Simulation of terrestrial water storage dynamics in Illinois using the Community Land Model augmented with a model of an unconfined aquifer

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Abstract

We evaluate the ability of an augmented version of the Community Land Model, version 3 (CLM3) (Niu et al., 2006) to represent monthly changes in soil moisture and groundwater storage from 1997–2005. We drive the model offline on a 1/8º grid using North American Land Data Assimilation System meteorological forcing data. The version of CLM3 used here represents water-table dynamics using a one-dimensional, lumped unconfined aquifer model and is one of the first land-surface models (LSMs) to represent bidirectional communication between the unsaturated and saturated zones.

Soil moisture and water table measurements obtained by the Illinois State Water Survey are used to assess the model's ability to simulate monthly changes in total soil-column water storage. We explore the degree to which the augmented version of CLM3 realistically partitions the total change in terrestrial water storage between subsurface reservoirs. CLM3 augmented with the aquifer model outperforms its predecessor in the representation of the magnitude of changes in terrestrial water storage; however, the CLM3 with the aquifer model is unable to realistically partition changes in terrestrial water storage between subsurface reservoirs. It performs best in wet years when the water table is shallow. Neither a modification that increases vertical communication between the aquifer and the soil profile nor a modification that incorporates topographic variation in baseflow calculations measurably improves the simulated terrestrial water storage dynamics, although increasing recharge slightly improves the amplitude of the simulated seasonal cycle in groundwater storage. Additional preliminary conclusions are discussed, and future work is outlined.

Introduction

The transfer of water between land-surface reservoirs and the atmosphere determines the surface energy balance and the transfer of energy. Effectively modeling the transfer of water between land-surface reservoirs and the atmosphere is essential to realistic numerical weather forecasting and weather prediction. Accurate characterization of terrestrial water storage dynamics is necessary for a range of water-resources and agricultural applications, such as long-term water-resources planning, drought prediction, and the timing of crop planting.

The land-surface modeling community has recently recognized aquifers as potentially important drivers of spatial and temporal variation in the terrestrial water storage and land-surface–atmosphere mass fluxes. Researchers have incorporated one-dimensional water-table dynamics into a range of models of the land surface that are used to provide lower boundary fluxes in numerical weather and climate models (e.g., York and Gutowski, 2002; Liang et al., 2003; Yeh and Eltahir, 2005; Maxwell and Miller, 2005; Niu et al., 2006). The ability of the augmented models to simulate terrestrial water storage variation has yet to be tested.

Our objective is to characterize the ability of a land-surface model (LSM) to simulate terrestrial water storage dynamics on a regional scale. We take advantage of the relatively high spatial and temporal resolution of the ground-based hydrologic observations obtained by the Illinois State Water Survey (Hollinger and Isard, 1994; Robock et al., 2000) to evaluate the ability of an augmented version of the Community Land Model, version 3 (CLM3) (Bonan et al., 2002; Oleson et al., 2004; Niu et al., 2006)

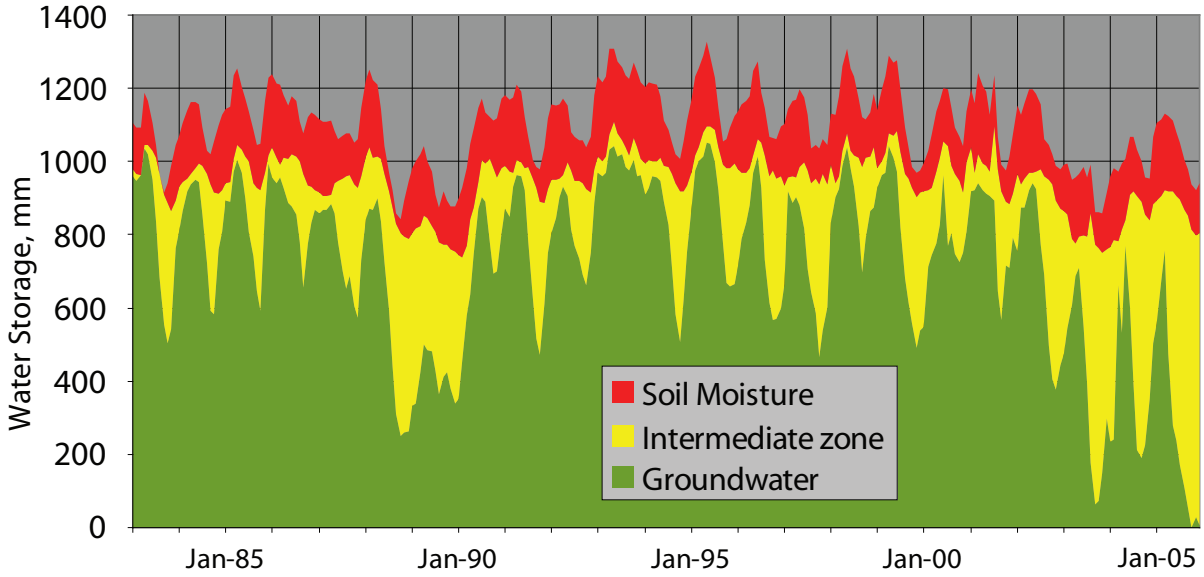
to represent changes in terrestrial water storage over a regional domain. The state of Illinois covers approximately 145,800 km^2; cropland and grassland dominate the landscape in much of the state, which is characterized by relatively low topographic relief. The climate is temperate and continental. For additional discussion of the hydrology and hydrogeology of Illinois, see Changnon et al., 1988, Yeh et al., 1998, and Hollinger and Isard, 1994.

