

## **Kalman filters for assimilating near-surface observations in the Richards equation – Part 3: Retrieving states and parameters from laboratory evaporation experiments**

**H. Medina, N. Romano, and G. B. Chirico**

### **Reply to Referee#II**

We thank Referee#2 for the appreciation of our work and for the fruitful suggestions. Below we provide our replies to the Referee comments.

#### **Ref#2**

*1. I think the section describing the context of this contribution is rather poor. The subject of dual state parameter estimation is not new (Boulet et al. (2002), Moradkhani et al. (2005), Qin et al. (2009), Montzka et al. (2011), Liu and Gupta (2007), De Lannoy et al. (2007) to name a few). One common theme in these studies is that the state augmentation methods ignore the time-invariance property of the parameters, which is how these soil parameters are handled in most modeling systems. In this study also, this issue is ignored. In fact, Liu and Gupta (2007) provides a description of the limitation of the joint state and parameter estimation approaches. I suggest that the authors revise the introduction section and provide a better context of this work in view of all these prior works.*

#### **Reply**

We will expand the introduction as suggested. Certainly the implementation of a dual (or a joint) exercise for parameter-state estimation demands more caution, as compared with a standard KF approach.

In this study we implemented a dual approach, based on two parallel filters with separate state-space representations for the states and the parameters. The alternative would be a joint approach, with a single filter applied to an augmented state vector, including states and parameters.

Liu and Gupta (2007), talking about the joint approach, stated: “[The joint approach] *may render the estimation process unstable and intractable because of complex interactions between states and parameters in nonlinear dynamic systems (Todini, 1978a, 1978b). In addition, since parameters generally vary much more slowly than the system states, unstable problems may also result from the fact that both model states and parameters are updated at each observation time step in this method. This same argument may apply to the dual state-parameter estimation methods presented by Moradkhani et al. (2005a, 2005b).*” This can be seen as the price to be paid for a more accurate result.

#### **Ref#2**

*2. Line 25 (p 13375): What is "noise observations.." ? In fact, this whole sentence is awkward.*

#### **Reply**

We will improve this sentence. Here we refer to observations corrupted by (noise) observation errors.

#### **Ref#2**

*3. Line 10 (p 13377): "Actually, data assimilation ..." - this sentence looks out of place, including the reference.*

#### **Reply**

We will remove this sentence while improving the overall introduction.

#### **Ref#2**

*4. Since the authors have control of the laboratory environment, I wonder why some of these parameters (Ks) weren't measured directly (instead of relying on an earlier published work)?*

#### **Reply**

In a previous work (Medina, 2012; companion paper) we used a synthetic experiment for comparing estimated and “actual” states and parameters, providing several insights about parameter identification employing this dual approach.

In the study by Romano and Santini (1999) the authors not only provided a valuable experimental dataset for evaluating this approach, but also supported the comparison between a sequential and a non sequential inverse method.

We also judge helpful evaluating new methods by examining a case study already discussed in the literature.

### **Ref#2**

*5. The trends in Figures 2 and 3 are interesting. Why is it that the values of alpha converge to a higher value, though the starting point is closer to the reference truth? Similar trends can also be seen in n where it is moving away from the reference value.*

### **Reply**

As stated in pag. 13389, L. 15, we attribute this behaviour to the fact that the assimilation algorithm is implemented by exploiting the soil water content as observation variable, whilst Romano and Santini (1999) employed pressure head values measured at three depths. Parameter  $\alpha$  acts as a scaling factor of the pressure head values with respect to the soil moisture in the VGM model and its identifiability with inverse methods is highly affected by the type of information employed (e.g. Simunek and van Genuchten, 1996; Ritter et al., 2004; Wöhling and Vrugt, 2011).

The final results are also influenced by the narrow range covered by the state variables in the considered experiment as well as the high correlation between the van Genuchten parameters. Several authors evidence the difficulties for the identification of the VGM parameters, as imposed by the narrow variability of naturally occurring boundary conditions (Scharnagl et al., 2011; Vrugt et al., 2001, 2002). The issues related to the correlation between VGM parameters are widely documented (e.g., Romano and Santini, 1999; van Dam, 2000; Vrugt et al., 2003).

