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Research paper

Spatial and Temporal Assessment of Titiwangsa Lake Water Quality Using Chemometrics Analysis

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Abstract

Titiwangsa Lake is a renowned recreational lake in Kuala Lumpur, Malaysia. The present study was purposely to define the current status of Titiwangsa Lake water quality and propose a water quality monitoring program to conserve and sustain the health of this lake. Samples were collected in January 2017 during the day and night-time periods. Spatial classification using hierarchical agglomerative cluster analysis (HACA) has clustered the sampling stations into low, medium and high contaminated areas. Temporal classification of discriminant analysis (DA) forward stepwise mode has highlighted DO, chlorophyll-a and E-coli are the significant variables. They showed a lower range of data during the day-time period compared to night-time period. DA backward stepwise model showed significant variables of total suspended solid (TSS) and total phosphate (TP) were higher in concentration during the day-time period as compared to night-time period. The significant of varimax factors (VFs) in the principal component analysis (PCA) might contribute by the landscaping, small-scale domestic wastewater, urban stormwater and land erosion. In a nutshell, based on HACA classification, samples can be collected at only three stations represent each cluster during the next water quality monitoring activities as this could reduce the time and cost of sampling and sample analysis.

Keywords: *Discriminant analysis; hierarchical agglomerative cluster analysis; principal component analysis; Titiwangsa Lake, Malaysia; water quality.*

1. Introduction

Lake is a localized water basin, surrounded by land and separated from rivers and streams. There are two types of lake namely the freshwater and saline water lake. The freshwater lake makes up relatively small percentage of the earth's water body with 0.26% out of all freshwater on the earth [1]. Despite of the small proportion, the freshwater lake is a noticeable freshwater resource in the environment. They provide habitat for a diverse range of organisms and support a broad range of human activities namely the tourism, transportation, agriculture, aquaculture and many more. Since the surrounded land normally used for residential, recreational, industrial and agriculture purposes, the lake is highly susceptible to the anthropogenic pollutants through the land-based run-off and atmospheric depositions. Additionally, limitation of lake water movement and the intensity of the pollutants introduced to the lake water specify the degree of pollution in the lake. Commonly, pollutants which have been deposited into the lake water will either settle down to the surface sediment bed or circulate in the water column. Furthermore, excessive amounts of pollutants could endanger the aquatic organisms, human and the lake ecosystem health [2].

Water quality is an expression of chemical, physical and biological condition of the water. Generally, water quality sustains the ecosystem balance in order to maintain the vegetation, aquatic organisms and wetlands. In addition, it also controls the quality of human and environmental health [3]. The surface water quality is regularly controls by natural processes of rock and soil weathering as well as anthropogenic input. However human activities are known to contribute significant amount of pollutants which will generate pressure to the ecosystem, then lead to habitat loss and decrease the quality of the organism's life inhibit the water system [4-5].

Recently, numerous monitoring studies have revealed that anthropogenic pollutants originated from different land uses could

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bring influences on the water quality and the surface water ecosystem health [6-12]. Therefore, it is an absolute necessity to define the changes in the ecosystem and an essential to implement a regular monitoring program on surface water quality due to protect and sustaining the ecosystem health. Commonly, water quality monitoring program generates a large and complex dataset, containing multiple physico-chemical parameters which is difficult to interpret the monitored data, extract the information and deliberate a significant conclusion [3]. Despite of that, the classification of water quality parameters of a station may lead to a variety of quality classes as some data could be closed or far from a limit [5]. Therefore, many recent researches have employed the multivariate statistical analysis to clarify and properly manage the water quality parameters classification [3, 5, 10-11, 13].

