OPEN ACCESS

ARTICLE

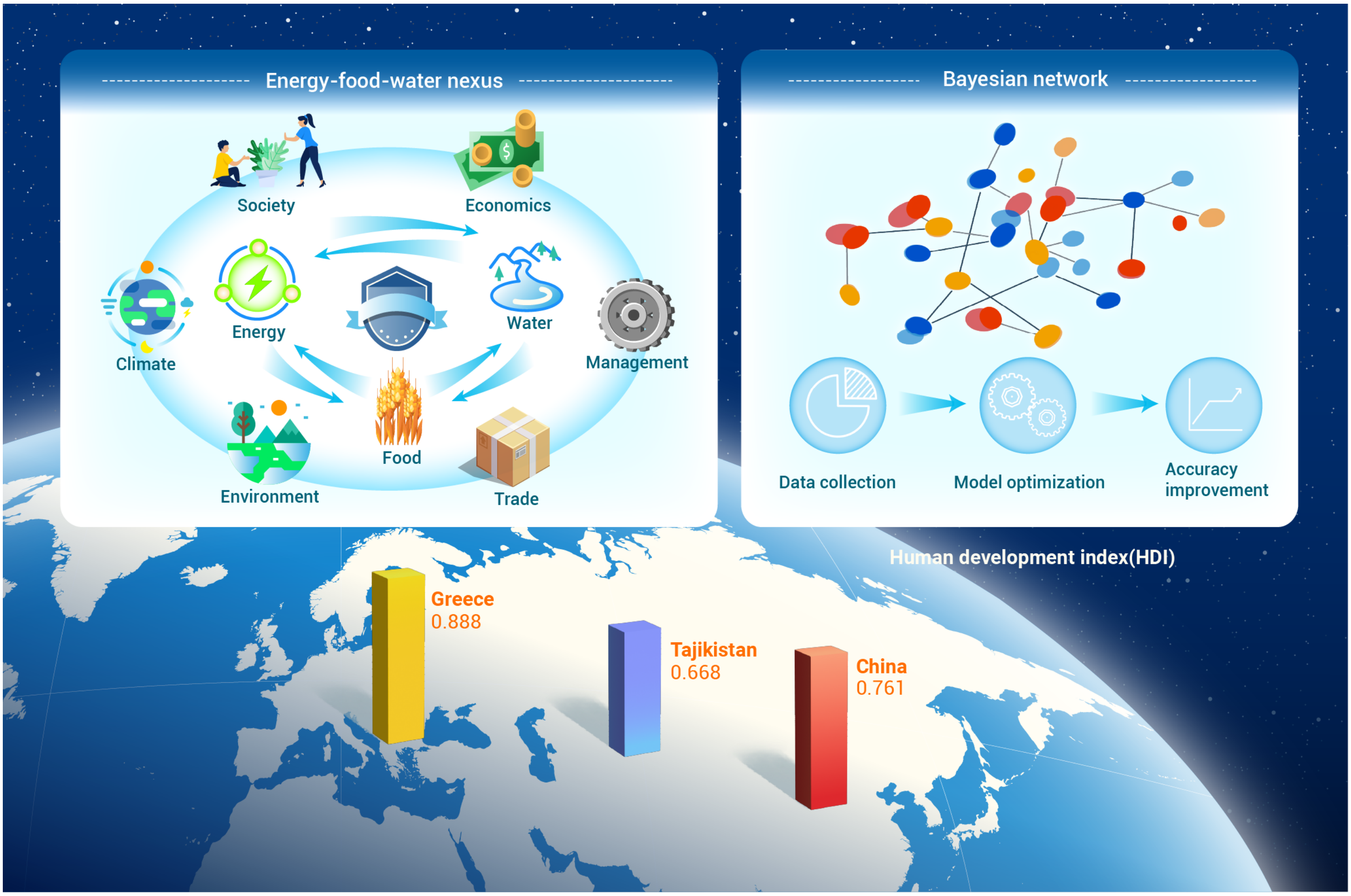
Decoding resources strategies: Food-energy-water nexus across varied development stages

Yaxin Shi,[1,2] Yao Wang,[1,2] Suning Liu,[3,*] and Haiyun Shi[1,2,4,5,*]

*Correspondence: u3002906@connect.hku.hk (S.L.); shihy@sustech.edu.cn (H.S.)

Received: February 16, 2025; Accepted: November 10, 2025; Published Online: November 17, 2025; https://doi.org/10.59717/j.xinn-geo.2025.100172

GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Multiple factors act upon the food-energy-water nexus and thus affect the security of the entire system.
- An enhancement in the accuracy rate was observed after the Bayesian network model was optimized.
- Validation and application of the model in varying development levels countries enables its broader promotion.

ARTICLE

Decoding resources strategies: Food-energy-water nexus across varied development stages

Yaxin Shi,[1,2] Yao Wang,[1,2] Suning Liu,[3,*] and Haiyun Shi[1,2,4,5,*]

[1]State Key Laboratory of Soil Pollution Control and Safety, Southern University of Science and Technology, Shenzhen 518055, China

[2]Guangdong-Hong Kong Joint Laboratory for Soil and Groundwater Pollution Control, School of Environmental Science and Engineering, Southern University of Science and Technology, Shenzhen 518055, China

[3]Department of Ocean Science and Engineering, Southern University of Science and Technology, Shenzhen 518055, China

[4]Shenzhen Key Laboratory of Precision Measurement and Early Warning Technology for Urban Environmental Health Risks, School of Environmental Science and Engineering, Southern University of Science and Technology, Shenzhen 518055, China

[5]State Environmental Protection Key Laboratory of Integrated Surface Water-Groundwater Pollution Control, School of Environmental Science and Engineering, Southern University of Science and Technology, Shenzhen 518055, China

*Correspondence: u3002906@connect.hku.hk (S.L.); shihy@sustech.edu.cn (H.S.)

Received: February 16, 2025; Accepted: November 10, 2025; Published Online: November 17, 2025; https://doi.org/10.59717/j.xinn-geo.2025.100172

Citation: Shi Y., Wang Y., Liu S., et al. (2025). Decoding resources strategies: Food-energy-water nexus across varied development stages. *The Innovation Geoscience* **3**:100172.

Globalization, climate change, and socioeconomic pressures intensify food-energy-water (FEW) nexus complexity and challenges, but existing models are constrained by regional biases and data gaps, limiting their generalization and adaptability for large-scale cross-regional analysis. This study develops a national-scale Bayesian network model using open-access datasets (e.g., FAO, World Bank) to ensure data availability across most countries, combined with an Expectation-Maximization (EM) algorithm to achieve 90% prediction accuracy under 10% data missingness, effectively overcoming regional and data constraints. Parameter optimization improves model accuracy by 18% compared to the lowest scenario, while it decreases accuracy by 2% compared to the highest scenario but improving prediction precision by 25%. Framework optimization extended the applicability of the model to multi-scenario application, including internal mechanism analysis, influencing factor analysis, and scenario analysis. Analyses of Greece, China, and Tajikistan indicate that the food system dominates FEW nexus in Greece and China, while the water system is dominant in Tajikistan. Socioeconomic development significantly influences all three countries. Greece faces severe energy risks (Energy dependence rate, EDR 74.9% - 81.3%), China has prominent water risks (Water stress, WS 39.7% - 42.0%), and Tajikistan confronts concurrent water and energy risks (WS 42.8% - 54.9%, EDR 33.5% - 43.7%). It is suggested that the dominant subsystems be given priority for control and management to enhance the regulatory efficiency, balance socioeconomic development with resource carrying capacity, address the cross-border water resources issue in Tajikistan and Greece's dependence on energy imports through international cooperation to strengthen system resilience.

INTRODUCTION

As the basic resources for socioeconomic development, food, energy, and water are all important factors in achieving Sustainable Development Goals (SDGs).[1] However, due to factors such as climate change, globalization, population growth, and economic development, these basic resources are facing increasing challenges since they are in short supply to varying degrees.[2,3,4]The intensifying resource crisis is undermining global sustainable development. The traditional departmental management mode is difficult to deal with the complex coupling relationships among resource departments. In this context, the concept of food-energy-water (FEW) nexus has been proposed to comprehensively manage food, energy and water resources from an interdepartmental and interdisciplinary perspective.[5]

Many researchers have conducted studies on FEW nexus at different scales, including household, community, watershed, national, and global scales. A variety of simulation and quantitative assessment tools have been developed based on methodologies such as, computable general equilibrium,[6] system dynamic model,[7] life cycle analysis,[8] agent-based model,[9] and composite index method.[10] However, most models exhibit limitations in their generalization capacity, hindering their application in different regions and cross-regional comparative analysis. The main reasons for this limitation include the regional limitations of the models and the availability of data.

In previous studies, many FEW nexus analytical models have been developed for specific regions, with their frameworks deeply coupled to region-specific factors. Specifically, the setting of model parameters and the boundary conditions of model are highly dependent on the inherent characteristics of the target region, including natural endowments (e.g., water resource availability, crop varieties, and energy conditions) and socioeconomic status (e.g., energy technologies, policy regulation mechanisms).[11] Meanwhile, the divergent resource constraints and management objectives across different regions further drive model developers to demonstrate geographically biased preferences in indicator selection.[12,13] For example, model developed for coastal regions affected by saline intrusion is difficult to be directly adapted in inland regions.[14] Ecological indicators designed to address soil salinization, sandstorms, and lake shrink in arid regions cannot be directly applied to other geographical contexts.[15] Such region-specific models may experience operational failures or trigger systemic errors during cross-geographical transplantation due to mismatches in fundamental conditions, severely constraining their broad applicability.

Data gap is the key constraint factor for model generalization. The limited accessibility of data such as data held by private sectors or specific industries, and the incompatibility between available datasets and the requirements of FEW nexus analysis tools, are the primary factors hindering the generalization of models.[16] However, most models such as agent-based model and life cycle approaches have high data requirements, leading to limited applicability.[17] In recent years, the Bayesian network has become an emerging tool for FEW nexus due to its obvious advantages in handling incomplete data and uncertainties.[18] However, there are still significant deficiencies in its application. The accuracy of the Bayesian network model is highly sensitive to data discretization strategies in parameterization, resulting in the limitation of the model's accuracy rate.[19] However, in most Bayesian FEW nexus studies, the selection of discretization strategies is overly simplistic and subjective, which may compromise their accuracy.[20,21] In the Bayesian network model of FEW Nexus for the Beijing-Tianjin-Hebei region, Wang et al. directly applied the equal frequency discretization method to categorize all variables into high, medium, and low levels, without adequately considering the method's applicability or variations in data precision among the variables.[22] Similarly, studies by Chen et al. in the Ningxia irrigation district[23] and Chai et al. in China[21] utilized the equal interval discretization method, yet likewise provided insufficient justification for methodological selection and also simply discretized all variables into three states. Furthermore, the model of China incorporated merely nine variables, resulting in an overly simplified structure that inadequately captures the underlying complexities of FEW nexus. Shi et al. developed a Bayesian network model of FEW nexus for the Syr Darya River basin, leveraging expert knowledge to guide the discretization process.[20] This discretization approach relies on experts' understanding of the specific region, which may achieve reasonable results in specific region yet impedes model transferability and broader applicability. Simultaneously, constrained by statistical data availability, certain inputs in this model were processed through aggregation of regional datasets or population-proportion-weighted averaging, potentially compromising data accuracy. This involves an often-overlooked factor beyond data availability, the data scale. Due to the

