Integrated Water Risk Early Warning Framework for Semi-arid Transitional Zones Based on Water Environmental Carrying Capacity (WECC) (Postprint)

Authors: XIE Yuxi, ZENG Weihua, QIU Jie, QIU Jie

Date: 2023-02-15T00:00:00+00:00

Abstract

Water risk early warning systems based on the water environmental carrying capacity (WECC) are powerful and effective tools to guarantee the sustainability of rivers. Existing work on the early warning of WECC has mainly concerned the comprehensive evaluation of the status quo and lacked a quantitative prejudgement and warning of future overload. In addition, existing quantitative methods for short-term early warning have rarely focused on the integrated change trends of the early warning indicators. Given the periodicity of the socioeconomic system, however, the water environmental system also follows a trend of cyclical fluctuations. Thus, it is meaningful to monitor and use this periodicity for the early warning of the WECC. In this study, we first adopted and improved the prosperity index method to develop an integrated water risk early warning framework. We also constructed a forecast model to qualitatively and quantitatively prejudge and warn about the development trends of the water environmental system. We selected the North Canal Basin (an essential connection among the Beijing- Tianjin-Hebei region) in China as a case study and predicted the WECC in 25 water environmental management units of the basin in 2018–2023. We found that the analysis of the prosperity index was helpful in predicting the WECC, to some extent. The result demonstrated that the early warning system provided reliable prediction (root mean square error of 0.0651 and mean absolute error of 0.1418), and the calculation results of the comprehensive early warning index (CEWI) conformed to the actual situation and related research in the river basin. From 2008 to 2023, the WECC of most water environmental management units in the basin had improved but with some spatial differences: the CEWI was generally poor in areas with many human disturbances, while it was relatively good in the upstream regions with higher forest and grass covers as well as in the downstream areas with larger water volume. Finally, through a sensitivity analysis of the indicators, we proposed specific management measures for the sustainability of the water environmental system in the North Canal Basin. Overall, the integrated water risk early warning framework could provide an appropriate method for the water environmental administration department to predict the WECC of the basin in the future. This framework could also assist in implementing corresponding management measures in advance, especially for the performance evaluation and the arrangement of key short-term tasks in the River Chief System in China.

Full Text

Preamble

Integrated Water Risk Early Warning Framework of the Semi-Arid Transitional Zone Based on the Water Environmental Carrying Capacity (WECC)

XIE Yuxi[1], ZENG Weihua[1,2], *QIU Jie*[3]

[1] School of Environment, Beijing Normal University, Beijing 100875, China
[2] Northwest Institute of Plateau Biology, Chinese Academy of Sciences, Qinghai 810008, China
[3] Nanjing Institute of Environmental Sciences, Ministry of Ecology and Environment, Nanjing 210042, China

Abstract: Water risk early warning systems based on the water environmental carrying capacity (WECC) are powerful and effective tools for guaranteeing river sustainability. Existing research on WECC early warning has primarily focused on comprehensive evaluation of the current status, lacking quantitative pre-judgment and warning of future overload conditions. Furthermore, existing quantitative methods for short-term early warning have rarely addressed the integrated change trends of early warning indicators. However, given the periodicity of socioeconomic systems, the water environmental system also follows cyclical fluctuation patterns. Thus, monitoring and utilizing this periodicity for WECC early warning is meaningful. In this study, we adopted and improved the prosperity index method to develop an integrated water risk early warning framework. We also constructed a forecast model to qualitatively and quantitatively pre-judge and warn about development trends in the water environmental system. We selected the North Canal Basin—a critical connection in the Beijing-Tianjin-Hebei region—as a case study and predicted WECC for 25 water environmental management units in the basin from 2018-2023. Our analysis demonstrated that the prosperity index was helpful for predicting WECC to some extent. The early warning system provided reliable predictions (root mean square error of 0.0651 and mean absolute error of 0.1418), and the comprehensive early warning index (CEWI) calculations aligned with actual conditions and related research in the basin. From 2008-2023, WECC improved in most water environmental management units, though with spatial differences: CEWI was generally poor in areas with significant human disturbance, while relatively good in upstream regions with higher forest and grass coverage and in downstream areas with larger water volumes.

Finally, through sensitivity analysis of indicators, we proposed specific management measures for sustaining the water environmental system in the North Canal Basin. Overall, the integrated water risk early warning framework provides an appropriate method for water environmental administration departments to predict future WECC in basins. This framework can also assist in implementing management measures in advance, particularly for performance evaluation and arrangement of key short-term tasks in China' s River Chief System.

Keywords: water risk; early warning system; water environmental carrying capacity; prosperity index; water management; North Canal (Beiyun River)

Citation: XIE Yuxi, ZENG Weihua, QIU Jie. 2023. Integrated water risk early warning framework of the semi-arid transitional zone based on the water environmental carrying capacity (WECC). *Journal of Arid Land*, 15(2): 145-163. https://doi.org/10.1007/s40333-022-0083-z

Corresponding authors: ZENG Weihua (E-mail: zengwh@bnu.edu.cn); QIU Jie (E-mail: qiujie@nies.org)

Received 2022-07-25; revised 2022-09-26; accepted 2022-09-30

1 Introduction

Rapid socioeconomic development has caused a series of water environmental issues. Increased water demand has led to river depletion, while pollutant discharge has caused water quality deterioration, particularly in semi-arid areas lacking abundant water resources [**?**, **?**]. Environmental degradation has also restricted regional sustainable development [**?**, **?**]. Sustainable water management represents a significant solution to this risk [**?**, **?**], and water environmental carrying capacity (WECC) serves as an effective indicator for evaluating regional sustainability [**?**, **?**]. In China, as water environmental management has shifted from end-of-pipe treatment after pollution discharge to forward-looking environmental prevention, numerous policy documents have proposed establishing monitoring and early warning mechanisms for resources and environmental carrying capacity. Since 2016, Chinese government ministries have established monitoring and early warning mechanisms for WECC and issued technical guidance documents (e.g., *Monitoring and Early Warning Techniques of Resources and Environment Carrying Capacity* and *National Water Resources Carrying Capacity Monitoring and Early Warning Technology Outline*). However, these efforts have primarily focused on comprehensive evaluation of the status quo, lacking quantitative pre-judgment and warning of future overloaded states.

