

# **Analyzing the water environment and social-economic effects for integrated water resource management**

Course of Environmental and Ecological System  
Graduate Programs in Environmental Systems  
Graduate School of Environmental Engineering  
The University of Kitakyushu, Japan

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Kitakyushu, Japan, September 2022

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# Acknowledgments

I sincerely thank my supervisor Professor Takaaki Kato for his kind help. During the three years, he guided me in the selection of my research method and in improving it and guiding me in writing my paper. I am grateful to his kindly guiding.

I am grateful to my parents for their encouragement and support, which helped me to complete my doctoral studies. Thanks to my husband. He encourages finish my doctor research.

Thanks to friends in the research lab. They also helped me a lot

Finally, I am very honored to have completed my doctoral studies at Kitakyushu University

# Abstract

Because of urbanization and climate change, the water environment faces a terrible vulnerability trend. This study is to study the urban water vulnerability. This study includes three kinds of methods, indicators, vector auto regression model (VAR) and spatial analysis. This indicator is established to quantify water resource vulnerability through urban water scarcity, urban water stress, urban water pollution, urban water productivity and sanitation water, containing development pressure and management capability. The vector auto regression model was used to study the spatial-temporal characteristics of the urban water resource management indicators. Regression analysis is used to study the connection of indicators under the urban water environment and the spatial connection of these indicators, aimed to estimate agricultural water supply internalization and examine the influence of urbanization on water supply internalization. The study area is China, there are three types of study areas, the whole China province; Four province-level municipalities, Beijing, Tianjin, Shanghai, and Chongqing, and its neighboring provinces in China; and four provinces in North China. The four provinces consist of 30 cities in four provinces in North China: Beijing, Tianjin, Hebei, and Shandong.

The result indicates that east area has more vulnerability water environment, compared with other area. Social development has a significant positive impact on our indicators of urban water vulnerability, especially in urban productivity and urban water pollution. If properly managed, urbanization provides benefits for resource savings and environmental protection. Urban water resource vulnerability indicators have a regional relationship, with the same development pressure and management capability. In the

future, cooperative development could be strengthened to achieve the sustainable urban water environment. Urban development impacts agricultural water supply internalization through urban water supply internalization and agriculture. Spatial agglomerations of urban and agricultural activities have effects on agricultural water supply internalization.



# **1 Introduction**

## **1.1 Background**

### **1.1.1 Water situation**

Climate change will cause the water shortage. Freshwater ecosystems in river basins with large populations of urbanites with insufficient water will likely experience flows insufficient to maintain the ecological process. Economic development is expected to lead to an 80% increase in water demand by 2050, which negatively affects the water environment for areas in the primary stages of economic development (Grossman et al., 1995). Extreme weather events such as Hurricanes Harvey and Sandy, and Australia's Millennium drought have brought water security. The water quality problem also leads to water scarcity. The United Nations survey showed that about 40% of the steady flow of global rivers has been polluted.

In addition, there is an increase in the population. The world population has reached 7.753 billion by the year 2020. A large part of the 900 million people in rural areas that have an income below the one-dollar-per-day poverty line lack access to water for their livelihoods. Lack of access to safe drinking water and sanitation, combined with poor personal hygiene, is estimated to cost the lives of 2.18 million people, three-quarters of whom are children younger than 5 years old (Pruss et al., 2002). In the urban area, currently, 150 million people live in cities with perennial water shortages, defined as having less than 100 L per person per day of sustainable surface and groundwater flow within their urban extent. By 2050, It will increase to almost 1 billion people. Cities in certain regions will struggle to find enough water for the needs of their residents

(McDonald, 2011)

### **1.1.2 Urban and rural situation--Social factors**

As the economy has developed, the social structure has changed. This world is getting more urbanized than ever. By 2050, nearly 7 of 10 people in the world will live in cities (World Bank, 2019). Rural and urban areas are economically, socially, and environmentally interlinked. Ecosystem services are among the major areas of rural-urban linkages in which their interdependence is highly manifested.

There is urban-rural migration, which will affect the pressure on the environment. Urban and rural areas have different development patterns and therefore lead to different water use characteristics. Rural water use is high and economically inefficient but provides basic food. Urban water use is economically efficient. A strong rural-urban linkage in this context has a higher potential for reducing these urban area problems. Rural and urban areas face water conflict. In water scarcity background, there are urban-rural water conflicts. The most rapid population growth period was from 1994 to 2018, with most large cities with 5 million or more people nearly doubling their population. It led to more and more populations that suffer from water scarcity. 3.9 billion people lived in cities in 2014 (UN, 2014). This trend is expected to continue: 66% of the global population is expected to live in cities by 2050, compared to 54% in 2014. The relationship between urbanization and water security is a multi-faceted one (Srinivasan et al., 2013).

Urban water environments face many challenges because of urban development. Urban development is the core of modern economic and social growth. The annual growth rate of the urban population worldwide was 2.15% by the end of 2015 (UN-Habitat, 2016; United Nations, 2015).

Under climate change, urban areas will produce a surface water deficit of 1,386–6,764 million m<sup>3</sup> per year worldwide (Flörke et al., 2018). Agricultural water accounts for the highest proportion of water consumption amounts; its withdrawals will increase by 13% and reach 2975 km<sup>3</sup> in 2050 versus 2000 (Chartzoulakis and Bertaki, 2015).

In modern life, with the development of urban areas, the water environment has become increasingly harsh. Urban area and population development have led to an 80% increase in water demand by 2050 globally (Flörke et al., 2018). The threat of climate change brings pressure to urban areas. A serious shortage of water resources and progressive deterioration of the water environment restrict urban development and urban residents' lives (Kraas et al., 2013).

Rapid urbanization brings anthropological system effects on agriculture and the water environment. Urban areas rely on rural areas to meet their demands for food and water (Gebre and Gebremedhin, 2019). Water has connections with energy and food (Endo et al., 2020, 2021) and has been studied in the framework of water–energy–food nexus. Food consumption structures have changed with urbanization, and food demand is a function of population growth (UN, 2004). Meanwhile, urban water has direct competition with rural water (Falkenmark, 1995).

### **1.1.3 Water management**

Raising water demands and insufficient freshwater resources are the main reasons of water conflicts in transboundary watersheds. Existing development needs to reconcile economic development with the ecological environment.

With the development of economy, the water environment will have download and upload curve, the environmental Kuznets curve. In the process, Water management is necessary. The sustainable utilization of water resources while ensuring the

conservation and environmental protection is fundamental to sustainable development. Water management needs to coordinate economic development with the ecological environment and therefore requires holistic water management.

A useful management solution is integrated water resource management (IWRM), a multi-criterion planning and decision-making process. IWRM is a useful way to harmonize the differences in industrial, ecological, and social-economic development, to achieve equity and efficiency. IWRM is a multi-criterion planning and decision-making process with a flexible development strategy (GWP, 2000; WWAP, 2003; Hooper, 2006). An IWRM plan has been proposed to promote coordinated development and water resource management via integrated assessment, based on establishing a framework in which the evaluation of water management and decision-making. IWRM aims to maximize the economic benefits and social welfare of the use of water without jeopardizing the sustainability of the ecosystem.

It is known that the environment should be considered to achieve sustainable development. Integrating water resource management (IWRM) is a good way to solve the conflict between water imbalance distribution and socio-economic development. When combined with an indicator, it can be used to assess the water environment, for example, groundwater resources management in Iran (Hosseini et al., 2019). Pires (2017) summarized four categories of indicators: social, economic, environmental, and institutional sustainability.

Under the IWRM framework, many indicators combine with other factors provide information for decision-making, such as the water footprint combined with climate factors (Vanham et al., 2017; Xu et al., 2019). The driver–pressure–state–impact–response (DPSIR) approach combines social factors (Sun et al., 2017), and city water management combines with urban factors (Chang et al., 2020). Intensive

industrialization, rapid urbanization, and prompt modernization have aggravated water conflicts among different stakeholders in the development process. They developed a vulnerability assessment methodology by prioritizing the key issues of IWRM, containing DPSIR, which uses policy-relevant indicators to quantify water resource vulnerability to environmental change (Huang and Cai, 2009).

## **1.2 Research questions**

Population and social-economic development led to Water scarcity. There is Water quantity and Water quality scarcity. The development of modern society has led to the problem of water quantity scarcity. water contamination led to water quality scarcity.

An increase in population and increased environmental pressure without a significant increase in freshwater resources. The increase in population lead to increase environmental pollution and further aggravated the water quality scarcity. Water management under IWRM is very important.

In climate change situations, humans face more water pressure in many areas of the world. Ribeiro et al. (2003) noted the importance of water vulnerability under climate change conditions. Some researchers have studied environmental vulnerability, for example, groundwater vulnerability (Nasri et al., 2021) and urban ecosystem vulnerability (Shen et al., 2016). However, further studies are needed to develop tools to identify causes of water vulnerability in metropolises with significantly large populations. We want to study the urban water resource vulnerability. Urban development has a significant impact on water scarcity (Gebre and Gebremedhin, 2019).

Next, we want to study the system effects of urban development on urban and agricultural water consumption under rural–urban development transformation situations. The system effect includes direct and path effects, where direct effects

include agricultural activities and urban water scarcity, which directly affect agricultural water scarcity. Path effects include direct and indirect path effects. The direct path effect reflects the direct water conflict due to increasing urban water demand, which is the urban effect on agricultural water through urban water scarcity. The indirect path effect refers to indirect water conflict due to urban area expansion, which is the urban effect on agricultural water through a change in agricultural activities. Some researchers have studied path effects using system models. For example, Wu et al. (2013) and Jeong and Adamowski (2016) used system models to study the social impacts on water stress. However, these studies have two limitations: first, they ignored the impact of urbanization on agricultural water; second, they ignored the effect of the spatial distribution of urban and agricultural activities.

However, the natural distribution of resources and the spatial location of human activities that demand water for society significantly also affect the environment. Spatial agglomeration refers to the geographical pattern where the same feature appears in proximity to each other (Billings and Johnson, 2016). The spatial agglomeration of agricultural and urban activities affects the environment. Zhong et al. (2020) found that the economic and social development of the surrounding cities impacted local agricultural activities. Urbanization, urban population agglomeration, and industrialization significantly impact air quality (Liu, 2017). Agricultural agglomeration can improve the efficiency of agricultural water use efficiency (Wang et al., 2019). We use spatial models to consider the effects of spatial agglomeration of urban and agricultural activities on water stress.

We use a relatively novel approach of combining system models with spatial models and address four research questions: first, how does agricultural development affect agricultural water stress directly? Second, how do urban activities affect agricultural

water stress via urban water stress? This question concerns the direct and indirect path effects. Third, are agricultural water stress and agricultural activities affected by urban development? This question concerns the indirect path effect. Fourth, what is the spatial agglomeration effect of urban and agricultural development on agricultural water stress?

From the problem statement, three research questions are considered in the thesis:

1 How can we comprehensively measure water quality and water quantity for cities to address water vulnerability? 2 How can we consider the diverse characteristics of urbanization in water vulnerability analysis? 3 Which factors are important among the changes in the social structure for agricultural and urban water security?

### **1.3 Study area**

The study area is China region. Water scarcity is serious in China, according to the Chinese Statistic Year Book 2018, the urban population has grown from 551.5 million in 1951 to 1390.1 million in 2017. The urban population percentage increased from 11.78% in 1951 to 58.52% in 2017. The population increase has led to serious water shortages. Seriously unbalanced water distribution aggravates water scarcity (Jia et al., 2018), especially in North China. The water unbalance distribution also leads to conflicts in urban and agricultural areas (Cai, 2008). Significant regional unbalance water resource endowment is between the east area and west area of China (Fan et al., 2017). North China faces more intensified conflict between ecosystems and human development, especially east area of North China.

China faces severe water scarcity, attributed to rapid economic development and urbanization, especially with a large and growing population (Jiang, 2009). The urban population percentage increased from 11.78% in 1951 to 58.52% in 2017 (NBS, 2018). Rapid Urbanization brings anthropogenic system effects on agriculture and the

environment. Urban development has an impact on water scarcity (Gebre, 2019).

Under the limitation of water resources, the contradiction of water allocation of urban and agricultural activity is prominent (Meng et al., 2018). Now, China's food production depends significantly on irrigation (Wang et al., 2017). Urbanization leads to an increase in agricultural water.

In China development process, Eastern provinces are more suitable for urban development. Because the geographical distance is relatively close to the coastal areas and more suitable for the concentration of urban activities. More urban areas are in the Eastern provinces rather than in Western provinces. The Eastern provinces are more densely populated than the Western and interior regions. and in higher urban development levels. There are also significant regional differences observed in its water resource endowment (Fan et al., 2017), Unbalanced development and unbalanced precipitation distribution in China cause problems, leading to urban development in Eastern China. China's climate leads to prominent differences in precipitation between the Southern and Northern provinces. The North and Northwest regions account for half of China's total area but have less than 20% of the total national available water resources.

Water shortages and uneven geographical and temporal distribution of water resources have led to complex water problems in China. Particularly in Northern China, water use conflict between ecosystems and human development has intensified, including upstream and downstream agricultural and industrial conflicts (Cai, 2008). The water environment carrying capacity in China is different across different areas (Jia et al., 2018), and Northern China faces severe water problems.





Fig 1-1 Map of provincial administrative divisions in China

## 1.4 Research Objectives

According to these research questions, his study focuses on three aspects

1 How can we comprehensively measure water quality and water quantity to address water vulnerability?

A1 Create a water vulnerability indicator for cities, including the totality of agriculture and urban areas

A2 State of urban water vulnerability indicator

A3 Compare different areas

2 How can we consider the diverse characteristics of urbanization in water analysis?

B1 Create an urban water vulnerability indicator

B2 Conduct spatial-temporal analysis

3 Which factors are important among the changes in social structure on agricultural and

urban water security?

C1 Analyze urban and agricultural water interactions

C2 Identify factors influencing urban water security

C3 Identify factors influencing rural water security

## 1.5 Research method

We want to use two aspects of method, indicators and spatial and temporal analysis. Indicators is used to measure the water environment. spatial-temporal analysis to analysis the water environment geological characters. Spatial stimulations model and Spatial Autorepression model is used to study the influencing factors

Table1-1 Method

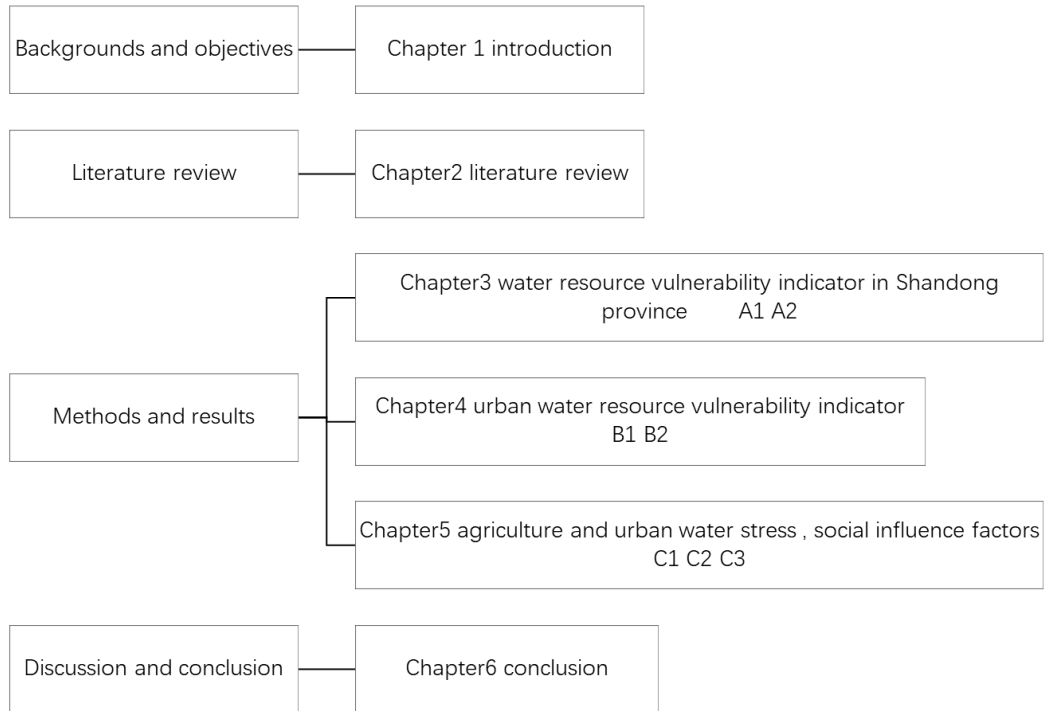
Classification	Method	Object	Chapter
Indicator	Water resource vulnerability (WRVI)	Water vulnerability	Chapter3
	Urban water resource vulnerability (UWRVI)	Urban water vulnerability	Chapter3 4
	Agriculture water stress	Water use pressure	Chapter5
	Urban water stress	Water use pressure	Chapter5
Temporal analysis	Vector auto regression	Urban water vulnerability connection	Chapter4
Spatial analysis	Spatial stimulations model		Chapter5
	Spatial autorepression model		Chapter5

## 1.6 Chapter plan

This dissertation includes 6 chapter. The outline diagram of the dissertation is

shown in Fig1-2

Fig 1-2 Chapter outline



## 2 Literature review

The increasing concentration of people in large, densely settled cities on the coast is likely to exacerbate water scarcity (Mekonnen and Hoekstra, 2016). With the development of population and economy, the water environment will have the download .and upload curve. The curve is the environmental Kuznets curve, when the economic development reaches a certain level, after reaching a certain critical point or "inflection point", with the further increase of per capita income, the degree of environmental pollution tends to decrease, and the degree of environmental pollution gradually slows down and the quality of the environment gradually improves.

Water security was first articulated as a policy challenge at the World Water Forum in 2000 in the United Nations Ministerial Declaration of the Hague on Water Security in the Twenty-first Century and it has remained on the agenda of international organizations since then (United Nations, 2000; UN Water, 2013;)

In China, rapid economic development and urbanization with a large and growing population contribute to China's water scarcity (Jiang, 2009). According to Chinese statistics years book 2018, the urban population percentage increased from 11.78% in 1951 to 58.52% in 2017. China's food production significantly depends on irrigation (Wang,2017). Urbanization leads to an increase in agricultural water.

There is a principle that urban development should not affect the supply of rural ecosystem services and rural life at all. Furthermore, the rural population should be given policy attention to the ecosystem services the rural areas are providing and the rural area's ecosystem should be protected for its sustainable service delivery. (Gebre & Gebremedhin, 2019)

Urban areas are where the population of secondary and tertiary industries is the main residents instead of agriculture. In China, urban areas include cities and towns established under the national administrative system (Ministry of Construction of the People's Republic of China, 1999).

## **2.1 IWRM definition**

Traditional water management uses two methods to solve the problem of imbalanced development of water demand and supply: the hard path (i.e., engineering solutions; Gleick, 1998) and the soft way (seek to make the available water supply more sustainable and productive instead of attempting to identify new sources; Gleick, 2003). Both have limitations. The hard way is more likely to harm the environment, the soft way faces the restricted water quantity.

A valuable solution to this hard and soft way limitation is integrated water resource management (IWRM), a multi-criterion planning and decision-making process. IWRM is a valuable way to harmonize the differences in industrial, ecological, and social-economic development to achieve equity and efficiency. An IWRM plan proposed to promote coordinated development and water resource management through the integrated assessment based on establishing a framework for evaluating water management and decision-making.

IWRM aims to maximize the economic benefits and social welfare of water use without jeopardizing the ecosystem's sustainability”, according to WWAP (2003). Coordination between the management of national water resources and economic development is necessary for IWRM requirements. As for the definition of IWRM, The Global Water Partnership (GWP, 2000) defines it as “a process which promotes the coordinated development and management of water, land and related resources, to

maximize the resultant economic and social welfare equitably without compromising the sustainability of vital ecosystems.” IWRM involves cross-sectoral collaboration and adaptive management rather than a single sector (Hooper, 2006) It needs greater participation of different groups of stakeholders, such as policy- and decision-makers, planners, managers, scientists, and the general public (UN, 1992).

Integrated water resources management (IWRM), is a comprehensive and flexible strategy of development and implementation to holistically evaluate all areas of urban water cycle and the collective impacts, as well as its links to other management sectors. It is a multi-criterion planning and decision-making process. It is an important and critical subject in every city and country (Cai et al., 2017; Wang et al., 2018).

## **2.2. Practice Function of IWRM**

Many researchers have combined ecological and social-economic aspects to study the water environment and water management. The expansion of IWRM philosophies has given rise to improvements in decision-making.

As for ecology, ecological Increasing importance is being placed on coupling with IWRM. Regarding climate change, Pessacg et al. (2015) have used the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model to focus on the impact of precipitation users” of water in the allocation of water-related services of ecosystems engage stakeholders in management and decision-making processes. Xue et al. (2017) have proposed a participatory ecosystem service (ES) - the Bayesian network model. At different levels of management, different areas exist. In the river basin area, Crase et al. (2018) have summarized integrated management in balancing multiple objects and multiple sites upstream and downstream.

About economic sectors, Guan and Hubacek (2008) study the linked interactions in

the economic system and interactions in the hydrological system. They used economic input-output modeling combined with a mass-balanced hydrological model. The system of environmental-economic accounting for water (SEEA-W), can be used to assess the water balance in river basins in a hydrological model, including the rain runoff water balance and the economic balance. (Pedro-Monzonis et al., 2016).

IWRM provides for decision-makers who need hydrological and economic information for water management. Pahl-Wostl et al., (2020) have used a transdisciplinary diagnostic method for multi-level water government. In addition, Wang, et al., (2019) have examined basin water management in Canada. Hosseini et al. (2019) have studied environment sustainable groundwater management (ESGM), based on weighted aggregation indicators, through a multi-criterion decision-making model.

### **2. 3. IWRM used in water allocation**

In the process, finding suitable ways of allocating water is important in IWRM. The most effective time to implement IWRM is the initial allocation of water resources. In modern society, the initial allocation of water resources is relatively controllable and can give full play to the maximum efficiency of water resources. The existing method is based on quota and market regulation, both they exist problems, such as lack of flexibility based on quota and lack of fairness in market regulation. This paper makes a thorough study of these two ways of distribution and puts forward some suggestions

Water allocation should achieve a multi-objective compromise between environmental, social, and economic preferences(Roozbahani, Schreider, & Abbasi, 2015). Sustainable water allocation can be a resolution for water disputes as it addresses simultaneously economic, social, and environmental benefits. Water allocation is not enough to solve the social-ecology problem.

Prioritization of water allocation can reduce economic losses and protect the environment (Eamen et al., 2020). Water allocation can be undertaken through administered systems, market-based systems, or a combination of the two (Zhao et al., 2013)

Water allocation is affected by many factors, such as economic development, social equity, and the environment. Integrated interconnections linking multiple aspects, such as upstream and downstream, water resource quality and quantity, economic and environmental needs, and technical and political decisions, are the principles of IWRM (Ludwig et al., 2013).

IWRM is a framework for considering water allocation in different areas and different sectors. For example, generally interact agricultural production and other water-use sectors, interact with the upstream and downstream systems (George et al., 2011; Han et al., 2013; Letcher et al., 2007). The relationships in coordinating the social economy and water environment are considered on an urban scale (Cui et al., 2019). Water allocation is useful, but the issues of equity and efficiency must be addressed in the redistribution of water resources (Garrick et al., 2013).

A water allocation policy should integrate equity, efficiency, and environmental consciousness for the sustainable and coordinated development of socio-economic and water environmental systems in urban cities. In supplement to water deficit, water transfer, and groundwater utilization (Zhang et al., 2015), should consider the spatial heterogeneity of water availability and delivery facilities, based on water storage, water demand, and water management institutions.

The hydrological model provides information for water allocation. The hydrological models that fall in this category include MODSIM-DSS (Fredericks et al., 1998), MIKEBASIN (Bangash et al., 2012; DHI, 2006), WEAP (Yates et al., 2005; McCartney



and Arranz, 2007), and SWAT (Wu et al., 2018; Wurbs, 2015). The hydrological model provides information for decision-makers. The outputs from the REALM model provide information on the likely hydrological impacts of changes in the state of nature and the data required to complete the economic assessment of the simulated change (Perera et al., 2005; George et al., 2011).

Economic analysis has a key role in providing valuable information to aid in both the decision-making process and the development of river basin management plans (Wang, 2019). An Integrated Modelling System can be used (Welsh, 2013) to achieve a nationally compatible market, regulatory, and planning-based system for managing surface and groundwater resources for rural and urban use that optimizes economic, social, and environmental outcomes. Cost-benefit analysis, including how the domestic and industrial uses of water are determined, has been presented (Davidson et al., 2009). Roozbahani (2015) has used a multi-objective model to study social and other factors representing economic and environmental preferences, to facilitate sustainable water allocation.

## **2. 4 Model construction ———indicator analysis**

Water scarcity connects with social development. The driving Force-Pressure-State-Impact-Response (DPSIR) framework is designed to provide a more comprehensive approach to analyzing environmental connections with problems. The DPSIR framework organizes the indicators according to the cause-effect schema: Drive Forces, Pressure, State, Impact, and Response. DPSIR is based on the pressure-state-response (PSR) introduced by the OECD (1994). The DPSIR is the most widely used framework for environmental indicators. (WWAP, 2003). Adopting a framework is especially important in the case of indicators related to sustainable development, which

encompasses many subjects and dimensions. it is a relevant tool for structuring communication between scientists and end-users of environmental information, while it is inappropriate as an analytical tool. (Environmental, economic, social, and political) (Laura Maxim 2009)

This framework comprises information categories based on a chain of causal relations that encompass these phenomena and has been widely adopted in various ecosystems, with application and development. Cooper (2013) improved the framework using constituent information categories to make the framework represent the socio-environmental system more clearly. In the case study, Sun (2016) studied the impact of changes in socio-economic development and the consumption structure of the residents of Bayannur, Inner Mongolia, using DPSIR combined with AHP.

