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Covariabilities of spring soil moisture and summertime United States precipitation in a climate simulation

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Abstract:

This paper explores the space-time connections between springtime soil moisture and summer precipitation over the continental United States by applying a singular value decomposition (SVD) method to a 50-year climate simulation. The first two SVD modes were analyzed. The two leading SVD modes account for 43% of the squared covariance between spring soil moisture and summer precipitation. Their corresponding components explain 14% of the soil moisture variance and 19% of the precipitation variance, respectively, which is larger than that contributed by tropical Pacific sea-surface temperatures (SSTs). The temporal correlations between the two expansion coefficients of each SVD mode are 0.83 and 0.88, respectively, indicating a significant association between spring soil moisture variation and summer precipitation variability. Both positive and negative cross-correlations exist over different regions of the United States in the two modes. Linear regression relates surface relative humidity and surface air temperature to the soil moisture SVD time series. The patterns revealed by the SVD analysis show where the local soil moisture-precipitation coupling contributes to the model's simulation of precipitation. Copyright © 2006 Royal Meteorological Society

KEY WORDS climate simulation; soil moisture-precipitation coupling; land-atmosphere interaction; SVD

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INTRODUCTION

The influence of soil moisture on near-surface atmosphere and climate via land-atmosphere interaction has been recognized as important for decades (e.g. Manabe, 1969; Walker and Rowntree, 1977; Rind, 1982; Mintz, 1984; Dickinson and Henderson-Sellers, 1988; Avissar and Verstraete, 1990; Chahine, 1992; Betts *et al*., 1996; Koster *et al*., 2003). Soil moisture variations affect subsequent precipitation through the feedbacks between the land and the atmosphere, and hence provide land surface memory (e.g. Delworth and Manabe, 1988, 1989; Dirmeyer and Shukla, 1993; Koster and Suarez, 1995; Schär *et al*., 1999; Pal and Eltahir, 2001; Koster *et al*., 2003). The typical timescale of soil moisture variability is about 2–3 months in midlatitudes, as inferred from both observations and model simulations (e.g. Delworth and Manabe, 1988, 1989; Vinnikov *et al*., 1996; Liu and Avissar, 1999; Entin *et al*., 2000; Wu *et al*., 2002), suggesting that the impact of such land surface memory on precipitation could last up to seasonal timescales.

Various previous studies have related spring soil moisture to summer precipitation. For example, Namias (1991) suggested that reduced soil moisture during late winter and/or spring over a mid-continental region (such as the central United States) could help induce and amplify a warm and dry summer over the same region, in part by reduction of the local evaporation, as well as by modifying the large-scale atmospheric circulation. Schubert *et al*. (2004) examined the causes of the US Great Plains droughts using ensembles of long-term (1930–2000) simulations with an atmospheric general circulation model forced with observed sea-surface temperatures (SSTs). Their study indicated that only about one-third of the total low-frequency rainfall variance in the Great Plains is forced by SST anomalies, with the remaining low-frequency variance of precipitation resulting from interactions with soil moisture.

The above studies have indicated that soil moisture may enhance the precipitation variability via local land-atmosphere feedbacks. The basic mechanisms that affect precipitation variability are the land surface's ability to store moisture and then to deliver it to the atmosphere (Milly and Dunne, 1994), the atmosphere's ability to recycle the evaporated moisture from the land into precipitation (Brubaker *et al*., 1993), and the dependency of atmospheric thermodynamic profiles on surface fluxes. The physical processes relating the formation of precipitation to soil moisture dynamics and their feedbacks are extremely complex. While the soil moisture feedback is usually positive, negative feedback may exist in certain regions or atmospheric regimes (e.g. Findell and Eltahir,

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2003; Ek and Holtslag, 2004). The present study further addresses this issue of soil moisture – precipitation correlation on interannual timescales.

This study selects the continental United States as an ideal midlatitude example with typical soil memory of roughly 2–3 months to clarify the relationship between soil moisture and precipitation. The relative importance of the land and ocean influences on precipitation changes with the seasons. The influence of the land surface is strongest when the continents are warmer than the surrounding oceans and surface evaporation is large, and varies greatly as a function of terrain and vegetative cover. SST anomalies during the cold season, however, can indirectly affect warm season rainfall by contributing to the initial springtime soil moisture conditions and vegetative cover, which can subsequently influence the climate during the warm season by influencing surface air temperature and evaporation. To establish that soil moisture affects precipitation is difficult with observational or model data, because the other direction of causality is much stronger – precipitation has a first-order impact on soil moisture. This study examines the associations between springtime soil moisture and summertime precipitation. Its primary focus is to identify the correlations between spring soil moisture variations and summer precipitation anomalies for interannual timescales.

Section 2 describes the data and methods used for the study, while Section 3 reviews the coupling of Common Land Model (CLM) with National Center for Atmospheric Research Community Climate Model Version 3 (NCAR CCM3), which provides the long-term soil moisture and precipitation data for the study, and the evaluation of its performance. In Section 4, the results of correlations between spring soil moisture and summer precipitation in the US are presented and discussed. Further discussion is made in Section 5 and conclusions from the study are summarized in Section 6.

METHODOLOGY

Modeling

The third version of NCAR CCM (Kiehl *et al*., 1998) coupled with multilayer land model CLM (Dai *et al*., 2003) was used to simulate climatic variations in the United States land-atmospheric system. The NCAR CCM3 is a spectral atmospheric model with T42 truncation (approximately $2.8^{\circ} \times 2.8^{\circ}$ horizontal resolutions), 18 vertical levels, and a 20-min time step. It employs comprehensive parameterizations of deep convection, shallow and nonprecipitating convection, shortwave and longwave radiation, and atmospheric boundary layer turbulence. The SSTs and sea ice are prescribed from observed monthly mean fields over 1950–2000.

