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Spatio-temporal analysis of the Brantas river water quality status by using principal component weighted index (PCWI)

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Abstract. River, as one of the surface water resources, has faced many contaminations due to domestic and industrial activities in its surrounding, and thus routine water quality monitoring is required. This activity yields a large number of water quality characteristics that can be very useful to evaluate the status of river quality status. In this study, we integrated a statistical multivariate analysis such as Principal Component Analysis (PCA) and conventional Water Quality Index (WQI) measure to produce a data-driven composite index for water quality assessment. We implemented this technique to evaluate the status of Brantas River, the largest river in East Java Province-Indonesia, using a long-term dataset collected from 2012 to 2021. The study area was divided into three classes: upstream, midstream, and downstream. Results of the study suggested that the pollution level in the Brantas River fluctuates yearly. Meanwhile, the degree of contamination increased from upstream to downstream.

Keywords: multivariate analysis; principal component analysis; surface water; water quality evaluation; WQI.

1. Introduction

River is surface water resource that flow from the upstream to the downstream. It is highly used for human activities both domestic and industrial purposes (Wikurendra et al., 2022). However, these will lead to the contamination of the aquatic system and thus causing deterioration of river water quality (Dunca, 2018). Therefore, a routine water quality monitoring and management is essential to preserve the quality as well as the availability of the water to support human life (Biswas & Tortajada, 2019). Any river water shortage will affect the well-being of surrounding community as well as the public health (Mishra et al., 2021).

Many standards related to water quality have been set both at the international and national levels to facilitate monitoring and evaluation of water resources. However, it only provides an assessment based on certain factors and does not represent the overall picture (Kannel et al., 2007; Rosemond et al., 2008). Therefore, a composite index for water quality assessment was developed, such as the Water Quality Index (WQI), to monitor and evaluate the characteristics of surface water (Banda & Kumarasamy, 2020).

WQI is a method that resumes various water quality parameters into a single value, making it easier to interpret water quality evaluations (Horton, 1965; Brown et al., 1970).

WQI value classification is very useful for measuring system heterogeneity using a simple additive weighting approach, which incorporates independent criteria whose relative relevance is reflected by subjective weights (Praus, 2019). Water quality varies widely geographically and temporally, so a high frequency of monitoring will result in large and complex data sets, with a large number of water quality parameters. This results in difficulty in interpreting the data obtained. A number of statistical techniques applied in the ecological field, especially unconstrained ordination techniques which are multivariate, can be used to help facilitate the interpretation of multidimensional data and reduce subjectivity in the water quality evaluation process (Kazi et al., 2009; Esdras et al., 2017).

One unconstrained coordination technique for dimension reduction is Principal Component Analysis (PCA). This technique is used to determine the inter-relationships between the original variables and convert them into independent principal components (Jolliffe & Cadima, 2016). When water quality parameters are related to each other, the resulting WQI index will give an inappropriate classification. In addition, the use of PCA also allows the efficiency of the number of water quality parameters without significantly losing the information contained in the system (Mahapatra et al., 2012)

The Brantas River is the longest river in East Java, where along the river it is widely used for various agricultural, industrial, household activities, and so on (Buwono et al., 2021). Evaluation of water quality in the Brantas River with an objective and efficient method is needed to support long-term development. In this paper, we aim to integrate PCA and WQI to produce water quality hybrid index of the Brantas River which more objective. In addition, this will also help help address water quality management policy issues more efficiently.

2. Materials And Methods

2.1. Study Area

Data used in this study obtained from the water quality monitoring of the Brantas River at the Water Quality Laboratory, Brantas River Center Surabaya, East Java in time range 2012–2021. The sampling points are grouped to three categories (upstream, midstream, and downstream) which indicating the parts of river. The upstream was represented with 6 sampling points which located in Batu, Malang and Blitar Regency, while 4 sampling points denoted the central parts located in Kediri, Nganjuk, and Jombang Regency. Finally, the 4 points that indicated the downstream area was taken at Jombang and Mojokerto. The sampling points is presented in Figure 1. Furthermore, water quality parameters employed in this study presented in Table 1.

