

Climate Drift in a Coupled Land–Atmosphere Model

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ABSTRACT

A coupled land–atmosphere climate model is examined for evidence of climate drift in the land surface state variable of soil moisture. The drift is characterized as pathological error growth in two different ways. First is the systematic error that is evident over seasonal timescales, dominated by the error modes with the largest saturated amplitude: systematic drift. Second is the fast-growing modes that are present in the first few days after either initialization or a data assimilation increment: incremental drift. When the drifts are robust across many ensemble members and from year to year, they suggest a source of drift internal to the coupled system. This source may be due to problems in either component model or in the coupling between them. Evidence is presented for both systematic and incremental drift. The relationship between the two types of drift at any given point is shown to be an indication of the type and strength of feedbacks within the coupled system. Methods for elucidating potential sources of the drift are proposed.

1. Introduction

Climate drift is a characteristic of coupled climate model systems. It is defined as the separation over time of the pattern and magnitude of one or more simulated state variables from the observed state in a systematic, repeatable way. The individual components in a coupled system, when allowed to evolve in the absence of data assimilation or other constraints, will come to a quasi-stable balance with one another. This state may not be close to the system's initial state, nor to the observed state. If the feedbacks between two systems are not well balanced, an incorrect equilibrium may be attained.

Climate drift has long been acknowledged and addressed in coupled ocean–atmosphere model systems. Manabe et al. (1991) among others have applied a flux adjustment to correct for inconsistencies at the interface between coupled ocean and atmosphere models. Another approach is to apply corrections to state variables near the interface within one of the component models (e.g., Huang and Schneider 1995). These adjustments usually are attempts to relax model quantities toward some observed or uncoupled mean climate. An alternative is to tune physical parameters carefully within one or both models to minimize drift (e.g., Schneider

et al. 1997). In addition, initialization procedures may be applied to the component models to attempt to minimize imbalances at the start of an integration. Last, one may use an anomaly coupling approach (e.g., Ji et al. 1994; Kirtman et al. 1997) in which one or both component models are not exposed to the mean state (and thus the systematic error) of the opposing model, but only to perturbations from the mean model climates.

Climate drift also exists in coupled land–atmosphere models. However, it is more difficult to verify because accurate data on land state variables (e.g., soil wetness or snow water mass) are very sparse in comparison with ocean state variables (e.g., sea surface temperature). Also, it is difficult to correct, because the relationships defining the land state and evolution are more varied, less well understood, and more empirical than the equations defining the state and evolution of fluids such as the atmosphere and ocean.

As with ocean–atmosphere models, drift can be caused by either component model, as well as by the coupling method itself. For a land–atmosphere system, one can visualize how systematic errors in the atmospheric general circulation model (AGCM) may affect near-surface fluxes of energy (e.g., by problems in the radiation or cloud parameterizations, or neglect of the radiative consequences of aerosols), and water (via problems in the parameterization of convection, or simulation of boundary layer humidity, which regulates evapotranspiration). These problems are very common across AGCMs, particularly those that stem from poor simulation of clouds and associated moist processes,

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because clear-sky radiative transfer and dry thermodynamics and fluid dynamics are generally well understood and duplicated in models.

The land surface scheme (LSS) may also have errors that affect the fluxes of heat, water, and momentum. Problems exist in the basic data on vegetation and soil properties and their distribution. There are vast areas of the globe where basic properties of the land surface on large scales are not well observed or documented. In addition, the means by which such information should be applied within an LSS are not completely understood. In many cases, quantities that are observable do not correspond directly with model parameters. Last, the parameterizations within an LSS that are designed to determine the storage and exchange of heat and moisture between atmosphere and land are in many cases based not on a complete physical understanding of the system but on an incomplete empirical sampling of a limited number of sites extrapolated to global application.

Last, there is demonstrable sensitivity, and thus uncertainty, to the way in which an AGCM and an LSS are coupled. Empiricism also exists in the parameterization of the planetary boundary layer in the AGCM and its connection to the land surface, the formulation of atmospheric stability, and near-surface turbulence (and thus the exchange of fluxes). Even the numerics of the coupling, which are designed to handle properly the shortcomings of finite spatial and temporal resolution in an efficient manner, can directly affect the balance between system components.

Drift is normally quantified as the growing difference between model and observed states over time when the model is initialized from an observed state. This cannot be done on a large scale with the land surface because important land surface state variables are not observed on large scales. Remote sensing can be used to observe global skin temperature, and in some regions a near-surface soil wetness index, but these variables tend to have a fast response time strongly driven by the atmosphere. Slowly varying land state variables, which integrate cumulative errors such as water content in the top meter of soil, would be an ideal metric. Unfortunately, these data are not available as part of an operational global observing network. However, one can apply a proxy to observed soil wetness, with the added bonus that the proxy is consistent with the LSS interpretation of soil wetness, namely, a soil wetness field generated offline in an uncoupled mode, where the same LSS is driven by observed/analyzed hydrometeorological forcings. Using an offline product as a substitute for “ground truth,” one can begin to identify and to quantify drift in coupled land–atmosphere models.

In this paper, drift in one coupled land–atmosphere climate model will be quantified and examined. Section 2 defines the two kinds of “drift” analyzed in this paper. Section 3 describes the LSS and AGCM used in this study, the generation of the observed soil moisture proxy, and the coupled land–atmosphere modeling ex-

periments. Sections 4 and 5 describe the two kinds of drift as observed in this coupled model system. Section 6 synthesizes the two kinds of drift into a single representation related to feedbacks in the coupled system. Conclusions are given in section 7.

2. Definitions of drift

Before proceeding, it will be necessary to define climate drift for coupled land–atmosphere models in a quantifiable fashion. In this paper, only soil moisture will be examined. Drift can be defined in more than one way. Two unique definitions will be used in here. The first is analogous to the systematic error of soil moisture in the coupled land–atmosphere model, essentially the accumulated effect of the drift over a season. At every grid box in the LSS, a water balance is maintained:

$$P - E - R - \Delta S = \Delta W, \quad (1)$$

where P is the precipitation rate (positive downward flux of moisture); E is evapotranspiration rate (positive from land to atmosphere); R is surface and subsurface runoff rate (positive out of the grid box); ΔW is the rate of change in the soil reservoir, that is, the rate of change in column-integrated soil moisture; and ΔS is the rate of change in other storage, such as snowpack and moisture intercepted by the canopy. Over time, errors in the left-hand side will accumulate in the ΔW term. The drift on the time scale of a season can be defined as

$$D_s = \int (\Delta W_{\text{MODEL}} - \Delta W_{\text{OBS}}) dt. \quad (2)$$

Note that the change in soil moisture itself is not the drift; there may be a real observed seasonal change. Here, D_s is the difference between the coupled model’s evolution of ΔW and that which is observed. If D_s is robust in its magnitude and spatial patterns across many integrations of the coupled model, it serves as a measure of the systematic error in surface water fluxes.

