Influence of "Realistic" Land Surface Wetness on Predictability of Seasonal Precipitation in Boreal Summer

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ABSTRACT

Outputs from two ensembles of atmospheric model simulations for 1951–98 define the influence of "realistic" land surface wetness on seasonal precipitation predictability in boreal summer. The ensembles consist of one forced with observed sea surface temperatures (SSTs) and the other forced with realistic land surface wetness as well as SSTs. Predictability was determined from correlations between the time series of simulated and observed precipitation. The ratio of forced variance to total variance determined potential predictability. Predictability occurred over some land areas adjacent to tropical oceans without land wetness forcing. On the other hand, because of the chaotic nature of the atmosphere, considerable parts of the land areas of the globe did not even show potential predictability with both land wetness and SST forcings.

The use of land wetness forcing enhanced predictability over semiarid regions. Such semiarid regions are generally characterized by a negative correlation between fluxes of latent heat and sensible heat from the land surface, and are "water-regulating" areas where soil moisture plays a governing role in land–atmosphere interactions. Actual seasonal prediction may be possible in these regions if slowly varying surface conditions can be estimated in advance. In contrast, some land regions (e.g., south of the Sahel, the Amazon, and Indochina) showed little predictability despite high potential predictability. These regions are mostly characterized by a positive correlation between the surface fluxes, and are "radiation-regulating" areas where the atmosphere plays a leading role. Improvements in predictability for these regions may require further improvements in model physics.

1. Introduction

Variations in soil moisture have been hypothesized to affect precipitation on monthly-to-seasonal time scales, and on regional-to-continental area scales. Atmospheric general circulation model (AGCM) studies have shown that soil moisture significantly influences precipitation during boreal summer (e.g., Shukla and Mintz 1982), especially in semiarid zones between wet and dry climates (e.g., Koster et al. 2000, 2004b). Better model representation and understanding of this land impact on the atmosphere could improve seasonal precipitation forecasts. For example, successful forecasts of heavy precipitation in North America that caused the Mississippi River flood in the summer of 1993 required model soil moisture that was much wetter than normal (Beljaars et al. 1996). Schubert et al. (2004) demonstrated that soil moisture variability was an important factor on interannual variability of precipitation in an AGCM hindcast simulation for the 1930's Dust Bowl in the U.S. Great Plains. Remote sensing could be used in the practical implementation of a prediction system. Some studies (e.g., Hirabayashi et al. 2003) have al-

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ready shown that remotely sensed, surface soil moisture information introduced into an AGCM has the potential to improve seasonal-scale precipitation prediction.

There has also been considerable speculation as to whether land surface moisture anomalies may remotely influence precipitation through continental-scale changes in land–ocean thermal contrasts and atmospheric circulations. For example, the influence of winter snow cover over Eurasia on subsequent summer Asian monsoon precipitation has been extensively studied. An inverse snow–monsoon precipitation relationship was initially found (e.g., Hahn and Shukla 1976). However, a more recent study using observational records (Robock et al. 2003) showed that the inverse snow–monsoon precipitation relationship held only from the 1960s through the 1980s in the twentieth century. "Atmospheric memory" cannot persist for a few months, so winter snow alone is not the key to the inverse snow–monsoon precipitation relationship. Previous model studies have speculated that persistent soil moisture anomalies into summer that follow anomalous winter snows affect continental-scale atmospheric circulations of the summer Asian monsoon (e.g., Yasunari et al. 1991). Soil moisture anomaly seems therefore a key to seasonal predictability. However, other recent studies that analyzed observed soil moisture records in Eurasia suggest that soil moisture memory is also short after snowmelt (Robock et al. 2003; Ueda et al. 2003). This short soil moisture memory is inconsistent with long-lasting effects of snow anomalies through soil wetness anomalies. Ongoing research on the relationship between land surface wetness and precipitation is expected to reconcile the contrasting conclusions.

Long-term in situ observations of soil moisture and snow amount are limited in time and space, although efforts on compiling such data have been in progress, and a globally gridded observational dataset is not yet available. Globally distributed snow cover data have only been available since the beginning of the satellite era. These relatively short and few observational records have placed limitations on statistical analyses that only use observed time series to clarify land wetness influences on precipitation. AGCMs are therefore a necessary tool to investigate such influences. The use of AGCMs is also relevant because such studies also seek to improve the accuracy of dynamical seasonal climate predictions. Past simulations with an AGCM used soil moisture and snow calculated in the coupled land–atmosphere system of the AGCM. Soil moisture and snow characteristics produced in the coupled land–atmosphere model did not necessarily match the characteristics of the real land surface. Such simulations can reveal the strength of land–atmosphere couplings in AGCMs (Koster et al. 2004b), but validation with observations is difficult.

Dirmeyer (1999, 2000) incorporated into an AGCM a global soil wetness dataset that was produced in an independent land surface simulation under the Global Soil Wetness Project (GSWP; Dirmeyer et al. 1999). These studies benefited from realistic specifications of soil moisture, and allowed a comparison between simulated and observed precipitation. However, soil wetness calculations of GSWP were limited to 1987–88. Thus, improvements in simulation could not be fully examined in terms of interannual variability.

