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Beyond Dissolved Oxygen: Integrated Assessment of Multistage Vortex Aeration Effects on Urban Reservoir Water Quality

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Abstract

Aeration is widely used to increase the oxygen concentration in urban reservoirs, but its broader effect on nutrients, organic matter, and integrated water quality status remains uncertain. This study evaluated the response of the Jangrim reservoir, Busan, Republic of Korea, to a multistage vortex aerator (MVA) using monthly monitoring data from the Water Environment Information System by the Ministry of Environment from 2020 to 2025. The dataset was divided into pre-MVA and post-MVA periods, and water quality changes were assessed using descriptive statistics, box plots, percentage change, time-series regression, Pearson's correlation analysis, principal component analysis, and three water quality indices: CCME-WQI, RT-WQI, and NSF-WQI. After MVA installation, dissolved oxygen increased from 8.7 mg/L, corresponding to a 72.4% increase. TN and TP decreased by 41.2% and 59.6%, respectively. In contrast, organic matter indicators showed mixed responses: BOD decreased by 18.8%, whereas COD and TOC increased by 4.6% and 13.2%, respectively. WQI scores improved after MVA operation, but CCME-WQI remained in the Poor class. PCA showed that urban pond system water quality was controlled by oxygen-related, nutrient, and organic–particulate factors. Overall, MVA improved oxygen conditions and partially reduced nutrient pressure, but aeration alone was insufficient for full urban pond system restoration.

Keywords: dissolved oxygen; urban reservoir; multistage vortex aerator; multivariate statistical analysis; nutrients; organic pollution; water quality index

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1. Introduction

Water is essential for life and daily human needs. Maintaining dependable, secure, and economical water access remains a fundamental objective that faces significant global challenges in the 21st century [1]. The volume and conditions of inflowing water strongly affect nutrient loading and overall water quality. Shallow urban pond systems are particularly vulnerable because watershed inputs often carry elevated concentrations of pollutants, nutrients, organic matter, and suspended solids [2,3]. Seasonal precipitation affects both

the volume and quality of inflows to these water bodies. Water quality frequently degrades due to organic depletion, eutrophication, heavy metal contamination, and urban runoff, leading to significant impacts that compromise socioeconomic functions such as water supply, recreation, and aesthetics while also disrupting ecological processes by altering community structure and biodiversity. Moreover, factors such as land use change [4], hydraulic alteration [5], the introduction of toxic chemicals and nutrients [6], and increased water demand due to urbanization [7,8] have substantially deteriorated water quality. This decline has resulted in the abandonment of certain water bodies, as they no longer serve as sustainable sources of potable water. Effective treatment techniques and water quality information are crucial for the prevention and management of water contamination.

Contaminated water bodies are typically managed via four main approaches: physical, chemical, biological, and ecological restoration techniques [9]. Physical, chemical, and biological treatments are generally performed in situ, whereas restoration is an ex situ strategy. Aeration and dredging are effective physical approaches; however, they are frequently expensive, energy-intensive, and labor-intensive [10,11]. The efficiency of aeration-based systems also depends on hydraulic and design conditions. For example, laboratory-scale analysis of air diffuser systems showed that plume spacing can strongly influence destratification efficiency, indicating that aeration performance is controlled not only by oxygen supply but also by mixing configuration and flow interaction [12]. Chemical treatments are rapid but may induce secondary contamination [13]. Biological methods, such as biofilms and aquatic plant filtration, are ecologically sustainable yet exhibit reduced efficacy and slower rates in complicated environments. Ex situ restoration involves the transportation of contaminated water and sediments for offsite remediation, which requires substantial resources and presents difficulties in sediment disposal [14]. In this context, the introduction of pure oxygen aeration via a multistage vortex aerator (MVA) (Section 2.2) presents an effective in situ option with minimal risk of secondary pollution. However, it should be noted that MVA technology is designed primarily for small, shallow urban water bodies, as scaling it to massive reservoirs with storage volumes in the tens or hundreds of millions of cubic meters would require multi-unit networks or different aeration systems altogether. Park et al. [15] developed a gas-transfer model for the MVA and showed that the system can rapidly increase DO by combining high-purity oxygen injection, additional gas–water pressure, and vortex-induced mixing. The study reported that DO could reach more than 40 mg/L within 60 min, confirming the high oxygen transfer capacity of the device. Ghosh et al. [16] further demonstrated the field applicability of MVA in the Geojeongcheon stream, where DO increased by up to 7.05 mg/L and water quality improved to a good grade. This study also reported reductions in odor, total phosphorus, and suspended solids, suggesting that MVA can support aerobic purification in polluted urban streams.

In addition, ongoing evaluation of water quality is essential for monitoring contaminants and facilitating water resource management through spatial-scale assessments [17]. Previous research frequently included graphical methodologies (Piper plots, bivariate diagrams) when combined with univariate statistical analysis [18] as well as an IoT-based water pollution monitoring system [19]. Owing to the variability in water quality across locations and seasons, programs must monitor multiple physicochemical variables across different sites and times, resulting in high costs and complicated data matrices that are challenging to analyze. Consequently, monitoring networks need to be refined to utilize a more concise, representative variety of characteristics, locations, and sampling intervals while maintaining critical information [20].

Multivariate statistical techniques (MSTs) and the water quality index (WQI) are frequently utilized in the evaluation of stream water quality and serve essential functions in water resource management [17,21–25]. The MST facilitates comprehensive analysis

of complex water quality data, identifies sources of pollution, and clarifies the natural or human-induced processes that influence temporal and spatial variations [24,26,27]. WQI is a quantitative instrument that combines various water quality parameters into a singular value, reflecting the condition of surface water [28,29]. Numerous water quality indices have been formulated and utilized for assessment, including the National Sanitation Foundation Water Quality Index (WQI), Florida Stream Water Quality Index (FWQI), British Columbia Water Quality Index, Oregon Water Quality Index, and Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI) [22,30].

While conventional aeration studies predominantly focus on surface dissolved oxygen (DO) elevation and deep-water anoxia control in deep reservoirs, this study provides a novel, integrated assessment of multistage vortex aeration (MVA) in a shallow urban pond system subjected to continuous anthropogenic pressure. The scientific novelty of this work rests on three key pillars: (1) moving beyond simple reaeration metrics to systematically evaluate how MVA operation differentially impacts distinct organic pollution pools (BOD vs. COD and TOC) and nutrient dynamics (TN and TP); (2) evaluating physical circulation and water quality responses under oxic baseline conditions (DO = 8.71 mg/L); and (3) coupling modified multi-parameter water quality indices (CCME-WQI, RT-WQI, and NSF-WQI) with Promax-rotated principal component analysis (PCA) to establish a long-term empirical framework for tracking urban aquatic ecosystem recovery over an extended operational window (2020–2025).

2. Materials and Methods

2.1. Research Site

The study area, the Jangrim reservoir, is a narrow, 0.7 km long urban water body consisting of three small ponds situated within the Saha district of Busan, Republic of Korea (35°04′–35°05′ N; 128°57.6′–128°57.9′ E) (Figure 1). Integrated into the 57,298 m^2 Jangrim Ecological Park, this shallow urban pond system operates under intense anthropogenic pressure. It is characterized by a surface water area of approximately 6540 m^2, an estimated total water volume of 13,800 m^3, and an average water depth ranging between 1 and 3 m with a continuous artificial circulation flow rate of 3 m^3/min.



