An Evaluation of the Strength of Land–Atmosphere Coupling

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ABSTRACT

Two ensembles of 1-month integrations of a coupled land–atmosphere climate model that differ only in their treatment of land surface boundary conditions have been generated from initial conditions chosen from the July states taken from each year of a 17-yr integration from the second Atmospheric Model Intercomparison Project (AMIP2). Both ensembles have specified sea surface temperature from one randomly chosen year, but one ensemble has the land surface state variables specified in each member at each time step to be identical to those from a single member of the other ensemble. Comparisons with the 17-yr AMIP2 integration provide an estimate of the role of interannually varying SST in affecting climate variability. Comparison between the two ensembles helps to quantify the role of land surface variability on the variance of surface fluxes and the climate. In this model system, the impacts of suppressed ocean variability on intra-ensemble spread are generally stronger than for suppressed land surface variability. The impacts of land surface variability on climate variability are clearer on monthly timescales than on synoptic timescales. Absolute measures of the impact of surface variability on the synoptic scale are not strong, but the time evolution of variability is consistent with expectations that the land surface does exert some control on climate variability.

1. Introduction

In recent years, interest in the role of the land surface in climate has been increasing. There have been a number of modeling studies that have investigated the response of climate to realistic land surface variability on seasonal to interannual timescales. Most studies have focused on the response of mean climate, or climate anomalies, to the treatment of the land surface. For example, Dirmeyer (2000) and Douville and Chauvin (2000) each showed how, in a coupled climate system model, specification of soil moisture calculated offline by driving the same land surface scheme with analyses of near-surface meteorological conditions improved the simulation of climate anomalies. Viterbo and Betts (1999) performed similar experiments with soil wetness from global reanalysis. Bounoua et al. (2000) examined how the remotely sensed range of variations of vegetation affect climate simulations.

Koster and Suarez (1995) and Koster et al. (2000b) examined the impact on climate variability of the ocean and land surface. In their experiments, sea surface temperature (SST) and evaporation efficiency (the ratio of evaporation to potential evaporation) were manipulated in multicentury integrations to test the response of the atmosphere to variability at the lower boundary. In their coupled land–atmosphere model, there was significant sensitivity to land variability over a large fraction of the land surface, largely corresponding to the transition zones between humid and dry regions.

Recently an economical climate modeling study has been endorsed by both the Global Energy and Water Cycle Experiment Global Land–Atmosphere System Study project, and the Seasonal to Interannual Modeling and Prediction working group of the United States Climate Variability and Predictability effort within the World Climate Research Programme. The study involves generation of an ensemble of 1-month simulations leveraged off participation in the second Atmospheric Model Intercomparison Project (AMIP2; Gleckler 1996). A preliminary study has been completed that assesses, in two different climate models, the roles of land and ocean variability on climate variability at timescales of a month or less. In Koster et al. (2000a), the National Center for Atmospheric Research (NCAR) Community Climate Model (CCM), version 3 (Kiehl et al. 1998), coupled to the Biosphere–Atmosphere Transfer Scheme (Dickinson et al. 1993), and the National Aeronautics and Space Administration Goddard Earth Observing System climate atmospheric general circulation model (AGCM) with the “Mosaic” land surface scheme (Koster and Suarez 1992, 1995) were compared. In particular, disparity between the results of the two models provides simulation to assess the strength of land–atmosphere coupling and the relative roles of land and ocean within the Center for Ocean–Land–Atmosphere Studies (COLA) climate model system.
This study attempts to address a pair of questions relating to variability in the climate system, one absolute and one relative. How much control does the land surface exert on the atmosphere in the face of the chaotic nature of the variability of the general circulation? How strong is the impact of the land surface state on the atmosphere as compared with the impact of the ocean state? I have leveraged off of an existing multiyear integration, performing a number of 1-month integrations to construct two additional complementary ensembles that can be used to address these questions.

Section 2 describes the atmospheric and land surface models that are used in the coupled model system and describes the construction of the experiments. Section 3 examines the effect of ocean and land surface variability (or more accurately the suppression of variability) on the variation of specific surface hydrologic fluxes and near-surface atmospheric variables on the monthly timescale. The study of land–atmosphere coupling and interaction is extended to submonthly scales in section 4. Conclusions are presented in section 5.