An alternative to this long-timescale definition is one based on the initial errors or corrections in a data assimilation context: the increments. Here, the water balance equation becomes

$$P - E - R - \Delta S + I = \Delta W, \quad (3)$$

where I is the analysis increment for soil moisture, added periodically to adjust the soil moisture based on an a priori criterion, such as the minimization of near-surface temperature or humidity errors (Douville et al. 2000). Thus, a definition for incremental drift would be the average of these short-timescale increments over the same time period as in (2), with the seasonal evolution included:

$$D_t = \frac{1}{N} \sum_{n=1}^N (\Delta W_{\text{MODEL}^*} - I), \quad (4)$$

where N is the number of data assimilation increments

during the period. Note that the change in model soil moisture here is not the same as in (2), given that in this case the integration is constrained by the data assimilation. Thus, if the increments I are chosen to keep the model soil moisture close to observations, then $\Delta W_{\text{MODEL}^*}$ should more closely resemble ΔW_{OBS} than ΔW_{MODEL} . Where there is substantial short-term drift, D_i will be dominated by the increment.

Also, D_i will not necessarily resemble D_s in magnitude or structure. The increment (and thus D_i) is in some sense a reflection of the fastest-growing error mode or modes, whereas D_s will resemble the modes with the largest amplitude on seasonal scales. There is no reason to expect that the fastest-growing error modes should also be the ones that saturate at the largest magnitude (cf. Kirtman 2001, manuscript submitted to *J. Geophys. Res.*). Thus, these two indices of drift give us complementary views of error growth in the coupled land-atmosphere model system.

3. Models and experiments

The LSS examined in these experiments is the simplified version of the Simple Biosphere model (SSiB; Xue et al. 1991, 1996; Dirmeyer and Zeng 1997). Because there are no global datasets of observed soil wetness, we use as a proxy the global gridded fields for 1987 and 1988 produced by SSiB as a participating LSS in the Global Soil Wetness Project (GSWP; Dirmeyer et al. 1999; Dirmeyer and Zeng 1999). These fields are produced by driving the LSS with observed/analyzed meteorological data. The resulting fields of soil wetness may be more useful than a global observed data set in this context, because the fields are inherently consistent with the SSiB LSS. This may facilitate a clean comparison between soil wetness produced in coupled model integrations, and that created from observed/analyzed forcing. Over ocean, boundary conditions of sea surface temperatures (SST) are specified from the weekly analysis of Reynolds and Smith (1994).

The AGCM is version 1.12 of the Center for Ocean-Land-Atmosphere Studies (COLA) GCM at a spectral resolution of R40 (1.8° lat by 2.8° long on the corresponding Gaussian grid) and 18 discrete vertical levels. It is a research version of the global spectral model described by Sela (1980). This version of the model is very similar to that described by Kinter et al. (1997), with the principal differences being that this version uses a relaxed Arakawa-Schubert convection parameterization (DeWitt 1996) and a cloud radiation scheme based on that used in the Community Climate Model, version 3 (DeWitt and Schneider 1996).

Seasonal integrations from boreal spring/summer are used to assess drift. Ensembles of nine integrations are conducted for 1987 and 1988. Two kinds of integrations are performed. The control ensembles are initialized on 1 May, and the coupled land-atmosphere model evolves freely throughout the integrations until their termination

at the end of August. The second set is identical to the first, except that every five days the global fields of soil wetness are reset to the values interpolated from the offline GSWP simulation with the same SSiB LSS. Thus, in the “GSWP” climate model ensembles, the soil moisture is constrained toward a state that is analogous to observations for this LSS. The adjustment that is made every five days is essentially a data assimilation increment; a relaxation with a time scale of zero. The GSWP soil wetness is used in lieu of true observations. See Dirmeyer (2000) for a complete description of the methodology and an assessment of the ensemble integrations.

4. Systematic drift

The ensemble-mean drift in root-zone soil wetness (D_s) is shown in Fig. 1, where seasonal rates of change are calculated from the monthly mean fields (August minus May) of 1987 and 1988. There is much detailed structure in the distribution of D_s , but several general characteristics are evident. First, the structure and magnitude of the systematic drift is very similar between the two seasons. The spatial correlation between the two fields is 0.78 and is higher if the fields are smoothed to leave only large-scale variations. Individual ensemble members also show the same large-scale differences. Thus, the systematic drift appears to be systematic from year to year, even though only two years are shown.

Second, the systematic drift is predominantly negative. That is, the soil in the unconstrained control integrations of the coupled land-atmosphere climate model tends to dry excessively (or in monsoon areas, not moisten enough) from spring to summer in comparison with what would be expected from driving the LSS offline with observed/analyzed meteorological conditions. The drying is particularly severe over eastern North America, much of the high latitudes of Eurasia, and most of the Southern Hemisphere. There is also an indication of insufficient moistening over much of southern and Southeast Asia. There are areas of positive systematic drift over northern China and Mongolia, portions of sub-Saharan West Africa, the eastern Amazon basin, Scandinavia, the Arctic islands of Canada, and much of the mountainous regions of the Americas.

