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Accounting for carbon emissions in social water cycle system in nine provinces along the yellow river and analysis of influencing factors

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Abstract

Background Water resources is an essential factor to ensure the sustainable development of the society, but along with the utilization and treatment of water resources, a large amount of carbon emissions will be generated. The study of carbon emissions in social water cycle system is of great significance in promoting the achievement of carbon peaking and carbon neutrality. This study calculated the carbon emissions generated in social water cycle system in nine provinces along the Yellow River, used the Tapio decoupling model to analyze the decoupling relationship between water and carbon emissions, and constructed the STIRPAT expanded model to analyze the main influencing factors of carbon emissions.

Results (1) The total carbon emissions of the nine provinces showed an increasing trend over time, with a growth rate of 25.13%. (2) The carbon emission intensity of water use (1.60kg/m^3) and drainage (1.45kg/m^3) system is higher, the carbon emission intensity of water supply (0.30kg/m^3) and water withdrawal (0.56kg/m^3) system is lower. (3) The relationship between water resources utilization and carbon emissions along the Yellow River is generally in a state of negative decoupling and coupling. (4) Energy structure and population growth are the main factors affecting carbon emissions in social water cycle system, while water supply quantity and water use system are secondary factors.

Conclusions Water use system is the main body of carbon emissions in social water cycle system, and as the water consumption increases, the carbon emissions will continue to increase. In order to reduce carbon emissions and mitigate climate change, carbon emission factors should be incorporated into water resources management.

Keywords Social water cycle system, Carbon emissions, Decoupling relationship, STIRPAT model, Influencing factors

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Background

Adequate water supply is an essential foundation for social water security. However, with rapid economic development and population growth, the demand for water resources is increasing, leading to increased energy consumption in the social water cycle and a significant increase in carbon emissions (CE).[1] The resulting climate change will have a severe impact on the hydrological cycle, increasing the frequency of extreme hydrological events such as droughts and floods, and jeopardizing the supply of water resources and social water security. Research has shown that CE in the urban social water cycle system (SWCS)[2] can account for 2% of the total CE in cities, and the structure and intensity of CE in different links vary significantly [1]. Therefore, it is important to identify the main carbon emitters and influencing factors in SWCS to mitigate the impact of climate change on water security.

As early as 1997, British scholar Stephen Merrett proposed the concept of the "hydrosocial cycle" based on the hydrological cycle [2]. Subsequently, many scholars have introduced similar concepts, but these lacked a theoretical system [3]. In 2011, Wang Hao established the scientific definition and connotation of the social water cycle, providing a theoretical foundation for constructing a research framework for the social water cycle [4]. The social water cycle refers to the cyclical process of “water withdrawal-water supply-water use-drainage” formed in the social system and its related areas under the influence of human being [4]. The water withdrawal system extracts, treats, collects and processes available water resources through both engineering and non-engineering measures to meet the demands of human society, mainly including surface water lifting, groundwater extraction, water lifting from storage project, recycled water collection, and inter-basin water transfer, etc. [5] Water supply system distributes and allocates available water resources to various sectors, mainly including raw water treatment and tap water allocation, etc. [6] Water use system refers to a series of activities designed to maximize the economic, social and ecological functions of water resources to meet human activity, mainly including domestic, industrial, agricultural and ecological water utilization, etc. The drainage system mainly collects domestic sewage and industrial wastewater for centralized treatment, involving sewage collection, sewage treatment and discharge [7]. These systems also generate CE while ensuring social water use, and the different systems are characterized by complexity, linkage and change. Among them, the CE of water collection, water supply and water use systems mainly come from energy consumption, while the CE of drainage systems include methane emissions and material consumption in the sewage treatment process in addition to energy consumption [8].

Research on CE in SWCS inherently involves exploring the "water-energy" relations. Scholars such as Venkatesh and Brattebø [9], Valek et al. [10], Jiang [11], Xiang and Jia [12] have quantitatively analyzed the water-related energy consumption in various regions and examined the "water-energy" nexus through coupling simulations, which provides a reference basis for the calculation of energy consumption in SWCS. Building on this foundation, many scholars have further investigated the CE effects in SWCS. For example, Chen et al. explored the carbon emission intensity (CI)[3] and spatial distribution characteristics of CE during the sewage treatment in Chinese cities [13]. Ma et al. quantitatively analyzed the impact of CE on urban water supply efficiency [14]. Zhu et al. explored the relationship between agricultural water and CE under different irrigation modes [15]. These studies offer theoretical support for the selection of energy-saving and carbon reduction paths in different links of SWCS. In addition, Rothausen and Conway provided a comprehensive overview of energy consumption and greenhouse gas emissions in SWCS, recommending their inclusion in water resource management to address the upcoming challenges of water resource management and climate change [16]. Zhao et al. took Zhengzhou city as an example, conducted a comprehensive accounting of CE from the water system, and predicted the trend of CE from the urban water system under different scenarios [1]. Zuo et al. integrated the concepts of carbon emissions and carbon sinks, developed a framework for calculating water-related carbon emissions, and summarized formulas for calculating carbon emissions from 16 different water resource activities. Additionally, he constructed an analysis function table for carbon emission calculations [5].

In summary, research in this field primarily focuses on carbon emissions at the micro scale, such as groundwater extraction, urban water supply, and sewage treatment, as well as the study of CE in the overall social water circulation system at the macro scale. However, in general, the existing studies predominantly emphasize the micro scale. There are relatively few studies on the distribution characteristics, trends and influencing factors of CE in SWCS at the macro-scale, as well as the analysis of the ‘water-CE’ relationship. In this paper, nine provincial-level administrative regions along the Yellow River Basin (YRB)[4] are taken as the research area, and only the CE

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[1] CE: the abbreviation of carbon emissions.

[2] SWCS: the abbreviation of social water cycle system.

[3] CI: the abbreviation of carbon emissions intensity.

[4] YRB: the abbreviation of Yellow River Basin.

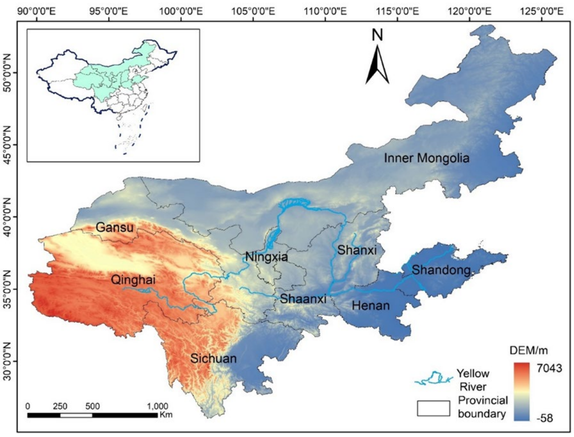


Fig. 1 Location of the study area (DEM: digital elevation model)

effect is considered to calculate the CE in SWCS of different provinces. Identify the main body of CE and its influencing factors, reveal the correlation characteristics between water resources utilization and CE.

