https://doi.org/10.5194/hess-2022-244
Preprint. Discussion started: 18 July 2022

Hydrology and Earth System Sciences
Discussions

Disentangling natural streamflow from reservoir regulation practices in the Alps using generalized additive models

Manuela Irene Brunner[1] and Philippe Naveau[2]

[1]Institute of Earth and Environmental Sciences, University of Freiburg, Freiburg, Germany
[2]Laboratoire des Sciences du Climat et l'Environnement (LSCE, EstimR) CNRS, Gif-sur-Yvette, France

Correspondence: Manuela I. Brunner (manuela.brunner@hydrology.uni-freiburg.de)

Abstract. Reservoir regulation affects various streamflow characteristics from low to high flows with important implications for downstream water users. Still, information on past reservoir operations is rarely publicly available and it is hardly known how reservoir operation signals, i.e. information on when water is stored in and released from reservoirs, vary over a certain region. Here, we develop a statistical model to reconstruct reservoir operation signals from observed streamflow time series that encompass a period before and a period after a known year of reservoir construction. In a first step, a generalized additive model (GAM) regresses streamflow time series from the unregulated pre-reservoir period on four covariates including temperature, precipitation, day of the year, and glacier mass balance changes. In a second step, this GAM, which represents natural conditions, is applied to predict natural streamflow, i.e. streamflow that would be expected in the absence of the reservoir, for the regulated period. The difference between the observed regulated streamflow signal and the predicted natural baseline should correspond to the reservoir operation signal. We apply this approach to reconstruct the seasonality of reservoir regulation, i.e. information on when water is stored in and released from a reservoir, from a dataset of 74 catchments in the Central Alps with a known reservoir construction date. We group these reconstructed regulation seasonalities using functional clustering to identify groups of catchments with similar reservoir operation strategies. We find that reservoir management varies by catchment elevation, with seasonal redistribution from summer to winter being strongest in high-elevation catchments. These elevational differences suggests a clear relationship between reservoir operation and climate and catchment characteristics, which has practical implications. First, these elevational differences in reservoir regulation can and should be considered in hydrological model calibration. Furthermore, the reconstructed reservoir operation signals can be used to study the joint impact of climate change and reservoir operation on different streamflow signatures, including extreme events.

1 Introduction

Reservoir regulation affects various streamflow characteristics – including variability (Eisele et al., 2004; Ferrazzi et al., 2019), seasonality (Biemans et al., 2011; Adam et al., 2007; Rottler et al., 2019), and extreme events (Verbunt et al., 2005; He et al., 2017; Wang et al., 2017; Wan et al., 2017; Vicente-Serrano et al., 2017; Mahe et al., 2013; Tijdeman et al., 2018; van Oel et al., 2018; Volpi et al., 2018; Brunner, 2021) – in almost 50% of the world's large rivers (>1000 m^3 s^{-1}) and in 8% of the rivers overall (Lehner et al., 2011). Regulation patterns may vary across regions and hydro-climates as reservoirs are operated

https://doi.org/10.5194/hess-2022-244
Preprint. Discussion started: 18 July 2022

for different purposes including irrigation, energy production, water supply, and recreation, in some cases in a multi-purpose way (Lehner et al., 2011; Brunner et al., 2019a). However, information on these reservoir operation signals, i.e. on when water is stored in and when it is released from reservoirs, is hardly publicly available, despite its importance for model calibration and impact assessments (Yassin et al., 2019; Speckhann et al., 2021; Brunner et al., 2021; Steyaert et al., 2022). In some cases, reservoir operation records are made available by the operating agencies (e.g. Steyaert et al. (2022)), however, this is the exception rather than the rule. As a consequence, it is often unclear how reservoir regulations vary across a region and whether and how the regulation patterns are related to catchment characteristics – knowledge that might be useful to transfer reservoir regulation information to basins without such information. Because of the lack of reservoir regulation information, hydrological and land-surface models often use generic reservoir operation schemes that don't necessarily reflect local behavior, which is particularly problematic when simulating streamflow at sub-monthly resolution or when modelling extreme events (Hanasaki et al., 2006; Yassin et al., 2019; Turner et al., 2021).

Various attempts have been made to infer reservoir operation signals from different types of data sources including optical and altimetry remote sensing (Peng et al., 2006; Eldardiry and Hossain, 2019; Hou et al., 2021; Du et al., 2022), reservoir purpose, simulated inflows and water withdrawals (Hanasaki et al., 2006; Voisin et al., 2013) or in- and outflows (Turner et al., 2021). To identify the time scales most affected by reservoir operation, White et al. (2005) and Shiau and Huang (2014) used the wavelet transform on both observed in- and outflow time series and compared their wavelet power spectra. To estimate reservoir release policies, Coerver et al. (2018) used fuzzy rules to link inflow and storage with reservoir release for a set of reservoirs in Asia and North America and Turner et al. (2021) developed harmonic regression models using observed and simulated daily reservoir in- and outflows for large reservoirs in the continental United States (Steyaert et al., 2022). To map input–output relationships for dams around the world, Ehsani et al. (2016) used artificial neural networks and data on inflow, release and storage. While these approaches are very helpful for reservoir signal reconstruction in case both in- and outflow data are available, inferring the reservoir operation signal based on outflow information only remains challenging.

Here, we shed light on spatial variations in reservoir regulation signals and their relationship to catchment characteristics, by developing a statistical two-step approach for reservoir signal reconstruction. The approach is based on a generalized additive model (GAM) that enables reconstructing reservoir operation signals from observed streamflow time series measured downstream of a reservoir or a set of reservoirs and encompassing the period before and after a known year of reservoir construction.

Generalized additive models (GAMs) extend the linear regression setup. The classical additive linear link, $\sum \beta_j X_j$, between the observational vector Y and the explanatory variables $(X_1, \dots, X_p)^T$ is replaced by a sum of smooth functions $\sum f_j(X_j)$ (see, e.g. Hastie and Tibshirani, 1986). Hence, GAMs represent nonlinear relationships between covariates and the target variable. Each smooth function $f_j(.)$ corresponds to a linear projection on a given basis, here a cubic smoothing spline representation (see, e.g. Hastie and Tibshirani, 1986; Wood, 2017). Typically, a GAM is written as

$$y_t = \sum_{j=1}^{p} f_j(x_{tj}) + \sigma\, \epsilon_t, \qquad (1)$$

https://doi.org/10.5194/hess-2022-244
Preprint. Discussion started: 18 July 2022

where $\sigma > 0$ and ϵ_t represents a standardized random noise. In this study, the response variable y_t corresponds to streamflow time series in mm/d (units). The index t represents the time evolution in days and spans the time period before reservoir construction, which varies by catchment. For example, the construction of the Mauvoisin reservoir in 1957 can be clearly identified in the streamflow time series of the catchment Drance de Bagnes (gauge Le Châble, Figure 2). In this study, the set of explanatory variables, $(X_1, \ldots, X_p)^T$, contains three climatological parameters: temperatures, precipitation, seasonality (day of year), and modelled glacier mass balance changes. During the unregulated pre-reservoir period, the GAM learns the non-linear relationship between streamflow time series and corresponding climatological parameters. Then, the estimated transfer function f_j calibrated on unregulated periods will be applied via (1) to regulated periods. The difference between the observed regulated streamflow signal and the predicted natural baseline according to our definition corresponds to the reservoir operation signal.

