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Type Drive Analysis of Urban Water Security Factors

Li Gong*, Hong Wang*, Chunling Jin*, Lili Lu*, and Menghan Ma*

Abstract

In order to effectively evaluate the urban water security, the study investigates a novel system to assess factors that impact urban water security and builds an urban water poverty evaluation index system. Based on the contribution rates of Resource, Access, Capacity, Use, and Environment, the study adopts the Water Poverty Index (WPI) model to evaluate the water poverty levels of 14 cities in Gansu during 2011–2018 and uses the least variance method to evaluate water poverty space drive types. The case study results show that the water poverty space drive types of 14 cites fall into four categories. The first category is the dual factor dominant type driven by environment and resources, which includes Lanzhou, Qingyang, Jiuquan, and Jiayuguan. The second category is the three-factor dominant type driven by Access, Use, and Capability, which includes Longnan, Linxia, and Gannan. The third category is the four-factor dominant type driven by Resource, Access, Capability, and Environment, which includes Jinchang, Pingliang, Wuwei, Baiyin, and Zhangye. The fourth category is the five-factor dominant type, which includes Tianshui and Dingxi. The driven types impacting the urban water security factors reflected by the WPI and its model are clear and accurate. The divisions of the urban water security level supply a reliable theoretical and numerical basis for an urban water security early warning mechanism.

Keywords

Water Poverty Index (WPI), Type Drive, Urban, Water Security

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1. Introduction

Urban water security is an important part of regional water security that guarantees harmonious development of the urban economy, society, and ecology. In order to further analyze the connotations and denotations of urban water security, it should be studied not only in the hydroscience field but also in the fields of economics, environmental science, safety science, and geography. The Water Poverty Index (WPI) theory expands research on water security from the single field of water resources to comprehensive urban development and the economy and society fields. By combining the exploitation, utilization, and management problems in water security with the water use approach, water use influence, and water use capability of human life, we try to supply new ways of thinking about water security problems and provide a theoretical basis for water security evaluation and new approaches for solving urban water security problems.

Based on the water poverty theory framework, this study uses an urban area to investigate water

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Corresponding Author: Li Gong (gongl@mail.lzjtu.cn)
* School of Civil Engineering, Lanzhou Jiaotong University, Lanzhou, China (gongl@mail.lzjtu.cn, 643255901@qq.com, jinchunling@mail.lzjtu.cn, 805746509@qq.com, 1906941296@qq.com)

security drive factors. It uses the least variance method to analyze driving types affecting urban water security and supplies a new way of thinking about water security theory development.

In urban water security research, early scholars focused on water security in relation to natural hazards, such as flooding, drought, river diversions, and so on. Attention on water security has become much greater with the development of the social economy and in-depth scientific research [1,2]. Jin and Gong [3] adopted the improved pressure-state-response (PSR) model to evaluate the water security state in Lanzhou. Gong and Jin [4] conducted deep research on the water security evaluation index and proposed evaluation indicators that are adapted to the urban security state in China. De Souza et al. [5] combined the institutional matrix with environment monitoring tools to visualize potential pollution sources related to the regulation and management of apartments. Wang and Chen [6] applied the krill foraging algorithm to optimize the maximum entropy projection pursuit model to evaluate regional water security. Marcantonio [7] studied cross factors that impact water security. Wang et al. [8] used the Dempster composition rule of evidence theory and proposed the multi-factor information fusion theory to evaluate urban water security. Alekseev et al. [9] applied the fuzzy logic element in the plant–soil–air system to conduct a water security evaluation. Mohammed et al. [10] combined the artificial neutral network (ANN) and support vector machine (SVM) to predict water security in the conduit.

This study considers urban water security problems including resource shortage, pollution, flooding, drought, and sudden water events. Urban water security in the external form includes water quality security, water quantity guarantee security and disaster prevention. The extension of urban water security includes all kinds of social urban water security caused by having less water, more water, or viscous water. The key components are urban ecology security, economy security, and society security.