Herein, we present a water quality monitoring study of Titiwangsa Lake, Kuala Lumpur City Center of Malaysia. Titiwangsa Lake is a large lake located in the middle of Titiwangsa recreational park at the north-eastern fringe of Kuala Lumpur. This 57 hectares' lake is situated closed to National Art Gallery and National Theatre, has the facilities for jogging, canoeing, aqua-biking and many more outdoor activities. Titiwangsa Lake is an important tourist spot in Malaysia since it offers the Malaysian natural scenic beauty addition with outdoor facilities for visitors [14-15]. The study area is considerably one of the densely populated in Malaysia. Deterioration of surface water within this area has long anticipated due to lack of treated discharge from the point sources of pollution. This study investigates any possible pollution sources which have contaminated the Titiwangsa Lake water quality since the land use activities are dominance by the domestic and commercial areas. The collected water quality parameters were classified according to National Water Quality Standards (NWQS) using chemometrics approach. NWQS is a national water quality standard for Malaysia, created by Malaysian Department of Environment. This standard defines six classes (I, IIA, IIB, III, IV and V) which referred for classification of rivers or river segments based on the descending order of water quality vis-ávis Class I being the 'best' and Class V being the 'worst' [16]. For the present study, the collected water quality data from Titiwangsa Lake was compared to Class IIB (recreational use with body contact) since this lake is largely dominated by recreational activities.

2. Methodology

2.1. Data and Monitoring Sites

The water quality data was obtained from 12 sampling points in the Titiwangsa Lake (Figure 1) during the period of 9th January 2017 to 12th January 2017. Water quality parameters were collected and measured in-situ using BOD check Modern Water, Turbidimeter, TSS Meter and YSI Multiparameter. Lake water in-situ analysis was conducted at every 1-meter depth interval from surface to bottom water layer. In the meantime, samples for metal in the sediment were oven dried, digested with mixed concentrated acids under the microwave oven heating [17] and analysis using Inductively Coupled Plasma Optical Emission Spectrometry (ICP-OES).

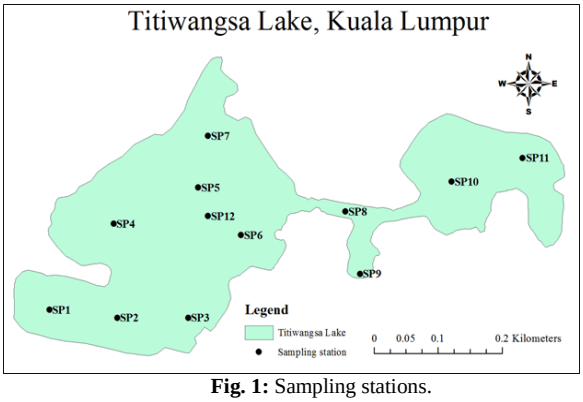


Fig. 1: Sampling stations.

2.1. Statistical Analysis

15 water quality parameters were collected from 12 sampling stations for spatial and temporal analysis. They are pH, temperature, dissolved oxygen (DO), turbidity (Tur), total dissolved solid (TDS), biological oxygen demand (BOD), chemical oxygen demand (COD), total suspended solid (TSS), oil and grease (OG), ammonical nitrogen (AN), total nitrogen (TN), total phosphorus (TP), Chlorophyll-a, Escherichia coli (E.coli), and coliform. Additionally, 22 heavy metals parameters were also analyzed for sediment samples at five sampling points, namely arsenic (As), mercury (Hg), aluminium (Al), cadmium (Cd), chromium (Cr), copper (Cu), iron (Fe), lead (Pb), magnesium (Mg), manganese (Mn), selenium (Se), argentum (Ar), tin (Sn), zinc (Zn), barium (Ba), boron (B), calcium (Ca), nickel (Ni), potassium (K), strontium (Sr), vanadium (V) and cobalt (Co). Data matrix for the present study involved (11 parameters x 12 sampling points) for surface water quality analysis; (5 parameters x 8 different depths) for different depth of water quality analysis; and (22 parameters x 12 sampling points) for lake sediment analysis.

Mann-Kendall non-parametric test of trend were applied to determine the spatial water quality trend [18] due to the sampling depth

2.2.1. Discriminant Analysis

Discriminant analysis (DA) determines the variables that discriminate between two or more naturally occurring clusters. It constructs a discriminant function (DF) for each group [26]. DFs are calculated using Equation (1) as follow:

$$f(Gi) = ki + \sum_{j=1}^{n} Wij\ Pij \quad (1)$$

where *i* is the number of groups *(G)*, *ki* is the constant inherent to each group, *n* is the number of parameters used to classify a set of data into a given group and *Wj* is the weight coefficient assigned by DF analysis (DFA) to a given parameter *(Pj)*.

