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Authors
Syed, Tajdarul Hassan
Lakshimi, V
Paleologos, E
et al.

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Analysis of process controls in land surface hydrological cycle over the continental United States

Tajdarul Hassan Syed,[1,2] Venkat Lakshmi,[1] Evan Paleologos,[1] Dag Lohmann,[3] Kenneth Mitchell,[3] and James S. Famiglietti[2]

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[1] The paper uses two years (1997–1999) of data from the North American Land Data Assimilation System at National Centers for Environmental Prediction to analyze the variability of physical variables contributing to the hydrological cycle over the conterminous United States. The five hydrological variables considered in this study are precipitation, top layer soil moisture (0–10 cm), total soil moisture (0–200 cm), runoff, and potential evaporation. There are two specific analyses carried out in this paper. In the first case the principal components of the hydrological cycle are examined with respect to the loadings of the individual variables. This helps to ascertain the contribution of physical variables to the hydrological process in decreasing order of process importance. The results from this part of the study had revealed that both in annual and seasonal timescales the first two principal components account for 70–80% of the variance and that precipitation dominated the first principal component, the most dominant mode of spatial variability. It was followed by the potential evaporation as the secondmost dominant process controlling the spatial variability of the hydrologic cycle over the continental United States. In the second case each hydrological variable was examined individually to determine the temporal evolution of its spatial variability. The results showed the presence of heterogeneity in the spatial variability of hydrologic variables and the way these patterns of variance change with time. It has also been found that the temporal evolution of the spatial patterns did not resemble white noise; the time series of the scores of the principal components showed proper cyclicity at seasonal to annual timescales. The northwestern and the southeastern parts of the United States had been found to have contributed significantly toward the overall variability of potential evaporation and soil moisture over the United States. This helps in determining the spatial patterns expected from hydrological variability. More importantly, in the case of modeling as well as designing observing systems, these studies will lead to the creation of efficient and accurate land surface measurement and parameterization schemes. *INDEX TERMS:* 1836 Hydrology: Hydrologic budget (1655); 1854 Hydrology: Precipitation (3354); 1818 Hydrology: Evapotranspiration; 1899 Hydrology: General or miscellaneous; 1869 Hydrology: Stochastic processes; *KEYWORDS:* hydrological cycle, land surface, principal components

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1. Introduction

[2] Surface hydrologic processes play a significant role in global climate change as well as in the interactions between different components in the Earth system. Changes in the soil moisture affect the vertical and horizontal fluxes in the water and energy cycle [*Wu et al.*, 2002; *Beljaars et al.*, 1996; *Yoo et al.*, 1998]. Runoff is known to affect a very crucial connection between the land, ocean, and atmosphere, namely the thermohaline circulation in the ocean. The shutting down or slowing of the thermohaline circulation due to flux of excess fresh water in the North Atlantic is known to have been the trigger for the Younger Dryas or the little ice age in Europe [*Manabe and Stouffer*, 1993; *Broecker and Denton*, 1990].

[3] Soil moisture conditions also play a role in the Earth's energy cycle by the partitioning of outgoing energy flux into latent and sensible heat fluxes due to its control over surface albedo [*Delworth and Manabe*, 1989]. Results from their study showed that the variability of soil wetness conditions significantly affected the fluctuations in the near-surface relative humidity and temperature.

[1]Department of Geological Sciences, University of South Carolina, Columbia, South Carolina, USA.

[2]Department of Earth System Science, University of California, Irvine, California, USA.

[3]Environmental Modeling Center, National Weather Service, National Centers for Environmental Prediction, NOAA, Suitland, Maryland, USA.

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[4] In spite of its manifold importance, there exists uncertainty in the understanding of the physics of the water and energy cycles over the continents. This lack of understanding is reflected in the global climate and hydrologic models, outputs of which in some cases differ significantly from in situ data. One of the primary reasons behind the discrepancy can be attributed to the lack of understanding of the process controls in the surface hydrologic cycle and in the scales in which they operate, which pertain to both the time and space domains. Hence a proper understanding of the spatial and temporal variability of the hydrologic cycle and the process controls can lead us to a better understanding of the role of land-atmosphere interactions in driving climate variability and also help us to better parameterize land surface variables in hydroclimatological studies.

[5] In this paper we define the problem of proper characterization and understanding of process controls in the spatial variability in the hydrologic cycle over the continental United States. Analysis has been proposed in both seasonal and annual timescales to identify the changes in the underlying processes controlling the variability of the hydrologic cycle. The method that has been used for the analysis is principal component analysis (PCA) in which the principal components can be identified as physically independent processes controlling the variance in the hydrological variables of the continental hydrologic cycle.

[6] *Vinnikov et al.* [1999] addressed the issue of level of monitoring by questioning whether the relatively high density networking stations for soil moisture observation in Oklahoma provided more accurate estimates of soil moisture than the lesser dense Illinois network. The work also revealed two major components in the soil moisture variability, one of which is related to large-scale atmospheric forcing with a temporal scale in the order of a few months. The second component is related to land surface dynamics composed of short-term hydrological processes such as infiltration, surface runoff, and gravitational drainage. Temporal and spatial scales of observed soil moisture variations in the extratropics have been investigated by *Entin et al.* [2000]. The study of spatial autocorrelation functions of soil moisture yielded a constant spatial scale of correlation of several hundred kilometers for both the upper 10 cm and upper 1 m soil layer in all locations. These authors also found that the spatial scales of soil moisture exhibited good agreement with the spatial scales of monthly averaged precipitation, which was considered the main factor behind the spatial variability of soil moisture for most of the regions in the extratropics. The work of *Koster and Suarez* [1996] showed that the soil moisture memory is mainly controlled by four distinct factors: (1) nonstationarity in the statistics of the forcing, as induced by seasonality, (2) reduction in anomaly differences through the functional dependence of evaporation on soil moisture, (3) reduction in anomaly differences through the functional dependence of runoff on soil moisture, and (4) correlation between initial soil moisture and subsequent atmospheric forcing, as induced by land-atmosphere feedback.

[7] Additional relevant prior research was the work by *Famiglietti et al.* [1995]. Principal component analysis was performed on both seasonal and annual hydrological cycles to determine the dominant modes of spatial variability and also to propose a classification scheme for the continental United States on the basis of the hydroclimatological similarity. The results showed that the first two components accounted for 92% of the variability in the continental-scale hydrological cycle. The first mode of variability is dominated by precipitation accounting for $\sim$58% of the variability in the continental-scale hydrological cycle. The second component, however, was related to both snowmelt runoff and time variability of weather and explained 34% of the variability. However, the proposed classification scheme based on hydroclimatological similarity exhibited inconsistencies in the distinction between regions that were hydrologically and climatologically different (such as the Northern Great Plains and northern Mexico).

