Dear anonymous referee #1:

We thank you for providing such thoughtful comments to improve our manuscript. The responses of the comments are highlighted in blue. The new paragraphs/sentences that were added to the revised manuscript are marked in red. As an additional note to the reviewer, after re-evaluation of our datasets, we now have more sites included in this revised manuscript (58 sites now compared to 51 in the last version). This is because analysis of the last version was focused on the sites where both SMAP 9km dataset and SMAP 36km datasets pass the quality control and we only used the 36km dataset. But here in this version, we focus on 36km data product. Therefore, more sites are available as some sites did not have 9km data. In addition, after re-checking the time of DCA observations, we found that the DCA brightness temperature time field were slightly miss aligned in our prior analysis by ~12hrs. We have corrected such mistake in this version. These adjustments have not signifyingly altered our results or conclusions drawn in this paper.

Compared to the previous version, the methodology is presented in a clearer way.

1. The fact that the results are treated by type of surface makes it possible to enrich the discussion. However, these groupings do not respond to the suggestion made, i.e. to treat all the surfaces together for the calculation of entropy in order to properly reflect the model's capacity to treat different surfaces. By calculating the parameters site by site and comparing the results to local statistics one can arrive at a wrong interpretation of the statistics. I find it counter-intuitive that the best results are obtained when the information is redundant rather than synergistic. One explanation for this is that the best correlation is obtained on surfaces where the vegetation cover is less important (with larger range of value and little vegetation effects). This is also the situation where Tbh and TBv are the most correlated, hence the high R. To say that R can be a good indicator to evaluate a model is a bit hazardous in this case. A comment on this point should be made in the discussion.

Response: We have now also computed the uncertainties by lumping all the datasets together and have shown the results in "Lumped" column of table 1 in the revised manuscript. In addition, we also did the partial information decomposition using the "Lumped" dataset. The results are shown in revised version of table 2. We explored the relationship between these information components and different metrics such as vegetation density, vegetation homogeneity, informational total uncertainty etc. We found that these quantities are all marginally related to the informational components (S, R, U_h, U_v). We think high R (lower S) is both physically affected by vegetation and how the algorithm processes the T_{Bh} and T_{Bv}. Therefore, our S and R is an integration of these factors. We have added "These information components were found to be marginally correlated with factors such as vegetation density (the Pearson correlation of average LAI with R, S, U_h U_v are 0.23, -0.38, -0.54, and -0.19 respectively) and vegetation heterogeneity (the Pearson correlation of LAI standard deviation with R, S, U_h, U_v are 0.22, -0.39, -0.54, and -0.22 respectively). Additionally, these informational components were also found to be correlated with the mutual information shared between brightness temperatures and DCA estimates (the Pearson correlation of $I(T_{Bh},T_{Bv}; DCA)$ with R, S, U_h, U_v are 0.6, -0.28, 0.22, and -0.16 respectively), the informational total uncertainty (the Pearson correlation of I_{Tot} with R, S, U_h, U_v are -0.76, 0.62, 0.56, and 0.68 respectively), informational random uncertainty (the Pearson correlation of I_{Rnd} with R, S, U_h, U_v are -0.42 , 0.29, 0.05, and 0.15 respectively), and informational model uncertainty (the Pearson correlation of I_{Mod} with R, S, U_h, U_v are -0.63, 0.56, 0.66, and 0.75 respectively).

This indicates that these informational components in the DCA system are not only physically driven by both vegetation density and heterogeneity but also other factors such as how algorithm processes the information from T_{Bh} and T_{Bv} to produce the DCA outputs. It is more likely to observe higher *R* and lower *S* in locations where vegetation is denser and more heterogeneous, yet the correlation of these variables with model quality (0.47 for mean LAI and 0.42 for the standard deviation of LAI) are weaker than the correlations found between *R* and *S* and model quality shown in Figure 7." to 4.2 Model evaluation from another perspective. The following paragraph "In addition, we find the proportion of informational uncertainty increases as the data is lumped together relative to averaging these statics calculated on a site-by-site basis (Table 1). Treating all the surfaces together as a whole does not reduce the informational total uncertainty because the lumping process contains both "high quality" and "low quality" (as assessed by the Pearson correlation between *in situ* and DCA soil moisture) datasets. The uncertainties in these datasets may accumulate while lumping them together and result in an increase in total informational uncertainty." was also added to 4.1 DCA informational uncertainties."

