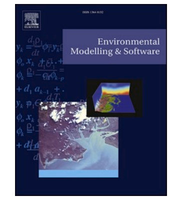
Environmental Modelling and Software 133 (2020) 104802

Contents lists available at ScienceDirect

Environmental Modelling and Software

journal homepage: http://www.elsevier.com/locate/envsoft



GRAPS: Generalized Multi-Reservoir Analyses using probabilistic streamflow forecasts

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ARTICLE INFO

Keywords:
Reservoir modeling
Software development
Simulation
Optimization
Water resources management

ABSTRACT

A multi-reservoir simulation-optimization model GRAPS, Generalized Multi-Reservoir Analyses using Probabilistic Streamflow Forecasts, is developed in which reservoirs and users across the basin are represented using a node-link representation. Unlike existing reservoir modeling software, GRAPS can handle probabilistic streamflow forecasts represented as ensembles for performing multi-reservoir prognostic water allocation and evaluate the reliability of forecast-based allocation with observed streamflow. GRAPS is applied to four linked reservoirs in the Jaguaribe Metropolitan Hydro-System (JMH) in Ceará, North East Brazil. Results from the historical simulation and the zero-inflow policy over the JMH system demonstrate the model's capability to support monthly water allocation and reproduce the observed monthly releases and storages. Additional analyses using streamflow forecast ensembles illustrate GRAP's abilities in developing storage-reliability curves under inflow-forecast uncertainty. Our analyses show that GRAPS is versatile and can be applied for 1) short-term operating policy studies, 2) long-term basin-wide planning evaluations, and 3) climate-information based application studies.

1. Introduction

Water allocation among municipal, industrial, and agricultural sectors requires thorough integration of current supply and demand along with potential climate change, population growth and ecological considerations over the river basin (Singh et al., 2015). Most large river systems typically have multiple reservoirs that are regulated to meet its design uses (e.g., irrigation, water supply, hydropower) considering several ecosystem and environmental constraints (Wang et al., 2015a). Thus, multi-purpose multi-reservoir operations encompass detailed analyses considering trade-offs among conflicting uses (Kasprzyk et al., 2009). For instance, too little release may affect water quality and recreation, while too much release may cause flooding (Singh et al., 2015). The opposing nature of benefits associated with storing the water and profits associated with releasing the water contributes to the complexity of multi-reservoir system operations (Yeh, 1985; Koustosyiannis et al., 2003; Li et al., 2015). To understand the tradeoffs in multi-sectoral water allocation over the river basin, it is important the reservoir modeling framework should be capable of providing the tradeoffs under observed flows and forecasted flows, which is typically represented in the form of ensembles (Sankarasubramanian et al., 2009).

The main intent of this study is to develop and validate a multi-reservoir multi-purpose reservoir modeling framework that can take probabilistic seasonal/annual inflow forecasts for allocating water for multiple uses. The operation of a reservoir system is likely to be subjected to both supply and demand variations, which are typically provided as forecasts at subseasonal (weekly to monthly) to seasonal/annual time scale. It is important to analyze how these supply and demand variations impact the reliability of a given user and the probability of violating the target storage, which are specified as rule curves (Sankarasubramanian et al., 2009; Golembesky et al., 2009). Currently, reservoir modeling platforms typically use either deterministic forecasts, provided as forecast mean/median, which ignores the probabilistic information and the forecast uncertainty on the mean. A more rigorous approach is to analyze the multi-reservoir system using probabilistic inflow forecasts specified as ensembles to support proactive and

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https://doi.org/10.1016/j.envsoft.2020.104802
Received 6 April 2020; Received in revised form 19 June 2020; Accepted 20 July 2020
Available online 27 August 2020
1364-8152/

adaptive water management policies. The utility of a multi-reservoir modeling system is to support reservoir managers and operators for meeting different target demands and testing adaptive strategies including drought contingency plans based on the potential supply and demand (Maurer and Lettenmaier, 2004).

Several formulations of multi-reservoir models have been in the literature, which are well documented in several review papers (Yeh, 1985; Labadie, 2004; Ahmad et al., 2014). Commonly used mathematical programming techniques include linear programming models (Loucks et al., 1981; Belaineh et al., 1999), network flow models (Hsu and Cheng, 2002) and interior-point method (Seifi and Hipel, 2001). Similarly, non-linear programming models have relied on sequential analyses to ensure convergence such as sequential linear programming (Barros et al., 2003), sequential quadratic programming (Finardi et al., 2005), and using generalized reduced gradient technique (Peng and Buras, 2000). Studies have also used both dynamic programming and stochastic dynamic programming models (Alaya et al., 2003). To reduce the dimensionality in the above mathematical programming models, studies have suggested using simulation-optimization models (Koustasyiannis and Economou, 2003; Sankarasubramanian et al., 2009). Application of several novel heuristic techniques such as genetic programming, tabu search and particle swarm optimization have also been used to solve multi-reservoir models (Rani and Moreira, 2009, Baltar and Fontane, 2008; Reddy and Kumar, 2007 and references therein).

Several agencies, universities and private corporations have also developed multi-reservoir modeling software packages. HEC-ResSim by U.S. Army Corps of Engineers is used to simulate reservoir operations for flood risk management, and real-time decision support (Klipsch and Hurst, 2013). Another popular software is MODSIM, a generalized river basin software designed as a tool for making improved basin-wide and regional strategies for management and water rights analysis (Labadie, 2010). California Department of Water Resources developed a general-purpose reservoir–river basin simulation model, CalSim, that permits specifications of system description and operational constraints through a new water resources engineering simulation language (Draper et al., 2004). A water resource planning tool, WEAP, developed by Stockholm Environment Institute, is capable of simulating water demand, supply, flows, and storage, and pollution generation, treatment and discharge (Sieber and Purkey, 2015). WaterWare is a proprietary, decision-support river-basin planning system that employs rule-based concepts for developing operating criteria and policies (Jamieson and Fedra, 1996). Another proprietary popular river basin modeling software is RiverWare developed by the Center for Advanced Decision Support for Water and Environmental Systems (CADSWES) (Zagona et al., 2001). RiverWare is a river basin modeling tool that includes an extensible library of modeling algorithms, solvers, and a language for the expression of operating policy and is extensively used by many operating agencies such as Bureau of Reclamation and Tennessee Valley Authority. Despite the availability of many multi-reservoir models, the implementation of these models under probabilistic inflow forecasts, represented as ensembles, requires running the model subsequently for each member or its deterministic form (i.e., mean/median of the forecast). However, detailed application of seasonal-to-interannual inflow forecasts for reservoir management shows the importance and incorporation of probabilistic constraints on target storage and release (Sankarasubramanian et al., 2009; Georgakakos and Graham, 2008), which cannot be handled by most of the above models.

The skill of seasonal climate forecasts over the last decade has improved considerably through a better understanding of teleconnection between the slowly evolving boundary conditions such as SSTs in the tropical oceans and local hydroclimatology (Goddard et al., 2003; Devineni et al., 2008 in GRL; Wang et al., 2015b). Low-frequency climate variability such as El Nino Southern Oscillation (ENSO) has been proven to influence streamflow in many parts of the world (Dettinger and Diaz, 2002). Utilizing these climate forecasts with updated and corrected land-surface conditions have resulted in improved streamflow and soil moisture forecasts (Wood et al., 2002; Sinha and Sankarasubramanian, 2013; Mazrooei et al., 2019). Despite these advancements, error propagation in downscaling and disaggregation of climate forecasts in developing streamflow forecasts (Wood et al., 2005; Sankarasubramanian et al., 2009; Mazrooei et al., 2015) have caused the application of climate forecasts for real-world water allocation to face challenges due to forecast uncertainty as well as due to institutional hierarchy (Pagano et al., 2001; Pagano et al., 1999; Broad et al., 2007). These challenges necessitate the translation of uncertainty in climate forecasts into corresponding uncertainty in reservoir releases and storages (Li et al., 2014; Lu et al., 2017).

Seasonal to interannual water allocation using a reservoir model based on climate-information requires combining the initial storage conditions with the conditional distribution of streamflow, specified as ensembles, to develop with the forecasted probability of meeting the target storage for the user-specified release (Sankarasubramanian et al., 2009). Georgakakos and Graham (2008) considered a single reservoir to obtain an optimal solution for minimizing the squared deviation from the end-of-the-season target storage under inflow forecast uncertainty. Maurer and Lettenmaier (2004) evaluated the long-lead hydrologic predictability, represented as deterministic inflow forecast, for improving hydropower generation from six reservoirs in the Missouri River basin using an aggregated reservoir system representation. Probabilistic inflow forecasts developed from combining multiple GCMs for a single reservoir, Falls Lake in North Carolina (NC), has been demonstrated to be valuable in invoking drought restrictions (Golembesky et al., 2009). Li et al. (2014) considered inter-basin transfer between two NC reservoirs – Falls Lake and Lake Jordan – using two separate single reservoirs for maintaining quality pool and water supply pool elevations under inflow forecast uncertainty. Wang et al. (2015a) used a single reservoir model to identify the trade-offs between hydropower generation and ecological demands under inflow forecast uncertainty. Lu et al. (2017) utilized multi-time scale forecasts, represented as ensembles, in a single reservoir model for improving hydropower generation and reducing flood risk for a major hydropower reservoir in India. Thus, most studies have used a single reservoir model or a simplified aggregated representation of a reservoir network for evaluating the utility of deterministic/probabilistic inflow forecasts to improve water allocation. To address this, we propose a detailed multi-reservoir simulation-optimization model, GRAPS (Generalized Reservoir Analyses using Probabilistic Streamflow forecasts), that considers the probabilistic inflow forecasts, specified as ensembles, along with probabilistic constraints on meeting the target storage (i.e., rule curves) to quantify the reliability of meeting the user-specified releases.

