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Original Research

Spatial spillovers and nonlinear drivers of water-supply carbon emissions in China

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ABSTRACT

Water supply systems are critical components of urban infrastructure and significant contributors to global carbon emissions. These systems face an emerging challenge in balancing the increasing demands of water security with international climate mitigation goals. To combat water scarcity, many regions have transitioned toward energy-intensive water sources such as inter-basin water transfer and desalination, which significantly increase electricity-dependent indirect emissions. Concurrently, the global shift toward clean energy in electricity generation has provided a crucial mechanism for mitigating these emissions. However, the complex interactions among shifting water-source mixes, energy transitions, and socioeconomic drivers remain poorly understood, often obscuring the effectiveness of decarbonization strategies. Existing quantification frameworks frequently overlook the spatial spillover effects of economic development and the risk that new water security strategies will offset decarbonization gains. Here we show that China's carbon emissions from water-supply processes rose to 228 Mt CO_2 yr^{-1} by 2022, despite initial declines driven by clean energy expansion. Using a three-stage quantification–decomposition–attribution framework, we find that while economic development generally suppresses emission in neighboring regions via technology diffusion, it exhibits a national U-shaped relationship with carbon output. Crucially, central China displays an inverted U-shaped pattern, suggesting a localized risk of high-carbon lock-in as industries and water demands shift. These findings reveal a critical paradox in the water–energy–carbon nexus where water security measures may inadvertently undermine climate targets. Our results advocate for integrated regional governance and differentiated policy interventions to safeguard both water and climate stability in rapidly developing regions.

1. Introduction

Water supply systems are a vital part of urban infrastructure and a significant source of carbon emissions. These systems support urban economies and societies by processing water through extraction, treatment, and distribution. Unlike industrial and transport sectors, carbon emissions from water-supply processes (CEWS) are primarily indirect, stemming mainly from electricity consumption, and are often overlooked in climate policy discussions [1,2]. Globally, water supply systems account for approximately 3–5% of urban electricity consumption [3], making the sector a non-negligible contributor to carbon emissions [4,5]. As such, quantifying and managing CEWS has become an emerging challenge for the global water sector.

A key tension exists between ensuring water security and achieving carbon reduction goals. To address water scarcity, water supply systems have shifted progressively from reliance solely on rivers and lakes to the inclusion of energy-intensive water sources, such as seawater desalination [6], wastewater recycling [2], and inter-basin water transfer [7]. These measures, while essential for securing supply, significantly increase electricity use and CEWS [8,9]. Meanwhile, the share of clean energy in global electricity

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generation increased from 32.3% in 2012 to 38.9% in 2022 [10]. Since fossil fuel-based electricity emits 3–5 times more carbon than clean energy [11], this shift has helped mitigate CEWS growth. This dynamic creates a paradox: while the expansion of clean energy helps curb carbon emissions, the growing reliance on energy-intensive water sources offsets these gains. Consequently, these two opposing forces obscure the historical changes in CEWS and complicate the identification of its main driving factors.

To address the uncertainty in CEWS changes, a robust quantification framework grounded in the water–energy–carbon nexus is necessary. Existing CEWS assessment methods fall into two categories: top–down and bottom–up. Top–down approaches, such as the input–output, computable general equilibrium, and system dynamics models, use macroeconomic data to estimate embedded carbon emissions [12–14]. However, their high level of sectoral aggregation makes it difficult to capture the heterogeneity of carbon emissions during the transition of water supply systems toward energy-intensive sources [15]. In contrast, bottom–up methods, particularly life-cycle assessment (LCA), offer more detailed insights [16] but often focus narrowly on specific water treatment technology characterizations [17,18]. Previous reviews of China's water–energy policy have anticipated potential climate change conflicts between the water and energy sectors [19]. However, existing CEWS assessments still fail to account for the offsetting effects between the expansion of clean energy and the growing reliance on energy-intensive water sources.

While quantification of CEWS is essential, it only reflects the outcomes of complex water–energy–carbon interactions. Effective decarbonization strategies require an understanding of the drivers of carbon emissions, especially the role of economic development. Macro-level models such as the environmental Kuznets curve (EKC) explore the direct impact of economic development but lack transparency in how structural and technological changes influence carbon emissions [20,21]. Decomposition methods such as the logarithmic mean Divisia index (LMDI) can attribute the total carbon emission changes to the contributions of various internal factors, yet they fail to explain the socioeconomic forces behind them [22,23]. Therefore, a research gap lies in how economic development affects CEWS through these internal mechanisms. This gap is particularly relevant given the interconnected nature of water supply systems shaped by cross-regional power grids and inter-basin water transfer projects. For example, electricity supply regions may bear higher carbon emissions, while consumption regions may reduce carbon emissions through imports [24,25]. Similarly, the spatial distribution of CEWS may be influenced by inter-basin water transfer [9]. This networked structure implies that the economic development of any given region inevitably exerts spatial spillover effects on the CEWS of its neighbors [26]. However, these spatial spillover effects are often overlooked in analyzing the transmission mechanisms of economic development impacts on carbon emissions.

To bridge these gaps, we propose a three-stage framework of quantification–decomposition–attribution, aiming to link economic development with CEWS. The quantification stage develops a CEWS assessment model that integrates water source mix and clean energy dynamics. The decomposition stage identifies the internal drivers, such as electricity consumption intensity, for changes in CEWS. The attribution stage uses spatial econometric modeling to reveal how economic development drives these internal factors, which in turn shape CEWS. The contribution of this study lies in establishing a causal link between CEWS quantification, internal factor analysis, and socioeconomic drivers, offering deeper insights into CEWS dynamics.

This paper is organized as follows. Section 2 outlines the system boundaries and describes the methodology. Section 3 presents the results, covering the characteristics of national and provincial CEWS, internal factors influencing CEWS, the transmission mechanisms, and spatial spillovers of economic development affecting CEWS. Section 4 discusses the impact of water–energy co-evolution, the relationship curve between economic development and CEWS, and policy recommendations.

2. Methods

2.1. System boundaries

This study focuses on the operational stage of the water supply system, where carbon emissions are sensitive to variations in both the water source mix and the carbon emission intensity of electricity consumption. While expanding energy-intensive water sources requires the construction of large-scale infrastructure, such as desalination plants and pumping stations, the resulting carbon emissions are one-time and relatively small, accounting for less than 10–20% of the total life-cycle carbon emissions of water supply systems [27]. In contrast, carbon emissions from water supply system operations dominate. Therefore, the carbon emissions associated with the construction of pumping stations, dams, and electricity generation facilities were excluded.