The present study extends those noted above, demonstrating the influence of "realistic" land surface wetness on the predictability of seasonal precipitation during boreal summer. A major focus is the reproducibility of interannual variability of summer precipitation. A 48-yr dataset of realistic land surface wetness is used as an AGCM boundary condition. The realistic land surface wetness for 48 yr was derived from an independent global land surface simulation driven by observed atmospheric forcings (see Hirabayashi et al. 2005, hereafter H05, for details). This design is therefore an analog to AGCM experiments that use an observed sea surface temperature (SST) dataset over several decades as a boundary condition in studies on the impact of El Niño.

2. Experimental design

Two AGCM ensembles that were forced with different boundary conditions composed this study. Each ensemble consisted of five numerical integrations for 1951–98. The global spectral AGCM used in this study was developed by the Center for Climate Systems Research at The University of Tokyo and the National Institute for Environmental Studies (Numaguti et al. 1997). The model has T42 horizontal resolution (corresponding to spacing of approximately 2.8° latitude and longitude), and 20 vertical levels. The land surface scheme of the AGCM is MATSIRO (Takata et al. 2003), an SiB2-type (Sellers et al. 1996) land surface scheme with an explicitly modeled vegetation canopy. Soil moisture was modeled in five layers from a thin, 5-cm layer at the top, to the bottom at 2 m. Snow was modeled in three layers, and a partial snow cover scheme was used for cases with small amounts of snow. Observed monthly SST data (Rayner et al. 1996) from 1951 to 1998 were used as a boundary condition.

In the first ensemble (control experiment, hereafter referred to as CTL), only the observed SST data were specified as a lower-boundary condition. Land surface wetness was not specified, and the coupled land–

atmosphere system evolved freely. The second ensemble (hereafter LND) was forced with both SST fields and the realistic land surface wetness from 1951 to 1998.

The realistic land surface wetness was output every 24 h from a separate land surface simulation (H05) that also used MATSIRO, the same land surface model used in the AGCM. The land surface simulation is detailed in H05, but a concise summary follows. Offline land surface simulations require global atmospheric data as forcings; these include precipitation, surface air temperature and humidity, and radiation components at time intervals that correspond to the simulation time step, which is hourly in H05. Input atmospheric-forcing data were derived from a dataset compiled by the Climate Research Unit (CRU; Mitchell et al. 2004, manuscript submitted to *J. Climate*). The dataset includes observed monthly precipitation totals, number of precipitation days in each month, and maximum and minimum temperatures in each month. Statistical and empirical equations were applied to the monthly dataset, yielding atmospheric input-forcing data (precipitation, surface temperature and humidity, and radiation components) at the simulation time resolution, and a $1° \times 1°$ spatial resolution. MATSIRO was then forced with these data for 1901–2000 (outputs for 1951–98 were used in the AGCM simulations in this study) to yield global soil moisture, snow amount, runoff, latent heat flux, and other land surface variables at $1° \times 1°$ resolution. In the calculation, the state of soil moisture and snow never feeds back on the input forcings. Calculated soil moisture and snow in this separate MATSIRO simulation were spatially interpolated onto boundary conditions for LND, and were specified at every time step of AGCM simulations with temporally linear interpolation. In other words, soil moisture and snow were replaced with the H05 values at every time step in the LND experiment.

H05 assessed the outputs of the separate land surface simulation. A brief summary is included here. H05 compared simulated and observed summer soil moisture in Mongolia. Nineteen observation stations were averaged for a comparison that showed good interannual correlation ($r = 0.755$) with the simulation. H05 also successfully replicated the upward trend in summer soil moisture observed from 1960 to 1990 in Mongolia (Robock et al. 2000). Offline land surface simulations are generally easier for soil moisture in humid regions, and H05 should give better correlations in such regions. As for runoff, globally, many places showed high correlation coefficients for simulated and observed annual runoff. An exception was cold regions, where predicted runoff time series were poorly correlated with observations, despite good simulations of time series of snow cover. Some unknown processes like frozen soil and frozen river may cause the prediction errors in cold regions.

The hindcast of snow cover in H05 was compared to satellite-based observations. Both spatial patterns and time variability in modeled snow-covered areas compared favorably with observations. For example, H05 reproduced the smaller snow cover area over Europe and larger snow cover area over North America observed in satellite data between 1975 and 1985. Correlation coefficients between H05 and satellite observations of the interannual variability of snow-covered areas in spring (March and April) were 0.731 in North America and 0.577 in northern Eurasia. Correlations in midwinter were higher. Correlations in spring were smaller because of difficulties in simulating snowmelt. Note that the interannual variability of snow may not greatly affect the results in this paper because potential predictability of precipitation is lacking at higher latitudes, as described later.

Resolution differences result in global distributions of land cover and soil type in the AGCM differing slightly from distributions in H05. Land cover and soil types are represented as discrete numbers, and land surface physical processes in each grid are nonlinear. There is therefore no method to spatially interpolate the land surface hydrological variables from H05 to the AGCM grids that does not introduce differences. Simple linear interpolation was used in this study for land surface wetness.

A possible option that is not used in this study is the "normalization of anomalies" (Koster et al. 2004a). This option transforms the anomalies of land wetness from the offline land surface simulation into the anomalies for an AGCM with the utilization of averages and standard deviations of land wetness from both the offline simulation and an AGCM simulation like CTL. This option is relevant for precisely extracting land impacts. However, the option is not used here because this study intends to show the "maximum" predictability of precipitation (and maximum potential predictability of precipitation) due to the incorporation of realistic land wetness. Thus, the realistic land wetness is directly applied without normalization.

