Response Letter

The value of satellite soil moisture and snow cover data for the transfer of hydrological model parameters to ungauged sites

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In the following document, we reproduce all the comments of the Referees in italic characters followed by our responses in blue.

Response to editor

Thank you for your responses to the reviewer comments. From what I can understand you aim to make some useful changes that will improve the manuscript. I would say the reviewers are mixed in their assessment of your paper but I believe with major changes to your approaches and results then the paper could become a useful contribution. I do accept that applying spatial data and in a multi-objective approach to the regionalization problem warrants a novel enough approach to be included in the literature,

We would like to thank the Editor for the evaluation of the manuscript.

however I do wish to make the following points for the next evaluation of this paper:
1) I do not agree that in your response to referee #2 that you are really dealing with the core uncertainties in this process. I'd like to see some significant justification as to why you can possibly consider that the adjustment of weights is fundamentally the most important source of uncertainty that your experimental design faces or really that this in some way relates to the core matters the reviewer is trying to get you to address. You are using multi-objectives here, and spatial information, you are currently treating them all as if they are deterministic. I think when we use multi response data we have to care and mind what they represent and their accuracy. Here you provide no evidence to justify your methods and this needs to change

We agree with the Editor about the importance of providing insights into the various uncertainty sources of the data and the experimental design. During the conceptualization of the analysis we considered the following potential sources of uncertainty:

(a) model inputs
(b) model structure
(c) accuracy of satellite data

(d) model calibration
(e) model parameter regionalization

We considered the impact of sources (a) to (c) to be smaller than (d) and (e) for the following reasons. The uncertainty of model inputs (a) is generally mainly due to the spatial interpolation of point (precipitation and air temperature) observations, as catchment averages are needed for water balance reasons, and this is a topic that has traditionally attracted a lot of interest in hydrology (e.g. Faurès et al. 1995). In this study, the model inputs (mean daily precipitation and air temperature) are estimated from the gridded SPARTACUS dataset with a grid resolution of 1 km that is small relative to the median catchment size 167 km². Hiebl and Frei (2018) show the accuracy of the precipitation interpolation used in SPARTACUS to be high, and the monthly biases to be very small (values are within ±2%). The cross-validation of the air temperature interpolation (Hiebl and Frei, 2016) indicates no systematic overestimation or underestimation, i.e. the compound mean error is 0 °C, the root mean square error is 1.4 °C.

Model structure (b) is of course more difficult to evaluate and previous studies in the context of regionalization performance (e.g. Petheram et al. (2012), Parajka et al., 2013, Yang et al., 2020) have shown that the simpler models are not superior to complex models (nor much worse) in predicting daily hydrographs in ungauged catchments, and more generally the difference between hydrological models tends to be small (Petheram et al., 2012). Parajka et al. (2013) grouped models according to the number of model parameters and showed that the median of the regionalisation performance (Nash-Sutcliffe efficiency) for each group of models is around 0.65. Yang et al. (2020) compared four daily rainfall-runoff models (GR4J, WASMOD, HBV and XAJ, with 6, 8, 13, and 17 parameters) and reported that the difference in model structure has a smaller impact on the regionalization model performance than the difference in climate conditions. Yang et al. (2020) shows that the average Nash-Sutcliffe runoff efficiency values are, for the best regionalization method (Physical similarity methods with output averaging), larger than 0.6 for all tested model structures. These findings suggest that the model structure error (when measured as the difference in performance between different model types) tends to be small in a regionalisation context.

The evaluation of MODIS snow cover (source (c)) of Tong et al. (2021) indicates an overall classification accuracy of the most recent MODIS snow cover product of larger than 97% which implies much smaller uncertainties than most of the other sources. The accuracy assessment of the experimental S1ASCAT dataset at the regional scale is still work in progress. A preliminary assessment (Panic et al., 2020, https://presentations.copernicus.org/EGU2020/EGU2020-16222_presentation.pdf) demonstrates S1ASCAT to compare well with point-scale and area-representative *in situ* root zone measurements. The correlation between observed *in situ* (i.e. TDR soil network and Cosmic-Ray Neutron Probe) and S1ASCAT soil moisture is 0.59 and 0.51, respectively. These correlations are higher than those obtained between *in situ* and existing COPERNICUS soil moisture products (SSM 1km and SWI 1km), and it is to be expected that only a part of the differences between the data types is due to the satellite data, as also TDR soil probes and Cosmic-Ray Neutron Probes have some level of uncertainty.

