The interplay between reservoir storage and operating rules under evolving conditions

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Abstract. Reservoir storage helps manage hydrological variability, increasing predictability and productivity of water supply. However, there are inevitable tradeoffs, with control of high frequency variability coming at the expense of robustness to low frequency variability. Tightly controlling variability can reduce incentives to maintain adaptive capacity needed during events that exceed design thresholds. With multiple dimensions of change projected for many water supply systems globally, increased knowledge on the role of design and operational choices in balancing short-term control and long-term adaptability is needed. Here we investigated how the scale of reservoir storage (relative to demands and streamflow variability) and reservoir operating rules interact to mitigate shortage risk under changing supplies and/or demands. To address these questions, we examined three water supply systems that have faced changing conditions: the Colorado River in the Western United States, the Melbourne Water Supply System in Southeastern Australia, and the Western Cape Water Supply System in South Africa. Moreover, we parameterize a sociohydrological model of reservoir dynamics using time series from the three case studies above. We then used the model to explore the impacts of storage and operational rules. We found that larger storage volumes lead to a greater time before the shortage is observed, but that this time is not consistently used for adaptation. Additionally, our modeling results show that operating rules that trigger withdrawal decreases sooner tend to increase the probability of an

adaptive response; the findings from this model are bolstered by the three case studies. While there are many factors influencing the response to water stress, our results demonstrate the importance of: i) evaluating design and operational choices in concert, and ii) examining the role of information salience in adapting water supply systems to changing conditions.

Keywords: drought, reservoir, robustness, fragility, system dynamics, sociohydrology

1.0 Introduction

A prolonged drought affected the Western Cape region (South Africa) region from 2014 to 2017 and the city of Cape Town experienced an extreme water crisis approaching "Day Zero", i.e. when there would be no stored water to deliver (Otto et al., 2018). A couple of years before, between 2014 and 2015, extended areas of Sao Paolo (Brazil) received water only two days per week during a severe, but not unprecedented, drought (Muller, 2018; Otto et al., 2015). In both cases, extensive systems of reservoirs, aqueducts, canals and pumps, engineered to reliably supply water, along with the organizations responsible for management and operation, were unable to meet water demands during extreme drought conditions (Otto et al., 2018, 2015).

Increasing variability of streamflow and growing water consumption intensify the risk of water stress and shortage (K. P. Georgakakos et al., 2012; Rodell et al., 2018; Vorosmarty et al., 2000). Since reservoirs are typically designed based on historic conditions, their ability to buffer streamflow variability is expected to decline in the coming decades (A. P. Georgakakos et al., 2012). In addition to reducing the impacts of streamflow variability, the buffer provided by reservoirs can maintain stability in water supply as conditions change. For example, as demands increase, stored water mitigates the risk of water shortage and allows time for adaptive actions such as demand management or acquisition of new supplies. Similarly, they can provide a buffer as changes in climate or upstream developments increase the variability of streamflow or reduce average streamflow. The performance of reservoir systems is influenced not only by the designed characteristics of the physical infrastructure, but also by the reservoir operating rules that guide reservoir managers in balancing multiple objectives, including maximizing present benefits while minimizing future risks (You and Cai, 2008a).

Under conditions of low streamflow or high demand, reservoir operators must determine how to balance present and future impacts of water shortage. There are multiple ways of formulating this decision problem. Bower et al. (1962) developed one approach known as standard operating policy (SOP). Under SOP the releases are made as close to the quantity demanded as feasible (You and Cai, 2008a). SOP is the optimal policy to minimize the expected cost of water shortages when the cost function is linear. However, the cost of water shortage often increases non-linearly (Draper and Lund, 2004; Gal, 1979). Hedging policy responds to the fact that large shortages have disproportionate impacts by accepting a small reduction in releases to reduce the risk of a severe shortage later (Bower et al., 1962). SOP results in lower shortage frequency while hedging results in a lower maximum shortage magnitude (Cancelliere et al., 1998). There are many forms of hedging which vary in both complexity and goals including policies developed for multi-reservoir systems and to meet ecosystem goals (Adams et al., 2017; Zeng et al., 2014). Simply put, both SOP and hedging identify conditions which trigger a reduction in releases and specify the degree of reduction as a function of the system state, serving as a feedback controller for the system.

[Figure 1]

Controlling variability aims to increase predictability and productivity (Anderies, 2015). Reservoirs combine two approaches for controlling variability: a modification of system structure (i.e. the addition of storage) and feedback control which acts to reduce variability (i.e. the operational rules) ([Figure 1). In particular, the combination of structural and feedback approaches, such as those applied in reservoir systems, is very effective at reducing high frequency variability. However, there are inevitable tradeoffs, with control of high frequency variability coming at the expense of robustness to low frequency variability (Bode, 1945; Csete and Doyle, 2002). Examples of tradeoffs that have been identified in water systems are the levee effects and other safe development paradoxes (Burton et al., 1968; Di Baldassarre et al., 2018; Viglione et al., 2014). Research in social-ecological systems suggests that tightly controlling short-term variability generates fragilities in the long-term by suppressing information needed for adaptation (Carpenter et al., 2015). Ecological systems are not a perfect analogy for heavily engineered-human dominated systems. In contrast to ecological systems, in engineered systems information can be deliberately collected and directed to key decision makers or archived for later use.