Methods

Observed dataset

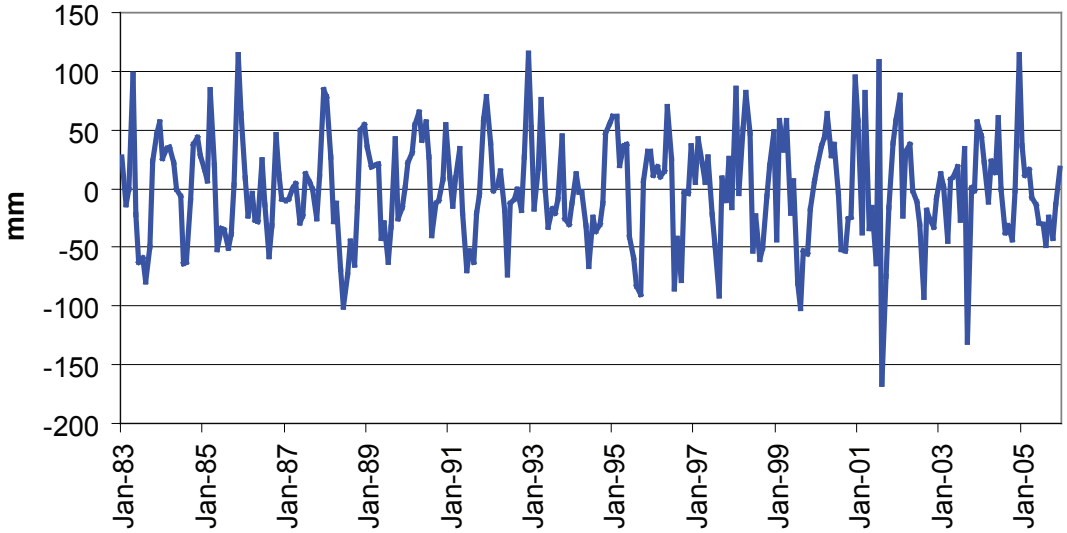
As a measure by which to evaluate the ability of CLM3 to simulate changes in terrestrial water storage, we used ground-based measurements of soil moisture and water-table variations obtained from across the state of Illinois, USA, by the Illinois State Water Survey (ISWS) (Hollinger and Isard, 1994; Robock, 2000). We extended the terrestrial water storage time series of Rodell and Famiglietti (2001) to include data for the years 1996–2005. The resulting time series (spanning the years 1983–2005) describes the components of statewide average terrestrial water storage in Illinois (Figure 1).

Figure 1. Illinois statewide average terrestrial water storage variations (area-weighted average derived from ISWS observations).



The time series partitions total-column terrestrial water storage into three parts: (1) water stored in the saturated zone, (2) water stored in the top two meters of the soil profile, and (3) water stored between the water table and two meters below the land surface (termed the "intermediate zone"). From the component time series, we computed the monthly change in water stored in each of the three components and the subsurface as a whole. Figure 2 shows the time series of monthly change in water stored in the total subsurface.

Figure 2. Monthly change in total-column terrestrial water storage (statewide area-weighted average derived from interpolated ISWS point observations).



