Supplement of Hydrol. Earth Syst. Sci., 26, 1779–1799, 2022
https://doi.org/10.5194/hess-26-1779-2022-supplement

Hydrology and Earth System Sciences
Open Access

Supplement of

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

Rui Tong et al.

Correspondence to: Rui Tong (tong@hydro.tuwien.ac.at)

Supplement

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).

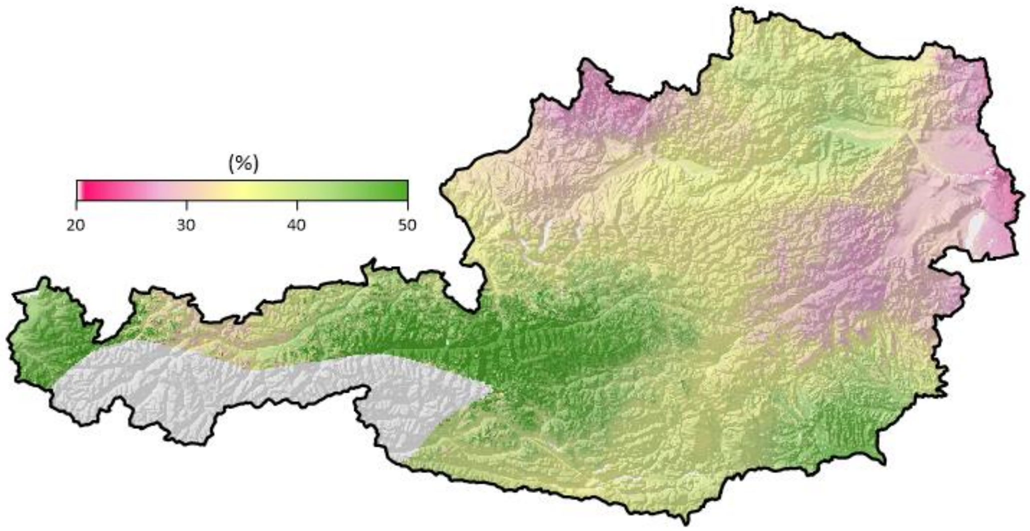

Figure S1. Relative root zone soil moisture from ASCAT on May 15, 2016 in Austria. Grey colour indicates masking because of snow cover.

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.

