AGU ADVANCING EARTH AND SPACE SCIENCE

Water Resources Research

RESEARCH ARTICLE
10.1029/2022WR033893

National-Scale Detection of Reservoir Impacts Through Hydrological Signatures

S. Salwey[1], G. Coxon[1,2], F. Pianosi[2,3], M. B. Singer[4,5,6], and C. Hutton[7]

[1]School of Geographical Sciences, University of Bristol, Bristol, UK, [2]Cabot Institute, University of Bristol, Bristol, UK, [3]Department of Civil Engineering, University of Bristol, Bristol, UK, [4]School of Earth and Environmental Sciences, Cardiff University, Cardiff, UK, [5]Earth Research Institute, University of California Santa Barbara, Santa Barbara, CA, USA, [6]Water Research Institute, Cardiff University, Cardiff, UK, [7]Wessex Water Services Ltd., Bath, UK

Key Points:

- Hydrological signatures can be used to identify reservoir-induced hydrological alteration using only downstream flow timeseries
- Application to 186 catchments across Great Britain finds reservoirs often induce losses in the water balance and reduce flow variability
- Signatures provide insights into reservoir operations which will help to design and evaluate new operation schemes in hydrological models

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

S. Salwey,
saskia.salwey@bristol.ac.uk

Citation:

Salwey, S., Coxon, G., Pianosi, F., Singer, M. B., & Hutton, C. (2023). National-scale detection of reservoir impacts through hydrological signatures. *Water Resources Research*, *59*, e2022WR033893. https://doi.org/10.1029/2022WR033893

Received 14 OCT 2022
Accepted 3 MAY 2023

Abstract

Reservoirs play a vital role in the supply and management of water resources and their operation can significantly alter downstream flow. Despite this, reservoirs are frequently excluded or poorly represented in large-scale hydrological models, which can be partly attributed to a lack of open-access data describing reservoir operations, inflow and storage. To help inform the development of reservoir operation schemes, we collate a suite of hydrological signatures designed to detect the impacts of reservoirs on the flow regime at large-scales from downstream flow records only. By removing the need for pre-and-post-reservoir flow timeseries (a requirement of many pre-existing techniques), these signatures facilitate the assessment of flow alteration across a much wider range of catchments. To demonstrate their application, we calculate the signatures across Great Britain in 111 benchmark (i.e., near-natural) catchments and 186 reservoir catchments (where at least one upstream reservoir is present). We find that abstractions from water resource reservoirs induce deficits in the water balance, and that pre-defined flow releases (e.g., the compensation flow) reduce variability in the downstream flow duration curve and in intra-annual low flows. By comparing signatures in benchmark and reservoir catchments, we define thresholds above which the influence of reservoirs can be distinguished from natural variability and identify 40 catchments significantly impacted by the presence of reservoirs. The signatures also provide insights into local reservoir operations, which can inform the development of tailored reservoir operation schemes, and identify locations where current modeling practices (which lack reservoir representation) will be insufficient.

Plain Language Summary

Reservoirs play a vital role in the supply and management of water resources. However, reservoirs are frequently either excluded, or poorly represented in large-scale river flow simulations due to a lack of open-access data describing their operation. To help inform the representation of reservoirs, we use a suite of simple metrics to detect where and how rivers are being impacted by upstream reservoirs from records of downstream flow. We apply these metrics over hundreds of gauges across Great Britain and find that abstractions for water supply reduce the volume of water in rivers downstream of reservoirs, and that controlled water releases reduce downstream flow variability. The application of the metrics defined in this study enable us to gain insights into how upstream reservoirs are operated and will help to improve our ability to simulate and predict river flow under changing climate and water demand.

1. Introduction

Reservoirs play a vital role in the supply and management of water resources. The number of reservoirs and their cumulative storage volume has increased rapidly over the last six decades, and it is estimated that there are more than 16 million reservoirs worldwide with a combined storage capacity of over 8 million cubic meters (MCM) (Lehner et al., 2011). Depending on their management and operation, reservoirs may have major impacts on downstream river basins, and the resultant flow alterations have been identified globally across a number of scales (Adam et al., 2007; Döll et al., 2009; Tebakari et al., 2012; Vörösmarty et al., 2003). Despite impacts to various parts of the flow regime, reservoirs are frequently either excluded, or poorly represented in large-scale hydrological models, resulting in degraded model performance and model simulations that miss key aspects of reservoir-induced streamflow behavior (Dang et al., 2020; Wada et al., 2017). Consequently, many researchers are now focusing their efforts on the challenge of appropriately incorporating reservoirs into large-scale hydrological models (He et al., 2017; Qiu et al., 2019; Shin et al., 2019; Turner et al., 2020; Yassin et al., 2019). Improving the representation of reservoirs in hydrological models is essential for enhancing our capacity to simulate current and future water resource availability, and will help inform national and international water management under nonstationary conditions of supply and demand (Brown et al., 2015; Dang et al., 2020; Turner & Galelli, 2016; Wagener et al., 2010).

Incorporating reservoirs into large-scale hydrological modeling still faces several key challenges (Wada et al., 2017). Firstly, there are very few places in the world where operating rules are publicly available, particularly across large scales (Brown et al., 2015; Masaki et al., 2017). In many countries the water industry is privatized and water is managed by regional companies, resulting in a lack of consistent national-scale data and often a higher level of data protection (Steyaert et al., 2022). Reservoir regulation frequently draws on detailed and undocumented decision-making processes, and thus it is rarely possible to implement control curves or operational rules directly into simulations. In some cases, operations are further complicated by the role of reservoirs in larger conjunctive use systems. In these locations, operation at singular reservoirs should be considered part of a coordinated network, managing resources over a wider area, with a more complex set of objectives and trade-offs (Rougé et al., 2019). Moreover, even where operating rules are available at individual locations, the application, or generalization, to a larger domain is problematic. Reservoir operation is often designed for a specific set of local or regional objectives and studies have found that ignoring individual operational nuances can result in significant errors when simulating downstream flow (Turner et al., 2020; Yassin et al., 2019). In deriving reservoir rules from generic characteristics, such as reservoir type or location, one assumes that operations will be consistent across a sample of reservoirs with similar properties, as well as through time, which is often not the case (Haddeland et al., 2006; Hanasaki et al., 2006; Masaki et al., 2017). Although in many cases this baseline level of reservoir representation still improves streamflow simulations compared with not including reservoirs, there remains significant room for improvement before performance reaches a level capable of informing water management across large scales (e.g., national scales).

Some studies have demonstrated the potential for assessing flow alteration, and even inferring operational rules, by comparison of inflow and outflow timeseries, or dividing a record into pre-and-post impoundment (Gao et al., 2009; Magilligan & Nislow, 2005; Richter et al., 1996; Singer, 2007; Tebakari et al., 2012; Turner et al., 2021). Despite the success of techniques such as the Indicators of Hydrologic Alteration (IHA) for assessing small-scale reservoir impact, in most cases the necessary data is not available for these techniques to be upscaled. Inflow and outflow, or suitably long (pre- and post-dam) timeseries are rarely available across large spatial domains; neither are suitable paired catchments nor naturalized timeseries, which in some cases can also facilitate an assessment of flow alteration (Arheimer & Lindstrom, 2014; Brunner, 2021; Döll et al., 2009). Consequently, in many locations, little is known about how reservoirs are impacting the flow regime and there is a lack of guidance or data for how they should be represented in hydrological models. In response to this, Steyaert et al. (2022) have collated a national scale database for inflow, outflow and storage data at 679 major reservoirs across the contiguous United States. This dataset has allowed reservoir operations to be inferred nationally, and operation schemes derived from this data have been shown to outperform generic alternatives when forced with observed inflows (Turner et al., 2020, 2021). While this new dataset represents an unrivaled level of data availability, to our knowledge, no other country has a similar dataset that has been collated and made openly available. Consequently, here we highlight the need for a data analysis methodology which can detect and characterize reservoir-induced flow alteration from more widely available public data, to support the identification of reservoir impacts and their implementation into hydrological models.

To fill this gap, we introduce a suite of hydrological signatures designed to quantify the large-scale (e.g., can be applied over hundreds to thousands of catchments) impact of reservoirs on the flow regime from only downstream flow records. The signatures are designed to capture the principal components of reservoir-induced flow alteration relevant to hydrological modeling, including impacts on the water balance (WB), flow variability and the relationship between streamflow and precipitation at annual, monthly, and daily timescales. We calculate these signatures across a large sample of catchments in Great Britain, where the flow gauging network typically postdates the construction of reservoirs, resulting in a lack of upstream or pre-construction flow timeseries that would facilitate the use of standard approaches (e.g., IHA). To distinguish reservoir impacts from naturally occurring streamflow variability, we compare hydrological signatures between 186 catchments where we know one or more reservoir is present ("reservoir catchments") and 111 benchmark catchments across Great Britain (i.e., catchments where human influence on river regime should be negligible). By calculating signatures across these two groups of catchments (reservoir and benchmark), we use the benchmark variability to define thresholds enabling the detection of reservoir catchments exhibiting significant flow alteration. Our study demonstrates the feasibility of using hydrological signatures to detect and quantify the large-scale influence of reservoirs on downstream flow, whilst supporting diagnosis of upstream reservoir operation. We suggest that national-scale insights into streamflow manipulation that result from such an effort will be vital to inform the development of necessary reservoir operation schemes and will guide their inclusion in large-scale hydrological modeling frameworks.

2. Data and Catchment Selection

We used a large sample of catchments across Great Britain to test whether our suite of hydrological signatures could detect and quantify the influence of reservoirs on the flow regime over hundreds of gauges. To achieve this, we collated reservoir and hydrometeorological data for two sets of catchments: (a) benchmark catchments: a sample of near-natural catchments where flows should be almost completely unaffected by human activities and (b) reservoir catchments: a sample of catchments that include one or more reservoirs upstream of the flow gauge station.

2.1. Reservoir Data

The location, capacity, use and construction date of reservoirs was obtained from the UK reservoir inventory (Durant & Counsell, 2018), which contains data on UK reservoirs with storage exceeding 1.6 MCM and a selection of smaller ones. After cross-referencing the UK Reservoir Inventory with the Global Reservoir and Dam Database (Lehner et al., 2011), it was apparent that some of the Scottish reservoirs in GranD were not included in the UK inventory, and in several locations the capacities were significantly different (see Text S5 in Supporting Information S1). Consequently, in Scotland, the UK reservoir inventory has been supplemented with data on 84 reservoirs from the Scottish Environment Protection Agency (SEPA). Of these additional reservoirs, 65 have no use category, and thus their purposes (e.g., hydroelectricity generation, flood control, water supply) have been classified as unknown. Where mismatches in capacities were identified, the UK Reservoir Inventory has been updated using the supplementary SEPA data.

We excluded 82 of the UK Reservoir Inventory reservoirs from this analysis, either because there was no gauge downstream of the reservoir (37), they were outside of Great Britain (2) or because they could not be placed on the river network (43), largely because their outflow or inflow location was unclear (see Figure S1 in Supporting Information S1). Similarly, we have also removed reservoirs built to supply canals, those with multiple uses and those designed for flood storage. Since there were less than 5 reservoirs in each of these categories we were unable to draw any robust conclusions about their impact. In total, 232 reservoirs remained for analysis (Figures 1b–1d). Reservoirs with the highest capacity tend to be located in the west of Great Britain, where rainfall is substantially higher and where there is relatively high basin relief. A vertical belt of reservoirs run from north to south through Wales, and similarly through the center of England. There are very few reservoirs in central southern England where supply is more groundwater dominated, or along the Welsh border. In Scotland, reservoir coverage is reasonably widespread, with some gaps in the North East of Scotland and along the West coast and Islands. Water resource reservoirs make up the largest proportion of reservoirs in this study (65%) followed by hydropower reservoirs (10%), and the remaining portion have an unknown use (25%).

