

The Hydrologic Feedback Pathway for Land–Climate Coupling

PAUL A. DIRMEYER

Center for Ocean–Land–Atmosphere Studies, Calverton, Maryland

(Manuscript received 31 May 2005, in final form 28 November 2005)

ABSTRACT

The impact of improvements in land surface initialization and specification of observed rainfall in global climate model simulations of boreal summer are examined to determine how the changes propagate around the hydrologic cycle in the coupled land–atmosphere system. On the global scale, about 70% of any imparted signal in the hydrologic cycle is lost in the transition from atmosphere to land, and 70% of the remaining signal is lost from land to atmosphere. This means that globally, less than 10% of the signal of any change survives the complete circuit of the hydrologic cycle in this model. Regionally, there is a great deal of variability. Specification of observed precipitation to the land component of the climate model strongly communicates its signal to soil wetness in rainy regions, but predictive skill in evapotranspiration arises primarily in dry regions. A maximum in signal transmission to model precipitation exists in between, peaking where mean rainfall rates are 1.5–2 mm day⁻¹. It appears that the nature of the climate system inherently limits to these regions the potential impact on prediction of improvements in the ability of models to simulate the water cycle. Land initial conditions impart a weaker signal on the system than replacement of precipitation, so a weaker response is realized in the system, focused mainly in dry regions.

1. Introduction

In recent years there has been increasing attention on the land surface as a source of enhanced seasonal climate predictability beyond what can be attained through knowledge of the evolution of sea surface temperature (SST) and its effect on the general circulation of the atmosphere. The land surface state includes variables such as soil moisture and temperature, snowpack and other surface water stores, and the state of vegetation. Of these, soil moisture is perhaps the most important (Dirmeyer 1995). The relatively poor skill of boreal summer hindcasts, compared to winter, by several climate models in the Dynamical Seasonal Prediction (DSP) Project (Shukla et al. 2000) was shown by Dirmeyer et al. (2003). However, Dirmeyer (2003) showed that while SST appears to be the dominant factor in providing skill to boreal winter forecasts over land, in other seasons the land surface state affects skill. The degree of impact of the land surface on climate varies from model to model (Koster et al. 2002, 2004), but

numerous studies in recent years have shown significant positive impacts on the skill of seasonal hindcasts by careful application of realistic soil wetness initial conditions (Fennessy and Shukla 1999; Koster and Suarez 2003; Kanamitsu et al. 2003), boundary conditions (Dirmeyer 2000; Douville 2003; Dirmeyer and Zhao 2004), and even snow cover (Yang et al. 2001; Schlosser and Mocko 2003).

Studies of the land surface's role in regional climate anomalies and variability have focused on key events and regions and met with mixed results. Simulations of the 1988 drought over central North America have largely shown that the feedback between dry soil and the atmosphere can be a contributing factor to amplify the drought (Atlas et al. 1993; Fennessy and Shukla 1999; Sud et al. 2003), whereas somewhat conflicting results have been found for the 1993 floods in the same region (Beljaars et al. 1996; Paegle et al. 1996; Bosilovich and Sun 1999). Diedhiou and Mahfouf (1996) found that the choice of land surface parameterizations significantly affected the simulation of climate over the Sahel. Garric et al. (2002) and Douville et al. (2001) found that soil moisture feedbacks are important over the Sahel, but Douville et al. (2001) found less sensitivity over South Asia. Timbal et al. (2002) conclude that soil wetness feedbacks play an important role in

Corresponding author address: Paul A. Dirmeyer, Center for Ocean–Land–Atmosphere Studies, 4041 Powder Mill Road, Suite 302, Calverton, MD 20705-3106.
E-mail: dirmeyer@cola.iges.org

the climate of Australia. Douville (2002) found evidence that even remote soil moisture variations could impact monsoon regions. Globally, regions of sensitivity can be very spotty (Douville 2003) and can vary greatly among models (Koster et al. 2006).

Why are there such large discrepancies between different regions and different models of the estimates of the sensitivity of the climate system to variations in the land surface state? Guo et al. (2006) suggest that differences among models can be related to the variance of surface evapotranspiration over land, and the degree to which precipitation parameterizations respond to changes in evaporation. In other words, there are distinct coupling strengths associated within the land (how soil moisture controls evapotranspiration), and between land and atmosphere (from evapotranspiration to precipitation). The experiment of Koster et al. (2006) and Guo et al. (2006) involved specification of soil wetness, so the coupling from atmosphere to land (precipitation to soil wetness) was not directly tested.

Dirmeyer and Zhao (2004) and Dirmeyer (2005) took a different approach, specifying the downward fluxes of precipitation and radiation over land. The goal was to examine the impact that more realistic downward fluxes would have on the simulation of soil wetness, and how the signal propagates back to the atmosphere as reflected in changes to the simulation of near-surface air temperature and precipitation. The motivation for this approach came from the realization that errors in downward fluxes contributed to strong drift of soil wetness to extreme values in the climate model, reducing the sensitivity of the atmosphere to anomalies in initial soil wetness, and thus potentially reducing the predictability of the climate system. Dirmeyer and Zhao (2004) found that flux replacement indeed reduced systematic errors and improved the simulation of climate anomalies in seasonal hindcasts. Dirmeyer (2005) found that the drift in the uncorrected model leads to unrealistically low variability, and that flux replacement brings about significant improvements in hydrologically important regions such as central North America, Europe, South Asia, and the Sahel. These studies suggest that given proper meteorological forcing, the land surface can convey climate anomalies back to the atmosphere.