Our quantification framework of CEWS was developed from a water–energy coupling perspective, focusing on the interdependence between the electricity-consuming water supply system and the electricity-generating energy system (Fig. 1). Within the water supply system, our assessment covered the complete water supply life cycle, including freshwater intake, treatment, and delivery, wastewater treatment, and recycling. We focused on indirect carbon emissions from electricity consumption, which account for over 80% of the total carbon emissions in China's water supply sector [28]. In addition, electricity is consumed throughout all stages of the water supply [3]. For example, electricity

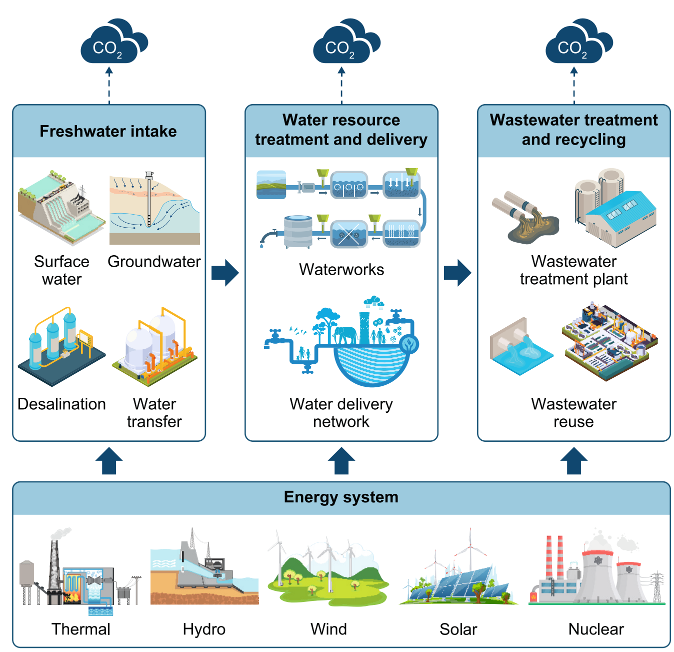

Fig. 1. Conceptual diagram and system boundaries of carbon emissions from water-supply processes.

consumption for freshwater intake comes mainly from groundwater extraction, reservoir operation, and inter-basin water transfer. The use of equipment and chemicals in water resource treatment also consumes electricity. During the water resource distribution process, pumping stations consume electricity to maintain pressurization and ensure smooth delivery to water users. In the final water-supply process, wastewater treatment and recycling, electricity is used to operate aeration and wastewater treatment equipment. In contrast, direct carbon emissions from fossil fuel combustion and fugitive emissions are relatively minor [29] and were therefore excluded from this analysis.

In the energy system, we focused on the factors that determine the carbon emission intensity of electricity consumption. The first factor was the local electricity generation mix. The energy system evaluated in this study included China's five major electricity generation methods: thermal power, hydropower, wind power, solar power, and nuclear power. Since thermal power consumes primary energy, it is the primary source of carbon emissions, while electricity from other methods is considered clean energy. The second factor was inter-regional electricity exchange. China's electricity grid operates on three interconnected levels: the national, regional, and provincial electricity grids. As a result, a province's electricity consumption reflects both local generation and cross-regional transfers. Therefore, our analysis of the energy system focused primarily on the combined effects of the electricity generation mix and inter-regional electricity transmission on CEWS dynamics.

2.2. Life-cycle assessment model for CEWS quantification

We employed bottom–up analysis to quantify CEWS across China's 30 provinces throughout the water supply life cycle [30]. The LCA method, a tool that analyzes the environmental impact of a given good or service throughout its life cycle, is increasingly gaining attention in assessing the impact of human activities on the environment [31]. The entire life cycle of the water supply system covers freshwater intake, treatment, and delivery, wastewater treatment, and recycling. The sum of the carbon emissions from these four stages can be expressed by equation (1):

$$C_{i,t} = \sum_{m=1}^{4} C_{m,i,t} = \sum_{l=1}^{L} \sum_{m=1}^{4} \left(W_{l,m,i,t} \times e_{l,m,i,t} \times a_{i,t} \right) \tag{1}$$

where $C_{i,t}$ represents carbon emissions from water-supply processes in ith province at year t (kg CO_2 yr^{-1}); $W_{l,m,i,t}$ represents the water supply quantity of water source type l at the mth stage of water supply in ith province at year t (m^3 yr^{-1}); $e_{l,m,i,t}$ represents the electricity consumption intensity at the mth stage of water supply in ith province at year t (kWh m^{-3}); $a_{i,t}$ represents the carbon emission intensity of electricity consumption in ith province at year t (kg CO_2 kWh^{-1}); L represents the number of water sources. The detailed calculation equation for a is explained in Supplementary Text S1.

2.3. Analyzing the transmission mechanism linking economic development to changes in CEWS

In this section, we systematically reveal the transmission mechanisms of macroeconomic drivers by coupling the LMDI method with a spatial econometric model. First, the LMDI method is introduced to decompose changes in CEWS into contributions from key internal factors (e.g., carbon emission mix, electricity consumption intensity). Subsequently, the spatial econometric model is applied to explain the changes in CEWS by linking the decomposed factors to macroeconomic drivers, such as economic development.

2.3.1. Decomposition using the logarithmic mean Divisia index

The LMDI method is essentially a generalization of the Kaya identity [32]. It allows changes in the research object to be decomposed into a combination of variables, enabling the calculation of each variable's influence on the considered factor [33]. It performs complete decompositions, resulting in no residuals. In addition, the LMDI method satisfies the Fisher factor reversal test, ensuring the convergence of the results [34]. Therefore, in the decomposition stage, we adopted the LMDI method to decompose the driving factors of CEWS. The detailed calculation equations for the LMDI method are expressed by the following equation:

$$\begin{aligned} C_{i,t} &= \sum_{m=1}^{4} C_{i,m,t} = \sum_{m=1}^{4} \left(\frac{C_{i,m,t}}{C_{i,t}} \times \frac{C_{i,t}}{P_{i,t}} \times \frac{P_{i,t}}{E_{i,t}} \times \frac{E_{i,t}}{S_{i,t}} \times \frac{S_{i,t}}{L_{i,t}} \times L_{i,t} \right) \\ &= \sum_{m=1}^{4} \left(\delta_{i,m,t} \times \varepsilon_{i,t} \times \theta_{i,t} \times \iota_{i,t} \times \sigma_{i,t} \times \tau_{i,t} \right) \end{aligned} \tag{2}$$

where $P_{i,t}$ represents the primary energy consumption of electricity generation in ith province at year t (kg yr^{-1}); $E_{i,t}$ represents the electricity consumption from the water-supply process in ith province (kWh yr^{-1}); $S_{i,t}$ represents the total water supply in ith province at year t (m^3 yr^{-1}); $L_{i,t}$ represents the local water supply scale in ith province, including reservoir water, diversion water, pumping water, and groundwater at year t (m^3 yr^{-1}); δ_m is the proportion of carbon emissions at the mth stage of water supply, representing carbon emissions mix (CEM) in the carbon emissions within the water supply life cycle; ε is the carbon emission intensity (CEI), defined as the ratio of the total carbon emissions and the primary energy consumption; θ is the ratio of the total primary energy consumption and the electricity consumption from water-supply process, representing the primary energy consumption intensity (PECI); ι is the ratio of the electricity consumption and the total water supply, denoting electricity consumption intensity (ECI); σ is the water source mix (WSX), defined as the ratio of the total water supply to the local conventional water supply—when $\sigma > 1$, the water supply includes inter-basin water transfer, seawater desalination, and wastewater recycling, and the greater the value, the greater the supply of these water sources; and τ is the local water supply (LWS) scale.