Information on the state of the system is necessary, but insufficient, to inform response to changing conditions. Just as a thermostat senses the temperature and compares it to the goal temperature to determine when to heat or cool a space, operators use information on the state of water supply system (e.g. current demands, volume of stored water, forecasted inflows) to inform actions such as water withdrawals and opening spillways. However, when it comes to changing the rules (e.g. enacting new demand management policies, altering reservoir operating rules) the availability of information is insufficient as rule change requires aligning attention and resources in a policy making environment with competing priorities and limited resources. Adaptive action can be both financially and politically costly, creating incentives to delay response to changing conditions.

Even in cases where the need for change is acknowledged (e.g. Tenney, 2018), it can be challenging to act because substantial policy change requires political and financial support as well as a technical motivation (Garcia et al., 2019; Treuer et al., 2017). In other words, to overcome policy making inertia the information must be both available and salient (Eshbaugh-Soha, 2006).

Salience refers to the observation that when attention is directed to one part of the environment, that part is given disproportionate weight in decision making (Kahneman and Tversky, 1979). The concept of salience is valuable in understanding the link between a change in water demand or supply and policy action because increasing the salience of an issue can change policy makers' and consumers' cost benefit calculation under risk (Bordalo et al., 2012). Research on stochastic environmental processes, such as flooding or wildfire, shows that the occurrence of extreme events redirects attention, increasing the weigh these risks are given in decision making (Dessaint and Matray, 2015; Hand et al., 2015). In the water supply sector, increased water issue salience is positively correlated with the implementation of demand management policies and lower per capita water demand (Garcia and Islam, 2019; Quesnel and Ajami, 2017).

Water supply systems are multi-level systems within a nested, hierarchical structure with multiple subsystems operating at a range of scales (Ostrom and Janssen, 2005; Pahl-Wostl, 2009). Intervention at one level in the system to control the variability of key flows reduces the incentives for investment in adaptive capacity elsewhere in the system (Burton et al., 1968; White, 1945), though information related rules and norms influence these decisions. Adaptive capacity in the water supply systems takes many forms across system levels, from household storage tanks and farm grain stores to regional levee and reservoir systems. Large-scale reservoirs decrease the variability of streamflow enabling lower variability in agriculture, industrial production, and domestic water service, altering the incentives to invest in and maintain adaptive capacity at other levels (Di Baldassarre et al., 2018). In other words, reservoirs are embedded in ecological and social systems that become fine-tuned for efficiency at a low level of variability (Carlson and Doyle, 2002). Under changing conditions, many reservoir systems will reach a threshold beyond which they can no longer attenuate as much variability, and will pass along greater variability to other levels of the system.

Reservoirs, as intended, decrease the frequency of drought impacts on water usage and can temporarily mask reductions in reliability by providing a buffer as the ratio of demands-to-supplies rises, or variability increases, by delaying impact. Even when information on supply and/or demand change is available to decision makers, it may have lower salience as impacts are differed and delay adaptive action. This delay increases the scale of corrective action needed. Further, both infrastructure expansion and demand management policy can generate substantial opposition (Feldman, 2009; Muller, 2018), slowing and sometimes halting action. Delays are fundamental features of dynamical systems with storage and can have either positive or negative effects on system dynamics. Delays can cause oscillation (overshooting of system capacity and subsequent overcorrection) and instability, or moderate variability and allow decision makers time to respond to change (Sterman, 2000). In sum, reservoirs both buffer variability and postpone response by delaying information and impact (Garcia et al., 2016). Importantly, the rules and norms on information collection, information processing and decision making shape these tradeoffs, and how environmental variability shapes policy change (Anderies et al., 2018). Reservoir operating rules are one example of the set of rules and norms shaping this relationship. The tradeoffs in tightly controlling hydrological variability with reservoirs combined with the role of rules in shaping those tradeoffs, motivates this analysis and raises questions about how decisions made in designing the reservoir and its operating rules influence this phenomenon. In this paper, we address two specific questions: 1) How does the scale of reservoir storage (relative to demands and streamflow variability) affect long-term reliability? 2) How do reservoir operating rules in place mitigate shortage risk under changing supplies and/or demands? We address these questions by applying a sociohydrological model to three cases of reservoir operation under change. After evaluating model adequacy through case application, we explore the model state space through a sensitivity analysis in order to address both questions in more general terms.

This paper is organized as follows. First, we describe three cases to illustrate delay effects associated with reservoirs: the Colorado River Reservoir System, the Western Cape Water Supply System, and the Melbourne Water Supply Reservoir System. Second, we present a simple model of reservoir operations, which is applied to each case to analyze the effects of reservoir capacity and operation on long-term performance patterns. Then, we use the model to explore the state space through a sensitivity analysis. Lastly, we discuss the results and limitations of the study and summarize our conclusions.

2.0 Case studies

We address the research questions in the context of three cases: the Colorado River Reservoir System in the Western United States, Western Cape Water Supply System in Cape Town, South Africa, and the Melbourne Water Supply Reservoir System in Southeastern Australia. We have selected these cases to explore how infrastructure design (i.e. capacity) and policy choices (i.e. operational rules) interact in a range of scales, hydro-climatic regimes, and governance contexts using a sociohydrological model.

2.1 Colorado River Reservoir System, Western United States

The Colorado River watershed spans 630,000 km^2, including seven U.S. states and Mexico, and supplies water to more than 40 million people, irrigates 22,000 km^2, and provides 4,200 megawatts of electricity generation capacity (USBR 2012). The watershed is predominately semi-arid, receiving an average precipitation around 400 mm/year (Christensen and Lettenmaier, 2007). There are numerous reservoirs on the main stem of the Colorado River with an approximate total capacity of 74,000 GL (60 Million acre-foot; MAF) or four times the average annual flow (Rajagopalan et al., 2009). Lake Mead (34,000 GL; 27.6 MAF) and Lake Powell (32,000 GL; 26.2 MAF) are multipurpose reservoirs providing water supply, flood control and hydropower that together account for ~89% of the main stem storage capacity. The maximum surface area of these two reservoirs (A_{res}) is 1298 km^2.

