Assessing Socioeconomic Drought Based on a Standardized Supply and Demand Water Index

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Abstract
Socioeconomic drought occurs when a water shortage is caused by an imbalance between the supply and demand of water resources in natural and human socioeconomic systems. Compared with meteorological drought, hydrological drought, and agricultural drought, socioeconomic drought has received relatively little attention. Hence, this study aims to construct a universal and relatively simple socioeconomic drought assessment index, the Standardized Supply and Demand Water Index (SSDWI). Taking the Jianjiang River Basin (JJRB) in Guangdong Province, China, as an example, we analyzed the socioeconomic drought characteristics and trends from 1985 to 2019. The return periods of different levels of drought were calculated. The relationships among socioeconomic, meteorological, and hydrological droughts and their potential drivers were discussed. Results showed that: (1) SSDWI can assess the socioeconomic drought conditions well at the basin scale. Based on the SSDWI, during the 35-year study period, 29 socioeconomic droughts occurred in the basin, with an average duration of 6.16 months and average severity of 5.82. Socioeconomic droughts mainly occurred in autumn and winter, which also had more severe droughts than other seasons. (2) In the JJRB, the joint return periods of “∪” and “∩” for moderate drought, severe drought, and extreme drought were 8.81a and 10.81a, 16.49a and 26.44a, and 41.68a and 91.13a, respectively. (3) Because of the increasing outflow from Gaozhou Reservoir, the occurrence probability of socioeconomic drought and hydrological drought in the JJRB has declined significantly since 2008. Reservoir scheduling helps alleviate hydrological and socioeconomic drought in the basin.

Keywords Socioeconomic drought · Standardized supply and demand water index · Copulas · Joint return period · Jianjiang River basin
1 Introduction

Drought is a complex natural disaster that depends on a variety of influencing factors, but it stems primarily from insufficient precipitation for prolonged periods. Droughts have large impacts on normal water supplies, crop irrigation, ecological environment, and subsequently people’s lives, in addition to threatening property safety (Cammalleri et al. 2017; Fang et al. 2019; Mishra and Singh 2010; Stoll et al. 2011; Trenberth 2001; Wilhite 2000; Yoo et al. 2016). The four types of drought are meteorological, hydrological, agricultural, and socioeconomic (Ams 2004; Wilhite 2006; Wilhite and Glantz 1985). Socioeconomic drought occurs when water demand exceeds water supply and consequently causes various social, economic, and ecological problems (Dinar and Mendelsohn 2011; Hayes et al. 2011; Ren et al. 2019; Vandenberghhe et al. 2011; Zseleczky and Yosef 2014). Among the drought types, socioeconomic drought is the only one driven by unnatural factors (Tu et al. 2018). With the growth of populations and industries, regional water demands have increased and socioeconomic drought has become a major problem facing the economic development of many countries and regions (Arab et al. 2010; Madani 2014; Montanari 2015; Sivapalan 2015; Van Beek et al. 2011; Vogel et al. 2015; Wada et al. 2011; Wheater and Gober 2015).

In general, drought indices are the most powerful tools available for studying the various types of drought events. Over the past decades, various new indices have been proposed and used to solve different drought issues. Commonly used indices include Palmer’s drought severity index (PDSI; (Palmer 1965)), surface water supply index (SWSI; Shafer and Dezman 1982), standardized precipitation index (SPI; Mckee et al. 1993), vegetation condition index (VCI; Kogan 1995), standardized runoff index (SRI; Shukla and Wood 2008), and standardized precipitation evapotranspiration index (SPEI; Vicente-Serrano et al. 2010). These indices have been used widely to assess the impact of meteorological drought, hydrological drought, and agricultural drought, having proven their superiority and universality through continuous improvement and application. In terms of socioeconomic drought, however, because of relatively recent developments of the field, universally available and simple drought indices are still lacking.