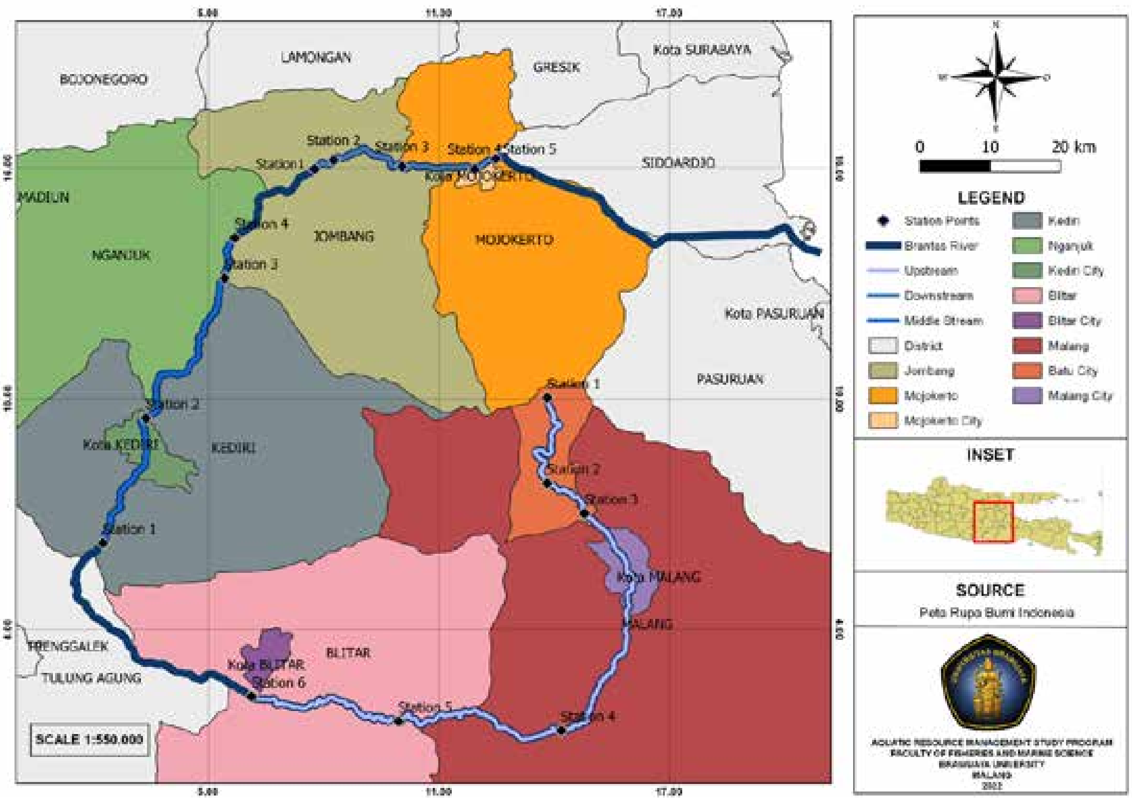


Figure 1. Map of study location area

Table 1. List of water quality parameters used in this study

No.	Parameter	Unit
1	Temperature	^oC
2	Total suspended solid (TSS)	mg/L
3	Total dissolved solid (TDS)	mg/L
4	pH	-
5	Dissolved oxygen (DO)	mg/L
6	Biological oxygen demand (BOD)	mg/L
7	Chemical oxygen demand (COD)	mg/L
8	Ammonia	mg/L
9	Nitrate	mg/L
10	Nitrite	mg/L
11	Phosphate	mg/L
12	Total coliform	MPN/100mL

2.2. Data Analysis

2.2.1. Principal Component Weighted Index (PCWI)

PCWI is a method that integrate WQI and PCA to derive a hybrid index to evaluate water quality status of an aquatic system (Lusiana et al., 2022). WQI is a classic water quality index which accommodate a weight that shows importance of each water quality parameter in its formula as expressed below

$$I = \frac{(Mi - Ii)}{(Si - Ii)} \text{ x } 100 \quad (1)$$

$$WQI = \frac{\Sigma_{i=1}^{p} W_i Q_i}{\Sigma_{i=1}^{p} W_i} \quad (2)$$

where:

Q_i = weight of the i-th water quality parameter

W_i = unit weight for i-th water quality parameter

M_i = observed value of the i-th water quality parameter

I_i = ideal value of i-th water quality parameter

S_i = standard value for i-th water quality parameter.

Unit weights () in WQI determined subjectively according to recommended values suggested from previous studies (Praus, 2019). Meanwhile, PCA approach in this method replaces the unit weights () and weight () with eigenvalue () and principal component (), respectively. The formula of PCWI described as follows:

$$PCWI = \frac{\Sigma_{i=1}^{n} \lambda_i PC_i}{\Sigma_{i=1}^{p} \lambda_i} \quad (3)$$

where:

λ_i = eigenvalue of i-th component

PC_i = the i-th principal component.

