Henley, Benjamin J.; Thyer, Mark Andrew; Kuczera, George Alfred
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Climate driver informed short-term drought risk evaluation

Benjamin J. Henley,[1] Mark A. Thyer,[2] and George Kuczera[1]

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[1] This study proposes a methodology for quantifying the impact of climate drivers on water supply drought risk. Climate driver informed short-term drought risks are evaluated for future time steps following conditioning on the initial state of climate drivers and initial reservoir storage level. The methodology is demonstrated using a case study in eastern Australia. Simulations of future rainfall are provided by the climate-informed multitime scale stochastic (CIMSS) model, which is used to incorporate Pacific decadal variability exhibited by the Pacific Decadal Oscillation-Interdecadal Pacific Oscillation. The climate driver informed drought risks are compared to a traditional approach that evaluates long-term drought risks using a nonclimate driver informed rainfall model. The case study considers four scenarios describing a range of different climate driver initial conditions. For the PDO-IPO positive initial state scenarios, the short-term risks are found to be higher than traditional long-term risks by 20%–100%. Furthermore, the elevated short-term risks can last up to 30 years with the CIMSS model but <10 years with the traditional model. The implication of these results is that traditional approaches can significantly underestimate the severity and duration of drought risk. The case study demonstrates a practical and general approach for incorporating the influence of climate drivers and initial storage conditions into drought risk analyses, which could be adapted to other regions and climate drivers. The results prompt a recommendation to water resource planners to carefully integrate climate variability over a range of time scales into water supply system planning and operation.

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1. Introduction

[2] The provision of adequate drought security is a key responsibility for managers of water supply systems. Typically, simulations from stochastic hydrological models are used as inputs to reservoir system models to estimate drought risk, test management strategies, and optimize system performance. Traditional approaches for the assessment of water supply drought risk have relied on estimating the long-term probability of storage levels falling below specified thresholds. In this study, drought risk evaluated over the full simulation period is referred to as the long-term drought risk. Water managers, engineers, and system operators have designed and operated reservoir systems under the basis that there are known and stationary long-term risks of particular thresholds being violated and that these risks represent the key risks to water supply system security.

[3] However, traditional approaches that rely on long-term drought risk evaluation have a number of shortcomings. Long-term drought risk approaches obscure the time evolution of drought risk due to hydrological variability on interannual to multidecadal timescales. Low long-term risks of failure have little meaning and offer little comfort to water managers at times when water supply systems are significantly drawn down due to persistent drought conditions. For example, from 1997 to 2010, water supply systems and natural ecosystems across much of Australia were forced to endure a long and severe drought sequence, termed the "Big Dry" [*Sohn*, 2007] or "Millennium Drought" [*Whitaker*, 2005]. The drought led many Australian water authorities to commission desalination plants. At such times, well-informed drought risk analysis methods are crucial.

[4] A variety of methods have been proposed to improve upon traditional methods for evaluating drought risk. Examples of recent work include: the improved allowance for streamflow persistence in estimating the average return period [*Douglas et al.*, 2002], clarifying the characteristics of drought such as the duration, severity (magnitude or intensity), spatial extent, and frequency or return period [*Cancelliere and Salas*, 2004], improved identification of significant drought episodes using the joint distribution of drought duration and magnitude from paleoclimate data [*Biondi et al.*, 2005], the comparison of operating rules and management procedures [*Cancelliere et al.*, 1998; *Westphal et al.*, 2007], and the direct simulation of drought

[1]Discipline of Civil, Surveying and Environmental Engineering, The University of Newcastle, Callaghan, New South Wales, Australia.
[2]School of Civil, Environmental and Mining Engineering, The University of Adelaide, Adelaide, South Australia, Australia.

Corresponding author: B. J. Henley, Discipline of Civil, Surveying and Environmental Engineering, The University of Newcastle, Callaghan, NSW 2308, Australia. (ben.henley@uon.edu.au)

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characteristics [*Bonaccorso et al*., 2003; *Cancelliere and Salas*, 2010].

[5] Although drought risk is commonly evaluated by calculating long-term probabilities, conditional methods have also been widely employed. For example, position analysis [*Hirsch*, 1978] is a tool used by water managers to forecast risks associated with a specific operating plan over a future period, conditioned on current storage levels and anticipated inflows [*Tasker and Dunne*, 1997]. *Hirsch* [1978] presented a risk analysis model to investigate the long-term marginal probabilities of entering emergency restrictions in any year and also the risk in a given year conditional on emergency restrictions being imposed in the previous year. *Tasker and Dunne* [1997] used position analysis to investigate a streamflow simulation scheme that used bootstrapping of the residuals from a stochastic model.

[6] Position analysis can use as its input a single trace of projected inflows, inflow prediction procedures and/or replicates of inflows generated from a stochastic model to provide drought risk estimates in the short-term (for example, the next 1–10 years). One method is to project forward using the lowest observed inflow series on record. While this method is generally considered to be a conservative approach, it does not quantify the likelihood of such a scenario, nor does it allow for the possibility of drought conditions more severe than those which have occurred in the observed record. In this paper, conditional methods will be extended to include conditioning on scenarios that explicitly incorporate variability from climate drivers.

[7] Although water supply drought risk is most commonly assessed using a long-term approach, large-scale climate drivers, such as the El Niño Southern Oscillation (ENSO), Indian Ocean dipole (IOD), and the Interdecadal Pacific Oscillation and the closely related Pacific Decadal Oscillation (PDO-IPO), are known to influence rainfall and streamflow patterns in Australia, and similar ocean-atmosphere circulation mechanisms affect other regions around the world.