Early warning was first applied in macroeconomics, originating from the theoretical hypothesis of economic cycles proposed by British economists in 1875

[?, ?]. The concept of a global environmental monitoring system called "early warning" was later introduced to the environmental field [?, ?]. Nevertheless, most related studies have concentrated on flood forecasting [?, ?], early warning of water shortage and water resource carrying status [?, ?, ?], and prediction of water quality and pollutants [?, ?, ?, ?], with very few addressing comprehensive early warning of water environmental system risk.

Although WECC lacks a uniform definition, it is a broad concept related to water' s environmental properties that focuses on interaction mechanisms in human (socioeconomic)-water environmental systems [?, ?]. The essence of WECC is to seek balance between the water environmental system and socioeconomic development. Water environmental system risk represents the uncertainty of overload caused by imbalance between these systems. Thus, WECC can quantitatively measure risk to the water environmental system by evaluating overload situations [?, ?]. Early warning of water risk based on WECC is therefore a powerful and practical tool for guaranteeing river sustainability and can provide a quantitative basis for watershed management [?, ?].

Unlike long-term early warning (three to five years) that supports long-term planning, short-term early warning (one to two years) is mainly used for assessing and predicting water environmental situations in the next year' s watershed management. However, existing quantitative methods and models for short-term early warning of water environmental systems are based primarily on future trend prediction of single, independent indicators and have rarely focused on integrated change trends. These methods include variable fuzzy pattern recognition (VFPR) [?, ?], autoregressive moving average model (ARMA) [?, ?], multiple linear regression model (MLRM) [?, ?], gray forecast model (GM) [?, ?], and artificial neural networks (ANNs) [?, ?, ?, ?, ?]. In reality, however, socioeconomic system changes are cyclical and affected by temporal patterns (e.g., monthly, quarterly, and annual changes). As a comprehensive concept influenced by socioeconomic development and environmental endowment, WECC indicators should also exhibit cyclicality due to socioeconomic fluctuations. Thus, learning from economic early warning concepts and analyzing the periodicity of economic activities' environmental impact on WECC would provide valuable references for future socioeconomic decision-making and environmental management.

According to Mitchell and Burns' [?, ?] "measuring business cycles," this economic cycle change is also called the "boom-bust cycle," referring to regular expansion and contraction experienced by economic activities following a general development trend. Prosperity index (boom or climate index) analysis is commonly used in economic early warning to measure economic cycle variation status and trends through fluctuations caused by economic activities [?, ?]. It evaluates whether the economy is booming or in recession, as exemplified by the Babson barometer of economic activity and Business Climate Index. Building on Mitchell and Burns [?, ?], Moore [?, ?] selected 21 representative indicators (leading, coincident, and lagging categories from nearly a thousand economic indicators) to develop the diffusion index (DI) and later collaborated with Shiskin to compile the composite index (CI) [?, ?]. The CI effectively overcomes DI deficiencies by predicting business cycle turning points and indicating fluctuation intensity. Prosperity index analysis can qualitatively judge future trends through fluctuation analysis.

This study identified correlations between socioeconomic indicators and WECC to improve the prosperity index analysis method and establish an integrated water risk early warning framework based on WECC. We constructed a comprehensive early warning index (CEWI) and its forecast model by simultaneously considering periodic trends of pressure and support indicators to qualitatively and quantitatively pre-judge and warn about water environmental system development trends.

The Beijing-Tianjin-Hebei region is a crucial transition zone between semi-arid and semi-humid areas in China. The North Canal Basin serves as an essential connection among this region. The North Canal is a typical water-short river, with 70% of its water coming from reclaimed sources. Inadequate self-purification capacity causes severe water pollution and degradation of river ecological functions, endangering resident health [?, ?]. We selected the North Canal Basin as our case study to verify the integrated water risk early warning framework' s feasibility and propose suggestions for water environmental system sustainability. This framework can also provide a scientific method for performance evaluation and key task arrangement in China' s River Chief System, where local government chief officers serve as regional river chiefs responsible for water resources management [?, ?].

2 Study Area

The North Canal (Beiyun River) originates in Beijing and runs through the Beijing-Tianjin-Hebei region [Figure 1: see original paper]. The mainstream is 143 km long, covering an area of 6166 km^2, including 25 water environmental management units divided based on water quality control sections. In 2020, the basin' s annual gross domestic product (GDP) was approximately 3.51$×10ˆ{12}$ CNY, with a permanent population of around 24.0$×10ˆ{6}$ [?, ?, ?, ?], and an annual water volume of 10.48$×10ˆ{6}$ m^3 [?, ?].

