

Article

A Triangular Fuzzy Number-Based Water Quality Assessment Model for Evaluating the Impacts of Floating Photovoltaic Projects on Reservoir Water Quality Under Uncertainty

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Abstract

This study developed a Photovoltaic–Reservoir Water Quality Impact Model (PVRWQIM) based on triangular fuzzy number theory (TFN) to address data sparsity and measurement uncertainty in conventional water quality assessment. The model consists of two components: a TFN-based exceedance-risk module for quantifying the likelihood of water quality parameters exceeding predefined risk thresholds, and a transitional TFN module for evaluating changes in exceedance risk before and after floating photovoltaic (FPV) construction. The model was applied to Junshan Reservoir in Jiangxi Province, China, using 15 observations each from before and after FPV construction. The results indicate the following: (i) Before construction, the exceedance probabilities for water temperature (T), dissolved oxygen (DO), permanganate index (COD_{Mn}), total phosphorus (TP), total nitrogen (TN), chlorophyll a (Chla), and cyanobacterial density (CD) were 16.7%, 16.1%, 31.3%, 33.7%, 33.3%, 32.7%, and 31.3%, respectively. After construction, the exceedance probabilities for T, DO, COD_{Mn}, TP, and TN increased to 93.1%, 89.7%, 82.5%, 83.5%, and 83.3%, respectively ($p < 0.01$), while the probabilities of exceedance for Chla and CD decreased to 14.8% and 14.2%, respectively ($p < 0.05$). (ii) T and DO are the primary threat factors triggered by FPV construction, with a probability of increased ecological risk of approximately 90%. (iii) The model reveals a statistical correlation pattern: the probability of reduced ecological risk for CD and Chla is 62%, while the probability of increased ecological risk for COD_{Mn}, TP, and TN is 77%. The two sets of indicators exhibit opposite trends, suggesting that FPV shading may directly suppress algae growth while simultaneously weakening self-purification capacity indirectly through cooling and reduced water flow, thereby contributing to nutrient accumulation. It should be noted that, based on limited observational data, this study reveals correlations rather than proven causal mechanisms; the aforementioned causal interpretations require further validation through controlled experiments or mechanistic models in the future. (iv) The proposed PVRWQIM provides a practical tool for quantifying reservoir water quality risks under sparse data and measurement uncertainty and can support environmental assessment of similar FPV projects.

Keywords: photovoltaic power generation project; water quality assessment model; triangular fuzzy number; Junshan Reservoir

Academic Editors: Leszek Sobkowiak and David Post

Received: 27 April 2026

Revised: 22 June 2026

Accepted: 24 June 2026

Published: 30 June 2026

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1. Introduction

The depletion of conventional fossil fuels and the increasing challenges posed by global climate change have made the development and utilization of renewable energy an urgent priority. As one of the most abundant renewable energy sources, solar energy provides an important pathway for achieving low-carbon and sustainable development through photovoltaic (PV) technology [1]. Against the background of increasing land scarcity, floating photovoltaic (FPV) technology, which deploys PV systems on water surfaces, has attracted growing global attention because of its distinctive environmental and technical advantages [2,3].

FPV systems alleviate the conflict between energy development and land availability by utilizing water surfaces instead of valuable land resources. Their main advantages include the following: (i) Water bodies can lower the operating temperature of photovoltaic panels, slowing down performance degradation and improving power generation efficiency. For example, experimental research by Mohamad et al. in semi-arid regions of Jordan showed that FPV systems have a power generation efficiency 5–15% higher than that of land-based systems [4]. (ii) Covering water bodies with FPV panels reduces water evaporation. A study by Santos et al. on the Passaúna Reservoir in Brazil confirmed that an FPV system covering an area of 1265.14 m² reduced water evaporation by 60.20% [5]. Jin et al. further estimated the global potential of deploying FPV on reservoirs regarding renewable energy production, water conservation, and land protection, indicating that this technology offers significant comprehensive benefits [6]. (iii) FPV avoids land-use conflicts with agriculture, ecological conservation, and urban development by utilizing idle water surfaces for power generation. For China, where land resources are relatively scarce, this technology provides an effective pathway to efficiently utilize water surface resources to meet energy demands [7]. (iv) FPV can be integrated with existing hydropower stations to form a “hydro–solar complementary” operating model. As a supplementary energy source, FPV can provide electricity when hydropower output is insufficient, thereby enhancing grid stability and reliability and optimizing the energy mix [8]. (v) The shading effect of FPV panels reduces the solar radiation received by the water body, which, in turn, suppresses excessive algal growth and lowers the risk of algal blooms [9].

In recent years, domestic and international scholars have conducted extensive empirical research on the impact of floating photovoltaic (FPV) systems on the aquatic environment in reservoirs and lakes. In their study of the fish–solar complementary project at Liuyanjie Reservoir, Zhang et al. [10] found that the eutrophication index at irrigation intake points in areas covered by photovoltaic panels had significantly increased; Liu et al. [11] reviewed the potential feedback mechanisms of FPV on aquatic ecosystems and regional climate; Vincent Bax [12] et al. revealed differences in the impact of installation methods on water quality by comparing three different FPV system designs; Niu et al. [13] as well as Alhejji and Mosaad et al. [14] separately confirmed that photovoltaic shading reduces water temperature and dissolved oxygen levels and inhibits algal growth; and Wu et al. [15] indicated that photovoltaic arrays weaken water flow by altering the wind field over the water surface. Although these phenomenological observations have enriched our understanding of PV–aquatic environment interactions, existing studies largely remain descriptive, lacking assessment models capable of systematically quantifying water quality risks under FPV influence. The uncertainty of environmental impacts has become a major factor contributing to public and stakeholder concerns regarding PV projects [16], further highlighting the necessity of developing water quality risk assessment tools suitable for environments characterized by uncertainty. Table 1 summarizes representative case studies of FPV installations in natural water bodies (reservoirs and lakes) in recent years. Although previous studies have reported various effects of FPV on

water temperature, dissolved oxygen, algae, and nutrients, methodological innovations at the “assessment model” level remain relatively scarce. This gap constitutes the necessity and novelty of this study.

The current water quality evaluation methods can be categorized into four types: deterministic models, probabilistic statistical models, machine learning models, and fuzzy logic models. Deterministic models (such as single-factor evaluation methods, water quality indices, and nutrient status indices [17,18]) are simple to operate and provide intuitive results, and they are based on national standards (GB 3838-2002) [19]. However, their fundamental limitation lies in treating measured values as precise and certain numbers, making them unable to account for errors and uncertainties arising from sampling, transportation, and laboratory analysis [19]. Probabilistic statistical models (e.g., Monte Carlo simulation and Bayesian networks) can quantify random errors and provide probability intervals; however, they typically require large sample sizes to fit reliable distribution functions, making them difficult to apply to reservoirs with low monitoring frequencies and short data series (especially small reservoirs in remote areas) [20]. Machine learning models (such as artificial neural networks and support vector machines) have achieved some success in water quality prediction due to their nonlinear mapping capabilities. However, they require large amounts of historical data for training, have poor adaptability to sparse data, and offer limited model interpretability, making it difficult to reveal their internal mechanisms. Their ability to handle uncertainty typically requires integration with other methods (such as Monte Carlo simulation), while their capacity to characterize spatial heterogeneity depends on how input features encode spatial information [21]. Fuzzy mathematical models, based on fuzzy set theory, use membership functions to describe imprecise or uncertain concepts. They can effectively handle subjectivity, imprecision, and uncertainty, and their results better align with human cognitive habits. The model is insensitive to a small number of outliers. The establishment of membership functions and fuzzy rules requires expert knowledge or experience and involves a degree of subjectivity. Model outputs are typically fuzzy levels rather than precise numerical values [22].

When assessing the impact of photovoltaic projects on aquatic environments, traditional methods still face three key challenges: (i) measured values are subject to sampling and measurement errors and are inherently uncertain variables, yet traditional methods treat them as certain values; (ii) photovoltaic construction alters the hydrological rhythms of reservoirs, leading to uneven spatial distribution of pollutants; (iii) government agencies currently lack the monitoring data required to support approval and permitting processes. Therefore, there is an urgent need to develop a new water quality assessment model capable of functioning effectively under conditions of limited data and measurement uncertainty.

To address this gap, this study developed a Photovoltaic–Reservoir Water Quality Impact Model (PVRWQIM) based on triangular fuzzy number (TFN) theory. The model comprises two submodules: (i) a TFN model for water quality standard exceedances, used to quantify the probability of exceedance for each indicator under conditions of measurement uncertainty, and (ii) a transitional TFN model, used to assess trends in the risk of water quality exceedances before and after PV construction. Seven key indicators—water temperature (T), dissolved oxygen (DO), permanganate index (COD_{Mn}), total phosphorus (TP), total nitrogen (TN), chlorophyll a (Chla), and cyanobacterial density (CD)—were selected. Taking the Junshan Reservoir in Jiangxi Province as the study site, a comparative analysis of water quality risks before and after PV construction is conducted. The primary objectives of this study included the following: (i) establishing and validating the applicability of the PVRWQIM under conditions of sparse data and measurement uncertainty; (ii) quantitatively identifying the primary threat factors induced by PV construction; (iii)

revealing the direction and magnitude of the ecological risks posed by PV projects to various water quality indicators in the reservoir; (iv) providing a scientific basis for government departments in the approval and environmental management of reservoir PV projects.

