Modeling the Correlation between Water Resources Carbon Emission and Water Consumption

Jiang Hu[1], Juanjuan Wen[2, *]
[1]Department of Design, Central and Southern China Municipal Engineering Design & Research Institute Co., Ltd., Wuhan, 430010, China
[2]Department of Construction Management and Real Estate, Chongqing Jianzhu College, Chongqing, 400072, China

Abstract: Study the influencing factors and future changes of consumption carbon emissions and water consumption, and provide scientific support for the formulation of targeted policies in the region. Analyze the mechanism of energy consumption structure on carbon intensity, calculate the carbon emission of water intake system, water supply system, drainage and sewage treatment system; use the idea of carbon emission decomposition model to build a water consumption decomposition model. LMDI is used to decompose all factors without residual error, and the trend coefficient of gray correlation degree is used to judge the growth trend of energy consumption and carbon emission. The Baiyangdian Lake Basin is selected as the research water area. Based on the statistical data from 1986 to 2018, the direct path coefficients of the respective variables can be obtained. The absolute value of the respective variable t value is greater than t0.01(25) = 2.496, indicating that the path coefficient of the respective variable to the dependent variable is extremely significant. The growth rate of total energy consumption and certain energy consumption is less than the growth rate of CO2 emissions, and the minimum detected carbon emissions per unit time is not less than 20Kg, indicating that the proposed method has certain monitoring efficiency and monitoring stability.

Key words: Energy consumption structure; Carbon emission decomposition model; Water resource consumption decomposition; LMDI; Grey relational trend

1. Introduction

Cities are the places where human economic activities are most concentrated, as well as the areas where water and energy resources are most concentrated, and their greenhouse gas emissions account for more than 70% of the global total. Therefore, seeking a solution for urban carbon emission reduction is the key to alleviating the global climate change problem [1]. Climate change is a severe challenge faced by mankind. As a responsible major country, China is facing increasing pressure on carbon emissions and carbon reduction. At the 2015 Paris Climate Conference, China promised: China will reach the peak of carbon emissions around 2030 and strive to achieve it as soon as possible [2]. By 2030, carbon dioxide emissions per unit of GDP will be reduced by 60%-65% compared to 2005. With the increasing demand for water resources, China's water resources have gradually become the same as coal and other non-renewable resources, subject to pressure caused by water shortages and water pollution, and have increasingly become a factor restricting economic and social development [3].

At present, many scholars apply simulation technology, dynamic programming analysis and other related optimization theories, combined with system dynamics, input-output models, multi-objective decision-making models, gray system models, multiple statistical regression analysis methods and other methods. Researched the relevance and optimization of regional economic and industrial structure development changes and water resources [4]. Few scholars have analyzed the correlation between Beijing's economic development and water resources consumption and utilization. Domestic and foreign scholars have developed energy planning models through energy-economic models, energy technology models and energy-economy-environment models, while China's energy forecasting models rely on energy-economic models of resources and the environment. Although the environmental impact is currently being considered, the focus is still on the establishment of energy technology models. The energy supply and demand forecasting method are relatively simple, and the development trend of energy supply and demand cannot be fully demonstrated [5-7].

This paper proposes a modeling study on the correlation between water resources carbon emissions and water consumption. Analyze the mechanism of energy consumption structure on carbon intensity, and calculate carbon emissions from water intake systems, water supply systems, drainage and sewage treatment systems. With the help of the carbon emission decomposition model, the water consumption decomposition model is constructed, the LMDI is used to decompose all factors without residual error, and the gray correlation degree trend coefficient is used to judge the growth trend of energy consumption and carbon emissions.

2. Water carbon emissions

Human development and utilization of water resources run through the entire process of urban water system operation. The operation of urban water system (water intake, water supply, water use, sewage treatment, etc.) requires huge energy consumption, behind which is considerable carbon emissions [8]. Whether it is the extraction of deep groundwater resources, long-distance water diversion, unconventional water reuse, expansion of urban drainage networks, increased industrial and domestic water consumption, or improved sewage treatment levels. Both mean that the urban water system needs to consume more energy during the operation process, resulting in more energy consumption and carbon emissions [9]. The mechanism analysis of the effect of energy consumption structure on carbon intensity is shown in Figure 1.

