

Comparing the Degree of Land-Atmosphere Interaction in Four Atmospheric General Circulation Models

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Abstract

Land-atmosphere feedback, by which (for example) precipitation-induced moisture anomalies at the land surface affect the overlying atmosphere and thereby the subsequent generation of precipitation, has been examined and quantified with many atmospheric general circulation models (AGCMs). Generally missing from such studies, however, is an indication of the extent to which the simulated feedback strength is model dependent. Four modeling groups have recently performed a highly controlled numerical experiment that allows an objective inter-model comparison of land-atmosphere feedback strength. The experiment essentially consists of an ensemble of simulations in which each member simulation artificially maintains the same timeseries of surface prognostic variables. Differences in atmospheric behavior between the ensemble members then indicates the degree to which the state of the land surface controls atmospheric processes in that model. A comparison of the four sets of experimental results shows that feedback strength does indeed vary significantly between the AGCMs.

1 Introduction

The impact of precipitation anomalies on soil moisture anomalies is self-evident – heavy rains induce wet soil, whereas extended dry periods induce dry soil. Less obvious is the impact of soil moisture anomalies on the precipitation itself. Conceivably, a wetter soil can produce higher evaporation, which in turn can induce additional precipitation through both local recycling and modifications in the large-scale circulation. This land-atmosphere feedback, if strong, is of great interest. It may allow, for example, the translation of soil moisture anomalies into short-term and seasonal predictions of precipitation. It also helps determine the climatic impacts of land-use change (e.g., deforestation).

Atmospheric general circulation models (AGCMs) are popular tools for examining land-atmosphere feedback, largely because they include parameterizations for many of the physical processes involved and because these parameterizations can be manipulated easily in controlled experiments. The list of published feedback studies is extensive [e.g., *Shukla and Mintz*, 1982; *Henderson-Sellers and Gornitz*, 1984; *Delworth and Manabe*, 1989; *Oglesby and Erickson*, 1989; *Dirmeyer*, 1994; and *Lau and Bua*, 1998; to name only a few]. Necessarily missing from single-AGCM experiments, however, is an analysis of the degree to which the experimental results are model-dependent. Models can certainly differ in their simulation of feedback; differences in land-surface parameterizations, for example, can lead to differences in the response

of evaporation to precipitation anomalies, and differences in boundary layer and convection parameterizations can lead to differences in the atmosphere's response to surface evaporation and sensible heat flux. Clearly, in any feedback study, an evaluation of simulated feedback strength against observations is desirable.

Unfortunately, while a few indirect approaches have been employed at the regional scale [e.g., *Findell and Eltahir*, 1997], the direct quantification of real-world feedback strength at the global scale from available observations is extremely difficult, if not impossible. The validation of simulated feedback strength is indeed beyond the scope of this paper. This paper instead focuses on a lesser, but still very important, aspect of the problem: the extent to which simulated feedback strength varies between different AGCMs. This variation is a measure of the degree to which feedback-related model results are model dependent. In a sense, it measures the uncertainty inherent in our understanding of feedback and our ability to model it.

The problem of intermodel variation in feedback strength is addressed here by having several AGCMs perform the same, highly controlled numerical experiment. Four models participated in the intercomparison: the NASA Seasonal-to-Interannual Prediction Project (NSIPP) AGCM, the Center for Ocean-Land-Atmosphere Studies (COLA) AGCM, the National Center for Atmospheric Research Community Climate Model Version 3 coupled to the Biosphere-Atmosphere Transfer Scheme (CCM3/BATS), and the

United Kingdom Meteorological Office AGCM (HadAM3). The experiment is described in section 2, and the results of the intercomparison are presented in section 3. Section 4 offers some interpretation of the results.

2 Experiment Design

The design of the experiment is illustrated in Figure 1. The experiment has two parts. In the first part, the AGCM, fully coupled to its own land surface model (LSM) but forced by prescribed sea surface temperatures (SSTs), is run over a selected month. At each time step in this simulation (hereafter labeled simulation W, for “write”), the values of all land surface prognostic variables at every grid cell are recorded into a special data file. The recorded prognostic variables include soil moisture contents at all vertical levels, temperatures at all vertical levels, canopy interception reservoir content, and various variables characterizing snow, if snow is present. The one-month experiment is then repeated 15 more times, using 15 different sets of atmospheric and land surface initial conditions, to obtain an ensemble of 16 one-month simulations (simulations W2-W16). The prognostic variables, however, are only recorded during Simulation W1.

