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Special Section:
Resilient Decision-making for a Riskier World

Key Points:
- A stochastic resilience optimization model is developed to allocate water between consumptive and nonconsumptive uses
- The model allows decision-makers to measure resilience in relation to adverse shocks on water storages or inflow with weather uncertainty
- The model is calibrated to a basin and a subcatchment with sensitivity analyses to show value added to decision-making at multiple scales

Supporting Information:
- Supporting Information S1
- Data Set S1

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Resilience, Decision-making, and Environmental Water Releases

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Abstract Tensions between delivering water for human uses versus environmental benefits are increasing in many arid and semiarid regions, potentially causing irreversible environmental consequences. The issue of how to balance these competing uses of water is of fundamental importance, especially with projected increases in the variability of water resources due to climate change. In response, a stochastic resilience optimization model is developed to assist decision-makers to optimally determine water releases from storages for environmental purposes and to measure the resilience of a system for given risk tolerances. The model, with sensitivity analyses, provides a valuable tool for water planners to minimize the risk of irreversible consequences and to optimize for resilience taking into account weather uncertainty, existing environmental conditions, and water storage levels. A calibration of the model to the Murray-Darling Basin and also the Goulburn-Broken catchment region in Australia highlights its potential to improve decision-making at multiple spatial scales and over time.

1. Introduction

Overextraction of water and climate change both pose significant threats to economic and ecological sustainability. Driven by demographic and economic growth, global water extraction has tripled over the period 1960–2010 (Wada & Bierkens, 2014). This has resulted in substantial, and possibly irreversible, ecological consequences in key rivers of the world (Grafton et al., 2012; Vörösmarty et al., 2000). An increasing trend of water extraction is projected to continue (Haddeland et al., 2014; Shen et al., 2008; Wada & Bierkens, 2014), thus raising the future risks to economic and ecological systems (Haddeland et al., 2014; Shen et al., 2008; Wada & Bierkens, 2014).

Climate variability and climate change exacerbate and multiply the risk that there will be another 620 million people living with chronic water shortages, and an up to 300% increase in drought incidence by the 2050s (King et al., 2016). While there is no panacea for these threats (Meinzen-Dick, 2007), optimizing the use of water through better planning and improved water allocation is key to ensuring that the sustainable development goals are achieved (World Bank, 2016).

The question of how to allocate water across consumptive (such as irrigation) and nonconsumptive (such as streamflows) uses is fundamental to ensuring sustainable development (Garrick et al., 2017). In catchments where water storages and river flows are regulated, a trade-off exists between consumptive and nonconsumptive uses that may require water (re) allocation and thus an assessment of different payoffs of water across space and time. Successfully managing these trade-offs is necessary to promote sustainable development which is defined as "meeting the needs of the present without compromising the ability of future generations to meet their own needs." (WCED, 1987:27).

There are two broad sustainability perspectives that influence how trade-offs are assessed in terms of water reallocation: "weak sustainability" (Pearce & Atkinson, 1993) and "strong sustainability" (Neumayer, 2003). Weak sustainability assumes complete or full substitutability between human-made assets and natural capital. If there is complete substitutability across human-made assets and natural capital, then decision makers can (1) directly compare the value of water used for consumptive and nonconsumptive purposes and (2) reallocate water so as to maximize the social benefits from competing water uses in monetary terms (Akter et al., 2014; Grafton et al., 2011). A challenge with weak substitutability is that it does not, typically, represent the accepted understanding of the economy and natural capital (Ekins et al., 2003:166). Further, optimization with weak substitutability requires accurate valuation of environmental assets in monetary terms, which is often difficult to achive in practice (Arrow et al., 2003; Ekins et al., 2003:168) because many environmental assets are nonpriced and nonmarket public goods (Smith & Krutilla, 1979:29). By contrast, strong sustainability implies that the range over which human-made assets and natural capital are substitutes is very limited. Thus, optimization with strong sustainability is much more concerned with ensuring the sustainability of natural capital in its “safe” range to ensure that it provides ongoing and beneficial ecosystem services.

Here we develop a general and widely applicable model for water (re) allocation between consumptive and nonconsumptive uses informed by the strong sustainability concept and the “tolerable window” approach (Bruckner et al., 2003). Our model provides a method to decide when to release water from reservoirs (and how much) over a multiple-year planning period so as to maintain environmental conditions within a defined window while ensuring that storage levels in reservoirs are above a specified reserve level. This approach assists decision makers to maintain both the state of the environment and the water storage levels within a tolerable range (or window) beyond which irreversible environmental consequences might occur.

Our modeling approach provides three key contributions in terms of risk, resilience, and decision-making. First, the (re) allocation of water between consumptive and nonconsumptive uses does not require environmental assets to be valued in monetary units, as in the weak sustainability approach. This particular feature greatly reduces the data requirements for decision making and the epistemic uncertainty arising from incomplete or erroneous knowledge or data about the substitutability of human-made assets and natural capital (Settre et al., 2017; Walker et al., 2003:f1).

Second, the model explicitly accounts for stochastic uncertainty in water availability. In particular, the stochastic uncertainty in water availability includes both annual variability in river flows and the correlation pattern in weather (e.g., a dry year is more likely followed by another dry year). Stochasticity requires better planning for water (re) allocation in intertemporal contexts, especially when both the water storage levels and environmental conditions are close to irreversibility thresholds. In this context, the stochasticity makes it impossible to guarantee any particular outcome with certainty, and the optimal response is to minimize the risk of moving out of the tolerable window (or crossing an undesirable threshold) and to maximize the probability of recovery given the dynamic constraints.

Third, our model provides a tool to quantify resilience for water management in an uncertain world. Holling (1973:14) concept of resilience is commonly interpreted as the ability of a system to absorb changes in state variables and for the key characteristics of the system to persist. One general approach to measure the resilience of water systems is employed by Fiering and Holling (1974) and Hashimoto et al. (1982), where resilience is defined as the average recovery time following a shock. This approach has been applied widely to measure how fast a water system can recover after a failure (Ajami et al., 2008; e.g., Fowler et al., 2003; Jain & Bhunya, 2008; Huizar et al., 2018; McMahon et al., 2006; Srdjevic et al., 2004). An alternative approach measures resilience via changes in the state variables that a system can absorb while still producing satisfactory outcomes with a certain target probability (Fiering, 1976:766).

