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Evaluation of the land surface water budget in NCEP/NCAR and NCEP/DOE reanalyses using an off-line hydrologic model

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Abstract. The ability of the National Centers for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) reanalysis (NRA1) and the follow-up NCEP/Department of Energy (DOE) reanalysis (NRA2), to reproduce the hydrologic budgets over the Mississippi River basin is evaluated using a macroscale hydrology model. This diagnosis is aided by a relatively unconstrained global climate simulation using the NCEP global spectral model, and a more highly constrained regional climate simulation using the NCEP regional spectral model, both employing the same land surface parameterization (LSP) as the reanalyses. The hydrology model is the variable infiltration capacity (VIC) model, which is forced by gridded observed precipitation and temperature. It reproduces observed streamflow, and by closure is constrained to balance other terms in the surface water and energy budgets. The VIC-simulated surface fluxes therefore provide a benchmark for evaluating the predictions from the reanalyses and the climate models. The comparisons, conducted for the 10-year period 1988-1997, show the well-known overestimation of summer precipitation in the southeastern Mississippi River basin, a consistent overestimation of evapotranspiration, and an underprediction of snow in NRA1. These biases are generally lower in NRA2, though a large overprediction of snow water equivalent exists. NRA1 is subject to errors in the surface water budget due to nudging of modeled soil moisture to an assumed climatology. The nudging and precipitation bias alone do not explain the consistent overprediction of evapotranspiration throughout the basin. Another source of error is the gravitational drainage term in the NCEP LSP, which produces the majority of the model's reported runoff. This may contribute to an overprediction of persistence of surface water anomalies in much of the basin. Residual evapotranspiration inferred from an atmospheric balance of NRA1, which is more directly related to observed atmospheric variables, matches the VIC prediction much more closely than the coupled models. However, the persistence of the residual evapotranspiration is much less than is predicted by the hydrological model or the climate models

1. Introduction

Global reanalyses, which are the result of retrospective analyses produced using "frozen" versions of coupled land-atmosphere models and assimilation systems [e.g., *Kalnay et al.*, 1996, *Gibson et al.*, 1997], have provided the research community with new opportunities to understand continental and global water and energy budgets that are not possible directly from observations. Reanalysis products have the advantage of being consistent and continuous in space and time, for periods as long as five decades in the case of the cooperative reanalysis project of the National Centers for Environmental Prediction (NCEP) and National Center for Atmospheric Research (NCAR) [*Kalnay et al.*, 1996] and over 20 years for the reanalysis project of NCEP and the Department of Energy (DOE). These products can be used to characterize the land surface water and energy budgets for decadal trends, interannual variability, and seasonal, monthly, and diurnal cycles, as well as to evaluate forecasting skill and potential improvements in the operational models on which the reanalysis products are based. These sets of comprehensive model output also offer an opportunity to diagnose the land surface parameterizations for systematic biases in predicted parameters. This opportunity arises because of the move toward consolidation of parameterizations across an array of forecasting models within the various weather and climate modeling centers. For instance, NCEP is moving toward use of a common

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land surface scheme across its weather, intermediate range forecast, and long-term climate forecast models.

The sensitivity of atmospheric models to land surface conditions has been documented in many studies [e.g. *Mintz*, 1984; *Milly* and *Dunne*, 1994; *Betts et al.*, 1996a]. These studies and others like them have motivated atmospheric modelers to use more sophisticated land surface parameterizations (LSPs), and to represent land-atmosphere interactions as coupled processes, rather than boundary conditions as was once the case. In this context it is important to produce consistent, realistic estimates of those land surface properties (especially soil moisture and/or vegetation evaporative stress) that control the partitioning of net radiation into latent, sensible, and ground heat flux. This, in turn, requires accurate representation of the surface hydrologic cycle, specifically water balance processes such as the partitioning of precipitation into infiltration and direct runoff, which directly affects soil moisture and evapotranspiration. The coupled surface energy and water cycles are likewise closely linked to properties such as albedo and surface roughness, which influence evapotranspiration, surface temperature, and boundary layer properties in complex, nonlinear relations.

Soil moisture plays a crucial role in a LSP, since it directly or indirectly controls several processes that affect the partitioning of both precipitation and net radiation. For instance, *Huang et al.* [1996] summarized the interaction between soil moisture, surface albedo and roughness, relative humidity, surface temperature, and upper level atmospheric circulation, all of which affect simulated atmospheric dynamics. *Betts et al.* [1996a] noted that soil moisture is analogous to, and potentially as important as, sea surface temperature (SST), which is the critical state variable defining the ocean boundary in global weather forecasts. From an observational standpoint, *Dirmeyer* [1995] argued that soil moisture is more poorly specified than sea surface temperature, due in part to the absence of global networks, and high spatial heterogeneity. *Delworth and Manabe* [1988] showed that soil moisture is a red noise process, due to the low pass filtering represented by moisture accumulation processes in the soil column, applied to precipitation, which is nearly a white noise process. Soil moisture responds relatively slowly to changes in hydrologic inputs, and provides a mechanism for persistence in medium- and long-range weather forecasts. *Van den Dool et al.* [1986], *Huang and van den Dool* [1993], *Huang et al.* [1996], *Durre et al.* [2000], *Roads et al.* [1999], and others have shown that this long-term memory can be exploited to improve long-range forecasts of air temperature over the central United States in summer, when soil moisture memory is the dominant process affecting persistence of weather.

A similar solution exists at longer forecast lead times, such as for climate forecasting. In this case a global model is run with prescribed SST, but the land and atmosphere are allowed to interact. Downscaling may be achieved by nesting a regional model within the global model. When run for long periods of decades to centuries, the land surface and atmosphere tend toward a dynamic equilibrium. It is especially important, therefore, that land-atmosphere interactions be properly represented, as they can have important implications for moisture recycling over the continents. For instance, *Koster and Suarez* [1995] and *Koster et al.* [2000] have shown the importance of the land surface in controlling the variability and predictability of precipitation over the continents, even having a greater influence than the oceans, particularly in the Northern Hemisphere summer.

The need to represent land-atmosphere interactions in numerical weather prediction, which is an initial value problem, is less obvious. Until the last decade or so, the traditional thinking was that land surface conditions could be prescribed, as they were unlikely to change much over the time horizon of weather forecasts (now typically 4, to about 10, days). *Betts et al.* [1996a], however, showed that the initial land surface conditions specified for numerical weather prediction models can have a profound influence on the simulated atmospheric dynamics and resulting computed fluxes, perhaps for periods as long as 200-300 days [*Pielke et al.*, 1999]. Recently, *Viterbo and Betts* [1999] investigated forecast sensitivities with specific initial conditions of wet and dry soil moisture fields, and showed that forecasts of precipitation could change by as much as 40% due to differences in initial soil moisture. In addition to initial conditions for numerical weather forecast models, a climatological balance of the land surface can also be important over the weather forecast time horizon. For example, *Beljaars et al.* [1996] showed how the accuracy of 2-3 day precipitation forecasts is improved by incorporation of an improved LSP in the coupled forecast model.

While research results show the need for better representation of the land surface for both weather and climate prediction, how best to achieve this is complicated, and most work to date has focused on model improvements. The quandary in specifying initial conditions is the absence of surface observational networks of state variables, for example, of soil moisture, which could be used to update surface conditions. If such observations were available, they might be used in the same manner that free atmosphere variables (typically soundings of temperature, humidity, and wind) are used to update the atmospheric states at the time of forecast. The alternative approach has been to incorporate LSPs driven by model surface forcings to represent excursions of surface conditions from long-term climatologies. As we will show in this paper, this approach has problems as well, due in part to two factors. These are the accumulation of errors in the land surface resulting from biases in surface forcings, especially precipitation, and the difficulty in representing the complex, nonlinear dynamics of the land-atmosphere system with LSPs that are simplified sufficiently to economize on computational demands in a coupled setting. An alternative approach now being pursued by NCEP is the Land Data Assimilation System (LDAS) [*Mitchell et al.*, 1999], which essentially makes a parallel off-line run of the same LSP that is coupled to the weather prediction model, using observed forcings up to the time of forecast. The land surface states (soil moisture, snow extent and water equivalent or depth, and surface temperature) are then used as initial conditions for the forecast, in lieu of direct observations. The NCEP Climate Prediction Center has applied this conceptual approach experimentally on a monthly basis, based on the work by *Huang et al.* [1996].

An important, and largely unresolved, problem specific to the incorporation of LSPs in numerical weather prediction models is the tendency of LSPs to seek their own soil moisture equilibrium. This equilibrium may not be consistent with the surface fluxes required by the boundary layer formulation to produce accurate forecasts. Current practice is to counteract the tendency of soil moisture "drift" toward a dynamic equilibrium by "nudging" the predicted soil moisture back toward a prescribed climatology. This is achieved by injecting or extracting water from the soil column periodically as part of the forecast update (data assimilation) process. Soil moisture nudging is performed by both the NCEP/NCAR and the

European Centre for Medium-Range Weather Forecasts (ECMWF) reanalyses [*Roads and Betts*, 2000]. In the case of the NCEP/NCAR reanalysis [*Kalnay et al.*, 1996] (hereinafter referred to as NRA1), the soil moisture nudging results in significant nonclosure of the surface water budget, and has implications for the ability of the coupled model to simulate interannual persistence, as well as the natural variability of the system [*Maurer et al.*, 2001]. The followup reanalysis by NCEP and DOE, which also integrates some fields from the Atmospheric Model Intercomparison Project (AMIP-II), NCEP/DOE AMIP-II reanalysis (hereinafter referred to as NRA2) [*Ebisuzaki et al*, 1998; *Kanamitsu et al*, 2000], includes a much smaller adjustment, which is somewhat different from the nudging in NRA1 as it is a correction based on observed precipitation fields.

One difficulty in evaluating the performance of LSPs is the paucity of observations of land surface variables over large continental regions for long time periods. Some methods that have been used to evaluate LSPs in coupled models include comparisons of model-predicted evapotranspiration with that derived from an atmospheric water balance [*Lohmann et al.*, 1998a], model comparison with observations over specific, intensive study sites [*Betts et al*, 1996b], comparison of LSP runoff against annual streamflow [*Koster et al.*, 1999], and intercomparison of different soil moistures produced by coupled models with multiyear observations taken across large regions [*Robock et al.*, 1998]. These approaches are valuable for the parameter or region of study, but do not allow an evaluation of the interaction of the water balance components over large regions for long periods.

In this study, NRA1 and NRA2 are evaluated using the output from a physically based macroscale hydrologic model, similar in concept to what will be produced in real time by LDAS. This work is similar to an earlier study by *Maurer et al.* [2001] that provided a framework for diagnosing biases in the NRA1 land surface fluxes and state variables. Because the hydrologic model closes the surface water balance by construct and is driven by gridded observed precipitation and temperature, we argue that the hydrologic model simulations, which are produced as space-time fields, should be reasonably accurate, at least over the long term. They can therefore be viewed as baseline pseudo-observations for purposes of evaluating the reanalysis surface fluxes. In a slightly different manner, the hydrologic model output can be used to evaluate the statistics of surface variables simulated using long-term global climate model simulations, which are "freewheeling" in the sense that only sea surface temperatures are prescribed. The use of the hydrologic model output as psuedo-observations offers an opportunity to diagnose the land surface water budgets of the reanalyses and climate models. Furthermore, evaluation of soil moisture fields produced by the coupled models offers insights into the potential improvements that can be realized by utilizing LDAS soil moisture to initialize the forecast model.

2. Modeling Approach

Land surface fluxes and state variables represented by the LSP used in NRA1 and NRA2 are compared with predictions of the same variables using an off-line simulation of the hydrologically based variable infiltration capacity (VIC) model [*Liang et al.*, 1994, 1996]. This comparison is facilitated by the inclusion of two additional model simulations: a relatively unconstrained global climate simulation using the NCEP global spectral model; and a more highly constrained regional climate simulation using the NCEP regional spectral model, both of which incorporate the same LSP used in the reanalyses. The analysis domain is the Mississippi River basin, which is subdivided into five major subbasins for this analysis (see Figure 1). A 10-year simulation period (1988-1997) is used to compare the coincident period with the coupled models, which is sufficient to identify major differences between the two sets of model-derived fields.

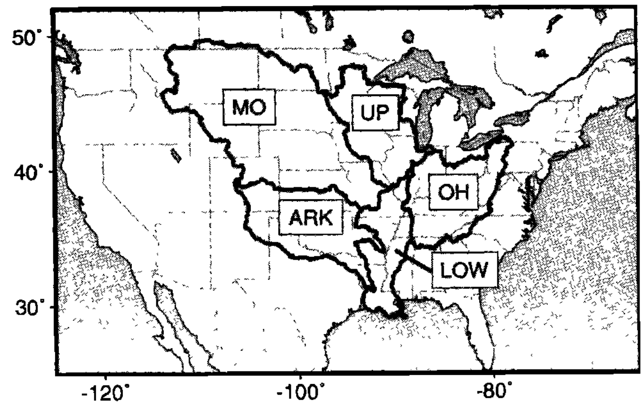

Figure 1. Mississippi River Basin with subbasin locations for lower Mississippi River (LOW), Arkansas-Red Rivers (ARK), Missouri River (MO), upper Mississippi (UP), and Ohio River (OH) basins.

2.1. Meteorological Forcing Data

The VIC model is forced with observed meteorological data, which ideally would include temperature, precipitation, wind, vapor pressure, and incoming longwave and shortwave radiation. Because only temperature and precipitation are measured routinely at a reasonably large number of locations within the Mississippi River basin, we use established relationships relating these to other meteorological variables. For example, dew point temperature is calculated using the method of *Kimball et al.* [1997], which relates the dew point to the daily minimum temperature, and downward shortwave radiation is calculated based on the daily temperature range and the dew point temperature using a method described by *Thornton and Running* [1999].

The precipitation data consist of daily totals from the National Oceanic and Atmospheric Administration (NOAA) Cooperative Observer (co-op) Stations (approximately one station for every five grid cells). The raw precipitation data were gridded to a 1/8° grid (the specified resolution used for this VIC simulation) using the SYMAP algorithm of *Shepard* [1984] as implemented by *Widmann and Bretherton* [2000]. The gridded daily precipitation data for the VIC model were then scaled to match the long-term average of the parameter-elevation regressions on independent slopes model (PRISM) precipitation data set [*Daly et al.*, 1994, 1997], which is a comprehensive data set of monthly means for 1961-1990 that is statistically adjusted to capture local variations due to complex terrain. The daily precipitation total is distributed evenly over each time step. The minimum and maximum daily temperature data for the Mississippi River basin, also obtained from the co-op stations (approximately one station for every seven grid cells), were combined with a digital elevation model and the temperatures lapsed to the grid cell mean elevation. Temperatures at each time step were interpolated by fitting an asymmetric spline through the daily maxima and minima. Because surface observations of wind speed are very sparse and are biased toward certain geographical settings (e.g., airports), daily 10-m wind fields were obtained from the NCEP/NCAR reanalysis [*Kalnay et al.*, 1996], and regridded from the T62 Gaussian grid (approximately 1.9° square) to the 1/8° grid using a linear interpolation.