[8] The study by *Henley et al*. [2011] showed that the PDO-IPO negative state coincides with higher annual rainfall over a large area of the coast of NSW, around 1000 km in length and extending inland around 100 km. A number of studies have shown the influence of the PDO-IPO on Australian hydrological regimes, particularly in this region, including *Power et al*. [1999], *Arblaster et al*. [2002], *Kiem and Franks* [2004], *Micevski et al*. [2006], *Westra and Sharma* [2009], and *Speer et al.* [2011]. *Meinke et al.* [2005] identified decadal and interdecadal variability as important components of rainfall variability globally.

[9] As climate drivers oscillate, water supply drought risk also fluctuates. Traditional long-term drought risk evaluation could therefore be viewed as an overall marginal probability, integrating out, or less kindly, being ignorant of, the time-varying influence of climate drivers.

[10] The studies by *Kiem and Franks* [2004], *Verdon and Franks* [2007], and *Verdon-Kidd and Kiem* [2010] investigated the impact of climate drivers on long-term drought risk; however, these studies did not investigate conditional drought risk using position analysis. Of the studies that have investigated conditional position analysis, none to date have explicitly investigated the conditional impacts of climate drivers on drought risk.

[11] This study therefore proposes a methodology for investigating the impact of climate drivers on water supply systems. Termed "climate driver informed short-term drought risk," the method evaluates the conditional water supply drought risk at each time step, given an initial storage level and the current state of one or more climate drivers. To demonstrate the method, this study uses the CIMSS model developed by *Henley et al*. [2011] to investigate the influence of the PDO-IPO on climate driver informed short-term drought risk at a site on the east coast of Australia. The PDO-IPO is chosen as the climate driver for this study due to its predictability several years into the future and its known impact in this region.

[12] This study is organized as follows. Section 2 describes the methodology, including the two rainfall models used in this study, the climate driver informed multitime scale stochastic (CIMSS) model of *Henley et al*. [2011], and the nonclimate driver informed lag-one autoregressive model (section 2.2), as well as the reservoir simulation approach (section 2.3). The climate driver informed short-term drought risk methodology is introduced in section 2.4, including a range of initial climate driver state scenarios and time-based drought risk thresholds. Section 2.5 outlines the traditional long-term drought risk approaches. Section 3 presents the results, including the comparison of short and long-term drought risk and the CIMSS model against traditional nonclimate informed stochastic rainfall models. Section 4 assesses the sensitivities of the results to the initial storage, capacity, and yield. The study concludes with a discussion in section 5 of the implications of the heightened drought risk evident during the PDO-IPO positive state and the significance of a highly variable and changing climate on the future reliability and security of water supply systems, and a statement of the key findings in section 6.

2. Methodology

2.1. Overview

[13] The general approach for performing climate driver informed drought risk evaluation is outlined in Figure 1. The key differences from traditional drought risk simulation are as follows: (1) development of stochastic model for the hydrological inputs includes a stochastic model for the climate driver(s) and their relationship with hydrological inputs, (2) stochastic simulations of hydrological inputs are conditioned on the initial state of the climate driver(s), (3) simulations of water supply system behavior are conditioned on initial reservoir conditions, and (4) drought risk evaluation is undertaken on a short-term basis in each year following initialization. The following sections provide a detailed description of each component of the approach and its specific application to the case study.

2.2. Stochastic Models

[14] The CIMSS model of *Henley et al*. [2011] utilizes a Bayesian hierarchical approach for incorporating climate mechanisms and their impacts on hydrological data. In general, physical phenomena operating at multiple timescales are simulated with stochastic models. In the *Henley et al.* [2011] study, a two-level hierarchy was adopted and is also used in this study. The upper level simulates the positive/negative states of the PDO-IPO with a gamma distribution

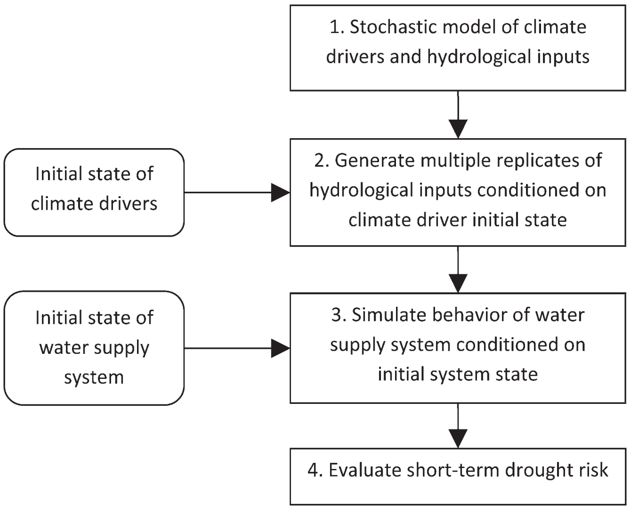

Figure 1. Major components of the climate driver informed drought risk approach.

calibrated to paleoclimate PDO-IPO data. The paleo data used here is the combined paleo IPO (CPIPO) index, which merges seven paleo sources from around the Pacific and dates back around 440 years prior to instrumental IPO records [*Henley et al.*, 2011]. The lower level of the CIMSS model simulates rainfall using two seasonal lag-one autoregressive models with Box-Cox transformation (AR(1)-BC) with parameters conditioned on the upper level PDO-IPO model. The nonclimate driver informed lag-one autoregressive model with Box-Cox transformation (AR(1)-BC model) was described by *Frost et al.* [2007].

2.3. Reservoir System

[15] The reservoir model used here is a simple water balance model at the annual time step. The simplicity in its configuration is such that the ensuing drought risk assessment is not clouded by idiosyncracies of a particular water supply system configuration. In doing so, it is suggested that this analysis maintains a broader applicability.

