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Exploring City Development Modes under the Dual Control of Water Resources and Energy-Related CO_2 Emissions: The Case of Beijing, China

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Abstract: Water and energy are basic resources for urban development. It is of extreme importance to balance economic development, water and energy security, and environmental sustainability at the city level. Although many studies have focused on energy-related CO_2 emissions or water resources, individually, in relation to socioeconomic development, few studies have considered water and energy-related CO_2 emissions as synchronous limiting factors. Here, taking Beijing as an example, a partial least squares STIRPAT model—a method that combines partial least squares with the STIRPAT (stochastic impacts by regression on population, affluence, and technology) model—was used to determine the main driving factors of water use and energy-related CO_2 emissions at the regional scale from 1996 to 2016. The empirical results showed that the population, per capita gross domestic product (GDP), urbanization level, technology level, and service level, are all important factors that influence the total water use and energy-related CO_2 emissions. Additionally, eight scenarios were established to explore suitable development modes for future years. Consequently, a medium growth rate in socioeconomic status and population, and a high growth rate in the technology and service level, were found to be the most appropriate development modes. This scenario would result in a total water use of 4432.13 million m^3 and energy-related CO_2 emissions of 173.64 million tons in 2030. The results provide a new perspective for decision makers to explore suitable measures for simultaneously conserving water resources and reducing energy-related CO_2 emissions in the context of urban development.

Keywords: partial least squares STIRPAT model; water resources; energy-related CO_2 emissions; scenario analysis; Beijing

1. Introduction

Water and energy have become two bottlenecks restricting sustainable socioeconomic growth [1]. The long-term requirement for water and energy is increasing with population and economic development, which has aggravated the global fragility of water and energy systems, both regionally and nationally, in the past few decades [2]. Water, energy, and environmental status are especially threatened in countries or regions experiencing high-speed economic and urbanization development. Among such countries, China is a typical instance in which water and energy status are particularly challenging for high-speed economic development and the aquatic ecosystems and environment are highly stressed [3,4]. Cities are gathering places where population, industry, and wealth are highly concentrated, and large amounts of resources are consumed. In China, city regions account for 75% of the total energy consumption and are responsible for 85% of energy-related CO_2 emissions [5]. Additionally, water resources are one of the main factors in urban economic development. The city development modes and policy choices have a significant impact on ensuring water and energy security and sustainable environmental development.

To date, multiple studies have analyzed the impact of policy trends on the environment. For example, Yang et al. investigated the climate impact of U.S. policy choices based on the assumption of whether the U.S. follows its proposed nationally determined contribution and makes use of technological innovation [6]. Pan et al. studied the implications of different effort-sharing principles of China's energy system transformation with regard to achieving the 2 °C goals [7]. Feyera et al. developed the water evaluation and planning (WEAP) model to test various policy options to determine which one could achieve sustainable water use in Kenya [8]. We should choose appropriate city development modes to ensure not only city economic development, but also water and energy security and environmental sustainability.

In addition, multiple studies have explored the driving forces of energy-related CO_2 emissions to ensure energy conservation and emission reduction [9–11]. For example, Pao and Tsai forecasted the CO_2 emissions, energy consumption, and economic growth in Brazil by applying a grey prediction model (GM) and autoregressive integrated moving average (ARIMA) model [12]. Meng et al. proposed a hybrid model for projecting energy-related CO_2 emissions of China and compared the results with those from the GM [13]. Liddle presented the STIRPAT (stochastic impacts by regression on population, affluence, and technology) model to explore the carbon emissions elasticities for income and population, and found that the carbon emissions elasticity of income is highly robust, in contrast to the carbon emissions elasticity of the population [14]. Additionally, previous studies have investigated the relationship between social development and water resources. Chenoweth used scenario analysis to analyze whether the water resources of Israel, Palestine, and Jordan are adequate to enable social and social development in the future [15]. Wang et al. evaluated the impact of socioeconomic development on water resources use [16]. Jason Scott et al. selected fractional water allocation and capacity sharing as a method of allocating and managing water entitlements to encourage sustainable economic growth and social development in South Africa [17]. Zhao et al. explored the influencing factors of population, affluence, urbanization level, and diet structure on the agriculture product-related water footprint change based on an extended STIRPAT model to address China's current water resource pressures [18]. Although these studies have forecasted future CO_2 emission or water resources from different perspectives, and have provided meaningful policy implications, many studies have tended to regard water and energy security as isolated factors, rather than consider them in conjunction in formulating long-term policies.

The newly born concept of the water–energy nexus has emerged over the past decade, and is closely related to population growth, urbanization, diminishing resources, and climate change [19]. Immense amounts of fundamental research have been conducted to analyze the link between water and energy, i.e., water is needed to produce energy, and energy is consumed to maintain a water supply. For example, He et al. evaluated the needed energy for various water supply sectors in 2020 and 2030 in China, and predicted that the urban domestic sector will overtake the agricultural sector as the most energy-intensive sector in 2030 [20]. Sun et al. investigated the water–energy nexus in the Beijing–Tianjin–Hebei region from the perspective of the electricity sector, and found that the insufficient water demand of power generation can be mitigated, to a certain degree, due to power structure adjustment and technological advancement, but that the trend towards water shortages cannot be avoided [21]. Lam et al. calculated and compared the energy consumption for water provision in thirty cities of the Middle East and North Africa [22]. However, most of these studies have concentrated on the physical linkages of water and energy resources to make planning and policy implications, and lack any integrated analysis exploring the common driving factors of the two from the aspect of social development to ensure water and energy security, and environmentally sustainable development.

