https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hydrology and Earth System Sciences
Open Access
EGU
Discussions

Comparison of Generalized Non-Data-Driven Reservoir Routing Models for Global-Scale Hydrologic Modeling

Joseph L. Gutenson[1*], Ahmad A. Tavakoly[1,2], Mark D. Wahl[1], Michael L. Follum[1]
[1]Research Civil Engineer (Hydraulics), US Army Engineer Research and Development Center, Coastal and Hydraulics Laboratory, 3909 Halls Ferry Rd., Vicksburg, MS 39056
University of Maryland, Earth System Science Interdisciplinary Center, College Park, Maryland, USA
[*]Corresponding Author: joseph.gutenson@noaa.gov

Abstract: Large-scale hydrologic simulations should account for attenuation through lakes and reservoirs when flow regulation is present. Generalized methods for approximating outflow are required since reservoir operation is complex and specific real-time release information is typically unavailable at global scales. There is currently no consensus on the best approach for approximating reservoir release rates in large spatial scale hydrologic forecasting. This research compares two parsimonious reservoir routing methods previously implemented in large-scale hydrologic modeling applications, requiring minimal data so as not to limit their usage. The methods considered are those proposed by Döll et al. (2003) and Hanasaki et al. (2006). This paper compares the two methodologies across 60 reservoirs operated from 2006-2012 by the U.S. Army Corps of Engineers. The authors vary empirical coefficients for both reservoir routing methods as part of a sensitivity analysis. The Döll method generally outperformed the Hanasaki method at a daily time step, improving model skill in most cases beyond run-of-the-river conditions. The temporal resolution of the model influences performance. The optimal model coefficients varied across the reservoirs in this study and model performance fluctuates between wet years and dry years, and for different configurations such as dams in series. Overall, the Döll and Hanasaki Methods could enhance large scale hydrologic forecasting, but can be subject to instability under certain conditions.

Hydrology and Earth System Sciences
Discussions

1. Introduction

1.1. Importance of Dams in Hydrologic Simulations

Improvements in numerical weather prediction, the increasing abundance of computational power, and greater precision of remotely sensed observations make global hydrologic forecasting and flood warning systems increasingly feasible (Alfieri et al., 2013; Wu et al., 2014; Emerton et al., 2016; Salas et al., 2017). Lack of information concerning anthropogenic influences on runoff is a major deficiency of large-scale flood forecasting systems (Emerton et al., 2016). Reservoir operations tend to distort natural flow patterns, effectively redistributing surface water spatially and temporally (Zhou et al., 2016). Impoundments significantly influence the downstream flow regime at small and large spatial scales (Batalla et al., 2004; Magilligan and Nislow, 2005). Over half of the world's large river systems are now substantially altered by dams (Nilsson et al., 2005) resulting in a seven-fold increase in water storage within the global river system (Vörösmarty et al. 1997). Furthermore, the cumulative alterations from global reservoir impoundments are so significant that it has been suggested that they could buffer global sea-level rise (Chao et al., 2008).

Dams primarily impact the hydrologic cycle by changing the magnitude and timing of the discharges downstream (Haddeland et al., 2006; Döll et al., 2009; Biemans et al., 2011; Wu et al., 2014; Zajac et al., 2017), often with the specific intent to mitigate hydrologic extremes (i.e., floods and droughts) (Zajac et al., 2017). Dams reduce peak discharges by roughly a third on average while dampening the daily variation by a similar amount (Graf, 2006). In hydrologic forecasting, accuracy of the timing and magnitude of hydrologic extremes is fundamentally important to the usefulness of the forecasts.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Therefore, the significant impacts from dams make inclusion of reservoir operations, or reservoir routing, critical.

At continental scales, no current forecasting operations systematically account for dam and reservoir influences (Emerton et al., 2016). Integrating dam operations within large-scale hydrologic models is shown to improve model performance downstream of reservoir locations (Snow et al., 2016; Tavakoly et al., 2017; Salas et al., 2017; Zajac et al., 2017). This is often not feasible at large-scales since there may be multiple entities responsible for regulating flow, particularly with respect to transboundary waters. Among other things, operational knowledge, site-specific rule curves, reservoir uses, and local decision-making practices at each individual project dictate dam releases. Thus, dam operations are typically non-linear, complex processes, driven by anthropogenic and environmental influences. This makes generalizing reservoir operations difficult, particularly in the context of predicting dam-induced hydrologic responses. Heuristically accounting for dams within existing routing schemes should improve forecast results when scheduled releases are not readily known.

Reservoir routing methodologies are generally divided into the two basic categories: data-driven and non-data-driven. Machine-learning, artificial intelligence (Coerver et al., 2017; Macian-Sorribes and Pulido-Velazquez, 2017; Ehsani et al., 2016; Mohan and Ramsundram, 2016; Ticlavilca and McKee, 2011; Chaves and Chang, 2008; Khalil et al., 2005), and remote sensing (Bonnema et al., 2016; Yoon and Beighley, 2015) are examples of data-driven approaches. Such data-driven methodologies can be effectively applied to dynamic non-linear systems, particularly when the governing influence on the system does not follow any particular deterministic model. These types of

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

approaches require training data or specific knowledge of a particular reservoir to effectively parameterize and apply them. This is often an insurmountable limitation for data-driven approaches. For that reason, the focus of this paper is on non-data-driven reservoir routing methodologies as an incremental improvement over schemes that effectively neglect dams when information is scarce.

1.2. Non-Data-Driven Reservoir Storage and Outflow Simulation

Non-data-driven approaches to reservoir routing rely on conceptualizing reservoir responses without explicitly observing the actual reservoir operations. The optimal method for a given application depends on a balance between complexity and available information (De Vos, 2015). Therefore, this manuscript focuses on selecting for parsimony.

Existing non-data-driven reservoir models range from simple approaches to sophisticated methods. Solander et al. (2016) showed that temperature-based schema best fits the modeling of discharge, $Q_{out,t}$. The Solander et al. (2016) rule is driven by temperature shifts at each model time step above and below the mean temperature. The Solander et al. (2016) method indicates that temperature is the main proxy governing reservoir release, due to the assumption that seasonality drives agricultural production and reservoir operation. However, the Solander et al. (2016) study focuses on long-term climatic forecasting. Diurnal temperature variations will not likely describe day-to-day reservoir operations. Zhao et al., (2016) developed a reservoir routing scheme based on reservoir stage and storage rules. However, real-time insights related to current reservoir stages throughout a region can involve considerable remotely sensed information. The stage information must then be related somehow to storage volume making this a much more a data-driven process. Burek et al. (2013) also developed a non-data-driven approach

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hydrology and Earth System Sciences Discussions

to reservoir routing which was implemented by Zajac et al. (2017). This approach is built into the LISFLOOD model. The Burek et al. (2013) model requires a number of assumptions about storage capacity limits and naturalized streamflow thresholds. For example, the minimum, normal, and maximum storage are assumed to be 0.1, 0.3, and 0.97, respectively. To maintain the objective of investigating parsimonious models, the approach by Burek et al. (2013) was not included in this evaluation. Döll et al. (2003) and Wisser et al. (2010) were presented non-data-driven methods to simulate reservoirs operation that can be considered as simple approaches.

The Wisser et al. (2010) method follows a simple, rule-based approach to define the reservoir outflow at each time step ($Q_{out,t}$). The rule that Wisser et al. (2010) enact is that when the inflow at each model time step moves above and below long-term average inflow, the behavior of the reservoir release changes. De Vos (2015) suggested that this model is too simple to effectively model reservoir outflow. Döll et al. (2003) derived a natural lake reservoir routing scheme. Hence, this methodology is applicable to man-made reservoirs and natural water bodies. The Döll et al. (2003) methodology found genesis in the reservoir outflow model proposed by Meigh et al. (1999). Meigh et al. (1999) proposed a simple reservoir release methodology, which intended to mimic outflow at reservoirs from a theoretical rectangular weir. A more substantive version of the Meigh et al. (1999) method is formulated by Döll et al. (2003). Despite its simplicity, the Döll method demonstrated good performance compared to several other methods previously mentioned (De Vos, 2015). Compared to the aforementioned methods, Hanasaki et al. (2006) derived a demand driven approach to reservoir routing, which can be considered as complicated non-data-driven reservoir routing model. They distinguished between irrigation and non-

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hydrology and Earth System Sciences
Discussions

irrigation reservoirs and offered two distinct algorithms for each. Water demands for irrigation, domestic, and industrial uses are considered in the irrigation reservoirs, whereas the releases from non-irrigation reservoirs are simply a ratio of inflow.

De Vos (2015) also proposed a within-year/over-year reservoir routing method, which they considered a non-data-driven approach. Within-year reservoir operations are driven by yearly fill and release cycles and typically have a small storage capacity relative to their total annual demand. Thus, water accumulates during wet periods and decreases during dry periods. Over-year reservoir operation, on the other hand, is based on long-term, multi-year drawdowns. Over-year reservoirs have storage which is sufficiently large, relative to inflow, so that yearly cycles of water storage and release are not necessary (Adeloye and Montaseri, 2000; Vogel et al., 1999). De Vos (2015) compared his methodology to the Hanasaki et al (2006), Döll et al. (2003), and Neitsch et al. (2011). The De Vos (2015) over-year simulation assumes knowledge of the mean and standard deviation of reservoir storage and is still too data-driven for the purposes of this study.

