Dear anonymous referee #2:

Thank you for providing such valuable suggestions and comments on our manuscript. Please find the response to these comments (in blue). The sentences or paragraphs that were added to the revised manuscript are in red.

The topic of the manuscript is certainly important and interesting for HESS readers. However, the manuscript contains a large number of typos, things that should be explained in more detail and assumptions that are not discussed and could affect the results. The authors cite (Lines 84-86) just two of the possible uncertainty sources of the retrieval model, however the method discussed in this manuscript is based on in situ measurements. Therefore, the uncertainty of in situ measurements must be taken into account, and it is not at all. In situ measurements are here considered as "ground truth". Unfortunately "ground truth" does not exist, as all measurements, they have errors. But probably more important is the uncertainty of the spatial representativeness (satellite Tbs are representative of a spatial scale of tens of kilometer while in situ measurements are single point measurements) and depth representativeness (sensors measure at a given depth while the Tbs are representative of a different/changing depth). These effects must be mentioned and discussed and their possible effects on the results should be analyzed.

Response: We thank the reviewers for these overall constructive comments. We agree and admit that part of the uncertainty is due to scale mismatch between point measurements of *in situ* and SMAP data product. We also acknowledged that the sensing depth of the SMAP may vary, though the designated sensing depth is up to 5cm. In practice, the sensing depth may be even shallower. 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. We added the following paragraph "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." to the revised manuscript

In addition, why using 9km Tbs instead of the original Tbs in the 36 km grid which is closer to the instrument resolution (_ 50 km). The SM dataset that is provided in a grid with 9-km sampling has been obtained using a Backus-Gilbert interpolation. Surprisingly this is not mentioned at all in the manuscript. How could this choice affect the results as this is another uncertainty source that is not taken into account?

Response: We thank the reviewer for this comment. We compared informational uncertainty from both the 9km SMAP datasets and 36km SMAP datasets to address the resolution effects. 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 when we were obtaining the 36km SMAP product. Thus, we decided to switch to the newest 9km and 36km SMAP data product for the comparisons of resolution effects. We have also included the soil effective temperature (T_{eff}) in the uncertainty decomposition analysis since this information is important in the DCA modeling process. We found that the differences in informational uncertainties between SMAP DCA 36km and 9km product are not pronounced (Figure 1 below). The results from a two-sample t-test between SMAP 9km and SMAP 36km information uncertainties shown that there is no significant different between SMAP 9km and SMAP 36km in informational uncertainties ($p > 0.05$). Given no pronounced resolution effects on informational uncertainties, we decided to proceed by using the original SMAP 36km product for this study.

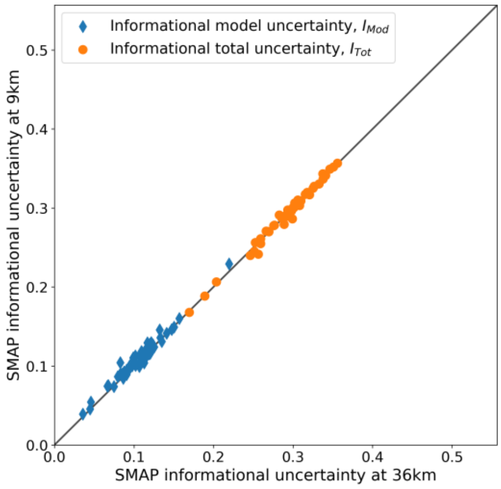

Figure 1. Informational uncertainty comparisons between 36km and 9km SMAP DCA products

If MDCA is better (at least taking into account that using together Tbh and Tbv adds 15 % of information) why SCA is the official SMAP algorithm and gives better results ? "There is strong interest in the MDCA approach because of its independent estimation of vegetation water status". I probably agree, but this if very very challenging using a single incidence angle. SMOS can do it because it provides multi-incidence angle Tbs. Konings et al. "How Many Parameters Can Be Maximally Estimated From a Set of Measurements?," in IEEE Geoscience and Remote Sensing Letters, vol. 12, no. 5, pp. 1081-1085 have already explained that not because there are two measurements it is possible to actually retrieve two parameters.