Specification of downward fluxes also provides a different starting point than Koster et al. (2006) and Guo et al. (2006) for examining the propagation of information around the hydrologic cycle. We envision the hydrologic cycle over land as a loop, where variations in upstream components affect the behavior of the downstream components to varying degrees, depending on location, season, synoptic situation, etc. At its simplest,

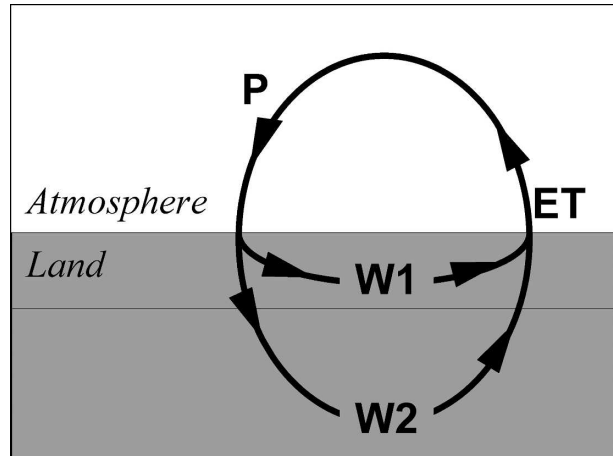


FIG. 1. Simple schematic of the local hydrologic cycle between land and atmosphere.

this can be viewed as an entirely local phenomenon. Figure 1 presents this concept as a simple schematic. Precipitation (P) falling on the land surface goes into the soil matrix, where it can reemerge to the atmosphere by one of two paths, either as direct evaporation from the surface (W1), or as transpiration through the vascular systems of the vegetation, whose roots can tap soil moisture below the surface (W2). Together, these sources of evapotranspiration contribute a latent heat flux (LH) back to the atmosphere, which influences future precipitation both by supplying water to the atmosphere and thermodynamically by contributing heat to destabilize the boundary layer, aiding the formation of convection.

This view is admittedly a gross oversimplification. First, the process is not entirely local, as advection and the general circulation of the atmosphere can easily transport water and moist static energy horizontally (Brubaker and Entekhabi 1996). There also are horizontal transports at the land surface that may be important for the hydrologic cycle in some parts of the world. For example, some portion of precipitation will run off into rivers, where it can be transported laterally downstream. There it may evaporate from rivers, lakes, wetlands, or be diverted for agriculture where it may evaporate or infiltrate and transpire. The horizontal transport of evapotranspiratable water can be especially important where major rivers flow through semi-arid or arid regions.

Second, even locally there is more going on than Fig. 1 would suggest. Evapotranspiration is not only a function of available soil moisture, but also the availability of energy to drive evaporation (net radiation), as well as the near-surface humidity, temperature, and winds. The state of the vegetation also imposes an additional

control on latent heat flux. In the atmosphere, precipitation is the result of the condensation of water vapor from rising air. This mechanism can be driven by dynamic or thermodynamic forcings that may or may not be sensitive to the evapotranspiration occurring at the bottom of the atmospheric column.

Thus, the loop portrayed in Fig. 1 is not truly a closed system. It is that fact that leads to the deterioration of “signal” as one traces the impact of a perturbation in one component of the hydrologic cycle around through the system. Can the loss of signal be quantified in a meaningful way? If so, it may serve as a means to quantify the strength of the hydrologic coupling between land and atmosphere (Koster et al. 2006). The strength of coupling cannot be established reliably in the real world, but climate models give us a laboratory where we can make an estimate. By interrupting the hydrologic cycle in the model at various locations in the feedback loop, we may increase our understanding of the roles of the processes involved. This paper aims to contribute to this understanding.

Section 2 describes the datasets used in this study, as well as principal calculations conducted. Main results for the estimation of the land–atmosphere coupling strength along each branch of the feedback loop ascertained through the flux replacement method are given in section 3. A more practical elaboration in terms of the impact of land surface initial conditions on climate forecasts is presented in section 4. Section 5 presents conclusions.

2. Data and methods

Eighteen sets of seasonal integrations of the Center for Ocean–Land–Atmosphere Studies (COLA) climate model (Kinter et al. 1997; Schneider 2002) containing the Simplified Simple Biosphere land surface model (SSiB; Xue et al. 1991, 1996; Dirmeyer and Zeng 1999a) were generated for boreal summer covering 1982–99. The simulations are at a 2.8° resolution and consist of 10-member ensembles following the method of the DSP Project (Shukla et al. 2000). Complete descriptions of the climate model components, initial conditions, and boundary conditions in the context of these DSP simulations are provided in Dirmeyer and Zhao (2004). For the current study, we examine three specific cases. In the first case, called CTL, the climate model is initialized with climatological land initial conditions, derived from an SSiB 2-yr mean climatology from the Global Soil Wetness Project (GSWP; Dirmeyer et al. 1999) as described by Dirmeyer and Zeng (1999b). In the second case, LIC, interannually varying land initial conditions are applied, taken from a 21-yr offline integration of SSiB called the Global Offline Land surface

Dataset (GOLD; Dirmeyer and Tan 2001). Note that the land surface initial condition is just a particular land surface state supplied to the climate model from which the predicted land state variables evolve. The final case, P, uses the same initialization as LIC, but the precipitation over land is specified in the land surface model from the same hybrid observation–reanalysis forcing data used to drive SSiB in producing the GOLD dataset. In other words, the land model does not “feel” the atmospheric model’s precipitation, but only the specified observed precipitation (see Dirmeyer and Zhao 2004 for details). There is no coupling of land surface runoff to river discharge into the ocean, as the ocean is a specified observed boundary condition in these integrations (Reynolds and Smith 1994).

The three cases can be viewed as lying sequentially on a spectrum of climate simulations. CTL can only simulate, at best, the contribution to seasonal climate predictability of atmospheric initial conditions and the specified observed SST. LIC adds the contribution of the land surface initial conditions, which may influence climate through the persistence and feedback of soil wetness anomalies from late boreal spring. In the P case, we might expect that the specification of observed precipitation would help constrain the model’s soil wetness relatively close to realistic values throughout the 4-month period, long beyond the initial state. Presumably, each subsequent case should encompass a more realistic simulation of climate than the previous. Beyond case P in this spectrum lie the observed climate states.

To validate the global performance of the model in simulating components of the surface hydrologic cycle, the GOLD product is used, since the only observational data records are point measurements and are very limited in number. GOLD contains monthly means of soil moisture, evapotranspiration, and runoff. Since GOLD is produced with the same SSiB model driven by a proxy of actual surface meteorology and radiation, it represents our best estimate of SSiB’s response to observed forcing. We refer to the GOLD estimates of land surface state variables and surface fluxes throughout this paper as “verification data” and use them as a proxy for the true quantities. However, precipitation is compared to an actual observational dataset: the Climate Prediction Center (CPC) Merged Analysis of Precipitation (CMAP; Xie and Arkin 1997). Note that although observed precipitation is specified over the model land surface in case P, the atmospheric model continues to simulate rainfall, and that is the quantity validated. In essence, the climate model’s predicted rainfall is the end of the line for the hydrologic pathway in case P.