The partitioning, use, and management of the Colorado River is governed by a collection of federal and state statutes, interstate compacts, international treaties, court decisions and contracts with the federal government known as the "Law of the River" (Morris et al., 1997). Water allocations to each of the basin states were set by the 1922 Colorado River Compact (USBR 1922) and the 1928 Boulder Canyon Project Act, and Mexico's allocation was set by the 1944 Mexican Water Treaty. These allocations, totaling 20,300 GL (16.5 MAF), were based average annual flow at Lees Ferry, Arizona of around 21,000 GL (17.0 MAF), which was computing using the early 20th century streamflow data available at the time and ignoring inconvenient evidence of historic droughts (Kuhn and Fleck, 2019; MacDonald, 2010).

In the years since, it has become clear that the estimation of the long-term average flow was based on a historically wet period. The long-term average flow is currently estimated around 20,200 GL (16.4 MAF), which is less than the allocated quantity (USBR, 2012). For many years, this structural deficit was not obvious as some states were not using their full allocation. Growing demand brought the structural deficit to light, especially during drought. Note water use in Figure 1c does include Mexico's water use as the population data was not available. Between 2000 and 2014, river flows have been 19% below the 1906-1999 average ([Figure 2a) (Udall and Overpeck, 2017). In response, the basin states negotiated the 2007 Interim Guidelines for Lower Basin Shortages which allocated shortages among the basin states and incentivized conservation (Grant, 2008). The shortage guidelines effectively reduced water use, but reservoir levels continued to fall as the drought persisted. By the beginning of 2018, Lakes Mead and Powell were collectively 35% full, compared to 70% full in 2000 (Figure 2b). The U.S. Bureau of Reclamation responsible for operating the river's water supply reservoirs has warned that without action the Lake Mead could drop to dead storage by the mid-2020's (James, 2018). The basin states negotiated a temporary drought contingency plan in 2019 (Sullivan et al., 2019). However, an estimated 1/6 to 1/2 of the decrease in streamflow during the 2000's drought is due to above average temperatures and projections of a continued rise in temperature increase the possibility of long-term streamflow decline or aridification in the basin (Udall and Overpeck, 2017). Given this potential, and the structural deficit, more than a temporary drought plan is needed to restore stability to the basin in the long-term.

[Figure 2 (Maupin et al., 2018; US Bureau of Reclamation, 2019, 2016, 2012)*]*

2.2 Melbourne Water Supply Reservoir System, Southeastern Australia

Melbourne is the capital of the State of Victoria in south-eastern Australia. The city is located beside the large Port Philip Bay approximately 60 km from the sea. It extends toward the Dandenong and the Macedon Ranges, the Mornington Peninsula and the Yarra Valleyrise. The annual rainfall is about 660 mm evenly distributed through the year, with a slight maximum in October (Zhou et al., 2000).

Water for consumption in Victoria is withdrawn from reservoirs, streams and aquifers under entitlements issued by the Victorian Government and authorized under the Water Act 1989 (Victoria State Government, 1989) ([Figure *3*a,b). The water supply system for Melbourne relies on 10 storage reservoirs with a total capacity of 1,812 GL. The maximum surface area of these reservoirs (A_{res}) is 241 km^2. There are two types of storage reservoir: i) on-stream reservoirs and ii) off-stream reservoirs, which receive water transferred from on-stream reservoirs or other sources.

Melbourne is the second most populous city of Australia and its water supply history is an example of how reservoir expansions can enable increased water consumptions (Di Baldassarre et al., 2018), ([Figure *3*d). The Thomson Reservoir is the most recent and was built to "drought-proof" Melbourne, after a period of drought occurred in the years 1982-1983, by increasing storage capacity of 250%.

The Millennium Drought occurred in the period 2001-2009, [Figure *3*a, and it was the worst drought on record for southeast Australia (Van Dijk et al., 2013). The river ecosystems and irrigated dryland agriculture in Victoria and the Murray-Darling were especially hard hit (Leblanc et al., 2012). The drought contributed to compulsory water restrictions, increased electricity prices and major bushfires. The Australian Bureau of Agricultural and Resource Economics and Science estimated that annual drought losses exceeded A$5 billion from 2006 to 2007 in terms of the gross value of agricultural production (Australian Bureau of Agricultural Resource Economics, 2008). The drought also had a social cost, e.g. 6000 jobs were lost, and farmers were increasingly suffering from depression and exhaustion (Sherval et al., 2014). In the Melbourne metropolitan area, different strategies to decrease demand and increase the supply were pursued. For instance, desalination and water recycling plants were built ([Figure *3*c). Water use restrictions included banning consumptive activities (e.g., car washing) and promoting more efficient water use (e.g., requirements for shutoff valves on hoses). Besides these temporary restrictions the Victoria Uniform Drought Water Restrictions Guidelines outlined permanent restrictions (Low et al., 2015).