Taking the derivative of both sides of equation (2):

$$\frac{\mathrm{d}C_{i,t}}{\mathrm{d}t} = \sum_{m=1}^{4} \left(\frac{\mathrm{d}\delta_{i,m,t}}{\mathrm{d}t} \times \frac{C_{i,m,t}}{\delta_{i,m,t}} + \frac{\mathrm{d}\varepsilon_{i,t}}{\mathrm{d}t} \times \frac{C_{i,m,t}}{\varepsilon_{i,t}} + \frac{\mathrm{d}\theta_{i,t}}{\mathrm{d}t} \times \frac{C_{i,m,t}}{\theta_{i,t}} + \frac{\mathrm{d}\iota_{i,t}}{\mathrm{d}t} \times \frac{C_{i,m,t}}{\iota_{i,t}} + \frac{\mathrm{d}\sigma_{i,t}}{\mathrm{d}t} \times \frac{C_{i,m,t}}{\sigma_{i,t}} + \frac{\mathrm{d}\tau_{i,t}}{\mathrm{d}t} \times \frac{C_{i,m,t}}{\tau_{i,t}} \right) \tag{3}$$

Integrating both sides of equation (3):

$$\int_{T_0}^{T}\frac{\mathrm{d}C_{i,t}}{\mathrm{d}t}\mathrm{d}t=\Delta C_i$$
$$=\sum_{m=1}^{4}\int_{T_0}^{T}\left[\left(\frac{\mathrm{d}\delta_{i,m,t}}{\mathrm{d}t}\times\frac{1}{\delta_{i,m,t}}+\frac{\mathrm{d}\varepsilon_{i,t}}{\mathrm{d}t}\times\frac{1}{\varepsilon_{i,t}}+\frac{\mathrm{d}\theta_{i,t}}{\mathrm{d}t}\times\frac{1}{\theta_{i,t}}+\frac{\mathrm{d}\iota_{i,t}}{\mathrm{d}t}\times\frac{1}{\iota_{i,t}}+\frac{\mathrm{d}\sigma_{i,t}}{\mathrm{d}t}\times\frac{1}{\sigma_{i,t}}+\frac{\mathrm{d}\tau_{i,t}}{\mathrm{d}t}\times\frac{1}{\tau_{i,t}}\right)\times C_{i,m,t}\right]\mathrm{d}t \quad (4)$$
$$=\sum_{m=1}^{4}\int_{T_0}^{T}\left[\left(\frac{\mathrm{d}(\ln\delta_{i,m,t})}{\mathrm{d}t}+\frac{\mathrm{d}(\ln\varepsilon_{i,t})}{\mathrm{d}t}+\frac{\mathrm{d}(\ln\theta_{i,t})}{\mathrm{d}t}+\frac{\mathrm{d}(\ln\iota_{i,t})}{\mathrm{d}t}+\frac{\mathrm{d}(\ln\sigma_{i,t})}{\mathrm{d}t}+\frac{\mathrm{d}(\ln\tau_{i,t})}{\mathrm{d}t}\right)\times C_{i,m,t}\right]\mathrm{d}t$$

Since it is challenging to directly calculate equation (4), Ang and Liu proposed an exponential decomposition method to obtain reasonable decomposition results [35]. By introducing the logarithmic mean weight function, the following weight function was defined:

$$\omega_{i,m}=\mathrm{L}(C_{i,m,T},\ C_{i,m,T_0})=\begin{cases}\dfrac{C_{i,m,T}-C_{i,m,T_0}}{\ln C_{i,m,T}-\ln C_{i,m,T_0}}, & C_{i,m,T}\neq C_{i,m,T_0}\\ C_{i,m,T}, & C_{i,m,T}=C_{i,m,T_0}\end{cases} \quad (5)$$

where L () represents the logarithmic mean of carbon emissions between the calculation year T and the baseline year T_0.

Therefore, equation (4) can be transformed into the following:

$$\Delta C_i=C_{i,T}-C_{i,T_0}=\sum_{m=1}^{4}\left[\omega_{i,m}\times\left(\ln\frac{\delta_{i,m,T}}{\delta_{i,m,T_0}}+\ln\frac{\varepsilon_{i,T}}{\varepsilon_{i,T_0}}+\ln\frac{\theta_{i,T}}{\theta_{i,T_0}}+\ln\frac{\iota_{i,T}}{\iota_{i,T_0}}+\ln\frac{\sigma_{i,T}}{\sigma_{i,T_0}}+\ln\frac{\tau_{i,T}}{\tau_{i,T_0}}\right)\right]=\Delta C_{\delta_i}+\Delta C_{\varepsilon_i}+\Delta C_{\theta_i}+\Delta C_{\iota_i}+\Delta C_{\sigma_i}+\Delta C_{\tau_i} \quad (6)$$

where ΔC_i represents the change in CEWS in ith province from the baseline year T_0 to calculation year T (kg CO_2 yr^{-1}); and ΔC_{δ_i}, ΔC_{ε_i}, ΔC_{θ_i}, ΔC_{ι_i}, ΔC_{σ_i}, and ΔC_{τ_i} represent the contributions of CEM, CEI, PECI, ECI, WSX, and LWS to the change in CEWS, respectively (kg CO_2 yr^{-1}).

2.3.2. Attribution using the spatial econometric model

In the attribution stage, we selected the internal effect factors obtained from the LMDI as the dependent variables in the spatial econometric models. To systematically identify the macro-level factors influencing the evolution of CEWS, we adopted the classic stochastic impacts by regression on population, affluence, and technology (STIRPAT) model [36]. This model is widely used for its established robustness in capturing macro-level environmental factors [37]. For the population, we used population density to capture how settlement patterns influence electricity and water provision and demand. High-density areas can benefit from economies of scale in centralized supply, reducing distribution losses, but they may also experience higher aggregate demand that increases total consumption. We chose per capita GDP to represent the level of affluence, which can increase carbon emissions by stimulating water demand or reduce them by enabling investment in clean technologies. Technological change was captured using patent counts as an indicator of upgrading.