We thus decided to focus on the uncertainties resulting from model calibration (source (d) and selection of regionalization method (source (e)). The impact of using different time periods for the prediction of runoff hydrographs is evaluated by the split-sample uncertainty assessment proposed by Klemes (1985). Regionalization studies typically refer only to regionalisation model efficiencies obtained for the same period as used for model calibration. Our results indicate that regionalization efficiencies obtained in an independent validation period generally show a small decrease (loss) in runoff model performance. The median of the loss in Nash-Sutcliffe efficiency varies between 0.02 and 0.07, depending on the regionalization method and calibration weight. In the lowlands the average median loss is 0.06 while it is 0.03 in the alpine basins. The results also show that the median loss of runoff efficiency tends to be smaller for multiple-objective variants (average median loss of 0.05) than for variants using parameters calibrated to runoff only (average median loss of 0.06). The largest relative improvement of soil moisture efficiency is found in alpine catchments (more than 70%), but the absolute value of the correlations (on average 0.31) are still lower than in lowland catchments (average correlation 0.59). These numbers suggest that the differences in performance (which are an indicator of the uncertainties to be expected) are quite significant for uncertainty source (d).

The evaluation of the uncertainty of runoff prediction using different regionalization methods (source (e)) shows that the variability in medians of runoff regionalization efficiency is smaller between regionalization methods than between different calibration variants (i.e. runoff weights). For example, the standard deviation of the medians obtained for eleven runoff weights for the local similarity regionalization method in alpine catchments is 0.17. The standard deviation of the medians between eight regionalization methods ranges (depending on the runoff weight) between 0.04 and 0.11. The differences are somewhat smaller in lowland catchments (i.e. the standard deviation of medians between runoff weights and regionalization methods are 0.14 and about 0.09, respectively).

In response to this comment, we extended the Discussion section to discuss the additional sources of uncertainty as follows:

“The transfer of model parameters to ungauged sites and the efficiency of different approaches for predicting runoff hydrographs are affected by different sources of uncertainty. During the conceptualization of the analysis we considered the following potential sources of uncertainty: (a) model inputs; (b) model structure; (c) accuracy of satellite data; (d) model calibration and (e) model parameter regionalization. We considered the impact of sources (a) to (c) to be smaller than (d) and (e) for the following reasons. The uncertainty of model inputs (a) is generally mainly due to the spatial interpolation of point (precipitation and air temperature) observations, as catchment averages are needed for water balance reasons, and this is a topic that has traditionally attracted a lot of interest in hydrology (e.g. Faurès et al. 1995). In this study, the model inputs (mean daily precipitation and air temperature) are estimated from the gridded SPARTACUS dataset with a grid resolution of 1 km that is small relative to the median catchment size 167 km². Hiebl and Frei (2018) show the accuracy of the precipitation interpolation used in SPARTACUS to be high, and the monthly biases to be very small (values are within ±2%). The cross-validation of the air temperature interpolation (Hiebl and Frei, 2016) indicates no systematic overestimation or underestimation, i.e. the compound mean error is 0 °C, the root mean square error is 1.4 °C.

Model structure (b) is of course more difficult to evaluate and previous studies in the context of regionalization performance (e.g. Petheram et al. (2012), Parajka et al., 2013, Yang et al., 2020) have shown that the simpler models are not superior to complex models (nor much worse) in predicting daily hydrographs in ungauged catchments and more generally the difference between hydrological models tends to be small (Petheram et al., 2012). Parajka et al. (2013) grouped models according to the number of model parameters and showed that the median of the regionalisation performance (Nash-Sutcliffe efficiency) for each group of models is around 0.65. Yang et al. (2020) compared four daily rainfall-runoff models (GR4J, WASMOD, HBV and XAJ, with 6, 8, 13, and 17 parameters) and reported that the difference in model structure has a smaller impact on the regionalization model performance than the difference in climate conditions. Yang et al. (2020) shows that the average Nash-Sutcliffe runoff efficiency values are, for the best regionalization method (Physical similarity methods with output averaging), larger than 0.6 for all tested model structures.

