ResORR: A Globally Scalable and Satellite Data-driven Algorithm for River Flow Regulation due to Reservoir Operations

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Abstract: We propose a globally scalable algorithm, ResORR (Reservoir Operations driven River Regulation), to predict regulated river flow and tested it over the heavily regulated basin of the Cumberland River in the US. ResORR was found able to model regulated river flow due to upstream reservoir operations of the Cumberland River. Over a mountainous basin dominated by high rainfall, ResORR was effective in capturing extreme flooding modified by upstream hydropower dam operations. On average, ResORR improved regulation river flow simulation by more than 50% across all performance metrics when compared to a hydrologic model without a regulation module. ResORR is a timely software algorithm for understanding human regulation of surface water as satellite-estimated reservoir state is expected to improve globally with the recently launched Surface Water and Ocean Topography (SWOT) mission.

Keywords: River Regulation, Reservoir Operations, Hydrological Modeling, Satellite Remote Sensing

Highlights:

- A globally scalable algorithm, called ResORR, to predict regulated flow from naturalized flow and upstream reservoir storage is proposed.
- ResORR requires globally available satellite-based reservoir storage and satellite-forced hydrologic model.
- ResORR was tested on the heavily regulated river basin of the Cumberland river in Tennessee, USA.
- On average, ResORR improved regulation river flow simulation by more than 50% across all performance metrics when compared to a hydrologic model without a regulation module.
- ResORR is a timely software algorithm that can be further improved of its skill with reservoir storage data from the Surface Water and Ocean Topography (SWOT) mission.

Data and Software Availability: The model code developed during this study is available on GitHub (https://github.com/UW-SASWE/ResORR) under the MIT license. Documentation on ResORR is available at - https://resorr.readthedocs.io/en/latest/? The github repository was created by first author Pritam Das (pdas47@uw.edu). Author's experimental CPU environment used Linux Ubuntu OS, Intel Xeon Scalable Gold 6242 at 2.8GHz (16-Core), 192GB RAM.

1. Introduction

Rivers have provided humans with food, water and energy security since human civilization first started to take shape in ancient valleys of Tigris-Euphrates, Indus and Nile rivers. This has only been made possible by means of control structures such as dams and reservoirs, which allow storage and release of water from the river according to human needs. Usually, water from the river is stored in reservoirs when the river naturally has higher flows, resulting in a net reduction in the downstream flow of the river. This storage is driven by human needs such as flood control or to meet future freshwater demand when natural availability may be insufficient. The converse happens during naturally occurring periods of low flows, when release of water from reservoirs artificially increases the downstream flow rate during the dry season to meet demand for water. This regulation of surface water, in the form of alteration of the streamflow from its natural pattern of discharge under pristine conditions, can be termed as river regulation.

River regulation can change how the basin responds to a hydro-meteorological event in the form of precipitation or snowmelt, affecting its natural variability and streamflow timing. For instance, Wisser and Fekete (2009) found that the average residence time has increased by 42 days globally over the past century due to construction of reservoirs. Such disruption and alteration of natural conditions is even more profound at a regional scale, for instance, Bonnema and Hossain, (2017) note about 11-30% streamflow alteration in the Mekong basin, with the residence time of reservoirs varying from 0.09 to 4.04 years. Vu et al., (2021) estimate that reservoirs in the Mekong hold 50% of its dry season flow and 83% of its wet season flow. As a result, the high flows of the Mekong-river have reduced by 31%, while the low-flows have increased by 35%.

River regulation can also have serious ecological repercussions. For instance, the unique annual flow reversal of the Tonle Sap River (TSR) leading to filling up the Tonle Sap Lake (TSL) during the wet season and draining it during dry season may cease to exist if the flood pulse of the Mekong River dampens by 50% and is delayed by a month (Pokhrel et al., 2018). The absence of this unique flow reversal may have a negative impact on aquatic biodiversity, particularly for fisheries and paddy planting (Marcaida et al., 2021). Similarly, in European rivers, high-flows appear to be down by 10% while low-flows are up by 8% (Biemans et al., 2011). Negative consequences are not limited to only ecological aspects but can also influence the regional demand-and-supply of resources, with the potential to escalate pre-existing water conflicts. The construction and filling up of the Grand Ethiopian Renaissance Dam (GERD) on the Nile River has been a source of contention between Ethiopia and the other riparian countries – Egypt and Sudan. Eldardiry and Hossain, (2021) estimate that if unprepared, the High Aswan Dam (HAD) – a dam of existential importance to Egypt for its water-food-energy security – may take anywhere from 2 years to 7 years to fully recover following the filling-up of the GERD. Although, they also optimistically estimate that with cooperation and planning between the riparian countries, the recovery period can be limited to immediate 2 years.

Apart from the direct alteration of streamflow timing of rivers, regulation due to dam and reservoir operations can have an indirect effect on other components of the eco-system. For instance, river regulation disturbs the natural sediment flow, resulting in a net reduction in sediment deposition along shorelines of rivers, estuaries and oceans (Dunn et al., 2019; Li et al., 2021). River water temperature anomalies owing to thermal stratification in reservoirs have also been widely recognized (Ahmad et al., 2021; Cheng et al., 2020). Considering the sensitivity of aquatic life to the water temperature changes (Caissie, 2006), river regulation can negatively affect the environmental suitability for aquatic organisms (Cheng et al., 2022). Such negative environmental consequences are a direct result of human decisions – which many consider necessary to support the demands of a rapidly growing population. A better understanding of human regulation of river flow, exacerbated by a changing climate and increasing freshwater demand, is urgently required to ensure a sustainable future.

The coupled nature of human-water resources has led to developments in explicitly modeling reservoir operations in Large-Scale Hydrological Models (LHMs) and Global Circulation Models (GCMs) (Hanasaki et al., 2018; Wada et al., 2017). Existing methods to represent human activities in hydrological models rely on modeling the optimal reservoir release based on operating parameters such as the design role of the reservoir (Hanasaki et al., 2006), land-water management schemes, downstream demand for water and energy (Alcamo et al., 2003; Biemans et al., 2011; Haddeland et al., 2006; Vanderkelen et al., 2022). Many of these human activities are often assumed or 'parameterized' due to lack of sufficient observational data on reservoir operations. Using such a parameterized approach, Zhou et al. (2016) found that in highly regulated basins, such as the Yellow and the Yangtze rivers, the seasonal reservoir storage variations can contribute up to 72% of the variability of the basin's total storage. While such key insights can be obtained using generic schemes of reservoir operations, the underlying assumption of optimal reservoir operations may not always hold true. Stakeholders and reservoir managers must often deviate from optimal operating conditions based on a variety of reasons, such as adapting to regional water and energy demands, new hydro-political reality, environmental regulations, and changing weather and climate patterns that result in river flow to exceed the bounds of pre-dam historical flow records.

In the past, modeling human decisions of reservoir operations using parameterizations or criteria-based assumptions has been the primary way for characterizing river-regulation due to a lack of publicly available observations on dam operations. However, to better understand river regulation, which is representative of the intricacies of operation of individual reservoirs, we need to characterize and quantify river regulation grounded in observations of reservoir operations (Biswas et al., 2021; Das et al., 2022; Zhou et al., 2016). Earth observing satellites, with their vantage of space and a multi-decadal record of observations on reservoir operations now provide an opportunity to fill this data availability gap by inferring reservoir operations from space (Bonnema & Hossain, 2017).

