Authors response to the referee report C5106 of the anonymous referee #2

We would like to thank the anonymous referee #2 for the very helpful comments on our manuscript (hess-2014-400). We have carefully considered the reviewer's comments and will include them into the revised version of the manuscript. Please find below a point by point response to the reviewer's comments.

Comment 1: Page 10861, line 13 (P61, L13): As the sink term is defined as water extraction, and increasing water extraction decreases water storage, it seems more appropriate to have the sign "-" in front of S(z,t).

Response: We agree with the reviewer and we will change equation (1) (P61, L13) according to the reviewer's suggestion to:

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z}\left[K(h)\left(\frac{\partial h}{\partial z} + 1\right)\right] - S(z,t)$$

Comment 2: P62, L13: This method does not specifically neglect "vertical" soil water flow, it neglects soil water flow more generally.

Response: Here, we also agree with the reviewer. The sentence will be changed as follows:

Old:
However, a disadvantage is that the depletion of soil water is assumed to occur only by root water uptake and soil evaporation, and vertical soil water fluxes are negligible (Hupet et al., 2002).

New:
However, a disadvantage is that the depletion of soil water is assumed to occur only by root water uptake and soil evaporation, and **soil water fluxes are negligible** (Hupet et al., 2002).

Comment 3: P62, L27: The cited studies do not fit parameters of "time constant RWU profiles" as their RWU profiles are not time constant. Their RWU model parameters are time constant but as soil matric potential and transpiration vary, their RWU profiles change. The following ("whereas …" L27-29) does not contradict the cited studies then.

Response: Yes, this is right fort he cited studies. We have changed the sentence accordingly and to show that the models implicitly assume relations between observables (like root distribution, soil water content) and root water uptake profiles, when uptake profiles depend on other biotic regulations as well.

Old:

Another problem is that the applied models for soil water flow ignore biotic processes. For example Musters et al. (2000) and Hupet et al. (2002) tried to fit parameters of time constant root water uptake profiles, whereas empirical data strongly suggest that plants adjust the distribution of root water uptake dynamically depending on soil moisture storage (Green and Clothier, 1995; Lai and Katul, 2000; Li et al., 2002; Garrigues et al., 2006).

New:

Another problem is that the applied models for soil water flow potentially ignore biotic processes. For example Musters et al. (2000) and Hupet et al. (2002) tried to fit parameters for root distributions in a model determining uptake profiles from water availability **whereas empirical and modeling studies suggest that adjustment of root water uptake distribution may also be from physiological adaptations (Jackson et al., 2000; Zwieniecki et al., 2003; Bechmann et al., 2014)**.

Comment 4: P64, L18: Here it could also be mentioned that a RWU model is used in addition of a soil water flow model.

Response: Thank you for the useful hint. We will change the sentence as follows:

Old:

In this study, synthetic time series of volumetric soil water content generated by a soil water flow model (section 2.3), were treated as measured data and are used as the basis for all methods (section 2.2) estimating the sink term $\widetilde{S}(z)$ and total evapotranspiration $\widetilde{E}$.

New:

In this study, synthetic time series of volumetric soil water content generated by a soil water flow model coupled **with a root water uptake model** (section 2.3), were treated as measured data and are used as the basis for all methods (section 2.2) estimating the sink term $\widetilde{S}(z)$ and total evapotranspiration $\widetilde{E}$.

Comment 5: P65, L20: During dry periods, non-null "q" may occur as capillary rise (q is then negative), especially if the water table is no deeper than 2 meters. A possible justification to prevent capillary rise from happening in the synthetic dataset would be to define the "water table" as the bottom of a lysimeter. Didn't capillary rise occur during dry periods in the synthetic dataset?

Response: Yes, there is capillary rise in our synthetic dataset from the shallow water table, which is also realistic for our scenario. Overall, the capillary rise flux is smaller than drainage in magnitude, but it does introduce uncertainty to the method (Fig. AC2.1). However, our aim was to generate a scenario as realistically as possible to evaluate the particular methods and also show their drawbacks, and we therefore prefer to not make the proposed adjustment. It is true that this introduces an additional error to the ssml method, and we will point this out in the revision.

Comment 6: P66, L2: A more precise definition of dry period should be provided here. I believe that later in the manuscript it is mentioned that the dry periods start 24 hours after the end of rain events. Was there no leaching later than that? I insist on these points (5 and 6) because they could be a major reason why the method ssml fails to predict accurate evapotranspiration.

Response: We are aware that percolation can occur also up to several days after a rainfall event, especially in deeper layers. This is the case for the investigated summer period, which started one day after a rainfall event, and percolation was considerable for more than a week in the deep soil layers (Fig AC2.1 c). However, this period was chosen deliberately to investigate whether the particular data-driven methods can deal with leaching fluxes.
This is also discussed in section 4, P79, L13-20: “In those simpler soil water balance methods any change in soil moisture is assigned only to root water uptake (Rasiah et al., 1992; Musters et al., 2000; Hupet et al., 2002). However, even several days after a rainfall event the vertical matrix flow within the soil can be similar in magnitude to the root water uptake (Schwärzel et al., 2009) and this leads to considerable overestimation of the sink term, when soil water flow is not accounted for. This error sums up, when the sink term is integrated over depth and leads to a great bias in 20 the evapotranspiration estimate.”
We agree with the reviewer’s comment that a more precise definition of the applied dry period should be provided. We will change sentence P66, L2 accordingly:

<u>Old:</u>
Additionally, rainfall measurements are required to select dry periods.