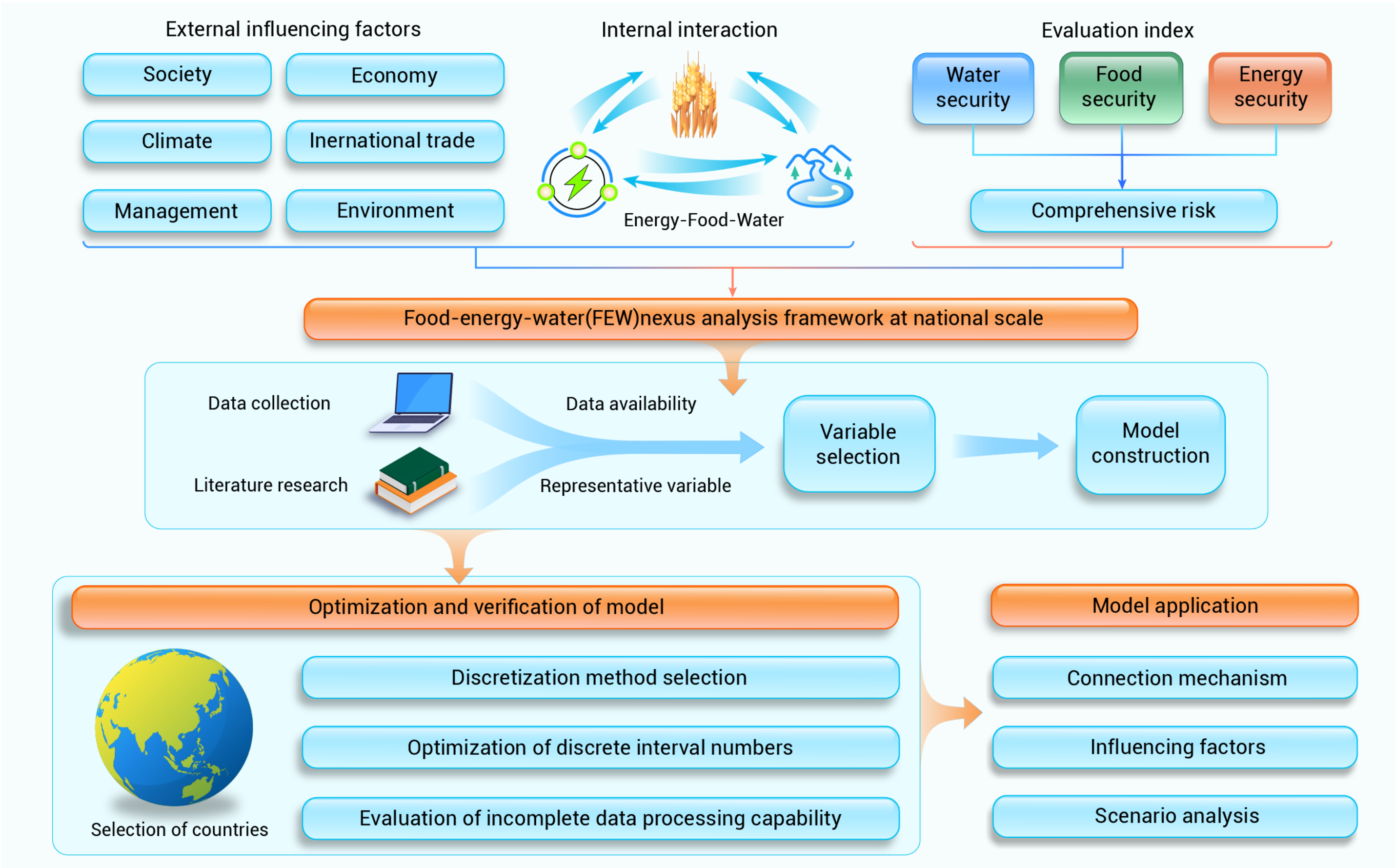


Figure 1. The flowchart of this study.

selection of different research scales, there is a situation where the scales of the regional model and the data boundaries are inconsistent. The data needs to be further processed to meet the requirements of the model scale, which will affect the reliability and accuracy of the results.[14] In addition, the focus points of models at different scales will also limit their applicable scenarios.

Beyond limitations in generalization capabilities, the existing model framework requires further refinement. Many researchers analyze internal interactions in FEW nexus by examining its conceptual meanings and coupling mechanisms.[24,25] As the research deepens, many influencing factors have been incorporated into the analytical framework of FEW nexus, and the impacts of external factors have also been analyzed in depth,[17] such as climate,[26] land use,[27] carbon emissions,[28] and socioeconomics.[21] Some scholars have also developed index systems to evaluate the security and sustainability of FEW nexus, aiming to propose targeted management strategies, such as FEW nexus sustainability and FEW nexus system resilience.[29,30] However, there is still a lack of integration between the analytical framework and evaluation index system for FEW nexus. This makes it impossible to assess the joint response mechanisms of the nexus security status when internal interactions or external influencing factors change, thereby limiting to some extent the applied value of FEW nexus research in promoting secure and sustainable resource management.

To address the aforementioned constraints, this study proposes a novel Bayesian network model for FEW Nexus. The model is established at the national scale. Although there is no optimal scale for FEW nexus research, the sound policy framework and implementation capacity at the national scale can facilitate the formulation and implementation of sustainable policies.[31] Furthermore, comprehensive databases aligned with research boundaries at this scale significantly streamline data processing and enhance model reliability. The main contributions of this study are as follows: (1) the model effectively transcends geographical constraints by capturing common characteristics of FEW nexus and mitigating region-specific factors; (2) the constraints of data are mitigated through the use of publicly available datasets from authoritative institutions (e.g., FAO, World Bank, IEA) combined with the missing data handling mechanism powered by the Expectation-Maximization (EM) algorithm; (3) the model enables direct integration between FEW nexus system analysis and the assessment of system security status by embedding evaluation indicators within FEW nexus system, which can provide decision-making support through scenario analysis; (4) this study proposes a set of parameter optimization methods for Bayesian networks to enhance the accuracy and simulation precision of the model. Through these innovative initiatives, the model is positioned to serve as a potent analytical tool for comprehensive management of FEW nexus, offering actionable guidance for sustainable resource governance.

Figure 1 illustrates the main research steps of this study. First, a new national analysis framework for FEW nexus incorporating evaluation indicators was established. Subsequently, representative variables for each subsystem are screened based on data availability and common characteristics of FEW nexus. Next, a Bayesian network model is constructed based on interactions between variables. Then, the model parameterization process is optimized and validated to improve the accuracy and simulation precision of the model. Concurrently analyze the processing capability of the model for missing data to determine the upper limit of missing values while maintaining model accuracy. Finally, the model is applied to countries with different development levels (Greece, China, and Tajikistan) to analyze their FEW nexus and provide comprehensive management recommendations.

MATERIALS AND METHODS

Basic theory of Bayesian network

Bayesian network can represent multilateral connections among different variables, which can explain multiple issues rather than a specific problem, and thus can reflect the complex connection mechanism in FEW nexus.[14,21] Moreover, the machine learning algorithms which are used to parameterize the Bayesian network models, such as EM algorithm, can use incomplete data to perform parameter estimates,[32,33] which can reduce the requirements for data. Bayesian network can also express uncertainty through probability distribution,[34] and integrate expert knowledge and stakeholders' suggestions, which is of great significance to model application.[35] In our previous study,

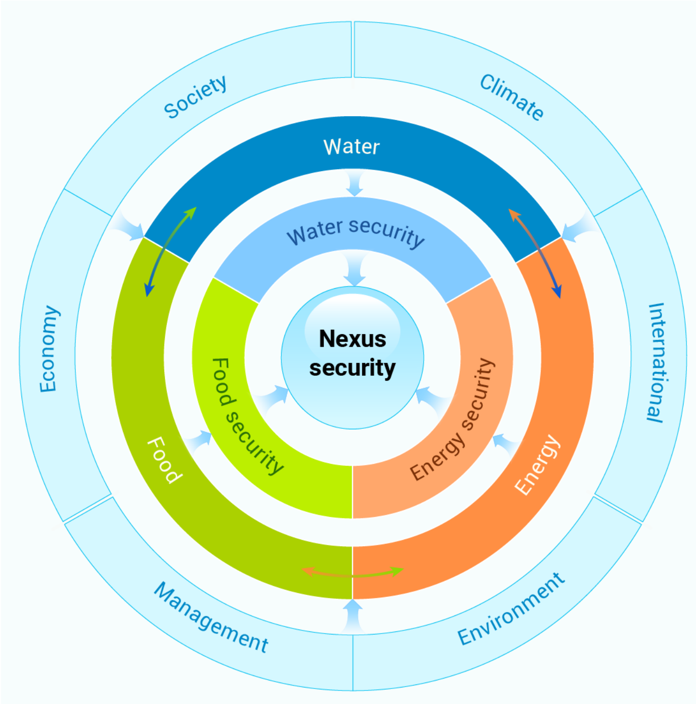


Figure 2. The FEW nexus analysis framework at national scale International means international trade.

the basic theories of Bayesian network and the sensitivity analysis method have been introduced in detail,[14] so we will not repeat them here. In this study, the Bayesian network is implemented by Netica software and is parameterized with the EM algorithm.[22]

Interrelations and interactions of FEW nexus

There exist intricate interdependencies among food, energy and water in FEW nexus.[25] The nexus connections encompass pairwise interactions (water-food, water-energy, food-energy) and tripartite synergies.[36] These connections manifest through cross-sectoral interactions in resource production and consumption processes. For instance, irrigation water supply directly impacts crop yields,[37] power generation relies on water resources for cooling,[38] and agricultural production consumes energy for machinery and fertilizers.[39]

With the deepening of research, numerous external influencing factors have been incorporated into the analytical framework of FEW nexus, such as the impacts of climate, socioeconomics,[26] land use,[27] or directly coupled external influencing factors with nexus, such as "food-energy-water-CO_2 nexus" incorporating carbon emissions[28] and "water-energy-food-economy-society-environment nexus" integrating socioeconomic and environmental dimensions.[21] These studies analyze not only interactions among the food, energy and water subsystems but also the interplay between external influencing factors and these subsystems, thereby examining how external influencing factors affect FEW nexus. However, most of these studies focus on single or a few factors, lacking a macro-level, comprehensive analysis of multiple external influencing factors. Therefore, this study integrates common external influencing factors into FEW nexus framework, where these factors affect the entire FEW nexus by influencing different variables in food, energy and water subsystems.

In addition to analyzing interactions among variables within FEW nexus, evaluating the nexus is critical for understanding it. Existing studies have developed evaluation index for FEW nexus from multiple dimensions, including system coupling degree and coordination,[40,41] system benefits,[42] system efficiency,[43] sustainability indicators,[29] supply-demand risk,[22] system security indices,[30] and Sustainable Development Goals (SDGs).[10] However, there is still a lack of direct integration of these evaluation index into the nexus analytical framework. This study innovatively incorporates water security, food security, energy security, and comprehensive risk indices, establishing a complete influence chain of "external influencing factors - resource subsystem variables - resource subsystem security status - systemic comprehensive risks". This framework enables direct assessment of resource security status under different scenarios, thereby expanding the application value of the model.

FEW nexus analysis framework at national scale

The connections between food, energy, and water are complex. To clarify these complex connections, the FEW nexus analysis framework is first established to guide model construction. The analytical framework needs to consider food system, energy system, and water system that reflect the production and consumption of food, energy, and water, as well as external influencing factors. Common external factors are climate system, society system, and economy system.[5,44,45]

Management measures and environmental pressure are also important influencing factors of FEW nexus.[46,47] Management measures such as adjusting the input of food and energy production materials will certainly affect food, energy, and water resources. Also, the production and consumption of food, energy, and water will affect the sustainable development of society when the environmental pressure is too large. In addition, in the context of globalization, international trade has great impacts on the development of different countries in various aspects, including food, energy, and water resources security. International trade allows the exchange of various materials and resources at a global scale, which makes the relationship between food, energy, and water more complicated.[48,49]

In addition to the internal interactions and external influencing factors of FEW nexus, we have also incorporated the evaluation index system into the framework. By establishing the connection between variables and evaluation index, the direct connection between the operation of FEW nexus and the evaluation index can be achieved. This not only enables the assessment of FEW nexus security status but also provides references for regulatory agencies based on the security status under different states. Based on this, a national scale FEW nexus analysis framework is constructed (Figure 2), which mainly includes internal core factors (e.g., food system, energy system, and water system), external influencing factors (e.g., society system, economy system, climate system, environment system, management system, and international trade system), and security evaluation index system.

