14.5 # Parameter Retrieval in a Land-Surface Model

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1. Introduction.

The parameter retrieval method (Marchuk 1981; Louis 1979; Backus and Gilbert 1970; Qiu and Chou 1988) can be applied to determine the optimal values of certain parameters in sophisticated numerical models. The method can be utilized to determine the values of interrelated parameters in a complex numerical model, thus making the parameter calibration more objective.

In this study, we apply a parameter retrieval method to a land surface model, the SHEELS (Smith et al. 1993), inside the ARPS (Xue et al. 1995; 2000) framework. The Oklahoma Atmospheric Surface-layer Instrumentation System (OASIS) soil and surface measurements (Brotzge 2000) are used as the ground truth for the parameter retrieval and validation.

The soil textural description at the Norman, Oklahoma OASIS site is given in Table 1. Typically, parameters in land surface models are specified using tables based on the soil categories. For example, the saturated hydraulic conductivity to be retrieved in this study can be specified according to Table 1 (in the last column) for SHEELS after Dickinson et al. (1993). The alternative is to use parameter retrieval methods and measurement data to determine the 'optimal' parameter values that produce forecasts with best fit to data. The second approach is the focus of this work.

2. The Land-surface model: SHEELS

The SHEELS model describes the physics of the surface and subsurface (Smith et al. 1993) of the soil layers. It evolved from the BATS (Dickinson et al. 1986) model and has enhanced soil thermal and hydrological features. The model uses only one canopy layer and allows fractional coverage of the ground by vegetation. The partially vegetated surface is divided into four domains centered on the in-canopy air. Instead of using a nested soil layer approach, three adjacent zones are used to describe the subsurface, each of which is treated differently for moisture and root distribution. SHEELS also allows division of the soil zone into sub-layers. Although the soil properties as input are usually specified only for each of the three soil zones (limited by data availability), the water fluxes and heat conductance are diagnosed for the sub-layers, i.e., there is a vertical-moisture-content-gradient driven water exchange, a temperature-gradient driven heat exchange between the adjacent layers, and a soil-water-content-dependent plant transpiration. SHEELS as used in this study is a 1-D model (there is no lateral moisture and heat transfer) that differentiates 11 soil categories (the 11 textural classes in United States Department of Agriculture textural triangle) and 6 land cover classes.

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3. The Parameter retrieval method

The parameter retrieval method we use is based on the small perturbation theory described in Marchuk (1981). With this method, a set of linear system of equations is formed, with the solution to be found being the parameter perturbations and the coefficients of the equations being the gradients of a cost function with respect to the parameters. When more data than the number of parameters are used, the equation system is over-determined and the system can be solved using a general linear inversion method (Backus and Gilbert 1970; Qiu and Chou 1988).

Although the above optimization problem would best be solved by using minimization techniques based on model ajoint (LeDimet and Talagrand 1986), application of the method does require the adjoint code of the forward model, and the coding of the adjoint for a model like SHEELS is not straightforward due to the use of discontinuous functions and complex logics in the formulation. With the current procedure, the gradients of the cost function with respect to the parameters are obtained by running the forward model multiple times, each time using a different parameter value perturbed within its possible range. With the gradients, i.e., the coefficients of the linear system of equation, being known, the equations are solved to obtain corrections to the parameters that give a better match between the model prediction and the observations when measured in terms of the cost function. Iterations are usually performed to improve the accuracy of retrieval.

In this study, the saturated hydraulic conductivity, K_{sat}, the minimum stomatal resistance, R_{smin}, and the fractional soil moisture at which permanent wilting occurs, f_{wilt}, are chosen as the target parameters for retrieval. They play direct roles in determining the soil hydrological processes that will finally affect the surface water and energy fluxes. Their values in field conditions are generally uncertain and their canonical values are usually obtained under laboratory conditions.

The three parameters to be retrieved are functions of soil properties only. Ideally, the optimization process should be carried out with observational values over time periods containing a broad range of meteorological and biophysical conditions. To simplify the problem, we selected periods with fine weather conditions only. OASIS provides routine half-hourly measurements of soil moisture contents at four different depths, it is therefore not hard to have enough observations to make the inversion problem over-determined hence solvable.

In general, parameters of very different sensitivity should not be retrieved at the same time. This is true for K_{sat}, and R_{smin} and f_{wilt}. We therefore retrieve first the value of K_{sat} for all the different vertical sub-layers, then fix it at its optimal value and repeat the procedure to retrieve R_{smin}

and f_{wilt} together. Again, iterations can be performed to refine the retrievals.

To start the procedure, the initial guess values for the target parameters need to be specified and the closer are they to the true values the better. Published categorical values from previous studies are used here. The setting of the range of parameters should bracket the initial guess and be wide enough to cover plausible limits of their variations. In our procedure, the model-derived soil volumetric water contents are compared with the corresponding OASIS measurements. An optimal solution was chosen on the basis of root mean square (*rms*) difference. We choose to terminate the iteration procedure when the decrease of *rms* error is three orders of magnitude smaller than the initial value based on first guess parameter values.