The North Canal Basin covers most of Beijing' s urban area and serves as the primary drainage system, receiving 80% of reclaimed water from factories and sewage plants annually [?, ?]. Dense population and developed economy have negatively impacted the water environmental system. Within Beijing' s portion of the North Canal in 2020, 6% of the water body was inferior to Grade V water quality (the standard for agricultural and general landscape water areas) according to China' s National Environmental Quality Standards for Surface Water (GB3838-2002) [?, ?] [?, ?].

3 Methods

The early warning framework includes six main steps [Figure 2: see original paper]. First, defining the warning situation constructs the indicator system after analyzing impact factors on the water environmental system. Second, identifying warning sources organizes indicators for WECC characterization through time-difference correlation analysis. Third, judging the warning trend evaluates WECC tendencies using the prosperity index (fluctuation). Fourth, quantitative prediction of the warning situation constructs the CEWI and forecasts its future values. Fifth, dividing warning levels and setting signal lights. Sixth, making suggestions for warning removal and WECC improvements.

3.1.1 Establishment of the Indicator System

WECC focuses on interaction mechanisms in human–water environmental systems and serves as an important index for investigating human life and production impacts, affected by numerous factors including water resources, water quality, economy, and population [?, ?, ?]. As this study explored impact factor fluctuations and forecasted basin sustainability using WECC, we selected indicators from different perspectives based on whether they applied pressure or support to socioeconomic and water environmental systems. The water environmental system can be classified into water quantity and quality, involving ecosystem water conservation (water interception) and water quality purification (pollution interception) capabilities. Indicator selection also ensured data availability. Table 1 describes the indicator system.

Specifically, we selected 17 pressure indicators from socioeconomic development activities affecting the water environmental system, including population, GDP, water consumption, and wastewater/pollution discharge (e.g., chemical oxygen demand (COD), ammonia nitrogen (NH_4), and total phosphorus (TP)). We also selected 13 indicators describing water environmental system support capacity, including water resources, sewage treatment capacity, water conservation capacity, water purification capacity (related to natural vegetation around water bodies), and environmental protection investment.

We required a benchmark indicator to directly reflect WECC with suitable periodicity, determining the time lag of pressure and support indicators in subsequent time-difference correlation analysis. This study selected a comprehensive water environmental carrying rate (CWECR) as the benchmark indicator:

$$CWECR = \frac{[Average(R_{WR}, R_{WE})]}{[Max(R_{WR}, R_{WE})]}$$

where R_{WR} is the water resources carrying rate; R_{WE} is the water environmental carrying rate; U_{WR} (m^3) is water utilization; Q_{WR} (m^3) is water resources amount; P_{COD} (t), P_{NH4} (t) and P_{TP} (t) are pollutant discharges of COD,

NH_4, and TP, respectively; and W_{COD} (t), W_{NH4} (t), and W_{TP} (t) are water environmental capacities for COD, NH_4, and TP, respectively.

3.1.2 Data Collection

Most data were obtained from statistical yearbooks: Beijing Area Statistical Yearbook \cite{Beijing Municipal Bureau Statistics, 2009-2018}, Tianjin Statistical Yearbook \cite{Tianjin Municipal Bureau Statistics, 2009-2018}, Hebei Statistical Yearbook \cite{Hebei Provincial Bureau of Statistics, 2009-2018}, Langfang Economic Statistical Yearbook \cite{Langfang Municipal Bureau Statistics, 2009-2018}, Hebei Rural Statistical Yearbook \cite{Hebei Provincial Bureau of Statistics, 2008-2017}, Yearbook of Tianjin Beichen \cite{Local Chronicles Office of Beichen District, 2015-2017}, Yearbook of Wuqing \cite{Local Chronicles Office of Wuqing District, 2015-2017}, Tianjin Water Resources Bulletin \cite{Tianjin Water Authority, 2008-2017}, Beijing Water Resources Bulletin \cite{Beijing Water Authority, 2008-2017}, Hebei Water Resources Bulletin \cite{Department of Water Resources of Hebei Province, 2008-2017}, and other unpublished departmental statistics.

Environmental pollution discharge data, sewage treatment, and waste reuse information came from China' s secondary pollution investigation (conducted in 2017). Beijing University of Chemical Technology provided non-point pollution data. Water environmental capacity data came from our research group' s previous results. Land use data (30 m resolution) were interpreted from Landsat remote sensing images. Considering data availability, the study time span is 2008-2017, with a forecast period of 2018-2023.

3.2 Identification of Warning Sources

For early warning accuracy, we must determine key factors consistent with WECC fluctuation cycles. We used time-difference correlation analysis to classify indicators into leading and synchronous (coincident) categories (lagging indicators were not considered). This analysis identified correlation (time-difference) between the benchmark indicator and selected indicators using SPSS (Statistical Package for Social Science).

The formula is:

$$R_l = \frac{\sum_{t=1}^{N-l}(X_{t+l} - \bar{x})(Y_t - \bar{y})}{\sqrt{\sum_{t=1}^{N-l}(X_{t+l} - \bar{x})^2 \sum_{t=1}^{N-l}(Y_t - \bar{y})^2}}$$

where R_l is the time-difference correlation coefficient; l is the time-difference or time lag (positive = lagging, negative = leading, zero = synchronous); t is time; N is the number of indicators; X is the impact indicator ($X = \{X_1, X_2, \dots, X_N\}$); Y is the benchmark indicator ($Y = \{Y_1, Y_2, \dots, Y_N\}$); and $\bar{x}$ and $\bar{y}$ are average values of X and Y. If R_l is largest when $l = 0$, indicator X is synchronous with Y. If R_l is largest when l is negative, X is a leading indicator of Y.