Studies have used satellite remote sensing-based reservoir operations monitoring techniques to model the resulting regulation of streamflow. Reservoir releases are obtained by typically assuming water mass balance at the reservoirs, by modeling the inflow and storage change of the reservoirs. For instance, Yoon & Beighley, (2015) and Yoon et al., (2016) model the inflow at reservoirs in the Cumberland basin due to surface runoff and upstream releases using the Hillslope River Routing (HRR) model. The storage change is estimated using historical record of reservoir operations by Yoon & Beighley, (2015) and by simulating SWOT-like storage change estimates by Yoon et al., (2016). The performance of the simulated discharges in both cases improves with the inclusion of reservoirs. Han et al., (2020) also take the approach of simulating reservoir operations by deriving the operating curve of reservoirs using satellite observations. Reservoir releases from upstream reservoirs were added to the inflow of downstream reservoirs in a cascade reservoir system in the Mekong River basin. However, in this case the inclusion of upstream releases did not improve the performance of regulated streamflow estimates drastically. Dong et al., (2023) use historical satellite observations of reservoir water level to calibrate parameters of a reservoir operation scheme. The reservoir releases are routed downstream using the Coupled Land Surface and Hydrologic Model System (CLHMS). All the existing studies rely on specific hydrological routing models to route the runoff and releases downstream. There doesn't exist a method to leverage existing hydrological model setups, that are usually calibrated using data that is only accessible to local stakeholders. Furthermore, the availability of high frequency satellite observations near-real time provides an opportunity to move away from parameterization and simulation driven estimation of reservoir operations to a direct observation-based approach for modeling reservoir releases. Rather than relying on parameterized or criteria-based assumptions of reservoir operations, we can now use actual observation-based reservoir operations to quantify the regulation of flow in physical models. Because satellite observations today can track the dynamic state of reservoirs comprising surface area, water surface elevation, evapotranspiration losses, storage change and even outflow (Cooley et al., 2021; Hossain et al., 2017; Lee et al., 2010; Okeowo et al., 2017; Zhao et al., 2022), there is now a stronger argument to move away from assumptions and parameterizations in representing human flow regulation in physical hydrologic models.

Satellites such as the Landsat, Sentinel, and Jason series have been extensively monitoring hydrologically relevant aspects of the Earth's surface, such as surface reflectance and elevation, at the global scale. For instance, Gao et al., (2012) were able to recreate storage variations of large reservoirs using observations from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite platform. Cooley et al., (2021) used NASA's ICESat-2 satellite observations of water level height to estimate that about 3/5th of the Earth's surface water storage variability takes place due to reservoirs. Moreover, the recently launched terrestrial hydrology-focused Surface Water and Ocean Topography (SWOT) satellite is now expected to improve the monitoring of surface water resources at an unprecedented scale and accuracy (Biancamaria et al., 2016). Together, these Earth-observing satellites provide an opportunity to independently track various aspects of the hydrological cycle, including reservoir operations (Bonnema & Hossain, 2017; Hossain et al., 2017). Using multi-sensor satellite data on surface water, we can now build comprehensive, distributed, and scalable modeling platforms to simulate reservoir-river systems. The Reservoir Assessment Tool (RAT) is one such modeling platform that can estimate reservoir fluxes, comprising inflow to the reservoir, storage change, evaporative losses and outflow, solely using satellite data and hydrological modeling (Biswas et al., 2021; Das et al., 2022). More recent developments have made it easier to monitor reservoirs using RAT, further democratizing the availability of surface water data at the granular level for regulated river systems (Minocha et al., 2023). This has allowed for both global and regional scale studies of the anthropogenic impact on terrestrial water storage (Biswas & Hossain, 2022) and floods (Suresh et al., 2024), especially in the regions of the world that lack a robust data collection and sharing infrastructure.

Considering the importance and urgency of an observations-driven understanding of river regulation, there is now a need to develop methods to quantify river regulation due to reservoir operations that can be scaled globally based on publicly and globally available satellite observables. The wide availability of satellite-based reservoir operations data will only keep increasing with the recent launch of the SWOT mission that is optimized for surface water tracking, particularly for lakes and reservoirs. Here, the multi-satellite observations used by RAT to estimate storage change (Das et al., 2022) can be directly used as observations to quantify river regulation, obviating the need to separately model reservoir operations based on parameterizations or operating assumptions, which can be both difficult and unrepresentative of actual reservoir operations. Given the availability of multi-decadal satellite observations of surface water that are now made widely accessible due to advancements in information technology, we are now uniquely positioned to predict regulated flow at a level of granularity that was not possible before. Estimation of river regulation grounded in observational data inherently represents the actual or likely decisions made by reservoir operators. The primary research question that this paper addresses is – *How can river regulation due to operation of reservoirs be formulated in a globally scalable format using primarily satellite observations?* The objectives of the paper are as follows:

1. To develop a globally scalable river-regulation algorithm based on satellite observables or satellite derived reservoir data for predicting the human regulation of surface water.
2. To investigate incorporation of the river-regulation algorithm in the RAT modeling platform for regulated rivers, and quantify its skill in capturing river flow regulation at a basin scale.

2. Study area and Data

2.1. The Cumberland River in Tennessee, US

The Cumberland River is highly regulated by a system of 10 major dams and reservoirs with varying primary use cases, making it one of the most heavily regulated basins. The United States Army Corps of Engineers (USACE) Nashville District, own and operate 10 such multi-purpose dam/reservoir projects on the Cumberland River, with the first dams being built in 1950s. These dams are used for hydropower generation, flood control, recreation, commercial navigation, public water supply, and fisheries and wildlife management – bringing in immense economic benefits to the region (Robinson, 2019). Figure 1 compares the daily discharge in the Cumberland River for two time-periods corresponding to unregulated conditions (1916-1920) and regulated conditions (2016-2020). The effect of regulation can be clearly seen in the figure, in the form of reduced range and variability in the discharge hydrograph. Studies suggest that such regulation has caused a sharp decline in the population and species variety of Mussels in the basin, which were plentiful when the river was unregulated (Neel & Allen, 1964; Tippit et al., 1995; Wilson & Clark, 1914). In addition to the highly regulated status of the basin, the availability of long periods of in-situ observational data from the operating agencies makes this basin an ideal test bed for investigating anthropogenic river regulation (Bonnet et al., 2015).