2. The Research Method and Data Sources Used to Assess Urban Water Security

2.1 Water Poverty

In 2002, Lawrence et al. [11] from the Center for Ecology and Hydrology (CEH) first proposed the conception of the WPI. The so-called WPI is a parameter that can be used to evaluate water pressure and water scarcity. It is an interdisciplinary definition that combines the naturally acquired water characteristics with socioeconomic variables to reflect the water poverty degree. Originally, WPI model was used to estimate the influence of the water resource scarcity degree on social economic development. The WPI has high practicability and applicability as well as being easy to understand and calculate.

The WPI calculates factors with different scale spaces and broad applicability. In order to easily obtain the data for each indicator included in the WPI, the WPI is usually applied in a country or a region. The indicator data differ among different countries and regions. The function of the WPI in the water security field is similar to that of the Consumer Price Index (CPI) in the economic field. The CPI is the barometer of economy development. Similarly, the WPI is the standard evaluation model for water industry development, and water resource management can better satisfy the urban water security demand when it is used. WPI includes five sub-indexes: *Resource* (R), *Access* (A), *Use* (U), *Capacity* (C), and *Environment* (E). The range of the WPI and its sub-indexes is [0,100]. The larger the value, the better the water resource is. The contents of the WPI and its sub-indexes are shown in Table 1 [12]. This study adopted the following WPI formula to calculate WPI:

$$WPI = \frac{w_r R + w_a A + w_c C + w_u U + w_e E}{w_r + + w_a + w_c + w_u + w_e} \tag{1}$$

where w_r, w_a, w_c, w_u, and w_e are the weights of every subsystem. When w_r, w_a, w_c, w_u, and w_e are set to 1, we have

$$WPI = \frac{R + A + C + U + E}{5} \tag{2}$$

Table 1. Data and calculation methods for the subsystems of the Water Poverty Index (WPI)

WPI subsystem	Calculation method and basis	Indicators in China	Weights	Value
Resource (R)	Surface water evaluation by hydrology	Quantity of surface water resources (m^3)	0.539	Positive
	Quantitative and qualitative evaluation of resources	Water supply to demand ratio (%)	0.245	Positive
	Underwater evaluation by hydrogeology	Overdraft rate of groundwater (%)	0.126	Negative
	Quantitative and qualitative evaluation of water quality	Qualified ratio of drinking water quality (%)	0.090	Positive
Access (A)	Access to clean water	Ratio of tap water users to the total population	0.256	Positive
	Access to water	Urban water use popularizing rate	0.256	Positive
	Ratio of member of the population with access to health facilities compared with the total population	Urbanization rate (%)	0.345	Positive
	Access to irrigation	Irrigation area rate (%)	0.143	Positive
Utility (U)	Per capita household water consumption	Per capita daily domestic water use (L/person per day)	0.324	Positive
	Per capita agricultural water consumption	Water consumption per agricultural area unit (m^3/ha)	0.126	Negative
	Per capita industrial water consumption	Industrial water consumption per 10^4 Yuan output ($m^3/10^4$ Yuan)	0.211	Negative
	Time of water collection	Water efficiency (%)	0.339	Positive
Capacity (C)	GDP per capita	Water consumption per 10^4 Yuan GDP ($m^3/10^4$ Yuan)	0.235	Negative
	Education level	College students per 10^4 people (/10^4 people)	0.156	Positive
	Household consumption level	Urban family annual income (Yuan per year)	0.246	Positive
	Gini coefficient	Urban Engel coefficient (%)	0.256	Negative
	Health indicator	Infant mortality	0.107	Negative
Environment (E)	Water quality observation	Comprehensive pollution index of surface drinking water	0.356	Negative
	Environment management and governance	Urban domestic sewage treatment rate (%)	0.321	Negative
	Water pollution load	Industrial wastewater emission amount of particular pollutants	0.134	Positive
	Biological diversity	Green coverage ratio (%)	0.189	Positive

2.2 Least-Square-Error Method

The American geographer John C. Weaver first proposed the least-square-error (LSE) method for use in agricultural zoning [13]. Variance occurs as the sample data fluctuate around their average number, and this method shows trends in data dispersion. Generally, the variance of a set of data decreases at first and then increases. The minimum variance denotes the minimum deviation value between the actual distribution and theoretical distribution. Generally, the minimum variance value reflects the actual state of a certain region [14].

