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Assessing socioeconomic drought based on a standardized supply and demand water index

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Abstract: Socioeconomic drought is a phenomenon of water shortage caused by an imbalance between the supply and demand of water resources in natural and human socioeconomic systems. Occurrence of these droughts is closely related to sustainable socioeconomic development. However, compared with meteorological drought, hydrological drought and agricultural drought, socioeconomic drought has received relatively little attention. Therefore, this paper proposes 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, socioeconomic drought characteristics and trends during 1985-2019 were analyzed. The return period of different levels of drought were calculated using a copula function to estimate the risk of socioeconomic drought in the basin, and the relationship between socioeconomic, meteorological, and hydrological droughts and their potential drivers were discussed. The results showed that: (1) SSDWI was a better index for characterizing socioeconomic drought in the JJRB. 29 socioeconomic droughts occurred in the basin during the past 35 years, with an average duration of

6.16 months and an average severity of 5.82 per events. 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 ‘ $\square$ ’ and ‘ $\cap$ ’ 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) Due to the increasing outflow from Gaozhou Reservoir, the risk of socioeconomic drought and hydrological drought in the JJRB has significantly declined since 2008. The reasonable operation of the reservoir has played an important role in alleviating the 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 stems primarily from insufficient precipitation for prolonged periods. Droughts have large impacts on normal water supplies, crop irrigation, ecological environment and subsequently can affect people's lives and threaten property safety (Wilhite, 2000; Trenberth, 2001; Mishra and Singh, 2010; Stoll et al., 2011; Yoo et al., 2016; Cammalleri et al., 2017; Fang et al., 2019a). There are four types of drought: meteorological, hydrological, agricultural and socioeconomic (Wilhite and Glantz, 1985; American Meteorological Society, 2004; World Meteorological Organization, 2006). 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; Vandenberghe et al., 2011; Zselezky and Yosef, 2014; Ren et al., 2019). 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 of the world. (Arab et al., 2010; L.P.H. van Beek et al., 2011; Yoshihide Wada et al., 2011; Madani, 2014; Sivapalan, 2015; Wheeler and Gober, 2015; Vogel et al., 2015; Montanari, 2015).

In general, drought indices are the most powerful tools available for studying the various types of drought events. Over the past decades, a variety of new indices have been proposed and used to study 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). The above indices have all been widely used to assess the impact of meteorological drought, hydrological drought, agricultural drought and have proven their superiority and universality as they have been continuously improved and applied. However, in terms of socioeconomic drought, due to relatively recent development of the field, there is still a lack of universally available and simple drought indices.

Under a backdrop of drastic global climate change (Kunkel, 2003;Hanson and

Weltzin, 2000; Hirabayashi et al., 2008; Ahn et al., 2016; Mehran et al., 2015; Tsanis & Tapoglou, 2019; Vicuna et al., 2013; Zhou et al., 2020a, 2020b; Aherne et al., 2006; Tietjen et al., 2017), more and more researchers have focused on the study of socioeconomic drought and a series of indicators to measure socioeconomic drought have been proposed (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). These indicators can be divided into two main categories, related to either reservoir resilience or river runoff deficit.

As a main component of artificial infrastructure, reservoirs help address the uneven distribution of water in space and time, and increase a society's ability to resist extreme events (such as floods and droughts). Reservoir management plays an important role in water supply and demand security while also preventing the adverse effects of socioeconomic droughts (Mehran et al., 2015; Bai et al., 2015; Fang et al., 2017). By the end of the last century, about 20% of the all annual freshwater flow globally was controlled by artificial reservoirs, and 70% of global freshwater production was supplied by these reservoirs (Fekete et al., 1999; Shiklomanov et al., 2000; Vörösmarty and Sahagian, 2000). These statistics illustrate indicating the importance of reservoirs in providing global human water resilience and their close relationship between reservoirs and human socioeconomic systems (Zhang et al., 2014b; Mehran et al., 2015). Therefore, considering the regulated capacity of reservoirs, Mehran et al. (2015) used multivariate standardized reliability and resilience index (MSRRI) to identify socioeconomic drought events; Huang et al. (2016a) applied the

