



# Analysis of the Water-Food-Energy Nexus and Water Competition Based on a Bayesian Network

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## Abstract

Water competition is a key issue in the study of the water-food-energy nexus (WFEN), which can affect water, food, and energy security and can generate notable challenges in water resource management. Since Bayesian network can express parameter uncertainty with a certain probability distribution while reflecting the dependencies of each variable, this study used a Bayesian network to model the WFEN in the Pearl River Region (PRR). The network structure can intuitively represent complex causal relationships, and the form of the probability distribution can effectively reflect the variable uncertainty. The responses of the Bayesian network model under different scenarios were used to analyse the major influencing factors, and water competition relationships in various sectors were explored. The results indicated that water competition between the different sectors was very complex and could dynamically change under the different scenarios. For example, an increase in hydropower and flow to sea could lead to a decrease in irrigation water, but an increase in irrigation water did not necessarily reduce hydropower and flow to sea. Water for hydropower generation and salt tide alleviation were obviously affected by the total offstream water use, but there existed no obvious water competition between these aspects in general. However, when offstream water use remained stable, a competitive relationship was observed between hydropower and flow to sea. Overall, the outcomes of this study could be of great significance to further analyse the WFEN in other regions.

**Keywords** Water-Food-Energy Nexus · Water Competition · Bayesian Network · Pearl River Region

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## 1 Introduction

As basic resources for social and economic development, water, food, and energy resources are important for the achievement of sustainable development goals (UN, 2015). However, due to the growth in population and gross domestic product (GDP), the demand for water, food, and energy will continue to increase in the future, which will greatly challenge the security of water, food and energy (FAO, 2014; US NIC, 2012). Since these three resources are closely related, it is necessary to jointly solve water, energy and food issues to rationally utilize these three resources under limited resource conditions and to meet the needs of socioeconomic development. Therefore, the concept of the water-food-energy nexus (WFEN) was developed to address sustainability issues related to water, food and energy resources under climate change and socioeconomic development from an inter-disciplinary and cross-sectoral perspective (Hoff 2011; Zhang et al. 2018).

Scholars have proposed that water constitutes the core of the WFEN (Hoff 2011; D'Odorico et al. 2018). Water resources are not only the main limiting resources restricting food production growth (Porkka et al. 2017) but also an indispensable part of the extraction, production, distribution and use of energy (Wu and Chen 2013). Since food and energy growth depends on limited water resources, there exists fierce water competition between food and energy in the WFEN (D'Odorico et al. 2018). Water competition between the food and energy sectors undoubtedly aggravates the WFEN complexity and generates more challenges in water resource management.

Due to the complexity and uncertainty in water resource research, Bayesian networks have become a popular method. A Bayesian network exhibits a flexible structure that can express the dependency between various variables, and this method can combine various sources of information for probabilistic reasoning. Consequently, this approach can suitably address highly uncertain and complex problems (Marcot and Penmanb 2019). Bayesian networks have been widely used in related fields, such as precipitation prediction, water pollutant analysis, water environmental protection and water ecological restoration, supervision and management of water supply networks, and integrated water resource management (Legasa and Gutierrez 2020; Bonotto et al. 2018; Tang et al. 2019; Govender et al. 2021).

The WFEN contains a number of water-related issues and is highly complicated due to its inter-departmental and inter-disciplinary characteristics, while the Bayesian method is undoubtedly a suitable method for WFEN research. However, there are few applications of the Bayesian method in WFEN research. In existing relevant studies, scholars have used Bayesian networks to analyse the contradiction between the supply and demand in the WFEN and water resource management of upstream and downstream cross-border rivers in the WFEN (Chai et al. 2020; Wang et al. 2021; Shi et al. 2020). However, there is a lack of research on water competition between different sectors in the WFEN.

The Pearl River Basin contains abundant water resources and exhibits a well-developed hydropower industry, but this basin is easily affected by salt tides, and the relationships within the WFEN in this region are complex. Scholars have conducted WFEN studies in the Pearl River Delta (Ouyang et al. 2021) and have optimized reservoir dispatch in the East River to reduce water supply shortages and improve the hydropower efficiency by estimating the irrigation water demand (Wu and Chen 2013). Nevertheless, there remains a lack of studies of the WFEN in the entire Pearl River region (PRR) and water competition between the different sectors.

This study used Bayesian network theory to construct a Bayesian network model based on the WFEN in the PRR to analyse causal relationships in the WFEN. First, the proposed model was parameterized with available data, and the parameterized Bayesian network was used to represent the causal relationship between different variables and the inherent uncertainty. Subsequently, sensitivity and diagnostic analysis experiments of the proposed model were performed to identify important model variables and the main influencing factors of the WFEN. Then, the complex water competition relationships among the different sectors were explored with the proposed model. Finally, combined with socioeconomic development plans, future water competition between the different sectors was predicted. Based on the proposed model, the key factors of the WFEN could be recognized, and current and future water competition considerations could be examined. Compared to the existing literatures, the study area (i.e., the PRR) is a new application area, and the factor of salt tides has been less considered in previous WFEN studies. In addition, water competition among the different sectors was investigated after analysis of the relationships within the WFEN. This study considered novel aspects, and the outcomes can provide references for local water resource management.