3.3 Judgement of Warning Trend

The prosperity index reflects comprehensive changes in WECC impact indicators, enabling indirect (qualitative) judgment of WECC deterioration or improvement trends in the next period. The prosperity index is generally divided into DI and CI.

The DI evaluates and measures fluctuation status of impact indicators, essentially indicating whether half of the indicators are increasing annually [?, ?]. When DI exceeds 50 (prosperous line), more than half of impact indicators are in a prosperous state. Under the benchmark indicator, WECC is a negative indicator (higher WECC = worse carrying situation). Thus, if more than half of pressure indicators increase or more than half of support indicators decrease, WECC worsens. When DI is below 50, more than half of impact indicators are depressed—meaning more than half of pressure indicators decrease or more than half of support indicators increase—and WECC improves. The leading degree of the leading DI to the synchronous DI (time lag l) indicates that WECC changes will appear after l years.

The CI, also called the "prosperity composite index," is commonly used independently in economic early warning studies. It represents a weighted average of indicator changes and can predict fluctuation turning points while reflecting the degree (amplitude) of indicators' influence on WECC. When CI exceeds 100 (prosperous line), impact indicators are booming (increasing) and WECC worsens. When CI is below 100, impact indicators are in a downturn (declining) and WECC improves. The leading degree of the leading CI to the synchronous CI (time lag l) indicates WECC changes will occur after l years.

3.3.1 Calculation of the DI The DI represents the percentage of variables with increasing time-series changes:

$$DI_t = \frac{IP + IS}{n} \times 100$$

where DI_t is the diffusion index at time t, representing the ratio of increasing pressure indicators and decreasing support indicators in the next period to all indicators; n is the total number of indicators; IP is the number of increased pressure indicators; $X_{i,t}$ is the value of the ith indicator at time t; $X_{i,t-1}$ is the value at time $t-1$; and IS is the number of reduced support indicators.

3.3.2 Calculation of the CI CI calculation is more complex than DI. The process involves:

First, obtaining the symmetrical change ratio for each indicator by finding the time series of relative cyclic fluctuations based on original indicator time series:

$$C_i(t) = \frac{X_{i,t} - X_{i,t-1}}{(X_{i,t} + X_{i,t-1})/2} \times 100$$

where $C_i(t)$ is the symmetrical change ratio of each indicator.

Second, quantifying the normalization factor of sequence A_i:

$$A_i = \frac{\sum_{t=1}^{h} |C_i(t)|}{h}$$

where h is the number of periods.

Third, calculating the standardized symmetrical change ratio S_i:

$$S_i(t) = \frac{C_i(t)}{A_i}$$

Fourth, determining the average rate of change $R(t)$:

$$R(t) = \frac{\sum_{i=1}^{n} W_i S_i(t)}{\sum_{i=1}^{n} W_i}$$

where W_i represents the weight of the ith indicator, determined by its time-difference correlation coefficient.

Assuming $I(t) = 100$ (no fluctuation trend), we have:

$$I(t) = I(t-1) \times \frac{200 + R(t)}{200 - R(t)}$$

Finally, the CI formula is:

$$CI(t) = \frac{I(t)}{I(t)_o} \times 100$$

where $I(t)_o$ is the average value of $I(t)$ in the reference period.

By calculating CI separately from pressure and support indicators, we obtain the integrated CI as the ratio of pressure CI to support CI:

$$CI(t)_{integrated} = \frac{CI(t)_{pressure}}{CI(t)_{support}}$$

where $CI(t)_{integrated}$ is the integrated CI, and $CI(t)_{pressure}$ and $CI(t)_{support}$ are CI values from pressure and support indicators, respectively.

3.4 Prediction of Warning Situation

Using selected leading pressure and support indicators, we constructed the CEWI to reflect comprehensive carrying capacity in advance. To avoid correlation between indicators that could bias the early warning index by strengthening pressure or support trends, we adopted factor analysis to extract common factors and calculate CEWI. We used principal component analysis to extract common factors and applied maximum variance rotation. Kaiser-Meyer-Olkin (KMO) and Bartlett' s sphericity tests measured suitability for factor analysis, requiring KMO > 0.50 and Bartlett' s significance < 0.05 [**?**, **?**]. Component scores were calculated using the regression method in SPSS.

The formulas are:

$$T_i = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$

$$F_i = \sum_{i=1}^{m} Coe_i \times T_i$$

$$EWI_P \text{ (or } EWI_S) = \sum_{i=1}^{m} W_i \times F_i$$

where T_i is the normalized indicator; X_i is the leading pressure or support indicator selected in step 2; X_{max} and X_{min} are maximum and minimum values; F_i is the factor; m is the total number of factors; Coe_i is the component score coefficient; EWI_P and EWI_S are pressure and support early warning indices; and W_i is each factor' s contribution rate.

Referencing the CI calculation formula, we constructed a prediction model for CEWI in the next period, related to the change rate of the leading integrated CI and CEWI values from the last two periods. The change rate of the leading integrated CI for the next period can be calculated through time-series analysis:

$$CEWI_{t+1} = CEWI_t \times \frac{200 + RCI_{t+1}}{200 - RCI_{t+1}} + (CEWI_t - CEWI_{t-1})$$

where $CEWI_{t+1}$ is the comprehensive early warning index for period $t+1$; $CEWI_t$ and $CEWI_{t-1}$ are indices at times t and $t-1$; and RCI_{t+1} is the change rate of the leading integrated CI for period $t+1$.

