water

MDPI

Article

Risk Assessment and Prediction of Reclaimed Water Utilization in Yuyao City, China

Xiaomeng Song [1,*], Chenxu Guo [1], Dexin Wang [1,2] and Xiaojun Wang [3,4,5,*]

[1] School of Resources and Geosciences, China University of Mining and Technology, Xuzhou 221116, China; ts24010179p31@cumt.edu.cn (C.G.); ts22010187p31@cumt.edu.cn (D.W.)
[2] Zhangweinan Canal Administration Bureau, Haihe River Water Conservancy Commission, Ministry of Water Resources, Dezhou 253009, China
[3] The National Key Laboratory of Water Disaster Prevention, Nanjing Hydraulic Research Institute, Nanjing 210029, China
[4] Technology Innovation Center for Efficient Utilization of Unconventional Water Sources, Ministry of Water Resources, Nanjing 210029, China
[5] Research Center for Climate Change, Ministry of Water Resources, Nanjing 210029, China
* Correspondence: xmsong@cumt.edu.cn (X.S.); xjwang@nhri.cn (X.W.)

Abstract

Reclaimed water can alleviate urban water scarcity, but its utilization involves risks across production, transmission, utilization, and management. This study established an 18-indicator assessment system for Yuyao City. Analytic hierarchy process (AHP) and entropy weights were combined using a game-theory-based procedure, while a fuzzy matter-element model assessed historical risks during 2020–2023. Nonlinear autoregressive models generated three output settings for seven time series, forming 2187 nonprobabilistic input combinations for 2025, 2030, and 2035. Historical risk remained within the medium-risk class but declined annually. Production and utilization received the largest criterion weights (0.352 and 0.336, respectively). The proportion of reclaimed water usage, reclaimed water utilization rate, green space rate in built-up areas, investment proportion, and industrial water reuse rate received the highest indicator weights. Across the constructed combinations, risk indices ranged from 0.361 to 0.469 in 2025, 0.376 to 0.420 in 2030, and 0.286 to 0.339 in 2035, with arithmetic means of 0.413, 0.395, and 0.312, respectively. All ranges remained within the medium-risk class. Further risk reduction requires coordinated improvements in production capacity, pipeline coverage, utilization, and institutional support. Future studies should use longer time series, time-ordered validation, and sensitivity tests of weights and thresholds.

Keywords: reclaimed water utilization; risk assessment; fuzzy matter-element model; game-theory-based weighting; nonlinear autoregressive model; Yuyao City

Check for updates

Academic Editor: Carmen Teodosiu

Received: 27 September 2026
Revised: 23 October 2026
Accepted: 27 October 2026
Published: 29 October 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

Freshwater scarcity is increasingly perceived as a global systemic risk, with about two-thirds of the global population facing severe water scarcity conditions [1], particularly in these regions (e.g., China, India) due to the conflict between water resource availability and local water demand [2,3]. In addition, pollution may exacerbate this imbalance and risk of water scarcity due to poor water quality under global climate change and rapid urbanization [4–6]. To effectively alleviate the various issues arising from water scarcity, a range of solutions has been proposed. Through extensive research and practical applications in water conservation, reclaimed water has emerged as a focal point in the field due to its

numerous advantages, including a substantial and stable supply, ease of collection and treatment, and environmental benefits [7]. Reclaimed water has found widespread usage across various sectors, including agriculture [8,9], industry [10], urban miscellaneous uses, environmental water use [11], and ecological water replenishment [12,13]. However, the reuse of reclaimed water also introduces a range of potential risks. These encompass not only threats to human health and the ecological environment posed by chemical substances and microorganisms [14,15] but also economic and social risks stemming from factors such as technology, management, and funding [16]. Moreover, cognitive biases and low public acceptance at the societal level may impede its broader implementation [17].

While considerable progress has been made in current research, certain limitations persist. Most studies tend to focus on a single stage of the process, such as health risks associated with water quality, or they perform static assessments at a macro level. There is a notable lack of systematic risk assessment research that addresses the typical county scale in the Yangtze River Delta, covering the entire "production–transmission–utilization–management" process. Additionally, many studies provide limited analysis of possible future risk conditions under alternative input configurations, which restricts forward-looking risk management. Consequently, it is important to combine whole-process historical risk assessment with exploratory analysis of possible future input conditions for reclaimed water utilization at the county scale in the Yangtze River Delta.

Thus, this study aims to assess the historical and possible future risk conditions of reclaimed water utilization in Yuyao City. Specifically, the study: (1) establishes an 18-indicator risk assessment system covering the production, transmission, utilization, and management stages; (2) combines analytic hierarchy process (AHP) and entropy weights through a game-theory-based procedure and applies a fuzzy matter-element model to assess historical risks from 2020 to 2023; (3) uses nonlinear autoregressive (NAR) models to generate lower, reference, and higher output settings for seven basic time series and constructs $3^7 = 2187$ input combinations for 2025, 2030, and 2035; and (4) identifies stage-specific priorities for reclaimed water risk management. Compared with previous studies, the main contribution of this study is the integration of whole-process risk assessment with exploratory future input construction at the county scale, thereby linking historical diagnosis with forward-looking risk screening.

2. Literature Review

Currently, research on risk assessment for reclaimed water can be broadly categorized into two categories. The first is health risk assessment, which focuses on the direct and indirect effects of pollutants in reclaimed water on human health and ecosystems. This type of risk assessment is characterized by a significant degree of variability and is primarily influenced by water quality. The internationally recognized assessment method is the "four-step process" proposed by the U.S. National Academy of Sciences, namely hazard identification, exposure assessment, dose–response relationship, and risk characterization [18,19]. The second is whole-process risk assessment, which considers reclaimed water as a component of the social system and evaluates the comprehensive risks to the economy and society during its utilization. For instance, Li et al. [20] constructed a risk evaluation index system for urban reclaimed water utilization; Yang et al. [21] applied the AHP-entropy weight method to identify economic factors as key influencing factors; Lu et al. [22] and Li and Wang [23] applied the fuzzy matter-element model to risk assessment of reclaimed water utilization at urban and regional scales, respectively, achieving favorable results. Collectively, these studies have categorized the risks associated with reclaimed water utilization into various stages, including production [24], transmission, utilization, and management, thereby establishing a foundation for systematic risk management. In summary, previous

studies have primarily emphasized contaminant exposure, human-health effects, ecological responses, and public acceptance [14,15], whereas whole-process studies have generally used indicator-based approaches to evaluate technical, infrastructure, utilization, and management conditions [14,15]. However, comprehensive assessments integrating all four stages remain relatively limited, particularly at the county scale.

The determination of indicator weights is a fundamental aspect of risk assessment. The primary methodologies for this process can be categorized into subjective and objective weighting methods. Subjective weighting methods, such as the AHP [25] and the Delphi expert consultation, leverage the knowledge and experience of experts; however, they may introduce biases into the decision-making process. Conversely, objective weighting methods, such as the entropy weight method [26], depend on the relationships within objective data but may neglect practical experience. Given the limitations of any single approach, some scholars have begun to adopt combined weighting approaches, integrating the strengths of different methods through techniques such as linear weighting, to enhance the reliability and efficiency of the assessment.

A variety of technologies and methodologies have been employed for the utilization of reclaimed water and its associated risk assessment. Notably, Fuzzy matter-element models are capable of integrating diverse indicators that may vary in units, attributes, and risk thresholds, and they have proven effective in environmental evaluations [27]. Additionally, autoregressive and neural-network methodologies have been utilized to characterize nonlinear temporal relationships within urban water-demand data [28]. However, these methodologies are rarely combined into a cohesive reclaimed water risk framework that synthesizes historical assessments with potential future conditions. It is also important to emphasize that outputs generated by these models should not be interpreted as scenarios for socioeconomic development or probabilistic forecasts unless they are supported by appropriate assumptions and probabilities of occurrence.

3. Methods

3.1. Study Area

Yuyao City, situated on the southern bank of Hangzhou Bay and administered by Ningbo City, as shown in Figure 1, covers an area of 1526.86 km^2 with a population of 1.265 million. The city has a subtropical monsoon climate, leading to significant spatiotemporal disparities in water resource availability. As an industrial center specializing in new materials, optoelectronics, and new energy vehicles, Yuyao faces a substantial demand for industrial water. The city's reclaimed water infrastructure is centered around the Xiaocaoe Wastewater Treatment Plant, which has a capacity of 225,000 m^3/day, and a coastal industrial water plant, currently operating at 10,000 m^3/day, with plans to expand to 50,000 m^3/day. Reclaimed water is primarily utilized for industrial cooling in the China-Italy Ningbo Ecological Industrial Park, as well as for municipal greening and road sprinkling. Despite recent advancements, the utilization rate of reclaimed water was just 2.6% in 2023, significantly lower than the national advanced level.

3.2. Data Sources

The research data were collected from four categories: (1) statistical yearbooks, including the Ningbo Statistical Yearbook (2008–2023) and the China Urban and Rural Construction Statistical Yearbook (2020–2023); (2) departmental reports, such as the Yuyao Water Resources Bulletin (2019–2023) and monthly operation records from local wastewater treatment plants and reclaimed water facilities; (3) planning documents, specifically the 14th Five-Year Development Plan for Municipal Infrastructure of Yuyao City and the Revised Special Plan for Water Supply Engineering of Yuyao City (2022–2035); and (4) primary data

obtained through expert interviews and on-site investigations conducted between 2023 and 2024 with Yuyao's water management authorities and the coastal reclaimed water plant.