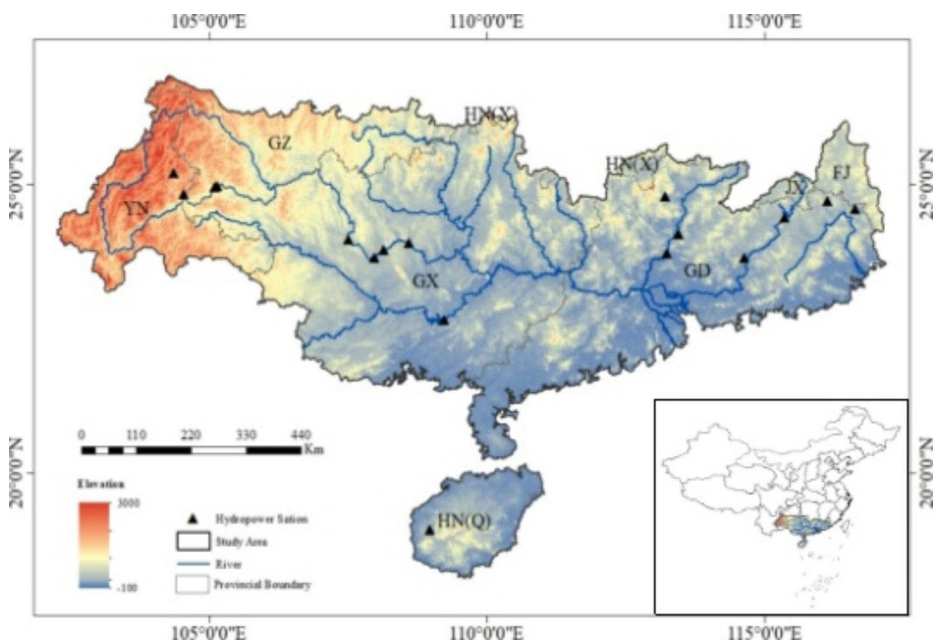


Fig. 1 Location of the PRR

## 2 Study area and data

### 2.1 Study area

The PRR is located in South China, including the Pearl River Basin and the rivers along the South China Coast. The study area covers eight provinces (i.e., Yunnan, Guizhou, Guangxi, Guangdong, Hunan, Jiangxi, Fujian, and Hainan), with a total area of 579 thousand km<sup>2</sup> (Fig. 1). This region contains abundant water resources, with an average annual rainfall of approximately 1200–2000 mm and an average annual runoff of 338.1 billion m<sup>3</sup>. The rivers in this region exhibit a high natural slope, which provides a high potential for hydropower development and plays an important role in supporting the socioeconomic development process in this region. The effective irrigation area of farmland in this region is 4480.98 thousand ha, and irrigation water accounts for a large proportion of the total water consumption. In 2020, farmland irrigation water in the PRR reached 40.68 billion m<sup>3</sup>, accounting for 52.6% of the total water consumption. In recent years, frequent droughts and salt tide disasters have greatly affected water use and the WFEN in this region.

### 2.2 Data

This study collected data on climate, water resources, water use, agriculture, society and economy in the PRR (please refer to Table 1). There were only individual years with agricultural and societal and economic statistical data at the PRR scale, resulting in the absence of available data series. Therefore, agricultural and societal and economic data series were obtained by converting provincial statistical data according to the proportion of provincial administrative divisions in the study area to the total province. Then, final agricultural and societal and economic data series values were obtained for calculation purposes after prof-

**Table 1** Data description and sources

Data	Description	Source
Evaporation	Weather station and daily scales	Meteorological Science Data Center
Precipitation	Annual scale	Water Resources Bulletin
Water resources and water use	Annual scale	Water Resources Bulletin
Hydropower generation	Hydropower, installed hydropower capacity; annual and station scales	Almanac of China's Water Power, China electric power yearbook, Yearbook of China Water Resources
Agriculture	Irrigation area, sown area, and food output; annual and provincial scales	National Bureau of Statistics of China
Society and economy	Population and GDP; provincial scale	National Bureau of Statistics of China
Flow to sea	Annual scale	Water Resources Bulletin
Salt tides	Chlorinity of the Modaomen Waterway; highest value per year	Zhongshan Yearbook, Water Resources Bulletin of Zhongshan

reading the converted data series based on the proportional coefficient. The proportional coefficient is the ratio between the statistical values at the PRR scale for individual years and the converted values of relevant data, and statistical data were obtained from Pearl River Continued Records and China Water Resources Statistical Yearbook.

Evaporation data for calculation purposes were obtained via spatial interpolation obtained by summing daily-scale station data. Missing daily-scale data were replaced with annual data. Since it was difficult to obtain complete hydropower production data, only representative sites with relatively complete data series were selected to represent hydropower stations in the entire study area. The highest chlorinity at the Quanlu Water Plant in the Pearl River Estuary was used to reflect the impact of salt tides on the Pearl River Basin, and missing values were classified based on yearbook records and relevant literature (Lu et al. 2011; Liu and Huang 2000). Over the past two decades, the total population and GDP in this region have exhibited a significant upward trend. Therefore, if these data were directly used in modelling, future development could likely exceed a certain threshold. Therefore, the population and GDP growth rates were used to express social and economic development conditions, respectively

### 3 Methods

#### 3.1 Bayesian network model

Bayesian network is a directed acyclic graph that uses nodes to represent variables and arcs between nodes to represent the causal connection between variables. If there exists a directed arc from variables  $X$  to  $Y$ ,  $X$  is the parent node of  $Y$ , and  $Y$  is the child node of  $X$ . The causal connection between these nodes can be expressed by the conditional probability  $P(Y|X)$ . When node  $Y$  exhibits multiple parent nodes,  $\text{parents}(Y)$  can be used to represent all parent nodes of  $Y$ , and the conditional probability of  $Y$  can then be expressed as  $P(Y|\text{parents}(Y))$ . Each node of the Bayesian network is associated with a certain probability distribution. If a node has a parent node, this probability distribution can be expressed with a given conditional probability. When there is no parent node, the probability distribution can be represented as an edge distribution. Thus, the joint distribution of the Bayesian network can be expressed as Eq. (1) if the variables in the Bayesian network are  $X_1, X_2, \dots, X_n$ .

