RC: Reviewer Comment, AR: Author Response, ☐ New Manuscript text

Dear Referee,

We would like to thank you very much for your effort in reviewing our manuscript. Please find our responses to your comments below. These should be considered as preliminary (part of the interactive discussion) as implementation of the final changes also depends on another referee report that is still pending.

Kind regards,

Chansheng He

(on behalf of all the authors)

The comments of editor and reviewers are in black with bold text, the author's answers are indicated in blue color, as well as old text passages. New text passages are indicated in green color.

General Comments

Overall, the paper is well written, and the data are valuable. However, I still have some main concerns:

AR: We thank the reviewer for the evaluation and the comments.

Major Comments

RC: **The authors give a good description of the SHP and SM datasets. However, they fail to clarify the accuracies of the ground-based datasets. Errors exist in either ground measurements or products. Direct comparisons between ground measurements and products can not help us understand the quality of the ground measurements. Although it is still challenging to quantify errors within the in-situ measurement, methods like triple collocation do exist that can give uncertainties of the in-situ measurements. I would strongly recommend the authors to try to explain the**

accuracy of the ground measurements, at least to cite some previous validation work to prove that the validation results of SHP and SM products in this work are consistent with them. This will make the quality of the ground measurements to be convincing.

AR: Thank you for your comments. Yes, errors exist in either ground measurements or products. Firstly, we have tried to collect SM using two sensors at the same depth at a station within the study area (Figure R1 (a)). However, as a distance needs to be maintained between the two sensors to prevent interference (Cobos and Chambers, 2010), and SM has strong spatial heterology even at centimeter scale (Liang et al., 2011; Zhang et al., 2018; Guo et al., 2019; Guo et al., 2020), it’s difficult to say that the two sensors are measuring SM at the same place. Results also showed that the two sensors at the same depth have different SM dynamics (Figure R1 (b)). Thus, the triple collocation will introduce additional errors when obtaining the local SM. Secondly, the harsh mountainous environment makes it difficult to collect data and maintain the large-scale SM network over QTP. What’s more, we usually need to replace several SM sensors each year, which are always broken by the animals (rat, yak, etc.) during the long period (Figure R2). The limited funding also makes it difficult to maintain the long-term SM monitoring over large scale of QTP using the triple collocation method.

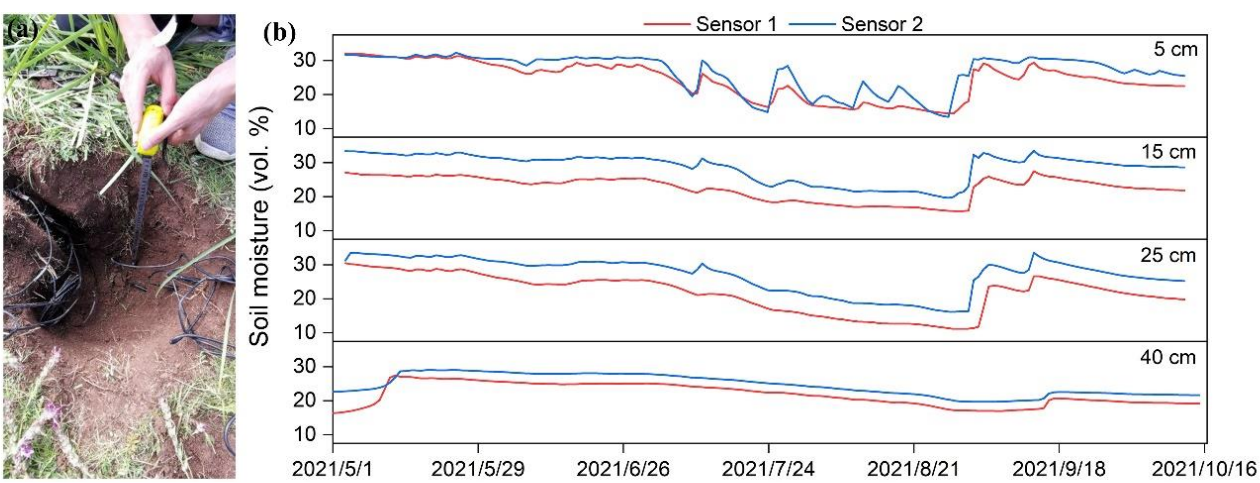

Figure R1. (a) The installation of two 5TE sensors at the same layer at one site within the study area, (b) the comparison of measured SM during 2021/5/1-2021/10/15 at the first four depths.

Figure R2. (a) Datalogger damage caused by water ingress, (b) the stolen of 5TE sensor and datalogger in the field (only the broken white waterproof box remains), (c)-(f) the damage of 5TE sensor in the field.

Meanwhile, we have checked our results thoroughly and corrected a mistake when evaluating the SMAP_L4 product in our previous analysis (the SMAP_L4 product version during 2015-2016 is different from the data product after 2016). What's more, in order to compare our results with the previous evaluations, we evaluated the SM products using the metrics of Pearson's R, bias, and ubRMSE (Figures 12 and 13). The results about evaluations of the SM products have been revised in the manuscript accordingly.

