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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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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 sensors (*SWC*) 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 critical 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 continue 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,

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they generally require complex model parameterizations and inputs, some of which are not readily available (e.g., soil hydraulic parameters and plant physiological parameters; 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 are 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 LSMs grid cells to less than 1 km (Wood et al., 2011).

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) eddy covariance site in eastern Nebraska, USA. The remainder of the paper is organized as follows. In the methods section we will describe the widely used VZM, Hydrus-1D (Simnunek 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 the calibrated VZM with independent ET_a estimates provided by EC observations. Finally, 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).

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 (Soil Survey Staff, 2016), the soils at the site are comprised mostly of silt loam and silty clay loam. 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). In this study, hourly latent heat flux measurements were integrated to daily values and then used for calculating daily 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 (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, 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 Cosmos-Ray Neutron Probe (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 CNRP 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. For a more general integration of CRNP data into the NOAH LSM data assimilation framework, we refer to the work of Shuttleworth et al. (2013) and Rosolem et al. (2014). The areal footprint of the CRNP is ~250+/-50 m radius circle (see Desilets and Zreda (2013) and Kohli et al. (2015) for details). Here we assume for simplicity the EC and CRNP footprints are both representative of the areal-average field conditions.

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 details 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 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) Beer's law 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 extiction coefficient with a value set to 0.5 (Wang et al., 2009b) and LAI (L^2/L^2) is leaf area index described above. The root water uptake, which was assumed to be equal to actual transpiration, was simulated according to the Feddes model, based on T_p and root density distribution (Feddes et al., 1978). 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:

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Hydrology and Earth System Sciences
Open Access
Discussions

$$\begin{cases} if\ D < MRD \\ D = \frac{AGDD}{GDD_{Silking}} MRD \\ else \\ D = MRD \end{cases} \quad (4)$$

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* approximatly 60-70 days after crop emergence). *GDD* for each growing season day was calculated as:

$$GDD = \frac{T_{max} - T_{min}}{2} - T_{base} \quad (5)$$

where T_{max} and T_{min} are the maximum and minimum daily temperature (^{o}C), respectively, and T_{base} is the base temperature set to be 10^{o} C following McMaster and Wilhelm (1997) and Yang et al. (1997).

2.2.2 Inverse modeling to estimate soil hydraulic parameters

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

$$\theta(h) = \begin{cases} \theta_r + \frac{\theta_s - \theta_r}{(1+|\alpha h|^n)^m}, h < 0 \\ \theta_s,\ h \geq 0 \end{cases} \quad (6)$$

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-437, 2016
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Published: 26 August 2016

$$K(S_e) = K_s \times S_e^{l} \times [1-(1-S_e^{1/m})^m]^2 \quad (7)$$

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 ($=(\theta-\theta_r)/(\theta_s-\theta_r)$) (-) 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 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 (i.e., 0-15 cm, 15-35 cm, 35-75 cm, and 75-175 cm), which led to a total of 24 hydraulic parameters to be optimized (θ_r, θ_s, α, n, K_s, and L). In order to efficiently optimize the parameters, we used the method outlined in Turkeltaub et al. (2015). Specifically, the van Genuchten parameters of the upper two layers were first optimized, while the parameters of the lower two layers were fixed, since water contents of the lower layers changed more slowly and over a smaller range than the upper layers. Then, the optimized van Genuchten parameters of the upper two layers were kept fixed, 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 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,

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-437, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 26 August 2016

and 2011-2012 were used as the spin-up, calibration, and validation periods, respectively. Moreover, to minimize the impacts of freezing conditions on *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. In addition, soil properties were assumed to be homogeneous throughout the simulated soil column with a length of 175 cm. Since 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 on the van Genuchten parameters used are given in Table 1. With respect to the goodness-of-fit assessment, four performance criteria were selected to evaluate the model results, including R-squared (R^2), Mean Average Error (MAE), Root Mean Square Error (RMSE), and the Nash-Sutcliffe Efficiency (NSE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - O_i| \quad (8)$$

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

$$NSE = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O}_i)^2} \quad (10)$$

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. Finally, based on the best scores (i.e., lowest MAE and RMSE, and highest NSE scores), the best optimized soil parameter values at each location were selected. Using the selected parameters, the Hydrus model was run in a forward mode in order to estimate ET_a between 2007 and 2012. We note 2004-2006 was used as a spin-up period for the forward model.

3. Results and Discussions

3.1 Inverse Vadose Zone Modeling Results

The time series of the average *SWC* from the four TP locations along with one standard deviation at each depth is plotted in Figure 4. Despite the small spatial scale in this study (~65 ha), Figure 4 clearly shows that *SWC* varies considerably across the site, particularly during the growing season. The comparison between *SWC* data from the CRNP and spatial average of *SWC* data at four TP locations in the study field (*i.e.* average of 10 and 25 cm depths at each location) is presented in Figure 5 and 6. The daily RMSE between the spatial average of the TPs and CRNP data is 0.037 cm^3/cm^3, which is consistent with other studies that reported similar values in semiarid shrublands (Franz et al., 2012), German Forests (Bogena et al., 2013, Baatz et al., 2014), montane forests in Utah (Lv et al., 2014), sites across Australia (Hawdon et al., 2014), and a mixed land use agricultural site in Austria (Franz et al. 2016). Note we would expect lower RMSE (~<0.02 cm^3/cm^3) with additional point sensors located at shallower depths and in more locations spatially. Never-the-less, the consistent behavior between the spatial mean *SWC* of TPs and the CRNP allows us to explore spatial variability of soil hydraulic properties within footprint using inverse modeling. This will be described in the next sections. The study period (2007-2012, Figure 7) contained significant interannual variability in precipitation. During the spin-up period in 2007, the annual precipitation

(942 mm) was higher than the mean annual precipitation (784 mm), 2008 was a wet year (997 mm), 2009-2011 were near average years (715 mm), and 2012 was a record dry year (427 mm) with a widespread drought across the region. Therefore, both wet and dry years were considered in the inverse modeling simulation period.

