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Regional Assessment of Land and Water Carrying Capacity and Utilization Efficiency in China

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Abstract: In response to the severe situation of water and land resources in China, this paper uses the DPSIR (driving force–pressure–state–impact–response) model and two-stage network DEA (data envelopment analysis) model to evaluate the carrying capacity and utilization efficiency of land and water resources in 31 provinces of China from 2009 to 2017. The empirical results show that the carrying capacity and the efficiency values of land and water resources in most areas of China do not perform well and show a downward trend during the sample period. Specifically, the carrying capacity of land and water resources show a decreasing trend from north to south and from east to west. In addition, the response to the current situation of land and water resources has an important influence on the carrying capacity. The utilization efficiency of water and soil resources is significantly different in the two stages in most regions, indicating that the efficiency of economic benefit transformation is far greater than land and water resources development. Our results shed some insights on land and water utilization efficiency management and provide political recommendations for different regions.

Keywords: carrying capacity; DPSIR model; network DEA model; utilization efficiency

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1. Introduction

With the rapid growth of population and industrialization, as well as urbanization, global water and land resources security is facing severe challenges [1,2]. From the perspective of production function, expanding the number of production factors and improving the utilization efficiency of production factors are the two main driving forces of economic growth [3]. In the past rough economic growth mode, land and water resources have been widely used as major inputs in industrial manufacturing, agricultural production, and urban infrastructure construction. However, the economic growth mainly depends on increasing the amount of water and land resources to improve the output value, which could further aggravate the deterioration of the environment such as serious land erosion, land desertification, and water resource depletion. The contradiction between natural resource consumption and economic development has increasingly become the focus of scholars and policy-makers.

As a developing country, China, has the largest population in the world, with only a quarter of the world's per capita water resources and less than a third of the land area [4]. Some policies and regulations are made by the Chinese government to realize "high-quality development" with lower resources consumption. However, due to the imbalance of economic development and spatial distribution of resources, there is a significant regional difference in terms of water and land resources usage pattern. For example, the distribution of water resources in the south of China is much more abundant than that in the north region. It is necessary to make individual regulations for different areas by fully considering the condition of resources' carrying capacity and utilization performance for each area.

The carrying capacity of water and land resources are two important indicators to measure the space of regional development. Water resources carrying capacity refers to the reasonable scale that enables regional water resources system to support sustainable social and economic development under a certain level of economic, social, and technological development [5,6]. Additionally, UNESCO defines the land resource carrying capacity as "the intensity of human activities that can be carried by a region while maintaining an acceptable standard of living" [7]. However, the water resources and land resources should be combined and used together in the real-life world. In this way, the comprehensive carrying capacity of land and water resources can be defined as the maximum supporting capacity that can provide for the social and economic development of each region corresponding to its resource endowment and utilization efficiency under existing strict environmental regulations.

The majority of existing studies have only focused on the evaluation of the carrying capacity with a single factor, in which water resources and land resources carrying capacity are usually considered as independent systems to conduct evaluation, respectively. This paper intends to use the DPSIR model and the network DEA model to analyze the carrying capacity and utilization efficiency of water and land resources. The structure of this paper is organized as follows. Corresponding studies have been reviewed in Section 2. Section 3 describes the methodology and the data sources. Section 4 presents the analysis of the empirical results. The last section concludes the main findings and provides policy implications.

2. Literature Review

Some scholars have performed research to analyze the capacity of water resources or land resources. Dou et al. established a distributed quantitative model to analyze the water resources' carrying capacity of 60 districts in Henan province during different development periods [8]. Deng et al. quantified the water resource carrying capacity of the Hanjiang River Basin in China and predicted that the water consumption would be on the rise in 2035 while the water resource carrying capacity would decline [9]. In terms of land carrying capacity, Luo et al. investigated the evolution of China's land carrying capacity from the perspective of carrier-load [10]. Xue et al. established a three-stage mixed model to evaluate the comprehensive carrying capacity of land resources in Yangtze River Delta urban agglomeration and further determine the key factors affecting the carrying capacity [11]. Most of the existing research about carrying capacity calculation has been operated from the angle of resource endowment while utilization efficiency should be another important factor in determining resource carrying capacity.

In addition to the carrying capacity of land and water resources, many studies have focused on measuring the utilization efficiency of water and land resources combining with some output variables. The efficiency of resource utilization can be interpreted as producing the same quantity of goods and services with fewer resources or producing more output with a certain quantity of resources [12]. Most of these studies use a DEA (data envelopment analysis) approach to compute the efficiency of land and water resources, because it could measure multiple input and output variables without considering the functional relationship between input and output. For example, Ali and Klein used the DEA model and Malmquist index to estimate the agricultural water use efficiency of agricultural irrigation areas in southern Alberta from 2008 to 2012 [13]. Xie et al. used the super-efficiency slack-based measurement (SBM) model to calculate the land-use efficiency [14]. There is a lack of study about measuring the comprehensive carrying capacity of water and land resources.

The conventional methods for evaluating resource carrying capacity include the comprehensive index evaluation method [15,16], multiple objective decision method [17], principal component analysis [18], TOPSIS (technique for order preference by similarity to an ideal solution) method [19,20], and PSR (pressure state response) method [4]. The DPSIR model (driving force pressure state impact response framework) is an extension of the PSR model proposed by the OECD (Organization of Economic Cooperation and Development), which improves the comprehensiveness of the index system and has been widely applied in ecology, environment, and resources studies. [21–23] since the DPSIR model is suitable for dealing with complex feedback systems, which could be used to evaluate and analyze the carrying capacity of the integrated system of land and water resources.

It is obvious that measuring the carrying capacity of resources is an important research topic for maintaining regional sustainable development. However, few studies can calculate a comprehensive carrying capacity for both water and land resources. In order to fill the research gaps and satisfy practical needs, this paper will analyze the carrying capacity and utilization efficiency of water and land resources in China by using the DPSIR and network DEA model. Our empirical analysis is considerably different from existing studies in at least two aspects. On one hand, while existing studies employ the DPSIR model to analyze the carrying capacity of water or land resources in a local region, we study the carrying capacity of both water and land resources at a whole national level in China. On another hand, in terms of the utilization efficiency of water and land resources, various studies treat the production process as a "black box" while the internal structure of the production process is ignored. Thus, we introduce the network DEA model by dividing the whole production process into the resource exploitation sub-process and the transformation of the economic benefit sub-process.