2. Models and experiment structure

This investigation uses version 2.2 of the COLA AGCM. This model consists of a dynamical core taken from the NCAR CCM3 (Williamson and Olson 1994; Kiehl et al. 1998) combined with a package of physical parameterizations assembled at COLA. These parameterizations include the shortwave radiation parameterization of Lacis and Hansen (1974) as modified by Davies (1982), the longwave radiation parameterization of Harshvardhan and Corsetti (1984), the Mellor and Yamada (1982) turbulence scheme with level-2.0 closure, the relaxed Arakawa–Schubert scheme for convective precipitation of Moorthi and Suarez (1992), and Tiedtke (1984) shallow convection.

One feature that distinguishes version 2.2 of the COLA AGCM is a significant update to the land surface scheme (LSS). The LSS is based on the simplified version of the Simple Biosphere model (SiB; Sellers et al. 1986) called SSiB (Xue et al. 1991, 1996). The modifications for use in version 2.2 include spatially and temporally varying vegetation parameters and spatially varying soil parameters based on the International Satellite Land Surface Climatology Project Initiative I land surface data (Meeson et al. 1995). The implementation allows for a more realistic distribution of soil and vegetation properties than could be specified in earlier versions of SiB (Dirmeyer and Zeng 1997, 1999). In addition, the full two-stream calculation for surface radiation has been reintroduced (Sellers 1985), and a three-layer temperature diffusion scheme replaces the original force–restore soil temperature scheme (Viterbo and Beljaars 1995).

This numerical experiment leverages off of integrations being produced for AMIP2. Integrations for AMIP2 were performed at a spectral horizontal resolution of R40 (approximately 1.8° lat by 2.8° long) with a time step of 12 min. The period of integration for GCMs participating in AMIP2 is from January 1979 through February 1996, preceded by a recommended spinup period of more than one year. Experimental subproject 1 of AMIP2 involves an ensemble integration of the AMIP2 study period, with ensemble members differentiated by distinct initial conditions. This experiment makes use of one of the ensemble members as a control case with specified SST derived from a blend of Reynolds and Smith (1994) optimal interpolation SST and the Hadley Centre Global Ice and SST (GISST2.2a) data (Rayner et al. 1996). The nine prognostic state variables at the land surface are the temperature and soil wetness in the surface, root, and deep soil layers; a radiometric skin temperature; water storage on the canopy; and snow liquid water mass on the ground. The AGCM and LSS are fully coupled and evolve in tandem.

I take the combined atmosphere–land state on 1 July during each of the 17 years of the AMIP2 integration and use them as unique initial conditions for two ensembles of 1-month test integrations using the same coupled AGCM–LSS system. In addition, we take the 17 Julys from the AMIP2 integration as a third ensemble. Because the AMIP integration has a prognostic atmosphere and land surface as well as interannually varying SST, I will refer to this ensemble as case ALO (signifying that interannual variability exists in Atmosphere, Land, and Ocean).

One year was chosen at random to represent the “control” member of the ensembles. I have chosen 1986, though any year would suffice. The AMIP2 integration for July 1986 was repeated so that the land surface state variables could be saved from each time step during that month. These land surface state variables were then used as specified boundary conditions in a new ensemble of 1-month integrations, which also all used the same 1986 SST for all members. Because only the initial (and subsequent) atmospheric states vary among the members of this ensemble, I refer to it simply as case A. The last ensemble is integrated with 1986 SST but with the land surface free to evolve in the coupled system. This ensemble also has variability in the initial land surface conditions, which are taken from the same years as the atmospheric initial conditions in the chosen AMIP2 integration. This case is called AL. Table 1 summarizes the experiments.