Given the robust spatial structure of the systematic drift in soil wetness, one might readily implicate systematic errors in the downward fluxes of energy and water from the atmosphere. Indeed, there is a strong connection. Figure 2 shows the ensemble mean error in the simulation of precipitation by the control integrations over the same periods as in Fig. 1. Comparison is made to the Climate Prediction Center Merged Analysis of Precipitation (Xie and Arkin 1997) monthly precipitation dataset. Note that the areas of positive drift do align well with areas of positive rainfall errors. However, there are significant positive rainfall errors over many of the regions where there is a dry drift. In fact,

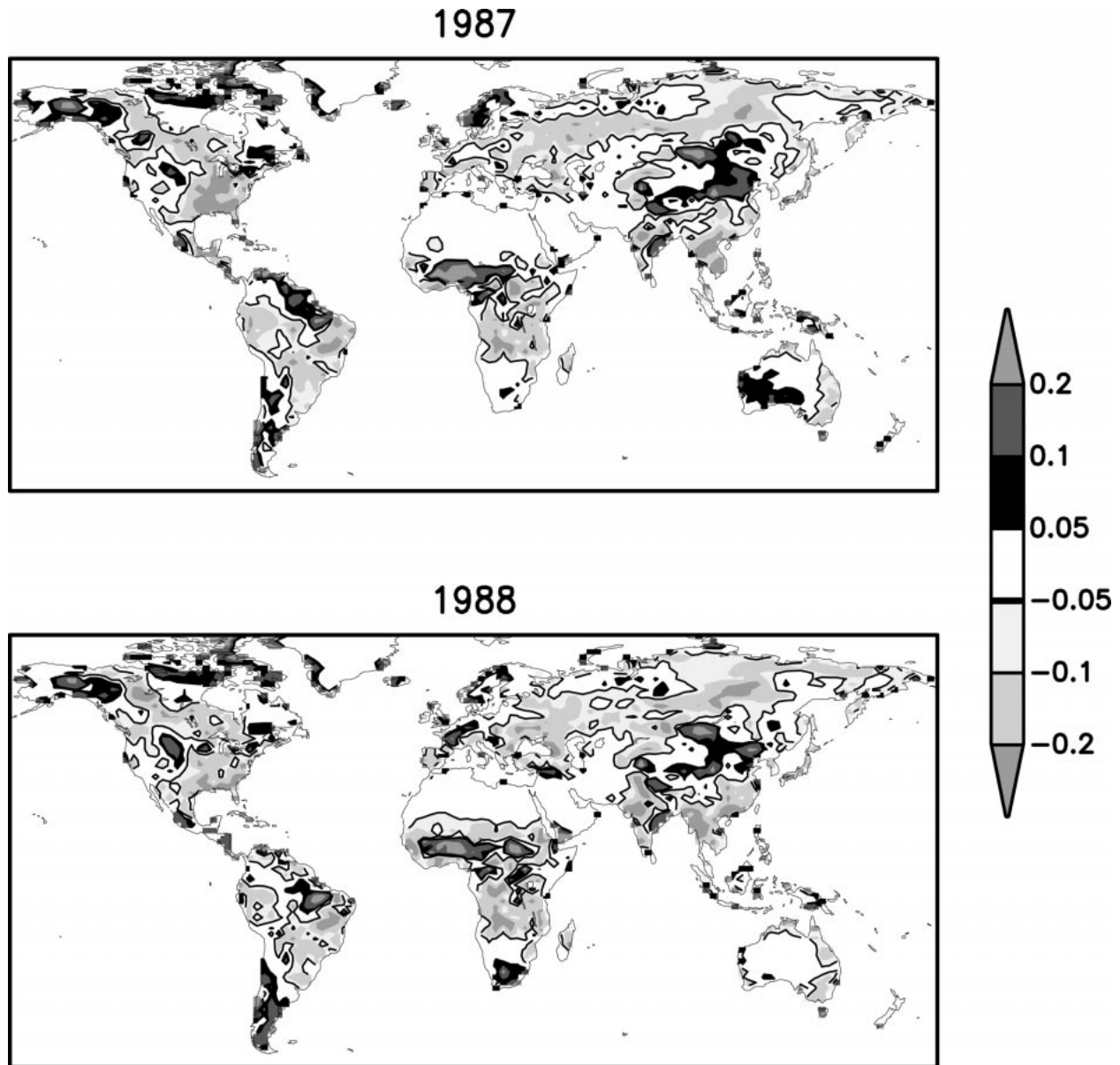


FIG. 1. Four-month (May, Jun, Jul, and Aug) systematic drift in root-zone soil wetness during 1987 and 1988. Units are fraction of saturation.

the patterns are more similar between Fig. 1 and Fig. 2 if one offsets the zero crossing.

This offset is explained by examining another large systematic error in the AGCM: the downward shortwave radiation at the surface (Fig. 3). Errors are relative to the estimates from the International Satellite Cloud Climatology Project (Darnell et al. 1992). With the exception of a few areas in the winter hemisphere, almost all land areas in the coupled climate model are receiving excessive solar radiation. The errors are particularly large over the Tibetan highlands and the Asian monsoon region but are also large over much of Europe and North America. Excess rainfall will moisten the soil, but ex-

cess radiative energy will dry it, so errors of the same sign in these two quantities will tend to offset one another.

If the rainfall errors in Fig. 2 are converted from millimeters per day to Watts per meter squared by making the appropriate time conversions and multiplying by the latent heat of condensation, the effects of the two errors can be combined. Figure 4 shows the effect of these combined systematic errors. It is now evident that the net effect over most areas would lead to a drying of soils and a negative systematic drift in soil wetness. The large cumulative errors over desert regions have little effect on soil wetness, because those soils are al-