The Yellow River Basin is an important economic zone and key ecological reserve in China, flowing through nine provincial-level administrative regions, and covering more than 30% of the country's administrative area, population, arable land, and food production [17]. In 2021, the Communist Party of China Central Committee and the State Council have jointly issued an outline document titled 《Outline of the Yellow River Basin's Ecological Protection and High-quality Development Plan》 emphasizing ecological governance to mitigate human impacts and foster balanced economic, social, and ecological development in the region [18]. However, the YRB faces challenges from human activities and climate change. Future projections indicate a steady increase in temperatures at a rate of 0.039–0.056 °C per year, exacerbating the frequency and intensity of droughts and floods [19]. This scenario significantly increases water demand for agriculture and domestic use [20, 21], leading to intense competition among different water sectors. Analyzing the characteristics of CE in SWCS along the YRB administrative regions and exploring pathways towards "carbon neutrality" in the water resources sector are crucial for mitigating the pressures on water resources stemming from climate change and human activities. The location of the study area is shown in (Fig. 1). The elevation data is provided by the Copernicus Digital Elevation Model from the European Space Agency [22].

Methods

Data sources

The data for the study were mainly obtained from the governmental statistics in China. Among them, the total water supply, surface water supply, groundwater supply, domestic water consumption, agricultural irrigation water consumption, industrial water consumption, and effective irrigated area of agriculture were obtained from China Water Resources Bulletin (2004–2021); the data of water supply from storage projects, diversion projects and water lifting projects, water transfer across basins are from the Provincial Water Resources Bulletin(2004–2021); the amount of sewage discharge, sewage treatment, and sewage recycling are from China Urban–Rural Construction Statistical Yearbook (2004–2021); the socio-economic data are from CHINA STATISTICAL YEARBOOK.

Models and methods

Accounting methodologies for carbon emissions

The study uses energy intensity and CE factors to account for the relevant CE. First of all, based on the analysis of the sources of CE in SWCS, combined with the actual operational mode of each system in the study area, the links of SWCS with CE effects are identified.

The SWCS consists of four subsystems: water withdrawal, water supply, water use and drainage. The water withdrawal system generates CE from surface water lifting, groundwater extraction, water lifting from storage project, inter-basin water transfer, and recycled water collection; the water supply system includes raw water treatment and tap water allocation, the water use system includes domestic, agricultural and industrial water utilization, the drainage system includes sewage collection, sewage treatment and discharge, and the CE generated by the sewage discharge process are relatively small and are not included in this calculation.

Referring to the existing research results, select the appropriate accounting method and construct the CE accounting table. Specific CE links and their corresponding accounting formulas and parameter selection basis are shown in (Table 1).

Tapio decoupling model

The decoupling theory, which emerged in the mid-twentieth century, describes the relationship between economic growth and resource consumption (or environmental pressure) [29].The Tapio decoupling method, on the other hand, employs elastic analysis to assess the ratio of the change rate of CE in the base period and the current period to the change rate of the driving variable for CE [30]. The study utilizes the Tapio decoupling model to analysis the decoupling status between water resource utilization and CE across different provinces. The decoupling could be calculated by Eq. (1):

Table 1 Accounting table of CE in social water cycle system

Subsystem	Subsegment	Methods of accounting	Parameter description
Water withdrawal	Surface water lifting	$C_1 = Q_1 \times E_1 \times EF$	C_i is the CE equivalent produced by each link in the social water cycle (kg). E.g., C_1 is the CE equivalent produced by surface water lifting; Q_1 is the volume of water withdrawn from surface water (m^3); E_i is the energy intensity of each link in the social water cycle. E.g., E_1 is the energy intensity of surface water lifting, kWh/m^3, the specific value is shown in Table 2 [11]; EF is the amount of carbon emitted per unit of energy, kg/kW·h, the specific value is shown in Table 2 [5]
	Groundwater extraction	$C_2 = Q_2 \times E_2 \times EF$	Q_2 is the volume of water withdrawn from groundwater (m^3); E_2: Table 2;
	Water lifting from storage project	$C_3 = C_T + C_S$ $C_S = Q_S \times E_S \times EF$ $C_T = Q_T \times E_T \times EF$	CE from water lifting in the storage project consist of two parts: CE from daily operation of equipment and CE from water lifting process, which are expressed by C_S、C_T respectively; Q_S is the volume of water storage (m^3); E_S: 0.14 kW • h/m^3 [5]; Q_T is the amount of water lifting (m^3); E_T: Table 2 [11]
	Inter-basin water transfer	$C_4 = Q_4 \times E_4 \times EF$	Q_4 is the water transferred across basins (m^3); E_4: Table 2 [12]
	Recycled water collection	$C_5 = Q_5 \times E_5 \times EF$	Q_5 is the amount of recycled water collected (m^3); E_5: 0.82 kW • h/m^3 [11]
Water supply	Raw water treatment	$C_6 = Q_6 \times E_6 \times EF$	Q_6: amount of raw water treatment (m^3); E_6: Table 2 [11]
	Tap water allocation	$C_7 = Q_7 \times E_7 \times EF$	Q_7: amount of tap water (m^3); E_7: Table 2 [11]
Water use	Domestic water utilization	$C_8 = Q_8 \times E_8 \times EF$	Q_8: amount of domestic water (m^3); E_9: 7.43 kW • h/m^3 [23]
	Agricultural water utilization	$C_9 = Q_9 \times C_{FAG}$	Q_9 is effective irrigated area in agriculture (m^2); C_{FAg} is the CE from water used for agricultural irrigation, 25 kg/hm^2 [24]
	Industrial water utilization	$C_{10} = Q_{10} \times E_{10} \times EF$	Q_{10} is the amount of industrial water (m^3); E_{10}: 5.003 kW • h/m^3 [1]
Drainage	Sewage collection	$C_{11} = Q_{11} \times E_{11} \times EF$	Q_{11} is the amount of wastewater collected (m^3); E_{11}: 0.013 kW • h/m^3 [25]
	Sewage treatment	$C_{12} = C_E + C_w + C_{CH4}$ $C_{12} = Q_{12} \times E_{12} \times EF$ $C_W = Q_{12} \times C_{FW}$ $C_{CH_4} = Q_{12} \times \Delta BOD \times EF_{CH_4} \times GWP$	CE in the wastewater treatment process mainly come from the consumption of energy and materials as well as methane emitted in the biochemical process respectively [26], and are expressed as C_E、C_W、C_{CH_4}; Q_{12} is the amount of wastewater treatment (m^3); E_{12}: 0.013 kW • h/m^3 [25]; C_{FW} is the CE from the materials consumed to treat a unit of sewage, 0.03 kg/t; ΔBOD is the concentration difference of BOD before and after wastewater treatment (0.58 kg/m^3) [27]; EF_{CH_4} is CO_2 emission factor of CH_4, 0.086 [28]; GWP is the global warming potential of CH_4, 25

$$\varepsilon(C, W) = ((C_1 - C_0)/C_0)/(W_t - W_0/W_0)) \qquad (1)$$

where Ɛ represents the decoupling index during the calculation period. C_0 and W_0 represents the CE and total water supply in the base period. C_t and W_t represents the CE and total water supply in period t.