The metric used for measuring the impact on predictability of land surface initial conditions and specification of downward fluxes is the “gain in predictability,” or simply “gain.” Gain is defined as the percentage of unrealized predictability attained from one case to another, measured in terms of the temporal correlation of interannual variations in anomalies between climate model and observations. This calculation is made independently for every grid point of the model. By this metric, a perfect climate prediction would capture the interannual variations in a variable X exactly, even if the model possesses a mean bias and an incorrect magnitude of variability. Presumably, such static errors in model statistics could be easily corrected a posteriori using a model output statistics (MOS) correction. In fact, since we are using the mean of a 10-member ensemble as our forecast, the variance of the ensemble mean must be lower than the variance of a single model realization, so a climate model with perfect interannual variability must have comparatively weak interannual variance of the ensemble mean.

All calculations in this study use either monthly or seasonal means. If we define the temporal anomaly correlation coefficient (ACC) across 18 yr at a location for variable X of the control case as r_{CTL} , then the signed explained variance is

$$R_{CTL} = r_{CTL}|r_{CTL}|. \quad (1)$$

The reason we do not use the conventional formulation for explained variance, r^2 , is that our formulation for gain requires calculation of differences, where the sign affects the meaning of the result; there exists information in the sign of the correlation. We assume that each year is independent from the others, so at each location there are 18 data points, and 16 degrees of freedom for estimation of statistical significance. The unrealized predictability is $1 - R_{CTL}$, which can vary from 0 to 2. When realistic land initial conditions are used (LIC), there will be a different signed explained variance: R_{LIC} . The gain in predictability due to use of realistic land initial conditions is defined as

$$G_{LIC} = \frac{R_{LIC} - R_{CTL}}{1 - R_{CTL}}. \quad (2)$$

Similarly, the further gain from the specification of observed precipitation fluxes at the surface is defined as

$$G_P = \frac{R_P - R_{LIC}}{1 - R_{LIC}}. \quad (3)$$

The gain is the increase in explained variance, and can be negative (a loss) if the ACC decreases. In the figures and tables we express it as a percentage on a 100-point scale. For any one case in the context of Fig. 1, the gain

in predictability of the terms progressing around the hydrologic cycle is depleted as the signal of the imposed initial or boundary condition erodes around the pathway. By calculating the gain at each point in the cycle, we can see where the signal is being lost. This locates the weak links in the coupling between land and atmosphere. By applying this analysis globally, we may find regional differences in predictability gain and signal loss within the hydrologic cycle, which may give clues to the causes of each.

To easily quantify the gains on a larger scale, we can calculate spatial averages over land points. However, a simple average is not appropriate (DelSole and Shukla 2006). The average over N land grid points for a gain G is calculated as

$$G_{Land} = \frac{-\sum_{i=1}^N A_i \ln(1 - G_i)}{2 \sum_{i=1}^N A_i}, \quad (4)$$

where A_i is the area of grid box i . This approach follows the concept of localized mutual information (DelSole and Shukla 2006), including the penalization for negative correlations incorporated into Eq. (1).

3. Gain from specified precipitation

The ability of this model to simulate the mean components of the global water cycle was illustrated by Dirmeyer (2003), Dirmeyer and Zhao (2004), and Dirmeyer (2005). Figure 2 shows the statistical significance of R_{LIC} for the four terms labeled in Fig. 1. Surface soil wetness (W1) has generally lower correlation than root zone soil wetness (W2) at the seasonal time scale because the water-holding capacity of the surface layer, and thus its memory of initial conditions, is so small ($\sim 13 \text{ kg m}^{-2}$). However, both soil wetness fields show greater memory of initial conditions in dry regions, where there is less noise in the form of heavy precipitation events to erase the persistent signal of the initial conditions. There are also significant correlations in some of the humid coastal regions of the Tropics (e.g., the Atlantic coast of South America) and regions of the Southern Hemisphere (e.g., eastern Australia) that result from SST controls on terrestrial precipitation there (P). Skill in LH resembles that for soil wetness but is slightly weaker and largely absent from humid forested regions.

When atmospheric model precipitation is replaced by observed precipitation as an input to the land model in the coupled land-atmosphere climate system, changes occur in the terms of the hydrologic cycle. Figure 3 shows the gain in predictability G_P of seasonal means

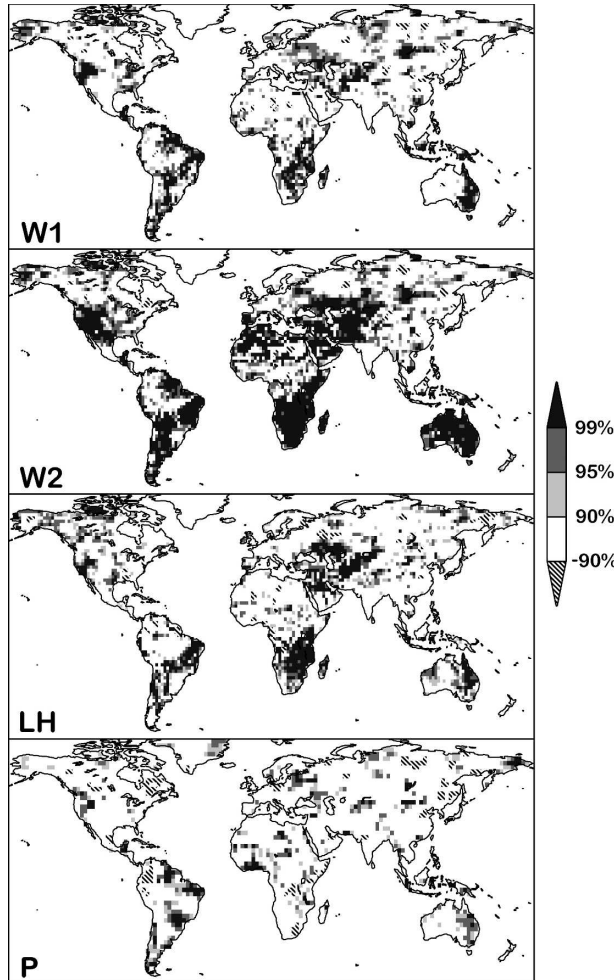


FIG. 2. Significance of temporal correlations over 18 yr between case LIC and observations (R_{LIC}) of JJAS mean surface soil wetness (W1); root zone soil wetness (W2); latent heat flux (LH); and precipitation (P).