Here we use the ability of state variables to absorb a negative shock to quantify resilience. In particular, we employ a target probability that irreversible changes to environmental assets will not occur and then measure resilience by the magnitude of adverse shocks in reservoir inflows or storage that a system under stress can absorb or withstand when the recovery probability is optimized. As a result of this optimization, the risk tolerance varies across the states of nature including the length of a drought and water storage levels in the context of water scarcity.

The remainder of the paper is organized as follows. In section 2, we describe the problem context. In section 3, the model is formulated using the viability analysis framework that helps decision makers optimize the chance that the state of nature remains within a well-defined range over a planning period (Béné et al., 2001; Doyen et al., 2007; Durand et al., 2012; Mouysset et al., 2014). Section 4 calibrates the model to the entire Murray Darling Basin (MDB) in Australia. This case provides a stylized aggregate picture of water allocation at a basin scale. The second case, in section 5, is calibrated to the Goulburn-Broken (GB) catchment located within the MDB. This second case shows how the model can improve decision-making in a single-reservoir system. Both cases include sensitivity analyses with respect to climate scenarios and the levels of water diversions for consumptive purposes. These sensitivity analyses illustrate the relative effectiveness of supply and demand-based methods to respond to water scarcity for the two cases. Section 6 highlights the applicability of the model, while section 7 concludes.

2. Problem Context

The context is a general problem where a decision is made each year concerning the volume of water released for the environment, a nonconsumptive use. We assume that decision makers consider both the benefits for the environment and potential impacts on the security of supply to other water users (Williams, 2017). In this case, the optimal environmental release depends on how much water is available for reallocation, the condition of wetlands and habitats, and the anticipation of the likelihood of dry weather in future. The decision makers decide on the volume of nonconsumptive water required to minimize the risk of either the water storage level being reduced to a certain level, which can disrupt water supplies to human activities, or the risk that wetlands become irreversibly degraded from inadequate flows of water.

Our model considers three types of wetlands. The conditions of the wetlands vary with inundation flows and their drought resistance. Near wetlands that are closest to river banks only need small floods to be inundated, but they need to be inundated more frequently. Far wetlands that are most distant to river banks need larger inundation for the water to reach them but require less frequent floods. In-between wetlands require greater (lesser) inundation than near (distant) wetlands and less (more) frequent inundation. All three types of wetlands require some inundation within a finite period of time or they may fail to recover following a drought characterized by below normal inflows. The "drought resistance" or resilience of the wetlands differs across the three types. We assume that the objective of the decision makers is to determine when to release water to deliver a flood so as to minimize the negative consequences from insufficient inundation in all three types of wetlands.

The two cases where we apply the model are the MDB in Australia and one of its subregions, the GB catchment. An important feature of water management in Australia is that, typically, volumes of available water are allocated for streamflows or for nonconsumptive purposes as a fixed share of catchment inflows (Stewardson & Guarino, 2018). Current water policy in the MDB seeks to increase the volumes allocated for streamflows, and this is being implemented via a sustainable diversion limit (SDL) in each catchment within the Basin and also at the basin scale (MDBA, 2010). Our approach provides a multiobjective optimization approach to reservoir management (Alais et al., 2017; Yang et al., 2015). Model calibration to the two cases shows the potential societal benefits from optimizing the release of water from storages for streamflows or environmental purposes.

3. Model Description

3.1. Modeling Weather Correlations

We use the term "weather" to refer to the level of water inflows and classify weather into three types (dry, normal, and wet) corresponding to a low, medium, and high range of water inflows. We use a variable W with three possible values $\{d, n, w\}$ corresponding to the three weather types. The time step is 1 year. Weather correlation is modeled via the probabilistic distribution of next year's weather given this year as in equation (1) with $t = 0..T-1$, where T is a finite time planning horizon.

$$P(W_{t+1} = i | W_t = j) = P_{ij} \text{ with } i, j \in \{d, n, w\} \text{ and } \sum\nolimits_i P_{ij} = 1 \quad (1)$$

3.2. Water Balance

Water balance is modeled such that the storage level next year is the current storage plus the change in storage. The change in storage is the difference between inflows into water storages and all outflows. The outflows include planned releases from reservoirs (e_t) that can be used for either human consumption or environmental purposes and leakages (e.g., evaporation). Water storage is limited by a maximum capacity, and excessive inflows will cause overspill if the capacity is exceeded.

Using R_t for the storage level at time t, $\overline{R}$ for the storage capacity, η for the evaporation/leakage rate, and o_t for the overspill, the water balance for water storages can be represented by equation (2), and the overspill water, if any, can be represented in equation (3), both with all $t = 0..T - 1$. In these equations, $\Phi(W_t)$ is the weather-dependent mean inflow into reservoirs and ϵ_t is the difference between the actual inflow and the mean.

$$R_{t+1} = \min\left\{[\Phi(\mathrm{W_t}) + \epsilon_t] - e_t - \eta R_t + R_t, \overline{R}\right\} \tag{2}$$

$$o_t = \max\left\{[\Phi(\mathrm{W_t}) + \epsilon_t] - e_t - \eta R_t + R_t - \overline{R}, 0\right\} \tag{3}$$

We denote unregulated inflows—the flows from unregulated tributaries downstream of the reservoirs which also depend on weather—as $\phi(W_t)$, and the water balance is specified in equation (4). The left-hand side of this equation is the total inflow into the downstream that consists of the overspill water (if any), the planned release from water storages, and the unregulated inflows. The right-hand side includes three components: human diversions (i), conveyance or minimum passing flow (δ), and an annually varying streamflow component for environmental purposes, which we define as environmental flows and that include in-channel flow pulses that are not required every year (E_t).

$$o_t + e_t + \phi(W_t) = i + \delta + E_t \tag{4}$$

3.3. Wetland Types, Expected Inundation Recurrence Intervals, Flood Intensity, and Delivery Flows

We classify wetlands into three types based on their distance to river banks, namely, near or close, in-between and distant or far wetlands. These types are indexed as (c, b, f), respectively. Distant or far wetlands require large flows to be inundated, while near or close wetlands only need small flows. After being inundated, wetlands will not require water for a given period of time. This period of time is the expected inundation recurrence intervals (or frequency). We denote the expected inundation recurrence intervals of the three types of wetlands as (Π_c, Π_b, Π_d), where $0 < \Pi_c < \Pi_b < \Pi_f$, which implies that distant wetlands need less frequent inundation than near wetlands.