Although we followed exactly the methods of Rodell and Famiglietti (2001) to derive the updated time series of terrestrial water storage in Illinois, the updated version of the dataset does not exactly coincide with the original dataset during the period of overlap (1983–1996). The sources of the slight discrepancies are fourfold: (1) We neglected surface reservoirs and snow as sources of terrestrial water storage variation Rodell and Famiglietti (2001) showed that in midlatitude regions such as Illinois, changes in water stored in snow and surface reservoirs are very small when compared to the magnitude of the variation in water stored in soil and groundwater. (2) Because data for the original sites were not continuous through 2005, we used a slightly different set of observation sites to provide inputs for the area-weighted state average. (3) When processing the soil-moisture data for the lowest soil layer (190–200 cm), we considered a larger portion of the data to be unreliable, which resulted in somewhat different

intermediate zone calculations. (4) The different mean and minimum values for terrestrial water storage components resulting from the longer record altered several relative measures (e.g., groundwater storage, which is computed as the total less the minimum value for the record).

Community Land Model and variations

Our investigation was composed of four model runs, each of which used a different version of the Community Land Model, version 3 (CLM3) (Oleson et al., 2004; Bonan et al., 2002). The Community Land Model is representative of current-generation LSMs used in comprehensive models of the climate system.

Run 1 ("No Aquifer")

Our first run employed the standard version of CLM3 (Oleson et al., 2004; Bonan et al., 2002), which represents the entire soil profile with a 10-layer, 3.43-m soil column. It contains no representation of an aquifer, thereby implicitly assuming that the intermediate zone and groundwater are at steady state.

Run 2 ("Low Recharge")

The second in our suite of runs used an augmented version of CLM3 (Niu et al., 2006; hereafter the "Niu et al. CLM3"), which contains an unconfined aquifer model that represents vertical exchange of water between a single-layer unconfined groundwater model and the unsaturated soil column. We made slight modifications to the parameters used to generate baseflow. The runoff generation mechanism used by the Niu et al. CLM3 is different from the standard version of CLM3. Following the assumptions of

Topmodel (Beven and Kirkby, 1979; Silvapalan et al., 1987) and Topmodel-inspired land-surface models (e.g., Stieglitz et al., 1997), the Niu et al. CLM3 calculates baseflow (R_{sb}) as an exponentially decaying function of grid-cell–mean depth to water (see Niu et al. [2005] for a detailed description):

$$R_{sb} = R_{sb\max} e^{-f z_{\nabla}} \tag{1a}$$

Niu and colleagues (2005) treat R_{sbmax} as a single, globally constant tuning parameter. The researchers replaced a product of several terrain-specific parameters used in other models with R_{sbmax}:

$$R_{sb\max} = \alpha \frac{K_{sat} e^{-\lambda}}{f} \tag{1b}$$

Where K_{sat} is the saturated hydraulic conductivity at the ground surface, f is the e-folding depth of saturated hydraulic conductivity (which is assumed to decay exponentially with depth), λ is the grid-cell-mean topographic index, and α is an "anisotropic factor," which is used to correct for the smoothing of high-frequency topographic variation that occurs when coarse-resolution elevation is used to derive the grid-cell mean topographic index. We used region-specific f and λ values to calculate a reasonable region-specific R_{sbmax}.

We calculated the e-folding depth, f, following the work of Miguez-Macho et al. (2006), who define f as a function of terrain slope (terrain slope = rise/run):

$$f = \frac{a}{1 + b\beta} \tag{2}$$

Where parameter a = 120, parameter b = 75, and β is the terrain slope (= rise/run). We used ArcGIS to calculate the terrain slope from USGS GTOPO30 DEM data that we had resampled to a 1/8º grid. The mean terrain slope in Illinois is ~ 0.128; using Equation 2,

the statewide average value for f is 11.32. The mean topographic index for the state of Illinois is 11.70. We used 2000 as the anisotropic factor. CLM3 empirically calculates saturated hydraulic conductivity from soil texture data. Using the Lawrence and Chase (2006) soil texture dataset, the CLM3-computed statewide-mean saturated hydraulic conductivity is 3.16×10^{-5} mm s^{-1}. The resulting statewide mean R_{sbmax} for Illinois was 5.93×10^{-6}.

Niu et al.'s model calculates vertical flux between the aquifer and the soil column according to Darcy's Law. The model parameterizes vertical hydraulic conductivity (K_{vert}) as a function of depth of the intermediate zone:

$$K_{vert} = \frac{\int_{z_{bot}}^{z_{\nabla}} K_{bot} e^{-f(z_{\nabla} - z_{bot})} dz}{(z_{\nabla} - z_{bot})} \qquad (3)$$

Where K_{bot} is the hydraulic conductivity of the bottom layer of the soil column, f is the e-folding depth of hydraulic conductivity (Equation 2), z_{∇} is the depth of the water table, and z_{bot} is the depth of the bottom interface of the soil column.

