Multimodeling – An Emerging Approach to Improving Process-Based Modeling of Soil Systems

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Abstract
Environmental systems usually are approximated in mathematical terms by making simplifying assumptions that lead to multiple model structures which may produce results that are equally consistent with available observations. An increasing number of papers are now being published on various applications of multimodeling in which predictions from various independent models are combined, rather than attempting to find the best model. Multimodeling consists of assigning weights to the simulation results from the various models, and then combining these results into a single prediction. We constructed a multimodel using 14 independent Richards equation-based individual models by employing different pedotransfer functions. The individual models were not calibrated. Soil water contents were monitored for 300 days with multisensory capacitance probes at eight depths in four locations. Simulations using seven different methods to assign weights to individual models were compared with observed soil water time series. The multimodel was by far more accurate and reliable than the individual models. The concurrent use of several models, and mutimodeling in particular, presents an opportunity to better understand and forecast soil processes.

Key Words
Multimodeling, concurrent use, model weights, soil water, pedotransfer functions.

Introduction
Having a multiplicity of models of the same process or phenomenon is commonplace when modelling environmental processes, especially when the soil-plant-atmosphere system is considered. The multiplicity relates to differences in the simplifications needed to express observed natural complexities in mathematical terms, differences in model emphasis, and differences in scales at which models were developed or the natural system was observed (Beven, 2002). A massive effort in developing criteria for selecting the best model has thus far not produced a univocal solution. All error-based methods condition the evaluation and comparison of models on the available data. Using the reasonability of forecasts to evaluate models, e.g. with the GLUE methodology (Beven and Binley, 1992), does not exclude the subjective element of selecting cutoffs and defining reasonability. Invoking measures of model complexity based on the number of model parameters is problematic for nonlinear models. The uncertainty of the model structure is in most cases difficult to include in the criteria statistics (van Ness and Sheffer, 2005).

The last 10 years has seen a marked interest in making use of different conceptual approaches instead of attempting to find the best model or using a single preferred model. Several approaches to the concurrent use of several models are currently being pursued. One approach is multimodeling, which consists of assigning weights to the simulation results from different models, and then combining results from the individual models into a single prediction (Burnham and Anderson, 2002). Multimodeling has been shown to improve both deterministic and probabilistic performances of predictions (Hagedorn *et al.* 2005). The objective of this work was to investigate and demonstrate the applicability of multimodeling to water flow in variably saturated field soils.

Methods
Multimodeling
The use of the term "multimodel" in publications has grown exponentially during the past ten years. To deal with uncertainties in model selection, multimodel prediction has emerged as a popular technique in climate prediction (Barnston *et al.* 2003), but later propagated also to surface hydrology (e.g., Regonda *et al.* 2006), subsurface hydrology (Neuman, 2002; Guber *et al.* 2009), and ecological modeling (Link and Barker, 2006). Since its introduction, multimodel prediction based on combining results from more than one model has been subject to much debate that can be summarized into two questions: (a) is a multimodel prediction better than

the single best forecast, and (b) what is the best approach to weigh predictions obtained with the different models. The improvement in predictions has been attributed to the fact that the multimodel provides better coverage of system parameter space. The relation between the average capability of the single model and the performance of the multimodel is not linear, especially when the probabilistic diagnostics is considered (Hagedorn *et al.* 2005). Selection of weights in multimodels is currently still a topic of research. Alternative methods for weighing have been reviewed by Armstrong (2001) and Burnham and Anderson (2002), among others. The most often used methods are:

1) arithmetic averaging of results from all models (AA),
2) superensemble forecasting (SF) where the multimodel result is the multiple linear regression with individual forecasts as the independent variables (Krishnamurti *et al.* 2000),
3) superensemble with singular value decomposition (SVD) to alleviate effects of multicollinearity caused by similarity in the predictions of individual models (Kharin and Zwiers, 2002),
4) Bayesian model averaging (BA), (Neuman, 2002),
5) using information theory (IT) to select weights by minimizing the information loss, for example by using Akaike criteria (Poeter and Andersen, 2005), and
6) using weights inversely proportional to the accuracy of each model on a training dataset (IW).

The multimodel in this study was built using 14 individual models. Each of the models employed the Richards flow equation, the Brooks-Corey-Campbell or van Genuchten-Mualem equations for water retention and the unsaturated hydraulic conductivity, and one of 14 pedotransfer functions (PTFs) to estimate the hydraulic parameters from basic soil properties: (1) Rosetta (Schaap *et al.* 2001), (2) Vereecken et al. (1989), (3) Varallyay et al. (1982), (4) Wösten et al. (1999), (5) Rawls and Brakensiek (1982), (6) Saxton et al. (1986), (7) and (8) Williams et al. (1992), (9) Campbell and Shiozawa (1992), (10) Oosterveld and Chang (1980), (11) Mayr and Jarvis (1999), (12) Gupta and Larson (1979), Tomasella and Hodnett (1998), and Rawls et al. (1983). References to these PTF sources are given by Pachepsky et al. (2007), while a computer code to compute water retention according these functions is available upon request from the first author. The saturated hydraulic conductivity of the different textural classes was estimated as described in Pachepsky and Rawls (2004). None of the individual models was calibrated.