[16] The reservoir's inflow is represented by the variable q_i, with the reservoir's outflows, such as the restricted demand (supply), evaporation, and other losses represented by the variable d_i. System storage proportion s_i at time i is therefore computed by

$$s_i = \begin{cases} s_{\text{temp}} & \text{if} \quad 0 < s_{\text{temp}} < 1, \\ 1 & \text{if} \quad s_{\text{temp}} >= 1, \\ 0 & \text{if} \quad s_{\text{temp}} <= 0, \end{cases} \tag{1}$$

where

$$s_{\text{temp}} = \frac{s_{i-1} \times C + q_i - d_i}{C}, \tag{2}$$

and C is the reservoir capacity. Water restrictions are simulated with a 5% reduction in demand for every 10% reduction in storage below 50%, down to a 20% reduction in demand at storage levels of 20% and below.

[17] Reservoir inflow simulations are obtained by nonparametric sampling from the observed streamflow record, conditioned on the stochastic rainfall simulated by the models described in section 2.2. A k-nearest neighbor (kNN) approach is used to conditionally sample annual reservoir inflow from the observed distribution using simulated annual rainfall as the predictor with $k = \sqrt{n}$. Detailed investigations of this method have been presented previously by *Lall and Sharma* [1996], *Sharma et al.* [1997], and *Mehrotra and Sharma* [2006].

[18] In this study, a range of different storage capacities and demands are trialed, based on the dimensionless ratios, C/Q_{av}, and D/Q_{av}, where Q_{av} is the annual average inflow and D is the reservoir yield (the annual supply level that satisfies the drought risk criteria). This provides insight into how the short-term drought risk compares for different water supply system characteristics.

2.4. Climate Informed Short-Term Drought Risk

2.4.1. Definition

[19] An approach for evaluating short-term drought risk based on stochastic rainfall simulations conditioned on climate and initial storage is described here. The short-term drought risk $r_{i,\text{st}}$ is the proportion of replicates in which the system storage $s_{i,j}$ falls below a threshold, τ, in time step i:

$$r_{i,\text{st}} = \frac{\sum_{j=1}^{n_{\text{reps}}} c_{i,j}}{n_{\text{reps}}}, \tag{3}$$

$$c_{i,j} = \begin{cases} 1 & \text{if} \quad s_{i,j} <= \tau \\ 0 & \text{if} \quad s_{i,j} > \tau \end{cases}, \tag{4}$$

where i ranges from 1 to n_{data} and j is a Monte Carlo inflow replicate ranging from 1 to n_{reps}.

2.4.2. A Time-Based Drought Risk Threshold

[20] Traditional drought risk analyses typically use arbitrarily chosen thresholds (τ) such as 5% for the drought security threshold, and around 40%–60% for reliability thresholds. However, absolute thresholds do not take into account the system yield relative to the inflow (q_i) or capacity (C), nor the *time* taken for storage levels to deplete.

[21] For a large reservoir system, 5% storage could represent several months of remaining water supply; however, for a small system, complete failure could be imminent. Emergency drought management plans that include, for example, the commissioning of desalination or wastewater recycling plants, are often limited by planning approval and construction time lines, as highlighted by *Berghout* [2008]. Such timelines are unlikely to be any faster in the case of smaller storage systems nearing depletion. A more useful criterion would be the risk of triggering such an emergency drought management plan, where the threshold is a function of *time* instead of storage.

[22] It is therefore proposed in this study that the threshold τ for the drought risk determination be equal to 1 year's yield (D) expressed as a proportion of the reservoir storage capacity (C), so $\tau = D/C$. The risk $r_{i,\text{st}}$ can therefore be interpreted as the conditional probability that the reservoir will be within 1 year of a fully depleted (0%) storage, assuming no intervening inflows. This time-based approach to setting the drought risk threshold is more informative

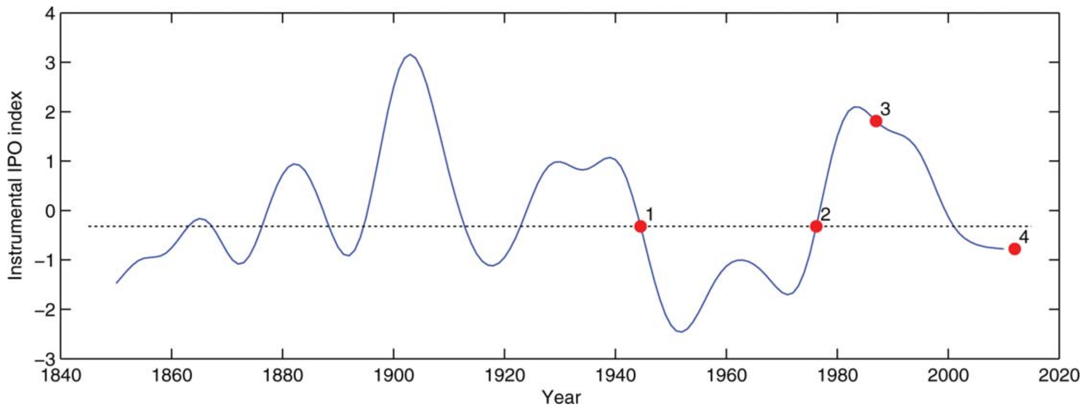

Figure 2. PDO-IPO scenarios used in conditional simulations.

and more amenable to assisting planning decisions which are time dependent.