3. Research Methods and Data Sources

3.1. Evaluation System for the Water and Land Resource Comprehensive Carrying Capacity

It is an integral problem-building tool that can be used to integrate knowledge from multiple disciplines to provide information and support for motivational decision-makers [24–26]. The key strength of this framework is that it can identify relationships in environmental management by establishing causal chains from 'driver forces', which put 'pressures' in the 'state' of society, thereby leading to certain 'impacts' that will lead to various 'responses' [27,28]. It is widely used in the study of environmental system evaluation due to its advantages in constructing complex environmental problems and determining solutions [29,30]. To be specific, in order to explore the carrying capacity of land and water resources, this study uses the DPSIR framework to divide the evaluation index of a natural system into five parts, including the driving force layer, the pressure layer, the state and the impact layer, and the response layer. The driving force layer (D) represents the factors for the change of land and water resources carrying capacity caused by human activities. The pressure layer (P) represents the direct pressure of human beings on water and land resources. The state layer (S) represents the situation of water and land resources under the constant pressure of human beings on the environment. The impact layer (I) represents the reverse effect of the change of land and water resources on the development of human society and economy. The response layer (R) represents the actions that humans take in the face of current environmental conditions and bite back.

3.1.1. Constructing Index System

In accordance with relevant research, this paper selects 18 representative indicators to construct the evaluation index system of the land and water resources carrying capacity of 31 provinces in China from the five aspects of driving force, pressure, state, impact, and response. Specific indicators and measurement approaches are shown in Table 1.

Table 1. Specific indicators and measurement approaches related to the DPSIR model.

	Indicator Layer	Units	Calculation Approach
Driving force	Per capita cultivated land area	hm^2	Area of cultivated land of the year/total population of the year
	Per capita GDP	Yuan	GDP of the year/total population of the year
	Population density	Person hm^2	Total population/land area of the year
	Water resources per capita	m^3/person	Total water resources/total population of the year
	Proportion of natural wetland area	%	Current wetland area/land area
Pressure	Total social water consumption	100 million m^3	The total amount of industrial, agricultural, domestic, and ecological water of the year
	Natural population growth rate	%	Natural population growth of the year/average population
	Water consumption rate of ecological environment	%	Eco environmental water consumption/average water resources
	Development and utilization rate of land resources	%	Cultivated land area/land area in curren year
	Water consumption per capita	m^3/person	Total social water consumption/total population of the year
State	Matching coefficient of water and land resources	Ten thousand m^3 hm^2	Total water resources/cultivated land area of the year
	Proportion of effective irrigation area	%	Effective irrigation area/total sown area of the year
	Crop yield per unit area	Kg hm^2	Total crop yield/sown area
Impact	Urbanization rate	%	Current urban population/total population
	Multiple crop index		Total sown area/cultivated area
Response	Agricultural mechanization degree	Kw hm^2	Total power of agricultural machinery/cultivated land area
	Proportion of afforestation area	%	Total afforestation area/land area in current year
	Agricultural water quota	m^3·ten thousand yuan^{-1}	Agricultural water consumption/total agricultural output value

3.1.2. Determination of Index Weight

Because the units of various evaluation indexes are different, they cannot be directly compared when evaluating the carrying capacity of water and land resources. Therefore, we first standardize the indexes and convert them into dimensionless values in order to eliminate the influence of dimensions [31].

Then, the mean square deviation method is used to measure the difference degree of the index value according to the deviation degree of the data from the mean value and then determine the contribution degree of the index. The greater the difference degree, the greater the contribution, that is, the greater the weight. The specific formula is as follows:

$$E(G_j) = \frac{1}{n}\sum_{i=1}^{n} x'_{ij} \tag{1}$$

$$\sigma(G_j) = \sqrt{\sum_{i=1}^{n} [x'_{ij} - E(G_j)]^2} \tag{2}$$

$$W_j = \sigma(G_j) / \sum_{i=1}^{m} \sigma(G_j) \tag{3}$$

where $E(G_j)$ is the mean value of j indicator, x'_{ij} is the standardized value of the indicator, $\sigma(G_j)$ is the standard deviation of j indicator, and W_j is the weight of the j indicator.

With the calculated weight, we can use Formula (6) to obtain the comprehensive score of water and land resources carrying capacity of 31 provinces in China from 2009 to 2017, where L_i represent the carrying capacity value.

$$L_i = \sum_{j=1}^{m} x'_{ij} \times W_j \tag{4}$$

3.2. Two-Stage Network DEA Model with Undesirable Outputs

Since the use of land and water resources is a complex and mutually influencing process, the classic DEA models as the CCR or BCC model may lead to unreasonable evaluation of the use efficiency, and at the same time, much important information will be lost. Different from the above DEA models, which regard each DMU as a black box, the two-stage network DEA model will consider the internal structure of the DMU [32,33], where the DMU represents decision-making units; it refers to each province participating in the evaluation. Therefore, based on the macro-economic level and the characteristics of water and land resource utilization, we divide the water and land resource utilization system into two sub-stages: the water and land resource development stage and the transforming into economic benefits stage. On this basis, considering that the production process using resources contains undesirable outputs such as pollutants, a two-stage DEA model with shared inputs and undesirable outputs is constructed. The model structure is shown in Figure 1.

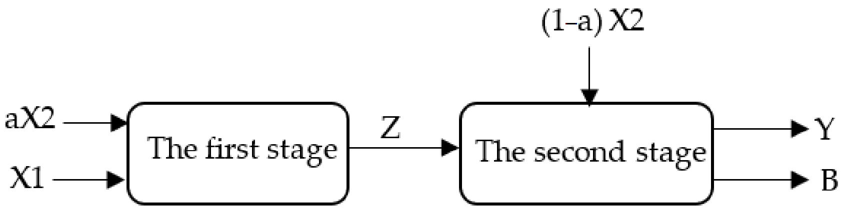

Figure 1. The two-stage DEA structure.

