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EVALUATION OF SURFACE WATER QUALITY USING MULTIVARIATE TECHNIQUES IN TERENGGANU RIVER BASIN

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ABSTRACT

Surface river water is seriously experiencing contamination which threatens human health, ecosystem and plants/animals life. Cluster analysis and principal component analysiswas used to evaluatethe spatial variation and contamination sources of surface water quality data sets initiated from Terengganu river basin and originated during 2003-2007 monitoring of 30 parameters at 13 sampling stations. CA grouped monitoring stations into two based on their similarity characteristics: low pollution source (LPS) and moderate pollution source (MPS). PCA yielded 8 varifactors with total variance of 73.62%. Besides, based on the land use activities PCA identifies mineral components, anthropogenic activities (agricultural, domestic sewage water, industrial waste) and natural processes (erosion and runoff) were the major pollution sources resulted in the variation of the river. Therefore, the results revealed the importance of multivariate statistical techniques for investigation and understanding the surface water quality.

INTRODUCATION

Truly water is the most important for sustaining life and resource in all economic activities associated with agriculture and industry. Surface waters are vulnerable to pollution as a result of natural processes such as erosion, precipitation input, weathering of crustal materials and anthropogenic activities viz: urban, industrial, agricultural activities (Sundaray *et al*., 2006; Carpenter *et al*., 1998; Jarvie *et al*., 1998). Rivers constitute the main inland water body for domestic, industrial, and agricultural field. The discharge of wastewaters, and industrial effluents weather treated or not, can be regarded a constant polluting source that dominate surface water quality, as well as non-point source pollution, caused by surface and runoff from agricultural areas and urban areas, which is a seasonal and affected by climate change (Singh *et al*., 2004; Juahir *et al*., 2010). Since, water forms the main inland water resource for domestic, industrial and agricultural purposes, it is vital to avert and control rivers pollution (Simeonova *et al*., 2003) and to have genuine information on water quality for effective management. Characterization of the spatial variation and source apportionment of water quality parameters can produce an improved understanding of the environmental situation and assist policy makers to design priorities for sustainable water management (Hung *et al*., 2010). The degree of water quality is determined by the content of physical, chemical and biological parameters available in it. Association between two parameters may cause to increases or decrease in the concentration of others. This association or relationship is usually achieved using multivariate statistical techniques (Mazlum *et al*., 1999; Jaji *et al*., 2007). The applications of different multivariate statistical techniques are used to reveal the information concealed in the quality monitoring network. Hence, the cluster analysis (CA) and principal component analysis (PCA) have increased tremendously in recent years for analysing environmental data and design meaningful information. These methods allow the identification of the possible pollution sources that affect water systems and offer a valuable for relievable management of water resources as well as rapid solution for pollution problems (Regunath *et al*., 2002; Vega *et al*., 1998; Kazi *et al*., 2009; Wunderlin *et al*., 2001; Shrestha and Kazama, 2007). Additionally, are the most common statistical techniques used in the interpretation of

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data (Praveena *et al*., 2007). Generally these techniques are applied to identify key variables for environmental monitoring purposes and similar contaminant sources (Looi *et al*., 2013). In this study multivariate statistical techniques were employed to dictate the water quality inputs and to cluster monitoring stations using surface water quality data from Department of Environment, Malaysia.

MATERIALS AND METHODS

Study Area

Terengganu river basin (4^0 41' – 5^0 20'N, $102^0$31' – 103^0 9 ' E) is located in Terengganu State; in east coast Peninsular Malaysia, has a length of 100 km and an aggregate catchment range of roughly 500 km2 (Noor, 2010). It begins from Lake Kenyir discharge through Kuala Terengganu and streams into South China Sea Figure 1. Terengganu River basin where included Nerus River, Telemong River, Bereng River, and Pueh River. The climate is tropical wet climate (Koppen Geiger Classification: AF) with no dry or cold season as it is constantly moist (year round rainfall).

