Utrecht University
Department of Physical Geography

Quantifying Reservoir Outflow Performance in PCR-GLOBWB 2 with the Implementation of the Downstream Demand Allocation Function

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Lars Streefland
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Supervisors:

Dr. Rens van Beek
Dr. ir. Niko Wanders

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Abstract

During the 20th century, anthropogenic reservoirs have been constructed to ensure flood protection and an increasing global water demand. Consequently, natural streamflow timing and streamflow have been altered significantly. Increasing the anthropogenic impact on the hydrological cycle. To understand the feedback between artificial water management and global scale hydrological processes, Global Hydrological Models (GHM) are developed. In this study, a demand allocation function is integrated into the second version of PCRaster GLOBal Water Balance model (PCR-GLOBWB2), which fully integrates water demand at each time step. PCR-GLOBWB2 includes approximately 7000 human-made reservoirs, which are dynamically included according to their construction year, available in the most recently published Global Reservoir and Dam (GRanD v1.3) database. By integrating the allocation function it allows the user to study the reliability of reservoirs to provide sufficient release for downstream demand. Initially, downstream reservoir demand was limited to environmental flow, while the integrated function implements irrigational, domestic, industrial, and livestock demand as an addition.

The performance of PCR-GLOBWBs reservoir scheme and the integrated function were tested for 40 globally distributed reservoirs. Performance is validated and compared using output of four model simulations and observed outflow data for a time-range of 31 years (1980-2010). Simulation products include discharge for natural conditions, the implementation of reservoirs, circumstances including reservoirs and initial demand settings, and a combination of reservoir availability and the integrated demand allocation function.

Error metrics were given for each reservoir on a monthly basis. For twelve reservoirs the Kling Gupta Efficiency (KGE) was positive (>0.0), with maximum performance obtained for Ghost (0.64) and American Falls (0.64). Trends for the components of KGE obtained overestimations for the bias (>1.0, 27/40 reservoirs) and peak values (>1.0, 29/40), and a relatively well performing correlation (>0.5, 18/40). Highest performance trends were predominantly obtained for hydropower and within-year reservoirs, for which the average residence time is less than a year.

The ability of a reservoir to satisfy downstream demand was quantified in cumulative number of months with unmet demand. The allocation derived an average increase of approximately 65 months between the model simulations with environmental flow and allocated demand. Trends for the unmet demand obtained low sensitivity for hydropower and within-year reservoirs, while high sensitivities were obtained for non-hydropower and multi-year reservoirs, for which the average residence time is more than a year.

Both performance and unmet demand were related to the quality of meteorological forcing data. More accurate release modelled is obtained for reservoirs located in more accurately forced river basins. In conclusion, the reservoir scheme resulted in a relatively moderate performance, and the allocation function performed a more realistic representation of the downstream reservoir demand.

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Contents

ABSTRACT .... **I**

ACKNOWLEDGEMENTS .... **II**

LIST OF FIGURES .... **V**

LIST OF APPENDIX FIGURES .... **VI**

LIST OF TABLES .... **VI**

LIST OF APPENDIX TABLES .... **VI**

1. INTRODUCTION **1**

1.1 BACKGROUND INFORMATION 1
1.2 PROBLEM DESCRIPTION AND RESEARCH OBJECTIVE 2
1.3 RESEARCH QUESTIONS 3
1.4 READING GUIDE 3

2. LITERATURE STUDY **4**

2.1 RESERVOIRS 4
2.2 SINGLE- AND MULTIPLE-RESERVOIR OPERATIONS 4
2.3 WITHIN- AND MULTI-YEAR RESERVOIRS 5
2.4 RESERVOIR OPERATIONS 5
2.4.1 Storage Levels/Stages 5
2.4.2 Environmental Flow Requirements 6
2.5 RESERVOIR PURPOSES 6
2.5.1 Hydropower 6
2.5.2 Flood Control 7
2.5.3 Water Supply & Irrigation 7
2.6 RESERVOIR IMPACTS 8
2.6.1 Hydrology 8
2.6.2 Downstream Sedimentation 9
2.6.3 Climate 9
2.7 RESERVOIR DATABASES 10

3. METHODOLOGY **12**

3.1 PCR-GLOBWB 2 12
3.1.1 Reservoir Strategies 12
3.1.2 Demand Routing 13
3.1.3 Demand Allocation 14
3.1.4 Model Forcing 15
3.2 MODEL PERFORMANCE 16
3.3 RESERVOIR DATA 17
3.3.1 Dataset 18
3.3.2 Data Revision 18
3.4 FLOW DURATION CURVES 19
3.5 UNMET DEMAND & RELIABILITY 20

4. RESULTS **23**

4.1 MODEL PERFORMANCE 23
4.1.1 Long-Term Statistics of Reservoir Outflow 23
4.1.2 Long-Term Statistics per Model Simulation 24
4.2 GROUPED PERFORMANCE 25
4.2.1 Seasonality 25

4.2.2 Number of Reservoirs per Grid Cell ... 25
4.3 Outflow Analysis ... 30
4.3.1 Evaluation of Long Term Monthly Release ... 30
4.3.2 Seasonality ... 30
4.3.3 Flow Duration Curves ... 30
4.4 Unmet Downstream Demand ... 31
4.4.1 General ... 31
4.4.2 Reservoir Purpose ... 32
4.4.3 Multi- and Within-Year ... 32

5. DISCUSSION ... 44

5.1 Model Performance ... 44
5.1.1 Outflow Analysis ... 45
5.1.2 Demand ... 45
5.1.3 Multiple Reservoirs in Cell ... 46
5.2 Limitations ... 46
5.2.1 Data ... 46
5.2.2 Previous Studies ... 47

6. CONCLUSIONS ... 49

7. RECOMMENDATIONS ... 50

8. REFERENCES ... 51

9. APPENDIX ... 56

9.1 A: Long-Term Monthly Statistics ... 56
9.2 B: Unmet Demand ... 58
9.3 C: Annual Regime Curves ... 59
9.4 D: Model Equations ... 61
9.4.1 Reservoir Model Functions ... 61
9.4.2 Routing Implementation ... 63
9.4.3 Reservoir Allocation ... 64
9.4.4 Demand Allocation ... 66
9.4.5 Variables in PCR-GLOBWB 2 Functions ... 67

List of Figures

Figure 1: Multiple-reservoir systems in series (left) and parallel (right) (Lund et al., 1999). ... 4
Figure 2: Example of a multiple-reservoir system located at the Missouri River Basin (Source: US Army Corps of Engineers). ... 5
Figure 3: The Global Reservoir and Dam (GRanD) database most recent version (v1.3). In yellow the reservoirs added since the first version (Source: globaldamwatch.org)... 11
Figure 4: Schematic diagram of the modelling framework in PCR-GLOBWB (Wada et al. 2014) ... 12
Figure 5: Overview of the global spatial reservoir distribution for observed data. The data is sorted by capacity and is subdivided in 5 groups corresponding to their capacity in Million Cubic Meters (MCM). ... 18
Figure 6: An example of a Flow Duration Curve (FDC) provided by Pechlivanidis et al., (2014). ... 19
Figure 7: Monthly average performance evaluation results for each individual PCR-GLOBWB 2 simulation sorted according to the KGE performance of the final simulation: **(a)** KGE performance metrics, **(b)** Amplitude performance metrics $\sigma s/\sigma o$. Simulation 1 is related to the natural conditions, simulation 2 contains reservoirs, simulation 3 has reservoirs and the basic water demand modules, and simulation 4 includes reservoirs and the additional water demand. ... 26
Figure 8: Kling Gupta Efficiency sorted per reservoir type, model run, and performance. These are sorted according to the ratio of reservoir capacity to mean annual inflow **(figure a)**, and according to their reservoir type **(figure b)**. ... 28
Figure 9: Hydrographs of monthly outflow for two in-series reservoirs, obtained for all simulations and is done with PCR-GLOBWB 2 between 1980 and 2010, including demand. Simulation 1 is related to the natural conditions, Simulation 2 contains reservoirs, Simulation 3 has reservoirs and the basic water demand modules, and Simulation 4 includes reservoirs and the additional water demand. ... 29
Figure 10: Hydrographs of monthly outflow for two in-series reservoirs, obtained for all simulations and is done for PCR-GLOBWB 2 between 1980-2010, including demand. Simulation 1 is related to the natural conditions, Simulation 2 contains reservoirs, Simulation 3 has reservoirs and the basic water demand modules, and Simulation 4 includes reservoirs and the additional water demand. ... 29
Figure 11: Regime curves of mean monthly discharge for the model runs in PCR-GLOBWB 2. Demand is applied for simulation 3 and 4. Regime curves for observed values are given to visually compare the difference between modelled and real-time data. The x-axes show months (1-12), and the y-axes show releasee ($m^3 s^{-1}$) on a symmetrical logarithmic scale. ... 33
Figure 12: Reservoir Storage in mean monthly volume for the model runs with reservoirs in PCR-GLOBWB 2. The x-axes show months (1-12), and the y-axes show storage (m^3). ... 35
Figure 13: Flow Duration Curves of observed and modelled (Runs) mean daily in- and outflow per reservoir sorted according to their median values. Simulation 1 is related to the natural conditions, simulation 2 contains reservoirs, simulation 3 has reservoirs and the basic water demand modules, and simulation 4 includes reservoirs and the additional water demand. ... 37
Figure 14: a, b, and c: Hydrographs of monthly discharge for run 4 in PCR-GLOBWB's over the period 1980-2010: an example of a reduced number of unmet demand months: **(a)** Joes Valley (c=0.83), an example of an enlarged number of unmet demand months **(b)** Flaming Gorge (c=2.42), and **(c)** an example of a reservoir retaining its number of unmet demand months at zero. ... 39

Figure 15: Unmet Demand in total and average number of months per reservoir between 1980 and 2010 for PCR-GLOBWB model runs 3 and 4. 40
Figure 16: Unmet Demand in total and average number of months between 1980 and 2010 for PCR-GLOBWB model runs 3 and 4. These are sorted according to their ratio between reservoir storage and annual outflow, respectively **(a)** Within-Year, **(b)** Multi-Year. 41
Figure 17: Unmet Demand in total and average number of months between 1980 and 2010 for PCR-GLOBWB model runs 3 and 4. These are sorted according to their reservoir purpose, respectively **(a)** Hydropower, **(b)** Secondary Hydropower, **(c)** Non - Hydropower, and **(d)** Hydropower & Secondary Hydropower combined. 42

List of Appendix Figures

Appendix Figure 1: Regime curves of mean annual discharge for the model runs in PCR-GLOBWB2. Demand is applied for simulation 3 and 4 and is given for these simulations. Observed values regime curves are given to visually compare the difference between modelled and real-time data. The x-axes show months (1-12), and the y-axes show release ($m^3 s^{-1}$) on a symmetrical logarithmic scale. 59

List of Tables

Table 1: Scenarios for PCR-GLOBWB 2 modelling 16
Table 2: Summary of reservoirs. 21

List of Appendix Tables

Appendix Table 1: Metrics of long term monthly averages per reservoir for every model scenario on the time period (1980-2010). 56
Appendix Table 2: Metrics of long term annual averages per reservoir for every model scenario on the time period (1980-2010). 57
Appendix Table 3: Unmet Demand for long term monthly average on the time period (1980-2010). 58
Appendix Table 4: Variables used in PCR-GLOBWB 2 reservoir and demand functions 67

1. Introduction

1.1 Background Information

These days concerns arise due to projected global climate changes ,which are directly coupled to enforced anthropogenic activities (IPCC, 2014). Consequently, contributing to enhanced demand for quantitative assessments of these changes (Schlosser et al., 2014). The hydrological system is one of the systems experiencing serious impacts caused by anthropogenic activities. It experiences high global stress levels and forces, for example, modifications in precipitation and evaporation patterns. In combination with an increased water consumption, caused by population growth and increased wealth, this leads to enforced global water stress (Cosgrove et al., 2015). At the beginning of the 20th century 1.7 billion people were living on earth, at the moment it is greater than 7.0 billion, and projections expect 9.3 billion in 2050 and 10.1 billion in 2100 (Bloom, 2011). To provide a steady temporal water demand and to secure safety, it is useful to construct dams, developing a more reliant way to ensure water and energy sources, and secure regions from flooding (Liu et al., 2016; Valdes et al., 1995; Yang et al., 2017). Globally, more than 45,000 large dams have been constructed and contain an estimated total storage capacity of 1.000 km^3 in 1950 up to 11.000 km^3 in 2007 (Hanasaki et al., 2006; Zhao et al., 2016). In perspective, global river discharge is approximately 45.000 km^3 (Widén-Nilsson et al., 2007). The redistribution of large volumes of surface water have changed the natural hydrological flow schemes significantly (Biemans et al., 2011; Haddeland et al., 2006). The natural hydrograph is modified by regulating the natural river flow, which attempts to secure a reliable source of water for a wide variety of human and environmental needs (Ehsani et al., 2017; Lehner et al., 2011). Earlier results show reduced ranges in peak and daily discharge by respectively 67% and 64% of many large dams on North American rivers (Graf, 1999). These globally distributed reservoirs serve a variety of purposes, for example, hydropower, flood control, water supply, navigation, fishery and recreation (Hogeboom et al., 2018; Skalak et al., 2013; Wu et al., 2012).

Reservoir performance and development rely on the chance of failure. Hashimoto et al. (1982) described the reservoir system performance in the following ways: i) how often the system fails (reliability), ii) how quickly the system returns to a satisfactory state after failure (resiliency), and iii) how significant the consequences of failure are. An alternate definition of reliability is the probability no failure occurs within a fixed period of time. Reliability is used to develop performance criteria capturing system performances, which are highly relevant during droughts, peak demands or extreme weather conditions (Hashimoto et al., 1982). In terms of artificial reservoirs, Ganji et al. (2012) defined reliability as the ability of a reservoir to perform its required functions under stated conditions throughout a specific period. For reliability the operational status of a reservoir can be described as either satisfactory or unsatisfactory. The mode of a failure is when a reservoir cannot fulfil its purpose and does not have outflow similar to the unregulated inflow.

Reservoirs are related to economic activities, social development, and ecological impacts. Contributing to human development by using the water for consumption, irrigation, cooling, transportation, construction, mills, power generation, fishing and recreation (Aleseyed et al., 1975; Hogeboom et al., 2018). Water scarcity affects economic development to a large extent, and can be the dominant factor of water scarcity in turn. In semi-arid or arid regions water withdrawal worsens water scarcity already (Wada et al., 2014). Water demand in these relatively dry areas often exceeds available water resources, which is caused by intensified irrigation (Wada et al., 2014). Ecological impacts of reservoirs are related to ecosystems, species, sediment transport, nutrient transport, and many other components. Many riverine species are highly sensitive to specific river flow patterns, for example spring peak floods or summer low flows (Lehner et al., 2011). Alterations to natural flow patterns cause serious deviations in ecological processes (Van Puijenbroek et al., 2019). To avoid disturbances from dam operations, ecologists and water resource planners are highly interested in the adaptation of dam operation toward releasing "environmental flows". These flows meet certain flow characteristics required to sustain and retain ecological activities and related human activities (Pastor et al., 2014). Besides flow regulation, dams result in the fragmentation of aquatic habitats and limit species movement, nutrient transport, and sediment movement (Skalak et al., 2013). Dam operations result in a decrease of sediment transports and reduce the riverine habitat-forming substrate available for critical life stages, for example fish nesting and refuge (Lehner et al., 2011; Skalak et al., 2013). These reduced sediment and nutrient transports significantly affect estuarine and coastal communities by sinking deltas, caused by reduced sediment transportation. Consequently, resulting in an increased vulnerability of anthropogenic activities depending on ecological providence (Syvitski et al., 2009).

Given these concerns, the role of dams and reservoirs has become a priority during the international debate about sustainable dam management (Lehner et al., 2011). Reservoirs affect geomorphological, ecological, economical, and social environments and it is essential to compromise in all of these. In addition, reservoirs result in a trade-off between reliability, in terms of demand, and ecological and geomorphological impacts. It is essential to acquire and study the maximum trade-off and turn this into maximum reward policies.

1.2 Problem Description and Research Objective

Nowadays, interest has shifted to the relevance of economic, ecological and geomorphological impacts of manmade dams. To provide information on the impact of globally distributed reservoirs, it is crucial to implement and consider reservoir operations in a Global Hydrological Model (GHM), capable of evaluating varying scenarios, for example in relation to anthropogenic climate change. Output of reservoirs in a GHM can be used to assess the impacts of reservoir release on ecosystem functioning and services, including among others water/energy supplies and flood protection. The value of such a model is, however, largely dependent on its skill and it is essential to understand reservoir outflow and establish model performance. Studies on reservoir operations are very complex, because real-time data is often limited and not publicly available. Moreover, large-scale hydrological models can only parameterize reservoir operations in general terms and often consider a single dam including a single purpose, which is detrimental for the model performance compared with actual observations. For example, PCR-

GLOBWB 2, the GHM used during this study, is able to parameterize reservoir outflow as a function of storage and downstream demand, but due to a lack of data, its reservoir scheme was globally implemented for a single dam type, which purpose is hydropower generation (Sutanudjaja et al., 2018). This single dam purpose provides inaccurate estimations of the reservoir effects, and potentially in relatively high levels of unmet downstream water demand. To improve the accuracy of the reservoir output it is necessary to characterize multiple reservoir purposes. PCR-GLOBWB 2 uses the most recent Global Reservoir and Dam (GranD, v1.3) dataset, which consists of 7320 globally distributed reservoirs (Lehner et al., 2011). This dataset excludes reservoirs smaller than 0.1 km^3, and limits the total amount of reservoirs available, which is estimated to be 45000 (Hanasaki et al., 2006).

Given the limited availability of data on reservoir operations and the general nature of the reservoir scheme in PCR-GLOBWB 2, the objective of this study is to assess the performance of its reservoir scheme for scenarios of different reservoir purposes (hydropower, water supply). To this end, modelled reservoir release is validated against reported values for a set of representative multi-purpose reservoirs across the world. To assess the chosen reservoir type and operations do not only lead to adequate performance in reservoir release, but also leads to an improvement in the water availability downstream of the dam, the reliability of the simulated reservoir operations is quantified in satisfied demand.

1.3 Research Questions

- Can reservoir release performance of PCR-GLOBWB 2 be quantified with observed outflow data to performance metrics for the most recent version of the GRanD (v1.3), and how are these metrics related to reservoir purposes, outflow characteristics, or within- and multi-year reservoirs?
- How vary discharges between reservoirs within- and multi-year reservoirs, and between reservoirs with and without a hydropower purpose?
- Can the total number of months with unmet downstream demand be quantified, and how does the allocation function affect the results between model simulations with and without the allocation function?

1.4 Reading Guide

This study consists of eight chapters fluently guiding you through all research steps. The following sections will provide background information, and introduce the reader to information about reservoirs, rivers, datasets, previous studies and the used model. Up next, the methodology is given, which outlines the research steps taken. Results are followed up upon and supply the main findings, and will be discussed in combination with the methodology. In the discussion a critical note is placed with regard to the results, methodology and the related research questions. Finally, the conclusion is given providing a brief research summary, the main findings, and conclusions.

2. Literature Study

2.1 Reservoirs

Reservoirs are anthropogenic structures with impacts to the land surface water balance and are locally and regionally important (Haddeland et al., 2006). Human made dams trap freshwater runoff and alter the timing of natural river flows. They are designed to serve a variety of purposes, for example hydropower, water supply, or flood protection. Design criteria are developed based on several procedures, which are mainly deterministic (Koutsoyiannis, 2005). An example of a deterministic design strategy is the mass curve analysis, which plots the cumulative inflow volumes as a function of time. The firm yield of a reservoir, which is defined as the maximum yield that could have been delivered without failure during the historical drought of record, is determined from this analysis. Other methods for reservoir design are simplified reliability-based procedures, which are analytical determinations of reservoir reliability fed by seasonality and arbitrary probability distribution (Koutsoyiannis, 2005). Probability-based theoretical analyses are used to determine the relations between reservoir size (c), demand (δ), and reliability (α). An example of a probabilistic approach is stochastic (Monte Carlo) simulation, in which long synthetic series of inflows are generated, which are transformed into series of storage values. Reliability is determined from the storage time series. Based on these findings the design of a reservoir can be specified to its specific purpose and reliability.

2.2 Single- and Multiple-Reservoir Operations

Reservoirs are grouped in single- and multiple-systems. Single operating reservoir systems are individual reservoirs and not aligned with other up- or downstream reservoirs. Multi-reservoir systems are defined as reservoirs in organized and connected series or as parallel units (see Figure 1). In Figure 2, an example is given of a multi-reservoir operation located at the Missouri River (U.S.). Other examples are the Columbia River (north western U.S.) and the Rio Grande (mid southern U.S.).

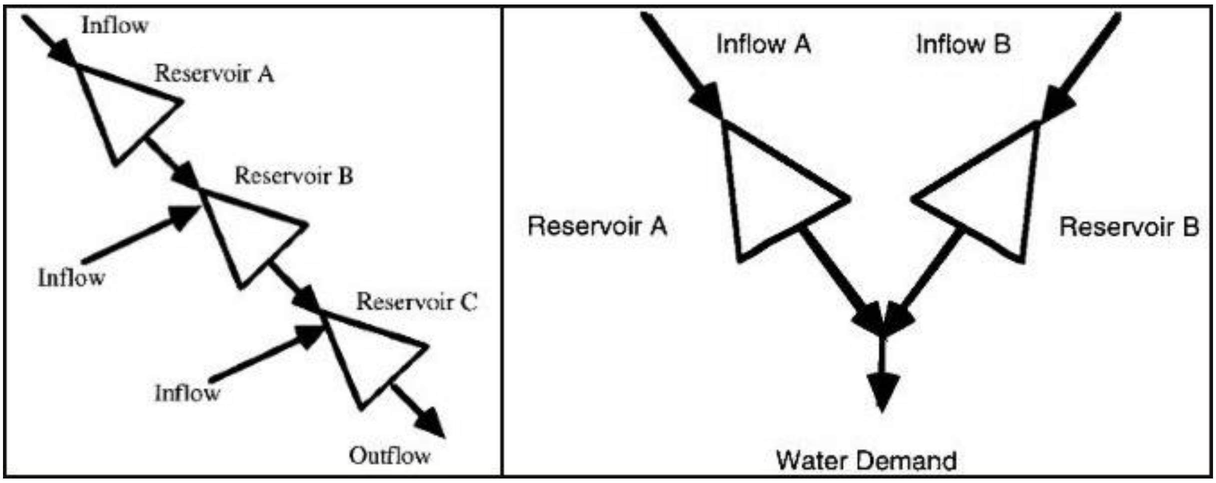


Figure 1*: Multiple-reservoir systems in series (left) and parallel (right)* (Lund et al., 1999).

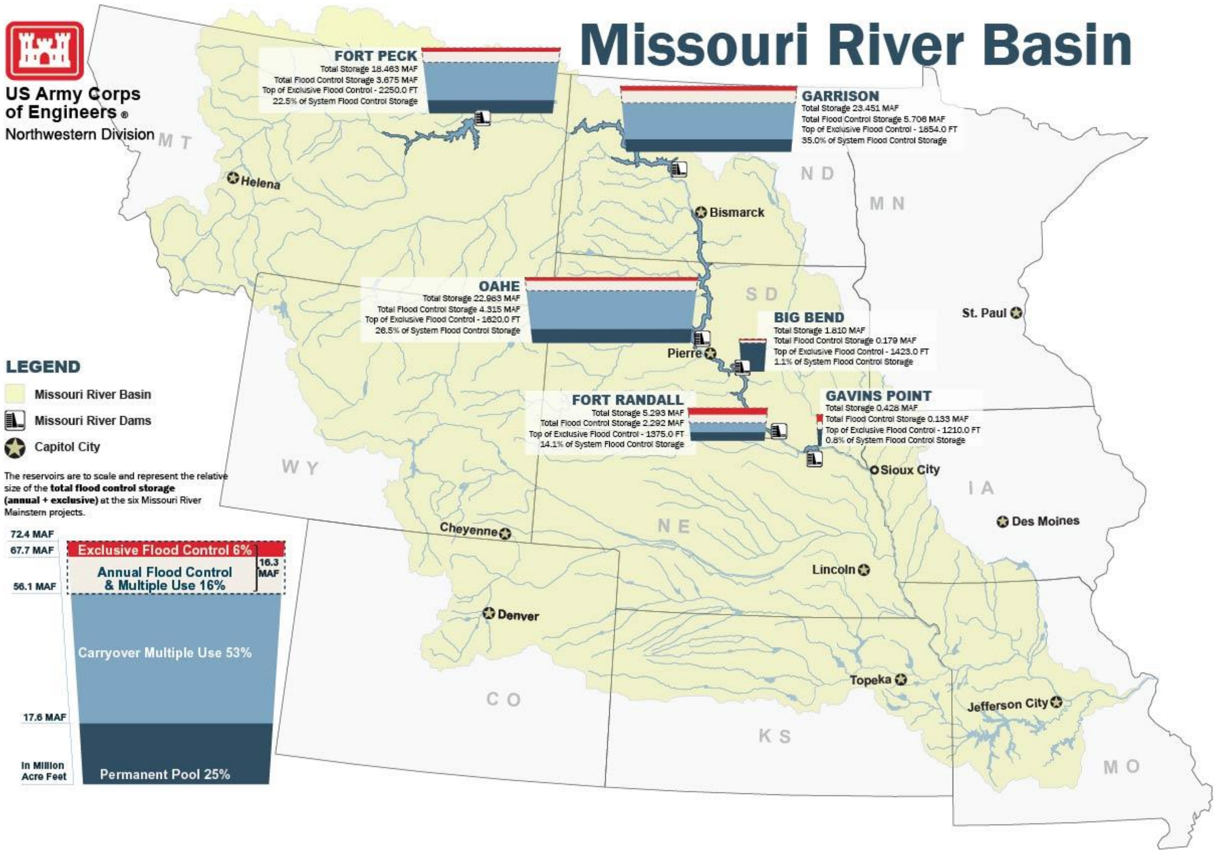


***Figure 2**: Example of a multiple-reservoir system located at the Missouri River Basin (Source: US Army Corps of Engineers).*

2.3 Within- and Multi-Year Reservoirs

Reservoirs can be arranged in single- and multi-year reservoirs depending on their characteristics of storage and inflow (Wu et al., 2012). Single-year reservoirs regulate their discharge at daily, monthly, seasonal or yearly temporal scale (Wu et al., 2012). Multi-year reservoir discharges are regulated interannual (Skaar et al., 2006). Related to Hanasaki et al., (2006) and Yassin et al., (2019) it can be defined as a within-year reservoir when the ratio between storage capacity and annual inflow (c) is less than 0.5, while multi-year is given with ratios of 0.5 and above. Other studies, for example from Wu and Chen (2012), used a value of 0.3.