Under a backdrop of drastic global climate change (Aherne et al. 2006; Ahn et al. 2016; Hanson and Weltzin 2000; Hirabayashi et al. 2008; Kunkel 2003; Mehran et al. 2015; Tietjen et al. 2017; Tsanis and Tapoglou 2019; Vicuña et al. 2013; Zhou et al. 2020), researchers have increasingly been focused on socioeconomic drought and have proposed a series of indicators to measure socioeconomic drought (Eklund and Seaquist 2015; Guo et al. 2019; Huang et al. 2016; Liu et al. 2020b; Mehran et al. 2015; Shi et al. 2018; Tu et al. 2018). These indicators can be divided into two main categories that are related to either reservoir resilience or river runoff deficit.

Reservoirs, primary components of artificial infrastructure, can address the uneven distribution of water in space and time as well as increase a society’s ability to manage extreme events (such as floods and droughts). As such, reservoir management is important in water supply security and must consider water demands while also preventing the adverse effects resulting from socioeconomic droughts (Bai et al. 2015; Fang et al. 2017; Mehran et al. 2015). By the end of the last century, about 20% of the annual freshwater flow globally was controlled by artificial reservoirs, and 70% of global freshwater was supplied by these reservoirs (Fekete et al. 1999; Vörösmarty and Sahagian 2000). These statistics illustrate the importance of reservoirs in securing global water supplies (Mehran et al. 2015; Zhang et al. 2014). Therefore, considering
the regulated capacity of reservoirs, Mehran et al. (2015) used a multivariate standardized reliability and resilience index (MSRRI) to identify socioeconomic drought events. Furthermore, Huang et al. (2016) applied this MSRRI framework to evaluate socioeconomic drought in the Heihe River Basin, China, and discussed the impacts of El Niño, Southern Oscillation and Atlantic Oscillation on socioeconomic drought. Guo et al. (2019) improved the MSRRI framework by combining it with reservoir operational strategies, using copula functions to calculate the return periods of different grades of drought in the upper Yellow River while also considering the effects of extreme climate change. Although the MSRRI framework can accurately quantify socioeconomic drought situations under the influence of reservoir operation, it has some limitations. Consequently, it is difficult to measure socioeconomic drought for basins or regions that lack reservoirs or have low reservoir storage capacities.

In general, most of the water supply in a basin is diverted from the river. When the river runoff is less than the minimum required to meet in-stream water demand (as determined by requirements for navigation, ecology, water quality, and water use), a socioeconomic drought event can be considered to have occurred. It is also feasible to view socioeconomic drought from the river runoff deficit perspective. In this way, Shi et al. (2018) proposed the socioeconomic drought index (SEDI) to predict future socioeconomic drought conditions from 2020 to 2099 in the East River Basin. Tu et al. (2018) defined socioeconomic drought events by establishing a flow threshold and discussed the role of reservoir regulation in alleviating socioeconomic drought risk. This method, however, is similar to the discriminatory method used for assessing hydrological drought, which could be confounded by the fact that, when hydrological drought occurs, there may be no socioeconomic drought.

The concept of “resilience” is based either on the characteristics of reservoirs or on the river runoff deficit, especially by the SEDI, which specifies that a socioeconomic drought event will not end until excess water in the subsequent period recuperates all previous water shortages. Therefore, the duration of socioeconomic drought calculated by this index is usually much longer than other droughts, but this may overestimate the impact of socioeconomic drought events (Liu et al. 2020b). A portion of the previous water deficit may never be recovered, whereas other portions do not need to be recovered. When drought occurs, watershed management departments usually prioritize ensuring domestic and industrial water supplies and appropriately reduce agricultural water use (Piao et al. 2010; Shao et al. 2009). Moreover, the limitation of irrigation water during arid periods may not significantly affect the growth of plants as they have physiologically adaptive mechanisms (Ingram and Bartels 1996). Other water resources (such as groundwater) also can be considered as backups, but water shortages in backups are almost irreparable when returning to normal water supply. For extreme cases, in which industrial and domestic water are also strained, actions must be taken to shut down industrial production to save water. When the water supply is restored to normal, the amount of water used by people for domestic and production increases to normal levels compared with the low water use during the drought. It is not necessary to make up for previous water shortages (policy restrictions) or to make up for only a small portion of the shortage (Boisson et al. 2014; Liu et al. 2020a; Paradis et al. 2020). Therefore, in this study, we explore the characteristics of socioeconomic drought without considering recovery and gap-filling.