2.4.3. PDO-IPO Scenarios of Initial Climate Driver State

[23] The choice of initial climate driver state can be based either on the current state of the climate drivers or on likely scenarios from historical information. For this case study, the initial climate driver states were based on four PDO-IPO scenarios (Figure 2). For scenarios 1 and 2 the CIMSS model is initialized so that the first PDO-IPO state in each replicate is a negative or positive state, representing the PDO-IPO state in 1945 and 1976, respectively. For scenario 3, the model is initialized 10 years into a positive PDO-IPO state, as was the case in 1987. Similarly, scenario 4 is initialized 12 years into a negative PDO-IPO state, representing the best estimate of the PDO-IPO condition at the time of writing (2013). Along with the PDO-IPO state initialization, the rainfall models are initialized to the rainfall in the prior year $y^1_{\mathrm{obs},t-1}$ for each of the four scenarios. These initial rainfall values were 1524, 958, 1621, and 1373 mm for scenarios 1–4, respectively.

[24] The aim here is to investigate a broad spectrum of initial climate driver state scenarios, including both at the commencement and at around a decade (approximately midway) into each PDO-IPO state. Scenarios 1 and 2 represent examples of the commencement of their respective PDO-IPO states. Scenario 3 starts at a relatively wet year (at the Stroud case study site) approximately 10 years into a PDO-IPO positive state. This combination enables a thorough comparison of the CIMSS and AR(1)-BC models. Scenario 4 represents the situation at the time of writing, and therefore has relevant practical significance.

2.5. Long-Term Drought Risk

[25] The performance of water supply systems is traditionally assessed based on the long-term probability of the storage level falling below specified thresholds. These probabilities are evaluated using Monte Carlo simulation of the modeled system, with the warm-up period discarded to remove the effect of initial conditions. The long-term drought risk r_{Lt} is defined here as

$$r_{\mathrm{Lt}} = \frac{\sum_{i=1}^{n_{n\mathrm{data}}} r_{i,\mathrm{st}}}{n_{\mathrm{data}}}. \quad (5)$$

2.6. Case Study

[26] A long-term rainfall record on the east coast of New South Wales (NSW), Australia, is selected here as a case study. The site (Stroud Post Office) is part of the Australian Bureau of Meteorology's high quality (HQ) rainfall gage network [*Lavery et al*., 1997]. Reservoir inflow data (1931–2007) is from Tillegra, NSW. This site is chosen because it is close to the rainfall data site and has previously been proposed as a major dam site for the Lower Hunter Region. The July-June water year is used in order to align with impact seasons of the CIMSS model of *Henley et al*. [2011].

[27] The rainfall and inflow transformation models are evaluated by comparing the simulated and observed annual distribution, autocorrelation, and scatterplots of rainfall and inflow. As the observed data is within the 90% limits of the simulated data, both models are deemed satisfactory.

3. Results

[28] The short-term drought risks are compared here for the CIMSS and AR(1)-BC rainfall models for two reservoir storage capacities of C/Q_{av} of 1.75 and 4.0. The simulations use an initial storage of 70%, an annual yield of $0.75Q_{\mathrm{av}}$, and 50,000 Monte Carlo replicates for each model run. Figure 3 shows the expected value of the short-term risks. The results are summarized in the following sections.

3.1. Short-Term Versus Long-Term Risks

[29] For the short-term drought risk, the results show an initial transient period due to the effect of initial conditions. During the initial period, the short-term risk is significantly higher (PDO-IPO-positive scenario) or lower (PDO-IPO-negative scenario) than the long-term risk for up to 20 years. Following this is a steady-state period where the short-term drought risk asymptotically approaches the long-term risk.

3.2. Differences Between Climate Driver Informed and Nonclimate Driver Informed Rainfall Models

[30] Whilst the long-term risks are similar for the CIMSS and AR(1)-BC models, the short-term risks are markedly different. The climate driver informed (CIMSS) model risks are highly dependent on the PDO-IPO scenario, whereas the nonclimate driver informed (AR(1)-BC) model risks do not change significantly between scenarios. For the