As shown in Figure 1, X1 represents independent input in the first stage, and X2 represents shared input. aX2 is used in the first stage of production, (1 − a) X2 is used in the second stage of production, where the "a" is the share ratio between the first and the second stages, between 0 and 1. Z represents intermediate outputs, which are obtained from the first stage production and enter into the second stage production as input, then the final desirable output Y and undesirable output B are obtained.

Based on the structure, a two-stage DEA model is constructed to calculate the sub-stage and overall efficiencies of water and land resources utilization. It is assumed that there are n DMUs, and each DMU has g independent input variables, m shared input variables, s final desirable output variables, t undesirable output variables, and q intermediate variables. α_i and

$1-\alpha_i$ ($0<\alpha_i\leq 1$, $i=1,2,\ldots,m$), respectively, denote the share ratio between the first and the second stages. The specific formula is as follows:

$$E_k=\max\frac{\sum\limits_{p=1}^{q}\omega_p^1 Z_{pk}+\sum\limits_{r=1}^{s}\mu_r Y_{rk}}{\sum\limits_{a=1}^{g}\lambda_a X_{ak}+\sum\limits_{i=1}^{m}\nu_i^1\alpha_i X_{ik}+\sum\limits_{i=1}^{m}\nu_i^2(1-\alpha_i)X_{ik}+\sum\limits_{p=1}^{q}\omega_p^2 Z_{pk}+\sum\limits_{b=1}^{t}\theta_b B_{bk}}$$
$$s.t.\begin{cases}\dfrac{\sum\limits_{p=1}^{q}\omega_p^1 Z_{pk}+\sum\limits_{r=1}^{s}\mu_r Y_{rk}}{\sum\limits_{a=1}^{g}\lambda_a X_{ak}+\sum\limits_{i=1}^{m}\nu_i^1\alpha_i X_{ik}+\sum\limits_{i=1}^{m}\nu_i^2(1-\alpha_i)X_{ik}+\sum\limits_{p=1}^{q}\omega_p^2 Z_{pk}+\sum\limits_{b=1}^{t}\theta_b B_{bk}}\leq 1, j=1,2,\cdots,n\\ \dfrac{\sum\limits_{p=1}^{q}\omega_p^1 Z_{pj}}{\sum\limits_{a=1}^{g}\lambda_a X_{aj}+\sum\limits_{i=1}^{m}\nu_i^1\alpha_i X_{ij}}\leq 1, j=1,2,\cdots,n\\ \dfrac{\sum\limits_{r=1}^{s}\mu_r Y_{rj}}{\sum\limits_{i=1}^{m}\nu_i^2(1-\alpha_i)X_{ij}+\sum\limits_{p=1}^{q}\omega_p^2 Z_{pj}+\sum\limits_{b=1}^{t}\theta_b B_{bj}}\leq 1, j=1,2,\cdots,n\\ 0<\alpha_i\leq 1,\nu_i^1,\nu_i^2,\lambda_a,\omega_p^1,\omega_p^2,\mu_r,\theta_b\geq\varepsilon; i=1,2,\cdots,m\end{cases} \tag{5}$$

where E_k is the objective function, i.e., the efficiency value, and X, Z, Y, and B represent input, intermediate output, expected output, and unexpected output, respectively. v_i^1 and v_i^2 are the weight of shared input between the first and second stages, respectively. λ_a is the weight of independent input in the first stage, ω_p^1 and ω_p^2 represent the weight of output and input of Z_{pj} in the first and second stages, respectively. μ_r and θ_b represent the weights of desirable and undesirable outputs in the second stage, respectively. ε is a small non-Archimedean number. According to the Charnes Cooper transformation, Model (5) can be simplified into the following mathematical programming model:

$$E_k=\max\sum_{p=1}^{q}W_p^1 Z_{pk}+\sum_{r=1}^{s}U_r Y_{rk}$$
$$s.t.\begin{cases}\sum\limits_{a=1}^{g}\lambda_a X_{ak}+\sum\limits_{i=1}^{m}\pi_i^1 X_{ik}+\sum\limits_{i=1}^{m}V_i^2 X_{ik}+\sum\limits_{i=1}^{m}\pi_i^2 X_{ik}+\sum\limits_{p=1}^{q}W_p^2 Z_{pk}+\sum\limits_{b=1}^{t}\delta_b B_{bk}=1\\ \sum\limits_{a=1}^{g}\lambda_a X_{aj}+\sum\limits_{i=1}^{m}\pi_i^1 X_{ij}-\sum\limits_{p=1}^{q}W_p^1 Z_{pj}\geq 0, j=1,2,\cdots,n\\ \sum\limits_{i=1}^{m}V_i^2 X_{ij}-\sum\limits_{i=1}^{m}\pi_i^2 X_{ij}+\sum\limits_{p=1}^{q}W_p^2 Z_{pj}+\sum\limits_{b=1}^{t}\delta_b B_{bj}-\sum\limits_{r=1}^{s}U_r Y_{rj}\geq 0, j=1,2,\cdots,n\\ \lambda_a, W_p^1, W_p^2, U_r, \delta_b\geq\varepsilon; V_i^2\geq\pi_i^2\geq\varepsilon; i=1,2,\cdots,m\end{cases} \tag{6}$$

Using linear programming (6), the optimal solution of the decision variable λ_a,$\alpha_i(\alpha_i=\frac{\pi_i^2}{V_i^2})$,$V_i^1(V_i^1=\frac{\pi_i^1}{\alpha_i})$,$V_i^2$,$W_p^1$,$W_p^2$,$\delta_b$ is obtained, then substituted into Equations (7) and (8) to obtain the efficiency values of the first and second stages of the production system, where E_k^1, E_k^2 is the efficiency value of the first and second stages, respectively, and the meaning of other variables is the same as Equation (5).

