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Comprehensive Water Quality Assessment Using Korean Water Quality Indices and Multivariate Statistical Techniques for Sustainable Water Management of the Paldang Reservoir, South Korea

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Abstract: The Paldang Reservoir (PDR) in South Korea is vital for supplying drinking water and maintaining ecosystems; thus, a comprehensive understanding of its water quality is necessary. Spatiotemporal changes in reservoir water quality were evaluated by applying Korean water quality indices and multivariate statistical techniques (MSTs). A dataset of 15 water quality parameters at five sites in the PDR were evaluated from 2017 to 2021. The organic matter, suspended matter, total phosphorus (TP), chlorophyll *a* (Chl-*a*), and total coliforms in the PDR exhibited a fair grade or higher. Chemical oxygen demand was found to correlate with biochemical oxygen demand, Chl-*a*, and TP. The average real-time water quality index (RTWQI) and average trophic state index (TSI_{KO}) of the PDR were excellent and mesotrophic, respectively, and 46% of eutrophic conditions occurred during the monsoon season. For a hierarchical cluster analysis (HCA), the five sites were grouped into three polluted areas and 12 months were grouped into dry and wet seasons. Principal component analysis and factor analysis identified four potential pollution sources (domestic sewage, industrial wastewater, intensive agricultural activities, and livestock wastewater) in the PDR and explained 79.7% of the total changes. Thus, the RTWQI, TSI_{KO}, and MSTs are useful tools for assessing freshwater quality in Korea, predicting potentially harmful conditions, and potentially assisting policymakers in PDR management.

Keywords: Paldang Reservoir; water quality index; trophic state index; sustainable water management; potential pollution source

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Citation: Cho, Y.-C.; Im, J.-K.; Han, J.; Kim, S.-H.; Kang, T.; Lee, S. Comprehensive Water Quality Assessment Using Korean Water Quality Indices and Multivariate Statistical Techniques for Sustainable Water Management of the Paldang Reservoir, South Korea. *Water* **2023**, *15*, 509. https://doi.org/10.3390/w15030509

Academic Editors: Zhongyao Liang, Feifei Dong, Chao Dai and Wei Gao

Received: 20 December 2022
Revised: 18 January 2023
Accepted: 25 January 2023
Published: 27 January 2023

1. Introduction

Reservoirs are important resources for freshwater ecosystems, providing drinking water, regulating the climate, maintaining biodiversity, and nitrate cycling [1]. Freshwater quality is affected by an increase in internal chemical oxygen demand (COD) caused by algal overproduction, the leaching of sediment pollutants, and incoming storm water runoff [2]. Anthropogenic factors, such as agricultural practices, urbanization, and industrialization, have gradually increased pressure and competition for sustainable water management in reservoirs [3,4]. Therefore, the efficient and systematic management of reservoirs is important for human health, maintaining freshwater ecosystem sustainability, and socioeconomic development [5,6].

Water quality assessment is helpful in identifying local pollution sources. To obtain reliable information on freshwater quality and to understand spatiotemporal changes in physical, chemical, and biological properties, continuous and reliable water quality assessments are crucial [7]. Water quality assessment is helpful in identifying local pollution sources. In recent years, researchers, limnologists, and water quality managers have proposed water quality assessment methods using various water quality indices (WQIs) depending on the research purpose, sample types, and size of the sampling area [8,9]. The WQI and trophic state index (TSI) are powerful mathematical tools created using comprehensive information on various complex water quality parameters to assess surface freshwater quality [10,11]. Moreover, they provide useful information for surface freshwater quality management by evaluating spatial and seasonal changes in water quality and nutritional status [12]. Various indices, such as the National Sanitation Foundation Water Quality Index, Florida Stream Water Index (FWQI), British Columbia Water Quality Index, Oregon Water Quality Index, and Canadian Council for Ministers of the Environment Water Quality Index (CCME WQI), have been successfully developed for and applied in water quality assessment [13,14]. These WQIs are usually applied to reflect specific local environments, such as water quality standards, toxic substances, and trace pollutants, or institutional conditions (e.g., water quality regulations, local environmental conditions, and trophic state) [12]. Since WQIs differ in statistical integration methods and parameter value interpretation, indices for the stable prediction of water quality, nutritional status, and comprehensive water quality assessment still need to be developed [15].

Multivariate statistical techniques (MSTs), such as agglomerative hierarchical cluster analysis (HCA), principal component analysis (PCA), and factor analysis (FA), are useful tools for interpreting large and complex water quality datasets in addition to evaluating their spatiotemporal variability [16,17]. An HCA was conducted to identify spatiotemporal water quality similarity information based on large-capacity entity data [18]. PCA and FA (PCA/FA) were used to identify the major factors that may affect water quality. MSTs have been widely applied in the identification of natural and anthropogenic factors that affect the physical, chemical, and biological properties of surface freshwater quality [18,19]; however, there are some limitations in applying MST alone to water quality assessment [20]. It cannot define the quantitative contributions of the identified pollution sources or surface freshwater quality. To minimize the limitations of MSTs and maintain their benefits, they must be combined with various WQIs, which will lead to the comprehensive assessment of surface freshwater quality (e.g., prediction of potentially harmful conditions, providing analysis insights, and decision-making solutions for water quality management and control) [21].

The Paldang Reservoir (PDR) in South Korea is an important water supply source for 27 million citizens in the Seoul metropolitan area (52% of the Korean population) and has been used for various purposes (e.g., fishing, recreation, irrigation, hydroelectric power) [22]; however, the Korean government has determined environmental policies with which to conserve the water quality of the PDR (e.g., areas for special countermeasures and total water pollution load management system (TPLMS)) and given priority to water quality management as well as safe water supply [23,24]. There is eutrophication and algal blooms in the PDR due to the increased human activities in the watershed (e.g., industrial wastewater discharge, intensive agriculture), changes in water circulation due to climate change (e.g., water temperature rise, dissolved oxygen reduction), and an increase in the inflow of nonpoint pollutants (e.g., N, P) [25,26]. According to a recent study, the water quality of reservoirs in Korea is closely related to the proportion of urban areas, farmland, and forests in the watershed (e.g., in the entire drainage basin) [27]. Moreover, during the stratification period, changes in the water temperature (WT) and dissolved oxygen (DO) concentrations lead to a series of water quality problems [2]. Currently, compared with other reservoirs in Korea, the PDR maintains fair water quality conditions in terms of biochemical oxygen demand (BOD) class Ib ($\leq$2 mg/L, good). Since there still exist uncertainties regarding future environmental changes in the PDR, data collection through regular monitoring programs as well as comprehensive water quality assessments for sustainable surface water quality management and control are required.

Sustainable water quality management and conservation can be achieved by accurately understanding the water quality and eutrophication status of the PDR in addition to determining the major factors that affect water quality. Therefore, this study aims to (1) evaluate the pollution characteristics of water quality parameters through quantitative analysis;

(2) examine the relationships among the quality parameters that affect the quality; (3) evaluate the spatiotemporal water quality and eutrophication status of the PDR by applying the Korean WQI and TSI_{KO}; and (4) identify major factors (natural and anthropogenic sources) that affect the spatiotemporal water quality of the PDR by applying MSTs.

2. Materials and Methods

2.1. Study Area

The PDR is a representative artificial lake constructed for the Paldang hydroelectric dam (37°31′35.0″ N, 127°16′44.6″ E) at a location joined by the South Han River (SHR), North Han River (NHR), and Gyoungan Stream (GAS) in 1974 [28,29]. The PDR is one of the largest reservoirs in Korea, with a surface area of 36.5 km^2 and a total capacity of 244×10^6 m^3. It has a mean depth of 6.5 m and a maximum depth of 25 m in front of the Paldang hydroelectric dam (PDD), and its annual water level fluctuation is very small [29]. It is very vulnerable to rainfall and pollutants because the average hydraulic residence time is relatively short (approximately 3.0–6.7 days) [11,26]. Additionally, PDR spatially exhibits various physical, chemical, and biological properties because the area from the inflow rivers (SHR, NHR, and GAS) to the PDD is longitudinally divided into river, transition, and lacustrine zones [30]. The SHR and NHR account for 55% and 42% of the inflow amount of the PDR, respectively, whereas the GAS represents only 3% [31]. The average annual temperature and precipitation of the PDR watershed over the past ten years (2012–2021) were 10.5 °C and 1319 mm, respectively, and it showed monsoon climate characteristics, in which approximately 54% of the precipitation occurred from June to August [32]. The land-use cover of the watershed was composed of 61.2% forest, 18.6% agricultural, 8.5% meadow, 5.8% urban, 2.5% barren, 2.5% water, and 1.0% wetland [33]. In this study, sampling sites were selected from the National Water Quality Monitoring Network (PD1–PD5) to identify the water quality characteristics of the PDR (Figure 1). The network forms a surveillance system with which to protect water supply sources and manage river water quality with prompt response measures in the event of a pollution accident by monitoring real-time water pollution accidents.