The evaluation of MODIS snow cover (source (c)) of Tong et al. (2021) indicates an overall classification accuracy of the most recent MODIS snow cover product of larger than 97% which implies much smaller uncertainties than most of the other sources. The accuracy assessment of the experimental S1ASCAT dataset at the regional scale is still work in progress. A preliminary assessment (Panic et al., 2020, https://presentations.copernicus.org/EGU2020/EGU2020-16222_presentation.pdf) demonstrates S1ASCAT to compare well with point-scale and area-representative *in situ* root zone measurements. The correlation between observed *in situ* (i.e. TDR soil network and Cosmic-Ray Neutron Probe) and S1ASCAT soil moisture is 0.59 and 0.51, respectively. These correlations are higher than those obtained between *in situ* and existing COPERNICUS soil moisture products (SSM 1km and SWI 1km), and it is to be expected that only a part of the differences between the data types is due to the satellite data, as also TDR soil probes and Cosmic-Ray Neutron Probes have some level of uncertainty.

We thus decided to focus on the uncertainties resulting from model calibration (source (d) and selection of regionalization method (source (e)). The impact of using different time periods for the prediction of runoff hydrographs is evaluated by the split-sample uncertainty assessment proposed by Klemes (1985). Regionalization studies typically refer only to regionalisation model efficiencies obtained for the same period as used for model calibration. Our results indicate that regionalization efficiencies obtained in an independent validation period generally show a small decrease (loss) in runoff model performance. The median of the loss in Nash-Sutcliffe efficiency varies between 0.02 and 0.07, depending on the regionalization method and calibration weight. In the lowlands the average median loss is 0.06 while it is 0.03 in the alpine basins. The results also show that the median loss of runoff efficiency tends to be smaller for multiple-objective variants (average median loss of 0.05) than for variants using parameters calibrated to runoff only (average median loss of 0.06). These results are consistent with Yang et al. (2020), who reported a small degradation of regionalization runoff performance from the calibration to the validation period. The largest relative improvement of soil moisture efficiency is found in alpine catchments (more than 70%), but the absolute value of the correlations (on average 0.31) are still lower than in lowland catchments (average correlation 0.59). These numbers suggest that the differences in performance (which are an indicator of the uncertainties to be expected) are quite significant for uncertainty source (d).

The evaluation of the uncertainty of runoff prediction using different regionalization methods (source (e)) shows that the variability in medians of runoff regionalization efficiency is smaller between regionalization methods than between different calibration variants (i.e. runoff weights). For example, the standard deviation of the medians obtained for eleven runoff weights for the local similarity regionalization method in alpine catchments is 0.17. The standard deviation of the medians between eight regionalization methods ranges (depending on the runoff weight) between 0.04 and 0.11. The differences are somewhat smaller in lowland catchments (i.e. the standard deviation of medians between runoff weights and regionalization methods are 0.14 and about 0.09, respectively)."

2) Secondly and partly related to the above and as I have noted in my editorial review, the methods section is extremely poor (still) on explaining how you are comparing these spatial information to your model framework and how commensurate they are (and the issues and assumptions that have to be dealt with). If your paper is a valuable contribution to introducing this type of spatial information into the regionalization process then I expect the paper to give this full and detailed consideration of the steps needed to make those comparisons effective and 'plausible' Here there is a smoke screen of how lower resolution information is disaggregated and related to a model that has only spatial elevation bands and homogeneous parameters for each catchment. The paper does not attempt to explain in detail the approach used to compare these quantities nor explains how soil moisture (for a certain depth average) can be related to a potential different depth average of a model conceptualization. I don't mind if this is fully detailed in appendices etc. but this has to be massively improved with appropriate figures and explanations. In conjunction with this there is almost no evaluation as to the trade offs and parameterizations across catchments to how well the model does compared to this information. This again needs to improve as the plots currently are too summarized to explain the real value of the information in the multi-objective analyses and thus the value to the regionalization approach.