<u>New:</u>
Additionally, rainfall measurements are required to select dry periods, where no percolation occurs. **These could start several hours up to several days after a rainfall event (Breña Naranjo et al., 2011), whereas it depends on the amount of rainfall and the site-location parameters like soil type and vegetation. In this study we waited 24 hours after the end of the precipitation event, before applying the model.**

We also approve that the statement in sentence P78, L22-24: “For the same reason, none of the water balance methods can be applied during times of fast soil water flow, for example during or shortly (one day) after a rainfall event.”, could be confusing and we will edit the sentence to:

<u>New:</u>
“For the same reason, none of the water balance methods can be applied during times of fast soil water flow, for example **during or after a rainfall event**.”

We agree that it is important to point the drawback of the ssml more out in the manuscript and we will specifically refer to the ssml in the above mentioned section in the revised manuscript.

Comment 7: P67, L20: The assumption that mflow does not change significantly between day and night is interesting and could be directly illustrated from the synthetic dataset as mflow is known at all times.

Response: Indeed, the manuscript would benefit from an illustration of the basic assumption of the msml method, that invariance of mflow during day and night. We correlated the mean fluxes in the nights before and after one particular day with the mean fluxes of the respective day, and found a strong correlation (R^2=0.99, p<0.001) (Fig. AC2.2). We will include this figure in the revised manuscript.

Comment 8: P67, L21: Here it is not clear to me which nights are included in mflow. Is "antecedent and preceding nights" limited to two nights? In case daytime mflow would be correlated to night-time mflow, I would expect that the highest correlation would be with mflow from the most recent night. What additional pieces of information would other preceding nights provide?

Response: Yes, "antecedent and preceding nights" is limited to one night before and after the considered day. We will make this more clear in the revised manuscript as follows:

Old:
The sink term can be calculated from Eq. (8a), assuming that m_{flow} can be estimated from Eq. (8b) and using the average of the antecedent and preceding nights $m_{flow,i}$.

New:
The sink term can be calculated from Eq. (8a), assuming that m_{flow} during the day can be estimated from Eq. (8b) and using the average of the **antecedent and the preceding night**.

Comment 9: P68, L22: I found the inverse model section quite confusing. It seems like the method of Zuo and Zhang is first explained, then for some reason a second method is explained. The first method would not be implemented though. I understand from the first sentences that the sink terms are optimized at each depth and each time step (while usually the RWU model parameters are optimized). Hopefully what follows can be clarified and made more concise.

Response: Obviously, this section leads to confusions and misunderstandings, for example that the method after Zuo and Zhang was not implemented. However, the method after Zuo and Zhang was implemented but we modified the termination process of the original iterative procedure. We agree that this section would benefit from a more concise and structured explanation. We restructured this section (Section 2.2.4 Inverse Model (im), P68, L6 - P70, L8) as follows (changes in bold letters) and will replace it in the revised manuscript.

New:

The fourth approach is the most complex. The *i*nverse *m*odel (*im*) estimates the average root water uptake by solving the Richards' equation (Eq. 1) and iteratively searching the sink term profile for each time step, which produces the best fit between the numerical solution and measured values of soil moisture content (Zuo & Zhang, 2002). **The advantage of this method is the estimation of root water uptake without the a priori estimation of rooting profile function parameters since they are highly uncertain as elucidated in the introduction. We implemented the inverse water balance approach after Zuo and Zhang (2002) with the Fast Richard's solver (Ross, 2003), which is available as FORTRAN 90 code. We modified the original method by changing the convergence criterion.**

In this section, we first introduce the iterative procedure as proposed by Zuo and Zhang (2002) and then explain the modification, which we conducted.

The iterative procedure by Zuo and Zhang (2002) runs the numerical model over a given time step (Δt) in order to estimate the soil water content profile $\tilde{\theta}_{\mathrm{i}}^{(\mathrm{v=0})}$ at the end of the time step, and assuming that the sink term ($\tilde{S}_{im,i}^{(v=0)}$) is zero over the entire profile. Here ~ depicts the estimated values at the respective soil layer i, and v indicates the iteration step. Next, the sink term profile $\tilde{S}_{im,i}^{(v=1)}$ is set equal to the difference between previous approximation $\tilde{\theta}_{\mathrm{i}}^{(\mathrm{v=0})}$and measurements θ_{i} while accounting for soil layer thickness and length of the time step for units.

In the following iterations, $\tilde{S}_{im,i}^{(v)}$ is used with Richards' equation to calculate the new soil water contents $\tilde{\theta}_{\mathrm{i}}^{(\mathrm{v})}$. The new average sink term $\tilde{S}_{im,i}^{(v+1)}$ is then determined with Eq. (10).

$$\tilde{S}_{im,\mathrm{i}}^{(v+1)} = \tilde{S}_{im,\mathrm{i}}^{(v)} + \frac{\tilde{\theta}_i^{(v)} - \theta_i}{\Delta t} \cdot d_{z,i} \tag{10}$$

This iteration process continues until a specified decision criterion ε_{ZZ} is reached:

$$\varepsilon_{ZZ} \geq \frac{1}{n}\sum_{i=1}^{n}\left[\frac{\tilde{\theta}_i^{(v)} - \theta_i}{\theta_i}\right]^2 \quad ,$$

(11)

where n is the number of soil layers in the soil column.

Since ε_{zz} is a normalized root mean square error over depth, good and poor estimations cancel between layers. This leads to termination of the iterative procedure even if the estimation of the sink term is very poor in several layers. **We therefore propose a slightly adapted termination process, which applies to separate soil layers, as follows.** The estimation of the sink term in general is applied as proposed by Zuo and Zhang (2002).