Beijing, as the capital of China, has been facing a water–energy predicament in balancing the inherent tradeoffs among water and energy security, economic competitiveness, and environmental sustainability. According to the Thirteenth Five-Year Plan (2016–2020), The gross domestic product (GDP) growth is expected to average 6.5% per year from 2016 to 2020. The total water use will be controlled at 4.3 billion m^3, and the water intensity per unit of GDP will be reduced by over 30% relative to the standards proposed in the Eleventh Five-Year Plan (2006–2010). The total energy consumption will be capped at 76 million tons of standard coal, and the energy intensity per unit of GDP is slated to drop by more than 17% in 2020. The proportion of high-quality energy will increase to more than 95%, and the proportion of renewable energy will exceed 8% [23], to achieve peak carbon dioxide emissions as soon as possible. It is important to consider the development modes of Beijing under the dual control of water resources and energy-related CO_2 emissions to fulfil future urban planning requirements. The specific objectives in the present paper are to (1) identify the significant common driving factors influencing water use and energy-related CO_2 emissions in Beijing; (2) design scenarios with driving forces at different levels according to the results; and (3) select a suitable way to simultaneously conserve water resources and reduce energy-related CO_2 emissions over the next fourteen years.

2. Materials and Methods

2.1. Study Area

Beijing is the capital of the People's Republic of China, and is located in the northern region of the North China Plain, adjacent to Tianjin and surrounded by Hebei province (Figure 1). The per capita GDP of Beijing was 16,789 USD in 2016, ranking second in China. The permanent population in 2016 was 21,729,000, and the urbanization rate reached 86.5%, which was second only to that of Shanghai in the whole country. The proportion of the tertiary industry exceeded 80% and reached 80.3% [24,25]. Advanced technology and the introduction or internalization of high-end talents have become the fundamental driving forces of Beijing's economic development. The construction of cultural centers and science and technology innovation centers has been promoted steadily [26].

Beijing is located in the Haihe River Basin, where water resources are scarce. The average per capita reserves of water resources in Beijing were 161 m^3 in 2016, or 1/60 of the global average [27]. The demand for water has already exceeded the supply capacity, due to the increase in urban population and economic development. The demand and supply balance have been maintained at the expense of the overdraft of groundwater, and has damaged the environment for many years [28]. The competition between supply and demand will become increasingly acute in the future as social development progresses. Additionally, the city has a small primary energy reserve and is a typical energy resource-poor city that relies heavily on foreign provinces [29]. Fossil energy accounts for up to 76% of the energy consumption structure. Energy is the basic resource of urban development and inevitably causes extensive CO_2 emissions [24,30]; thus, it is imperative to explore future development modes for achieving the goals of resources conservation and environmentally sustainable development in Beijing.

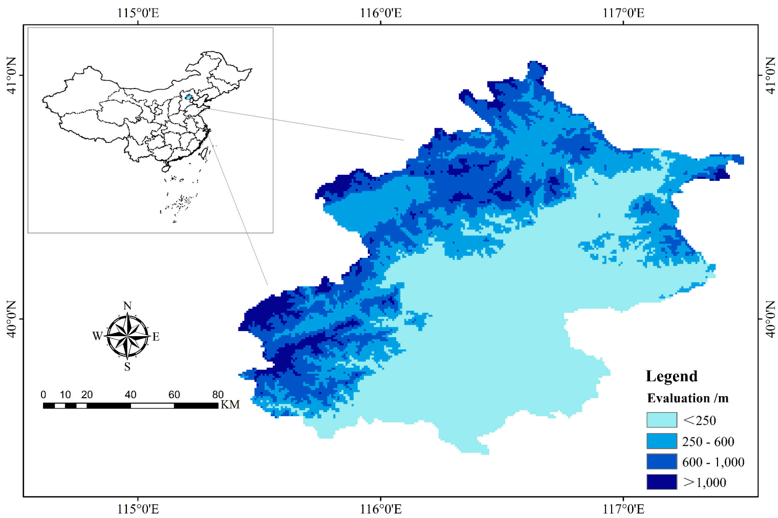

Figure 1. Simplified map of Beijing.

2.2. Methodology

2.2.1. Calculation of Energy-Related CO_2 Emissions

Energy-related CO_2 emissions were calculated based on the 2006 Intergovernmental Panel on Climate Change (IPCC, Geneva, Switzerland) Guidelines for National Greenhouse Gas Inventories as follows [31]:

$$ERCE = \sum_{i=1} E_i \times LCV_i \times CF_i \times O_i \times \frac{44}{12}, \tag{1}$$

where $ERCE$ represents the total energy-related CO_2 emissions (million tons), E_i is the total energy consumption of fuel i (million tons), LCV_i represents the lower calorific value of fuel i, CF_i is the unit calorific value of the ith kind of fuel in terms of carbon content, O_i is the oxidation rate of fuel i, and $LCV \times CF \times O$ contains the emission factors [32–34]. All emission factors for fuel combustion in this study were obtained from Mi et al. [35], and 44/12 is the ratio of the molecular weights of CO_2 and C.