It might be advantageous to specify only the slowly varying components of the land surface, such as snow or subsurface soil moisture, because only the slowly varying components are predictable. However, surface soil moisture (the first layer in the model) was also specified in this study to isolate the maximum predictability of precipitation.

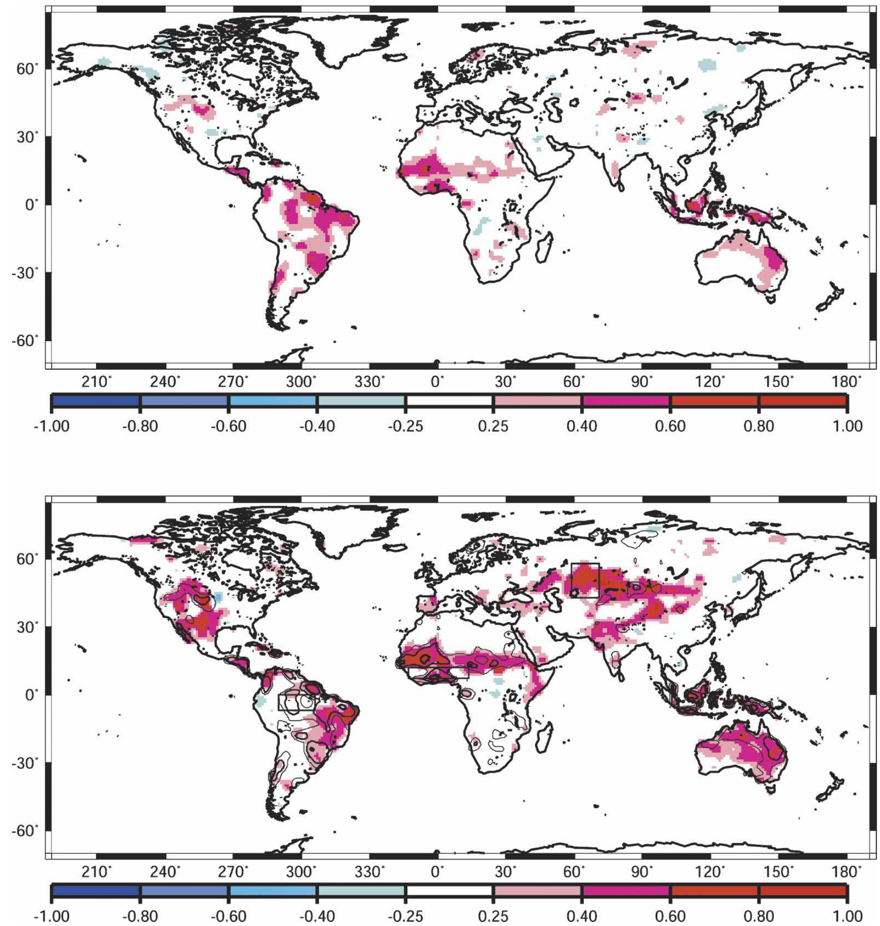

FIG. 1. (a) Correlation coefficients between interannual variability of simulated JJA precipitation from CTL and observed JJA precipitation from CRU. Shaded areas are statistically significant at the 5% level. (b) Same as in (a), but for LND [with the correlations in (a) shown as contours denoting 0.25, 0.4, and 0.6]. The boxes denote regions where predictability of precipitation does not exist whereas potential predictability of precipitation does exist.

3. Results

a. Global skills for correlation with observations

Monthly results in this study suggest that the specification of the land surface wetness mainly affects precipitation during boreal summer. Previous studies discussed in the introduction also show the greatest impacts in summer. Therefore, the focus here is on seasonal mean precipitation in June–August (JJA). JJA is a snow-free season, so the impact of soil moisture will be highlighted.

Figure 1a shows correlation coefficients between the interannual variability of simulated JJA precipitation in CTL and the observed JJA precipitation of CRU. Correlation calculations used ensemble mean time series of the five simulations of either CTL or LND. The CRU data were used as a global, gridded, observed precipitation dataset for comparison with the simulated ensemble mean time series. The CRU data are available only over land; they were used because they are available for a longer period, and because impacts were expected primarily over land. The CRU data were also used as input forcings in the separate land surface simulation in H05. However, validation of simulated precipitation against the CRU data that were already used as inputs is possible because of the complex nonlinear computational procedures in the AGCM.