Drought can be quantified according to the degree of water scarcity, and socioeconomic drought can be quantified by the degree to which water supply does
not meet water demand. Referring to the ideas of PDSI, SPEI, and other indices, we proposed a more universally applicable standardized supply and demand water index (SSDWI) as an indicator to measure socioeconomic droughts. First, we simulated the monthly water supplies and demands within a basin and then used the difference function to calculate SSDWI. We used the run theory (Muhammad et al. 2019; Yevjevich 1967; Zhao et al. 2014) to identify socioeconomic drought events, analyze their characteristics at different timescales, and determined the multivariate distribution of drought characteristics using copula functions. Furthermore, the binary joint return period can be calculated to characterize the potential occurrence probability of socioeconomic drought. In this study, the Jianjiang River Basin from 1985 to 2019 was taken as an example to calculate the SSDWI and the accompanying characteristics. Finally, the relationship between socioeconomic drought and meteorological hydrological drought and its changing trends were discussed along with an analysis of possible causes. The results of this study can provide a new approach to the understanding of regional socioeconomic drought and hold great significance for decision-makers seeking drought prevention and early warning.

2 Study Area and Data

The Jianjiang River Basin (JJRB), with a total watershed area of 9464 km², is located within 110°20′ to 111°20′E and 21°15′ to 22°30′N in the western part of Guangdong Province, China (Fig. 1). The Jianjiang River mainly flows through Maoming and Wuchuan with average annual water resources of 8.94 billion m³, making it the largest river in the coastal river system of Guangdong Province. The watershed is at the junction of subtropical monsoon and tropical monsoon regions with a humid climate. The annual average temperature is 20-21 °C, and the annual average rainfall is 1780 mm. Gaozhou Reservoir is a large and key regulation reservoir in the basin, with a total catchment area of 1022 km² and a total capacity of 1.28 billion m³. Its main functions are water supply, irrigation, power generation and facilitating shipping in the basin. Because of the monsoon climates and uneven spatial and temporal distribution of precipitation, 70% of the total annual precipitation occurs from April to September where there is strong solar radiation, high temperatures, high evaporation rates, and high crop transpiration. Seasonal droughts in this region have occurred frequently and have become an important factor in restricting sustainable socioeconomic development.

In the JJRB, agriculture represents the largest water demand, accounting for about 65% of all water usage in the basin. The water supply in the basin comes through water storage (reservoirs) and diversion, which account for about 70% of all water supplies. We collected monthly flow data from 1985 to 2019 at Huazhou Station, the main control station of the basin. The measured inflow and outflow data of the Gaozhou Reservoir also were collected. The annual water supply data from 1985 to 2019 were taken from the basin water resources bulletin. We collected and reasonably calculated the basin water quota, crop effective irrigation area, population, output value, and other social and economic data from the statistical yearbook of each city. We took the monthly water supply and use data from 2014 to 2019 from the operational data records of hydroelectric plants, main canals, and reservoirs.
3 Methodology

3.1 Simulation of Water Supply and Demand

Socioeconomic drought is a water shortage phenomenon caused by an imbalance between the supply of water resources in natural systems and the demand of human socioeconomic systems. Therefore, simulated time series of water supply and demand in the basin can be used to characterize the socioeconomic drought to a certain extent. We selected 1985...
– 2019 as the research period and determined the annual water supply during this period using the water resources bulletin and statistical yearbook of the basin. In the JJRB, the water supply can be divided into four parts: storage, diversion, withdrawal, and groundwater. Because of the lack of data, we estimated the intra-annual distribution ratios of different water supply components based on the monthly water supply data from 2014 to 2019 (Fig. 2a).