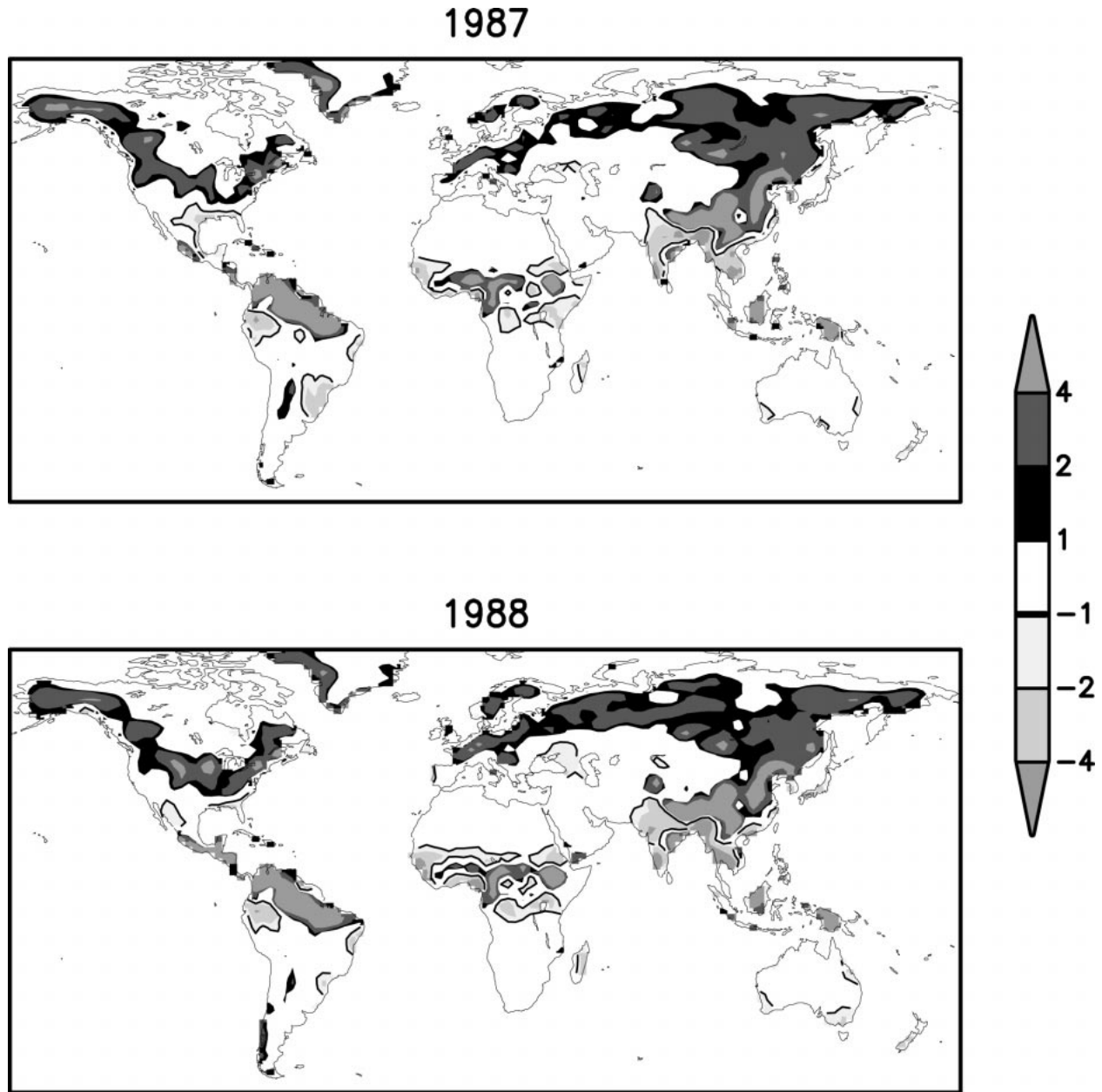


FIG. 2. As in Fig. 1 but for precipitation error (mm day^{-1}).

ready dry. However, over the Northern Hemisphere mid-latitudes and the monsoon regions of the Tropics and subtropics, there is good agreement between Fig. 4 and Fig. 1.

Table 1 shows the magnitude of the pattern correlations over land for several regions and for all global land points free of permanent ice. It is clear that the pattern of systematic drift is related to the precipitation errors. The significance thresholds vary for each region, but the correlation is significant at the 95% level over every region. Correlations with the errors in downward shortwave radiation are lower, but there are noteworthy

correlations over North America, Europe, and south Asia. When the systematic drift is compared with the combined effects of radiation and precipitation errors, these regions in particular show an even higher correlation, and the global correlation increases by another 7%.

There is also some interannual variability evident in the correlation coefficients. Correlations over South America and Australia are lower during 1988 than 1987 but are higher over Europe and Asia. Causes for these variations are not known.