We extract this reservoir signal from observed time series of 74 catchments in the Central Alps for which streamflow data are available before and after a known date of reservoir construction (Section 2.2). From this database of 74 extracted signals, we identify groups of catchments with similar reservoir operation strategies using functional data clustering (Section 2.3) (Chebana et al., 2012; Ternynck et al., 2016). The functional form is derived from discrete observations (Ramsay and Silverman, 2002) either by smoothing the data non-parametrically (Jacques and Preda, 2014) or by projecting the data onto a set of basis functions. The basis function (e.g. B-spline, Fourier, or wavelet bases) coefficients can be used for clustering (Cuevas, 2014). It has been shown in previous studies that functional data representations can be beneficial to identify groups of similar hydrographs over a range of temporal scales, such as spring flood events (duration of six months; Ternynck et al., 2016), flood events (duration of several days; Brunner et al., 2018), low flow events (Laaha et al., 2017), diurnal discharges (duration of one day; Hannah et al., 2000), yearly hydrographs (Merleau et al., 2007; Jamaludin, 2016), and streamflow regimes (Brunner et al., 2020). Here, we use functional data clustering to identify groups of catchments with similar reservoir operation seasonalities. We then assess whether and how catchments with different reservoir operation strategies differ in their location and catchment characteristics.

2 Methods

2.1 Dataset

The Central Alps are an interesting region to study different reservoir regulation patterns because this region is characterized by diverse hydro-climatic regimes (Bard et al., 2015), which are often heavily influenced by reservoirs (Lehner et al., 2005; Brunner et al., 2019a). Therefore, we identify a large sample of 74 regulated catchments in the headwater regions of the four major European rivers originating in the Central Alps, namely, the Rhine, Rhône, Danube, and Po for which the date of reservoir construction is known and for which observed daily streamflow data are available for both a period before and a period after reservoir construction (Figure 1). The observed streamflow time series were obtained from national agencies in Switzerland (Federal Office for the Environment, FOEN), Austria (Austrian Ministry of Sustainability and Tourism), and eastern France (Banque HYDRO) and regional agencies in southern Germany (regions Bavaria [Bayerisches Landesamt für

https://doi.org/10.5194/hess-2022-244
Preprint. Discussion started: 18 July 2022

Hydrology and Earth System Sciences
Discussions

Umwelt] and Baden-Württemberg [Landesanstalt für Umwelt Baden-Württemberg]). The streamflow records of the different catchments do not necessarily cover the same time period, however, each catchment has streamflow data for at least 10 years before and after reservoir construction (see Figure 2 for an example time series in the Swiss Alps). Northern Italy was excluded from the analysis because streamflow records provided by the regional agencies did not cover the pre-reservoir construction period.

In addition to streamflow, we derive daily meteorological time series (precipitation and temperatures) for each catchment from the gridded E-OBS dataset at 25 km spatial resolution for the period 1950–2020 (Cornes et al., 2018) by averaging over all grid cells within a catchment. Temperature and precipitation time series are smoothed over a moving time window of 5 days to remove noise and NA values are replaced by the mean flow across the whole time period. Furthermore, data on reservoir locations and construction dates are also obtained from national agencies (Switzerland: FOEN, Austria: Austrian Ministry of Sustainability and Tourism, France: Comité Francais des Barrages et Reservoirs (https://www.barrages-cfbr.eu/)) and open source databases (Germany: Speckhann et al. (2021)). To account for changes in glaciermelt contributions over time, we compute annual glacier mass balance changes for each of the selected catchments using simulated mass balance changes over the period 1951–2020 for the glaciers in the Randolph Glacier Inventory (RGI Consortium, 2017; Compagno et al., 2021). After estimating the average mass balance change for each glacier in a catchment by weighting changes across different elevation bands, each annual mass balance time series is dis-aggregated at a daily resolution. This smoothing avoids a step-like mass balance change time series.

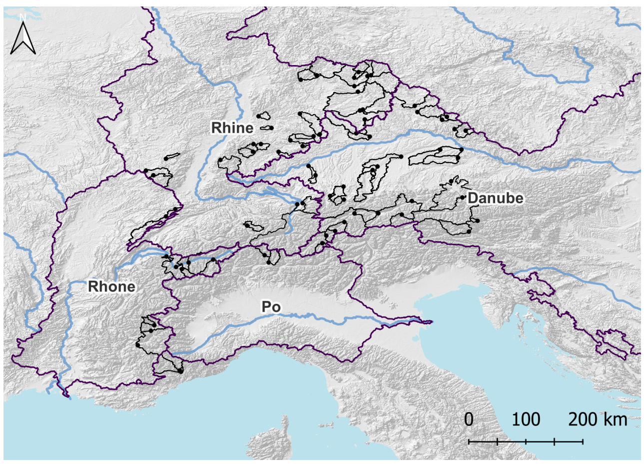

Figure 1. 74 catchments in the Central Alps with at least 10 years of streamflow data before and after reservoir construction (black catchment outlines).

https://doi.org/10.5194/hess-2022-244
Preprint. Discussion started: 18 July 2022

Hydrology and Earth System Sciences
Open Access
EGU
Discussions

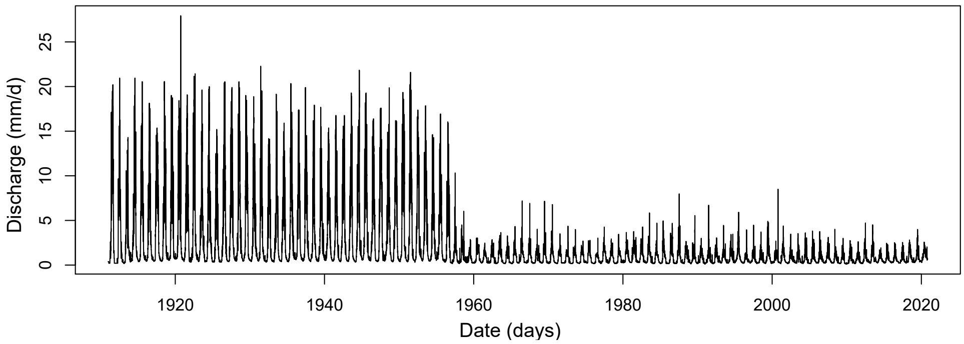

Figure 2. Streamflow time series for the catchment of the Drance de Bagnes (gauge Le Châble) illustrating streamflow changes induced by the construction of the Mauvoisin reservoir in 1957.