In response to this comment, we have extended the Methods section and added a Supplement section as suggested by the Editor. This revision provides more detailed information on why and how we have estimated the agreement between satellite and modelled soil moisture and a detailed description of how we relate modelled and satellite soil moisture.

Methods section:

"The rationale behind selecting the Pearson correlation as a measure of agreement is that it assesses the spatial and temporal correspondence of the satellite soil moisture and simulated root zone soil moisture time series. At the spatial resolution of original ASCAT dataset (ca. 12.5 km), the satellite estimates of root zone soil moisture reflect mainly regional rainfall and melt processes patterns, and are thus more closely related to altitudinal zonality than to morphometric characteristics of the terrain that operate at smaller scales. The calculation of O_{SM} from soil moisture averages for elevation zones thus allows representing the agreement in regional and seasonal soil moisture patterns. Choice of a correlation coefficient has the advantage of not being sensitive to the units. In a preliminary analysis, we tested different methods for calculating O_{SM} and found that the O_{SM} combining soil moisture estimated from different elevation zones better describes the soil moisture agreement than the correlation between soil moisture estimates averaged at the catchments scale (see Supplement, Fig. S3). Particularly in the alpine regions, correlation calculated from catchment averages masks the spatial variability in the agreement between ASCAT and hydrologic root zone soil moisture estimates. A similar approach has been used in previous studies (e.g., Parajka et al., 2006; Gruber et al., 2020; Beck et al., 2021). A more detailed description of the calculation of soil moisture agreement is presented in the Supplement."

Supplement section:

Soil moisture is one of the key controls of runoff response. Past studies have used ground soil moisture measurements to provide insight into spatial and temporal soil moisture patterns and their relation to terrain, and soil and vegetation characteristics (e.g. Bardossy and Lehmann, 1998, Western and Blöschl, 1999). However, ground-based measurements have spatial supports of only a few centimetres, and logistically, they can only cover relatively small areas. This makes it very difficult to estimate meaningful spatial averages over medium-sized to large catchments. Alternative more relevant for larger catchments are hydrological models and satellite observations (Babaeian et al., 2019). The main advantage of using hydrological models is that they explicitly represent areal averages, and soil moisture simulated by these models is considered vertically representative over the entire root zone (i.e. the critical zone for runoff generation) but they always need calibration for accurately representing hydrological processes in a particular case (Blöschl and Grayson, 2002).

The TUWmodel used in this study is a conceptual hydrologic model, which simulates soil moisture in the root zone. The changes in the soil moisture state result from changes in snowmelt, rainfall, evapotranspiration and runoff generation contributions. The parameterization of soil moisture and runoff generation has three model parameters (*FC*, *Beta*, *LP*), which are calibrated. The relationship between rainfall, melt, soil moisture storage and runoff generation is described by a non-linear function, which is an empirical curve that connects effective precipitation to simulated soil moisture storage and the model parameter field capacity (*FC*) (Bergström and Lindström, 2015). The contribution of rain (P_R) and snowmelt (M) to runoff is calculated by an explicit scheme as a function of the soil moisture *SSM* in the root zone, using the following non-linear relationship:

$$\Delta S_{UZ} = \left(\frac{S_{SM}}{FC}\right)^{Beta} \cdot (P_R + M),$$

where *FC* is the maximum soil moisture storage and *Beta* is a parameter that controls the characteristics of runoff generation. Similar concepts can, for example, be found in the Xinanjiang model (Zhao, 1992) and the VIC model (Liang and Lettenmaier, 1994). For a full description of the TUWmodel and its implementation see Viglione and Parajka (2020), Astagneau et al. (2021) and Jansen et al. (2021).