MSRRI framework to evaluate socioeconomic drought in the Heihe River Basin, China, and discussed the impacts of El Niño Southern Oscillation (ENSO)/Atlantic and Oscillation (AO) on socioeconomic drought; Zhao et al.(2019) used MSRRI to assess socioeconomic drought of the Datong River and analyzed the meteorological driving force by cross wavelet; Guo et al.(2019) improved the MSRRI framework by combining it with reservoir operational rules, 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. This framework can accurately quantify socioeconomic drought situation under the influence of reservoir operation, but it still has some limitations. It is difficult to use this indicator to assess the real socioeconomic drought scenarios for basins or regions that lack reservoirs or have low reservoir storage capacities.

Generally speaking, 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 assess socioeconomic drought from the river runoff deficit perspective. In this way, Shi et al.(2017) proposed the socioeconomic drought index (SEDI) to assess historical and future socioeconomic droughts conditions in the Dongjiang 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. However, this method 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 used either from the characteristics of reservoirs or from the deficit of river runoff, especially the SEDI, which specifies that a socioeconomic drought event will not end until all previous water shortages recover from excess water in the subsequent period. 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.,2020). In fact, a portion of the previous water deficit may never be recovered, while 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 & Bartels,1996). Other water resources (such as groundwater) can also be considered as a backup, and this part of water shortage is almost irreparable when returning to normal water supply. For more extreme cases, where industrial and domestic water is also strained, actions must be taken to shut down industrial production to save water. When the water supply is restored to normal, the domestic and industrial water is restored to normal. The previous part of water shortage does not need to be restored (policy restrictions) or only a small part of water shortage can be restored (Boisson et al., 2014; Paradis et al., 2020; Liu et al., 2020). So it is necessary to 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 as the degree to which water supply does not meet water demand. Referring to the ideas of PDSI, SPEI and other indices, this paper proposes a more universally applicable standardized supply and demand water index (SSDWI) as an indicator to measure socioeconomic droughts. This index first simulates the monthly water supplies and demands within a basin and then uses the difference function to calculate SSDWI. Then the run theory is used to identify socioeconomic drought events, analyze their characteristics at different time scales, and determine the multivariate distribution of drought characteristics using copula functions. Furthermore, the binary joint return period can be calculated to characterize the potential risk of socioeconomic drought. In this study, the Jianjiang River Basin from 1985 to 2019 was taken as an example for calculating the SSDWI and the accompanying characteristics. Then 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 perspective for better understanding of regional socioeconomic drought, and has a high value for decision makers seeking drought prevention and early warning.

2. Study area and data

The Jianjiang River Basin (JJRB) is located in the western part of Guangdong Province, China (Figure 1). The Jianjiang River mainly flows through Maoming and

Wuchuan with an 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 located within 110°20'~111°20'E and 21°15'~22°30'N, at the junction of subtropical monsoon and tropical monsoon regions with a humid climate. The total watershed area is 9464 km², the annual average temperature is 20-21°C, and the annual average rainfall is 1780 mm. Gaozhou Reservoir is the most important large reservoir in the basin, with a total catchment area of 1022 km² and a total reservoir capacity of 1.28 billion m³. Its main functions are water supply, irrigation, power generation and facilitating shipping in the basin. Due to the monsoon climates and uneven spatial and temporal distribution of precipitation, 70% of the total annual precipitation occurs from April to September, coupled with the strong solar radiation, high temperature, large evaporation and crop transpiration in western Guangdong. Seasonal and regional droughts have occurred frequently, which has become one of the important factors restricting the sustainable development of social economy.

