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Long-Term Water Quality Assessment in a Tropical Monsoon

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ABSTRACT

Multivariate statistical techniques such as principal component analysis (PCA) and cluster analysis (CA) were applied to water quality parameters in order to interpret complex matrices for better assessment of water quality and environmental status of a watershed. A study was conducted to assess water quality and to establish relationship among water quality parameters in Kelantan River basin. Water quality data was obtained from Department of Environment, (DOE) Malaysia from 2005-2014. Multivariate statistical techniques such as principal component analysis (PCA) and cluster analysis (CA) were applied to 15 water quality parameters in order to interpret complex matrices for better assessment of water quality and environmental status of the watershed. From the results, five PCs were extracted which are collectively accountable for controlling approximately 70% of the watershed's water quality. Results of cluster analysis indicated that three water quality parameters that included total suspended solids, total solids and turbidity control the water quality of the study area. These parameters were allocated into three clusters based on their similarity. The finding of this study will contribute to existing knowledge of the problems

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associated with water quality in the basin. This information can be put to use by land use managers and policy makers for future planning and development of the watershed.

Keywords: Cluster analysis, Kelantan, multivariate statistics, principal component analysis, water quality

INTRODUCTION

Water quality in Kelantan River basin has been under threat in the past few decades due to land use changes such as unrestricted deforestation for logging activities, agricultural activities and urbanization (Abdulkareem et al., 2017). In addition to this, natural factors such as soil type, geology, erosion, weathering of crustal materials, topography, vegetation cover, rainfall (intensity, duration and amount) have been reported to cause seasonal variation in water quality of the basin. While natural factors such as soil type, topography and rainfall are stable over a certain period of time, anthropogenic factors such as land use vary from time to time due to rapid increase in urbanization as well as for sustainable watershed management. The spatio-temporal differences existing in physicochemical properties make it necessary to have representative measurements of water quality parameters. However, monitoring activities are designed to cover periodic water samples collection at several locations aimed at determining several parameters which usually lead to collection of large data set that require complex interpretation (Simeonov et al., 2003; Yu et al., 2013).

Multivariate statistical techniques such as principal component analysis (PCA) and cluster analysis (CA) can be applied to water quality parameters in order to interpret complex matrices for better assessment of the chemistry and environmental status of the watershed. They can also be used in pinpointing sources controlling water quality and provide possible water management techniques as well as offers speedy response to pollution problems (Jalali, 2010). Several researchers in the past have utilized the use of multivariate statistical analysis in analyzing water quality data. For example, Dalakoti et al. (2018) used multivariate analyses (HCA [hierarchical cluster analysis] and PCA) to examine the potential similarities in pollution loads and the factors responsible for pollution at Nainital District in India. In Malaysia, Saiful et al. (2017) identified various types of pollution sources due to changes in land uses in Perlis River basin using HCA, PCA and CA. Multivariate analyses was applied in Lake Victoria, Kenya to evaluate the use of changes in pollution indicators (Kundu et al., 2017). The spatial variation and potential sources of pollution were identified by Juahir et al. (2011) using hierarchical agglomerative cluster analysis (HACA), PCA and CA in Langat River basin, Malaysia. Dalakoti et al. (2018) analyzed water quality data at wetland monitoring stations in South Florida, USA. They applied multivariate analysis with the aim of identifying variance in water depth and water quality variables due to changes in rainfall seasons for both wet and dry season. In another study, PCA and CA were utilized to assess spatial variations and to interpret water quality data of Lis River water, Portugal (Vieira et al., 2012). Different multivariate statistical techniques (CA, PCA and multiple regression) were applied by Simeonov et al. (2003) to datasets obtained from northern Greece for the assessment of surface water quality during a monitoring program.