<u>Run 3 ("High Recharge")</u>

Making recharge an exponentially decaying function of water table depth decouples the soil column and the aquifer when the water table is deep; however, this parameterization may make it difficult for the model to restore communication between the saturated and unsaturated zones when wet periods follow prolonged dry periods. The third run used the Niu et al. (2006) model, which we modified to increase recharge to the aquifer. In the High Recharge run, we assumed that the vertical hydraulic conductivity

between the unsaturated zone and the aquifer is equal to the hydraulic conductivity of the bottom soil layer (K_{bot}) and that it remains constant throughout the intermediate zone (i.e., it did not exponentially decay). This modification likely still underestimates the hydraulic conductivity of the intermediate zone because hydraulic conductivity is a highly nonlinear function of soil moisture, which increases with proximity to the water table.

Run 4 ("Topography")

Neglecting inter-cell variation in topographic characteristics (as is done implicitly when the model is provided with an R_{sbmax} that is constant across the model domain) neglects one of the fundamental assumptions used to derive the baseflow equation used by Niu et al.'s CLM3. The Topmodel baseflow function and its derivatives implicitly assume that a watershed's individual topographic characteristics help determine the watershed's characteristic baseflow response (e.g., Silvapalan, 1987). To test whether the use of a globally constant value of R_{sbmax} adversely affects modeled baseflow, water-table dynamics, or both, we modified the High Recharge version of CLM3 to allow the topography-related baseflow-generation parameters to vary within the model domain. For each model grid cell, we calculated a grid-cell–specific R_{sbmax} using the grid-cell topographic characteristics (f and λ) and soil hydraulic properties (K_{sat}). We used 1/8º grid-cell-mean topographic index data derived from USGS HYDRO1K DEM data.

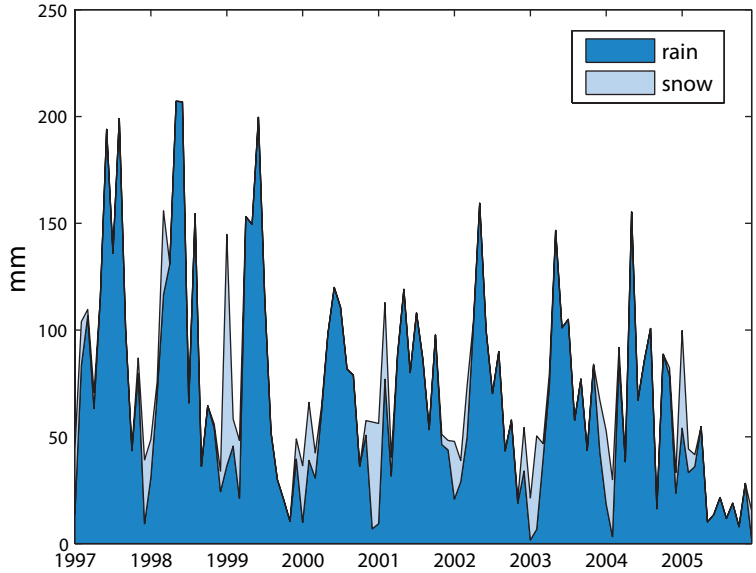
Run specifications, land-surface input data, and forcing data

A land-surface dataset derived from Moderate Resolution Spectroradiometer and Advanced Very High Resolution Radiometer satellite images (Lawrence and Chase,

2006) provided land-surface parameter initializations. The land-surface dataset has a native resolution of 1/20º; it was interpolated to a 1/8º grid. The model domain spanned 36.75N to 42.75N and –91.75E to –87.25E.

We used North American Land Data Assimilation System (NLDAS) meteorological forcing data (Cosgrove et al., 2003) to drive each of the four versions of CLM3 offline at 1/8º resolution from midnight January 1, 1997, to midnight January 1, 2006. NLDAS meteorological forcing data was chosen because of its high spatial resolution and quality. Figure 3 shows statewide average precipitation during the period simulated by the models.

Figure 3. Time series of cumulative precipitation averaged over the state of Illinois.



We initialized each run with the state variables from the end of a corresponding spin-up run. For each spin-up run, we used the NLDAS meteorological forcing data to drive the model from January 1, 1997, to January 1, 2006. For the three spin-up runs used to initialize the experiments employing Niu et al.'s CLM3 or a variation, we modified the

code according to the methods outlined by Niu et al. (2006) to increase the speed with which the modeled depth to water reaches equilibrium.

