We would like to thank the reviewer providing critical feedback to our manuscript. We provided a reply to each comment which is followed by the revisions we made to the manuscript. The text for the reviewer comments are in grey while our replies and revisions are in black.

Anonymous Referee #3
Received and published: 25 January 2018
This is a strong paper which makes a clear contribution. In particular, I appreciate the attempt to inject more rigor into the discussion surrounding vertically-coupling among multi-depth soil moisture measurements. I view the paper's contribution as being mainly methodological; however, some interesting preliminary conclusions regarding the occurrence of vertical de-coupling are presented (specifically, that – at least at one site – de-coupling is not limited to dry soil conditions). The overall presentation of the manuscript is very good and the topic is of sufficient interest for HESS' readership. Therefore, I recommend publication following adequate response to the following minor points:

1) The manuscript would benefit from a more detailed description of exactly how their approach(es) can be used to improve the performance of a land data assimilation system. There are really two issues here. The first is a fundamental observability issue (i.e., what is the upper limit on how effectively surface soil moisture can be used to constrain sub-surface soil moisture given a perfect data assimilation issue). The second issue is the vertical accuracy of the assimilation paper. That is, even if you have high theoretical observability (i.e. high vertical coupling) at a particular point, you can still squander this potential constraint by using an assimilation model that does not properly represent this coupling. This is the model accuracy issue addressed previously by the Kumar et al. 2009 JHM paper (already cited in the original paper). To me, the second point is really the most important; however, addressing it requires the additional step of cross-comparing observed vertical coupling to the vertical coupling predicted by the assimilation model (when run off-line). It sounds like this is the ultimate intention of the authors; however, it is not explicitly spelled out in the current manuscript. So, in summary, I would encourage the authors to be more specific/detailed in describing exactly how these results can be used to improve the performance of a land data assimilation system.

We thank the reviewer for pointing out this aspect. Our intention with this paper was to develop a data driven assumption free method. We agree completely with the cross-comparison of observed vs modeled vertical coupling, but as the focus in this paper is indeed on the methodology itself we discussed to what extent such a comparison should be included in this paper. Nonetheless, based on the suggestion of the reviewer we revised the manuscript largely in Section 5.2 to accommodate the reviewers suggestion in page 11 starting from line 26

"For data assimilation (DA) applications, the applied (de)coupling methods can be used for cross-comparison of the vertical coupling derived from DA model outputs with those observed from long term in situ measurements. This can aid in examining the adequacy of the assumed inherent connection between surface and subsurface values. As Kumar et al. (2009) pointed out, land surface models vary in their representation of the strength of this connection (e.g. weak or strong connection) which contributes the degree in which modeling results are improved. They also suggested that strong coupling is a more robust choice unless independent information suggests that a more decoupled surface-subsurface representation is more realistic. In this aspect, the analysis applied in this study could be a valuable tool in determining which type of surface-subsurface coupling is the more optimal choice. Furthermore, the assumed connection strength is adopted for the whole range of soil moisture values. The results of our analysis show that at any given site, decoupling will occur regardless of degree of soil moisture variability. We suggest that perhaps a variable coupling strength could be adopted based on the soil moisture range where decoupling is likely to occur rather than a single value for the whole range."

2) The discussion in Section 3.2.2 is not very accessible. For example, equation (1) is introduced as describing the time series of "outcomes" Y_t, yet Y_t only appears on the LHS of the equation as g(E(Y)). "g" is apparently a "monotonic link function" (??) and E is some kind of a an expectation operator (in space, in time, across an ensemble?). So it's hard for me to see how Yt is actually "described" here. In the next function sentence "s" is introduced as a "basis function" (?) and all this is before the actual DLNM model is introduced. I suspect that all this terminology is correct and adequate

for an applied math audience; however, HESS readership will likely need a bit more help and conceptual background to get through this section. I'd strongly recommend that the authors revise/expand Section 3.2.2 with an eye towards making it more accessible to a general earth science audience. Especially the early part of the section between equations (1) and (2)...I struggled there to follow the authors' approach.

Similar response to reviewer #1, comment #4.
We realize the difficulty encountered by the reviewer in following the description of methods applied using the DLNM. We completely revised 3.2.2 section of the manuscript.