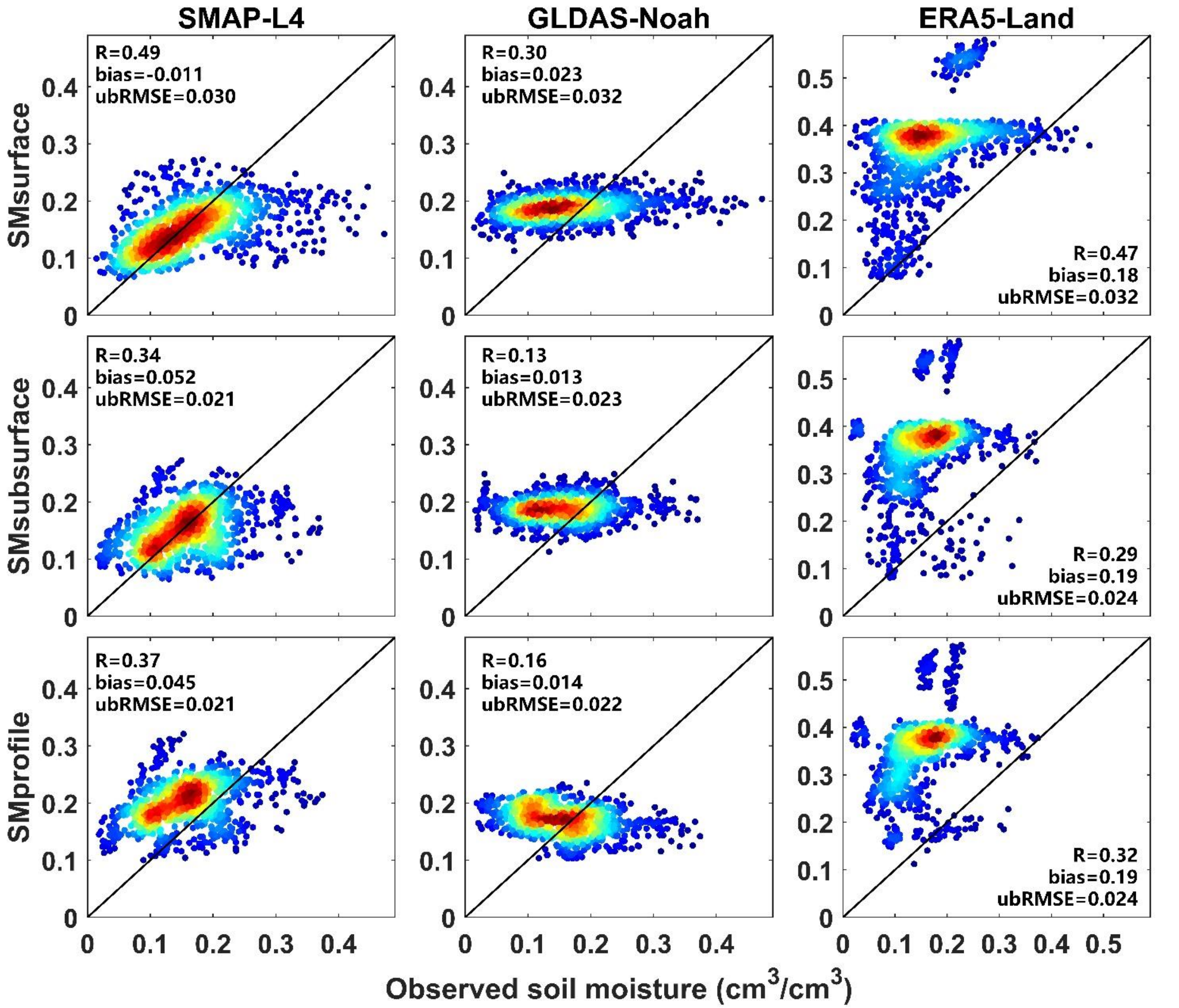

Figure 12. Scatterplots comparing the different derived SM products with the observed SM for different soil layers. The metrics within each plot show the mean value of the metrics for all stations.

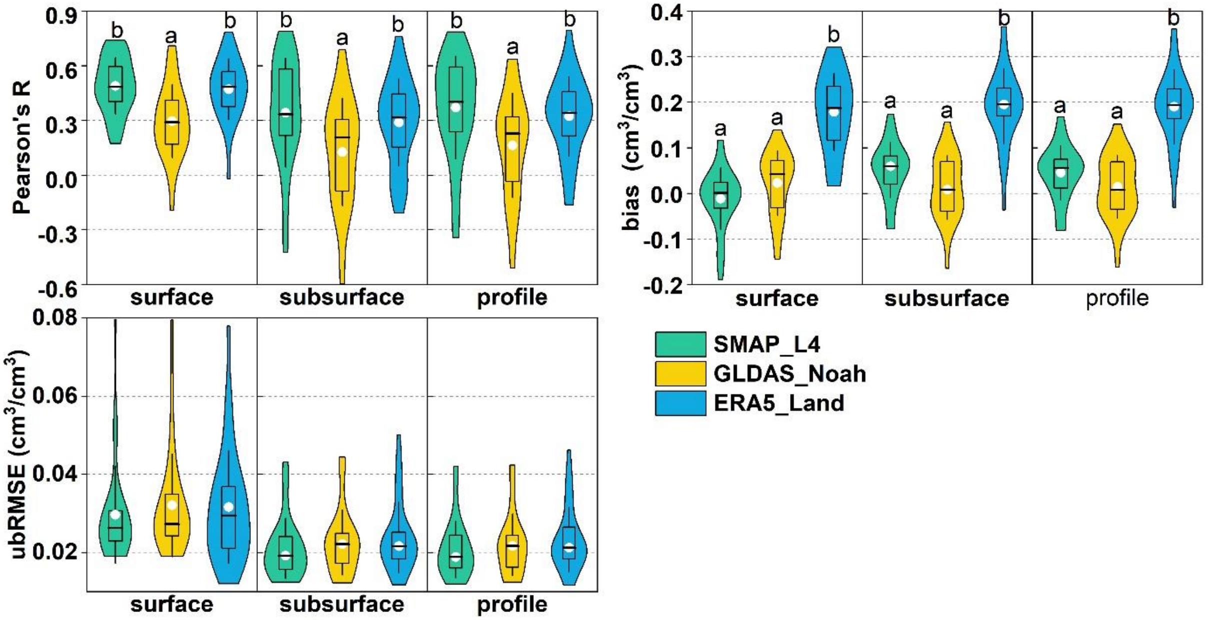

Figure 13. Metrics for comparing the different SM products (GLDAS_Noah, ERA5_Land, and SMAP_L4) with the in-situ SM observations for different layers. The different letters above the violin plot indicate the significant differences ($p < 0.05$) between different products for each soil layer, while no letter indicates the differences are not significant.

□ The results show that both SMAP_L4 (mean bias of -0.011 cm^3/cm^3, 0.052 cm^3/cm^3, and 0.045 cm^3/cm^3 for surface, subsurface, and profile soil layers, respectively) and GLDAS_Noah (mean bias of 0.023 cm^3/cm^3, 0.013 cm^3/cm^3, and 0.014 cm^3/cm^3 for surface, subsurface, and profile soil layers, respectively) have significantly ($p < 0.01$) lower bias than ERA5_Land (mean bias of 0.179 cm^3/cm^3, 0.191 cm^3/cm^3, and 0.190 cm^3/cm^3 for surface, subsurface, and profile soil layers, respectively). Both SMAP_L4 (mean R of 0.490, 0.343, and 0.371 for surface, subsurface, and profile soil layers, respectively) and ERA5_Land (mean R of 0.471, 0.289, and 0.323 for surface, subsurface, and profile soil layers, respectively) correlate with the observations with significantly ($p < 0.01$) higher R values than GLDAS_Noah does (with mean R of 0.296, 0.127, and 0.164 for surface, subsurface, and profile soil layers, respectively). After removing the bias, the mean ubRMSE of the three SM products are lower than 0.032 cm^3/cm^3, 0.024 cm^3/cm^3, and 0.024 cm^3/cm^3 for the surface, subsurface, and profile

SM, respectively. Therefore, the three SM products achieved the accuracy requirement of 0.04 cm^3/cm^3 (Chan et al., 2016) in the study area.