Because the Niu et al. CLM3 does not contain a state variable that tracks the water content of the intermediate zone, we could only infer the modeled variation in intermediate zone water storage. To estimate intermediate zone water storage changes, we assumed constant soil moisture throughout the intermediate zone equal to the aquifer specific retention. (Specific retention is the effective porosity of the aquifer less the aquifer specific yield. We assumed the effective porosity of the aquifer was equal to that of the bottom model soil layer and, following Niu et al. (2006), used 0.2 as the specific yield.)

Results

Statewide averages using model output were computed using a mask for the state of Illinois. Tables 1–3 show the correlation coefficient ($r_{m,o}$) of the model output with observations.

$$r_{m,o}(\tau) = \frac{\sum_{t=0}^{n-1} m_{t-\tau} o_t}{\sqrt{\sum_{t=0}^{n-1} m_{t-\tau}^{\ 2} \sum_{t=0}^{n-1} o_t^{\ 2}}} \qquad (4)$$

Where τ is the lag, n is the number of members in each series, and o and m are series. Likelihood estimates (see shaded values in the box at the bottom of each table) for the correlation coefficients between the model output and observations were determined using 100,000 Monte Carlo runs, in each which we calculated the correlation coefficient,

$r_{m,o}$, between two 107-member series x and y. In each Monte Carlo experiment, x and y were unique realizations of the probability density function describing Gaussian white noise. Future work will estimate confidence intervals for the correlation coefficients and more rigorous statistical analysis, if warranted.

TABLE 1.

Correlation coefficients of modeled change in soil-column water storage with observations ($r_{m,o}$)

	Lag (months)						
	-3	**-2**	**-1**	**0**	**1**	**2**	**3**
No Aquifer	0.251	0.423	0.667	0.324	0.322	-0.058	-0.311
Low Recharge	-0.099	0.175	0.624	0.478	0.461	0.205	-0.049
High Recharge	0.136	0.354	0.663	0.382	0.328	0.030	-0.239
Topography	0.136	0.354	0.662	0.381	0.328	0.030	-0.238

	Lag (months)						
	-3	**-2**	**-1**	**0**	**1**	**2**	**3**
No Aquifer	-0.079	-0.036	0.382	-0.117	0.300	0.039	-0.032
Low Recharge	-0.208	-0.108	0.449	0.066	0.174	0.045	-0.033
High Recharge	-0.138	-0.056	0.398	-0.054	0.189	0.064	-0.056
Topography	-0.138	-0.056	0.399	-0.054	0.189	0.064	-0.055

Likelihood*	0.900	0.950	0.990	0.999	0.9999
lower bound of |*r*| (107-member series)	0.161	0.190	0.248	0.314	0.369

* A "Likelihood" value here of 0.99 means that, if the true correlation coefficient of the two time series is 0 (i.e., they are random noise), then 99% of the time the absolute value of the estimated correlation coefficient will be lower than the correlation coefficient given.

TABLE 2.

Correlation coefficients of modeled change in groundwater storage with observations ($r_{model,obs}$)

	Lag (months)						
	-3	**-2**	**-1**	**0**	**1**	**2**	**3**
Low Recharge	-0.161	-0.156	-0.126	-0.021	0.097	0.168	0.241
High Recharge	-0.257	-0.180	-0.154	0.007	0.220	0.287	0.311
Topography	-0.257	-0.179	-0.154	0.007	0.221	0.288	0.311

	Lag (months)						
	-3	**-2**	**-1**	**0**	**1**	**2**	**3**
Low Recharge	0.028	0.046	0.029	0.045	0.062	0.018	0.032
High Recharge	0.026	0.089	-0.028	-0.009	0.062	0.011	0.005
Topography	0.026	0.089	-0.029	-0.010	0.062	0.011	0.005

Likelihood*	0.900	0.950	0.990	0.999	0.9999
lower bound of $\|r\|$ (107-member series)	0.161	0.190	0.248	0.314	0.369

* A “Likelihood” value here of 0.99 means that, if the true correlation coefficient of the two time series is 0 (i.e., they are random noise), then 99% of the time the absolute value of the estimated correlation coefficient will be lower than the correlation coefficient given.

TABLE 3.