2.2. Catchment Selection and Hydrometeorological Data

For the benchmark catchments, we selected gauging stations from the UK Benchmark Network, which are considered to be relatively free of human disturbance and that exhibit a natural flow regime (Harrigan et al., 2018). For the reservoir catchments, we selected all gauging stations in Great Britain from the UK National River Flow Archive, NRFA (https://nrfa.ceh.ac.uk/) that included at least one reservoir upstream from the reservoirs identified in Section 2.1. For each of these catchments, we collated open-access, nationally available rainfall, potential evapotranspiration (PET) and flow catchment daily timeseries (as detailed below) in order to calculate the hydrological signatures.

Daily rainfall data were extracted from the 1 km Centre for Ecology and Hydrology Gridded Estimates of Areal Rainfall (CEH-GEAR) (Tanguy et al., 2021) and daily PET data were extracted from the 1 km Climate Hydrology and Ecology research Support System Potential Evapotranspiration (CHESS-PE; which is calculated using the Penman-Monteith equation) (Robinson et al., 2017) using catchment boundaries from the National River Flow

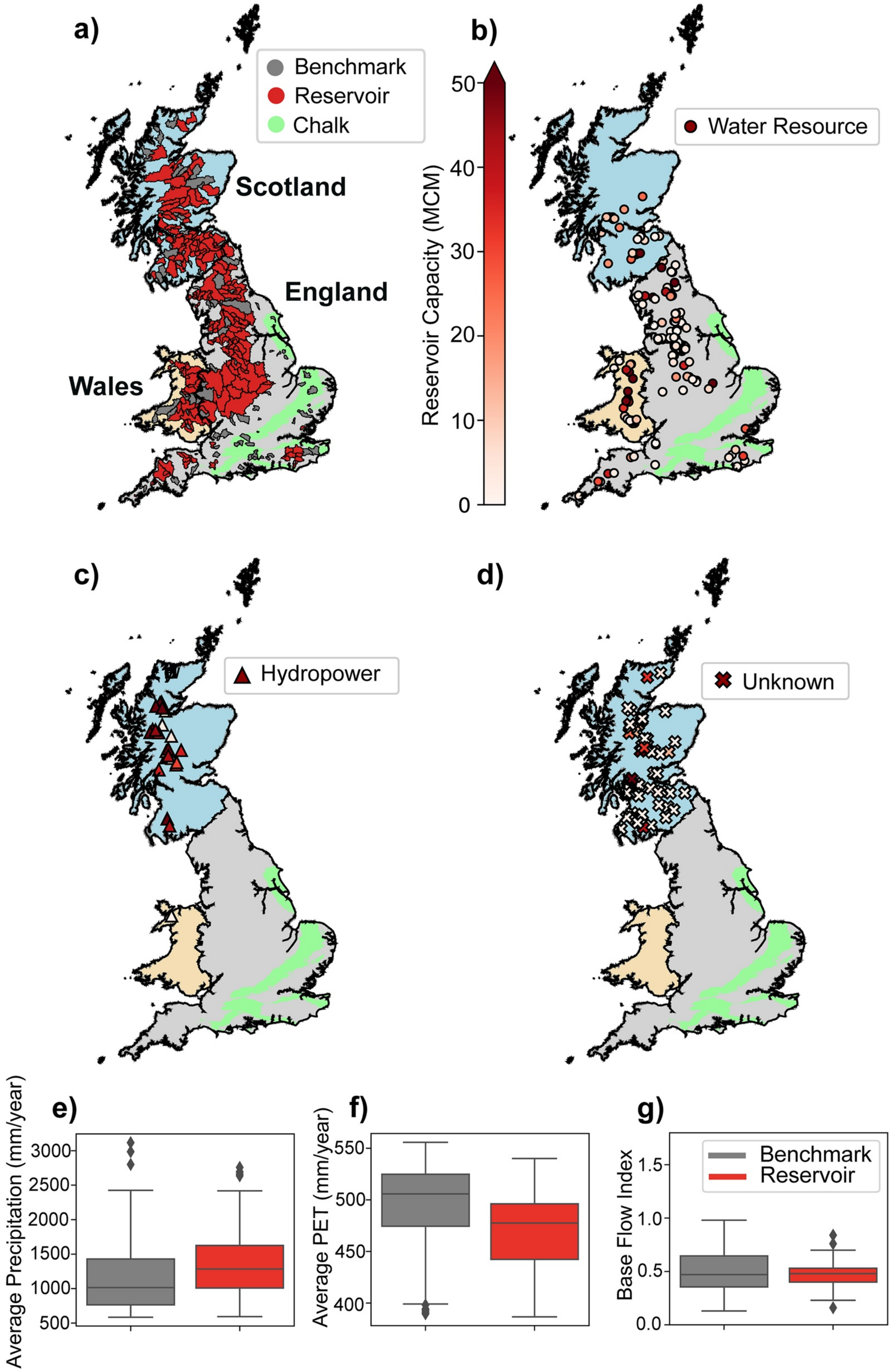

Figure 1. (a) Distribution of benchmark and reservoir catchments used in this analysis. (b, c, and d) Distribution of Water Resource, Hydropower and Unknown reservoirs. (a)–(d) Also display the regions underlain by chalk (in green). (e, f, and g) Comparison of average precipitation, average potential evapotranspiration and baseflow index across benchmark and reservoir catchment samples.

Archive (NRFA). Daily flow timeseries were obtained from the NRFA database. To ensure appropriately long time series were available for the robust calculation of the hydrological signatures, only gauges with NRFA daily flow timeseries spanning from 1980 to 2014 with 90% complete data were included in the analysis. Where data gaps were present, NaN (no data) values were forced into the precipitation and PET timeseries at the associated timesteps. The timeseries start date was set to 1980, since more than 95% of the reservoirs with known construction dates were completed by this point. Finally, we removed six of the benchmark catchments due to the presence of a reservoir in the upstream river network.

After applying these checks, 186 reservoir catchments and 111 benchmark catchments remained for analysis (Figure 1a). These two sets of gauges have national coverage, with a bias toward the west and north of Great Britain where most of the reservoirs and near-natural catchments are located. Our new database covers a wide diversity of hydrologic and climatic conditions across Great Britain, with meteorological characteristics largely consistent between the benchmark and reservoir catchments to ensure that any differences between the two sets of catchments are due to impacts from reservoirs (Figures 1e and 1f). Geology is characterized by the catchments' baseflow index (BFI) which measures the proportion of the river runoff that can be classified as baseflow (for more information see Gustard et al., 1992) and has been shown to reflect the underlying geology across Great Britain (Bloomfield et al., 2021). The benchmark sample has more variable BFI than the reservoir sample (Figure 1g), particularly at the upper end, where 12% (or 13) of the benchmark catchments have a BFI higher than recorded in any reservoir catchment. These are primarily chalk catchments where we expect there to be a significant groundwater influence (see Figure 1a) (H. Jones et al., 2000). Since this resource is often clean and cheap, catchments underlain by chalk tend to rely on groundwater resources more than surface water.

In comparison to the benchmark catchments, reservoir catchments have slightly higher average rainfall (1,285 mmyr^{-1} compared with 1,013 mmyr^{-1}) and lower average PET (478 mmyr^{-1} compared with 505 mmyr^{-1}). The upstream reservoir capacity ranges from 0.59 MCM to 8,356 MCM, with a median upstream reservoir capacity of 20.6 MCM. The distance between the gauges where downstream flows are recorded and the location of the nearest upstream reservoir ranges from 0.05 to 202 km with a median of 21 km.

3. Hydrological Signatures

Our approach investigates to what extent reservoir impact can be detected, quantified, and in many cases diagnosed by downstream flow timeseries. The statistical and dynamical properties of streamflow timeseries can be described by quantitative metrics, called hydrological signatures (see review by McMillan, 2020). For natural and near-natural catchments, hydrological signatures have been shown to provide useful insights into catchment behavior, and have been widely used to assess underlying processes and evaluate model structure and parameterization (McMillan et al., 2022). For example, event runoff ratios are used to explore the partitioning of fast and slow runoff processes, whilst the variability of flow can be connected to higher water storage (Estrany et al., 2010; McMillan et al., 2014). Signatures such as the flashiness index (which measures oscillations in flow relative to total flow) have also been used to quantify overall human impact, but on the whole, the metrics usually focus on natural processes (Baker et al., 2004; Gnann et al., 2021). In this study, we aim to define a suite of hydrological signatures that enable us to detect and quantify specific aspects of reservoir-induced streamflow behavior and that have tangible links to reservoir operation, such that their magnitude and subsequent investigation can provide insights into the upstream operational rules without the benefit of pre-and-post-reservoir flow data.

The selection of hydrological signatures used here focus on the WB, runoff coefficient, flow variability and the relationship between streamflow and precipitation at daily, monthly, and annual timescales. These signatures are designed to capture the principal components of reservoir management including exporting and importing water for water supply (WB and runoff coefficient) and the operation scheme which dictates how water is stored and released under normal and extreme conditions (flow variability and relationships between precipitation and streamflow). Most of the signatures defined in this paper rely on concepts (the runoff ratio, the flow duration curve (FDC), etc.) that are commonly used in the literature (McMillan, 2020; Sankarasubramanian et al., 2001; Sawicz et al., 2011; Yadav et al., 2007; Yilmaz et al., 2008), but here have been combined and adjusted to detect aspects of streamflow behavior specifically related to reservoir operation.

The following section will give a brief introduction to each signature.

3.1. Water Balance (WB)

The WB is a fundamental reflection of hydrological functioning in a catchment, which can be directly impacted by reservoir operations, particularly those related to abstractions (e.g., for water supply or irrigation) (Döll et al., 2009; Van Beek et al., 2011; Van Oel et al., 2008), pumped storage (where reservoir levels are sustained by imported water) (Ming et al., 2017) or inter-catchment transfers (Gupta & van der Zaag, 2008; Murgatroyd & Hall, 2020), which can lead to either net losses or gains. In this analysis, we quantify the reservoir-induced changes to the WB via a Budyko-type curve. The framework can be used to examine the catchment WB by considering the relationship between the catchment runoff coefficient (defined here as the ratio between catchment mean annual discharge and catchment mean annual precipitation) and the catchment aridity index (defined here as the ratio between catchment mean annual PET and catchment mean annual precipitation) (Budyko, 1974; C. Wang et al., 2016). The runoff coefficient quantifies how much precipitation is translated into streamflow, whilst the aridity index considers climatic deficits induced by the ratio of precipitation to PET. Considering the long-term WB, a catchment with no losses or gains can be represented by:

$$\frac{Q}{P} = 1 - \frac{PE}{P} \tag{1}$$

where Q, P and PE are the catchment average daily discharge, precipitation and potential evapotranspiration calculated from the entire available timeseries, all expressed in mm/day. Subsequently, Q/P represents the runoff coefficient and PE/P is the aridity index in a manner than establishes energy and water limitations for a particular catchment. The water balance signature (WB) measures the deviation from a closed WB and is calculated as:

$$\text{WB} = \frac{Q}{P} - \left(1 - \frac{\text{PE}}{P}\right) \tag{2}$$

This Equation 2 is represented by a dashed black line on the Budyko-type plot (Figure 3a). A negative value of the WB implies that a catchment experiences water losses which exceed the total PET while a positive value implies that a catchment gains more water than is delivered in precipitation. The magnitude of this signature can be used to assess the magnitude of water lost or gained by a catchment, with higher water losses or gains anticipated in the reservoir catchments.