The land component of climate models has evolved from the original single soil layer bucket schemes, based upon the original work of Budyko (1956) and the early work of Manabe (1969), to comprehensive multilayer diffusion schemes with root and canopy included (Dickinson *et al*., 1993; Sellers *et al*., 1996). The CLM is developed primarily on the basis of Biosphere-Atmosphere Transfer Scheme (BATS) (Dickinson *et al*., 1993), NCAR Land Surface Model (LSM) (Bonan, 1996), and the snow model from IAP94 (Chinese Academy of Sciences Institute of Atmospheric Physics Land Surface Model 1994 version) (Dai and Zeng, 1997) to establish a more physically-based soil–vegetation–atmosphere transfer scheme for climate studies. Its major model characteristics include 10 unevenly spaced layers to adequately represent soil temperature and soil moisture and a multilayer parameterization of snow processes, an explicit treatment of the mass of liquid water and ice water and their phase change within the snow and soil system, a runoff parameterization following the topography-based runoff prediction model (TOPMODEL) concept (detailed in Beven, 1997), a canopy photosynthesis-conductance model that describes the simultaneous transfer of CO_2 and water vapor into and out of vegetation, and a tiled treatment of sub-grid fraction of land cover which includes a separate computation of energy and water balance. A CCM-like vertical differencing is used, in which the mesh points are specified and interfaces are located halfway between two neighboring layers. The thermal properties (temperature, thermal conductivity, and volumetric heat capacity) and the hydraulic properties (volumetric soil water content, hydraulic conductivity, and metric potential) are defined at the node of each layer. Another relevant feature is the use of high-resolution vegetation data, including the global 1-km fractional vegetation cover and the International Geosphere–Biosphere Program (IGBP) land cover classification, both are pixel-dependent but seasonally independent (Zeng *et al*., 2000). The CLM has been extensively evaluated in off-line mode and by coupling runs with atmospheric models. Its testing data include those in the Project for Intercomparison of Land Surface Parameterization Schemes (Henderson-Sellers *et al*., 1992), a variety of multiyear point observational data for different land cover types and different climatological regimes over the world, regional data over the US Red-Arkansas River basin, and global data from the Global Soil Wetness Project (Dirmeyer *et al*., 1999). Dai *et al*. (2003) show that the CLM realistically simulates the state variables, such as soil moisture, soil temperature and snow water equivalent, and the flux terms, such as net radiation, latent heat flux, sensible heat fluxes and runoff.

The coupling of CLM to NCAR CCM3 is detailed in Zeng *et al*. (2002). They have evaluated a 15-year simulation of land surface climate from CLM-CCM3 by comparison with LSM-CCM3 and observations. The summer cold bias of surface air temperature in the LSM was found to be significantly reduced by an increase of sensible heat fluxes and decrease of latent heat fluxes. The winter warm bias over seasonally snow-covered regions was decreased. The CLM also significantly improves the simulation of the annual cycle of runoff and snow mass during the snow accumulation stage. The comparison of volumetric soil water between CLM and LSM showed

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a similar spatial distribution of soil water, but with CLM having slightly drier soils. The model simulates the principal spatial and seasonal features of the observed precipitation distribution to within 0.2 mm day^{-1} of that observed (Willmott *et al*., 1998) for most of the months over global land. In sum, the results reported by Zeng *et al*. (2002) suggest that the simulation of land climate in CCM3 has been substantially improved through use of the CLM.

The model output to be used in this study consists of monthly mean precipitation over the United States and soil water content to a depth of 1 m from 1950 to 2000. The water in the first meter of soil depth is expected to couple to the atmosphere on a timescale of a month or two. Near-surface water is exchanged more rapidly and deeper water more slowly. The quality of the soil moisture simulation data is described in Wu and Dickinson (2004) and will be briefly reviewed in Section 4. Spring and summer seasonal means are obtained by averaging the monthly means of March–April–May (MAM) and June–July–August (JJA), respectively. An anomaly is defined as the deviation of the seasonal mean from its long-term average.

SVD analysis

SVD is a technique to objectively identify coupled spatial patterns with the maximum temporal covariance between two fields. It has been applied in atmospheric research for decades (Wallace *et al*., 1992; Wang and Ting, 2000; Trenberth *et al*., 2002; Liu, 2003) and described in detail by Bretherton *et al*. (1992). Here we review its basic elements to help clarify the analysis.

Denote two fields as $u(t) = [u(x_k, t)]$ and $v(t) = [v(y_l, t)]$, where x_k and y_l are space locations; $k = 1, 2, \ldots, N_x$, $l = 1, 2, \ldots, N_y$, and N_x and N_y are the number of space locations for u and v, respectively; and t is time. SVD analysis separates each of the two fields into a sum of spatial patterns multiplied by temporal series,

$$u(t) = \sum_{k=1}^{N} a_k(t) p_k \tag{1}$$

$$v(t) = \sum_{k=1}^{N} b_k(t) q_k \tag{2}$$

where p_k and q_k are spatial patterns (principal components), $a_k(t)$ and $b_k(t)$ are temporal series (expansion coefficients), and N is the smaller of N_x and N_y. An SVD mode is composed of a spatial pattern and its corresponding temporal series. p_k and q_k are obtained as the eigenvectors (singular vectors) of $C_{uv}C_{uv}^T$ and $C_{uv}^T C_{uv}$, respectively, where C_{uv} is the cross covariance of $u(t)$ and $v(t)$. The correlation between a_k and b_k has the following feature: if the nonnegative eigenvalues (singular values) σ_k are put in decreasing order (i.e. $\sigma_\mathrm{i} \geq \sigma_\mathrm{j}$ for $i < j$), then the covariance between a_i and b_i is greater than or equal to that of a_j and b_j. Thus, the largest covariance occurs between the first pair of spatial patterns, the second largest covariance between the second pair, and so on. The first few pairs of modes, the SVD leading modes, may describe much of the total covariance. The contribution of the kth pattern to the total covariance of the two fields is measured by squared covariance function (SCF),

$$SCF_k = \sigma_k^2 \Big/ \sum_{l=1}^{N} \sigma_l^2 \tag{3}$$

In this study, the SVD analysis is performed on the basis of a covariance matrix between soil moisture and precipitation anomalies. Prior to the SVD analysis, these anomalies are area-weighted by a latitude parameter $cos(\pi\varphi/180)$, where φ is the latitude in degrees.