In the current study. IWRM consists of an indicator-based framework and system dynamics. Some of these tools have been used in case studies in China. The eastern developed regions of China are affected by particularly severe environmental problems with water resources, as a result of overexploitation. Cai, 2016 and Jia, 2018 use an indicator-base and system dynamics model to calculate water environment carrying capability. Their result shows that in China, the uneven spatial distribution of water resources, rapid economic development, and urbanization, in the presence of a large and growing population and poor water resource management, has led to water scarcity problems.

The indicator-based framework is used to integrate ecology and social-economy information, based on the DPSIR framework, Pires (2017) has proposed four sustainability criteria: social, economic, environmental, and institutional. In China, indicators are also used to evaluate the relationship between environmental and social resources to ensure sustainable and vital ecological integration of land and related

resources. Several researchers have developed an indicator-based framework, DPSIR (Sun, 2016), based on a case study of the sustainability of water utilization, changes in societal economic development, and the consumption structure of the residents of Bayannur, Inner Mongolia. An integrated approach has been adopted in various water resource modeling efforts to support socio-economic systems.

### **2.4.1 Indicator**

Indicators are defined more specifically as “quantitative measurements of progress toward or away from a stated goal” (Parris and Kates, 2003) or simply as metrics that are used to describe the “status, trend or performance of underlying complex systems” (McCool, 2004,). Indicator method is a standard method under integrate management.

Indicators of sustainability can be used to inform decision-making and can be instrumental in bringing about policy change. Despite their usefulness, indicators of sustainability have faced a variety of critiques. Sustainability indicators are critiqued for not applying to an appropriate spatial scale and therefore not discriminating between differential impacts on various social, economic, and geographic groupings (Briassoulis, 2001). For example, indicators are used to estimate the water environment under a sustainable development goals indicator framework (Vanham et al., 2018).

Water indicators play an important role in the assessment of the utilization water environment. There are defining and populating indicators to capture the different facets of water security. There are three categories of indicators through integration to assess the water environment. First, physical water scarcity contains two aspects of water scarcity. Water scarcity indicators often combine a water pollution index, such as the Falkenmark index (Falkenmark et al., 1989, 1992), water poverty index (Sullivan, 2002), and water stress (Zeng et al., 2012). Second, water use with social effect was

considered, such as Sun (2017) used the driver–pressure–state–impact–response approach to combine the water environment with social factors. Third, indicators were combined with other factors, such as the water footprint (Vanham et al., 2017; Xu et al., 2019). Table 2-1 is water indicators. There are qualitative and quantitative analyses of water indicators.

. Water security is also highly dynamic (Srinivasan et al., 2017), suggesting the need for indicators that can reflect changes at the local level. Local indicators are seen to be useful to reflect the very significant variation in water challenges between localities within a single country or river basin, allowing for more effective problem identification, and to provide a stronger link between indicators and decision-makers, as responsibility for many aspects of water policy is widely devolved to the local level (Rouse, 2013)

In this work, we are specifically interested in resource management objectives of urban water management. This includes supply security (which encompasses resource efficiency and internalization of supply), environmental protection (which encompasses sustainable management of water, energy and nutrient resources, and restoration of hydrological flows), and recognizing the diverse functions of urban water.

Categorizations of water management objective:

1 Resource use, consist of supply internalization and water efficiency. Supply internalizations aim to extend supplies and decrease reliance on water drawn from the environment by utilizing water sources available within the urban area, i.e. harvesting and utilizing water falling on urban areas (rainwater, storm- water) and the recycling of water (wastewater, greywater); Water efficiency here refers to the overall water efficiency in relation to water drawn from the environment.

2 Resource situation, resource situation is means protection of water resources and hydrological flows, refers to the sustainable management of water resources in terms of stocks, qualities and flows. This include (1) managing the volumes of water drawn from the environment for urban uses within the region's capacity to supply, (2) limiting the discharge of pollutants to the environment to maintain the quality of waterways, and (3) restoring natural hydrological flows altered by increased imperviousness.

3 Resource function, is to sustain habitat health and biodiversity, enabling economic activities (e.g. industrial, commercial, energy generation, agricultural, forestry, fisheries, livestock).

Table 2-1 Integrate Water indicators

Indicator	Main inputs	Main references
Green city index	Resource use	EIU, 2009
	Resource situation	EIU, 2011
City blueprint	Resource use	van Leeuwen 2012
	Resource situation	
	Resource function	
Water sensitive cities index	Resource use	CRC WSC, 2016
	Resource situation	
	Resource function	
Sustainable cities water index	Resource use	Arcadis, 2016.
	Resource situation	
	Resource function	
Urban metabolism indicates	Resource use	Renouf, et al,( 2017)
	Resource situation	
Urban water security indicators	Resource use	Jensen & Wu (2018)
	Resource function	

From the water users' perspective, the urban water environment is a subcategory of the whole water environment. The water environment is one of the bases of social development. Water user's indicators consist of urban water indicators and agriculture

water indicators. Some researchers have studied the water environment through water users and developed water indicators. For example, He (2021) studied agricultural water. Water environment indicators are important for assessing the water environment to ensure sustainable water management.

## **2.4.2 Urban water indicators**

Urban area is meaning city. There are five different city classifications, megacity, super metropolis, metropolis, medium city, and small city, determined by urban population (State Council, 2014). As a result, among 656 cities in China, six cities are classified as “Megacity” (including Shanghai, Beijing, Chongqing, Guangzhou, Tianjin and Shenzhen),

. Urban water management is important in achieving urban water environment conservation and sustainable utilization. Its main objectives are to maintain health, save human resources, conserve natural resources, and save financial resources (Hellström et al., 2000).

The key objectives of urban water management are in relation to access to water and sanitation, supply security, environmental protection, the functionality of urban water, risk management of extreme conditions, resilience to droughts and floods) and institutional aspects. They focus on the management of direct water (real flows of water from surrounding regions) and not on indirect water (that embodied in the goods and services produced using water from elsewhere) (Renouf and Kenway, 2016).

There are some urban indicators to measure urban water situation. Renouf (2017) summarized some city water indicators such as the green city indicator, water-sensitive cities indicator, city blueprint, sustainable cities water indicator, and Asian water development outlook. Exceptions are, the Water Sensitive Cities Index

(Chesterfield et al., 2016), which includes a range of indicators that align with the desired features of ‘water sensitive cities’, and the ADB's Asian Water Outlook, which has a set of indicators aligned to its goals. However, the indicators for these instruments are not currently quantified, and are instead evaluated qualitatively. Indicator development was guided by the visions and/or principles articulated in the concept of Water Sensitive Cities (Wong et al., 2013), Shields (2009) calculated the green city indicator for major European cities. Gleason (2021) estimated water-sensitive city indicators in Mexico.

An indicator that addresses water access in the context of sustainability should be a leading indicator that addresses the ability of the water system to maintain the population with access to water over time.

Table2-2 Urban water indicators

Indicator	Main inputs	Main references
Green city index	Resource use Resource situation	EIU, 2009 EIU, 2011
City blueprint	Resource use Resource situation Resource function	van Leeuwen 2012
Water sensitive cities index	Resource use Resource situation Resource function	CRC WSC, 2016
Sustainable cities water index	Resource use Resource situation Resource function	Arcadis, 2016.
Urban metabolism indicators	Resource use Resource situation	Renouf, et al, 2017
Urban water security indicators	Resource use Resource function	Jensen and Wu, 2018

### 2.4.3 Agriculture water indicator

Rapid urbanization brings anthropological system effects on agriculture and the water environment. Urban areas rely on rural areas to meet their demands for food and water (Gebre and Gebremedhin, 2019). Water has connections with energy and food , has been studied in the framework of water–energy–food nexus. Food consumption structures have changed with urbanization, and food demand is a function of population growth (UN, 2004). Meanwhile, urban water has direct competition with rural water (Falkenmark, 1995). There are two kind of agriculture indicators, water footprint and WECC.

Table 2-3 Agriculture water indicator

Indicator	Main inputs	Main reference
Water footprint	Resource function	Zhao et al, 2014
Agriculture WECC	Resource use Resource situation Resource function	He et al., 2021

Indicators tend to be comprehensive in evaluating water environmental and socio-economic. We use Chapter 3 to explores the full range of analysis indicators further<sup>2</sup> However, the spatio-temporal analysis of indicators is not sufficient. It is discussed in Chapter 4<sup>3</sup> For a more in-depth linkage between the different sectoral indicators, we conducted the study in Chapter 5.



# **3 Water resource vulnerability indicator and urban water resource vulnerability indicator**

## **3.1 Background**

The study is based on Sun and Kato (2020), and focus on urban water study. Urbanization is an essential part of modern society. Urban expansion, which is obviously unavoidable, comprises urban area growth and urban population growth. Urban population growth has a significant effect on the socio-environment. The urban population and the foreseeable threat to climate change bring pressures in urban areas and progressively emerge to severely hinder urban development (Kraas et al., 2013). The annual growth rate of the urban population was 2.15% at the end of 2015 (UN-Habitat, 2016; United Nations, 2015). All these factors lead to an increase in water demand. Economics and urban population drive the urban water demand quickly, leading to an 80% increase in demand by 2050 (Flörke, 2018). In particular, climate change alters the timing and distribution of water.

We believe that human development, especially urban development, considers the destructive and protective effects of development on the environment. We study the effects of urbanization that could promote industrial growth, industrial structural change, and sanitation improvement.

In urban water environment research, most studies considered single urban areas.

Urban areas are connected to other urban areas. We study the urban agglomeration in a province based on the development level and climate characteristics. Urban water environments in different development regions are different. The development level region was divided according to China Western Development in 2000. The natural environment in the Western region is relatively poor. This study explores the extent of development that the Western region can sustain and whether the Eastern region can improve its environmental quality.

Economic development imposes great pressure on the water environment. Comprehensive studies on city water resources vulnerability are important to sustainable development in China, especially for Shandong Province.

Due to the complexity of its internal mechanisms and diversity of regional environmental systems (including natural, social and economic environments), water is a kind of environmental properties as an integral part of the ecological environment, we consider vulnerability with respect to sustainable water resources only. In general, the vulnerability of a natural and socio-economic system can be determined by the character, magnitude, rate of a threat's development, and by the system's sensitivity and adaptive capacity on the other.

This study bases on the Driver Pressure State Impact and Response (DPSIR) model. (Kelble2013) . DPSIR model can capture cause and effect relationships between the social economic and environmental systems. It is a sustainability is and evaluation framework. In addition, the indicator-component index system is also used to find water resources in two main cities in Shandong Province. In the stable equilibrium of a subsystem, a small but a gradual change might rapidly lead to the collapse of the whole system.

## **3.2 Objectives**

We use indicators to measure the state of water scarcity and its factors. The application of indicators of water use and management can contribute to a better allocation of this limited resource and have important impact on policy making. The relevance of indicators for the decision-making process is one of the most important features of the indicators in relation to other forms of information. In the paper we calculate indicators for two water scarce cities in Shandong Province in order to measure the environmental situation and provide information for a response to make social and environmentally sustainable development.

Water vulnerability is by biophysical and social drivers operating in water environments. We want to study the urban water vulnerability concept to assess the connection between the water environment and socio-economic factors through water indicators. Urban water vulnerability analysis requires consideration both water stress and water management capabilities.

## **3.3 Methodology**

We calculate indicator, water resource vulnerability indicators. Water vulnerability depends on biophysical and social drivers operating at multiple scales. The assessment tools use a holistic approach to water resource management, specifically for IWRM (Plummer, 2012). We explore the social effect, especially the urban effect, on the water resource environment using the urban water resource vulnerability indicator (UWRVI).

According to UNEP (2002), the vulnerability can be defined as the interface between exposure to physical threats to human well-being and the capacity of people and communities to cope with those threats. Threats may arise from a combination of

social and physical processes, while the vulnerability is associated with many environmental concerns. Scholars have divided vulnerability into intrinsic and specific vulnerabilities. Intrinsic vulnerability refers to the vulnerability determined by human activities (Ribeiro et al., 2003). Some scholars consider specific vulnerability to be the sensitivity of water resources to a contaminant (Doerfliger et al. 1999; Gogu and Dassargues 2000).

From the driven pattern of water vulnerability indicator (WVI), the WVIs can be divided into supply-driven and demand-driven groups. Supply-driven WVIs include resource limitations, extreme events, and land cover. Demand-driven WVIs include demographic households and economies (Sullivan, 2011). The methods used to measure WVI include a multi-dimensional approach (Sullivan, 2011), a multi-criteria decision analysis method (Shen et al., 2016), and integration of climatic variables with reliability, resilience, and vulnerability indicators (Hazbavi, 2018). The creation of WVIs is sometimes combined with Analytic Hierarchy Process (AHP) (Nasri et al., 2021) and geographic information systems. From the perspective of research, there are WVIs regarding groundwater (Nasri et al., 2021), urban ecosystems (Shen et al., 2016), Arctic ecosystems (Alessa et al., 2008), and China Anhui (Pan et al., 2017).

This study combines supply- and demand-driven WVIs. Most previous studies focused on the environmental effect rather than the social effect on water. We study the social effect of urban development and the social impact on the water environment and create an urban water resource indicator using a multi-dimensional approach combined with the DPSIR framework.

Then we calculate indicator, urban water resource vulnerability indicators. We extend the research by Cai et al. (2017) and further study the relationship between development and the environment to promote sustainable development. We believe that

human development, especially urban development, considers the destructive and protective effects of development on the environment. We study the effects of urbanization that could promote industrial growth, industrial structural change, and sanitation improvement. In the end, we make comparison.

### **3.4 WRVI**

We chose water environmental vulnerability because it is important to measure the balance between economic and environmental development. Vulnerability is the degree to which a system is susceptible to, or unable to recover with, the adverse effects of environmental changes. Water environmental capacity and water resources constitute the foundation of the water vulnerability. It represents the self-sustaining, self-regulating and self-purification ability of water environment system. Water self-purification capacity is quantified in the form of water environmental capacity, which is the basis of the carrying capacity of water environment. Climate change is why assessments on water resources and water supply vulnerability, estimation of water scarcity, and analyses of droughts are necessary tools

As for framework can be developed and organized for the evaluation of sustainability. The DPSIR Driving Forces–Pressure–State–Impact–Response approach is the most widely used framework applied for environmental indicators. DPSIR framework designed to provide a more comprehensive approach to the analysis of environmental problems.

DPSIR is based on the pressure-state-response (PSR) introduced by the OECD(1994).The DPSIR framework organizes the indicators according to the cause–effect schema under these: Drive Forces, Pressure, State, Impact and Response. The adoption of a framework is especially important in the case of indicators related to

sustainable development, which encompasses many subjects and dimensions.

This system's view of analysis is that economic and social development, which is common driving forces (D). It is social, demographic and economic developments in societies and the corresponding changes in lifestyles which is overall levels of consumption and production. Patterns exert pressure (P). It is developments bring pressure in using of resources and the use of land on the environment, changes in the state (S). It represents indicator of condition of different environmental compartments and systems. Changes have impacts (I) Impacts on human beings, ecosystems and man-made capital resulting from changes in environmental quality. Because of these impacts, society responds (R) to these driving forces, or acts directly upon the pressure, state or impacts through preventive, adaptive, or curative solutions. Responses by groups (and individuals) and government in society attempts to prevent, compensate and adapt to changes in the state of the environment policy response options

In the paper, we focus on S state and use indicators to measure the water situation, impacts of economic development, and the pressure of environment. Economy growth is driving forces. At the same time due to economy and population growth, environment suffer more and more pressure (P). Understanding present situation is essential to Government and company to respond (R). We extend the research by Cai et al. (2017) and further compare different cities in Shandong provinces. They study resource stress; development pressure; ecosystem health; and management capability.

### **3.4.1 Indicators and data**

According to the DPSIR framework and indicator-component index system, an

index is established to qualify water resource vulnerability through water scarcity, water stress, water pollution, and water production efficiency. The different elements are combined for calculation water scarcity, water stress, water pollution, and water production efficiency and the Water Resources Vulnerability Index (WRVI), like: annual per capita water resources total water supply; annual total water resources total wastewater discharge annual gross domestic product (GDP). The Water Resources Vulnerability Index (WRVI) can be expressed as:

$$WRVI = (WSc + WSt + WPo + WPr) / 4$$

WSc is Water scarcity. WPo is Water pollution. Water stress (WSt) is urban water consumption as a proportion of the total amount of water resources. Water pollution (WPo) is the proportion of sewage emissions of total water resources. Water productivity (WPr) is water demand per unit of GDP

#### 1 Water scarcity (WSc)

Water scarcity is Indicators to measure resource stress, per capita water resources. its equation can be presented as

$$WSc = (1700 - WRP) / 1700 (WRP \leq 1700)$$

$$WSc = 0 (WRP > 1700)$$

As for WSc With regard to the value of 1700, it is a threshold value proposed by Falkenmark (1989). It indicates that there is no vulnerability in water scarcity if the WRP value reaches above 1700 m<sup>3</sup>/person. WRP - annual per capita water resources (m<sup>3</sup>/person)

#### 2 Water stress (WSt)

Water stress is Urban water consumption as a proportion of the total amount of water resources. It is to measure development pressure.

$$WSt = Wsu / WR$$

WSu - annual total water supply (m<sup>3</sup>) .WR - annual total water resources (m<sup>3</sup>)

### 3 Water pollution situation (WPo)

$WPo = WW / WR / 0.1$  ( $WW < 0.1 \times WR$ )

$WPo = 1$  ( $WW \geq 0.1 \times WR$ )

WR - annual total water resources (m<sup>3</sup>); WW - annual total wastewater discharge (m<sup>3</sup>);

As for WPo where WW is annual total wastewater discharge (m<sup>3</sup>). Regarding the value of 0.1, 1 unit of wastewater can make approximately 10 unit of unpolluted water totally unusable. It is to measure ecosystem health.

### 4 Water productivity(WPr)

It is to measure management capability.

$WPr = (40 - GDPWW) / 40$  ( $GDPWW \leq 40$ )

$WPr = 0$  ( $GDPWW > 40$ )

GDPWW - annual gross domestic product (GDP) in constant prices divided by annual total water withdrawal (RMB(yuan)/ m<sup>3</sup>); GDPWW - the global average WP (RMB(yuan)/ m<sup>3</sup>)

Under DPSIR framework, we studied the period from 2008 to 2018 to calculate the water resource vulnerability index. The water resource data come from Shandong Water Resource Bulletin 2015-2018, Jinan Water Resource Bulletin 2011-2014, and Shandong Statistic Yearbook 2008-2011. Water consumption data, population data, and GDP data come from the Jinan Statistic Yearbooks 2009-2019 and the Qingdao Statistic Yearbooks 2009-2019.

## 3.4.2 Study area

In view of industrial and agricultural economy, Shandong Province holds an important position in China. Shandong, as a big province of industry and agriculture,



ranks the third in China's GDP and first in the North China. With developed industry and agriculture, Shandong has a large population. During the primary stage of industrial development, it consumes a large amount of natural resource and damages the environment greatly. Water resources in Shandong Province are scarcely compared with other regions, for example up to 12% of the fruits and 13% of the vegetables in China were produced by Shandong Province using only 1% of China's water resources. We choose two cities in Shandong province. Jinan in inland area. Qingdao in Coastal area.

### **3.4.3 Results and discussion**

To facilitate the harmonious development of the water ecological environment and social economy the current management system for domestic basin resources and the environment aim to manage the resources and environment within the watershed boundary as a unit.

#### **1 Water resource vulnerability situation in Qingdao**

Table3-1 and Fig3-1 are water resource vulnerability situation in Qingdao. Water scarcity (WSc) keep a high level. Average is 0.91693. Water stress (WSt) is unstable and varies with precipitation. Water pollution situation (WPo) is unstable, it also varies with precipitation. Water productivity (WPr) keep high level.

Water scarcity(WSc) and Water stress(WSt) represent natural water scarcity. Water scarcity (WSc) keep high level. The water pressure range is larger, which is easily affected by the climate. As for water quality, the change of Water pollution range is bigger, because Water pollution emissions remain basically remain unchanged, but due to climate factors, the low rainfall, Water purification, poor ability of Water pollution to Water vulnerability has a greater impact. Water production remains stable and water consumption required for economic development remains constant.

Table 3-1 Water resource vulnerability index in Qingdao

Year	WSc	WStl	Wpo	Wpr	WRVI
2008	0.816	0.123	0.125	0.779	0.461
2009	0.936	0.360	0.383	0.797	0.619
2010	0.956	0.532	0.581	0.828	0.724
2011	0.860	0.163	0.197	0.853	0.518
2012	0.918	0.317	0.348	0.868	0.613
2013	0.907	0.271	0.334	0.870	0.596
2014	0.918	0.371	0.405	0.879	0.643
2015	0.981	1.000	1.000	0.908	0.972
2016	0.958	0.660	0.790	0.915	0.831
2017	0.935	0.451	0.524	0.921	0.708
2018	0.900	0.313	0.367	0.922	0.625
Average	0.917	0.415	0.460	0.867	0.665

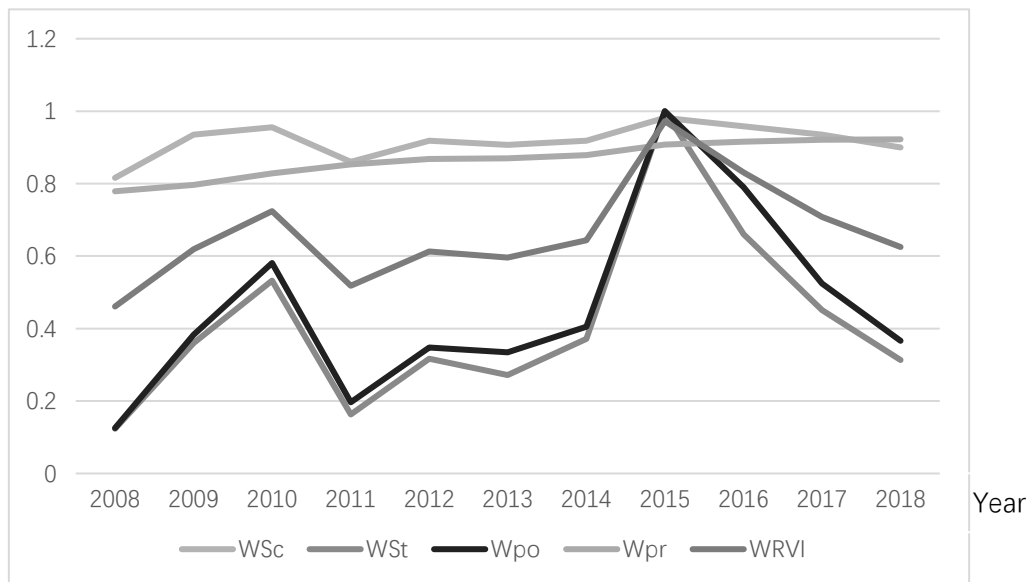


Fig.3-1 Trend of water resource vulnerability situation in Qingdao between 2008-2018

## 2 Water resource vulnerability situation in Jinan

Table3-2 and Fig3-2 are water resource vulnerability situation in Jinan. In water vulnerability, Water scarcity (WSc) keep a high level. Water stress (WSt) is unstable. It varies with precipitation. Water Stress (WSt) and Water Pollution (WPo) share the same trend and are affected by natural precipitation. Water Productivity (WPr) shows a linear growth trend, indicating that the Water consumption in social economy is increasing. Water pollution (WPo) is unstable, it also varies with precipitation. Water productivity (WPr) in low level. There are 2 peaks in Jinan, the first one appears on 2014 and the second one appears on 2017. The curve of WRVI is relative stable.