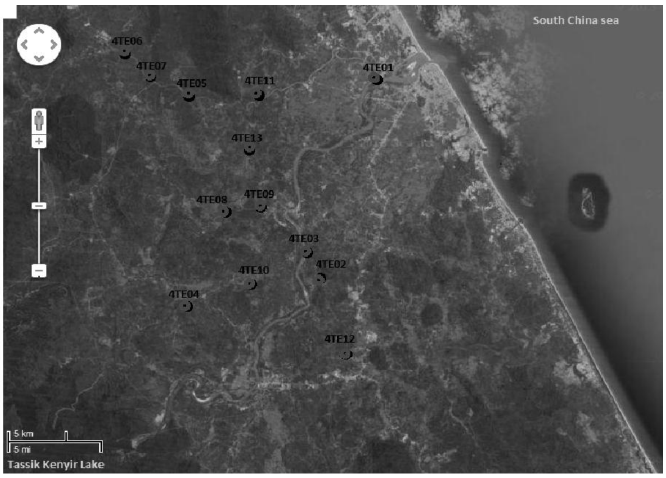


Figure 1. Showing study area and monitoring stations

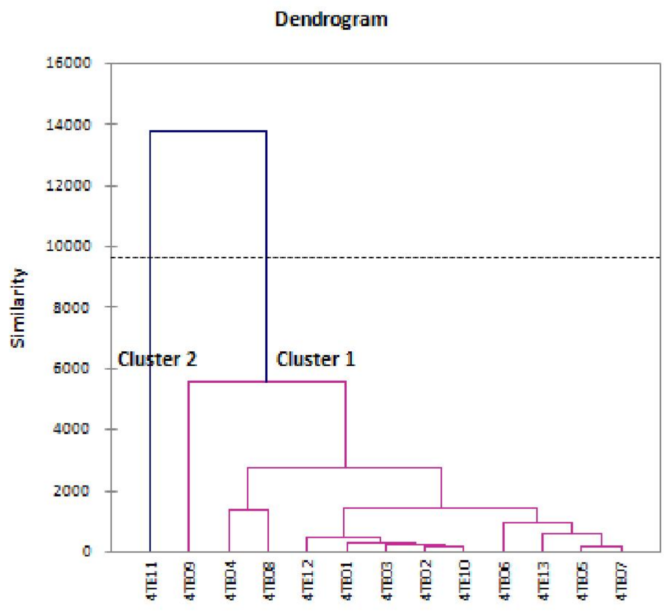


Figure 2. Dendogram showing the clusters of the monitoring stations

The annual average temperature is 26.7^{0}C (80^{0}F). Average monthly temperature varies by 3^{0}C (5.4^{0}F). Total annual precipitation averages 2911mm. On average there are 2412 hours of sunshine per year. There are two main types of monsoons the southwest monsoon season is usually established in the latter half of May or early June and ends in September. The northwest monsoon season usually starts in early November and ends in March (Terengganu, 2014). The study area has a population of 1,125,000 as at 2013 (DOSM, 2014) and is pristine environment in the upstream catchment area turning urbanized and industrialized downstream with the major settlement of Kuala Terengganu city at the mouth. Establishing and important land uses include forest, commercial plantation (e.g., oil palm, coconut, and rubber, cocoa), agriculture, rural/urban settlements, past mining activities and industry. The construction of a hydroelectric power dam upstream has altered the hydro geochemical compartments consisting of the Kenyir Lake and the main tributary of Terengganu River. Therefore, the rivers is influenced by residential and city waste, agricultural activities, run-off and industrial activities. Collectively, it is influenced by point source pollution and non-point source pollution. Indeed, is important to beat this obligation through deciding the progressions in water quality.

