Dear Prof. McCabe,

We would like to thank you and the three reviewers for your time and excellent comments regarding our manuscript, titled "Feasibility analysis of using inverse modeling for estimating field-scale evapotranspiration in maize and soybean fields from soil water content monitoring networks". After careful analysis of all the comments, we have made extensive revisions to our manuscript. You can find our detailed responses to the reviewers' comments (shown in red italics) and the changes we made to the manuscript in the following sections. We have also included a marked up version of the original manuscript.

On the behalf of all coauthors, I hope that this revised version would meet the publication standard of Hydrology and Earth System Sciences (HESS) and inclusion in the Eric F. Wood special issue. Please let us know if there are more questions and comments about the manuscript.

Sincerely,

Prof. Trenton E. Franz
School of Natural Resources
University of Nebraska-Lincoln, USA

Reply to the editor:

Thank you for the comments regarding our manuscript. Please see our detailed replies below.

1. All of the reviewers have requested some details on the type and manner of inverse modeling. Given the importance of this element to your work, it would be helpful to see some additional methodological paragraphs on this, rather than just referencing previous publications.

   Authors: Thank you for the suggestion. We have included more detail about the inverse methodology, which is more "off the shelf". We note that we use RMSE as our objective function to minimize in order to select parameters using the built in Hydrus software. We also have included other fitting metrics for completeness. Please see L231-234 for full details.

   L231-234: "With respect to the goodness-of-fit assessment, Root Mean Square Error (RMSE) between simulated and observed SWC was chosen as the objective function to minimize in order to estimate the soil hydraulic parameters. The built in optimization procedure in Hydrus-1D was used to perform parameter estimation."

2. Some further comment and discussion on the quality of the reproduced evaporation is warranted. Accurately (inversely) modeling the ET is clearly non-trivial and there are a multitude of possible reasons that could affect its simulation beyond just issues to do with the eddy-covariance approach. Outlining these and providing some insights and guidance where possible (e.g. the assessment of parameter uncertainty and influence on ET response) would add considerable value to the manuscript.

   Thank you for the suggestions. In order to investigate the key sources of error, as you suggested, we performed a set of preliminary sensitivity analysis experiments of effects of soil hydraulic parameters and plant root growth on the ETa and results are presented in part 3.3 (L383-L417) and figures 10 and 11. The preliminary sensitivity analysis on a number of key soil and plant parameters was very insightful and has improved the manuscript considerably. We also provide a description and a few key citations (Bastidas et al. 1999 and Rosolem et al. 2012) to undertake a more in depth sensitivity analysis in future work.

3. Certainly there is no need to overstate whether the approaches accurately match the eddy-covariance data: if the retrieval is judged to be relatively poor, the work still presents useful findings – especially if these can be related to either the interpretive model used or some other reason (parameter uncertainty, equifinality issues, measurement limitations).

Thank you for the comment. We tried to avoid overstating this in the manuscript and now provide a set of goodness of fit metrics based off RMSE. This is done for both soil water content (L278-L281) and ETa (L331-333).

L278-L281: "In this research we define RMSE values less than 0.03 cm^3/cm^3 between observed and simulated SWC values as well-matched and RMSE between 0.03 and 0.06 cm^3/cm^3 as fairly well-matched. We note the target error range of satellite SWC products (e.g. SMOS and SMAP) is less than 0.04 cm^3/cm^3 (Entekhabi et al., 2010).

L331-333: "In this research we consider RMSE values less than 1 mm/day between observed and simulated ET_a values as well-matched and RMSE values between 1 and 1.2 as fairly well-matched (Figure 9 and Table 6)."

4. Related to this, the paper would benefit by adding some detail of the evaporation sub-model, perhaps placing this in the context of other approaches that can be employed to estimate evaporation using the data that you have available (including the met data that would have been collected by the EC system). If it is a simplistic approach, perhaps it is unreasonable to expect an accurate reproduction?

   Thank you for the comment. Here we have focused on using two different data sources and HYDRUS to estimate evaporation and associated parameters. We found that the CRNP does a reasonable job (based off SWC and ETa RMSE scores and fit criteria) to constrain HYDRUS in the top layer. From the sensitivity analysis it seems constraining the soil hydraulic parameters n and alpha are critical for the top layer, indicating the CRNP may be useful in estimating evaporation, particularly when transpiration is relatively small. For more simple models we suggest that other widely used remote sensing and crop models may benefit from a constrained evaporation estimate from CRNP (L397-399).

   L397-399: "Moreover, the CRNP may be useful in helping constrain and parameterize soil hydraulic functions in simpler evaporation models used in remote sensing (c.f. Allen et al. 2007) or crop modeling (c.f. Allen et al. 1998)."

5. Where possible, reduce and merge figures and tables, only maintaining those that are directly relevant to the material being presented.

   Thank you for the comment. We tried to reduce and merge the figures as suggested by the reviewers. Reduced figures from 13 to 11 but added sensitivity analysis with same number of tables with new analyses suggested by reviewers.

Replies to Anonymous Reviewer #1

Thank you for the comments regarding our manuscript. Please see our detailed replies below.

1. The inverse methodology description is very weak. There is no description of which search method is used! What is the combined objective function? A detailed sensitivity analysis has to be given, especially in light of the mentioned problems of equifinality. It is extremely unlikely that all 24 parameters are sensitive and justify optimization. Also inverse modelling offers the opportunity to provide the reader with an estimate of the confidence intervals for each estimated parameter, which will also reveal the sensitivity and associated uncertainty.

With respect to the objective function, the central theme of the paper was to employ a standard publicity available model to test our hypothesis, not to devise new algorithms for inversion, and that is why we did not get into the inverse modeling details in great depth. As it was mentioned in the paper, more description about inverse modeling can be found in Mualem (1976), van Genuchten (1980), and Turkeltaub et al. (2015).

Moreover, Wang et al (2009) have done a detailed sensitivity analysis of groundwater recharge and evapotranspiration for soil hydraulic parameters in a single layer. The objective function we used was minimizing RMSE between observations and the model using the standard optimization algorithm provided in the HYDRUS software (L234). We provided the other goodness-of-fit metrics to further test and evaluate the model fit.

Thank you for the suggestions on the sensitivity analysis, it was very enlightening and has greatly improved the manuscript. In order to investigate the key sources of error, as you suggested, we performed a set of sensitivity analysis experiments of effects of soil hydraulic parameters and plant root growth on the ETa and results are presented in part 3.3 (L383-L417) and figures 10 and 11. We indeed found that 3 (alpha, n, Ks) of the 6 parameters were the most sensitive for the 4 soil layers. When preforming a full optimization with all 24 parameters we had an ETa RMSE of 0.911 mm/day compared to 1.511 mm/day using only 12 parameters (L402). Given that alpha, n, and Ks in the top layer were most sensitive, the CRNP may be beneficial to constrain these parameters during periods dominated by evaporation (L394). We also note that more in depth sensitivity analyses and multiple objective functions could be performed in the future as an extension of this work (L407).

Lastly, 95% confidence intervals were provided to all parameter estimates in Table 5.

Wang, T., V. A. Zlotnik, J. Simunek, and M. G. Schaap. 2009. Using pedotransfer functions in vadose zone models for estimating groundwater recharge in semiarid regions. Water Resources Research 45: 12. doi:10.1029/2008wr006903.

2. The results of simulated SWC seems to be reasonable from a SWC perspective, but it's important to also address the certainty/robustness and likelihood of the estimated soil parameters. Are they random parameter picks from an equifinal problem or are they physically reasonable and do their mutual differences fit into field/lab measurements (I assume soil samples exists from the sites)? The author has attempted to validate the spatial distribution of the estimated soil parameters based on a soil map, which is highly appreciated. However, it would have been interesting to utilize this information for regionalizing the soil parameters and thereby limiting the number of free parameters in the calibration. Likewise, the soil map could have been used to upscale the AET simulations to the field scale by including the soil map instead of a simple average of the four points.

   Thank you for the suggestion. As you suggested we upscaled ETa based on the SSURGO soil map and added the results in the manuscript (L329-L331, L350, and L363), figure 9, and tables 6 and 7. We also note that a set of hydrogeophysical maps using electromagnetic and cosmic-ray neutron rovers exist for the site and will be investigated in a companion manuscript in the future. Preliminary results indicate SSURGO zone definition is fairly accurate compared to the hydrogeophysics. However, certain boundaries appear off as a result of the limited information built into the SSURGO delineation. It is unclear how far off this lines are and if the hydrogeophysics can improve this lines for applications like precision agriculture.

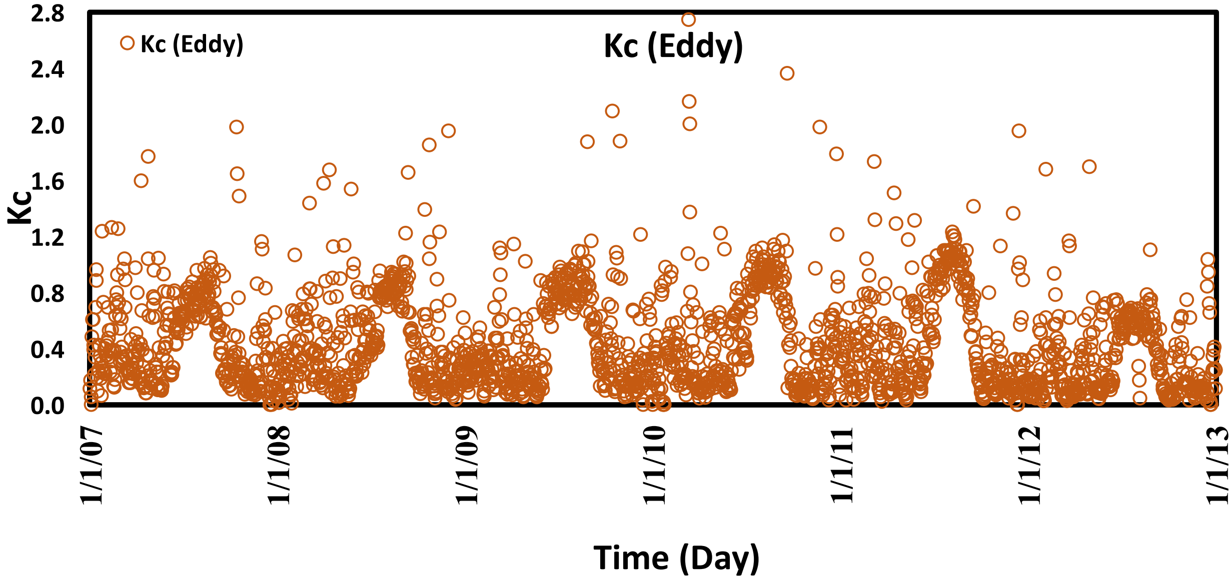
3. The results of the AET simulations seem to be very poor. I miss a critical view on the results regarding lacking ability to simulate even inter-annual variability (fig 11) and perhaps more importantly the apparently complete lack of predictive capability on the daily scale. The performance metrics in Table 6 indicate good R^2 and NSE, but that correlation is intrinsically given by the seasonality of the climate. The real test is if the model has any predictive power on estimating the evaporative fraction AET/PET. If you normalize the AET on a daily timescale by the daily PET and then calculate the R^2 and NSE, you probably get no explanation of variance. This can also be somewhat illustrated in table 6, if you add a column of RMSE in % of average daily AET, then you see that the RMSE is in the order of 50-80% of the daily AET (see attached table). In comparison most Remote sensing AET methods can, with calibration, achieve results in the order of RMSE of 25-30% of the daily mean AET.

   We compared the results with EC measured ET in this study just as a simple comparison as there was no other relatively accurate measured ET data available in the study area. As it was mentioned in the paper there are always different uncertainties involve in the Eddy-Covariance (EC) measurements. EC measurements can be bias by up to 20% or *even more. Considering this we cannot easily say since the simulated ET values are not perfectly matched with EC ET measured data that "the AET simulations seem to be very poor". We have now provided guidance on the goodness-of-fit RMSE metrics for both SWC (L278-281) and ETa (L331-333).*

L278-L281: "In this research we define RMSE values less than 0.03 cm^3/cm^3 between observed and simulated SWC values as well-matched and RMSE between 0.03 and 0.06 cm^3/cm^3 as fairly well-matched. We note the target error range of satellite SWC products (e.g. SMOS and SMAP) is less than 0.04 cm^3/cm^3 (Entekhabi et al., 2010).

L331-333: "In this research we consider RMSE values less than 1 mm/day between observed and simulated ET_a values as well-matched and RMSE values between 1 and 1.2 as fairly well-matched (Figure 9 and Table 6)."

Your suggestions are appreciated and if we had access to more accurate measured ET data, like Lysimeter measured ET, we could investigate such analysis. Because of the nature of EC ET measurements (which is not based on Kc values, but instead based on the flux measurements) such comparison may not be useful. As an example obtained Kc values from EC (2007-2012) are shown below. According to the graph, most of the times during mid-growing season, obtained Kc values from EC are less than 1 (we usually expect to have values of 1-1.2 during the mid-growth season). The average EC Kc value during July and August (2007-2012) is 0.81 with a minimum average Kc value of 0.58 in 2012 and maximum Kc value of 0.99 in 2011. On the other hand, sometimes Kc values exceed 4 while in the "real world" such Kc values do not exist. In addition, Kc values do not usually change suddenly during the growing season and it is rarely possible to have a Kc value of 1 in one day and Kc value of 0.4 for the next day, but according to the graphs in some of the days we can see this case in the EC Kc values. The inherent noise seen in Kc makes this comparison challenging without temporal smoothing.



4. Given the very little detail available on the AET model used (Feddes 1978) I can only speculate, but perhaps the simulated SWC is not accurate enough at the critical moments when AET is limited by water availability, or the AET model is not appropriate or the climate data are poor. But overall I do not find the results on simulated daily AET encouraging. An uncertainty analysis of the different model components would be appropriate (see comment below).

   Thank you for the suggestion. We added more details about Feddes (1978) model in the manuscript and that should make ETa estimation process clearer (L171-L176). Also, as previously mentioned we performed sensitivity analysis as you requested and results are presented in part 3.3 (L383-L417) and figures 10 and 11. This included a sensitivity analysis of the maximum dynamic rooting depth on ETa. The sensitivity to root distribution is more challenging and beyond the scope of the current paper.