2.2.2. STIRPAT Model

The well-known IPAT (Impact = Population × Affluence × Technology) model was first established by Ehrlish and Holdren in the early 1970s to detect the driving forces of environmental impact; the model can be described as follows: $I = PAT$ [36]. Here, I represents the environmental pressure (i.e., water use and energy-related CO_2 emissions in our case study), P represents the population size, A is affluence, and T refers to the technology level. The IPAT equation assumes that I is affected by the three driving factors P, A, and T, and that proportionality exists between the variables, which limits the application of the model in nonproportional scenarios. To overcome this constraint, Dietz and Rosa proposed the STIRPAT model, which has a stochastic form that can be expressed as follows [37]:

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

where a is the model constant; b, c, and d are the indexes of P, A, and T, respectively; and e is the error term. Equation (2) is often converted to logarithmic form in empirical studies, as follows:

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

Additional driving factors can be incorporated into the STIRPAT model to analyze their impact on environmental pressure. To obtain a deep understanding of the driving factors of water use and energy-related CO_2 emissions in Beijing, the urbanization rate, which is defined as the proportion of the total population living in the urban area, was introduced into the model to better reflect the population factor. The real per capita GDP was used to represent the affluence factor. The added value of tertiary industry relative to the real GDP was added to the model to reflect the impact of changes in service level on water use and CO_2 emissions. Finally, the technology level factors included the water use intensity and energy intensity. The extended STIRPAT model can be described as follows:

$$\ln WU = \ln a_0 + a_1 \ln P + a_2 \ln UR + a_3 \ln A + a_4 \ln ST + a_5 \ln TW + \ln e_1, \tag{4}$$

$$\ln ERCE = \ln b_0 + b_1 \ln P + b_2 \ln UR + b_3 \ln A + b_4 \ln ST + b_5 \ln TE + \ln e_2, \tag{5}$$

where WU represents the total water use (million m^3), P is the population size, $ERCE$ is the energy-related CO_2 emissions (million tons), UR is the urbanization rate, A is affluence in terms of per capita GDP (10^4 USD), ST is the proportion of added value from tertiary industry, and TW and TE are the water use intensity and energy intensity, which are expressed as water use and energy consumption per unit of GDP, respectively (m^3/10^4 USD, tons of standard coal per 10^4 USD).

2.2.3. Partial Least Squares (PLS) Regression

PLS regression is regarded as one of the most effective methods for eliminating the correlation between variables and is used for modeling under the condition of multicollinearity [38]. The steps of PLS are as follows [39]: (1) Normalize the dependent variable Y and independent variable X, and denote the resulting terms as F_0 and E_0, respectively; (2) extract the first components t_1 and u_1, which must carry the most variation information to represent X and Y as best as possible; and (3) establish a regression model such that t_1 and u_1 are the linear combination of $x_1, x_2, \ldots, x_p$ and $y_1, y_2, \ldots, y_3$. The calculation is ended when the prediction sum of squares ($PRESS_t$) achieves a minimum score, and the extracted t involves the optimal number of components.

The variable important in projection (VIP) value is adopted to reflect the explanatory potential of each independent variable for each dependent variable, and can be calculated as follows [40]:

$$\mathrm{VIP}_j = \sqrt{\frac{p}{R_d(I;(t_1,\cdots,t_m))}\sum_{h=1}^{m} R_d(I;t_h)w_{h\,j}^2} \tag{6}$$

where VIP_j represents the VIP of x_j (j = 1, 2, ..., p), p is the number of independent variables, and w is the j_{th} component of the w_h-axis, which can be used to measure the marginal contribution of x_j to t_j, where $\sum_j^k w_{hj}^2 = w_h' w_h = 1$ and h = 1, 2, ..., m.

2.3. Data

The annual total population (P), per capita GDP (A), urbanization rate (UR), water use intensity (TW), energy intensity (TE), and percentage of added value from tertiary industry (ST) data were collected or calculated from the *National Bureau of Statistics of China*, *Beijing Statistical Yearbook*, and *Beijing Energy Statistics Yearbook* [23,41,42]. GDP was corrected for inflation to remove the factors of price changes in calculating economic aggregates, to facilitate the comparison of aggregates over time [43].

3. Results and Discussion

3.1. Estimating Energy-Related CO_2 Emissions in Beijing

As shown in Figure 2, the total energy consumption in Beijing ranged from 37.35 to 69.62 million tons of standard coal from 1996 to 2016. The change trend of total energy consumption was mainly manifested in two stages. From 1996 to 2011, the total energy consumption increased relatively quickly, with an annual growth rate of 3.6%, showing a slight upward trend, while the growth rate of energy consumption gradually leveled off, with an average annual growth rate of 1.6% from 2012. This behavior is due to the transformation and upgrading of Beijing's industrial capacity. In addition, the economic growth changed sharply, ending a period of double-digit growth. According to Figure 3, the energy-related CO_2 emissions in Beijing showed an increasing trend from 33.96 million tons to 129.62 million tons during the study period. The energy-related CO_2 emissions increased by 95.66 million tons in 20 years. However, the emissions intensity, which refers to CO_2 emissions per unit of GDP (million tons/10^4 USD), showed a significant downward trend with an annual decline rate of 6.42%, indicating that Beijing has achieved partial success in building a low-carbon economy and developing clean energy.

