Impact of Soil Moisture Initialization On Seasonal Weather Prediction

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Abstract

The potential role of soil moisture initialization in seasonal forecasting is illustrated through ensembles of simulations with the NASA Seasonal-to-Interannual Prediction Project (NSIPP) model. For each boreal summer during 1997-2001, we generated two 16-member ensembles of 3-month simulations. The first, "AMIP-style" ensemble establishes the degree to which a perfect prediction of SSTs would contribute to the seasonal prediction of precipitation and temperature over continents. The second ensemble is identical to the first, except that the land surface is also initialized with "realistic" soil moisture contents through the continuous prior application (within GCM simulations leading up to the start of the forecast period) of a daily observational precipitation data set and the associated avoidance of model drift through the scaling of all surface prognostic variables. A comparison of the two ensembles shows that soil moisture initialization has a statistically significant impact on summertime precipitation and temperature over only a handful of continental regions. These regions agree, to first order, with regions that satisfy three conditions: (1) a tendency toward large initial soil moisture anomalies, (2) a strong sensitivity of evaporation to soil moisture, and (3) a strong sensitivity of precipitation to evaporation. The degree to which the initialization *improves* forecasts relative to observations is mixed, reflecting a critical need for the continued development of model parameterizations and data analysis strategies.

1 Introduction

Standard weather forecasts, which are based on the initialization of atmospheric variables in a numerical weather model, may extend out to about a week. Longer-lead forecasts are prevented by the chaotic nature of the atmosphere and the associated high speed with which atmospheric anomalies dissipate. The prediction of precipitation and temperature on seasonal to interannual timescales thus requires a different strategy: the seasonal prediction of "slower" components of Earth's climate system and a proper accounting of the atmosphere's response to these slower components. If, for example, we can predict a sea surface temperature (SST) anomaly field six months in advance, and if we know that the atmosphere responds in a characteristic way to this anomaly field, then some aspects of atmospheric behavior are predictable at six months.

The modeling and prediction of SSTs has been the main staple of seasonal forecasting efforts for some time (Shukla et al., 2000). This focus is appropriate, since SSTs are known to affect tropical and winter midlatitude meteorology, and they appear to be predictable a year or more in advance. The impact of SST fields on atmospheric properties in summer midlatitudes, however, appears quite small in various modeling studies (Kumar and Hoerling, 1995; Trenberth et al., 1998; Shukla, 1998; Koster et al., 2000). In fact, some studies show that in midlatitude summer, another "slow" component of Earth's climate system, soil moisture, dominates over SSTs in controlling continental precipitation (Koster et al., 2000). The implication is that the proper use of soil moisture data in a forecast system may, under certain circumstances, increase seasonal forecast skill.

Soil moisture data, however, are typically not employed in operational seasonal forecast systems. This is partly due to a dearth of relevant observational datasets and partly to a still limited understanding of the role soil moisture plays in seasonal prediction. Fortunately, the first limitation is being addressed by various ongoing land data assimilation efforts (e.g., Mitchell et al., 1999; Rodell et al., submitted), in which land surface models estimate soil moisture indirectly through their integration of observed precipitation and other forcing data. These efforts may someday be enhanced by the direct use of global, satellite-based estimates of soil moisture.

The second limitation – our limited understanding of soil moisture's impact – has been addressed by several recent atmospheric general circulation (AGCM) studies. These studies address many different aspects of the problem, as indicated by the following broad categorization. The examples listed within each category are not exhaustive.

(i) *Impact of "perfectly forecasted" soil moisture on the simulation of observed extreme events.* Studies by Atlas et al. (1993), Schubert (see Figure 1 of Entekhabi et al., 1999), and Hong and Kalnay (2000) have examined how the specification of soil moisture in a numerical model affects the simulation of rainfall associated with observed flood or drought conditions. The studies show that a proper soil moisture boundary condition is essential to the proper simulation of the precipitation extremes. Because the soil moisture is artificially maintained at prescribed values throughout the simulation period, these studies have relevance to precipitation forecasting only if soil moisture can be predicted into the simulation period – the studies do not address the prediction of soil moisture itself.

(ii) *Impact of "perfectly forecasted" soil moisture on the simulation of non-extreme interannual variations.* Studies by Delworth and Manabe (1988, 1989), Koster and Suarez (1995), Koster et al. (2000), Dirmeyer (2000, 2001), and Douville et al. (2001) have examined the impact of prescribed soil moisture on the interannual variation of model-generated precipitation, without a specific focus on observed "extreme" years. The upshot of these studies is that the specification of soil moisture (or evaporation efficiency) does exert significant control on the generation of precipitation, if only in certain regions. Koster et al. (2000) found that soil moisture affects precipitation mostly in the transition zones between arid and humid climates. These studies do not address the prediction of soil moisture itself, so they too address only part of the forecast problem.

(iii) *Impact of large, idealized soil moisture initial conditions on the evolution of subsequent model precipitation.* Many studies have examined how an initialized soil moisture anomaly affects precipitation in an AGCM (Rind, 1982; Oglesby and Erickson, 1989; Beljaars et al., 1996; Schar et al., 1999).

These studies do address the prediction of soil moisture, since it is not prescribed throughout the forecast period – soil moisture and atmospheric variables are free to evolve together. Nevertheless, the imposed soil moisture anomalies are idealized and are typically large, with the emphasis often being on the establishment of linkages between model precipitation and soil moisture rather than on the reproduction of observed precipitation anomalies. These studies generally find that a large initial soil moisture anomaly has a strong impact on subsequent precipitation.

(iv) *Idealized ensemble predictability studies, assuming a "perfect" model.* The studies of Wang and Kumar (1998) and Schlosser and Milly (in press) exemplify this type of predictability study, in which a set of soil moisture states that was attained by the model itself in a prior run (as opposed to a set of arbitrarily chosen anomalies) is used to initialize each member of an ensemble of parallel simulations. The inter-ensemble divergence of soil moisture over time and the impacts of this divergence on associated states and fluxes can provide a quantitative description of memory in the model, a description that is untainted by model "drift" because it avoids potentially uncharacteristic responses to artificial initial anomalies. Schlosser and Milly (in press) found significant temperature predictability but an almost negligible degree of precipitation predictability associated with soil moisture initialization in the GFDL AGCM.

(v) *Impact of "realistic" soil moisture initial conditions on the evolution of* *subsequent model precipitation.* An alternative to both idealized and model-generated soil moisture initial conditions are initial conditions inferred from observations, i.e., initial conditions that are reasonable proxies to the actual conditions occurring in the years studied. Fennessy and Shukla (1999), for example, used a proxy soil moisture dataset derived from the European Centre for Medium-Range Weather Forecasts analysis-forecast system. Douville and Chauvin (2000) initialized their model with soil moisture estimates derived from the Global Soil Wetness Project, and Viterbo and Betts (1999) examined the impact of soil moistures derived from ERA-15 reanalysis on the simulation of the 1993 Mississippi flood. Because forecasted precipitation fields can be compared to what actually happened, these studies allow a first look at the usefulness of soil moisture initialization in forecasting. The results, though suggestive and even encouraging, are still limited by the short data record and other issues, as discussed further in section 6.2 below.

All of these modeling studies, along with various statistically-based studies (e.g., Huang et al., 1996), contribute toward answering the most important question of all for seasonal prediction, namely, can an accurate soil moisture initialization lead to an improved forecast? In the present paper, we examine this question further with the forecasting system of the NASA Seasonal-to-Interannual Prediction Project (NSIPP). The approach we apply is a combination of categories (iv) and (v) above. Ensembles of AGCM simulations with the same non-idealized, model-consistent initial conditions for soil moisture provide a quantitative description of how initial anomalies are "remembered" into the forecast period and of how they influence precipitation and temperature forecasts. The initial conditions used in each simulated year, however, reflect the soil moisture conditions that occurred in nature during that year due to the application (prior to the forecast period) of observed precipitation rates into the model and the scaling of the resulting anomalies into model-consistent values, as described in section 3.

The main goals of the paper are twofold: (i) to document, for the NSIPP system, where soil moisture initialization affects precipitation and temperature forecasts during boreal summer (section 4), and (ii) to explain the global distribution of soil moisture impact in terms of climatological controls – to provide a possible means, in fact, for predicting the impact distribution that would be obtained with *any* forecasting system, based solely on its climatology (section 5). Note that these two goals could be achieved with an idealized ensemble-based experiment approach alone (category (iv) above). Because, however, the soil moisture initializations we use reflect real conditions, the experiment also lets us examine whether the initialization increases predictive skill (section 6). The improvement will prove to be mixed, setting the stage for a discussion of our current abilities to take full advantage of soil moisture initialization in seasonal forecasting.

2 Models Used

The present analysis uses the atmosphere and land components of the NSIPP forecasting system. The ocean component of the NSIPP system is replaced by prescribed sea surface temperatures (SSTs), as described in section 3.