The Data

Data sets of 30 water quality variables and 271 samples (30 × 271), over a period of five years (2003 – 2007) were monitored by Department of Environment, Malaysia (DOE) across 13 stations of Terengganu river basin (Figure 1). The monitored parameters aredissolved oxygen (DO), biological oxygen demand (BOD), Chemical oxygen demand (COD), Suspended solid (SS), PH, ammonia nitrate (NH_3-N), temperature, conductivity, salinity, turbidity, dissolved solid (DS), total solid (TS), nitrate (NO_3), chlorine (Cl), phosphate (PO_4), arsenic (As), mercury (Hg), chromium (Cr), cadmium (Cd), lead (Pb), zinc (Zn), calcium (Ca), iron (Fe), potassium (K), magnesium (mg), sodium (Na), oil and grease (OG), MBAS, E coli, and total coli form. Preparatory work was tendered on the datafollowing sorting, arranging and transformation of the data station by station. Non numerical variables were subjected to transformation. Data transformation helps to normalize the whole data set so as to fulfil the assumption of cluster and PCA (Voudouris *et al*., 2000).

Multivariate Statistical Techniques

Cluster Analysis

CA is a technique applied to group the data into clusters or classes. The aim is to develop a set of clusters where by the object in the same cluster are similar to each other but different from those in other clusters. Hierarchical agglomerative clustering is the most common approach, which provides intuitive similarity relationship between any one sample and the entire data set, and is typically illustrated by a dendogram (tree diagram) (McKenna, 2003). The groups are classified by their similar characteristics, which aid to clarify the data better. The current approach can be used to extract related variables and determine the processes that managed the water chemistry (Praveena *et al*., 2007; Cheni and Khemiri, 2009). However, in this study hierarchical agglomerative cluster analysis was performed on the normalized data set by ward method, using Squared Euclidean distance as a measure of similarity.

The Euclidean distance is a commonly used distance coefficient that usually gives the similarity between two samples and a "distance" that can be represented by the "difference" between analytical values from both the samples (Otto, 1998). It is one of the commonly adopted measures (Farham *et al*., 2000). The result of dendogram provides a visual conclusion of the clustering processes, displaying a picture of the groups and their proximity, with a reduction in dimensionality of the initial data (Shrestha and Kazama, 2007; Alkarkhi *et al*., 2000). Cluster analysis was used to categorize the sampling points into statistically significant groups based on their dissimilarities or similarities in pollution level of river water.

Principal Component Analysis

PCA is a statistical approach that can be applied to analyse interrelationships among a large number of variables base on their common underlying dimension by providing empirical estimates of the variables (Hair *et al*., 1995). The PCA is aimed to transform the original variables into new, uncorrelated variables (axes, known as principal components, which are linear combination of the original variables.A principal component is a linear combination of observed water quality variables, while a VF can include unobservable, hypothetical latent variables (Vega *et al*., 1998; Helena *et al*., 2000).

PCA gives information on the most significant parameters that describe the majority of the data set, affording data reduction with minimum loss of original information (Helena *et al*., 2000; Shrestha and Kazama, 2007). The principal component (PC) can be expressed as:

$$Z_{ij} = a_{i1}x_{1j} + a_{i2}x_{2j} + a_{i3}x_{3j} + \text{---------} + a_{im}x_{mj}$$

Where *z* is the component score, component loading is *a*, *x* is the measured value of variable, *i* is the component number, j the sample number of variables. XLSTAT2014 Excel software add-in was used for the Statistical analysis.

RESULTS AND DISCUSSION

Descriptive statistic

Table 1 present the range mean and standard deviation of all the parameters of the study area. It shows that coliform, E-coli, TS, EC, Tur, SS and DS were the dominant variables with high mean concentration of 40103 mg/L, 3411.3 mg/L, 74.59 mg/L, 67.1 mg/L, 53.5 mg/L, 44.057 mg/L and 31.55 mg/L respectively. This indicates that these parameters have common source of origin (anthropogenic activities). The mean value of pH is 6.68 units which are acidic. The concentration of COD and DO are 24.3 mg/L and 6.37 mg/L, indicating low anthropogenic pressure on the surface water.