[Figure 3 (Melbourne Water, 2020)]

2.3 Western Cape Water Supply System, South Africa

The metropolitan area of Cape Town is located on the Cape Peninsula within the Cape Floristic Region of South Africa. Most of Cape Town's suburbs are within the large flat plain that joins the Cape Peninsula with the mainland, i.e. the Cape Flats neighborhood. The geology of the region consists of a rising marine plain. The climate is Mediterranean, characterized by warm dry summers and cool, wet winters with strong winds. The nearby Table Mountain creates multiple local microclimates, with average annual rainfall ranging from about 400 mm in the wind-swept Cape Flats to up to 1,000 mm in the nearby mountain slopes in and around Constantia (Brown and Magoba, 2009).

The metropolitan area of Cape Town includes over 40 towns in South Africa. The population increased by approximately 64% since 1996 (Koopman and de Buys, 2018). It is estimated that about 14% of the total population lives in informal settlements either integrated in high-income suburbs or on the periphery of the city (Currie et al., 2017). The city's water is supplied by the Western Cape Water Supply System, which includes six major reservoirs with a total storage capacity of 898 GL (99.6% of the total). The largest one is the Theewaterskloof Dam on the Sonderend River, with a storage capacity of 480 GL, equal to 41% of the total storage. The Berg River Dam, the most recent addition, completed in 2009, increased storage from 768 GL to the present capacity. The maximum surface area of these reservoirs (A_{res}) is 67 km^2. Some dams are managed by the National Department of Water and Sanitation (DWS) and some by the City of Cape Town (CCT).

The 2015-2017 drought was the worst on record ([Figure 4a), Otto et al. (2018). The drought threatened to cut off tap water to around 4 million people (Figure 4c) as the water stress prompted the dramatic Day Zero narrative, attracting the attention at the national and international level. The drought was caused by the lowest rainfall since the 1880s (Wolski, 2018). The lack of rainfall caused a sharp drop of reservoir storage ([Figure 4b). To get through the drought, the DWS introduced restrictions to maintain dam levels above 15%, though water can be extracted to 10%. In 2016, the DWS initially imposed a 20% restriction on domestic and agriculture water use. Domestic water restriction was increased to 40% in October 2017 and then to 45% in December 2017. Day Zero was estimated to be in April 2018, and the campaign to avoid it began in January 2018. In February 2018, the water supply was limited to 50 liters per capita per day, leading people to queue to get water from sources, drill private boreholes, and buy bottled water. In March 2018, the mayor declared the CCT a disaster area. The reduction in water consumption, Figure 3c, prevented reservoir depletion. Then, the occurrence of rainfall replenished the dams, allowing to cancel the Day Zero campaign. The economic impact was estimated around US$200 million (Muller, 2018).

[Figure 4 (City of Cape Town, 2019; Climate Systems Analysis Group, 2020; Department of Water and Sanitation City of Cape Town, n.d.; Koopman and de Buys, 2018)]

3.0 Methodology

The methodology is presented in three steps: model development, model scaling and model application.

3.1 Model Description

The model described here is adapted from Garcia et al. (2016). Minor modifications are made to the withdrawal and population modules. The model can be applied with a range of time steps and is here applied with an annual time step. Streamflow, Q (L^3T^{-1}), is modeled using a first order autoregressive model (AR1), parameterized by mean (μ_H, L^3T^{-1}), standard deviation (σ_H, L^3T^{-1}), and lag one autocorrelation (ρ_H, unitless), Eq. 1. The final term, a_t (unitless) is a normally distributed random variable with a mean zero and a standard deviation of one. For three cases studies observed streamflow is used in place of modeled streamflow and the streamflow model would be adapted and adjusted as needed to reflect local streamflow patterns to explore projections or counterfactuals.

$$Q_t = \rho_H(Q_{t-1} - \mu_H) + \sigma_H(1 - \rho_H^2)^{0.5} a_t + \mu_H \quad (1)$$

At each time step, the amount of water in storage, V (L^3), in the reservoir is specified by a water balance equation where W is water withdrawal (L^3T^{-1}), Eq. 2. Dam reservoir evaporation in volume is given multiplying the evaporation in depth (LT^{-1}) which is specific for each dam and the maximum area of the corresponding reservoirs, A_{res} (L^2) (Kohli and Frenken, 2015). For simplicity, the use of water for irrigation purposes is not considered separately (i.e. all water uses are lumped) and there is a single water user on the river (i.e. no competition or interaction amongst users).

$$\frac{dV}{dt} = Q_t - W_t - E_t\, A_{res} \quad (2)$$

The evaporation in depth E is estimated as:

$$E_t = f\ PET \tag{3}$$

Where f is a weighting factor (unitless) which is 1 for open water surfaces and PET (L T^{-1}) is the monthly average potential evapotranspiration (L T^{-1}), in turn estimated from the saturated water pressure e_{sat} (L^{-1} M T^{-2}, mbar for this empirical equation) (Dingman, 2015):

$$PET_t = 0.00409\ e_{sat,t} = 0.00409 * 6.11 \exp\left[\frac{17.3\ T_t}{237.3+T_t}\right] \tag{4}$$

T is the monthly average air temperature (°C for this empirical equation) estimated for each site, applying the inverse distance weighted approach to all temperature stations in the proximity of the site.

