This manuscript produces a 3-hour, 1-km soil moisture (SM) dataset generated using a spatiotemporal fusion approach that integrates the 3-hour, 9-km SMAP L4 soil moisture product with the 1-day, 1-km Crop-CASMA soil moisture data. The resulting dataset is evaluated against in-situ SM observations. Overall, the manuscript is well-structured, and the generated SM dataset holds significant potential for the scientific community. However, several aspects require clarification and further discussion:

Response:

The authors gratefully appreciate your valuable comments and suggestions. We have carefully considered your comments and have responded as follows. The revised content is marked in red in the response.

1. Validation Approach: The methodology leverages the higher-accuracy SMAP L4 product to capture temporal variations while using the lower-accuracy but higher-resolution Crop-CASMA data to retain spatial details. Consequently, the accuracy of the fused product should theoretically be higher than that of Crop-CASMA but lower than SMAP L4.

Response:

We agree with your point. In this manuscript, both the 3-hour and daily validation were expressed in Sections 3.3 and 3.4. It can be seen that the validated results are consistent with the reviewer's view. That is, the accuracy of the simulated STF_SSM dataset is higher than that of the Crop-CASMA but smaller than that of the SMAP L4. Thank you for the comments.

2. Comparative Analysis: The authors compare their product only with SMAP L4 and Crop-CASMA but do not benchmark it against other 1-km resolution datasets or even higher-resolution (30-m) products (DOI: 10.1038/s41597-021-01050-2). Including such comparisons, or at least discussing them, would provide a more comprehensive evaluation of the dataset's performance.

Response:

Thank you for the comment. We have supplied a discussion in Section 4.3 to analyze six high-resolution SSM datasets. Considering the differences in validation methods, spatial and temporal coverages, and statistical metrics, it is not appropriate to quantify them under a standard. Hence, we suggested that other people select according to their requirements, before using the data.

4.3 Analysis of different fine SSM datasets

Currently, some high-resolution SSM datasets have been published and used. We listed six 1-km SSM datasets at a large scale and exhibited the details of these datasets in Table 6, such as the spatial resolution, temporal resolution, and accuracy. Given the differences in validation methods, spatial and temporal coverages, and statistical metrics, etc, it is difficult to harmonize these *datasets to the same standard to quantify accuracy. Therefore, before using the data, it is necessary to further select the more suitable SSM dataset according to the requirements.*

Table 6. *Comparative analysis for six high-resolution SSM datasets. Statistical metrics for accuracy include root mean square error (RMSE), unbiased root mean square error (ubRMSE), and unbiased root mean square deviation(ubRMSD).*

References	Area	Spatial resolution	Temporal resolution	Accuracy (m^3/m^3)
This study	CONUS	1-km	3-hour	ubRMSE = 0.057
(Vergopolan et al., 2021)	CONUS	30-m	6-hour	RMSE = 0.07
(Fang et al., 2022)	Global	1-km	daily	ubRMSE = 0.063
(Zheng et al., 2023)	Global	1-km	daily	ubRMSE = 0.045
(Han et al., 2023)	Global	1-km	daily	ubRMSE = 0.050
(Song et al., 2022)	China	1-km	daily	ubRMSD = 0.074

Fang, B., Lakshmi, V., Cosh, M., Liu, P., Bindlish, R., and Jackson, T. J.: A global 1-km downscaled SMAP soil moisture product based on thermal inertia theory, Vadose Zone Journal, 21, e20182, https://doi.org/10.1002/vzj2.20182, 2022.

Han, Q., Zeng, Y., Zhang, L., Wang, C., Prikaziuk, E., Niu, Z., and Su, B.: Global long term daily 1 km surface soil moisture dataset with physics informed machine learning, Sci Data, 10, 101, https://doi.org/10.1038/s41597-023-02011-7, 2023.

Song, P., Zhang, Y., Guo, J., Shi, J., Zhao, T., and Tong, B.: A 1 km daily surface soil moisture dataset of enhanced coverage under all-weather conditions over China in 2003–2019, Earth Syst. Sci. Data, 14, 2613–2637, https://doi.org/10.5194/essd-14-2613-2022, 2022.

Vergopolan, N., Chaney, N. W., Pan, M., Sheffield, J., Beck, H. E., Ferguson, C. R., Torres-Rojas, L., Sadri, S., and Wood, E. F.: SMAP-HydroBlocks, a 30-m satellite-based soil moisture dataset for the conterminous US, Sci Data, 8, 264, https://doi.org/10.1038/s41597-021-01050-2, 2021.