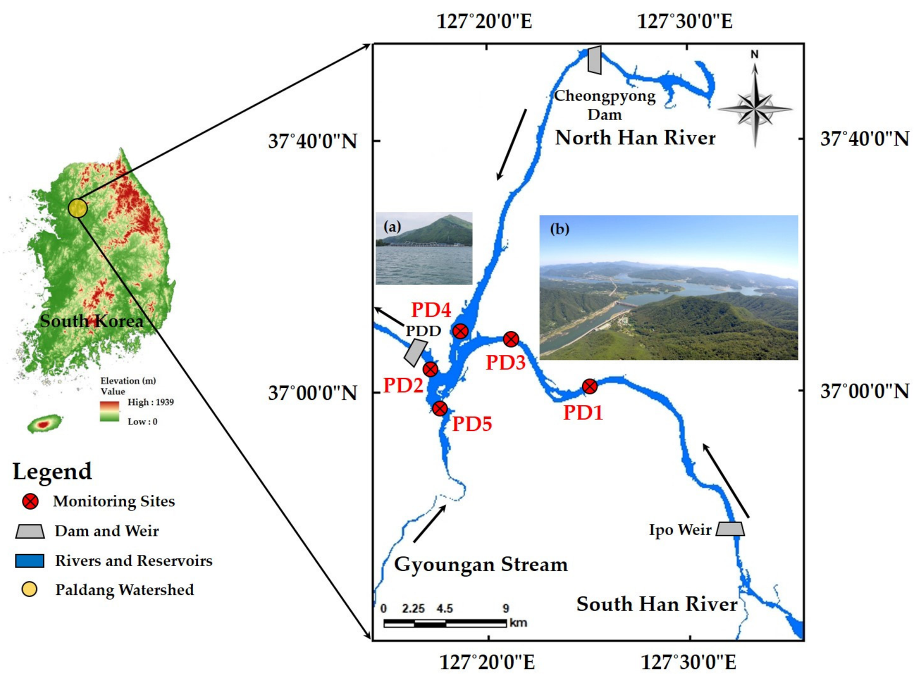

Figure 1. Map showing water quality monitoring network sites in the Paldang Reservoir (PDR), South Korea. (**a**) Paldang hydroelectric dam (PDD); (**b**) panoramic view of the PDR.

2.2. Water Sampling Collection and Analytical Methods

Water samples were collected once per month from January 2017 to December 2021. Water samples (280 in total) collected at the 5 monitoring sites were analyzed, and the information was interpreted. Sampling was performed at a surface point with the maximum water depth in the cross-section of each sampling site. At points with a maximum water depth of 5 m or higher, water from the surface, middle, and lower layers was mixed by using a water sampler (1010 Niskin Van Dorn sample bottle, 10 L) (only surface water was sampled at points with a maximum water depth of less than 5 m). The water samples were stored in polyethylene bottles (2 L), washed with 0.1 N HNO_3 solution, and transported to the laboratory in an ice box at 4 °C or less. Samples were collected, preserved, and transported according to water pollution process test standards (WPPTSs) [34].

The WT, potential of hydrogen (pH), electrical conductivity (EC), and DO were measured at the sites by using a multiparameter water quality sonde (EXO2, YSI Inc., Yellow Springs, OH, USA). The transparency of water was measured using a Secchi disk (ChemLab, Incheon, Republic of Korea) with a diameter of 30 cm. For the water samples, the concentrations of physical, chemical, and biological water quality parameters, including BOD, COD, total organic carbon (TOC), total suspended solids (TSSs), total nitrogen (TN), ammonium nitrogen (NH_3-N), nitrate nitrogen (NO_3-N), total phosphorus (TP), phosphate phosphorous (PO_4-P), chlorophyll *a* (Chl-*a*), and total coliforms (TCs), were determined according to the WPPTS method and standard protocol [35] (Table S1). Data quality (e.g., precision and accuracy) was verified through quality assurance and quality control (QA/QC) implementation in the laboratory. The laboratory owns an international proficiency test certificate in the field of water quality (WP289, W291) issued by the US Environmental Resource Associates in 2019 [36].

2.3. Real-Time Water Quality Index

In this study, the water quality of the PDR was assessed by applying the real-time water quality index (RTWQI) proposed by the National Institute of Environmental Research (NIER). The RTWQI is one of the WQIs created by modifying the CCME WQI model to fit the domestic water environment [37]. Unlike WQIs in many countries, the RTWQI can provide researchers, policymakers, and the general public with real-time water quality information through the Water Environment Information System (http://water.nier.go.kr/web (accessed on 14 November 2022)) [38]. The parameters required for the RTWQI calculation were WT, pH, EC, DO, turbidity, TOC, TN, and TP. In this study, the RTWQI was calculated by replacing turbidity with TSSs to investigate the influence of particulate matter on the PDR. Table S2 lists the reference ranges of the parameters for the RTWQI calculation [39]. The RTWQI was calculated by considering factors such as the number of parameters that exceeded the standards ($\boldsymbol{F_1}$), the frequency of water quality standards ($\boldsymbol{F_2}$), and the degree of violation ($\boldsymbol{F_3}$) (Table 1). The calculated RTWQI can be classified according to its score, as shown in Table 2.

Table 1. Detection parameters for RTWQI calculation [13,40,41].

Factor	Description	Formula
F_1 (scope)	This represents the extent of water quality guideline non-compliance over the time of interest; it is expressed by the percentage of variables (chemical indications) that do not meet the water quality standards (failed variables)	F_1 = (number of failed variables/total number of variables) × 100
F_2 (frequency)	This represents the frequency by which the objectives are not met; it is expressed by the percentage of individual tests that do not meet the quality standards ("failed tests")	F_2 = (number of failed tests/total number of tests) × 100

Table 1. *Cont.*

Factor	Description		Formula
F_3 (amplitude)	This represents the amount by which failed tests do not meet their objectives; it is calculated by an asymptotic function that scales the normalized sum of excursions (*nse*) from objectives to yield a range between 0 and 100		F_3 = (*nse*/0.01 nse + 0.01)
	Excursion	The number of times by which an individual concentration is greater than (or less than, when the objective is a minimum) the objective; it represents the relative deviation of a failed test from the guideline	$\text{excursion}_i = (\text{failed test value}_i / \text{Objective}_i) - 1$
	nse	This represents the collective amount by which individual tests are out of compliance	$nse = \left(\sum \text{excursion}_i\right) / \text{total number of tests}$
	RTWQI	Combines three measures of variance (F_1, scope; F_2, frequency; and F_3, amplitude) of excursions from objectives to produce a single unitless number that represents the overall water quality at a site relative to the benchmark chosen	$\text{RTWQI} = 100 - \sqrt{\frac{F_1^2+F_2^2+F_3^2}{3}}$

Table 2. Classification of surface water quality according to the RTWQI score and rating [39].

RTWQI Score	Rating	Signal	Description
$80 \leq \text{RTWQI} \leq 100$	Excellent		Water quality is protected with a virtual absence of threat or impairment; conditions very close to natural or pristine levels.
$60 \leq \text{RTWQI} \leq 79$	Good		Water quality is protected with only a minor degree of threat or impairment; conditions rarely depart from natural or desirable levels.
$40 \leq \text{RTWQI} \leq 59$	Fair		Water quality is usually protected but occasionally threatened or impaired; conditions sometimes depart from natural or desirable levels.
$20 \leq \text{RTWQI} \leq 39$	Marginal		Water quality is frequently threatened or impaired; conditions often depart from natural or desirable levels.
$0 \leq \text{RTWQI} \leq 19$	Poor		Water quality is almost threatened or impaired; conditions usually depart from natural or desirable levels.

