Socioeconomic Drought Under Growing Population and Changing Climate: A New Index Considering the Resilience of a Regional Water Resources System

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Abstract Socioeconomic drought occurs when water supply from a regional water resources system cannot meet the water demands. Even if a socioeconomic drought ends, the antecedent water deficit may continue to have impacts for some time, thus influencing the resilience of a regional water resources system. To take this into account, especially under growing population and changing climate, this study develops a new method through integrating a new index, Water Resources System Resilience Index (WRSRI), into socioeconomic drought event identification. The new index represents the percentage of the antecedent water deficit for a socioeconomic drought that can be recovered from the excess water during subsequent periods through analyzing records of a historical drought event. The methodology, implemented on the East River Basin in South China, involves three major steps: (1) calculation of WRSRI value; (2) analysis of key features of identified future socioeconomic drought events, that is, total number, longest duration (LD), and percentage on different drought levels; and (3) sensitivity analysis of WRSRI based on a total of 52 streamflow data sets generated from General Circulation Model outputs and using a macroscale hydrologic model. The results indicate that, for each data set, the total number decreases with an increase in WRSRI but the LD increases; moreover, for most data sets, the LD is less sensitive within the WRSRI range of [0, 0.6]. The outcomes of this study can enhance our capability in more effectively assessing the resilience of a regional water resources system, especially under changing future socioeconomic and environmental conditions.

1. Introduction

In recent years, socioeconomic drought has been attracting significant attention among hydrologists, water managers, social scientists, and economists, among others (Eklund & Seaquist, 2015; Guo et al., 2019a, 2019b; Huang et al., 2016; Liu et al., 2020; Mehran et al., 2015; Shi et al., 2018; Tu et al., 2018). Normally, a socioeconomic drought event, which is associated with the minimum in-stream water requirement (MIWR) against water supply, is considered to occur if the water supply from a regional water resources system cannot meet the water demand of the society (Shi et al., 2018). Similar to the other categories of drought (i.e., meteorological, agricultural, and hydrological) (American Meteorological Society, 2013), the major properties of socioeconomic drought, including duration, severity, and intensity, need to be identified (see Figure 1) (Mishra & Singh, 2010). For a given river basin, the MIWR value can be determined through combining the required water resources for water quality, ecology, navigation, water intake, and so on (Shi et al., 2018; Wu & Chen, 2013). Since streamflow is the main source of water supply in most river basins, with the use of the MIWR value as the threshold, it can be considered that water deficit (i.e., the negative values below the x axis in Figure 1) will occur if the streamflow at the control station of a river basin during a certain period (i.e., Δt in Figure 1) is less than the MIWR value during the same period. In contrast, if the streamflow is larger than the MIWR value, there will be excess water (i.e., the positive values above the x axis in Figure 1) during that period. This excess water will be the key to the recovery of the antecedent water deficit. In general, the moment when the difference between the streamflow and the MIWR value changes from positive to negative (i.e., t in Figure 1) is regarded as the start of a socioeconomic drought event, while the moment when the difference changes from negative to positive (i.e., t in Figure 1) is regarded as the...
end of this event (Mishra & Singh, 2010; Tu et al., 2018). However, even if a socioeconomic drought event ends, the antecedent water deficit may still result in continued negative impacts on a regional water resources system, including in terms of hydrology, ecology, and economy (Borgomeo et al., 2015; Exposito & Bethel, 2017; Kim & Kaluarachchi, 2016; Thomas et al., 2014; You & Cai, 2008a, 2008b). Therefore, the impact of a socioeconomic drought event will probably be underestimated without consideration of the recovery of the antecedent water deficit from the excess water during the subsequent periods.

In a recent study, Shi et al. (2018) proposed an index, namely, the SocioEconomic Drought Index (SEDI), for identifying a socioeconomic drought event, considering that a socioeconomic drought event would not end until all the antecedent water deficit has been recovered from the excess water during the subsequent periods. Such an index, however, may probably overestimate the impact of a socioeconomic drought event, since the reality is that a part of the antecedent water deficit cannot be recovered while another part of it does not need to be recovered. For example, it is impossible to make up for the shortage in industrial and domestic water that has already occurred, as the water consumption policy would be adjusted during the drought periods (Piao et al., 2010; Shao et al., 2009); in addition, the limits of water for planting during the drought periods would not significantly affect the growth of plants due to their physiological changes (Ingram & Bartels, 1996). However, not all the water deficit can be overcome by policy and self-adjustment. If and when policy and self-adjustment do not work to make up for all the water deficit, other water resources (e.g., groundwater) can usually be used. It is worth noting that this part of water can be recharged when there is additional surface water after all the human and ecological water demands are met in subsequent periods following the drought events (Boisson et al., 2014; Khepar et al., 2000; Paradis et al., 2020; Voisin et al., 2018). Since some of the antecedent water deficit cannot be recovered (e.g., water for hydropower) or does not need to be recovered (e.g., water restrictions for industrial or domestic consumption during the drought periods), only a certain percentage of the antecedent water deficit can be, and need be, recovered from the subsequent excess water. However, for a water resources system to be perfectly sustainable, it is necessary to seek harmony with the resources under different changing scenarios (e.g., population growth and climate change) (Garrote et al., 2007; Shao et al., 2009). It is also important to note that the resilience of water resources systems (belonging to repairable systems) has the specific definition as “the recovery capacity of repairable systems from the failure state to the safe state” (Li & Lence, 2007a; UNESCO/IHP, 1999). In this context, drought, which is normally regarded as one of the main reasons to cause the failure of a water resources system, may largely influence the resilience of a water resources system. Using the recoverable part of water deficit to quantify the resilience of a regional water resources system aids in better describing the transition of state (from failure to safe) of a water resources system. This issue is addressed in the present study.

Studying the resilience of a regional water resources system for socioeconomic droughts is likely to gain more significance in the future because of both population growth and climate change (Mehran et al., 2015). The United Nations (2012) reported that the global population would reach about 9.5 billion (under the medium projection scenario) by 2050. With population growth, projections by OECD (2012) indicate that the global water demand will increase by 55% between 2000 and 2050. It has also been reported that population growth, rather than climate change, would be the dominant factor determining the number of people...
likely to be directly exposed to human-induced droughts in the next few decades (Smirnov et al., 2016). Similar results can be found in the study of Chen et al. (2018), which showed that demographic change would be the primary contributor to population exposure to droughts (79.95%) during 2020–2039 in China, compared to climate change (29.93%) or the interaction between climate change and population growth (−9.88%). Therefore, controlling the rapid growth of population would be imperative for mitigating future drought risk (Ahmadalipour et al., 2019).