2.2. Hydrologic Model Implementation

Liang et al. [1994, 1996] described the VIC model in detail. VIC is a macroscale hydrologic model that balances both energy and water over a grid mesh, typically of resolution from a fraction of a degree to several degrees latitude by longitude. Macroscale in this context refers to areas above a critical scale at which subgrid hydrologic variability can be captured statistically [e.g., *Wood et al.*, 1988]. It has been successfully applied to many large global rivers [e.g., *Abdulla et al.*, 1996; *Lohmann et al.*, 1998b; *Nijssen et al*, 1997; *Wood et al.*, 1997; *Nijssen et al.*, 2001]. The VIC model computes the vertical energy and moisture fluxes in a grid cell based on a specification at each grid cell of soil properties and vegetation coverage. The VIC model includes the representation of subgrid variability in soil infiltration capacity, specification of a mosaic of vegetation classes in any grid cell, and spatially varying subgrid precipitation. At the 1/8° resolution, the model represents about 23,000 computational grid cells within the Mississippi River basin. For this study, the model was run for the 10-year simulation with full water and energy balance solutions at a 3-hour time step.

In the VIC model, drainage between soil layers is entirely gravity driven, and the unsaturated hydraulic conductivity is a function of the degree of saturation of the soil [*Campbell*, 1974]. Base flow is produced from the lowest soil layer using the nonlinear ARNO formulation [*Todini*, 1996]. To account for subgrid variability in infiltration, the VIC model uses a variable infiltration capacity scheme based on the work by *Zhao et al.* [1980]. This scheme uses a spatial probability distribution to characterize available infiltration capacity as a function of the relative saturated area of the grid cell. Precipitation in excess of the available infiltration capacity forms surface runoff.

Land cover characterization was based on the data set developed by *Hansen et al.* [2000], which has a resolution of 1 km, and a total of 14 different land cover classes. From this global data set we identify the land cover types present in each 1/8° grid cell in the model domain and the proportion of the grid cell occupied by each. The primary characteristic of the land cover that affects the hydrologic fluxes simulated by the VIC model is leaf area index (LAI). LAI is derived from the gridded (¼°) monthly global LAI database of *Myneni et al.* [1997], which is combined with the land cover classification to derive the monthly LAI corresponding to each vegetation classification for each grid cell. These LAI values do not change from year to year in this implementation of VIC. Rooting depth is specified for each land use type, typically with shorter crops and grasses drawing their water from the upper soil layers, and tree roots extending into the deeper layer. Infiltration, moisture flux between the soil layers, and runoff all vary with vegetation cover type within a grid cell. Grid cell total surface runoff and base flow are computed for each vegetation type and then summed over the component vegetation covers within each grid cell for each time step.

The VIC model as applied in this study uses a three-layer soil column, with depths of each layer specified for each grid cell. The soil characteristics used in the VIC model for the Mississippi River basin were derived from the 1-km resolution continental United States data set produced by Pennsylvania State University [*Miller and White*, 1998], which classifies the soil texture into 16 classes for each of 11 layers. Gridded 1/8° data sets have been developed as part of the LDAS project using this data set, inferring specific soil characteristics (e.g., field capacity, wilting point, saturated hydraulic conductivity) based on the work of *Cosby et al.* [1984] and *Rawls et al.* [1998]. These LDAS data sets were used to specify the relevant soil parameters required by the VIC model directly. For remaining soil characteristics (e.g., soil quartz content), values were specified using the soil textures from the 1-km database, which were then indexed to published parameter values (the primary source was *Rawls et al.* [1993]), and aggregated to the 1/8° model resolution.

2.3. Hydrologic Routing to Subbasin Outlet

The method of *Lohmann et al.* [1996] was used to route runoff generated by both the VIC model and the NCEP LSP (from NRA1) at each grid point or cell to the basin outlet. Since only monthly summary data were used in this study for NRA2, this precluded applying the daily flow routing to NRA2 runoff. The resulting predicted hydrographs at the mouth of the Mississippi and its major tributaries were then compared with observed streamflows, or, where available, naturalized flows that have been adjusted to remove anthropogenic effects (e.g., irrigation diversions, reservoir storage, and evaporation).

2.4. NCEP/NCAR Reanalysis (NRA1)

NRA1 has been described in detail elsewhere [*Kalnay et al.*, 1996]. The intent of the NRA1 project was to produce long-term analysis fields using a "frozen" state-of-the-art version of the NCEP data assimilation and operational forecast models, which was intended to result in continuous, consistent data sets. Reanalysis model output is archived every 6 hours, with surface flux fields saved on a T62 Gaussian grid. The NRA1 archive includes surface fluxes of both water and energy, including precipitation, soil moisture, runoff, downward and upward shortwave and longwave fluxes, and latent and sensible heat transfers. These variables are all denoted as "class C", which indicates that they are derived entirely from the data assimilation model and have no direct relationship to observations. Class "A" variables are those strongly linked to observed data, and class "B" variables are influenced by observations, but are also strongly influenced by the model. As reported by *Kalnay et al.* [1996] class "C" variables should be used with caution due to the high influence of the model on the predicted values. Nonetheless, reanalysis data, including the surface variables noted above, have been widely used in lieu of (or perhaps more accurately in the absence of) observations by studies such as the Atmospheric Model Intercomparison Project [*Glecker*, 1996].

While VIC has been used primarily in off-line simulations, that is, forced with observationally based forcings to simulate the land surface fluxes, the NCEP LSP is designed primarily to partition net radiation into latent and sensible heat. In this context, runoff and streamflow are primary outputs of VIC, but are essentially by-products of the NCEP LSP (and other

LSPs used in coupled settings). This essential difference is reflected in the structure of the LSP in NRA1, which is based on the model described by *Mahrt and Pan* [1984] and *Pan and Mahrt* [1987], with later modification by *Pan* [1990]. The soil column has two layers, a thin top layer of 10 cm thickness and a lower layer 190 cm in depth. In addition to the globally constant soil depth, most other parameters are fixed globally, including wilting point (0.12), critical point (0.25), and porosity (0.47). The soil hydraulic conductivity is a function only of the moisture content of the soil column. The percent of vegetation canopy coverage is also fixed at 70% for all grid cells. The NCEP LSP includes a representation of free drainage from the bottom of the soil column, which is controlled by the hydraulic conductivity of the lower soil layer, which in turn is a function of its moisture content. The water exiting the soil column as free drainage is included in the archived runoff. Soil moisture is adjusted to an assumed climatology of monthly values, which is discussed in greater detail below.

2.5. NCEP/DOE AMIP II Reanalysis (NRA2)

NCEP/DOE AMIP II reanalysis (NRA2) is a followup to NRA1 [*Ebisuzaki et al.*, 1998; *Kanamitsu et al.*, 2000]. The first phase of NRA2, completed in 2000, included the period 1979-1997. NRA2 uses the same raw data (e.g., measurements from rawinsondes, buoys, aircraft, etc.) as NRA1 and operates at the same resolution, but corrects some of the known errors in the NRA1, and makes other improvements to the model. It includes changes affecting snow cover and snowmelt, and improves the model representation of variables including precipitation, orography, shortwave radiation, clouds, and the planetary boundary layer. The most significant changes in NRA2 that directly affect the land surface water budget are the removal of the nudging of soil moisture toward a climatology, and the incorporation of a scheme to assimilate precipitation observations into the computation of soil moisture. This assimilation introduces a soil moisture correction analogous to nudging, in that additional moisture can be injected into or extracted from the soil column at each time step. The observed precipitation database used is the 5-day accumulated Xie-Arkin precipitation, which is a global data set based on both gauge and satellite estimates [*Xie and Arkin*, 1997].

Though modeled precipitation is not adjusted by the observations, infiltration is adjusted based on observed precipitation as follows. The assimilation considers two conditions: zero and nonzero modeled runoff. In the first case all modeled precipitation enters the soil column, in which case the a priori infiltration is adjusted to equal the observed precipitation. In the latter case the modeled infiltration is the modeled precipitation less the runoff, which in the assimilation process is constrained by an upper limit of the observed precipitation value. Therefore adjustments only occur when runoff is zero (in which case adjustments can be positive or negative), or when the modeled precipitation minus the modeled runoff exceeds the observed precipitation (in which case adjustments can only be negative and have the effect of removing water from the soil column). When neither of these conditions is met, the errors in modeled precipitation, compared to observations, are assumed only to affect modeled runoff and no adjustment is made. Adjustments are made after comparing 5-day accumulations and are made over the following 5-day period.

2.6. Climate Models

Two climate models were included in this study to provide an additional dimension to the diagnosis of the reanalysis land surface variables. These are the NCEP global spectral model (GSM) as applied in the AMIP II [*Glecker*, 1996], and the NCEP regional spectral model (RSM). Both the GSM and RSM use the same LSP as NRA1 and NRA2. The GSM includes the same model physics as NRA2, including identical ocean surface boundary conditions (that is, prescribed SSTs over the period of simulation), and is run at the same resolution. However, it is run in a "climate" mode, meaning that no data assimilation or reinitialization of the model occurs throughout the simulation period (see *Glecker* [1996] for a complete description of boundary conditions and other modeling details). This allows the interpretation of model intercomparisons with regard to the effect of the assimilation process on the model LSP results.

The RSM [*Juang and Kanamitsu*, 1994; *Juang et al.*, 1997] uses the same (atmospheric) model physics as NRA2, but it is run at a finer grid resolution than the reanalysis models (roughly 50-km resolution). The RSM is embedded within the lower-resolution NRA1 (which at T62 is roughly 200 km), and has been applied at a similar resolution over the United States in other studies [e.g., *Hong and Leetmaa*, 1999; *Roads and Chen*, 2000]. The RSM uses NRA1 base fields as forcings at the boundaries, and like the GSM, the surface variables are free to evolve through the simulation period. The RSM shares the same essential physics and model dynamics as the GSM and NRA2, and orography is better resolved, which results in improved predictability of surface fluxes. It is used in this study to examine the possible effect of resolution on the simulation of land surface water balance parameters. In addition, as *Roads and Chen* [2000] pointed out, it is more highly constrained to reproduce the large-scale climate of the reanalysis. While better regional climate depictions are ultimately to be expected from the incipient NCEP regional reanalysis, it is expected that regional models like this will still be used for regional climate forecasts.

2.7. Soil Moisture/Surface Water Adjustment

Because the LSPs use different numbers of soil layers (for example, two for NCEP and three for VIC) and have different soil depths and moisture storage capacities, direct comparisons between the soil moisture values would be misleading. In order to facilitate comparisons of soil moisture from the models, the reported soil moistures for each grid cell were adjusted by subtracting the hydrologically inactive column soil moisture, which is analogous to the dead pool storage in a water supply reservoir:

$$SM_i = \sum_{j=1}^{N_L} d_{ij} f_{ij} - \min \left\{ \sum_{j=1}^{N_L} d_{ij} f_{ij} \right\}, \qquad (1)$$

where SM_i is the adjusted soil moisture for grid cell i, *min* denotes the minimum daily soil moisture value in the 10-year period of simulation for the grid cell, d_{ij} is the depth of layer j in cell i, f_{ij} is the fractional volumetric soil moisture in layer j in cell i, and N_L is the number of layers in the soil column. While SM_i is averaged over only 1 month or a season, the minimum is still fixed as the minimum daily volumetric soil moisture over all days in the simulation. This adjustment applies equally when discussing total surface water (soil water plus snow water), since the minimum snow water is zero for all grid cells. All figures and data presented below use these adjusted soil moistures or surface waters, except where noted.

3. Methods of Comparison

The VIC land surface variables are compared with the coupled model surface field predictions for the period 1988-1997. To make the model domains comparable, the coupled model data were overlaid onto the same 1/8° grid used in the VIC simulation using a simple inverse distance relation with the four nearest neighbors. For comparison, the results are aggregated to monthly, seasonal, and annual totals for each of the surface water budget components.

3.1. Moisture Budgets

The surface water budget for the land surface can be expressed as [*Roads et al.*, 1999]

$$\frac{dW}{dt} = P - ET - N + U, \tag{2}$$

which represents the balance of precipitation P, evapotranspiration ET, runoff N, and the nudging/nonclosure term U, with the change in total moisture storage in the grid cell dW/dt, where W includes both soil moisture and snow water content. As shown in a time series analysis by *Roads et al.* [1999], the GSM used in the NRA1 has a tendency to drift to its own climatology. As noted above, NRA1 assumes a climatology (specifically, the average monthly soil moisture of *Mintz and Serafini* [1981, 1992]), and the nudging term U represents the nonclosure of the surface water budget due to nudging. As shown by *Maurer et al.* [2001], the nudging term for NRA1 is quite large. NRA2 also uses a nudging term, due to the precipitation assimilation procedure described above, but it does not assume a soil moisture climatology, and the magnitude of U is significantly smaller. Regardless of its magnitude, the nudging term U must be accounted for to assure closure of the water balance. For the GSM and RSM climate models, no surface water nudging is performed.

Because the VIC model balances the surface water budget by construct, there is no nonclosure term (U) in its budget. Unlike the LSPs the VIC model is calibrated by comparison of streamflow at the outlet of the major subbasins with observations (or, in the case of highly regulated subbasins like the Missouri, through comparison with naturalized flows, which have had the major anthropogenic effects removed). In order to compare the basin-wide and subbasin average monthly water budget components, we present monthly average values for each variable. To examine the effects of the LSP on interannual variations in the surface water budget, we evaluate time series of monthly values for the 10-year period of this study for each subbasin, as well as for the basin, as a whole.

3.2. Modeled and Derived Evapotranspiration Comparison

To estimate the degree to which the biases in the NRA1 evapotranspiration (ET) are caused by biases in the NRA1 precipitation (P) fields, we follow a method described by *Trenberth and Guillemot* [1998], which is based on the atmospheric water budget. In its simplest form, the atmospheric water budget can be expressed as

$$\frac{dP_W}{dt} = MC - (P - ET) + U_q, \tag{3}$$

where MC is the horizontal convergence of vertically integrated atmospheric water vapor, U_q is an atmospheric nudging term, part of the data assimilation process that is analogous to the surface water nudging term, and P_w is the precipitable water in the atmosphere:

$$P_W = \frac{1}{g}\int_0^{P_{sfc}} q\,dp, \tag{4}$$

where q is specific humidity, p is pressure, and P_{sfc} designates the pressure at the ground surface. Moisture convergence is defined by

$$MC = -\nabla \bullet \frac{1}{g}\int_0^{P_{sfc}} q\mathbf{v}\,dp, \tag{5}$$

where v is the horizontal wind velocity and g is gravitational acceleration. All of the variables are included in, or are readily derived from, the NRA1 fields. In particular, similar to the NRA1 model computations, horizontal and vertical moisture advection were first computed spectrally for each atmospheric model level (sigma). This spectral advection was then converted to physical space on the associated Gaussian transform grid (192 x 94 cells globally). The horizontal and vertical advection terms were then summed vertically and multiplied by the surface pressure at each grid point. To reduce spatial noise, the resulting integrated moisture divergence was spectrally transformed, filtered with a fourth-order Laplacian, and then once again transformed back to physical space. *Roads et al.* [1998] compared this method of calculating moisture convergence, using accumulated 6-hourly data, to exact accumulations over the Mississippi River basin and concluded that it can be used at least for first-order moisture convergence and residual computation.