Corresponding to the three types of wetlands, we classify flood intensities, which can refer to both the volume and duration of flows, into small, medium, and large floods, denoted as $\{s, m, l\}$. Floods are delivered if environmental flows (E_t) exceed a given threshold. We use three threshold levels $\Delta_l > \Delta_m > \Delta_s > 0$ to denote the minimum environmental flows that can deliver three types of floods, as in equation (5). Here we assume that water for consumptive use does not contribute to flood delivery flow and thus is "lost" (Kingsford, 2010:11) through diversions. We note that a certain proportion of water for consumptive use contributes to environmental flows and that may provide some ecological benefits (CSIRO, 2007), but because consumption is spread over a crop growing season, it has negligible impact on delivering floods or inundation events.

$$\begin{cases} \text{No flood} = E_t < \Delta_s \\ \text{Small flood} = E_t \in [\Delta_s, \Delta_m) \\ \text{Medium flood} = E_t \in [\Delta_m, \Delta_l) \\ \text{Large flood} = E_t \geq \Delta_l \end{cases} \tag{5}$$

3.4. No-Inundation Duration

A no-inundation duration is defined as the time since the most recent inundation event. It is preferable from an ecological perspective that wetlands are inundated *before* the no-inundation duration exceeds the expected inundation recurrence interval. The no-inundation duration and the impact of a flood on this duration vary across the three types of wetland and also the flood intensity. For example, when a small flood inundates near or close wetlands and the other two types of wetlands remain noninundated, the no-inundation duration of the near wetlands is reset to zero, while the no-inundation durations of the in-between and distant wetlands continue to rise. Similarly, when a medium flood inundates near and in-between wetlands, it resets the no-inundation durations of these two types, but not the distant wetland. Only a large flood inundates all three types of wetland and resets all three no-inundation durations to zero.

We denote the no-inundation durations of three types of wetlands as a three-dimensional vector $L_t \equiv \left[L_t^c, L_t^b, L_t^f\right]$, where $L_t^f \geq L_t^b \geq L_t^c \geq 0$. The dynamics of these variables is represented by equation (6).

$$\begin{cases} \left(L_{t+1}^c = L_t^c + 1; L_{t+1}^b = L_t^b + 1; L_{t+1}^f = L_t^f + 1\right) \text{ if no flood} \\ \left(L_{t+1}^c = 0; L_{t+1}^b = L_t^b + 1; L_{t+1}^f = L_t^f + 1\right) \text{ if small flood} \\ \left(L_{t+1}^c = 0; L_{t+1}^b = 0; L_{t+1}^f = L_t^f + 1\right) \text{ if medium flood} \\ \left(L_{t+1}^c = 0; L_{t+1}^b = 0; L_{t+1}^f = 0\right) \text{ if large flood} \end{cases} \text{for } t = 0..T-1 \tag{6}$$

3.5. Critical Resilience Thresholds and Recovery Probability

We denote the storage level below which there is a disruption to water supply as R^* and the no-inundation durations that cause irreconcilable damages for three types of wetlands as $L^* \equiv \left[L^{c^*}, L^{b*}, L^{f*}\right]$, respectively. These are critical resilience thresholds of the system. If the storage level is reduced to R^*, or any of the no-inundation durations reach their critical resilience thresholds L^*, then the consequences, either economic or ecological, are irreversible. The problem is to avoid these critical resilience thresholds.

Given an initial state (storage levels, no-inundation durations, and weather), the system's dynamics are described by equations (1)–(6) with a trajectory (R_t, L_t, W_t). Given that the weather is stochastic, it is impossible to guarantee that the storage R_t and the no-inundation durations L_t will not reach their resilience thresholds over the time horizon $t = 0..T-1$. Thus, the problem is to maximize the probability of not going beyond the resilience thresholds, as formulated in equation (7), where $\ll$ is the element-wise "not-greater-than" operator.

$$Pr(R_0, L_0, W_0) = \max_{<e_t>} \text{Prob}(R_t > R^* \& \ L_t \ll L^* : t = 0, 1..T-1) \ \text{given } R_0, L_0, W_0 \text{ subject to } (1) - (6) \tag{7}$$

3.6. Resilience Measure

The optimization problem in equation (7) can be solved using the stochastic viability framework (De Lara et al., 2015; Doyen & De Lara, 2010). The optimal recovery probability $\Pr(R_0, L_0, W_0)$ varies with the storage R_0. Thus, a storage or inflow decline shock (e.g., unexpectedly low inflows, below the average) will, typically, reduce the recovery probability. Consequently, we quantify system resilience as the maximum negative shock to storage/inflows that can be absorbed without having the recovery probability reduced below a certain target level γ, as defined by equation (8).

$$\text{Resilience} = \max \tilde{\epsilon} \geq 0 \,|\, \Pr(R_0 - \tilde{\epsilon}, L_0, W_0) > \gamma \tag{8}$$

4. Calibration to the Murray-Darling Basin, Australia

4.1. Overview of the Murray-Darling Basin

The MDB encompasses the combined catchments of the Murray and Darling Rivers and their many tributaries in South East Australia. The Basin covers 14% of mainland Australia (more than 1 million square kilometers), is home to 2.2 million people (approximately 8% of Australia's population), and contains 70% of irrigated land area of the country (ABS, 2011). Surface water is diverted for irrigated agriculture, urban water supply, and environmental needs. The region contains over 30,000 wetlands including 16 Ramsar-listed wetland sites (MDBA, 2010:t2.4) covering an area of around 25,000 km^2 and about 60,000 km^2 of floodplain area.

The Basin includes both highly regulated rivers, semiarid ephemeral streams, and numerous unregulated tributaries where surface water is not regulated by dams (MDBA, 2011:85). The average annual inflow into dams or weirs during the period 1892–2006 is 11,470 GL/yr (1 GL = 10^6 cubic meter), and the average total inflow is 28,700 GL (CSIRO, 2008a:30). Thus, the proportion of regulated inflows is approximately 40%, but this proportion varies widely across the Basin's catchments (MDBA, 2011).

The MDB is subject to periodic droughts and floods (Grafton, Pittock, et al., 2014; Williams, 2017). Water diversions diminish peak streamflows that are associated with flooding events in both their size and frequency.