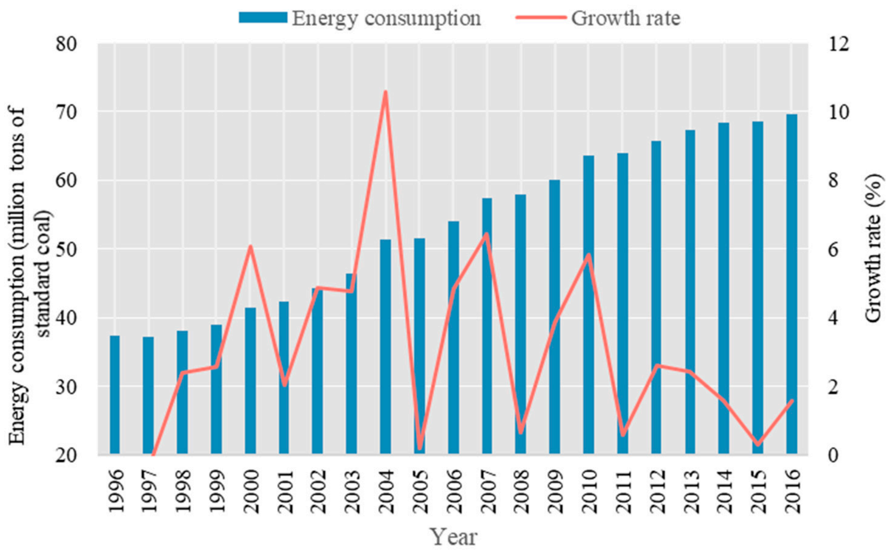

Figure 2. Total energy consumption and growth rate in Beijing from 1996 to 2016.

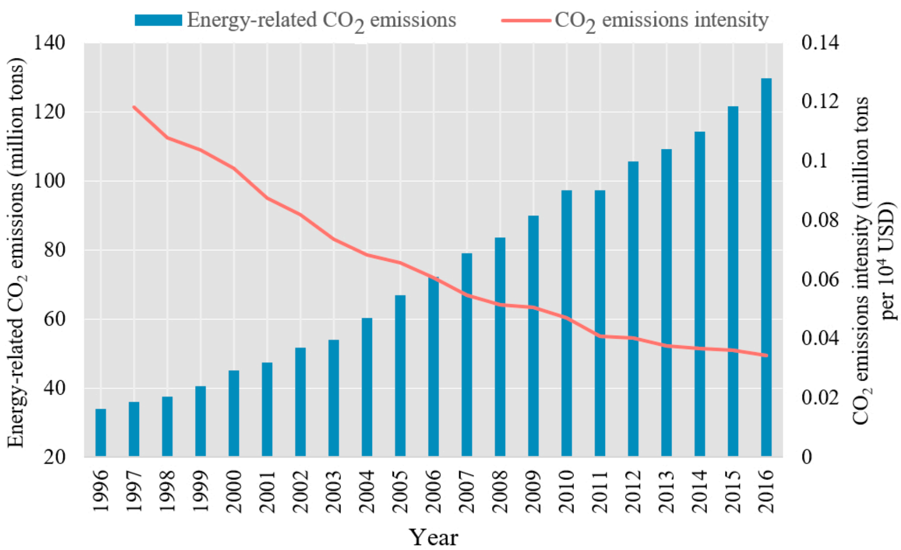

Figure 3. Energy-related CO_2 emissions and CO_2 emissions intensity in Beijing from 1996 to 2016.

3.2. Regression Analysis

3.2.1. Collinearity Diagnostics

A correlation test was carried out to test the collinearity between variables. There existed a relatively high correlation between variables, and most of the absolute values of the correlation coefficients were greater than 0.9 (Tables 1 and 2). Then, the ordinary least squares (OLS) method was adopted to further test whether there existed multicollinearity between a given dependent variable and the independent variables. All variance inflation factor (VIF) values were greater than 10 (Tables 3 and 4), indicating that there was substantial multicollinearity among these variables. Therefore, the regression results based on OLS were unreliable, and could not reflect the relationship between the driving factors and the associated water use and energy-related CO_2 emissions in Beijing. To eliminate the multicollinearity among variables, the PLS method was adopted to model the regression analysis.

Table 1. Matrix of correlation between variables (water use).

	ln*WU*	ln*P*	ln*A*	ln*UR*	ln*TW*	ln*ST*
ln*WU*	1					
ln*P*	−0.512 *	1				
ln*A*	−0.623 **	0.973 **	1			
ln*UR*	−0.629 **	0.953 **	0.974 **	1		
ln*TW*	0.652 **	−0.978 **	−0.997 **	−0.975 **	1	
ln*ST*	−0.643 **	0.933 **	0.979 **	0.935 **	−0.972 **	1

* Correlation is significant at the 0.05 level (2-tailed). ** Correlation is significant at the 0.01 level (2-tailed).

Table 2. Matrix of correlation between variables (energy-related CO_2 emissions).

	ln*ERCE*	ln*P*	ln*A*	ln*UR*	ln*TE*	ln*ST*
ln*ERCE*	1					
ln*P*	0.987 **	1				
ln*A*	0.997 **	0.973 **	1			
ln*UR*	0.977 **	0.953 **	0.974 **	1		
ln*TE*	−0.990 **	−0.982 **	−0.989 **	−0.948 **	1	
ln*ST*	0.967 **	0.933 **	0.979 **	0.935 **	−0.968 **	1

** Correlation is significant at the 0.01 level (2-tailed).

Table 3. OLS results.

