The manuscript presents a soil moisture dataset for the contiguous United States with fine temporal and spatial resolution. The authors disaggregate the fine soil moisture data from a daily level to a 3-hour level. I also note that the spatial coverage of soil moisture data is complete. It seems to make the dataset more useful.

Response:

Thank you very much for the positive comments and constructive suggestions. We have carefully considered your comments and have responded as follows. The revised content is marked in red in the response.

I have a concern. In section 4.1, the authors used the drought in four states as a case study to display the decline in soil moisture. However, since drought is always a slow process, it seems the data have potential to characterize changes in drought using the daily soil moisture data. I suggest that the authors supply fast-forming disasters as a case study further to amplify the importance of hourly soil moisture data.

Response:

Thank you for the valuable comment. We agree with the comment and admit that the fast-forming disasters indeed further reflect the advantages of the STF-SSM dataset in terms of fine temporal resolution. We think that flooding is an appropriate case to further illustrate the importance of the SSM dataset. First, there is a correlation between the occurrence of flooding and the change of SSM. Second, the variation of flooding is rapid enough to be observed with the 3-hour SSM data.

Specifically, two flooding events (in South Carolina and Texas) are selected to exhibit the advantages of the developed 3-hour SSM dataset. We found that the SSM variation is sensitive to flooding. Hence, we have revised Section 4.1 and supplied the description.

Lines 515-529

In addition to droughts, SSM is also sensitive to flooding. When a flooding event begins, the SSM value is usually rapidly increased over a short period. To highlight the advantages of the developed 3-hour SSM dataset, we portrayed the SSM variation under two flooding events. Figure 11a shows the flooding in 2015 in Williamsburg, South Carolina, because of extreme precipitation from 2015-10-01 to 2015-10-05. It can be seen that the SSM value in this region began to increase dramatically from the evening of 2015-10-01 to 2015-10-02, and remained at a high level until 2015-10-05. Figure 11b presents the flooding in 2017 in Jefferson, Texas, due to Hurricane Harvey. We found that the SSM value had started to rise on the evening of 2017-08-24 before Hurricane Harvey reached landfall fully (2017-08-25), and peaked on 2017-08-27.

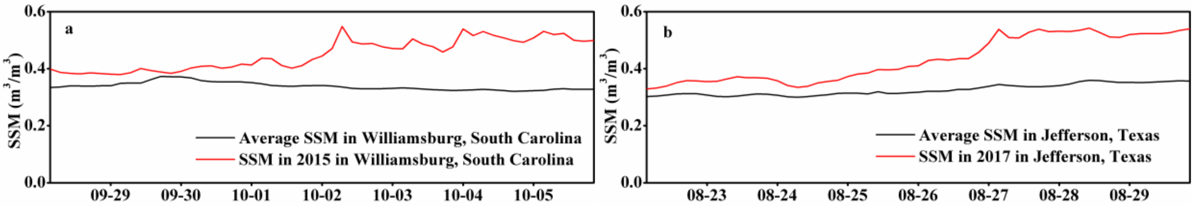

Figure 11. *Surface soil moisture (SSM) variations under flood events. Black lines represent the average SSM values calculated from 2015 to 2023. Red lines are the SSM values for the corresponding year. (a) the flood in Williamsburg, South Carolina in 2015. (b) the flood in Jefferson, Texas in 2017.*

There are also some minor suggestions as follows:

1). The units of RMSE, Bias, and ubRMSE in Tables 2-5 should be provided.

Response:

Thank you for the suggestions. We have supplied the units of RMSE, Bias, and ubRMSE in these tables.

2). Section 2.2: The VIPSTF model includes two different versions. Which version was used in the manuscript? Please explain it.

Response:

We gratefully appreciate your valuable comment. The VIPSTF model contains a spatial weighting- and a spatial unmixing-based version. Considering the difference of accuracy, the selection in this manuscript is the spatial weighting-based version. Also, we have added the corresponding description in the latest manuscript.

Section 2.2.2

In this study, the virtual image pair-based spatio-temporal fusion (VIPSTF) model was employed to generate the 3-hour, 1-km STF_SSM dataset, due to its stable performance, superior computational efficiency, and flexible usage ***(Wang et al., 2020; Yang et al., 2023)****. The spatial weighting version of the VIPSTF model was adopted in this study, because of the reliable accuracy.*

3). Line 265: What is the size of the soil moisture dataset? What is the data format? I suggest the authors to provide more detailed information about the STF_SSM dataset.