realized from case LIC to case P. The effect that precipitation has on the surface soil wetness is evident in the sharp gains seen for W1 over rainy regions of the globe. Whereas random synoptic events have the capacity to erase soil wetness signals, specified observed precipitation reinforces them. The gains are somewhat weaker in root zone soil wetness. Comparing to the corresponding panels in Fig. 2, it is clear that the gains are realized mainly in regions that had little or no skill in case LIC, and that there was little predictability to be gained in the arid regions, perhaps because there is little precipitation signal there to begin with. Huge gains are seen for latent heat flux, which are sharply confined to drier regions (notice the strong gradients in locations such as the Great Plains of the United States and the Sahel region of Africa). This pattern of response appears to be tied to vegetation. Forests have

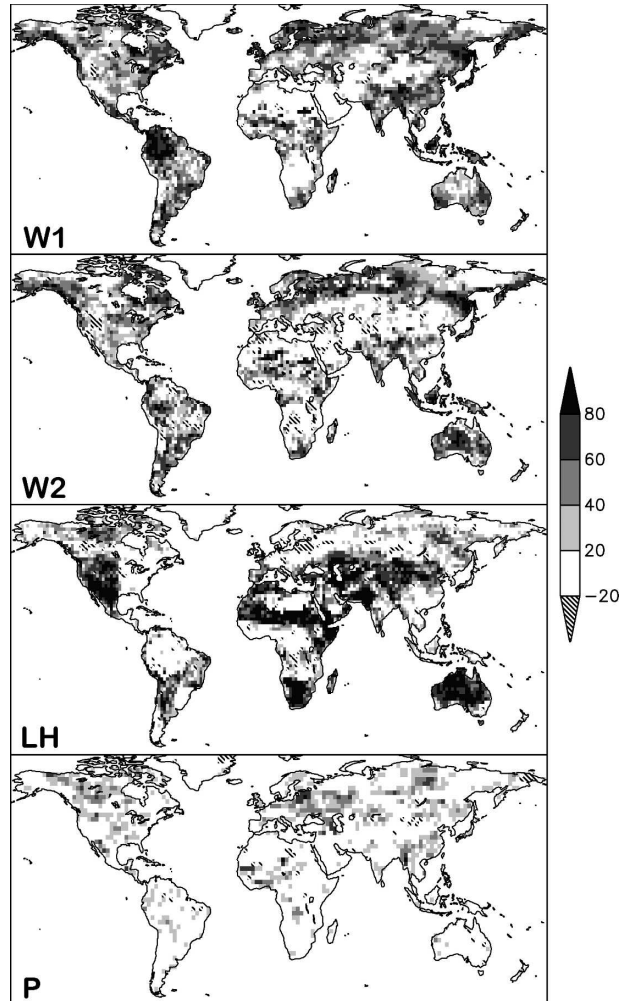


FIG. 3. The gain in predictability, G_p , from case LIC to P during JJAS.

deep roots and a relatively stable rate of transpiration over a wide range of soil wetness in this and other land surface models (see Fig. 5 of Dirmeyer et al. 2000). Water is not the limiting factor here. Rather, evapotranspiration is controlled by other factors such as the availability of net radiation and the near-surface relative humidity. In the dry regions, evapotranspiration is water limited, and thus strongly tied to the time series of rainfall. Rain that does occur goes almost entirely into evapotranspiration, and does not remain long in the soil matrix. The atmospheric model precipitation shows broad areas with relatively weak gains in predictability ($>20\%$), yet almost no areas with losses of predictability of more than 20%. It appears that the specification of observed precipitation over land imparts a signal in the hydrologic cycle that survives transit through the land surface to improve the model's simulation of precipitation over many areas.

TABLE 1. Global mean of percentage gain in predictability from case LIC to P (G_P) for the terms as shown in Fig. 3.

	Jun	Jul	Aug	Sep	JJAS
Specified precipitation	100	100	100	100	100
Surface soil wetness	32	38	31	30	29
Root zone soil wetness	21	31	26	27	23
Latent heat flux	25	29	32	37	37
Model precipitation	3	7	8	9	7

Table 1 quantifies G_{Land} , the global average of G_P (land only between 60°S and 80°N), for the variables of the hydrologic cycle during each month of the season, as well as for the seasonal mean. One may read down each column of the table as a progression along the hydrologic cycle illustrated in Fig. 1. The first row, specified precipitation, is listed merely as a reference point where the signal, and thus the gain in predictability, is presumed to be perfect and complete. The gain realized in the predictability of soil wetness is 30%–38% at the surface, and around 10% lower for the root zone. Latent heat flux lies between the two. The gain in the heretofore unrealized predictability of precipitation is less than 10% on the global scale. This suggests that in this model on the global scale, the hydrologic feedback loop is not very strong.

Global means mask a great deal of regional variability, evident in Fig. 3. Figure 4 shows G_{Land} for each variable during June–September (JJAS) composited based on mean model precipitation. Each bin shows G_{Land} averaged only over those terrestrial grid boxes where the mean rainfall lies within the ranges shown on the bottom axis. The bars show the percentage of land area that falls within each bin—the COLA model tends to have a precipitation distribution that overweighs high and low rainfall rates, with too small an area showing moderate precipitation.

Gains in predictability of soil wetness are greater in wet regions than in dry. Gains in W2 peak for rainfall rates around 3 mm day⁻¹, while gains in W1 continue to grow with increasing precipitation. More interesting is the response of LH and P . Latent heat flux shows very high average gains over arid regions and small gains in wet zones. This is consistent with the hypothesis of Guo et al. (2006) that coupling in the land segment of the hydrologic cycle is strongest in dry areas. Guo et al. (2006) also contend that the atmospheric state (namely, low moist static energy and high lifting condensation levels) preconditions the planetary boundary layer to have low sensitivity of precipitation to LH variations over deserts, but high sensitivity in humid regions where the atmosphere is conditionally unstable. The result of these two opposing spectra of sensitivity is a

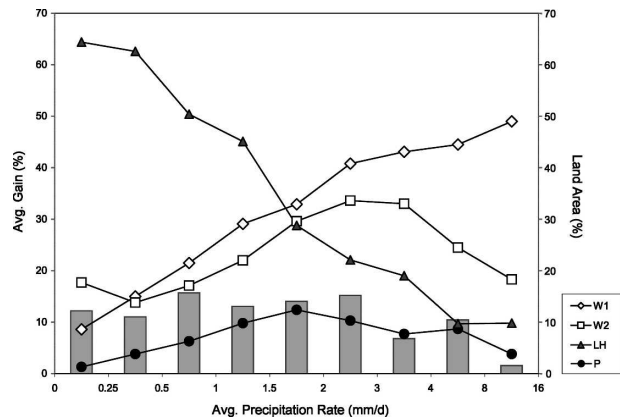


FIG. 4. Spatially averaged G_P for JJAS categorized by mean model precipitation rate. Bars indicate the percentage of total land area (between 60°S and 80°N) in each category.

peak in the responsiveness of precipitation to soil wetness variations in the transition zone between wet and dry climates (Koster et al. 2003). This structure is reflected in the gain for P in Fig. 3, which is small at both extremes but peaks between 1.5–2 mm day⁻¹.