[8] The present study is based on the 2-year data set of land surface variables from the NOAH (National Centers for Environmental Prediction (NCEP), Oregon State University, Air Force Weather Agency, and National Oceanic and Atmospheric Administration's (NOAA) Office of Hydrology) Land Surface Model in the North American Land Data Assimilation Systems (NLDAS) project [*Mahrt and Pan*, 1984; *Ek and Mahrt*, 1991; K. Mitchell, The Community NOAH Land-Surface Model (LSM), User's Guide, available through the Environmental Modeling Center's Web site at http://www.emc.ncep.noaa.gov/mmb/gcp/noahlsm/README_2.2.htm]. The objective of this work can be considered twofold: to accomplish a proper characterization and understanding of the process controls on the spatial variability of the hydrologic cycle over the continental United States and to evaluate the usefulness of principal components as climatological indices. The aim is to examine whether the gross features of the spatial variance in the land surface variables can be represented by a smaller number of indices that account for a significant proportion of the total variance.

[9] The paper is organized as follows. Section 2 describes the data analyzed in this study and the methods employed for the analysis. Specifically, it explains the difference between case I with multivariable principal components and case II with a single-variable principal component analysis. Section 3 describes the results for both case I and case II. Finally, section 4 describes the major conclusions and provides discussion for future studies.

2. Data and Methods

[10] The primary source of the data was the input and output from the NOAH Land Surface Model in the NLDAS project. The NOAH Land Surface Model (LSM) is an uncoupled, stand-alone one-dimensional column model designed to execute both single site and land surface simulations. The model is driven by near-surface atmospheric forcing data, which are obtained from various sources, including both satellite and ground observations. This LSM simulates soil moisture (both liquid and frozen), soil temperature, skin temperature, snowpack depth, snowpack water equivalent (and hence snowpack density), canopy water content, and the energy and water fluxes and surface water balance.

[11] Although the model outputs include numerous land surface parameters, only a few are analyzed in this paper. The original model outputs are in 1/8° grid boxes (with a spatial extent of 12.5×12.5 km) and are given at an hourly

Table 1. Detailed Description of the Variables

Parameters	Spatial Resolution	Temporal Resolution	Time Span
Precipitation	$1^\circ \times 1^\circ$	biweekly sum	Oct. 1997 to Sept. 1999
Total soil moisture (0–200 cm)	$1^\circ \times 1^\circ$	biweekly instantaneous values	Oct. 1997 to Sept. 1999
Top layer soil moisture (0–10 cm)	$1^\circ \times 1^\circ$	biweekly instantaneous values	Oct. 1997 to Sept. 1999
Runoff	$1^\circ \times 1^\circ$	biweekly sum	Oct. 1997 to Sept. 1999
Potential evaporation	$1^\circ \times 1^\circ$	biweekly average	Oct. 1997 to Sept. 1999

timescale. In our analysis the data were spatially aggregated to $1^\circ \times 1^\circ$ grid boxes and temporally aggregated to biweekly sum and instantaneous or biweekly average depending on the underlying process by which they interact within the terrestrial hydrologic cycle. The data set analyzed in this study extends from October 1997 to September 1999. The model runs on individual grid cells, so the values of the parameters at each node are individually calculated instead of being interpolated from the value of each parameter from the surrounding data points. Each grid is characterized by a dominant soil and texture type; in the case of bare soil, the secondmost dominant type is considered to be the characteristic class of each grid. Similarly, the dominant vegetation type also characterizes each grid box, and it is determined by calculating the fractional coverage amount of the different types of vegetation in a 1×1 km area. The number of such boxes within each $1/8^\circ$ grid box is calculated to determine the dominant vegetation type in that particular grid cell.

[12] The details of the different land surface parameters that have been used in the current work are given in Table 1. The method that has been used is principal component analysis (PCA). PCA is an important tool for identifying patterns in a multivariate data set, such as the one used for the current work. The method also helps in expressing the data so as to highlight the similarities and differences which otherwise are hard to analyze. This is particularly important where the variables vary simultaneously in multiple dimensions such as space (two dimensions) and time (one dimension). Understanding of the variances in this type of data can only be accurate when the analysis is based on the covariance amongst the variables instead of variance, thus making this method appropriate for this research.

[13] The principal components (PC) are the eigenvectors of the covariance matrix between the variables. The contribution of each PC toward the total variance is given by the corresponding eigenvalue, which is also an effective measure of its relative importance, hence a tool for variable selection [*King and Jackson*, 1999]. The principal components are identified as physically independent processes controlling the variance in the important parameters of the continental hydrological cycle. This helps us to determine the relative importance of each variable in controlling the overall covariance amongst the different land surface parameters in this case. The relative importance is based on the amount of variance explained by each of the principal components. Apart from this the method can also be used to understand the spatiotemporal variability. The representation and understanding of the spatiotemporal variability is discussed in case II of the current research. This part of the study is aimed at illustration of the spatial patterns of variance of each variable and how these patterns change with time, thereby providing us with valuable information about the temporal evolution of the most dynamic regions. The relevance of PCA for the current analysis is mainly due to three reasons: (1) it can represent the variance of scalar field with a comparatively fewer independent coefficients; (2) it can remove redundant variables in a multivariate data set; and (3) PC have the ability to represent physically independent processes. PCA has so far been extensively used in meteorological studies toward the establishment of the gross patterns, trends, and modes of interannual to interdecadal variability in geophysical fields [*Kidson*, 1975; *Widmann and Schar*, 1997; *Sengupta and Boyle*, 1998; *Kawamura*, 1994; *Horrel*, 1981]. *Basalirwa et al.* [1999] identified climatological regions in Tanzania on the basis of similar rainfall characteristics by performing PCA on rainfall records for the years 1961–1990. Analysis has been carried out in both seasonal and annual timescales to identify the changes in the underlying processes controlling the variability of the hydrological cycle.