Table 1. Major studies on the impact of floating PV projects on water quality in China and abroad.

Country	Project Name	Reservoir Type	Research Focus	Assessment Method	Key Findings
China	Xiangjiaba Reservoir	Hydroelectric reservoir	Temperature	Numerical simulation	Impact on water temperature in deep-water reservoirs; assessment of potential benefits [2]
Greece	Lake Kremasta	Oligotrophic artificial reservoir	Water quality	Hydrodynamic and water quality models	Potential impacts on water quality are still in the early stages of development [23]
Brazil	Passaúna Reservoir	Water storage reservoir	Water evaporation rate	Experimental study	Reduction in water evaporation rate [5]
India	Srisaillam Dam	Hydropower reservoir	Potential assessment	Case study	Assessment of floating PV potential [8]
Romania	Mihăilești Reservoir	Multipurpose reservoir	Water temperature, dissolved oxygen, chlorophyll a, etc.	Hydrodynamic modeling and solar radiation assessment	Impacts water temperature, DO, Chla, etc. [24]
Singapore	Tengku Reservoir	Multipurpose reservoir	Temperature and water quality	3D hydrodynamic-ecological lake model	Impacts hydrodynamics and water quality [25]

2. Methods and Materials

2.1. Study Area

As shown in Figure 1, Junshan Reservoir is located in Leping City, Jiangxi Province, on the south bank of a tributary in the middle and lower reaches of the Le'an River. Its geographical coordinates are 117°22'48" E and 28°53'00" N. The reservoir is approximately 40 km from downtown Leping City. It has a water surface area of 528,143.73 m², a normal water level of 40.80 m, and a total storage capacity of 6.21 million m³. It is a small Type-I reservoir primarily used for irrigation and flood control and serves as an important water source for agricultural production and regional development in Leping City. The reservoir provides irrigation water for approximately 3.33 km² of downstream farmland while also supporting regional flood control.

The Junshan Reservoir PV Project is a key component of the “90 MW PV Project in Zhongbu Town and Mingkou Town, Leping City, operated by Guoneng Huangjinbu Power Generation Co., Ltd.” The photovoltaic array employs a floating installation method; the main technical parameters are detailed in Table 2.

Table 2. Key technical parameters of the Junshan Reservoir Photovoltaic Project.

Parameter	Value	Description
PV module mode	535 Wp monocrystalline silicon solar modules	Peak power of 535 Wp per module
Number of modules	168,252	Junshan Reservoir area
Total DC installed capacity	90 MWp	Total output power at peak power
Junshan Reservoir site area	0.36 km ²	Actual water surface area occupied by the PV array
Total reservoir water surface	0.53 km ²	Total water area of Junshan Reservoir

Water surface coverage rate	Approx 68.4%	PV array area/total reservoir water surface area
Installed power density per unit water surface area	Approx 166 W/m ²	Total installed capacity/PV array area
Substation voltage level	220 kV	Dedicated substation, with one 220 kV transmission line
Expected increase in generation efficiency	5–10%	Due to the water cooling effect, floating systems on water achieve higher efficiency than land-based systems of the same specifications

Note: The parameters are derived from the public notice regarding the environmental protection acceptance inspection upon project completion and the EPC general contracting tender documents; some of these parameters represent aggregate data for the entire Junshan Reservoir FPV project.

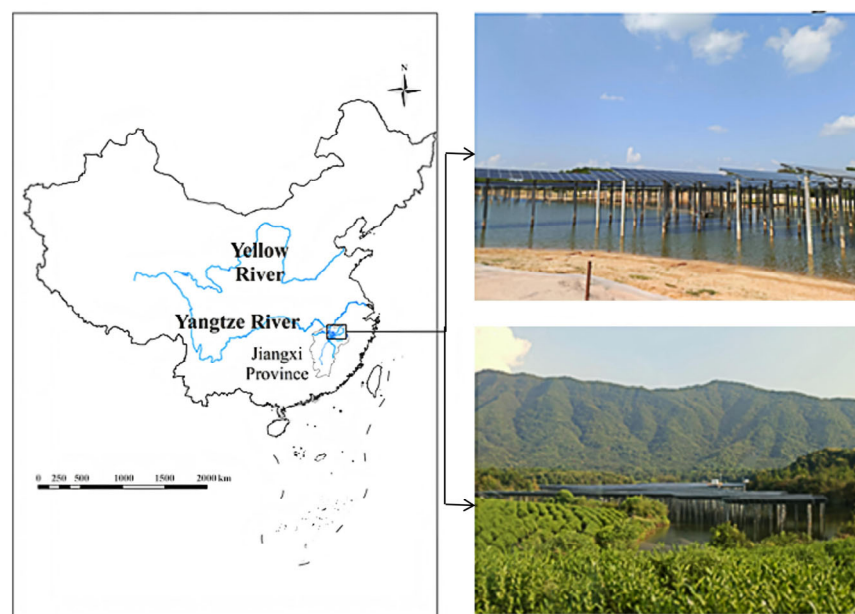


Figure 1. Schematic Map of the Geographical Location of Junshan Reservoir.

2.2. Sampling and Monitoring Methods

The assessment data used in this study were obtained from an environmental survey conducted by the Jiangxi Provincial Key Laboratory of Poyang Lake. As shown in Figure 1, five monitoring sites were established across Junshan Reservoir. In March 2021, before FPV construction, and March 2022, after FPV construction, three independent environmental replicate samples were collected at each monitoring site, yielding 15 observations for each period. Sampling was conducted in the same month in both years to minimize the influence of seasonal variations in water temperature, light intensity, and aquatic biological activity. This design helped ensure that pre- and post-construction comparisons primarily reflected changes associated with the FPV project rather than seasonal fluctuations.

Water temperature (T) and dissolved oxygen (DO) were measured in situ using a portable multiparameter water quality analyzer (Hach, Loveland, CO, USA). The permanganate index (COD_{Mn}) was determined using the acidic potassium permanganate method (Sinopharm Chemical Reagent Co., Ltd., Shanghai, China). Total phosphorus (TP) was measured using the ammonium molybdate spectrophotometric method (Sinopharm

Chemical Reagent Co., Ltd., Shanghai, China), and total nitrogen (TN) was measured using the alkaline potassium persulfate digestion–UV spectrophotometric method (Shimadzu, Kyoto, Japan; Hach, Loveland, CO, USA). Chlorophyll *a* (Chl*a*) was determined by acetone extraction spectrophotometry (Shimadzu, Kyoto, Japan), and cyanobacterial density (CD) was determined by microscopic counting (Olympus, Tokyo, Japan). Water quality classification and threshold selection followed the Surface Water Environmental Quality Standards of China (GB 3838-2002), and laboratory analyses were conducted according to the relevant national standard methods.

To control analytical errors, two field blanks and two laboratory blanks were included in each batch of samples. In addition, one duplicate sample was inserted for every 10 samples for repeated analysis. The relative deviation of parallel sample analyses was controlled within 10%, and the spiked recovery rate was maintained between 85% and 115% [26]. These quality control measures ensured the reliability and reproducibility of the analytical results. All analyses were conducted by the Jiangxi Provincial Key Laboratory of Poyang Lake.

It should be noted that the three water samples collected at each monitoring point are independent environmental parallel samples (that is, three water samples collected independently at the same monitoring point and under the same sampling conditions), rather than repeated samples analyzed by the laboratory. These three samples were pre-processed and tested, respectively, and the test results were used to characterize the random variation caused by the microscopic spatial heterogeneity of the water body in the monitoring point. Therefore, in the subsequent Mann–Whitney U test, three independent samples of each monitoring point were included in the analysis as independent statistical observations (15 independent data points each before and after construction). This processing method can more truly reflect the overall distribution characteristics of water quality parameters before and after the construction of photovoltaic power stations, and also meets the basic requirements of sample independence for non-parametric testing.

March was selected as the sampling period for three reasons. First, Junshan Reservoir is primarily used for downstream farmland irrigation. The water temperature in March, averaging approximately 15.2 °C before construction, represents typical spring conditions in subtropical regions, falling between winter lows and summer highs. In addition, large-scale spring ploughing had not yet begun, and agricultural non-point source pollution inputs were relatively low, making this period suitable for reflecting the reservoir's baseline water quality. Second, March avoids the peak period of summer algal blooms, which helps distinguish the potential effects of FPV shading from natural seasonal fluctuations in algal growth. Third, the post-construction sampling campaign was conducted in March 2022, shortly after project completion, to capture the short-term effects of the FPV project on reservoir water quality while minimizing interference from longer-term environmental variability. Table 3 summarizes the measurement ranges of various water quality parameters at Junshan Reservoir prior to PV construction, the corresponding water quality categories under GB 3838-2002, and the thresholds for determining exceedances used in this study. All data are presented as mean $\pm$ standard deviation. The Mann–Whitney U test was used to compare differences between the two independent samples (pre- and post-construction), with a significance level set at $\alpha = 0.05$. A *p*-value < 0.05 was considered significant, and a *p*-value < 0.01 was considered highly significant [27].