The decoupling status is categorized according to the amount of the decoupling index and the positive or negative changes in CE and water supply, as shown in Fig. 2 [31].

The theory of decoupling suggests that the separation between economic growth and resource consumption

Table 2 Average CO_2 emission factor and energy intensity in different provinces

Province	EF (kg/kW·h)	Energy intensity (kW·h/m³)					
		E_1	E_2	E_T	E_4	E_6	E_7
Ningxia	0.8184	2.200	0.27	0.037	/	0.445	0.375
Sichuan	0.2891	0.210	0.300	0.029	/	0.242	0.374
Gansu	0.6124	1.870	0.500	0.031	0.300	0.305	0.399
Qinghai	0.2236	1.590	0.520	0.016	/	0.162	0.399
Inner Mongolia	0.8503	0.950	0.300	0.033	/	0.414	0.495
Shaanxi	0.8696	0.430	0.640	0.064	/	0.221	0.520
Shanxi	0.8798	0.390	0.620	0.072	1.782	0.574	0.625
Henan	0.8444	0.190	0.30	0.081	0.760	0.296	0.42
Shandong	0.9236	0.080	0.470	0.084	1.047	0.281	0.332

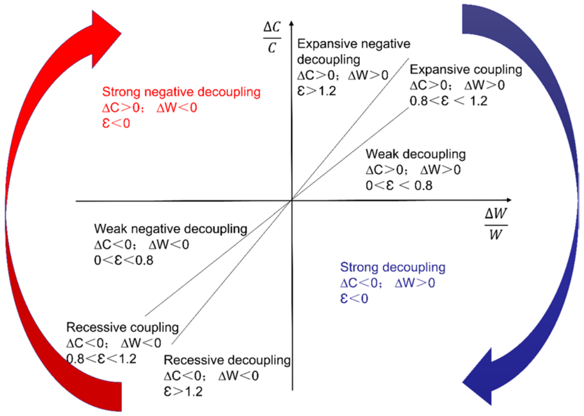


Fig. 2 The partition standard of decoupled States Image from

can be achieved through technological innovation, energy transformation and effective management of resources. Therefore, decoupling behavior is not a short-term process and requires a certain period of technological change and structural adjustment. However, most of the current studies have used the decoupling index in the form of chain ratio, i.e., based on the data of the adjacent years before and after, which is difficult to reflect the influence of technological innovation or policy adjustment on the trend of "decoupling" in a longer period [32]. In order to more accurately describe the relationship between water resource utilization and CE, this paper takes into account the length of the time period and divides it into three phases: 2004–2009, 2010–2015, and 2016–2021, and takes the starting year of each phase as the base period for calculation.

STIRPAT model

The STIRPAT model originates from the IPAT accounting model: I = PAT [33]. Where I denotes environmental impact, including consumption of resources and emissions of waste (including greenhouse gases), etc.; P denotes population size; A denotes the degree of affluence, which is usually indicated by per capita GDP; and T denotes the degree of technological progress. The IPAT model allows for a concise articulation of the key drivers of environmental changes and reflects the fact that no one factor can be held singularly responsible for environmental impacts [34]. However, as a mathematical identity, it assumes that the relationship between the prior factors is proportional, it is not easy to consider the non-proportional and non-monotonic influence relationship; and T is usually unknown and can only be calculated based on the other three variables, making it easy to attribute some of the demographic and economic impacts to technology. To overcome this weakness, Rosa and Dietz expanded IPAT into a stochastic model that can be used to empirically test hypothesis [35]. The STIRPAT model:

$$I = aP^{b}A^{c}T^{d}\varepsilon \tag{2}$$

The constant a scale the model; b, c, and d are parameters to be estimated, also known as ecological elasticity coefficients, which show the relationship between environmental impacts and their drivers; t is the error coefficient.

Compared with the IPAT model, which regards T as a black box, the STIRPAT model allows T to be decomposed and refined to include other driving factors. In the follow-up study, the author proposed the criterion of factor decomposition: the decomposed factors can be used as part of the technology and are conceptually consistent with the multiplication specification of the model. In addition, the model can also add a quadratic term or polynomial term to explain the non-monotonic and non-proportional influence relationship [34].

In order to eliminate the influence of heteroscedasticity and facilitate estimation and hypothesis testing, all variables can be logarithmically processed to construct an additive regression model:

$$\ln I = \ln a + b\ln P + c\ln A + d\ln T + \ln\varepsilon \tag{3}$$

In order to accurately explain the influencing factors of CE in SWCS, this study constructs the extended STIRPAT model based on the factor decomposition criterion and the analysis of the results of CE, selecting the population, affluence, water supply quantity, CI of the water use system, energy structure, and the industrial water as the main influencing factors:

$$\begin{aligned}\ln C =& \ln a + b\ln P + c\ln A + d\ln W + e\ln UI \\ &+ f\ln ES + g\ln IR + \ln\varepsilon\end{aligned} \tag{4}$$

where C denotes total CE; P denotes population; A denotes per capita GDP; W denotes total water supply quantity; UI denotes CI of water use system; ES denotes energy structure; and IR denotes the rate of industrial water to total water consumption.