However, the impacts of climate change on future socioeconomic droughts cannot be ignored either (AghaKouchak et al., 2014; Ahn et al., 2016; Shi et al., 2018; Tietjen et al., 2017; Wang et al., 2018). The Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC, 2013) reported that the average global land and ocean surface temperature experienced a fast warming of 0.12°C/decade during 1951–2012. With this rise in temperature, corresponding changes in precipitation and evapotranspiration can cause changes in stream flow, which can lead to more stress on water supply and more frequent socioeconomic drought events (Mehran et al., 2015; Shi et al., 2017; Tsanis & Tapoglou, 2019; Vicuna et al., 2013; Zhou et al., 2020a, 2020b). Based on data from 190 countries all over the world, Smirnov et al. (2016) pointed out that 68% of the selected countries would experience an increase in drought exposure primarily due to climate change, compared to 12% primarily due to population growth and 20% primarily due to the interaction effect. For China in particular, considering two warming scenarios of 1.5°C and 2.0°C above the preindustrial level, the difference in economic loss caused by drought disasters may reach 100 billion Chinese Yuan (Su et al., 2018). Therefore, it is important and necessary to consider the impacts of both population growth and climate change on socioeconomic droughts to mitigate economic losses through investigating the recovery and adaptation capacity of a regional water resources system in the face of water shortage caused by socioeconomic droughts.

The present study develops a new method for assessing socioeconomic droughts under growing population and changing climate, considering the resilience of a regional water resources system. The new method is developed through proposing a new index, termed as the Water Resources System Resilience Index (WRSRI), and integrating the index into the socioeconomic drought event identification process. This new index represents the percentage of the antecedent water deficit for a socioeconomic drought that can be recovered from the excess water during the subsequent periods through analyzing the records of a historical drought event. The methodology involves three major steps: (1) calculation of the WRSRI value of the river basin; (2) analysis of the key features of the identified future socioeconomic drought events, that is, the total number (TN), the longest duration (LD), and the percentage on different drought levels (PDDL); and (3) sensitivity analysis of the WRSRI based on a total of 52 streamflow data sets generated from General Circulation Model (GCM) outputs and using a macroscale hydrologic model. In this study, a long-term water demand projection model considering both population growth and economic development (Chen et al., 2015) is used for future MIWR calculation. The Variable Infiltration Capacity (VIC) model (Liang et al., 1994) is used for future streamflow simulation. The SEDI (Shi et al., 2018) is used for future socioeconomic drought event identification. The methodology is implemented on the East River Basin (ERB) in South China as the study area. The outcomes of this study can provide new avenues to recognize the importance of the resilience of a regional water resources system in socioeconomic drought analysis, especially in the context of population growth and climate change.

### 2. Materials and Methods

Figure 2 presents the flowchart of the major steps involved in this study. First, a variety of data is collected for the study area, including the GCM outputs, socioeconomic data (population and gross domestic product [GDP] data), and historical streamflow data (see section 2.1 for details). Second, the MIWR for a given river basin, which is regarded as the threshold for identifying socioeconomic drought events, is calculated based on the historical data for the past and a water demand projection model for the future (see section 2.2 for details). Third, with the historical streamflow data and the future streamflow simulated using the VIC
model and the GCM outputs (see section 2.3 for details), socioeconomic drought events are identified using the SEDI proposed by Shi et al. (2018) (see section 2.4 for details). Moreover, the WRSRI is integrated into the process of identification of socioeconomic drought events to consider the resilience of a regional water resources system (see section 2.5 for details). Finally, a sensitivity analysis of WRSRI is conducted to assess the impacts of the resilience of a regional water resources system on the socioeconomic drought event identification (see section 2.6 for details).

2.1. Study Area and Data

The East River (see Figure 3) in China originates in the Jiangxi Province and serves a number of mega cities with high economic development in the country. It is an important tributary of the Pearl River, which is the second largest river in China in terms of river discharge. The basin area of the East River is about 27,040 km², and the length of the main stream is about 562 km (Shi et al., 2018; Zhang et al., 2015). The average annual discharge of the East River is about 23.8 km³, and the main water use in this river basin is focused on socioeconomic purposes (Zhang et al., 2013). Therefore, the East River plays a vital role in the sustainable development of one of the most rapidly developing regions of China (i.e., South China) by providing water resources for socioeconomic purposes. The largest reservoir in the ERB, that is, the Xin-fengjiang Reservoir (see Figure 3), was built during 1958–1962, with a drainage area of 5,740 km² and total storage capacity of 13.9 km³. Its main uses include flood control, water supply, and hydropower generation (Wu & Chen, 2013).

Table 1 lists all the different types of data used in this study. For simulation of streamflow, the projected data sets (including precipitation, maximum/minimum air temperature, and wind speed) under different climate change scenarios are used as the forcing meteorological data for running the VIC model. The outputs from 17 GCMs are collected, including 16 IPCC the Fourth Assessment Report (AR4) GCMs under three scenarios.

Table 1
Summary of Data Used in This Study

| Data                  | Description                                                                 |
|-----------------------|-----------------------------------------------------------------------------|
| IPCC AR4 GCMs         | Number | Data set | Modeling center/country     | Spatial resolution/period |
|                       | 1       | bcc_r_cm2_0.1 | Bjerknes Centre for Climate Research/Norway | 0.5° × 0.5°/1951–2099 |
|                       | 2       | ncar_ccsm3_0.1 | National Center for Atmospheric Research/United States | 0.5° × 0.5°/1951–2099 |
|                       | 3       | cccma_c_gcm3_1.1 | Canadian Center for Climate Modeling and Analysis/Canada | 0.5° × 0.5°/1951–2099 |
|                       | 4       | cnrm_cm3.1 | Centre National de Recherches Meteorologiques/France | 0.5° × 0.5°/1951–2099 |
|                       | 5       | csiro_mk3_0.1 | Commonwealth Scientific and Industrial Research Organization/Australia | 0.5° × 0.5°/1951–2099 |
|                       | 6       | mpi_echam5 | Max Planck Institute/Germany | 0.5° × 0.5°/1951–2099 |
|                       | 7       | miub_echo_g.1 | Meteorological Institute of the University of Bonn/Germany | 0.5° × 0.5°/1951–2099 |
|                       | 8       | gfdl_cm2.0.1 | Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric Administration/United States | 0.5° × 0.5°/1951–2099 |
|                       | 9       | gfdl_cm2.1.1 | Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric Administration/United States | 0.5° × 0.5°/1951–2099 |
|                       | 10      | giss_model_e_r.1/2 | National Aeronautics and Space Administration Goddard Institute for Space Sciences/United States | 0.5° × 0.5°/1951–2099 |
|                       | 11      | inmcm3_0.1 | Institute of Numerical Mathematics, Russian Academy of Science/Russia | 0.5° × 0.5°/1951–2099 |
|                       | 12      | ipsd_cm4.1 | Institut Pierre Simon Laplace/France | 0.5° × 0.5°/1951–2099 |
|                       | 13      | miro3_2_medres.1 | Center for Climate System Research and National Institute for Environmental Studies and Frontier Research Center for Global Change/Japan | 0.5° × 0.5°/1951–2099 |
|                       | 14      | mri_cgm2_2.2a1 | Meteorological Research Institute/Japan | 0.5° × 0.5°/1951–2099 |
|                       | 15      | ncar_pcm1.1a | NCAR/United States | 0.5° × 0.5°/1951–2099 |
|                       | 16      | ukmo_hadcm3.1 | Met Office/United Kingdom | 0.5° × 0.5°/1951–2099 |
| IPCC AR5 GCM Streamflow data | 17 | HadGEM2-ES | Met Office Hadley Centre/United Kingdom | 0.5° × 0.5°/2000–2099 |
| Socioeconomic data    | Observed at Boluo station: temporal resolution = monthly; period = 1954–1988 | 0.5° × 0.5°/2000–2099 |
|                       | Population data: temporal resolution = annual; period = 2000–2099 | 0.5° × 0.5°/2000–2099 |
|                       | GDP data: temporal resolution = annual; period = 2000–2018 | 0.5° × 0.5°/2000–2099 |