With these three ensembles, one can investigate the role of ocean variability (AL vs ALO) and land variability (A vs AL) in determining the statistical properties of the atmosphere on monthly timescales. In so doing, the relative roles of the two principal components of the lower boundary with respect to the atmosphere can be assessed. I also save the daily precipitation from each integration in cases A and AL to examine the links between land surface and atmospheric variability on submonthly timescales.
3. Variability of monthly means

I will mainly examine the effects that surface variability has on the variance of atmospheric properties. However, I start by showing the impacts on the mean precipitation, because it is helpful to understand some of the response characteristics shown later in this paper. Figure 1 shows the difference in the ensemble mean, monthly mean precipitation between cases A and AL. Because all of the members of ensemble A have specified the land surface state from the 1986 member of ALO, the difference between this ensemble member and the AL ensemble mean is also shown. It is clear that, over land, many of the precipitation differences evident between A and AL arise from the anomalies in 1986. In particular, the dry conditions over much of central North America, the Arctic margins of Russia, and the fine structure of dry and wet anomalies over South Asia are nearly identical. Nevertheless, there are land areas where the anomalies are not reproduced, such as the bands of wet anomalies over central Siberia, Greenland, Patagonia, and most of the structure over Australia. Also, there are features evident in the A minus AL plot, such as the drying over the Sahel, that are not evident in the precipitation from the control year. Overall, there appears to be a tendency for dry anomalies to be transmitted better through the land surface state variables to the A ensemble than are the wet anomalies. This result may be due to the tendency for land-forced dry climate anomalies to be more persistent (Entekhabi et al. 1992) and for surface fluxes to be relatively insensitive to soil moisture variations in wet soil conditions (Dirmeyer et al. 2000). Differences over ocean are not communicated from the AL case to the A case, because the SSTs are identical throughout all members of both cases. There are differences over open ocean in Fig. 1, but they lie predominantly in the model storm tracks and convergence zones and are not significantly large.

Table 1. Initial and boundary conditions for the 17-member ensembles. Where the year 1986 is not specified, conditions for each ensemble member are taken from 1 Jul of each year (1982–98) of the AMIP2 simulation. Here, IC is initial conditions.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>SST</th>
<th>Land state</th>
<th>Atmosphere IC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALO</td>
<td>Observed</td>
<td>Free (AMIP2 IC)</td>
<td>From AMIP2 integration</td>
</tr>
<tr>
<td>AL</td>
<td>1986</td>
<td>Free (AMIP2 IC)</td>
<td>From AMIP2 integration</td>
</tr>
<tr>
<td>A</td>
<td>1986</td>
<td>Specified 1986 ALO</td>
<td>From AMIP2 integration</td>
</tr>
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This experiment provides evidence that information about the model rainfall in the simulation of July 1986 can be communicated through the land surface state variables to reproduce similar conditions in the other ensemble members. The focus, however, is on the impact on atmospheric variability from the land and ocean. Figure 2 shows the impact on the intra-ensemble variability of monthly mean near-surface air temperature (actually the canopy air space temperature in SSiB) by suppressing intra-ensemble variability of the land surface (top) and the ocean (bottom). This is expressed as the ratio of the intra-ensemble variances:

\[
\frac{S_{\text{land}}}{S_{\text{ocean}}} = \frac{v_A}{v_{AL}}, \quad \frac{S_{\text{ocean}}}{S_{\text{AL}}} = \frac{v_{AL}}{v_{ALO}}. \tag{1}
\]

Throughout this section, all references to variance or variability will mean this intra-ensemble variance. In Fig. 2 and all subsequent figures showing the variability impacts, the two tails of 5% significance, based on a Fisher’s F test, are shaded—dark gray for a significant decrease in variance and medium gray for a significant increase.

It is obvious from Fig. 2 that there is a direct overwhelming local impact on near-surface air temperature. There is evidence in the bottom panel that some land areas are affected by maritime variability. In particular, the eastern part of the Amazon basin and the islands of Indonesia appear to respond to the suppressed variance over the neighboring oceans, perhaps because these areas lie in the path of the surface tropical easterlies blowing directly from the ocean. Yet there are very few coastal areas that are thermally dominated by SST. On the other hand, there are land regions in the top figure for which there is no significant response of near-surface air temperature to variability in the soil temperature or wetness. Again, the eastern Amazon basin and Indonesia are evident, as are equatorial Africa and parts of the Andes and Bolivian Plateau.