A modified logistic growth model is used to simulate population change. In absence of significant demand change, the population, P (persons), nears the carrying capacity as growth occurs, Eq. 5. However, the impact of this approach to carrying capacity (per capita demand, D (L^3T^{-1}), multiplied by P, and divided by μ_H) does not have a continuous influence on growth rates. Rather, the proximity to carrying capacity is not reflected in population time series during wet periods or when stored water is available for use. However, when shortages are occurring or have recently occurred this effect is hypothesized to be significant. To capture the effect, the carrying capacity term is multiplied by the shortage awareness, M_t. δ_{NG} (T^{-1}) is the average population growth rate.

$$\frac{dP}{dt} = \delta_{NG}[1 - M_t P_t D_t / \mu_H] P_t \tag{5}$$

Water withdrawals, W, are determined by the reservoir operating policy in use, Eq. 6. As there is only one source, water withdrawn is equivalent to the quantity supplied. We determine the withdrawal by employing linear hedging, where Kp is the slope of the release function (for further background and illustrations see (Shih and Revelle, 1994; You and Cai, 2008a)). While simple, linear hedging is found to be effective under realistic approximations of the utility function (Draper and Lund, 2004). When the hedging slope, *Kp* (unitless), is 1 (equivalent to standard operating policy), water withdrawals are equivalent to demands except if the available water is insufficient to meet demands, in the latter case, all water available is withdrawn. When $Kp > 1$, reductions in withdrawals begin when available water is less than *KpDP*. If streamflow plus stored water exceeds reservoir capacity, excess water is discharged. T (T) is the reference time (here 1-year).

$$W_t = \begin{cases} V_t/T + Q_{t-1} - V_{Max}/T & for\ V_t/T + Q_{t-1} \geq D_tP_t + V_{Max}/T \\ D_tP_t & for\ D_tP_t + V_{Max} > V_t + Q_{t-1} \geq K_PD_tP_t \\ \frac{V_t/T + Q_{t-1}}{K_P} & for\ K_PD_tP_t > V_t/T + Q_{t-1} \end{cases} \quad (6)$$

When the water withdrawal is less than the quantity demanded by the users, a shortage, S [$L^3\ T^{-1}$], occurs.

$$S_t = \begin{cases} D_tP_t - W_t & for\ D_tP_t > W_t \\ 0 & otherwise \end{cases} \quad (7)$$

There are three terms in the shortage salience, *M* (unitless), equation, Eq. 8. The first term is the shortage impact which is a convex function of the shortage volume. This term assumes that the least costly options to manage demand will be undertaken first and that the contribution of an event to shortage salience is proportional to the shortage cost. This portion of the equation includes *D* [L^3T^{-1} $person^{-1}$], per capita demand. At high levels of shortage salience only a large shortage will lead to a significant increase. The adaptation cost is multiplied by one minus the current shortage awareness to account for this effect. The third term in the equation incorporates the decay of shortage salience, μ_S (T^{-1}), i.e. the decrease in attention to water shortage risk and its relevance to decision making that occurs over time (Di Baldassarre et al., 2013). *M* has a range from 0 to 1.

$$\frac{dM}{dt} = \left(\frac{S_t}{D_t P_t}\right)^2 (1 - M_t) - \mu_S M_t \quad (8)$$

The last equation is the change in per capita water demand, Eq. 9. Here per capita water demand is the total demand in the reservoir system service area divided by population. It is inclusive of residential, industrial, and agricultural water usage. There are two parts to the per capita equation demand change equation: shock stimulated logistic decay with a maximum rate of α (T^{-1}) and a background decay rate, β (T^{-1}). The decrease of per capita water demand accelerates in a time interval if water users are motivated by recent personal experience with water shortage (i.e. $M > 0$). As a certain amount of water is required for basic health and hygiene, there is ultimately a floor to water efficiencies, specified here as D_{min} (L^3T^{-1}). Reductions in per capita water usage become more challenging as this floor is approached; a logistic decay function is used to capture this effect. The background decay rate captures the increasing water efficiency observed in both urban and agricultural settings (Coomes et al., 2010; International Water Management Institute, 2007). Note that the background decay is context specific and in some cases it would not be relevant (such as a developing region with expanding per capita water use).

$$\frac{dD}{dt} = -D_t \left[M_t \alpha \left(1 - \frac{D_{min}}{D_t}\right) + \beta\right] \quad (9)$$

3.2 Model Scaling

Scaling is a technique to express a model in an equivalent dimensionless form (Anderies et al., 2002). The key advantage of scaling analysis is that it reveals where combinations or ratios of parameters rather than single parameters control model behavior. Socio-hydrological systems of the same class vary widely. For example, reservoir-based water supply systems are present around the world, but vary significantly in scale (e.g. reservoir capacity, population size, total demand) and variability (e.g. streamflow and demand temporal variation). Scaled or dimensionless models of these systems can help to highlight the drivers of common or divergent dynamics. Additionally, this technique decreases the amount of model input as a reduced number of parameter ratios, rather than individual parameters, must be specified.

The model presented above is scaled using the following relationships where "$\hat{x}$" is used to indicate the non-dimensional version of "x":

$$\widehat{\sigma_H} = \frac{\sigma_H}{\mu_H} \tag{10}$$

$$\widehat{V_{max}} = \frac{V_{max}}{\sigma_H T} \tag{11}$$

$$\widehat{D_{min}} = \frac{D_{min}}{\mu_H} \tag{12}$$

$$\widehat{E_v} = \frac{E * A_{res}}{\mu_H T} \tag{13}$$

The first relationship normalizes streamflow standard deviation by mean streamflow (Eq. 10), the second normalizes reservoir capacity by the streamflow standard deviation and the reference time (Eq. 11), the third normalizes the minimum demand by the mean streamflow (Eq. 12), and the forth relationship normalizes the reservoir evaporation by the streamflow mean and the reference time (Eq. 13). Note that $\widehat{D_{min}}/\mu_H$ is also equal to one over the carrying capacity of the system.