Shaded areas in Fig. 1 show where the correlation is statistically significant at the 5% level. Minor changes in the significance level (e.g., 5%–1% or 5%–10%) do not influence the major impressions of Fig. 1 or subsequent figures. Significant correlations occasionally occur over land in Fig. 1a. Examples include eastern South America, Central America, parts of the Sahel and the coast of Guinea, northeastern Australia, and the Indonesian archipelago. The shaded areas are

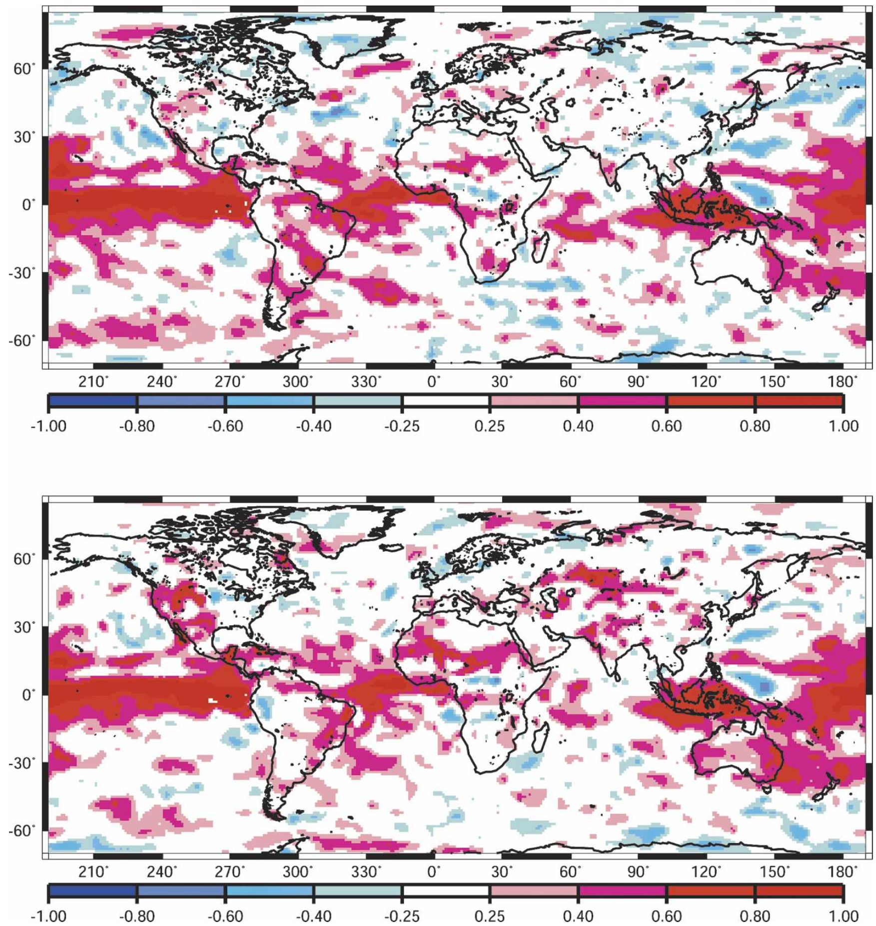

FIG. 2. Same as in Fig. 1, but from GPCP.

where predictability of seasonal precipitation can occur given only SST information. The word "predictability" is used in this study to denote a significant correlation between the time series of simulated outputs and observations. Significant correlations are rare in Fig. 1a in mid- and high latitudes, for example, over Eurasia, North America, and much of Africa.

Figure 1b shows correlations between LND and CRU. Differences between Figs. 1a and 1b highlight areas where the realistic land surface wetness impacts predictability. Significant signals appear over central Asia and northern India, middle and western North America, the Sahel, and Australia. Parts of some of these regions showed significant correlations in Fig. 1a. However, areas of significant correlation are much broader and more significant in Fig. 1b. The expansion in predictability results from specifying the land surface wetness. Most of these regions are located between dry and wet climates (henceforth referred to as semiarid regions), where soil moisture is dry enough to effectively control surface fluxes and the atmosphere is wet enough to allow precipitation (Koster et al. 2004b).

Figure 2a shows correlation coefficients between CTL and another global precipitation dataset by the Global Precipitation Climatology Project (GPCP; Adler et al. 2003), which was compiled from surface observations and satellite-derived estimates. GPCP data are only available after 1979, but are used here to show correlations over the oceans. There are significant correlations (predictability) over the tropical oceans, particularly the central and eastern equatorial Pacific, the equatorial Atlantic, and the oceans around Indonesia. Some shaded land areas in Fig. 1a (i.e., the east coast of Brazil, Indonesia, Central America, and the Guinea coast) are adjacent to such tropical oceans with high correlations. Precipitation variability over these land areas is likely controlled by SST variability. In contrast, significant correlation is rare over the western Pacific and the northern Indian Ocean, two major regions in the summer Asian Monsoon system. Land areas with significant correlations in Fig. 2a resemble those in Fig. 1a. Differences over land between Figs. 1a and 2a arise from differences in sampling periods or compilation methods between CRU and GPCP. Figure 2b shows correlation coefficients between LND and GPCP. Conclusions stated above for Fig. 2a are also relevant for Fig. 2b.

b. *Global skills of potential predictability based on the ratio of forced variance*

Next, we calculated the "potential predictability" of precipitation from each simulation ensemble using the analysis of variance as in Rowell et al. (1995) and Rowell (1998). First, the ratio (ρ) of interannual variance caused by boundary forcings to total interannual variance was calculated at each grid point. The "ensemble mean perfect model correlation skill" $r_{\mathrm{EMPM}} = \rho n^{1/2}[\rho(n-1)+1]^{-1/2}$ (n = the number of simulations in an ensemble) was then derived. Here, $r_{\mathrm{EMPM}} = \rho$ if $n = 1$, and $r_{\mathrm{EMPM}} > \rho$ if $n > 1$. For a perfectly behaving model, r_{EMPM} is expected to be the same as the correlation between the ensemble mean time series of simulated outputs and the time series of observations. In a model with errors, the correlation will be less than r_{EMPM}. Therefore, r_{EMPM} is the theoretical upper limit of "ensemble mean predictability" (shown in Figs. 1 and 2), and is an indicator of potential predictability for an ensemble of simulations with a set of boundary conditions.