Results

Characterizing of carbon emissions

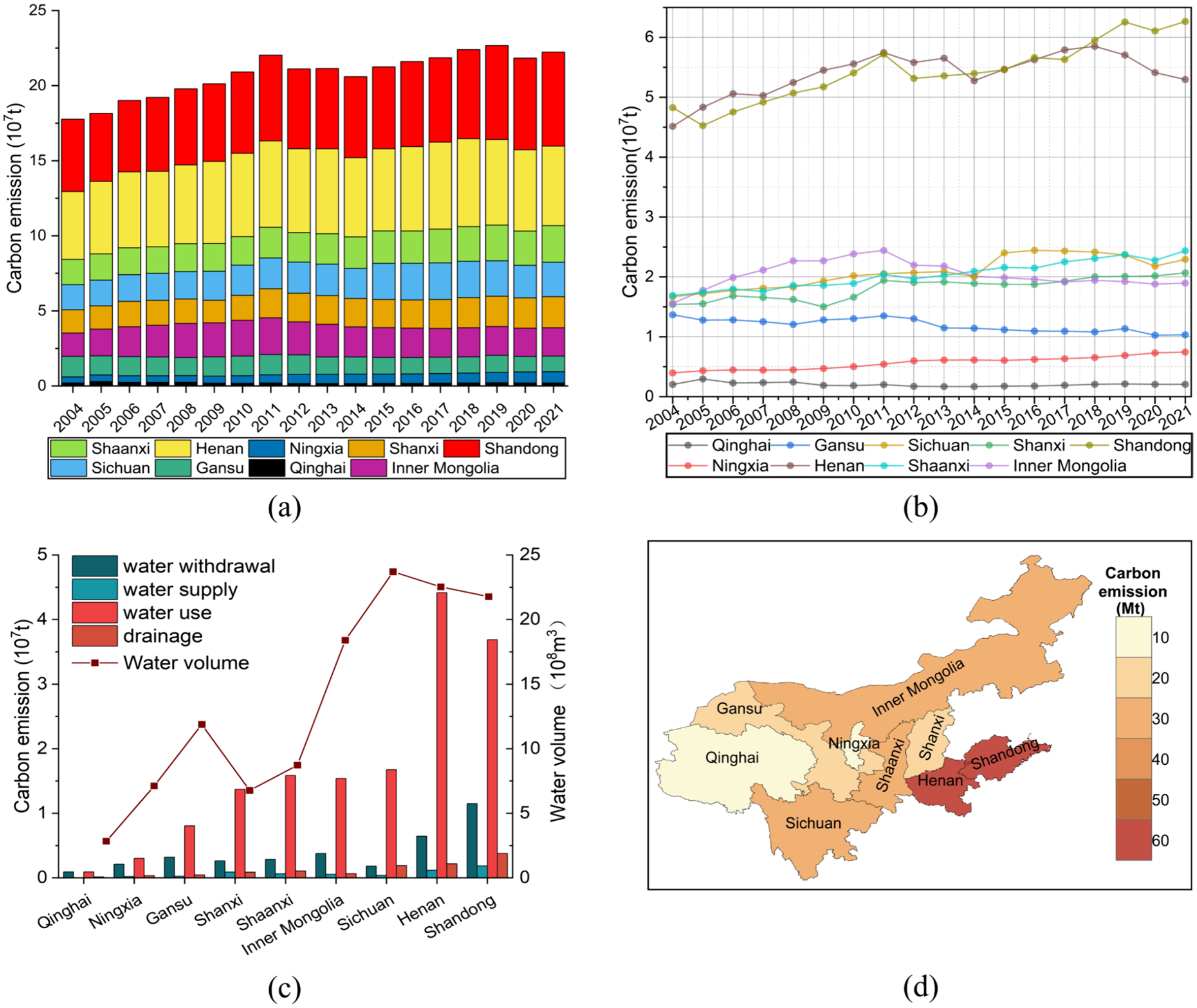
(a: Stacked Columns of Total CE of the Nine Provinces Along the YRB, 2004–2021; b: Trends in total CE by province; c: Annual average CE from subsystems of the social water cycle and annual average total water supply, 2004–2021; d: Spatial distribution of annual average CE by province).

CE in SWCS of the nine provinces in China from 2004 to 2021 are accounted for and counted, the results are shown in Fig. 3. The total CE of the nine provinces showed an increasing trend over time, from 178 million tons in 2004 to 222 million tons in 2021, with a growth rate of 25.13% and an average annual growth of 2.48 million tons. However, there were periods of localized decline observed during 2012–2014 and 2019–2021. The decrease during 2012–2014 was mainly attributed to the implementation of the most stringent water resources management polices in China in 2011, which significantly improved the efficiency of domestic water use. In 2012 alone, the total domestic water utilization in nine provinces decreased by 1.67 billion m^3, and CE decreased by 11.68 million tons. During 2019–2021, the reduction in industrial output due to the COVID-19 pandemic resulted in decreased industrial water consumption. In 2020, the total industrial water consumption decreased by 3.16 billion m^3, contributing to a reduction in CE by 9.17 million tons.

Of the nine provinces, only Gansu and Qinghai show a decreasing trend in CE from 2004 to 2021, with decreases of 24% and 0.6%, respectively; this is mainly due to a decrease in CE from water-use systems (28% and 29% in Gansu and Qinghai, respectively) caused by a reduction in the amount of industrial water use (59% and 52% in Gansu and Qinghai, respectively). The trend in the remaining provinces is roughly the same as the trend in total CE in the nine provinces.

As seen in Fig. 3(c), the primary source of CE is the water use system, followed by the water withdrawal system. Additionally, the annual average water supply across the provinces generally aligns with the trend in CE, indicating a correlation between water consumption and CE. However, in certain regions, such as Shanxi, Shaanxi, Henan, and Shandong provinces, the annual average water consumption shows a declining trend while the annual average CE continue to rise. This suggests that factors other than water usage also influence CE.

From the spatial distribution of CE, it is evident that the upper and middle reaches of the YRB have relatively low CE. For instance, Qinghai's annual average emissions account for only 3% of the total emissions across the nine provinces. In contrast, the downstream regions exhibit higher CE, with Henan and Shandong each accounting for 13% of the total annual emissions. This variation is primarily influenced by regional differences in water use. The upper and middle reaches of the YRB are characterized by sparse populations, lagging economic development, and relatively low water demand, with agriculture being the dominant industry. Agricultural water use has relatively low CI. For example, from 2004 to 2021, the water withdrawal from the YRB in Qinghai, Gansu, and Shanxi was relatively small, with annual average shares of 3.37%, 8.62%, and 8.90% respectively. In contrast, Ningxia, Inner Mongolia, and Shaanxi had higher water withdrawal shares, at 14.62%, 19.75%, and 12.2% respectively, but primarily for agricultural irrigation, resulting in lower carbon emissions. The downstream regions, on the other hand, have dense populations and developed economies, leading to higher demands for agricultural, industrial, and urban water use, and consequently higher CI. For example, Henan and Shandong accounted for 13.64% and 17.39% of water withdrawals, respectively, with significant industrial and domestic water use, contributing to higher overall system carbon emissions. Therefore, the CE from SWCS across the provinces along the YRB generally increase from the upstream to the downstream regions. Furthermore, although the YRB flows through Sichuan, the basin area within Sichuan is only 18,700 km^2, resulting in minimal water withdrawal from the YRB, accounting for just 0.06% of the total water withdrawal in the basin. Sichuan's primary water sources are from the Yangtze River Basin. However, given that Sichuan is also included in China's strategic plan for high-quality development of the YRB, it is still selected as a study area in this research.



