International Journal on Advanced Science Engineering Information Technology

Vol.13 (2023) No. 4
ISSN: 2088-5334

Assessment of Water in Terengganu River, Malaysia Using Multivariate Statistical Techniques and Fuzzy DEMATEL

Mohamad Ammar Pairan [a], Nurnadiah Zamri [a,*], Azimah Ismail [b]

[a] Faculty of Informatics and Computing, Universiti Sultan Zainal Abidin, Besut Campus, Besut, Terengganu, Malaysia
[b] East Coast Environment Research Institute, Universiti Sultan Zainal Abidin, Gong Badak Campus, Kuala Nerus, Terengganu, Malaysia
Corresponding author: *nadiahzamri@unisza.edu.my

***Abstract*—Water is essential in our daily life for life purposes and other activities. Significant water quality degradation due to natural factors and human activities can harm human health and ecosystems. Therefore, water quality monitoring is always necessary for public health and a good ecosystem. This study focuses on assessing river water quality in Terengganu involving several parameters and the location of water monitoring stations along the Terengganu River, which is linked to the second-largest dam in Malaysia. This study uses multivariate analysis such as Principal Component Analysis (PCA) and Agglomerative Hierarchical Clustering (AHC) to assess water quality in the Terengganu River. PCA investigates the origin of each parameter that contributes to river pollution. Before AHC, WQI categorized monitoring stations based on different river pollution zones. The AHC method groups all water monitoring stations based on the level of river pollution zones. Then, this study was continued with the Fuzzy Decision-Making Experiment and Evaluation Laboratory (FDEMATEL) to determine the relationship between river pollution factors. The PCA results yielded five significant factors that accounted for 55.33% of the total variance. AHC classifies three clustered areas: low, medium, and high pollution. Criterion (agricultural and irrigation run-off) is the main causal relationship from FDEMATEL. The results of this study help reveal important information about river water quality in Terengganu to control pollution sources, thus helping to maintain the health of the local population and ecosystem.**

***Keywords*—Water quality; principal component analysis; agglomerative hierarchical clustering; fuzzy DEMATEL; Terengganu River.**

Manuscript received 7 Jun. 2022; revised 30 Apr. 2023; accepted 16 May 2023. Date of publication 31 Aug. 2023.

I. INTRODUCTION

Quality, clean, and safe water resources are needed to grow human beings and other living things in daily life and endeavors in the future. Access to high-quality, clean, safe water is essential to improving health and reducing poverty [1]. River quality assessment is crucial in environmental water management [2]. Parameters can be accessed via river quality assessment using Water Quality Index (WQI). For example, [3] combined WQI with self-organizing maps of Kohonen (SOM) to monitor long-term water quality at 10 sample points in the Mesta River watershed area in Bulgaria. [4] developed two models for accessing water quality: 1) using water quality assessment with WQI and 2) using an evaluation model called WQImin that used six key parameters. From 2008 to 2018, both models were used in the Yilong Lake dataset to evaluate water quality using thirteen water quality parameters.

Besides WQI, multivariate statistical techniques are practical approaches for identifying temporal and spatial variations in water quality parameters. For example, [5] analyzed surface water pollution sources using multivariate statistical analysis techniques such as regression analysis, Principal Component Analysis (PCA), and Absolute Principal Component Score-Multiple Linear Regression (APCS-MLR). These methods were utilized to assess fifteen physicochemical factors and twelve socio-economic parameters. Their study discovered that industrial operations and population expansion caused ammonium nitrogen and total nitrogen pollution. Total Phosphorus (TP) came from domestic discharge and poultry breeding activities. Moreover, [6] found the anions bicarbonate, sulfate, nitrate, and chloride, and the cations sodium, calcium, and magnesium as significant ion concentrations from 70 groundwater samples from Suzhou, Huaibei Plain, China. The study also used multivariate statistical analysis to evaluate all samples. [7] analyzed water quality in the BahrMouise canal in El-Sharkia

Governorate using PCA and Agglomerative Hierarchical Clustering (AHC) techniques. Their water quality studies aim to preserve soil, reduce the risk of degradation, and assist decision-makers in achieving agricultural sustainability, which is especially significant given the region's lack of underwater irrigation and limited agricultural acreage.

Malaysia is a tropical rainforest country rich in water resources and has around 672 rivers. Due to its status as a developed country, Malaysia faced high uncontrolled sewage treatment or discharge from manufacturing and agro-based industries [8]. Ammoniacal Nitrogen (NH_3-N), Biochemical Oxygen Demand (BOD), and Suspended Solids (SS) are the most crucial parameters that cause river pollution. Effluent and ineffective sewage treatment from manufacturing and agro-based industries can produce high BOD. Meanwhile, uncontrollable domestic sewage and animal farming can contribute to high NH_3-N. Besides, improper land clearing activities and earthworks can contribute to high SS [8]. Continuous water quality statistics on these river pollution hotspots are needed to categorize which areas are polluted and must be treated. Several previous studies have discussed water quality assessment in Malaysia, such as [9] the spatial water quality assessment of selected river basins in Malaysia's three states. The spatial variance of the most significant water quality parameters was analyzed using envirometric techniques such as Cluster Analysis (CA), PCA, and Discriminant Analysis (DA). The technique used water quality data from the Juru River Basin, Kuantan River Basin, and Johor River Basin to determine the source of contamination. [10] in Tanjung Karang, Selangor, Malaysia, assessed the pesticide concentration in surface water, the effectiveness of pesticide removal in a conventional drinking water treatment plant (DWTP), and the potential health risk to consumers. Due to the importance of the water quality assessment towards our health and ecosystems, this study continues to assess water quality assessment towards the Terengganu River.

Terengganu River Basin is located on Malaysia's East Coast in Terengganu State. It is main upstream originates from Kenyir Lake in northeast Malaysia and flows through Kuala Terengganu, the state capital of Terengganu. Terengganu River is chosen in this study because it has Malaysia's second-biggest Kenyir dam. Besides, Terengganu is also a commercial trade center and has become one of the modern cities known for tourism, fishing, and industry. Since then, various studies have also focused on the Terengganu River. For example, [11] used the PCA approach to study the similarities and inequalities across stations and determine the effect of pollution sources on the water parameters of the Nerus River. Then, [12] used the gravimetric method to evaluate the total suspended solids (TSS) in the Terengganu River basin and determine the deterioration of water quality. The study showed that TSS and ammoniacal nitrogen (AN) are two important parameters that cause water deterioration in the Terengganu River.

Furthermore, river pollution caused by anthropogenic activities is concentrated downstream to the middle of the river. However, many studies have discussed on Terengganu River water quality evaluation. However, new research is still needed due to the increasing data with different parameters and pollution locations. Besides, previous studies have failed to determine the causes of the pollution.

Therefore, this study proposes an extension of water quality assessment in the Terengganu River with the updated data and new parameters. The PCA method investigates the most important component of the river parameters by decreasing the dataset's dimensionality and enhancing interpretability while reducing information loss. Then, WQI is implemented to categorize the monitoring stations based on different pollution zones. Next, the AHC is applied to cluster all the pollution areas based on the same characteristics generated by AHC. Finally, the Fuzzy Decision-Making Trial and Evaluation Laboratory (FDEMATEL) based Multi-Criteria Decision Making (MCDM) is applied to generate the most important causes contributing to pollution by identifying the cause-effect chain components of pollution. Twelve experts from the environmental department, universities, agricultural sector, and public are evaluated to find the Terengganu River's best pollution causes. The rest of this paper is arranged as follows. Section II presents this study's materials and methods, including the study area, data pre-treatment, and methods. Section III discusses the findings and discussions, including pH analysis, PCA, AHC, and FDEMATEL. Lastly, the conclusion is drawn in Section IV.