The judgement of the main driving factors for water poverty conditions requires a standard to be built. According to the ideal division standard of Weaver, the scores of theoretical data and actual water poverty conditions differ, so it is inaccurate to directly use them. Thus, the minimum variance theory was introduced. When the variance is minimum, the theoretical value is closest to the actual value. We calculated the contribution rates of the subsystems of water poverty based on the minimum variance method and sorted them by size. The specific method used was as follows:

(1) Obtain the ideal value of each subsystem. When the driving factor is 1, the ideal value of a subsystem with the maximum contribution rate is 100%, while the rest of the ideal values are 0.
(2) Calculate the absolute value of the difference between the ideal value and the actual value.
(3) Calculate the quadratic sum of all absolute values in the subsystem.
(4) Calculate the average value of all quadratic sums.

The average value is the variance when the driving factor is 1; it is also called single factor driving. The subsystem number when the variance is the smallest is the main driving factor number of water poverty. So, the variance when the driving factor is 2, 3, 4, and 5 is dual factor driving, three factor driving, and so on.

2.3 Data Standardized Method

The range standardization processing method was conducted on all factors, and the higher the score was, the lower the water poverty degree was. The standardized data y_{ij} obtained by range transform was $0 \leq y_{ij} \leq 1$. The calculation transforms the forward and backward factors to the forward factors, so it is good for subsequent judgment. For the forward factor, the larger the factor is, the greater its positive contribution to the system is, as shown in Fig. 1. For the backward factor, the larger the factor is, the greater its negative contribution to the system is, as shown in Fig. 2.

For the forward factor, the calculation formula is

$$y_{ij} = \frac{x_{ij} - \min\limits_{1 \leq j \leq n}(x_{ij})}{\max\limits_{1 \leq j \leq n}(x_{ij}) - \min\limits_{1 \leq j \leq n}(x_{ij})} \tag{3}$$

For the backward factor, the calculation formula is

$$y_{ij} = \frac{\max\limits_{1 \leq j \leq n}(x_{ij}) - x_{ij}}{\max\limits_{1 \leq j \leq n}(x_{ij}) - \min\limits_{1 \leq j \leq n}(x_{ij})} \tag{4}$$

where y_{ij} is the standardized value of the factor, x_{ij} is the value of the factor, and $\max(x_{ij})$ and $\min(x_{ij})$ are the maximum and minimum values of factor x_{ij}.

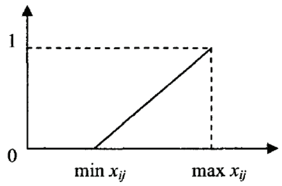

Fig. 1. Positive index.

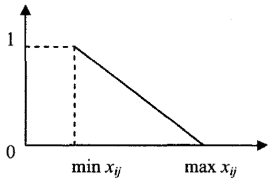

Fig. 2. Negative index.

3. Study Region Situation and Index System Construction

3.1 Region Situation

Gansu Province is located in the geographic center of China on the upper reaches of the Yellow River. The area of Gansu is 4.54 × 105 km^2. It is between longitudes 92°13′ and 108°46′ east and latitudes 32°11′ and 42°57′ north. The city is 130.8 km long from north to south and 94.8 km long from east to west. There are 14 cities in Gansu: Lanzhou, Baiyin, Dingxi, Wuwei, Tianshui, Longnan, Pingliang, Qingyang, Jinchang, Zhangye, Jiayuguan, Jiuquan, Linxia, and Gannan. The total annual runoff volume of rivers in Gansu is about 6.03 × 10^{10} m^3 with the total energy reserves being about 1.4264×10^7 kW. There are 78 rivers with a runoff volume of 1 × 10^8 m^3 from all rivers in Gansu. The water resources in Gansu are divided into 3 basins—the Yellow River, Changjiang River, and inland rivers—which include 9 river systems.