   We appreciate the reviewer's thoughts, but most of the comments are made based on the apparent difference between the EC measured ET and simulated ET. The Hydrus model is a widely used method based on a solution to the Richards Equation. The Mead Site 3 flux tower is a long standing Ameriflux tower and continues to be a part of the core network. In order to address the comments, we performed a sensitivity analysis of all 24 soil hydraulic properties building on Wang et al. (2009). A full sensitivity analysis of the root model parameters is beyond the current scope of the paper and we refer the reviewer to Guswa (2012) and Rosolem et al. 2012 for a more robust treatment.

L171-176: "The root water uptake, S(h), was simulated according to the model of Feddes et al. (1978)

$S(h) = \alpha(h)S_p$ (4)

where α(h) is the root-water uptake water stress response function, is dimensionless and varies between 0 and 1 depending on soil matric potentials, and S_p is the potential water uptake rate and assumed to be equal to T_p. The summation of actual soil evaporation and actual transpiration is ET_a."

Guswa, A. J. 2012. Canopy vs. Roots: Production and Destruction of Variability in Soil Moisture and Hydrologic Fluxes. Vadose Zone Journal 11:3. doi:10.2136/vzj2011.0159.

Rosolem, R., H. V. Gupta, W. J. Shuttleworth, X. B. Zeng, and L. G. G. de Goncalves (2012), A fully multiple-criteria implementation of the Sobol' method for parameter sensitivity analysis, J. Geophys. Res.-Atmos., 117. doi:10.1029/2011jd016355.

Q: footprint analysis? EC footprint of 250 m radius is very large, what is the height of the EC mast?

Thank you for your comment. We added more information about the EC height in the manuscript (L119-L123).

The height on the EC mast varies with crop height. According to Suyker et al. (2004):

"To have sufficient upwind fetch (in all directions) representative of the cropping system being studied, eddy covariance sensors were mounted at 3.0 m above the ground while the canopy was shorter than 1.0 m, and later moved to a height of 6.2 m until harvest."

The footprint of the tower will there change over the season, ~100 times the tower height. This is a long running Ameriflux site and the variable footprint is a part of the method and its inherent uncertainty.

Suyker, A. E., S. B. Verma, G. G. Burba, T. J. Arkebauer, D. T. Walters, and K. G. Hubbard. 2004. Growing season carbon dioxide exchange in irrigated and rainfed maize. Agric. For. Meteorol. 124:1-2: 1-13. doi:10.1016/j.agrformet.2004.01.011.

L119-L123: "At this field, sensors are mounted at 3.0 m above the ground while the canopy is shorter than 1.0 m. At canopy heights greater than 1.0 m, the sensors are then moved to a height of 6.2 m until harvest in order to have sufficient upwind fetch (in all the directions) representative of the cropping system being studied (Suyker et al., 2004)."

5. Please explain the reasoning behind eq. 2 and 3?

We explained the reason in the response and explain in the manuscript that they are one of the model inputs (L167-L170). We needed to introduce potential evaporation (Ep) and potential transpiration (Tp) values to the Hydrus model. By using Beer's law we were able to divide ETp to Ep and Tp. Based on LAI values, with equation 2 we can calculate the Ep values and then by having the Ep value we can use equation 3 to calculate the Tp values. More information can be found in Šimunek et al, (2013).

Šimunek, J., Šejna, M., Saito, H., Sakai, M., van Genuchten, M.T. (2013). The HYDRUS-1D Software Package for Simulating the One-Dimensional Movement of Water,Heat, and Multiple Solutes in Variably-Saturated Media, Version 4.17.Department of Environmental Sciences, University of California Riverside, Riverside, California, USA, 307 pp.

6. L168: The Actual Transpiration is calculated using Feddes 1978 based on Tp and root density distribution. That must be a key component of this approach, please give more details on the application of the Feddes model.

Thank you for your comment. We added more details about Feddes (1978) model in the manuscript and that should make ETa estimation process clearer (L171-L176).

L171-176: "The root water uptake, S(h), was simulated according to the model of Feddes et al. (1978)

$$S(h) = \alpha(h)S_p \qquad (4)$$

where α(h) is the root-water uptake water stress response function, is dimensionless and varies between 0 and 1 depending on soil matric potentials, and S_p is the potential water uptake rate and assumed to be equal to T_p. The summation of actual soil evaporation and actual transpiration is ET_a."

7. L198-204: Optimized against which objective function? What was the calibration target? Which optimization algorithm (gradient based/global etc.) is used? That has to be clear up front? Also what was the result of the sensitivity analysis? Which type of sensitivity analysis, was it necessary to optimize all parameters? And why not calibrate all four layers simultaneous?

Thank you for your questions. We added a description of the objective function to the manuscript (L231-L235) and we explained why we calibrated the two upper layers first and then we calibrated the two deeper layers (L208-L213) based on minimizing RMSE between observations and model simulations. Also, as previously mentioned we performed a sensitivity analysis with results presented in part 3.3 (L383-417) and figures 10 and 11.

We note that we could not optimize all the layers simultaneously because the maximum number of parameters that we can be optimized by the Hydrus-1D model is 15. We have followed the same procedure as Turkeltaub et al. (2015) and Wang et al. (2015, 2016). Since we wanted to use standard software for parameter estimation, developing a new algorithm was beyond the scope of the paper. Certainly other algorithms that can estimate many parameters exist in hydrologic modeling (c.f. Vrugt et al. 2003).

Vrugt, J. A., H. V. Gupta, W. Bouten, and S. Sorooshian (2003), A Shuffled Complex Evolution Metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters, Water Resources Research, 39(8). doi:10.1029/2002wr001642.

L231-235: "With respect to the goodness-of-fit assessment, Root Mean Square Error (RMSE) between simulated and observed SWC was chosen as the objective function to minimize in order to estimate the soil hydraulic parameters. The built in optimization procedure in Hydrus-1D was used to perform parameter estimation."

L208-213: "Since Hydrus-1D is limited to optimizing a maximum of 15 parameters at once and that the SWC of the lower layers changes more slowly and over a smaller range than the upper layers, the van Genuchten parameters of the upper two layers were first optimized, while the parameters of the lower two layers were fixed. Then, the optimized van Genuchten parameters of the upper two layers were kept constant, while the parameters of the lower two layers were optimized. The process was continued until there were no further improvements in the optimized hydraulic parameters or until the changes in the lowest sum of squares were less than 0.1%."

8. L220-224: It might be obvious, but please state clearly, which observation data the performance metrics are based on.

Thank you for your question. We added that it is based on soil water content into the manuscript (L206).

9. L230: How are the best defined, what are the weights and how was your combined objective function defined?

   We chose the selected optimized sets of soil parameters values based on RMSE but the other metrics were included for completeness (L231-L233).

   L231-233: "With respect to the goodness-of-fit assessment, Root Mean Square Error (RMSE) between simulated and observed SWC was chosen as the objective function to minimize in order to estimate the soil hydraulic parameters."

10. L265-266: Of course the upper layers are better you calibrated them first and then kept them fixed while calibrating the lower layers, so they have had significantly more freedom in the optimization. Try to calibrate the lower first and then fix them and calibrate the upper, then you might get different results.

    The Hydrus-1D can just optimize up to 15 parameters simultaneously and we decided to optimize the upper 2 layers first and then the 2 lower layers. The SWC data in the 2 upper layers has more dynamics than the 2 lower layers. As previously mentioned we performed sensitivity analysis as requested and results are presented in part 3.3 (L383-417) and figures 10 and 11. The sensitivity analysis was very insightful about model behavior indicating that n and alpha in the top zone were the most sensitive to ETa (L391-399), thus creating opportunities for use of the CRNP.

    L391-399: "We found that n and α were the most sensitive, particularly in the shallowest soil layer. This sensitivity to the shallowest soil layer provides an opportunity to use the CRNP observations, particularly in the early growing season (i.e. when evaporation dominates latent energy flux), to help constrain estimates of n and α. As the crop continues to develop additional information in deeper soil layers should be used to estimate soil hydraulic parameters or perform data assimilation. Moreover, the CRNP may be useful in helping constrain and parameterize soil hydraulic functions in simpler evaporation models used in remote sensing (c.f. Allen et al. 2007) or crop modeling (c.f. Allen et al. 1998)."

11. L336: "the various ETa estimation techniques performed well." I disagree.

    We softened the language (L367-L371) and added specific guidelines on their performance (L331-333).

    L367-L371: "However, we note that given the fact that EC ET_a estimation can have up to 20% uncertainty (Massman and Lee, 2002, and Hollineger and Richardson, 2005), and *accounting for the natural spatial variability of ET_a due to soil texture and root depth growth uncertainties, the various ET_a estimation techniques performed fairly well."*

L331-333: "In this research we consider RMSE values less than 1 mm/day between observed and simulated ET_a values as well-matched and RMSE values between 1 and 1.2 as fairly well-matched (Figure 9 and Table 6)."

12. L337: "In fact, it is difficult to identify which is the clear solution if any." Please rephrase.

    We rephrased the sentence (L371-L372).

    L371-L372: *"In fact, it is difficult to identify which ET_a estimation method is the most accurate method."*

13. Fig 9: How come the simulated values cannot go down to 0.20-0.25 for the Cosmic ray calibration, when that is possible for the TP calibrations?

    We corrected the figure (Figure 8).

14. Fig 11: The proposed method seems to not capture the inter-annual variability, try to plot the annual values of EC against simulated annual values in a scatterplot to see if there is any correlation on an annual basis?

    Thank you for your comment. We deleted the figure and presented the results just in table 6.

15. Fig 13: You need to plot the daily obs vs. simulated AET in a scatterplot, the accumulated curves gives no indication of the performance of the daily model simulations! The bias of the Scatter plot will however give you the same information as the offset in accumulated values.

    Thank you for your suggestion. We changed the figure to Scatter plot (Figure 9).

16. Table 6: Needs units.

    Thank you for your comment. We have added units to table 3, 4, and 6.

Replies to Anonymous Reviewer #2

Thank you for the comments regarding our manuscript. Please see our detailed replies below.

P6, L114-119: Mention the instrument height above canopy for the EC tower. This would serve as a reference to validate your claim of the footprint size.

Thank you for your comment. We added more information about the EC height in the manuscript (L119-L123).

The height on the EC mast varies with crop height. According to Suyker et al. (2004):

"To have sufficient upwind fetch (in all directions) representative of the cropping system being studied, eddy covariance sensors were mounted at 3.0 m above the ground while the canopy was shorter than 1.0 m, and later moved to a height of 6.2 m until harvest."

The footprint of the tower will there change over the season, ~100 times the tower height. This is a long running Ameriflux site and the variable footprint is a part of the method and its inherent uncertainty.

Suyker, A. E., S. B. Verma, G. G. Burba, T. J. Arkebauer, D. T. Walters, and K. G. Hubbard. 2004. Growing season carbon dioxide exchange in irrigated and rainfed maize. Agric. For. Meteorol. 124:1-2: 1-13. doi:10.1016/j.agrformet.2004.01.011.

L119-L123: "At this field, sensors are mounted at 3.0 m above the ground while the canopy is shorter than 1.0 m. At canopy heights greater than 1.0 m, the sensors are then moved to a height of 6.2 m until harvest in order to have sufficient upwind fetch (in all the directions) representative of the cropping system being studied (Suyker et al., 2004)."

P7, L138-139: The reference to integration of CRNP data into the NOAH LSM seems extraneous here, and would be better deleted.

We deleted the reference from the manuscript.

P7, L141-142: No numbers are given for the footprint size of the EC tower. So there's no way for the reader to decide if this assumption is valid or not. Further, with the assumption made, a discussion on the implications of this assumption later in the manuscript would be a good addition.

Thank you for your comment. We added more information about the EC height in the manuscript (L119-L123). The assumption is that both the EC and CRNP are representative of the average conditions of the crop. This is by equivalency the same as to what an LSM grid would assume.

The height on the EC mast varies with crop height. According to Suyker et al. (2004):

"To have sufficient upwind fetch (in all directions) representative of the cropping system being studied, eddy covariance sensors were mounted at 3.0 m above the ground while the canopy was shorter than 1.0 m, and later moved to a height of 6.2 m until harvest."

The footprint of the tower will there change over the season, ~100 times the tower height. This is a long running Ameriflux site and the variable footprint is a part of the method and its inherent uncertainty.

Suyker, A. E., S. B. Verma, G. G. Burba, T. J. Arkebauer, D. T. Walters, and K. G. Hubbard. 2004. Growing season carbon dioxide exchange in irrigated and rainfed maize. Agric. For. Meteorol. 124:1-2: 1-13. doi:10.1016/j.agrformet.2004.01.011.

L119-L123: "At this field, sensors are mounted at 3.0 m above the ground while the canopy is shorter than 1.0 m. At canopy heights greater than 1.0 m, the sensors are then moved to a height of 6.2 m until harvest in order to have sufficient upwind fetch (in all the directions) representative of the cropping system being studied (Suyker et al., 2004)."

P8, L163: Please provide references to the Beer's law.

We added the reference to the Beer's law (L167) for the Hydrus code.

P8, L167: It may be better to mention that the LAI was described in the previous or study area section, rather than "above".

We changed it as you suggested (L171).

L171*: "where k is an extinction coefficient with a value set to 0.5 (Wang et al., 2009b) and LAI (L^2/L^2) is leaf area index described in the previous section."*

P8, L168: A brief description of how the Feddes model makes use of the potential transpiration and the root density distribution is necessary. Further, no details of the root density used in the study are given, which should be rectified.

Thank you for the suggestion. We added more details about Feddes (1978) model in the manuscript that should make the ETa estimation process more clear (L171-L176). Also, more information about root distribution model was provided in the manuscript (L189-L190).

L171-L176: "The root water uptake, S(h), was simulated according to the model of Feddes et al. (1978)

$S(h) = \alpha(h)S_p$ (4)

where α(h) is the root-water uptake water stress response function, is dimensionless and varies between 0 and 1 depending on soil matric potentials, and S_p *is the potential water uptake rate and assumed to be equal to* T_p*. The summation of actual soil evaporation and actual transpiration is* ET_a*."*

L189-L190: "Finally, the Hoffman and van Genuchten (1983) model was used to calculate root distribution. Further details about the model can be found in Šimunek et al., 2013."