Figure 3 shows the global distribution of r_{EMPM}. Here, we refer first to Fig. 3b, which shows results from LND that include the specification of both land and ocean conditions. High potential predictability occurs over semiarid regions (central Asia, the middle and western parts of North America, and the Sahel), over the central and eastern equatorial Pacific and Central America, over land and ocean near Indonesia, and over the equatorial Atlantic and adjacent regions of South America and the coast of Guinea. These are also regions of significant predictability (Figs. 1b, 2b). High potential predictability also occurs over the northern Indian Ocean and the western Pacific (and adjacent land areas, e.g., Indochina), although significant predictability in these areas is not present in Figs. 1b and 2b. Figure 3b also shows that potential predictability is missing over many parts of mid- to high latitudes, even when both land wetness and ocean conditions are specified as boundary conditions.

The difference between Figs. 3a and 3b, the "absolute" impact of the land wetness specification on potential predictability, is shown in Fig. 3c. In addition, Figs. 3a,b are combined in Fig. 4 to demonstrate the "relative" importance of the land wetness specification on potential predictability. Colors in Fig. 4 denote the ratio of potential predictability of CTL to the potential predictability of LND, which is equivalent to the relative magnitude of the land wetness impacts to the SST impacts. Potential predictability over northern South America, Central America, the coast of Guinea, and land areas of Indonesia arises from the variability of SSTs, as was already inferred in a previous subsection. Potential predictability over parts of South America, such as Nordeste and the Parana River basin, requires land wetness information. Potential predictability over the Sahel and the adjacent land region to the south appears as a mixture of impacts from SSTs and land wetness, with larger impacts of land wetness in the eastern part. Over the middle and western parts of North America, potential predictability mostly requires land wetness information, while SSTs mainly influence the west coast and the northeastern edge of the potentially predictable region. Similarly, potential predictability over central Asia is greatly influenced by the land surface wetness. Potential predictability arising from the land wetness specification is also present over a region from the Mediterranean to the Caspian Sea. However, less or no significant predictability is present there as shown in Figs. 1 and 2. Further study in this region may be warranted.

There are some land areas where predictability of precipitation does not exist whereas potential predictability of precipitation does exist (Figs. 1b and 3b). Examples of such regions include areas south of the Sahel (and north of the coast of Guinea) around 10°N [hereafter referred to as Sudan, after Rowell et al. (1995), and shown as a box in Figs. 1b, 3b, 5, and 6], and (a part of) the Amazon (also shown as a box in the figures). In these regions, potential predictability of evaporation shown in Fig. 5 is likely a key to the inconsistency between predictability and potential predictability of precipitation. Both Sudan and the Amazon show relatively smaller potential predictability of evaporation than semiarid regions like the Sahel, middle and western North America, and most of central Asia. It is speculated for these semiarid regions, in view of higher potential predictability of evaporation in Fig. 5 and relatively large impacts from land wetness in Figs. 3c and 4, that evaporation variability locally induces precipitation variability. In contrast, over Sudan and the Amazon, relatively low potential predictability of evaporation as well as prevailing SST impacts suggest that the variability of precipitation is remotely controlled, with less influence from the local evaporation variability. Predictability of precipitation there was likely absent because natural remote effects on the atmosphere in those regions were not well reproduced in the model. It is unknown whether this is a common shortcoming of AGCMs. Low potential predictability of evaporation at the northwestern part of central Asia (shown as a box