[14] The results of the analysis are discussed under two categories, namely, case I and case II. In case I, principal component analysis was done on the four major components of the land surface hydrologic cycle, averaged over the whole time span, with the purpose of understanding the relative importance of the major drivers in the continental hydrologic cycle. This would help in deciphering the process controls over the hydrologic cycle, thereby narrowing down the range of uncertainties and unpredictability in the understanding and characterization of the land surface hydrologic cycle. In case II, also principal component analysis was carried out on a single variable that varied both in space and time. This part of the current work is aimed at the simultaneous representation of the space-time variability in the major driving forces of the continental hydrologic cycle identified from the results in case I. The analysis will contribute toward a better understanding of the temporal variations in a spatially distributed data set. The use of principal components to visualize and represent space-time variability is not only a unique way of representation but also a time- and cost-effective way. The emphasis will be on the identification of the centers or areas of maximum variability, depicted by the areas with the values of maximum variance over a particular time span and the changes in variability over time which will have severe implications on the modeling and designing of observational networks for the study of soil moisture. In case I the variables that were used were precipitation (PRCP), runoff (RUNOFF), total soil moisture (TSOILM), and potential evaporation (POTEVP). Calculations were made on both annual and seasonal timescales for the 2 years separately (from October 1997 until September 1998 and from October 1998 until September 1999). This analysis is aimed toward the establishment of process controls that underlie the spatial variability of the hydrologic cycle

over the continental United States. The term spatial variability of the hydrologic cycle refers to the temporal changes in the spatial patterns of the controlling process and the spatial scales over which they vary. These help us to understand the heterogeneity in the land surface climatology over the continental United States and the changes in heterogeneity over time.

[15] The four variables considered here are key components of a water balance equation [*Delworth and Manabe*, 1988]. Following is a conceptual version of the water balance parameterization put forward by *Delworth and Manabe* [1988]:

$$\mathrm{TSOILM}(t+1) = \mathrm{TSOILM}(t) + \mathrm{PRCP} - \mathrm{RUNOFF} - \mathrm{POTEVP}.$$

The future state of soil moisture (TSOILM ($t + 1$)) is given by the present soil moisture state denoted by the total soil moisture (TSOILM (t)) and the positive and negative fluxes. The positive flux in the above mentioned water balance equation is precipitation, and the negative fluxes are runoff and potential evaporation which leads to an increase or decrease in the magnitude of moisture content in the soil. Precipitation plays an important role of a random driving force in the hydrologic cycle. Soil moisture is the key response variable dependent on both precipitation and potential evaporation. It can be used as an index for characterizing the role of different land surface variables in the hydrologic cycle. In this study the total soil moisture is considered in order to analyze the bigger picture of their variance instead of considering the top layer soil moisture whose variability can be due to various other reasons. Runoff is a measure of the loss in the hydrologic cycle. The potential evaporation represents the abstraction parameter and is calculated by the model. It is the maximum evaporation that can take place in a particular area under given atmospheric conditions. Potential evaporation was chosen because it takes into account other atmospheric forcing such as radiation, wind speed, air temperature, and surface pressures and therefore can be considered as a driving variable for the energy balance and also representative of the atmospheric forcing. Precipitation and runoff fall in the category of water budget components with precipitation considered the prime forcing variable and runoff the response. Similarly, potential evaporation, although an abstract variable calculated by taking into account different aspects of land surface climatology such as wind speed, humidity, and temperature, is mostly representative of the incoming solar radiation. Hence potential evaporation can be considered as the forcing variable and the total soil moisture as the response variable. However, the total soil moisture is not solely dependent on energy budget components, but the spatial patterns of the soil moisture are driven in part by the incoming solar radiation.

[16] The representation of the spatial structure of the hydrological variables has been perceived as an issue [*Lohmann et al.*, 1998; *Vinnikov et al.*, 1999; *Yoo et al.*, 1998]. In most cases the representation of the spatial structure of a space-time varying parameter is carried out by shrinking one of the dimensions, either space or time. This restricts the proper representation of the parameters and hence the understanding of its spatiotemporal variability. Principal component analysis on the variable of interest varying in both time and space can lead to the establishment of the spatial structure of the variance, in time and space. The analysis was aimed at the establishment of the spatio-temporal distribution of variance with a smaller number of orthogonal components and, most importantly, without any loss of vital information. In most common applications of PCA to geophysical fields the data matrices are dimensioned ($n \times K$) in time and space, respectively, since data at K locations in space are sampled at n different time steps. Thus the data can be considered to be composed of K time series where the index of time, t, extends from 1 to n. The principal component scores $u_m(t)$ are given by the following equation:

$$u_m(t) = \sum_{k=1}^{K} e_{km} x_k(t),$$

where m is the number of principal components, e is the eigenvectors of the covariance matrix of the original centered data, also known as the loadings, and x is the original data set. The above mentioned equation emphasizes the fact that if the original data, x, consist of a set of time series, then the principal component scores (u_m) can be considered as the time series, representative of the original data but in a different coordinate system (defined by the eigenvectors of the correlation matrix) and that of reduced dimensionality. Hence the temporal evolution of the spatial patterns can be captured by the time series of the principal component scores. Similarly, while considering the spatial distribution of the fields, the eigenvectors of the correlation matrix also known as the loadings of the principal components can be displayed graphically in an informative way. This is because each of the eigenvectors has the same dimension as that of the original data and has one-to-one correspondence with the K locations in space of the data from which the principal components are calculated. Thus the spatial plot of the loadings will clearly depict the locations which contribute the most in the explanation of the variance in each of the principal components. Plots of the loadings of each component can be considered as spatial patterns of standing oscillations; thus areas with the highest values represent areas with the maximum variance over a particular time span. One thing to be noted is the fact that the areas with the highest loadings do not necessarily represent the areas with the highest absolute values of the parameter but the areas with the maximum variability.