2.4. Korean TSI

The influence of the eutrophication of rivers and reservoirs on humans and water bodies may differ depending on the region and country. In this study, the spatial and temporal nutritional status of the PDR was evaluated by using the Korean trophic state index (TSI_{KO}) proposed by the NIER. The TSI_{KO} is an indicator that excludes transparency and reflects COD instead of considering the characteristics of domestic reservoirs, which have short residence times and are considerably affected by allochthonous organic matter [42]. The TSI_{KO} is usefully expressed by using empirical equations for the water quality parameters (e.g., COD, Chl-*a*, and TP) surveyed in major domestic reservoirs, as shown in Equations (1)–(3) [12]:

$$TSI_{KO}\ (COD) = 5.8 + 64.4 \log\ (COD\ mg/L) \tag{1}$$

$$TSI_{KO}\ (Chl\text{-}a) = 12.2 + 38.6 \log\ (Chl\text{-}a\ mg/m^3) \tag{2}$$

$$TSI_{KO}\ (TP) = 114.6 + 43.3 \log\ (TP\ mg/L) \tag{3}$$

The TSI_{KO} (total) was calculated by assigning a weight of 50% to allochthonous COD and a weight of 25% to Chl-*a* and TP, which are autochthonous organic matter indicators, as shown in Equation (4):

$$TSI_{KO}\ (total) = 0.5\ TSI_{KO}\ (COD) + 0.25\ TSI_{KO}\ (Chl\text{-}a) + 0.25\ TSI_{KO}\ (TP) \tag{4}$$

The calculated TSI_{KO} was classified into four nutritional states: oligotrophic (≤30); mesotrophic (31–50); eutrophic (51–70); and hypertrophic (>71).

2.5. Data Treatment and MST

Prior to the statistical analysis, a Kolmogorov–Smirnov single-sample test was conducted to test the goodness-of-fit for the normal distribution of the water quality data [11,20]. A one-way analysis of variance (ANOVA) was conducted to identify significant spatial and temporal changes in the water quality parameters ($p < 0.05$). To examine the relationships between two or more variables, Pearson's correlation coefficient, which was statistically significant at $p < 0.05$, was considered.

HCA uses Ward's method and squared Euclidean distance to cluster the sampling sites and seasons as well as express them in a dendrogram ($D_{link}/D_{max} \times 100$) [17]. After the HCA, one-way ANOVA and post hoc analyses were conducted in order to examine which clusters had differences [36]. To test the suitability of the data for PCA/FA, the Keiser–Meyer–Olkin (KMO) and Bartlett's sphericity tests were conducted [19]. In this study, principal components (PCs) with an eigenvalue of 1.0 or higher were extracted, and varimax rotation was used to interpret the PCA results [17]. The loading of PCs generates verifactors (VFs), which are new orthogonal variables, through varimax rotation [7]. In this study, the VFs were classified as "strong", "moderate", and "weak" if their absolute loading values were >0.75, 0.75–0.50, and 0.50–0.30, respectively. HCA and PCA/FA were applied to standardized experimental data through z-scale transformation to eliminate the influence of the measurement unit and avoid the misclassification caused by large differences in data dimensions [20,43]. Multivariate statistical analysis was performed by using the Statistical Package for the Social Sciences (SPSS, ver. 22.0; IBM Corp., Armonk, NY, USA) software. Excel 2019 (Microsoft Corp., Redmond, WA, USA) was used for data processing and basic statistical analysis. Origin Pro 2021b (Origin Lab Corp., MA, USA) software was used for box plots and contour color filling to visualize the data analysis results.

3. Results and Discussion

3.1. Pollution Characteristics of Water Quality Parameters

In this study, 280 samples were collected at the National Water Quality Monitoring Network (PD1–PD5) points for five years (2017–2021) in order to investigate the pollution characteristics of the PDR water. Table 3 summarizes the descriptive statistical values of the 15 water quality parameters at the five sampling sites. In this study, the physicochemical and biological parameters, except WT, pH, and DO, showed significant spatial differences among the sites ($p < 0.05$). In particular, EC and TCs exhibited very large standard deviations compared with the other parameters. Such spatial changes in parameters indicate that the influence of anthropogenic factors is greater than that of natural factors [9].

WT is a critical parameter that regulates chemical reaction rates and affects aquatic microbes as well as material transfer [44]. The WT in the PDR ranged from 2.2 to 29.9 °C, with the average WT value being the lowest at site PD2 (13.5 °C). As PD2 is located in front of the PDD, it has the maximum water depth and a large watershed area, which remained the least affected by atmospheric temperature; pH, a measure of the acidity (pH of <7) or alkalinity (pH of >7) of water, is an index that represents the hydrogen ion concentration [45]. The average pH of the PDR was 8.0, indicating a weak alkalinity. EC is directly related to the concentration of solids dissolved in water and directly affects drinking and irrigation [45,46]. The EC value of the PDR varied considerably from 101 to 389 µS/cm. The highest average EC value (306 µS/cm) was observed at PD5. This was because the effluent discharged from a wastewater treatment plant (WWTP) was introduced into the GAS, which passes through the cities of Yongin and Gwangju [47]. DO is important for microbial metabolism and redox reaction regulation [48]. The average DO value of the PDR (10.7 mg/L) belonged to the Korean Water Pollution Standard (KWPS) Ia class (≥7.5, excellent), ensuring clean ecosystems without pollutants; however, hypoxia conditions (4.3 mg/L) were observed at PD2 because anaerobic conditions, where DO is insufficient or completely absent, were maintained in low layers of PD2 due to continuous thermocline formation in summer [49]. The natural mixing of water can supplement the oxygen in reservoirs and eliminate stratification [50]. The transparency of PDR ranged from 0.4 to 4.8 m. Site PD4 under the influence of the effluent from the Cheongpyong Dam (CPD) showed the highest average transparency value of 2.1 m.

Table 3. Descriptive statistics summary of physicochemical and biological parameters in monitoring sites and overall PDR water.

