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Key Points:

- Defines socioeconomic drought by linking climate variability, local resilience, and demand
- Presents a novel approach combining climatic variability and local resilience
- Improved description of water stress onset and persistence

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A hybrid framework for assessing socioeconomic drought: Linking climate variability, local resilience, and demand

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Abstract Socioeconomic drought broadly refers to conditions whereby the water supply cannot satisfy the demand. Most previous studies describe droughts based on large-scale meteorological/hydrologic conditions, ignoring the demand and local resilience to cope with climate variability. Reservoirs provide resilience against climatic extremes and play a key role in water supply and demand management. Here we outline a unique multivariate approach as a measure of socioeconomic drought, termed Multivariate Standardized Reliability and Resilience Index (MSRRI). The model combines information on the inflow and reservoir storage relative to the demand. MSRRI combines (I) a "top-down" approach that focuses on processes/phenomena that cannot be simply controlled or altered by decision makers, such as climate change and variability, and (II) a "bottom-up" methodology that represents the local resilience and societal capacity to respond or adapt to droughts. MSRRI is based on a nonparametric multivariate distribution function that links inflow-demand reliability indicator to water storage resilience indicator. These indicators are used to assess socioeconomic drought during the Australian Millennium drought (1998–2010) and the 2011–2014 California drought. The results show that MSRRI is superior to univariate indices because it captures both early onset and persistence of water stress over time. The suggested framework can be applied to both individual reservoirs and a group of reservoirs in a region, and it is consistent with the currently available standardized drought indicators. MSRRI provides complementary information on socioeconomic drought development and recovery based on reservoir storage and demand that cannot be achieved from the commonly used drought indicators.

1. Introduction

Many areas of the world face water scarcity and water availability challenges as a result of deteriorating water quality, increasing water demand, and climatic variability and change [*Trenberth*, 2001; *Stoll et al.*, 2011; *Sivakumar*, 2011; *Wood et al.*, 1997; *Schewe et al.*, 2014; *Veldkamp et al.*, 2015; *Haddeland et al.*, 2014; *Schewe et al.*, 2014]. Semiarid and arid regions are particularly vulnerable to climatic variability and change impacts on water availability and distribution [*Cayan et al.*, 2008; *Seager and Vecchi*, 2010; *Israel and Lund*, 1995; *Medellín-Azuara et al.*, 2008; *Connell-Buck et al.*, 2011]. As population and industry grow and water demand increases, socioeconomic drought becomes a major concern in many regions of the world [*Arab et al.*, 2010; *Chen and Fu*, 2011; *Wada et al.*, 2011; *Madani*, 2014; *Sivapalan*, 2015; *Wheater and Gober*, 2015; *Loucks*, 2015; *Vogel et al.*, 2015; *Montanari*, 2015]. Socioeconomic drought refers to conditions whereby the water demand outstrips the supply, leading to societal, economic, and environmental impacts [*Dinar and Mendelsohn*, 2011; *Zseleczky and Yosef*, 2014; *Hayes et al.*, 2011]. Reservoirs are one of the main man-made infrastructures providing resilience against extremes (e.g., floods and droughts), and they play a key role in managing water supply and demand and reducing the impacts of socioeconomic droughts. Currently, man-made reservoirs [*Vörösmarty and Sahagian*, 2000] control approximately 20% of the total global annual river discharge [*Fekete et al.*, 1999; *Shiklomanov et al.*, 2000]. Approximately 70% of global freshwater withdrawal comes from reservoirs [*Shiklomanov et al.*, 2000], which gives some indication of reservoirs' importance in providing resilience for human water use globally [*Zhang et al.*, 2014].

Human influence on the hydrological cycle and redistribution of water [*Wada et al.*, 2013] is already apparent, as can be seen in Figure 1, where comparison of the natural inflow to Shasta Lake in California and its controlled outflow shows a shift in the maximum mean monthly runoff from March to July. The figure highlights the anthropogenic influence on the water supply leading to a substantial change in the distribution of the water relative to the natural conditions. The primary objective of this redistribution is to store water for the time it is needed most (i.e., dry season) and to build resilience in the system against socioeconomic droughts.

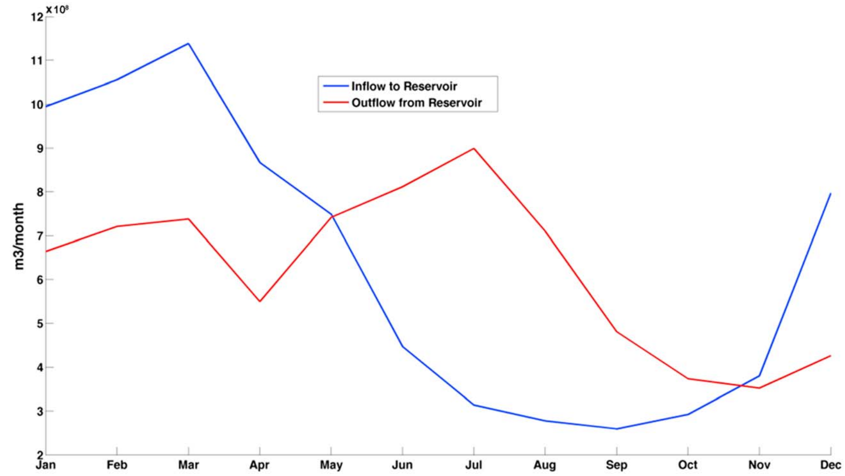

Figure 1. Mean monthly inflow versus mean monthly outflow at Shasta Lake, California.

Studying socioeconomic drought is likely to grow more important as the climate changes and the population grows. Changes in seasonality of precipitation or snowmelt combined with population and agricultural and industrial growths can lead to more stress on water supply.

Many statistical performance indices have been introduced to measure or describe a system under stress. One of the first sets of indicators designed for this purpose was by *Hashimoto et al*. [1982] who elaborated the use of three basic statistical indices: reliability, resilience, and vulnerability. Together, these measures were used to explain the performance of a system (e.g., a water storage reservoir designed to cope with socioeconomic drought). Reliability was defined as the probability that no failure occurs within a fixed period of time (e.g., planning/operation period). Resiliency was described as how quickly a system is likely to recover or bounce back from failure once failure has occurred. Vulnerability was referred to as the likely magnitude of a failure, if one occurs. These indicators have been widely used to assess the effect of climate variability on water resources [*Kundzewicz et al*., 2008].