The second part of the experiment consists of another 16-member ensemble of one-month simulations, using solar forcing for the same month as before and using the same prescribed SSTs. Again, the ensemble members use different atmospheric initial conditions. At every time step of every simulation,

the updated values of all land surface prognostic variables are discarded and then replaced by the corresponding values for that time step from the data file written in Simulation W1. Thus, in this ensemble, all member simulations (simulations R1-R16, where R denotes “read”) are forced to maintain precisely the same time series of (geographically-varying) land surface states.

We focus mainly on precipitation in this study. The idea is simple: we examine the degree to which the time series of precipitation rates in simulations R1-R16 are similar. If they are similar, even after “subtracting out” the effects of SSTs and other intramonthly signals through an analysis of simulations W1-W16, then we can say that the evolution of the atmosphere is indeed largely governed by land surface conditions. The degree to which the intra-ensemble similarity differs between GCMs provides one measure of how land-atmosphere feedback strength varies between models.

The set-up of the experiment did differ slightly between the four participating GCMs. For example, for various reasons, each GCM used its own set of prescribed SSTs, though each was derived from datasets used in various phases of the Atmospheric Model Intercomparison Project [*Gates, 1992*]. These differences, which should not affect the basic outcome of the experiment, are outlined in Table 1.

3 Results

To quantify the degree of “similarity” in the time series of precipitation amongst the members of an ensemble, we employ an approach used by *Koster et al.* [2000]. First, we choose an aggregation period. In the analysis below, we look at 3-day totals of precipitation, P ; each July simulation thus provides a times series of ten 3-day totals. We then compute an ensemble average time-series, \hat{P} . For each time period n , we compute

$$\hat{P}_n = \frac{1}{16} \sum_{i=1}^{16} P_{ni}, \quad (1)$$

where i loops over the 16 ensemble members. Next, we compute the variance, σ_P^2 , of P across all ensemble members and time periods (i.e., across 160 values) and the variance, $\sigma_{\hat{P}}^2$, of \hat{P} across all time periods (i.e., across 10 values). This allows us to compute Ω_P , a measure of time series similarity:

$$\Omega_P = \frac{16\sigma_{\hat{P}}^2 - \sigma_P^2}{15\sigma_P^2}. \quad (2)$$

Note that if each ensemble member produces exactly the same time series of P , then $\sigma_{\hat{P}}^2$ will equal σ_P^2 , and Ω_P will equal 1. If, however, the time series are completely uncorrelated, then $\sigma_{\hat{P}}^2$ will be approximately $\sigma_P^2/16$, and Ω_P will be about 0. Thus, Ω_P varies from 0 to 1, with values closer to 1 indicating a greater degree of precipitation similarity.

Ω_P essentially measures the ratio of the signal variance to the total variance. (A similar diagnostic was suggested by *Rowell et al.* [1995]). Figure

2 illustrates the nature of Ω_P graphically. The top plot in the figure shows the time series of precipitation at a specific grid cell for each of the 16 simulations in the NSIPP R ensemble. Note that the precipitation is low for the month until day 20, when it shoots up for each simulation. The obvious coherence between the different time series is reflected in the high Ω_P value (0.85) at this grid cell. In the bottom plot, which shows the 16 time series at a different grid cell, the coherence is absent – the precipitation generated in one simulation is essentially independent of that in any other simulation. Precipitation at this cell is thus controlled by chaotic atmospheric dynamics rather than by SST or land conditions. Ω_P for this grid cell is very low (0.07).

To relate Ω_P to land control, we must properly account for seasonal variations in SSTs and anything else outside of the land surface that can induce intra-monthly trends in precipitation. We do this simply by calculating Ω_P separately for the R and W ensembles. $\Omega_P(R)$ represents the similarity in precipitation induced by all factors, including the specified set of land states. $\Omega_P(W)$ represents the similarity induced by everything but the specified land states. The difference $\Omega_P(R) - \Omega_P(W)$ thus gives a first-order indication of the land’s impact on the evolution of the atmosphere.