Table 1. Descriptive Statistics

Variables	Minimum	Maximum	Mean	Std. Deviation
DO mg/L	1.76	8.33	6.374	1.23
BOD mg/L	1	142	2.768	9.849
COD mg/L	15	329	24.339	22.937
SS µS	0.5	1040	44.057	84.754
pH unit	3.17	8.84	6.683	0.787
NH_3-N	0.005	10.21	0.306	0.9
TEMP ^{0}C	23.05	82.2	27.56	3.753
COND	0	979	67.1	112.155
SAL %	0.01	0.47	0.031	0.054
TUR nut	0	626.6	53.502	82.405
DS mg/L	6	569	31.554	69.966
TS mg/L	0	1054	74.598	107.535
NO_3 mg/L	0.005	1.29	0.183	0.145
Cl mg/L	0.5	92	3.592	7.132
PO_4mg/L	0.005	1.25	0.037	0.1
As mg/L	0.001	0.005	0.001	0.001
Hg mg/L	0	0.128	0.001	0.008
Cd mg/L	0.001	0.003	0.001	0
Cr mg/L	0.001	0.018	0.001	0.002
Pb mg/L	0.005	0.015	0.005	0.001
Zn mg/L	0.005	0.6	0.035	0.048
Ca mg/L	0.05	20.7	1.627	2.373
Fe mg/L	0.005	14.5	0.767	1.31
K mg/L	0.05	121	2.562	8.03
Mg mg/L	0.05	22	0.987	2.434
Na mg/L	0.05	29.1	4.131	3.382
OG mg/L	0.5	51	0.749	3.087
MBAS	0.025	0.025	0.025	0
E-coli	0	41000	3411.255	6216.669
Coliform	0	970000	40102.59	99760.99

Table 2. Summary of Descriptive statistics of the parameters for the stations

Stations	Number of Variable	Mean	Standard Deviation
4TE01	30	87.6	4.082
4TE02	30	89.56	2.945
4TE03	30	88.84	3.923
4TE04	30	81.44	5.37
4TE05	30	86.08	4.281
4TE06	30	86.04	8.044
4TE07	30	88.52	3.906
4TE08	30	83.8	9.925
4TE09	30	79.32	13.02
4TE10	30	88.36	2.97
4TE11	30	66.16	13.28
4TE12	30	92.08	2.886
4TE13	30	86.8	5.605

Table 2 shows the summary of the average mean and standard deviation of all parameters for each station. This describe station 4TE11 has the highest concentration of mean. Therefore, this station was classified as polluted.

Spatial Similarities and Monitoring Grouping

Categorically CA grouped 13 monitoring stations into two low pollution source (LPS) and moderate pollution source (MPS), based on their similarity characteristics features and natural back ground. The output of CA is illustrated in Figure 3 (dendogram). The dendogram gives clearly image of the number of groups or clusters which explain the principal process that accounted spatial variation (Boyaciaglu and Boyaciaglu, 2007). Cluster 1 comprises the following stations (4TE01, 4TE02, 4TE03, 4TE04, 4TE05, 4TE06, 4TE07, 4TE08, 4TE09, 4TE10, 4TE12 and 4TE13) and Cluster 2 station (4TE11).