Table 3. Background information on water quality at Junshan Reservoir and criteria for determining exceedances.

Evaluation Indicator	Unit	Pre-PV Meas. Range	Mean $\pm$ Stand-ard Deviation	GB 3838-2002 Category	Non-Compliance Threshold	Source of Threshold
T	°C	14.5–16.6	15.2 $\pm$ 0.9	—	≤ 15 °C	Minimum temperature for rice growth and development
DO	mg/L	1.76–2.63	2.17 $\pm$ 0.36	Class V or worse	≤ 2 mg/L	GB 3838-2002 Class V
COD _{Mn}	mg/L	13.34–15.96	14.90 $\pm$ 1.09	Class V or worse	≥ 15 mg/L	GB 3838-2002 Class V
TP	mg/L	0.16–0.23	0.19 $\pm$ 0.03	Class V or worse	≥ 0.2 mg/L	GB 3838-2002 Class V
TN	mg/L	1.75–2.15	1.97 $\pm$ 0.17	Class V or worse	≥ 2.0 mg/L	GB 3838-2002 Class V
Chla	µg/L	27.36–31.65	29.76 $\pm$ 1.76	—	≥ 30 µg/L	Eutrophication Classification Standard
CD	$\times 10^6$ cells/L	41.5–56.5	47.6 $\pm$ 6.2	—	$\geq 5 \times 10^7$ cells/L	Algal Bloom Classification Standard (Moderate)

Note: Under GB 3838-2002, the threshold values for DO, COD_{Mn}, TP, and TN correspond to Class V surface water standards, which are applicable to agricultural water use areas and waters with general landscape requirements. Classes I–III apply to drinking water source protection areas, while Class IV applies to industrial water use areas. Water quality inferior to Class V is classified as worse than Class V. No official GB 3838-2002 limits are specified for T, Chla, or CD; therefore, their risk thresholds were determined based on the minimum temperature required for rice growth, eutrophication classification criteria, and algal bloom classification criteria, respectively.

2.3. Single-Factor Evaluation Method and Its Limitations

The single-factor evaluation method is commonly used for classifying water quality grades as per the Surface Water Environmental Quality Standards (GB 3838-2002) [19]. This method involves selecting appropriate evaluation indicators for reservoirs, calculating the single-factor index for each indicator to determine whether it meets the standards, and assigning an overall water quality category based on the grade corresponding to the indicator with the poorest performance [28]. All seven parameters monitored in this study (T, CD, Chla, DO, COD_{Mn}, TP, and TN) had a significant impact on water quality. According to the single-factor evaluation method, if DO, COD_{Mn}, TP, or TN exceed Class V standards, the reservoir water quality is considered extremely unhealthy and unsuitable for agricultural use [19]. Furthermore, when the water temperature drops below 15 °C, rice growth is adversely affected [29]. A CD value exceeding 5×10^7 cells/L indicates moderate algal blooms, while a Chla concentration exceeding 30 µg/L indicates significant eutrophication [30]. These exceedance thresholds are summarized in Table 3.

However, when assessing the impact of PV projects on reservoir water quality and pollutant threats, single-factor evaluation methods face the following three key challenges. (i) Uncertainty in measured values: Due to sampling and measurement errors, measured pollutant values are inherently uncertain variables, whereas traditional methods treat them as certain values [31]. (ii) Spatial heterogeneity: The construction of PV projects alters the hydrological rhythms of reservoirs, leading to uneven distribution of pollutants in the water body and thereby increasing the uncertainty of measured values [32]. (iii) Sparse data: Reservoirs are typically located in remote areas, resulting in insufficient environmental monitoring data [33]. Consequently, traditional methods struggle to comprehensively assess the impact of PV projects on the aquatic environment and their patterns of change. The aforementioned challenges introduce uncertainty into the assessment of reservoir water quality under PV influence, creating an urgent need to develop improved methods capable of handling uncertainty and suitable for small-sample data. To this end, this paper introduces triangular fuzzy number theory to construct a PV–Reservoir Water Quality Impact Model.

2.4. Triangular Fuzzy Number Theory (TFN)

TFN is an uncertainty analysis method based on fuzzy set theory, which can be represented by $T(x) = (x_L, x_Q, x_S)$, where x_L , x_Q and x_S are the lower limit, most likely value and upper limit of x , respectively [34]. The calculation method of the membership function $u(x)$ is as follows:

$$u(x) = \begin{cases} 0 & x < x_L \text{ or } x > x_S \\ \frac{x - x_L}{x_Q - x_L} & x_L \leq x \leq x_Q \\ \frac{x_S - x}{x_S - x_Q} & x_Q < x \leq x_S \end{cases} \quad (1)$$

Accordingly, $u(x)$ is illustrated in Figure 2.

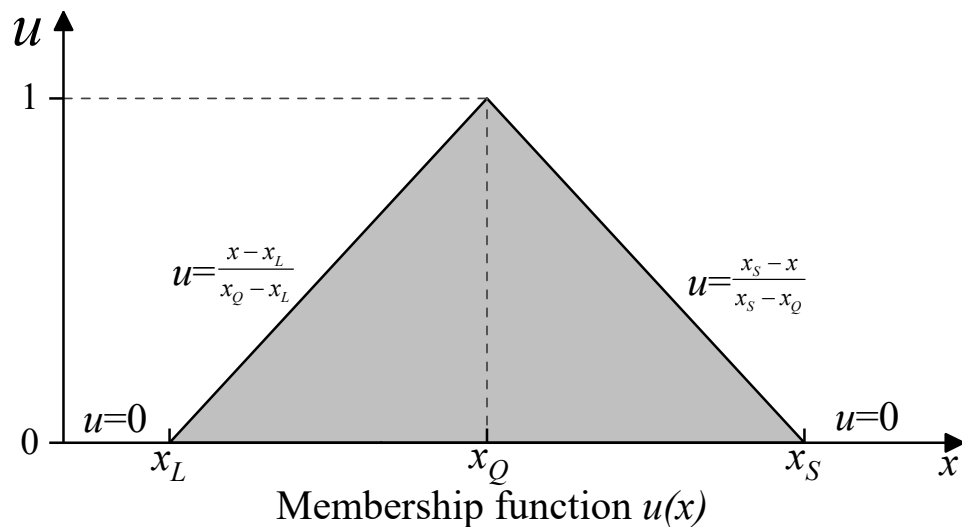


Figure 2. Membership function $u(x)$.

TFN has lower requirements for measured data compared with methods such as conventional mathematical statistics, time-series analysis, and machine learning methods that require larger sample sizes. According to [35], the range of one ecological risk class is defined as $x \in [a, b]$. The membership-area-based probability that the object belongs to this grade can be expressed as:

$$P = \frac{\int_{x=a}^b u(x) dx}{\int_{x=-\infty}^{+\infty} u(x) dx} \quad (2)$$

In addition, $T(x) = (x_L, x_Q, x_S)$ and $T(y) = (y_L, y_Q, y_S)$, with two different TFNs, satisfy the following subtraction rule [36]:

$$T(x) - T(y) = (x_L - y_S, x_Q - y_Q, x_S - y_L) \quad (3)$$

In general, TFN can effectively reflect the main uncertainty information of pollutants with fewer numerical features. Consequently, TFN is widely applied to uncertainty analysis in water resources management with insufficient survey data and provides an effective analytical tool for managers [37].

2.5. PVRWQIM

The Photovoltaic–Reservoir Water Quality Impact Model (PVRWQIM) was developed based on triangular fuzzy number theory. It consists of two components: a TFN-based exceedance-risk model and a transitional TFN model. The exceedance-risk model is used to quantify the probability that water quality parameters exceed predefined risk thresholds under uncertainty. The transitional TFN model is used to evaluate changes in exceedance risk before and after FPV construction.

2.5.1. Water Quality Standard Exceeding TFN Model

As described in Section 2.1, the measured values of monitoring indicators are subject to uncertainty. In this study, it is assumed that there are n monitoring points in the monitoring area, and the i th monitoring datum at the j th monitoring point is expressed as x_{ij} . Moreover, the TFN constructed in this study takes the lower, mean, and upper limits of the monitoring data as x_{iL} , x_{iQ} , and x_{iS} , respectively. Therefore, the TFN belonging to the i th monitoring datum is expressed as $T(x_i) = (x_{iL}, x_{iQ}, x_{iS})$.

According to Table 3, CD, Chla, COD_{Mn}, TP, and TN are indicators for which higher values indicate poorer water quality. When measured values exceed the permissible threshold (X), the water quality of the reservoir is extremely unhealthy. Conversely, the indicators of T and DO are worse after smaller values. When measured values are lower than X , the reservoir's water quality is affected. Based on the water quality index evaluation method, this study is divided into two types of indicator models for calculation.

The assessment standards for judging whether the water quality exceeds the health standard cannot be applied directly, as the measured value is a TFN consisting of an upper limit, a lower limit, and the mean value. To solve this problem, the total area of $T(x_i)$ is defined as A_T and the area of water quality exceeding the standard as A_E , according to the quartile calculation method in TFN. Then, the ratio of A_T and A_E represents the possibility of water quality exceeding the standard, which can be defined by R . The formula is as follows:

$$R = \frac{A_E}{A_T} \quad (4)$$

The schematic diagram of $T(x_i)$ is shown in Figure 3.