In order to perform PCA, there are two underlying assumption that should be met (Johnson & Wichern, 2013). First, sampling adequacy criteria by using KMO test (Greenacre & Primicerio, 2013). Second, data homogeneity by using Bartlett test (Hair et al., 2010).

2.2.2. Standard Dataset Transformation

Since the research variables' units varied, we used standard normal transformation transformation) for every variable in this study as seen in following equation (Lusiana & Mahmudi, 2020):

$$Z_{ij} = \frac{X_{ij} - \bar{X}_i}{S_i} \quad (4)$$

where:

Z_{ij} = standard normal transformation value for the i-th variable, j-th observation

$\bar{X}_{ij}$ = measured value of i-th variable, j-th observation

X_i = average value of the i-th variable

S_i = standard deviation of the i-th variable

$i = 1, 2, \ldots, p$

$j = 1, 2, \ldots, n$

p = number of variables

n = sample size

2.2.3. Spatio-Temporal Analysis of PCWI

Spatial and temporal analysis of PCWI were performed by classifying it in accordance to Shewhart control chart (Praus, 2019), then comparing them descriptively by using box-whisker plot. Furthermore, significance test carried out by employing with one-way ANOVA and Tukey test (Midway et al., 2020; Musa et al., 2020).

3. Results And Discussions

3.1. Descriptive summary of variables

The water quality parameter that was observed from the Brantas River is summarized in Table 2 below. The standard value applied in this research was based on Indonesia Ministry of Environment regulations from 2001 (Ministry of Environment, 2001). The result indicated that mean value of each parameter met the standard value, except for TSS, BOD, phosphate, and total coliform at all river parts. In specific, ammonia and nitrite values in downstream parts are exceeding the standard value.

3.2. Correlation between Variables

According to Figure 2, it can be seen that some water quality parameters are correlated to each other. The pattern

