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Mapping of river water quality through spatial K'luster analysis by tree edge removal

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ABSTRACT

Mapping is one of the steps that is useful for monitoring changes in water quality, planning and management, increasing public awareness, and analyzing the impact of climate change. This study aims to obtain river water quality mapping through statistical clustering methods, namely grouping observation points to points with excellent and bad quality are obtained. This research increases accuracy and efficiency in monitoring and managing water resources, thereby supporting more appropriate decision-making to preserve the environment in the area. This method is called spatial cluster analysis by tree edge removal, which is a data grouping method that considers geographical aspects between observations. Obtained secondary data from The Special Region of Yogyakarta (DIY), which was then carried out statistical analysis using spatial cluster analysis with spatial K'luster analysis (SKATER). The clustering results are then presented to the mapping. This study uses chemical oxygen demand (COD), pH, total phosphate, nitrate, and ammonia parameters at 43 river sample points in the DIY. SKATER produces 3 clusters, each consisting of 32 locations, 2 locations, and 9 locations. The results of the study showed that the cluster with the highest average COD was cluster 2, which was 29 mg/L and was located in the Winongo and Oya rivers. Likewise, phosphate, pH, and ammonia levels were higher than in other locations. The results are used as indicators for controlling pollution at these cluster points. This result is different from several similar studies that carried out clustering without considering the geographical aspects of the observations. This information is used as a reference for controlling pollution and reducing COD and other parameters at river locations. The challenge of adapting the SKATER method to different river characteristics limits research on rivers in the Yogyakarta region, and implementing the method requires technological support and expertise that do not yet fully exist in the region.

Keywords: enviromental, geographical aspect, polution, spatial, statistic analyzing.

INTRODUCTION

Monitoring river water quality is a critical component of sustainable water resources management. With increasing pressures from industrial activities, urbanization, and climate change, it is essential to systematically monitor water quality to ensure the health of aquatic ecosystems and human safety. River water quality mapping using state-of-the-art technology offers an effective way to identify and address potential water quality issues in a timely manner.

Several implementations of clean river programs through government policies have not had a significant impact on the management and protection of clean and healthy river environments, as indicated by the still poor quality of rivers in several major cities in Indonesia (Asri, 2023). Based on data from river water observations in the Special Region of Yogyakarta, rivers that have COD values that exceed the quality standards are the Bedog River with a COD value of 34 mg/L, the Winongo River 29 mg/L, and the Belik River 25 mg/L.

One of the important parameters for measuring water quality is chemical oxygen demand (COD). COD is an important parameter in assessing water quality because it measures the amount of oxygen needed to oxidize organic matter and some chemicals in the water. High COD indicates significant organic contamination, which can have a negative impact on river ecosystems and water quality. The increase in COD values in these rivers is typically caused by a variety of factors. These factors include industrial and domestic waste disposal, agricultural activities, solid waste disposal, fishing activities, clean water treatment, riparian vegetation degradation, and construction activities. Changes in weather and rainfall patterns also have an impact. In addition, erosion caused by strong water flow can carry organic particles into the river, increasing COD. In some large cities, many recreational and tourist attractions also have an impact.

COD monitoring is critical in efforts to effectively manage river water quality. If the water contains a lot of inorganic waste, the amount of oxygen needed by microorganisms to break down the waste will be large, so the COD figure will also be high. High COD in river water indicates organic pollution that can reduce dissolved oxygen, threatening the survival of fish and other aquatic organisms. Inadequate treatment can lead to the formation of more persistent and difficult to decompose toxic compounds (Aguilar et al., 2023).

