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Improvement of runoff simulation efficiency using satellite soil moisture data for typical monthly runoff regimes in Austria

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The availability of remote sensing data opened possibilities for assimilating these into rainfall-runoff models. We examined the quality of the simulated monthly runoff regime in catchments in which the inclusion of a new satellite soil moisture dataset (ASCAT SW1) into the calibration of the TUW rainfall-runoff model outperformed in the model verification the conventional runoff-only calibration in 198 Austrian basins. Using k-means clustering, catchments with similar mean monthly runoff regimes were grouped. Three variants of the multi-objective approach were analysed for each month of the year in Carinthia, Styria and Upper and Lower Austria regions. Improvement in the simulated monthly runoff using the ASCAT data was mainly noticeable in the winter and spring months. The runoff simulation efficiency decreased in the driest summer and autumn months. It has also been confirmed that improvements in the simulations can be expected in the flat river basins compared to the hilly types and in river basins with lower average slopes. The findings refine previous recommendations regarding when hydrological models could benefit from considering information beyond the runoff signatures in their calibration.

KEY WORDS: ASCAT, TUW dual-layer model, soil moisture assimilation, multi-objective calibration, runoff regime

Introduction

Recently the hydrological community significantly increased efforts to improve soil moisture estimation by incorporating remotely-sensed soil moisture data into hydrological studies. The potential of using remotely soil moisture through remote sensing in hydrology was described, e.g. in Brocca et al. (2017). The areas of applications of satellite-based soil moisture data in rainfall-runoff modelling cover three areas in general: Estimating antecedent soil moisture for rainfall-runoff models (e.g., Sunwoo and Choi, 2017; Jadidoleslam et al., 2019); assimilation of satellite data for runoff forecasting (e.g., Meng et al., 2017; Ciupak et al., 2019; Jun et al., 2021, Rončák et al., 2021); multi-objective calibration of continuous hydrological models (e.g., Li et al., 2018; Tong et al., 2021; Kuban et al., 2021, 2022).
Multi-objective calibration of rainfall-runoff models helps to reduce model and parameter uncertainty and improves predictions in general (Efstratiadis and Koutsoyiannis, 2010). The advantages of the multi-objective calibrations using satellite data were demonstrated in several case studies (see, e.g., Nijzink et al., 2018; Demirel et al., 2019; Széles et al., 2020). In addition, microwave satellite sensors increased the applicability of remote sensing of soil moisture. Consequently, the availability of satellite soil moisture datasets is growing, including a new ASCAT Soil Water Index (SWI) data product used in this paper (Paulik et al., 2014). The ASCAT application used here benefits from a new vegetation parameterisation of the ASCAT surface soil moisture retrieval algorithm and improved spatial representation based on a new directional resampling method (Tong et al., 2021; Kuban et al., 2021).
When calibrating rainfall-runoff models to soil moisture and discharge data concurrently, improvements in the representation of internal soil moisture state variables and fluxes were typically achieved. However, joint enhancement in soil moisture and runoff simulation efficiency has not always been observed (Kuban et al. 2021, 2022). Furthermore, other studies also noted deteriorated performance in runoff simulations (Brocca et al., 2017). Therefore, situations leading to benefits from including satellite soil moisture data in rainfall-runoff modelling (both for data assimilation and model calibration) need further clarification.
This paper is based on three various multi-objective calibrations of the dual-layer conceptual TUW rainfall-runoff model in 209 catchments in Austria (Kuban et al., 2021, 2022). It analyses the quality of the simulated monthly runoff regime in those catchments in which the inclusion of a new satellite soil moisture dataset (ASCAT SW1) into the calibration outperformed the conventional runoff-only calibration results in the model verification

for 198 catchments. We used identical model calibrations as in Kuban et al. (2021), which are based on the combinations composed of three multi-objective functions: on the runoff and soil moisture in the root zone; on the runoff and soil moisture in the topsoil layer; and on the runoff and soil moisture both in the root and topsoil layers, respectively. These included the exact finer spatial resolution of the ASCAT product for the topsoil and root zone, reported by Tong et al. (2021). Catchments with improvements in the multi-objective runoff simulations for each calibration scheme as compared to the single objective runoff-only calibration are selected and clustered based on the similarity of their interannual mean monthly runoff distribution. Comparisons of measured and simulated monthly runoff regimes are analysed. The results are expected to permit inferences about the physiographic properties of catchments with typical water balance, where the value of the scatterometer data for hydrological modelling proves helpful.