Global maps of $\Omega_P(R) - \Omega_P(W)$ are provided in Figure 3 for all four AGCMs. The salient result is a wide disparity in the diagnostic between the models. The impact of land conditions on atmospheric processes is clearly largest for the NSIPP model. The COLA and CCM3/BATS models have

similar $\Omega_P(R) - \Omega_P(W)$ distributions, with values of 0.2 or less almost everywhere, and the HadAM3 model has what appears to be an even weaker land-atmosphere connection.

Because the choice of a 3-day averaging period was somewhat arbitrary, other averaging periods were examined as well. The relative behavior of the models is similar when the precipitation is averaged over 1-day and 6-day periods (not shown). In general, however, $\Omega_P(R) - \Omega_P(W)$ for a given model increases as the precipitation aggregation period increases.

4 Discussion

4.1 Coherence of Surface Fluxes

One potential explanation for low values of $\Omega_P(R) - \Omega_P(W)$ in Figure 3 involves the response of the surface turbulent fluxes to the imposed surface states. Due to variations in the atmospheric forcing, the time series of evaporation or sensible heat flux amongst the members of an ensemble may not look the same, even given identical time series of soil moisture and temperature. If the time series of turbulent fluxes were not the same, and if the effect of the land surface on precipitation were mostly through these fluxes, then the derived values of $\Omega_P(R) - \Omega_P(W)$ would necessarily be low.

A warning is in order here — the response of precipitation to land surface conditions may be more complex than this. For example, the temperature and humidity conditions in the atmospheric boundary layer, which help de-

termine precipitation, may be strongly guided by surface temperature and moisture states. Although the surface fluxes are responsible for communicating the surface states to the boundary layer, the state of the boundary layer may nevertheless correlate better with the surface states themselves than with the *time-integrated* surface fluxes examined in this section.

With this caveat, we analyze the time series of evaporation rates produced by the GCMs by defining, in direct analogy to Ω_P , the diagnostic Ω_E :

$$\Omega_E = \frac{16\sigma_E^2 - \sigma_E^2}{15\sigma_E^2}. \quad (3)$$

where σ_E^2 is the variance of evaporation across all ensemble members and σ_E^2 is the variance of evaporation in the ensemble mean time series. Ω_E thus measures the degree of similarity among the time series of evaporation rates (and loosely, via energy balance considerations, among the time series of sensible heat fluxes) produced by the different members of an ensemble. As with Ω_P , a value of 1 implies that all 16 time series are identical, whereas a value of zero implies that the 16 time series are completely uncorrelated.

Figure 4 shows the global distribution of $\Omega_E(R) - \Omega_E(W)$ for each of the AGCMs. In each case, Ω_E is high over much of the globe. Indeed, in many regions, specifying surface moisture and temperature states in this experiment is roughly equivalent to specifying time series of the surface turbulent fluxes. If Ω_P is correspondingly low in these regions, as it is in particular for the COLA, CCM3/BATS, or HadAM3 GCMs, then we can conclude that the modeled atmosphere in these regions does not respond strongly to the

local surface fluxes. That is, a low Ω_P value in the presence of a high Ω_E value is probably best explained by the model’s atmospheric formulations, presumably those of boundary layer processes and moist convection, though it might also (or instead) result from a low Ω_E value in a critical remote region.

In some regions, Ω_E is indeed fairly low. Both the CCM3/BATS and the HadAM3 models, for example, show low values over a large fraction of northeastern Asia, and the HadAM3 model also shows low values over much of North America. Such findings for HadAM3 are consistent with *Gedney et al.’s* [2000] suggestion that evaporation in the HadAM3 model is rarely moisture limited. If the land surface’s effect on precipitation is mostly through the surface fluxes, and if this effect is mostly local, then Figure 4 does identify some regions for which the land-atmosphere coupling is weakened by an insensitivity of surface moisture and energy fluxes to the surface prognostic states.