Parameter	PD1	PD2	PD3	PD4	PD5	Overall
WT (°C)	15.1 [a] ± 7.3 [b] (3.3 [c]–27.5 [d])	13.5 ± 7.5 (2.2–26.5)	15.2 ± 7.4 (3.4–28.3)	14.8 ± 7.5 (2.7–28.3)	16.8 ± 8.1 (2.9–29.9)	15.0 ± 7.6 (2.2–29.9)
pH	8.0 ± 0.4 (7.3–8.8)	7.9 ± 0.4 (7.2–9.7)	8.1 ± 0.4 (7.4–9.0)	7.9 ± 0.3 (7.0–8.7)	8.0 ± 0.4 (6.7–8.8)	8.0 ± 0.4 (6.7–9.7)
EC (μS/cm)	268 ± 33 (183–345)	197 ± 33 (125–253)	264 ± 35 (178–342)	156 ± 25 (101–210)	306 ± 41 (183–389)	237 ± 63 (101–389)
DO (mg/L)	10.7 ± 2.1 (6.5–14.0)	10.3 ± 2.2 (4.3–14.1)	10.9 ± 2.0 (6.9–14.4)	10.8 ± 1.8 (7.3–14.1)	10.9 ± 1.6 (6.8–14.3)	10.7 ± 2.0 (4.3–14.4)
Transparency (m)	1.7 ± 0.8 (0.5–4.8)	3.6 ± 1.7 (0.5–3.6)	1.5 ± 0.7 (0.4–4.1)	2.1 ± 0.8 (0.6–4.6)	1.1 ± 0.4 (0.4–1.9)	1.7 ± 0.8 (0.4–4.8)
BOD (mg/L)	1.3 ± 0.7 (0.4–3.1)	1.1 ± 0.3 (0.6–1.9)	1.6 ± 0.7 (0.5–3.4)	1.1 ± 0.3 (0.6–2.3)	2.2 ± 0.6 (1.2–7.2)	1.4 ± 0.7 (0.4–3.7)
COD (mg/L)	3.9 ± 0.7 (2.7–5.6)	3.8 ± 0.5 (3.0–5.2)	4.2 ± 0.8 (2.8–6.8)	3.5 ± 0.5 (2.8–5.5)	5.2 ± 0.8 (3.6–7.2)	4.1 ± 0.9 (2.7–7.2)
TOC (mg/L)	2.3 ± 0.4 (1.6–3.0)	2.2 ± 0.3 (1.5–2.7)	2.4 ± 0.4 (1.7–3.3)	2.0 ± 0.3 (1.5–2.8)	3.0 ± 0.5 (2.0–4.0)	2.3 ± 0.5 (1.5–4.0)
TSSs (mg/L)	6.1 ± 5.5 (1.0–36.3)	5.8 ± 3.7 (1.5–24.8)	6.9 ± 5.5 (1.4–36.2)	3.8 ± 2.1 (1.1–10.8)	9.1 ± 6.1 (2.0–43.4)	6.3 ± 5.1 (1.0–43.4)
TN (mg/L)	2.7 ± 0.4 (1.7–3.6)	2.2 ± 0.3 (1.4–3.0)	2.6 ± 0.4 (1.6–3.7)	1.9 ± 0.2 (1.4–2.4)	2.7 ± 0.7 (1.3–4.0)	2.4 ± 0.6 (1.3–4.0)
NH_3-N (mg/L)	0.059 ± 0.050 (0.005–0.313)	0.047 ± 0.029 (0.009–0.172)	0.051 ± 0.040 (0.008–0.247)	0.031 ± 0.026 (0.005–0.141)	0.097 ± 0.072 (0.009–0.350)	0.056 ± 0.051 (0.005–0.350)
NO_3-N (mg/L)	2.271 ± 0.365 (1.303–2.978)	1.838 ± 0.301 (1.105–2.374)	2.227 ± 0.395 (1.275–2.953)	1.578 ± 0.214 (1.159–1.973)	2.111 ± 0.625 (0.779–3.148)	2.003 ± 0.478 (0.779–3.148)
TP (mg/L)	0.044 ± 0.026 (0.014–0.156)	0.032 ± 0.019 (0.009–0.117)	0.047 ± 0.029 (0.018–0.179)	0.020 ± 0.010 (0.011–0.052)	0.049 ± 0.026 (0.020–0.188)	0.038 ± 0.026 (0.009–0.188)
PO_4-P (mg/L)	0.017 ± 0.017 (0.001–0.063)	0.007 ± 0.009 (0.001–0.048)	0.016 ± 0.018 (0.001–0.074)	0.003 ± 0.003 (0.001–0.012)	0.007 ± 0.008 (0.001–0.042)	0.010 ± 0.013 (0.001–0.074)
Chl-*a* (mg/m^3)	11.6 ± 9.8 (0.5–37.1)	13.0 ± 5.5 (5.2–31.2)	16.5 ± 10.8 (1.5–52.2)	11.1 ± 6.5 (2.8–40.6)	27.6 ± 14.8 (5.0–67.5)	15.8 ± 11.6 (0.5–67.5)
TCs (CFU/100 mL)	559 ± 1181 (1–4867)	348 ± 693 (2–3567)	703 ± 2126 (2–13,667)	430 ± 1007 (1–4500)	1046 ± 3102 (4–17,000)	607 ± 1830 (1–17,000)

Notes: [a] Mean; [b] standard deviation; [c] minimum; and [d] maximum. WT: water temperature; pH: potential of hydrogen; EC: electrical conductivity; DO: dissolved oxygen; BOD: 5-day biological oxygen demand; COD: chemical oxygen demand; TOC: total organic carbon; TSS: total suspended solids; TN: total nitrogen; NH_3-N: ammonium nitrogen; NO_3-N: nitrate nitrogen; TP: total phosphorus; PO_4-P: phosphate phosphorous; Chl-*a*: chlorophyll *a*; and TCs: total coliforms.

BOD is an important indicator for evaluating the pollution levels of rivers and reservoirs by using biodegradable organic matter. The average BOD value of the PDR was 1.4 mg/L, which corresponds to the KWPS Ib class (≤2.0, good). At most sampling sites, the average BOD value belonged to the KWPS II class (≤3.0, slightly good) or higher, ranging from 1.1 to 2.2 mg/L, indicating that there was enough pollution by organic matter. Unlike BOD, COD and TOC are indicators for evaluating the pollution level via total organic matter, including biodegradable and nonbiodegradable organic matter. The average COD and TOC values of the PDR were 4.1 and 2.3 mg/L, respectively, which correspond to the KWPS III class (≤5.0, fair) and Ib class (≤3.0, good), respectively, for the PDR. Site PD5 exhibited the highest average BOD/COD ratio (0.42), indicating that the proportion of biologically decomposed organic matter was higher than that of chemically decomposed organic matter. On the contrary, site PD2 had the lowest average BOD/COD ratio (0.30) as a large amount of nonbiodegradable organic matter is introduced to and accumulated at the site because of its location (in front of the PDD). The movement of suspended matter in reservoirs is affected by natural erosion and sediment transport processes [46]. The TSSs value of the PDR varied considerably from 1.0 to 43.4 mg/L and belonged to the KWPS III class (≤15.0, fair), with an average of 6.3 mg/L. The lowest average TSSs value was observed at site PD4 (3.8 mg/L) under the influence of the effluent from the CPD, which is located upstream [29].

Nutrients, such as nitrogen, phosphorus, and inorganic nitrogen (ammonia and nitrate), limit the growth of freshwater algae and play an important role in the eutrophication process [51]. The average TN value of the PDR (2.408 mg/L) exceeded the acceptable limit of the KWPS (≤1.5 mg/L). The average TP value of the PDR was 0.038 mg/L, which corresponded to the KWPS III class (≤0.05, fair) or higher. Nutrient pollution was highest at site PD5, which was related to agricultural runoff during the monsoon season, manure wastewater from human activities, and the use of fertilizers as well as pesticides from agricultural activities [47]. Since high levels of TP, TN, and other nutrients may further deplete DO by accelerating eutrophication, careful water quality management is required [45].

Chl-*a* is an important indicator that is used to manage eutrophication in rivers and reservoirs. The Chl-*a* value of the PDR ranged from 0.5 to 67.6 mg/m^3, with an average of 15.8 mg/m^3 and the highest average Chl-*a* value (27.6 mg/m^3) at PD5. There is no domestic criterion for Chl-*a* concentration in rivers and reservoirs, but the US Environmental Protection Agency proposed a Chl-*a* concentration of >30 μg/L in eutrophic rivers [52]. The average Chl-*a* concentration at the five sampling sites was ≤30 μg/L. Based on the Chl-*a* parameter, eutrophic rivers can reduce DO as well as interfere with the function of aquatic ecosystems, and long-term eutrophication may lead to algal blooms. TCs are a water pollution indicator that respond rapidly to environmental changes and are generally related to the commercial development of a target area [53]. The sources of TCs include rainwater discharge and agricultural as well as urban runoff [52]. The TCs of the PDR ranged considerably, from 1 to 17,000 CFU/100 mL. According to the KWPS, the water quality condition was found to be class Ib (≤500, good) at sites PD2 and PD4, class II (≤1000, slightly good) at sites PD1 and PD3, and class III (≤5000, fair) at site PD5.

3.2. Correlation of Physical, Chemical, and Biological Parameters

Important relationships between physicochemical and biological parameters were confirmed by using a Pearson correlation matrix ($p < 0.05$, Figure 2). There was a statistically significant positive correlation between COD and TOC in the PDR ($r = 0.914$, $p < 0.01$). COD was significantly positively correlated with BOD ($r = 0.851$, $p < 0.01$), Chl-*a* ($r = 0.801$, $p < 0.01$), and TP ($r = 0.509$, $p < 0.01$). COD showed higher correlation with TOC because organic matter decomposition was higher than BOD. TP showed a statistically positive correlation with TSSs ($r = 0.895$, $p < 0.01$) and TCs ($r = 0.520$, $p < 0.01$). Phosphorus in inorganic pollution is a nutrient indicator, and increasing nutrients increases organic matter concentration. Water pollution by these pollutants may occur because of agricultural activities, domestic wastewater, and aquaculture [9]. Since nutrients can flow into the PDR together with organic matter and cause algal blooms based on these correlations, urgent measures and management are required for water pollution control [52]. There was a statistically significant negative correlation between WT and DO ($r = -0.850$, $p < 0.01$) because the solubility of oxygen in water decreases with an increase in temperature [54]. There was a statistically positive correlation between pH and DO ($r = -0.499$, $p < 0.01$), indicating that a high photosynthesis rate increases the pH of the water [10]. EC was significantly positively correlated with TN ($r = 0.544$, $p < 0.01$) and TOC ($r = 0.462$, $p < 0.01$). EC can be increased by wastewater discharge from the local WWTP and drainage returned from agricultural irrigation along rivers [19]. The PDR, a river reservoir in the Han River system, is exposed to all of these effects [29]. TSSs showed a statistically significant positive relationship with TP ($r = 0.895$, $p < 0.01$), indicating that suspended particles tend to adsorb phosphorus [55]. Chl-*a* had the highest statistically positive correlation with BOD ($r = 0.854$), followed by COD ($r = 0.801$) and TP ($r = 0.746$) ($p < 0.01$). Changes in algae that feed on high concentrations of inorganic nutrients cause an increase in organic matter in rivers and reservoirs [56]; however, Chl-*a* showed no statistically significant correlation with DO, which is important for microbial metabolism ($p > 0.05$). There was a strong positive correlation between TP and TC levels ($r = 0.520$, $p < 0.01$). This indicates that nutrient enrichment in a reservoir considerably affects TC growth and may determine the utility of the water [46].