Following *Roads et al.* [1994], we apply equation (3) using the atmospheric moisture convergence and rate of change in precipitable water from NRA1 (both of which are derived from class "B" variables, which by NRA1 classification should be more reliable than the water balance produced by the LSP, which relies on class "C" forcing variables), and combine this with the gridded observed precipitation to compute values for ET. Since NRA1 precipitable water and atmospheric moisture flux data are used, along with observed precipitation, the U_q is implicitly included in the residual ET. However, as concluded by *Trenberth and Guillemot* [1998], for areas such as North America this residual method of computing ET (using NRA1 atmospheric data) produces better estimates than the NRA1 model. *Gutowski et al.* [1997] examined ET-P computed from NRA1 atmospheric data over the Ohio and upper Mississippi River basins, and identified errors relative to long-term runoff. Using gridded observed P values from the current study, the resulting residual ET would have errors of 20% to 26% relative to VIC ET. This shows a considerable improvement over the NRA1 model output, which is overestimated by 85% to 98% relative to VIC for these basins.

This residual ET estimate is not independent of the LSP and the NRA1 P, because LSP effects are reflected in atmospheric conditions through model feedback. However, it does

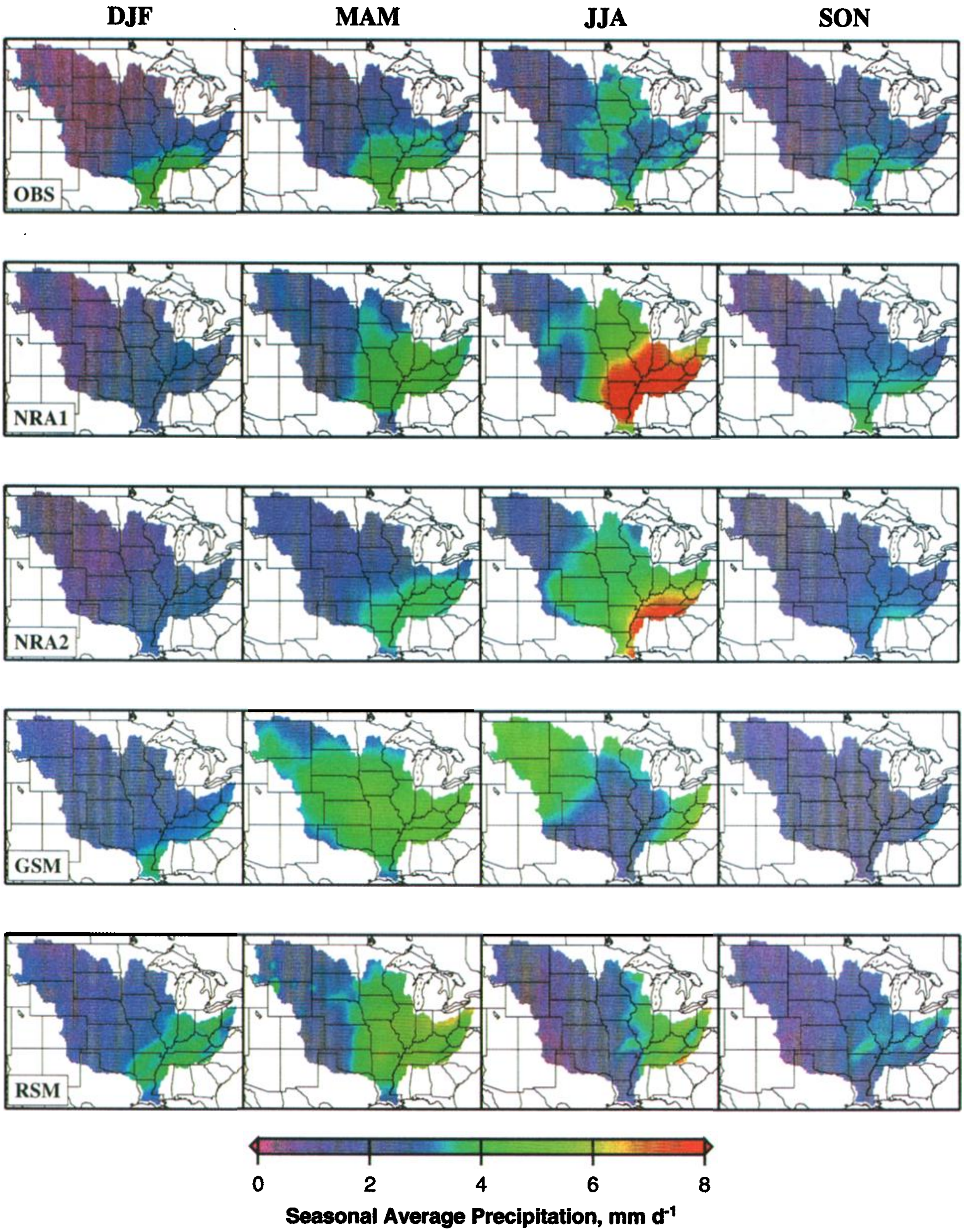

Plate 1. Comparison of seasonal average precipitation for the gridded observations (OBS), reanalyses (NRA1 and NRA2) and climate models (global spectral model (GSM) and regional spectral model (RSM)).

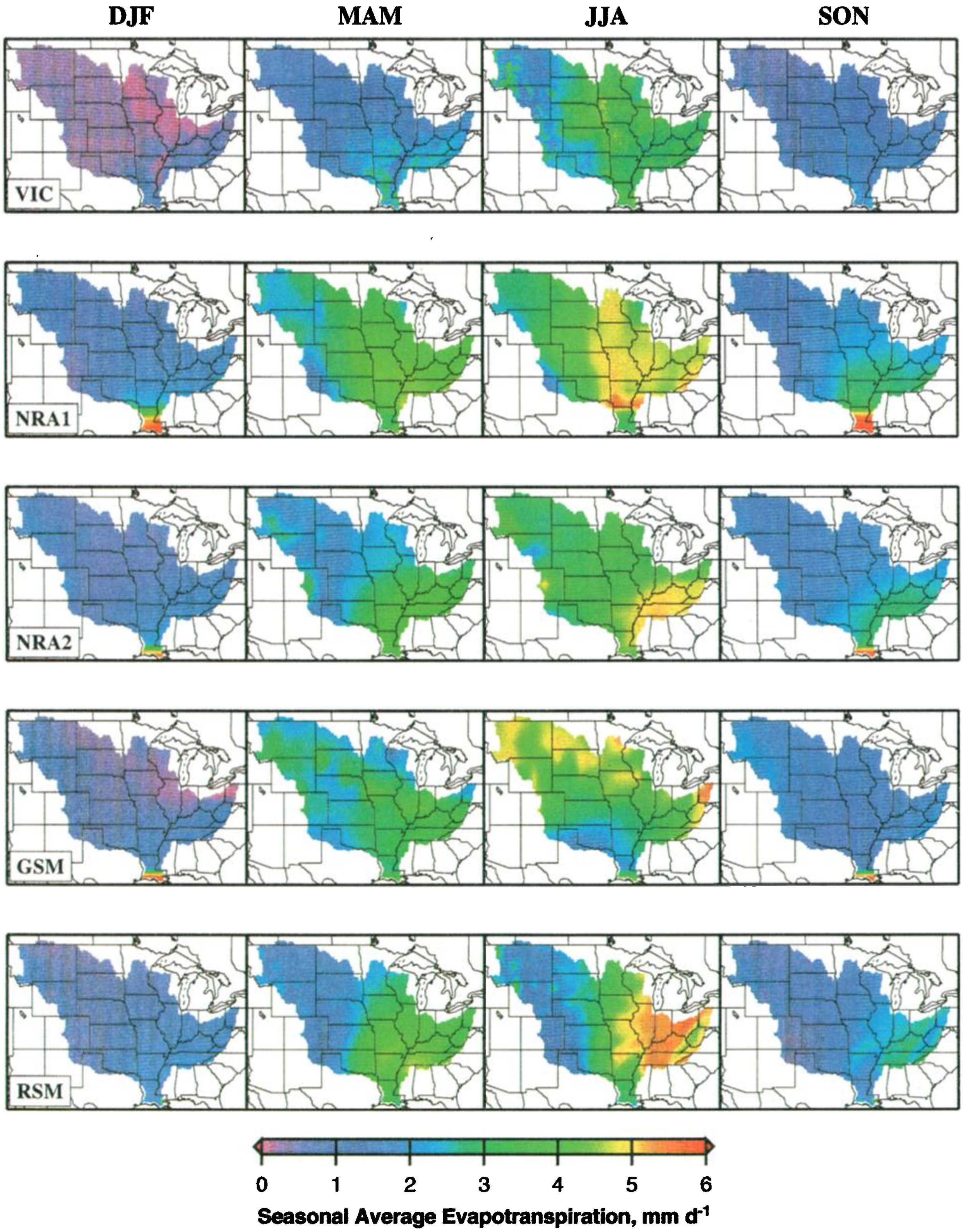

Plate 2. Comparison of seasonal average evapotranspiration for the VIC model, reanalyses, and climate models.

Table 1. Mean and Standard Deviation (Std. Dev.) for the Period 1988-1997 for the VIC model, Reanalyses, and Climate Models [a]

	P, mm		*ET*, mm		*N*, mm	
Model	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
VIC [b]	800	73.4	535	20.8	259	40.2
NRA1 [c]	1021	88.9	977	17.6	175	22.1
NRA2 [d]	861	113.0	855	58.6	203	44.3
GSM [e]	985	96.7	808	44.9	334	50.5
RSM [f]	896	112.9	773	70.2	93	33.7

[a] Precipitation (*P*), evapotranspiration (*ET*), and runoff (*N*) are expressed as annual totals.
[b] Variable infiltration capacity model.
[c] National Centers for Environmental Prediction and National Center for Atmospheric Research (NCEP/NCAR) reanalysis
[d] NCEP/Department of Energy reanalysis.
[e] Global spectral model.
[f] Regional spectral model.

provide a convenient method of separating the LSP NRA1 *P* fields from the *ET* estimate and can be used to compare the VIC model and NRA1 *ET* in order to assess the sources of biases in the LSP *ET* predictions. Since only monthly summary data were used for NRA2 in this study, an equivalent analysis of residual *ET* for NRA2 was not performed.

4. Results and Discussion

By comparing surface water budgets, we assess the spatial and temporal differences between the VIC model and the coupled models over the Mississippi River basin. Table 1 provides a summary of the mean annual *P*, *ET* and *N*, with the variation of annual values for the 10-year study period. Much of the analysis is performed on a seasonal basis, with seasons defined as winter (December, January, and February), spring (March, April, and May), summer, (June, July, and August), and fall (September, October, and November).

4.1. Characterization of the Mississippi River Basin

The Mississippi River basin covers an area of 3,200,000 km^2 in the central United States, which constitutes nearly 40% of the area of the continental United States. As discussed by *Entekhabi et al.* [1992], interior portions of a continent are generally more prone to persistence of anomalous wet and dry periods and also correspond to areas where precipitation recycling (where precipitation has as its source evaporation from some defined "local" region) tends to be strongest. For the Mississippi River basin, recycling ratio estimates generally fall in the range of 0.30–0.36 for the summer, and 0.10-0.17 for the winter [*Brubaker et al.*, 1993; *Dirmeyer et al.*, 2000; *Bosilovich et al.*, 2000]. These studies indicate the existence of a strong land-atmosphere feedback, especially in the summer, which highlights the importance of accurate land surface simulation in coupled models.

4.2. Evaluation of the VIC Hydrologic Model Predictions

To evaluate the ability of the VIC model to reproduce the hydrologically important characteristics of the Mississippi River basin, the simulated daily runoff from each grid cell was routed to points near the outlets of four of the subbasins. The comparisons of the simulated and observed (naturalized in the case of the Missouri) flows are shown in Figure 2. Also included in this figure is the daily runoff from NRA1, routed to the same point using the same routing algorithm. Because only monthly summary data were used for NRA2, GSM, and RSM, they were not included in the routing. It should be noted that the Arkansas River has significant withdrawals, and naturalized flows were not available for the period of study. Therefore the VIC model high flows are expected to be higher than the observations. Elsewhere, though, the VIC model is

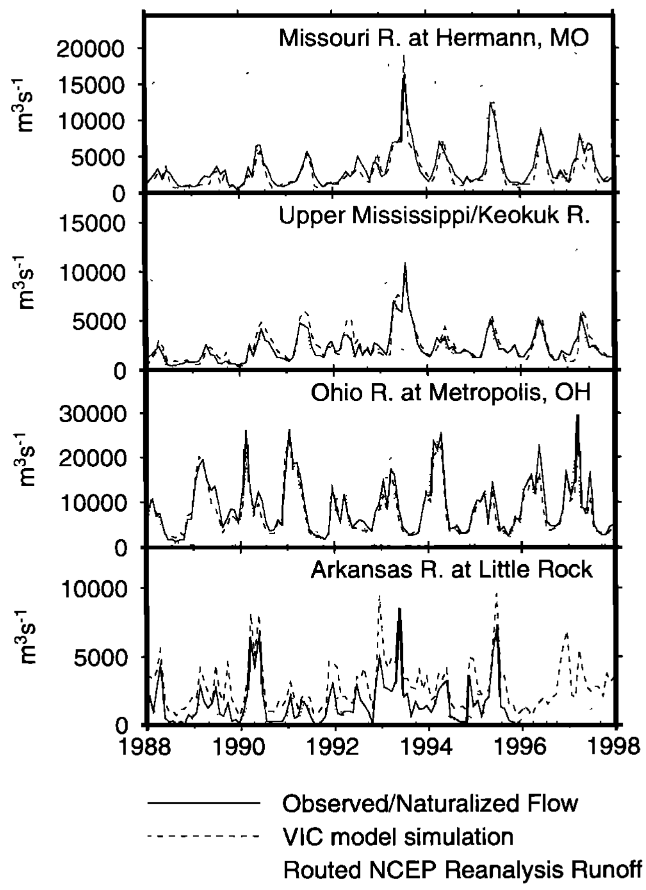

Figure 2. Hydrographs of monthly routed flows for the 10-year study period at outlet points in the Mississippi River basin for the variable infiltration capacity (VIC) model, NCEP/NCAR reanalysis (NRA1), and observed or naturalized flows.