It should be noted that water demand is dominated by agricultural, industrial, and domestic components calculated according to the quota method. These quotas came from a central authority. We determined the annually allocated proportion of water demand for each component based on their monthly water consumption in the basin from 2014 to 2019 (Fig. 2b).

### 3.2 Standardized Supply and Demand Water Index

Because socioeconomic drought is essentially an imbalance between supply and demand of water, the SSDWI can be calculated by referring to the methods for the SPEI that utilize the monthly differences between water supply and demand. First, monthly deficit or surplus is calculated as follows:

$$X_i = S_i - D_i (i = 1, 2, \ldots, 12)$$  

where $X_i$ represents the monthly deficit or surplus of water; $S_i$ represents monthly supply; $D_i$ represents monthly demand; $i$ represents a specific month. This calculation can be made for any timescale, like SPI. For subsequent operations, the $X_i$ sequence is normalized so that it is

|   | Norm | GEV | Log | Log-Log | Log-Norm |
|---|------|-----|-----|---------|----------|
| $X_{i-1}$ | 0.9187 | 0.9811 | 0.6941 | 0.6204 | 0.4444 |
| $X_{i-3}$ | 0.6259 | 0.7765 | 0.3981 | 0.4107 | 0.6129 |
| $X_{i-6}$ | 0.7144 | 0.6924 | 0.4372 | 0.3956 | 0.5718 |
| $X_{i-12}$ | 0.6017 | 0.6404 | 0.4790 | 0.4425 | 0.5147 |

Fig. 2 Distributions of (a) water supply and (b) water demand proportions throughout the year
that its average value is 0 and the standard deviation is 1. For fitting, we selected the normal distribution (Norm), generalized extreme value (GEV) distribution, logistic distribution (Log), log-logistic distribution (Log-Log), and log-normal distribution (Log-Norm). The Kolmogorov-Smirnov (K-S) test was used to find the optimal cumulative function (Table 1).

The results showed that the GEV distribution was the best optimal cumulative function for the 1-, 3-, and 12-month timescales, and the suboptimal choice for the 6-month timescale. Therefore, we chose the GEV distribution as the best distribution. The cumulative GEV distribution function is as follows:

\[
F(x) = \exp \left\{ -\left[ 1 + \rho \left( \frac{x - \mu}{\sigma} \right) \right]^{\frac{1}{\rho}} \right\}
\]

where \( \rho \) is the shape parameter; \( \mu \) is the unknown parameter; \( \sigma \) is the scale parameter. The three parameters are all estimated by the maximum likelihood method. The SSDWI can be obtained as the standardized values of \( F(x) \) by following the classical approximation of Abramowitz and Stegun (1964):

\[
W = \begin{cases} 
\sqrt{-2\ln(1 - F(x))} & F(x) \leq 0.5 \\
\sqrt{-2\ln F(x)} & F(x) > 0.5 
\end{cases}
\]

\[
\begin{align*}
\text{SSDWI} &= -W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \\
\text{SSDWI} &= \left( W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \right) \\
\end{align*}
\]

where \( C_0 = 2.515 \, 517 \), \( C_1 = 0.802 \, 853 \), \( C_2 = 0.010 \, 328 \), \( d_1 = 1.432 \, 788 \), \( d_2 = 0.189 \, 269 \), and \( d_3 = 0.001 \, 308 \).

### 3.3 Run Theory

In this study, we used the run theory (Yevjevich 1967) to identify socioeconomic drought events and extract characteristics, such as drought duration, severity, and intensity. Drought duration is the duration of a drought event from its initiation to end. Drought severity is the cumulative value of the drought index during this drought event (usually taken as the sum of opposite numbers). Drought intensity is the ratio of drought severity to drought duration.