Other definitions of reliability, resilience, and vulnerability as well as different performance metrics have been developed and discussed in the literature [e.g., *Moy et al*., 1986; *Jinno*, 1995; *Kundzewicz*, 1995; *Vogel and Bolognese*, 1995; *Kundzewicz and Kindler*, 1995; *Srinivasan et al*., 1999; and *Vogel et al*., 1999; *Ward et al*., 2013; *Moody and Brown*, 2013; *Steinschneider and Brown*, 2012]. In recent studies, more parametric rules are developed for multireservoir systems [*Nalbantis and Koutsoyiannis*, 1997]. *Miller et al*. [2010] identified a major difficulty in integrating resilience and vulnerability performance indices—namely, that differences existed between the use of these terms in concept and theory, in methodologies to assess them, and in the real-world practice of addressing climate change [*Jain and Bhunya*, 2008].

The definition of vulnerability has evolved over time. In the Fourth Assessment Report of Intergovernmental Panel on Climate Change (IPCC), vulnerability was defined as the degree to which a system is susceptible and unable to cope with climate variability and extreme weather events, as well as sensitivity and the adaptive capacity of the system to this variability [*Intergovernmental Panel on Climate Change*, 2007]. In the more recent IPCC report [*Intergovernmental Panel on Climate Change*, 2012], the social implication of vulnerability is emphasized and is generally referred to as the tendency or susceptibility of a system to be adversely affected, while such susceptibility establishes an internal characteristic of the affected element. Recent definitions of vulnerability indicate that it is a relative concept, and possible statements about vulnerability must clearly specify the entity that is vulnerable, the stimulus to which it is vulnerable, and the preference criteria to calculate the result of the interaction between them [*Ionescu et al*., 2009].

Although there are many similarities between the performance indices' approaches (e.g., vulnerability and reliability), they have been kept separate from each other and studied in parallel tracks [*Preston et al*., 2011]. Integrating different aspects of the same crisis—while acknowledging the value of multiple perspectives—would benefit the different communities involved [*Miller et al*., 2010]. The integrated and multidimensional nature of water resources problems and hydrological systems, such as socioeconomic drought, has convinced researchers in the fields of resilience and vulnerability to choose hybrid approaches. For example, *Ziervogel et al.* [2006] has explored local adaptations due to climate variations in different social and environmental stresses and proved that using a combination of approaches is more successful than single-method approaches [*Miller et al.*, 2010].

Another frequent distinction in vulnerability and drought assessment studies arises from the "top-down" and "bottom-up" methodologies [*Dessai and Hulme*, 2004]. A top-down methodology comes from climate variability or climate change impacts assessments and focuses on biophysical vulnerability while considering different meteorological or climate conditions and impact models. In other words, "top-down" focuses on climatic and meteorological conditions that cannot be simply controlled or altered by decision makers. A "bottom-up" methodology focuses on the capacity of people, societies, and governments to respond or adapt to climate extremes or water availability challenges placed on them. A bottom-up approach considers the human dimension and societal response such as water reuse and conservation as ways to cope with water stress [*Mastrandrea et al.*, 2010]. The bottom-up relies on the available infrastructure, institutional capacity, social conditions, and perception of water vulnerability.

In this study, the vulnerable entity is defined as the total water storage in reservoirs to cope with socioeconomic drought, and water stress refers to lack of inflow and/or storage to satisfy the demand (i.e., socioeconomic drought). The stimulus to which the water storage in reservoirs is vulnerable is the seasonal or interannual change in surface runoff. The preference criterion used to assess the result of the interaction between the entity and the stimulus is to satisfy water demand during a certain time frame by using both the current storage and inflow to the system. Furthermore, in this paper, the term resilience corresponds to the storage available to cope with socioeconomic droughts or, in general, climatic variability and water availability challenges. Building resilience into the system is considered a bottom-up approach to address socioeconomic droughts.

In this paper, a methodology is proposed that integrates both top-down and bottom-up approaches for assessing socioeconomic drought and water stress. The approach includes an inflow versus water demand reliability indicator that is dominated by climatic and meteorological conditions (top-down) and a water storage resilience index that considers the man-made infrastructure to cope with climate variability (bottom-up). The two indicators are combined using a multivariate statistical framework as a measure of socioeconomic droughts. The model offers a unique approach for estimating the overall water stress through water supply vulnerability including the effect of system resilience (here reservoirs). The final outcome is a hybrid indicator that combines the above mentioned top-down and bottom-up approaches for assessing socioeconomic drought.

2. Classical Methods for Reliability, Resilience, and Vulnerability Assessment

There are different definitions for reliability, resilience, and vulnerability [e.g., *Hashimoto et al.*, 1982; *Srinivasan et al.*, 1999; *Vogel et al.*, 1999]. Before presenting the methodology, the classical definitions for methods for reliability, resilience, and vulnerability are briefly reviewed, and their definitions in this study are clarified. Performance measures of reliability, resilience, and vulnerability have been defined and widely used in the past decades [e.g., *Harberg*, 1997]. A commonly used definition is based on the probability of no failure over the operating period. In case of a surface water reservoir, failure can be defined as the inability of the reservoir system to deliver the desired water demand [*Vogel and Bolognese*, 1995]. *Hashimoto et al.* [1982] introduced reliability as

$$\alpha = pr\{X_t \in S_a\} \quad (1)$$

where X is the system's output state/status at time t and S_a is all satisfactory conditions/outputs. Reliability is interpreted as the probability that no failure occurs.

The concept of resilience in reservoir systems was first introduced by *Hazen* [1914] and later redefined by *Sudler* [1927], *Hurst* [1951], *Matalas and Fiering*, [1997], *Hashimoto et al.* [1982], *Fiering* [1982], and *Moy et al.* [1986]. Basically, resilience can be expressed as [*Hashimoto et al.*, 1982]

$$\gamma = \frac{pr\{X_t \in F \& X_{t+1} \in S_a\}}{pr\{X_t \in F\}} \quad (2)$$

where F represents the failure of the system, X is the system's output/status at times t and $t+1$, and S_a is all satisfactory conditions/outputs. Resilience in classical methods was interpreted as the failure occurrence of the system that is followed by satisfactory condition/output. However, in this study, resilience refers to the storage available to cope with socioeconomic droughts.