The manuscript is organized as follows: The generalized model formulation is presented in section two that can adapt to the complexity of interlinked reservoir systems by sequentially routing the flow from upstream to downstream. GRAPS is then applied to a system of reservoirs in Ceará, Brazil to demonstrate GRAPS' capabilities in reservoir modeling and its abilities to accurately reproduce historical storage and flows. Results of the simulation are finally assessed under inflow forecasts and the performance of the forecast-based application is validated with historical observations.

2. GRAPS formulation

GRAPS is extended from a water allocation framework, as outlined in Arumugam et al. (2003) and Sankarasubramanian et al. (2009), that utilizes the benefits of ensemble forecasts of reservoir inflows to issue annual water contracts. Unlike many mainstream reservoir-modeling tools, GRAPS is well suited to handle streamflow ensembles, which translates forecast uncertainty into storage and release reliabilities. Fig. 1 provides an overview of variables, storages, inflows, and outflows, for a given reservoir within the multi-reservoir system. The mathematical formulation for GRAPS is outlined below.

Assume there are N_R reservoirs in a given basin with the index s (s =

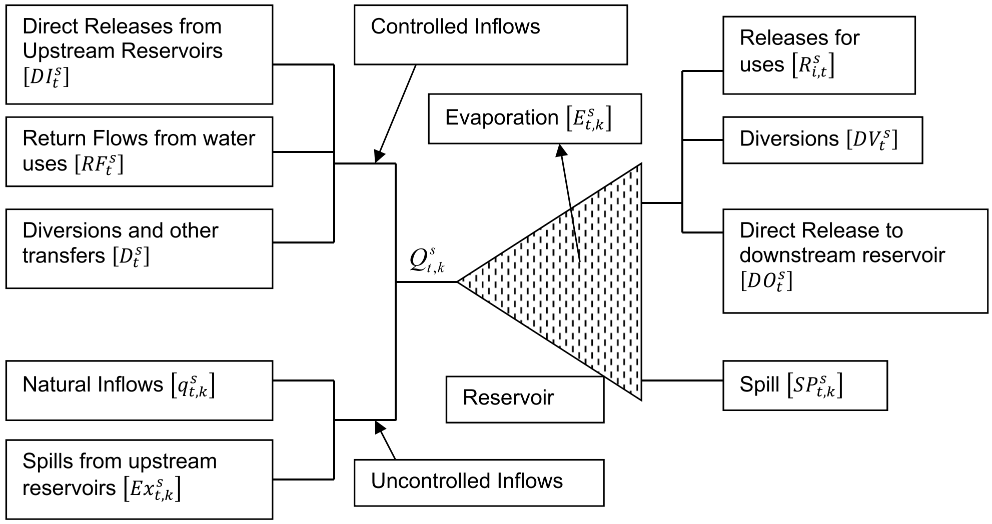

Fig. 1. Inflow and outflow variables allocated with reservoir water balance.

$1 \ldots N_R$) denoting a particular reservoir. The number of upstream reservoirs for the reservoir s is denoted by U_S which includes reservoirs that contribute flows indirectly into reservoir s. Inflows into any reservoir could be grouped into two categories: uncontrolled inflows and controlled flows. Uncontrolled flows are provided as ensembles denoting the conditional distribution. Two types of uncontrolled flows are considered in the model for the reservoir s: natural inflows into the reservoir ($q_{t,k}^s$) and spillage from the upstream reservoirs ($Ex_{t,k}^s$). Controlled flows are of three types: (1) releases and direct inflows from upstream reservoirs, (2) return flows from command areas and wastewater from municipal and industrial use, and (3) diversions and water from inter-basin transfers or other sources. Controlled flows are expressed as functions of the decision variables of the multi-reservoir water allocation model.

2.1. Reservoir variables

2.1.1. Natural inflow

Natural inflows, $q_{t,k}^s$ for time $t = 1, \ldots, T$, $k = 1 \ldots K$, $s = 1, \ldots, N_R$ is the probabilistic streamflow forecasts with indices, 't' 'k' and 's' representing the time step (monthly and above), ensemble member and reservoirs respectively. Inflows, both observed and forecasted ensembles, are provided exogenously to the model by the user.

2.1.2. Spillage

Spillage is a result of uncontrolled spillway discharge. Net spillage from upstream reservoirs, $Ex_{t,k}$, is the sum of the spill from all the upstream reservoirs after accounting conveyance losses, which is estimated based on the past spill data at the reservoir and the reported streamflow in the downstream location (i.e., reservoir/node). The term, $SP_{t,k}^{s'}$, from reservoir s is a derived conditional distribution of spill after accounting for releases, diversions, and evaporation.

$$Ex_{t,k} = \sum_{s'=1}^{U_s} SP_{t,k}^{s'} \tag{1}$$

2.1.3. Return flows from uses

Assuming there are n_s uses in each reservoir, and releases for each use, $R_{i,t}^{s'}$, return flows from the uses released from the upstream reservoirs, U_S, could be calculated. Let NL be the number of lags, the number of time-steps it takes return flow to reach the reservoir. Then, return flow in time step t into reservoir s, RF_t^s, can be estimated as,

$$RF_t^s = \sum_{s'=1}^{U_s} \sum_{i=1}^{n_s} \sum_{t'=t}^{t-NL} f_{t',i}^{ss'} R_{i,t}^{s'} \tag{2}$$

where $f_{t',i}^{ss'}$ is the fraction of monthly releases from reservoir s' that contribute to the current reservoir s with the contribution effective from previous releases (NL months).

2.1.4. Direct release from upstream reservoirs

Direct outflows from upstream reservoirs, $DO_t^{s'}$ results as part of instream requirement as well as excess water being released for hydropower generation and additional downstream needs. Here, s' denotes the upstream reservoir to the current reservoir s. This can be expressed as

$$DI_t^s = \sum_{s'=1}^{U_S} \partial^{ss'} DO_t^{s'} \tag{3}$$

where $\partial^{ss'}$ is the fraction which quantifies the losses on the upstream reservoir, s', releases, $DO_t^{s'}$, to the direct inflow of the downstream reservoir, s. $\partial^{ss'}$ is usually estimated based on historical upstream release and downstream recorded release between reservoirs s' to s. The optimization model treats $DO_t^{s'}$ as a decision variable, which could be either considered as a hydropower plant if present or as a user with an ecological flow requirement to be met. Here, we are treating the direct outflow, $DO_t^{s'}$, from the release term, $R_{i,t}^{s'}$, for uses to indicate that they are not return flows and their consumptive use is very small.

2.1.5. Diversions and other transfers

Diversions for wildlife protection and other environmental/interbasin transfers could contribute to additional inflows.

$$D_t^s = \sum_{d=1}^{ND_s} \eta_{sd} D_{td} \tag{4}$$

η_{sd} is the fraction representing the losses in the diverted quantity D_{td}. D_{td} must be specified as part of the exogenous input to the model.

2.1.6. Net inflows

Net inflows, $Q_{t,k}^s$, is the sum of uncontrolled and controlled inflows into reservoir s (Fig. 1). It is important to note that RF_t^s and DI_t^s are functions of decision variables of the allocation model, whereas D_t^s must be specified as an input to the model. This variable is not required but is used to simplify the equations.

$$Q^s_{t,k} = RF^s_t + DI^s_t + D^s_t + Ex^s_{t,k} + q^s_{t,k} \quad (5)$$

2.2. Reservoir simulation

The minimum (dead), maximum, and initial storages of reservoir s are represented by $S^s_{\min}$, $S^s_{\max}$, and S^s_0. H^s and $SP^s_{\max}$ are the elevation of spillway crest level and maximum spillway discharge, respectively. δ^s_1 and δ^s_2 are the storage-area curve coefficients of the reservoir. In line with the water contract specification (see Section 2.5), different restriction levels are imposed if the actual inflows are less than the forecasted inflows. These restriction levels are defined as pr^s_l, where $l = 1, \ldots, n^s_j$ and r denotes the number of restriction level in a particular reservoir s. ψ^s_t represents the monthly evaporation rates in each reservoir s.

To simulate reservoir operation, the following mass balance equation is used to solve for the end-of-time-step storage for each time-step t for each ensemble member k.

$$S^s_{t,k} = S^s_{t-1,k} + Q^s_{t,k} - E^s_{t,k} - \sum_{i=1}^{n_s} R^s_{i,t} - DO^s_t - DV^s_t - SP^s_{t,k} + SD^s_{t,k} \quad (6)$$

For t = 1, $S^s_{t-1,k} = S^s_0$ indicates the observed storage in each reservoir s. Equation (6) states that the end-of-time-step storage is equal to the current storage plus the net inflow and any deficit, SD^s_t, minus spill, SP^s_t, all releases ($R^s_{i,t}$) for uses, direct downstream release from the reservoir (DO^s_t), diversions to other basins (DV^s_t), and evaporation ($E^s_{t,k}$). The outflow term from the reservoir (DO^s_t) will provide the direct inflow to the downstream reservoir based on equation (3) after accounting the instream losses. $R^s_{i,t}$ and DO^s_t, are decision variables to the optimization model; however, diversion flows (DV^s_t) are specified exogenously. Equations (7) and (8) calculate the spill and deficit for each time step t.