Water quality monitoring, such as COD, can be done using several steps and techniques to ensure accurate and comprehensive data on water conditions, including mapping, statistical analysis, and a combination of both. Mapping is the process of creating and using maps to depict geographic and spatial information about an area. This process involves the collection, analysis, and representation of data related to locations and features on the earth's surface. In river water quality monitoring, mapping provides many functions to understand and manage the health of aquatic ecosystems. Other benefits are identifying sources of pollution, monitoring changes in water quality, analyzing contaminant distribution, planning and management, compiling risk maps, increasing public awareness, and analyzing the impact of climate change.The use of QGIS for the analysis of potential flood impacts in the Nabaoy Watershed and combining it with remote sensing in his research (Seneris, 2022). The mapping results from QGIS provide information that the upstream area of the Nabaoy Watershed has low to very low flood vulnerability, while the downstream area has moderate to very high vulnerability. Furthermore, Latwal et al. (2024) uses mapping through remote sensing that allows real-time and spatial monitoring of water quality, which is important for sustainable management of tropical reservoirs. The results of this monitoring are very important for water quality information in tropical areas, which is very important for maintaining the health of ecosystems and water resources, especially in reservoirs.

Monitoring through statistical analysis can use various models, such as regression analysis, clustering, to forecasting. Clustering is a method for grouping objects based on several characteristics or data variables. This method can be used to group locations, observation points, or river basin areas based on predetermined water quality parameters. The grouping results will show locations with low to high parameter values, low to high pollution, and so on.

Several studies have conducted statistical analysis. With a descriptive approach, channel roughness and physical conditions of the river have a major impact on pollutant concentrations based on COD parameters (Marlina et al., 2017). Research conducted by Caphra et al. (2021) shows that river water temperature affects COD. Higher temperatures can accelerate the rate of chemical and biological reactions in water, thereby increasing the rate of organic matter degradation. This in turn increases COD because more oxygen is needed to oxidize decomposed organic matter. In addition, increased water temperature can increase turbulence in river water, which can help spread pollutants more evenly and increase their interaction with microorganisms that break down organic matter, thereby contributing to increased COD.

Environmental parameters pH, dissolved oxygen (DO) and temperature have a very strong correlation and are inversely proportional to COD in lakes (Komala et al., 2019). Total coliforms have a significant impact on water COD. The presence of total coliform bacteria indicates organic matter contamination, which requires oxygen for decomposition. This decomposition process increases COD because it requires more dissolved oxygen to oxidize organic matter. Research shows that total coliforms are often used as indicators of water microbiological quality and have a direct relationship with other water quality parameters, including COD (Aram et al., 2021). Clustering has also been widely applied for factor analysis on other river water quality. Meanwhile, Suphawan and Chaisee (2021) predicted the water quality index (WQI) in the Ping River, Thailand, using three statistical models: multiple linear regression (MLR), artificial neural network (ANN), and gaussian process regression (GPR). Hierarchical clustering has been used to group water quality indices for assessing groundwater and surface water quality in mining communities (Anang et al., 2023). The application of K-Means clustering to grouping river water sample points in DIY has been carried out by (Novianta et al., 2023).

Some studies that have been discussed have not considered the spatial aspect or the relationship between observations. So this study applies spatial K'luster analysis by tree edge removal (SKATER) as one of the spatial cluster methods. Other clustering methods can be used, such as the Kulldorf spatial scan statistics method (Tango, 2010) and Moran's I (Lee and Wong, 2001).

The SKATER method was introduced (Assunção, 2006). This method uses an algorithm that transforms regional data into partition graphs. This method partitions locations that are not adjacent and do not share similar characteristics. Next, Bekti and Rachmawati (2014) used this method to classify factors that influence infant birth and death in Bogor Regency, West Java. Meanwhile, (Jian et al., 2019) used SKATER in the regionalization process. The SKATER method's advantage is that its grouping uses identification of neighbors between locations, which is an important part of spatial analysis.

One work in clustering COD of the rivers in The Special Region of Yogyakarta (DIY) using K-means has been performed by Novianta et al. (2023). This research revealed that K-means fails to capture a significant amount of data due to its sensitivity to outliers, irregular shapes, and clusters of varying sizes. Therefore, a different clustering system is required to obtain more comprehensive data. This research aims to carry out a more comprehensive cluster-based spatial analysis for regional, geographic, or environmental planning using SKATER.