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 via water storage (reservoirs) and diversion, which account for about 70% of all water supplies. The monthly flow data from 1985 to 2019 were collected at Huazhou Station, the main control station of the basin. The measured inflow and outflow data of the Gaozhou Reservoir were also collected. The annual water supply data from 1985 to 2019 were taken from the basin water resources bulletin. The basin water quota, crop effective irrigation area, population, output value and other social and economic data were

collected from the statistical yearbook of each city and reasonably calculated. The monthly water supply and use data from 2014 to 2019 were taken from the operational data records of waterworks, main canals and reservoirs.

Fig. 1 Water reservoirs and stations in the Jianjiang River Basin, South China

3. Methodology

3.1 Simulation of water supply and demand

Socioeconomic drought is a water shortage phenomenon caused by an imbalance between supply of water resources in natural systems and 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. 1985 – 2019 was selected as the research period, and the annual water supply during this period was determined using the water resources bulletin and statistical yearbook of the basin. In the JJRB, the water supply is usually divided into four parts: storage, diversion, withdrawal and groundwater. Due to the lack of data, the intra-annual distribution ratios of different water supply components were estimated based on the monthly water supply data from 2014 to 2019 (Fig. 2 (a)).

Water demand is dominated by agricultural, industrial and domestic components, which are calculated according to the quota method. The main calculation methods are shown in Table 1. The annually allocated proportion of water demand for each component part was determined based on their monthly water consumption in the basin from 2014 to 2019 (Fig. 2 (b)). The relevant data used in the calculation were obtained from the statistical yearbooks and water resource bulletins of local cities.

Table 1 Calculation of annual total water demand in the JJRB

Water demand column(10^4 m^3)	Method of calculation	Annotation
Agriculture	$WA_t = \frac{m \cdot A}{\theta}$	m- Irrigation quota, m^3/hm^2 ; A- Planting area of crops, 10^4 hm^2 ; θ - Utilization coefficient of irrigation

		water;
		P_1 and P_2 represent urban and rural population
Life	$WL_t = P_1 k_1 + P_2 k_2$	respectively; k_1 and k_2 represent urban and rural domestic water quota respectively, $m^3/(p.a)$
Industry	$WI_t = Y(1 - r)g$	Y- Total industrial output value, 10^4 yuan; r- Repetition rate of industrial water; g- Water consumption per 10^4 yuan of industrial output value, $m^3/10^4$ yuan
Total	$D_t = WA_t + WL_t + WI_t$	D_t -Total annual water demand of basin

Fig. 2 Distributions of water supply(a) and water demand(b) proportions throughout the year

3.2 Standardized supply and demand water index

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

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

where, X_i represents the monthly deficit or surplus of water; S_i represents monthly supply; D_i represents monthly demand; and i represents a specific month. This

calculation can be made for any time scale, like SPI. For subsequent operations, the X_i sequence is normalized so that its average value is 0 and standard deviation is 1. For fitting, the normal distribution (Norm), generalized extreme value distribution (GEV), logistic distribution (Log), log-logistic distribution (Log-Log) and log-normal distribution (Log-Norm) were selected (Fig. 3). In the abscissa, 100 indicates a perfect balance between water supply and demand, numbers over 100 indicate a surplus of water, and numbers under 100 indicate that demand exceeds supply, and the difference compared to 100 is the deficit or surplus water(10^8 m^3). At the same time, the Kolmogorov-Smirnov (K-S) test was used to find the optimal cumulative function (Table 2).

Fig. 3 Empirical values using the normal, GEV, logistic, log-logistic and lognormal distributions of the X_i series at the time scales of 1, 3, 6 and 12 months

Table 2 Optimization of the cumulative distribution function

	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}	0.8541	0.8909	0.5215	0.4541	0.6234
X _{i-12}	0.6017	0.6404	0.4790	0.4425	0.5147