Further, system vulnerability was defined as the likely magnitude of a failure, if one occurs. It can also be defined as the expected maximum severity of a failure state into the set of unsatisfactory states [*Hashimoto et al*., 1982], shown as

$$\vartheta = \sum\nolimits_{t \in F} e_t Se_t \ \text{ and } \ e_t = pr\{X_t \in F\} \tag{3}$$

where e_t is the probability of a temporal failure state and Se_t is the indicator of its severity at time t. Based on this definition of vulnerability, the severity of a failure state is more important than its duration. There are alternative definitions for vulnerability developed for different applications [e.g., *Kundzewicz and Kindler*, 1995; *Kjeldsen and Rosbjerg*, 2004], such as the ratio of maximum deficit to the target water demand [*McMahon et al*., 2006].

3. Methodology

In general, there are two major classes of reservoir systems [*Vogel and Bolognese*, 1995]: over-year and within-year systems. The within-year systems are typically refilled by the end of each year, and as a result, this system is very sensitive to seasonality and other temporal variations in the system (e.g., monthly inflow, monthly water demand, and evaporation). In contrast, over-year systems do not refill by the end of each year and are sensitive to long-term water supply deficit (drought). The latter is more common in areas where long-term dry conditions are expected frequently. This classification signifies the importance of variations, especially the time period that is affecting the reservoir system. Here there is a time frame defined for each reservoir system that is either 6 months (for within-year systems) or 12 months (for over-year systems) depending on the category of the reservoir system. It should be noted that the presented model is general and can be used for assessment over different time frames.

In this study, the proposed method to investigate socioeconomic drought is a multivariate approach that relies on two individual (univariate) indicators. At first, a time frame is defined based on the type of reservoir system (within-year or over-year). After defining the time frame, two new indicators are defined as follows: water storage resilience indicator and inflow-demand reliability indicator. Inflow-demand reliability (IDR) indicator is derived by computing the sum of the percent change of inflow with respect to water demand during the projected time frame:

$$\alpha_t = \frac{\sum_{i=t-m+1}^{t} Q_{\text{in}_i} - Q_{\text{est}_t}}{Q_{\text{est}_t}} \quad , Q_{\text{est}_t} = \begin{cases} \sum_{i=t-12}^{t-13+m} (Q_{\text{out}})i, & \text{if} \quad m = 6 \\ \sum_{i=t-m+1}^{t} (Q_{\text{out}})i, & \text{if} \quad m = 12 \end{cases} \tag{4}$$

where Q_{in_i} is the monthly inflow to the reservoir (i ranges from month 1 to N, which is the sample size), m is the selected time frame in months (6 months for within-year and 12 for over-year systems), Q_{est_t} is the total estimated water demand during projected time frame, and time step t ranges from month 13 to N ($t = 13,.., N$). Here the first 6 or 12 months (depending on the type of the reservoir system) of the data are used to estimate the demand in the projected time frame. The total water demand for the projected time frame (next m months) is estimated based on the same period in the previous year. For this reason, the index can only be estimated starting from the second year of the data ($t = 1,\ldots, 12$).

This indicator (inflow-demand reliability) corresponds to the "top-down" approach where the available inflow is assessed relative to the water demand. In other words, this indicator shows whether the available water (inflow to the system) is sufficient to satisfy water demand, regardless of the storage in the reservoir.

The other indicator introduced here in respect to "bottom-up" methodology is the water storage resilience indicator. This indicator is defined based on monthly inflow, monthly water demand, monthly storage, and total water demand during the time frame. Water storage resilience (WSR) indicator is computed on a monthly basis and shows whether the reservoir storage is sufficient to satisfy water demand for the selected time period (m):

$$\beta_t = \frac{St_t + Q_{\text{in}_t} - Q_{\text{out}_t} - O_{\min} - Q_{\text{est}_t}}{Q_{\text{est}_t}} \tag{5}$$

where St_t is the reservoir storage at month t, where $t = 13,\ldots, N$, $O_{\min}$ is the reservoir minimum operational storage, Q_{in_i} is the monthly inflow to the reservoir at month t, Q_{est_t} is the total estimated water demand during projected time frame (either 6 or 12 months) as discussed before, and Q_{out_t} is the monthly water demand at month *t*. If reservoir storage is not available, then a reservoir model is needed to estimate the storage based on the inflow and outflow (demand).

For convenience and easy cross comparison, the two indicators are standardized using the standard normal distribution. First, the marginal probabilities of both indicators (water storage resilience and inflow-demand reliability) are calculated [*Gringorten*, 1963].

$$P(x_t) = \frac{I - 0.44}{N + 0.12} \tag{6}$$

where *N* is the sample size, *I* denotes the rank of nonzero indicator (α or β) data from the smallest to largest, and $P(x_t)$ is the corresponding empirical probability at month *t*. The empirical probabilities are then transformed into a standardized index (*SI*) as

$$SI(x) = \varphi^{-1}(P(x)) \tag{7}$$

$$SI(P(x)) = \begin{cases} \text{if } \; 0 < P(x) \le 0.5, & +\left(k - \dfrac{C_0 + C_1 k + C_2 k^2}{1 + d_1 k + d_2 k^2 + d_3 k^3}\right) \text{ and } k = \sqrt{\ln\left({}^{1}/_{\mathrm{P(x)}^2}\right)} \\ \text{if } \; 0.5 < P(x) \le 1, & -\left(k - \dfrac{C_0 + C_1 k + C_2 k^2}{1 + d_1 k + d_2 k^2 + d_3 k^3}\right) \text{ and } k = \sqrt{\ln\left[{}^{1}/_{(1-\mathrm{P(x)})^2}\right]} \end{cases} \tag{8}$$