As an illustration, Figure 8 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 four performance criteria (e.g., R^2, MAE, RMSE, and NSE) between simulated and observed *SWC* data at TPs and CRNP locations are presented in Tables 2 and 3.

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 TPs 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 throughout the whole period. However, the match between the simulated and observed *SWC* are better in the shallower depths of 10 and 25 cm (Figure 8 and Table 2). In addition, the simulated and observed data were well matched during the validation period (2011-2012), except during the second half of 2012 when the extreme drought occurred. 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 indicate the feasibility of using these data to estimate effective soil hydraulic parameters (Table 3). Based on the performance criteria (Table 3), the simulated data are fairly well-matched with the observed *SWC* data during both the calibration and validation periods. However, as the crops extracted water from deeper soil layers and due to the fact that the CRNP observational depth is limited to near surface layers (~20 cm), it is clear from the data that the comparison between the simulated and observed values deteriorates over the growing season (Figure 9). The results suggest that it might be more appropriate to use the CRNP data for inverse modeling during periods that are dominated by soil evaporation (Jana et al., 2016) and/or for sites with shallow rooted vegetation only. 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 is beyond the scope of this study and future investigations are still needed.

Table 4 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 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 4), in most of the soil layers, the TP 4 location possesses 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 were used to explore whether the optimized van Genuchten parameters from the inverse modeling (Figure 10 and Table 5) agreed 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 good agreement with the spatial distribution of soil texture in the study field, indicating the capability of using inverse VZM modeling to infer soil hydraulic properties.

3.2 Comparison of modeled ET_a with observed ET_a

Using the best fit soil hydraulic parameters for the four TP sites and the CRNP site, the Hydrus-1D model was run in a forward mode to calculate ET_a over the entire study period. The simulated daily ET_a was then compared with the independent EC ET_a measurements using the same four performance criteria that were used to evaluate the simulated SWC time series (Table 6). The performance criteria 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 and Figure 11). However, based on the performance criteria from inverse modeling results and based on the Web Soil Survey Data, one can conclude that partly due to the spatial heterogeneity of soil texture in the study field, spatial variation in ET_a rates likely exist over the field (e.g., less ET_a occurs at the TP 4 location than from the other part of the field). In addition, higher surface runoff can be expected at the TP 4 location due to finer-textured soils and therefore less stored water to support ET_a. 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.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-437, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 26 August 2016

Given that CRNPs have a limited observational depth and 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 (e.g., RMSE of 1.26 mm/day at the CRNP location versus mean RMSE value of 1.07 mm/day at 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 non-growing and early growing seasons in comparison to the EC ET_a measurements; however, with the development of deeper root systems after mid-June, the simulation results of daily ET_a did slightly deteriorate (Figure 13).

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 7). 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, Figure 12 and Figure 13), 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 model's ability to estimate ET_a accurately during the drought year (2012). 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, the various ET_a estimation techniques performed well. In fact, it is difficult to identify which is the clear solution if any. 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).

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.

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Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-437, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 26 August 2016

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Published: 26 August 2016

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List of Figures

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-437, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 26 August 2016

Figure 10. Variability of soil texture in the study field based on Web Soil Survey data (available at http://websoilsurvey.sc.egov.usda.gov/App/HomePage.htm).

Figure 11. Annual actual Evapotranspiration (ET_a) estimation in different location at the study site (2007-2012).

Figure 12. Mean Annual Actual Evapotranspiration (ET_a) estimation in different location at the study site (2007-2012).

Figure 13. Cumulative simulated actual ET versus cumulative observed actual ET in different locations at the study site (2007-2012).