3.2 WPI System and Weight

3.2.1 WPI system

In the WPI system, the indicators differ in different regions and countries and are determined by the conditions there. The indicators have different degrees of importance and contribution rates in water security evaluation. In the calculation, two parameters, weight and value, show the contribution rates of the indicators. This study performed a series of improvements and adjustments to the original WPI and theory system.

3.2.2 Calculation of weights

The eigenvalue method was adopted to calculate the weights. Fig. 3 shows a flow chart of the eigenvalue method. The calculation results are shown in Table 1.

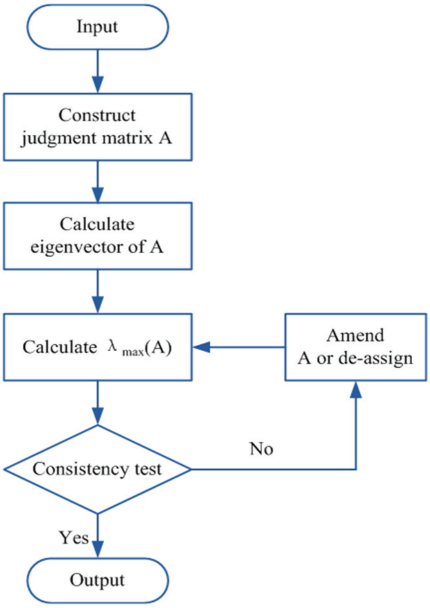

Fig. 3. Flow block diagram of the eigenvalue method.

3.3 Water Poverty Level and Driving Type

According to the WPI evaluation index system, we calculated the water poverty level and driving type of 14 cities in Gansu. The computation process is shown as follows:

(a) Normalization processing was conducted on all indicators. A lower score indicated poorer water, meaning that the indicator should be processed by cost standardization. A higher score indicated richer water, meaning that the indicator should be processed by efficiency standardization.

(b) The eigenvalue method was adopted to calculate the weights of the indicators in the WPI subsystem, and we obtained the evaluation scores of five subsystems for 14 cities in Gansu province.

The weights were calculated by the eigenvalue method, and then the indicators were weighted and processed by the following steps.

(c) The weighted sum of the scores of all subsystems was calculated to get the total score of the WPI for each city. Finally, standardization processing was conducted on the scores of all subsystems. The proportion of each weighted subsystem score from the total score of WPI was determined to get the water poverty driving effect contribution degree of each subsystem.

(d) The contribution rate of each subsystem was determined by the least variance method to obtain the water poverty driving types of 14 cities in Gansu. The results are shown in Table 2.

Table 2. WPI values, driving effect contribution rates, and driving effect types of 14 cities in Gansu

Rank	City	Scores of WPI	Drive type	R_{ef}%	A%	C_{ef}%	U_{ef}%	E_{ef}%
1	Jinchang	65.36	Four factors	26.21	38.25	12.55	15.67	7.32
2	Jiuquan	60.22	Dual factors	35.25	4.26	40.12	9.14	11.23
3	Lanzhou	59.14	Dual factors	26.31	12.54	12.63	17.28	31.24
4	Jiayuguan	58.24	Dual factors	12.36	29.31	32.44	15.40	10.49

Table 2. (Continued)