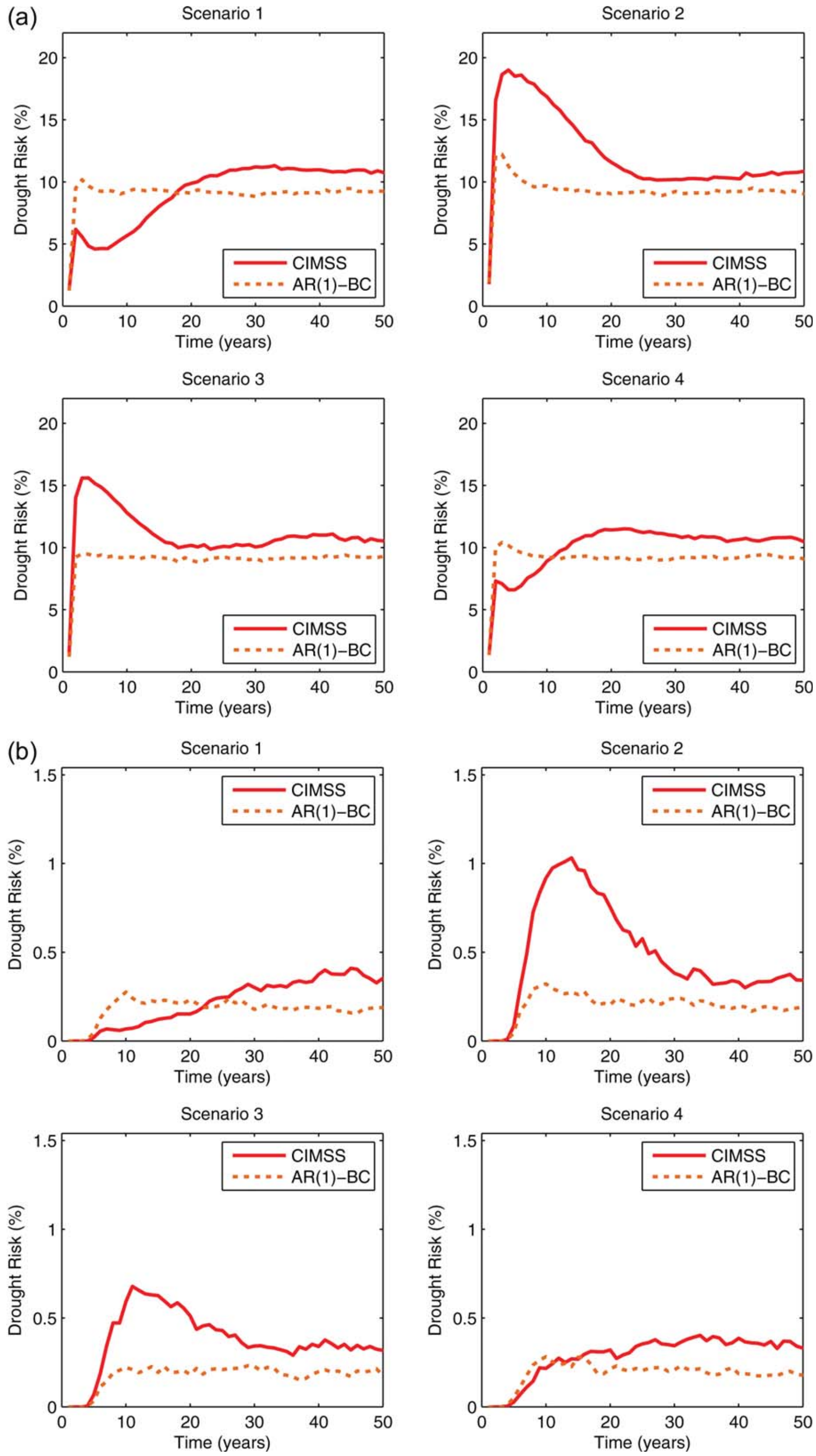

Figure 3. Short-term drought risks for two reservoir capacities (a, $C/Q_{\mathrm{av}} = 1.75$ and b, $C/Q_{\mathrm{av}} = 4.0$), four PDO-IPO scenarios, $s_0 = 70\%, D/Q_{\mathrm{av}} = 0.75, \tau = D/C$, and 50,000 model replicates.

smaller reservoir capacity ($C/Q_{\mathrm{av}} = 1.75$), the highest short-term risks for the CIMSS model (19%) occur at approximately 5 years into the PDO-IPO positive state of scenario 2, and stay well above the long-term risk for almost 20 years. In comparison, for the AR(1)-BC model the short-term risk only reaches 12% and persists above the long-term risk for only 5 years. For scenario 3, which starts when the PDO-IPO is 10 years into a positive state, the

CIMSS model exhibits almost as high a short-term risk as scenario 2. For the AR(1)-BC model, the higher than average rainfall value in 1986 results in virtually no peak in the risk, despite a positive PDO-IPO state producing drier than average conditions. For scenarios 1 and 4, the CIMSS model short-term risk rises initially due to the initial conditions, then falls due to the higher inflows in the PDO-IPO negative state, before rising to the long-term risk. The slightly higher initial peak for scenario 4 is due to it having a lower initial rainfall (1373 mm) than scenario 1 (1524 mm). The AR(1)-BC model does not show any significant change between scenarios, except for slightly higher peak risk for scenario 2, which has the lowest initial rainfall of 958 mm.

[31] Since the CIMSS model takes into account the state and persistence of PDO-IPO Pacific decadal variability and the AR(1)-BC model does not, it is apparent that system simulations that utilize nonclimate driver informed models, such as the annual AR(1)-BC rainfall model will overestimate short-term drought risk at the commencement of an PDO-IPO negative state (scenario 1) and underestimate short-term drought risk at the commencement of an PDO-IPO positive state (scenario 2). The clear propensity for the AR(1)-BC model, in particular, to *underestimate* risk in this situation provides a strong impetus for utilizing climate driver informed models.

3.3. Reservoir Capacity Effects

[32] Qualitatively similar results are obtained for the larger reservoir ($C/Q_{\mathrm{av}} = 4.0$, Figure 3b), with the key difference being that the drought risks are more than 1 order of magnitude lower and the peak short-term risks are delayed several years due to the buffering effect of the larger reservoir. This is further investigated in section 4.2.

3.4. Conditional Reservoir Level Distributions

[33] Given that the four scenarios used in Figure 3 are based on the joint occurrence of a particular PDO-IPO state and a specific initial storage (70%), it is worthwhile evaluating the probability of switching from a PDO-IPO negative to positive state if $s_i \leq 70\%$, and similarly for a switch from PDO-IPO positive to negative state.

[34] The probabilities are computed using Bayes' theorem from the Monte Carlo simulations, as described by *Henley* [2012]. The results are

$$P(Y(i-1) < 0 | s_i \leq 70\%, Y(i) > 0) = 0.40,$$

$$P(Y(i-1) > 0 | s_i \leq 70\%, Y(i) < 0) = 0.60,$$

where $Y(i)$ is the simulated PDO-IPO value at time step i.

[35] There is a higher probability that the previous PDO-IPO state was positive (a switch to negative state occurred) if the reservoir storage level is at or below 70%. It is however still relatively likely that the reservoir is at or below 70% storage at the time of a crossing from PDO-IPO negative to positive conditions. This shows that while the conditional simulation scenario 2 is less likely than scenario 1, the initialization of the storage level (s_0) at 70% coincident with the commencement of a PDO-IPO positive state is still a likely scenario.