In this study, DA was applied to determine whether the groups differ with regard to the mean of a variable and to use that variable to predict group membership. The dataset was divided into two groups which are the day time and night time sampling periods. These two groups were tested for temporal DA using the standard, forward stepwise and backward stepwise modes. In temporal DA, the sampling period, i.e. day and night time were identified as dependent variables whereas measured parameters were acted as independent variable. In the forward stepwise mode, variables are included step by step beginning with the most significant variable until no significant changes were obtained. In the backward stepwise mode, variables are removed step by step beginning with the less significant variable until no significant changes were obtained.

2.2.2. Principal Component Analysis

Principal component analysis (PCA) is a most powerful pattern recognition technique that is usually coupled with HACA. It provides information on the most significant parameters due to spatial and temporal variations. It also describes the whole data set by excluding the less significant parameters with minimum loss of original information [25, 27]. The principle component (PC) can be expressed as follow:

$$Z_{ij} = a_{i1}x_{1j} + a_{i2}x_{2j} + a_{i3}x_{3j} + a_{im}x_{mj} \quad (2)$$

where *Z* is the component score, *a* is the component loading, *x* is the measured value of the variable, *i* is the component number, *j* is the sample number and *m* is the total number of variables.

PCA usually utilized factor analysis (FA) method to interpret a large complex data matrix and offers a powerful means of detecting similarities among variables or samples [28]. The basic concept of FA is expressed as follow:

$$zij=af1f1i+af2f21+....+afmfmi+efi \quad (3)$$

where z is the measured value of a variable, a is the factor loading, f is the factor score, e is the residual term accounting for errors or other sources of variation, i is the sample number, j is the variable number, and m is the total number of factors.

Since generated PCs are sometimes not readily to be interpreted; therefore, it is advisable to rotate the PCs using varimax rotation. Varimax rotations are commonly applied on the significant PCs with Eigen values greater than 1 [29-30], in order to obtain new groups of variables, known as varimax factors (VFs). The number of VFs obtained by varimax rotations is equal to the number of variables in accordance with common features. VFs can be classified as 'strong', 'moderate' and 'weak' significant factor loadings with the value of greater than 0.75, 0.75 – 0.50 and 0.50 – 0.30 respectively [31]. In this study, PCA/FA was applied to the datasets of the lake water quality of 11 variables for 10 different sampling stations temporally, i.e. day and night-time periods.

3. Results and Discussion

3.1. Determination of Lake Water Pollution Risk According to NWQS Class IIB Standard

12 water quality parameters of Titiwangsa Lake were examined spatially at 12 sampling points. Data obtained was evaluated based on Class IIB of NWQS. Table 1 shows the assessment of water quality parameters which were complied and not-complied with Class IIB for both day and night-time sampling. 75% of the total sampling station shows that BOD was not comply with Class IIB and 100% of the total sampling station shows OG has similar classification for both sampling periods. In the meantime, the remaining ten water quality parameters were 100% complied with Class IIB during both monitoring periods.

BOD, OG and Coliform were identified as the main contributor to the lake water pollution. They have recorded the highest cumulative percentage of non-complied to Class IIB during both sampling periods. This finding has highlighted the necessity for the local authority to be more proactive in controlling pollutants around Titiwangsa Lake, particularly the untreated direct discharge.

Table 1: The assessment of Titiwangsa Lake water quality in comparison with Class IIB.