P10, L199-205: What were the objective functions and methodology used to optimize these parameters? No description of any sort is provided, which makes it very difficult to assess the applicability.

We added objective function to the manuscript (L231-L235) and we explained that why we calibrated two upper layers first and then we calibrated the two deeper layers (L207-L214). Note, we could not optimize all the layers simultaneously because the maximum number of parameters that we can be optimized by the Hydrus-1D model is 15. We have followed the same procedure as Turkeltaub et al. (2015) and Wang et al. (2015, 2016). We used RMSE as our objective function. We performed sensitivity analysis as you requested and results are presented in part 3.3 (see L383-L415) and figures 10 and 11.

L231-235: "With respect to the goodness-of-fit assessment, Root Mean Square Error (RMSE) between simulated and observed SWC was chosen as the objective function to minimize in order to estimate the soil hydraulic parameters. The built in optimization procedure in Hydrus-1D was used to perform parameter estimation."

L207-214: "In order to efficiently optimize the parameters, we used the method outlined in Turkeltaub et al. (2015). Since Hydrus-1D is limited to optimizing a maximum of 15 parameters at once and that the] SWC of the lower layers changes more slowly and over a smaller range than the upper layers, the van Genuchten parameters of the upper two layers were first optimized, while the parameters of the lower two layers were fixed. Then, the optimized van Genuchten parameters of the upper two layers were kept constant, while the parameters of the lower two layers were optimized. The process was continued until there were no further improvements in the optimized hydraulic parameters or until the changes in the lowest sum of squares were less than 0.1%."

P11, L223: R-squared has a name. It is called the Coefficient of Determination. Also, while the other metrics are described in equations, R-squared is not.

We added the name to the manuscript (L236) and we described the equation (eq 10, L240).

P12, L230: What about R-squared?

We changed the sentence.

P12, L236: This may be a matter of semantics, but I feel that the subsection is better titled as "Vadoze Zone Inverse Modeling Results". You are performing inverse modeling of the vadose zone, not modeling of the inverse vadose zone.

Thank you for the suggestion. We changed the title as you suggested.

P12, L238/239/250: Figures 4 and 7 are interchanged. Fig. 4 shows the annual precipitation, and fig 7 shows the temporal evolution of daily SWC.

We corrected the figure numbers (Now Figures 4 and 6).

P12, L239: Not so clear. It may be good to mention that the large standard deviation values show this. Also, I was surprised to see that the upper layers had smaller SD values than the deeper layers! As the authors themselves mention elsewhere, the soil moisture variability is expected to reduce with depth. Any discussion on this phenomenon would be welcome.

We modified the sentence (L254-256).

L254-256: "Based on the large standard deviation values (Figure 4), despite the relatively small spatial scale (~65 ha) and uniform cropping at the study site, SWC varies considerably across the site (c.f. standard deviation in Figure 4), particularly during the growing season."

P13, L272-273: Based on the numbers in Table 3, I am not sure the data are "fairly well matched". R-squared < 0.1 in the validation period (and < 0.4) in the calibration period), along with a negative NSE, tells me that the model and observation were not behaving alike. Maybe addition of distribution-level metrics could help bring out the relationship (if any) between the two better.
Also, here, and through the rest of the discussion, the authors use terms such as "fairly well matched" or "performed well" or similar language. These are highly subjective terms, and no analyses of numbers are provided to support these statements. It is necessary to establish at the beginning of the section what the authors consider as a "good" or "fairly good" etc., performance means in terms of absolute numbers. While the

performance metrics are provided in the tables, no discussion is made regarding them and the reasoning for considering a particular statistic good.

Thank you for your comments. We defined each error term for SWC and ETa, and added a section at the beginning to explain those error terms (L278-281 and L331-333).

L278-281: "In this research we define RMSE values less than 0.03 cm^3/cm^3 between observed and simulated SWC values as well-matched and RMSE between 0.03 and 0.06 cm^3/cm^3 as fairly well-matched. We note the target error range of satellite SWC products (e.g. SMOS and SMAP) is less than 0.04 cm^3/cm^3 (Entekhabi et al., 2010)."

L331-333: "In this research we consider RMSE values less than 1 mm/day between observed and simulated ET_a values as well-matched and RMSE values between 1 and 1.2 as fairly well-matched (Figure 9 and Table 6)."

P14, L282: How do these soil hydraulic parameters obtained from the inverse estimation compare with the textures used in the optimization? Further, while you mention earlier in the text that 6 different soil textures were used in the optimization, you omit mentioning which textures they are.

The six textures are now included in the manuscript (L217-218). The difference in the optimized hydraulic properties roughly match with the SSURGO textural descriptions (comparison of Table 1 vs. 5 and see discussion in L299-321).

L217-218: "including sandy clay loam, silty clay loam, loam, silt loam, silt, and clay loam"

P14, L289: Provide a reference or hyperlink to the Web Soil Survey Data.

We added the hyperlink to the text (L107).

P15, L315: The infiltration rate in fine textured soil is lower, leading to higher surface runoff, as the authors mention. However, the water holding capacity of such soils is higher than coarse soils, leading to higher stored volume. I think a better argument here may be that the plant/root would have to overcome higher pressures to extract water from the fine soil, thus leading to lower ET.

Thank you for your suggestion. We added that to the manuscript (L338-L341).

L338-341: "Here smaller ET_a rates at TP 4 location are likely due to finer soil texture at this location which makes it more difficult for the plant/roots to overcome potentials to extract water from the soil, thus leading to a lower ET_a rate and greater plant stress."

P16, L330: Do you mean Figures 11 and 12 here? Figure 11 is never discussed in the entire manuscript.

We changed the figure numbers.

P16, L330-334: generally, the phenomenon of roots extracting water from deeper layers is seen in more mature vegetation such as trees, and not in seasonal agricultural crops. Also, even accepting that the plants may be drawing from layers deeper than the model domain, the phenomenon should not be so apparent in the clayey soils (TP4). A clayey soil restricts root penetration, and usually a shallow root depth is seen in such soils.

Thank you for your comments. We explained the phenomenon in more detail in the manuscript (L363-L367) and also we performed a root growth sensitivity analysis and presented the results in part 3.3 (L408-L417) and Figure 11. We also refer the reader to Guswa (2012) for a more complete discussion.

L363-367: "This shows that although 2012 was a very dry year, the plants found most of the needed water by extracting water from deeper soil reservoirs. As previously mentioned we defined a maximum root depth for the model that could greatly impact the results. To further illustrate this point, a sensitivity analysis was performed on the maximum rooting depth and presented in the following section. "

L408-417: "A sensitivity analysis of ET_a by varying rooting depth is illustrated in Figure 11. As would be expected with increasing rooting depth, higher ET_a occurred. In addition, Figure 11 illustrates a decreasing RMSE against EC observations for up to 200% increases. Again it is unclear if the EC observations are biased high or in fact rooting depths are much greater than typically considered in these models. The high observed EC values in the drought year of 2012 indicate that roots likely uptake water from below the 1 m observations. Certainly the results showed here further indicate the importance of root water uptake parameters in VZMs and LSMs, even in homogeneous annual cropping systems. While beyond the scope of this paper we refer the reader to the growing literature on the importance of root water uptake parameters on hydrologic fluxes (c.f. Schymanski et al. 2008 and Guswa 2012)."

Guswa, A. J. 2012. Canopy vs. Roots: Production and Destruction of Variability in Soil Moisture and Hydrologic Fluxes. Vadose Zone Journal 11:3. doi:10.2136/vzj2011.0159.

P16, L337: Clear solution to what?

We soften the language (L367-L371).

L367-L371: " However, we note that given the fact that EC ET_a estimation can have up to 20% uncertainty (Massman and Lee, 2002, and Hollineger and Richardson, 2005), and accounting for the natural spatial variability of ET_a due to soil texture and root depth growth uncertainties, the various ET_a estimation techniques performed fairly well."

Figures and Tables: I feel that, overall, the number of figures and tables can be reduced. As mentioned earlier, Figures 4 and 7 are interchanged.

Thank you for your comments. We tried to reduce the figures and tables and deleted some of the figures. Since we performed a sensitivity analysis we added additional figures per the reviewers suggestions.

Figures 5 and 6: Keep any one of these two. No extra information is extracted by having two figures showing the same information here.

We kept just figure 5.

Figure 10: This can be merged with fig. 1.

We merged with Figure 1.

Figure 11: This figure is never discussed in the text. Figure 12: This could be merged into fig. 11 as another panel. Also, in the text, this figure is discussed after fig. 13.

We changed the figures and discussion as suggested.

Table 1: These numbers can be discussed in the text instead of adding a single row table. As mentioned in an earlier comment, almost none of the numbers from the tables are discussed in context.

Thank you for the suggestion. We have decided to keep table to make it easier to understand expected range of parameters and understanding of sensitivity analysis presented.

Table 3: Can be merged with tab. 2.

Thank you for suggestion. Since calibration and validation are different years we decided to keep both tables for clarity.

Table 7: There is no need for this table. The numbers can be mentioned in figs. 11 and 12. That would also make those figures easier to interpret.

Thank you for suggestion. We decided to keep the tables for clarity instead of including numbers in text and in other tables.

Technical comments:
P4, L75: Should read as "… hyper-resolution LSM grid cells…" P5, L93: Check the spelling of the name "Simunek". P7, L135: "The CRNP measurement depth…" P7, L147: "… explained in detail by …" P9, L176: "… GDD approximately 60-70…" P10, L195: The abbreviation TP has not been established earlier. P10, L198: the parameter "l" should be in lower case. P13, L262: "… criteria at TP locations…" P15, L302: "… inverse VZM modeling…" VZM already includes model. P16, L333: "VZM model" Same as above. References: Ensure uniform formatting of all the bibliography. Some end in page numbers, some in years, some in journal names, and some in volumes/ issues. Table 4, Column 8: Use lower case "l" for tortuosity. Table 5, Column 6: Hectares in Field.

We have made the changes, thank you.

Replies to Anonymous Reviewer #3

Thank you for the comments regarding our manuscript. Please see our detailed replies below.

Authors estimated field scale evapotranspiration (ET) by calibrating a 1D unsaturated zone model (HYDRUS-1D) using soil water content measurements, and compared simulated ET with observed ET from an eddy covariance tower. The HYDRUS-1D soil hydraulic parameters were calibrated using daily soil water content measurements from four theta monitoring probes at multiple depths and one cosmic ray neutron probe. While this is an interesting study, the novelty of the current study is not clear. Based on presented results, large differences exist between simulated ET and eddy covariance data and results of soil moisture simulations are not entirely satisfactory given the negative NSE during calibration and small coefficient of determination for soil moisture simulations at certain depths. In particular, authors have not discussed the implications of their results and what can be done to improve model estimation. While the focus of the inverse modelling was on soil hydraulic parameters estimation, the study can benefit from a detailed model sensitivity experiment to soil hydraulic and root growth function model parameters. I suggest authors to perform a detailed uncertainty estimation approach to identify the sources of errors (model input, parameters, or model structure) in

ET and soil water content estimates. This can help to identify why the model did not perform well in some cases and how authors can improve their results.

Thank you for the suggestions. In order to investigate the key sources of error, as you suggested, we performed a set of sensitivity analysis experiments of effects of soil hydraulic parameters and plant root growth on the ETa *and results are presented in part 3.3 (L383-L417) and figures 10 and 11. The preliminary sensitivity analysis on a number of parameters was very insightful and has improved the manuscript considerably. We also provide a description and a few key citations (Bastidas et al. 1999 and Rosolem et al. 2012) to undertake a more in depth sensitivity analysis in future work.*

1. Introduction, the rational and implications of the current study are not entirely clear. I suggest authors outline the main objectives of their study and discuss how their results advance our understanding of ET estimation using unsaturated zone models. It is not clear whether authors try to develop a benchmark for soil moisture or ET estimation or how their soil hydraulic parameter estimation can help parametrize hyper-resolution land surface models? These are the ideas that are discussed in the Introduction but their links with the current study are not clear.

The introduction was modified for clarity. Specifically, the manuscript lays out the methodology for taking SWC observations to estimate ETa. Both SWC and ETa are key benchmarks needed by the LSM community. The final paragraph in the introduction lays out the motivation and key outcomes (L89-100). The abstract also discusses the societal need for these value added products from SWC monitoring alone.

L89-100: "The aim of this study is to examine the feasibility of using inverse VZM modeling for estimating field scale ET_a based on long-term local meteorological and SWC observations for an Ameriflux (Baldocchi et al., 2001) EC site in eastern Nebraska, USA. We note that while this study focused on one particular study site in eastern Nebraska, the methodology can be easily adapted to a variety of SWC monitoring networks across the globe (Xia et al., 2015), thus providing an extensive set of benchmark data for use in LSMs. The remainder of the paper is organized as follows. In the methods section we will describe the widely used VZM, Hydrus-1D (Šimunek et al., 2013), used to obtain soil hydraulic parameters. We will assess the feasibility of using both profiles of in-situ SWC probes as well as the area-average SWC technique from Cosmic-Ray Neutron Probes (CRNP). In the results section we will compare simulated ET_a resulted from calibrated VZM with independent ET_a estimates provided by EC observations. Finally a sensitivity analysis of key soil and plant parameters will be presented."

2. Section 2.2.1. It seems authors have used a different growth root model compared to the HYDRUS-1D root growth model for annual vegetation. Have authors performed any experiments to assess how the results of the two root growth models compare?

   Since we had annual cultivation rotation between soybean and maize we had to introduce the root depth to the model and we could not use the default values inside the model. Likewise, as default values were constant and cannot be changed for different type of crops in different years during the simulation, we were not able to compare the models. This parameterization is not available in the standard HYDRUS package and a limitation of using it with crop rotations. We wanted to keep intact the cropping history to minimize impact on SWC between years. Clearly the topic of root water uptake deserves more investigation. We did perform a root depth sensitivity analysis summarized in Figure 11.

3. Section 2.2.1. It will be very useful if authors can report Kc parameters and root growth model parameters as they can impact the results of ET estimation.

   As it was mentioned, we performed a root growth sensitivity analysis and presented the results in part 3.3 (L408-L417) and Figure 11 to investigate the impact of root depth on ETa. A discussion of observed Kc values can be found above in response to reviewer 1 (graph on page 6).