(1) Calculate the difference between the estimated and measured soil water content (Eq. 12) and compare the change of this difference to the difference of the previous iteration (Eq. 13).

$$e_i^{(v)} = \left|\theta_i - \tilde{\theta}_i^{(v)}\right| \tag{12}$$

$$\varepsilon_{GH,\mathrm{i}}^{(v)} = e_i^{(v-1)} - e_i^{(v)} \tag{13}$$

(2) In soil layers where $\varepsilon_{GH}^{(v)} < 0$: Set the root water uptake rate back to the value of the previous iteration ($\tilde{S}_{im,\mathrm{i}}^{(v+1)} = \tilde{S}_{im,\mathrm{i}}^{(v-1)}$), since the current iteration was no improvement. Only if $\varepsilon_{GH,\mathrm{i}}^{(v)} \geq 0$: go to step (3). This prevents acceptance of the estimated sink term $\tilde{S}_{im,\mathrm{i}}^{(v)}$ even if it leads to a worse fit than the previous iteration.

(3) If $e_\mathrm{i}^{(v)} > 1.0\text{e-}4$: Calculate $\tilde{S}_{im,\mathrm{i}}^{(v+1)}$ according Eq. (10); else the current iteration sink term ($\tilde{S}_{im,\mathrm{i}}^{(v+1)} = \tilde{S}_{im,\mathrm{i}}^{(v)}$) is retained as it results in a good fit between estimated and measured soil water contents.

The iteration process continues until the convergence criterion $\varepsilon_{GH}^{(v)}$ (Eq. 13) does not change anymore between iterations (i.e. all layers have reached a satisfactory fit), or after a specified number of iterations (we chose 3000).

The required input information are besides the soil water content measurements and the rainfall, the soil hydraulic parameters.

Comment 10: P70, L21: Here I did not find the spatial resolution of the simulation (1 cm?).

Response: The spatial resolution of the simulation is according to the measurement depths 15-15-30-40-40-40-40 cm. The advantage of the applied soil water flow model is that the water fluxes are calculated with the matrix flux potential (Kirchhoff transformation), which allows a spatial discretization with large nodal spacing (Ross, 2006). The inversion of the soil model to estimate root water uptake benefits from this lower spatial discretization, which reduces computation times. This was the reason to choose this model.
We compared the model results for simulated soil water contents of the applied spatial discretization and one model with 1 cm spatial resolution. The obtained $R^2 = 0.98$ between both datasets justified the application of the coarse spatial resolution.
We will include a comment on the spatial resolution in the revised manuscript.

Old:
The model was set up for a one dimensional homogeneous soil profile, 220 cm deep. Measurement points were set in depths of 15, 30, 60, 100, 140, 180 and 220 cm. We used a maximum rooting depth of 140 cm, with 60% of root length density located in the top 15 cm of the root zone, which corresponds to mean values measured on the field site (Ravenek et al., 2014).

New:
The model was set up for a one dimensional homogeneous soil profile, 220 cm deep. Measurement points were set in depths of 15, 30, 60, 100, 140, 180 and 220 cm. **The spatial resolution of the soil model is according to the measurement points 15-15-30-40-40-40-40 cm. The advantage of the applied soil water flow model is that the water fluxes are calculated with the matrix flux potential (Kirchhoff transformation), which allows a spatial discretization with large nodal spacing (Ross, 2006).** We used a maximum rooting depth of 140 cm, with 60% of root length density located in the top 15 cm of the root zone, which corresponds to mean values measured on the field site (Ravenek et al., 2014).

Comment 11: P72, L4-5: This sentence could be removed as its content is repeated in more detail in the next sentence.

Response: Thank you for the useful hint. We will remove the indicated sentence in the revised manuscript.

Comment 12: P74, L16: According to Table 2 the best result (b=0.89%) corresponds to the measurement frequency of 12h, not 24h. The captions of Table 2 and 4 do not specify what variable prediction is evaluated. From the rest of the text I believe it is the daily averaged ET though.

Response: Yes, 0.89 % is for the frequency of 12 h (according to Table 2). We apologize for the typing error and we will change it to 12 h in the indicated sentence in the revised manuscript.

We will change the captions of Table 2 and 4 in the revised manuscript as follows:

Old:
Table 2: Comparison of the model performance of the four data-driven methods regarding time resolution of soil moisture measurements. The model performance is expressed as correlation coefficient R, relative variability in simulated and reference values RV and relative bias (b) for the period 25 July to 26 August 2009. Days at which rainfall occurs were excluded for the data analysis.

Table 4: Comparison of the model performance of the Multi Step Multi Layer Regression and the Inverse Model regarding soil moisture measurement uncertainty. The model performance is expressed as correlation coefficient R, relative variability in simulated and reference values RV and relative bias (b) for the period 25 July to 26 August 2009. The precision uncertainty is abbreviated by prec err, the calibration uncertainty by cali err and the combined uncertainty by com err.

New:
Table 2: Comparison of the model performance of the four data-driven methods **for reproducing daily evapotranspiration for the particular time resolution** of soil moisture measurements. The model performance is expressed as correlation coefficient R, relative variability in simulated and reference values RV and relative bias (b) for the period 25 July to 26 August 2009. Days at which rainfall occurs were excluded for the data analysis.

Table 4: Comparison of the model performance **with considering soil moisture measurement uncertainties for the Multi Step Multi Layer Regression and the Inverse Model for reproducing daily evapotranspiration.** The model performance is expressed as correlation coefficient R, relative variability in simulated and reference values RV and relative bias (b) for the period 25 July to 26 August 2009. The precision uncertainty is abbreviated by prec err, the calibration uncertainty by cali err and the combined uncertainty by com err.

Comment 13: P75, L14: “The results show that lesser complex methods better reproduce ET”. Isn’t it the opposite, more complex methods (msml and im) better predict ET?

Response: The reviewer is right, more complex methods better predict ET. The focus of the indicated sentence was more on the temporal resolution of the applied soil moisture data rather than a comparison between the methods. Lesser complex methods perform better when using soil water measurements with higher temporal resolution (e.g. of 1 and 3 h).

We rephrased this section to make this more obvious.