Material and methods

The TUW-dual rainfall-runoff model and its calibration and validation

In this paper, the TUW-dual conceptual rainfall-runoff model's output time series were used as calibrated by Kuban et al. (2021) in 209 Austrian catchments. The TUW hydrological model follows the structure of the well-known HBV model (Bergstrom, 1992). Parajka et al. (2009) developed it at the Vienna University of Technology as a lumped or semi-distributed conceptual rainfall-runoff model. Precipitation, air temperature, and potential evapotranspiration inputs are required to model catchment runoff on a daily or shorter-step basis. Model inputs can be spatially differentiated with the catchment elevation.

Consequently, the meteorological inputs, soil moisture and snow water equivalent were independently defined for each elevation zone. These were considered to have a 200 m altitudinal range in this research. The limitation of the approach used here was that the model parameters were identical in each elevation zone. Even with this limitation, the TUW-dual can still be regarded as a semi-distributed conceptual model.

Compared with the original TUW model, in the dual version, the soil layer was split into two zones, i.e., the shallow surface soil layer (topsoil) and the deep root zone soil layer. Separate storage represents each layer. The ASCAT data are directly indexed into the surface soil layer. The Soil Water Index (SWI) for the root zone layer is based on an infiltration model, which relates the surface and root zone soil moisture as a function of time. Conceptually it represents the soil moisture content in the first meter of the soil in relative units, ranging between the wilting level (0 %) and field capacity (100 %). Paulik et al. (2014) compared the ASCAT SWI dataset with at-site soil moisture measurements. They found that the SWI better agrees with the in-situ soil moisture from the deeper layers than the original ASCAT set of soil surface moisture data.

The surface zone soil storage is fed by rain and snowmelt and produces direct runoff. Bidirectional moisture flux connects both storages. The field water capacity parameter limits the root zone storage capacity, and it also produces (slow) runoff. In both soil storages, the water is reduced by the actual evapotranspiration, which is the function of the actual water level in these. Kuban et al. (2021, 2022) contain the detailed algorithm and the parametrisation of the layers.

The original TUW single soil layer model has 15 parameters, which need to be calibrated. In the TUW-dual model, 18 parameters had to be considered because of the dual soil layer structure. In addition, three new parameters for the surface soil storage layer were added. The single-objective and multi-objective calibration of the TUW-dual model methodology is described in Kuban et al. (2021, 2022). The analysis in this paper was based on the results achieved therein. For the sake of completeness, the main concepts are therefore repeated here.

The multi-objective calibrations were initially performed with data from the period 2007–2014 calibration period on 209 catchments and were published in Kuban et al. (2021). In this study, as in Kuban et al. (2022), we analysed the model performance to simulate runoff on a subset of 198 basins, where data were available for the validation period of 1991–2000. The model parameters from the calibration period were used (Kuban et al., (2021) in the verification. The validation catchments were divided into two groups, as in Kuban et al. (2022): catchments where the multi-objective calibration approach using the ASCAT SWI data improved or did not improve the values of runoff model efficiency criterion.

The multi-objective calibrations by Kuban et al. (2021) were performed with four functions (OF). The function labelled OF_Q was based on runoff only; OF_{Q+SR} was built from the runoff and soil moisture in the root zone; OF_{Q+SS} was assembled from data on the runoff and soil moisture in the topsoil layer, and $OF_{Q+SR+SS}$ was based on the runoff and soil moisture both in the root and topsoil layers.

The objective functions in multi-objective calibration were a weighted linear combination of the individual single-objective functions OF_Q, OF_{SR}, and OF_{SS}:

$$OF_{Q+SR} = OF_Q \times w_Q + OF_{SR} \times w_{SR} \tag{1}$$

$$OF_{Q+SS} = OF_Q \times w_Q + OF_{SS} \times w_{SS} \tag{2}$$

$$OF_{Q+SS+SR} = OF_Q \times w_Q + OF_{SS} \times w_{SS} \times OF_{SR} \times w_{SR} \tag{3}$$

where

w_Q, w_{SR}, w_{ST} – are the weights based on the results of Tong et al. (2021) and Kuban et al. (2021), and which were set as 1/2 and 1/3, respectively.

The Spearman correlation coefficient between the measured and simulated soil moisture values was used as an objective function for both soil moisture layers. For the runoff, we chose the average of the Nash-Sutcliffe coefficient (NSE) and the logarithmic NSE as the objective functions (Nash and Sutcliffe, 1970):

$$NSE = 1 - \frac{\Sigma_{i=1}^{n}(Qobs(i) - Qsim(i))^2}{\Sigma_{i=1}^{n}(Qobs(i) - \bar{Q}obs)^2} \quad (4)$$

$$logNSE = 1 - \frac{\Sigma_{i=1}^{n}(logQobs(i) - logQsim(i))^2}{\Sigma_{i=1}^{n}(logQobs(i) - log\bar{Q}obs)^2} \quad (5)$$

where
Qsim(i), Qobs(i) – are the simulated and observed runoff at time *i*;
$\bar{Q}obs$ – is the average of the observed runoff.