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Table 1
Weather Correlation Parameters (Historical Climate)

	Prob($W_{t+1} = d$)	Prob($W_{t+1} = n$)	Prob($P_{t+1} = w$)
$W_t = d$	0.36	0.50	0.14
$W_t = n$	0.23	0.53	0.25
$W_t = w$	0.21	0.41	0.38

Median annual flows at the Basin's Mouth are less than 30% of their pre-development levels (CSIRO, 2008b). Reduced streamflows from water consumption have also contributed to widespread degradation along the Murray River (MDBC, 2003).

At the Basin's Mouth there is high salinity and exposed acid-sulfate soils that generate water acidity that can result in fish die offs (Parliament of Australia, 2008). Toward the end of the Millennium Drought that began in the late 1990s and ended at the close of the noughties, Norris (2010:23–24) summarized the effect of drought and overextraction of water on the key environmental assessments in the MDB. In particular, he observed evidence of poor ecological conditions in many of the Basin's rivers compared to before the Millennium Drought.

4.2. Parameter Values

In this application of the model described in section 3, the historical weather parameters are estimated using the inflow data over 115 years, from 1892 to 2006. The classification of dry, normal, and wet weather is similar to the approach used by Grafton et al. (2011), that is, dry weather (*d*) is when the inflow is below the 25th percentile, wet weather (*w*) is when the inflow is above the 75$^{\text{th}}$ percentile, and normal weather (*n*) exists for the remaining years. Given this classification, the probabilistic distribution of weather is reported in Table 1. Each cell in the table indicates the probability of weather in year $t + 1$ given the weather in year t, so the sum of each row equals 1. Table 1 indicates a pattern of weather correlation; that is, a dry year is more likely followed by another dry year (probability of 0.36) than a counter balance wet year (probability 0.14), and a wet year is more likely followed by another wet year (probability 0.38) rather than a counter balance dry year (probability 0.21).

The means of the regulated inflows for dry, normal, and wet weather in the historical climate scenario are calculated by the average of the actual inflows in years with corresponding weather during the 115-year data record. The unregulated inflows that are not directly managed are estimated using the average degree of regulation for the whole MDB of 40%, as per section 4.1. The annual rate of evaporation from reservoirs, lakes, and channels is set at 13.5% and is an approximation from the water balance of the MDB (CSIRO, 2008a:30).

The flood augmentation flows are estimated at 40 GL/d × 30 days, 40 GL/d × 60 days, and 60 GL/d × 60 days that correspond to small, medium, and large floods with the expected flood recurrence intervals of 2, 5, and 8 years, respectively (MDBA, 2011:f8.1,f8.2). The minimum conveyance flow is assumed to be 2,000 GL/yr (MDBA, 2011:100). The storage capacity in the MDB is 22,663 GL (MDBA, 2010:36). These parameters are summarized in Table 2 together with the data sources.

We consider two climate scenarios and two diversion levels for each case to illustrate the decision-making insights associated with the model. The two climate scenarios are (1) the historical climate as presented in Table 2 and (2) a climate change scenario where water availability in the MDB declines by 11% (CSIRO, 2008b:8). The two diversion levels are set at 12,175 GL/yr—the highest diversion level since the imposition of a cap on surface water diversions in 1995 and a lower SDL of 10,873 GL/yr that accords with the MDB Basin Plan (MDBA, 2017) and increased volume of water, on average, allocated to environmental flows (Grafton & Wheeler, 2018).

Table 2
Model Parameter Values for the MDB With Historical Climate

Parameter description	Notation	Value	Sources/assumptions
Regulated inflow (GL)	$\Phi(W_t)$	(4,680; 9,930; 21,500) for dry, normal, and wet weather	Inflow data 1982–2006
Unregulated inflow (GL)	$\phi(W_t)$	(5,200; 10,400; 23,833) for dry, normal, and wet weather	Average degree of regulation of 40% (section 4.1)
Flood-augment flow (GL)	$(\Delta_s,\Delta_m,\Delta_l)$	(1,200; 2,400; 3,600) for medium and large floods	(MDBA, 2011:f8.1,f8.2)
Expected inundation recurrence interval (years)	(Π_c, Π_b, Π_f)	(2;5;8)	(MDBA, 2011:f8.1,f8.2)
Conveyance (GL)	δ	2,000	(MDBA, 2011:100)
Evaporation rate	η	13.5%	(CSIRO, 2008a:30)
Storage capacity (GL)	$\overline{\text{R}}$	22,633	(MDBA, 2010:36)

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Table 3
Basin Scale: Optimal Response and Recovery Probability With Historical Climate and the Diversions of 12,715 GL/yr

		Optimal response					Optimal recovery probability				
Current weather	Storage level	$L = 1$	$L = 2$	$L = 3$	$L = 4$	$L = 5$	$L = 1$	$L = 2$	$L = 3$	$L = 4$	$L = 5$
Dry	20%										
	30%						<5%	<5%	<5%	<5%	
	40%						29.0%	29.0%	29.0%	<5%	
	50%				r/s		64.1%	64.1%	60.4%	16.6%	
	60%			r/s	r/s		74.5%	74.2%	63.0%	63.0%	
	70%			r/s	r/s		85.2%	83.7%	72.6%	72.6%	
	80%			r/s	r/s		88.7%	84.8%	83.9%	83.9%	
	90%		r/s	r/s	r/s		91.9%	88.4%	88.4%	88.4%	
	100%		r/s	r/s	r/s		93.0%	91.7%	91.7%	91.7%	
Normal	20%										
	30%				r/m		94.1%	91.6%	91.6%	91.5%	
	40%				r/m		94.7%	94.0%	94.0%	93.6%	
	50%				r/m		>95%	>95%	>95%	>95%	
	60%				r/m		>95%	>95%	>95%	>95%	
	70%	r/m	r/m	r/m	r/m		>95%	>95%	>95%	>95%	
	80%	u/s	r/m	r/m	r/m		>95%	>95%	>95%	>95%	
	90%	u/l	u/l	u/l	u/l		>95%	>95%	>95%	>95%	
	100%	u/l	u/l	u/l	u/l		>95%	>95%	>95%	>95%	
Wet	20%										
	30%	u/l	u/l	u/l	u/l		>95%	>95%	>95%	>95%	
	40%	u/l	u/l	u/l	u/l		>95%	>95%	>95%	>95%	
	50%	u/l	u/l	u/l	u/l		>95%	>95%	>95%	>95%	
	60%	u/l	u/l	u/l	u/l		>95%	>95%	>95%	>95%	
	70%	u/l	u/l	u/l	u/l		>95%	>95%	>95%	>95%	
	80%	u/l	u/l	u/l	u/l		>95%	>95%	>95%	>95%	
	90%	u/l	u/l	u/l	u/l		>95%	>95%	>95%	>95%	
	100%	u/l	u/l	u/l	u/l		>95%	>95%	>95%	>95%	

Notes.
1. 12,715GL/yr is the highest diversion level since the imposition of a cap on surface water diversions in 1995.
2. Storage level is measured as % of the total storage capacity.
3. Blackened cells = the thresholds for irreversible consequences. Empty cells = no floods.
4. r = regulated flood, u = unregulated flood (i.e., caused by natural flows).
5. l = large flood (3,600 GL), m = medium flood (2,400 GL), s = small flood (1,200 GL).