II. Material and Method

A. Study Area

Terengganu River originates from the Terengganu state, one of the states in Peninsular Malaysia, and is chosen as the main research location for this study. This river flows through the Kenyir Dam (Empangan Tasik Kenyir) in Hulu Terengganu and ends in Kuala Terengganu (downstream part) towards the South China Sea. This river basin is in the North-Eastern coastal area of Peninsular Malaysia, between latitudes 4°40'N-5°20'N and longitudes 102°30'E-103°09'E. Fig. 1 shows the locations for the sampling station at the Terengganu River. The Terengganu River basin has sixteen major tributaries with a total catchment area of around 5000 km2 [13]. The largest basin among sixteen basins is the Nerus River basin. All rivers flow through many socio-economic activities, including aquaculture, agriculture, commercial industries, farming, urban and rural communities, tourism, reserves, and forests (Taman Negara). This study includes 14 monitoring stations, 21 water quality parameters, and 405 samples. These 405 water samples were taken from all around the Terengganu River basins. These 14 main sampling stations include Rum Whereas, whereas 21 water quality parameters include Dissolved Oxygen (DO), Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Suspended Solids (SS), pH, Ammoniacal nitrogen (NH_3-N), Temperature (TEMP), Nitrate (NO_3), Chlorine (CI), Phosphate (PO_4), Arsenic (As), Chromium (Cr), Lead (Pb), Zinc (Zn), Calcium (Ca), Iron (Fe), Potassium (K), Magnesium (Mg), Sodium (Na), E-Coli, Total Coliform.

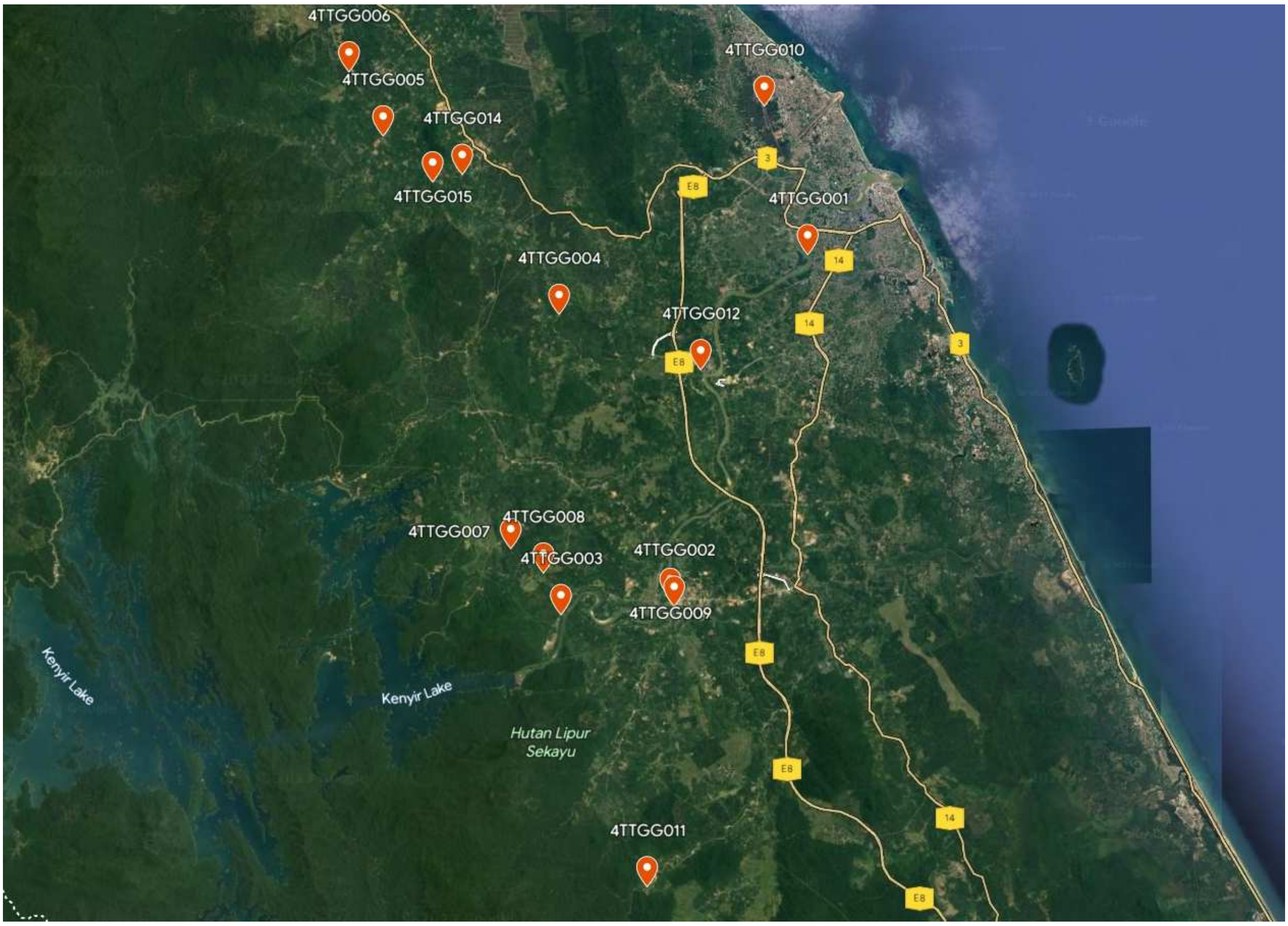

Fig. 1 Location of the water monitoring stations in Terengganu River

B. Data Pre-Treatment

The data used in this study are secondary data retrieved from the Department of Environment Terengganu, which needs to be sorted according to the water sampling stations. The data requires pre-treatment to identify any symbols, missing data, and unreadable symbols that can lead to inaccurate pre-processing data processes. Approximation using an average of the nearest neighboring data was performed. In contrast, some data that are closed or under the limitation of measurement, which can be identified with the mathematical figure (≤) in front of the parameter value, were set to half of its detection limit to make it legitimate XLSTAT to analyze the data. This process is essential to increase the effectiveness of the data pre-processing using our next multivariate analysis and MCDM method.

C. Methods

This study used three different methods to pre-process the data. In Phase 1, the PCA method explores the inherent pattern in the water quality dataset. The varimax rotation in PCA is applied to retrieve the maximum factor loading variance and select the most important principal components (PCs) parameters for the eigenvalues greater than 1.0. Next, in Phase 2, WQI is implemented to categorize the monitoring stations based on different pollution zones. Then, AHC is applied to cluster the patterns of the sampling sites concerning water quality. This AHC used Ward distance metrics and Euclidean distance to create a dendrogram, reflecting the variability in the water quality characteristics. The last phase, Phase 3, offers the FDEMATEL method based on MCDM to develop a causal relationship between water quality factors. Data from a group of water quality experts were gathered using a survey method. Empirical data were calculated using the FDEMATEL method's seven steps, in which the initial decision matrix was converted into a total relation matrix before constructing a cause-and-effect diagram. Visualizing the causal relationship between water quality parameters using a digraph is the key finding of this FDEMATEL. The result shows that most activities affect the Terengganu River's pollution. The whole of this phase is summarized in Fig. 2 as follows.

III. Result and Discussion

A. Summary Statistics of Terengganu River Datasets

pH is an essential biological element used to indicate pollution [14]. The pH of water influences the number of chemical components, such as nutrients and heavy metals, that may be dissolved in the water [15]. Analyzing the pH measurement is essential before running the pre-processing method. This will help to identify the characteristics of each sampling site.

