



Improving land-surface model hydrology: Is an explicit aquifer model better than a deeper soil profile?

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[1] We use Monte Carlo analysis to show that explicit representation of an aquifer within a land-surface model (LSM) decreases the dependence of model performance on accurate selection of subsurface hydrologic parameters. Within the National Center for Atmospheric Research Community Land Model (CLM) we evaluate three parameterizations of vertical water flow: (1) a shallow soil profile that is characteristic of standard LSMs; (2) an extended soil profile that allows for greater variation in terrestrial water storage; and (3) a lumped, unconfined aquifer model coupled to the shallow soil profile. North American Land Data Assimilation System meteorological forcing data (1997–2005) drive the models as a single column representing Illinois, USA. The three versions of CLM are each run 22,500 times using a random sample of the parameter space for soil texture and key hydrologic parameters. Other parameters remain constant. Observation-based monthly changes in state-averaged terrestrial water storage (dTWS) are used to evaluate the model simulations. After single-criteria parameter exploration, the schemes are equivalently adept at simulating dTWS. However, explicit representation of groundwater considerably decreases the sensitivity of modeled dTWS to errant parameter choices. We show that approximate knowledge of parameter values is not sufficient to guarantee realistic model performance: because interaction among parameters is significant, they must be prescribed as a congruent set. **Citation:** Gulden, L. E., E. Rosero, Z.-L. Yang, M. Rodell, C. S. Jackson, G.-Y. Niu, P. J.-F. Yeh, and J. Famiglietti (2007), Improving land-surface model hydrology: Is an explicit aquifer model better than a deeper soil profile?, *Geophys. Res. Lett.*, 34, L09402, doi:10.1029/2007GL029804.

1. Introduction

[2] With the growing recognition of groundwater–atmosphere interaction as a potentially significant influence on spatial and temporal climate variability, researchers in the field of terrestrial hydrometeorology have focused increasing attention on improving the process representations of subsurface hydrology within land-surface models (LSMs).

Existing process representations fall within three broad classes: (1) multi-layered, relatively shallow soil columns in which groundwater storage is implicitly represented because the model conserves mass [e.g., Oleson *et al.*, 2004]; (2) many-layered, deep soil columns whose lower boundaries are beneath the climatological depth to the water table [Koster *et al.*, 2000; Maxwell and Miller, 2005]; and (3) multi-layered soil columns coupled to lumped, unconfined aquifer models [York *et al.*, 2002; Liang *et al.*, 2003; Yeh and Eltahir, 2005; Fan *et al.*, 2007; Niu *et al.*, 2007].

[3] Which of these methods best represents subsurface hydrology at a monthly time scale? We address this question for three different levels of parameter uncertainty: (1) when an optimal set of subsurface hydrologic parameters (e.g., percent sand, porosity, and specific yield) can be inferred from observations (the “ideal” case); (2) when no information about effective parameters can be obtained (the “worst” case); and (3) when only ranges for parameter values are known (the “real life” case).

[4] To ensure a fair comparison between methods, we isolate process representation as the primary source of uncertainty in model predictions. To limit input-data uncertainty, we employ the same meteorological forcing data and land-surface data for all runs. We use a Monte Carlo approach to explore the impact of parameter uncertainty. Unlike calibration studies, the underlying goal of this work is not to identify the optimal parameter set; instead our primary goal is to evaluate and compare the added value of process representations.

[5] Three questions frame our analysis: (1) When given a surrogate optimal parameter set, which of the ways to represent subsurface hydrology results in the most realistic simulation of monthly change in terrestrial water storage? (2) When no reliable information regarding effective subsurface hydrologic parameters exists, which process representation most consistently gives the best performance? (3) Does knowledge of approximate values for hydrologic parameters guarantee reasonably accurate simulation of monthly change in terrestrial water storage? Our results will inform LSM model development; more important, they characterize the level of confidence that can be placed in LSM-generated hydrologic predictions, especially when observations are scarce.

2. Methods

[6] We use the National Center for Atmospheric Research’s Community Land Model (CLM) [Bonan *et al.*, 2002; Oleson *et al.*, 2004; Niu *et al.*, 2005] as the host model in which to test three methods for representing vertical water flow within the LSM soil column. The

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Table 1. Ranges and Distributions of Randomly Sampled Subsurface Hydrologic Parameters

Parameter	Range	Distribution
Sand ^a	5 to 90%	uniform
Clay ^a	5 to (100 - [% sand])%	semi-uniform
Porosity	0.01–0.50 m ³ m ⁻³	uniform
e-folding depth of saturated hydraulic conductivity	0.1–100 m	uniform
Maximum rate of baseflow (rsbmax)	1 × 10 ⁻¹¹ –1 × 10 ⁻³ m s ⁻¹	log uniform
Specific yield ^b	0.01–0.25	uniform

^aCLM calculates hydraulic conductivity and matric potential as a function of percent sand and percent clay according to the methods of *Clapp and Hornberger* [1978] and *Cosby et al.* [1984]. Percent silt is 100–(% sand + % clay).