2.4 Reservoir Operations

2.4.1 Storage Levels/Stages

Reservoirs contain specific storage volumes and are in general divided in five stages. Yassin et al. (2019) divided them in the dead, critical, normal, flood and emergency storage. Each storage zone has predefined rules developed during reservoir development and vary with seasonal fluctuations and meteorological forecasts. A lack of data availability for reservoir dead storages result in the assumption of 10% maximum storage as definition for the dead storage (Döll et al., 2009; Yassin et al., 2019). If the storage volume is equal or greater than the dead storage, then reservoir release returns empty. On top of the dead storage is the critical storage located and release avoids storage depletion, while supporting environmental flow requirements. In the third zone the outlet is only forced by reservoir storage, and increasing storage volumes are related to intensified release. In the fourth zone, release is a function of reservoir volume and the inflow. A certain reservoir level is required for flood control, while water storage is required for remaining purposes. For multi-purpose reservoir storages are divided in conservation and flood storage volumes. This flood level differs according to the season and contains annual variation (Valdes et al., 1995).

2.4.2 Environmental Flow Requirements

Reservoirs affect downstream flow patterns significantly and result in reduced ecological variety. Those impacts on downstream ecosystems extend to hundreds of kilometres (Richter et al., 2007). Reservoir development alters water temperature, chemistry, sediment transpose, floodplain vegetation, and downstream estuaries. Those consequences are further outlined in Section 2.6. The main priority during reservoir operation development is to ensure water demand and secondly to protect the downstream riverine ecosystem (Yin et al., 2011).

Environmental flows are defined as the minimum river flow volume needed to maintain healthy conditions of riverine ecosystems (Yin et al., 2011). It is related to the hydrological regime instead of a minimum discharge volume. Nowadays, the ecological impact of reservoirs is more significantly considered in policy development and bring higher variability into reservoir schemes. In reservoir modelling a minimum environmental flow requirement is often assigned to retain minimum reservoir release for maximum ecological preservation. Yin et al. (2011) mentions the consequence of these minimum release volumes causing a reduction in discharge variability.

Reservoir schemes can be adapted to environmental flows when historical discharge data is available before dam development. The historical data of an unaffected river provides details about the variety in high, low, and mean flows. If it is assumed that ecological diversity is at a maximum value for historical flows, then a maximum trade-off can be made between ecological diversity and human water needs (Suen et al., 2006; Yin et al., 2011).

2.5 Reservoir Purposes

Reservoirs can serve a variety purposes, including flood control, water supply (irrigation), hydropower generation, navigation, fishery and recreation (Wang et al., 2019). They serve multiple purposes to contribute to local, regional or national scale demands. Hydropower, water supply, and flood control are most relevant during this study.

2.5.1 Hydropower

Hydropower reservoirs serve as global electricity generators and affect riverine ecosystems by abruptly changing flow conditions, and are limited by minimum releases and maximum release variety (Olivares, 2008). In terms of a hydropower dam its main relevance is to generate a specific energy demand. Hydropower generator system efficiency can be around 85%, while thermal-electric plants are less than 50%. Unexploited hydropower electricity production could be increased by almost ten times (Martin Dorber, 2019). Hydropower dam policies are mainly focused on a continuous power demand and will, in comparison to other reservoir schemes, have a limited empty release. Those built for generating hydroelectricity have the most pronounced fluctuations in water level and are a direct result from varying electricity demands. Hydroelectric dams contain a fluctuating release during the day as consequence of daily varying power demands. This variation is relatively small to avoid loss of hydraulic head and reduction in power production (Nilsson, 2009).

2.5.2 Flood Control

The main purpose of a flood control dam is to prevent overflow damage downstream of the reservoir and to retain safety of the reservoir itself (Valdes et al., 1995). Release is restricted to the maximum allowable non-damaging channel capacity downstream. Crucial in flood control governing are storage capacity and expected inflow magnitude from an incoming flood (Zhou et al., 2018). In rivers with flood flows unable to be controlled by a single storage, multiple reservoirs work together to prevent these flood control points from flooding (He et al., 2017, Section 2.2). Combined reservoir systems are more effective in terms of peak delay than the equivalent storage capacity combined in one reservoir. Water cascading out of a reservoir produce a multi-peaked hydrograph. In terms of management practices these peaks can be delayed to reduce damage along the downstream river system (Valdes et al., 1995; Wu et al., 2012). Hydrographs of flood control dams result in unexpected high discharge volumes caused by intensified upstream rainfall events. To prevent downstream regions from flooding, this peak is delayed and gradually released afterwards. These dams often have multiple purposes, and also serve as water supply, irrigation or hydropower dam.

An example of a reservoir with flood-control as main function and recent failure is Lake Oroville. Intensified precipitation events upstream of the reservoir resulted in flooding and demolition of the spillway. Remarkable is the occurence during a flood scenario, which is the main design function (Koskinas et al., 2019). Scenarios similar to lake Oroville promote topics about reestablishment of the trade-off between risk-assessment and meeting downstream demands.

2.5.3 Water Supply & Irrigation

Water supply reservoirs are used as buffer during periods with less water availability. These periods, so called meteorological droughts, occur because of long-term rainfall shortage or an extended period with limited rainfall, and develop into an agricultural drought owing to a lack of moisture in the soil, which develops into a hydrological drought (Kim et al., 2018). As consequence, water supply storages will be forced by seasonal behaviour (Wang et al., 2006). Hydrological droughts develop into socioeconomic droughts, causing severe damages (Kim et al., 2018). To prevent those droughts, precautionary measures are taken by constructing water supply reservoirs. These reservoirs are used for industrial, municipal or irrigation purposes (Hanasaki et al., 2006). Typical for a water supply dam hydrograph is the moderate outflow compared to inflow. Peak inflows are tempered and stored to be used for more reliant demand periods. This is mainly used for irrigational purposes, while industrial or domestic purposes benefit from a more continuous outflow over time.

Irrigational reservoirs are used as agricultural water suppliers. Those systems are capable of transforming relatively dry areas into intensified agricultural regions (Biemans et al., 2011). Seasonal dependence of crop growth and annual variability in discharge and runoff are controlled by reservoir reserve features. Crops need a specific moisture content to optimize growth. During growing seasons this moisture content is often not available and cause a moisture shortage, which is fulfilled with water withdrawals. Irrigational reservoirs have a reservoir scheme with relatively low release compared to pre-dam operations. Water withdrawal from a reservoir in terms of irrigation is lost by transpiration and evaporation, and these make up the irrigation water consumption. Irrigational water consumption and the corresponding flow reduction is mainly high in semi-arid and arid areas with intensive irrigational activities (Döll et al., 2009). Irrigational withdrawals can be relatively high during dry periods and accounts for more than 90% of the global consumptive water use (Döll et al, 2009). Dry riverbeds are a common phenomenon at irrigational reservoirs. Characteristic for an irrigation reservoir is the strong seasonal fluctuation in reservoir outflow.

Water supply and irrigational reservoirs alter natural flow in terms of cumulative in- and outflow, and their corresponding timing of peak outflow. Inflow is stored at the reservoir during intensified precipitation events and is released when needed in downstream areas. This results in a delay of the peak outflow between natural flow, without reservoirs, and anthropogenically modified conditions. Besides, water supply reservoirs result in a reduction of the cumulative annual outflow. This is a result of local withdrawals and water body evaporation.

2.6 Reservoir Impacts

Reservoirs have positive and negative impacts on up- and downstream areas. The negative effects include alteration of the natural river dynamics of water, sediments, and nutrients; habitat fragmentation and loss of biodiversity (Biemans et al., 2011). To evaluate reservoir impacts on available water resources, ecosystems, and economics for anthropogenic use and future water stress, human alterations to the hydrological cycle need to be included.

2.6.1 Hydrology

Hydrological impact affects the downstream area with changes of the seasonal hydrological regime and flooding frequency, change in total discharge (water loss by irrigation, diversion and evaporation), short-term flow fluctuations (hydro-peaking), water level fluctuations (draw down zones in reservoirs and downstream lakes), hydraulic changes in rivers and lakes, groundwater level shift and salt intrusions near estuaries, thermal stratification in reservoirs, and alterations in temperature (Wüest, 2014).

Reservoirs alter the seasonal hydrological regime threefold: (1) a reduction in flow during the summer, (2) a drastic increase of winter discharge, and (3) a reduction in frequency and amplitude of extreme flows (floods and minimum flows) (Döll et al., 2009; Wüest, 2014; Zhang et al., 2018). Döll et al. (2009) provides a global overview of the impacts of anthropogenic water consumption and reservoirs on river flow regimes. Döll et al. (2009) related six indicators of river flow alterations to their relevance for the freshwater ecosystem health. These consist of biodiversity, the numerous and complex functions of reservoirs, reservoir operations, including the release to generate hydropower and to supply water downstream, and the storage of water during floods can significantly affect river discharges. Biemans et al. (2011) found a 5% decrease in global discharge from irrigational extraction and reservoir management. Between October to March an increase in discharge of up to 2% is caused by increased releases from non-irrigation reservoirs during months with low-flow. Biemans et al. (2011) found a mean annual decrease in global discharge of 2,1% or 930km^3.

2.6.2 Downstream Sedimentation

Wüest (2014) summarizes six sediment transport and river morphology impacts that are a direct result of artificial reservoir operations. Dam constructions can lead to reservoir siltation and reservoir filling, reduction of particle transport, increased clarity/reduced turbidity, turbidity peaks (extreme values during reservoir flushing), floodplain and bank deterioration (reduced flooding), delta retreat and coastal erosion (reduced sediment supply), and geomorphological stagnation of rivers and riverbed erosion (reduced sediments and bedload).

Reservoir siltation and reservoir filling is a consequence of sediment input from side-rivers. The sediment cycle is a continuous process of mechanical and chemical processes along a river basin and three main processes can be distinguished: sediment production, sediment transport and sediment deposition. Reservoir filling is caused by the accumulation of sediments and slowly fills and reduce the storage capacity (Schleiss et al., 2016). Another consequence is the reduction of particle transport downstream of the reservoir. Compared to rivers without reservoirs it causes erosion downstream of the dam instead of sedimentation. After a reservoir establishment on the Missouri River in the United States, the low water level dropped by more than 2.5m, ant the flood level increased by 1m in the lower reaches (Yang et al., 2017).

2.6.3 Climate

2.6.3.1 Greenhouse Gas Emissions

Freshwater reservoirs are a known source of greenhouse gas (GHG) emissions to the atmosphere (Prairie et al., 2017). All inland aquatic systems are sites where active carbon processing and transport occur, and receive carbon in dissolved or particulate fractions of inorganic and organic material (Prairie et al., 2017). Carbon fractions convert one species to another and some can be emitted into the atmosphere or being buried. Due to biochemical activities in reservoirs, methane is formed, which is a 34 times more powerful GHG than carbon dioxide in terms of warming potential (Kemenes et al., 2007). Drops in hydrostatic pressure during relatively dry periods enhance methane bubbling (Deemer et al., 2016). More frequent alterations in hydrostatic pressure give rise to enhanced emissions. Although just a relatively small percentage of terrestrial surface is covered with freshwater reservoirs, their net contribution to the atmosphere is of the same order as the flux between oceans and atmosphere (Prairie et al., 2017). Changes in reservoir management should implement the impacts of reservoirs on climate to release schemes.

2.6.3.2 Energy Balance

As a consequence of reservoir development, alteration trends in the regional energy balance, and its corresponding hydrological cycle, are observed (Degu et al., 2012). Effects of reservoirs on the energy balance and water cycle are divided in direct and indirect consequences. Indirect consequences of reservoir development lead to an increase of the average precipitation and a decrease of average observed temperatures, and are predominantly located in arid or semi-arid regions (Lehner et al., 2011; Pizarro et al., 2013). Increases of precipitation and temperature are caused by enhanced irrigational activities close to reservoirs (Degu et al., 2012; Pizarro et al., 2013). Direct consequences of reservoir developments are increased numbers of extreme rainfall events and the precipitation volume (Pizarro et al., 2013). These are mainly observed closer to reservoirs ($\leq\ 5\,km$) and in more arid regions.

During the pre-reservoir situation flows proceed continuously downstream until it reaches lower lain lakes or oceans. In the situation with reservoir it generates an increase of potential evaporation due to enlarged surface area.

$$R_n = H + \lambda E + S \qquad \textit{Eq. 2.6.3.2.1}$$

Where R_n is the net radiation $[W\,m^{-2}]$, H the sensible heat flux $[W\,m^{-2}]$, λE the latent heat flux $[W\,m^{-2}]$, λ as latent heat of vaporization in $[J\,kg^{-1}]$, E is the evaporation rate in $[kg\,s^{-1}\,m^{-2}]$, and S is the change of energy storage in the lake $[W\,m^{-2}]$ (Liebe, 2009). From this equation it becomes clear that surface area is one of the key elements for the latent heat flux, which is forced by evaporation. For increased surface areas this means an increase in total evaporation, causing an increase in moisture availability and more frequent precipitation events.

2.7 Reservoir Databases

Databases with reservoir information are used to provide and categorize relevant information concerning dams and reservoirs. Those datasets contain information regarding to reservoir name, construction-year, spatial coordinates, capacity and other relevant information. Examples of widely used reservoir datasets are GRanD, FHRED, ICOLD, or FAO AQUASTAT (Lehner et al., 2011; Zarfl et al., 2014). With ICOLD being limited in its use due to limited access, and FAO AQUASTAT being used as main input for the GRanD.

The Global Reservoir and Dam (GRanD) database provides information for 7320 dams and reservoirs and includes dam and reservoir names, spatial coordinates, construction year, surface area, storage capacity, dam height, main purpose, and so on. The largest combined reservoir volumes are concentrated in Canada, Russia, United States, Brazil and China. This most recent version, published in 2019, unifies and extends previous versions. It expands the database by 458 new dam locations built between 2000 and 2016. This brings the total to 7320 dams and adds a reservoir storage capacity of 667 km^3. For 5759 of the 7320 global reservoirs, information is available for the main and side purposes of reservoirs. Please note, after the year 2000 only 450 reservoirs were attached to the global reservoir system, while, for example, between 1950 and 1970 approximately 2500 dams have been built. Reservoirs nowadays are mainly built in rapidly developing regions, for example South-East Asia (see Figure 3), where water demand is increasing at an intensified rate.

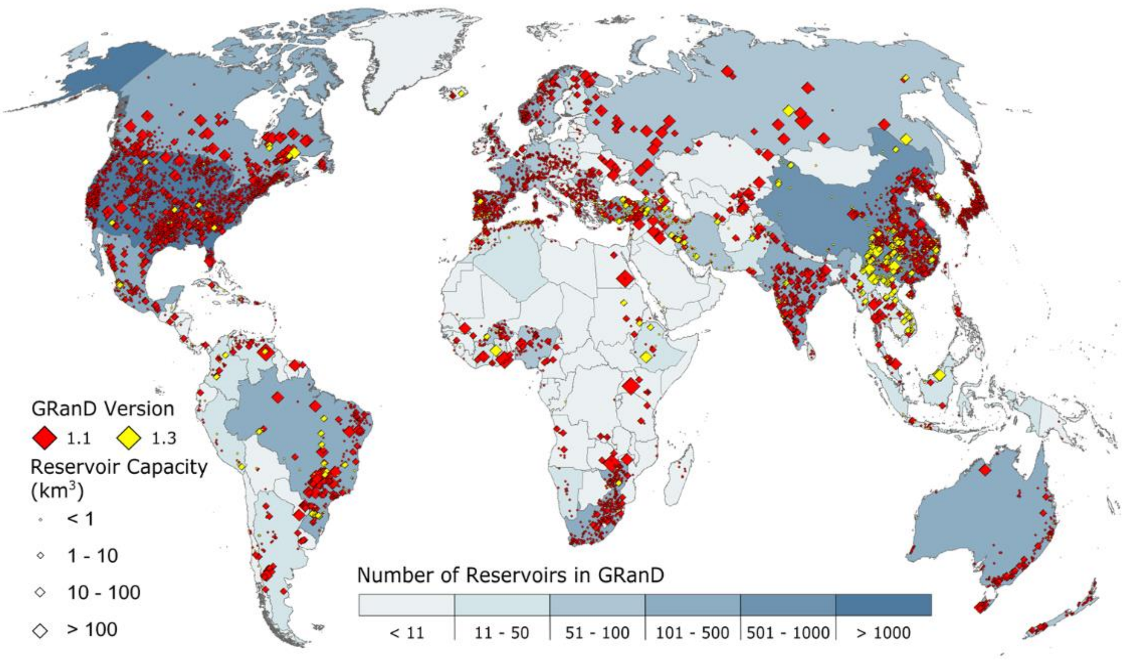


***Figure 3**: The Global Reservoir and Dam (GRanD) database most recent version (v1.3). In yellow the reservoirs added since the first version (Source: globaldamwatch.org).*

3. Methodology

3.1 PCR-GLOBWB 2

PCR-GLOBWB 2 (PCRaster Global Water Balance) is one of the most recently developed Global Hydrology Models (GHM) and is used during this study. It is a grid-based global hydrological model developed at the Department of Physical Geography, Utrecht University (Van Beek et al., 2011; Sutanudjaja et al., 2018; Van Beek and Bierkens, 2009). This version, compared to others, fully integrates water use (see Figure 4). Sector-specific water demand, water withdrawal, water consumption, and return flows are calculated at every time-step and interact directly and dynamically with the simulated hydrological processes (Sutanudjaja et al., 2018). The first version of PCR-GLOBWB was performed at relatively coarse resolution of 30 arcmin (50 by 50 km at the equator), limiting their sub regional or local applications. This second version of the model is able to simulate the water balance at a finer spatial resolution of 5 arcmin. This allows an improved representation of globally distributed alterations in topography, soil, and vegetation on hydrological processes. An improved resolution for visualization supports decision-makers and stakeholders (Sutanudjaja et al., 2018).

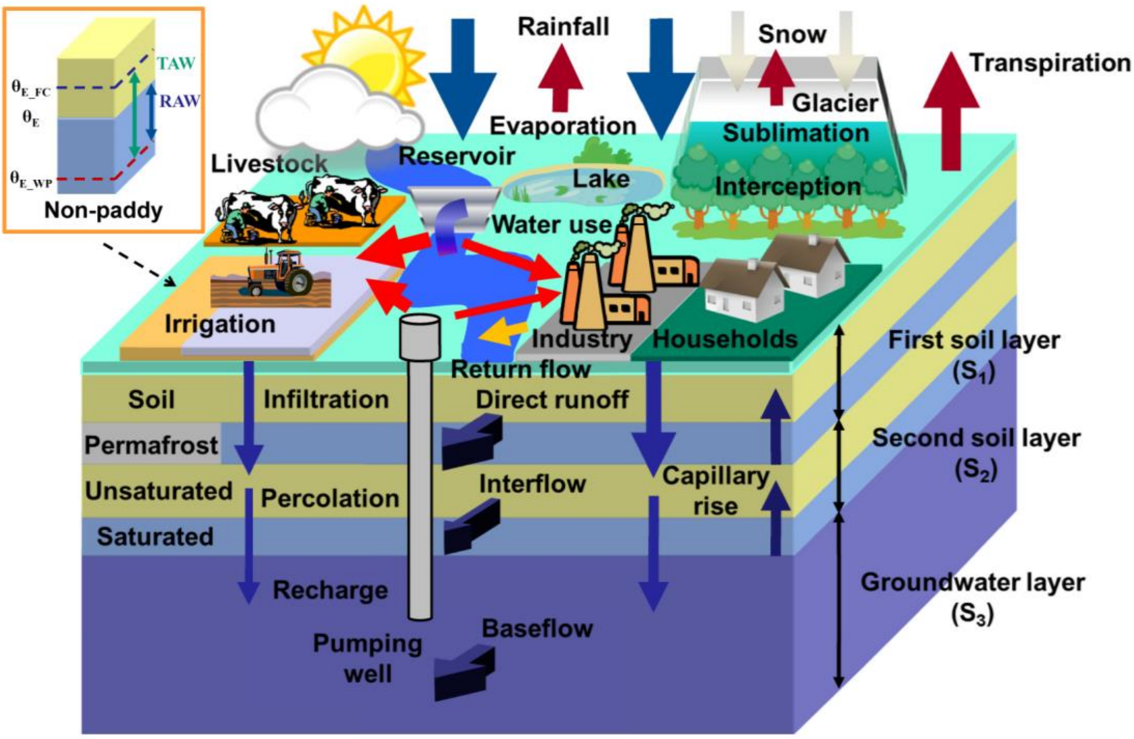


***Figure 4**: Schematic diagram of the modelling framework in PCR-GLOBWB* (Wada et al. 2014)

3.1.1 Reservoir Strategies

PCR-GLOBWB 2 dynamically implements reservoirs at the start of each year and is done to realize an improved representation of reservoir development over time. Unfortunately, resulting in an annual parameterization for each reservoir. Reservoir outflow is developed as function in PCRaster programming language, is integrated into the routing scheme, and uses average outflow, inflow and reservoir storage as conditional statements for outflow regulation. The functions in PCR-

GLOBWB 2, resulting in reservoir outflow, are given in Appendix 9.4.1 and are implemented in the model as decision statements to return reservoir outflow $\left(Q_{resvOutflow}\right)$.

If lakes and reservoirs are introduced to the scheme, then average outflow $\left(Q_{\mu_{outflow}}\right)$ is set to the maximum value between average outflow, channel discharge $\left(Q_{\mu_{channel}}\right)$ and inflow $\left(Q_{\mu_{inflow}}\right)$ (see Eq. 9.4.1.1 - Eq. 9.4.1.3). If average outflow, in upcoming time steps, is greater than zero, then this value is used in the next decision variable. The second step introduces a reduction factor $(F_{reduction})$ which limits reservoir outflow to empty the reservoir below dead-storage (see Eq. 9.4.1.4- Eq. 9.4.1.6) and uses reservoir storage (S), capacity $\left(S_{capacity}\right)$, and minimum $(R_{minFrac})$ and maximum $(R_{maxFrac})$ reservoir fraction. Without reservoir outflow limitation it returns a value of one, and does not limit the reservoir outflow. To limit reservoir outflow for dry conditions, caution is taken by limiting reservoir outflow to the inflow.

In the next statement (see Eq. 9.4.1.8) the downstream demand $(D_{downstream})$ is implemented and assigned to reservoirs. The computation and allocation of downstream reservoir demand is further outlined in section 3.1.3 and is, for now, implemented in the reservoir outflow function. Again, a reduction factor $(F_{reductionDemand})$ is attached to prevent reservoir outflow from continuously satisfying downstream demand values (see Eq. 9.4.1.7). It is related to the minimum reservoir fraction as function of the reservoir capacity. If reservoir storage is close to its dead storage, the model limits downstream demand satisfactory to its maximum outflow capacity. Dead storage is predefined, because this part of the waterbody volume cannot be used for outflow, as it is predominantly below outflow level.

The final step in PCR-GLOBWB's reservoir outflow function is to prevent a reservoir from flooding, and is done with multiple decision variable functions (see Eq. 9.4.1.10 - Eq. 9.4.1.16) using estimated storage $(S_{estimated})$ for the next timestep in combination with storage capacity, maximum and minimum reservoir fraction, bankfull ratio $\left(R_{Qbankfull}\right)$, average outflow, and reservoir outflow. Flood outflow (Q_{Flood}) returns empty when estimated storage is less than storage capacity multiplied by the maximum reservoir fraction, and if the bankfull ratio multiplied by the average outflow and subtracted by previous calculated reservoir outflow, is less than zero. Conditions with intense precipitation events, forcing high runoff volumes, can result in overflowing reservoir volumes. To prevent storage volumes greater than its capacity, a function forces a maximum reservoir outflow to prevent figurative dam failures. It relates reservoir outflow and inflow, and if reservoir volumes are greater than the maximum allowed storage capacity, then it will equalize the reservoir outflow to the inflow. Throughout the program in PCR-GLOBWB 2 it uses conditional statements to satisfy the most accurate outflow value for each time step.

3.1.2 Demand Routing

Water supply in PCR-GLOBWB-2 is subdivided in irrigational, industrial, livestock and domestic demands. Without this module, water availability and demand were calculated independently (Wada et al., 2014). In this second version of the model both computations are integrated to dynamically simulate water consumption at a daily time step. This represents a more reliable interaction between human water use and terrestrial water fluxes (Wada et al., 2014). Irrigational water demands are calculated based on the crop composition and the irrigated area per cell (Sutanudjaja et al., 2018). Those irrigated areas change over time. Furthermore, crops are separated in fractions of paddy and non-paddy irrigation, and crop composition per month. These fractions are predetermined, while the total irrigated area per cell changes over time (Sutanudjaja et al., 2018). The non-irrigational water demand function is prescribed by population, electricity demand, and gross domestic product (GDP) per capita (Sutanudjaja et al., 2018). Domestic water demands are forced by seasonal variations in temperature. Both industrial and domestic water demands are computed by a country specific recycling ratio (RC), which is associated with the GDP and the access to domestic water demand. Water withdrawal in PCR-GLOBWB2 is equalized to gross water demands unless sufficient water is not available (De Graaf et al., 2014; Sutanudjaja et al., 2018; Wada et al., 2014). With insufficient water availability the withdrawal is downscaled to available water sources and allocated per sector (Sutanudjaja et al., 2018). If river discharge, under naturalized conditions, drops below one-tenth of the average yearly discharge, then the surface water withdrawal is ceased. In PCR-GLOBWB 2 a module is implemented, consisting of water desalination in coastal areas (Wada et al., 2014). This module calculates water abstractions from salt water and contributes this to the total gross demand and withdrawals.

3.1.3 Demand Allocation

A recently developed function, capable of allocating downstream demand to upstream reservoirs, is implemented in PCR-GLOBWB2. In this section the allocation function, contributing to the reservoir outflow, is briefly outlined to contribute to the understanding of this operation onto the overall routing scheme. A description of the demand allocation function, implemented in PCR-GLOBWB, will be given. Followed by a specification of the implementation into the routing scheme. The full list of functions, statements, and routing implementations are given in sections 9.4.2, 9.4.3, 9.4.4.

The function begins with the allocation of reservoirs based on their capacity. Reservoir parameterization is done on an annually, because PCR-GLOBWB2 dynamically implements reservoirs regarding to their construction year. The implementation of the reservoir allocation starts with a decision statement (see Eq. 9.4.3.1) which defines whether the reservoirs and demand need to be allocated or not. Then the characteristic flow velocity is calculated based on average discharge, channel width and channel depth (Eq. 9.4.3.2). Reservoirs satisfy local and downstream demands that could be reached within $\sim 600\, km$ or to a next downstream reservoir, and result in average flow velocities of approximately $1\, m\, s^{-1}$ (Van Beek et al., 2011; Hanasaki et al., 2006; Wada et al., 2014). It is used as input for the allocation scheme. This scheme is given in section 9.4.3 and allocates the total capacity and downstream serving area of the upstream reservoirs. The downstream allocation function uses this total capacity to assign a weight for the demand per reservoir (Eq. 9.4.3.13). This allocated downstream demand is recalculated with the implementation of the environmental flow requirements, which are added to the downstream demand when a reservoir is available in a cell (Eq. 9.4.2.9).

Conditions where downstream demand is not allocated to a reservoir, or demand is absent, the reservoir outflow is a function of active storage. This mainly results in increased storage values, because it does not need to satisfy any downstream demand and is defined as a hydropower purpose reservoir. If downstream demand is allocated to upstream reservoirs and storage volumes allows to, then the scheme tries to satisfy this demand. Again, if the dead storage is reached, then the outflow is limited and allocated demand values cannot be fulfilled.