2.2 Reservoir signal reconstruction using GAMs

Here, we propose a modelling approach to reconstruct the reservoir operation signal from observed streamflow time series measured downstream of a reservoir before and after reservoir construction, representing natural and regulated conditions, respectively. Before the reservoir construction date, a regression scheme can learn the natural link between streamflow times series and some appropriate meteorological explanatory variables. In this work, this natural baseline signal is obtained by applying a generalized additive model (GAM) (Hastie and Tibshirani, 1986) during the pre-reservoir time period. After the reservoir construction, the reservoir operation signal can be defined as the difference between the regulated streamflow time series and the signal that would have been measured without the reservoir. The later signal was never observed but it can be estimated by applying the learning GAM link to post-reservoir meteorological explanatory variables. These covariates include the following three climatological drivers: (1) smoothed daily temperatures, (2) smoothed daily precipitation, and (3) day of the year (seasonality), and interpolated daily glacier mass balance changes (for details on datasets see 2.1). The last variable takes into account non-stationarities induced by changing glacier melt. Discharges during the natural and regulated period can have different magnitudes as a result of water diversions, e.g. in the case of hydropower production. Therefore, we standardize both the natural and regulated streamflow time series by subtracting the mean. Such standardization makes natural and regulated flow magnitudes comparable. As positive and skewed random variables, it is unlikely that streamflow time series follow a Gaussian distribution given the four covariates. To handle this issue, we choose a Gamma family within the GAM approach and study the following additive link

$$f_1(p_t) + f_2(h_t) + f_3(d_t) + f_4(g_t), \tag{2}$$

where p_t corresponds to smoothed precipitation, h_t to smoothed temperature, d_t to the day of the year, and g_t to the interpolated glacier mass balance changes (for the implementation, we used the R-package mgcv (Simon Wood, 2022; Wood, 2017)). We assess the model's performance by comparing observed with predicted streamflow values (Figure 3). The model captures the observed values and their distribution quite well, as illustrated by comparisons of observed vs. predicted values (panel a), observed and predicted quantiles (panel b), and observed and predicted time series (panel c).

https://doi.org/10.5194/hess-2022-244
Preprint. Discussion started: 18 July 2022

Hydrology and Earth System Sciences
Discussions

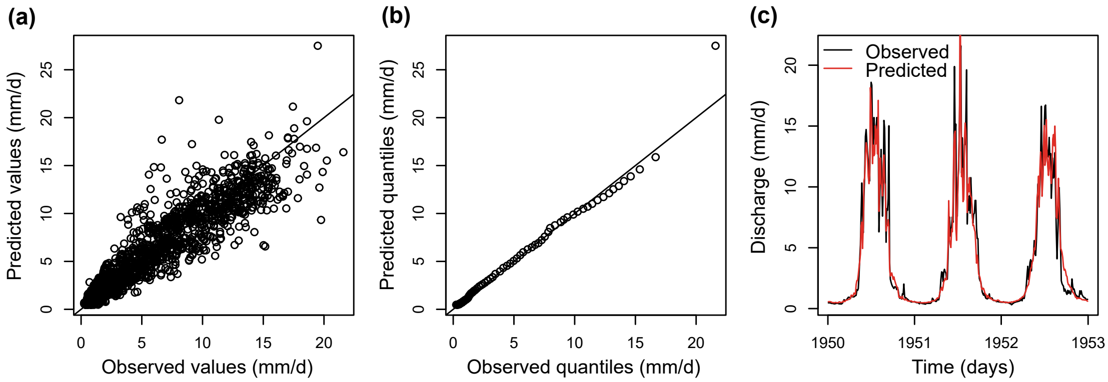

Figure 3. Evaluation of the GAM model fitted using natural streamflow data of the Drance de Bagnes (before reservoir construction [1911–1956]) and used to predict streamflow with precipitation, temperature, day of year, and glacier mass balance changes as predictors. (a) Observed vs. predicted values (1911–1956), (b) Q-Q plot, observed vs. simulated quantiles (1911–1956), and (c) observed vs. predicted time series (3-years 1911–1913).

Next, we apply this model to deduce the never-observed “natural" flow after the reservoir construction. In this case, the GAM inputs are the same four covariables: temperature, precipitation, day of year, and glacier mass balance changes, but taken over the period after the reservoir construction. As an application example, Figure 4 compares the natural streamflow regime (i.e. the mean annual hydrograph) of the Drance de Bagnes derived using the model for the regulated period (red) with the natural observed (grey) and the regulated observed streamflow regimes (black). The observed regulated regime has a seasonality distinct from the simulated natural regime. We assume that the difference between the observed regulated streamflow signal and the predicted natural baseline represents the reservoir operation signal.

https://doi.org/10.5194/hess-2022-244
Preprint. Discussion started: 18 July 2022

Hydrology and Earth System Sciences
Discussions

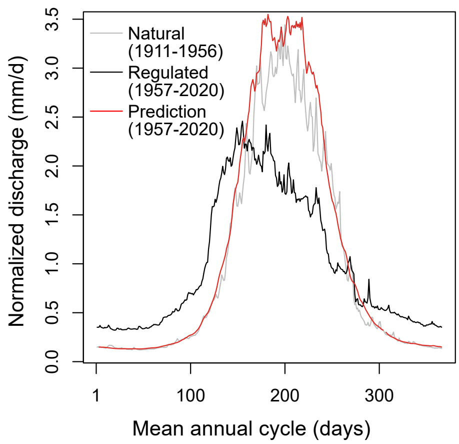

Figure 4. Comparison of the observed natural streamflow regime (i.e. the mean annual hydrograph) of the Drance de Bagnes before reservoir construction (grey, 1911–1956), observed regulated regime after reservoir construction (black, 1957–2020), and simulated natural regime for period after reservoir construction (red, 1957–2020).