3. Results

3.1. Case I: Multivariable Principal Components

[17] The principal components are calculated from the covariance matrix of all the four variables given in Table 1. Hence the variances accounted by each of the principal components represent a percentage of the overall variance of the data set that includes four variables which vary in both the space and time domain. The percentage of variances explained by the different principal components of seasonally/annually averaged hydrologic variables for the 2 separate years are given in Table 2. Two features of the principal components are evident from Table 2. The per-

Table 2. Percentage of Variances Explained by Each Principal Component

Principal Component	Percentage of Variance 1997–1998	1998–1999
	Annual	
First	58.8	54.7
Second	29.6	33.0
Third	10.1	10.7
Fourth	1.5	1.6
	Autumn	
First	56.6	52.1
Second	26.8	27.5
Third	12.9	14.4
Fourth	3.7	6.0
	Winter	
First	57.2	59.0
Second	26.8	26.6
Third	14.3	11.7
Fourth	1.7	2.7
	Spring	
First	63.1	62.2
Second	24.2	21.6
Third	9.4	11.5
Fourth	3.3	4.7
	Summer	
First	57.8	55.1
Second	27.6	28.2
Third	11.5	14.0
Fourth	3.1	2.7

centage of variances explained by the successive principal components are more or less similar at the seasonal and annual timescales for both years (in spring the first component accounts for 6% more variance than the other seasons). Apart from that it can also be seen that the spatial-temporal variability in the continental-scale hydrology over the United States were explained by the first two components. The first principal component explained about 55–59% of the total variance, the second another 22–23%, and the third an additional 10–12%. Hence the first two principal components together roughly account for 83–88% of the variability, or in physical terms, that delineation of the mechanism or the process control associated with the first and the second principal components can account for most of the variability present in the major components of the continental hydrological cycle.

[18] For the understanding of the process controls underlying the first three modes of spatial variability, the loadings (or weights) of the different land surface hydrologic variables in each of the principal components were examined. The loadings associated with the variables in each of the principal components for the year October 1997 until September 1998 are shown in Figure 1 for the annual cycle. The loadings of each of the hydrologic variables in the individual principal components are summarized in Table 3. The values in Table 3 represent the contribution of each variable toward the determination of individual principal components.

[19] Analysis of the relative magnitudes and signs of the loadings of the variables indicates that the first principal component (or the most dominant mode of spatial variability) is highly correlated with the spatial pattern of precipitation for the annual and most of the seasonal cycles for the year 1997–1998. It can be seen from Table 3 that for most of the timescales considered, the loadings for precipitation are consistently the highest, indicating its strong influence on the first and the most dominant mode of spatial variability. Hence the most important feature of the first principal component is that it is dominated by precipitation for the annual cycle and most of the seasonal cycles except for winter and spring where it is dominated by runoff. In Figure 1 the values of the loadings for all the variables in the first principal component are all positive, indicating that all the other hydrologic variables vary in phase with precipitation as the annual/seasonal precipitation controls annual/seasonal wetness and thus evaporation and runoff. The first principal component represents the hydrological processes connected with precipitation and the water balance. Increased precipitation increases soil moisture and runoff. It can be seen that in terms of the first principal component the only change observed in seasonal patterns is in the autumn and winter cycles, where the variable POTEVP has sign opposite to those in the spring and summer cycles and reverse to all the other variables. This could be due to the fact that precipitation in the winter and fall creates wet conditions that are coupled with low evapotranspiration, but in the case of spring and summer the evapotranspiration is high, and wet conditions are followed by high evaporation.

[20] The principal components are known to be uncorrelated with each other and thus representative of mechanisms controlled by physically independent factors. Therefore, in theory, the interpretation of the second principal component must be unrelated to precipitation, but the physical interpretation of the principal components is limited by a fundamental constraint. While it is often possible to clearly associate the first principal component with a known physical process, this becomes much more difficult as one

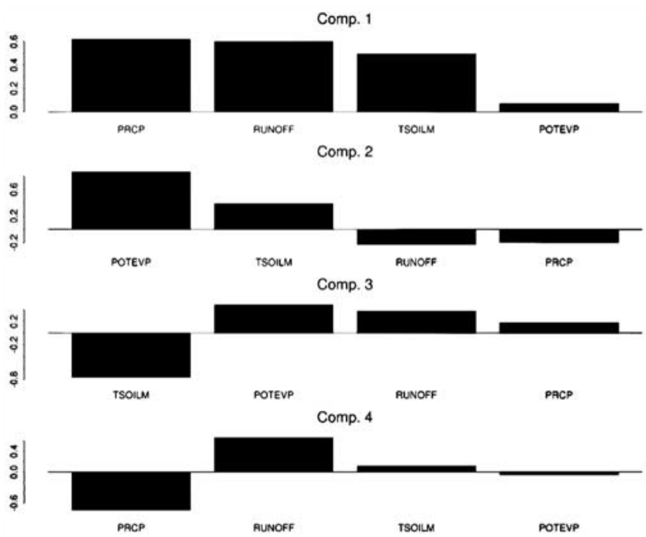

Figure 1. Plot of the loadings of principal components for the annual cycle of October 1997 to September 1998. PRCP is precipitation, RUNOFF is runoff, TSOILM is total soil moisture, and POTEVP is potential evaporation.

Table 3. Loadings of the Principal Components for the Seasonally/Annually Averaged Timescales for 1997–1998[a]

Variables	Principal Components Loadings: Component 1	Component 2	Component 3	Component 4
		Annual		
TSOILM	0.495	0.397	**−0.763**	0.124
PRCP	**0.621**	−0.197	0.182	**−0.736**
POTEVP		**0.867**	0.490	
RUNOFF	0.602	−0.228	0.380	0.664
		Autumn		
TSOILM	0.487	0.361	**0.791**	
PRCP	**0.620**		−0.321	**0.715**
POTEVP	−0.106	**0.918**	−0.366	−0.110
RUNOFF	0.606	−0.160	−0.371	−0.685
		Winter		
TSOILM	0.436	0.461	**−0.768**	
PRCP	0.621		0.374	−0.684
POTEVP	−0.147	**0.883**	0.446	
RUNOFF	**0.635**		0.266	**0.725**
		Spring		
TSOILM	0.530	−0.177	**0.829**	
PRCP	0.564	0.321	−0.298	−0.700
POTEVP	0.267	**−0.893**	−0.361	
RUNOFF	**0.574**	0.262	−0.305	**0.713**
		Summer		
TSOILM	0.472	−0.461	**−0.734**	−0.165
PRCP	**0.586**	0.358		**0.727**
POTEVP	0.371	**−0.664**	0.648	
RUNOFF	0.544	0.467	0.206	−0.666

[a]TSOILM, total soil moisture; PRCP, precipitation; POTEVP, potential evaporation; RUNOFF, runoff. Bold entries are the largest values.

proceeds to explain the second- and higher-order principal components because they are constrained to be orthogonal to the first principal component. However, real world processes do not need to have orthogonal patterns or uncorrelated indices.