Figure 3. Map of the East River Basin, including the locations of the Boluo station and the Xin-fengjiang Reservoir.
and one IPCC AR5 GCM under four scenarios (i.e., Representative Concentration Pathway [RCP] 2.6/4.5/6.0/8.5) (IPCC, 2013); see Table 1 for the names of these 17 GCMs and some basic details. As a result, this study selects a total of 52 (=16 × 3 + 1 × 4) projected data sets for future streamflow simulation. In addition, the observed monthly streamflow data at the Boluo station (see Figure 3) during 1954–1988 are collected to identify the representative socioeconomic drought event during this period, the duration of which is used to determine the rational WRSRI value of the ERB (see section 3.1 for details); the socioeconomic data (population data during 2000–2099 and the GDP data during 2000–2018) in the ERB are collected to project the long-term water demand and calculate the MIWR value of the basin.

2.2. Calculation of MIWR

The MIWR value is regarded as the minimum water requirement for domestic and industrial consumption, navigation, water quality, and the maintenance of aquatic habitat (Wu & Chen, 2013). The MIWR value can be calculated as

\[ MIWR = \max\{Q_1, Q_2, Q_3, Q_4\} + Q_s \]  

(1)

where \( Q_1 \) is the required value for maintaining water quality, \( Q_2 \) is the required value for ecology, \( Q_3 \) is the required value for navigation, \( Q_4 \) is the required value for preventing seawater intrusion, and \( Q_s \) is the required value for water intake. Among these, the \( Q_1, Q_2, Q_3, \) and \( Q_4 \) values can usually be obtained from past assessments of annual water resources, while the \( Q_s \) value can be estimated using water demand projection models. In the present study, \( Q_s \) is estimated using a long-term water demand projection model, considering both population growth and economic development (see Chen et al., 2015, for details). This model selects population as the most important driving force and GDP as the indicator of classifying different levels of socioeconomic development for water demand projection. Five stages of water demand, which correspond to five levels of socioeconomic development and have their own features of water demand (Table 2), are identified from the GDP data; therefore, the equations for estimating the water demand in each stage will be different. For water demand components closely related to population (e.g., agricultural and domestic water demands), per capita water demand is projected, and the total water demand for these components is estimated as the product of the projected per capita water demand and population; for other water demand components (e.g., industrial water demand), the total water demand is directly projected without considering the influence of population. This model has been proved to be applicable to several regions, including Hong Kong, the United Kingdom, and the Pearl River basin (PRB) and the ERB in South China (Chen et al., 2015). Therefore, in this study, the MIWR value of the study area (i.e., the ERB in South China), which indicates the future water demand of the study area, is calculated with this model. The equations to calculate the different water demand components of the \( Q_s \) value of the ERB are listed in Table 3. It is worth noting that the stage of water demand of the ERB will turn to 5 from 4 around 2060 and, thus, the equations are different for the periods of 2015–2060 and 2061–2100.

Based on previous studies (Lee et al., 2007; PRBWRPB et al., 2000; Wu et al., 2001; Wu & Chen, 2013), the \( Q_1, Q_2, Q_3, \) and \( Q_4 \) values of the ERB are found to be 317, 230, 210, and 150 m³/s, respectively, and they are also assumed to be invariable over time (Shi et al., 2018), for use in Equation 1. Therefore, the maximum value among \( Q_1, Q_2, Q_3, \) and \( Q_4 \) is 317 m³/s. For the \( Q_s \) value, Shi et al. (2018) provided the future water demand in the ERB under three projection scenarios (i.e., high, medium, and low) and indicated that the \( Q_s \) value would vary between 150 and 176 m³/s under the medium projection scenario during 2020–2099. With these, the MIWR value of the ERB will vary between 467 (=317 + 150) and 493 (=317 + 176) m³/s during the same period, which is used as the threshold to identify future socioeconomic drought events. However, not considering the uncertainties may have an impact on the results.
2.3. Streamflow Simulation

In this study, the future streamflow under different climate change scenarios are simulated with the VIC model (Liang et al., 1994), which has been widely applied to numerous river basins around the world (Andreadis et al., 2005; Nijssen et al., 2001; Wang et al., 2012), including the ERB and PRB (Niu et al., 2014, 2017; Niu & Chen, 2010; Wang et al., 2019). The VIC model, a macroscale land surface hydrological model that can solve full water and energy balances, was originally developed by Liang et al. (1994) and further improved by Hamman et al. (2018). The VIC model shares several basic features with other land surface models that are commonly coupled to the GCMs. Moreover, routing of streamflow is performed separately from the land surface simulation using a separate model originally developed by Lohmann et al. (1996, 1998). It has been updated to be the RVIC streamflow routing model, which is used as a postprocessor with the VIC model.

The studies by Niu and Chen (2010) and Niu et al. (2014) indicated that the streamflow simulated with the VIC model were comparable to the observed streamflow data recorded at 10 hydrological stations over the PRB at the monthly scale. The Nash-Sutcliffe efficiency coefficients for most of the 10 hydrological stations were higher than 0.80, and the relative biases were generally within the range of ±0.25, which can satisfy the performance ratings suggested by Moriasi et al. (2007). Moreover, using the same parameters as that in these two studies, Shi et al. (2018) simulated the monthly streamflow for the period 1954–1988 over the ERB, a subbasin of the PRB. The comparison of the simulations against the observations recorded at the control station of the ERB (i.e., Boluo station) demonstrated that the simulation accuracy was satisfactory. Therefore, this study also directly uses the same parameters to run the VIC model for future streamflow simulation over the ERB at the monthly scale.

2.4. Identification of Socioeconomic Drought Event

In this study, the SEDI, proposed by Shi et al. (2018), is adopted for identification of the socioeconomic drought events over the ERB at the monthly scale. This index can consider both the water shortage level (WSL) and the drought duration level (DDL) of a socioeconomic drought event. Both the WSL and the DDL have four values, that is, 1, 2, 3, and 4.

For the WSL determination, reservoir storage percentage (RSP), which is a variable related to typical reservoir storage (usually equal to the effective storage capacity of a reservoir) in a given river basin (Denver Water, 2002), is used as an indicator to classify different levels (see Shi et al., 2018, for details):

1. WSL = 1 denotes a socioeconomic drought event with RSP ∈ [0, 40%);
2. WSL = 2 denotes a socioeconomic drought event with RSP ∈ [40%, 60%);
3. WSL = 3 denotes a socioeconomic drought event with RSP ∈ [60%, 80%); and
4. WSL = 4 denotes a socioeconomic drought event with RSP ∈ [80%, +∞).

For the DDL determination, a socioeconomic drought event at the quarterly (1–3 months), semiannual (4–6 months), annual (7–12 months), or longer (more than 1 year) scale is assigned the values of 1, 2, 3, and 4, respectively.