Monte Carlo confidence interval estimation

The Monte Carlo estimation method is used to test significance levels for this study. It is a type of resampling process used to produce a probability estimate. The original data samples consist of n independent units $(x_j, j = 1, 2, \ldots, n)$. The order of the data is randomly rearranged multiple times, in principle, destroying the correlation of u and v and thus providing a statistical distribution of uncorrelated data for null hypothesis testing. We (1) resample from the original data, x_j, to generate a sample, x_j^*; (2) compute the statistic of interest for the realized sample, such as correlation coefficient in our study; (3) repeat the above two-steps a large number of times M (say, $M = 1000$, 5000, or more); (4) order the computed sample statistics in a distribution f_x^*, called the 'Monte Carlo distribution' of the statistic; (5) on this estimated distribution f_x^*, identify the density values corresponding to the 95th and 5th percentiles, respectively, to obtain the lower and higher limits of a 95% confidence (or 5% significance) interval. A Monte Carlo confidence interval need not be symmetrical. More details about Monte Carlo methods can be found in Noreen (1989).

RESULTS AND DISCUSSION

Summer rainfall variability

Figure 1 shows the simulated summer rainfall climatology and corresponding standard deviations, with Willmott–Matsuura observational results (Willmott and Matsuura, 2001) displayed in Figure 2 for comparison. The summer rainfall rates range from less than 0.5 mm day^{-1} in the Western coastal regions to more than 4 mm day^{-1} in the Eastern coastal regions. The Gulf Coast has greater than 5 mm day^{-1}, and the Northern and Central Plains about 3 mm day^{-1} precipitation on average. The distribution of precipitation reflects the geographical dependence of summer precipitation in the US on a seasonal timescale, with the largest variability in the Southeast and the Northern Central Plains. Over the Southeast and Southern Great Plains, the standard deviation values are

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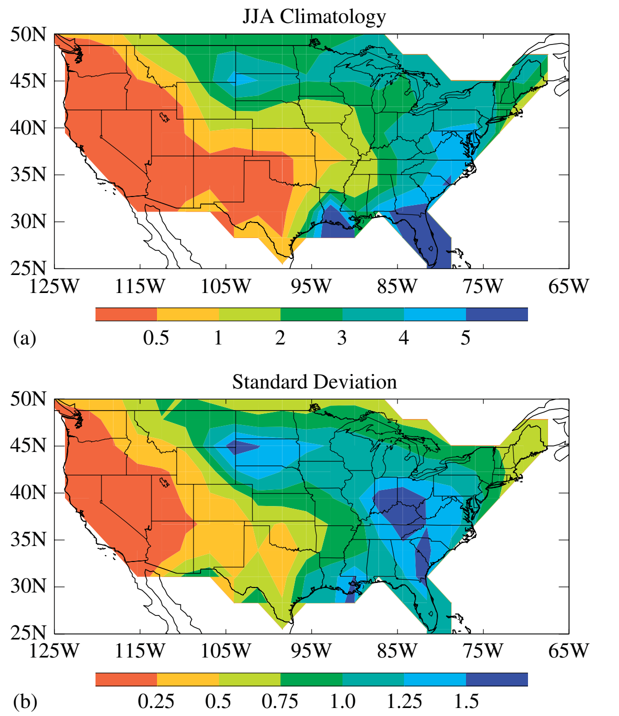

Figure 1. Simulated climatology of summer precipitation and corresponding standard deviation. Units are mm day^{-1}

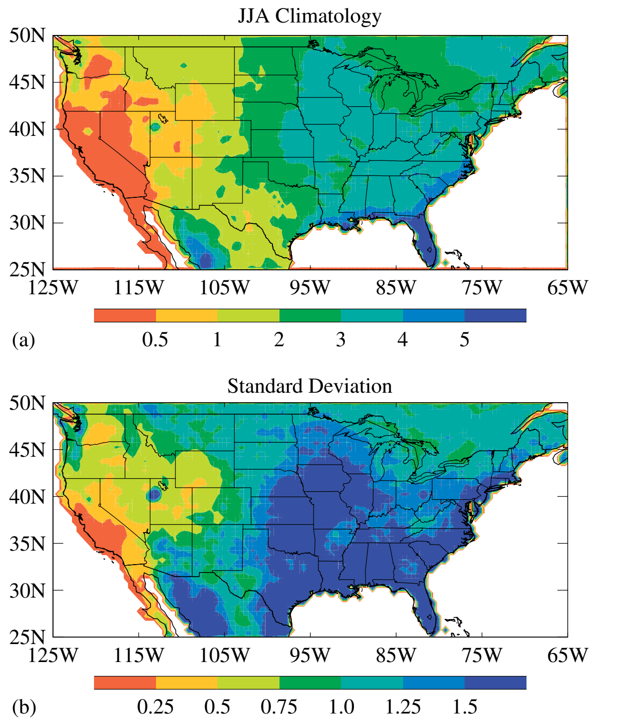

Figure 2. Summer precipitation from Willmott–Matsuura observations and corresponding standard deviation. Units are mm day^{-1}

as large as their corresponding climatologic magnitudes. Compared with the same climatology and standard deviation from 50-year observations of Willmott and Matsuura (2001), the simulated precipitation has mostly captured the observed spatial patterns both qualitatively and quantitatively across the country, but with a dry bias shown in the Southern Great Plains extending as far east as Louisiana. Such a bias has always existed in CCM simulations and is generally attributed to the orographic effect of the highly smoothed Rocky Mountains presented in the model.