Table 3-2 Water resource vulnerability index in Jinan

Year	WSc	WSt	Wpo	Wpr	WRVI
2008	0.875	0.214	0.189	0.453	0.433
2009	0.768	0.107	0.105	0.503	0.371
2010	0.769	0.099	0.121	0.576	0.391
2011	0.810	0.150	0.152	0.623	0.434
2012	0.852	0.205	0.222	0.635	0.479
2013	0.847	0.193	0.244	0.705	0.497
2014	0.925	0.394	0.492	0.707	0.629
2015	0.889	0.269	0.334	0.737	0.557
2016	0.842	0.196	0.203	0.751	0.498
2017	0.908	0.356	0.345	0.786	0.599
2018	0.871	0.202	0.024	0.825	0.480
Average	0.851	0.217	0.221	0.664	0.488

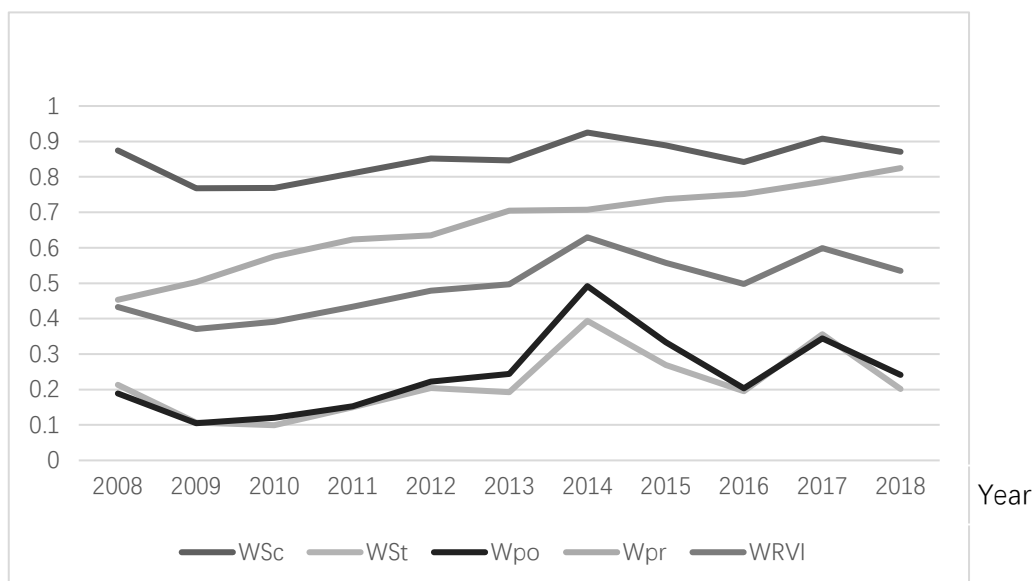


Fig.3-2 Trend of water resource vulnerability situation in Jinan between 2008-2018

The obtained result indicates that drought has a huge impact on water resource vulnerability. Additionally, Qingdao is more vulnerable than Jinan. The variance and Mean WRVI of Qingdao are larger than Jinan, and water scarcity is 7.8% higher than Jinan. Water stress is 91.4% higher. Water pollution is 107.99% higher. Water productivity is 30.7% higher. In summary, Mean WRVI in Qingdao is 36.2% more vulnerable than Jinan. Variance of WRVI is 204.31% higher.

The highest WRVI point of Qingdao appeared as 0.972 in 2015, and the highest WRVI point of Jinan appeared as 0.629 in 2014. Natural endowment has a greater impact on WRVI. In 2015, Qingdao had 30.9% of the average water resources. In 2014, Jinan had 40.4% of the average water resources. In 2015 both cities finish reform of the laddered water price.

Due to the limitations of available data, the present study mainly considers water resource factors, water environment factors, and some economic factors, which correlates with the ecological environment changes caused by human activities. At present, the water resource environment is fragile. It is necessary for government and

enterprise to respond to protect the fragile water environment and keep sustainable development.

### **3.5 UWRVI**

Urbanization is an essential part of modern society. Urban expansion, which is obviously unavoidable, comprises urban area growth and urban population growth. Urban population growth has a significant effect on the socio-environment. The urban population and the foreseeable threat to climate change bring pressures in urban areas and progressively emerge to severely hinder urban development (Kraas et al., 2013). The annual growth rate of the urban population was 2.15% at the end of 2015 (UN-Habitat, 2016; United Nations, 2015). All these factors lead to an increase in water demand. Economics and urban population drive the urban water demand quickly, leading to an 80% increase in demand by 2050 (Flörke, 2018). In particular, climate change alters the timing and distribution of water.

In China, the urban population had grown rapidly from 551.5 million in 1951 to 1390.1 million in 2017. The urban population percentage increased considerably from 11.78% in 1951 to 58.52% in 2017 (NBS, 2018). Nearly 60% of the Chinese population is agglomerated in urban areas to exacerbate water stress in cities, especially in megacities. China is representative because it is the biggest developing countries in the world and a good example to study the effect of urban development to environment.

In China development process, Eastern provinces are more suitable for urban development. Because the geographical distance is relatively close to the coastal areas and more suitable for the concentration of urban activities. More urban areas are located in the Eastern provinces rather than in Western provinces. The Eastern provinces are more densely populated than the Western and interior regions. and in higher urban

development level. There are also significant regional differences were observed in its water resource endowment (Fan et al., 2017), Unbalanced development and unbalanced precipitation distribution in China cause problems, leading to urban development in Eastern China. China's climate leads to prominent differences in precipitation between the Southern and Northern provinces. The North and Northwest regions account for half of China's total area but have less than 20% of the total national available water resources.

Water shortages and uneven geographical and temporal distribution of water resources have led to complex water problems in China. Particularly in Northern China, water use conflict between ecosystems and human development has intensified, including upstream and downstream agricultural and industrial conflicts (Cai, 2008). The water environment carrying capacity in China is different across different areas (Jia et al., 2018), and Northern China faces severe water problems.

It is known that environment should be considered to achieve sustainable development. The sustainable utilization of water resources while ensuring conservation and environmental protection is fundamental to sustainable development. Integrating water resource management (IWRM) is a way to solve the conflict between water imbalance distribution and socio-economic development. IWRM is a multi-criterion planning and decision-making process with a flexible development strategy (GWP, 2000; WWAP, 2003; Hooper, 2006). When combined with an indicator, it can be used to assess the water environment, for example, groundwater resources management in Iran (Hosseini et al., 2019). Pires (2017) summarized four categories of indicators: social, economic, environmental, and institutional sustainability.

Under the IWRM framework, many indicators combine with other factors provide information for decision-making, such as the water footprint combined with climate

factors (Vanham et al., 2017; Xu et al., 2019). The driver–pressure–state–impact–response (DPSIR) approach combines with social factors (Sun et al., 2017), and city water management combines with urban factors (Chang et al., 2020). Intensive industrialization, rapid urbanization, and prompt modernization have aggravated water conflicts among different stakeholders in the development process. They developed a vulnerability assessment methodology by prioritizing the key issues of IWRM, containing DPSIR, which uses policy-relevant indicators to quantify water resource vulnerability to environmental change (Huang and Cai, 2009). Cai et al. (2017) performed a Spatio-Temporal analysis of water vulnerability in China during 2003–2017.

We extend the research by Cai et al. (2017) and further study the relationship between development and the environment to promote sustainable development. We believe that human development, especially urban development, considers the destructive and protective effects of development on the environment. We study the effects of urbanization that could promote industrial growth, industrial structural change, and sanitation improvement.

In urban water environment research, most studies considered single urban areas. Urban areas are connected to other urban areas. We study the urban agglomeration in a province based on the development level and climate characteristics. Urban water environments in different development regions are different. The development level region was divided according to China Western Development in 2000. The natural environment in the Western region is relatively poor. This study explores the extent of development that the Western region can sustain and whether the Eastern region can improve its environmental quality.

### **3.5.1. Water vulnerability and indicators**

DPSIR contains indicators closely related to the economy, population, technology, and the environment and can reflect regional sustainability. Indicators are powerful decision-making tools, and their adoption can evaluate and monitor progress toward sustainability. The DPSIR framework has been used to identify relevant information in several ecosystems, such as biodiversity (Young et al., 2014).

DPSIR is based on the Pressure–State–Response framework (PSR) (OECD, 1993, 2003). This framework comprises information categories based on a chain of causal relations that encompass these phenomena and has been widely adopted in various ecosystems, with application and development. Cooper (2013) improved the framework using constituent information categories to make the framework represent the socio-environmental system more clearly. In case study, Sun (2016) studied the impact of changes in socio-economic development and the consumption structure of the residents of Bayannur, Inner Mongolia, using DPSIR combined with AHP. In the current study, we combined WVI and DPSIR to measure the relationship between society and the environment.

Some scholars have used a similar method that combines WVI with DPSIR to study the impact of social development levels on water resources (Huang and Cai, 2009; Cai et al., 2017). In a relatively new research direction, we expand the range of WVI and refine the DPSIR category using UWRVI to study more detailed effects of society on the water environment. We study the effect of urban development, which is the most important development method in modern life. In previous studies, few studies have focused on urban effects, especially urban agglomerations, on the water environment. The constituent information categories of DPSIR need to be further expanded to measure the social effect of UWRVI. Economic development and population growth



bring driving force (D) and pressure (P) to the environment. We study the impact (I) of change, describe the state (S), and provide information for decision-making (R).

### **3.5. 2 Study area**

In this study we divided China in different region for two principles, development level and climate characters. China was divided into Eastern and Western areas according to the Western Development Plan in 2000 to measure development levels and five parts to measure climate characteristics. The Eastern provinces were divided into Northeast China, North China, and Southeast China. The Western provinces are divided into two parts: Northwest and Southwest.

- 1) Northeast China (Heilongjiang, Jilin, and Liaoning);
- 2) North China (Beijing Tianjin Shanxi Hebei Henan Shandong)
- 3) Northwest China (Inner Mongolia, Shaanxi, Xinjiang, Gansu, Qinghai)
- 4) Southeast China (Jiangsu, Zhejiang, Shanghai, Guangdong, Fujian, Jiangxi, Anhui, Hainan)
- 5) Southwest China (Guangxi, Yunnan, Sichuan, Chongqing, Guizhou, Tibet)

Different areas of China have different characteristics of nature and the socio-economy. Because one urban area depends on other urban areas, we study different urban agglomeration levels of provinces and the effect of development on the water resource environment. At the administrative district of the provincial level, the interdependency of different cities is obvious.

### 3.5.3 Material and methods

We modified the indicators of Cai et al. (2017) and created our indicator. The main difference between the indicator by Cai et al. (2017) and our indicators is that we use the water data of urban areas in each province, while Cai et al. used water data from all areas. Water requirements and consumption refer to the water resource demand for developing a region (Liu et al., 2012). We use the four components of our indicator to calculate UWRVI using equation (1). Urban resource stress was measured using urban water scarcity (UWSc), urban development pressure using urban water stress (UWSt), urban ecosystem health by urban water pollution (UWPo), and urban management capability by urban water productivity (UWPt) and sanitation water (SW). We followed Cai et al. (2017)'s approach and assigned equal weights to different indicators in the same component category and among different components. According to Cai et al. (2017) and modified a little, we interpret the indicator values between 0 and 0.2 as low, 0.2, and 0.4 as moderate, 0.4, and 0.6 as high, and above 0.6 as severe.

$$UWRVI = \frac{UWSc+UWSt+UWPo+\frac{UWPt+SW}{2}}{4} \quad (1)$$

#### 3.2.1 Urban resource stress

Equation (2) of the UWSc was adopted from Cai et al. (2017). Urban areas are inseparable from surrounding environments. The threshold value of 1700 was proposed by Falkenmark (1989). The indicator of water scarcity in provinces is regarded as an indicator of urban water scarcity.

$$\begin{cases} UWSc = \frac{1700-WRP}{1700} (WRP < 1700) \\ UWSc = 0 (WRP \geq 1700) \end{cases} \quad (2)$$

In this study, WRP is the annual per capita water resource (m<sup>3</sup>/ person).

### 3.2.2 Urban development pressure

It is important to assess the degree of water resource exploitation in urban areas to keep the hydrological process healthy and renewable. Among the two indicators considered by Cai et al. (2017) within this component, we consider water stress. We do not consider safe drinking water accessibility because it is not a problem in urban areas. Equation (3) of urban water stress (UWSt) was adopted from Huang and Cai (2009) and Cai et al. (2017), but we focus on urban water use.

$$UWSt = \frac{WUS}{WR} \quad (3)$$

In this study, WR is the annual water resource (m<sup>3</sup>), and WUS is the urban water supply (m<sup>3</sup>).

### 3.2.3 Urban ecosystem health

Urban ecosystem health was measured using **urban water pollution and treated situation (UWPo)**. In water hydrologic processes, human activity produces waste and pollutes water resources, which deteriorates ecological health. (Huang and Cai, 2009). We modified the equation in Cai et al. (2017) to consider the reduced ecosystem impacts of water pollution due to sewage treatment. The treatment of wastewater is a human effort to protect the environment. Wastewater treatment industrial is developing with urban development. This effort can be measured by the ratio between untreated wastewater discharge and total water resources.

$$\begin{cases} UWPo = \frac{WUP-TS}{WR} & (WUP - TS < WR) \\ UWPo = 1 & (WUP - TS \geq WR) \end{cases} \quad (4)$$

In this study, WUP is the annual total urban water discharge (m<sup>3</sup>), and TS is the annual amount of treated sewage (m<sup>3</sup>).

### 3.2.4 Urban management capacity

Urban management capacity is measured by urban water productivity (UWPt) and sanitation water (SW). According to the World Bank (2016), the whole water productivity, GDPWR, is expressed as the annual gross domestic product in constant prices divided by annual total water withdrawal. GDPWRg is the average GDPWR.

$$\begin{cases} \text{UWPt} = \frac{\text{GDPWRg} - \text{GDPWR}}{\text{GDPWRg}} (\text{GDPWR} \leq \text{GDPWRg}) \\ \text{UWPt} = 0 (\text{GDPWR} > \text{GDPWRg}) \end{cases} \quad (5)$$

In this study, GDPWR is the annual urban industrial, domestic product at constant prices divided by the annual total urban water withdrawal. Industries, except agricultural products that cannot be produced at scale in cities, are all related to cities. Urbans are very important transshipment and trading centers and production bases. To simplify equation (5), GDPWRg can be regarded as 100.

$$\begin{cases} \text{UWPt} = \frac{100 - \text{GDPWR}}{100} (\text{GDPWR} \leq 100) \\ \text{UWPt} = 0 (\text{GDPWR} > 100) \end{cases} \quad (6)$$

The urban water management system should strive to meet the basic livelihood needs of the urban population, particularly accessibility to improved sanitation. The sanitation water indicator (SW) equation was adopted from Cai et al. (2017), but our study considers only the urban population. The indicator calculates the ratio of urban population Pa with access to improved sanitation facilities (persons) relative to urban population P.

$$\text{SW} = 1 - \frac{\text{Pa}}{\text{P}} \quad (7)$$

### **3.5.4 Data**

This study assessed 31 provinces in mainland China from 2003 to 2017. Due to the unavailability of relevant data, Hong Kong, Macau, Taiwan, and other areas among the land claimed by the Chinese government were excluded. The data were collected from environmental statistics, environmental statistical yearbooks, and statistical yearbooks of Chinese central and local governments. Data on urban water supply (UWS), urban water pollution (UWP), treated sewage (TS), and population sanitation water (SW) were collected from environmental statistics (2003–2014) and environmental statistics yearbook (2015–2017). Annual water resource amount (WR), per capita water resources (WPR), GDPWR, and population (P) were collected from the statistical yearbook. Due to the absence of official data on Tibet's water pollution, the values were assumed to be zero in this study.

### **3.5.5 UWRVI result**

The national average of UWRVI in 2003 was 0.46 and 0.09 in 2017. UWRVI values vary at the provincial scale. Based on the average during 2003–2017, three provinces were identified, having severe levels of vulnerability; Beijing (0.65), Tianjin (0.65), and Shanghai (0.78), all of which are metropolitan cities. Ningxia (0.60) is in high UWRVI level (Fig3-3). In 2003, 11 provinces did not have a low UWRVI value, especially, Ningxia, Beijing, Tianjin, and Shanghai are at the severe level (Fig3-3). In 2017, Tianjin (0.57) and Shanghai (0.37) had a UWRVI value above 0.2. Tianjin was at a high level, Shanghai at a moderate level, and the others were low (Fig3-3).

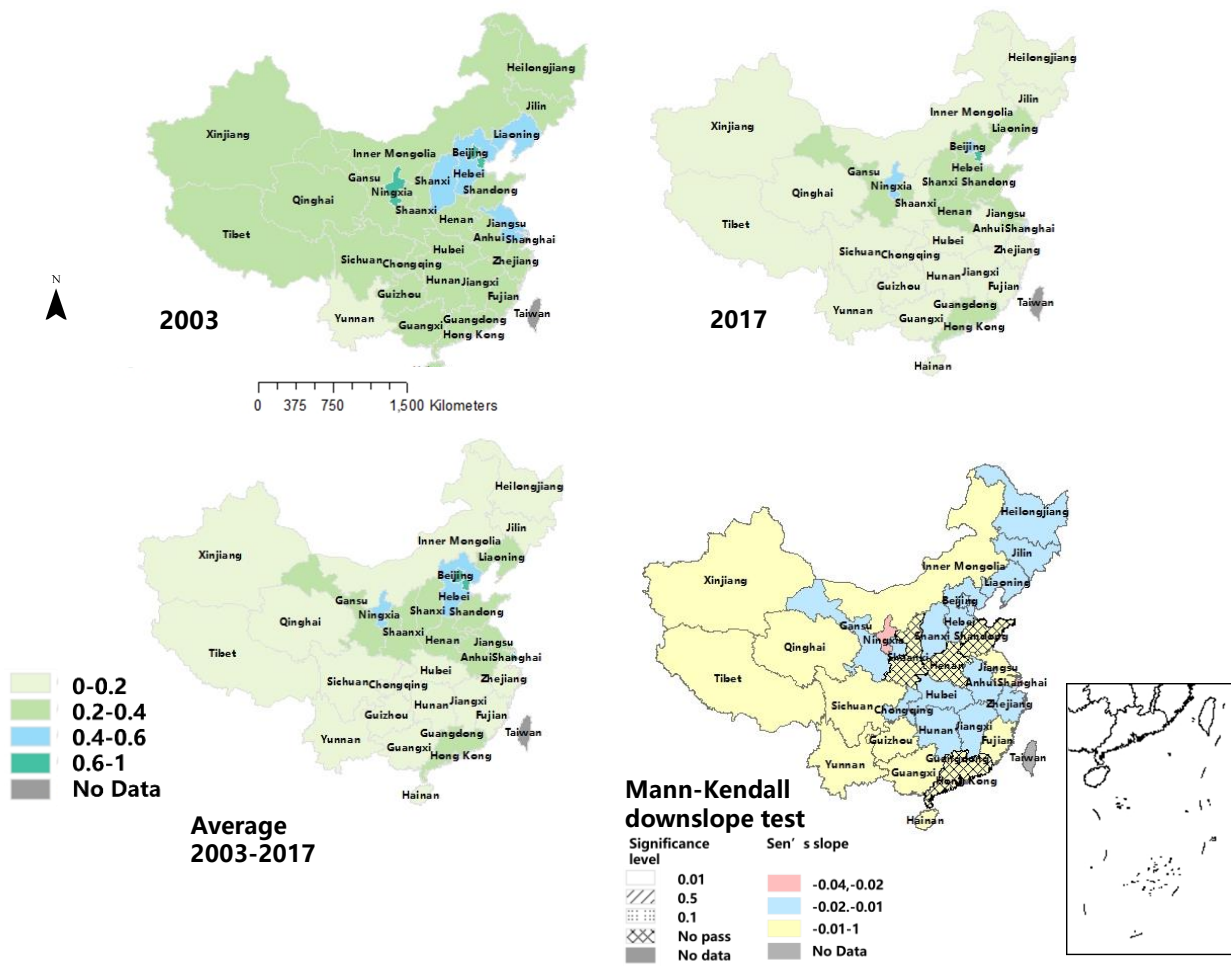


Fig. 3-3. Indicator results of urban water resource vulnerability in 2003, 2017, average 2003-2017; and Mann-Kendall downslope test

Urban water scarcity

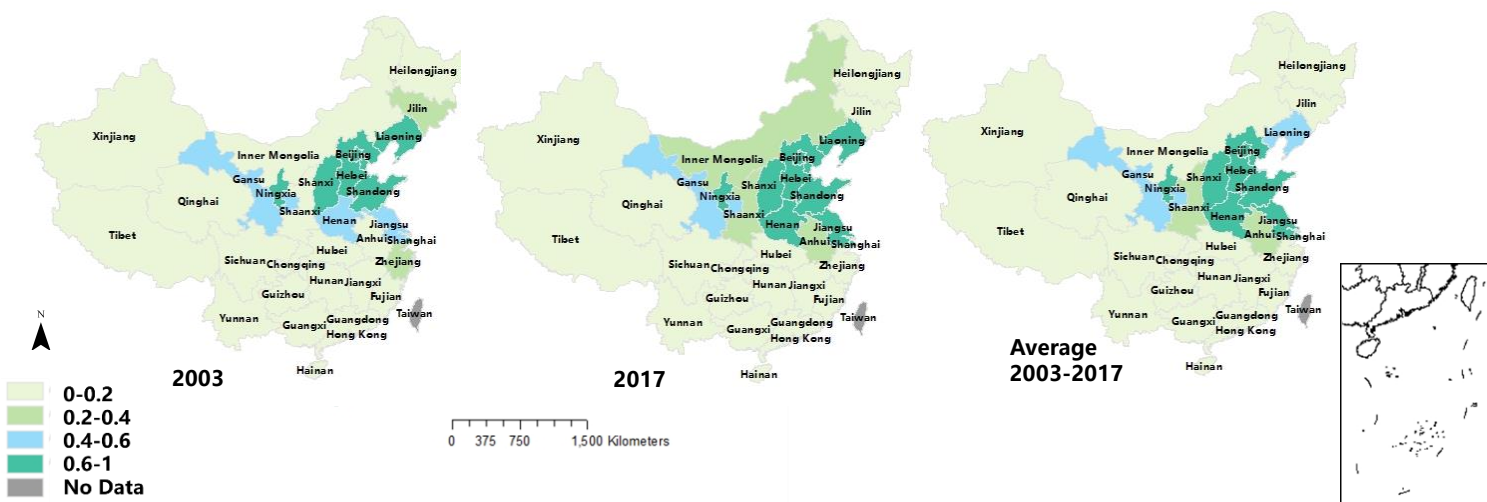


Fig 3-4 Indicator results of urban water scarcity in 2003(left),2017(middle) and average 2003-2017(right)

On the national scale, for both 2003 and 2017, the annual average value for urban water scarcity was 0, indicating no vulnerability. At the provincial scale, severe vulnerabilities were identified in eight provinces, viz. Beijing (0.93), Tianjin (0.93), Shanghai (0.93), Hebei (0.87), Ningxia (0.88), Liaoning (0.69), Shandong (0.68), and Shanxi (0.76) in 2003(Fig2). In 2017, 10 provinces had severe levels of water scarcity, viz. Beijing (0.92), Tianjin (0.93), Shanghai (0.90), Hebei (0.88), Ningxia (0.91), Liaoning (0.58), Shandong (0.82), Shanxi (0.82), Jiangsu(0.66), and Henan(0.76)(Fig3-4). The average value over 2003–2017 shows that Beijing, Tianjin, Hebei, Shandong, Shanxi, Ningxia, Jiangsu, and Shanghai had severe water scarcity levels, Gansu and Liaoning had a high level, and Shaanxi and Anhui were at a moderate level. Over the past 15 years, an increasing number of provinces have faced severe urban water scarcity, especially in Inner Mongolia, Shaanxi, and Anhui(Fig3-4).

Urban water stress

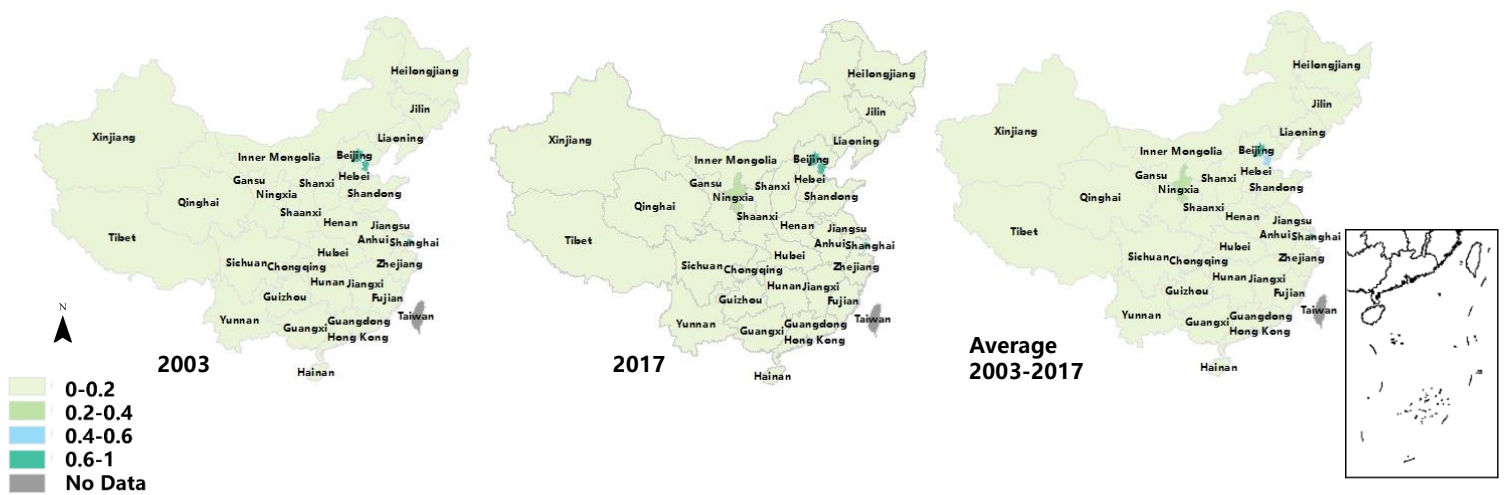


Fig 3-5 Indicator results of urban water stress in 2003(left),2017(middle) and average 2003-2017(right)

The average urban water stress in 2003–2017 for Beijing (0.64), Tianjin (0.56), Shanghai (1), and Ningxia (0.29) were above 0.2. Beijing and Shanghai had a severe water stress level, Tianjin at a high level, and Ningxia was moderate (Fig3). In 2003, the vulnerability of urban water stress was above 0.2 for Beijing (0.70), Tianjin (0.61), and Shanghai (1), while in 2017, it was above 0.2 for Beijing (0.64), Tianjin (0.56), Shanghai (1), and Ningxia (0.31) (Fig3-5). In 2003, the three provinces of Hebei, Liaoning, and Ningxia had a vulnerability value of 0.1–0.2. There were four provinces, Hebei, Liaoning, Jiangsu, and Shandong, within this range in 2017(Fig3-5). This indicator showed an increasing trend.