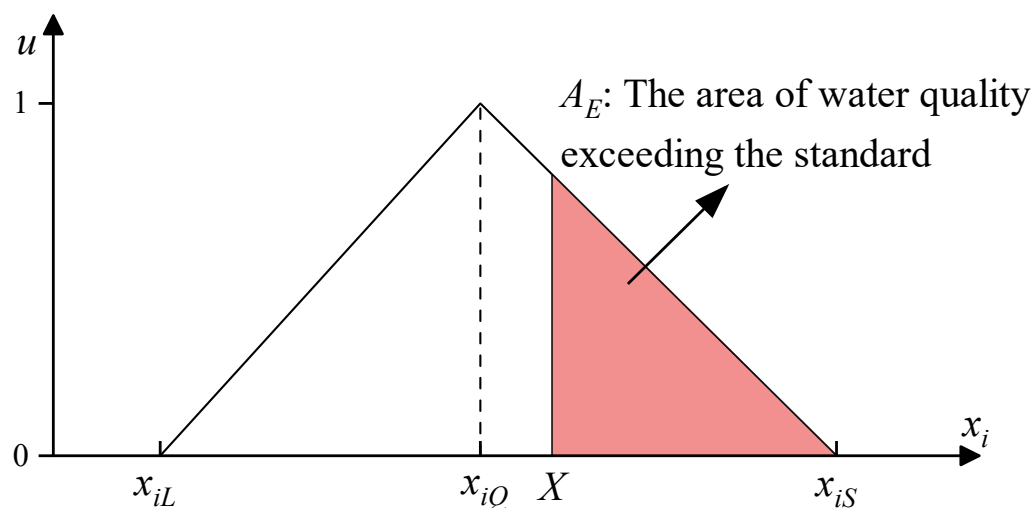


Figure 3. The schematic diagram of $T(x_i)$.

As shown in Figure 3, this study designs an over-standard risk vector (p_R^L) to quantify the probability of the reservoir water quality risk exceeding the standard based on its risk definition. The probability calculation rule for TFN can be generated according to Equation (2).

The indicator that is worse after a higher value.

$$p_R^L = \begin{cases} 1 & X \leq x_{iL} \\ 1 - \frac{(X - x_{iL})^2}{(x_{iS} - x_{iL}) \cdot (x_{iQ} - x_{iL})} & x_{iL} < X < x_{iQ} \\ \frac{(x_{iS} - X)^2}{(x_{iS} - x_{iL}) \cdot (x_{iS} - x_{iQ})} & x_{iQ} < X \leq x_{iS} \\ 0 & x_{iS} \leq X \end{cases} \quad (5)$$

The indicator that is worse after a smaller value.

$$p_R^L = \begin{cases} 1 & X \leq x_{iL} \\ \frac{(X - x_{iL})^2}{(x_{iS} - x_{iL}) \cdot (x_{iQ} - x_{iL})} & x_{iL} < X < x_{iQ} \\ 1 - \frac{(x_{iS} - X)^2}{(x_{iS} - x_{iL}) \cdot (x_{iS} - x_{iQ})} & x_{iQ} < X \leq x_{iS} \\ 0 & x_{iS} \leq X \end{cases} \quad (6)$$

2.5.2. Transitional TFN Model

The water quality standard exceeding the TFN model can assess the risk of excessive water quality with uncertainty. However, it cannot directly indicate how reservoir water quality risk changes after FPV construction. Therefore, a transitional TFN model was developed to evaluate the direction and magnitude of changes in exceedance risk.

The TFNs of the i th monitoring index before and after PV construction are defined as $T(x_i) = (x_{iL}, x_{iQ}, x_{iS})$ and $T(x_i^*) = (x_{iL}^*, x_{iQ}^*, x_{iS}^*)$, respectively. Then, a difference E_i is introduced according to Equation (3). The difference between two TFNs is $T(E_i) = \{E_{iL}, E_{iQ}, E_{iS}\}$, which is calculated as:

$$T(E_i) = \{E_{iL}, E_{iQ}, E_{iS}\} = T(x_i^*) - T(x_i) = \{x_{iL}^* - x_{iL}, x_{iQ}^* - x_{iQ}, x_{iS}^* - x_{iS}\} \quad (7)$$

The schematic diagram of $T(E_i)$ is shown in Figure 4.

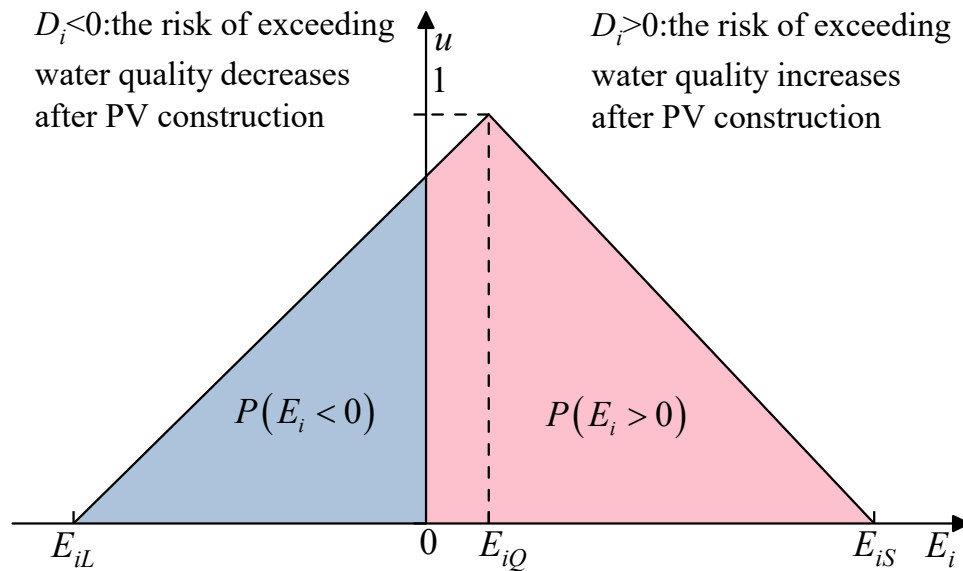


Figure 4. The schematic diagram of $T(E_i)$.

As shown in Figure 4, $T(E_i)$ represents the changes in water quality exceeding the standard caused by the construction of the PV. Furthermore, when $E_i > 0$, it indicates that the risk of exceeding the limit for the i th monitoring indicator increases after PV construction for the indicator which is worse after higher value, and it decreases when $E_i < 0$. Correspondingly, when $E_i > 0$, the risk for the i th monitoring indicator decreases after PV construction for the indicator which is worse after smaller value, and it increases when $E_i < 0$.

Accordingly, it can be considered that the probability of $P(E_i > 0)$ and $P(E_i < 0)$ can be quantified as the changing trend in the risk hazard of reservoir water quality exceeding the standard caused by PV construction. According to Equation (2), $P(E_i > 0)$ and $P(E_i < 0)$ can be generated:

$$P(E_i > 0) = \begin{cases} 1 & 0 < E_{iL} \\ 1 - \frac{E_{iL}^2}{\{E_{iS} - E_{iL}\} \cdot \{E_{iQ} - E_{iL}\}} & E_{iL} \leq 0 < E_{iQ} \\ \frac{C_{iS}^2}{\{E_{iS} - E_{iL}\} \cdot \{E_{iS} - E_{iQ}\}} & E_{iQ} \leq 0 < E_{iS} \\ 0 & E_{iS} \leq 0 \end{cases} \quad (8)$$

$$P(E_i < 0) = \begin{cases} 0 & 0 < E_{iL} \\ \frac{E_{iL}^2}{\{E_{iS} - E_{iL}\} \cdot \{E_{iQ} - E_{iL}\}} & E_{iL} \leq 0 < E_{iQ} \\ 1 - \frac{E_{iS}^2}{\{E_{iS} - E_{iL}\} \cdot \{E_{iS} - E_{iQ}\}} & E_{iQ} \leq 0 < E_{iS} \\ 1 & E_{iS} \leq 0 \end{cases} \quad (9)$$

3. Results and Discussion

3.1. Measured Values of Water Quality Indicators

According to the environmental survey results, the measured values of the selected water quality indicators before and after FPV construction are shown in Figures 5–7.

As shown in Figure 5, the average water temperature (T) and dissolved oxygen (DO) levels in the Junshan Reservoir before construction were 15.2 °C and 2.17 mg/L, respectively; after construction, these values were 14.1 °C and 1.80 mg/L, representing decreases of 7.4% and 17.2%, respectively. The Mann–Whitney U test indicated that the pre- and post-construction changes in T and DO exhibit extremely significant differences ($p < 0.01$). As shown in Figure 6, the average values of cyanobacterial density (CD) and chlorophyll a (Chla) after construction were 4.76×10^7 cells/L and 29.76 µg/L, respectively, representing a decrease of approximately 2.2% compared with pre-construction levels, with a significant difference ($p < 0.05$). COD_{Mn}, TP, and TN exhibited opposite trends. As shown in Figure 7, the average concentrations of COD_{Mn}, TP, and TN before construction were 14.90, 0.19, and 1.97 mg/L, respectively; after construction, these values changed to 15.99, 0.21, and 2.11 mg/L, respectively. COD_{Mn} and TN increased by 7%, while TP increased by 12.6%, with both showing highly significant differences ($p < 0.01$).