Detailed comments

Comment est calculé teff (a mettre dans la section 2 plutôt que 4)

2. L241 coarse

Response: We thank the reviewer for this comment. The typo has been corrected.

3. L244 …more sensitive …. In situ soil moisture: I don't undersdand

Response: We thank the reviewer for the comment. I acknowledge that such statement may confuse the reader. Therefore, we have replaced "can be more sensitive to surface meteorological conditions and more random than the actual *in situ* soil moisture." by "was found to vary wet or dry surface soil conditions (Escorihuela et al., 2010; Raju et al., 1995)".

4. L244 you can consider the following papers dedicated to sampling depth.

M.-J. Escorihuela, A. Chanzy, J.-P. Wigneron, et Y. H. Kerr, « On the effective soil moisture depth of L-band radiometry: a case study », Remote Sensing of Environment, vol. 114, p. 995 1001, 2010, doi: doi:10.1016/j.rse.2009.12.011.

S. Raju, A. Chanzy, J. P. Wigneron, J. C. Calvet, Y. Kerr, et L. Laguerre, « Soil moisture and temperature profile effects on microwave emission at low frequencies », Remote Sensing of Environment (NLD), vol. 54, no 2, p. 85 97, 1995.

Response: We thank the reviewer for providing these papers. We have cited them in revised paper. Please refer to the response in Comment 3

5. L246 is it really an overestimate.

Response: We thank the viewer for point out this. We acknowledge this can be overestimate or underestimate. Therefore, we have changed "result in an overestimate the actual informational uncertainties" to "bias the estimation of informational uncertainty" in the revised manuscript.

6. L294 what you mean by high quality data set?

Response: We thank the reviewer for this comment. The high-quality dataset here is referred to as the high Pearson correlation coefficient between the SMAP DCA soil moisture and *in situ* soil moisture. We have added the following to clarify this "(higher correlation between *in situ* soil moisture and SMAP DCA soil moisture)".

7. L305: This indicates ...: see my general comment. The DCA is designed to take profit of TBh and the difference between TBh and TBv. Physically this statement is wrong and probably requires deeper discussion.
Response: We thank the reviewer for this insightful comment. We have removed such statement from the revised manuscript.

8. L320'321 How can you say that?
Response: We thank the reviewer for such comment. We have replaced such statement "Mutual information can provide a way of unambiguously define the best achievement performance of a model that is able to completely transform the available information to the desired target given a set of the input data" with "It offers an opportunity of partitioning the total informational uncertainty in the DCA to the uncertainty due to the input datasets and the uncertainty due to model structure and model parameterizations. This partition cannot be achieved by leveraging the common DCA assessment metrics (Chan et al., 2018) (e.g., Pearson correlation, ubRMSE) that only involve the DCA soil moisture and *in situ* soil moisture".

9. L333 why schrubland are less sensitive to water availability.
Response: We thank the reviewer for this comment. We acknowledge that such statement might be erroneous. Therefore, we have removed this sentence.

10. L374 Tbh and TBv are correlated but Tbv-Tbh give an orthogonal information linked to the roughness and the vegetation. This is the essence of DCA. Taking care of sweeping the physic like this on the basis of your statistic that might be not well posed.
Response: We thank the reviewer for this comment. We have removed this sentence from the paragraph mentioned.

11. For the originality of the approach, the quality of presentation this paper deserve publication but apparent conflict between the physic and the results need a bit more discussion and some final statement might a bit tempered.
Response: We thank the reviewer for supporting our article. We have added the explanation regarding this partial information decomposed components in the discussion and have tempered the overall conclusion in the revised manuscript.