### Urban water pollution



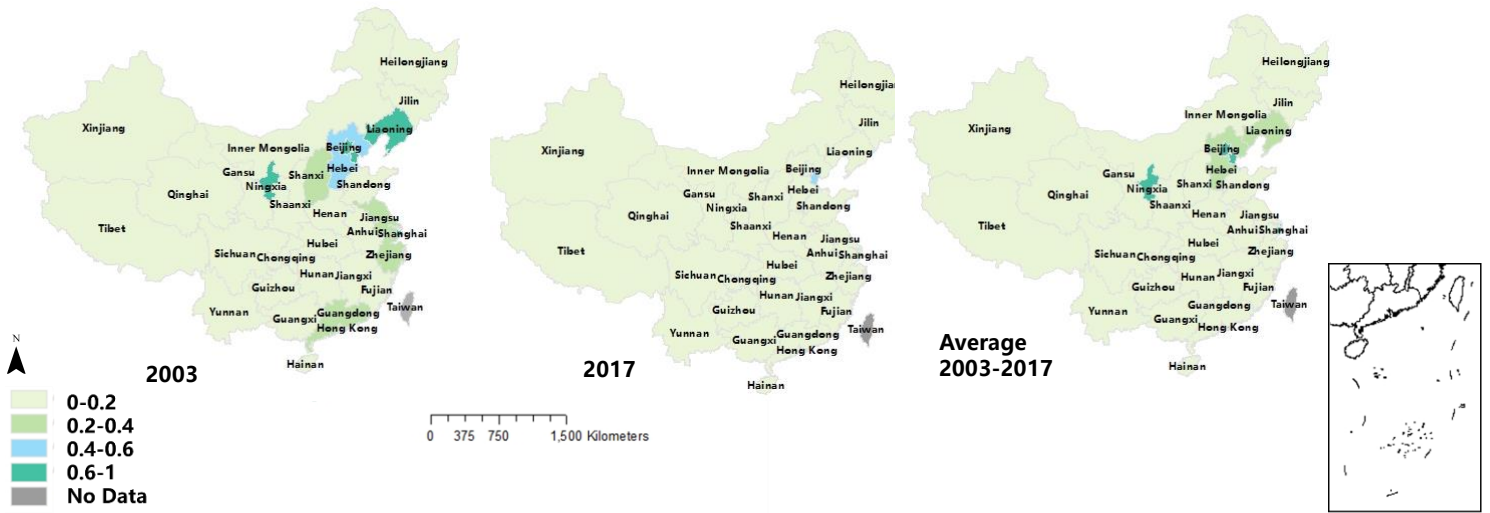


Fig 3-6 Indicator results of urban water pollution in 2003(left),2017(middle) and average 2003-2017(right)

As for urban water pollution, ten provinces were identified to have indicator values above 0.2 in 2003, viz. Zhejiang (0.20) Guangdong (0.24) Hebei (0.57) Shanxi (0.20), Jiangsu (0.38) Liaoning (0.72) Ningxia (1) Beijing(1)Shanghai(1) and Tianjin(1) and two provinces with values above 0.2 in 2017; viz. Shanghai (0.37) and Tianjin (0.57). In 2003, 5 provinces have severe urban water pollution. In 2007, no province have severe urban water pollution (Fig3-6). On average, during 2003–2017, Beijing (0.89), Shanghai (0.96), Tianjin (0.80), and Ningxia (0.64) had severe urban water pollution (Fig3-6).

#### Urban Water productivity

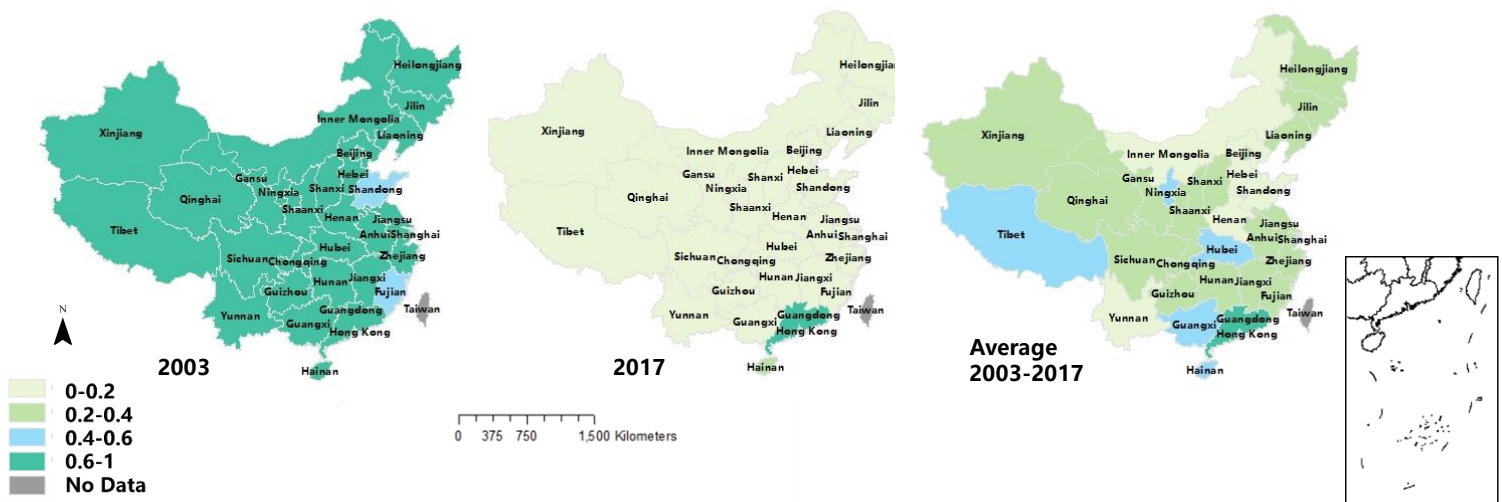


Fig 3-7 Indicator results of urban water productivity in 2003(left),2017(middle) and average 2003-2017(right)

In 2003, most of China faced severe water productivity vulnerability, except in Shandong (0.56) and Fujian (0.60), which have high level(Fig3-7). In 2017, only Guangdong (0.85) faced severe vulnerability. Hainan (0.23) had a high level(Fig3-7). On average, during 2003–2017, Guangdong (0.78) faced severe vulnerability, and Hubei (0.41), Ningxia (0.44), Guangxi (0.44), Hainan (0.54), and Tibet (0.50) faced a high level. This indicator showed a downward trend(Fig3-7).

#### Sanitation water

For China as a whole, the indicator values during the study period varied. However, the area with a vulnerability below 0.6 expanded. In 2003, Shanghai (0.05), Tianjin (0.33), Beijing (0.34), and Liaoning (0.58) had a score below 0.6. In 2017, Shanghai (0), Zhejiang (0), Beijing (0.14), Liaoning (0.49), Guangdong (0.52), Chongqing (0.57), Jilin (0.58), Ningxia (0.58), and Jiangsu (0.60) had a vulnerability below 0.6. On average, during the study period, most provinces were at a severe level, except for Beijing, Shanghai, Tianjin, Liaoning, Zhejiang, and Guangdong. (Fig3-8)

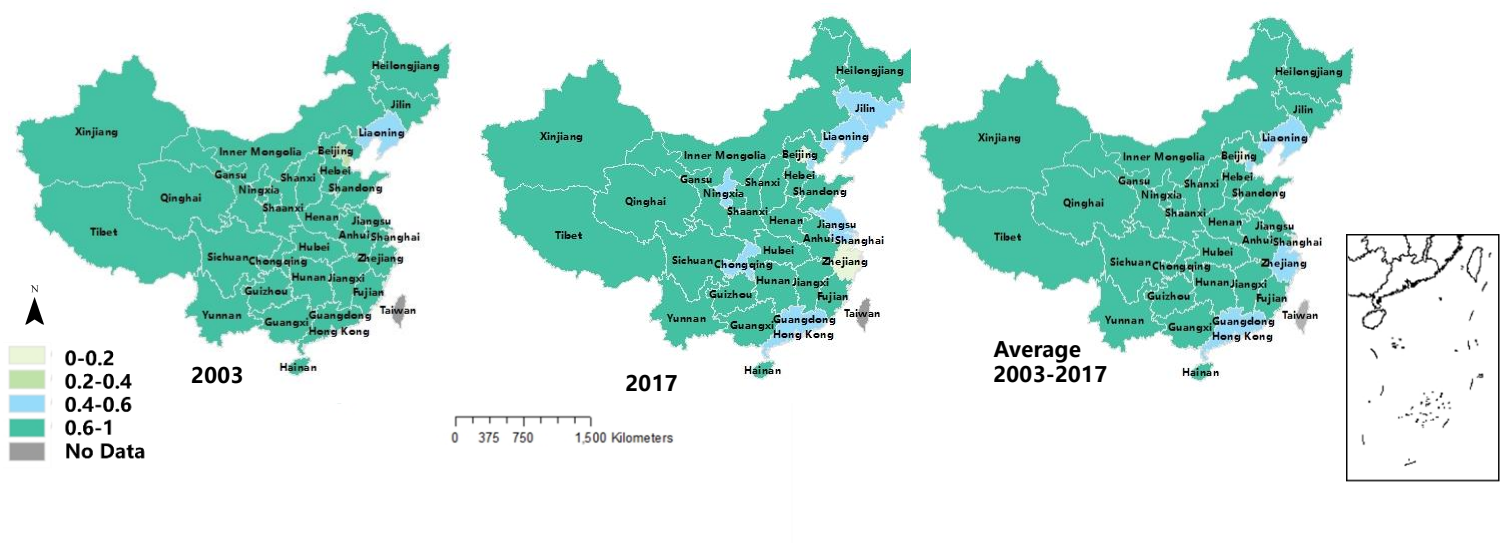


Fig 3-8 Indicator results of sanitation water in 2003(left),2017(middle) and average 2003-2017(right)

### 3.6 Discussion

The difference in vulnerability between urban water and overall water

In Cai et al. (2017), water scarcity, stress, productivity, and pollution tend to worsen vulnerability. In the urban agglomerations of provinces in our study, the vulnerability related to water pollution, productivity, and sanitation decreased over time, indicating that urbanization is beneficial in mitigating some vulnerable areas. Our study shows that urban development, under regional development, is a way to solve the problem of the Western environment. In the development of Western China, cities did not exert much pressure on the Western region, and their vulnerability did not worsen. The only exception was Ningxia.

Unbalanced development is widespread in China, especially in urban areas. The coastal sub regions of Eastern China have greatly benefited from economic reforms,

their socio-economic development, such as urbanization and per capita GDP. Urban development cannot exist alone and needs to be compared with the development in the whole of China, where there is spatial heterogeneity, both nature, and social heterogeneity, leading to water resource environment problems (Jia et al., 2018).

We analyzed the urban water vulnerability from three aspects. First, different development regions were horizontally compared with different precipitation regions. Second, time trends were compared among the different development levels. Third, we compare urban sectors and the entire socio-economic sector.

Eastern and central provinces in China could be considered as economically developed and population-concentrated areas. The Eastern provinces represent the worst water environment carrying status. However, most of the Western provinces exhibit a better water environment carrying status. The most severely congested areas are mainly distributed in North China. Intensive human activities have caused enormous environmental pressures in these areas. Eastern China is the regions that have a higher degree of water resource vulnerability. Northern China, in particular, is the most water vulnerability region in China and has the most serious water conflicts. Metropolises Beijing and Shanghai are also the regions with the most severe UWRVI. On average, North China and Northwest China(except for Qinghai, Xinjiang, Inner Mongolia),Shanghai, Liaoning, and Guangdong, are not low. Thus, UWRVI has a strong relationship with the development stages. We then examined the characteristics of the four component indicators of the UWRVI.

Geographical features and climate conditions do not directly reflect urban resource stress. On average, in 2003–2017, all provinces located in North China were at a severe stress level. In Northwest China, the three provinces were above the low level, Gansu and Ningxia were vulnerable. Gansu was at a high level, and there were provinces above

the low level in Southeast China and Northeast China. This indicates that North China faces a more severe water resource environment for development than Northwest China.

Regarding urban development pressure, metropolises exert great pressure on the environment. Beijing in North China exerted severe urban development pressure. On average, between 2003 and 2017, metropolises (Beijing, Tianjin, and Shanghai) and Ningxia urban water use were beyond the water carrying capability. The indicators in Jiangsu and Shandong also increased, but not beyond their water-carrying capability. There was an increase in water stress in Southeast China. The urban water pressure of Shanghai is severe, inconsistent with the geographical characteristics of the rich precipitation in Shanghai. Thus, geographic features and climate conditions are not decisive factors in the disparity between water resources and socio-economic development.

The average urban ecological health levels are not low in Beijing, Tianjin, Hebei, Liaoning, Ningxia, and Shanghai. In metropolises that pressure their environmental health, and in other places, contradictions cause great pressure on the ecological health of water. However, most parts of the country maintain a balance between the amount of sewage being discharged and the amount of sewage being treated, with minimal impact on nature.

Regarding urban management capability, on average, the urban water productivity of Guangdong, Guangxi, Xizang, and Ningxia are at the highest level, and this indicator is closely related to the degree of development. However, North China performs better in this indicator, indicating that the contradiction between human activities and water is prominent in North China, but the urban industrial structure is healthy. Sanitation water was highly correlated with the degree of development, and the values were small in the metropolis. On average, Liaoning, Zhejiang, and Guangdong have high levels,

while others are serious.

The UWRVI in China experienced a decline in most provinces. Urban development is becoming increasingly environment- and people-friendly. Most provinces pass the Mann-Kendall test of decreasing trends. However, provinces in North China, such as Shandong, Shanxi, Henan, and Guangdong, and Shandong, did not pass this test (see Fig. 1). Despite rich precipitation, Guangdong, with its two large cities, Guangzhou and Shenzhen, experienced a decline in UWRVI.

Regarding urban water scarcity, in 2003, the North China provinces, Ningxia Liaoning, and Shanghai experienced the worst water scarcity. Our indicator for urban water scarcity is comparable to the water scarcity indicator of Cai et al. (2017). After Cai et al.'s research period ended in 2013, our extended result shows that the water scarcity of Inner Mongolia in Northwest China and Northeast China has improved in the following five years. However, with population increase and environmental changes, water scarcity has not been alleviated in China.

Regarding urban water stress, our results show that cities have a growing impact on the environment, and metropolises and North China faced pressure earlier. The provincial urban aggregate in Southern China has faced urban water pressure over time, Jiangsu showed an increase in 2017. In the Northwest, Ningxia and other provinces did not face the urban water pressure because the Northwest was underdeveloped. With the development of Shandong and Jiangsu, more provinces will face this problem in the future. Currently, there is no significant increase in the Northwest.

Urban water productivity in China has improved over the last 15 years. In 2003, there were 29 provinces with severe levels of water productivity. All 31 provinces were above the high level. In 2017, only Guangdong was at a severe water productivity level, and Hainan was at a moderate level. Urban development provides incentives for improving

water use efficiency.

The promotion of sewage treatment has improved the environment and reduced urban water pollution, which is beneficial to the environment. Economic growth and technology encourage humans to find ways to protect resources and the environment. Regarding sanitation water, the indicator values in the developed areas for sanitation water are small. The vulnerability in developing areas, such as Tibet, was high. The local economy and cities along the Southeast coast of North China are well developed, and the degree of development is more relevant. Still, there is a downward trend in the coastal provinces of North and Southeast China.

### **3.7 Conclusion**

An indicator system for urban water vulnerability was established by careful quantification of integrated indicators. In China, there are more overloading provinces in the North and less in the South, roughly the same as the distribution of precipitation. This was due to different locations along the main rivers and spatial distribution of natural reserves. In the Northern provinces and several other provinces in Southeast provinces, urban water scarcity had been worsening, with the growth of population and the development of economy. Urban water stress is relatively stable, just metropolis (Beijing Tianjin Shanghai) and Ningxia (in Northwest China) face severe or high urban water stress. Urban water productivity efficiency improved across China, particularly in economically advanced areas. This is partly due to the changing economic structure of the rapidly developing tertiary industry and the diminishing role of the water-dependent industries. Thus, development is partly a consequence of the evolution of China's economy to be less dependent on water and may only, to a limited extent, due to water sector-related factors. Urban water pollution has improved in approximately

half of China. A positive trend was observed in many water-stressed areas, which is a challenge. A positive development was observed throughout China in improving access to sanitation. Large parts of the country also exhibited positive development in water supply coverage, particularly in less advanced parts of China, with more scope for improvement. The conflict between humans and nature may continue, but urban development has not brought much pressure to the water resource environment. An urban agglomeration is more environment-friendly than metropolitanization. Table 3-3 is Innovation point.

Table 3-3 Innovation point

items	Most important findings/innovations	Most important previous papers	Innovation relative to the previous papers
3.1	5 water indicators showed similar time trends both in Qingdao and Jinan	Cai et al 2017	Compared different cities instead of different provinces
3.2			I studied each year between 2008 and 2018 instead of two years and general trend
3.3			We considered a long period
3.4	Analysis of the urban part of provinces revealed that some	Cai et al 2017	Used urban province level instead of province level
3.5	indicators showed larger regional differences than the results from the analysis of whole province data		The province which has higher rate of agriculture GDP has less urban water vulnerability. Urban province-level municipalities have large water vulnerability.
3.6			Water productivity of the urban part of provinces showed significantly larger regional differences than the province level analysis.



# **4 Spatial-temporal analysis of urban water resource vulnerability in China**

## **4.1 Background**

This study is based on Sun and Kato (2021). The method is based on chapter3, we make further Spatial-temporal analysis This study focuses on metropolises and their neighboring provinces in China. Metropolises represent the most developed urban level. They are characterized by a dense population and economic development within a relatively limited area. Compared with other cities, metropolises exert more pressure on nature and face a bad urban water environment. At the same time, metropolises have relatively good management capabilities to deal with water pressure. In this study, we chose four province-level municipalities; Beijing, Tianjin, Shanghai, and Chongqing. We studied the urban water environment of metropolises and their relationship with their neighboring provinces. We further tested whether there were regional differences in spatial-temporal relationship of development pressure, management capability.

The Spatio-temporal relationship among metropolises is relevant to the coordinated development across these areas. Coordinated development means that different stakeholders collaborate to achieve a common goal. Coordinated development can also be used in water management. The Global Water Partnership (GWP, 2000) use coordinated development as part of integrated water resource management. We want to

study whether coordinated development exists in metropolises and whether there are differences in coordinated development performance across metropolises.

## **4.2 Objectives**

Our contributions are threefold. First, we developed a new indicator system to evaluate the urban water environment. We combined development pressure and management capability with the whole water environment indicator. The connection between development pressure and management capability was also considered. Second, we analyzed the urban water environments in China. We compared the urban water environments with different regional characteristics and development trends. Third, we combined the analysis of contemporaneous effects, Granger causality, and variance decomposition to identify water vulnerability causes across different types of metropolises and provided policy recommendations.

## **4.3 Methodology**

This section is used to describe the indicator system and spatial-temporal analysis. We want to compare different urban environments on a special and temporal scale through four steps; Step 1, calculate new indicator; Step 2, calculate system; Step 3 perform regression to test the indicator relationship and different indicator relationships in different areas; Step 4, estimate vector autoregressive models (VAR) to test the spatial-temporal relationship of different indicators in different regions.

## **4.3.1 Method**

### **4.3.1.1 Indicators**

We aimed to study the water environment in urban areas. Urban areas are where the population of secondary and tertiary industries is the main residents instead of agriculture. In China, urban areas include cities and towns established under the national administrative system (Ministry of Construction of the People's Republic of China, 1999). The objectives of urban water management are five-fold: urban areas have enough water, urban development has little effect on urban water, urban residents have enough safe water, urban water pollution is controlled, and urban areas avoid flooding (Hellström, 2000; Brown, 2009).

From the water users' perspective, the urban water environment is a subcategory of the whole water environment. The water environment is one of the bases of social development. Water users comprise urban and agricultural areas. Some researchers have studied the water environment through water users and developed water indicators. For example, He (2021) studied agricultural water. Water environment indicators are important for assessing the water environment to ensure sustainable water management.

Based on water resource vulnerability (Huang and Cai, 2009) and the objectives of urban water management, we developed UWRVI. In water environment, socioeconomic development not only put pressure on the environment, but also improves water management capacity (Sun et al ,2016). We wanted to test whether this exists in an urban water environment. Huang and Cai (2009) used the Drivers, Pressures, State, Impacts and Responses framework and separated water management factors from other causes of water vulnerability that are relevant to pollution, economic and population factors. Thus, we separated UWRVI into two domains: development

pressure and management capability. We used three sub-systems to measure the development pressure, urban resource stress (URS), urban development pressure (UDP), and urban ecosystem health (UEH). These sub-systems are directly related with pollution, economic situation, and population. Management capability was measured by the sub-indicators of urban management capability (UMC).

Table 1 lists the details of the indicator calculation process. URS contain B1 (water scarcity). UDP is the pressure brought about by the human economy, and quality of life improves. UDP contains B2 (water stress) and B3 (improved sanitation water), and UEH is the water quality/water pollution sub-indicators. The UEH contains B4 (water pollution). Urban management capability (UMC) has sub-indicators of B5 (water use efficiency), B6 (sewage treatment), and B7 (urban flood management). We referred to the water vulnerability indicators for whole Chinese provinces by Cai et al. (2017) to design some of our sub-indicators.

Table 4-1 Indicator construct of UWRVI

Domain	Subsystem	Indicator	Equation
Develop Pressure Indicators	URS	B1 Water scarcity	$\begin{cases} UWS_c = \frac{1700 - WRP}{1700 - 500} (500 < WRP < 1700) \\ UWS_c = 1 (WRP \leq 500) \\ UWS_c = 0 (WRP \geq 1700) \end{cases}$
	UDP	B2 Water stress	$UWSt = \frac{WUS}{WR}$
		B3 Improved sanitation water	$URLs = 1 - \frac{UAW}{TUAW}$
	UEH	B4 Water pollution	$\begin{cases} UWP_o = \frac{WUP * 10}{WR} (WUP < WR) \\ UWP_o = 1 (WUP \geq WR) \end{cases}$
Management capability indicators	UMC	B5 Water use efficiency	$\begin{cases} UWPt = \frac{GDPWR}{GDPWRg} (GDPWR \leq GDPWRg) \\ UWPt = 1 (GDPWR > GDPWRg) \end{cases}$
		B6 Sewage treatment	$UST = 1 - \frac{TS}{WUP}$
		B7 Urban flood management	$UED = 1 - \frac{UAd}{UA}$

B1: WRP = annual provincial water resource/provincial population (m<sup>3</sup>/ person). UWSc takes 0 when WRP is above 1700 and 1 when WRP is less than 500. Five hundred is the threshold for absolute scarcity. These threshold values are credited to Falkenmark (1989, 1992).

B2: WR is the annual provincial water resource (m<sup>3</sup>), and WUS is the annual amount of urban water supply (m<sup>3</sup>).

B3: UAW = annual amount of urban life water (L) / urban population (person) TUAW is the average UAW of all provinces in 2003–2017. The accurate value of the TUAW was 191.25. To simplify the calculation, this value was considered to be as 200.

B4: WR is the annual provincial water resource (m<sup>3</sup>), and WUP is the annual amount of urban wastewater discharge (m<sup>3</sup>).

B5: GDPWR = provincial no-agriculture water use (m<sup>3</sup>) / provincial no-agriculture GDP (10000 yuan); GDPWRg is the average GDPWR of all provinces in 2003–2017. The accuracy value was 95.84. To simplify the calculation, the GDPWRg value was regarded as 100 (m<sup>3</sup>/ 10000 yuan). (GDP will be inflation effect, we make GDP deflator indicators to make the deflator.)

B6: TS is the annual amount of treated urban sewage (m<sup>3</sup>). WUP is the annual amount of urban wastewater discharge (m<sup>3</sup>).

B7: *UAd* is the length of the drainage pipe in the urban area (100 m), and *UA* is the urban area size (km<sup>2</sup>)

Hereafter, we calculate three indicator values: UWRVI, development pressure indicator, and management capability indicator. These indicators are the weighted averages of the relevant sub-indicators. Equations (1)–(3) show the calculation process for the three indicators. In these equations,  $w_n$  ( $n = 1$  to  $n = 7$ ) represents the weights of different indicators.

The UWRVI summarizes seven sub-indicators.

$$UWRVI = \frac{B1 \times w1 + B2 \times w2 + B3 \times w3 + B4 \times w4 + B5 \times w5 + B6 \times w6 + B7 \times w7}{w1 + w2 + w3 + w4 + w5 + w6 + w7} \quad (1)$$

The development pressure indicator summarizes four sub-indicators.

$$Development\ presure\ indicator = \frac{B1 \times w1 + B2 \times w2 + B3 \times w3 + B4 \times w4}{w1 + w2 + w3 + w4} \quad (2)$$

Finally, the management capability indicator summarizes three sub-indicators.

$$Management\ capability\ indicator = \frac{B5 \times w5 + B6 \times w6 + B7 \times w7}{w5 + w6 + w7} \quad (3)$$

#### 4.3.1.2 Weights

Calculating indicator weights is important in the indicator quantification process. Traditionally, there are three ways to calculate weights: the analytical hierarchy process (AHP) (Forman et al., 2001), the entropy weight method (EWM), and principal component analysis (PCA). PCA was invented by Karl Pearson and developed by Hotelling (1933). Because EWM and PCA are more objective methods, we used them to calculate the weights instead of AHP. After the calculation, we selected a better result between PCA and EWM. Some researchers have used EWM in environmental studies (Li et al, 2020). Some researchers compared PCA and EWM (Kim et al., 2021) in water environment study.