We used root mean square error (RMSE) and mean absolute error (MAE) to evaluate prediction model performance [**?**, **?**]. RMSE reflects absolute deviation between predicted and actual values, while MAE represents relative deviation. Lower values indicate better model performance.

3.5 Division of Warning Levels and Setting of Signal Lights

CEWI is the ratio of pressure early warning index to support early warning index (Eq. 16). We set 1.000 as the non-overloading status with 0.500 intervals. Early warning signal lights represent WECC status. Warning levels and explanations are given in Table 2 .

Table 2. Classification of warning levels and corresponding explanation

Signal light	Warning level	Range of CEWI	Explanation
Red light	Heavy warning	>1.500	Water environmental system is seriously overloaded; emergency measures needed to prevent irreversible deterioration.
Yellow light	Medium warning	1.000–1.500	Socioeconomic development significantly affects the system, exceeding carrying capacity. Restrict growth and reduce pressure.
Green light	Slight warning	0.500–1.000	Impact of socioeconomic development on water environmental system is moderate.

Signal light	Warning level	Range of CEWI	Explanation
Deep green light	No warning	<0.500	Socioeconomic and water environmental systems develop in harmony.

3.6 Suggestions for Warning Removal

We conducted sensitivity analysis to identify indicators with the most significant impact on future CEWI. We decreased each leading pressure indicator by 10% or increased each leading support indicator by 10% at time t, then recalculated the resulting CEWI_{t+1} decrease. Based on this analysis and related North Canal Basin research, we proposed risk elimination measures for high-risk units, focusing on two aspects: alleviating/decreasing pressures and enhancing carrying capacities (increasing supports).

4 Results

4.1 Identification of Warning Sources

While some studies use all indicators for water safety analysis or WECC evaluation without secondary screening [?, ?, ?], we retained only indicators with correlation coefficients > 0.500 to improve early warning accuracy. Classification results [Figure 3: see original paper] revealed 11 leading indicators (seven pressure, four support) and seven synchronous indicators (three pressure, four support). Synchronous indicators reflected current WECC, with current pressure derived mainly from agricultural water consumption, non-point-source COD pollution discharge, and NH_4 pollution discharge intensity. Related research confirms the North Canal is relatively polluted by organic substances and NH_4 [?, ?]. These leading indicators provide WECC early warning with a time lag of approximately one to two years, suggesting that measures to improve WECC should be taken one to two years in advance, particularly for reducing point-source NH_4 and TP pollution (correlation coefficient > 0.700). Specifically, preventing potential phosphorus leaching is most needed in downstream sections, while cutting off external pollutants could help control nitrogen pollution [?, ?, ?].

4.2 Analysis of Prosperity Index

4.2.1 Analysis of the DI The DI represents the percentage of increasing pressure indicators or decreasing support indicators, demonstrating whether WECC is improving or worsening. From the synchronous DI [Figure 4a: see original paper], values exceeded 50 in 2010, 2014, and 2017, indicating worse WECC in those years. Examining cycle peaks and troughs to judge indicator adaptability [?, ?], we found a time lag (zero to two years) between synchronous and leading DI, confirming excellent advancement of leading indicators. Based on this lag, we inferred the synchronous DI might peak next in 2017, 2018, or 2019. The leading DI trended downward in 2017, suggesting WECC would likely improve or at least not worsen significantly in the next period.

4.2.2 Analysis of the CI The CI simultaneously presents fluctuation trends and degrees, comprehensively reflecting WECC [?, ?]. The synchronous integrated CI [Figure 4b: see original paper] was generally consistent with the benchmark indicator (CWECR), indicating it could evaluate WECC changes. Similar to DI analysis, synchronous integrated CI peaked in 2010 and 2014, suggesting worse WECC in those years. Cycle analysis revealed a time lag (zero to two years) between synchronous and leading integrated CI, confirming leading indicators as good early warning indices. The synchronous integrated CI would continue upward, but despite the leading integrated CI' s uptrend, its value remained below 100, indicating WECC would not worsen significantly in the next period.

4.3 Analysis and Prediction of CEWI

4.3.1 Analysis of CEWI in 2008-2017 To avoid indicator correlation, we conducted factor analysis on leading pressure and support indicators. Results showed KMO values > 0.500 (0.742 and 0.559 for pressure and support indicators, respectively) and Bartlett' s sphericity test significance < 0.001 (0.000 for both), indicating selected indicators passed correlation tests and were suitable for factor analysis [?, ?]. The accumulated contribution rate of the first three factors reached 82.293% for pressure indicators and 89.657% for support indicators, so we extracted three common factors for each.

We calculated CEWI for 25 water environmental management units in the North Canal Basin [FIGURE:5a1-a5]. After 2013, lower reaches' WECC improved, and by 2017, overall basin WECC improved, especially in middle and upper reaches (Beijing areas). Box plots [Figure 5b: see original paper] show CEWI generally declined year-over-year since 2009, with most values remaining below 1.000 despite slight upward fluctuation after 2014. Box-shape changes stabilized after 2013, implying regional WECC differences gradually reduced and overall status improved. These results align with actual conditions.

Since 2013, Beijing's government issued two "Three-Year Action Plans" for water environmental treatment and established the River Chief System covering over 1200 river reaches, built 18 new reclaimed water plants, and upgraded three sewage treatment plants [?, ?, ?], making treatment effects obvious. Box plots for different management units [Figure 5c: see original paper] show urban central areas have poor and unstable WECC. Unit B-13' s CEWI exceeded 1.000 with large data distribution span, while unit B-14 risked overload with higher CEWI (near 0.800). Units B-3 and B-16 showed significant CEWI variation, indicating substantial WECC improvement and corresponding water quality improvement [?, ?, ?].