4.2 Idealized Nature of Experiment

One curious aspect of Figure 3 is the geographical structure of the NSIPP model’s Ω_P distribution, which differs somewhat from the distribution of seasonal Ω_P values derived by *Koster et al.* [2000] with the same AGCM. *Koster et al.* [2000] place the largest Ω_P values in the transition zones between arid and humid regions, whereas Figure 3 places them in somewhat different areas, farther to the north, for example, in North America. The difference

presumably results from the different designs of the experiments. *Koster et al.* [2000] effectively prescribe only land surface soil moisture contents. This has direct relevance to predictability studies, since soil moistures may be predictable (and thus effectively “specified”) on seasonal timescales due to their inherent memory. The present experiment prescribes diurnal variations of both surface moisture conditions and surface temperatures. Apparently the added specification of temperature leads to a significant increase in Ω_P in certain areas.

This last point underscores the idealized nature of the present experiment. The experiment does not address the long-term predictability of precipitation in the participating models. It simply allows a highly controlled comparison of the models’ coupling behavior – a comparison of the degree to which the generation of precipitation is guided by the full land surface state rather than by chaotic atmospheric dynamics or external forcings (SSTs). Clearly the models disagree about the strength of land-atmosphere coupling. This uncertainty is often not acknowledged in land-atmosphere feedback studies.

We must emphasize again that the proper level of land-atmosphere feedback — the proper range of Ω_P (or even Ω_E) — is simply not known. This analysis makes no attempt to state which model’s coupling behavior is the most realistic. For a proper evaluation, long-term observational studies of boundary layer behavior are required. Furthermore, the low Ω_P values in Figure 3 for the COLA, CCM3/BATS, and HadAM3 models do not imply

that these models have a low potential for predictability. The COLA group recently performed a series of experiments similar to those of *Koster et al.* [2000]. An analysis of these experiments shows that the coupling behavior of the COLA model on seasonal timescales is similar to that of the NSIPP model — in effect, Ω_P for both models is high over a significant fraction of the earth. Apparently the noise behind the COLA model’s low Ω_P values in Figure 3 is smoothed out at much longer timescales.

5 Summary

A highly-idealized, simple, and inexpensive AGCM experiment has been devised that illustrates some key aspects of simulated land-atmosphere coupling behavior. Four AGCM groups have performed the experiment for the present study, and a comparison of their results shows that the apparent strength of land-atmosphere coupling on short (daily to weekly) timescales does vary significantly between the models. A strict evaluation against observations is not provided, since the strength of coupling in the real world is difficult, if not impossible, to measure. Nevertheless, the intermodel differences are important in themselves, since they illustrate the uncertainty with which we understand the various processes (particularly atmospheric boundary layer and convection processes) that control the coupling. Further studies of coupling strength are needed, particularly with field observations, given the central role played by land-atmosphere feedback in many published and ongoing

numerical studies of climate variability and predictability.

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Figure Captions

Fig. 1 Basic design of the experiment, as performed by all participating models.

Fig. 2 Superposed time series of precipitation for two grid cells: one in which Ω_P is high (top), and one in which Ω_P is low (bottom).

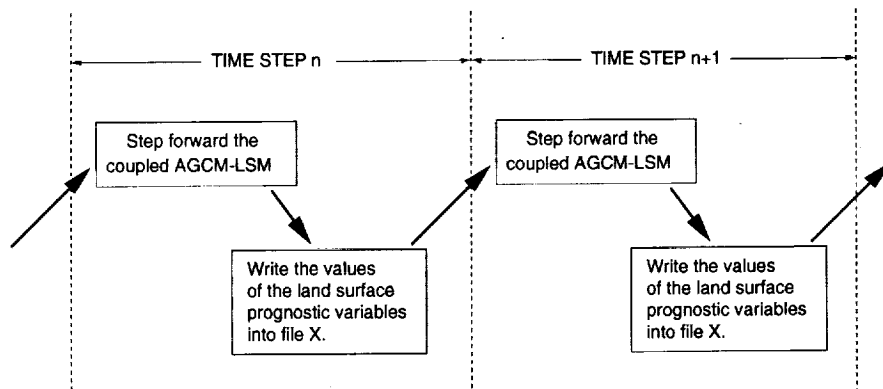
Fig. 3 Global fields of $\Omega_P(R) - \Omega_P(W)$, as generated by each of the participating AGCMs.

Fig. 4 Global fields of $\Omega_E(R) - \Omega_E(W)$, as generated by each of the participating AGCMs. The values of this diagnostic over the ocean were not available for HadAM3.