3.2. Dry/Wet Runoff Ratio (DWRR)

By storing and redistributing water across the year, reservoirs have the potential to alter the monthly runoff coefficient through sustaining downstream flow, releasing water for downstream abstraction or withholding water to increase storage or releasing additional water received from pumped storage (J. A. Jones & Hammond, 2020; Tang et al., 2021; Z. Yin et al., 2021). In natural catchments in Great Britain, we expect the monthly runoff coefficient to follow a seasonal cycle, with higher runoff coefficients in winter (or wet season) when PET is lower and rainfall totals are higher. The Dry/Wet Runoff Ratio (DWRR) assesses deviations in the seasonal cycle by comparing the mean runoff coefficient in the dry (in this case summer, April–September) and wet (winter, October–March) season, calculated as:

$$\text{DWRR} = \left(\frac{Q}{P}\right)_{\text{dry}} \Big/ \left(\frac{Q}{P}\right)_{\text{wet}} \tag{3}$$

where $(Q/P)_{\text{dry}}$ is the mean runoff coefficient using daily data from April–September (i.e., Q and P are the average of daily flow and precipitation in the dry season only), and $(Q/P)_{\text{wet}}$ is the mean runoff coefficient using daily data from October–March. A value exceeding 1 implies that the dry runoff coefficient is higher than the wet runoff coefficient and suggests that reservoirs are redistributing water throughout the year or receiving large imports. Comparatively, a value near 0 implies that there is a large contrast between high wet season and low dry season runoff.

3.3. Segmentation of the Flow Duration Curve (Seg-FDC)

A central component of reservoir management is determining how much water is released and when. To characterize this, this signature is based on the FDC, which quantifies the cumulative frequency of flow (or the percentage of time a specific flow is equaled or exceeded). Many studies have defined signatures based on the slope of the central part of the FDC, or on specific quantiles (Farmer et al., 2003; Yilmaz et al., 2008). However, in theory, reservoirs have the potential to modify the full range of flow. After comparing the FDCs from benchmark and reservoir catchments, we found that in some reservoir catchments, the FDC shows abrupt changes and flat segments (examples of this can be seen in Section 5.3), as reservoir outflows are often kept at the same constant value (e.g., the compensation flow) for long periods of time. This signature (Segmentation of the Flow Duration Curve (Seg-FDC)) thus first fits a sigmoidal function to the observed cumulative distribution function and then measures how closely the data follows that "natural" (sigmoidal) shape. The sigmoidal function takes the form:

$$\hat{f} = -a * \log\left(\frac{1}{1-x}\right) + b \tag{4}$$

where a and b are parameters optimized for each catchment based on a nonlinear least squares regression of the catchment FDC (based on historical daily flows) between the 5th and the 95th percentiles, and x is the flow exceedance probability. The deviation of the observed FDC from the sigmoidal function of Equation 4 are then quantified by the root mean square error, normalized by the standard deviation of the (log) flow, that is,:

$$\text{Seg} - \text{FDC} = \sqrt{\frac{\sum_{i=1}^{N} \left(\log(Q_i) - \hat{f}_i\right)^2}{N}} * \frac{1}{\sigma} \tag{5}$$

where N is the number of data points (i.e., the length of the time series), Q_i is the daily flow value in the ith position of the observed FDC, $\hat{f}_i$ is the corresponding flow according to the sigmoidal function of Equation 4, and σ the standard deviation of the (log) flow timeseries. A value close to 0 implies that there is a close match between the observed FDC and the sigmoidal one, suggesting that the shape of the observed FDC is "natural." The higher the Seg-FDC metric, the larger the deviations from the sigmoidal function, which suggests significant modification to the natural flow variability.

3.4. Low Flow Variability (LFV)

By storing and redistributing water, reservoir operations can help to sustain (and sometimes elevate) low flows and retain high flows, minimizing the seasonal cycles observed in natural catchments (Gibbins et al., 2001; J. A. Jones & Hammond, 2020; Singer, 2007; Tang et al., 2021; Tijdeman et al., 2018). To protect downstream ecosystems, reservoir releases must often abide by a "compensation flow," which is a pre-defined minimum volume that must be released wherever possible (Maynard & Lane, 2012; X. A. Yin et al., 2011). To ensure that reservoirs maximize storage, the compensation flow often becomes the default release volume when a reservoir is not full. This signature identifies the effects of the compensation flow by considering how the low flow regime changes throughout the year. If a reservoir has a constant, pre-defined release volume, it is likely that this will remove or reduce the low flow seasonality, thereby lowering intra-annual variability, highlighting the control of a reservoir over the flow regime. This signature focuses on the flow that is exceeded 80% of the time (or the 20th percentile of flow, referred to as the Q_{80}), since this has been used as threshold value for drought definition (Van Loon et al., 2016) and should capture the compensation flow. For each catchment, this signature calculates the difference between the maximum and the minimum monthly Q_{80} (normalized by the mean daily discharge, for comparability across catchments):

$$\text{LFV} = 1 - \frac{\max_{m=1,\ldots,12}(Q_{80,m}) - \min_{m=1,\ldots,12}(Q_{80,m})}{Q} \tag{6}$$

where $Q_{80,\text{m}}$ is the 20th flow percentile in month m (e.g., $Q_{80,1}$ is the 20th percentile of the all daily flow data recorded in the month of January across the entire 34 years timeseries) and Q is the mean daily discharge in mm/day. A high value of this signature implies that there is minimal intra-annual variation in Q_{80} values, or that the low flow regime is unaffected by seasonal change. Comparatively, a low value implies that there is a more variable low flow regime, usually because Q_{80} reflects seasonal flow patterns and is highest in winter and lowest in summer. We expect locations where pre-defined reservoir releases (such as the compensation flow) control low flows to exhibit lower Low Flow Variability (LFV) values than are seen in benchmark catchments.

3.5. Streamflow Elasticity (E)

By design, reservoirs are intended to facilitate the redistribution of flow by storing water for release or abstraction. This can occasionally break down following extremely dry (or wet) periods, but in general, reservoirs will often be able to control the downstream regime independent of precipitation (J. A. Jones & Hammond, 2020; Tijdeman et al., 2018). Streamflow elasticity characterizes the relationship between precipitation and flow on an annual timescale (Sawicz et al., 2011) and thus can characterize this relationship. This Streamflow Elasticity (E) signature is calculated with the equation:

$$E = \text{median}\left(\frac{\Delta Q_{\text{year-on-year}}}{\Delta P_{\text{year-on-year}}}\right) * \frac{P}{Q} \tag{7}$$

where P and Q are, as usual, the average daily precipitation and discharge in a catchment, whereas $\Delta Q_{\text{year-on-year}}$ (or $\Delta P_{\text{year-on-year}}$) represents the change in mean annual streamflow (or precipitation) from 1 year to the next in the available time series (i.e., with 34 years we have 33 values of ΔQ and ΔP, from which we take the median). In line with previous studies, we find that the median is the most stable form of this metric (Sawicz et al., 2011). A value of 1 implies that the percentage change in precipitation from 1 year to the next will be matched by the percentage change in streamflow. Values which exceed 1 suggest a catchment is more sensitive to precipitation change, whilst a value of less than 1 implies that catchment flow is insensitive to changes in precipitation. A negative value of streamflow elasticity suggests that there is an inverse relationship between streamflow and precipitation.

4. Application of Hydrological Signatures

Having defined the above five signatures, we compare their values across the benchmark and the reservoir sample to (a) detect whether significant alterations are found in any of the reservoir catchments (Section 4.1); (b) investigate whether we can link the magnitude of these alterations to the characteristics of the reservoir catchments (Section 4.2).

4.1. Detecting Significant Alteration

To distinguish reservoir-driven impacts from naturally occurring streamflow behavior a threshold is defined for each signature, based on the maximum or minimum value recorded in the benchmark sample. In some cases, anomalous catchments are excluded from the threshold definition, where they are considered to exhibit significantly different behavior to any in the equivalent reservoir sample. For example, when defining the WB threshold, we exclude 6 chalk catchments with significant groundwater water gains/losses, since this signature does not account for groundwater processes. Once the thresholds have been calculated, any reservoir catchment with a signature crossing the associated threshold is considered to exhibit significant flow alteration (see Section 5.6 for more detail).

4.2. Catchment Descriptors

Throughout this study, we use two catchment descriptors to examine the link between the magnitude of flow alteration, as measured by our hydrological signatures, and the associated reservoir characteristics. Previous studies have used descriptors based on factors such as the reservoir capacity, catchment area, distance upstream, annual flood volume or mean annual inflow to anticipate the impacts of reservoirs on, for example, flood attenuation or river fragmentation (Arheimer et al., 2017; Cipollini et al., 2022; Jumani et al., 2022; Scarrott et al., 1999; Singer, 2007; W. Wang et al., 2017). We trialled several descriptors, finding clear links between the size and location of upstream reservoirs and the associated flow alteration. Thus in this study, we focus the descriptors on reservoir capacity, catchment precipitation and catchment area. The first descriptor is the percentage of the overall catchment surface area that is drained through reservoirs. This is termed the "contributing area" and is expressed as:

$$\text{Contributing Area}\,(\%) = \frac{\text{catchment area drained by reservoirs}\,(\text{km}^2)}{\text{total catchment area}\,(\text{km}^2)} \times 100 \tag{8}$$

The second descriptor, referred to as the "normalized upstream capacity," compares the capacity of a reservoir to the average volume of precipitation received by the catchment in a year. A value of 1 suggests that the reservoir is large enough to store 1x the average annual rainfall, similarly a value of 2 means a reservoir can store 2x the average rainfall and so on, the descriptor is expressed as:

$$\text{Normalized Upstream Capacity} = \frac{\text{total upstream reservoir capacity}\,(\text{mm}^3)}{\text{total catchment area}\,(\text{mm}^2) * \text{average annual catchment precipitation}\,(\text{mm})} \tag{9}$$

This descriptor complements the Contributing Area by accounting for the increased potential of large reservoirs to manipulate flow, whilst accounting for differences in water availability across catchments. Both metrics are

10.1029/2022WR033893

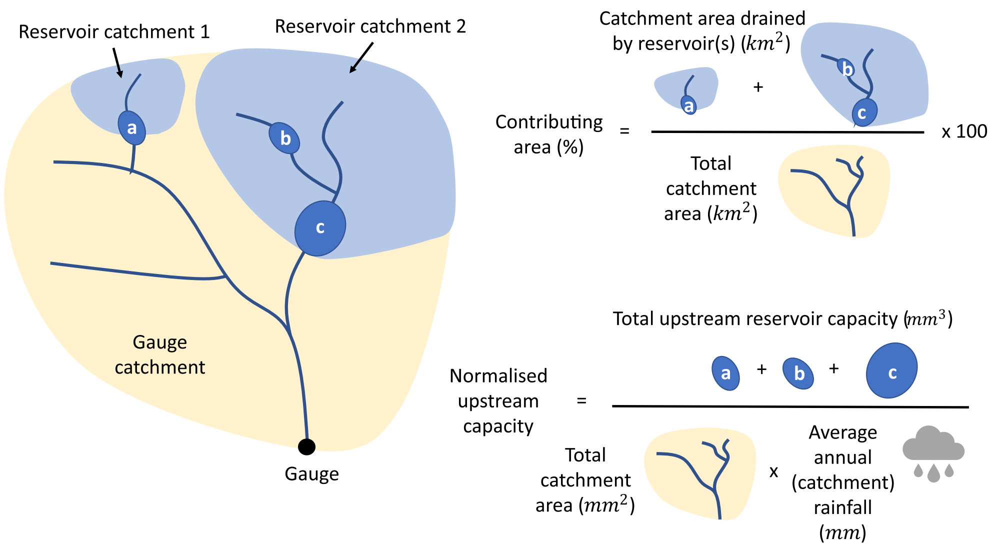

Figure 2. Schematic visualizing catchment descriptors and their equations for reservoir catchments. As demonstrated, the contributing area is the sum of reservoir catchments 1 and 2 divided by the total gauge catchment area, whilst the normalized upstream capacity is the sum of reservoirs 1, 2 and 3 capacities divided by the gauge area multiplied by the average annual (catchment) rainfall.

illustrated below in Figure 2. Finally, we also contextualize flow alteration by considering the purpose of upstream reservoirs. If this is unknown for all reservoirs in the catchment, then the category has been classified as Unknown. However, where at least one reservoir has a use, the catchment is either classified as a Water Resource or Hydropower catchment, or where both types lie upstream, a catchment is considered to have Multiple Types (Figure 1b).