$$E_k^1=\frac{\sum\limits_{p=1}^{q}\omega_p^1 Z_{pk}}{\sum\limits_{a=1}^{g}\lambda_a X_{ak}+\sum\limits_{i=1}^{m}\nu_i^1\alpha_i X_{ik}}=\frac{\sum\limits_{p=1}^{q}W_p^1 Z_{pk}}{\sum\limits_{a=1}^{g}\lambda_a X_{ak}+\sum\limits_{i=1}^{m}V_i^1\alpha_i X_{ik}} \tag{7}$$

$$E_k^2=\frac{\sum\limits_{r=1}^{s}U_r Y_{rk}}{\sum\limits_{i=1}^{m}V_i^2(1-\alpha_i)X_{ik}+\sum\limits_{p=1}^{q}W_p^2 Z_{pk}+\sum\limits_{b=1}^{t}\delta_b B_{bk}} \tag{8}$$

3.3. The Data Source and Illustration of Variables

Considering the availability of data, combined with China's major policy planning in recent years, we finally chose the nine years of China's rapid economic development, and accurate data can be found for the research period. The data of 31 provincial administrative regions, including total water resources, land resources (land area), and index of carrying capacity of land and water resources, are collected from the National Bureau of Statistics, China Statistical Yearbook, from 2009 to 2017 and local statistical yearbooks. Additionally, the interpolation method is used to supplement some missing data.

In the development stage of land and water resources, water resources and total land area are the independent input indexes in the first stage, labor and fixed asset investment are the shared investment indexes, and water supply and construction land area are selected as the intermediate output indexes. Then, the intermediate output index, labor force, and fixed asset investment are taken as the input in the transformation stage of economic benefits. The total domestic production is viewed as the desirable output index of the second stage, and the total discharge of industrial wastewater, industrial waste gas, and industrial solid waste was taken as the undesirable output indexes of the second stage.

4. Results and Discussion

4.1. Analysis on the Results of Carrying Capacity of Water and Land Resources

By calculating Equations (1)–(4), the scores of the land and water-carrying capacity of each province from 2009 to 2017 can be calculated, respectively, and the results of 31 provinces are presented in Table 2. As shown in Table 2, the average values of all provinces in China range from 0.287 to 0.508, which means that regional difference widely exists. According to the Chinese government, the country is divided into four regions, i.e., the northeast region, east region, west region, and central region. Among the four regions, the east region has the highest comprehensive carrying capacity of land and water resources, followed by the central region, then the west region and the northeast region. Figure 2 shows the change trend of the average carrying capacity of water and land resources in four regions and the whole country from 2009 to 2017. The x-axis represents the year, and the y-axis represents the average carrying capacity score of regions. The results mean that the overall carrying capacity of land and water resources in China remains unchanged during 2009–2017. However, the carrying capacity shows a trend of first increase and then decrease for the northeast region, and the western region shows a stable trend, while the eastern and central regions show a fluctuating upward trend.

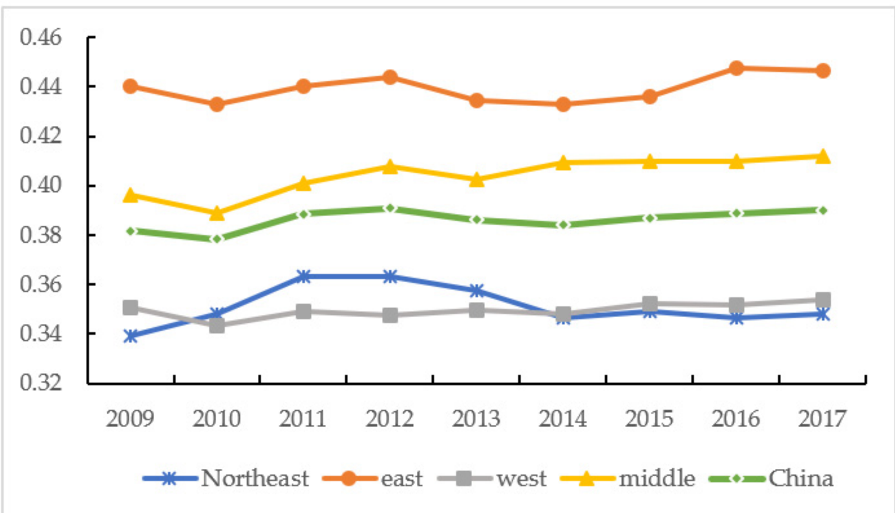

Figure 2. Annual changes in carrying capacity by regions.

Table 2. Comprehensive carrying capacity values of water and land resources in four regions.