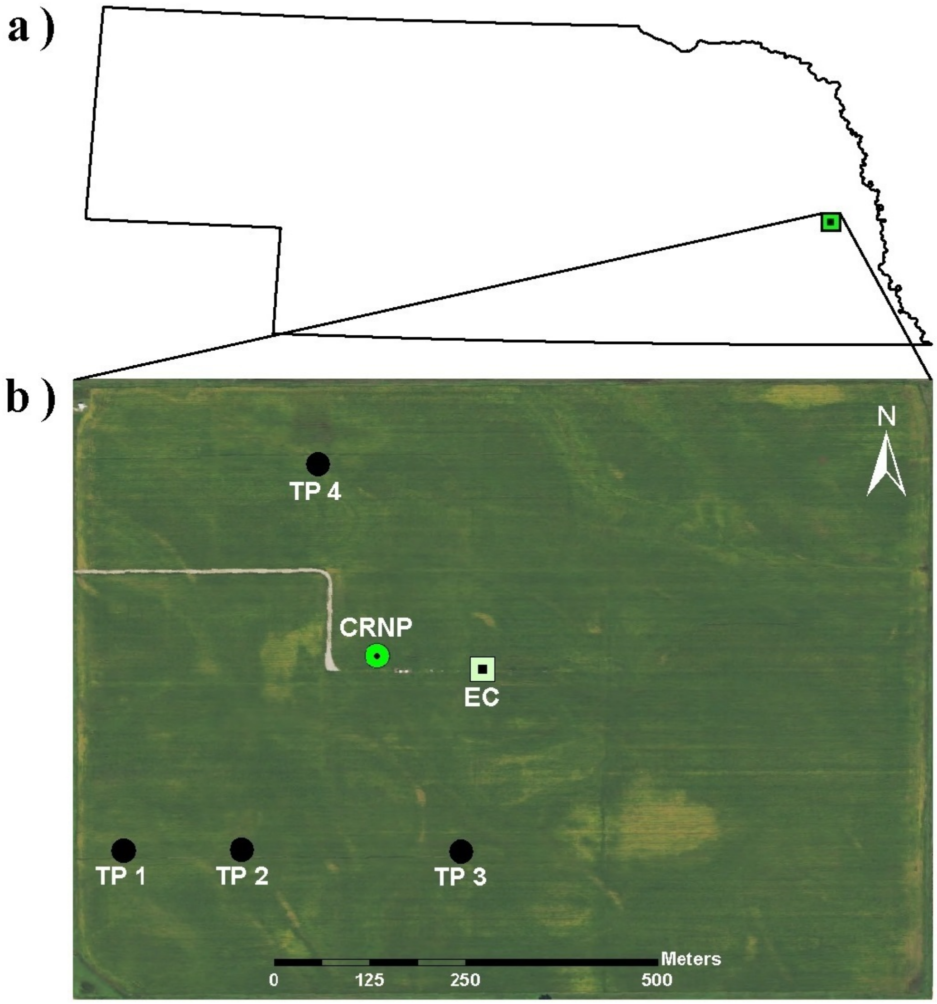


Figure 1. Study site (Mead Rainfed/US-Ne3) location in Nebraska (a) and locations of Eddy-Covariance Tower (EC), Cosmic-Ray Neutron Probe (CRNP) and Theta Probes (TPs) at the study site, 2014 (b).

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-437, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 26 August 2016

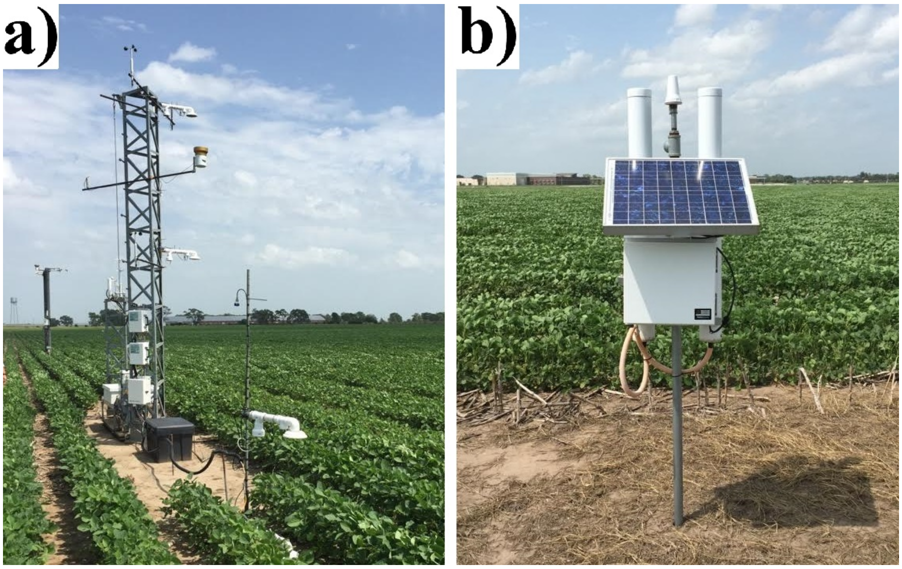


Figure 2. Eddy-Covariance Tower (a) and Cosmic-Ray Neutron Probe (b) Located at the Mead Rainfed (US-Ne3) Site.

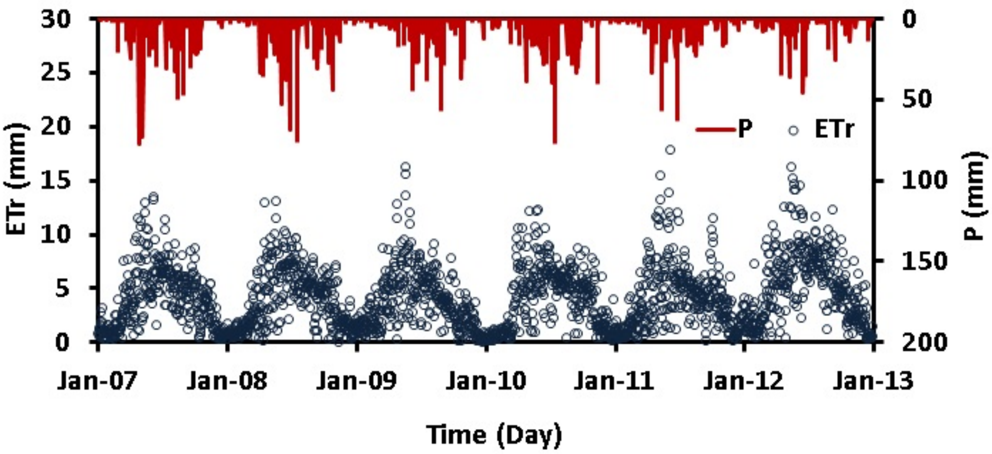


Figure 3. Daily precipitation (P) and reference evapotranspiration (ET_r) during the calibration (2008–2010) and validation (2011–2012) periods at the Mead Rainfed (US-Ne3) Site.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-437, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 26 August 2016