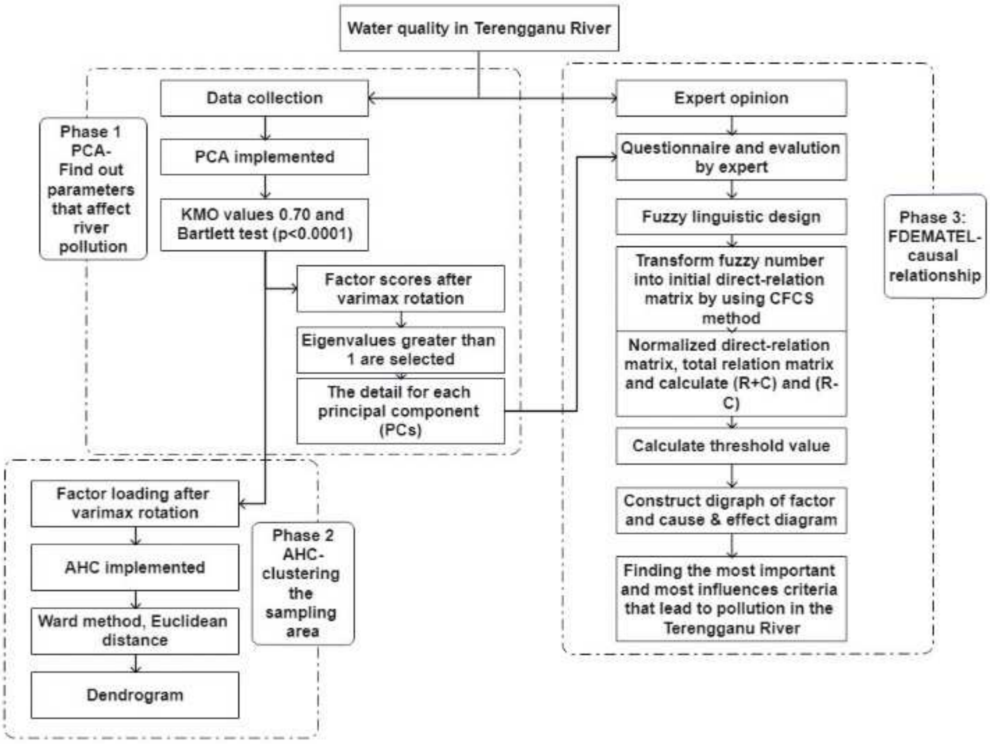

Fig. 2 Research flow chart

Therefore, Table 1 lists the summary for all water parameters, including pH measurements for the whole Terengganu River dataset. Based on Table 1, pH for the Terengganu River ranges from 3.79 to 8.88, whereas DO ranges from 2.39 to 8.74, BOD ranges from 2.0 to 17.0, and COD ranges from 8.0 to 42.0. The rest of the other parameters are listed in Table 1. Summary statistics are essential to summarize and provide information about the Terengganu River datasets.

TABLE I
SUMMARY OF STATISTICS

Parameters	Min	Max	Mean	Standard Deviation
DO (mg/l)	2.394	8.746	6.773	1.390
BOD (mg/l)	2.000	17.000	4.405	1.908
COD (mg/l)	8.000	42.000	14.738	6.141
SS (mg/l)	1.000	203.000	34.155	40.224
pH	3.791	8.883	7.183	0.980
NH3-N (mg/l)	0.005	10.300	0.778	1.789
TEMP (°C)	23.704	31.854	27.513	1.672
NO3 (mg/l)	0.005	122.000	9.061	20.211
Cl (mg/l)	0.500	217.000	12.101	26.398
PO_4 (mg/l)	0.005	4.430	0.187	0.598
As mg/l	0.001	0.004	0.001	0.001
Cr (mg/l)	0.001	0.002	0.001	0.000
Pb (mg/l)	0.001	0.005	0.001	0.001
Zn (mg/l)	0.012	0.132	0.033	0.020
Ca (mg/l)	0.200	28.400	2.886	4.860
Fe (mg/l)	0.005	33.400	0.995	3.605
K (mg/l)	0.300	364.000	11.979	44.341
Mg (mg/l)	0.100	48.200	2.562	6.118
Na (mg/l)	1.600	41.000	5.867	6.652
E-coli (cfu/100ml)	0.500	9600.000	861.018	1545.132
Total Coliform (cfu/100ml)	76.000	610000.000	85082.762	119043.712

B. Computational and Results of Principal Component (PCA)

Validity testing is an important step before applying the PCA method. The validity test uses Bartlett's sphericity test and Kaiser-Meyer-Olkin (KMO). The result shows significant at $p < 0.0001$ for Bartlett's sphericity test and 0.68 for KMO. Once both results are significant, PCA can be used for the next evaluation of this study. The PCA results (refer to Table 2) show that the first five PCs retrieved an eigenvalue of more than one. This explained 55.33% of the total variance from all the Terengganu River parameters, where PC1 (24.754%), PC2 (11.439%), PC3 (8.055%), PC4 (8.055%), and PC5 (4.868%). From Table 2, parameters with more than 0.7 varimax factor values are selected for the next evaluation (refer to the bold value).

TABLE II
FACTOR LOADING VALUES OF ALL PARAMETERS AFTER VARIMAX ROTATION

Parameters	PC1	PC2	PC3	PC4	PC5
DO (mg/l)	-0.379	-0.398	-0.010	-0.207	0.009
BOD (mg/l)	0.107	**0.955**	-0.027	-0.065	0.020
COD (mg/l)	0.226	**0.764**	0.003	0.400	-0.035
SS (mg/l)	0.042	0.038	**0.863**	0.246	-0.011
pH	0.137	-0.346	-0.045	-0.095	0.100
NH3-N (mg/l)	0.640	0.126	-0.008	0.032	-0.054
TEMP (°C)	0.152	0.093	-0.176	-0.014	0.071
NO_3 (mg/l)	-0.064	-0.008	0.010	-0.008	**0.987**
Cl (mg/l)	**0.930**	0.092	-0.012	0.079	-0.053
PO_4 (mg/l)	**0.930**	0.087	-0.011	-0.035	-0.008
As mg/l	0.668	0.155	0.007	0.130	-0.044
Cr (mg/l)	0.354	0.121	-0.041	0.048	-0.092
Pb (mg/l)	-0.087	-0.068	**0.937**	-0.083	0.021
Zn (mg/l)	-0.076	0.203	0.046	-0.080	0.070
Ca (mg/l)	0.473	0.618	-0.063	0.111	-0.050
Fe (mg/l)	0.011	0.089	0.079	**0.979**	-0.007
K (mg/l)	**0.971**	0.031	-0.013	-0.019	-0.007

Parameters	PC1	PC2	PC3	PC4	PC5
Mg (mg/l)	**0.936**	0.197	-0.052	0.015	-0.033
Na (mg/l)	0.159	0.267	-0.118	0.121	-0.062
E-coli (cfu/100ml)	0.198	-0.015	-0.012	-0.021	-0.012
Total Coliform (cfu/100ml)	0.333	0.012	0.068	-0.014	-0.036
Eigenvalue	7.054	3.310	1.985	1.359	1.216
Variability (%)	24.754	11.439	8.055	6.215	4.868
Cumulative (%)	24.754	36.193	44.248	50.463	55.332

#Bold represents a strong factor in loading

Based on Table 2, parameters that achieved 0.7 and above varimax factors for PC1 are Cl, PO_4, K, and Mg. Then, PC2 reveals high positive loading of BOD and COD with 11.44% of the variance. PC3 explains 8.06% of the total variability, with strong positive loading on SS and Pb. Next, PC4 represents 6.22% of the total variability, with strong positive loading on Fe. The presence of iron in rivers is familiar. Lastly, PC5 accounted for 4.87% of the total variability, with strong positive NO_3. Based on PCA results, the WQI method is extracted to categorize different types of pollution, and the AHC method is implemented to classify 14 monitoring stations based on different pollutants.

C. Section Headings Computational and Results of Water Quality Index (WQI)

This study used the univariate clustering technique to implement WQI to categorize the monitoring station area before running the AHC (Section 3.4). The WQI results show three categories of pollution: Low pollution zone, Moderate pollution zone, and High pollution zone. These weighted values retrieved from the WQI are explained as follows:

1) Low pollution zone. The weighted values for this category range from -29.71 to -9.43. This area is less vulnerable to water pollution, with the lowest WQI reading. These areas are mostly in areas less associated with pollutants based on the activity characteristics at the sampling station.