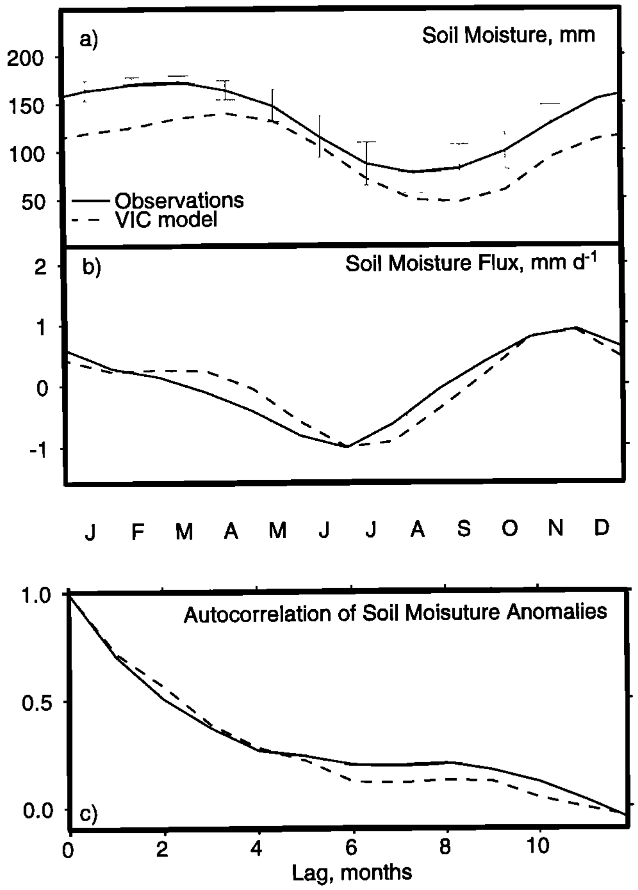

Figure 3. Comparison of monthly average soil moistures between Illinois data of *Hollinger and Isard* [1994] for 1988-1996 and the VIC simulation for 1988-1997: (a) volumetric soil moisture (adjusted as described in text), with 95% confidence intervals for observed data, (b) average monthly soil moisture flux, and (c) autocorrelation of monthly normalized soil moisture anomalies.

quite successful in capturing the peak flows, the autumn low flows, and the interannual variation of streamflows throughout the Mississippi River basin. The success at reproducing runoff hydrographs, taken together with the use of observed P, and the physical representations of soil moisture and runoff generation processes within the model, suggests that the model simulations of other surface flux and state variables (e.g., ET, total soil moisture storage, and snow) are probably reasonable representations of the true system. This gives us some confidence in using the space-time fields of water budget components as benchmarks against which to compare the coupled model products. On the other hand, Figure 2 shows obvious problems with the NRA1-derived streamflow. The flows peak unrealistically early in the year and are much too large for the Missouri and upper Mississippi subbasins. In the Arkansas-Red basin, almost no flow is predicted.

To further evaluate the VIC model output, we compare the soil moisture predicted by the model to observations. In the Mississippi River basin, there are few systematic soil moisture records of a length sufficient for comparison to the 10-year VIC model simulation. The soil moisture database described by *Hollinger and Isard* [1994], extended through August 1996 as described by *Robock et al.* [2000], is unique in the length and detail of collected soil moisture measurements. These data are based on periodic observations at 19 sites in Illinois. These report soil moistures at 11 different depths to a total of 2 m, with measurements reported approximately every 2 weeks on average, less frequently in the winter. Figure 3a compares the Illinois monthly average data for 1988-1996 with the VIC model simulation for 1988-1997, adjusting both data sets by subtracting the minimum as described in section 2.7. The greatest seasonal difference is in winter, when the VIC model simulation underestimates the observed data by 25%. It should be noted that 800 grid cells (bounded by latitudes 42.5° and 37.5°, and longitudes –88° and –90.5°) with varying land covers were averaged in the VIC model, compared to an averaging of 19 point measurements at grassland sites for the observations. Figure 3b shows that the VIC simulation captures the seasonal cycle in observed soil moisture fluxes, indicating that the VIC simulation produces soil moisture storage changes that are physically realistic and consistent with observations. Figure 3c illustrates that the autocorrelation of soil moisture anomalies in the VIC model closely matches that of observed data, indicating reasonable simulation of hydrologic persistence.

4.3. Water Balance Comparison

4.3.1. Entire Mississippi basin. Figure 4a shows the average monthly variation of the components of the surface water budget, with the state variable W, for the entire Mississippi basin. The figure shows an overall tendency of NRA1 to overestimate precipitation in comparison with the gridded observed values in the summer months, to overpredict ET in all months, to simulate earlier runoff, and to exhibit greater annual fluctuations in soil moisture as compared with the VIC simulation. The most prominent feature of the NRA1 land surface water balance is the magnitude of the nudging term, U. The NRA1 nudging has an average (absolute) magnitude of 1.6 mm d^{-1}, which is comparable to the basin-wide average precipitation of 2.2 mm d^{-1}. That is, the nudging of soil moisture toward a climatology, which is accomplished by injecting water into the system in the winter and removing water in the summer, has an impact on the water budget nearly as large as the principal forcing mechanism for the land surface water balance. While some adjustment of the soil moisture occurs in NRA2, the magnitude is much smaller (annual average of 0.5 mm d^{-1}), and the large imposed seasonal cycle from NRA1 is removed from U. It is also interesting to note that U in NRA2 is positive in all months, which shows that the predominant effect of the assimilation of observed P occurs when runoff is absent and observed P exceeds modeled P. This also implies that the majority of the overpredicted summer P for NRA2 is partitioned by the LSP into runoff. The VIC model closes its water budget by construct and therefore has no U term. The RSM has only a minor nonclosure of its water budget (computed as U for this figure) with an average magnitude of 0.05 mm d^{-1}. Although the GSM uses no adjustment of the soil moisture, a nonclosure (U) appears in winter months due to a model error related to snowmelt and evaporation, the average annual magnitude of which is 0.4 mm d^{-1}.

As shown in Table 2, the VIC model produces a basin-wide average ET that exceeds P in the summer months, whereas in NRA1 the summer P is so large that it exceeds even the model's overpredicted ET. NRA2 reduces the summer P bias

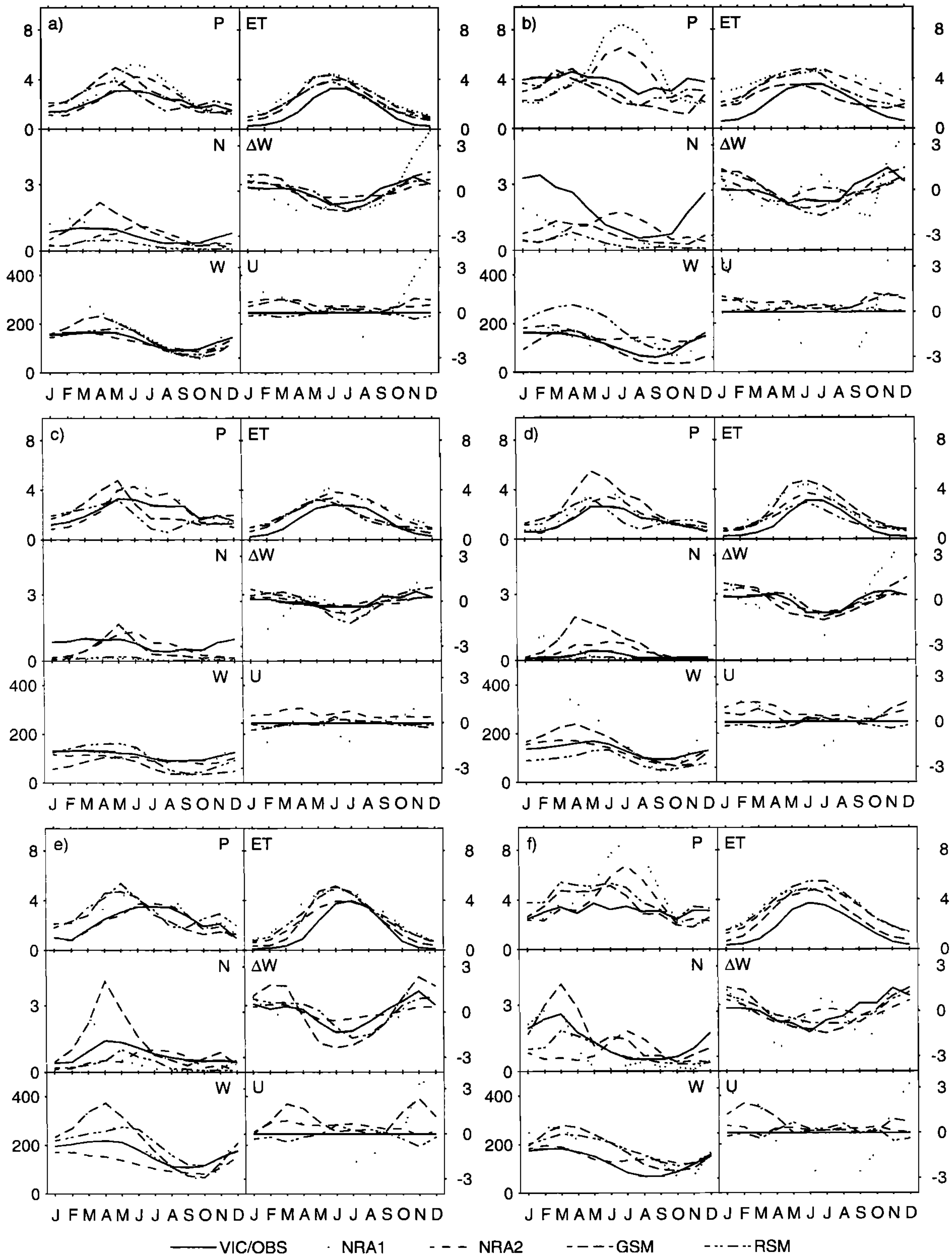

Figure 4. Average monthly surface water balance components and state variables (precipitation P (mm d^{-1}), evapotranspiration ET (mm d^{-1}), runoff N (mm d^{-1}), surface water W (mm), surface water flux ΔW (mm d^{-1}), and nonclosure or nudging term U (mm d^{-1})) for the VIC model, reanalyses, and climate models for (a) entire Mississippi River basin, (b) lower Mississippi basin, (c) Arkansas-Red basins, (d) Missouri basin, (e) upper Mississippi, and (f) Ohio basin.

Table 2. Mean Summer (June, July, and August) Precipitation (P) and Evapotranspiration (ET) for the Entire Mississippi River Basin for 1988-1997

Model	Average Summer P, mm d^{-1}	Average Summer ET, mm d^{-1}
VIC	2.8[1]	3.1
NRA1	4.7	4.0
NRA2	3.9	3.7
GSM	3.4	3.8
RSM	2.3	3.3

[1] Precipitation values are gridded observed.

by 42%, and the ET bias falls by 33%, though the remaining bias in P is still large enough so that P exceeds ET in the summer. This apparent connection between the summer ET and P biases is confounded by the interaction between ET and P in the GSM and RSM, which use the same LSP. For example, the RSM underpredicts summer P by 18%, while overpredicting ET by 18%. For all models the positive ET bias is present for most months, regardless of whether P is underpredicted or overpredicted. We examine this effect in more detail for each subbasin below. The overprediction of summer P does not occur to the same degree in the GSM and RSM, but a spring P bias exists of comparable magnitude to the NRA2 summer P bias (Figure 4a). Because these models use essentially the same physics as NRA2, this temporal shift is probably attributable to the assimilation process used in the reanalyses.

A final observation regarding the monthly average water balance components for the entire basin is that the timing of the runoff without nudging or adjustment of the soil water is changed significantly. The runoff in NRA1 responds predominantly to the excessive soil moisture in the winter and early spring, and is an artifact of the large nudging term. The surface water (including both soil moisture and snow water equivalent) annual fluctuation in NRA1 has an amplitude nearly 5 times that of the VIC model. This indicates that the climatology to which the LSP is being nudged overestimates the range of soil moisture variations for the basin. In NRA2 the high soil moisture cycle caused by nudging is removed, which allows the runoff to respond to the other components in the water balance. This is evidenced by the fact that the runoff peak occurs later than with NRA1 (and later than with the VIC model), because it is forced largely by the overpredicted summer P. With the GSM and RSM, which do not nudge the land surface water budget, the timing of the runoff is also more or less in phase with P, as moderated by soil moisture and snow storage and release.

4.3.2. Subbasins. Figures 4b through 4f show the water budget components and the state variable W for the major subbasins. The NRA1 budgets show substantial regional biases in some subbasins, most notably a 150% overestimation in summer P over the Ohio basin (Figure 4f) and a 125% overestimation over the lower Mississippi basin (Figure 4e). High regional P biases over the southeastern United States in NRA1 have been recognized in several global studies [*Mo and Higgins*, 1996; *Janowiak et al.*, 1998; *Trenberth and Guillemot*, 1998], as well as in studies focused over the central United States [*Higgins et al.*, 1996; *Betts et al.*, 1996b]. The P bias is reduced in NRA2, due to revisions in the convection parameterization and boundary layer physics in the model. Similar reductions in bias were seen in a previous comparison of NRA1 with the RSM [*Hong and Leetmaa*, 1999; *Roads and Chen*, 2000]. However, substantial bias still exists in the modeled summer P for the Ohio and lower Mississippi basins in NRA2, which are 86% and 72% greater than gridded observations, respectively. The P biases in the GSM and RSM do not follow the same seasonal pattern as NRA1 or NRA2. Because the models share both atmospheric and land surface physics, this difference is probably due to the assimilation process in the reanalyses. In the Ohio basin the mean absolute errors (relative to gridded P observations) in NRA2, GSM, and RSM are comparable at 1.0, 0.9, and 1.1 mm d^{-1}, respectively; however, the highest biases in NRA2 are for summer, as opposed to spring (extending through June) for GSM and RSM. The spatial distribution of these patterns by season is shown in Plate 1.

ET is consistently overestimated in all subbasins in NRA1 relative to the VIC model. In NRA2 this bias is virtually unchanged in the Ohio and Arkansas-Red basins, while the lower Mississippi basin has a slightly reduced bias in the fall and winter months. The largest change is in the Missouri and upper Mississippi basins, where the spring bias is reduced, though a bias of nearly 1 mm d^{-1} remains for each basin, and the summer ET bias is close to zero. The GSM and RSM produce less ET than VIC in the lower Mississippi, Arkansas-Red, and Missouri subbasins (Figure 4b, 4c, and 4d). In each of the cases the underprediction occurs in July and August, and it is always accompanied by a P underestimation, usually of longer duration. Even with instances of underprediction in P in both the Ohio and upper Mississippi subbasins, ET is not underpredicted in these basins. The spatial variation in the ET produced by the different models is shown in Plate 2.