As one moves away from the surface state variables toward more derived and removed quantities, interesting patterns emerge. Figure 3 shows the same ratio of variances for surface evapotranspiration. The response to suppressed SST variability is largely confined to the Tropics. Across the extratropics and even within the subtropical ridges there is no significant reduction of variability in evaporation. Only in the vicinity of the boundary currents, where the interannual variability of SST in the regions of sharp temperature gradients has been eliminated in the AL case, are there significant reductions of variability in the northern extratropics.

When the land state variables are specified, most land areas show the expected reduction in evapotranspiration variability. Yet there are exceptions. In high latitudes, at which strong baroclinicity in the atmosphere may lead to unusual gradients of temperature or humidity between the unresponsive land and the changeable atmosphere, surface flux variations are enhanced. In a similar way, over desert regions such as the Sahara, Arabia, central
Australia, and the Mojave–Sonora, an occasional rainy day in the 1986 control run can generate the possibility for abnormally strong evaporation in the other members of case A when the elevated soil wetness is specified at the land surface. The nonlinear nature of the Clausius–Clapeyron relationship can lead to very high evaporation rates where potential evaporation is high, and specified wet soil essentially provides an unlimited moisture source.

Precipitation is further removed from the surface state variables than evapotranspiration in the hydrologic cycle. As a result, the signal in precipitation variance is weaker still (Fig. 4). When land state variables are specified, the pattern of the response is like that of evaporation but with a much more limited area of significant reductions. The largest coherent area is over North America, largely where there was reduced rainfall in Fig. 1. Thus, this result may be an artifact of the year chosen for the control case, although the area of suppressed variability does extend farther to the south and west. Elsewhere, there are large areas showing a reduction in precipitation variance over central South America, Southeast Asia, central
Asia north of the Himalayan range, eastern Europe, and parts of both northern and southern Africa. The only coherent area of increased variability over land is in the vicinity of Namibia.

The response to suppressed ocean variability is actually very comparable to the impact on evaporation variance. This similarity suggests a very direct connection between local evaporation and precipitation variability over the warm oceans. The only areas in low latitudes where precipitation variance is not suppressed like evaporation variance are the regions of the eastern Pacific cold tongue and the stratus decks of the eastern oceanic margins.

Evaporation and near-surface air temperature are determined by the state of the surface and the lowest layer of the atmosphere. Precipitation involves vertical motion of moist air through the atmospheric column, and so the van response in precipitation variance may be attributable to the distance of its production mechanism from the surface. Thus, it is worth seeing how the signals induced by the suppression of land surface variability among ensemble members propagate up through the at-
Fig. 3. As in Fig. 2, but for surface evaporation. Unshaded areas have evaporation rates less than 0.01 mm day\(^{-1}\) in the ALO case.

mosphere. Figures 5 and 6 show the spatial distribution of air temperature variance at the 1st and 5th of the 18 model layers, centered at \(\sigma = 0.995\) and \(\sigma = 0.8565\), respectively, where \(\sigma\) denotes a coordinate system based on relative pressure. As in the previous figures, the impacts of suppressed land and ocean variability are each shown.

The reduced temperature variance at \(\sigma = 0.995\) brought about by suppressed ocean variability is evident across the global oceans, except over the stormiest regions of the Southern Hemisphere and the tropical western Pacific. Moving up to \(\sigma = 0.8565\), areas of reduced variance are confined to the Tropics and the subtropical ridges. An increase of variance becomes evident over many areas. These correspond to areas of stratus cloud in the AGCM, off the west coasts of continents and over the high latitudes.

Over land, there is remarkably little signal at the lowest model level. However, at \(\sigma = 0.8565\) there are coherent regions of reduced variability over the northern Great Plains, the Amazon basin, India, Southeast Asia, and smaller areas over Central America, southern Alaska, Russia, and China. There are also areas of increased variance over the subtropical margins of Africa and the Americas. The arc of increased variance over the Sahel is particularly prominent.