The specific method used to identify drought events at the monthly timescale is as follows: (1) we set three truncation levels \( X_0 = 0 \), \( X_1 = -0.3 \), \( X_2 = -0.5 \) (\( X \) is the drought index value); (2) when the drought index was less than \( X_1 \), we preliminarily determined that a drought had occurred in that month; (3) when the drought index was greater than \( X_3 \), for a drought event lasting 1 month, we determined that there was no drought in that month and eliminated the event; (4) when the time interval between two adjacent droughts was only 1 month, and the drought index value within that month was less than \( X_0 \), we combined the two adjacent droughts into one drought event. In the last case, the drought duration was the sum of the two drought duration events plus one event, and the drought severity was the sum of two drought events.
3.4 Copulas

Copula functions are highly recognized and widely used multidimensional joint analysis methods. They take advantage of the fact that each factor does not require a uniform distribution function to be applied in the field of multivariate research. In this study, we selected the two-dimensional copula function for drought return period analysis, expressed as follows:

\[ C(u, v) = \varphi^{-1}(\varphi(u), \varphi(v)) \tag{5} \]

where \( \varphi \) denotes the convex function; and \( u \) and \( v \) represent the two variables. Generally, the three main types of copulas are elliptical, Archimedean, and quadratic. The elliptical copula can be used to construct an abnormal extreme relationship, and therefore it is better for describing extreme events. The Archimedean copula is simple to construct and has strong representability. Both elliptical and Archimedean connection functions are widely used in hydrological frequency analysis (Chen et al. 2015; Reddy and Ganguli 2012; Song and Singh 2010). Therefore, in this study, we used three Archimedean copulas (Clayton, Frank, Gumbel) and two elliptical copulas (Gaussian, \( t \)) to simulate the joint probability of marginal distribution of drought duration and severity and used the maximum likelihood method to estimate the copula parameters (Joe 1997).

In addition, we selected the ordinary least squares (OLS) minimum criterion and Akaike information criterion (AIC) to test the goodness of fit and determine the optimal copula function. The formulas of the inspection methods follow:

\[ \text{OLS} = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (P_{ei} - P_{i})^2} \tag{6} \]

\[ \text{AIC} = n \ln \left[ \frac{1}{n-1} \sum_{i=1}^{n} (P_{ei} - P_{i})^2 \right] + 2l \tag{7} \]

where \( P_{ei} \) is the joint empirical probability of two-dimensional variables, \( P_{i} \) is the joint distribution value of the copula function, \( n \) is the number of samples, and \( l \) is the number of parameters contained in the model. The smaller the values of OLS and AIC, the closer the joint distribution probability value calculated by the copula function to the empirical probability value and the better the fit would be.

3.5 Joint Return Period Calculation

The drought return period indicates the average interval between the occurrence of two drought phenomena (Ge et al. 2016; Motevali Bashi Naeini et al. 2021; Thilakarathne and Sridhar 2017; Tsakiris et al. 2016). The joint return period is the reciprocal of the joint probability of two variables and can be used to represent the occurrence probability of drought events. Salvadori and De Michele (2004) proposed two return periods: “or (\( \cup \))” joint return period and “and (\( \cap \))” joint return period. Suppose two
random variables X and Y, and the thresholds of X and Y are set to x and y, respectively. Then, the “∪” joint return period is the time interval in which at least one variable (X or Y) is higher than the threshold \(T(X > x) \cup (Y > y)\); and the “∩” joint return period refers to the time interval in which both X and Y exceed their own thresholds \(T(X > x) \cap (Y > y)\).