The $2^\circ \times 2.5^\circ$ multi-level primitive equation atmospheric model used by Koster and Suarez (2001) is used in this analysis as well. The NSIPP-1 AGCM includes penetrative convection with the Relaxed Arakawa-Schubert scheme (Moorthi and Suarez 1992), Richardson number-dependent fluxes in the surface layer, and a sophisticated treatment of radiation, including a recent parameterization of longwave radiation (Chou and Suarez 1996) and the calibration of the cloud parameterization scheme with ERBE and ISCCP data. The numerics include fourth-order advection of vorticity and all scalars, and the atmospheric dynamics are coded as a dynamical core (Suarez and Takacs 1995). The climatology of this AGCM is described by Bacmeister et al. (2000).

The land surface model (LSM) used with the AGCM is the Mosaic LSM of Koster and Suarez (1992, 1996), a scheme that separates each grid cell into subgrid "tiles" based on vegetation class and then performs separate energy and water balance calculations over each tile. Following the approach of Sellers et al. (1986), vegetation explicitly affects the balance calculations within a tile in several ways: (a) stomatal conductance increases during times of environmental stress, thereby reducing transpiration; (b) vegetation phenology helps determine the albedo and thus the net radiation; and (c) the "roughness" of the vegetation affects the transfers of both momentum and the turbulent fluxes. All tile quantities (evaporation, radiation, etc.) are aggregated to grid cell totals prior to performing the analyses below.

The total water holding capacity of a tile is an important parameter for this study because it helps determine soil moisture memory. Three vertical soil layers are followed in each tile: a thin surface layer, a root zone layer, and a deep soil layer that can store moisture and provide it to the root zone during dry periods. The water holding capacity of these layers varies with vegetation type. Typically, forest tiles can hold a maximum of about 1500 mm of water, grassland tiles can hold about 620 mm, and bare soil tiles can hold about 140 mm. For an expanded discussion, the reader is referred to Koster and Suarez (2001), who provide a global map of "effective" water holding capacity in the model, i.e., a map of effective grid cell values that accounts for the different hydrological activity of component tiles.

3 Experiment Design

The analysis of initialization and predictability in the NSIPP-1 AGCM system is centered around a number of ensembles of 3-month simulations. In each simulation, SST fields are prescribed from observations but the atmospheric and land variables evolve together, following the approach used in the Atmospheric Model Intercomparison Project (AMIP; Gates, 1992). Each simulation begins on June 1. Five different boreal summers (1997-2001) are examined.

For each of the five summers, two distinct ensembles are produced: an "AMIP" ensemble and a "SoilInit" ensemble. These types differ only in the way the land surface variables are initialized. In the AMIP ensemble, the initial conditions used for the land variables differ between members. In the "SoilInit" ensemble, on the other hand, all members are initialized with the same set of surface conditions, conditions that are considered realistic because they reflect observed antecedent precipitation. The impact of soil moisture initialization on forecasted summertime precipitation and temperature is isolated by comparing the fields generated by the two ensembles.

Table 1 provides a summary of all simulations performed, including the supplemental simulations (the "GPCP" ensemble) used to initialize the SoilInit ensembles. Specific details regarding the model runs are now provided.

3.1 AMIP Ensembles

Observed monthly SSTs from Reynolds and Smith (1994) allowed NSIPP to produce a 16-member ensemble of multi-year AMIP-style simulations, that is, simulations in which these SSTs are prescribed but land and atmospheric variables evolve together. Half of these simulations had been integrated for multiple decades prior to 1995, and the other half began in 1995, with land variables initialized from randomly chosen years of the multi-decade simulations; thus, the impact of spin-up on model behavior in 1997 and beyond is negligible. For the present study, we examine "subset ensembles" of the 16-member AMIP-style ensemble. For each year in 1997-2001, we extract the June through August model results from each ensemble member, thus producing an ensemble of sixteen 3-month AMIP simulations. Note that for any given year, the different ensemble members have different (yet model consistent) land moisture conditions on 1 June.

3.2 GPCP Ensemble

The 5-member "GPCP ensemble" is run for one purpose only – to provide initial soil moisture conditions for the SoilInit ensembles. The strategy behind each member simulation in the GPCP ensemble is illustrated in Figure 1. First note that in typical AGCM simulations, including the AMIP simulations discussed above, the atmospheric model drives its LSM at every time step with values of precipitation, downwelling radiation, surface pressure, near-surface humidity, near surface air temperature, and wind speed. A GPCP simulation is run in the same way, except for one important difference – the precipitation computed by the GCM is not allowed to fall on the land surface. Instead, the land surface is forced by the *observed* precipitation for the given day, that is, a precipitation total derived from a daily dataset produced by the Global Precipitation Climatology Project (GPCP; George Huffmann, personal communication). This observed precipitation is applied uniformly over the day; past experience with the Mosaic LSM indicates that this uniform application will not strongly affect the model's behavior.

The underlying assumption of this experimental set-up is that in nature, interannual variations in precipitation are, to first order, responsible for interannual variations in soil moisture. Variations in radiation, surface humidity and other atmospheric fields may also have an impact but are of secondary importance. Under this assumption, the soil moisture fields that evolve in the GPCP simulations can be considered the most "realistic" moisture variables possible for initializing supplemental LSM runs (such as the SoilInit ensembles) because they reflect realistic antecedent precipitation *and* they are consistent with the LSM's own internal physics.

As of this writing, daily GPCP precipitation data are available for 5 years, starting in January, 1997. The availability of daily data defines, in fact, the period over which we perform our analyses. Monthly GPCP precipitation data, however, are available for many years before this, and we use two years of these data (1995-1996) to avoid spin-up problems. Daily values for 1995-1996 are artificially constructed from the monthly values using the temporal partitioning inherent in the 1997 daily data. At a given grid cell, if $P_{i,m,1997}$ is the daily precipitation during day i of month m in 1997, and if $P_{m,1995}$ and $P_{m,1997}$ are the monthly precipitation totals for month m of 1995 and 1997, respectively, then the corresponding daily total for 1995 is taken to be:

$$P_{i,m,1995} = P_{i,m,1997} \frac{P_{m,1995}}{P_{m,1997}}. \qquad (1)$$

This approach, which is similar to that used by *Sellers et al.* [1996] to disaggregate data for the ISLSCP Initiative 1 dataset, produces a time series of 1995 and 1996 precipitation data with reasonable temporal statistics and with accurate monthly means.

We begin the five GPCP runs on 1 January 1995 (initializing both the atmosphere and the land with 1 January 1995 conditions from five of the AMIP runs) and extend them through 1 June 2001. The land surface prognostic variables on a given date are averaged across the five ensemble members to get a single, best estimate of land surface conditions on that date.

3.3 SoilInit Ensembles

The SoilInit ensembles match the AMIP ensembles in size – on each 1 June during 1997-2001, we begin a 16-member ensemble of 3-month simulations. The initialization of the land surface prognostic variables is based on the values for 1 June produced during the GPCP ensemble, while the sixteen sets of atmospheric initial conditions are taken directly from the AMIP ensembles.

Climate drift prevents us from initializing the land variables directly with the mean 1 June states from the GPCP ensemble. The problem is that the mean GCM climate, while realistic to first order, does differ from that of the real world. Figure 2 illustrates the problem with an exaggerated example. Consider a hypothetical surface tile with the indicated probability density functions (pdfs) for soil moisture, across all years. The pdfs for the mean AGCM climate and for the GPCP ensemble presumably differ because of large differences in modeled and measured mean precipitation. Now suppose that during a given year, the GPCP ensemble produced a degree of saturation in the soil of 0.5. The 0.5 value clearly reflects a very dry year in the GPCP ensemble and thus in nature, and yet it would represent a very wet year in the free-running GCM. If we were to initialize the tile with 0.5 in the SoilInit ensemble, we would unrealistically initialize it wet.

To address this issue, we use standard normal deviates. At each land surface tile, we compute the mean ($\overline{w}$) and standard deviation (σ_w) of June 1 soil moisture for both the GPCP runs and the AMIP runs, across the 5 years of interest (1997-2001). Then, if the GPCP-based June 1 soil moisture for a particular year n (averaged over the five ensemble members) is $w_n^{[\mathrm{GPCP}]}$, the corresponding value $w_n^{[\mathrm{SoilInit}]}$ used to initialize the SoilInit ensemble in that year is that which satisfies:

$$\frac{w_n^{[\mathrm{SoilInit}]} - \overline{w^{[\mathrm{AMIP}]}}}{\sigma_w^{[\mathrm{AMIP}]}} = \frac{w_n^{[\mathrm{GPCP}]} - \overline{w^{[\mathrm{GPCP}]}}}{\sigma_w^{[\mathrm{GPCP}]}} \tag{2}$$

This approach ensures that a dry condition in the GPCP ensemble will translate to a roughly equivalent dry condition in the SoilInit ensemble. It also helps to prevent climate drift, since the initial conditions produced by (2) will necessarily be within the realm of the coupled model's own variability.

The same procedure, in fact, is used to initialize all of the land surface variables. Note that in the regions where the GCM reproduces the atmospheric forcing accurately, the land surface conditions from the GPCP ensemble are, in effect, used without modification in the initialization of the SoilInit runs.