The planning horizon is 10 years (T = 10). We specify $R^* = 0.2\times\overline{R}$, which implies that a water supply may be disrupted when the storage level declines to 20% of the accessible capacity—approximately the average storage level during the noughties that was contemporaneous with the decade-long Millennium Drought. The critical resilience thresholds for the no-inundation durations for three types of wetlands are 5, 11, and 17 years, respectively. This implies that the wetlands may not be able to recover if they are not inundated for more than twice of the expected inundation recurrence intervals, that is, $L^* = 2 \times (\Pi_n, \Pi_i, \Pi_d) + 1 = (5,11,17)$.

4.3. Results for the MDB

The model controls for a large number of all possible combinations of storage levels, weather realizations, and drought conditions in each of the three types of wetlands. For brevity, we summarize the results focusing on a typical situation where a drought (no-flood) period has commenced in all three types of wetlands. Full results for all combinations are available on request.

The optimal response to a drought is reported in Table 3. The column with $L = 1$ refers to cases where all three types of wetlands have not been inundated for a year, and the column with $L = 4$ refers to a drought that has

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Table 4
Basin-Scale Resilience Measurement: Absorbable Inflow/Storage Decline Shocks in Dry Periods (as % of Storage Capacity)

		High diversions 12,715 GL/yr					Low diversions 10,873 GL/yr				
	Storage level	$L = 1$	$L = 2$	$L = 3$	$L = 4$	$L = 5$	$L = 1$	$L = 2$	$L = 3$	$L = 4$	$L = 5$
Historical weather	20%										
	30%										
	40%						3.3%	3.2%	2.2%		
	50%	2.2%	2.2%	1.7%			13.3%	13.2%	12.2%	2.6%	
	60%	12.2%	12.2%	11.7%	2.1%		>20%	>20%	>20%	12.6%	
	70%	>20%	>20%	>20%	12.1%		>20%	>20%	>20%	>20%	
	80%	>20%	>20%	>20%	>20%		>20%	>20%	>20%	>20%	
	90%	>20%	>20%	>20%	>20%		>20%	>20%	>20%	>20%	
	100%	>20%	>20%	>20%	>20%		>20%	>20%	>20%	>20%	
Climate change	20%										
	30%										
	40%										
	50%						2.4%	2.4%	1.7%		
	60%	0.7%	0.4%	0.4%			12.4%	12.4%	11.7%	1.3%	
	70%	10.7%	10.4%	10.4%	0.8%		>20%	>20%	>20%	11.3%	
	80%	>20%	>20%	>20%	10.8%		>20%	>20%	>20%	>20%	
	90%	>20%	>20%	>20%	>20%		>20%	>20%	>20%	>20%	
	100%	>20%	>20%	>20%	>20%		>20%	>20%	>20%	>20%	

Notes.
1. 12,715 GL/yr is the highest historical surface water diversion since the imposition of a cap on surface water diversions in 1995.
2. The low diversions of 10,873 GL/yr is the current SDL in the Basin Plan.
3. Storage level is measured as % of the total storage capacity.
4. Resilience measure is evaluated by calculating when recovery is a more likely outcome than no recovery (i.e., at least 50% recovery probability).
5. The climate change scenario is evaluated by a 11% reduction in water availability (CSIRO, 2008b:8).
6. Blackened cells represent the thresholds for irreversible consequences.
7. Grayed cells represent situations where there is less than 50% recovery chance even without storage/inflow decline shocks.

been in place for 4 years. The column with $L = 5$ is in black, which implies that irreversibility occurs if the adjacent wetlands are not inundated for 5 years, that is, more than double of its expected inundation recurrence interval. The rows where the storage is 20% are also blackened to reflect the storage threshold under which water supply may be disrupted.

The left-hand side of Table 3 reports the flood augmentation to achieve the optimal recovery probability. For example, with a 40% storage level and 4-year drought, no floods should be augmented in dry weather. This is because the inflow in dry weather is too low. As a result, there is not enough water to satisfy, together, the consumptive use, the minimum conveyance flow, and also deliver a sufficient volume of water for a flood without imposing a high risk of reducing water storages below 20%. The optimal response, in this scenario, is to wait for better weather that may result in additional inflows. By contrast, if the weather is normal and given the same level of storage and drought conditions, the optimal response is to deliver a medium flood to inundate the near and in-between wetlands because they are already close to their irreversibility thresholds. When the weather is wet, there is no need to release water for the environment because the spill from dams and unregulated flows provide for an unregulated flood that meets the needs of the wetlands. In general, dam releases for environmental flows are more likely with higher water storage levels and more severe drought conditions.

The optimal rule for water releases for environmental flows in Table 3 represents a pulse effect (Junk et al., 1989). This arises because floods will occur in some years and no water, beyond minimum conveyance flows, is released for environment flows in other years. Thus, dam releases for environmental flows are postponed until a drought has lasted for a given period of time. Outside of the model context, the flood cycle may not be

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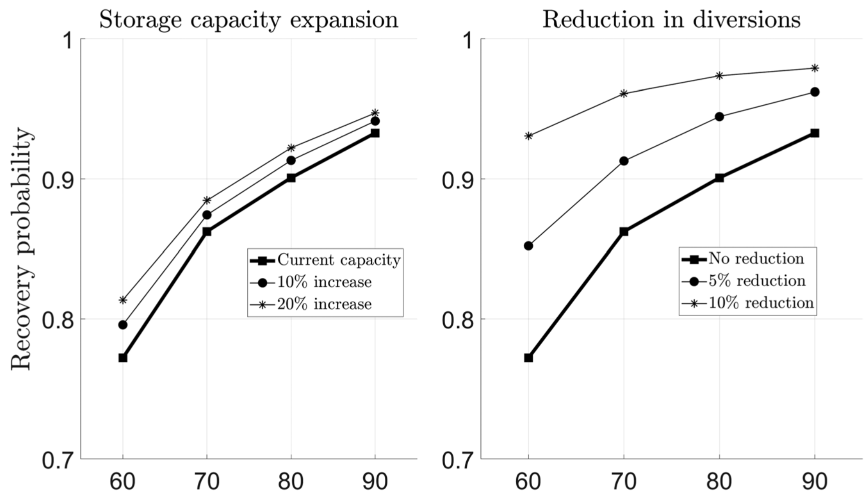

Figure 1. Murray Darling Basin scale: the impact of storage capacity expansion and reduction in diversions for consumptive water use.

regular because the period between two planned floods will vary depending on the actual realization of the weather and the water inflows, both of which are random variables.