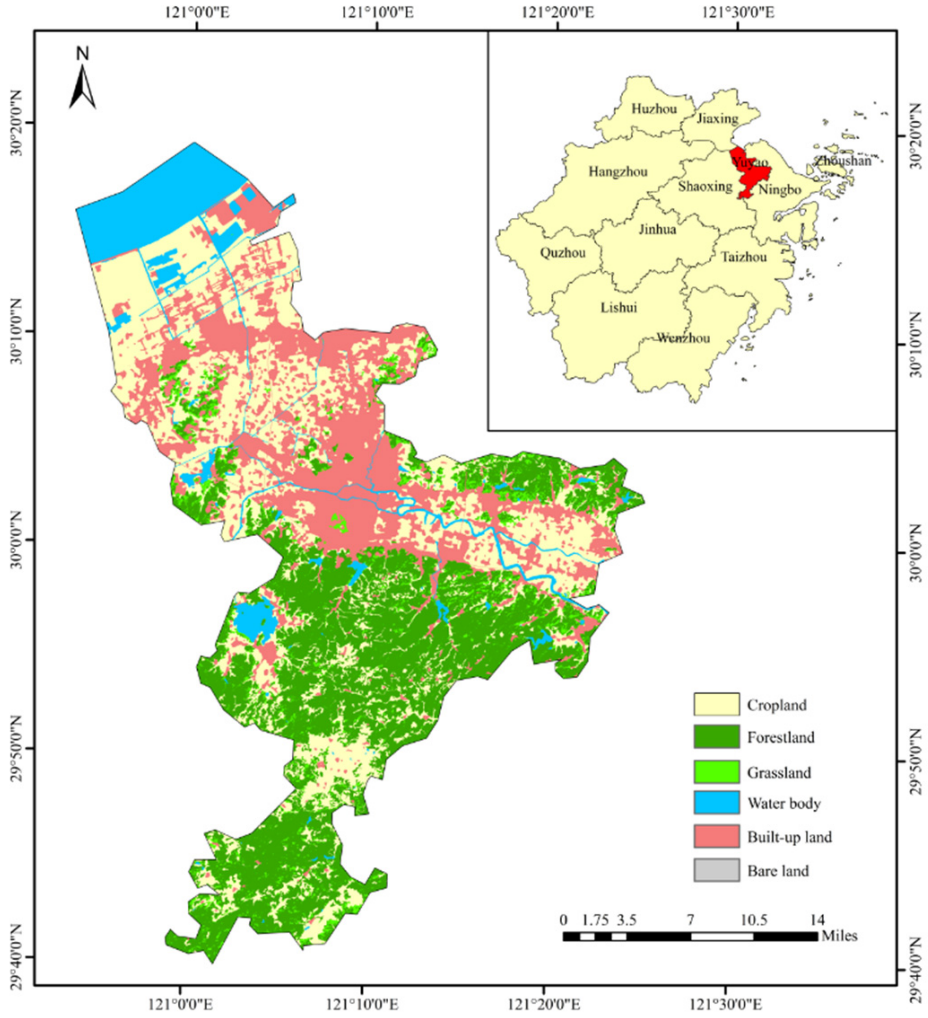


Figure 1. Map of Yuyao City.

3.3. Risk Assessment Index System

Following the life-cycle perspective, reclaimed water utilization was divided into four stages: production, transmission, utilization, and management. Candidate indicators were identified from previous studies, relevant standards, local reclaimed water practices, and the characteristics of the four stages. Indicators were retained according to four criteria: relevance to reclaimed water utilization risk, clear meaning and measurability, relative independence to avoid duplication, and data availability. The selected indicators cover water quality, treatment capacity, pipeline infrastructure, end-use demand, investment, and institutional support.

The Delphi consultation panel consisted of five specialists: one technical manager from a chemical enterprise, one specialist from a water management authority, two managers responsible for reclaimed water plant operation, and one researcher in water treatment. Their expertise covered industrial water use, water resources management, reclaimed water facility operation, and water treatment technology. Based on the literature review, indicator-selection criteria, data availability, and expert consultation, 18 indicators were retained to construct the risk assessment system (Table 1).

Table 1. Index system for risk assessment of reclaimed water utilization.

Criterion Layer	Indicator Layer	Definition/Calculation	Unit	Attribute	Data Source
Production (B1)	Influent Ammonia Nitrogen (T1)	Annual mean of the monthly ammonia nitrogen concentrations in the influent of the reclaimed water facility	mg/L	−	A
	Influent Chemical Oxygen Demand (COD) (T2)	Annual mean of the monthly COD concentrations in the influent of the reclaimed water facility	mg/L	−	A
	Sewage Treatment Rate (T3)	Annual sewage treatment volume/annual sewage discharge volume × 100%	%	+	A, B
	Sewage Treatment Load (T4)	Annual sewage treatment volume/annual design treatment capacity × 100%	%	−	A
	Reclaimed Water Production Load (T5)	Annual reclaimed water utilization volume/annual design production capacity × 100%	%	−	A
	Reclaimed Water Utilization Rate (T6)	Annual reclaimed water utilization volume/annual sewage treatment volume × 100%	%	+	A
Transmission (B2)	Reclaimed Water Pipeline Density (T7)	Total length of reclaimed water pipelines/built-up area	km/km^2	+	A, B
	Sewage Pipeline Density (T8)	Total length of sewage pipelines/built-up area	km/km^2	+	B
	Water Supply Loss Rate (T9)	Annual water supply loss volume/total annual water supply volume × 100%	%	−	B
Utilization (B3)	Effluent Ammonia Nitrogen (T10)	Annual mean of the monthly ammonia nitrogen concentrations in the effluent of the reclaimed water facility	mg/L	−	A
	Effluent COD (T11)	Annual mean of the monthly COD concentrations in the effluent of the reclaimed water facility	mg/L	−	A
	Proportion of Reclaimed Water Usage (T12)	Annual reclaimed water utilization volume/total annual water consumption × 100%	%	+	A, C
	Road-Area-to-Built-Up-Area Ratio (T13)	Road area within the built-up area/total built-up area × 100%; used as a proxy for reclaimed water demand for road sprinkling and street cleaning	%	−	B
	Green Space Rate in Built-up Areas (T14)	Green space area within the built-up area/total built-up area × 100%; used as a proxy for reclaimed water demand for urban irrigation	%	−	B
	Industrial Water Reuse Rate (T15)	Reused industrial water volume/total industrial water consumption × 100%; used as a proxy for industrial reclaimed water demand	%	−	D

Table 1. *Cont.*

Criterion Layer	Indicator Layer	Definition/Calculation	Unit	Attribute	Data Source
Management (B4)	Investment Proportion (T16)	Annual investment in sewage treatment and reclaimed water utilization/total annual fixed-asset investment × 100%	%	+	D, E
	Incentive Policies (T17)	1 if a reclaimed water incentive policy was in effect during the year; otherwise, 0	–	+	E
	Management Measures (T18)	1 if a reclaimed water management measure was in effect during the year; otherwise, 0	–	+	E

Note: "+" denotes a benefit-type indicator, for which a higher value corresponds to a lower risk, whereas "−" denotes a cost-type indicator, for which a higher value corresponds to a higher risk. Annual design treatment and production capacities were calculated from the corresponding daily design capacities multiplied by 365 days. Data sources were as follows: A, monthly operational and administrative records provided by local treatment plants, reclaimed water facilities, and water-management authorities; B, China Urban and Rural Construction Statistical Yearbook (2020–2023); C, Yuyao Water Resources Bulletin (2019–2023); D, Ningbo Statistical Yearbook (2008–2023); and E, official policy and management documents and expert interviews and on-site investigations conducted in 2023–2024.

The low-, medium-, and high-risk levels of each indicator were determined using national and local standards, including GB/T 19923-2024 [29], GB/T 18920-2020 [30], and DB33/2169-2018 [31], together with regional planning targets and historical reference values (Table 2). Incentive policies (T17) and management measures (T18) were represented as binary indicators, where 1 denotes that the corresponding policy or measure was in effect and 0 denotes its absence. The road-area-to-built-up-area ratio (T13) was calculated as the road area divided by the built-up area. It was used as a proxy for potential municipal reclaimed water demand associated with road sprinkling and street cleaning. Under limited reclaimed water supply, a higher ratio indicates greater demand-side pressure and was therefore treated as a negative indicator.

Table 2. Classification of risk indicator levels.

Indicator	Low Risk	Medium Risk	High Risk
T1	(0, 5)	(5, 8)	(8, ∞)
T2	(0, 50)	(50, 100)	(100, ∞)
T3	(97.5, 100)	(95, 97.5)	(0, 95)
T4	(0, 60)	(60, 85)	(85, 100)
T5	(0, 50)	(50, 90)	(90, 100)
T6	(50, 100)	(25, 50)	(0, 25)
T7	(0.5, ∞)	(0.2, 0.5)	(0, 0.2)
T8	(25, ∞)	(5, 25)	(0, 5)
T9	(0, 9.5)	(9.5, 10)	(10, 100)
T10	(0, 5)	(5, 8)	(8, ∞)
T11	(0, 60)	(60, 100)	(100, ∞)
T12	(25, 100)	(5, 25)	(0, 5)
T13	(0, 8)	(8, 12.5)	(12.5, 100)
T14	(0, 20)	(20, 40)	(40, 100)

Table 2. *Cont.*

Indicator	Low Risk	Medium Risk	High Risk
T15	(0, 50)	(50, 70)	(70, 100)
T16	(50, 100)	(20, 50)	(0, 20)
T17	1	0	0
T18	1	0	0

Note: The thresholds for T1 and T2 were based on DB33/2169-2018, whereas those for T10 and T11 were based on GB/T 18920-2020 and GB/T 19923-2024. The thresholds for T3 and T6 were based on national planning targets and provincial reference values, and that for T9 was based on the national target for public water supply network loss control. The thresholds for T7, T8, and T13 were based on municipal reference values in Zhejiang Province, while those for T14 and T15 were based on published studies. We determined the remaining thresholds using local historical data and planning targets. T17 and T18 are binary indicators: 1 indicates the presence of the corresponding policy or management measure, and 0 indicates its absence.