where φ is the standard normal distribution function and *P*(*x*) is the empirical probability. One can also standardize the empirical probability values by a commonly used approximation (equation (8)), in which $C_0 = 2.515517$, $C_1 = 0.802583$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$ [*Abramowitz and Stegun*, 1965; *Naresh Kumar et al.*, 2009; *Edwards*, 1997; *Farahmand et al.*, 2015]. Substituting α and β with *x* from equations (6) to (8) leads to standardized indices for inflow-demand and water storage resilience (hereafter $SI(\alpha)$ and $SI(\beta)$). The two univariate indicators are then combined using a multivariate framework [*Yue et al.*, 1999; *Hao and AghaKouchak*, 2014; *Hao and Singh*, 2015]

$$P_{j_t} = \Pr(SI(\alpha) \le SI(\alpha_t),\; SI(\beta) \le SI(\beta_t)) \tag{9}$$

where P_{jt} is the joint (multivariate) empirical probability at month *t*, calculated using the two indices: inflow-demand reliability index $SI(\alpha_t)$ and water storage resilience index $SI(\beta_t)$. Having the two univariate indicators, the joint empirical probability can be derived using the multivariate model of the Gringorten plotting position introduced by *Yue et al*. [1999]:

$$P_{j_t}(SI(\alpha_t), SI(\beta_t)) = \frac{I - 0.44}{N + 0.12} \tag{10}$$

where *I* is the number of occurrences of the pair ($SI(\alpha_t)$, $SI(\beta_t)$) for $SI(\alpha) \le SI(\alpha_t)$ and $SI(\beta) \le SI(\beta_t)$, and *N* is the sample size. We define the Multivariate Standardized Reliability and Resilience Index (MSRRI) by standardizing the joint distribution function of the inflow-demand reliability index and water storage resilience index [*Hao and AghaKouchak*, 2014]:

$$\mathrm{MSRRI} = \varphi^{-1}\left(P_j\right) \tag{11}$$

where the joint empirical probability P_j can be standardized using equation (8). The final index (MSRRI) is not only a hybrid index (consisting of two fundamentally different indicators) but also covers both common approaches in vulnerability studies (top-down and bottom-up). MSRRI can be considered as a measure of socioeconomic drought since it evaluates the supply and storage relative to the demand. Similar to other standardized drought indicators, positive values indicate sufficient water to satisfy demand, while negative values indicate shortage of water relative to the demand. Here the standardization is based on a nonparametric approach that does not require parameter estimation or any a priori assumption on the underlying distribution function of the original data [*Farahmand and AghaKouchak*, 2015; *Hao et al.*, 2014]. The values of MSRRI and the corresponding socioeconomic drought severity can be interpreted similar to the commonly available drought indicators such as the Standardized Precipitation Index (SPI) [*McKee et al.*, 1993]—i.e., a negative value indicates socioeconomic drought, while a positive value represents a wet period. Figure 2 summarizes the steps for deriving MSRRI based on the two univariate indicators. It is worth pointing out that for socioeconomic drought monitoring, MSRRI does not require projections of the water supply. The model only requires projected demand which can be estimated from historical data (typically, the latest demand information for the target season).

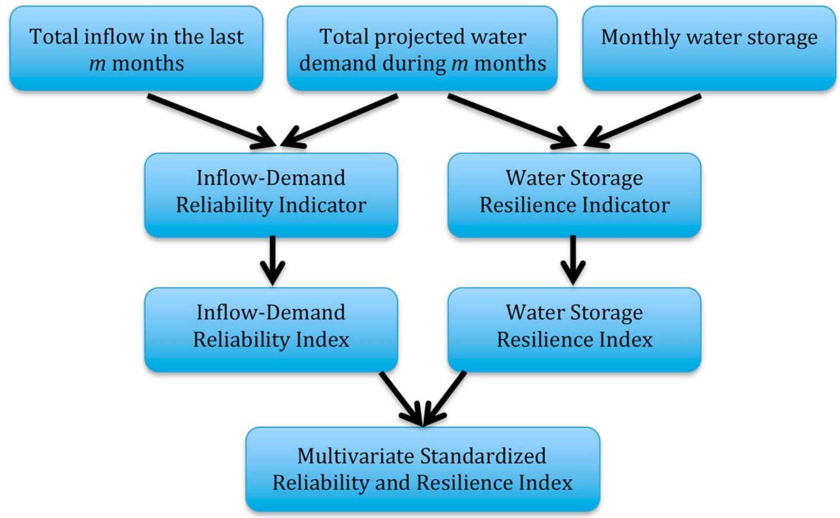

Figure 2. Components of the Multivariate Standardized Reliability and Resilience Index (MSRRI).

4. Results and Discussion

In the following section, the proposed indicators have been applied to case studies in Melbourne, Australia, and California, U.S. The presented method can be used for a group of reservoirs (Figure 3) that serves a region or an individual reservoir (Figures 4–6). First, an example application is provided for Melbourne major reservoirs (Thomson, Maroondah, O'Shannassy, and Upper Yarra reservoirs) that provide 80% of Melbourne's water demand. This reservoir system is categorized as an over-year system as they take more than 1 year to fill. Therefore, the time frame for this system is defined as 12 months. Melbourne's freshwater supply mostly depends on surface runoff, so substantially below average precipitation and inflow could lead to water scarcity in the region [*Grant et al.*, 2013].

Figure 3 displays the water storage resilience (WSR) and inflow-demand reliability (IDR) indicators as well as MSRRI. As shown, the IDR and WSR indicators behave differently in trend and severity providing information on climatic and reservoir conditions, respectively. The differences between IDR and WSR can explain the differences between meteorological and local reservoir conditions (both relative to the demand). For example,