Figure 1. Location of the study area showing the MVA installation site and outlet in the Jangrim reservoir, Busan, Republic of Korea. Source: Google Earth.

Hydrologically, the water body receives baseflow, urban drainage, and localized wastewater inputs from upstream settling basins and adjacent industrial zones (Figure 1). The urban pond system terminates near the Busan Environmental Corporation (BECO) wastewater treatment plant (WWTP), placing it at a sensitive urban–industrial interface before discharging via the designated outflow point (Figure 1). Due to its shallow geometry and continuous artificial circulation driven by the multistage vortex aerator (MVA) installed in 2022, the system remains vertically well-mixed without developing persistent thermal stratification. Furthermore, seasonal ice formation is minimal and highly transient during winter months owing to ongoing water movement and regional temperate conditions. Throughout the multi-year monitoring period (2020–2025), surrounding land use practices, industrial zoning, and municipal drainage inputs remained stable, ensuring continuous background anthropogenic loading across both the pre- and post-aeration phases.

2.2. Multistage Vortex Aerator (MVA)

The MVA is an in-line oxygen dissolution unit integrated into the existing circulation system of the urban pond system. A submerged pump pulls water through the device while pure oxygen is injected at the inlet. Inside a series of partitioned vortex chambers, the spinning flow stretches and thins the gas–liquid boundary layer and greatly increases the contact area, so oxygen dissolves quickly and efficiently (Figure 2). The treated, high-DO water is then recirculated throughout the basin, uniformly distributing oxygen, improving redox conditions, and preventing the formation of low-oxygen, odor-generating hotspots [15].

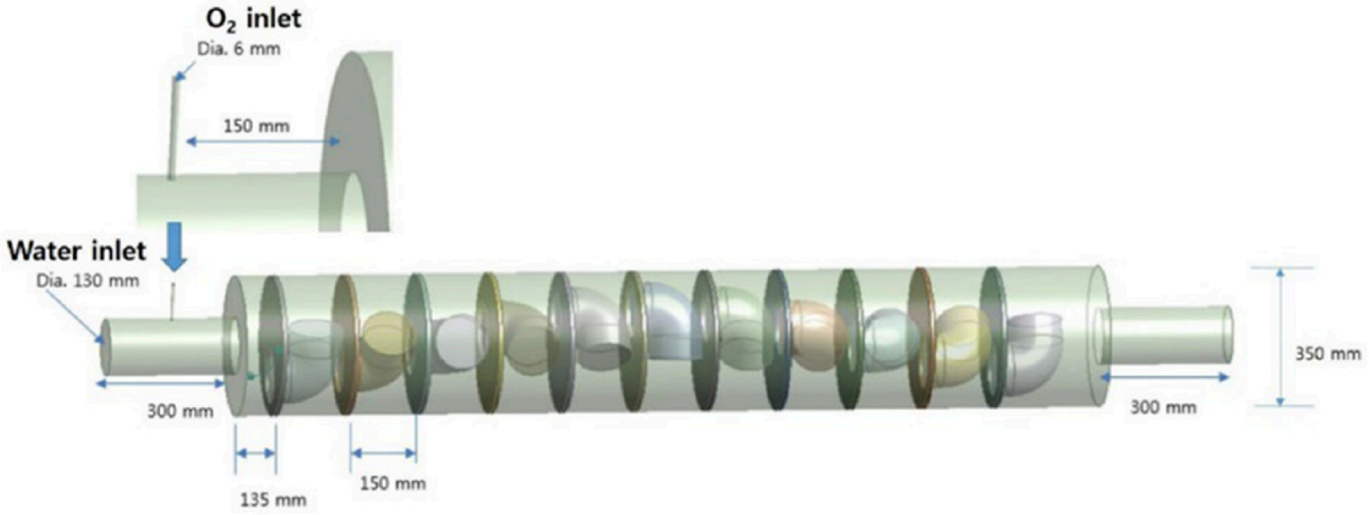


Figure 2. Schematic illustration of the MVA. Redrawn with permission from reference [15].

The system comprises a pure oxygen generator and an oxygen dissolver, which together enable rapid aeration of the whole urban pond system without the need for additional surface equipment. The oxygen transfer efficiency is governed by the thickness of the gas–liquid interface film, which is reduced through increased contact time and the frequency of phase collisions, thereby increasing dissolution. As previously reported by Lewis and Whitman [31], the diffuser demonstrates significantly improved performance over conventional aeration devices, such as fine-pore diffusers, which are susceptible to issues such as inorganic scaling and biological fouling, resulting in reduced transfer efficiency and increased head loss [32].

Figure 3 shows the structural and operational layout of the multistage vortex aerator (MVA) system. According to technical specifications given in Table S1, the installation comprises a 100 L/min oxygen generator and three vortex dissolvers that utilize high-velocity gas–liquid mixing to produce super-oxygenated water. This treated effluent is distributed via a 0.6 km longitudinal underground pipeline (redline, Figure 1) that transports oxygenated water (DO > 5 mg/L) along the urban pond system's axis, discharging strategically to facilitate aerobic purification and prevent sediment nutrient leaching across the 13,800 m^3 urban pond system capacity. With an oxygen transfer efficiency 3.3–7.3 times greater than that of conventional diffusers, this configuration provides an appropriate in situ system for evaluating targeted oxygenation in small, high-load urban aquatic ecosystems.

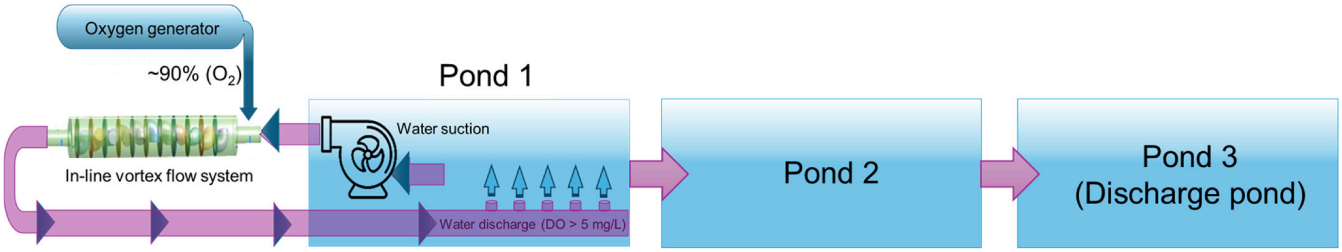


Figure 3. Schematic diagram of urban pond system treatment via a multistage vortex aerator (MVA).