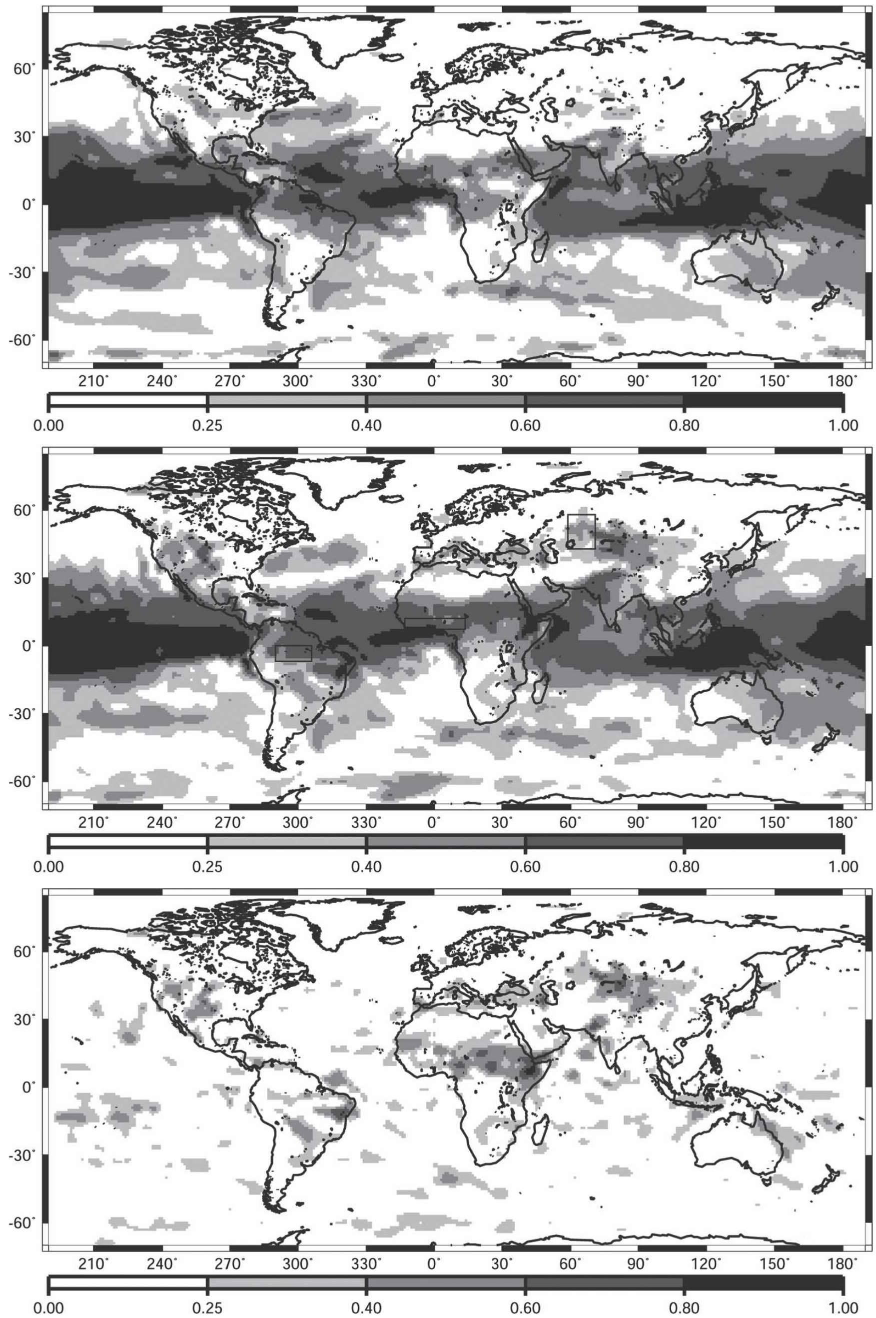

FIG. 3. (a) Potential predictability of simulated JJA precipitation in CTL. (b) Same as in (a), but for LND. (c) The difference between (b) and (a). The square root of the difference between the square of (b) and the square of (a) is presented in order to harmonize the dimension.

in Fig. 5) indicates that remote effects also dominate there. Because this area is far from the ocean and relatively strong land wetness impact is seen (see Fig. 4), land wetness variability from somewhere else may be the remote cause of precipitation variability over this area.

c. Predictability in the Asian monsoon regions

Previous studies (e.g., Rasmusson and Carpenter 1983) have suggested that interannual variability of precipitation at many locations in monsoonal Asia is correlated with equatorial Pacific SST variability. There-

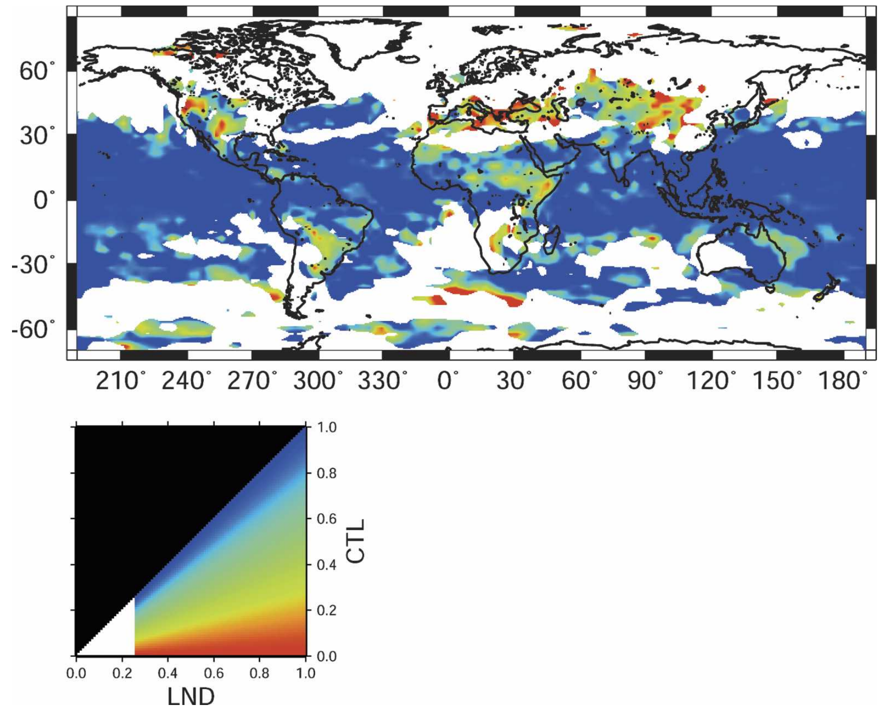

FIG. 4. The ratio of potential predictability of JJA precipitation in CTL relative to that in LND. Only values above 0.25 are shaded.