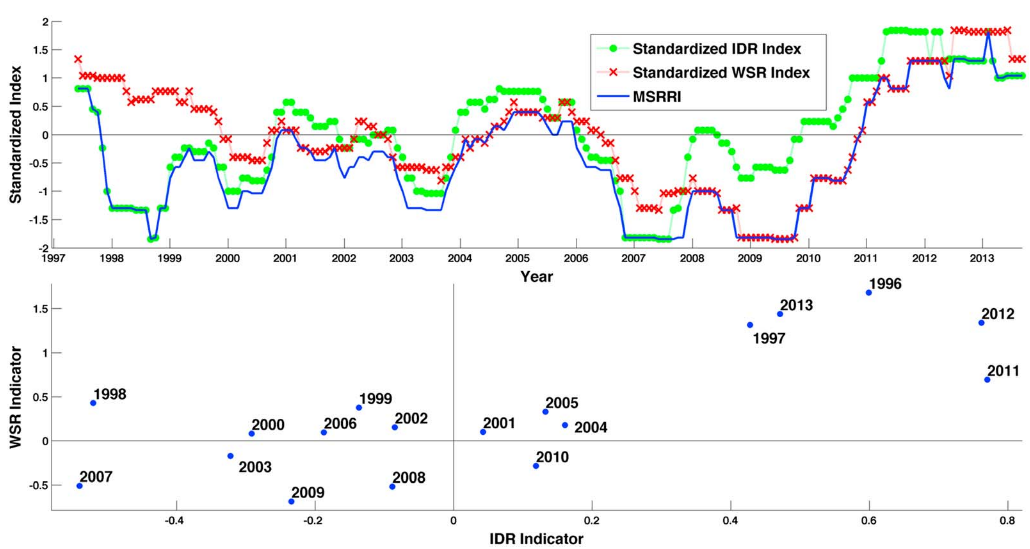

Figure 3. Melbourne's major reservoirs; (top) Standardized Water Storage Resilience (WSR) Index, inflow-demand reliability (IRD) index, and Multivariate Standardized Resilience and Reliability Index (MSRRI); (bottom) annual Water Storage Resilience indicator versus annual inflow-demand reliability indicator.

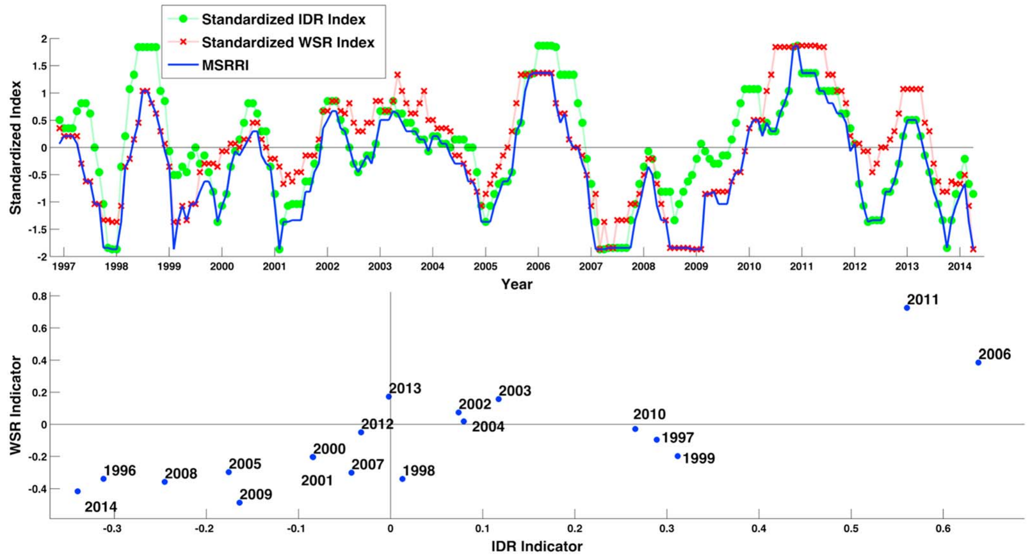

Figure 4. Shasta Lake; (top) Standardized Water Storage Resilience (WSR) Index, inflow-demand reliability (IRD) index, and Multivariate Standardized Resilience and Reliability Index (MSRRI); (bottom) annual Water Storage Resilience indicator versus annual inflow-demand reliability indicator.

IDR < 0 and WSR > 0 indicate onset of a low-inflow condition (i.e., hydrologic drought [*Van Loon*, 2015; *Prudhomme et al*., 2014]) based on input relative to demand (IDR < 0), while there is sufficient storage to satisfy the demand (WSR > 0). This corresponds to a situation whereby the hydrologic conditions indicate onset of a drought; however, the demand can still be satisfied with the available storage (i.e., hydrologic drought has not led to a socioeconomic drought). On the other hand, IDR > 0 and WSR < 0 indicate above average inflow relative to demand (IDR > 0), while storage is still below average and cannot satisfy the demand (WSR < 0). This means that there is apparent hydrologic drought based on input to reservoirs, while the system is suffering from a socioeconomic drought since the available storage cannot satisfy the demand. MSRRI combines these two indicators and provides information on the overall condition of the system. This

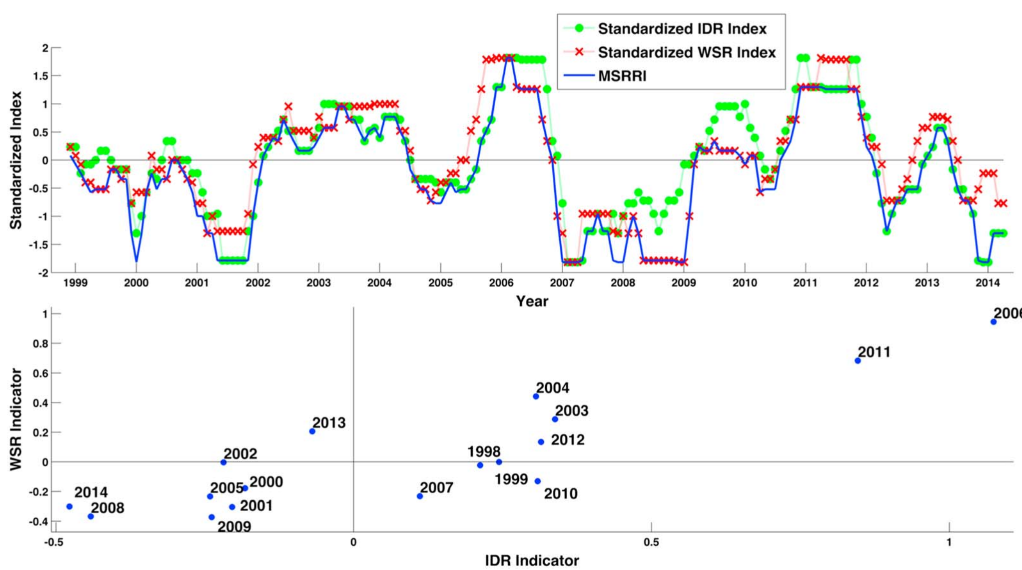

Figure 5. Lake Oroville; (top) Standardized Water Storage Resilience (WSR) Index, inflow-demand reliability (IRD) index, and Multivariate Standardized Resilience and Reliability Index (MSRRI); (bottom) annual Water Storage Resilience indicator versus annual inflow-demand reliability indicator.