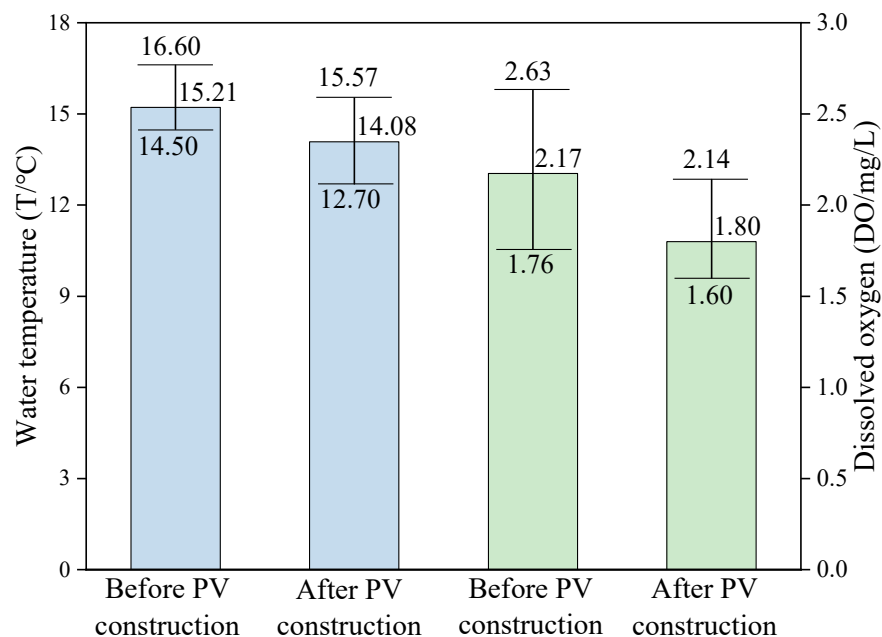


Figure 5. Concentrations of T and DO before and after PV construction.

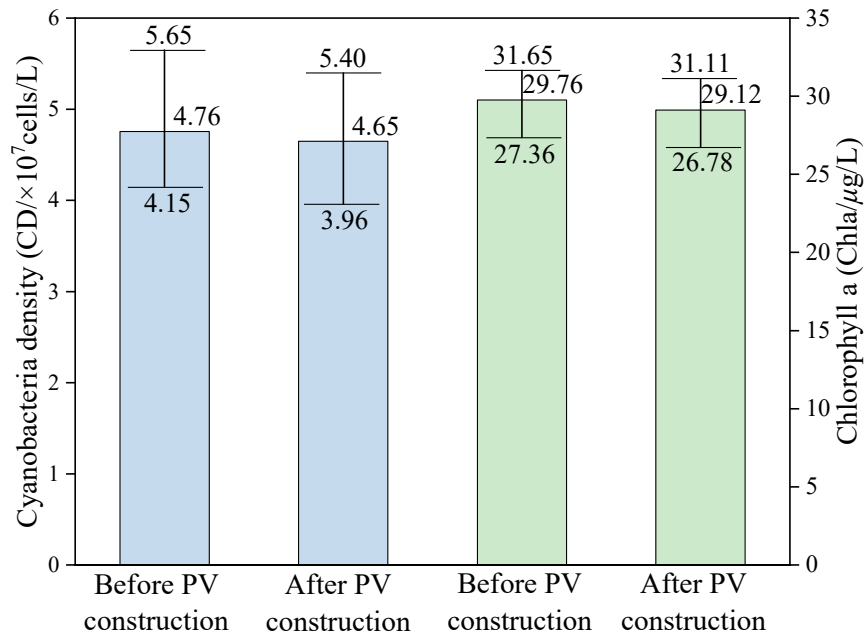


Figure 6. Concentrations of CD and Chla before and after PV construction.

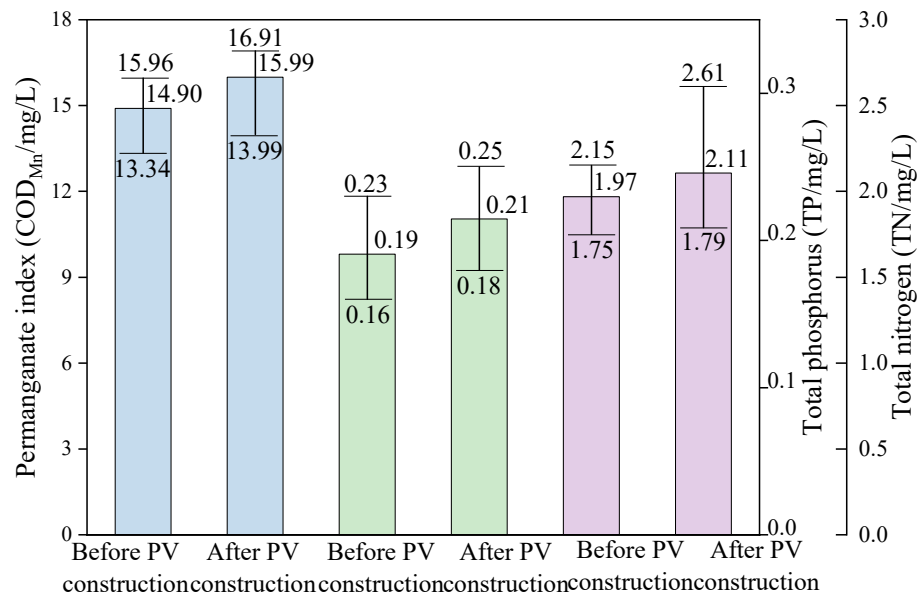


Figure 7. Concentrations of COD_{Mn} , TP and TN before and after PV construction.

These observed changes may be related to two main processes.

(i) The relationship between photovoltaic construction and changes in light intensity at the water surface

The shading effect of PV panels can reduce incoming solar radiation and prevent direct solar heating of the water surface, thereby lowering water temperature. At the same time, reduced light availability may weaken phytoplankton photosynthesis, which is associated with lower oxygen production [38]. This mechanism is consistent with the observed decline in DO after FPV construction.

Cyanobacteria generally prefer warm and high-light conditions. In addition, Chla is commonly used as an indicator of phytoplankton biomass and is closely associated with photosynthetic activity [39]. Therefore, reduced light availability under FPV shading may

suppress algal growth and photosynthesis, which is consistent with the observed decreases in CD and Chla.

By contrast, COD_{Mn}, TP, and TN may respond differently to reduced light and oxygen conditions. COD_{Mn} is often negatively associated with DO because organic matter degradation consumes oxygen and may increase chemical oxygen demand [40]. In addition, lower water temperature and reduced light availability may weaken microbial decomposition and nutrient transformation processes [41]. As a result, TP and TN may accumulate more readily in the water column after FPV construction.

(ii) The Relationship Between Photovoltaic Construction and Changes in Water Flow

Large-scale FPV panels can reduce wind disturbance and surface mixing, thereby decreasing the contact between water and the atmosphere [25]. Consequently, temperature, wind speed, and water flow may all decrease. According to a study by Pastore et al. [42], water flow velocity increases the contact area between oxygen and water, which may enhance the dissolution rate of DO. Furthermore, PV panels may block the disturbance of surface water by water flow and wind, potentially reducing atmospheric reoxygenation [11]. Consequently, with PV construction, overall DO levels in the water body may decrease, and COD_{Mn} and Chla concentrations may also decline.

However, slow-moving water may impede the movement of suspended solids, increasing the risk of sedimentation [43,44]. Pollutant concentrations may more easily lead to water quality deterioration and elevated COD_{Mn} levels. Furthermore, reduced water flow may diminish the water body's self-purification capacity and dilution–degradation capabilities [45]. Consequently, TP and TN may accumulate more readily, resulting in increased concentrations.

The objective of this study is to reveal statistical correlations among water quality indicators before and after PV construction, rather than to demonstrate causal mechanisms. The mechanism hypotheses proposed in the literature (e.g., that shading affects water temperature, dissolved oxygen, algae, and nutrients) are theoretical inferences; the observational data from this study alone cannot distinguish between PV effects and other confounding factors (such as interannual climate variability or construction activities within the watershed).

3.2. Risk Assessment of Exceeding Water Quality Standards

According to the water quality standard exceeding the TFN of PVRWQIM, the TFNs of each indicator in Junshan Reservoir before and after PV construction are shown in Figures 8–14.