Station No.	Parameters											
	DO	pH	BOD	COD	TSS	OG	AN	TN	TP	Chl-a	Coliform	*E.coli*
DAY												
SP1												
SP2												
SP3												
SP4												
SP5												
SP6												
SP7												
SP8												
SP9												
SP10												
SP11												
SP12												
NIGHT												
SP1												
SP2												
SP3												
SP4												
SP5												
SP6												
SP7												
SP8												
SP9												
SP10												
SP11												
SP12												
Limit	5	6.0 - 9.0	6	50	150	0.04	0.9	5	5	10	50000	5000

Note: -below limit; -above limit;

3.2. Spatial Classification of Lake Water Quality Parameters Using HACA

Spatial variation determination on the water quality for Titiwangsa Lake was carried out using HACA for both sampling periods. 12 water quality parameters were analyzed from 12 sampling points. Based on the HACA dendogram for spatial clustering according to Class IIB, the day-time sampling period generated three significant clusters. Cluster 1 comprises station SP9; station SP5 and SP8 are classified under Cluster 2 whereas the other sampling stations, i.e. SP2, SP12, SP10, SP11, SP1, SP4, SP6, SP3 and SP7 are assigned under Cluster 3. In the meantime, night-time sampling period also generated three significant clusters. Station SP7 was clustered under Cluster 1, Cluster 2 comprises of nine sampling points (SP8, SP2, SP6, SP10, SP3, SP11, SP5, SP1 and SP12) plus the remaining two sampling points, i.e. SP4 and SP9 were grouped under Cluster 3. Thus, based on HACA spatial classification, for the future sampling activities, samples can be collected at only three stations, represents three different clusters during both periods

3.3. HACA Spatial Classification of Heavy Metals in the Surface Sediment

During both sampling periods, there were 22 parameters of heavy metals collected at 12 sampling stations. 17 parameters were selected for further classification analysis since the other five parameters did not show any significant variance. HACA dendogram has classified the similarity of heavy metals concentration in the surface sediment of Titiwangsa Lake spatially into three clusters. The clusters were interpreted as High Contaminated Sampling Point (HCSP), Moderate Contaminated Sampling Point (MCSP) and Low Contaminated Sampling Point (LCSP). HCSP consists of station SP1, SP10 and SP11; MCSP consists of SP2, SP4, SP7, SP8, SP9 and SP12; whereas LCSP consists of point SP3, SP5 and Point SP6. Therefore, based on the HCSP, LCSP and MCSP clusters, the cost and time of the future heavy metals contamination monitoring in Titiwangsa Lake can be reduced.

Figure 2 shows the water quality index (WQI) calculated for Titiwangsa Lake samples according to NWQS. In general, samples from all stations during both sampling periods were classified into Class II which is beneficial for water supply that requires a conventional treatment, suitable for sensitive aquatic species as well as appropriate for body contact recreational uses. Other than that, the water sample during day time from station SP7 was the only water sample which was classified into Class III, i.e. beneficial for water supply that requires for an extensive treatment and suitable for common of economic value and tolerant aquatic species and livestock drinking.

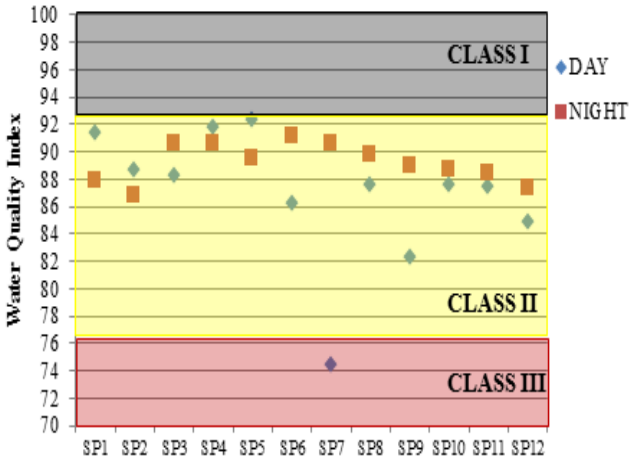


Fig. 2: Calculated WQI for Titiwangsa Lake based on NWQS.