References

Chan, S. K., Bindlish, R., O'Neill, P., Jackson, T., Njoku, E., Dunbar, S., Chaubell, J., Piepmeier, J., Yueh, S., Entekhabi, D., Colliander, A., Chen, F., Cosh, M. H., Caldwell, T., Walker, J., Berg, A., McNairn, H., Thibeault, M., Martínez-Fernández, J., Uldall, F., Seyfried, M., Bosch, D., Starks, P., Holifield Collins, C., Prueger, J., van der Velde, R., Asanuma, J., Palecki, M., Small, E. E., Zreda, M., Calvet, J., Crow, W. T. and Kerr, Y.: Development and assessment of the SMAP enhanced passive soil moisture product, Remote Sens. Environ., 204, 931–941, doi:10.1016/j.rse.2017.08.025, 2018.
Escorihuela, M. J., Chanzy, A., Wigneron, J. P. and Kerr, Y. H.: Effective soil moisture sampling depth

of L-band radiometry: A case study, Remote Sens. Environ., 114(5), 995–1001, doi:10.1016/j.rse.2009.12.011, 2010.
Raju, S., Chanzy, A., Wigneron, J.-P., Calvet, J.-C., Kerr, Y. and Laguerre, L.: Soil moisture and temperature profile effects on microwave emission at low frequencies, Remote Sens. Environ., 54(2), 85–97, doi:10.1016/0034-4257(95)00133-L, 1995.

Dear anonymous referee #2:

We thank you for your valuable comments. The replies to the comments are highlighted in blue. The new text added to the revised manuscript are marked in red. As an additional note to the reviewer, after re-evaluation of our datasets, we now have more sites included in this revised manuscript (58 sites now compared to 51 in the last version). This is because analysis of the last version was focused on the sites where both SMAP 9km dataset and SMAP 36km dataset pass the quality control and we only used the 36km dataset. But here in this version, we focus on 36km data product. Therefore, more sites are available as some sites did not have 9km data. In addition, after re-checking the time of DCA observations, we found that the DCA brightness temperature time field were slightly miss aligned in our prior analysis by ~12hrs. We have corrected such mistake in this version. These adjustments have not significantly altered our results or conclusions drawn in this paper.

The manuscript has improved significantly in readability, the methodology explanation is much clearer in the new version. The analysis per land cover classes is an interesting addition. Using the SMAP data set which is provided in a 36 km, closer to the instrumental resolution, is a good choice as well. A plot was provided in the authors answer to my previous comments comparing the results using the "36 km" or the "9 km" SMAP data sets, showing no significant differences. This is expected as providing a 50 km resolution data set in a 9 km grid or in a 36 km grid should not affect the results of this study.

I have a number of comments:

1. "Higher redundant information provided by Tbh and Tbv tends to be found in land covers with less woody components". This is surprising, the effet of those woody components is to create a depolarisation making TbH and Tbv more similar. In this sense, I would expect that they are more redundant when the vegetation cover is denser. The manuscript will still improve if such affirmations are interpreted in relation with our physical understanding of the signal. My feeling is that the analysis in terms of "redundancy" is only showing that the for the easiest sites (those with more homogeneous land covers, topography, roughness, meteorological conditions, those for which remote sensing estimations agree the best with in situ measurement), the results are good using either TbH or Tbv. This does not imply that "redundancy" is the reason of the better results. Regarding the affirmation "The informational redundancy between these remotely sensed observations can be used as independent metric to assess the retrieval quality of the algorithms". I do not agree until the physical insight mentioned above is included.

Response: We thank this reviewer for such insightful comment. We found that the redundant component is related to many factors. We explored the relationship between the redundant component (R) and site vegetation density and surface vegetation homogeneity as indicated by LAI values the site LAI standard deviation. As suggested by the reviewer, we found that vegetation density is marginally correlated with R (Pearson correlation [$\boldsymbol{r}$(LAI; R)] of 0.22). In addition, the vegetation homogeneity is also marginally correlation with R ($\boldsymbol{r}$(LAI std; R)] of 0.23). The R is also correlated with mutual information between T_{Bh}, T_{Bv} and SMAP DCA ($\boldsymbol{r}(I(\mathrm{DCA}; T_{Bh},T_{Bv}); R)$ of 0.6) as well as the informational model and random uncertainties. Therefore, the metric R is not only integrating information about how surface vegetation (vegetation density and vegetation homogeneity) may affect the algorithm performance, but also provided insights into how the SMAP DCA processes these the brightness temperature data streams. The correlation between *R* and the DCA model quality is higher than the correlation of the mean (or std) of LAI with the model quality. Furthermore, the correlation between R and the DCA model quality is also higher than that of the direct correlation of T_{Bh} and T_{Bv} with the model quality. This suggests that the *R* is more informative, and integrates across, these multiple effects (both physical and computational).