Note that the AGCM cannot solely be implicated for

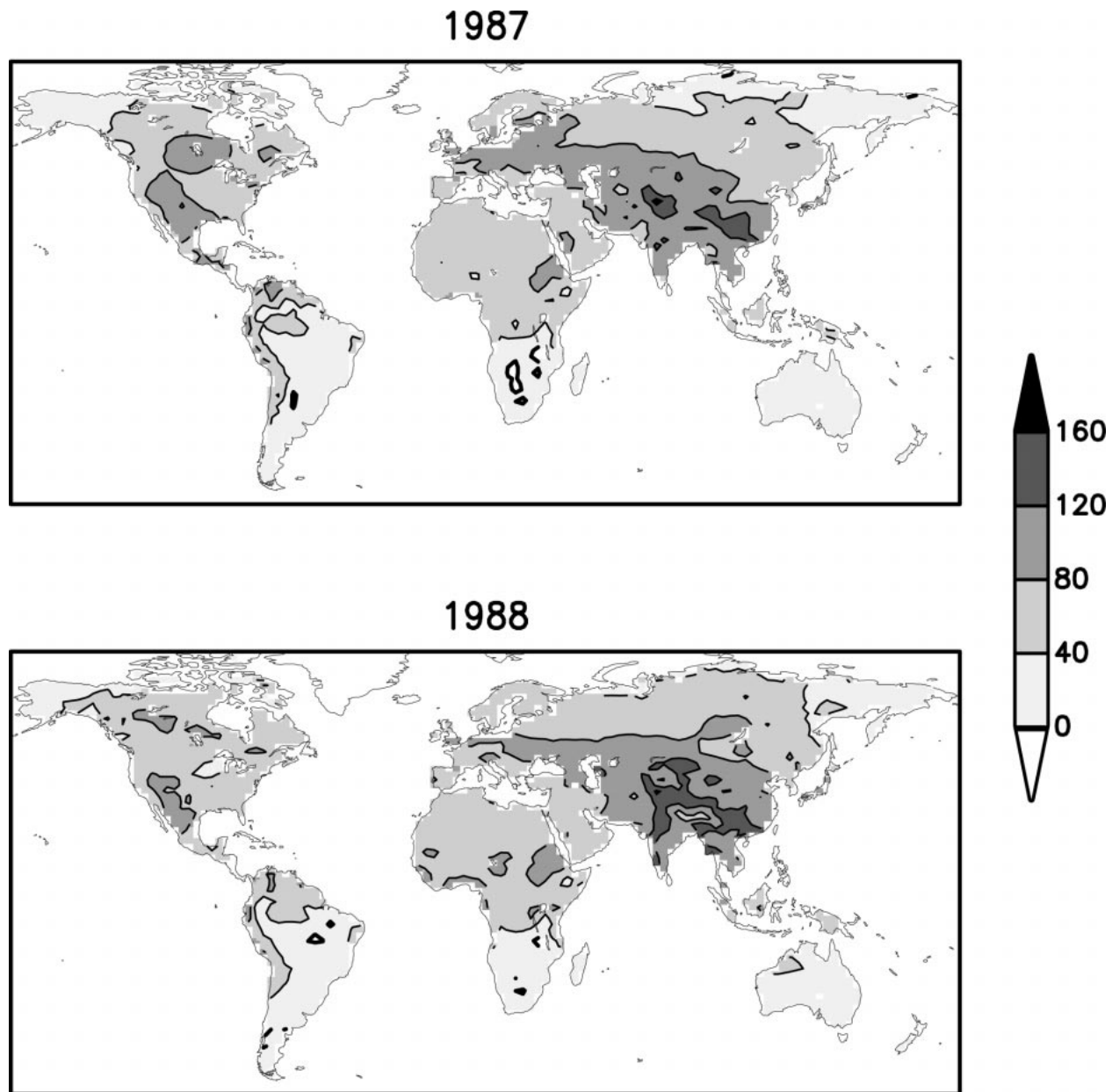


FIG. 3. As in Fig. 1 but for error in downward solar radiation at the surface (W m^{-2}).

these systematic errors by this analysis. It may be that the LSS is contributing to the errors in radiation, and particularly rainfall, through some feedback mechanism. I illustrate how to determine the extent of this feedback in section 6.

5. Incremental drift

The drift in soil wetness described in the previous section is the ultimate result of several months of divergence in the modeled state of the land, largely driven by systematic errors in the coupled climate model. Here I will look at the earliest phases of that drift—the di-

vergence in soil wetness that occurs in the first five days after soil wetness data is assimilated into the LSS. This is the incremental drift defined as D_I in (4).

Figure 5 shows the spatial distribution of D_I . Note that this drift is strongly dominated by the assimilation increment, and the seasonal change in soil wetness contributes little to D_I . The pattern of incremental drift is different than that of the systematic drift shown in Fig. 1. The pattern of incremental drift is more similar to the precipitation errors seen in Fig. 2. In particular, there is very good agreement over the areas of excessive model rainfall. This agreement should not be surprising. Rainfall wets the soil immediately, but drying by evapo-

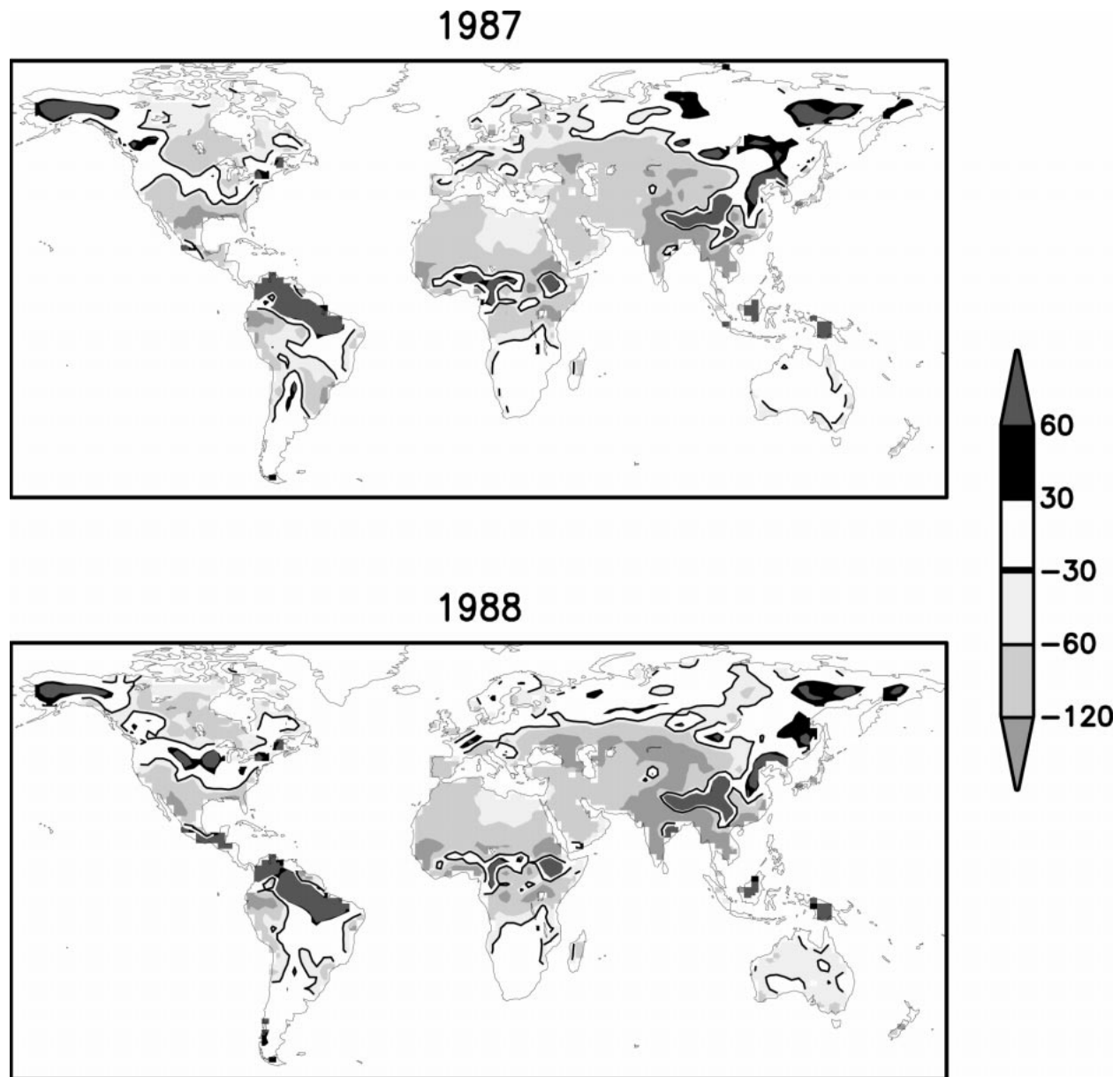


FIG. 4. As in Fig. 1 but for error in energy flux (precipitation latent heat content minus the downward solar radiation; W m^{-2}).

transpiration takes place over time from days to weeks. In five days there is time for the soil moisture to react to rainfall errors, but not much time to respond to errors in solar radiation.