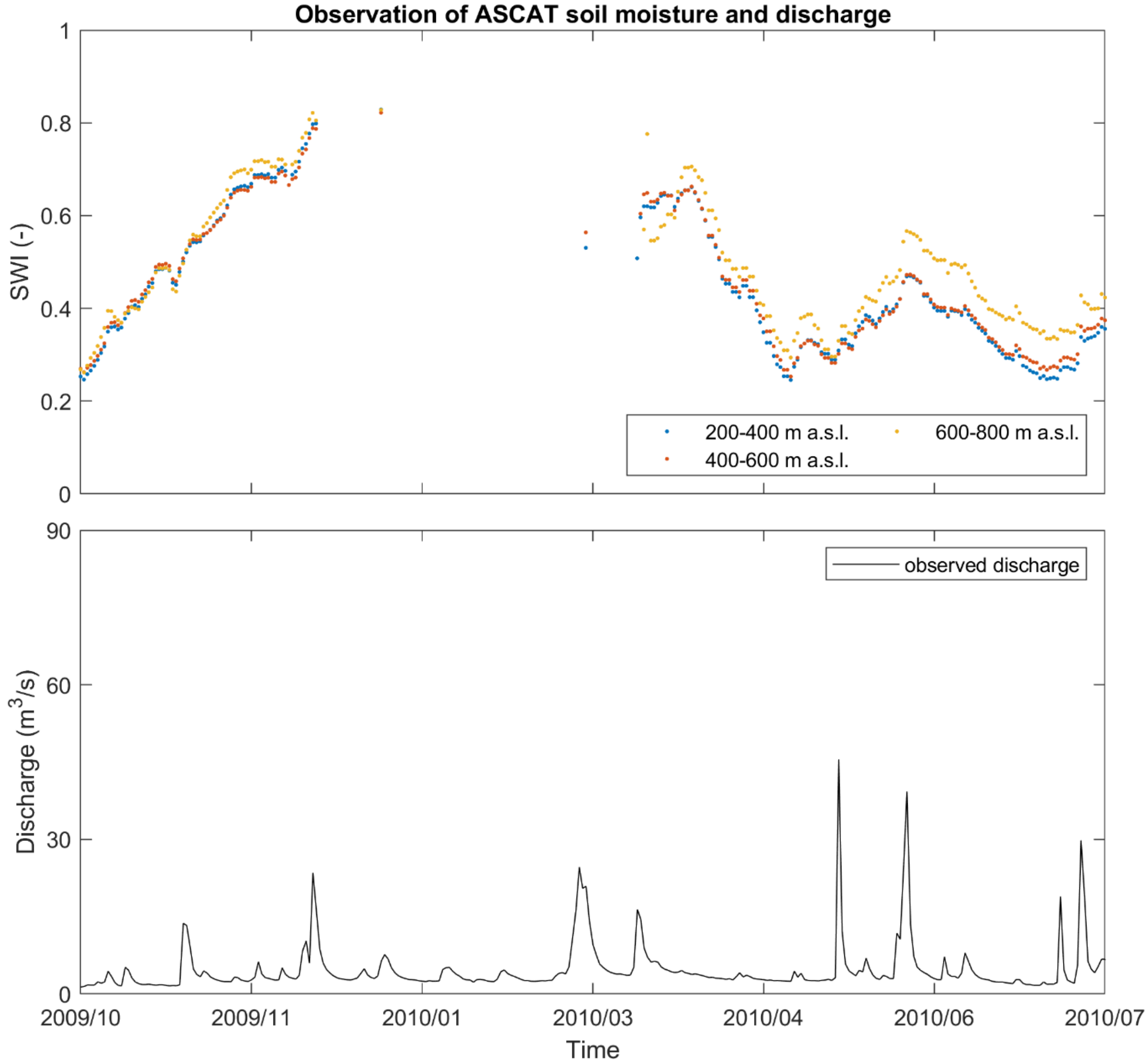

Figure S2. Time-series of observed S1ASCAT soil moisture in different elevation zones and observed discharge for the Pramerdorf-Pram catchment (341 km²) in Upper Austria.

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).