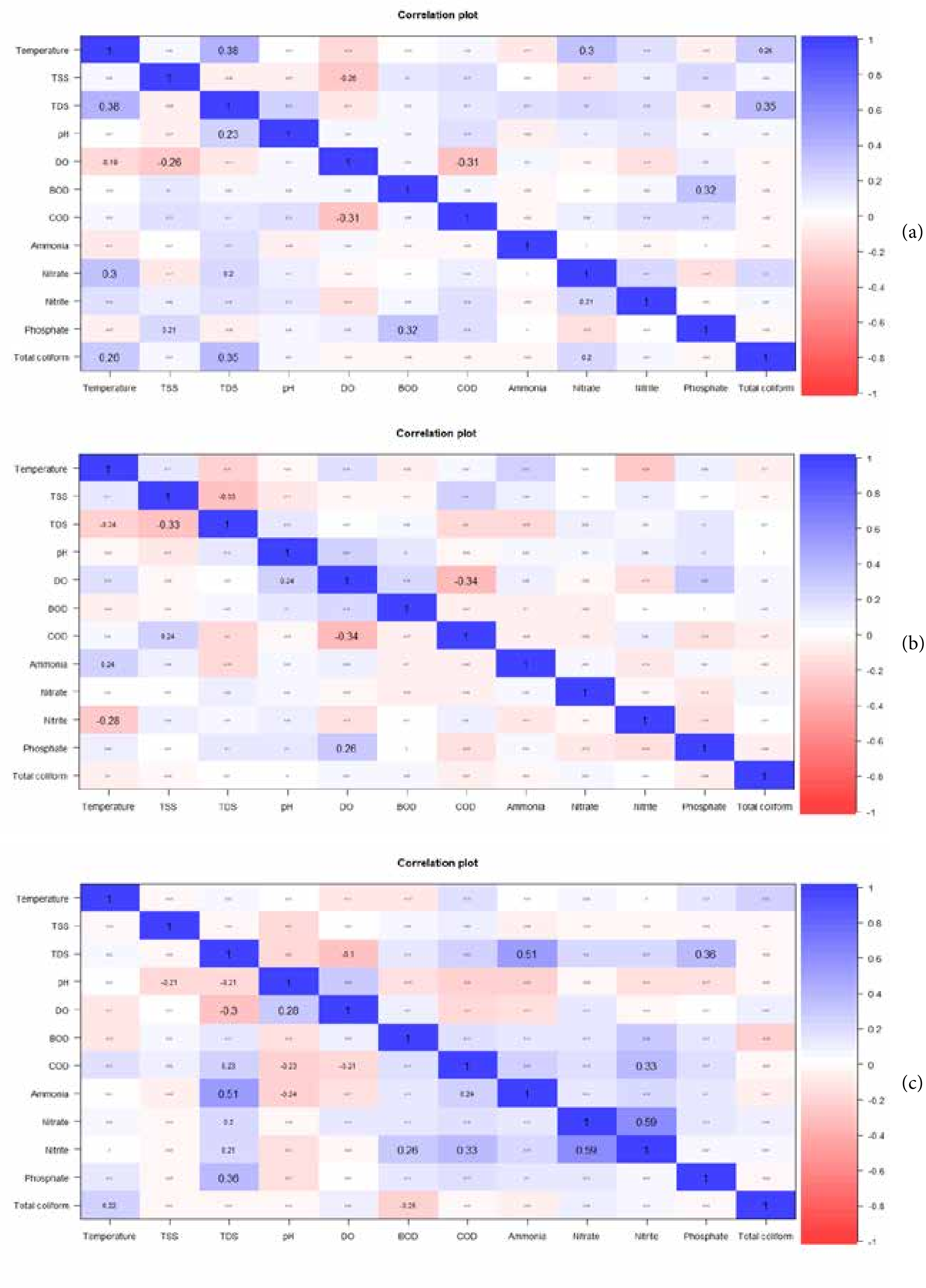


Figure 2. Heat plot of water quality characteristics correlation in Brantas River (a) Upstream; (b) Midstream; (c) Downstream

Table 2. Measurement result of water quality parameter in the Brantas River

No	Parameter	Standard Value	Upstream	Midstream	Downstream
1	Temperature (°C)	Deviation 3	24.92	28.94 ± 1.479	29.72 ± 1.506
2	TSS (mg/L)	50	127.95 ± 851.771	105.06 ± 152.146	142.73 ± 400.811
3	TDS (mg/L)	1000	184.07 ± 80.320	198.39 ± 55.887	281.89 ± 174.696
4	pH	6–9	7.64 ± 0.531	7.63 ± 0.426	7.72 ± 0.386
5	DO (mg/L)	4	6.92 ± 1.086	6.61 ± 0.974	6.86 ± 1.029
6	BOD (mg/L)	3	8.40 ± 14.803	7.34 ± 4.902	8.60 ± 5.371
7	COD (mg/L)	25	11.01 ± 11.140	12.94 ± 12.956	15.62 ± 16.897
8	Ammonia (mg/L)	0.2	0.18 ± 1.258	0.13 ± 0.184	2.08 ± 8.312
9	Nitrate (mg/L)	10	2.76 ±1.439	2.41 ± 1.132	2.87 ± 3.356
10	Nitrite (mg/L)	0.06	0.05 ± 0.079	0.04 ± 0.028	0.16 ± 0.854
11	Phosphate (mg/L)	0.2	1.35 ± 2.595	0.92 ± 1.210	1.72 ± 3.289
12	Total coliform (MPN/100mL)	5000	7099.23 ± 9659.882	15434.93 ± 21513.769	5377.64 ± 8076.218

of variable correlation in upstream and centre area of Brantas river is quite similar, while opposite pattern found in downstream area. Temperature has high correlation with nitrogen compound, such as nitrate, nitrite, and ammonia, as well as phosphate correlated with DO and BOD in upstream and centre area. On the other hand, in downstream part, TDS and COD has great association with ammonia, nitrate, nitrite, and phosphate. Therefore, this result strengthening the relevance usage of PCA for water quality assessment (Lusiana et al., 2022).

3.2. Results of Principal Component Analysis on Water Quality Parameters of Brantas River

Prior to PCA, two assumption tests should be performed to test the data appropriateness (Rencher & Christensen, 2012). The KMO test results for data adequacy suggested that the data collected from upstream, midstream, and downstream parts of Brantas River met the requirement (larger than 0.50), as the test statistics were 0.61, 0.52, and 0.57, respectively. On the other hand, Bartlett test statistics p-value were all less than 0.05, meaning that the used data were homogeny. Therefore, PCA can be implemented for water quality characteristics for each part in Brantas River.

The proportions for every principal component's variance explained are depicted in Figure 2. The scree plot assists us in selecting core components and examine data structure. According to (Rencher & Christensen, 2012), the accumulated proportion of the variation, which denotes the quality to meet for extracting features in PCA, may possibly explain a minimum of 80 percent of the total variability. Therefore, the first eight to nine principal components were retained and accounted for 84.6% (upstream), 82,32% (midstream), and 84.1% (downstream) of the variance in the dataset.