This study aims to obtain river water quality mapping through statistical clustering methods, namely grouping observation points to points with excellent and bad quality are obtained. The clustering method used is SKATER, which has advantages in grouping data by considering geographical aspects between observations. Furthermore, the clustering results are presented to the mapping to visualize the results of clustering river observation points so that it is easier to find out which locations are prone to pollution. The resulting clusters tend to be more spatially consistent, making more sense for situations involving pollution distribution patterns along rivers. This study conducted mapping of river water quality COD and influencing factors (pH, total phosphate, nitrate, and ammonia) in DIY based on SKATER. This method is used with the consideration that the identification of previous studies showed a spatial relationship between locations. With this grouping, a grouping of river locations with the same characteristics will be obtained. The use of the new SKATER method in rivers in the Yogyakarta region will provide greater insight into spatial patterns of water quality. In addition, this method is expected to increase accuracy and efficiency in monitoring and managing water resources, thereby supporting more appropriate decision-making to preserve the environment in the area.

MATERIALS AND METHODS

Data collection

This study uses secondary data from The Special Region of Yogyakarta (DIY) for the period September-October 2023. The data is in the form of 43 sample points where river water quality parameters were measured (Fig. 1). The rivers include Bedog, Belik, Bulus, Gadjah Wong, Kenteng, Kuning, Oyo, Tambakbayan, Winongo, and Opak. The variables used are river water quality parameters: COD, pH, ammonia, phosphate, and nitrate. In addition, geographic location is also included in the calculation indicated by longitude and latitude.

Spatial K'luster analysis by tree edge removal (SKATER)

The analysis SKATER steps are 1) Descriptive analysis, 2) Dependency test with Moran's I to determine whether there is a spatial effect, 3) the SKATER method and 4) its mapping. The SKATER method uses an algorithm, which is a strategy for converting regional data into partition graphs. SKATER is performed in two steps (Reis et al., 2007). The first step is to determine the Minimum Spanning Tree (MST). The MST describes the neighborhood graph between locations based on certain variables.

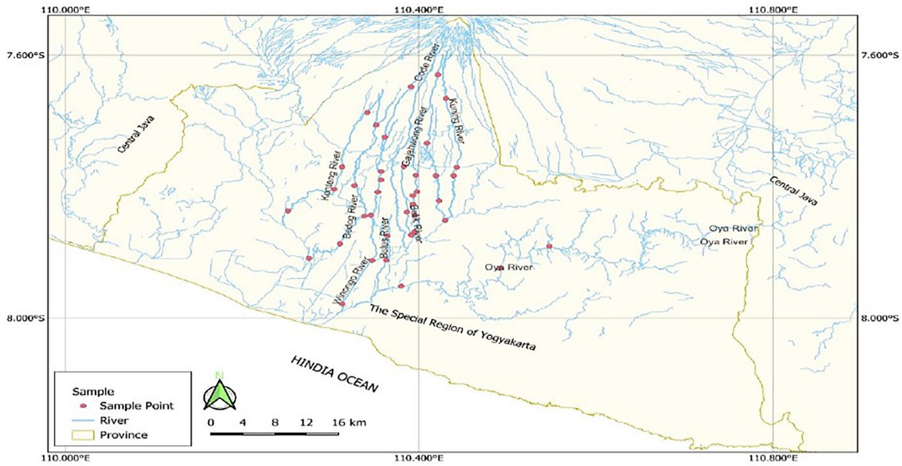

Figure 1. Maps of the research

Consider a set of locations O with variables {A1, A2,...., An}. Each location has a vector of variables x={a1, a2,..., an} where a1 is all possible values of the variable A1. The topology of a data set shows a connection graph G = (V,L) with a set of vertices V and a set of edges L. Connections between vertices vi and vj occur when locations i and j are close to each other (neighbors). The proximity is measured by the Euclidean distance. The Euclidean distance formula for vectors xi and xj is:

$$d_{ij} = d\left(x_i, x_j\right) = \sum_{l=1}^{n}\left(x_{il} - x_{jl}\right)^2 \quad (1)$$

where: d_{ij} – Euclidean distance between i-th observations;i, j – 1, 2, …, n with n being the number of observations; x_{ik} – vector variable ke-k di amatan ke-i.