4 Results: Simulated Memory

Figure 3 shows, for June, July, and August of 1999, differences (SoilInit minus AMIP) in the ensemble mean fields of soil moisture, precipitation, and temperature over southern North America. Differences are plotted only where they are statistically significant at the 95% level, as determined from a Student's T test. In other words, differences are plotted only where we can be reasonably sure that initialization has had some impact on the fields.

In this particular year (1999), the land initialization produced a wet soil moisture anomaly in the central United States that persisted through June, July, and August (left column of Figure 3). In much of the eastern and western United States, the spread of soil moisture values across the SoilInit ensemble increased enough, even in June, to render the distinction between the SoilInit and AMIP ensembles insignificant. The impact of soil moisture initialization on precipitation and temperature is shown in the middle and right columns, respectively. The areas of impact lie within those identified for soil moisture. The precipitation and soil moisture anomalies presumably help maintain each other through feedback. The associated evaporation anomalies induce the temperature anomalies via latent cooling.

Figure 3 highlights a relatively large impact of soil moisture initialization on the GCM fields in North America, compared to that seen in other years. The interannual variability of the impact is suggested in Figure 4, which shows, for each of the five years, differences (SoilInit minus AMIP) in the ensemble mean precipitation totals for JJA. Again, the differences are plotted only when they are significant at the 95% level. For some years (e.g., 1997), soil moisture initialization has very little impact on forecasted precipitation in North America.

A global composite measure of initialization's impact on JJA means is shown in Figure 5. The figure was constructed by first computing, at each grid cell and for each year n, the probability, $1 - \mathcal{P}_n$, that the initialization had no impact at all on the variable in question. A Student's T test provided the necessary values for $1 - \mathcal{P}_n$, with $1 - \mathcal{P}_n$ set equal to 1 if the ensembles were indistinguishable at the 75% level. The product of $1 - \mathcal{P}_n$ over all of the years is thus the probability that the initialization never had an impact on the variable. The probability, $\mathcal{P}$, that initialization had some impact (at least once) during the 5 years is thus computed with

$$\mathcal{P} = 1 - \prod_{n=1997}^{2001} (1 - \mathcal{P}_n) \tag{3}$$

Values of $\mathcal{P}$ exceeding 99% are shown in the figure for soil moisture, precipitation, and temperature.

As might be expected, the impact of initialization on seasonally-averaged soil moisture is extensive, covering most of the globe. The impacts on seasonally-averaged precipitation, on the other hand, are much more spatially limited. The main areas of impact for precipitation lie in the center of the North American continent, to the south and west of the Amazon, in tropical Africa, and across a swath in western Asia centered over the Caspian and

Black Seas. The areas over which initialization affects seasonally-averaged temperature are much more extensive, though not as extensive as those for soil moisture.

5 Geographical Variation of Soil Moisture Impact on Precipitation

Koster et al. (2000; see Fig. 13) found that a prescribed soil moisture boundary condition (or more specifically, a prescribed evaporation efficiency) had a significant impact on precipitation in transition zones between very dry and very wet climates. The areas they identify are more extensive than those in the middle panel of Figure 5, for two reasons. First, different versions of the NSIPP AGCM were used in the two studies, and the climates simulated by the two versions are somewhat different. Second, and much more important, the fields generated by Koster et al. (2000) show the response of precipitation to surface boundary conditions, that is, they identify the regions where precipitation can be predicted *if soil moisture itself can be predicted.* Initialization has an impact over a smaller area (middle panel of Figure 5) simply because the impact requires both (i) this strong response to land surface boundary conditions and (ii) soil moisture memory. Koster and Suarez (2001), in their analysis of soil moisture memory in the NSIPP system, show that memory is small (for example) in southern Asia, the middle of the Amazon, and the Sahel. Thus, despite the fact that Koster et al.

(2000) found a significant land-atmosphere connection in these regions, the impact of initialization there is low.

Thus, one way to predict the geographical distribution of impact in Figure 5 is to perform experiments similar to those in Koster et al. (2000) and then scale the results with a memory factor. These experiments, however, are as computationally expensive as the forecast experiments themselves. We want to establish a simpler, alternative approach, one that predicts the geographical distribution of impact from standard AGCM diagnostics – diagnostics typically available from any pre-existing AGCM simulation, as performed by any modeling group. To do this, we identify several factors that underpin land feedback on precipitation. In order for feedback to occur, conditions conducive to each of these factors must be adequate. The areas for which all conditions are adequate will be shown to agree, to first order, with the areas highlighted in the middle panel of Figure 5.

A simple line of reasoning identifies the factors we consider. We assume that in order for soil moisture initialization to have an impact on precipitation, (i) the soil moisture anomaly must be large enough to begin with, (ii) evaporation must be sensitive to soil moisture, so that the soil moisture anomaly can induce an evaporation anomaly, and (iii) precipitation must be sensitive to evaporation, so that an evaporation anomaly can induce a precipitation anomaly. These three factors and their combined effects are now discussed in turn.

5.1 Size of Soil Moisture Anomalies

The characteristic size of the initial soil moisture anomalies in the SoilInit ensemble is measured in terms of the standard deviation, σ_w, of total soil water in a grid cell (expressed as a degree of saturation) on the first of June. Recall that the initial soil moistures used in the ensemble, though based on observed antecedent precipitation, have been scaled with (2) to be consistent with the model's climatological means and standard deviations, as determined from AMIP simulations spanning the five years of study. Thus, one measure of σ_w for the total grid cell soil water could be derived from the $\sigma_w^{[\mathrm{AMIP}]}$ values used in (2), which correspond to individual water prognostic variables in tile space. For logistical reasons, and to ensure an accurate, independent calculation, we instead estimate σ_w by processing the June 1 soil moistures generated in archived multi-decadal NSIPP AGCM simulations (Koster and Suarez, 2001). Perhaps the most correct value of σ_w would be obtained by first determining, for each of a number of calendar years, the standard deviation of the June 1 moisture generated in an ensemble of parallel simulations. The standard deviation would then be averaged over the years, so that σ_w would be less likely to reflect interannual SST variations. We instead use the interannual value because it better represents the type of data accessible to most modeling groups.

The global field of σ_w is shown in the top plot of Figure 6. In the NSIPP system, initial anomalies tend to be especially large in central North America, parts of tropical Africa, and southeast Asia. They tend to be small in deserts and in certain very wet regions (e.g., the Amazon), where the soil moistures tend to cluster around their minimum and maximum values, respectively.

5.2 Evaporation's Sensitivity to Soil Moisture

Koster and Suarez (2001) show that a simple linear function can approximate the Mosaic LSM's much more complicated relationship between mean profile soil moisture, w_{n}, and evaporative fraction $E_{\mathrm{n}}/R_{\mathrm{n}}$, where E_{n} is the time-averaged evaporation and R_{n} is the time-averaged net radiation during time period n. This simple function,

$$\frac{E_{\mathrm{n}}}{R_{\mathrm{n}}} = cw_{\mathrm{n}} + d, \tag{4}$$

is determined via linear regression on simulated pairs of $E_{\mathrm{n}}/R_{\mathrm{n}}$ and w_{n} values. Koster and Milly (1997) show that for diagnostic purposes, such an approximation can be used to characterize the behavior of LSMs in general.

For the present study, we revisit the multi-decadal NSIPP AGCM simulations examined by Koster and Suarez (2001) to obtain "climatological" values of c and d for the June through August (JJA) period at every grid cell. Each $E_{\mathrm{n}}/R_{\mathrm{n}}$ value used in the linear regression is determined from three-month E and R totals from a particular year of simulation, whereas the corresponding w_{n} value is estimated (for various logistical reasons) from instantaneous w values on June 1, July 1, August 1, and September 1 of the same year.

The derived value of c at each grid cell is then multiplied by the climatological mean net radiation, $\overline{R}$, at that cell (for JJA) to produce a quantitative measure of the sensitivity of evaporation itself to soil moisture, one of the assumed requirements for land-atmosphere feedback. The global field of $c\overline{R}$ is shown in the middle panel of Figure 6. The figure indicates that evaporation is largely insensitive to soil moisture variations in eastern and northern North America, the eastern half of Asia, Scandinavia, the Amazon, and tropical Africa north of the equator. Thus, in these regions, we expect little impact of soil moisture initialization on precipitation.

5.3 Precipitation Sensitivity to Evaporation

Establishing a quantitative measure of the sensitivity of precipitation to evaporation is much less straightforward. One simple approach is to consider the difference between the two types of precipitation generated by the NSIPP-1 AGCM. The first type, moist convective precipitation, results from vertical air motion induced by moist static instability. Evaporation affects the onset of moist convection by influencing the structure and stability (relative to higher layers) of the atmospheric boundary layer. The second type, large-scale condensation, results from the horizontal movement of large, moist air masses into cooler regimes. Since these movements are mostly controlled by the large-scale atmospheric circulation, local evaporation presumably has little impact on the triggering of large-scale condensation events.

Under the assumption that only moist convection responds directly to local evaporation, we use the convective fraction, i.e., the ratio of convective precipitation to total precipitation, as a crude measure of precipitation's sensitivity to local evaporation. The convective fraction is plotted in the bottom panel of Figure 6. Moist convection is minimal in southern hemisphere midlatitudes (due to wintertime conditions) and in the far north of northern hemisphere continents. Thus, we expect little land-atmosphere feedback in these regions.