The results showed that the GEV distribution was the best optimal cumulative function for the 1-month, 3-month, 6-month and 12-month time scales. The cumulative GEV distribution function is as follows:

$$F(x) = \exp \left\{ - \left[1 + \rho \left(\frac{x-\mu}{\sigma} \right) \right]^{-\frac{1}{\rho}} \right\} \quad (2)$$

where, ρ is the shape parameter, μ is the unknown parameter, and σ is the scale parameter. The three parameters are all estimated by the maximum likelihood method. The SSDWI can easily be obtained as the standardized values of $F(x)$. For example, by following the classical approximation of Abramowitz and Stegun(1965),

$$\begin{cases} SSDWI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} & F(x) \leq 0.5 \\ SSDWI = - \left(W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \right) & F(x) > 0.5 \end{cases} \quad (3)$$

where,

$$W = \begin{cases} \sqrt{-2 \ln(1 - F(x))} & F(x) \leq 0.5 \\ \sqrt{-2 \ln F(x)} & F(x) > 0.5 \end{cases} \quad (4)$$

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, the run theory (Yevjevich, 1967) was used 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 the drought event (usually taken as the sum of opposite numbers). The drought intensity is calculated as the ratio of drought severity to drought duration. The specific methods of identifying drought events at the monthly time scale using run theory are as follows (Fig. 4): (1) 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 is less than X_1 , it is preliminarily determined that a drought had occurred in that month; (3) when the drought index is greater than X_2 , for a drought event lasting one month, it is determined that there was no drought in that month and eliminated; and (4) when the time interval between two adjacent droughts processes is only one month, and the drought index value within that month is less than X_0 , the two adjacent droughts processes are combined into one drought event. In this last case, the drought duration is the sum of the two drought durations plus one, and the drought severity is the sum of two drought events. Otherwise, it is two independent drought processes.

After extracting the drought characteristics such as duration, severity and intensity, the joint return period under different levels of drought can be calculated using their distribution.

Fig. 4 Identification of socioeconomic drought events and their characteristics using run theory

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 paper, we chose the two-dimensional copula function for drought return period analysis, expressed as follows:

$$C(u, v) = \varphi^{-1}(\varphi(u), \varphi(v)) \quad (5)$$

Where, φ denotes the convex function; and u and v represent the two variables. Generally, there are three main types of copulas: elliptical, Archimedean and quadratic. The elliptical copula can be used to construct an abnormal extreme relationships, so 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 (Genest et al., 2007; Song and Singh,

2010; Chen et al., 2015; Reddy and Ganguli, 2012). Therefore, in this study, three Archimedean copulas and two elliptical copulas were used to simulate the joint probability of marginal distribution of drought duration and severity (Table 3), and the maximum likelihood method was used to estimate the copula parameters (Joe, 1997).

Table 3 Expression and definition domain of the Copula functions

Copula function		Expression	θ Definition
Archimedean copulas	Clayton	$\max[(u^{-\theta} + v^{-\theta} - 1)^{-1/\theta}, 0]$	$(0, +\infty)$
	Frank	$-\frac{1}{\theta} \ln \left[1 + \frac{(e^{-\theta u} - 1)(e^{-\theta v} - 1)}{e^{-\theta} - 1} \right]$	$\mathbb{R}$
	Gumbel	$\exp \{ -[(-\ln u)^\theta + (-\ln v)^\theta]^{1/\theta} \}$	$[1, +\infty)$
elliptical copulas	Gaussian	$\int_{-\infty}^{\theta^{-1}(u)} \int_{-\infty}^{\theta^{-1}(v)} \frac{1}{2\pi\sqrt{1-\theta^2}} \exp \left\{ -\frac{s^2 - 2\theta st + t^2}{2(1-\theta^2)} \right\} ds dt$	$(-1, 1)$
	t	$\int_{-\infty}^{t_k^{-1}(u)} \int_{-\infty}^{t_k^{-1}(v)} \frac{1}{2\pi\sqrt{1-\theta^2}} \exp \left\{ 1 + \frac{s^2 - 2\theta st + t^2}{k(1-\theta^2)} \right\}^{-\frac{k+2}{2}} ds dt$	$(-1, 1), k \neq 0$

In addition, the Ordinary Least Squares (OLS) minimum criterion and Akaike Information Criterion (AIC) were selected to test goodness of fit and determine the optimal copula function. The formulas of the inspection methods are:

$$\text{OLS} = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (P_{ei} - P_i)^2} \quad (6)$$

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

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 are, the closer the joint distribution probability value calculated by the copula function is to the empirical probability value, and the better the fitting effect is.