A recent study by Ruiz-Barradas and Nigam (2005) on warm season rainfall variability over the US Great Plains, using observations, reanalysis data, and model simulations, finds that the Great Plains precipitation variability is represented rather differently between models and the reanalysis data. Their intercomparison results indicate that models (NCAR CAM and NASA NSIPP) generate nearly all the Great Plains precipitation from deep convective processes. They suggest that precipitation over the Great Plains is more stratiform (large-scale condensation) than given in the models, and that modeled precipitation recycling may be unrealistically efficient. Inadequately represented soil moisture memory in a climate model may contribute to the underestimation of precipitation, especially in dry regions (Wu and Dickinson, 2005).

As mentioned in the introduction, it would not be easy to establish the impacts of soil moisture on precipitation interaction even if good observations were available, because of the strong causality in the other direction. An awareness of the potential mechanisms alone does not necessarily lead to improved simulations and predictions of variability. The relative importance of the mechanisms in nature, and the extent to which the key factors are represented in climate models will determine the quality of the simulations and predictions.

SVD patterns

To examine the links between spring soil moisture variations and summer precipitation variability in the United States, an SVD analysis is performed using the covariance matrix of the two fields. The first two SVD modes are selected for analysis based on their statistical characteristics. Their statistics are listed in Table I, including the percentage of squared covariance explained by each mode, the temporal correlation between pairs of expansion coefficients, and the variance in individual fields that are explained by each mode. The squared covariance for any one SVD mode measures its contribution to the total covariance of the two fields. The 1st SVD mode explains 27% of the squared covariance between spring soil moisture and summer precipitation, with its individual patterns explaining 9% of the total spring soil moisture variance and 10% of the total summer precipitation variance, respectively. The 2nd mode explains 16% of the squared covariance between the two fields. Together, these two leading modes account for 43% of the squared covariance between spring soil moisture and summer precipitation, and the corresponding components explain 14% of the spring soil moisture variance and 19% of the summer precipitation variance, respectively. By contrast,

Table I. Statistics of the first two leading SVD modes of spring soil moisture and summer precipitation

Mode	Squared covariance (%)	Temporal correlation	Soil moisture variance (%)	Precipitation variance (%)
1	27	0.83	9	10
2	16	0.88	5	9

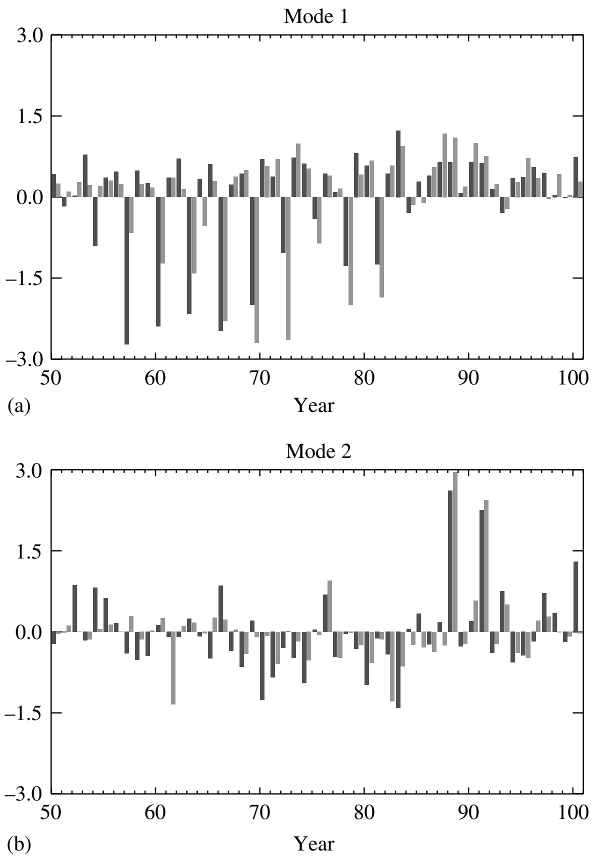

Figure 3. Normalized expansion coefficient time series of the first two SVD modes for spring soil moisture (dark bar) and summer precipitation (light bar) during the simulation period of 1950–2000

Ting and Wang (1997) and Wang and Ting (2000) found that Pacific SSTs associated with El Nino–Southern Oscillation (ENSO) can only explain 7% of summer precipitation variance and 11% of winter precipitation variance. The correlation coefficients between spring soil moisture and summer precipitation for the two pairs of expansion coefficient time series are 0.83 and 0.88, respectively, indicating a strong temporal relationship between the corresponding SVD patterns of the two fields.

The time series of the expansion coefficients for the two SVD modes are shown in Figure 3. The spring soil moisture and the summer precipitation time series exhibit coherent fluctuations in most of the years. In particular, both time series display large fluctuations during 1957–1981 in mode 1, and the two largest fluctuations in 1988 and 1991 in mode 2, respectively. Figure 3 also shows an asymmetric behavior between positive and negative extremes, e.g. multiple large negatives in mode 1, and two large positives in mode 2. Such behavior has been seen in observed time series of precipitation and soil moisture (refer to Figure 1 in Wu *et al.*, 2002).