3.4. Risk Assessment and Future Analysis Framework

Figure 2 presents the methodological framework adopted in this study. Following data preprocessing and construction of the risk assessment indicator system, AHP and entropy weights were integrated using a game-theory-based combination weighting method. Historical and exploratory future risk assessments were subsequently conducted using the fuzzy matter-element model.

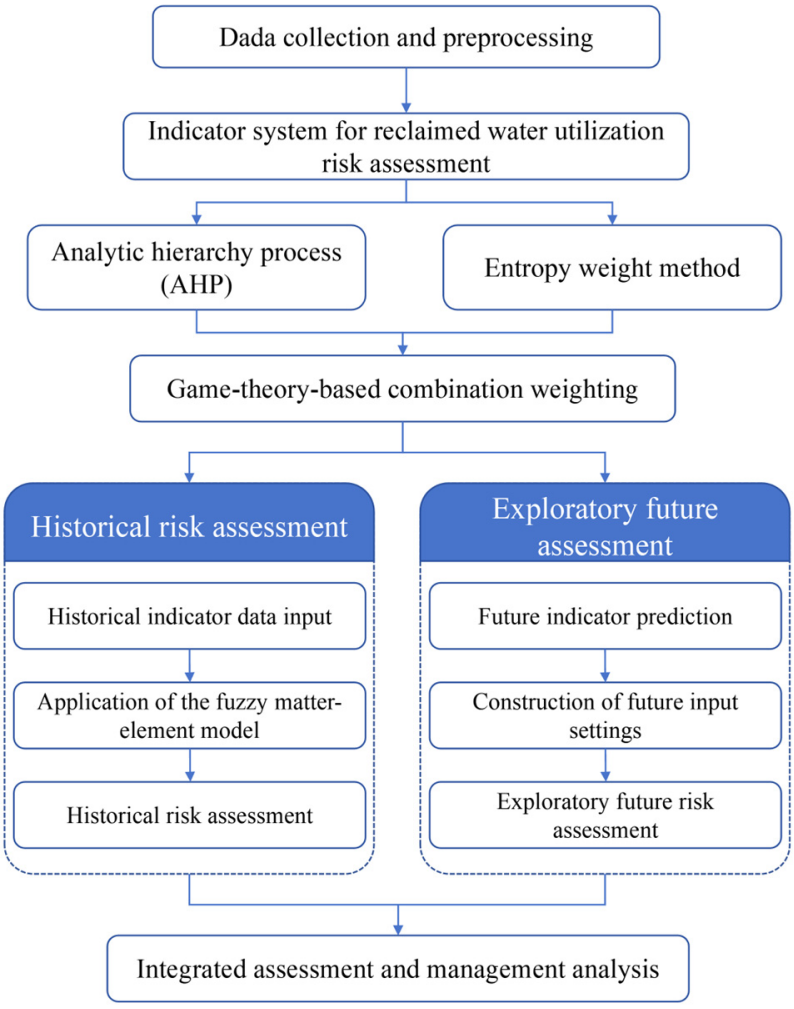


Figure 2. Methodological framework for reclaimed water utilization risk assessment.

3.4.1. Combined Weighting Method Based on Game Theory

To integrate expert experience and objective data, a game-theory-based combined weighting method was adopted. Subjective weights calculated via the AHP and objective weights derived from the entropy weight method are optimally integrated to determine the comprehensive weights of all indicators [27]. A three-level hierarchy (target, criterion, and indicator layers) was established based on Table 1. Five experts performed pairwise comparisons using the 1–9 scale (Table 3). Consistency was assessed using the consistency ratio (CR), with CR < 0.10 as the acceptance criterion. The subjective weight ω_{1j} was calculated as the average of the five experts' global weights for indicator j.

Table 3. Scale values of judgment matrix elements and their meanings.

Scale Value	Meaning
1	The two factors are equally important.
3	The former is slightly more important than the latter.
5	The former is obviously more important than the latter.
7	The former is strongly more important than the latter.
9	The former is extremely more important than the latter.
2, 4, 6 and 8	Intermediate values

Objective weights were derived using the entropy weight method. Let $Q = (q_{ij})_{n\times m}$, where i denotes a historical assessment sample, j denotes an indicator, n is the number of samples, and m = 18. The normalization formulas are:

$$\begin{cases} r_{ij} = \frac{q_{ij} - min_i(q_{ij})}{max_i(q_{ij}) - min_i(q_{ij})} (positive) \\ r_{ij} = \frac{max_i(q_{ij}) - q_{ij}}{max_i(q_{ij}) - min_i(q_{ij})} (negative) \end{cases} \quad (1)$$

where $max_i(q_{ij})$ and $min_i(q_{ij})$ are the maximum and minimum values of indicator j across the historical assessment samples. A positive indicator represents an indicator for which a larger value indicates a more favorable condition, whereas a negative indicator represents an indicator for which a smaller value indicates a more favorable condition. The normalized value r_{ij} is dimensionless and ranges from 0 to 1.

The information entropy H_j and entropy weight ω_{2j} were then computed as:

$$H_j = -\frac{1}{ln\, n}\sum_{i=1}^{n} \frac{r_{ij}}{\sum_{k=1}^{n} r_{kj}} ln\left(\frac{r_{ij}}{\sum_{k=1}^{n} r_{kj}}\right) \quad (2)$$

$$\omega_{2j} = \frac{1 - H_j}{m - \sum_{k=1}^{m} H_k} \quad (3)$$

In Equation (2), H_j is the information entropy of indicator j, and the term $0ln0$ is defined as 0. If the values of an indicator are constant across all historical samples, $H_j = 1$ and $\omega_{2j} = 0$ are assigned. In Equation (3), ω_{2j} is the objective entropy weight of indicator j. Both H_j and ω_{2j} are dimensionless.

Let $\omega_1 = (\omega 11, \ldots, \omega 1\mathrm{m})$ and $\omega_2 = (\omega 21, \ldots, \omega 2\mathrm{m})$ denote the normalized subjective and objective weight vectors, respectively. Both are $1 \times m$ row vectors. In the game-theory-based combination, the combination coefficients were determined by minimizing the deviation between each individual weight vector and the combined weight vector:

$$\min_{a_{k\geq 0}} \left\| \sum_{l=1}^{2} a_l \omega_l^T - \omega_k^T \right\|_2^2, k = 1, 2 \quad (4)$$

where a_l is the combination coefficient of weight vector ω_l, and $\|\cdot\|_2$ denotes the Euclidean norm. The simultaneous first-order conditions give:

$$\begin{bmatrix} \omega_1\omega_1^T & \omega_1\omega_2^T \\ \omega_2\omega_1^T & \omega_2\omega_2^T \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} \omega_1\omega_1^T \\ \omega_2\omega_2^T \end{bmatrix} \tag{5}$$

The coefficients are normalized as $\alpha_k = a_k/(a_1 + a_2)$, where $k = 1, 2$. The comprehensive weight vector is defined as:

$$\omega = \alpha_1\omega_1^T + \alpha_2\omega_2^T \tag{6}$$

The combination coefficients used in this study were $\alpha_1 = 0.48$ and $\alpha_2 = 0.52$, corresponding to the subjective AHP weights and objective entropy weights, respectively. Therefore, the combined weight of indicator j was calculated as $\omega_j = 0.48\omega_{1j} + 0.52\omega_{2j}$. Criterion-level weights were obtained by summing the combined weights of the corresponding indicators. The weights ω_{1j}, ω_{2j}, and ω_j, as well as the coefficients a_k and α_k, are dimensionless.

3.4.2. Fuzzy Matter-Element Model

The fuzzy matter-element model was used to calculate the risk value [27]. For each indicator, the optimal membership degree η_{ij} was determined according to its positive or negative attribute:

$$\begin{cases} \eta_{ij} = \frac{q_{ij}}{max(q_{ij})} (Positive\ indicator) \\ \eta_{ij} = \frac{min(q_{ij})}{q_{ij}} (Negative\ indicator) \end{cases} \tag{7}$$

The reference fuzzy matter-element is constructed from the maximum favorable membership degree of each indicator within the fixed reference dataset and represents the most favorable state of the reclaimed water utilization system. For sample i, the favorable membership degree of indicator j is denoted by η_{ij}, and the corresponding membership degree of the reference sample is denoted by η_{0j}. The Euclidean closeness degree C_i measures the proximity of the sample to this favorable reference state:

$$C_i = 1 - \sqrt{\sum_{j=1}^{m} \omega_j \left(\eta_{0j} - \eta_{ij}\right)^2} \tag{8}$$

where m = 18 is the number of assessment indicators, and ω_j is the combined weight of indicator j, with $\omega_j \geq 0$ and $\sum_{j=1}^{m} \omega_j = 1$. A larger C_i indicates greater proximity to the favorable reference state and therefore a lower level of risk. To express the assessment on a scale that increases with risk, the risk index R_i is defined as:

$$R_i = 1 - C_i = \sqrt{\sum_{j=1}^{m} \omega_j \left(\eta_{0j} - \eta_{ij}\right)^2} \tag{9}$$

Both C_i and R_i are dimensionless and range from 0 to 1 when the membership degrees lie within this interval. A larger R_i indicates greater deviation from the favorable reference state and a higher level of reclaimed water utilization risk.