4. Sensitivity to Capacity, Yield, and Initial Storage Level

4.1. Sensitivity to Capacity and Yield

[36] The sensitivity of short-term drought risks to reservoir capacity and yield is examined here for PDO-IPO scenario 2 using $\tau = D/C$ and a range of D/Q_{av} and C/Q_{av}. The results are shown in Figure 4.

[37] The short-term drought risks are highly sensitive to both yield and capacity, with an apparent exponential relationship between the capacity/yield and the peak short-term drought risk. The low C/Q_{av} and high D/Q_{av} combinations exhibit very high peak short-term drought risks. The peak is reached earlier in time for the smaller storage (after 1–2 years for $C/Q_{\mathrm{av}} = 1.5$) than the larger storage (after 10–15 years for $C/Q_{\mathrm{av}} = 4.0$). The peak is sooner and much more pronounced for high D/Q_{av} and low C/Q_{av} combinations. The buffering effect of the larger storage against the persistent lower inflows during the PDO-IPO positive state is evident in the strong reduction in peak short-term risks for higher C/Q_{av}. For example, increasing C/Q_{av} from 1.5 to 2.0 has the effect of reducing short-term peak risk from 20% to 9% for the $D/Q_{\mathrm{av}} = 0.7$ case. A similar reduction in short-term peak risk is obtainable by reducing yield from $D/Q_{\mathrm{av}} = 0.7$ to 0.6.

4.2. Sensitivity to Initial Storage Level

[38] The sensitivity of short-term drought risks to the initial storage level is examined here for PDO-IPO scenario 2. The CIMSS and AR(1)-BC models are compared. Initial storage levels range between 1.0 and 2.2 times annual yield (D). This range equates to 41.3% to 90.8% of the capacity of the reservoir. The results are shown in Figure 5.

[39] The short-term drought risks are highly sensitive to the initial storage conditions. The CIMSS model produces higher drought risks for essentially all of the timeframe and initial storages (for scenario 2). The risks are >20% for initial storages of $<1.5D$ within 6 years of the simulation commencing for the CIMSS model, but reach >20% for only the first 1–3 years for the AR(1)-BC model. The CIMSS model risks show that this PDO-IPO scenario results in a severe exacerbation of the stress on the reservoir that would be produced by low initial storage volumes. However, this intensification of short-term drought risk from the commencement of a PDO-IPO positive state is much less for the AR(1)-BC model.

5. Discussion

5.1. Comparing Long-Term and Climate-Informed Short-Term Risks

[40] The two stochastic rainfall models produce similar results for the long-term drought risks. This is because the impacts of the two oscillating PDO-IPO states in the CIMSS model tend to average out over the long-term. The marginal distributions and lag-one autocorrelations of the rainfall simulations from both models are similar, which gives rise to similar long-term risks.

[41] For the positive PDO-IPO scenarios for the CIMSS model, the short-term drought risks are significantly higher than the long-term risks. The peak short-term drought risk over the 5–20 years following the crossing to the PDO-IPO