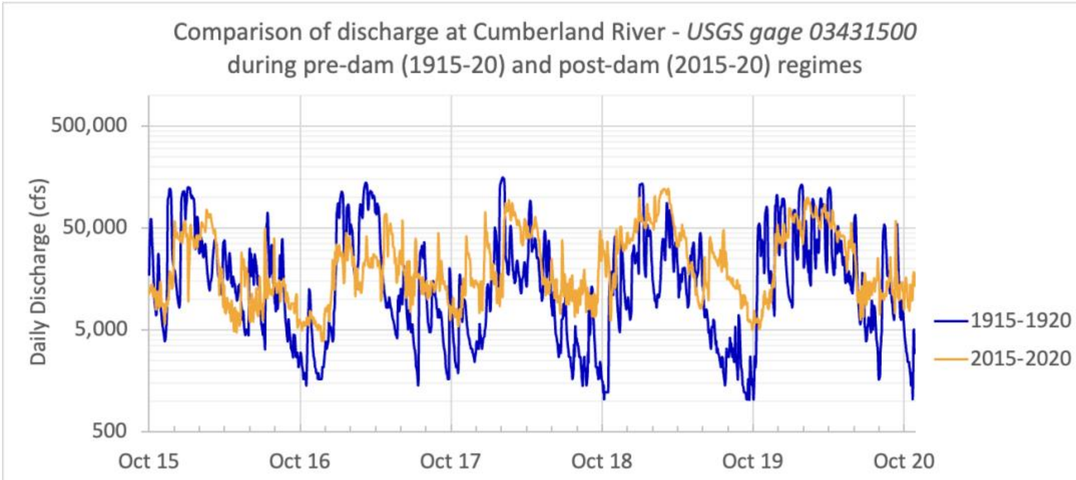

Figure 1: Comparison of 5 years of daily discharge during (a) unregulated conditions, prior to construction and operation of major dams (1916-1920), and (b) regulated conditions, as observed in the Cumberland River near Nashville, TN. The flow rate in a regulated regime has a markedly attenuated peak-trough range – with low flows rarely dropping below 5000 cfs as compared to the unregulated regime when flow rates naturally used to drop to 1000 cfs. Source: United States Geological Survey (USGS).

Originating in the Appalachian Mountains, the Cumberland River flows westwards through the states of Kentucky and Tennessee in the United States, draining a region of about 18,000 sq. miles (~45,000 sq. km), before merging into the Ohio River. Ten dams – Martins Fork, Laurel, Wolf Creek, Dale Hollow, Cordell Hull, Center Hill, Old Hickory, J. Percy Priest, Cheatham, and Barkley dams – are operated by USACE, with some additional dams operated by the Tennessee Valley Authority (TVA) (Robinson, 2019). Limited by the availability of in-situ reservoir operations data, 8 of the USACE owned dams were included in this study. Based on the conclusions of the study, the authors believe that the results are not affected by the exclusion of the 2 USACE dams owing to their relatively insignificant (Martin's Fork dam) to no storage (Cheatham dam). The region generally has a temperate, warm, and humid climate, with most of the precipitation occurring from December through May.

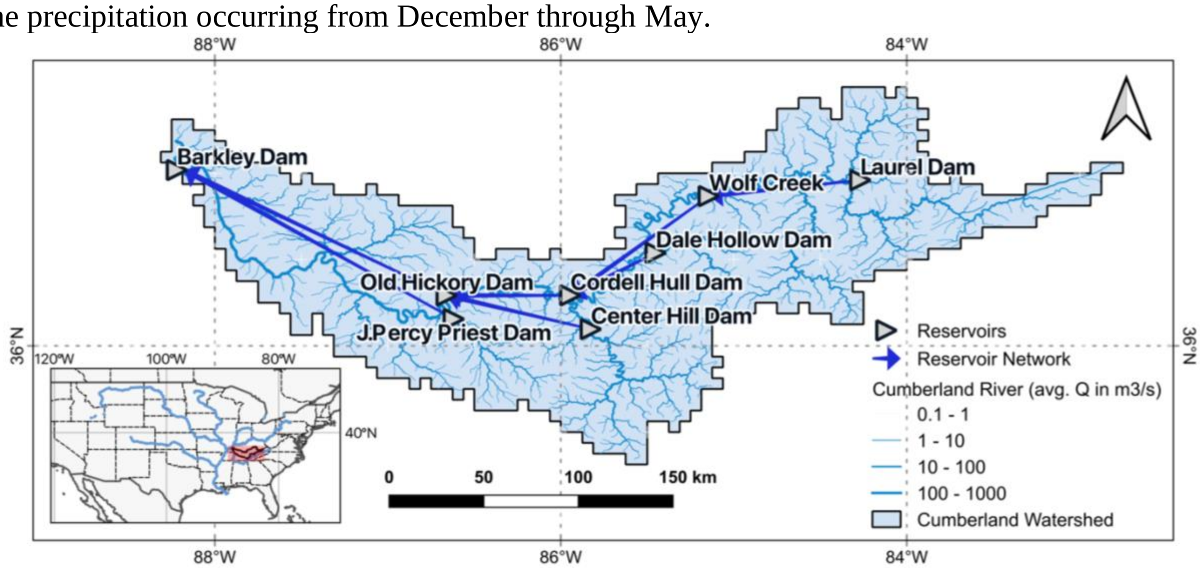

Figure 2: Map of the Cumberland basin, showing locations of the reservoirs, the reservoir network and the location of the Cumberland basin in the US.

2.2. In-situ and satellite observations of reservoir dynamics

To develop, test and validate the river-regulation algorithm, observed in-situ data pertaining to reservoir operations – inflow, outflow, and storage – were used, which were obtained from the ResOpsUS (Steyaert et al., 2022) dataset. This dataset is a compilation of in-situ reservoir operations data for 679 major dams in the US, including 8 of the USACE dams in the Cumberland basin and one dam operated by the TVA, until November 2019. Daily storage change was calculated using the storage values in the dataset for all but 2 dams – Old Hickory and J. Percy Priest – which had missing storage data from July 2015 onwards. The storage change for these reservoirs were obtained by subtracting the reported Outflow from the Inflow ($\Delta S = I - O$). Readers are referred to section 7.2 for more discussion on this data preparation step. The in-situ data was also used to force the river-regulation model in certain experiments to compare the sensitivity of the river-regulation model to the accuracy of input data – a detailed discussion is provided in section 4.1. Additionally, the in-situ Area-Elevation Curve (AEC) of all the USACE reservoirs were also obtained from the Access to Water Resources Data – Corps Water Management System (CWMS) Data Dissemination tool (USACE, n.d.).

The latest version of Reservoir Assessment Tool (RAT 3.0) was used to obtain the storage change and river flow under pristine (naturalized) conditions (assuming no upstream reservoirs). Originally developed by Biswas et al., (2021), the RAT framework is designed to improve access to information on reservoir dynamics, especially with recent developments leading to both a higher performance and accessibility (Das et al., 2022; Minocha et al., 2023). Using the default hydrological model of RAT, Variable Infiltration Capacity (VIC) (Liang et al., 1994), rainfall-runoff modeling was performed at a 0.0625° spatial resolution. The inflow to each reservoir's location under natural conditions was estimated using the VIC-Routing model (Lohmann et al., 1998), which uses the linearized Saint-Venant equation to route streamflow within the watershed. The default VIC parameters, and sources of temperature and wind data used in RAT 3.0 were used to force the hydrological model. The precipitation was obtained from the ERA-5 reanalysis dataset (Hersbach et al., 2020). It must be noted here that the VIC-based reservoir inflow in RAT 3.0 does not take upstream reservoir operations into account, and hence the need to develop a model that can supplement the RAT framework by taking upstream regulation into consideration. A detailed discussion on how the hydrological model's estimated inflow in pristine conditions is used in the river regulation model can be found in section 3.1. Since the in-situ AEC of the TVA-owned reservoir was not available, the default AEC option in RAT 3.0 was applied based on the Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM) (Earth Resources Observation And Science (EROS) Center, 2017).