3.1.4 Model Forcing

During this research the 30 arcmin spatial resolution is used with a time range from 1980 to 2010. This time range is a consequence of the limited historical data availability and the maximum length of meteorological forcing data. Outputs, in terms of discharge, were modelled as daily or monthly averages. In PCR-GLOBWB2 the GRanD v1.3 is used as input for general information, for example location or reservoir capacity, about earth's major artificial reservoirs. Antarctica and Greenland are not implemented in PCR-GLOBWB2. A new reservoir dataset, GRanD v1.3 is introduced to the most recent version of the model.

The performed model simulations are forced by WATCH Forcing Data methodology applied to ERA-Interim data (WFDEI). This dataset is useful for modelling hydrological impacts in large catchments, because bias correction preserves the spatial continuity of large-scale or frontal precipitation events with half-degree grid boxes (Weedon et al., 2014). Most of the grid data in WFDEI is provided by the CRU TS3.1/3.2 and GPCCv5/v6 data sets. It contributes to temperature, precipitation and potential reference evapotranspiration.

Every model simulation, processed during this study, is given in Table 1. For PCR-GLOBWB 2 two versions are available, which are one with a relatively low spatial resolution of 30 arcmin in lat- and longitude and one with higher resolution of 5 arcmin (Sutanudjaja et al., 2018). The spatial resolution of 30 arcmin is used to reduce time interval in between model simulations. During those model simulations the spin-up is set at one year, so it can use the first year to perform dynamic state equilibrium.

Four model simulations (see Table 1) are performed to gradually implement multiple conditions. The first simulation is used as initial situation and is limited to natural conditions. Followed by a model simulation including man-made dams. The third simulation includes initial demand modules and at last a simulation is done including the allocated demand function.

***Table 1**: Scenarios for PCR-GLOBWB 2 modelling*

Model simulation	**Properties**	**Model Output**	**Spatial Resolution (Arcmin)**	**Simulation period**
1st	In the first model run PCR-GLOBWB 2 is used in naturalized conditions without reservoir impacts or water demands.	Outflow	30	1980-2010
2nd	The second model run uses PCR-GLOBWB 2.0 without water withdrawals but includes reservoirs.	Outflow	30	1980-2010
3rd	Includes all water demand modules (Wada et al. 2014) and reservoirs (GRanD v1.3)	Outflow, Demand	30	1980-2010
4th	Includes all water demand modules (Wada et al., 2014), reservoirs and additional water demand allocation (Sections 3.1.2 & 3.1.3)	Outflow, Demand	30	1980-2010

3.2 Model Performance

Hydrological models are sources of uncertainty, because each model implements different schemes for land surface, or river routing processes and uses different spatial resolutions (Masaki et al., 2017). Even natural flows differ significantly considerably among GHMs (Global Hydrological Models) (Masaki et al., 2017). For this study model performance is obtained for 40 reservoirs with observed outflow data (see section 3.3). Afterwards it can be used to obtain a generic scheme with indicators for reservoir features and model performance.

The Kling Gupta Efficiency is used to establish model performance for long term metrics (Gupta et al., 2009; Sutanudjaja et al., 2018; Yassin et al., 2019). To analyse model performance it is assumed that at least ten years of daily validation data is required (Van Beek et al., 2011; Yassin et al., 2019). This is not fully applied due to limited observed data availability. If this minimum time-range is not established, then it can be assumed that these performance metrics are less accurate. The acquisition of statistical performance methods is done with Hydrostats, a Python module developed by Roberts et al. (2018). It includes five separate modules: analyze, data, ens_metrics, metrics, and visual, and contributes to the simplification of data processing, analysing and visualising. The metrics module contains 70, widely used, hydrological metrics for hydrological model verification, including the Kling Gupta Efficiency of Gupta et al., (2009). This version of the Kling Gupta Efficiency is used instead of the more recent version (Kling et al., 2012), because for model performance comparison it is highly relevant to use similar statistical acquisition methods as in previous studies (Sutanudjaja et al., 2018). With the interconnection of modules in Python programming language (van Rossum, 1995), Pandas (McKinney, 2010), Numpy (Van Der Walt et al., 2011), and Hydrostats it was possible to develop a data analysis method, able to obtain data frames from Network Common Data Form (NetCDF) files and translate this into performance and statistical analyses between observed and modelled data.

The Kling Gupta Efficiency (KGE) is used, because it weighs the importance of various components(Gupta et al., 2009; Pechlivanidis, Jackson, McMillan, & Gupta, 2014). Gupta et al. (2009) mentioned the concern of using the Nash Sutcliffe efficiency with the observed mean as baseline. This led to overestimations of model performance for seasonal variables like runoff in snowmelt dominated basins. Especially in a GHM it is essential to eliminate these overestimations. The KGE is used to analyse the model performance instead of the widely used mean squared error or the Nash-Sutcliffe efficiency (Gupta et al., 2009; Kling et al., 2012; Nash & Sutcliffe, 1970; Sutanudjaja et al., 2018).

The Kling-Gupta Efficiency (KGE) is defined as follows:

$$KGE = 1 - ED \qquad \textit{Eq. 3.2.1}$$

$$KGE_s = 1 - ED_s \qquad \textit{Eq. 3.2.2}$$

with: *Eq. 3.2.3*

$$ED = \sqrt{(r-1)^2 + (\beta-1)^2 + (\alpha-1)^2} \qquad \textit{Eq. 3.2.4}$$

$$\alpha = \frac{\sigma_s}{\sigma_o} \qquad \textit{Eq. 3.2.5}$$

$$\beta = \frac{\mu_s}{\mu_o} \qquad \textit{Eq. 3.2.6}$$

$$r = \frac{Cov_{so}}{\sigma_s * \sigma_o} \qquad \textit{Eq. 3.2.7}$$

where ED (Eq. 3.2.4) is defined as the Euclidian Distance from the ideal point. The Kling Gupta Efficiency (Gupta et al., 2009; Kling et al., 2012) can be interpreted as high performing when values are close to 1, and a low performance below zero. A KGE value of, for example, 0.6 means that the worst component is ≥0.6 (Kling et al., 2012). With α (Eq. 3.2.5) and β (Eq. 3.2.6) are defined as high performance close to 1 and low when it highly deviates from 1. With α as a measure of relative variability in the data values, and β representing the bias. r (Eq. 3.2.7) is defined as the correlation, ranges between 1 and -1, and defines the timing of an in- or decrease between two datapoints. If two alterations match in their directions, then it will result in a value of 1, and -1 for mismatching. In other words it is an analytical tool to provide information about the timing between two data samples.

3.3 Reservoir Data

The study area ranges from site specific reservoirs and their individual behaviour to outputs of the global hydrological model (GHM) PCR-GLOBWB 2. Individual reservoirs are mainly provided for North-American data with open access, while other reservoir data, outside of the USA, are provided by Yassin, Fuad (2018). For 40 reservoirs the real-time observed data is obtained to be compared with PCR-GLOBWB2 outflow data. Performance of these reservoirs in PCR-GLOBWB 2, compared to observed data, is quantified with the method given in section 3.2.

Reservoirs are grouped regarding to their socio-economical and climatological relevance. These features generate a certain dam height, width, and volume. Climatologically, reservoirs are shaped to prevent potential downstream damage done by intense precipitation events, or to delay the outflow for future dry periods (water supply). Causing deviations in, for example, within- or multy-year characteristics of reservoirs. This ratio is defined with the variable "c" and is given in Table 2 for each reservoir.

The most relevant reservoir purposes for this study are hydropower, water supply, and flood control. This is related to the most abundant reservoir purposes in the GRanDv1.3 dataset. Other purposes, for example fishery, navigation or recreation, were limited available and assumed to be unusable. This assumption is grounded upon the reduced chance to match a reservoir for its main purpose with observed data and the limitation of PCR-GLOBWB2 in relation with minor purposes. Furthermore, most of these other purposes are limited as secondary purpose.

3.3.1 Dataset

To validate simulation results, long term monthly or daily operational records of observed outflow data were obtained (see Table 2). Unfortunately, the data was unequally distributed and was mainly available in North-America, where reservoir operation data has open access from the worldwide web. Poor data availability for reservoirs, river hydrographs and dams make it difficult to analyse trends in globally distributed reservoir purposes (Zajac et al., 2017). For global variation the dataset of Yassin, Fuad (2018) is included, which contained data availability for Central- and Far East Asia. The obtained real-time reservoir data can be subdivided in four regions: North-America, Central Asia, Southeast Asia and Oceania. Due to difficulties in reservoir data acquisition it was not possible to obtain high quality data from South-America, Africa and Europe. Furthermore, it was hard to obtain data outside of the VS, because of limited access, expensive datasets, and little or no respond on data requests in other countries. The globally obtained reservoirs and their size are presented in Figure 5.

Figure 5*: Overview of the global spatial reservoir distribution for observed data. The data is sorted by capacity and is subdivided in 5 groups corresponding to their capacity in Million Cubic Meters (MCM).*

3.3.2 Data Revision

Data revision is done to prevent inaccuracies in the results. For the outflow analysis, accomplished with flow duration curves (FDCs), it is a prerequisite to have complete outflow records, causing a minimum of 360 days per year of discharge data to be useful for outflow analysis (Searcy, 1959; Vogel & Fennessey, 1995). The data obtained from American rivers is given in cubic feet per second (*cfs*) and needed to be converted to cubic meter per second (*cms*). For some of the reservoirs, provided by Yassin, Fuad (2018), a temporal resolution of 10 days was available. This temporal resolution is, combined with other reservoir features, given in Table 2.

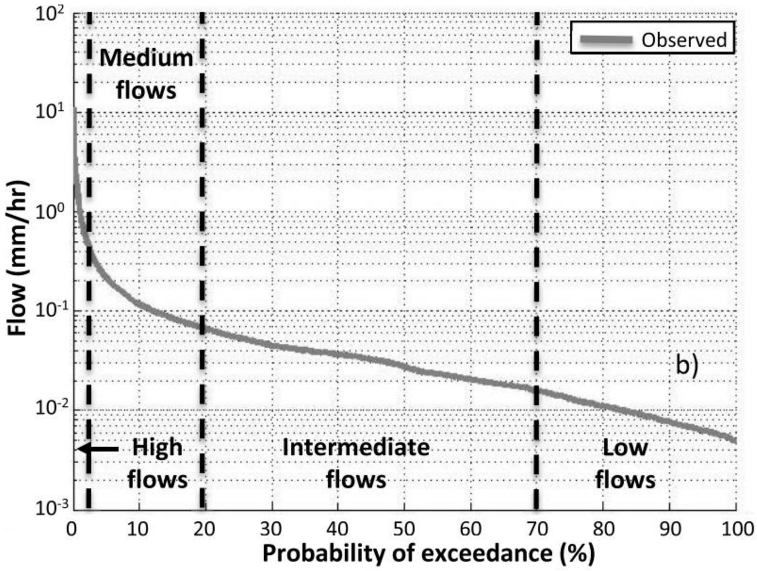


Figure 6*: An example of a Flow Duration Curve (FDC) provided by Pechlivanidis et al., (2014).*

3.4 Flow Duration Curves

To analyse reservoir release, the evaluation method, used in Yassin et al. (2019), Searcy (1959), Döll et al. (2009) and Biemans et al., (2011), is combined. They normalized reservoir scheme parameters and their ranges across different types and sizes of reservoirs with Cumulative Distribution Function (CDFs). Those CDFs are used to obtain trends and changes between observed and simulated release, and are a measurement tool to integrate the effect of climate, topography and geology on the distribution of runoff frequencies and magnitudes in a single graph. With flows arranged to their frequency of occurrence and the CDF plotted, it presents the effect of these factors (Searcy, 1959; Vogel et al., 1995). For reservoir release they are defined as Flow Duration Curves FDCs and visualize the discharge against the exceedance probability (Searcy, 1959). The Weibull plotting formula was used to construct the FDCs for regulated and unregulated flows (Jiang et al., 2009; Yassin et al., 2019):

$$P = \frac{\left(100 * \frac{M}{n+1}\right)}{Q_{max}} \qquad \textit{Eq. 3.4.1}$$

where P is defined as the probability a given flow will be equalled or exceeded in percentage of time, M is the ranked position on the list and n is the number of events for period of record (Sugiyama et al., 2003). Figure 6 shows an example of a FDC, which marks specific regions for low, intermediate, medium and high flows. These phases are used to characterize reservoir outflows per reservoir purpose. Different to the Weibull plotting formula is the introduction of Q_{max}, which enables the user to analyse the data for each probability of exceedance relative to the maximum observed median outflow. This reduced the complexity to compare in between reservoirs.

During this study the calendar-period method is used, which positions all discharges in classes according to their magnitude (Searcy, 1959). A FDC, constructed on a daily temporal base, provides most detailed flow representations and is used as analysis method (Jiang et al., 2009). A method to eliminate differences in volumes is to express discharge per median exceedance probability. One of the marks for a FDC is the 90 percent exceedance discharge, which is the discharge volume $(m\,s^{-1})$ exceeded 90% of the time (Q_{90}) and is defined as low flow. Alterations in Q_{90}, Q_{50} (median flow), and Q_{05} (peak flow) are used as main components for the comparison between observed and modelled reservoir outflow for each purpose (Vogel et al., 1995). The exceedance probability per discharge volume is taken for each year to obtain the all-time median. This excludes years with extraordinary high or low flows in minimum, average, and maximum sense and gives a long-period trend. These non-exceedance probabilities are compared for anthropogenically regulated and unregulated conditions.

3.5 Unmet Demand & Reliability

In Eq. 3.5.1 the function quantifying unmet demand on a long term average monthly base is given. Where average demand is defined with D_{μ}, modelled average outflow as $Q_{\mu_{modelled}}$ and unmet demand with D_{Unmet}. The number of months when demand is unmet $(D_{Unmet} < 0.0)$ is summed and defined as the total number of months with unmet demand. This is done on a monthly base and can have a maximum value of 372, which is the number of months in between 1980 to 2010. D_{Unmet} is only computed for model simulation 3 and 4, because those included water demand and withdrawal in their model scheme.

$$D_{Unmet} = \sum_{i=1}^{n} (Q_{\mu_{modelled}} - D_{\mu}), \quad D_{unmet} > 0 \qquad \textit{Eq. 3.5.1}$$

With the implementation of the allocation function, downstream demand in model simulation three consists of environmental outflow, while simulation number four implements the allocation of the downstream irrigational, domestic, and livestock demand. This gives a lower satisfactory rate for reservoirs in simulation four, but is used to mention the difference. Trends in the number of months with unmet demand will be evaluated in relation to their purpose or mean cumulative inflow to storage volume ratio (within- or multi-year).

Table 2: *Summary of reservoirs.*

Dam Name	***Country***	***Year***	***Main Purpose*** [a]	$c = \frac{Capacity}{MAI}$	***Dam Height (m)***	***Capacity (MCM)*** [b]	***Reservoirs in PCR-GLOBWB2 Cell*** (n)	***Temp-oral Res.***	***Data period***	***Source***
Albeni Falls	USA	1955	HF	0.07	55	1424.7	1	1-D	1980-2010	www.cbr.washington.edu
American Falls	USA	1977	IHR	0.30	32	*2062*	1	1-D	1978-1994	Yassin, Fuad (2018)
Bhumibol	Thailand	1964	IHWF	2.61	154	*13462*	1	1-D	1980-1995	Yassin, Fuad (2018)
Big Sandy	USA	1952	H	0.10	6	67.1	2	1-D	1990-2018	www.usbr.gov/rsvrWater
Blue Mesa	USA	1965	H	0.73	119	923.2	2	1-D	1980-2018	www.usbr.gov/rsvrWater
Buffalo Bill	USA	1909	HWI	0.72	107	746.0	2	1-D	1980-2018	www.usbr.gov/gp/hydromet/
Chardara	Kazakhstan	1965	HI	0.36	27	*6700*	1	10-D	2001-2010	Yassin, Fuad (2018)
Charvak	Uzbekistan	1977	HI	0.28	168	*2000*	1	10-D	2001-2010	Yassin, Fuad (2018)
Copeton	Australia	1976	IHW	5.53	113	*1364.0*	1	1-D	2009-2010	www.waternsw.com.au/
Fall River	USA	1948	F	0.84	29	316.3	1	1-D	2000-2009	www.swt-wc.usace.army.mil/
Flaming Gorge	USA	1963	WHF	2.42	153	4336.3	4	1-D	1980-2010	Yassin, Fuad (2018)
Fort Peck Dam	United States	1957	FHIR	2.64	78	*23560*	1	1-M	1970-1999	Yassin, Fuad (2018)
Garrison	United States	1953	FHIR	1.55	64	*30220*	2	1-M	1970-1999	Yassin, Fuad (2018)
Ghost	Canada	1929	H	0.05	42	*132*	1	1-D	1990-2010	Yassin, Fuad (2018)
Grand Coulee	USA	1941	IF	0.07	168	6395.6	2	1-D	2000-2013	www.usbr.gov/pn/hydromet/
Int. Amistad	Mexico	1969	IH	2.61	87	6330.0	1	1-D	1977-2006	Yassin, Fuad (2018)
Int. Falcon	Mexico	1953	IHWF	1.40	53	3920.0	1	1-D	1958-2006	Yassin, Fuad (2018)
Joes Valley	USA	1965	IF(H)	0.80	59	67.7	2	1-D	1995-2018	www.usbr.gov/rsvrWater
Kayrakkum	Tajikistan	1957	HI	0.20	32	4160.0	1	10-D	2001-2010	Yassin, Fuad (2018)
Keystone	USA	1964	HI	0.32	37	*2063,1*	3	1-D	2007-2010	www.swt-wc.usace.army.mil/
Lake Helena	USA	1972	I	0.01	6	*60,5*	3	1-D	1980-2010	www.usbr.gov/gp
Lake Kemp	USA	1923	FWH	0.42	35	1282.8	4	1-D	2006-2010	www.swt-wc.usace.army.mil/

Dam Name	Country	Year	Main Purpose [a]	$c = \frac{\text{Capacity}}{\text{MAI}}$	Dam Height (m)	Capacity (MCM) [b]	Reservoirs in PCR-GLOBWB2 Cell (n)	Temp-oral Res.	Data period	Source
McPhee	USA	1983	IHW	0.62	90	282.5	2	1-D	1985-2018	www.usbr.gov/rsvrWater
Nurek[c]	Tajikistan	1980	IH	0.50	300	*10500*	1	10-D	2001-2010	Yassin, Fuad (2018)
Oldman	Canada	1991	IH	1.31	76	490.0	1	1-D	1996-2011	Yassin, Fuad (2018)
Oahe	United States	1966	FHIR	0.45	75	29110.0	1	1-M	1970-1999	Yassin, Fuad (2018)
Oroville	USA	1968	FHIWR	0.72	235	4366.5	5	1-D	1995-2010	Yassin, Fuad (2018)
Powell (Glen Canyon)	USA	1966	HW	2.23	216	25070	1	1-D	1980-2010	https://www.usbr.gov/
Rafferty	Canada	1991	IFWR	72.87	20	632.4	1	1-D	1998-2010	
Red Fleet	USA	1979	IWR	0.75	53	*29.6*	4	1-D	1989-2018	www.usbr.gov/rsvrWater
Ririe	USA	1976	FIR	0.03	77	*99,3*	1	1-D	1976-2018	www.usbr.gov/
Ross	USA	1949	HFR	0.75	165	1791.9	2	1-D	1980-2019	www.nwd-wc.usace.army.mil
Seminoe	United States	1938	IHR	1.04	90	*1255*	1	1-D	1951-2013	Yassin, Fuad (2018)
Sirikit	Thailand	1974	IHWF	1.83	114	9510.0	1	1-D	1981-1996	Yassin, Fuad (2018)
Split Rock	Australia	1988	IW	5.19	66	372.0	1	1-D	1996-2018	www.waternsw.com.au/
St. Mary	Canada	1951	I	0.50	62	394.7	1	1-D	2000-2011	Yassin, Fuad (2018)
Thief Valley	USA	1931	I	0.14	22	21.5	1	1-D	1984-2018	www.usbr.gov/
Travers	Canada	1954	I	0.87	41	317.0	1	1-D	1979-1988	Yassin, Fuad (2018)
Tuyen Quang	Vietnam	2008	H	0.23	92	2245.0	1	1-D	2007-2011	Yassin, Fuad (2018)
Waterton	Canada	1963	I	0.26	55	172.7	1	1-D	2000-2011	Yassin, Fuad (2018)

[a] Main purpose: H = Hydropower, I = Irrigation, W = Water Supply, F = Flood Control and R = Recreation. Multiple letters should be interpreted as: 1. Main Purpose, 2. Secondary Purpose, 3. Secondary Purpose, etc. [b] Capacity, with unity MCM, is defined as million cubic meter. Data period is defined as the acquired period of data in years. Temporal resolution (Temp. Res.) is given in number of days(1-D or 10-D) or monthly(M).

4. Results

This chapter presents the results of the model performance, outflow analysis, and unmet demand findings. To maximize the readability it is subdivided in multiple sections. It begins with the model performance to validate the quality of the model in relation to observed outflow. Subsequently, the results continue with an outflow and unmet demand analysis. To maximize the interpretation and understanding of the results, some findings, interpretations, and potential causes will already be discussed in this chapter. Conclusions on these trends will be discussed in the discussion.

4.1 Model Performance

The overall performance results for the 40 reservoirs are presented in Figure 7 and Figure 8. The exact results per reservoir are given in Appendix Table 1 and Appendix Table 2. Model performance is defined with the Kling Gupta Efficiency (KGE) and its individual components (see Section 3.2). These findings were obtained for the period between 1980 to 2010 and compares PCR-GLOBWB 2 monthly average outflow data with observed data. High performance is defined for performance with KGE values greater than 0.0, moderate performance between -1.0 and 0.0, and low performance less than -1.0. A value of 1.0 marks a perfect fit for (α), (β), and (R). Please note, Tuyen Quang is given in the results but did not produce output for simulation 2, 3, and 4, and produced incorrectly acquired data, but is given as the highest performing reservoir for performance sorting.

4.1.1 Long-Term Statistics of Reservoir Outflow

The model performance of the final simulation, including demand allocation, resulted in 12 reservoirs with a $KGE > 0.0$, 11 with $-1.0 < KGE < 0.0$, and 16 with a $KGE < -1.0$. Low performance $(KGE < -1.0)$ is highly related to the overestimation of peak values (α) and the bias (β) (see Figure 7), which resulted in values greater than 4.0 (see Figure 7b and d). In terms of ratio a value of 0.5 indicate an underestimation of twice the observed outflow, while 2.0 indicate a double overestimation. Correlation (R), given in Figure 7c, performed relatively well for low performing $(KGE < 0.0)$ reservoirs. McPhee and Nurek, two overall low performing reservoirs in PCR-GLOBWB 2, did show a high correlation value (> 0.75) for monthly outflow values, which is greater than or equal to other high performing reservoirs. Even the lowest performance at the final simulation, given by Red Fleet reservoir $(KGE = -83)$, resulted in a correlation greater than 0.5. Corresponding to a relatively high performance of release timing in PCR-GLOBWB2. High performing reservoirs $(KGE > 0.0)$ resulted in a relatively small under- or overestimation of α and β, but mainly remained in between a ratio of 0.5 and 2.0.

The overall trend is predominantly low performing, observed for $16/40$ reservoirs, and is related to extreme overestimations of the bias or peak values (see Figure 7b and d). The lowest performing reservoirs in PCR-GLOBWB 2 highly overestimated both of these parameters, while for reservoirs performing close to the edge with moderate performance the peak values were mainly overestimated. For moderate performance a subdivision is observed between reservoirs with over- and underestimation of the outflow for both bias and peak values. With Travers, Powell, and Big Sandy Dike as examples of clear underestimations of both (α) and (β).

4.1.2 Long-Term Statistics per Model Simulation

The reservoir scheme of PCR-GLOBWB 2 had a hard time to reproduce release volumes, statistically defined by (α) and (β). It had a good sense of timing for most reservoirs, because relatively high correlation values were obtained for each category (high, moderate, low). Figure 7c shows the relation between overall model performance and correlation, because high correlation values reduce for descending performance, but it does not result in a similar downward trend as observed in Figure 7a. In terms of performance per simulation it did not result in significant improvements between ex- and including the allocation function. The only reservoir with a visible change in KGE, between the final simulations, was Lake Helena. This is caused by an increased overestimation in peak values. In between model simulation 1, 2 and 3 an improvement is observed, which can be related to the more realistic simulation in ascending order. With simulation 1 excluding reservoirs, simulation 2 including reservoirs, and simulation 3 including reservoirs and global demand. The similar outflow response of simulation 4, compared to simulation 3, can partially be related to the inability of this demand function to force reservoirs to deliver downstream demands. It allocated downstream demand to be more satisfactory over time compared to the previous situation. Unfortunately, other reservoir scheme rules can still reduce the reservoir outflow.

The low performance of a large group of reservoirs can possibly be related to the in-series feature of multiple reservoirs. This could have resulted in similar inaccurate model outputs for the similar river basin. Two examples are given in Figure 9 and Figure 10, and show two reservoirs in series, and were outperforming compared to observed outflow. Int. Amistad and Int. Falcon are given in Figure 9, which are two reservoirs with directly in-series features. This means outflow of Int. Amistad directly flows into Int. Falcon without a significant intervening input. Another example is given in Figure 10, where a comparison between two reservoirs in Kazakhstan is visualized. Both examples resulted in low performing KGE values for each reservoir. Unfortunately, the impact of an upstream in series reservoir directly affected the storage volume over time for downstream reservoirs. Due to the usage of storage volume in the function for reservoir outflow, this directly resulted in similar behaviour of reservoirs downstream. Therefore, it is highly plausible reservoirs in series result in similar performance values. Charvak, a reservoir, which outflow is added to the flow between Kayrakkum and Chardara (example in Figure 10) resulted in a relatively high performance value $(KGE > 0.3)$ and is not directly affected by an upstream reservoir, which resulted in independent performance. Fort Peck and Oahe resulted in similar low performance and were in-series without significant input. Another reason for low performance availability at multiple reservoirs, for example Bhumibol and Sirikit, could be the presence of these reservoirs at similar main river basins. These in series reservoirs are available in PCR-GLOBWB 2 at the main stream of the flow-map. It did not clarify the performance of the reservoir scheme in PCR-GLOBWB 2, but noticed the importance in accuracy of forcing at a specific river basin.

4.2 Grouped Performance

In this section, model performance is sorted according to reservoir purposes or annual inflow against storage volume ratio. Performance findings, only given for KGE, are shown in Figure 8a and b.

High performance is predominantly observed for within-year reservoirs, reservoirs with hydropower purposes, and non-hydropower purposes. Low performance is obtained for multi-year reservoirs and secondary hydropower purposes. Keep in mind multi-year reservoirs are indicated by a mean annual inflow to storage capacity ratio greater than 0.5 ($c > 0.5$). Most of these multi-year reservoirs with a low performance featured a secondary hydropower purpose (see Figure 8). Moderate performing reservoirs ($-1 < KGE < 0$) were not specifically related to "c" or a reservoir purpose. For most multi-year reservoirs it resulted in an overestimation of the outflow. A possible source of the low performance can be the impact of outflow of reservoirs upstream. For example, Chardara and Kayrakkum reservoirs were available on the same stream flow. With Kayrakkum being the first reservoir to implement outflow to the stream. Outflow performance could be more sensitive to geographical location than the relevance of purpose or annual regime. Upstream precipitation events, causing runoff and discharge, force the model to generate a certain response. In terms of reservoirs this incoming discharge resulted in a modified sensitivity of storage volumes, which directly affected the outflow. Low performance of upstream regions could have been the main cause of inaccuracies for reservoir outflow and the river basin in general. This indicates the potential difficulty of drawing conclusions on reservoir release performance in moderate or low performing river basins.