Table 3. Factor loading after varimax rotation

Parameters	VF1	VF2	VF3	VF4	VF5	VF6	VF7	VF8
DO	-0.365	-0.112	-0.299	0.206	-0.015	-0.024	-0.556	0.057
BOD	0.04	0.972	0.108	0.041	0.074	0.024	0.005	-0.004
COD	0.042	0.944	0.165	0.122	0.094	0.027	0.007	0.016
SS	-0.032	0.077	-0.017	0.915	0.045	-0.012	0.01	-0.023
PH	-0.534	0.029	0.164	-0.135	-0.014	-0.26	-0.473	0.07
NH3-NL	0.393	0.148	0.751	-0.053	0.018	-0.052	0.081	-0.036
TEMP	0.09	-0.015	-0.062	-0.248	-0.046	-0.069	0.567	0.058
COND	0.889	0.043	0.301	-0.005	0.014	0.044	0.091	-0.001
SAL	0.888	0.045	0.299	0.003	0.015	0.035	0.099	-0.008
TUR	-0.077	0.15	-0.014	0.772	0.102	-0.059	-0.131	-0.031
DSs	0.902	0.017	0.264	0.021	-0.046	0.113	0.141	-0.007
TS	0.557	0.075	0.152	0.734	0.007	0.06	0.115	-0.026
NO3	-0.049	-0.084	-0.041	0.443	0.225	-0.01	-0.333	0.096
Cl	0.396	0.048	0.801	-0.026	0.057	0.155	-0.035	-0.002
PO4	0.052	0.04	0.831	0.007	-0.126	-0.074	0.08	-0.079
As	-0.046	-0.043	0.481	0.139	0.044	0.024	0.509	0.053
Hg	-0.017	0.009	0.006	-0.018	-0.02	-0.011	0.049	0.981
Cd	0.108	0.021	-0.026	-0.052	-0.003	0.867	0.063	-0.02
Cr	0.066	0.026	0.764	0.001	0.122	-0.017	0.052	0.116
Pb	0.674	-0.023	-0.17	-0.079	0.025	-0.282	0.031	-0.006
Zn	0.504	0.011	-0.081	0.028	-0.209	0.326	-0.052	0.056
Ca	0.742	0.006	0.314	0	0.007	0.281	0.096	-0.042
Fe	0.861	0.03	-0.02	0.094	-0.047	-0.179	0.157	0.003
K	0.198	0.045	0.911	0.014	-0.017	-0.001	0.03	-0.038
Mg	0.702	0.003	0.459	-0.019	-0.002	0.009	0.02	-0.03
Na	0.634	-0.021	0.288	-0.122	-0.046	0.294	-0.124	0.03
OG	-0.004	0.922	-0.08	0.059	0.019	-0.026	-0.036	-0.005
MBAS	0	0	0	0	0	0	0	0
E-coli	-0.054	0.253	0.062	0.049	0.831	-0.014	0.046	-0.011
Coliform	-0.035	-0.046	-0.01	0.189	0.868	-0.016	-0.042	-0.012
Eigenvalue	8.284	3.351	2.864	2.214	1.378	1.166	1.082	1.011
Variability (%)	28.565	11.555	9.876	7.636	4.75	4.02	3.732	3.486
Cumulative %	28.565	40.119	49.995	57.631	62.381	66.401	70.132	73.618

Bold indicates strong and moderate loading

The finding vividly shows for rapid evaluation of water quality only, one station in each cluster is required to serve as good in spatial assessment of the water quality of the entire network. Figure 4 shows the following DS, Conductivity, Salinity, Fe, Ca, Mg, Pb, Na, TS and Zn concentration of these parameters have been observed in station 4TE11. Clearly, it is evident that cluster analysis method is meaningful in offering reliable classification of surface water in the entire region and can yield to construct proper possible evaluation in a good form.

Identification of Pollution Sources

Principal component analysis was applied on the treated data (30 × 271), so as to reduce thehuge dimensions of the initial data sets and also identify the latent pollution influencing the water quality of Terengganu river basin. Principal component after rotation gives eights VFs based on Eigen value >1 and Scree plot Figure 3. An Eigenvalue 1 or >1 is considered as significant (Shrestha and Kazama, 2007). Classification of principal component is thus, “strong”, “moderate”and “weak” corresponding absolute loading values of >0.75, 0.75 - 0.50 and 0.50 - 0.30 respectively (Liu *et al.*, 2003). However, the whole PCA explain 73.62% of the total variance in the water quality data sets. VF1 with 28.57% of the total variance has a strong loading on DS, conductivity, salinity, Fe, Ca, Mg, and moderate loading factor on Pb, Na, TS and Zn these were 0.902, 0.889, 0.888, 0.861, 0.742, 0.702, 0.674, 0.634, 0.557 and 0.504 as shown in Table 3. Strong loading between the parameters indicates correlation in polluting the river water quality.