3.3.1. Spatial Variation of Water Quality in Different Water Depth

Table 2 and Figure 3 show the spatial variation of Titiwangsa Lake water quality based on Mann-Kendall non-parametric trend. Throughout the observation pH, temperature and DO exhibit the downward trend, in contrary, TDS demonstrates the significant upward trend. Based on data analysis (Figure 3), station with the deepest water level indicated the lowest value of pH, temperature and DO. Apparently, the variation in pH levels was strongly related to water depth due to the increasing of carbon dioxide (CO_2) level produced during the aquatic organisms' respiratory activities and the decomposition of organic materials below the thermocline layer [32-33]. In the freshwater system, CO_2 will react with water molecule to form carbonic acid (H_2CO_3). The produced H_2CO_3 can easily lose one or both the hydrogen ions which will reduce the water pH. In the meantime, the concentration of DO increased with the increasing of pressure. DO saturation decrease by 10% per meter with the increasing of water depth due to hydrostatic pressure [34-35]. The concentration of TDS showed increased with the increasing of water depth. Commonly, high concentration of TDS will increase the water temperature but decrease the concentration of DO. This could be caused by the heat absorption by the suspended particles from the solar radiation.

Next, the absorbed heat was transferred to the surrounding water column. Besides that, high temperature could decrease the solubility of DO in the water bodies [35]. This will demonstrate a significant decline in DO concentration towards the deeper water layer. Other than that, an increasing of water surface temperature could cause lake water to stratify. Water stratification normally does not allow mixing between the upper and lower water layers. Commonly, the decomposition of organic materials and respiration of aquatic organisms occurs in the lower layer of the lake water column. They create a hypoxia phenomenon which aggravates the organisms and stressing the lake ecosystem.

Figure 3 shows pH, temperature and DO showed a decrease of value with the increasing of water depth. Likewise, TDS increased with the increasing of water depth. Mann-Kendall non parametric test in Table 2 reveals the insignificant trend of turbidity ($p>0.05$). Recorded turbidity shows significant fluctuates trend spatially. The turbidity level declined in the water depth lower than 1.0 m but sharply inclined as the water depth increased to 3.0 m, before reaching the constant state between the water depths of 3.0 to 4.0 m. Next, the turbidity level was dramatically decreased as the water level increased to 5.0 m, before a sharp increased to 3.15 NTU, downward to the lake bottom.

Table 2: Mann-Kendall non parametric test of lake water quality in different water depth.

Variable	Kendall's tau	S	Trend	p-value
pH	-1.000	-36.000	↓	0.000
Temp.	-0.944	-34.000	↓	0.000
DO	-0.944	-34.000	↓	0.000
Turbidity	0.389	14.000	NT	0.180
TDS	0.833	30.000	↑	0.001

Note: ↑-upward trend; ↓-downward trend; NT-no trend

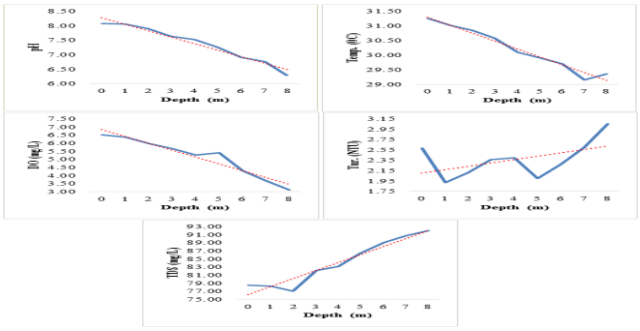


Fig. 3: Spatial water quality variation with water depth of Titiwangsa Lake.

3.4. Temporal Variation of Lake Water Quality

3.4.1. Determination of Temporal Variation of Water Quality Parameters Using DA

Temporal DA was carried out to define the variation within the water quality raw dataset in correlation with different sampling period. For instance, in the present study, sampling was carried out during day-time and night-time periods. Temporal DA was carried out by treating the sampling period as the dependent variables, while the water quality parameters were treated as the independent variables. DA was performed through standard, forward stepwise and backward stepwise model. The calculated discriminant function (DF) for standard mode was 100% with 12 discriminant variable; 86.96% for forward stepwise mode with three discriminant variables, as well as 95.65% for backward stepwise mode with five discriminant variables (Table 3).