With these, SEDI is defined as the larger one of WSL and DDL. Therefore, SEDI also has four values, that is, 1, 2, 3, and 4, corresponding to the four levels of socioeconomic drought, that is, SEDI = 1 for low level,
SEDI = 2 for moderate level, SEDI = 3 for severe level, and SEDI = 4 for extreme level. As mentioned above, SEDI will overestimate the impact of a socioeconomic drought event, because it considers that all the antecedent water deficit must be recovered from the excess water during the subsequent periods, which is inconsistent with the actual situation. Therefore, in this study, WRSRI, which represents the percentage of the antecedent water deficit that can be recovered from the excess water during the subsequent periods, is integrated into the process of socioeconomic drought event identification to evaluate the resilience of a regional water resources system. This integration is described next.

2.5. Integration of WRSRI

As can be seen from Figure 1, severity of a socioeconomic drought event, which is one of the key properties of a socioeconomic drought event, can be directly described as the water shortage caused by a socioeconomic drought event (i.e., shadow in Figure 1). The present study assumes that only a certain percentage of the antecedent water deficit can be recovered from the excess water during the subsequent periods. To account for this, a new index, that is, WRSRI, is proposed to represent such a percentage and consider the resilience of a regional water resources system. Since the value of this percentage should be between 0 and 1, WRSRI has the value within the range of [0, 1]. Thus, when the difference between the streamflow and the MIWR value changes from negative to positive (i.e., $t_e$ in Figure 1), the recoverable part is calculated as the severity multiplied by WRSRI (e.g., shadow within the red triangle below the x axis in Figure 1). This part can be recovered when there is excess water (e.g., blank within the red triangle above the x axis in Figure 1) in the subsequent periods. It is worth noting that, if the recoverable part is not large (e.g., less than the excess water in the next period after $t_e$), it can be easily recovered in this period; otherwise, the excess water in the next few periods after $t_e$ will be needed. In this study, a socioeconomic drought event will not be considered to end until the moment when the recoverable part is totally recovered. Consequently, if water deficit occurs again before that moment, socioeconomic drought will continue.

For the sake of clarity and understanding, several terms involved in the process of the WRSRI integration are defined, including antecedent water deficit ($AWD$), difference between the streamflow and the MIWR value ($D$), and recoverable part ($RP$). Among these, $AWD$ and $D$ are both intermediate variables that can be easily acquired during the original process of socioeconomic drought event identification, while $RP$ is a newly generated variable during the process of WRSRI integration. Then, during the updated process of the socioeconomic drought event identification, the WRSRI integration is conducted as follows:

1. If $AWD_{t-1} \geq 0$ and $D_t \geq 0$, then
   \[ AWD_t = AWD_{t-1} + D_t \]  

2. If $AWD_{t-1} < 0$ and $D_t < 0$, then
   \[ AWD_t = AWD_{t-1} + D_t \]  

3. If $AWD_{t-1} \geq 0$ and $D_t < 0$, then
   \[ AWD_t = D_t \]  

4. If $AWD_{t-1} < 0$ and $D_t \geq 0$, then
   \[ RP_t = AWD_{t-1} \times WRSRI \]
   \[ AWD_t = RP_t + D_t \]  

where $AWD_t$ and $AWD_{t-1}$ denote the values of the antecedent water deficit in the current period $t$ and the previous period $t-1$, respectively; $D_t$ denotes the difference between the streamflow and the MIWR value in the current period $t$; and $RP_t$ denotes the recoverable part in the current period $t$.

The WRSRI can play a vital role in the fourth case above. For a given river basin, the WRSRI value should be relatively stable, because the basic features of a river basin are considered to be invariant (Shi et al., 2020).
Thus, the WRSRI value of a river basin can be calculated using the historical data. However, due to rapid urbanization (Shi & Chen, 2018) and some artificial measures (Khepar et al., 2000), the resilience of a regional water resources system may change. That is why it is necessary to conduct a sensitivity analysis of WRSRI.

2.6. Sensitivity Analysis of WRSRI

It is worth noting that WRSRI = 1 corresponds to the case that all the antecedent water deficit must be recovered during the process of socioeconomic drought event identification (Shi et al., 2018). In contrast, WRSRI = 0 is the case of identifying a socioeconomic drought event without considering the resilience of a regional water resources system (Mishra & Singh, 2010; Tu et al., 2018). Whether a change in WRSRI will have significant impacts on socioeconomic drought is worth studying, especially for the values close to the WRSRI value determined from the historical data. Therefore, a sensitivity analysis of WRSRI is performed in the present study, setting a value of 0.1 as the interval within the WRSRI range of [0, 1]. Several features of the identified socioeconomic drought events are discussed, including the TN, the LD, and the PDDL.

2.7. Indicator for Comparison Analysis

As mentioned earlier, the resilience of a water resources system has the specific definition as the recovery capacity of the water resources system from the failure state to the safe state (Li & Lence, 2007a).

Therefore, given a moment of time \( t_1 \) and a later moment of time \( t_2 \), the resilience of a regional water resources system can be defined as (Li & Lence, 2007a)

\[
Re(t_1, t_2) = \frac{P[g(t_2) \geq 0, g(t_1) < 0]}{P[g(t_1) < 0]} = \frac{P_\cap P_{\text{gt}1 \text{t}1}}{P_{\text{gt}1}} \tag{7}
\]

where \( Re(t_1, t_2) \) denotes the conditional probability that a given water resources system failure at \( t_1 \), it will recover at \( t_2 \); \( g(t_1) \) and \( g(t_2) \) denote the performance functions at \( t_1 \) and \( t_2 \), respectively; \( P[.] \) denotes the probability; \( P_{\text{gt}1} \) denotes the failure probability; and \( P_\cap \) denotes the intersection probability that a water resources system fails at \( t_1 \) and recovers at \( t_2 \).

Several methods have been developed for estimating \( P_\cap \) or its derivatives (Andrieu-Renaud et al., 2004; Li & Lence, 2007b). One of these methods uses sampling by calculating the number of failures and successes among a set of data series (Fowler et al., 2003; Kjeldsen & Rosbjerg, 2004). Therefore, \( Re(t_1) \) is estimated as

\[
Re(t_1) \approx \frac{N_{\text{gt}1 \text{t}1}}{N_f(t_1)} \tag{8}
\]

where \( N_f(t_1) \) denotes the number of failure realizations in the \( g(t_1) \) ensemble, while \( N_{\text{gt}1 \text{t}1} \) denotes the number of success realizations in the \( g(t_2) \) ensemble that evolve from the failure realizations in the \( g(t_1) \) ensemble.