Satellite observations similarly provide an integral value over an area which allows direct comparisons with hydrologic models. Most satellite datasets are available globally with relatively high temporal resolution, so they are also suited for ungauged catchment predictions. However, microwave-based datasets have limited penetration depths and poor estimation under dense vegetation, on frozen ground and for snow-covered conditions. Because of the limited penetration depth of a few centimetres, further processing is needed to obtain soil moisture estimates over a deeper soil layer.

The satellite estimates of root zone soil moisture used in this study are based on the change detection method of Wagner et al. (1999) which relates surface soil moisture and satellite backscatter. The surface soil moisture is determined by extrapolating the backscatter coefficient to a reference angle of 40° and accounting for surface roughness and vegetation characteristics. A simple two-layer water balance model then estimates the root zone soil moisture. The first layer represents the remotely sensed topsoil layer, and the second layer represents a reservoir connected to the surface layer. It is assumed that the surface wetness observations from the scatterometer reflect the high soil moisture dynamics due to precipitation, evaporation, and surface runoff and indicate the wetting and drying trend of the moisture content in the lower soil profile. The water flux between the two layers is assumed to be proportional to the volumetric water content in the surface layer and the reservoir. The result of this model is a Soil water index, which represents the profile soil moisture in relative units ranging between wilting point and field capacity. This method has been validated and compared with ground-based and modelled root-zone soil moisture estimates in numerous studies (e.g. Paulik et al., 2014). It has become a part of the processing algorithms providing operational and experimental soil moisture products, such as S1ASCAT used in this study (Bauer-Marschallinger et al., 2018).

One of the aims of this study is to compare the hydrologic model and satellite soil moisture predictions in ungauged basins. The procedure consists of transferring model parameters to ungauged basins, running the model, and estimating runoff, soil moisture and snow cover. We use a semi-distributed hydrologic model for the modelling and calculate the soil moisture and snow cover in individual elevation zones in each catchment. The catchments are partitioned into elevation zones of 200 m vertical width. The main idea of our approach is to keep the number of model parameters small (to allow an effective transfer to ungauged sites), but to represent the spatial (mostly altitudinal) variability of runoff processes, including snowmelt in alpine areas. Our approach uses lumped model parameters (i.e. the same parameters in all elevation zones of a catchment), but the model inputs and state variables differ between elevation zones. This methodology has been widely used in the past (e.g. Paris Anguela et al., 2008, Parajka et al., 2009).

The individual steps of the methodology are documented in Figs S1-S4. Fig. S1 shows an example of the regional patterns of root zone soil moisture estimated from the ASCAT satellite, indicating that the spatial resolution reflects mainly the large scale rainfall patterns and antecedent melt processes, rather than the morphometric characteristics of the terrain (e.g. differences between concave and convex landforms).

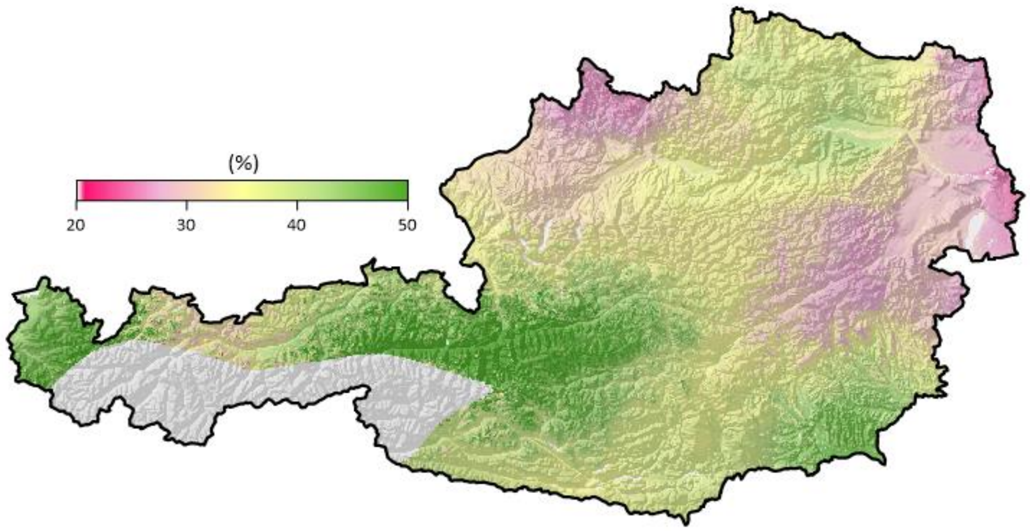

Figure S1. Relative root zone soil moisture from ASCAT on May 15, 2016 in Austria. Grey colour indicates masking because of snow cover.