Old:
The results show that lesser complex data-driven methods, except the ssml, better reproduce the actual evapotranspiration, when using soil water measurements with higher temporal resolution of 1 and 3 h.

New:
Our results also show that lesser complex data-driven methods, also perform better at higher temporal resolution (1 and 3 h), except for the ssml.

Comment 14: P75, L27: It is explained that the standard deviation of z_25%, z_50% and z_90% from the synthetic dataset is almost 0. In consequence the RV index tends to values too high to be indicative, and its numerator (std dev of estimated z_25%, z_50% and z_90%) is used instead. Smaller std dev of estmations then become indicator of quality of fit, which makes sense. I am surprised though that the authors (i) insist in the introduction and discussion on the dynamism of RWU which adapts itself to soil moisture distribution, (ii) use a RWU model that has compensation implemented, but eventually generate a synthetic dataset that does not seem to have significant variations of RWU relative distribution…

Response: Our aim was to generate a realistic scenario from a known experimental field site to evaluate the particular methods. In the case study there was no water stress and thus there was no redistribution of water uptake within the soil layers necessary although the applied model can reproduce different root water uptake patterns. Nevertheless, the uniformity of the root water uptake patterns has no technical influence on the application of the investigated data-driven methods. We will add this as a comment in the method section of the revised manuscript.

Comment 15: P80, L17: The word "uptake" probably missing between "root water" and "model".

Response: We apologize for the typing error and we will add "uptake" in the indicated sentence in the revised manuscript.

Comment 16: P81, L12: The word "and" between "calibration error" and "but"…

Response: Thank you for the hint. We will delete the word "and" in the indicated sentence in the revised manuscript.

Comment 17: P95: More results could be provided in Table 4, if not within the body of the article, it could be added in appendix.

Response: We will add the values of the mean relative bias between synthetic and predicted values of evapotranspiration and the depths where 25, 50, 90 % of water extraction occurs, according to Fig. 6 of the manuscript.

New:

Table 4: Comparison of the model performance with considering soil moisture measurement uncertainties for the Multi Step Multi Layer Regression and the Inverse Model for reproducing daily evapotranspiration and the mean depths where 25 %, 50 % and 90 % water extraction occurs. The model performance is expressed as correlation coefficient R, relative variability in simulated and reference values RV and relative bias (b) for the period 25 July to 26 August 2009. The precision uncertainty is abbreviated by prec err, the calibration uncertainty by cali err and the combined uncertainty by com err. The relative bias for reproducing evapotranspiration is abbreviated with b_{ET} and for reproducing mean depths where 25 %, 50 % and 90 % water extraction occurs is abbreviated with $b_{25\%}$, $b_{50\%}$ and $b_{90\%}$, respectively.

	Multi Step Multi Layer Regression			Inverse Model		
Time resolution of measurements	1h			24h		
Criterion	prec err	cali err	com err	prec err	cali err	com err
R	0.90	0.89	0.91	-0.027	0.847	-0.054
RV	1.35	1.50	1.35	1.51	1.25	1.85
Median bias b_{ET} (%)	-6.2	-4.9	-6.1	-10.3	498.1	483.3
Median bias $b_{25\%}$ (%)	19.6	3.6	19.5	25.2	531.1	405.1
Median bias $b_{50\%}$ (%)	28.0	5.4	27.7	42.0	622.4	659.1
Median bias $b_{90\%}$ (%)	80.8	27.7	84.7	128.5	757.6	569.0

Comment 18: P98: If found the successive grey and white bands for respectively day and night to be sort of confusing as dark is commonly associated to night.

Response: We agree that the distribution of the grey bands is confusing. Indeed, the figure would benefit from a change of the grey and white bands (grey=night, white=day). We will edit the figure accordingly in the revised manuscript (Fig. AC2.3).

Comment 19: Page 10901: The coloured bands are not all visible due to overlapping.

Response: We agree that Figure 5 does not show clearly the coloured bands. We adjusted the figure so that the bands for the precision error is now visible (Fig. AC2.4). The bands for the combined and the calibration error do really overlap almost completely. We will mention this in the figure legend to improve reading the figure.

General comment: An illustration displaying what goes wrong with the im method for an isolated simulation would be helpful in addition to the confidence intervals of Fig. 5.

Response: Thank you for the useful suggestion. We included a Figure showing the evolution of the inverse procedure (im) for the simulation with undisturbed soil moisture data (Fig. AC2.5) and for one isolated simulation with soil moisture data including a randomly selected calibration uncertainty (Fig. AC2.6). From figure AC2.6 it is evident that the inverse procedure is unable to close the water balance for the entire soil profile, especially if the sensors in the measurement transect have a different uncertainty range. The im fit the simulated soil moisture on the imprecise measured values at the expenses of the root water uptake, and thus overestimates the root water uptake in individually layers (Fig. AC2.6 d, e) and evapotranspiration. We will include figure AC2.6 as Figure 7 in the revised manuscript in addition to the discussion on page 88, line 27 to page 89, line 1 as follows.

<u>Old:</u>
This "calibration error" renders the evolution of the vertical potential gradients inconsistent with the evolution of the vertical sink term distribution, and thus introduces forbidding overestimation of evapotranspiration for the considered time steps

<u>New:</u>
This "calibration error" renders the evolution of the vertical potential gradients **and soil moisture profile** inconsistent with the evolution of the vertical sink term distribution, and thus introduces forbidding overestimation **of root water uptake and** evapotranspiration for the considered time steps **(Fig. 7)**.

Additional reference:

Bechmann, M., Schneider, C., Carminati, A., Vetterlein, D., Attinger, S., and Hildebrandt, A.: Effect of parameter choice in root water uptake models – the arrangement of root hydraulic properties within the root architecture affects dynamics and efficiency of root water uptake, Hydrol. Earth Syst. Sci., 18, 4189-4206, doi:10.5194/hess-18-4189-2014, 2014.