The vertical profiles of the ratio of temperature variances over four rectangular regions are given in Fig.
7. Three regions of generally reduced variance are shown (Great Plains, Amazon, and India) as well as a box over the region of increased variance in the Sahel. The response in temperature variance is not strongest in the atmospheric layer next to the surface, from which the signal is driven. Instead, the greatest reduction in variance appears to be in layer 2 or 3. Where there are considerable reductions in temperature variance, a significant signal permeates the lowest 30% of the atmosphere. Over the Sahel, the increase of variance is predominantly aloft, with significant increases up to approximately 500 hPa. However, as in the other regions, variance is most damped in layer 2 of the AGCM. Over ocean, the ratio of variances from AL and ALO (not shown) indicates that the temperature signal penetrates throughout the troposphere in the Tropics, through the lower half of the troposphere in the subtropics, and only through the lowest few layers in the midlatitudes.

The reason for the counterintuitive increase in temperature variance over the Sahel may be a southward shift of the arid margin in case A, which serves to move both the latitude of peak convective heating (near the African coast) and the peak in temperature variance (over the Sahara) also toward the south. Over other subtropical land regions, there is a genuine increase in temperature variability in the lower troposphere.

Figure 8 shows the horizontal distribution of the impact on specific humidity variance in the lowest model
FIG. 5. As in Fig. 2, but for air temperature in the lowest AGCM layer. Unshaded areas have a temperature variance of less than 0.05 K² in cases (top) AL and (bottom) ALO.

Vertical profiles of the ratio of humidity variances over the same four regions as Fig. 7 are presented in Fig. 9. Where a reduction in variance is evident, the penetration of a significant signal is only through the lowest 15%-20% of the atmospheric column. For humidity, the strongest effects are indeed at the lowest model layer. The Sahel shows no significant change in variance, outside of one layer near 700 hPa.

Why are the impacts on temperature variability not most significant in the lowest model layer, while for humidity the impacts match intuition? This is particularly puzzling given that, in the coupled AGCM–LSS system, the surface and near-surface temperatures and humidity are solved simultaneously in a semi-implicit scheme. This result may be caused not so much by the impact of suppressed land surface variability in case A, but rather by the characteristics of lower-tropospheric variability and its connection to the land surface in the fully coupled model. In case AL, intra-ensemble variance in specific humidity is greatest at the lowest model layer.
layer, but intra-ensemble temperature variance in the model typically peaks 2–4 layers above the surface. Variance of both variables then drops quickly with height. This relative damping of temperature variability in the lowest 1–3 layers of the atmosphere is the result of the thermal inertia of the soil— intra-ensemble temperature variance continues to decrease down through the soil column. In case A in which the land surface variability between ensemble members is nil, the profiles of variability for temperature and humidity are small and are nearly constant throughout the lower one-half of the atmosphere. Thus, the profiles of the variance ratios displayed in Figs. 7 and 9 are predominantly determined by the profiles of $v_{\text{AL}}$, the baseline variance of the control ensemble, giving the impact on temperature profiles somewhat more significance away from the lower boundary.

4. Daily variability

If the land surface state exerts a strong level of control over the atmosphere, one might expect the individual members of an ensemble of integrations with different initial atmospheric states to be herded toward a common state over time by identically specified land surface states. This might be manifest in a reduction of the intra-ensemble spread of precipitation over time or a measurable coherence among ensemble members in the time series of a quantity such as daily rainfall at any given location. If precipitation does not respond in a linear

![Impact on $T_{w=0.857}$ Variance Specifying Land State Variables](image1)

![Impact on $T_{w=0.857}$ Variance Specifying Sea Surface Temperature](image2)

**Fig. 6.** As in Fig. 5, but for air temperature in the 5th layer from the bottom of the AGCM.
Fig. 7. Vertical profile of the ratio of intra-ensemble variances ($y_A$ over $y_{AL}$) of monthly mean temperature averaged over the indicated regions.

fashion to changes in the state of the land surface, then one might not expect to find a difference in $y_A$ as compared with $y_{AL}$.