Figure S1 shows higher soil moisture in central and western (alpine) parts of Austria due to rainfall on May 14, 2016 and preceding snowmelt than in the eastern lowlands. Wetter soils in the South-east reflect local rainfall events on May 14 and 15. Both the seasonal precipitation and melt processes have strong altitudinal variability, so we decided to estimate the agreement in soil moisture for individual elevation zones in each catchment. We extracted for each day the average satellite soil moisture in each elevation zone in each catchment. The example in Figure S2 shows the S1ASCAT root-zone soil moisture averages for different elevation zones at the top and observed daily discharge at the bottom.

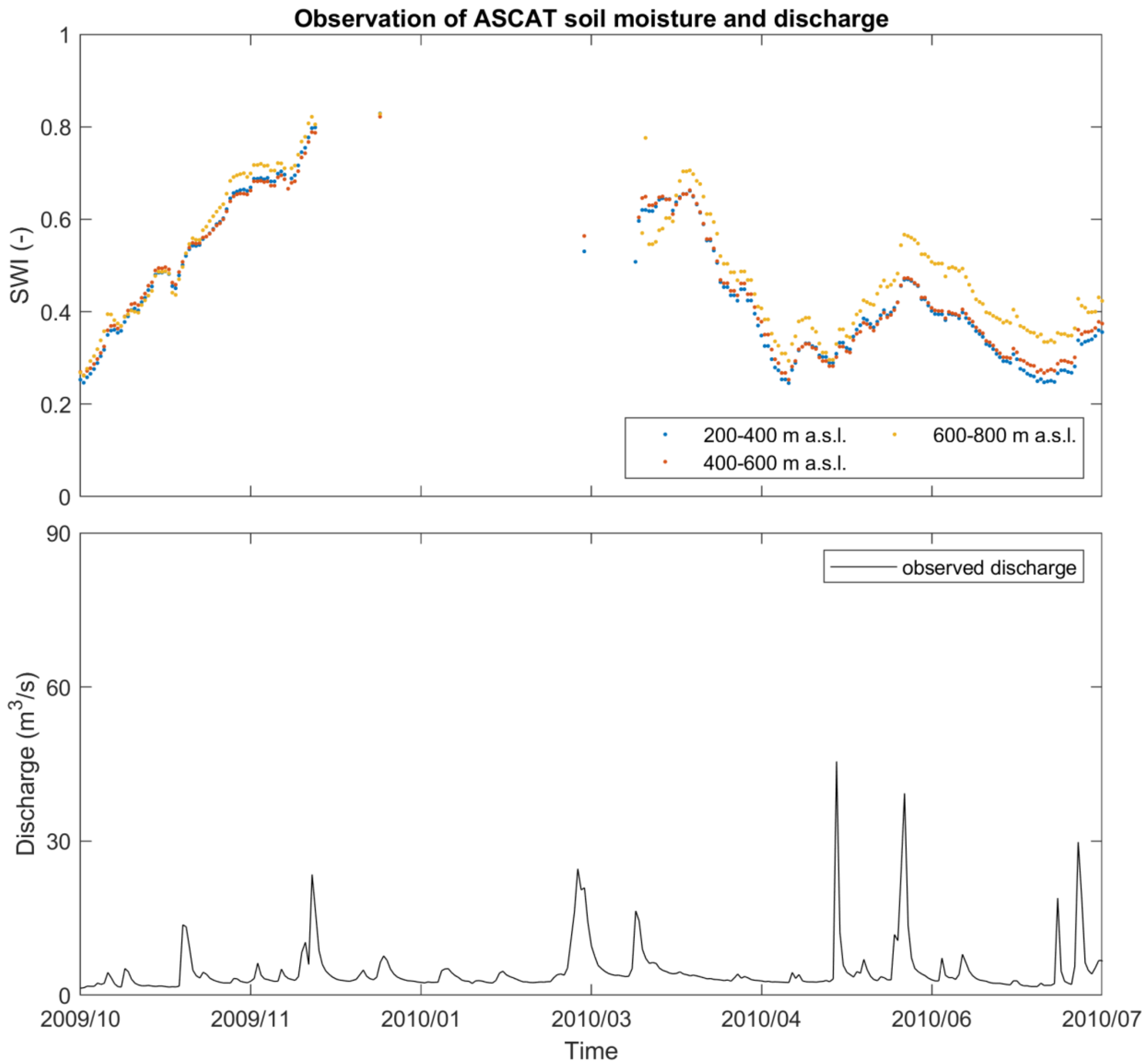

Figure S2. Time-series of observed S1ASCAT soil moisture in different elevation zones and observed discharge for the Pramerdorf-Pram catchment (341 km²) in Upper Austria.

In a next step we considered (in turn, leave one out) each catchment as ungauged and transferred calibrated model parameters to it by using different regionalization methods. The model parameters had been calibrated in a previous study of Tong et al. (2021) using a multiple-objective framework. We tested 11 different sets of model calibrations representing different runoff weightings and satellite snow cover and soil moisture objective functions. While the weight w_Q=1 represents a traditional calibration to runoff only, w_Q=0 represents a calibration to snow cover and soil moisture only. Values of w_Q between 0 and 1 represent different tradeoffs between these objectives. Regionalization model performance in each catchment was then evaluated against runoff and satellite data. The soil moisture efficiency compares the correlation (OSM) between the simulated relative root zone soil moisture and the ASCAT snow water index. In a preliminary testing phase, we tested different methods for calculating the OSM agreement. We found that the OSM combining soil moisture estimated from different elevation zones allows more robust description of the OSM agreement than the correlation between soil moisture estimates averaged over the entire catchment (Fig. S3).