Risk classification is based on R_i. Two virtual boundary samples are constructed using the indicator values separating low from medium risk and medium from high risk in Table 2. Their risk indices are calculated using the same membership transformation, reference sample, and indicator weights applied to the assessment samples. The resulting thresholds are denoted by τ_L and τ_H, respectively, where $0 \leq \tau_L < \tau_H \leq 1$. The risk grades are defined as follows:

$$Risk\ level_i = \begin{cases} \text{Low risk}, & 0 \leq R_i \leq \tau_L \\ \text{Medium risk}, & \tau_L < R_i \leq \tau_H \\ \text{High risk}, & \tau_H < R_i \leq 1 \end{cases} \tag{10}$$

The membership transformation, reference sample, indicator weights, and classification thresholds were held constant across the historical and exploratory future assessments to ensure that the resulting risk indices were comparable.

For the historical samples, the relative contribution score of each indicator was calculated using the factor contribution method [28]. First, the original indicator values were converted into dimensionless risk-oriented standardized values:

$$z_{ij} = \begin{cases} \frac{q_{ij} - q_j^{\min}}{q_j^{\max} - q_j^{\min}}, \text{for a cost-type indicator,} \\ \frac{q_j^{\max} - q_{ij}}{q_j^{\max} - q_j^{\min}}, \text{for a benefit-type indicator,} \end{cases} \quad (11)$$

where q_{ij} is the original value of indicator j in historical year i, and $q_j{}^{\min}$ and $q_j{}^{\max}$ are the minimum and maximum values of indicator j in the fixed normalization dataset, including the historical observations and corresponding risk-level reference values. Thus, a larger z_{ij} indicates a less favorable condition and a higher level of risk.

The relative contribution score of indicator j in year i was calculated as:

$$RC_{ij} = \frac{\omega_j z_{ij}}{\sum_{k=1}^{m} \omega_k z_{ik}}, \mathrm{j} = 1, 2, \ldots, m \quad (12)$$

where RC_{ij} is the dimensionless relative contribution score, ω_j is the comprehensive weight of indicator j, and m = 18 is the number of indicators. For each historical year, $\sum_{j=1}^{m} RC_{ij} = 1$. A larger RC_{ij} indicates a larger weighted risk-oriented standardized value within the adopted assessment framework. The contribution score is used for the relative comparison and ranking of indicators and does not represent a causal effect.

3.4.3. NAR Neural Network and Exploratory Future Input Construction

A nonlinear auto-regressive (NAR) neural network [28] was adopted to predict seven basic time-series indicators: wastewater treatment volume, wastewater discharge volume, total water consumption, built-up area, sewage pipeline length, road area, and green space area. The NAR model uses the historical values of the target variable as inputs and can be expressed as:

$$\mathrm{Y}(t) = \mathrm{f}[\mathrm{y}(t-1), \mathrm{y}(t-2), \ldots, \mathrm{y}(t-d)] + e(t) \quad (13)$$

where d denotes the delay order and $e(t)$ is the residual term. Compared with a static mapping model, the feedback structure of the NAR network enables it to represent nonlinear temporal relationships in urban water-use and infrastructure-development indicators.

For each indicator, the model was developed using 15 annual observations from 2008 to 2022. The original model implementation specified a nominal training, validation, and testing ratio of 70:15:15, and each model was run 100 times. Because the available records do not retain the year-by-year allocation of observations among the three subsets, the nominal ratio should not be interpreted as a strictly chronological holdout validation. Given the short annual series, the NAR outputs were used primarily to construct exploratory future input settings.

Model fitting was evaluated using the mean relative error (MRE), defined as the mean absolute percentage deviation between the modeled and observed values:

$$\mathrm{MRW} = \frac{100}{\mathrm{N}} \sum_{\mathrm{t}=1}^{\mathrm{N}} \left| \frac{\mathrm{Y}(t) - \mathrm{y}(t)}{\mathrm{y}(t)} \right| \quad (14)$$

where N is the number of evaluated observations, $\mathrm{Y}(t)$ is the modeled value, and $\mathrm{y}(t)$ is the corresponding positive observed value. The available model records provide only the overall historical MRE rather than separate training, validation, and testing errors. Runs with an overall historical MRE below 10% were retained for future input construction.

This criterion measures agreement with the available historical observations but does not establish independent out-of-sample forecasting accuracy.

For each retained model, lower, reference, and higher output settings were constructed from the minimum output, the output of the run with the lowest historical MRE, and the maximum output, respectively. The remaining indicators were assigned using planning targets, policy settings, or historical reference values. The three settings for the seven NAR-predicted series formed $3^7 = 2187$ candidate combinations for each target year. These constructed combinations have no assigned occurrence probabilities; their arithmetic mean describes the selected combination ensemble rather than an expected future risk.

4. Results

4.1. Index Weights and Relative Importance of Indicators

Based on the game-theory-based combination weighting method, the subjective weights calculated by the AHP and the objective weights calculated by the entropy weight method were optimally combined. The resulting comprehensive weights of the risk assessment index system for reclaimed water utilization in Yuyao City are presented in Table 4. These weights represent the relative importance assigned to each indicator within the assessment framework rather than its actual contribution to risk in a particular year. The annual risk contribution of an indicator depends on both its weight and its normalized observed value.

Table 4. Comprehensive weighting of the index system.

Criterion Layer	Indicator Layer	Objective Weights	Subjective Weights	Final Weights	Criterion Weight
Production (B1)	T1	0.051	0.029	0.040	0.352
	T2	0.047	0.029	0.038	
	T3	0.064	0.078	0.071	
	T4	0.075	0.042	0.058	
	T5	0.066	0.069	0.067	
	T6	0.032	0.122	0.077	
Transmission (B2)	T7	0.030	0.058	0.044	0.143
	T8	0.034	0.037	0.036	
	T9	0.091	0.035	0.063	
Utilization (B3)	T10	0.036	0.037	0.036	0.336
	T11	0.043	0.037	0.040	
	T12	0.040	0.126	0.083	
	T13	0.030	0.043	0.037	
	T14	0.101	0.043	0.072	
	T15	0.058	0.079	0.069	
Management (B4)	T16	0.068	0.072	0.070	0.169
	T17	0.067	0.034	0.050	
	T18	0.067	0.031	0.049	

At the criterion level, production (B1) and utilization (B3) received the largest comprehensive weights, at 0.352 and 0.336, respectively, followed by management (B4, 0.169) and transmission (B2, 0.143). This distribution indicates that the assessment framework assigns greater relative importance to production- and utilization-related indicators. The comparatively lower weight of the transmission stage reflects its relative position within the adopted weighting structure and does not imply that transmission-related risks are negligible or adequately controlled.

At the indicator level, the five largest comprehensive weights were assigned to the proportion of reclaimed water usage (T12, 0.083), reclaimed water utilization rate (T6, 0.077), green space rate in built-up areas (T14, 0.072), investment proportion (T16, 0.070), and industrial water reuse rate (T15, 0.069). Together, these indicators accounted for 37.1% of the total weight. T12 and T6 describe the scale and efficiency of reclaimed water utilization, T14 and T15 represent components of the demand structure, and T16 represents financial support for system development.

4.2. Historical Risk Evolution Analysis

The risk index R_i for reclaimed water utilization in Yuyao City from 2020 to 2023 was calculated using the fuzzy matter-element model. The risk levels were classified as low risk ($0 \leq R_i \leq 0.249$), medium risk ($0.249 < R_i \leq 0.714$), and high risk ($0.714 < R_i \leq 1$), as shown in Figure 3. The evaluation results show that the risk of reclaimed water utilization in Yuyao City from 2020 to 2023 remained at a medium level, with a year-over-year decline. The lower risk index in 2023 coincided with changes in several indicators. In terms of process upgrading, the Binhai Reclaimed Water Plant completed its "ultrafiltration + reverse osmosis" dual-membrane renovation by the end of 2022, achieving effluent quality superior to tap water in key indicators such as conductivity and chloride concentration. Effluent ammonia nitrogen (T10) and COD (T11) dropped well below low-risk thresholds. Reclaimed water and sewage pipeline densities increased in 2023, corresponding to lower transmission-stage risk contributions. In terms of policy implementation, the issuance of incentive policies (T17) and management measures (T18) in 2022 coincided with lower risk contributions from these indicators in 2023. Regarding water demand structure optimization, the built-up road area ratio decreased from 21.86% to 18.28%, corresponding to a lower risk contribution from T13. Nevertheless, a considerable gap remains in the low-risk range. Persistent issues, such as the reclaimed water utilization rate (T6) remaining below 5% and the sharply increasing production load (T5), have yet to be resolved, indicating that risk management still faces challenges.

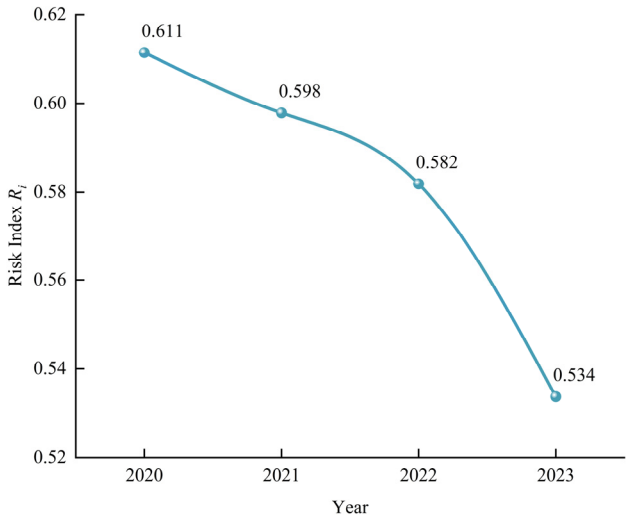


Figure 3. Risk assessment results of reclaimed water utilization in Yuyao City.