		2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
Northeast	Liaoning	0.357	0.363	0.392	0.397	0.389	0.367	0.363	0.357	0.356	0.371
	Jilin	0.345	0.362	0.377	0.369	0.366	0.361	0.376	0.376	0.379	0.368
	Heilongjiang	0.316	0.319	0.321	0.324	0.317	0.311	0.309	0.306	0.309	0.315
East	Beijing	0.523	0.501	0.527	0.548	0.533	0.488	0.475	0.485	0.494	0.508
	Tianjin	0.518	0.499	0.492	0.477	0.462	0.465	0.453	0.476	0.488	0.481
	Hebei	0.453	0.441	0.45	0.456	0.451	0.458	0.444	0.463	0.447	0.451
	Shanghai	0.472	0.467	0.461	0.477	0.461	0.464	0.469	0.49	0.486	0.472
	Jiangsu	0.404	0.407	0.407	0.414	0.407	0.409	0.409	0.422	0.425	0.411
	Zhejiang	0.436	0.436	0.43	0.432	0.416	0.416	0.42	0.43	0.423	0.427
	Fujian	0.379	0.377	0.413	0.404	0.402	0.397	0.434	0.442	0.434	0.409
	Shandong	0.485	0.48	0.491	0.49	0.484	0.502	0.487	0.5	0.496	0.49
	Guangdong	0.37	0.374	0.378	0.384	0.373	0.378	0.411	0.404	0.405	0.386
	Hainan	0.362	0.347	0.355	0.358	0.356	0.349	0.359	0.365	0.365	0.357
West	Inner Mongolia	0.341	0.335	0.346	0.352	0.356	0.342	0.338	0.338	0.342	0.343
	Guangxi	0.332	0.321	0.323	0.326	0.327	0.323	0.331	0.33	0.335	0.328
	Chongqing	0.353	0.383	0.395	0.398	0.394	0.393	0.4	0.405	0.394	0.39
	Sichuan	0.304	0.292	0.3	0.292	0.296	0.293	0.308	0.321	0.329	0.304
	Guizhou	0.32	0.307	0.303	0.304	0.325	0.331	0.348	0.347	0.364	0.328
	Yunnan	0.326	0.311	0.315	0.313	0.313	0.308	0.317	0.317	0.313	0.315
	Tibet	0.483	0.487	0.496	0.493	0.494	0.494	0.499	0.517	0.504	0.496
	Shaanxi	0.344	0.323	0.338	0.339	0.34	0.34	0.338	0.328	0.33	0.336
	Gansu	0.29	0.281	0.292	0.288	0.287	0.286	0.294	0.282	0.286	0.287
	Qinghai	0.358	0.343	0.346	0.331	0.318	0.319	0.322	0.328	0.331	0.333
	Ningxia	0.409	0.39	0.395	0.404	0.403	0.4	0.386	0.382	0.381	0.395
	Xinjiang	0.351	0.346	0.338	0.333	0.346	0.345	0.348	0.323	0.334	0.34
Central	Shanxi	0.365	0.361	0.379	0.378	0.38	0.38	0.356	0.34	0.34	0.364
	Anhui	0.376	0.371	0.38	0.388	0.413	0.421	0.432	0.425	0.426	0.404
	Jiangxi	0.427	0.414	0.415	0.423	0.374	0.374	0.387	0.4	0.398	0.401
	Henan	0.476	0.441	0.451	0.452	0.446	0.456	0.446	0.446	0.45	0.452
	Hubei	0.344	0.352	0.362	0.373	0.381	0.388	0.391	0.39	0.404	0.376
	Hunan	0.389	0.394	0.419	0.433	0.421	0.436	0.447	0.458	0.454	0.428

Figure 3 visually shows the average carrying capacity of 31 provinces during 2009–2017. In order to evaluate the ultimate carrying capacity of water and land resources more clearly, this paper establishes a grading evaluation standard by referring to the existing research data and combining with the empirical results. The score is between 0 and 1; the higher the score, the stronger the carrying capacity of water and land resources. The specific classification is as follows: poor carrying capacity (less than 0.35), below average carrying capacity (0.35~0.4), above-average carrying capacity (0.4~0.45), and high carrying capacity (more than 0.45). Specifically, the poor carrying capacity category consists of 10 provinces, i.e., Inner Mongolia (NMG), Xinjiang (XJ), Shaanxi (SN), Qinghai (QH), Guizhou (GZ), Guangxi (GX), Yunnan (YN), Heilongjiang (HLJ), Sichuan (SC), and Gansu (GS). The below-average carrying capacity category includes eight provinces, i.e., Ningxia (NX), Chongqing (CQ), Guangdong (GD), Hubei (HB), Liaoning (LN), Jilin (JL), Shanxi (SX), and Hainan (HI). Hunan (HN), Zhejiang (ZJ), Jiangsu (JS), Fujian (FJ), Anhui (AH), and Jiangxi (JX) belong to the above-average carrying capacity category. The last category contains seven provinces, i.e., Beijing (BJ), Tibet (XZ), Shandong (SD), Tianjin (TJ), Shanghai (SH), Henan (HA), and Hebei (HE).

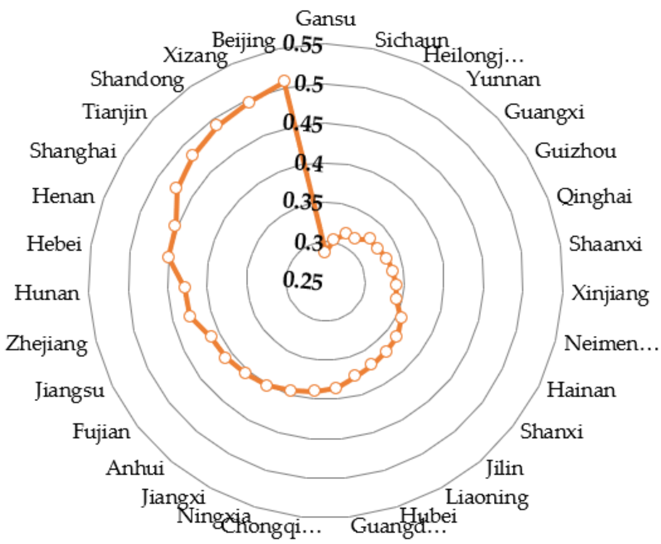

Figure 3. Radar map for average carrying capacity of 31 provinces during 2009–2017.

In order to further compare the relations between quantity and the comprehensive carrying capacity of water and land resources, the two-dimensional coordinate systems are depicted in Figures 4 and 5. The x-axis in Figures 4 and 5 represents the water resources and land resources content of each province, respectively, and the y-axis represents the average carrying capacity score of regions. In the following two figures, the x-axis denotes the quantity of water and land resources in each province by a min–max standardization, respectively. The y-axis denotes the comprehensive carrying capacity of water and land resources, in which the value in each province is also converted by a min–max standardization.

As shown in Figure 4, the provinces are divided into four categories in terms of the values between the quantity of water resources and comprehensive carrying capacity. Twelve provinces located in the "low–high" category, respectively, are Beijing, Shandong, Tianjin, Shanghai, Henan, Hebei, Jiangsu, Zhejiang, Anhui, Fujian, Hunan, and Jiangxi, in which the water resources are relatively not abundant but the comprehensive carrying capacity is relatively good. Seventeen provinces such as Guizhou and Gansu belong to the "low–low" category, which indicates that more than half of the provinces in China face both water shortage and bad carrying capacity problems. In addition, Tibet is located in the "high–high" category, while Sichuan is located in the "high–low" category. Turning to the relations between land resources and comprehensive carrying capacity, most provinces are concentrated in the second third quadrants, which means that the comprehensive carrying capacity of different provinces is diverse, although they are lacking in land resources.