5. Results

5.1. Reservoirs Mainly Induce Deficits in the Water Balance

Figure 3a examines the WB across benchmark and reservoir catchments by relating the runoff coefficient to the Aridity Index in a Budyko-type curve. The largest deficits (i.e., points significantly below the bisector line with a

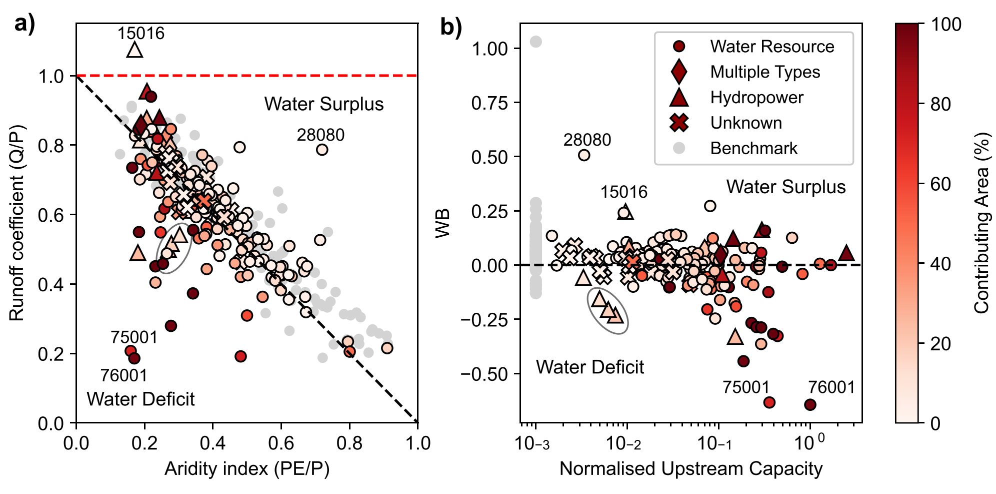

Figure 3. (a) Budyko-type curve investigating the relationship between runoff coefficient and aridity index. Benchmark catchments are shown in gray and reservoir catchments are colored by their contributing area. Circled in gray are the three hydropower catchments on the River Spey. Points falling below the diagonal (dashed line) indicate catchments where the runoff deficit exceeds total potential evapotranspiration. The Water Balance (WB) signature is the vertical distance between a point and the diagonal. (b) Plot showing the relationship between normalized upstream capacity and WB signature. Benchmark catchment variability is displayed parallel to the *Y* axis.

low WB metric such as the St Johns Beck at Thirlmere Reservoir (75001) and the Haweswater Beck at Burnbanks (76001)) are primarily seen in catchments with a water resource reservoir upstream, particularly those with high contributing area (Figures 3a and 3b). In these catchments, runoff deficits significantly exceed total PET suggesting that water is being removed from the catchment (most likely by abstraction for public water supply). The St Johns Beck at Thirlmere Reservoir (75001) and the Haweswater Beck at Burnbanks (76001) have the largest WB signature (and water deficit), demonstrating how in these catchments more than ~60% of incoming water is abstracted from the reservoir. Despite a low contributing area, some hydro-power catchments also have notable deficits, such as the three gauges on the river Spey in Scotland (circled in gray on Figure 3) where the WB signature decreases from −0.15 to −0.21 to −0.23 as contributing area increases from 13.4% to 18%–22.2%. Although large deficits are recorded in these catchments, the lower contributing area demonstrates how at hydropower catchments, our chosen catchment descriptors are not as successful at anticipating flow alteration. Contrastingly, Figure 3b also shows several catchments with high contributing area and normalized upstream capacity which still have a WB metric close to zero, where there appear to be no significant deficits or surpluses. Here reservoirs do not appear to be manipulating the WB.

There are two catchments where the runoff coefficient is larger than 1, these are the Tay at Kenmore (15016) and the Wey at Broadwey (44009) which have runoff coefficients of 1.07 and 1.43 (latter catchment not shown on Figure 3a due to axis height). The former is a hydro-power catchment which, despite low reservoir storage, receives substantial imports as part of the Breadalbane Hydro Scheme. The latter is a groundwater-dominated benchmark catchment with significant water gains (note: we are not constraining groundwater contributions to streamflow in this framework). Although water deficits are most prominent in the reservoir sample, there are several reservoir catchments with notable water surpluses (i.e., points significantly above the bisector line). The Tame at Lea Marston Lakes (28080) has the largest positive WB signature of 0.5, despite a contributing area of only 6%, implying there is a substantial water import. Within the benchmark sample, the four catchments with the highest WB signature and the two with the lowest all have a BFI ≥ 0.9 and are primarily chalk catchments, suggesting that these losses/gains may be driven by groundwater (Oldham et al., 2022).

5.2. Reservoirs Alter the Seasonal Runoff Patterns

Figure 4 shows the variability of the runoff coefficient over the year and the associated Dry/Wet Runoff Ratio (DWRR) signature. There are four water resource reservoir catchments (the St Neot at Craigshill Wood, the Clywedog at Bryntail, Brenig at the Llyn Brenig outflow, and Tryweryn at the Llyn Celyn outflow; 48009, 54081, 67003 and 67017) where the intra-annual runoff coefficient peaks in July (Figure 4a) and the dry/wet runoff ratio exceeds 1 (Figures 4c and 4d). This is not seen in the benchmark and remaining reservoir catchments (see Figure S2 in Supporting Information S1 for full reservoir results), which have a runoff peak either in the winter, or in April under the influence of snow. Catchments with April peaks have the highest elevation ranges and are often located in higher elevation regions of Scotland (Figure 4b). The reservoir-induced summer runoff peaks imply that in summer months, these catchments have streamflow exceeding the supplied precipitation, where reservoirs are likely to be releasing additional water to sustain downstream abstractions or downstream flow. In all four of these catchments the increased dry (summer) runoff coefficient translates into a higher DWRR. When considering the dry/wet runoff ratio in the context of the annual precipitation (Figure 4c), it is apparent that as well as the high dry/wet runoff ratios, there is a second group of water resource reservoir catchments with low DWRR signatures compared to the benchmark catchments with similar precipitation. This is likely driven by the artificial reduction in runoff coefficient during the drier months as reservoirs store water for public supply and the relationship between spill flows and heavy rain.

5.3. Catchments Downstream of Reservoirs Have Segmented Flow Duration Curves

The second component of the flow regime examined in this analysis was the FDC. We defined the Seg-FDC metric to quantify deviations from a "natural," that is, smooth, FDC (Figure 5a). The higher the Seg-FDC metric, the more the FDC shows abrupt changes and flat segments (i.e., Figures 5b–5d), which are distinctly unnatural. Figure 5e shows that reservoir catchments with the highest Seg-FDC signature also have a higher contributing area and normalized upstream capacity, demonstrating that the flow variability is impacted the most at gauges close to large reservoirs. There are some exceptions to this, notably the Ness at Ness-side (6007) which has high normalized upstream capacity and high contributing area (4,718 mm and 97%) despite low Seg-FDC, and contrastingly, the Tame at Lea Marston Lakes (28080) which has a low contributing area and normalized upstream capacity (6.3% and 5.43 mm) despite a high Seg-FDC.

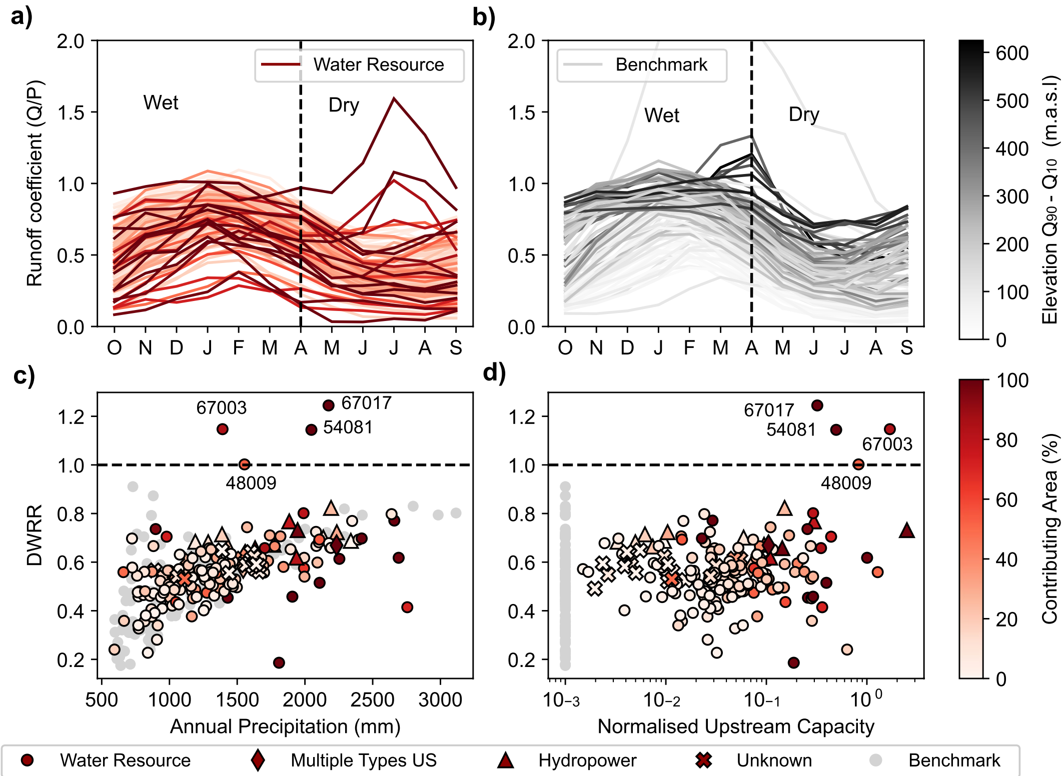

Figure 4. (a and b) Intra-annual variability in monthly runoff coefficient of (a) water resource reservoir catchments colored by their contributing area and (b) benchmark catchments colored by their elevation range. See Text S2 and Figure S2 in Supporting Information S1 for results from Hydropower, Unknown and Multiple Types catchments. (c) Dry/Wet Runoff Ratio (DWRR) plotted against a catchments annual precipitation, benchmark catchments are displayed in gray and reservoir catchments are colored by their contributing area. (d) Plot showing the relationship between normalized upstream capacity and the DWRR signature. Reservoir catchments are colored by their contributing area and benchmark catchment variability is displayed parallel to the *Y* axis.