Specifically, for the analysis of socioeconomic drought, the present study defines \( N_f(t_1) \) as the number of socioeconomic drought events with a duration of at least \( t_1 \) months and \( N_{\text{gt}1 \text{t}1} \) as the number of socioeconomic drought events with a duration of \( t_1 \) months that ends in the following month. For example, \( N_f(3) \) is the number of socioeconomic drought events with a duration of at least 3 months, while \( N_{\text{gt}1}(3, 4) \) is the number of socioeconomic drought events with a duration of only 3 months. As a result, for a given data set, if the LD of all the identified socioeconomic drought events is \( n \), then the resilience of a water resources system (Re) can be estimated as

\[
Re = \sum_{i=1}^{n} Re(t_i) \approx \frac{N_{\text{gt}1}(1, 2)}{N_f(1)} + \frac{N_{\text{gt}1}(2, 3)}{N_f(2)} + \ldots + \frac{N_{\text{gt}1}(n, n+1)}{N_f(n)} \tag{9}
\]

3. Results and Discussion

3.1. WRSRI Value of the ERB

In this study, the observed monthly streamflow data recorded during the period 1954–1988 at the Boluo station are considered. According to previous studies (Shi et al., 2018; Wu & Chen, 2013), the MIWR value of the
ERB during the period 1954–1988 was 467 m$^3$/s. Thus, the historical socioeconomic drought events can be identified based on this MIWR value. He and Chen (2014) reported that there was an extremely serious drought event in 1963, starting in September 1962 and ending in May 1963. Therefore, this event is used here to determine the WRSRI value of the ERB. Figure 4 shows the cumulative water differences of three cases at the monthly scale during the 1963 drought event. These cases are (1) WRSRI = 0 (i.e., the antecedent water deficit need not be recovered); (2) WRSRI = 1 (i.e., all the antecedent water deficit must be recovered); and (3) WRSRI = 0.58 (i.e., a certain percentage of the antecedent water deficit can be recovered). Since the maximum positive value is over 15, the y axis of Figure 4 is truncated at 1.0 in order to clearly present the curves below the zero value on the y axis. It is observed that the identified socioeconomic drought events in these three cases would start from the same month, that is, December 1962; however, their ends are quite different.

Since WRSRI = 1 denotes the case that all the antecedent water deficit must be recovered during the process of socioeconomic drought event identification, the identified socioeconomic drought event would last for the LD (i.e., 18 months) and end in May 1964 (i.e., the red dashed line in Figure 4). In contrast, WRSRI = 0 denotes the case that the antecedent water deficit need not be recovered during the process of socioeconomic drought event identification; therefore, the identified socioeconomic drought event would last for the shortest duration (i.e., 6 months) and end in May 1963 (i.e., the blue dashed line in Figure 4). As is clear, the durations of the identified socioeconomic drought events in both these cases do not match with the actual duration of the drought (i.e., around 9 months from September 1962 to May 1963) (He & Chen, 2014). Therefore, a rational WRSRI value should be determined to make the identified duration of the 1963 drought event to be consistent with the actual situation. To this end, the duration of the 1963 drought event is calculated for each WRSRI value within the range of [0, 1] with an interval of 0.01, using the method mentioned in section 2.5, until the calculated duration is found to be equal to the actual duration. Based on the results from such calculation, it is observed that the identified socioeconomic drought event would last for 9 months, starting in December 1962 and ending in August 1963, when WRSRI = 0.58 (i.e., the black solid line in Figure 4). Therefore, this study regards the WRSRI value of the ERB as 0.58, which is used for subsequent analysis.

3.2. Features of the Identified Future Socioeconomic Drought Events

In this study, future socioeconomic drought events during 2020–2099 are identified based on the following: the simulated monthly streamflow under the abovementioned 52 climate change scenarios, the MIWR value of the ERB (i.e., between 467 and 493 m$^3$/s), and the WRSRI value of the ERB (i.e., 0.58). Moreover, the results from the two special cases of WRSRI, that is, WRSRI values of 0 and 1, are used for comparison. Three representative features, that is, the TN, the LD, and the PDDL of all the identified future socioeconomic drought events, are selected for analysis.

3.2.1. TN

One of the key features in the assessment of the resilience of a regional water resources system is the TN of all the identified future socioeconomic drought events. Figure 5 presents the TN of future socioeconomic drought events for all the 52 streamflow data sets (i.e., corresponding to the 52 climate change scenarios) and for the three cases of WRSRI (=0, 0.58, and 1) considered in this study. The results for the A1B, A2, and B1 scenarios for the case of the 16 AR4 GCMs are presented in Figures 5a–5c, respectively, while the results for the single AR5 GCM for the four RCPs are presented in Figure 5d. Based on these results, the following two broad observations can be made: (1) The variations among the different data sets are basically consistent, that is, the data set with the larger TN when WRSRI = 0.58 normally has the larger TNs also when WRSRI = 0 and 1; and (2) for each data set, the TN in the case when WRSRI = 0.58 is larger than that in the case when WRSRI = 1 and smaller than that in the case when WRSRI = 0. The reason for the second observation is as follows: In the case when WRSRI = 0, there is no need to recover the antecedent water deficit; once the difference between the streamflow and the MIWR value changes from negative to positive in a month, it is regarded as the end of a socioeconomic drought event. This means that a large number of drought events with relatively shorter durations might be identified. Along with an increase in WRSRI,
more water is needed to recover the antecedent water deficit, and the streamflow beyond the MIWR value (but with relatively smaller magnitude) would not be able to provide enough water to end a drought event that already occurred. In such a case, the adjacent drought events with relatively shorter durations that are identified in the case when WRSRI is lower may be pooled to be new drought events with relatively longer durations, leading to a decrease in the TN. It is also worth noting that several previous studies (Madsen & Rosbjerg, 1995; Tu et al., 2018; Zelenhasic & Salvai, 1987; Zhang et al., 2013) have considered the criterion for pooling mutually dependent drought events even when WRSRI = 0, suggesting a critical duration (i.e., 6 months) and a critical ratio between the excess volume during interevent time and the antecedent deficit volume (i.e., 0.3). Since quarterly (1–3 months) and semiannual (4–6 months) drought events are also identified in the present study, the above critical duration (of 6 months) is not applicable here. Nevertheless, the results of the TN considering the above criterion, that is, WRSRI = 0 (pooled), are also shown in Figure 5. It is observed that, for each data set, the TN considering this criterion is normally smaller than that in any of the three WRSRI cases (i.e., WRSRI = 0, 0.58, and 1).

With reference to the specific numbers, the TNs identified from the 16 AR4 GCMs are overall larger than those identified from the single AR5 GCM for the same case. This is mainly due to the fact that different data sets may yield different performances on drought assessment; the AR5 GCMs are found to provide more optimistic estimation on future drought situation than the AR4 GCMs (Shi et al., 2018). For the 16 AR4 GCMs under three scenarios (i.e., SRES A1B/A2/B1), the variations in the TNs are fairly similar (see Figures 5a to 5c). For example, when WRSRI = 0.58, the TNs vary within the ranges of 100–128 (SRES A1B), 102–130 (SRES A2), and 103–129 (SRES B1), and the mean values of the TNs are 115 (SRES A1B), 116 (SRES A2), and 116 (SRES B1). For the single AR5 GCM under four scenarios (i.e., RCP 2.6/4.5/6.0/8.5) in the case

Figure 5. Total numbers of the identified socioeconomic drought events for 16 AR4 GCMs under (a) A1B (b) A2 (c) B1 scenarios and (d) 1 AR5 GCM in the three WRSRI cases (i.e., WRSRI = 0, 0.58, and 1) in the ERB.
when WRSRI = 0.58, the TNs are 102 (RCP 2.6), 97 (RCP 4.5), 103 (RCP 6.0), and 96 (RCP 8.5), which are much smaller than the mean values obtained above for the 16 AR4 GCMs. The observations made for the other two cases of WRSRI, that is, when WRSRI = 0 and 1, are more or less consistent with those made when WRSRI = 0.58.