4. DATA: OASIS measurements

The OASIS data set at Norman super site used here was provided by J. Brotzge, and has been used for model calibration purposes (Brotzge and Weber 2002). The Norman site is flat and the vegetation is classified as scrub and its immediate surroundings can be considered uniform within a range of several kilometers and has an elevation of 360 m.

The available measurements that can be used to force to the land-surface model include surface temperature, water vapor mixing ratio, wind speed and direction, surface pressure (mb), and precipitation rate (m s^{-1}). At the OASIS site, an infrared sensor records surface skin temperature and data are collected at 5 min intervals. The soil moisture and soil temperature are measured using the 229-L sensors every half an hour at 0.05 m, 0.25 m, 0.60 m and 0.75 m from the surface downward. Details of the measurements, including theory, sensor calibration and data manipulation are described in Basara (2001).

Like the soil data, vegetation data are also recorded every half an hour. The vegetation parameters include vegetation type, leaf area index (LAI), vegetation coverage, and NDVI index.

OASIS measurements of soil moisture contents from May 20 through May 24, 2000 are used in our parameter retrieval scheme to determine the optimal parameters. This period represents synoptically-quiescent spring days characterized by warm temperatures (maximum temperature of 28° C), a moderately moist soil and vigorous vegetation growth (NDVI = 0.61). From the Norman OASIS site, a vegetation cover of 75% was estimated for the period. The retrieved values of parameters are then applied to the period of May 11-15, 2000 to validate the retrievals. The weather condition of this period is similar to that of the first period. To better match OASIS data which contain measurements of soil temperature and soil moisture for soil depths of 0.05, 0.25, 0.6 and 0.75 m, SHEELS is used as a 5-layer model. The first four layers are centered at the measurement depths and the bottom layer is included to facilitate the implementation of zero-gradient boundary condition.

5. Results and analysis

OASIS-measured soil moistures at 0.05, 0.25, 0.6 and 0.75 m show that before the rainfall at 06UTC, May 25th, there is a steady drying down trend for the deep soil moistures (all except that measured at 0.05 m) (Fig.1). The soil moisture at the surface layer (0.05 m) has an apparent daily cycle. However, counter-intuitively, soil water content increases during daytime (Fig. 1.). Zoom-in of the figure reviews that the phase of soil moisture variation at 0.05 m depth is opposite to that of 0.25 m, suggesting water redistribution among this slab of soil perhaps due to the activity of shrubs (Brotzge, personal communication).

Because the process responsible to the kind of diurnal cycle in the moisture in the upper most soil layer is not modeled in SHEELS, and to remove other noises in the observational data, we compare daily averaged values of model against the observed ones during the period of May 20 to May 24, 2000 in our retrieval experiment.

The retrieved values of the parameters are given in Table 2. In Fig. 2, we can see that the daily mean soil moisture contents at different depths for the May 11- 15, 2000 period are much better predicted when using the retrieved values than using the original category-based values.

The retrieved parameters are generally not far from the categorical values. For example, starting from the first guess values of f_{wilt}=0.18 and R_{smin}=150 s m^{-1} derived from Dickinson et al. (1993), we obtain the retrieved values of 0.19 and 200 s m^{-1}, respectively. The vegetation type at Norman is not exactly one category in SHEELS' classifications. Such a situation of mixed types is even more difficult for the category-based approach.

In summary, our preliminary results show that a simple, non-adjoint-based parameter retrieval procedure can be quite successful in retrieving important parameters in a soil-vegetation model, and the model prediction can be significantly improved when the optimal retrieved parameter values are used.

Acknowledgement

This work was supported by a grant from the Federal Aviation Administration.

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Table 1. Soil characteristics of Norman OASIS super site

	Texture Class	% Sand	% Silt	% Clay	% Gravel	Saturated hydraulic conductivity (m s^{-1})
5 cm depth	Silt loam	19.06	56.62	24.32		8.9×10^{-6}
25 cm depth	Silty clay	14.17	43.17	42.66		1.1×10^{-6}
60 cm depth	Silty clay	18.49	39.66	41.85	1.91	1.1×10^{-6}
75 cm depth	Silty clay	16.45	41.32	42.23	2.60	1.1×10^{-6}

Table 2. Retrieved vs. classification-specified saturated hydraulic conductivity ($\times 10^{-6}$ m s^{-1}), minimum stomatal resistance and wilting point. At the time of convergence, the mean square error rms=1.48×10^{-3} for soil moisture contents at all four levels.