Under this assumption, we derive the reservoir operation signal by subtracting the predicted 'natural signal' from the observed regulated signal (Figure 5a). To remove noise and retrieve a clear signal, we smooth the signal using regression splines (Figure 5b). Positive values represent release conditions as the regulated signal is higher than the natural signal, while negative values represent storage conditions as the natural signal would be higher than the observed regulated signal. The reconstructed signal informs about regulation at a daily scale but can also be aggregated to mean daily values to represent regulation seasonality, i.e. the regulation regime. We here derive reservoir regulation seasonality by averaging the reconstructed daily signals for each day of the year (Figure 5c).

https://doi.org/10.5194/hess-2022-244
Preprint. Discussion started: 18 July 2022

Hydrology and Earth System Sciences
Discussions

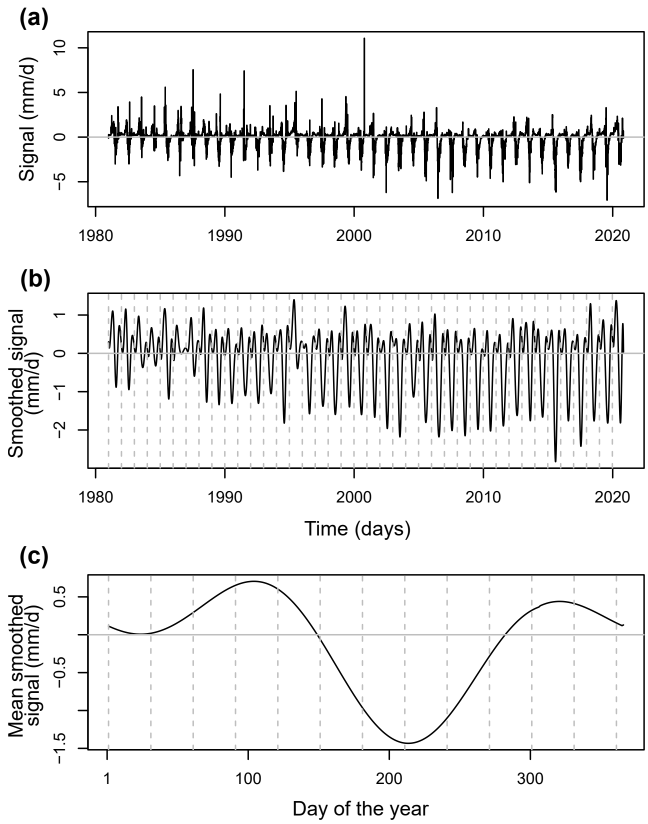

Figure 5. Reservoir signal for the Drance de Bagnes reconstructed for the period 1960–2020 using the GAM predictions by subtracting predicted natural discharge from observed regulated discharge, where positive and negative values indicate release and storage, respectively: (a) Raw daily signal, (b) smoothed signal (spline smoothing), and (c) mean seasonal signal.

2.3 Reservoir signal variation analysis

We apply the GAM modelling approach introduced in the section above to reconstruct the mean reservoir signals (i.e. reservoir seasonality) of 74 catchments in the Central Alps with streamflow data for a period before and after reservoir construction. We then use these reconstructed reservoir seasonalities to identify groups of catchments with similar reservoir operation patterns using functional data clustering (Ramsay and Silverman, 2002). To do so, we follow the approach proposed by Brunner et al. (2020) to cluster streamflow regimes, i.e. mean annual streamflow hydrographs. First, we project the discrete observations, i.e. the reconstructed reservoir operation seasonalities at daily resolution, to a set of B-spline basis functions (R-package fda; Ramsay et al., 2014). Similar to Brunner et al. (2020), we use five spline basis functions of order four, which corresponds to a minimal number of basis functions still allowing for sufficient flexibility in representing diverse shapes of reservoir operation seasonalities. The projection of the observed reservoir operation seasonalities to the five basis functions results in five coefficients per observed operation signal, one per spline base. The analysis is performed in R using the packages *fda.usc* (Febrero-Bande and Oviedo de la Fuente, 2012) and *fda* (Ramsay et al., 2014). Second, we compute a Euclidean distance ma-

https://doi.org/10.5194/hess-2022-244
Preprint. Discussion started: 18 July 2022

trix using the matrix of $n = 74 \times 5$ spline coefficients. Third, we use a hierarchical clustering algorithm (*hclust*) with Ward's minimum variance criterion, which minimizes the total within-cluster variance (Ward, 1963). We cut the tree at $k = 2$ clusters, because this seems to be the most suitable number of clusters given the symmetry of the tree.

3 Results

Reservoir operation in the Central Alps varies by season and across catchments (Figure 6). While some catchments are strongly regulated (i.e. those with strong signal amplitudes), less water is stored and released in other catchments (i.e. those with weak amplitudes). Independent of magnitude, the seasonal release-storage signal appears to be similar in most catchments. Water is mostly stored in summer (negative values), when snowmelt, precipitation, and runoff are abundant (Frei and Schär, 1998; Brunner et al., 2019b; Vorkauf et al., 2021), and released in winter (positive values) when electricity demand is high because of cold temperatures and elevated heating needs (Thornton et al., 2016; Wenz et al., 2017).

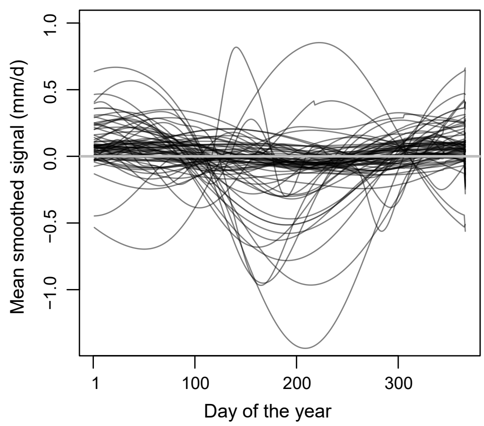

Figure 6. Reservoir regulation seasonality reconstructed using the GAM modelling approach for the 74 catchments in the Central Alps, where positive and negative values indicate release and storage, respectively.

This regulation seasonality is particularly pronounced in the catchments in the Central Alps, which are identified as a first cluster of catchments sharing similar reservoir operation patterns (Figures 7a and 8). In this region, reservoirs are mostly operated for hydropower production (Panduri and Hertach, 2013; Brunner et al., 2019a). In contrast, reservoir operation seasonality is weaker in the catchments in the pre-Alps and lowland areas (Figures 7b and 8), the second cluster of catchments with similar reservoir operation signals. In this region, reservoirs are operated for a wider variety of purposes including flood protection, recreation, energy production, water and industrial supply (Speckhann et al., 2021).

https://doi.org/10.5194/hess-2022-244
Preprint. Discussion started: 18 July 2022

Hydrology and Earth System Sciences
Discussions

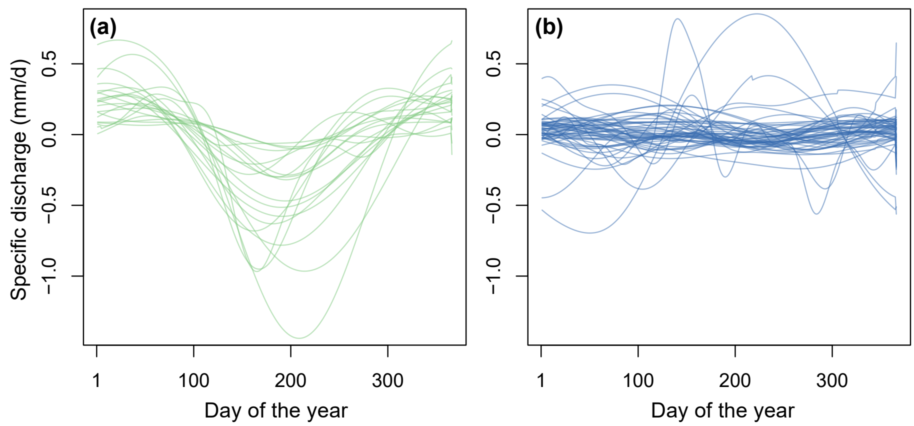

Figure 7. Reservoir regulation seasonality patterns clustered into two groups: (a) release in winter and storage in summer and (b) weak seasonal storage pattern.