2) Moderate pollution zone: The weighted values for this category range from -8.45 to -9.50. Sampling stations in this category are classified as moderately contaminated groups with relatively high K, Mg, PO4, COD, and SS parameters. Therefore, simple treatment methods are required before water can be used.

3) High pollution zone. The weighted values for this category range from 11.66 to 41.75. High weighted values with high concentrations for the parameters Cl, K, Mg, COD, BOD, Pb, SS, and PO_4 indicate that river pollution at the sampling site can cause the water quality of the area to be affected. Due to that, it needs to control and treated before use. Next, AHC is extracted to find which monitoring stations are based on pollution zones.

D. Computational and Results of Agglomerative Hierarchical Clustering (AHC)

This study used the univariate clustering technique to implement WQI to categorize the monitoring station area. Cluster analysis is a method for unsupervised pattern classification to categorize and create current data set structures without making future assumptions about data organization. This section uses AHC to classify 14 monitoring sites based on their characteristics (see Fig. 3).

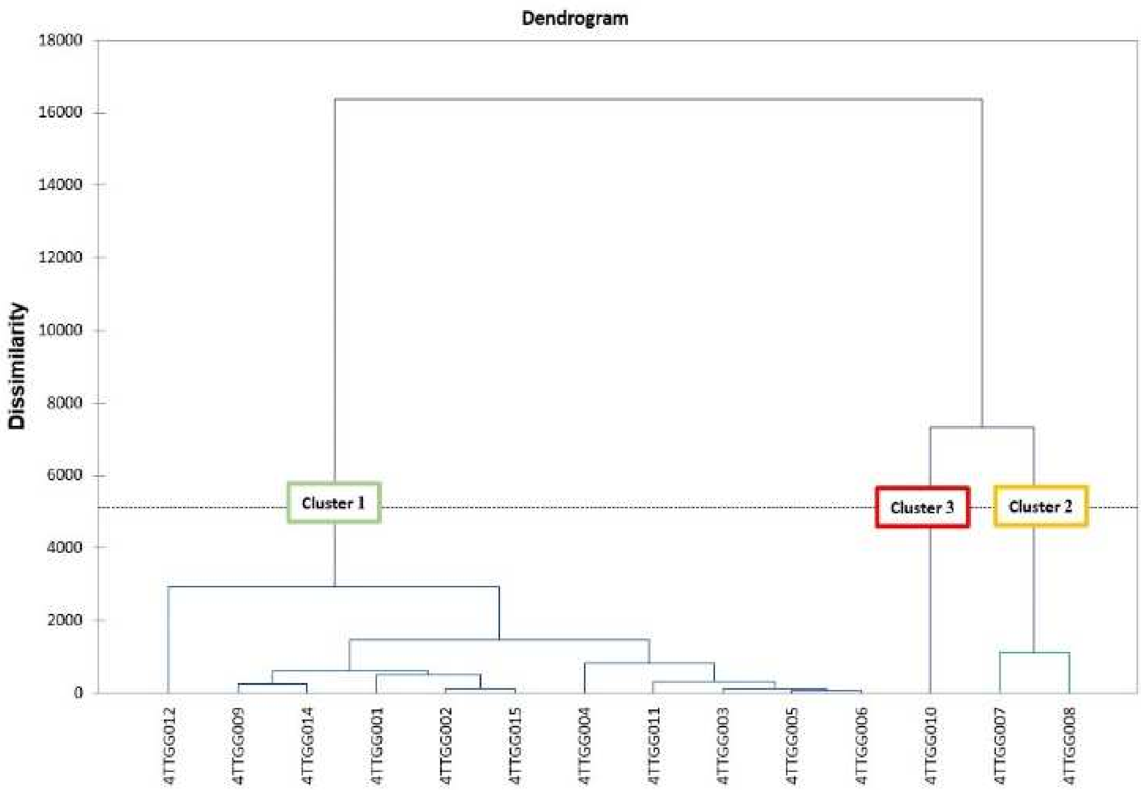

Fig. 3 Different clustering based on water quality parameter

Based on the AHC results, three different clusters are retrieved. Cluster 1 consists of 11 stations, namely 4TTGG012 (Telemong River), 4TTGG009 (Terengganu River), 4TTGG014 (Nerus River), 4TTGG001 (Terengganu River), 4TTGG002 (Berang River), 4TTGG015 (Nerus River). 4TTGG004 (Nerus River), 4TTGG011 (Berang River), 4TTGG003 (Terengganu River), 4TTGG005 (Nerus River), and 4TTGG006 (Nerus River). Cluster 2 consists of 2 stations, namely 4TTGG007 (Pueh River) and 4TTGG008 (Pueh River). Cluster 3 consists of 1 station, 4TTGG010 (Nerus River). It can be concluded that Cluster 1 is a low pollution zone, Cluster 3 is a medium pollution zones, and Cluster 2 is a high pollution zone.

This result is inlined with the description for each zone, where 11 stations in Cluster 1 are mostly situated in the residential areas and recreational sites. These areas have fewer agriculture activities and slow development and are covered by forest greenery. Cluster 3 seems to be medium pollution due to these two monitoring stations at oil palm farming activities. The use of regressive fertilizers from agricultural activities contributes to the medium pollution of the river. Lastly, Cluster 2 has high pollution rates due to the active industrial activities near this river. The area rapidly develops and carries out several industrial activities, such as iron mills, recycling centers, and food-based factories [16]. Besides, this area is also located in an urban area with a high population. Due to that, this area is highly contaminated with the SS and heavy metals parameter captured from the industrial and residential activities. The following section covers the FDEMATEL method to identify the causes that change the Terengganu River's water quality.

E. Computational and Results of Fuzzy DEMATEL

The causes that change the Terengganu River's water quality can be retrieved using FDEMATEL. Twelve criteria to consider in FDEMATEL include Population growth and economic development (A), Land use development (B), Urbanisation (C), Untreated domestic sewage (D), Industrial discharge (E), Agricultural run-off and irrigation (F), Municipal water pollution from home and business (G), Soil erosion (H), Mining operation (I), Housing and road development (J), Logging and forest clearing (K), and Poultry farm and wet market activities (L). Twelve experts from different backgrounds will evaluate these twelve criteria, such as the environmental department, universities, agricultural sector, and public, to select the most suitable causes contributing to the Terengganu River. Details on twelve criteria are explained in Table 3 as follows:

TABLE III
ACTIVITIES THAT CAN CAUSE RIVER POLLUTION

Criteria	Descriptions	Research
(A) Population growth and economic development	Uncontrolled development affects water quality and the deterioration of river ecosystems.	[17]–[21]
(B) Land use development	Changes in land use harm river water quality and water ecology.	[22]–[24]
(C) Urbanization	Affect water quality in terms of the enrichment of dissolved inorganic nutrients.	[25]–[27]
(D) Untreated domestic sewage	Untreated household sewage impacted the stream's water quality.	[28], [29]
(E) Industrial discharge	Pollutants from industrial processes affect the aquatic environment.	[30], [31]
(F) Agricultural run-off and irrigation	Run-off from the agricultural sector can significantly increase the chloride content in river water.	[32], [33]
(G) Municipal water pollution	Untreated sewage leads to the deterioration of river quality	[34]–[36]
(H) Soil erosion	Soil erosion is one of the most significant variables influencing the water quality of the precipitation basin.	[37], [38]
(I) Mining operation	Mining operations have a negative influence on water quality.	[39], [40]
(J) Housing and road development	The expanding population's desire for homes and roads greatly strains water quality.	[41], [42]
(K) Logging and forest clearing	Malaysian deforestation has increased land-use changes and their influence on water quality.	[43], [44]
(L) Poultry farm and wet market activities	Animal feces from markets and farms are important sources of microbes and suspended particles in rivers	[45]–[47]

TABLE IV
FACTOR LOADING VALUES OF ALL PARAMETERS AFTER VARIMAX ROTATION

Criteria	Sum Row, R	Sum Column, C	R+C	R-C
A	5.9453	6.6211	12.566	-0.676
B	6.5416	7.3156	13.857	-0.774
C	6.3612	6.6533	13.015	-0.292
D	6.3157	7.1208	13.437	-0.805
E	6.6978	7.1515	13.849	-0.454
F	6.3545	5.2855	11.640	1.069
G	6.535	6.6316	13.167	-0.097
H	6.4864	6.3008	12.787	0.186
I	6.5843	6.0308	12.615	0.824
J	6.3856	5.4467	11.832	0.939
K	6.2504	6.6385	12.889	-0.388
L	6.2787	5.5403	11.819	0.738

Table 4 shows the prominence and relation of the criteria. The prominence is calculated as the row and column values (R+C), which show the importance criteria. Similarly, the difference in row and column values (R-C) was related, separating the criteria into a cause-and-effect group.