Correlation of modeled change in TWS with observations ($r_{model,obs}$)

	Lag (months)						
	-3	**-2**	**-1**	**0**	**1**	**2**	**3**
No Aquifer	0.258	0.291	0.456	0.177	0.171	-0.135	-0.346
Low Recharge	0.181	0.267	0.465	0.241	0.153	-0.070	-0.231
High Recharge	0.304	0.196	0.250	0.063	-0.022	-0.308	-0.421
Topography	0.303	0.197	0.246	0.063	-0.023	-0.308	-0.423

	Lag (months)						
	-3	**-2**	**-1**	**0**	**1**	**2**	**3**
No Aquifer	-0.089	-0.120	0.215	-0.034	0.263	0.064	-0.074
Low Recharge	-0.054	-0.090	0.185	-0.071	0.018	-0.034	-0.039
High Recharge	-0.067	-0.231	0.000	-0.049	0.126	-0.077	-0.142
Topography	-0.069	-0.229	-0.004	-0.048	0.125	-0.076	-0.145

Likelihood*	0.900	0.950	0.990	0.999	0.9999
|*r*| at lower bound of interval (107-member series)	0.161	0.190	0.248	0.314	0.369

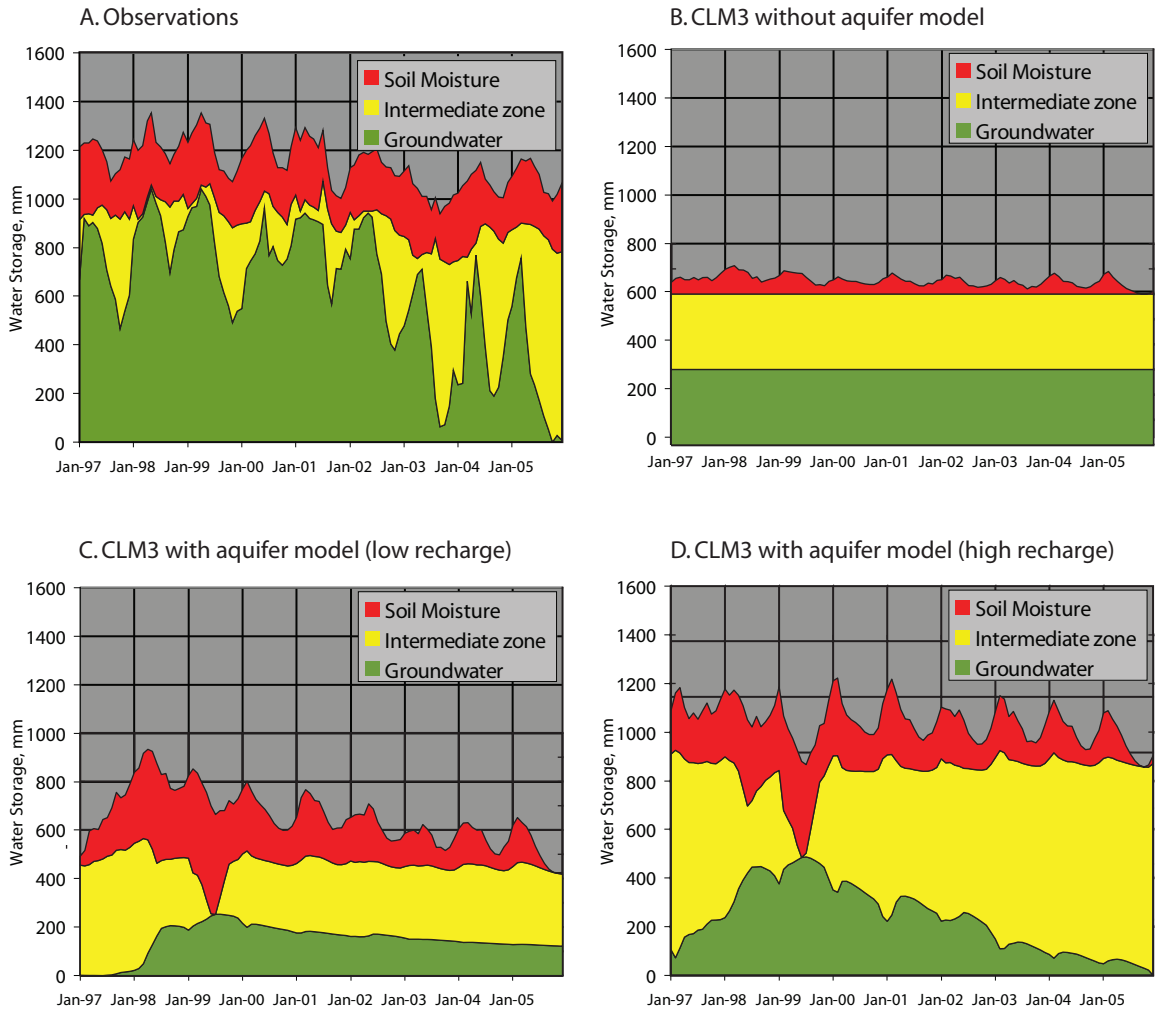
* A "Likelihood" value here of 0.99 means that, if the true correlation coefficient of the two time series is 0 (i.e., they are random noise), then 99% of the time the absolute value of the estimated correlation coefficient will be lower than the correlation coefficient given.