Rank	City	Scores of WPI	Drive type	$R_{ef}\%$	$A\%$	$C_{ef}\%$	$U_{ef}\%$	$E_{ef}\%$
5	Pingliang	51.86	Four factors	13.23	9.12	35.47	14.25	27.93
6	Longnan	48.38	Three factors	47.32	13.45	11.25	10.21	26.77
7	Baiyin	47.68	Five factors	18.46	19.24	20.21	22.38	19.71
8	Zhangye	46.52	Four factors	20.21	15.21	17.24	30.21	17.13
9	Linxia	46.3	Three factors	28.19	10.21	4.21	7.29	50.10
10	Wuwei	44.98	Four factors	12.26	31.25	20.27	26.97	9.25
11	Tianshui	44.18	Four factors	28.27	15.58	19.25	18.88	18.02
12	Gannan	41.2	Three factors	27.14	9.25	6.19	8.26	49.16
13	Qingyang	39.58	Dual factors	18.52	14.38	29.34	23.36	14.40
14	Dingxi	33.78	Five factors	17.25	21.25	17.64	20.15	23.71
	Gansu	49.10	Four factors	17.17	25.14	19.53	25.14	13.02

4. Result Analysis

4.1 Water Poverty Degree Analysis

According to the calculation results, the score range of water poverty for the 14 cities in Gansu is 33.78–65.3. The lower the score, the more severe the water poverty state is. We statistically analyzed the WPI scores of 14 cities in Gansu and classified the water poverty degree by the clustering method. The clustering analysis results show that the water poverty degree falls into five levels: No Water Poverty, Slight Water Poverty, Moderate Water Poverty, Serious Water Poverty, and Extreme Water Poverty. Of the 14 cities, only Jinchang was identified as a No Water Poverty region. The results are shown in Fig. 4.

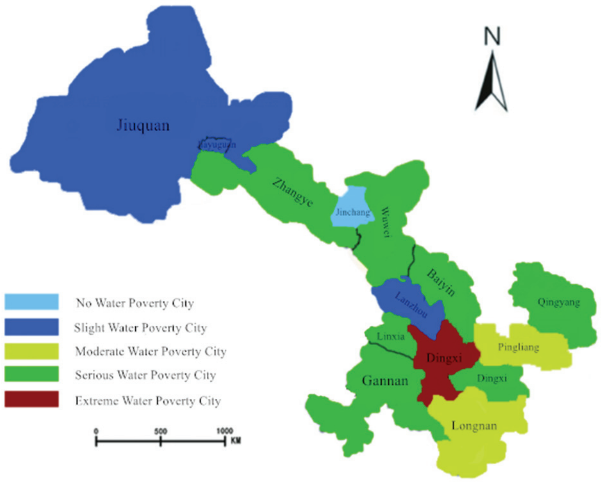

Fig. 4. Water poverty levels of 14 cities in Gansu.

4.2 Spatial Drive Type Analysis

In order to further analyze the causes of water poverty and the spatial drive types, the least variance method was adopted to calculate the *Resource*, *Access*, *Use*, *Capacity*, and *Environment* factors of 14 cities. The results are shown in Fig. 5.

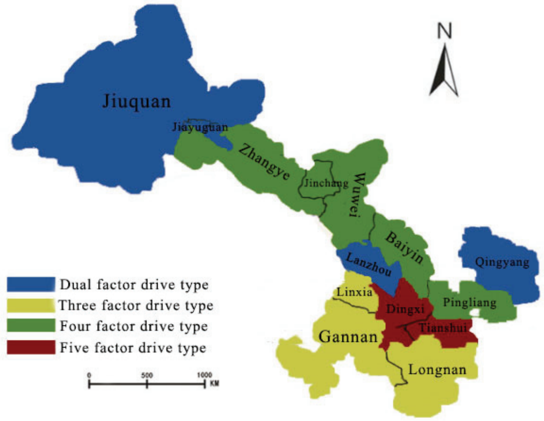

Fig. 5. Water poverty drive types in Gansu.