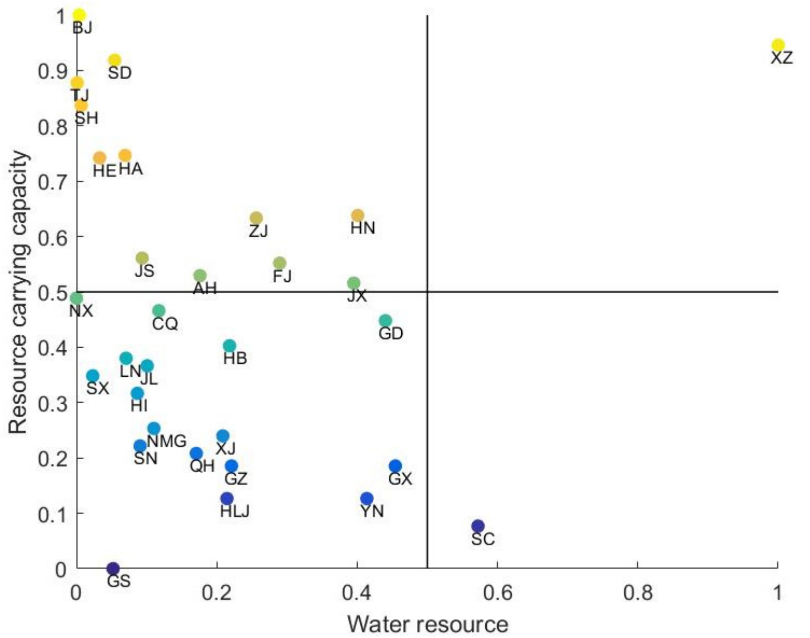

Figure 4. Water and land resources carrying capacity score and water resource distribution.

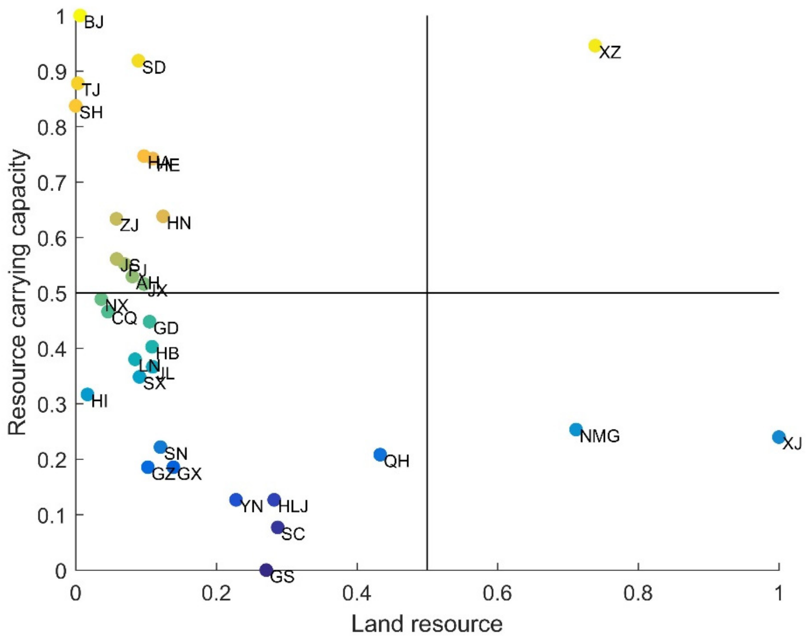

Figure 5. Water and land resources carrying capacity score and land resource distribution.

Then, using the index weights obtained from Equation (3) and combining with Equation (4), we can calculate the scores of 31 provinces under the driving force system (D), pressure system (P), state system (S), impact system (I), and response system (R), respectively. The average values of each province are shown in Table 3.

Table 3. Average scores of 31 provinces in China under five systems.

	D	Rank	P	Rank	S	Rank	I	Rank	R	Rank
Beijing	0.093	6	0.196	2	0.076	5	0.070	5	0.072	7
Tianjin	0.082	11	0.195	3	0.066	8	0.065	7	0.072	8
Hebei	0.063	26	0.178	7	0.052	13	0.049	16	0.109	1
Shanxi	0.065	24	0.179	6	0.019	27	0.037	24	0.065	11
Inner Mongolia	0.116	1	0.131	26	0.030	23	0.041	22	0.025	29
Liaoning	0.077	13	0.148	20	0.056	11	0.045	18	0.044	22
Jilin	0.089	7	0.157	13	0.064	9	0.035	26	0.022	30
Heilongjiang	0.113	3	0.110	30	0.035	21	0.041	21	0.016	31
Shanghai	0.105	4	0.151	17	0.078	4	0.108	1	0.029	27
Jiangsu	0.100	5	0.111	29	0.069	6	0.076	4	0.055	16
Zhejiang	0.085	9	0.150	19	0.078	3	0.053	14	0.060	15
Anhui	0.066	23	0.172	8	0.043	18	0.059	12	0.063	14
Fujian	0.079	12	0.140	23	0.067	7	0.059	11	0.064	12
Jiangxi	0.062	29	0.146	21	0.050	15	0.070	6	0.074	6
Shandong	0.074	18	0.199	1	0.062	10	0.060	10	0.096	3
Henan	0.060	31	0.192	4	0.047	17	0.064	8	0.087	5
Hubei	0.074	17	0.137	24	0.050	16	0.060	9	0.055	17
Hunan	0.062	27	0.133	25	0.056	12	0.076	3	0.100	2
Guangdong	0.076	14	0.118	28	0.051	14	0.078	2	0.063	13
Guangxi	0.061	30	0.144	22	0.028	25	0.048	17	0.047	20
Hainan	0.069	21	0.181	5	0.032	22	0.044	19	0.033	25
Chongqing	0.070	20	0.164	11	0.030	24	0.059	13	0.068	10
Sichuan	0.064	25	0.121	27	0.038	19	0.050	15	0.031	26
Guizhou	0.062	28	0.172	9	0.005	31	0.036	25	0.053	19
Yunnan	0.066	22	0.154	15	0.014	29	0.034	28	0.046	21
Tibet	0.114	2	0.154	16	0.134	1	0.000	31	0.095	4
Shaanxi	0.071	19	0.156	14	0.014	30	0.041	20	0.054	18
Gansu	0.075	15	0.150	18	0.017	28	0.019	30	0.026	28
Qinghai	0.075	16	0.158	12	0.023	26	0.035	27	0.043	23
Ningxia	0.082	10	0.170	10	0.037	20	0.037	23	0.069	9
Xinjiang	0.088	8	0.074	31	0.107	2	0.033	29	0.038	24