5.4 Combined Impact of the Three Factors

Again, all three factors plotted in Figure 6 are assumed critical to the translation of an initial soil moisture anomaly into a significant precipitation anomaly. The product of the three factors (σ_w, $c\overline{R}$, and convective fraction) can serve as a crude index of their combined effect, for if any one factor is small, the product will be small as well. In fact, the product of the first two, $\sigma_w c\overline{R}$, is essentially a measure of the interannual range of evaporation rates on the first date of the forecast period. It is thus a measure of the degree to which the surface energy balance can vary.

The product of the three factors is shown in the top panel of Figure 7. In North America, the product is high only in the center of the continent. From Figure 6, low values of the product in the east and north of the continent stem from a low evaporation sensitivity, whereas low values in the west stem from a low characteristic size of soil moisture anomalies. The product of σ_w, $c\overline{R}$, and convective fraction is also high along a swath south of the Amazon, in tropical Africa below the equator, in a thin swath across central Asia, and along the coast of the Bay of Bengal.

The patterns in the top plot of Figure 7 can be directly compared to those in the bottom plot, which shows where soil moisture initialization did affect the seasonal precipitation. (The bottom plot is a repeat of the middle plot in Figure 5.) A perfect agreement is not expected, given the statistical nature of the test and the limited duration of five years for the analysis. Nevertheless, the patterns agree quite well, particularly in the western hemisphere and in central Asia. The agreement in tropical Africa is less satisfying but still adequate.

Overall, the comparison in Figure 7 suggests that the aforementioned three requirements for an impact of soil moisture initialization on precipitation (namely, that the initial soil moisture anomaly be large enough, that the evaporation be sensitive to soil moisture, and that the precipitation be sensitive to evaporation) can indeed be represented together as a product of three distinct GCM diagnostics (namely, σ_w, $c\overline{R}$, and the convective fraction). This result is especially intriguing because it may provide a simple, albeit crude, way to characterize seasonal forecast systems in general. Of course, the robustness of the result over a variety of modeling systems must yet be demonstrated.

6 Usefulness of Soil Moisture Initialization

6.1 Evaluation of Forecasts

The preceding sections have quantified the impact of soil moisture initialization on forecasted precipitation and temperature anomalies. As noted in the introduction, this analysis could have proceeded using any set of model-consistent initial conditions. A key motivation for our experimental design (Figure 1), however, is the generation of crude estimates of realistic initial soil moisture conditions for the SoilInit ensemble, estimates that should allow a first look at the impact of the initialization on forecast skill. The SoilInit and AMIP ensemble forecasts can be validated against measured precipitation and temperature during the forecast period to provide a flavor for the advantages of land initialization.

Figure 8, for example, shows the 1997 JJA precipitation and temperature anomalies in central Asia for the SoilInit and AMIP ensembles (averaged over the component members) and for observations. All anomalies are relative to the means for the 5-year period. Precipitation observations are derived from the GPCP dataset, and temperature observations are taken from a global surface meteorology station dataset compiled by the National Climate Data Center (the "Global Surface Summary of Day Data") and thereafter gridded by NASA's Data Assimilation Office (M. Bosilovich, personal communication). For ease of comparison, the anomalies are shown only in those areas for which the SoilInit and AMIP ensemble-average forecasts differ significantly at the 95% level. Note also that observed temperature anomalies are simply not available in parts of the southeastern section of the map, so that a certain amount of "mental interpolation" is needed to fill in the gaps. For this particular season, the initialization of soil moisture has led to a significant improvement in forecasted seasonal precipitation and temperature over the western Asia areas identified earlier as having potential for predictability.

The success seen in Figure 8, however, is not typical, at least for the 5-year data record examined. Figure 9 shows the opposite extreme, a particularly poor forecast of JJA 2001 precipitation and temperature in the central U.S. The inaccurate SoilInit forecast of high precipitation in this region stems from very wet initial conditions there, which in turn stem from higher-than-average May 2001 precipitation rates in the GPCP dataset. In other words, in the real world during 2001, the central U.S. experienced a relatively wet spring followed by a relatively dry summer, whereas in the model, the wet spring tended to produce, on average, a wet summer.

Figure 10 summarizes the precipitation forecast results over regions in North America and western Asia that are known (Figure 5) to be characterized by high potential predictability. In both regions, soil moisture initialization seems to improve the forecast (at least in terms of reproducing the direction of the observed anomaly) in 1997 through 1999. The impact of initialization, however, appears negligible in 2000, and, in agreement with Fig. 9, initialization led to a poorer forecast over the North American region in 2001. Overall, the results are mixed; for the modeling system and initialization approach used here, and for the short period considered, soil moisture initialization does not unambiguously lead to an improved seasonal forecast.

6.2 Context of Experiment

As discussed in section 1, many studies support the idea that accurate soil moisture initialization may someday improve seasonal precipitation forecasts. The mixed results in section 6.1 reflect the difficulty associated with meeting this goal. Showing that precipitation in the NSIPP AGCM is strongly controlled by an artificially maintained soil moisture state (Koster et al., 2000) and is even influenced by soil moisture initialization (section 4) has proven much easier than showing conclusively that the initialization improves skill.

The mixed results in section 6.1, however, need not be viewed as pessimistic. Rather, they are probably indicative of current needs for improved model formulations, improved initialization strategies, and a more lengthy validation dataset. Any number of model and data deficiencies may have affected the comparisons in Figures 8-10. The following is a partial list:

(i) The model may locate incorrectly its areas of soil moisture initialization impact. If the locations of significant impact shown in Fig. 5 are shifted from the true locations (i.e., those operating in the real world) by even 5 or 10 degrees in latitude or longitude, the model would have problems; it might, for example, translate a soil moisture anomaly into a precipitation anomaly in a place where the land has little impact in the real world, and in an adjoining region, where soil moisture should have an impact, the model might let atmospheric chaos dominate. Errors in Fig. 5 could result from an inaccurate simulation of soil moisture variability, evaporation sensitivity to soil moisture, or convective fraction (see section 5).

(ii) Other model deficiencies may significantly bias the estimation of initial soil moisture contents, the strength of land-atmosphere feedback, or other aspects of Earth's climate system that affect forecast skill. In particular, the AGCM's climatological precipitation fields are imperfect relative to observations, necessitating the use of (2) in the initialization process. Even if the model's mean precipitation fields were accurate, antecedent precipitation anomalies could overestimate or underestimate initial soil moisture anomalies if surface processes such as runoff are parameterized poorly.

(iii) The soil moisture initial conditions used by the ensemble members are tied to observations, but the atmospheric conditions are not; the initial atmospheric fields, though consistent with the given year's SSTs, are culled from AGCM archives rather than from an atmospheric data assimilation system, as used in operational weather forecasting. In principle, taking advantage of predictable weather during the first week or so of a forecast – taking advantage of slow modes of variability inherent in the atmospheric fields – could lead to a more reliable soil moisture boundary condition over the remainder of the forecast period. An investigation of atmospheric initialization techniques for seasonal forecasting is warranted.

(iv) Only variations in observed precipitation are used to set the initial soil moisture contents. Observed variations in other fields (notably radiation, near-surface temperature, and near surface humidity) prior to the start of the forecast are ignored but could have an important effect on soil moisture evolution. In principle, a superior soil moisture data set for initialization would be produced by a full data assimilation system, one that combines the integration of all available forcing data (e.g., Mitchell et al., 1999) with the assimilation into the model of soil moisture observations wherever they exist (e.g., Walker and Houser, 2001). This superior data set might in turn lead to an improved forecast.

(v) The GPCP data are not perfect. Potential errors affect both the initialization of the soil moisture and the verification of the forecast.

Each of these model and data deficiencies could lead to a significant decrease in forecast skill. Even if the model and data were perfect in every way, however, we would still face a very difficult problem in evaluation: nature in this experimental design provides only five "realizations" of precipitation and temperature fields, not nearly enough to demonstrate statistically the success or failure of the approach. This limitation is clearly illustrated in the top plot of Fig. 11, which compares the observed JJA 2001 precipitation anomaly over the central U.S. region in Fig. 10 with the anomalies generated by the individual members of the SoilInit ensemble. Recall from Fig. 10 that, for this region and year, soil moisture initialization appeared to have a particularly negative impact on the accuracy of the forecast. Accordingly, Fig. 11 shows that most of the SoilInit simulations incorrectly predicted a wet summer in 2001. Note, however, that a few of the ensemble members do predict a dry summer, even dryer than what actually occurred. Thus, despite appearances in Fig. 10, the SoilInit forecast for JJA 2001 was *not* inconsistent with the observations. The observed dry summer was given a low, but nonetheless nonzero, probability of occurrence.