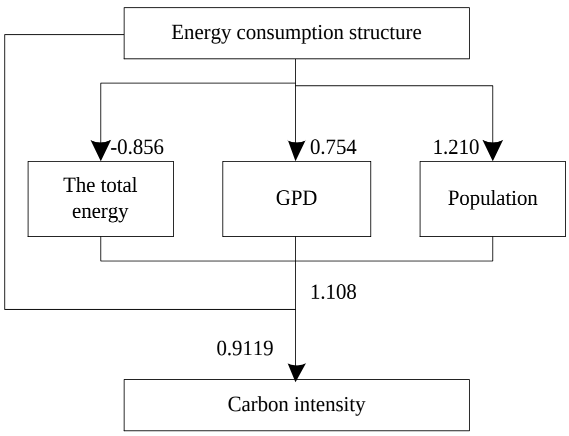

Figure 1. The effect mechanism of energy consumption structure on carbon intensity

It can be seen from Figure 1 that the direct effect of energy consumption structure on carbon intensity is -0.189, which directly inhibits the growth of carbon intensity, but the total effect is 0.919, which promotes [10]. The reason is that the energy consumption structure has reached 1.964 through the indirect promotion of GDP and the total population, which offsets the sum of the direct energy consumption structure and its indirect restraint through the total amount of energy. The cheapness and availability of coal meets the needs of my country's economic development, making GDP highly dependent on coal. For a long period of time, my country's GDP has grown rapidly and the total population has remained high. The level of management and technology have been high. If it is impossible to optimize and upgrade in a short period of time, adjust the energy structure and reduce the proportion of coal (removing coal used for power generation). At the same time, the total energy must be controlled. The carbon intensity cannot be reduced, but it will increase.

2.1 Carbon emission accounting of water intake system

Water storage project water supply carbon emission accounting: surface water storage projects mainly include reservoirs, ponds (small mountain reservoirs), ponds and dams [11]. The energy consumption and carbon emissions of this link mainly come from the energy consumption (power consumption) of the operation and maintenance of the water storage project infrastructure (such as the control of gates and monitoring equipment, lighting, air conditioning, and heating, etc.). It also involves some of the energy consumption caused by the loss of water head along the water delivery.

The energy intensity of the water storage process generally has no regional difference, and the value of its energy intensity is in the range of 0.018~0.2k Wh/m^3. In this study, the average value of the energy intensity range (0.109k Wh/m^3) was used to calculate the energy consumption and carbon emissions of the surface water storage project in Zhengzhou City [12]. The specific calculation formula is as follows:

$$C_X = Q_X \times W_X \times EF_{CO_2} \tag{1}$$

In the formula, C_X is the water supply carbon emission of the water storage project, in kg. Q_X is the water supply volume of the storage project, in m^3. W_X is the energy intensity of the water storage project's water supply, with a value of 0.109k Wh/m^3, and EF_{CO_2} is the electricity carbon emission coefficient, with a value of 0.801kg/k Wh.

Carbon emission calculation of water supply for surface water lifting projects: Surface water lifting projects refer to directly lifting water from rivers or lakes, lifting the water body from a lower position to a higher position, so as to use the drop for subsequent water diversion [13]. Surface water lifting projects mainly use water lifting pumping stations to convert electrical energy into energy to lift water bodies. The energy consumption of the water lifting project and the resulting energy consumption and carbon emissions are closely related to the water lifting lift, the efficiency of the pumping station and the water lifting volume.

Assuming that the average lifting lift for surface water lifting is 29m, according to the principle of energy conversion, the carbon emission calculation formula for energy consumption of surface water lifting projects is:

$$C_B = \frac{g \times h \times Q \times \rho}{3.6 \times 10^6 \times \eta} \times EF_{CO_2} \tag{2}$$

In the formula, C_B is the carbon emission of the surface water lifting project, in kg; g is the acceleration of gravity, with a value of 9.8m/s. h is the lifting lift, the unit is m. Q is the amount of surface water lift, in m3. ρ is the density of water, with a value of 1×10kg/m^3. η is the efficiency of the pumping station, with a value of 0.75. EF_{CO_2} is the electric carbon emission coefficient, with a value of 0.801kg/k Wh.