Variables selection and model construction

The national scale model analyzes FEW nexus from a macro perspective, focuses on the interactions between departments, and hopes to ensure resource security through policy coordination. Therefore, from the macro perspective, model variables are selected based on data availability and the common characteristics of FEW nexus. The core of FEW nexus is the production, consumption, and interaction of food, energy, and water. Currently, studies on FEW nexus are mostly conducted from the perspective of total resources, but seldomly consider the influences of resource structure.[21,22] In this study, major food crops and major primary energy sources are selected to reflect the influences of food structure and energy structure. Wheat, rice, maize, and soybeans are the four major crops, accounting for two-thirds of the world's food calories.[50] Thus, these four crops are selected to reflect the different interactions between different food crops and other factors in the system. According to "Statistical Review of World Energy 2022", oil, coal, and natural gas are the most dominant energy sources, accounting for 31%, 27%, and 24% of the total energy, respectively.[51] In addition, renewable energy is becoming more and more important in the fight against global warming, and the consumption of renewable energy has been increasing in recent years.[52] Therefore, oil, coal, natural gas, and renewable energy are chosen as the main energy sources representing the energy structure. In addition, it is necessary to consider some management measures in the production process of these resources, such as agricultural fertilization and energy industry investment. Fertilizer input affects crop yields and agricultural water use, thereby acting on FEW nexus.[53] In modern agriculture, pesticides are also commonly used alongside fertilizers to enhance yields.[54] Additionally, land use, particularly changes in cultivated land area, is directly impacts agricultural production.[55] Furthermore, these factors ultimately affect FEW nexus through their impacts on agricultural systems. Therefore, this study selects fertilizers consumption, pesticides consumption and agricultural land as relevant management measures for the food system. Energy input is crucial for energy production and meeting energy demand, typically reflected by energy infrastructure investment.[56,57] However, due to data limitations, this study uses installed capacity to represent energy input, the feasibility of which has been demonstrated in "Input indicator of the energy industry" section.

The tension between population size and food, energy, and water resources is the major obstacle to sustainable development,[58] and therefore, society system usually chooses the population as a representative variable.[21] Economy system includes Gross Domestic Product (GDP) growth, price, industrial added value, and other indicators. Since GDP growth is closely related to resource consumption, it is usually selected to represent the economy system.[14] Based on the trend of globalization, food and energy imports as well as foreign direct investment are selected to reflect the impacts of international trade. Climate system is a complex system that involves many variables. To simplify the model, precipitation is often selected to reflect impacts of climate change, which directly affects regional water resources and crops production.[22] In addition, considering the global warming trend, temperature is selected to further enrich the influences of climate factors. At the same time, with global warming, carbon emission has become a hot topic, and carbon emission is closely related to FEW nexus.[59] Therefore, carbon emission is chosen as the representative variable of environmental pressure.

The security evaluation of FEW nexus is commonly measured by resource supply-demand risks.[22] However, based on the statistical data from the dataset used in this study, the supply and consumption of water, food, and energy resources are generally balanced, rendering the supply-demand risks inadequate for distinguishing differences in resource security status. Therefore, this study selects food dependence rate (FDR), energy dependence rate (EDR), and water stress (WS), which can also reflect the security status of water, food, and energy resources is used as an evaluation index. Then, the composite risk index (CRI) is constructed based on these three indexes. The calculation formulas of the indexes are expressed as Equations (1)-(4):

$$WS = \frac{\textit{Total water withdrawal}}{\textit{Total water resources} - \textit{Environmental flow requirement}} \times 100\% \quad (1)$$

$$FDR = \frac{\textit{Food net imports}}{\textit{Food consumption}} \times 100\% \quad (2)$$

$$EDR = \frac{\textit{Energy net imports}}{\textit{Energy consumption}} \times 100\% \quad (3)$$

$$CRI = (WR + FDR + EDR)/3 \quad (4)$$

In summary, representative variables for the model were selected based on the shared characteristics of FEW nexus and data availability. Except for the evaluation indices, all variables and their data sources are listed in Table S1. Based on the calculation formulas presented in this section, the data series of all variables in the model can be obtained. To ensure the integrity of the data, the data from 1990 to 2019 are selected for the model. The situation of data missing is shown in Table S2. Since the data used in this study are statistical data with uniform format, no prior preprocessing is needed. The Bayesian network model can directly handle incomplete data via the EM algorithm, so no data imputation is required. However, the model requires discretization in calculation; details are shown in the following sections "Discretization method selection" and "Optimization of discrete interval numbers and model verification". Based on the selected variables, the FEW nexus analysis model is constructed by Bayesian network, and the specific structure of the model is shown in Figure 3. It is worth noting that due to the complexity of FEW nexus, some variables in the model may exist in multiple subsystems at the same time, but this does not affect the calculation of the model. Also, there are some countries that do not produce the individual food types or energy types in the model, so these variables can be removed when building the model.

MODEL OPTIMIZATION AND VERIFICATION

The model optimization method

This study implements optimization for Bayesian network model parameterization. First, models are parameterized using different discretization methods. The accuracy of the model under different discretization methods is calculated, and the discretization method that yields the highest model accuracy is selected as the optimal one. Second, the number of discrete intervals for different variables under the discretization method with higher accuracy is optimized. To maximize the model's precision and accuracy, dynamic optimization is performed on the number of discrete intervals for different variables. The value ranges of variables are standardized, and the relative sizes of the variables value ranges are calculated. The threshold for the relative size of the variables value ranges is set, and the number of discrete intervals for different variables is dynamically calculated based on this threshold. The optimization workflow is illustrated in Figure S1, with implementation details provided in the following subsection.

Selected countries as case studies

To ensure the reliability of the results, countries with different levels of socioeconomic development are selected to verify the model. The latest "human development report" released by United National Development Program divides the countries into four categories according to human development index (HDI), namely, very high human development, high human development, medium human development, and low human development. We select one country from each category to verify the model, so as to ensure the applicability of the model in countries with different development levels. However, due to the lack of data in the low human development countries and the small number of these countries, they are temporarily ignored in this study. In addition, considering that the follow-up research will be carried out in countries along the Belt and Road, the verification countries are selected from the countries that joined the Belt and Road in the early stages. Crucially, the selected countries must have relatively complete data to ensure the operability of model validation. In summary, taking into account the socioeconomic development level, follow-up research plans, and data availability, we select three countries, i.e., Greece (very high human development), China (high human development), and Tajikistan (medium human development), for model validation. The locations of the three selected countries are shown in Figure 4.

Greece, located at the southernmost tip of the Balkan Peninsula in Europe, covers an area of 13,200 km^2 and has a coastline of about 15,000 km. It has the subtropical Mediterranean climate, mainly mountainous terrain, narrow plain and rich in mineral resources.[60,61] In 2021, its total population was 10.64 million, GDP was US$ 214.87 billion, and the per capita GDP was US$ 20,192.[62] Greece is a developed country, which has a very high human development. China is located in the east of Asia, on the west coast of the Pacific Ocean. The total land area is about 9.6 million km^2, with the terrain high in the west and low in the east, showing stratification. There are many combinations of temperature precipitation, forming a variety of climate.[63] The eastern half has a monsoon climate, the Qinghai-Tibet Plateau forms a unique high-cold climate, and the northwestern region forms inland drought climate. In 2021, its total population was 1.41 billion, GDP was US$ 17.73 trillion, and the per capita GDP was US$ 12,556.[62] China is a fast-developing country, and the HDI belongs to high human development. Tajikistan is a landlocked country in southeast Central Asia with an area of 143,100 km^2. Tajikistan is mountainous and has a continental climate.[64] In 2021, Tajikistan had a total population of about 9.75 million, with the GDP of US$ 8.75 billion and the per capita GDP of US$ 897.[62] Tajikistan has a low level of economic development and living standards, with a medium human development index.

Discretization method selection

After the structure of the Bayesian network is constructed, the conditional probability distributions of nodes in the network can be learned through sample data. This process is referred to as the parameterization of the Bayesian network model. Prior to parameterization, data generally undergoes discretization, which maps infinite data into finite intervals. Discretization can effectively improve algorithmic accuracy and computational efficiency.[65] Equal interval and equal frequency are common methods for data discretization in Bayesian network models.[21,22] Equal interval discretization is to divide data into multiple intervals with the same length from minimum to maximum. Equal frequency discretization is to divide the data into intervals with same samples size.

Following data discretization, the model parameters can be estimated using the EM algorithm. For the parameterized Bayesian network, the accuracy of Bayesian parameters can be evaluated by K-fold cross-validation.[66] The specific process is as follows: The data is randomly divided into K parts, one of which is reserved as test data while other K-1 parts are used for training the model. The accuracy of the model is evaluated by comparing the error

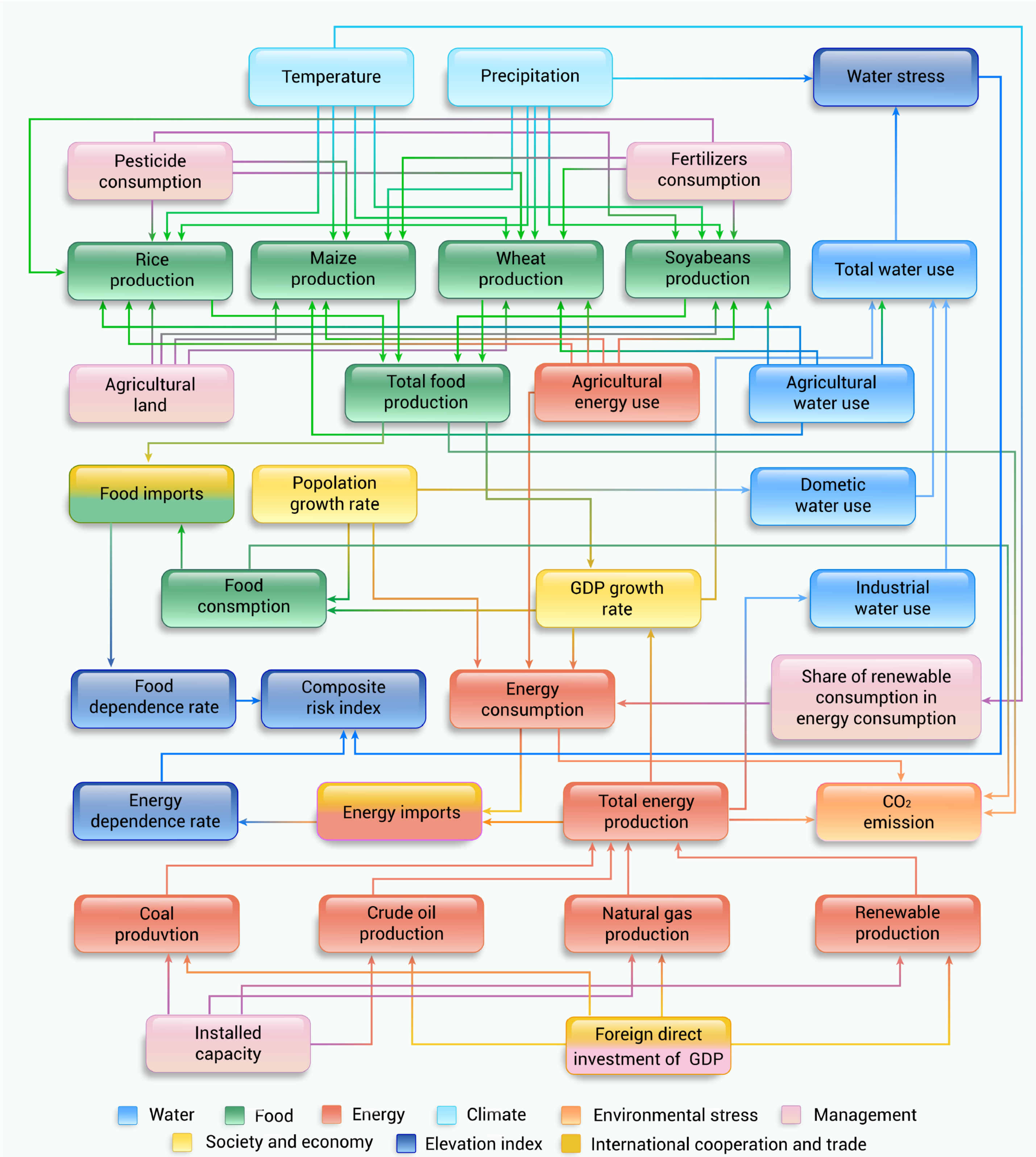


Figure 3. Bayesian network structure of the FEW nexus analysis model.

between the maximum posteriori probability state and the actual state. Through repeating this process for K times and recording each result, the average of the K results is taken as the final accuracy rate. Through the above process, the model accuracy can be calculated. But the different discretization methods in the parameterization process will affect the accuracy of the model.[19] Therefore, the optimization of discretization method and K-fold cross-validation are carried out at the same time. Firstly, the accuracy of the model under different discretization methods is compared, and the discretization method with the highest accuracy is selected. Secondly, in addition to the discretization methods, the model results can be affected by the number of discretization intervals, which are also optimized in this study.