3.2.2. LD

Another key feature in assessing the resilience of a regional water resources system is the LD of all the identified future socioeconomic drought events. Figure 6 presents the LD results of future socioeconomic drought events for all the 52 streamflow data sets and for the three cases of WRSRI considered in this study. Unlike the TNs, the LDs vary greatly among the different data sets; however, for each data set, the LD in the case when WRSRI = 0.58 is larger than that in the case when WRSRI = 0 and smaller than that in the case when WRSRI = 1. The reason for this is deduced from the explanation presented earlier (section 3.2.1); that is, along with an increase in WRSRI, the new drought events pooled from adjacent drought events with relatively shorter durations identified in the case when WRSRI is lower should have longer durations. Specifically, for a given new drought event, its duration is equal to the sum of the durations of the adjacent drought events and the interval between the adjacent drought events (Tu et al., 2018). Moreover, the results of the LD considering the criterion WRSRI = 0 (pooled) are also shown in Figure 6. It is observed that, for each data set, the LD considering this criterion is normally comparable to that in the case when WRSRI = 0.58.

With reference to the specific numbers, the LDs identified from the 16 AR4 GCMs are generally larger than those identified from the single AR5 GCM for the same case. Further, for the 16 AR4 GCMs under the three scenarios (i.e., SRES A1B/A2/B1), the variations in the LDs are nearly the same. For example, when

Figure 6. Longest durations of the identified socioeconomic drought events for 16 AR4 GCMs under (a) A1B (b) A2 (c) B1 scenarios and (d) 1 AR5 GCM in the three WRSRI cases (i.e., WRSRI = 0, 0.58, and 1) in the ERB. Note: The dashed lines denote the mean values in the case when WRSRI = 0.58.
WRSRI = 0.58, the LDs vary within the ranges of 11–33 (SRES A1B), 10–32 (SRES A2), and 11–33 (SRES B1), and the mean values of the LDs are 21 (SRES A1B), 23 (SRES A2), and 21 (SRES B1). For the AR5 GCM under the four scenarios (i.e., RCP 2.6/4.5/6.0/8.5) in the case when WRSRI = 0.58, the LDs are 11 (RCP 2.6), 10 (RCP 4.5), 11 (RCP 6.0), and 10 (RCP 8.5), which are much smaller than the mean values obtained for the 16 AR4 GCMs under the three scenarios. Moreover, the observations made for the other two cases of WRSRI, that is, when WRSRI = 0 and 1, are more or less consistent with those when WRSRI = 0.58. In addition, for a majority of the data sets (i.e., 31 out of 52 or about 60%), the differences between the LDs in the cases when WRSRI = 1 and 0.58 are larger than the differences between the LDs in the cases when WRSRI = 0.58 and 0, indicating that the LD of the identified socioeconomic drought events is less sensitive when WRSRI is below 0.58 (see section 3.3 for further details).

3.2.3. PDDL

Figure 7 presents the percentages of the identified future socioeconomic drought events on different drought levels for 16 AR4 GCMs under (a) A1B (b) A2 (c) B1 scenarios and (d) 1 AR5 GCM when WRSRI = 0.58 in the ERB.

Figure 7. Percentages of the identified future socioeconomic drought events on different drought levels for 16 AR4 GCMs under (a) A1B (b) A2 (c) B1 scenarios and (d) 1 AR5 GCM when WRSRI = 0.58 in the ERB.

WRSRI = 0.58, the LDs vary within the ranges of 11–33 (SRES A1B), 10–32 (SRES A2), and 11–33 (SRES B1), and the mean values of the LDs are 21 (SRES A1B), 23 (SRES A2), and 21 (SRES B1). For the AR5 GCM under the four scenarios (i.e., RCP 2.6/4.5/6.0/8.5) in the case when WRSRI = 0.58, the LDs are 11 (RCP 2.6), 10 (RCP 4.5), 11 (RCP 6.0), and 10 (RCP 8.5), which are much smaller than the mean values obtained for the 16 AR4 GCMs under the three scenarios. Moreover, the observations made for the other two cases of WRSRI, that is, when WRSRI = 0 and 1, are more or less consistent with those when WRSRI = 0.58. In addition, for a majority of the data sets (i.e., 31 out of 52 or about 60%), the differences between the LDs in the cases when WRSRI = 1 and 0.58 are larger than the differences between the LDs in the cases when WRSRI = 0.58 and 0, indicating that the LD of the identified socioeconomic drought events is less sensitive when WRSRI is below 0.58 (see section 3.3 for further details).

3.2.3. PDDL

Figure 7 presents the percentages of the identified future socioeconomic drought events on different drought levels for all the 52 streamflow data sets when WRSRI = 0.58. For all the 48 data sets from the 16 AR4 GCMs, the percentages on low level (SEDI = 1), moderate level (SEDI = 2), severe level (SEDI = 3), and extreme level (SEDI = 4) vary within the ranges of 26–50%, 12–35%, 17–41%, and 2–23%, respectively, and the mean percentages on these four levels are 40%, 21%, 28%, and 11%, respectively. Moreover, the differences among the three scenarios (i.e., SRES A1B/A2/B1) are not significant. It is observed that extreme socioeconomic drought events under the SRES A2 scenario (Figure 7b) account for a relatively larger percentage than those under the other two scenarios (i.e., SRES A1B/B1; Figures 7a and 7c), mainly due to the fact that the SRES A2 scenario describes an unevenly developed world with medium to high emission (IPCC, 2007). For the four data sets from the single AR5 GCM considered in this study (Figure 7d), the percentages on low level (SEDI = 1), moderate level (SEDI = 2), severe level (SEDI = 3), and extreme level (SEDI = 4) vary within the ranges of 20–25%, 31–44%, 32–43%, and 0–3%, respectively, and the mean percentages on these four levels are 22%, 40%, 37%, and 1%, respectively. On average, fewer low and extreme socioeconomic drought events are identified for the four data sets from the single AR5 GCM, while a greater number of moderate and severe socioeconomic drought events are identified.

In addition to the above, the percentages of the identified future socioeconomic drought events on different drought levels for all the 52 streamflow data sets when WRSRI = 0 or 1 are also calculated (figures not
shown). For all the 48 data sets from the 16 AR4 GCMs, the mean percentages on these four levels are 54%, 19%, 18%, and 9%, in the case when WRSRI = 0, while 35%, 20%, 34%, and 11%, in the case when WRSRI = 1. For the four data sets from the single AR5 GCM, the mean percentages on these four levels are 39%, 47%, 13%, and 1%, in the case when WRSRI = 0, while 19%, 25%, 55%, and 1%, in the case when WRSRI = 1. The results are summarized in Table 4, and the following key observations are made: (1) Compared to the case when WRSRI = 0.58 on an average sense, there will be higher percentages of low and moderate (i.e., less serious) socioeconomic drought events but lower percentages of severe and extreme (i.e., more serious) socioeconomic drought events when WRSRI = 0; and (2) compared to the case when WRSRI = 0.58 on an average sense, there will be lower percentages of less serious socioeconomic drought events but higher percentages of more serious socioeconomic drought events when WRSRI = 1. This is reasonable because a larger WRSRI value means that more water is needed for recovering the antecedent water deficit in a regional water resources system, which leads to more socioeconomic drought events with longer durations (see section 3.2.2 for details). Since DDL is one of the two indicators to determine the levels of socioeconomic drought (see section 2.4 for details), there will be a larger number of more serious socioeconomic drought events at least from the perspective of higher DDLs due to longer durations.