3.5 Joint return period calculation

After selecting the optimal copula function, the return period of drought occurrence can be calculated. Joint return period is the reciprocal of the joint probability of two variables, which can be used to represent the risk of drought events. Salvadori and Michele (2004) proposed two return periods: ‘or($\square$)’ joint return period and ‘and($\cap$)’ joint return period. Suppose two random variables are X and Y, and the thresholds of X and Y are set to x and y, respectively. ‘ $\square$ ’ joint return period is the time interval in which at least one variable (X or Y) is higher than the threshold ($T_{(X>x)\square(Y>y)}$); and ‘ $\cap$ ’ joint return period refers to the time interval in which both X and Y exceeding their own thresholds($T_{(X>x)\cap(Y>y)}$).

The socioeconomic drought duration and severity were tested 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):

$$T_{(D>d)\cup(S>s)} = \frac{E(\Delta T)}{1-C(F_D(d),F_S(s))} \quad (8)$$

$$T_{(D>d)\cap(S>s)} = \frac{E(\Delta T)}{1-F_D(d)-F_S(s)+C(F_D(d),F_S(s))} \quad (9)$$

where, $T_{(D>d)\square(S>s)}$ and $T_{(D>d)\cap(S>s)}$ are ‘ $\square$ ’ and ‘ $\cap$ ’ joint return period, respectively; C represents the copula function; $C(F_D(d), F_S(s))$ stands for the joint distributions of drought duration and intensity, which are combined using the copula function; $F_D(d)$ and $F_I(i)$ are the marginal distribution of drought duration and intensity, respectively;

and $E(AT)$ 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 was actually drought inter-arrival time.

4. Results

4.1 Socioeconomic drought events and their features

The socioeconomic drought events and SSDWI statistical results in the JJRB from 1985 to 2019 are shown in Figure 5 and Figure 6.

Fig. 5 Monthly SSDWI in the JJRB from 1985 to 2019

Fig. 6 Socioeconomic drought events during 1985-2019 in the JJRB

On the monthly scale, a total of 29 socioeconomic drought events occurred in the JJRB over the 35 years study period, with an average duration of 6.16 months per drought event and an 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. Compared with meteorological drought and hydrological drought, the duration of socioeconomic drought tended to be longer.

On the seasonal scale (Fig. 7), it is considered that 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 almost never occurred in summer due to the high rainfall, river flow, and high water supply rate during this season.

On the yearly scale, drought events were generally considered to be divided into

four levels: slight ($-0.5 \sim -1$), moderate ($-1 \sim -1.5$), severe ($-1.5 \sim -2$) and extreme (< -2). Based on these categories, severe droughts occurred in the JJRB in 2000 and 2003, while moderate droughts occurred in 1986, 1991 and 2008.

Fig. 7 Frequency and severity of socioeconomic drought in the JJRB in different seasons

4.2 Marginal distribution fitting of drought duration and severity

In order to accurately determine the critical values for different grades of drought events, the Weibull distribution, GEV distribution, normal distribution, logistic distribution, log-logistic distribution and generalized Pareto (GP) distribution were used to fit the duration and severity of droughts. The distribution with the best goodness of fit was selected by K-S test. All distributions met the 0.05 significance threshold, and the results are shown in Table 4. The empirical and theoretical distributions are shown in Figure 8. Table 4 shows that the best fitting distributions for drought duration and severity were the logistic and GP distributions, respectively. Figure 8 further

demonstrates the reliability of the marginal distribution selection.