In addition, we included other control variables to mitigate the risk of omitted-variable bias. Industrial structure was measured as the proportion of secondary industry in total GDP, reflecting the extent of industrial activity and its implications for intersectoral coordination and water-use intensity [38]. The electricity generation mix, proxied by the proportion of thermal power in total electricity generation, captured the carbon emission intensity of electricity consumption [39]. Finally, water use intensity—defined as water use per CNY 10,000 of GDP—was included to capture differences in regional water use efficiency [40]. Definitions of all variables are provided in Table 1.

Previous studies have found that the impact of economic development on the environment follows the EKC [41,42]. Therefore, a square term for economic development was introduced to capture the nonlinear relationship. In addition, to eliminate the impact of magnitude and units, all variables were processed by a natural logarithm. Finally, the following spatial econometric model was established:

$$\ln Y_{i,t}=\alpha+\rho\sum_{j\neq i}^{N}\boldsymbol{W}_{i,j}\ln Y_{j,t}+\beta_1\ln D_{i,t}+\beta_2(\ln D_{i,t})^2+\sum_{k=1}^{K}\vartheta_k X_{k,i,t}+\varphi_1\sum_{j\neq i}^{N}\boldsymbol{W}_{i,j}\ln D_{j,t}+\varphi_2\sum_{j\neq i}^{N}\boldsymbol{W}_{i,j}\left(\ln D_{j,t}\right)^2+\sum_{k=1}^{K}\xi_k\sum_{j\neq i}^{N}\boldsymbol{W}_{i,j}X_{k,j,t}+\mu_i+\nu_t+\epsilon_{i,t} \quad (7)$$

where $Y_{i,t}$ represent the dependent variable in ith province at year t; $D_{i,t}$ represents the level of economic development in ith province at year t, which is the independent variable; $X_{k,i,t}$ is control variable; α is a constant term; ρ represents the spatial autoregression coefficient; $\boldsymbol{W}$ denotes the spatial weight matrix; β, ϑ, φ, and ξ are parameters to be estimated; μ_i and ν_t denote region fixed effects and time fixed effect, respectively; $\epsilon_{i,t}$ represents the random error term; N and K are the number of spatial provinces and control variables, respectively.

Selecting an appropriate spatial weight matrix is crucial, as its structure defines the transmission channels of spatial interactions, thereby shaping the results. To capture inter-provincial linkages, we adopted two matrices—the spatial adjacency matrix and the geographic distance matrix—and compared results across specifications as a robustness check. In the spatial adjacency matrix, $\boldsymbol{W}_{i,j} = 1$ if province i and j are adjacent, $\boldsymbol{W}_{i,j} = 0$ otherwise. For the geographic distance matrix, we assumed that spatial correlation decays with distance and specified inverse-squared geographic distance weights. The calculation equation is as follows:

$$\boldsymbol{W}_{i,j} = \begin{cases} \dfrac{1}{d_{i,j}^2} \; i \neq j \\ 0 \; i = j \end{cases} \tag{8}$$

$$d_{i,j} = R \times \arccos\left[\cos\chi_i \cos\chi_j \cos\left(\psi_i - \psi_j\right) + \sin\chi_i \sin\chi_j\right] \tag{9}$$

where $d_{i,j}$ represents spherical distance between provinces (km); R represents the radius of the earth (km); χ_i and χ_j represent the latitude angles of provinces i and j, respectively (°); ψ_i and ψ_j represent the longitude angles of provinces i and j, respectively (°).

Spatial econometric models can be divided into three types of interaction effects: interactions among exogenous independent variables, interactions among endogenous dependent variables, and interactions among error terms. These correspond to the spatial error model (SEM), spatial autoregression (SAR) model, and spatial Durbin model (SDM) [43]. Therefore, before regressing the spatial econometric model, we conducted relevant fitness tests to determine the appropriate model to adopt, including robustness tests, Wald spatial lag tests, spatial error tests, and others. To account for regional heterogeneity, we divided China into four regions: northeast China, east China, central China, and west China (Supplementary Fig. S1).

2.4. Data sources

This study focuses on the period 2010–2022, which spans China's rapid expansion of clean energy and growing reliance on energy-intensive water sources [44,45]. For CEWS calculations, the electricity consumption intensity of each water-supply process was taken from the literature (Supplementary Table S1). Water supply volumes at each supply stage were derived from the China Water Resources Bulletins [46] and the China Urban–Rural Construction Statistical Yearbook [47]. We calculated the carbon emission intensity of electricity consumption using primary energy consumption in the thermal power process and total electricity generation, obtained from the China Energy Statistical Yearbook [48] and the Compilation of Statistical Data on the Power Industry [49]. The socioeconomic data involved in the LMDI and spatial econometric models were sourced from the China Statistical Yearbook [50].

3. Results

3.1. Patterns of carbon emissions from water-supply process in China

Between 2010 and 2022, China experienced fluctuations in both its CEWS and the proportions of different water-supply stages. Although China's total water usage remained relatively stable at around 600 billion $m^3\ yr^{-1}$ (Supplementary Fig. S2), national CEWS increased from 210 Mt $CO_2\ yr^{-1}$ in 2010 to 219 Mt $CO_2\ yr^{-1}$ in 2011 before declining to the lowest level of 196 Mt $CO_2\ yr^{-1}$ in 2014. Subsequently, as the carbon emission intensity of electricity consumption slowed and inter-basin water transfer and wastewater recycling increased, CEWS began to rise again after 2014 (Fig. 2a). Regarding the composition of CEWS over the years 2010–2022, carbon emissions from the freshwater intake process accounted for over 70% of total CEWS, while their proportion gradually declined over time. In contrast, the share of carbon emissions from other water-supply processes increased. Specifically, comparing 2022 levels with those in 2010, the proportion of carbon emissions from water resource treatment and delivery, wastewater treatment, and wastewater recycling increased by 1%, 4%, and 3%, respectively (Fig. 2b).

Provincial CEWS generally declined between 2010 and 2022 (Fig. 3a). Specifically, 20 of 30 provinces showed declines, with Yunnan, Qinghai, and Jilin recording the largest decreases of 59.1%, 28.5%, and 27.5%, respectively. However, the remaining 10 provinces experienced increasing CEWS to varying degrees. Among these provinces, Beijing, Tianjin, and Hebei had the highest growth rates in CEWS, which were 145.1%, 281.0%, and 172.8%, respectively. At each water-supply stage, while carbon emissions from the freshwater intake process accounted for more than 30% of CEWS in most provinces, the provincial water-use structure significantly shaped the carbon-emission mix. Specifically, in provinces with a higher proportion of domestic and industrial water use, such as Jiangsu, Zhejiang, Guangdong, Chongqing, Sichuan, and Guizhou, carbon emissions from the water resource treatment and delivery process accounted for a larger share than in other regions.