Field data

Field data were obtained from a 10x10 m plot at the research site of the Beltsville Agricultural Research Center, Maryland, USA. Soils at the site are classified as a coarse-loamy, siliceous, mesic Typic Hapludult, either well or excessively well drained. On average, the soils have a coarse loamy sand surface horizon (0-25 cm, organic matter 1.2-5.1%), followed by a sandy loam horizon (25-80 cm), and a loam horizon (80-120 cm), with loamy sand and fine-textured clay loam lenses between 120 and 250 cm. Soil water content measurements were taken with multi-sensor capacitance probes, MCPs (EnviroSCAN, SENTEK Pty Ltd., South Australia), at four locations within the plot. Data were recorded each 15 minutes from January 1 through October 23, 2007, at depths from 10 cm to 80 cm at 10 cm increments. The MCPs were connected to a CR-10X datalogger. Collected data were acquired using a Redwing 100 Airlink modem (Campbell Scientific, Inc., Logan, Utah) once a day. Soil texture, bulk density and organic carbon content were measured at each location at depths from 10 cm to 100 cm at 10 cm increments. Rainfall at the site was measured with a pluviograph, while other weather data were obtained from the energy balance meteorological station with an eddy covariance tower located in 100 m from the plot. Daily evaporation rates were estimated using the Pennman-Monteith equation. We used the HYDRUS-1D software for all of the simulations.

Results

Basic soil properties and multimodeling results

Basic soil properties varied substantially across the plot and with depth. Bulk density increased from 1.35-1.55 g/cm^3 at 5 cm depth to 1.70-1.95 g/cm^3 at 90 cm. Sand content varied between 55 and 65 % at the surface and between 50 to 70 % at the 90 cm depth. The organic matter content did not show substantial variability, decreasing exponentially with depth from 2% at 5 cm depth to 0.2 % at 90 cm. The variations in texture and bulk density resulted in differences in the soil water regimes among the different locations (Figure 1). The multimodel provided accurate simulations of the daily average water contents at all depths (Figure 1). The lowest RMSE values were obtained with singular value decomposition (SVD) weighing. RMSEs were within the range of 0.018 cm^3/cm^3 to 0.061 cm^3/cm^3 at the depth of 10 cm, and within the range of 0.005 cm^3/cm^3 to 0.019 cm^3/cm^3 below 10 cm at four locations. The best individual model performed markedly worse than the multimodel.

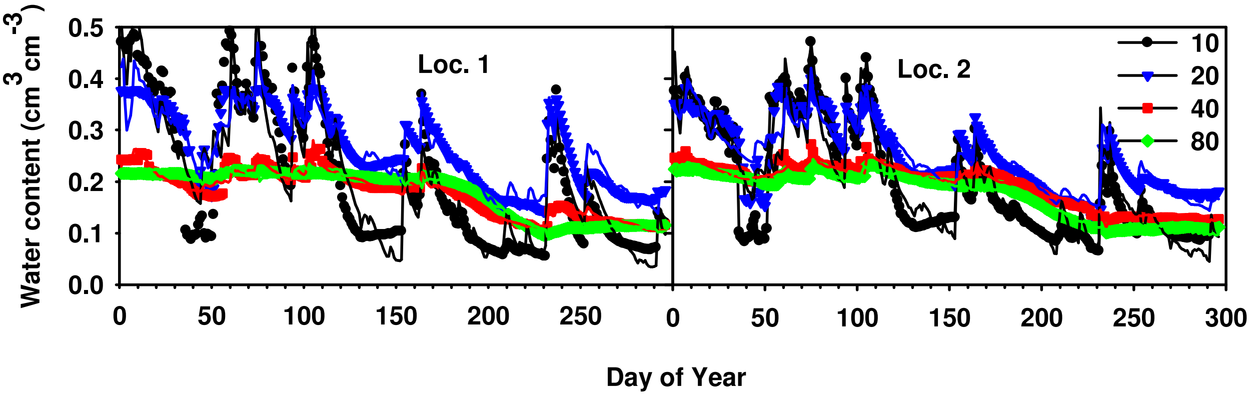

Figure 1. Examples of the multimodel accuracy at different depths at two monitoring locations. Symbols and lines show observed and simulated soil water content time series, respectively; the legend shows depth in cm.

Reliability of multimodeling results

Each water content time series was split into a training and a testing dataset. Training datasets were defined within time windows from 10 to 150 days long, and then moved across the whole observation period. All data outside the windows were used to test the multimodel prediction. The best fit of the multimodel to the daily water contents in the training sets were obtained using weights. The various weighing methods were evaluated in terms of their accuracy and uncertainty (i.e., average and standard deviation) in reproducing the measured water contents of the training datasets (Figure 2).