3. Methods

3.1. Reservoir Operations driven River Regulation (ResORR) – Conceptual algorithm

The core assumption of the ResORR algorithm is that the volume of water entering the reservoir, Inflow (I), is composed of two components – natural and regulated. The Natural Runoff

(NR) is defined as the component of surface runoff that flows naturally into the reservoir without passing through any upstream reservoirs. Similarly, the Regulated Runoff (RR) is the component of surface runoff that first gets intercepted by an upstream reservoir before being released based on the reservoir's operations policy. The partitioning of the inflow to a reservoir is defined by the following equation,

$$I = NR + RR \tag{1}$$

Essentially, the problem of estimating the inflow at any reservoir is decomposed into the two parts of estimating the natural and regulated components of the incoming streamflow. A detailed discussion on estimating these sub-components of inflow is provided later in the section. The estimated inflow to a reservoir in this scheme will, hence, be affected by regulation due to upstream reservoir operations.

For example, consider the example of a two-reservoir system (A and B), where reservoir B is downstream of reservoir A, depicted in the schematic in Figure 3(a). In this scenario, the inflow at reservoir B would have contributions from the outflow of the upstream reservoir A in the form of RR (i.e., $RR \neq 0$), in addition to the NR. On the other hand, since reservoir A has no upstream reservoirs, the inflow to the reservoir would be fully natural, i.e., $RR = 0$ and $I = NR$.

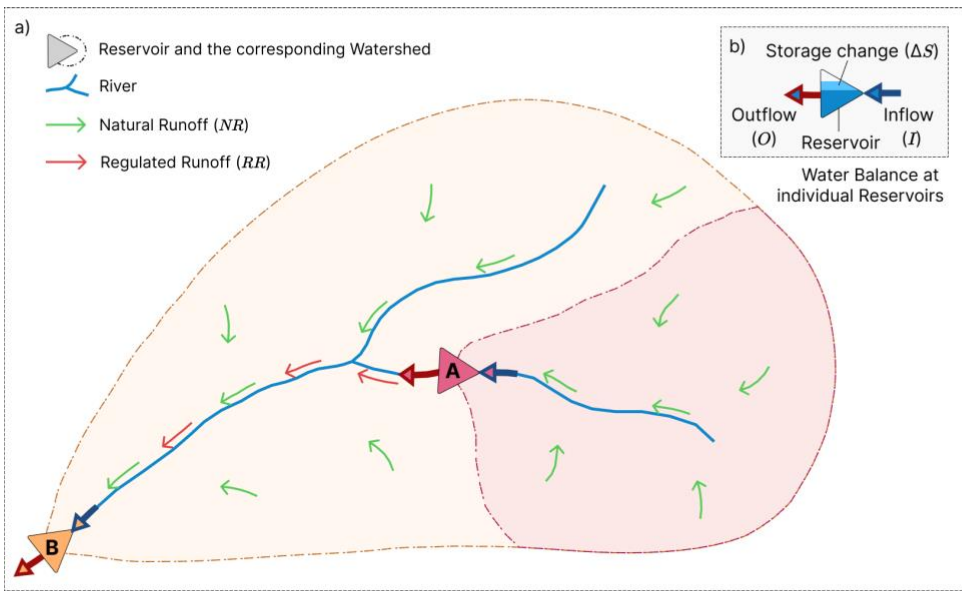

Figure 3: Conceptual schematic of the ResORR model. Panel (a) depicts the flow of surface runoff and streamflow, along with the contribution of the natural (green arrows) and regulated (red arrows along the stream) components, referred to in this paper as Natural Runoff (NR) and Regulated Runoff (RR) to the Inflow ($I = NR + RR$) to a reservoir. Panel (b) describes the components of the water balance equation ($O = I - \Delta S$) used at the reservoir to obtain the outflow from the reservoir, which is treated as the regulated component of the downstream streamflow.

As discussed above, the RR is defined as the component of inflow to a reservoir due to upstream reservoir releases. It is estimated as the sum of all Outflow (O) of the upstream reservoirs.

$$RR_i = \sum_j^N O_j \tag{2}$$

Where RR_i is the incoming Regulated Runoff to reservoir i; O_j is the Outflow from the j^{th} upstream reservoir; N is the total number of upstream dams for reservoir i.

The NR is defined as the volume of water inflow to the reservoir due to surface runoff unaffected by any upstream reservoir operations., i.e., the generated surface runoff drains directly to the reservoir, without passing through any other reservoir. This surface runoff is generated in the part of the watershed which is not shared by any other upstream dams. For instance, in Figure 3, the orange and red shaded regions of the watershed will generate the NR for reservoirs B and A respectively. The NR for a reservoir can be estimated using the theoretical inflow into a reservoir if there were no upstream dams, which is referred to as the Theoretical Natural Runoff (TNR) in this paper. The Theoretical Natural Runoff (TNR) refers to the inflow to a reservoir if none of the upstream dams existed. The TNR can be calculated using the following equation –

$$TNR_i = NR_i + \sum_{j}^{N} NR_j \tag{3}$$

Where, TNR_i is the Theoretical Natural Runoff of reservoir i; NR_i is the Natural Runoff to reservoir i; and N is the total number of upstream dams of reservoir i along the same river network. For example, in the schematic in Figure 3, the TNR of reservoir A and B would be NR_A and $NR_B + NR_A$ respectively.

Since the TNR represents streamflow into a reservoir in pristine conditions (without considering upstream reservoirs), it is analogous to the modeled inflow at reservoirs using traditional hydrologic models which do not take reservoir operations into account. The NR of any reservoir can be obtained by rearranging the terms of (3, and calculating the NR for reservoirs by iteratively moving downstream for each time-step. The NR for any reservoir can hence be obtained using the TNR of the reservoir, and the NR of the upstream reservoirs using the following equation –

$$NR_i = TNR_i - \sum_{j}^{N} NR_j \tag{4}$$

Using the estimated NR and RR components, the inflow to a reservoir under regulated conditions is then calculated using (1. Using the storage change of the reservoir, obtained either in-situ or using satellite estimates, the outflow can then be calculated using the water balance equation –

$$O = I - \Delta S \tag{5}$$

Where O, I and ΔS are the outflow, inflow and storage change of a reservoir respectively. In the current form of the mass balance equation of the reservoir fluxes, the evaporative losses are not considered. For semi-arid to arid parts of the world, such as the Western US, the Middle East, and Australia, evaporation from reservoirs can play an important role in reservoir water balance (Zhao et al. 2022). For the application ResORR over the Cumberland basin, which has a humid subtropical climate and is a relatively wet region. Here, the evaporative losses from reservoirs do not play a major role in the water balance and was hence safely ignored. For instance, the evaporation from the Wolf Creek reservoir is about only 1-2% of the total inflow to the reservoir annually.