The bottom plot in Fig. 11 shows the corresponding histogram for the June 2001 forecast. In this plot, the observed anomaly lies outside the range indicated by the SoilInit ensemble, implying that the forecast system is probably biased, perhaps for the reasons enumerated above. Still, at least one of the ensemble members produced an anomaly of similar magnitude to the observed anomaly, and thus even for this more stringent test, the forecast is not conclusively wrong. The examples in Fig. 11 underscore the difficulties associated with evaluating a probabilistic ensemble forecast against a small sample of observations. The examples are in some ways even pessimistic, for such a large spread in the forecasts may imply a limited usefulness of the soil moisture initialization. Our hope is that a reduction of model and data errors will significantly improve such comparisons with the observations, perhaps in part by reducing this spread.

In any case, a proper statistical evaluation would require a great many more years of global precipitation data, not just monthly data for the summer validation period but also daily data for the generation of the initial soil moisture contents. The GPCP daily dataset currently spans the five years studied here. For a proper statistical analysis, an equivalent dataset covering several decades (with similar accuracy) would be needed.

7 Summary

We examined ensembles of simulations performed with the NASA Seasonal-to-Interannual Prediction Project AGCM to determine the impact of soil moisture initialization on seasonal forecasts of precipitation and temperature. Through the use of the technique outlined in Figure 1, the initial soil moisture anomalies in the SoilInit ensemble have "realistic" values for the five years examined – if, for example, precipitation observations indicate that a region experienced a wetter-than-average May, then the June 1 initial conditions for that region would be duly wet, in a manner consistent with internal land surface model physics and the AGCM's own mean climate. Output from the SoilInit ensemble was directly compared to that from the AMIP ensemble, which does not make use of a specific soil moisture initialization.

Two main results fall out of this study. First, as shown in Fig. 3-5, the impact of soil moisture initialization on seasonal precipitation prediction is significant over only a small fraction of the globe. Over most of the globe, the pdf of JJA precipitation derived from a SoilInit ensemble is statistically indistinguishable from that derived from the corresponding AMIP ensemble. This suggests that for seasonal precipitation prediction, soil moisture information will be useful only in certain limited areas. Note, however, that the impact of soil moisture initialization on seasonal temperature prediction is much more extensive, covering roughly half of Earth's land surface (Fig. 5).

The second main result is that an analysis of the forecast system's climatology allows us to predetermine, to a large extent, where soil moisture initialization should have an impact on the precipitation forecast. Three sensible criteria for a significant impact are identified: (i) the initial soil moisture anomaly must be large enough; (ii) evaporation must be adequately sensitive to a given soil moisture anomaly; and (iii) precipitation must be adequately sensitive to a given evaporation anomaly. Diagnostic measures of these three criteria for the NSIPP system are combined in Fig. 7, and the combination successfully reproduces (for the most part) the areas of influence seen in the forecast experiments. This result may have broad implications. By performing the same kind of diagnostic analysis, other modeling groups may get a sense for where soil moisture initialization will be important in their own forecast system, prior to performing the computationally-intensive ensembles described in this paper.

Finally, the analysis serves as a springboard for describing the difficulties associated with evaluating soil moisture-influenced forecasts against observations. A hint of an improvement in the seasonal forecasts of precipitation and temperature can arguably be attributed to soil moisture initialization (Fig. 10), but a proper evaluation is rendered impossible at this time by an insufficient data record – a great many more years of data would be required for a proper statistical analysis. Of course, model and data processing deficiencies, as enumerated in section 6.2, further cloud the comparisons. Our hope is that the correction of these deficiencies will eventually lead to a clearer demonstration of the impact of soil moisture initialization on seasonal predictive skill.

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Figure Captions

Fig. 1 Schematic of the strategy used for the GPCP model runs, which provide the initial conditions for the SoilInit ensembles.

Fig. 2 Illustration of the impact of climate bias in the GCM, using hypothetical, extreme example. Note that a relatively dry state in the GPCP ensemble corresponds to a relatively wet state for GCM's mean climatology (in the absence of GPCP forcing).

Fig. 3 Impact of soil moisture initialization on the monthly averaged soil moisture (left column), precipitation (middle column) and temperature (right column).

Fig. 4 Impact of soil moisture initialization on JJA precipitation for each of the five years considered in the experiment.

Fig. 5 Composite maps showing the locations where soil moisture initialization had a significant impact, at least once during the 5 years studied, on soil moisture (top), precipitation (middle), and surface temperature (bottom). Significance is at the 99% level.

Fig. 6 Factors affecting strength of land-atmosphere feedback. Top: characteristic size of initial soil moisture anomaly, as measured by the standard deviation of total June 1 soil water (in units of degree of saturation). Middle: Product of the mean net radiation and the slope of the evaporation ratio versus soil moisture relationship (in W/m^2). Bottom: Convective fraction (dimensionless).

Fig. 7 Top: Product of the three factors hypothesized to contribute to soil moisture initialization's impact on precipitation. Bottom: Composite map showing the locations where soil moisture initialization had a significant impact, at least once during the 5 years studied, on precipitation. Significance is at the 99% level.

Fig. 8 Comparison of JJA precipitation and temperature forecasts with observations in 1997. Top: forecasted anomalies obtained with SoilInit ensemble, that is, with specific soil moisture initialization. Middle: forecasted anomalies obtained with AMIP ensemble, that is, without specific soil moisture initialization. Bottom: Observed anomalies.

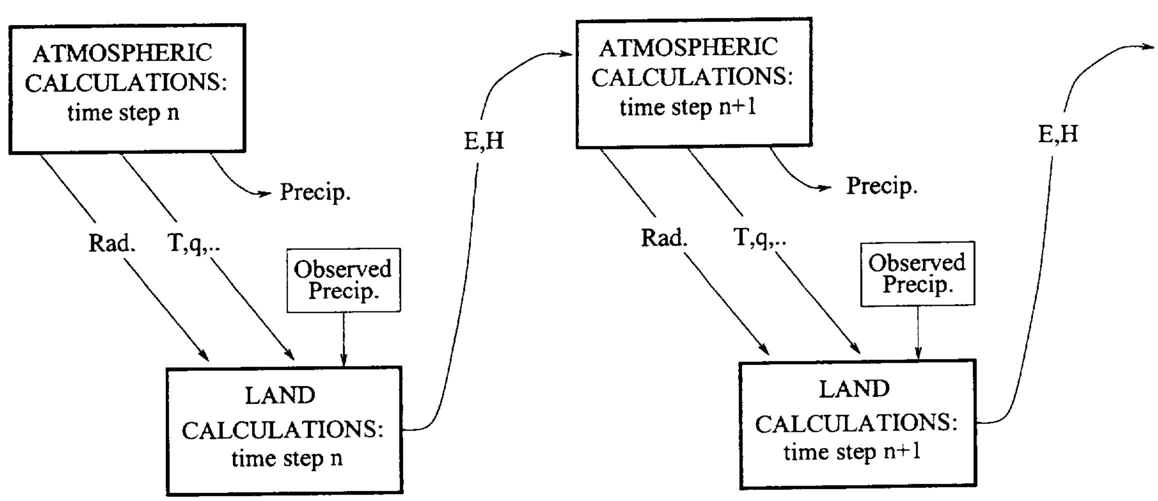
Fig. 9 Comparison of JJA precipitation and temperature forecasts with observations in 2001. Top: forecasted anomalies obtained with SoilInit ensemble, that is, with specific soil moisture initialization. Middle: forecasted anomalies obtained with AMIP ensemble, that is, without specific soil moisture initialization. Bottom: Observed anomalies.

Fig. 10 Summary of forecast results over the two indicated regions, one in central North America (left two columns) and one in western Asia (right two columns). Shown in the first column of each pair of columns are the mean JJA precipitation anomaly (in mm day^{-1}) for the SoilInit ensemble (leftmost bar), the mean JJA precipitation anomaly for the AMIP ensemble (middle bar), and the observed JJA precipitation anomaly (crosshatched bar), for each year of study. Shown in the second column of each pair of columns are the corresponding values for the JJA temperature anomalies (in °K).

Fig. 11 Top: JJA 2001 precipitation anomalies (in mm day^{-1}) generated by the individual members of the SoilInit ensemble, ranked by size. The observed precipitation anomaly is shown as the crosshatched bar. Bottom: Same, but for June 2001 precipitation.

	AMIP ensembles	"GPCP-style" runs	SoilInit ensembles
1995 - 1996	16-member ensemble covering both years.	5-member ensemble covering both years; monthly GPCP precip. applied, using artificial temporal disaggregation.	
1997	16-member ensemble continues through year. We examine June-August periods of these simulations.	5-member ensemble continues through year; daily GPCP precip. applied.	16-member ensemble of 3-month simulations, beginning on June 1. Initial land conditions taken from GPCP ensemble.
1998	Same as for 1997.	Same as for 1997.	Same as for 1997.
1999	Same as for 1997.	Same as for 1997.	Same as for 1997.
2000	Same as for 1997.	Same as for 1997.	Same as for 1997.
2001	Same as for 1997.	Same as for 1997.	Same as for 1997.

Table 1: Summary of runs used in this study.