Model	SSTs Used	Surface Grid Res.	Key References for AGCM	Notes
NSIPP	July 1988	4° (long.) × 5° (lat)	Dynamics: <i>Suarez and Takacs</i> [1995] Land: <i>Koster and Suarez</i> [1992, 1996] Convection: <i>Moorthi and Suarez</i> [1992]	Initial atmosphere and land states for W and R from July 1 1988 conditions in 16 parallel AMIP runs.
COLA	July 1986	1.8° × 2.8°	Physics: <i>Kinter et al.</i> [1997] Dynamics: <i>Kiehl et al.</i> [1998] Land: <i>Xue et al.</i> [1991], <i>Dirmeyer et al.</i> [1999] Convection: <i>DeWitt et al.</i> [1996]	Full description of experiments in <i>Dirmeyer et al.</i> [2001].
CCM3/ BATS	July 1983	2.8° × 2.8°	GCM: <i>Kiehl et al.</i> [1998] Land: <i>Dickinson et al.</i> [1993] GCM-Land comb.: <i>Hahmann and Dickinson</i> [2001]	W2-W16 began June 15 (first 15 days thrown out); June 15 land states were identical; June 15 atmosphere states from 16 sequential days.
HadAM3	July 1981	3.75° × 2.5°	General: <i>Pope et al.</i> [2000] Land: <i>Cox et al.</i> [1999] Convection: <i>Gregory and Rowntree</i> [1990]	Initial atmosphere and land states for W from a previous AMIP run: July 1 1979-1994 inclusive. Prescribed land states for R from 1981 run, with land states initialized to climatology.

Table 1: Models used in the experiment and details of the experimental set-up.

PART 1: ESTABLISH A TIME SERIES OF SURFACE CONDITIONS (Simulation W1).



(Repeat without writing to obtain simulations W2-W16.)

PART 2: RUN 16-MEMBER ENSEMBLE, WITH EACH MEMBER FORCED TO MAINTAIN THE SAME TIME SERIES OF SURFACE PROGNOSTIC VARIABLES (Simulations R1-R16).

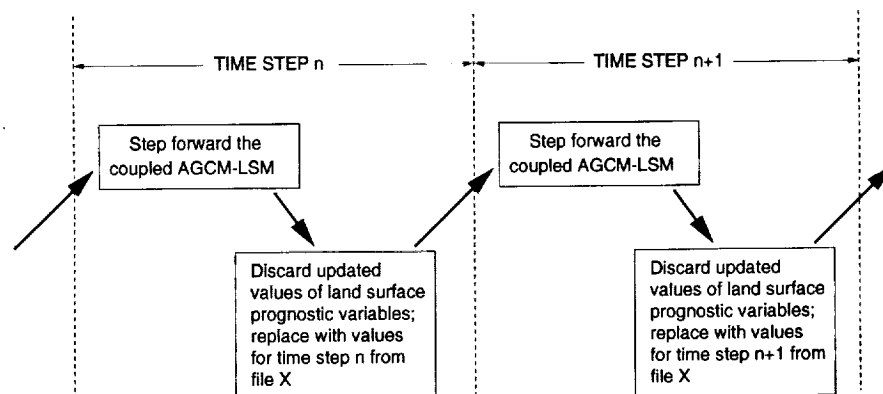


Figure 1: Basic design of the experiment, as performed by all participating models.