### **References**

- Liu, Y. and Gupta H. V.: Uncertainty in hydrologic modeling: Toward an integrated data assimilation framework, *Water Resour. Res.*, 43, W07401, doi:10.1029/2006WR005756, 2007.
- Medina, H., Romano, N. and Chirico, G. B.: Kalman filters for assimilating near-surface observations in the Richards equation – Part 2: A dual filter approach for simultaneous retrieving of states and parameters, *Hydrol. Earth Syst. Sci.*, 2012, (companion paper).
- Moradkhani, H., Sorooshian, S., Gupta, H. V., and Houser, P.: Dual state-parameter estimation of hydrological models using Ensemble Kalman filter, *Adv. Water Resour.*, 28, 135–147, 2005a.
- Moradkhani, H., K.-L. Hsu, H. V. Gupta, and Sorooshian, S.: Uncertainty of hydrologic model states and parameters: Sequential data assimilation using the particle filter, *Water Resour. Res.*, 41, W05012, doi:10.1029/2004WR003604, 2005b.
- Ritter, A., Muñoz-Carpena, R., Regalado, C. M., Vanclooster, M., and Lambot, S.: Analysis of alternative measurement strategies for the inverse optimization of the hydraulic properties of a volcanic soil, *J. Hydrol.*, 295, 124–139, 2004.
- Romano, N. and Santini, A.: Determining soil hydraulic functions from evaporation experiments by a parameter estimation approach: Experimental verifications and numerical studies, *Water Resour. Res.*, 35, 3343–3359, 1999.
- Scharnagl, B., Vrugt, J. A., Vereecken, H., and Herbst, M.: Inverse modelling of in situ soil water dynamics: investigating the effect of different prior distributions of the soil hydraulic parameters, *Hydrol. Earth Syst. Sci.*, 15, 3043–3059, doi:10.5194/hess-15-3043-2011, 2011.
- Šimunek, J. and M. T. van Genuchten: Estimating Unsaturated Soil Hydraulic Properties from Tension Disc Infiltrometer Data by Numerical Inversion, *Water Resour. Res.*, 32(9), 2683–2696, doi:10.1029/96WR01525, 1996.
- Todini, E.: Mutually interactive state/parameter estimation (MISP) in hydrological applications, in *Identification and Control in Environmental Systems*, edited by G. C. Vansteenkiste, Elsevier, New York, 1978a.

- Todini, E.: Mutually interactive state/parameter estimation (MISP), in Application of Kalman Filter to Hydrology, Hydraulics and Water Resources, edited by C.-L. Chiu, Univ. of Pittsburgh, Pittsburgh, Pa, 1978b.
- Van Dam, J.C., 2000. Field-scale water flow and solute transport. SWAP model concepts, parameter estimation, and case studies. PhD-thesis, Wageningen University, Wageningen, The Netherlands, 167 p.
- Vrugt, J. A., Bouten, W., and Weerts, A. H.: Information content of data for identifying soil hydraulic parameters from outflow experiments, *Soil Sci. Soc. Am. J.*, 65, 19–27, 2001.
- Vrugt, J. A., Bouten, W., Gupta, H. V., and Sorooshian, S.: Toward improved identifiability of hydrologic model parameters: the information content of experimental data, *Water Resour. Res.*, 38, 1312, doi:10.1029/2001WR001118, 2002.
- Vrugt, J.A., Bouten, W., Gupta, H.V., and Hopmans J.W.: Toward improved identifiability of soil hydraulic parameters: On the selection of a suitable parametric model, *Vadose Zone Journal*, 2, 98-113, 2003.
- Wöhling, Th. and Vrugt, J.A.: Multi-response multi-layer vadose zone model calibration using Markov chain Monte Carlo simulation and field water retention data. *Water Resources Research*, 47, W04510, doi:10.1029/2010WR009265, 2011.