This section first selects the optimal discretization method, and the specific process is as follows: the data collected in this study for the same variable are primarily derived from a single data source and can therefore be

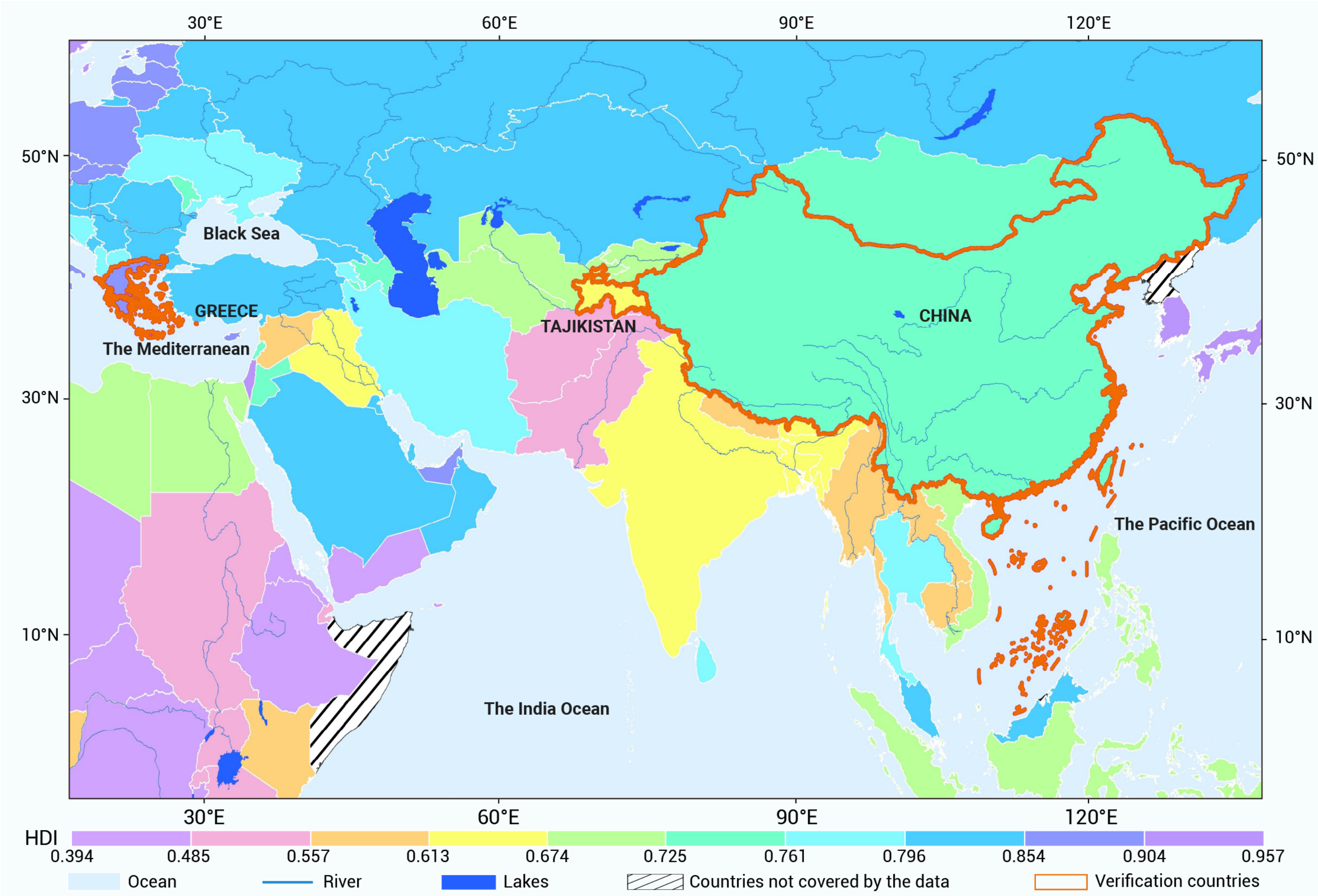


Figure 4. Location of the three selected countries for verification.

directly applied to the discretization process. The number of discretization intervals is temporarily set as the most common 3 intervals (The intervals can be represented by high, medium and low, and each interval of each variable has a corresponding specific value). Set the K value to 3 according to the number of samples. Specifically, data from 1990 to 2019 are randomly partitioned into three equal subsets. One subset is selected as the validation set, while the remaining data are utilized to parameterize the Bayesian network. The model's accuracy is then validated with the selected subset. This process is repeated three times, with each subset serving as the validation set once. The model's accuracy is calculated as the average of the three validation results. Variables of WUT, FPT, EPT, FC, and EC reflecting resources production and consumption and CRI reflecting risk level are selected as verification variables to show the cross-validation results. The accuracy of the model under different discretization methods is shown in Figure S2.

From the perspective of the single variable, the accuracy of the model with equal interval discretization is greater than or equal to the accuracy of the model with equal frequency discretization for all verification variables in different countries. From the perspective of the average accuracy of the six variables, the accuracy of the model with equal interval discretization is greater than the accuracy of the model with equal frequency discretization in different countries, with 19.33% higher in Greece, 4.57% higher in China, 18.09% higher in Tajikistan and 14% higher for average of the three countries. Therefore, from either the comparison of a single variable or the comprehensive consideration of six variables, the model with equal interval discretization has outperformed that with equal frequency discretization. It can then be concluded that the equal interval discretization has obvious advantages over the equal frequency discretization for the proposed model.

Optimization of discrete interval numbers and model verification

In the previous section, it was found that the accuracy of the model under equal interval discretization is higher than that under equal frequency discretization. In this section, the number of discrete intervals for different variables under equal interval discretization will be optimized to further improve the model accuracy. There are a lot of variables in the model, and the value ranges of different variables vary greatly. If such a difference is not considered, i.e., all variables are discretized with a unified fixed interval, it may lead to large differences in the precision of different variables, resulting in inaccurate fitting results.

To improve the accuracy and precision of the model as much as possible, different interval numbers are set for different variables according to their value ranges. We propose a method to optimize the discretization interval number of different variables (noted as Z). First, the relative size of the variable range is defined as X_r, which is calculated as follows:

$$X_r = \left| \frac{X_{\max} - X_{\min}}{X_{\min}} \right| \tag{5}$$

where $X_{\max}$ is the maximum value in the variable X data series, and $X_{\min}$ is the minimum value in the variable X data series. The larger X_r is, the larger the data difference of variables is, and more intervals are needed to reflect the data characteristics. The smaller X_r is, the number of intervals can be appropriately reduced. Therefore, set the thresholds m and n of X_r, and determine the Z value according to the relationship between X_r and the threshold. When m and n are different values, different Z will be obtained, and the accuracy of the model will also change. When the model accuracy is highest, the values of m and n are the optimal threshold of X_r, which can be used to determine the Z-values for the remaining cases.

To compare the optimization effect, the case of the fixed number of discretization intervals is calculated first. Four and five discretization intervals are set for comprehensive comparison under equal interval discretization method, combined with the calculation results of three discretization

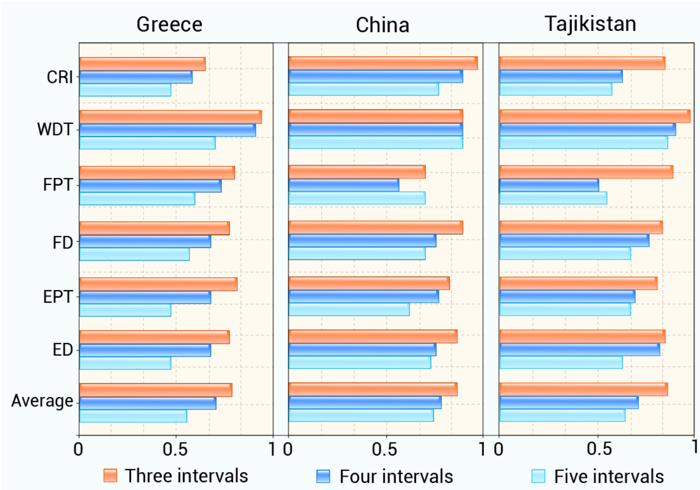


Figure 5. The accuracy of model with different discretization intervals The meaning of the abbreviated variables in the figure has been given in Table S1, and the average here represents the average of the six variables.

intervals. The relevant results are shown in Figure 5.

For most variables except for FPT of China and FPT of Tajikistan, the more discretization intervals, the lower accuracy of the model. This is because the more the number of discretization intervals, the more accurate the value of each interval range, and the higher the precision requirements of model, so the accuracy of the model will be reduced. For the average values of six variables, after the number of discretization intervals increased from 3 to 4, the accuracy of models in Greece, China, and Tajikistan decreased by 11.27%, 9.38%, and 17.71%, respectively. After the number of discretization intervals increased from 4 to 5, the accuracy of models in Greece, China, and Tajikistan decreased by 25.39%, 4.83%, and 9.37%, respectively. Therefore, the accuracy of model can be enhanced by reducing the number of discretization intervals. However, excessive reduction would degrade model precision, as overly large intervals increase prediction uncertainty. As for the abnormality of FPT of China and FPT of Tajikistan, it may be the linkage influences caused by the mismatch of data discretization intervals precision of the two variables and other related nodes in the network. It indicates that the fixed discretization intervals number may lead to data precision mismatches across variables, thereby degrading simulation performance. Thus, the number of discretization intervals must be customized for each variable based on its data distribution characteristics, ensuring coordination of precision among interconnected nodes and optimizing the trade-off between model precision and predictive accuracy.

Following the method described earlier, the Z value must be first determined. If the Z value is too small, the data accuracy is not enough, and if the Z value is too large, the difference between the data in different intervals is too small, which is not conducive to model calculation. Therefore, we optimize the values of Z from 3, 4, and 5. At the same time, it is considered that Z has the following relationship with the two thresholds m and n of X_r: when $X_r < m$, $Z = 3$; when $m < X_r \leq n$, $Z = 4$; and when $X_r > n$, $Z = 5$. When setting different value schemes of m and n, the value step should be first determined. By comparing the data structures, it can be found that when the X_r values of variables are small, their values are concentrated, mostly between 0 and 2. Instead, when the X_r values of the variables are large, their values are scattered, mostly between 2 and 10. There are also some variables with X_r values greater than 10, but these values are too large so that they have less effect on discretization. Therefore, the data sequence of m is 0.5, 0.75, 1, 1.25, 1.5, 1.75, and 2 with the step size of 0.25, and the data sequence of n is 4, 5, 6, 7, 8, 9, and 10 with the step size of 1.

The model accuracy is compared under different schemes; known from Figures S3a & b, the number of variables with accuracy greater than 0.7 is the largest when $n = 7$ and the number of variables with accuracy greater than 0.8 is the largest when $m = 1.5$. Figure S3c shows that the average accuracy of all verification variables reaches the extreme value when $m = 1.5$ and $n = 7$. In addition, according to Figure S3a, when $m = 1.5$ and $n = 7$, the accuracy of all verification variables is greater than or equal to 0.7, which guarantees the lower limit of accuracy for any single variable while ensuring the high overall accuracy. Therefore, set the threshold $m = 1.5$ and $n = 7$ to calculate the Z value for different variables in different countries.

The optimized model achieved an average accuracy of 83% across three countries, outperforming equal frequency discretization with 3 intervals (75%) by 8% and equal interval discretization with 5 intervals (65%) by 18%. Although the average accuracy decreased by 2% compared to equal interval discretization with 3 intervals (85%), it reduces prediction intervals by 25% for six key variables among the 18 validated variables across three countries: EPT and EC in China, and FPT, FC, EC, and CRI in Tajikistan, thereby enhancing predictive precision while maintaining high accuracy. In this case, the 2% loss in accuracy is negligible.