4.2.1 Seasonality

In Figure 8 reservoir performances are sorted according to their purpose and annual inflow to reservoir storage ratio. Within-year reservoirs resulted in the highest overall performance. A visually interpretation of the monthly average outflow (see Figure 11) indicates those reservoirs with a more accurate sense of timing compared to multi-year reservoirs. For these relatively small reservoirs, compared to their mean annual inflow, it looks easier to reproduce seasonal delay caused by a reservoir compared to multi-year reservoirs. For multi-year reservoirs this delay is not observed or is shifted too much compared to observed values. In terms of purpose this resulted in relatively high performance values for hydropower reservoirs, and low performance for non-hydropower reservoirs. Unfortunately, it will be difficult to draw conclusions on observed trends related to their purpose, because low performing reservoirs are probably more related to misinterpretations of upstream discharge than to reservoir purposes.

4.2.2 Number of Reservoirs per Grid Cell

Table 2 shows the number of reservoirs for each grid cell where the reservoir is located. PCR-GLOBWB2 cumulates the available reservoir capacity in a single grid cell. Multiple reservoirs available on a single grid cell have resulted in overestimations of peak-values and bias. This is observed for Red Fleet (4), Oroville (5), and Lake Kemp (4), especially the bias is highly overestimated, while the peak flows are relatively tempered. For grid cells with one reservoir an underestimation of the outflow is observed, for example for Waterton or Split Rock Dam.

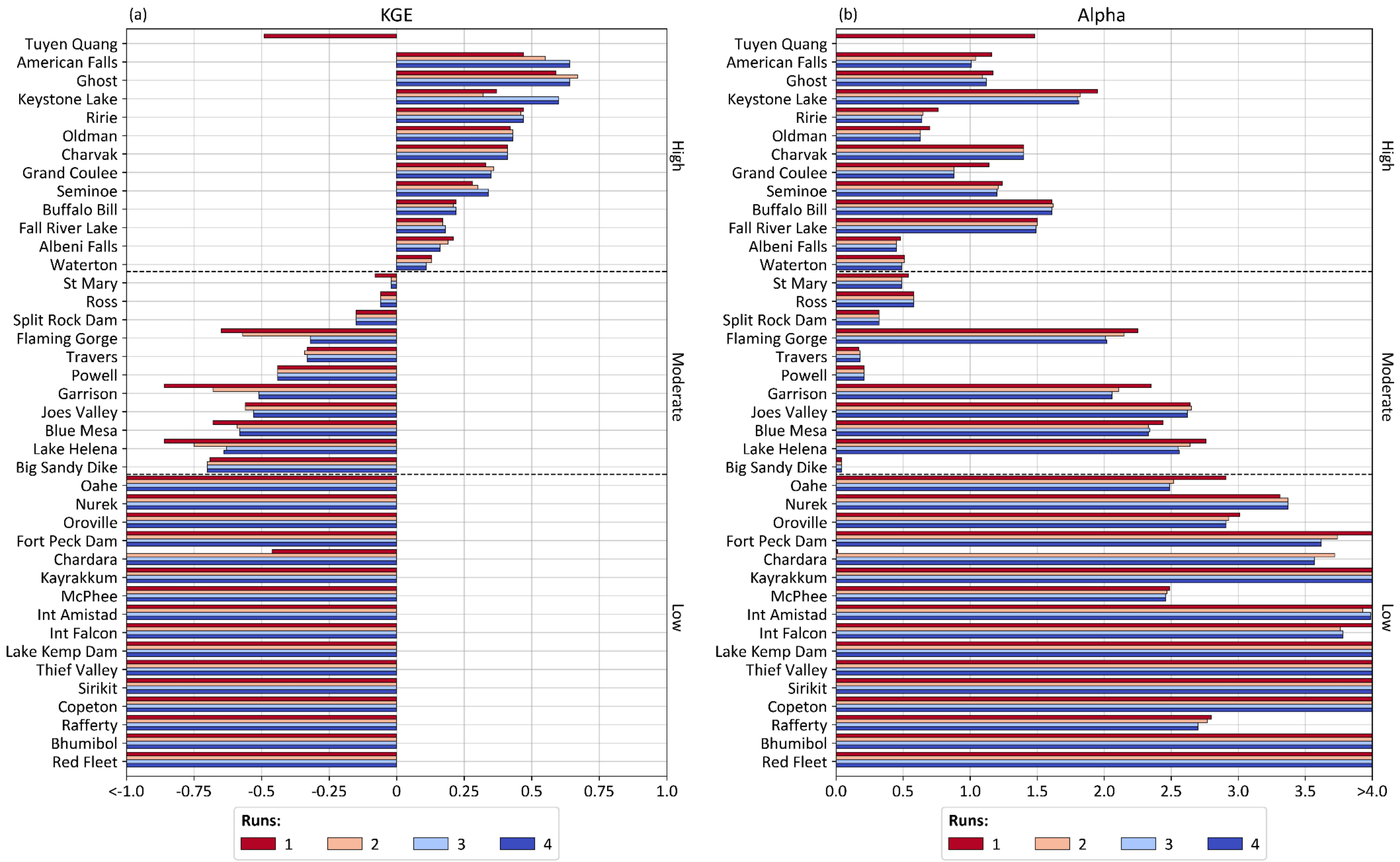


***Figure 7**: Monthly average performance evaluation results for each individual PCR-GLOBWB 2 simulation sorted according to the KGE performance of the final simulation: **(a)** KGE performance metrics, **(b)** Amplitude performance metrics $\left(\frac{\sigma_s}{\sigma_o}\right)$. Simulation 1 is related to the natural conditions, simulation 2 contains reservoirs, simulation 3 has reservoirs and the basic water demand modules, and simulation 4 includes reservoirs and the additional water demand.*

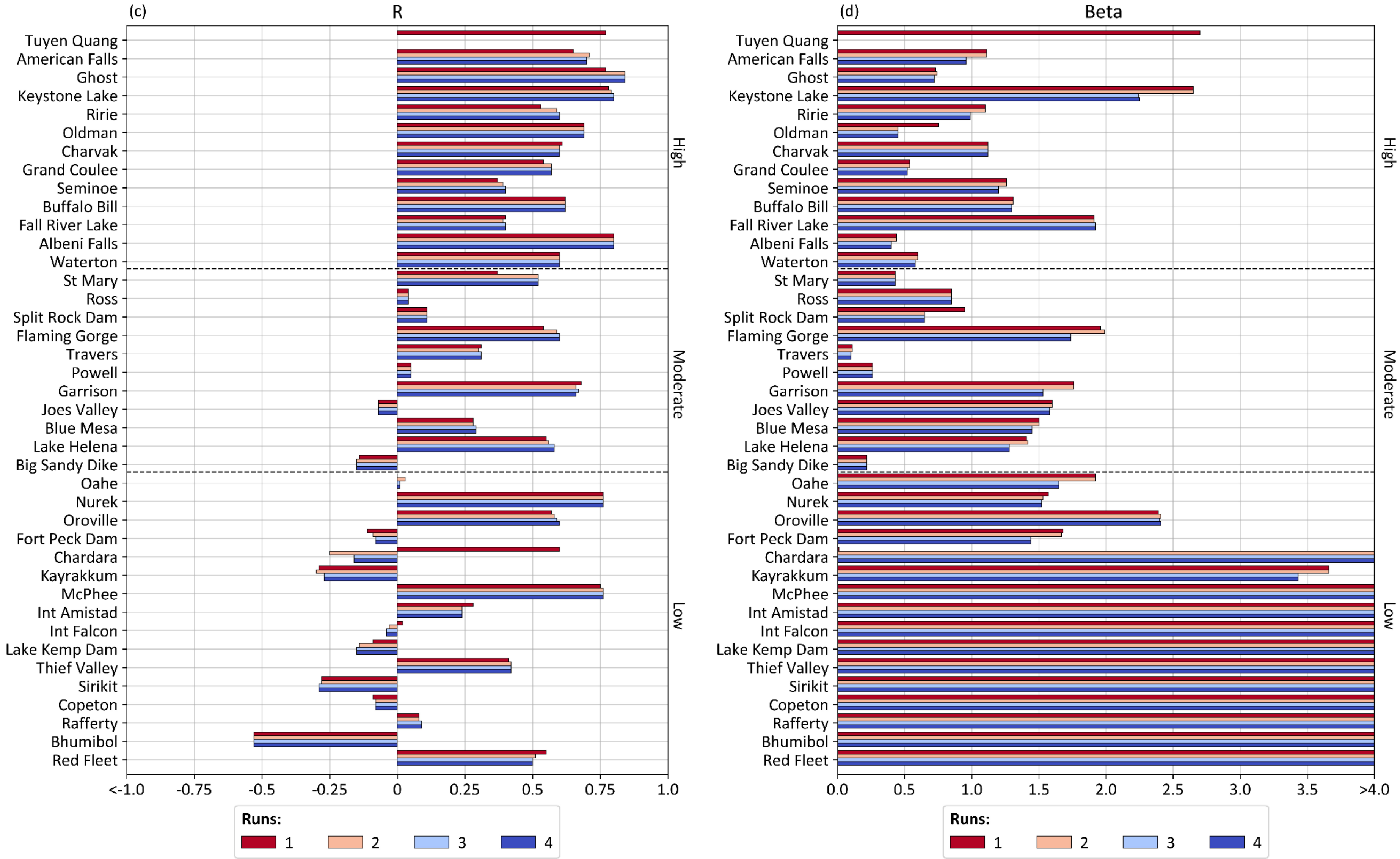


Figure 7 *(continued):* ***(c)*** *Bias performance metrics* $\left(\frac{\mu_s}{\mu_o}\right)$, *and* ***(d)*** *Correlation performance metrics* $\left(\frac{Cov_{so}}{\sigma_s * \sigma_o}\right)$. *Performance metrics are sorted from high to low performance, with the KGE as categoriser.*

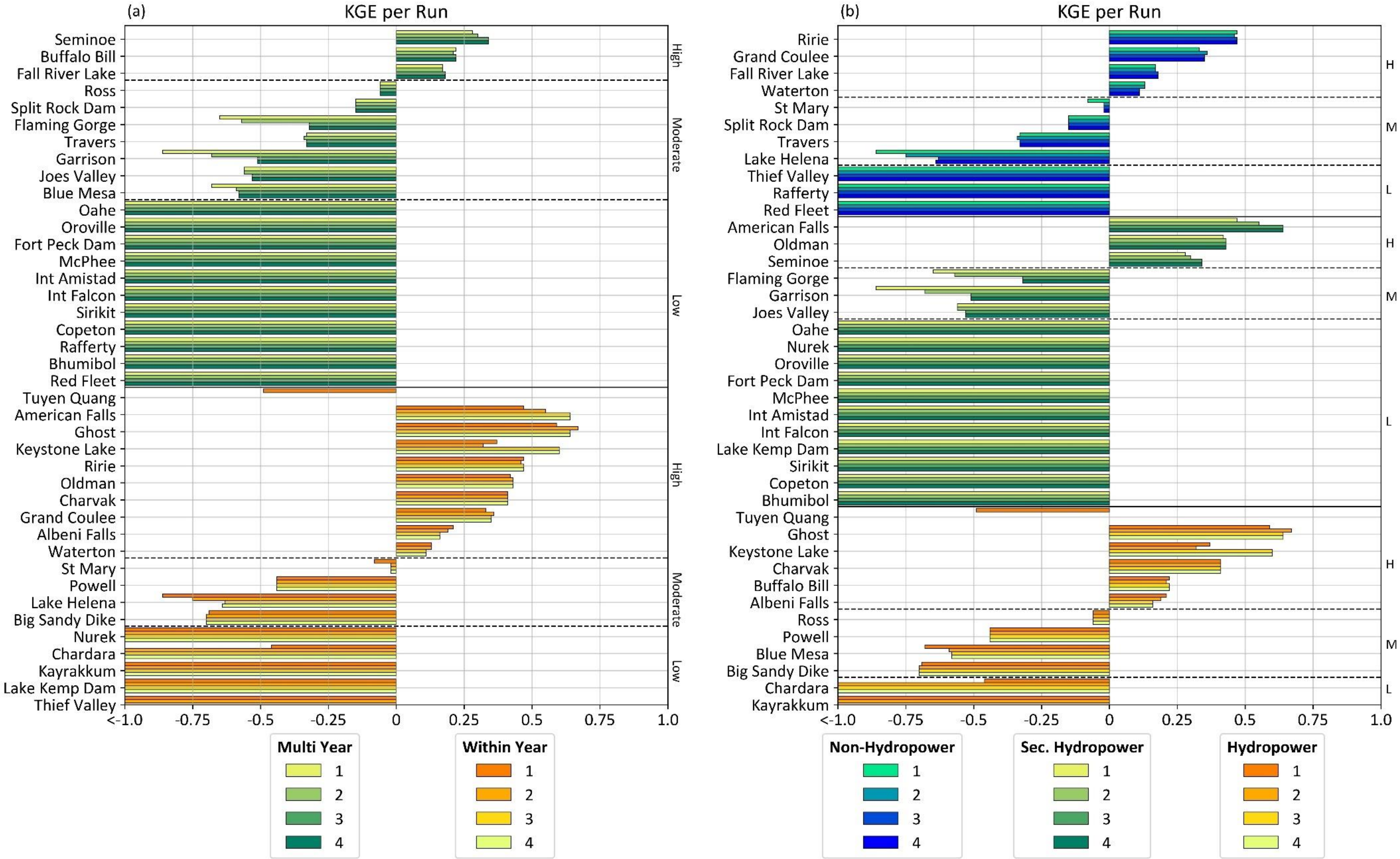


***Figure 8**: Kling Gupta Efficiency sorted per reservoir type, model run, and performance. These are sorted according to the ratio of reservoir capacity to mean annual inflow **(figure a)**, and according to their reservoir type **(figure b)**.*

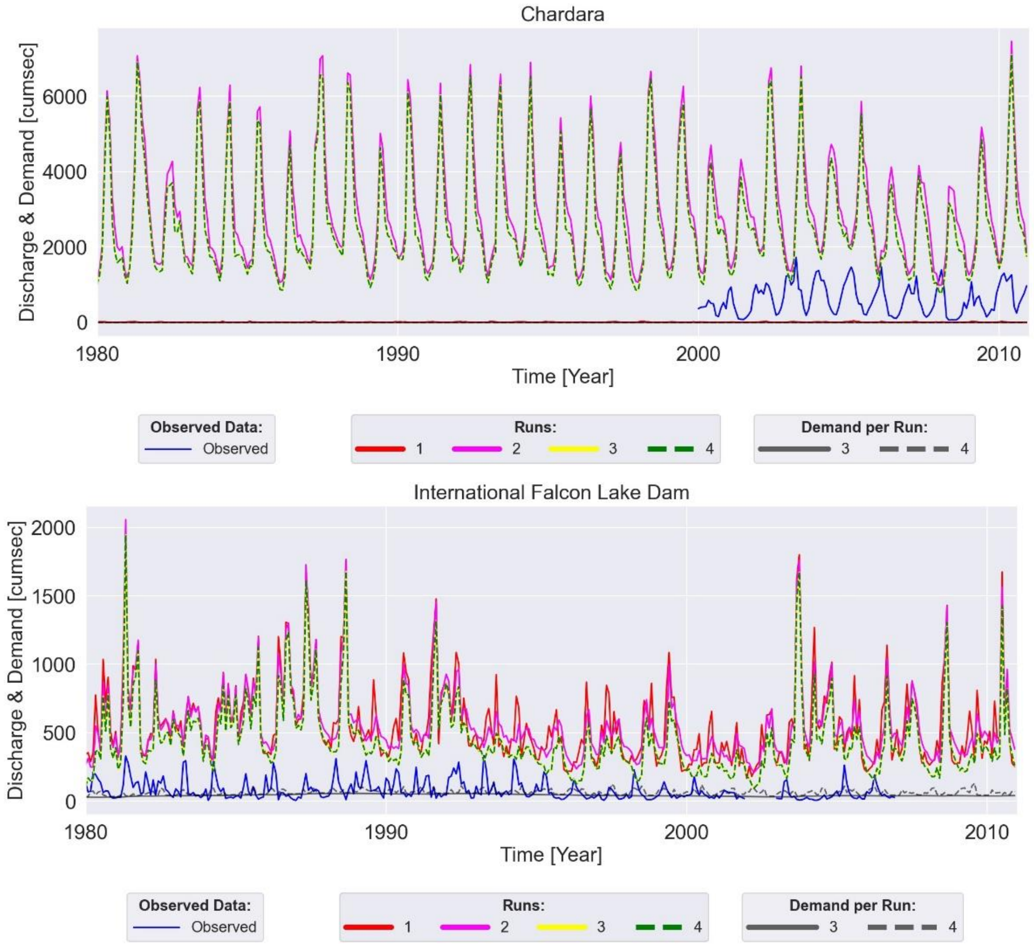


***Figure 9**: Hydrographs of monthly outflow for two in-series reservoirs, obtained for all simulations and is done with PCR-GLOBWB 2 between 1980 and 2010, including demand. Simulation 1 is related to the natural conditions, Simulation 2 contains reservoirs, Simulation 3 has reservoirs and the basic water demand modules, and Simulation 4 includes reservoirs and the additional water demand.*

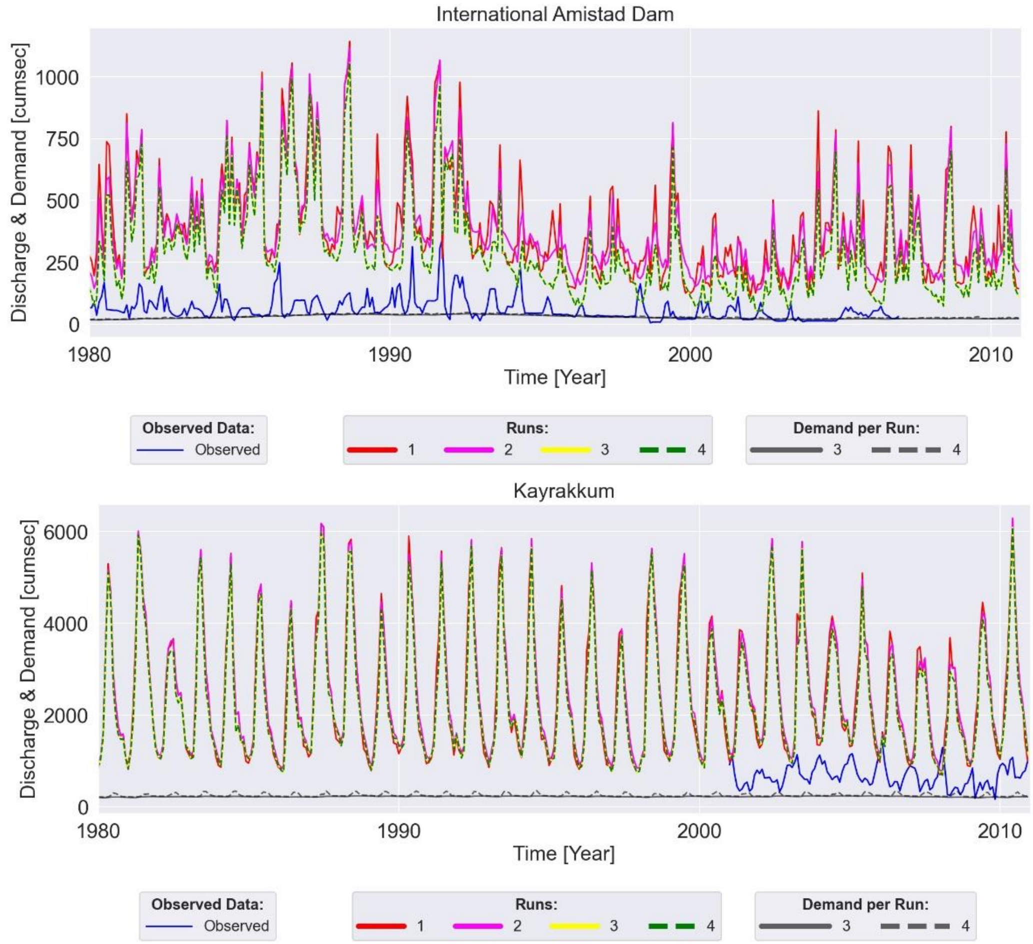


***Figure 10**: Hydrographs of monthly outflow for two in-series reservoirs, obtained for all simulations and is done for PCR-GLOBWB 2 between 1980-2010, including demand. Simulation 1 is related to the natural conditions, Simulation 2 contains reservoirs, Simulation 3 has reservoirs and the basic water demand modules, and Simulation 4 includes reservoirs and the additional water demand.*

4.3 Outflow Analysis

Considering the overall and sorted model performances, trends could be observed in outflow regimes. This will be subdivided in overall trends and more specific for distinctive and single purpose reservoirs. An overview of the outflow findings is presented in Figure 11 and Figure 13. During this analysis the model performance is used to be related to outflow. The monthly average sensitivity of reservoir storage to outflow is given in Figure 12.

4.3.1 Evaluation of Long Term Monthly Release

The first trend, observed for most reservoirs, is the attenuation of monthly average outflow over time. Reservoirs are known for their attenuation feature in peak flow and seasonal delay. Examples of reservoirs without this limitation are Buffalo Bill and Charvak, which did not show any change over time between natural or human impacted discharge. This could be the result of the ability of PCR-GLOBWB2 to satisfy peak flow and bias at any time or due to similar in- and outflow forced by maximum storage volumes. An example of a reservoir resulting in a reduction and delay of the peak flow is Grand Coulee. Figure 13 shows this reservoir resulted in an increased minimum outflow (Q_{90}) and a decreased peak outflow (Q_{05}). Please note, these flow duration curves are normalized to their median maximum monthly outflow value. This trend is mainly observed for non- or secondary hydropower driven reservoirs, while peak flow reduction was mainly expected for hydropower driven reservoirs.

4.3.2 Seasonality

Delay and reduction of outflow are two of the consequences taken in mind during the construction of a reservoir. This sensitivity of a reservoir to incoming flow volumes is expressed in reduced outflow volumes or sensitivity in terms of storage limitation. In Figure 12 are the reservoir storages given and can be linked to the findings in Figure 11. Reservoirs with a low sensitivity for outflow delay or reduction showed a similar trend for storage volume. Relatively large reservoirs with high discharge rates, but not specifically within- or multi-year reservoirs, resulted in an enforced delay between natural and human impacted discharge. An exception on this rule is Bhumibol reservoir, which was one of the largest reservoirs in the dataset, but did not result in a strong delay or reduction in the modelled outflow. This could have been the result of the overestimation of river basin flow data, earlier mentioned in Section 4.1.

4.3.3 Flow Duration Curves

For the $FDCs$ trends are analysed for Q_{90}, Q_{50}, and Q_{05} (see Figure 13). Hydropower dams resulted in a trend, which is marked by a minimum outflow value of approximately 20% for Q_{90}. Important for these reservoirs is the relatively high minimum base-flow, which is essential in terms of downstream demand. In terms of demand satisfaction it is more useful to have a relatively large discharge, but a small angle between Q_{90} and Q_{05}, which indicated more continuous outflow with less fluctuations. Examples of well performing reservoirs for hydropower reservoirs in both observed as modelled outflow are Ghost, Albeni Falls, and Powell. A low performing reservoir is given by Buffalo Bill. Non-hydropower reservoirs show for observed and modelled reservoirs a relatively low Q_{90} value ($Q_{90} < 10\%$) and often close to dry riverbed conditions. This is predominantly not related to extremely high peak flows, which could have reduced the outflow. Secondary hydropower reservoirs, mainly serving a water supply function, result in a greater deviation between Q_{90} and Q_{05}. This indicates a less continuous outflow, but shows improvement compared to non-hydropower reservoirs. For example, Int. Amistad and Int. Falcon resulted in a relatively high baseflow for both observed and modelled outflow.

For within-year reservoirs the $FDCs$ resulted in a relatively steep increase of the slope between Q_{50} and Q_{05}. This indicates a lower ability for within-year reservoirs to reduce the peak flows and retain the water for future water demands. Logically, this is a consequence of the limited ability of a within-year reservoir to store water longer than a water year. In contrast, multi-year reservoirs resulted, especially for modelled outflow, in relatively high Q_{90} values ($Q_{90} > 20\%$) or in very low Q_{90} values, close to dry riverbed. This contrast is probably related to multi-year features of reservoirs with a relatively low mean annual inflow volume and relatively small storage volumes. This resulted into small reservoirs with a multi-year feature and a model having difficulties to reproduce accurate model simulations.

4.4 Unmet Downstream Demand

For reservoir demand an analysis is done, which describes the observed trends for unmet demand downstream of a reservoir (see Figure 15, Figure 16, and Figure 17). Exact findings per reservoir are given in Appendix Table 3. This is, similar to the model performance analysis, sorted according to reservoir purpose or within- or multi-year reservoirs. Please note, reservoirs with low model performance directly result in a non-representative estimation of the unmet demand, because this is a function of reservoir outflow, which is highly under- or overestimated by the model for low performing.

4.4.1 General

The allocation of the demand to upstream reservoirs resulted in an overall increase of the unmet demand between the model simulation without and with demand allocation (see Figure 15). Model simulation three, excluding demand allocation, implemented the environmental flow conditions, while the simulation with demand allocation, also applied the downstream demand and returned this to the downstream demand in the model function. Weights are assigned to reservoirs to allocate the downstream demand to their capacity. Based on the outflow and performance analysis it can be suggested low unmet demand values are related to reservoirs with extraordinary high outflow values. For example, Chardara, Kayrakkum, Int. Amistad, and Int. Falcon reservoirs, which showed outflow values much greater than observed release, especially in contrast to the observed outflow in Figure 11. This low performance and high overestimation of the model for these reservoirs resulted in an inaccurate estimation of the unmet demand.

The reservoir allocation weight, forced by total downstream demand and reservoir capacity, generated an increase of the total amount of months with unmet demand. Single demand dependence to a reservoir can be a potential cause. This strong increase in downstream reservoir dependence is observed for three out of five reservoirs in Asia. Similar to other observations, this strong increase in downstream reservoir dependence resulted in an increase of unmet demand months for multi-year reservoirs.

4.4.2 Reservoir Purpose

Reservoirs with hydropower as main function resulted for both model simulations in the lowest mean value for number of months with unmet demand (see Figure 17). Five out of ten hydropower reservoirs did not have months with unmet demand during the entire modelling period. The intensified increase of unmet demand for Buffalo Bill reservoir can be argued by the misinterpretation of reservoir outflow timing and the peak in downstream demand (see Figure 11).