One may also consider the problem in terms of a perfect precipitation signal being lost as one progresses through the hydrologic cycle (100% – G_{Land}). From this perspective according to Table 1, globally 60%–70% of the signal is already lost in the surface soil wetness. This is largely because other factors regulating surface evaporation, such as temperature, humidity, and downward radiation (available energy) are not controlled so are still free to vary in case P. Degradation in root zone soil wetness is slightly more severe, in the order of 70%–80%. Latent heat flux maintains its signal in arid regions, but completely loses it in humid regimes, as indicated in Fig. 3. The net result is a 65%–75% loss of signal globally. Over 90% of the signal is lost in a complete circuit of the hydrologic cycle, as indicated by the remaining gains for precipitation.

This train of thought, given the conceptual model of the hydrologic cycle presented in Fig. 1, requires W1 to have the highest values of G_{Land} , followed in order by W2, LH, and finally P . An increase in gain along this sequence denotes an apparent recovery of lost signal. In fact, signal recovery is impossible. Rather, this pattern shows where the simple pathway model of Fig. 1 is not valid, or where random variations have created a bogus region of apparent signal recovery. Figure 4 shows disagreement to be the case over dry regions. In these areas the memory of surface soil wetness is very short, as described previously. The nearly direct link between specified precipitation and surface evaporation creates a stronger signal than between specified precipitation and soil wetness, leading to an inversion

in the chain of decreasing gains. Over humid vegetated regions, as stated previously, that evapotranspiration is largely decoupled from precipitation, so there is a large loss of signal from soil wetness to latent heat flux in these areas.

The loss of signal from latent heat flux to model precipitation is severe over arid regions. Here the air is so dry, and the boundary layer so far from moist convective instability, that fluctuations in evaporation have little impact on the likelihood of rainfall. However, in humid regions the remaining signal, though weak, appears to be largely preserved.

There exist a number of areas in humid climates with negative gain in latent heat flux (Fig. 3). Replacement of precipitation with observations without the concomitant replacement of observed downward radiation may introduce inconsistencies that have a detrimental impact on the skill of the surface evapotranspiration. When integrations are performed where shortwave and longwave fluxes are also replaced, the areas of large negative gain in latent heat flux disappear (Dirmeyer and Zhao 2004). In some regions such as Southeast Asia, tropical Africa, and Siberia, it seems that sensible heat flux may provide the pathway for the precipitation signal (not shown). This illuminates one of the complicating factors in this simple analysis approach—because the hydrologic cycle shown in Fig. 1 does not operate in isolation, but is intertwined with the surface energy balance, atmospheric thermodynamics, and the general circulation, substitution of precipitation can have unintended consequences. For example, there exists a thermal feedback between surface temperature, sensible heat flux, and the general circulation through the development and maintenance of surface pressure features (e.g., thermal lows) and upper-level ridges. Although it may be initiated by soil wetness anomalies, this pathway is not through the hydrologic cycle. Yet it can have major impacts on regional hydrology, such as changing moisture flux convergence. Specification of only one of the upper boundary conditions to the land model can introduce irregularities beyond the simple loop of Fig. 1 that can reemerge within the hydrologic cycle through its connections with the broader climate system. This caveat should be kept in mind when regarding regional details of this analysis.

To summarize the effects of specifying observed precipitation on the simulation of the hydrologic climate anomalies in this model, we can make the following statements. The schematic presented in Fig. 1 has flaws that appear in both wet and dry regimes. In moisture-limited regions, specified precipitation anomalies are expressed almost immediately as LH anomalies that compare well with verification data but with little last-

ing response in soil wetness on monthly–seasonal time scales. Yet these improvements in simulated surface fluxes of moisture do not improve much the simulation of P . In wet regions the circuit depicted in Fig. 1 is a more accurate representation of the process, but there is significant degradation at each step in the terrestrial section of the pathway. Thus little of the signal of specified P is expressed in LH. In the transition areas cumulative loss of signal is minimized, and coupling around the entire pathway appears to be best preserved. Biases in precipitation in the COLA model may weaken its overall hydrologic feedback, because moderate precipitation rates are underrepresented in the model climatology.

4. Gain from land initial conditions

The process for analyzing the propagation of signals in precipitation around the hydrologic cycle also can be applied to understand how initial conditions of soil wetness affect the forecast of precipitation. Figure 5 shows the gains in predictability on the seasonal (JJAS) scale from the use of realistic initial land surface conditions at 1 June (G_{LIC}). The gains are stronger in the subsurface soil wetness than at the surface because of the larger reservoir and thus longer memory there. The strongest gains are over arid regions, dry-season monsoon areas of the Southern Hemisphere, and Mediterranean climates of the Northern Hemisphere. In these regions there is essentially no rainfall, so anomalies of subsurface soil wetness can persist until rains begin again. Patterns of the gains in predictability of latent heat flux resemble those of W2, but are generally weaker. There is essentially no significant signal apparent in precipitation.