These equations were solved for the reservoirs mapped in

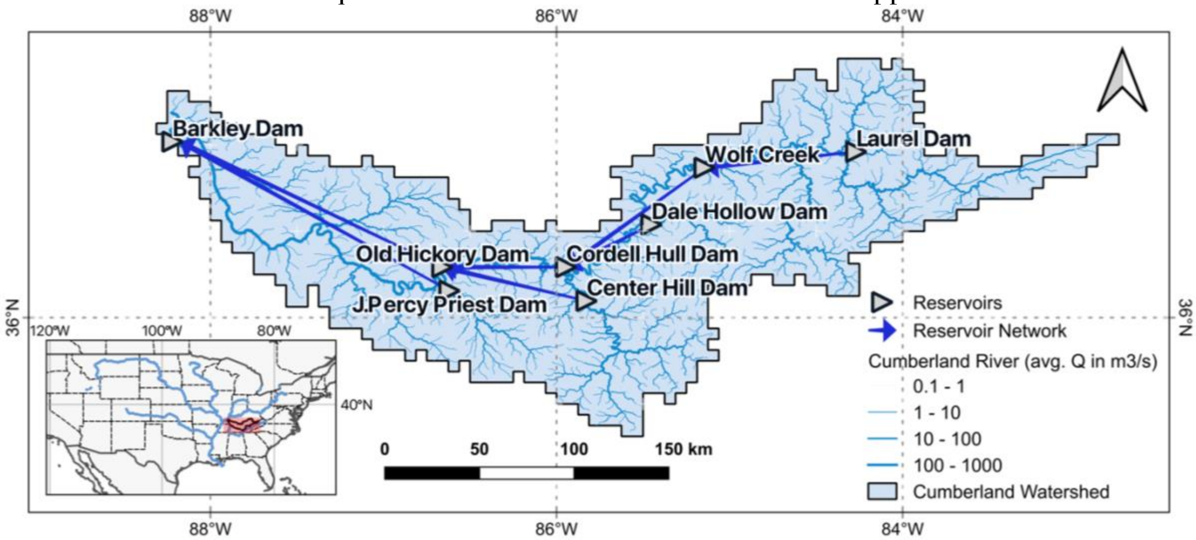

Figure 2 by traversing down the network of reservoirs for each time-step. Since the TNR is obtained by routing water through the watershed, the travel time of water between the reservoirs is inherently considered in the subsequent calculations that depend on this routed hydrograph. The proposed methodology is not a routing scheme, rather it operates on precomputed hydrographs obtained by routing water through a watershed using traditional routing algorithms. The proposed algorithm uses observational reservoir operations, either from in-situ or satellite platforms to adjust the streamflow for regulation due to upstream reservoir operations in a post-processing fashion.

To assess the performance of the model, sensitivity to uncertainties in the model inputs, and generally investigate the limitations of the model, various experiments were setup which are discussed in section 4.1. To test the theoretical robustness of the proposed river regulation algorithm as a mass conserving scheme, we set up a two inter-connected linear reservoir problem where outflow is proportional to water storage and according to the elevation head available at the outlet. Using this set up we generated regulated inflow that should theoretically happen at the second reservoir (reservoir 2) based on storage and regulation effect of the upstream reservoir (reservoir 1). Consequently, we tested the algorithm’s ability to mimic the same regulated inflow to reservoir 2 using storage and upstream unregulated inflow of reservoir 1 that would be available in a globally scalable manner from satellite observations and modeling platforms such as RAT 3.0. Our algorithm demonstrated perfect theoretical consistency as a mass conserving scheme. More details on this theoretical robustness check of the ResORR algorithm are provided in the appendix (section 7).

3.2. Reservoir network

The reservoir network represents the connectivity of the reservoirs in the model and is represented by a directed tree data structure, with the nodes representing the reservoirs and the links depicting their connectivity, while preserving the order of reservoirs. The model first topologically sorts the reservoir network, to order them such that the water balance computations of upstream reservoirs are performed before the subsequent downstream reservoir. At each time-step, the model iterates over the topologically sorted reservoir network, and solves the series of equations discussed in 3.1.

The reservoir network is generated using the location of reservoirs and the Global Dominant River Tracing (DRT) dataset (Wu et al., 2011). Since the river-regulation model is designed as an add-on to the RAT framework, the script to generate the reservoir network can use the inputs and intermediary outputs of RAT to generate the reservoir network.

4. Experiments and Results

4.1. River regulation experiment setups using in-situ data

The ResORR algorithm is fully described by equations (1)-(5), which uses estimates of streamflow under pristine conditions from a hydrological model. However, the uncertainties in the estimations of hydrological model may propagate as uncertainty in the river-regulation model. Experiments were performed to isolate the performance of the core of the algorithm, its ability to partition the inflow between the natural and regulated components using in-situ observations in place of hydrological model and satellite estimates. By reducing uncertainties in certain parts of the algorithm, the performance of the individual components could be investigated, shedding light on the sensitivity of the algorithm components to the input data accuracy. Moreover, the observed in-situ ΔS was used in these experiments to gauge the baseline performance of ResORR using best available reservoir operations data, avoiding the higher uncertainties normally associated with satellite estimates of storage change.

To investigate the strengths and weaknesses of ResORR, especially in terms of scalability, the experiment designs were iteratively modified and updated in order from E1 to E4 over the period of 2015-2019. Details about the experiment designs and the rationale behind the experiments are summarized in Table 1.

Table 1: Summary of the experiments performed on the river regulation model along with the corresponding symbols used in the performance comparison plot (Figure 4).

Exp.	In-situ data used	Description	Rationale
E1 ○	ΔS	In-situ ΔS was used in eqn. (5) to estimate O. VIC hydrologic model was not calibrated for estimating natural inflow.	Uncertainties in satellite estimates of ΔS are minimized in this experiment.
E2 □	O	Observed O was used in eqn. (3) to estimate RR.	Uncertainties in otherwise estimated O, due to uncertainties in modeled I are minimized. The RR obtained as such would reflect the "theoretically" best estimate of incoming regulated streamflow.
E3 △	I, ΔS	Observed I was used in eqn. (4) only at the most upstream dam, where NR = TNR = I. In-situ ΔS was used in (5) to estimate O.	For upstream-most reservoirs all the incoming streamflow would be due to natural runoff, hence, by using the observed I, the uncertainties due to modeled I are minimized. The RR in this

			case would reflect the "theoretical best estimate" of the downstream regulated streamflow.
E4	ΔS	In-situ ΔS resampled to a 16-day frequency was used in eq (5) to estimate O. The VIC hydrological model, forced with satellite data, was calibrated at upstream most dams of Center Hill Dam, Dale Hollow Dam, and Laurel Dam.	The modeled inflow to the upstream most dams were calibrated using the observed inflow, essentially, minimizing the uncertainties at the upstream boundary of the reservoir network. This represents the ResORR in its globally scalable form under the scenario of perfect ΔS. The resampling to 16-day frequency was done to simulate the observational frequency of the satellite used later in this study.