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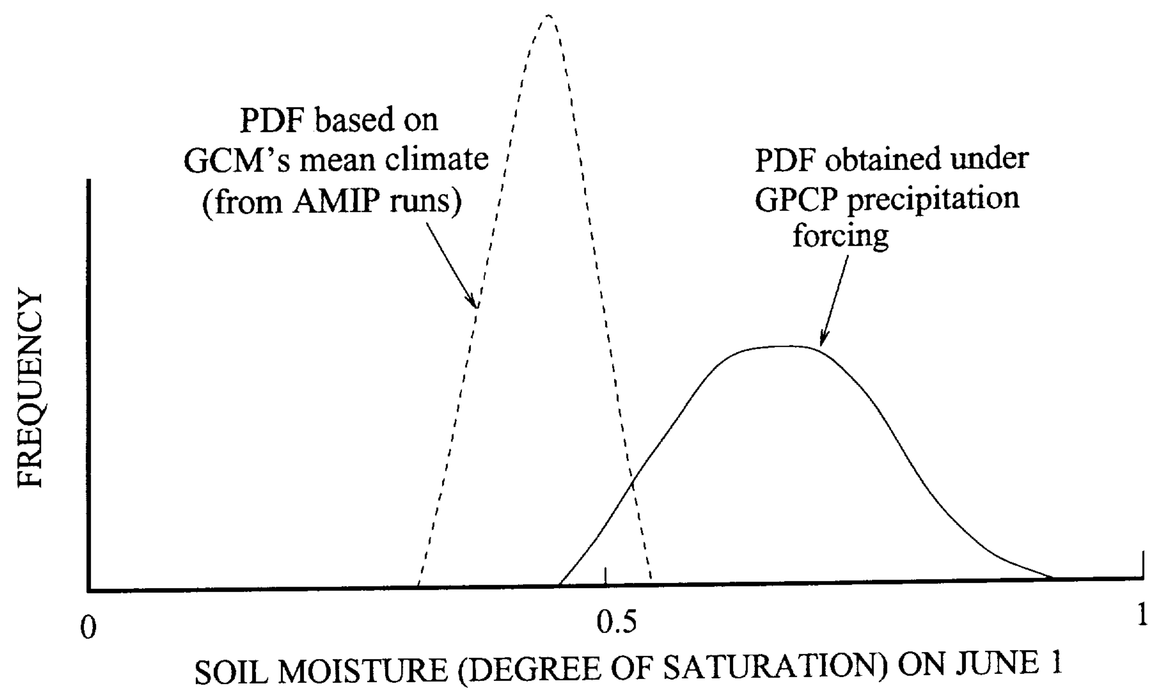

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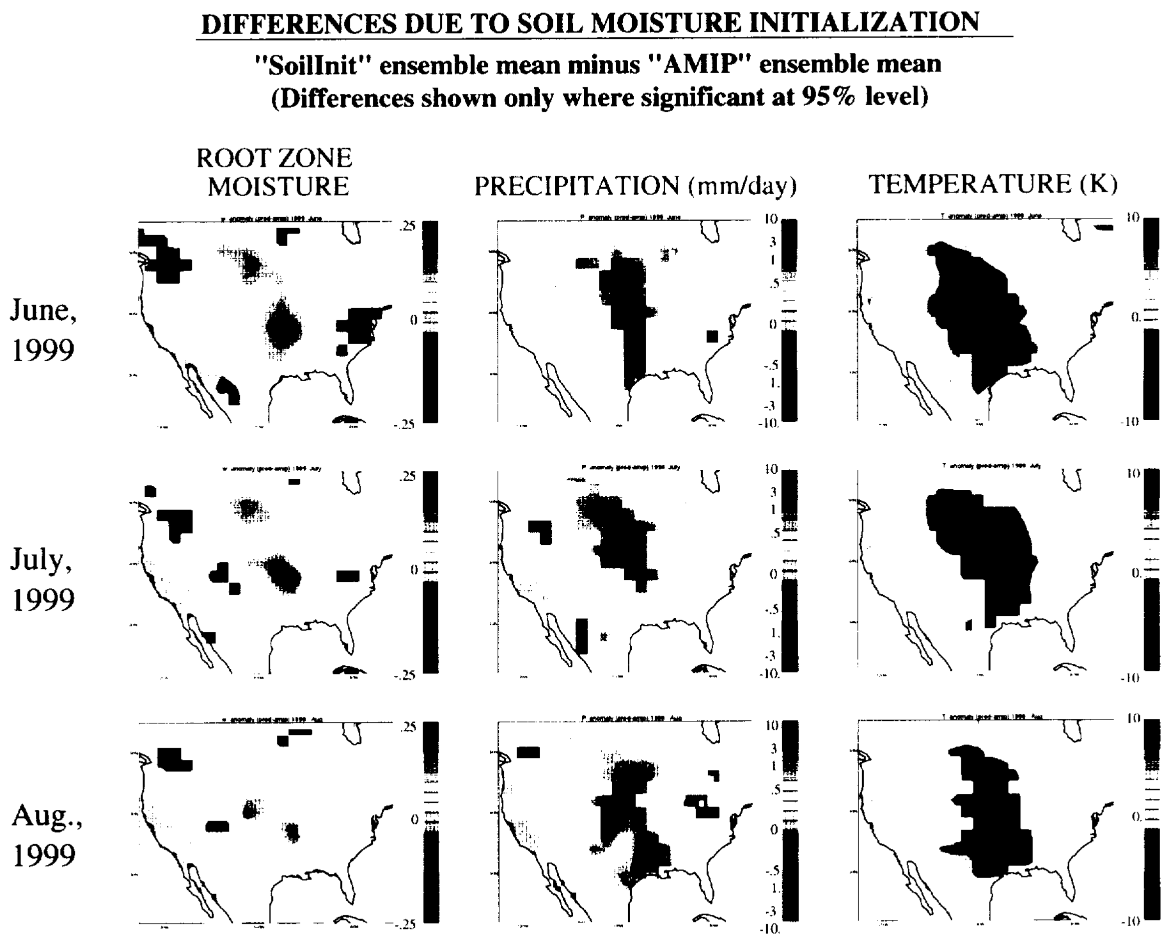

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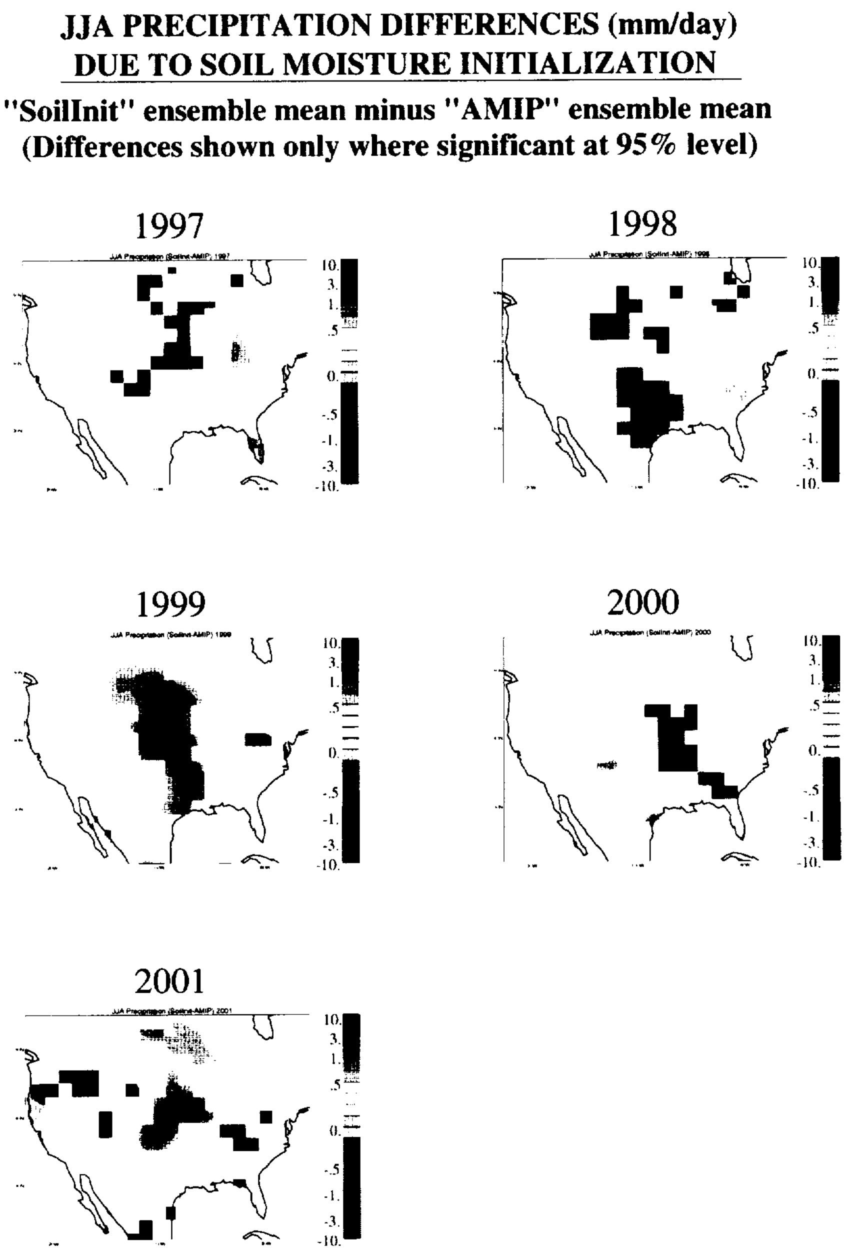
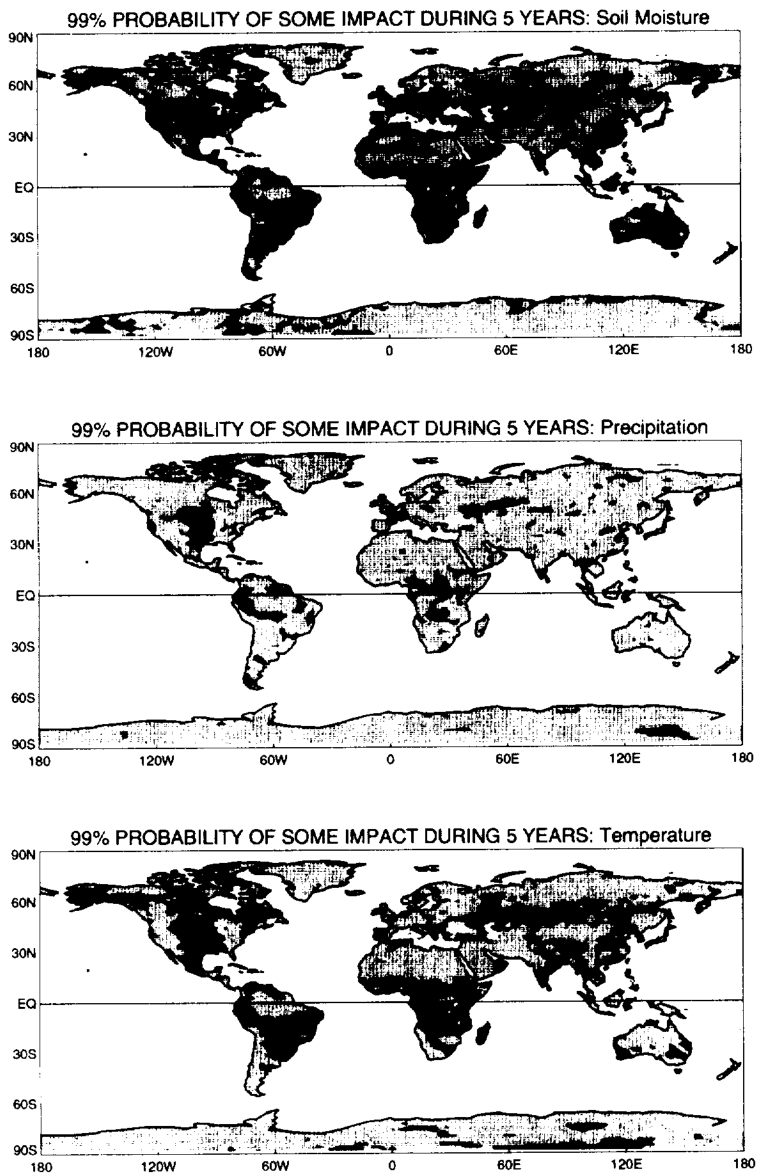