Furthermore, we reviewed existing studies on FEW nexus based on Bayesian networks (Table 1). Given that existing national-scale studies on this topic are relatively scarce, studies conducted at other scales were incorporated for comparative analysis. Some studies (including existing national-scale models) have not validated model accuracy, representing a limitation in the current research. Moreover, in studies that validated model accuracy, only a single indicator is selected to measure model accuracy, which is insufficient for the overall representativeness of the model. In contrast, the model in this study has selected more variables for validation, and its accuracy is higher than that of most existing studies. These comparative results demonstrate the superior performance of the model in this study.

Incomplete data processing capability of EM algorithm

The EM algorithm addresses missing data but remains vulnerable to severe data gaps, which may degrade accuracy. Despite the study area's data integrity, validating the model's missing-value tolerance is critical for cross-border generalizability. Although the EM algorithm can handle incomplete data, excessive levels of data missingness can still affect the model accuracy. While the data series in this study are relatively complete, to ensure the generalized model can be successfully applied in other countries, it is necessary to evaluate its capability to process incomplete data.

The selected data series in this study are relatively complete, with 0.1% missing in Greece, 0.3% missing in China, and 5% missing in Tajikistan. Therefore, the original data is regarded as complete data. The remaining data after being randomly deleted a part from the original data is defined as incomplete data. The incomplete data is used to parameterize the model, and the original data is used as test data to verify the accuracy of the model. The higher the accuracy, the better the interpolation effect of EM algorithm on the incomplete data. For comparison, the following scenarios are set: 10% (S_1), 30% (S_2), and 50% (S_3) of all data series are deleted randomly. The verification results are shown in Table S3.

The more missing data, the lower the accuracy of the model. When the missing data accounts for 10%, the accuracy rate of verification variables in different countries can be maintained above 90%. Within the 30% missing data, the accuracy of most verification variables can still be above 70%, and some verification variables in China are slightly lower than 70%. When the missing data accounts for 50%, none of the three counties can guarantee that the accuracy of all verification variables is above 70%. It can be concluded that EM algorithm has certain processing ability for incomplete data. When the missing data is within a certain range, the accuracy of the model can be guaranteed. Therefore, this model can be applied to regions with incomplete data, but attention needs to be paid to the balance between missing rate and accuracy rate.

RESULTS

The Bayesian network model for FEW nexus at the national scale has been optimized and validated in the previous section. This section will use this model to analyze FEW nexus in Greece, China, and Tajikistan. Sensitivity analysis is a common method in Bayesian network, which can quantify the sensitivity of output results to input variables and clarify the explanatory degree between variables. Therefore, sensitivity analysis can quantify the interactions between variables. With the sensitivity analysis indicators, it is possible to analyze the linkage mechanisms of food, energy and water, and quantify the influence intensity of external influence factors. Mutual Information (MI) and Variance of Belief (VB) are common indicators for sensitivity analysis in Bayesian networks.[14] A larger MI or VB value between two variables indicates a stronger dependency relationship between them. In addition to analyzing the complex interwoven relationships among various vari-

Table 1. Accuracy of existing Bayesian network models for FEW nexus.

Reference	Study area	Research scale	Number of validation indicators	Accuracy rate
14	The Pearl River Basin	River basin scale	0	No validation
20	Syr Darya River basin	Transboundary river basin scale	1	70%
21	China	National scale	0	No validation
22	Beijing-Tianjin-Hebei region	Regional scale	1	73.30%
67	Yangtze River Economic Belt	Regional scale	1	77.20%

ables in the system, Bayesian networks can directly calculate the posterior probabilities of other variables when input parameters change. Therefore, the model can be used to predict variable values under different scenarios and conduct scenario analysis. This allows for the determination of variable values under diverse scenarios, enabling the model to support prediction and scenario analysis.

Connection mechanism of FEW nexus

The internal connection mechanism of FEW nexus is the logical expression of the mutual influences and interactions among various variables. Thus, sensitivity analysis index reflecting interactions among various variables can be used to show the internal connection mechanism. The sensitivity indicator VB is employed to quantify the interactions among the food, energy, and water systems. Variables such as total food production (FPT), food consumption (FC), total energy production (EPT), energy consumption (EC), and total water consumption (WUT) are selected and the sensitivities between them are calculated to show the connection mechanism between food system, energy system, and water system.

As shown in Figure 6, different countries have different FEW nexus internal connection mechanisms. For Greece, the interactions between FC and other variables are the most significant, and food system has a stronger effect on the variables of other subsystems than water system and energy system, so food system is the dominant subsystem of FEW nexus. Similarly, in China, the interaction between FC and other variables is the most significant, and food system is also the dominant subsystem. In Tajikistan, the interaction between water system and other variables is most significant, and water system is the dominant subsystem.

Changing the priorities of management actions may lead to different effects on FEW nexus.[68] Due to the significant effect of the dominant subsystem of FEW nexus on other variables, the management policy for the dominant subsystem will achieve a broader regulatory effect. Therefore, identifying the dominant subsystem of FEW nexus has important guiding significance for the formulation of the integrated management strategy of FEW nexus. In Greece, food is the greatest impact resource in FEW nexus.[69] Although the Mediterranean climate in Greece results in relatively scarce water resources, the region predominantly cultivates drought-resistant crops with high agricultural value, and the thriving tourism industry drives steady demand for premium local agricultural products,[70] making agriculture vital to Greece's economy. Additionally, EU agricultural subsidies further elevate the importance of agriculture.[71] Consequently, the food system constitutes the most socioeconomically significant core of Greece's FEW nexus. However, in Greece's SDGs, two agriculture-related indicators lag behind those of the European Union, so agriculture of Greece should be promoted.[72] This is also consistent with our results. In FEW nexus of China, agriculture is the largest consumer of resources,[73] and the food sector in particular plays a leading role in water stress.[74] China exhibits diverse climates, but its core grain-producing regions experience a temperate monsoon climate with significant seasonal and interannual precipitation variability. To ensure grain production, many areas rely on groundwater irrigation.[75] Pressures from a massive population, strategic goals for absolute food security, and social stability requirements collectively elevate food security to a central position. China has implemented numerous policies to safeguard it.[76] Consequently, food system holds critical importance within China's FEW nexus. In Tajikistan, water resources are the most critical variables affecting FEW nexus security.[31] Tajikistan possesses exceptionally abundant water resources relative to its land area and population size. These resources directly translate into hydropower, which plays a decisive role in the country's energy security and economic operation.[77] Simultaneously, water resource management is deeply intertwined with regional geopolitics.[78] Consequently, water resources, serving both as water itself and as a carrier for hydropower, constitute the most fundamental, strategic, and dominant element within Tajikistan's FEW nexus. These conclusions confirm the outcomes of the proposed model, prove the effective role of the model in the analysis of FEW nexus, and provide policy recommendations for management institutions.

Influencing factors of FEW nexus security

Sensitivity analysis can also reflect the effects of different influencing factors on the variable by calculating the sensitivity between the variable and influencing factors. For FEW nexus security evaluation indicators WS, FDR, EDR and CRI, we analyze the influences of other external factors on them except the variables of food system, energy system, and water system. In addition to international trade system, food import and energy import also belong to food system and energy system, respectively, and their impacts are significantly greater than other external influencing factors, so, these two variables are not considered in this analysis for the convenience of comparison. The results are shown in Figure 7. To facilitate comparison, mutual information (MI) and VB are both normalized to the range of 0~100% to obtain MI ratio and VB ratio.

As shown in Figure 7, CP is the most influential factor on WS in these three countries, indicating that water security is greatly affected by precipitation. Precipitation increase is an important factor to solve water security.[79] The factors that most influence FDR in these three countries are all socioeconomic development factors, and the influences of GDPGR and PGR are not much different in Greece, while PGR is much larger than GDPGR in China and Tajikistan. Both economic growth and population growth affect food security, but the positive or negative impacts of population growth on food security depend on the ability of economies to keep up with food productivity growth.[80] Among the socioeconomic development factors, GDPGR has a certain impact on EDR in these three countries, among which the impact is the largest in Greece, while the impacts of energy management measures in China and Tajikistan are greater than GDPGR. Energy investment and energy infrastructure can withstand energy risks and improve energy security.[81] Compared with developed countries, developing countries are more likely to face energy poverty due to the lack of reliable energy infrastructure for financial, technological and other reasons.[82] For CRI, among the three countries, GDPGR, PGR and CE are the most influential factors.

It is worth noting that, the higher the development level, the greater the impacts of socioeconomic factors on CRI; the lower the development level, the greater the impact of CE on CRI. This may be because the higher the development level of a country, the more complete the infrastructure. Consequently, the risks of food, energy, and water resources mainly lie in the supply of human life and economic development. Countries with lower development levels are more constrained by environmental pressures, so CRIs are vulnerable to CE limits. On the whole, socioeconomic development factors have greater impacts on FEW nexus security. Even for WS, which is greatly affected by CP, socioeconomic development factors also have significant impacts on it. In addition, CE and energy measures also have significant impacts on FEW nexus security.

Scenario analysis

As mentioned before, socioeconomic development factors have greater impacts on FEW nexus security. To ensure the secure and sustainable development of FEW nexus, this study calculates the demand levels and evaluates the security status of food, energy and water resources based on current socioeconomic development level. Recommendations for the secure and sustainable development of FEW nexus are then proposed according to the

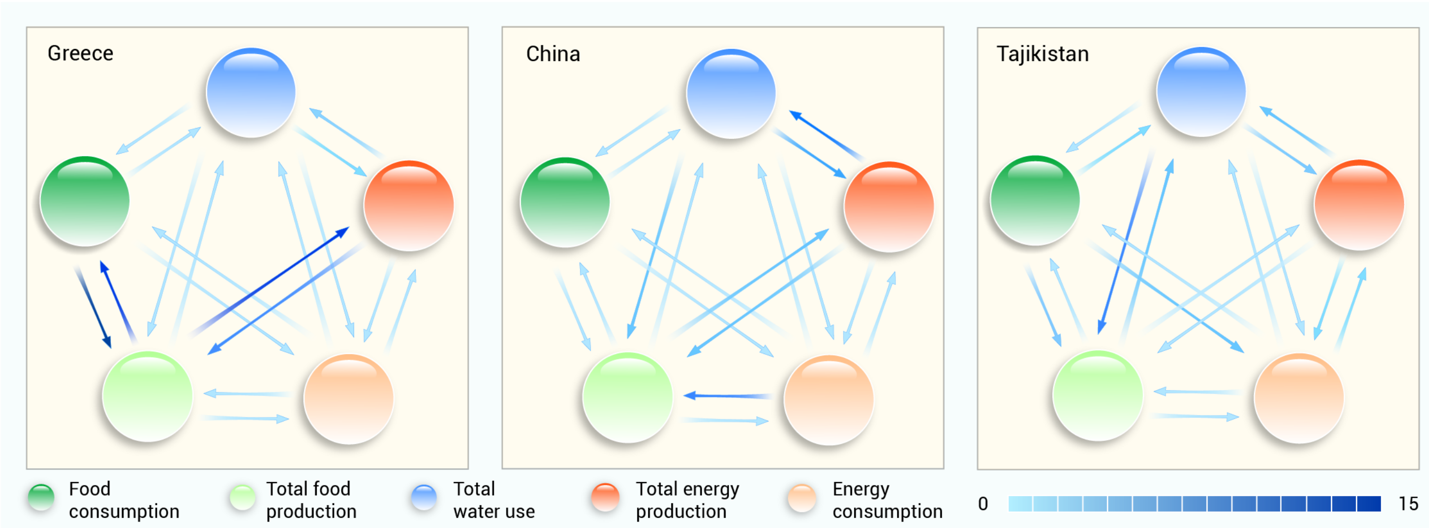


Figure 6. Connection mechanism of food, energy, and water systems The color depth of the arrow indicates the degree of connection.

results. The specific operation is as follows: Based on the available data, the average PGR and GDPGR reflecting the socioeconomic development level of each country are calculated, and the values of PGR and GDPGR are input into the model to calculate the values of other variables. The results are shown in Table S4.