The regulated inflows obtained at the 4 dams, which have at least one upstream dam were compared against the observed inflow at those same dams. The comparison statistics measuring the performance of the river regulation model against observed inflow data are summarized in Figure 4. To understand how the river regulation algorithm is performing under various input scenarios and assumptions, one should compare the relative position of the symbols for each dam along the horizontal axis only. The TNR, obtained from the VIC hydrological model are denoted using grey and black circles, corresponding to the streamflow modeled using default parameter values and calibrated parameters. Formulation of performance metrics are provided in Appendix (section 7).

Figure 4: River regulation model performance for E* experiments using in-situ reservoir dynamics data.

Compared to the uncalibrated VIC streamflow estimates, the performance of the river regulation model in the E1 experiment in improving the accuracy of regulated inflow seems to be reduced. In other words, ResORR using in-situ ΔS, but with uncalibrated VIC flow at upstream most location does not improve the skill in predicted regulated inflow at downstream dam locations. However, on taking a closer look at the hydrographs comparing modeled inflow, TNR and observed inflow in Figure 5, it is apparent that the variability in the observed inflow, which is regulated inflow, is more closely replicated by the variability in the modeled inflow than the TNR. This likely suggests that even though the overall performance of ResORR gets reduced as a regulated streamflow predictor, the signature of human regulation is still captured well.

While analyzing the observed inflow hydrographs of two consecutive dams (Cordell Hull and Old Hickory dams) in Figure 6, a closer relationship between the downstream inflow and upstream outflow can be noted. It is clear that the upstream outflow plays a dominant role in dictating the downstream and regulated inflow at the next downstream dam as would be normally expected in the event of no lateral flow diversion. This relationship is further explored in the E2 experiment, where the daily in-situ outflow is used to calculate the RR to the downstream dam. Overall, the results improve across the board in the E2 experiment, underlining the role of upstream reservoir releases in predicting the downstream regulated streamflow. The E2 experiment also stresses the importance of having high accuracy estimates of reservoir storage data.

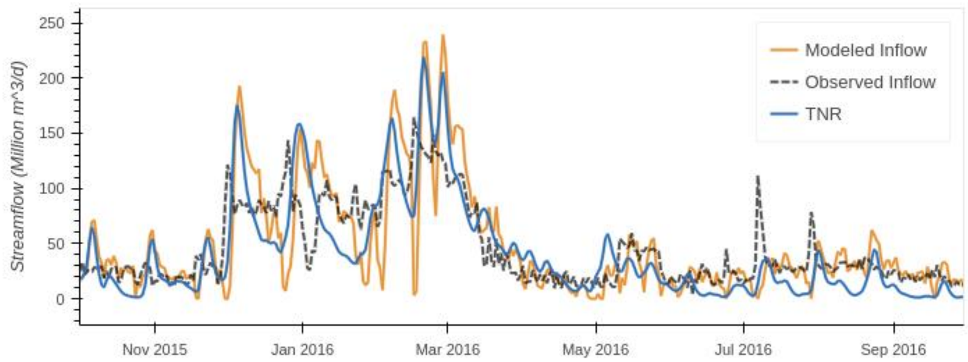

Figure 5: Hydrographs comparing the Modeled, Observed and TNR at Old Hickory Dam, which is the second most downstream dam in the network. The observed inflow is regulated inflow.

In the E3 experiment, the observed inflow to the upstream most dams was used as the NR. In most cases, the performance of the streamflow predictions still improved when adjusted for upstream regulation, as compared to the TNR. While this experiment suggests that if the accuracy of inflow estimates at the upstream most boundary conditions are accurate, that can improve the regulated streamflow estimates along that downstream network as well. Following this, the final E4 experiment, representative of the performance of the proposed and scalable river regulation model under accurate ΔS was performed. Here the VIC hydrological model was calibrated using the observed inflow at the upstream most dams. The result of this experiment shows overall improvement for nearly all the reservoirs. These results indicate that using in-situ reservoir dynamics, specifically storage change, and inflow hydrograph modeled without considering reservoirs (TNR) can be used to improve the performance of downstream streamflow estimates.

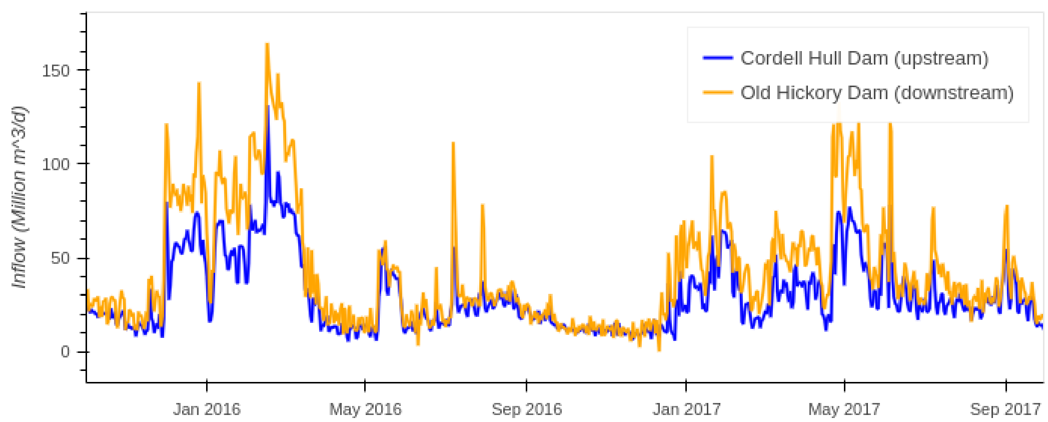

Figure 6: Observed inflows at two consecutive dams. The upstream Cordell Hull Dam drains into the downstream Old Hickory Dam, with the effect of upstream reservoir dynamics.

Moreover, the experiment results also shed light on the relationship between the model performance and the number of upstream dams. For instance, taking the case of the Wolf Creek dam (7.4 km^3 storage capacity), which only has one upstream dam (Laurel Dam, 0.5 km^3 storage capacity), the performance of the model does not improve as significantly as compared to the TNR. On the other hand, Cordell Hull Dam (run-of-the-river) is highly regulated and has two upstream dams, the Dale Hollow dam (2.1 km^3) and the Wolf Creek dam, and the performance of the streamflow estimates improves significantly by almost 50% across all the dams in the basin.

Overall, the results show that considering the effect of upstream regulation improves the performance of the streamflow estimates at the downstream dams.