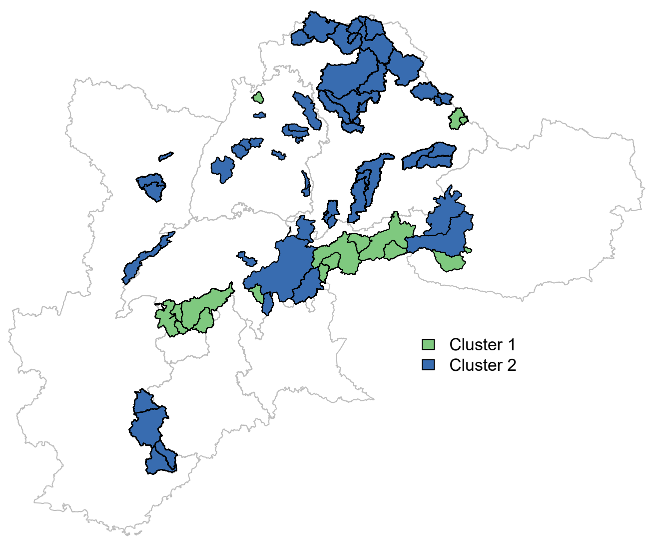

Figure 8. Catchments belonging to cluster 1 (green) and 2 (blue) with similar seasonal regulation patterns.

The catchments belonging to the two clusters clearly differ by elevation and to a weaker degree in catchment area (Figure 9). That is, high-elevation catchments show much stronger regulation signals than low-elevation catchments.

https://doi.org/10.5194/hess-2022-244
Preprint. Discussion started: 18 July 2022

Hydrology and Earth System Sciences
Discussions

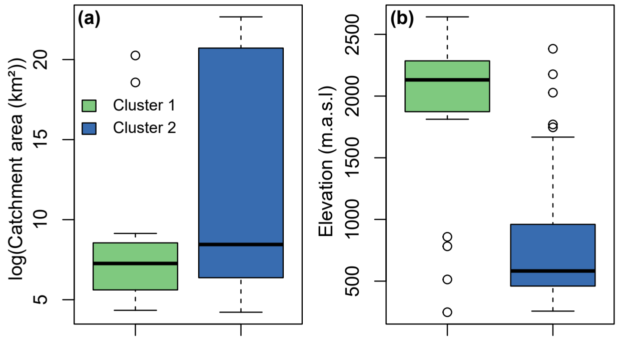

Figure 9. Characteristics of catchments belonging to the two reservoir regulation clusters: (a) logarithm of catchment area, (b) elevation.

175 These high-elevation catchments with strong regulations tend to be the catchments with glacier- and/or snowmelt-influenced streamflow regimes (i.e. mean annual hydrographs) (Figure 10a), while the low-elevation catchments are more rainfall-dominated with some still being substantially snowmelt influenced (Figure 10b).

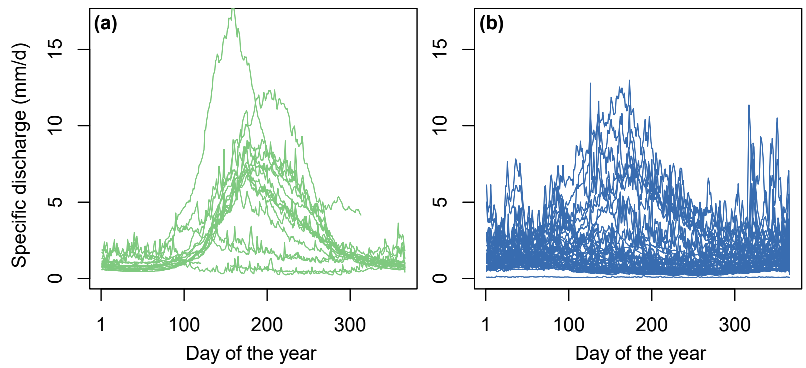

Figure 10. Natural streamflow regimes (computed using the undisturbed streamflow time series before reservoir construction) belonging to the two reservoir regulation clusters.

4 Discussion and Conclusions

We proposed a generalized additive modelling approach to reconstruct the seasonality and magnitude of reservoir operation
180 using observed streamflow time series, including a period before and after reservoir construction. This statistical approach has the advantage of being observation-based and computationally inexpensive. It does not require setting up a hydrological model to simulate natural streamflow. However, the approach also has some limitations. First, it is only applicable in catchments where streamflow observations are available for a natural period before and a regulated period after reservoir construction. This means that the approach is not applicable in ungauged catchments and in catchments where streamflow is only available for
185 a post-reservoir construction period. Turner et al. (2021) proposed a regionalization approach for reservoir operation signals.

Our signals may also be regionalized by establishing a relationship between group membership and catchment characteristics, e.g. elevation, which seems to be strongly related to the type of reservoir regulation signal observed (Figure 7). Second, while the predictive performance of the GAM is satisfactory, there is room for improvement with respect to the simulation of extreme events, which are as in other approaches not perfectly represented. The residuals not only represent the reservoir operation signal, but also include residual model error. Nonetheless, by smoothing the residuals, we are able to reconstruct a regular pattern representing reservoir regulation. As an alternative to GAMs, we tested the use of Generalized Additive Models for Location, Scale and Shape (GAMlss) said to be more appropriate for modelling time series following extreme value distributions. However, such model adaptation did not improve model performance and new statistical modelling frameworks are needed to better represent extreme events. Third, separating flow changes induced by reservoir operation and other types of changes induced by climate change, such as glaciermelt contributions, is challenging. While the GAM representing natural conditions can theoretically consider changes in glaciermelt contributions by including glacier mass balance changes, these effects are in practice not perfectly represented because glacier mass balance changes are observed and simulated at a coarse resolution (annual). This means that the signal reconstructed by comparing the simulated natural signal with the observed regulated signal may not solely represent reservoir operation, but to some degree also changes in glaciermelt contributions not accounted for by the model. A better separation of the confounding changes – glaciermelt and reservoir operation – may be achieved if more detailed information about glacier mass balance were available or in cases where the seasonality of reservoir regulation is clearly different from the seasonality of glaciermelt.