Response: We thank the reviewer for this comment. We did not state that the MDCA/DCA perform better than the SCA. The objective of our study is to partition the overall informational uncertainty into the uncertainty caused by the DCA input data streams and that caused by the model itself. We also thank the reviewer for providing this valuable paper reference. We mentioned the dual channel is interesting not only because it provides soil moisture but provided vegetation optical depth estimation that cannot be independently estimated through the SCAs. It is reasonable to assume that the vegetation optical depth may not be accurate as there are large uncertainties in the DCA. Hence, finding where the information is lost (informational uncertainties) in the DCA can be helpful for DCA soil moisture estimations and hence more accurate estimation of vegetation optical depth. We thank the reviewer for providing this valuable reference and have cited this reference in the following "There is strong interest in the DCA approach because of its independent estimation of vegetation opacity in lieu of the specified vegetation climatology employed by the SCA. Additionally, it has been suggested that using a time-integrated vegetation opacity, as is employed in the multi-temporal dual channel algorithm (MT-DCA) for instance (Piles et al., 2016), improves the estimates of soil and vegetation state. These contrasting approaches, as well as other studies on SMAP's temporal polarized ratio algorithm (TPRA) (Gao et al., 2020) and regularized dual channel algorithm (RDCA) (Chaubell et al., 2019), suggested there is still uncertainty about how SMAP observations of horizontal and vertical brightness temperature can be best translated into estimates of surface properties. Although SMAP can provide spatially explicit soil moisture estimates that have been shown to be useful to understand a set of ecohydrological problems (Jadidoleslam et al., 2019), the soil moisture retrievals are still subject to significant amount of uncertainty due to the imperfection of the model and the forcing datasets. The success of retrieving soil moisture and vegetation opacity are interdependent (Konings et al., 2017) and it is important to consider the how the amount of duplicate information carried within a set of observations limits the number of parameters to be inferred (Konings et al., 2015). Therefore, it is critical to diagnosis and quantify the causality of the uncertainty caused by the SMAP algorithm in order to improve the soil moisture and vegetation opacity retrieval quality." of the introduction

Other comments ——————

Line 18: raw data here is undefined. The authors should be more specific so that the abstract is self-explicative

Response: We thank the reviewer for this comment. The "raw data" has been explicitly replaced by "T_{Bh}, T_{Bv} and T_{eff}" that are the inputs to the DCA.

Line 21: "inadequacy" is not a scientific term. What is that inadequacy? Where does it come from?

Response: We thank the reviewer for this comment. We have replaced "inadequacy" with the term "a lack of additional explanatory power beyond T_{Bh}, T_{Bv} and T_{eff}" in the revised manuscript.

Line 67: Peggy O'Neill et al. should be O'Neill et al.

Response: We thank the reviewer for the comment. The citation style has been corrected as suggested.

Line 79: 0.04 m3/m3 accuracy target? Which is the metric the authors refer to ?

Response: We thank the reviewer for this comment. The metric that we are referring to is ubRMSE. We have specified the metric in the revised manuscript.

Line 136: The tau-omega model is not inverted at all. It is used as a forward model and the modeled Tbs are compared to the observed ones varying parameters such as SM. When the Tb's are similar to the observed ones, SM is assumed to be close the real value. There is no inversion of the model giving SM as a function of Tb.

Response: We thank the reviewer for this comment. This sentence has been rephrased as "It requires the brightness temperatures as the main inputs, soil effective temperature as an ancillary input, and is parameterized based on overlaying vegetation and soil surface information. The DCA iteratively feeds the '*tau-omega'* model with initial guesses of soil moisture and vegetation optical depth." in the revised manuscript.

Line 144: it is the uncertainty or the variable that is denoted as H(Yobs) ?

Response: We thank the reviewer for this comment. We have dropped this term in the revised manuscript and have provide a more explicit definition.

Line 150: The following sentence is meaningless "Although the detailed structure of best achievable model performance maybe remain unknown, mutual information, denoted as I(XInputs; Yobs) where XInputs are the available inputs and Yobs is the in situ measured variable of interest, can provide a good benchmark measure". Please, rephrase.

Response: We thank the reviewer for this comment. The above statement has been rephrased to "Mutual information between the model inputs and *in situ* observations of model output can be used as a useful and effective measure of best achievable performance model because it links the model inputs and *in situ* observations only through the joint and marginal probability mass functions that do not involve any priori model assumptions (Gong et al., 2013)."

Line 167: Eq. 2, what is the sense of writing an inequality comparing "mutual informations" (I) with the uncertainty of the variable of interest (H(Yobs))? H and I should not be in the same inequality.
Response: We thank the reviewer for this comment. We found that these inequalities may introduce unnecessary confusions to the readers. Therefore, we have dropped this equation (1) and equation (2) in the revised manuscript. The explanation is that the entropy *H*(.) can be interpreted as the uncertainty inherent in a random variable or the amount of information requires to describe a random variable. The maximum information of another or other explanatory random variables can provided/capture the information about such random variable should be the entropy of this random variable.