The right-hand side of Table 3 reports the recovery probability associated with the optimal response. For example, if the current weather is dry, the storage is 40% of the capacity, and the drought has been in place for 3 years ($L = 3$), the likelihood of avoiding disruption of the water supply to consumption and irreversible drought consequences is 29% during the planning period. The recovery probability increases to 94% or more than 95% if the current weather is normal or wet, respectively, if all else is unchanged. This increase in the recovery probability arises from the difference in inflows associated with different weather and also from the weather correlation, whereby a dry year is more likely to be followed by a dry year rather than a wet year (see Table 1).

We quantify the resilience of the system by calculating the maximum negative shock to inflows/storage that can be absorbed while still having the chance that wetland recovery is more likely than no recovery at any time in the future (irreversible consequence), that is, target the recovery probability to be at least 50%. To be comparable across scenarios, the magnitude of the shocks is measured as percentage points of the storage capacity. Results are reported in Table 4 for each combination of climate and diversion levels for consumptive water use, as well as the storage and drought conditions.

In the historical weather scenario, if the storage level is 60% with diversions for consumptive water use of 12,715 GL/yr, and a drought in place for 3 years, the system can absorb a decline in inflows or storage of 11.7% of the storage capacity, but a larger shock will make irreversibility more likely than a wetland recovery. If a drought has been in place for 4 years, the maximum shock that the system can withstand is reduced to 2.1%. The grayed cells represent situations where the system cannot absorb any declines in storage or inflows without the probability of irreversibility exceeding the probability of recovery. In general, the higher is the storage level and the less severe is the drought condition, the larger is the negative shock the system can withstand in terms of reduced inflows and thus greater is the resilience.

The results in Table 4 can be used to assess the possible effects of climate variability and climate change on system resilience. Projected climate change, with a lower level of water availability, substantially reduces the resilience in all situations, but the impact is more pronounced with higher levels of diversions for consumptive water use. Under the climate change scenario and the higher level of diversions 12,715 GL/yr, the resilience is low; with 60% storage, the system can absorb a shock of less than 1% during the first 3 years of a drought. With the lower level of diversions (10,873 GL/yr), if all else is unchanged, the system can better withstand some adverse shocks of more than 10%. These results show that reducing the diversions for consumptive water use will strengthen resilience and thereby mitigate the possible negative impacts of climate change.

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Table 5
Model Parameter Values for GB Region With Historical Climate

Parameter description	Notation	Value	Source/assumptions
Regulated inflow (GL)	$\Phi(W_t)$	(695; 1,408; 2,354) for dry, normal and wet weather	Inflow data 1986–2008
Unregulated inflow (GL)	$\phi(W_t)$	(751; 1,698; 3,569) for dry, normal and wet weather	Inflow data 1986–2008
Flood-augment flow (GL)	$(\Delta_s, \Delta_m, \Delta_l)$	(172; 267; 568)	Cottingham et al. (2003)
Expected inundation recurrence interval (years)	(Π_s, Π_m, Π_l)	(2;3.5;10)	Cottingham et al. (2003)
Conveyance (GL)	δ	222.65	Cottingham et al. (2003)
Evaporation rate	η	13.5%	(CSIRO, 2008a:30)
Storage capacity (GL)	$\overline{R}$	3,345	Farquharson et al. (2017)

A sensitivity analysis was undertaken to evaluate the impact of extending storage capacity (increased accessible supply) and reducing the level of diversions (reduced effective demand) for consumptive water on the recovery probability. This sensitivity analysis evaluates the effectiveness of supply augmentation and demand management. The results are depicted in Figure 1 with different levels of storage under the assumption that a drought commenced in a dry year.

The left panel of the figure shows the recovery probability if the storage capacity remains at the current level, or if it is extended by 10% and 20%, respectively. A higher storage capacity improves the chance of recovery. The right panel shows the recovery probability with different levels of reductions in diversions for consumptive water use. Comparing the two panels suggests that a reduction in diversions is more effective that expanding storage capacity in improving the resilience of the system in the sense that for the same proportional change there is a larger increase in the probability of recovery.

5. Calibration to Goulburn-Broken Region

5.1. Overview of the Region

The GB region is in the southern part of MDB, based around the Goulburn and Broken Rivers. It covers 2% of the total area and population of the MDB, respectively. The region generates approximately 11% of the runoff and accounts for around 14% of the surface water diverted for irrigation in the MDB (CSIRO, 2008a). About half the region is devoted to dryland cereal cropping and grazing, and about one-twelfth is irrigated dairy pasture and horticultural cropping. An extensive irrigated area stretches from south and east of Shepparton to west of Tatura and Kyabram.

The lower Goulburn River and the floodplain downstream of Loch Garry are nationally important wetlands (CSIRO, 2008a). The river influences the Ramsar-listed Barmah-Millewa Forest and Gunbower Forest wetlands during periods of high flows. The river and its associated floodplain and wetland habitats contain many important cultural heritage sites, support River Red Gum forests, and many threatened species such as Murray Cod, Trout Cod, Squirrel Glider, and Eastern Great Egret. The river also supports a variety of recreational activities such as fishing and boating.

5.2. Parameter Values

The historical weather parameters are estimated using the data for regulated and unregulated inflows over 113 years, from 1896 to 2008. The calibration for the weather correlation parameters follows the procedure which is applied to the MDB in section 4.2. The expected inflows from regulated and unregulated tributaries for dry, normal, and wet weather in the historical climate scenario are calculated by the average of the actual inflows in years with corresponding weather during the 113 years. The conveyance flow is assumed to be the minimum flow of 610 ML/d or 222.65 GL/yr, as recommended by Cottingham et al. (2003:49). Lake Eildon is the main storage of the region and has a capacity of 3,345 GL (Farquharson et al., 2017). Hydrological parameters for GB region are summarized in Table 5 together with their data sources.