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^n P(X_i | \text{parents}(X_i)) \quad (1)$$

Based on the joint distribution, probabilistic inference can be conducted with the parameterized Bayesian network. Given the states of a group of evidence variables, the states of query variables can be inferred, and probability distributions of the different variables in various states can then be obtained, as expressed in Eq. (2).

$$P(Q|E) = \frac{P(Q, E)}{P(E)} \quad (2)$$

where  $Q$  is the query variable and  $E$  is the evidential variable. The inference process can be simplified according to the characteristics of the network structure, and Bayesian networks can thus be applied to complex and large-scale structures (Zhang and Guo 2006).

### 3.2 Bayesian network parameterization

In this study, the BNT toolbox in MATLAB was used for parameter learning of the Bayesian network. Maximum likelihood estimation and Bayesian estimation are common parameter estimation methods for Bayesian networks. Bayesian estimation assumes that the parameters are random and can be calculated with prior knowledge, which is intuitive and more reasonable than is maximum likelihood estimation (Zhang and Guo 2006). Therefore, this study chose the Bayesian estimation method for parameter learning. Moreover, likelihood equivalent uniform Bayesian Dirichlet (BDeu) priors provided by the BNT toolbox were selected for parameterization. The BDeu is a very common prior distribution for Bayesian networks that provides undifferentiated objective priors with equal probabilities (Heckerman et al. 1995). Although no information is provided, this distribution can control overfitting. After prior distribution setting, the weight of prior knowledge must also be set. In prior weight setting, it is necessary to ensure that the sample data obtain enough weight information. In this study, the prior weight was set to 2, which is equivalent to expressing the prior into two virtual samples.

### 3.3 Sensitivity analysis and diagnostic analysis of the bayesian network

Sensitivity analysis and diagnostic analysis are often used for Bayesian network evaluation (Pollino et al. 2007). Sensitivity analysis can identify the impact of varying variables on the query variable by observing the magnitude of change in the probability of the query variable after change the varying variable. The magnitude of change can be represented by mutual information ( $MI$ ) and variance in belief ( $VB$ ) (Zou and Yue 2017).  $MI$  and  $VB$  can be calculated with Eqs. (3) and (4), respectively (Pearl 1988; Neapolitan 1990).

$$MI = H(Q) - H(Q|F) = \sum_q \sum_f P(q, f) \log \frac{P(q, f)}{P(q)P(f)} \quad (3)$$

$$VB = \sum_f \sum_q P(q, f) [P(q, f) - P(q)]^2 \quad (4)$$

where  $Q$  is the query variable,  $q$  is the state of  $Q$ ,  $F$  is varying variables, and  $f$  is the state of  $F$ . The larger the  $MI$  and  $VB$  values are, the higher the dependence of  $Q$  and  $F$ .  $MI$  and  $VB$  are 0 if  $Q$  is independent of  $F$ .

In contrast, diagnostic analysis aims to determine the influence of the target variable on the other variables by observing the magnitude of change in the probability of the other variables after setting a specific state of the target variable. The result is generally expressed by the degree of change in the probability value.

Sensitivity analysis and diagnostic analysis can effectively measure the relationship between the variables in the Bayesian network model. These methods can identify the importance of different nodes in the network and the degree of information a node can

respond to according to the responses of the other nodes under input parameter variation. Consequently, the major influencing factors and their effects can be determined among the other variables to help decision-makers in the formulation of management measures.

### 3.4 Bayesian network model based on the water-food-energy nexus (WFEN-BN)

Water, food and energy are the core factors of the WFEN, and these factors are influenced by external factors such as social, economic and environmental factors (Molajou et al. 2021; El-Gafy and Apul 2021). In recent decades, the population, economy, and urbanization in the PRR have rapidly increased, which has increased the demand for water, grain, energy and other resources in this region. At the same time, climate change has affected water resources in this region and caused frequent droughts (Deng et al. 2018). These factors have impacted the water supply in different sectors (Yan et al. 2018). Changes in water resources and water use can affect the relationship between water, food and energy and can aggravate water competition between energy and food. Moreover, the intensity of salt tides in the Pearl River Estuary has increased, and the salty boundary has significantly moved upwards since the 21st century because of climate change and local socioeconomic development, which can threaten local water use (Chen et al. 2014). To alleviate the effects of salt tide disasters, local governments have released additional water from upstream reservoirs to suppress up-