4.3. Indicator Contribution Analysis

To compare the relative contributions of individual indicators in each assessment year, the indicator contribution values were calculated using the standardized indicator values and comprehensive weights. Figure 4 presents the results for 2020–2023. These values

represent the relative contributions of the indicators to the calculated risk index within the adopted assessment framework and do not establish causal effects.

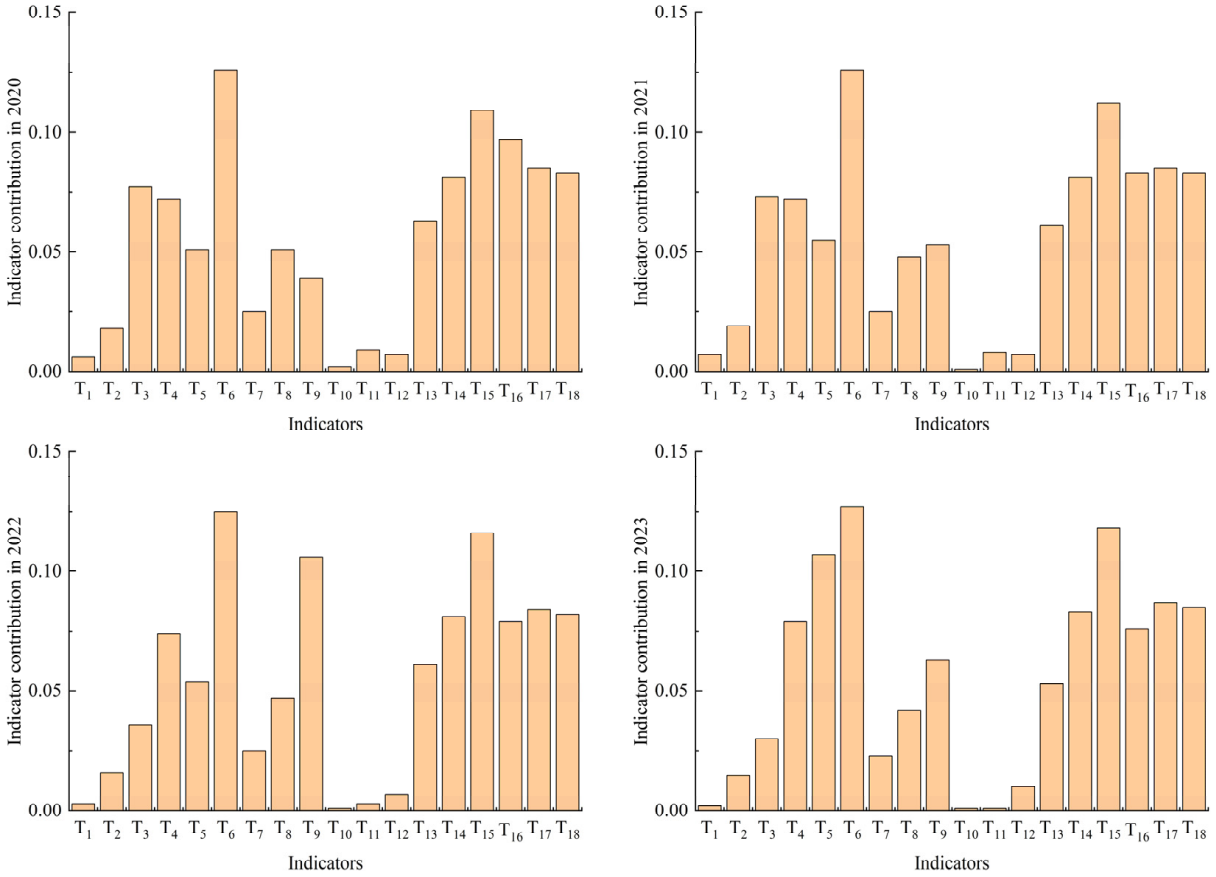


Figure 4. Contributions of individual indicators to the calculated risk index (2020–2023).

The reclaimed water utilization rate (T6) and industrial water reuse rate (T15) had the two largest calculated contributions in each year from 2020 to 2023. In 2020 and 2021, the investment proportion (T16), incentive policies (T17), and management measures (T18) were also among the five largest contributors. In 2022, the water supply loss rate (T9) entered the five largest contributors, while in 2023, the reclaimed water production load (T5) did so. These results show that utilization-related indicators remained prominent throughout the assessment period, whereas the relative contributions of other indicators varied among years.

4.4. Exploratory Future Risk Assessment

The seven fundamental time series were projected through repeated NAR runs, which were subsequently integrated with the planning-based indicator settings. Table 5 provides a summary of the model parameters utilized in this process. Figures 5 and 6 depict the projected trajectories and the progression of historical fitting errors, respectively. In conclusion, the findings indicate the variability in the overall historical mean relative error (MRE) throughout the model training phase. The retained runs demonstrated an overall historical MRE that remained below 10%, suggesting a satisfactory alignment between the fitted and observed historical values. However, it is important to note that the absence of separate training, validation, and testing errors necessitates a cautious interpretation of these results. Therefore, they should be viewed primarily as indicators of historical fitting performance rather than as measures of independent out-of-sample forecasting capabilities.

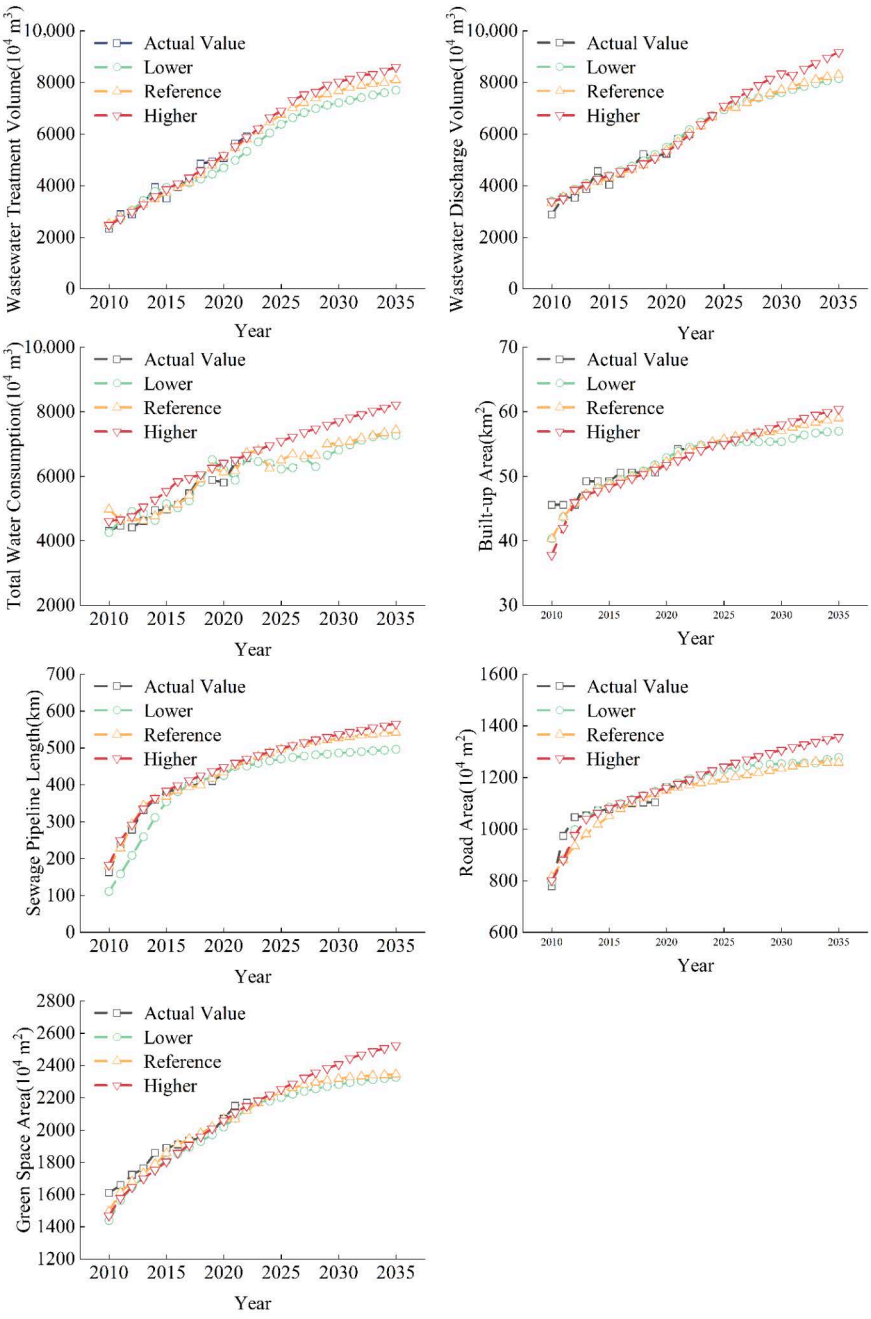


Figure 5. Observed and NAR-projected trajectories of the seven basic variables.

Table 5. NAR model parameters for the seven basic time series.

