Response to Comments from Reviewer 2

Note that the reviewer's comments are in italic black, and responses in blue.

We thank the effect and time of the reviewer. Here, we carefully address the issues raised by the reviewer.

Main comments: 1. The title says different blending methods were to be used. However, in the manuscript, only LSW and AVE were used to blend SM data. This needs to be made consistent.

Thank you for your suggestion. We will also change our title to "Blending SMAP, Noah and In Situ Soil Moisture Using Multiple Error Estimation Methods" in the revised manuscript.

2. In the abstract "The in situ-based product performs better when the sample density is high, while the simple-averaged product performs better when the station density is low, or measurement sites are less representative." This sentence is misleading. It seems encouraging a sparse SM network. The author should specify what level of accuracy this sentence is referring to.

Thank you for your comment. This study identified two potential datasets, one is in situ-based soil moisture and the other is the simple-averaged product form in situ-based and Noah soil moisture. The sentence you mentioned intends to explain the applicability of each dataset rather than encouraging either dense or sparse SM networks.

According to your suggestion, we would modify the sentence to "Absolute error (MAE) is lower when sampling density is higher, and when this is the case the in situ-based product has the lower relative error. However, when the sampling density is lower, the simple-average product has lower relative error."

3. In terms of the four knowledge gaps: "1) of the lack of in-situ soil moisture inclusion in product blending" 3.1) If the high resolution in-situ based soil moisture product is available, then why bother blending it with coarser SM products? Please the author clarify what is the information gain/loss on this point.

Although station-based soil moisture observations are usually assumed as the most accurate data, this does not mean station measurements are perfect and have no limitations. In fact, each source of soil moisture information has its advantages and disadvantages. The advantage of in situ observations is that they are the only source of in ground soil moisture information, and thus are often used as a benchmark for models. The primary disadvantages of in situ observations are 1) sparse spatial density and 2) limited spatial representativeness. Similarly, model and satellite remote sensing soil moisture have the advantage of representing a larger spatial area and, for the most part, a finer spatial resolution. Of course, the primary disadvantage of models and satellites is that they are indirect representations of soil moisture variations and not direct measurements. Therefore, these three soil moisture data sources are complementary and, as we show in this study, can be combined to improve soil moisture monitoring. We will add this clarification to the introduction section in our revised manuscript.

On the other hand, averaged product AVE(K, N) from blending in-situ based K-API with NLDAS soil moisture, presents similar and sometimes smaller errors than K-API in places where in-situ measurements are sparse, such as the central to the south of Texas and east Arkansas (Fig. 10). This indicates when in-situ measurements are sparse, using additional sources of soil moisture information (such that from NLDAS) may help to increase the accuracy (lines 705-710). This is the gain from blending in-situ based soil moisture with other coarser SM products. Fig. 12 further confirmed this point by assessing K-API and AVE(K, N) with varying numbers of sampling points and different sampling schemes. The conclusion is also summarized in lines 763-767 in the original manuscript.

3.2) The RK was used to derive gridded SM utilizing API, relying on precipitation as the main predictor of soil moisture variations. Nevertheless, plenty of studies show the control of LST and vegetation on SM, together with topographic variables and soil textures. This reviewer is wondering why the authors neglect these perspectives.

Thanks for your comments. Yes, LST, vegetation, topographic variables, and soil textures may all impact the soil moisture variation, and incorporating them in SM interpolation using RK may further improve the results. However, the focus of this study is not identifying the best set of auxiliary variables for SM interpolation using RK, but to blend SM products from in-situ, remote sensing, and model simulations. Here, the simplest RK model was developed by using precipitation as the only auxiliary variable, given precipitation is the chief driver of soil moisture. If the simplest RK model works, then the future study can be conducted to improve the RK model by incorporating other auxiliary variables. We would add a sentence in the discussion alluding to potential benefits of adding other auxiliary variables in future work.

3.3) The API uses a fixed k, as in equation (1). However, this reviewer expect the k value will be a function of different climates, vegetation covers, topography and soil textures. Please the author clarify.

Thanks for your comment. We agree it is possible k could vary as a function of different climates, vegetation covers, topography and soil textures. However, the focus of this study is not on one source of soil moisture (e.g., the interpolated SM using API and RK), but to blend soil moisture from multiple sources. Therefore, future studies can be conducted to further improving API estimation by considering k as a function of multiple variables. We would add a sentence in the discussion alluding to varying k as a function of multiple variables in future studies.

"2) There is no comprehensive evaluation of different data blending methods" 3.4) From the title, it seems the author would like to use multiple blending methods. On the other hand, it turns out only LSW and AVE used. This reviewer does not agree with this knowledge gap.

Thank you for the helpful suggestion. We will revise this knowledge gap to "(2) lack of understanding on the impact of estimated error variance over soil moisture blending. Currently,

there are a variety of methods for estimating error variance of different datasets, such as TC, Kriging and Relative Error Variance (REV) (Vinnikov et al., 1996; Ford and Quiring, 2019). It would be helpful to compare these methods and identify their impact on soil moisture blending."
We will also change our title accordingly.

"(3) The impact of measurement units (e.g., volumetric water content, soil moisture anomalies, and percentiles) is unknown" This is to me physically nonsense. They are not all measurement units even. Volumetric water content is a unit, but anomalies? percentiles?

Thank you for your comment. We will change the sentence to "The impact of soil moisture representation (e.g., volumetric water content, soil moisture anomalies, and percentiles) is unknown" in our revised manuscript.

4) A simple and operational methodology is still needed for accurate daily soil moisture mapping with high spatial resolution. This is not a knowledge gap, but rather improving the current technology. For example, people are using UAV to derive SM for precision agriculture.

Thank you for your comment. We will be more specific with this knowledge gap and revise it to "(4) A simple and operational methodology is still needed to leverage multiple, diverse sources of soil moisture information for accurate daily soil moisture mapping at high spatial resolution".