2.2 Carbon emission accounting of water supply system

Agricultural water carbon emissions accounting: The carbon emissions of agricultural water are mainly related to the energy consumed in the process of water extraction and pressure transmission of agricultural irrigation water. Since the irrigation transmission and distribution link after the water source reaches the field is the conversion of field water and soil water in the root layer of crops and the redistribution of soil water, the consumption link is the conversion of non-runoff soil water resources to gaseous water [14]; The drainage link is to drain excess water out of the agricultural system. The consumption process of these links is mainly driven by gravitational potential energy, solar energy, biological potential energy and capillary potential energy. Basically, no energy consumption occurs, and accordingly it will not cause energy consumption and carbon emissions [15]

Assuming that the agricultural irrigation mode is the joint supply of multiple water sources, the irrigation water source mainly uses surface water from the Yellow River, followed by the exploitation of groundwater, and also includes the use of a small amount of water storage engineering water sources, rainwater and sewage water sources [16]. The energy intensity of agricultural irrigation water is in the range of 0.052~0.62k Wh/m^3. The index value of the energy intensity of agricultural irrigation water refers to the existing research results, and the median value is 0.336k Wh/m^3. The formula for calculating the energy consumption and carbon emissions of agricultural water is as follows:

$$C_N = Q_N \times W_N \times EF_{CO_2} \tag{3}$$

In the formula, C_N is the carbon emission of agricultural water in kg. Q_N is agricultural water consumption in m3. W_N is the energy intensity of agricultural water use, with a value of 0.336k Wh/m^3. EF_{CO_2} is the electricity carbon emission coefficient, with a value of 0.801kg/k Wh.

Energy consumption and carbon emissions of industrial water: Combine factors such as the amount of electricity and raw coal used in the industrial water process of Zhengzhou, heat generation, and carbon emission coefficient. The carbon emission coefficient of the comprehensive energy consumption of industrial water in Zhengzhou City converted by weight is 0.642kg/k Whitherever, the formula for calculating the energy consumption and carbon emissions of industrial water is as follows:

$$C_G = Q_G \times W_G \times G_{CO_2} \tag{4}$$

In the formula, C_G is the carbon emission of industrial water, in kg. Q_G is industrial water consumption in m3. W_G is the energy intensity of industrial water, with a value of 5.033k Wh/m3. G_{CO_2} is the carbon emission coefficient of industrial water comprehensive energy consumption, with a value of 0.642kg/k Wh.

2.3 Carbon emission accounting for drainage and sewage treatment systems

Under normal circumstances, urban sewage can use gravity to achieve gravity collection and transportation from the sewage point to the sewage treatment plant. This process does not produce energy consumption [17]. However, under the influence of special terrain and obstacles, it is necessary to pressurize the sewage to lift the sewage from the low terrain to the high place to achieve normal sewage collection and transportation. The pressurized transportation link will cause a certain amount of energy consumption and bring about carbon emissions. In the current design of urban sewage pipe networks, sewage pipes are usually laid at a fixed slope. At the same time, taking into account economic factors and construction and maintenance issues, the deepest buried depth of the sewage pipeline is basically a fixed value in a certain area. Therefore, the calculation formula for energy consumption and carbon emissions from the sewage collection process from the discharge point to the sewage treatment plant is as follows:

$$W_S = \frac{H \times Q}{\eta} \times EF_{CO_2} \tag{5}$$

$$H = L \times G \tag{6}$$

In the formula, W_S is the energy consumption and carbon emissions in the sewage collection process, in kg; Q is the sewage lift volume, in m3; η is the pump efficiency, generally taken as 0.75; EF_{CO_2} is the electricity carbon emission coefficient, which is 0.801kg/k Wh. H is the total lift lifted by the pump, in m. L is the straight-line distance of sewage lifting, in m. G is the average slope value of the sewage pipe network, which is generally 1‰? Under normal circumstances, the energy consumption of the sewage collection process is calculated in the energy consumption of the sewage treatment plant's inflow lifting pump station. That is to say, they are all classified as the energy consumption of sewage treatment, so this article does not separately calculate and analyze the energy consumption and carbon emissions of the sewage collection process.