4.3.2 Prediction of CEWI in 2018–2023 Before predicting CEWI for the next period, we validated the model using historical data. Since CEWI values were relatively stable after 2014 [Figure 5: see original paper], we simulated values for 2014–2017 (100 total samples) and verified them against actual values. Results demonstrated good fit (RMSE = 0.0651, MAE = 0.1418), confirming the prediction model' s reliability [?, ?].

As shown in Figure 6 [Figure 6: see original paper], except for some units (B-12, B-19, B-20, B-21, B-22, B-23, B-24, and B-25), CEWI values for the remaining 17 units improved in 2017, consistent with recent water environmental system improvements. The proportion of water bodies inferior to Grade V decreased from 60% in 2017 to 6% in 2020 \cite{Beijing Municipal Ecology and Environment Bureau, 2017–2019, 2020}. Results showed prosperity index fluctuation analysis helped predict WECC to some extent.

Spatial CEWI distribution indicated upstream and downstream regions would have better WECC in 2023, primarily due to high vegetation cover and less human interference upstream, plus large flow enhancing WECC downstream. Sustainability levels would be higher in middle reaches (city center locations). Although overload situations would improve, risk remains in unit B-13 (CEWI = 0.880) due to high population density, large domestic water use, and significant pollution discharge in central Beijing. Unit B-21' s CEWI would significantly increase in 2023, requiring strengthened water environmental management.

4.4 Suggestions for Warning Removal

Sensitivity analysis results [Figure 7: see original paper] demonstrated that total population reduction, domestic water consumption reduction, and water purification capacity enhancement were the three most effective measures for improving basin WECC, while decreasing point-source NH_4 pollution was key for central city areas (units B-13 and B-14). If all assumed measures were taken, unit B-13' s CEWI would drop below 1.000. Improvement potential existed in units B-6, B-11, B-12, B-14, and B-17 (accumulated CEWI decline > 0.100).

Based on this analysis, we suggest the North Canal Basin (especially Beijing) should control population size where possible. According to regional water-saving management measures, district governments should create water use plans, implement strict water quota management, and pursue laddered water pricing for water consumption units, particularly high-consumption enterprises. Governments should strengthen water-saving education and publicity while encouraging water-saving equipment renovation/installation through appropriate compensation. To enhance ecosystem water purification capacity, governments should optimize land use patterns. Research shows North Canal Basin eco-environmental quality improvement relates to increased vegetation cover [?, ?], especially water quality improvement through forestland increase [?, ?]. Governments should increase ecological conservation areas in urban planning, restrict construction land expansion, and reduce built-up land and impervious surface aggregation [?, ?]. Since wastewater treatment plants remain the main pollution source [?, ?], stricter effluent standards should be set to optimize central city water quality.

5 Conclusions

From an economic fluctuation perspective, this study utilized the prosperity index to construct a water risk early warning system based on WECC and applied it to the North Canal Basin. Results demonstrated that prosperity index analysis helped predict WECC status, the early warning system was reliable (RMSE = 0.0651, MAE = 0.1418), and CEWI calculations aligned with actual conditions and related research. This index provides an appropriate method for water environmental administration departments to predict future basin WECC and assists in implementing management measures in advance, particularly for performance evaluation and key short-term task arrangement in China' s River Chief System.

The case study suggested that while most North Canal Basin water environmental management units' WECC improved, middle reaches face water environmental system overload risk. Specific management measures are needed, including population control, water quota management, water conservation publicity and education, water-saving equipment renovation/installation, land use structure optimization, and stricter effluent standards.

Acknowledgements: This research was supported by the National Key R&D Program of China (2021YFB3901104). The authors thank Beijing University of Chemical Technology for providing non-point pollution data.

References

Bafarasat A Z. 2021. Is our urban water system still sustainable? A simple statistical test with complexity science insight. *Journal of Environmental Management*, 280: 111748, doi: 10.1016/j.jenvman.2020.111748.

Bai W R, Gu H, Ji L N, et al. 2018. Experimental study on joint regulation of water quality and quantity in the lower reaches of the North canal. *Beijing Water*, (6): 20–24. (in Chinese)

Beijing Municipal Bureau Statistics. 2009–2018. *Beijing Regional Statistical Yearbook*. Beijing: China Statistics Press. (in Chinese)

Beijing Municipal Bureau Statistics. 2021. *Beijing Regional Statistical Yearbook*. Beijing: China Statistics Press. (in Chinese)

Beijing Municipal Ecology and Environment Bureau. 2017–2019. *Beijing Ecological and Environment Statement* (2017–2019). [2021-03-02]. http://sthjj.beijing.gov.cn/. (in Chinese)

Beijing Municipal Ecology and Environment Bureau. 2020. *Beijing Ecological* *and Environment Statement* (2020). [2022-02-16]. http://sthjj.beijing.gov.cn/. (in Chinese)

Beijing Water Authority. 2008–2017. *Beijing Water Resources Bulletin* (2008–2017). [2021-03-02]. http://swj.beijing.gov.cn/zwgk/szygb/. (in Chinese)

Beijing Water Authority. 2020. *Beijing Water Resources Bulletin* (2020). [2022-02-16]. http://swj.beijing.gov.cn/zwgk/szygb/. (in Chinese)

Cao R X, Zhang K X, Zeng W H, et al. 2021. Research on the early-warning method of water environment carrying capacity based on BP neural network: A case study of Beiyunhe River Basin. *Acta Scientiae Circumstantiae*, 41(5): 2005–2017. (in Chinese)