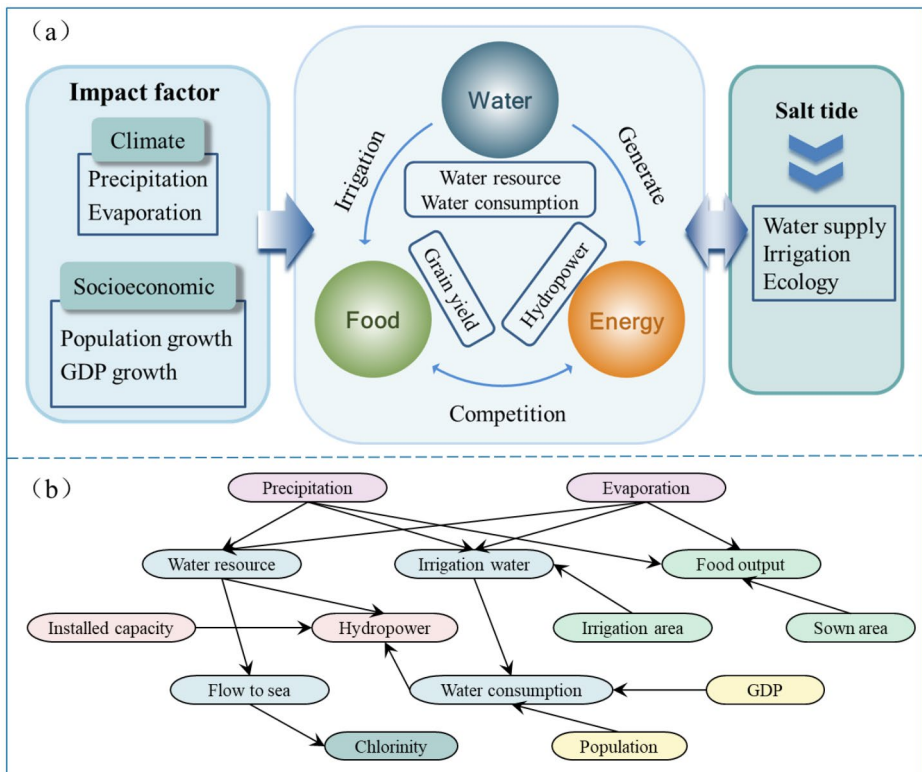


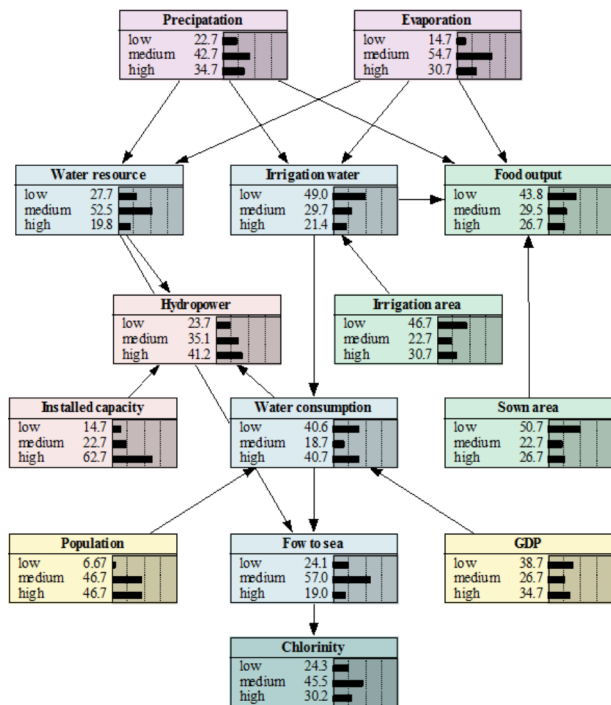
Fig. 2 Framework and structure of the WFEN-BN for the PRR

bound salt tides, which can inevitably affect the WFEN. Considering all these problems, the framework of the WFEN-BN for the PRR was constructed (Fig. 2 (a)). The framework of

**Table 2** Description and status of the variables after discretization

Variable	Description	Low	Medium	High	Unit
Precipitation		7300~8500	8500~9700	9700~10,900	10 <sup>8</sup> m <sup>3</sup>
Evaporation		940~1020	1020~1100	1100~1620	mm
Water resources		3500~4500	4500~5500	5500~6500	10 <sup>8</sup> m <sup>3</sup>
Irrigation area	Farmland	3500~4200	4200~4400	4400~4600	10 <sup>3</sup> ha
Irrigation water	Farmland	420~450	450~480	480~510	10 <sup>8</sup> m <sup>3</sup>
Sown area	Food crops	6500~7300	7300~8300	8300~9300	10 <sup>3</sup> ha
Food output	Food crops	3000~3200	3200~3700	3700~4200	10 <sup>4</sup> t
Population	Growth rate	<0	0~0.015	>0.015	%
GDP	Growth rate	<0.1	0.1~0.15	>0.15	%
Water consumption		810~840	840~860	860~890	10 <sup>8</sup> m <sup>3</sup>
Installed capacity	Hydropower station	440~560	560~680	680~800	10 <sup>4</sup> kW
Hydropower generation		170~240	240~310	310~390	10 <sup>8</sup> kW·h
Flow to sea	Sum of all the inlets in the entire region	3000~4000	4000~5000	5000~6000	10 <sup>8</sup> m <sup>3</sup>
Chlorinity	Annual maximum value at the Quan Lu Water Plant	0~2200	2200~5200	5200~8200	mg/L

**Fig. 3** Parameterized WFEN-BN for the PRR





the WFEN-BN simplifies conditions according to the research theme in this study, and the Bayesian network structure can be established based on this framework (Fig. 2 (b)).

## 4 Results

### 4.1 Parameterization of the WFEN-BN

To reduce the computational complexity, relevant data were discretized. Discretization methods include objective methods, such as equal-frequency or equal-interval methods, and expert-based subjective methods (Farnaz et al. 2017; Shi et al. 2020). The discretization process in this study combined objective and subjective methods. The equal-interval discretization method was first used, after which appropriate adjustments were made according to the actual sample conditions. Finally, the variables could be divided into three states (i.e., low, medium, and high) according to the sample size (Table 2).

We parameterized the model with the obtained discretized data, and the results are shown in Fig. 3. This model reflects the quantitative dependence between the variables, which can reveal and assess the WFEN.

### 4.2 Sensitivity analysis

Representative WFEN-BN variables were selected as query variables in sensitivity analysis. In this study, water consumption, food output, hydropower, and chlorinity, which are impor-