Breña Naranjo, J. A., Weiler, M., and Stahl, K.: Sensitivity of a data-driven soil water balance model to estimate summer evapotranspiration along a forest chronosequence, Hydrol. Earth Syst. Sci., 15, 3461-3473, doi:10.5194/hess-15-3461-2011, 2011.

Jackson, R. B., Sperry, J. S., and Dawson, T. E.: Root water uptake and transport: using physiological processes in global predictions, Trends Plant Sci., 5, 482–488, 2000.

Ross, P.J.: Fast Solution of Richards' Equation for Flexible Soil Hydraulic Property Descriptions, Land and Water Technical Report, CSIRO, 39/06, 2006.

Zwieniecki, M. A., Thompson, M. V., and Holbrook, N. M.: Understanding the Hydraulics of Porous Pipes: Tradeoffs Between Water Uptake and Root Length Utilization, J. Plant Growth Regul., 21, 315–323, 2003.

Figures for „Author comment - response to referee #2"

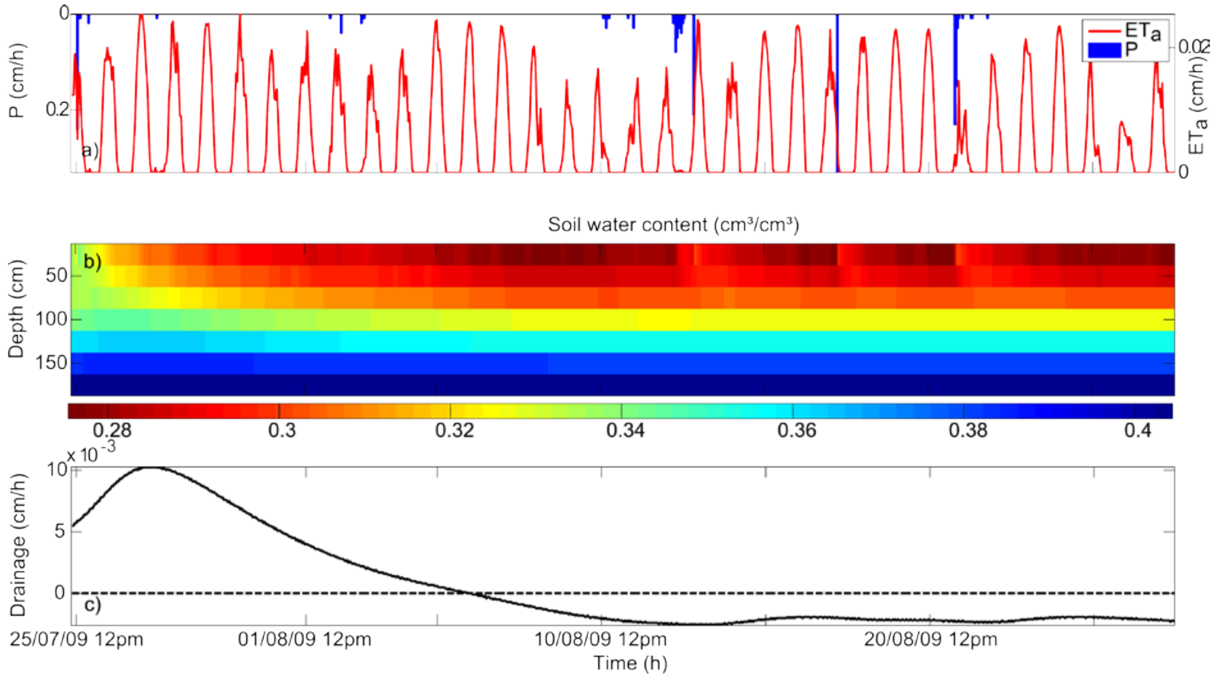

Figure AC2.1: Precipitation (P) and actual evapotranspiration (ET_a) from 25th July to 28th August (a), temporal and spatial evolution of soil water content (b) and drainage flux out of the soil column in 220 cm. Positive drainage indicate outflow and positive drainage indicate capillary rise.