Of course, the gain from initial conditions ought to be strongest during the first month. This is shown in Table 2. Nevertheless, we see that soil wetness initialization has only a weak impact on latent heat flux even in June. By July, only root zone soil wetness preserves any memory of the initial condition information, and it does not appear to convey that information to other parts of the hydrologic cycle. Deviations are again a function of regional climate variations. Figure 6 shows the area averages of the seasonal gains G_{LIC} binned by precipitation rates (relative areas for each bin are the same as in Fig. 4). Also shown as small symbols with no connecting lines are June values. As evident in Table 2, the gain from land initial conditions skips W1 and goes straight to W2. This is an artifact of the short memory of the surface soil layer, and not a signal recovery. The surface soil layer, which is only 30 mm thick in this model, has such a small capacity that its soil moisture can easily be extracted by evaporation in a single day. Gains in the

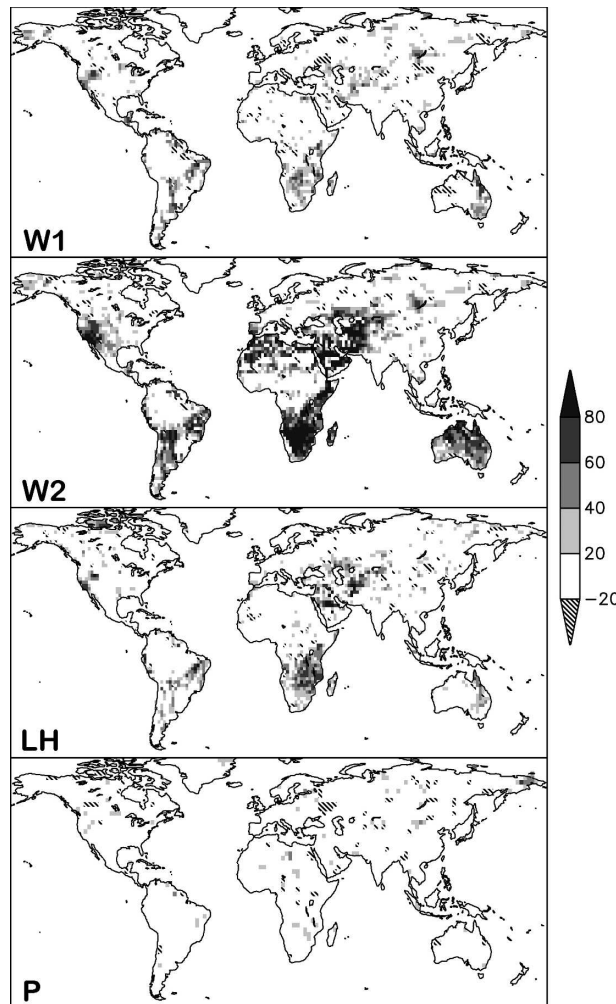


FIG. 5. The gain in predictability, G_{LIC} , from case CTL to LIC during JJAS.

other terms stratify in accordance with the conceptual model of Fig. 1 for all precipitation regimes. Gains in W2 are very strong in dry regions, but taper off sharply as mean precipitation increases. Gains in LH are also much stronger in arid regions than in humid ones, but overall are much weaker than the gains in W2. There are only tiny gains in P in any rainfall regime.

The gains for the first month of the simulations are

TABLE 2. As in Table 1 for G_{LIC} .

	Jun	Jul	Aug	Sep	JJAS
Specified precipitation	100	100	100	100	100
Surface soil wetness	8	0	-1	-1	4
Root zone soil wetness	40	21	15	11	23
Latent heat flux	8	2	1	0	6
Model precipitation	0	0	-1	0	0

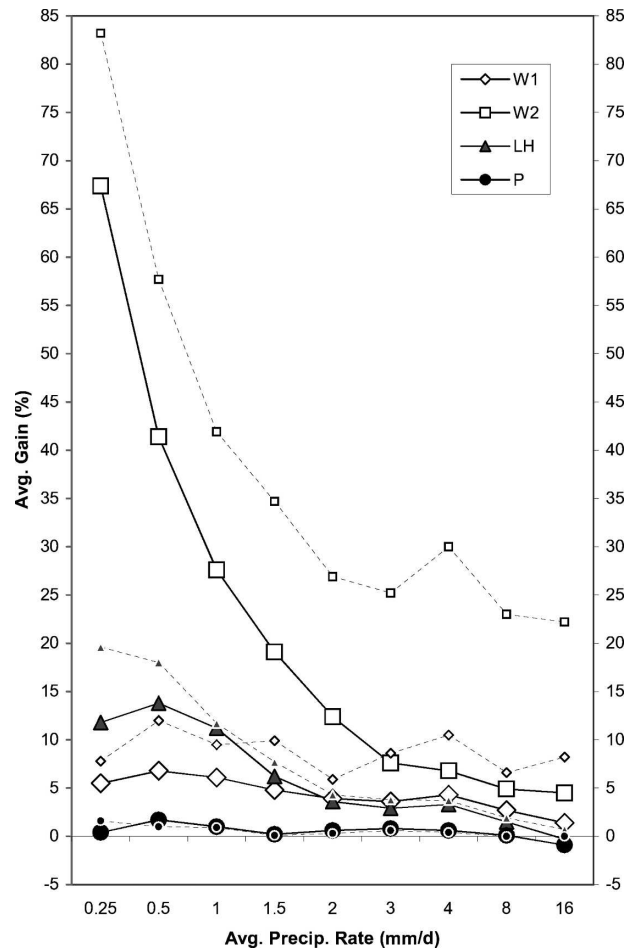


FIG. 6. Spatially averaged G_{LIC} for JJAS categorized by mean model precipitation rate. Small unconnected symbols show G_{LIC} for June only.

much larger than for the seasonal mean for both soil wetness terms (the W2 gain for the driest bin is off the scale at 83%). However, these higher values are transmitted to LH only in the driest two bins, and have almost no signature in precipitation.

As described above, barren deserts lack a direct mechanism to convey water from the subsurface to the atmosphere, so the root zone soil wetness signal cannot be manifest easily in latent heat. This helps to preserve rather than erase the soil wetness anomalies. In sparsely vegetated areas transpiration is an active mechanism for linking the subsurface to the atmosphere. Here lies a domain where initial soil wetness anomalies can be expressed in the latent heat flux term over the course of months, since moisture stress on vegetation in this region is high and transpiration rates are small. But the dry atmosphere in these areas is not motivated to generate rainfall anomalies by the small variations in latent heat flux, so the signal is lost within

the atmospheric boundary layer. The humid regions lose their root zone soil wetness signal quickly. The magnitude of the initial anomalies is relatively small compared to the monthly rainfall or evapotranspiration totals in those areas, and they are quickly erased.