4. Section 2.2.2. Additional details regarding the inverse modelling algorithm and an objective function that is used for parameter estimation are required.

   We added a description of the objective function to the manuscript (L233-L235) and we explained why we calibrated the two upper layers first and then we calibrated the two deeper layers (L209-L212) based on minimizing RMSE between observations and model simulations. Also, as previously mentioned we performed a sensitivity analysis with results presented in part 3.3 (L383-417) and figures 10 and 11.

   We note that we could not optimize all the layers simultaneously because the maximum number of parameters that we can be optimized by the Hydrus-1D model is 15. We have followed the same procedure as Turkeltaub et al. (2015) and Wang et al. (2015, 2016). Since we wanted to use standard software for parameter estimation, develop a new algorithm was beyond the scope of the paper. Certainly other algorithms that can estimate many parameters exist in hydrologic modeling (c.f. Vrugt et al. 2003).

   Vrugt, J. A., H. V. Gupta, W. Bouten, and S. Sorooshian (2003), A Shuffled Complex Evolution Metropolis algorithm for optimization and uncertainty assessment of

hydrologic model parameters, Water Resources Research, 39(8). doi:10.1029/2002wr001642.

5. Section 2.2.2. Line 206- Can authors provide further details about initial soil hydraulic parameters that they used in the modelling experiment? Did they use soil hydraulic parameters based on soil texture class information? Similarly, authors used the same parameter bounds for model calibration for all soil texture classes. It will be useful if authors can incorporate the soil texture information to define priors and initial parameter values.

   The initial values were just the default values in the Hydrus-1D model which are based on the different soil types. Agreed, priors could be used with pedotransfer functions to improve results. Unfortunately, the connection between hydrologic fluxes and soil texture classes is unclear (Groenendyk et al. 2015). This work continues on that disconnection. The comparison between the SSURGO textural classes and the optimized soil hydraulic functions (Tables 1 to 5) deserves more attention in future work.

   Groenendyk, D. G., T. P. A. Ferre, K. R. Thorp, and A. K. Rice. 2015. Hydrologic-Process-Based Soil Texture Classifications for Improved Visualization of Landscape Function. PLoS One 10:6: 17. doi:10.1371/journal.pone.0131299.

6. Section 2.2.2. Why homogeneous soil type was used for simulating water content for the Cosmos-Ray neutron probe while for the Theta probes variability in vertical hydraulic conductivity is considered?

   As a first cut we used a single layer. Since the CRNP only sees the top 20 cm we wanted to see how well it could or not reproduce ETa values. Clearly more investigation is needed about the use of CRNP to estimate ETa. The sensitivity analysis indicates that constraining alpha, n, and Ks in the top layer is most important for estimates of ET. The CRNP could be used to estimate these in periods where evaporation controls Latent Energy flux as suggested in L391-393.

   L391-393: "Moreover, the CRNP may be useful in helping constrain and parameterize soil hydraulic functions in simpler evaporation models used in remote sensing (c.f. Allen et al. 2007) or crop modeling (c.f. Allen et al. 1998)."

7. Why the spin-up period is varied between the inverse modelling approach and the forward model? What criteria authors used to define model spin-up?

Because the longer sets of climatic data exist, compared to the SWC at the study site (L247-L247).

L247-L249: "Finally, we note that the years 2004-2006 were used as a model spin-up period for the forward model and evaluation of ET_a because of the longer climate record length."

8. Table 2-Why negative NSE is obtained during calibration period particularly in deeper soil layers? Even R2 values are pretty small for a VZM model that is calibrated to observations. Can authors describe the reasons for this mismatch? Similarly results of soil moisture simulation are not satisfactory for the CRNP calibration based on Table 3.

   We defined each error term for SWC and ETa, and added a section at the beginning to explain those error terms (L278-281 and L331-333). We note that the model is optimized by RMSE whereas NSE and R2 are additional evaluation metrics. We deemed well matched as RMSE between 0 and 0.03 cm3/cm3 per satellite remote sensing standards. With respect to the difference in ETa, I suspect the root zone depth and distribution will greatly impact this as indicated by our preliminary sensitivity analysis (Figure 11). Clearly more work devoted to root water uptake parameters is needed.

   L278-281: "In this research we define RMSE values less than 0.03 cm^3/cm^3 between observed and simulated SWC values as well-matched and RMSE between 0.03 and 0.06 cm^3/cm^3 as fairly well-matched. We note the target error range of satellite SWC products (e.g. SMOS and SMAP) is less than 0.04 cm^3/cm^3 (Entekhabi et al., 2010)."

   L331-333: "In this research we consider RMSE values less than 1 mm/day between observed and simulated ET_a values as well-matched and RMSE values between 1 and 1.2 as fairly well-matched (Figure 9 and Table 6)."

9. Authors indicate that inverse modelling based on CRNP data is most useful during the periods that soil evaporation is dominant. Can authors further explain why that is the case? One would expect that CRNP should provide better estimate of ET as its footprint is likely to overlap the EC tower footprint.

   Since the CRNP only sees the top 20 cm we wanted to see how well it could or not reproduce ETa values. We hypothesize that at roots development into deeper layers and Transpiration becomes more important in the latent energy term the information content in the CRNP would diminish. Clearly this topic requires more investigation. The sensitivity analysis indicates that constraining alpha, n, and Ks in the top layer is most *important for estimates of ET. The CRNP could be used to estimate these in periods where evaporation controls Latent Energy flux as suggested in L397-399.*

L397-399: "Moreover, the CRNP may be useful in helping constrain and parameterize soil hydraulic functions in simpler evaporation models used in remote sensing (c.f. Allen et al. 2007) or crop modeling (c.f. Allen et al. 1998)."

10. Section 3.2. Authors relate variability in performance of the model in ET simulation to variability in soil texture. However, one important information that is missing is vegetation type at the location of the probes and the EC tower footprint scale. Perhaps, authors should combine ET estimates from multiple probes to estimate ET at a field scale.

    As you suggested we upscaled ETa based on the SSURGO soil map to the field scale and results added in the manuscript (L329-L331, L350, and L363), Figure 9, and tables 6 and 7.

11. It will be useful if authors can provide information about deep drainage from model simulations at multiple locations.

    For the interested reader, the deep drainage can be calculated by the using mass balance with precipitation, ET, and runoff provided in the manuscript (L341-345). Since deep drainage was not discussed in the results it is unclear what this would provide to the main objective of the paper. For detailed discussion of deep drainage in Neb we suggest the reader see Wang et al. 2016.

    L341-345: "In addition, higher surface runoff can be expected at the TP 4 location due to finer-textured soils. According to the simulation results the average surface runoff at the TP 4 location was about 44.8 mm/year from 2007 to 2012, while the average surface runoff at the other three locations (TPs 1-3) was around 10.6 mm/year, which partially accounts for the lower ET_a rates."

    Wang, T., Franz, T. E., Yue, W., Szilagyi, J., Zlotnik, V. A., You, J., et al. (2016). Feasibility analysis of using inverse modeling for estimating natural groundwater recharge from a large-scale soil moisture monitoring network. Journal of Hydrology, 533, 250-265.

12. Line 166- Extinction

Change made, thank you.

13. Line 238-Please revise the Figure number to 7.

We corrected the figure numbers (Figures 4 and 6).

14. Figure 5- Can authors describe the reason for large differences between the spatially averaged TP and CRNP by the end of year 2014?

We suspect that there is an issue with the TP data at that point in time, perhaps due to frozen soils?

Feasibility analysis of using inverse modeling for estimating field-scale evapotranspiration in maize and soybean fields from soil water content monitoring networks

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Keywords**:** Evapotranspiration; Soil Water Content; Inverse Modeling; Soil Hydraulic Parameters; Cosmic-Ray Neutron Probe

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Abstract

In this study the feasibility of using inverse vadose zone modeling for estimating field scale actual evapotranspiration (ET_a) was explored at a long-term agricultural monitoring site in eastern Nebraska. Data from both point scale soil water content (*SWC*) sensors and the area-average technique of Cosmic-Ray Neutron Probes were evaluated against independent ET_a estimates from a co-located Eddy-Covariance tower. While this methodology has been successfully used for estimates of groundwater recharge, it was essential to assess the performance of other components of the water balance such as ET_a. In light of the recent evaluation of Land Surface Model (LSM) performance from the plumber experiment, independent estimates of hydrologic state variables and fluxes are critically needed benchmarks. The results here indicate reasonable estimates of daily and annual ET_a from the point sensors, but with highly varied soil hydraulic function parameterizations due to local soil texture variability. The results of multiple soil hydraulic parameterizations leading to equally good ET_a estimates is consistent with the hydrological principle of equifinality. While this study focused on one particular site, the framework can be easily applied to other *SWC* monitoring networks across the globe. The value added products of groundwater recharge and ET_a flux from the *SWC* monitoring networks will provide additional and more robust benchmarks for the validation of LSM that continues to improve their forecast skill. In addition, the value added products of groundwater recharge and ET_a often have more direct impacts on societal decision making than *SWC* alone. Water flux impacts human decision making from policies on the long-term management of groundwater resources (recharge), to yield forecasts (ET_a), and to optimal irrigation scheduling (ET_a). Illustrating the societal benefits of *SWC* monitoring is critical to insure the continued operation and expansion of these public datasets.

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1. Introduction

Evapotranspiration (ET) is an important component in terrestrial water and surface energy balance. In the United States, ET comprises about 75% of annual precipitation, while in arid and semiarid regions ET comprises more than 90% of annual precipitation (Zhang et al., 2001; Glenn et al., 2007; Wang et al., 2009a). As such, an accurate estimation of ET is critical in order to predict changes in hydrological cycles and improve water resource management (Suyker et al., 2008; Anayah and Kaluarachchi, 2014). Given the importance of ET, an array of measurement techniques at different temporal and spatial scales have been developed (c.f., Maidment, 1992; Zhang et al., 2014), including lysimeter, Bowen ratio, Eddy-Covariance (EC), and satellite-based surface energy balance approaches. However, simple, low-cost, and accurate field-scale measurements of actual ET (ET_a) still remain a challenge due to the uncertainties of available estimation techniques (Wolf et al., 2008; Li et al., 2009; Senay et al., 2011; Stoy, 2012). For instance, field techniques, such as EC and Bowen ratio, can provide relatively accurate estimation of local ET_a, but are often cost prohibitive for wide-spread use beyond research applications (Baldocchi et al., 2001; Irmak, 2010). By comparison, satellite-based remote sensing techniques are far less costly for widespread spatial coverage (Allen et al., 2007), but are limited by their accuracy, temporal sampling frequency (e.g., Landsat 8 has a 16-day overpass), and technical issues that further limit temporal sampling periods (e.g., cloud coverage during overpass) (Chemin and Alexandridis, 2001; Xie et al., 2008; Li et al., 2009; Kjaersgaard et al., 2012).

As a complement to the above mentioned techniques, recent studies have used process-based vadose zone models (VZMs) for estimating field-scale ET_a with reasonable success, particularly in arid and semi-arid areas (Twarakavi et al., 2008; Izadifar and Elshorbagy, 2010; Galleguillos et al., 2011; Wang et al., 2016). Although VZMs are time and cost effective for estimating field-scale ET_a, they generally require complex model parameterizations and inputs, some of which are not readily available (e.g., soil hydraulic parameters and plant physiological parameters; c.f. Wang et al., 2016). In order to address the issue of missing soil hydraulic parameters, a common approach is to use pedotransfer functions to convert readily available soil information (e.g., texture, bulk density, etc.) to soil hydraulic parameters (Wösten et al., 2001); however, significant uncertainties are usually associated with this method for estimating local scale water fluxes (Wang et al., 2015). In fact, Nearing et al. (2016) identified soil hydraulic property estimation as the largest source of information lost when evaluating different land surface modeling schemes versus a soil moisture benchmark. Poor and uncertain parameterization of soil hydraulic properties is a clear weakness of land surface models (LSMs) predictive skill in sensible and latent heat fluxes (Best et al., 2015). This problem will continue to compound with the continuing spatial refinement of hyper-resolution LSM grid cells to less than 1 km (Wood et al., 2011).

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In order to address the challenge of field scale estimation of soil hydraulic properties, here we utilize inverse modeling for estimating soil hydraulic parameters based on field measurements of soil water content (*SWC*) (c.f. Hopmans and Šimunek, 1999; Ritter et al., 2003). While VZM-based inverse modeling approaches have already been examined for estimating groundwater recharge (e.g., Jiménez-Martínez et al., 2009; Andreasen et al., 2013; Min et al., 2015; Ries et al., 2015; Turkeltaub et al., 2015; Wang et al., 2016), its application for ET_a estimation has not been adequately tested. Moreover, we note that simultaneous estimation of *SWC* states and surface energy fluxes within LSMs is complicated by boundary conditions, model parameterization, and model structure (Nearing et al., 2016). With the incorporation of regional soil datasets in LSMs like Polaris (Chaney et al., 2016), effective strategies for estimating ground truth soil hydraulic properties from existing *SWC* monitoring networks (e.g., SCAN, CRN, COSMOS, State/National Mesonets, c.f. Xia et al. (2015)) will become critical for continuing to improve the predictive skill of LSMs.

The aim of this study is to examine the feasibility of using inverse VZM modeling for estimating field scale ET_a based on long-term local meteorological and *SWC* observations for an Ameriflux (Baldocchi et al., 2001) EC site in eastern Nebraska, USA. We note that while this study focused on one particular study site in eastern Nebraska, the methodology can be easily adapted to a variety of *SWC* monitoring networks across the globe (Xia et al., 2015), thus providing an extensive set of benchmark data for use in LSMs. The remainder of the paper is organized as follows. In the methods section we will describe the widely used VZM, Hydrus-1D (Šimunek et al., 2013), used to obtain soil hydraulic parameters. We will assess the feasibility of using both profiles of in-situ *SWC* probes as well as the area-average *SWC* technique from Cosmic-Ray Neutron Probes (CRNP). In the results section we will compare simulated ET_a resulted from calibrated VZM with independent ET_a estimates provided by EC observations. Finally a sensitivity analysis of key soil and plant parameters will be presented.