Non-hydropower reservoirs resulted in a very large increase of unmet demand between the model simulation with and without allocation. This is mainly caused by misinterpretations of the outflow. For example, Travers reservoir does not show extraordinary high demand for the model simulation with demand allocation, but shows a clear misinterpretation with actual outflow. Visual analysis of this reservoir in Figure 11 shows it could satisfy the demand more often in relation to actual outflow. Furthermore, the increase in unmet demand can be related to the extremely low environmental flow conditions for the model simulation without demand allocation, which were almost equal to dry riverbed conditions. Similar trends are observed for St. Mary, Waterton, and Joes Valley. Another observed trend is the availability of extremely high allocated demand values resulting in unmet demand even with high reservoir release volumes. This is observed for Bhumibol and Sirikit reservoir. A potential cause for this extraordinary acquisition can be large demand weights as a result of large storage volumes. This extraordinary trend is only observed for these reservoirs, and can be related to the misinterpretation of its river basin, especially for observed reservoir outflow, which is less than the downstream demand. Reservoirs with a secondary hydropower function respond similar to reservoirs with hydropower as main purpose. Similar to non-hydropower reservoirs a trend is observed between unmet demand and model performance. Examples are Int. Amistad and Int. Falcon, presenting absence of unmet demand, while the performances were very low against the obtained outflow.

4.4.3 Multi- and Within-Year

Multi-year reservoirs, which have a storage to mean annual inflow ratio greater than 0.5, resulted in a stronger increase in unmet demand than within-year reservoirs (see Figure 16). Only three reservoirs, Lake Kemp, Waterton, St. Mary resulted in a large increase of unmet demand. These were within-year reservoirs without a hydropower function, while within-year hydropower serving reservoirs did relatively well and were able to keep up when allocated demand was included. Multi-year reservoirs, mainly containing a relatively large storage volumes, were assigned a large weight for demand and resulted in high demand values compared to their average outflow. Those were predominantly, except for Buffalo Bill, non- or secondary hydropower driven reservoirs, forcing a stronger seasonality and lower base-flow value, it is plausible to assume these multi-year reservoirs to be less satisfactory in terms of downstream demand than within-year reservoirs.

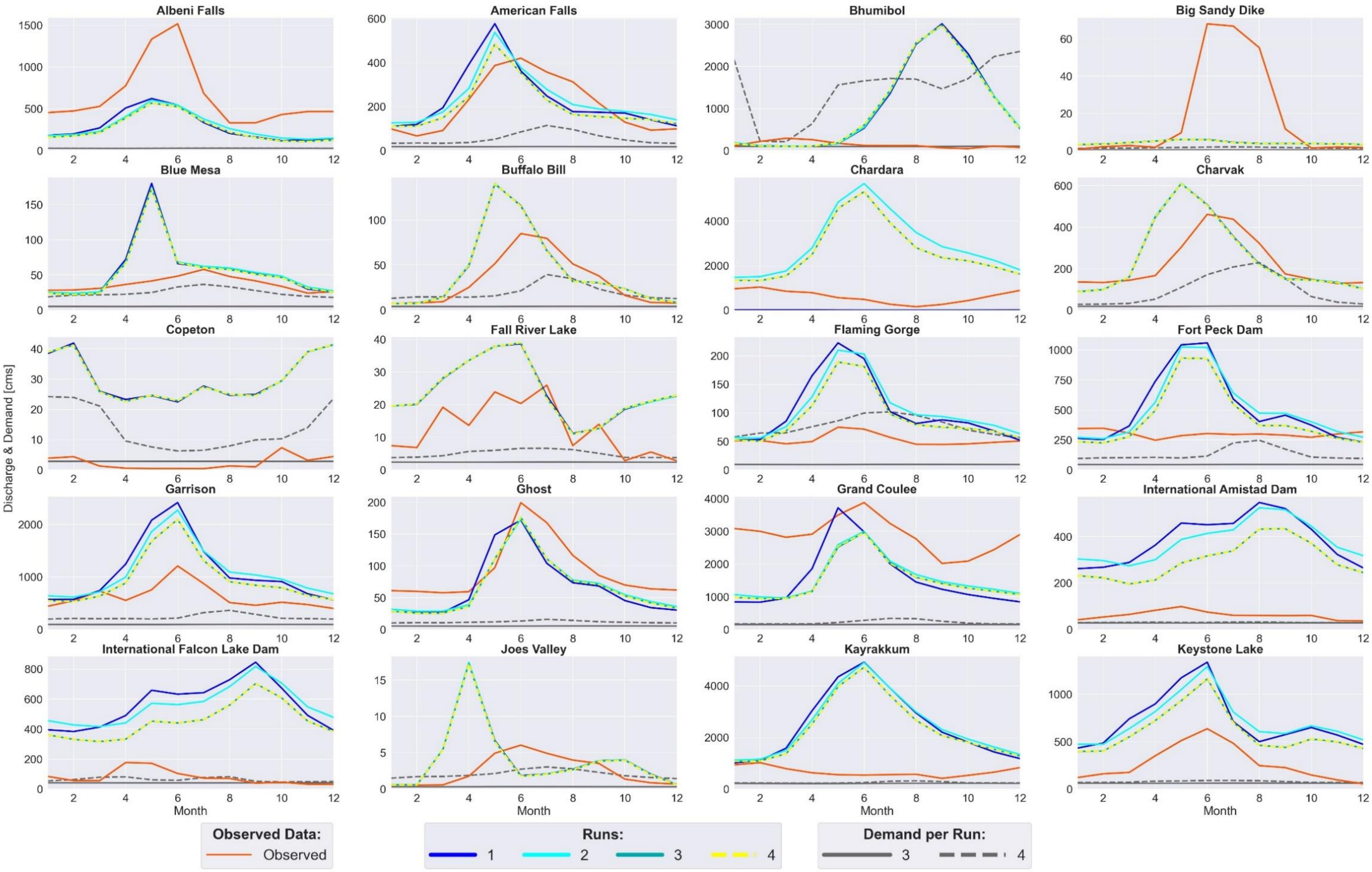


***Figure 11**: Regime curves of mean monthly discharge for the model runs in PCR-GLOBWB 2. Demand is applied for simulation 3 and 4. Regime curves for observed values are given to visually compare the difference between modelled and real-time data. The x-axes show months (1-12), and the y-axes show releasee (m^3 s^{-1}) on a symmetrical logarithmic scale.*

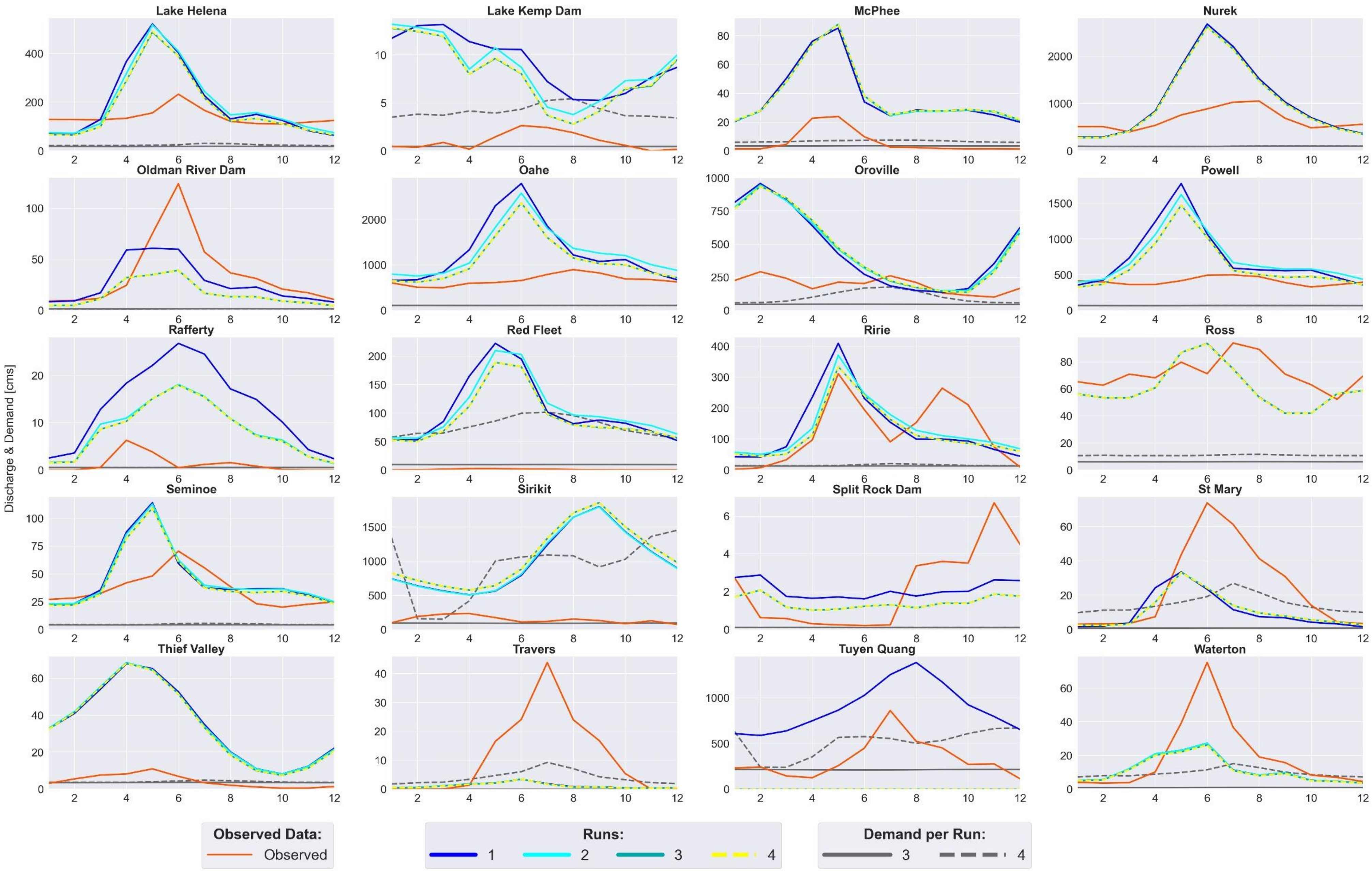


***Figure 11**: (Continued)*

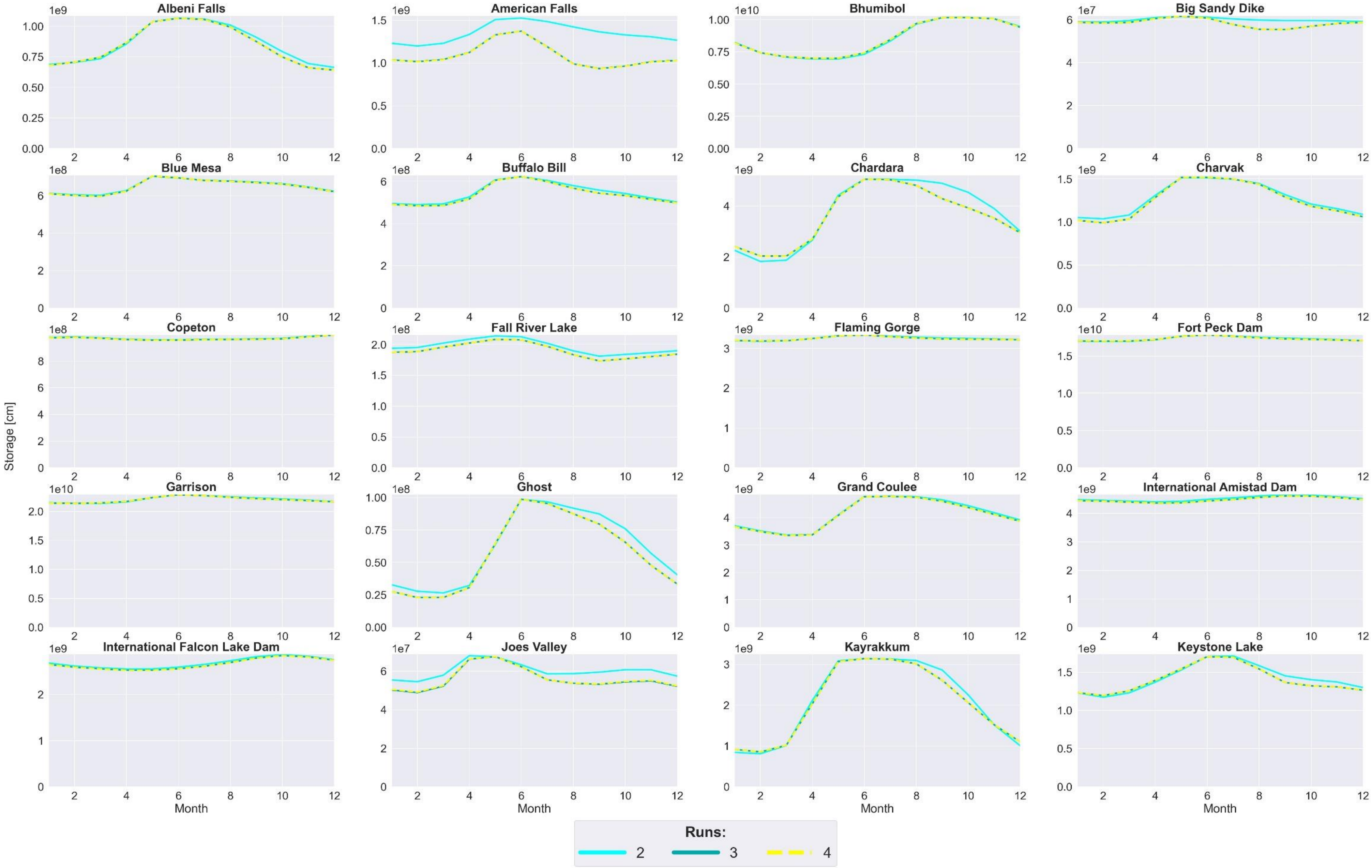


Figure 12*: Reservoir Storage in mean monthly volume for the model runs with reservoirs in PCR-GLOBWB 2. The x-axes show months (1-12), and the y-axes show storage (m³).*

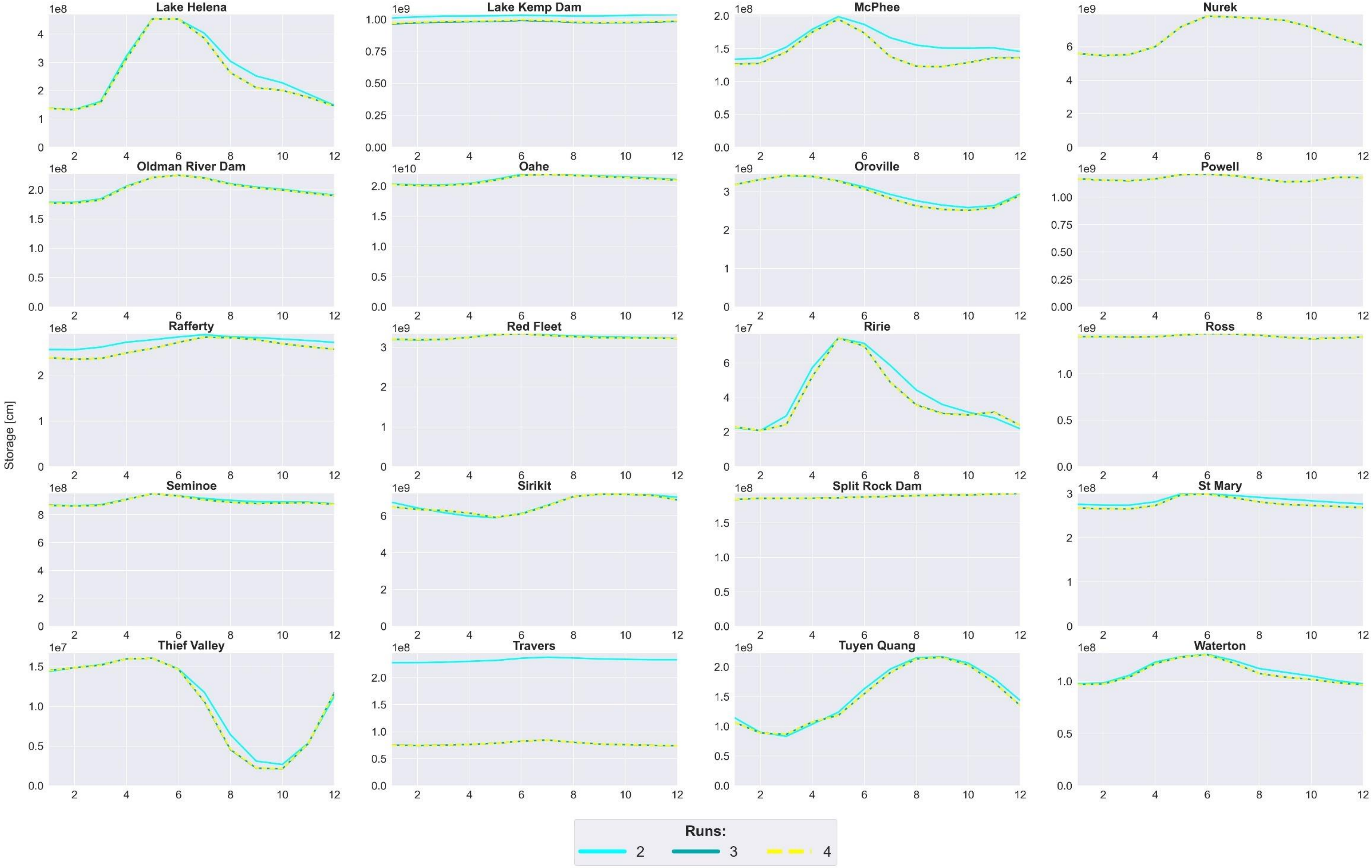


Figure 12: *Continued*

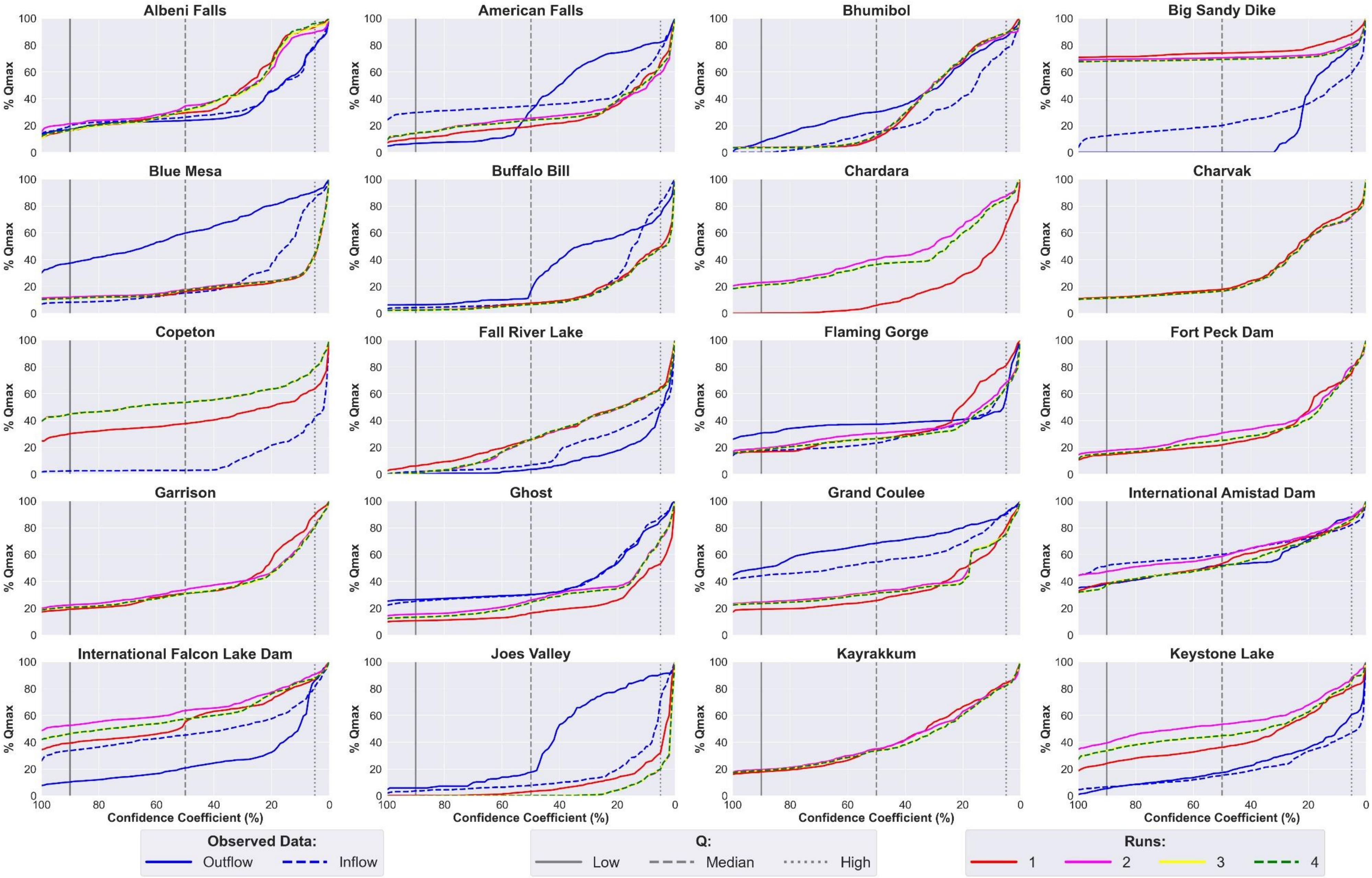


Figure 13*: Flow Duration Curves of observed and modelled (Runs) mean daily in- and outflow per reservoir sorted according to their median values. Simulation 1 is related to the natural conditions, simulation 2 contains reservoirs, simulation 3 has reservoirs and the basic water demand modules, and simulation 4 includes reservoirs and the additional water demand.*

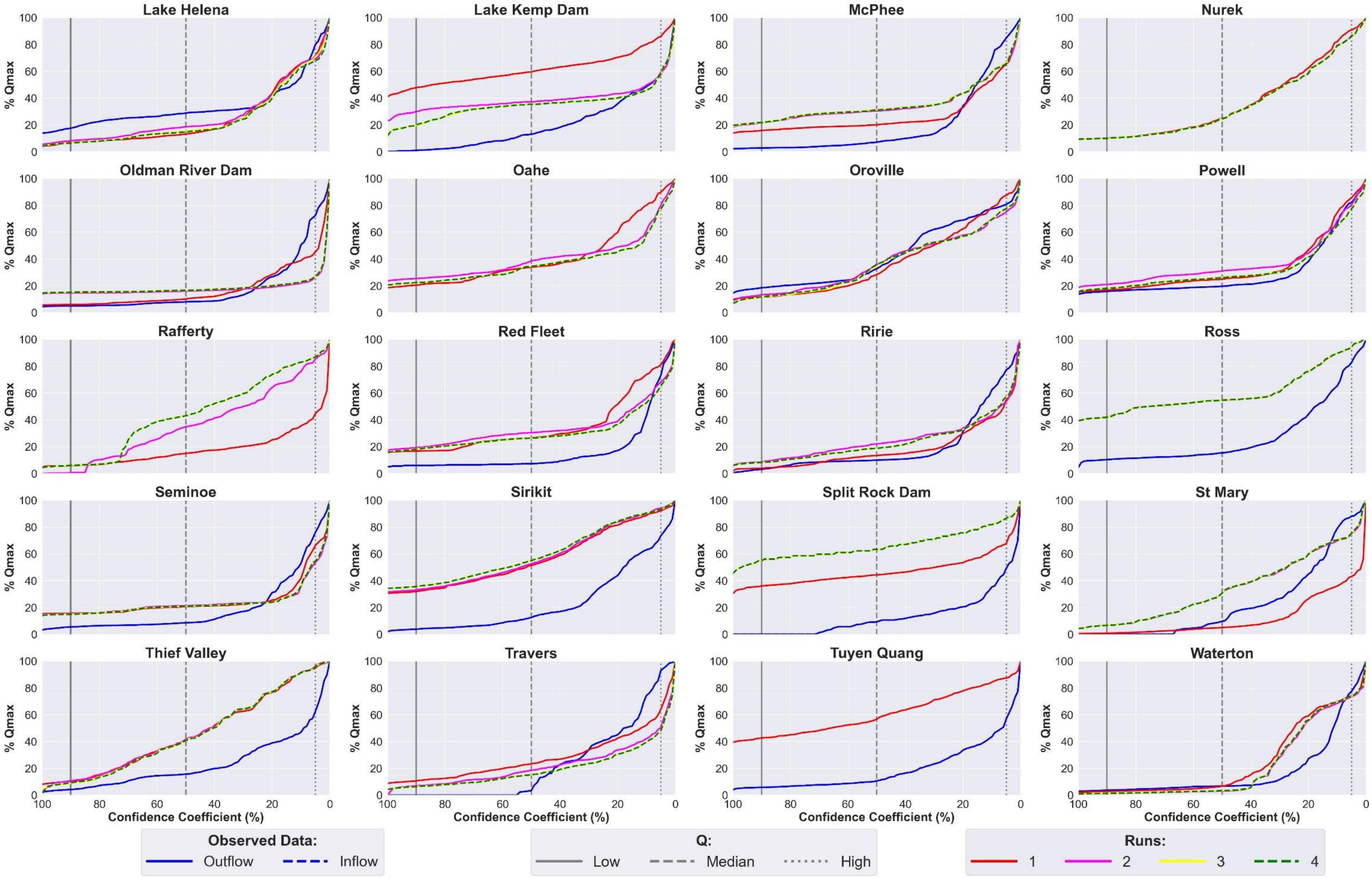


Figure 13: (Continued)