Variable	Coefficient	*t*-Statistic	Sig.	VIF
1. OLS results (water use)				
C	−16.947	−12.760	0.000	
ln*P*	0.800	8.316	0.000	78.800
ln*A*	0.978	10.927	0.000	296.370
ln*UR*	−0.221	−1.020	0.026	24.818
ln*TW*	0.905	15.813	0.000	293.144
ln*ST*	−0.641	−2.808	0.015	110.544
***R* squared**	0.993			
***F*-statistic**	147.858			
Sig.	0.000			
2. OLS results (energy-related CO_2 emissions)				
C	−0.738	−0.570	0.079	
ln*P*	0.732	7.143	0.000	69.817
ln*A*	0.686	6.873	0.000	287.886
ln*UR*	0.605	1.705	0.014	51.666
ln*TE*	0.149	−2.213	0.047	131.445
ln*ST*	0.543	1.171	0.064	356.158
***R* squared**	1.000			
***F*-statistic**	3986.371			
Sig.	0.000			

Table 4. Cumulative variance explanation of the results by PLS analysis.

PLS Component	Variance of X	Cumulative Variance of X	Variance of Y	Cumulative Variance of Y	Adjusted R^2
1. Water use					
t1	0.974	0.974	0.377	0.377	0.342
t2	0.009	0.983	0.332	0.709	0.674
t3	0.006	0.989	0.100	0.809	0.773
t4	0.010	0.999	0.040	0.848	0.808
t5	0.001	1.000	0.126	0.975	0.966
2. Energy-related CO_2 emissions					
t1	0.972	0.972	0.994	0.994	0.994
t2	0.013	0.986	0.003	0.998	0.997
t3	0.005	0.991	0.001	0.998	0.998
t4	0.007	0.998	0.000	0.999	0.999
t5	0.001	0.999	0.000	0.999	0.999

3.2.2. PLS Regression of the STIRPAT Model

The PLS method was adopted to correct the STIRPAT model in the presence of multicollinearity among variables. By PLS theory, R^2X is the ability of the extracted principal components to interpret the independent variables X, and R^2Y is the ability to explain the dependent variable Y. When water use was the dependent variable and the number of principal components equaled 5, maximum values of R^2X (cum) = 1.000, R^2Y (cum) = 0.975 and adjusted R^2 = 0.966 were attained, indicating that this scenario represented the best explanation of both the dependent and independent variables (Tables 4 and 5). Additionally, when energy-related CO_2 emissions were the dependent variable and the number of principal components equaled 5, maximum values of R^2X (cum) = 0.998, R^2Y (cum) = 0.999 and adjusted R^2 = 0.999 were found, indicating that this scenario represented the best interpretation of both the dependent and independent variables (Tables 4 and 5). Thus, both the independent variables and dependent variables could be interpreted by the principal components with a satisfactory regression. We can conclude from this result that the future total water use and energy-related CO_2 emissions could be estimated based on the PLS-STIRPAT model (Table 5). The associated regression models can be defined as follows:

$$\ln WU = -18.390 + 0.975 \ln P + 1.017 \ln A - 0.194 \ln UR - 0.215 \ln ST + 0.965 \ln TW \quad (7)$$

$$\ln ERCE = -1.812 + 0.702 \ln P + 0.748 \ln A + 0.242 \ln UR - 0.130 \ln ST + 0.096 \ln TE \quad (8)$$

The VIP values, which reflect the importance of the independent variables to a dependent variable, are shown in Figure 4. These factors demonstrated similar importance in energy-related CO_2 emissions, for which all the VIP values ranged within 0.985–1.019. The influences of the factors on energy-related CO_2 emissions in Beijing were ranked as follows: ln$P$ (1.019) = ln$A$ (1.019) > lnTE (1.007) > lnUR (0.992) > lnST (0.985). However, when water use was considered as the dependent variable, the VIP values of the independent variables were distinct and ranged within 1.554−0.884. The influences of the factors on water use in Beijing were ranked as follows: lnTW (1.554) > ln$P$ (1.152) > ln$A$ (1.012) > lnST (0.894) > lnUR (0.880). The VIP values of the independent variables were all greater than 0.8, indicating that those variables were significant in explaining the dependent variable [44].

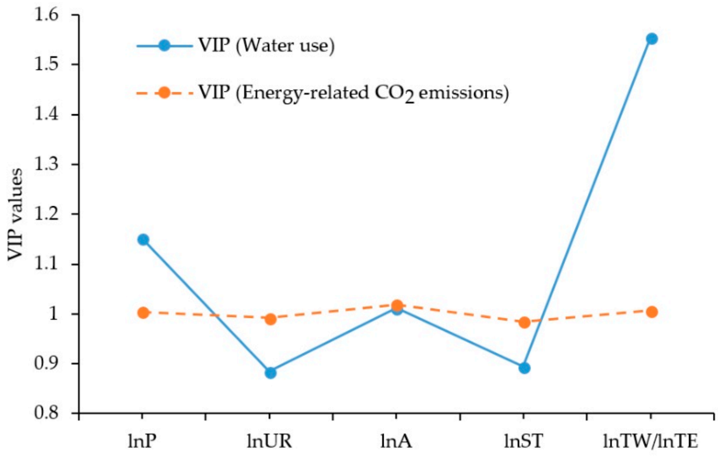

Figure 4. VIP values.