2. Materials and Methodology

2.1 Study Site

The study site is located in eastern Nebraska, USA at the University of Nebraska Agricultural and Development Center near Mead. The field site (US-Ne3, Figure 1a, 41.1797° N, 96.4397° W) is part of the Ameriflux Network (Baldocchi et al., 2001) and has been operating continually since 2001. The regional climate is of a continental semiarid type with a mean annual precipitation of 784 mm/year (according to the Ameriflux US-Ne3 website). According to the Web Soil Survey Data

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(Soil Survey Staff, 2016, http://websoilsurvey.nrcs.usda.gov/), the soils at the site are comprised mostly of silt loam and silty clay loam (Figure 1b and Table 1). Soybean and maize are rotationally grown at the site under rainfed conditions, with the growing season beginning in early May and ending in October (Kalfas et al., 2011). Since 2001, crop management practices (i.e., planting density, cultivars, irrigation, and herbicide and pesticide applications) have been applied in accordance with standard best management practices prescribed for production-scale maize systems (Suyker et al., 2008). More detailed information about site conditions can be found in Suyker et al. (2004) and Verma et al. (2005).

An EC tower was constructed at the center of the field (Figure 1 and Figure 2a), which continuously measures water, energy, and CO_2 fluxes (e.g., Baldocchi et al., 1988). At this field, sensors are mounted at 3.0 m above the ground when the canopy is shorter than 1.0 m. At canopy heights greater than 1.0 m, the sensors are then moved to a height of 6.2 m until harvest in order to have sufficient upwind fetch (in all directions) representative of the cropping system being studied (Suyker et al., 2004). In this study, hourly latent heat flux measurements were integrated to daily values and then used for calculating daily EC ET_a integrated over the field scale. Detailed information on the EC measurements and calculation procedures for ET_a are given in Suyker and Verma (2009). Hourly air temperature, relative humidity, horizontal wind speed, net radiation, and precipitation were also measured at the site. Destructive measurements of leaf area index (*LAI*) were made every 10 to 14 days during the growing season at the study site (Suyker et al., 2005). We note that the *LAI* data were linearly interpolated to provide daily estimates. Theta probes (TP) (Delta-T Devices, Cambridge, UK) were installed at 4 locations in the study field with measurement depths of 10, 25, 50, and 100 cm at each location to monitor hourly *SWC* in the root zone (Suyker et al., 2008). Here, we denote these four locations as TP 1 (41.1775° N, 96.4442° W), TP 2 (41.1775° N,

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96.4428° W), TP 3 (41.1775° N, 96.4402° W), and TP 4 (41.1821° N, 96.4419° W) (Figure 1b). Daily precipitation (*P*) and reference evapotranspiration (ET_r) computed for the tall (alfalfa) reference crop using the ASCE standardized Penman-Monteith equation (ASCE-EWRI 2005) are shown in Figure 3 for the study period (2007–2012) at the study site.

In addition, a CRNP (model CRS 2000/B, HydroInnova LLC, Albuquerque, NM, USA, 41.1798 N°, 96.4412° W) was installed near the EC tower (Figure 1b and 2b) on 20 April 2011. The CRNP measures hourly moderated neutron counts (Zreda et al., 2008, 2012), which are converted into *SWC* following standard correction procedures and calibration methods (c.f., Zreda et al., 2012). In addition, the changes in above-ground biomass were removed from the CRNP estimates of *SWC* following Franz et al. (2015). The CRNP measurement depth (Franz et al., 2012) at the site varies between 15-40 cm, depending on *SWC*. Note for simplicity in this analysis we assume the CRNP has an effective depth of 20 cm (mean depth of 10 cm) for all observational periods. The areal footprint of the CRNP is ~250+/-50 m radius circle (see Desilets and Zreda 2013 and Köhli et al., 2015 for details). Here we assume for simplicity the EC and CRNP footprints are both representative of the areal-average field conditions.

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2.2. Model setup

2.2.1 Vadose Zone Model

The Hydrus-1D model (Šimunek et al., 2013), which is based on the Richards equation, was used to calculate ET_a. The setup of the Hydrus-1D model is explained in detail by Jiménez-Martínez et al. (2009), Min et al. (2015), and Wang et al. (2016), and only a brief description of the model setup is provided here. Given the measurement depths of the Theta Probes, the simulated soil profile

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length was chosen to be 175 cm with 176 nodes at 1 cm intervals. An atmospheric boundary condition with surface runoff was selected as the upper boundary. This allowed the occurrence of surface runoff when precipitation rates were higher than soil infiltration capacity or if the soil became saturated. According to a nearby USGS monitoring well (Saunders County, NE, USGS 411005096281502, ~2.7 km away), the depth to water tables was greater than 12 m during the study period. Therefore, free drainage was used as the lower boundary condition.

Daily ET_r was calculated using the ASCE Penman-Monteith equation for the tall (0.5 m) ASCE reference (ASCE-EWRI, 2005), and daily potential evapotranspiration (ET_p) was calculated according to FAO 56 (Allen et al., 1998):

$$ET_p(t) = K_c(t) \times ET_r(t) \quad (1)$$

where Kc is a crop-specific coefficient at time t. The estimates of growth stage lengths and Kc values for maize and soybean suggested by Allen et al. (1998) and Min et al. (2015) were adopted in this study. In order to partition daily ET_p into potential transpiration (T_p) and potential evaporation (E_p) as model inputs, Beer's law (Šimunek et al., 2013) was used as follows:

$$E_p(t) = ET_p(t) \times e^{-k \times LAI(t)} \quad (2)$$

$$T_p(t) = ET_p(t) - E_p(t) \quad (3)$$

where k [-] is an extinction coefficient with a value set to 0.5 (Wang et al., 2009b) and LAI [L^2/L^2] is leaf area index described in the previous section. The root water uptake, $S(h)$, was simulated according to the model of Feddes et al. (1978):

$$S(h) = \alpha(h) \times S_p \quad (4)$$

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where $\alpha(h)$ [-] is the root-water uptake water stress response function and varies between 0 and 1 depending on soil matric potentials, and S_p is the potential water uptake rate and assumed to be equal to T_p. The summation of actual soil evaporation and actual transpiration is ET_a.

Since the study site has annual cultivation rotations between soybean and maize, the root growth model from the Hybrid-Maize Model (Yang et al., 2004) was used to model the root growth during the growing season

$$\begin{cases} if\ D < MRD,\ D = \frac{AGDD}{GDD_{Silking}} MRD \\ or\ D = MRD \end{cases} \quad (5)$$

where D (cm) is plant root depth for each growing season day, MRD is the maximum root depth (assumed equal to 150 cm for maize and 120 cm for soybean in this study following Yang et al. 2004), $AGDD$ is the accumulated growing degree days, and $GDD_{Silking}$ is the accumulated GDD at the silking point (e.g., accumulated plant GDD approximately 60-70 days after crop emergence). GDD for each growing season day was calculated as:

$$GDD = \frac{T_{max} - T_{min}}{2} - T_{base} \quad (6)$$

where T_{max} and T_{min} are the maximum and minimum daily temperature (°C), respectively, and T_{base} is the base temperature set to be 10° C following McMaster and Wilhelm (1997) and Yang et al. (1997). Finally, the Hoffman and van Genuchten (1983) model was used to calculate root distribution. Further details about the model can be found in Šimunek et al. (2013).

2.2.2 Inverse modeling to estimate soil hydraulic parameters

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Inverse modeling was used to estimate soil hydraulic parameters for the van Genuchten-Mualem model (Mualem, 1976; van Genuchten, 1980):

$$\theta(h) = \begin{cases} \theta_r + \frac{\theta_s - \theta_r}{(1+|\alpha h|^n)^m}, h < 0 \\ \theta_s,\ h \geq 0 \end{cases} \quad (7)$$

$$K(S_e) = K_s \times S_e^{\,l} \times [1-(1-S_e^{1/m})^m]^2 \quad (8)$$

where θ [L^3/L^3] is volumetric *SWC*; θ_r [L^3/L^3] and θ_s [L^3/L^3] are residual and saturated moisture content, respectively; h [L] is pressure head; K [L/T] and K_s [L/T] are unsaturated and saturated hydraulic conductivity, respectively; and S_e (=(θ–θ_r)/(θ_s–θ_r)) [-] is saturation degree. With respect to the fitting factors, α [1/L] is inversely related to air entry pressure, n [-] measures the pore size distribution of a soil with m=1–1/n, and l [-] is a parameter accounting for pore space tortuosity and connectivity.

Daily *SWC* data from the four TP locations and CRNP location were used for the inverse modeling. Based on the measurement depths of the TPs, the simulated soil columns were divided into four layers for TP locations (i.e., 0-15 cm, 15-35 cm, 35-75 cm, and 75-175 cm), which led to a total of 24 hydraulic parameters (θ_r, θ_s, α, n, K_s, and l) to be optimized based on observed *SWC* values. In order to efficiently optimize the parameters, we used the method outlined in Turkeltaub et al. (2015). Since Hydrus-1D is limited to optimizing a maximum of 15 parameters at once and that the *SWC* of the lower layers changes more slowly and over a smaller range than the upper layers, the van Genuchten parameters of the upper two layers were first optimized, while the parameters of the lower two layers were fixed. Then, the optimized van Genuchten parameters of the upper two layers were kept constant, while the parameters of the lower two layers were optimized. The process was continued until there were no further improvements in the optimized hydraulic parameters or until the changes in the lowest sum of squares were less than 0.1%. Given the sensitivity of the

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optimization results to the initial guesses of soil hydraulic parameters in the Hydrus model, soil hydraulic parameters from six soil textures were used as initial inputs for the optimizations at each location (Carsel and Parish, 1988), including sandy clay loam, silty clay loam, loam, silt loam, silt, and clay loam. Based on the length of available *SWC* data from the TP measurements, the periods of 2007, 2008-2010, and 2011-2012 were used as the spin-up, calibration, and validation periods, respectively. Moreover, to minimize the impacts of freezing conditions on the quality of *SWC* measurements, data from January to March of each calendar year were removed (based on available soil temperature data) from the optimizations.

In addition to the TP profile observations, we used the CRNP area-average *SWC* in the inverse procedure to develop an independent set of soil parameters. The CRNP was assumed to provide *SWC* data with an average effective measurement depth of 20 cm at this study site. The observation point was therefore set at 10 cm. As a first guess and in the absence of other information, soil properties were assumed to be homogeneous throughout the simulated soil column with a length of 175 cm. Because the CRNP was installed in 2011 at the study site, the periods of 2011, 2012-2013, and 2014 were used as spin-up, calibration, and validation periods, respectively, for the optimization procedure.

The lower and upper bounds of each van Genuchten parameter are provided in Table 2. With respect to the goodness-of-fit assessment, Root Mean Square Error (RMSE) between simulated and observed *SWC* was chosen as the objective function to minimize in order to estimate the soil hydraulic parameters. The built in optimization procedure in Hydrus-1D was used to perform parameter estimation. A sensitivity analysis of the six soil model parameters was performed. In addition, three additional performance criteria, including Coefficient of Determination (R^2), Mean

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Average Error (MAE), and the Nash-Sutcliffe Efficiency (NSE) were used to further evaluate and validate the selected model behavior:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \quad (9)$$

$$R^2 = \left(\frac{n(\sum_{i=1}^{n} P_i O_i) - (\sum_{i=1}^{n} P_i)(\sum_{i=1}^{n} O_i)}{\sqrt{[n\sum_{i=1}^{n} P_i^2 - (\sum_{i=1}^{n} P_i)^2][n\sum_{i=1}^{n} O_i^2 - (\sum_{i=1}^{n} O_i)^2]}}\right)^2 \quad (10)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - O_i| \quad (11)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O}_i)^2} \quad (12)$$

where n is the total number of *SWC* data points, O_i, and P_i, are respectively the observed and simulated daily *SWC* on day i, and $\bar{O}_i$ is the observed mean value. Based on the best scores (i.e., lowest RMSE values), the best optimized set of soil hydraulic parameters at each location were selected. Using the selected parameters, the Hydrus model was then run in a forward mode in order to estimate ET_a between 2007 and 2012. Finally, we note that the years 2004-2006 were used as a model spin-up period for the forward model and evaluation of ET_a because of the longer climate record length.

3. Results and Discussions

3.1 Vadose Zone Inverse Modeling Results

The time series of the average *SWC* from the four TP locations along with one standard deviation at each depth are plotted in Figure 4. Based on the large standard deviation values (Figure 4), despite the relatively small spatial scale (~65 ha) and uniform cropping at the study site, *SWC*

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As an illustration, Figure 7 shows the daily observed and simulated *SWC* during the calibration (2008–2010) and validation (2011–2012) periods at the TP 1 location (the simulation results of the other three sites can be found in the supplemental Figures S1, S2, and S3). The results of objective function criterion (RMSE) and the other three performance criteria (e.g., R^2, MAE, and NSE) between simulated and observed *SWC* values at TPs locations are presented in Table 3.

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In this research we define RMSE values less than 0.03 cm^3/cm^3 between observed and simulated *SWC* values as well-matched and RMSE between 0.03 and 0.06 cm^3/cm^3 as fairly well-matched. We note the target error range of satellite *SWC* products (e.g. SMOS and SMAP) is less than 0.04 cm^3/cm^3 (Entekhabi et al., 2010). Similar to previous studies (e.g., Jiménez-Martínez et al., 2009; Andreasen et al., 2013; Min et al., 2015; Wang et al., 2016), the results of all the performance criteria at TP locations show the capability of inverse modeling in estimation of soil hydraulic parameters. The results of the calibration period (2008-2010) indicate that the simulated and observed *SWC* values are in good agreement (i.e. well matched as defined above) throughout the entire period at most locations and depths (Figure 7 and Table 3). In addition, the simulated and observed *SWC* data are fairly well-matched at most locations and depths during the validation period (2011-2012), with notable differences during the second half of 2012 during the extreme drought conditions (Figure 7 and Table 3). Reasons for this disagreement in the observed and simulated *SWC* data will be discussed in the following sections.

The results of inverse modeling using the CRNP data also indicate the feasibility of using these data to estimate effective soil hydraulic parameters (Figure 8 and Table 4). Based on the performance criteria (Table 4), the simulated data are fairly well-matched with the observed *SWC* data during both the calibration and validation periods. Additional information from deeper soil probes or more complex modeling approaches such as data assimilation techniques (Rosolem et al., 2014, Renzullo et al., 2014) may be needed to fully utilize the CRNP data for the entire growing season. However, this was beyond the scope of the current study and merits further investigation given the global network of CRNP (Zreda et al., 2012) dating back to ~2011.