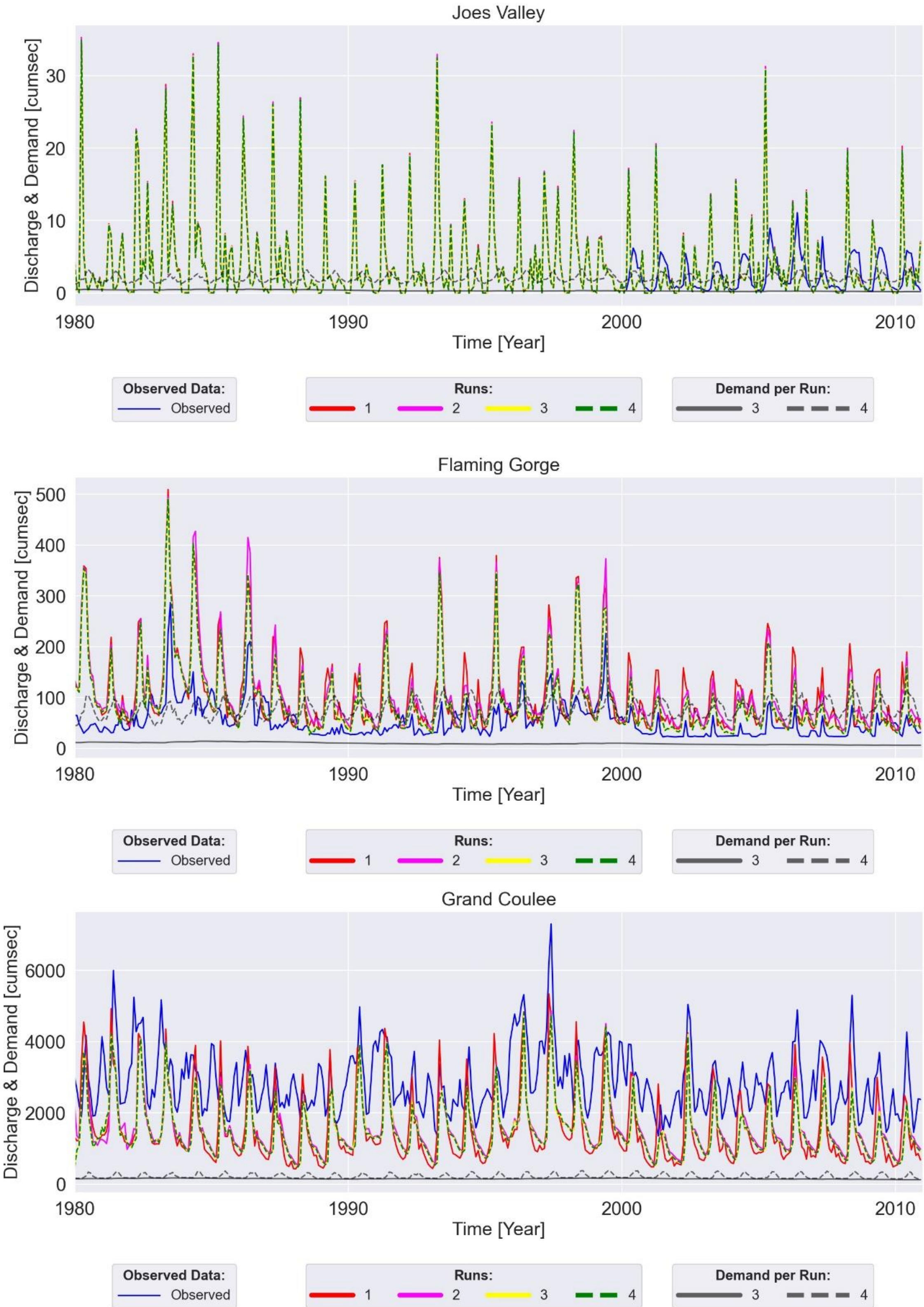


Figure 14: *a, b, and c: Hydrographs of monthly discharge for run 4 in PCR-GLOBWB's over the period 1980-2010: an example of a reduced number of unmet demand months:**(a)** Joes Valley (c=0.83), an example of an enlarged number of unmet demand months **(b)** Flaming Gorge (c=2.42), and **(c)** an example of a reservoir retaining its number of unmet demand months at zero.*

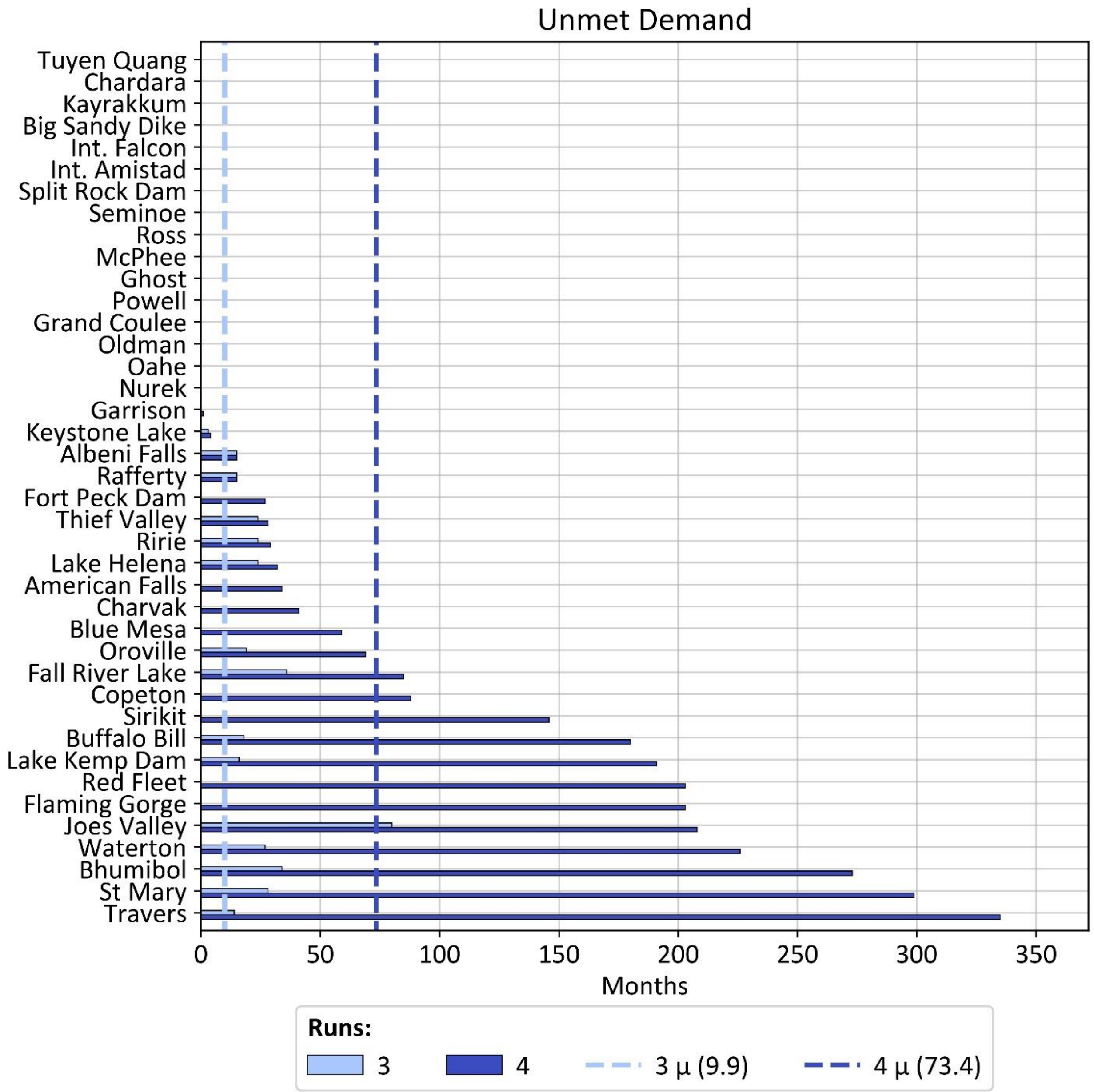


***Figure 15**: Unmet Demand in total and average number of months per reservoir between 1980 and 2010 for PCR-GLOBWB model runs 3 and 4.*

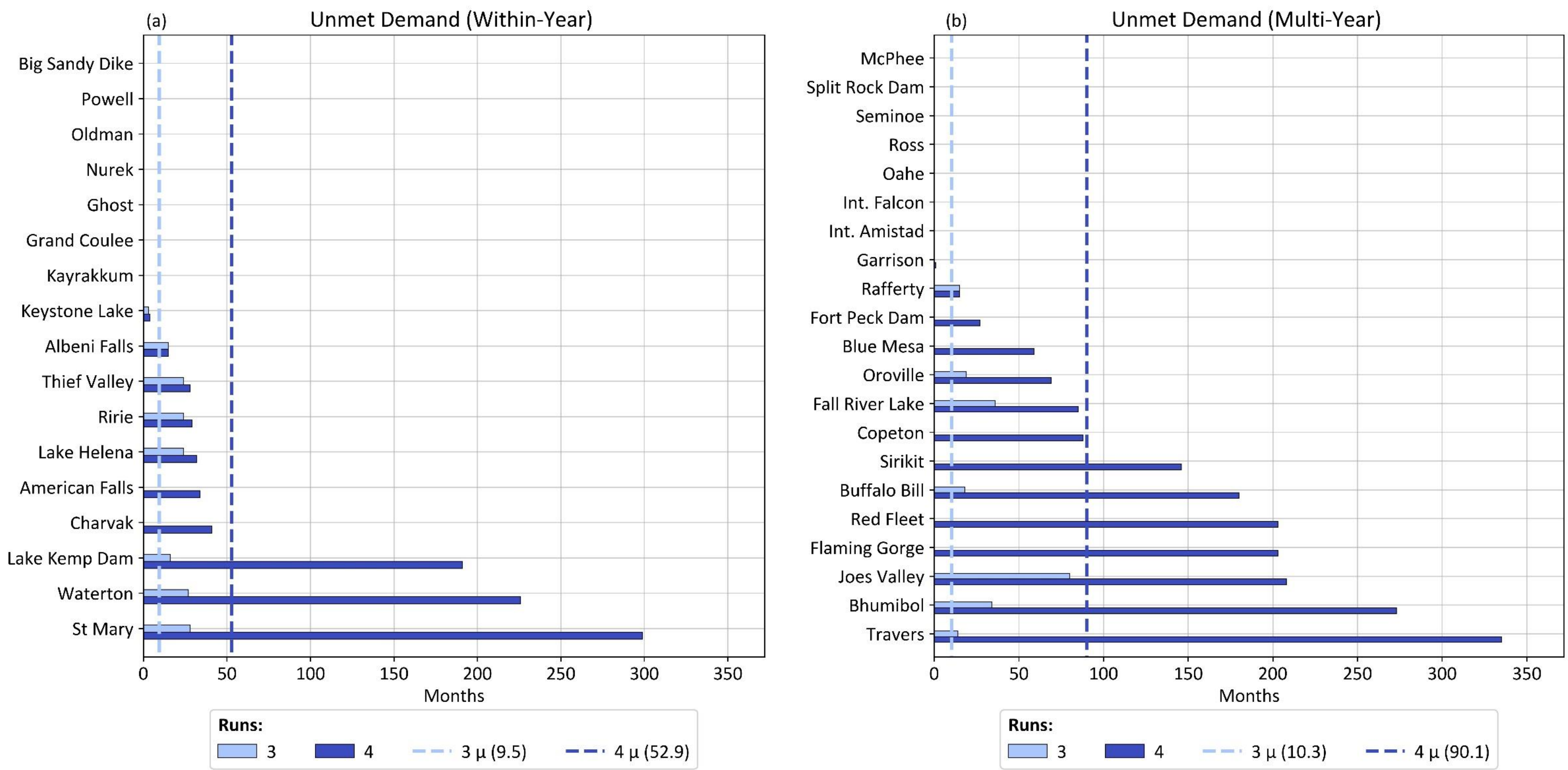
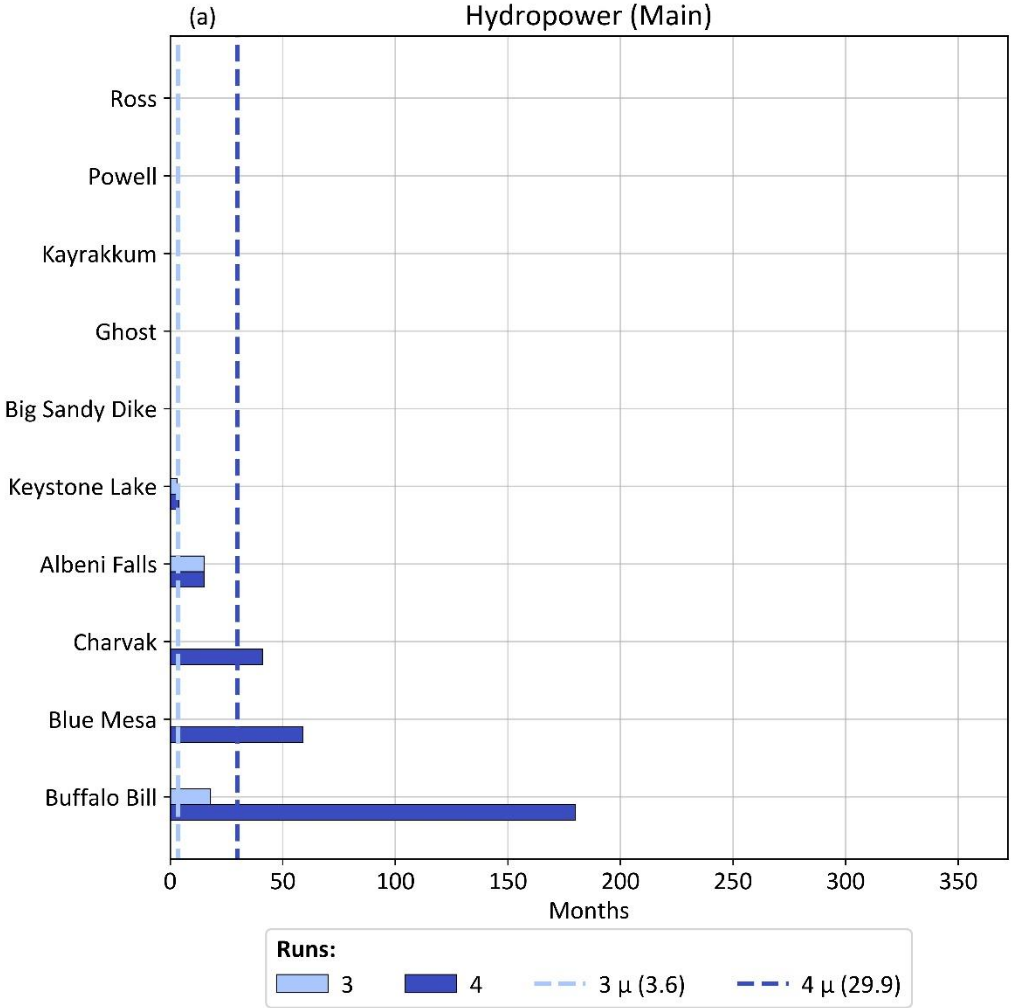


***Figure 16**: Unmet Demand in total and average number of months between 1980 and 2010 for PCR-GLOBWB model runs 3 and 4. These are sorted according to their ratio between reservoir storage and annual outflow, respectively **(a)** Within-Year, **(b)** Multi-Year.*



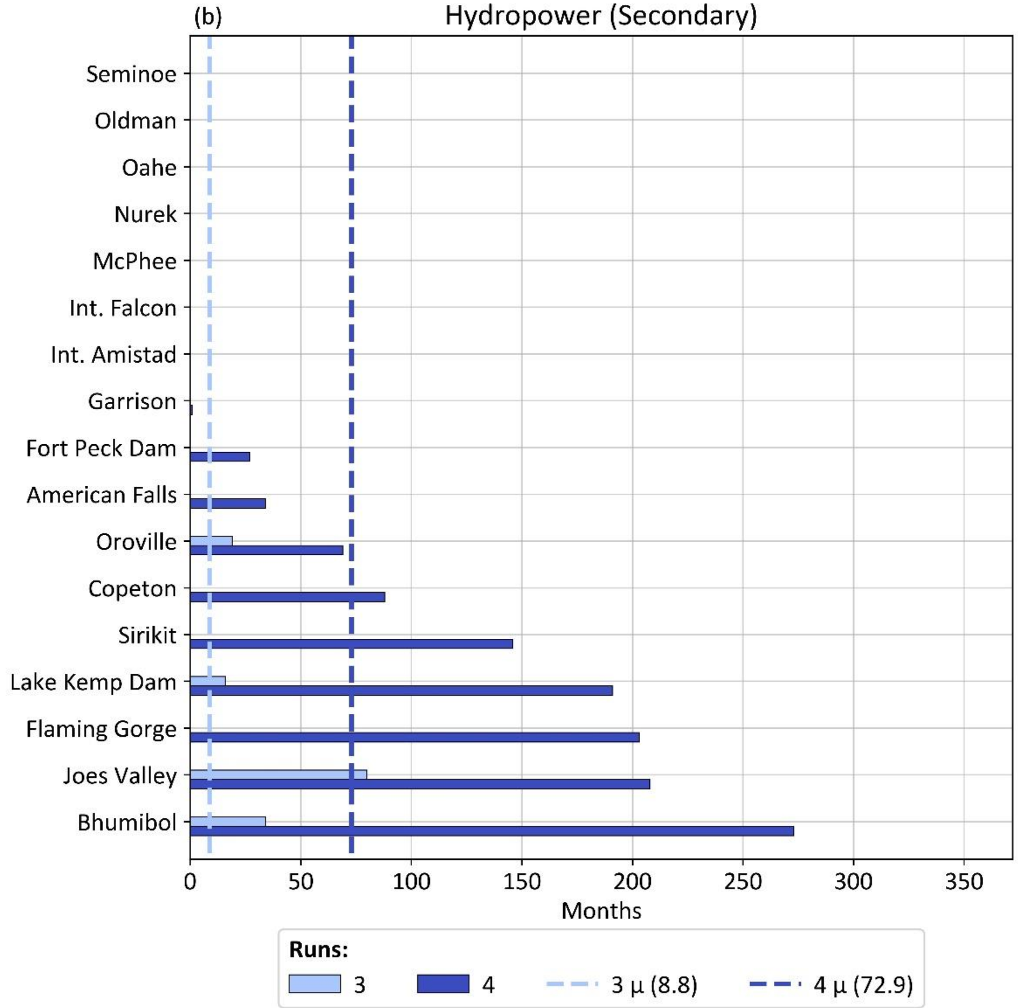
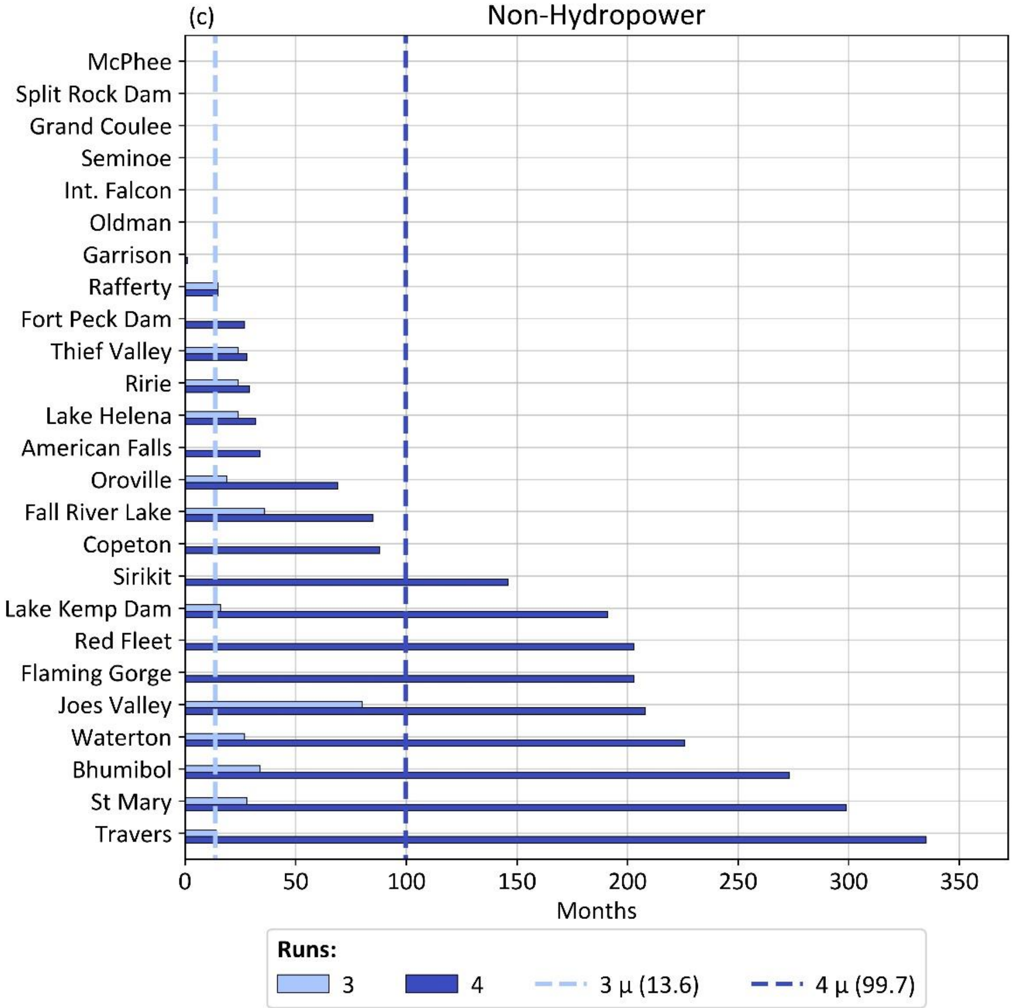


Figure 17*: Unmet Demand in total and average number of months between 1980 and 2010 for PCR-GLOBWB model runs 3 and 4. These are sorted according to their reservoir purpose, respectively* ***(a)*** *Hydropower,* ***(b)*** *Secondary Hydropower,* ***(c)*** *Non -Hydropower, and* ***(d)*** *Hydropower & Secondary Hydropower combined.*



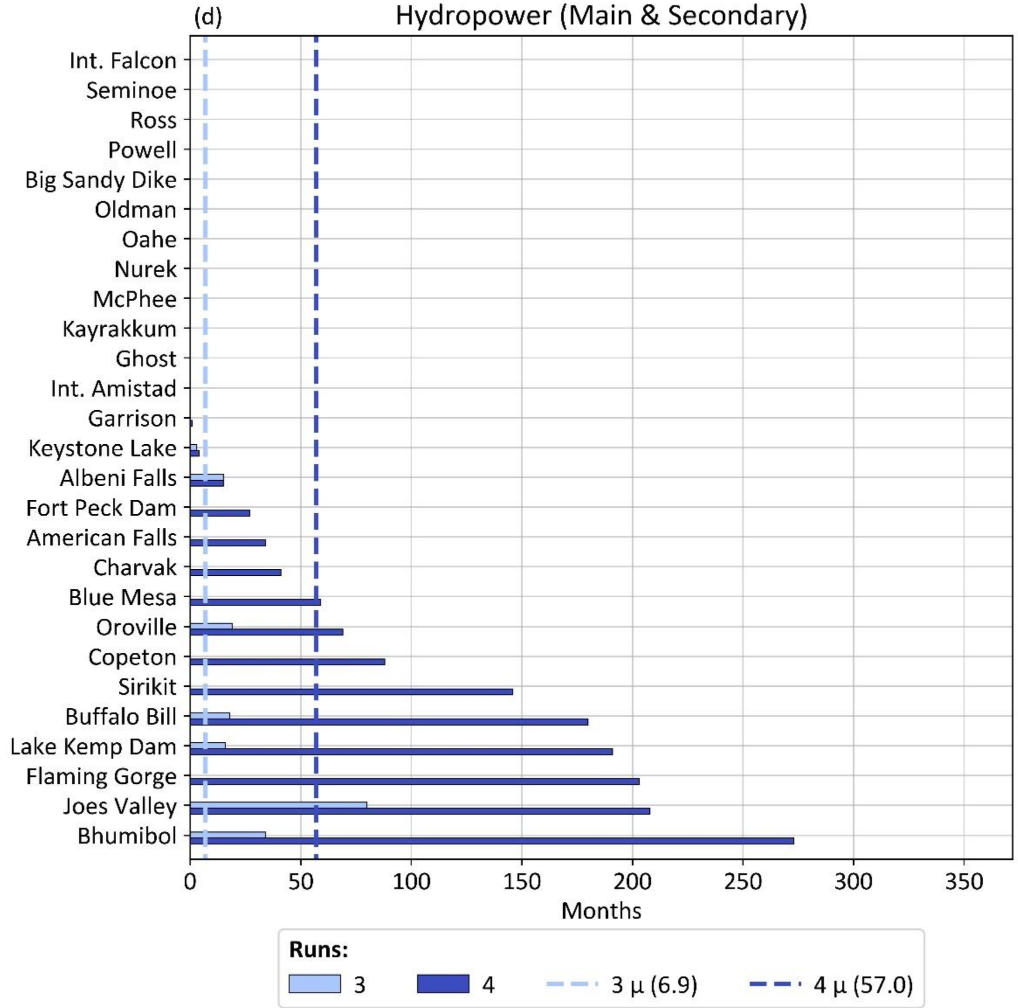


***Figure 17**: (Continued)*

5. Discussion

The main findings, study limitations, and future study objectives are discussed in the upcoming section.

5.1 Model Performance

Varying high and low performances are obtained during this study. Differences in performance results are related to reservoir processes, functions and sensitivity of PCR-GLOBWB 2, or to limitations in data availability.

High performance reservoir outflow is mainly related to within-year hydropower reservoirs, and is associated to the sensitivity of the according river basin. To obtain a more accurate estimation of the performance of distinctive reservoir purposes it is highly recommended to sort reservoirs in PCR-GLOBWB 2 according to their usability. This can be denoted by a discharge performance per river basin to estimate the potential accuracy of reservoirs.

Model performance was highly sensitive for upstream river basin characteristics. Reduction of reservoir performance is related to reservoirs located in the main stream of its corresponding river, resulting in extraordinary overestimations of reservoir outflow values. Besides, in-series reservoirs, in contrast to parallel, and located on the main stream, did result in similar, mainly low, performance findings (see examples in Figure 9 and Figure **10**). Excellent examples were the Kayrakkum, Chardara reservoirs, which were in-series reservoirs and resulted in relatively low performance, while Charvak, located at a tributary, resulted in high model performance. This was similar for Int. Falcon and Int. Amistad. The findings suggest reservoirs in series, and directly located on the main stream, are forced into low performance. Failure or low accuracy in upstream areas result in downstream over- or underestimations. This does not relate the performance of the reservoir scheme in PCR-GLOBWB 2, but describes the failure of model reproduction for a specific river basin. Data was mainly available for reservoirs at similar river basins. This made it hard to conclude on global observed trends found for the dataset. In future studies it could be useful to study river basin performance at first, prevent the usage of multiple reservoirs on one tributary, and limit the usage of in-series reservoirs for performance analysis. Difficulties regarding to this improvement are further discussed in Section 5.2.1.

Low performing multi- and within-year reservoirs like Rafferty, Copeton, Red Fleet, Lake Kemp, and Nurek were highly related to limited data availability, low observed outflow values, or incomplete datasets. An example of a reservoir resulting in low performance, due to limited data availability, was Copeton, which contained only two years of data. For Rafferty, Red Fleet, and Lake Kemp outflow was constantly close to null, which made it highly difficult for PCR-GLOBWB 2 to simulate without containing any peak values or clear bias. An incomplete dataset was given for Nurek, which limited the statistical model performance in its accuracy. According to the analysis of long-term flow schemes it can be assumed very low performance is more a direct consequence of the observed dataset, than reservoir purpose or annual inflow to storage ratio.

Red Fleet is located on a grid cell, containing another substantial larger reservoir. It contained Flaming Gorge, which generated a relatively high performance value compared to Red Fleet. A reason for low performing reservoirs is the availability of multiple reservoirs on a single grid cell. This means modelled validation data is used for multiple observed data sets. This could not result in similar performance values, because observed outflow is not similar. For these grid cells it is observed that highest outflow volumes perform better. This was the case for Flaming Gorge and Red Fleet. The performance findings of Red Fleet reservoirs can therefore be interpreted as less usable, but is interpreted as a desired interpretation and pre-study assumption for future reservoir scheme studies with PCR-GLOBWB2.

5.1.1 Outflow Analysis

PCR-GLOBWB2 reservoir outflow showed limited performance for dry riverbed conditions, while relatively small reservoirs, in potentially relatively dry regions, resulted in empty riverbed conditions for observed outflow. These trends, where PCR-GLOBWB 2 is challenging with dry riverbeds and high peak volumes, resulted in low performance.