Nonetheless, there are regions of strong positive incremental drift where rainfall errors are negative (and vice versa) that cannot be explained easily by this argument. In fact, there are many points where D_s and D_l are of opposite sign. That is, over the seasonal time period the soil wetness of the control model drifts in one direction, while the incremental drift is in the opposite direction. Two examples are compared in Fig. 6. The evolution in time of root-zone soil wetness at two selected grid points is shown for the 1988 ensembles.

In the GSWP ensemble integrations, the incremental adjustments are seen as abrupt steps in soil wetness every five days. The top panel is for a point in the United States centered over eastern Wyoming. This point has a positive seasonal precipitation bias, evidenced by the fact that the control ensemble mean soil wetness is progressively greater than the GSWP ensemble mean ($D_s > 0$). Likewise, the analysis increments, indicated by the sharp adjustments to soil moisture every five days in the GSWP ensemble, are negative in the net and cumulatively larger than the total change in soil moisture from the beginning to the end of the integrations ($D_l > 0$). Thus, if it were not for the periodic adjustments to the soil wetness in the GSWP integrations,

TABLE 1. Correlation coefficient between the systematic drift in root-zone soil wetness with errors in the variables shown for May–Aug 1987 (left columns) and 1988 (right columns). Only land points are considered over the following regions: global (57°S–75°N), North America (15°–75°N, 169°–55°W), South America (60°S–15°N, 90°–30°W), Australia (50°–10°S, 100°–160°E), Africa (50°S–35°N, 30°W–55°E), Europe (35°–75°N, 15°W–55°E), northern Asia (40°–80°N, 55°E–169°W) and southern Asia (10°–40°N, 55°–140°E).

	Correlation of systematic drift in root-zone soil wetness with errors in:					
	Precipitation		–(Downward shortwave)		$P - SWD$	
Global	0.38	0.38	0.13	0.17	0.40	0.41
North America	0.46	0.49	0.31	0.27	0.56	0.58
South America	0.48	0.30	–0.01	0.02	0.52	0.29
Australia	0.50	0.40	0.21	–0.28	0.55	0.30
Africa	0.42	0.40	–0.15	–0.03	0.33	0.35
Europe	0.41	0.56	0.31	0.48	0.50	0.63
Northern Asia	0.44	0.49	–0.04	0.15	0.32	0.44
Southern Asia	0.33	0.50	0.24	0.31	0.37	0.55

they would converge to the wetter control state. One might say that this case follows the logic behind data assimilation. The periodic adjustments to the soil moisture are marshaling the model away from the erroneous climate state toward which it drifts because of the excessive rainfall.

A different situation is evident in the bottom panel, for a point in Louisiana near the Gulf of Mexico. Here, the control integration dries out excessively over time ($D_s < 0$). Yet it is seen that, by mid-June, the GSWP ensemble is beginning to inch toward even wetter states, and the increments from this point throughout the remainder of the season are negative in order to maintain “correct” soil wetness ($D_l > 0$). Here the model is attempting to run away to a much wetter equilibrium than was attained by any of the control ensemble members. Roughly two months into the integration, a positive feedback has been realized between the wetter specified GSWP soil moisture state and rainfall.

These locations were chosen because they are especially unambiguous examples of negative and positive feedbacks. By applying an objective metric, such as the signs of D_s and D_l , one can find examples of each possible combination of the two-by-two contingency table on each continent, although the strengths of some of the drifts are small. Situations where the control run has a wet systematic drift but a dry incremental drift appear to be the rarest, although they do appear with some frequency at high latitudes in this model.

6. The feedback mechanism

It is obvious that a precipitation event has a direct and immediate effect on soil wetness. However, this event will have a diffused impact on evapotranspiration over a period of days or weeks. Thus, the potential feedback on subsequent precipitation will be difficult to measure. In addition, other surface properties are also

affected that can affect fluxes, such as the surface temperature and soil heat capacity.

The strength of the response in evapotranspiration to a perturbation in soil wetness is a function of the background soil wetness (Dirmeyer et al. 2000). When soil wetness is high, additional water in the soil will have little effect on evapotranspiration, which is occurring near the potential rate already. When soils are dry, there can be a large relative impact but a small absolute impact on evapotranspiration. Between these extremes is the region of greatest absolute sensitivity of evapotranspiration to soil wetness. In such a way, the state of the land surface can modulate the strength of feedbacks between land and atmosphere.

Even when there is a substantial increase in latent heat fluxes from the land surface to the atmosphere, there may be aspects of the large-scale circulation that suppress the effect of these increased moisture and heat fluxes. For example, if large-scale dynamics are inducing subsidence over a region, it may take a very large anomaly to overcome the positive feedback (Charney 1975) and shift the local climate from dry to wet (Entekhabi et al. 1992). In a similar way, large-scale low-level convergence may retard feedbacks that would attempt to drive local climate to a drier state. So the state of the atmospheric circulation can also help to determine the potential strength of feedbacks.

In the situation over Wyoming shown in the previous section, model rainfall is too large, driving up soil wetness and evapotranspiration. The soil wetness increment is fighting against this trend, but excessive rainfall continues. The high rainfall is being driven by a process external to the local land–atmosphere coupling in this instance. In fact, this AGCM has a long-standing and well-documented tendency to simulate excessive rainfall on the eastern slopes of the Rocky Mountains at this latitude, probably related to systematic errors in the general circulation interacting with the model orography.

Over Louisiana, rainfall is too low and soil wetness drops considerably from spring to summer. The assimilated soil wetness maintains a wetter soil, which by summer is capable of flipping the local climate to a wetter state. Here, land–atmosphere interactions probably are determining the rainfall regime. When soil moisture is assimilated, evapotranspiration accelerates and there is an increase in local moist static energy that drives increased low-level moisture flux convergence, drawing on the adjacent moisture source provided by the Gulf of Mexico. Perhaps the default land–atmosphere coupling in this area is too strong or is poorly calibrated with respect to the atmospheric response to soil moisture (Betts et al. 1998).