(a) (b)

(c) (d)

Fig. 3 The variation characteristics of CE in the nine provinces, 2004–2021

Analysis of Carbon emissions intensity

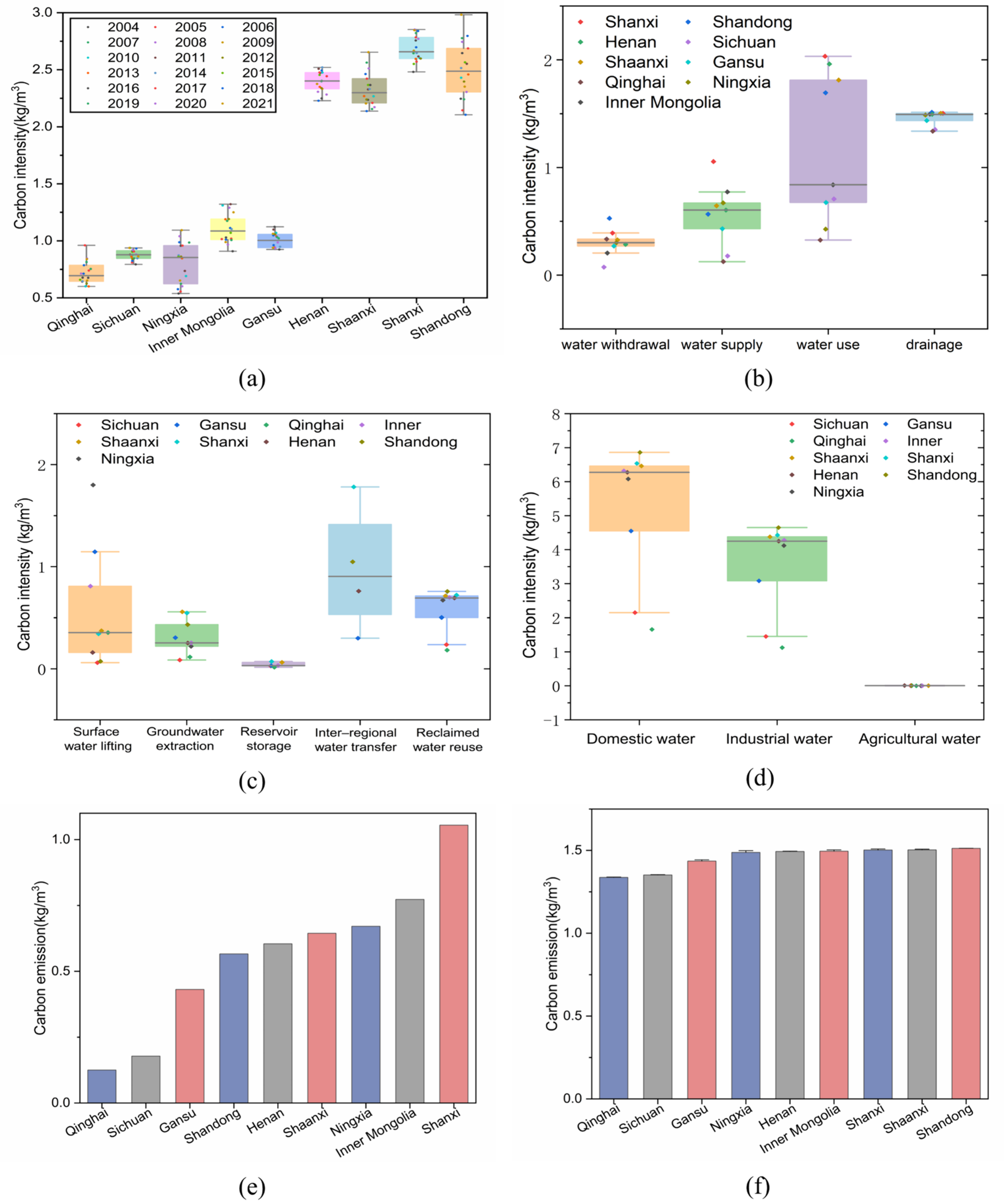
(a: Trends in CI by province; b: Distribution of CI of subsystems in the social water cycle in nine provinces; c: Distribution of CI of Water Withdrawal System by Segment in Nine Provinces; d: Distribution of CI of Water Use System by Segment in Nine Provinces; e: CI of water supply systems by province; f: CI of drainage systems by province) In order to evaluate the CI in SWCS of each province, the following indicators were introduced in this study:

$$I = C/Q \tag{5}$$

where I denotes the intensity of CE in SWCS (kg/m^3); C denotes the CE produced by each system (kg); Q denotes the amount of water involved in each system (m^3); where the CI of the overall SWCS is calculated by dividing the total CE of each province by the total amount of water used.

The calculation results are shown in Fig. 4 and analyses as follows:

(I) The CI of water use system (average value is 1.60kg/m^3) and drainage system (average value is 1.45kg/m^3) is higher, and the CI of water supply system (average value is 0.30kg/m^3) and water withdrawal system (average value is 0.56kg/m^3) is lower. The primary reason for the higher intensities in water use and discharge systems is the significant energy consumption required for treating and processing water resources, along with significant CH_4 dur-



(a) (b)

(c) (d)

(e) (f)

Fig. 4 CI in SWCS in the nine provinces, 2004–2021

ing wastewater treatment, which increases carbon emissions. Therefore, the trend of CI of SWCS in each province from 2004 to 2021 is similar to that of water use system.

(II) The CE of the water system mainly comes from energy consumption, and the CI will be affected by the energy structure. The CI of domestic (average value is 5.21kg/m^3) and industrial water utilization (average value is 3.53kg/m^3) is higher, and the CI of agricultural water utilization is lower (average value is 0.005kg/m^3). The CI of water withdrawal system is mainly affected by the way of water withdrawal, among which the average CI of inter-basin water transfer is the largest (0.97kg/m^3), and the CI of water lifting from storage project is the lowest (0.19kg/m^3). The CI of water supply and drainage systems is mainly affected by the treatment technology and scale.

