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Hydrology and Earth System Sciences
Discussions

Interactive comment on "Sensitivity of water stress in a two-layered sandy grassland soil to variations in groundwater depth and soil hydraulic parameters" *by* M. Rezaei et al.

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The authors would like to thank the first reviewer for the careful review of our manuscript and for providing us with his/her valuable comments and the suggestions. The following responses have been prepared to address all of the reviewers' comments in a point - by - point fashion. In the following text, the responses from the authors are in plain, followed by details of changes/modifications in the text (in plain and bold type). The page and line numbers are refer to the current version.

In model calibration:

Indeed, the choice of the calibration period may have influence on the results of the analysis. On the other hand, the observed soil water range and dynamics, rainfall intensity and ETo were similar in calibration and validation periods in which a similar model response and performance is expected in other different period. However, we tested parameter sensitivity and optimization for 2013 growing season period which as we expected they were similar model outputs as calibration period 2012 (results not shown in this paper). We will modify the text as follows:

In page 6893, line 14: "For accurate parameter estimation, the longer period such a growing season (i.e. 2012) with several drying and wetting events was selected. It is also suggested by Wöhling et al. (2009); Wöhling et al. (2008). Therefore, the period . . ."

In page 6893, line 15: "We used a time interval of two hours, resulting in 12960 soil water content records based on hourly precipitation and evaporation input data. Based on our experience we found out those number of data are sufficient for optimization purposes."

Model evaluation and statistical analysis:

We would adopt the text and add the justification as follows:

In page 6894, line 6: "The performance of models can be evaluated with a variety of statistics (Neuman and Wierenga, 2003). It has been known that there is no efficiency criteria which performs ideally. Each of the criteria has specific pros and cons which have to be taken into account during model calibration and evaluation. It suggested a combination of different efficiency criteria to assess of the absolute or relative volume error (Krause et al., 2005). The root-mean-square errors (RMSE), the coefficient of determination (r2), and the Nash–Sutcliffe coefficient of model efficiency (American Society of Civil Engineers, 1993), are popular and widely used performance criteria to evaluate the difference between observed and modeled data (Gandolfi et al., 2006; Nasta et al., 2013; Verbist et al., 2009; Verbist et al., 2012; Vrugt et al., 2004; Wöhling and Vrugt, 2011; Wollschlager et al., 2009). They are calculated .. . ."

In results & discussion:

Generally, we would like to stress that at the field scale non-uniform irrigation distribution (water supply in dryer parts with groundwater level below 120 cm) would be necessary and resulting in cost saving for the farmer in one hand. On the other hand, improper timing in irrigation strategy could be improved by considering soil water status, crop condition and weather forecast using combined hydrological and crop growth model in irrigation management and precision agriculture. We have tried to simplify the parameterization scenarios in the calibration and validation stage of model development. Current study provides adequate procedure to apply hydrological model in combination with crop growth model for irrigation scheduling by the practitioners. This simple approach of modeling for precision agricultural managements may extend from a local to regional scale and different crops such as the study area. The link with similar modeling exercises focusing on sensitivity analysis is already made in the current version page 6885, lines 5-8 and page 6895 lines 21-22, and also here in the following paragraphs. However, many studies did aggregate the sensitivities of different aspects and/or time steps to summarizing sensitivity indices e.g. (Li et al., 2012; Mertens et al., 2005; Verbist et al., 2012; Zhou et al., 2012). The latter makes it difficult to compare the current contribution with other papers in literature. However, we would address the following text in the manuscript:

In P 6895, lines 5-8: "Generally, all soil hydraulic parameters showed higher sensitivity in dry periods as compared to wet periods. On the other hand, there is a clear effect of parameter variability in layer 1 on water content estimation at 10 cm, and the effect is slightly declining at 20 and 30 cm, which suggested the great importance and influence of upper boundary variables especially evapotranspiration. Similar results were observed by Rocha et al. (2006). They found soil water content and pressure heads were most sensitive to hydraulic parameters variation in the dry period near the soil surface using local sensitivity analysis of Hydrus."