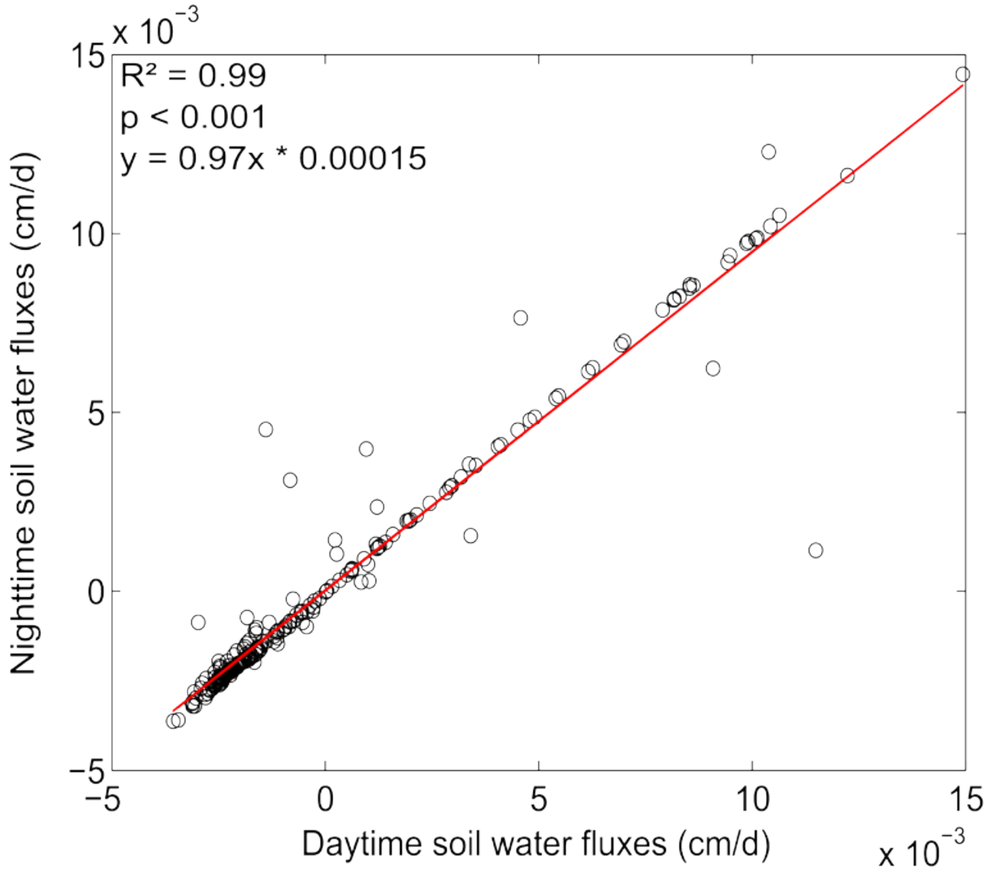

Figure AC2.2: Correlation between the mean fluxes of the respective day and the mean fluxes in the nights before and after one particular day. The analysis was conducted with the LinearModel.fit function of the Statistics toolbox in Matlab R2012.b.

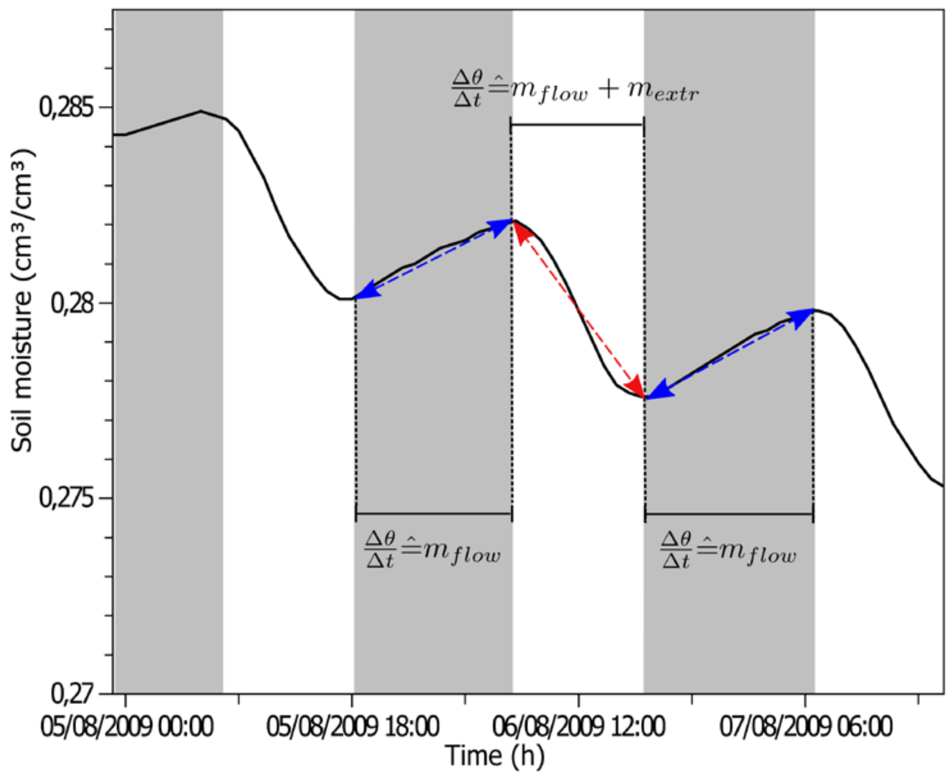

Figure AC2.3: Short term fluctuations of soil moisture in 15 cm depth during August 2009, showing the rewetting of soil at night times (blue line) and the water extraction at the day (red line); dashed lines depict the change between times with soil water extraction (white) and rewetting of soil (grey).