Next, Table 5 lists all values higher than the threshold value (h). The threshold value is used as a guideline when designing a diagram. For example, $t_{AB}\ (0.5781) > h(0.5329)$ shows that criteria B (Land use development) is affected by criteria A (Population growth and economic development). Detailed relationship among criteria is listed in Table 6 and Fig. 4. Both Table 6 and Fig. 4 explain and visualize the causal relationship between the evaluation criteria

TABLE V

TOTAL-RELATION MATRIX, T

criteria	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*L*
A	0.4487	**0.5781**	0.5164	**0.5584**	**0.5625**	0.4114	0.5217	0.4993	0.4688	0.4291	0.5184	0.4325
B	**0.5733**	**0.5454**	**0.5774**	**0.6142**	**0.6194**	0.4548	**0.5658**	**0.5422**	0.5247	0.4718	**0.5719**	0.4807
C	**0.5560**	**0.6137**	0.4824	**0.6006**	**0.5992**	0.4410	**0.5595**	0.5264	0.5030	0.4549	**0.5572**	0.4673
D	**0.5489**	**0.6090**	**0.5493**	0.5126	**0.5965**	0.4404	**0.5542**	0.5324	0.5047	0.4568	**0.5512**	0.4597
E	**0.5823**	**0.6418**	**0.5857**	**0.6242**	**0.5460**	0.4737	**0.5868**	**0.5561**	**0.5363**	0.4833	**0.5902**	0.4914
F	**0.5565**	**0.6179**	**0.5693**	**0.6021**	**0.5939**	0.3828	**0.5533**	0.5230	0.5044	0.4438	**0.5540**	0.4535
G	**0.5719**	**0.6319**	**0.5827**	**0.6175**	**0.6152**	0.4506	0.4940	**0.5398**	0.5216	0.4658	**0.5704**	0.4736
H	**0.5646**	**0.6232**	**0.5651**	**0.6023**	**0.6150**	0.4564	**0.5661**	0.4660	0.5220	0.4627	**0.5706**	0.4724
I	**0.5672**	**0.6314**	**0.5781**	**0.6131**	**0.6211**	0.4623	**0.5736**	**0.5488**	0.4528	0.4764	**0.5761**	0.4834
J	**0.5542**	**0.6120**	**0.5527**	**0.5989**	**0.6048**	0.4502	**0.5614**	0.5204	0.5036	0.3966	**0.5620**	0.4688
K	**0.5468**	**0.6035**	**0.5470**	**0.5897**	**0.5901**	0.4344	**0.5448**	0.5165	0.4915	0.4528	0.4730	0.4603
L	**0.5507**	**0.6077**	**0.5472**	**0.5872**	**0.5878**	0.4275	**0.5504**	0.5299	0.4974	0.4527	**0.5435**	0.3967

bold represents a value greater than the threshold

TABLE VI

DETAIL RELATIONSHIP FIG. 4

1	Criteria A is influenced by criteria C, F, G, H, I, J, K, and L. It shows that criteria A mutually influences criteria B, D, and E.
2	Criteria F, I, J, and L influence criteria B. It shows that criteria B has a mutual influence with criteria A, C, D, E, G, H, K, and itself.
3	Criteria C is influenced by criteria F, H, I, J, and L and also influences criteria A. It shows that criteria C mutually influences criteria B, D, E, G, and K.
4	Criteria D is influenced by criteria F, H, I, J, and L. It shows that criteria D mutually influences criteria A, B, C, E, G, and K.
5	Criteria E is influenced by criteria F, J, and L. It shows that criteria E has a mutual influence with criteria A, B, C, G, H, I, K, and itself.
6	Criteria F is influenced by criteria A, B, C, D, E, G, and K.
7	Criteria G is influenced by criteria F, I, J, and L and also influences criteria A. It shows that criteria G mutually influences criteria B, C, D, E, H, and K.
8	Criteria H is influenced by criteria I and A, C, D, and K. Criteria H mutually influence criteria B, E, and G.
9	Criteria I is influenced by criteria A, B, C, D, G, H, and K. It shows that criteria I mutually influence criteria E.
10	Criteria J is influenced by criteria A, B, C, D, E, G, and K.
11	Criteria K is influenced by criteria F, H, I, J, and L and also influences criteria A. It shows that criteria K mutually influences criteria B, C, D, E, and G.
12	Criteria L is influenced by criteria A, B, C, D, E, G, and K.