Spill

$$SP^s_{t,k} = \begin{cases} S^s_{t,k} - S^s_{\max} & S^s_t \geq S^s_{\max} \\ 0 & Otherwise \end{cases} \text{ with } s = 1, \ldots, N_R \quad (7)$$

Deficit

$$SD^s_{t,k} = \begin{cases} S^s_{\min} - S^s_{t,k} & S^s_t \leq S^s_{\min} \\ 0 & Otherwise \end{cases} \text{ with } s = 1, \ldots, N_R \quad (8)$$

Equation (9) requires that all reservoirs operate between their minimum and maximum storage levels.

$$S^s_{t,k} = \min\left(S^s_{t,k}, S^s_{\max}\right), \quad S^s_{t,k} = \max\left(S^s_{t,k}, S^s_{\min}\right) \quad (9)$$

Evaporation, E^s_t, is computed as a function of average storage for the current time-step, using the initial storage and the end-of-time-step storage with the storage-elevation relationship.

$$E^s_{t,k} = \psi^s_t \delta^s_1 \left(\left(S^s_{t,k} + S^s_{t-1,k}\right)/2\right)^{\delta^s_2} \quad (10)$$

The depth of evaporation, ψ^s_t, is specified exogenously to the model. Because both S^s_t and E^s_t are unknown, evaporation must be calculated implicitly. This is done using the secant method for root finding (Press et al., 1986).

2.3. Hydropower

Hydropower P is computed as a function of generator efficiency, η, the density of water ρ, gravity, g, and the height difference between the reservoir level and the tailwater, h^{TW}_t. The reservoir level is given as a function of the storage-elevation coefficients, β^s_1 and β^s_2, and the average storage between time-steps.

$$P^s_{t,k} = \eta \rho g \left(\beta^s_1 \left(\left(S^s_{t,k} + S^s_{t-1,k}\right)/2\right)^{\beta^s_2} - h^{TW}_t\right) NR^s_t \quad (11)$$

Net release, NR^s_t, consists of release for hydropower as well as the releases for other uses that go through the turbines. GRAPS identifies hydropower as a separate use and also requests details on turbines along with details on whether the outlet for a particular use (e.g., irrigation) is available for hydropower generation. Although generator efficiency varies with elevation and flow rate, the efficiency is considered constant for simplicity. Based on the above equation, GRAPS determines an ensemble of hydropower generation for conventional hydropower plants and pumped storage hydropower plants. Generation from run-of-river hydropower plants cannot be determined as they have little/no storage.

2.4. Net benefit from the water allocation

When GRAPS is optimized, the objective is to maximize the net utility of water allocations across all uses. Equation (12) describes the mathematical formulation of the objective function, O, denoting the basin-wide net benefit from the allocation. The revenue, φ^s_i ($R^s_{i,t}$) is the tariff paid for the release in each time period t, allocated over the season for the ith water use from reservoir s. Tariffs in GRAPS are expressed as functions of release to allow users to represent linear, increasing-block, and decreasing-block tariff structures. Compensations to users for not meeting the specified use, $R^s_{i,t}$, is subtracted from the total revenue generated in the second term of the objective function. These compensations are defined for each reservoir with $\gamma^s_{i,j}$ indicating the compensation to user i if restriction level j is imposed and $W^s_{i,j}$ is the demand deficit for the entire modeled period for user i and restriction level j. ν^s_i is the compensation schedule for user i if the supply falls below the maximum allowed deficit. The contract penalty, ν^s_i, is invoked if the difference between the total deficit for user i, W^s_i, and the maximum allowable deficit for user i, $W^s_{i,\max}$ (equations (12) and (13)). For further details of the above contract structure, see Sankarasubramanian et al. (2009).

$$O = \sum_{s=1}^{N_s} \sum_{i=1}^{n} \sum_{t=1}^{T} \varphi^s_i\left(R^s_{i,t}\right) - \sum_{s=1}^{N_s}\left[\sum_{i=1}^{n}\sum_{j=1}^{n_i} \gamma^s_{i,j} W^s_{i,j} + \sum_{i=1}^{n} \nu^s_i \nabla\left(W^s_i - W^s_{i,\max}\right)\right] \quad (12)$$

$$\text{Where} \cdot \nabla(x) = \begin{cases} 1 & x > 0 \\ 0 & otherwise \end{cases} \quad (13)$$

2.5. Model constraints

GRAPS is subjected to both deterministic and probabilistic constraints. The following deterministic constraints (14–17) are prescribed in the model for each reservoir for each time step t.

Demand Constraint

$$R^s_{i,\min} \leq R^s_{i,t} \leq R^s_{i,\max} \text{ with } i = \{1 \cdots n_s\} \; s = \{1 \cdots N_R\} \quad (14)$$

Inflow Requirement between two reservoir segments ss'

$$DI^{s'}_{t,\min} \leq NR^{ss'}_t \leq DI^{s'}_{t,\max} \text{with } s = \{1 \cdots N_R\} \quad (15)$$

Diversion Demands

$$D^s_{t,\min} \leq D^s_t \leq D^s_{t,\max} \text{ with} s = \{1 \cdots N_R\} \quad (16)$$

Spillway Constraint

$$0 \leq SP^s_{t,k} \leq SP^s_{\max} \text{ with } s = \{1 \cdots N_R\} \quad (17)$$

Target Storage Constraint

$$\Pr\left(S^s_T \leq S^s_{Tr}\right) = \frac{n\left(S^s_T \leq S^s_{Tr}\right)}{N} \leq p_s \text{ with} s = \{1 \cdots N_R\} \quad (18)$$

User Reliability Constraint

$$\Pr\left(W_i^s \geq W_{i,\max}^s\right) = \frac{n\left(W_i^s \geq W_{i,max}^s\right)}{N} \leq pf_i^s \text{ with } i = \{1 \cdots n_s\} \; s = \{1 \cdots N_R\} \tag{19}$$

Using ensemble input, GRAPS calculates the probabilistic constraints and also reports the probability of spill and deficit by counting how many times an event occurs (e.g. meeting target storage), represented as the operator $n(.)$, and dividing that by the number of members, N, in the ensemble. In equation (18), S_T^s and S_{Tr}^s represent the simulated end-of-time-period storage and the target storage respectively, for each reservoir s. The model estimated $\text{Prob}(S_T^s \leq S_{Tr}^s)$ should be lesser than the target constraint p_s. In equation (19), W_i^s is the restriction level for user i at reservoir s and $W_{i,\max}^s$ is the maximum allowable restriction level for a user at a reservoir. Based on this, the model meets specified the user reliability, $(1 - pf_i^s)$, where pf_i^s denotes the model estimated failure probability for the current release patterns. In addition to these probability performance measures, GRAPS also provides ensembles of hydropower, spill and deficit for each reservoir at each time step.

GRAPS can also operate under observed flows in which the probabilistic constraints in (18) and (19) are converted into deterministic constraints with the total number of ensembles K being equal to 1. The deterministic form of (18) and (19) ensures by forcing p_s and pf_i^s being equal to zero.

2.6. Optimization-simulation framework

GRAPS equations specified in equations (1)–(19) could be used in a stand-alone simulation mode or in an optimization-simulation mode. Under simulation mode, GRAPS performs the simulation across the cascade using equations (1)–(11) based on the user specified decision variables, $R_{i,t}^s$ and DI_t^s and computes the model outputs such as ensembles of spill, hydropower generation and storages along with the net benefit and probabilistic constraints (12)–(19). Under the optimization-simulation mode, GRAPS maximizes the net benefit in (12) based on the deterministic and probabilistic constraints in (14)-(19) to obtain the decision variables, $R_{i,t}^s$ and DI_t^s, using feasible sequential quadratic programming (Zhou and Tits, 1992). Add a line on observed flows. FSQP obtains the decision variables by solving both the deterministic and probabilistic constraints. FSQP optimizes continuous functions and their derivatives and also considers finite differences when continuous derivatives are not available for the objective function and the constraints. In this study, we used both simulation mode and the optimization-simulation mode to obtain the releases using finite difference approximation of constraints and objective function using both observed flows and climatological ensembles.

2.7. GRAPS model characteristics

2.7.1. Node-link representation

Similar to many other existing water resources systems modeling programs, GRAPS adopted a node-link representation to characterize physical river basin networks. Even though the shapes of the rivers and reservoirs are arbitrary, the underlying spatial configuration can be simplified and represented in the program by a two-dimensional interconnected directed network of nodes and links. Each node in the model can represent one of six entities: watersheds, reservoirs, inter-basin transfers, users, junction-nodes, and sinks. Reservoirs, watersheds, and users are represented by system blocks, and diversion locations and flow confluences are designated by junction nodes. Rivers, streams, and channels are designated as links and are defined with a direction and upper and lower bounds on flow capacity. In such a node-link representation, a reservoir system begins from a watershed node and ends at a sink node. A representation of this node-link structure is shown in Fig. 2. Such node-link formulation provides an efficient and simple representation of the underlying reservoir system.