Furthermore, in the example of Eq.1 X is Tbs, Y is Ymodel and Z is Yobs as i) one measures the Tbs, ii) apply the model, iii) Compare to "ground truth". Therefore I(X,Y) >= I(X,Z) should be I(X_inputs, Ymodel) >= I(X_inputs, Yobs) instead of what is written
in Eq. 2
Response: We thank the reviewer for this comment. We have dropped this equation. The explanation of the inequalities can be found in this paper (Gong et al., 2013).

Lines 175-180. The manuscript will be clearer if it is stated how to compute those quantities from the actual SM time series records (taking into account the uncertainties)
Response: We thank the reviewer for this comment. The details about how we calculated entropy, mutual information and informational uncertainties in the DCA systems has been provided in the revised manuscript.

Line 193 Eq. 5 Why the "mutual information" is compared to uncertainties? Why
uncertainties are assumed to be additive?
Response: We thank the reviewer for this comment. The reason why uncertainties is assumed to be additive is because the way informational random uncertainty and informational model uncertainty are defined in (Gong et al., 2013). We have provided the following descriptions "For a given system in which the inputs and output are linked via mathematical functions, the mutual information between model outputs and *in situ* observation can never exceed the entropy of the *in situ* observations. This information gap is defined as informational total uncertainty (I_{Tot}). The mutual information between the *in situ* observations and the available explanatory variables is also always smaller than the entropy of *in situ* observations. This information gap, defined as informational random uncertainty (I_{Rnd}), is caused by the existence of inherent data uncertainty of the explanatory variables and a lack of complete explanatory variables to fully capture the information in the *in situ* observations." in the revised manuscript.

Line 195: Eq. 5 expresses I as a function of HCN, how Hcn(Ymdca, Yobs) could be estimated by replacing anything in Eq. 5. Do the authors mean I(Ymdca, Yobs) can be ..." ?
Response: We thank the reviewer for this comment. We have added the following equations to the revised manuscript "

$$H(\mathrm{X}, \mathrm{Y}) = -\sum_{x \in X} \sum_{y \epsilon Y} p(x, y) log_2\, p(x, y), \quad (1)$$

where $p(x, y)$ is the joint probability mass function associated with X and Y that is estimated by the same method mentioned above. The same normalization and correction method of eq. (2) is applied to joint entropy of eq. (3). The entropy after the correction and normalization is formulated as

$$H_{CN}\,(\mathrm{X}, \mathrm{Y}) = \frac{H(\mathrm{X,Y}) + \frac{K-1}{2n}}{log_2\, n}, \quad (2)$$

where H_{CN}(X, Y) is the corrected and normalized joint entropy of random variable associated with $\{X, Y\}$, H(X, Y) is the uncorrected entropy from eq. (3), n is the number of data points that were used to calculate the normalized joint entropy (hereafter joint entropy), K is the number of non-zero joint probabilities based on the Freeman and Diaconis method (Freedman and Diaconis, 1981). All the joint entropies that are associated with two or more random variables in the later equations (i.e., H_{CN}(*in situ*, DCA), $H_{CN}(T_{Bh}, T_{Bv}$, DCA), $H_{CN}(T_{Bh}, T_{Bv}, T_{eff}$, *in situ*) etc.) are computed using the combination of eq. (3) and eq. (4) with the replacement of $p(\bullet)$ by their joint probability mass functions, respectively. "

Eq 10. What is -II ?
Response: We thank the reviewer for this comment. II is the interaction information and -II is the negative number of II.

—- Typos Line 193 Eq. 5 TBv should be T_{B_v}.
Response: We thank the reviewer for this comment. We have corrected the typo.

Line 177. "is" and "the" are lacking. "Where p IS THE probability..."
Response: We thank the reviewer for this comment. We have corrected the typo.

Line 194: ... and H_CN() ARE the estimated joint ENTROPIES that ...
Response: We thank the reviewer for this comment. We have corrected the typo.

Line 196. It IS worth
Response: We thank the reviewer for this comment. We have corrected the typo.

Eq 8: U_1 should be U_2
Response: We thank the reviewer for this comment. We have corrected the typo.

Line 232: H_CN(h,v) should be H_CN(Tbh, Tbv)
Response: We thank the reviewer for this comment. We have corrected this typo.

Line 345. Please correct "theoretic"
Response: We thank the reviewer for this comment. We have corrected this.

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