The non-data driven reservoir routing methods developed by Döll et al. (2003) and Hanasaki et al. (2006), which will be referred to as Döll and Hanasaki methods, were considered in this research for several reasons. Both models require minimal input data to implement. They consider only reservoir inflow and storage volume, i.e. current, minimum, and maximum storage volume that can be estimated when detailed reservoir information is not available. Additionally, both models have been implemented in large-scale hydrologic models. The Döll method was used in the WaterGAP model and the application of the Hanasaki method was implemented in the TRIP model by the same authors.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hydrology and Earth System Sciences
Discussions

The aim of this study is to assess non-data-driven reservoir routing methods for use in hydrologic forecasting schemes applicable across the global domain. The Döll and Hanasaki methods were found to be sufficiently parsimonious for wide-scale implementation. The following research questions are addressed with respect to the two approaches: (1) How well do the chosen reservoir routing models improve outflow estimates relative to simulation of naturalized flow (i.e. neglecting dams altogether)? (2) How do reservoir routing coefficients affect model performance? (3) How does the time step affect model performance and stability? This is a critical point for the current regional- to continental-scale forecasting schemes that operate at daily, or sub-daily, time steps. (4) How sensitive are the reservoir routing schemes to various real-world dam operations and climate variability?

To achieve research objectives of the study, reservoir data including daily inflow and outflow from 2006-2012, for 60 USACE reservoirs were used to evaluate the reservoir routing schemes. The data were obtained from nine USACE districts: Pittsburg, Nashville, St. Paul, Rock Island, Omaha, Tulsa, Sacramento, Los Angeles, and Vicksburg. The selected dams are representative of a wide range of reservoir sizes, flow regimes, and climatologic settings. The results of this analysis will benefit readers in determining if the reservoir routing models implemented within existing large-scale hydrologic models adequately represent reservoir effects.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

2. Methodology

2.1. Simulation Specifications

The storage ratio (Vogel et al., 1999) or Impoundment Ratio (impoundment ratio) is an important metric in previous work generalizing reservoir operation by De Vos (2015) and Hanasaki et al., (2006). The impoundment ratio is described as follows:

$$IR = \frac{(S_{max} - S_{min})}{Q_{in} * 86400 * 365} \qquad (1)$$

where S_{max} and S_{min} are the maximum and minimum volumes of the reservoir's active storage, and Q_{in} is the mean annual inflow to the reservoir.

A higher impoundment ratio indicates that the capacity of the reservoir is large relative to mean inflows, while the opposite is true of low IR values. De Vos (2015) considered IR values greater than unity "large" reservoirs, as they are capable of storing the average yearly volume of water flowing into them. To utilize the Hanasaki method, the release coefficient (k_r) needs to be determined.

$$k_r = \frac{S_{begin}}{\alpha S_{max}} \qquad (2)$$

where S_{begin} is the storage at the beginning of the each year and α is a dimensionless coefficient, which was set to 0.85 in the Hanasaki et al. (2006) study. In the current study, the α parameter was varied from 0.45-0.95 by increments of 0.10 and solve k_r for each α value.

Outflow is the quantity of most interest for hydrologic forecasting. The Hanasaki Method relates outflow based on the incoming flow. In this study, only the non-irrigation methodology from the Hanasaki Method was used to simulate reservoir outflow at each time step ($Q_{out,t}$) since one cannot assume seasonal irrigation demands will be known

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

globally. Further, the primary of selected reservoirs is not irrigation. Hanasaki estimates outflow as follows:

$$Q_{out,t} = \begin{cases} k_r Q_{in,t} & (IR = 0.5) \\ (\frac{IR}{0.5})^2 Q_{in,t} + Q_{in,t}\left\{1 - \left(\frac{IR}{0.5}\right)^2\right\} & (0 < IR < 0.5) \end{cases} \quad (3)$$

where $Q_{in,t}$ is the inflow at time t and k_r is the release coefficient which is calculated based on Equation 2. The 0.5 threshold value for IR is an empirical condition derived by Hanasaki et al. (2006).

Unlike Hanasaki method, the Döll method relates outflow ($Q_{out,t}$) to current available storage capacity of the reservoir:

$$Q_{out,t} = \frac{k_{rd}}{\Delta t}(S_t - S_{min})\frac{(S_t - S_{min})}{(S_{max} - S_{min})}^{1.5} \quad (4)$$

Where Döll empirically derives the release coefficient, k_{rd} = 0.01, Δt is the simulation time step (s), and S_t is the current volume of storage at time "t". For analysis of the Döll methodology, k_{rd} was varied at values of 0.01, 0.02, 0.04, 0.06, 0.08, 0.10, 0.20, 0.40, 0.50, 0.60, 0.70, 0.80, and 0.90 in this study. The results for the sensitivity analysis are discussed in the section 3.3.

The sensitivity analysis can provide useful information on how coefficients may vary based on geographical and reservoir characteristics such as the impoundment ratio. The two methods were evaluated and results compared to actual outflow records provided by the USACE Districts. Two approaches were used to evaluate model performances: hydrograph assessment of daily and monthly reservoir outflow and statistical evaluation. the statistical evaluation was performed for daily and monthly averaged simulated results vs. observations using the Kling-Gupta efficiency (KGE, Gupta et al., 2009), coefficient of determination (R-Squared), and root mean square error (RMSE). The KGE value ranges from negative infinity to one. Four levels of performance were defined for KGE in this study (Tavakoly et al., 2017): poor performance (KGE < 0), acceptable (0 < KGE < 0.4), good (0.4 < KGE < 0.7), and very good (0.7 < KGE). Goodness-of-fit values were evaluated to compare simulated discharge to the actual outflow records provided by the USACE Districts. These are indicators of how well the models perform. The same goodness-of-fit values are calculated to compare actual discharge with observed inflow to assess baseline performance. The baseline condition represents the treatment of reservoir outflow as naturalized, altogether neglecting reservoir operations. Thus, the baseline condition is that inflow into the reservoir equals outflow from the reservoir. To be viable, the reservoir routing scheme should improve results over the baseline condition in virtually all cases.

2.2. Study Area

The model tests and evaluation were conducted on 60 reservoirs in the United States maintained by the U.S. Army Corps of Engineers (USACE). Figure 1 illustrates reservoirs used in this study. The primary purpose of 43 of the reservoirs are flood control, six are hydroelectric, four are recreation, three are water supply, two are classified as other, one is irrigation, and one is a fish and wildlife pond. Table 1 describes pertinent characteristics of each reservoir in this analysis.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hydrology and Earth System Sciences
Discussions
Open Access
EGU

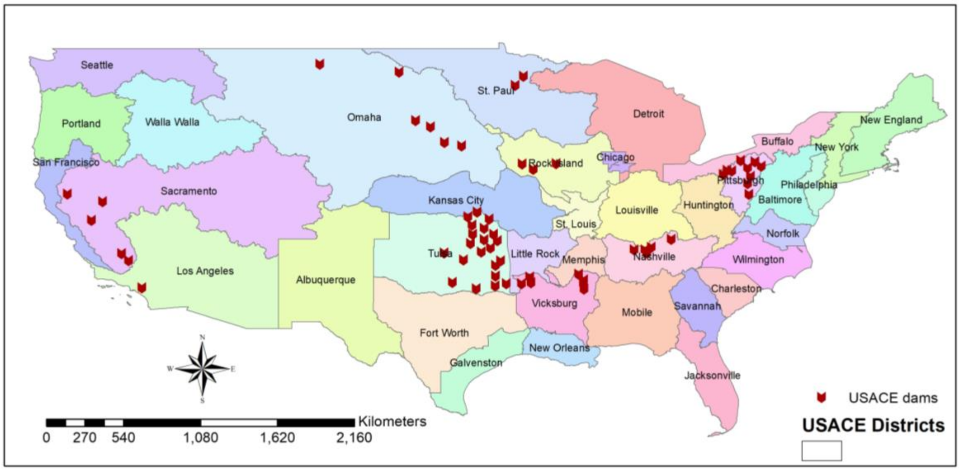


Figure 1. USACE districts and location of reservoirs in this study.

Table 1. Select statistical characteristics of reservoirs analyzed in this study.

Characteristic	Minimum	Maximum	Mean	Standard Deviation
Minimum Storage (MCM)	0	12,377	827	2,553
Maximum Storage (MCM)	25	32,070	2,695	6,184
Annual Inflow (cms)	0.64	780	118	202
Annual Outflow (cms)	0.66	776	113	195
Impoundment Ratio	0.03	15.50	1.96	2.33

3. Results and Discussion

3.1. Overall Model Performances

The goodness-of-fit metrics were calculated for each reservoir in the study. Observed inflow is compared with observed outflow to establish a benchmark used to show whether implementing the two non-data driven reservoir routing schemes improves

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

estimates for reservoir outflow over simply treating as unregulated flow. Figure 2 illustrates the comparison of skill metrics between baseline (the use of inflow as an estimate of outflow) and the use of the Döll and Hanasaki methods to simulate outflow. The KGE, R-Squared, and RMSE for the Döll and Hanasaki methods in Figure 2 represent the best fit results from the sensitivity study. Data points in Figure 2 that fall below the dashed line represent instances where KGE, R-Squared, and RMSE are lower for the reservoir routing method compared to the baseline. Data points falling above the dashed line indicate instances where higher KGE, R-Squared, and RMSE were obtained than the baseline for this study. The Hanasaki Method tends to produce minimal utility over the baseline scenario. In general, the Hanasaki Method does not appear to make outflow estimates worse. Estimates that have acceptable KGE values in the baseline scenario tend to produce acceptable results using the Hanasaki Method. On the other hand, Figure 2 illustrate that the Döll Method generally tends to increase KGE and R-Squared, and decrease RMSE. Thus, the general conclusion is that selecting the optimum Döll release coefficient will ultimately produce an improved estimate of reservoir outflow compared to the baseline. Generally, the Hanasaki Method will produce an estimated reservoir outflow that performs

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hydrology and Earth System Sciences
Open Access
Discussions

similarly to the baseline scenario.