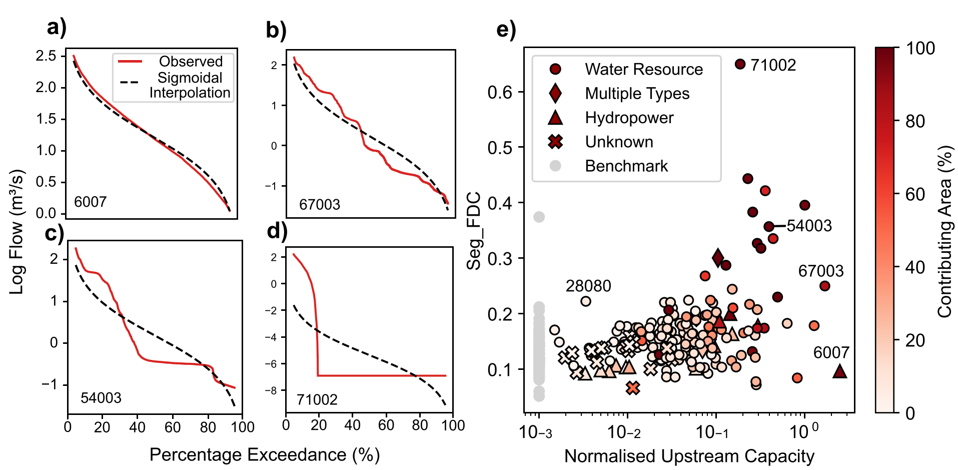

Figure 5. (a–d) Observed flow duration curves (red) at selected reservoir catchments and their sigmoidal interpolation (black dashed). (e) Plot showing the relationship between normalized upstream capacity and Segmentation of the Flow Duration Curve (Seg-FDC) signature for the reservoir catchments. Reservoir catchments are colored by their contributing area and benchmark catchment variability is displayed parallel to the *Y* axis.

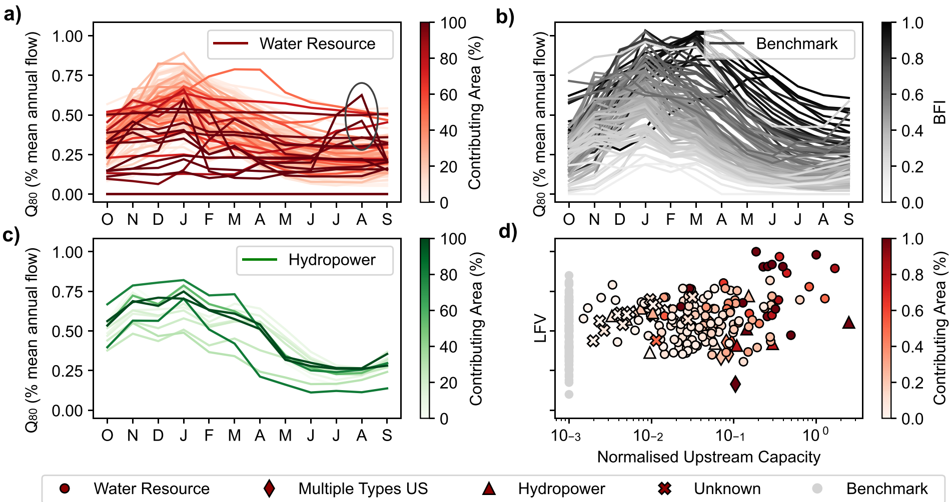

Figure 6. Intra-annual variations in monthly Q_{80} expressed as a percentage of mean annual flow at (a) water resource reservoir catchments colored by their contributing area, here catchments 54081, 67003 and 67017 have been circled in gray to highlight their peak in July/August (b) benchmark catchments colored by their baseflow index (BFI) and (c) hydropower catchments colored by their contributing area. See Text S3 and Figure S3 in Supporting Information S1 for results from Unknown and Multiple Types catchments. (d) Plot showing the relationship between normalized upstream capacity and Low Flow Variability signature. Points are colored by their contributing area. Benchmark catchment variability is displayed parallel to the *Y* axis.

5.4. Reservoir Operation Can Reduce Intra-Annual Low Flow Variability

Figures 6a–6c plot the monthly Q_{80} at water resource, benchmark and hydropower catchments normalized by the mean annual flow (see Figure S3 in Supporting Information S1 for full results). In the benchmark sample (Figure 6b) a seasonal cycle can be seen, with higher Q_{80} in winter and lower Q_{80} in summer. The color coding also shows that catchments with higher BFI (and potentially higher groundwater contributions) have higher Q_{80} as a percentage of mean flow. While many of the water resource (Figure 6a) and hydropower reservoir catchments (Figure 6c) exhibit a similar pattern to the benchmark catchments, where Q_{80} is highest in January and lowest in summer, there are some water resource catchments with high contributing area that exhibit a different pattern. In several of these catchments, Q_{80} remains constant throughout the year, demonstrating a disconnect between low flows and seasonal change. This translates into a high LFV signature displayed in Figure 6c. There is also a second cluster of reservoir catchments which can be distinguished from the benchmark sample by their Q_{80} peak in the summer months. The Clywedog at Bryntail, Brenig at the Llyn Brenig outflow, and Tryweryn at the Llyn Celyn outflow (54081, 67003 and 67017, with their peaks circled in Figure 6a) all have notable peaks in July/August, which coincide with their peaks in intra-annual runoff coefficient and high DWRR signatures (Figure 4). This is likely to be driven by their need to sustain downstream abstraction and although this can be seen in Figure 6a, the effect is not captured by the LFV signature.

5.5. Reservoirs Can Both Strengthen and Weaken the Relationship Between Streamflow and Precipitation

Finally, Figure 7a shows the relationship between streamflow elasticity (E) and a catchment's annual precipitation. When compared against those with similar annual precipitation values, it is clear that reservoir catchments with the highest contributing area behave differently to the benchmark sample. This is particularly true for those catchments with annual precipitation exceeding 1,350 mm, which in benchmark catchments have an elasticity from ~1 to 1.5, whilst in reservoir catchments elasticity ranges from ~0 to 2.5. This suggests that in these wetter catchments, reservoir catchments are both more and less sensitive to precipitation than benchmark catchments. The increased variability in catchments with high normalized upstream capacity and contributing area can also be seen in Figure 7b. Although no benchmark catchments have an elasticity of less than 0.5, five reservoir catchments can be identified below this threshold.

10.1029/2022WR033893

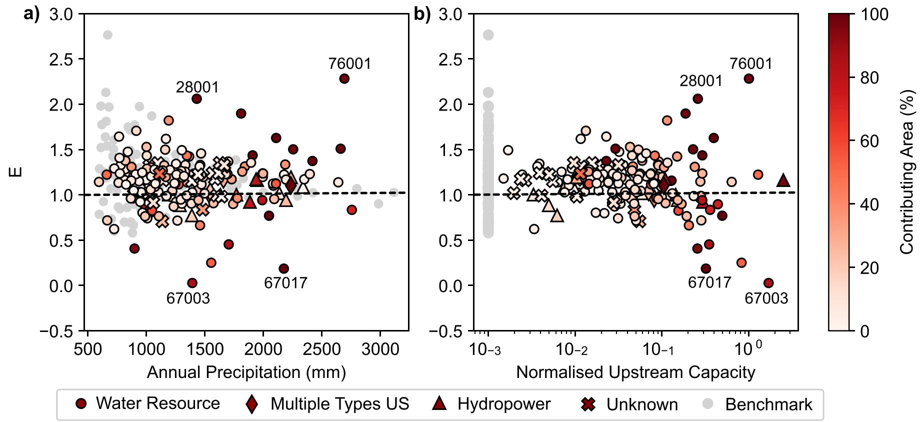

Figure 7. Streamflow elasticity against (a) annual precipitation and (b) normalized upstream capacity. Benchmark catchments are displayed in gray, whilst reservoir catchments are colored by their contributing area. Flow in catchments falling above the black dashed line is more sensitive to changes in precipitation, whilst flow in catchments falling below the line is less sensitive to changes in precipitation.

5.6. Defining Signature Thresholds to Identify Reservoir-Impacted Catchments

Figure 8 shows the full range of signatures calculated across all catchments. Thresholds of benchmark variability were calculated using the maximum and minimum signature values from the benchmark sample and are represented by dashed gray lines, above (or below) which reservoir signatures classify a catchment as having significant flow alteration, distinguishing a catchment from the benchmark sample. For some signatures, we alter the thresholds to exclude anomalous catchments, which is discussed below.

Forty of the 186 reservoir catchments cross at least one signature threshold and thus are considered to be significantly altered by upstream reservoir operation. There are no catchments that are identified by all four metrics, but eight water resource catchments exceed the benchmark threshold for three of the five signatures (WB, Seg-FDC and LFV). The Seg-FDC signature identifies 22 catchments of which 13 have a contributing area of more than 70%. The threshold chosen for this signature disregards one benchmark catchment, the West Glen at Easton Wood (31023). This catchment is ephemeral and flow is recorded as 0 from the 60th percentile upwards causing a large plateau in flow values. In total, the WB metric identifies 24 catchments below the negative threshold and 4 above the positive threshold, where 13 have a contributing area exceeding 70% or normalized upstream capacity of over 300 mm. When defining thresholds for this signature, benchmark variability (and hence the chosen threshold) excludes 6 chalk catchments with significant groundwater gains/losses. The WB signature does not account for groundwater and we assume that the manipulations to the WB in these catchments are not relevant to the definition of the reservoir-induced flow alteration threshold. The LFV signature identifies nine catchments in excess of the benchmark signature threshold. These are all water resource catchments and all have a contributing area over 70% and normalized upstream capacity of more than 0.18. Similarly five water resource catchments are identified by the streamflow elasticity metric, of which four have contributing area exceeding 84% and normalized upstream capacity of over 0.26 and 2 are not picked up by any other signature. The DWRR signature picks up the smallest number of catchments (4) which all have a contributing area exceeding 50%.

6. Discussion

6.1. Signatures and Catchment Descriptors as Methods of Detection

This study introduces a novel suite of hydrologic signatures that can be used to detect and quantify reservoir-induced flow alteration solely from downstream flow timeseries. Hydrologic signatures have been widely used to quantify and better understand “natural” hydrologic processes (Addor et al., 2018; Euser et al., 2013; Gnann et al., 2021; Sawicz et al., 2011), but to our knowledge this is the first study to have focused on hydrological signatures linked to reservoir operation schemes that only require downstream flow (McMillan, 2020). The suite of hydrological signatures introduced in this study have tangible links to reservoir operation, such that their magnitude and subsequent investigation can provide insights into the upstream operational rules.