The approach proposed here can be used to reconstruct reservoir operation signals in other parts of the world. Depending on the hydro-climate, the type of predictors used in the GAM might need to be adjusted. For example, the glaciermelt part can be removed in non-alpine regions where streamflow is uninfluenced by glaciermelt. The GAM modelling approach introduced here can also be used to assess changes in reservoir operation over time. Such adaptation in reservoir operation might be necessary to account for changing environmental conditions (Feng et al., 2017).

By applying our GAM model to 74 regulated catchments in the Central Alps, we identify two main groups of regulated catchments (Figure 8): those in the Central Alps with storage in summer and release in winter and those in the pre-Alps and lowland regions with a less pronounced operation seasonality and generally weaker storage and release cycles (Figure 7). The catchments with pronounced regulation cycles in group 1 are mainly operated for hydropower production (Brunner et al., 2019a), while those with less pronounced regulation seasonality in group 2 are operated for a variety of purposes (Speckhann et al., 2021). This finding that lowland catchments have weak reservoir regulation seasonality is in line with findings by Eisele et al. (2004) who have shown that reservoir regulations in Baden-Württemberg have a very small impact on the timing of hydrological extremes. Applied at a larger or even global scale, the GAM approach could help us to even better understand spatial variations in reservoir operation. The reservoir signals reconstructed using the GAM modelling approach may be used to inform hydrological model development and calibration. Furthermore, the reconstructed signals could inform the representation of reservoir operation in hydrological models. Improving such representation is crucial to advance the field of change attribution as it will allow for a better separation of climate and regulation signals, which both influence streamflow characteristics.

https://doi.org/10.5194/hess-2022-244
Preprint. Discussion started: 18 July 2022

Hydrology and Earth System Sciences
Discussions

Data availability. data used for our analysis will be published on HydroShare upon acceptance of this manuscript.

Author contributions. MIB developed the concept and jointly with PN the methodology of this study. MIB performed all analyses, produced the figures, and wrote the first draft of the manuscript, which was revised and edited by PN.

Competing interests. The authors declare no competing interests. MIB is an editor with HESS.

Acknowledgements. We thank the German Research Foundation (grant 2100371301), the French national programs (FRAISE- LEFE/INSU and 80 PRIME CNRS-INSU), and the European H2020 XAIDA (Grant agreement ID: 101003469) for supporting this research. We acknowledge the E-OBS dataset from the EU-FP6 project UERRA (https://www.uerra.eu) and the Copernicus Climate Change Service, and the data providers in the ECA&D project (https://www.ecad.eu). Philippe Naveau also acknowledges the support of the French Agence Nationale de la Recherche (ANR) under reference ANR-20-CE40-0025-01 (T-REX project), and the ANR-Melody (ANR-19-CE46-0011). We thank Loris Compagno for providing the simulated glacier mass balance time series.

https://doi.org/10.5194/hess-2022-244
Preprint. Discussion started: 18 July 2022

References

Adam, J. C., Haddeland, I., Su, F., and Lettenmaier, D. P.: Simulation of reservoir influences on annual and seasonal streamflow changes for the Lena, Yenisei, and Ob' rivers, Journal of Geophysical Research Atmospheres, 112, 1–22, https://doi.org/10.1029/2007JD008525, 2007.

Bard, A., Renard, B., Lang, M., Giuntoli, I., Korck, J., Koboltschnig, G., Janža, M., D'Amico, M., and Volken, D.: Trends in the hydrologic regime of Alpine rivers, Journal of Hydrology, 529, 1823–1837, https://doi.org/10.1016/j.jhydrol.2015.07.052, 2015.

Biemans, H., Haddeland, I., Kabat, P., Ludwig, F., Hutjes, R. W. A., Heinke, J., Von Bloh, W., and Gerten, D.: Impact of reservoirs on river discharge and irrigation water supply during the 20th century, Water Resources Research, 47, 1–15, https://doi.org/10.1029/2009WR008929, 2011.

Brunner, M. I.: Reservoir regulation affects droughts and floods at local and regional scales, Environmental Research Letters, 16, 124 016, https://doi.org/10.1088/1748-9326/ac36f6, 2021.

Brunner, M. I., Viviroli, D., Furrer, R., Seibert, J., and Favre, A.-C.: Identification of flood reactivity regions via the functional clustering of hydrographs, Water Resources Research, 54, 2017WR021 650, https://doi.org/10.1002/2017WR021650, 2018.

Brunner, M. I., Björnsen Gurung, A., Zappa, M., Zekollari, H., Farinotti, D., and Stähli, M.: Present and future water scarcity in Switzerland: Potential for alleviation through reservoirs and lakes, Science of the Total Environment, 666, 1033–1047, https://doi.org/10.1016/j.scitotenv.2019.02.169, 2019a.

Brunner, M. I., Farinotti, D., Zekollari, H., Huss, M., and Zappa, M.: Future shifts in extreme flow regimes in Alpine regions, Hydrological Earth System Sciences, 23, 4471–4489, https://doi.org/10.5194/hess-23-4471-2019, 2019b.

Brunner, M. I., Newman, A., Melsen, L. A., and Wood, A.: Future streamflow regime changes in the United States: assessment using functional classification, Hydrology and Earth System Sciences, 24, 3951–3966, https://doi.org/10.5194/hess-24-3951-2020, 2020.

Brunner, M. I., Slater, L., Tallaksen, L. M., and Clark, M.: Challenges in modeling and predicting floods and droughts: A review, WIREs Water, 8, e1520–, https://doi.org/10.1002/wat2.1520, 2021.

Chebana, F., Dabo-Niang, S., and Ouarda, T. B. M. J.: Exploratory functional flood frequency analysis and outlier detection, Water Resources Research, 48, W04 514, https://doi.org/10.1029/2011WR011040, 2012.

Coerver, H. M., Rutten, M. M., and Van De Giesen, N. C.: Deduction of reservoir operating rules for application in global hydrological models, Hydrology and Earth System Sciences, 22, 831–851, https://doi.org/10.5194/hess-22-831-2018, 2018.

Compagno, L., Eggs, S., Huss, M., Zekollari, H., and Farinotti, D.: Brief communication: Do 1.0, 1.5, or 2.0° C matter for the future evolution of Alpine glaciers?, Cryosphere, 15, 2593–2599, https://doi.org/10.5194/tc-15-2593-2021, 2021.

Cornes, R. C., van der Schrier, G., van den Besselaar, E. J. M., and Jones, P. D.: An ensemble version of the E-OBS temperature and precipitation data sets, Journal of Geophysical Research: Atmospheres, 123, 9391–9409, https://doi.org/10.1029/2017JD028200, 2018.