We tested the socioeconomic drought duration and severity against the gamma function, Weibull function, GEV function, lognormal function, and log-logistic function for the best fit of the marginal distribution and to select the most suitable distribution function. After selecting the distribution function, the two marginal distributions were fitted using the copula, and the two drought return periods were calculated as follows (Guo et al. 2019):

\[
T(D > d) \cup (S > s) = \frac{E(\Delta T)}{1 - C(F_D(d), F_S(s))}
\]

\[
T(D > d) \cap (S > s) = \frac{E(\Delta T)}{1 - F_D(d) - F_S(s) + C(F_D(d), F_S(s))}
\]

where \(T(D > d) \cup (S > s)\) and \(T(D > d) \cap (S > s)\) are “∪” and “∩” joint return periods, respectively; \(C\) represents the copula function; \(C(F_D(d), F_S(s))\) stands for the joint distributions of drought duration and severity, which are combined using the copula function; \(F_D(d)\) and \(F_S(s)\) are the marginal distribution of drought duration and severity, respectively; and \(E(\Delta T)\) denotes the expected of drought events interval time and is the sum of the average of drought duration and non-drought duration. Here drought interval is drought interarrival time.

4 Results

4.1 Socioeconomic Drought Events and Their Features

On the monthly scale, a total of 29 socioeconomic drought events occurred in the JJRB over the 35-year study period, with an average duration of 6.16 months per drought event and average severity of 5.82. The durations of most drought events were concentrated in 6-8 months, with few lasting less than 4 months or more than 10 months. We found that the average drought duration of SEDI (Shi et al. 2018) was about 10, MSRRI (Mehran et al. 2015) was about 12, and IMSRRI (Guo et al. 2019) was about 14. Compared with SEDI, MSRRI, and IMSRRI, the drought duration and severity identified by SSDWI were smaller because we had not considered reliability and resilience.

On the seasonal scale (Fig. 3), spring is January to March, summer is April to June, autumn is July to September, and winter is October to December. Winter and autumn generally had more frequent and more severe socioeconomic droughts. Socioeconomic droughts rarely occurred in summer because of the high rainfall, river flows, and sufficient water supply during this season.

On the yearly scale, drought events generally could be divided into four levels: slight (-0.5 to -1), moderate (-1 to -1.5), severe (-1.5 to -2), and extreme (< -2). Based on these categories, severe droughts occurred in the JJRB in 2000 and 2003 and moderate droughts occurred in 1986, 1991, and 2008.
4.2 Marginal Distribution Fitting of Drought Duration and Severity

To accurately determine the critical values for different grades of drought events, we used the Weibull, GEV, normal, logistic, log-logistic, and GP distribution to fit the duration and severity of droughts. We selected the distribution with the best goodness of fit according to the K-S test. All distributions met the 0.05 significance threshold. The empirical and theoretical distributions were shown in Fig. 4. The K-S test results showed that the best fitting distributions for drought duration and severity were the logistic (0.8093) and GP (0.7515)
distributions, respectively. Fig. 4 further illustrated the reliability of the marginal distribution selection and a significant positive correlation between drought duration and severity. In addition, the critical values for different grades of socioeconomic drought events corresponding to the cumulative probability could be obtained from Fig. 4. Socioeconomic drought events can be classified into four grades based on duration and severity. The duration of slight, moderate, severe, and extreme drought was less than 4 months, 4-7 months, 7-10 months, and greater than 10 months, respectively. The severity of slight, moderate, severe, and extreme drought was less than 3, 3-7, 7-10, and greater than 10, respectively.