The efficiency of the validation model runs was evaluated with respect to the simulated runoff. Therefore the same combinations of NSE and the logarithmic NSE were considered as the Runoff Model Efficiency RME:

$$RME = OF = \frac{(NSE + logNSE)}{2} \quad (6)$$

The evolution strategy by Storn and Price (1997), also known as the differential evolution (DE), was used to optimize the multi-objective parameter. DE is considered successful in finding the global optimum of a real-valued function of real-valued parameters and does not need continuous or differentiable objective functions. The DEoptim version was used here as described in Mullen et al. (2011).
The improvement in the multi-objective against the single-objective calibration was calculated as the difference between Relative Volume Errors (RVE):

$$RVE = \sum\left(\frac{Qobs(i) - Qsim(i)}{Qobs(i)}\right) * 100\% \quad [\%] \quad (7)$$

Improvement in the multi-objective calibration (IMO) = $\left|RVE_{single-objective}\right|$ - $\left|RVE_{multi-objective}\right|$
[%] (8)

In this study we decided to cluster the catchments into groups with a similar interannual distribution of normalised mean monthly runoff. We sought to determine how the inclusion of satellite data in such groups can improve the model efficiency in a typical runoff regime. Runoff simulations using the multi-objective approaches were considered separately.
We have applied the cluster analysis to group catchments according to the respective normalised runoff regimes represented by the interannual distribution of the long-term means of the monthly discharges divided by the long-term mean annual runoff. Cluster analysis is a multivariate method that aims to classify a sample of subjects (or objects) based on a set of measured variables into several different groups so that similar subjects are placed in the same group. The cluster analysis method has several variants; in this study, the *k*-means clustering was used (e.g., Hartigan, 1975).
This standard algorithm, which defines the total within-cluster variation as the sum of squared Euclidean distances between items and the corresponding centroid, has the following formula:

$$W(C_k) = \sum_{xi \in Ck}(x_i - \mu_k)^2 \quad (9)$$

where
x_i – is a data point belonging to the cluster C_k,
μ_k – is the mean value of the points assigned to the cluster C_k.

The choice of distance measures is a critical step in clustering. It defines how the similarity of two elements (*x*, *y*) is calculated and it will influence the shape of the clusters. The classical method for distance measure is the Euclidean distance calculated as:

$$d_{\mathrm{euc}}(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (10)$$

where,
x and *y* – are two vectors of length *n*.

The K-means algorithm iteratively assigns each observation to the nearest centre and re-iterates this process until a new iteration no longer re-assigns any observations to a new cluster. The algorithm is considered to have converged at this point, and the final cluster assignments constitute the clustering solution. More details about this method are presented, e.g., in Hartigan and Wong (1979).

Data

In this paper, 198 catchments from the whole country of Austria were selected (Fig. 1). These catchments were also used in the previous studies (Kuban et al., 2022, 2021; Tong et al., 2021; Sleziak et al., 2020), and represent river basins with no significant anthropogenic influences. The catchments have various geomorphological characteristics. The catchments' area varies between 13.7 (Micheldorf, Krems River) to 6214 km^2 (Bruck an der Mur under Muerz, the Mur River), and the average slope varies from 1.74% to 43.91%. The mean annual precipitation is less than 400 mm year^{-1} in the east and more than 2500 mm year^{-1} in the west of Austrian. The mean daily air temperature was −2.83°C in the Alpine catchments and up to 10.30°C in the lowland catchments.
The Austrian hydrological and meteorological data that we used in this study were provided by the Central Hydrographical Bureau (HZB; https://ehyd.gv.at/, last access: 17 March 2021) and the Zentralanstalt für Meteorologie und Geodynamik (ZAMG). The data from all 198 gauged stations from the period 1991–2000 were used to validate the model in a daily time step. The discharge time series were not influenced by dams or hydropower structures. The climatic model inputs (mean daily precipitation and mean daily air temperature) have been derived from the gridded SPARTACUS data set (Hiebl and Frei, 2016, 2017). This data set provides daily 1 km gridded spatial resolution maps covering the whole territory of Austria. These data have been