EWM can be described as follows:  $x_{\theta ij}$  is the observed value of subsystem indicator  $j$  in the year  $\theta$  (2003-2017), in the  $i_{th}$  province. The total number of subsystem-indicators  $n$  is the number of years, which is 15, multiplied by the number of provinces with available data, which is 31 for this study. Eqs. (4)- (6) shows the EWM calculation process. These indicator values were already standardized and, thus, the mean information content for indicator  $j$ ,  $em_j$ , is

$$em_j = -\frac{1}{\ln(n)} \sum_{\theta=2003}^{2017} \sum_{i=1}^{31} x_{\theta ij} \ln(x_{\theta ij}). \quad (4)$$

Then, the mean information content was modified so that a larger value indicates means a larger variation of the indicator.

$$emj_j = 1 - em_j \quad (5)$$

The weight for the subsystem indicator  $j$  becomes

$$W_j = \frac{emj_j}{\sum_{j=1}^7 emj_j}. \quad (6)$$

### 4.3.2 Study areas

We focus on four metropolises and their neighboring provinces in China. These are four province-level municipalities in China: Beijing, Tianjin, Shanghai, and Chongqing. These province-level municipalities are located in different areas of China. They include coastal and inland areas, Northern and Southern China, and East and West area of China, and represent different areas, development stages, and development patterns. The characteristics of the metropolises are shown in Table 2. These metropolises are the core cities and at the highest development level in the neighboring provinces. We study whether there is coordinated development between the metropolis and neighboring provinces.

We created the province groups according to development levels and climate. First, according to different economic development regions, the scheme can be divided into three areas: East area, Central area, and West area (1986, The "Seventh Five-Year Plan"); the East area of China includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, Hainan Liaoning, Jilin, and Heilongjiang. The Central area of China contains Shanxi, Inner Mongolia, Anhui, Jiangxi, Henan, Hubei, and Hunan. The West area of China contains Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The East area is most of the coastal areas and is easy to develop. The East and Central areas contained dense populations.

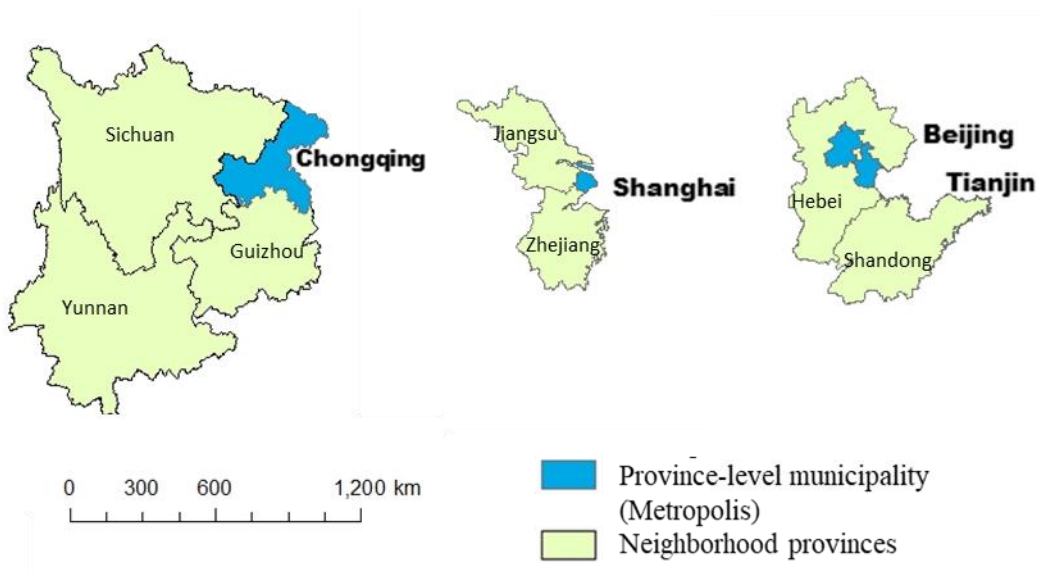


Fig. 4-1 Map of metropolises and neighborhood provinces



Second, we considered the climate characteristics. According to the 800 mm iso-precipitation line by Qinling and Huaihe, China has two mainly climate areas, Northern China and Southern China, Northern China is colder and drier. The minimum temperature in winter was below zero, and the precipitation was less than 800 mm. Provinces located in the same development area and climate area were regarded as neighborhood areas. The East area can be further divided according to the relationship between regional economic development. Because of the limited urban development of Tibet, we regard Chongqing's neighborhood provinces as Sichuan Yunnan and Guizhou. The map and some attributes of the four groups of metropolises and neighborhood provinces are shown in Fig. 4-1, Table 4-2

Table 4-2 Metropolises and neighborhood provinces and metropolises situation

Metropolis	Neighborhood province	Economic region	GDP (Billion yuan per year)	Population (10 thousand)	Climate region	Temperature (Annual average)	Precipitation (mm/per year)
Beijing	Tianjin, Hebei, Shandong	East area	1189.2	1925.45	Northern	13.4 °C	531
Tianjin	Beijing, Hebei, Shandong	East area	788.1	1335.29	Northern	14.2 °C	555
Shanghai	Jiangsu, Zhejiang	East area	2155.7	2167.33	Southern	17.7 °C	1300
Chongqing	Sichuan, Guizhou, Yunnan	West area	1106.3	2977.09	Southern	19.0 °C	1147

Note: Values were averaged between 2003 and 2017; Data of population and GDP from Chinese Statistic Year Book(2003-2018) ; Data of climate from China Meteorological Administration

### 4.3.3 Data

This study used data from 31 provinces and focuses on 11 provinces in mainland China from 2003 to 2017. Because of the unavailability of relevant data, Hong Kong,

Macau, Taiwan, and other areas were excluded. Data on annual provincial water resources, provincial non-agricultural GDP, provincial population, urban population, and urban area were collected from the statistical yearbook (2004–2018). Data on the annual amount of urban water supply, annual amount of urban life water, annual amount of treated urban sewage, provincial no-agriculture water use, annual amount of urban wastewater discharge, length of drainage pipe in an urban area, and annual provincial water resources were collected from environmental statistics (2003–2014) and environmental statistics yearbook (2016–2018).

#### **4.3.4 Data analysis**

In this study, we perform an indicator relationship analysis and Spatial-temporal analysis of different indicators. The aims were to study the relations between different indicators, and the relationships between metropolises and neighborhood provinces. These indicators include the development pressure indicator, management capability indicator, and UWRVI. Statistics software Stata was used to perform the analysis.

##### **4.2.4.1 Regression analysis**

We first examine the contemporaneous relationship between the management capability indicator and the development pressure indicator for different metropolises. The ordinary least squares (OLS) model equation is Eq. (7);  $j$  denotes metropolis;  $t$  denotes the year;  $C$  denotes a constant term; and  $\epsilon$  denotes an error term.  $\beta$  where is the parameter to be estimated.

$$y_{management\ capability\ indicators,j,t} = \beta y_{development\ pressure\ indicators,j,t} + C + \epsilon$$

(7)

We then study the contemporaneous effect of neighborhood provinces on metropolises. The OLS equations are shown in Eqs. (8)-(10):  $j$  denotes the metropolis,  $r$  denotes a different neighborhood province,  $t$  denotes the year,  $C$  denotes a constant term, and  $\epsilon$  denotes an error term.  $\beta_r$  where  $r$  is the parameter to be estimated.

$$Y_{development\ pressure\ indicators,j,t} = \sum_{r=1}^{number\ of\ neighbour\ provinces\ of\ metropoice\ j} \beta_r Y_{development\ pressure\ indicator,r,t} + C + \epsilon \quad (8)$$

$$Y_{management\ capability\ indicators,j,t} = \sum_{r=1}^{number\ of\ neighbour\ provinces\ of\ metropoice\ j} \beta_r Y_{managemet\ capability\ indicator,r,t} + C + \epsilon \quad (9)$$

$$UWRVI_{j,t} = \sum_{r=1}^{number\ of\ neighbour\ provinces\ of\ metropoice\ j} \beta_r UWRVI_{r,t} + C + \epsilon \quad (10)$$

#### 4.2.4.2 Vector autoregression models

We then used the vector autoregression model (VAR) to combine spatial and temporal analysis (Sims, 1980) to examine the possibility of coordinated development between the metropolis and neighboring provinces. Appendix B shows some details of the VAR model. In this study, we estimated a VAR model for each of the development pressure, management capability, and UWRVI for the four metropolitan areas.

#### 4.2.4.3 Granger causality and coordinated development.

Granger causality (Granger, 1969) was tested to examine the effects of exogenous variables. In this study, we use Granger causality to test whether one metropolis is affected by neighborhood provinces in terms of water vulnerability. According to

Tobler's First Law of Geography (Tobler, 1970), everything is related to everything else, but near areas are more related to each other. One region is easily affected by the neighborhood region. This effect is regarded as a neighborhood effect. The existence of the neighborhood effect is the basis of coordinated development that enables jointly achievement of the same goal in a metropolis area.

#### **4.2.4.4 Variance decomposition**

Variance decomposition of VAR was introduced by Lütkepohl (2007). It can explain how much of the variation of a metropolis indicator is explained by the past shock in the indicators by the metropolis itself and neighboring provinces. Measuring shock is a core technology in variable decomposition. Variable decomposition has used in spatial analyses. Chudik and Fratzscher (2011) forecast and analyze different countries economic situation differences between the forecast and estimated equations. They study which countries have a greater effect on variance of one country economic situation. Variance decomposition has been also used in environmental studies. For example, Mamipour (2019) used it to forecast and analyze the differences between the forecast and estimated equations. They study social, economic, and environmental factors, which will have a greater effect on the variables of different factors.

In this study, we use variance decomposition of VAR in UWVRI analysis of four metropolises to explore the exogenous and endogenous effects. We want to study whether the coordinated development model works for metropolises.

## 4.4 Result

### 4.4.1 Weights and indicator values

Table4- 3 Sub-indicator weights

	P1	P2	P3	EWM
B1	0.262	0.261	-0.096	0.176
B2	0.298	0.135	0.310	0.253
B3	0.043	0.327	-0.569	0.12
B4	0.300	0.136	0.290	0.265
B5	-0.207	0.045	0.375	0.028
B6	-0.181	0.400	-0.298	0.059
B7	-0.143	0.570	-0.111	0.099

We used PCA and EWM to calculate the indicator weights as shown in Table 3. The first three columns show the principal components obtained from PCA and, the last column shows the weights due to EWM. As for PCA, seven indicators were summarized into three principal components because the three eigenvalues exceeded one. We designed UWRVI as a one-dimensional indicator and P1, which had the largest eigenvalue and thus was the most important principal component, can be a candidate set of indicator weights. However, P1 assigns negative weights to the management capability domain. Because a smaller value of sub-indicators in both the development pressure and management capability domains mean less water vulnerability, it is inappropriate to place negative weights to sub-indicators. Thus, we employed the EWM weights.

Table 4 shows the 15-year average of the UWRVI and the four sub-indicators for each province. Smaller values indicate lower vulnerability. We found significant differences between the metropolises and other provinces. In terms of UWRVI, Beijing (0.537), Tianjin (0.523), and Shanghai (0.628) are the most vulnerable provinces. There are differences between metropolises. As the neighboring provinces of Beijing and Tianjin, Hebei (0.311) and Shandong (0.294) are less vulnerable than the metropolises. As the neighboring provinces of Shanghai, Jiangsu (0.251) and Zhejiang (0.062) are less vulnerable than Shanghai. Chongqing (0.110) is less vulnerable than the other metropolitan areas. The neighboring provinces of Yunnan (0.105), Guizhou (0.107), and Sichuan (0.072) are also less vulnerable. Different metropolises and their neighboring provinces have different UWRVI and subsystem indicator values. Metropolis, located in Northern China or East area of China, is more vulnerable; Metropolis, located in Southern China and West area of China, is the least vulnerable. Neighborhood provinces have similar vulnerability patterns.

Regarding the sub-system indicators, there are differences between metropolises and neighboring provinces. For the URS, Beijing, Tianjin, and Shanghai were 1. This means that the annual per capita water resources are below 500 m<sup>3</sup>/year. Their neighborhood provinces also face terrible water scarcity situations. Shandong and Hebei had values of 1. Jiangsu is 0.916. Chongqing and its neighboring provinces have relatively abundant water resources. As for UDP, Shanghai (0.885), Beijing (0.645), and Tianjin (0.685) are vulnerable, but Chongqing is not. As for UEH, Shanghai (0.702), Beijing (0.572), and Tianjin (0.556) are highly vulnerable, but Chongqing is not. As for UMC, Chongqing had the highest value of 0.304 compared to the other three metropolises.

Table 4-4 UWRVI and sub-indicators

	Development pressure			Management	UWRVI
	URS	UDP	UEH	capability UMC	
Beijing	1.000	0.645	0.572	0.224	0.537
Tianjin	1.000	0.685	0.556	0.111	0.523
Hebei	1.000	0.259	0.099	0.227	0.311
Shandong	1.000	0.260	0.103	0.126	0.294
Shanghai	1.000	0.885	0.702	0.186	0.628
Jiangsu	0.916	0.114	0.087	0.204	0.251
Zhejiang	0.064	0.043	0.022	0.181	0.062
Chongqing	0.062	0.148	0.014	0.304	0.110
Sichuan	0.000	0.044	0.006	0.318	0.072
Guizhou	0.000	0.122	0.004	0.398	0.107
Yunnan	0.000	0.147	0.003	0.351	0.105

Values were averaged over the period between 2003 and 2017

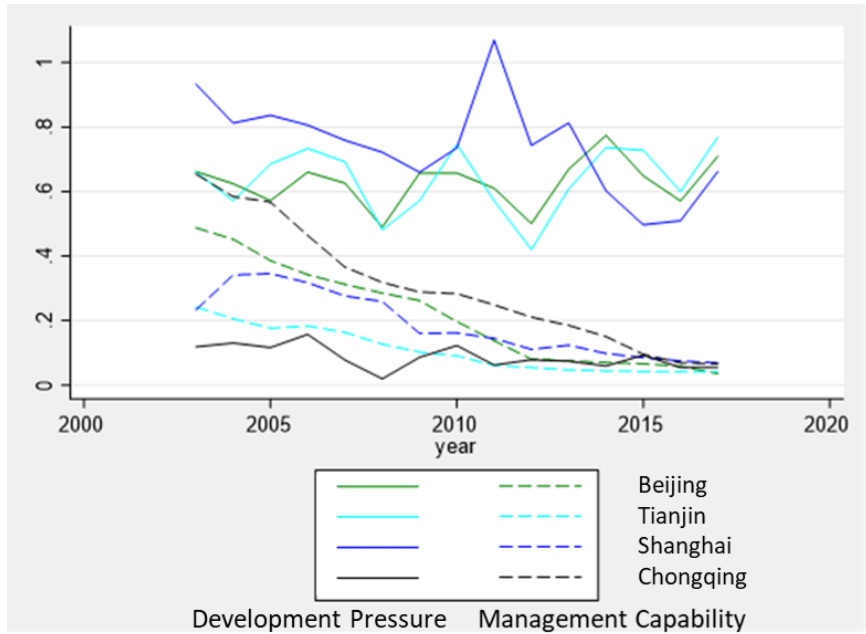


Fig 4-2 Timeline of development pressure and management capability indicators in metropolises

Figure 4-2 shows the timeline of development pressure and management indicators for the four metropolises between 2003 and 2017. The development pressures of Beijing, Tianjin, and Shanghai were unstable and maintained relatively high vulnerability levels. The development pressure in Chongqing was low. The vulnerability of management capability in the four metropolises maintained downward trends.

## 4.4.2 Regression analysis

### 4.4.2.1 Development pressure and management capability

Table 4-5 shows the relationship between management capability indicators and development pressure indicators in metropolises. We found that development pressure indicators significantly effect on management capability in metropolitan areas in Southern China, namely Shanghai and Chongqing. In areas with more abundant



precipitation, management capability is more easily affected by development pressure.

Table 4-5 Effects of development pressure to management capability

Metropolises	Development pressure coefficient	constant	R-squared
Beijing	-0.306 (0.591)	0.409 (0.265)	0.021
Tianjin	0.025 (0.903)	0.092 (0.431)	0.001
Shanghai	0.318* (0.073)	-0.050 (0.787)	0.228
Chongqing	3.376*** (0.009)	0.001 (0.809)	0.415

\* 10% significance, \*\* 5% significance, \*\*\* 1% significance, P-values in parentheses

#### 4.2.2.2 Contemporaneous effects of neighborhood provinces

Table 4-6 shows the indicator relationships between metropolitan and neighboring provinces. In the management capability sector, all models have high R-squared values. The development pressure sector results have similar R-squared values to the UWRVI results. The patterns of statistically significant influence from neighborhood provinces are similar between the UWRVI and the management capability sub-indicators for Beijing, Tianjin, and Chongqing. However, Shanghai's UWRVI result is similar to that of the development pressure sub-indicator.

Table 4-6 Regression result of contemporaneous special effects

		Tianjin	Hebei	Shandong	constant	R2
Beijing	Development pressure	0.317 (0.150)	0.804 (0.338)	0.387 (0.440)	0.009 (0.967)	0.648
	Management capabilities	2.255*** (0.001)	-0.220 (0.579)	0.241 (0.443)	-0.007 (0.770)	0.971
	UWRVI	0.338* (0.066)	1.016* (0.071)	0.010 (0.983)	0.041 (0.767)	0.701
		Beijing	Hebei	Shandong	constant	R2
Tianjin	Development pressure	0.563 (0.150)	1.671 (0.121)	0.269 (0.690)	-0.395 (0.140)	0.681
	Management capabilities	0.278*** (0.001)	0.268** (0.34)	-0.089 (0.422)	0.001 (0.921)	0.982
	UWRVI	0.810* (0.066)	0.265 (0.778)	0.700 (0.341)	-0.200 (0.338)	0.628
		Jiangsu	Zhejiang	cons	-	R2
Shanghai	Development pressure	1.001 (0.138)	2.589*** (0.002)	0.306 (0.134)	-	0.583
	Management capabilities	0.020 (0.965)	0.784 (0.157)	0.039 (0.144)	-	0.780
	UWRVI	0.810 (0.209)	2.209*** (0.004)	0.287* (0.085)	-	0.587
		Sichuan	Guizhou	Yunnan	constant	R2
Chongqing	Development pressure	0.239 (0.867)	0.728 (0.479)	-0.197 (0.703)	0.040 (0.166)	0.469
	Management capabilities	1.034*** (0.000)	-0.033 (0.836)	0.071 (0.556)	-0.037 (0.345)	0.973
	UWRVI	1.126** (0.019)	-0.308 (0.609)	0.185 (0.727)	0.042 (0.178)	0.748

\* 10% significance, \*\* 5% significance, \*\*\* 1% significance, P-values in parentheses

### 4.4.3 VAR model

The VAR model is a system of equations in which more than one variable is treated

as endogenous, and the values of variables are regressed against lagged dependent variables in the system. For example, Mamipour (2019) used a VAR model to study the relationship between the environmental economy and society. Some researchers use VAR to study spatial relationships; for example, Pesaran (2004) uses a global VAR model to test different countries' economic situations. An example system of these equations is shown below.  $y_{r,t}$  denotes the indicator value at time  $t$ , and in province  $r$ .  $p$  denotes the number of lagged stages.  $A_p$  denotes the matrix of coefficients. where  $C_r$  denotes a constant term.  $\epsilon_r$  denotes an error term.

To test the of VAR model, there are three ways. Firstly, different lagged joint significance of the model. We found the model is significance at different lagged. Secondly, the residual test. Through autocorrelation test, we found the residual has no autocorrelation and is stationary. So, the residual is white noise. Thirdly, we test the stationary of the VAR Model of UWRVI. Because, we make variable discompose of UWRVI model, it is part of forecast and need relative stationary of the model. The model is stationary. The VAR model could be accepted.

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{r,t} \end{bmatrix} = A_1 \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ \vdots \\ y_{r,t-1} \end{bmatrix} + \dots + A_p \begin{bmatrix} y_{1,t-2} \\ y_{2,t-2} \\ \vdots \\ y_{r,t-2} \end{bmatrix} + \begin{bmatrix} C_1 \\ C_2 \\ \vdots \\ C_r \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_r \end{bmatrix}$$

$$A_1 = \begin{bmatrix} A_{11,1} & \dots & A_{1r,1} \\ \vdots & \ddots & \vdots \\ A_{r1,1} & \dots & A_{rr,1} \end{bmatrix}, \dots, A_p = \begin{bmatrix} A_{11,p} & \dots & A_{1r,p} \\ \vdots & \ddots & \vdots \\ A_{r1,p} & \dots & A_{rr,p} \end{bmatrix}$$

#### 4.4.3.1 Stationary tests

We combined the DF-GLS and KPSS tests (Rothenberg and Stock, 1996; Kwiatkowski et al., 1992) to examine whether the time series has a unit root or whether it is stationary. The results of these tests contradict each other. We recognized the

stationarity of a time series when either the DF-GLS test rejected the null or the KPSS test maintained the null hypothesis. The results in Table 4-7 show that the indicator time series for all 11 provinces cannot reject stationarity. Thus, we used the original time series for further analyses. Table C.2 shows the results from the residual white noise test where all the time series were admitted with white noise errors.

Table 4-7 Stationarity tests of time series

Metropolis		DF-GLS	KPSS	Neighborhood province	DF-GLS		KPSS
Beijing	Development pressure	-3.975***	0.245	Hebei	Development pressure	-2.298*	0.211
	Management capabilities	-1.974*	0.273		Management capabilities	-4.419***	0.534**
	UWRVI	-2.269*	0.811***		UWRVI	-1.111	0.583**
Tianjin	Development pressure	-2.302*	0.131	Shandong	Development pressure	-1.083	0.514**
	Management capabilities	-2.361*	0.171		Management capabilities	0.165	0.531**
	UWRVI	-4.757***	0.794***		UWRVI	-11.705***	0.167
Shanghai	Development pressure	-1.878*	0.474**	Jiangsu	Development pressure	-2.264*	0.196
	Management capabilities	-1.86*	0.567**		Management capabilities	-2.389*	0.578**
	UWRVI	-2.106*	0.734**		UWRVI	-3.554**	0.394*
				Zhejiang	Development pressure	-4.363***	0.502**
					Management capabilities	-2.86**	0.579**
					UWRVI	-3.436***	0.542**
Chongqing	Development pressure	-4.15***	0.678**	Sichuan	Development pressure	-1.466	0.616**
	Management capabilities	-3.407*	0.545**		Management capabilities	-0.738	0.591**
	UWRVI	0.329	0.802***		UWRVI	-0.074	0.61**
				Yunnan	Development pressure	-2.089*	0.231
					Management capabilities	-1.31	0.572**
					UWRVI	-2.003*	0.54**
				Guizhou	Development pressure	-0.681	0.787***
					Management capabilities	-0.841	0.606**
					UWRVI	-1.218	0.598**

\* 10% significance, \*\* 5% significance, \*\*\* 1% significance

#### 4.4.3.2 System model of the metropolis

The VAR models require information on the number of lags. We used the final prediction error (FPE) and likelihood ratio (LR) to determine the number of lagged stages for the metropolis system models. We chose the minimum number of lags among the appropriate ranges to maximize the effective sample size. The resulting lagged stage was 2. Table C.2 and Fig C.1 present the results of some VAR specification tests. The residual white noise test examines whether the residual is white noise. The residuals were found to be white noise. The model used for variance decomposition was stationary. These results showed the VAR model was acceptable.

Table 4-7 shows that the metropolises except for Shanghai had negative feedback from their past indicator values of development pressure. The UWRVI of Beijing, Tianjin and Chongqing was affected by the past indicator values of all of their neighboring provinces and themselves. Shanghai's UWRVI was affected by Zhejiang but not by Jiangsu.

#### **4.4.4 Granger causality**

The results of the Granger causality test for the UWRVI are presented in Table 8. For most metropolises, neighborhood provinces have Granger causality. The two metropolises in Northern China have connections with neighboring provinces. Among the two metropolises in Southern China, Shanghai is less likely to be affected by neighboring provinces.

Tables 4-9 and 4-10 show the results for the development pressure indicators and management capability indicators. Development pressure and UWRVI showed similar Granger causality patterns in North China, where the development pressure was high. Management capability indicators were different. All the metropolises, including Shanghai, were affected by at least some of the neighboring provinces.