^bSpecific yield is used only by the AQUIFER runs, not by the SHALLOW or DEEP runs.

versions of CLM calculate surface and subsurface runoff (i.e., baseflow) as a function of topographic characteristics [*Niu et al.*, 2005] and are identical except for the method that they use to represent vertical water transfer in the soil column.

[7] The first version of CLM (hereafter “SSOIL”) uses the standard 10-layer, relatively shallow 3.43-m soil profile with topography-based runoff parameterizations [*Niu et al.*, 2005]. Because it conserves mass, the model implicitly represents groundwater dynamics; however, the true depth to the water table often exceeds the depth of the model’s lower boundary. The second model (hereafter “DEEP”) is identical to SSOIL except that it uses a 30-layer, 11.2-m soil profile, thereby extending the depth of the model soil profile to encompass a wider range of groundwater fluctuations. The third version (hereafter “AQUIFER”) couples a lumped unconfined aquifer model to the standard 10-layer soil profile [*Niu et al.*, 2007]; it allows two-directional vertical water transfer between the unsaturated zone and the aquifer down a hydraulic gradient.

[8] We run each version of the model as a single column representing the state of Illinois, USA. Illinois covers ~146,000 km². Crops and grass dominate the landscape. The climate is temperate and continental, and the topographic relief is relatively low. (See *Changnon et al.* [1988] and *Yeh et al.* [1998] for detailed descriptions of regional climate and hydrogeology.)

[9] Meteorological forcing and land-surface input data are the area-weighted arithmetic averages of high-resolution datasets over the state of Illinois. The forcing is provided by the North American Land Data Assimilation System [*Cosgrove et al.*, 2003]. A CLM-compatible land-cover dataset derived from Advanced Very High Resolution Radiometer and Moderate Resolution Imaging Spectroradiometer data [*Lawrence and Chase*, 2007] provides vegetation type distributions, biomass densities, and soil colors.

[10] A Monte Carlo approach allows us to extensively explore the range of model responses across parameter space. We run SSOIL, DEEP, and AQUIFER 22,500 times each. A unique set of subsurface hydrologic parameters is used for each run. We randomly sample uniform or semi-uniform distributions that span physically reasonable ranges of values for soil texture parameters and other hydrologic parameters (Table 1). Each Monte Carlo run is initialized

with a spun-up dataset created by running the model three times through the period 1997–2005 using default parameters. To allow for additional spin-up, the first year of each run is omitted from the analysis.

[11] We assess the accuracy of model output using the statewide-average change in total column terrestrial water storage (dTWS), which we constructed from soil moisture and groundwater observations obtained by the Illinois State Water Survey (ISWS) [*Hollinger and Isard*, 1994; *Robock et al.*, 2000] following the methods of *Rodell and Famiglietti* [2001]. dTWS is a suitable constraint because it integrates the hydrologic behavior of the landscape; it is directly observable everywhere on Earth using Gravity Recovery and Climate Experiment (GRACE) measurements [*Chen et al.*, 2006]; and it properly represents the land storage term of the coupled atmospheric-terrestrial water budget.

[12] Looking only at data from 1998–2005, we score parameter sets with the following metric:

$$F = \text{RMSE} \times (1 - r) \quad (1)$$

where RMSE is the root mean square error between modeled and observed dTWS:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (o_i - m_i)^2} \quad \begin{array}{l} n = \text{length of time series} \\ o_i = \text{observed dTWS at time } i \\ m_i = \text{modeled dTWS at time } i \end{array} \quad (1a)$$

and r is the correlation coefficient, defined as:

$$r = \frac{\sum_{i=1}^n (o_i - \bar{o})(m_i - \bar{m})}{\left(\sum_{i=1}^n (o_i - \bar{o})^2 \sum_{i=1}^n (m_i - \bar{m})^2 \right)^{1/2}} \quad \begin{array}{l} n, o_i, m_i \text{ defined in (1a)} \\ \bar{o} = \text{mean observed dTWS} \\ \bar{m} = \text{mean modeled dTWS} \end{array} \quad (1b)$$

We use F because it allows us to select parameter sets for which both the timing and amplitude of the modeled seasonal cycle match observations. We define the best parameter set as that which minimizes F ; we use it as a surrogate optimum. We perform the exhaustive parameter exploration, which mimics a single-criteria manual calibration.

4. Conclusions and Implications

[19] When a surrogate optimal parameter set is used, the model with the 3.43-m, 10-layer soil profile; that with the 30-layer, 11.2-m soil profile; and that in which a lumped unconfined aquifer is coupled to the shallow soil profile are equivalently adept at simulating monthly dTWS over the state of Illinois. When knowledge of subsurface hydraulic parameter values is limited, the coupled aquifer model makes CLM significantly less sensitive to errant parameter values; that is, the explicit aquifer representation is the most robust of the three parameterizations. However, knowledge of ranges for individual parameters is insufficient to guarantee realistic simulation of monthly dTWS.