Indicators	Hidden Layer Nodes	Delay Order	Learning Rate
Wastewater Treatment Volume (10^4 m^3)	10	1	0.005
Wastewater Discharge Volume (10^4 m^3)	15	2	0.001
Total Water Consumption (10^4 m^3)	10	2	0.05
Built-up Area (km^2)	13	1	0.01
Sewage Pipeline Length (km)	12	1	0.005
Road Area (10^4 m^2)	13	1	0.01
Green Space Area (10^4 m^2)	14	1	0.01

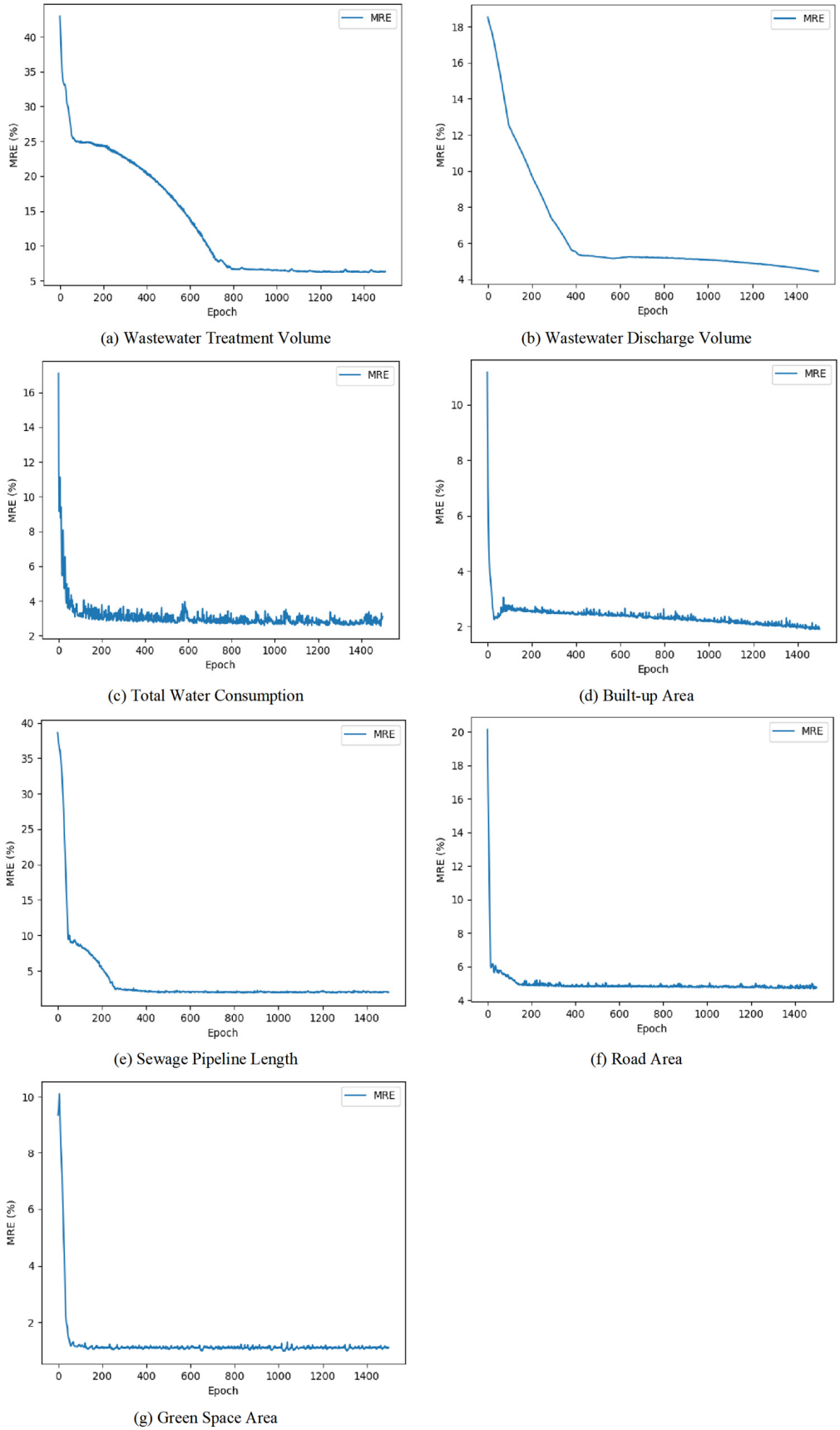


Figure 6. Variation in historical fitting MRE during the training of the seven NAR models.

Table 6 presents the lower, reference, and higher numerical settings for the seven projected series. These settings explore variation in model outputs and are not assigned

socioeconomic or policy narratives. The reference setting follows the run with the lowest historical MRE. Combining the settings across indicators explores alternative input configurations rather than three mutually exclusive urban development pathways.

Table 6. Numerical settings of the projected basic variables for 2025, 2030, and 2035.

Indicators	Output Setting	2025	2030	2035
Wastewater Treatment Volume (10^4 m^3)	Lower	6750	7980	9120
	Reference	6901	8224	9587
	Higher	7050	8510	10,050
Wastewater Discharge Volume (10^4 m^3)	Lower	6880	8050	9250
	Reference	7027	8346	9682
	Higher	7200	8680	10,120
Total Water Consumption (10^4 m^3)	Lower	28,500	30,200	31,800
	Reference	29,134	31,125	33,015
	Higher	29,800	32,100	34,500
Built-up Area (km^2)	Lower	106.5	115.2	122.8
	Reference	108.3	118.5	127.6
	Higher	110.2	122.0	133.0
Sewage Pipeline Length (km)	Lower	1220	1450	1680
	Reference	1265	1526	1807
	Higher	1310	1605	1940
Road Area (10^4 m^2)	Lower	1980	2150	2280
	Reference	2026	2222	2375
	Higher	2075	2300	2480
Green Space Area (10^4 m^2)	Lower	1520	1710	1880
	Reference	1553	1763	1956
	Higher	1590	1820	2040

Indicators constrained by planning targets or policy assumptions were assigned common values across the constructed combinations for each target year. These include water supply loss rate, proportion of reclaimed water usage, industrial water reuse rate, investment proportion, incentive policies, and management measures. Investment proportion was set to its historical median for 2003–2022, while incentive policies and management measures were assumed to remain active. The seven NAR-predicted basic series were combined using the lower, reference, and higher settings, yielding 2187 candidate combinations for each target year (Figure 7). The ellipsis in Figure 7 represents the three additional NAR-predicted series—built-up area, sewage pipeline length, and road area—which follow the same lower, reference, and higher settings; the crossing lines indicate all possible combinations among the seven predicted series.

The constructed input combinations were evaluated using the fuzzy matter-element model (Figure 8). The risk ranges were 0.361–0.469 in 2025, 0.376–0.420 in 2030, and 0.286–0.339 in 2035, with arithmetic means of 0.413, 0.395, and 0.312, respectively. Under the stated classification thresholds, all three ranges fall within the medium-risk class. Their widths were 0.108, 0.044, and 0.053, respectively: the ranges for 2030 and 2035 were narrower than that for 2025, but the width did not decrease monotonically. These ranges describe dispersion across constructed input combinations, not statistical prediction intervals or changes in the probability of future outcomes.

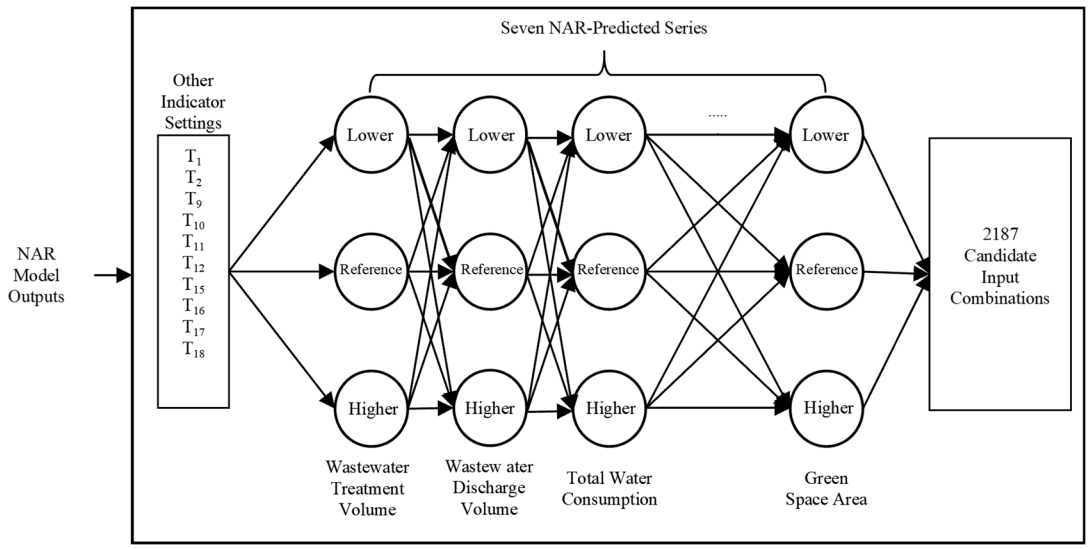


Figure 7. Construction of the 2187 candidate input combinations for future risk assessment.

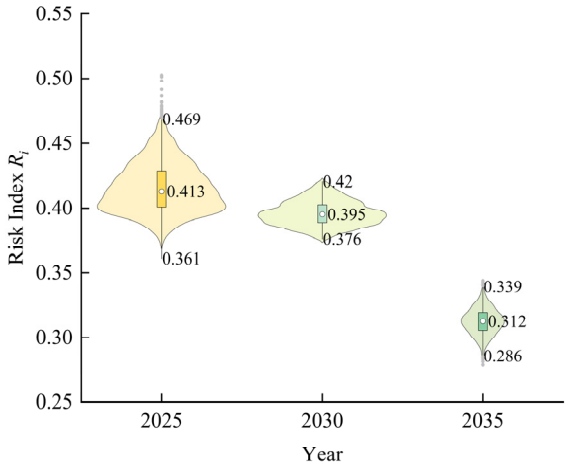


Figure 8. Distribution of reclaimed water utilization risk indices across the constructed input combinations in 2025, 2030, and 2035.