2.3. Data Collection and Analytical Framework

Official water quality data for the Jangrim reservoir were obtained from the National Water Environment Information System (NIER) (https://water.nier.go.kr/web, accessed on 15 April 2026) of Republic of Korea. The dataset encompasses a 6-year longitudinal period from January 2020 to December 2025, specifically focusing on the monitoring station at the MVA outlet to evaluate the system's operational impact. Ten physicochemical and organic parameters were selected: temperature (Temp), pH, electrical conductivity (EC), dissolved oxygen (DO), biological oxygen demand (BOD), chemical oxygen demand (COD), total organic carbon (TOC), suspended solids (SS), total nitrogen (TN), and total phosphorus (TP). To evaluate the restoration efficiency, the data were categorized into pre-MVA (number of samples—n = 45) installation (January 2020–September 2023) and post-MVA (n = 27) installation (October 2023–December 2025). By focusing the localized monitoring solely on the MVA outlet, this study isolates the mechanical influence of the MVA on the urban pond system's metabolic recovery, ensuring that the reported improvements are directly attributable to the MVA's operational discharge.

Water quality monitoring was conducted continuously at the MVA outlet sampling location. Due to the shallow depth and narrow geometry of the urban pond system, rapid hydrodynamic mixing induced by the MVA discharge ensures that the measured water quality parameters at this outlet represent the overall state of the urban pond system.

2.4. WQI Model Calculations

In this study, three distinct indices, CCME-WQI, RT-WQI, and NSF-WQI, were employed to evaluate the ecological status of the Jangrim reservoir. These indices were selected to provide a comparative synthesis of the urban pond system's health, translating complex physicochemical datasets into single, communicable scores. The calculation framework involved: (1) parameter selection based on data availability, (2) conversion of concentrations into standardized sub-indices, (3) application of weighting factors to reflect the relative ecological importance of each variable, and (4) aggregation via index-specific cumulative formulas [33] (Table 1).

Table 1. Summary of the water quality index (WQI) models applied to the Jangrim reservoir.

Index	Parameter (Units)	Weight [a] (W_i)	Objective Values (V_0)	Formula	WQI Range & Class
CCME-WQI [34,35]	pH (-) DO (mg/L) BOD (mg/L) COD (mg/L TDS (mg/L) TN (mg/L) TP (mg/L)	-	$6.5 \leq$ pH ≤ 9.0 DO ≥ 7.5 BOD ≤ 2.0 COD ≤ 2.0 TDS ≤ 500 TN ≤ 3.0 TP ≤ 0.04	CCME-WQI = $100 - \frac{\sqrt{F_1^2+F_2^2+F_3^2}}{1.732}$ F_1—scope F_2—frequency F_3—amplitude	95–100 Excellent; 80–94 Good; 60–79 Fair; 45–59 Marginal; 0–44 Poor
RT-WQI (NIER/CCME-style, real-time) [34,36]	Temp (°C) pH (-) EC (µS/cm) TOC (mg/L) DO (mg/L) TN (mg/L) TP (mg/L)	-	[b] -10 °C $\leq$ Temp $\leq$ [b] $+10$ °C $6.5 \leq$ pH ≤ 9.0 EC ≤ 200 TOC ≤ 3.0 $0.8 \times DO_{sat} \leq DO \leq 1.3 \times DO_{sat}$ TN ≤ 3.0 TP ≤ 0.1	RT-WQI = $100 - \frac{\sqrt{F_1^2+F_2^2+F_3^2}}{1.732}$ F_1—scope F_2—frequency F_3—amplitude	80–100 Excellent; 60–79 Good; 40–59 Fair; 20–39 Marginal; 0–19 Poor
NSF-WQI (Brown model; subset) [37]	Temp (°C) pH (-) DO (%) BOD (mg/L) TP (mg/L) TN (mg/L) SS (mg/L)	0.132 0.145 0.224 0.145 0.132 0.132 0.092	-	NSF-WQI = $\sum_{i=1}^{n} Q_i W_i$ Q_i = sub-index values W_i = relative weights	90–100 Excellent; 70–89 Good; 50–69 Fair; 25–49 Poor; 0–24 Very poor

Note(s): (1) [a]—relative weights are used in this calculation. (2) [b]—monthly mean for 1 year temperature.

2.4.1. Canadian Council of Ministers of the Environment Water Quality Index (CCME-WQI)

CCME-WQI is a globally recognized tool for disseminating water quality status based on three factors: scope (F_1), frequency (F_2), and amplitude (F_3). While the index typically utilizes parameters such as pH, DO, COD, BOD, TN, TP, TDS (total dissolved solids) and fecal coliform, this study adapted the input variables based on data availability at the MVA outlet. Specifically, seven parameters were utilized: pH, DO, TN, TP, COD, BOD and TDS. TDS was estimated from EC using the following relationship proposed by Rusydi (2018) [38]:

$$\text{TDS} = 0.65 \times \text{EC} \quad (1)$$

Because each removed parameter modifies the denominator, this exclusion has an impact on the size of the F_1 score. F_1 is the percentage of parameters that, at least once during the study period, fall short of the water quality targets (Equation (2)). F_2 is the proportion of individual tests that fail to meet water quality objectives (Equation (3)). F_3 represents the magnitude by which failed tests exceed objectives (Equations (4)–(7)). The final CCME-WQI values and its score are calculated by combining these three factors (Table 1).

$$F_1 = \left(\frac{n\ of\ failed\ variables}{n\ of\ variables}\right) \times 100 \quad (2)$$

$$F_2 = \left(\frac{n\ of\ failed\ tests}{n\ of\ tests}\right) \times 100 \quad (3)$$

$$EXCURSION_i = \left(\frac{Failed\ test\ value}{Objective}\right) - 1 \quad (\text{when test value} > \text{objective}) \quad (4)$$

$$EXCURSION_i = \left(\frac{Objective}{Failed\ test\ value}\right) - 1 \quad (\text{when test value} < \text{objective}) \quad (5)$$

$$NSE = \frac{\sum_{i=1}^{n} EXCURSION_i}{n\ of\ tests} \quad (6)$$

$$F_3 = \frac{NSE}{0.01NSE + 0.01} \quad (7)$$

2.4.2. Real-Time Water Quality Index (RT-WQI)

The RT-WQI, developed by Republic of Korea's Ministry of Environment (MOE), is based on the CCME-WQI framework and is originally designed for high-frequency automated monitoring data. In this study, the RT-WQI was modified to fit the monthly monitoring data available for the Jangrim reservoir. Therefore, each monthly observation was treated as one assessment cycle, and the calculated index is referred to as a modified monthly RT-WQI. Based on data availability, seven RT-WQI-related parameters were used: Temp, pH, EC, DO, TOC, TN, and TP. Turbidity was excluded because it was not available in the dataset. Although BOD, COD, and SS were available, they were not included in the RT-WQI calculation because they are not part of the standard RT-WQI parameter set. RT-WQI was computed by evaluating criteria including the quantity of parameters beyond the standards (F_1), the frequency of adherence to water quality standards (F_2), and the degree of violations (F_3) [35] (Equations (2)–(7)). The RT-WQI score is classified into five grades: Excellent (100–80), Good (79–60), Fair (59–40), Caution (39–20), and Poor (19–0), as illustrated in Table 1.