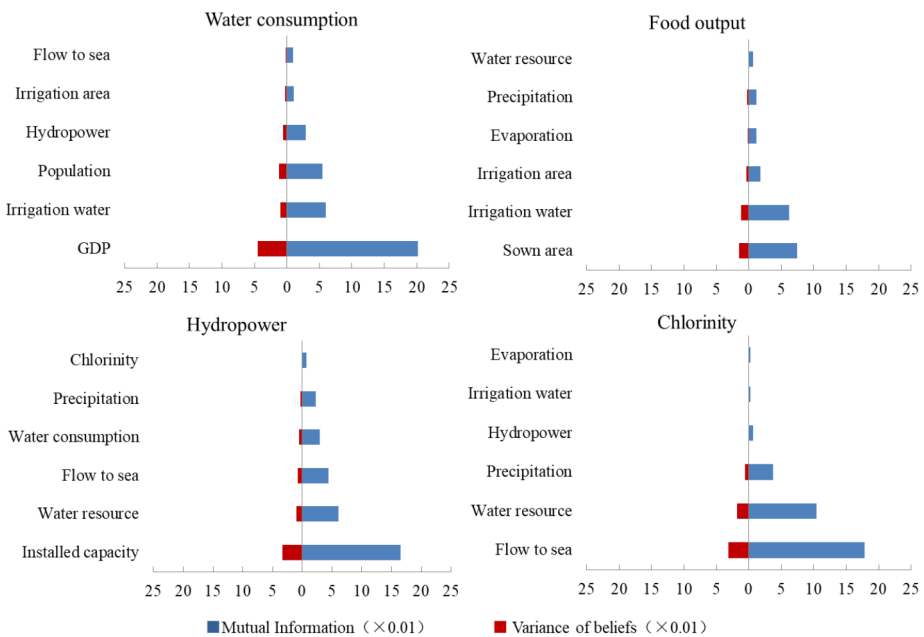
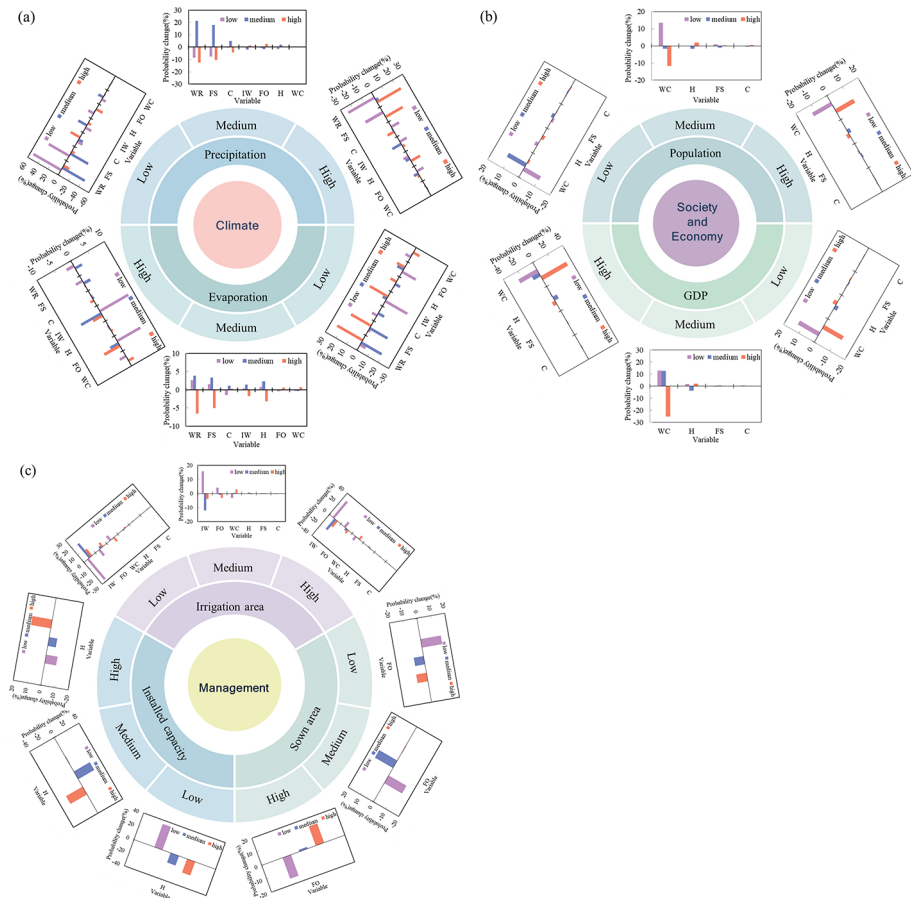


Fig. 4 Sensitivity analysis of the essential WFEN-BN variables

tant elements of the water, food production, hydropower generation and salt tide systems, respectively, were selected.

As shown in Fig. 4, the sensitivity analysis results based on *MI* (blue bars) and *VB* (red bars) basically revealed consistent trends. The variables with the greatest impacts on water consumption, food output, hydropower, and chlorinity were the GDP, sown area, installed capacity, and flow to sea, respectively, all located in the parent node of the target variable within the network. This indicates that the factors directly influencing the query variable generated notable impacts. By comparing the sensitivity analysis results among the four target variables, water resources highly impacted the food output, hydropower, and chlorinity. At the same time, the sensitivity index value of water consumption was significantly higher than that of the other target variables. These results all verified that the water system is highly important for the entire network. In addition, as shown in Fig. 5, the *MI* and *VB*