available since 1961 and have been consistently interpolated using the same consistent station network throughout the entire period (Duethmann et al., 2020).
For the multi-objective calibration, the new experimental data of the Soil Water Index (ASCAT SWI) were used from the experimental version of the ASCAT DIREX Soil Water Index (ASCAT SWI) product, similarly as in Tong et al. (2021). The original ASCAT SWI surface soil moisture dataset at a 12.5 km spatial resolution is based on a new parametrisation for the correction of vegetation (Hahn et al., 2020), which has shown better soil moisture results for Austria (Pfeil et al., 2018). The process of disaggregation consists of a directional resampling method using a connection between regional (12.5 km) and local (0.5 km) scale Sentinel-1 backscatter observations, which temporarily retain stable soil moisture patterns that are also reflected in the radar backscatter measurements (EODC, 2021). The ASCAT SWI product provides estimates of the Soil Water Index describing the soil-water content profile on a 0.5 km spatial sampling grid, whereas the effective spatial resolution is believed to be within the range of 5–15 km, depending on the location. It is derived from directionally downscaled ASCAT surface soil moisture by computing the Soil Water Index. A key strength of this product is its consistency over long periods of time, as its temporal behaviour is only determined by the backscatter measurements acquired by the intercalibrated ASCAT sensors flown onboard the Metop-A/B/C, which belongs to the EUMETSAT-operated Metop ASCAT (Advanced Scatterometer) satellite mission.

Results and discussion

We apply the K-means clustering methods to cluster the catchments analysed with similar mean monthly runoffs for all three multi-objective variants of the runoff simulation. Only catchments with an improvement in the runoff simulation for the individual approaches of the model multi-objective calibration were considered.
Four clusters were formed for all three multi-objective approaches tested. Fig. 2 presents the spatial division of

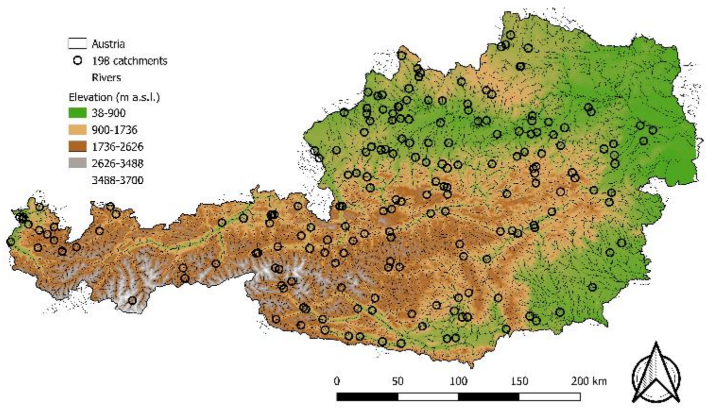

Fig. 1. Location of the 198 catchments selected on the territory of Austria.

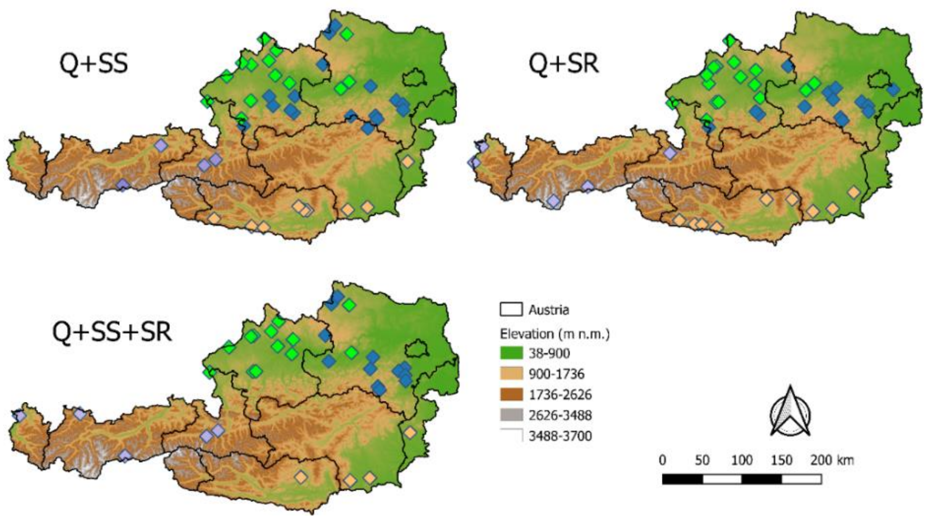

Fig. 2. Groups of the catchments with similar runoff regimes, with an improvement in the runoff simulation for the three multi-objective approaches (Q+SS, Q+SR, and Q+SS+SR) in the 1991–2000 validation period.