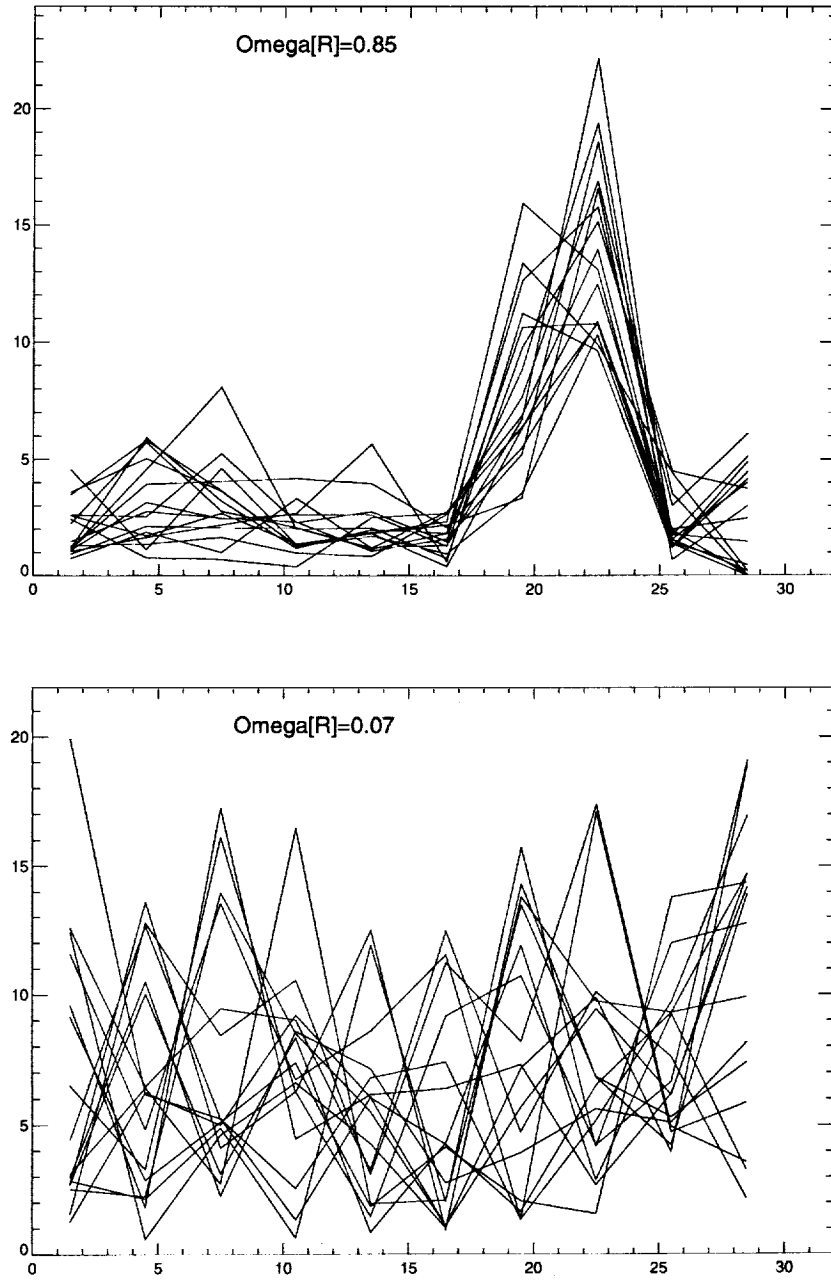


Figure 2: Superposed time series of precipitation for two grid cells: one in which Ω_P is high (top), and one in which Ω_P is low (bottom).