We consider two climate scenarios and two diversion levels for consumptive water use. The two climate scenarios are the historical climate, as presented in Table 5, and a climate change scenario where water availability in the GB region declines by 30% given the fact that future annual runoff in the region is projected to fall by 2%–44% (CSIRO, 2008a:28). The two diversion levels are 1,760 GL/yr, a previous high level of diversions, and 1,311 GL/yr, the current SDL in the Basin Plan (MDBA, 2010:t4.10). Similar to the MDB case, we assume

Table 6
GB Catchment: Optimal Flood Delivery in Dry Weather

		High diversions (1,760 GL/yr)					Low diversions (1,310 GL/yr)				
	Storage level	*L* = 1	*L* = 2	*L* = 3	*L* = 4	*L* = 5	*L* = 1	*L* = 2	*L* = 3	*L* = 4	*L* = 5
Historical weather	20%										
	30%										
	40%									r/s	
	50%								r/s	r/s	
	60%				r/m			r/s	r/s	r/s	
	70%				r/m			r/s	r/s	r/s	
	80%			r/m	r/m			r/s	r/s	r/l	
	90%			r/m	r/m			r/s	r/s	r/l	
	100%		r/m	r/m	r/m			r/s	r/l	r/l	
Climate change	20%										
	30%										
	40%										
	50%										
	60%									r/m	
	70%				r/m					r/m	
	80%				r/m				r/m	r/m	
	90%				r/m				r/m	r/m	
	100%				r/m			r/m	r/m	r/m	

Notes.
1. Storage level is measured as % of the total storage capacity.
2. The climate change scenario is evaluated by an average 30% reduction in water availability (CSIRO, 2008a).
3. The high level of diversions is the baseline diversion limit (MDBA, 2010:t4.10), while low diversions are the current SDL in the Basin Plan.
4. Blackened cells represent the thresholds for irreversible consequences.
5. r/s = regulated small flood (172 GL), r/m = regulated medium floods (267 GL), and r/l = regulated large floods (568 GL).
6. Empty cells mean no floods.

the planning horizon is 10 years, and the storage threshold under which water supply can be disrupted is given as 20% of the capacity. The critical resilience thresholds for the three types of wetlands are also assumed to be twice the expected inundation recurrence intervals, so $L^* = 2 \times (\Pi_c, \Pi_b, \Pi_f) + 1 = (5, 8, 21)$.

5.3. Results for the Goulburn-Broken Catchment

The calibration to the GB catchment area includes a large number of possible states. As with the calibration for the whole MDB, we focus on the scenario where a drought has commenced in all three types of wetlands. Table 6 reports the optimal flood response for the GB region in dry weather. The results suggest that floods are more likely with higher levels of storage or more severe drought conditions, although their intensities vary. The optimal intensity of a regulated flood (if any) is medium with diversions for consumptive water use of 1,760 GL/yr, while small floods are more common with diversions of 1,310 GL/yr. A key reason for this result is that lower levels of diversions for consumptive water use allow more water to be available for environmental flows. Thus, the optimal response is to deliver a flood even when the drought conditions are not yet close to the irreversibility thresholds. This, in turn, explains why more floods are delivered with lower levels of diversions for consumptive water use, as shown in Table 6.

The results in Table 6 show which threshold, storage or drought, is more likely to be reached when the system is under stress. For example, in the historical climate scenario, with 60% storage and a 4-year drought, the optimal response is to augment a medium flood. This optimal response will be to inundate two types of wetlands (i.e., near and in-between wetlands) because the distant or far wetlands can survive for a longer period without being flooded. Thus, at this point of time, the drought does not yet pose an immediate risk of irreversibility on the far wetlands. This inundation response, however, reduces the water storage level and increases the risk of the storage level falling below its threshold. When the storage level is 50% or less, it is not optimal to trigger an inundation. In this scenario, the optimal response is to wait for weather events to bring additional inflows.

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Table 7
GB Catchment Region's Resilience Measurement: Absorbable Inflow/Storage Decline Shocks in Dry Periods (as % of Storage Capacity)

		High diversions (1,760 GL/yr)					Low diversions (1,310 GL/yr)				
	Storage level	*L* = 1	*L* = 2	*L* = 3	*L* = 4	*L* = 5	*L* = 1	*L* = 2	*L* = 3	*L* = 4	*L* = 5
Historical weather	20%										
	30%										
	40%						3.7%	3.6%	3.0%	0.6%	
	50%						13.7%	13.6%	13.0%	10.6%	
	60%	1.7%	1.6%	1.6%			>20%	>20%	>20%	>20%	
	70%	11.7%	11.6%	11.6%	1.7%		>20%	>20%	>20%	>20%	
	80%	>20%	>20%	>20%	11.7%		>20%	>20%	>20%	>20%	
	90%	>20%	>20%	>20%	>20%		>20%	>20%	>20%	>20%	
	100%	>20%	>20%	>20%	>20%		>20%	>20%	>20%	>20%	
Climate change	20%										
	30%										
	40%										
	50%										
	60%						0.7%	0.3%	0.3%		
	70%						10.7%	10.3%	10.3%	0.9%	
	80%						>20%	>20%	>20%	10.9%	
	90%						>20%	>20%	>20%	>20%	
	100%						>20%	>20%	>20%	>20%	

Notes.
1. Storage level is measured as % of the total storage capacity.
2. Resilience measure is evaluated by targeting that recovery is a more likely outcome than irreversibility (i.e., at least 50% recovery probability).
3. The climate change scenario is evaluated by assuming 30% reduction in water availability (CSIRO, 2008a).
4. The high level diversion is the baseline diversion limit (MDBA, 2010:t4.10), while low diversion is the current SDL in the Basin Plan.
5. Blackened cells represent the thresholds for irreversible consequences.
6. Grayed cells represent situations where there is less than 50% recovery chance even without storage/inflow decline shocks.