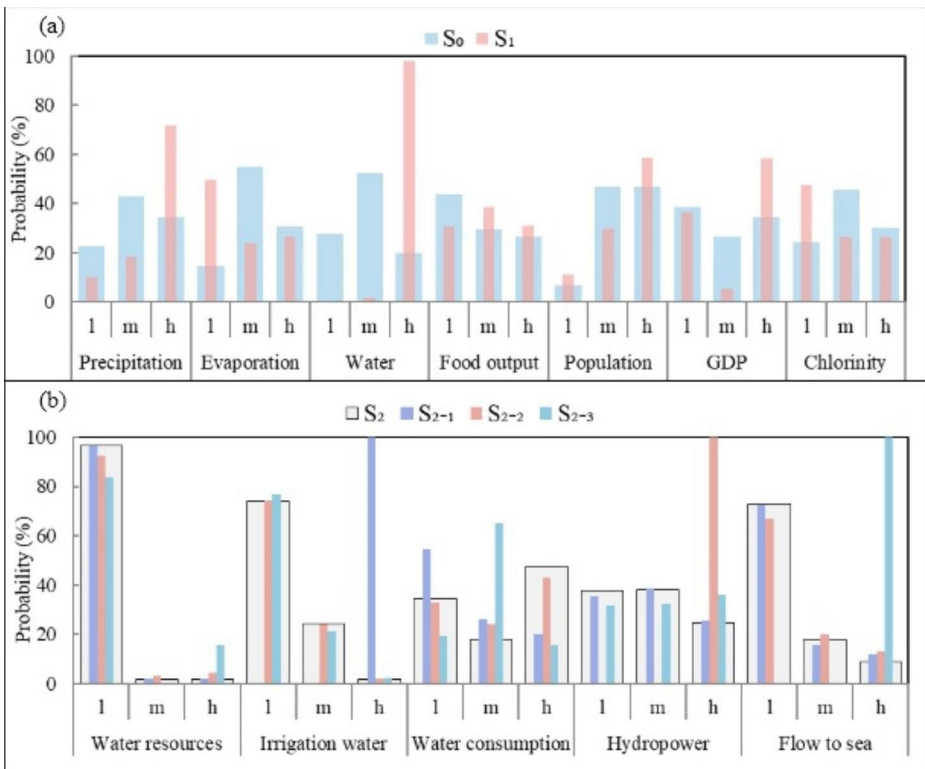


**Fig. 5** Diagnostic analysis of (a) climate factors, (b) society and economy factors, and (c) management factors of the WFEN-BN. Note: WR denotes water resources, FS denotes the flow to sea, C denotes the chlorinity, IW denotes irrigation water, FO denotes the food output, WC denotes the water consumption, and H denotes hydropower

values for the different influencing factors and query variables greatly differed. The primary and secondary influencing factors of the target variable could be distinguished according to the mutation position of the ranking index values and could be further divided according to the number of decrease stages. The identification results for the influencing factors of query variables could provide a reference for managers in the formulation of management strategies.

### 4.3 Diagnostic analysis

The influencing factors of the WFEN can be divided into climate factors, society and economy factors, and management measures in diagnostic analysis. The results are shown in Fig. 5. From the perspective of the influence scope, which refers to the number of variables influenced by a given factor, climate factors most notably impacted the network. Both precipitation and evaporation affected seven variables within the network, followed by the irrigation area among the management measures, which affected six variables within the network. The population size and GDP among the society and economic factors impacted four variables. The sown area and installed capacity among the management measures exerted the smallest impact on the network, affecting only one variable. From the perspec-



**Fig. 6** Response of the network model under the different scenarios. The letters l, m, and h indicate the three states of low, medium, and high, respectively

tive of the influence intensity, which refers to the change in probability value when the probability of more than one variable is adjusted, the most notable variable was chosen for comparison, and precipitation exerted the greatest impact on the network, followed by the installed capacity, GDP, irrigation area, evaporation, sown area and population. Combining these two aspects, climate factors highly impacted the WFEN. Climate factors can impact the state of regional water resources, and water resources can play a vital role in sustainable WFEN development. In addition, the irrigation area can significantly impact the entire network. Hence, irrigation area construction and management are of great significance to the development and utilization of water resources in this region.

#### 4.4 Water competition in the different sectors

Since the development of each sector requires a large amount of water, we established an extreme scenario  $S_1$  with a high water consumption: the states of irrigation water, hydropower, flow to sea, and water consumption were all high. The states of the other variables under  $S_1$  were compared to the variable states under the base scenario  $S_0$ , which is the combination of the variable states in the Bayesian network in subsection 4.1, and the requirements of a high water guarantee rate and obtainable benefits were analysed (Fig. 6 (a)). High water resource requirements cannot always be satisfied. Thus,  $S_2$  was established with low precipitation and high evaporation levels, resulting in low water resources, and  $S_{2-1}$  (high irrigation water),  $S_{2-2}$  (high hydropower), and  $S_{2-3}$  (high flow to sea) were set under the base scenario  $S_2$ . The corresponding probability distribution of the variables in the network under these scenarios was compared to analyse the water competition between the various water sectors under water resource constraints (Fig. 6 (b)).

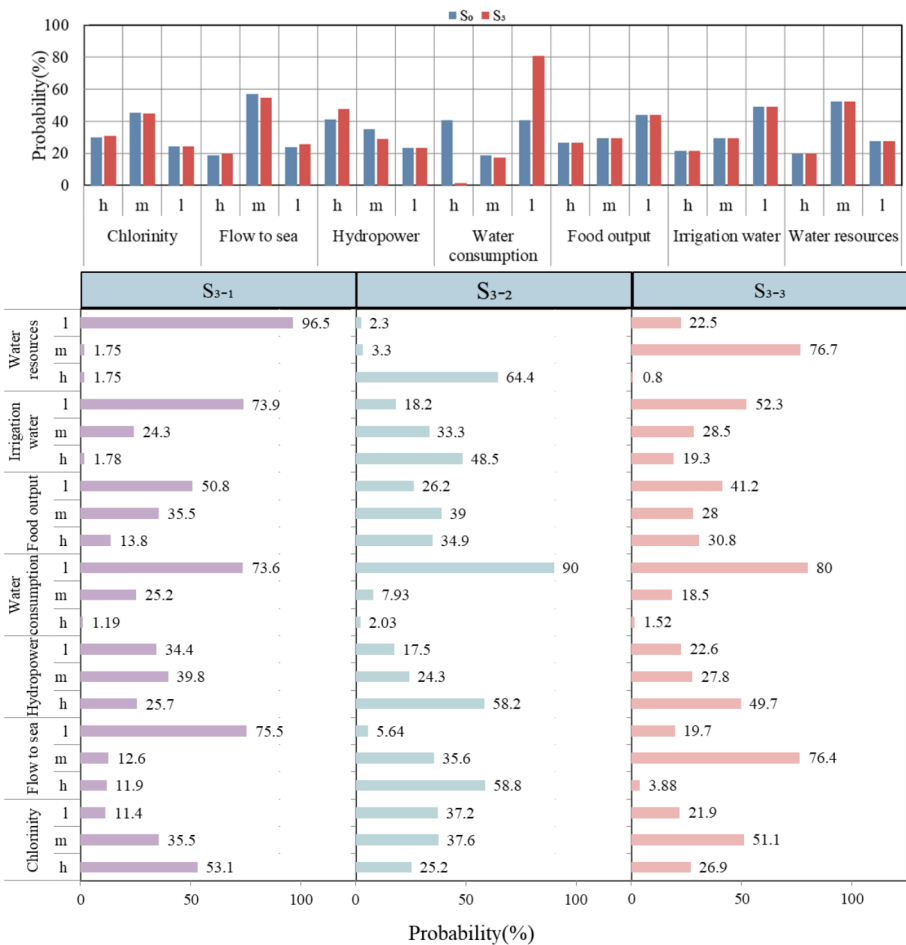
As shown in Fig. 6 (a), high water consumption could support rapid population and economic growth, provide more food resources for social development, guarantee the highest benefits of hydropower generation, and reduce the risk of salt tide damage. However, to ensure a high water consumption, the probability of both high precipitation and low evaporation levels must provide high water resources for an adequate water supply. Under limited water resources, water competition can differ when the water supply in different sectors is prioritized. Under  $S_{2-1}$ , when irrigation water is first guaranteed, hydropower generation and flow to the sea tend to increase. Under  $S_{2-2}$ , when hydropower generation is first guaranteed, flow to the sea tends to increase, and the amount of irrigation water tends to decrease. Under  $S_{2-3}$ , when flow to the sea is first guaranteed, hydropower generation tends to increase, and the amount of irrigation water tends to decrease.

