a storm may last a few days and promote future storms (Koster et al. 2003). However, there is also possibility that this persistence of precipitation is caused by the internal atmospheric dynamics or some other external forcing (e.g., SST) and has nothing to do with soil moisture memory (Wei et al. 2008).

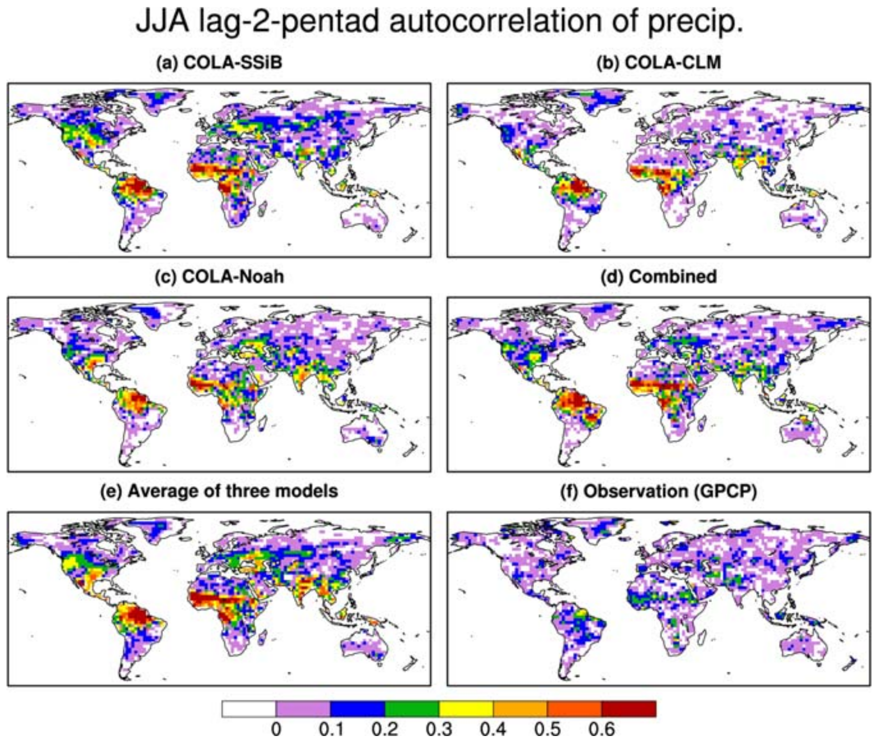

Fig. 3 The JJA lag-2-pentad autocorrelation of precipitation across 1987-2004. (a) COLA-SSiB. (b) COLA-CLM. (c) COLA-Noah. (d) Combined experiment. (e) Calculated with the average precipitation of the three individually coupled simulations. (f) From the observational dataset of GPCP (Xie et al. 2003). The model results are interpolated to the same grid as that of GPCP data (2.5°×2.5°). Values larger than 0.11 are over 95% confidence level. Seasonal cycles are not removed in this calculation; removing them can lead to results with similar patterns but smaller amplitude.

It can be seen in Figure 3 that all the model simulations show a largely similar pattern of precipitation persistence, but regional differences between models exist. The result from the combined simulation is within the range of the three individually coupled simulations. The average of the three individual simulations shows a precipitation persistence larger than any of the individual simulations because the averaging tend to suppress the short time scale precipitation variations that are inconsistent among the models. Although the memories of surface LH and SH are much lower in Noah (not shown), it does not show an overall lower precipitation persistence than the other two models in the individually coupled simulations. This suggests that the land surface heat fluxes do not play a dominant role in the global pattern of precipitation variability, but regional impacts may still exist. Compared to the observation, all the simulations here have overestimated the precipitation persistence in many areas.

4. Land-atmosphere coupling strength and its relationship to precipitation variability

Figure 4 shows the GLACE **Ω** values of total precipitation for ensembles W and S and their difference **Ω**(S)-**Ω**(W) (see definitions in Appendix). No matter which LSS the AGCM is coupled with, **Ω** show similar patterns, with largest values in the tropical rain belt, where the SST forcing has strongest influence. The patterns of W and S are very close, with large differences (**Ω**(S)-**Ω**(W)) mainly over the regions with high **Ω** values. This indicates that the land-atmosphere coupling strength is strongly influenced by external forcing. Globally, the COLA-SSiB has the strongest land-atmosphere coupling strength, while the coupling strength for COLA-Noah is the weakest. The difference should be mainly from the different land models because they are coupled to the same AGCM.