Similar situations for weak and strong feedbacks can be envisioned for areas with positive increments. Remember also that there are large errors in solar radiation in this model that may also affect the strength and range of sensitivity of land–atmosphere feedbacks.

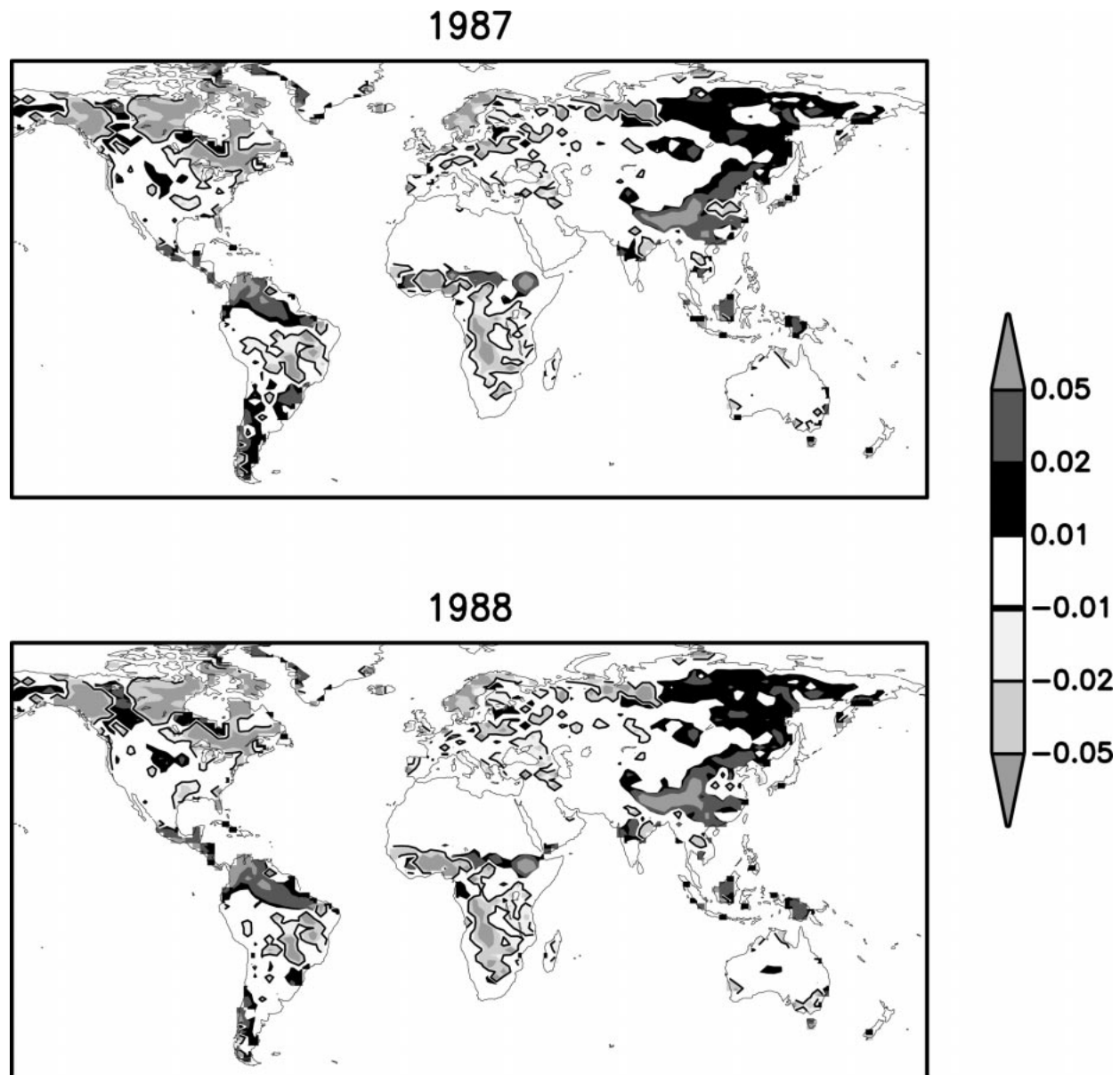


FIG. 5. As in Fig. 1 but for the average incremental drift in root-zone soil wetness. Units are fraction of saturation.

There are other ways to quantify and to address climate drift other than that applied in this study. With respect to land–atmosphere interactions, there are at least three approaches that can be taken. Figure 7 shows these approaches schematically. The first is to make adjustments in the fluxes from the land to the atmosphere. This adjustment is done based on some predefined set of criteria to minimize errors or to investigate the sensitivity of the system. Koster and Suarez (1995) and Koster et al. (2000) are examples of this approach, in which sensitivity was investigated by prescribing an element of the evaporation based on long coupled integrations. This study is an example of the approach

illustrated in the center panel. Here, a land surface state variable has been adjusted in a coupled climate model, based on an offline integration. In the last panel, intervention occurs where fluxes from the AGCM are passed to the LSS. This intervention can be done to correct known systematic errors in the AGCM (e.g., precipitation or radiation). In each case, the changes at one point of the coupled system will propagate around through the system to varying degrees. By carefully designing experiments in each of these three approaches with the same coupled system, a more complete picture of feedbacks and the causes of drift and errors can be realized.