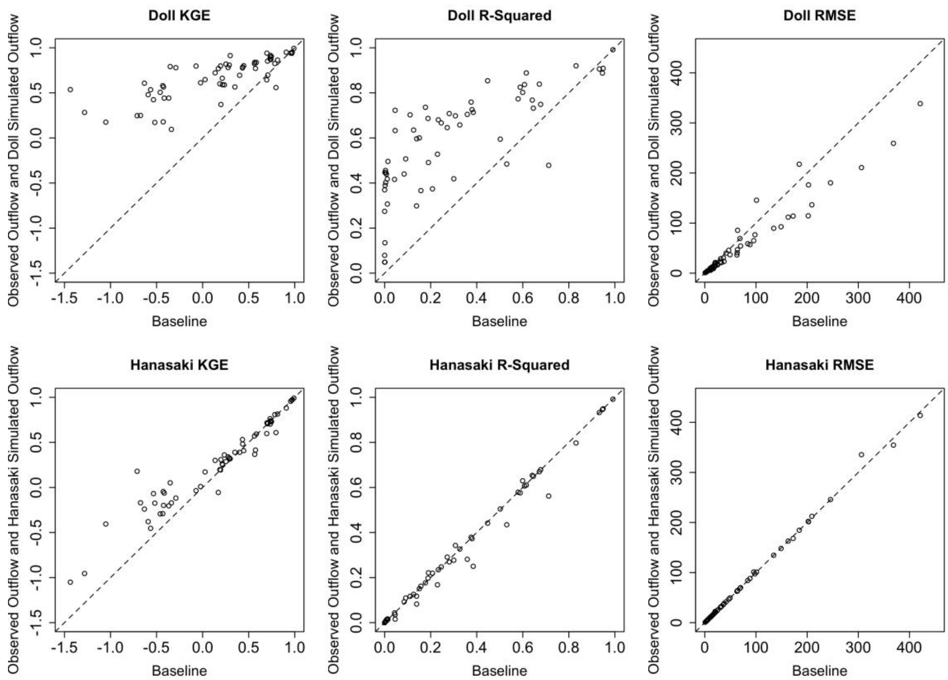


Figure 2. Scatter plots of skill metrics between the use of daily observed inflow as outflow (Baseline) and simulated outflow. The dashed line indicates the plane separating increased and decreased skill that results from using either reservoir routing method.

Figure 3 is a geographic representation of the KGE values from the baseline scenario as well as the two routing models for each reservoir. In general, the Döll Method outperforms the baseline and Hanasaki Method, particularly in the Tulsa and Pittsburg Districts. Furthermore, the Döll Method tends to improve KGE values at nearly all reservoirs and tends to preserve high KGE values at locations where the baseline is already good or very good estimator of outflow. Figure 3a illustrates the wide range of reservoir operating conditions present in the study. The reservoir dataset contains reservoirs in which the outflow correlates poorly with the inflow regime as others that correlates well. Figure 3a also portrays significant geographic clustering where reservoirs in certain regions tend

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

to be less correlated with inflow and other clusters where observed inflow and observed outflow correlate strongly. This could indicate that operations at these reservoirs may have a particularly regional context and may bias towards a particular reservoir routing scheme. However, it can be seen that correlation between observed inflow and observed outflow and geographic proximity of the reservoirs do not influence the implementation of either the Döll or Hanasaki method. Thus, the results of this research indicate no significant geographic constraints in the context of this study.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hydrology and Earth System Sciences
Open Access
Discussions

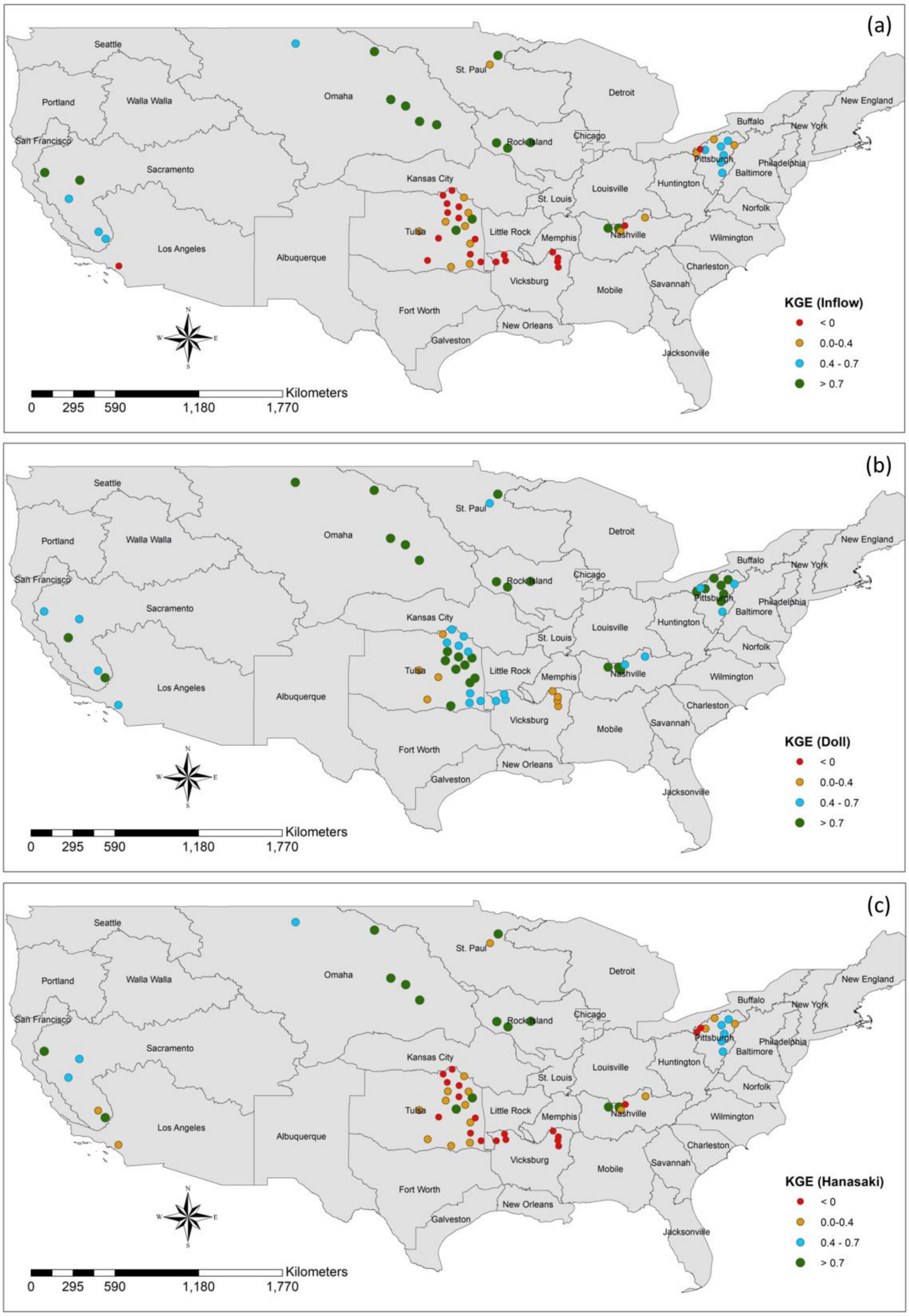


Figure 3. Spatial distribution of KGE comparing observed daily outflow to the each estimate of outflow: a) observed inflow b) Döll Method simulated outflow, c) Hanasaki Method simulated outflow for all reservoirs in this study. KGE values for the Döll Method and the Hanasaki Method are the maximum KGE from all coefficient treatments.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hydrology and Earth System Sciences
Open Access
Discussions

From multivariate comparison, a substantial negative relationship between two of the best fit results (KGE and R-Squared) and reservoir IR was found. Figure 4 illustrates this comparison between IR and each goodness of fit metric for the baseline, Döll, and Hanasaki methods. Based upon Figure 4, KGE in particular appears to non-linearly correlated to IR. A similar, yet less significant, negative relationship was found between IR and R-Squared. Little statistical correlation appears to occur between IR and RMSE. However, KGE and R-Squared values in Figure 4 indicate that the ability to predict outflow using the reservoir routing techniques applied in this study decreases with reservoir with high IR values. Proceeding sections investigate some of the possible reasons for this relationship between reservoir routing model performance and IR.

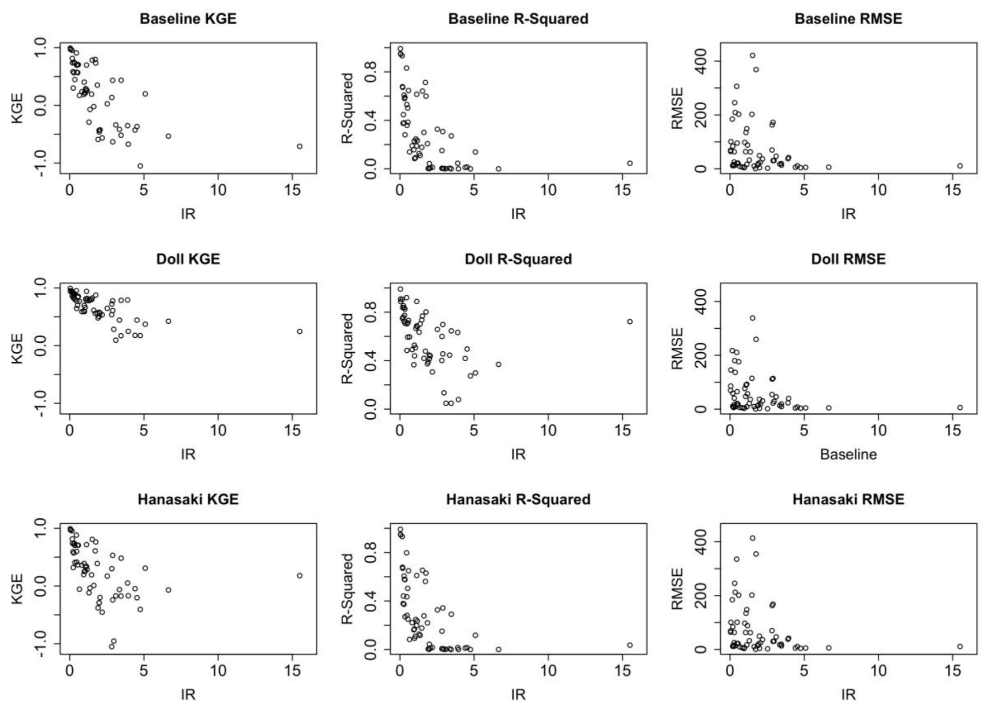


Figure 4. Comparison of IR and KGE from goodness of fit metrics.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