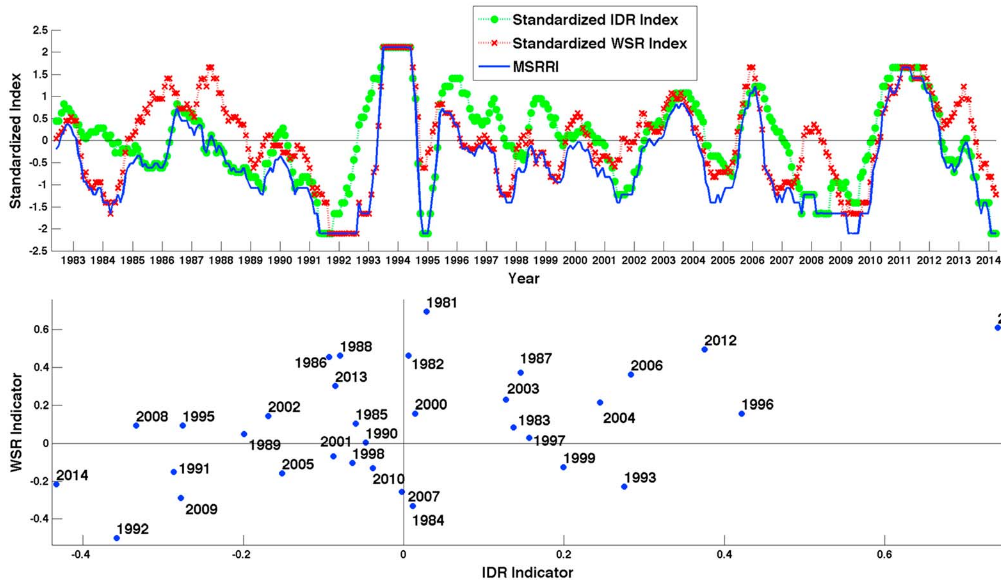

Figure 6. Trinity Lake; (top) Standardized Water Storage Resilience (WSR) Index, inflow-demand reliability (IRD) index, and Multivariate Standardized Resilience and Reliability Index (MSRRI); (bottom) annual Water Storage Resilience indicator versus annual inflow-demand reliability indicator.

information is particularly important when describing the onset and recovery from a socioeconomic drought relative to inflow, storage, and demand.

Figure 3 (top) shows the three indices together for Melbourne's major reservoirs on a monthly scale. We focus on the Melbourne's Millennium drought [*Grant et al*., 2013; *Dijk et al*., 2013] which started in 1998 and lasted over a decade. As shown in Figure 3, IDR shows deficit starting 1998, while WSR slowly changes and shows a deficit in 2000. In other words, the input deficit starts in 1998; however, the water supply can satisfy the demand because of the storage until 2000. This indicates that a socioeconomic drought occurred around 2 years after the beginning of the hydrologic drought. The lag between the onset of a hydrologic and socioeconomic drought can be considered as the local resilience of the system. In Figure 3, IDR shows drought recovery at the end of 2009 based on inflow relative to demand, while WSR does not show a full recovery until 2011 when the reservoir storage has recovered (i.e., the socioeconomic drought in the region recovers around 2 years after the end of the hydrologic drought). Relying on a univariate index (either inflow-demand reliability or water storage resilience) cannot clearly reveal the severity of water stress. MSRRI detects the onset and persistence of the socioeconomic drought throughout the Millennium drought based on both IDR and WSR. In fact, given that MSRRI is based on the joint distribution of IDR and WSR, MSRRI indicates the onset of the stress based on the onset of the hydrologic drought (here IDR) and recovery of the system from a socioeconomic perspective (i.e., based on WSR). This behavior of MSRRI provides an assessment of the overall stress on the system including the system resilience.

In Figure 3 (bottom), the annual IDR indicator is plotted against WSR indicator. This figure shows four possible combinations of IDR and WSR: IDR $>$ 0 and WSR $>$ 0; IDR $<$ 0 and WSR $<$ 0; IDR $<$ 0 and WSR $>$ 0; and IDR $>$ 0 and WSR $<$ 0 (see Table 1). For example, a positive value WSR indicator and a negative value of IDR indicator imply that the water storage can satisfy the demand for the next time frame, while the inflow cannot (i.e., hydrologic drought not transformed into a socioeconomic drought). In other words, the climatic condition (top-down) is not favorable, but the local reservoirs (bottom-up) can satisfy the demand. Figure 3 (bottom) shows that in 1996 both of the indicators are positive (the top right corner of the plot), but they decrease and reach a record low in 2009, indicating significant water scarcity with respect to both inflow and storage. In 2009, the inflow and storage were not sufficient to satisfy the demand for another year. However, significant rainfall in 2010 improved the condition (IDR $>$ 0 showing hydrologic drought recovery), and the socioeconomic drought terminated by 2011 (i.e., the system fully recovered with respect to both inflow and storage).

As mentioned earlier, the presented method can also be applied to individual reservoirs. In the following, MSRRI is evaluated against univariate water stress indicators for Shasta Lake, Lake Oroville, and Trinity

Table 1. Four Categories of Reservoir Conditions Based on Inflow-Demand Reliability and Water Storage Resilience Indicators

Water Storage Resilience Indicator	Inflow-Demand Reliability Indicator	Water Storage Can Satisfy Demand	Inflow Can Satisfy Demand
Positive	Positive	Yes	Yes
Positive	Negative	Yes	No
Negative	Positive	No	Yes
Negative	Negative	No	No

Lake, which outflow to the Sacramento River, the Feather River, and the Trinity River, respectively. The time frames are 6 months for Shasta Lake and Lake Oroville and 12 months for Trinity Lake. California, like Melbourne, often experiences prolonged droughts and water stress due to its semiarid and variable climate and high population [*Gao et al*., 2012]. Nearly 41% of California's water demand is provided by surface runoff; therefore, reservoirs are very important for water management [*Stanton and Fitzgerald*, 2011]. California has been in a prolonged drought during 2012–2015 resulting in record low storage and significant water stress on the system [*Shukla et al*., 2015; *AghaKouchak et al*., 2014a, 2014b; *Cook et al*., 2015; *Griffin and Anchukaitis*, 2014; *Swain et al*., 2014; *Diffenbaugh et al*., 2015; *Mann and Gleick*, 2015; *Mao et al*.,2015].