Chen L Y, Li C F, Li S Y. 2011. Measurement and prospect of China' s price boom-based on the analysis of constructing the price boom diffusion index. *Price: Theory and Practice*, (5): 53–54. (in Chinese)

Chen W T, Xia Q, Su J, et al. 2022. Evaluation and early warning of water environmental carrying capacity in Baiyangdian basin based on time-difference correlation analysis and fuzzy neural network. *Environmental Engineering*, 40(6): 261–271. (in Chinese)

Dai D, Sun M D, Lv X B, et al. 2022. Comprehensive assessment of the water environment carrying capacity based on the spatial system dynamics model, a case study of Yongding River Basin in North China. *Journal of Cleaner Production*, 344: 131137, doi: 10.1016/j.jclepro.2022.131137.

Department of Water Resources of Hebei Province. 2008–2017. *Hebei Water Resources Bulletin* (2008–2017). [2021-03-02]. http://slt.hebei.gov.cn/. (in Chinese)

Ding X W, Zhang J J, Jiang G H, et al. 2017. Early warning and forecasting system of water quality safety for drinking water source areas in three gorges reservoir area, China. *Water*, 9(7): 465, doi: 10.3390/w9070465.

Hebei Provincial Bureau of Statistics. 2008–2017. *Hebei Rural Statistical Yearbook*. Beijing: China Statistics Press. (in Chinese)

Hebei Provincial Bureau of Statistics. 2009–2018. *Hebei Statistical Yearbook*. Beijing: China Statistics Press. (in Chinese)

Hebei Provincial Bureau of Statistics. 2021. *Hebei Statistical Yearbook*. Beijing: China Statistics Press. (in Chinese)

Imani M, Hasan M M, Bittencourt L F, et al. 2021. A novel machine learning application: water quality resilience prediction model. *Science of The Total Environment*, 768: 144459, doi: 10.1016/j.scitotenv.2020.144459.

Ji L N, Liu Z J. 2021. The practice process of aquatic ecological environment protection and restoration of North Canal. *Beijing Water*, (3): 17–21. (in Chinese)

Jin T, Cai S B, Jiang D X, et al. 2019. A data-driven model for real-time water quality prediction and early warning by an integration method. *Environmental Science and Pollution Research*, 26: 30374-30385.

Kang P, Xu L Y. 2012. Water environmental carrying capacity assessment of an industrial park. *Procedia Environmental Sciences*, 13: 879-890.

Karunasingha D S K. 2022. Root mean square error or mean absolute error? Use their ratio as well. *Information Sciences*, 585: 619-629.

Knedlik T. 2014. The impact of preferences on early warning systems—The case of the European Commission' s Scoreboard. *European Journal of Political Economy*, 34: 157-166.

Langfang Municipal Bureau Statistics. 2009-2018. *Langfang Economic Statistical Yearbook*. Beijing: China Statistics Press. (in Chinese)

Li Y J, Liu C Y. 2016. *Principle and Application of Multivariate Analysis*. Beijing: Economic Science Press, 94-107. (in Chinese)

Liao R K, Hu J Y, Li Y K, et al. 2020. Phosphorus transport in riverbed sediments and related adsorption and desorption characteristics in the Beiyun River, China. *Environmental Pollution*, 266: 115153, doi: 10.1016/j.envpol.2020.115153.

Liu D, Wang X, Zeng W H, et al. 2019. Research on overload warning of water environment carrying capacity based on ARMA model. *Water Resources Protection*, 35(1): 52-55, 69. (in Chinese)

Liu J, Shen Z Y, Chen L. 2018. Assessing how spatial variations of land use pattern affect water quality across a typical urbanized watershed in Beijing, China. *Landscape and Urban Planning*, 176: 51-63.

Liu J, Yan T Z, Shen Z Y. 2021. Sources, transformations of suspended particulate organic matter and their linkage with landscape patterns in the urbanized Beiyun river watershed of Beijing, China. *Science of The Total Environment*, 791: 148309, doi: 10.1016/j.scitotenv.2021.148309.

Liu X J, Pan Y, Zhang W H, et al. 2019. Achieve sustainable development of rivers with water resource management - economic model of river chief system in China. *Science of The Total Environment*, 708: 134657, doi: 10.1016/j.scitotenv.2019.134657.

Local Chronicles Office of Beichen District. 2015-2017. *Yearbook of Tianjin Beichen*. Changchun: Jilin People' s Publishing House. (in Chinese)

Local Chronicles Office of Wuqing District. 2015-2017. *Yearbook of Wuqing*. Tianjin: Local Chronicles Editing Committee Office of Wuqing District of Tianjin. (in Chinese)

Lu J H, Tang D S. 2019. Study on water resources bearing capacity early warning based on PSR and matter-element extension model. *Water Resources* *and Hydropower Engineering*, 50(1): 58–64. (in Chinese)

Lu Y, Xu H W, Wang Y X, et al. 2017. Evaluation of water environmental carrying capacity of city in Huaihe River Basin based on the AHP method: A case in Huai' an City. *Water Resources and Industry*, 18: 71–77.

Maier H R, Jain A, Dandy G C, et al. 2010. Methods used for the development of neural networks for the prediction of water resource variables in river systems: Current status and future directions. *Environmental Modelling & Software*, 25(8): 891–909.

