The author's answers are indicated in red color, as well as old text passages. New text passages are indicated in green color.

1. The aim of this study is ambiguous. Is it comparison of different methods, improvement of methods, or evaluation of satellite products?

Response:

The aim of this study is to use multi-station in situ SM observations and remotely sensed SM data from the Qilian Mountains, a prime example of a high and cold mountainous area, to characterize the relationship between surface SM and deeper SM in order to obtain the spatial distribution of profile SM.

In the revised manuscript, we have deleted some contents that are not important for the analysis, and we made a drastic restructuring and reorganization to make the revised manuscript easier to understand.

The revised manuscript is now divided into three parts. Firstly, we evaluated the different methods for estimating subsurface soil moisture (SM). The ExpF method was found to be the most suitable method for further application in the study area.

Secondly, our results indicate that the median value of T_{opt} can be used for application of the ExpF method in the study area.

Finally, the ExpF method derived with the median value of T_{opt} was combined with the SMAP_L3 surface SM product to estimate the subsurface SM. The subsurface SM was also compared to the SMAP_L4 root zone SM product (a widely used large-scale root zone SM product). Results indicated that the combination of the ExpF method with the SMAP_L3 surface SM product can significantly improve the estimation of profile SM in mountainous areas. Furthermore, the combination of SMAP_L3 and the ExpF method (with the median value of Topt) was applied to estimate the temporal and spatial distribution of profile SM in the study area.

2. Does the ExpF method with optimum Topt perform better than the ANN? If not, why does the author apply the ExpF method to expand SMAP?

Response:

Thank you for your comment and suggestion. The ANN method is statistically superior to those from the other two methods. However, we prefer the ExpF approach as it is simpler to apply and more process-based than the ANN method. in the revised manuscript. (Line 213-223)

As expected, all metrics showed that the performance decreased with depth. The results indicate that for two out of the three statistical measures (RSR and NSE), the ANN method was statistically superior to the other two methods. Specifically, the ANN method resulted in the lowest estimation error, while the ExpF method was better able to capture SM dynamics. A similar finding was reported by Zhang et al. (2017a), who found that the ExpF method had a significantly higher correlation coefficient along with a higher mean bias compared to the ANN method. Results also demonstrated that both ANN and ExpF method were able to provide accurate estimates of subsurface SM for layer 2, layer 3 and profile SM.

Overall, both the ANN and ExpF method are useful for estimating subsurface SM from surface SM in our study area, and ANN was the statistically superior method. However, the ExpF method is a simpler approach as it only needs one parameter (T_{opt}), and can thus be easily applied in data-scarce mountainous areas. Therefore, the ExpF method was used to estimate subsurface SM in the remainder of this study.

3. In the introduction, the author mentions there are four groups of methods, what are their advantages and disadvantages? Why did the author choose the three methods in this study?

Response:

In the introduction, we introduced five groups of methods, which are data assimilation of remote sensing data into land surface model (Han et al., 2013), physically-based methods (Manfreda et al., 2014), (semi-) empirical approaches (Albergel et al., 2008), data-driven methods (Kornelsen and Coulibaly, 2014; Zhang et al., 2017a), and statistical methods (Gao et al., 2019). Among them, the application of both data assimilation and physically based methods are limited due to the large amount of required input data, e.g. soil properties, which are often not available for data-scarce mountainous areas (Jin et al., 2015; Li et al., 2017; Dai et al., 2019). As we want to evaluate the methods that can be used in data-scarce mountainous areas, we exclude both data assimilation and physically based methods, and evaluated the other three methods in this study.

4. In section 4.1, there are lag time between soil moisture data at different layers and at surface. How did the author consider the impacts of the lag time in applications of these methods?'

Response:

Thanks for your suggestion. We wanted to evaluate the coupling strength between surface soil moisture and subsurface soil moisture. However, there is no satisfying criterion to conclude whether the coupling strength is strong or not according to the results of the cross-correlation analysis. Thus, we have deleted the contents related to the cross-correlation analysis in the revised manuscript.

5. The performance of the ANN method is significantly related to the training data. In this study, 70 % data was used as training data according to Zhang's study. However, Zhang's study focused on the US., is 70 % suitable for the high mountainous area? Moreover, even with a ratio of 70%, there are lots of data combinations, what's the principle to choose these data? Does the author compare the performance of the ANN method with different data combinations?