Zheng, C., Jia, L., and Zhao, T.: A 21-year dataset (2000–2020) of gap-free global daily surface soil moisture at 1-km grid resolution, Sci Data, 10, 139, https://doi.org/10.1038/s41597-023-01991-w, 2023.

3. Temporal Variability Discussion: It is recommended that the authors expand their discussion on the temporal variations of the generated SM dataset within a single day, in addition to the analysis presented in Figures 6 and 7. This would help highlight the advantages of the product in capturing sudden SM changes compared to daily-scale products.

Response:

To address this problem, we have added a case of sudden change of SSM in Section 4.1, i.e., two flooding events in Texas and South Carolina. According to two flooding events, the SSM time-series have been exhibited in Figure 11. On this basis, we can estimate the duration and occurrence of flooding on a 3-hour scale. In this case, the advantages of the 3-hour SSM dataset can be further amplified.

In addition, the two SSM time-series within a single day are displayed in Figure 5. It can be seen that the Pixel 2 in Figure 4 was experiencing precipitation, because the SSM values are increased from 1:30 to 7:30. The intra-day variation of SSM is difficult to be observed by daily-scale data.

Thank you for the valuable suggestions.

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.

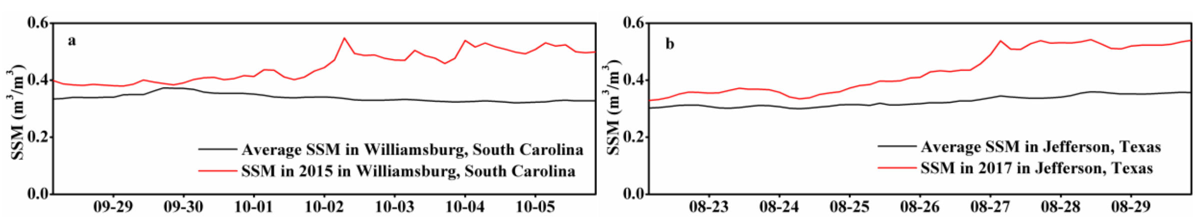

Figure 11. *Surface soil moisture (SSM) variations under flood events. Black lines represent the average SSM values calculated from 2015 to 2023. Red lines are the SSM values for the corresponding year. (a) the flood in Williamsburg, South Carolina in 2015. (b) the flood in Jefferson, Texas in 2017.*

4. Figure 3: The date and time of the SM data should be explicitly stated in the figure title for clarity.

Response:

In the updated version, we have revised the title of Figure 3 and supplied the detailed date and time. We appreciate your suggestions.

Figure 3. *Spatial pattern of Surface Soil Moisture (SSM) in the Crop-CASMA SSM dataset (left), SMAP L4 SSM product (middle), and the STF_SSM dataset (right) on 2015-04-01 (01:30), 2017-06-08 (07:30), 2019-08-16 (13:30), and 2021-10-25 (19:30). Both the SMAP L4 and STF_SSM datasets are exhibited at the 3-hour scale, while the Crop-CASMA SSM dataset is displayed at the daily scale. The basemap is from Esri, Earthstar Geographics, and the GIS User Community.*

5. Figure 8 / Table 4: It is recommended that the authors provide the number of validation sites corresponding to each land cover type, either in Figure 8 or Table 4, to enhance transparency in the validation process.

Response:

Thank you for the suggestion. The number of validation sites for each land cover type has been added to Table 4. Moreover, we have also revised the title of Figure 8 and supplied the corresponding number for each land cover type.