After summarizing the previous works about SM products validation, we found that our results are consistent with the previous studies. For example, Xing et al. (2021) found that for the surface SM, SMAP_L4 has a better performance than ERA5_Land with the higher R and lower bias. For the root zone SM, SMAP_L4 and ERA5_Land have higher R values than the GLDAS_Noah, while SMAP_L4 and GLDAS_Noah have a lower bias than the ERA5_Land (Xing et al., 2021), which are consistent with our results. On the other hand, previous research also displayed a broad range of bias, ubRMSE, and R when evaluating the three SM products (Table R1, Bi et al., 2016; Qu et al., 2019; Xing et al., 2021). Thus, our evaluations are consistent with the previous studies with a reasonable variation range. Additionally, previous studies demonstrated that the performance of different SM products varies from one site to the other (Xing et al., 2021; Bi et al., 2016; Zeng et al., 2015). Generally, the SM products overestimate SM under dry condition, while underestimate SM under wet condition, and the SM products show worse performance in the sites with strong landscape heterogeneity (Zeng et al., 2015; Qu et al., 2019; Xing et al., 2021). Our study showed similar results that the bias is negatively correlated with the soil water content significantly for the three SM products (Figure R3). In summary, the evaluations of SM products based on our SM dataset are consistent with the previous studies. The discussion about the quality of SM datasets has been revised in the manuscript.

Table R1 the comparison of the evaluation metrics for ERA5_Land, GLDAS_Noah, and SMAP_L4 from previous studies over QTP with that of our study (mean value)

product	layer	bias		ubRMSE		R		source
		reference	our study	reference	our study	reference	our study	
ERA5_Land	surface	-0.01~0.59	0.179	0.018~0.095	0.032	-0.23~0.84	0.471	(Xing et al., 2021)
	profile	0.04~0.45	0.190	0.013~0.089	0.024	-0.22~0.96	0.323	
GLDAS_Noah	surface	-0.15~0.108	0.023	0.037~0.058	0.032	0.287~0.785	0.296	(Bi et al., 2016; Qu et al., 2019; Xing et al., 2021)
	subsurface	--	0.013	0.021~0.054	0.023	-0.245~0.824	0.127	
	profile	-0.24~0.16	0.014	0.005~0.084	0.022	-0.19~0.79	0.164	
SMAP_L4	surface	-0.20~0.16	-0.011	0.017~0.086	0.030	0.14~0.78	0.490	(Xing et al., 2021)
	profile	-0.16~0.14	0.045	0.01~0.08	0.021	0.24~0.94	0.371	

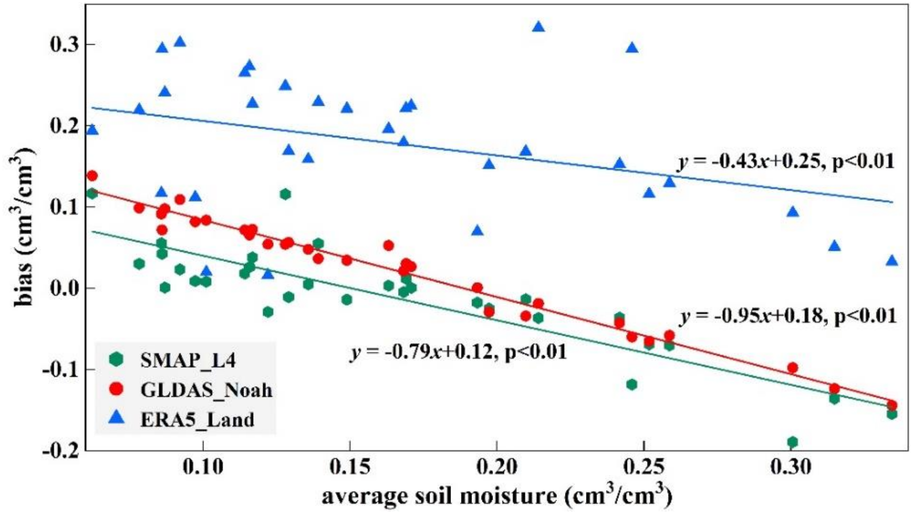

Figure R3. The relationship between the bias of different SM products and average SM at surface layer.

□ The evaluations of SM products are consistent with the previous results over QTP (Xing et al., 2021; Bi et al., 2016; Qu et al., 2019).

For the SHP dataset, Zhao et al. (2018) evaluated the soil properties products based on measurements at Maqu, Naqu, and Ngari stations over QTP. The comparisons of our evaluation and results of Zhao et al. (2018) are shown in Table R2. Zhao et al. (2018) found that the evaluation of SHP datasets varied significantly at different regions of QTP. Table R2 shows that our evaluation is consistent with the results of Maqu site, which is the nearest site to our study area.

Table R2. The comparisons of the bias of the evaluation of SHP datasets (HWSD and Soilgrid_250m) between Zhao et al. (2018) and this study.

Dataset	site	clay (%)	silt (%)	sand (%)	BD (g/cm^3)	Source
HWSD	Ngari	12.60	21.30	-34.20	-0.17	(Zhao et al., 2018)
	Naqu	10.90	10.50	-21.50	-0.19	
	Maqu	6.49	-28.00	21.90	0.36	
	Heihe	13.16	-22.38	9.43	0.21	This study
Soilgrid250	Ngari	8.43	14.70	-22.80	-0.27	(Zhao et al., 2018)
	Naqu	9.33	13.20	-22.50	-0.37	
	Maqu	9.70	-20.50	11.40	0.12	
	Heihe	11.48	-24.15	12.78	0.02	This study

Furthermore, the values of measured soil properties were compared to those available in the literature to cross-check whether they are within a reasonable range. Firstly, we found that the SHPs varied significantly at different sites. For example, the sand content is 84.54 ± 8.28 (mean ± standard deviation) and 26.95±10.55 for the Ngari and Maqu, respectively (Zhao et al., 2018). Thus, we only compare our results to the previous studies near our study area (at Qilian Mountain, Table R3). Table R3 shows that the values of SHPs in our study have a reasonable range.

Table R3 the comparisons of SHP values in our dataset (mean±standard deviation) with the value ranges of previous studies in the Qilian Mountains

SHP	Value	Source
clay (%)	6.66±1.49	this study
	0.3~19	(Hu et al., 2019; Hu et al., 2020; Yang et al., 2017; Zhi et al., 2017)
silt (%)	64.1±12.31	this study
	17~90	(Hu et al., 2016; Hu et al., 2019; Hu et al., 2020; Yang et al., 2017; Zhi et al., 2017)
sand (%)	29.23±13.25	this study
	1~79	(Hu et al., 2016; Hu et al., 2019; Hu et al., 2020; Yang et al., 2017; Zhi et al., 2017)
SOC (%)	4.53±4.03	this study
	0.07~27	(Hu et al., 2016; Hu et al., 2019; Song et al., 2016; Zhi et al., 2017)
BD (g/cm^3)	1.17±0.24	this study
	0.3~1.8	(Hu et al., 2019; Hu et al., 2020; Yang et al., 2017; Yang et al., 2020; Zhi et al., 2017)
$\log_{10}K_S$ (cm/day)	1.4±0.5	this study
	0.07~3.6	(Hu et al., 2020; Liu et al., 2013; Yang et al., 2020)

Moreover, collecting the SM and SHP datasets since 2013, we have done lots of work based on the datasets. For example, based on the SHP dataset, we have analyzed the spatial distribution of the saturated soil hydraulic conductivity and soil properties (Zhao et al., 2014; Tian et al., 2017), exploring the scaling method of soil texture (Li et al., 2018), the application and improvement of hydrological models (Jin et al., 2015; Zhang et al., 2016). Based on the SM dataset, we have done the analysis of the spatial-temporal variation of SM (Tian et al., 2019), estimation of soil water storage (Tian et al., 2020), analysis of preferential flow (Kang et al., 2022), validation and improvement of the SM products (Zhang et al., 2017; 2019; Bai et al., 2020), and the validation of hydrological models (Su et al., 2020).