4.2.1 Dual factor drive type regions

In dual factor drive type regions, the water poverty state is dominated by the *Resource* drive effect and the *Environment* drive effect. The dual factor drive type regions include Lanzhou, Jiayuguan, Qingyang, and Jiuquan. These four cities have relatively higher social and economic levels and greater scientific and technological strength. As the provincial capital, Lanzhou is regulated and controlled by the government and has many high schools. So, its water use efficiency is high, and its domestic water, industrial and agricultural water, and water facilities level are the best in Gansu. While Lanzhou has a large population, the per capita water resources quantity is in the water-deficient area, especially considering the dual water shortage for the population and zoology. Economic development puts a large amount of pressure on water resources, so Lanzhou is a *Resource* type water shortage city. Water development and use are high in Jiayuguan and Jiuquan, and the ecological environment load of the two cities is heavy. These two cities should enhance their input and management to control agricultural pollution and improve the water quality. After comprehensively comparing various factors, water shortage and ecological environment deterioration were identified as the dominant factors causing water poverty. Water quantity in Qingyang is limited, rainfall is scarce, the distribution of runoff is uneven, the mineralization of rivers is high, and the water quality is weak, so input into improving the water quality and ecology should be increased.

4.2.2 Three factor drive type regions

Three factor drive type regions include Longnan, Linxia, and Gannan, which are dominated by *Access*, *Use*, and *Capacity* drive effects. The three cities have a good water resource basis, low pressure, and a complete ecological environment. However, the social and economic development levels of the three cities are low—they are in the last three positions in Gansu—so the urban sewage treatment is low, the density of the drainage system is low, and the production capacity and government finance self-sufficient ability are low. In particular, the technology and education levels in Linxia are low. Meanwhile, agricultural water consumption is large, representing a large proportion of the total water consumption. Additionally, the agricultural water use efficiency is not high and the industrial water reuse rate is very low. So, these cities reduce their water poverty level by improving their overall social level and adaptive capacity, and social economic development comes at the cost of damaging the ecological environment.

4.2.3 Four factor drive type regions

The four factor drive type regions include five cities—Jinchang, Pingliang, Wuwei, Baiyin, and Zhangye—which are dominated by the *Resource, Access, Capacity,* and *Environment* drive effects. These cities have a weak water resource basis and low water distribution density, and they are zoological shortage regions. The characteristics of these cities are that they have small populations and higher per capita water quantities than the extreme water shortage standard. Self-financing of the local government is weak, the social economic development level is low, the per capita total output value is low, and the ratio of governmental expenditure to the GDP is high. The levels of science and education are low, the illiteracy rate is high, and the undergraduate proportion is at a low level in China. Their total water use efficiency is low, the main water use is agricultural water use, the per mu irrigation water use quantity is high, and the level of agriculture development is low, so there is no clear better trend to represent the state of these regions. The control rate of urban industrial sewage treatment is low, and drainage facilities require improvement. In Zhangye, the water use rate is high, so it relieves the water use pressure to some extent. In Pingliang, there is a weak water resource state, and its level of hydraulic engineering facilities is low.

Inadequate natural endowment is a common phenomenon, leading to the day after tomorrow disorder and whole body ill hydraulic engineering. For hydraulic engineering in Pingliang, one-third of systems are in the normal operating state, one-third are in a sick running state, and one-third are in an outage or scrap state. Of the 32 reservoirs in Pingliang, there are 17 sick and dangerous reservoirs which not only cannot store water normally but also carry potential risks. In Jinchang, the water resource occupation rate is low, but the per capita water consumption, irrigation norm, GDP water consumption, and water resource development rate are high. In particular, the water resource development rate is the highest in the country. So, the water poverty state is collaboratively driven by the factors *Resource, Access, Capacity,* and *Environment*. The self-social adaptability in the above cities should be improved to relieve water poverty.