3.2. Sensitivity Analysis of Models

Because the Döll method consistently outperforms the Hanasaki method at daily time steps, the Döll Method was selected for the sensitivity analysis at daily time steps. The value of k_{rd} coefficient was introduced as 0.01 in the Döll et al. (2003) study. In this study, k_{rd} values were varied to obtain maximum KGE and R-Squared and minimum RMSE. Figure 5 demonstrates the dispersion of k_{rd} values which maximum the model skill to simulate reservoir routing for all selected reservoirs in this study. For all model skill metrics, k_{rd}=0.90 tends to be the most prevalent k_{rd} value that maximizes model skill. In only two of the 60 reservoirs (Sardis Dam and Enid Dam) k_{rd} = 0.01 maximizes R-Squared and minimizes RMSE for the range of k_{rd} coefficients. This research suggests

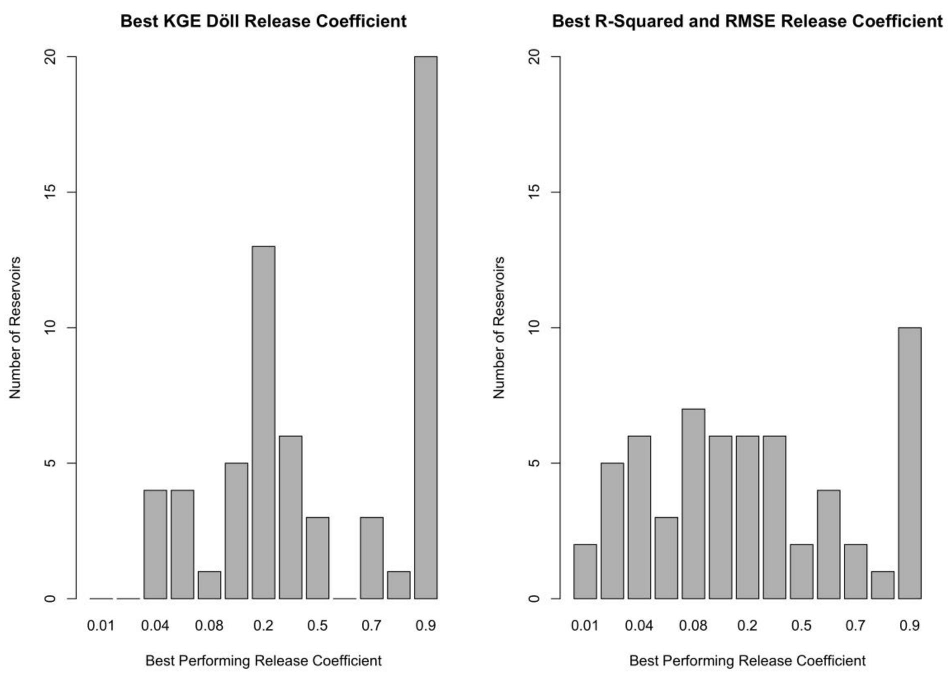


Figure 5. Bar charts of $\boldsymbol{k_{rd}}$ values that maximize KGE and correlation and minimize nRMSE.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

that the $k_{rd} = 0.01$ is not necessarily the optimum coefficient to maximize model performance.

Investigating the linkage between dam characteristics and the best performing k_{rd} yields no clear relationship. Evaluation of correlation between impoundment ratio, coefficient of variation of inflow, ratio of average inflow to average outflow, and geographic location shows low correlation between each variable and best performing k_{rd} value. However, the range of best performing k_{rd} within this analysis and as demonstrated in Figure 5 suggests that the value is not constant across all reservoirs. Thus, as one implements the Döll Method within their hydrologic modeling framework, k_{rd} may be adjusted when comparing streamflow estimates to gage observations, like those curated by the Global Runoff Data Centre (GRDC, 2017).

3.3. Dam Systems and Reservoir Routing

Reservoirs in the Vicksburg and Omaha districts were selected to evaluate performance of the Döll Method in complex drainage systems. Although these reservoirs are not directly connected, the reservoir operators coordinate in order to minimize flooding in the Louisiana Delta regions near the mouth of the Mississippi River. The operation of these reservoirs presents an interesting case in which the non-date driven models in this study do not characterize the nature of the dam releases well. The modeled results at four Vicksburg District dams yield only minimal improvement over unregulated (i.e. naturalized) flow at these reservoirs. The decrease in reservoir routing performance can be attributed to the large impoundment ratios at these dams indicating the reservoir storage is large relative to annual volume of inflow.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hydrology and Earth System Sciences Discussions

The reservoirs of interest in the Vicksburg District include Arkabutla, Sardis, Enid, and Grenada. These dams function in parallel on tributaries of the lower Mississippi River, namely the Coldwater River, Little Tallahatchie River, Yocona River, and Yalobusha River, respectively. Together, these dams control flooding in northern Mississippi as part of the Yazoo Basin Headwaters Project (USACE, 2017; USACE, 1987). The Yazoo Basin reservoirs discharge directly into the heavily regulated Mississippi River (Meade and Moody, 2010). The reservoirs operate to ensure high releases are not concurrent with large flows upstream on the Mississippi to avoid devastating flooding to the low-lying Louisiana delta regions. This requires a high level of coordination throughout the Yazoo Basin Headwater Project and with regulation upstream on the Mississippi. Additionally, each of the Yazoo Basin reservoirs have a substantial impoundment ratio, ranging from 2.96-3.95. In other words, the reservoirs are capable of containing large volumes of water to mitigate downstream impacts. Thus, current pool levels and forecasted inflow at these four reservoirs do not substantially influence release decisions. The reservoirs also have the capacity to absorb large flood events. As a result, they do not seem follow the same functional form as other dams in this study.

Figure 6 from Sardis Dam in the Yazoo Basin Headwaters Project demonstrates the hydrograph comparing observed inflow and outflow and the modeled outflow that provides the highest KGE (Döll method, k_{rd}=0.90) for the year 2008. Figure 6 demonstrates that peak outflows do not tend to correspond to the time at which peak inflow occurs. In fact, release rates at Sardis Dam are at a minimum during the peak inflow time period. This pattern repeats at each of the reservoirs in the Yazoo Basin Headwaters Project indicating that inflow and consumed storage are not substantial predictors of outflow timing at these

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

reservoirs. This exemplifies the lack of correlation between observed inflow and observed outflow at reservoirs within the Yazoo Basin Headwaters Project.

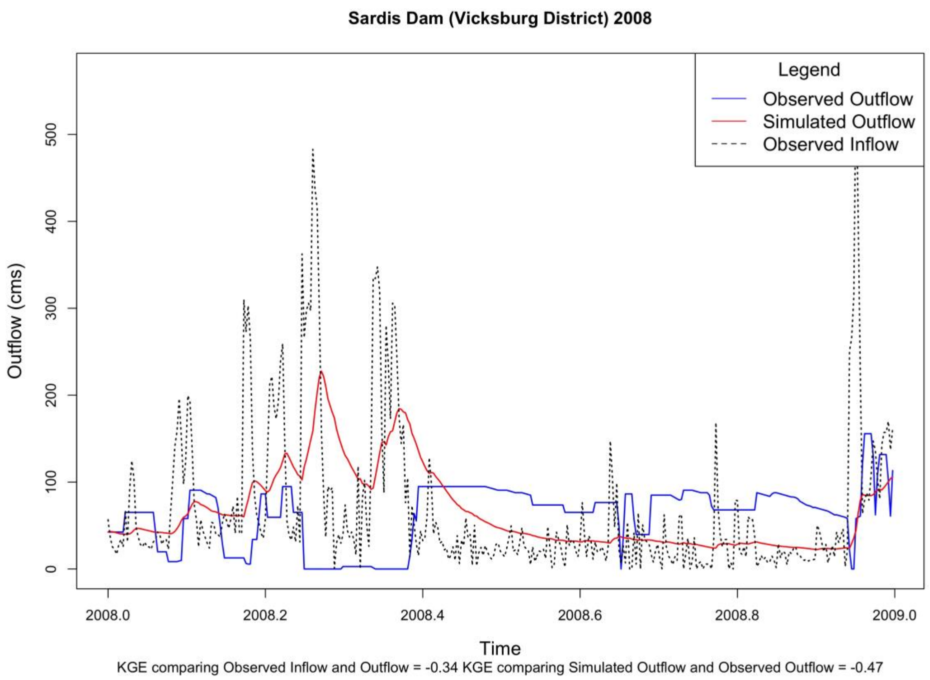


Figure 6. Hydrographs of observed inflow and outflow versus simulated outflow with the highest KGE value at Sardis Dam (Döll method k_r=0.90). KGE comparing observed Inflow and outflow = - 0.34; KGE comparing simulated and observed outflows= 0.095

Dams operating in series represent a specific case where compounding model error is a particular concern. USACE operates several large dams in series on the Missouri River. These include Fort Peck, Garrison, Oahe, Big Bend, Fort Randall, and Gavins Point within in the Omaha District (Lund and Ferreira, 1996). For this cascading system on the Missouri River, inflow appears to be a progressively stronger predictor of outflow from upstream to down. At the upstream end inflow yielded a KGE=0.43 at Fork Peck with a KGE=0.99 downstream at Gavins Point Dam. Figure 7 provides a comparison of observed inflow and outflow along with simulated outflow for Gavins Point Dam. The Döll method tends to

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hydrology and Earth System Sciences
Discussions

provide a slightly better estimate of outflow compared with inflow, except in the instance of Big Bend Dam. At Big Bend Dam, the Hanasaki method produces an estimate of outflow more consistent with observed outflow than either the Döll method or inflow alone. However, the differences are almost trivial considering how well inflow alone performed in this case. The Döll method is particularly accurate during peak inflow conditions, for example the large hydrologic event in mid-2011 at Gavins Point Dam in Figure 7. The performance of non-data driven approaches in this instance is promising since compounding errors are a large concern in this type of system. Other instances involving dams in series should be evaluated to find out if these findings hold more generally.