Table 4-8 The UWRVI Granger causality result

Metropolis	Hypothesis	Chi-square statistics	P value	Conclusion
Beijing	Tianjin does not Granger cause	24.75	0	reject
	Hebei does not Granger cause	38.243	0	reject
	Shandong does not Granger cause	37.039	0	reject
	All of neighborhood provinces do not Granger cause	72.408	0	reject
Tianjin	Beijing does not Granger cause	21.609	0	reject
	Hebei does not Granger cause	13.726	0.001	reject
	Shandong does not Granger cause	43.221	0	reject
	All of neighborhood provinces do not Granger cause	49.048	0	reject
Shanghai	Jiangsu does not Granger cause	0.398	0.816	Not reject
	Zhejiang does not Granger cause	2.955	0.204	Not reject
	All of neighborhood provinces do not Granger cause	3.557	0.432	Not reject
Chongqing	Yunnan does not Granger cause	56.268	0	reject
	Sichuan does not Granger cause	118.44	0	reject
	Guizhou does not Granger cause	56.273	0	reject
	All of neighborhood provinces do not Granger cause	167.05	0	reject

Table 4-9 Development pressure indicator Granger causality result

Metropolis	Hypothesis	Chi-square statistics	P value	Conclusion
Beijing	Tianjin does not Granger cause	162.52	0	reject
	Hebei does not Granger cause	298.52	0	reject
	Shandong does not Granger cause	398	0	reject
	All of neighborhood provinces do not Granger cause	722.81	0	reject
Tianjin	Beijing does not Granger cause	36.148	0	reject
	Hebei does not Granger cause	23.599	0	reject
	Shandong does not Granger cause	75.56	0	reject
	All of neighborhood provinces do not Granger cause	77.407	0	reject
Shanghai	Jiangsu does not Granger cause	1.635	0.442	Not reject
	Zhejiang does not Granger cause	3.812	0.149	Not reject
	All of neighborhood provinces do not Granger cause	4.961	0.291	Not reject
Chongqing	Yunnan does not Granger cause	29.446	0	reject
	Sichuan does not Granger cause	53.198	0	reject
	Guizhou does not Granger cause	0.896	0.641	Not reject
	All of neighborhood provinces do not Granger cause	66.439	0	reject

Table 4-10 Management capability indicator Granger causality result

Metropolis	Hypothesis	Chi-square statistics	P value	Conclusion
Beijing	Tianjin does not Granger cause	4.5322	0.104	Not reject
	Hebei does not Granger cause	7.3161	0.026	reject
	Shandong does not Granger cause	2.8211	0.244	Not reject
	All of neighborhood provinces do not Granger cause	36.721	0	reject
Tianjin	Beijing does not Granger cause	62.793	0	reject
	Hebei does not Granger cause	152.44	0	reject
	Shandong does not Granger cause	89.222	0	reject
	All of neighborhood provinces do not Granger cause	734.95	0	reject
Shanghai	Jiangsu does not Granger cause	9.2812	0.01	reject
	Zhejiang does not Granger cause	39.212	0	reject
	All of neighborhood provinces do not Granger cause	59.473	0	reject
Chongqing	Yunnan does not Granger cause	8.0055	0.018	reject
	Sichuan does not Granger cause	1.6304	0.443	Not reject
	Guizhou does not Granger cause	39.396	0	reject
	All of neighborhood provinces do not Granger cause	85.983	0	reject

### 4.4.5 Variance decomposition of UWRVI

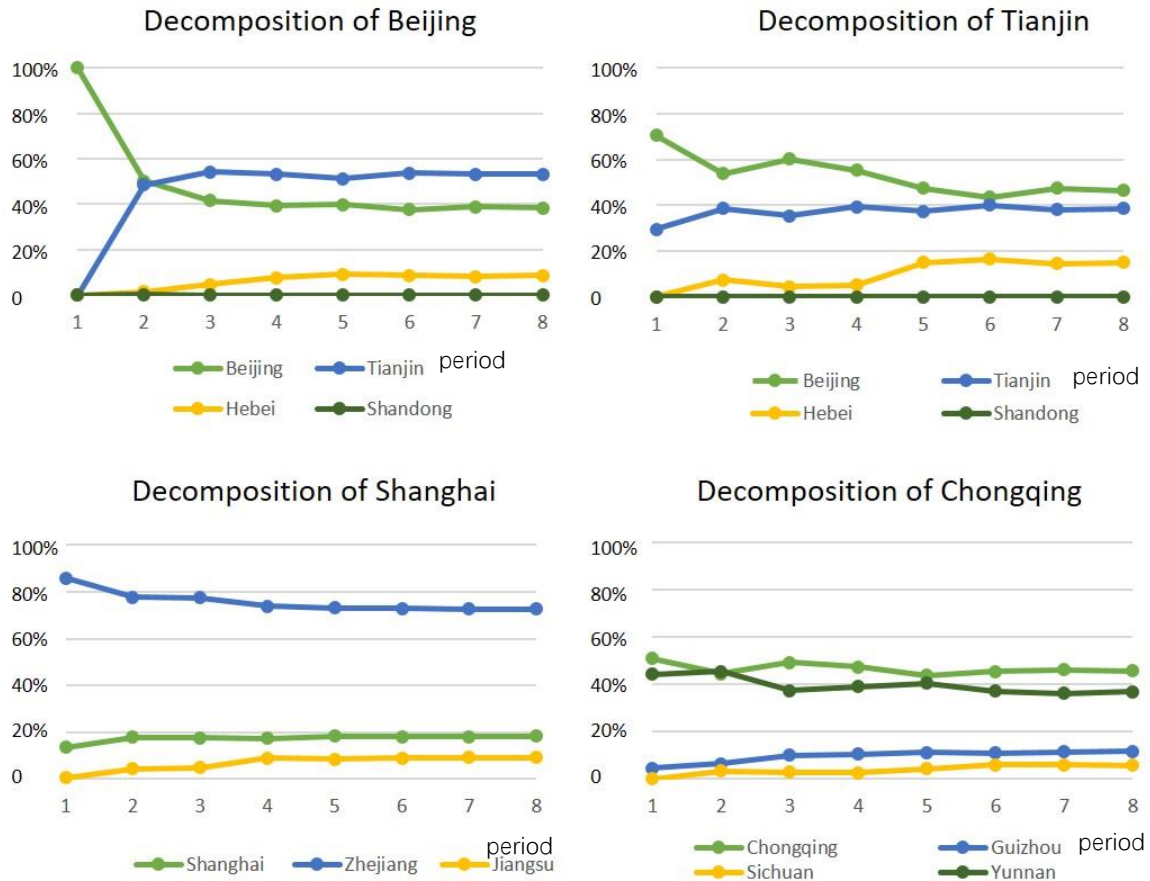




Fig 4-3 Variance decomposition of UWRVI

Figure 4-3 shows the results of the variance decomposition of UWRVI. In Beijing, 38%–51% of the variations between the 2<sup>nd</sup> and 8<sup>th</sup> periods were explained by themselves, while 48%–54% were explained by Tianjin. In Tianjin, 29%–39% were explained by Tianjin. Chongqing had a greater effect on themselves and explained 45%–51% of the subsequent variations. Shanghai itself explained only 13%–19% of the temporal variations, and the impact of Zhejiang's indicator value change on Shanghai was outstanding. Variance decomposition is means prediction of the future.

## **4.5 Discussion**

### **4.5.1 Merits of the UWRVI indicator**

We developed a new indicator system for urban areas based on current water indicators regarding whole areas. Current vulnerability indicators such as Cai (2017) did not considered the differences due to social structures and the urbanization levels. We focused on water use in urban areas and distinguished two types of water vulnerability relevant to either development pressure or management capability. By comparing the performance in these two areas across metropolises and neighborhood provinces, we can analyze water vulnerability and its cause from a new angle as discussed in the next section.

### **4.5.2 Different types of vulnerability across metropolises and their causes**

An investigation of the UWRVI and sub-indicators in Table 3 helps distinguish three

types of metropolises in terms of water vulnerability. Chongqing has a small UWRVI, which indicates less vulnerability. The sub-indicators further divide the remaining metropolises into two groups. Beijing and Tianjin have moderate values of UDP and UEH, while Shanghai shows critical vulnerability in these two areas.

Our indicators suggest that the main cause of vulnerability in Beijing and Tianjin is the natural limitation of water resources, while that in Shanghai is anthropogenic. The large values of UDP and UEH in Shanghai show that artificial water stress, sanitation, and water pollution are significant causes of water vulnerability. The management capability indicator of Shanghai was not as good as that of in Beijing and Tianjin suggesting less efficient water management in Shanghai. The large population and regional GDP of Shanghai shown in Table 2 should be relevant to these anthropogenic water problems. The source of water vulnerability in Beijing and Tianjin is mainly due to URS, which is caused by the limited precipitation in the northern area as shown in Table 2. Zhang (2010) concluded that the main cause of water problems in Beijing was the excess population relative to its ecologically available water resources. However, our analysis using comprehensive urban water indicators enabled us to determine the relative importance of natural and anthropogenic factors. This resulted in a different interpretation of water vulnerability in Beijing.

### **4.5.3 Relationships of metropolis and neighborhood provinces**

Our method for investigating inter-provincial relationships of UWRVI using VAR models enables us to identify different types of relationships across the four megacity areas. According to Tables 4-8 -10, UWRVI has spatio-temporal relationship between the metropolis and neighborhood provinces except for in the Shanghai area. The development pressure sub-indicators had a similar pattern (see Table 9). The special-

temporal relationships across a metropolis and its neighboring provinces may be a product of coordinated development in the area.

A comparison across Tables 4-6, 8, 9, and 10 provides further insight into regional characteristics. Some provinces have contemporaneous relationships with the adjacent metropolis but lack Granger causality. An example is the relationship among the development pressure indicators of Zhejiang and Shanghai. Some provinces have Granger causality but lack contemporaneous relationships such as the case of development pressure in Beijing and Tianjin. Jiangsu's development pressure indicator and UWRVI lack both contemporaneous relationship and Granger causality to Shanghai. Some provinces have both contemporaneous relationships and Granger causality. These relationships are summarized in Table 11.

These different types of relationships with metropolises reflect different regional development patterns. Having contemporaneous relationships but lacking Granger causality means, the province shares the same short-term water limiting or water policy factors as the adjacent metropolis. Having Granger causality but lacking contemporaneous relationships is caused when a metropolis depends on a significant part of the water supply in neighboring provinces, but short-term water limiting factors are regionally diverse.

Table 4-11 Relationships of metropolis and neighborhood provinces

	The province that has Granger causality	The province that does not have granger causality
The province that has contemporaneous relationship	Tianjin to Beijing (Management capability, UWRVI) Hebei to Beijing (Management capability, UWRVI) Beijing to Tianjin (Management capability, UWRVI)	Zhejiang to Shanghai (Development pressure, UWRVI)
The province that does not have contemporaneous relationship	Tianjin to Beijing (development pressure) Hebei to Beijing (development pressure) Shandong to Beijing (management capability, UWRVI) Beijing to Tianjin (development pressure) Shandong to Tianjin (management capability) Zhejiang to Shanghai (management capability)	Jiangsu to Shanghai (Development pressure, UWRVI)

The causes of water vulnerability are relevant to the different patterns of UWRVI dependency between the metropolis and neighborhood provinces, as shown in Fig. 3. Beijing and Tianjin, which had nature-caused vulnerability, were affected mainly by the history of UWRVI of their own and those of the provinces that have contemporaneous relationships with the metropolises. The contemporaneous relationships between the metropolis and neighborhood provinces can be caused by the same natural cause of water limitation in the area. During this event, there is no room for the provinces to relieve the water problem of the metropolises, and thus, the UWRVI of both the metropolises and provinces worsens. It is interesting that the provinces with contemporaneous relationships with the metropolises have long-lasting impacts on the metropolises as well. This may be caused by the regional cooperation of water management/policy areas.

Shanghai, whose vulnerability is mainly due to human causes, was affected more by the change in indicators in the neighboring provinces compared to the other three metropolises. The urban water vulnerability in Shanghai is extremely high, but its close neighbor, Zhejiang, is less vulnerable. Thus, Shanghai relies heavily on Zhejiang for its water supply. Zhejiang, in turn, caused long-lasting effects on Shanghai's water

vulnerability as shown in Fig. 4-3.

#### **4.5. 4 Policy suggestion**

To alleviate metropolis water stress, the current water policy of the Chinese government mainly focuses on Northern China, and mainly to relieve nature causes vulnerability. Examples include the Yellow River Water Right Allocation Policy, Relative Water Withdraw Policy and others (SC, 1987; YRCC, 1994). As for different domains, the current policy mainly aims to relieve development pressure and encourage water efficiency. Some researchers have also focused on four provinces-level municipalities and water transfer to alleviate metropolis problems (Zhao, 2017). We put more stress on the regional cooperation among neighborhood provinces and metropolises as a whole.

Metropolises with natural vulnerability have shown obvious geographical dependencies in development pressure, management capability, and UWRVI. Beijing and Tianjin are located in water-scarce area. Because their neighborhood provinces have similar natural limitations of water resources, long-distance water transfer, such as the South to North Water Transfer Project, may be necessary as a core of water policy. However, improving the effectiveness of coordinated development with neighborhood provinces regarding water resources may also play important roles given the large environmental impacts of long-distance water transfer. The river chief system studied by Liu et al (2020) may work as an effective regional water allocation mechanism.

In Shanghai, where human vulnerability is a problem, only the management capability has close relationships with its neighboring provinces suggesting some linkage of regional water policy in the water management area. However, Shanghai has

the ability and responsibility to improve water efficiency, because it is the core city in the Shanghai-Nanjing-Hangzhou urban agglomeration. Water efficiency is a way to combine socioeconomic development and water protection (Wang et al., 2019). Just focusing on water protection may lead to the loss of economic benefits (Ren et al., 2016). Fan et al. (2017) noted that developing economies can benefit from water conservation by increasing investment in water efficiency. Their development pressure is also high and requires countermeasures. Shanghai may increase investment in water reuse in order to reduce water pollution and increase water supply. They can also strengthen the regional cooperation discussed for the metropolises with nature causing vulnerability.

## **4.6 Conclusions**

In this study, we developed a new water indicator system, the UWRVI, to measure the urban water environment in the metropolis and neighborhood provinces. The indicator system comprises the development pressure and management capability domains. The calculation results showed that the UWRVI and its sub-domains have different regional characteristics because of the unbalanced distribution of natural resources and unbalanced development. We suggest that humans could reduce urban water resource vulnerability by coordinated development of development pressure and management capabilities. Table 4.12 is Innovation point.

Table 4.12 Innovation point

items	Most important findings/innovations	Most important previous papers	Innovation relative to the previous papers
4.1	Further spatial-temporal analysis, study urban water resource vulnerability in different region, and study the timely change. Use vector auto regression model (VAR)	Cai et al 2017	Study the relationship between metropolis and neighborhood province, use granger causality under VAR model, to test the relationship
4.2			Forecast the future effect from different area, use variable decomposition. the vulnerability of metropolis is both affected by metropolis themselves and neighborhood provinces.
4.3			Separately studied the development pressure and management capability. these two domains have different region relationship. Management capability have more relationship

Appendix: Model estimation results and relevant statistics

Table C.1 VAR model result

Variables	Development pressure	Management capability	UWRVI	Variables	Development pressure	Management capability	UWRVI	Variables	Development pressure	Management capability	UWRVI
Dependent variable: Beijing				Dependent variable: Chongqing				Dependent variable: Shanghai			
Beijing				Chongqing				Shanghai			
L1	-0.155*	0.203	-0.453	L1	-0.766***	1.650***	-0.228	L1	0.969**	-0.548***	0.772*
L2	-0.913***	0.038	-1.300***	L2	-0.482***	-0.167*	-0.763***	L2	-0.671	0.285**	-0.596
Tianjin				Sichuan				Jiangsu			
L1	0.466 ***	0.22	0.535**	L1	-3.567***	-0.302***	1.334**	L1	0.63	-0.428***	0.613
L2	-0.361***	0.563	-0.361***	L2	-5.019***	-0.430***	0.933	L2	-1.09	-0.199*	-0.33
Hebei				Guizhou				Zhejiang			
L1	-3.813 ***	0.373	-2.328***	L1	3.548***	0.393***	-0.957	L1	-4.062	1.255**	-2.895
L2	1.537***	0.23	3.124***	L2	3.870***	0.446***	-1.435***	L2	2.645**	0.737	2.641*
Shandong				Yunnan				Constant			
L1	2.591***	-0.171	2.231***	L1	0.381	-0.124	0.766	Constant	0.707**	-0.01	0.433*
L2	-0.235	-0.191	-1.156*	L2	-0.028	-0.321***	1.125***				
Constant	1.196***	-0.051 ***	0.805***	Constant	0.039*	-0.010***	0.110***				
R <sup>2</sup>	0.988	0.994	0.911	R <sup>2</sup>	0.853	0.998	0.856	R <sup>2</sup>	0.403	0.989	0.403
Dependent variable: Tianjin				Dependent variable: Sichuan				Dependent variable: Jiangsu			
Beijing				Chongqing				Shanghai			
L1	-0.678**	-0.048	-0.666	L1	-0.124	1.962**	-0.069	L1	0.386***	0.454**	0.269***
L2	-1.444***	0.239***	-1.793***	L2	-0.04	-0.205	-0.222***	L2	-0.072	0.261**	-0.071
Tianjin				Sichuan				Jiangsu			
L1	0.959***	-0.013	0.784*	L1	-0.689**	-0.514**	0.520**	L1	-0.311*	0.601***	-0.11
L2	-0.259	-0.291***	-0.198	L2	-1.195***	-0.459*	0.717***	L2	-0.467***	-0.340***	-0.105
Hebei				Guizhou				Zhejiang			
L1	-4.301***	0.470***	-2.520***	L1	0.899***	0.854***	0.123	L1	-1.720***	2.618***	-0.981*
L2	2.541***	-0.031	3.562***	L2	1.128***	0.456***	-0.528***	L2	0.706***	-2.270***	0.818
Shandong				Yunnan				Constant			
L1	5.282***	-0.321***	4.473***	L1	-0.301*	-0.535***	-0.208	Constant	0.330***	-0.014**	0.182***
L2	-1.867***	0.215***	-2.071*	L2	-0.16	-0.315***	0.516***				
Constant	0.330***	-0.014**	0.182***	Constant	0.027***	-0.130***	0.015				
R <sup>2</sup>	0.899	0.999	0.851	R <sup>2</sup>	0.894	0.992	0.963	R <sup>2</sup>	0.699	0.991	0.580

L1: first-order lag, L2: second-order lag

\* 10% significance, \*\* 5% significance, \*\*\* 1% significance.

Table C.1 VAR model result (continued)

Variables	Development pressure	Management capability	UWRVI	Variables	Development pressure	Management capability	UWRVI	Variables	Development pressure	Management capability	UWRVI
Dependent variable: Hebei				Dependent variable: Guizhou				Dependent variable: Zhejiang			
Beijing				Chongqing				Shanghai			
L1	-0.242**	-0.293**	-0.063	L1	-0.269***	-2.319**	-0.344**	L1	0.055	-0.186***	0.034
L2	-0.369***	-0.534***	-0.443***	L2	-0.250***	-0.026	-0.143	L2	-0.125*	0.030	-0.106
Tianjin				Sichuan				Jiangsu			
L1	0.347***	0.103	0.127	L1	-0.366	1.152**	1.070**	L1	0.203	-0.131***	0.168
L2	-0.078	0.905***	-0.123	L2	-1.901***	1.620***	-0.349	L2	0.155	-0.081**	0.246**
Hebei				Guizhou				Zhejiang			
L1	-1.278***	-0.099	-0.669*	L1	0.698***	-0.549	1.226***	L1	-0.358	0.577***	-0.189
L2	0.941***	0.482***	1.423***	L2	2.144***	-0.570***	-0.063	L2	0.405*	0.630***	0.401*
Shandong				Yunnan				Constant			
L1	1.301***	0.332***	1.019***	L1	-0.087	0.773**	-0.984**	Constant	-0.012	0.000	-0.026
L2	-0.775***	0.566***	-0.469	L2	-0.276*	0.256	0.695**				
Constant	0.488***	0.050***	0.176*	Constant	0.033***	0.215***	0.012				
R <sup>2</sup>	0.787	0.998	0.7143	R <sup>2</sup>	0.968	0.944	0.811	R <sup>2</sup>	0.358	0.998	0.582
Dependent variable: Shandong				Dependent variable: Yunnan							
Beijing				Chongqing							
L1	0.170	0.792***	0.598***	L1	-0.094	-0.481	-0.19				
L2	-0.131	-0.565***	-0.073	L2	-0.147***	-0.596**	-0.096				
Tianjin				Sichuan							
L1	0.036	0.569	-0.285**	L1	-0.295	-0.302	0.345				
L2	-0.100	-0.123	-0.126**	L2	-2.425***	1.569***	-0.201				
hebei				Guizhou							
L1	-1.450	-0.202	-1.360***	L1	-0.531***	0.105	1.535**				
L2	0.381	-0.408*	0.287	L2	2.391***	0.084	0.159				
Shandong				Yunnan							
L1	1.104	0.847***	0.781***	L1	0.389***	0.619**	-0.894*				
L2	0.157	0.167	0.907**	L2	-0.453***	0.068	0.571				
Constant	0.300	0.037**	0.063	Constant	0.076***	-0.105**	-0.027				
R <sup>2</sup>	0.758	0.991	0.848	R <sup>2</sup>	0.902	0.981	0.707				

L1: first-order lag, L2: second-order lag

\* 10% significance, \*\* 5% significance, \*\*\* 1% significance.



Table C.2 Model specification tests

Metropolis			Chi2 (Joint significance test)	Q (residual white noise test)	P	DFGLS (Residual stationary)
Beijing& Tianjin	Development pressure	L1	16023.150***	3.298	0.1922	-1.681*
		L2	8939.205***			
	Management capability	L1	8602.949***	0.770	0.6804	-1.603**
		L2	12113.780***			
	UWRVI	L1	37416.650***	3.062	0.2164	-1.239*
		L2	14518.990***			
Shanghai	Development pressure	L1	38.626***	0.162	0.9220	-2.839*
		L2	51.647***			
	Management capability	L1	360.088***	1.757	0.4154	-2.469**
		L2	135.988***			
	UWRVI	L1	20.562**	0.008	0.9960	-2.209**
		L2	53.069***			
Chongqing	Development pressure	L1	151.027***	0.011	0.9944	-1.239*
		L2	296.369***			
	Management capability	L1	39286.680***	1.771	0.4124	-1.025*
		L2	28377.760***			
	UWRVI	L1	2544.710***	1.714	0.4245	-2.526**
		L2	2515.021***			

L1: first-order lag, L2: second-order lag

\* 10% significance, \*\* 5% significance, \*\*\* 1% significance.

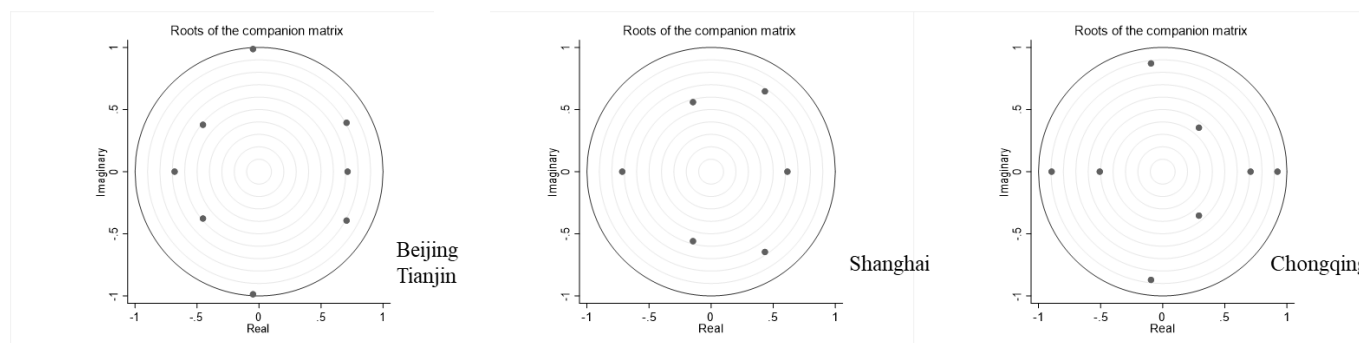


Fig C.1 Model stationarity test

# **5 The effect of urbanization on agricultural water supply internalization: Combining system and spatial models**

## **5.1 Background**

The development of urban and agricultural areas faces water scarcity problems worldwide. Urban development has a significant impact on water scarcity (Gebre and Gebremedhin, 2019). Under climate change, urban areas will produce a surface water deficit of 1,386–6,764 million m<sup>3</sup> per year worldwide (Flörke et al., 2018). Agricultural water accounts for the highest proportion among water consumption amounts; its withdrawals will increase by 13% and reach 2975 km<sup>3</sup> in 2050 versus 2000 (Chartzoulakis and Bertaki, 2015).

Rapid urbanization brings anthropological system effects on agriculture and the water environment. Urban areas rely on rural areas to meet their demands for food and water (Gebre and Gebremedhin, 2019). Water has connections with energy and food (Endo et al., 2020, 2021) and has been studied in the framework of water–energy–food nexus. Food consumption structures have changed with urbanization, and food demand is a function of population growth (UN, 2004). Meanwhile, urban water has direct competition with rural water (Falkenmark, 1995).

China faces severe water scarcity, attributed to rapid economic development and urbanization, especially with a large and growing population (Jiang, 2009). According to the Chinese Statistics Yearbook 2018, the urban population percentage increased from 11.78% in 1951 to 58.52% in 2017. Under the limitation of water resource, the contradiction of water allocation of urban and agricultural activity is prominent (Meng et al., 2018). Now, China's food production depends significantly on irrigation (Wang et al., 2017). Urbanization leads to an increase in agricultural water.