The Beijing–Tianjin–Hebei region exhibited the most significant increase in carbon emissions per unit of water supply (CEPWS) between 2010 and 2022 (Fig. 3b). In 2010, the highest estimated CEPWS values were found in Henan and Tianjin (0.9 kg $CO_2e\ m^{-3}$), followed by Shandong and Beijing (0.8 kg $CO_2e\ m^{-3}$) and Hebei (0.6 kg $CO_2e\ m^{-3}$). Over the study period, CEPWS increased significantly in Beijing, Tianjin, and Hebei. Consequently, the three

Table 1
Selection and definitions of variables for the spatial econometric model.

Category	Variable name	Variable measurement
Dependent variable	Internal effect factors (IEF)	CEM/CEI/PECI/ECI/WSX/LWS
Independent variable	Economic development level (EDL)	GDP per capita
Control variable	Industry structure (IS)	Proportion of secondary industry
	Technological upgrading (TU)	Number of patents
	Population density (PD)	Ratio of permanent population to administrative area
	Electricity generation mix (EGX)	Proportion of thermal power generation
	Water use intensity (WUI)	Water use per CNY 10,000 of GDP

Note: CEM: carbon emissions mix in the carbon emissions within the water supply life; CEI: carbon emission intensity of primary energy consumption; PECI: primary energy consumption intensity of the electricity consumption; ECI: electricity consumption intensity in the water-supply process; WSX: water source mix; LWS: local water supply.

provinces with the highest CEPWS in 2022 were Hebei (2.3 kg CO_2e m^{-3}), Beijing (1.7 kg CO_2e m^{-3}), and Tianjin (1.6 kg CO_2e m^{-3}). Over the same period, 18 provinces exhibited a downward trend in CEPWS, with the largest decreases occurring in Yunnan, Heilongjiang, and Jilin, while Qinghai, Sichuan, and Yunnan maintained the lowest CEPWS, with values remaining below 0.2 kg CO_2e m^{-3} (Fig. 3b).

3.2. Decomposition of the internal factors influencing CEWS

The changes in China's CEWS exhibited three distinct stages, including 2010–2011, 2011–2014, and 2014–2022. Therefore, to identify the primary internal driving factors of CEWS in different periods, we decomposed CEWS changes across four temporal segments: the entire study period (2010–2022) and the three aforementioned subperiods.

ECI was identified as a primary driver for the increase in national CEWS. Between 2010 and 2022, while CEM, CEI, and WSX contributed to this increase, ECI had the greatest positive impact, accounting for 69.2 Mt CO_2 yr^{-1} (Fig. 4). However, the effect of ECI on CEWS growth varied substantially across provinces. For example, ECI accounted for over 90% of the increase in CEWS in Nei Mongol and Shanghai, and exceeded 60% in Beijing, Tianjin, and Hebei. In contrast, in provinces such as Hubei, which benefit from available water resources with relatively low electricity intensity, the contribution of ECI to CEWS growth was minimal.

The extent to which ECI drove CEWS growth varied across different time periods. At the national level, ECI had the strongest promoting effect on CEWS (52.9 Mt CO_2 yr^{-1} increase) in the 2014–2022 period, followed by 2011–2014 (12.4 Mt CO_2 yr^{-1} increase) and 2010–2011 (1.7 Mt CO_2 yr^{-1} increase) (Fig. 4). During 2010–2011, ECI contributed to CEWS growth in only half of the provinces. Between 2011 and 2014, ECI became a universal driver of CEWS growth across all provinces. During this period, Shanghai's ECI was the sole contributor to its CEWS increase. Over the years from 2014 to 2022, ECI continued to drive CEWS growth in most provinces. However, the effect of ECI on CEWS growth continued to weaken (Supplementary Fig. S3). For example, Shanghai's reduction in electricity consumption during the water resource treatment and delivery process negatively affected CEWS growth.

PECI played a crucial role in reducing CEWS. Between 2010 and 2022, PECI contributed to a 54.9 Mt CO_2 yr^{-1} decrease in national CEWS, far exceeding the 12.7 Mt CO_2 yr^{-1} reduction attributed to LWS (Fig. 4). Although LWS suppressed national CEWS growth after 2014, it is noteworthy that with the expansion of local water resources, LWS began to promote CEWS growth from 2021 (Supplementary Fig. S3). At the provincial level, the increase in water demand in provinces such as Jiangsu and Hubei also caused LWS to contribute to an increase in CEWS. In contrast, PECI generally suppressed CEWS growth across most provinces. In several provinces that experienced rapid clean energy expansion, including Shanxi, Jiangsu, Jiangxi, Hunan, Hainan, Sichuan, Yunnan, and Xinjiang, PECI accounted for over 90% of their CEWS reduction.

The influence of PECI on CEWS growth was initially positive but became negative in later stages. From 2010 to 2011, during the early stages of clean energy development, PECI promoted CEWS growth in 19 provinces. However, with clean energy generation gradually expanding, primary energy consumption per unit of electricity generation decreased, amplifying PECI's mitigating effect. This suppressive influence peaked between 2011 and 2014, accounting for a 34.1 Mt CO_2 yr^{-1} reduction in national CEWS (Fig. 4). During the 2014–2022 period, while PECI continued to exert a negative influence on CEWS growth, its contribution decreased to 23.7 Mt CO_2 yr^{-1}. However, during this same period, PECI contributed positively to CEWS growth in provinces such as Hubei, Guangxi, Chongqing, and Guizhou.

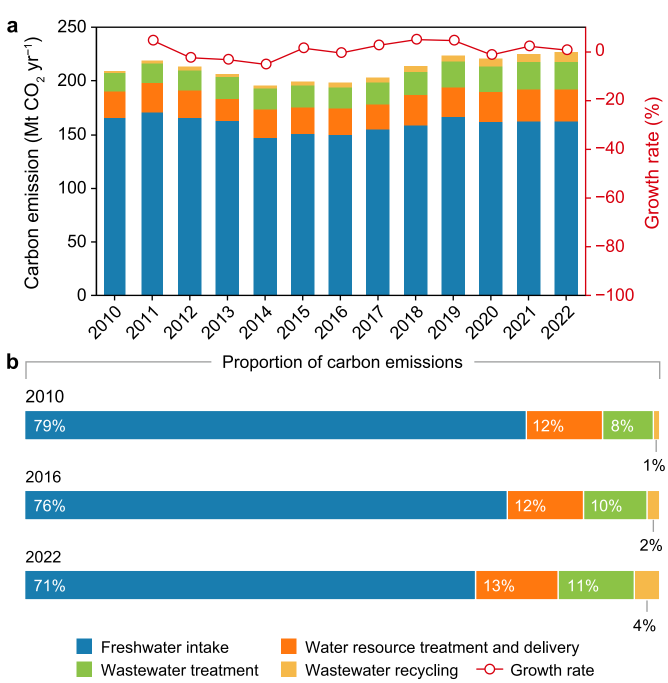

Fig. 2. National carbon emissions from water-supply and their distribution across supply stages (2010–2022). **a**, Annual carbon emissions from water-supply processes (stacked bars; left axis), disaggregated into freshwater intake, water resource treatment and delivery, wastewater treatment, and recycling. The red line indicates the annual growth rate (right axis). **b**, Proportion of carbon emissions attributable to each water-supply stage.