The very slight differences in the correlation coefficients observed between the High Recharge and Topography runs, in combination with other model output (not shown), demonstrate that allowing the topographic characteristics of each grid cell to vary within the model domain (as was done in the Topography runs) did not have a large effect on the statewide average terrestrial water storage dynamics. (Because there was so little difference between the statewide averages of these runs, only some of the figures that follow contain output from both runs. If output from both runs is not shown, it was

deemed too similar to merit separate inclusion.) This is a somewhat unexpected result and will be analyzed further in future work. It is possible that allowing topographic characteristics to vary between model grid cells will have a larger effect in regions with greater topographic relief than Illinois: the standard deviation of the topographic index in Illinois is ~0.9.

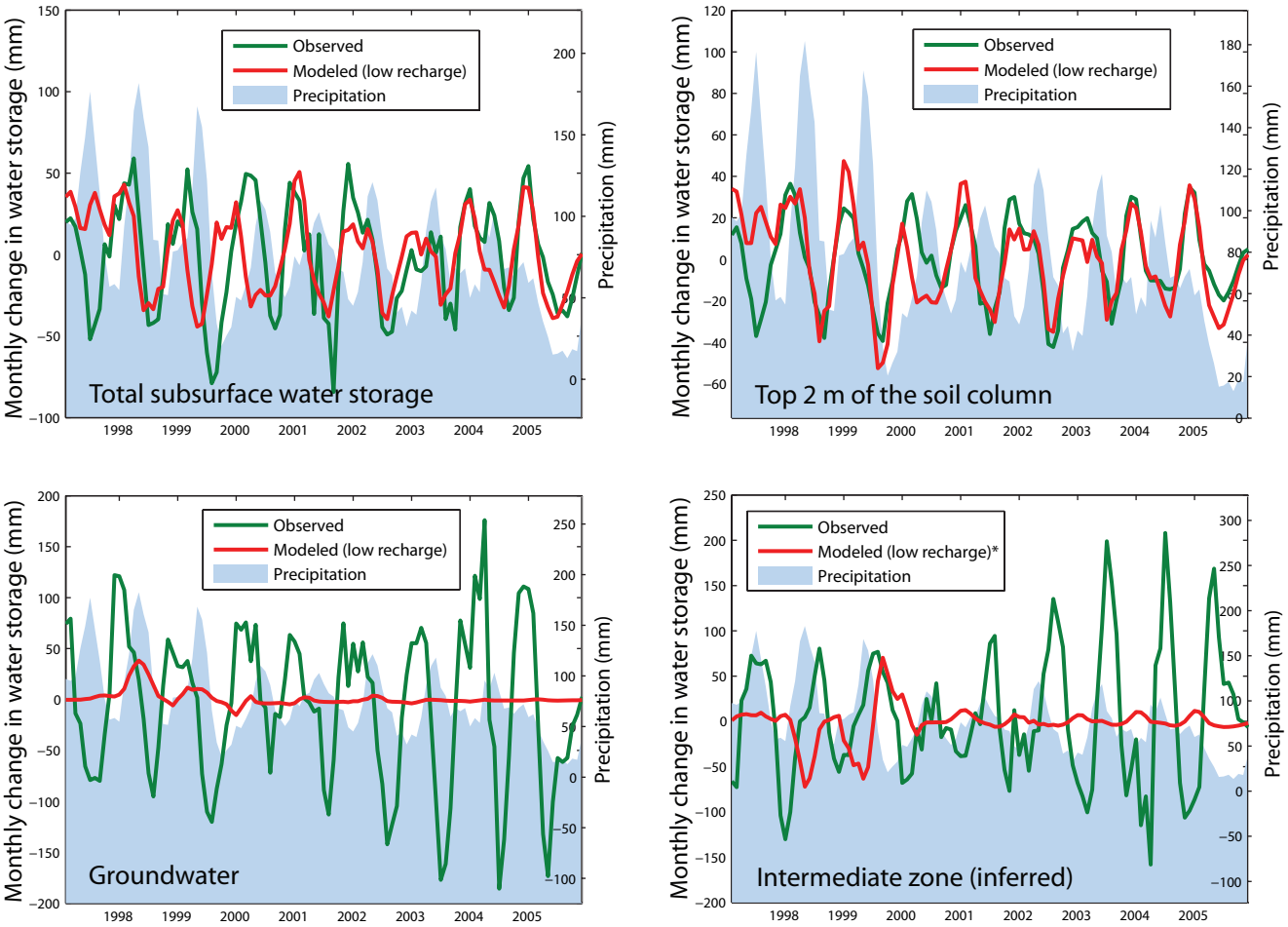
Although the increase in communication between the groundwater and the soil column slightly improved the partitioning of terrestrial water storage between subsurface reservoirs, none of the aquifer-equipped models realistically partition changes in terrestrial water storage into component reservoirs (Figure 4). (Note that in Panel B of Figure 4, the baseline CLM3, which does not contain a representation of groundwater, does not represent changes in the intermediate zone or groundwater. Constant storage was added to represent the assumption implicit in the model.) Figure 4 shows that the inclusion of an aquifer model significantly increases the skill of the model when representing the magnitude of variation in total-column terrestrial water storage.