4.2. River regulation using satellite estimates of reservoir storage change

Now that E4 results established robustness of the proposed river regulation algorithm, we explore how well ResORR fares with satellite-derived ΔS that will have higher uncertainty. The inundation area of the reservoirs were obtained using the Landsat-8 and Sentinel-1 satellite data from June 2018 to October 2019, using the TMS-OS algorithm described by Das et al., (2022). The storage change of the reservoirs were then obtained using these surface area estimates and in-situ Area-Elevation Curve (AEC), using the following equation –

$$\Delta S_t = \frac{A_t + A_{t-1}}{2} \times (h_t - h_{t-1}) \tag{6}$$

Here the ΔS in equation 6 is the total volumetric storage change, A is the inundation area, and h is the water level height corresponding to the inundation area, obtained using the AEC relationship. The date of satellite observation is denoted by t, with $t-1$ referring to the last satellite observation. For instance, since Landsat-8 has a revisit period of 16 days, the estimated storage change would refer to the volumetric storage change within those 16 days. These storage change estimates were transformed to daily values by linearly distributing the volumetric change over 16 days. Based on the findings of the previous section, the VIC hydrological model was calibrated at the upstream most dams, like the E4 experiment. The modeled inflow as such and the streamflow estimates from VIC were compared against the observed in-situ inflow. The results are summarized in Figure 7.

Similar to the results in the previous section, for the Cordell Hull and Old Hickory, both run-of-the-river dams having upstream dams with large storage capacities, ResORR performance increases significantly across all metrics. For the Wolf Creek dam, adjusting for the upstream Laurel Dam's operations, ResORR performance does not increase as drastically, which can be explained due to the relatively smaller size of the upstream Laurel Dam. In contrast, the performance increases the most for the Cordell Hull Dam, which is preceded by two large dams, Wolf Creek Dam and Dale Hollow dam. The improvement in performance gradually reduces downstream with marginal improvement for the downstream most Barkley Dam. This can be explained by the run-of-the-river nature of the upstream dams, the storage change dynamics of which can be difficult to quantify using satellite observations. Overall, the results suggest that river regulation due to dams can be characterized by the proposed ResORR algorithm using satellite estimates of reservoir storage dynamics. Adjusting for flow regulation due to upstream reservoir storage change improves the overall inflow predictions in a regulated basin.

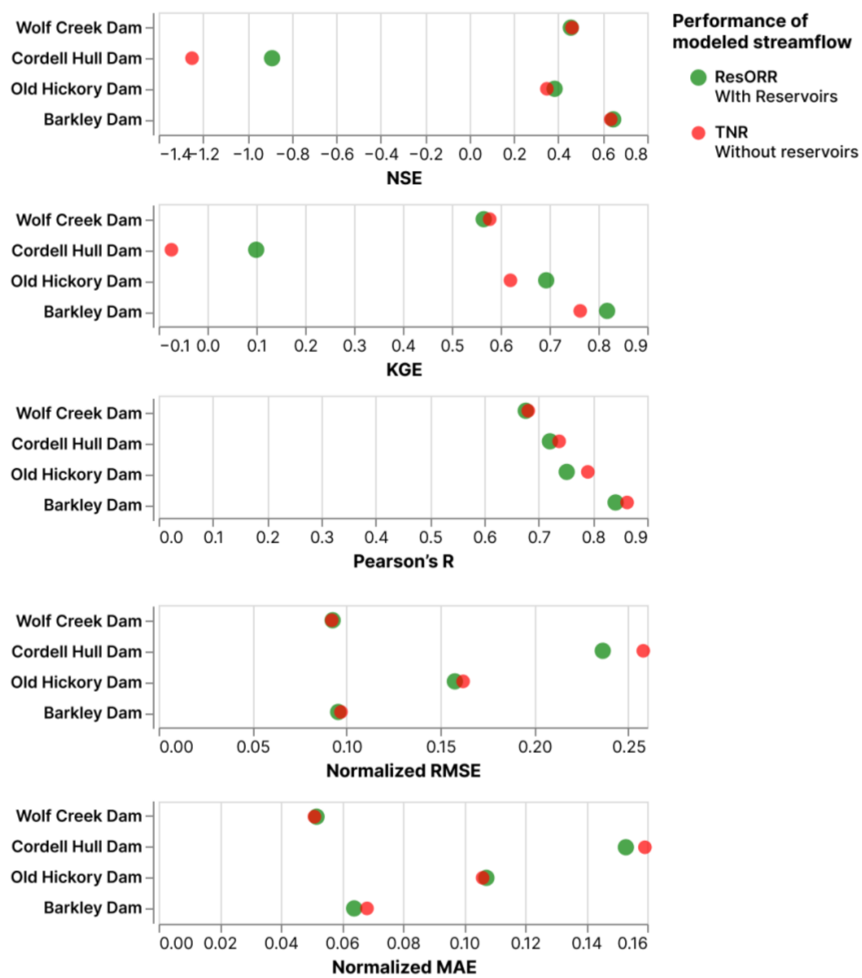

Figure 7: ResORR model performance using satellite derived reservoir storage change.

5. Conclusions and Discussion

Rivers of the 21st century are marked with numerous reservoirs, which store, and release water based on their primary objectives, playing a vital role in providing food, water, and energy security. However, such reservoir operations can alter the natural streamflow patterns, reducing the water availability downstream by storing water during high flows, and *vice versa*. In this study, we developed and tested a scalable river regulation model, ResORR, to predict the regulation of streamflow due to upstream reservoir operations. Overall, we find that adjusting for upstream reservoir operations via storage change improves the accuracy of downstream streamflow predictions. The theoretical basis of the ResORR model was tested using in-situ data in the heavily regulated Cumberland basin. The results stress the importance of having high accuracy estimates of both the storage change and the hydrological model. Moreover, we find that if the hydrological model can be calibrated for boundary conditions of the reservoir network, *i.e.*, at the upstream most dams, significant improvement can be achieved in predicting regulated inflow at all the downstream dam locations.

Currently, the reservoir network is automatically generated using the dam locations and the DRT flow directions, and hence, any inter- or intra-basin diversions between reservoirs or lateral diversions cannot yet be modeled. The regulation caused by reservoirs is also determined by its storage capacity, and in a case where a small reservoir drains into a larger reservoir, the algorithm adds little value to the streamflow predictions. Moreover, if the storage change of the upstream reservoir is relatively low, the performance improvement of regulated streamflow estimation downstream can be limited. Such a case was experienced in a case-study of the devastating flood due to extreme precipitation in the state of Kerala, India, in 2018. Due to high precipitation leading up to the main extreme precipitation event, the reservoirs were already at full supply level. All the incoming inflow due to the extreme precipitation event had to be released by the upstream reservoir, with little to no storage change. Even with these limitations, the ResORR algorithm can play an important role in quantifying the regulation of river flow due to reservoirs in changing the world's river systems.

With advancements in satellite observations-based reservoir dynamics tracking, especially the RAT 3.0, which has democratized access to reservoir operations information, it is now possible to easily track the operations of reservoirs globally. Building on top of the RAT framework, the proposed river regulation algorithm ResORR would also be able to characterize the regulation of river flow using only satellite-tracked reservoir states at the global scale. The algorithm was developed over the Cumberland basin which is in a humid region. The evaporative losses from the reservoirs therefore play a relatively minor role compared to the inflow into the reservoir due to surface runoff. Hence, the evaporative losses were not considered while calculating the outflow. However, the evaporative losses play an important role in arid region. For application over such regions, the evaporation from the reservoirs can be included in the water mass balance of the reservoirs in eq. (5). The ResORR software architecture is also designed to work seamlessly within the RAT framework, i.e., it can run entirely using the RAT model outputs and intermediary files. With this river regulation tool, the RAT framework will be able to not only infer reservoir dynamics, but also quantify the regulation of streamflow caused by the upstream reservoir operations. We can expect ResORR to soon become a truly scalable algorithm based on the globally available reservoir storage change data of unprecedent accuracy from the Surface Water and Ocean Topography mission.