Table 5 summarizes the optimized van Genuchten parameters for the four different depths of the four TP locations and the single layer for the CRNP location. The optimized parameters were

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then used to estimate ET_a for the entire study period as an independent comparison to the EC ET_a data. The results of the ET_a evaluation will be discussed in the next section. According to the simulation results (Table 5), in most of the soil layers, the TP 4 location results in lower n, K_s, and higher θ_r values than the other 3 locations (TPs 1-3), suggesting either underlying soil texture variability in the field or texture dependent sensor sensitivity/calibration. As a validation for the simulation results, the publicly available Web Soil Survey Data (http://websoilsurvey.nrcs.usda.gov/) was used to explore whether the optimized van Genuchten parameters from the inverse modeling (Figure 1b and Table 2) agreed qualitatively with the survey data. Based on the Web Soil Survey Data, the soil at the TP 4 location contains higher clay percentage than the other locations. Meanwhile, the optimized parameters reflect the spatial pattern of soil texture in the field as shown by the Web Soil Survey Data (e.g., lower n and K_s values and higher θ_r values at the TP 4 location with finer soil texture). Physically, finer-textured soils generally have lower K_s and higher θ_r values (Carsel and Parrish, 1988). Moreover, the shape factor n is indicative of pore size distributions of soils. In general, finer soils with smaller pore sizes tend to have lower n values (Carsel and Parrish, 1988). The observed *SWC* at the TP 4 location is consistently higher than the average *SWC* of the other three locations (Figure S4 in supplemental materials), which can be partly attributed to the higher θ_r values at the TP 4 location (Wang and Franz, 2015). Overall, the obtained van Genuchten parameters from the inverse modeling are in qualitatively good agreement with the available spatial distribution of soil texture in the study field, indicating the capability of using inverse VZM to infer soil hydraulic properties. Further work on validating the Web Soil Survey Data soil hydraulic property estimates is of general interest to the LSM community.

3.2 Comparison of modeled ET_a with observed ET_a

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Because a longer set of climatic data was available at the study site (as compared to *SWC* data), we used 2004-2006 as a spin-up period. Using the best fit soil hydraulic parameters for the four TP locations and the single CRNP location, the Hydrus-1D model was then run in a forward mode to calculate ET_a over the entire study period (2007-2012). The simulated daily ET_a was then compared with the independent EC ET_a measurements using RMSE (Eq. (9)) as the evaluation criterion. In order to upscale TP ET_a estimation to the field/EC scale, we used the soil textural boundaries and areas defined by the Web Soil Survey Data map to compute a weighted average ET_a. In this research we consider RMSE values less than 1 mm/day between observed and simulated ET_a values as well-matched and RMSE values between 1 and 1.2 as fairly well-matched (Figure 9 and Table 6). The performance criterion results indicate that the simulated daily ET_a is in a better agreement with EC ET_a measurements at the TP 1-3 locations than at the TP 4 and CRNP locations (Table 6). However, based on the performance criteria from inverse modeling results and on the Web Soil Survey Data, we conclude that spatial heterogeneity of soil texture in the study field results in significant spatial variation in ET_a rates across the field (e.g., less ET_a occurs at the TP 4 location than from the other parts of the field). Here smaller ET_a rates at the TP 4 location are likely due to finer soil texture at this location, which makes it more difficult for the plant/roots to overcome potentials to extract water from the soil, thus leading to a lower ET_a rate and greater plant stress. In addition, higher surface runoff can be expected at the TP 4 location due to finer-textured soils (as we observed during our field campaigns). According to the simulation results the average surface runoff at the TP 4 location was about 44.8 mm/year from 2007 to 2012, while the average surface runoff at the other three locations (TPs 1-3) was around 10.6 mm/year, which partially accounts for the lower ET_a rates. We note that future work using historic yield maps may also be used to further

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elucidate the soil hydraulic property differences given the direct correlation between transpiration and yield.

Given that CRNPs have a limited observational depth and that only one single soil layer was optimized in the inverse model for the CRNP, one could expect the simulated daily ET_a from the CRNP to have larger uncertainty. Here we found an RMSE of 1.14 mm/day using the CRNP versus 0.91 mm/day for the upscaled TP locations. However, when the optimized soil parameters obtained from the CRNP data were used to estimate ET_a, the model did simulate daily ET_a fairly well during both non-growing and growing seasons in comparison to the EC ET_a measurements.

On the annual scale, ET_a measured by the EC tower accounted for 87% of annual P recorded at the site during the study period (Figure 6). Overall, the simulated annual ET_a at all the TP and CRNP locations is comparable to the annual ET_a measured by the EC tower, except during 2012 (Table 7), in which a severe drought occurred in the region. One explanation is that the plants extract more water from deeper layers under extreme drought conditions than what we defined as a maximum rooting depth (150 cm for maize and 120 cm for soybean) for the model, thus limiting the VZM ability to estimate ET_a accurately during the drought year (2012). In fact, based on the EC ET_a measurements at the study site, there was just 8.18% reduction in annual ET_a in 2012 than the average of the other years (2007-2011), while there were 29.58% and 35.75% reduction in annual simulated ET_a values respectively in upscaled TP and CRNP. This shows that although 2012 was a very dry year, the plants probably found most of the needed water by extracting water from deeper soil reservoirs. As previously mentioned we defined a maximum rooting depth for the model that could greatly impact the results. To further illustrate this point, a sensitivity analysis was performed on the maximum rooting depth and presented in the following section. However, we note that given the fact that EC ET_a estimation can have up to 20% uncertainty (Massman and Lee, 2002, and

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Hollineger and Richardson, 2005), and accounting for the natural spatial variability of ET_a due to soil texture and root depth growth uncertainties, the various ET_a estimation techniques performed fairly well. In fact, it is difficult to identify which ET_a estimation method is the most accurate method. These results are consistent with the concept of equifinality in hydrologic modeling given the complexity of natural systems (Beven and Freer, 2001). Moreover, the findings here are consistent with Nearing et al. (2016) that show information lost in model parameters greatly affects the soil moisture comparisons against a benchmark. However, soil parameterization was less important in the loss of information for the comparisons of ET/latent energy against a benchmark. Fully resolving these issues remains a key challenge to the land surface modeling community and the model's ability to make accurate predictions (Best 2015). The following section provides a detailed sensitivity analysis of the soil hydraulic parameters and root depth growth functions in order to begin to understand the sources of error in estimating ET_a from *SWC* monitoring networks.

3.3 Sensitivity analysis of soil hydraulic parameters and rooting depth

In this research we compared simulated ET_a with the measured EC ET_a. As expected some discrepancies between simulated and measured ET_a values existed. In order to begin to understand the key sources of error we performed a set of sensitivity analysis experiments on the estimated soil hydraulic parameters. Building on Wang et al. (2009b), a sensitivity analysis for a single homogeneous soil layer (6 parameters) and a 4-layer soil profile (24 parameters) was performed over the study period (2007–2012). Here we performed a preliminary sensitivity analysis by changing a single soil hydraulic parameter one at a time while keeping the other parameters constant (i.e. at the average value). Figure 10 illustrates the sensitivity results on simulated ET_a, indicating the soil hydraulic parameters have a range of sensitivities with tortuosity (*l*) being the least. We found that

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n and α were the most sensitive, particularly in the shallowest soil layer. This sensitivity to the shallowest soil layer provides an opportunity to use the CRNP observations, particularly in the early growing season (i.e. when evaporation dominates latent energy flux), to help constrain estimates of n and α. As the crop continues to develop (and transpiration contributes a relatively larger component of latent energy) additional information about deeper soil layers should be used to estimate soil hydraulic parameters or perform data assimilation. Moreover, the CRNP may be useful in helping constrain and parameterize soil hydraulic functions in simpler evaporation models widely used in remote sensing (c.f. Allen et al. 2007) and crop modeling (c.f. Allen et al. 1998).

Following the sensitivity analysis, we repeated the optimization experiment using only α, n, K_s, and used model default estimates for the other parameters in each layer. We found that the RMSE values were significantly higher (1.511 vs. 0.911 mm/day) than when considering all 24 parameters. We suspect that given the high correlation between soil hydraulic parameters (Carsel and Parrish 1988), that fixing certain parameters leads to a degradation in overall performance. We suggest further sensitivity analyses, in particular changing multiple parameters simultaneously or using multiple objective functions, be used to fully understand model behavior (c.f. Bastidas et al. 1999 and Rosolem et al. 2012).

A sensitivity analysis of ET_a by varying rooting depth is summarized in Figure 11. As would be expected with increasing rooting depth, higher ET_a occurred. In addition, Figure 11 illustrates a decreasing RMSE against EC observations for up to 200% increases. Again it is unclear if the EC observations are biased high or in fact rooting depths are much greater than typically considered in these models. The high observed EC values in the drought year of 2012 indicate that roots likely uptake water from below the 1 m observations. Certainly the results shown here further indicate the importance of root water uptake parameters in VZMs and LSMs, even in homogeneous annual

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Deleted: that investigation in root water uptake is an area that deserves more attention in LSMs cropping systems. While beyond the scope of this paper we refer the reader to the growing literature on the importance of root water uptake parameters on hydrologic fluxes (c.f. Schymanski et al. 2008 and Guswa 2012).

4. Conclusions

In this study the feasibility of using inverse vadose zone modeling for field scale ET_a estimation was explored at an agricultural site in eastern Nebraska. Both point *SWC* sensors (TP) and area-average techniques (CRNP) were explored. This methodology has been successfully used for estimates of groundwater recharge but it was critical to assess the performance of other components of the water balance such as ET_a. The results indicate reasonable estimates of daily and annual ET_a but with varied soil hydraulic function parameterizations. The varied soil hydraulic parameters were expected given the heterogeneity of soil texture at the site and consistent with the principle of equifinality in hydrologic systems. We note that while this study focused on one particular site, the framework can be easily applied to other networks of *SWC* monitoring across the globe (Xia et al., 2015). The value added products of groundwater recharge and ET_a flux from the *SWC* monitoring networks will provide additional and more robust benchmarks for the validation of LSM that continue to improve their forecast skill.

5. Data availability

The climatic and EC data used in this research can be found at http://ameriflux.lbl.gov/. The TP *SWC* and *LAI* data in the study site are provided by Dr. Andrew Suyker and CRNP *SWC* are

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provided by Dr. Trenton E. Franz and both sets of data can be requested directly from the authors. The US soil taxonomy information is provided by Soil Survey Staff and is available online at http://websoilsurvey.nrcs.usda.gov/ (accessed in July, 2016). The remaining datasets are provided in the supplemental material associated with this paper.

Acknowledgments

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List of Figures

Figure 1. Study site (Mead Rainfed/US-Ne3) location in Nebraska (a) and locations of Eddy-Covariance Tower (EC), Cosmic-Ray Neutron Probe (CRNP), Theta Probes (TPs), and variability of soil texture based on Web Soil Survey data at the study site, 2014 (b). See table 1 for soil descriptions.

Figure 2. Eddy-Covariance Tower (a) and Cosmic-Ray Neutron Probe (b) Located at the Mead Rainfed (US-Ne3) Site.

Figure 3. Daily precipitation (*P*) and reference evapotranspiration (ET_r) during the calibration (2008–2010) and validation (2011–2012) periods at the Mead Rainfed (US-Ne3) Site.

Figure 4. Temporal evolution of daily *SWC* (*θ)* at different soil depths. The black lines represent daily mean *SWC* (*θ)* calculated from TPs in 4 different locations at study site and the blue areas indicate one standard deviation.

Figure 5. Time series of daily CRNP and spatial average TP *SWC* (*θ)* data.

Figure 6. Annual precipitation (*P*) and annual actual evapotranspiration (ET_a) at the Mead Rainfed (US-Ne3) Site.

Figure 7. Daily observed and simulated *SWC* (*θ)* during the calibration (2008–2010) and validation (2011–2012) periods at TP 1 location. See supplemental figures for other comparisons.

Figure 8. Daily observed and simulated *SWC* (*θ*) during the calibration (2012–2013) and validation (2014) periods at the location of Cosmic-Ray Neutron probe.

Figure 9. Simulated daily *ETa* versus Observed daily *ETa* in different locations at the study site (2007-2012).

Figure 10. Sensitivity Analysis of Effect of Soil Hydraulic Parameters on average annual *ETa* values (2007-2012) for a single homogeneous soil layer (6 parameters) and for a 4-layer soil profile (24 parameters).

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Figure 11. Sensitivity Analysis of Effect of Root Depth on *ETa* estimation for a single homogeneous soil layer profile. Note that root depth is in terms of percent depth as it is dynamic over the growing period.

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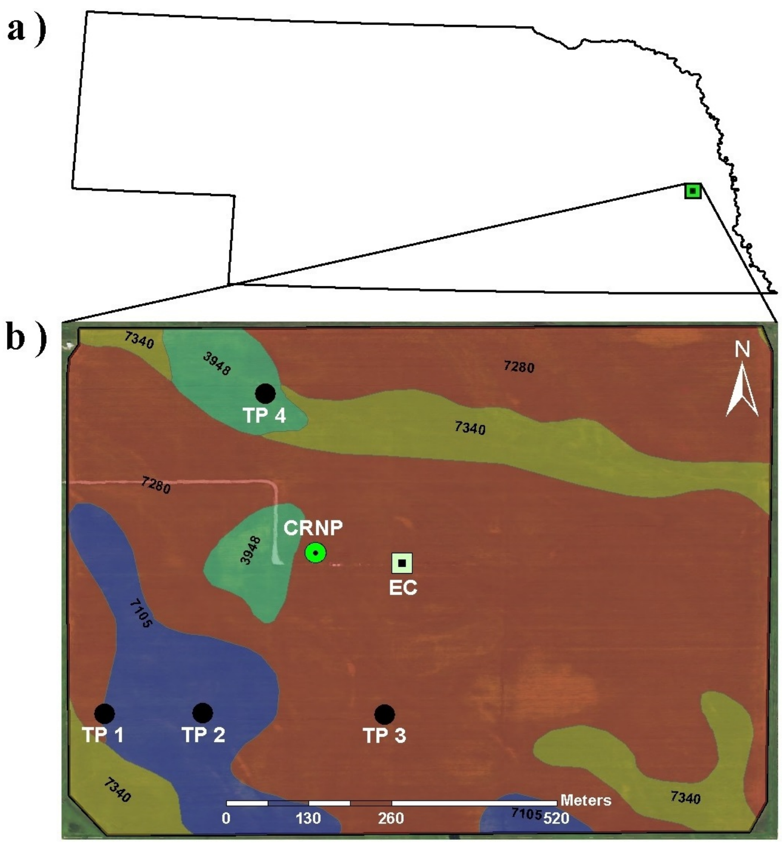

Figure 1. Study site (Mead Rainfed/US-Ne3) location in Nebraska (a) and locations of Eddy-Covariance Tower (EC), Cosmic-Ray Neutron Probe (CRNP), Theta Probes (TPs), and variability of soil texture based on Web Soil Survey data at the study site, 2014 (b). See table 1 for soil descriptions.