The formation of MST is based on the Prims algorithm, which is to form connections between nodes and edges at each location. The algorithm is:

1. Suppose the connection G = (V, L) consists of several nodes V and edges L. The first tree is denoted T1. Choose a vi from V, then we get Tk = T1 = ({vi}, ϕ).
2. Choose an edge from the smallest cost (l') from L that connects Tk to vj.
3. Choose vj and l' on the Tk tree and then build the Tk + 1 tree.
4. Repeat the second step until all nodes enter the Tn tree.

The second step, after the MST is formed, SKATER performs a recursive partition of the MST to obtain a grouping. The result of the grouping is the homogeneity of variables within the group. To form a partition, k-1 edges are removed from the MST. Each will produce a tree-shaped group. The partition produces a graph G* consisting of trees T1, T2,..., Tn. Each tree, while connected, lacks nodes and shares primary edges with other trees. Edge selection is performed using the sum of squared deviations between groups (SSDi), which is intended to minimize (Assunção, 2006).

$$Q(\Pi) = \sum_{l=0}^{k} SSD_i \quad (2)$$

where:

$$SSD = \sum_{j=1}^{m}\sum_{i=1}^{n_k}\left(x_{ij} - \bar{x}_j\right)^2 \quad (3)$$

where: n_k is the number of spatial objects in tree k; x_{ij} is the jth attribute of spatial object i; m is the number of attributes considered in analysis; and $\bar{x}_j$ is the average value of the j-th attribute for all objects in tree k.

RESULTS AND DISCUSSION

Spatial distribution patterns

COD measures the amount of oxygen needed to decompose organic matter in water, pH indicates the acidity or alkalinity of water, and total phosphate, nitrate, and ammonia are important indicators of pollutants that can affect the health of aquatic ecosystems. Figures 2 to 6 describe the characteristics of the five variables at 43 DIY river water sample points. This mapping image explains the variation of data at each location.

The COD parameter has an average of 10.571 mg/L. The lowest recorded figure is 3.00 mg/L, while the highest value is 34.00 mg/L. The range of COD values shows a significant variation in the level of organic pollution in water samples. There a quality standard limit of 25 mg/L, there

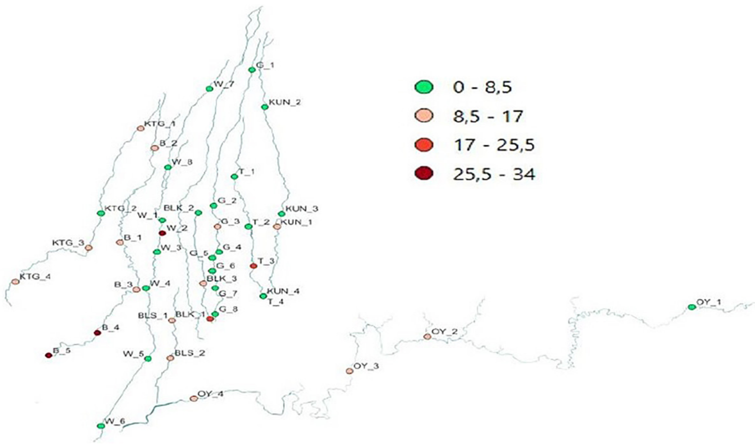

Figure 2. COD spatial pattern

are 4 locations that have COD above the quality standard. These locations are in the Bedog, Belik, Winongo, and Opak rivers.

This location is in an industrial area, so there is potential for an increase in COD levels. Industrial activities, especially textiles, produce liquid waste with high COD, this is due to the chemicals used in production activities (Indarsih, 2016; Marlina et al., 2017). High concentrations of COD are related to the presence of organic matter in water originating from high-density residential areas (Komarudin et al., 2015).