2.7.2. Ensemble input framework

By using probabilistic streamflow ensembles, GRAPS can be used to investigate climate change effects on basin management and reservoir systems. Fig. 3 illustrates how the simulation model is executed with a streamflow ensemble. Performing reservoir mass balance for all the traces in the ensemble, as opposed to going over the entire cascade for each trace in the ensemble, can also facilitate parallelization in computing, which we are currently working on incorporating in GRAPS. The model simulates the most upstream reservoir time steps 1 to T and for ensembles 1 to K then goes to the next reservoir. If a reservoir has multiple branches flowing into it, such as the case with reservoir 3 in Fig. 3, GRAPS will simulate all reservoirs on all of the branches upstream of that reservoir before simulating that reservoir.

2.7.3. Python interface

Using Python 3.7 and PyQt5, a graphical user interface was developed to increase the usability of GRAPS. This interface streamlines the creation of the data files required to run GRAPS and provides a method for visualizing the network cascade. It is designed to allow a user to use intuitive keystrokes and mouse movements to create the network cascade and then use input dialogs for each system block to enter information. An example network created with the interface is shown in Fig. 2.

2.7.4. Input

Like many other advanced water allocation models, GRAPS requires information on basin hydrology, reservoir, and users. For a generalized reservoir model like GRAPS, input files are prepared and tailored to each reservoir system. These input files specify the connectivity, reservoir characteristics, reservoir management and user demands of the modeled system. Of these files, the most crucial input to the program is naturalized flow or streamflow that represents natural hydrology, into every reservoir.

2.7.5. Output

To model the reservoir system, specific information describing individual reservoirs must be provided. This information includes the area-storage relationship, current reservoir storage, and water demands for disparate water uses. The user is required to provide reservoir system-specific information regarding network and diversion blocks. Specific details about users, such as information about demands and water contracts, must also be provided. Simulation results comprise of variables such as storage, reservoir releases, releases to users, hydropower generation, spill, and deficit. The main result of the ensemble simulations is the reliability of meeting end-of-period target storage for each reservoir.

2.7.6. Connectivity

The reservoir network is represented as an acyclic directed graph with a single terminal node, the sink. A hierarchical tree structure, in which nodes and users ordered from upstream to downstream, is used to store the reservoir network. In the model, each network must have at least one watershed and exactly one sink. To simulate a network with multiple sinks, one can use junction nodes in place of the individual sinks, and then connect the junctions to a single, artificial sink. Fig. 4 shows how individual elements of the reservoir network can be connected.

3. GRAPS application using ensemble forecast for a multi-reservoir system

3.1. Study area: Jaguaribe valley, Ceará, Brazil

The purpose of this case study is to demonstrate GRAPS′ modeling capability to accurately simulate historical operations. The case is based on the Jaguaribe River Basin (Fig. 5), a basin situated in the semiarid

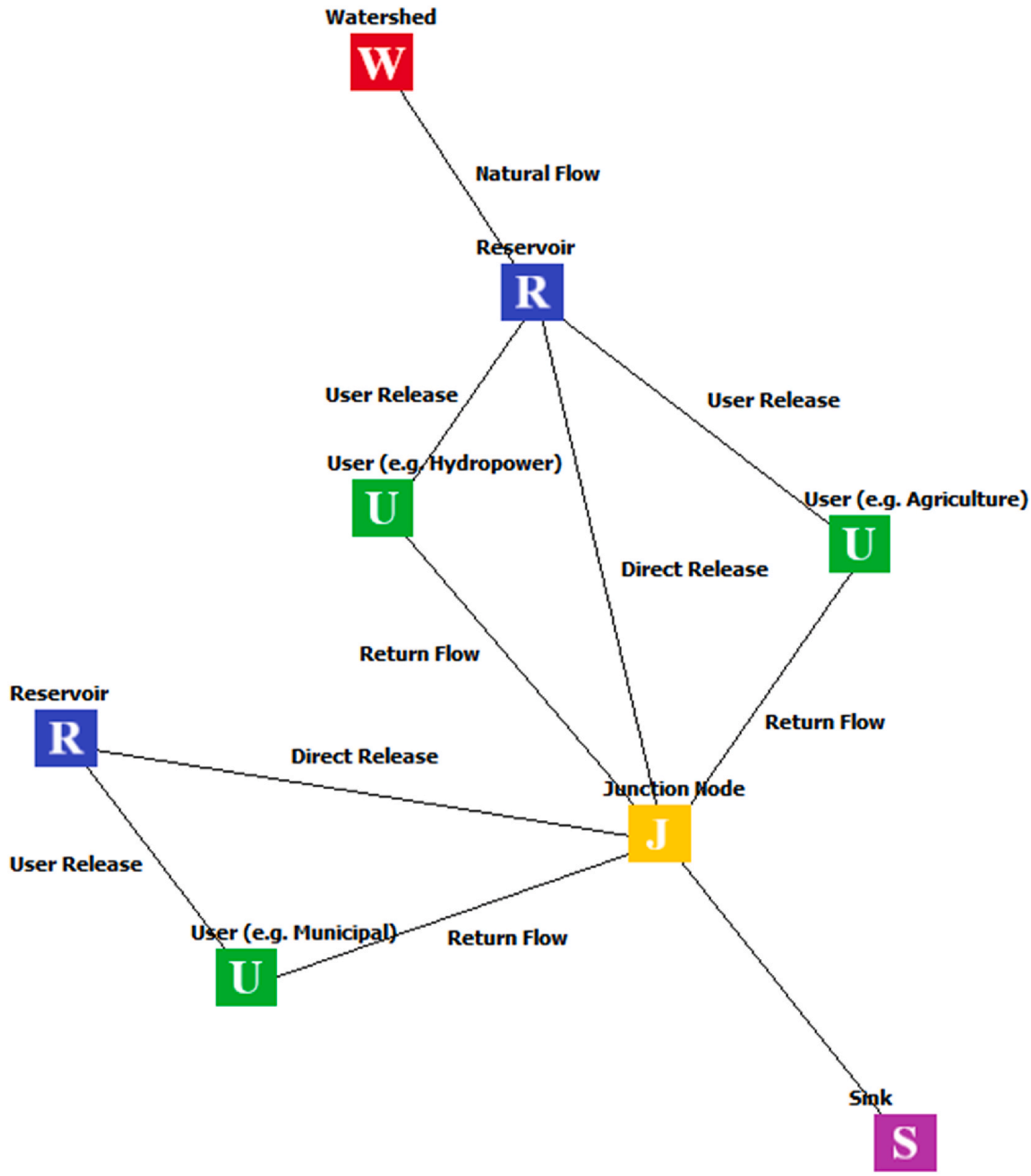

Fig. 2. Python interface depiction of a reservoir system in GRAPS with major modeling components within the River basin.

state of Ceará in the northeastern part of Brazil. With a drainage basin covering an area of 75,961.07 km^2, the Jaguaribe River extends for about 610 km and its discharge can range from zero to 7000 m^3/s (Campos et al., 2000). The main water management challenge in the region is to retain water in reservoirs in rainy years and to manage it such that it will last for several years (Johnsson and Kemper, 2005). Another challenge is the increasing dependence of the capital Fortaleza, one of the largest and fastest-growing cities in Brazil (Johnsson and Kemper, 2005). In a 2007 study, Broad et al. (2007) pointed out that a third of Ceará's population is rural, and most of the population is in the agricultural sector. Persistent poverty and drought have created an ongoing vulnerability. The reservoirs in the upper Jaguaribe River basin provide water for agricultural uses, including agribusiness and small family farming. The downstream reservoirs provide water for municipal use for the city of Fortaleza and other small towns in the region.

3.2. Modeled reservoirs

The generalized model is applied to 4 reservoirs in the Jaguaribe River Basin. The modeled reservoirs in this case study are Orós, Banabuiú, Pacajus, and Pacoti. Water is diverted from the Jaguaribe River Basin to the Pacajus reservoir via Canal do Trabalhador (Worker's Canal). The Canal is a diversion medium that supplies water to any user along the way. Through a small canal via a pump station, water is again delivered from Pacajus reservoir to Pacoti reservoir.

Table 1 summarizes the four modeled reservoirs in this case study. The largest reservoir in this study is Orós, with a maximum storage of 1940 hm^3. Pacajus reservoir, on the other hand, is the smallest reservoir with a maximum storage of 240 hm^3. Due to the aridity of the region, the minimum storages for all the reservoirs are low. Additionally, most of the annual inflow happens from January to June. Pacoti and Pacajus have higher minimum storages due to their role in ensuring water supply to the nearby city of Fortaleza.

3.3. Input

Historical streamflow and reservoir data were provided by Dr. de Assis de Souza Filho at the Federal University of Ceará, Fortaleza, Brazil.

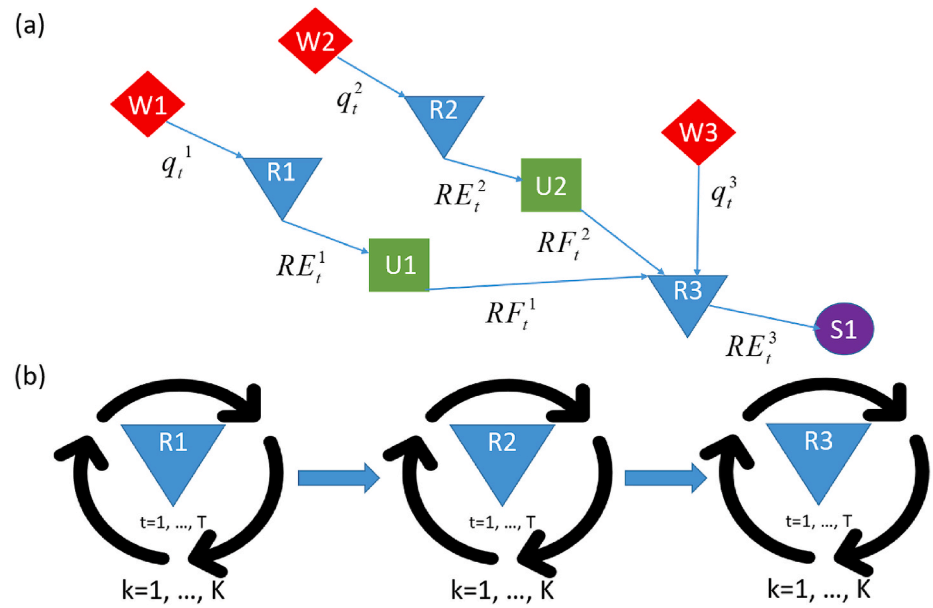

Fig. 3. Model execution diagram. (a) Sample reservoir cascade. (b) GRAPS stepping down the cascade, simulating reservoirs for all time steps and all ensembles before moving to the next reservoir.