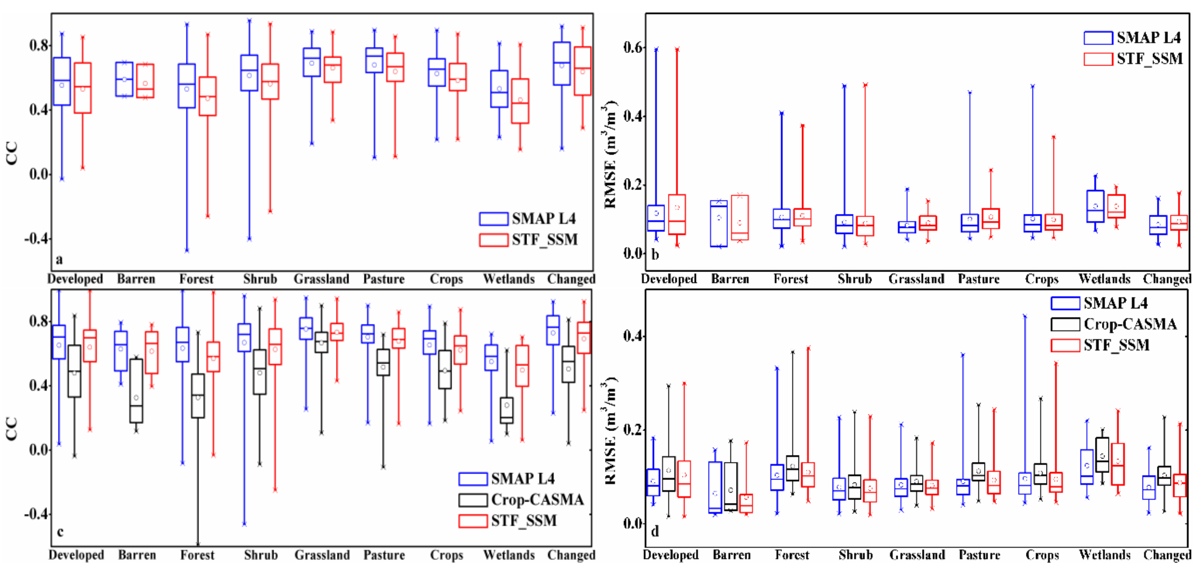

Figure 8. *Accuracy of the surface soil moisture (SSM) datasets under different land cover types. The "changed" type refers to areas where land cover type changed between 2015 and 2023. (a) and (b) are the correlation coefficient (CC) and the root mean square error (RMSE) of SSM datasets at the 3-hour scale. (c) and (d) are the CC and RMSE of SSM datasets at the daily scale.*

For each land cover type, the number of validation sites is 45 (developed), 7 (barren), 190 (forest), 211 (shrub), 148 (grassland), 97 (pasture), 69 (crops), 10 (wetlands), and 49 (changed), respectively.

Table 4. Mean correlation coefficient (CC) and root mean square error (RMSE) of surface soil moisture (SSM) datasets under different land cover types.

Land cover type (number of validation sites)	*3-hour*				*Daily*					
	SMAP L4		*STF_SSM*		*SMAP L4*		*Crop-CASMA*		*STF_SSM*	
	CC	*RMSE (m^3/m^3)*	*CC*	*RMSE (m^3/m^3)*	*CC*	*RMSE (m^3/m^3)*	*CC*	*RMSE (m^3/m^3)*	*CC*	*RMSE (m^3/m^3)*
Developed (45)	*0.554*	*0.117*	*0.530*	*0.135*	*0.653*	*0.091*	*0.480*	*0.114*	*0.640*	*0.104*
Barren (7)	*0.591*	*0.105*	*0.564*	*0.083*	*0.601*	*0.103*	*0.208*	*0.117*	*0.576*	*0.092*
Forest (190)	*0.530*	*0.151*	*0.472*	*0.156*	*0.634*	*0.104*	*0.327*	*0.123*	*0.570*	*0.110*
Shrub (211)	*0.615*	*0.091*	*0.562*	*0.089*	*0.669*	*0.078*	*0.481*	*0.083*	*0.627*	*0.076*
Grassland (148)	*0.691*	*0.083*	*0.662*	*0.089*	*0.753*	*0.083*	*0.669*	*0.090*	*0.734*	*0.082*
Pasture (97)	*0.680*	*0.101*	*0.639*	*0.107*	*0.704*	*0.091*	*0.517*	*0.112*	*0.678*	*0.093*
Crops (69)	*0.626*	*0.102*	*0.585*	*0.099*	*0.654*	*0.097*	*0.494*	*0.108*	*0.623*	*0.095*
Wetlands (10)	*0.532*	*0.138*	*0.463*	*0.138*	*0.551*	*0.124*	*0.279*	*0.145*	*0.498*	*0.134*
Changed (49)	*0.677*	*0.084*	*0.639*	*0.094*	*0.730*	*0.078*	*0.505*	*0.104*	*0.693*	*0.088*
Mean	*0.611*	*0.108*	*0.569*	*0.110*	*0.661*	*0.094*	*0.440*	*0.111*	*0.627*	*0.097*

6. Figure 9: If feasible, the authors are encouraged to analyze and present the relationship between RMSE, slope, and altitude, as this could provide additional insights into the dataset's accuracy under varying topographic conditions.

Response:

We appreciate your suggestions to make our manuscript complete. In the latest version, we have modified the content in Section 3.5. Meanwhile, the relationship between RMSE, slope, and elevation has been supplied (Figures 9e to 9h). The results further prove the advantage of the generated STF_SSM dataset.