In this study, Kelantan River basin was selected due to its flood prone nature in Malaysia. Several factors are responsible for flood in the watershed such as mismanaged drainage system, unpredictable nature of weather conditions and unplanned development by human activities. LULC changes and climate change have significant impact on the natural hydrologic conditions and ecological process of the watershed. LULC changes increase the occurrence of flooding, presenting a significant management problem. Furthermore, extensive LULC changes recorded 1980s to 2000s, especially in relation to deforestation (due to logging activities) and transformation to agricultural land (mostly for rubber and oil palm production) have been reported by several authors (Adnan & Atkinson, 2011; Abdulkareem et al., 2018a; Abdulkareem et al., 2018b; Jamaliah, 2007; Wan, 1996). In view of this, this work was carried out to assess water quality and to establish a relationship among water quality parameters.

MATERIALS AND METHODS

Monitoring Area

Kelantan River basin is in the northeastern part of Peninsular Malaysia between latitudes 4° 40’ and 6° 12’ north, and longitudes 101° 20’ and 102° 20’ East. The catchment has a maximum length and breadth of about 150 km and 140 km respectively. The watershed has an area of approximately 13,100 km^2, with the main river lying about 248 km long occupying more than 85% of the Kelantan state. The estimated quantity of the annual rainfall in the basin is about 2383±120 mm, a large amount of which occurs during the Northeast monsoon between mid-October and mid-January. Kelantan River is the major river in the Peninsular State of Kelantan located in the Northeastern part of Malaysia. The river originated at the convergence of Galas and Lebir rivers close to Kuala Krai where it meanders near the coastal plain finally meeting South China Sea, about 12 km north of Kota Bharu the capital city of Kelantan state (Figure 1). Kelantan River’s main reach possess larger tributaries that are located downstream. Furthermore, Galas and Lebir are known to also possess many tributaries escalated into the forested mountains of the country and are known to provide majority of the flow into the main Kelantan River. River Galas has two major tributaries viz., Pergau and Nenggiri that contribute to about 8000 km^2 or 54% from the total surface area of Kelantan’s catchment (approximately 13,100 km^2). Figure 1 shows map of the study area with water quality monitoring sites.

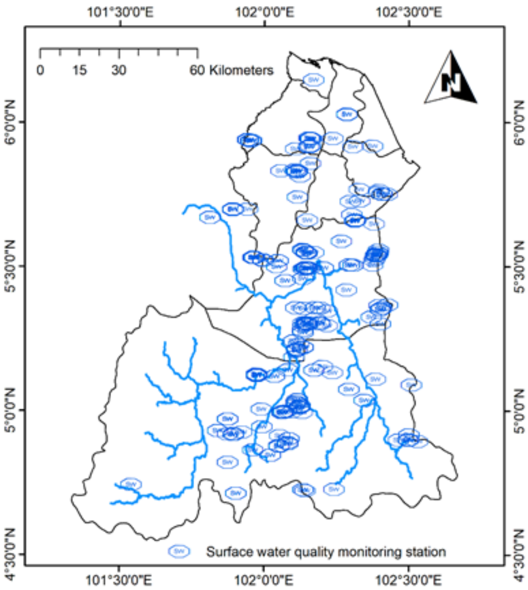

Figure 1. Map of the study showing sampling locations

Water Quality Data

Water quality data was obtained based on spatio-temporal availability from the Department of Environment, (DOE) Malaysia from 2005-2014. Fifteen water quality parameters that included total suspended solids (SS), pH, ammonium nitrate (NH_4-N), temperature (TEMP), conductivity (COND), turbidity (TUR), total dissolve solutes (DS), total solids (TS), nitrate (NO_3), chloride (Cl), phosphate (PO_4), calcium (Ca), potassium (K), magnesium (Mg) and sodium (Na) from several water quality monitoring sites were chosen for this study (Figure 1).

Statistical Analyses

Statistical analyses were conducted using multivariate statics such as Pearson correlation; PCA and CA in assessing water quality and establishing relationship between water parameters.