		Connect From					
	System Blocks	**Watershed**	**Inter-basin Transfer**	**Reservoir**	**Junction Node**	**User**	**Sink**
Connect To	**Watershed**	Invalid	Invalid	Invalid	Invalid	Invalid	Invalid
	Inter-basin Transfer	Invalid	Invalid	Invalid	Invalid	Invalid	Invalid
	Reservoir	**Valid**	**Valid**	**Valid**	**Valid**	**Valid**	Invalid
	Junction Node	**Valid**	**Valid**	**Valid**	**Valid**	**Valid**	Invalid
	User	Invalid	Invalid	**Valid**	**Valid**	Invalid	Invalid
	Sink	**Valid**	**Valid**	**Valid**	**Valid**	**Valid**	Invalid

Fig. 4. Connectivity diagram between different nodes within GRAPS.

However, historical inflow and reservoir levels were dated before the year 2000. Castanhão reservoir, a sizable reservoir in the region was constructed after 2000. Consequently, Castanhão reservoir was not included in the model.

3.4. *Streamflow ensemble*

Considering the lag-one correlation between the annual flows is close to zero, an ensemble of climatological streamflow forecasts was developed from the historical inflows for the corresponding month from 1913 to 2000 to populate 100 ensemble forecasts (Arumugam et al., 2003). This ensemble of forecasts was generated by bootstrapping, a simplistic resampling technique that draws randomly from a set of data points and allows replacement.

3.5. *Zero inflow policy*

Since half of the year (July–December), there is zero inflow into the Orós reservoir, the water management agency in Ceará, Brazil, COGERH, assumes zero inflow for the upcoming twelve months. For additional details on the zero-inflow assumption and its merits in water allocation, see Sankarasubramanian et al. (2009). This conservative approach allocates water based on the beginning of the year storage. As a result, when the reservoir is simulated with the observed inflow, the reservoir may spill in some instances.

3.6. *Schematic representation of the modeled system*

Fig. 6 illustrates how the multi-reservoir system is schematically represented in the program. The network contains reservoirs connected in series and parallel. At the very top of the graph are Orós and Banabuiú reservoirs. Since the agriculture sector dominates the state and most of the users are agriculture users, we simplify the modeling by assigning Orós and Banabuiú to have only one aggregated agriculture user each. Node 1 (a junction node) is used to represent a point of river confluence and to gather upstream reservoir and user releases from Orós and Banabuiú. Canal do Trabalhador is represented in the network as a node and is modeled as a user that delivers water from node 1 to the Pacajus reservoir. Due to its function as a small relay reservoir, Pacajus reservoir only has one user, a pump that delivers water from the reservoir to Pacoti reservoir. Finally, Pacoti reservoir supplies all the drinking water to the city of Fortaleza, which is represented as a municipality user node.

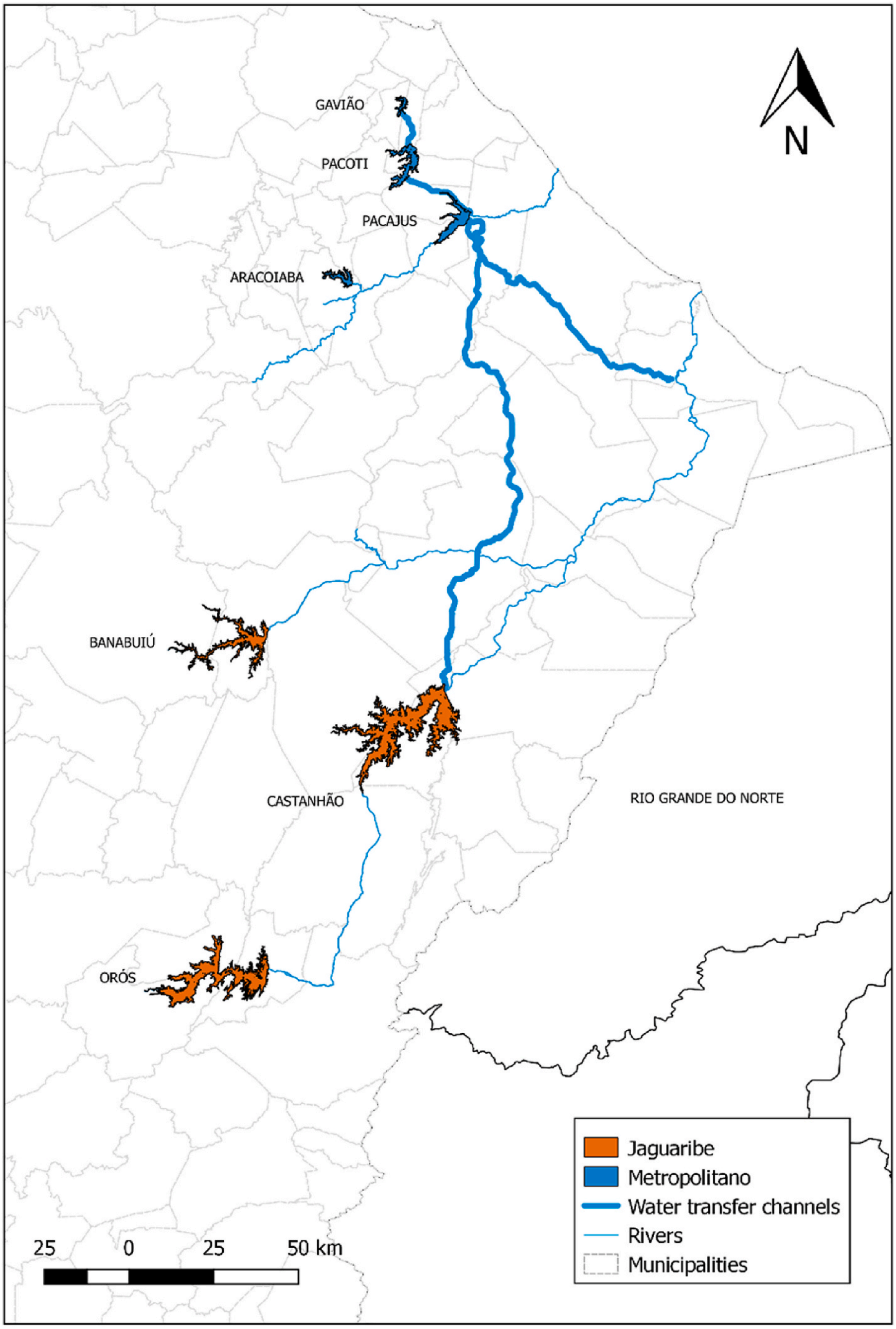

Fig. 5. Jaguaribe valley river and irrigation system.

Table 1
Reservoir information.

	Latitude	Longitude	County	Basin	S_{max}(hm3)	S_{min}(hm3)
Orós	9310493	508313	Orós	Alto Jaguaribe	1940	16.87
Banabuiú	9411109	508724	Banabuiú	Banabuiú	1675	0.186
Pacajus	9533300	568400	Pacajus	Metropolitanas	240	34.7
Pacoti	9554155	552178	Horizonte	Metropolitanas	380	21.74

Although there are two distinctive watersheds, interbasin transfer is not needed as the two watersheds are represented within one system model. Denoted as a sink, the Atlantic Ocean receives return flows from Lower Jaguaribe agriculture, Node 1, Pacoti reservoir, and the city of Fortaleza.