Figure 4: Impact of soil moisture initialization on JJA precipitation for each of the five years considered in the experiment.



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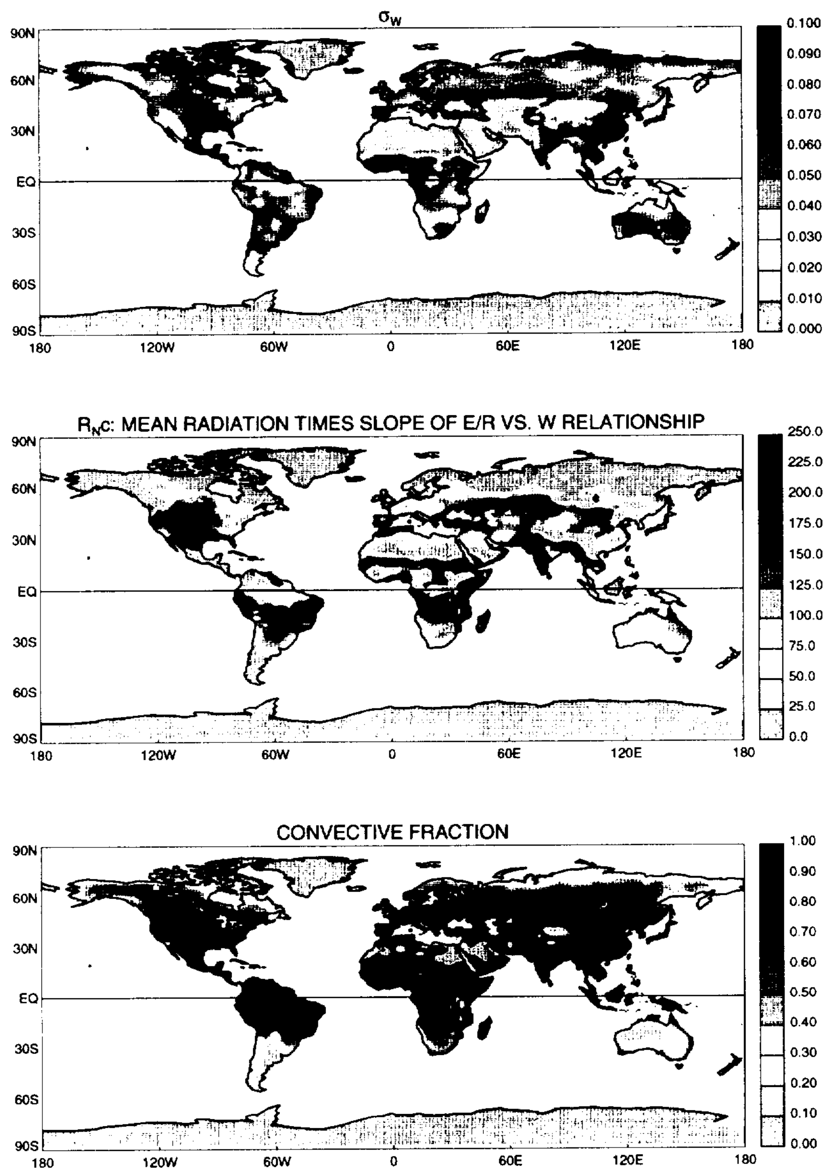

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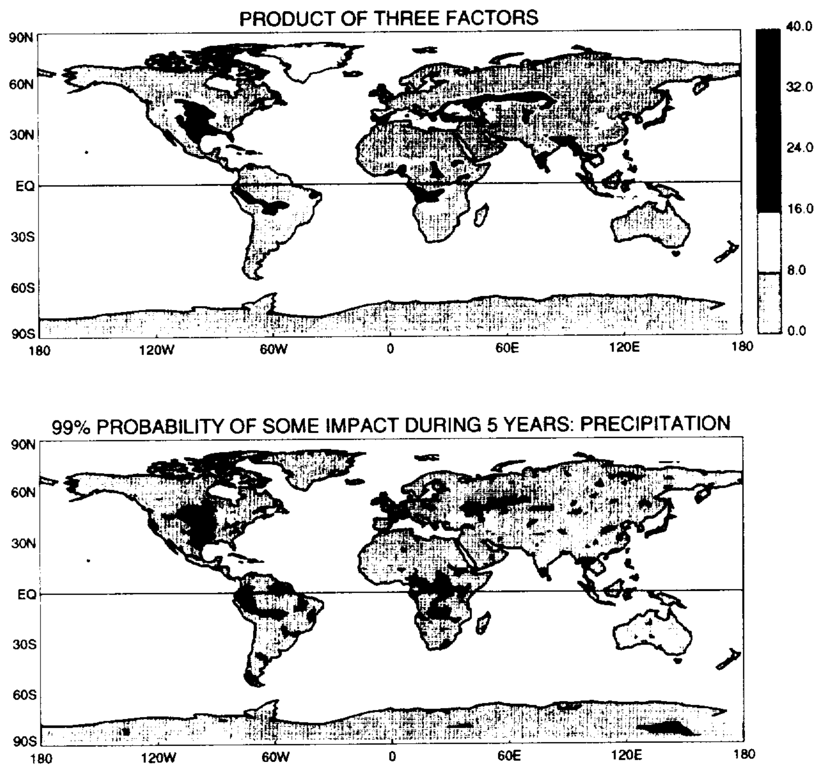