Principal Component Analysis (PCA). It is advisable to always determine the Kaiser-Mayer-Olkin (KMO) before performing PCA. This will help to assess how suitable it is to perform PCA on the intended data and to determine the sufficiency of the samples. The analysis can proceed if KMO value is found to be ≥ 0.5. In the current study; the value of KMO value was found to be 0.719. The PCA is the most commonly utilized multivariate statistical analysis. It functions by extracting variables into groups called principal components (PCs). These groups (PCs) are extracted along with their eigenvalues, variability (%) and cumulative values (%) (Ranjan et al., 2013). PCA was used in detecting patterns in data, which were presented based on their resemblances and dissimilarities. Pattern identification in a complex data is a difficult task, hence, the use of PCA is such scenario helps in providing good assessment (Smith, 2002).

Cluster Analysis (CA). This is a type of multivariate analysis that categorizes data into clusters according to their resemblance to each other and difference to other groups. CA is performed without making assumptions on the intended data so that structures or patterns can be discovered on the original data set (Mohapatra et al., 2011).

RESULTS AND DISCUSSIONS

Statistical Summary

The statistical summary of water quality parameters from 2005-2015 is shown in Table 1. The pH of the water in rivers of Kelantan showed both acidic and alkaline values (5.18 and 8.73 respectively). However, high SS (3380 mg L^{-1}) and high TS (3397 mg L^{-1}) might be because of high anthropogenic activities on the rivers. Urbanization around the river banks might influence the chemical reactions in the area due to leaching caused by sewage release (Abdulkareem et al., 2018). High TDS values ranging from 8.25 to 204 mg L^{-1} could also be attributed to anthropogenic activities such as agriculture. The order of availability of anions in the watershed is Cl>NO_3>PO_4 while that of cations were Na>Ca>Mg>K. There was high sedimentation in the area, which was evident from high values of turbidity (2780.00 NTU) in the basin.

Pearson Correlation

Guildford rule of thumb (Guilford & Fuchter, 1965) as presented in Table 2 was used in interpreting the relationship between water quality parameters. Results of the Pearson correlation matrix that describe the relationship between water quality parameters (Mor et al., 2009) are presented in Table 3. The results showed that most of the parameters were not correlated with one another even though high correlation existed in some few cases such as Turbidity-SS ($r = 0.856$, $p < 0.01$), DS-TS ($r = 0.982$, $p < 0.01$), DS-conductivity ($r = 0.82$, $p < 0.01$), DS-Turbidity ($r = 0.85$, $p < 0.01$), Na-Cl ($r = 0.76$, $p < 0.01$). While a moderate correlation was observed in the following parameters; Ca-conductivity ($r = 0.61$, $p < 0.05$), Ca-TDS ($r = 0.66$, $p < 0.05$), Mg-DS ($r = 0.52$, $p < 0.05$) and K-Mg ($r = 0.54$, $p < 0.05$).

Table 1

Summary statistics of water quality parameters in Kelantan River from 2005-2014

Parameters	Unit	Minimum	Maximum	Mean	Std. deviation
TSS	mg L^{-1}	1.00	3380.00	132.78	247.99
pH	-	5.18	8.73	7.11	0.55
NH_4-N	mg L^{-1}	0.01	2.60	0.07	0.17
Temperature	^{0}C	18.72	34.30	26.50	2.08
Conductivity	µS cm^{-1}	14.00	440.00	58.29	32.31
Turbidity	NTU	0.00	2780.00	155.09	259.47
TDS	mg L^{-1}	8.25	204.00	29.04	14.94
TS	mg L^{-1}	0.00	3397.00	158.12	246.10
NO_3	mg L^{-1}	0.01	1.72	0.19	0.20

Table 1 *(Continued)*

Parameters	Unit	Minimum	Maximum	Mean	Std. deviation
Cl	mg L^{-1}	0.52	74.00	2.91	4.02
PO_4-P	mg L^{-1}	0.01	1.00	0.03	0.06
Ca	mg L^{-1}	0.10	35.46	4.89	4.15
K	mg L^{-1}	0.10	11.05	1.34	0.82
Mg	mg L^{-1}	0.10	18.66	1.16	1.14
Na	mg L^{-1}	0.10	39.08	4.02	2.45