(III) There are significant differences in CI among provinces. In the middle and lower reaches of the YRB, provinces such as Shaanxi, Shanxi, Henan, and Shandong exhibit higher CI, ranging from 2.0 to 3.0kg/m^3. In contrast, the upstream provinces have lower CI, ranging from 0.5 to 1.5kg/m^3. This variation is mainly influenced by industrial scales and water use structures. The middle and lower reaches are more economically developed, with a higher proportion of industrial and domestic water use, leading to greater CI.Additionally, the differences in energy structures contribute to these variations. For instance, Shandong province having the largest carbon emission coefficient of the electric power system (0.9236kg/kW·h), while Sichuan province, due to its abundance of clean energy, has the lowest emission coefficient (0.2891kg/kW·h).

Analysis of Water-Carbon emissions decoupling relationship

The results of Tapio decoupling model are shown in Fig. 5 and Fig. 6. Shaanxi Province, Sichuan Province, Henan Province, Shandong Province and Shanxi Province have been in the state of expansive negative decoupling and strong negative decoupling for a long time. The Ningxia Hui Autonomous Region has been in a strong negative decoupling state. Qinghai Province was in an expansive negative decoupling state from 2004 to 2008, basically in a decoupling state from 2009 to 2016, and in a strong negative decoupling state for a long time since 2016. Gansu Province was in a state of recessive coupling from 2004 to 2009, in a state of expansive negative decoupling from 2010 to 2012, since 2013, it has changed from a strong decoupling state to a recessive coupling state. Inner Mongolia was in a state of expansive negative decoupling between 2004 and 2012, and was in a state of recessive decoupling for a long time after 2012. Decoupling behavior is not a short-term process, but a long-term adjustment process that requires a certain period and cost input. Therefore, it can be concluded that the decoupling of water resources utilization and CE has not been realized in the nine provinces along the YRB during the investigation period. Fig. 7

It is found that there are three main factors affecting the decoupling relationship:

(I) The way of water withdrawal. Due to the different CE generated by different water withdrawal methods, the change in the way of water withdrawal will affect the decoupling relationship. For instance, the increase of surface water utilization in Ningxia Hui Autonomous Region leads to the increase of CE, which is detrimental to achieving decoupling state.

(II) Water consumption and structure. Industrial and domestic water use contributes significantly to CI, making CE highly responsive to changes in their water consumption. In contrast, agricultural water use has a very low CI, meaning significant changes in agricultural water use do not notably affect CE. Therefore, the change of water consumption and

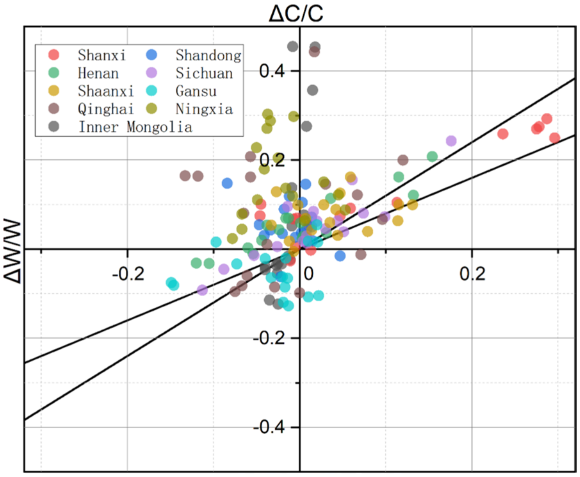


Fig. 5 The change rate of water resources utilization and CE in each province, 2004–2021

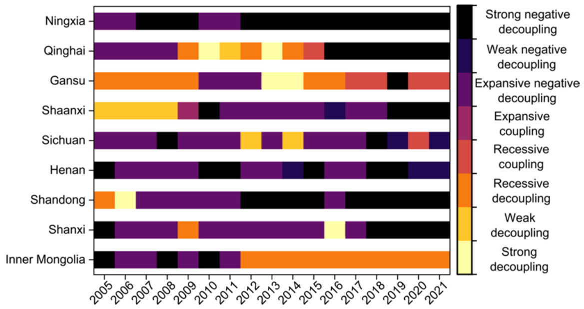


Fig. 6 The decoupling relationship between water resources utilization and carbon emissions

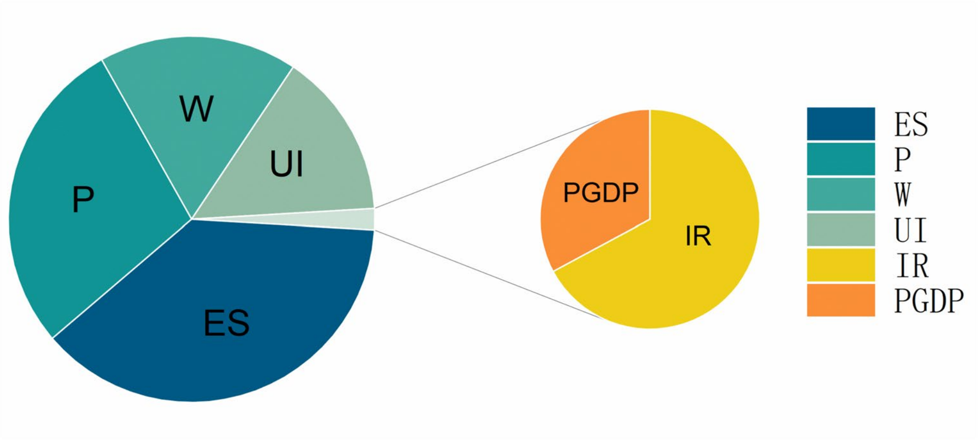


Fig. 7 The order of factors in terms of impact

the adjustment of water structure will have an impact on the decoupling state.

(III) Sewage treatment volume. A large amount of CH_4 emitted during the sewage treatment process and the energy consumed will produce a large amount of CE. In order to alleviate the pressure of water resources, the amount of sewage treatment is increasing, which is also not conducive to the realization of the decoupling state.

At present, in SWCS, the utilization of water resources, the way of water withdrawal and sewage treatment are mainly affected by the natural endowment conditions, the water demand of society and human activities in the region, with the aim of ensuring water security, and do not prioritize the carbon emission effect. However, in order to cope with the threat of extreme climate to water security, mitigate the impact of CE on climate, and achieve the decoupling of water resources utilization and carbon emissions, effective measures should be taken. Improving the extraction process of water resources, improving water conservation techniques, improving the construction of basic water supply facilities. Improving the efficiency of sewage collection and treatment, optimizing the layout of drainage facilities, reduce the amount of sewage treatment and its energy consumption, improving the utilization of clean energy, optimize energy structure and energy management, reduce the scale of industries with high water and high energy consumption while ensuring economic development.