Figure 4 displays the SVD correlation patterns of soil moisture (a) and precipitation (b). Physically, the contour values represent correlations between soil moisture fields and corresponding SVD expansion time series of precipitation, and between precipitation fields and corresponding SVD expansion time series of soil moisture. The soil moisture pattern of mode 1 (Figure 4(a)) exhibits large negative values in the West and positive values in the Southeast, while the precipitation pattern (Figure 4(b)) displays large negative loadings in the West and the Southeast and the slight positive values in the Northern Great Plains. In mode 2, large positive values are shown in the Southern Great Plains and the Southwest for soil moisture pattern (Figure 4(c)), and large negative loadings in the Great Plains and the West for precipitation pattern (Figure 4(d)). Maximum soil moisture anomalies in both modes in the southern United States occur over regions of negative precipitation anomaly. This negative correlation is especially pronounced where the two leading SVD modes for soil moisture are in phase, around the point of 92 °W and 34 °N. Over this region, both modes have correlation values above the 5% significance level, as estimated by the Monte Carlo tests.

We have examined how such correlations change with time by performing the same calculations but with one-month to three-month lagged data. For example, we examined how soil moisture in May correlates with precipitation in June, July, and August, respectively. The monthly SVD patterns are not as prominent as the seasonal SVD patterns, consistent with the conclusion of Liu (2003) that the seasonal prediction skill is higher compared to the monthly prediction skill. In addition, the average of top 1-m soil moisture as used here does not show the rapid decay of memory that dominates the shallow layers. In the above SVD analysis, the precipitation series lags the soil moisture series by one season. How similar would patterns be from a contemporary SVD analysis? Still using summer precipitation as an example, we examined its SVD patterns associated with the soil moisture in summer (JJA) rather than for spring MAM. The results are shown in Figure 5 and the corresponding statistics are listed in Table II. In-phase relations that are similar to those seen in Figure 4 dominate in both leading modes, while out-of-phase features still exist over the Great Plains in mode 1 and the Southwest in mode 2, similar to those described by Findell and Eltahir (2003), but these are not statistically significant. The concurrent correlation between soil moisture and precipitation is relatively strong (Table II), presumably mainly due to the direct impact of precipitation on soil moisture.

Wallace *et al.* (1992) identified that in the absence of any relationship between the two fields, the empirical

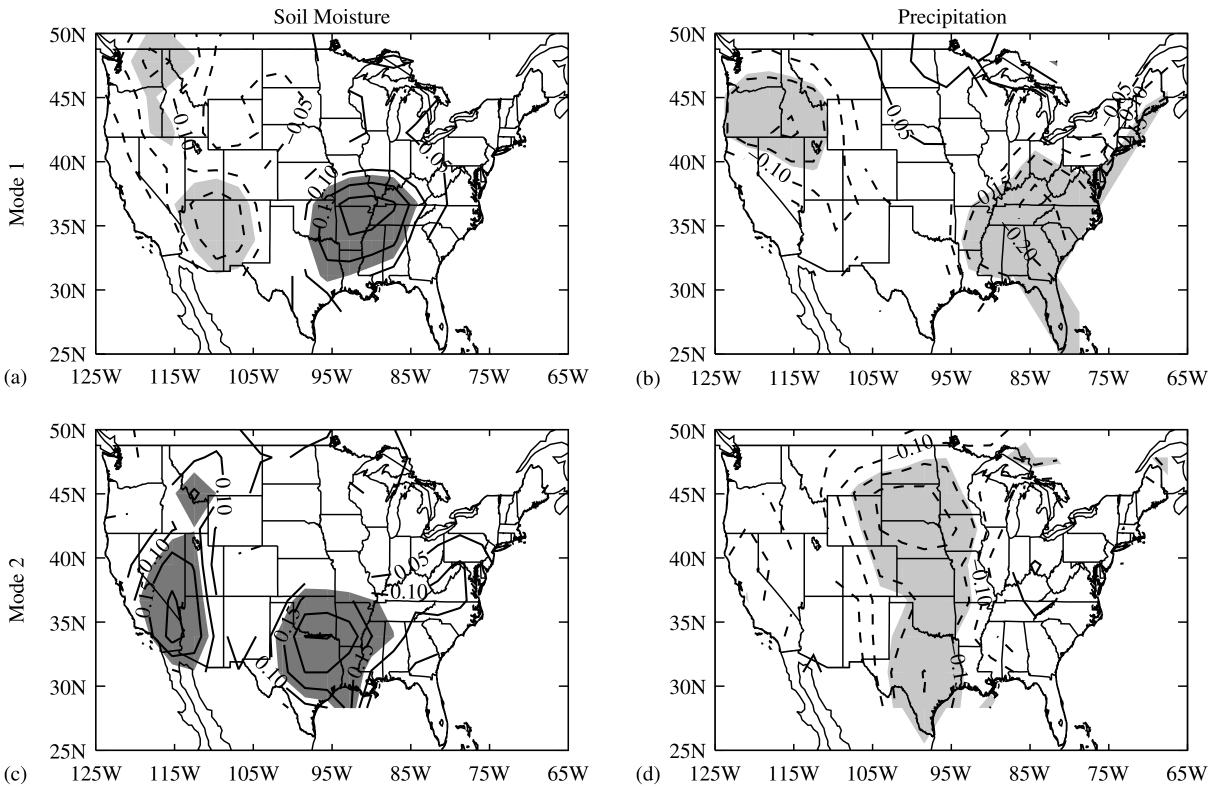

Figure 4. Cross-correlations of the first two SVD modes between spring soil moisture, (a) and (c), and summer precipitation, (b) and (d). Contours are smoothed by a 3-grid window. Contour interval is 0.05, and negative contours are dashed. Areas of positive (negative) values above the 5% Monte Carlo statistical significance level are shaded dark (light)