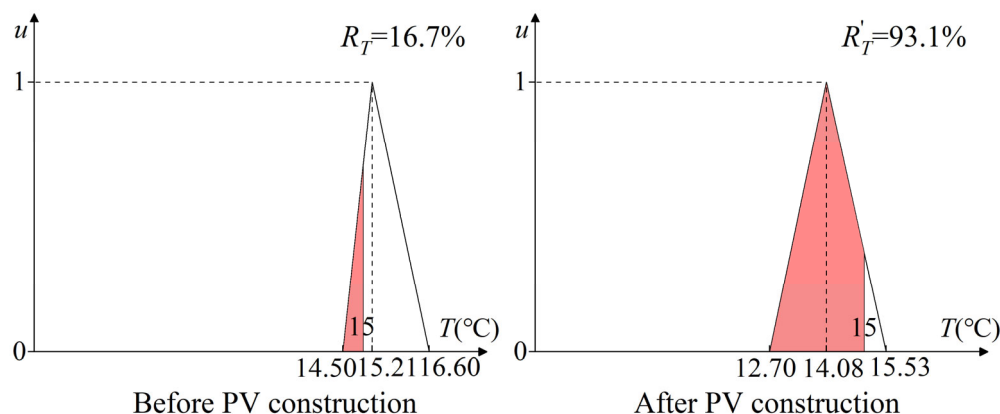


Figure 8. T TFNs in Junshan Reservoir before and after PV construction.

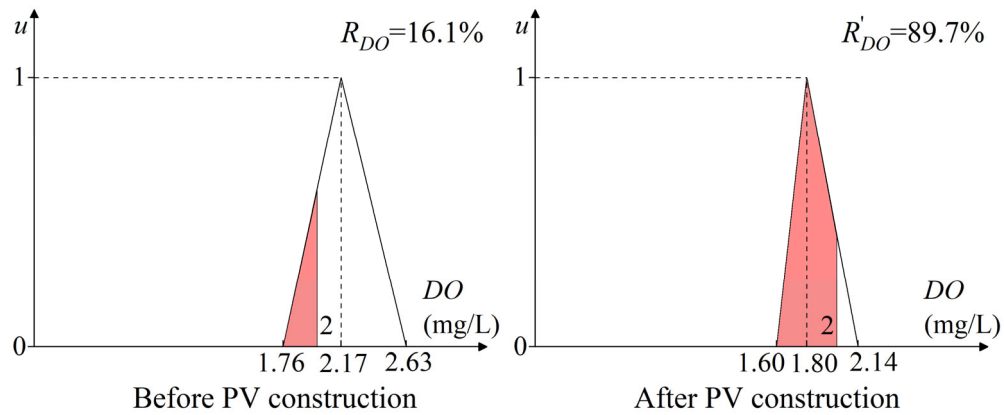


Figure 9. DO TFNs in Junshan Reservoir before and after PV construction.

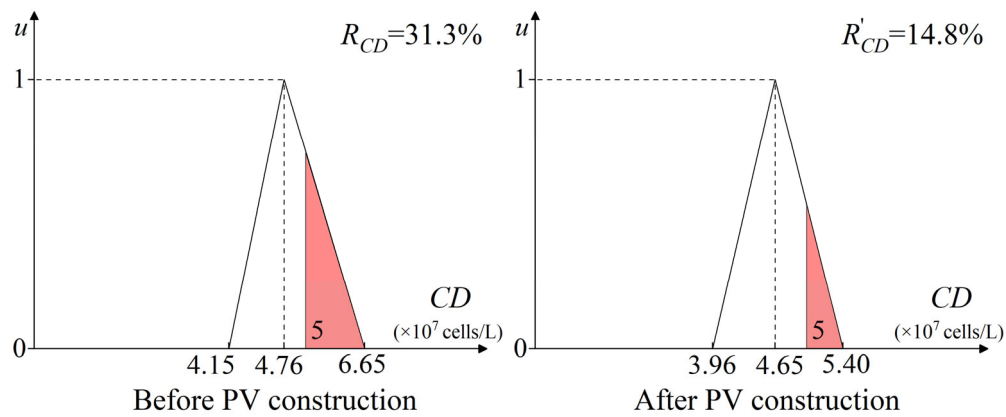


Figure 10. CD TFNs in Junshan Reservoir before and after PV construction.

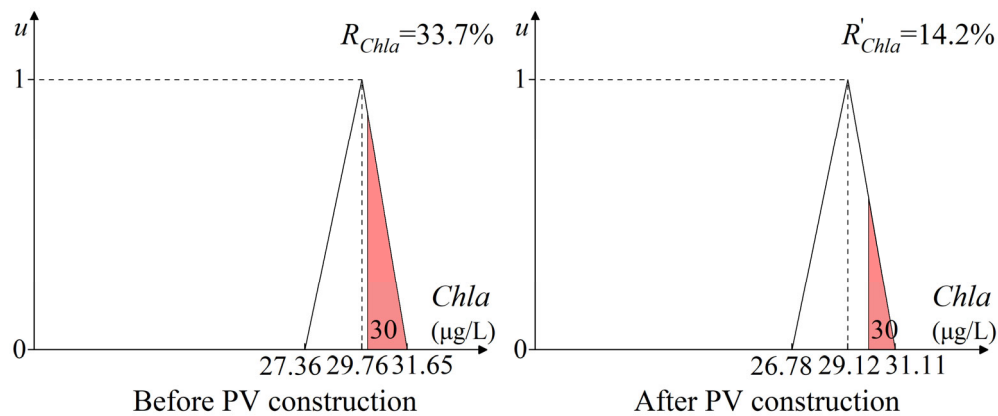


Figure 11. Chla TFNs in Junshan Reservoir before and after PV construction.

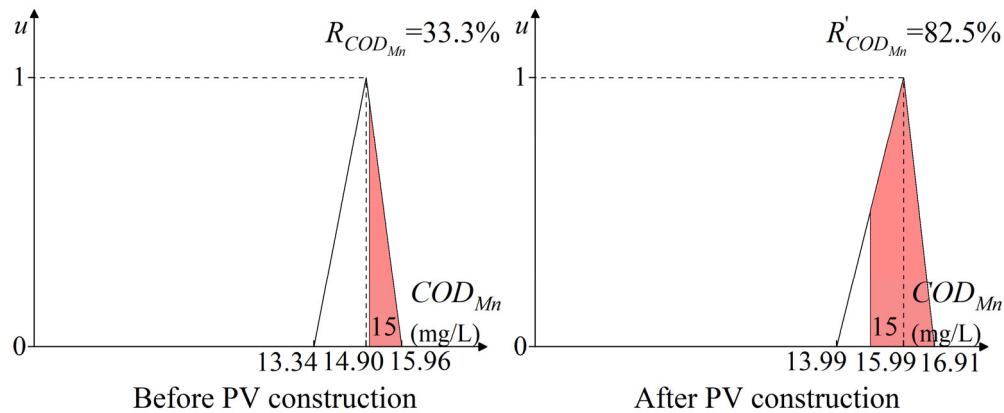


Figure 12. COD_{Mn} TFNs in Junshan Reservoir before and after PV construction.

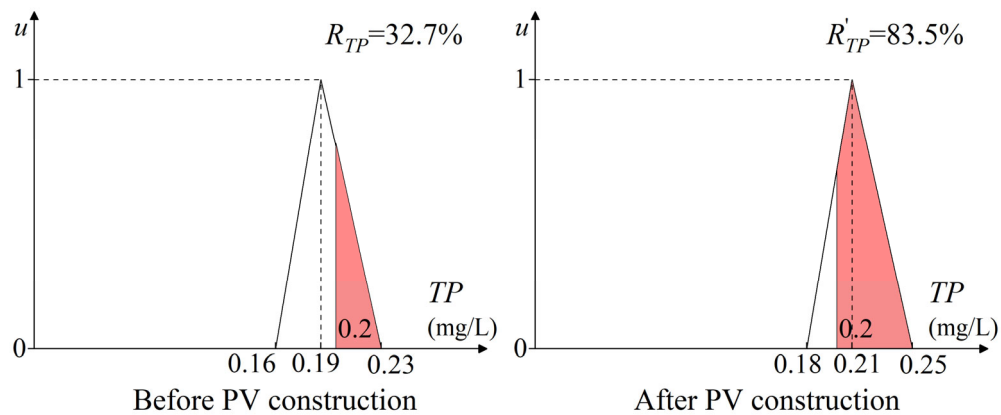


Figure 13. TP TFNs in Junshan Reservoir before and after PV construction.

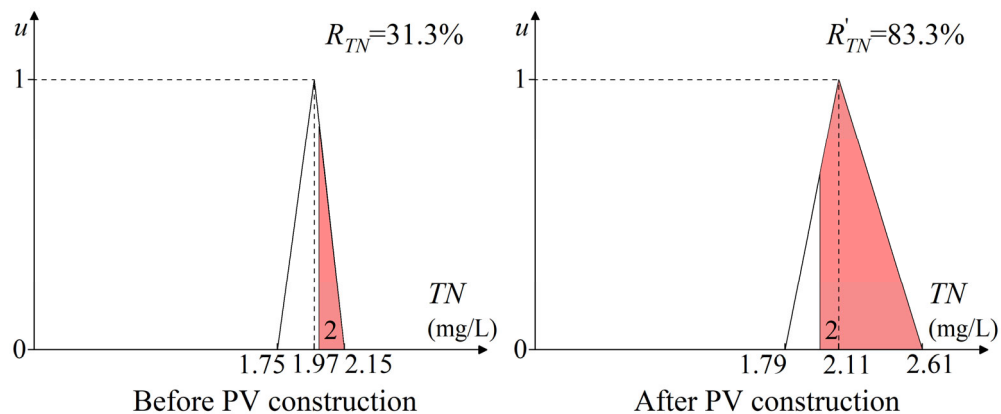


Figure 14. TN TFNs in Junshan Reservoir before and after PV construction.