	Saturated hydraulic conductivity($\times10^{-6}$ m s^{-1})				R_{smin}	f_{wilt}
	5 cm	25 cm	60 cm	75 cm		
Based on classifications	8.9	1.1	1.1	1.1	150.0	0.18
Retrieved using OASIS observations	8.86	4.54	0.8	0.8	200.0	0.19

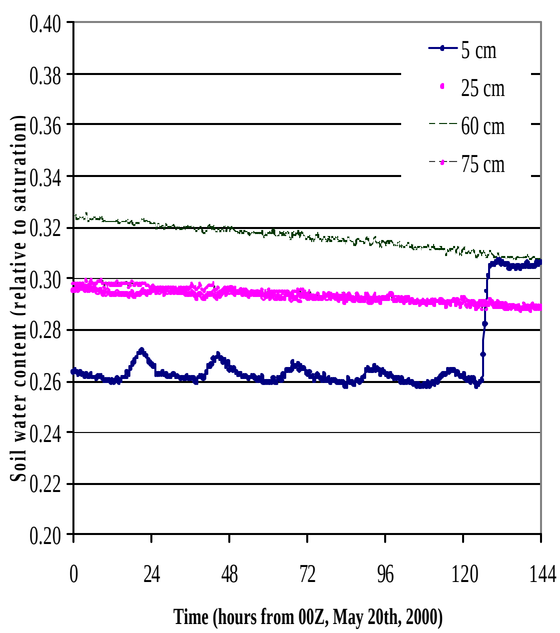

Fig.1. OASIS measured soil moistures at 5 cm, 25 cm, 60 cm and 75 cm, respectively.

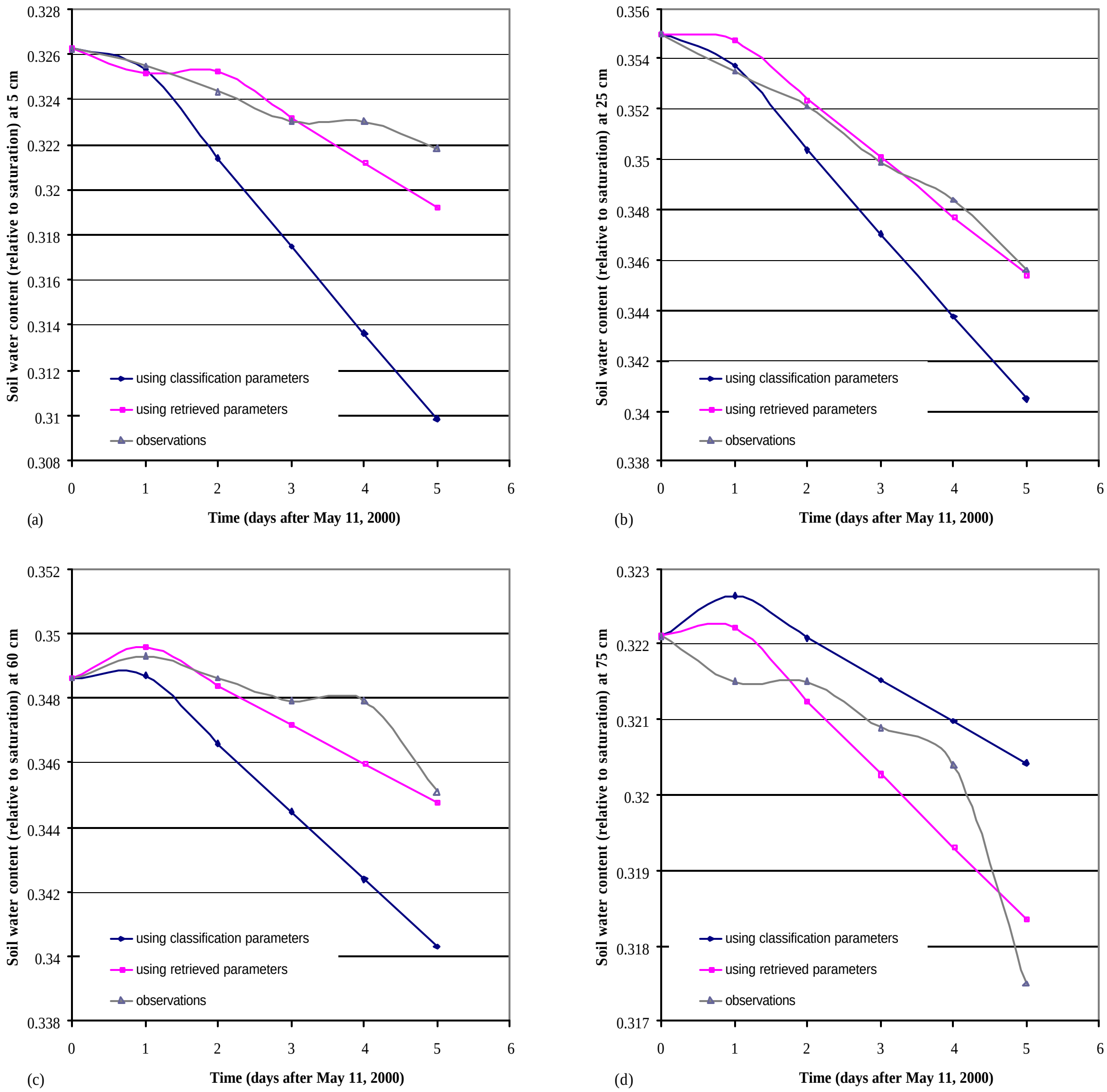

Fig. 2. A comparison of model predicted (using the lookup table and the retrieved parameters) and observed values of soil water content at the 5 cm (a), 25 cm (b), 60 cm (c), and 75 cm (d) levels.