4.3 Selection of the Optimal Copula Function

According to the optimal distribution of drought duration and severity in Sect. 4.2, we selected the Log distribution and GP distribution to fit the marginal distribution of drought duration and severity, respectively. The Kendall and Spearman rank correlation coefficients between drought duration and severity were 0.62 and 0.76, respectively. Therefore, the copula function can be used to construct the joint probability distributions of drought duration and severity. We estimated the copula parameter $\theta$ using the maximum likelihood method. We used AIC and OLS as parameters to select the best fitting copula. It was obvious that the t-copula was the most suitable copula because it had the smallest AIC and OLS values (Table 2). These results indicated that the t-copula had the best fit for drought duration and severity. Therefore, we selected the t-copula to construct the drought occurrence probability model in this study. The contours of drought duration and severity were shown in Fig. 5.

| Table 2 | Optimization of copula functions |
|---------|----------------------------------|
| Selection basis | Clayton | Frank | Gumbel | gaussian | t |
| AIC     | -15.58 | -18.28 | -17.06 | -20.25   | -20.99 |
| OLS     | 0.0541 | 0.0516 | 0.0527 | 0.0499   | 0.0492 |

Fig. 5 Contours diagram of socioeconomic drought duration and severity in the JJRB
4.4 Calculation of Drought Return Periods of Different Grades

After we identified the copula function that best fit drought duration and severity, we calculated the joint return periods (“∪” and “∩”) in the two cases to characterize the socio-economic drought in the JJRB. The results were shown in Fig. 6. The possibility of socio-economic drought with return period “∪” was higher than that with return period “∩”. With increasing drought duration and severity, the joint return periods of “∪” and “∩” increased. The joint return period was calculated for each grade of drought except for the slight drought. The joint return periods of “∪” and “∩” under moderate drought conditions were 8.81 years and 10.81 years, respectively, whereas those under severe drought conditions were 16.49 and 26.44 years, respectively. Furthermore, the joint return periods of “∪” and “∩” under extreme drought conditions were 41.68 and 91.13 years, respectively.

5 Discussion

5.1 Relationships Among Socioeconomic, Meteorological, and Hydrological Drought

In general, meteorological drought is the main driver behind the other two kinds of drought. The abnormal shortage of rainfall leads to reduced river runoff and water shortages for domestic and industrial water demands. To explore the relationships among meteorological, hydrological, and socioeconomic drought, we used the data of rainfall, temperature, and river runoff data measured in the JJRB to calculate SPEI (Vicente-Serrano et al. 2010) and SDI (Nalbantis and Tsakiris 2009) and to characterize meteorological and eco-

| Scale  | SPEI and SDI | SPEI and SSDWI | SDI and SSDWI |
|--------|--------------|----------------|----------------|
| Month  | 0.5231       | 0.2811         | 0.5097         |
| Season | 0.5984       | 0.3579         | 0.6381         |
| Year   | 0.6437       | 0.5338         | 0.7682         |
hydrological drought from 1985 to 2019. We analyzed the relationships among SPEI, SDI, and SSDWI indices at monthly, seasonal, and annual scales using the Pearson correlation coefficient (significance level of 0.01). As shown in Table 3, the three drought types were most strongly correlated at the 12-month timescale. The correlations of SSDWI with SPEI and SDI were all greater than 0.5, indicating that SSDWI could measure socioeconomic drought characteristics well in the JJRB. Compared with meteorological drought, hydrological drought was more closely related to socioeconomic drought. Sufficient river runoff volume is important in preventing saltwater intrusion, ensuring river ecological health, facilitating ship navigation, and supplying water intake outside the river. Therefore, under the premise of prioritizing ecological flow and navigable flow, when river flow is abnormally low, meeting the water demands outside the river (i.e., agricultural demands) is often impossible. When an imbalance exists between water supply and demand between the natural systems and human social systems, a socioeconomic drought occurs. Therefore, hydrological drought is the most direct causes of socioeconomic drought.