First, Inner Mongolia has the highest score (0.116) in terms of the score of the driving force system, indicating that the carrying capacity of land and water resources in Inner Mongolia is greatly driven by the local population and the total amount of natural resources, followed by Xizang (0.114) and Heilongjiang (0.113). These areas have rich land and water resources and low population density, so the score is high in terms of driving force. The province with the lowest score of driving force is Henan (0.06), and other provinces with similar performance included Jiangxi (0.062), Guangxi (0.061), Guizhou (0.062), and other central and western regions with relatively low economic development and per capita resources.

Second, the pressure of land and water resources is triggered by the driving force, which will cause the response of government management. The maximum pressure scores are found in Shandong (0.199), Beijing (0.196), and Tianjin (0.195), all of which are in the eastern region with relatively high economic development, where humans have exerted great pressure on local water and land resources. Xinjiang (0.074) has the lowest pressure score, followed by Heilongjiang (0.110). The pressure caused by driving forces is relatively small.

Third, according to the score of the state system, the state of water and land resources varies in different provinces. The provinces with high land and water resources states included Xizang (0.134), Xinjiang (0.107), Zhejiang (0.078), Shanghai (0.078), and Beijing (0.076). Some provinces have a high state because of their excellent resource performance with respect to low pressure on resources, while others have a high state because of their relatively good performance with respect to the driving force of social factors. In contrast, the provinces with a poor state of land and water resources include Guizhou (0.005), Shaanxi (0.014), and Yunnan (0.014).

Fourth, the score of the impact factor of land and water resources carrying capacity is induced by the state of resources. The high impact score refers to the large adverse effect of the change of land and water resources on human beings and the social economy, represented by Shanghai (0.108), Guangdong (0.078), Hunan (0.076), and other eastern or central regions, which are highly dependent on water and land resources. Tibet (0.000), Gansu (0.019), Xinjiang (0.033), and Yunnan (0.034) are the low-impact regions, whose social economy and human activities are not negatively affected by the state of water and land resources.

Fifth, the score of the response system shows the management policy and implementation strength formulated by the government department when facing the deterioration of land and water resources and the negative impact on human life. Hebei (0.109), Hunan (0.100), Shandong (0.096), and other central and eastern regions have taken relatively strong policy measures. However, Beijing (0.072) and Zhejiang (0.060), which scored well in other systems, performed moderately. The response score of Shanghai (0.029) was particularly poor among China's 31 provinces and cities. The lowest response intensity was found in Heilongjiang (0.016), Jilin (0.022), and Inner Mongolia (0.025).

Through the evaluation of carrying capacity, it is found that the scores of the driving force system and the resource state system have a higher effect on the carrying capacity than the other three systems. Specifically, the pressure system has no significant relationship with the carrying capacity, which means that the carrying capacity of land and water resources in a region was not mainly determined by the resource pressure. The scores of the impact factors of land and water resources show that the areas with greater pressure on land and water resources have a great negative impact on the development of human society and economic operation. Therefore, all provinces should pay more attention to the protection of land and water resources. The negative impacts also increase in provinces with high driving forces and pressure scores. The score of the response system indicates that some provinces under great pressure (such as Zhejiang and Shanghai) have not taken corresponding response measures, and there is still room for further improvement of the carrying capacity of land and water resources. As long as the government finds out the problems and relevant policies in time and actively implements them, the state of water and land resources in this region will not be too bad. Thus, provinces can obtain higher resource carrying capacity, such as Beijing, Tianjin, and Xizang, and vice versa, such as Xinjiang and Inner Mongolia.

4.2. Analysis of the Results of Utilization Efficiency of Water and Land Resources

Based on Equations (6)–(8), we can calculate the utilization efficiency of each province in the whole and two stages from 2009–2017, respectively. The results are shown in Table 4. First, we take the average efficiency of all DMUs to obtain the efficiency of China in the first stage, the second stage, and the whole system during 2009–2017, respectively. Figure 6 draws the change trend of the efficiencies during the observation period. The x-axis here represents the year, and the y-axis represents the average efficiency score.

Figure 6 shows that the overall efficiency value is basically consistent with the change trend of the second stage, which maintains a continuous and slow decline trend before 2015. After significant growth in 2016, the overall efficiency value drops in 2017. The results indicate that the efficiency of the economic benefit transformation stage plays a leading role in the overall utilization efficiency of water and land resources. Additionally, for the first stage of water and land resources development, the efficiency change trend is not obvious and only fluctuates in a small range. Comparing the beginning and ending of the observation period, the efficiency value in the first stage has slightly increased, but the efficiency value in the second stage drops significantly. As a result, the overall efficiency value of the whole system decreases during the observation period.

Table 4. Overall and sub-stage efficiencies of water and land resources utilization in 31 provinces of China.

Province	Overall Efficiency	First Stage Efficiency	Second Stage Efficiency	Province	Overall Efficiency	First Stage Efficiency	Second Stage Efficiency
Beijing	1.000	0.130	1.000	Hubei	0.596	0.195	0.598
Tianjin	0.822	0.208	0.823	Hunan	0.544	0.239	0.541
Hebei	0.577	0.283	0.579	Guangdong	0.579	0.197	0.581
Shanxi	0.605	0.332	0.607	Guangxi	0.477	0.264	0.142
Inner Mongolia	0.788	1.000	0.636	Hainan	0.609	0.139	0.615
Liaoning	0.535	0.285	0.536	Chongqing	0.586	0.115	0.587
Jilin	0.528	0.284	0.555	Sichuan	0.574	0.186	0.579
Heilongjiang	0.616	0.604	0.254	Guizhou	0.603	0.207	0.604
Shanghai	0.742	1.000	0.655	Yunnan	0.590	0.227	0.592
Jiangsu	0.696	0.189	0.697	Tibet	0.995	0.406	0.900
Zhejiang	0.621	0.071	0.622	Shaanxi	0.740	0.266	0.741
Anhui	0.579	0.263	0.580	Gansu	0.638	0.553	0.669
Fujian	0.604	0.136	0.605	Qinghai	0.860	0.517	0.001
Jiangxi	0.496	0.196	0.496	Ningxia	0.520	1.000	0.195
Shandong	0.674	0.146	0.676	Xinjiang	0.789	1.000	0.053
Henan	0.552	0.235	0.552	number (=1)	1	4	1