Known from Table S4, according to the socioeconomic development level in the past 30 years, Greece has a high EDR (74.9% - 81.3%) and is prone to energy risks. To ensure energy security, it is necessary to improve the energy self-sufficiency rate or maintain the energy import trade to ensure the stable supply of energy imported resources. Among the FEW nexus security indicators in China, except WS (39.7% - 42.0%), which is slightly larger, other indicators are less risky. Due to its vast territory and diverse climates, China has uneven distribution of precipitation and water resources.[83,84] Water security has long been a major concern of China, and measures such as South-to-North Water Transfer Project has been built to solve the water problem.[85] Both water and energy risks are obvious in Tajikistan (WS 42.8% - 54.9%, EDR 33.5% - 43.7%). Tajikistan and even the whole Central Asia are facing water security issues due to transboundary rivers.[86] To address Tajikistan's water security issues, transboundary water relations must be managed well. Tajikistan has a high consumption of energy and water per unit of GDP, and there is an urgent need to improve the efficiency of resource utilization.[87]

Overall, Greece has the largest comprehensive risk due to its significant energy risk, followed by Tajikistan, whose water risk and energy risk are more obvious. Except for water risk, food risk and energy risk are relatively small in China, so the comprehensive risk is the smallest in the three countries. This may be attributed to the distinct resource advantages and disadvantages of Greece and Tajikistan, which lead to large differences in the values of different indicators and prominent risks of individual indicators. Although China is much larger than the other two countries in terms of volume, its demand for water, food, and energy is huge compared with the other two countries, China's overall development is more balanced, so China's comprehensive risk is small.

DISCUSSION AND IMPLICATIONS

Input indicator of the energy industry

Energy industry investment can better reflect the input of energy industry well.[56,57] However, it is difficult to obtain specific data on investment in the energy industry for most countries based on existing publicly available databases. Therefore, installed capacity is selected as the alternative to reflect the input of energy industry in this study. The installed capacity can represent the level of infrastructure construction in the energy industry, so to some extent, it can reflect the input of energy industry.[88,89] To confirm this representativeness, installed capacity and energy industry investment are respectively used as energy industry input indicators to construct models, and the effects of these two indicators on other variables are compared. Since the amount of investment in energy industry varies greatly every year, it is normalized into the ratio of investment in energy industry to the whole industry to facilitate calculation.

The specific process is as follows: use the installed capacity (EIC) and the ratio of investment in energy industry to the whole industry (EIR) as energy industry input indicator to construct models, calculate the sensitivity of EIC and EIR to other variables in their respective models, and compare the correlation between the two groups of sensitivities. If the correlation is good, the EIC can represent the EIR as an indicator of the energy industry input.

Due to data limitation, only the energy industry investment data of China can be obtained from the "National Bureau of Statistics" of China, and therefore, only these data can be used for verification. Known from Figure S4, the determination coefficients R^2 of the two groups of sensitivity under the MI and VB are 0.98 ($P < 0.01$) and 0.95 ($P < 0.01$), respectively (P represents the significance level). It shows that the effects of EIC and EIR on other variables in the model are significantly correlated. The EIC can represent the EIR to some extent. So, the energy industry input indicator setting in this study is reasonable. Of course, in practical applications, if the model is built for a country whose energy investment data can be collected through other ways, the energy investment data can also be used as energy industry input indicator.

Model innovation and limitations

This study developed a national-scale Bayesian network model for FEW nexus, with its parameterization process optimized and validated to enhance model accuracy and simulation precision. Grounding in the interactions among food, energy, and water resources, the model innovatively integrates multidimensional external influence factors and evaluation indices. The incorporation of extensive relevant variables expands the model applicability, enabling multidimensional applications including internal connection mechanisms, assessment of external influencing factors, system security evaluation, and scenario analysis. Additionally, the variable selection strategy of the model significantly ensures its applicability in most regions. Meanwhile, the processing capability of the EM algorithm for handling incomplete data was systematically evaluated, with its applicability level in data-deficient regions quantitatively determined, thereby establishing a scientific foundation for the model implementation and broader application. These innovations significantly enhance the model generalization ability, enabling it to break through geographical limitations and lay the foundation for its wide-scale promotion and application. This makes it possible for the model to become a technical platform supporting large-scale horizontal comparisons, providing scientific support for cross-regional collaborative analysis of resource systems in the context of global change.

Nevertheless, there are still some limitations in this model. Although we have collected the relevant factors of water, food, and energy as much as possible, there may be omissions. At the same time, due to the limitations of data availability and model size, not all relevant factors can be displayed in the model. For example, in the climate system, only precipitation and temperature are considered, while other climate factors are ignored. However, it is undeniable that the model can display most types of the relevant factors.

Figure 7. Influencing factors of FEW nexus security in different countries The meaning of the abbreviated variables in the figure has been given in Table S1.

That is, to a certain extent, the model has fully reflected FEW nexus. Moreover, in the proposed model, food, energy, and water are taken as three equally important factors to calculate the comprehensive risk index, without considering the priority among different factors caused by different national policies. This problem will be further considered in future studies. In addition, although this model can process the incomplete data, too much missing data will inevitably affect the accuracy of the model. Therefore, attention should be paid to the balance between the missing data and the accuracy of the model. Moreover, this model is constructed at the national scale, although we have verified the universality of the model at this scale, it has not been verified at other scales. Therefore, this model is only suitable for national scale studies. To apply the model to other scales, the model needs to be adjusted and re-verified. For example, the resource import between nations should be replaced by the resource transfer between regions. At the same time, attention should be paid to the influences of the difference in data statistical caliber on the model. However, the modeling idea can provide valuable reference for models at other scales.

Overall, a national scale analysis model to assess FEW nexus in countries with different development levels is proposed. Although the proposed model still has some limitations, in general, we provide a powerful tool for getting a full grasp of FEW nexus and provide strong technical support for managers' decision-making. In future studies, the model will be used to conduct a more in-depth analysis of FEW nexus, and therefore, to expand the application of the model.

Furthermore, while this study touched upon climatic factors, it did not delve into the impacts of extreme events on FEW nexus. In recent years, frequent occurrences of extreme events such as droughts and floods have significantly impacted FEW nexus.[90,91] Given this, the influence of extreme events is poised to become a key research focus in this field. However, current research predominantly concentrates on single extreme events, with insufficient consideration for compound extreme events.[92,93] Moreover, while numerous studies analyze the effects of extreme events on individual elements (food, energy or water), research examining their system-wide impacts on the integrated FEW nexus remains a significant gap.[94] Additionally, many studies focus on attribution or prediction, with insufficient integration into policy practice.[92] Therefore, there is broad research potential in the future to explore how to achieve stable and sustainable integrated management of FEW nexus under the context of compound extreme events.

Policy recommendations

This study systematically analyzed FEW nexus of Greece, China, and Tajikistan by using Bayesian network. Given the significant differences in their socioeconomic development levels and resource endowments, FEW nexus characteristics of the three countries also exhibit distinct features. This study summarizes the characteristics of their FEW nexus and proposes targeted recommendations based on practical conditions. Moreover, the implementation results of some specific measures were obtained through Bayesian network model.

In Greece, FEW nexus is dominated by the food system, with its interaction with water and energy systems significantly stronger than those between other systems. However, government investment of Greece in agriculture lags behind the EU average,[72] and risks in the food system could impact the entire nexus. Meanwhile, it faces high energy demand risk, insufficient energy self-sufficiency, heavy reliance on imports, and uncertainties in supply stability, resulting in prominently high energy security risks (EDR) and nexus comprehensive risk (CRI). To address these challenges, Greece should increase agricultural investment, enhance technological innovation, and adjust its industrial structure to drive the collaborative development of water and energy systems through the optimization of the food system. Concurrently, it should establish diversified energy security pathways by promoting renewable energy development, improving energy self-sufficiency, clean energy production, and energy efficiency, establishing strategic reserves for energy imports, expanding import channels, and deepening trade partnerships to reduce external supply risks. For example, by increasing energy investment to maintain installed capacity within the medium state (12498, 164880), energy imports would shift from high (32631, 38952], probability: 39.5%) to low (19972, 26311], probability: 39.1%). This reduces the probability of high energy risk (EDR) by 3.2% and lowers the probability of comprehensive high risk (CRI) by 3.2%.

In China, the comprehensive risk (CRI) of FEW nexus is the lowest among the three countries, with generally manageable risks in its food and energy systems (FDR and EDR). However, water security (WS) remains a significant challenge due to the uneven spatial and temporal distribution of precipitation.[83] Although projects such as the South-to-North Water Diversion have significantly alleviated China's water resource risks, long-term water security and stability still face significant challenges. Additionally, the food system plays a dominant role in FEW nexus, while the interaction between total energy production and total water use is also relatively significant. To address these issues, China should adopt a dual approach. On the one hand, through measures such as promoting agricultural water-saving technologies, optimizing crop spatial layout, cultivating drought-resistant crop varieties, optimizing the energy structure, and improving energy production technologies to systematically reduce water intensity in agricultural and energy production and minimize water consumption. On the other hand, strengthen cross-regional collaborative governance, leverage basin-level platforms to improve resource allocation efficiency, and promote coordinated development across regions. For example, if agricultural water use and industrial water use are kept in a low state through water-saving technologies (WFU: (315, 333]; WIU: (78, 103]), then the probability of high risk of water stress (WS) decreases by 2.5%.

In Tajikistan, the water system dominates in FEW nexus. The country is situated in an arid region and reliant on transboundary rivers, which has exacerbated water resource risks in the region. Additionally, the country faces extremely high energy and water consumption per unit of GDP, low resource utilization efficiency, and supply instability caused by weak energy infrastructure,[87] combined with limitations from environment (CE), significantly exacerbating water security and energy poverty risks. To address these challenges, Tajikistan should take the following measures. First, establish a collaborative governance mechanism for transboundary water resources by conducting multilateral consultations with Central Asian neighbors, establishing a joint management framework, clarifying water resource allocation rules, ecological protection responsibilities, and joint monitoring mechanisms, and avoiding water resource disputes. Second, improve resource utilization efficiency by promoting energy and water-saving technologies in industrial and agricultural sectors, upgrading energy and water conservancy infrastructure, and reducing resource consumption intensity per unit of output. Third, promote the transformation of high-energy-consuming industries, reduce dependence on high-energy-consuming traditional energy sources, and enhance energy supply autonomy and risk resistance capabilities. For example, by employing water-saving technologies to maintain agricultural water use at the low state (5180, 7109] and developing renewable energy to reduce dependence on conventional energy, thereby keeping the share of renewable consumption in energy consumption at the high state (52.3 to 65], this approach can reduce the probability of high water risk (WS) by 16.36%, decrease the probability of high energy risk (EDR) by 4.86%, and lower the probability of comprehensive high risk (CRI) by 3.1%.

The differences in FEW nexus among the three countries highlight the importance of identifying dominant subsystems, analyzing influencing factors, assessing security status, and implementing targeted policy interventions to maintain FEW nexus security and sustainability. Prioritizing the management of dominant subsystems (such as food system in Greece and the water system in Tajikistan) can achieve broader regulatory effects. Targeted strategies can be formulated based on FEW nexus security status and its significant influencing factors. However, at the common level, socioeconomic development factors (PGR, GDPGR) generally have a significant impact on FEW nexus security, necessitating a balance between development and resource carrying capacity. Meanwhile, transboundary resource issues (e.g., water in Tajikistan) and global trade dependencies (e.g., Greece's energy imports) require international collaboration to enhance overall resilience. Through a combination of strategies, the security and sustainability of FEW nexus can be systematically enhanced.