Fig. 8 Empirical and theoretical CDFs fitted to drought duration and severity

Table 4 K-S test of drought duration and severity marginal distribution fitting

K-S Test value	WBL	GEV	NORM	Log	Log-Log	GP
Duration	0.4156	0.6482	0.6553	0.8093	0.7977	0.0707
Severity	0.4128	0.7473	0.7232	0.6403	0.6050	0.7515

In addition, the critical values for different levels of socioeconomic drought events corresponding to the cumulative probability could be obtained from Figure 8. The results are shown in Table 5. The drought events that lasted for 7 – 10 months and had severities between 7 – 10 were identified as severe, while the drought events that were longer than 10 months and had a severity greater than 10 were identified as extreme drought.

Table 5 Gradation of socioeconomic drought events according to duration and intensity

Socioeconomic drought event	Duration	Severity
Slight drought	<4 months	<3
Moderate drought	4~7 months	3~7
Severe drought	7~10 months	7~10
Extreme drought	>10 months	>10

4.3 Selection of the optimal copula function

According to the optimal distribution of drought duration and severity in Section 4.2, the Log distribution and GP distribution were selected to fit the marginal distribution of drought duration and severity, respectively. Figure 6 shows a significant positive correlation between drought duration and severity. 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. The copula parameter θ was estimated using the maximum likelihood method. AIC and OLS were used as parameters to select the best fitting copula. The results are shown in Table 6.

It was obvious that the t-copula was the most suitable copula because it had the smallest AIC and OLS values (Table 6). These results indicated that the t-copula had the best fit for drought duration and severity. Therefore, the t-copula was chosen to construct the drought risk model in this study. The resulting joint distributions and contours of drought duration and severity are shown in Figure 9 and Figure 10, respectively.

Table 6 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. 9 Cumulative distribution diagram of socioeconomic drought duration and severity in the JJRB

Fig. 10 Contours diagram of socioeconomic drought duration and severity in the JJRB

4.4 Calculation of drought return periods of different grades

After the copula function of drought duration and severity is optimally fitted, the joint return periods ($'\cup'$ and $'\cap'$) in the two cases were calculated to characterize the socioeconomic drought in the JJRB. The results are shown in Figure 11, and the joint return periods of different grades of socioeconomic droughts are shown in Table 3.

Obviously, the possibility of socioeconomic drought with return period ‘ $\cup$ ’ is higher than that with return period ‘ $\cap$ ’. With increasing drought duration and severity, the joint return periods of ‘ $\cup$ ’ and ‘ $\cap$ ’ increased. The joint return periods of ‘ $\cup$ ’ and ‘ $\cap$ ’ under moderate drought conditions were 8.81 years and 10.81 years, respectively. while those under severe drought conditions were 16.49 and 26.44 years, respectively. Furthermore, the joint return periods of ‘ $\cup$ ’ and ‘ $\cap$ ’ under extreme drought conditions were 41.68 years and 91.13 years, respectively.

Table 7 Joint return periods for different grades of socioeconomic drought in the JJRB

Drought scenarios	‘ $\cup$ ’ joint return period (year)	‘ $\cap$ ’ joint return period (year)
Moderate drought	8.81	10.81
Severe drought	16.49	26.44
Extreme drought	41.68	91.13

Fig. 11 ‘ $\cup$ ’ (a) and ‘ $\cap$ ’ (b) joint return period of drought duration and severity