3. Water consumption

To build a water consumption decomposition model with the help of carbon emission decomposition model [18]. This article believes that water consumption is relative to three industries, that is, agricultural water is defined as the primary industry, industrial water is the secondary industry, and domestic and environmental water is the tertiary industry [19]. That is, the additive form of the decomposition of total water consumption is shown in the following formula:

$$W=\sum_{n=1}^{3}\frac{W_n}{GDP_n}\cdot\frac{GDP_n}{GDP}\cdot\frac{GDP}{p}\cdot p=\sum_{n=1}^{3}\omega_n\cdot\omega_n\cdot s\cdot p \tag{7}$$

In the formula, W represents the total water consumption; $W_n\left(n=1,2,3\right)$ represents the water consumption of the first, second and tertiary industries; and GDP_n represents the GDP of the nth industry. ω_n , s, a, and p represent four factors: water consumption intensity, industrial structure, per capita wealth, and population.

$$\Delta\omega_n=f\left(\omega_n^0,\omega_n^T\right)\cdot\ln\frac{\omega_n^T}{\omega_n^0} \tag{8}$$

In the formula, $f\left(\omega_n^0,\omega_n^T\right)=\dfrac{\omega^T-\omega^0}{\ln\left(\omega^T/\omega^0\right)}$, and the calculation of water consumption caused by the three factors of s, a, P, etc. is similar to the following formula, and n can be used instead of m.

The decomposition method of energy consumption effect generally includes exponential decomposition method and structural decomposition method, among which the widely applicable methods include Laspeyres and Divisia. Research by Ang et al. showed that LMDI can decompose all factors without residuals, and can even be applied to the decomposition of partial incomplete data sets [20]. This article defines the effect of changes in energy consumption carbon emissions as ΔCO_2. According to the LMDI decomposition model, ΔCO_2^P is equal to the sum of changes caused by Δk, Δe, Δs, Δa and Δp in all production industries, and CO_2 is equal to the sum of ΔCO_2^L , Δc, Δu and Δp in the living sector. The decomposition formula of the measurement factor (X) is:

$$\Delta X_m=f\left(CO_{2m}^0,CO_{2m}^T\right)\cdot\ln\frac{X_m^T}{X_m^0} \tag{9}$$

In the formula, X can represent k, e, s, a, P, u, etc., $f\left(CO_{2m}^0,CO_{2m}^T\right)$, and the f function based on industry m can be substituted into m. The setting of 0 and T is to study the change or cumulative change from the starting year to a certain target year.

4. Modeling the correlation between water carbon emissions and water consumption

IPAT is a universally recognized formula for analyzing the impact of human activities on the environment. IPAT appeared in the Ehrlich-Holdren/Commone debate on the main driving force of man-made environmental impacts in the early 1970s. It is widely used as a framework for analyzing the driving forces of environmental change:

$$I = P * A * T \tag{10}$$

In the formula, I represents environmental impact, P represents population size, A represents wealth, and T represents technological level. In order to overcome the shortcomings of this formula being limited to limited driving factors, the traditional PAT formula was transformed into a stochastic form-STIRBAT model. The original STIRBAT model expression is:

$$I = aP^h A^c T^d e \tag{11}$$

In the formula, a represents a constant term, and b, c, and d are the elastic coefficients corresponding to P, A, and T, respectively. That is, when P, A, T changes by 1%, I will change $b\%$, $c\%$ and $d\%$ respectively. e is a random error term. At the time of $a = b = c = d = e = 1$, the IPAT model can be seen as a special form of the STIRBAT model.

To identify the spatial correlation and agglomeration characteristics of a certain observation value between regions, the Moran's-I index measurement is generally selected at present, which is defined as:

$$Moran'sI = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(Y_i - \bar{Y}\right)\left(Y_j - \bar{Y}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{12}$$

In the formula, $\bar{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i$ and $\bar{Y}$ represent the mean value of Y, and Y_i and Y_j respectively represent the variables of the location i and location j where the observation value is studied, and spatial correlation should be considered; S^2 $S^2 = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)$, is the variance of Y, and w_{ij} represents the element in the i-th row and j-th column in W of the normalized spatial weight matrix of the study observation; n is the number of observations in the study. The value range of the Moran index is generally $-1 \le Moran'sI \le 1$, which is a very important method for testing spatial correlation; When the Moran index is greater than zero, it proves that there is a positive correlation in the spatial distribution of injuries. The larger the value, the stronger the positive correlation. When the Moran index is less than zero, there are different attributes between the positions of adjacent observations, and the smaller the value, the greater the difference; When it is $Moran'sI = 0$, it indicates that the observation objects in different positions in the space obey the random distribution. The statistical test uses asymptotic normal distribution and random distribution to test the results of the $Moran'sI$ index. The standardized expression formula is:

$$Z(d) = \frac{Moran'sI - E(Moran'sI)}{\sqrt{VAR(Moran'sI)}} \tag{13}$$

Calculating the expected value of standardized $Moran'sI$ is based on the distribution of geospatial data, and the formula is as follows:

$$E_n(Moran'sI) = \frac{1}{n-1} \tag{14}$$

Assuming the spatial data of normal distribution, the variance formula is:

$$VAR_n(Moran'sI) = \frac{n^2 w_1 + n w_2 + 3 w_0^2}{w_0^2 (Moran'sI)} - E_0^2(Moran'sI) \tag{15}$$

From the above formula, we can get the Z value-the test statistic, and distinguish the significance of the null hypothesis according to its value. If the test statistic Z obeys a normal distribution, its absolute value is greater than the critical value 1.65 (or 1.95). If the significance level is below 0.05 (or 0.1), then in terms of spatial distribution, the carbon emissions and water resources of each city have significant agglomeration.

The calculation of the gray correlation degree shows that the gray correlation degree between energy consumption and carbon emissions of various industries is fixed, in order to analyze the growth trend of the reference series X_0 and the comparison series X_1. The gray correlation degree trend coefficient is used to judge the relative development of the energy consumption growth trend and the carbon emission growth trend. The trend coefficient is defined as follows:

$$r = \begin{cases} 1, x_i'(k) - x_0'(k) > 0 \\ -1, x_i'(k) - x_0'(k) < 0 \end{cases} \tag{16}$$

In the formula, $x_i'(k) = x_i(k) / x_i(1)$; $x_0'(k) = x_0(k) / x_0(1)$. When the data growth rate in the comparison series is greater than the data growth rate of the reference series, the gray correlation degree is positive; on the contrary, when the data growth rate in the comparison series is less than the data growth rate of the reference series, the gray correlation degree is negative.

5. Case Analysis

The Baiyangdian River Basin is located in the entire North China Plain and the central part of the Haihe River Basin, and the northern part of the Diandong Plain of the Daqing River. The geographical coordinates are about 113°40E~116°48E, 38°10N~40°03N.The basin borders the Taihang Mountain in the west, the Yongding River Basin in the north, the Ziya River Basin in the south, and the Duliujian River in the east to Quanhai Bay. The drainage area is about 34875.25km2, accounting for about 23.44% of the Daqing River Diandong Basin and 10.9% of the Haihe River Basin. Among them, mountainous areas accounted for about 34.2%, hills accounted for about 12.5%, and plains accounted for about 53.1%. The basin flows through Shanxi Province, Hebei Province and Beijing.

Based on the statistical data from 1986 to 2018, the direct path coefficients of the respective variables (the direct influence effects of the respective variables on the dependent variable) can be obtained, as shown in Table 1.

Table 1. Direct path coefficients of respective variables

Partial correlation coefficient	The numerical	The correlation coefficient	The numerical
p_{1y}	1.739	r_{1y}	-0.831
p_{2y}	-0.333	r_{2y}	0.930
p_{3y}	-0.076	r_{3y}	-0.450
p_{4y}	-0.52	r_{4y}	-0.840
p_{5y}	-1.327	r_{5y}	-0.999
p_{6y}	-0.166	r_{6y}	-0.798

Since the path coefficients of the independent variables x3 and x6 are small and fail the t test, consider deleting the independent variables x3 and x6 and recalculate the direct path coefficients of the remaining variables. It is estimated that the mechanism model diagram of the low-carbon economy is obtained, as shown in Figure 2.