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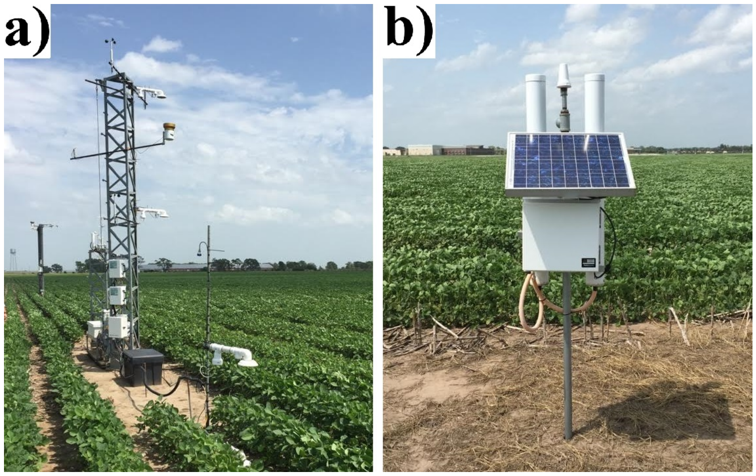

Figure 2. Eddy-Covariance Tower (a) and Cosmic-Ray Neutron Probe (b) Located at the Mead Rainfed (US-Ne3) Site.

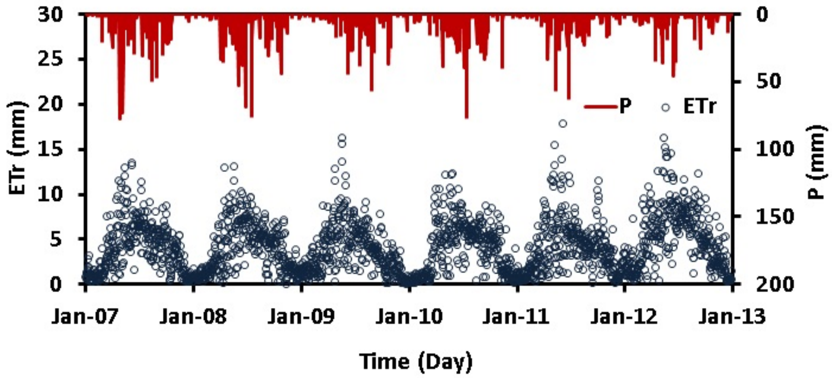

Figure 3. Daily precipitation (P) and reference evapotranspiration (ET_r) during the calibration (2008–2010) and validation (2011–2012) periods at the Mead Rainfed (US-Ne3) Site.

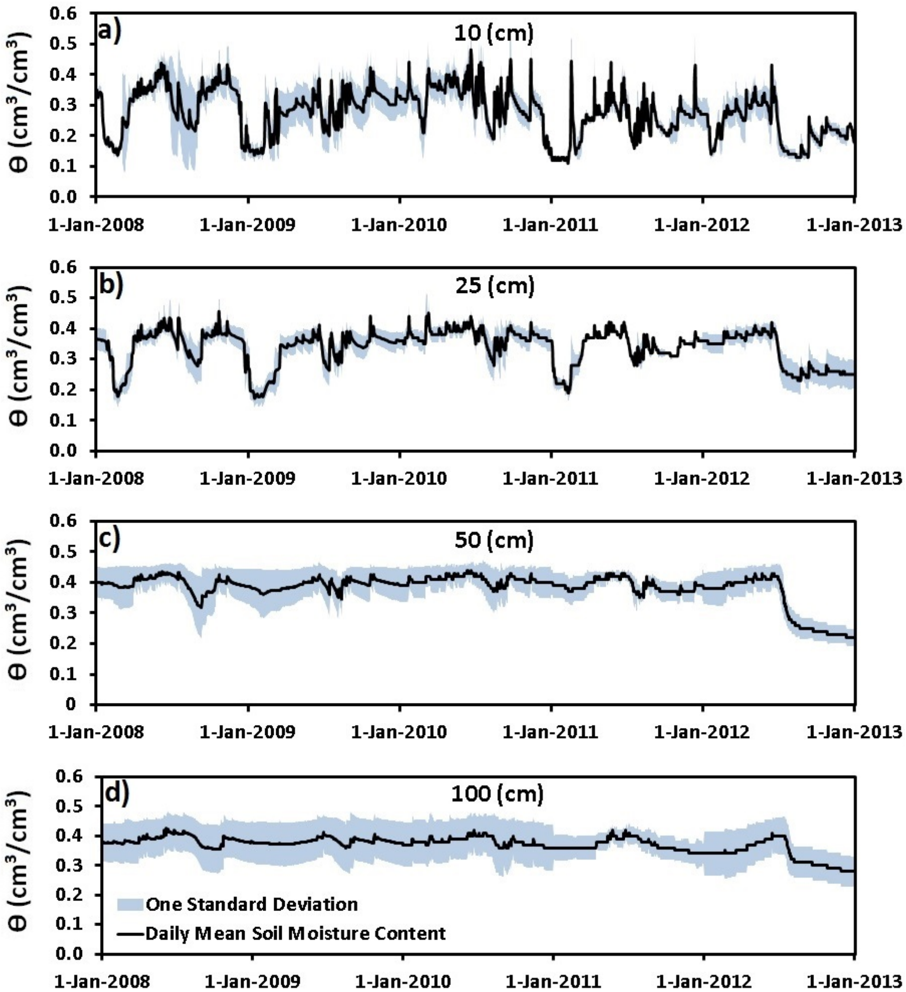

Figure 4. Temporal evolution of daily *SWC* (*θ)* at different soil depths. The black lines represent daily mean *SWC* (*θ)* calculated from TPs in 4 different locations at study site and the blue areas indicate one standard deviation.

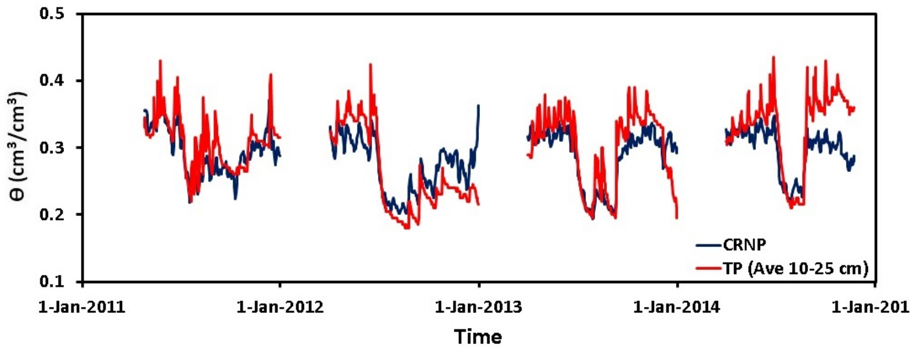

Figure 5. Time series of daily CRNP and spatial average TP *SWC* (*θ)* data.

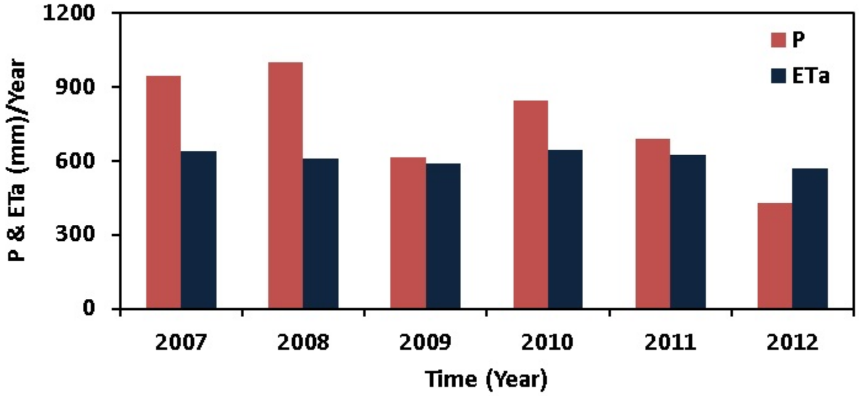

Figure 6. Annual precipitation (P) and annual actual evapotranspiration (ET_a) at the Mead Rainfed (US-Ne3) Site.

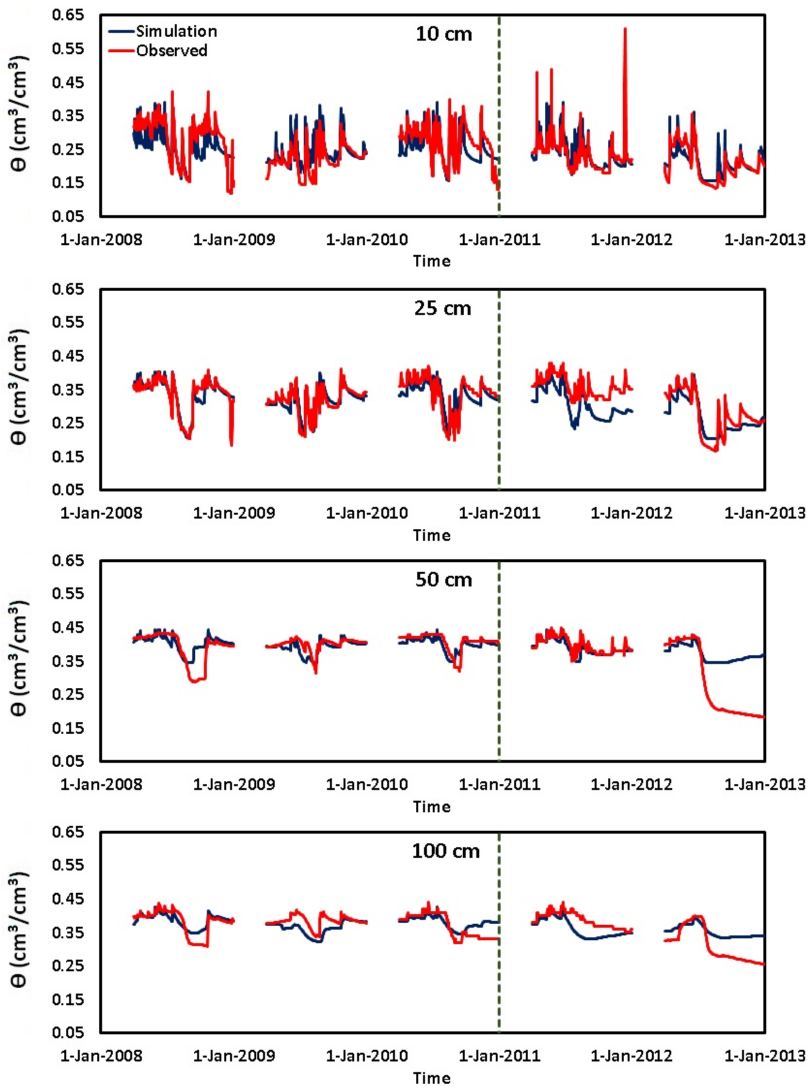

Figure 7. Daily observed and simulated *SWC* (*θ*) during the calibration (2008–2010) and validation (2011–2012) periods at TP 1 location. See supplemental figures for other comparisons.

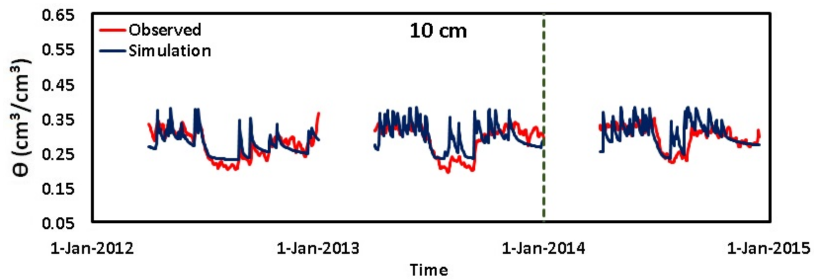

Figure 8. Daily observed and simulated *SWC* (*θ*) during the calibration (2012–2013) and validation (2014) periods at the location of Cosmic-Ray Neutron probe.

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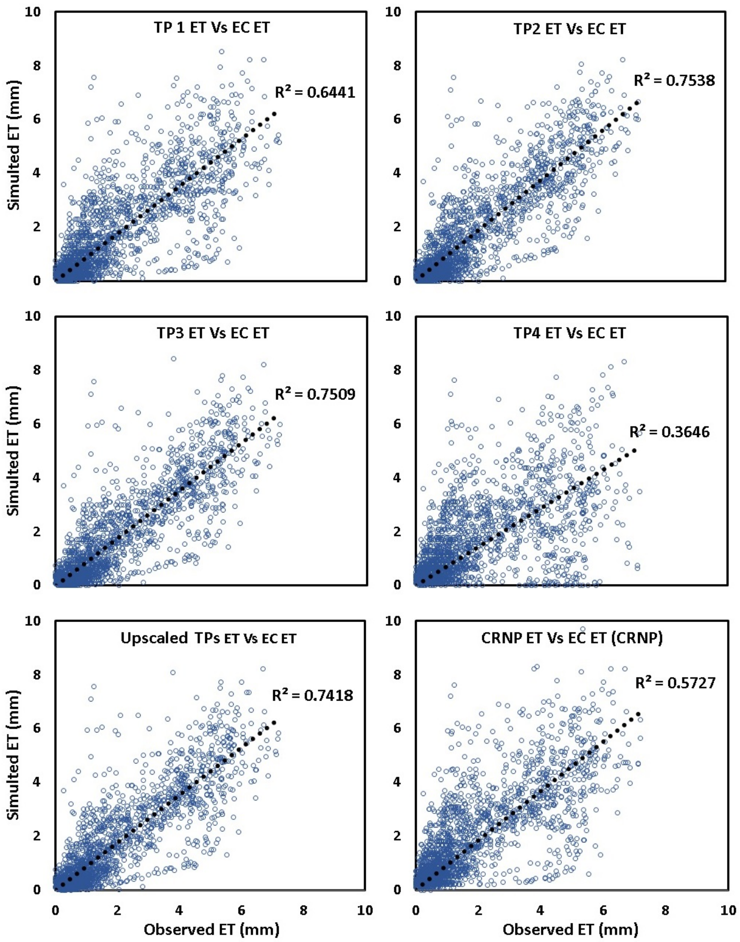

Figure 9. Simulated daily ET_a versus observed daily ET_a at different locations in the study site (2007-2012).