Through the above analysis, it can be concluded that a high water consumption can yield higher benefits across all sectors, but this scenario requires high water resources. When the state of water resources is low, no matter which sector is prioritized to ensure water consumption, the water consumption in the other sectors is affected. The states of hydropower and flow to the sea exhibit the same change trend, and when these states first change, the change trend of irrigation water is the opposite. However, when the state of irrigation water first changes, the change trends of hydropower and flow to the sea are the same. These results indicate that there occurs no obvious water competition between hydropower generation and salt tide control. However, there exists water competition between these sectors and irrigation, but this competition is not obvious when irrigation water is prioritized. This

can be attributed to the influence of the other water use sectors, which is further analysed in the Discussion section.

### 4.5 Potential water competition in the future

According to the development plan of the administrative agency of the PRR, the average annual population and GDP growth rates from 2020 to 2025 were calculated to determine the socioeconomic development scale of the PRR over the next five years. Moreover, this was defined as the base scenario  $S_3$ . Under  $S_3$ , we established  $S_{3-1}$  (low precipitation and high evaporation),  $S_{3-2}$  (high precipitation and low evaporation), and  $S_{3-3}$  (medium pre-



**Fig. 7** Response of the network variables under the different scenarios in the future. The upper part shows a comparison between the probability distributions of the different variables under the government’s future socioeconomic development plan and  $S_0$ , and the lower part shows the probability distribution of the variables under the different climate conditions

precipitation and medium evaporation) and compared the responses of the network variables under these scenarios to analyse the limitations of water resources on the WFEN under different climate conditions in the future. The results are shown in Fig. 7.

Under scenario  $S_3$ , the states of irrigation water, hydropower, and flow to sea slightly changed, water consumption exhibited a decreasing trend, and water competition was not further intensified. Under  $S_{3-1}$ , the state of water resources was low, and flow to sea, hydropower, and irrigation water all tended to decrease, which resulted in a decrease in hydropower benefits and the food output and aggravated salt tide disasters. Under  $S_{3-2}$ , the state of water resources was high, and flow to sea, hydropower, and irrigation water all tended to increase, which improved hydropower benefits and the food output and weakened salt tide disasters. Under  $S_{3-3}$ , the probability distributions of the other variables did not fluctuate much. Irrigation water and flow to sea slightly decreased, and hydropower slightly increased. The change trends of hydropower and flow to sea were the opposite, indicating that there existed a restrictive relationship between these water use sectors, which suggests that there may also occur water competition. This is contrary to the conclusion in subsection 4.5, which may be caused by water competition between upstream and downstream sectors. In addition, irrigation water was reduced and the food output increased with opposite trends under  $S_{3-3}$ , which may be related to the improvement in irrigation technology and water efficiency. These questions are answered in the Discussion section.

## 5 Discussion

### 5.1 Opposite trends in irrigation water and food output

Under  $S_{3-3}$ , food output and irrigation water exhibited opposite trends under a low variation in irrigation water consumption. This occurs because water-saving technology can effectively reduce excess water consumption, such as soil evaporation, which can reduce irrigation water on a regional scale (Zhou et al. 2021). Improvement in irrigation technology can increase water productivity so that high grain yields can still be obtained under the condition of irrigation water savings (Aziz et al. 2018). In recent years, the PRR has continued to promote water-saving irrigation technology. According to statistical data retrieved from the China Water Conservancy Statistical Yearbook, the water savings irrigation area of the Pearl River Basin increased by 817,000 hectares (~69.3%) from 2008 to 2019. From 2000 to 2019, the irrigation water amount per mu decreased by 23.9%. However, the grain yield per mu increased by 7.5%. Water-saving renovation projects can improve irrigation and drainage engineering systems and can provide important basic support for stable food production. Moreover, the effective utilization coefficient of irrigation water can be enhanced to reduce irrigation water pressure and alleviate water competition.