Ions such as Ca and Mg are the most abundant in rivers (Wollast & Mackenzie, 1983) while presence of Na and Cl with high correlation between them indicates the intrusion of saline water into rivers (Panteleit et al., 2001). SS is a major water quality parameter whose significance lies not only on the physical (light penetration) and ecological productivity (Parkhill & Gulliver, 2002; Rügner et al., 2013) but also is an indicator of other parameters such as phosphorus that are transferred on the surfaces of suspended sediments (Jones et al., 2011; Rügner et al., 2013). SS in the studied basin are a result of frequent flooding of the studied catchment.

Table 2
Guildford rule of thumb for interpreting correlation coefficient (Guilford & Fuchter, 1965)

r-value	Interpretation
0.0 to 0.29	Negligible or little correlation
0.3 to 0.49	Low correlation
0.5 to 0.69	Moderate or marked correlation
0.7 to 0.89	High correlation
0.9 to 1.00	Very high correlation

High correlation obtained between SS and turbidity in this study is attributed to the presence of suspended particles in rivers that causes high turbidity of the water by scattering light. The relationship between SS and TS and that of TS and turbidity were also found to be highly correlated in this study. These relationships are however, dependent on size, shape and type particles (Rügner et al., 2013). In Kelantan River basin where high agricultural and other anthropogenic activities are common along the riverbanks and where flow conditions in rivers are high during floods, more coarse particles may be suspended leaving smaller particles submerged. The moderate correlation between DS and Ca, DS and Mg and Mg and K can be interpreted as the mineral component of the river. High correlation between Na and Cl is an indication of seawater intrusion in northern part of Kelantan that is closed to South China Sea.

Table 3

Correlation matrix of water quality parameters in Kelantan River basin

Parameters	TSS	pH	NH_4-N	Temp	Cond	Tur	TDS	TSS	NO_3	Cl	PO_4-P	Ca	K	Mg	Na
TSS	1														
pH	-0.027	1													
NH_4-N	0.083	0.016	1												
Temperature	0.003	0.050	0.040	1											
Conductivity	-0.036	0.103	-0.004	0.12	1										
Turbidity	0.856**	-0.051	0.069	-0.01	-0.03	1									
TDS	-0.049	0.025	0.014	0.14	0.82**	-0.02	1								
TS	0.982**	-0.028	0.080	0.01	0.01	0.85**	0.01	1							
NO_3	0.264	-0.025	0.292	-0.01	0.10	0.25	0.08	0.249	1						
Cl	-0.016	-0.097	0.034	0.07	0.27	0.00	0.39	0.014	0.068	1					
PO_4-P	-0.037	0.051	-0.020	0.01	0.03	-0.01	0.01	-0.034	-0.076	0.060	1				
Ca	-0.013	0.091	-0.033	0.11	0.61*	-0.03	0.66*	0.032	0.119	0.128	-0.016	1			
K	0.114	-0.031	0.087	0.21	0.20	0.15	0.28	0.130	0.257	0.357	0.024	0.113	1		
Mg	-0.024	-0.017	0.022	0.09	0.46	-0.01	0.52*	0.013	0.114	0.335	0.009	0.482	0.54*	1	
Na	-0.038	-0.050	0.002	0.16	0.40	-0.04	0.49	-0.018	0.078	0.76**	0.046	0.194	0.494	0.483	1

Notes: * *significant correlation at $p < 0.05$ (2 tailed),* ** *highly significant correlation at $p < 0.01$ (2 tailed)*

Extraction of Components

Fifteen water quality parameters were subjected to PCA where 15 PCs (Table 4-5 and Figure 2) were identified but only 5 PCs were considered most useful because of their eigenvalue that is >1 (Arslan, 2013; Pathak & Limaye, 2011). PCs with higher eigenvalue contribute greater in controlling water quality (Abdi, 2003). In order to infer factors that are of utmost importance without altering the variance, varimax factor rotation was utilized (Kaiser, 1960). The eigenvalue-one criterion otherwise known as Kaiser criterion suggests that only PCs with eigenvalue value >1 should be adopted and interpreted. This is on the account that every one of the detected variables is responsible for one unit of variance to the total variation in the data.