We want to study the system effects of urban development on urban and agricultural water consumption under rural–urban development transformation situations. The system effect includes direct and path effects, where direct effects include agricultural activities and urban water scarcity, which directly affect agricultural water scarcity. Path effects include direct and indirect path effects. The direct path effect reflects the direct water conflict due to increasing urban water demand, which is the urban effect on agricultural water through urban water scarcity. The indirect path effect refers to indirect water conflict due to urban area expansion, which is the urban effect on agricultural water through a change in agricultural activities.

However, the natural distribution of resources and the spatial location of human activities that demand water for society significantly also affect the environment. Spatial agglomeration refers to the geographical pattern where the same feature appears in proximity to each other (Billings and Johnson, 2016). The spatial agglomeration of agricultural and urban activities affects the environment. Zhong et al. (2020) found that the economic and social development of the surrounding cities impacted local agricultural activities. Urbanization, urban population agglomeration, and industrialization significantly impact air quality (Liu, 2017). Agricultural agglomeration can improve the efficiency of agricultural water use efficiency (Wang et

al., 2019). We use spatial models to consider the effects of spatial agglomeration of urban and agricultural activities on water supply internalization.

Some researchers have studied path effects using system models. For example, Wu et al. (2013) and Jeong and Adamowski (2016) used system models to study the social impacts on water stress. However, these studies have two limitations: first, they ignored the impact of urbanization on agricultural water; second, they ignored the effect of the spatial distribution of urban and agricultural activities.

We use a relatively novel approach of combining system models with spatial models and address four research questions: first, how does agricultural development affect agricultural water supply internalization directly? Second, how do urban activities affect agricultural water supply internalization via urban water supply internalization? This question concerns the direct and indirect path effects. Third, are agricultural water supply internalization and agricultural activities affected by urban development? This question concerns the indirect path effect. Fourth, what is the spatial agglomeration effect of urban and agricultural development on agricultural water supply internalization?

## **5.2 Objectives**

We want to study the system effects of urban development on urban and agricultural water consumption under rural–urban development transformation situations. We want to study which factors are important among the changes in social structure on agricultural and urban water security? It consists of analyzing urban and agricultural water interactions, identifying factors influencing urban water security, and identifying factors influencing rural water security.

## 5.3 Method

### 5.3.1 Indicator

Under the sustainable development goals indicator framework, water supply internalization is important in measuring the levels of the water environment and development pressure (Vanham et al., 2018). Water consumption sectors can be divided into agricultural and urban water sectors. Different water consumption supply internalization could be used in water environment study. He et al. (2021) studied the agricultural water sector, and Li et al. (2020) considered water stress in agriculture. In this study, water supply internalization is the ratio of water consumption to water resource amount (see Equations (1) and (2)). Agricultural water (AW) is the amount of water consumed by the agricultural industry. Urban water (UW) is the amount of water that is not used by the agricultural industry among the total water consumption in an area. The water resource (WR) is the amount of blue water that humans can withdraw from nature (Hoekstra et al., 2011), and it consists of freshwater lakes, rivers, and aquifers.

Agricultural water supply internalization (AWS):

$$AWS = \frac{AW}{WR} \quad (1)$$

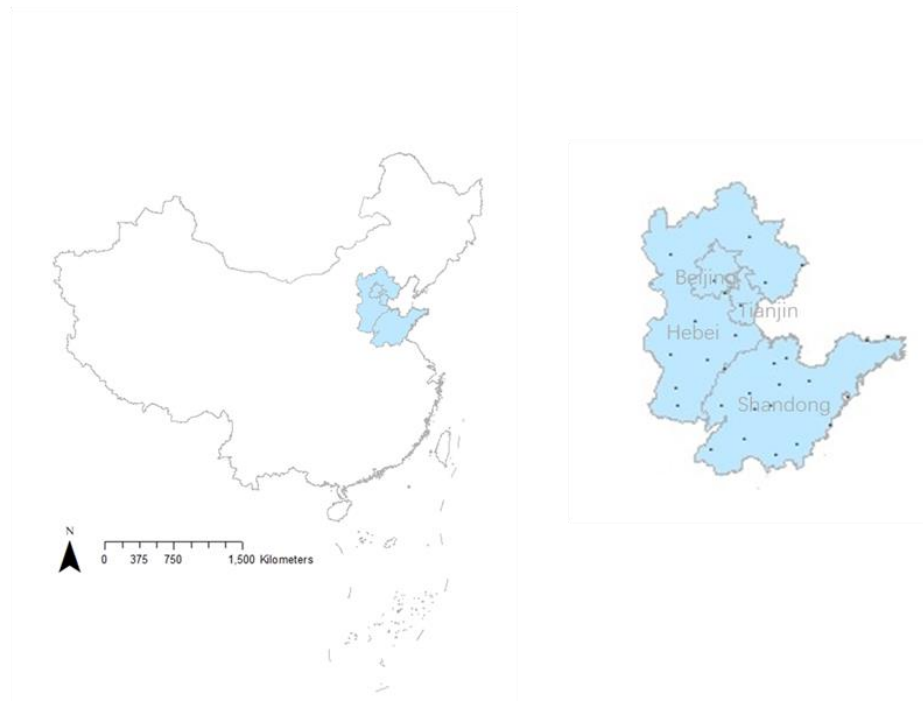
Urban water supply internalization (UWS):

$$UWS = \frac{UW}{WR} \quad (2)$$

### 5.3.2 Study area

We studied the North China Plain, which is a water scarcity area in China, especially in four East coastal provinces: Beijing, Tianjin, Hebei, and Shandong (Figure 5-1). The

annual water per person in the four provinces is less than 500 m<sup>3</sup> (China Statistic Year Book and China Water Bulletin). According to Falkenmark (1989, 1992), water scarcity areas are defined by per capita water amounts below 500 m<sup>3</sup> annum. We studied 30 cities in the four provinces. These cities have faced conflicts between agricultural and urban activities. These four provinces are the main producing areas for water-consuming crops. Wheat production in Henan, Shandong, and Hebei provinces accounts for more than 50% of the total national production (Tang, 2018). The growth cycle of winter wheat in North China is winter and spring with little rainfall, and wheat consumes a large amount of blue water (Govere et al., 2020). Besides, it is developed urban areas. It has the capital of China and Beijing. Beijing and Tianjin were designated province-level cities. Shandong and Hebei experienced rapid urbanization. The urban population ratio of Shandong increased from 48.32% in 2009 to 60.58% in 2017. Hebei's grew from 43.74% in 2009 to 55.01% in 2017.



### **5.3.3 Theoretical framework**

#### **1 System model**

System dynamics (SD) and simultaneous equation modeling (SEM) are among our chosen methods. Wu et al. (2013) and Jeong and Adamowski (2016) used SD to study water and social effects. Some researchers have used SEM to study the simultaneous social effects on water (Maas et al., 2020; Shiferaw, 2008). The SD model is complex and can be used to study multiple paths. SEM simplifies the paths and performs a single-path analysis using intermediate variables. SEM produces more consistent and efficient estimates (Goldberger, 1972). To compare the different mechanisms by which urban development affects agricultural water use, we compare single-the equation model and SEM model to estimate the direct effect and direct /indirect path effect. This study includes three kinds of models.

First, we defined a simple single-equation model to study the direct effect. Agricultural activities and urban water supply internalization affect agricultural water supply internalization. This is illustrated in Figure 5-2.

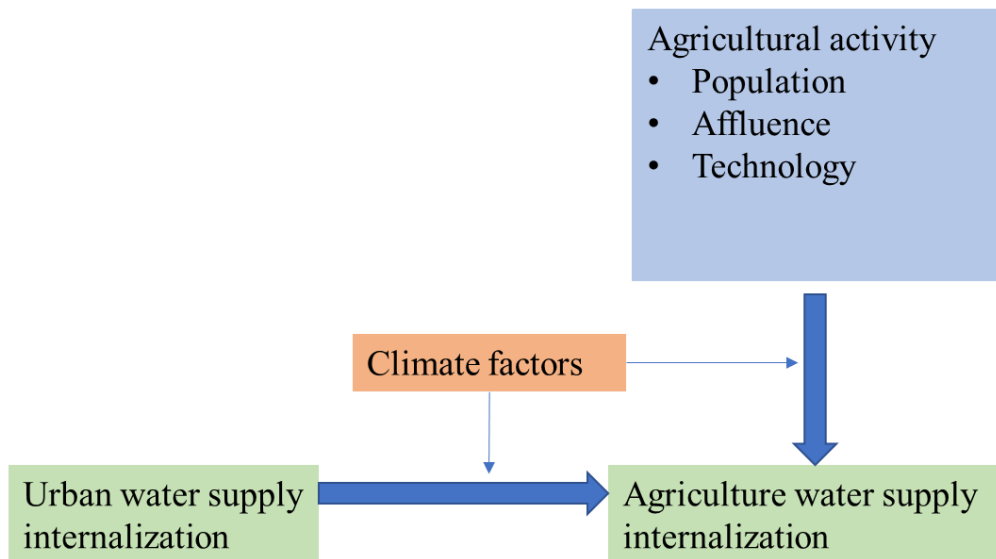


Fig. 5-2 Direct effect

Second, we examined the direct path effect. This is a direct water conflict due to urban water demand. Urban development has led to an increase in urban water consumption. Fan (2017) noted that urban water consumption is affected by meteorological factors, socioeconomic status, water supply, and conservation factors. An increase in urban water consumption leads to water conflicts between urban and agricultural water. Agriculture is high in water consumption but low in economic efficiency. Human society needs to coordinate water uses across different sectors (Mohan, 2021). Antoci et al. (2017) conducted a theoretical analysis to determine the relationship between the competing water use sectors. As shown in Figure 5-3, the relationship between the different water sectors is affected by social factors, such as the price mechanism brought about by the overall economic situation of the population. The direct path effect is related to the effects of urban activities on agricultural water supply internalization via urban water supply internalization.



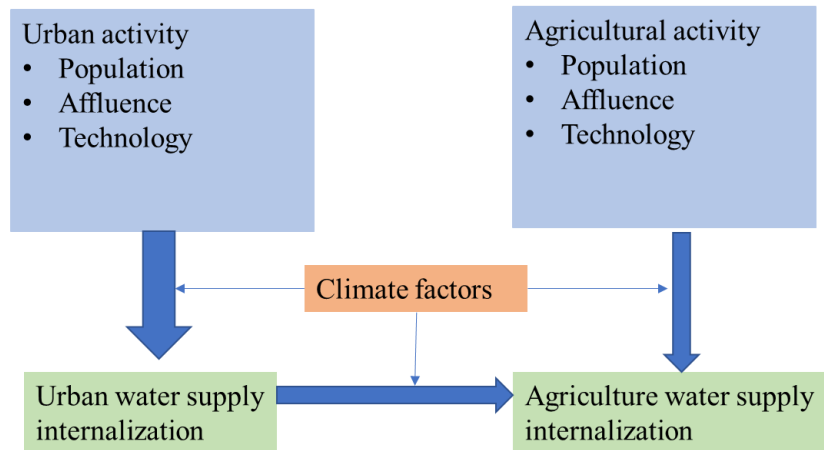


Fig. 5-3 Direct path effect from urban activity to agricultural water supply internalization via urban water supply internalization

Third, we examined the indirect path effect. Under the rural-urban development transformation situation, population migration from rural areas is a common feature (De Brauw et al., 2014). Urban areas sprawl into agricultural land (Yang et al., 2018) and increase the demand for agricultural products (Gebre and Gebremedhin, 2019). Urban development has indirect connections with agricultural water supply internalization via agricultural activities, as shown in Figure 5-4.

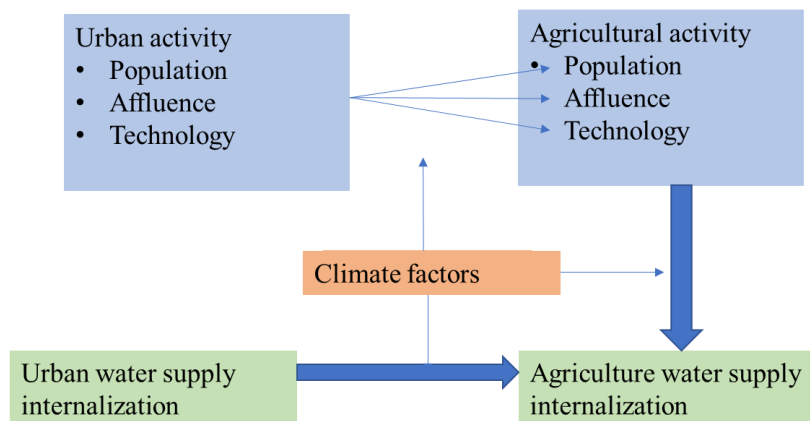


Fig 5-4 Indirect path effect from urban activity to agricultural water supply internalization via agricultural activities

## 2 Spatial agglomeration indicator and model

We used a spatial agglomeration indicator and a spatial model to study the spatial connection between cities. Since the natural and economic environments are linked across regions, the influence of spatial location needs to be considered in the system model. According to Tobler's First Law of Geography, everything is related to everything else, but one region is easily affected by the neighborhood region (Tobler, 1970). This spatial spillover effect produces a spatial agglomeration. Paelinck and Klaassen (1979) proposed a spatial econometric model. The Global Moran's I can explain the similarity of the attribute values between adjacent areas to determine whether there is water supply internalization spatial agglomeration. The Moran's I statistic is one of many ways spatial autocorrelation can be represented (Moran, 1950). The Global Moran's I emphasize the covariance between regional statistics and mean values (see Equation (5)). Some researchers have conducted spatial analyses of agriculture and water. Li et al. (2020) studied the Moran Index for irrigation water. Wang et al. (2019) conducted a spatial analysis of the agricultural water. Wu et al. (2020) conducted a spatial analysis of the agricultural energy efficiency.

There are two step to test the spatial agglomeration effect. The first step is to examine Global Moran's I of the global spatial autocorrelation of agricultural and urban water supply internalization. We measured agricultural water supply internalization and urban water supply internalization using Global Moran's I over 2001-2016. The second step was to measure the spatially influential factors on water supply internalization using spatial models.

$$I_{ws} = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^n (X_i - \bar{X}) \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad (3)$$

The Global Moran's  $I$ ,  $I_{ws}$  is calculated across cities ( $j, j = 1-30$ ).  $W_{ij}$  represents the spatial weight; if the two cities are spatially adjacent, the value is 1; otherwise, it is 0 (adjacency matrix).  $X$  is the agricultural water supply internalization or urban water supply internalization, and  $\bar{X}$  represents the average of those values. The Global Moran's  $I$  is between - 1 and 1. When  $I < 0$ , it indicates that the water supply internalization is negatively correlated across the adjacent cities; when  $I > 0$ , it indicates a positive correlation, and when  $I = 0$ , it indicates that there is no spatial correlation.

For spatial analysis, we used two different spatial models to measure the spatial influencing factors of water supply internalization: spatial autoregressive model (SAR) and spatial simultaneous equation model (SSEM). SAR is fitted using datasets containing observations of geographic areas or units with a spatial representation (Griffith, 2009). A linear model with autoregressive errors and spatial lags of the dependent and independent variables was fitted. SSEM uses the generalized spatial three-stage least squares (GS3SLS) method, as suggested by Kelejian and Prucha (2004). SSEM with cross-sectional data can address the two-way mechanisms. SSEM can be regarded as a simultaneous equation model combined with spatial analysis. Long (2020) studied foreign direct investment and carbon productivity using SSEM. For our empirical analysis, the Stata external command was used for the model estimation. We wanted to test which spatial factors had a greater impact.

The types of data used in this study is panel data. Panel data could consider different regions. In panel data analysis, fixed-effects models are suitable for studying different regional data. However, regional characteristic variables could not be used in the fixed-effects models. This will have multicollinearity. Auci and Vignani (2021) also consider the limitations of the fixed-effect model in agricultural water studies. Since we focused on regional characteristics, we used pooled data analysis for simultaneous models.

### 5.3.4 Variables and data

As for dependent variables, we used two types of dependent variables. First, urban water supply internalization and agricultural water supply internalization; second, agricultural factors and agricultural water supply internalization. The independent variables included both social and climate factors. Auci and Vignani. (2021) studied the social and climate factors of variable in irrigation water studies. Agricultural variables are not only related to agricultural activities and climate, but also have connections with the entire social aspect. China's water efficiency in different regions is different (Hu et al, 2017).

Table 5-1 summarizes the dependent and independent variables used in the study. Independent variable includes agriculture sectors, urban sectors, climate factors and others. As for the agricultural sector, affluence is the agricultural GDP. This population is an agricultural population. As for technology, we used two aspects to measure: agricultural asset technology and crop typology. Agricultural asset technology refers to the power of agricultural machines. Machine power has been used in many agricultural studies, such as Chen and Song (2008). We used crop typology to reflect the different crop cultivated areas. Crop typology is an important part of social agricultural change. Auci and Vignani (2021) studied crop typology in irrigation water. Agricultural economic efficiency is important (Petrescu-Mag et al., 2019). We considered traditional plant planting area, which consists of grains and oilseeds, and vegetable planting areas. Vegetable planting brings more economic value and higher profits, including capital and technology (Siciliano, 2012).

As for the urban part, urban GDP, urban population, and degree of industrialization represent affluence, population, and technology, respectively. As for industrialization,

we used the industrial asset ratio of the whole GDP (industrialization = industrial asset/industrial GDP). Some researchers measure industrialization through the ratio of GDP, as in Dong et al. (2019).

As for climate factors, we used temperature and precipitation as two variables, temperature and precipitation, which separately represent the yearly annual temperature and the yearly amount of precipitation. Auci and Vignani (2021) studied the climatic factors that affected agricultural water. As for location variable, the convenience of water use is indicated. We used four levels to represent the different locations. One indicates that the city is located in the Yellow River basin. Two indicates that the city is in the Yellow River water transfer project area. Only seven cities are not located in the Yellow River basin or Yellow River water transfer project area. In these seven cities, three important cities have plans for south-to-north water transfer projects. These three cities were regarded as Level 3. Others are regarded as Level 4. A larger level indicates more difficulty in accessing large water resources.

We used data from 2001 to 2016. Social factor data are from the local statistical yearbook; the local statistical year book includes the Beijing statistical yearbook, Tianjin Statistical yearbook, Hebei statistical yearbook, and Shandong statistical yearbook. Missing data were filled using local averages. Population data were obtained from the local statistical yearbook. Affluence includes agricultural and urban GDP from local statistical data. Technology includes industrialization from local statistical yearbooks. Plant area of Beijing Tianjin and Shandong were taken from local statistical yearbooks. The plant area of Hebei was obtained from the Hebei Rural Statistical Yearbook. The temperature data were obtained from the China Meteorological Administration. Local water resource, precipitation and agricultural water consumption amounts were compiled from the Beijing Water Resources Bulletin, Tianjin Water

Resources Bulletin, Hebei Water Resources Bulletin, and Shandong Water Resources Bulletin. Water resource bulletin. Hebei agricultural water amount was taken from the Hebei rural statistics yearbook.

Table 5-1 Variables

Variable type and abbreviation	Variable name and definition	Mean	Standard deviation	Max	Min
Agricultural population: agr <sub>1</sub>	Agricultural population (10,000 person)	369.939	199.802	940.028	53.491
Agricultural affluence: agr <sub>2</sub>	Agricultural GDP (100 million yuan)	4.938	0.037	598.98	1.589
Agricultural technology: agr <sub>3</sub>	Agricultural machine power (10,000 kilowatts)	9019.674	128920.9	2000000	68.891
Agricultural technology: agr <sub>4</sub>	Vegetable planting areas (1,000 hectares)	438778.149	5251670	278637	16172
Agricultural technology: agr <sub>5</sub>	Traditional plant planting areas (1,000 hectares)	172560.534	5298969	1300000	39512.3
Urban population: urn <sub>1</sub>	Urban Population (10,000 person)	281.256	302.515	1879.6	40.16
Urban affluence: urn <sub>2</sub>	Urban GDP (100 million yuan)	7.211	0.046	25539.3	111.4
Urban technology: urn <sub>3</sub>	Industrial assets rate (100 million yuan / 100 million yuan )	0.129	0.062	0.675	0.013
Climate factor 1: C <sub>1</sub>	Temperature (°C)	12.714	1.243	14.821	8.069
Climate factor 2: C <sub>2</sub>	Precipitation (100 million m <sup>3</sup> )	69.445	39.536	236.3	10.1
Location: L	Water accessibility (4 levels)	2	1.001	4	1
Urban water supply internalization: UWS	water supply internalization (m <sup>3</sup> / m <sup>3</sup> )	0.452	0.442	5.104	0.009
Agricultural water supply internalization: AWS	water supply internalization (m <sup>3</sup> / m <sup>3</sup> )	1.07	1.259	11.944	0.058

Note: GDP – Gross Domestic Product

### 5.3.5 Models

We used Model 1 to study the direct effect shown in Figure 2. Model 1A (Equation (4)) is used to study the direct effect without spatial variables. The prefix “ln” of the

variables means that the variables were logarithmically transformed. Model 1B in Equation (5) is used to study the direct effect with spatial effect. It is the SAR model.

$$\ln AWS_{it} = \sum_{a=1}^5 \alpha_a \ln agr_{ita} + \sum_{c=1}^2 \beta_c \ln cli_{itc} + \gamma_1 \ln UWS_{it} + \gamma_2 \ln L_i + \gamma_3 + \mu_{it} \quad (4)$$

$$\ln AWS_{it} = \sum_{a=1}^5 \alpha_a \ln agr_{ita} + \sum_{c=1}^2 \beta_c \ln cli_{itc} + \gamma_1 \ln UWS_{it} + \gamma_2 \ln L_i + \gamma_3 \sum_i^{30} w_{ij} \ln AWS_{it} + \gamma_4 + \mu_{it}$$

(5)

The symbols  $i$  and  $t$  denote city and year, respectively.  $agr_a$  denote the different agriculture factors ( $agr_1$ – $agr_5$ ) and  $\alpha_a$  represents the coefficient of agricultural factors.  $\beta_c$  denotes the coefficient of climate factor  $c$ .  $\gamma_1$  through  $\gamma_4$  represent the coefficients of the other variables;  $w_{ij}$  is adjacency weight;  $w_{ij} \ln AWS$  is spatial lagged variable, and  $\mu_{it}$  is an error term.

We used Model 2 to study the direct path effect shown in Figure 3. The joint-dependent variables were agricultural water supply internalization and urban water supply internalization. Model 2A considers the direct path effect without spatial effects. Model 2A is SEM and consists of Equations (6) and (7).  $\alpha_{Aa}$ ,  $\beta_{Ac}$ ,  $\gamma_1$ , through  $\gamma_3$  are the coefficients of the agricultural water supply internalization equation.  $\alpha_{Ua}$ ,  $\beta_{Uc}$ ,  $\delta_1$ , and  $\delta_2$  are the coefficients of the urban water supply internalization equation.  $\mu_{Ait}$ , and  $\mu_{Uit}$  are the error terms.

Equation of agricultural water supply internalization:

$$\ln AWS_{it} = \sum_a^5 \alpha_{Aa} \ln agr_{ita} + \sum_c^2 \beta_{Ac} \ln cli_{itc} + \gamma_1 \ln UWS_{it} + \gamma_2 \ln L_i + \gamma_3 + \mu_{Ait} \quad (6)$$

Equation of urban water supply internalization:

$$\ln UWS_{it} = \sum_a^3 \alpha_{Ua} \ln urn_{itu} + \sum_c^2 \beta_{Uc} \ln cli_{itc} + \delta_1 \ln AWS_{it} + \delta_2 + \mu_{Uit} \quad (7)$$

Model 2B analyzes the direct path effect by considering the spatial effect. Model 2B is SSEM and consists of Equations (8) and (9). The spatial lagged variables are  $w_{ij} \ln AWS_{it}$  and  $w_{ij} \ln UWS_{it}$ .

Spatial equation of agricultural water supply internalization:

$$\ln AWS_{it} = \sum_a^5 \alpha_{Aa} \ln agr_{ita} + \sum_c^2 \alpha_{Ac} \ln cli_{itc} + \beta_1 \ln UWS_{it} + \beta_2 \ln l_{it} + \beta_3 \sum_j^{30} w_{ij} \ln AWS_{jt} + \beta_4 \sum_j^{30} w_{ij} \ln UWS_{jt} + \beta_5 + \mu_{Ait}$$

(8)

Spatial equation of urban water supply internalization:

$$\ln UWS_{it} = \sum_a^3 \alpha_{Ua} \ln urn_{itu} + \sum_c^2 \beta_{Uc} \ln cli_{itc} + \gamma_1 \ln AWS_{it} + \gamma_2 \sum_j^{30} w_{ij} \ln AWS_{jt} + \gamma_3 \sum_j^{30} w_{ij} \ln UWS_{jt} + \gamma_4 + \mu_{Uit}$$

(9)

We used Model 3 to study the indirect path effect, as shown in Figure 4. Model 3A is SEM using Equations (10) and (11) that ignore the special effect. Equation (13) considers the effect of urban activity on agricultural features. We considered one of the agricultural features of different models as the dependent variable of this equation.

Equation of agricultural water supply internalization:

$$\ln AWS_{it} = \sum_a^5 \alpha_{Aa} \ln agr_{ita} + \sum_c^2 \alpha_{Ac} \ln cli_{itc} + \beta_1 \ln UWS_{it} + \beta_2 \ln l_{it} + \beta_3 + \mu_{Ait}$$

(10)

Equation of agricultural feature:

$$\ln (\text{agriculture})_{it} = \sum_a^3 \alpha_{Ua} \ln urn_{itu} + \sum_c^2 \alpha_{Uc} \ln cli_{itc} + \gamma_1 \ln AWS_{it} + \gamma_2 + \mu_{Uit}$$

(11)

Model 3B is SSEM using Equations (12) and (13), which considered the spatial effect.