2.4.3. National Sanitation Foundation Water Quality Index (NSF-WQI)

NSF-WQI, proposed by Brown et al. [37] and developed with the U.S. National Sanitation Foundation, provides an overall measure of water quality. NSF-WQI was also applied to evaluate the overall water quality of the Jangrim reservoir. The original NSF-WQI uses nine parameters: Temp, DO, fecal coliform, pH, BOD, phosphate, nitrate, turbidity, and total solids. However, because the available Jangrim reservoir dataset did not include fecal coliform, turbidity, and nitrate, NSF-WQI was modified according to data availability. In this study, the modified NSF-WQI was calculated using the available NSF-related parameters: Temp, DO, pH, BOD, TP, TN, and SS. TP and TN were used as nutrient-related indicators, while SS was used as the available solids-related parameter. Since several original NSF-WQI parameters were unavailable, the parameter weights were adjusted by normalizing the weights of the included parameters so that their total equaled 1.0. The modified NSF-WQI calculation is given in Table 1, where Q_i is the sub-index score of parameter i, W_i is the relative weight of parameter i, and n is the number of parameters included in the calculation. The resulting NSF-WQI scores were used to classify water quality and compare temporal changes before and after MVA installation. Because the calculation was based on the available monthly dataset, the index is referred to as a modified monthly NSF-WQI.

2.5. Statistical Tools

All statistical analyses and graphical visualizations were performed using the OriginPro 2026 software. Before conducting statistical analysis, all water mquality parameters were transformed into Z-scores [39]. This standardization was applied from the initial stage of analysis to reduce the influence of different measurement units and scales among variables, such as mg/L, °C, µS/cm, and pH, and to support more consistent comparison among monthly observations. Descriptive statistics, including mean, standard deviation, minimum, and maximum values, were calculated for each parameter. Time-series linear regression analysis was applied to evaluate temporal trends in water quality parameters before and after MVA operation. Each parameter was regressed against time, and the regression slope was used to determine whether the parameter showed an increasing or decreasing trend. Statistical significance was evaluated at $p < 0.05$. This method was considered more suitable than simple group comparison tests because the dataset consisted of monthly time-series observations.

Data quality flags provided by the National Water Environment Information System (NIER) (https://water.nier.go.kr/web, accessed on 15 April 2026) database were checked before analysis. Values marked as missing or moving-average-estimated were not interpreted as directly measured pollution events. These flagged values were considered cautiously in temporal interpretation to avoid overestimating short-term water quality peaks.

Multivariate statistical analysis, including Pearson's correlation analysis and principal component analysis (PCA) were used to explore the relationships among water quality parameters and identify the dominant factors controlling urban pond system water quality variability. Pearson's correlation analysis was applied to assess associations among physicochemical, nutrient, organic matter, and ionic indicators [36,40,41]. To simplify the factor structure and enhance interpretability, principal component analysis (PCA) was performed on the normalized water quality dataset using Promax rotation, and the final interpretation was based on the rotated component loadings and components with eigenvalues greater than 1.

3. Results and Discussion

3.1. Descriptive Statistics and Time-Series Trend Analysis of Water Quality Parameters

Descriptive statistics were calculated to compare water quality conditions before and after MVA installation in the Jangrim reservoir. The results are presented in Table S3, and the distribution of each parameter is shown using box plots in Figure 4. One extreme outlier in the post-MVA electrical conductivity (EC) dataset (17,930 μS/cm) was screened out for descriptive plotting to eliminate scale distortion and prevent statistical variance inflation (Mean − 1SD). Sensitivity checks confirmed that screening this single measurement anomaly did not alter the overall trend or interpretation of urban pond dynamics, and all reported raw EC values remained strictly positive. Monthly variations in selected key parameters are shown in Figure 5, where the red lines indicate fitted linear regression trends over the entire monitoring period. To maintain visual clarity while emphasizing critical system dynamics, detailed time-series trends are presented for parameters exhibiting high seasonal responsiveness or direct operational sensitivity to aeration (e.g., DO, BOD, TN, TP). Parameters displaying near-static baselines or low variance (e.g., pH, SS) are visually summarized via distribution boxplots. These approaches are consistent with previous water quality studies that used statistical and graphical methods to evaluate temporal changes in monitored water bodies [20,36,42–44]. Time-series linear regression was applied to identify increasing or decreasing trends during the study period. The regression slope was used to indicate the direction and magnitude of the trend, and statistical significance was evaluated at $p < 0.05$ (Table S2).

The clearest post-MVA change was observed for DO. The mean DO concentration increased from 8.71 mg/L in the pre-MVA period to 15.02 mg/L in the post-MVA period, corresponding to an increase of approximately 72.4% (Table S3). The box plot also shows a clear upward shift in DO after MVA installation, with the median increasing from 9.0 mg/L to 16.0 mg/L (Figure 4). The time-series regression showed a significant increasing trend for DO over the entire monitoring period, with a positive slope of 0.13584 mg/L per month ($p < 0.001$) (Figure 5f; Table S2). These results indicate that MVA installation coincided with a substantial improvement in oxygen conditions in the urban pond system. Similar findings have been reported in aeration-based water remediation studies, where oxygen transfer systems increased DO and improved water conditions [15,16].

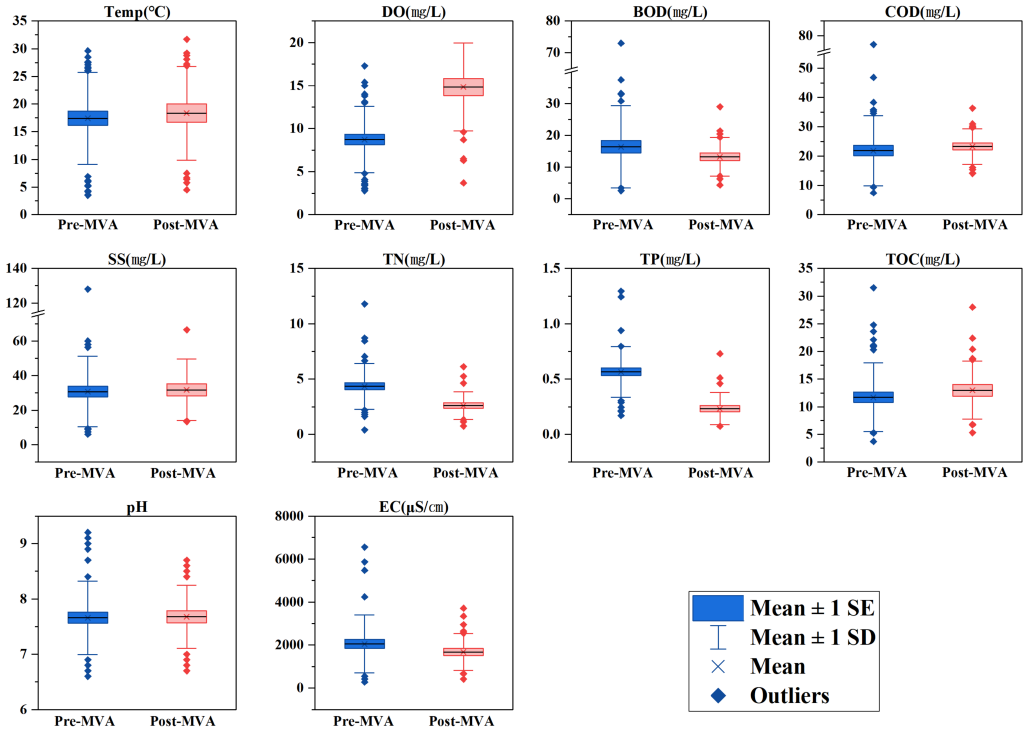


Figure 4. Box plots of water quality parameters during the pre-MVA (n = 45) and post-MVA (n = 27) periods.