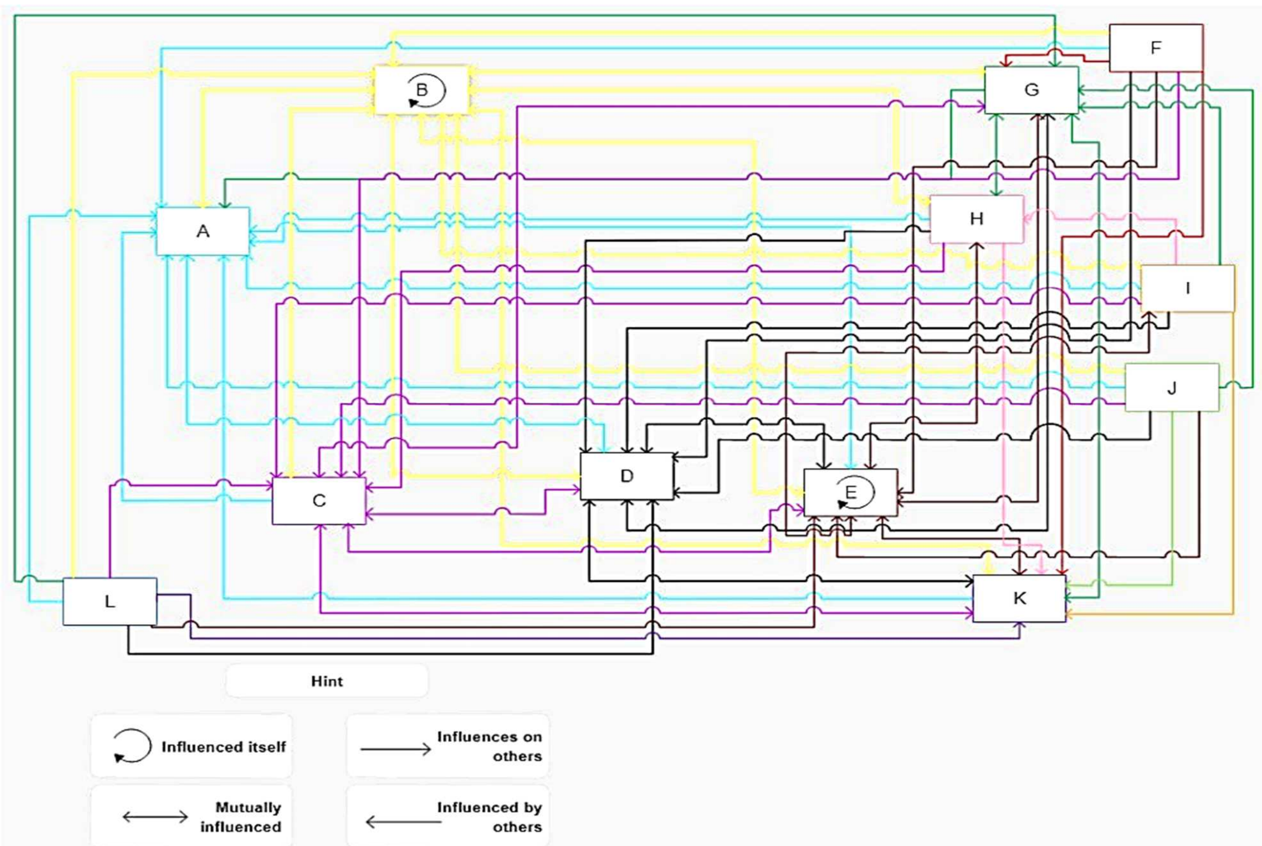

Fig. 4 Relationship digraph for each evaluation criteria

Lastly, the values (R-C) and (R+C) are mapped onto the Cartesian coordinate to construct the causal diagram. It is shown in Fig. 5. Based on the information from the causal diagram (see Table 4), the evaluation criteria are divided into two groups by the x-axis. The cause evaluation criteria are Criteria F, H, Criteria I, Criteria J, and Criteria L, as the (R-C) is positive. On the other hand, the effect evaluation criteria are Criteria A, Criteria B, Criteria C, Criteria D, Criteria E, Criteria G, and Criteria K, as the (R-C) is negative. This result indicates that Criteria F (Agricultural run-off and irrigation) is the essential evaluation criterion for determining the best factors influencing Terengganu River water quality.

Criteria F (Agricultural run-off and irrigation) has the highest (R-C) value from all the evaluation criteria at 1.069. This result is seen in line with the PCA and AHC results. PCA and AHC results also indicate that (Agricultural run-off and irrigation) contribute to river water pollution. It is due to the fertilizer used in agriculture that contains phosphorus and nitrogen. Usually, 60% of the fertilizer will be absorbed by the soil [29]. The rest, 40%, will flow into the river when it reaches a high concentration and can no longer be absorbed by the soil. Then, Criteria J (Housing and road development) has the second highest (R-C) value at 0.939.

The growing population rate, especially in developing areas such as Kuala Nerus, has further boosted the area's economic growth and construction activities. Infrastructure development that includes the construction of houses, buildings, and roads affects water quality changes and threatens aquatic life [30]. Usually, the criteria for the effect group are easily influenced by other criteria and can become unsuitable to be used as critical success factors. However, it is still necessary to measure the characteristics of each criterion. Among all 12 Criteria, Criteria B (Land use development) has the highest value (R+C). Big changes in the soil structure can affect the environment, including water and air around that area [31].

On the other hand, it changes the function of ecosystem services [31]. Land use development includes all the agricultural, residential, and industrial activities near the river [32]. Lastly, Criteria G (Municipal water pollution from home and business) is in the effect group and retrieves (R-C) value slightly below zero, which is -0.097.

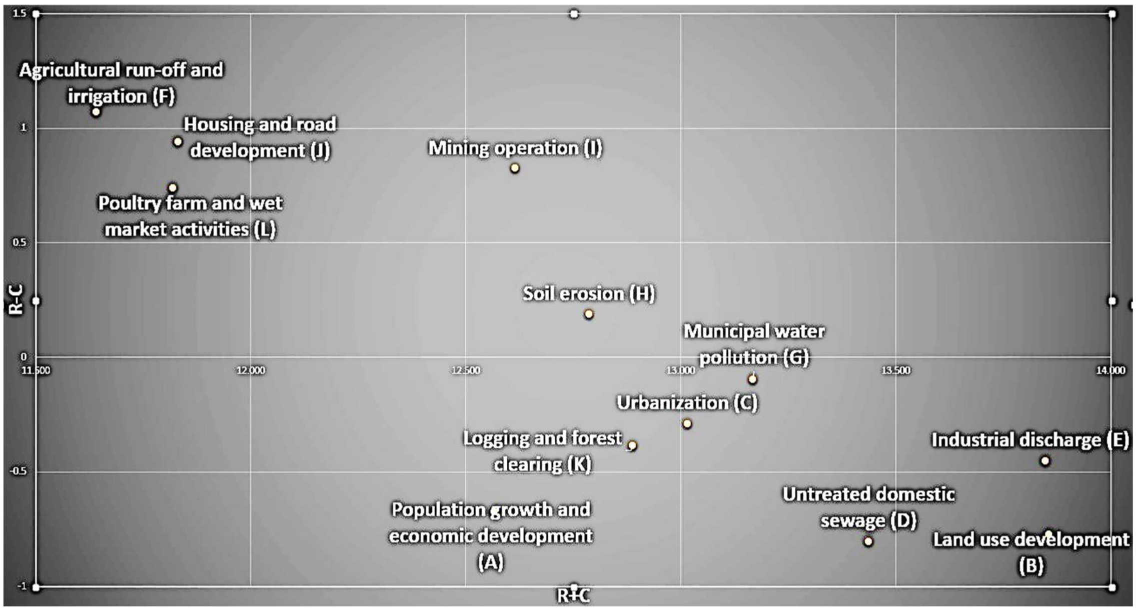

Fig. 5 Causal relationship

IV. Conclusion

This study successfully showed that the analysis used multivariate approaches to identify water parameters leading to pollution, particularly in the Terengganu River. The PCA method was successfully used to analyze 21 water parameters. In this study, PCA retrieved five significant factors with a total variance of 55.33%. Then, WQI generated three pollution zones: Low, Moderate, and High. Next, AHC gathered 14 water quality monitoring stations in three groups based on PCA's factor scores: less polluted, moderate, and polluted. Most monitoring stations are in category one instead of categories 2 and 3.

Furthermore, the FDEMATEL method identifies causal relationships between human activities and river pollution based on experts' opinions using two visual ways: causal diagram and digraph. Twelve experts are from different backgrounds: authorities, lecturers, the agricultural sector, and the public. FDEMATEL method results show that the cause group (positive R-C) consists of five criteria; Criteria F, H, I, J, and L. Whereas, the effect group (negative R-C) consists of Criteria A, B, C, D, E, G, and K. Criteria F (Agricultural run-off and irrigation) has the highest (R-C) value from all the evaluation criteria at 1.069. This finding is consistent with the PCA and AHC results. Both PCA and AHC results also indicate that (Agricultural run-off and irrigation) contribute to the contamination of river water. It is due to the fertilizer used in agriculture containing phosphorus and nitrogen. This phosphorus and nitrogen may produce eutrophication and algal blooms in the river, affecting water quality and threatening drinking water safety. Finally, these results (PCA, AHC, and FDEMATEL) are believed to be helpful for the local authorities to effectively manage the source of river pollution in the examined area and as a reference for further research in the future. Lastly, future research could extend this by adopting machine learning and deep learning approaches, generating more exciting and robust results.

ACKNOWLEDGMENT

The authors are grateful to the Department of Environment Malaysia for the permission to conduct this study. Enormous gratitude and special thanks to the Department of Environment Malaysia experts, universities, and the public for their valuable contribution to this study. We thank Malaysia's Ministry of Higher Education (MOHE) for supporting this research FRGS-RACER: RACER/1/2019/STG06/UNISZA//)

REFERENCES

[1] X. He, P. Li, J. Wu, M. Wei, X. Ren, and D. Wang, "Poor groundwater quality and high potential health risks in the Datong Basin, northern China: research from published data," *Environ. Geochem. Health*, vol. 43, no. 2, pp. 791–812, Feb. 2021, doi: 10.1007/S10653-020-00520-7.