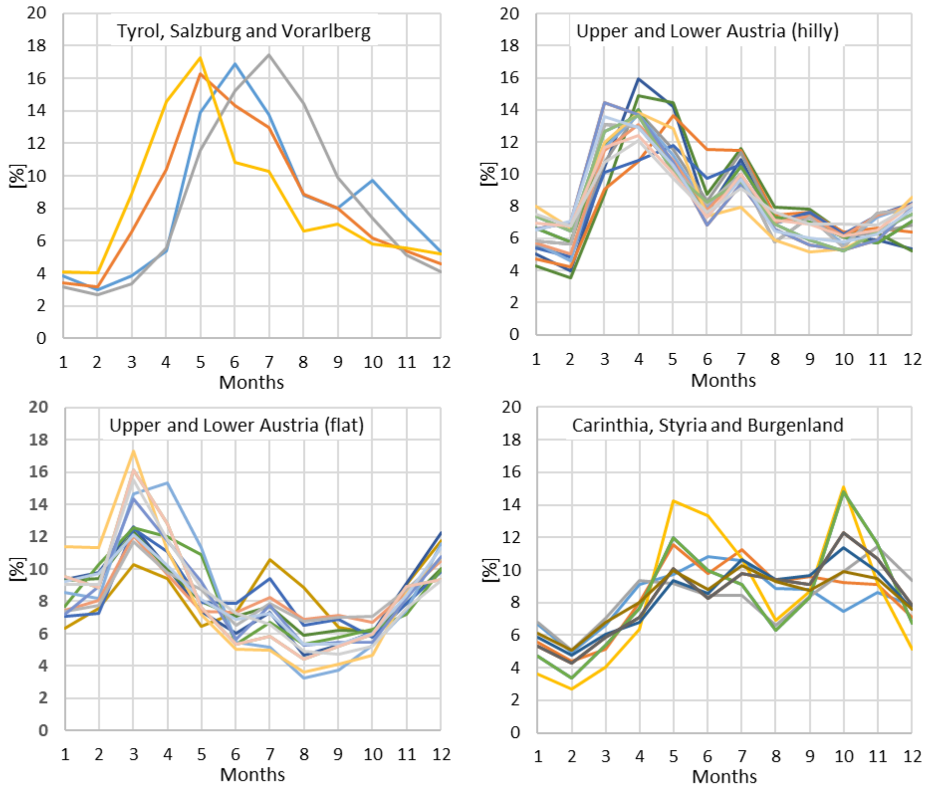

Fig. 3. *Normalized mean monthly runoff for the catchments where we have detected an improvement in the runoff simulation with the multi-objective approach (Q+SS) for 1991–2000.*

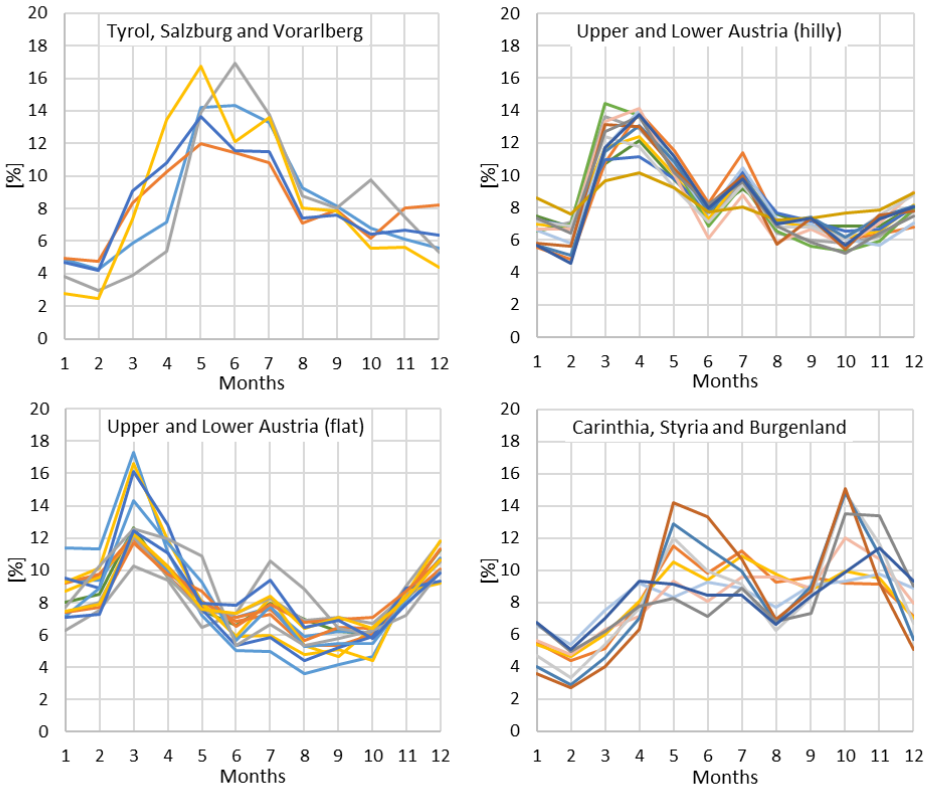

Fig. 4. *Normalized mean monthly runoff for the catchments where we have detected an improvement in the runoff simulation with the multi-objective approach (Q+SR) for 1991–2000.*