Response:

We have further added the detailed STF_SSM data format in the manuscript. Specifically, a total of 25567 scenes were produced, and the STF_SSM dataset occupied approximately 1.78 TB of storage space. The Pete supercomputer in Oklahoma state university was employed for data generation, which can provide 6688 processor cores and more than 2 petabytes of storage. Each STF_SSM scene requires approximately 73.0 MB of storage space and takes around 680 seconds to produce. Given the difference in computational efficiency of different computers, we only show the size of the dataset in the latest manuscript. Thank you for the comments.

Section 2.2.3

Finally, a total of 25,567 STF_SSM scenes were produced, accounting for approximately 1.78 TB. Each STF_SSM scene requires approximately 73.0 MB of storage space. The Pete High-Performance Computing (HPC) facility at Oklahoma State University was employed for data generation.

4). Figure 3: Is the scene in the first column an average of all the intraday scenes? Please clarify the specific time for each scene.

Response:

Thank you for the comments. The temporal resolution of the Crop-CASMA SSM data is daily. Hence, the exhibited Crop-CASMA SSM scene in Figure 3 is not an average of all the intraday scenes. By comparison, the temporal resolution of the SMAP L4 SSM and STF_SSM datasets is 3 hours, so we have exhibited some SSM scenes at special time points. We have described this information in the title of Figure 3.

5). Line 475: The potential for hourly soil moisture data applications needs to be further emphasized. That is the main driver of fine soil moisture dataset development.

Response:

Thank you for the valuable suggestions. We have selected two flooding events to exhibit the advantages of the developed 3-hour SSM dataset. Since the SSM is always increased for a short period, when a flooding event occurs. Hence, we have revised Section 4.1 and supplied the corresponding contents.

Lines 505-519

In addition to droughts, SSM is also sensitive to flooding. When a flooding event begins, the SSM value is usually rapidly increased over a short period. To highlight the advantages of the developed 3-hour SSM dataset, we portrayed the SSM variation under two flooding events. Figure 11a shows the flooding in 2015 in Williamsburg, South Carolina, because of extreme precipitation from 2015-10-01 to 2015-10-05. It can be seen that the SSM value in this region began to increase dramatically from the evening of 2015-10-01 to 2015-10-02, and remained at a high level until 2015-10-05. Figure 11b presents the flooding in 2017 in Jefferson, Texas, due to Hurricane Harvey. We found that the SSM value had started to rise on the evening of 2017-08-24 before Hurricane Harvey reached landfall fully (2017-08-25), and peaked on 2017-08-27.

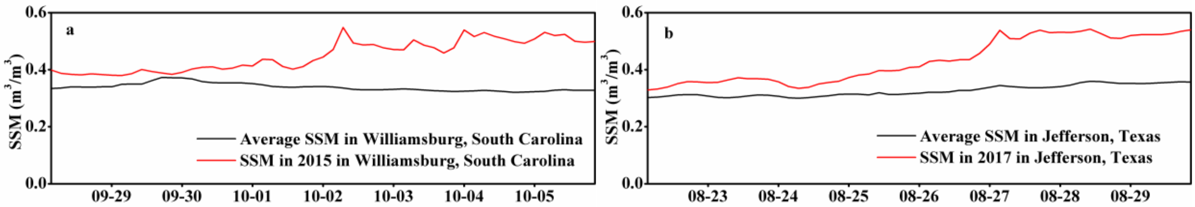

Figure 11. *Surface soil moisture (SSM) variations under flood events. Black lines represent the average SSM values calculated from 2015 to 2023. Red lines are the SSM values for the corresponding year. (a) the flood in Williamsburg, South Carolina in 2015. (b) the flood in Jefferson, Texas in 2017.*

6). The references listed also provide 1-km soil moisture data or downscaling methods, which may be helpful to your work. In addition, what the difference is between the proposed and listed methods.
https://doi.org/10.1016/j.jag.2023.103572
https://doi.org/10.1016/j.rse.2022.113334
https://doi.org/10.1016/j.rse.2024.114579

Response:

Thank you very much for the suggestions. The mentioned references mainly contain the use of synthetic spatial radar (SAR) data to estimate high-resolution SSM data. The proposed methods mainly consider the optical/thermal-infrared data to predict the fine SSM data. Both methods can effectively estimate SSM and improve its spatial resolution. We admitted that using the SAR data is also reliable and accurate. However, this method is limited by the coarse revisit period and narrow swath width of SAR data, especially for estimating a large, high temporal resolution SSM dataset. We have revised the introduction and supplied this description in the latest manuscript.

Lines 126-131

In addition, synthetic aperture radar (SAR) data are also beneficial for generating high-resolution SSM datasets. Since microwave signals can penetrate the cover of clouds or haze, the SSM estimation can avoid the influence of weather factors. However, producing a large-scale, fine temporal resolution SSM product is limited by the coarse revisit period and narrow swath width of SAR data ***(Wang et al., 2023; Zhu et al., 2023; Fan et al., 2025)****.*

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