The results across the constructed input combinations were further examined in relation to the indicator settings for the production, transmission, utilization, and management stages. In the production stage, increases in wastewater treatment and reclaimed water production loads may place greater pressure on available capacity. In the transmission stage, pipeline expansion that lags behind the growth of the built-up area may reduce pipeline density. In the utilization stage, low reclaimed water utilization may limit further risk reduction. In the management stage, stable investment, incentive policies, and management measures remain important for supporting system operation and infrastructure development. Overall, coordinated improvements in production capacity, pipeline coverage, reclaimed water utilization, and institutional support are needed to further reduce future risk.

5. Discussion

5.1. Interpretation of Historical and Exploratory Future Risk Patterns

The historical assessment results show that the overall risk index of reclaimed water utilization in Yuyao City decreased from 0.611 in 2020 to 0.534 in 2023, while remaining within the medium-risk class. At the criterion level, the production and utilization stages

received the largest comprehensive weights, followed by the management and transmission stages. These weights represent the relative importance assigned to the four stages by the combined weighting method rather than their actual annual contributions to the calculated risk. At the indicator level, the proportion of reclaimed water usage (T12), reclaimed water utilization rate (T6), green space rate in built-up areas (T14), investment proportion (T16), and industrial water reuse rate (T15) received relatively large weights. However, the contribution of an indicator in a particular year also depends on its standardized indicator value.

The year-specific contribution analysis provides additional information beyond the weight results. The reclaimed water utilization rate (T6) and industrial water reuse rate (T15) had the two largest calculated contributions throughout 2020–2023. The investment proportion (T16) was among the five largest contributors in 2020 and 2021, while the water supply loss rate (T9) and reclaimed water production load (T5) entered the five largest contributors in 2022 and 2023, respectively. Incentive policies (T17) and management measures (T18) also remained among the indicators with relatively large contributions. This variation indicates that the annual assessment results were influenced by both the comprehensive weights and the observed indicator values. It also shows that the transmission and management stages should not be considered unimportant solely because their criterion weights were lower.

The 2187 constructed input combinations for each target year provide an exploratory perspective on possible future risk conditions. The calculated risk indices ranged from 0.361 to 0.469 in 2025, from 0.376 to 0.420 in 2030, and from 0.286 to 0.339 in 2035, with arithmetic means of 0.413, 0.395, and 0.312, respectively. All three ranges remained within the medium-risk class. The corresponding range widths were 0.108, 0.044, and 0.053. Although the ranges for 2030 and 2035 were narrower than that for 2025, their widths did not decrease monotonically. Because the constructed combinations were not assigned occurrence probabilities, these ranges should not be interpreted as statistical prediction intervals, and their arithmetic means represent summaries of the constructed combination ensembles rather than expected future risk values.

5.2. Management Implications for the Reclaimed Water System

The assessment results indicate that risk management should address the production, transmission, utilization, and management stages in a coordinated manner. In the production stage, increases in wastewater treatment volume and reclaimed water demand may place pressure on production capacity if facility expansion and process reliability do not keep pace. Future measures should therefore coordinate capacity expansion with demand growth, strengthen influent and effluent monitoring, and promote graded water-quality supply according to the requirements of different users.

In the transmission stage, pipeline development should be coordinated with the expansion of built-up areas and the spatial distribution of reclaimed water users. If pipeline construction grows more slowly than the serviced urban area, reclaimed water pipeline density may decline even when the total pipeline length increases. Reclaimed water pipelines should therefore be incorporated into urban infrastructure planning together with wastewater collection and conventional water supply systems. Pipeline extension, leakage control, and pressure management are also important for improving transmission reliability.

In the utilization stage, the reclaimed water utilization rate and the proportion of reclaimed water usage remain important constraints. Reclaimed water applications may be extended beyond existing industrial cooling and municipal greening uses to other suitable non-potable industrial uses, municipal miscellaneous uses, and ecological replenishment, pro-

vided that water-quality and planning requirements are satisfied. Incentive policies may also be linked more closely to actual reclaimed water consumption and water-saving performance.

In the management stage, stable investment, enforceable technical standards, and regular performance evaluation are needed to support the operation and expansion of the reclaimed water system. Diversified financing and performance-based incentives may help reduce the dependence of infrastructure development on short-term fiscal expenditure. Together, these measures can improve coordination among production capacity, pipeline coverage, effective demand, and institutional support.

5.3. Comparison with Previous Studies

Previous studies have applied indicator systems, combined weighting methods, and fuzzy matter-element models to reclaimed water risk assessment [20,21]. The present study extends this work by explicitly organizing the indicators into production, transmission, utilization, and management stages and applying the framework at the county scale. This stage-based structure links the assessment results with specific components of the reclaimed water system and supports the identification of management priorities.

Methodologically, the game-theory-based weighting procedure combines the AHP and entropy weights by minimizing the deviation between the combined and basic weight vectors, thereby reducing dependence on a single weighting method. The NAR models provide alternative numerical settings for seven basic time series, which are subsequently combined with planning- and policy-based indicator settings. The resulting 2187 combinations are used to examine how alternative input configurations correspond to different risk indices. Therefore, the contribution of the combined framework lies in exploratory risk screening and management support rather than probabilistic forecasting of future events.

5.4. Limitations and Future Work

Several limitations should be considered when interpreting the results. First, each NAR model was developed using only 15 annual observations from 2008 to 2022. Under the nominal 70:15:15 division, the validation and testing subsets necessarily contain very few observations. Moreover, the retained modeling records contain only the overall historical MRE and do not preserve the exact year-by-year subset allocation or subset-specific performance statistics. Therefore, the nominal division cannot be regarded as strict chronological out-of-sample validation, and the possibility of overfitting cannot be excluded. The projected trajectories should consequently be interpreted as exploratory future input settings rather than independently validated forecasts. Future studies should use longer time series, apply time-ordered or rolling-origin validation, report training, validation, and testing performance separately, and compare the NAR results with simpler forecasting methods.

Second, the different data periods serve different analytical purposes. The 2008–2022 series were used for the seven NAR-predicted variables, the 2020–2023 period was used for the historical assessment because complete data for all 18 indicators were available only for these years, and the 2003–2022 investment series was used to obtain a longer-term reference value. These periods should not be interpreted as a single common calibration window.

Third, the 2187 combinations are constructed from predefined lower, reference, and higher settings and have no assigned occurrence probabilities. Their distribution depends on the selected NAR outputs, planning targets, and policy assumptions. In addition, the indicator weights and risk thresholds were fixed in the present assessment. Future research should examine the robustness of the results through systematic perturbation of the weights and thresholds and, where sufficient evidence is available, incorporate probability-informed scenario analysis.

Finally, some management indicators are represented as binary variables and therefore do not fully describe policy intensity, coverage, or implementation effectiveness. The water-quality indicators also focus on conventional parameters and do not include trace contaminants or pathogenic microorganisms. Future studies could develop continuous management indices, incorporate quantitative microbial and ecological risk assessments, and compare reclaimed water systems across counties with different industrial and infrastructure conditions.

6. Conclusions

This study developed an integrated framework for assessing historical and future reclaimed water utilization risks in Yuyao City by combining game-theory-based weighting, the fuzzy matter-element model, nonlinear autoregressive models, and constructed input combinations. The historical assessment showed that the overall risk decreased from 2020 to 2023 but remained within the medium-risk class. The production and utilization stages received the largest comprehensive weights. The proportion of reclaimed water usage, reclaimed water utilization rate, green space rate in built-up areas, investment proportion, and industrial water reuse rate were identified as important indicators. For the constructed input combinations, the risk indices ranged from 0.361 to 0.469 in 2025, from 0.376 to 0.420 in 2030, and from 0.286 to 0.339 in 2035, with arithmetic means of 0.413, 0.395, and 0.312, respectively. All three ranges remained within the medium-risk class. These values summarize the selected combination ensemble and should not be interpreted as probability-weighted forecasts.

Further risk reduction requires coordinated measures across the reclaimed water system. Production capacity and water-quality monitoring should be strengthened in response to increasing treatment and production loads. Pipeline construction should be coordinated with urban development, while leakage control and network coverage should be improved. Reclaimed water applications should be expanded where water-quality and planning requirements are satisfied, supported by stable investment, enforceable technical standards, and performance-based incentives. Future research should use longer time series and independent or rolling-origin validation, examine the sensitivity of the results to indicator weights and risk thresholds, and incorporate more detailed indicators of policy implementation, emerging contaminants, pathogens, and ecological effects.