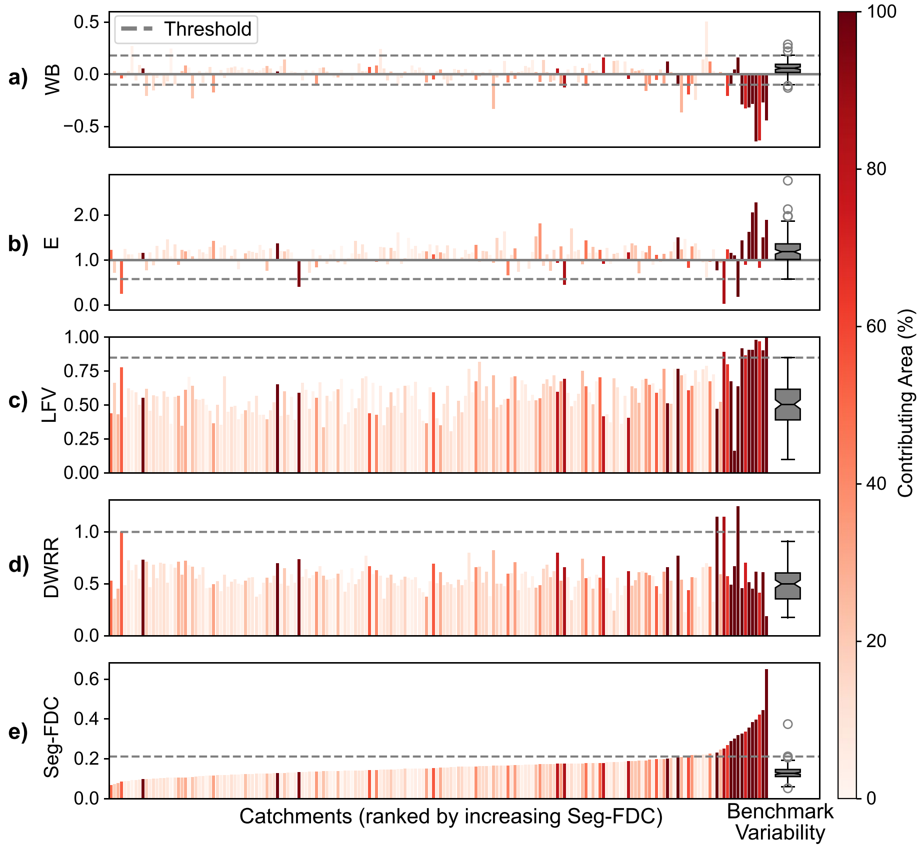

Figure 8. Bar charts which demonstrate the signature values recorded in the reservoir catchment sample. Catchments are ordered by increasing Segmentation of the Flow Duration Curve (Seg-FDC) signature (panel e). The same order is used for all other signatures (a–d) to enable comparison across plots. Benchmark variability is displayed in gray boxplots to the right of the reservoir sample. Reservoir catchments are colored by their contributing area and signature thresholds are marked by the gray dashed line(s) for each metric.

Using thresholds from the set of benchmark catchments, we detect significant flow alteration in 40 of the 186 reservoir catchments. Catchments with the highest degree of alteration, or those flagged by multiple signatures, usually also have high contributing area (>70%) and normalized upstream capacity (>0.2). In line with other studies, this finding highlights the importance of a reservoirs size and location for determining the magnitude of flow alteration at a given downstream gauge location (Arheimer et al., 2017; Cipollini et al., 2022; Jumani et al., 2022; Ruhi et al., 2019; Singer, 2007). These catchment descriptors could therefore be useful for environmental flow planning and forecasting significant flow alteration (Grantham et al., 2014). However, there are several exceptions to this pattern, where the nuances of individual reservoir operation schemes highlight the difficulties involved in generalizing the downstream impacts of reservoirs (Turner et al., 2020). We find examples of large reservoirs with high contributing area having a non-distinguishable impact on downstream flow (e.g., the Dee at Bala Lake which has a contributing area of 80% and normalized upstream capacity of 0.29 but has no significant alteration), as well as identifying flow alteration at locations significantly far from a reservoir outflow (e.g., the Carron at Headswood which despite contributing area of 10% and normalized upstream capacity of 0.09 is flagged by both the WB and Seg-FDC signatures). Importantly, in those catchments where we do not detect significant alteration, we acknowledge that this does not mean reservoir operations are not influencing flow, rather their impact cannot be detected at the downstream gauge with the signatures we have used.

As found in previous studies (Ferrazzi & Botter, 2019; Ruhi et al., 2019; Singer, 2007), our results highlight the importance of using a suite of signatures. None of the reservoir catchments are above/below the benchmark thresholds for all five signatures, one is picked up by four of the five signatures (the Brenig at the Llyn Brenig outflow; 67003; picked up by all but the WB signature) and 10 catchments exceed the benchmark thresholds for three of the five metrics. The WB signature (WB) detects the largest number of catchments (28), but this signature alone still only detects 70% of the total impacted catchments.

6.2. How Are Reservoirs Impacting the Flow Regime?

Using our suite of signatures, we find that reservoirs across Great Britain can induce deficits in the WB, alter flow variability and manipulate streamflow elasticity, aligning with findings elsewhere in the literature (Döll et al., 2009; Maynard & Lane, 2012; Tebakari et al., 2012; Tijdeman et al., 2018). We see the most widespread impacts on the WB and FDC, and suggest that accounting for pre-defined reservoir releases and abstractions will be essential for adequately simulating flow downstream of reservoirs in impacted catchments. In light of water scarcity and changing patterns of rainfall and evapotranspiration (Dobson et al., 2020; Watts et al., 2015), we also highlight the importance of accounting for a reservoirs compensation flow requirements, which in many cases dominate the low flow regime.

Whilst water resource catchments are detected by all five metrics, hydropower catchments only show significant alterations to the WB. These catchments induce both water deficits and surpluses, which in some cases, suggests that they exchange water between one another. In agreement with Rougé et al. (2019) this confirms that multi-reservoir coordination can be a vital aspect of local and regional reservoir operation and consideration of the propagation/dissipation effects on the flow regime through the river network is important (Singer, 2007). These apsects may be missed when considering reservoirs in isolation. We hypothesize that in many cases hydropower gauges are not detected by the remaining metrics due to a smaller (or lack of) influence from compensation flows. This requirement is most dominant at water resource reservoirs (Black et al., 2005) and as well as inducing flat segments in the FDC, it drastically reduces the LFV in water resource catchments.

6.3. Implications for Hydrological Modeling

By using signatures to detect reservoir-impacted catchments, this study has provided a large-scale framework to identify where current hydrological modeling practices are missing vital reservoir representation and to inform the development of a reservoir operation scheme. The signatures proposed in this study can be used to add local observational insight into tailored reservoir operation schemes, and to tune parameters based on the diagnostic power of the metrics extracted from downstream flow.

Our WB signature can provide an indication of how abstraction volumes relate to total streamflow, whilst the Seg-FDC metric can identify routine release volumes, and the LFV signature can pinpoint where compensation flow dominates the flow regime and estimate its magnitude. Figure S4 and Text S4 in Supporting Information S1 provide an example of the diagnostic capability of the signatures for inferring reservoir operations at the Vyrnwy Reservoir (54003). As well as for the definition of reservoir operation schemes, signatures might also be used to evaluate simulated streamflow after reservoirs have been included in a large-scale hydrological model, as each signature can link to a different parameter from the operation scheme. This approach to model evaluation has significant advantages over commonly used aggregate measures of performance (e.g., Nash Sutcliffe Efficiency or Mean Squared Error) which often struggle to isolate the influence of specific model components on the output (McMillan, 2020; Yilmaz et al., 2008).

Furthermore, many of our results have confirmed the notion that generic operation schemes (such as those which are defined based on reservoir use categories) may miss key differences in reservoir operation (Masaki et al., 2017). For example, for reservoirs categorized as "water resource" reservoirs, we found a cluster of three catchments in Wales (the Clywedog at Bryntail, Brenig at the Llyn Brenig outflow, and Tryweryn at the Llyn Celyn outflow; 54081, 67003 and 67017) with much higher DWRR signatures than the remaining water resource reservoirs. Here, abstractions are carried out downstream of the gauges, and although reservoirs are still significantly altering downstream flow variability, we observe no changes to the overall WB (unlike the deficits seen elsewhere). As well as the DWRR, the downstream abstractions can also be identified by the unnatural peaks in the monthly runoff coefficient and Q_{80} in summer months. This behavior is not seen in the other catchments with water resource reservoirs (where abstractions are directly taken from reservoirs) and highlights a difference that should not be ignored (as is often the case in generic schemes) when introducing reservoirs into a large-scale hydrological model.

6.4. Future Work and Limitations

Although this suite of signatures aims to highlight the most significant impacts of reservoirs on the flow regime, this is not exhaustive. 76% of the reservoirs in the UK reservoir inventory are designed for water resources (Durant & Counsell, 2018), and consequently, the hydrological signatures introduced here have bias toward the effects of this type of management. Similarly, the signatures are also based on several assumptions surrounding the climate, hydrology and reservoir management practices of Great Britain. In many other locations signatures may have to consider the specific impacts of flood control, hydropower or irrigation reservoirs in more detail (Arheimer & Lindstrom, 2014; Ferrazzi & Botter, 2019), and may find differing management practices reduce the applicability of this suite of metrics. Both the Seg-FDC and LFV signatures look for deviations in a seasonal climatic regime, whilst the WB signature assumes that catchments have a largely closed WB. These assumptions may not always hold in other locations, and we hope that the future application of these signatures across more catchments will help to inform the generalizability of the metrics. The signature thresholds we have defined in this study are also specific to Great Britain, although following a similar procedure in other countries could lead to the definition of new thresholds, and we suggest that this may be a focus for future work.

We also suggest future work should focus on developing the threshold definition process. Here we adopt a simple method which, whilst largely successful, could be enhanced to better identify reservoir catchments with significant alteration. In some cases we find reservoir catchments to exhibit notably different behavior to the benchmark sample when considered in the context of their annual precipitation (see Figures 4c and 7a), but these are not detected by thresholds based solely on the range of benchmark variability. To overcome this we suggest that in future it may be preferable to develop a threshold which varies with climatic, or geological variability, or to adopt a classification based technique which increases the discriminatory power of the signatures. Whilst our two samples of catchments were deemed to have a comparable spread of climatic and geological variables, in some cases we still had to exclude small clusters of catchments from the threshold definition. Although this could be improved by a more advanced threshold approach, this also emphasizes the importance of using two comparable catchment samples. Future work might also consider calculating the signatures over different time periods and consider their applicability to data-scarce regions where the robustness of the signatures may be affected by missing data. A simple sensitivity analysis of our results to timeseries length and percentage of missing data suggest that our approach would (overall) produce similar results in a more data-scarce environment (see Text S6 and Table S1 in Supporting Information S1), but this would benefit from further testing. In this study we also assumed that reservoir operations were static over time, which is unlikely to be the case.

Finally, to test the diagnostic ability of our signatures we recommend that further work should apply them to the definition and development of reservoir operation schemes within large-scale hydrological models. Incorporating reservoirs into hydrological models may significantly influence flow simulations, particularly under drought conditions, which is increasingly relevant given projections of increasing water scarcity and changing patterns of rainfall and evapotranspiration (Dobson et al., 2020; He et al., 2017; Watts et al., 2015).

7. Conclusions

This study introduces a novel suite of hydrologic signatures that can be used to detect and quantify reservoir-induced flow alteration solely from downstream flow timeseries. We have demonstrated the use of these hydrological signatures in a new framework that aims to detect and estimate the magnitude of reservoir-driven flow alteration and have demonstrated its feasibility by applying the framework nationally across Great Britain. This methodology differs from others of its kind for its minimal data requirements, large-scale applicability and diagnostic power. We find that in Great Britain, the main impacts on the flow regime are driven by abstractions and periods of constant release, where the compensation flow is particularly significant. The magnitude of alteration can be related to a catchments contributing area and normalized upstream capacity, where these catchment descriptors have potential for predicting the degree of flow alteration experienced at a downstream catchment. We hope these signatures will facilitate the diagnostic evaluation of reservoir operation schemes built into hydrological models, and that in Great Britain, the knowledge gained from this study will aid the development of national-scale reservoir representation, emphasizing the locations at which our current modeling practices may be insufficient.