3.3. Transmission mechanisms of economic development affecting CEWS and their regional heterogeneity

Based on the results in Supplementary Text S2, it was reasonable to use SDM to analyze the mechanisms by which economic development affects CEWS. At the national level, economic development influenced CEWS through multiple internal factors, including CEM, CEI, PECI, ECI, WSX, and LWS, which exhibited some heterogeneity (Table 2). Specifically, economic development was negatively correlated with CEI (total effect coefficient = −0.1, $p < 0.05$) and WSX (total effect coefficient = −0.6, $p < 0.01$), thereby contributing to a reduction in CEWS. In contrast, economic development positively influenced CEM (total effect coefficient = 1.9, $p < 0.01$) and LWS (total effect coefficient = 0.5, $p < 0.01$), driving CEWS growth. However, the limited contributions of these four internal factors in driving CEWS changes mean that economic development had a negligible impact on CEWS growth through these transmission pathways.

The primary transmission mechanisms through which economic development influenced CEWS were ECI and PECI, both of which exhibited contrasting spatial spillover effects. Specifically, local economic development exerted a significant positive direct effect on local PECI (effect coefficient = 1.1, $p < 0.01$), indicating that local economic growth increased local primary energy consumption intensity, thereby promoting local CEWS. Conversely, local economic development exerted a significant negative indirect effect on both PECI (effect coefficient = −0.9, $p < 0.1$) and ECI (effect coefficient = −13.9, $p < 0.01$). This indicates that local economic development significantly suppressed increases in

Fig. 3. Provincial trends in carbon emissions from water-supply processes (2010–2022). **a**, Carbon emissions by water-supply stage for each province over time. The red and blue numbers represent changing rates in carbon emissions in 2022 relative to 2010. **b**, Carbon emissions per unit of water supplied for each province over time.

electricity and primary energy consumption intensities in neighboring provinces, thereby mitigating CEWS growth. Considering the total effects, economic development did not exhibit a statistically significant effect on PECI (effect coefficient $= 0.3$, $p > 0.1$) but significantly reduced ECI (effect coefficient $= -12.7$, $p < 0.01$). Consequently, economic development exerted a net negative impact on CEWS by significantly lowering ECI.

ECI and PECI were important factors that influenced CEWS. In all regions except central China, economic development negatively affected CEWS growth. Specifically, in northeast China, while

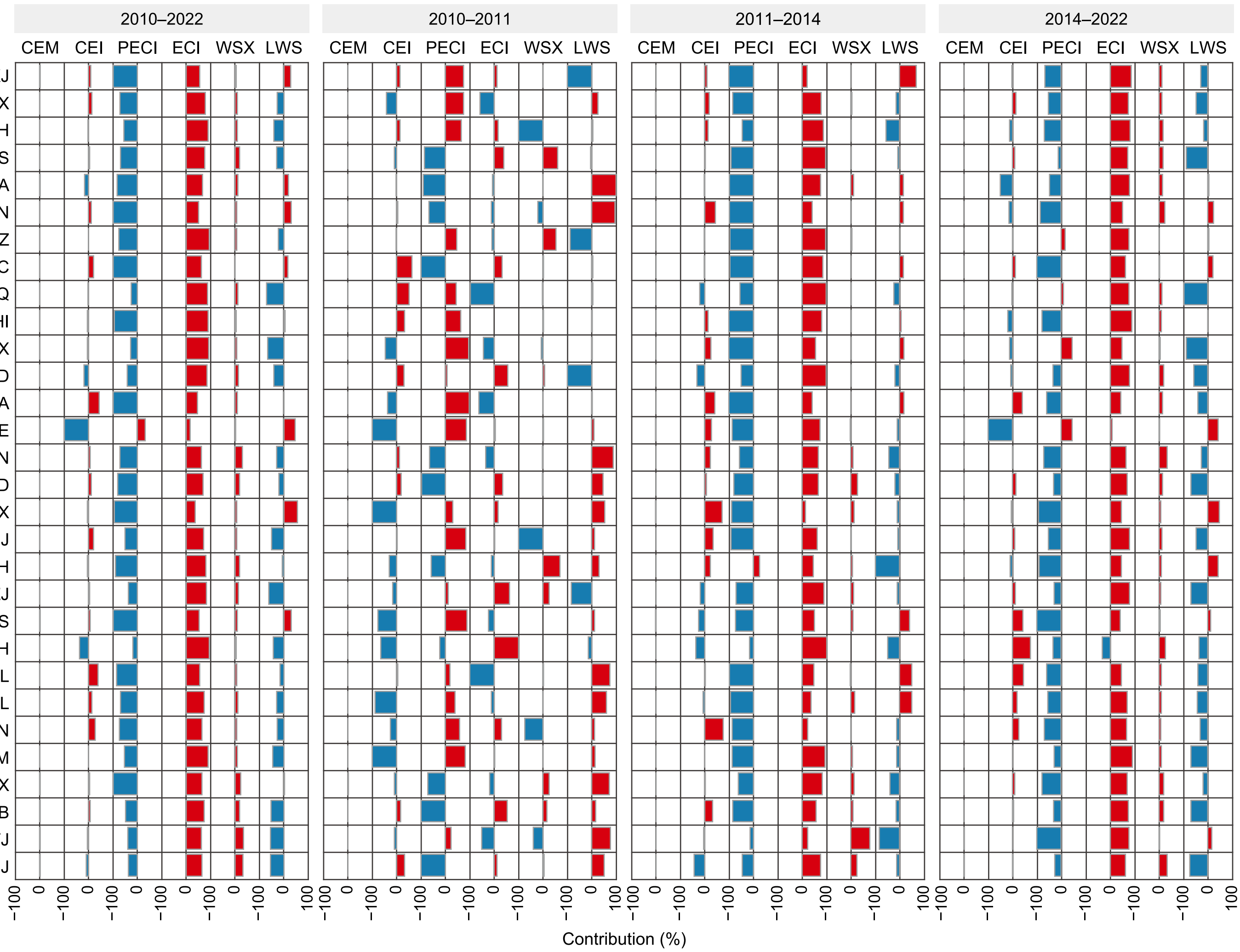

Fig. 4. Contribution of six internal factors to the changes of carbon emissions from water-supply processes from thirty provinces in different periods. The abbreviations of each province are shown in Supplementary Table S2. CEM: carbon emissions mix in the carbon emissions within the water supply life; CEI: carbon emission intensity of primary energy consumption; PECI: primary energy consumption intensity of the electricity consumption; ECI: electricity consumption intensity in the water-supply process; WSX: water source mix; LWS: local water supply.

economic development had no statistically significant effect on ECI, its direct effect coefficient on PECI was −41.6 ($p < 0.01$; Fig. 5a). This suggests that in northeast China, economic development mitigated CEWS growth by reducing local PECI. In contrast, economic development in east China reduced CEWS mainly by suppressing the growth of ECI and PECI in neighboring areas (Fig. 5b).