fore, SST specification should produce a certain predictability of precipitation in these regions. Specification of realistic land surface wetness is unlikely to degrade predictability. In fact, even an enhancement in predictability can be expected if, for example, continental surface wetness affects monsoon strength as described in the introduction. However, Figs. 1b–3b and 4 show that although potential predictability is present, little predictability is seen over the South and Southeast Asian monsoon regions from the northern Indian Ocean to the western Pacific. Recently, Wang et al. (2004) demonstrated that over the monsoon regions, specifically over the oceans, SST anomalies and observed precipitation anomalies have a negative correlation, although SST anomalies and precipitation anomalies simulated by AGCMs have a positive correlation. The lack of predictability of precipitation over those monsoonal oceans may be linked with the odd

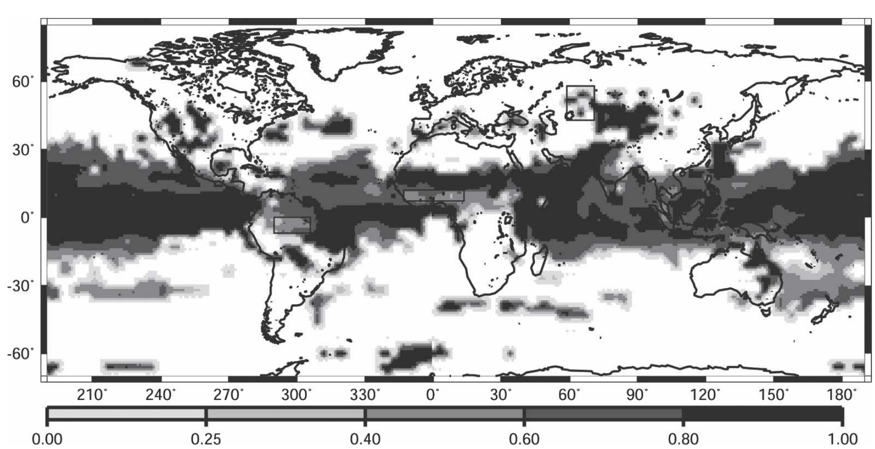

FIG. 5. Same as in Fig. 3, but for evaporation in LND. Areas where potential predictability of precipitation exceeds 0.4 are shaded in order to investigate the cause of potential predictability of precipitation.

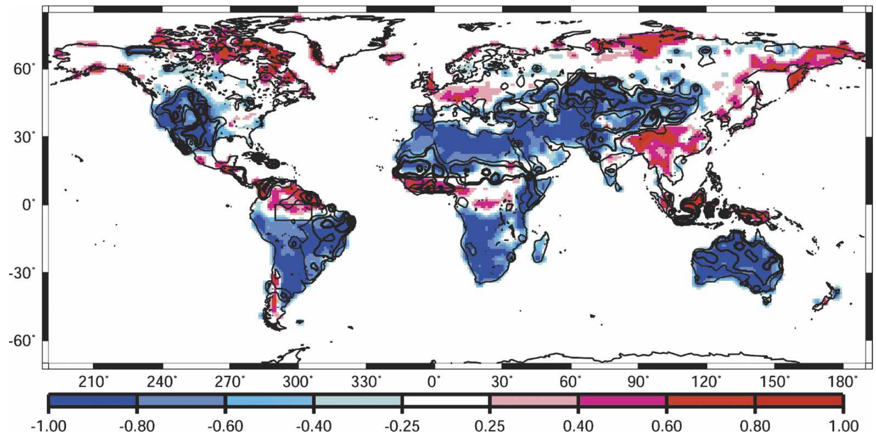

FIG. 6. Same as in Fig. 1, but for JJA mean sensible heat flux and latent heat flux in LND. (Contours show the same values as in Fig. 1b.)

representation of the SST–precipitation relationship in the model.

There is no predictability over Indochina where potential predictability occurs. In an atmospheric model study, Kanae et al. (2002) found that precipitation variability over Indochina is remotely controlled by SST variability around Southeast Asia and in the western Pacific. In fact, Fig. 4 shows that ocean effects dominate there. Thus, improvements in predictability for Indochina, and probably for similar land areas adjacent to those oceans, may also require improvements in the SST–precipitation relationship over those oceans. An exception is northern India where considerable predictability occurred because of the specification of land surface wetness (Fig. 1).

In the East Asian monsoon region, where the mei-yu (baiu) front is a major source of JJA precipitation, potential predictability does not appear over most of the continent (Fig. 3b). However, this may not reflect true predictability because an accurate simulation of the mei-yu (baiu) front is a challenge for current AGCMs (Ninomiya et al. 2002). In future improvements of mei-yu (baiu) simulations, land surface roles may not be negligible because energy and moisture supplied from the land surface each play an important role (Shinoda and Uyeda 2002).

d. *"Water regulating" versus "radiation regulating"*

Surface energy flux variability has an interesting property in semiarid regions where the impact of land wetness is most important. Figure 6 shows correlation coefficients between fluxes of latent and sensible heat calculated from the data for 1951–98 of LND. Areas where latent heat flux is negatively correlated with sensible heat flux are similar to the semiarid areas. An exception is arid regions where the lack of precipitation seems to inhibit predictability. Semiarid and arid regions can be characterized by this negative correlation, which suggests that "water" regulates the variability of surface fluxes. Namely, if soil is wetter than normal, latent heat flux will be above normal and sensible heat flux will be below normal. In contrast, a positive correlation implies that "radiation" regulates the variability of surface fluxes; both latent heat flux and sensible heat flux will be below normal when the input radiation energy to the surface is below normal, presumably because of cloud cover anomalies. Land surface water has little influence in this case, and the atmosphere plays a leading role on an interannual basis in contrast to semiarid and arid regions. It is reasonable to conclude that water-regulating locations, where land conditions actively control the surface fluxes and therefore the atmosphere, likely correspond to areas where the positive influence of the realistic land surface wetness on precipitation predictability is apparent. It is also reasonable that Sudan, the Amazon, and Indochina, where remote effects on precipitation variability are likely present, are radiation-regulating rather than water-regulating regions. Indonesia and Central America, regions affected by the tropical oceans, are also radiation regulating.