Based on the PVRWQIM triangular fuzzy number model for water quality exceedances, the triangular fuzzy numbers of the seven water quality indicators before and after FPV construction are shown in Figures 8–14. Figures 8–14 illustrate the triangular fuzzy distributions of various indicators before and after the PV project construction. Specifically, the triangular fuzzy values for T and DO were {14.50, 15.21, 16.60} and {1.76, 2.17, 2.63}, respectively, before construction, and changed to {12.70, 14.08, 15.53} and {1.60, 1.80,

2.14}, respectively, with the probability of exceeding standards rising from 16.7% to 93.1% and from 16.1% to 89.7%, respectively. These results indicate that the risk of water temperature and dissolved oxygen exceeding standards is more certain after construction, which may render the water unsuitable for agricultural use and make it difficult to sustain aquatic life and support rice paddy irrigation. For algal-related indicators, the pre-construction triangular fuzzy values for CD and Chla were {4.15, 4.76, 5.65} and {27.36, 29.76, 31.65}, and after construction, they were {3.96, 4.65, 5.40} and {26.78, 29.12, 31.11}, respectively. The exceedance probabilities decreased from 31.3% to 14.8% for CD and from 33.7% to 14.2% for Chla. This suggests that FPV construction may have reduced the risk of algal bloom and eutrophication indicators, although longer-term monitoring is required to confirm this trend.

Critical discussion of the decline in algal indices: It should be noted that the decrease in CD and Chla should not be simply regarded as a positive ecological effect. First, algae are primary producers in aquatic ecosystems, and an excessive reduction in their biomass may weaken the energy base of the food web, thereby affecting the survival and reproduction of higher-trophic-level organisms such as zooplankton and fish. Second, the decline in algae in this study was accompanied by significant increases in total nitrogen (TN), total phosphorus (TP), and permanganate index (COD_{Mn}) ($p < 0.01$), indicating that the water body may have entered a “low-algae, high-nutrient” non-steady state. Under these conditions, once light conditions are restored (e.g., during the cleaning or replacement of solar panels), the accumulated nutrients may trigger algal blooms that are more severe than those observed prior to construction. Third, the reduction in algae implies a decrease in photosynthetic oxygen production, while respiratory oxygen consumption may relatively increase. This would exacerbate diurnal fluctuations in dissolved oxygen levels, potentially leading to more severe hypoxia, particularly during summer nights, thereby threatening the survival of aquatic organisms. Therefore, the decline in CD and Chla cannot simply be regarded as a positive ecological benefit of PV projects; rather, it should be comprehensively evaluated within the context of the entire ecosystem’s response. Future research should integrate food web analysis and long-term monitoring to fully assess the actual impact of reduced algal populations on reservoir ecosystems.

Regarding nutrient and organic matter indicators, the pre-construction values for COD_{Mn} , TP, and TN were {13.34, 14.90, 15.96}, {0.16, 0.19, 0.23} and {1.75, 1.97, 2.15}, respectively, and after construction, they were {13.99, 15.99, 16.91}, {0.18, 0.21, 0.25}, and {1.79, 2.11, 2.61}, respectively. The probability of exceeding standards increased from 33.3% to 82.5%, from 32.7% to 83.5%, and from 31.3% to 83.3%, respectively. These preliminary results suggest that water quality may deteriorate following construction, but longer-term monitoring is needed to confirm the potential impact on ecosystem water demands.

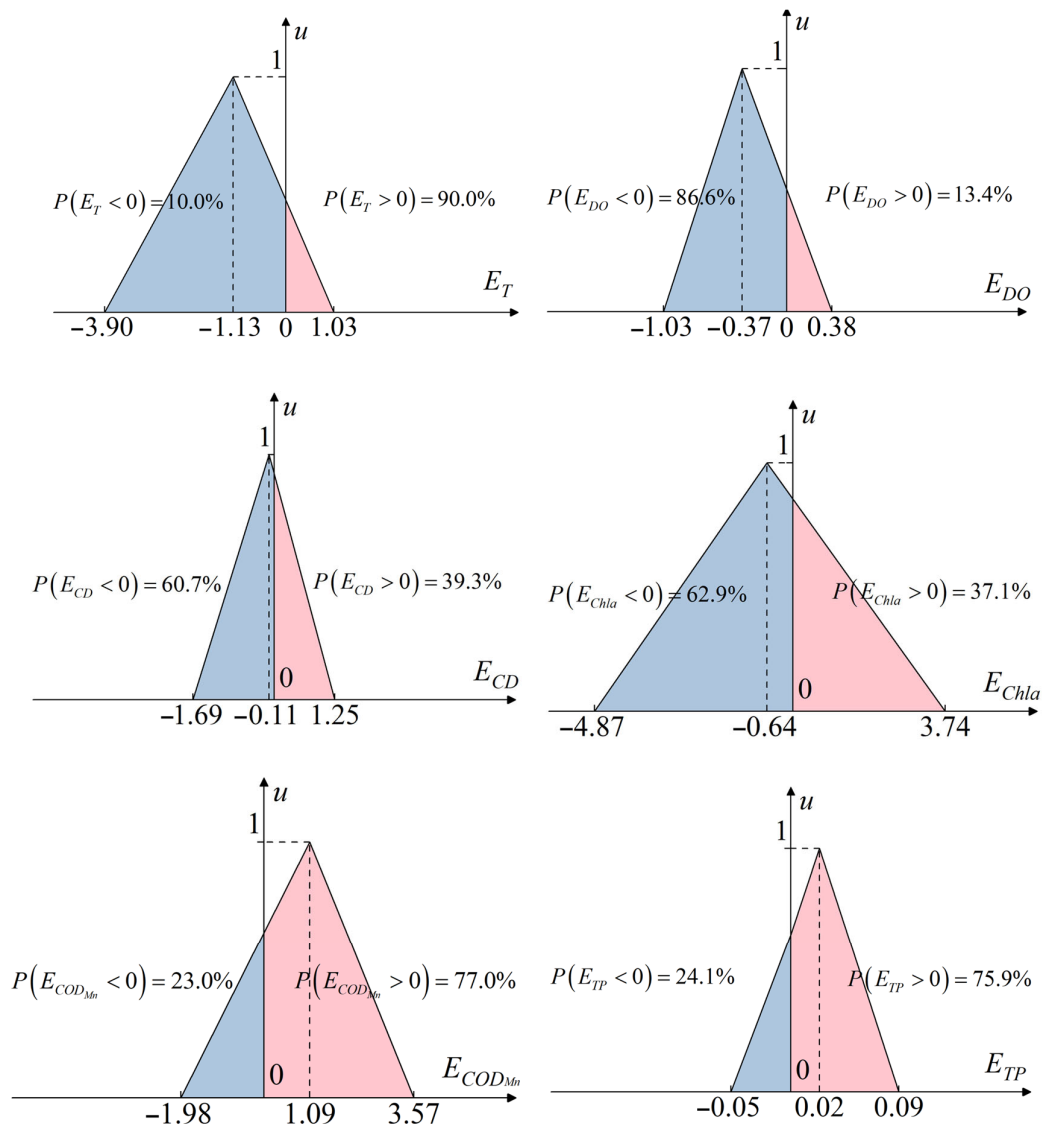
Overall, these changes may be associated with FPV-induced alterations in solar radiation, wind disturbance, water temperature, hydrodynamic exchange, and dissolved oxygen. These factors can jointly influence algal growth, nutrient cycling, and organic matter degradation [46,47]. Consequently, increased nutrient concentrations may pose additional ecological risks to downstream water users. However, this inference requires further validation through long-term monitoring and mechanistic studies.

To verify the validity of the PVRWQIM’s outputs, we compared the trends in water quality parameters from this study with results reported in recent literature. Yang et al. [25] found in their study of tropical reservoirs in Singapore that areas covered by photovoltaic panels exhibited an approximately 10% increase in total nitrogen, a 30% increase in total phosphorus, a 30% decrease in chlorophyll a, a 50% decrease in dissolved oxygen, and a slight increase in water temperature beneath the panels. Liu et al. [11] conducted a

systematic review of the multifaceted effects of PV on water temperature, dissolved oxygen, nutrients, and algae, noting that shading effects are the key drivers of these changes. Mentzafou et al. [23] simulated the impact of PV on Lake Kremasta in Greece and found that the effects on water quality were limited to the installation area and exhibited only minor variations. In this study, total nitrogen increased by 7%, total phosphorus by 12.6%, dissolved oxygen decreased by 17.2%, and chlorophyll a decreased by 4.9%. The direction of change in these indicators is highly consistent with the aforementioned literature (increases in nutrients, decreases in dissolved oxygen and chlorophyll a), indicating that the PVRWQIM outputs exhibit reasonable ecological consistency. Differences in the magnitude of changes across studies may stem from variations in water body type, climatic conditions, and PV coverage; the influence of these factors on PVRWQIM parameters warrants further investigation in the future.

3.3. Impact of Junshan Reservoir PV on Water Environmental Risks

According to the transitional TFN model of PVRWQIM, the ecological risk changes before and after PV construction in Junshan Reservoir are listed in Figure 15.