Table 2
Spatial spillover effects of economic development on various internal factors.

Variable	Direct effect	Indirect effect	Total effect
CEM	1.0*** (0.2)	0.9*** (0.3)	1.9*** (0.4)
CEI	−0.1 (0.1)	−0.1 (0.1)	−0.1** (0.1)
PECI	1.1*** (0.3)	−0.9* (0.5)	0.3 (0.4)
ECI	1.2 (0.8)	−13.9*** (2.2)	−12.7*** (2.3)
WSX	−0.3*** (0.1)	−0.3* (0.2)	−0.6*** (0.2)
LWS	0.5*** (0.1)	0.1 (0.1)	0.5*** (0.1)

Note: CEM: carbon emissions mix in the carbon emissions within the water supply life; CEI: carbon emission intensity of primary energy consumption; PECI: primary energy consumption intensity of the electricity consumption; ECI: electricity consumption intensity in the water-supply process; WSX: water source mix; LWS: local water supply. Values in parentheses are robust standard errors. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

In west China, only the indirect effect of economic development on ECI was significant (effect coefficient = −0.4, $p < 0.05$; Fig. 5c), indicating that economic development mitigated CEWS growth by reducing ECI in the surrounding areas. In central China, this pattern was reversed. First, both the direct and indirect effects coefficients of economic development on ECI were 3.9 ($p < 0.01$) and 7.5 ($p < 0.05$), respectively. Furthermore, its direct effect on PECI was significantly positive, with a coefficient of 5.5 ($p < 0.01$; Fig. 5d). This indicates that economic growth in central China increased both local ECI and PECI and stimulated ECI growth in neighboring provinces, thereby driving CEWS upward.

4. Discussion

4.1. Carbon reduction benefits of clean energy are offset by the increased use of energy-intensive water sources

China's water supply system exhibits a carbon-emissions paradox: efforts to enhance water security by relying on energy-intensive water sources may undermine the goal of decarbonization. On the one hand, China is navigating significant decarbonization pressure by increasing the use of clean energy, with its share of total electricity generation rising from 20.3% in 2010 to 33.5% in 2022 (Supplementary Fig. S4). This shift reduced the carbon emission intensity of electricity consumption in China from 0.8 kg CO_2e kWh^{-1} in 2010 to 0.6 kg CO_2e kWh^{-1} in 2022 (Supplementary Fig. S5). On the other hand, unlike developed countries such as the Netherlands and Sweden, where water supply systems operate at low energy intensity [51], China continues to address water scarcity by expanding energy-intensive water sources [52]. For example, the contribution of large-scale inter-basin water transfer projects (e.g., the South-to-North Water Diversion Project) to total water supply increased from 2.0% in 2010 to 3.8% in 2022 [46]. However, these nontraditional water sources increased China's water-supply electricity consumption from 0.4 kWh m^{-3} in 2010 to 0.6 kWh m^{-3} in 2022. As a result, the decarbonization gains from a cleaner power grid were offset by the expansion of energy-intensive water sources, resulting in a net increase in national CEWS.

This carbon emissions paradox reveals a key risk to China's fragmented governance structure, in which strategies in one sector can precipitate negative outcomes in another [53]. Our findings provide empirical validation of sectoral conflicts within China's water–energy nexus [19]. Although both energy transition and water security are critical national strategies in China, they conflict from a carbon-emissions perspective [54,55]. Consequently, this carbon paradox highlights the need for a fundamental governance shift toward an integrated water–energy–carbon nexus approach [56]. Such a shift calls for enhanced interdepartmental coordination to align water management, energy planning, and climate target objectives. For example, carbon emissions assessments should be integrated into planning and decision-making processes for energy-intensive water sources [57,58]. Information sharing should be fostered across authorities to strengthen coordinated decision-making in managing the water–energy–carbon nexus.

4.2. Economic development has nonlinear spatial spillover effects on carbon emissions from water-supply process

At the national level, the mitigating effect of economic development on CEWS growth is primarily attributable to interprovincial spatial spillovers. Specifically, economic development in one province significantly suppresses electricity consumption intensity in the water-supply processes of neighboring regions. This finding underscores that carbon emissions from water-supply process are a regionally interconnected system. We attribute this phenomenon to regional integration policies and the resulting agglomeration economies [59]. Such integration strengthens the exchange of technology and expertise through inter-regional trade networks, facilitating the diffusion of advanced water-saving technologies and low-carbon operational practices from economically developed provinces to less developed ones [60]. Consequently, a province's economic growth can catalyze decarbonization in its neighbors' water supply systems, even in the absence of explicit cross-regional governance policies.

Consistent with trends observed in other sectors [61,62], a U-shaped nonlinear relationship exists between national economic development and CEWS. Initially, the transition to centralized water supply systems and a decline in high-water-consuming industries allowed economic growth to suppress CEWS. However, as economies advance, rising demands for higher water quality and increasing reliance on energy-intensive water sources drive CEWS upward. This nonlinearity underscores that economic growth alone is an unreliable decarbonization strategy for the water supply system. However, this relationship is not spatially uniform. In central China, the relationship between economic development and CEWS follows an inverted U-shape. This pattern is closely linked to the siphon effect, whereby developed regions attract technology and talent while transferring water-intensive industries to central China [63,64]. As a result, the region faces systemic disadvantages relative to more developed regions, manifested as constrained technological upgrading, suboptimal infrastructure, and weaker institutional frameworks. This dynamic may risk trapping central China in a long-term "high-carbon lock-in", which would severely impede its ability to escape the "middle-income trap" [65,66].

Overall, these findings highlight the dual impact of economic development on CEWS: it can promote positive inter-regional spillovers while simultaneously creating perilous high-carbon lock-in risks for specific regions. Therefore, a uniform decarbonization policy for the water supply system is insufficient and may even be counterproductive under sustained economic growth. A combined strategy incorporating national coordination and region-specific interventions is essential. At the national level, policies should leverage spillover effects through inter-provincial collaborative governance [67]. At the regional level, high-carbon lock-in regions, such as central China, require stricter environmental entry standards and targeted technological guidance to ensure the sustainability of economic growth and the decarbonization of water supply systems [68].