Runoff is underestimated in all subbasins in NRA1, with the exception of January through April in the upper Mississippi and January through March in the Missouri basin, when the runoff mirrors the high soil moistures. This indicates that the nearly saturated soil column may cause the precipitation to run off, although excessive gravity drainage from the soil column encouraged by the high soil moisture may also contribute to the high runoff. (A more specific diagnosis here is limited by the fact that surface runoff, bottom drainage from the soil column, and soil moisture adjustment are not archived separately in NRA1, or the other coupled models included in this study.) The exaggerated NRA1 annual fluctuation in the soil moisture cycle is also prominent in the upper Mississippi and Missouri basins, with overestimation in the winter and spring, and underestimation in the late summer and fall. As in the entire basin, the NRA1 nudging term has a substantial influence on the water budget in each subbasin. Even modest biases in runoff are important in hydrologic studies. As shown by *Maurer et al.* [2001], small absolute differences in runoff production will produce large relative differences in routed streamflows. The response of the runoff term in NRA2 to the reduction of U in NRA1 is evident in the shift of seasonal peak runoff in NRA2. This shift is especially evident in the Ohio and lower Mississippi basins, where in NRA1 the excessive P was withdrawn from the system by the nudging process so that the annual runoff cycle was unrealistic. Plate 3 shows the wide variation in temporal and spatial runoff biases relative to VIC for all of the coupled models and the difficulty in producing late season runoff with the LSP.

Neither NRA1 nor NRA2 accurately simulates the accumulation and melting of snow as represented by VIC (Plate 4).

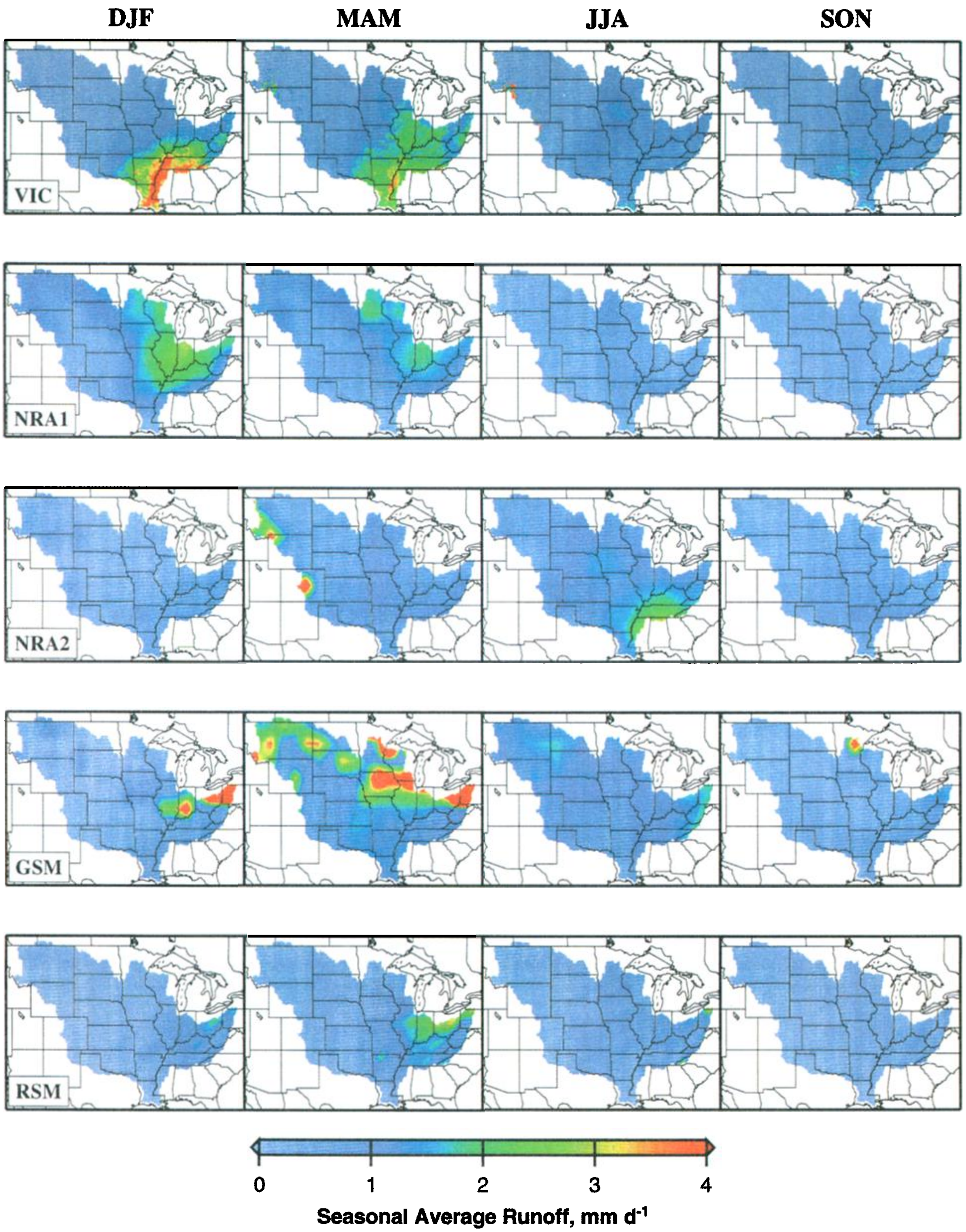

Plate 3. Comparison of seasonal average runoff for the VIC model, reanalyses, and climate models.

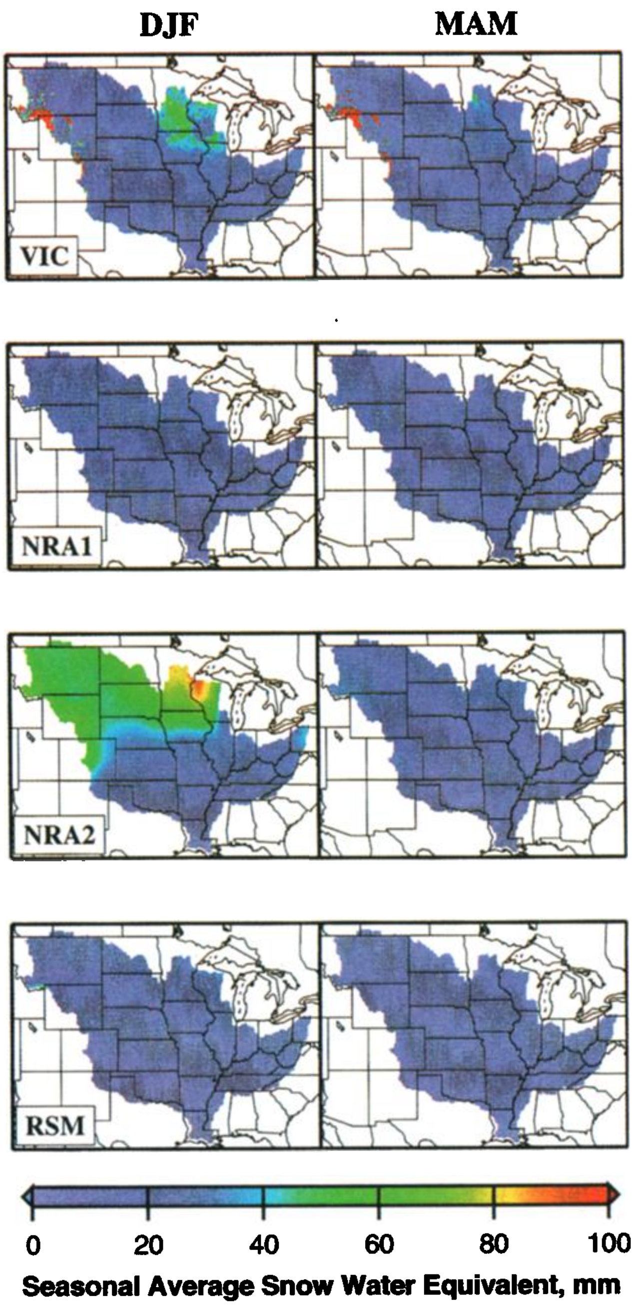

Plate 4. Winter and spring seasonal average snow water equivalent for the VIC model, the reanalyses, and the RSM.

The GSM output utilized in this study did not separate snow water storage from soil moisture and hence is not shown. The VIC average snow water equivalent on the ground for November through March for the Missouri basin is 15 mm, while NRA1 estimates it as 10 mm, NRA2 as 38 mm, and RSM as 4 mm. A known error in NRA1, in which the snow cover extent updating scheme in the NRA1 used 1973 data for the period 1974-1994, contributes to a portion of the difference between the NRA1 and VIC results. However, the underprediction of snow water equivalent by NRA1 is consistent both from 1988-1994 and from 1995-1998, which included the corrected snow initialization. For the Missouri basin the underestimation of snow in NRA1, relative to the VIC model, results primarily from the inability of the NRA1 to capture the intense precipitation and very deep winter snowpack over spatially limited areas at high elevations in the Rocky Mountains at the eastern edge of the basin. The underprediction is not surprising because the NRA1 spatial scale is much coarser than VIC and cannot resolve these localized extremes. By contrast, NRA2 has a positive bias throughout the Missouri basin. For the upper Mississippi basin the differences in snow water equivalent are largest, with an average snow water equivalent of 29 mm, 7 mm, 40 mm, and 7 mm for VIC, NRA1, NRA2, and RSM, respectively, for November through March. The timing of the melt in NRA1 and NRA2 is earlier than in VIC, especially in the Missouri subbasin. Delayed, slower melt has the effect of recharging soil moisture later into the spring. This soil moisture is available for evapotranspiration or emergence as base flow later in the year, which is one mechanism for hydrologic persistence in the basin. In addition to the hydrologic impact of the differences, snow has a profound effect on the surface energy balance, through increased albedo, changed surface roughness, insulation of the ground surface, and ultimately the transfer of latent and sensible heat to the atmosphere.

4.4. Time Series Analysis of Water Budget Components

To assess the interannual variability of the water balance components (and states) in the different models, the monthly time series for each model for the 10-year simulation is shown for the entire Mississippi River basin in Figure 5. As shown in the monthly average plots at the basin-wide scale (Figure 4), the tendency for NRA1 to overestimate the summer P is apparent, as is the overestimation of ET. As noted above, this ET bias is reduced somewhat in NRA2, though the pattern of the bias on the basin-wide level is consistent between the two reanalyses, as well as for GSM and RSM.

Figure 5 shows that the runoff in NRA1 responds strongly to the soil water, which peaks every January and February due to the large nudging term. Figure 5 also shows that the NRA1 runoff is close to zero for the late summer and autumn of nearly every year, an effect that is shifted later in the year for NRA2, GSM, and RSM. This is most discernable during the winter of 1993-1994, when soil moistures were at their highest wintertime levels in the 10-year study period, a condition that would produce high base flow. This state is captured by NRA2 and RSM soil moisture, yet simulated runoff is near zero. This illustrates the inability of the LSP to reproduce the late season portion of the hydrographs, when base flow dominates the runoff.

This difficulty of the LSP in simulating late season base flow was evaluated for the period September-December 1993, focusing on NRA2. The time series of soil moisture for each subbasin (not shown) reveal that the high surface water conditions during these months are largely due to high soil moisture levels in the Missouri and upper Mississippi subbasins. The anomalously high late season runoff for September-December 1993 originates in different subbasins each month (Table 3). An examination of these months reveals an important property of the NRA2 LSP. Specifically, nearly all precipitation infiltrates into the soil column, and most of the runoff is due to the free drainage from the bottom of the soil column (H.-L. Pan, personal communication, 2000). This characteristic was also identified by *Lohmann et al.* [1998a], where the LSP (run off-line) produced a greater proportion (over 80%) of its total runoff from soil column drainage than did any of the other 15 land surface models compared in the

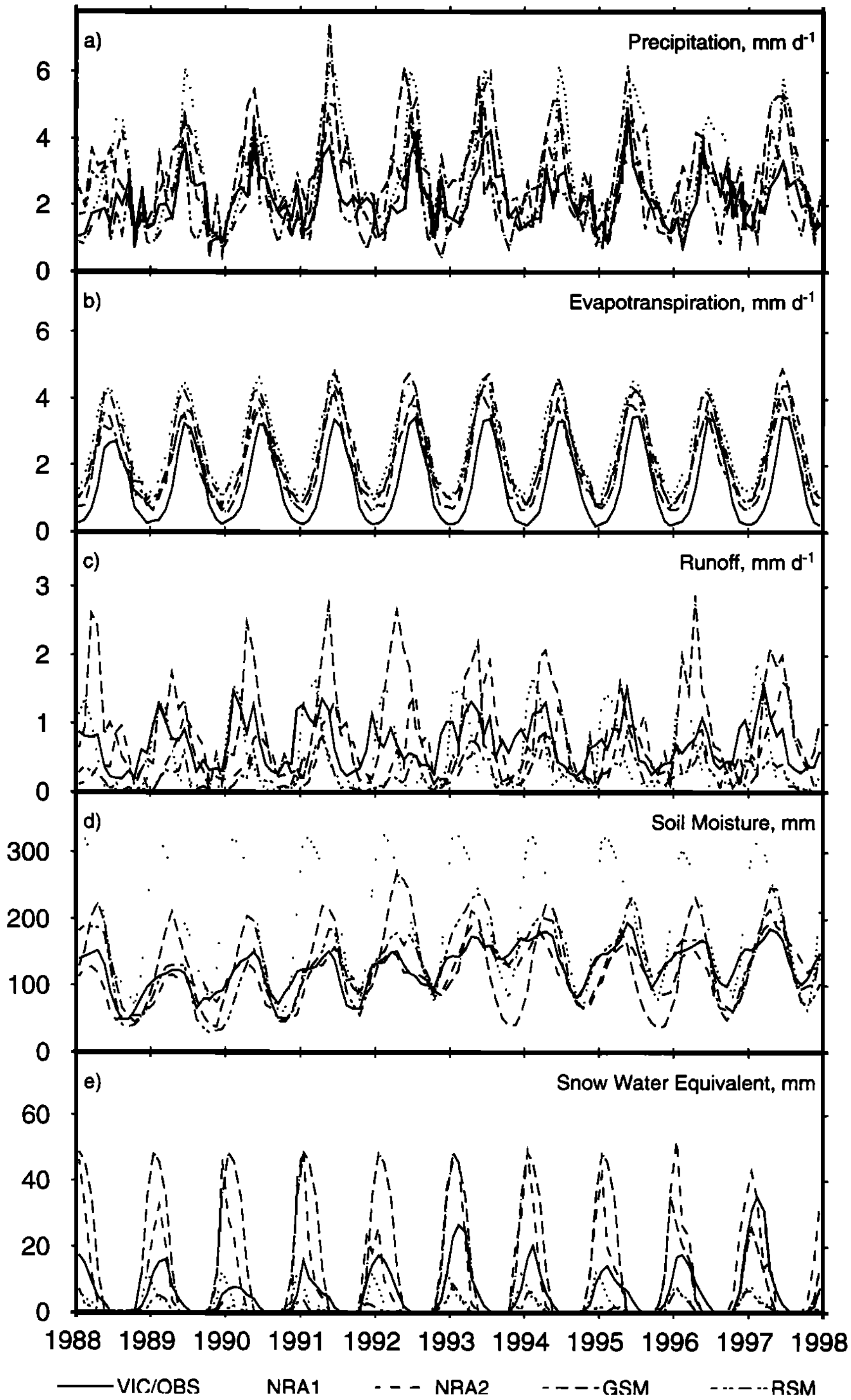

Figure 5. Time series of water budget components and state variables for entire Mississippi River Basin for 1988-1997, for VIC, reanalyses, and climate models.

project for intercomparison of land surface parameterization schemes (PILPS)-2c. In the Missouri subbasin, where VIC simulates the greatest proportion of base flow contribution to runoff, the LSP in NRA2 shows a correlation of soil moisture to runoff anomalies (during the same month) that is very similar to VIC (0.59 and 0.62, respectively). In the upper Mississippi subbasin they differ by a greater amount (0.28 for NRA2, 0.87 for VIC), and in the lower Mississippi subbasin by even more (0.15 for NRA2, 0.80 for VIC). The runoff response to the elevated soil moisture in the LSP is closer to VIC during September, when the Missouri runoff anomaly dominates that simulated for the entire basin (Figure 5), than in October, when the upper Mississippi subbasin is dominant. In November the lower Mississippi subbasin provides the dominant runoff anomaly (as simulated by VIC) at the basin-wide scale, and as with the upper Mississippi basin in October, even with a positive soil moisture anomaly in November 1993, a negative runoff anomaly is predicted by NRA2. This

Table 3. Average Monthly Runoff for the Entire Mississippi River Basin Simulated by VIC and NRA2, and the Subbasin Having the Greatest Impact on the Runoff Anomaly Each Month, as Simulated by VIC

	Average Monthly Runoff, mm d^{-1}		
Month	VIC	NRA2	Dominant Subbasin
Sept. 1993	0.77	0.63	Missouri
Oct. 1993	0.58	0.20	Upper
Nov. 1993	0.82	0.24	Lower
Dec. 1993	0.93	0.11	Upper

indicates that the mechanism for discharging soil moisture as runoff in the LSP may underestimate the strength of the relationship between soil moisture and drainage.