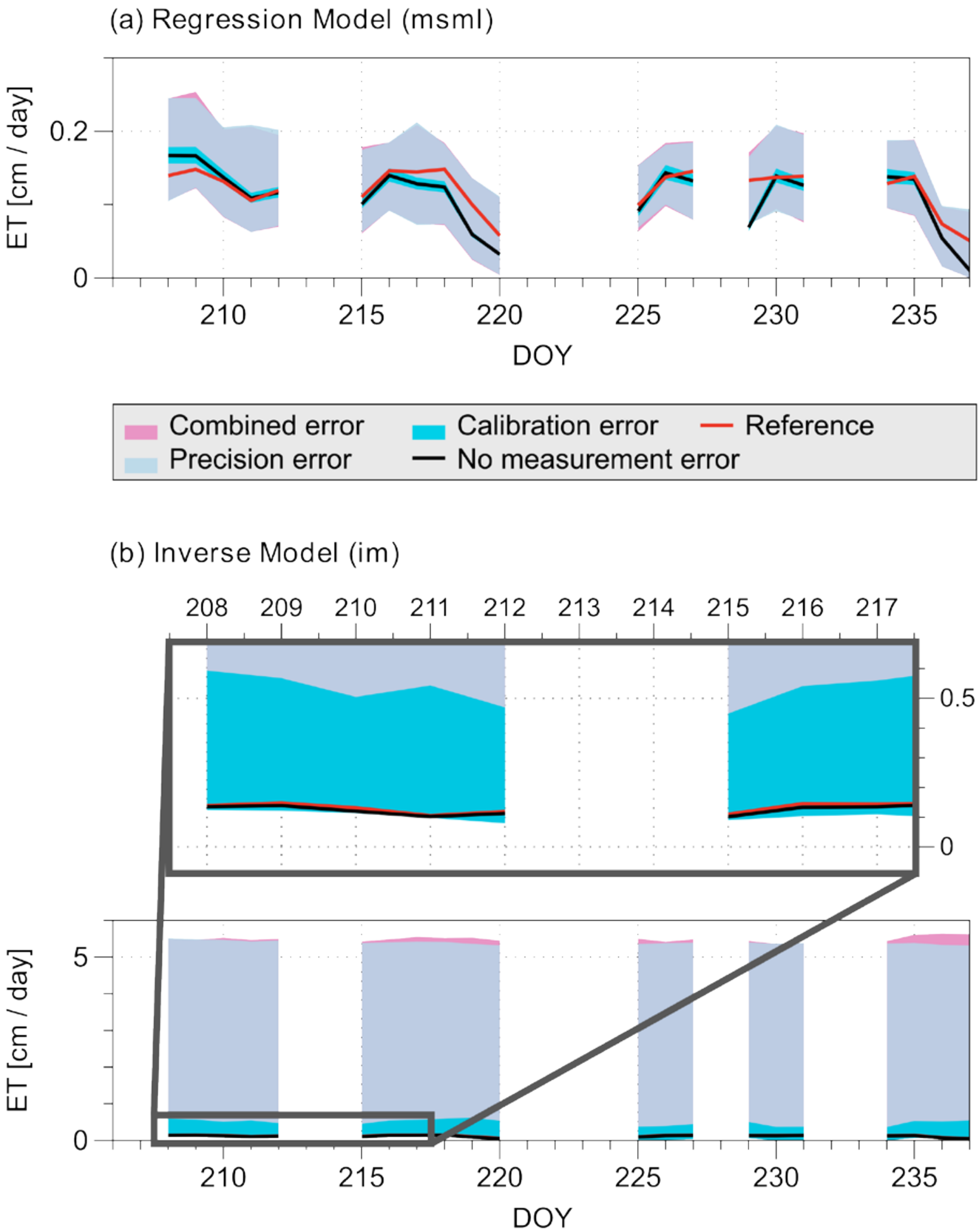

Figure AC2.4: Influence of soil moisture uncertainty on evapotranspiration estimated with the Multi Step Multi Layer Regression (Regression Model - msml) (a) and the Inverse Model (im) (b). The red line is the evapotransiration from the synthetic data (Reference). The colored bands indicate the 95% confidence intervals.