3.7. *Assumptions*

For simplicity and illustration, several assumptions were made in modeling the Ceará reservoir system. Both Orós and Banabuiú are linked

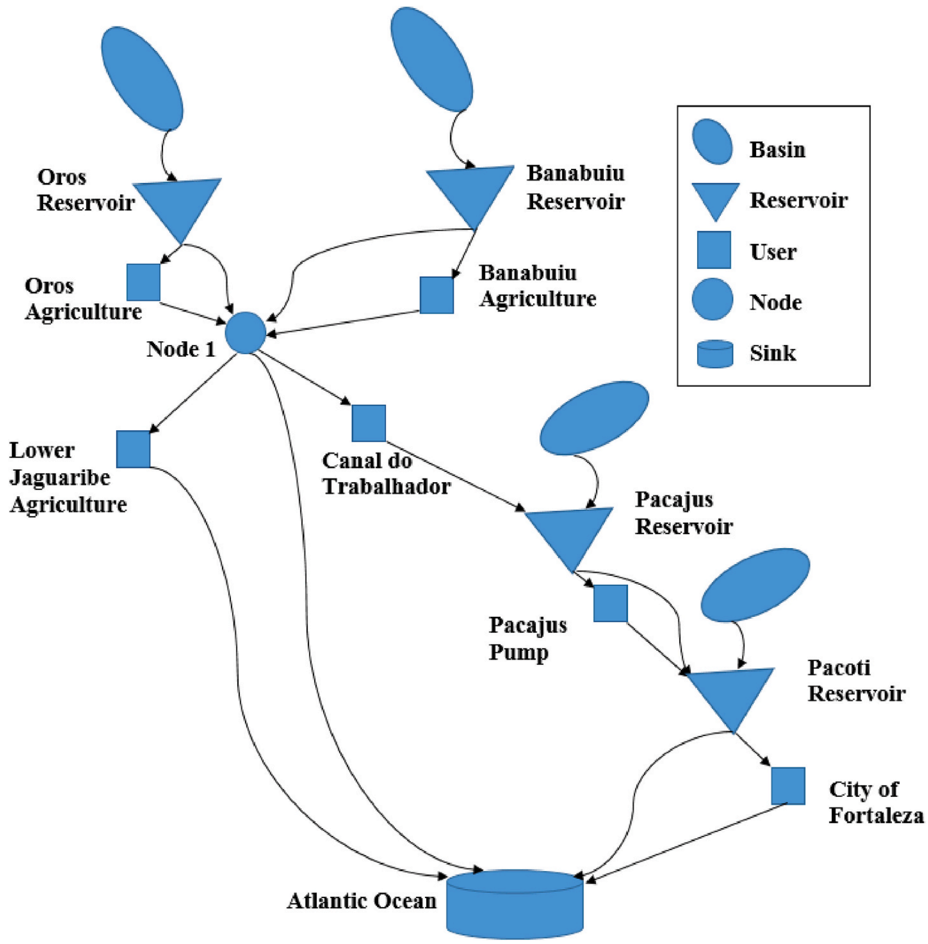

Fig. 6. Network diagram of the modeled reservoirs within the Jaguaribe-Metropolitan system.

to only agriculture users as the municipal demand in the rural area is very small. Given that the Jaguaribe-Metropolitan system is primarily operated based on priority-based allocation (see Sankarasurbamanian et al., 2009; Broad et al., 2007), the application of GRAPS was primarily implemented as a simulation model. Additionally, the simulation period is chosen to be from January 1997 to December 1999 as it encompasses a wet (1997), normal (1998) and dry (1999) years. Lower Jaguaribe Agriculture is the only user in the lower Jaguaribe River and represents all the water demands in that area. To account for water loss due to consumptive use, it is assumed that return flows from agricultural (municipal and industrial) users are 40% (90%) of the water allocation.

4. Results and discussion

The primary objectives of the case study are to demonstrate GRAPS′ capability to model a complex reservoir system and validate the program's ability to accurately compute flows and reservoir storages and to generate storage reliability curves from ensemble inputs. The multi-reservoir system is modeled for an entire calendar year and for a three year period with monthly time-steps. In this case, travel time for return flows it is not useful, so it is not considered. Simulation results are presented in the following subsections.

4.1. Model validation

Fig. 7 shows simulated flow routing for different seasons in 1998. For this purpose, GRAPS was run in a simulation mode with observed flows (i.e., total number of ensembles $K = 1$ and the RHS of equations (18) and (19) are set to zero). As shown in the network diagram (Fig. 6), Orós and Banabuiú are the two uppermost reservoirs and receive natural inflow. As a result, inflow into Orós and Banabuiú is part of the flow routing demonstration. Proper routing is an important function of any multi-reservoir simulation program. The preceding result indicates that the program is routing various flows (natural flows, reservoir releases, and user return flows) correctly from upstream to downstream and through junction nodes. GRAPS allows for the specification of loss fractions to incorporate consumptive use. Because a junction node is a place for gathering releases and return flows from upstream and distributing the flow to downstream without using the water, total inflow into Node 1 is the same as the total outflow from Node 1.

To demonstrate GRAPS' ability to model and optimize reservoir systems over a multi-year time horizon, the Ceará system is optimized using observed inflows (i.e., total number of ensembles $K = 1$ and the RHS of equations (18) and (19) are set to zero) from January 1997 to December 1999 using FSQP (Fig. 8). This period is chosen because 1997 is an abnormally wet year 1999 is a dry year for the region. In 1998 the inflow into the system is near the long-term averages. The high inflow in 1997 results in three months of spill from Orós and Banabuiú and two months of spill from Pacajus. Because spill from Orós and Banabuiú can flow directly to the Atlantic Ocean, their spill flow does not impact the storages of Pacajus and Pacoti. In April of 1999, releases for industrial use taper off and become zero. This can be attributed to the critical need of municipal use during dry years.

4.2. Optimized reservoir system analysis using climatological inflow ensemble

In Fig. 9, the impact of three different inflow scenarios –

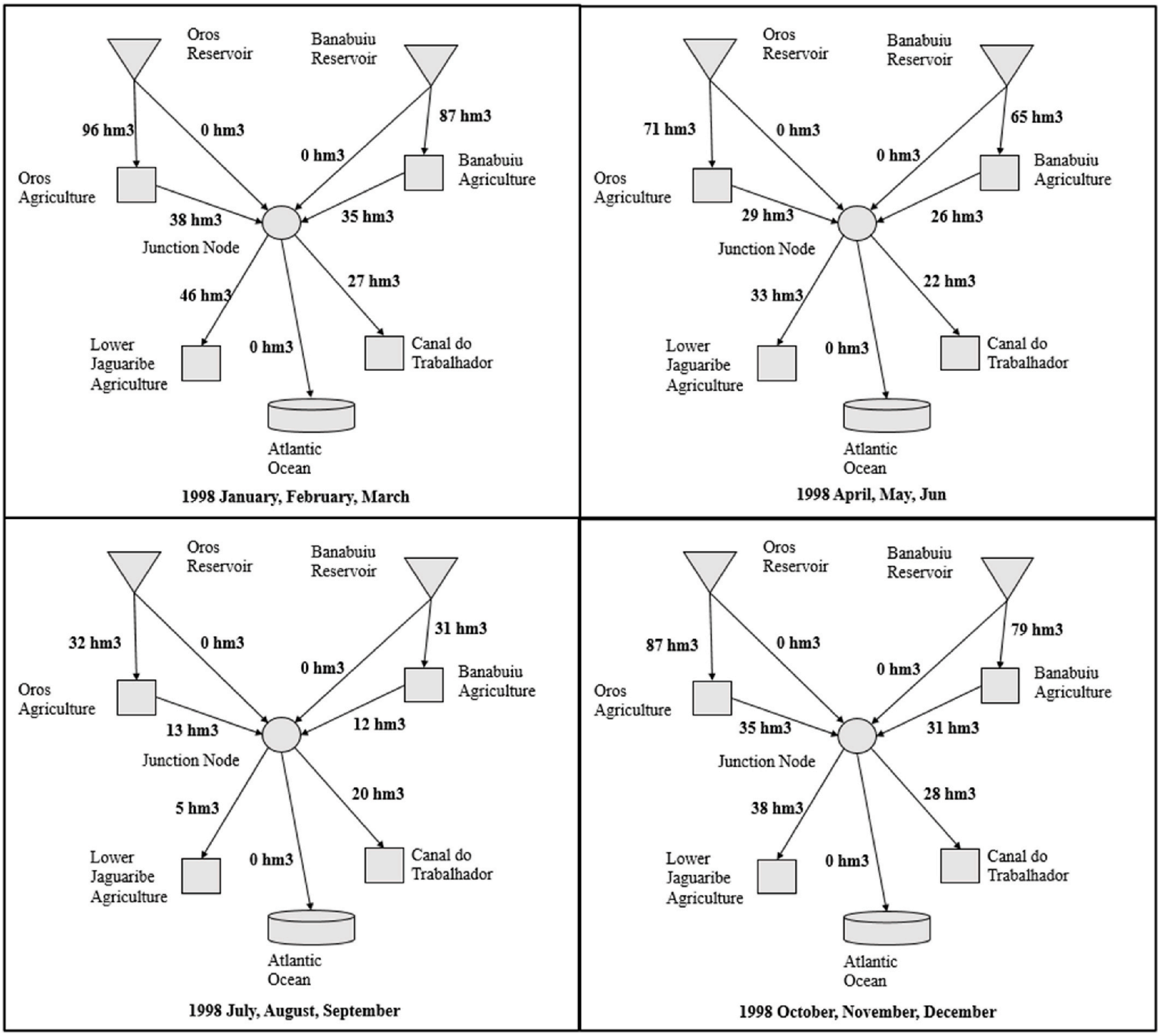

Fig. 7. Flosw routing through the junction node for different seasons in 1998.