"3.2.2Distributed lag model
We incorporated delayed or lagged effects in evaluating the relation between surface and subsurface values, and eventually in determining (de)coupled values. It should be emphasized that the analysis was primarily focused on examining the trends and relations between surface and subsurface soil moisture. Moreover, it was not intended to contradict or replace other models for estimating soil moisture or examining its patterns.

A distributed lag non-linear model (DLNM) developed by Gasparrini et al. (2010) was applied to the 5 cm and 40 cm time series datasets at the study sites. Briefly, the model is capable of simultaneously representing both functional dependency and delayed response between exposure and response values. We considered surface soil moisture as the exposure values that produced delayed effects to the response values at the subsurface. A non-linear model was selected in order to capture the non- linear dynamics of flow and transport along the soil profile (Mohanty and Skaggs, 2001; Kim and Barros, 2002). Furthermore, DLNM offered enough flexibility to model a variety of dependencies in the time series dataset by selecting a suitable basis function. DLNM could be thought of as equivalent to a linear time series model (e.g. autoregressive model) just as a generalized linear model is equivalent to a linear model.

In assessing lagged dependence, event scale patterns were of interest rather than large scale trends within the time series (Wilson et al., 2004). This required seasonal patterns to be addressed prior to applying the DLNM. This was done by fitting a loess function to the time series and then subtracting it from the original soil moisture values (Cleveland et al., 1990). Removal of seasonality was further justified by the scatterplot results (see Section 4.1). The influence of seasonality on the vertical soil moisture variability is indicated by clustering of observation points occurring within the same months (fig.4). De-seasonalized soil moisture values were used for identifying (de)coupled soil moisture conditions.

For consistency in modeling, the range of surface soil moisture values used was from 0-0.50 cm 3 cm -3 . This was based on the highest surface soil moisture value encountered among the four sites. A lag value of up to 30 days was considered long enough to investigate delayed effects. This period also approximated the recurrence of heavy rainfall within the study sites. A spline function was the basis function chosen to represent the functional dependence as well as delayed effects as it offered
flexibility to capture non-linearities. In addition, contributions from daily rainfall data were used to incorporate current and past meteorological conditions. This was applied as a covariate and was represented with an additional basis function. We only considered delayed effects in vertical flow as lateral movement is deemed negligible in flat to slightly sloping terrain (Table.1). The analysis was performed in R software using dlnm (Gasparrini, 2011) and mgcv (Wood, 2006a) packages.

The following section concisely describes the mathematical formulation of a DLNM. However, the reader may choose to skip this section as the general methods applied have already been described in the text above. For a more detailed explanation, readers are referred to Gasparrini et al. (2010) and Gasparrini et al. (2017).

3.3 Evaluating (de)coupled soil moisture values
Application of a DLNM resulted in the estimation of parameter β for each surface soil moisture value. This indicated the strength of dependence between surface and subsurface soil moisture. Higher β values indicated stronger dependence or coupling between the two. Hence, we referred to β as the relative influence of surface soil moisture on subsurface values."
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####Some lines for the mathematical description of DLNM is not included here. The structure of this section was not revised#########

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3) The analysis here is based solely on vertically-discrete soil moisture measurements (i.e. soil moisture observed at a depth of 40 cm). However, in remote-sensing, modeling and data assimilation, soil moisture estimates reflect vertically-integrated values (within the measurement depth of the remote sensor or across the vertically-discrete soil layer specified in a land model). Will the transition between vertically-discrete versus vertically-averaged soil moisture values affect the applicability of these results in a modeling or data assimilation context? I would recommend more discussion on this point.

We thank the reviewer for raising this point. We added another paragraph in section 5.2 in page 12 starting from line 4 to tackle this topic.

"Although the study focused on vertically discrete values, the results are also applicable for depth-average values commonly used in remote sensing and DA applications. This requires that the vertically discrete values adequately capture the overall dynamics within zone being investigated. In such a case, we infer that the translation to depth-averaged values would result in (de)coupled values that are close, but not identical, to the values obtained when only comparing two discrete depths. As an illustration, we calculated the depth-average values using all the available measurements at each site (i.e. 5, 10, 20 and 40 cm depth) following the formula from Qiu et al. (2014). Figure 9 (left) reveals highly similar dynamics for both discrete and depth-average values. Therefore, it can be expected that the results from a regression and DLNM analyses using depth-average values would be highly similar to the original results in fig.5 and fig.8. However, if the vertically discrete values insufficiently represent the subsurface dynamics, larger deviations in the resulting decoupled values can be expected."