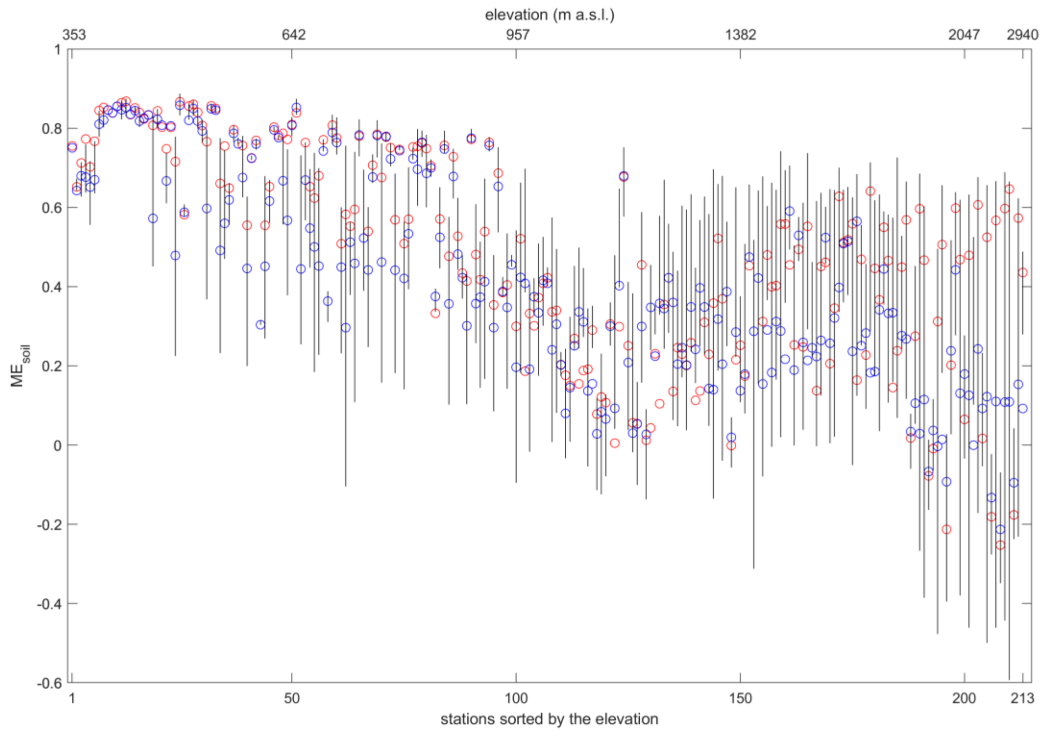

Figure S3. Comparison of the Pearson correlation coefficient (MEsoil) estimated from the mean catchment averages (red symbols) and from elevation zone averages (blue symbols) in 213 catchments. The black bars show the variability of Pearson correlation calculated for the elevation zones within each catchment. The Pearson correlation is estimated between ASCAT root zone soil moisture and hydrologic model relative root zone soil moisture in the calibration period.

Particularly in the alpine (higher altitude) regions, correlations calculated from the catchment averages of soil moisture estimates hide the spatial variability in the agreement between ASCAT and hydrologic root-zone soil moisture estimates, because in catchments with large altitudinal variability, the correlation between catchment averages is often large (red symbols in Fig. S3), but the soil moisture agreement