Table 5. Overview of the PLS regression results.

Variable	Water Use (ln*WU*)	Energy-Related CO_2 Emissions (ln*ERCE*)
Constant	−18.390	−1.812
ln*P*	0.975	0.702
ln*A*	1.017	0.748
ln*UR*	−0.194	0.242
ln*TW*/ln*TE*	0.965	0.094
ln*ST*	−0.215	−0.130
R^2X (cum)	1.000	0.998
R^2Y (cum)	0.975	0.999
Adjusted R^2	0.966	0.999

3.3. Model Verification

To further test the robustness of the STIRPAT model, both total water use and energy-related CO_2 emissions from 2011 to 2016 were calculated based on Equations (7) and (8), and compared with actual values. The estimated values were almost equal to the actual values, and the average relative errors of water use and energy-related CO_2 emissions were 0.99% and 1.29%, respectively (Table 6). Therefore, the PLS-STIRPAT model could be adopted to forecast future total water use and energy-related CO_2 emissions in Beijing.

Table 6. Comparison between actual values and estimated values of water use and CO_2 emissions from 2011 to 2016 in Beijing.

Year	Water Use			Energy-Related CO_2 Emissions		
	Actual Values (Million m^3)	Estimated Values (Million m^3)	Relative Error (%)	Actual Values (Million tons)	Estimated Values (Million Tons)	Relative Error (%)
2011	3596	3575	0.59%	97.23	99.84	2.65%
2012	3588	3566	0.61%	105.49	106.06	0.54%
2013	3638	3608	0.83%	109.05	109.17	0.11%
2014	3749	3711	1.01%	114.31	114.58	0.24%
2015	3820	3855	1.70%	121.5	119.33	1.73%
2016	3880	3832	1.21%	129.62	126.45	2.45%

3.4. Scenario Analysis and Prediction of Water Use and Energy-Related CO_2 Emissions in Beijing

Scenarios aimed at estimating future water use and energy-related CO_2 emissions were designed based on the PLS-STIRPAT model. Generally, population factors and affluence factors may lead to an increasing trend in total water use and CO_2 emissions, while technology factors, such as energy intensity, water use intensity, and service level, are negative factors that may have a negative influence on dependent variables. Therefore, we divided these variables into two parts, and assumed that the trends of variation in driving factors would be consistent within each part. Additionally, considering that the urbanization rate of Beijing has been relatively high and remained almost stable from 2010 to 2016, the urbanization rate is not considered in this study. The future trends of each driving factor were divided into three situations with diverse speeds: low (L), medium (M), and high (H). The combination of these factors formed eight scenarios, which are shown in Table 7, and the annual variation rates of each factor are shown in Table 8.

The predicted total water use and energy-related CO_2 emissions in Beijing from 2016 to 2030 are displayed in Figures 5 and 6. The total water use and CO_2 emissions will clearly continuously increase over the next fifteen years. The scenario-specific total water use in 2030 can be ranked in increasing order as "S5", "S7", "S4", "S6", "S2", "S1", "S3", and "S8", and the corresponding values are 4432.13, 5236.39, 5576.53, 5956.89, 6194.79, 7047.16, 7794.33, and 8866.78 million m^3, respectively. In addition, the energy-related CO_2 emissions in 2030 can be ranked in increasing order as "S7", "S5", "S6", "S2", "S1", "S4", "S3", and "S8", which is a different order from that of predicted water use; the corresponding values are 162.36, 173.64, 182.32, 195.19, 206.59, 215.40, 230.72, and 242.52 million tons, respectively.

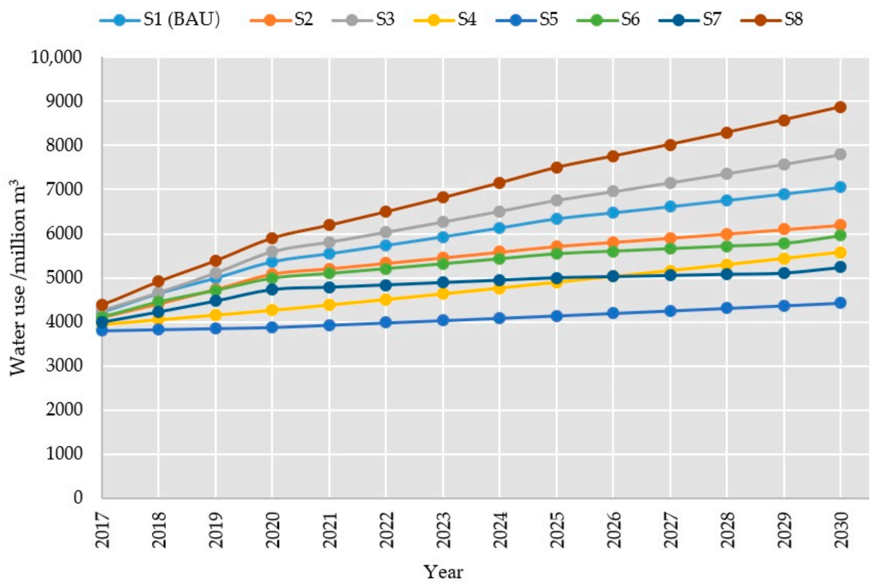

Figure 5. Predicted water use in Beijing from 2017 to 2030.