Table 4
Eigenvalue, variability and cumulative % of extracted factors

Factors	Eigenvalue	Variability %	Cumulative %
PC1	3.70	24.67	24.67
PC2	2.95	19.64	44.31
PC3	1.49	9.94	54.25
PC4	1.21	8.07	62.32
PC5	1.07	7.16	69.48
PC6	0.98	6.52	76.00
PC7	0.87	5.80	81.80
PC8	0.81	5.42	87.22
PC9	0.64	4.29	91.50
PC10	0.42	2.79	94.30
PC11	0.29	1.96	96.26
PC12	0.21	1.41	97.66
PC13	0.18	1.21	98.88
PC14	0.15	1.02	99.90
PC15	0.02	0.10	100.00

Therefore, PCs with an eigenvalue more noteworthy than 1.00 are considered to contribute more variation than those with eigenvalue <1. PCA is conducted with the goal of reducing the number of experimental data into smaller components without damaging the actual meaning of the data sets involved. As such keeping PCs with less variance (eigenvalue <1) at the expense of those with more variance (eigenvalue >1) will defeat the aim at which PCA is conducted (O'Rourke et al., 2005).

Table 5
Factor loadings after Varimax rotation

Parameters	PC1	PC2	PC3	PC4	PC5
SS	0.07	0.96	0.08	-0.14	0.02
pH	0.01	-0.07	0.36	0.12	0.62
NH_4-N	0.07	0.18	-0.15	0.75	0.13
Temperature	0.24	-0.02	-0.06	0.05	0.55
Conductivity	0.76	-0.13	0.43	-0.02	-0.04
Turbidity	0.08	0.91	0.05	-0.16	0.01
DS	0.84	-0.13	0.32	-0.04	-0.09
TS	0.12	0.95	0.10	-0.16	0.01
NO_3	0.24	0.39	-0.08	0.62	-0.09
Cl	0.62	-0.06	-0.52	-0.20	-0.05
PO_4-P	0.03	-0.06	-0.08	-0.29	0.57
Ca	0.64	-0.10	0.58	0.05	-0.09
K	0.59	0.15	-0.44	0.12	0.15
Mg	0.75	-0.07	-0.03	0.03	-0.06
Na	0.75	-0.10	-0.46	-0.16	0.01
Eigenvalue	3.70	2.95	1.49	1.21	1.07
Variability %	24.67	19.64	9.94	8.07	7.16
Cumulative %	24.67	44.31	54.25	62.32	69.48