4. Summary and discussion

A couple of AGCM ensembles for 1951–98 help to assess whether land surface wetness information is necessary for the prediction of interannual variability in boreal summer precipitation. Previous studies (e.g., Dirmeyer et al. 2003) have suggested that adequate land surface initial and boundary conditions could improve the accuracy of boreal summer climate predictions. This study shows the enhancement of predictability (based on correlations with the observations) and potential predictability (through the analysis of variance) of precipitation on an interannual basis with prior knowledge of land surface wetness. Potential predictability is not apparent over many land areas, particularly at mid- and high latitudes, even when land surface wetness and SSTs are both specified as boundary conditions to the AGCM. Over land areas, both predictability and potential predictability were present mostly over semiarid regions (e.g., central Asia, parts of North America, and the Sahel) and regions adjacent to the equatorial oceans (e.g., Central America, Indonesia, and the Guinea coast). Prescribed land surface wetness in semiarid regions induces high potential predictability of evaporation, which leads to high potential predictability of precipitation and then to the realization of significant correlations with observed precipitation. Information on land surface wetness is indispensable for accurate seasonal precipitation simulations and forecasts in semiarid regions. However, we should note that actual seasonal prediction is an initial condition problem, and this study was constructed as a boundary condition problem. "Predictability" in this study carried out as a boundary condition problem shows the upper boundary of real predictability in a practical prediction system. Thus, a set of numerical experiments as an initial condition problem, like as a subseasonal forecast study by Koster et al. (2004a), are warranted to further verify the feasibility of seasonal precipitation prediction systems incorporating land surface wetness information of those regions.

The semiarid regions basically overlap with regions where previous studies (e.g., Koster et al. 2002, 2004b) found strong land–atmosphere coupling. Coupling strength depends on the internal dynamics of the land–atmosphere system in the AGCM, so comparison with observations is difficult. The validity of the coupling strength is, to an appreciable extent, verified in this study.

Predictability of precipitation is highest over water-regulating areas, with the exception of arid regions where very little precipitation is expected. Determining whether a location is "water regulating" or "radiation regulating" in the real world will help to determine if land surface wetness information at that location will improve predictions of precipitation. Identifying regions where such locations are clustered, with utilizations of in situ observations, remote sensing, and data assimilation techniques, will help the future planning and expansion of global hydrometeorological observation networks.

Remote effects control precipitation variability over some land regions (e.g., Sudan, the Amazon, and Indochina). Winds from tropical oceans prevail in these regions (not shown), and the regions are classified as radiation regulating. Predictability of precipitation was lacking in these regions where remote effects are important, although potential predictability exists. In addition to these regions, there are other land and ocean areas with little predictability, but with high potential predictability of precipitation. Because potential predictability exists, further improvement in seasonal precipitation prediction over such regions may yet occur as atmospheric models improve.

The results presented here depend on the AGCM used. A different AGCM may produce different results. For example, in previous studies with another experimental design, the strength of land–atmosphere coupling over each location exhibited a wide variety among AGCMs (Koster et al. 2002, 2004b). Thus, a multi-AGCM analysis is required for more reliable conclusions. For example, Dirmeyer (2000) showed that soil moisture greatly impacts precipitation in the Asian monsoon regions, a conclusion that is at odds with this study. The many differences in experimental design between the previous and present study preclude a direct comparison. However, a coordinated multimodel experiment and analysis could reconcile such differences. Phase 2 of GSWP (GSWP2) is now under way (Dirmeyer et al. 2002). In that study, 10-yr (1986–95) land surface hydrological variables are calculated in a highly controlled manner using a dozen land surface models. Each land surface model can be attached to an AGCM. So, GSWP2 outputs could be used in a multi-AGCM analysis.

The specified "realistic" land surface hydrological components sometimes diverge from observations, as discussed in H05. In particular, the simulation of hydrology at high latitudes in the Northern Hemisphere could be improved. This shortcoming does not necessarily degrade findings in this study, however, because potential predictability of precipitation in mid- to high latitudes in the Northern Hemisphere is generally low. Of course, future improvements in the separate land surface simulation are essential.

A higher-resolution AGCM study could reveal other influential land areas that cannot be identified using the resolution of this study. For example, a regional climate model study with a finer resolution demonstrated a plausible land impact on precipitation over Indochina (Kanae et al. 2001). The semiarid nature of that location depends on mountains on the eastern and western sides of the peninsula, and is rarely reproduced in a coarse-resolution model. Similar areas in other parts of the globe will be revealed in future higher-resolution AGCM experiments.

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