Identification of factors affecting Carbon emissions

In order to more clearly reveal the main factors affecting CE in SWCS, the research constructs a STIRPAT model for analysis. The existing data has two dimensions of cross-Sect. (9 provinces) and time (2004–2021), which is suitable for solving the STIRPAT model by using the estimation strategy of panel data. The main information of the sample is shown in (Table 3).

Pooled (POOL) model, fixed-effect (FE) model and random-effect (RE) model are the most commonly used to the estimation of the panel data [36]. In order to determine which strategy has the best regression effect, it is necessary to use the F-test to decide whether to choose the POOL model or the FE model, the Breusch Pagan test to decide whether to choose the RE model or the POOL model, and the Hausman test to decide whether to choose the RE model or the FE model. The test results (Table 3) show that the FE model has better estimation performance. However, our empirical model may eliminate some additional factors affecting CE, which leads to endogeneity issue and hinders unbiased estimation. In order to address this potential endogeneity issue, the generalized method of moments (GMM) provided by Arellano and Bond was chosen [37] and existing research has shown that the GMM estimation method significantly outperforms the FE model both in terms of parameter-efficiency and parameter-consistency in the finite-sample case ($n<30$, $T<30$) [38]. There are two types of GMM-based estimators: Difference GMM (DIFF-GMM) and System GMM (SYS-GMM) [39]. When the individual effect is fixed effect, the estimation results of SYS-GMM are non-consistent, which may lead to erroneous empirical results, while difference GMM is still consistent estimation [40], and CE may be affected by time-varying factors, so the final choice is to use DIFF-GMM. The results are shown in (Table 4).

Table 4 shows the estimation results based on RE, FE, FE-trend and DIFF-GMM, respectively. The effects of population (lnP), water supply (lnW) and energy mix (lnES) on CE in SWCS are statistically significant

Table 3 Basic data characteristic distribution table of the sample

Variable		Mean	Std.dev	Min	Max	Observations
lnTC	Overall	7.36	0.99	5.13	8.74	N = 162
	Between		1.04	5.31	8.60	n = 9
	Within		0.12	7.03	7.74	T = 18
lnP	Overall	8.03	1.00	6.29	9.23	N = 162
	Between		1.06	6.34	9.18	n = 9
	Within		0.03	7.91	8.12	T = 18
lnPGDP	Overall	1.06	0.62	−0.43	2.18	N = 162
	Between		0.23	0.63	1.41	n = 9
	Within		0.58	−0.26	1.96	T = 18
lnEF	Overall	−0.40	0.49	−1.49	0.00	N = 162
	Between		0.52	−1.43	−0.02	n = 9
	Within		0.02	−0.46	−0.32	T = 18
lnW	Overall	4.73	0.69	3.19	5.59	N = 162
	Between		0.72	3.34	5.46	n = 9
	Within		0.07	4.54	4.92	T = 18
lnUI	Overall	−0.05	0.67	−1.43	0.78	N = 162
	Between		0.70	−1.14	0.71	n = 9
	Within		0.11	−0.35	0.29	T = 18
lnIR	Overall	−2.03	0.47	−3.14	−1.28	N = 162
	Between		0.44	−2.85	−1.53	n = 9
	Within		0.22	−2.88	−1.40	T = 18

in all estimation strategies. The DIFF-GMM estimation strategy passes each hypothesis test: $P(AR(1)) < 0.1$, $P(AR(2)) > 0.1$, $P(\text{Sargan-test}) > 0.1$, $P(\text{Hansen-test}) > 0.1$, indicating that the parameter estimation is reliable. As shown in Fig. 7, ES has the greatest impact on carbon emissions, followed by P, W, UI, IR, and PGDP.

By analyzing the regression results of DIFF-GMM, it can be found that for every 1% increase in water supply quantity (W) at the 1% significance level, CE will increase by 0.684%, an increment of less than 1%, indicating that although an increase in water supply will lead to an increase in CE, this effect can be attenuated by effective measures., such as optimizing the energy structure and water use structure, and improving the efficacy of sewage treatment. At the same time, this underscores that water conservation is an effective approach to reducing carbon emissions.

Energy structure (ES) is the main factor affecting CE. According to the calculation, at the 1% significance level, every 1% increase in the CE coefficient of energy will increase the total CE by 1.474%. It indicates that CE mainly come from the consumption of energy, and saving energy while increasing the use of clean energy can effectively reduce CE.

Population (P) likewise has a significant impact on CE. At the 1% level of significance, for every 1% increase in population, CE will increase by 1.096%. The population effect can be categorzed into three categories: (I) Population size effect. Population growth directly increase the demand for water resources, resulting in a large amount of CE. (II) Synergistic effect. The expansion of population size led to urban expansion, which in turn promote the increasing demand for water resources in infrastructure construction, industrialization construction, agricultural modernization and other activities, resulting in an increase in CE. (III) Threshold effect. When population growth exceeds the carrying capacity of water resources, additional water sources are needed, such as inter-basin water transfer, seawater desalination, and reclaimed water reuse. These activities are often accompanied by high energy consumption and high CE.

The CI of water use system (UI) will increase by 0.573% for every 1% increase in UI at the 1% significance level, indicating that the water use system is the main body of CE, and that energy consumption of water use system is higher than other systems. Therefore, the water use system should be taken as the core link in the implementation of water resources management.

For every 1% increase in the rate of industrial water use (IR) at the 1% significance level, CE will increase by 0.049%, indicating that the adjustment of the proportion of industrial water use will not have a significant impact on CE. Industrial water use is the link with the highest CI in SWCS, but the amount of industrial water use is small,

Table 4 Regression results of carbon emissions

Method	RE	FE	FE-trend	DIFF-GMM
_cons	2.966***	−3.318**	−4.022*	
	(0.000)	(−0.030)	(−0.067)	
lnP	0.178***	0.960***	1.022***	1.096***
	(−0.001)	(0.000)	(−0.003)	(0.009)
lnPGDP	0.064***	−0.014	0.1	−0.024***
	(0.000)	(−0.246)	(−0.115)	(0.003)
lnW	0.648***	0.792***	0.803***	0.684***
	(0.000)	(0.000)	(0.000)	(0.000)
lnES	0.219**	1.544***	1.087**	1.474***
	(−0.016)	(0.000)	(−0.032)	(0.001)
lnUI	0.740***	0.752***	0.737***	0.573***
	(0.000)	(0.000)	(0.000)	(0.000)
lnIR	0.02	0.046***	0.059*	0.049*
	(−0.213)	(−0.007)	(−0.076)	(0.081)
L.lnTC				0.077**
				(0.036)
F-test		82.39(0.000)	78.56(0.000)	
Breusch Pagan test	1754.64(0.000)			
Hausman test		53.64(0.000)		
Wooldridge test		2.882(0.128)		
AR(1)				−1.67(0.089)
AR(2)				−1.47(0.193)
Sargan test				108.91(0.326)
Hansen test				3.08(1.000)

(a)RE、FE、FE-trend and DIFF-GMM indicate random effects, fixed effects, two-way fixed effects model and difference GMM estimator respectively. (b) lnIR and lnUI: the endogenous variable, lnP and lnES: the instrumental variables, L.lnC (the lagged term of dependent variable): the predetermined variable. (c): values in (): Standard errors; (d): ***, ** and *: significance at the 1%, 5% and 10% levels. (e):AR (1) and AR (2): the first and second-order autocorrelations tests respectively

accounting for about 15% of the total water use, and only adjusting the proportion of industrial water use cannot achieve the purpose of carbon reduction.