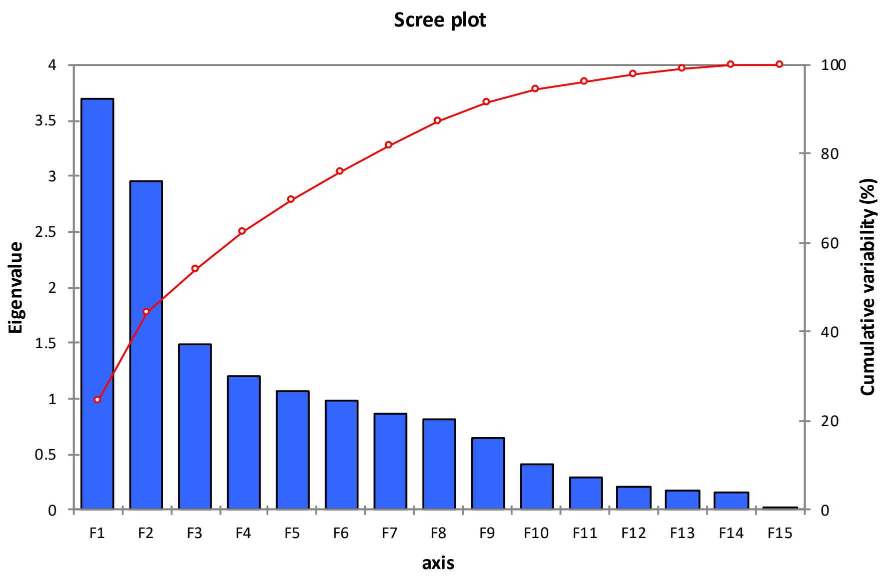

Figure 2. Scree plot of extracted factors (factors with Eigenvalue ≥ 1 are considered the most significant)

From the results of PCA (Table 4-5 and Figure 2) five PCs were identified which account for a cumulative value of 69% in the water quality. PC1 with eigenvalue of 3.70 recorded 24.67% of the total variance making it the PC controlling the most important processes influencing water quality (Yidana et al., 2010). In this PC, all the water quality parameters were observed even though some of the parameters recorded very little loading. A strong positive loading between electrical conductivity, TDS, Mg and Na was observed signifying that these parameters were dependent upon the contribution of other parameters. Ca was observed to be lower than both Na, which might be due to cation exchange activity that occurred naturally when ions of higher charges were replaced by those with lower charges ($Ca2+$ is replaced by $Na+$ at the exchange site). PCA is of utmost importance in hydrochemical analyses due to its ability to give inferences according to specific or multiple hydrochemical processes (Suk & Lee, 1999). A single PC can have one or more processes (Arslan, 2013; Kumaresan & Riyazuddin, 2008; Yidana et al., 2010) as observed in PC1 (Table 5) where high loading of DS and electrical conductivity resulting from seawater intrusion. Other processes such as Ca and Mg loading are because of weathering process (Kumaresan & Riyazuddin, 2008) although seawater intrusion may have dominated the whole scenario.

PC2 contribute 19.64% of the variability and it comprises a strong loading of parameters like SS, turbidity and TS (Table 5). The strong loading of SS, turbidity and TS may be because of influence of human activities along the riverbanks of Kelantan River basin making the water to attract more microorganisms. While the negative pH loading observed may be caused by high runoff activities in the watershed and leaching of sewage. An eigenvalue of 1.49 was observed in PC3 (Table 5) with a total variability of 9.94%. This PC shows a positive weak loading of pH, electrical conductivity and DS while a positive moderate loading of Ca and a moderate negative of Cl were observed. The positive moderate loading of Ca can be explained by weathering process occurring in the watershed. The weak loading of DS is an indication of small amounts of organic matter content in the water. PC4 has a total variability of 8.07% and eigenvalue of 1.21 (Table 5). A strong loading of NH4-N and a moderate loading of NO3 were observed in this PC. This strong and moderate loading of nitrogen containing compounds is a clear indication of pollution caused by anthropogenic activities resulting from agricultural activities, sewage disposal and other domestic activities, which lead to build up of microorganisms (Sundaray, 2010). PC4 was reported to have a strong loading of pH and a moderate loading of temperature and PO4-P. The moderate loading of temperature is an indication of natural weather where high ambient air temperatures directly affect river temperatures. High loading of pH is an indication of photosynthetic activities caused by microorganisms such as algae and other aquatic plants United States Environmental Protection Agency (US EPA, 2012).

