Dear anonymous referee #3:

Thank you for your valuable comments. Below we respond (highlighted in blue) to the reviewer's comments. The text that were added to the revised manuscript are marked in red.

The paper by Li and Good tackles a very important problem of trying to understand the contributions of the sources (observations and model) of uncertainty in SMAP soil moisture retrieval. In general I found the paper easy to read, typographic errors not withstanding, and as a non-expert in information theory I followed the logic of the arguments well. However, as an avid user of SMAP products, I would have like to have seen some attempt to translate the findings into the soil moisture units (mˆ3/mˆ3) and discussion of how the findings may be useful when next I process large time series of the SM estimates.

Response: We thank the reviewers for these overall constructive comments concerning about this work. Unfortunately, this study cannot translate the information quantities into the specific soil moisture unit of (m^3/m^3). We did not observe a strong relationship between the RMSE and the information uncertainties/decomposed mutual information components, likely in part to the large differences in the soil moisture regimes at different sites. RMSE as an absolute metric is more sensitive to these absolute differences while the correlation coefficient, being normalized by the variance at the site itself is less sensitive and more comparable across sites. The redundant components can be very helpful for large time series processing. For instance, the larger the redundant components of T_{Bh}, T_{Bv} to the DCA algorithm, the more likely we can obtain high quality datasets. The tolerance of the data quality depends on the user's need. In general, redundant information between T_{Bh}, T_{Bv} to the DCA of a value greater than 0.1 can be indicative of a better overall retrieval quality (~0.75 in Pearson correlation). We have added the following to the revised manuscript "Given the strength of this relationship, the *R* could be potentially used as a DCA evaluation metric that doesn't depend on *in situ* measurement and ancillary dataset. It is also useful for SMAP DCA soil moisture users to have a rough estimation of how high the quality of the obtained DCA soil moisture without actually knowing the *in situ* soil moisture. However, this depends on specific user requirements for data quality. In general, the DCA soil moisture tends to be in high end in term retrieval quality (~ 0.75 in Pearson correlation) when the *R* is greater 0.1.".

Specific comments:

Clarify the denominator in Eq. (4)

Response: We thank the reviewer for this comment. We have clarified this in the revised manuscript.

Scale disparity between in situ and image pixels resolution is not well addressed and I dare say a major contributor to the uncertainty. The conclusion that 88% of the uncertainty is attributable to uncertainty in Tb is a little hard to accept.

Response: We thank the reviewer for this comment and now better clarify where this estimate comes from. We have switched the 9km SMAP datasets to 36km SMAP datasets to address the comments from another reviewer who would like to know how the choice of different resolution of SMAP products may affect the overall analysis. Therefore, we obtained the 36km SMAP product and we found that the newly obtained 36km SMAP product no longer provides the MDCA soil moisture and is replaced by the Dual Channel Algorithm (DCA) soil moisture with some data updates. Thus, we decided to switch to the newest 9km and 36km SMAP data product. We have also found that we did not included the soil effective temperature (T_{eff}) in the uncertainty decomposition analysis. Hence, the results from the updated manuscript are now based on the consideration of soil effective temperature. In general, we found that 64% percent of the information total uncertainty is caused by informational random uncertainty from the input datasets of DCA. For now, we have classified the uncertainty induced by the sensing depth and spatial mismatch as part of the informational random uncertainty. This is because the model does not contain the resolution itself and the uncertainty induced by sensing depth is more of imperfection of the sensor. However, it is extremely hard to sperate what's the proportion of informational random uncertainty is specifically caused by spatial mismatch. We have added the following text in the revised manuscript "It is important to acknowledge that we used the point based *in situ* soil moisture as the ground truth in this analysis. Due to course spatial resolution of SMAP products, we acknowledge that *in situ* soil moisture may not be able to represent the spatial averaged soil moisture well. Although the nominal sensing depth of L-band SMAP soil moisture is 5 cm, the penetration depth was found to be even shallower in wetter regions (Shellito et al., 2016). In fact, the L-band sensing depth was found to as little as ~1cm (Jackson et al., 2012) and can be more sensitive to surface meteorological conditions and more random than the actual *in situ* soil moisture. The heterogeneity in each pixel relative to the *in situ* observations together with the sensing depth disparity may negatively influence the results of this study and result in an overestimate the actual informational uncertainties. We also acknowledge the existence of upscaling methods for matching the *in situ* soil moisture to satellite footprint (Crow et al., 2012). However, most of upscaling methods are achieved under the assistance of additional reference soil moisture datasets. This process introduces additional pieces of information in the DCA system making the separation of the uncertainty induced by the upscaling algorithm or additional dataset from other informational uncertainties much harder. Additionally, we used the hourly *in situ* data to best match the SMAP DCA soil moisture retrievals in time (within an hour). Therefore, it is hard to find a reference dataset at with high frequency in time domain and good spatial coverage. Here we consider the informational uncertainty caused by the spatial mismatch and sensing depth mismatch between *in situ* and DCA soil moisture as part of the informational random uncertainty (I_{Rnd}). Because the DCA essential is a mathematical function and does not inherently require the inputs to be at a specific resolution. The spatial resolution is often the inherent attribute of the data. The sensing depth is more of imperfection L-band sensor. The reader should also keep these in mind while interpreting and adopting the results in this study."