climatological ensemble, zero-inflow forecast and perfect forecast (i.e., observed flows) – on the estimated spill for Orós and Banabuiú in 1997 is analyzed by optimizing the releases using FSQP. The optimized releases for three inflow scenarios were run with the observed flows to evaluate how the system would have performed under each inflow scenario. The climatological ensemble ($K = 100$) was developed by bootstrapping the observed flows over the period 1913–2000 by assuming each year has the equal probability of occurrence. For the zero inflow (for T = 12 months) and observed inflow policies, K was set to 1 and the deterministic form (18) and (19) was considered for optimization using FSQP. Because extended severe droughts are prone in the Jaguaribe River basin, a zero-inflow policy was applied as a conservative measure by the local government for seasonal water allocation (see Sankarasubramanian et al., 2009). This zero-inflow policy is considered here as well as using the observed monthly inflows and the climatological ensemble. The spill distribution for the optimized release under climatological ensemble is smoothened with a guassian kernel density estimator (Fig. 9). The spill that would have occurred for the optimized release under three inflow scenarios is also shown (three straight lines, spill volume indicated in legend), which is obtained by running GRAPS in a simulation mode with the respective releases under each inflow scenario. The zero-inflow policy resulted in the most spill for Orós, followed by the climatological flows and then the observed flows. This is along the expected lines as zero-inflow policy being conservative has estimated lower release resulting in higher spill. This is followed by lesser spill based on the release under climatological ensemble and the optimized release under perfect forecast (i.e., observed flows) result in the lowest spill. For Banabuiú, all three policies result in similar yearly spill volumes due to its limited storage. The results from the climatological spill indicate that Orós (Banabuiú) forecasted spill is 10% (7%) probability. Analyzing the spill density, it is evident that most of the inflow ensemble members result in no or very little spill for both reservoirs. At the beginning of 1997, Orós and Banabuiú each have approximately 900 hm^3 of unused storage, thereby the forecasted climatological spill distribution is small. Though the ensemble used in this analysis is simplistic with no forecast skill, the ability of GRAPS to effectively handle inflow ensembles and optimize the release under inflow uncertainty is effectively demonstrated.

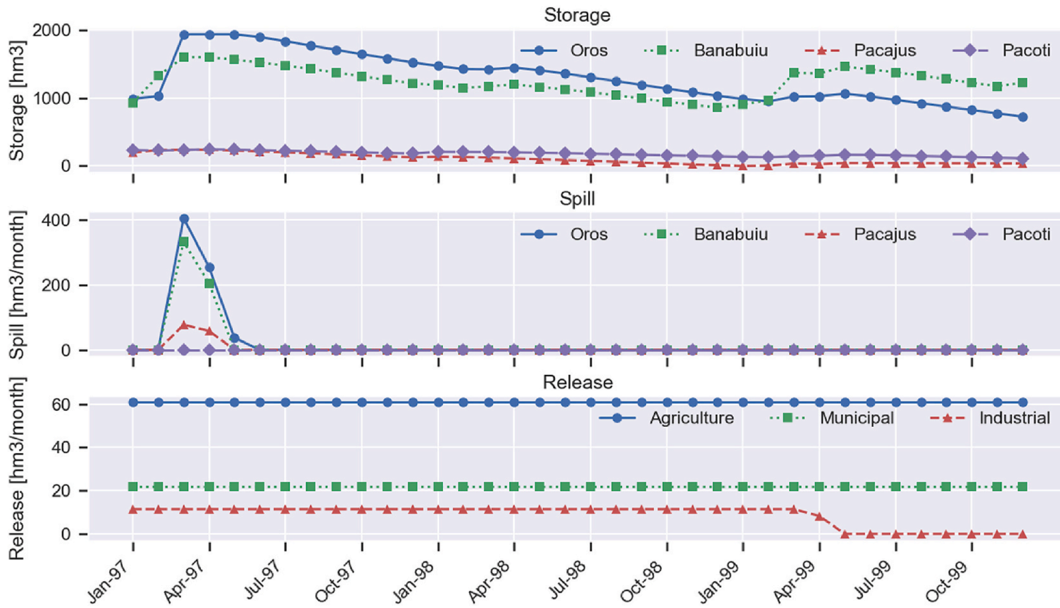

Fig. 8. Optimized releases, storages and spill for three years of allocation (1997–1998) using observed flows with FSQP.

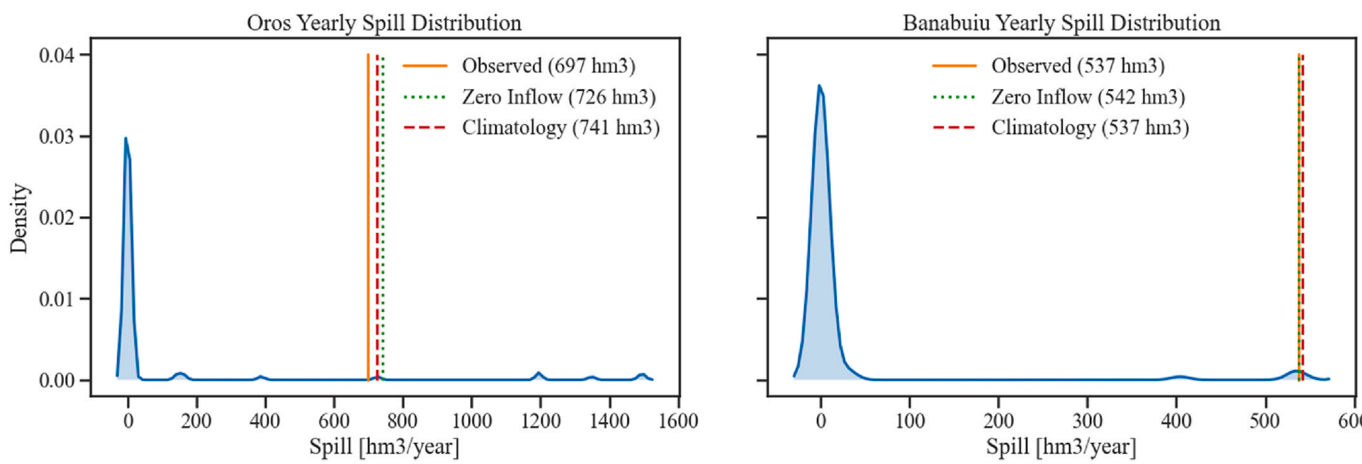

Fig. 9. Spill for Orós and Banabuiú Reservoirs in 1997 for zero inflow policy, climatology, and perfect forecast (observed). The density plot shows the spill distribution obtained by optimizing the release using the climatological inflow ensemble.

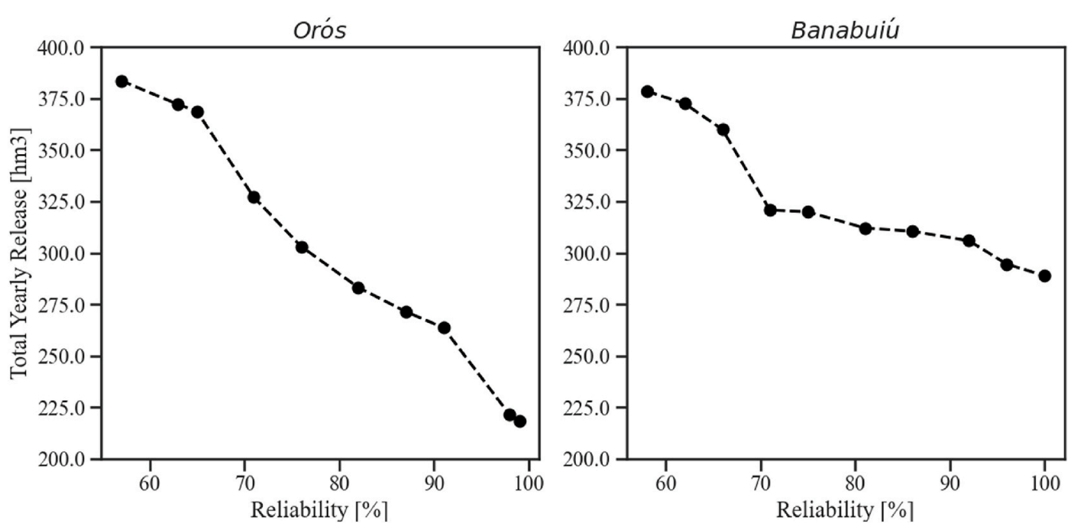

Fig. 10. – Optimal yearly agricultural release versus target storage reliability (p_s) for Orós and Banabuiú reservoirs in 1998 given fixed initial and target storages.

Fig. 10 shows the ability of GRAPS in estimating the optimal releases that meet various target storage reliabilities (p_s) using climatological ensemble for the year 1998. Target storage reliability is a critical constraint in ensuring enough water at the end of the planning period (Golembesky et al., 2009; Li et al., 2014). For Fig. 10, the Feasible Sequential Quadratic Programming (FSQP) algorithm is used to maximize the system benefits given a bootstrapped climatological ensemble for the natural inflow into the two reservoirs in the JMH system. The target storages for Orós (1100 hm^3) and Banabuiú (400 hm^3) are chosen to provide enough storage to meet demand from multiple sectors given two years of no inflow into the reservoirs (Sankarasubramanian et al., 2009). The initial storage for both reservoirs is set as the observed storages at the beginning of January 1998 (1425.4 hm^3 for Orós and 728.9 hm^3 for Banabuiú). The end-of-the-season target storage reliability is computed by counting the number of times end-of-period storage equal or above the target storage over the entire ensemble and the specified p_s is given as a constraint in (18). The target storage reliability (p_s) is increased in increments of 5% from 55% to 100% as a constraint in the optimization-simulation model to obtain the optimal releases under each case using climatological ensemble. As the target storage reliability increases, the optimal yearly release decreases. For Banabuiú, the relationship flattens for reliabilities greater than 70%, i.e. small changes in release result in large changes in reliability. This suggests that the low flow years for Banabuiú are similar and, because the Jaguaribe River is known to go long periods of time with little to no flow, likely nearly zero inflow years. Because the climatological inflow provided is bootstrapped from historical inflow data, it shows the drier nature of flows occurring over the arid JMH basin. Such discrete and continuous nature of inflow ensemble can cause large discontinuities in the reliability constraints in (18) and (19). Under these situations, the optimal solutions from FSQP typically ends indicating that the new solution is numerically equivalent to the previous best solution which indicates that the objective function has flattened out in the search space. Even though this sounds logical under the discrete (i.e., zero flows) and continuous nature of the density of inflows, evaluation of the optimized solutions with other optimization algorithms such as Particle Swarm Optimization and Iterative Linear Programming, could reduce the uncertainty in the optimal solutions. Given GRAPS is designed to work with any optimization algorithms as a stand-alone optimization-simulation model, our future effort will evaluate various algorithms in providing optimal solutions with GRAPS.