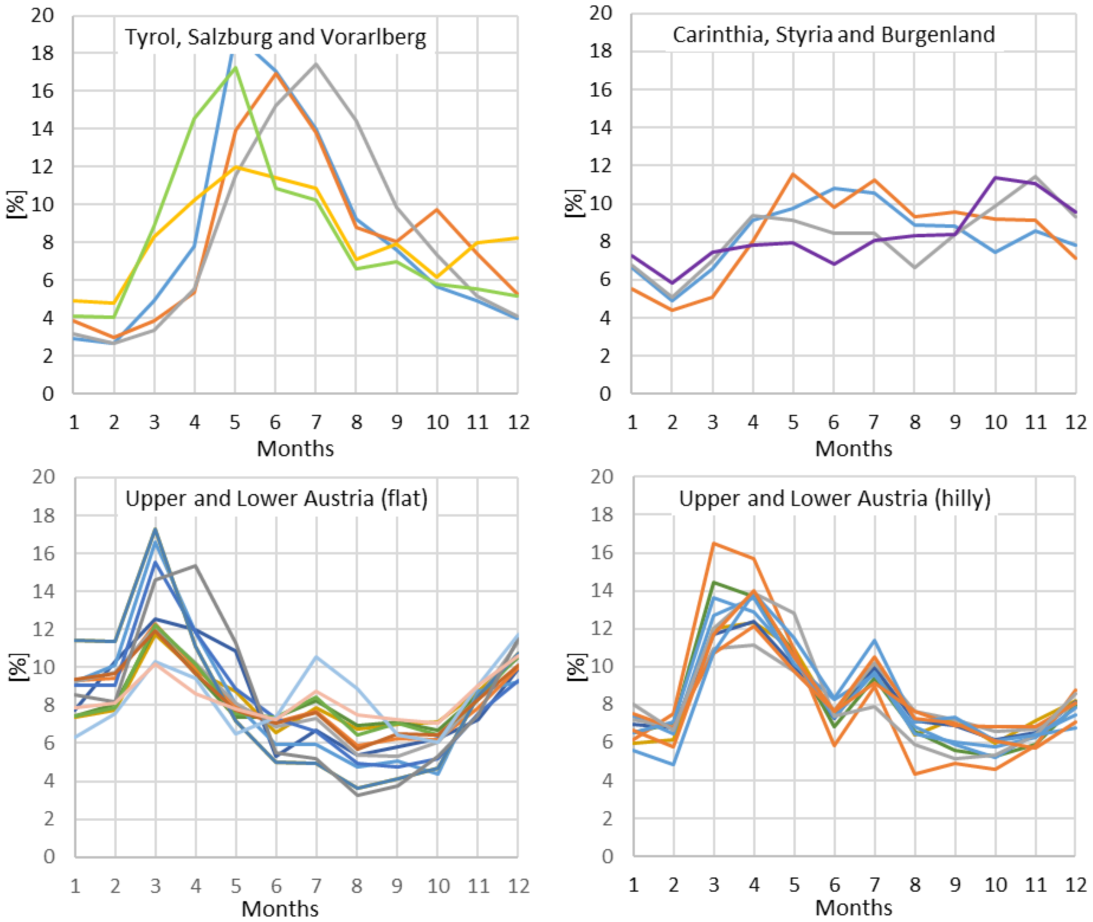

Fig. 5. Normalized mean monthly runoff for the catchments where we have detected an improvement in the runoff simulation with the multi-objective approach (Q+SS+SR) for 1991–2000.

the catchments into four clusters. We can see that the catchments form very comparable clusters, which are located in the following federal republics (regions) of Austria: Tirol and Salzburg (marked by purple colour points), Upper and Lower Austria (green and blue colour points), and Styria, Carinthia, and Burgenland (orange colour points).

Figs. 3–5 presents the typical mean monthly runoff regimes for the catchments analysed. We can see that the catchments located in the regions of Tyrol and Salzburg are characterised by the highest amount of runoff from May to July and by the driest periods in the winter months. This regime is typical of the high mountainous regions in the Alps. The catchments in the Upper and Lower Austria regions were divided by clustering into two groups, which represent hilly and flat catchments. The differences in these catchments can also be seen in the specific runoff and geomorphological characteristics. The runoff regime from snowmelt in the spring season is earlier in the flat catchments than the hilly ones. The catchments located in the regions of Carinthia and Styria are specific, with a higher monthly runoff regime in the spring and autumn that has an interconnection with the precipitation regime influenced by the cyclonic tracks from the Mediterranean Sea.