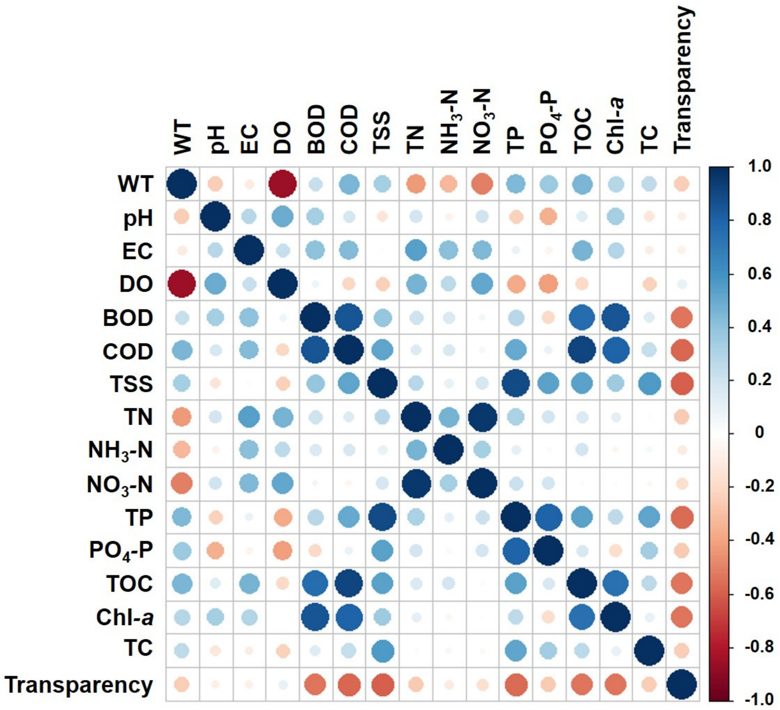

Figure 2. Pearson correlation matrix between physicochemical and biological parameters in the PDR.

3.3. Korean WQI Assessment

3.3.1. Spatial and Seasonal Characteristics of the RTWQI

To determine the utility and potential pollution level of PDR water, the RTWQI was calculated at the five sampling sites, considering eight different physical and chemical water quality parameters (Table S3). The RTWQI of PDR water ranged from fair (45) to excellent (100) during the monitoring period, with an average score of 81, which corresponds to the excellent grade, indicating clean water quality with few pollutants (Table S3). The Korean RTWQI shows cleaner water quality as its score increases (Table 2). The RTWQI of the PDR was distributed in the order of good (48%) > excellent (44%) > fair (8%). Figure 3 shows the average RTWQI calculated at the five PDR sampling sites. Site PD4, which had the highest average RTWQI score (95), showed excellent (98%) and good (2%) grades during the monitoring period. Site PD2 (85) exhibited the second highest average RTWQI score, followed by PD1 (79), PD3 (77), and PD5 (66). Relatively good water quality was maintained at all sampling sites because the grades were higher. WQIs with a low score are mainly affected by industrial and domestic wastewater, agricultural runoff, and various anthropogenic activities, including the direct drainage of untreated water from factories [56,57]. In particular, PD5 was included in the good water quality category, but its RTWQI score was low because the concentrations of EC, TSSs, TOC, and TN, which affect the calculation of the RTWQI, were relatively higher than those at other sampling sites (Figure 4).

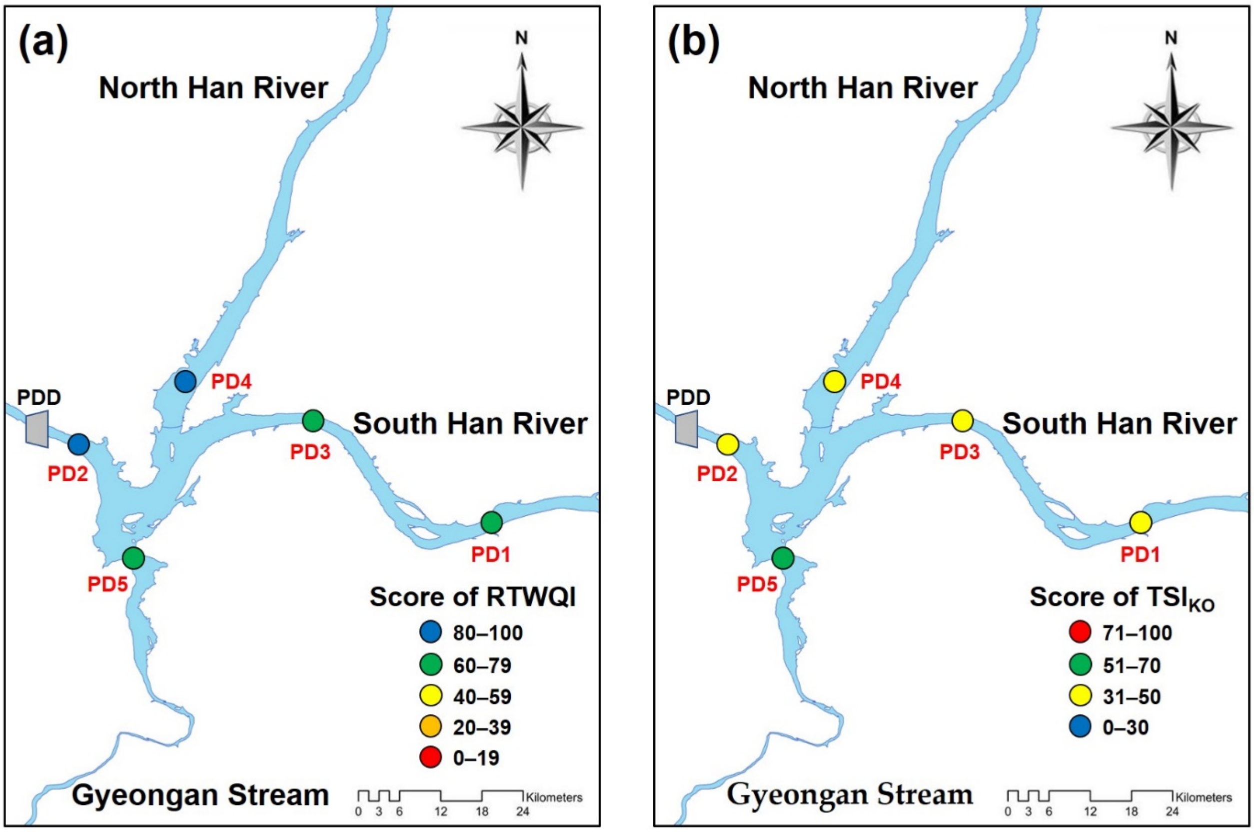

Figure 3. Korean water quality indicators in the PDR. (**a**) Real-time water quality index (RTWQI); (**b**) Korean trophic state index (TSI_{KO}).

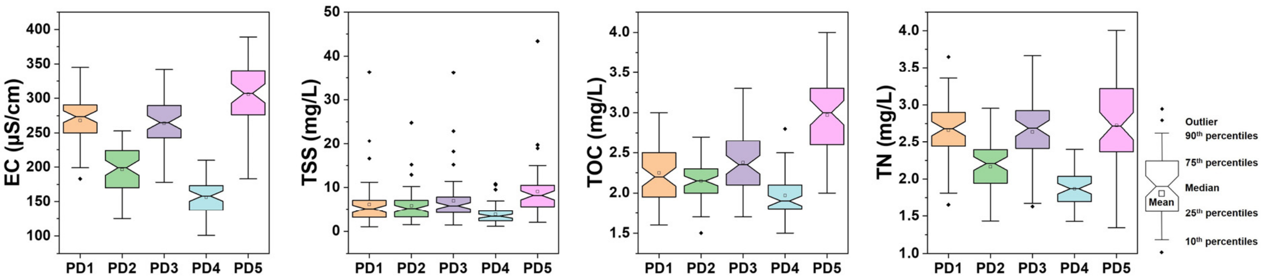

Figure 4. Boxplot graph of water quality parameters that affect the calculation of the RTWQI.