### 5.2 Complex water competition processes between the different sectors

Water competition between the different scenarios, as described in subsections 4.5 and 4.6, suggests that irrigation water can exhibit opposite change trends to those of hydropower and flow to sea. Notably, with increasing hydropower and flow to sea, irrigation water can decrease, which suggests that hydropower generation and salt tide control can consume

water otherwise used for irrigation. However, hydropower and flow to sea do not strictly exhibit opposite change trends to that of irrigation water, which indicates that irrigation may not necessarily consume water at the expense of hydropower generation and salt tide control. In fact, hydropower and flow to sea revealed opposite trends to water consumption, which includes water for agriculture, forestry, fishery animal husbandry, livelihood, manufacture and ecological greening. This could be considered offstream water use, while water for hydropower generation and salt tide control remained within the river water body, so there occurred clear competition between these two sectors. Irrigation water only comprises part of offstream water use, which is affected by hydropower and flow to sea, but this water use sector does not strictly affect hydropower and flow to sea, while offstream water use inevitably affects hydropower and flow to sea.

In most situations, the change trends of hydropower and flow to sea are similar, but under  $S_{3-3}$ , opposite trends were observed. Under most conditions, both hydropower and flow to sea compete with offstream water use, but there also exists competition for water resources between upstream and downstream river areas. Hydropower stations require a height drop, most of which occurs upstream, while flow to sea only focuses on downstream areas. Hydropower involves water storage, while flow to sea entails water release. Therefore, when the offstream water use does not change much, competition between hydropower and flow to sea can occur.

Water competition between the different sectors is complex, and there exist distinct competition relationships under the different scenarios. To alleviate water resource competition, it is necessary to determine key objectives and major contradictions so that effective management measures can be proposed.

### 5.3 Application of the bayesian network in the WFEN

There are many types of connection relationships in the WFEN. Different concepts can be obtained from different perspectives (Proctor et al. 2021), and the relationships between the different variables are nonlinear and contain high uncertainty (Li et al. 2019). With the use of a Bayesian network to model the WFEN, the network structure can intuitively reflect the complex causal relationships in the WFEN, and the probability distributions can effectively express the uncertainty in the variables. In this study, the Bayesian method was used to analyse the WFEN. Compared to qualitative analysis (Smajgl et al. 2016), this study quantified the relationship between the considered variables. In contrast to variable quantification through other methods, the Bayesian method in this study does not require complex mathematical equations to express the relationship between variables (Li et al. 2019).

The parameter learning stage of a Bayesian network requires a certain amount of sample capacity, but the data of some related variables are difficult to collect, and certain samples exhibit an insufficient size. In addition, the more variables there are, the more detailed the description of the research problem, but this also suggests a more complex network structure, more data samples, and a larger calculation amount. Therefore, a trade-off between these aspects must be achieved in Bayesian network construction. This study examined the WFEN issue at the watershed scale and focused on water competition between the different sectors. Therefore, in network construction, this study focused on the water system and water use-related variables and simplified the remaining issues. In addition, under different research scales and concerns and scales of data statistics (Zhang et al. 2018), the application

effect of Bayesian networks may be different. The research problem in this study is considered at the watershed scale, but some data occur at the provincial scale, which can affect the reliability of the results. Even if the data and research scales were consistent, different effects may be obtained at different research scales. Therefore, it is necessary to investigate the issue of different scales in future WFEN studies based on Bayesian networks and simultaneously balance the model complexity, expression effect and number of data samples in the modelling process during network construction.

## 6 Conclusions

Combined with Bayesian network theory and actual conditions in the PRR, this study established a Bayesian network model based on the WFEN (i.e., the WFEN-BN) for this region, which could effectively express the complex causal relationships in the WFEN and uncertainty in its variables. The major influencing factors were identified through sensitivity and diagnostic analysis methods. The connection relationships in the WFEN under different conditions were simulated based on the responses of network variables under different scenarios, and the complex water competition conditions between different sectors were analysed based on the proposed model. The main conclusions can be summarized as follows:

(1) The water system plays an important role in the WFEN, affects all WFEN aspects and is highly sensitive to other variables. Moreover, water consumption is greatly affected by socioeconomic development. In addition, the network is the most obviously affected by climate factors.

(2) A large amount of water resources is required to ensure that each sector contains enough water to support high benefits. When the water resource amount is insufficient to ensure high water consumption levels in all water-consuming sectors, water competition can occur between these sectors. The water resource competition relationship is not a steady-state relationship, and under the different scenarios, different water resource competition relationships are obtained between the various sectors.

(3) Hydropower and flow to sea can affect irrigation water, but irrigation water does not necessarily impact either sector. Offstream water use exhibits a clear water competition relationship affecting the sectors of hydropower and flow to sea. Under normal circumstances, water competition between hydropower and flow to sea is not significant, but when the offstream water consumption remains relatively stable, water competition between these two sectors can occur.

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**Data Availability** Evaporation data can be accessed at [http://101.200.76.197/data/detail/dataCode/SURF\\_CLI\\_CHN\\_MUL\\_DAY\\_V3.0.html](http://101.200.76.197/data/detail/dataCode/SURF_CLI_CHN_MUL_DAY_V3.0.html). Water Resources Bulletin data can be accessed at <http://www.pearlwater.gov.cn/zwgkcs/lygb/szygb/andhttp://www.mwr.gov.cn/sj/#tjgb>. Societal and economic data can be accessed at <http://https--data--stats--gov--cn--e4192.proxy.www.stats.gov.cn/easyquery.htm?cn=C01>. Salt tide data



in the Water Resources Bulletin of Zhongshan can be accessed at <http://water.zs.gov.cn/xxml/zwgk/szygb/index.html>. The other data in this study were retrieved from published yearbooks, which are available by purchasing the yearbooks.

## Declarations

**Ethical approval** This paper does not contain any studies involving human participants or animals performed by any of the authors.

**Consent to participate** Not applicable.

**Consent to Publish** Not applicable.

**Competing Interests** The authors declare that there are no conflicts of interest regarding the publication of this paper.

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