Meng Y, Miao C C, Li L, et al. 2016. Investigation and evaluation of outlet of North Canal main inflow river. *Water & Wastewater Engineering*, 52(s1): 17–19. (in Chinese)

Ministry of Ecology and Environment of the People' s Republic of China. 2002. *National Environmental Quality Standards for Surface Water of China* (GB3838-2002). [2022-02-16]. https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/shjbh/shjzlbz/. (in Chinese)

Mitchell W C, Burns A F. 1947. *Measuring Business Cycles*. Cambridge, MA: National Bureau of Economic Research, 3–22.

Moore G H. 1950. *Statistical Indicators of Cyclical Revivals and Recessions*. Cambridge, MA: National Bureau of Economic Research, 3–31.

Plate E J. 2008. Early warning and flood forecasting for large rivers with the lower Mekong as example. *Journal of Hydro-environment Research*, 1(2): 80–94.

Ren Y T, Lu J, Fu Q. 2017. Sanjiang plain water safety warning research system based on evaluation index. *Yellow River*, 39(3): 75–80. (in Chinese)

Shi C Y, Zhang Z. 2021. A prediction method of regional water resources carrying capacity based on artificial neural network. *Earth Sciences Research Journal*, 25(2): 169–177.

Shiskin J, Moore G H. 1968. *Composite Indexes of Leading, Coinciding, and Lagging Indicators*. Cambridge, MA: National Bureau of Economic Research, 316–356.

Song L L, Wang Z S, Wu J N, et al. 2022. Performance evaluation for implementation of National Water Pollution Control and Management Technology Major Project in Beijing-Tianjin-Hebei region—A case study of Beiyun River Basin. *Environmental Protection Science*, 48(4): 46–51. (in Chinese)

Su S, Gong Z N, Zhang W J, et al. 2022. Change of vegetation coverage and assessment of ecological environment quality in Beiyun River Basin. *Acta Scientiae Circumstantiae*, 42(1): 19–27. (in Chinese)

Sun S Y, Meng Y, Li L, et al. 2022. Temporal and spatial distribution characteristic and evaluation analysis of surface water quality in Beiyun River. *Beijing*

Water, (1): 29-34. (in Chinese)

Tan Q, Huang G H, Cai Y P. 2013. Multi-source multi-sector sustainable water supply under multiple uncertainties: an inexact fuzzy-stochastic quadratic programming approach. *Water Resources Management*, 27(2): 451-473.

Taylor J R. 2015. *An Introduction to Error Analysis: The Study of Uncertainties in Physical Measurements*. Wang Z Y (translation). Beijing: Higher Education Press, 89-105. (in Chinese)

Tianjin Municipal Bureau of Statistics. 2009-2018. *Tianjin Statistical Yearbook*. Beijing: China Statistics Press. (in Chinese)

Tianjin Municipal Bureau of Statistics. 2021. *Tianjin Statistical Yearbook*. Beijing: China Statistics Press. (in Chinese)

Tianjin Water Authority. 2008-2017. *Tianjin Water Resources Bulletin* (2008-2017). [2021-03-02]. http://swj.tj.gov.cn/. (in Chinese)

Tu X J, Wang M Z, Sun K, et al. 2016. China Internet industry state analysis and prosperity indexes. *China Communications* (English version), 13(10): 245-252.

Usama A M, Choong W W, Low S T, et al. 2015. Investigating the environmental Kuznets curve (EKC) hypothesis by utilizing the ecological footprint as an indicator of environmental degradation. *Ecological Indicators*, 48: 315-323.

Wang G, Xiao C L, Qi Z W, et al. 2021. Water resource carrying capacity based on water demand prediction in Chang-Ji economic circle. *Water*, 13(1): 16, doi: 10.3390/w13010016.

Wang T X, Xu S G. 2015. Dynamic successive assessment method of water environment carrying capacity and its application. *Ecological Indicators*, 52: 134-146.

Xie Y X, Wu H, Cui D, et al. 2019. Chinese early warning of environmental carrying capacity based on the climate index method. *China Environmental Science*, 39(1): 440-448. (in Chinese)

Yu C X, Li Z Y, Yang Z F, et al. 2020. A feedforward neural network based on normalization and error correction for predicting water resources carrying capacity of a city. *Ecological Indicators*, 118: 106724, doi: 10.1016/j.ecolind.2020.106724.

Yu Y, Wu J, Wang X Y, et al. 2012. Degradation of inorganic nitrogen in Beiyun River of Beijing, China. *Procedia Environmental Sciences*, 13: 1069-1075.

Yuan J C. 1987. Research status and development trend of environmental management information system. *Environmental Science*, 8(5): 75-79. (in Chinese)

Zhang L, You Y, Gao C D, et al. 2020. Dissolved organic nitrogen structural and component changes in overlying water along urban river at molecular and material levels-Beiyun basin case study. *Journal of Cleaner Production*, 287: 125570, doi: 10.1016/j.jclepro.2020.125570.

Zhang Y J. 2007. *Research on Econometric Analysis Method and Application of Economic Prosperity*. Beijing: Economic Press China, 49-111. (in Chinese)

Zhang Y J, Yue Q, Wang T, et al. 2021. Evaluation and early warning of water environment carrying capacity in Liaoning province based on control unit: a case study in Zhaosutai river Tieling city control unit. *Ecological Indicators*, 124: 107392, doi: 10.1016/j.ecolind.2021.107392.

Zhou X Y, Zheng B H, Khu S T. 2019. Validation of the hypothesis on carrying capacity limits using the water environment carrying capacity. *Science of The Total Environment*, 665: 774-784.

Note: Figure translations are in progress. See original paper for figures.