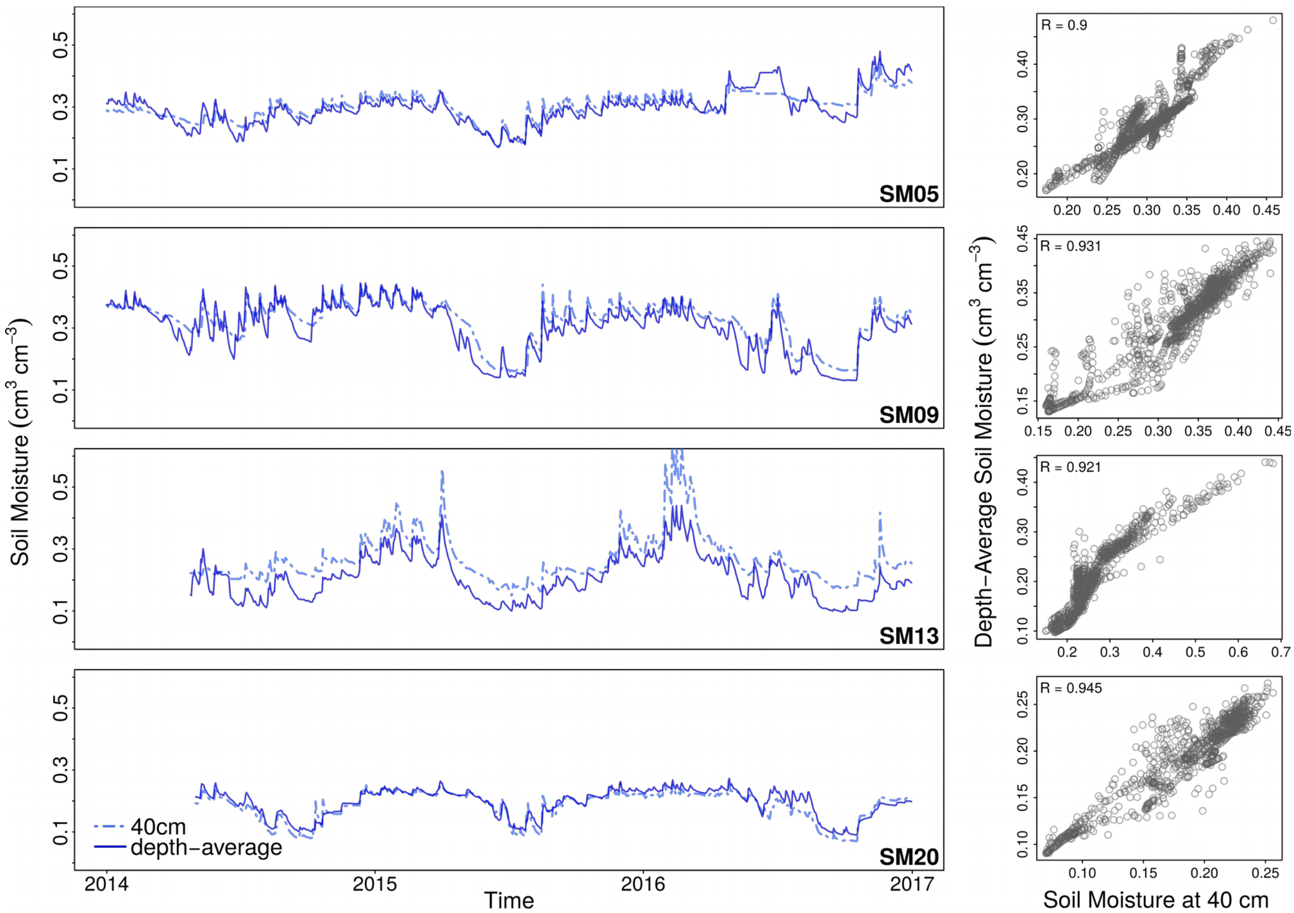

Figure 9. Subsurface soil moisture dynamics from vertically-discrete (40cm) and depth-average value. Left: Time series of soil moisture at 40 cm and depth-averaged values. The dynamics observed for depth-average values are highly similar to those at 40 cm. The scatterplots on the right further confirms that these two sets of values are highly correlated.

4) While the manuscript is generally well-written, it does contain a large number of minor English usage errors. Additional proof-reading is recommended.

There was another round of proof reading to check for textual and grammatical errors.