To investigate the seasonal characteristics of the RTWQI of the PDR, a heatmap was drawn by calculating the monthly average RTWQI score at the sampling sites (Figure 5a). The collected data were divided into pre-monsoon (January to June), monsoon (July to September), and post-monsoon (October to December) data to evaluate RTWQI characteristics by season. The average RTWQI was 83 (57–100) and 82 (53–100) in the post-monsoon and pre-monsoon seasons, respectively, which correspond to an excellent grade; however, in the monsoon season, a good grade was observed with an average of 74 (45–100). Therefore, the seasonal RTWQI of the PDR showed no significant difference ($p > 0.05$), and the RTWQI of the PDR was found to be more affected by anthropogenic factors than the season. There were significant changes in the parameters (EC, TSSs, TOC, TN and TP), except for WT, pH, and DO, that affected the RTWQI calculation.

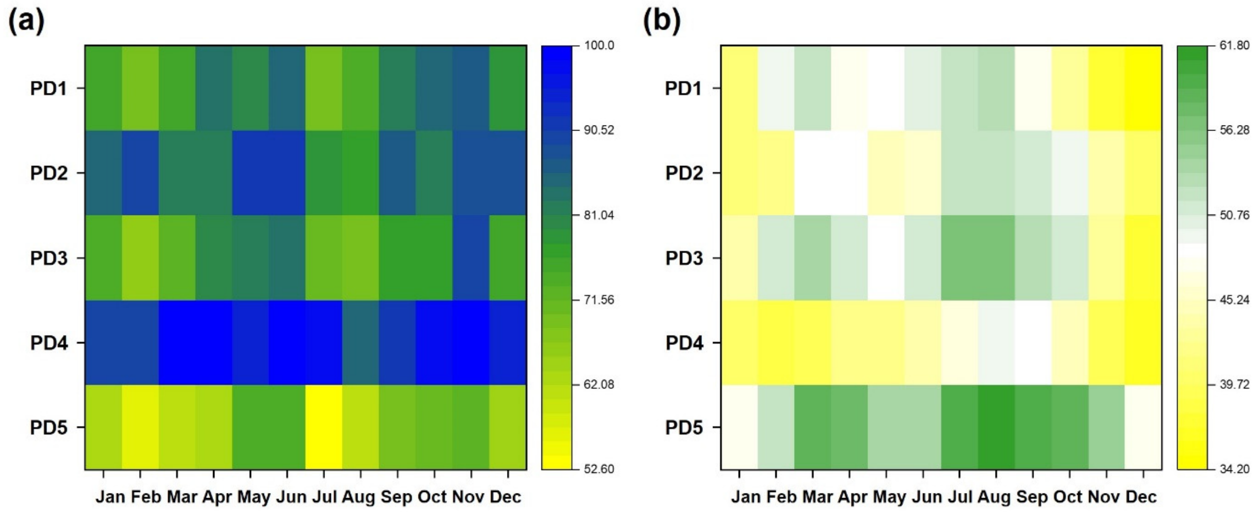

Figure 5. Temporal variations (heat map) graphic of Korean water quality indicators in the PDR. (**a**) RTWQI; (**b**) TSI_{KO}.

The excellent grade of the PDR was more dominant in the post-monsoon season (50%) than in the pre-monsoon (46%) and monsoon seasons (28%); however, the good and fair grades were more dominant in the monsoon season (52%) than in the pre-monsoon and post-monsoon seasons (20%). In particular, the excellent grade was always maintained at sites PD2 and PD4 in the pre-monsoon and post-monsoon seasons, except during the monsoon season. On the other hand, a fair grade (70%) was continuously observed at site PD5 during the monsoon season. Therefore, it is necessary to perform effective water quality management and control by identifying factors and pollutants that spatially and seasonally affect the RTWQI through an on-site survey of site PD5.

3.3.2. Spatial and Seasonal Characteristics of TSI_{KO}

The TSI_{KO} was calculated by applying the water quality data collected from the five sampling sites once a month to Equations (1)–(4) (Figure 3b). Furthermore, the period was divided into pre-monsoon (January to June), monsoon (July to September), and post-monsoon (October to December) in order to evaluate the seasonal TSI_{KO} characteristics of the PDR (Figure 5b). The nutritional status of the PDR showed spatial and seasonal changes based on TSI (COD), TSI (TP), and TSI (Chl-*a*). These results are similar to those of a study on the nutritional status of Korean reservoirs [58]. The TSI_{KO} of the PDR spatially showed oligotrophic to eutrophic conditions and maintained mesotrophic conditions on average. The average TSI_{KO} for each site was evaluated as mesotrophic at PD1 (47), PD2 (47), PD3 (50), and PD4 (43), except for site PD5. Site PD4 showed mesotrophic conditions during the entire period, whereas site PD2 exhibited mesotrophic conditions in the pre- and post-monsoon seasons. In particular, site PD5 was found to be eutrophic over the entire period compared with the other sites (Figure 3b). Regardless of the season, eutrophication can decrease DO, interfere with ecosystem functions, and affect the quality of intake water in the PDR [46]. As site PD5 is located in the GAS, the stagnation caused by the increased residence time of the SHR and NHR has a large impact on the drinking water quality of the PDR due to a marked increase in algal-growth-limiting nutrients [59].

The average TSI (COD) of the PDR was not eutrophic during any season. In contrast, the average TSI (TP) and TSI (Chl-*a*) showed eutrophic conditions during the monsoon season. The PDR was oligotrophic mainly in the post-monsoon season, and hypertrophic conditions did not occur in all of the seasons; however, mesotrophic and eutrophic conditions were observed over the entire period. In particular, the mesotrophic condition of the PDR was dominant in the pre-monsoon season (49%) and eutrophic conditions were dominant in the monsoon season (46%). The eutrophic condition of the PDR was aggravated in the monsoon season because an environment suitable for algal growth was created as nutrients were introduced from upstream areas due to low rainfall compared with normal years, and both intermittent rainfall as well as WT were increased by recent heat waves. Considering the results of this study, it is necessary to prepare appropriate measures with which to control the spatial and seasonal occurrence of eutrophic conditions in the PDR.

3.4. Multivariate Statistical Analysis

3.4.1. Spatial Similarity Grouping

In this study, an HCA was used to classify the spatial (sampling sites) and temporal (seasonal) water quality similarities in the PDR into groups. The HCA group showed high internal homogeneity and external heterogeneity [46]. The spatial HCA of the PDR formed a dendrogram in which all five sampling sites were grouped into three clusters that were statistically significant at $(D_{link}/D_{max}) \times 100 < 50$ (Figure 6; $p < 0.05$). The dendrogram is used to provide a visual summary of the clustering process, and it presents a description of groups and proximity to considerably reduce the dimensions of the original dataset [36]. Cluster 1 consisted of two sites (PD1 and PD3), which were affected by the effluent from the Ipo Weir located in the SHR. Cluster 2 also consisted of two sites (PD2 and PD4), which were affected by the clean effluent from the CPD located in the NHR. Site PD5 of cluster 3 was affected by the GAS and wastewater that was directly discharged from the two WWTPs. Therefore, the spatial HCA of the PDR suggests that the sampling sites were affected by similar sources and natural backgrounds (geographical locations) [16]. To identify the water quality characteristics of the clusters, the average values and standard error (SE) of the water quality parameters are presented in Table 4. For cluster 3, COD, Chl-*a*, and TC concentrations exhibited substantially higher pollution (HP) than the other clusters, except for the pH, DO, and transparency parameters; however, for cluster 2, very low pollution (LP) was observed for all of the water quality parameters. Cluster 1 showed moderate water pollution between clusters 2 and 3. This also indicates that the NHR has the highest quality of water, followed by the SHR and the GAS. A one-way ANOVA and a post hoc analysis were conducted to examine the reliability of the HCA and the average difference between the clusters. The one-way ANOVA results showed that WT, DO, TSSs, Chl-*a*, and TCs at site PD5 (cluster 2) were remarkably different from those at sites PD2 and PD4 (cluster 3) ($p < 0.05$). The post hoc analysis results showed that there was no statistically significant difference between clusters 2 and 3 ($p > 0.05$), and that cluster 1 was significantly different from clusters 2 and 3 ($p < 0.05$).