[2] N. Hien Than, C. Dinh Ly, and P. Van Tat, "The performance of classification and forecasting Dong Nai River water quality for sustainable water resources management using neural network techniques," *J. Hydrol.*, vol. 596, p. 126099, May 2021, doi: 10.1016/j.jhydrol.2021.126099.

[3] G. Yotova, M. Varbanov, E. Tcherkezova, and S. Tsakovski, "Water quality assessment of a river catchment by the composite water quality index and self-organizing maps," *Ecol. Indic.*, vol. 120, p. 106872, Jan. 2021, doi: 10.1016/J.ECOLIND.2020.106872.

[4] T. Wu, S. Wang, B. Su, H. Wu, and G. Wang, "Understanding the water quality change of the Yilong Lake based on comprehensive assessment methods," *Ecol. Indic.*, vol. 126, p. 107714, Jul. 2021, doi: 10.1016/J.ECOLIND.2021.107714.

[5] H. Zhang, H. Li, D. Gao, and H. Yu, "Source identification of surface water pollution using multivariate statistics combined with physicochemical and socio-economic parameters," *Sci. Total Environ.*, vol. 806, p. 151274, Feb. 2022, doi: 10.1016/j.scitotenv.2021.151274.

[6] K. Chen, Q. Liu, W. Peng, and X. Liu, "Source apportionment and natural background levels of major ions in shallow groundwater using multivariate statistical method: A case study in Huaibei Plain, China," *J. Environ. Manage.*, vol. 301, p. 113806, Jan. 2022, doi: 10.1016/j.jenvman.2021.113806.

[7] M. K. Abdel-Fattah, S. K. Abd-Elmabod, A. A. Aldosari, A. S. Elrys, and E. S. Mohamed, "Multivariate Analysis for Assessing Irrigation Water Quality: A Case Study of the Bahr Mouise Canal, Eastern Nile Delta," *Water 2020, Vol. 12, Page 2537*, vol. 12, no. 9, p. 2537, Sep. 2020, doi: 10.3390/W12092537.

[8] Jabatan Alam Sekitar Malaysia, "Environmental Quality Report," pp. 1–195, 2019.

[9] A. Masthurah, H. Juahir, and N. B. Mohd Zanuri, "Case study Malaysia: Spatial water quality assessment of Juru, Kuantan and Johor River Basins using environmetric techniques," *Surv. Fish. Sci.*, vol. 7, no. 2, pp. 19–40, 2021, doi: 10.18331/SFS2021.7.2.2.

[10] N. Elfikrie, Y. Bin Ho, S. Z. Zaidon, H. Juahir, and E. S. S. Tan, "Occurrence of pesticides in surface water, pesticides removal efficiency in drinking water treatment plant and potential health risk to consumers in Tengi River Basin, Malaysia," *Sci. Total Environ.*, vol. 712, p. 136540, Apr. 2020, doi: 10.1016/J.SCITOTENV.2020.136540.

[11] H. M. A. Alssgeer, M. B. Gasim, M. M. Hanafiah, E. R. A. Abdulhadi, and A. Azid, "GIS-based analysis of water quality deterioration in the Nerus river, Kuala Terengganu, Malaysia," *Desalin. Water Treat.*, vol. 112, pp. 334–343, 2018, doi: 10.5004/dwt.2018.22335.

[12] T. J. Xin, H. Shaari, A. Ghazali, N. B. Ibrahim, and K. S. Rine, "Data on monthly physicochemical variation of Tropical Island groundwater of Pulau Bidong, South China Sea," *Data Br.*, vol. 30, p. 105527, Jun. 2020, doi: 10.1016/j.dib.2020.105527.

[13] N. Zamri, M. A. Pairan, W. N. A. W. Azman, and L. Abdullah, "An assessment of water pollutions area in Terengganu River, Malaysia using unsupervised machine learning," *Procedia Comput. Sci.*, vol. 215, pp. 920–928, Jan. 2022, doi: 10.1016/J.PROCS.2022.12.094.

[14] B. M. Saalidong, S. A. Aram, S. Otu, and P. O. Lartey, "Examining the dynamics of the relationship between water pH and other water quality parameters in ground and surface water systems," *PLoS One*, vol. 17, no. 1 1, p. e0262117, Jan. 2022, doi: 10.1371/journal.pone.0262117.

[15] USGS, "pH and Water." pp. 1–4, 2019. https://www.usgs.gov/special-topics/water-science-school/science/ph-and-water#overview

[16] M. Bagheri *et al.*, "Land-use suitability assessment using delphi and analytical hierarchy process (D-ahp) hybrid model for coastal city management: Kuala terengganu, peninsular malaysia," *ISPRS Int. J. Geo-Information*, vol. 10, no. 9, 2021, doi: 10.3390/ijgi10090621.

[17] A. Ghosh *et al.*, "Application of hexagonal fuzzy mcdm methodology for site selection of electric vehicle charging station," *Mathematics*, vol. 9, no. 4. pp. 1–28, 2021, doi: 10.3390/math9040393.

[18] E. E. Karsak and M. Dursun, "An integrated fuzzy MCDM approach for supplier evaluation and selection," *Comput. Ind. Eng.*, vol. 82, pp. 82–93, 2015, doi: 10.1016/j.cie.2015.01.019.

[19] M. S. Adnan, H. Roslen, and S. Samsuri, "The Application of Total Maximum Daily Load (TMDL) Approach in Water Quality Assessment for the Batu Pahat River," in *IOP Conference Series: Earth and Environmental Science*, 2022, vol. 1022, no. 1, p. 012074, doi: 10.1088/1755-1315/1022/1/012074.

[20] C. Yao *et al.*, "Water Quality Degradation in Urban Rivers of Dar es Salaam, Tanzania: Changes, Status, and Causes," *Water. Air. Soil Pollut.*, vol. 234, no. 4, pp. 1–19, Apr. 2023, doi: 10.1007/S11270-023-06237-4/FIGURES/7.

[21] Z. Feng *et al.*, "Analysis of long term water quality variations driven by multiple factors in a typical basin of Beijing-Tianjin-Hebei region combined with neural networks," *J. Clean. Prod.*, vol. 382, p. 135367, Jan. 2023, doi: 10.1016/j.jclepro.2022.135367.

[22] Y. Kazancoglu and Y. D. Ozkan-Ozen, "Analyzing Workforce 4.0 in the Fourth Industrial Revolution and proposing a road map from operations management perspective with fuzzy DEMATEL," *J. Enterp. Inf. Manag.*, vol. 31, no. 6, pp. 891–907, Oct. 2018, doi: 10.1108/JEIM-01-2017-0015.

[23] A. Bylak *et al.*, "Small stream catchments in a developing city context: The importance of land cover changes on the ecological status of streams and the possibilities for providing ecosystem services," *Sci. Total Environ.*, vol. 815, p. 151974, Apr. 2022, doi: 10.1016/J.SCITOTENV.2021.151974.

[24] C. Cheng, F. Zhang, J. Shi, and H. Te Kung, "What is the relationship between land use and surface water quality? A review and prospects from remote sensing perspective," *Environ. Sci. Pollut. Res. 2022 2938*, vol. 29, no. 38, pp. 56887–56907, Jun. 2022, doi: 10.1007/S11356-022-21348-X.

[25] M. Manoj, V. D. Kumar, M. Arif, E. R. Bulai, P. Bulai, and O. Geman, "State of the Art Techniques for Water Quality Monitoring Systems for Fish Ponds Using IoT and Underwater Sensors: A Review," *Sensors*, vol. 22, no. 6. Multidisciplinary Digital Publishing Institute, p. 2088, 08-Mar-2022, doi: 10.3390/s22062088.