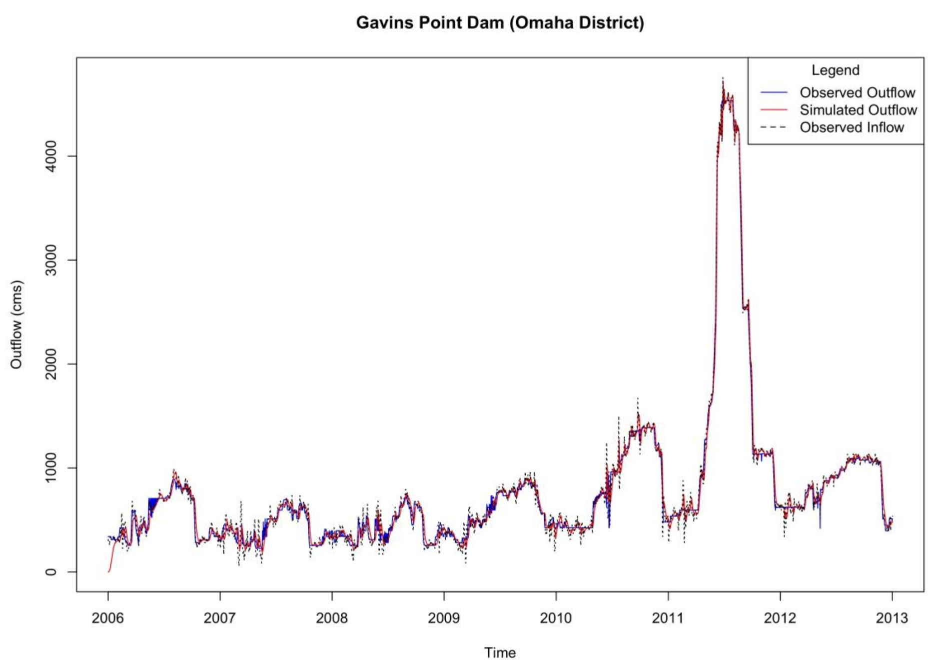


Figure 7. Hydrographs of observed inflow and outflow versus simulated outflow with the highest KGE value at Gavins Point Dam (Döll method kr=0.04). KGE comparing observed Inflow and outflow = 0.99; KGE comparing simulated and observed outflows= 0.99.

The reservoir management is unique in both the Yazoo Basin Headwaters Project and the Missouri River. The operators of dams within the Yazoo Basin Headwaters Project

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

tend to regulate outflow in a manner that is more in line with downstream conditions. The attention to downstream conditions is due mainly to the impact that downstream floods will have on the low-lying communities within the Louisiana Delta. The dams in the Yazoo Basin Headwaters Project have among the highest impoundment ratios, which inherently reduces the influence of upstream conditions in discharge decisions. The non-data driven approaches evaluated here do not account for downstream conditions and thus do not perform well in this instance, particularly where large impoundment ratios allow operators considerable leeway.

On the other hand, the non-data driven approaches tend to perform well when inflow conditions dictate discharge decisions as we see on the Missouri River system. Reservoirs with smaller impoundment ratios are naturally more responsive to inflow requiring greater consideration for upstream conditions. The Döll Method showed relatively small improvement of outflow estimates compared to inflow as a predictor of outflow in the Yazoo Basin Reservoirs, while the method provided reasonable estimates in dam systems like the Missouri River system. Therefore, it can be inferred that the Döll method is more applicable for dam systems where reservoir management focuses on upstream hydrologic conditions, while large impoundment ratios may be indicative of reservoirs where downstream conditions are more likely to prevail. This would likely apply for the Hanasaki Method as well since that method links outflow more directly.

3.4. Wet and Dry Year Comparison

Figure 8 shows results for wet and dry years at two reservoirs considered to be representative of this study. The Döll Method provides a relatively good estimate of outflow at Union City Dam (Pittsburg District) in Figure 8a and Figure 8c. It performs

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

relatively poorly at Arcadia Lake (Tulsa District) in Figure 8b and Figure 8d. In the case of Union City Dam, the Döll Method tends to produce a noticeable improvement in model skill during both a relatively wet year and a relatively dry year. The performance (Figure 8a and Figure 8c) seems to be independent of wet or dry conditions, at least on an annual basis. This does not hold for Arcadia Lake. The model shows modest skill at Arcadia Lake during the wet year (Figure 8b), but almost none during the dry year.

There appears to be a difference in the timing discharges between at the two locations in Figure 8. The Döll Method appears to estimate the right amount of volume released during the wet year at Arcadia Lake (Figure 8b). However, the actual release is delayed from the estimate given by the model. The lag could indicate that water is being retained, possibly for use in irrigation or domestic supply. In this instance, Arcadia Lake supplies water to the city of Edmond, Oklahoma which may influence release decisions (Arcadia Lake Park Office, 2018),

The Döll Method performs much more poorly during the 2006 dry year at Arcadia Lake (Figure 8d). The model does not predict the sporadic releases throughout the year. The inflow events in that year are not substantial enough to affect storage meaningfully, thus we see almost no response in the modeled output. Observed outflows demonstrate that beyond two relatively high-volume reservoir releases during 2006, the reservoir releases are restricted to practically no outflow the rest of the year. The Döll Method does not anticipate the two large releases, as the reservoir storage does not dramatically shift in either instance. Arcadia Dam appears to be operating in a conservation mode for nearly the entire year. The Döll Method does not account for this. Instead, it estimates a near constant discharge over the entire year with almost no storage change.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hydrology and Earth System Sciences
Discussions
Open Access

Results for wet years and dry years appear to be fairly mixed. Indications are that the performance of the Döll Method could be somewhat site specific. However, reservoirs that tend to be less responsive to storage fluctuations are not represented well in the Döll Method since storage fluctuations drive the model. Arcadia Lake has an IR of about 4.75 which is relatively high. Union City Dam has an IR of about 0.24, which is relatively low. IR is a good indicator of reservoir responsiveness to storage fluctuations. A lack of reservoir responsiveness to storage fluctuations could result in two different types of error when the Döll Method is implemented within a large-spatial-scale hydrologic model. First, forecasted outflow could easily mistime a hydrologic event, particularly during wet years, as Figure 8b demonstrates. Second, the authors anticipate that if the storage does not dramatically fluctuate during a dry year the estimated reservoir release likely will not anticipate sporadic releases for irrigation and other purposeful discharges. Unaccounted for, these large but short duration releases may lead to a consistent overestimation of reservoir outflow for the entire dry year period.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

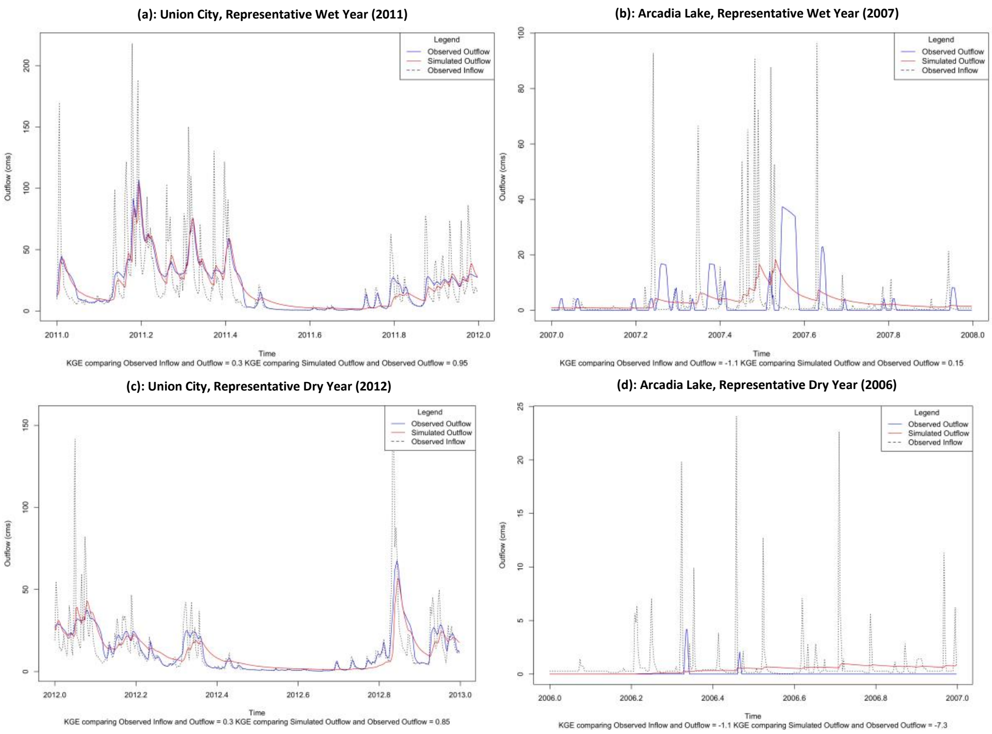


Figure 8. Two reservoirs where the Döll Method tends to perform very good and poor: outflow: a) wet year Union City Dam 2011; b) wet year Arcadia Lake 2007; c) dry year Union City Dam 2012; and d) dry year Arcadia Lake 2006.

3.5. Effects of Time Step on Model Performance

Model comparisons are conducted for daily and monthly time steps. Table 2 illustrates the results at Fort Peck, Garrison Dam, Oahe Dam, and Fort Randall Dam, each of which appears in the Hanasaki et al. (2006) study and this research. Table 2 also contains Sardis Dam, Mosquito Creek Dam, and Prado Dam, which are not included in Hanasaki et al. (2006). Results illustrate that the time scale can influence simulation results. The monthly comparison amongst Fort Peck, Garrison, Oahe, and Fort Randall is in agreement with the conclusions of Hanasaki et al. (2006). However, when the simulation time step changes to a daily time step, the skill of Hanasaki Method and the Döll method reverse and the Döll method tends to outperform the Hanasaki Method. In additional reservoirs (Sardis

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hydrology and Earth System Sciences
Open Access
Discussions

and Prado), the results indicate that the Döll method outperformed the Hanasaki Method at both daily and monthly time steps, based upon KGE. However, the results at Mosquito Creek reservoir tend to follow the original Hanasaki et al. (2006) results.