Nutrient concentrations also decreased after MVA installation. The mean TN concentration decreased from 4.35 mg/L to 2.56 mg/L, corresponding to a reduction of approximately 41.2%, while TP decreased from 0.56 mg/L to 0.23 mg/L, corresponding to a reduction of approximately 59.6% based on the calculated dataset values (Table S3). These decreases are also visible in the box plots and time-series plots, where both TN and TP shifted to lower values during the post-MVA period (Figures 4 and 5b,c). Linear regression showed significant decreasing trends for TN and TP over the full study period, with slopes of −0.03921 mg/L per month and −0.00720 mg/L per month, respectively ($p < 0.001$) (Table S2). Previous studies have shown that nutrient control often requires additional nitrogen and phosphorus removal strategies beyond aeration alone. Lake nitrogen reduction depends on both watershed nitrogen load management and in-lake nitrogen removal processes [45]. For phosphorus, struvite crystallization has been reported as an effective recovery method, removing up to 70% of soluble phosphorus from water and wastewater [46]. In addition, calcium-rich biochar derived from waste mussel shells and spent coffee grounds showed high phosphate adsorption capacity and high removal efficiency in real water samples [47]. Therefore, although MVA improved DO and was associated with TN and TP reductions, long-term nutrient control in the Jangrim reservoir may require complementary nutrient management strategies. Improved aerobic conditions may support nitrification by promoting the oxidation of reduced nitrogen forms, while higher oxygen availability near the sediment–water interface can also reduce phosphorus release from sediments under some conditions.

However, because nitrogen transformation rates, sediment fluxes, and external inflow loads were not directly measured in this study, the observed TN and TP reductions should be interpreted as associated post-MVA improvements rather than direct mechanistic evidence of nutrient removal. Previous studies have shown that nitrogen and phosphorus can be reduced using biological treatment, sediment control, chemical precipitation, and adsorption methods. Therefore, although MVA improved DO and reduced TN and

TP, additional nutrient control methods may still be needed for long-term urban pond system restoration.

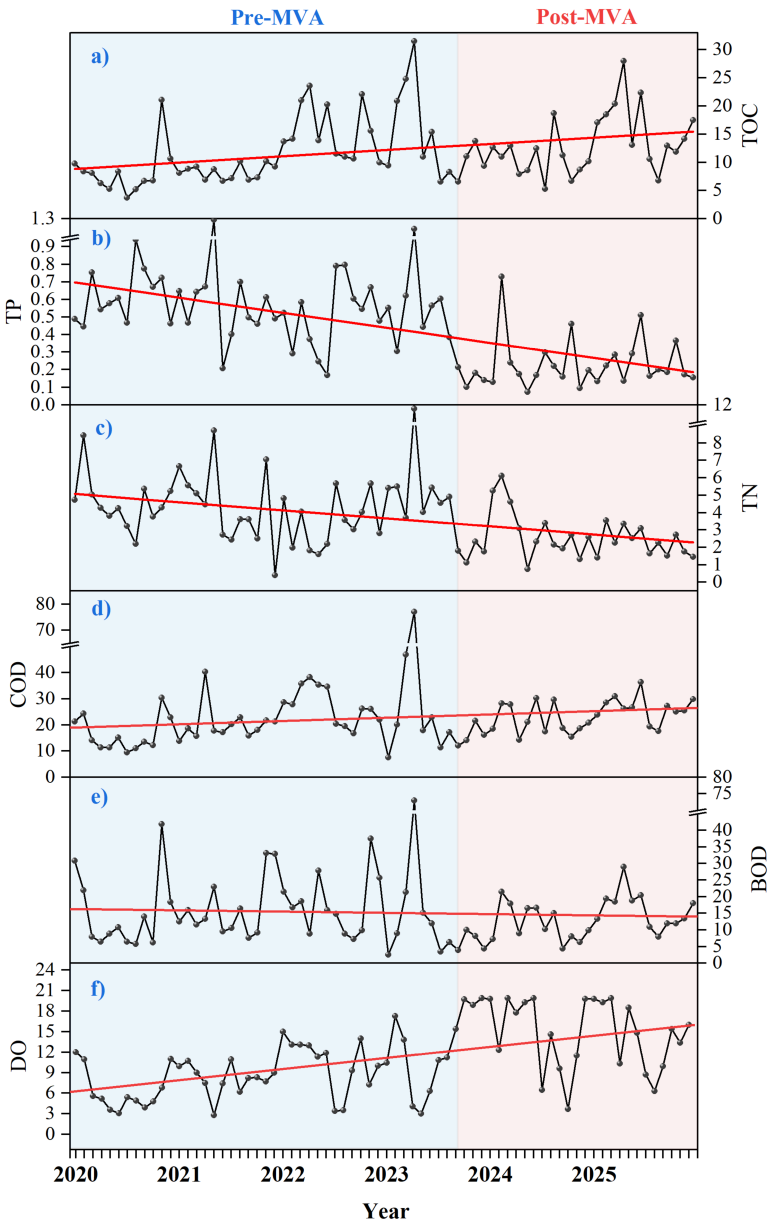


Figure 5. Time-series variation in selected water quality parameters pre- and post-MVA installation: (**a**) TOC, (**b**) TP, (**c**) TN, (**d**) COD, (**e**) BOD, and (**f**) DO.

Organic matter indicators showed mixed responses. BOD decreased from 16.35 mg/L to 13.28 mg/L, corresponding to an approximate reduction of 18.8% (Table S3; Figures 4 and 5e), but the time-series regression did not show a statistically significant trend (Table S2). COD increased slightly from 22.32 mg/L to 23.35 mg/L, corresponding to an approximate increase of 4.6% (Table S3; Figure 5d), and its increasing regression trend was not statistically significant (Table S2). TOC increased from 11.60 mg/L to 13.13 mg/L, and the regression result showed a significantly increasing trend over the study period (Table S3; Figure 5a; Table S2). The observed decoupling between BOD reduction (−18.8%) and elevated TOC (+13.2%) provides key insights into the operational mechanisms of MVA. Enhanced oxygenation accelerates the aerobic breakdown of readily bioavailable (labile) organic matter, leading to a net decrease in BOD. However, this process yields incomplete organic mineralization, transforming labile compounds into refractory, bio-resistant organic

fractions (e.g., humic and fulvic substances) that contribute directly to measured TOC and COD pools. This persistent baseline of COD and TOC demonstrates that external urban runoff and anthropogenic loading into this shallow pond remained active throughout the monitoring period, with surrounding catchment land use practices remaining stable. These results indicate that organic matter conditions were not consistently improved after MVA installation. This mixed response is reasonable because BOD, COD, and TOC represent different fractions of organic pollution: BOD mainly reflects biodegradable organic matter, COD represents chemically oxidizable substances, and TOC includes the total organic carbon pool, including less biodegradable organic fractions. Therefore, these indicators may respond differently to aeration and oxygen enrichment [48].