The forward stepwise mode showed that DO, Chlorophyll-a and E.coli are the significant variables. It indicates that these parameters have high variation in terms of their temporal distribution. DO, Chlorophyll-a and E.coli showed a lower range of data during the daytime with 6.37 mg/L, 7.36 mg/m^3 and 31 MPN/100 mL respectively. During the night time, collected data on these parameters were slightly increased with 7.87 mg/L of DO, 1.88 mg/m^3 of Chlorophyll-a and 99 MPN/100 mL of E.coli. In the meantime, the five significant variables of backward stepwise mode are DO, Chlorophyll-a, E.coli, TSS and TP. In contrast to DO, Chlorophyll-a and E.coli, the concentration of TSS (µDay = 3.42 mg/L; µNight = 2.92 mg/L) and TP (µDay = 0.019 mg/L; µNight = 0.016 mg/L) were slightly higher during the daytime compared to the night time. This pattern was anticipated due to the watering activities of plants and home ornaments landscaping during the daytime. Apart from that, the phosphate-rich fertilizer and soil were run-off into the drains during the watering activities and finally were flushed into the lake water bodies. The remaining eight water quality parameters showed no significant difference ($p > 0.05$) between both sampling periods. The box and whisker plots of DO, Chlorophyll-a and E.coli throughout both sampling periods proved that these parameters have the highest variability due to the most significant ($p < 0.05$) data variation in backward stepwise DA model. These highlighted data are the only water quality parameters that will be carry on for further discussion.

Table 3: Classification matrix of DA temporal variations in Titiwangsa Lake.

Time	Time assign by DA		Total	% correct
	Day	Night		
Standard mode DA				
Day	11	0	11	100.00%
Night	0	12	12	100.00%
Total	11	12	23	100.00%
Stepwise forward DA				
Day	9	2	11	81.82%
Night	1	11	12	91.67%
Total	10	13	23	86.96%
Stepwise backward DA				
Day	11	0	11	100.00%
Night	1	11	12	91.67%
Total	12	11	23	95.65%

3.4.2. The Identification of Possible Pollution Sources Using PCA

PCA was employed to the data set in order to compare the compositional patterns between the examined water parameters as well as to identify the factors that influence the variation of Titiwangsa Lake water quality. Three PCs were obtained, with eigenvalues larger than one, summing almost 77.6%, of the total variance in the data set. Corresponding varimax factors (VFs), variable loadings, and variance are presented in Table 4.

Table 4: Loadings of environmental variables on the varimax-rotated PCs for water quality data in Titiwangsa Lake.

Variables	D1	D2	D3
DO	-0.136	-0.002	0.962
pH	0.797	-0.390	0.044
BOD	0.601	0.680	0.122
COD	-0.679	0.022	0.479
TSS	0.053	0.952	0.044
OG	0.000	0.000	0.000
AN	-0.687	-0.131	0.395
TN	0.704	0.291	0.096
TP	0.631	0.315	-0.400
Chl-a	-0.008	0.006	-0.946
Coliform	-0.019	0.928	-0.067
E.coli	-0.042	0.834	-0.094
Eigenvalue	3.944	2.813	1.776
Variability (%)	35.857	25.570	16.148
Cumulative %	35.857	61.428	77.575

Throughout both monitoring periods, VF1 accounted the highest variance with 35.86% of the total variance. VF1 has the strong positive loadings on the variables namely pH (0.797), TN (0.704) and TP (0.631). Since Titiwangsa Lake is a recreational lake, the strong positive loadings on pH, TN and TP indicated the chemically changing of water quality which could possibly cause by the acidic pollutants. Commonly, they are related to anthropogenic sources and possibly derived from the landscaping and a small scale of domestic wastewater. The hydrolysis of these acidic materials in the lake water column will decrease the water pH [37].

TP measures the total amount of phosphorus in both the organic and inorganic forms. It is the principal nutrients in urban storm water. The major sources of nutrients in urban storm water are lawn fertilizers which derived from garden and residential landscapes, atmospheric deposition, automobile exhaust, soil erosion, animal waste and detergents [38]. The degree to which nitrogen and phosphorus are present in a lake can determine the trophic status and the amount of algal biomass produced. Excess nutrients tend to increase the primary biological productivity. The major impact associated with nutrient over enrichment is an excessive growth of algae that leads to nuisance algal blooms and eutrophic conditions. Additionally, the decomposition of organic materials requires high demand of dissolved oxygen. Therefore, this process normally decreases the concentration of DO in the bottom lake water column.