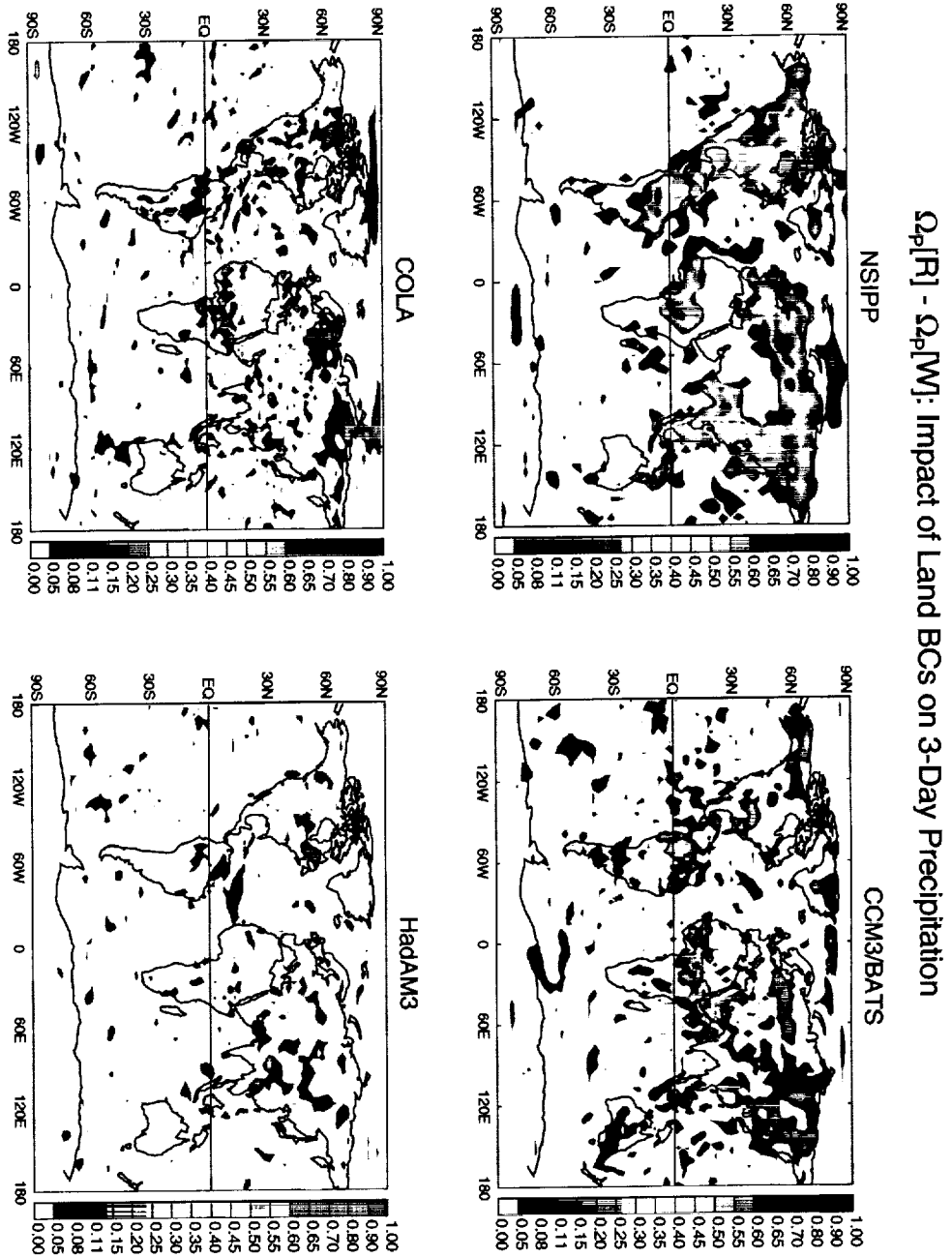


Figure 3: Global fields of $\Omega_P(R) - \Omega_P(W)$, as generated by each of the participating AGCMs.