Although the magnitudes of the annual precipitation for the entire Mississippi basin vary between observed and the coupled models, the monthly correlations between modeled values and gridded observations tend to be strong (e.g., r=0.84 for NRA1, r=0.85 for NRA2), which suggests that the general pattern of the monthly anomalies is well represented on a basin-wide level. By contrast, the lower Mississippi basin observed and NRA1 monthly precipitation are poorly correlated, though correlation is somewhat higher for NRA2 (r=0.09 for NRA1, r=0.32 for NRA2), which indicates that for this subbasin the occurrence of precipitation in NRA1 and NRA2 is not well represented. Likewise, for the Ohio basin the monthly correlation is low (r=0.31 for NRA1, r=0.50 for NRA2). These results illustrate the general success of NRA1 and NRA2 in capturing continental-scale patterns, but with considerable regional errors. For the finer-resolution RSM, driven by NRA1 base data, the results are somewhat improved (for the lower Mississippi basin, r=0.64; for the Ohio, r=0.59), although this increase is not seen for all subbasins.

4.5. Interannual Variability and Persistence

The discussion in the previous section concentrates on identifying biases in land surface variables predicted by the LSP used in NRA1, NRA2, GSM, and RSM. A major difference between off-line and coupled land-atmosphere models is the ability of a coupled model, principally through soil moisture, and also through snow in some regions, to simulate feedbacks between the land surface and the atmosphere. In so doing, the coupled model should represent persistence observed in, for instance, extended wet or dry periods. In this section the ability of the models to reproduce the VIC simulated interannual variability and persistence is evaluated.

In order to compare all models using the same variable, soil moisture and snow water are lumped into the term surface water, W. This does not appreciably change the variability or persistence characteristics related to soil water alone, due to the relatively small contribution of snow to the total water storage at the scale of the defined subbasins. The interannual variability in NRA1 W is lower than that simulated by the VIC model, as reflected in the low coefficient of variation (CV) for annual average W shown in Table 4. This result, as shown by *Maurer et al.* [2001], is a manifestation of the nudging, which pushes the NRA1 soil moisture to the prescribed climatology, which itself has no interannual variability. This argument is bolstered by the fact the NRA2, GSM, and RSM all show a much greater coefficient of variation (CV) for the entire basin for W. The discrepancy between the VIC and NRA1 CV is greatest in the Missouri and upper Mississippi subbasins, where the W persistence is strongest. This illustrates the effect on interannual variability of imposing a climatology on the soil moisture conditions in the LSP, especially with the relatively short relaxation time constant of 60 days. *Roads et al.* [1999] also showed the large nudging term effectively limits the predictability to the relaxation time. *Betts et al.* [1998] noted that the incorporation of nudging reduces the interannual variability in the soil moisture content with subsequent negative impact on the ability of the model to represent persistent wet or dry periods. *Viterbo and Betts* [1999] evaluated the ECMWF reanalysis and also reported a reduction in variability resulting from the use of soil moisture nudging.

The low interannual variability in NRA1 reflects the inability of the LSP, when used with the large nudging, to simulate low-frequency variations in the hydrologic system. This is seen in the contrasting levels of persistence provided by the memory of soil moisture conditions in NRA1 and the VIC model, reflected in Figure 5. The high soil moisture conditions in 1993 in the VIC simulation are carried into the following year, while in NRA1 the annual cycle is forced to its assumed climatology and no significant interannual persistence is observed. Figure 5 also shows that NRA2 and RSM generally follow the VIC soil moistures closely for the entire basin, and simulate the successively wetter winter W levels

Table 4. Mean Surface Water (Adjusted as Described in the Text) With Standard Deviation (Std. Dev.) and Coefficient of Variation (CV), Defined as the Standard Deviation Divided by the Mean

Statistic	VIC	NRA1	NRA2	GSM	RSM
	Entire Mississippi Basin				
Mean, mm	135	191	129	144	132
Std. Dev., mm	22.2	10.2	27.4	20.8	32.4
CV	0.16	0.05	0.21	0.14	0.24
	Lower Mississippi Basin				
Mean, mm	121	176	152	94	188
Std. Dev., mm	5.5	22.0	47.5	22.2	42.0
CV	0.04	0.12	0.31	0.24	0.22
	Arkansas-Red Basin				
Mean, mm	115	131	99	64	107
Std. Dev., mm	12.9	10.2	28.4	22.1	30.0
CV	0.11	0.08	0.29	0.35	0.28
	Missouri Basin				
Mean, mm	132	221	129	151	89
Std. Dev., mm	39.0	11.4	44.2	24.5	31.4
CV	0.30	0.05	0.34	0.16	0.35
	Upper Mississippi Basin				
Mean, mm	169	207	127	211	202
Std. Dev., mm	32.6	15.2	42.7	26.7	69.1
CV	0.19	0.07	0.34	0.13	0.34
	Ohio Basin				
Mean, mm	130	166	149	180	183
Std. Dev., mm	12.4	11.1	29.1	33.1	31.8
CV	0.10	0.07	0.19	0.18	0.17

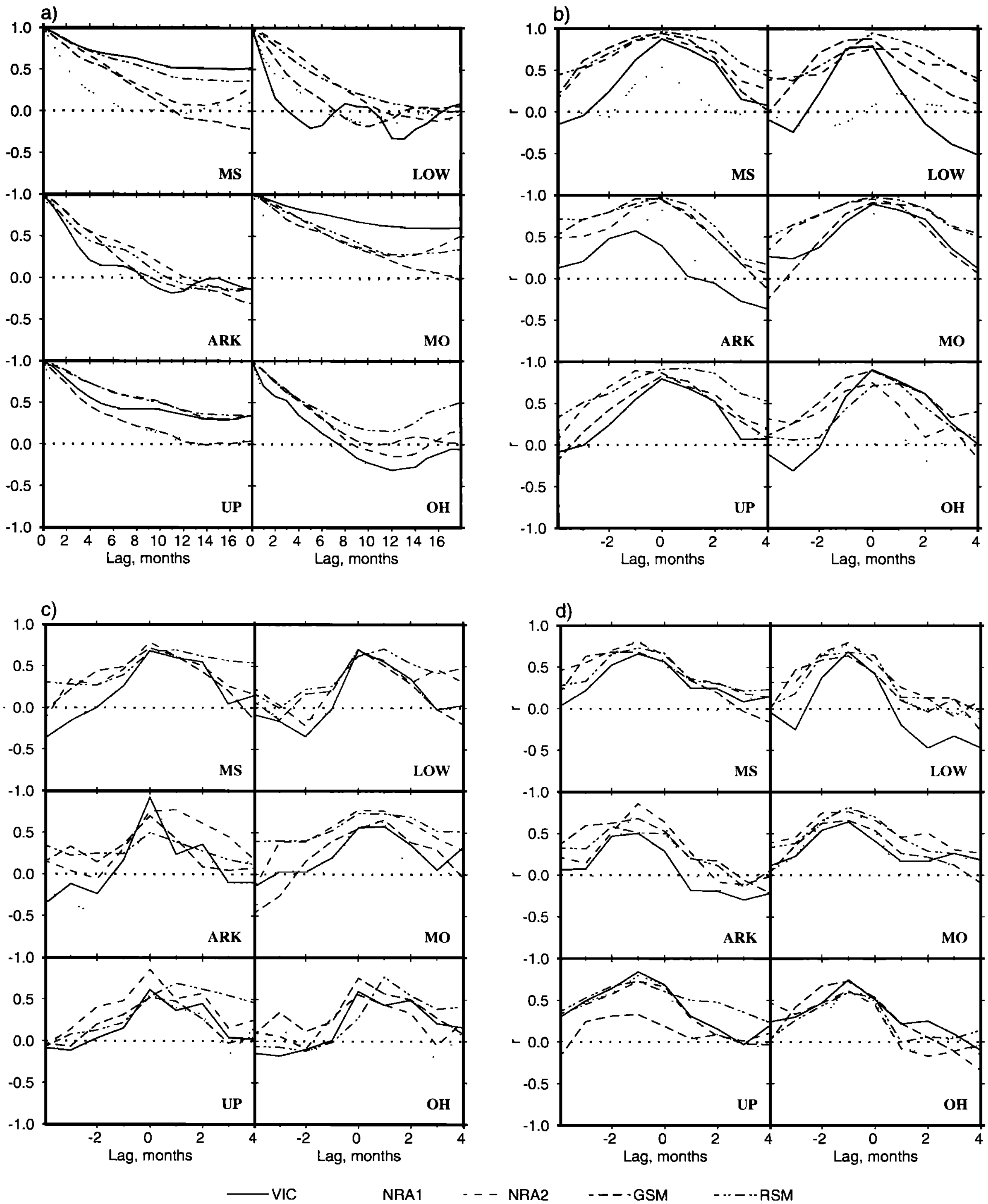

Figure 6. (a) Autocorrelation of normalized monthly surface water anomalies, and correlations of (b) surface water with evapotranspiration anomalies, (c) precipitation with evapotranspiration anomalies, and (d) surface water with precipitation anomalies. Subbasins are identified as in Figure 1, with the entire Mississippi River basin (MS).

Table 5. Surface Water Decay Timescales for the Mississippi River Basin and Subbasins

	Decay Timescale, months				
Basin	VIC	NRA1	NRA2	GSM	RSM
Entire Mississippi	30.7	3.0	7.4	7.0	14.9
Lower Mississippi	1.5	3.0	6.8	3.6	6.4
Arkansas-Red	3.1	1.9	7.6	5.4	5.9
Missouri	38.5	2.9	9.2	8.8	10.0
Upper Mississippi	11.5	1.9	12.7	5.3	13.6
Ohio	3.9	1.8	5.6	5.4	6.4

from 1991-1993 and the drying in 1994. While Table 4 shows the CVs for *W* for NRA2, RSM, and GSM are comparable to VIC for the entire basin, it also shows that by subbasin the patterns diverge from VIC, which shows much greater variability by subbasin. This again illustrates the stronger ability of the coupled models to simulate continental-scale dynamics, and their reduced skill at reproducing surface conditions at the subbasin scale.

The variation in *W* persistence for the different models and the subbasins is shown in plots of the autocorrelation of *W* anomalies for the Mississippi River basin and for each subbasin (Figure 6a). It should be noted that these, and all other anomalies discussed below, are normalized to remove the seasonal cycle in variance and the climatological monthly means. Although the variance in soil moisture anomalies in the Mississippi River basin does not display a significant seasonal cycle, *ET*, for example, has a high variance in the summer and much lower variance the rest of the year. Therefore nonnormalized anomalies can produce artificially inflated correlations due to the seasonal cycle of the variance. A convenient measure of persistence is the decay timescale (or *e*-folding time) used by *Delworth and Manabe* [1988], which is the lag at which the autocorrelation function reduces to $1/e$ (0.37). This is shown in Table 5 for the different models and subbasins. The VIC decay timescale varies considerably between subbasins, and is longest for the Missouri and upper Mississippi basins. For these subbasins the decay timescale is no longer small relative to the 10-year study period; hence the uncertainty would be greater. The pattern of persistence is consistent with the global study of *Delworth and Manabe* [1988], who identified a general trend of increasing decay timescale with latitude, and with *Huang et al.* [1996], who concluded that areas with lower temperatures (hence lower potential *ET*) and lower precipitation will experience higher soil moisture persistence (see also *Roads et al.* [1999]).

The decay timescale in NRA1 varies little between subbasins and shows almost identical values in the driest and wettest subbasins. This again reflects the inability of the model to simulate significant hydrologic memory beyond the damping timescale of the nudging. For NRA2 and RSM the decay timescales are comparable to VIC in pattern, although they tend to overpredict persistence for basins showing low *W* persistence (lower Mississippi and Arkansas-Red basins) and underpredict for the Missouri basin. This effect was also noted by *Roads et al.* [1999], who compared NRA1 with the NCEP GSM run without soil water nudging or assimilation of observations. Their results showed larger variation and persistence than NRA1 for *W* over the Mississippi River basin. The RSM more closely captures the persistence simulated by VIC than the other models for the entire Mississippi River basin, but overpredicts other subbasins, most noticeably producing high persistence in the lower Mississippi basin, which has almost no persistence in VIC. This comparison reveals the difficulty with capturing local variability using the LSP in the coupled models, especially at the level of subbasins with very short or very long persistence within a continental scale watershed. Further evidence of the scale effect may be seen by comparing the decay timescales for the subbasins (Table 5) for the coupled models. While all of the coupled models exhibit far less variation in decay timescale across the subbasins, the RSM shows the greatest variability between subbasins.