5. Discussion and concluding remarks

GRAPS, a next-generation multi-reservoir simulation program, is presented and detailed as an optimization-simulation model. The program uses simulation for reservoirs and junction nodes and optimizes the releases for multiple users that maximizes the net benefit from allocation by considering deterministic constraints and probabilistic constraints on target storage and user deficits. In this study, we demonstrated the optimization using FSQP, but in principle, GRAPS can be called using any non-linear programming solvers. GRAPS can also be run in a simulation mode to obtain the target storage reliability and reliability of obtaining user-specified releases (equations (19) and (19)). GRAPS can perform water allocation using observed inflows or using the seasonal/annual inflow forecast ensemble. GRAPS uses a node-link representation with reservoirs, watersheds, junction nodes and users represented as nodes and rivers, streams, and channels represented as links. The program routes the flow of water from upstream to downstream both spatially and temporally through a connected network of different reservoir elements. As opposed to existing reservoir models such as RiverWare and Hec-ResSim, GRAPS can handle ensemble forecast to translate the inflow uncertainty into appropriate probabilistic information on the target storage (equation (18)) and the reliability of allocating the user-specified amount (equation (19)) by optimizing/simulating the releases. Unlike a site-specific reservoir model, GRAPS can be applied to any reservoir systems and to help the process of setting up, a python user interface is developed. In contrast to commercial software, GRAPS is free to use for noncommercial and educational purposes and can be downloaded from (https://github.com/lcford2/GRAPS.git).

GRAPS formulation is tested in a simulation mode (Fig. 7) in routing the flow through the four reservoirs (Fig. 7) and also evaluated in an optimization-simulation mode by performing multi-sectoral water allocation (Fig. 8) using observed flows for the JMH basin in Ceara, North East Brazil. GRAPS was also evaluated in estimating the spill by optimizing the releases under three inflow scenarios – climatological ensembles, zero inflow and perfect forecast (i.e., observed flows) – during a wet year (Fig. 9). Analyses show zero inflow forecast estimate the highest spill amount, followed by climatological ensembles with the perfect forecast providing the least amount of spill when the optimized release for the three scenarios were run as a simulation using observed flows. GRAPS was also evaluated in optimizing the releases in meeting different target storage reliability, p_s, values under climatological ensembles. Analyses show clearly as p_s increases, total release for all uses decreases using FSQP, but to get convergence on the optimized release, it is important that the inflow forecast ensembles should be well calibrated. Otherwise, the uncertainty in optimized releases should be analyzed with various optimization solvers.

GRAPS maximizes the net benefit from multi-sectoral water allocation considering seasonal/annual inflow uncertainty. Challenges in estimating the target storage reliability, particularly during dry years, as the nature of the inflow distribution tends to be mixture (i.e., discrete and continuous) distribution. Thus, estimation of target storage reliability and reliability of allocating the user demand depends on the skill of inflow forecasts and their ability to predict the observed frequencies of various events. This implies that apart from the accuracy (e.g., correlation) of the inflow forecasts, it is important that the forecast needs to be well calibrated between the forecast probability of wet/dry years with their observed frequencies. Multimodel forecasts developed by combining multiple climate forecasts and hydrologic models to develop well-calibrated inflow forecasts (Sinha and Sankarasubramanian, 2013). Application of multimodel inflow forecasts have benefitted in improving the hydropower generation (Oludhe et al., 2013) and in setting up restrictions during drier years (Golembesky et al., 2009). Thus, providing an inflow forecast that is skillful and well-calibrated could result in reliable estimation of the conditional probabilities related to management attributes (p_s and pf_i), which is critical if the forecast skill is significant only during a particular season (e.g., winter/spring). Given GRAPS can also work with other solvers, the optimized releases should also be tested with other solvers for ensuring global optima. This is particularly important if the number of decision variables (i.e., (N_s+ N_R)*T) increases for a large system that has multiple uses.

GRAPS is designed to maximize the expected net benefit in considering the revenue and penalties in allocating water for multiple uses. This study considered only three uses (i.e., municipal, industrial and irrigation), but other uses such as hydropower, flood control and recreation could also be considered. Formulation on hydropower is already included and it could be included in the revenue part of the net benefit. Flood control benefits could be considered explicitly if the simulated storages do not violate the flood control space. Previous deterministic reservoir modeling efforts have suggested approaches for incorporating flood control benefits (Simonovic and Marino, 1982). Similarly, recreation benefits can also be incorporated if the monthly simulated storages within the desired reservoir levels that support recreational benefits. Any violation of those storage spaces could also be considered as a penalty into the net benefit specified in equation (12). For additional details on estimating recreational benefits, see Cordell and Bergstrom (1993). Other ecological benefits such as instream flow maintenance could also be incorporated explicitly by considering ecosystem maintenance as a user. Incorporation of these additional benefits could be implemented by modifying the 'get_net_ben' subroutine related to the net benefit function or by defining them as a user in the system.

GRAPS is primarily designed to support multi-sectoral water allocation considering seasonal/annual inflow forecasts. It has not yet been applied for daily streamflow forecasts in which the routing and loss coefficients (i.e., coefficients in equations (2)–(4)) could be quite significant depending on the inflow conditions. As GRAPS can estimate the monthly/seasonal forecasted hydropower potential, it can also be linked with power system model for supporting seasonal power generation planning and maintenance. Efforts are currently underway in linking GRAPS with an energy system model TEMOA (https://temoacloud.com/) for the TVA system that includes 28 hydropower reservoirs, 3 nuclear power plants, and 23 fossil fuel (coal and natural gas) plants (Ford et al., 2019). Similarly, GRAPS can also be extended for long-term planning studies considering climate change projections (e.g., Singh et al., 2006). Under such conditions, the inflow forecast will become inflow projections developed multiple climate model's projections. Under such long-term planning conditions, the initial conditions of the reservoirs play a limited role, but the future demand and inflow conditions play a critical role. Even though GRAPS cannot explicitly estimate modified rule curves for potential capacity expansion, it can estimate the probability of meeting the target storage, p_s, and probability of meeting the user-specified demand, pf_i, under projected inflow and demand conditions. By estimating the target storage for different p_s and pf_i, for different storage values, one could choose the target storage that will ensure desired target storage probability and reliability for different uses under projected climate and demand scenarios. These are critical modeling efforts that link water system with both energy and food systems for analyzing their performance under changing climatic conditions.

Software availability

GRAPS is written in Fortran 90 and uses the Fortran Feasible Sequential Quadratic Programming (FFSQP) for optimization package (Zhou and Tits, 1992). GRAPS was developed by the authors of this article and is available as free and open-source software on GitHub at https://github.com/lcford2/GRAPS. Contained in the repository is the source code, along with pre-compiled executables for Linux and Windows. Compilation was performed using intel compilers for Fortran. This repository was made public in March 2019. The source code is less than 200 KB and the executable is slightly more than 1 MB, depending on the operating system and the compiler used. An example is included in the repository that is based on the reservoir system in Ceará, Brazil along with explanations of the input files.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This material is based on work supported by the National Science Foundation under Grant No. 1442909 and Grant No. 1805293. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

Notations

Variables noted with a star (*) are represented as ensembles in GRAPS

DI	Direct inflow from upstream reservoir
DO	Direct outflow to downstream reservoir
DV	Diversion releases from a reservoir
NR	Net release through reservoir turbines
∂	Loss fraction
N_R	Total number of reservoirs
U_s	Upstream reservoirs
T	Number of time-steps
NL	Number of lags
RF	Return flow
n_s	Number of uses for each reservoir
n_r	Number of restriction levels for each reservoir
f	The fraction of monthly releases from an upstream reservoir that contribute to the current reservoir with the contribution effective from previous releases (NL months)
β	Monthly demand fraction
ND	Number of diversions
D	Diversion inflow into a reservoir
η	Diversion loss fraction
q	* Natural inflow
Ex	* Spill inflow from upstream reservoirs
k	Ensemble number
SP	* Spill outflow from a reservoir
SD	Deficit
Ex	Net spillage
Q	Net inflow
R	Release for each use
p_f	Failure probability
pr_l	Restriction level probability
$S_{\min}$	Minimum storage
$S_{\max}$	Maximum storage

S_0	Initial storage
S	Reservoir storage
H	Elevation of spillway
$SP_{\max}$	Maximum spillway discharge
δ	Storage-elevation curve coefficients
E	* Evaporation
ψ	Evaporation rate (lake evaporation depth)
P	Hydropower
K	Generator efficiency
ρ	Density of water
g	Gravity constant
h	The height difference between headwater and tailwater elevations
N	Total number of ensembles
w	User restriction level
W	User demand deficit

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envsoft.2020.104802.

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