SS showed almost no change between the two periods. The mean SS concentration slightly decreased from 31.50 mg/L to 31.10 mg/L, corresponding to only an approximate 1.3% reduction (Table S3). Combined pressures from land-based inflows, construction activity, suspended solids, and hydrological modification often affect urban and coastal water bodies in Korea. Previous work on Busan New Port and Jinhae Bay showed that large-scale coastal development can alter water quality and suspended solid dynamics [49]. These findings highlight the need to consider external and hydrodynamic pressures when evaluating restoration technologies in urban water bodies. This suggests that MVA operation had limited influence on particulate matter. SS is commonly controlled by external inflow, runoff, sediment resuspension, and hydraulic conditions rather than aeration alone. In addition, organic matter and suspended solids can continue to enter the urban pond system through watershed-related pollution sources, which have been widely reported as important controls on reservoir and river water quality [3,25,50].

Temperature, pH, and EC showed only minor average changes after MVA installation. Temperature increased slightly from 17.45 °C to 17.88 °C, while pH remained near neutral, increasing from 7.65 to 7.72. EC increased from 2039.50 μS/cm to 2277.37 μS/cm.

Overall, the pre/post comparison indicates that MVA installation was associated with a clear improvement in oxygen conditions and reductions in TN and TP. However, organic matter indicators, suspended solids, and ionic conditions did not show consistent improvement. These findings suggest that MVA operation can support oxygen enhancement in the Jangrim reservoir, but aeration alone is not sufficient to fully control organic pollution, particulate matter, or ionic inputs. Therefore, MVA should be considered as one component of an integrated reservoir management strategy, together with external load control, inflow management, and continuous water quality monitoring.

3.2. Multivariate Statistical Analysis

3.2.1. Correlation Analysis

Pearson's correlation analysis was conducted separately for the pre-MVA and post-MVA periods to evaluate changes in the relationships among water quality parameters after MVA operation. The analysis was used to identify shifts in parameter interactions rather than as direct evidence of MVA effectiveness. The significance levels were considered to identify statistically reliable associations (significance level marked as * $p < 0.05$, ** $p < 0.01$) (Figure 6). Before MVA operation, organic and particulate indicators showed strong and significant positive correlations, particularly BOD-COD, BOD-SS, COD-SS, COD-TOC, and SS-TOC, indicating that organic matter and suspended solids behaved as a closely connected pollution group [51] (Figure 6a). After MVA operation, these relationships remained mostly significant but became weaker in some cases, especially COD–SS, which decreased from r = 0.92 to r = 0.51 (Figure 6b). This suggests that the linkage between suspended solids and oxidizable organic matter was partially reduced under improved oxygen conditions.

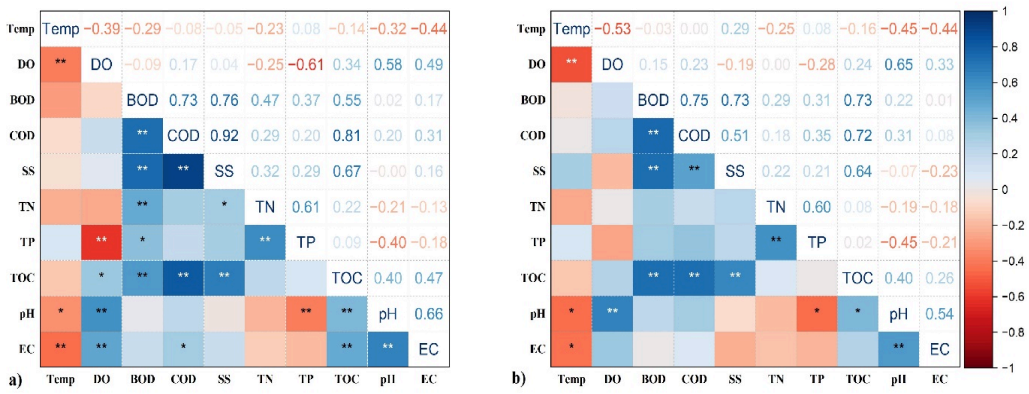


Figure 6. Pearson's correlation matrix for water quality parameters; (**a**) pre-MVA and (**b**) post-MVA installation period (* $p < 0.05$, ** $p < 0.01$).

DO showed a significant negative relationship with temperature in both periods (r = −0.39 and r = −0.53), confirming that seasonal thermal control continued to influence oxygen availability [36]. However, the DO–TP relationship weakened after MVA operation, from r = −0.61 to r = −0.28, suggesting that the association between low-oxygen conditions and phosphorus behavior became less pronounced. In contrast, the DO–pH relationship remained positive and significant, increasing from r = 0.58 to r = 0.65, indicating stronger coupling between oxygenation and physicochemical conditions after aeration. Overall, the significant correlations confirm that MVA operation was associated with a shift in the internal water quality structure, mainly affecting oxygen-related physicochemical interactions rather than uniformly changing all organic and nutrient parameters. These findings support Section 3.1, where DO showed the clearest improvement, while organic matter and nutrient responses were more variable and seasonally influenced. Similar correlation-based interpretations have been used in water quality studies to identify dominant parameter associations and pollution processes [16,36,40].

3.2.2. Principal Component Analysis (PCA)

Principal component analysis (PCA) was applied to ten selected water quality parameters to identify the dominant factors controlling water quality variation during the pre-MVA and post-MVA periods. PCA is widely used in water quality studies to reduce complex datasets and identify major pollution gradients or controlling processes [20,36,42,52]. PCs with an eigenvalue of 1.0 or greater were considered significant and therefore selected. The Promax method was selected as the rotation method because environmental parameters in reservoir systems naturally interact and exhibit inter-factor correlations [53,54]. The first two principal components explained 63.0% of the total variance, with PC1 and PC2 accounting for 34.2% and 28.8%, respectively. PC1 was mainly associated with COD, BOD, SS, and TOC, indicating an organic–particulate pollution gradient (Figure 7). These parameters loaded in the same direction, suggesting that oxidizable organic matter, biodegradable organic matter, suspended solids, and organic carbon behaved as a connected pollution group [36]. This result is consistent with the correlation analysis, where BOD, COD, SS, and TOC showed strong positive relationships. PC2 separated oxygen-related physicochemical parameters, mainly DO, pH, and EC, from nutrient- and temperature-related parameters, including TN, TP, and Temp. Post-MVA samples were relatively shifted toward the DO, pH, and EC vectors, while pre-MVA samples were more widely distributed toward organic matter, suspended solids, nutrients, and temperature (Figure 7). However, the overlap between the two groups indicates that MVA operation did not completely separate the pre-MVA and post-MVA conditions. Therefore, PCA suggests a partial shift in water quality

structure, mainly related to improved oxygen conditions, while organic matter and nutrient responses remained influenced by seasonal variation and external or internal loading.