Figures 4–6 display IDR, WSR, MSRRI, and WSR versus IDR for Shasta Lake, Lake Oroville, and Trinity Lake, respectively. Shasta Lake univariate and multivariate indicators, plotted in Figure 4, show that despite high inflows (IDR > 0) during 1997, 1998, 1999, and 2010 as compared to the other years, lack of sufficient storage resulted in WSR < 0. This is an example situation in which a typical drought indicator based on just climatic information would indicate drought but lack of sufficient storage results in a socioeconomic drought. In contrast, in 2013, although the water storage was sufficient to satisfy the total water demand, the net inflow to the reservoir was the main driver of water stress in the following year (compare IDR and WSR in Figure 4 (top) and see Figure 4 (bottom)). Given that MSRRI is based on the joint distribution function of IDR and WSR, it responds to changes in either or both of the indicators (i.e., supply and storage relative to the local demand). Figure 4 (top) shows that in 2004 MSRRI begins to decline much earlier than both IDR and WSR indicators, showing an earlier detection of a socioeconomic drought. According to the California Department of Water Resources data, in 2006 Shasta Lake had the highest volume of water storage. In contrast, it experienced the lowest volume of water storage in 2008 [*California Data Exchange Center-Reservoirs, California Department of Water Resources*, 2013]. As shown in Figure 4, MSRRI is consistent with Shasta Lake observations.

Analysis of Lake Oroville (Figure 5) reveals that during 2007 and 2010, the study area is net positive (wet condition) with respect to inflow relative to the demand. This means above average inflow and precipitation in the region. However, MSRRI indicates that with respect to storage, Lake Oroville has a deficit and the system has not recovered (i.e., hydrologic drought ended, but the socioeconomic drought continued). The storage recovers in 2011; however, between 2012 and 2013 the inflow relative to the demand (IDR) decreases. By the end of 2013, the storage is still sufficient to satisfy the demand. In 2014, with a record low IDR, significant stress is observed in WSR and MSRRI, leading to a record socioeconomic drought. A similar figure is provided for Trinity Lake from 1980 to 2013 (Figure 6). The dry and wet signals based on MSRRI, precipitation and reservoir storage data from the California Department of Water Resources [*California Data Exchange Center-Reservoirs, California Department of Water Resources*, 2013], are consistent (not shown here for brevity). For example, the three reservoirs show positive MSRRI values in 2006, which is consistent with the observed above average precipitation (see Figure 7a) and Palmer Drought Severity Index (PDSI) [*Palmer*, 1965] (Figure 7f). Also, the three reservoirs show that the inflow and reservoir conditions were above average in 2011 (see Figures 7b and 7g). However, 3 years of consecutive dry conditions (see Figures 7c–7e and 7h–7j) led to critical conditions in 2014 (i.e., record low IDR and near record low WSR).

When assessing socioeconomic droughts, all sectors that require water should be considered. In the above example, demand includes not only the human and industrial needs but also environmental water demand. The demand information used in this study was specifically reservoir demand and did not include the demand met with groundwater. If the demand on a reservoir is not known and only the overall demand of a basin is available, groundwater can be addressed in two different ways: (a) the portion of the overall demand satisfied with groundwater can be removed from the demand used as input to MSRRI and (b) if the recharge (inflow), groundwater storage, and groundwater demand are known, MSRRI can also be derived for a groundwater basin

