

Reviewer 1:

The author demonstrates the need to use PTFs for LSMs and propose to use DA to calibrate PTF parameters with COSMOS-UK soil moisture measurements. The calibrated PTF parameters for Cosby PTFs were used to run JULES, and a better match with in-situ SM measurements was found. Although the structure of the manuscript is clear, there are some unclear points needed clarification.

The authors thank the reviewer for their useful comments, which will help improve the manuscript. We respond to the reviewer's main stated concerns here; each of these is repeated in black text. Our responses are given in blue text and planned changes to the manuscript are given in green. Please also see the attached supplement for responses to comments in the annotated pdf provided by the reviewer.

1. In the conclusion, the author claimed that "Calibrating PTFs for the soils on which they are to be used and at the scales at which they are applied, rather than on small-scale field or lab soil samples, will ultimately improve the performance of land surface models." First of all, I agreed with the author that the LaVenDAR DA framework was used to calibrate the Cosby PTF parameters (k1-k12). On the other hand, there is a very strong assumption the author is making here, which is that they deemed the soil texture information as from HWSD is the one very close to the in-situ conditions. This is not always true as demonstrated by the work below: Zhao, H., Zeng, Y., Lv, S. & Su, Z. 2018, Analysis of soil hydraulic and thermal properties for land surface modeling over the Tibetan Plateau, Earth system science data. 10, 2, p. 1031 This actually means that the better match between predicted SM and the COSMOSUK SM measurement, as demonstrated in this study, can be achieved with any other soil texture information input (e.g., SoilGrids, or FAO-UNESCO). But then, this is very dangerous then, as it will lead to a speculation that the in-situ measured soil information is not important

This work is based on the assumption that the soil texture data is correct, and we will make this clearer in the manuscript. We plan to add the following text at line 156.

We assume that the soil texture values from the HWSD are correct; they are not changed during the data assimilation process. We used a global soil dataset rather than locally available soil texture observations to ensure that our method has the potential for extension to areas without local measurements. Other open source global soil texture products are also available (e.g. SoilGrids Hengl et al (2017)). We acknowledge that there may be discrepancies between the HWSD and local measurements (e.g. Zhao et al (2018)), but our choice to use the HWSD here follows recent successful integration of soil texture data from the HWSD with JULES in studies such as Martinez de la Torre (2019), Ritchie et al (2019) and Ehsan Bhuiyan et al (2019) '

2. For the subsections 3.2 & 3.3, they are not independent. Furthermore, the subsection titles seem need further critical thinking (see specific comments). 'Effect of Data Assimilation on ' does not reflect the contents and seems not justified, especially when the k1-k12 were used as the state vector, which is supposed to be updated with DA and therefore the soil physics properties via Eq. 2-11.

We plan to add text to the start of sections 3.2 and 3.3 to make clearer the distinction between direct updating of the state vector (k1-k12) and subsequent adjustments to the JULES soil physics parameters.

3.2 'The data assimilation algorithm in this study acts directly on the PTF constants k_1 - k_{12} which make up the state vector. The resulting changes to the JULES soil physics parameters through equations (2) - (11) are presented here in section 3.2. Figures 8 and 9 show changes in the eight JULES soil physics parameters used for the topsoil and subsoil layers respectively. (Section 3.3 shows how the underlying PTF constants are updated).'

3.3 'In this section we present the changes to the 12 PTF constants k_1 - k_{12} . These updates are the direct result of applying the data assimilation algorithm.'

3. How were the COSMOS-UK SM measurements calibrated is not clear. It is understood that there were previous publications. However, some specific descriptions on how the CRNP measurements were calibrated in the table3 will help readers to understand why this or that station works. The relevant part of discussion on this is too thin.

We will add more detail about the calibration process in section 2.2

The CRNS at each site counts fast neutrons within the sensor's footprint. These counts are corrected for local meteorological conditions using in situ measurements and also background neutron intensity using data from a neutron monitoring station (Evans et al., 2016). The corrected counts are then calibrated for site-specific soil properties determined from destructive soil sampling conducted after site installation. Soil samples were collected from each site following Köhli et al. (2015) and were returned to UKCEH for laboratory analysis. The results were used to determine reference soil moisture, lattice and bound water, bulk density and organic matter for the day of sampling, and are subsequently used to derive soil water content from the corrected CRNS counts.

Further reviewer's comments were provided as annotations to a pdf. Please see the attached supplement for our responses to these.

References:

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