[21] Although in most cases it is almost impossible to refer to the principal components as physically independent processes, in the current analysis we can see that the near-zero values of the loadings for precipitation in the second principal component for both the annual and seasonal timescales indicate that the physical mechanism responsible for this mode of variability is relatively independent of the precipitation. Apart from this the loadings for the potential evaporation were generally found to be higher than all the other variables of interest for both the annual and seasonal timescales. The signs of the weighting coefficients or the loadings of potential evaporation and total soil moisture were opposite to those of the precipitation and runoff. The fact that the signs in the loadings for the total soil moisture and potential evaporation were opposite to those of precipitation and runoff suggests a mechanism of variability in which, when the total soil moisture and potential evaporation were high, the runoff was low and vice versa. The large weighting for the potential evaporation in the second principal component relates to the fact that the variability of potential evaporation is the secondmost dominant factor controlling the variability of the hydrologic cycle over the continental United States. The reason for the above mentioned result is kind of intuitive because of the dependence of potential evaporation on incoming solar radiation which, in turn, is the key driver behind both the water and energy cycle. The possible reason for the potential evaporation not showing up as the most dominant mode of variability for the continental hydrologic cycle is because of its dependence on factors other than solar radiation. A secondary process that might be contributing in part toward the second principal component is the opposite signs of the loading of potential evaporation and total soil moisture with respect to runoff and precipitation and vice versa. The mechanism can be interpreted as time variability of storm and interstorm events. As during a storm event the runoff increases and potential evaporation decreases, just the opposite happen in an interstorm event. We observe that it is not a single event or process that is controlling the spatial structure of the second principal component, but both potential evaporation and the time variability of storm and interstorm events have a control over the secondmost dominant mode of spatial variability.

[22] The third principal component is dominated by the spatial patterns of the total soil moisture, which has in all cases an opposite sign from all other variables. Therefore the redistribution of the soil wetness controls the third most dominant mode of spatial variability, which, in turn, can be attributed to the variability in other factors like the soil properties, vegetation, and topography.

[23] Our results show that for both seasonal and annual hydrologic cycles the most dominant pattern of spatial variability is controlled by precipitation, the water balance component of the hydrologic cycle. The secondmost dominant mode of spatial variability is highly influenced by potential evaporation, the energy balance component of the

Table 4. Loadings of the Principal Components for the Seasonally/Annually Averaged Timescales for 1998–1999[a]

Variables	Principal Component Loadings: Component 1	Component 2	Component 3	Component 4
		Annual		
TSOILM	0.454	−0.494	**0.725**	0.157
PRCP	**0.626**	0.286		**−0.724**
POTEVP	0.166	**−0.770**	−0.602	−0.128
RUNOFF	0.612	0.283	−0.333	0.659
		Autumn		
TSOILM	0.513	0.276	**−0.784**	−0.212
PRCP	**0.596**	−0.157	0.499	**−0.609**
POTEVP	0.233	**0.846**	0.367	0.310
RUNOFF	0.572	−0.429		0.699
		Winter		
TSOILM	0.484	−0.385	**−0.786**	
PRCP	0.591	0.307	0.206	0.717
POTEVP	0.332	**−0.743**	0.569	−0.118
RUNOFF	**0.554**	0.453	0.126	**−0.687**
		Spring		
TSOILM	0.562		**−0.556**	0.612
PRCP	0.440	0.733	−0.140	−0.500
POTEVP	0.465	**−0.680**	−0.111	−0.556
RUNOFF	**0.524**		0.812	**0.257**
		Summer		
TSOILM	0.431	−0.488	**−0.758**	
PRCP	**0.603**	0.353		**−0.711**
POTEVP	0.302	**−0.715**	0.603	
RUNOFF	0.599	0.356	0.149	0.701

[a]Bold entries are the largest values.

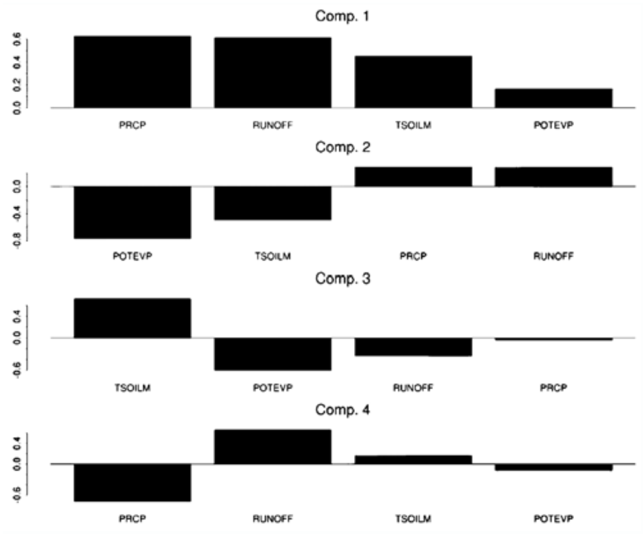

Figure 2. Plot of the loadings of principal components for the annual cycle of October 1998 to September 1999.

hydrologic cycle, and the third by the pattern of redistribution of soil moisture in the soil column.

[24] The analysis not only leads to a better understanding of the hydrologic cycle but also distinguishes between the two dominant spatial scales of variability in the hydrologic cycle over the continental United States. The process controls for the first two components can be considered factors with large scales of variability, i.e., precipitation and potential evaporation. The third principal component is influenced by total soil moisture, which has a shorter scale of variability; it is mostly dependent on soil properties and topography, and these can vary within very short distances and times. Our results indicate that the variability in the hydrologic cycle exhibits two spatial scales, a large spatial scale that is dominated by atmospheric variables, such as precipitation, evaporation, solar radiation, wind speed, air temperature, and surface pressure, and a short scale of spatial variability due to factors such as soil property, topography, or, in general, the catchment's hydrology.

[25] To test the consistency of the process controls over the space-time variability in the hydrologic cycle over the continental United States, principal component analysis was also performed for the following year, 1998–1999, with the same variables. The loadings of each of the variables in the individual principal components are given in Table 4. The plot of the loadings for each variable in the annually averaged principal component is shown in Figure 2.