Hydrology and Earth System Sciences
Discussions
Open Access

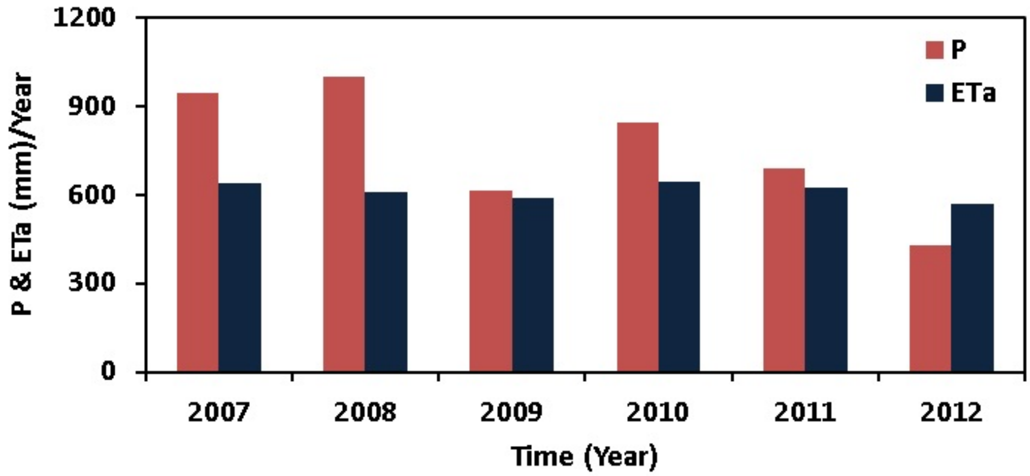


Figure 4. Annual precipitation (P) and annual actual evapotranspiration (ET_a) at the Mead Rainfed (US-Ne3) Site.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-437, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 26 August 2016

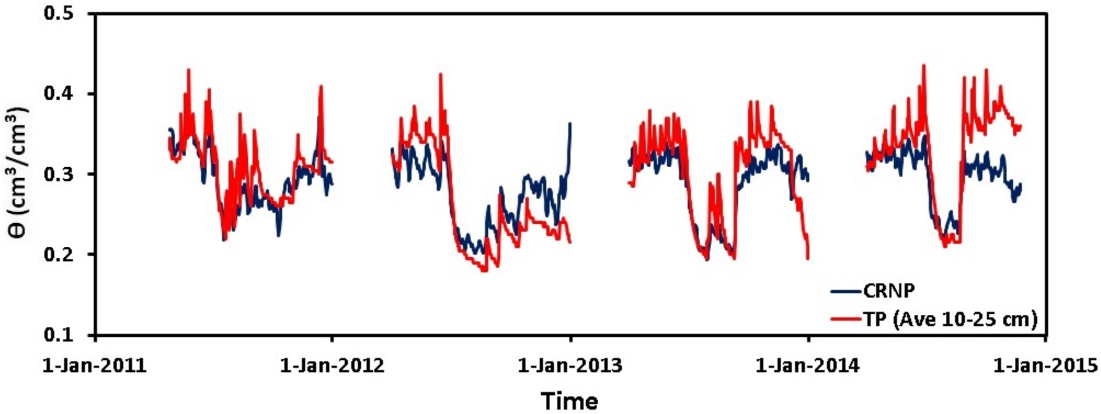


Figure 5. Time series of daily CRNP and spatial average TP *SWC* (*θ)* data.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-437, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 26 August 2016