Cuevas, A.: A partial overview of the theory of statistics with functional data, Journal of Statistical Planning and Inference, 147, 1–23, https://doi.org/10.1016/j.jspi.2013.04.002, 2014.

Du, T. L. T., Lee, H., Bui, D. D., Graham, L. P., Darby, S. D., Pechlivanidis, I. G., Leyland, J., Biswas, N. K., Choi, G., Batelaan, O., Bui, T. T. P., Do, S. K., Tran, T. V., Nguyen, H. T., and Hwang, E.: Streamflow prediction in highly regulated, transboundary watersheds using multi-basin modeling and remote sensing imagery, Water Resources Research, 58, https://doi.org/10.1029/2021wr031191, 2022.

Ehsani, N., Fekete, B. M., Vörösmarty, C. J., and Tessler, Z. D.: A neural network based general reservoir operation scheme, Stochastic Environmental Research and Risk Assessment, 30, 1151–1166, https://doi.org/10.1007/s00477-015-1147-9, 2016.

https://doi.org/10.5194/hess-2022-244
Preprint. Discussion started: 18 July 2022

Hydrology and Earth System Sciences
Open Access
Discussions

Eisele, M., Steinbrich, A., and Leibundgut, C.: Assessment of the human impact on the temporal variability of stream flow in meso-scale river basins, in: Hydrology: Science & Practice for the 21st Century, pp. 375–382, 2004.

Eldardiry, H. and Hossain, F.: Understanding reservoir operating rules in the transboundary nile river basin using macroscale hydrologic modeling with satellite measurements, Journal of Hydrometeorology, 20, 2253–2269, https://doi.org/10.1175/JHM-D-19-0058.1, 2019.

Febrero-Bande, M. and Oviedo de la Fuente, M.: Statistical computing in functional data analysis: The R package fda.usc, Journal of Statistical Software, 51, 1–3, https://doi.org/10.18637/jss.v051.i04, 2012.

Feng, M., Liu, P., Guo, S., Shi, L., Deng, C., and Ming, B.: Deriving adaptive operating rules of hydropower reservoirs using time-varying parameters generated by the EnKF, Water Resources Research, 53, 6885–6907, https://doi.org/10.1002/2016WR020180, 2017.

Ferrazzi, M., Vivian, R., and Botter, G.: Sensitivity of regulated streamflow regimes to interannual climate variability, Earth's Future, 7, 1206–1219, https://doi.org/10.1029/2019EF001250, 2019.

Frei, C. and Schär, C.: A precipitation climatology of the Alps from high-resolution rain-gauge observations, International Journal of Climatology, 18, 873–900, https://doi.org/10.1002/(SICI)1097-0088(19980630)18:8<873::AID-JOC255>3.0.CO;2-9, 1998.

Hanasaki, N., Kanae, S., and Oki, T.: A reservoir operation scheme for global river routing models, Journal of Hydrology, 327, 22–41, https://doi.org/10.1016/j.jhydrol.2005.11.011, 2006.

Hannah, D. M., Smith, B. P. G., Grunell, A. M., and McGregor, G. R.: An approach to hydrograph classification, Hydrological Processes, 14, 317–338, 2000.

Hastie, T. and Tibshirani, R.: Generalized additive models, Statistical Science, 1, 297–318, 1986.

He, X., Wada, Y., Wanders, N., and Sheffield, J.: Intensification of hydrological drought in California by human water management, Geophysical Research Letters, 44, 1777–1785, https://doi.org/10.1002/2016GL071665, 2017.

Hou, J., van Dijk, A., Beck, H., Renzullo, L., and Wada, Y.: Remotely sensed reservoir water storage dynamics (1984–2015) and the influence of climate variability and management at global scale, Hydrology and Earth System Sciences, p. in press, https://doi.org/10.5194/hess-2021-350, 2021.

Jacques, J. and Preda, C.: Model-based clustering for multivariate functional data, Computational Statistics & Data Analysis, 71, 92–106, https://doi.org/10.1016/j.csda.2012.12.004, 2014.

Jamaludin, S.: Streamflow profile classification using functional data analysis : A case study on the Kelantan river basin, in: The 3rd ISM international statistical conference, vol. 1842, pp. 1–11, https://doi.org/10.1063/1.4982836, 2016.

Laaha, G., Gauster, T., Tallaksen, L. M., Vidal, J.-P., Stahl, K., Prudhomme, C., Heudorfer, B., Vlnas, R., Ionita, M., Lanen, H. A. J., Adler, M.-J., Caillouet, L., Delus, C., Fendekova, M., Gailliez, S., Hannaford, J., Kingston, D., Loon, A. F. V., Mediero, L., Osuch, M., Romanowicz, R., Sauquet, E., Stagge, J. H., and Wong, W. K.: The European 2015 drought from a hydrological perspective, Hydrology and Earth System Sciences, 21, 3001–3024, https://doi.org/10.5194/hess-21-3001-2017, 2017.

Lehner, B., Czisch, G., and Vassolo, S.: The impact of global change on the hydropower potential of Europe: A model-based analysis, Energy Policy, 33, 839–855, https://doi.org/10.1016/j.enpol.2003.10.018, 2005.

Lehner, B., Liermann, C. R., Revenga, C., Vörömsmarty, C., Fekete, B., Crouzet, P., Döll, P., Endejan, M., Frenken, K., Magome, J., Nilsson, C., Robertson, J. C., Rödel, R., Sindorf, N., and Wisser, D.: High-resolution mapping of the world's reservoirs and dams for sustainable river-flow management, Frontiers in Ecology and the Environment, 9, 494–502, https://doi.org/10.1890/100125, 2011.

Mahe, G., Lienou, G., Descroix, L., Bamba, F., Paturel, J. E., Laraque, A., Meddi, M., Habaieb, H., Adeaga, O., Dieulin, C., Chahnez Kotti, F., and Khomsi, K.: The rivers of Africa: Witness of climate change and human impact on the environment, Hydrological Processes, 27, 2105–2114, https://doi.org/10.1002/hyp.9813, 2013.

Merleau, J., Perreault, L., Angers, J.-F., and Favre, A.-C.: Bayesian modeling of hydrographs, Water Resources Research, 43, W10 432, https://doi.org/10.1029/2006WR005376, 2007.

Panduri, R. and Hertach, M.: Dokumentation minimales Geodatenmodell Stauanlagen unter Bundesaufsicht, Tech. rep., Bundesamt für Energie BFE, Ittigen, 2013.

Peng, D., Guo, S., Liu, P., and Liu, T.: Reservoir storage curve estimation based on remote sensing data, Journal of Hydrologic Engineering, 11, 165–172, https://doi.org/10.1061/ASCE1084-0699200611:2165, 2006.