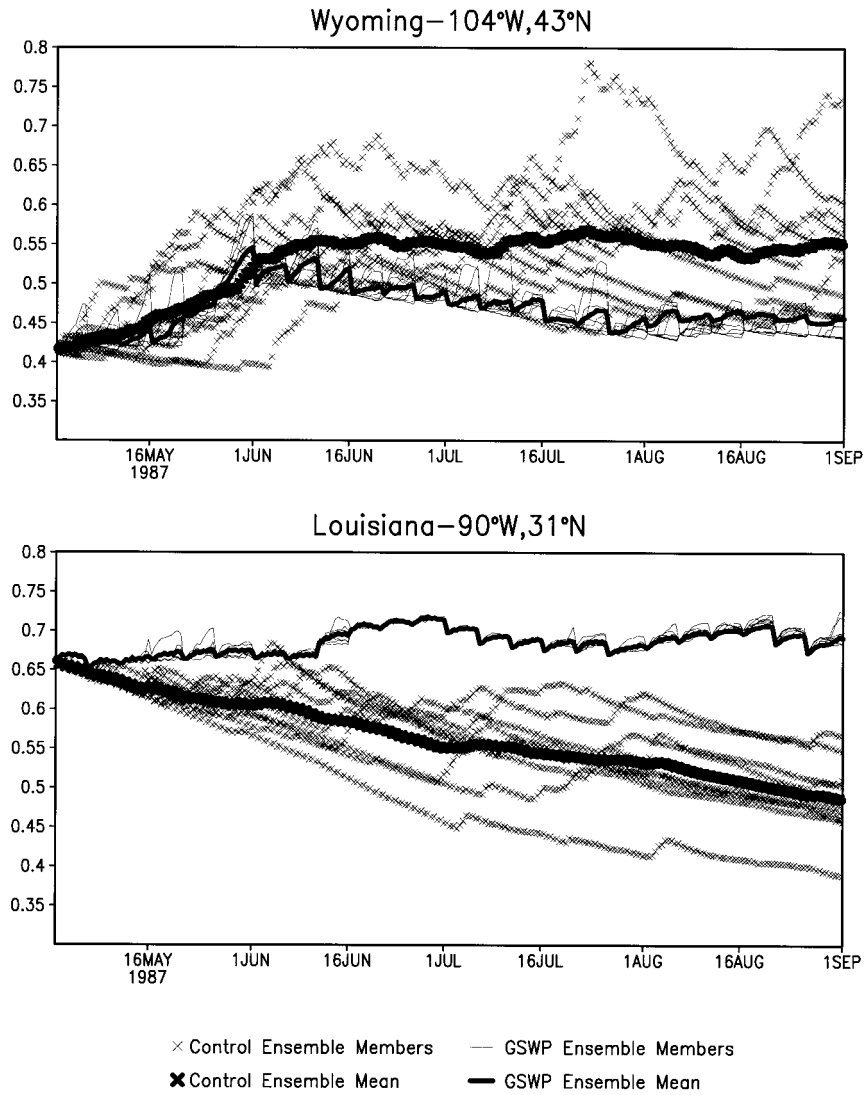


FIG. 6. Time evolution of root-zone soil wetness at two grid points in each of the nine ensemble members from the control and GSWP cases and for the ensemble means. Units are fraction of saturation.

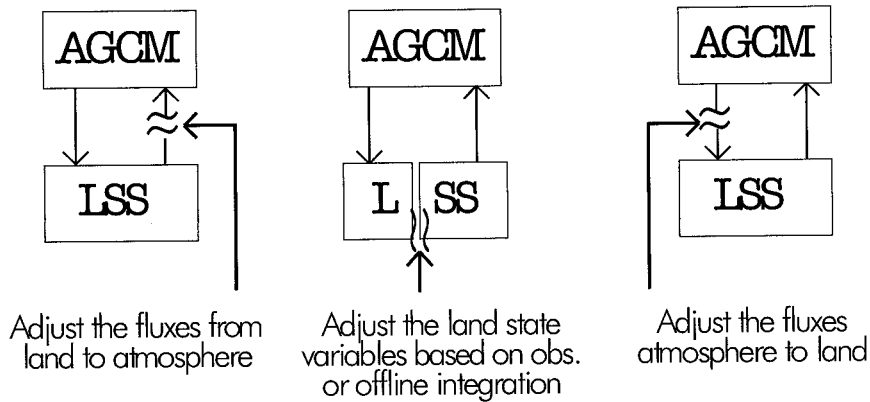


FIG. 7. Schematic representation of three approaches to quantify and to address climate drift in coupled land-atmosphere models.

7. Conclusions

Climate drift in root-zone soil wetness has been found in the coupled climate system of the COLA atmospheric GCM and SSiB LSS. Ensembles of seasonal control integrations were compared with integrations in which soil moisture was reset every five days to values calculated with the LSS driven by observations and analyses alone. The periodic resetting of soil wetness is in effect a blunt land data assimilation. Two different years were examined.

Two kinds of climate drift have been defined and explored. The first is essentially the long-term systematic drift that is evident on timescales of a season and that consists of the sum of all growing error modes that saturate during that time. The second kind of drift is a short-timescale incremental drift that reflects the fastest-growing error modes, evident in the first few days after initialization or a data assimilation increment. Not addressed here are longer multiyear drifts in deep soil moisture that can arise when soil wetness initialization is poor, particularly in arid regions. This long-term drift does not have a significant effect on surface fluxes beyond the scales examined here.

The errors at both daily and seasonal timescales are not random in nature, but in fact are very robust in sign and structure within ensembles and from year to year. The systematic drift has a spatial structure and character that may be largely controlled by errors in precipitation and downward solar radiation at the land surface. The incremental drift is dominated by errors in rainfall alone. This difference is due to the fact that soil wetness is, to first order, a balance between rainfall and evapotranspiration. Evapotranspiration responds slowly over time to errors in radiation and thus affects soil moisture slowly, whereas rainfall errors have an immediate, abrupt effect on soil wetness via rapid infiltration.

Often the systematic drift and incremental drift act in the same manner (e.g., a dry bias may be evident in both at a given location). This suggests the cause of the drift may be in part external to the local coupled system. However, there are many locations where a correction of systematic drift invokes an opposite incremental drift. That is, a regime change occurs in which a seasonal dry bias, for instance, when corrected by data assimilation, becomes an incremental drift toward wetter conditions (or vice versa). The correction by data assimilation has pushed the local system into a different regime, presumably through the changes in evapotranspiration that supply moisture and heat to the local system. A positive feedback has been triggered. It is not known whether such bimodality is widespread in this model, provided the proper range of soil wetness is crossed. It may be that, with the limited adjustments made in this experiment, only a few of many possible cases have been stumbled upon.

Drift itself may be caused by errors in either component of the coupled land-atmosphere model, or in the

actual coupling between the atmospheric GCM and the LSS. A methodology is described to determine better the sources of drift by systematically adjusting the fluxes from atmosphere to land and from land to atmosphere, as well as adjusting land surface state variables as was done here. Making adjustments to each, in turn, and following the propagating effects around the coupled loop between land and atmosphere may reveal a clearer picture of error propagation, sensitivity, and feedback. This approach will be the subject of continuing investigations.

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