Figure 4. Terrestrial water storage variation and its components in Illinois: comparison of observations with modeled output.



Although the annual cycle of groundwater storage is least realistic in the Low Recharge run, the time series of change in total-column terrestrial water storage change simulated by Low Recharge run has the highest correlation with observations. Figure 5 juxtaposes total NLDAS precipitation with modeled and observed change in the amount of water stored in each of the three subsurface reservoirs. Note that all series in the Figure 5 have been smoothed by convolution of each time series with a length-3 boxcar filter ([1/3, 1/3, 1/3]).

Figure 5. Modeled change in components of terrestrial water storage (from the Low Recharge run) juxtaposed with corresponding observations and NLDAS total precipitation.



Preliminary conclusions and future work

The aquifer model introduced into CLM3 by Niu et al. (2006) improves the magnitude of water storage variations in the modeled soil moisture. Future work will quantify this improvement and will address whether a similar result could be obtained by simply increasing the depth of the modeled soil column.

The Niu et al. CLM3 does a poor job of partitioning terrestrial water storage change between subsurface reservoirs. It significantly underestimates the amplitude of

the annual cycle water stored in the saturated zone. After relatively wet years in the late 1990s the Low Recharge model (Niu et al.'s original version) simulates very little recharge. The amplitude of the annual cycle of groundwater storage simulated by the High Recharge model is better than that simulated by the Low Recharge model; however, increasing recharge degrades the correlation of the modeled total terrestrial water storage with the observed.

Initial visual assessment of model output implies that the aquifer-equipped CLM3, regardless of modification outlined above, does a better job at representing water table dynamics during wet years when the water table is shallow. This is to be expected: the deeper the water table, the less physically realistic the transfer of water from the upper soil layers, through the intermediate zone, to the aquifer at depth. Comparison of model skill at individual observation sites will help provide additional information regarding model skill and potential improvements.

Future work will compare the model skill during wet and dry years and between wet and dry sites. Investigation into the seasonality of model skill (e.g., whether the model performs best when the modeled water table is falling) may also point the way toward potential efficient improvements in the parameterization.

The representation of aquifer dynamics in CLM3 provides an opportunity for effective use of parameter optimization and calibration techniques. Subsurface water transfer in nature—and in physically based models—depends in large part on the value of hard-to-measure, highly spatially variable hydraulic properties (e.g., hydraulic conductivity). It is possible that on the large spatial scales represented by regional LSMs,

the model is no longer particularly sensitive to the values of subsurface hydrogeologic parameters; more likely, models require detailed parameter inputs. Parameter optimization techniques applied to CLM3 using the rich observational dataset of Illinois as an objective will help highlight directions for future research and observation campaigns.

Similar analyses will be made using a gridded version of the Catchment Land Surface Model (Koster et al., 2000; Ducharne et al., 2000), which contains an implicit representation of water table dynamics. The Catchment Land Surface Model will be run at ¼º using NLDAS forcing data over Illinois using the Land Information System (Kumar et al., 2006).

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