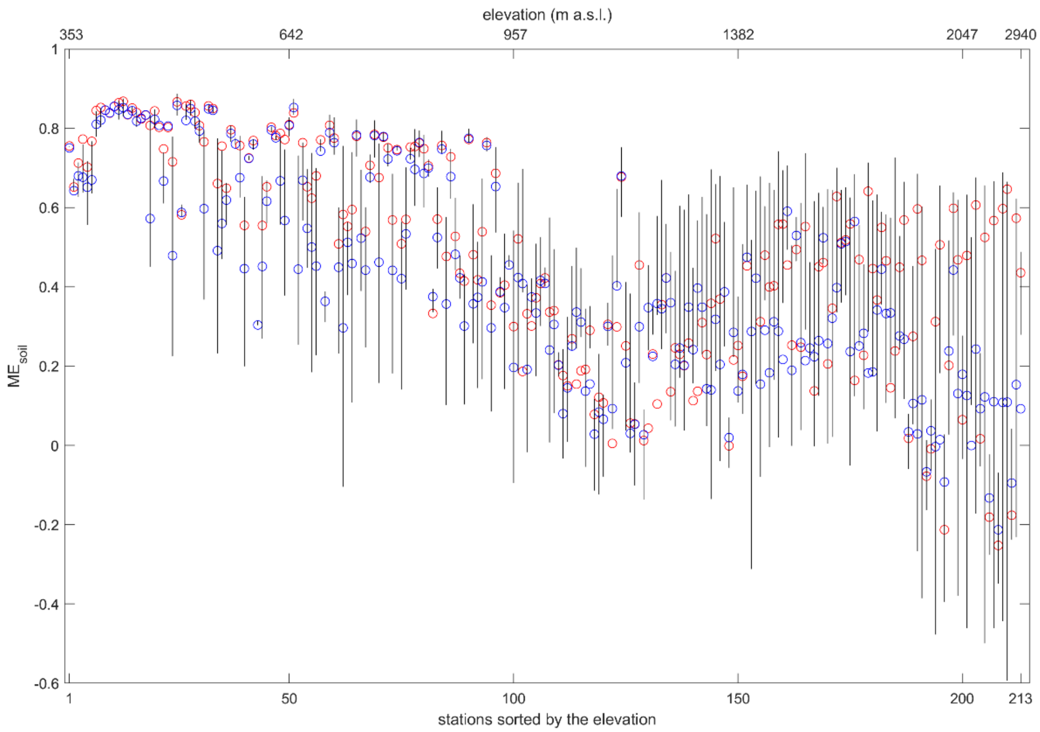

Figure S3. Comparison of the Pearson correlation coefficient (MEsoil) estimated from the mean catchment averages (red symbols) and from elevation zone averages (blue symbols) in 213 catchments. The black bars show the variability of Pearson correlation calculated for the elevation zones within each catchment. 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.

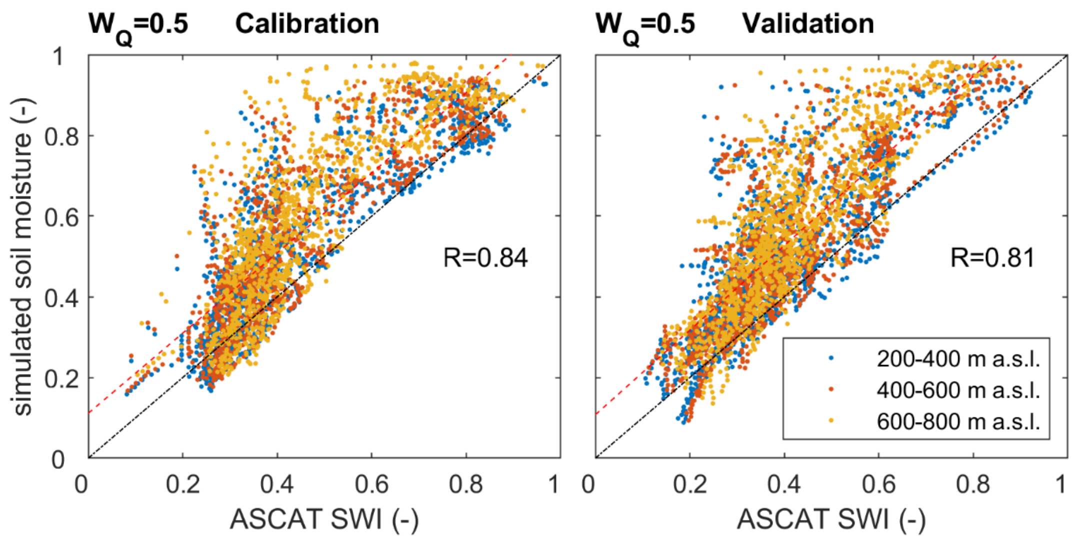

Figure S4 Example of soil moisture agreement (correlation) for the Pramersdorf-Pram catchment in the calibration and validation periods.

References

Astagneau, P. C., Thirel, G., Delaigue, O., Guillaume, J. H. A., Parajka, J., Brauer, C. C., Viglione, A., Buytaert, W., and Beven, K. J.: Hydrology modelling R packages: a unified analysis of models and practicalities from a user perspective, Hydrol. Earth Syst. Sci. Discuss., 2020, 1-48, 10.5194/hess-2020-498, 2020.

Babaeian, E., Sadeghi, M., Jones, S. B., Montzka, C., Vereecken, H., and Tuller, M.: Ground, Proximal, and Satellite Remote Sensing of Soil Moisture, Reviews of Geophysics, 57, 530-616, https://doi.org/10.1029/2018RG000618, 2019.