5.2 Trends of Socioeconomic, Hydrological, and Meteorological Drought

As shown in Fig. 7, SSDWI-12 followed an increasing trend since 1985, and its value was 0.067 < 0.1 after passing the Pettitt test. This result indicated that there was a mutation point in the index sequence at some time in the 35-year study period, and the mutation point was 2008. The mean value of SSDWI before 2008 was -0.37, but afterwards, it was 0.76, which indicated that occurrence probability of socioeconomic drought in the JJRB had been significantly reduced. This reduction was caused by the significant decline in the frequency and severity of socioeconomic drought in recent years. Similarly, because of the high correlation between hydrological drought and socioeconomic drought, the change in 2008 was reflected in hydrological drought as well. The average SDI was -0.35 before 2008 and 0.51 after 2008, indicating that the hydrological drought had significantly improved and that river runoff in the dry season was more reliable. SPEI did not change significantly, however, with mean values before and after 2008 of -0.15 and 0.13, respectively, indicating that there was no significant climate change in the JJRB in the past 35 years.

5.3 Possible Causes

Among the evaluated socioeconomic drought indicators, reservoirs have been identified as indispensable in ensuring sufficient river runoff and water supply in the basin during dry periods. Gaozhou Reservoir is the most important water storage project in the JJRB. Under the assumption that there has been no remarkable change in the climate
in recent years, the reservoir operation in the basin likely has alleviated hydrological and socioeconomic drought since 2008. Therefore, we analyzed the daily average discharge of Gaozhou Reservoir in spring, autumn, and winter (mainly used for flood management in summer) from 1985 to 2019. We found that the reservoir discharge has been increasing and that this increase has been more pronounced since 2008. The mean discharge before and after 2008 was 62.3 m$^3$/s and 117.9 m$^3$/s, respectively. This change was, due to the improved operation and utilization of the reservoir by the basin management department, which significantly reduced the frequency and severity of hydrological drought and socioeconomic drought. Proper management has ensured the river runoff during the dry season; thus, the normal water supply and the intake by users have rarely been limited.

6 Conclusions

In this study, we proposed a new indicator for characterizing socioeconomic drought—a standardized supply and demand water index. Taking the JJRB as an example, we discussed the characteristics of socioeconomic drought without considering the need for water recuperation. We also analyzed the occurrence of drought along different timescales and the characteristics of drought duration and severity using copula functions. Then, we calculated the return periods of socioeconomic drought and discussed the trends of droughts in the basin along with the possible underlying causes thereof. The main conclusions were as follows:

1. SSDWI was suited to characterizing the socioeconomic drought at the basin scale. The JJRB experienced 29 socioeconomic drought events from 1985 to 2019, with an average duration of 6.16 months and average severity of 5.82. Socioeconomic droughts predominantly occurred in autumn and winter, which also experienced more serious drought than other seasons.
2. In the JJRB, the joint return periods of “U” and “∩” for moderate drought, severe drought, and extreme drought were 8.81a and 10.81a, 16.49a and 26.44a, and 41.68a and 91.13a, respectively.
3. The occurrence probability of socioeconomic drought and hydrological drought in the JJRB has dropped significantly since 2008 because of the increased outflow from the Gaozhou Reservoir. Reservoir scheduling has played an important role in alleviating hydrological drought and socioeconomic drought in the basin.

This study provided a new perspective to identify and assessed socioeconomic droughts in changing environments. The findings of this study could assist the management of local water resources and the prevention of socioeconomic drought. However, this approach could be improved. Future studies could further investigate how water conflicts and water competition are reflected in actual socioeconomic drought scenarios; how socioeconomic drought specifically affects water users; how the dynamic process of water supply and demand can be described; and how water resources management departments can use the drought index to improve social utility.

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**Authors' Contributions** J.W. Zhou: Conceptualization, Investigation, Methodology, Formal analysis, Writing—original draft. X.H. Chen: Supervision, Data curation, Funding acquisition, Writing—review & editing. C. Xu & W. Pan: Writing—review & editing.

**Data Availability** The data has been obtained through surveys and Guangdong Hydrographic Bureau. If necessary, the database could be made available.

**Declarations**

**Competing Interest** The authors declared that they have no conflicts of interest to this work.

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