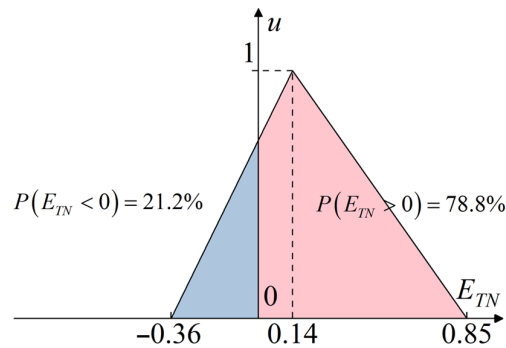


Figure 15. Transitional risk TFNs in Junshan Reservoir.

As shown in Figure 15, the transition triangular fuzzy numbers for T and DO exceeding standards are $\{-3.90, -1.13, 1.03\}$ and $\{-1.03, -0.37, 0.38\}$, respectively, with probabilities of being less than 0 of 0.900 and 0.866, respectively. This indicates that after the PV project was completed, the risk of T and DO exceeding standards showed a significant upward trend. At the same time, the triangular fuzzy numbers for the transition to exceedance of CD and Chla, which are related to algal blooms, are $\{-1.69, -0.11, 1.25\}$ and $\{-4.87, -0.64, 3.74\}$, respectively, with probabilities of being less than 0 at 0.607 and 0.629, respectively. After the construction of the PV project, the risk of exceedance for CD and Chla showed a downward trend.

In contrast, the triangular fuzzy transition numbers for exceedance of COD_{Mn} , TP, and TN are $\{-1.98, 1.09, 3.57\}$, $\{-0.05, 0.02, 0.09\}$, and $\{-0.36, 0.14, 0.85\}$, respectively. The probabilities that these triangular fuzzy numbers are greater than 0 are 0.770, 0.759, and 0.788, respectively. Therefore, the risk is induced and shows an upward trend after the PV project is constructed.

Overall, the ecological risks associated with T, DO, COD_{Mn} , TP, and TN increased after FPV construction, whereas those associated with CD and Chla decreased. This pattern is consistent with the measured changes in water quality indicators discussed in Section 3.1. Compared with the probability of reduced algal-related risk, the probability of increased nutrient and organic-matter risk was slightly higher. This suggests that although FPV construction may reduce algal bloom risk through shading, it may simultaneously increase nutrient accumulation and organic pollution risk.

According to the study in Reference [48], changes in reservoir temperature conditions caused by PV installations are the primary factor contributing to this phenomenon. Under natural conditions, water bodies maintain a certain temperature. After PV construction, water temperatures decrease significantly due to the shading effect of the PV panels. Additionally, the PV area blocks wind, thereby affecting dissolved oxygen concentrations [49]. However, winds from non-PV areas mitigate the wind-suppressing effect on the PV area. Consequently, changes in reservoir water temperature become more pronounced.

3.4. Limitations and Future Directions

The sampling in this study covered only two time points—before construction (March 2021) and after construction (March 2022)—with five monitoring sites; no control reservoir without a photovoltaic system was established. Although seasonal factors were controlled by scheduling both sampling rounds in the same month (March), driving factors such as seasonal variations, meteorological conditions, hydrological fluctuations (runoff and water level changes), and external nutrient inputs were not incorporated into the current model. These factors may independently or synergistically affect reservoir water quality, and their interactions with photovoltaic effects remain unclear. Furthermore,

following the completion of the PV project in 2022, simultaneous slope stabilization and supporting construction works were carried out in the watershed, altering the land surface conditions. This may have led to changes in surface runoff, soil erosion, and nutrient transport patterns, thereby exerting an additional impact on reservoir water quality. Since sampling occurred during the construction period, it was impossible to completely separate the PV effects from those of the watershed modifications, which constitutes another significant limitation of this study.

The current TFN model has the following weaknesses that require improvement: First, it employs linear triangular membership functions, assuming that indicator values vary uniformly within a given range; however, actual water quality data (such as nutrient concentrations) often exhibit skewed distributions. In the future, asymmetric TFN or trapezoidal fuzzy numbers could be introduced. Second, the model assumes that each indicator is independent and does not account for correlations between indicators (e.g., negative correlation between DO and COD_{Mn} , positive correlation between TP and TN). In the future, multidimensional TFN or fuzzy copula methods could be developed. Third, the exceedance thresholds use fixed values (e.g., $\text{DO} \leq 2 \text{ mg/L}$) and do not distinguish between seasonal and diurnal variations; in the future, time-varying thresholds could be introduced to adapt to management needs during different irrigation periods and ecologically sensitive periods. Fourth, the estimation of TFN parameters (lower bound, most probable value, upper bound) is not robust enough with small sample sizes; reliability could be improved by combining the Bootstrap resampling method.

To assess the impact of floating photovoltaic systems on reservoir water quality, the following research should be conducted in the future: Design a long-term continuous monitoring program using the BACI method (lasting at least 2–3 years, covering all four seasons, and including monitoring sites within the photovoltaic area, at the edges, and in a control area without photovoltaics) to disentangle the combined effects of photovoltaic impacts, seasonal fluctuations, interannual meteorological variability, and watershed modifications. Conduct comparative studies across multiple reservoirs (with varying coverage rates and nutrient conditions) to establish quantitative relationships between coverage and water quality responses and to identify ecological thresholds. Develop hydrodynamic–water quality–ecological coupling models (e.g., EFDC, Delft3D) to simulate water temperature stratification, dissolved oxygen distribution, and algal dynamics under different PV layouts, with particular attention to the impact of irrigation discharge periods on downstream water quality. Assess the water environmental risks associated with the full life cycle of PV panels (cleaning, replacement, and disposal). Increase monitoring of phytoplankton, zooplankton, benthic organisms, and fish communities to assess changes in the food web structure.

4. Conclusions

Based on triangular fuzzy number theory, this study developed the Photovoltaic–Reservoir Water Quality Impact Model (PVRWQIM) and applied it to the Junshan Reservoir in Jiangxi Province. The aim was to verify the model's ability to quantify changes in the risk of water quality exceedances before and after photovoltaic construction under conditions of sparse data and measurement uncertainty. The main conclusions are as follows:

(i) PVRWQIM successfully quantified the exceedance probabilities of seven water quality indicators. After FPV construction, the exceedance probabilities of T, DO, COD_{Mn} , TP, and TN increased from 16.7%, 16.1%, 33.3%, 32.7%, and 31.3% to 93.1%, 89.7%, 82.5%, 83.5%, and 83.3%, respectively. In contrast, the exceedance probabilities of CD and Chl_a decreased from 31.3% and 33.7% to 14.8% and 14.2%, respectively. These results indicate

that the model can capture differentiated responses among multiple water quality indicators under uncertainty.

(ii) The model revealed a statistically significant correlation pattern: “reduced algal risk” coexists with “increased risk of nutrient and organic matter accumulation” in the data. This pattern aligns with existing theoretical expectations: PV shading reduces light exposure, thereby inhibiting algal growth; simultaneously, shading may indirectly weaken the water body’s self-purification capacity through cooling, reduced water flow, and lower dissolved oxygen levels, which in turn is associated with nutrient accumulation. It should be noted that, based on limited observational data, this study reveals correlations rather than established causal mechanisms; the aforementioned causal explanations require further validation through controlled experiments or mechanistic modeling in the future.

(iii) Based on the current limited dataset, the model results suggest a potential trend toward increased risk of nutrient and organic matter exceedances in reservoirs following PV construction; however, this preliminary finding requires confirmation through longer-term, more intensive monitoring. It is recommended to establish sampling points both inside and outside the PV areas for monthly sampling and to install additional online sensors. Concurrently, improvement measures such as artificial aeration, artificial circulation, and the restoration of submerged vegetation should be considered to mitigate the potential risk of water quality deterioration. This model can be extended to other reservoir PV projects with limited data. Future research should refine the membership function, conduct year-round monitoring, and establish a coupled hydrodynamic–water quality model.

The list of symbols and abbreviations is shown in Table 4.

Table 4. Symbols and abbreviations.

Abbreviation	Full Name	Description
PV	Photovoltaic	Solar power generation
FPV	Floating Photovoltaic	Photovoltaic systems installed on water surfaces
TFN	Triangular Fuzzy Number	Uncertainty analysis method
PVRWQIM	PV-Reservoir Water Quality Impact Model	Proposed model in this study
COD _{Mn}	Permanganate Index	Indicator of organic matter in water
CD	Cyanobacterial Density	Algal cell concentration
Chla	Chlorophyll-a	Indicator of algal biomass
DO	Dissolved Oxygen	Oxygen content in water
TP	Total Phosphorus	Nutrient indicator
TN	Total Nitrogen	Nutrient indicator
T	Water Temperature	Temperature of water body

Author Contributions: Y.L. performed the writing—original draft preparation; M.Z. performed the data curation and investigation; F.Y. performed the conceptualization, methodology, and writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Water Science and Technology Projects of Water Resources Department of Jiangxi Province (grant numbers: 202527ZDKT08, 202527ZDKT10, and KT201736).

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

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

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