REFERENCES

1. United Nations. (2015). Transforming our world: The 2030 agenda for sustainable development. https://sdgs.un.org/publications/transforming-our-world-2030-agenda-sustainable-development-17981
2. Vinca A., Parkinson S., Riahi K., et al. (2021). Transboundary cooperation a potential route to sustainable development in the Indus basin. *Nat. Sustain.* **4**:331–339. DOI:10.1038/s41893-020-00654-7
3. Mdee A., Ofori A., Lopez-Gonzalez G., et al. (2022). The top 100 global water questions: Results of a scoping exercise. *One Earth* **5**:563–573. DOI:10.1016/j.oneear.2022.04.009
4. Kornhuber K., Lesk C., Schleussner C.F., et al. (2023). Risks of synchronized low yields are underestimated in climate and crop model projections. *Nat. Commun.* **14**:3528. DOI:10.1038/s41467-023-38906-7
5. Hoff J. (2011). Understanding the nexus background paper for the Bonn 2011 Conference: The water, energy and food security nexus. Bonn, Germany, Stockholm Environment Institute (SEI): Stockholm, Sweden. https://www.sei.org/publications/understanding-the-nexus/
6. Bardazzi E. and Bosello F. (2021). Critical reflections on water-energy-food nexus in computable general equilibrium models: A systematic literature review. *Environ. Modell. Softw.* **145**:105201. DOI:10.1016/j.envsoft.2021.105201
7. Zeng Y.J., Liu D.D., Guo S.L., et al. (2022). A system dynamic model to quantify the impacts of water resources allocation on water-energy-food-society (WEFS) nexus.

Hydrol. Earth Syst. Sci. 26:3965–3988. DOI:10.5194/hess-26-3965-2022
8. Li P.C. and Ma H.W. (2020). Evaluating the environmental impacts of the water-energy-food nexus with a life-cycle approach. *Resour. Conserv. Recycl.* 157:104789. DOI:10.1016/j.resconrec.2020.104789
9. Elkamel M., Valencia A., Zhang W., et al. (2023). Multi-agent modeling for linking a green transportation system with an urban agriculture network in a food-energy-water nexus. *Sust. Cities Soc.* 89:104354. DOI:10.1016/j.scs.2022.104354
10. Yuan M.H. and Lo S.L. (2020). Developing indicators for the monitoring of the sustainability of food, energy, and water. *Renew. Sust. Energ. Rev.* 119:109565. DOI:10.1016/j.rser.2019.109565
11. Qin J., Duan W.L., Chen Y.N., et al. (2022). Comprehensive evaluation and sustainable development of water–energy–food–ecology systems in Central Asia. *Renew. Sustain. Energy Rev.* 157:112061. DOI:10.1016/j.rser.2021.112061
12. Si Y., Li X., Yin D.Q., et al. (2019). Revealing the water-energy-food nexus in the Upper Yellow River Basin through multi-objective optimization for reservoir system. *Sci. Total Environ.* 682:1–18. DOI:10.1016/j.scitotenv.2019.04.427
13. Ravar Z., Zahraie B., Sharifinejad A., et al. (2020). System dynamics modeling for assessment of water–food–energy resources security and nexus in Gavkhuni basin in Iran. *Ecol. Ind.* 108:105682. DOI:10.1016/j.ecolind.2019.105682
14. Shi Y.X., Liu S.N. and Shi H.Y. (2022). Analysis of the water-food-energy nexus and water competition based on a Bayesian network. *Water Resour. Manag.* 36:3349–3366. DOI:10.1007/s11269-022-03205-1
15. Song S.R., Chen X., Liu T., et al. (2023). Indicator-based assessments of the coupling coordination degree and correlations of water-energy-food-ecology nexus in Uzbekistan. *J. Environ. Manag.* 345:118674. DOI:10.1016/j.jenvman.2023.118674
16. Daher B., Saad W., Pierce S.A., et al. (2017). Trade-offs and decision support tools for FEW nexus-oriented management. *Curr. Sustain. Renewable Energy Rep.* 4:153–159. DOI:10.1007/s40518-017-0075-3
17. Zhang C., Chen X.X., Li Y., et al. (2018). Water-energy-food nexus: Concepts, questions and methodologies. *J. Hydrol.* 195:625–639. DOI:10.1016/j.jclepro.2018.05.194
18. Mayfield H.J., Smith C., Gallagher M., et al. (2020). Considerations for selecting a machine learning technique for predicting deforestation. *Environ. Model. Softw.* 131:104741. DOI:10.1016/j.envsoft.2020.104741
19. Nojavan A.F., Qian S.S. and Stow C.A. (2017). Comparative analysis of discretization methods in Bayesian networks. *Environ. Modell. Softw.* 87:64–71. DOI:10.1016/j.envsoft.2016.10.007
20. Shi H.Y., Luo G.P., Zheng H.W., et al. (2020). Coupling the water-energy-food-ecology nexus into a Bayesian network for water resources analysis and management in the Syr Darya River basin. *J. Hydrol.* 581:124387. DOI:10.1016/j.jhydrol.2019.124387
21. Chai J., Shi H.T., Lu Q.Y., et al. (2020). Quantifying and predicting the water-energy-food-economy-society-environment nexus based on Bayesian networks - A case study of China. *J. Clean Prod.* 256:120266. DOI:10.1016/j.jclepro.2020.120266
22. Wang Y., Zhao Y., Wang Y.Y., et al. (2021). Supply-demand risk assessment and multi-scenario simulation of regional water-energy-food nexus: A case study of the Beijing-Tianjin-Hebei region. *Resour. Conserv. Recycl.* 174:105799. DOI:10.1016/j.resconrec.2021.105799
23. Chen B., Duan Q., Zhao W., et al. (2023). Oasis sustainability is related to water supply mode. *Agric. Water Manag.* 290:108589. DOI:10.1016/j.agwat.2023.108589
24. Yan X., Fang L. and Mu L. (2019). How does the water-energy-food nexus work in developing countries. An empirical study of China. *Sci. Total Environ.* 716:134791. DOI:10.1016/j.scitotenv.2019.134791
25. D'Odorico P., Davis K.F., Rosa L., et al. (2018). The global food-energy-water nexus. *Rev. Geophys.* 56:456–531. DOI:10.1029/2017RG000591
26. Wang K., Liu J.G., Xia J., et al. (2021). Understanding the impacts of climate change and socio-economic development through food-energy-water nexus: A case study of mekong river delta. *Resour. Conserv. Recycl.* 167:105390. DOI:10.1016/j.resconrec.2020.105390
27. Wolde Z., Wei W., Likessa D., et al. (2021). Understanding the impact of land use and land cover change on water–energy–food nexus in the Gidabo watershed, east African rift valley. *Nat. Resour. Res.* 30:2687–2702. DOI:10.1007/s11053-021-09819-3
28. Xu Z.C., Chen X.Z., Liu J.G., et al. (2020). Impacts of irrigated agriculture on food-energy-water-CO_2 nexus across metacoupled systems. *Nat. Commun.* 11:5837. DOI:10.1038/s41467-020-19520-3
29. Wang Q., Li S.Q., He G., et al. (2018). Evaluating sustainability of water-energy-food (WEF) nexus using an improved matter-element extension model: A case study of China. *J. Clean Prod.* 202:1097–1106. DOI:10.1016/j.jclepro.2018.08.213
30. Nuez-lopez J.M., Cansino-Loeza B., Sánchez-Zarco X.G., et al. (2022). Involving resilience in assessment of the water-energy-food nexus for arid and semiarid regions. *Clean Technol. Environ. Policy* 24:1681–1693. DOI:10.1007/s10098-022-02273-6
31. Hao L.G., Wang P., Yu J.J., et al. (2022). An integrative analytical framework of water-energy-food security for sustainable development at the country scale: A case study of five Central Asian countries. *J. Hydrol.* 607:127530. DOI:10.1016/j.jhydrol.2022.127530
32. Lauritzen L. (1995). The EM algorithm for graphical association models with missing data. *Comput. Stat. Data Anal.* 19:191–201. DOI:10.1016/0167-9473(93)E0056-A
33. Uusitalo L. (2007). Advantages and challenges of Bayesian networks in environmental modeling. *Ecol. Model.* 203:312–318. DOI:10.1016/j.ecolmodel.2006.11.033
34. Zheng Y., Xie Y.Z. and Long X.J. (2021). A comprehensive review of Bayesian statistics in natural hazards engineering. *Nat. Hazards* 108:63–91. DOI:10.1007/s11069-021-04729-2
35. Aguilera P.A., Fernández A., Fernández R., et al. (2011). Bayesian networks in environmental modeling. *Environ. Modell. Softw.* 26:1376–1388. DOI:10.1016/j.envsoft.2011.06.004
36. Endo A., Tsurita I., Burnett K., et al. (2017). A review of the current state of research on the water, energy, and food nexus. *J. Hydrol. Reg. Stud.* 1:20–30. DOI:10.1016/j.ejrh.2015.11.010
37. Du T.S., Kang S.Z., Zhang J.H., et al. (2015). Deficit irrigation and sustainable water-resource strategies in agriculture for China's food security. *J. Exp. Bot.* 66:2253–2269. DOI:10.1093/jxb/erv034
38. Macknick J., Newmark R., Heath G., et al. (2012). Operational water consumption and withdrawal factors for electricity generating technologies: a review of existing literature. *Environ. Res. Lett.* 7:045802. DOI 10.1088/1748-9326/7/4/045802
39. Yang Y.C.E., Ringler C., Brown C., et al. (2016). Modeling the agricultural water–energy–food nexus in the indus river basin, Pakistan. *J. Water Resour. Plan. Manage.* 142:04016062. DOI:10.1061/(ASCE)WR.1943-5452.0000710
40. Xu S.S. He W.J., Shen J.Q., et al. (2019). Coupling and coordination degrees of the Core water-energy-food nexus in China. *Int. J. Environ. Res. Public Health* 16:1648. DOI:10.3390/ijerph16091648
41. Qi Y.Y., Farnoosh A., Lin L., et al. (2021). Coupling coordination analysis of China's provincial water-energy-food nexus. *Environ. Sci. Pollut. Res.* 29:23303–23313. DOI:10.1007/s11356-021-17036-x
42. Tabatabaie S.M.H. and Murthy G.S. (2021). Development of an input-output model for food-energy-water nexus in the pacific northwest, USA. *Resour. Conserv. Recycl.* 168:105267. DOI:10.1016/j.resconrec.2020.105267
43. Han D.N., Yu D.Y. and Cao Q. (2020). Assessment on the features of coupling interaction of the food-energy-water nexus in China. *J. Clean. Prod.* 249:119379. DOI:10.1016/j.jclepro.2019.119379
44. El-Gafy I. and Apul D. (2021). Expanding the dynamic modeling of water-food-energy nexus to include environmental, economic, and social aspects based on life cycle assessment thinking. *Water Resour. Manag.* 35:4349–4362. DOI:10.1007/s11269-021-02951-y
45. Food and Agriculture Organization. (2014). Walking the nexus talk: Assessing the water-energy-food nexus in the context of the sustainable energy for all initiative. Rome: Food and Agriculture Organization (FAO). https://agris.fao.org/search/en/providers/122621/records/6473966668b4c299a3fb4b4b
46. Campana P.E., Lastanao P., Zainali S., et al. (2022). Towards an operational irrigation management system for Sweden with a water–food–energy nexus perspective. *Agric. Water Manage.* 271:107734. DOI:10.1016/j.agwat.2022.107734
47. Rubinsin N.J., Daud W.R.W., Kamarudin S.K., et al. (2021). Modelling and optimisation of oil palm biomass value chains and the environment-food-energy-water nexus in peninsular Malaysia. *Biomas Bioenerg.* 144:105912. DOI:10.1016/j.biombioe.2020.105912
48. Owen A., Scott K. and Barrett J. (2018). Identifying critical supply chains and final products: An input-output approach to exploring the energy-water-food nexus. *Appl. Energy* 210:632–642. DOI:10.1016/j.apenergy.2017.09.069
49. Taherzadeh O., Bithell M. and Richards K. (2021). Water, energy and land insecurity in global supply chains. *Glob. Environ. Change -Human Policy Dimens.* 67:102158. DOI:10.1016/j.gloenvcha.2020.102158
50. Kim W., Iizumi T. and Nishimori M. (2019). Global patterns of crop production losses associated with droughts from 1983 to 2009. *J. Appl. Meteorol. Climatol.* 58:1233–1244. DOI:10.1175/jamc-d-18-0174.1
51. BP. (2022). BP statistical review of world energy 2022. BP. https://www.bp.com/en/global/corporate/energy-economics/energy-outlook/energy-outlook-downloads.html
52. Dietzenbacher E., Kulionis V. and Capurro F. (2020). Measuring the effects of energy transition: A structural decomposition analysis of the change in renewable energy use between 2000 and 2014. *Appl. Energy* 258:114040. DOI:10.1016/j.apenergy.2019.114040
53. Chen B., Zhang X. and Gu B. (2025). Managing nitrogen to achieve sustainable food-energy-water nexus in China. *Nat. Commun.* 16:4804. DOI:10.1038/s41467-025-60098-5
54. Gao Y., Zhang Y., He S., et al. (2019). Fabrication of a hollow mesoporous silica hybrid to improve the targeting of a pesticide. *Chem Eng J.* 364:361–369. DOI:10.1016/j.cej.2019.01.105
55. Guo A., Yue W., Yang J., et al. (2023). Cropland abandonment in China: Patterns, drivers, and implications for food security. *J. Clean. Prod.* 418:138154. DOI:10.1016/j.jclepro.2023.138154
56. Bamisile O., Ojo O., Yimen N., et al. (2021). Comprehensive functional data analysis of China's dynamic energy security index. *Energy Rep.* 7:6246–6259. DOI:10.1016/j.egyr.2021.09.018
57. Matsumoto K. and Matsumura Y. (2022). Challenges and economic effects of introducing renewable energy in a remote island: A case study of Tsushima Island, Japan. *Renew. Sust. Energ. Rev.* 162:112456. DOI:10.1016/j.rser.2022.112456
58. Scanlon B., Ruddell B.L., Reed P.M., et al. (2018). The food-energy-water nexus: Transforming science for society. *Water Resour. Res.* 53:3550–3556. DOI:10.1002/