The time-scale effect upon model performance may relate to how well observed inflow correlates with observed outflow. Examining Table 2, Hanasaki Method outperforms the Döll Method when observed inflow and observed outflow are relatively well correlated. The effect is nullified when the inverse is true. The Hanasaki Method estimates outflow as a ratio of inflow, which may be a better estimate of outflow at the monthly time scale, particularly when discharge tracks closely with inflow. However, the Hanasaki Method will fluctuate at the smaller time steps due to inherent variations in inflow. The Döll Method tends to vary less at a daily time step and may be a better estimate of outflow at sub-monthly time steps.

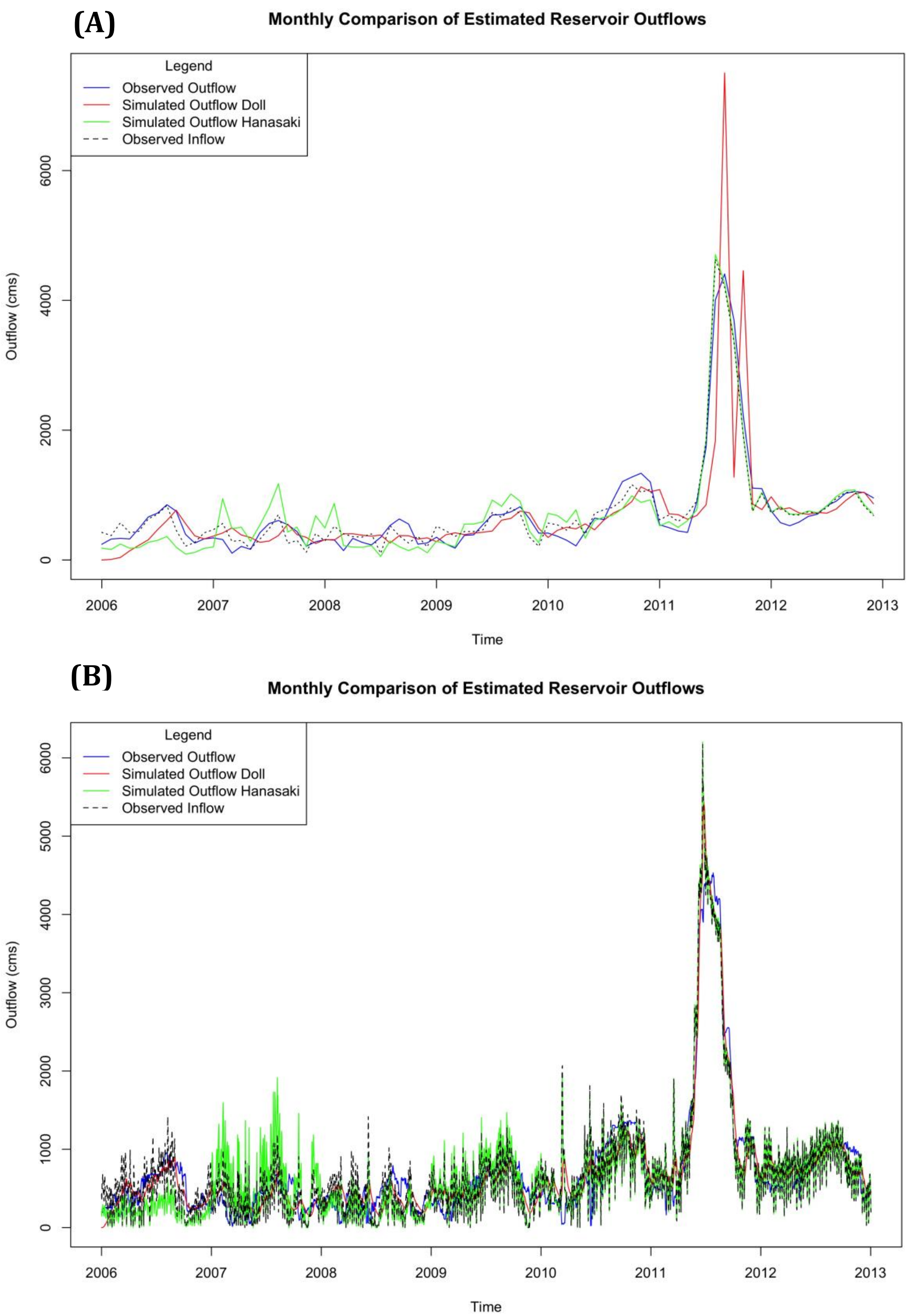
The hydrographs from Fort Randall Dam further illustrate the relationships between time step and model skill, particularly during high flow events. Daily and monthly comparisons between observation and simulations for Fort Randall Dam are shown in Figure 9. This figure compares the daily and monthly simulations with observations. Figure 9a shows that the Hanasaki simulations perform better than the Döll Method for monthly time steps, particularly during the high inflow events in 2011. The Döll method tends to overestimate reservoir outflow, while the Hanasaki Method correlates well with inflow and better matches the peak flow of 2011. At a diurnal time step (Figure 9b), the Hanasaki Method tends to be hypersensitive to inflow variations and overestimates outflow, whereas the Döll method provides a better approximation of outflow during the 2011 high flow event.

Table 2. Comparison of daily and monthly KGE values at selected reservoirs. The α and k_{rd} values represent the highest KGE values for Hanasaki and Döll methods respectively.

Reservoir	**Daily KGE**			**Monthly KGE**		
	Inflow	**Hanasaki**	**Döll**	**Inflow**	**Hanasaki**	**Döll**
Fort Peck **α=0.95 k_{rd}=0.04**	0.43	0.53	0.78	0.54	0.62	0.51
Garrison Dam **α=0.95 k_{rd}=0.06**	0.73	0.76	0.88	0.78	0.80	0.59
Oahe Dam **α=0.95 k_{rd}=0.20**	0.78	0.81	0.83	0.84	0.86	0.76
Fort Randall Dam **α=0.95 k_{rd}=0.20**	0.91	0.88	0.95	0.96	0.93	0.67
Sardis Dam **α=0.95 k_{rd}=0.90**	-0.34	-0.17	0.09	0.06	-0.03	0.16
Mosquito Creek Dam **α=0.45 k_{rd}=0.70**	-0.46	-0.29	0.51	0.49	0.60	0.39
Prado Dam **α=0.95 k_{rd}=0.50**	-0.02	0.01	0.61	0.32	0.61	0.71

It is possible that the conclusions of Hanasaki et al. (2006) suggesting better performance of the Hanasaki Method at the monthly-scale depend on how closely discharge from the dam tracks inflow. The Döll method may be a better candidate for integration into daily flow forecasting models.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019



468 Figure 9. Comparison of simulated outflow for the Fort Randall Dam with Hanasaki and Döll methods for (a) monthly and (b) daily time steps

3.6. Model Stability

Although the Döll Method outperformed the Hanasaki Method when using a daily time step, the Döll Method demonstrated some instability for high k_{rd} values. This instability occurs at three reservoirs in this study. The cause of the instability is a combination of a reservoir having a low impoundment ratio and a sharp change in the inflow to a reservoir. For instance, inflow into Old Hickory Dam in the Nashville District (IR = 0.04) increased by roughly two orders of magnitude in a matter of a few days in May 2010. During this event, the available storage filled up, necessitating a substantial increase in release flow to prevent overtopping. This occurred within a single time step in the model (Döll Method) and the outflow responded in kind in the next subsequent time step which then drained the reservoir below the specified minimum storage resulting in a non-computable imaginary number as the next solution.

Several solutions are posited to address Döll Method instability. One solution could be to varying k_{rd} values dynamically to mimic reservoir behavior. During large hydrologic events the value of k_{rd} could reduce the peak of the outflow hydrograph, and then increase during normal events. Another solution is the inclusion of rules and an expanded system of equations that govern the solution. Because the intention of the Döll Method is to approximate flow at a free-flowing weir, coupling operational rules with the simulation may better approximate reality. The rules may be as simple as switching behavior or the algorithm when storage approaches either minimum or maximum reservoir storage. A simple condition was tested for when storage drops below the minimum storage during the daily time step:

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

$$if\ S_t \le S_{\min} \Rightarrow \begin{cases} S_t = S_{\min} \\ Q_{out} = Q_{in} + \dfrac{S_t - S_{\min}}{\Delta t} \end{cases} \tag{5}$$

This condition prevents the reservoir from falling below the minimum storage. Outflow from Old Hickory Dam was re-simulated with $k_{rd} = 0.9$ and the new minimum storage condition (Equation 5). The proposed modification resulted in simulated outflow shown in Figure 10. Outflow is substantially overestimated for one-time step and drops to zero at the next time step. While an oversimplification of actual operations, this condition is similar to an emergency spillway discharge to prevent overtopping. The dam releases tremendous flow for a brief period, when the maximum storage is nearly exceeded and then inhibits the discharge when the storage is at the minimum capacity. The benefit of this modification is that additional reservoir information is not required. However, further testing and evaluation should be performed to validate this refinement.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hydrology and Earth System Sciences
Discussions
Open Access
EGU