The pH variable ranged from 6.7 to 8.5 with an average of 7.49 (Fig. 3). This indicates that the water tends to be neutral to slightly alkaline, which is in accordance with water quality standards for most uses. All locations are still on the threshold of the quality standard, which is 6–8.

This research is in accordance with research conducted by Djumanto et al. (2013), which states that the pH is neutral in the Gajah Wong River. The Gajahwong River is one of the rivers that flows from the slopes of Mount Merapi in the north and meets the Opak River in the south. This river passes through rural, forest, and agricultural areas in Sleman Regency, then urban residential areas and home industries in Kodya Yogyakarta, as well as agricultural, fishing, and residential areas in Bantul Regency. The pH of river water ranges from 4 to 9. The pH range suitable for aquatic organisms is different depending on the type of organism (Cech, 2005).

Total phosphate ranges from 0.0100 mg/L to 1,420 mg/L (Fig.4) with an average of 0.3 mg/L. There are 36 locations that exceed the quality standard of 0.2 mg/L. The Gadjahwong and Konteng rivers, which pass through densely populated areas, have very high phosphate levels. This high phosphate can cause eutrophication, which has a negative impact on the aquatic ecosystem (Listantia, 2020). The use of fertilizer contributes to the phosphorus compounds that enter rivers, while in residential areas, the diversification of detergents and waste organic materials from

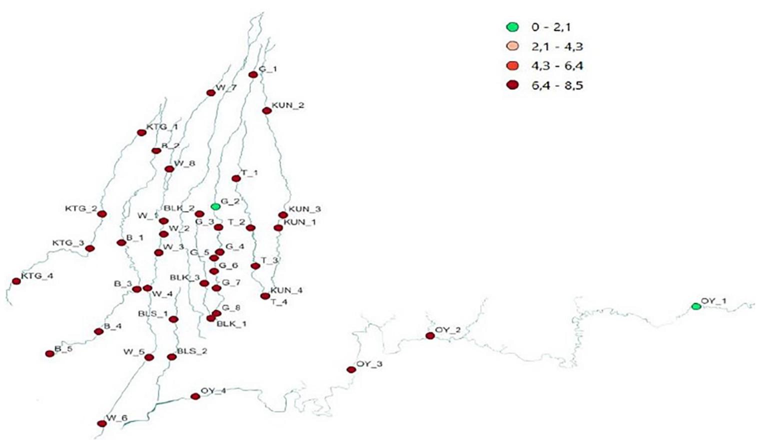

Figure 3. pH spatial pattern

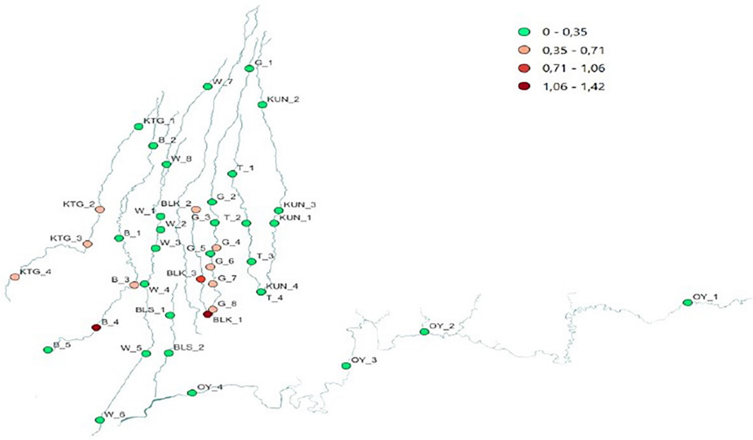

Figure 4. Total fosfat spatial pattern

household activities leads to the phosphorus compounds that enter waterways.