Lastly, the saturated soil hydraulic conductivity (K_S, Tian et al., 2017) of our dataset has contributed as a representative K_S network in the SoilKsatDB, a global database of K_S (Gupta et al., 2021, Earth System Science Data).

In summary, the comparisons of our results with the previous studies, cross-checking with the available literature, and the applications of our SHP and SM datasets indicate that the quality of our dataset is good and has been accepted by research community. The discussion about the quality of the datasets has been revised in the manuscript.

- ☐ Our evaluations of SHP datasets are consistent with the results of Zhao et al. (2018).
- ☐ Additionally, the value ranges of SHPs in our dataset are consistent with the previous studies within the study area (Hu et al., 2016; Hu et al., 2019; Hu et al., 2020; Liu et al., 2013; Song et al., 2016; Yang et al., 2017; Yang et al., 2020; Zhi et al., 2017).

RC: **I believe that the long-time series point SM measurements are valuable and meaningful. However, I do not think they are suitable for validating coarse SM products. Since the in-situ measurements are all obtained from single stations, spatial heterogeneity impacts on the validation results can not be ignored. They should be considered, especially when evaluating SM products with a spatial resolution of tens kilometers using in-situ point measurements. Actually, dense in-situ SM observation networks are an effective way to minimize the impacts of spatial heterogeneity. Several dense in-situ SM observation networks within the Qinghai Tibet Plateau, such as Heihe network constructed during HiWATER, Naqu and Pali of the CTP-SMTMN networks and Maqu and Ngari of the Tibet-Obs networks, have provided long time-series SM measurements which can be well used for SM evaluation. Therefore, I would suggest the authors use point SM measurements in different applications on a small scale to clarify their quality.**

AR: Thanks for your suggestion. On the one hand, the mismatch of scale between the SM measurements and the SM products is still a challenge in validating SM products (Jin et al., 2017), particularly in hard to reach, data lacking, topographically complex high mountain areas such as the Qilian Mountain Ranges and QTP, and has been discussed in the revised manuscript. On the other hand, the point SM measurements have been applied successfully as follows: (1) The response of SM at different layers to rainfall under different land covers and its control factors (Tian et al., 2019, Agricultural and Forest Meteorology, 271(15): 225-239). (2) The coupling of surface SM and subsurface SM and the estimation of profile SM from surface SM (Tian et al 2020, Hydrology and Earth System Sciences, 24(9): 4659-4674). (3) Analysis of the occurrence and controls of preferential flow (Kang et al., 2022, Journal of Hydrology, 607: 127528). (4) The estimation of rainfall from SM (Lai et al., 2022, Journal of Hydrology, 606: 127430). (5) Validation of hydrological modeling at different sites (Su et al., 2020, Journal of Geophysical Research: Atmospheres, 125(18): e2020JD032727). (6) Evaluation of the SMAP and SMOS products using our SM dataset (Zhang et al., 2017, Remote Sensing, 9(11): 1111; 2019, Science China Earth Sciences, 62(4): 703-718).

Additionally, based on the point SM measurements, we also analyzed the variation of SM with elevation in this study, and we find the increasing of SM with the increasing elevation (Figure S4 in the supplement), which is consistent with the previous studies (Geng et al., 2017).

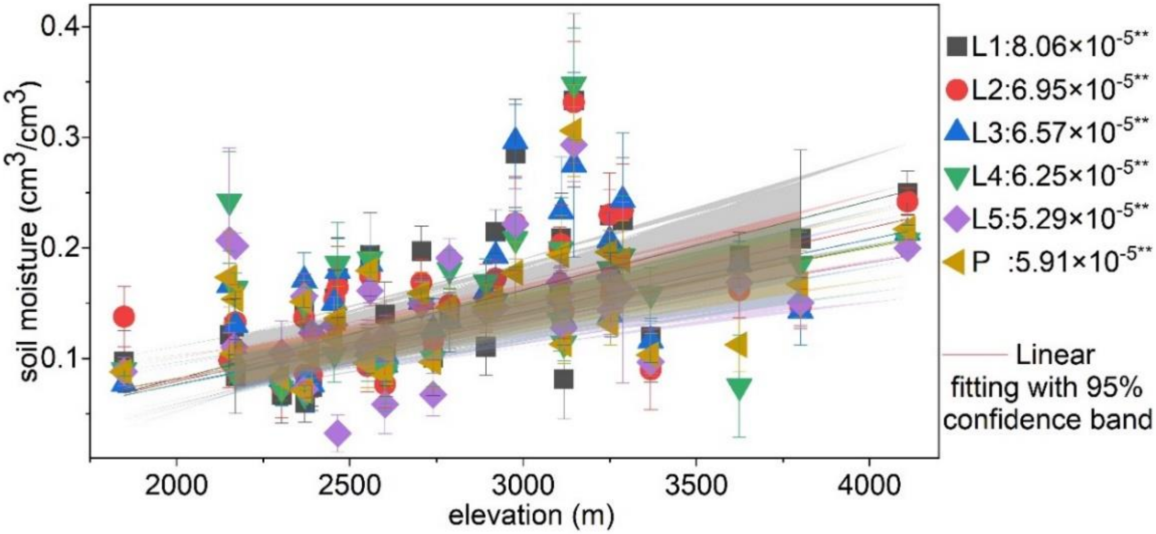

Figure S4. The variation of SM with elevation for different soil depths based on the observed temporal mean value (and standard deviation) at each station and the station elevation, including the linear fitting result with the 95% confidence band. L1 represents SM for layer 1, ** indicates the slope of the linear regression is significant at the 0.01 level.

- ☐ Notably, the scale mismatch between the point location of in-situ SM measurements and the footprints of SM products will introduce additional errors in the evaluation of the SM products (Jin et al., 2017).

Specific Comments

RC: L40, it is arbitrary to say "highly uncertain".

AR: We have changed the statement in the revised manuscript.

- ☐ the uncertainty associated with information about SHP datasets and SM products still exists

RC: L105, in our stud area

AR: We have changed it to "in our study area".

RC: L130, make sure that it is "at the long-term SM monitoring stations" or "at the random sampling

AR: We have changed it to "from each layer of long-term SM monitoring station".

RC: Table 1, suggest to list spatial resolutions for HWSD, SoilGrid, ShangYG and DaiYJ.