[26] It can be seen that for the year 1998–1999 the first principal component is highly correlated with the spatial patterns of the seasonally/annually averaged precipitation and the second principal component exhibits features similar to the previous year (1997–1998). In the secondmost dominant mode of spatial variability the sign of the loadings for the total soil moisture is opposite to that of runoff, and the potential evaporation has the highest value of the loadings for all the timescales that are considered, hence referring to the process of the time variability of weather events and of potential evaporation. The only exception is seen in the spring cycle (not shown here), where there is a significant difference in the values of the loadings for the different variables in each component. In the spring cycle of 1997–1998 the first principal component is dominated by runoff along with precipitation, whereas in the year 1998–1999 the total soil moisture is dominant. Similarly, for the second and third components, the spring cycle of 1997–1998 is strongly influenced by potential evaporation and soil moisture, respectively, whereas for the spring cycle 1998–1999 the second and the third components are dominated by precipitation and runoff. Hence the process controls over the spatiotemporal variability in the hydrologic cycle over the continental United States appear to be very similar for the time span of October 1997 to September 1998 and October 1998 to September 1999. Although the main objective of the principal component analysis is data reduction (which it serves in this case), in some cases it can reveal relation amongst different variables (that were not expected) and thereby allow interpretation of the influence of the variables in the different modes of variability based on the magnitude and signs of their weighting coefficients or loadings. In case I of our study, insight into the process controls of the continental water balance components and better characterization of the hydrologic cycle improved estimation of fewer land surface variables, rather than concentrating on a large number of variables, temporally and spatially varying. The results from the analysis of case I show that better estimation of the precipitation and potential evaporation can lead to enhanced characterization of the hydrologic cycle. It can also be inferred that the spatial and temporal structure of these two variables can be considered as good estimators of spatial and temporal structures of other land surface parameters.

3.2. Case II: Single Variable Principal Components

[27] The analysis of case I has given insight into the hydrologic cycle and also helped us reduce the dimensionality of the data set without significant loss of information. In case II the principal component analysis was carried out on a single variable that varied both in time and space. In section 3.1 we discussed the relative importance/contribution of a single variable in the hydrological system variability. In the present analysis we analyzed multiple variables simultaneously to determine the spatial variability of each of the variables. For the purpose of analysis the two most important forcing variables, precipitation and potential evaporation, are considered along with that of the top layer (0–10 cm) soil moisture and runoff.

[28] The plot of the spatial distribution of the first two components for the biweekly averaged precipitation, potential evaporation, top layer soil moisture, and runoff is shown in Figures 3, 4, 5, and 6, respectively. The first two components of the empirical orthogonal functions (EOFs) EOF1 and EOF2 explain ~70% of the variability present in the data set for each of the variables considered.

[29] The regions with the highest loadings are the areas with the largest variance within the time frame. We can therefore locate the areas where there have been changes in the value of the parameter throughout the time span. Areas with loading near zero are areas that do not exhibit any variance for this particular variable. The absolute value of the loading represents the extent of variability or the

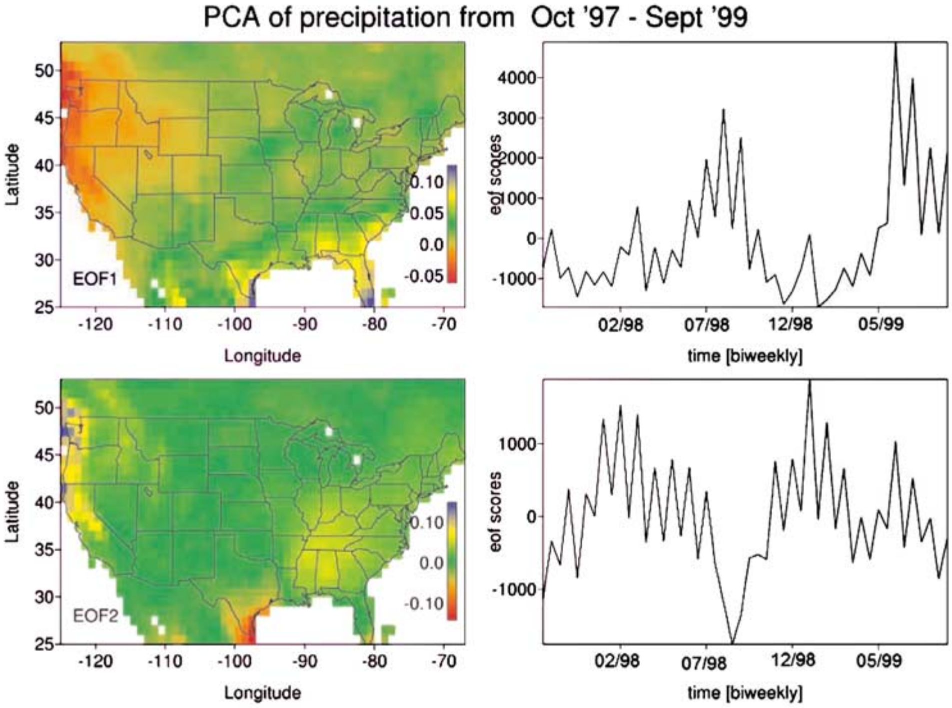

Figure 3. Plot of the loadings and scores for EOF1 and EOF2 of precipitation.

magnitude of the variance in the whole data set. The negative signs on the loadings indicate a negative correlation. In Figure 4 for EOF2 the areas with red and blue are the regions where most of the variability is encountered. The plot of the first principal component shows the most dominant spatial pattern of the variance within the 2 years of consideration and, similarly, the plot of loadings for EOF2 or the second principal component represent the secondmost dominant pattern for the spatial-temporal variability present in the data set. The spatial patterns of the first two components are representative of the pattern of variability for the whole data set, consisting of 2 years of daily values for the whole of the continental United States. In Figure 3 we observe that for the dominant mode of spatial variation of precipitation, most of the variability is concentrated on the northwestern parts of the United States, and