Data Availability Statement

The outputs of this study (signature values and catchment descriptors) can be found in the Supporting Information (Data Set S1). The code for calculating the signatures from this paper and producing the associated plots has been published by Salwey (2023) through Zenodo and is accessible at https://doi.org/10.5281/zenodo.7712750. The UK Reservoir Inventory (Durant & Counsell, 2018), CEH-GEAR (Tanguy et al., 2021) and CHESS-PE (Robinson et al., 2017) datasets are all publicly available through the CEH Environmental Information Data Centre. Flow timeseries and catchment BFI can be obtained on the NFRA website. Geological information was obtained from the British Geological Survey. The DECIPHeR model code from Coxon et al., 2019 has been provided by Coxon and Dunne (2019) through Zenodo and is accessible at https://doi.org/10.5281/zenodo.2604120, this was used to obtain the data for calculating the catchment descriptors.

Acknowledgments

This work is funded by a NERC GW4+ Doctoral Training Partnership studentship from the Natural Environmental Research Council (NE/S007504/1) and Wessex Water Ltd. Francesca Pianosi is partially funded by the Engineering and Physical Sciences Research Council (EPSRC) "Living with Environmental Uncertainty" Fellowship (EP/R007330/1) and Gemma Coxon was supported by a UKRI Future Leaders Fellowship award (MR/V022857/1). Michael Bliss Singer was supported by The National Science Foundation (BCS-1660490, EAR-1700555) and the Department of Defense's Strategic Environmental Research and Development Program (RC18-1006). We gratefully acknowledge discussions with Ross Woods, Thorsten Wagener and Jim Freer which strengthened the analysis of this paper.

References

Adam, J. C., Haddeland, I., Su, F., & Lettenmaier, D. P. (2007). Simulation of reservoir influences on annual and seasonal streamflow changes for the Lena, Yenisei, and Ob' rivers. *Journal of Geophysical Research*, *112*(D24), D24114. https://doi.org/10.1029/2007jd008525

Addor, N., Nearing, G., Prieto, C., Newman, A. J., Le Vine, N., & Clark, M. P. (2018). A ranking of hydrological signatures based on their predictability in space. *Water Resources Research*, *54*(11), 8792–8812. https://doi.org/10.1029/2018wr022606

Arheimer, B., Donnelly, C., & Lindstrom, G. (2017). Regulation of snow-fed rivers affects flow regimes more than climate change. *Nature Communications*, *8*(1), 1–9. https://doi.org/10.1038/s41467-017-00092-8

Arheimer, B., & Lindstrom, G. (2014). Electricity vs ecosystems - Understanding and predicting hydropower impact on Swedish river flow. In *Evolving water resources systems: Understanding, predicting and managing water-society interactions* (Vol. 364, pp. 313–319). https://doi.org/10.5194/piahs-364-313-2014

Baker, D. B., Richards, R. P., Loftus, T. T., & Kramer, J. W. (2004). A new flashiness index: Characteristics and applications to Midwestern Rivers and streams 1. *JAWRA Journal of the American Water Resources Association*, *40*(2), 503–522. https://doi.org/10.1111/j.1752-1688.2004.tb01046.x

Black, A. R., Rowan, J. S., Duck, R. W., Bragg, O. M., & Clelland, B. E. (2005). DHRAM: A method for classifying river flow regime alterations for the EC Water Framework Directive. *Aquatic Conservation: Marine and Freshwater Ecosystems*, *15*(5), 427–446. https://doi.org/10.1002/aqc.707

Bloomfield, J. P., Gong, M., Marchant, B. P., Coxon, G., & Addor, N. (2021). How is Baseflow Index (BFI) impacted by water resource management practices? *Hydrology and Earth System Sciences*, *25*(10), 5355–5379. https://doi.org/10.5194/hess-25-5355-2021

Brown, C. M., Lund, J. R., Cai, X. M., Reed, P. M., Zagona, E. A., Ostfeld, A., et al. (2015). The future of water resources systems analysis: Toward a scientific framework for sustainable water management. *Water Resources Research*, *51*(8), 6110–6124. https://doi.org/10.1002/2015wr017114

Brunner, M. I. (2021). Reservoir regulation affects droughts and floods at local and regional scales. *Environmental Research Letters*, *16*(12), 124016. https://doi.org/10.1088/1748-9326/ac36f6

Budyko, M. I. (1974). *Climate and life*. Academic press.

Cipollini, S., Fiori, A., & Volpi, E. (2022). A new physically based index to quantify the impact of multiple reservoirs on flood frequency at the catchment scale based on the concept of equivalent reservoir. *Water Resources Research*, *58*(2), e2021WR031470. https://doi.org/10.1029/2021WR031470

Coxon, G., & Dunne, T. (2019). uob-hydrology/DECIPHeR: DECIPHeR V1 (v1.0) [Software]. Zenodo. https://doi.org/10.5281/zenodo.2604120

Coxon, G., Freer, J., Lane, R., Dunne, T., Knoben, W. J. M., Howden, N. J. K., et al. (2019). DECIPHeR v1: Dynamic fluxEs and ConnectIvity for Predictions of HydRology. *Geoscientific Model Development*, *12*(6), 2285–2306. https://doi.org/10.5194/gmd-12-2285-2019

Dang, T. D., Chowdhury, A. F. M. K., & Galelli, S. (2020). On the representation of water reservoir storage and operations in large-scale hydrological models: Implications on model parameterization and climate change impact assessments. *Hydrology and Earth System Sciences*, *24*(1), 397–416. https://doi.org/10.5194/hess-24-397-2020

Dobson, B., Coxon, G., Freer, J., Gavin, H., Mortazavi-Naeini, M., & Hall, J. W. (2020). The spatial dynamics of droughts and water scarcity in England and Wales. *Water Resources Research*, *56*(9), e2020WR027187. https://doi.org/10.1029/2020WR027187

Döll, P., Fiedler, K., & Zhang, J. (2009). Global-scale analysis of river flow alterations due to water withdrawals and reservoirs. *Hydrology and Earth System Sciences*, *13*(12), 2413–2432. https://doi.org/10.5194/hess-13-2413-2009

Durant, M., & Counsell, C. (2018). Inventory of reservoirs amounting to 90% of total UK storage [Dataset]. NERC Environmental Information Data Centre. https://doi.org/10.5285/f5a7d56c-cea0-4f00-b159-c3788a3b2b38

Estrany, J., Garcia, C., & Batalla, R. J. (2010). Hydrological response of a small Mediterranean agricultural catchment. *Journal of Hydrology*, *380*(1–2), 180–190. https://doi.org/10.1016/j.jhydrol.2009.10.035

Euser, T., Winsemius, H. C., Hrachowitz, M., Fenicia, F., Uhlenbrook, S., & Savenije, H. H. G. (2013). A framework to assess the realism of model structures using hydrological signatures. *Hydrology and Earth System Sciences*, *17*(5), 1893–1912. https://doi.org/10.5194/hess-17-1893-2013

Farmer, D., Sivapalan, M., & Jothityangkoon, C. (2003). Climate, soil, and vegetation controls upon the variability of water balance in temperate and semiarid landscapes: Downward approach to water balance analysis. *Water Resources Research*, *39*(2), 1035. https://doi.org/10.1029/2001wr000328

Ferrazzi, M., & Botter, G. (2019). Contrasting signatures of distinct human water uses in regulated flow regimes. *Environmental Research Communications*, *1*(7), 071003. https://doi.org/10.1088/2515-7620/ab3324

Gao, Y. X., Vogel, R. M., Kroll, C. N., Poff, N. L., & Olden, J. D. (2009). Development of representative indicators of hydrologic alteration. *Journal of Hydrology*, *374*(1–2), 136–147. https://doi.org/10.1016/j.jhydrol.2009.06.009

Gibbins, C. N., Soulsby, C., Jeffries, M. J., & Acornley, R. (2001). Developing ecologically acceptable river flow regimes: A case study of Kielder reservoir and the Kielder water transfer system. *Fisheries Management and Ecology*, *8*(6), 463–485. https://doi.org/10.1046/j.1365-2400.2001.00274.x

Gnann, S. J., Coxon, G., Woods, R. A., Howden, N. J. K., & McMillan, H. K. (2021). TOSSH: A toolbox for streamflow signatures in hydrology. *Environmental Modelling & Software*, *138*, 104983. https://doi.org/10.1016/j.envsoft.2021.104983

Grantham, T. E., Viers, J. H., & Moyle, P. B. (2014). Systematic screening of dams for environmental flow assessment and implementation. *BioScience*, *64*(11), 1006–1018. https://doi.org/10.1093/biosci/biu159

Gupta, J., & van der Zaag, P. (2008). Interbasin water transfers and integrated water resources management: Where engineering, science and politics interlock. *Physics and Chemistry of the Earth*, *33*(1–2), 28–40. https://doi.org/10.1016/j.pce.2007.04.003

Gustard, A., Bullock, A., & Dixon, J. (1992). *Low flow estimation in the United Kingdom*. Institute of Hydrology.

Haddeland, I., Skaugen, T., & Lettenmaier, D. P. (2006). Anthropogenic impacts on continental surface water fluxes. *Geophysical Research Letters*, *33*(8), L08406. https://doi.org/10.1029/2006gl026047

Hanasaki, N., Kanae, S., & Oki, T. (2006). A reservoir operation scheme for global river routing models. *Journal of Hydrology*, *327*(1–2), 22–41. https://doi.org/10.1016/j.jhydrol.2005.11.011

Harrigan, S., Hannaford, J., Muchan, K., & Marsh, T. J. (2018). Designation and trend analysis of the updated UK Benchmark Network of river flow stations: The UKBN2 dataset. *Hydrology Research*, *49*(2), 552–567. https://doi.org/10.2166/nh.2017.058

He, X., Wada, Y., Wanders, N., & Sheffield, J. (2017). Human water management intensifies hydrological drought in California. *Geophysical Research Letters*, *44*(4), 1–19. https://doi.org/10.1002/2016GL071665

Jones, H., Morris, B., Cheney, C., Brewerton, L., Merrin, P., Lewis, M., et al. (2000). *The physical properties of minor aquifers in England and Wales* (British Geological Survey Technical Report, WD/00/4, p. 234). Environment Agency R&D Publication 68, Derby, Saxon Graphics Ltd.