Response:

Firstly, for the ANN method, the sample number of training has no relation with the location, and 70% is usually selected as the number of the training samples (e.g. Kornelsen and Coulibaly, 2014; Zhang et al., 2017). The training with 70% of the data was also used in the estimation of soil moisture time series from passive microwave data using the ANN method in the Heihe River watershed (Lu et al., 2017).

Secondly, we used random sampling with uniform distribution in this study, which can best balance the induced error by data sampling. Then, the combination with the best metric (minimum RMSE) was selected for the ANN method.

6. In section 4.3.2, Topt is estimated by precipitation and clay ratio. However, the main advantage of the RBF method is its requirement of few data in introduction. Thus, the improvement in this study is meaningless. What's the insight of this improvement in other regions?

Response:

The correlation between ln-transformed LAI and precipitation is significant (Pearson's R=0.80, $P<0.01$). Furthermore, we tested the partial correlation analysis of the ln-transformed LAI, precipitation and Topt. The results showed that the relationships between ln-transformed LAI and T_{opt} are nonsignificant under the control of precipitation. Meanwhile, the relationships between precipitation and T_{opt} under the control of ln-transformed LAI are not valid for all layers. Thus, this section about the control factors of T_{opt} is not convincing. Furthermore, as the control factors and regression of Topt are not applied to the further estimation of subsurface soil moisture from the SMAP_L3 product, this part is not important for the manuscript. Therefore, we have deleted the section on the control factors and regression of T_{opt} in the revised manuscript.

We improved the estimation of profile soil moisture in data-scarce mountainous areas as follows. Our study evaluates four methods to estimate T_{opt} in the data-scarce Qilian mountains, and the results show that the area-specific estimation of T_{opt} (site-specific T_{opt}, area-generalized T_{opt}) has significantly higher performance than the widely-used T_{opt} (T_{Warger} and T_{Qiu}), which has been applied in cold mountainous areas (e.g. the utility of T_{opt}=20 days for profile SM estimation in east Asia in Muhammad et al. (2017)).

Furthermore, the results indicate that there is a non-significant difference between the performance of a site-specific T_{opt} and an area-generalized T_{opt}. Thus, the area-specific Topt can be combined with ExpF method to estimate profile soil moisture with good performance. The reference T_{opt} for the estimation of profile and subsurface soil moisture in the study area are provided in the manuscript, and provide a reference for future studies in similar areas.

Finally, we compared the estimation of profile soil moisture based on the combination of the SMAP_L3 surface product and the ExpF method (with a median value of T_{opt} of SMAP) with a widely-used profile soil moisture product (SMAP_L4 root zone product). Results showed that our method can improve the profile soil moisture estimation significantly in our study area. Thus, based on the large-scale in-situ observations, we believe that our study improves the estimation of profile soil moisture in cold mountain areas, which will be useful for water resources management in inland river basins.

7. The author evaluates both SMAP_L3 and SMAP_L4 products against in situ observations. The SMAP_L4 is the assimilation results of satellite data and model simulation. What's the impacts of their original biases of SMAP_L3 and SMAP_L4 respectively? What's the impacts of scale-mismatch between footprint scale of satellite products and point scale of in situ observations?

Response:

In this study, we have we partitioned the bias in the SMAP-based estimation of profile SWI

("SMAP-observed profile SWI", Fig. S8(c)) in bias associated with the ExpF method and bias due to SMAP original differences to get insight into the major source of error in SMAP-based estimates of profile SWI. Results showed that the major error stems from the SMAP_L3 product.

The SMAP_L4 product is widely-used large-scale root zone soil moisture product. It is used as reference to test whether our method can improve profile soil moisture estimation. The results indicate that the ExpF method combined with the SMAP_L3 can significantly improve profile soil moisture estimation.

We have noted the problem of scale mismatch between the in-situ observations and the SMAP product. We have added a discussion about the introduced error from the scale mismatch in the revised manuscript (Line 297-300).

Notably, the SMAP_L3 product has a spatial posting of 9 km×9 km, while the in-situ measurements are point-based and soil moisture has a strong spatial variability in mountainous areas (Tian et al., 2019). Thus, the disparity of spatial scales between points and satellite footprints will introduce additional errors in the validation of the satellite products (Jin et al. 2017).

Reference:

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