Initial conditions can also be specified in non-dimensional terms:

$$\widehat{P_0} = \frac{P_0 D_{min}}{\mu_H} \tag{14}$$

$$\widehat{V_0} = \frac{V_0}{V_{max}} \tag{15}$$

$$\widehat{D_0} = \frac{D_0}{D_{min}} \tag{16}$$

3.3 Model Application

The scaled model was applied to each of the three cases. Initial conditions were set based on the time series data and simulation start date. Historic streamflow was used for these cases in place of the autoregressive streamflow model. Parameters were informed by both quantitative and qualitative case data. Sensitivity analysis was conducted to assess the impact of parameter values selected on model output and interpretation.

Lastly, the scaled model was used to simulate a generic system to directly explore the influence of reservoir volume and operating rule choice on water supply reliability and the interactions between these two choices. The hedging parameter Kp was varied between 1 (SOP) and 3 (conservative hedging) and the scaled reservoir volume (storage volume relative to streamflow standard deviation) was varied between 2 and 12. Five hundred streamflow traces were generated using the lag-1 autoregressive model and the same five hundred traces were used with each parameter set to ensure comparability across the sensitivity analysis.

Normalized values of parameters are reported in Table 1.

Table 1: Normalized parameters values and initial conditions used in each case study model run and the sensitivity analysis.

Parameter	Sensitivity Analysis	Colorado	Melbourne	Cape Town
σ_H/μ_H	0.25	0.31	0.32	0.33
$V_{max}/\ \sigma_H\Delta t$	{2, 4, …, 12}	11.08	10.42	4. 34
μ_H/D_{min}	5000000	77981681	8784629	10697075
$D_0/\ D_{min}$	2	3.30	3	2
P_0/P_c	0.25	0.18	0.31	0.24
V_0/V_{max}	0.5	0.55	0.33	0.70
ρ_H	0.60	0.29	0.35	0.95
μ_S	0.05	0.05	0.05	0.05
α	0.15	0.001	0.1	0.1
β	0.001	0.001	0.005	0.001
δ_{NG}	0.05	0.03	0.008	0.03
Kp	{1, 1.5, …, 3}	3	3	1.5

4.0 Results

4.1 Case Results

The socio-hydrological model was run for the three case studies of the Colorado River Basin, Melbourne and the City of Cape Town. The modeled water use, reservoir storage, issue salience and shortage volume are described below and compared to case data. As the model is highly stylized, the aim is not to fit observations precisely. Rather the aim is to assess the model's ability to qualitatively reproduce patterns (Sterman, 2000) in three distinct hydrological and operational environments.

In the Colorado River case, multi-years droughts occurred in the late 1970's, late 1980's, and the 2000's (Figure 5a). The impact of drought on stored water is clear in both the reservoir storage observations ([Figure 2b) and the modeled storage (Figure 5b). The model reproduced key features including the period of high storage from mid-1970's to mid-1980's, a decline in the late 1980's, recovery in the late 1990's, and decline followed by stabilization in the 2000's. The model is parameterized for conservative hedging policy (Kp = 3). This triggers water conservation well in anticipation of physical limits and is consistent with the case history. Over the study period, basin-wide water use increases before reaching a peak in 2001 ([Figure 2c). The increase in water use is driven by an increasing population ([Figure 2d), with higher water efficiency working against this trend (Coomes et al., 2010). Weather driven variation in demand as well as the ability of water users to substitute groundwater or alternative surface water sources increases the variability of water use (e.g. Porse et al., 2017). While this simple stylized model cannot reproduce all observed variability in water use, it does simulate increasing water use until the early 2000's followed by a period of decrease and stabilization (Figure 5e). Further, the model captures the trend in decreased demand per capita (Figure 5c). We have no observational data on salience at the basin scale. However, since the early 2000's there has been increased interest in demand management and development of alternate sources at the local level (e.g. Garcia & Islam, 2018; Porse et al., 2017) and increased inter-state policy developed addressing shortage allocation (Department of the Interior, 2007; US Bureau of Reclamation, 2018). The modeled salience shows a small increase in response to the late 1980's drought and a sharp rise in the early 2000's at the onset of intense drought (Figure 5d), consistent with these local and regional patterns. The shortage volume is representative of the variability in water availability (Figure 5f).

[Figure 5]

The model was then used to simulate reservoir management in Melbourne in response to droughts ([Figure *6*). The streamflow shows two drought events occurring at the beginning of the 1980's and in the late 1990's into the 2000's (Figure 3a). The drought beginning in the late 1990's, known as the Millennium drought, stressed the water supply system leading to falling reservoir storage and decreased water use ([Figure *3*a, b). The model reproduced the key features including a period of above average storage from late 1980's to mid-1990's, followed by rapidly falling storage from the late 1990's into the first decade of the 2000's (Figure 6b). The hedging parameter (Kp=3) simulates a conservative policy and thus water conservation is employed in advance to reduce the risk of severe shortage. This parameterization is consistent with the case history. However, the model simulation shows the minimum storage value at years 2005-2006 (Figure 6b), three years before the actual minimum was observed ([Figure *3*b). After a drop due to the first drought, the water usage increases as the population increases, before decreasing during the Millennium drought (Figure 3d,c). The model captures the declining water use during the Millennium drought but cannot reproduce water use patterns prior to the drought (Figure 6e). As in the Colorado River case, salience is modeled but is not directly observed. The first drought triggers a small increase in salience, which fades as memory of the drought weakens. Then, the more severe Millennium drought prompts a larger increase in salience (Figure 6d). High levels of salience persist throughout the drought though, consistent with empirical studies of long drought, peak levels are not maintained (Garcia et al., 2019). The modeled pattern of salience is consistent with the case history, including the implementation of water use restrictions. During the early 1980's drought, only Stage 1 water restriction were used. The second drought was longer and more severe, requiring a series of water restrictions. First, in 2002, the Stage 1 water restriction was imposed, then, in January 2007 and in April 2007 water Stage 3 and 3a restrictions were launched, reflecting the rising interest in demand management. The shortage volume represents the gap between supply and demand (Figure 6f).