In PCA, the principal component interpretation that is necessary to understand the data structure is frequently included. The rotated component loadings summarized in Table 3 would be used to describe relations between input variables. The principal components in PCA is ordered by its variance contribution to the overall variability as described in Figure 3. Meanwhile, the loading factors measured the effect of each raw variables to the relevant principal components. Hence, the first principal component (PC1) has the highest explained variance and thus variables with absolute high loading factors to this component regarded as the determinant of overall variability of water quality dynamics (Lusiana et al., 2022). It can be seen from Table 3 that TSS and TDS as the major variable for PC1 in all river parts. Meanwhile, DO, BOD, nitrite, and nitrate had an impact on PC2 in midstream and downstream part of Brantas River. Meanwhile, these factors also effect on higher principal component in upstream parts, implying that they are less important in this river part.

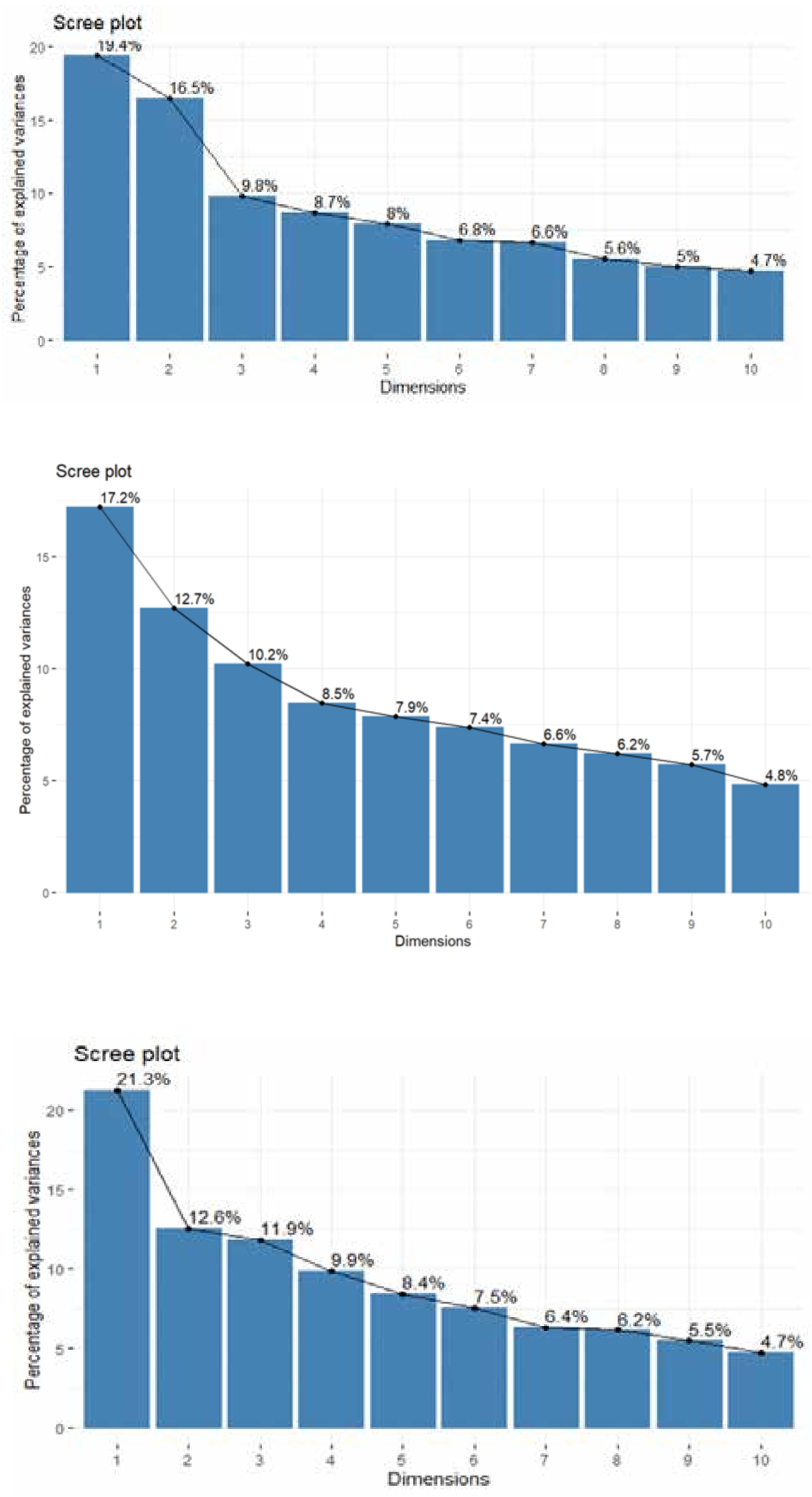
TSS in water often consists of inorganic material (such as silt, sand, and aquatic minerals), organic elements (such as detrital particulate comprised of carbohydrates, proteins, and lipids), and water-insoluble microbes. TSS content is an important criterion for characterizing water quality (Rossi et al., 2006). TSS content might have a direct and considerable impact on the visual characteristics of water involving sunlight reflection and absorption (Jafar-Sidik et al., 2017). As a result, the production of phytoplankton may be impacted, and the aquatic species' habitats may be altered, which would negatively impact the benthic population (Bilotta & Brazier, 2008). Meanwhile, TDS is a comprehensive measurement of how many soluble substances are present inside a lake or a river. The specific ions and concentrations that attribute to TDS could have ecotoxicological effects (Weber-Scannell & Duffy, 2007). Additionally, TDS may breach drinking water