A long *e*-folding time of soil moisture describes the hydrologic persistence in the soil water system, but to evaluate persistence in land-atmosphere interactions, the strength of the relationship between surface water and the atmosphere must be examined. Correlations between *W* and *ET* anomalies provide some insight into this effect. Because more than 50% of the annual *ET*, and more than 50% of the *ET* anomalies, occur during summer, the correlation of normalized *W* anomalies with normalized *ET* anomalies for summer will be stronger where the land-atmosphere interaction is strongest. For the VIC model, Figure 6b shows that four of the five subbasins show a strong correlation between *W* and *ET* at lag 0 (i.e., concurrent month), with the Missouri, upper Mississippi, and Ohio subbasins maintaining a correlation coefficient at or above 0.5 with up to a 2-month lag of *ET*. Although the correlations shown for the Missouri and upper Mississippi subbasins are close to zero at a lag of 4 months, it should be noted that two additional factors affect these results. First, only summer *W* is used, and at lags of 4 months the late fall and winter *ET* is much smaller, transpiration is inhibited, and hence the capability for soil moisture to interact with the atmosphere is most limited in the subbasins at higher latitudes. Second, these two subbasins were shown to have surface water persistence of the order of a year or more, though with the 10-year period used in this study it is difficult to establish these longer timescale relationships.

Again, considering the VIC data, one curious feature in Figure 6b is the stronger correlation at small negative lags for the Arkansas-Red basin than for a lag of 0. This is explained by the use of summer soil moistures, which results in negative lags including spring *ET*. The summer *ET* in the Arkansas-Red subbasin responds very strongly to *P*, as shown by the very high correlation at lag 0 in Figure 6c. Therefore lower radiative forcing in spring could result in a greater proportion of *P* anomalies translating into soil anomalies, hence stronger correlation of spring *P*, and subsequently *ET*, with a later summer *W* anomaly. This hypothesis is supported by the strong correlation of summer *W* with *P* anomalies at lags of -1 and -2 months seen in Figure 6d for the Arkansas-Red subbasin. This correlation is also present in other subbasins that do not share as high a *P-ET* correlation and hence do not display the larger correlation of *W-ET* at negative lags. Also, consistent with the stronger correlation of *W* with *ET* in the Missouri, upper Mississippi, and Ohio subbasins, Figure 6c shows that the correlation of *P* with *ET* anomalies is lower for these three subbasins (at lag 0) compared with the lower Mississippi and Arkansas-Red subbasins. This reflects the relative roles played by *W* and *P* as the water supply, or control, on *ET* anomalies in the subbasins. One further feature that seems counterintuitive is the negative correlation of *W* with *ET* anomalies and *W* with *P* anomalies in the lower Mississippi subbasin for summer beginning at a lag of 2 months. This is due to the negative summer P anomaly autocorrelation at lags of several months for the lower Mississippi basin observed during the 10-year study period.

Comparing the coupled models' ability to simulate these land-atmosphere interaction characteristics, it is first seen that NRA1 underestimates this interaction, represented in Figure 6b, in all basins, with the exception of the Arkansas-Red, where the interaction is dominated by P, and at longer lags in the lower Mississippi basin, where VIC shows a negative correlation. In the other three coupled models this interaction is stronger, equaling or exceeding the VIC values in most subbasins and in most months. Since all models use the same LSP, this underestimation in NRA1 probably is not characteristic of the LSP, but is a result of the implementation of the LSP in NRA1 and the strong effect of nudging. It is apparent that the overprediction of interaction between summer W and ET is greatest in the lower Mississippi and Arkansas-Red subbasins, especially at positive lags. The tendency to overpredict persistence in these basins can also be noted in Figure 6a and Table 5, where NRA2, GSM, and RSM overestimate the decay timescale. In the Missouri and upper Mississippi subbasins the summer W interaction with ET indicated by Figure 6b is also overpredicted by NRA2 and RSM, while GSM exhibits similar interaction to VIC.

Generally, the LSP in the coupled models displays a tendency to overpredict W persistence in all but the subbasins with the longest decay timescales. Also, in most subbasins the interaction between W and ET is overpredicted by the LSP in the coupled models, while the interaction of W with P is only consistently overpredicted by all models for the lower Mississippi and Arkansas-Red subbasins. This indicates that the LSP may partition too great a proportion of P into infiltration for some subbasins. This is not a basin-wide bias and perhaps indicates the lack of spatial variation in the soil characteristics in the LSP. However, the influence of W anomalies on ET several months later is overestimated throughout most of the subbasins. Likewise, as discussed in section 4.4, the interaction between W and N (through free drainage) is often underestimated. In other words, especially for subbasins that display little persistence in VIC, W anomalies remain in the system for several months too long in the LSP, favoring dissipation through ET rather than free drainage. This difference between the LSP and VIC, which parameterizes both slow drainage as well as the faster interflow drainage of the soil column through a nonlinear function, could explain the LSP overprediction of W persistence in all subbasins except the Missouri, where 87% of the P eventually leaves the system as ET (as simulated by VIC), as compared with 51% to 68% for the other subbasins.

4.6. Evapotranspiration Computation From Atmospheric Water Balance

In NRA2 it is seen that P observations can be used to improve estimates of soil water infiltration. Therefore it would be useful to explore the potential benefit of assimilating P observations more directly into the ET predictions. Combining the gridded observed daily P fields used in the VIC simulation with the atmospheric water budget from NRA1 can assess this possibility. Because ET is overestimated in all of the coupled models for nearly all months and subbasins, and because precipitation is overestimated predominantly in the summer

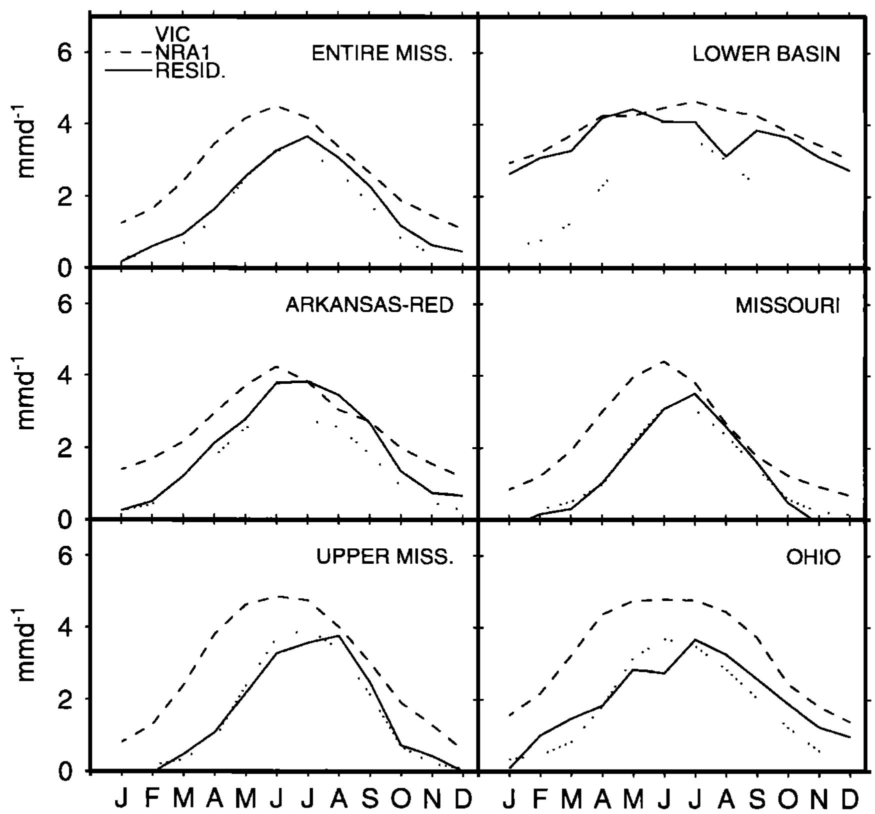

Figure 7. Comparison of evapotranspiration from the VIC model and NRA1 with the residual evapotranspiration computation from the atmospheric water balance.

Table 6. Mean Annual Evapotranspiration Rate (*ET*) for the Mississippi River Basin and Subbasins

	Mean Annual *ET*, mm d^{-1}					
Basin	Residual	VIC	NRA1	NRA2	GSM	RSM
Entire Mississippi	1.70	1.47	2.68	2.34	2.21	2.12
Lower Mississippi	3.51	1.95	3.86	3.45	2.45	3.08
Arkansas-Red	1.94	1.46	2.54	2.28	1.69	1.79
Missouri	1.20	1.26	2.21	1.92	2.27	1.46
Upper Mississippi	1.46	1.50	2.78	2.18	2.18	2.51
Ohio	1.96	1.74	3.29	3.07	2.54	3.35

months, the difference between the *ET* derived from the NRA1 assimilation model and the *ET* derived using this method are attributable largely to the LSP. From the moisture convergence and change in precipitable water from NRA1 and the observed *P*, a residual *ET* is calculated using equation (3). This is plotted along with *ET* from the VIC model and NRA1 in Figure 7, and is summarized in Table 6.

The significant change in computed *ET* is evident, with values derived from the NRA1 atmospheric variables and observed precipitation closely following the VIC simulated evapotranspiration. The average basin-wide residual *ET* is 1.7 mm d^{-1}, which is much closer to the VIC *ET* of 1.5 mm d^{-1} than the coupled models (NRA1 ET=2.7 mm d^{-1}; NRA2, GSM, and RSM ET=2.1-2.3 mm d^{-1}). This decrease in bias is interesting on several levels. First, the LSP in the coupled models is driven by the least reliable class "C" variables, whereas residual *ET* is computed excluding variables in this class and is therefore arguably more accurate. This shows that by closing the atmospheric water budget with observed *P*, the resulting *ET* approaches that simulated by VIC, which uses observed *P* and closes its water budget by construct. The greatest improvement in the residual *ET* estimate relative to the VIC values is in the Missouri and upper Mississippi basins, whereas the greatest precipitation bias is in the Ohio basin. This is further evidence that the LSP, as well as the precipitation bias, is responsible for errors in the reanalysis *ET*.

One interesting response of the system to using the atmospheric residual to produce the *ET* estimates for this basin is the loss of persistence in the system. For example, the basin-wide monthly anomalies in the computed residual *ET* have an autocorrelation at a lag of 1 month with r=0.06, while for the VIC model, r=0.30, and even in the presence of the large nudging term NRA1 has an r of 0.15. Without the large nudging, the LSP, as noted above, produces much greater persistence, with the autocorrelation at a lag of one month of 0.35, 0.26, and 0.62 for NRA2, GSM, and RSM, respectively. This shows that while the magnitude of the mean *ET* can be improved with the assimilation of precipitation, the persistence of the system is lost in the absence of a LSP.

5. Conclusions

A macroscale hydrology model with spatially variable land surface characteristics that is closely constrained to preserve the long-term river-basin-scale water balance is used to evaluate the land surface fluxes predicted by coupled land-atmosphere models. The LSP implemented in the NRA1, the followup NRA2, and two additional coupled models are shown to have some significant regional and temporal biases, as compared with observations and with fluxes predicted by the VIC hydrologic model. Precipitation is generally overpredicted relative to gridded observations by the reanalysis models, especially in the summer in the southeast. In the less constrained climate models, the bias tends to occur earlier in the spring and is shifted northward. In all models, evapotranspiration exceeds the off-line hydrologic model predictions in the majority of months, with the winter and spring biases being the most consistent across basins and models. This is shown to be most likely a product of the LSP, and not solely an effect of the precipitation bias or nudging in the coupled models.

Relative to the VIC simulation, snow extent and duration are underestimated in NRA1, and NRA2 produces excessive accumulation over wide areas, though melt continues to occur earlier than in the hydrologic model. This affects both the surface water balance of the coupled models and the feedback through surface radiation exchange to the atmosphere.

Intra-annual variations in soil moisture are too large in NRA1, and interannual variation and persistence of soil moisture are low as compared with the hydrologic model simulations. These are shown to be largely a result of a large soil moisture nudging term, which is used to maintain an assumed land surface climatology and which for large portions of the Mississippi River basin appears inappropriate. In the coupled models with a small or no nudging term, there is generally excessive interaction between the surface water (soil water plus snow) and *ET* during the summer. Late season runoff is underpredicted, which may be a result of the LSP underestimating drainage of soil water through base flow. The generally excessive *ET* in the LSP tends to dissipate soil moisture anomalies more quickly, while slow drainage favors retaining them longer. The relative strengths of these two effects vary through the basin, with hydrologic persistence being overestimated in the more humid subbasins, which are characterized by generally low persistence, and underestimated in the Missouri subbasin, which displays the strongest persistence and highest contribution of base flow in the hydrologic model simulations.

Estimation of *ET* from the NRA1 atmospheric moisture budget, using observed precipitation, significantly improves the estimated *ET* compared to the coupled models. This is encouraging as the atmospheric moisture budget is arguably more closely linked to observations than is the surface budget. However, while this approach produces *ET* values closer to the hydrologic predictions, the predicted interannual persistence of the atmospheric budget estimates is much less than of those produced by the hydrologic model or the LSP without large soil moisture nudging. Furthermore, the atmospheric budget method, although producing better results than the surface budget of the reanalysis, is not independent of the reanalysis surface *ET* predictions, due to the interaction between the LSP and the atmospheric model. More study may elucidate the source of differences in *ET* persistence and could evaluate the potential benefits of assimilating precipitation observations into schemes to update surface flux predictions derived from coupled land-atmosphere models.

Because *ET* is the final product of the LSP in the coupled models and controls the partitioning of atmospheric net radiation at the surface into latent and sensible heat, any bias is of great concern for forecasting or climate studies. The diagnoses presented here can help in formulating further comparative studies taking advantage of concurrent simulations with continental-scale hydrologic models for extended periods.

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References

Abdulla, F.A., D.P. Lettenmaier, E.F. Wood, and J.A. Smith, Application of a macroscale hydrologic model to estimate the water balance of the Arkansas-Red River basin, *J. Geophys. Res.*, *101*(D3), 7449-7459, 1996.

Beljaars, A.C., P. Viterbo, M.J. Miller, and A.K. Betts, The anomalous rainfall over the United States during July 1993: Sensitivity to land surface parameterization and soil moisture anomalies, *Mon. Weather Rev.*, *124*, 362-383, 1996.

Betts, A.K., J.H. Ball, A.C.M. Beljaars, M.J. Miller, and P.A. Viterbo, The land surface-atmosphere interaction: A review based on observational and global modeling perspectives, *J. Geophys. Res.*, *101*(D3), 7209-7225, 1996a.

Betts, A.K., S.-Y. Hong, and H.-L. Pan, Comparison of NCEP-NCAR reanalysis with 1987 FIFE data, *Mon. Weather Rev.*, *124*, 1480-1498, 1996b.

Betts, A.K., P. Viterbo, A. Beljaars, H.-L. Pan, S.-Y. Hong, M. Goulden, and S. Wofsy, Evaluation of land-surface interaction in ECMWF and NCEP/NCAR reanalysis models over grassland (FIFE) and boreal forest (BOREAS), *J. Geophys. Res.*, *103*(D18), 23,079-23,085, 1998.