We have added the following paragraph to 4.2 Model evaluation from another perspective. "These information components were found to be marginally correlated with factors such as vegetation density (the Pearson correlation of average LAI with *R, S,* U_h U_v are 0.23, -0.38, -0.54, and -0.19 respectively) and vegetation heterogeneity (the Pearson correlation of LAI standard deviation with *R, S,* U_h, U_v are 0.22, -0.39, -0.54, and -0.22 respectively). Additionally, these informational components were also found to be correlated with the mutual information shared between brightness temperatures and DCA estimates (the Pearson correlation of $I(T_{Bh},T_{Bv};\text{DCA})$ with *R, S,* U_h, U_v are 0.6, -0.28, 0.22, and -0.16 respectively), the informational total uncertainty (the Pearson correlation of I_{Tot} with *R, S,* U_h, U_v are -0.76, 0.62, 0.56, and 0.68 respectively), informational random uncertainty (the Pearson correlation of I_{Rnd} with *R, S,* U_h, U_v are -0.42 , 0.29, 0.05, and 0.15 respectively), and informational model uncertainty (the Pearson correlation of I_{Mod} with *R, S,* U_h, U_v are -0.63, 0.56, 0.66, and 0.75 respectively). This indicates that these informational components in the DCA system are not only physically driven by both vegetation density and heterogeneity but also other factors such as how algorithm processes the information from T_{Bh} and T_{Bv} to produce the DCA outputs. It is more likely to observe higher *R* and lower *S* in locations where vegetation is denser and more heterogeneous, yet the correlation of these variables with model quality (0.47 for mean LAI and 0.42 for the standard deviation of LAI) are weaker than the correlations found between *R* and *S* and model quality shown in Figure 7. The *R* and *S* metric in this study can thus not only integrate information about how the surface vegetation density and heterogeneity influence the algorithm performance but provided insight into how effectively DCA algorithm uses the information from T_{Bh} and T_{Bv}.

Compared with other ancillary and *in situ* independent metrics such as correlation strength between Pearson correlation of T_{Bh} with T_{Bv} and the Pearson correlation between *in situ* and DCA soil moisture (0.67), the correlation strength of *S* and *R* with Pearson correlation of *in situ* and DCA soil moisture are tighter (0.79 and -0.82 for *R* and *S*). This suggests the complex non-linear relationship between of T_{Bh}, T_{Bv} with DCA soil moisture is better captured by *R* and *S* as compared to the direct correlation between the two brightness temperatures themselves. Given the strength of this relationship, the *R* and *S* holds the potential to be used as a DCA evaluation metric that does not 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 (as characterized as the correlation strength between DCA and *in situ*) of the obtained DCA soil moisture without actually knowing the *in situ* soil moisture."

2. Same for Figure 7. The higher correlations of DCA SM and in situ measurements would be found when the unique information of TBv is the lowest, when the unique information of TBh is the lowest and when the synergistic information is the lowest... could the physical mechanisms be explained?

Response: We thank the reviewer for this comment. We found that these informational components are correlation with both physical factors such as LAI, the standard deviation of LAI and informational uncertainties. Such relationships are driven by the collected effect of land surface characteristics and how the algorithm process these data streams. Therefore, no single factor can totally explain why the higher correlation of DCA soil moisture and *in situ* soil moisture is more likely to be found in low U_h and U_v. Please also refer to the response of comment 2.

3. Regarding physical insight, Fig 4b could be interesting, but it is not commented in the text. The mutual information of TbH, TbV and Teff with respect to in situ do show a correlation with the entropy of the in situ measurements, in contrast to I(DCA, in situ). Could this be interpreted in terms of dynamics of the time series ? More dynamics, more entropy, more information content of TbH, TbV and Teff with respect to in situ ?