Hydrology and Earth System Sciences
Open Access
Discussions

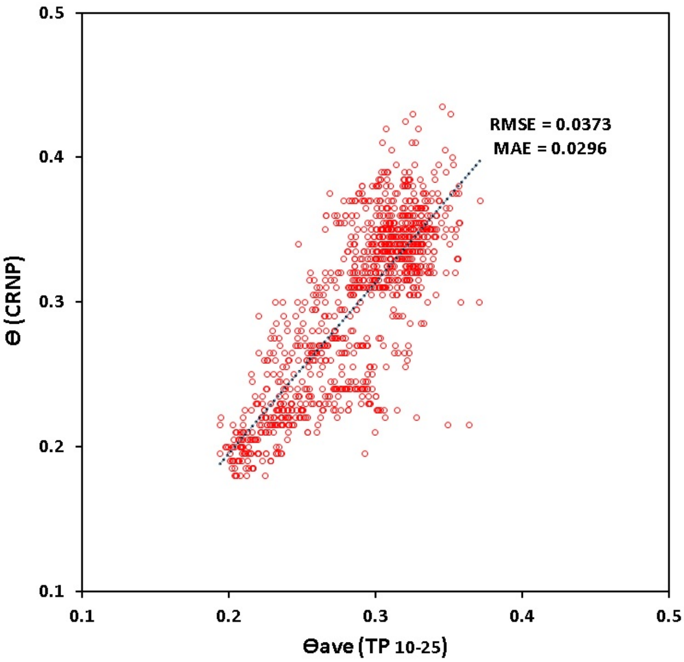
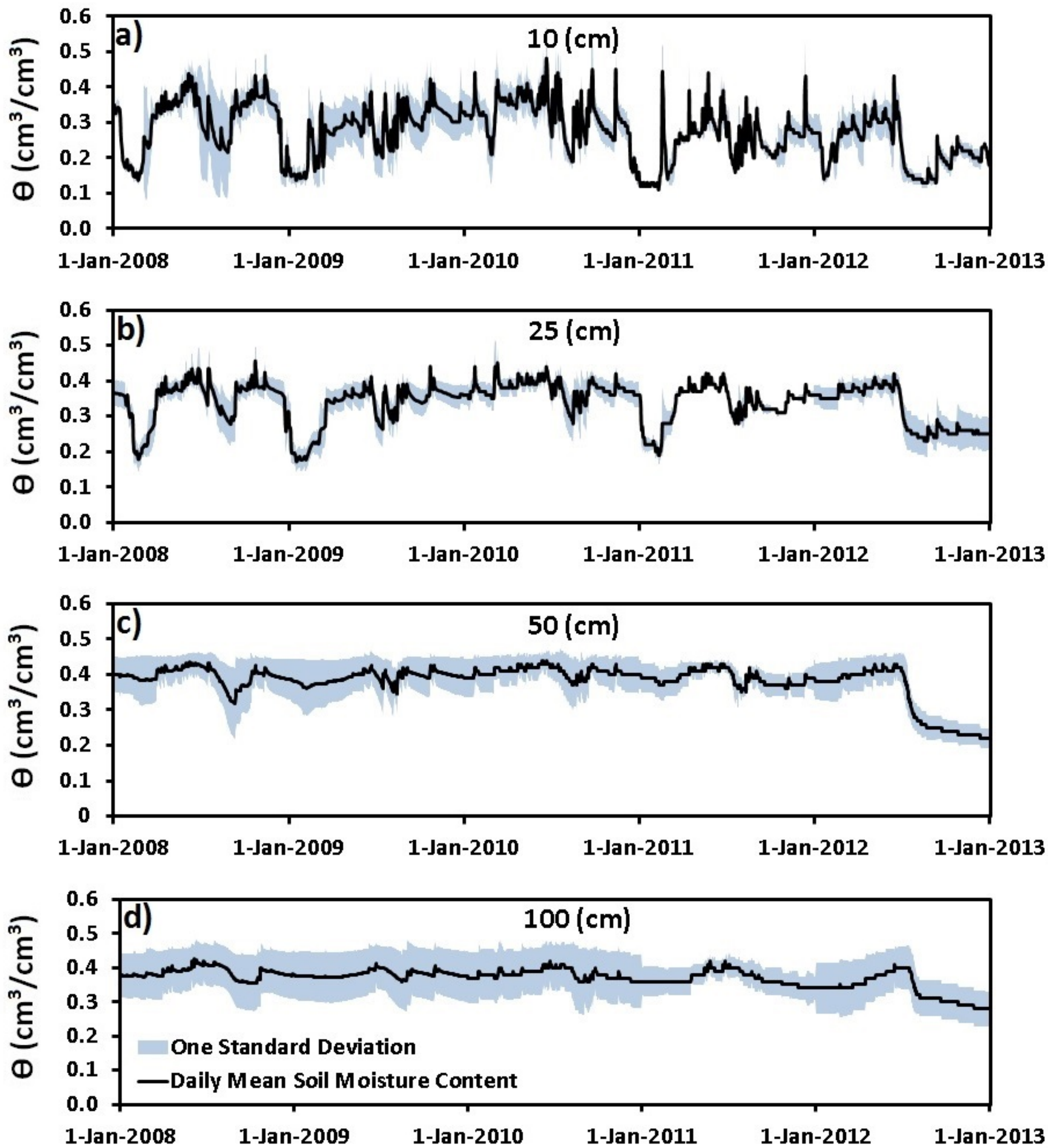


Figure 6. Comparison between daily CRNP and spatial average TP *SWC* (*θ*) data.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-437, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 26 August 2016



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640 Figure 7. Temporal evolution of daily *SWC* (*θ*) at different soil depths. The black lines represent
641 daily mean *SWC* (*θ*) calculated from TPs in 4 different locations at study site and the blue areas
642 indicate one standard deviation.