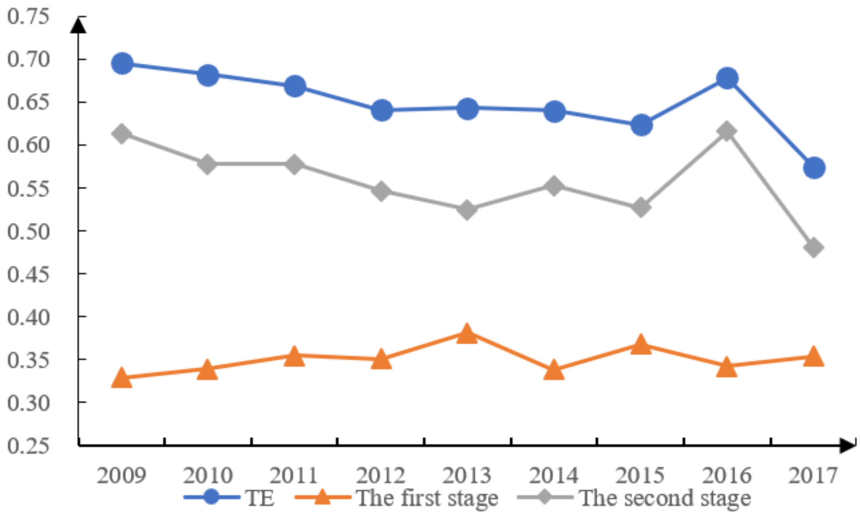

Figure 6. Change trend of stage and overall efficiencies from 2009 to 2017 at the national level.

Although the average efficiency value can reflect the national utilization status of water and land resources, the efficiency values of each province are not analyzed. Therefore, we hope to obtain more effective information about regional water and land use from Table 4.

From the perspective of the overall efficiency of water and land resources utilization, the efficiency value of Beijing is 1, which is the most effective area of water and land resources utilization among 31 provinces. On the contrary, Guangxi has the lowest efficiency value, 0.477. According to overall efficiency values, 31 provinces can be divided into four categories: high efficiency, relatively high efficiency, middle efficiency, and low efficiency. To be specific, the high-efficiency category includes Beijing, Tibet, Qinghai, and Tianjin. The relatively high-efficiency category consists of Xinjiang, Inner Mongolia, Shanghai, Shaanxi, Jiangsu, and Shandong. The middle efficiency category includes Gansu, Zhejiang, Heilongjiang, Shandong, and so on. The low-efficiency category consists of 11 provinces such as Hainan, Shanxi, Fujian, Guizhou, Hubei, Yunnan, and Chongqing. In general, the overall utilization efficiency of water and land resources in most provinces is still at the middle and low levels.

For the first stage, the four provinces with an average efficiency of 1, respectively, are Inner Mongolia, Shanghai, Ningxia, and Xinjiang. The result means that the four provinces have the best performance in the stage of water and land resources development. However, the efficiency values of other provinces in the first stage are very low, which indicates that there are significant differences in the development of water and land resources of different provinces in China. For the second stage, it is found that the efficiency value for each province is close to the overall efficiency value of the whole system. In addition, similar to the first stage, provincial difference also exists in the economic benefit transformation stage in terms of efficiency value. For example, the efficiency value of Beijing is 1 while the efficiency value of Qinghai is only 0.001.

5. Conclusions and Suggestions

5.1. The Main Conclusions of This Paper

This study applies the DPSIR model and two-stage network DEA model to analyze the comprehensive carrying capacity and utilization efficiency of water and land resources of 31 provinces from 2009 to 2017 in China. The major findings are as follows:

In terms of the comprehensive carrying capacity of water and land resources, except for Beijing, Tianjin, and Shanghai, most provinces perform relatively poorly. In addition, the carrying capacity gradually decreases from north to south and from east to west with the geographical location. Moreover, it is found that the score of the response system is basically consistent with the ranking of the comprehensive bearing capacity, which indicates that this system has an important impact on the bearing capacity.

In terms of comprehensive utilization efficiency of water and land resources, the average overall efficiency of China shows a gradual downward trend during the observation period. Specifically, the overall efficiency of most provinces is at a relatively low level. Considering the sub-stages, the efficiency of the transformation stage of economic benefits in most provinces is much greater than that of the development stage.

In general, it is found that the carrying capacity and utilization efficiency of most provinces belong to medium–poor, medium–medium, and poor–medium types. In addition, Beijing, Tianjin, and Tibet perform relatively well in both aspects, while Guangxi and Sichuan have a relatively low level of carrying capacity and utilization efficiency.

5.2. Policy and Recommendations

Based on the empirical study in this paper, some policy suggestions are provided for corresponding managers. First, different levels of environmental regulations should be made for different China's regions based on the empirical results, in which the western and southern regions should be restricted by stringent regulations because of the lower level of carrying capacity and utilization status of water and land resources. Second, managers need to consider various kinds of environmental protection measures, which include not only environmental laws and regulations but also some encouraging policies to strengthen the supervision and publicity of Water and Land Conservation Prevention. Third, a strict approval system should be constructed to control the total development of water and soil resources and formulate a clear upper limit of water and land use in combination with local economic development. Fourth, increasing attention should be paid to the influence factors to reduce the pressure of carrying capacity of water and land resources, such as expanding the scope of agricultural mechanization, increasing the area of afforestation, and saving agricultural water. Finally, the function of technological innovation on water saving and land pollution controlling should be emphasized, and the corresponding enterprises to develop and apply advanced technology should be promoted.

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