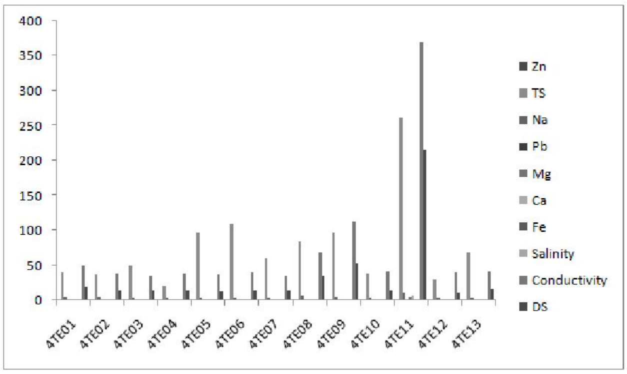


Figure 3. Zinc, Total solids, Sodium, Lead, Magnesium, Calcium, Iron, Salinity, Conductivity and Dissolved solid concentrations at the river monitoring stations

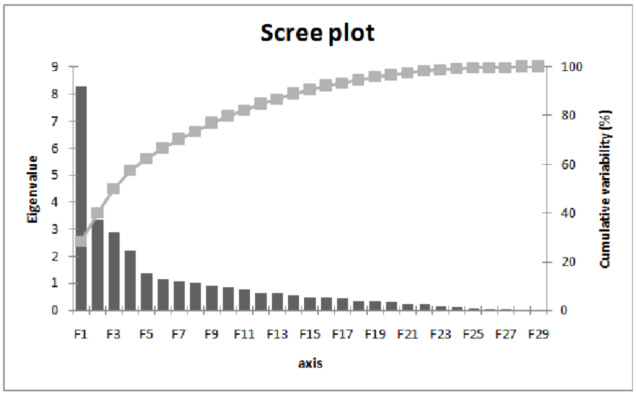
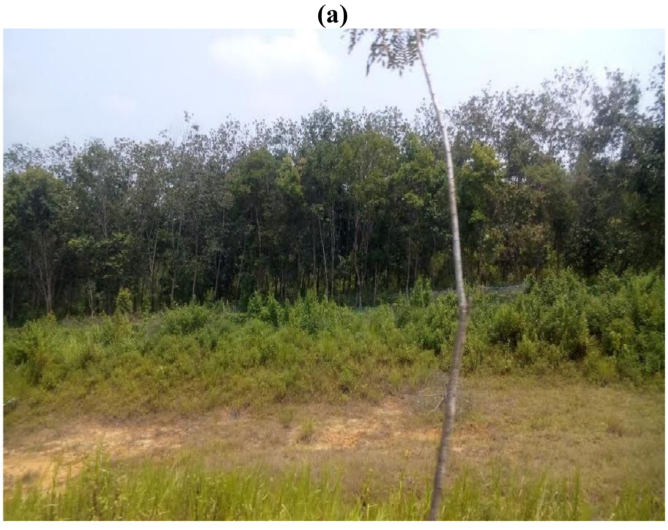


Figure 3. Scree plot showing Eigen values

This factor can be related to minerals component of the river. This reflect the geological strata of the river basin formed from rock features, likely from dissolved solids of marl, sandstone, gypsium soil and limestone (Al-Tamir, 2005). The high loading of dissolved solid may resulted river to be salty, and the overall dissolved solid is considered salinity. In addition, the moderate loading on TS and Zn stand as pollution associated with anthropogenic activities since agricultural activities are taking place along the river. VF2 shows 11.56% of the total variance with a strong loading on BOD, COD and OG having 0.972, 0.944 and 0.922. This factor suggests organic pollution from domestic and industrial waste disposed to the river from Terengganu town. And represent anthropogenic activities with much domestic impacts. River water is affected with organic and inorganic pollutants (Otokunfor and Obiukwu, 2005). VF3 has K, PO_4, CL, Cr and NH_3 – N (0.911, 0.831, 0.801 and 0.764) with strong loading describing 9.88% of the total variance. It indicates deposit of dust, pebbles and rock (geological deposits) and natural organic matter decomposition (Boyaciaglu and Boyaciaglu, 2007). PO_4 and K resulted due to agricultural activities as a result of fertilizerusage (Figure 4a,b).