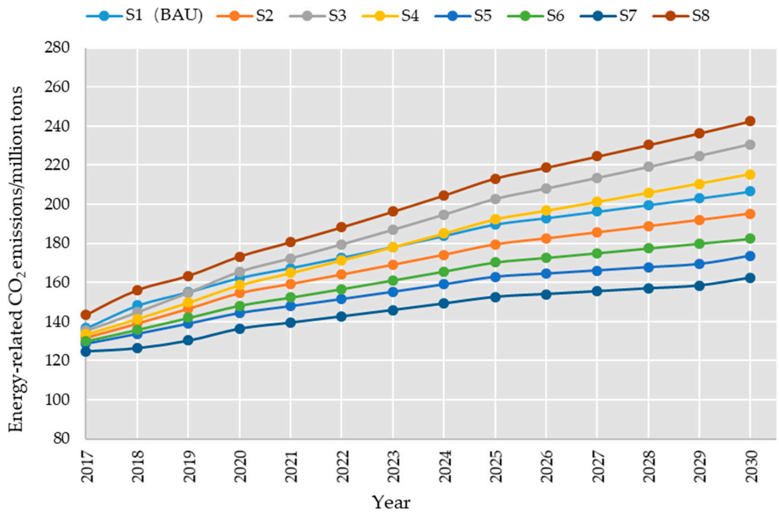

Figure 6. Predicted energy-related CO_2 emissions in Beijing from 2017 to 2030.

In the business-as-usual (BAU) scenario of S1, the total water use and energy-related CO_2 emissions will rise quickly to 7047.16 million m^3 and 206.59 million tons in 2030, respectively, representing a 78.96% and 59.39% increase, respectively, relative to the values in 2016. In S2, with an emphasis on adopting innovative technology to improve water efficiency and energy efficiency, and an increased focus on industrial restructuring, the total water use and energy-related CO_2 emissions will reach 6194.79 million m^3 and 195.19 million tons in 2030, respectively, or 13.8% and 5.8% less than the values for S1. Under a hypothetical situation with developing social and economic prosperity and rapid population growth in S3, the total water use and energy-related CO_2 may inevitably increase due to rapid urban development. The predicted total water use in 2030 is 7794.33 million m^3, which is a 25.8% increase relative to that in S2, while the energy-related CO_2 emissions will be 230.72 million tons, a 10.35% increase over S2. In S4, the government of Beijing continues to pursue prosperity in terms of social and economic development, while paying more attention to controlling the environmental pressure on water resources and energy. The total water use will decrease by 39.8%, while the CO_2 emissions will be reduced by 7.1% relative to the values in S3. In S5, with a medium increase in population and per capita GDP, high technological innovation and high industrial structure optimization, the total water use will be 4432.13 million m^3 in 2030, which is the minimum value among the eight scenarios, while the energy-related CO_2 emissions will be 173.64 million tons, which is the second-lowest value. Although the minimum energy-related CO_2 emissions appear in S7 with a value of 162.36 million tons, this scenario may be unacceptable, due to the low speed of economic development, which cannot approach the annual growth rate of 6.5% established in the Thirteenth Five-Year Plan (2016–2020) of Beijing as closely as S6 can. S8 shows an extensive social development mode that focuses more on rapid economic growth and population expansion, and neglects technological investment and industrial adjustment. Consequently, the total water use and energy-related-CO_2 emissions in S8 reach their peak values among the eight scenarios. From this analysis, positive technology innovation and industrial restructuring have a significant impact on reducing the total water use, while controlling economic growth and population expansion can effectively control energy-related CO_2 emissions. This conclusion is inconsistent with the calculated VIP values. In general, socioeconomic status and population grow in the medium-increase mode, and high growth rates in the technology and service levels correspond to the most suitable urban development mode under the dual control of water use and energy-related CO_2 in Beijing. In this urban development mode, the total water use will be 4432.13 million m^3, and the energy-related CO_2 emissions will be 173.64 million tons in 2030, representing reductions of 37.1% and 18.9%, respectively, relative to the BAU scenario in S1.

Table 7. Future development scenarios for the city of Beijing.

Scenario	Scenario Description	Affluence (*A*)	Population Size (*P*)	Technology Level (*TW*/*TE*)	Service Level (*ST*)
S1 (BAU)	This scenario is set as the basic situation. We assume that economic growth can meet the projections in the Thirteenth Five-Year Plan (2016–2020) and that the growth rate is slowly decreasing. Population growth has been consistent for the past five years and will gradually slow in the next decade. The technology level can meet the resource-saving targets, while the industrial structure follows the current development trend.	M	M	L	L
S2	S2 is based on S1, and emphasizes faster technical progress and an adjustment of the industrial structure to target resource saving.	M	M	M	M
S3	This scenario is based on S2 and focuses more on rapid development of the economy and population.	H	H	M	M
S4	The driving factors of per capita GDP and population remain high, and the CO_2 emissions are controlled due to the application of energy-saving or water-saving technology.	H	H	H	H
S5	Relative to S4, medium economic-development and population-growth modes are adopted to reduce energy-related CO_2 emissions.	M	M	H	H
S6	Risks and challenges lead to a decline in economic and population growth. Furthermore, the development of technology moves slowly.	L	L	L	L
S7	Relative to S6, S7 focuses more on environmentally friendly industries.	L	L	M	M
S8	This scenario attaches excessive importance to economic development and population growth while largely ignoring the pressure on the environment. This social development mode is unsustainable, and may lead to a waste of resources.	H	H	L	L

Table 8. Annual change rates for each factor in the L, M, and H scenarios (%).