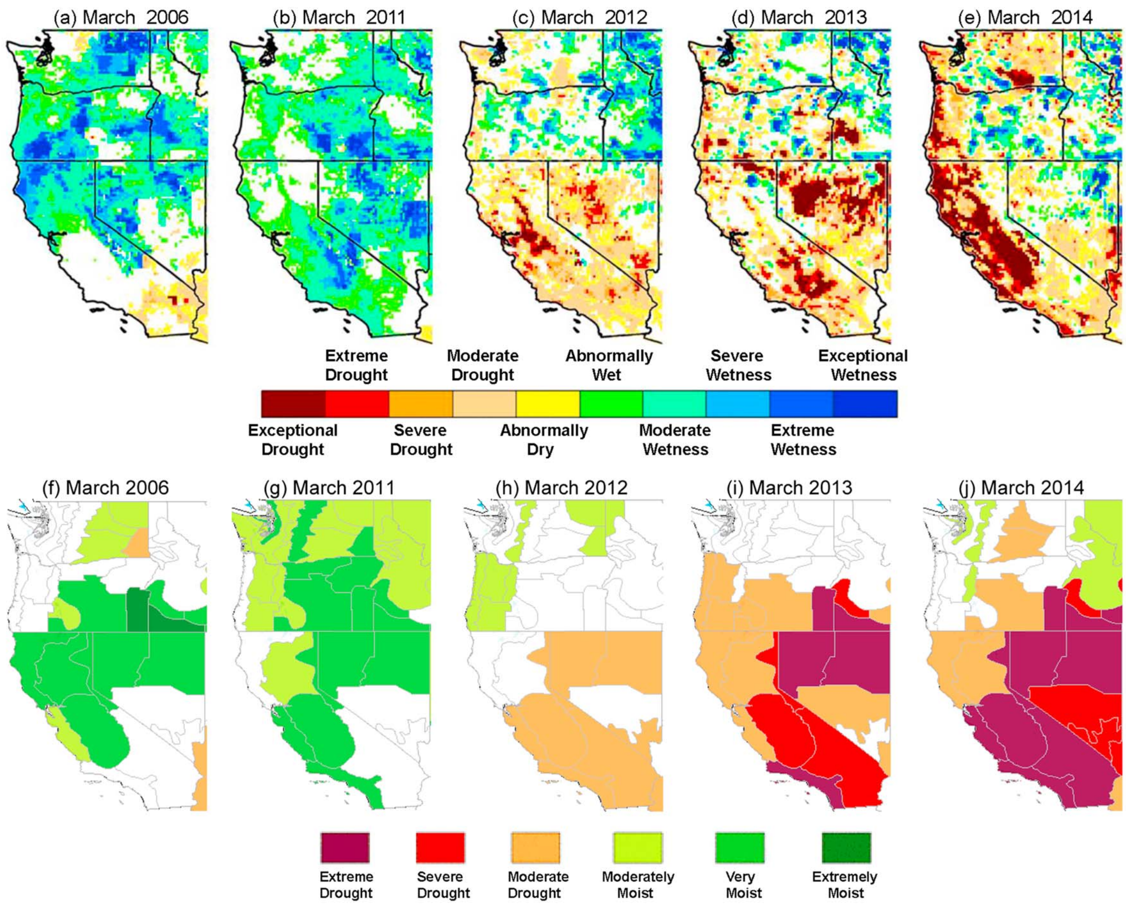

Figure 7. Dry and wet conditions in March 2006, 2011, 2012, 2013, and 2014 based on 6 month Standardized Precipitation Index (SPI) and the Palmer Drought Severity Index (PDSI). SPI data are obtained from the Global Integrated Drought Monitoring and Prediction System (GIDMaPS; http://drought.eng.uci.edu/). PDSI information is retrieved from the National Climatic Data Center (http://www.ncdc.noaa.gov/).

similar to a surface water reservoir. It is worth pointing out that in snow-dominated regions such as in California [*Bales et al*., 2006], snowmelt should be considered in estimating MSRRI. In California, for example, snowmelt is the main source of surface water in the dry season. For this reason, in this study, MSRRI is estimated based on inflow and reservoir storage that includes snow information. In general, because of seasonality in precipitation and snowmelt timing, etc., MSRRI may be more informative in a certain period of the year than other periods. Therefore, MSRRI should not be considered as the only source of information. Instead, it should be evaluated along with other water stress indicators to ensure comprehensive understanding of water availability and stress.

For drought monitoring, MSRRI does not require projections of the water supply; it only relies on observed inflow, water storage, and estimated short-term demand. However, if projections of inflow are available, MSRRI can be computed for future conditions. Applying MSRRI to future inflow (e.g., estimated from climate model simulations) requires using a reservoir model to estimate the storage levels corresponding to different inflow and demand scenarios.

MSRRI can be used not only for monitoring socioeconomic drought but also for addressing specific research questions. Having two of the main three MSRRI inputs (inflow, storage, and demand), one can use scenario analysis to answer questions such as the following: What inflow is required to recover from a socioeconomic drought given a certain storage and downstream demand? What is the likelihood of recovering from a certain observed socioeconomic drought (i.e., what is the likelihood of an inflow that leads to drought recovery based on MSRRI)? How much of the demand should be reduced to cope with an ongoing drought? The latter, for example, can be evaluated by computing MSRRI based on observed inflow and storage but with different water conservation scenarios (i.e., assessing the effects of 5%, 10%, or 25% reduction in water demand in severity of the socioeconomic drought).

5. Conclusion

A wide variety of indicators have been developed to describe droughts based on different perspectives. Socioeconomic drought, defined as conditions whereby the water supply is not sufficient to satisfy the local demand, is the least investigated type of drought. Most available indicators ignore the local water demand as well as the local reservoirs designed to cope with climatic extremes. Performance indices such as resilience, reliability, and vulnerability have been used for quantifying the complex interplay of climate variability and water availability. These indices help understanding water stress based on different factors, including large-scale meteorological and climatic conditions (top-down) representing climate variability and change. Furthermore, there are indicators that can describe local resilience of the water resources system (bottom-up) to cope with variability and extreme conditions (i.e., considering the effect of reservoirs). These indicators are often used separately and do not provide a comprehensive assessment of socioeconomic drought. In this paper, a model is suggested as a measure of socioeconomic drought that integrates both top-down and bottom-up approaches for assessing water stress due to both climatic conditions and local reservoir levels. The suggested model considers both large-scale variability and the local capacity for coping with extremes.

The indicator representing a top-down approach is termed inflow-demand reliability (IDR) indicator. The indicator describing the system resilience is named water storage resilience (WSR) indicator. Both indicators are described relative to the average demand to consider the human dimension of the socioeconomic droughts. The hybrid framework that combines the top-down and bottom-up concepts is termed the Multivariate Standardized Reliability and Resilience Index (MSRRI). This model offers a unique approach for describing socioeconomic drought by describing the overall water stress relative to the local demand and the capacity to cope with extremes.

In this study, MSRRI and individual univariate indicators (IDR and WSR) are used to assess water stress in Melbourne, Australia, and California, U.S. The results show that MSRRI is superior to univariate indices because it captures both early onset and persistence of socioeconomic drought over time. Furthermore, MSRRI shows whether a hydrologic drought turns into a socioeconomic drought. MSRRI provides information on not only inflow deficit (i.e., hydrologic drought) but also how long it takes to recover from a socioeconomic drought based on both inflow and reservoir levels. A positive value of MSRRI indicates that the demand can be satisfied during the time frame of analysis, regardless of the inflow conditions. Example applications of MSRRI for several extreme wet and dry conditions are provided including the Australian Millennium drought (1998–2010) and the 2014 California drought.

One interesting feature of MSRRI is that it is standardized similar to the currently available standardized drought indicators such as the Standardized Precipitation Index (SPI) [*McKee et al.*, 1993]. This means that values of MSRRI can be compared with the commonly used drought indicators. Current drought indicators do not consider the local water demand and the capacity to cope with dry conditions. MSRRI, on the other hand, can provide complementary information that cannot be achieved from the commonly used drought indicators such as SPI.

It is stressed that drought assessment should be based on a wide variety of information, as well as drought indicators. MSRRI provides unique information about socioeconomic drought; however, it should not be used as the only source of information. Ideally, MSRRI should be used along with other drought indicators to ensure a thorough understanding of the cause of water stress (e.g., hydrologic drought, high demand, or low storage or a combination of the water stress drivers). Finally, MSRRI can be used for evaluating different demand scenarios on the overall socioeconomic drought. Having a certain projected demand (e.g., average 6 month drought based on historical data), by using MSRRI, one can assess the impacts of water conservations (e.g., 25% reduction in the demand) on the overall socioeconomic drought by changing the projected demand in the model.

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