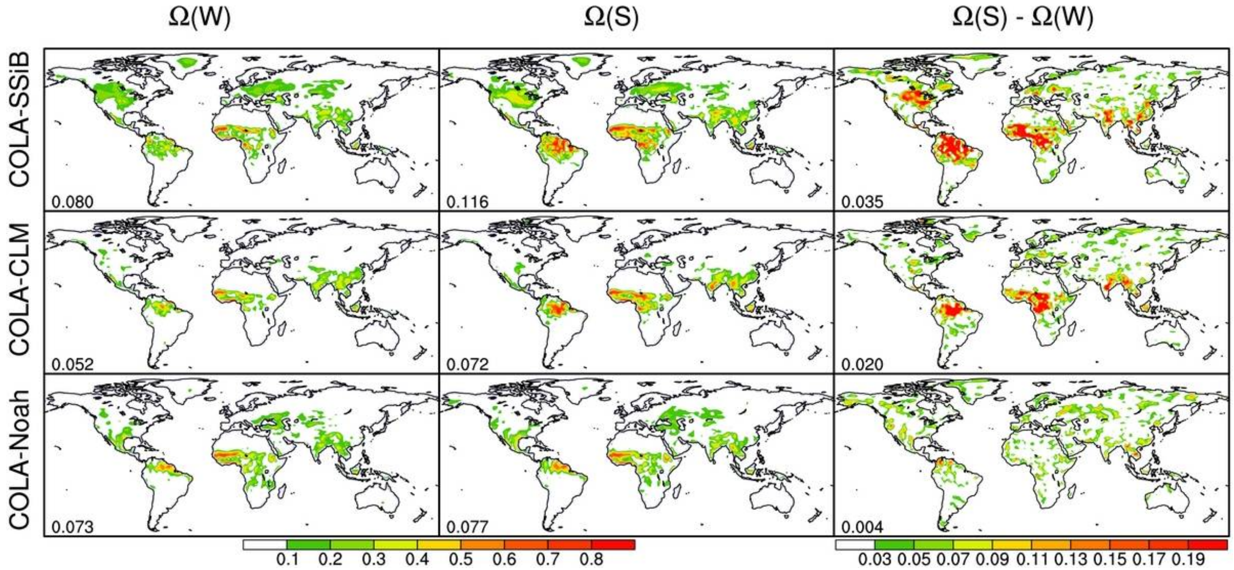

Fig. 4 The GLACE parameter Ω for precipitation from ensembles W (left column) and S (middle column), and their difference (right column). Top row: COLA-SSiB. Middle row: COLA-CLM. Bottom row: COLA-Noah. The global mean value of each panel is shown at the left corner.

It is shown in Wei et al. (2009b) that most of the precipitation predictability (**Ω**) and land-atmosphere coupling strength (**Ω**(S)-**Ω**(W)) are associated with the intraseasonal component of precipitation in the models, although they only account for a small percentage (~20%) of the total variance. The GLACE coupling strength can be conceptually decomposed into the impact of the slow varying external forcing (F) and the local impact of soil moisture. The external F and local soil moisture combine to determine the pattern of the coupling strength. From the output of the GLACE models, we find that most models have overestimated the low-frequency variance percentage and underestimated the high-frequency variance percentage of precipitation. It suggests that the specific mode of land-atmosphere coupling described in GLACE may be over-represented in the models. Based on the findings in this study, we adjust the land-atmosphere coupling strength estimated by GLACE. It is found that the adjusted coupling strengths are generally weaker than that from GLACE but the patterns are nearly the same.

Appendix: Global Land-Atmosphere Coupling Experiment (GLACE)

GLACE (Koster et al. 2004, 2006) is a model intercomparison study focusing on evaluation of the role of land state in numerical weather and climate prediction. It consists of three sets of 16-members ensembles of AGCM experiment: W, R and S. We only discuss W and S two sets here. Ensemble W is an ensemble of free runs with different initial land and atmosphere conditions but forced by the same SST of 1994; ensemble S is the same as ensemble W except that, at each time step, the subsurface soil moisture in the land model is replace by that from one member chosen from ensemble W. All runs cover the period of 1 June 1-31 August, 1994. A diagnostic variable **Ω** is defined:

$$\Omega = \frac{16\sigma^2{}_{<X>} - \sigma^2{}_X}{15\sigma^2{}_X}$$

where σ^2_x is the intraensemble variance of variable *x*, and $\sigma^2_{<x>}$ is the corresponding variance of ensemble mean time series. In calculating the variance, the first 8 days of data of each run is discarded to avoid model initial shock, and the remaining 84 days are aggregated into 14 six-day totals. Therefore, σ^2_x is a variance of 224 (16x14) six-day totals from all the ensemble members, and $\sigma^2_{<x>}$ is a variance of 14 six-day totals from the ensemble mean time series.

Theoretically, if the 16 members of an ensemble have the same time series of *x*, $\sigma^2\langle x\rangle$will be equal to σ^2_x and **Ω** will be 1; if the *x* time series of the 16 members are completely independent, $\sigma^2\langle x\rangle$ will be equal to $\sigma^2_x/16$ and **Ω** will be 0. Without sampling error, **Ω** will be between 0 and 1. **Ω** measures the similarity (or predictability) of the time series in 16 ensemble members, and is equivalent to the percentage of variance caused by the slowly varying oceanic, radiative, and land surface processes. The difference of **Ω** from the two ensembles, **Ω**(S)-**Ω**(W), is equivalent to the percentage of variance caused by the prescribed subsurface soil moisture, and is a measure of land-atmosphere coupling strength in GLACE.

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