An index of coherence for annual mean precipitation has been proposed by Koster et al. (2000b), which may be applied readily to daily mean precipitation:

$$
\Omega = \frac{Iv_p - v_p}{(I - 1)v_p},
$$

where $v_p$ is the variance among $I$ ensemble members and $N$ daily totals of precipitation and $v_{p}$ is the variance of the ensemble mean daily precipitation across $N$ days. Values of $\Omega$ approaching 1 indicate that there is little difference between the variances $v_p$ and $v_{p}$, and thus the individual ensemble members track one another precisely. A value of $\Omega = 0$ suggests that the time series of the individual ensemble members cannot be distinguished from a set of random, unrelated series (i.e., $v_p \rightarrow v_{p}/I$).

The top panel of Fig. 10 shows the coherence index for case A ($\Omega_A$). There is little indication from this index of any appreciable land surface control on the synoptic-scale variability of precipitation in this coupled AGCM–LSS system. Comparison with Koster et al. (2000a) suggests that the COLA climate model may exhibit relatively weak land–atmosphere coupling as compared with other models. Implicit in the formulation of $\Omega$ is that an ensemble lacking suppression of land surface variability should show $\Omega = 0$. A plot of $\Omega_{AL}$ (middle panel of Fig. 10) shows that to be largely but not wholly the case. Much of the suppressed synoptic variability over tropical oceans is endemic to the model regardless of the specification of the land surface and presumably results from the submonthly variation of the 1986 July SST in the integrations. Only when the difference between $\Omega_A$ and $\Omega_{AL}$ is taken does a coherent signal emerge over land. Granted, the changes are small in magnitude, but they are unilaterally positive over land. It may be that, on synoptic timescales, there is an effect from land surface variability on the variance of precipitation in this model. Nonetheless, the impact is not as robust as on monthly timescales.

There is a growth of coherence from the beginning of the integrations, when the member atmospheres have
vastly different states, to the end of the integrations when the land surface has had a full month to affect the physical state of the member atmospheres. This is true even if the integrations are extended an extra month. Figure 11 shows the ratio of variances between A and AL cases for precipitation averaged over the first three days and last three days of August. Some signal over land is evident immediately, particularly over drier land regions. By the end of the period, it is clear that ensemble spread has been reduced in the A case relative to the AL case over many of the continental areas. Over ocean, there is an increase in spread over some of the coastal seas, including the Mediterranean and North Seas. I do not have an explanation as to why decreased precipitation spread over land should lead to increased spread over adjacent oceans. Over open ocean, there are equal numbers of small patches of increased and decreased variance that reflect the internal noise of the atmosphere.

To illustrate the evolution of ensemble spread (or its reduction) over time, I average the daily precipitation variance over all land and ocean grid boxes between 60°S and 85°N in both the A and AL cases and then plot the ratio of those area-averaged variances in Fig. 12. There are two distinct elements to the change in variance illustrated over land. First, there is an immediate reduction in variance over land on the order of 5%–10% on the first day. This reduction stems from the
fact that in case AL the initial land state is different in each member of the ensemble, whereas in case A they are necessarily identical. If identical initial land surface conditions had been used in case AL, then the ratio of variances would have started at unity. Second, there is an uneven but progressive decrease in variance among the members of case A relative to case AL over the course of the integration. This decrease is evidence of the accumulating influence of the land surface boundary conditions over the atmosphere. The evolution of precipitation in the individual members of ensemble A is being discernibly marshaled by the end of the first month.

To see whether the impact of the land surface on rainfall variance continues to grow and if the results found here for one month extend to longer timescales, both ensembles were extended forward through August. Results are, if anything, more robust. The decrease in variance among the members of case A relative to case AL seen in Fig. 12 is slightly ameliorated in August, but the ratio is still near 0.9. The ensemble spread in case A over ocean actually increases, and the ratio is near 1.05 throughout August, so that the contrast between ocean and land variability changes is maintained in the second month. The differences in coherence index (Fig. 10) for a 2-month average are stronger and more pronounced over land, and the contrasts in the variability of monthly means described in section 3 are maintained throughout the second month.