in higher elevation zones (lines representing the range of correlation in Fig. S3) is much smaller. We thus decided to estimate the correlation for elevation zones rather than catchment averages. The final correlation coefficient is calculated as average over all elevation zones for every day where soil moisture is available. Days for which elevation zone average satellite soil moisture cannot be estimated (due to missing pixel values that indicate snow cover or frozen ground) are excluded from the correlation estimation. An example of the soil moisture agreement (correlation) for the Pramersdorf-Pram catchment in the calibration and validation period is presented in Figure S4.

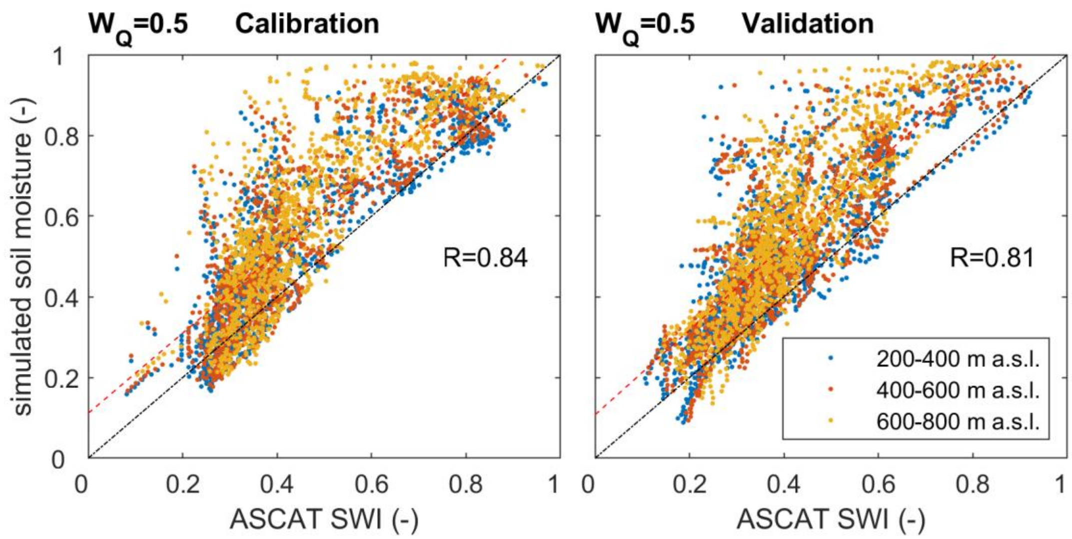

Figure S4 Example of soil moisture agreement (correlation) for the Pramersdorf-Pram catchment in the calibration and validation periods.

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