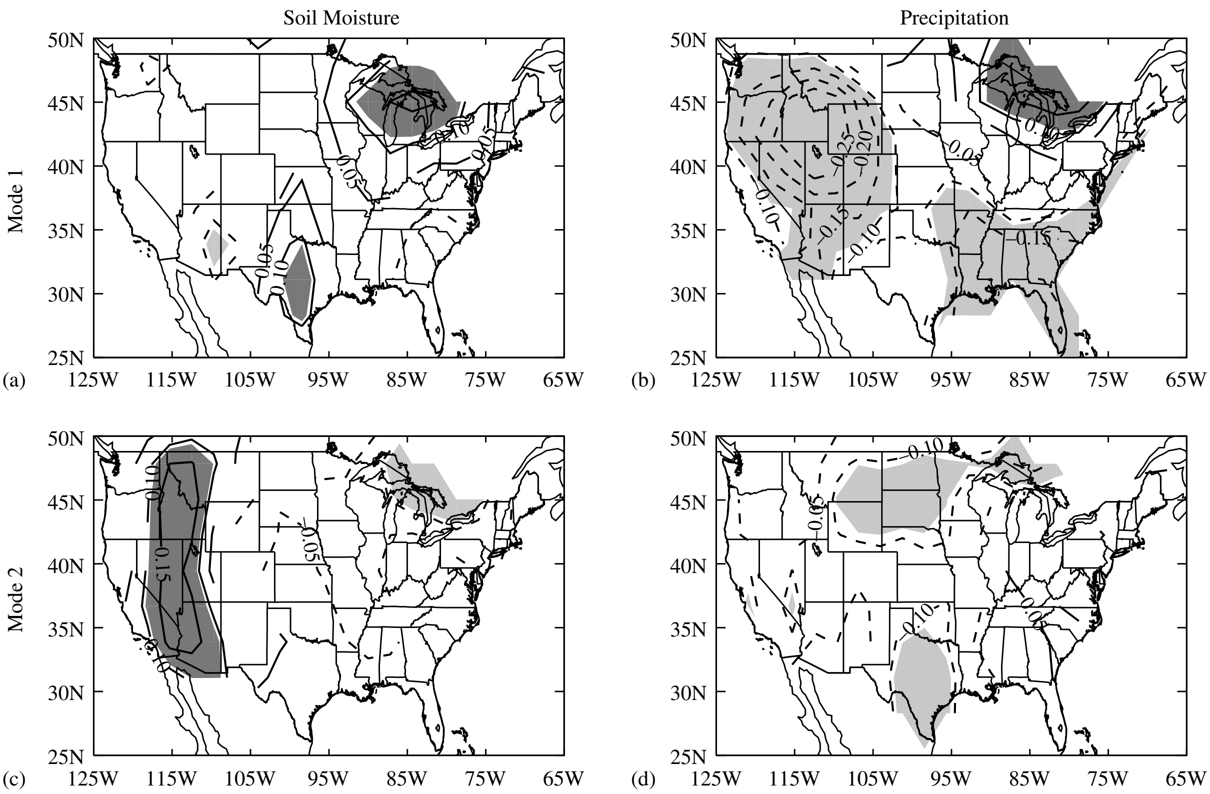

Figure 5. Same as in Figure 4 but for summer soil moisture (a and c) and summer precipitation (b and d)

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Table II. Statistics of the first two leading SVD modes of concurrent summer soil moisture and precipitation

Mode	Squared covariance (%)	Temporal correlation	Soil moisture variance (%)	Precipitation variance (%)
1	33	0.96	14	11
2	18	0.93	10	9

orthogonal functions (EOFs) of the field with fewer spatial degrees of freedom (i.e. the field whose variance tends to be more strongly concentrated in the leading EOFs of its temporal variance matrix) would tend to dominate the SVD solutions. To examine this possibility, an EOF analysis is performed on the summertime precipitation anomalies. Figure 6 displays the two leading modes with 16 and 9% variance explained, respectively. The overall spatial EOF patterns for the two leading modes are consistent with those identified in Ting and Wang (1997) for summertime US precipitation variability related to the Pacific SST. According to their results, the first mode is related to the tropical El Niño-La Niña SST variation and the second mode is linked to the North Pacific SST and atmospheric internal variability. The SVD patterns in Figures 4 and 5 appear to be relatively uncorrelated with the EOFs of Figure 6 with loadings in other regions such as the southern plains and the northwest. Thus, the SVDs appear to be distinct from the leading EOF patterns.

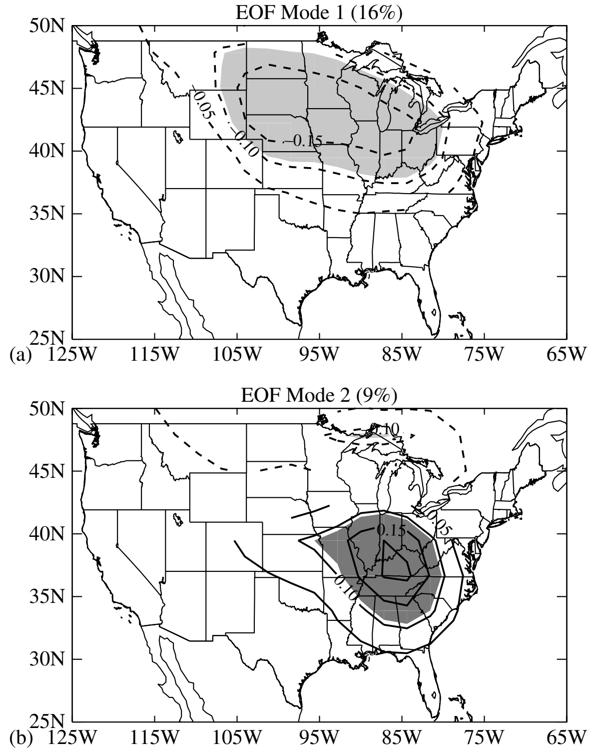

Figure 6. Two leading EOF modes for summer (JJA) precipitation. Contours are smoothed by a 3-grid window. Contour interval is 0.05, and negative contours are dashed. Areas of positive (negative) values above the 5% Monte Carlo statistical significance level are shaded dark (light)