AR: We have listed the spatial resolutions of SHP datasets in Table 1.

□ **Table 1. Calculation of SHPs at different depths (5 cm, 25 cm, 0–30 cm) for evaluating the soil property datasets.**

Depth	HWSD	SoilGrid	ZhangYG	DaiYJ	observation
Spatial resolution	30″	250 m	1 km	30″	-
5 cm	-	$SG_{0\text{-}5}$	$ZhangYG_{0\text{-}5}$	$DaiYJ_{0\text{-}5}$	obs_{5}
25 cm	-	$SG_{15\text{-}30}$	-	-	obs_{25}
0-30 cm	$HWSD_{0\text{-}30}$	$(5\bullet SG_{0\text{-}5}+10\bullet SG_{5\text{-}15}+15\bullet SG_{15\text{-}30})/30$	-	-	$(obs_{5}+obs_{25})/2$

Note: *SG* and *obs* represent soil properties from the SoilGrid dataset and from observations, respectively. The subscript gives the soil depths for the SoilGrids properties, and "-" indicates that data for a specific layer are not available in the datasets.

RC: Table 2, suggest to list spatial resolutions for GLDAS, ERA5 and SMAP SM products.

AR: We have listed the spatial resolutions of SM products in Table 2.

□ **Table 2. Calculation of the soil moisture at different depths (surface, subsurface and profile) from different datasets.**

Product	Spatial resolution	Surface (0-10 cm)	Subsurface (10-100 cm)	Profile (0-100 cm)
GLDAS	0.25°	$sm_{0\text{-}10}$	$(30\bullet sm_{10\text{-}40}+60\bullet sm_{40\text{-}100})/90$	$(10\bullet sm_{0\text{-}10}+30\bullet sm_{10\text{-}40}+60\bullet sm_{40\text{-}100})/100$
ERA5_Land	9 km	$(7\bullet sm_{0\text{-}7}+3\bullet sm_{7\text{-}28})/10$	$(18\bullet sm_{7\text{-}28}+72\bullet sm_{28\text{-}100})/90$	$(7\bullet sm_{0\text{-}7}+21\bullet sm_{7\text{-}28}+72\bullet sm_{28\text{-}100})/100$
SMAP_L4	9 km	$sm_{0\text{-}10}$	$(10\bullet sm_{0\text{-}100}\text{-}sm_{0\text{-}10})/9$	$sm_{0\text{-}100}$
Observation	-	sm_{5}	$(10\bullet sm_{15}+10\bullet sm_{25}+20\bullet sm_{40}+50\bullet sm_{60})/90$	$(10\bullet sm_{5}+10\bullet sm_{15}+10\bullet sm_{25}+20\bullet sm_{40}+50\bullet sm_{60})/100$

Note: *sm* is soil moisture, and subscripts indicate the range of depth. For the derived products, the depth is a range (e.g., 0-10, representing 0–10 cm), while for the observations, *sm* is reported at the observed depths of 5 cm, 15 cm, 25 cm, 40 cm, and 60 cm.

RC: Line 230, double-check the numbers here. I can not well relate some of the numbers here to those listed in Table 3. For example, why n ranges within 0.09 and 0.12? why cv of clay ranges within (0.18, 0.28)? etc.

AR: Thank you for your reminder, we have checked and revised the numbers thoroughly according to Table 3.

□ The results show that C_V of the n (ranged within 0.1–0.134 at different depths) of Van Genuchten model is less than 0.16, which is a relatively low spatial variability. Meanwhile, C_V for clay ranged from 0.156 to 0.287, and ranged from 0.174 to 0.237 for silt. C_V of θ_s ranged from 0.187 to 0.223, and the C_V of BD ranged from 0.195 to 0.238. These SHPs therefore show a relatively moderate variability according to Wilding (1985). C_V of sand ranged between 0.439 and 0.618, θ_r ranged between 0.472 and 0.654, C_V of K_S ranged between 0.293 and 0.534, and C_V of α ranged from 0.707 to 1.094. The C_V values of these SHPs were mostly higher than 0.36, indicating strong spatial variability. Thus, the soil texture for clay and silt had the lowest spatial heterogeneity, while both K_S, θ_r, and α had high spatial variability in the study area.

Table 3. The descriptive statistics (median and coefficient of variation) for soil properties at different depths.

depth (cm)	clay (%)	silt (%)	sand (%)	BD* (g/cm³)	SOC (%)	$\log_{10}K_S$* (cm/d)	α (cm⁻¹)	n (-)	θ_s* (cm³/cm³)	θ_r (cm³/cm³)
5	6.600 (0.224)	66.562 (0.192)	26.686 (0.453)	1.153 (0.207)	4.024 (0.889)	1.445 (0.356)	0.022 (0.896)	1.370 (0.119)	0.550 (0.189)	0.107 (0.564)
15	6.356 (0.156)	66.607 (0.174)	26.008 (0.439)	1.151 (0.195)	1.466 (1.019)	1.564 (0.293)	0.026 (0.877)	1.382 (0.100)	0.533 (0.187)	0.126 (0.472)
25	6.381 (0.243)	65.776 (0.237)	27.362 (0.513)	1.189 (0.228)	2.077 (0.945)	1.454 (0.381)	0.026 (0.707)	1.349 (0.134)	0.514 (0.214)	0.094 (0.654)
40	6.656 (0.203)	64.831 (0.222)	29.213 (0.505)	1.189 (0.233)	1.327 (0.998)	1.436 (0.405)	0.027 (0.948)	1.412 (0.117)	0.462 (0.223)	0.129 (0.603)
60	6.848 (0.287)	70.089 (0.233)	20.724 (0.618)	1.238 (0.238)	1.240 (1.05)	1.114 (0.534)	0.021 (1.094)	1.394 (0.104)	0.502 (0.216)	0.146 (0.544)
all	6.552 (0.227)	66.323 (0.21)	26.85 (0.486)	1.168 (0.219)	1.473 (1.008)	1.449 (0.37)	0.024 (0.887)	1.374 (0.117)	0.526 (0.200)	0.113 (0.566)

*indicates that the soil property is significantly ($p < 0.05$) different at different depths. $\log_{10}K_S$ is the $\log_{10}$ transformed K_S. α and n are the parameter of Van Genuchten model (Supplement). θ_s and θ_r are the saturated SM and residual SM, respectively (Supplement).

RC: L250, is it -0.66?

AR: Sorry for the error. It has been changed to "-0.66" in the revised manuscript.

RC: L255, wrong space place in "… significant ,except…"

AR: Thank you. It has been changed to "significant, except"

RC: Figure 5, keep the soil property name consistent with those in the text. E.g., bulk to bulk density or BD, s in logks should be a subscript

AR: Thank you, the names of SHPs have been changed to be consistent with those in the text (Figure 5).