5. Conclusions

Two ensembles of 1-month July integrations of the COLA coupled AGCM–LSS system with different initial conditions have been compared with each other and with a 17-yr AMIP2 integration to assess the relative roles of ocean and land surface variability on atmospheric variability. Additional examination of daily rainfall time series among all members of the ensembles provides insight into the effect of specified land surface state variables on reducing the spread of precipitation within the ensemble.

The two ensembles have individual members with initial conditions chosen from the 1 July states from each year of an AMIP2 integration. Both ensembles have SST specified from one randomly chosen year.
(1986). In one ensemble (A), the land surface state is specified in each member at each time step to be identical to that from a single member freely integrated with 1986 initial conditions and SST. In the other (AL), the land surface state is predicted in the coupled system. The Julys from the AMIP2 integration are combined as a third ensemble (ALO) with a predicted land surface and interannually varying SST.

Fig. 10. Coherence index (top) $\Omega_A$ and (middle) $\Omega_{AL}$ as defined in the text; (bottom) difference $\Omega_A - \Omega_{AL}$. Units are dimensionless.
Fig. 11. Impact on intra-ensemble precipitation variance of identically specified land surface state variables applied in all ensemble members during (top) the first three days of a 1-month integration and (bottom) the last three days of the same integration. Shading as in Fig. 2; unshaded areas have precipitation variance less than $10^{-3}$ mm$^2$ day$^{-2}$ in case AL.

Specification of 1986 SST greatly reduces the variability of temperature in the lower troposphere over all oceans and in the middle and upper troposphere in the subtropics and Tropics, reduces lower-troposphere humidity over the tropical and subtropical oceans, reduces evaporation over the tropical oceans, and reduces variability in precipitation over parts of the tropical and subtropical oceans. Specification of 1986 land surface state variables reduces variability in near-surface air temperature and precipitation over more than six large contiguous continental areas but reduces variance in evapotranspiration and near-surface humidity over a much larger fraction of the land surface. There is an increase in variance in evapotranspiration and temperature over many semiarid and arid regions. A statistically significant impact on temperature variability penetrates vertically through the lowest 30% of the atmosphere over the regions with the most evident influence. Humidity impacts penetrate the lowest 15%–20% of the atmospheric column.

The coherence of time series of precipitation amongst ensemble members of case A is very low. Nonetheless, there is a discernible increase in coherence across nearly all land areas over what is evident in case AL. There
is an immediate impact on precipitation spread from the very first day of the month, but the reduction in spread becomes gradually stronger as the month goes on, with the ratio of variances averaged over all land areas between case A and AL dropping from 0.93 to about 0.8.

Overall, the impacts of suppressed ocean variability on the variability within an ensemble of monthly climate simulations are stronger than for suppressed land surface variability, suggesting the coupling between land and atmosphere is weak in comparison with that between ocean and atmosphere in this model system. The impacts of land surface variability on climate variability are clearer on monthly timescales than on synoptic timescales. Absolute measures of the impact of surface variability on atmospheric variability (such as coherence) are not strong in this model system, but the relative impacts (A vs AL or AL vs ALO) are clear.

Results such as these are likely to be model dependent. It would be useful to know how the spectrum of coupled GCM–LSS systems currently in use behaves and, specifically, how well they agree. A preliminary comparison of these results with those from a few other model systems is being conducted. It suggests the coupling between land and atmosphere may be weak in comparison with that of other climate model systems, and this disparity among models leaves open the question: What is the strength of the coupling between land and atmosphere in the real world? It is not clear how to proceed in quantifying the strength of land–atmosphere coupling in the real world. However, applying a simple and computationally inexpensive test such as this one to a wide range of existing land–atmosphere models would help us to understand our current level of certainty and, perhaps, suggest how different LSSs; model resolutions; and parameterizations of the planetary boundary layer, convection, and clouds affect sensitivity.

If indeed this coupled land–atmosphere model is representative of the real climate system, then it suggests that variability in the state variables of the land surface cannot have wide-ranging impact on the boreal summer circulation, because the signal of land surface variability is confined predominantly to the lower atmosphere and does not appear to communicate much beyond the coastlines. However, the surface state can indeed have a strong local and regional impact over land, perhaps serving to modulate climate anomalies driven by SST or internal variability in the climate system.

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