In page 6895, lines 8-12: "Soil-water content is sensitive to variations of α, n, and Ks in both layers. The sensitivity is the largest for n, α and less so for Ks in the first layer. For the second layer, soil-water content was most sensitive to α followed by n and Ks. Abbasi et al. (2003) reported that n, θs and Ks were most sensitive parameters in their study which more pronounced in deeper parts, however they also observed some sensitivity near the soil surface during the drier conditions. The most sensitive parameters were θs, n and α and less sensitive parameter was Ks in study of Schneider et al. (2013) using Hydrus-1D. They found large interaction (correlation) among sensitive parameters. In contrast, Wegehenkel and Beyrich (2014) found that only θr and θs are more sensitive than α, n, and Ks input parameters for soil water content simulation using hydrus-1D."

Regards to underline a bit more the limitations inherited in our LSA: It is indeed correct that the manuscript does not elaborate about the drawbacks of a local sensitivity analysis. However, we are convinced that the selection of a LSA is justified, notwithstanding the impossibility of getting more insight in higher order parameter interaction. We do agree with the referee that the reader should be informed about these limitations. As such, we adapted the text, justifying the selection of a LSA as follows:

Page 6891-6892 lines 17-23: "The effect of each input factor or parameter to the model output is determined by a local sensitivity analysis (SA), using a one-at-a-time (OAT) approach. We used this approach because it allows a clear identification of single parameter effects. Relevant parameters have major effects on output variables with only a small change in their value (Saltelli et al., 2008). Sensitivity analysis is, among other purposes, used to find the most relevant parameters which enable a reduction of the number of parameters that need to be optimized. In a local sensitivity analysis, only the local properties of the parameter values are taken into account in contrast to global sensitivity analysis which computing a number of local sensitivities. Since similar to the global sensitivity analysis such as Morris (1991) which requires a total number of runs of the number of examined parameters and provides qualitative results and our interest in this study goes specifically to the measured values in the field, a local sensitivity analysis is chosen. Furthermore, an OAT approach (local or global) does not provide direct information about higher and total order parameter interaction as is provided by variance based sensitivity analysis (Saltelli et al., 2008). However, by evaluating the parameter sensitivities in time, insight is given about potential interaction when similar individual effects are observed. The latter can be quantified by a collinearity analysis (Brun et al., 2001), but will be done graphically in this contribution. Here, a dynamic (time-variable) local. . ."

Regards to potential impact of that on generalizing the results - use in the future: We do already emphasize the importance of correct parameterizing the hydraulic parameters for irrigation management, specifically because of the importance in dry periods (which are essential for a correct irrigation management) (page 6896, lines 15-20). The application of a time variant sensitivity analysis is crucial to this respect. However, we do not want to generalize the results of the SA itself too much towards other applications, due to the case-specific aspects. Each field is specific (sometimes referred to as uniqueness of place, (Beven, 2000)) and should be treated as such. Local sensitivity analysis is a straightforward methodology, which we consider as an essential step within the modeling workflow to learn about model behavior and to identify key parameters. Applying it time variant instead of aggregating the sensitivity in a single metric is crucial to derive this kind of information. It could be interesting to compare the results with other applications in sandy two-layered soil under grass in a temperate maritime climate, but the application of the SA is as important as the result itself and will be useful in a wide set of conditions, climates and soil types. Therefore, we deliberately inform the reader in the conclusions part about the case-specific conclusions eg. [p6901, lines 20], [p6902, line 2],. . . To make this more clear, we'll adapt the text as follows:

Page 6902, line 16: ". . . they generate. We showed that it is sufficient to estimate limited amount of key parameters for which the temporal variant information of the

sensitivity is crucial. Furthermore, that optimization strategies involving multiple. . ."

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