The comparison of the improvement in the runoff simulation using the multi-objective against the single-calibration approach was evaluated for the individual months using box plots, see Figs. 6–8. The box plots show the percentage of the improvement or deterioration in relative volume errors for the three multi-objective approaches (Q+SS, Q+SR, and Q+SS+SR) against the single-calibration approach for a specific month in the period 1991–2000 (Equations 7, 8).

The evaluation showed that the improvements occurred in different months for each group of catchments, where we detected an improvement in the runoff simulation with the multi-objective approach. For the Tyrol and Salzburg regions, there was a significant improvement in the runoff simulation between September and December and only a slight improvement from January to April. In the Upper and Lower Austria regions for the hilly river basins, there was only a slight improvement in the spring months of March-May for the multi-objective (Q+SS+SR) simulation and June. For the flat river basins in Upper and Lower Austria, there was a significant improvement in the runoff simulation from October to March, a slight decrease in May, and a subsequent improvement in June. In the states of Carinthia and Styria, there was an improvement in the runoff

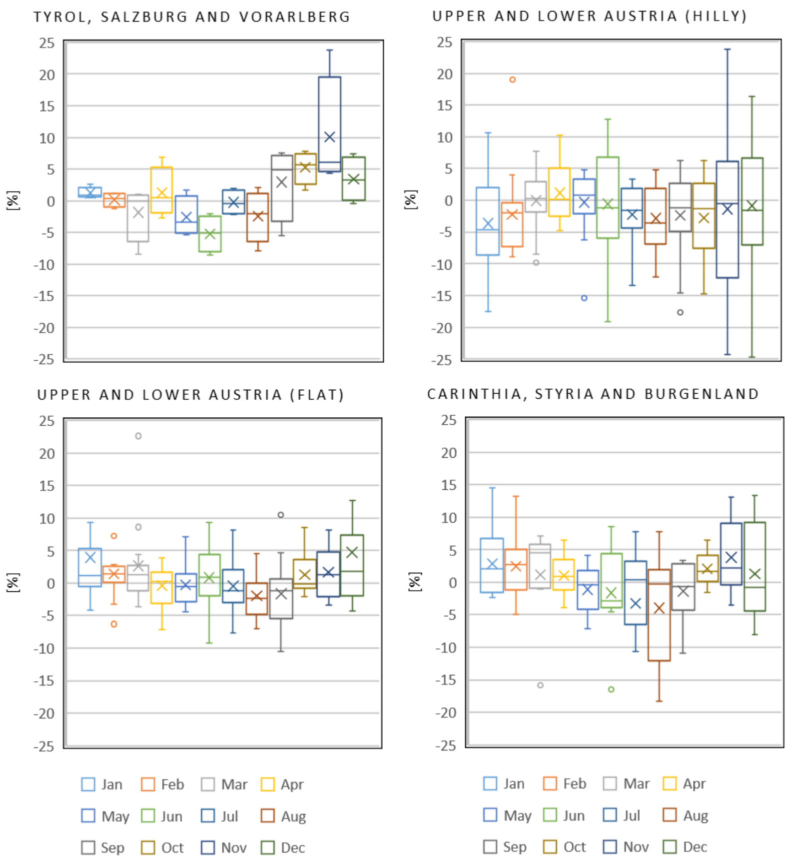

Fig. 6. Improvement in relative volume errors in [%] for multi-objective (Q+SS) calibration vs single-objective calibration in individual months for 1991–2000.