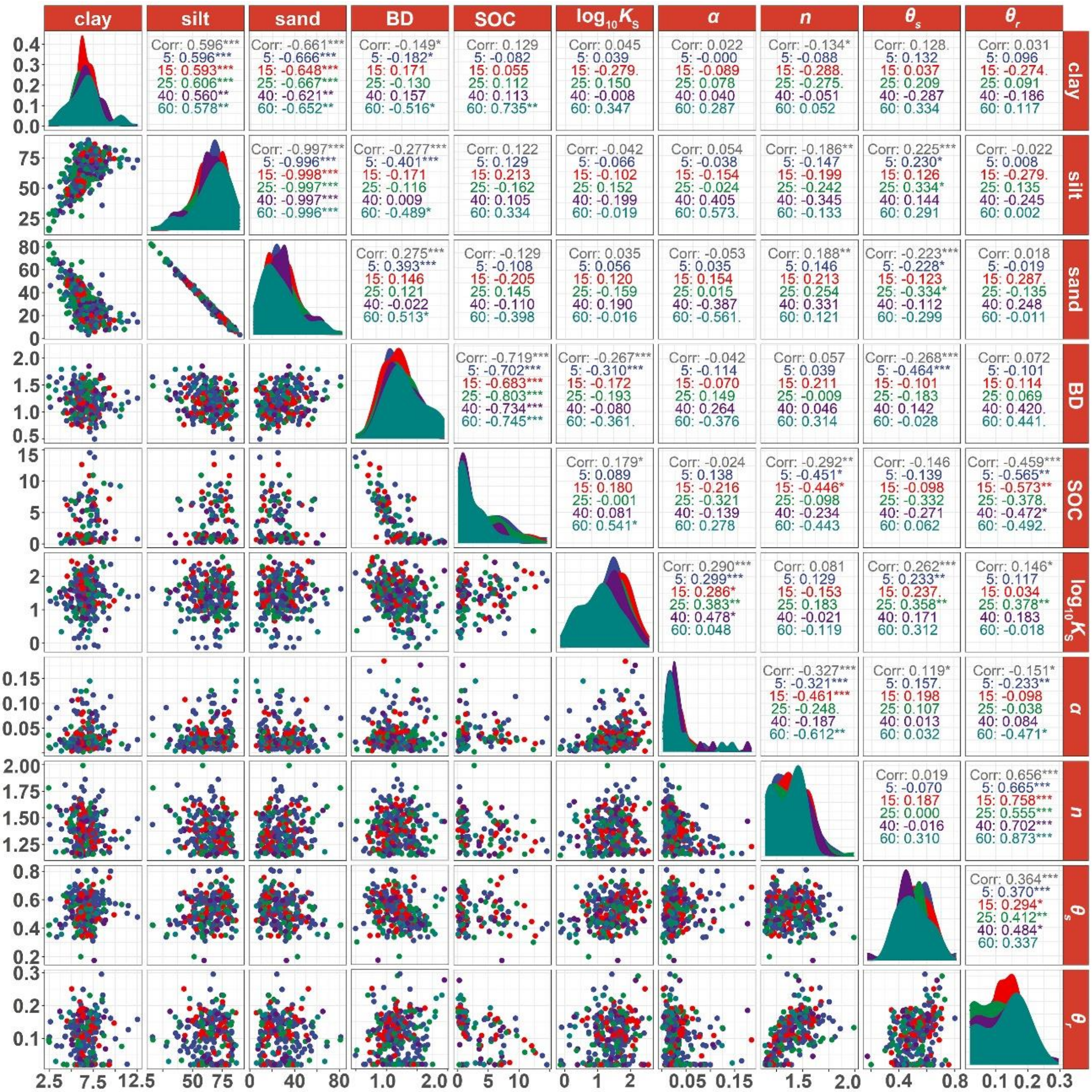

Figure 5. Correlations between different SHPs. Different colors indicate different soil layers. The lower triangle of the figure area shows the scatterplots between different SHPs of different layers. The upper triangle lists the Peason's correlation coefficients (R) of different SHPs, and the first number in each box (Corr:) is the R value calculated by combining data from all soil depths. Plots running diagonally across the figure area represent the distribution of each SHP.

RC: L280, Theta_r and theta_s should be written formally.

AR: We have changed the Theta_r and Theta_s into θ_r and θ_s, respectively (Figure 6).

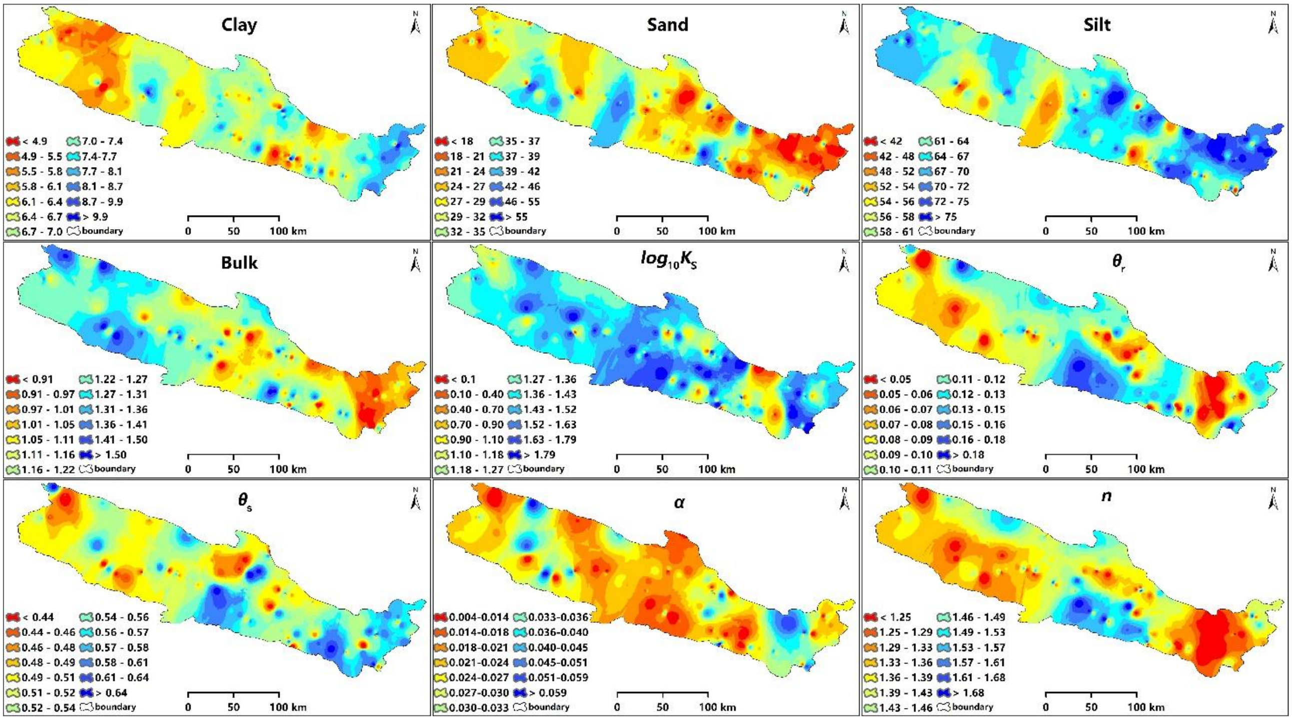

Figure 6. The spatial distribution of soil texture (sand, silt, clay, %), BD (g/cm^3), $\log_{10}K_S$ ($\log_{10}$ transformed K_S, cm/d), θ_r (cm^3/cm^3), θ_s (cm^3/cm^3), α, and n in the study area.