Although the correlation coefficient for per capita GDP (PGDP) is significant, the effect on CE is very small. At the 1% significance level, for every 1% increase in per capita GDP, CE will decrease by 0.024%. Many studies have examined the relationship between economic growth and carbon dioxide, but there is no clear conclusion, and even the same scale of study (individuals countries or groups of countries) can lead to conflicting conclusions, and most of the studies believe that CE are associated with economic growth through energy consumption [41]. Therefore, combining the results of the regression analysis, it can be concluded that economic growth does not directly have a significant impact on CE in SWCS.

Discussion

This study develops a framework for calculating CE within the SWCS across nine provinces along the YRB, focusing on four key stages: water withdrawal, water supply, water use, and discharge. It examines the characteristics of carbon emissions within the SWCS and the factors that influence them. The framework outlines common water-related activities in society and provides a detailed analysis of the sources of carbon emissions from each activity, along with their quantification methods. Previous studies have often focused on individual stages of the water cycle or specific cities, which fail to capture the large-scale impact of water-related social activities on carbon emissions [42]. Although Zuo et al. also developed a carbon accounting framework for the entire water system, they approached it from the perspective of water resource conservation [5]. In their study, agricultural crops were considered as carbon sinks, and they deducted the amount of carbon dioxide absorbed by crops when calculating carbon emissions from agricultural water use. Additionally, they overlooked the CE generated by the reuse of reclaimed water, emphasizing only the water-saving benefits. As a result, their framework does not fully reflect the actual carbon emissions of the water system. In contrast, this study focuses solely on direct carbon emissions within the SWCS, aiming to analyze and compare the contributions of different water-related activities to CE. This approach helps integrate carbon emission factors into comprehensive water resource management strategies.

The results of this study indicate that the CE and CI of the water use system are significantly higher than those of other stages, aligning with the findings of Zhao et al. [1] and Zuo et al. [5]. However, their research did not delve into the relationship between the water and CE within regions or the key factors influencing changes in water system carbon emissions. This paper identifies that the water-carbon relationship within the SWCS across the nine provinces along the YRB remains undetached, emphasizing that water conservation is directly linked to energy conservation. Furthermore, the study identifies several factors—such as energy structure, population growth, water extraction methods, water use patterns, and wastewater treatment—that have a significant impact on the water-carbon relationship and the increase in CE. This underscores the importance of utilizing clean energy and enhancing integrated water and energy management to achieve carbon neutrality. In addition to ensuring water security, maintaining and improving water supply infrastructure and developing advanced wastewater treatment technologies offer further benefits. In water-scarce regions, long-distance water transfers and groundwater extraction are commonly employed to access usable water resources, which often leads to increased energy consumption. Therefore, integrating traditional and non-traditional water supply systems (such as unconventional water use) can enhance water security, with careful selection of water sources based on water quality considerations [43]. Similarly, in densely populated areas, improving water supply and usage technologies can effectively reduce CE [13].

Due to the numerous stages involved in the SWCS analyzed in this study, it was challenging to obtain detailed carbon intensity parameters for each stage in every region. As a result, the carbon emission accounting results may not fully reflect the differences across regions caused by the use of varying technological processes. Instead, the results primarily highlight the impact of regional differences in energy structure, water extraction methods, water use patterns, and the scale of wastewater treatment on carbon emissions. This limitation has, to some extent, affected a more detailed analysis of the research findings.

Conclusions

This study accounts for the carbon emissions in social water cycle system in the nine provinces along the YRB in China, analyzed the variation characteristics of carbon emissions and carbon emission intensity, and the water-carbon decoupling relationship. The factors affecting carbon emissions are identified by the STIRPAT model. The main conclusions are as follows:

(1) From 2004 to 2021, the total carbon emissions of the nine provinces showed an increasing trend, with a growth rate of 25.13% and an average annual growth of 2.48 million tons. There are notable differences in carbon emissions and carbon emission intensity among provinces. With Henan Province and Shandong Province have the highest carbon emissions, and Qinghai Province has the lowest carbon emissions. The carbon emission intensity is higher in the middle and lower reaches of the Yellow River, ranging between 2.0 to 3.0 kg/m^3, whereas it is lower in the upstream regions, ranging between 0.5 to 1.5 kg/m^3.

(2) Water withdrawal system and water use system are the main carbon emitters in social water cycle system, accounting for 16% and 70% of the total carbon emissions, respectively. The carbon emission intensity of water use (average value is 1.60kg/m^3) and drainage (average value is 1.45kg/m^3) system is higher, the carbon emission intensity of water supply (average value is 0.30kg/m^3) and water withdrawal (average value is 0.56kg/m^3) system is lower.

(3) From 2004 to 2021, the water utilization and carbon emissions in the provinces along the YRB are generally in a state of negative decoupling and coupling, indicating that the increase of water resources utilization under the existing conditions will still lead to the continuous growth of carbon emissions, which is mainly affected by the way of water withdrawal, water consumption and structure, and sewage treatment volume.

(4) In the study, STIRPAT model is used to decompose the factors affecting carbon emissions into six main parts, and the impact of each factor was estimated. The results showed that: Energy structure and population growth are the main factors affecting carbon emissions (regression coefficient is greater than 1), water supply quantity and carbon intensity of water use system are secondary factors (regression coefficient is greater than 0 and less than 1), and economic development and water use structure do not directly have a significant impact on carbon emissions (regression coefficient tends to be 0).

Abbreviations

CE	Carbon emissions
SWCS	Social water cycle system
CI	Carbon emissions intensity
YRB	Yellow River Basin

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Author contributions
C.L. and F.W. wrote the main manuscript, H.L. prepared formal analysis, H.Z. and J.S. prepared data curation. All authors reviewed the manuscript.

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No datasets were generated or analysed during the current study.

Declarations

Competing interests
The authors declare no competing interests.

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