[Figure 6]

In the City of Cape Town, two drought events occurred: a minor one in 2002-2003 and a major one in 2015-2017 ([Figure 4a). The impact in terms of water storage is evident for these droughts in both observations (Figure 4b) and model results (Figure 7b). The model reproduces the observed reductions in storage in 2002-2003, 2010, and 2015-2017, while it does not capture the moderate drop in 2005 (Figure 4b, Figure 7b). The model is parameterized for a moderate hedging policy (Kp=1.5). This implies that water conservation is triggered in advance, but not far in advance, of physical limits. This is confirmed by observed data as the reservoirs were nearly drained before water restrictions were issued. Observed water use follows an increasing trend until 2015 which tracks population growth. However, this trend is interrupted by periods of temporarily high use, likely driven by climatic and economic variability (Figure 4c,d). While the model is not able to reproduce all features of the observed water use, simulation results do reproduce the temporary decrease seen around 2005 and peak water use in 2015, followed by a decrease (Figure 7e). There are no direct observations of salience in the area. However, the case history includes events likely to be correlated with increased salience of water issues (Treuer et al., 2017). Level 2 water restrictions were implemented in January 1, 2005. Later in the 2015-2017 drought, the first restriction (20%) was launched in 2016. Then, in October 2017, a 40% reduction was further launched, up to the dramatic day in January 2018, when the day Zero was estimated to occur in April of the same year. The model simulates an increase in salience at around 2002 driven by the first drought. Salience from this event fades over time with moderate increase from subsequent droughts until rising sharply in 2014 with severe drought (Figure 7d).

[Figure 7]

4.2 Sensitivity Analysis

Having gained confidence about the ability of the model to qualitatively simulate patterns in various (hydrological and operational) environments, , we apply the model to further address our research questions: 1) How does the scale of reservoir storage affect long-term reliability? 2) How do reservoir operating rules in place mitigate shortage risk under changing supplies and/or demands?

To explore the interaction of ratio between V_{max} and σ_H and the hedging factor Kp, we performed a sensitivity analysis running simulations of all combinations of these two parameters. Five hundred traces of stochastic streamflow, generated by a lag 1 autoregressive model, are used to understand performance across a range of streamflow patterns. [Figure *8* shows the ratio of t shortage volume to total demand over time across these simulations. Moving from left to right we can see the effect of increasing reservoir volume, relative to the variability of streamflow. [Figure *8* shows that the larger the reservoir the more shortage is delayed and the higher the maximum shortage. Moving from top to bottom we can examine the effects of changing operations from reactive (SOP or Kp =1) to proactive (Kp = 3). [Figure *8* shows that at higher values of Kp, shortages, relative to total demand, occur earlier but are lower in magnitude. Examining the full set of plots, we can see an interesting phenomenon as we move diagonally from top left to bottom right. Along the diagonals in [Figure *8*, the period of time before shortage occurs is constant but the magnitude increases. Additionally, we see decreasing variability across the simulations as we move diagonally from top left to bottom right.

[Figure 9a,b summarizes the relationships between the two parameters, Kp and the ratio between V_{max} and σ_H, and the mean and maximum shortage volumes over the simulation period. First, Kp was sampled at 0.05 intervals and the ratio was sampled at 0.25 intervals to better assess changes across the range. Second, mean and maximum shortage were computed for each simulation run. Finally, local regression (LOESS) was applied to describe the relationship. [Figure 9a shows a decrease in maximum shortage with a slight increase in mean shortage as Kp increases. This is consistent with the evidence that Kp = 1 is most effective at reducing average shortage volumes in the short term (Cancelliere et al., 1998; Garcia et al., 2015). [Figure 9b shows that maximum shortage increases substantially, and mean shortage slightly increases, as the ratio between V_{max} and σ_H increases. [Figure 9c,d illustrate the relationship between Kp and ratio between V_{max} and σ_H, and the lag between demand surpassing average supply and the first occurrence of shortage. Note that in some cases the first shortage occurs before demand surpassing average supply when low flows coincide with low storage, resulting in a negative lag. A negative lag is evidence of reduced demand in anticipation of demand overshooting average supply, or a proactive response. A positive lag implies a demand reduction after overshoot or a reactive response. [Figure 9c shows that as Kp increases the lag decreases with negative lags occurring with Kp > 1.75. [Figure 9d illustrates an increasing lag with a higher V_{max} and σ_H ratio. Examined together [Figure *8* and [Figure 9 demonstrate that the choice of more conservative hedging policy for reservoir operation can mitigate the unintended consequences of larger reservoir storage volumes.