RC: Figure 7, bulk, theta_s, Theta_r, and alpha should be written formally.

AR: We have changed the Theta_r, Theta_s, and bulk into θ_r, θ_s, and BD, respectively (Figure 7).

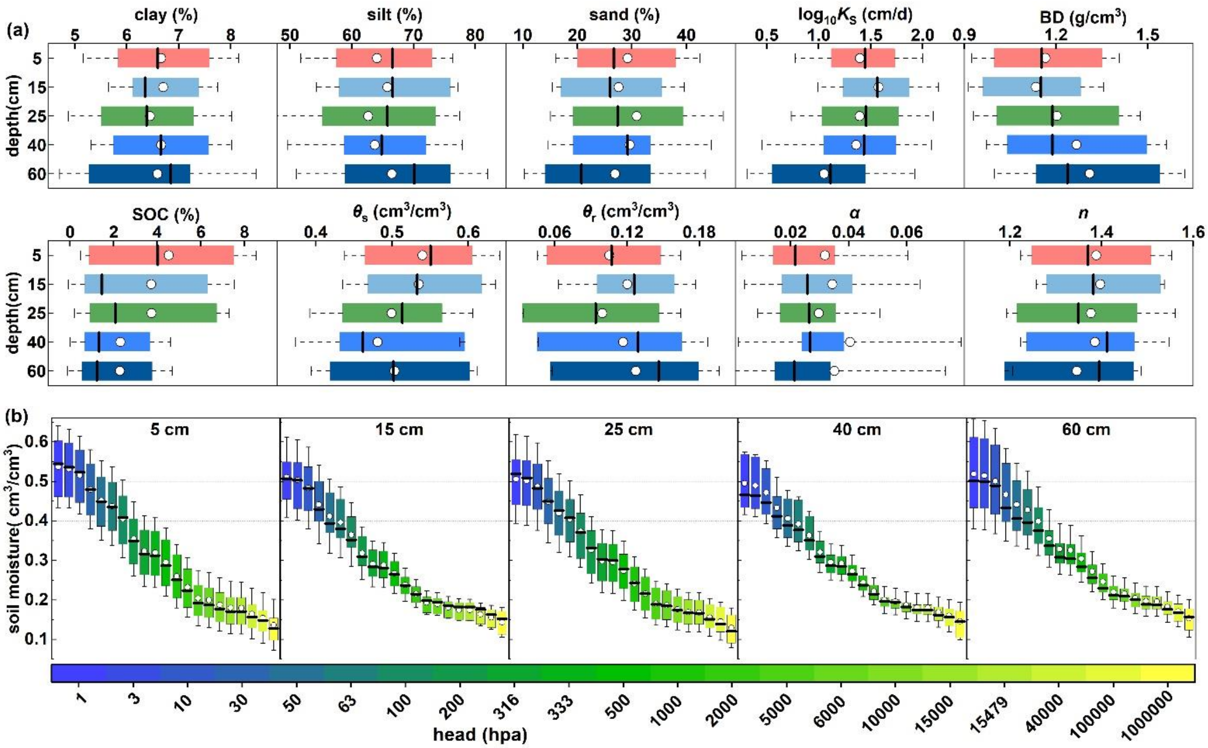

Figure 7. (a) The vertical distribution of sand, clay, silt, $\log_{10}K_S$, BD, SOC and the parameters of the Van Genuchten model for fitting the soil water retention curve (θ_r, θ_s, α, and n) in the study area; (b) boxplots show the distributions of the soil water retention curves for different soil layers.

RC: L330, Figure 11 here should Figure 10? The "higher" in "…and this is higher than the temporal…" should be "lower"?

AR: Thank you. Yes, it should be Figure 10. And the C_V of temporal variation should be lower than that of spatial variation (Figure 10). We have changed it in the revised manuscript.

☐ The spatial variability of SM varies from 0.32 to 0.65 over the study area, with a mean C_V of 0.45, and this is higher than the temporal variability of SM over the study period (2014–2020), which varied from 0.03 to 0.52, with a mean C_V of 0.18 (Figure 10).

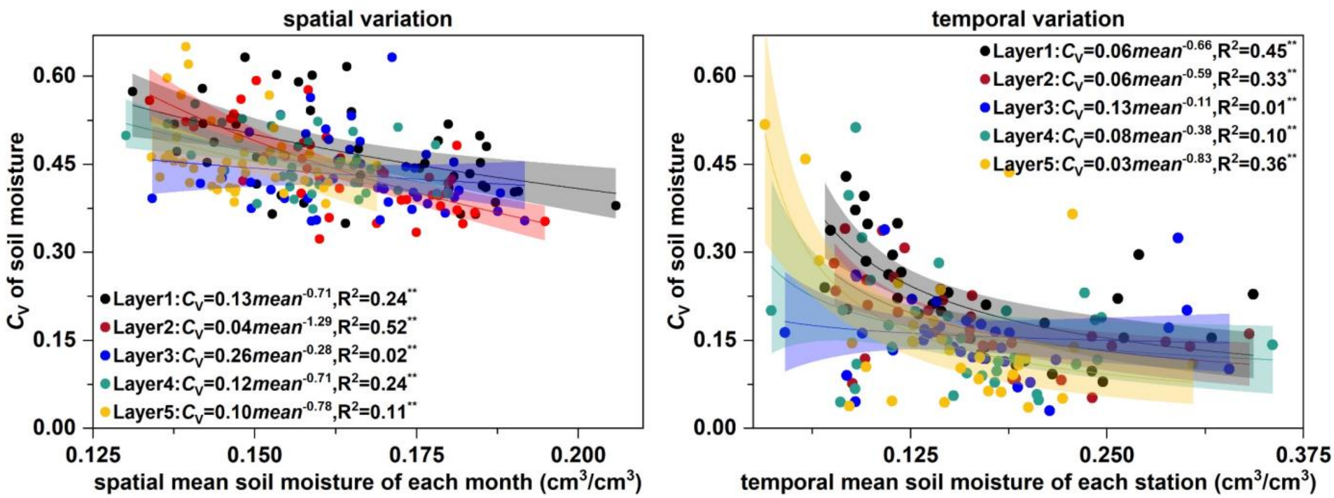

Figure 10. (a) The relationship between the spatial C_V and mean SM for each month for different soil layers; (b) the relationship between the temporal C_V and mean SM for each station for different soil layers. The curve and shading in each plot show the fitted curve and the 95% confidence interval, and the legend shows the fitting equation between C_V and mean SM for each soil layer. ** shows where the fitted curves are significant at the 0.01 level.