4.2.4 Five factor drive type regions

Five factor drive type regions include two cities, Tianshui and Dingxi, which are dominated by *Resource, Access, Capacity, Use,* and *Environment* drive effects. The water resource bases of the two cities are different, but the five subsystems have the same drive effects on the water poverty conditions. The results analysis of the 14 cities in Gansu showed that the water basis of Tianshui is better, and infrastructure construction, the economy development level, and the ecological environment are better without obvious weaknesses. In contrast, Dingxi has bad natural conditions, a weak resource base, a low economy level, and weak capability and infrastructure. All factors related to its subsystems need to improve. So, the water poverty state is collaboratively driven by five subsystems.

5. Conclusion

This study constructed an index system containing five subsystems with 21 factors. The water poverty degrees of 14 cities were calculated and analyzed. The following conclusions were made:

(1) Supported by the WPI theory and the least square method, this study took the cities as objects and analyzed the contribution rates of five subsystems—*Resource*, *Access*, *Capacity*, *Use*, and

Environment—in the urban water poverty state. In this study, the drive types were divided into four categories: the dual factor drive type, the three factor drive type, the four factor drive type, and the five factor drive type. All of them were shown to better reflect the water poverty drive factors and special distribution states. The research supplies the necessary data and theoretical basis for water resources management departments to conduct water management and make decisions.

(2) The evaluation index system in this study began with the five subsystems of *Resource*, *Access*, *Capacity*, *Use*, and *Environment* and combined the status of cities in China to determine the 21 main factors that lay a foundation for urban water poverty evaluation.

(3) The spatial distribution of water poverty drive types shows that *Resource* is the drive factor for the water poverty state in most cities in Gansu, denoting the weak water resource base across the whole of Gansu. In the cities with a low economy development level, *Access* and *Capacity* are the main drive factors of the water poverty state. In cities with a better water resource base in Gansu, *Use* is the main drive factor of the water poverty state for the lower development levels there.

(4) The water poverty space drive types of 14 cites in Gansu fall into four categories. Driven by environment and resource, the dual factor dominant type cities include Lanzhou, Qingyang, Jiuquan, and Jiayuguan. Driven by Access, Use, and Capability, the three factor dominant type cities include Longnan, Linxiam and Gannan. Driven by *Resource*, *Access*, *Capacity*, and *Environment*, the four factor dominant type cities include Jinchang, Pingliang, Wuwei, Baiyinm and Zhangye. The five factor dominant type cities include Tianshui and Dingxi. The drive types impacting the urban water security factors reflected by WPI and its model are clear and accurate. The divisions of the urban water security levels act as a reliable theory and numerical basis for an urban water security early warning mechanism.

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Li Gong **https://orcid.org/0000-0002-4824-5109**

He received B.S. degree in North China University of Water Resources and Electric Power in 2000, M.S. degree in Northwest A&F University in 2007, and a Ph.D. degree in Lanzhou Jiaotong University in 2014. Now he is a professor at the School of Civil Engineering, Lanzhou Jiaotong University, Lanzhou, China.

Hong Wang **https://orcid.org/0000-0003-0234-3851**

Since September, 2018, he is from Lanzhou Jiaotong University as a M.S. candidate. And he is with the School of Civil Engineering, Lanzhou Jiaotong University, Lanzhou, China.

Chunling Jin **https://orcid.org/0000-0002-8068-0055**

She received B.S. degree in North China University of Water Resources and Electric Power in 2000, and the M.S. degree in Lanzhou Jiaotong University in 2005. She is a professor at the School of Civil Engineering, Lanzhou Jiaotong University, Lanzhou, China.

Lili Lu **https://orcid.org/0000-0002-0592-6692**

Since September, 2018, she is from Lanzhou Jiaotong University as a M.S. candidate. And she is with the School of Civil Engineering, Lanzhou Jiaotong University, Lanzhou, China.

Menghan Ma **https://orcid.org/0000-0002-9597-7214**

Since September 2018, she is from Lanzhou Jiaotong University as a M.S. candidate. And she is with the School of Civil Engineering, Lanzhou Jiaotong University, Lanzhou, China.