Bárdossy, A., and Lehmann, W.: Spatial distribution of soil moisture in a small catchment. Part 1: geostatistical analysis, Journal of Hydrology, 206, 1-15, https://doi.org/10.1016/S0022-1694(97)00152-2, 1998.

Bauer-Marschallinger, B., Paulik, C., Hochstöger, S., Mistelbauer, T., Modanesi, S., Ciabatta, L., Massari, C., Brocca, L., and Wagner, W.: Soil moisture from fusion of scatterometer and SAR: Closing the scale gap with temporal filtering, Remote Sensing, 10, 1030, 2018.

Bergström, S., and Lindström, G.: Interpretation of runoff processes in hydrological modelling—experience from the HBV approach, Hydrological Processes, 29, 3535-3545, https://doi.org/10.1002/hyp.10510, 2015.

Blöschl, Günter, and Rodger Grayson. "Flächendetaillierte Niederschlag-Abfluss Modellierung." *Wiener Mitteilungen* 164: 33-55, 2002.

Jansen, K. F., Teuling, A. J., Craig, J. R., Dal Molin, M., Knoben, W. J. M., Parajka, J., Vis, M., and Melsen, L. A.: Mimicry of a Conceptual Hydrological Model (HBV): What's in a Name?, Water Resources Research, 57, e2020WR029143, https://doi.org/10.1029/2020WR029143, 2021.

Liang, X., Lettenmaier, D. P., Wood, E. F., and Burges, S. J.: A simple hydrologically based model of land surface water and energy fluxes for general circulation models, Journal of Geophysical Research: Atmospheres, 99, 14415-14428, https://doi.org/10.1029/94JD00483, 1994.

Parajka, J., Naeimi, V., Blöschl, G., and Komma, J.: Matching ERS scatterometer based soil moisture patterns with simulations of a conceptual dual layer hydrologic model over Austria, Hydrol. Earth Syst. Sci., 13, 259-271, 10.5194/hess-13-259-2009, 2009.

Paris Anguela, T., Zribi, M., Hasenauer, S., Habets, F., and Loumagne, C.: Analysis of surface and root-zone soil moisture dynamics with ERS scatterometer and the hydrometeorological model SAFRAN-ISBA-MODCOU at Grand Morin watershed (France), Hydrol. Earth Syst. Sci., 12, 1415-1424, 10.5194/hess-12-1415-2008, 2008.

Paulik, C., Dorigo, W., Wagner, W., and Kidd, R.: Validation of the ASCAT Soil Water Index using in situ data from the International Soil Moisture Network, International Journal of Applied Earth Observation and Geoinformation, 30, 1-8, https://doi.org/10.1016/j.jag.2014.01.007, 2014.

Ren-Jun, Zhao: The Xinanjiang model applied in China, Journal of Hydrology, 135, 371-381, https://doi.org/10.1016/0022-1694(92)90096-E, 1992.

Tong, R., Parajka, J., Salentinig, A., Pfeil, I., Komma, J., Széles, B., Kubáň, M., Valent, P., Vreugdenhil, M., Wagner, W., and Blöschl, G.: The value of ASCAT soil moisture and MODIS snow cover data for calibrating a conceptual hydrologic model, Hydrol. Earth Syst. Sci., 25, 1389-1410, 10.5194/hess-25-1389-2021, 2021.

Viglione, A., and Parajka, J.: TUWmodel, Lumped/Semi-Distributed Hydrological Model for Education Purposes. R package version 1.1-1. https://CRAN.R-project.org/package=TUWmodel, 2020

Wagner, W., Lemoine, G., and Rott, H.: A Method for Estimating Soil Moisture from ERS Scatterometer and Soil Data, Remote Sensing of Environment, 70, 191-207, https://doi.org/10.1016/S0034-4257(99)00036-X, 1999.

Western, A. W., and Blöschl, G.: On the spatial scaling of soil moisture, Journal of Hydrology, 217, 203-224, https://doi.org/10.1016/S0022-1694(98)00232-7, 1999.