RC: **Figure 9, the text 0.75 in the legend is wrong? Should it be 0.075? In addition, clarify in the text how to obtain figure 9? Same as figure 6 using Kriging method in ArcGIS to interpolate?**

AR: Thank you, the value should be 0.075 and the spatial distribution of SM is obtained through the Kriging method in ArcGIS. We have changed the value and clarified the method in the revised manuscript (Figure 9).

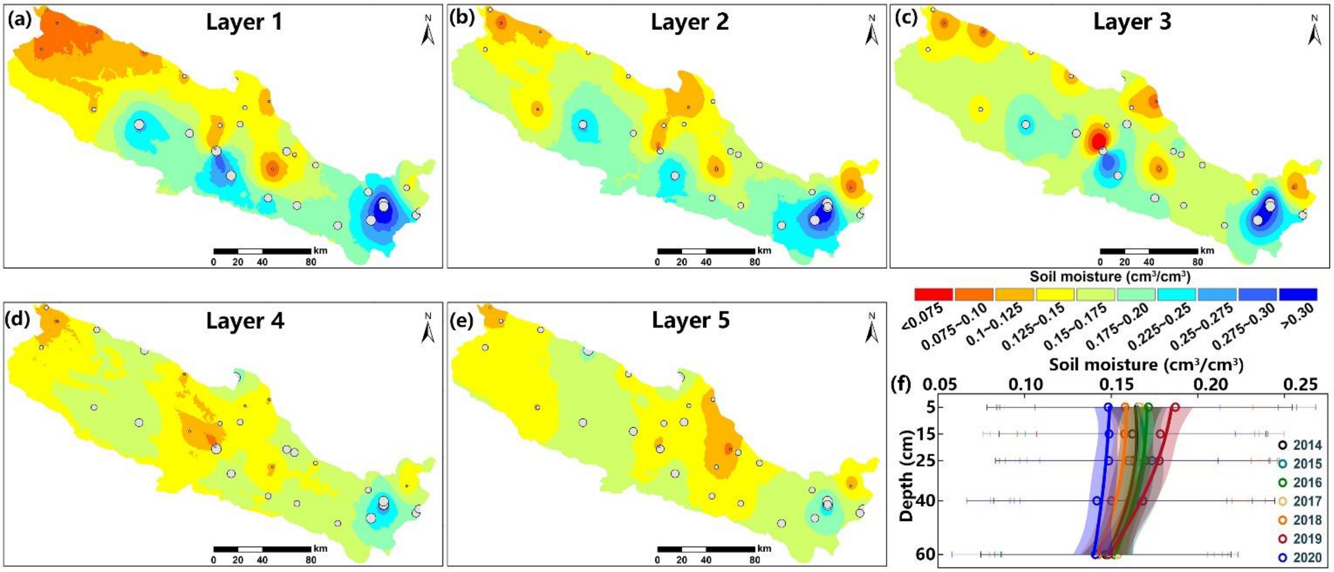

Figure 9. (a)-(e) The spatial distribution of the average SM during the study period for (a) layer 1 to (e) layer 5 through the Kriging method. Circles with different sizes show SM measurements from stations with different mean values over the study period. (f) The variation of the average SM with depth in different years, the line and shading show the fitted curve and the 95% confidence interval.

RC: L350, two meanings for PBIAS here. One is positive bias, the other is percent bias.

AR: Yes. The PBIAS can reflect both the positive or negative bias of the datasets and the percent of the bias. As the value ranges of SHPs such as soil texture and bulk density varied at a different order of magnitude, we used PBIAS instead of "bias" to compare the evaluations of different SHP datasets. The equation of the metrics used in this study has been listed in the revised supplement.

$$\mathrm{PBIAS} = 100 \times \frac{\sum(M-O)}{\sum O} \tag{1}$$

where M, O are the estimation values and observations, respectively.

RC: Figure 11, use BD instead of bulk.

AR: We have changed it in Figure 11.

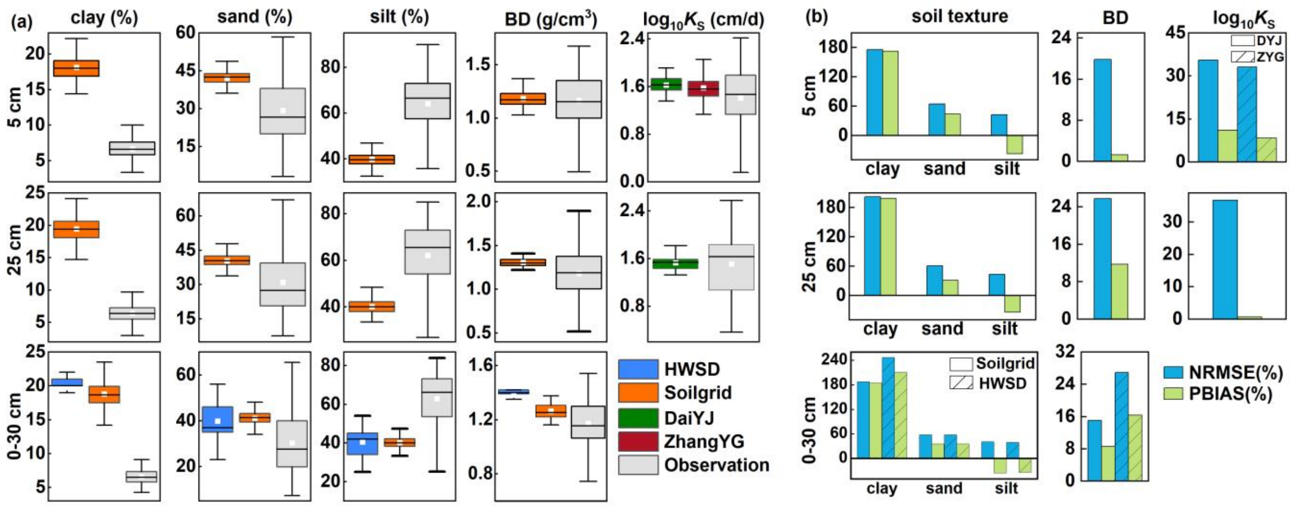

Figure 11. (a) Boxplots show the distributions for the evaluated derived datasets (soil texture and BD from the SoilGrid and HWSD datasets, $\log_{10}K_S$ from the ZhangYG and DaiYJ datasets), with the corresponding distributions for the observations. (b) Metrics to compare the existing derived soil datasets with the corresponding observations in the study area.

RC: L410, how can you conclude that "our SM dataset provides new accurate in-situ SM measurements covering …"?

AR: We have changed our statement in the revised manuscript.

☐ Our SM dataset provides an in-situ SM measurements covering 2014–2020 over a large-scale mountainous area

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