Nitrate concentrations varied from 0.200 mg/L to 4.000 mg/L with an average of 1.405 mg/L. All locations are still below the quality standard. The nitrate indicator provides information about human activities, which originate from human and animal waste. One source of pollution that produces a lot of nitrates is boarding houses and livestock pens (Permana, 2013) (Fig. 5)

Meanwhile, ammonia levels range from 0.01000 mg/L to 0.90000 mg/L, with an average of 0.066 mg/L (Fig. 6). With a quality standard of 0.2 mg/L, there are 3 locations that are above

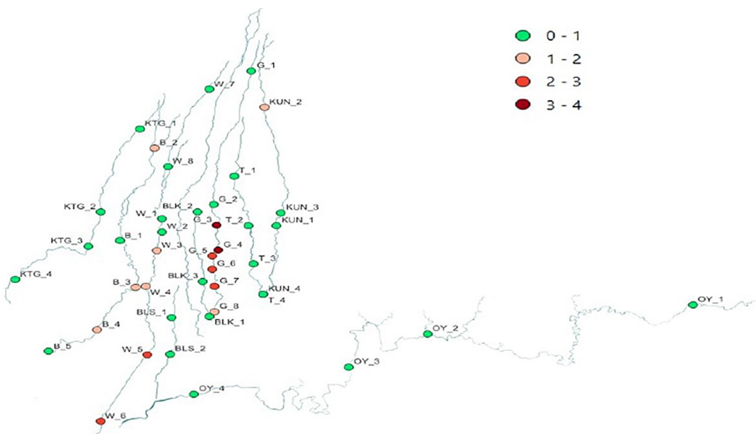

Figure 5. Nitrat spatial pattern

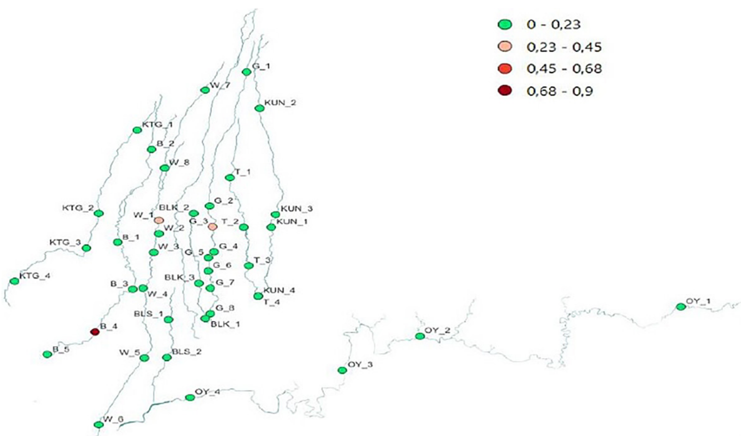

Figure 6. Amonnia spatial pattern

the quality standard. When it is in the Winongo, Bedog, and Gadjahwong Rivers. High levels of ammonia can harm aquatic life and indicate organic waste pollution.

The high concentration of ammonia in the rainy season causes runoff from drainage channels and domestic and non-domestic waste to enter water bodies. In the dry season, ammonia concentrations can be very low because the influence of high water temperatures can affect the nitrification process (Effendi, H. 2003). Furthermore, the Moran's I spatial effect test in Table 1 indicates that there is spatial autocorrelation.

Overall, the Moran's I test results revealed that only Nitrate exhibited significant spatial autocorrelation, indicating a spatial pattern where Nitrate values clustered in specific areas, as indicated by the P-value of less than 0.05. Other variables (COD, pH, Total Phosphate, and Ammonia) did not show significant spatial autocorrelation. The presence of spatial autocorrelation indicates that the sample points' locations are interconnected, so the SKATER spatial statistic is the statistical method used.

Mapping based on SKATER

Mapping is done through clustering with the SKATER method. This clustering is based on four variable characteristics, namely COD, Ph, Total Phosphate, and Ammonia. The first step is to determine the minimum spanning tree (MST) generator. This decision is based on the differences in location pairs. Figure 7 displays the MST results, which are in the form of connection lines between 40 river locations. Locations 31 and 9 form the first connection, while locations 6 and 4 form the second connection. Locations 13 and 12 form the final connection.