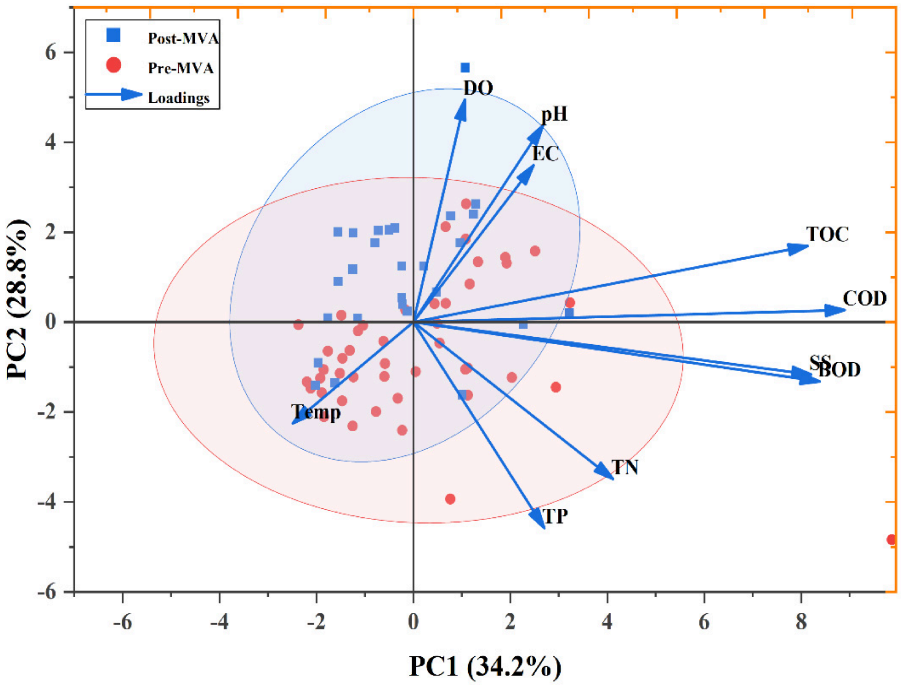


Figure 7. PCA biplot of the ten selected parameters for the pre- and post-MVA installation periods.

Promax-rotated (PR) PCA was used because water quality parameters are naturally related to each other, and this rotation provided a clearer factor structure with fewer cross-loadings [54]. Loadings with absolute values > 0.50 were considered meaningful for interpretation, following common practice in water quality PCA studies [20,25,36]. The results identified three main factors controlling water quality variation in the Jangrim reservoir (Table 2). PR1 had strong loadings for COD, SS, TOC, and BOD, with values of 0.954, 0.953, 0.842, and 0.739, respectively. This factor represents an organic–particulate pollution factor, showing that organic matter and SS were closely related. Similar organic and particulate groupings have been reported in previous water quality studies using PCA [20,36,51], which are often linked to external inflow, surface runoff, and sediment resuspension as key drivers of aquatic water quality [3,25,50]. In this study, PR2 represents a nutrient–oxygen interaction factor characterized by high positive loadings for total nitrogen (TN = 0.896) and total phosphorus (TP = 0.897) alongside a strong negative loading for dissolved oxygen (DO = −0.629). While this inverse relationship highlights nutrient enrichment driving oxygen depletion through heightened organic decomposition, higher DO levels serve a critical regulatory role by maintaining an oxic micro-layer at the sediment–water interface, which is consistent with previous studies linking nutrient enrichment and increased oxygen concentration in aquatic systems [16,36]. This supports the trend analysis, where DO increased while TN and TP decreased after MVA operation. PR3 was mainly related to temperature, pH, and EC, with loadings of −0.928, 0.651, and 0.752, respectively. This factor represents seasonal and physicochemical variation, indicating that temperature changes and ionic conditions also influenced urban pond system water quality. Seasonal physicochemical effects on water quality variation have also been reported in previous multivariate water quality studies [42,44,53].

Table 2. Promax-rotated PCA loadings of selected water quality parameters in the urban pond system.

Variables	Promax-Rotated PCAs			Main Factor
	PR1	PR2	PR3	
Temp (°C)	0.180	−0.339	**−0.928**	Seasonal/temperature
DO (mg/L)	0.128	**−0.629**	0.410	Nutrient–oxygen
BOD (mg/L)	**0.739**	0.393	0.104	Organic pollution
COD (mg/L)	**0.954**	−0.021	−0.023	Organic pollution
SS (mg/L)	**0.953**	0.055	−0.268	Particulate pollution
TN (mg/L)	0.106	**0.896**	0.225	Nutrient
TP (mg/L)	0.051	**0.897**	−0.025	Nutrient
TOC (mg/L)	**0.842**	−0.157	0.158	Organic carbon
pH	0.121	−0.309	**0.651**	Physicochemical
EC (μS/cm)	−0.009	−0.051	**0.752**	Ionic/physicochemical
Eigenvalue	3.42	2.88	1.41	
Variance explained (%)	34.21	28.84	14.10	
Cumulative variance (%)	34.21	63.06	77.01	

Note(s): Bold values show significant marks.

Overall, the Promax-rotated PCA showed that water quality variation was mainly controlled by organic–particulate pollution, nutrient–oxygen interaction, and seasonal physicochemical conditions. These results support the finding that MVA mainly improved oxygen and nutrient-related conditions, while organic matter and ionic characteristics remained affected by external and internal urban pond system processes. This interpretation is consistent with previous studies showing that multivariate analysis can identify dominant pollution sources and control processes in complex water quality datasets [20,36,50].

3.3. WQI Assessment and Relationship with PCA Results

Water quality was evaluated using CCME-WQI, RT-WQI, and NSF-WQI to compare the overall condition of the Jangrim reservoir before and after MVA operation. The WQI distributions are shown in Figure 8. Because these indices use different parameter sets, aggregation procedures, objective criteria, and weighting systems, their scores were interpreted separately rather than directly compared as equivalent values [34–36].

All three WQI models showed an upward shift after MVA installation, indicating an overall improvement in the integrated water quality condition. However, the magnitude and classification of improvement differed among the indices. CCME-WQI remained the most conservative index, increasing from 21.87 in the pre-MVA period to 28.74 in the post-MVA period while remaining within the Poor class (Figure 8b). This indicates that although some improvement occurred, several parameters continued to exceed the objective-based criteria. This result is consistent with the structure of CCME-WQI, which strongly reflects the frequency, amplitude, and number of water quality standard exceedances [34].

RT-WQI also increased after MVA operation, showing a moderate upward shift in the post-MVA period. The box plot and time-series pattern indicate that RT-WQI values became generally higher after installation, although fluctuations remained. This suggests that the post-MVA improvement was not uniform across all months. NSF-WQI showed the highest overall scores among the three indices and increased after MVA operation, indicating improvement from a conventional weighted-index perspective. However, because NSF-WQI uses a weighted aggregation approach, it may be less sensitive to individual parameter exceedances than CCME-WQI. Therefore, NSF-WQI can indicate moderate improvement even when some parameters remain problematic. The WQI results are consistent with the main water quality parameter analysis. The improvement in RT-WQI and NSF-WQI was mainly associated with the increase in DO and the reductions in TN and TP after MVA

installation. In contrast, the limited improvement in CCME-WQI reflects the continued influence of organic matter, suspended solids, ionic conditions, and remaining exceedances of water quality objectives. This interpretation is also supported by the PCA results, which showed that water quality was controlled by organic–particulate pollution, nutrient–oxygen interaction, and physicochemical variation, as commonly reported in previous water quality PCA studies [20,36,50,53].