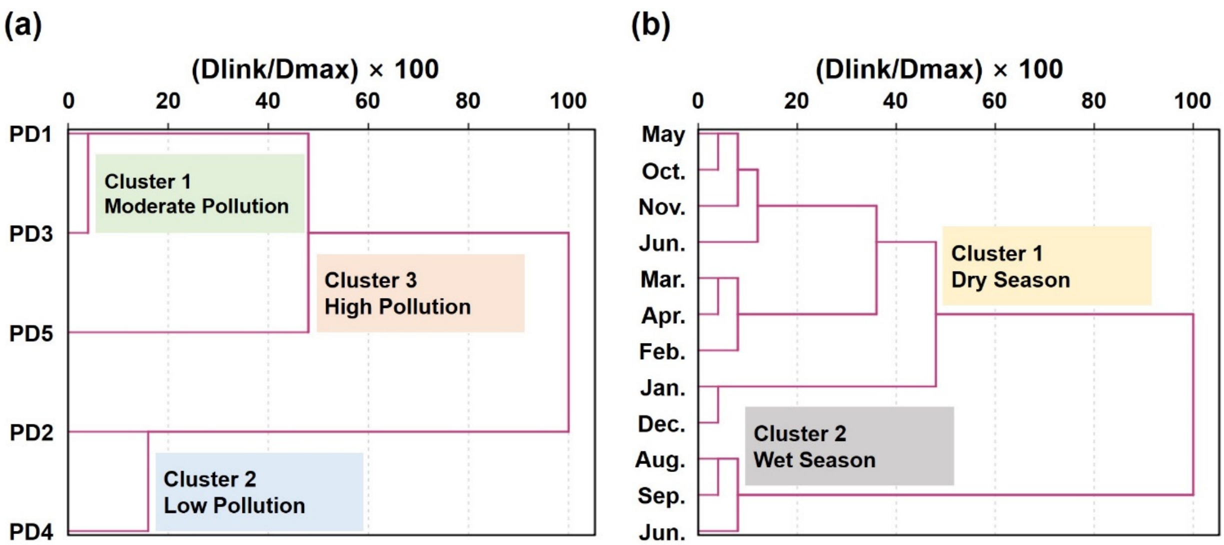

Figure 6. Dendrogram showing hierarchical clustering of (**a**) sampling sites; (**b**) seasons according to Ward's method with squared Euclidean distance.

Table 4. Mean values with standard error (SE) and ANOVA for water quality parameters in clusters of the sampling sites.

Parameter	LP		MP		HP	
	Mean	SE	Mean	SE	Mean	SE
WT	14.1	7.54	15.2	7.40	16.8	8.13
pH	7.9	0.39	8.1	0.37	8.0	0.39
EC	177	35.67	266	34.53	306	41.89
DO	10.5	2.04	10.8	2.04	10.9	1.61
Transparency	1.9	0.76	1.6	0.78	1.1	0.38
BOD	1.1 (Ib)	0.32	1.4 (Ib)	0.74	2.2 (II)	0.62
COD	3.6	0.49	4.1	0.80	5.2	0.85
TOC	2.1 (Ib)	0.27	2.3 (Ib)	0.40	3.0 (Ib)	0.52
TSS	4.9	3.18	6.5	5.50	9.1	6.17
TN	2.023 (VI)	0.33	2.651 (VI)	0.42	2.726 (VI)	0.70
NH_3-N	0.039	0.03	0.055	0.05	0.097	0.07
NO_3-N	1.714	0.29	2.249	0.38	2.111	0.63
TP	0.026 (Ib)	0.02	0.045 (III)	0.03	0.049 (III)	0.03
PO_4-P	0.005	0.02	0.016	0.02	0.007	0.01
Chl-*a*	12.1 (II)	6.07	14.0 (II)	10.64	27.6 (IV)	14.91
TC	387	861.06	629	1716.44	1046 (III)	3131.83

Notes: Units (mg/L), except for pH, WT (°C), EC (μS/cm), Chl-*a* (mg/m^3), and TCs (CFU/100 mL). LP: low pollution (cluster 2); MP: moderate pollution (cluster 1); and HP: high pollution (cluster 3). The Korean Water Pollution Standard classes are Ia (very good), Ib (good), II (slightly average), III (fair), IV (slightly poor), V (poor), and VI (very poor).

3.4.2. Seasonal Similarity Grouping

The seasonal HCA of PDR grouped 12-month data for five years (2017–2021) into two clusters that were statistically significant at $(D_{link}/D_{max}) \times 100 < 50$ (Figure 6b; $p < 0.05$). The two clusters corresponded closely to the dry season (DS) and wet season (WS) according to precipitation in Korea. In the one-way ANOVA results, all parameters, except BOD, showed a statistically significant seasonal difference ($p < 0.05$) (Table S4). A previous study reported that summer in Korea had a significant influence on hydrology, suspended solids, and nutrient concentrations in reservoirs compared with other seasons owing to the concentration of precipitation ($p < 0.05$) [60]. COD and TOC concentrations in the PDR were higher in the WS than in the DS (Table S4). This supports the view that the summer monsoon is the main driver of high levels of organic matter in reservoirs in East Asian countries such as China and Japan [61]. Organic matter in reservoirs can have allochthonous or autochthonous origins [46]. While allochthonous organic matter is mainly introduced into water systems through runoff derived from terrestrial water flow during rainfall events, autochthonous organic matter is generated through photosynthesis by phytoplankton [59]. TSS, TP, and Chl-*a* also exhibited higher concentrations in WS than in DS (Table S4). Regression analysis results between TSS and TP in WS showed that approximately 88% of the variation in TSS could be explained by TP (Figure S1). This indicates that TSS may act as a nutrient carrier in the PDR [62]. This also explains why autochthonous production by Chl-*a* is important for phosphorus accumulation. Therefore, for the seasonal water quality characteristics of the PDR, it can be said that WS poses a larger water pollution threat than DS. The HCA technique used in this study was found to be useful for clustering spatial and seasonal water quality similarities across the PDR. It also showed that future sampling strategies can be developed in an optimal manner for economic feasibility and efficiency of sampling.

3.4.3. PCA/FA

PCA/FA was conducted on the normalized dataset for the 15 water quality parameters over five years (2017–2021) at the five sampling sites in the PDR. The PCA/FA extracted PCs that affected the water quality of the PDR and identified potential pollution sources. The KMO and Bartlett's sphericity tests were conducted to determine the validity of the

PCA. For the KMO test, the validity increases as the value of the variable for the data is closer to 1.0, and values less than 0.5 are not allowed [63]. The Bartlett's sphericity test was used to test the null hypothesis that the correlation matrix between variables is a unit matrix. The relationship becomes more significant as the correlation between the variables increases, and the significance increases as the value approaches zero [36]. For the normalized dataset of the PDR, the KMO and Bartlett's sphericity test results were 0.742 and 5307 (df = 120, $p < 0.001$), respectively. This rejects the null hypothesis that the correlation matrix is a unit matrix and explains that PCA can be performed because there is a statistical significance between the water quality variables. When PCA was conducted, eigenvalues that explained 79.7% of the total variance extracted were >14 PCs. Table S5 explains the total variance and shows the amount of data that can be interpreted by each PC, as well as its proportion and cumulative amount. The scree plot also showed changes in eigenvalues according to the number of PCs (Figure 7) [16]. This means that the 15 variables can be explained by using the four PCs.