Hydrology and Earth System Sciences
Open Access
Discussions

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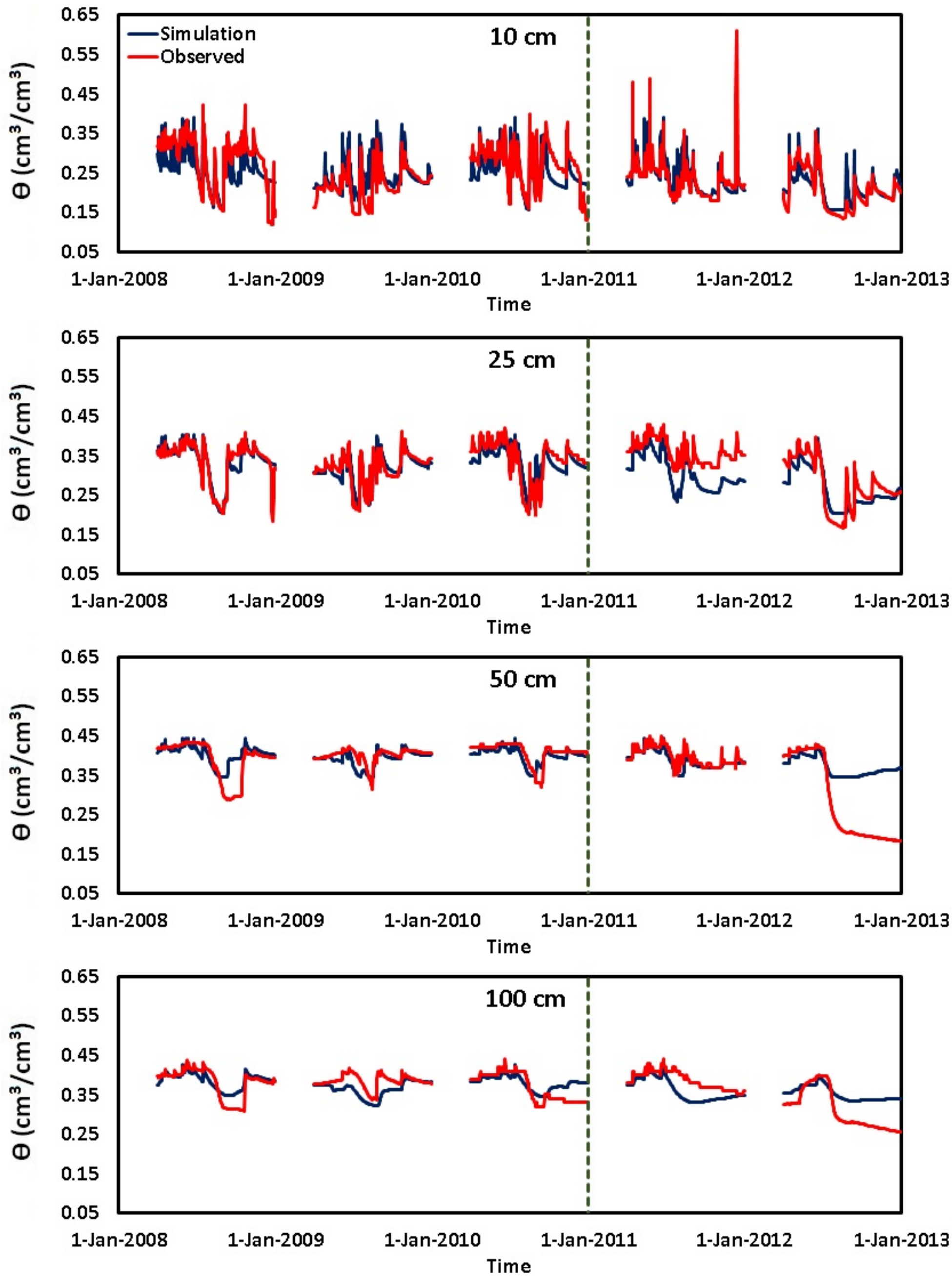


644 Figure 8. Daily observed and simulated *SWC* (*θ*) during the calibration (2008–2010) and validation
645 (2011–2012) periods at TP 1 location.

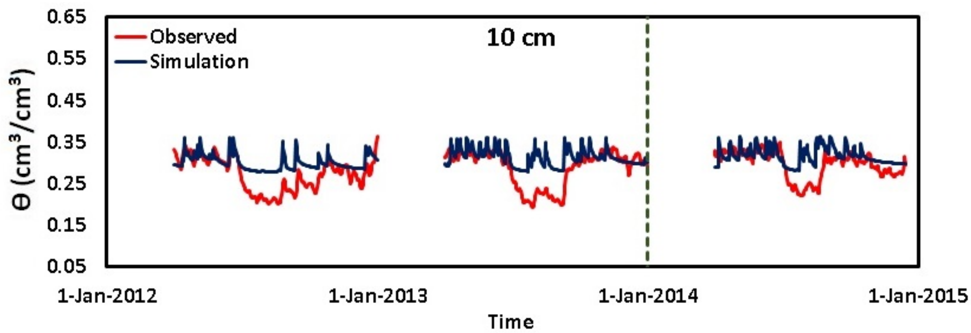
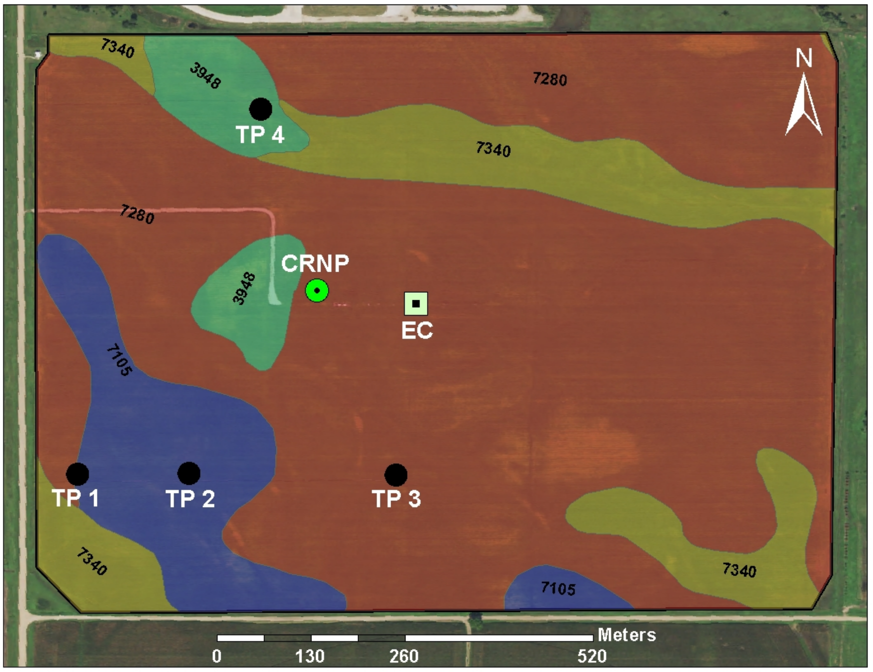