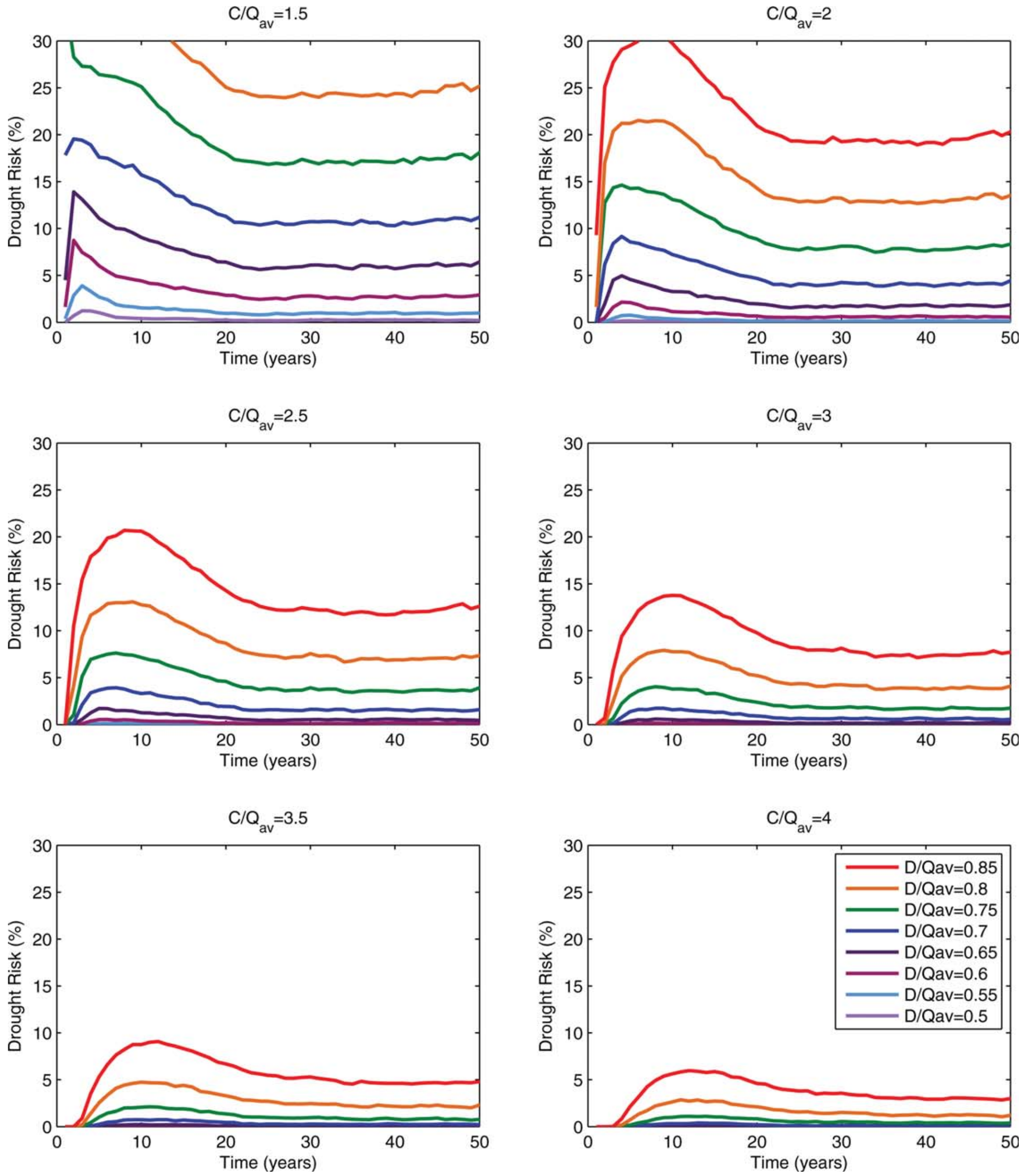

Figure 4. Short-term drought risks for scenario 2 with a range of capacities (C) and yields (D) as a proportion of the annual average inflow (Q_{av}) using $\tau = D/C, s_0 = 70\%$.

positive state in scenario 2 was found to be 19% using $D/Q_{\mathrm{av}} = 0.75, C/Q_{\mathrm{av}} = 1.7$ and an initial storage of 70%. In comparison, the long-term drought risk approached only around $10\% - 11\%$. A qualitatively similar peak in the short-term risks was observed for the larger reservoir ($C/Q_{\mathrm{av}} = 4.0$).

[42] These results show that whilst a traditional long-term drought risk analysis might reveal relatively low drought risks, the short-term (e.g., 5–20 year) risk of being within 1 year of reservoir depletion can be much higher than what might otherwise be expected. This comparison brings into question the usefulness of evaluating long-term drought risk. For a water resource planner who has a reservoir level at, say, 50%–60% of capacity ($1.2 - 1.4D$ in Figure 5), it is little comfort knowing that the long-term risk of the storage falling below 5% capacity is less than 0.1% (as drought risk is traditionally expressed) or that the long-term risk of the storage falling below 1 year's demand is less than 10% (from Figure 3), if the short-term risk of falling below 1 year's demand *in the next5 years* is actually 20%–30% (Figure 5).

[43] The climate driver informed short-term drought risk approach therefore arguably provides a more meaningful estimate of current system risks in the short-term than

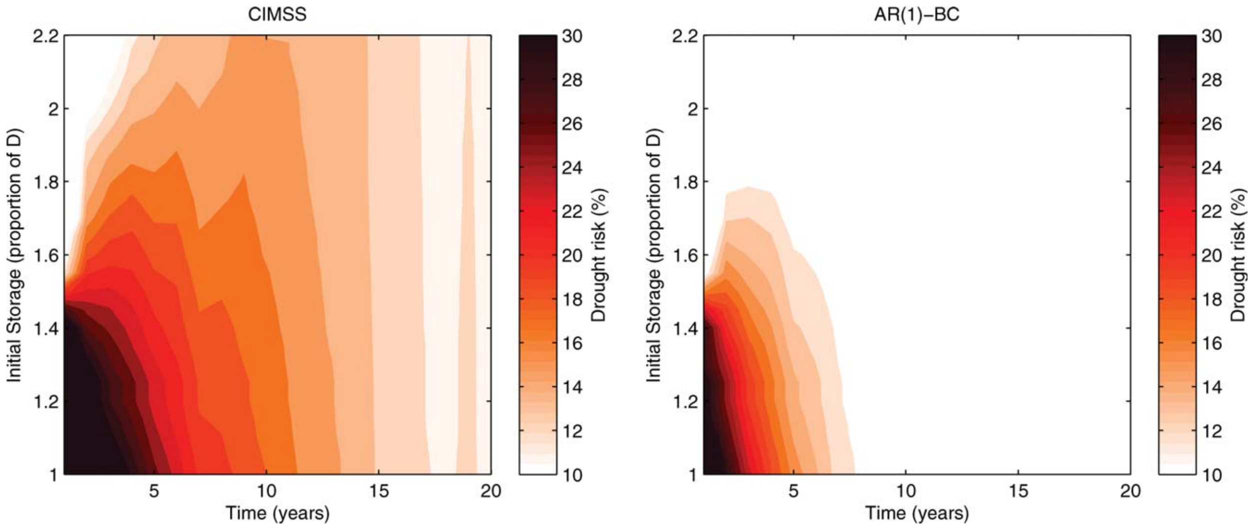

Figure 5. Short-term drought risks for the CIMSS model for scenario 2 with a range of initial storage levels expressed as a proportion of the annual yield $D, C/Q_{\mathrm{av}} = 1.75, D/Q_{\mathrm{av}} = 0.75, \tau = D/C$; note that the 70% initial storage used in Figures 3 and 4 equates to 1.70D.

either the long-term risk approach or the short-term risk conditioned only on initial storage.