Bosilovich, M.G., S. Schubert, A. Molod, and L.L. Takacs, Precipitation recycling in the NASA GEOS data assimilation system, paper presented at 15th Conference on Hydrology, Am. Meteorol. Soc., Long Beach, Calif., Jan. 9-14, 2000.

Brubaker, K.L., D. Entekhabi, and P.S. Eagleson, Estimation of continental precipitation recycling, *J. Clim.*, *6*, 1077-1089, 1993.

Campbell, G. S., A simple method for determining unsaturated conductivity from moisture retention data, *Soil Sci.*, *117*, 311-314, 1974.

Cosby, B.J., G.M. Hornberger, R.B. Clapp, and T.R. Ginn, A statistical exploration of the relationships of soil moisture characteristics to the physical properties of soils, *Water Resour. Res.*, *20*(6), 682-690, 1984.

Daly, C., R.P. Neilson, and D.L. Phillips, A statistical-topographic model for mapping climatological precipitation over mountainous terrain, *J. Appl. Meteorol.*, *33*, 140-158, 1994.

Daly, C., G.H. Taylor, and W.P. Gibson, The PRISM approach to mapping precipitation and temperature, paper presented at 10th Conference on Applied Climatology, Am. Meteorol. Soc., Reno, Nev., Oct. 20-24, 1997.

Delworth, T.D., and S. Manabe, The influence of potential evaporation on the variabilities of simulated soil wetness and climate, *J. Clim.*, *1*, 523-547, 1988.

Dirmeyer, P. A., Problems in initializing soil wetness, *Bull. Am. Meteorol. Soc.*, *76*, 2234-2240, 1995.

Dirmeyer, P. A., K.L. Brubaker, F. Bernal, A. Sudradjat, and B. Levy, The evaporative sources of moisture supplying rainfall over the Mississippi basin, in Proceedings, Second WCRP International Conference on Reanalyses, Reading, UK, *Rep. WCRP-109*, World Meteorol. Org., Geneva, 2000.

Durre, I., J.M. Wallace, and D.P. Lettenmaier, Dependence of extreme daily maximum temperatures on antecedent soil moisture in the contiguous United States during summer, *J. Clim.*, 13, 2641-2651, 2000.

Ebisuzaki, W., M. Kanamitsu, J. Potter, and M. Fiorino, An overview of Reanalysis-2, paper presented at 23rd Climate Diagnostics and Prediction Workshop, National Oceanic and Atmospheric Administration, Climate Prediction Center, Miami, Fla., Oct. 26-30, 1998.

Entekhabi, D., I. Rodriguez-Iturbe, and R.L. Bras, Variability in large-scale water balance with land-atmosphere interaction, *J. Clim.*, *5*, 798-813, 1992.

Gibson, J.K., P. Kallberg, S. Uppala, A. Hernandez, A. Nomura, and E. Serrano, *ERA Description, Reanalysis Proj. Rep. Ser.*, vol. 1, Eur. Cent. for Medium-Range Weather Forecasts, Reading, England, 1997.

Glecker, P. (Ed.), AMIP II guidelines, *AMIP Newslett. 8*, Lawrence Livermore Natl. Lab., Livermore, Calif., 1996.

Gutowski, W.J., Y. Chen, and Z. Otles, Atmospheric water vapor transport in NCEP-NCAR reanalyses: Comparison with river discharge in the central United States, *Bull Am Meteorol. Soc.*, *78*, 1957-1969, 1997.

Hansen, M.C., R.S. DeFries, J.R.G. Townshend, and R. Sohlberg, Global land cover classification at 1 km spatial resolution using a classification tree approach, *Int. J Remote Sens. 21*(6), 1331-1364, 2000.

Higgins, R.W., K.C. Mo, and S.D. Schubert, The moisture budget of the central United States as evaluated in the NCEP/NCAR and the NASA/DAO reanalyses, *Mon. Weather Rev.*, *124*, 939-963, 1996.

Hollinger, S.E., and S.A. Isard, A soil moisture climatology of Illinois, *J Clim.*, *7*, 822-833, 1994.

Hong, S.-Y., and A. Leetmaa, An evaluation of the NCEP RSM for regional climate modeling, *J Clim.*, *12*, 562-609, 1999.

Huang, J., and H.M. van den Dool, Monthly precipitation-temperature relations and temperature prediction over the United States, *J. Clim.*, *6*, 1111-1132, 1993.

Huang, J., H.M. van den Dool, and K.P. Georgakakos, Analysis of model-calculated soil moisture over the United States (1931-1993) and applications to long-range temperature forecasts, *J Clim.*, *9*, 1350-1362, 1996.

Janowiak, J.E., A. Gruber, C.R. Kondragunta, R.E. Livezey, and G.J. Livezey, A comparison of the NCEP NCAR reanalysis precipitation and the GPCP rain gauge satellite combined dataset with observational error considerations, *J. Clim.*, *11*, 2960-2979, 1998.

Juang, H.-M. H., and M. Kanamitsu, The NMC nested regional spectral model, *Mon. Weather Rev*, *122*, 3-26, 1994.

Juang, H.-M. H., S.-Y. Hong, and M. Kanamitsu, The NCEP regional spectral model: An update, *Bull. Am. Meteorol. Soc.*, *78*, 2125-2143, 1997.

Kalnay, E., et al., The NCEP/NCAR 40-year reanalysis project, *Bull. Am. Meteorol Soc.*, *77*, 437-471, 1996.

Kanamitsu, M., W. Ebisuzaki, J. Woolen, J. Potter, and M. Fiorino, An overview of NCEP/DOE Reanalysis-2, in Proceedings, Second WCRP International Conference on Reanalyses, *Rep. WCRP-109*, World Meteorol. Org., Geneva, 2000.

Kimball, J.S., S.W. Running, and R. Nemani, An improved method for estimating surface humidity from daily minimum temperature, *Agric. For. Meteorol.*, *85*, 87-98, 1997.

Koster, R.D., and M.J. Suarez, Relative contributions of land and ocean processes to precipitation variability, *J. Geophys. Res.*, *100*(D7), 13,775-13,790, 1995.

Koster, R.D., T. Oki, and M.J. Suarez, The off-line validation of land surface models: Assessing success at the annual timescale, *J. Meteor. Soc. Jpn.*, *77*(1B), 257-263, 1999.

Koster, R.D., M.J. Suarez, and M. Heiser, Variance and predictability of precipitation at seasonal-to-interannual timescales, *J Hydrometeorol.*, *1* (1), 26-46, 2000.

Liang, X., D.P. Lettenmaier, E. Wood, and S.J. Burges, A simple hydrologically based model of land surface water and energy fluxes for general circulation models, *J. Geophys. Res.*, *99*(D7), 14,415-14,428, 1994.

Liang, X., D. P. Lettenmaier, and E. F. Wood, One-dimensional statistical dynamic representation of subgrid spatial variability of precipitation in the two-layer variable infiltration capacity model, *J. Geophys. Res.*, *101*(D16), 21,403-21,422, 1996.

Lohmann, D., R. Nolte-Holube, and E. Raschke, A large-scale horizontal routing model to be coupled to land surface parameterization schemes, *Tellus, 48A*(5), 708-721, 1996.

Lohmann, D., et al., The project for intercomparison of land-surface parameterization schemes (PILPS) phase 2(c) Red-Arkansas basin experiment, 3, Spatial and temporal analysis of water fluxes, *Global Planet. Change, 19*, 161-179, 1998a.

Lohmann, D., E. Raschke, B. Nijssen, and D.P. Lettenmaier, regional scale hydrology, II, Application of the VIC-2L model to the Weser River, Germany, *Hydrol. Sci. J.*, *43*(1), 131-141, 1998b.

Mahrt, L., and H. Pan, A two-layer model of soil hydrology, *Boundary Layer Meteorol.*, *29*, 1-20, 1984.

Maurer, E.P., G.M. O'Donnell, D.P. Lettenmaier, and J.O. Roads, Evaluation of NCEP/NCAR reanalysis water and energy budgets using macroscale hydrologic model simulations, in *Land Surface Hydrology, Meteorology, and Climate: Observations and Modeling*, edited by V. Lakshmi, J. Albertson, and J. Schaake, *Water Sci. Appl. Ser.*, AGU, Washington, D.C. in press, 2001.

Miller, D.A., and R.A. White, A conterminous United States multi-layer soil characteristics data set for regional climate and hydrology modeling, *Earth Interactions 2*(1), 1-15, 1998.

Milly, P.C.D., and K.A. Dunne, Sensitivity of the global water cycle to the water-holding capacity of land, *J. Clim.*, 7, 506-526, 1994.

Mintz, Y., The sensitivity of numerically simulated climates to land-surface boundary conditions, in *The Global Climate*, edited by J.T. Houghton, pp. 79-105, Cambridge Univ. Press, New York, 1984.

Mintz, Y., and Y.V. Serafini, Global fields of soil moisture and land surface evapotranspiration, in Research Review 1980/81, *NASA Tech. Memo. 83907*, 178-180, 1981.

Mintz, Y., and Y. V. Serafini, A global monthly climatology of soil moisture and water balance, *Clim. Dyn.*, *8*, 13-27, 1992.

Mitchell, K., et al., The GCIP Land Data Assimilation (LDAS) Project – Now underway, *GEWEX News*, *9*(4), 3-6, 1999.

Mo, K.C., and R.W. Higgins, Large-scale atmospheric moisture transport as evaluated in the NCEP/NCAR and the NASA/DAO reanalyses, *J. Clim.*, *9*, 1531-1545, 1996.

Myneni, R.B., R.R. Nemani. and S.W. Running, Estimation of global leaf area index and absorbed PAR using radiative transfer models, *IEEE Trans. Geosci. Remote Sens.*, *35*(6), 1380-1393, 1997.

Nijssen, B., D.P. Lettenmaier, X. Liang, S.W. Wetzel, and E. Wood, Streamflow simulation for continental-scale basins, *Water Resour. Res.*, *33*(4), 711-724, 1997.

Nijssen, B., G.M. O'Donnell, D.P Lettenmaier, D. Lohmann, and E.F. Wood, Predicting the discharge of global rivers, *J. Clim.*, in press, 2001.

Pan, H.-L., A simple parameterization scheme of evapotranspiration over land for the NMC medium-range forecast model, *Mon. Weather Rev.*, *118*, 2500-2512, 1990.

Pan, H.-L., and L. Mahrt, Interaction between soil hydrology and boundary-layer development, *Boundary Layer Meteorol.*, *38*, 185-202, 1987.

Pielke, R.A., G.E. Liston, J.L. Eastman, and L. Lu, Seasonal weather prediction as an initial value problem, *J. Geophys. Res.*, *104*(D16), 19,463-19,479, 1999.

Rawls, W.J., L.R. Ahuja, D.L. Brakensiek, and A. Shirmohammadi, Infiltration and soil water movement, in *Handbook of Hydrology*, edited by D. Maidment, pp. 5.1-5.51, McGraw-Hill, New York, 1993.

Rawls, W.J., D. Gimenez, and R. Grossman, Use of soil texture, bulk density, and slope of the water retention curve to predict saturated hydraulic conductivity, *Trans. ASAE*, *41*(4), 983-988, 1998.

Roads, J., and A. Betts, NCEP/NCAR and ECMWF reanalysis surface water and energy budgets for the Mississippi River basin, *J. Hydrometeorol.*, *1*(1), 88-94, 2000.

Roads, J.O., and S.-C. Chen, Surface water and energy budgets in the NCEP regional spectral model, *J. Geophys. Res.*, *105*(D24), 29,539-29,550, 2000.

Roads, J.O., S.-C. Chen, A.K. Guelter, and K.P. Georgakakos, Large-scale aspects of the United States hydrologic cycle, *Bull Am. Meteorol. Soc.*, *75*, 1589-1610, 1994.

Roads, J. O., S-C, Chen, M. Kanamitsu, and H. Juang, Vertical structure of humidity and temperature budget residuals over the Mississippi River basin, *J. Geophys. Res.*, *103*(D4), 3741-3759, 1998.

Roads, J.O., S.-C. Chen, M. Kanamitsu, and H. Juang, Surface water characteristics in NCEP global spectral model reanalysis, *J. Geophys. Res.*, *104*(D16), 19,307-19,327, 1999.

Robock, A., C.A. Schlosser, K.Y. Vinnikov, N.A. Speranskaya, J.K. Entin, and S. Qiu, Evaluation of the AMIP soil moisture simulations, *Global Planet. Change, 19*, 181-208, 1998.

Robock, A., K.Y. Vinnikov, G. Srinivasan, J.K. Entkin, S.E. Hollinger, N.A. Speranskaya, S. Liu, and A. Namkhai, The global soil moisture data bank, *Bull Am. Meteorol. Soc.*, *81*, 1281-1299, 2000.

Shepard, D.S., Computer mapping: The SYMAP interpolation algorithm, in *Spatial Statistics and Models*, edited by G.L. Gaile and C.J. Willmott, pp. 133-145, D. Reidel, Norwell, Mass., 1984.

Thornton, P.E., and S.W. Running, An improved algorithm for estimating incident daily solar radiation from measurements of temperature, humidity, and precipitation, *Agric. For. Meteorol.*, *93*, 211-228, 1999.

Todini, E., The ARNO rainfall-runoff model, *J. Hydrol.*, *175*, 339-382, 1996.

Trenberth, K.E. and C.J. Guillemot, Evaluation of the atmospheric moisture and hydrological cycle in the NCEP/NCAR reanalysis, *Clim. Dyn.*, *14*, 213-231, 1998.

van den Dool, H.M., W.H. Klein, and J.E. Walsh, The geographical distribution and seasonality of persistence in monthly mean air temperatures over the United States, *Mon. Weather Rev.*, *114*, 546-560, 1986.

Viterbo, P., and A.K. Betts, Impact of the ECMWF reanalysis soil water on forecasts of the July 1993 Mississippi flood, *J. Geophys. Res.*, *104*(D16), 19,361-19,366, 1999.

Widmann, M., and C.S. Bretherton, Validation of mesoscale precipitation in the NCEP reanalysis using a new grid-cell data set for the northwestern United States, *J. Clim.*, *13*, 1936–1950, 2000.

Wood, E.F., M. Sivapalan, K. Beven, and L. Band, Effects of spatial variability and scale with implications to hydrologic modeling, *J. Hydrol.*, *102*, 29-47, 1988.

Wood, E.F., D. Lettenmaier, X. Liang, B. Nijssen, and S.W. Wetzel, Hydrological modeling of continental-scale basins, *Annu. Rev. Earth Planet. Sci.*, *25*, 279-300, 1997.

Xie, P., and P.A. Arkin, Global precipitation: A 17-year monthly analysis based on gauge observations, satellite estimates, and numerical model outputs, *Bull Am. Meteorol. Soc.*, *78*, 2539-2558, 1997.

Zhao, R.-J., L.-R. Fang, X.-R. Liu, and Q.-S. Zhang, The Xinanjiang model, in Hydrological Forecasting, Proceedings, Oxford Symposium, *IAHS Publ. 129*, 351-356, 1980.

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