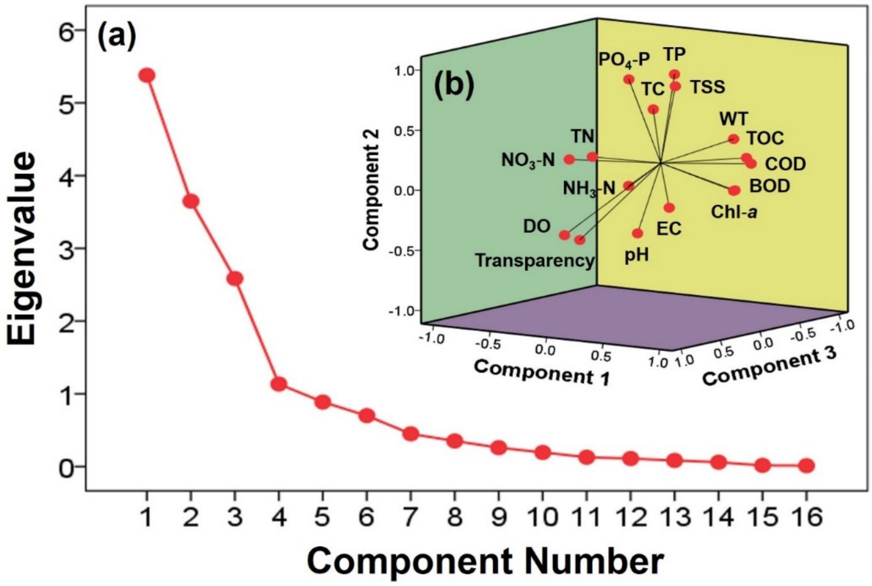

Figure 7. Principal component analysis of measured parameters by (**a**) screen plot of the characteristic roots (eigenvalues); (**b**) component plot in rotated space.

The FA identified four VFs through varimax rotation on the extent to which each PCs can interpret different variables. Table 5 presents the variable loadings for each VF. In this study, VFs with a correlation higher than 0.70 were considered strong. VF1, which represents 26.67% of the total variance, showed strong positive loading (>0.70) for BOD, Chl-*a*, COD, and TOC, as well as moderate negative loading (>0.50) for transparency. VF1 represents the organic matter concentration in the PDR because phytoplankton growth becomes an organic matter supply source in the reservoir and represents a considerable portion of the organic carbon concentration. Additionally, the negative contribution of transparency is related to high levels of organic matter and algal growth [46]. VF2, which represents 22.07% of the total variance, showed strong positive loading (>0.70) for TP, TSS, and PO_4-P in addition to moderate positive loading (>0.50) for TCs. This indicates that VF2 is related to the sediment deposited at the bottom of the water body as well as untreated domestic and municipal sewage. VF3, which represented 17.62% of the total variance, exhibited strong positive loading (>0.70) for DO and NO_3-N in addition to strong negative loading (>0.70) for WT. It also showed moderate positive loading (>0.50) for TN and pH. VF3 explains the ionic substances introduced from the runoff caused by seasonal changes, as well as livestock and agricultural activities in the reservoir. VF4, which represents 13.20% of the total variance, exhibited strong positive loading (>0.70) for EC and NH_3-N. VF4 can explain the influence of effluents from the WWTPs. Based on the PCA/FA results, municipal sewage, domestic sewage, industrial wastewater, intensive agricultural activities, and livestock wastewater were identified as potential sources of water pollution in the PDR.

Table 5. Loading of the 15 experimental variables on significant principal components for the dataset.

Variable	VF1	VF2	VF3	VF4
WT	0.337	0.301	**−0.772**	−0.207
pH	0.441	−0.277	*0.591*	−0.181
EC	0.401	−0.134	0.134	**0.751**
DO	−0.012	−0.298	**0.868**	0.137
Transparency	*−0.565*	−0.536	−0.116	0.033
BOD	**0.929**	0.052	0.074	0.117
COD	**0.896**	0.236	−0.195	0.204
TOC	**0.838**	−0.536	−0.116	0.260
TSS	0.350	**0.851**	−0.017	0.025
TN	0.072	0.329	*0.634*	0.632
NH_3-N	0.026	0.007	0.111	**0.778**
NO_3-N	−0.084	0.302	**0.705**	0.526
TP	0.247	**0.920**	−0.154	0.161
PO_4-P	−0.214	**0.820**	−0.233	0.134
Chl-*a*	**0.926**	0.053	0.051	−0.054
TC	0.114	*0.626*	−0.074	−0.139
Kaiser–Mayer–Olkin measure of sampling adequacy				0.742
Bartlett's test of sphericity				0.000

Note: Bold and italic values represent strong and moderate loadings, respectively.

To develop a prediction model for VFs, multiple linear regression analysis was conducted using VFs as dependent variables and the factor scores obtained from the FA as independent variables. The prediction model of VFs can explain the causal relationships between the variables, as shown in Table 6. Since the R^2 value of each VF was close to 1, ranging from 0.827 to 0.948, it can be said that the prediction of the regression equations is valid. This indicates that 82.7% to 94.8% of the information possessed by the dependent variables (VFs) can explain the variation in the independent variables. In addition, the regression equations can be said to be statistically significant because the significance probability (*p*-value) of the *F* statistic is less than the significance level of 0.05, as determined by one-way ANOVA results.

Table 6. Stepwise multiple linear regression model for VFs.

Model	Regression Equation	R^2	Sig.
VF1	Y= −2.576 + 0.509 BOD + 0.035 Chl-*a* + 0.195 COD + 0.208 TOC	0.948	0.000
VF2	Y= −0.999 − 2.546 TP + 39.758 PO_4-P + 0.103 TSS	0.932	0.000
VF3	Y = −9.096 + 0.194 DO + 1.524 NO_3-N + 0.744 pH − 0.675 TN − 0.022 WT	0.911	0.000
VF4	Y= −2.557 + 11.019 NH_3-N + 0.008 EC	0.827	0.000

Note: Sig.—statistical significance.

4. Conclusions

For sustainable water quality management in the PDR, which is an important as well as the largest regional water supply source in South Korea, a comprehensive water quality assessment was performed by applying the RTWQI, TSI_{KO}, and MSTs. The correlation analysis results showed that COD has a statistically significant correlation with BOD (r = 0.851, p < 0.01), Chl-*a* (r = 0.801, p < 0.01), and TP (r = 0.509, p < 0.01). As organic matter and phosphorus can flow into the PDR and cause eutrophication based on these correlations, it is necessary to limit the loads of organic matter and nutrients. The average RTWQI and TSI_{KO} of the PDR showed excellent and mesotrophic conditions, respectively, indicating clean water quality. The management and control of pollution sources has been prioritized owing to the Korean government's environmental policies for water quality preservation. The RTWQI of the PDR showed no remarkable seasonal difference, and 46% of eutrophic conditions occurred during the monsoon season (July to September). In particular, eutrophic conditions occurred at site PD5 over the entire period due to the increase in algae and nutrients. For the HCA, the five sites were grouped into three polluted areas while the seasons were grouped into dry and wet. PCA and FA identified four potential pollution sources in the PDR, namely domestic sewage, industrial wastewater, intensive agricultural activities, and livestock wastewater, and explained 79.7% of the total changes. Therefore, sustainable water management in the PDR should be performed with careful consideration of organic matter load, nutrient load, and other factors. The RTWQI, TSI_{KO}, and MSTs, which were used in this study, were found to be effective approaches for freshwater quality assessment. In particular, the Korean RTWQI and TSI_{KO} can be used as tools to predict potentially harmful conditions in domestic rivers and reservoirs, as they have the potential to assess the overall influence of water quality management and assist decision making.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/w15030509/s1, Figure S1: Regression analysis between TSSs and TP during the wet season; Table S1: Information on the analytical methods and instruments; Table S2: Reference range for water quality parameters for RTWQI calculation; Table S3: Descriptive statistics of the RTWQI; Table S4: Mean values of physicochemical and biological parameters in different seasons in the PDR; Table S5: Results of principal component analysis of normalized data: total variance explained.

Author Contributions: Conceptualization, Y.-C.C., J.-K.I. and S.L.; methodology, Y.-C.C. and J.-K.I.; formal analysis, Y.-C.C.; data curation, Y.-C.C., J.H. and S.L.; writing—original draft preparation, Y.-C.C.; writing—review and editing, Y.-C.C. and S.L.; supervision, S.-H.K. and S.L.; project administration, S.-H.K. and T.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Institute of Environmental Research (NIER), grant number NIER-2021-01-01-134.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data from this study are available in a publicly accessible repository that does not issue DOIs. Publicly available datasets were analyzed in this study. This data can be found at http://water.nier.go.kr (accessed on 14 November 2022).

Acknowledgments: This research was funded by the National Institute of Environmental Research (NIER), under the Ministry of Environment (MOE) of the Republic of Korea, grant number NIER-2021-01-01-134.

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

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