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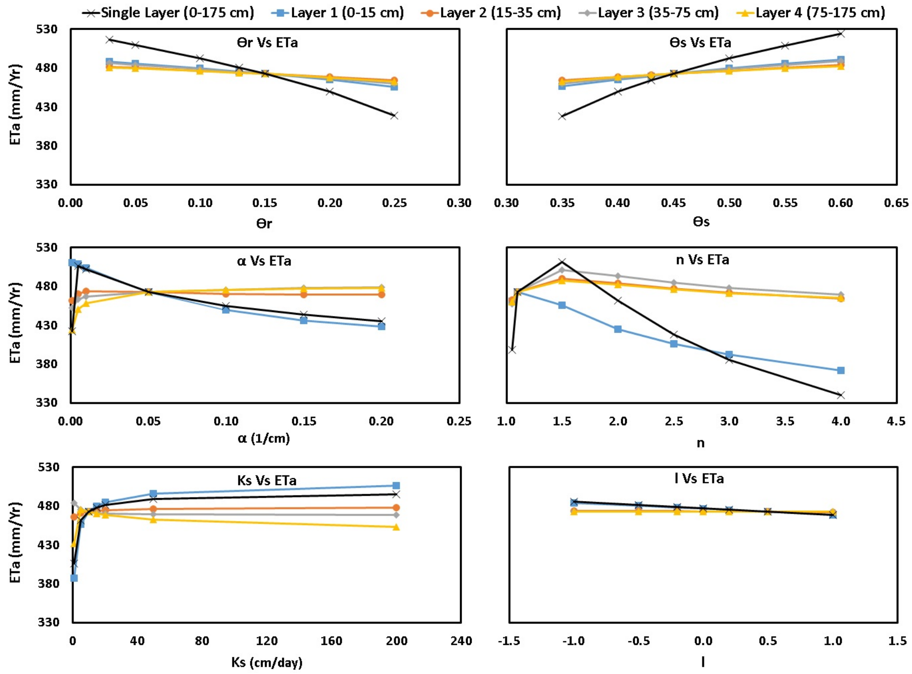

Figure 10. Sensitivity analysis of the effect of soil hydraulic parameters on average annual ET_a values (2007-2012) for a single homogeneous soil layer (6 parameters) and for a 4-layer soil profile (24 parameters).

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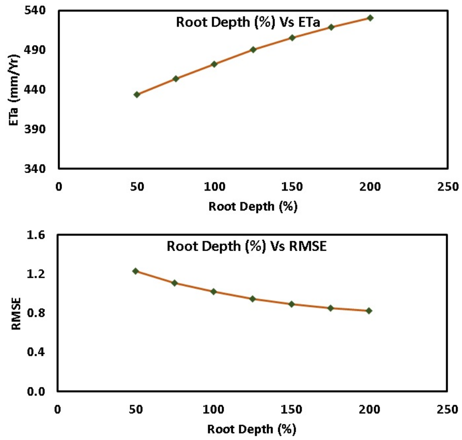

Figure 11. Sensitivity analysis of root depth on *ETa* estimation for a single homogeneous soil layer profile. Note that root depth is in terms of percent depth as it is dynamic over the growing period.

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List of Tables

Table 1. Variability of soil texture in the study field based on Web Soil Survey data (http://websoilsurvey.sc.egov.usda.gov/App/HomePage.htm).

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Table 1. Variability of soil texture in the study field based on Web Soil Survey data (http://websoilsurvey.sc.egov.usda.gov/App/HomePage.htm).

Map Unit Symbol	Map Unit Name	Clay (%)	Silt (%)	Sand (%)	Hectares in Field	Percent of Field
3948	Fillmore silt loam, terrace, occasionally ponded	41.7	51.0	7.3	3.24	4.9%
7105	Yutan silty clay loam, terrace, 2 to 6 percent slopes, eroded	25.8	59.4	14.8	6.88	10.3%
7280	Tomek silt loam, 0 to 2 percent slopes	32.3	61.6	6.1	47.23	70.8%
7340	Filbert silt loam, 0 to 1 percent slopes	41.4	51.7	6.9	9.34	14.0%
Total Area of Field					66.69	100.0%

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Table 2. Bounds of the van Genuchten parameters used for inverse modeling.

Soil Parameter	θ_r (-)	θ_s (-)	α (1/cm)	n (-)	K_s (cm/day)	l (-)
Range	0.03–0.30	0.3–0.6	0.001–0.200	1.01–6.00	1–200	-1–1

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Table 3. Goodness-of-fit measures for simulated and observed *SWC* data at different depths during the calibration period (2008 to 2010) and validation period (2011-2012) at TPs locations. Note we assume a good fit as an RMSE between 0-0.03 cm^3/cm^3 and fair as between 0.03-0.06 cm^3/cm^3.

Location	Depth (cm)	Calibration Period (2008-2010)				Validation Period (2011-2012)			
		R^2	MAE (cm^3/cm^3)	RMSE (cm^3/cm^3)	NSE	R^2	MAE (cm^3/cm^3)	RMSE (cm^3/cm^3)	NSE
TP 1	10	0.542	0.024	0.036	0.533	0.532	0.016	0.033	0.503
	25	0.742	0.014	0.022	0.739	0.716	0.029	0.040	0.486
	50	0.409	0.013	0.023	0.407	0.603	0.041	0.074	0.157
	100	0.352	0.015	0.022	0.343	0.419	0.027	0.038	0.358
TP 2	10	0.330	0.044	0.066	0.305	0.287	0.047	0.061	0.052
	25	0.623	0.010	0.020	0.604	0.718	0.038	0.055	0.135
	50	0.551	0.015	0.026	0.074	0.683	0.040	0.055	0.202
	100	0.424	0.019	0.027	-2.055	0.344	0.048	0.073	-0.473
TP 3	10	0.269	0.034	0.051	0.256	0.534	0.086	0.102	-4.265
	25	0.512	0.011	0.017	0.509	0.852	0.010	0.015	0.793
	50	0.549	0.015	0.023	-0.214	0.658	0.022	0.033	0.652
	100	0.238	0.018	0.029	-3.156	0.669	0.018	0.025	0.178
TP 4	10	0.412	0.029	0.044	0.406	0.580	0.051	0.071	-0.116
	25	0.434	0.016	0.025	0.350	0.594	0.029	0.042	0.490
	50	0.151	0.009	0.015	-13.400	0.443	0.041	0.073	0.036
	100	0.001	0.013	0.021	-12.058	0.292	0.026	0.039	0.238

Table 4. Goodness-of-fit measures for simulated and observed *SWC* data during the calibration period (2012 to 2013) and validation period (2014) at CRNP location.

Location	Depth (cm)	Calibration Period (2012-2013)				Validation Period (2014)			
		R^2	MAE (cm^3/cm^3)	RMSE (cm^3/cm^3)	NSE	R^2	MAE (cm^3/cm^3)	RMSE (cm^3/cm^3)	NSE
CRNP	10	0.497	0.018	0.027	0.456	0.192	0.020	0.032	-0.310

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Table 5. Optimized van Genuchten parameters in different locations at the study site. Note, 95% confidence intervals are in parentheses.

Location	Depth (cm)	θ_r (-)	θ_s (-)	α (1/cm)	n (-)	K_s(cm/day)	l (-)
TP 1	0-15	0.134 (0.130-0.137)	0.423 (0.417-0.429)	0.027 (0.026-0.027)	1.475 (1.456-1.494)	8.119 (7.965-8.273)	0.546 (0.525-0.567)
	15-35	0.136 (0.132-0.141)	0.408 (0.404-0.412)	0.007 (0.007-0.007)	1.345 (1.322-1.367)	11.540 (11.137-11.939)	0.480 (0.466-0.4[illegible]
	35-75	0.191 (0.188-0.194)	0.448 (0.443-0.453)	0.024 (0.024-0.025)	1.097 (1.088-1.105)	8.057 (7.879-8.235)	0.285 (0.278-0.292)
	75-175	0.071 (0.068-0.073)	0.430 (0.424-0.436)	0.025 (0.024-0.025)	1.069 (1.061-1.077)	9.807 (9.540-10.073)	0.364 (0.354-0.375)
TP 2	0-15	0.211 (0.195-0.227)	0.446 (0.431-0.461)	0.027 (0.018-0.035)	1.567 (1.431-1.703)	8.120 (4.660-11.580)	1.000 (0.411-1.589)
	15-35	0.197 (0.105-0.289)	0.434 (0.425-0.442)	0.006 (0.003-0.008)	1.191 (1.076-1.306)	8.655 (0.953-16.357)	0.022 (-0.194-0.[illegible]
	35-75	0.110 (0-0.258)	0.424 (0.406-0.441)	0.015 (0.007-0.023)	1.239 (1.040-1.438)	4.605 (0-9.214)	0.723 (-1.210-2.655)
	75-175	0.109 (0-0.275)	0.408 (0.357-0.459)	0.020 (0-0.044)	1.302 (0.965-1.639)	6.780 (0-20.523)	0.000 (-0.045-0.045)
TP 3	0-15	0.281 (0.276-0.287)	0.464 (0.463-0.465)	0.035 (0.033-0.036)	1.487 (1.446-1.528)	7.096 (6.742-7.450)	0.400 (0.385-0.416)
	15-35	0.072 (0.069-0.075)	0.402 (0.398-0.407)	0.012 (0.011-0.012)	1.085 (1.076-1.095)	29.960 (28.470-31.457)	0.353 (0.340-0.3[illegible]
	35-75	0.081 (0.076-0.087)	0.498 (0.481-0.515)	0.037 (0.034-0.039)	1.128 (1.108-1.149)	24.440 (22.013-26.872)	0.527 (0.472-0.583)
	75-175	0.085 (0.077-0.092)	0.500 (0.482-0.518)	0.039 (0.036-0.042)	1.147 (1.124-1.170)	17.540 (15.995-19.088)	0.496 (0.454-0.539)
TP 4	0-15	0.082 (0.069-0.096)	0.481 (0.474-0.489)	0.034 (0.030-0.038)	1.172 (1.158-1.186)	7.773 (6.913-8.632)	0.953 (0.772-1.133)
	15-35	0.200 (0.175-0.225)	0.426 (0.420-0.433)	0.013 (0.010-0.017)	1.217 (1.173-1.262)	14.060 (9.248-18.873)	0.044 (0.027-0.0[illegible]
	35-75	0.250 (0.240-0.260)	0.477 (0.472-0.481)	0.009 (0.007-0.011)	1.079 (1.066-1.092)	1.045 (0.952-1.138)	0.353 (0.168-0.538)
	75-175	0.200 (0.185-0.214)	0.487 (0.481-0.494)	0.012 (0.009-0.014)	1.070 (1.057-1.083)	1.454 (1.146-1.762)	0.985 (0.706-1.264)
CRNP	0-15	0.100 (0.098-0.103)	0.392 (0.386-0.398)	0.019 (0.018-0.019)	1.054 (1.145-1.164)	6.931 (6.786-7.076)	0.547 (0.545-0.5[illegible]

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Table 6. Goodness-of-fit measures for simulated and observed daily ET_a during the simulation period (2007-2012) at study site.

Location	R^2	MAE (mm/day)	RMSE (mm/day)	NSE
TP 1	0.644	0.696	1.062	0.618
TP 2	0.754	0.610	0.907	0.746
TP 3	0.751	0.601	0.904	0.728
TP 4	0.365	0.878	1.387	0.168
TPs Weighted Average	0.742	0.599	0.911	0.714
CRNP	0.573	0.742	1.143	0.562

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Table 7. Summary of simulated yearly and average actual evapotranspiration (ET_a) (mm) and observed yearly and average actual evapotranspiration (ET_a) (mm) from Eddy-Covariance tower during 2007 to 2012.

Location	Year						
	2007	2008	2009	2010	2011	2012	Average
EC	656.8	608.4	589.7	646.1	622.2	570.1	612.5
TP 1	646.1	629.0	559.8	642.1	573.9	415.5	579.5
TP 2	614.3	598.4	576.7	620.5	576.9	429.5	574.7
TP 3	529.0	556.1	556.4	590.4	549.8	405.2	545.4
TP 4	652.2	576.1	529.9	677.3	458.2	381.2	525.3
Upscaled TPs	613.9	564.1	556.3	600.3	547.7	405.9	548.0
CRNP	745.3	707.1	603.0	721.8	642.2	439.3	643.1

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which were performed to identify the sources of the errors in both ET_a estimation and soil hydraulic parameters optimization processes

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to identify the sources of the errors in *ETa* estimation and

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Based on the analysis for homogeneous single soil layer and 4-layer soil profile (F

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s on both *ETa* estimation and soil hydraulic parameters optimization except

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which did not have a significant effect on the results

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Even though we discovered that almost all the soil hydraulic parameters have effects on *ETa* estimation, we tried to limit the optimized factors (e.g., we just optimized α, n, K_{s}, and used model default for the other parameters) to see if that can help us to improve the results and obtain more accurate *ETa* estimation but after simulations we acquired higher RMSE values between measured and simulated *ETa* values. In fact, the results showed that more model input would help to have more robust output which are soil hydraulic parameters and *ETa* values here in this research.

Also, effect of root depth growth was investigated to see if it has an effect on simulations. Results of

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