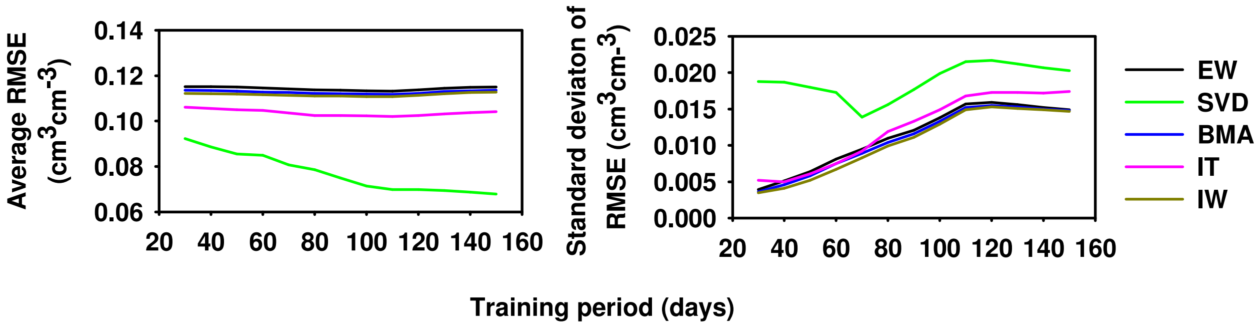

Figure 2. Changes in the multimodel error (RSME) of the test datasets with the duration of the multimodel training period. Colors show different weighting methods; abbreviations are explained in the text.

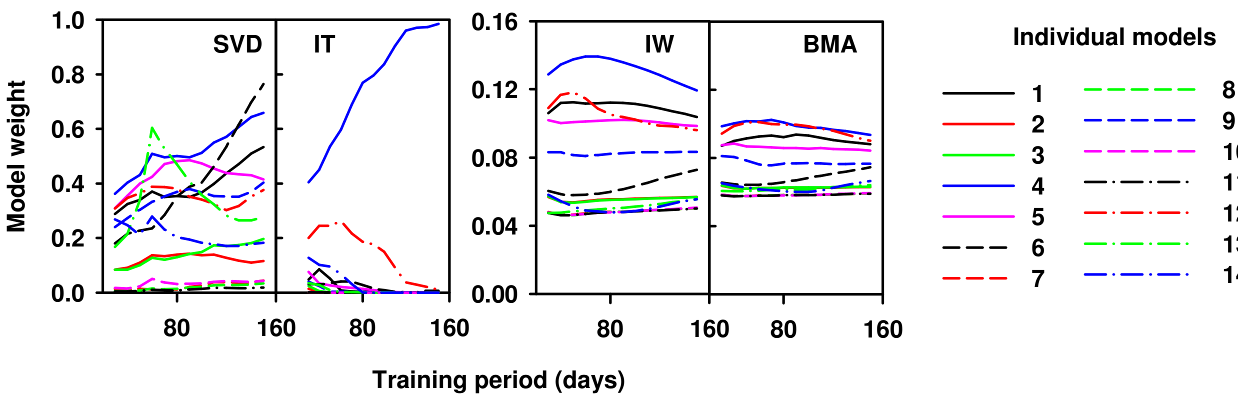

Figure 3. Changes in the weights of individual models with the length of the multimodel training period for the SVD, IT, IW and BMA weighting methods. See text for abbreviations and PTF numbers.

The length of the training period affected the accuracy of the predictions. In most cases, the average RMSE decreased and the standard deviation of the RMSE increased with an increase in the training period for all models and locations. Individual models had different weights at different depths, with the weights of some of the weighting methods also being dependent upon the duration of training period (Figure 3).

Discussion and conclusion

Multimodeling was found to be very effective approach to improving the accuracy of the flow simulations.

Accuracy and reliability of the multimodeling approach in our study varied among the six weighing methods. Overall, the best predictions were obtained with the SVD weighting method, probably because this method is well suited to decrease the effects of the multicollinearity of the inputs from the individual models. The main uncertainty factors were variation in soil properties, and the length of the training period. The reliability of the multimodeling approach increased with the length of the training period.

The excellent results obtained in this study indicate much promise in using the multimodeling methodology for analysing field-scale water flow data. Still, multimodeling is not the only way to take advantage of the concurrent use of existing models. Other approaches, such as model abstraction, have proved to be effective also. Model abstraction systematically simplifies a more complex model into a series of simpler models, and then uses these to (a) learn more about the system, (b) improve robustness of the predictions, (c) improve communication between the modeling results, and (d) improve performance of the modeling system as a whole (Pachepsky *et al.* 2007). Overall, the concurrent use of several models presents an important avenue for improving our understanding of soil processes.

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