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7. Appendix

7.1. River-regulation algorithm ResORR tested in a theoretical two-reservoir system using synthetic data

A theoretical two inter-connected linear reservoir system with artificially generated headwater flow inputs was used to test the theoretical robustness of the mass conserving and numerical stability of the ResORR algorithm. This classic problem (Figure 8) also helped visualize the outputs of ResORR algorithm and verify if mass balance is maintained.

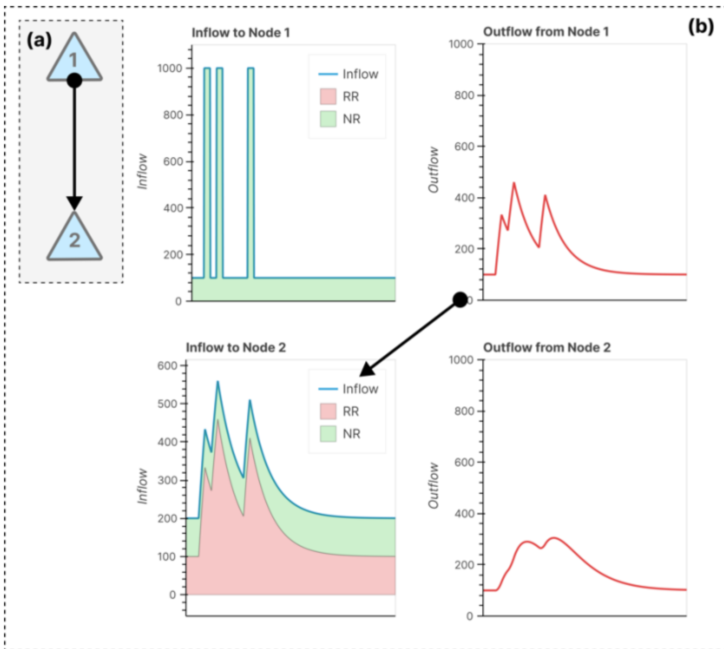

Figure 8: (a) Schematic showing the two-reservoir system setup. The black arrow denotes the direction of flow of water. (b) Hydrographs showing inflow and outflow from nodes 1 and 2. In this case, three input pulses of 1000 L^3/T units were fed into node 1, and its outflow was treated as the inflow to the downstream node 2. The inflow and outflow at node 2 represent the 'theoretical' answer for the ResORR algorithm to be theoretically valid.

A system of two interconnected linear reservoirs were set up, like the schematic shown in Figure 8. To understand how the outflow from an upstream reservoir would affect the inflow to the downstream reservoir, we first generated a synthetic headwater inflow hydrograph for reservoir 1and then applied ResORR to predict the regulated inflow to the downstream reservoir at node 2. Both the reservoirs were provided with a constant water influx of 100 L^3/T units in the form of natural runoff, NR. Additionally, the upstream reservoir, at node 1, was provided with three pulses of high inflow volumes of 1000 L^3/T units. The reservoirs were treated as linear reservoirs, where the outflow from a reservoir at any given time as a linear function of the instantaneous storage, and can be defined as follows –

$$O = K \times S$$

Where, $K\ [T^{-1}]$ is the reaction factor, which determines how quickly the reservoir drains ($K = 0.01$ in this experiment). The outflow from the upstream reservoir at node 1 was then treated as the regulated runoff, RR for the downstream reservoir, node 2. Using the inflows and outflows obtained at both the reservoirs, the storage change was obtained using (5). The theoretical natural runoff, TNR, was also obtained using (3). The ResORR was then run using this simulated storage change and TNR information as inputs, to model the inflow at both the reservoirs. The modeled inflow of ResORR was then compared with the synthetically generated inflow at the downstream node 2, with a perfect match between them. The closure of water balance was also tested by comparing the total inflow volumes in the modeled and synthetic inflow.

7.2. Performance metrics used for assessing ResORR

The following five commonly used performance metrics were used in this study to quantify the skill of the river regulation model -

Metric	Equation	Description
Nash-Sutcliffe Efficiency (NSE) (Nash & Sutcliffe, 1970)	$1-\frac{\sum_{t=1}^{T}(Q_O^t-Q_M^t)^2}{\sum_{t=1}^{T}(Q_O^t-\overline{Q_O})^2}$ Where, Q_O^t and Q_M^t are observed and modeled streamflow respectively. $\overline{Q_O}$ is the mean observed streamflow.	The NSE can vary between $-\infty$ and 1. A value of 1 indicates a perfect match between observed and modeled values. A value of 0 indicates that the model predictions are as performant as using the mean of the observed values as a predictor. Higher values are better.
Kling-Gupta Efficiency (KGE) (Gupta et al., 2009)	$1-\sqrt{(r-1)^2+(\alpha-1)^2+(\beta-1)^2}$ Where, r is the linear correlation between modeled and observed values, $\alpha=\left(\frac{\sigma_M}{\sigma_O}-1\right)^2$, σ_M and σ_O are the standard deviations of the modeled and observed values, $\beta=\left(\frac{\mu_M}{\mu_O}-1\right)^2$, μ_M and μ_O are mean modeled and observed values.	The KGE varies between $-\infty$ and 1. A value of -0.41 indicates model performance equal to using the mean of the observed values as a predictor (Knoben et al., 2019). Higher values are better.
Pearson's R	$\frac{cov(Q_O,Q_M)}{\sigma_O\sigma_M}$ Where, $cov(Q_O,Q_M)$ is the covariance of the observed and modeled values. σ_M and σ_O are the standard deviations of the modeled and observed values	The Pearson's R can vary from -1 to 1, where 1 indicates a perfect positive linear correlation. A value of 0 indicates no correlation.
Normalized Root-Mean Squared Error (NRMSE)	$\frac{\sqrt{\frac{\sum_{i=1}^{N}(Q_O-Q_M)^2}{N}}}{\max(Q_O)-\min(Q_O)}$ Where, $\max(Q_O)$ and $\min(Q_O)$ are the maximum and minimum observed streamflow values.	The NRMSE represents the standard deviation of the residuals as a fraction of the range of the observed values. Lower values are better.

Normalized Mean Absolute Error (NMAE)	$$\frac{\frac{\sum_{i=1}^{N} \lvert Q_M - Q_O \rvert}{N}}{\max(Q_O) - \min(Q_O)}$$ Where, N is the number of observations, $\lvert Q_M - Q_O \rvert$ is the absolute difference of modeled and observed values	The NMAE represents the average absolute difference between observed and modeled values as a fraction of the range of observed values. Lower values are better.

7.3. Handling missing In-situ storage data

Two dams in the basin, Old Hickory and Laurel, had missing in-situ storage data after April 2015, due to which storage change could not be calculated using observed (in-situ) storage. This missing data was filled by assuming water mass-balance owing to inflow and outflow from the reservoirs, $\Delta S = I - O$.