Author Contributions: Conceptualization, X.S. and D.W.; methodology, D.W.; software, D.W.; validation, X.S., C.G. and D.W.; formal analysis, X.S. and C.G.; investigation, X.W.; resources, X.S.; data curation, X.W.; writing—original draft preparation, X.S. and C.G.; writing—review and editing, X.S., C.G., D.W. and X.W.; visualization, C.G.; funding acquisition, X.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (No. 51979271), Research Project of Ministry of Natural Resources (No. 20210103), Water Science and Technology Project of Department of Water Resources of Zhejiang Province (No. RB2406), Young Top-Notch Talent Support Program of National High-level Talents Special Support Plan, Six Talents Peak Project of Jiangsu Province (No. JNHB-068), 333 High-level Talents Cultivation Project of Jiangsu Province.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding authors.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	Full term
AHP	Analytic Hierarchy Process
COD	Chemical Oxygen Demand
CR	Consistency Ratio
MRE	Mean Relative Error
NAR	Nonlinear Autoregressive

References

1. Mekonnen, M.M.; Hoekstra, A.Y. Four billion people facing severe water scarcity. *Sci. Adv.* **2016**, *2*, e1500323. [CrossRef] [PubMed]
2. Li, J.X.; Huang, K.; Yu, Y.J.; Qu, S.; Xu, M. Telecoupling China's City-Level Water Withdrawal with Distant Consumption. *Environ. Sci. Technol.* **2023**, *57*, 4332–4341. [CrossRef] [PubMed]
3. Yang, L.; Wang, Y.T.; Wang, R.R.; Klemes, J.J.; de Almeida, C.M.V.B.; Jin, M.Z.; Zheng, X.Z.; Qiao, Y.B. Environmental-social-economic footprints of consumption and trade in the Asia-Pacific region. *Nat. Commun.* **2020**, *11*, 4490. [CrossRef] [PubMed]
4. Jones, E.R.; Bierkens, M.F.P.; van Vliet, M.T.H. Current and future global water scarcity intensifies when accounting for surface water quality. *Nat. Clim. Chang.* **2024**, *14*, 629–635. [CrossRef]
5. Li, J.L.; Yang, J.X.; Liu, M.M.; Ma, Z.W.; Fang, W.; Bi, J. Quality matters: Pollution exacerbates water scarcity and sectoral output risks in China. *Water Res.* **2022**, *224*, 119059. [CrossRef] [PubMed]
6. Ma, T.; Sun, S.; Fu, G.T.; Hall, J.W.; Ni, Y.; He, L.H.; Yi, J.W.; Zhao, N.; Du, Y.Y.; Pei, T.; et al. Pollution exacerbates China's water scarcity and its regional inequality. *Nat. Commun.* **2020**, *11*, 650. [CrossRef] [PubMed]
7. Feng, H.Y.; Xu, J.R.; Shi, J.; Wang, Z.Y.; Li, Q.; Yang, M.J.; Shi, W.; Zhang, X.B. Resource and environmental benefits of reclaimed water reuse: Evidence from the northern arid and semiarid region of China. *Sustain. Cities Soc.* **2025**, *135*, 106989. [CrossRef]
8. Vanella, D.; Consoli, S.; Continella, A.; Chinnici, G.; Milani, M.; Cirelli, G.L.; D'Amico, M.; Maesano, G.; Gentile, A.; La Spada, P.; et al. Environmental and Agro-Economic Sustainability of Olive Orchards Irrigated with Reclaimed Water under Deficit Irrigation. *Sustainability* **2023**, *15*, 15101. [CrossRef]
9. Chen, Y.; Liu, H.L.; Lu, T.T.; Li, Y.; Zheng, Z.H.; Wang, Y.T. Effects of Reclaimed Water Irrigation on Grain Quality and Endogenous Estrogen Concentrations of Winter Wheat. *Water* **2023**, *15*, 3671. [CrossRef]
10. Badruzzaman, M.; Anazi, J.R.; Al-Wohaib, F.A.; Al-Malki, A.A.; Jutail, F. Municipal reclaimed water as makeup water for cooling systems: Water efficiency, biohazards, and reliability. *Water Resour. Ind.* **2022**, *28*, 100188. [CrossRef]
11. He, Y.; Li, X.; Li, H.; Wei, L.; Jiang, C.; Jiang, D.; Li, K. Characteristics of Epiphytic Bacterial Community on Submerged Macrophytes in Water Environment Supplemented with Reclaimed Water. *Environ. Sci.* **2024**, *45*, 2707–2714. [CrossRef] [PubMed]
12. Du, C.L.; Guo, W.; Li, G.W.; Bai, M.X.; Zhu, Q.H.; Tian, Z.J.; Li, M.T.; Zhao, C.; Zhang, L.Y. Biomanipulation as a strategy for minimizing ecological risks in river supplied with reclaimed water. *Environ. Res.* **2023**, *228*, 115801. [CrossRef] [PubMed]
13. Verma, K.; Thattaramppilly, R.M.; Manisha, M.; Jayakumar, S.; Marigoudar, S.R.; Pranesh, A.T.; Rao, L.K.A.R.Y.A. Determination of degradation/reaction rate for surface water quality of recycled water using Lake2K model for large-scale water recycling. *Environ. Sci. Pollut. Res.* **2023**, *30*, 120207–120224. [CrossRef] [PubMed]
14. Finnerty, C.T.K.; Childress, A.E.; Hardy, K.M.; Hoek, E.M.V.; Mauter, M.S.; Plumlee, M.H.; Rose, J.B.; Sobsey, M.D.; Westerhoff, P.; Alvarez, P.J.J.; et al. The Future of Municipal Wastewater Reuse Concentrate Management: Drivers, Challenges, and Opportunities. *Environ. Sci. Technol.* **2023**, *58*, 3–16. [CrossRef] [PubMed]
15. Zhao, X.H.; Xie, E. Reclaimed water influences bacterioplankton and bacteriobenthos communities differently in river networks. *Water Res.* **2023**, *243*, 120389. [CrossRef] [PubMed]
16. Hu, H.Y.; Chen, Z.; Lu, Y.; Wei, D.B.; Wu, Y.; Wu, Q.; Wang, W.; Huang, N. Challenges and future perspectives on the ecological uses of reclaimed water. *Water Ecol.* **2025**, *1*, 100020. [CrossRef]
17. Ding, Y.Z.; Liu, X.J. The impact of information provision on public willingness to use recycled water for flushing from the perspective of risk perception. *Front. Env. Sci.* **2024**, *12*, 1403953. [CrossRef]
18. Chen, M.H.; Shi, L.L.; Liu, G.; Wu, X.J.; Lu, Y. Aerosol exposure assessment during reclaimed water utilization in China and risk evaluation in case of. *Front. Env. Sci. Eng.* **2022**, *16*, 95. [CrossRef]
19. Liu, X.J.; Liang, C.Z.; Liu, X.H.; Zhao, F.; Han, C. Occurrence and human health risk assessment of pharmaceuticals and personal care products in real agricultural systems with long-term reclaimed wastewater irrigation in Beijing, China. *Ecotoxicol. Environ. Saf.* **2020**, *190*, 110022. [CrossRef] [PubMed]
20. Li, J.; Lu, L.; Zuo, Y. Discussion of Risk Assessment Index System of Utilization of Urban Reclaimed Water. *South-To-North Water Transf. Water Sci. Technol.* **2013**, *11*, 52–56.

21. Yang, K.; Fu, L.; Liu, J.; Zhong, J.; Qiu, G.; Gu, G.; Zhao, M.; Liang, Y. Sensitivity Analysis of Influencing Factors of Comprehensive Development of Reclaimed Water in Yunnan Province. *Water Resour. Power* **2018**, *36*, 40–43, 121.
22. Lu, X.; Yang, K.; Liu, J.; Qiu, G.; Liu, L.; Liang, Y.; Yang, W. Application of Fuzzy Matter-element Method in Risk Evaluation of Urban Reclaimed Water Utilization. *Water Power* **2018**, *44*, 18–21.
23. Li, M.; Wang, Y. The risk evaluation of reclaimed water resources use based on the fuzzy matter element mode. *West. China Dev.* **2017**, *2*, 10–14.
24. Meng, Y.; Liu, W.Y.; Fiedler, H.; Zhang, J.L.; Wei, X.R.; Liu, X.H.; Peng, M.; Zhang, T.T. Fate and risk assessment of emerging contaminants in reclaimed water production processes. *Front. Environ. Sci. Eng.* **2021**, *15*, 104. [CrossRef]
25. Mudashiru, R.B.; Sabtu, N.; Abdullah, R.; Saleh, A.; Abustan, I. A comparison of three multi-criteria decision-making models in mapping flood hazard areas of Northeast Penang, Malaysia. *Nat. Hazards* **2022**, *112*, 1903–1939. [CrossRef]
26. Malekinezhad, H.; Sepehri, M.; Pham, Q.B.; Hosseini, S.Z.; Meshram, S.G.; Vojtek, M.; Vojtekova, J. Application of entropy weighting method for urban flood hazard mapping. *Acta Geophys.* **2021**, *69*, 841–854. [CrossRef]
27. Shan, C.J.; Dong, Z.C.A.; Lu, D.B.; Xu, C.D.; Wang, H.; Ling, Z.; Liu, Q. Study on river health assessment based on a fuzzy matter-element extension model. *Ecol. Indic.* **2021**, *127*, 107742. [CrossRef]
28. Adamowski, J.; Chan, H.F.; Prasher, S.O.; Ozga-Zielinski, B.; Sliusarieva, A. Comparison of multiple linear and nonlinear regression, autoregressive integrated moving average, artificial neural network, and wavelet artificial neural network methods for urban water demand forecasting in Montreal, Canada. *Water Resour. Res.* **2012**, *48*, W01528. [CrossRef]
29. *Standard's GB/T 19923-2024*; Reuse of Urban Recycling Water—Water Quality Standard for Industrial Uses. Standardization Administration of China: Beijing, China, 2024.
30. *Standard's GB/T 18920-2020*; The Reuse of Urban Recycling Water—Water Quality Standard for Urban Miscellaneous Use. Standardization Administration of China: Beijing, China, 2020.
31. *Standard's DB33/2169-2018*; Discharge Standard of Major Water Pollutants for Municipal Wastewater Treatment Plant. Zhejiang Provincial People's Government: Hangzhou, China, 2018.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.