$\Omega_E[R] - \Omega_E[W]$: Impact of Land BCs on 3-Day Evaporation

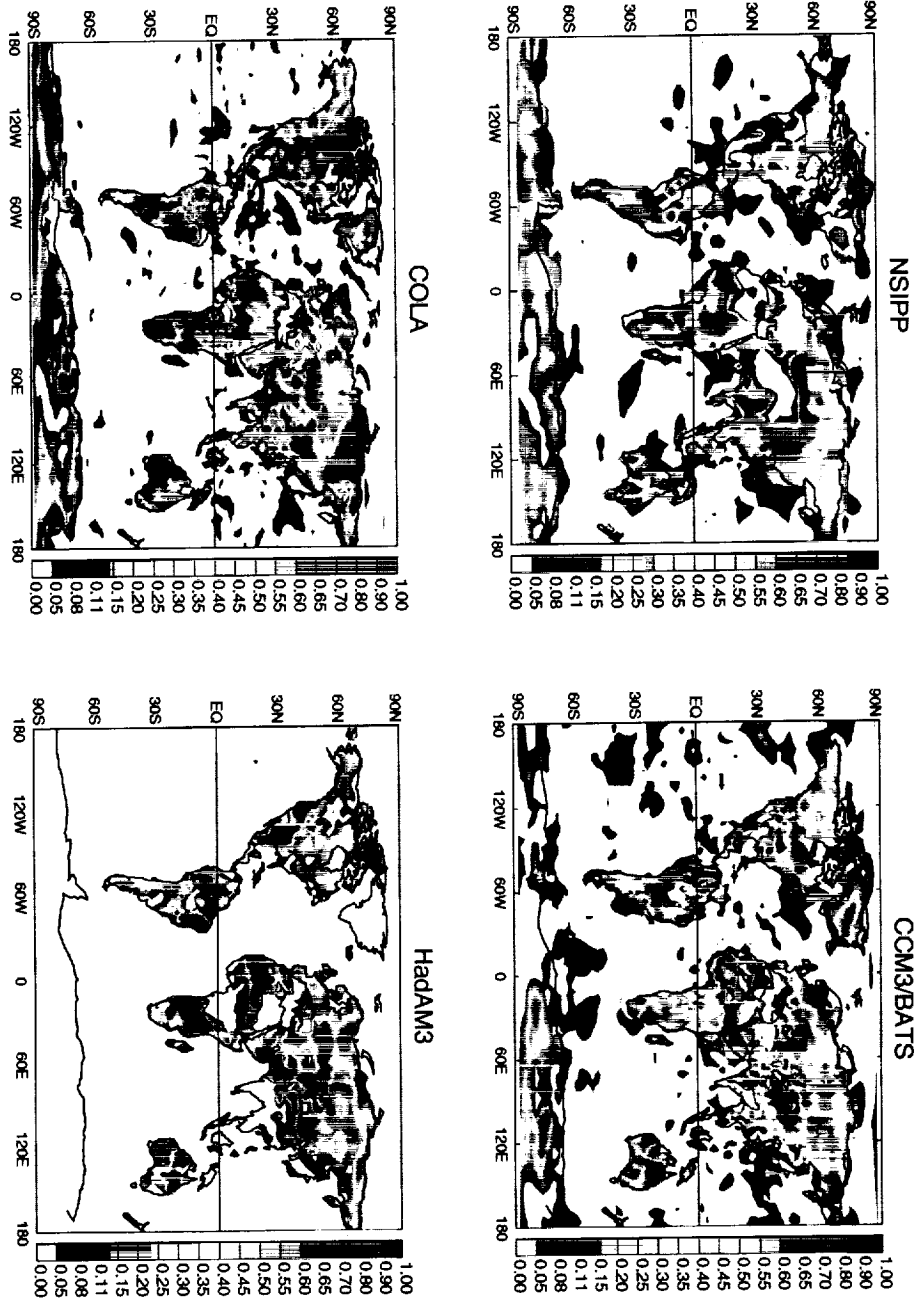


Figure 4: Global fields of $\Omega_E(R) - \Omega_E(W)$, as generated by each of the participating AGCMs.

Popular Summary:

"Comparing the Degree of Land-Atmosphere Interaction in Four Atmospheric General Circulation Models", by R. Koster, P. Dirmeyer, A. Hahmann, R. Ijpelaar, L. Tyahla, P. Cox, and M. Suarez

A wet soil that results from a rainstorm may lead to higher evaporation rates in the weeks to follow, and this higher evaporation may induce additional precipitation, either through local moisture recycling or through changes in the large-scale atmospheric circulation. Similarly, a drought may lead to dry soil and thus low evaporation rates, and the low evaporation may help stifle subsequent precipitation, thereby prolonging the drought. These are examples of land-atmosphere feedback, by which atmosphere-induced land surface anomalies in turn affect the atmosphere. Land-atmosphere feedback is extremely difficult, and often impossible, to quantify in the real world. Given its importance, though, it *has* been examined extensively with many atmospheric general circulation models (AGCMs).

Unfortunately, many of these studies give conflicting results. This leads to some obvious questions: (1) To what extent is the strength of simulated feedback model dependent? (2) How can we quantify intermodel differences in feedback strength in an objective way? In this paper, we address these questions with a carefully-devised AGCM experiment, an experiment with two very important characteristics. First, it directly quantifies land-atmosphere feedback in the AGCM. This is achieved by imposing the same land surface states in each member of a 16-member ensemble and then examining the similarity of the precipitation generated by the different ensemble members. Second, the experiment is simple enough and computationally inexpensive enough to be accessible to many different modeling groups. Indeed, for the present paper, four groups performed the experiment.

The models do show substantial differences in the simulated strength of land-atmosphere feedback. Such differences, objectively determined here for the first time, underline the uncertainty inherent in our understanding of land impacts on climate. The four-model comparison demonstrates the viability of the intercomparison experiment, which we hope will expand to include a great many more models in the near future.