[Figure 8]

[Figure 9]

5.0 Discussion and Conclusions

Reservoir storage is intended to protect water users from the variability inherent in streamflow. In each of the three cases, we see that the ability of reservoir systems to buffer drought effects decreases as demand increases and/or streamflow patterns shift. This is, of course, to be expected. However, the impact is not felt immediately as the stored water intended to meet demands during drought can be used to fill the gap between supply and demand temporarily. When Kp is equal to one, reductions in water use are not made until physically necessary (i.e. insufficient water in inflow and storage to meet the full demand) (Eq. 6). When Kp is increased, reductions in withdrawals are triggered sooner raising salience and subsequently leading to reductions in per capita demand (Figures 8 & 9). The magnitude of both reductions in withdrawals and increases in salience are lower when Kp is higher. Therefore, the rate of change in demand is slower, but, importantly, it starts sooner. Reducing demand sooner both slows the decline in (and eventually stabilizes) the volume of stored water, making future abrupt reductions in water use less likely to be needed. Additionally, the rate of demand change is important. A rapid shift in water available for use would be a significant shock to economic and public health, which water managers and reservoir operators would seek to avoid.

Reservoir storage provides a buffer of time to adapt to changing conditions. The sensitivity analysis illustrates this, as larger storage volumes lead to a greater time before the shortage is observed (Figures 8 & 9). Decision makers do not always use this time for adaptation, as illustrated in the three cases. In Melbourne, the response to intense drought and growing demand was fast and effective (Low et al., 2015) and was accomplished via strict water restrictions which were launched during the Millennium drought to avoid Day Zero, while in Cape Town the response to growing demands only occurred late into a historic drought leading to water delivery reductions (Muller, 2018). In the Colorado River Basin, the story is more nuanced and not yet complete. As stored water declined in the 2000's Lower Basin States developed a collaborative agreement to reduce use as reservoir levels declined (Department of the Interior, 2007). While this agreement reduced the risk of draining the reservoir, it proved to be insufficient, prompting an addendum in 2018, the Drought Contingency Plan (Sullivan et al., 2019). Further renegotiations to set operational rules beyond this are in process.

Reservoir storage can help manage hydrological variability (e.g. coping; Wamsler and Brink, 2014), as it dampens its effects, but if not paired with appropriate operating rules and water management policy, it has the potential to delay the actions and the countermeasures necessary to adapt to changing conditions. We hypothesize that the ability of stored water to delay impacts reduces the salience of the problem, increasing the challenge of major infrastructure or policy change and leading to delays in adaptation. This delay is particularly problematic when external forces drive increases in demand or population, increased streamflow variability, or decreased streamflow (Di Baldassarre et al., 2018). Additionally, the salience of water stress information, rather than just the presence of such information, is important in understanding response (Garcia et al., 2019; Quesnel and Ajami, 2017). The absence of salient information on the limits of water supply means that the potential negative feedback loops that could drive corrective action remains un-activated.

However, water supply management consists of more than just physical infrastructure. The rules used to operate reservoirs, sometimes referred to as soft infrastructure (Anderies et al., 2016), shape their performance. By testing alternate values of the operating parameter, Kp, we observe the effects of operational rules. The relationship between increases in Kp and decreasing shortage magnitude and increased frequency of shortages shown in [Figure *8* and [Figure 9, is the expected result of hedging policy (You and Cai, 2008b, 2008a). What is novel here is how the storage volume and operating rules interact with each other and the broader system of water supply and use. Under hedging policy (Kp >1) water managers decrease withdrawals before it is physically required thus increasing the salience of water shortage risk at higher volumes of stored water. This increases the probability of a timely adaptive response. Further, [Figure *8* and [Figure 9 illustrate that the choice of operating rule can either exacerbate or alleviate the tendency to delay response with increased reservoir capacity. In other words, the advantages of large supply reservoirs, such as the ability to buffer variability and thus alleviate the effects of drought, can be achieved while minimizing the risk of delayed response to change by pairing large reservoirs with conservative hedging to create salience and prompt adaptive action. While this is not the only way to drive increases in problem saliency through policy, these results can inspire further investigation of policy design aimed at reducing delays in response to changing conditions, particularly in contexts where changing environmental conditions significantly impacts the ability to meet societal goals.

While these analyses demonstrated the importance of storage volume and operating rules in explaining long-term reservoir performance under changing conditions, it is clear from the diversity of three cases that storage and operating rules alone do not determine the response. A variety of other factors including institutional arrangements (Garcia et al., 2019), financial resources (Hughes et al., 2013), leadership skill (Pahl-Wostl et al., 2007), the presence of motivated actors (Porter et al., 2015), and risk perception (Dobbie and Brown, 2014; Ridolfi et al., 2019) all influence the nature and speed of policy response to changing conditions.

The three cases demonstrate the model’s ability to reproduce key features, though not all patterns, in water use and storage. The model presented here is unavoidably simplified, leaving several opportunities for future improvements. It does not account for the large number of options for water management from more sophisticated and time varying operating rules to source substitution. Further data collection, covering both a broader range of variables and cases, could inform such model refinements. Additionally, the operational strategies of the reservoir are considered constant across time, while in practice they often change in response to new knowledge, performance, and changing conditions. Though the operational strategy modeled here, linear hedging policy, is only an approximation, it does offer insights into the effect of storage capacity and operational choices under changing conditions. Further, this analysis highlights when a change in operation policies would be advantageous. In sum, the case applications and sensitivity analysis presented here illustrate how infrastructure and policy design choices combine, in some cases non-linearly, to impact system performance.

Authorship Contribution Statement. Margaret Garcia: conceptualization, data acquisition, model development, writing, editing. **Elena Ridolfi:** data acquisition, analysis, visualization, writing. **Giuliano Di Baldassarre:** conceptualization, data acquisition, editing.

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