Table 3. Loading factor of each principal components

Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Upstream								
Temperature	**0.394**	-0.044	0.155	-0.009	0.308	-0.034	-0.300	-0.060
TSS	-0.004	**-0.592**	0.127	0.195	0.095	-0.005	0.212	-0.018
TDS	**0.503**	0.081	-0.128	0.227	-0.132	0.102	0.036	-0.188
pH	0.165	0.034	-0.428	-0.292	-0.118	0.307	**0.566**	-0.013
DO	-0.186	0.294	-0.251	0.194	0.303	-0.161	**0.414**	0.108
BOD	-0.023	-0.134	**-0.564**	0.110	0.229	-0.249	-0.360	-0.247
COD	0.144	-0.276	-0.193	-0.338	-0.414	0.136	-0.221	**0.448**
Ammonia	0.032	0.051	-0.018	**0.489**	-0.561	-0.508	0.134	0.145
Nitrate	0.284	0.090	0.045	-0.288	0.234	-0.507	0.037	**0.545**
Nitrite	0.213	-0.154	-0.075	-0.411	0.019	**-0.463**	0.223	-0.443
Phosphate	-0.089	-0.243	**-0.547**	0.201	0.130	0.053	-0.155	0.244
Total coliform	0.318	0.023	0.084	0.272	**0.371**	0.205	0.178	0.307
Midstream								
Temperature	-0.107	**0.494**	-0.246	0.136	0.015	-0.037	0.214	0.098
TSS	**-0.508**	0.154	0.146	-0.437	-0.089	0.017	-0.069	-0.053
TDS	**0.352**	-0.216	0.097	-0.400	0.181	0.126	0.156	0.142
pH	0.190	0.089	0.301	-0.078	-0.086	**-0.659**	-0.036	0.494
DO	0.176	**0.444**	0.403	0.054	-0.158	-0.058	-0.033	-0.052
BOD	0.069	0.007	0.482	0.077	-0.231	0.003	**0.538**	-0.374
COD	-0.383	-0.179	-0.105	0.113	0.177	-0.164	0.252	**0.454**
Ammonia	0.101	-0.028	-0.333	-0.336	**-0.506**	-0.195	0.299	0.089
Nitrate	-0.076	-0.411	0.175	-0.077	-0.012	-0.402	**-0.431**	-0.305
Nitrite	-0.032	**0.380**	-0.299	0.022	-0.164	-0.270	-0.333	-0.256
Phosphate	0.147	0.344	0.226	-0.175	**0.439**	0.161	-0.216	0.189
Total coliform	0.038	-0.077	0.133	0.061	-0.602	**0.459**	-0.368	0.402
Downstream								
Temperature	-0.060	0.115	**-0.571**	0.086	-0.232	0.459	-0.076	0.317
TSS	-0.023	0.122	0.183	0.692	-0.226	-0.204	**-0.538**	-0.003
TDS	**-0.441**	0.192	-0.039	-0.330	0.006	-0.244	-0.245	-0.088
pH	0.318	-0.267	-0.105	-0.372	0.090	0.311	**-0.493**	-0.017
DO	0.212	**-0.510**	0.074	-0.084	-0.379	-0.220	-0.214	0.417
BOD	-0.243	-0.212	**0.461**	0.001	-0.230	0.195	0.386	0.407
COD	-0.374	0.043	-0.084	0.246	0.016	**0.462**	-0.107	0.107
Ammonia	-0.386	0.162	0.047	-0.260	0.274	-0.231	-0.292	**0.527**
Nitrate	-0.302	**-0.545**	-0.171	0.057	0.049	-0.107	-0.124	-0.291
Nitrite	-0.380	**-0.468**	-0.056	0.156	0.240	0.081	0.072	-0.156
Phosphate	-0.264	0.095	-0.084	-0.279	**-0.745**	-0.049	0.020	-0.312
Total coliform	0.043	-0.071	**-0.601**	0.161	-0.001	-0.467	0.299	0.238

standards by contaminating groundwater through aquifer recharge. Rises in TSS or TDS in the river could be a sign of a human effect that can be looked into by looking at other measures of water quality and the amounts of its parts (Butler & Ford, 2018).