Corresponding atmospheric patterns

Soil moisture influences the near-surface atmospheric temperature and moisture content by affecting the surface fluxes of latent and sensible heat. The corresponding atmospheric patterns with respect to the soil moisture SVD modes are examined in order to verify consistency of the physical processes responsible for linking the spring soil moisture and summer precipitation and for assessing the impact of soil moisture–atmosphere feedbacks on atmospheric variability. Linear regression is used for this objective. Relative humidity is lowered and air temperature elevated in the absence of moisture fluxes because of dry soils. However, precipitation amounts can be elevated by a warmer atmosphere. Thus, correlations of temperature and precipitation can be of either sign (e.g. Trenberth and Shea, 2005). We carry out linear regressions of surface relative humidity and temperature anomalies on the soil moisture time series of the two SVD modes. The surface relative humidity and temperature time series are constructed similar to that of precipitation. A monthly relative humidity is calculated at each model grid point from the monthly mean atmospheric mixing ratio divided by the saturation mixing ratio corresponding to the monthly mean temperature and summer relative humidity constructed by averaging June, July and August values.

Figures 7 and 8 show summer surface relative humidity and air temperature patterns, respectively, scaled for one standard deviation positive anomaly of each SVD mode of the leading SVD modes of spring soil moisture time series. The significant correlations of summer relative humidity are in phase with those of the SVD precipitation (Figure 4), except for the absence of a relative humidity anomaly in the Northwest. Temperature anomalies are out-of-phase with those of relative humidity in Central and Eastern US, but that of mode 1 is in phase with precipitation in the Northwest. This in-phase relationship is consistent with Figure 5, indicating a lack of correlation between temperature and soil moisture in this region. Evidently, in this region, temperatures are determined by atmospheric processes rather than soil moisture. The strong negative correlation between spring soil moisture and summer precipitation in the Southern Great Plains does not map significantly onto any of the other summer climatologies.

FURTHER DISCUSSION

The strong spatial-temporal correlations between spring soil moisture and summer precipitation suggest that spring soil moisture may have a connection to summer precipitation when the interannual variations of climate patterns are superimposed on the seasonal cycle (Figure 9). The in-phase SVD patterns of the two fields are quite plausibly due to the direct hydrological relationship between soil moisture and precipitation. Here we

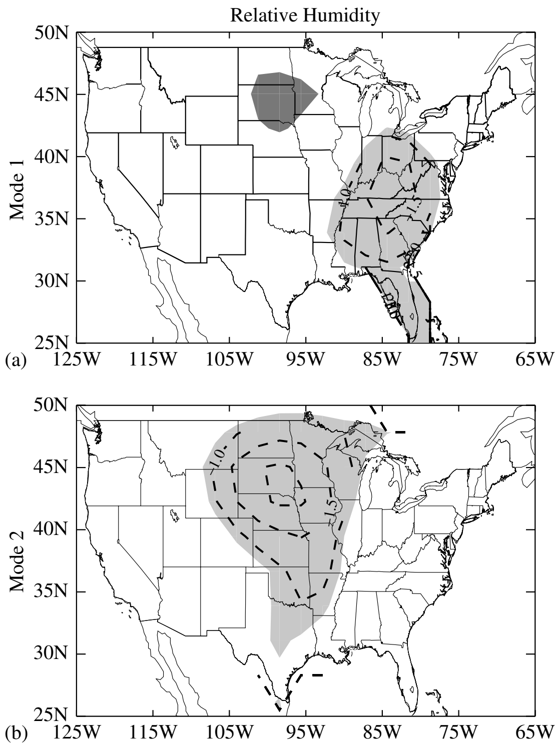

Figure 7. Patterns of the summer anomalous relative humidity regressed on the two leading SVD modes of spring soil moisture time series normalized to one positive standard deviation. Contours are smoothed by a 3-grid window. Contour interval is 0.5 (%), and negative contours are dashed. Areas of positive (negative) values above the 5% Monte Carlo statistical significance level are shaded dark (light)

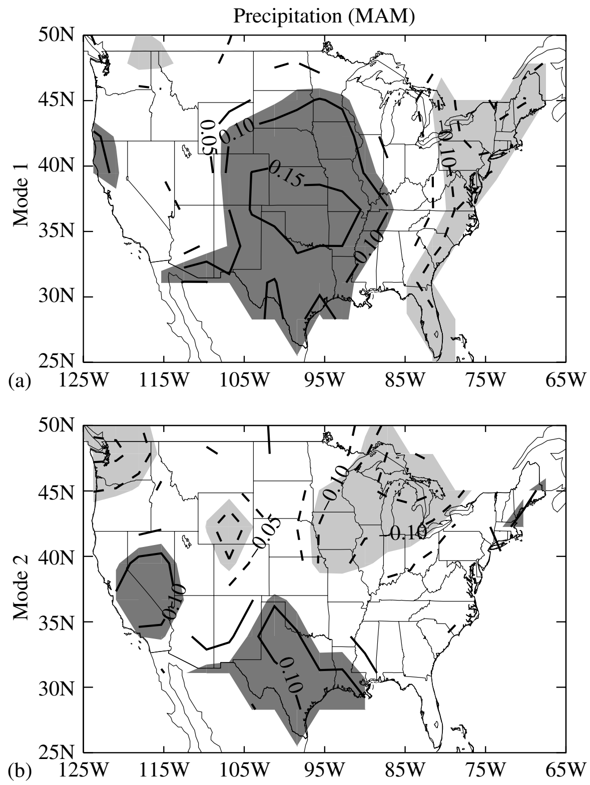

Figure 9. Spring precipitation (MAM) correlated with the summer precipitation time series of the two leading SVD modes. Contours are smoothed by a 3-grid window. Contour interval is 0.05, and negative contours are dashed. Areas of positive (negative) values above the 5% Monte Carlo statistical significance level are shaded dark (light)