Figure 9. Daily observed and simulated *SWC (θ)* during the calibration (2012–2013) and validation (2014) periods at the location of Cosmic-Ray Neutron probe.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-437, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 26 August 2016

Hydrology and Earth System Sciences
Open Access
Discussions



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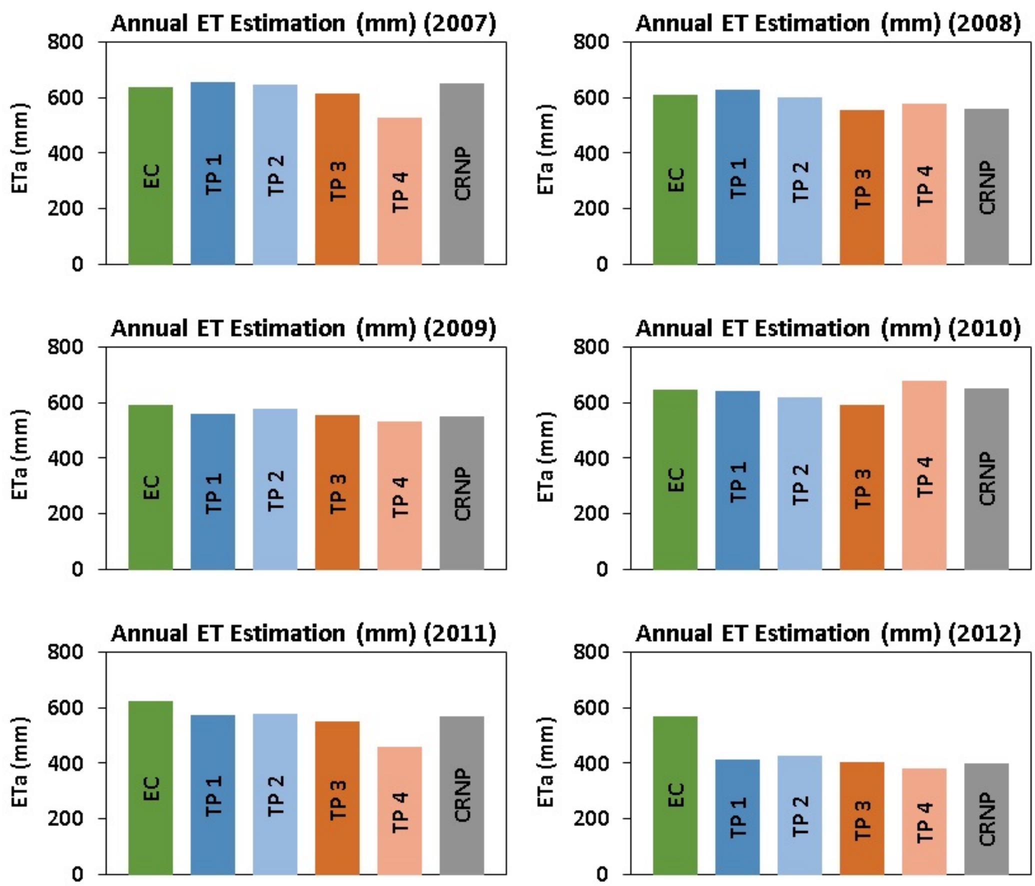
Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-437, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 26 August 2016

Hydrology and Earth System Sciences
Open Access
Discussions



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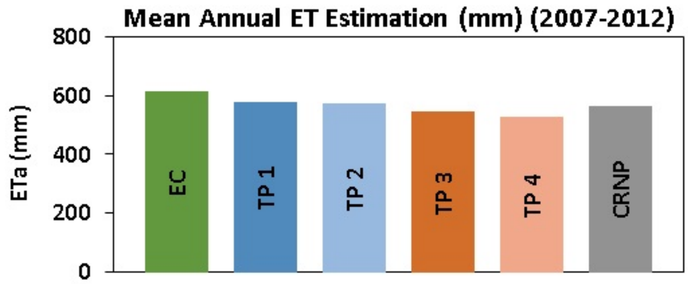