DO is the amount of oxygen gas dissolved in water. During the process of photosynthesis, it is taken in from the atmosphere or aquatic plants. Numerous aquatic species need well-oxygenated habitats, so dissolved oxygen is essential for their survival and the biogeochemistry of nutrients (North et al., 2014). The anaerobic condition, or low oxygen concentration, is also detrimental to the metabolic activities of animals such as fish. As a result, the DO concentration is the most important factor in determining the functioning of water bodies (Zhang et al., 2022). Meanwhile, BOD is a measure of organic load in freshwater ecosystems,



(a)

(b)

(c)

Figure 3. Variance explained scree plot

and it is linked to microbial contamination. High BOD concentration levels impair aquatic habitats and biodiversity, and inhibit water use. Human impacts of high BOD stresses into freshwater environments include domestic as well as agricultural inputs waste, industrial effluents, and municipal sewage overflows (Vigiak et al., 2019).

Nitrogen is required for the production of chlorophyll in plants, and nitrogen compounds are widely used in agricultural fertilizers to increase crop yields. The use of nitrogen fertilizers has increased significantly in recent years. Despite the fact that this has had a significant positive impact on global agricultural production, the broader ecosystem has been significantly harmed (Townsend et al., 2003). The majority of water-soluble nitrate and nitrite substances in soil come from nitrogen fertilizers, which can then be lost through surface runoff into groundwater, rivers, and drinking water (Picetti et al., 2022). Additional significant sources of nitrate pollutants in freshwater systems include industrial, human, and livestock manure (Shukla & Saxena, 2020). Excessive nitrate levels in drinking water can raise the risk of illnesses and health impacts such as methaemoglobinaemia, spontaneous abortion, thyroid disease, and stomach cancer (Ward et al., 2018). Even the presence of nitrite, has the potential to cause cancer. As a result, nitrogen pollution is a serious environmental issue that should be taken seriously (Xu et al., 2014).

3.4. Spatio-temporal assessment of PCWI in the Brantas River

Brantas River PCWI values were evaluated by categorizing them using a Shewhart control chart as a model (MacGregor & Kourti, 1995; Praus, 2019). In Table 4, the study's classification outcome is displayed. More than half of the PCWI values that indicate the water quality status of the Brantas River are classified as slightly contaminated (upstream) and fairly polluted (midstream and downstream). This suggests that the degree of contamination increased from upstream to downstream.

Furthermore, as shown in Figure 4, we used PCWI to examine the seasonal changes of water quality in the Brantas River throughout time. Figure 4(a) exhibits that the highest level of pollution in upstream of Brantas River occurred in 2012. Then, the pollution has significantly decreased until 2021 as denotes by the different letter notation resulted from Tukey test. Meanwhile, pollution level of midstream part of Brantas River, as depicted in Figure 4(b), relatively stable over the years. In contrast to the upstream, lowest water pollution in downstream part found at 2012, then the pollution significantly increased afterwards. This finding supports the result described in Table 4 which leads one to believe that the level of water contamination in Brantas River became increasingly severe as one moved downstream.