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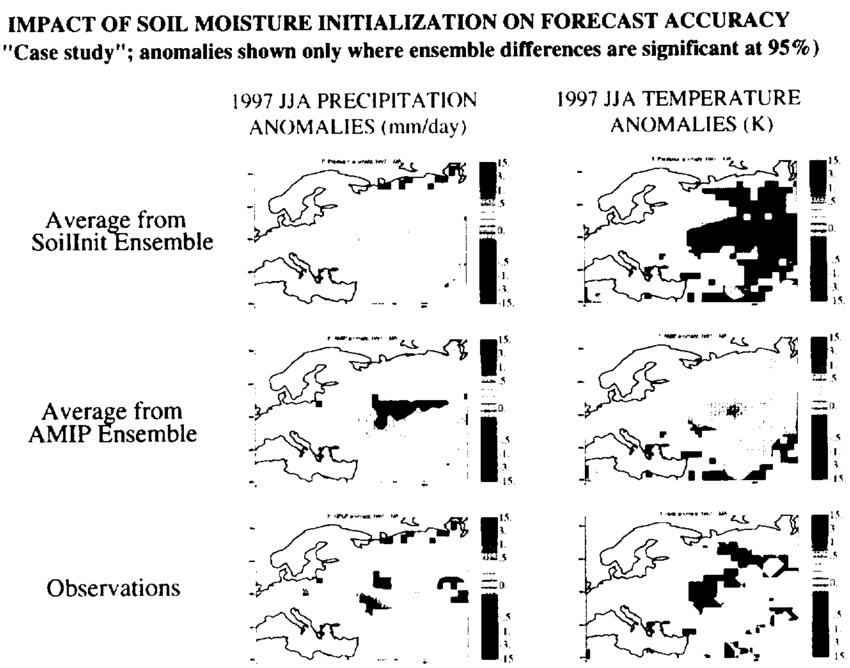

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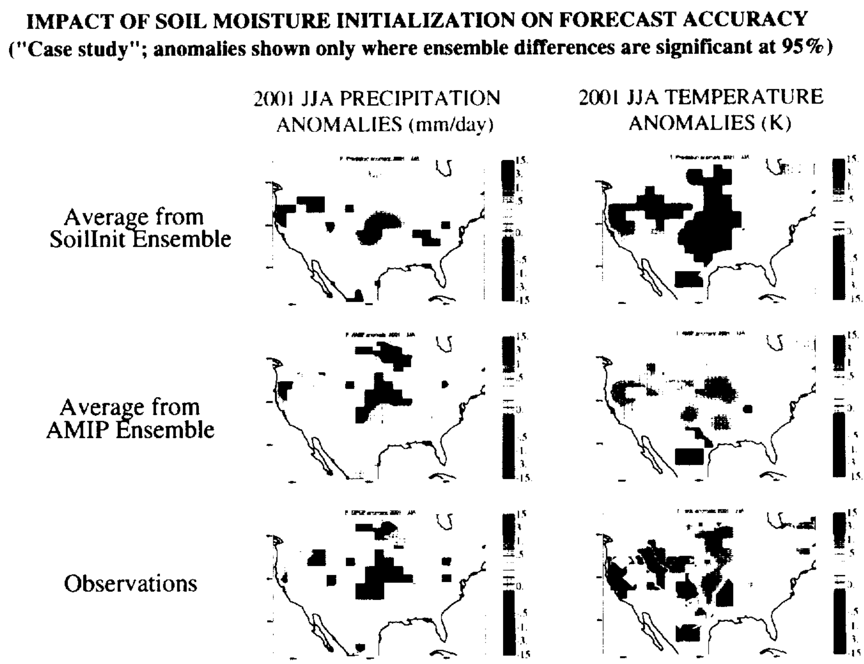

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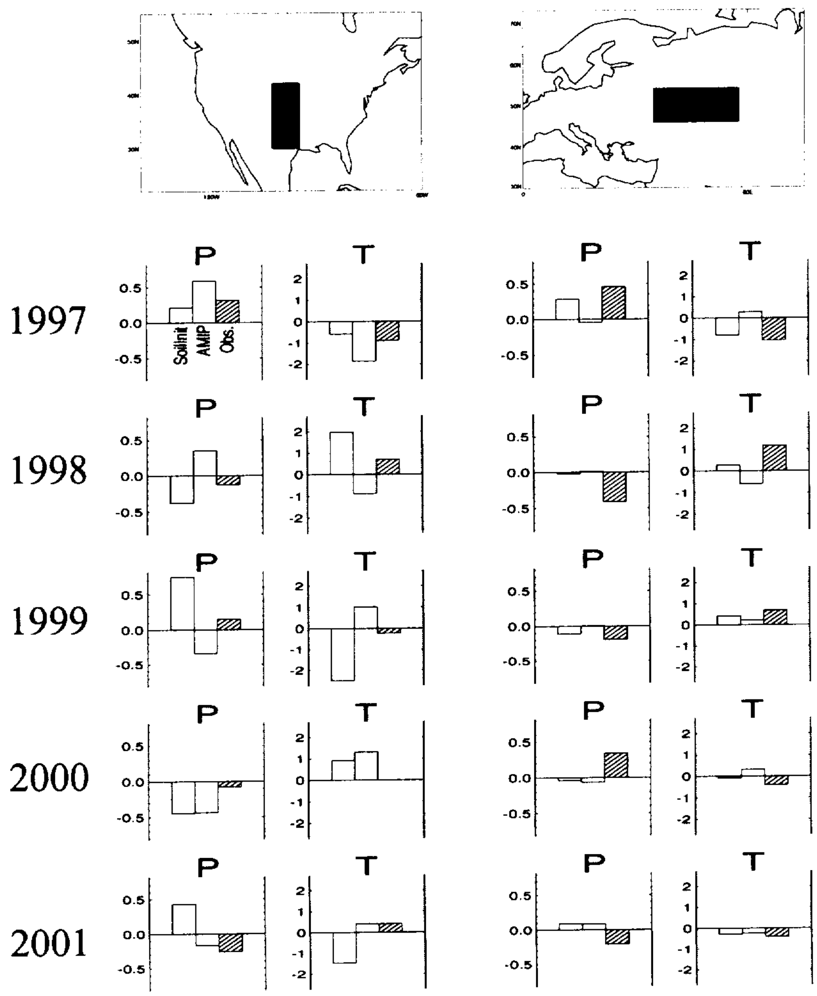

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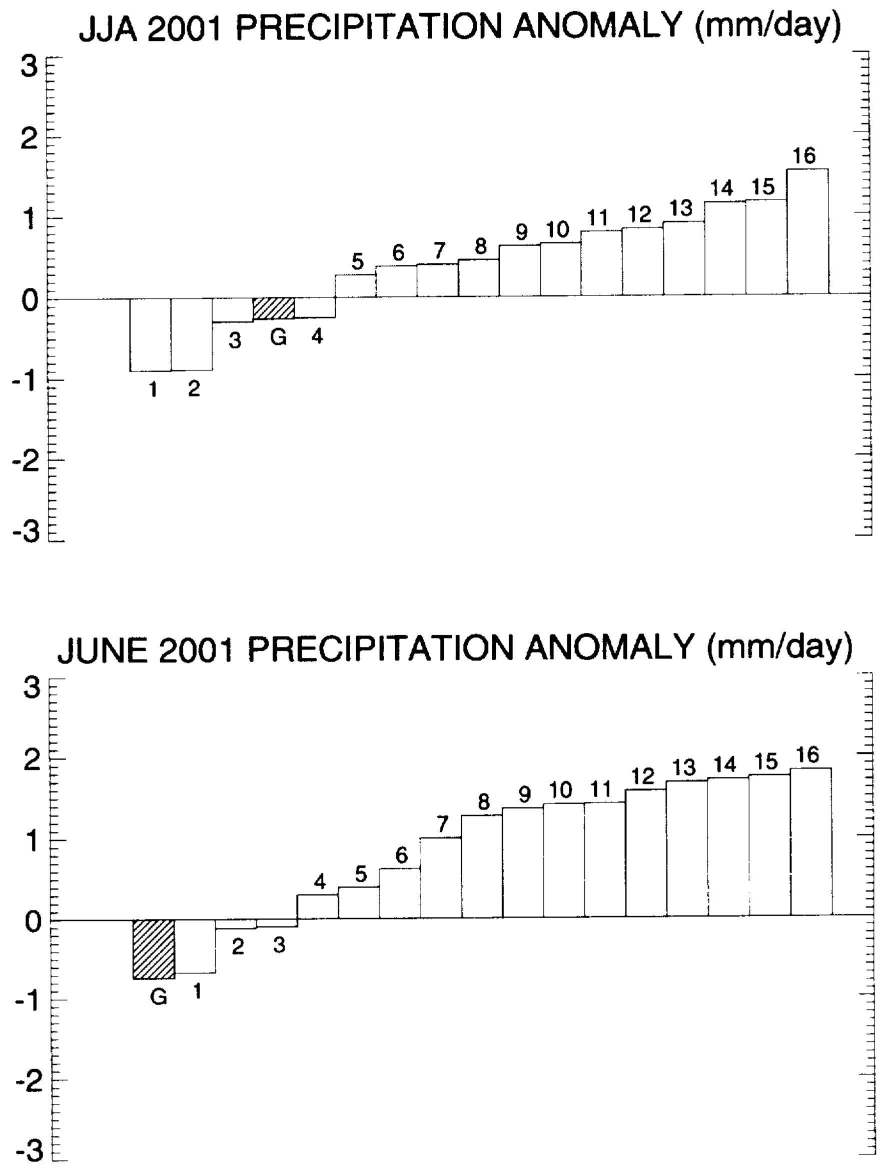

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