Spatial equation of agricultural water supply internalization:

$$\ln AWS_{it} = \sum_a^5 \alpha_{Aa} \ln agr_{ita} + \sum_c^2 \alpha_{Ac} \ln cli_{itc} + \beta_1 \ln UWS_{it} + \beta_2 \ln L_i + \beta_3 \sum_i^{30} w_{ij} \ln AWS_{it} + \beta_4 \sum_i^{30} w_{ij} \ln agr_{it} + \beta_5 + \mu_{Ait} \quad (12)$$

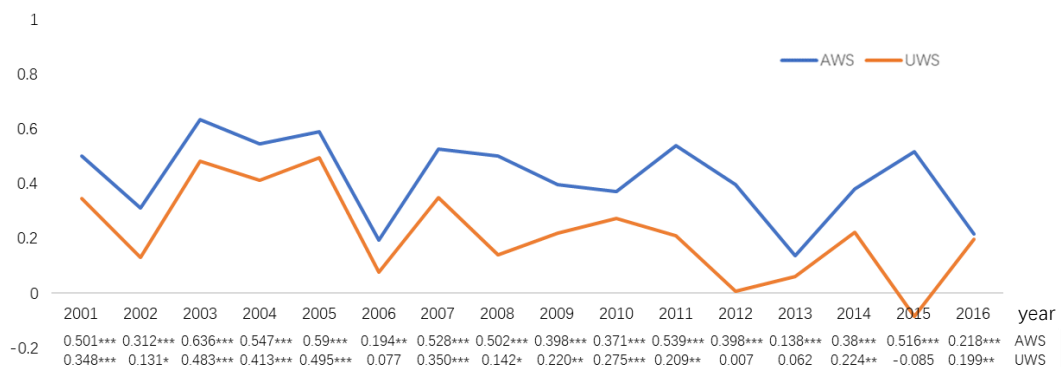
Spatial equation of agricultural feature:

$$\ln (\text{agriculture})_{it} = \sum_a^3 \alpha_{Ua} \ln urn_{itu} + \sum_c^2 \alpha_{Uc} \ln cli_{itc} + \gamma_1 \ln AWS_{it} + \gamma_2 \sum_i^{30} w_{ij} \ln AWS_{it} + \gamma_3 \ln \sum_i^{30} w_{ij} \ln agriculture_{it} + \gamma_4 + \mu_{Uit} \quad (13)$$

## 5.4 Result and discussion

### 5.4.1 Global Moran's I

Figure 5-5 shows that both agricultural water supply internalization and urban water supply internalization have had a positive significant correlation across the cities in most years over the studied period. The high value represents the high degree of agglomeration. The agricultural water supply internalization had a significant spatial agglomeration every year. Regarding the urban water supply internalization, some years did not have a significant spatial agglomeration. After 2010, this trend became more obvious and three years did not have spatial agglomeration.



\* 10% significance, \*\* 5% significance, \*\*\* 1% significance

Fig 5-5 Moran index

## 5.4.2 Model estimation

Table 5-2 shows the results of the models without special effects. Traditional plant areas, agricultural GDP, urban water supply internalization, precipitation, and temperature have significant effects on agricultural water supply internalization. The increase in traditional plant areas and urban water supply internalization has led to an increase in agricultural water supply internalization. An increase in temperature and precipitation tends to ease agricultural water supply internalization. Agricultural and vegetable plant areas did not significantly affect agricultural water supply internalization in some of the equations. In Model 3, the agricultural features considered were agricultural GDP, agricultural population, vegetable plant area, and traditional plant area. We chose these features because they were shown to have significant effects on agricultural water supply internalization in Model 1.

Table 5-2 Model estimate without spatial effects: Equation of agricultural water supply internalization

Variables	Model 1A	Model 2A	Model 3A			
			Agricultural GDP	Agricultural population	Vegetable areas	Traditional plant areas
ln (Agricultural Population)	0.107 (0.162)	- 0.766*** (0.007)	0.054 (0.491)	-0.766*** (0.007)	0.193*** (0.060)	-0.933*** (0.000)
ln (Agricultural GDP)	- 0.171*** (0.000)	- 0.254*** (0.000)	-0.301*** (0.000)	-0.254*** (0.000)	-0.157*** (0.000)	-0.302*** (0.000)
ln (Agricultural machine power)	-0.033 (0.305)	-0.026 (0.466)	-0.012 (0.706)	-0.026 (0.466)	-0.068 (0.112)	-0.276*** (0.000)
ln (Vegetable areas)	- 0.137*** (0.000)	- -0.058 (0.153)	-0.135*** (0.000)	-0.058 (0.153)	0.358** (0.035)	-0.287*** (0.000)
ln (Traditional plant area)	1.018*** (0.000)	1.753*** (0.000)	1.072*** (0.000)	1.753*** (0.000)	1.152*** (0.000)	2.894*** (0.000)
ln (Precipitation)	- 0.821*** (0.000)	- 0.788*** (0.000)	-0.736*** (0.000)	-0.788*** (0.000)	-0.809*** (0.000)	-1.198*** (0.000)
ln (Temperature)	- 1.968*** (0.000)	- 1.574*** (0.000)	-1.692*** (0.000)	-1.574*** (0.000)	-2.146*** (0.000)	-2.958*** (0.000)
ln (Water assess way)	- 0.153*** (0.005)	0.071 (0.393)	-0.141*** (0.010)	0.071 (0.393)	-0.150*** (0.008)	0.203** (0.035)
ln (Urban water supply internalization )	0.511*** (0.000)	0.445*** (0.000)	0.531*** (0.000)	0.445*** (0.000)	0.543*** (0.000)	0.457*** (0.000)
Constant	- 2.792*** (0.005)	- 9.394*** (0.000)	-3.750*** (0.000)	-9.394*** (0.000)	-1.969* (0.099)	- 14.010*** (0.000)
R <sup>2</sup>	0.765	0.698	0.755	0.698	0.743	0.500

\* 10% significance, \*\* 5% significance, \*\*\* 1% significance, P-values in parentheses  
Note: GDP – Gross Domestic Product

Table 5-3 shows the results of the spatial autoregression model and the SSEM of agricultural water supply internalization. It shows the non-spatial and spatial variables studied in this model.

Spatial agricultural water supply internalization affects the agricultural water supply internalization. An increase in neighborhood agricultural water supply internalization leads to an increase in agricultural water supply internalization, and neighborhood

agricultural factors have a significant effect on agricultural water supply internalization. An increase in agriculture leads to a decrease in agricultural water supply internalization.

Among the main variables, the agricultural population has a significant effect on agricultural water supply internalization in Model 1. Except for the equation of Model 1, the increase in agricultural GDP leads to a decrease in agricultural water supply internalization in all equations. Agricultural GDP has a significant effect. Agricultural machine power does not have a significant effect on agricultural water supply internalization in any of the equations. Different plant structures have a significant effect on agricultural water supply internalization. An increase in traditional plant areas leads to an increase in agricultural water supply internalization. This significant effect was observed in all equations. Vegetable areas had no significant effect on agricultural water supply internalization in the vegetable equation of Model 3B. However, there were significant effects on agricultural water supply internalization in the other equations of the model. The agricultural population had the same pattern. Water accessibility has different effects on the agricultural water supply internalization in the differential equations. In the equation of Model 1B, the agricultural population had no significant effect on agricultural water supply internalization. On the other equations of Models 2B and 3B, an increase in the agricultural population leads to a decrease in agricultural water supply internalization.

Table 5-3 Model estimate considering spatial effects: Equation of agricultural water supply internalization

Variables	Model 1B	Model 2B	Model 3B			
			Agricultural GDP	Agricultural population	Vegetable areas	Traditional plant areas
<b>Spatial effects:</b>						
ln (Agricultural water supply internalization )	0.288*** (0.000)	0.405*** (0.000)	0.130*** (0.002)	0.175*** (0.000)	0.177*** (0.000)	0.156*** (0.000)
ln (Agricultural population)				-0.227*** (0.001)		
ln (Agricultural GDP)			-0.209*** (0.000)			
ln (Urban water supply internalization )		-0.380*** (0.000)				
ln (Traditional plant areas)						-0.485*** (0.000)
ln (vegetable areas)					-0.185*** (0.009)	
<b>Main variables:</b>						
ln (Agricultural population)	0.252*** (0.001)	0.063 (0.334)	0.059 (0.417)	0.266 (0.169)	0.117 (0.145)	-0.018 (0.849)
ln (Agricultural GDP)	-0.026 (0.163)	-0.148*** (0.000)	-0.213*** (0.000)	-0.145*** (0.000)	-0.140*** (0.000)	-0.120*** (0.000)
ln (Agricultural machine power)	0.006 (0.842)	-0.028 (0.296)	0.002 (0.961)	-0.025 (0.371)	-0.033 (0.324)	-0.042 (0.167)
ln (Traditional plant areas)	0.337*** (0.005)	0.697*** (0.000)	1.013*** (0.000)	0.961*** (0.000)	0.832*** (0.000)	1.595*** (0.000)
ln (Vegetable areas)	0.164*** (0.006)	-0.058** (0.041)	-0.128*** (0.000)	-0.091*** (0.003)	0.102 (0.398)	-0.098*** (0.000)
ln (Precipitation)	-1.081*** (0.000)	-0.582*** (0.000)	-0.677*** (0.000)	-0.866*** (0.000)	-0.789*** (0.000)	-1.078*** (0.000)
ln (Temperature)	-0.03618 (0.921)	-1.529*** (0.000)	-1.378*** (0.000)	-1.740*** (0.000)	-1.672*** (0.000)	-2.261 (0.000)
ln (Water assess way)	0.067523 (0.703)	-0.104** (0.026)	-0.098* (0.053)	-0.047 (0.449)	-0.092* (0.071)	-0.049 (0.338)
ln (Urban water supply internalization )	0.223*** (0.000)	0.598*** (0.000)	0.503*** (0.000)	0.410*** (0.000)	0.448*** (0.000)	0.339*** (0.000)
Constant	-3.169* (0.070)	-1.653* (0.057)	-3.619*** (0.000)	-2.863* (0.066)	-2.081** (0.038)	-2.327** (0.038)
R <sup>2</sup>	0.8166	0.829	0.798	0.7918	0.7952	0.7421

\* 10% significance, \*\* 5% significance, \*\*\* 1% significance, P-values in

parentheses

Note: GDP – Gross Domestic Product

Table 5-4 presents the results of the remaining equations of SEM. Industrialization has significant effects on the agricultural features in Model 3B. An increase in industrialization led to a decrease in the four agricultural features. Warmer temperatures and larger precipitation are useful for improving agricultural output.

Table 5-5 shows the urban social effects on urban water supply internalization and

agricultural features. The table shows the non-spatial and spatial variables studied in this model. Spatial variables are spatial agricultural water supply internalization and (1) spatial agriculture GDP, (2) spatial agriculture population, (3) spatial vegetable planting area, and (4) spatial traditional plant plating areas. Model 2B shows that urban GDP and urban population affect urban water supply internalization. Since urban water supply internalization is related to agricultural water supply internalization, as shown in Table 5-2, urban industrialization has an impact on agricultural water supply internalization. In the four agriculture equation models of Model 3B, industrialization has significant effects on agricultural factors. An increase in industrialization leads to a decrease in agriculture. The urban population has significant effects on agricultural GDP. An increase in the urban population leads to a decrease in agricultural GDP. The urban population has significant effects on agricultural population and vegetable area. An increase in the urban population leads to an increase in agricultural population and vegetable area. Urban GDP has a significant effect on agricultural GDP, agricultural population, and vegetable plant area. Urban GDP increase leads to an increase in agricultural GDP and a decrease in agriculture, population, and vegetable plant area. The impacts of industrialization and urban GDP have significant effects on vegetable plant area. Both increases in industrialization and urban GDP led to a significant decrease in agricultural output.

Regarding the spatial variables, neighborhood agricultural water supply internalization increases lead to a decrease in urban water supply internalization and others. This relationship was significant. Agricultural GDP, agricultural population, vegetable area, and traditional plant areas in the neighboring cities have significant effects on the agricultural water supply internalization of a city. An increase in neighborhood agricultural features leads to an increase in the agricultural features of a

city.

Table 5-4 Model estimate without spatial effects: Equation of urban water supply internalization and agricultural feature

Variables Dependent variable	Model 2A Urban water supply internalization	Model 3A			
		Agricultural GDP	Agricultural population	Vegetable areas	Traditional plant areas
ln (agricultural water supply internalization)	0.384*** (0.000)	0.213*** (0.000)	0.373*** (0.000)	0.493*** (0.000)	0.539*** (0.000)
ln (Industrialization)	0.030 (0.608)	-0.647*** (0.000)	-0.322*** (0.000)	-0.227 *** (0.005)	-0.159*** (0.000)
ln (Urban population)	0.412 *** (0.000)	-0.360 (0.000)	0.216*** (0.000)	0.393*** (0.000)	0.014 (0.689)
ln (Urban GDP)	0.065 (0.140)	0.716*** (0.000)	-0.167*** (0.000)	0.393*** (0.000)	0.003*** (0.915)
ln (Precipitation)	-0.800*** (0.000)	0.623*** (0.000)	0.859*** (0.000)	0.741 *** (0.000)	1.046*** (0.000)
ln (Temperature)	-2.161*** (0.000)	1.413*** (0.000)	1.522*** (0.000)	0.463 (0.184)	2.409 *** (0.000)
Constant	5.155*** (0.000)	-5.763*** (0.000)	-2.144 *** (0.000)	6.109*** (0.000)	2.604*** (0.000)
R <sup>2</sup>	0.606	0.601	0.633	0.311	0.676

\* 10% significance, \*\* 5% significance, \*\*\* 1% significance, P-values in parentheses  
Note: GDP – Gross Domestic Product

Table 5-5 Model estimate considering spatial effects: Equation of urban water supply internalization and agricultural feature

Variables Dependent variable	Model 2B	Model 3B			
	Urban water supply internalization	Agricultural GDP	Agricultural population	Vegetable areas	Traditional plant areas
<b>Spatial effect</b>					
ln(Agricultural water supply internalization)	-0.516*** (0.000)	0.117** (0.025)	-0.102*** (0.001)	-0.024 (0.724)	-0.058* (0.056)
ln (Urban water supply internalization)	0.423*** (0.000)				
ln (Agricultural GDP)		0.099* (0.075)			
ln (Traditional plant areas)					0.519*** (0.000)
ln (Agricultural population)			0.458*** (0.000)		
wln (vegetable areas)				0.423*** (0.000)	
<b>Main variables</b>					
ln(Agricultural water supply internalization)	0.723*** (0.000)	0.109** (0.021)	0.330*** (0.000)	0.380*** (0.000)	0.383*** (0.000)
ln(Industrialization)	0.056 (0.294)	-0.662*** (0.000)	-0.200*** (0.000)	-0.160** (0.018)	-0.086*** (0.003)
ln (Urban population)	0.220*** (0.000)	-0.317*** (0.000)	0.089*** (0.009)	0.187** (0.012)	-0.014 (0.622)
ln (Urban GDP)	0.083** (0.032)	0.713*** (0.000)	-0.090*** (0.000)	-0.102** (0.048)	0.001 (0.965)
ln (Precipitation)	-0.477*** (0.000)	0.525*** (0.000)	0.644*** (0.000)	0.592*** (0.000)	0.719*** (0.000)
ln (Temperature)	-1.182*** (0.000)	1.164*** (0.000)	1.054*** (0.000)	0.536 (0.145)	1.459*** (0.000)
Constant	2.715*** (0.000)	-5.459*** (0.000)	-2.3748*** (0.000)	2.288* (0.075)	-0.295 (0.514)
R <sup>2</sup>	0.7427	0.620	0.762	0.518	0.8174

\* 10% significance, \*\* 5% significance, \*\*\* 1% significance, P-values in parentheses  
Note: GDP – Gross Domestic Product

## 5.5 Discussion

We compared SEM and SSEM to verify the existence of spatial correlation. A spatial correlation was observed. As shown in Tables 2-5, all spatial variables have significant effects. Thus, we believe that spatial models are more suitable for analyzing water supply internalization data. The following discussion is based on the spatial models. It consists of five aspects: direct effect, direct path effect, indirect effect, spatial effect, and others.



### **5.5.1 Direct effect**

In the direct effect, we studied the impacts of agricultural development on agricultural water (see Table 5-3). Agricultural population, affluence, and technology affect agricultural water. Modern agricultural development patterns have an increase in GDP or a decrease in population under rural-urban migration. This is because the efficiency of the rural economy increases (Siciliano, 2012).

### **5.5.2 Direct path effect**

The direct path effect includes two stages: the first stage is that urban water supply internalization and agricultural activities affect agricultural water supply internalization. The second stage is that urban activities affect urban water supply internalization. In the first stage (see Table 5-3), we found that urban water affected agricultural water supply internalization; it does not compete with agricultural water. This non-competition exists because of long-distance water transfers (south-to-north water transfer projects). Unlike the direct effect, in the first stage of the direct path effect, agricultural GDP affects agricultural water use, and the agricultural population does not. An increase in agricultural GDP and a decrease in the agricultural population represent modern agricultural development patterns. This pattern is compatible with agricultural water.

As for the second stage of the path effect (see Table 5-5), urban GDP and urban population are more likely to affect urban water. Urban development patterns have a significant impact on the environment.

### 5.5.3 Indirect path effect

The indirect path effect includes two stages. In the first stage, urban water supply internalization and agricultural activities affect agricultural water supply internalization. In the second stage, urban activities affect the features of agriculture. In the first stage, its characteristics are similar to the first stage of the direct path effect. This verifies the effect of modern agricultural patterns. In the second stage, an increase in urban development led to agricultural development. Urban development contributes to the development of agriculture. Urban populations contribute to plant growth. Industrialization and urban GDP have both positive and negative effects on agriculture. The urban population needs agricultural production, and the urban population has a positive effect on agriculture factors, except in traditional plant planting areas.

Urban development has a competition between rural and urban areas. Urban development may utilize water resources that could be used in agriculture and other resources. Competition refers to an increase in urban factors, leading to a decrease in agricultural factors. Industrialization leads to a decrease in agricultural activities and no significant effect on urban water supply internalization. Industrialization has a negative effect on agriculture. This confirms that competition exists between industrialization and agriculture. Urbanization development leads to an increase in the agricultural population migrating to urban areas, leading to a decrease in the agricultural population. Zhong et al. (2020) believe that urbanization contributes to urban agricultural development. We studied the social factors under industrialization, which have both positive and negative effects on agriculture. Agriculture is different from urban agriculture. Agricultural water supply internalization may be alleviated by adjusting crop typology. Auci (2021) found no impact of crop typology on irrigation water

consumption, which is different from our findings. This difference may be attributable to the use of a comprehensive plant structure.

#### **5.5.4 Spatial effect.**

There are three types of spatial effects. First, spatial agriculture water supply internalization, spatial urban water supply internalization, agricultural water supply internalization, and urban water supply internalization have an agglomeration phenomenon. Spatial water supply internalization agglomeration reduces the agricultural population and traditional plant areas. Second, there is an urban activity. Urban water has a spatial conflict with agricultural water. An increase in urban water supply internalization in neighborhood cities leads to a decrease in agricultural water supply internalization. Third is that the spatial agglomeration of agriculture is compatible with agricultural water supply internalization. An increase in neighborhood city agriculture leads to a decrease in agricultural water supply internalization. Agricultural agglomeration is beneficial to agricultural development.

#### **5.5.5 Other effects**

Different water supply internalization has important connections with climatic factors. As for climate, we found that precipitation decreases agricultural water supply internalization. In general, a suitable climate has a positive impact. However, high temperatures area shows low levels of agricultural water supply internalization. The average temperature represents the geographical location. water supply internalization is lower in the south of the geographical location. According to the average temperature of the study period, Tianjin is 12.67 °C, Beijing is 11.65 °C, Shandong is 13.40 °C, Hebei is 11.94 °C. The location variable, water assessment method, also verifies the

effect of location on agricultural water supply internalization. The more convenient the water use, the lower the water supply internalization.

## **5.6 Conclusions**

Agricultural development affects the agricultural water supply internalization. An increase in agricultural GDP and a decrease in the agricultural population reduce the agricultural water supply internalization. Urban activity has effect on agricultural water supply internalization in two ways: (1) urban water supply internalization has an effect on agricultural water supply internalization, and (2) urban development contributes to agricultural development and competition for agricultural resources. Agricultural aggregation reduces agricultural water supply internalization to achieve agricultural water sustainability goals. Table 5-6 is innovation points.

Table 5-6 innovation point

items	Most important findings/innovations	Most important previous papers	Innovation relative to the previous papers
5.1	Spatial analysis the agriculture effect factors.in 30 Chinese city in north china. Use Moran and Spatial simultaneous modeling	Auci (2021)	Combine agriculture effect factors with different water sector (agriculture water and urban water), urban water affect agricultural water.
5.2			System analysis of those agriculture effect factors, agriculture factors are affected by urban factors. Decrease of the Agriculture population and the increase of GDP decrease agriculture's water use.
5.3			Studied the spatial region agriculture water effect agriculture water. Spatial agriculture factors affect agricultural water. spatial urban factors contribute to agriculture development, spatial agriculture development decreases agriculture water supply internalization
5.4			Studied the different crop typology effects and found the effect crop typology change has effects on agricultural water. Traditional plant area has effects. Increase in area leads to increase in water use. Vegetable area increase will decrease water use.
5.5	Different water use sectors	Antoci et al. (2017)	al.Use theory study in the empirical analysis. They studied that water use conflicts in competing water use sectors can lead to economic conflicts and argued that water pricing would regulate them. I conducted an extended study. Between the two sectors of competing water use Specifically, to urban water consumption versus agricultural water use. Urban and agricultural areas have not only competed for water uses but also conflicting economic development issues. At the same time, there is a more visible pricing system for urban water use. It was found that there is an increasing relationship between urban and rural water use and that urban water consumption is spatially influenced by rural water consumption.

## 6 Conclusion

This study focuses on three aspects. Based on the objectives of our study, we have the following conclusions

1 How can we comprehensively measure water quality and water quantity to address water vulnerability? shown in chapter 3. It includes 3 aspects. 1 Use two kinds of indicators to measure the urban water environment. 2 Study the water environment in a different region. 3 province-level urban water environment and city-level water environment.

Two different indicators were calculated. In two different cities inland from the coast in a coastal province, the water environment in these two cities is not very different. In cities in different provinces, the difference is large

2 Measure the diverse characteristics of urbanization in water analysis, answering question 2, shown in chapter 4. It includes two aspects 1 Create an urban water vulnerability indicator. 2 Conduct spatial-temporal analysis.

The indicator system comprises the development pressure and management capability domains. The calculation results showed that the UWRVI and its sub-domains have different regional characteristics because of the unbalanced distribution of natural resources and unbalanced development.

3 Exploring the factors that are important among the changes in social structure on agricultural and urban water security. Answer question 3, shown in chapter 5. It includes 3 aspects. 1 Analyze urban and agricultural water interactions. 2 Identify factors influencing urban water security. 3 Identify factors influencing rural water security.

An increase in agricultural GDP and a decrease in the agricultural population lead

to a decrease in agricultural water supply internalization. Urban activity has system effects on agricultural water supply internalization. Urban water supply internalization has effects on agricultural water supply internalization. Urban development contributes to agricultural development and competing agricultural resource. Agriculture aggregation reduces agricultural water supply internalization, increasing agricultural water sustainability.

Humans need to reduce water use to make the environment sustainable while retaining sustainable development. Currently, China uses water transfer to relieve water stress. Long-distance water transfer project, such as the South to North Water Transfer Project, is one of the foundations of water policy. However, it may lead to water allocation problems, incurring further contradictions in different areas and industries.

In general, urban development is beneficial for agricultural development. Meanwhile, this environment restricts agricultural development. Balancing human society through agriculture and urban sectors is necessary. In addition, achieving region corporation is needed.

In the agriculture sector, which is the development of advanced agriculture, efficiency needs to be enhanced under the situation of the agricultural pattern of the low agricultural population and high agricultural value. There are two types of methods. First, agriculture should increase agricultural GDP and decrease the agricultural population. The technology needs to be improved. Mensah (2019) emphasized the importance of technology. Second, the plant structure must be adjusted. This led to suitable agricultural strategies and transformed urban service-oriented agriculture.

In terms of the relationship with urban water, urban and agricultural water need to be balanced under integrated water resource management. They do not compete, and so the increase in urban water uses and rural water use puts more pressure on long-distance

water transfers. Long-distance water transfers bring many economic and ecological costs. The Global Water Partnership (GWP, 2000) defines integrated water resource management (IWRM) as “a process which promotes the coordinated development and management of water, land, and related resources to maximize the resultant economic and social welfare equitably without compromising the sustainability of vital ecosystems.” Both the increase in urban population and urban GDP will increase urban water supply internalization. Urban areas need to improve urban water use patterns and increase their efficiency.

Urban development contributes to the development of agriculture while taking away agricultural resources. Agriculture should be developed in accordance with urban development. At the same time, agricultural production efficiency should be enhanced.

In terms of regional cooperation, the government should encourage the aggregation of agriculture and water-saving cooperation. Development of urban agriculture and strengthening the coordination of different cities are necessary. Strengthening regional agricultural cooperation will promote agricultural development.



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