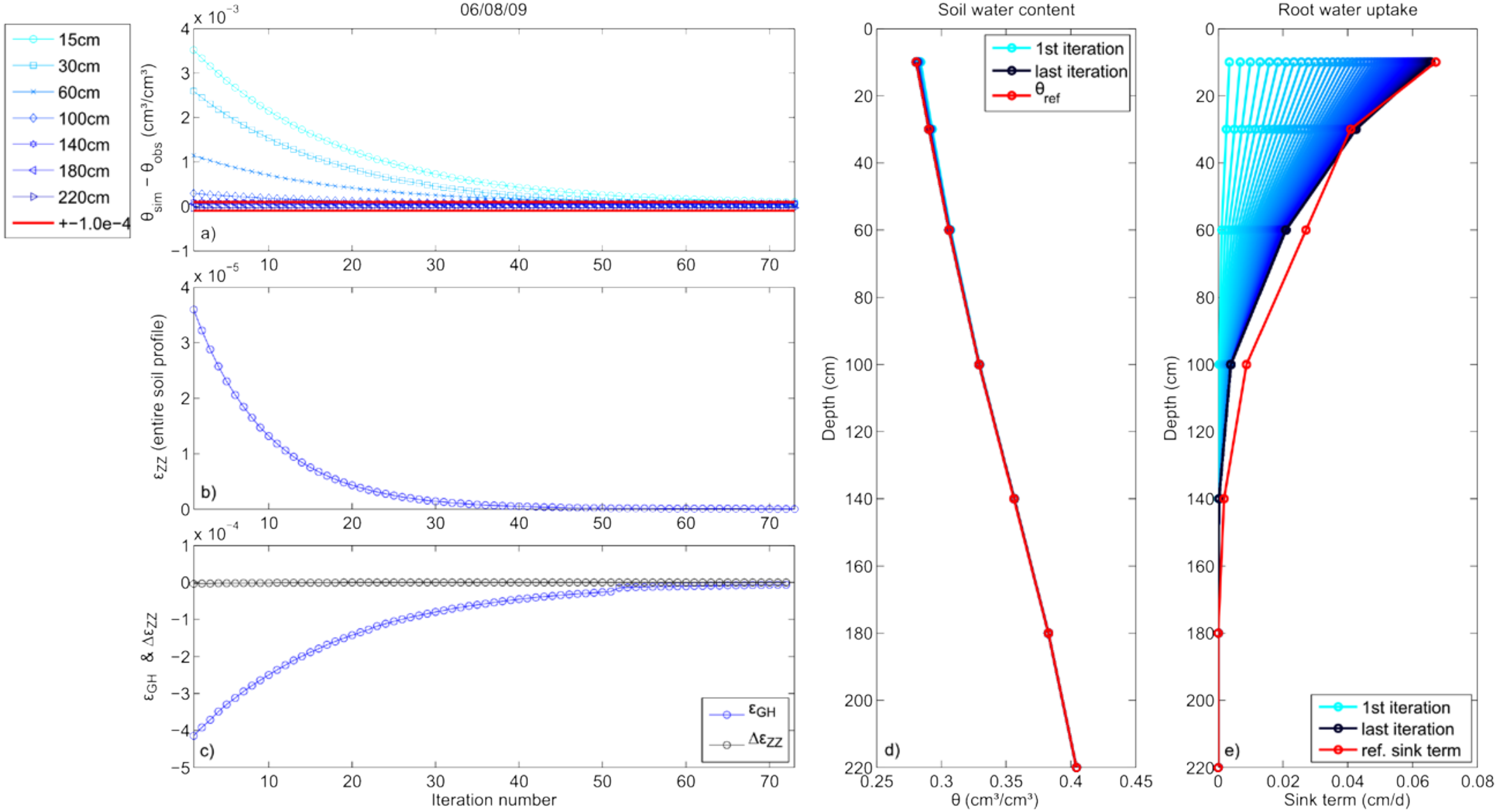

Figure AC2.5: Evaluation of the inversion process with undisturbed soil water content data of the im method (daily resolution). Subplot a) shows the difference of simulated (θ_{sim}) and observed soil water content (θ_{obs}) for each conducted iteration step in each depth. Suplot b) shows the evolution of the decision criteria ε_{ZZ} at each iteration step and c) depicts the convergence criteria $\Delta\ \varepsilon_{ZZ}$ and ε_{GH} for each iteration step until the reach their value for termination. Subplot d) shows the reference soil water content profile (θ_{ref}) which is in this case equal to θ_{obs} and the respective iterations. Subplot e) shows the reference sink term and the evaluation of the estimated sink term over depth for each conducted iteration.

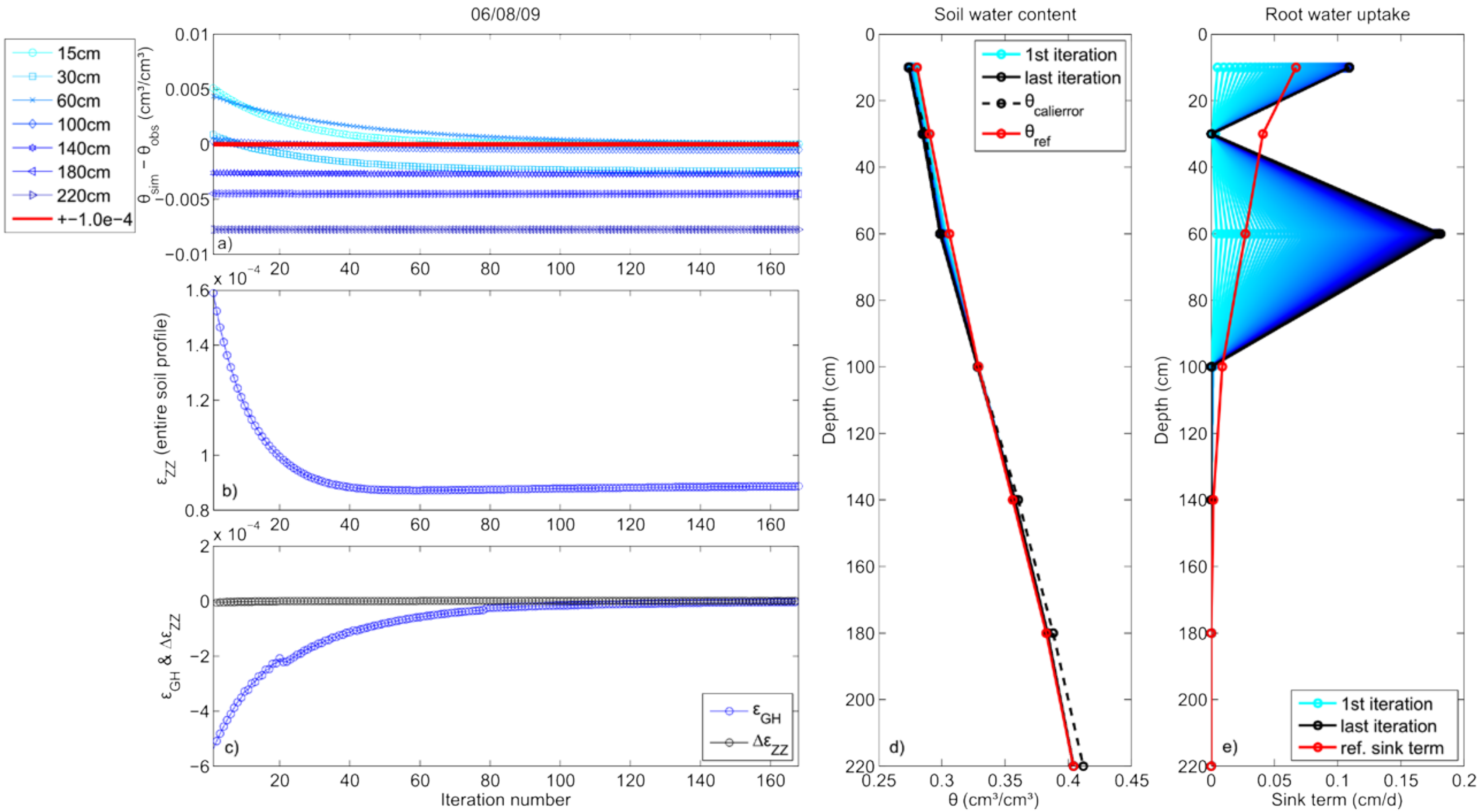

Figure AC2.6: Evaluation of the inversion process with disturbed soil water content data (calibration uncertainty) of the im method (daily resolution). Subplot a) shows the difference of simulated (θ_{sim}) and observed soil water content (θ_{obs}) for each conducted iteration step in each depth. Suplot b) shows the evolution of the decision criteria ε_{ZZ} at each iteration step and c) depicts the convergence criteria $\Delta\ \varepsilon_{ZZ}$ and ε_{GH} for each iteration step until the reach their value for termination. Subplot d) shows the reference soil water content profile (θ_{ref}), the perturbed soil moisture profile ($\theta_{calierror}$) and the respective iterations. Subplot e) shows the reference sink term and the evaluation of the estimated sink term over depth for each conducted iteration.