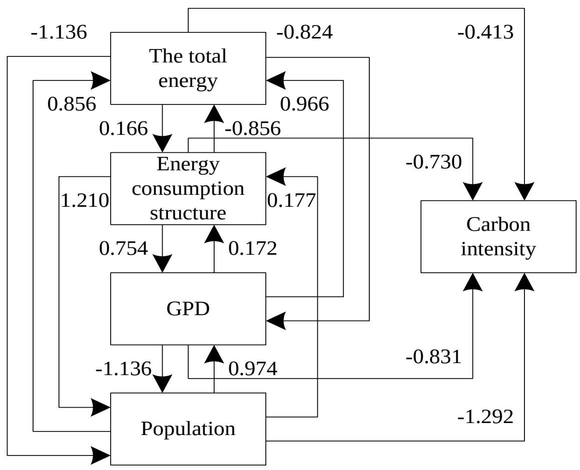

Figure 2. Mechanism model of low-carbon economy

The decision coefficient (comprehensive effect of the independent variable on the dependent variable) $R^2 = \sum_{i=1, i \neq 3}^{5} p_{iy} r_{iy} = 0.993$ has little precise effect on the result, and $p_{iy} r_{iy}$

is the indirect effect of a certain independent variable on the dependent variable through other independent variables. The residual effect $p_{ay} = \sqrt{1-R^2} = 0.83666$. The small residual effect shows that the path analysis has grasped the main factors and the internal quality of the model is ideal. Through the t test, the t values of the respective variables were obtained as t_1=5.607, t_2=2.678, t_4=-4.427, t_5=-21.385. The absolute value of the respective variable t value is greater than t0.01(25) = 2.496, indicating that the path coefficient of the respective variable to the dependent variable is extremely significant.

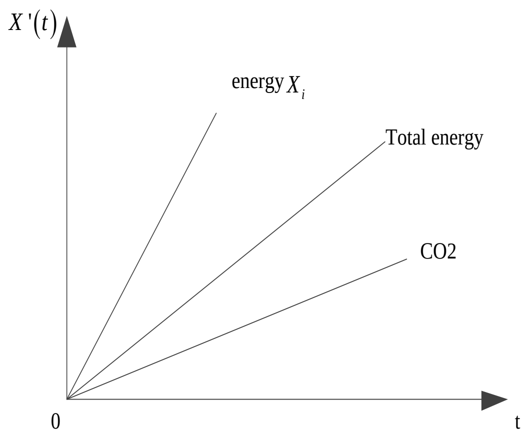

Figure 3. The growth rate of energy consumption is greater than the growth rate of carbon emissions

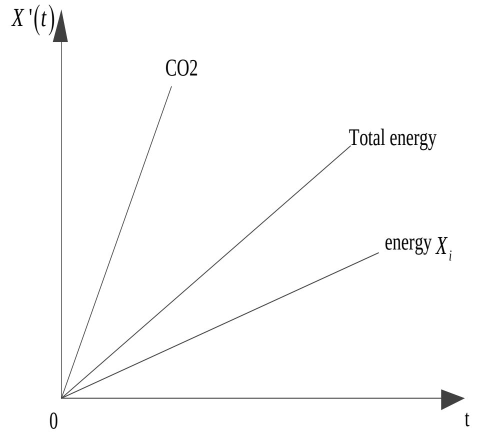

Figure 4 The growth rate of energy consumption is less than the growth rate of carbon emissions

Figure 3 shows that the unit carbon emission of energy consumption in this industry is very low, such as natural gas in industry, transportation \ warehousing and postal industry, wholesale \ retail and accommodation \ catering industry, other industries and living consumption. There is also electricity in the wholesale \ retail and accommodation \ catering industry, other industries, and life consumption. The growth rate of energy consumption is greater than the growth rate of carbon emissions. The growth rate of total energy consumption and certain energy consumption is less than the growth rate of CO2 emissions. In these industries, the use of this energy should be reduced, or the energy structure of these industries should be adjusted.

Water cycle element verification: The annual and monthly runoff measured values of the three hydrological stations of Hengshanling Reservoir, Wangkuai Reservoir and Xidayang Reservoir were used as reference for model verification and verification. Select the relative error between the simulated runoff and the measured runoff, and the efficiency comprehensive evaluation model simulation effect. The specific results are shown in Table 2.

Table 2 Water cycle verification results

time	parameter	parameter	Wang Kuai	Western Ocean
Pre-calibration (2010-2015)	Relative error	0.18	0.21	0.25
	nash coefficient	0.94	0.83	0.82
Post-validation (2016-2020)	Relative error	0.10	0.16	0.41
	nash coefficient	0.93	0.92	0.65

Comparing the measured value and the simulated value, the relative error of the approximate observation point is within. Due to the large model cell, this result is acceptable.