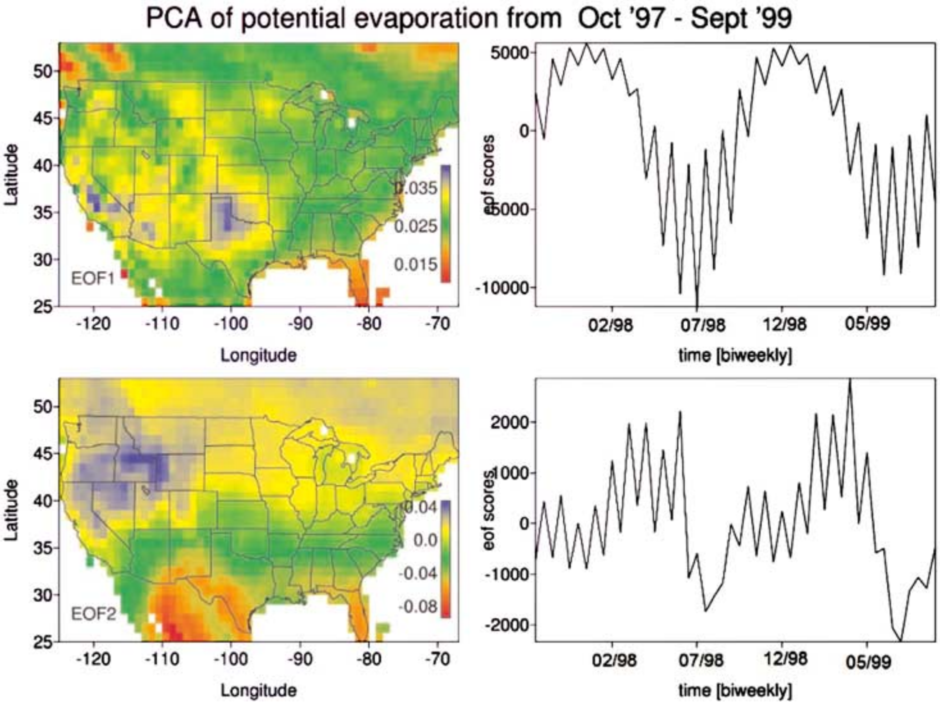

Figure 4. Plot of the loadings and scores for EOF1 and EOF2 of potential evaporation.

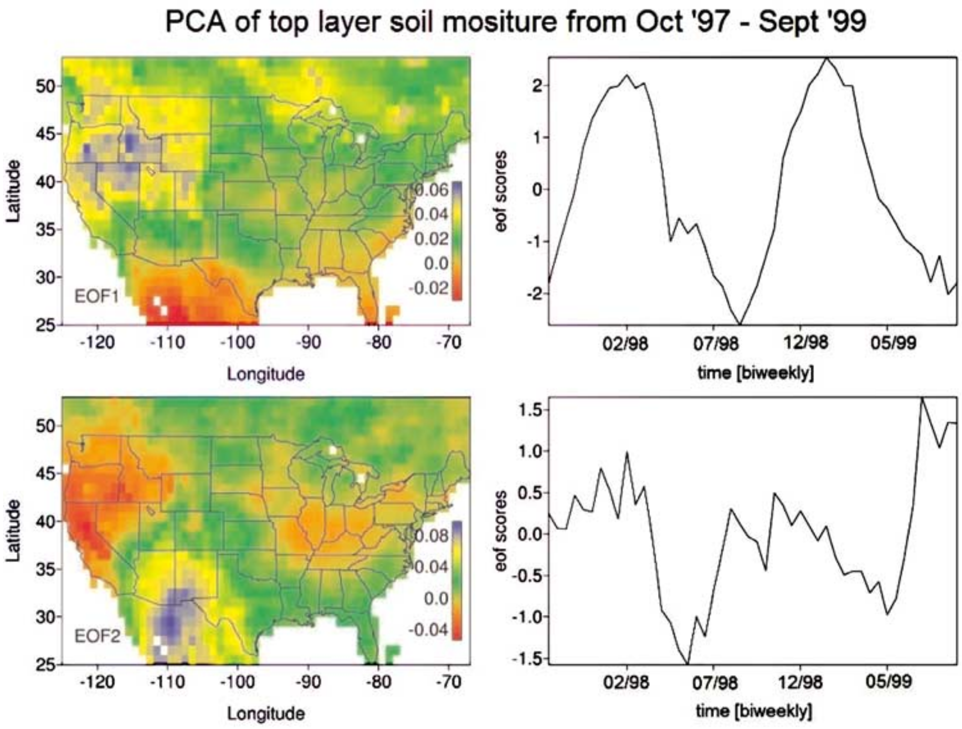

Figure 5. Plot of the loadings and scores of EOF1 and EOF2 for top layer soil moisture.

rest of the areas are more or less similar. The plot of the second principal component shows a uniform spatial distribution as most of the variation present in the precipitation was captured by the first principal component. The plot for the potential evaporation in Figure 4 shows that most of the variance is clustered near the central and southwestern parts of the United States although the maximum variance is seen in the state of Florida. The spatial plot of the second principal component shows that the areas of maximum variance are seen to be in the northwestern and south central parts of the United States. The time series of the EOF scores shows the temporal evolution of the variance in the areas of maximum variability or the areas with the maximum value of the loadings. The areas with the value of the loadings less

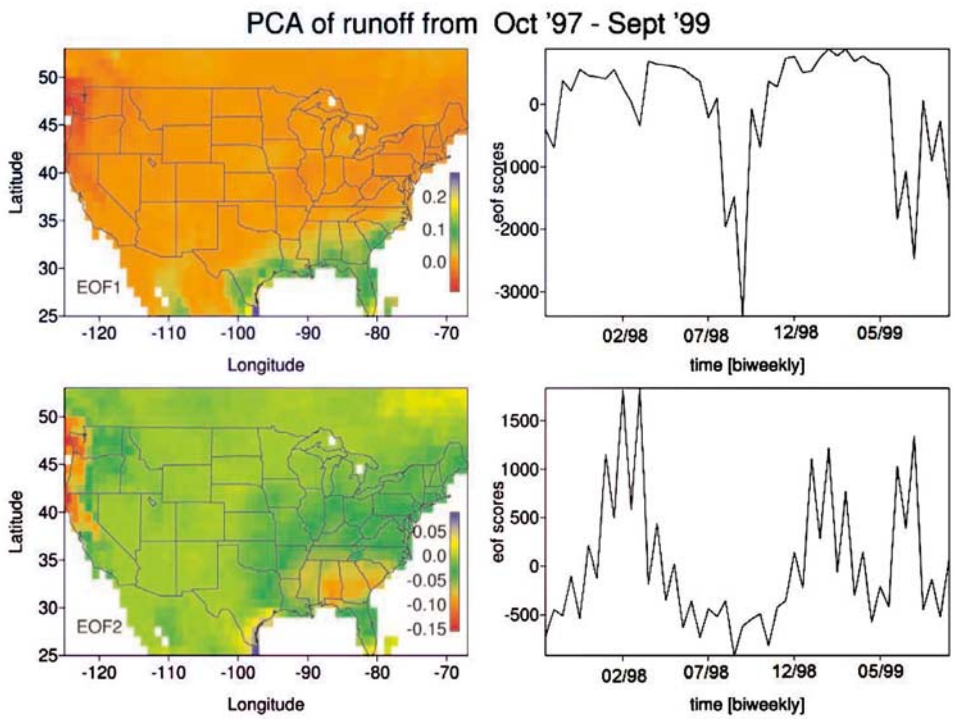

Figure 6. Plot of the loadings and scores of EOF1 and EOF2 for runoff.

than the maximum are influenced by the consecutive principal components. The time series of EOF scores in Figure 3 show that for EOF1 of precipitation, there is a seasonal variation unlike that of EOF2 where we see a more or less annual variability. However, in Figure 4 we see that for both EOF1 and EOF2 there is about a 10–11 month periodicity.