5. Conclusions

We have examined the impact of changes at particular segments of the hydrologic cycle (Fig. 1) on downstream branches, as a means to measure the strength of coupling between land and atmosphere in a climate model. Specifically, we define a signal (an increase in quality measured in terms of temporal correlations) generated by realistic initial conditions or prescribed observed precipitation input as an upper boundary condition for the land component of the climate model. We examine how this signal propagates around the feedback loop. By examining the resulting change in the simulation of monthly and seasonal climate anomalies of each component of the hydrologic cycle, the “gain in predictability,” we determine where most of the signal is lost.

Soil wetness and latent heat flux anomalies are most persistent in dry regions, where the capacity of the soil is large relative to the magnitude of water fluxes between atmosphere and land. This shows up clearly when realistic initial conditions of soil wetness are used (Fig. 2). This regional skill fails to manifest itself in model precipitation. The only skill in this quantity over land is in some coastal tropical and Southern Hemisphere locations where maritime advection or teleconnections convey information from the specified, interannually varying SSTs.

Specification of observed precipitation as the water input to the land surface component of the climate model conveys a signal through the hydrologic cycle that increases the skill in the simulation of soil wetness, latent heat flux, and even the predicted model precipitation over many areas. However, the average gain in unrealized predictability of rainfall was less than 10% when averaged over all land points, suggesting that the hydrologic feedback loop is not strong in this model.

When specifying observed precipitation, there is tremendous regional variability. The precipitation signal is conveyed strongly to soil wetness in rainy regions, but predictability gains in evapotranspiration arise primarily in dry regions. These differences are due to the different moisture stress regimes. In humid regions vegetation is deep rooted (primarily trees and shrubs) and usually unstressed, so evaporation is relatively insensitive to all but extreme rainfall anomalies. The anomalies survive to be expressed as soil wetness anomalies

throughout the season. Additionally, the magnitude of the underlying signal of specified P is greatest where P is greatest. In dry regions, potential evaporation is high, and most rainfall is quickly evaporated, leaving little imprint on soil wetness beyond a few days after the rain event. There is a peak in the gain for P between these extremes over regions of moderate mean precipitation. This is consistent with the multimodel results of Koster et al. (2006) and Guo et al. (2006), who show that the strongest land–atmosphere coupling (from W2 to P) exists in the transition zones between arid and humid climates.

Unlike the case of specified precipitation, use of realistic land surface initial conditions generates gains for soil wetness most strongly in arid regions. Given the relatively weak hydrologic feedback in this particular model, and its climate drift (Dirmeyer 2001, 2003), it is not surprising that there is no appreciable signal transmitted to model precipitation by the use of realistic soil wetness initialization. However, latent heat flux responds with gains in predictability over semiarid grasslands and savannahs, where transpiration is small but nonzero.

It should be noted that the feedback cycle is severed in the case of specifying observed precipitation, while it is not in the case of realistic land surface initial conditions. Thus, the apparent strength of the signal in the former case may be magnified because the system lacks a means to compensate through adjustment of the precipitation felt by the land surface. Of course, the feedback could be of either sign, so it is also possible that specification of rainfall subdued the signal in some locations. However, the magnitude of the precipitation errors in the climate model is typically much larger than the variations in evapotranspiration simulated across a range of soil wetnesses. Thus, it is doubtful that the effect of realistic initial land states could have as large an impact as correction of the precipitation biases in this model.

In this paper we try to put forward a new way of looking at the potential and realizable predictability that may be imparted on the global climate system through improved simulation of the hydrologic cycle over land. By examining what happens to a specific signal as it propagates around the hydrologic cycle, we may better appreciate the difficulty we face in making useful improvements to seasonal forecasts. Of course, only one climate model is examined here, but the following deduction is likely applicable to predictions with any dynamical climate model. The role of the land surface in contributing to useful improvements in the prediction of precipitation anomalies is likely to be limited to certain locations and times of year because a number

of other factors modulate the ability of climate signals to persist and propagate through the hydrologic branch of the coupled land–atmosphere system. Identification of the regions and seasons of strong sensitivity may help us to efficiently deploy enhancements to our observational network for collection of more and better data for forecast initialization, as well as guiding us to a better understanding and simulation of the global hydrologic cycle.

Acknowledgments. Thanks to Vasubandhu Misra for insightful comments and ideas, and to Michael Bosilovich and two anonymous reviewers for suggestions that have helped me to improve this paper. This work was conducted as part of omnibus research at the Center for Ocean–Land–Atmosphere Studies, supported by NSF Grant ATM-0122850, NOAA Grant NA16-GP2248, and NASA Grant NAG5-11656.