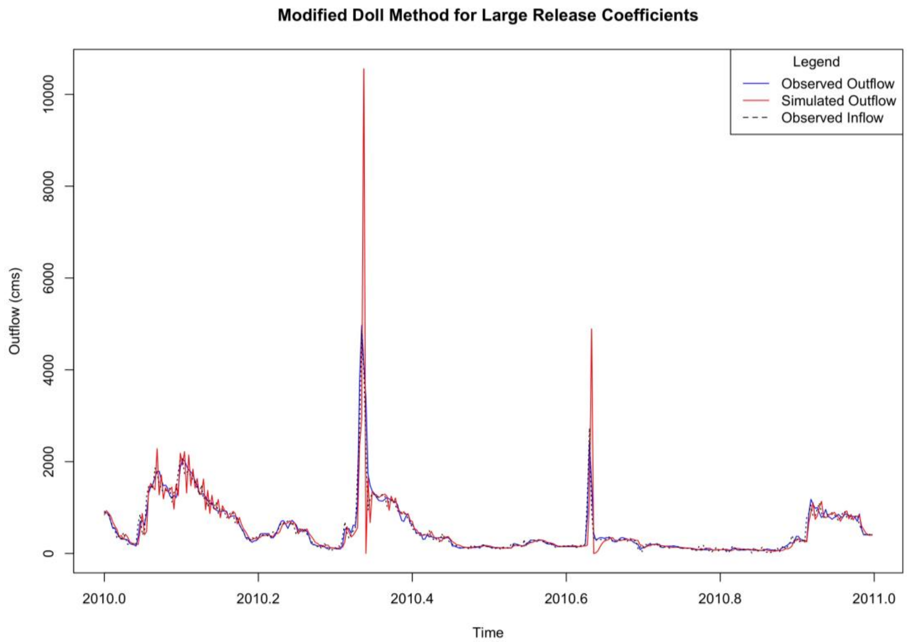


Figure 10. Outflow simulation for the Old Hickory Dam using the proposed modification of the Doll method for krd=0.4.

3.7. Limitations

This study is limited to models that require only reservoir inflow and storage, primarily to provide insight into the reliability of these measures as indicators of reservoir outflow. The inclusion of additional demand and evapotranspiration parameters could improve the results, but could also add considerable uncertainty. Of the two models, only Hanasaki et al. (2006) currently includes an estimate for withdrawals of any nature.

Another limitation of this study is the inflow that drives the simulations. All inflow utilized in this study, except for the Nashville district, is back-calculated from observed changes in storage and known discharges. This indirect method can lead to negative inflow values when losses due to seepage, evapotranspiration, or other types of withdrawals are

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hydrology and Earth System Sciences
Discussions
Open Access

underestimated. De Vos (2015) also noted that they used back-calculated inflow in their study. It is unclear whether Hanasaki et al. (2006) made use of direct observations, but it is worth noting that direct observations of total reservoir inflow are difficult to acquire.

3.8. Future Work

The non-data driven approaches evaluated consistently improved simulated streamflow estimates over naturalized flow conditions suggesting these approaches can potentially improve global streamflow forecasting. The Döll Method performed particularly well at daily time steps commensurate with many large-scale stream routing models. The incorporation of the Döll Method into to the RAPID code, a large-scale river routing model for simulating streamflow throughout distributed stream networks over large spatial extents (David et al., 2011), is under development. This will enable widespread testing and evaluation over large hydrologically diverse areas.

Reservoir routing schemes could be enhanced by assimilating remotely sensed data, e.g. near real-time changes in storage resolved from satellite altimetry, and eventually the planned NASA Surface Water and Ocean Topography (SWOT) Mission. This information could constrain reservoir simulations to improve global streamflow forecasts (Yoon and Beighley, 2015). These simulations could provide the training data necessary for more data intensive reservoir routing approaches, e.g. applying Artificial Intelligence and Machine Learning techniques to infer reservoir rule curves. Eventually, global streamflow forecasting models should leverage all available data to account for anthropogenic influence, utilizing techniques that range from simple to extremely complex.

4. Conclusions

This research compares two parsimonious reservoir routing methods that have previously been implemented in large-scale hydrologic modeling applications, namely the Döll and Hanasaki Methods. These methods were compared across 60 USACE operated reservoirs at a daily time step. Results show that the Döll Method tends to outperform the Hanasaki Method at a daily time step. An in depth examination of these results yields the following conclusions.

- The complexity and data requirements of both Döll and Hanasaki Methods are low and thus computationally inexpensive. Both can be feasibly implemented at large spatial scales at a daily or sub-daily time step.
- There is a significant relationship between reservoir IR and two of the skill metrics applied (KGE and R-Squared). Given that reservoirs with high IR typically are less responsive to short-term fluctuations in inflow and storage, the correlation between these variables is plausible. Further investigation of dam characteristics, such as if the dams operate in series or in parallel and wet and dry year considerations are further evidence of the correlation between the IR and Döll and Hanasaki Methods.
- Simulation time step plays an important part in reservoir routing skill. The comparison of the two methods by Hanasaki et al. (2006) are based on monthly reservoir outflows and conclusions may not hold within diurnal forecasting schemes. At overlapping locations, this study replicates the results reported by Hanasaki et al. for monthly time steps. However, the Hamasaki et al. findings do not hold for a daily time step.

- The best value for the empirical Döll coefficient, k_{rd}, can vary. Optimal values were typically greater than the k_{rd}=0.01 value which Döll et al. (2003) derived. This suggests that k_{rd} could be a potential calibration parameter within a large-scale hydrologic modeling framework much like a weir coefficient, which is specific to a particular type of weir.
- The Yazoo Basin Headwaters Project (USACE, 2017; USACE, 1987) is an interesting case study in how reservoir system complexity can be difficult to model. The Yazoo Basin Headwaters Project considers downstream flow conditions as the dominant criteria in dam operation. Thus, the inflow and available storage volume are poor predictors for determining reservoir discharge in this type of management scheme. The Döll Method appeared to scale flow correctly at these reservoirs and improve reservoir overall skill, but timing of the releases well represented and thus skill improvement is only minimal.
- Dam discharges in the Missouri River Reservoir System (Lund and Ferreira, 1996) are more correlated with storage volume and inflow conditions, which lends itself to the two non-data-driven approaches evaluated here. The Döll Method is particularly capable of accurately modeling reservoir outflows in reservoir systems that correlate well with storage and inflow fluctuations. Concerns related to model error being compounded through a series dams may be mitigated somewhat by the fact that inflow appears to be a progressively stronger predictor of outflow further downstream in these types of systems.
- Numerical stability of the Döll Method is a concern, particularly with higher k_{rd} values. These stability concerns originate at reservoirs with small active storage

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

capacity during high inflow events. Additional model refinement can overcome these stability concerns.

- The Döll Method showed minimal bias during relatively wet and dry years. Timing of releases can be influenced by wet years and the magnitude appears to be affected during dry years. The Döll Method appears to be most applicable for dam systems where reservoir management focuses on upstream hydrologic conditions. Large impoundment ratios could indicate reservoirs where downstream conditions are more likely to influence release decisions at the reservoir.

5. Acknowledgments

This project was partially funded by the Deputy Assistant Secretary of the Army for Research and Technology through the U.S. Army Engineer Research and Development Center (ERDC) Military Engineering (ME) work package entitled Austere Entry and the Geospatial Research and Engineering (GRE), Environmental Quality and Installations (EQI) work package entitled Climate Adaptive Mission Planning (CAMP), and Mississippi River Geomorphology and Potamology (MRG&P) Program, Project 470711. The MRG&P Program is part of the Mississippi River and Tributaries Program and is managed by the U.S. Army Corps of Engineers (USACE), Mississippi Valley Division (MVD). Data on lakes and reservoirs were obtained from U.S. Army Corps of Engineers Nashville, Omaha, Pittsburgh, Rock Island, St Paul, Tulsa, Vicksburg, Sacramento, and Los Angeles Districts. The authors would like to acknowledge the technical review and suggestion from Matthew W. Farthing, Scott D. Christensen, Elissa M. Yeates, Kayla A. Cotterman, and James W. Lewis all ERDC.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hydrology and Earth System Sciences Discussions

References

Arcadia Lake Park Office. (2018). Arcadia Lake. Retrieved from http://edmondok.com/338/Arcadia-Lake

Adeloye, A. J., & Montaseri, M. (1999). Predicting critical period to characterise over-year and within-year reservoir systems. *Water Resources Management*, *13*(6), 383–407. https://doi.org/10.1023/A:1008185304170

Alfieri L, Burek P, Dutra E, Krzeminski B, Muraro D, Thielen J, Pappenberger F. GloFAS-global ensemble streamflow forecasting and flood early warning. Hydrology and Earth System Sciences. 2013;17(3):1161–1175.

Batalla, R. J., Gómez, C. M., & Kondolf, G. M. (2004). Reservoir-induced hydrological changes in the Ebro River basin (NE Spain). *Journal of Hydrology*, *290*(1–2), 117–136. https://doi.org/10.1016/j.jhydrol.2003.12.002

Biemans, H., Haddeland, I., Kabat, P., Ludwig, F., Hutjes, R. W. A., Heinke, J., … Gerten, D. (2011). Impact of reservoirs on river discharge and irrigation water supply during the 20th century. *Water Resources Research*, *47*(3), 1–15. https://doi.org/10.1029/2009WR008929

Bonnema, M., Sikder, S., Miao, Y., Chen, X., Hossain, F., Ara Pervin, I., … Lee, H. (2016). Understanding satellite-based monthly-to-seasonal reservoir outflow estimation as a function of hydrologic controls. *Water Resources Research*, *52*(5), 4095–4115. https://doi.org/10.1002/2015WR017830

Burek, P., Knijff, J. v. d., & Roo, A. de. (2013). *LISFLOOD: Distributed Water Balance and Flood Simulation Model*. Luxembourg, Belgium. https://doi.org/10.2788/24719

Chaves, P., & Chang, F.-J. (2008). Intelligent reservoir operation system based on evolving artificial neural networks. *Advances in Water Resources*, *31*(6), 926–936. https://doi.org/10.1016/j.advwatres.2008.03.002

Coerver, H. M., Rutten, M. M., & van de Giesen, N. C. (2017). Deduction of Reservoir Operating Rules for Application in Global Hydrological Models. *Hydrology and Earth System Sciences Discussions*, (January), 1–27. https://doi.org/10.5194/hess-2016-660

David, C. H., Maidment, D. R., Niu, G., Yang, Z., Habets, F., & Eijkhout, V. (2011). River Network Routing on the NHDPlus Dataset. https://doi.org/10.1175/2011JHM1345.1

De Vos, J. (2015). *Non data-driven reservoir outflow and storage simulations in hydrological models*. TU Delft.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

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 Discussions*, *6*(4), 4773–4812. https://doi.org/10.5194/hessd-6-4773-2009

Döll, P., Kaspar, F., & Lehner, B. (2003). A global hydrological model for deriving water availability indicators: Model tuning and validation. *Journal of Hydrology*, *270*(1–2), 105–134. https://doi.org/10.1016/S0022-1694(02)00283-4

Ehsani, N., Fekete, B. M., Vörösmarty, C. J., & Tessler, Z. D. (2016). A neural network based general reservoir operation scheme. *Stochastic Environmental Research and Risk Assessment*, *30*(4), 1151–1166. https://doi.org/10.1007/s00477-015-1147-9

Emerton RE, Stephens EM, Pappenberger F, Pagano TC, Weerts AH, Wood AW, Salamon P, Brown JD, Hjerdt N, Donnelly C, et al. Continental and global scale flood forecasting systems. Wiley Interdisciplinary Reviews: Water. 2016;3(3):391–418.