[30] Analysis was also performed on the key response variables such as the top layer soil moisture and runoff for the purpose of detecting the similarity in the spatial patterns of the EOFs, and it can be seen from Figures 5 and 6 that the plot of EOF1 for the top layer soil moisture in Figure 5 is more or less similar to that of EOF2 of potential evaporation in Figure 4. The result shows that the soil moisture of the top layer is dictated by the secondmost dominant spatial pattern of potential evaporation, and the plot of EOF1 for the runoff in Figure 6 is guided by the most dominant spatial pattern of precipitation (Figure 3), which is not surprising, as the runoff is known to be a direct response variable of precipitation.

[31] One of the most interesting observations from case II is the ability of the analysis to represent the temporal variation in the spatial variability of certain land surface parameters. It can be seen from Figures 3–6 that the four variables under consideration show maximum spatial variability for EOF 1 (witnessed by the high EOF scores) at different periods of the year. Precipitation shows maximum spatial variability in late summer (for Figure 3, peaks in August–September), whereas top layer soil moisture depicts the same peaks in early spring (for Figure 5, peak in March) and exhibits minima in early winter (for Figure 5, minima in October). Potential evaporation depicts maximum spatial variability in winter (for Figure 4, peaks in November–December) and minima in late summer (August–September). Runoff, on the other hand, does not show any temporal pattern of spatial variability with an abrupt low in September–October (Figure 6). The temporal analysis of spatial variability shows interesting connections to the hydrological cycle. Dry periods (low precipitation) result in a maximum variability in top layer soil moisture due to the high spatial variability in the potential evaporation. The plot of the time series of EOF scores also revealed that there are certain characteristic temporal patterns of evolution in the spatial variability of hydrologic variables. Although the current work does not involve the delineation and characterization of the time periods of evolution of the variables, it does show that there are some patterns in the temporal evolution. Hence an extension of the present work can be directed toward the identification of the time periods of evolution of spatial patterns; for that, long-term data and proper time series analysis techniques will be required. From the current work a clear understanding of the surface hydrologic cycle will, in turn, help us to understand the links between hydrology and climate and the role of surface hydrology in land-atmosphere interactions.

4. Conclusion and Discussions

[32] In this study an attempt was made to understand the process controls in space-time variability of land surface parameters entering the description of the hydrologic cycle over the continental United States. Our results have shown that the hydrologic cycle is most strongly influenced by precipitation and potential evaporation and can be designated as the major driving force behind the continental hydrologic cycle over the conterminous United States. Our results are comparable to those of *Famiglietti et al.* [1995], in which the first principal component was shown to be strongly influenced by precipitation for both the annual and seasonal hydrologic cycles. The second principal component in our study was found to be dominated by the spatial pattern of potential evaporation, which can be perceived as a more realistic and a widely applicable phenomenon in comparison to that of snowmelt, which was found to be the variable that strongly influenced the second principal component in the work by *Famiglietti et al.* [1995]. Although snowmelt plays an important role under land surface hydrologic considerations, it can only be considered in restricted areas over the continental United States, hence such a generalization of snowmelt as the secondmost important variable controlling the continental hydrologic cycle seemed somewhat unrealistic for the whole continental United States. In our opinion, potential evaporation is the variable providing an authentic characterization of the hydrologic cycle and its variability. This is to some extent intuitive, as the calculation of potential evaporation also takes into account the amount of downwelling solar radiation which is the primary source of energy driving the hydrologic cycle both over land and ocean.

[33] Our study leads to the possibility that the hydrological cycle can be characterized by a few key physical variables. Accurate modeling of these variables is paramount to the success of land surface modeling. This also leads to an implication in terms of modeling strategy. These key variables should also be observed with improved spatial and temporal resolution to help (1) characterize spatial and temporal variability and (2) validate land surface models. Thus the second part of the current work dealt with the understanding and representation of the space-time variability in the most influential variables of land surface hydrology. The present work was able to delineate the areas of maximum variance and hence the areas of maximum activity over the continental United States in terms of land surface processes. Being able to point out the areas of major variability automatically calls for a need of better observations in those particular places. This can lead to a major step in the designing of observational networks, which are until now quite scanty and unnecessary at some places. A lot of time and effort is put into the selection and setting up of observation stations, and the current study takes the lead in trying to identify the spatial extent and locations of observational networks by the identification of the areas of maximum variability from an extended data set. Thus we can conclude that high-resolution observational networks are not needed for better characterization of certain variables over large areas, but better networks in the areas of high variability can do an equally good job if not better. This is directly evident from the results in case II of the current study. Figure 5 shows the first two components of the annual hydrologic cycles of the topsoil moisture. The plot shows that most dominant patterns of soil moisture variability are concentrated toward the eastern coast of the United States and also some parts of the northwestern United States and some in the Midwest; it also shows that

the variability in the areas other than those depicted as important by the principal component analysis have a very negligible contribution toward the variance of the parameter over the study area which in this case is the continental United States. The results discussed above are primarily aimed at the presentation of a method to identify areas with high variance. Therefore the current analysis on data with higher spatial and temporal resolutions over longer time periods will be able produce more widely applicable and robust results so as to influence the current designs of monitoring networks over the conterminous United States. Another interesting aspect of future research would be to compare and assimilate results from similar analysis on data from different land surface schemes that are currently available.

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J. S. Famiglietti, Department of Earth System Science, University of California, 230 Rowland Hall, Irvine, CA 92687-3100, USA.

V. Lakshmi, E. Paleologos, and T. H. Syed, Department of Geological Sciences, University of South Carolina, 701 Sumter Street, Columbia, SC 29208, USA. (vlakshmi@geol.sc.edu)

D. Lohmann and K. Mitchell, NOAA/NCEP, Environmental Modeling Center, W/NP2, Room 207, NOAA Science Center, 5200 Auth Road, Suitland, MD 20746-4304, USA.