L251-258, Fig. 4, and L347-350: This was confusing and can do with greater clarification to aid in the interpretation of the results. As I read it, the fraction of model-to-overall uncertainty is negatively correlated with the cor(in situ,MDCA), while positively correlated with error(in istu,MDCA). What does this mean and what are the implications for model refinement?

Response: We thank the reviewer for this comment. As we mentioned earlier, we changed the SMAP product in order to address the comment from the other reviewer. In the analysis of this new product, we found that there is no significant correlation between the RMSE and correlation between *in situ* soil moisture and DCA soil moisture. Therefore, we decided to exclude the RMSE plots. We have also plotted the actual informational model uncertainty against the Pearson correlation of *in situ* and DCA soil moisture. The implications of this analysis for model refinements are (1): more robust water body correction methods are needed for SMAP brightness temperature observations. The quality of the model effective soil temperature that goes to the SMAP DCA system need to be further evaluated (2): model uncertainties can be reduced potentially by a better parameterization scheme such as replacing time independent parameter with seasonal dependent parameters especially in locations where there are seasonal changes in landcover or vegetation phenology

References

Crow, W. T., Berg, A. A., Cosh, M. H., Loew, A., Mohanty, B. P., Panciera, R., de Rosnay, P., Ryu, D. and Walker, J. P.: Upscaling sparse ground-based soil moisture observations for the validation of coarse-resolution satellite soil moisture products, Rev. Geophys., 50(2), 634, doi:10.1029/2011RG000372, 2012.

Jackson, T. J., Bindlish, R., Cosh, M. H., Zhao, T., Starks, P. J., Bosch, D. D., Seyfried, M., Moran, M. S., Goodrich, D. C., Kerr, Y. H. and Leroux, D.: Validation of Soil Moisture and Ocean Salinity (SMOS) Soil Moisture Over Watershed Networks in the U.S., IEEE Trans. Geosci. Remote Sens., 50(5), 1530–1543, doi:10.1109/TGRS.2011.2168533, 2012.

Shellito, P. J., Small, E. E., Colliander, A., Bindlish, R., Cosh, M. H., Berg, A. A., Bosch, D. D., Caldwell, T. G., Goodrich, D. C., McNairn, H., Prueger, J. H., Starks, P. J., van der Velde, R. and Walker, J. P.: SMAP soil moisture drying more rapid than observed in situ following rainfall events, Geophys. Res. Lett., 43(15), 8068–8075, doi:10.1002/2016GL069946, 2016.