Overall, the WQI results indicate that MVA operation improved the integrated water quality status of the Jangrim reservoir, mainly through oxygen enhancement and partial nutrient reduction. However, the urban pond system did not reach a high-quality condition after MVA installation. The persistently low CCME-WQI values show that aeration alone was not sufficient to fully address organic matter, suspended solids, ionic pollution, and other remaining water quality exceedances. Therefore, MVA should be considered supporting restoration technology rather than a complete standalone solution for urban pond system water quality improvement.

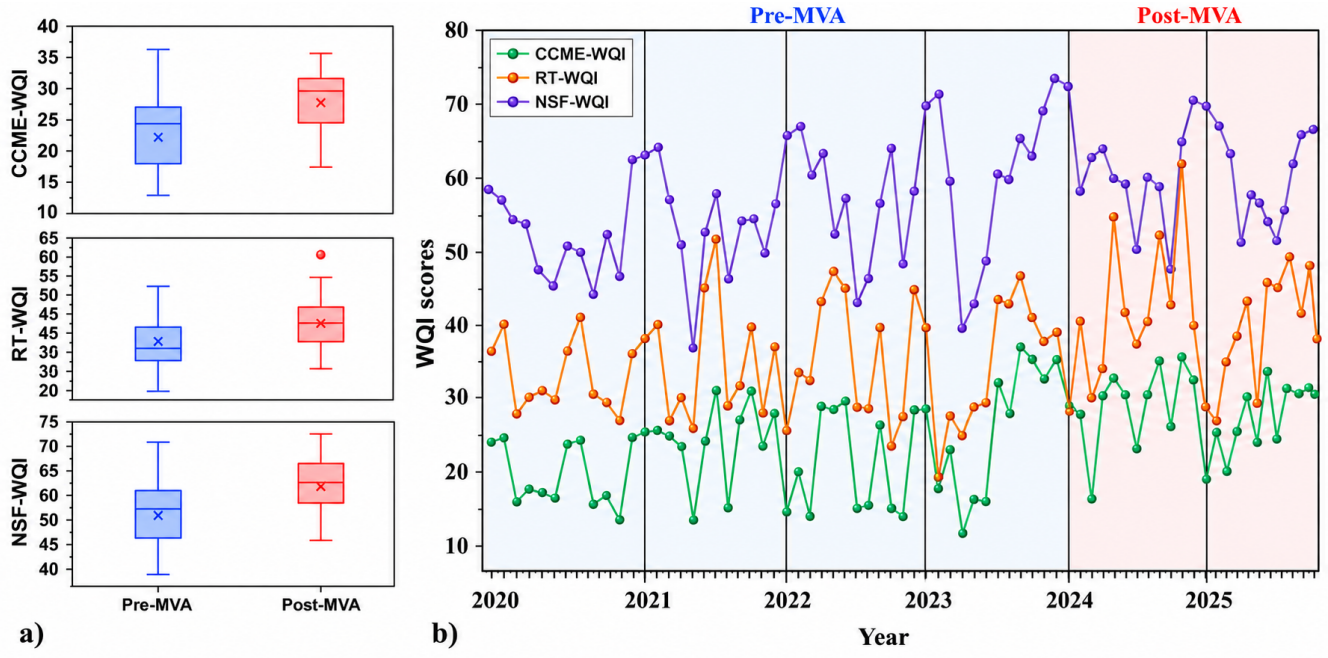


Figure 8. WQI variation before and after MVA installation: (**a**) box plots of CCME-WQI, RT-WQI, and NSF-WQI and (**b**) monthly time-series variation in the three WQI models.

3.4. Limitations of the Study

While this multi-year evaluation sheds light on the overall water quality responses associated with MVA in a shallow urban pond system, several practical and analytical limitations are worth keeping in mind. For starters, our monitoring focused on surface physicochemical and nutrient parameters without directly measuring sediment nutrient exchange rates, benthic oxygen demand, or microbial community shifts. Because of this, the observed drops in organic loading (BOD) and nutrients (TN and TP) reflect broader ecosystem trends rather than direct, measured proof of specific biochemical pathways.

Additionally, because the surface dissolved oxygen (DO) was already fairly well-oxygenated before installation (mean = 8.7 mg/L), our findings mostly capture physical mixing, water circulation, and redox-driven chemical changes. This naturally limits what we can conclude about how well MVA would handle reaeration and biological recovery in severely hypoxic or anoxic environments (DO < 2.0 mg/L). Tracking an open, urban water body over an extended window (2020–2025) also means dealing with natural environmental noise, like shifting weather patterns, seasonal rain, and variable urban runoff, which makes

it tricky to completely isolate MVA performance from external watershed inputs. Lastly, data availability meant that we had to omit a few traditional parameters (such as fecal coliforms and turbidity) when running our modified water quality indices (CCME-WQI, RT-WQI, and NSF-WQI). These index scores are best viewed as reliable internal benchmarks for tracking progress over time rather than direct matches for standard, full-parameter WQI models.

4. Conclusions

This study evaluated the multi-year water quality response of the Jangrim reservoir to multistage vortex aerator (MVA) operation using long-term monitoring data from 2020 to 2025. MVA deployment significantly improved system oxygenation, elevating mean dissolved oxygen (DO) from 8.7 to 15.0 mg/L (+72.4%). Concurrently, ambient nutrient concentrations decreased, with total nitrogen (TN) declining by 41.2% (from 4.35 to 2.56 mg/L) and total phosphorus (TP) by 58.9% (from 0.56 to 0.23 mg/L). These findings confirm that MVA-induced circulation and redox changes effectively alleviate surface nutrient pressure in urban pond systems.

However, the evaluation revealed key functional and operational insights:

(a) Artificial aeration alone failed to mitigate all organic and physical fractions. While BOD decreased by 18.8%, COD (+4.6%) and TOC (+13.2%) increased, SS remained virtually unchanged, and EC exhibited high variability due to ongoing watershed inputs and sediment dynamics.

(b) Despite localized parameter improvements, CCME-WQI remained within the "Poor" category, demonstrating that internal aeration cannot fully overcome external pollutant runoff or restore total system health.

(c) MVA operation elevated DO levels far above equilibrium (>15.0 mg/L), inducing rapid atmospheric off-gassing. Implementing automated feedback control systems to maintain target DO within an optimal range (6.0–10.0 mg/L) is essential to maximize transfer efficiency and prevent energy waste.

While MVA operation is a highly effective engineering tool for oxygenation and facilitating surface nutrient reductions, it cannot serve as a standalone restoration measure. Achieving sustainable water quality in urban reservoirs requires pairing artificial aeration with watershed-level external load reductions, runoff management, and targeted sediment control.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/w18172127/s1, Table S1. Technical specifications of the installed MVA system in the Jangrim reservoir, Table S2. Time-series linear regression trend analysis of selected water quality parameters over the study period, Table S3. Descriptive statistics of water quality parameters during the pre-MVA and post-MVA periods in the Jangrim reservoir.

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Conflicts of Interest: Author Jaebum Kim was employed by the company Joons Engineering Co., Ltd., 376, Mayu-ro, Siheung 15055, Republic of Korea. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationship that could be construed as potential conflicts of interest.

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