Model simulations performed well but showed a relatively moderate seasonal delay and reduction in average outflow. The model is not highly sensitive for the availability of reservoirs on a grid cell. Fortunately, it resulted in alterations between natural discharge and conditions with reservoirs. For reservoirs with obvious deviations it predominantly resulted in reduced maximum peak flows (Q_{05}) and increased minimum flow (Q_{90}), which is similar to the explanation of Vogel et al. (1995). Discharge values resulting in low vulnerability to reservoir availability contributed to a higher variability in reservoir storage. A lack of alteration between reservoir outflow is the direct result of PCR-GLOBWB 2 limiting the outflow to the average inflow, which is caused by a limiting maximum storage capacity.

5.1.2 Demand

During this study an allocation function for downstream reservoir demand was built into PCR-GLOBWB. It was built to find alterations, hypothesized as positive, in number of months with unmet demand. This function allocated water demand to all upstream reservoirs, based on their capacity, and limited to a maximum upstream distance defined in average river flow velocity for a certain time period. To evaluate this function, a sensitivity analysis is done for the number of months with unmet reservoir demand using two different scenarios.

It is hard to trustfully assume usability of the unmet demand analysis for its findings, because for a high number of reservoirs the performance metrics were too low to be useful. This resulted in non- or less representative findings for unmet demand. The goal was to allocate the downstream demand to make water supply reservoirs more reliable in PCR-GLOBWB 2. Unfortunately, due to low performance for a large number of these reservoirs, it is hard to conclude whether this model implementation is usable. An improvement in terms of accuracy for unmet demand could be the limitation of studying high performance reservoirs to perform this analysis.

The demand allocation assigned demand weights related to their storage capacities. If reservoir volume is limited by the minimum storage fraction, the reservoir is not capable of satisfying downstream demand, and returns the average inflow at the reservoir to maintain minimum storage. The limiting factors for downstream demand were given, and show demand cannot be allocated to the output of a reservoir if storage capacity is less than its minimum storage fraction. This limitation was observed for reservoirs with strong seasonality and empty riverbeds during dry periods. An improvement in PCR-GLOBWB 2 for future studies could be the implementation of a stronger seasonality, including attenuation of outflow, to improve the demand satisfactory.

5.1.3 Multiple Reservoirs in Cell

Model performance is highly sensitive for peak value and bias overestimations, which are caused by the availability of multiple reservoirs on a single grid cell. This made it hard to reproduce the total behaviour calculated by using the cumulative capacity, especially for small combined reservoirs including a significant larger one, which weight is more dominant on a grid cell. It is highly recommended in future studies with PCR-GLOBWB 2 and model performance to use the higher spatial resolution or sum the reservoir data for reservoirs contributing to the outflow of a grid-cell.

5.2 Limitations

Within- or multi-year reservoirs are based on sorting according to the mean annual inflow ratio to storage capacity, which was based on observed inflow data and the capacity given in the GRanD. Unfortunately, for multiple and especially small reservoirs these inflow values were close to zero, which assigned them a within-year feature. It is highly recommended to use modelled annual mean inflow and assign a ratio to a grid-cell instead of using observed inflow data. Stricter evaluation criteria for future reservoir studies would support an improved analysis based on reservoir features.

The example of Bhumibol, given in the result section, resulted in a remarkably low performance, while Sutanudjaja et al., (2018) mentioned the high performance of monsoon driven regions. This low performance is also generated for Sirikit, which is located in the same region as Bhumibol. The observed monthly average outflow of both reservoirs showed a shifted peak outflow towards the dry period in South-Eastern Asia (November to May). It suggests an extreme seasonal delay until the dry season, which is not applied by PCR-GLOBWB 2. An improvement in the reservoir scheme could be the implementation of stronger seasonality or attenuation in the outflow as function of the storage capacity and downstream demand.

5.2.1 Data

Deficient data availability for a global sensitivity analysis on reservoir outflow resulted in low and inaccurate performance metrics. A geographically wider spread dataset could have improved study results. Similar findings were found for specific river basins with reservoirs in series. Presenting a relatively good estimation of the performance of river basins in PCR-GLOBWB 2, but does not cooperate to evaluate reservoir scheme results.

During this study a large part of the dataset of (Yassin et al., 2019) was used. To limit the dependence of this dataset some reservoir data was obtained from other sources. Unfortunately, some of these obtained datasets resulted more often in dry riverbeds compared to other reservoirs. Furthermore, some of the reservoirs available in (Yassin et al., 2019) contained a low temporal resolution varying from 10-days to monthly. It is highly plausible it reduced the model performance, because it gives rise to difficulties in estimating timing, peak values, and bias. In addition to the temporal resolution, observed dataset length is crucial, but is not fully equipped, because data availability was limited and almost every available dataset was used. For example, Copeton, Keystone Lake, and Tuyen Quang are reservoirs with a limited time-range for observed data. Copeton and Tuyen Quang resulted in low performance values, while Keystone Lake generated a high performance. These limited time-periods $(< 10\,\text{year})$ did not result in low performance for certain, but are less representative for the overall quality. Low correlation values $(\mathrm{R} < 0.0)$ were mainly obtained for reservoirs with low temporal resolution data, or reservoirs with empty river banks for the observed data. The forcing of PCR-GLOBWB2 barely resulted in empty riverbeds. Related to these findings it can be recommended to use high temporal resolution data.

Grand Coulee reservoir, has, based on the GRanD database, an irrigational and flood control purpose, while Ortolano et al., (2002) mentioned the function of Grand Coulee to be both hydropower and irrigation. No information was found on closing this hydroelectric generator. Another misinterpretation has occurred for Tuyen Quang, marked in the results as not performing reservoir, and is the direct result of the construction date in 2008. It was not noticed and is therefore not yet interpreted in the model. Probably after completing the dam it did not result directly in outflow.

5.2.2 Previous Studies

Van Beek et al. (2011), who presented four reservoir outflow schemes obtained similar findings for Lake Oroville and Flaming Gorge. In its paper, the original reservoir scheme was implemented, and resulted in a greater reduction in release by reservoirs compared to this study. It is highly assumable the environmental flow conditions, implemented in PCR-GLOBWB 2, enforced the outflow to retain natural flow. Sutanudjaja et al. (2018) found performance values for KGE similar to those presented in this study. It showed approximately 21% of the river basins resulted in a KGE-value less than -1.0 for 30 Arcmin resolution. In comparison to Sutanudjaja et al., (2018), who acquired a dataset of 3597 locations, it can be concluded the reservoir dataset performed relatively well, especially for the limited and relatively poor dataset used during this study. PCR-GLOBWB 2 had a hard time producing outflow values comparable to the observed data. It was mainly related to the difficulty of computing the peak values and bias, which resulted in over- or underestimations. Fortunately, it resulted in a relatively high performance for correlation. It can highly be assumed that PCR-GLOBWB2s reproduction of timing for long-term monthly average outflow is relatively accurate. This is confirmed by Sutanudjaja et al. (2018) who predominantly found correlation values >0.0.

Van Beek et al. (2011); De Graaf et al. (2014); Sutanudjaja et al. (2018); Wada et al. (2014) used the CRU forcing data, while this study used WFDEI forcing data. It is uncertain whether this degraded the performance, but it can be used as argument to counter the regional low performance. It could be useful to do a study for reservoir performance with varying forcing data, similar to Weiland et al. (2015), who found discharge ranges up to 20% between different meteorological datasets.

In future studies to reservoir performance in PCR-GLOBWB 2 it is highly recommended to implement the performance of river basins before studying reservoir performance. This study demonstrated the sensitivity of reservoirs in PCR-GLOBWB 2 to inaccurate inflow, especially for reservoirs in series. The upstream reservoirs has to flood its high reservoir capacity caused by large discharge or runoff volumes and result in over- or underestimations at downstream dams. This potential inaccuracy of reservoirs in series was not implemented at the start of this research, and make it hard to draw conclusions.

6. Conclusions

This study quantified the performance of the ad-hoc reservoir scheme in PCR-GLOBWB 2, a global hydrological model, with the implementation of downstream demand allocation. This is established for 40 globally distributed reservoirs. Those reservoirs were mainly located in North-America, because globally distributed real-time outflow data is very limited. To compare model performance between natural discharge, and conditions with reservoirs and allocated downstream demand, four model simulations were processed for natural discharge, reservoir release, reservoir release with demand, and reservoir release with the allocated demand function. Output of those simulations were used to obtain performance metrics (KGE, α, β, r), release characteristics, and demand reliability (unmet demand).

- The reservoir scheme in PCR-GLOBWB 2 performed well for hydropower reservoirs with a relatively low mean annual inflow to storage capacity ratio (within-year) and is sensitive to river basins. Low performance is obtained for reservoirs located at the major tributary and being in-series, resulting in overestimations of peak values and biases. The model simulations resulted in an ascending performance for comprehensive simulations. Demand allocation did not result in significant improvements compared to the environmental flow conditions.
- Reservoir release resulted in characteristic outflow patterns per reservoir purpose, indicating the sensitivity of PCR-GLOBWB2 for within- and multi-year reservoirs. Unfortunately, it can be concluded PCR-GLOBWB2 has difficulties with the reproduction of reservoirs with long-term empty riverbeds.
- With the implementation of the demand allocation function a more realistic representation of the downstream reservoir demand is given. For the initial model simulation this was limited to environmental flow conditions, while domestic, irrigation, industrial, and livestock demands have been implemented with the allocation function. This did not improve the model performance, but returned an improved interpretation of the requested demand to reservoirs. Dynamic implementation of the allocated demand to specific reservoir stages could result in a more significant deviation in performance. Further research is required to establish this potential improvement.
- The observed trend in number of months with unmet demand between the model simulation with and without the allocation function is not reliable for low performing reservoirs. Unrealistic representations, compared to observed outflow, resulted in incorrect acquisitions for unmet demand.

Finally, it can be concluded that the implemented demand allocation function is a useful addition for the model to use as interpretation method for demand studies. Unfortunately, due to overestimations of PCR-GLOBWB2 in terms of biases and peak values it did not result in significant improvements. For future studies it is highly recommended to implement a more dynamic reservoir scheme capable of reducing seasonal reservoir outflow to retain storage volume for periods with intensified demand.

7. Recommendations

- A recommendation for future studies with the 30 arcmin spatial resolution reservoir scheme in PCR-GLOBWB2 is to consider the availability of multiple reservoirs on a grid cell. It caused overestimations of modelled outflow compared to observed. By cumulating real-time reservoir outflow for all reservoirs available on a grid cell it could result in improved model performances. Another solution is to study the possibilities of using the higher 5 arcmin spatial resolution available for PCR-GLOBWB2.
- Alterations between river basin forcing and its corresponding performance was not taken into account in advance of this study. It can be highly useful to compare model performance of the whole river basin in terms of discharge and runoff before using the reservoir data. Low performance of a river basin outlines the accuracy of PCR-GLOBWB2 instead of the implemented reservoir scheme.
- Due to the low-performance of the reservoir scheme in PCR-GLOBWB2 for multi-year reservoirs it is essential to implement a reservoir scheme able to distinguishes multi- and within-year reservoirs. This reservoir scheme should implement an improved sensitivity for long-term monthly peak values.
- An improvement for future modelling with reservoirs in PCR-GLOBWB2 could be the implementation of a function capable of reassigning downstream water demand to dynamic reservoir storages. This will enhance the sensitivity of outflow to downstream demand.
- To reduce the months with unmet demand it could be useful to force the outflow earlier over time to prevent empty outflow and a higher satisfaction in terms of downstream reservoir demand. Another improvement can be achieved by implementing a reservoir scheme, which is more sensitive for downstream demand, and estimates next year demand, which is established from average demand available from previous years. This will limit the outflow from a reservoir to meet upcoming demand values. Implementing such a function will implement a higher seasonal sensitivity, but could result in a higher flood frequency. This improved seasonality would mainly be sensitive for multi-year reservoirs, because these are more capable to delay water for future demand.

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9. Appendix

9.1 A: Long-Term Monthly Statistics

***Appendix Table 1**: Metrics of long term monthly averages per reservoir for every model scenario on the time period (1980-2010).*

Name	KGE Run1	KGE Run2	KGE Run3	KGE Run4	Alpha Run1	Alpha Run2	Alpha Run3	Alpha Run4	Beta Run1	Beta Run2	Beta Run3	Beta Run4	R Run1	R Run2	R Run3	R Run4
Albeni Falls	0.21	0.19	0.16	0.16	0.48	0.45	0.45	0.45	0.44	0.44	0.40	0.40	0.80	0.80	0.80	0.80
American Falls	0.47	0.55	0.64	0.64	1.16	1.04	1.01	1.01	1.11	1.11	0.96	0.96	0.65	0.71	0.70	0.70
Bhumibol	-10.33	-10.23	-10.34	-10.34	11.13	11.02	11.02	11.03	7.15	7.17	7.16	7.16	-0.53	-0.53	-0.53	-0.53
Big Sandy Dike	-0.69	-0.70	-0.70	-0.70	0.04	0.04	0.04	0.04	0.22	0.22	0.22	0.22	-0.14	-0.15	-0.15	-0.15
Blue Mesa	-0.68	-0.59	-0.58	-0.58	2.44	2.33	2.34	2.33	1.50	1.50	1.45	1.45	0.28	0.28	0.29	0.29
Buffalo Bill	0.22	0.21	0.22	0.22	1.61	1.62	1.61	1.61	1.31	1.31	1.30	1.30	0.62	0.62	0.62	0.62
Chardara	-0.46	-3.58	-3.00	-3.00	0.01	3.72	3.57	3.57	0.01	4.83	4.27	4.27	0.60	-0.25	-0.16	-0.16
Charvak	0.41	0.41	0.41	0.41	1.40	1.40	1.40	1.40	1.12	1.12	1.12	1.12	0.61	0.60	0.60	0.60
Copeton	-8.81	-8.77	-8.76	-8.76	6.95	6.98	6.99	6.99	11.30	11.26	11.28	11.28	-0.09	-0.08	-0.08	-0.08
Fall River Lake	0.17	0.17	0.18	0.18	1.50	1.50	1.49	1.49	1.91	1.91	1.92	1.92	0.40	0.39	0.40	0.40
Flaming Gorge	-0.65	-0.57	-0.32	-0.32	2.25	2.15	2.01	2.02	1.96	1.99	1.74	1.74	0.54	0.59	0.60	0.60
Fort Peck Dam	-2.59	-2.33	-2.17	-2.17	4.04	3.74	3.62	3.62	1.68	1.67	1.44	1.44	-0.11	-0.09	-0.08	-0.08
Garrison	-0.86	-0.68	-0.51	-0.51	2.35	2.11	2.06	2.06	1.76	1.76	1.53	1.53	0.68	0.66	0.67	0.66
Ghost	0.59	0.67	0.64	0.64	1.17	1.09	1.12	1.12	0.73	0.74	0.72	0.72	0.77	0.84	0.84	0.84
Grand Coulee	0.33	0.36	0.35	0.35	1.14	0.88	0.88	0.88	0.54	0.54	0.52	0.52	0.54	0.57	0.57	0.57
Int Amistad	-5.49	-5.20	-4.12	-4.12	4.34	3.93	3.99	3.99	6.31	6.21	4.86	4.86	0.28	0.24	0.24	0.24
Int Falcon	-6.08	-5.88	-4.72	-4.72	4.12	3.76	3.78	3.78	7.12	7.07	5.71	5.71	0.02	-0.03	-0.04	-0.04
Joes Valley	-0.56	-0.56	-0.53	-0.53	2.64	2.65	2.62	2.62	1.60	1.60	1.58	1.58	-0.07	-0.07	-0.07	-0.07
Kayrakkum	-3.97	-3.70	-3.44	-3.44	5.61	5.30	5.14	5.14	3.66	3.66	3.43	3.43	-0.29	-0.30	-0.27	-0.27
Keystone Lake	0.37	0.32	0.60	0.60	1.95	1.82	1.80	1.81	2.65	2.65	2.24	2.25	0.78	0.79	0.80	0.80
Helena	-0.86	-0.75	-0.63	-0.64	2.76	2.64	2.55	2.56	1.41	1.42	1.28	1.28	0.55	0.56	0.58	0.58
Kemp Dam	-6.17	-5.73	-5.00	-5.11	6.94	7.19	7.23	7.26	9.12	8.62	7.93	7.96	-0.09	-0.14	-0.15	-0.15
McPhee	-3.83	-3.89	-3.96	-3.96	2.49	2.47	2.46	2.46	6.02	6.09	6.13	6.13	0.75	0.76	0.76	0.76
Nurek	-1.25	-1.25	-1.24	-1.24	3.31	3.37	3.37	3.37	1.57	1.53	1.52	1.52	0.76	0.76	0.76	0.76
Oahe	-1.63	-1.32	-1.18	-1.18	2.91	2.52	2.49	2.49	1.92	1.92	1.65	1.65	0.00	0.03	0.01	0.01
Oldman	0.42	0.43	0.43	0.43	0.70	0.63	0.63	0.63	0.75	0.45	0.45	0.45	0.69	0.69	0.69	0.69
Oroville	-2.13	-2.09	-2.06	-2.06	3.01	2.93	2.91	2.91	2.39	2.41	2.40	2.41	0.57	0.58	0.59	0.60
Powell	-0.44	-0.44	-0.44	-0.44	0.21	0.21	0.21	0.21	0.26	0.26	0.26	0.26	0.05	0.05	0.05	0.05
Rafferty	-8.68	-9.17	-8.90	-8.90	2.80	2.77	2.70	2.70	10.64	6.77	6.60	6.60	0.08	0.08	0.09	0.09
Red Fleet	-99.55	-95.73	-83.41	-83.41	66.75	63.62	59.68	59.71	97.58	98.95	86.31	86.29	0.55	0.51	0.50	0.50
Ririe	0.47	0.46	0.47	0.47	0.76	0.65	0.64	0.64	1.10	1.10	0.99	0.99	0.53	0.59	0.60	0.60
Ross	-0.06	-0.06	-0.06	-0.06	0.58	0.58	0.58	0.58	0.85	0.85	0.85	0.85	0.04	0.04	0.04	0.04
Seminoe	0.28	0.30	0.34	0.34	1.24	1.21	1.20	1.20	1.26	1.26	1.20	1.20	0.37	0.39	0.40	0.40
Sirikit	-6.55	-6.56	-6.85	-6.85	5.70	5.71	5.62	5.62	6.90	6.90	7.42	7.42	-0.28	-0.28	-0.29	-0.29
Split Rock	-0.15	-0.15	-0.15	-0.15	0.32	0.32	0.32	0.32	0.95	0.65	0.65	0.65	0.11	0.11	0.11	0.11
St Mary	-0.08	-0.02	-0.02	-0.02	0.54	0.49	0.49	0.49	0.43	0.43	0.43	0.43	0.37	0.52	0.52	0.52
Thief Valley	-6.55	-6.56	-6.44	-6.44	4.72	4.74	4.78	4.78	8.17	8.16	8.01	8.01	0.41	0.42	0.42	0.42
Travers	-0.33	-0.34	-0.33	-0.33	0.17	0.18	0.18	0.18	0.11	0.11	0.10	0.10	0.31	0.30	0.31	0.31
Tuyen Quang	-0.49				1.48	0.00	0.00	0.00	2.70	0.00	0.00	0.00	0.77			
Waterton	0.13	0.13	0.11	0.11	0.51	0.51	0.49	0.49	0.60	0.60	0.58	0.58	0.60	0.60	0.60	0.60

Appendix Table 2*: Metrics of long term annual averages per reservoir for every model scenario on the time period (1980-2010).*

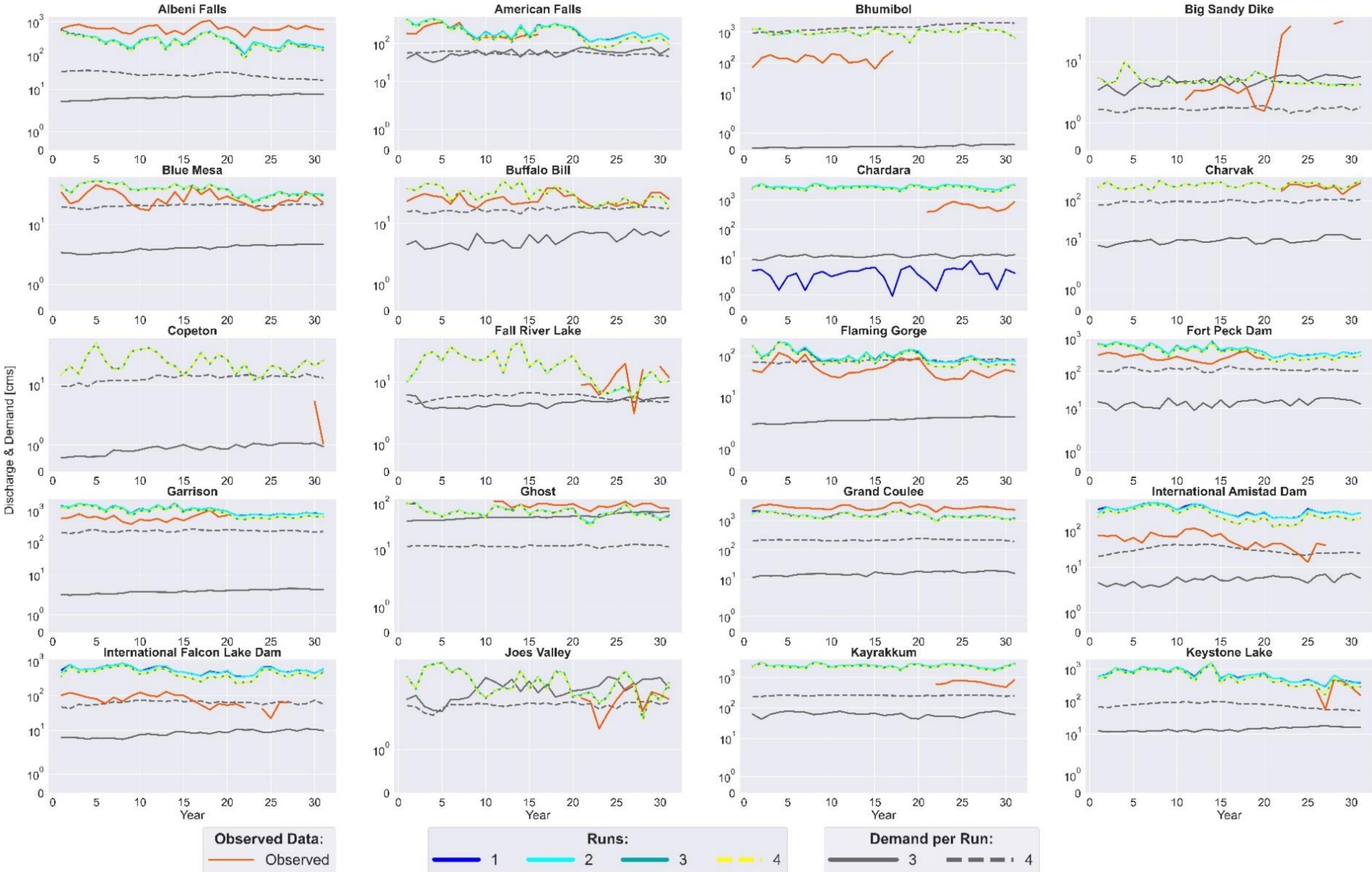
Name	KGE Run1	KGE Run2	KGE_ Run3	KGE Run4	Alpha Run1	Alpha Run2	Alpha Run3	Alpha Run4	Beta Run1	Beta Run2	Beta Run3	Beta Run4	R Run1	R Run2	R Run3	R Run4
Albeni Falls	0.30	0.30	0.27	0.28	0.71	0.69	0.72	0.72	0.44	0.44	0.40	0.40	0.71	0.72	0.71	0.71
American Falls	0.46	0.47	0.52	0.52	1.20	1.21	1.26	1.26	1.11	1.11	0.96	0.96	0.67	0.68	0.70	0.70
Bhumibol	-5.64	-5.66	-5.76	-5.76	5.04	5.06	5.06	5.06	7.21	7.22	7.22	7.22	-0.54	-0.54	-0.53	-0.53
Big Sandy Dike	-0.96	-0.96	-0.97	-0.97	0.05	0.05	0.05	0.05	0.23	0.23	0.22	0.22	-0.52	-0.52	-0.52	-0.52
Blue Mesa	0.41	0.41	0.45	0.45	1.07	1.08	1.10	1.10	1.50	1.51	1.46	1.46	0.71	0.71	0.70	0.71
Buffalo Bill	-0.08	-0.08	-0.07	-0.07	1.83	1.83	1.82	1.82	1.31	1.31	1.31	1.31	0.38	0.38	0.38	0.38
Chardara	-0.47	-3.01	-2.53	-2.53	0.01	2.17	2.29	2.29	0.01	4.84	4.28	4.28	0.56	0.80	0.80	0.80
Charvak	0.77	0.77	0.78	0.78	1.03	1.03	1.03	1.03	1.13	1.13	1.12	1.12	0.96	0.96	0.96	0.96
Copeton	-8.33	-8.29	-8.28	-8.28	5.86	5.89	5.88	5.88	10.88	10.85	10.86	10.86	-1.00	-1.00	-1.00	-1.00
Fall River Lake	0.00	0.00	0.03	0.03	2.28	2.27	2.26	2.26	1.91	1.90	1.91	1.91	0.20	0.20	0.23	0.23
Flaming Gorge	-0.09	-0.16	0.04	0.04	1.47	1.57	1.58	1.58	1.97	1.99	1.74	1.74	0.81	0.83	0.81	0.81
Fort Peck Dam	-0.62	-0.59	-0.51	-0.51	2.29	2.28	2.38	2.38	1.68	1.68	1.44	1.44	0.10	0.11	0.10	0.10
Garrison	-0.41	-0.40	-0.27	-0.28	2.03	2.04	2.12	2.12	1.76	1.76	1.53	1.53	0.29	0.28	0.27	0.27
Ghost	0.50	0.49	0.46	0.46	1.38	1.41	1.44	1.44	0.73	0.74	0.72	0.72	0.79	0.78	0.79	0.79
Grand Coulee	0.40	0.39	0.39	0.39	0.65	0.63	0.63	0.64	0.54	0.54	0.52	0.52	0.82	0.87	0.89	0.88
Int Amistad	-5.48	-5.41	-4.54	-4.54	4.27	4.29	4.57	4.57	6.32	6.22	4.86	4.86	0.66	0.64	0.62	0.62
Int Falcon	-6.34	-6.36	-5.49	-5.49	4.57	4.70	5.03	5.02	7.13	7.07	5.71	5.71	0.28	0.28	0.28	0.28
Joes Valley	0.26	0.26	0.28	0.28	2.10	2.10	2.08	2.08	1.60	1.59	1.57	1.57	0.60	0.60	0.60	0.60
Kayrakkum	-2.24	-2.27	-2.12	-2.12	2.69	2.69	2.74	2.74	3.66	3.67	3.44	3.44	0.57	0.57	0.57	0.57
Keystone Lake	0.37	0.37	0.70	0.70	1.89	1.95	1.96	1.97	2.65	2.65	2.24	2.25	0.90	0.89	0.89	0.89
Helena	-0.03	-0.03	0.03	0.03	1.90	1.90	1.89	1.89	1.41	1.42	1.28	1.29	0.71	0.71	0.72	0.72
Kemp Dam	-6.05	-5.29	-4.51	-4.61	6.39	5.92	5.99	5.99	9.05	8.56	7.87	7.90	-0.41	-0.42	-0.44	-0.44
McPhee	-3.94	-4.01	-4.07	-4.08	2.93	2.95	2.89	2.90	6.02	6.08	6.12	6.13	0.90	0.90	0.90	0.90
Nurek	-0.01	-0.01	0.00	0.00	1.84	3.24	3.24	3.24	1.59	1.55	1.55	1.55	0.63	0.63	0.63	0.63
Oahe	0.53	0.53	0.53	0.53	1.03	1.64	1.64	1.64	0.75	0.45	0.45	0.45	0.74	0.74	0.74	0.74
Oldman	-0.77	-0.75	-0.61	-0.62	1.93	1.94	2.02	2.02	1.93	1.92	1.66	1.66	-0.16	-0.15	-0.16	-0.17
Oroville	-1.98	-2.05	-2.03	-2.02	3.46	3.48	3.49	3.48	2.39	2.40	2.39	2.40	0.93	0.93	0.94	0.94
Powell	-0.40	-0.40	-0.40	-0.40	0.09	0.09	0.09	0.09	0.26	0.26	0.26	0.26	0.22	0.22	0.22	0.22
Rafferty	-8.54	-8.99	-8.73	-8.73	1.28	3.10	3.04	3.04	10.77	6.86	6.69	6.69	-0.07	-0.07	-0.01	-0.01
Red Fleet	-100.78	-102.66	-93.96	-93.89	98.85	105.44	106.52	106.52	97.46	98.87	86.23	86.21	0.44	0.43	0.44	0.44
Ririe	0.64	0.64	0.70	0.70	0.71	0.71	0.77	0.77	1.10	1.10	0.99	0.99	0.80	0.81	0.81	0.81
Ross	-0.07	-0.07	-0.07	-0.07	0.54	0.54	0.54	0.54	0.85	0.85	0.85	0.85	0.04	0.04	0.04	0.04
Seminoe	0.58	0.58	0.61	0.62	0.87	0.88	0.89	0.89	1.26	1.26	1.20	1.20	0.69	0.69	0.69	0.69
Sirikit	-5.28	-5.29	-5.68	-5.68	2.91	2.92	2.86	2.86	6.93	6.93	7.46	7.46	-0.44	-0.44	-0.46	-0.46
Split Rock	-0.32	-0.33	-0.33	-0.33	0.37	0.46	0.46	0.46	0.95	0.64	0.64	0.64	-0.13	-0.13	-0.13	-0.13
St Mary	0.20	0.22	0.22	0.22	0.98	0.98	0.98	0.98	0.43	0.43	0.43	0.43	0.72	0.74	0.73	0.73
Thief Valley	-6.45	-6.44	-6.32	-6.31	4.50	4.50	4.55	4.54	8.17	8.16	8.01	8.01	-0.06	-0.06	-0.05	-0.05
Travers	-0.07	-0.07	-0.07	-0.07	0.51	0.52	0.50	0.50	0.11	0.11	0.10	0.10	0.48	0.48	0.48	0.48
Tuyen Quang	-0.56				1.74	0.00	0.00	0.00	2.70	0.00	0.00	0.00	0.94			
Waterton	0.35	0.35	0.33	0.33	0.94	0.94	0.91	0.91	0.60	0.60	0.58	0.58	0.86	0.86	0.86	0.86