Table 7 reports the resilience measure for the GB. Similar to the MDB case, resilience is quantified by the maximum negative storage decline shock that can be absorbed without reducing the recovery probability to less than 50%. The table shows that the higher is the water storage level, or the less severe is the drought condition, the more likely it is the system can recover. We also find for the GB region that projected climate change

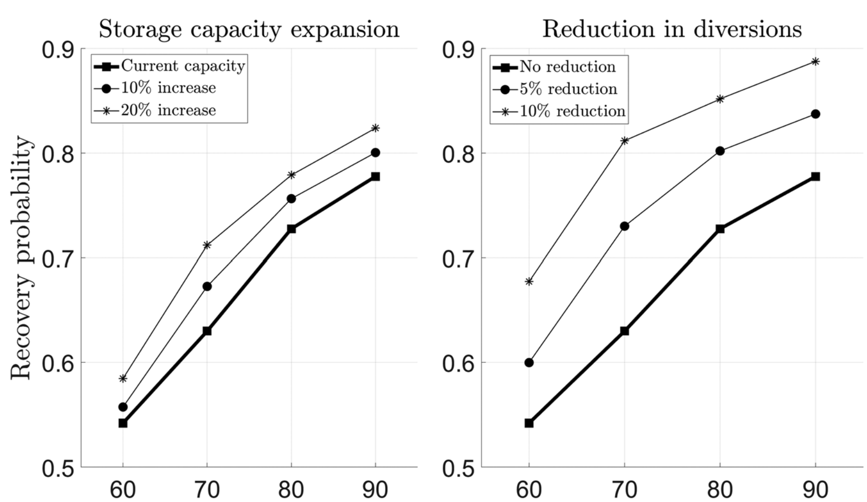

Figure 2. Goulburn-Broken catchment: the impact of storage capacity expansion and reduction in diversions.

worsens resilience, but reducing the diversions for consumptive water use from 1,760 to 1,310 GL/yr can mitigate the impacts of climate change on resilience.

Sensitivity analyses to evaluate the impact of augmenting the existing storage capacity and reducing the diversions for consumptive water use for the GB catchment are presented in Figure 2. Similar to the MDB, with a comparison based on a proportional change in either variable, the supply-based approach is less effective than the demand management at increasing resilience. We find that expanding the storage capacity by 20% can improve the resilience, but not as much as reducing diversions for consumptive water use by only 5%. This finding, as for the MDB, only applies for the particular parameters to calibrate the model and is not a general result.

6. Discussion

In response to the degraded ecological habitats in many river systems, scientists are increasingly arguing for the need to augment increased environmental flows (Arthington et al., 2010; Poff & Zimmerman, 2010). The dilemma faced by policy makers is that allocating more water for environment flows will, typically, mean less water for consumption and, in the case of MDB and GB, less water for irrigation. Our resilience optimization model helps decision makers by considering, in an optimization framework, the likely trade-offs while explicitly evaluating the risks. By using our model, and in a stochastic framework, water planners can (re) allocate water so as to maximize resilience which we define as minimizing the risk of irreversible environmental consequences.

Our resilience decision approach has general applicability. As we show in the two cases, the model can be applied with different spatial dimensions, either at a basin scale or at a single-reservoir scale, to determine when and how much water should be released in regulated river systems to increase environmental streamflows. Importantly, the model can be applied to optimally allocate water for consumption and environmental purposes in "data poor" circumstances and where there are missing data or no estimates of the economic value of environmental assets. This feature extends the applicability of the model relative to approaches that require monetary values for the environmental water that is released.

The two cases illustrate how decision makers are able to evaluate the sustainability of current and alternative water diversions for consumptive purposes. Thus, our approach is a valuable tool for decision makers who wish to optimally determine levels of water diversions for consumptive purposes that do not impose undue risks on the natural capital in river basins. In particular, our methods can be used to compare alternative diversion levels for consumptive water use and to quantify their possible effects on the resilience of environmental assets, such as wetlands. Further, decision makers can apply the model to evaluate the effects of climate change and to determine the optimal and timely adjustments in diversions for consumptive water use (if required) while keeping the risks to environmental assets to a defined level. This application is particularly important in arid and semiarid regions, including most of Australia, that are projected to have reduced and more variable precipitation (CSIRO & Bureau of Meteorology, 2015) that, in turn, exacerbate global water risks (Grafton et al., 2017) and the likelihood of weather extremes (Cai et al., 2015).

Our model can be used to compare the effectiveness of the two general solution approaches to addressing concerns about water security, namely, supply augmentation and demand management or conservation. Given the interannual variability in inflows, increasing storage capacity can intertemporally transfer water from wet periods to dry periods. In our two cases, we find that infrastructure augmentation might be not be cost-effective, or even necessary, if alternative water demand controls are available, for example, cap on water diversions (Grafton et al., 2015; Grafton, Chu, et al., 2014). Further applications in other catchments and basins, based on our approach, offer the possibility of improved decision-making in response to increased water insecurity.

We close with some caveats. First, while our approach allows for probabilistic forecasts of future weather and inflows in decision-making, it does so in a relatively simplistic way. That is to say, inflow forecasts in our model are based on only historical inflows. In some locations, advances in inflow forecasts already allow decision makers to use many other climate phenomena indices to obtain better forecasts (Hamlet & Lettenmaier, 1999; Yang et al., 2017). In addition, in our model, weather is classified into dry, normal, and wet states in a categorical format that employs the 25 and 75 quantile points of historical inflows. An alternative approach is to calculate the water year index from seasonal runoff data and then use the index for weather classification (Yang et al., 2016:1629,SI), where such data are available. Decision makers can also take into account more state variables such as the Multivariate-Standardized-Reliability-Resilience Index (Mehran et al., 2015) or the Sustainability-Robustness-Resilience Index (Huizar et al., 2018) which measure the reliability of water system in relation to satisfying water demands. These forecast advancements and model refinements should further enhance the applications of the model in practice provided such information is available to decision-makers.

7. Conclusion

We develop a resilience optimization model to determine optimal environmental water releases from regulated water storages while evaluating competing water uses premised on the notion of strong sustainability. In particular, the model accounts for stochasticity in weather and optimizes the probability of recovering from a drought that would negatively affect natural capital.

Our model is applied at a basin scale and also at a single catchment. Results from both cases, coupled with sensitivity analyses, show that the approach allows decision-makers to explicitly consider the risks of high levels of water diversions for consumptive water use and also climate change. Importantly, the approach allows for improved decision-making even under data-poor conditions and for comparisons of both supply and demand-based approaches to mitigate water scarcity. In sum, while further applications of the model are required, along with improvements in the modeling of weather and the use of more sophisticated weather forecasts, the approach offers an improvement over current practice of water (re) allocation while including the consideration of resilience and risk in decision-making.

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