(a)



(b)

Figure 4. Showing agricultural activities (a) Palm oil plantation (b) Rubber plantation

NH_3 – N is caused by domestic waste whereas chromium can be related to boat maintenance from fisher men.VF4 consist of SS, TS, and turbidity possesses 0.915, 0.772 and 0.73. This factor has strong loading, describing 7.64% of the total variance, resulted from soil erosion, runoff from agricultural activities. The presence of these parameters could have been related to anthropogenic activities (agricultural activities, land clearing and construction activities). Suspended particles, organic matter and silt lead to the formation of turbidity and total solids in the river, based on the visual inspection (Figure 5), TelemongRiveris turbid and contain suspended solids.

Figure 5. Shows the river turbid and contains particles

A total variance of 4.75% of VF5 have strong loading on E-coli and coli form is 0.831 and 0.868. This factor signifies that E-coliand coli form is considered from domestic and municipal sewage as well as wastewater treatment plant. This will definitely increase the percentage of virus and bacteria in the river due to discharge of these wastewaters. VF6 describe 4.02% of the total variance having strong loading on Cd (0.867). This factor was believed to have evolved from industries. Along Bereng and Telemong rivers mining activities are carried out this could lead to the contribution of this factor (Figure 6). According to a report by WHO (2003), industrial waste and agricultural activities (fertilizer) as well as leaching from dumpsite are causative agent of Cd. VF7 with a moderate loading factor on T and As these were 0.567 and 0.509 and explained 3.73% of the total variance. The moderate loading of temperature is related to seasonal changes.

Figure 6. Sand mining along the River Basin

The presence of arsenic could be related to fishing activities along the river basin, since it involved the use of boats having anti rusting paint. It is one of the carcinogenic agents, attributed to industrial waste. The VF8 accounted for 3.49% of the total variance, and has a strong factor loading on Hg (0.981). This factor has little percentage of the total variance among the factors. Hg takes it source from industrial activities. The factor has chemical parameters which show contamination from industrial waste (Papaioannou *et al*., 2010). This may happen as a result of industries around Gong Badak which discharge their waste into Nerus River. In view of the result of principal components, revealed the accompanying sources in charge of the variation in Terengganu River Basin: Mineral components, domestic and industrial waste (anthropogenic), natural processes (runoff and soil erosion), municipal and domestic sewage waste water pollution, waste from fishing activities, mining activities and industrial pollution.

Conclusion

Multivariate statistical methods including cluster analysis and principal component analysis can effectively be used to get data from the information set about the conceivable impacts of the earth on water quality and additionally recognize common groupings in the set of information. These strategies are essential to stay away from error of environmental monitoring information because of uncertainties. In this study, cluster analysis and principal component analysis were connected to data set obtained from Terengganu River Basin. Cluster analysis rendered two groups based on their similarity between the monitoring stations, low pollution source and moderate pollution source. PCA help in the recognizable proof of the prospective contamination sources brought about the variation of the water quality in the river. The PCA result gives eights varifactors with total variance of 73.62% and sources of contamination are mineral components, domestic and industrial waste (anthropogenic), natural processes (runoff and soil erosion), municipal and domestic sewage waste water pollution, waste from fishing activities, mining activities and industrial pollution. The results of this study indicated the sources of pollution responsible for water pollution in the Terengganu river basin and grouped the monitoring stations into two clusters based on their similarity features. Therefore, this confirmed the importance of the multivariate techniques for investigation and understanding of surface water quality information.

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