### Table 4

| Case     | AR4   | AR5   |
|----------|-------|-------|
|          | Low (%) | Moderate (%) | Severe (%) | Extreme (%) | Low (%) | Moderate (%) | Severe (%) | Extreme (%) |
| WRSRI = 0 | 54 | 19 | 18 | 9 | 39 | 47 | 13 | 1 |
| WRSRI = 0.58 | 40 | 21 | 28 | 11 | 22 | 40 | 37 | 1 |
| WRSRI = 1 | 35 | 20 | 34 | 11 | 19 | 25 | 55 | 1 |

3.3. Results of Sensitivity Analysis

As discussed in section 3.1, the historical WRSRI value of the ERB has been determined as 0.58, based on the 1963 drought. However, with the rapid development of a river basin and associated areas, such as the ERB, the resilience of a regional water resources system will probably change in the future due to a number of associated factors, for example, changes in the underlying surface and water utilization structure (Fang et al., 2020; Shi & Chen, 2018; Zhang et al., 2016). Therefore, it is necessary to explore how a potential change in the WRSRI value will affect the occurrences of socioeconomic drought events in the ERB. To this end, in this study, a sensitivity analysis of WRSRI is conducted separately for eight selected data sets. These are two data sets with the largest TN and LD values under the SRES A1B scenario (i.e., ncar_ccsm3_0.1 and cnrm_cm3.1, respectively), two data sets with the largest TN and LD values under the SRES A2 scenario (i.e., giss_model_e_r.1/2 and miub_echo_g.1, respectively), two data sets with the largest TN and LD values under the SRES B1 scenario (i.e., giss_model_e_r.1/2 and miroc3_2_medres.1, respectively), and two data sets of the AR5 model (HadGEM2-ES) with the lowest and highest emission scenarios (i.e., RCP 2.6 and RCP 8.5, respectively). Furthermore, the interval for the sensitivity analysis of WRSRI is set as 0.1 within the range of [0, 1]. With these, the results of the sensitivity analysis in terms of three features of the socioeconomic drought events, that is, the TN, the LD, and the PDDL, are presented next.

**3.3.1. TN and LD**

With an increase in WRSRI from 0 to 1, the changing trends in the TN and LD values are found to be opposite (see Figure 8). The TNs of the six data sets from the AR4 GCMs (i.e., Figures 8a to 8f) all decrease gradually with an increase in WRSRI, and the overall linear trends all have quite high coefficients of determination (i.e., $R^2 > 0.93$). Compared to the TNs of these six data sets, the changes in the TNs of the other two data sets from the AR5 GCM considered for the sensitivity analysis are quite different. For the data set of HadGEM2-ES with the lowest (i.e., RCP 2.6) emission scenario (i.e., Figure 8g), dramatic changes in the TNs are found within the WRSRI ranges of [0, 0.2] and [0.8, 1], leading to a relatively lower $R^2$ (i.e., 0.81); for the data set of HadGEM2-ES with the highest (i.e., RCP 8.5) emission scenario (i.e., Figure 8h; $R^2 = 0.77$), the changing features of the TNs within the WRSRI ranges of [0, 0.3] and [0.3, 1] are quite different, and thus, the $R^2$ (i.e., 0.77) of its linear trend is not high. In addition, differences between the TNs in the cases with two
adjacent WRSRI values (e.g., WRSRI = 0.2 and 0.3) are calculated. The mean value of all these differences for data sets from the AR4 GCMs is 4.0, which is twice as much as that for data sets from AR5 GCM (i.e., 2.0).

As can be seen from Figure 8, the LDs exhibit increasing trends with an increase in the WRSRI in a stepwise fashion for all the eight data sets considered in the sensitivity analysis. Moreover, for a majority of the data sets, the changes in the LDs in the cases when WRSRI is below 0.6 are less significant than the changes in the LDs in the cases when WRSRI is above 0.6, indicating that the LD is less sensitive within the WRSRI range of [0, 0.6]. This result is consistent with the observation made earlier in section 3.2.2.

In addition, the performances of the TNs and LDs in different cases are evaluated using the Taylor Diagram, which can summarize multiple aspects of the model performance (i.e., correlation, root mean squared error,  

Figure 8. Changes in the TNs and LDs with an increase in WRSRI from 0 to 1 in the ERB for six data sets from the AR4 GCMs ((a) to (f)) and two data sets from the AR5 GCM ((g) to (h)).
and standard deviation) in a single diagram (Taylor, 2001). The results are shown in Figure 9. It is clear that both the TNs and the LDs in the case when WRSRI = 0.6 are the closest to the reference point (i.e., the case when WRSRI = 0.58). Moreover, the performance of the TNs is basically better than that of the LDs, with TNs having higher correlation coefficients, lower centered root mean squared errors, and lower standard deviations.

3.3.2. Percentage of Socioeconomic Drought Events on Different Levels

Figure 10 presents the changes in the percentages of socioeconomic drought events on different levels with an increase in WRSRI from 0 to 1. The overall trend seems to be that there will be higher percentages of more serious socioeconomic drought events and lower percentages of less serious socioeconomic drought events. Moreover, the changes in the percentages for data sets from the AR5 GCM are more significant than those for data sets from the AR4 GCMs. For example, with reference to the specific values on an average sense, the percentage of more serious socioeconomic drought events changes from 24% (when WRSRI = 0) to 41% (when WRSRI = 1) for data sets from the AR4 GCMs, while the changing range is much wider for data sets from the AR5 GCM, which is [13%, 55%]. Based on the identified TNs for all the data sets (see section 3.2.1), the TNs for data sets from the AR4 GCMs are overall larger than the TNs for data sets from the AR5 GCM. However, when WRSRI is large, the percentage of more serious socioeconomic drought events for data sets from the AR5 GCM might be much higher than that for data sets from the AR4 GCMs. Thus, there might be a greater number of more serious socioeconomic drought events for data sets from the AR5 GCM. For example, the numbers of more serious socioeconomic drought events in the case when WRSRI = 0.9 are 48 and 43 for the two selected data sets from the AR5 GCM under RCP 2.6 and RCP 8.5 scenarios, respectively, while the numbers in the same case are only 37, 35, and 38 for the three selected data sets from the AR4 GCMs with the largest TNs under SRES A1B, SRES A2, and SRES B1 scenarios.