Table 1. Output Moran's I

Variable	Moran'I statistics	*p*-Value
COD (X1)	-0.0400	0.4166
pH (X2)	-0.0475	0.4614
Total fosfat (X3)	0.0243	0.1257
Nitrat (X4)	0.0316	0.0521
Amoniak (X5)	0.0900	0.0002

The second stage in SKATER is to partition the MST, and the results can be seen in Figure 8. This stage causes clustering in 40 river locations. In the figure, the clustering is indicated by different connection line colors. This stage produces 3 groups of river locations. For example, locations 6 and 4 form one group with a green description.

The complete grouping results can be seen in Figure 9. The three river groups are close together. Group 1 consists of 33 river locations that are close to each other, Group 2 consists of 2 river locations, and group 3 consists of 8 river locations that are close to each other. The second cluster has the highest average COD of 29 mg/L, which is in the Winongo and Oya rivers. Furthermore, cluster 1 has an average of 11.16 mg/L, and cluster 3 has an average of 4.44 mg/L. In other parameters, cluster 2 has a high average at pH 8.15, an average of phosphate 1.31 mg/L, and an average of ammonia 0.5 mg/L. Details of the characteristics of each cluster can be seen in Table 2.

This can happen because there is a lot of pollution around the point, Geographically, members of cluster 3, which have relatively low numbers on the parameters of pH, COD, phosphate, and ammonia, are in the same river flow, namely in the Tambakbayan and