Variable	Scenario	Years		
		2017–2020	2020–2025	2025–2030
P	L	0.5	0.25	0.15
	M	1	0.5	0.25
	H	2	1	0.5
A	L	5.5	3.5	1.5
	M	6.5	4.5	2.5
	H	7.5	5.5	3.5
TW	L	−5	−2.5	−1
	M	−6	−3	−1.5
	H	−7	−3.5	−2.5
TE	L	−3	−1.5	−1
	M	−4	−2	−0.5
	H	−5	−2.5	−1.5
ST	L	0.9	0.8	0.7
	M	1.0	0.9	0.8
	H	1.1	1.2	1.3

3.5. Uncertainty Analysis

In the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, two kinds of calculation methods were advanced for energy-related CO_2 emissions: the reference method and the sectoral method. The reference method is a top-down approach that focuses on terminal energy consumption, and multiplies the associated factors by the emission factors of different fuels to obtain the total energy-related CO_2 emissions, while the sectoral method is a bottom-up approach in which each department calculates the total carbon emissions and sums them to obtain the total carbon emissions. In this study, the energy-related CO_2 emissions were calculated from terminal consumption of different fuel types, rather than aggregated from all economic sectors. The results of the two various calculation method may include gaps. Furthermore, we used the emission factors, which play a vital role in calculating carbon emissions, provided by Mi et al. [35]. In their study, they proposed that the default values recommended by IPCC overestimated China's CO_2 emissions. Therefore, uncertainties may exist in the calculated energy-related CO_2 emissions.

4. Conclusions and Policy Implications

In this study, the PLS-STIRPAT model was established to explore future development modes in Beijing under the dual control of water resources and energy-related CO_2 emissions. The population, per capita GDP, urbanization rate, water (or energy) intensity, and the proportion of added value from tertiary industry were selected as the driving factors to predict the total water use (or energy-related CO_2 emissions). The VIP values of all factors indicated that all these factors are important in influencing the total water use and energy-related CO_2 emissions. Additionally, the scenario analysis results showed that the total water use and CO_2 emissions will continuously increase over the next fourteen years. Additionally, under the dual control of water use and energy-related CO_2 emissions, the most suitable urban development mode will enable the socioeconomic status and population to grow at a medium pace, and a high growth rate will be observed in the technology and service sectors. By 2030, the total water use will be 4432.13 million m^3, and the energy-related CO_2 emissions will be 173.64 million tons.

With its high-speed economic and urbanization development, Beijing will inevitably face pressures involving increased water demand and energy consumption. It is of prime importance to balance city economic development, water and energy security, and environmental sustainability. Based on our analysis, several suggestions are presented:

(1) The per capita GDP is the most significant factor influencing Beijing's energy-related CO_2 emissions, and has a significant influence on water use. Economic growth is necessary to achieve the basic goal of national survival and development, but inevitably applies environmental pressure. To fulfil targets of water and energy security and environment sustainability, Beijing needs to consider controlling the economic growth within a reasonable range, and change the strategies of economic growth to incorporate high-quality patterns. Moreover, it is essential to establish related regulations and laws on resource production to balance economic development, and water and energy security.

(2) In terms of goals for cutting CO_2 emissions and water security, population is another vital factor. Hence, it is recommended to continue to control the population size and attach importance to optimizing the population structure and quality in Beijing. Furthermore, the relevant authorities are suggested to enact efforts to raise people's environmental awareness and encourage households to maintain sustainable consumption patterns.

(3) The technology factors, including energy consumption intensity and water use intensity, play prominent negative impacts on energy-related CO_2 emissions and the total water use, respectively. Therefore, Beijing needs improved energy efficiency in energy-intensive industries, and to establish target-oriented responsibility systems and adopt low-carbon technology. Furthermore, it is recommended that government control be strengthened, and priority given to water conservation. Examples include adjusting crop configurations and promoting water-saving irrigation to improve water efficiency for agriculture, and improving the efficiency of cooling water (and reducing its use) to realize industrial water saving. In addition, the authorities concerned need to bring functions into full play to improve society's independent innovation ability. For example, it is suggested that increasing investment in science and supporting multiple enterprises with independent intellectual property rights and independent innovation capabilities will vigorously develop water-saving and low-carbon technologies, and improve economic growth's reliance on scientific-technical progress in Beijing.

(4) Water and energy are essential to human beings. However, policymaking efforts regarding optimization of the industrial structure, and ensuring water and energy security, are isolated from each other. It is of great important to improve policy integration related to these two resources. However, the research is still preliminary, and lacks specific energy use figures for the water sector. The preparation of the projections of energy use figures for the water sector are needed in the future. This study provides a theoretical foundation for Beijing to explore its city development mode under the dual control of water resources and energy-related CO_2 emissions, and provides a new perspective for establishing water and energy security integrally in formulating long-term policies for policymakers in other cities or countries.

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