We thank the reviewer for this comment. That is a good point. We think the interpretation from the reviewer maybe right. We have added the following to the discussion "As shown in figure 4b, the $I(T_{Bh}, T_{Bv}, T_{eff}; in\ situ)$ increase as there are more dynamics in the *in situ* soil moisture which is also reflected by high values of $H_{CN}(T_{Bh})$ and $H_{CN}(T_{Bv})$. The raw observations (T_{Bv}, T_{Bh}, and T_{eff}) provide more available information to the system, whereas such information is not properly captured by the algorithm as reflected by low correlation strength between $H_{CN}(in\ situ)$ and $I(DCA; in\ situ)$. Therefore, it is more likely to observe large information model uncertainties where the soil moisture is more dynamic which may cause a low efficiency of DCA to correctly transmit the available information."

4. What Konings et al (2017) actually shows is that not because there are two measurements one can retrieve simultaneously two variables with good accuracy (SM and VOD). SMOS can retrieve both SM and VOD because there are tens of Tb measurements for different incidence angles. This could have been mentioned explicitly in the introduction, and this could justify using DCA instead of MDCA. However, I think that in addition to Tbh, Tbv and Teff, the DCA algorithm use NDVI as input, in contrast to MDCA. What would be the implications for this work of not taking NDVI into account?

Response: We thank the reviewer for such comment. We have removed "The success of retrieving soil moisture and vegetation opacity is interdependent (Konings et al., 2017)". We've also added the following " Other L-band focused satellite mission such as Soil Moisture and Ocean Salinity (SMOS) retrieves both soil moisture and vegetation optical depth by using numerous brightness measurements for different incidence angles (Kerr et al., 2012)." to the introduction.

Vegetation water content climatology is derived from MODIS NDVI and these values, while different for each day of year and location combination, these values do not vary across different years. It is used to estimate the initial guess for the unknown vegetation optical depth. Here we consider this more of a dynamic parameter and not as an input data stream. However this parameter does potentially introduce additional information. We think including NDVI vegetation water content may decrease the estimated informational random uncertainty and increases the informational model uncertainty. We acknowledge this may be one of the limitations of this study. We have added the sentences below to the 4.3 Approach Limitations section "It is important to understand that SMAP DCA system retrieves soil moisture with the help of vegetation water content climatology derived from a MODIS NDVI data stream. This is specified as a set value for each location and day of year combination and is used to estimate the initial guess for the unknown vegetation optical depth (O'Neill et. al., 2020). The reader should keep in mind that this study considers such data as a dynamic time-varying parameter and it is not treated as a data input in this study. Adding NDVI as a data input would result in $I(T_{Bh}, T_{Bv}, T_{eff}, NDVI; in\ situ)$ being larger than or equal to $I(T_{Bh}, T_{Bv}, T_{eff}; in\ situ)$ in the calculation of I_{Rnd}, and therefore I_{Rnd} would decrease. Since, I_{Tot} only considers DCA output and *in situ* data it is not altered by adding dynamic parameters and I_{Mod} would therefore increase. Thus, consideration of additional dynamic parameters in this informational assessment would serve to shift uncertainties from those attributed to the input data themselves to uncertainties attributed to the model structure and parameterization."

5. Abstract Line 23-25: "Quality": please say explicitly which is the quality metric used. A few lines afterwards "Pearson correlations" are mentioned but again nothing is said of the variables used to compute that correlation.

Response: We thank the reviewer for this comment. We have added "denoted as the Pearson correlation coefficient between SMAP DCA soil moisture and *in situ* soil moisture" to the abstract.

6. Line 28: "... than FOR other land covers"

Response: We thank the reviewer for such comment. We no longer have that statement in the revised manuscript.

7. Line 31: "redundancy"

Response: Thank the reviewer for this comment. The wording is corrected as suggested.

8. Line 135: It would be good to add the list of the stations used to ensure the reproductivility of the results

Response: We thank the reviewer for this comment. We have provided a new table (table S1) that contains a list of stations used in this study in the supplementary materials.