9.2 B: Unmet Demand

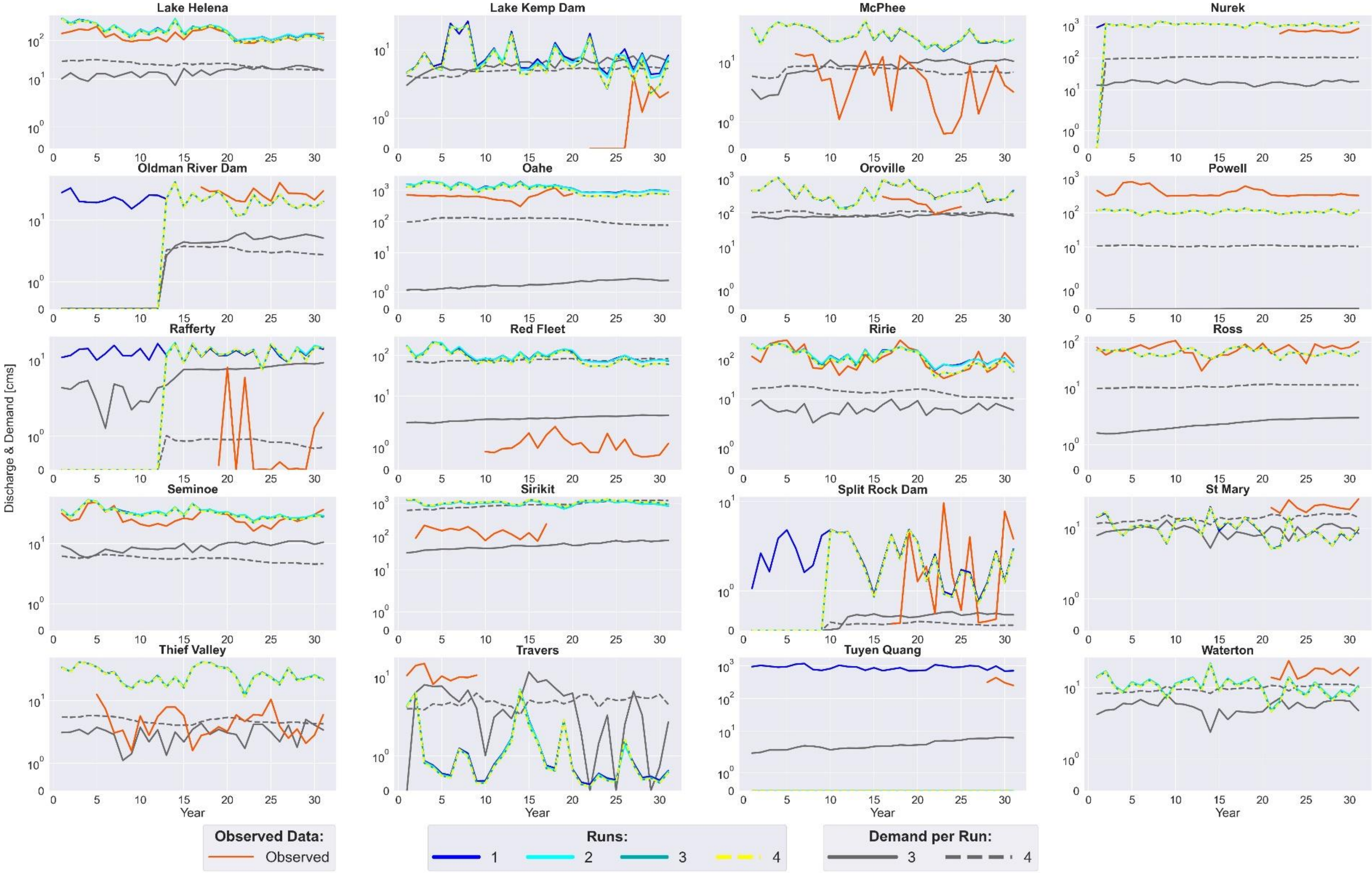
***Appendix Table 3**: Unmet Demand for long term monthly average on the time period (1980-2010).*

Name	*Month Run 3*	*Month Run 4*
Albeni Falls	15	15
American Falls	0	34
Bhumibol	34	273
Big Sandy Dike	0	0
Blue Mesa	0	59
Buffalo Bill	18	180
Chardara	-999	-999
Charvak	0	41
Copeton	0	88
Fall River Lake	36	85
Flaming Gorge	0	203
Fort Peck Dam	0	27
Garrison	0	1
Ghost	0	0
Grand Coulee	0	0
Int Amistad	0	0
Int Falcon	0	0
Joes Valley	80	208
Kayrakkum	0	0
Keystone Lake	3	4
Helena	24	32
Kemp Dam	16	191
McPhee	0	0
Nurek	0	0
Oahe	0	0
Oldman	0	0
Oroville	19	69
Powell	0	0
Rafferty	15	15
Red Fleet	0	203
Ririe	24	29
Ross	0	0
Seminoe	0	0
Sirikit	0	146
Split Rock	0	0
St Mary	28	299
Thief Valley	24	28
Travers	14	335
Tuyen Quang	-999	-999
Waterton	27	226

9.3 C: Annual Regime Curves



***Appendix Figure 1**: Regime curves of mean annual discharge for the model runs in PCR-GLOBWB2. Demand is applied for simulation 3 and 4 and is given for these simulations. Observed values regime curves are given to visually compare the difference between modelled and real-time data. The x-axes show months (1-12), and the y-axes show release (m^3 s^{-1}) on a symmetrical logarithmic scale.*



***Appendix Figure 1**: (Continued)*

9.4 D: Model Equations

9.4.1 Reservoir Model Functions

$$Q_{\mu_{outflow}} = Q_{\mu_{outflow}} \begin{cases} Q_{\mu_{outflow}}, & Q_{\mu_{outflow}} > 0.0 \\ max\ (Q_{\mu_{channel}}, Q_{\mu_{inflow}}, 0.001), & Q_{\mu_{outflow}} \leq 0.0 \end{cases} \qquad \textit{Eq. 9.4.1.1}$$

$$Q_{\mu_{outflow}} = Q_{\mu_{outflow}} \begin{cases} Q_{\mu_{outflow}}, & Q_{\mu_{outflow}} > 0.0 \\ downstream(lddMap, Q_{\mu_{outflow}}), & Q_{\mu_{outflow}} \leq 0.0 \end{cases} \qquad \textit{Eq. 9.4.1.2}$$

$$Q_{\mu_{outflow}} = areamaximum\left(Q_{\mu_{outflow}}, S_{id}\right) \qquad \textit{Eq. 9.4.1.3}$$

$$F_{reduction} = \min\left(1.0, max\left(0.0, \frac{(S - R_{minFrac} * S_{capacity})}{R_{maxFrac} - R_{minFrac}} * S_{capacity}\right), 0.0\right) \qquad \textit{Eq. 9.4.1.4}$$

$$Q_{resvOutflow} = F_{reduction} * Q_{\mu_{outflow}} * t \qquad \textit{Eq. 9.4.1.5}$$

$$Q_{resvOutflow} = \max\left(0.0, min\left(Q_{resvOutflow}, Q_{\mu_{inflow}} * t\right)\right) \qquad \textit{Eq. 9.4.1.6}$$

$$F_{reductionDemand} = getValDivZero\left(D_{downstream}, R_{minFrac} * S_{capacity}, smallNumber\right) \qquad \textit{Eq. 9.4.1.7}$$

$$D_{downstream} = \min(D_{downstream}, D_{downstream} * F_{reductionDemand}) \qquad \textit{Eq. 9.4.1.8}$$

$$Q_{resvOutflow} = \max\left(Q_{resvOutflow}, D_{downstream} * t\right) \qquad \textit{Eq. 9.4.1.9}$$

$$R_{Qbankfull} = 2.3 \qquad \textit{Eq. 9.4.1.10}$$

$$S_{estimated} = \max\left(0.0, S - Q_{resvOutflow}\right) \qquad \textit{Eq. 9.4.1.11}$$

$$\begin{aligned} Q_{Flood} = {} & \max\left(0.0, S_{estimated} - S_{capacity}\right) \\ & + cover\left(\frac{\max\left(0.0, S_{estimated} - R_{maxFrac} * S_{capacity}\right)}{(1.0 - R_{maxFrac}) * S_{capacity}}, 0.0\right) \\ & * \max\left(0.0, R_{Qbankfull} * Q_{\mu_{outflow}} * secondsPerDay - Q_{resvOutflow}\right) \end{aligned} \qquad \textit{Eq. 9.4.1.12}$$

$$Q_{Flood} = \max\left(0.0, min\left(Q_{Flood}, S_{estimated} - R_{maxFrac} * S_{capacity} * 0.75\right)\right) \qquad \textit{Eq. 9.4.1.13}$$

$$Q_{resvOutflow} = cover\left(Q_{resvOutflow}, 0.0\right) + cover\left(Q_{Flood}, 0.0\right) \qquad \textit{Eq. 9.4.1.14}$$

$$Q_{resvOutflow} = \begin{cases} \min(Q_{resvOutflow}, \max(0, S - R_{maxFrac} * S_{capacity} * 0.75), & S > (R_{maxFrac} * S_{capacity}) \\ Q_{resvOutflow}, & S \leq (R_{maxFrac} * S_{capacity}) \end{cases} \qquad \textit{Eq. 9.4.1.15}$$

$$Q_{resvOutflow} = \begin{cases} \max(0.0, Q_{resvOutflow}, Q_{\mu_{inflow}}), & S > (R_{maxFrac} * S_{capacity}) \\ Q_{resvOutflow}, & S \leq (R_{maxFrac} * S_{capacity}) \end{cases} \qquad \textit{Eq. 9.4.1.16}$$

$$Q_{resvOutflow} = \min(S, Q_{resvOutflow}) \qquad \textit{Eq. 9.4.1.17}$$

$$Q_{resvOutflow} = Q_{resvOutflow} \begin{cases} S_{id} > 0.0 \\ S_{type} = 2 \end{cases} \qquad \textit{Eq. 9.4.1.18}$$

9.4.2 Routing Implementation

$$S_{purpose} = \begin{cases} 1, & D_{allocation} = True \\ 0, & D_{allocation} = False \end{cases}$$ Eq. 9.4.2.1

$$V_{characteristic} = \min\left(10, max\left(0.1, \frac{5.0}{3.0} * \frac{Q_{\mu}}{C_{width} * C_{depth}}\right)\right)$$ Eq. 9.4.2.2

$$V_{characteristic} = cover\left(V_{characteristic}, areaaverage(V_{characteristic}, Landmask)\right)$$ Eq. 9.4.2.3

$$V_{characteristic} = \begin{cases} V_{characteristic}, & cover(S_{id}, 0) = 0 \\ cover(areaaverage(\{V_{characteristic}, S_{out} = True\}, S_{id}), & cover(S_{id}, 0) \neq 0 \end{cases}$$ Eq. 9.4.2.4

$$S_{allocation} = D_{allocation}$$ Eq. 9.4.2.5

$$S_{allocation} = S_{allocationUpdate}$$ Eq. 9.4.2.6

$$F_{allocation} = \{getValDivZero(SW_{allocated}, D_{PotentialGross}, SmallNumber), \quad Landmask = True$$ Eq. 9.4.2.7

$$SW_{Abstraction} = F_{allocation} * D_{PotentialGross} * C_{area}$$ Eq. 9.4.2.8

$$D_{downstream} = D_{downstream} + \begin{cases} Q_{environmental}, & cover(S_{out}, 0) = True \\ 0, & cover(S_{out}, 0) = False \end{cases}$$ Eq. 9.4.2.9

9.4.3 Reservoir Allocation

$$S_{id} = \begin{cases} S_{id}, & S_{capacity} > 0 \\ 0, & S_{capacity} \leq 0 \end{cases} \quad \text{Eq. 9.4.3.1}$$

$$S_{capacity} = \{cover(S_{capacity}, 0), \ Landmask = True \quad \text{Eq. 9.4.3.2}$$

$$S_{capacity} = \begin{cases} S_{capacity}, & S_{id} \neq 0 \\ 0, & S_{id} = 0 \end{cases} \quad \text{Eq. 9.4.3.3}$$

$$S_{purpose} = \begin{cases} \{cover(S_{purpose}, -1), \ Landmask = True\}, & S_{id} \neq 0 \\ 0, & S_{id} = 0 \end{cases} \quad \text{Eq. 9.4.3.4}$$

$$S_{additionalId} = \begin{cases} cover(S_{id}, 0), & (S_{allocated} = 0 \,\&\, S_{purpose} = S_{WaterSupply}) \\ 0, & otherwise \end{cases} \quad \text{Eq. 9.4.3.5}$$

$$S_{orderBasin} = areaorder(\{S_{capacity}, \ S_{additionalid} \neq 0\}, B) \quad \text{Eq. 9.4.3.6}$$

$$S_{orderBasin} = \{cover(S_{orderBasin}0), \ Landmask = True \quad \text{Eq. 9.4.3.7}$$

$$S_{MaxNumResBas} = cellvalue(mapmaximum(S_{orderBasin}), 1) \quad \text{Eq. 9.4.3.8}$$

$$S_{selectionMask} = True, \quad S_{orderBasin} == I_{update} \quad \text{Eq. 9.4.3.9}$$

$$S_{amount} = cellvalue(maptotal(scalar(S_{selectionMask})), 1) \quad \text{Eq. 9.4.3.10}$$

$$S_{I_{id}} = nominal(areamaximum\left(\begin{cases} scalar(S_{ids}), & S_{selectionMask} = True \\ 0, & S_{selectionMask} = False \end{cases}, \ Basins\right) \quad \text{Eq. 9.4.3.11}$$

$$S_{country} = nominal(areamaximum\left(\begin{cases} scalar(Countries), & S_{selectionMask} = True \\ 0, & S_{selectionMask} = False \end{cases}, \ Basins\right) \quad \text{Eq. 9.4.3.12}$$

$$S_{selCapacity} = areamaximum(S_{capacity}, B)\{S_{capacity}, \quad S_{selectionMask} = True \quad \text{Eq. 9.4.3.13}$$

$$S_{hOutlet} = areamaxim(S_{elevation}, B)\{S_{elevation}, \quad S_{selectionMask} = True \quad \text{Eq. 9.4.3.14}$$

$$P = path(ldd, S_{selectionMask}) \quad \text{Eq. 9.4.3.15}$$

$$S_{outletStreamOrder} = \{cover\big(areamaximum(\{Streamorder, P = True\}, B), ordinal\big(mapmaximum\big(scalar(Streamorder)\big) + 1\big), \ Landmask = True \qquad Eq.\ 9.4.3.16$$

$$Confluences = downstream(ldd, scalar(S_{selectionMask}) = 1) \qquad Eq.\ 9.4.3.17$$

$$Confluences = (Streamorder \geq S_{outletStreamOrder})\ \&\ downstream\big(ldd, scalar(P)\big) = 1\ \&\ pcrnot(P) \qquad Eq.\ 9.4.3.18$$

$$B_{sub} = subcatchment\left(ldd, nominal\big(uniqueid(confluences)\big)\right) \qquad Eq.\ 9.4.3.19$$

$$B_{sub} = nominal\left(areamaximum\left(\begin{cases} scalar(S_{ids}), & S_{selectionMask} = True \\ 0, & S_{selectionMask} = False \end{cases}, \ B_{sub}\right)\right) \qquad Eq.\ 9.4.3.20$$

$$x_{maxi} = t_{characteristic} * t_{sPerDay} \begin{cases} areaaverage(V_{characteristic}, P), & P = True \\ 0, & P = False \end{cases} \qquad Eq.\ 9.4.3.21$$

$$x_{path} = cover(accuflux(lddrepair(\{ldd, \ path = True\ ), (2 * cellarea)^{0.5}), \{scalar(0), \ Landmask = True) \qquad Eq.\ 9.4.3.22$$

$$P_{sel} = cover\left((x_{path} < x_{maxi}), 0\right) \qquad Eq.\ 9.4.3.23$$

$$P_{basins} = subcatchment\left(ldd, nominal\big(uniqueid(P_{sel})\big)\right) \qquad Eq.\ 9.4.3.24$$

$$M_{sel} = (P_{basins} \neq 0)\&\big\{cover\big(Countries = S_{country}, 0\big), \ Landmask = True \qquad Eq.\ 9.4.3.25$$

$$M_{sel} = M_{sel}\ \&\ \{cover(S_{elevation} \leq S_{hOutlet}, 0), \ Landmask = True \qquad Eq.\ 9.4.3.26$$

$$B_{sub} = \{cover(clump(\{B_{sub}, \ M_{sel} = True\}, \ Landmask = True \qquad Eq.\ 9.4.3.27$$

$$A_{allocated} = nominal(areamaximum\left(\begin{cases} scalar(S_{ids}), & S_{selectionMask} = True \\ 0, & S_{selectionMask} = False \end{cases}, \ B_{sub}\right) \qquad Eq.\ 9.4.3.28$$

$$S_{allocated} = \begin{cases} S_{ids}, & S_{selectionMask} = True \\ S_{allocated}, & S_{selectionMask} = False \end{cases} \qquad Eq.\ 9.4.3.29$$

$$S_{totalCapacity} = S_{totalCapacity} + \begin{cases} cover\big(S_{selCapacity}, 0\big), & A_{allocated} \neq 0 \\ 0, & A_{allocated} = 0 \end{cases} \qquad Eq.\ 9.4.3.30$$

9.4.4 Demand Allocation

$$D_{downstream} = cover(D_{downstream}, 0), \qquad Landmask = True \qquad \text{Eq. 9.4.4.1}$$

$$S_{id} = \begin{cases} S_{id}, & S_{capacity} > 0 \\ 0, & S_{capacity} \leq 0 \end{cases} \qquad \text{Eq. 9.4.4.2}$$

$$S_{id} = cover(S_{id}, 0), \qquad Landmask = True \qquad \text{Eq. 9.4.4.3}$$

$$S_{capacity} = cover(S_{capacity}, 0), \; Landmask = True \qquad \text{Eq. 9.4.4.4}$$

$$S_{capacity} = \begin{cases} S_{capacity}, & S_{id} \neq 0 \\ 0, & S_{id} = 0 \end{cases} \qquad \text{Eq. 9.4.4.5}$$

$$D_{allocated} = spatial(scalar(0)), \; Landmask = True \qquad \text{Eq. 9.4.4.6}$$

$$D_{original} = D_{downstream}, \qquad S_{total} > 0 \qquad \text{Eq. 9.4.4.7}$$

$$D_{original} = cellvalue(maptotal(D_{original}), 1) \qquad \text{Eq. 9.4.4.8}$$

$$D_{weight} = \begin{cases} S_{capacity}, & S_{id} = S_{allocatedid} \\ 0, & S_{id} = 0 \end{cases} \qquad \text{Eq. 9.4.4.9}$$

$$D_{weight} = areamaximum(D_{weight}, S_{allocatedid}) \qquad \text{Eq. 9.4.4.10}$$

$$D_{weight} = getValDivZero(D_{weight}, S_{total}, smallNumber) \qquad \text{Eq. 9.4.4.11}$$

$$D_{totalAllocated} = areatotal(D_{weight}, D_{downstream}, S_{allocatedid}) \qquad \text{Eq. 9.4.4.12}$$

$$D_{resvAllocated} = D_{allocated} + \begin{cases} D_{totalAllocated}, & S_{id} = S_{allocatedid} \\ 0, & S_{id} \neq 0 \end{cases} \qquad \text{Eq. 9.4.4.13}$$

$$D_{total} = cellvalue(maptotal(D_{resvAllocated}), 1) \qquad \text{Eq. 9.4.4.14}$$

9.4.5 Variables in PCR-GLOBWB 2 Functions

***Appendix Table 4**: Variables used in PCR-GLOBWB 2 reservoir and demand functions*

Variable	**Name**	**Unit**
$A_{allocated}$	*Allocated Area*	m^2
B	*Basins*	*Dimensionless*
B_{sub}	*Subbasins*	*Dimensionless*
C_{width}	*Channel Width*	m^1
C_{depth}	*Channel Depth*	m^1
$Confluences$	*Lowest Point of the Reservoir Path*	*Dimensionless*
$Countries$	*Mask for Countries*	*Dimensionless*
$D_{allocated}$	*Allocated Demand*	$m^3\ s^{-1}$
$D_{downstream}$	*Downstream Demand*	$m^3\ s^{-1}$
$D_{original}$	*Original Demand*	$m^3\ s^{-1}$
D_{weight}	*Weight of Demand per Reservoir given as Factor*	*Dimensionless*
$D_{totalAllocated}$	*Total Allocated Demand*	$m^3\ s^{-1}$
$D_{resvAllocated}$	*Allocated Reservoir Demand*	$m^3\ s^{-1}$
D_{total}	*Total Demand*	m^3
$F_{Allocation}$		
$F_{reduction}$	*Reservoir Outflow Reduction Factor*	*Dimensionless*
$F_{reductionDemand}$	*Downstream Demand Reduction Factor*	*Dimensionless*
$ID_{WaterSupply}$	*Water Supply Identifier*	*Dimensionless*
M_{sel}	*Selected Mask*	*Dimensionless*
P	*Path*	*Dimensionless*
P_{sel}	*Selected Path*	*Dimensionless*
P_{basins}	*Selects the Path within the Travel Time*	*Dimensionless*
$Q_{\mu_{outflow}}$	*Average Outflow*	$m^3\ s^{-1}$
$Q_{\mu_{channel}}$	*Average Channel Discharge*	$m^3\ s^{-1}$
$Q_{\mu_{inflow}}$	*Average Inflow*	$m^3\ s^{-1}$
$Q_{resvOutflow}$	*Reservoir Outflow*	$m^3\ s^{-1}$
Q_{Flood}	*Flood Outflow*	$m^3\ s^{-1}$
$R_{minFrac}$	*Minimum Reservoir Fraction*	*Dimensionless*
$R_{maxFrac}$	*Maximum Reservoir Fraction*	*Dimensionless*
$R_{Qbankfull}$	*Bankfull Ratio*	*Dimensionless*
S	*Reservoir Storage*	m^3
$Streamorder$	*The Streamorder*	*Dimensionless*
$S_{allocated}$	*Allocated Reservoirs*	*Dimensionless*
$S_{allocateid}$	*Allocated Reservoir Identification Numbers*	*DimensionLess*
$S_{capacity}$	*Reservoir Capacity*	m^3
$S_{estimated}$	*Estimated Reservoir Storage*	m^3
S_{id}	*Reservoir Identification Number*	*Dimensionless*
S_{ids}	*Reservoir Identification Numbers in a List*	*Dimensionless*
$S_{additionalId}$	*Additional Reservoir Identification Number*	*Dimensionless*
$S_{hOutlet}$	*Reservoir Outlet Elevation*	m^1
$S_{I_{id}}$		*Dimensionless*
$S_{id_{list}}$	*Obtain Additional Reservoir Identification Numbers To List*	*Dimensionless*
$S_{orderBasin}$	*Reservoir Order Per Basin*	*Dimensionless*
$S_{purpose}$	*Reservoir Purpose*	*Dimensionless*
$S_{MaxNumResBas}$	*Maximum Reservoirs per Basin*	*Dimensionless*
$S_{selectionMask}$	*Reservoir Selection Mask*	*Dimensionless*
$S_{selCapacity}$	*Selected Reservoir Capacity*	m^3
S_{amount}	*Total Number of Reservoirs on a Cell*	*Dimensionless*
$S_{country}$	*Reservoir Country*	*Dimensionless*
$S_{outletStreamorder}$	*Reservoir Streamorder*	*Dimensionless*
$S_{totalCapacity}$	*Total Reservoir Capacity*	*Dimensionless*
t	*Length of Time Step*	day^{-1}
$V_{characteristic}$	*Characteristic Velocity of Water in a Streamflow*	$\mathrm{m}^1\ \mathrm{s}^{-1}$
x_{path}		
x_{maxi}	*Maximum Travel Distance for Water at* $V_{characteristic}$	m^1