Cluster Analysis

When cluster analysis was performed on water quality parameters in Kelatan River basin, three major clusters were identified according to similarities existing between parameters and dissimilarities to other groups as outlined in Figure 3. Cluster 1 consisted of suspended solids, total solid and turbidity. The activities of microorganisms are directly related to turbidity (Mann et al., 2007). Higher activities of microorganisms in the river basin leads to oxygen depletion, which in turn affects dissolved oxygen concentration. In cluster 2, water quality parameters such as NH_4-N, NO_3, PO4-P, pH and temperature were observed. This cluster describes diverse processes involved in controlling the water quality of the basin. The presence of both NH_4-N and NO_3 is an indication of high level of anthropogenic activities taken place along the riverbanks in the watershed (Sundaray, 2010). In addition, pH and temperature are the major parameters controlling physiochemical and biological reactions taken place in water (Delpla et al., 2009; Nelson, 2000). Cluster 3 comprises electrical conductivity, dissolved solid, K, Na, Ca, Mg and Cl. This group gives an inference on the chemical activities in the watershed. The presence of Mg is an indication of freshwater recharge (Thilagavathi et al., 2012). While occurrence of Ca and Na signifies weathering processes taken in the river water while Cl may have been influenced by seawater intrusion as reported by Chidambaram et al. (2013).

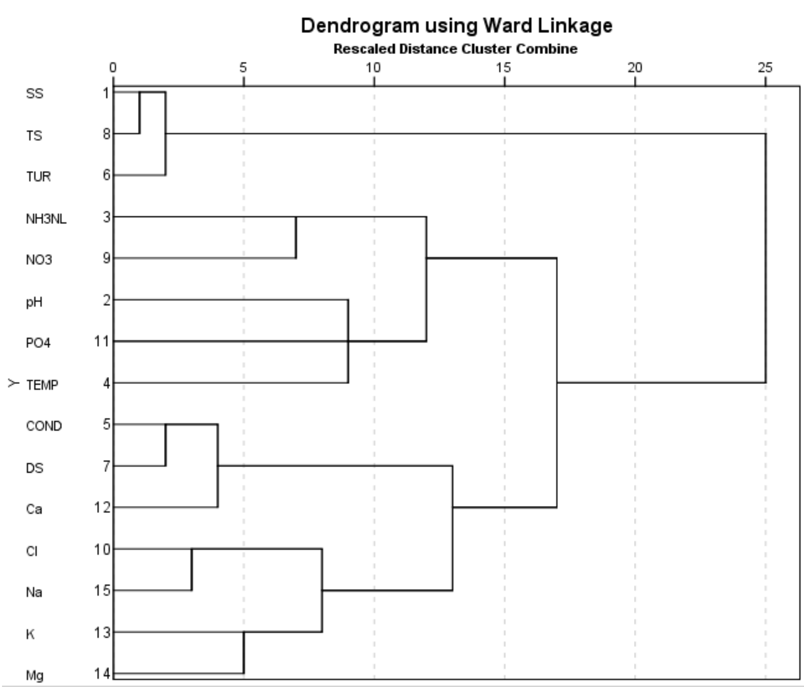

Figure 3. Dendrogram based on the clustering of water quality data in Kelantan

CONCLUSIONS

Fifteen water quality parameters from Kelantan River basin were used to conduct PCA and CA for identifying the parameters that influence water quality in the watershed. Water quality in the watershed is controlled by factors such as anthropogenic pollution, weather factors, seawater intrusion, weathering process and redox potential. PC1 was observed to be the most important component that is in control of water quality of the basin. Weathering processes and seawater intrusion are some of the processes that makes up the PC. Anthropogenic activities caused by high loadings of turbidity, suspended solids, total solids, NH_4-N and NO_3 are some of the processes influencing PC2 and PC4. Weathering activities also dominate PC3 due to moderate loading of Ca. High loading of pH and moderate loading of PO4-P suggesting that the PC is controlled by redox potential characterize PC5. Results of CA revealed that three clusters were observed. The first cluster comprises suspended solids, total solid and turbidity leading to the buildup of microbial activities. Cluster 2 is in control of diverse processes regulating water quality of the basin due to the presence of NH_4-N, NO_3, PO4-P, pH and temperature. The chemical activities involved in the watershed due to the presence of electrical conductivity, dissolved solid, K, Na, Ca, Mg and Cl are described by cluster 3. Results of this study will add to knowledge the specific water quality problems affecting the watershed, which can be utilized by land use managers and policy makers alike for future control planning.

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