9. Line 146: please give explicitly the quality flags and/or thresholds used to filter the data

Response: We thank the reviewer for this comment. We have provided the thresholds and quality flags used for SMAP DCA soil moisture, soil effective temperature and horizontally- and vertically polarized brightness temperature. The following sentences were added "The extracted data series were filtered by the internal quality flags of T_{Bh} ("tb_qual_flag_h"), T_{Bv} ("tb_qual_flag_v") and DCA ("retrieval_qual_flag_option3") as provided in SMAP data files. We retain data points at a particular SMAP observation time when they all simultaneous pass quality control and fall within their correspondent valid ranges (e.g., $0 \sim 330K$ for T_{Bh} and T_{Bv}, $253.15K \sim 313.15K$ for T_{eff}, $> 0.02 m^3/m^3$ for DCA soil moisture) as specified in the SMAP documentation (Chan, 2020)."

10. Line 147: "data points" here refer to time samples or in situ sites ?

Response: We thank the reviewer for this comment. Here we mean the time sample. We have added "We retain data points at a particular SMAP observation time" to the paragraph mentioned. Please also see the reply of comment 8.

11. Lines 270-276: Could you add an intuitive explanation on why the mutual information between model outputs and in situ observations cab never exceed the entropy of in situ observations ?

In terms of Eq 7 this would mean that H_CN(DCA)-H_CN(DCA, insitu) is necessarily negative. But personally, from the information given in the manuscript I still do not understand why.
Response: We thank the reviewer for this comment and have added an intuitive explanation. This reads as follows: "Conceptually, the entropies of model output and *in situ* observations can be considered as two circles (of equal or unequal sizes) and the mutual information between model output and *in situ* observation can be viewed as the overlapping area of these two circles (Uda, 2020). Therefore, the maximum mutual information shared between model output and *in situ* is the minimum of the entropy of model output and *in situ* observations, i.e: I(DCA, *in situ*) ≤ min[H(DCA), H(*in situ*)]. Intuitively, the overlapping area of two circles cannot be larger that of the smaller circle. Because we are focused on representing the observed soil condition, the information gap between *in situ* observations, H(*in situ*), and the mutual information shared between *in situ* observations and model output, I(DCA, *in situ*), is defined as informational total uncertainty (I_{Tot}). "

12. Line 354: "The sensing depth is more of imperfection L band sensor". I am afraid I do not agree. The representativeness of the two measurements (in situ or remote sensing) in depth is conceptually of the same characteristics of the spatial representativeness of both measurements. Both in depth or in space, in situ sensors or remote sensor simply measure different things.
Response: We thank the reviewer for this comment. We have removed such sentence from the revised manuscript.

13. Figure 7 x label of panel c: correct "inforamtion"
Response: We thank the reviewer for pointing out this typo. We have corrected this in the revised figure 7c.

References

Chan, S.: Soil Moisture Active Passive (SMAP) Level 2 Passive Soil Moisture Product Specification Document, Jet Propuls. Lab. Inst. Technol. Pasadena, USA, JPL D-72547 (Version 7.0), 63, 2020.
Kerr, Y. H., Waldteufel, P., Richaume, P., Wigneron, J. P., Ferrazzoli, P., Mahmoodi, A., Al Bitar, A., Cabot, F., Gruhier, C., Juglea, S. E., Leroux, D., Mialon, A. and Delwart, S.: The SMOS Soil Moisture Retrieval Algorithm, IEEE Trans. Geosci. Remote Sens., 50(5), 1384–1403, doi:10.1109/TGRS.2012.2184548, 2012.
O'Neill, P., Bindlish, R., Chan, S., Njoku, E., and Jackson, T.: Algorithm theoretical basis document: Level 2 & 3 soil moisture (passive) data products, Lev. 2 3 soil moisture data Prod. Jet Propuls. Lab. Inst. Technol. Pasadena, USA, JPL D-66480 (revision F), 100, 2020.
Uda, S.: Application of information theory in systems biology, Biophys. Rev., 12(2), 377–384, doi:10.1007/s12551-020-00665-w, 2020.