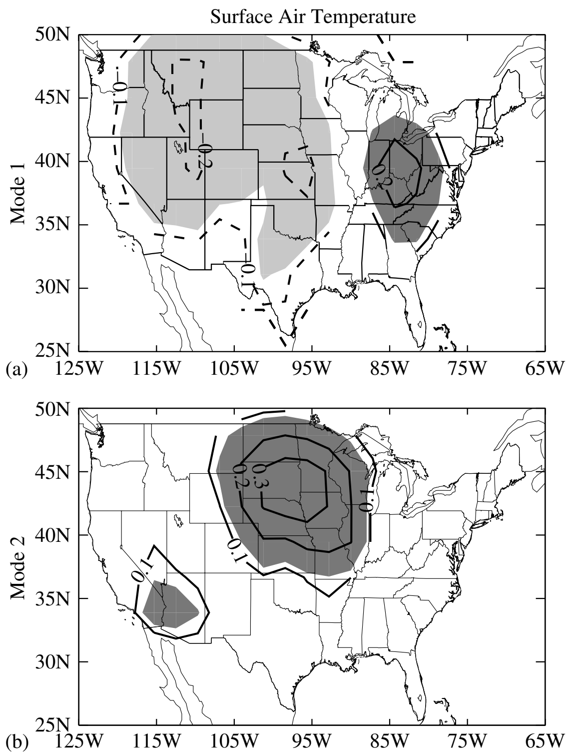

Figure 8. Same as in Figure 7 but for the summer anomalous surface air temperature. Contour interval is 0.1 (°K)

focus the discussion on the negative cross-correlations in order to better understand the above results and to guide future investigations.

The out-of-phase SVD patterns of the two fields suggest that both the variations of springtime soil moisture and summertime precipitation over the US may be caused by the same forcing, but in opposite ways. For example, Hoerling and Kumar (2003) showed that cold SSTs in the eastern tropical Pacific (150 °W–90 °W, 5 °N–5 °S, also the Niño 3 Region defined in Trenberth, 1997) and warm SSTs in the western tropical Pacific and Indian oceans (90 °E–150 °E, 15 °N–15 °S) contribute synergistically to widespread midlatitude drying. Over some regions, SST anomalies could cause systematic patterns of more precipitation in summer but less soil moisture (precipitation) in spring.

To further examine how the sign of soil moisture–precipitation correlations might change with different time-lags and -leads, four grid-points around the point of 92 °W and 34 °N are selected as an index that describes the temporal variability of a spatially coherent region. Figure 10 shows the spring soil moisture correlated with lagged seasonal precipitation from spring to the following winter. In this case, contemporary correlations of soil moisture and precipitation (i.e. spring soil moisture *vs.* spring precipitation) are significantly positive. The spring soil moisture correlates negatively with

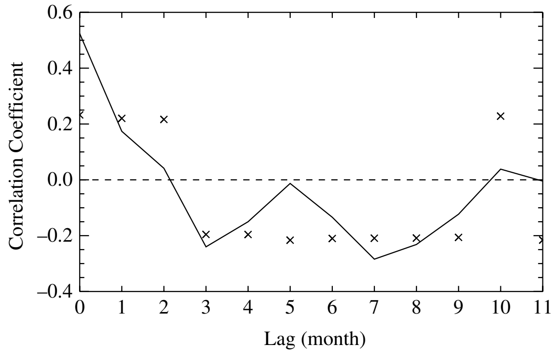

Figure 10. Correlations between spring soil moisture and lagged precipitation in the Southeast negative-feedback region, calculated by the area averaged time series. Crosses denote the 5% Monte Carlo statistical significance level

later season precipitation in JJA, JAS, although the latter is not above the 5% significance level; in addition, at longer lags, the spring soil moisture correlates negatively with later season precipitation in OND and NDJ. Apparently, the sign of soil moisture–precipitation correlations changes with different time-lags. As mentioned in Ruiz-Barradas and Nigam (2005), climate models such as those analyzed here may exaggerate local hydrological cycling. The model's lack of variability (compare Figures 1(b) with 2(b)), especially over the Southern Plains, suggests that the model's response to remote variations (e.g. ENSO, North American Monsoon) may be weak.

Although we are not aware of any previously reported lag relationship similar to those discussed above, many studies have discussed negative correlations between soil moisture and precipitation. Various studies (Findell and Eltahir, 2003; Ek and Holtslag, 2004) have shown how an out-of-phase contemporaneous correlation is possible. In a numerical study, Miller *et al.* (2005) find that cooling from evaporation can stabilize the atmosphere such that the evaporation does not contribute to precipitation. An inverse relationship between soil moisture and precipitation in the Southwest has been recognized directly or indirectly by previous studies (Lo and Clark, 2002; Kanamitsu and Mo, 2003; Mo and Juang, 2003; Zhu *et al.*, 2005). As early as over a decade ago, Meehl (1994) noted that the soil moisture-precipitation feedback could be either positive or negative for the south Asian monsoon.

Statistical modeling, referred to as 'Principal Oscillation Patterns' (von Storch and Zwiers, 1999), describes systems of two coupled variables in which the values of one correlate with the time tendency of the other on some timescales leading to negative lag correlations. Apparently, the climate model generates such an inverse relationship as documented by the SVD analysis.

CONCLUSIONS

The spatial-temporal associations between springtime soil moisture and summertime precipitation over the United States have been studied for a climate model simulation. Both in-phase and out-of-phase cross-correlations between spring soil moisture and summer precipitation are found over different regions in different leading SVD modes. The sign of the correlation changes with different time-lags. The patterns of summer precipitation connected with spring soil moisture are associated with consistent summer patterns of temperature and relative humidity.

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