3.5 SSM data accuracy across topographic conditions

As a significant soil-forming factor, terrain is one of the determinants of SSM variations. Particularly, SSM could have strong spatial variability in areas with complex topographic conditions. We analyzed the accuracy (including CC and RMSE) of the 1-km Crop-CASMA and STF_SSM datasets under different topographic conditions. As shown in Figures 9a and 9b, both the Crop-CASMA and STF_SSM datasets show a decrease in the CC value with increasing elevation. However, the STF_SSM dataset shows a slower decline in accuracy (with a slope of -

0.055) compared to the Crop-CASMA dataset (with a slope of -0.100). Under complex terrain conditions (i.e., larger slope), the accuracy of both SSM datasets is reduced. It can be seen from Figures 9c and 9d that the CC of the Crop-CASMA dataset decreases more sharply as the slope increases (with a slope of -0.023) while the CC in the generated STF_SSM dataset declines more gradually (with a slope of -0.011). Likewise, Figures 9e and 9f shows that the RMSE values of both SSM datasets increase with elevation. According to the intercept, the STF_SSM dataset has a slightly greater RMSE than the Crop_CASMA dataset, especially at high altitudes. Meanwhile, with an increase in slope, the STF_SSM dataset has a slower rise in RMSE values than the Crop-CASMA dataset (Figure 9g and 9h). This suggests that the STF_SSM dataset is more reliable than the Crop-CASMA dataset in complex terrain conditions.

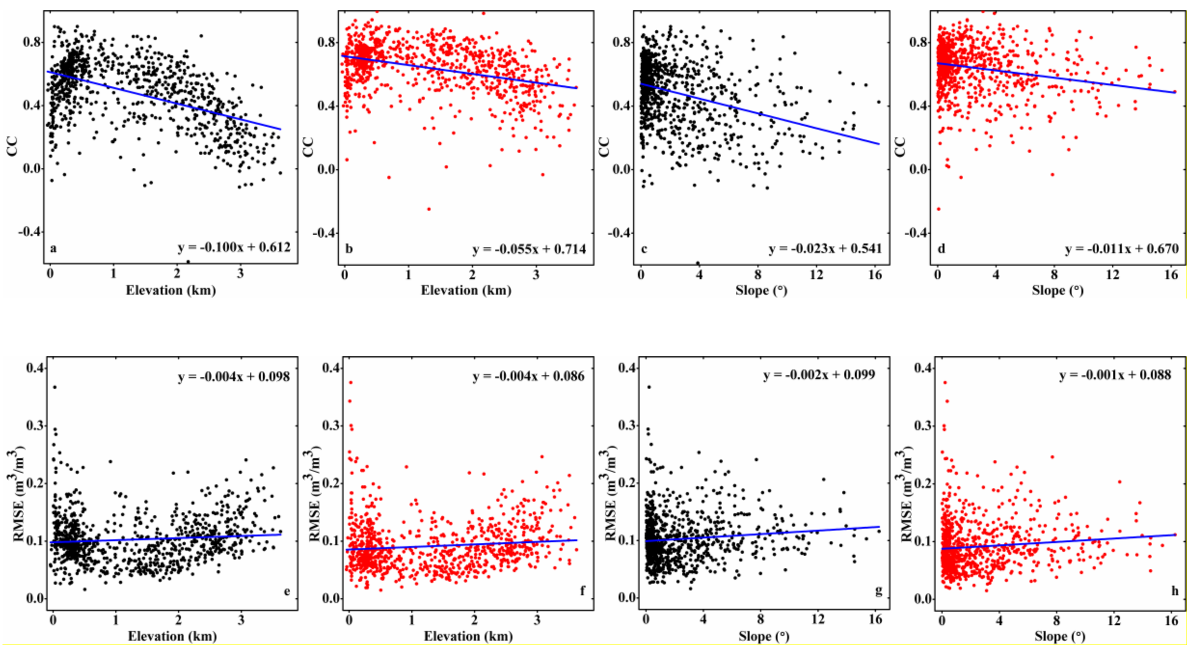

Figure 9. *Accuracy of the estimated surface soil moisture (SSM) from the 1-km Crop-CASMA and generated STF_SSM datasets along changing topographic conditions, denoted by elevation and slope. (a), (c), (e) and (g) refer to the 1-km Crop-CASMA SSM dataset. (b), (d), (f) and (h) are the generated STF_SSM dataset.*