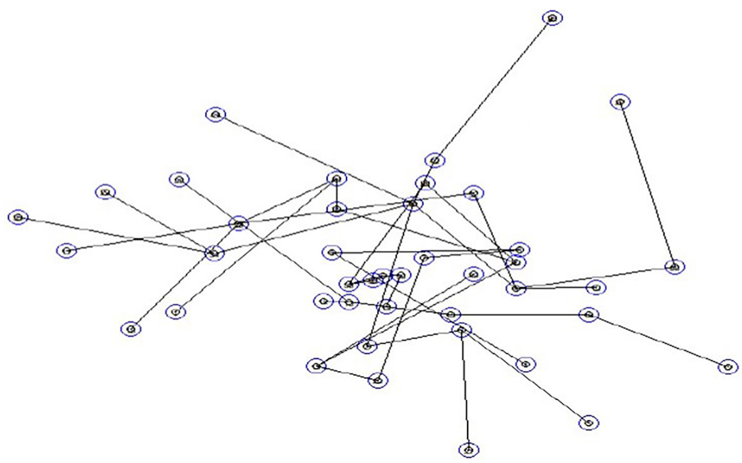

Figure 7. MST result

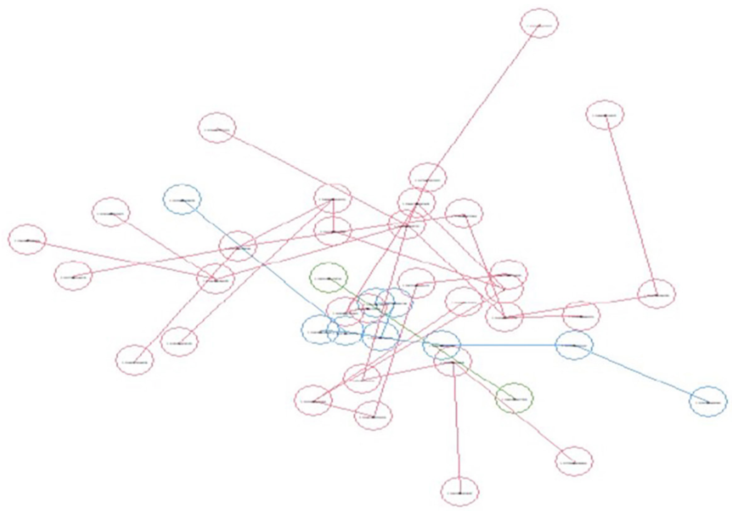

Figure 8. MST partition

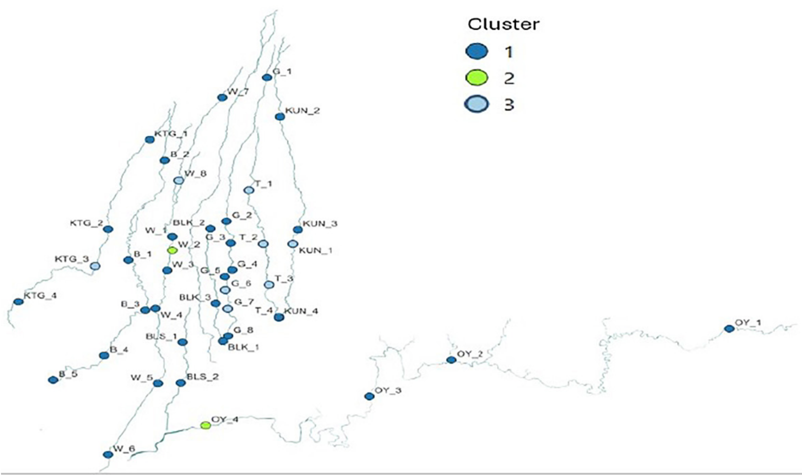

Figure 9. SKATER grouping results

Table 2. Data characteristics in each cluster

Cluster	Number of members	Average				
		pH	COD	Nitrat	Fosfat	Amonnia
1	33	7.54	11.16	0.97	0.24	0.04
2	2	8.15	29	1.5	1.31	0.5
3	8	7.17	4.44	2.89	0.31	0.07
Overall data	43	7.49	10.57	1.4	0.31	0.07

Gadjahwong Rivers. In contrast, two observations from cluster 2, which have relatively high parameter numbers, are located in different river flows. This phenomenon can occur due to the high level of pollution in the surrounding area. River pollution can occur due to anthropogenic activities such as industrial activities such as textiles (Auriga et al., 2023), agriculture, community behavior such as littering (Rachmawati et al., 2023), lack of public awareness about waste management (Yulia et al., 2022) and animal husbandry (Rachmawati et al., 2022).

As an evaluation of the clustering results, several clusterings were carried out with different numbers of clusters, and then an F test was carried out as in Table 3. The F test was carried out to determine the average difference between groups. The best number of clusters is the one with the

Table 3. F MANOVA

Amount kluster	F Statistics
2	4.53
3	10.12
4	9.49
5	7.44

largest F statistics value. Therefore, we conclude that SKATER, which has 3 clusters, is the best cluster with an F statistics value of 10.12. With this F statistic, it is also concluded that the average variables COD, pH, total phosphate, nitrate, and ammonia are significantly different between clusters. Between clusters already have high heterogeneity.

The mapping results in Figure 9 can be a warning that pollution control needs to be carried out at the second cluster points, namely in the Winongo and Oya Rivers. These results are different from several similar studies that conducted clustering without considering the geographical aspects of the observations. The government's role is crucial in controlling pollution, imposing strict sanctions on industrial players who dispose of waste without processing (Auriga et al., 2023), engaging in community development for river management (Rachmawati et al., 2023), establishing waste treatment installations at homes (Yulia et al., 2022), and enhancing monitoring of river quality and industrial activities (Prayogo et al., 2021).

CONCLUSIONS

After analysis and discussion, the COD parameter averages 10,571 mg/L. The lowest recorded value was 3.00 mg/l, while the highest was 34.00 mg/l. There are five locations with COD above the standard quality limit of 25 mg/L, namely in the Bedog, Belik, Winongo, and Opak Rivers. All locations maintain pH and phosphate levels within the standard quality threshold, with values ranging from 6 to 8. There are 36 locations with total phosphate levels that exceed the standard. There are 3 locations that have ammonia above the standard quality. Mapping through SKATER produces 3 clusters, namely cluster 1 (33 locations), cluster 2 (2 locations), and cluster 3 (9 locations). The cluster with the highest average COD is cluster 2, namely 29 mg/L which is located in the Winongo and Oya rivers. Likewise, phosphate, pH, and ammonia are higher than in other locations. This information is used as a reference for controlling pollution and reducing COD and other parameters at river locations.

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