Escobar, R., & Boulder, C. (2017). *Remote Sensing of Hydrological Extremes*. https://doi.org/10.1007/978-3-319-43744-6

Giacomoni, M. H., Kanta, L., & Zechman, E. M. (2013). Complex Adaptive Systems Approach to Simulate the Sustainability of Water Resources and Urbanization. *Journal of Water Resources Planning and Management*, *139*(June), 554–564. https://doi.org/10.1061/(ASCE)WR.1943-5452

Global Runoff Data Centre (GRDC). (2017). Welcome to the Global Runoff Data Centre. Retrieved January 8, 2018, from http://www.bafg.de/GRDC/EN/Home/homepage_node.html

Graf, W. L. (2006). Downstream hydrologic and geomorphic effects of large dams on American rivers. *Geomorphology*, *79*(3–4), 336–360. https://doi.org/10.1016/j.geomorph.2006.06.022

Gupta, H. V., Kling, H., Yilmaz, K. K., & Martinez, G. F. (2009). Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology*, *377*(1–2), 80–91. https://doi.org/10.1016/j.jhydrol.2009.08.003

Haddeland, I., Skaugen, T., & Lettenmaier, D. P. (2006). Anthropogenic impacts on continental surface water fluxes. *Geophysical Research Letters*. 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

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hejazi, M. I., Cai, X., & Ruddell, B. L. (2008). The role of hydrologic information in reservoir operation - Learning from historical releases. *Advances in Water Resources*, *31*(12), 1636–1650. https://doi.org/10.1016/j.advwatres.2008.07.013

Khalil, A., McKee, M., Kemblowski, M., & Asefa, T. (2005). Sparse Bayesian learning machine for real-time management of reservoir releases. *Water Resources Research*, *41*(11), 1–15. https://doi.org/10.1029/2004WR003891

Lehner, B., Liermann, C. R., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, P., … Frenken, K. (2011). *Global Reservoir and Dam (GRanD) database*. *European Environment*.

Lund, J. R., & Ferreira, I. (1996). Operating Rule Optimization for Missouri River Reservoir System. *Journal of Water Resources Planning and Management*, *122*(4), 287–295. https://doi.org/10.1061/(ASCE)0733-9496(1996)122:4(287)

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

McManamay RA. Quantifying and generalizing hydrologic responses to dam regulation using a statistical modeling approach. Journal of Hydrology. 2014;519(PA):1278–1296.

Meade, R. H., & Moody, J. A. (2010). Causes for the decline of suspended-sediment discharge in the Mississippi River system, 1940-2007. *Hydrological Processes*, *24*, 35–49. https://doi.org/10.1002/hyp

Meigh, J. R., McKenzie, A. A., & Sene, K. J. (1999). A grid-based approach to water scarcity estimates for eastern and southern Africa. *Water Resources Management*, *13*(2), 85–115. https://doi.org/10.1023/A:1008025703712

Mohan, S., & Ramsundram, N. (2016). Predictive Temporal Data-Mining Approach for Evolving Knowledge Based Reservoir Operation Rules. *Water Resources Management*, *30*(10), 3315–3330. https://doi.org/10.1007/s11269-016-1351-5

Neitsch, S., Arnold, J., Kiniry, J., & Williams, J. (2011). *Soil & Water Assessment Tool Theoretical Documentation Version 2009*. *Texas Water Resources Institute*. https://doi.org/10.1016/j.scitotenv.2015.11.063

Nilsson C, Reidy CA, Dynesius M, Revenga C. Fragmentation and Flow Regulation of the World's Large River Systems. Science. 2005;308(5720):405–408.

Patra, A., & Debbarma, N. (n.d.). Prediction of Reservoir Release using Genetic Programming and ANFIS Models Coupled with Wavelet Transform, 101–108.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Hydrology and Earth System Sciences Discussions

Salas FR, Somos-Valenzuela MA, Dugger A, Maidment DR, Gochis DJ, David CH, Yu W, Ding D, Clark EP, Noman N. Towards Real-Time Continental Scale Streamflow Simulation in Continuous and Discrete Space. Journal of the American Water Resources Association. 2017;92373(February 2018):7–27.

Snow, Alan D., Scott D. Christensen, Nathan R. Swain, James Nelson, Daniel P. Ames, Norman L. Jones, Deng Ding, Nawajish Noman, Cédric H. David, F. P. (2016). A High-Resolution National-Scale Hydrologic Forecast System from a Global Ensemble Land Surface Model. *Journal of the American Water Resources Association*, *in press* (4). https://doi.org/10.1111/1752-1688.12434

Solander, K. C., Reager, J. T., Thomas, B. F., David, C. H., & Famiglietti, J. S. (2016). Simulating Human Water Regulation: The Development of an Optimal Complexity, Climate-Adaptive Reservoir Management Model for an LSM. *Journal of Hydrometeorology*, *17*(3), 725–744. https://doi.org/10.1175/JHM-D-15-0056.1

Tavakoly, A. A., Snow, A. D., David, C. H., Follum, M. L., Maidment, D. R., & Yang, Z.-L. (2017). Continental-Scale River Flow Modeling of the Mississippi River Basin Using High-Resolution NHD Plus Dataset. *JAWRA Journal of the American Water Resources Association*, *78712*. https://doi.org/10.1111/1752-1688.12456

Ticlavilca, A. M., & McKee, M. (2011). Multivariate Bayesian Regression Approach to Forecast Releases from a System of Multiple Reservoirs. *Water Resources Management*, *25*(2), 523–543. https://doi.org/10.1007/s11269-010-9712-y

U.S. Army Corps of Engineers. (2017). Arkabutla Lake History. Retrieved July 13, 2017, from http://www.mvk.usace.army.mil/Missions/Recreation/Arkabutla-Lake/History-and-Mission/

U.S. Army Corps of Engineers. (1987). *Yazoo Basin Delta Flood Control: Environmental Impact Statement*. Vicksburg, MS.

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

Vogel, R. M., Lane, M., Ravindiran, R. S., & Kirshen, P. (1999). Storage Reservoir Behavior in the United States. *Journal of Water Resources Planning and Management*, *125*(5), 245–254. Retrieved from http://ascelibrary.org/doi/pdf/10.1061/(ASCE)0733-9496(1999)125:5(245)

Vörösmarty CJ, Sharma KP, Fekete BM, Copeland AH, Holden J, Marble J, Lough JA. The Storage and Aging of Continental Runoff in Large Reservoir Systems of the World. Ambio. 1997;26(4):210–219.

https://doi.org/10.5194/hess-2019-264
Preprint. Discussion started: 4 July 2019

Widén-Nilsson E, Halldin S, Xu C Yu. Global water-balance modelling with WASMOD-M: Parameter estimation and regionalisation. Journal of Hydrology. 2007;340(1-2):105–118.

Wisser, D., Fekete, B. M., Vörösmarty, C. J., & Schumann, A. H. (2010). Reconstructing 20th century global hydrography: a contribution to the Global Terrestrial Network-Hydrology (GTN-H). *Hydrol. Earth Syst. Sci*, *14*, 1–24. Retrieved from www.hydrol-earth-syst-sci.net/14/1/2010/

Wu H, Adler RFR, Tian Y, Huffman GJ, Li H, Wang J. Real‐time global flood estimation using satellite‐based precipitation and a coupled land surface and routing model. Water Resources …. 2014 [accessed 2014 Sep 15];50(3):2693–2717. http://onlinelibrary.wiley.com/doi/10.1002/2013WR014710/full

Wu, Y., & Chen, J. (2012). An Operation-Based Scheme for a Multiyear and Multipurpose Reservoir to Enhance Macroscale Hydrologic Models. *Journal of Hydrometeorology*, *13*(1), 270–283. https://doi.org/10.1175/JHM-D-10-05028.1

Yoon, Y., & Beighley, E. (2015). Simulating streamflow on regulated rivers using characteristic reservoir storage patterns derived from synthetic remote sensing data. *Hydrological Processes*, *29*(8), 2014–2026. https://doi.org/10.1002/hyp.10342

Zajac, Z., Revilla-Romero, B., Salamon, P., Burek, P., Hirpa, F. A., & Beck, H. (2017). The impact of lake and reservoir parameterization on global streamflow simulation. *Journal of Hydrology*, *548*, 552–568. https://doi.org/10.1016/j.jhydrol.2017.03.022

Zhao, G., Gao, H., Naz, B. S., Kao, S. C., & Voisin, N. (2016). Integrating a reservoir regulation scheme into a spatially distributed hydrological model. *Advances in Water Resources*, *98*, 16–31. https://doi.org/10.1016/j.advwatres.2016.10.014