TN is one of the common pollutants in the Klang Valley region. Normally it derives from the untreated sewage which has been discharged from the nearby restaurant into Titiwangsa Lake. Besides that, the decomposition of organic materials, mainly the food wastes in the waterways also affecting the quality of Titiwangsa Lake waters. In the meantime, COD and AN showed negatively loadings variables with -0.679 and -0.687 respectively. These two parameters were negatively contributed toward Titiwangsa Lake water quality as no industrial activity was observed within the proximity of this area and most of the domestic wastewater is channeled to Setapak treatment plant.

VF2 explains 25.57% of the total variance has strong loading on BOD (0.680), TSS (0.952), coliform (0.928) and E.coli (0.834). Coliform and E.coli are two parameters that are commonly discharged into the lake water system by the municipal sewage and wastewater treatment plants as well as domestic wastewater [39-40]. The presence of coliform and E.coli in lake water consumes a large amount of oxygen in order to decompose the organic materials. Therefore, it will result in increasing of BOD and decreasing of DO. However, if the concentration of DO keeps on increasing, Coliform and E.coli will experience the anaerobic fermentation process which will produce ammonia and organic acids in the lake water. Other than that, TSS is commonly derived from the urban storm water. Additionally, land erosion, atmospheric deposition and anthropogenic input also contribute a large amount of solid into the lake water.

VF3 explains 16.148% of the total variance with 0.962 strong loading on DO, contrary to Chlorophyll-a. The inverse relationship between these two parameters may cause by the verse pattern. DO show an increasing of concentration during night time period as compared to day time period. In the meantime, the concentration of Chlorophyll-a during the day time was slightly higher than night time period.

4. Conclusion and Recommendation

4.1. Conclusion

The spatial and temporal study conducted in Titiwangsa Lake is important in order to improve the lake water quality; since this lake is located in the middle of Kuala Lumpur City Centre and has been one of the famous tourist recreational areas. The determination of Titiwangsa Lake water quality is extremely crucial as it could aid the Kuala Lumpur City Council to come up with the pragmatic and precise decision making for the lake health. The CA revealed that the heavy metal concentrations in the lake were clustered in three groups namely HCSP, MCSP and LCSP. The concentration of DO decreased with the increasing of water depth. In the meantime, Coliform and E. coli are known to be harmful to the living communities in the lake. These two pollutants are commonly encouraged the decomposition of organic materials and bacterial respiration process in the bottom water layer. Furthermore, it creates a hypoxic condition at the bottom waters of the lake. The forward DA mode reveals DO, Chlorophyll-a, and E.coli are found to be the significant variables, temporally. In the meantime, PCA indicated the strong positive loadings of pH (0.797), TN (0.704), and TP (0.631). These strong positive loadings could be possibly contributed by the anthropogenic sources such as landscaping and domestic wastewater. The land erosion, atmospheric deposition and anthropogenic particles could contribute a large amount of TSS in the lake water bodies. TSS impedes the penetration of the sunlight to the lake bottom resulting in water turned murky. This phenomenon will reduce the lake health and give bad impression on the environmental care in Malaysia. Overall, the water quality status of Titiwangsa Lake was in good condition since the current lake management has managed to control the influence of pollutants in the lake. The present study could help the city council to improve the lake water quality with a low cost and efficient manner.

4.2. Recommendation

Maintaining the water quality of the Titiwangsa Lake is crucial to sustain the lake health. In fact, this is the best mechanism to guarantee the water quality to be preserved from human activities. The Kuala Lumpur City Council should prioritize the budget allocation of periodic monitoring of Titiwangsa Lake water quality. This is due to sustain and maintain the Titiwangsa Lake ecosystem health. Based on the present study, there are few recommendations should be taken as follow:

i. On-ground verification to reconfirm the point sources that discharge the pollutants into the lake corresponded to the lake water. This is to ensure the wastewater is treated before discharge into the lake.
ii. Control the pollutant point-sources prior the wastewater being treated.
iii. Determine the best water treatment technology to solve the water quality problem efficiently in order to meet the compliance of the NWQS Class IIB.

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