5. Discussion

5.1 Relationship between 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 in human life and production. In order to explore the relationship between meteorological, hydrological and socioeconomic drought, the data of rainfall, temperature and river runoff data measured in the JJRB were used to calculate SPEI (Vicente-Serrano et al.,2010) and SDI (Nalbantis I et al.,2009), and characterize meteorological and hydrological drought from 1985 to 2019. The relationships among SPEI, SDI, and SSDWI indices at monthly, seasonal, and annual scales were analyzed using Pearson correlation coefficient (significance level of 0.01). As shown in Table 8, the three droughts types were most strongly correlated at the 12-month scale. Compared with meteorological drought, hydrological drought was more closely related to socioeconomic drought. Therefore, it is appropriate to use flow deficit as a measure of socioeconomic drought. Sufficient river runoff volume is important in maintaining water quality, preventing saltwater intrusion, ensuring river ecological health, facilitating ship navigation and supplying water intake outside the river. Therefore, a river needs to meet the requirements of minimum ecological flow, navigable flow and basin water demand requirements. When the river flow is abnormally low, under the premise of prioritizing ecological flow and navigable flow, meeting the water demands outside the river (i.e., agricultural demands) is often impossible. In these scenarios, there is an imbalance between water supply and demand between the natural systems and human social systems, then a socioeconomic drought occurs. Therefore, hydrological drought is the most direct causes of socioeconomic drought, and the

relationship between them is relatively close.

Table 8 Pearson correlation coefficients among the three drought indices

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

5.2 Trends of socioeconomic, hydrological and meteorological drought

As shown in Figure 12, SSDWI-12 had an increasing trend since 1985, and its value was $0.067 < 0.1$ after passing the Pettitt test, This 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 0.76 afterwards, indicating that the risk of socioeconomic drought in the JJRB had been significantly reduced. The frequency and severity of socioeconomic drought in recent years have significantly declined. Similarly, due to 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, indicating that the hydrological drought occurrence and severity had been significantly improved, and the river runoff in the dry season was more reliable. However, SPEI did not change significantly, 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.

Fig. 12 Trends of socioeconomic drought (a), hydrological drought (b) and meteorological drought(c)

5.3 Possible causes

Among the previous socioeconomic drought evaluation indicators, reservoirs have been identified as indispensable in ensuring sufficient river runoff and water supply in the basin during dry periods. Gaozhou Reservoir is also the most important water storage project in the JJRB. Under the assumption that there has been no remarkable change in climate in recent years, reservoir operation in the basin is the likely reason for the obvious alleviation of hydrological and socioeconomic drought since 2008. Therefore, the daily average discharge of Gaozhou Reservoir in spring, autumn and winter (mainly used for flood management in summer) from 1985 to 2019 was analyzed. The results in Figure 13 show that, the discharge of the reservoir has been increasing, and the increase has been more pronounced since 2008. The mean discharge before and after 2008 were $62.3 \text{ m}^3/\text{s}$ and $117.9 \text{ m}^3/\text{s}$, respectively. This was, due to the improved operation and utilization of the reservoir by the basin management department that the runoff of the river during the dry season is guaranteed, and also include the normal water supply and the normal water intake of the water users, thus significantly reduces the frequency and severity of hydrological drought and socioeconomic drought.

Fig. 13 Daily average outflow of Gaozhou Reservoir in spring, autumn and winter from 1985 to 2019

6. Conclusions

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

(1) SSDWI was suited to characterizing the socioeconomic drought in the JJRB. There were 29 socioeconomic drought events in the basin from 1985 to 2019, with an average duration of 6.16 months and an average severity of 5.82. Socioeconomic droughts mainly occur in autumn and winter, which also experienced more serious drought than other seasons;

(2) In JJRB, the joint return periods of ‘ $\cup$ ’ and ‘ $\cap$ ’ 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 risk of socioeconomic drought and hydrological drought in the JJRB has dropped significantly since 2008 due to the increased outflow from the Gaozhou Reservoir. The reasonable operation of the reservoir plays an important role in alleviating hydrological drought and socioeconomic drought in the basin.

The research results of this paper provide a new perspective for the identification and assessment of socioeconomic droughts in a changing environments. The findings of this paper will be helpful in the management of local water resources and the prevention of socioeconomic drought. However, there are still many problems to be solved, such as how to calculate the monthly water supply and demand more finely and accurately, which part of the supply and demand chain has the greatest impact on socioeconomic drought, and how reservoirs and water supply projects work together to minimize the risk of socioeconomic drought, etc. These are the directions for further research.

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

Declaration of Competing Interest

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

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