REFERENCES

- Atlas, R., N. Wolfson, and J. Terry, 1993: The effect of SST and soil moisture anomalies on GLA model simulation of the 1988 U.S. summer drought. *J. Climate*, **6**, 2034–2048.
- Beljaars, A. C., P. Viterbo, M. J. Miller, and A. K. Betts, 1996: The anomalous rainfall over the United States during July 1993: Sensitivity to land surface parameterization and soil moisture anomalies. *Mon. Wea. Rev.*, **124**, 362–383.
- Bosilovich, M. G., and W.-Y. Sun, 1999: Numerical simulation of the 1993 midwestern flood: Local and remote sources of water. *J. Geophys. Res.*, **104**, 19 415–19 423.
- Brubaker, K. L., and D. Entekhabi, 1996: Analysis of feedback mechanisms in land–atmosphere interaction. *Water Resour. Res.*, **32**, 1343–1357.
- DelSole, T., and J. Shukla, 2006: Specification of wintertime North American surface temperature. *J. Climate*, **19**, 2691–2716.
- Diedhiou, A., and J. F. Mahfouf, 1996: Comparative influence of land and sea surfaces on the Sahelian drought: A numerical study. *Ann. Geophys.*, **14**, 115–130.
- Dirmeyer, P. A., 1995: Problems in initializing soil wetness. *Bull. Amer. Meteor. Soc.*, **76**, 2234–2240.
- , 2000: Using a global soil wetness data set to improve seasonal climate simulation. *J. Climate*, **13**, 2900–2922.
- , 2001: Climate drift in a coupled land–atmosphere model. *J. Hydrometeorol.*, **2**, 89–100.
- , 2003: The role of the land surface background state in climate predictability. *J. Hydrometeorol.*, **4**, 599–610.
- , 2005: The land surface contribution to the potential predictability of boreal summer season climate. *J. Hydrometeorol.*, **6**, 618–632.
- , and F. J. Zeng, 1999a: An update to the distribution and treatment of vegetation and soil properties in SSiB. COLA Tech. Rep. 78, 25 pp. [Available from Center for Ocean–Land–Atmosphere Studies, 4041 Powder Mill Road, Suite 302, Calverton, MD 20705.]
- , and —, 1999b: Precipitation infiltration in the simplified SiB land surface scheme. *J. Meteor. Soc. Japan*, **77**, 291–303.
- , and L. Tan, 2001: A multi-decadal global land-surface data set of state variables and fluxes. COLA Tech. Rep. 102, 43 pp. [Available from Center for Ocean–Land–Atmosphere Studies, 4041 Powder Mill Road, Suite 302, Calverton, MD 20705.]
- , and M. Zhao, 2004: Flux replacement as a method to diagnose coupled land–atmosphere model feedback. *J. Hydrometeorol.*, **5**, 1034–1048.
- , A. J. Dolman, and N. Sato, 1999: The Global Soil Wetness Project: A pilot project for global land surface modeling and validation. *Bull. Amer. Meteor. Soc.*, **80**, 851–878.
- , F. J. Zeng, A. Ducharne, J. C. Morrill, and R. D. Koster, 2000: The sensitivity of surface fluxes to soil water content in three land surface schemes. *J. Hydrometeorol.*, **1**, 121–134.
- , M. J. Fennessy, and L. Marx, 2003: Low skill in dynamical prediction of boreal summer climate: Grounds for looking beyond sea surface temperature. *J. Climate*, **16**, 995–1002.
- Douville, H., 2002: Influence of soil moisture on the Asian and African monsoons. Part II: Interannual variability. *J. Climate*, **15**, 701–720.
- , 2003: Assessing the influence of soil moisture on seasonal climate variability with AGCMs. *J. Hydrometeorol.*, **4**, 1044–1066.
- , F. Chauvin, and H. Broqua, 2001: Influence of soil moisture on the Asian and African monsoons. Part I: Mean monsoon and daily precipitation. *J. Climate*, **14**, 2381–2403.
- Fennessy, M. J., and J. Shukla, 1999: Impact of initial soil wetness on seasonal atmospheric prediction. *J. Climate*, **12**, 3167–3180.
- Garric, G., H. Douville, and M. Déqué, 2002: Prospects for improved seasonal predictions of monsoon precipitation over Sahel. *Int. J. Climatol.*, **22**, 331–345.
- Guo, Z., and Coauthors, 2006: GLACE: The Global Land–Atmosphere Coupling Experiment. Part II: Analysis. *J. Hydrometeorol.*, **7**, 611–625.
- Kanamitsu, M., C.-H. Lu, J. Schemm, and W. Ebisuzaki, 2003: The predictability of soil moisture and near-surface temperature in hindcasts of the NCEP seasonal forecast model. *J. Climate*, **16**, 510–521.
- Kinter, J. L., and Coauthors, 1997: Formulation. Vol. 1. The COLA atmosphere–biosphere general circulation model, COLA Tech. Rep. 51, 46 pp. [Available from Center for Ocean–Land–Atmosphere Studies, 4041 Powder Mill Road, Suite 302, Calverton, MD 20705.]
- Koster, R. D., and M. J. Suarez, 2003: Impact of land surface initialization on seasonal precipitation and temperature prediction. *J. Hydrometeorol.*, **4**, 408–423.
- , P. A. Dirmeyer, A. N. Hahmann, R. Ijpeelaar, L. Tyahla, P. Cox, and M. J. Suarez, 2002: Comparing the degree of land–atmosphere interaction in four atmospheric general circulation models. *J. Hydrometeorol.*, **3**, 363–375.
- , M. J. Suarez, R. W. Higgins, and H. Van den Dool, 2003: Observational evidence that soil moisture variations affect precipitation. *Geophys. Res. Lett.*, **30**, 1241, doi:10.1029/2002GL016571.
- , and Coauthors, 2004: Regions of coupling between soil moisture and precipitation. *Science*, **305**, 1138–1140.
- , and Coauthors, 2006: GLACE: The Global Land–Atmosphere Coupling Experiment. Part I: Overview. *J. Hydrometeorol.*, **7**, 590–610.
- Paegle, J., K. C. Mo, and J. Nogues-Paegle, 1996: Dependence of simulated precipitation on surface evaporation during the 1993 United States summer floods. *Mon. Wea. Rev.*, **124**, 345–361.
- Reynolds, R. W., and T. M. Smith, 1994: Improved global sea sur-

- face temperature analyses using optimal interpolation. *J. Climate*, **7**, 929–948.
- Schlosser, C. A., and D. M. Mocko, 2003: The impact of snow conditions in spring dynamical seasonal predictions. *J. Geophys. Res.*, **108**, 8616, doi:10.1029/2002JD003113.
- Schneider, E. K., 2002: The causes of differences between equatorial Pacific SST simulations of two coupled ocean–atmosphere general circulation models. *J. Climate*, **15**, 449–469.
- Shukla, J., and Coauthors, 2000: Dynamical seasonal prediction. *Bull. Amer. Meteor. Soc.*, **81**, 2593–2606.
- Sud, Y. C., D. M. Mocko, K.-M. Lau, and R. Atlas, 2003: Simulating the Midwestern U.S. drought of 1988 with a GCM. *J. Climate*, **16**, 3946–3965.
- Timbal, B., S. Power, R. Colman, J. Viviani, and S. Lirola, 2002: Does soil moisture influence climate variability and predictability over Australia? *J. Climate*, **15**, 1230–1238.
- Xie, P., and P. A. Arkin, 1997: Global precipitation: A 17-year monthly analysis based on gauge observations, satellite estimates, and numerical model outputs. *Bull. Amer. Meteor. Soc.*, **78**, 2539–2558.
- Xue, Y., P. J. Sellers, J. L. Kinter, and J. Shukla, 1991: A simplified biosphere model for global climate studies. *J. Climate*, **4**, 345–364.
- , F. J. Zeng, and C. A. Schlosser, 1996: SSiB and its sensitivity to soil properties—A case study using HAPEX-Mobilhy data. *Global Planet. Change*, **13**, 183–194.
- Yang, F., A. Kumar, W. Wang, H.-M. H. Juang, and M. Kanamitsu, 2001: Snow–albedo feedback and seasonal climate variability over North America. *J. Climate*, **14**, 4245–4248.