5.2. Comparing CIMSS and AR(1)-BC Rainfall Models

[44] The CIMSS rainfall model produced significantly different short-term drought risks to the AR(1)-BC model with all other parameters kept the same. For scenario 1, the PDO-IPO entering a negative state, the CIMSS-modeled short-term risk is significantly lower than that for the AR(1)-BC model for the transient period. The simulated higher inflows in the PDO-IPO negative state result in reduced drought risk in the short term. For scenario 2, the PDO-IPO entering a positive state, the CIMSS-modeled risks are significantly higher than those for the AR(1)-BC model. The AR(1)-BC model has no explicit mechanism to incorporate climate driver information. It is therefore suggested that the CIMSS model better depicts hydrological impacts of Pacific decadal-scale climate variability. It follows that the widely used AR(1)-BC model overestimates drought risk during the PDO-IPO negative state and underestimates drought risk during the positive state.

5.3. Sensitivity of Short-Term Risk to Capacity, Yield, and Initial Storage

[45] For the CIMSS model for scenario 2, the short-term drought risk generally increases with time until it reaches a peak, before decreasing beyond 15–30 years. The rise and fall is due to the cumulative effects of the stress on the supply system. The lower than average inflow in the positive PDO-IPO state, coincident with moderately high annual yield of $D/Q_{\mathrm{av}} = 0.75$, produces the peaking effect. The peak is reached earlier in time for the smaller storage (after 1–2 years for $C/Q_{\mathrm{av}} = 1.5$) than the larger storage (after 10–15 years for $C/Q_{\mathrm{av}} = 4.0$). The peak is sooner and much more pronounced for high D/Q_{av} and low C/Q_{av} combinations. To achieve short-term risks of lower than 1%, $C/Q_{\mathrm{av}} = 3.5$ is required for a demand of $D/Q_{\mathrm{av}} = 0.7$ and $C/Q_{\mathrm{av}} = 4.0$ is required for $D/Q_{\mathrm{av}} = 0.75$. The buffering effect of the larger storages against the persistent lower inflows during the PDO-IPO positive state is evident.

[46] The effects of initial storage were investigated for the PDO-IPO scenario 2 for the CIMSS and AR(1)-BC models. Initial storage is found to have a very strong effect on the short-term drought risks. The CIMSS model results show that this PDO-IPO scenario greatly exacerbates the stress on the reservoir that is produced by low initial storage volumes alone. However, this intensification of short-term drought risk from the commencement of a PDO-IPO positive state is not reproduced by the AR(1)-BC model.

6. Conclusion

[47] This study has introduced a new methodology for evaluating drought risk. The climate driver informed short-term drought risk methodology conditions simulations on climate information and reservoir initial storage. Climate informed simulations were provided by CIMSS model of *Henley et al*. [2011], which explicitly incorporates the impact of Pacific decadal-scale variability characterized by the PDO-IPO on hydrological simulations. This represents an advance on previous approaches that only considered the impact of initial reservoir conditions on short-term drought risk or the influence of decadal-scale climate variability on long-term drought risk.

[48] To demonstrate this new climate driver informed approach, rainfall and inflow data from a case study site on the east coast of Australia was used in a reservoir simulation to compare various drought risk scenarios. Drought risk from the climate driver informed short-term approach was compared with the traditional long-term approach and drought risk from a climate informed stochastic model

(CIMSS) was compared with a traditional nonclimate driver informed model (AR(1)-BC). The PDO-IPO was chosen as the climate driver for this study due to its predictability several years into the future and its known impact in this region.

[49] The short-term drought risk exhibits transient behavior, where the initial conditions of the simulations are affecting the drought risk, followed by a steady state in which the initial conditions are forgotten and the short-term risk approaches the long-term risk. For PDO-IPO positive scenarios, the increased short-term drought risk was considerably higher (up to 20%–100%) than the long-term drought risk for the case study region in eastern Australia. For water resource planners, this emphasizes the importance of analyzing short-term drought risks in undertaking water supply security assessments.

[50] The CIMSS model produced short-term drought risks that were significantly higher than the AR(1)-BC model for the PDO-IPO positive scenarios. Furthermore, the short-term risks from CIMSS were higher than the long-term risks for up to 20 years, whereas for the AR(1)-BC model the period of increased risk lasted only 5 years. This is despite the long-term risks being very similar. It is concluded that traditional long-term drought risks obscure the impact of decadal-scale variability because the drought risk is averaged in time over wet and dry periods. Furthermore, traditional nonclimate driver informed models, such as the AR(1)-BC model, can significantly underestimate the short-term drought risk. In contrast, the CIMSS model and the short-term climate driver informed drought risk approach provides an opportunity to better quantify the impact of decadal-scale climate variability on water supply drought risk. These results demonstrate the practical significance of the improved characterization of Pacific decadal-scale variability and the climate driver informed stochastic rainfall model developed by *Henley et al.* [2011].

[51] Furthermore, the effects of changing the nondimensional capacity (C/Q_{av}) and demand (D/Q_{av}) ratios and initial storage level on the short-term drought risk were investigated. The short-term risks were found to be highly sensitive to lower C/Q_{av} and higher D/Q_{av} combinations, as well as low initial storages. The increases in the short-term drought risks for PDO-IPO positive scenarios were exacerbated by low C/Q_{av}, high D/Q_{av} combinations and low initial storage. The severe impacts due to low initial storage were not reproduced by the AR(1)-BC model.

[52] In summary, the outcomes of this study present an opportunity for water resource planners to better quantify the risks due to decadal-scale hydrological variability. It is proposed that the climate driver informed short-term drought risk approach is a useful operational and strategic planning tool for water resource planners. It provides a more relevant and informative estimation of drought risk than traditional long-term approaches. The methodology demonstrated in this study is general and can be applied to other climate drivers and regions. Since current drought risk evaluation approaches do not routinely incorporate knowledge of climate mechanisms explicitly, they could be significantly underestimating the short-term risks of water supply system failure.

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