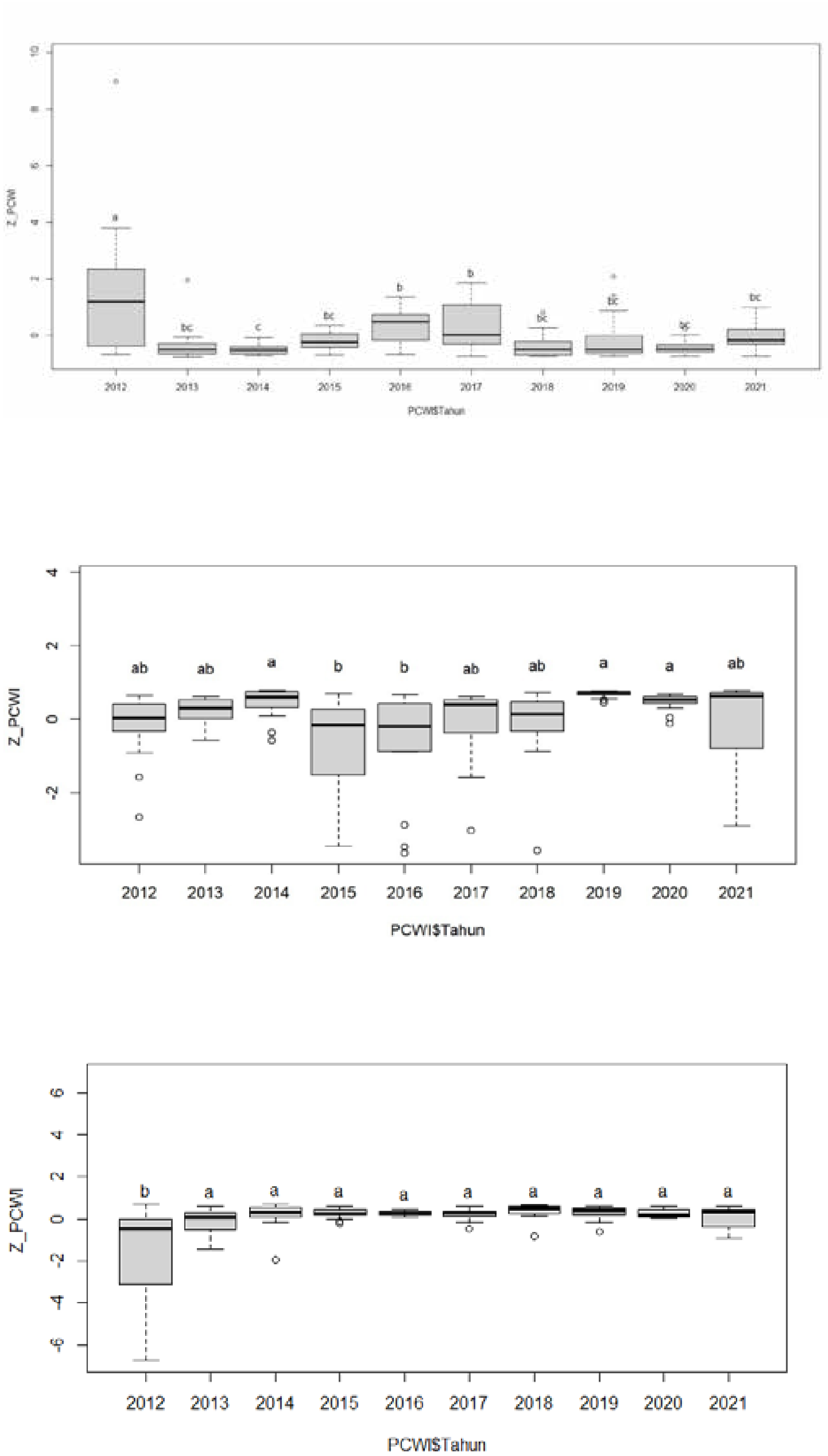
Our findings are consistent with those of Bisimwa et al. (2022), who discovered that the water quality of the Bukavu urban rivers in Kongo has degraded considerably from upstream to downstream, with high nutrient amounts that do not meet WHO quality standards for surface waters. Water quality in the downstream area tends to deteriorate for a variety of reasons. To begin, the quality of such water is heavily influenced by pollution expelled from an upstream watershed. Furthermore, elevated upstream water deposits reduce a river's dilution capacity, which can significantly degrade water quality in downstream river reaches (Yoon et al., 2015).

4. Conclusion

The finding in this study indicated that TSS, TDS, DO, BOD, nitrate, and nitrite as the most influential factors that determined the water quality dynamics in studied area. Moreover, temporal analysis of the PCWI values showed that the level of river contamination was fluctuated. On the other hand, the degree of pollution in downstream area significantly larger than the upstream.

Table 4. PCWI values classification of Brantas River parts

Class	Range	Upstream	Midstream	Downstream
Very good	< -3	0	5	5
Good	-3 to -2	0	6	1
Slightly polluted	-2 to 0	158	40	33
Fairly polluted	0 to 2	62	109	136
Heavily polluted	2 to 3	5	0	0
Unsuitable	>3	3	0	0



(a)

(b)

(c)

Figure 4. Box-Plot of PCWI in the Brantas River (a) upstream; (b) midstream; (c) downstream

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