4.3. Policy implications

First, the continuous development of clean energy represents a central strategy for carbon reduction. To continuously promote clean energy utilization, long-term development goals must be established and supported by sustained investment to enhance the efficiency of renewable technologies [69]. Concurrently, maximizing the overall absorption capacity of clean energy generation requires optimizing electricity system dispatch and strengthening inter-regional transmission from clean energy-rich areas to those with limited clean energy potential [70,71]. However, in regions with rapidly increasing CEWS, such as Beijing, Tianjin, and Hebei, additional measures are required, including improving the efficiency of pumping stations in water diversion, reducing electricity consumption in wastewater recycling, and enhancing overall water use efficiency [72].

Second, the positive spatial spillover effects of economic development on CEWS mitigation suggest that carbon reduction strategies should shift from province-led management toward multi-provincial collaborative management. This transition requires coordinated cross-provincial planning of water resource allocation and clean energy infrastructure to optimize resources and achieve synergistic carbon emission reduction. For instance, developed eastern provinces could lead by sharing best practices in low-energy water supply operations with less developed regions [73]. Meanwhile, cross-provincial benefit-sharing or carbon credit trading mechanisms could be introduced, allowing provinces that exceed CEWS reduction targets to exchange surplus carbon credits with those struggling to meet their goals [74].

Finally, the regional heterogeneity and nonlinear relationship between economic development and CEWS highlight the importance of a stage-specific, regionally differentiated policy design. In economically developed regions, policy efforts should focus on consolidating existing achievements and further reducing CEWS. For example, market-based water rights trading should be established in water-rich areas [75]. In addition, these provinces could focus on improving the energy efficiency of both existing and new water treatment infrastructure, such as long-distance water-transfer pumping stations and wastewater treatment plants. In contrast, in central China, where economic development may still

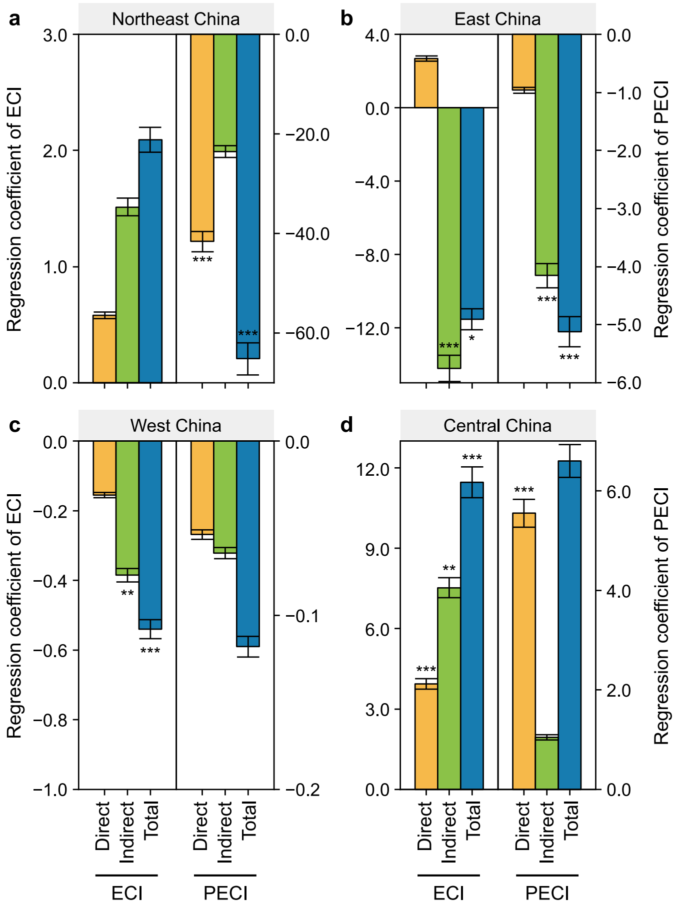

Fig. 5. Direct, indirect, and total effects of economic development on electricity consumption intensity in the water-supply process (ECI) and primary energy consumption intensity of the electricity consumption (PECI) for the four geographical subregions: northeast China (**a**), east China (**b**), west China (**c**), and central China (**d**). The provinces included in each geographic subregion were listed in Supplementary Table S2. Coefficients for ECI (left axis) and PECI (right axis) are plotted on separate scales. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

drive CEWS upward, policy should prioritize avoiding energy-intensive water-supply pathways. This entails enforcing stricter carbon-emission thresholds for new water supply projects, prioritizing low-carbon alternatives, such as floodwater harvesting [76], and introducing targeted subsidies or tax incentives to accelerate the adoption of low-energy treatment technologies [77].

4.4. Uncertainties and limitations

Given that the water supply system is a complex artificial system coupled with socioeconomic development, several limitations should be noted. First, although the proposed framework dynamically captures the evolution of both the electricity generation mix and the water source structure, it relies on static electricity consumption intensity across various water-supply processes. The value of electricity consumption intensity may vary over time due to technological innovations and efficiency improvements. Nonetheless, the findings of this study provide a robust baseline for understanding the historical evolution of CEWS. Second, while this study identified the carbon emissions paradox, it did not explicitly quantify the trade-off between enhancing water security through energy-intensive sources and the associated carbon-emissions costs. Future research should develop integrated assessment models capable of identifying coordinated pathways to achieve both water security and carbon mitigation goals.

5. Conclusions

This study proposed and applied an integrated framework of quantification–decomposition–attribution to analyze carbon emissions from water supply systems and their driving factors. By integrating LCA, LMDI, and SDM, the framework addresses the limitations of single-method approaches adopted in previous assessments. It not only provides a comprehensive account of CEWS dynamics in China but also reveals the nonlinear and spatially heterogeneous impact of economic development on CEWS. We identified the following key findings. First, despite the initial downward trend of CEWS, which benefited from clean energy development, rising reliance on energy-intensive water resources ultimately drove CEWS up to 228 Mt CO_2 yr^{-1} by 2022. Second, while freshwater intake accounted for over 70% of CEWS, its carbon emissions were declining, in contrast with the continued increase in carbon emissions from other water-supply processes. Third, at the national level, economic development significantly suppressed ECI growth in neighboring regions through spatial spillover effects, thereby inhibiting CEWS growth. Fourth, the relationship between economic development and CEWS generally followed a U-shaped pattern, but shifted to an inverted U-shaped pattern in central China. Our findings support the formulation of carbon reduction strategies in China's water supply sector that also safeguard water security. In addition, the analytical framework and generated insights provide a transferable reference for managing the water–energy–carbon nexus in other rapidly developing, water-scarce regions worldwide.

CRediT authorship contribution statement

Long Jiang: Writing - Original Draft, Visualization, Methodology, Data Curation, Conceptualization. **Zongzhi Wang:** Writing - Review & Editing, Methodology, Investigation, Funding Acquisition, Conceptualization. **Yong Jiang:** Writing - Review & Editing, Methodology, Conceptualization. **Kun Wang:** Writing - Review & Editing, Methodology. **Liang Cheng:** Writing - Review & Editing, Funding Acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ese.2026.100665.

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