Ramsay, J. O. and Silverman, B. W.: Applied functional data analysis: methods and case studies, Springer, New York, https://doi.org/10.1007/b98886, 2002.

Ramsay, J. O., Wickham, H., Graves, S., and Hooker, G.: Package 'fda': Functional data analysis, https://cran.r-project.org/web/packages/fda/fda.pdf, 2014.

RGI Consortium: Randolph Glacier Inventory 6.0 – A dataset of global glacier outlines, Tech. rep., RGI, Colorado, USA, https://doi.org/10.7265/N5-RGI-60, 2017.

Rottler, E., Francke, T., Bürger, G., and Bronstert, A.: Long-term changes in Central European river discharge 1869–2016: impact of changing snow covers, reservoir constructions and an intensified hydrological cycle, Hydrology and Earth System Sciences, 24, 1721–1740, https://doi.org/10.5194/hess-2019-487, 2019.

Shiau, J. T. and Huang, C. Y.: Detecting multi-purpose reservoir operation induced time-frequency alteration using wavelet transform, Water Resources Management, 28, 3577–3590, https://doi.org/10.1007/s11269-014-0688-x, 2014.

Simon Wood: mgcv: Mixed GAM Computation Vehicle with Automatic Smoothness Estimation, 2022.

Speckhann, G. A., Kreibich, H., and Merz, B.: Inventory of dams in Germany, Earth System Science Data, 13, 731–740, https://doi.org/10.5194/essd-13-731-2021, 2021.

Steyaert, J. C., Condon, L. E., W.D. Turner, S., and Voisin, N.: ResOpsUS, a dataset of historical reservoir operations in the contiguous United States, Scientific Data, 9, 34, https://doi.org/10.1038/s41597-022-01134-7, 2022.

Ternynck, C., Ali, M., Alaya, B., Chebana, F., Dabo-Niang, S., and Ouarda, T. B. M. J.: Streamflow hydrograph classification using functional data analysis, American Meteorological Society, 17, 327–344, https://doi.org/10.1175/JHM-D-14-0200.1, 2016.

Thornton, H. E., Hoskins, B. J., and Scaife, A. A.: The role of temperature in the variability and extremes of electricity and gas demand in Great Britain, Environmental Research Letters, 11, https://doi.org/10.1088/1748-9326/11/11/114015, 2016.

Tijdeman, E., Hannaford, J., and Stahl, K.: Human influences on streamflow drought characteristics in England and Wales, Hydrology and Earth System Sciences, 22, 1051–1064, https://doi.org/10.5194/hess-22-1051-2018, 2018.

Turner, S. W., Steyaert, J. C., Condon, L., and Voisin, N.: Water storage and release policies for all large reservoirs of conterminous United States, Journal of Hydrology, 603, https://doi.org/10.1016/j.jhydrol.2021.126843, 2021.

van Oel, P. R., Martins, E. S. P. R., Costa, A. C., Wanders, N., and van Lanen, H. A. J.: Diagnosing drought using the downstreamness concept: the effect of reservoir networks on drought evolution, Hydrological Sciences Journal, 63, 979–990, https://doi.org/10.1080/02626667.2018.1470632, 2018.

Verbunt, M., Groot Zwaaftink, M., and Gurtz, J.: The hydrologic impact of land cover changes and hydropower stations in the Alpine Rhine basin, Ecological Modelling, 187, 71–84, https://doi.org/10.1016/j.ecolmodel.2005.01.027, 2005.

Vicente-Serrano, S. M., Zabalza-Martínez, J., Borràs, G., López-Moreno, J. I., Pla, E., Pascual, D., Savé, R., Biel, C., Funes, I., Azorin-Molina, C., Sanchez-Lorenzo, A., Martín-Hernández, N., Peña-Gallardo, M., Alonso-González, E., Tomas-Burguera, M., and El Kenawy, A.: Extreme hydrological events and the influence of reservoirs in a highly regulated river basin of northeastern Spain, Journal of Hydrology: Regional Studies, 12, 13–32, https://doi.org/10.1016/j.ejrh.2017.01.004, 2017.

Voisin, N., Li, H., Ward, D., Huang, M., Wigmosta, M., and Leung, L. R.: On an improved sub-regional water resources management representation for integration into earth system models, Hydrology and Earth System Sciences, 17, 3605–3622, https://doi.org/10.5194/hess-17-3605-2013, 2013.

Volpi, E., Di Lazzaro, M., Bertola, M., Viglione, A., and Fiori, A.: Reservoir effects on flood peak discharge at the catchment scale, Water Resources Research, 54, 9623– 9636, https://doi.org/10.1029/2018WR023866, 2018.

Vorkauf, M., Marty, C., Kahmen, A., and Hiltbrunner, E.: Past and future snowmelt trends in the Swiss Alps: the role of temperature and snowpack, Climatic Change, 165, https://doi.org/10.1007/s10584-021-03027-x, 2021.

Wan, W., Zhao, J., Li, H., Mishra, A., Leung, L. R., Hejazi, M., Wang, W., Lu, H., Deng, Z., Demissisie, Y., and Wang, H.: Hydrological drought in the Anthropocene: Impacts of local water extraction and reservoir regulation in the U.S., Journal of Geophysical Research: Atmospheres, 122, 11 313–11 328, https://doi.org/10.1002/ 2017JD026899, 2017.

Wang, W., Li, H. Y., Leung, L. R., Yigzaw, W., Zhao, J., Lu, H., Deng, Z., Demisie, Y., and Blöschl, G.: Nonlinear filtering effects of reservoirs on flood frequency curves at the regional scale, Water Resources Research, 53, 8277–8292, https://doi.org/10.1002/2017WR020871, 2017.

Ward, J. H.: Hierarchical grouping to optimize an objective function, Journal of the American Statistical Association, 58, 236–244, https://doi.org/10.1080/01621459.1963.10500845, 1963.

Wenz, L., Levermann, A., and Auffhammer, M.: North–south polarization of European electricity consumption under future warming, Proceedings of the National Academy of Sciences of the United States of America, 114, E7910–E7918, https://doi.org/10.1073/pnas.1704339114, 2017.

White, M. A., Schmidt, J. C., and Topping, D. J.: Application of wavelet analysis for monitoring the hydrologic effects of dam operation: Glen canyon dam and the Colorado River at lees ferry, Arizona, River Research and Applications, 21, 551–565, https://doi.org/10.1002/rra.827, 2005.

Wood, S. N.: Generalized additive models. An introduction with R, CRC Press, Boca Raton, second edn., 2017.

Yassin, F., Razavi, S., Elshamy, M., Davison, B., Sapriza-Azuri, G., and Wheater, H.: Representation and improved parameterization of reservoir operation in hydrological and land-surface models, Hydrology and Earth System Sciences, 23, 3735–3764, https://doi.org/10.5194/hess-23-3735-2019, 2019.