Jones, J. A., & Hammond, J. C. (2020). River management response to multi-decade changes in timing of reservoir inflows, Columbia River Basin, USA. *Hydrological Processes*, *34*(25), 4814–4830. https://doi.org/10.1002/hyp.13910

Jumani, S., Deitch, M. J., Valle, D., Machado, S., Lecours, V., Kaplan, D., et al. (2022). A new index to quantify longitudinal river fragmentation: Conservation and management implications. *Ecological Indicators*, *136*, 108680. https://doi.org/10.1016/j.ecolind.2022.108680

Lehner, B., Liermann, C. R., Revenga, C., Vorosmarty, C., Fekete, B., Crouzet, P., et al. (2011). High-resolution mapping of the world's reservoirs and dams for sustainable river-flow management. *Frontiers in Ecology and the Environment*, *9*(9), 494–502. https://doi.org/10.1890/100125

Magilligan, F. J., & Nislow, K. H. (2005). Changes in hydrologic regime by dams. *Geomorphology*, *71*(1–2), 61–78. https://doi.org/10.1016/j.geomorph.2004.08.017

Masaki, Y., Hanasaki, N., Biemans, H., Schmied, H. M., Tang, Q., Wada, Y., et al. (2017). Intercomparison of global river discharge simulations focusing on dam operation-multiple models analysis in two case-study river basins, Missouri-Mississippi and Green-Colorado. *Environmental Research Letters*, *12*(5), 055002. https://doi.org/10.1088/1748-9326/aa57a8

Maynard, C. M., & Lane, S. N. (2012). Reservoir compensation releases: Impact on the Macroinvertebrate Community of the Derwent River, Northumberland, UK-A longitudinal study. *River Research and Applications*, *28*(6), 692–702. https://doi.org/10.1002/rra.2557

McMillan, H. (2020). Linking hydrologic signatures to hydrologic processes: A review. *Hydrological Processes*, *34*(6), 1393–1409. https://doi.org/10.1002/hyp.13632

McMillan, H., Gnann, S. J., & Araki, R. (2022). Large scale evaluation of relationships between hydrologic signatures and processes. *Water Resources Research*, *58*(6), e2021WR031751. https://doi.org/10.1029/2021WR031751

McMillan, H., Gueguen, M., Grimon, E., Woods, R., Clark, M., & Rupp, D. E. (2014). Spatial variability of hydrological processes and model structure diagnostics in a 50 km^2 catchment. *Hydrological Processes*, *28*(18), 4896–4913. https://doi.org/10.1002/hyp.9988

Ming, B., Liu, P., Chang, J. X., Wang, Y. M., & Huang, Q. (2017). Deriving operating rules of pumped water storage using multiobjective optimization: Case study of the Han to Wei Interbasin Water Transfer Project, China. *Journal of Water Resources Planning and Management*, *143*(10), 05017012. https://doi.org/10.1061/(Asce)Wr.1943-5452.0000828

Murgatroyd, A., & Hall, J. W. (2020). The resilience of inter-basin transfers to severe droughts with changing spatial characteristics. *Frontiers in Environmental Science*, *8*, 571647. https://doi.org/10.3389/fenvs.2020.571647

Oldham, L. D., Freer, J., Coxon, G., Howden, N., Bloomfield, J. P., & Jackson, C. (2022). Evidence-based requirements for perceptualising intercatchment groundwater flow in hydrological models. *EGUsphere*, 1–33. https://doi.org/10.5194/egusphere-2022-529

Qiu, J. L., Yang, Q. C., Zhang, X. S., Huang, M. Y., Adam, J. C., & Malek, K. (2019). Implications of water management representations for watershed hydrologic modeling in the Yakima River basin. *Hydrology and Earth System Sciences*, *23*(1), 35–49. https://doi.org/10.5194/hess-23-35-2019

Richter, B. D., Baumgartner, J. V., Powell, J., & Braun, D. P. (1996). A method for assessing hydrologic alteration within ecosystems. *Conservation Biology*, *10*(4), 1163–1174. https://doi.org/10.1046/j.1523-1739.1996.10041163.x

Robinson, E., Blyth, E., Clark, D., Comyn-Platt, E., Finch, J., & Rudd, A. (2017). Climate hydrology and ecology research support system meteorology dataset for Great Britain (1961-2015) [CHESS-met] v1. 2. https://doi.org/10.5285/b745e7b1-626c-4ccc-ac27-56582e77b900

Rougé, C., Reed, P. M., Grogan, D. S., Zuidema, S., Prusevich, A., Glidden, S., et al. (2019). Coordination and Control: Limits in standard representations of multi-reservoir operations in hydrological modeling. *Hydrology and Earth System Sciences Discussions*, *25*(3), 1–37. https://doi.org/10.5194/hess-25-1365-2021

Ruhi, A., Hwang, J., Devineni, N., Mukhopadhyay, S., Kumar, H., Comte, L., et al. (2019). How does flow alteration propagate across a large, highly regulated basin? Dam attributes, network context, and implications for biodiversity. *Earth's Future*, *10*(6), e2021EF002490. https://doi.org/10.1029/2021EF002490

Salwey, S. (2023). saskiasalwey/Reservoir_Impact_Signatures: Reservoir impact signatures (Version v2) [Dataset]. Zenodo. https://doi.org/10.5281/zenodo.7712750

Sankarasubramanian, A., Vogel, R. M., & Limbrunner, J. F. (2001). Climate elasticity of streamflow in the United States. *Water Resources Research*, *37*(6), 1771–1781. https://doi.org/10.1029/2000wr900330

Sawicz, K., Wagener, T., Sivapalan, M., Troch, P. A., & Carrillo, G. (2011). Catchment classification: Empirical analysis of hydrologic similarity based on catchment function in the eastern USA. *Hydrology and Earth System Sciences*, *15*(9), 2895–2911. https://doi.org/10.5194/hess-15-2895-2011

Scarrott, R., Reed, D., & Bayliss, A. (1999). Indexing the attenuation effect attributable to reservoirs and lakes. In *Flood estimation handbook* (Vols. 4–5). Institute of Hydrology.

Shin, S., Pokhrel, Y., & Miguez-Macho, G. (2019). High-resolution modeling of reservoir release and storage dynamics at the continental scale. *Water Resources Research*, *55*(1), 787–810. https://doi.org/10.1029/2018wr023025

Singer, M. B. (2007). The influence of major dams on hydrology through the drainage network of the Sacramento River basin, California. *River Research and Applications*, *23*(1), 55–72. https://doi.org/10.1002/rra.968

Steyaert, J. C., Condon, L. E., Turner, S. W. D., & Voisin, N. (2022). ResOpsUS, a dataset of historical reservoir operations in the contiguous United States. *Scientific Data*, *9*(1), 1–8. https://doi.org/10.1038/s41597-022-01134-7

Tang, Y. M., Chen, L. H., & She, Z. Y. (2021). Evaluation of instream ecological flow with consideration of ecological responses to hydrological variations in the downstream Hongshui River Basin, China. *Ecological Indicators*, *130*, 108104. https://doi.org/10.1016/j.ecolind.2021.108104

Tanguy, M., Dixon, H., Prosdocimi, I., Morris, D. G., & Keller, V. D. J. (2021). Gridded estimates of daily and monthly areal rainfall for the United Kingdom (1890-2019) [CEH-GEAR]. https://doi.org/10.5285/dbf13dd5-90cd-457a-a986-f2f9dd97e93c

Tebakari, T., Yoshitani, J., & Suvanpimol, P. (2012). Impact of large-scale reservoir operation on flow regime in the Chao Phraya River basin, Thailand. *Hydrological Processes*, *26*(16), 2411–2420. https://doi.org/10.1002/hyp.9345

Tijdeman, E., Hannaford, J., & Stahl, K. (2018). Human influences on streamflow drought characteristics in England and Wales. *Hydrology and Earth System Sciences*, *22*(2), 1051–1064. https://doi.org/10.5194/hess-22-1051-2018

Turner, S. W. D., Doering, K., & Voisin, N. (2020). Data-driven reservoir simulation in a large-scale hydrological and water resource model. *Water Resources Research*, *56*(10), e2020WR027902. https://doi.org/10.1029/2020WR027902

Turner, S. W. D., & Galelli, S. (2016). Water supply sensitivity to climate change: An R package for implementing reservoir storage analysis in global and regional impact studies. *Environmental Modelling & Software*, *76*, 13–19. https://doi.org/10.1016/j.envsoft.2015.11.007

Turner, S. W. D., Steyaert, J. C., Condon, L., & Voisin, N. (2021). Water storage and release policies for all large reservoirs of conterminous United States. *Journal of Hydrology*, *603*, 126843. https://doi.org/10.1016/j.jhydrol.2021.126843

Van Beek, L., Wada, Y., & Bierkens, M. F. (2011). Global monthly water stress: 1. Water balance and water availability. *Water Resources Research*, *47*(7), W07517. https://doi.org/10.1029/2010WR009791

Van Loon, A. F., Gleeson, T., Clark, J., Van Dijk, A. I., Stahl, K., Hannaford, J., et al. (2016). Drought in the Anthropocene. *Nature Geoscience*, *9*(2), 89–91. https://doi.org/10.1038/ngeo2646

Van Oel, P. R., Krol, M. S., Hoekstra, A. Y., & de Araujo, J. C. (2008). The impact of upstream water abstractions on reservoir yield: The case of the Orós Reservoir in Brazil. *Hydrological Sciences Journal*, *53*(4), 857–867. https://doi.org/10.1623/hysj.53.4.857

Vörösmarty, C. J., Meybeck, M., Fekete, B., Sharma, K., Green, P., & Syvitski, J. P. (2003). Anthropogenic sediment retention: Major global impact from registered river impoundments. *Global and Planetary Change*, *39*(1–2), 169–190. https://doi.org/10.1016/S0921-8181(03)00023-7

Wada, Y., Bierkens, M. F. P., de Roo, A., Dirmeyer, P. A., Famiglietti, J. S., Hanasaki, N., et al. (2017). Human-water interface in hydrological modelling: Current status and future directions. *Hydrology and Earth System Sciences*, *21*(8), 4169–4193. https://doi.org/10.5194/hess-21-4169-2017

Wagener, T., Sivapalan, M., Troch, P. A., McGlynn, B. L., Harman, C. J., Gupta, H. V., et al. (2010). The future of hydrology: An evolving science for a changing world. *Water Resources Research*, *46*(5), W05301. https://doi.org/10.1029/2009wr008906

Wang, C., Wang, S., Fu, B. J., & Zhang, L. (2016). Advances in hydrological modelling with the Budyko framework: A review. *Progress in Physical Geography: Earth and Environment*, *40*(3), 409–430. https://doi.org/10.1177/0309133315620997

Wang, W., Li, H. Y., Leung, L. R., Yigzaw, W., Zhao, J. S., Lu, H., et al. (2017). Nonlinear filtering effects of reservoirs on flood frequency curves at the regional scale. *Water Resources Research*, *53*(10), 8277–8292. https://doi.org/10.1002/2017wr020871

Watts, G., Battarbee, R. W., Bloomfield, J. P., Crossman, J., Daccache, A., Durance, I., et al. (2015). Climate change and water in the UK - Past changes and future prospects. *Progress in Physical Geography: Earth and Environment*, *39*(1), 6–28. https://doi.org/10.1177/0309133314542957

Yadav, M., Wagener, T., & Gupta, H. (2007). Regionalization of constraints on expected watershed response behavior for improved predictions in ungauged basins. *Advances in Water Resources*, *30*(8), 1756–1774. https://doi.org/10.1016/j.advwatres.2007.01.005

Yassin, F., Razavi, S., Elshamy, M., Davison, B., Sapriza-Azuri, G., & Wheater, H. (2019). Representation and improved parameterization of reservoir operation in hydrological and land-surface models. *Hydrology and Earth System Sciences*, *23*(9), 3735–3764. https://doi.org/10.5194/hess-23-3735-2019

Yilmaz, K. K., Gupta, H. V., & Wagener, T. (2008). A process-based diagnostic approach to model evaluation: Application to the NWS distributed hydrologic model. *Water Resources Research*, *44*(9), W09417. https://doi.org/10.1029/2007wr006716

Yin, X. A., Yang, Z. F., & Petts, G. E. (2011). Reservoir operating rules to sustain environmental flows in regulated rivers. *Water Resources Research*, *47*(8), W08509. https://doi.org/10.1029/2010wr009991

Yin, Z., Ottle, C., Ciais, P., Zhou, F., Wang, X. H., Jan, P., et al. (2021). Irrigation, damming, and streamflow fluctuations of the Yellow River. *Hydrology and Earth System Sciences*, *25*(3), 1133–1150. https://doi.org/10.5194/hess-25-1133-2021

Reference From the Supporting Information

United Utilities. (2022). Final drought plan.