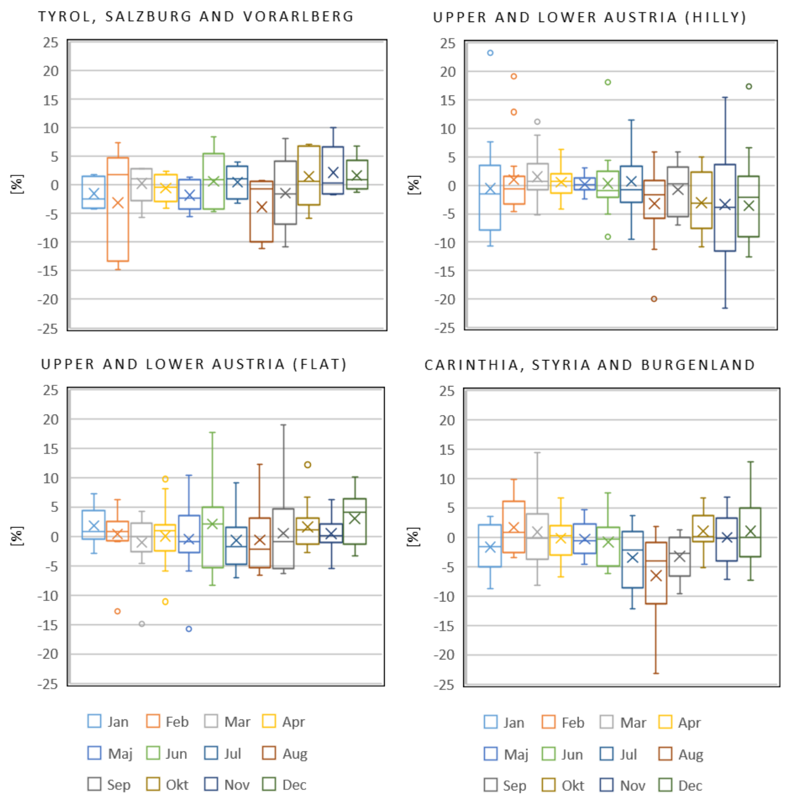

Fig. 7. Improvement in relative volume error in [%] for multi-objective (Q+SR) calibration vs single-objective calibration in individual months for 1991–2000.

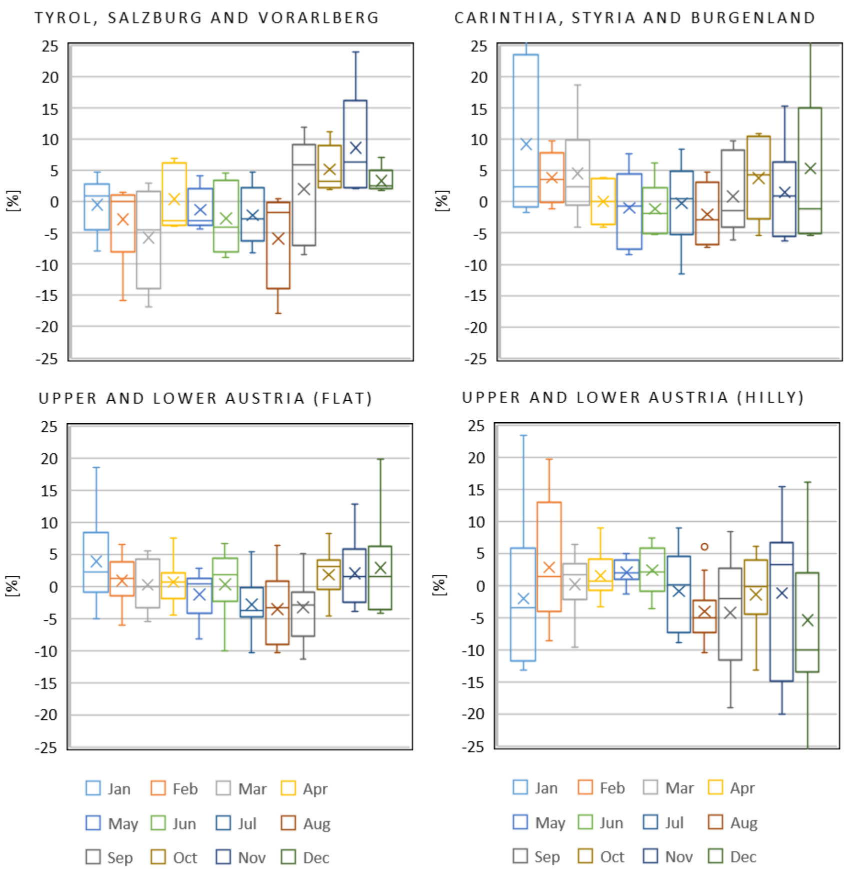

Fig. 8. Improvement in relative volume errors in [%]) for multi-objective (Q+SS+SR) calibration vs single-objective calibration in individual months for 1991–2000.

simulation using the multi-objective (Q+SS) approach from January to April and then in October to November, and for the multi-objective (Q+SR) approach from February to April. For the multi-objective (Q+SS+SR) approach, this improvement occurred in February-June and November.

Conclusion

In this study, we have examined the improvement of the simulated monthly runoff regime in catchments in which the inclusion of a new satellite soil moisture dataset (ASCAT SW1) into the calibration of the TUW rainfall-runoff model outperformed in the model verification, the conventional runoff-only calibration in 198 Austrian basins. Using k-means clustering, catchments with similar mean monthly runoff regimes were grouped for regions: Carinthia, Styria, and Upper and Lower Austria. Three variants of the multi-objective approach were tested for each month of the year. From the results, we can conclude that any improvement in the simulated runoff using ASCAT SWI data is mainly noticeable in the winter and spring months and vice versa; decreases in the simulation efficiency occurred in the driest summer and autumn months. This may be related to the ASCAT SWI product providing moderately distorted data for very dry soil (EODC, 2021). It has also been confirmed, e.g., in the Upper and Lower Austria regions, that better improvement in the simulations can be expected in the flat river basins compared to the hilly types, as well as in river basins with a lower average slope.

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