[26] B. Herut *et al.*, "Long-Term (2002–2021) Trend in Nutrient-Related Pollution at Small Stratified Inland Estuaries, the Kishon SE Mediterranean Case," *Water 2023, Vol. 15, Page 484*, vol. 15, no. 3, p. 484, Jan. 2023, doi: 10.3390/W15030484.

[27] A. B. Tahiluddin, S. N. Nuñal, and S. M. S. Santander–de Leon, "Inorganic nutrient enrichment of seaweed Kappaphycus: Farmers' practices and effects on growth and ice-ice disease occurrence," *Reg. Stud. Mar. Sci.*, vol. 55, p. 102593, Sep. 2022, doi: 10.1016/J.RSMA.2022.102593.

[28] M. Varol, "Use of water quality index and multivariate statistical methods for the evaluation of water quality of a stream affected by multiple stressors: A case study," *Environ. Pollut.*, vol. 266, p. 115417, Nov. 2020, doi: 10.1016/J.ENVPOL.2020.115417.

[29] Widyarani, D. R. Wulan, U. Hamidah, A. Komarulzaman, R. T. Rosmalina, and N. Sintawardani, "Domestic wastewater in Indonesia: generation, characteristics and treatment," *Environ. Sci. Pollut. Res.*, vol. 29, no. 22, pp. 32397–32414, May 2022, doi: 10.1007/S11356-022-19057-6/TABLES/4.

[30] M. Mokarram, A. Saber, and V. Sheykhi, "Effects of heavy metal contamination on river water quality due to release of industrial effluents," *J. Clean. Prod.*, vol. 277, p. 123380, Dec. 2020, doi: 10.1016/J.JCLEPRO.2020.123380.

[31] Vandana, M. Priyadarshanee, U. Mahto, and S. Das, "Mechanism of toxicity and adverse health effects of environmental pollutants," in *Microbial Biodegradation and Bioremediation: Techniques and Case Studies for Environmental Pollution*, Elsevier, 2022, pp. 33–53.

[32] J. R. Masoner *et al.*, "Contaminant Exposure and Transport from Three Potential Reuse Waters within a Single Watershed," *Environ. Sci. Technol.*, vol. 57, pp. 1353–1365, 2022, doi: 10.1021/acs.est.2c07372/suppl_file/es2c07372_si_002.xlsx.

[33] N. Laskar, U. Singh, R. Kumar, and S. K. Meena, "Spring water quality and assessment of associated health risks around the urban Tuirial landfill site in Aizawl, Mizoram, India," *Groundw. Sustain. Dev.*, vol. 17, p. 100726, May 2022, doi: 10.1016/J.GSD.2022.100726.

[34] A. S. Oleiwi and M. Al-Dabbas, "Assessment of Contamination along the Tigris River from Tharthar-Tigris Canal to Azizziyah, Middle of Iraq," *Water (Switzerland)*, vol. 14, no. 8, p. 1194, Apr. 2022, doi: 10.3390/w14081194.

[35] Y. Xie *et al.*, "Insight into impact of sewage discharge on microbial dynamics and pathogenicity in river ecosystem," *Sci. Rep.*, vol. 12, no. 1, pp. 1–12, Apr. 2022, doi: 10.1038/s41598-022-09579-x.

[36] R. Kumar, S. Parvaze, M. B. Huda, and S. P. Allaie, "The changing water quality of lakes—a case study of Dal Lake, Kashmir Valley," *Environ. Monit. Assess.*, vol. 194, no. 3, pp. 1–16, Mar. 2022, doi: 10.1007/S10661-022-09869-X/TABLES/1.

[37] R. Mohapatra, "Application of revised universal soil loss equation model for assessment of soil erosion and prioritization of ravine infested sub basins of a semi-arid river system in India," *Model. Earth Syst. Environ.*, vol. 8, no. 4, pp. 4883–4896, Nov. 2022, doi: 10.1007/S40808-022-01388-5.

[38] S. Chen *et al.*, "Mapping Potential Soil Water Erosion and Flood Hazard Zones in the Yarlung Tsangpo River Basin, China," *Atmos. 2023, Vol. 14, Page 49*, vol. 14, no. 1, p. 49, Dec. 2022, doi: 10.3390/ATMOS14010049.

[39] I. Lahmidi *et al.*, "Assessment of Soil and Surface Water Quality in Makhat's Watershed (Taza Province, Morocco)," *Ecol. Eng. Environ. Technol.*, vol. 24, no. 2, pp. 194–204, 2023, doi: 10.12912/27197050/156972.

[40] M. Ruhela *et al.*, "GIS-based impact assessment and spatial distribution of air and water pollutants in mining area," *Environ. Sci. Pollut. Res.*, vol. 29, no. 21, pp. 31486–31500, May 2022, doi: 10.1007/S11356-021-18009-W/figures/5.

[41] G. Asumadu *et al.*, "Analysis of risks factors associated with construction projects in urban wetlands ecosystem," *Int. J. Sustain. Dev. World Ecol.*, 2022, doi: 10.1080/13504509.2022.2130465.

[42] P. Zhang *et al.*, "Urban forest soil is becoming alkaline under rapid urbanization: A case study of Changchun, northeast China," *Catena*, vol. 224, p. 106993, May 2023, doi: 10.1016/j.catena.2023.106993.

[43] G. F. Akomolafe and R. Rosazlina, "Land use and land cover changes influence the land surface temperature and vegetation in Penang Island, Peninsular Malaysia," *Sci. Rep.*, vol. 12, no. 1, pp. 1–15, Dec. 2022, doi: 10.1038/s41598-022-25560-0.

[44] S. López and A. Maldonado, "New Insights on Water Quality and Land Use Dynamics in the Napo Region of Western Amazonia," *Socio-Environmental Res. Lat. Am.*, pp. 81–115, 2023, doi: 10.1007/978-3-031-22680-9_5.

[45] A. Jana, D. Dasgupta, T. Bhaskar, and D. Ghosh, "Poultry Waste Biorefinery," in *Biotic Resources*, CRC Press, 2022, pp. 85–108.

[46] S. Kaura, A. Mathur, and A. Kalra, "Bacteria and Pollutants," *Mod. Approaches Waste Bioremediation*, pp. 339–364, 2023, doi: 10.1007/978-3-031-24086-7_16.

[47] J. A. Nweze, S. Gupta, J. Akor, C. O. Nwuche, J. E. Nweze, and V. U. Unah, "Animal Waste: An Environmentally Sustainable Management Approach," *Clim. Chang. Mitig. Sustain. Bioenergy Harvest Through Anim. Waste*, pp. 1–33, 2023, doi: 10.1007/978-3-031-26224-1_1.

[48] M. Mahmoudi, M. Yousefian, S. V. Alavi, and M. Shahabian, "Investigation of Changes in Vegetative Growth, Yield and Qualitative Properties of Thomson Navel Orange Fruit with Emphasis on Optimal Consumption of Manure and Chemical Fertilizers," *J. Soil Manag. Sustain. Prod.*, vol. 11, no. 1, pp. 27–45, May 2021, doi: 10.22069/EJSMS.2021.17836.1938.

[49] M. Camara, N. R. Jamil, and A. F. Bin Abdullah, "Impact of land uses on water quality in Malaysia: a review," *Ecological Processes*, vol. 8, no. 1. 2019, doi: 10.1186/s13717-019-0164-x.

[50] R. Luo, S. Yang, Z. Wang, T. Zhang, and P. Gao, "Impact and trade off analysis of land use change on spatial pattern of ecosystem services in Chishui River Basin," *Environ. Sci. Pollut. Res.*, vol. 1, p. 3, 2021, doi: 10.1007/s11356-021-17188-w.

[51] S. Yadav, M. S. Babel, S. Shrestha, and P. Deb, "Land use impact on the water quality of large tropical river: Mun River Basin, Thailand," *Environ. Monit. Assess.*, vol. 191, no. 10, 2019, doi: 10.1007/s10661-019-7779-3.