3.4. Implications and Limitations

3.4.1. Implications

The results from the present study have some important implications. First, the proposed WRSRI, regarding that a water resources system has its own resilience under water deficit, can be used to evaluate the TNs and LDs of the potential socioeconomic drought events through considering different climate change scenarios in the future. Therefore, socioeconomic droughts can be integrally evaluated through directly indicating whether the influences of a socioeconomic drought event can be recovered from the water supplement during the subsequent periods. The results from this study reveal that the water deficit during a socioeconomic drought event can be partially recovered from the self-adaption of a water resources system or compensated from the economic goods by anthropogenic actions after the water deficit ends. When the resilience of a regional water resources system is considered, its impacts on socioeconomic drought events with low (SEDI = 1) and extreme (SEDI = 4) levels are not significant. However, its impacts on the moderate (SEDI = 2) and severe (SEDI = 3) socioeconomic drought events are remarkable. Therefore, WRSRI can play an important role in the assessment and allocation of water resources, especially under moderate and severe socioeconomic droughts events, and therefore must be considered in the future. Relying on WRSRI, the
water resources system can be evaluated in advance with its own resilience to tackle the potential water deficit when it occurs. In general, a higher value of WRSRI stands for more reliance on a water resources system on both the number and the duration of potential socioeconomic drought events. If a water resources system can achieve the recovery rate parallel with WRSRI, such a system can be regarded as the most resilient system to face future socioeconomic drought events. For example, the suggested WRSRI value of the ERB equals to 0.58, and for this case, the $R_e$ values calculated using Equation 9 vary within

Figure 10. Changes in the percentages on different drought levels with an increase in WRSRI from 0 to 1 in the ERB for six data sets from the AR4 GCMs ((a) to (f)) and two data sets from the AR5 GCM ((g) to (h)).
the range of \([3.69, 4.98]\) considering all the 52 streamflow data sets, with the mean of 4.58 and standard deviation of 0.30 (Table 5). For comparison, Table 5 also lists the ranges, means, and standard deviations of the Re values calculated using Equation 9 in the cases when WRSRI = 1 and 0. It is observed that the variation in the case when WRSRI = 0.58 is relatively smaller than that in the other two cases, although not significant (also see Figure 11).

Second, this study provides a new avenue to investigate future socioeconomic drought events from the perspective of assessment of the resilience of a regional water resources system. By changing water consumption and water resources allocation policy, the resilience has the potential to be improved. It is worth noting that this study not only develops a method to evaluate future socioeconomic drought events but also can provide a train of thought about facing other future challenges as well as realizing sustainable development.

3.4.2. Limitations

When applying the method proposed in this study, the following limitations should also be properly taken into consideration.

First, this study does not consider the ration of water for recovering the antecedent water deficit from different water sectors when experiencing socioeconomic drought events. Thus, this study cannot provide detailed information about the role of different water sectors in influencing the WRSRI value. Moreover, as this study mainly focuses on socioeconomic droughts, how other water uses (e.g., irrigation) may influence the WRSRI value is not explored either. Garrote et al. (2007) have pointed out that an effective method of water resources allocation should consider, especially under climate change, the reliability of different water resources to seek harmony with the resources. Therefore, this study, although providing a new perspective on self-adjustment of a regional water resources system to face future climate change by proposing a new index (WRSRI), can still be improved in future by considering the impacts of the adjustment policy on water use and the role of different water sectors in influencing the WRSRI value.

Second, when calculating MIWR, this study assumes that the required values for maintaining water quality, ecology, and navigation and preventing seawater intrusion are invariable over time. Such an assumption is not completely valid in most situations. For instance, there are seasonal variations in water resources and, hence, in the required values. Therefore, this assumption may affect the results, at least to some extent. As mentioned in section 2.2, these values are obtained from past assessments of water resources, which are all at the annual scale; moreover, the projected \(Q_s\) values are also at the annual scale. Therefore, seasonal variations of these values are not considered in this study. If data for a finer time scale(s) are available, the effects of this assumption can be evaluated.

Third, there should be a way to connect the statistics of the socioeconomic drought events to the actual economic losses. This study, however, does not allow establishing such a connection, mainly due to data constraints (e.g., the exact values of economic losses attributed to socioeconomic drought events). Furthermore, it is worth noting that only 16 IPCC AR4 GCMs and one IPCC AR5 GCM are used in this study in order to make comparison against the results in the study of Shi et al. (2018), namely, the case when WRSRI = 1. However, IPCC continues to intensively investigate future climate change, and a number of new climate change projections (e.g., CMIP6) are being issued by different institutions at present (Eyring et al., 2016; Matthes et al., 2017; Tokarska et al., 2020). Therefore, the performance of the proposed index can be, and needs to be, reassessed using the new data sets in future studies.

4. Conclusions

This study proposed a new index, termed as the WRSRI, considering the resilience of a regional water resources system, to assess socioeconomic droughts under changing future conditions, including
population growth and climate change. The assessment was done through integrating the proposed index WRSRI into the process of socioeconomic drought event identification. The method was applied to the ERB in South China. A total of 52 streamflow data sets, simulated with a macroscale hydrologic model (the VIC model) and with the outputs from 16 AR4 GCMs with three SRES scenarios and one AR5 GCM with four RCP scenarios, was used. Three selected features of the identified future socioeconomic drought events, namely, the TN, the LD, and the PDDL, were analyzed.

The major findings of this study are as follows. First, the WRSRI value of the ERB equals to 0.58, based on the 1963 drought. Using resilience of the water resources system (Re) as the indicator for comparison, the variation of the Re values in the case when WRSRI = 0.58 is less significant than that in the other two cases when WRSRI = 0 and 1, indicating that the recovery capacity from a drought event to a functional state is better in the case when WRSRI = 0.58. Second, for each data set, the TN of the identified socioeconomic drought events decreases with an increase in WRSRI; in contrast, the LD increases with an increase in WRSRI. Moreover, on an average sense, the number of the identified low and extreme socioeconomic drought events for the data sets from the AR5 GCM is fewer than that for the data sets from the AR4 GCMs. Third, the results from the sensitivity analysis of WRSRI based on eight selected data sets indicate that the LD is less sensitive to WRSRI than the TN, especially within the WRSRI range of [0, 0.6]; with reference to the PDDL, it seems that there will be higher percentages of more serious socioeconomic drought events and lower percentages of less serious socioeconomic drought events with an increase in WRSRI from 0 to 1.

The outcomes of the present study can improve our understanding of socioeconomic droughts in a region and help in more effectively assessing the resilience of a regional water resources system, especially in changing future socioeconomic and climatic conditions. This, in turn, can lead to a more sustainable planning and management of our water resources (Chen et al., 2016; Exposito & Bethel, 2017; Shi et al., 2019; Tang et al., 2007). In addition, in view of the limitations of this study, further studies can focus on (1) considering the role of different water sectors that influence the WRSRI value and (2) reassessing the performance of the proposed index using up-to-date data sets or in other regions.

Conflict of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The projected precipitation datasets under different climate change scenarios can be downloaded from https://www.wcrp-climate.org/wgcm-cmip. The observed monthly streamflow data at the Boluo station is provided by Pearl River Water Resources Commission and can be obtained from the corresponding author. The projected population data till 2100 can be obtained from https://www.un.org/en/development/desa/population/publications/database/index.asp. The GDP data can be obtained from http://data.stats.gov.cn/.

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