2017WR020889
59. Ghiat I. and Al-Ansari T. (2021). A review of carbon capture and utilisation as a CO_2 abatement opportunity within the EWF nexus. *J. CO2 Util.* 45:101432. DOI:10.1016/j.jcou.2020.101432.
60. Rovithakis A., Grillakis M.G., Seiradakis K.D., et al. (2022). Future climate change impact on wildfire danger over the Mediterranean: The case of Greece. Environ. Res. Lett. 17:045022. DOI 10.1088/1748-9326/ac5f94.
61. Mallinis G., Domakinis C., Kokkoris I.P., et al. (2023). MAES implementation in Greece: Geodiversity. *J. Environ. Manag.* 342:118324. DOI:10.1016/j.jenvman.2023.118324
62. World Bank. (2023). World Development Indicators. World Bank. https://databank.worldbank.org/reports.aspx?source=world-development-indicators
63. Jin H.Y., Chen X.H., Wu P., et al. (2021). Evaluation of spatial-temporal distribution of precipitation in mainland China by statistic and clustering methods. *Atmos. Res.* 262:105772. DOI:10.1016/j.atmosres.2021.105772
64. Wu H.W., Wu J.L., Li J.L., et al. (2020). Spatial variations of hydrochemistry and stable isotopes in mountainous river water from the Central Asian headwaters of the Tajikistan Pamirs. *Catena* 193:104639. DOI:10.1016/j.catena.2020.104639
65. Wang Y.L., Wang Z.W., He S.W., et al. (2019). A practical chiller fault diagnosis method based on discrete Bayesian network. *Int. J. Refrig.* 102:159–167. DOI:10.1016/j.ijrefrig.2019.03.008
66. Marcot B.G. and Hanea A.M. (2021). What is an optimal value of k in k-fold cross-validation in discrete Bayesian network analysis. *Comput. Stat.* 36:2009–2031. DOI:10.1007/s00180-020-00999-9
67. Chen Y., Pan Y. and Geng M. (2023). Identification of key brittleness factors and multi-scenario analysis of the water-energy-food-ecology nexus vulnerability based on NRS-BN. *Front. Environ. Sci.* 11:1273755. DOI:10.3389/fenvs.2023.1273755
68. Zhang J.Z., Wang S., Pradhan P., et al. (2022). Mapping the complexity of the food-energy-water nexus from the lens of Sustainable Development Goals in China. *Resour. Conserv. Recycl.* 183:106357. DOI:10.1016/j.resconrec.2022.106357
69. Laspidou C.S., Mellios N. and Kofinas D. (2019). Towards ranking the water–energy–food–land use–climate nexus interlinkages for building a nexus conceptual model with a heuristic algorithm. *Water* 11:306. DOI:10.3390/w11020306
70. Georgopoulou E., Mirasgedis S., Sarafidis Y., et al. (2017). Climate change impacts and adaptation options for the Greek agriculture in 2021–2050: A monetary assessment. *Clim. Risk Manag.* 16:164–182. DOI:10.1016/j.crm.2017.02.002
71. Kyriakopoulos G.L., Sebos I., Triantafyllou E., et al. (2023). Benefits and synergies in addressing climate change via the implementation of the common agricultural policy in Greece. *Appl Sci* 13:2216. DOI:10.3390/app13042216
72. Papadopoulou C.A., Papadopoulou M.P. and Laspidou C. (2022). Implementing water-energy-land-food-climate nexus approach to achieve the sustainable development goals in Greece: Indicators and policy recommendations. *Sustainability* 14:4100. DOI:10.3390/su14074100
73. Xiao Z.Y., Yao M.Q., Tang X.T., et al. (2019). Identifying critical supply chains: An input-output analysis for food-energy-water nexus in China. *Ecol. Model.* 392:31–37. DOI:10.1016/j.ecolmodel.2018.11.006
74. Niva V., Cai J.L., Taka M., et al. (2020). China's sustainable water-energy-food nexus by 2030: Impacts of urbanization on sectoral water demand. *J. Clean Prod.* 251:119755. DOI:10.1016/j.jclepro.2019.119755
75. Yuan K., Yang Z. and Wang S. (2021). Water scarcity and adoption of water-saving irrigation technologies in groundwater over-exploited areas in the North China Plain. *Irrig Sci* 39:397–408. DOI:10.1007/s00271-021-00726-2
76. Liu Y. and Zhou Y. (2021). Reflections on china's food security and land use policy under rapid urbanization. *Land Use Policy* 109:105699. DOI:10.1016/j.landusepol.2021.105699
77. Xu Z., Niu Y., Liang Y., et al. (2020). The integrated hydropower sustainability assessment in Tajikistan: A case study of Rogun Hydropower Plant. *Adv. Civ. Eng.* 2020:8894072. DOI:10.1155/2020/8894072
78. Wang X.X., Cui B.L., Chen Y.N., et al. (2024). Dynamic changes in water resources and comprehensive assessment of water resource utilization efficiency in the Aral Sea basin, Central Asia. *J. Environ. Manag.* 351:120198. DOI:10.1016/j.jenvman.2024.120198
79. Wehbe Y., Griffiths S., Al Mazrouei A., et al. (2023). Rethinking water security in a warming climate: Rainfall enhancement as an innovative augmentation technique. *NPJ Clim. Atmos. Sci.* 6:171. DOI:10.1038/s41612-023-00503-2
80. Ntiamoah E.B., Chandio A.A., Yeboah E.N., et al. (2023). How do carbon emissions, economic growth, population growth, trade openness and employment influence food security. Recent evidence from the East Africa. *Environ. Sci. Pollut. Res.* 30:51844–51860. DOI:10.1007/s11356-023-26031-3
81. Iyke B.N. (2024). Climate change, energy security risk, and clean energy investment. *Energy Econ.* 129:107225. DOI:10.1016/j.eneco.2023.107225
82. Salman M., Zha D.L. and Wang G.M. (2022). Assessment of energy poverty convergence: A global analysis. *Energy* 255:124579. DOI:10.1016/j.energy.2022.124579
83. Zhang A. and Zhao X. (2022). Changes of precipitation pattern in China: 1961–2010. *Theor. Appl. Climatol.* 148:1005–1019. DOI:10.1007/s00704-022-03986-w
84. Wang X., Xiao X.M., Zou Z.H., et al. (2020). Gainers and losers of surface and terrestrial water resources in China during 1989–2016. *Nat. Commun.* 11:3471. DOI:10.1038/s41467-020-17103-w
85. Su Q.M. and Chen X. (2021). Efficiency analysis of metacoupling of water transfer based on the parallel data envelopment analysis model: A case of the south–north water transfer project-middle route in China. *J. Clean. Prod.* 313:127952. DOI:10.1016/j.jclepro.2021.127952
86. Wang X.X., Chen Y.N., Li Z., et al. (2020). Development and utilization of water resources and assessment of water security in Central Asia. *Agric. Water Manag.* 240:106297. DOI:10.1016/j.agwat.2020.106297
87. Zhang S., Li Y., Huang G., et al. (2023). Developing a copula-based input-output method for analyzing energy-water nexus of Tajikistan. *Energy* 266:126511. DOI:10.1016/j.energy.2022.126511
88. Liu B.C., Song C.Y., Wang Q.S., et al., (2022). Forecasting of China's solar PV industry installed capacity and analyzing of employment effect: based on GRA-BiLSTM model. *Environ. Sci. Pollut. Res.* 29:4557-4573. DOI:10.1007/s11356-021-15957-1
89. Ma S.P., Liu Q.Q. and Zhang W.Z. (2022). Examining the effects of installed capacity mix and capacity factor on aggregate carbon intensity for electricity generation in China. *Int. J. Environ. Res. Public Health* 19:3471. DOI:10.3390/ijerph19063471
90. Seth K., Fernandes S.J. and Camargo S.J. (2015). Two summers of São Paulo drought: Origins in the western tropical Pacific. *Geophys. Res. Lett.* 42:10816–10823. DOI:10.1002/2015GL066314
91. Santos-Burgoa C., Sandberg J., Suárez E., et al. (2018). Differential and persistent risk of excess mortality from Hurricane Maria in Puerto Rico: A time-series analysis. *Lancet Planet. Health* 2:478–488. DOI:10.1016/S2542-5196(18)30209-2
92. McKinnon K.A. and Simpson I.R. (2022). How unexpected was the 2021 Pacific Northwest heatwave. *Geophys. Res. Lett.* 49:e2022GL100380. DOI:10.1029/2022GL100380
93. Iqbal A., Nazir H. and Khurshid N. (2024). Exploring the effects of floods in Pakistan: Pre/post flood analysis 2022. *I Int. J. Disaster Risk Reduct.* 115:105032. DOI:10.1016/j.ijdrr.2024.105032
94. Udall B. and Overpeck J. (2017). The twenty-first century colorado river hot drought and implications for the future. *Water Resour. Res.* 53:2404–2418. DOI:10.1002/2016WR019638

FUNDING AND ACKNOWLEDGMENTS

This study was supported by National Natural Science Foundation of China (42394132), National Key Technology R&D Program of China (2022YFC3201802), Shenzhen Key Laboratory of Precision Measurement and Early Warning Technology for Urban Environmental Health Risks (ZDSYS20220606100604008), High Level of Special Funds (G03050K001), Guangdong-Hong Kong Joint Laboratory for Soil and Groundwater Pollution Control (2023B1212120001), State Environmental Protection Key Laboratory of Integrated Surface Water-Groundwater Pollution Control, and State Key Laboratory of Soil Pollution Control and Safety, Southern University of Science and Technology. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

AUTHOR CONTRIBUTIONS

Y.S. conceived and designed the study and drafted the manuscript. H.S. and S.L. supervised the research and provided guidance. Y.S. and Y.W. prepared the figures and tables. Y.S., Y.W., H.S, and S.L. participated in reviewing and revising the manuscript. All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND CODE AVAILABILITY

Data of water is from AQUASTAT (https://www.fao.org/aquastat/en/), data of energy is from the IEA (https://www.iea.org/), data of food is from FAOSTAT (https://www.fao.org/faostat/en/#data), data of social and economic development is from World Bank (https://data.worldbank.org.cn), data of temperature is from the Berkeley Earth (https://berkeleyearth.org/data/), and data of precipitation is from WorldClim (https://www.worldclim.org/data/worldclim21.html). In addition, there is some supplementary data from Emissions Database for Global Atmospheric Research (https://edgar.jrc.ec.europa.eu/) and Energy Statistics Yearbook supplement data (https://unstats.un.org/unsd/energystats/pubs/yearbook/). And the specific source of the variables has been given in the text and references.

SUPPLEMENTAL INFORMATION

It can be found online at https://doi.org/10.59717/j.xinn-geo.2025.100172