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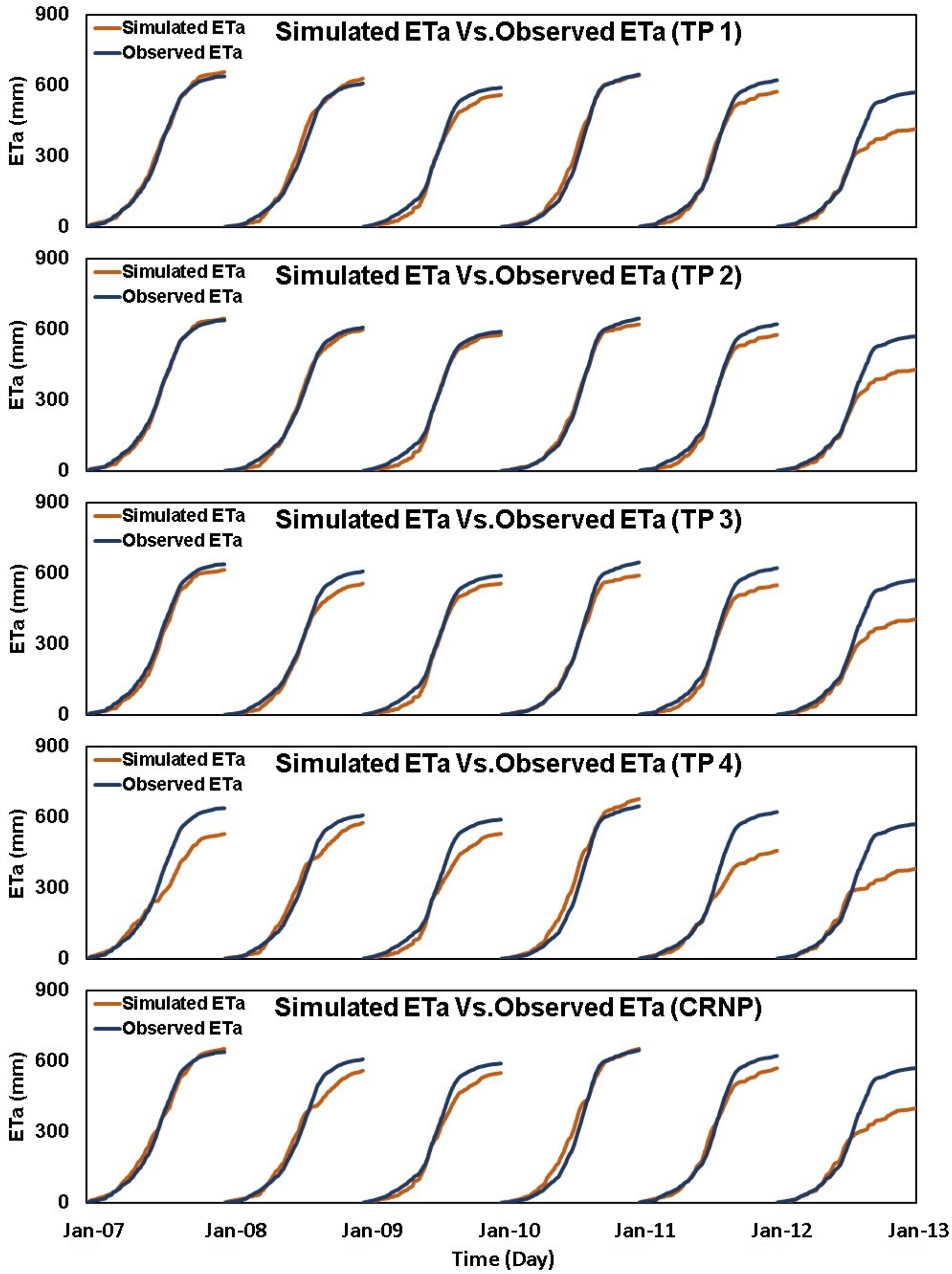
664 Figure 12. Mean Annual Actual Evapotranspiration (ET_a) estimation in different location at the
665 study site (2007-2012).

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-437, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 26 August 2016

Hydrology and Earth System Sciences
Open Access
Discussions



666

667 Figure 13. Cumulative simulated actual *ET* versus cumulative observed actual *ET* in different
668 locations at the study site (2007-2012).

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-437, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 26 August 2016

List of Tables

Table 1. 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

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-437, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 26 August 2016

Hydrology and Earth System Sciences
Open Access
Discussions

Table 2. 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.

Location	Depth (cm)	Calibration Period (2008-2010)				Validation Period (2011-2012)			
		R^2	MAE	RMSE	NSE	R^2	MAE	RMSE	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

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-437, 2016
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Published: 26 August 2016

Hydrology and Earth System Sciences
Discussions
Open Access

Table 3. 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	RMSE	NSE	R^2	MAE	RMSE	NSE
CRNP	10	0.352	0.024	0.038	-0.059	0.083	0.021	0.034	-0.454

730 Table 4. Optimized van Genuchten parameters in different locations at the study site.

Location	Depth (cm)	θ_r (-)	θ_s (-)	α (1/cm)	n (-)	K_s(cm/day)	L (-)
TP 1	0-15	0.134	0.423	0.027	1.475	8.119	0.546
	15-35	0.136	0.408	0.007	1.345	11.540	0.480
	35-75	0.191	0.448	0.024	1.097	8.057	0.285
	75-175	0.071	0.430	0.025	1.069	9.807	0.364
TP 2	0-15	0.211	0.446	0.027	1.567	8.120	1.000
	15-35	0.197	0.434	0.006	1.191	8.655	0.022
	35-75	0.110	0.424	0.015	1.239	4.605	0.723
	75-175	0.109	0.408	0.020	1.302	6.780	0.000
TP 3	0-15	0.281	0.464	0.035	1.487	7.096	0.400
	15-35	0.072	0.402	0.012	1.085	29.960	0.353
	35-75	0.081	0.498	0.037	1.128	24.440	0.527
	75-175	0.085	0.500	0.039	1.147	17.540	0.496
TP 4	0-15	0.082	0.481	0.034	1.172	7.773	0.953
	15-35	0.200	0.426	0.013	1.217	14.060	0.044
	35-75	0.250	0.477	0.009	1.079	1.045	0.353
	75-175	0.200	0.487	0.012	1.070	1.454	0.985
CRNP	0-15	0.102	0.369	0.019	1.075	6.450	0.555

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Table 5. 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 (%)	Hectors 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%

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	RMSE	NSE
TP 1	0.652	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	0.413	0.878	1.387	0.168
CRNP	0.499	0.787	1.259	0.349

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Discussions

760 Table 7. Summary of simulated yearly and average actual evapotranspiration (ET_a) (mm) and
761 observed yearly and average actual evapotranspiration (ET_a) (mm) from Eddy-Covariance
762 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
CRNP	656.8	559.6	549.9	652.8	570.7	400.1	564.2

763