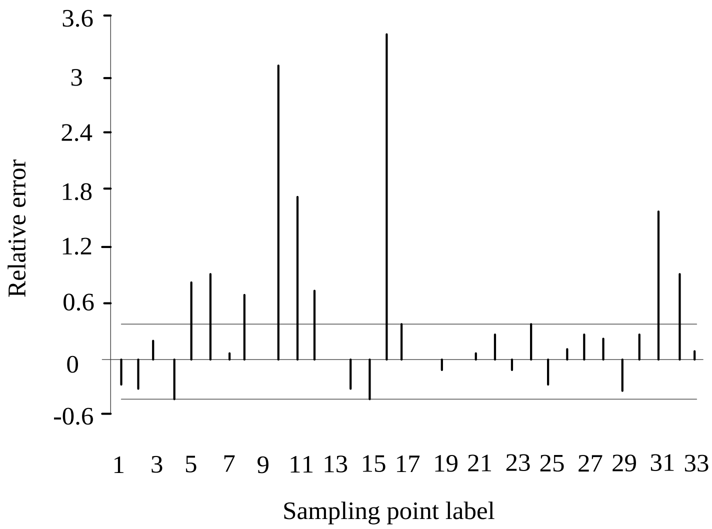

Figure 5. LAI relative error of sampling points

To further verify the carbon emission monitoring efficiency of the proposed method, compare the monitoring efficiency between the proposed method and the method in literature [6], and the comparison result is shown in Figure 6.

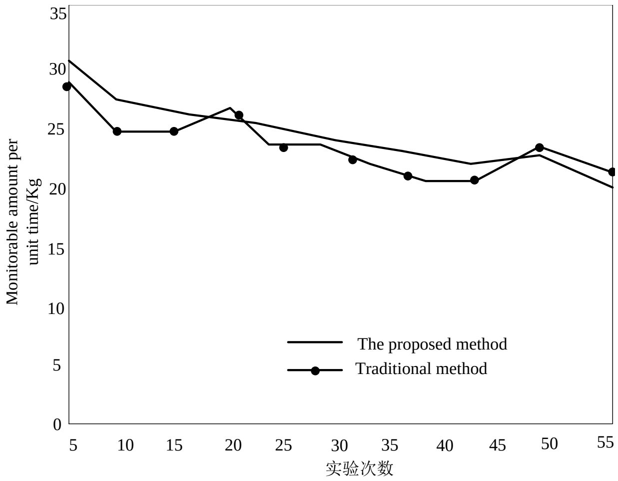

Figure 6. Comparison of monitoring efficiency

It can be seen from the comparison results in Fig. 6 that after many monitoring experiments, the monitorable quantity of the proposed method basically remains stable, and the minimum detection quantity per unit time is not less than 20Kg, indicating that the proposed method has certain monitoring efficiency and monitoring stability.

6. Conclusion

In order to deal with the problems of urban water shortage, urban waterlogging, water pollution and carbon emissions under the pressure of future urbanization and climate change. The rational planning of urban water system also needs to increase energy conservation and carbon emission reduction targets on the basis of existing design targets, in order to cope with the pressure of carbon emission reduction on the global and regional scales.

(1) Strengthen basic research on urban water system planning and design. The rationality of basic work will determine to a large extent whether the planning and design of urban water system is reasonable. Therefore, strengthening basic work research and exploring scientific prediction and analysis methods are the focus of future urban water system planning and design.

(2) Realize the centralized and decentralized layout of the overall structure of the urban water system. Increase the small and scattered urban water system infrastructure to realize the nearby treatment and utilization of water supply, sewage and rainwater. In this way, energy consumption and carbon emissions during long-distance transportation are reduced, and the potential harm of a single "large-scale centralized" water system facility to the city is reduced.

In terms of water reform, water rights trading is an important way to use market mechanisms to optimize the allocation of water resources, which is conducive to comprehensively improving water resources utilization efficiency and benefits, and provides strong support for the sustainable use of water resources and sustainable economic and social development. Therefore, implementing the most stringent water resources management system and promoting the optimal allocation and efficient use of Beijing’s water resources will help further promote the sustainable development of Beijing.

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