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RESEARCH

Analysis of Spatial and Temporal Variation of Water Quality: A Case Study of Kotagala Wetland, Nuwara Eliya, Sri Lanka

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ABSTRACT

Water quality of wetland ecosystems is a critical concern due to its implications on human health and aquatic life. This study was conducted to assess the spatial and temporal variation of water quality in Kotagala wetland to understand its impact on water safety for domestic uses and ecosystem health. Water samples were collected (n = 70) from six inlets and the wetland outlet from November 2021 to August 2022, and analyzed for pH, electrical conductivity (EC), salinity, total dissolved solids (TDS), total suspended solids (TSS), nitrate, and phosphate. The pH, EC, and nitrate showed significant correlations. Spatial clustering divided the monitoring sites into two clusters, as areas of higher and lower pollution levels. Discriminant analysis highlighted the significance of EC, pH, and nitrate concentrations in differentiating these clusters. Principal According to principal component analysis (PCA) 88.8% of the total variance of spatial variation in water quality was explained by the first two components. Temporal clustering following seasonal variations revealed the influence of rainfall pattern on water quality. EC, TDS, TSS, and nitrate concentrations emerged as the most important factors in this temporal categorization. In PCA, 76.8% of the total variance of temporal variation in water quality was explained by the first two components. Findings highlight the urgent need for sustainable strategies and policies to mitigate the impacts of human activities on wetland water quality, since water quality variations in the wetland was significantly impacted by direct human activities, and variations in rainfall trends in the area.

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INTRODUCTION

Wetlands, which occupy 4-6% of the earth's surface, are one of the most productive and intricate aquatic ecosystems. Wetlands are subjected to a variety of environmental stresses, including water abstraction, industrial and residential effluent discharge, agricultural run-off, changes in hydrology, ecosystem deterioration, and resource overexploitation (Singh et al., 2020). The surface water quality of wetlands is heavily influenced by both natural and anthropogenic inputs such as industrial and domestic wastewater, as well as agricultural sources. Most wetlands in Asia have severely degraded water, due to agricultural runoff with pesticides and fertilizers, as well as industrial and municipal wastewater discharges, all of which contribute to widespread eutrophication (Bassi & Kumar, 2017). Most wetlands in agricultural catchments are overburdened with extra fertilizers and other toxins due to heavy anthropogenic stress (Singh et al., 2021). Overexploitation of water resources, along with the discharge of untreated wastewater, contribute to the degradation of the surface water quality of wetlands. The presence of harmful pollutants in wetland water has an impact on the health of local residents who rely on these water sources to meet their daily needs. The quality of surface water is one of the most critical variables affecting the health of humans and aquatic species. Monitoring and evaluating water quality are crucial elements of environmental management because they guarantee the survival of aquatic ecosystems and the well-being of the human populations that depend on these resources.

Wetlands are dynamic and delicate ecosystems, and the expanding effects of human activity highlight the necessity for rigorous and specialized ways to monitor the water quality of these ecosystems (Kaur et al., 2017). Monitoring surface water to identify spatial and temporal water quality fluctuation is a key tool for managing water resources and their ecological services. Due to the dynamic character of these ecosystems, which include complicated hydrological patterns, different vegetation, and many microbiological interactions, monitoring water quality in wetlands is challenging. The potential identification of pollution sources depends significantly on this monitoring. (Seyedmohammadi et al., 2016). The creation of a specific water quality monitoring strategy for wetlands is essential to overcoming these constraints.

The Kotagala Wetland, which is situated in Nuwara Eliya district in Sri Lanka, is the subject of this case study. It is one of the largest wetlands in the upcountry of Sri Lanka. Kotagala wetland is vulenrable to deterioration of water quality brought on by urbanization, agricultural practices, and other human activities. Considering the ecological and socioeconomic importance of this wetland it is imperative to monitor the water quality and identify factors driving water quality deterioration. We suggest the creation of a thorough water quality monitoring program that is specifically suited to Kotagala Wetland in order to support the conservation efforts of this ecologically significant area. Therefore, objective of this study was to assess the spatial and temporal variation of water quality in Kotagala wetland to ensure water safety for domestic uses and ecosystem health.

METHODOLOGY

Study Area Description

The study was carried out in the Kotagala natural wetland, which is located in the central hilly area of Sri Lanka. It is one of the largest and rarely available wetlands in the Hatton valley. It belongs to Nuwara Eliya District under Nuwara Eliya DS division. The stream locally known as "*Kotagala Oya*" begins from the Kotagala wetland, which mainly supply water to attractive waterfalls in the downstream. The wetland is located within the coordinates of 53 ^{0} 30' N, 80 ^{0} 34' E and 57 ^{0} N, 80^0 38'E. The average annual rainfall over the catchment area of the wetland is 2929 mm. The mean maximum and minimum temperatures recorded in the area are 27 ˚C and 9 ˚C, respectively. The wetland is situated at an elevation range of 1724 - 1228 m with catchment area of 13 km^2. Tea plantations occupy most of the land extent in the catchment area as shown in Figure 1.

Data Collection and Analysis

Water samples were collected from 2021 November to 2022 August from 1 (S1) outlet and selected 6 inlets (S2- S7) (Figure 2) at monthly frequency. A total of 70 water samples were analyzed in this study.

A total of seven physicochemical parameters were analyzed to study the spatial and temporal water quality variation in selected sampling points. Nitrate, phosphate, TSS, TDS, pH, EC, and salinity were measured in the samples using standard methods (Table 1) at the laboratory of Department of Agricultural Engineering, University of Peradeniya, Sri Lanka and Joint Research and Development Center (JRDC), University of Peradeniya, Sri Lanka.

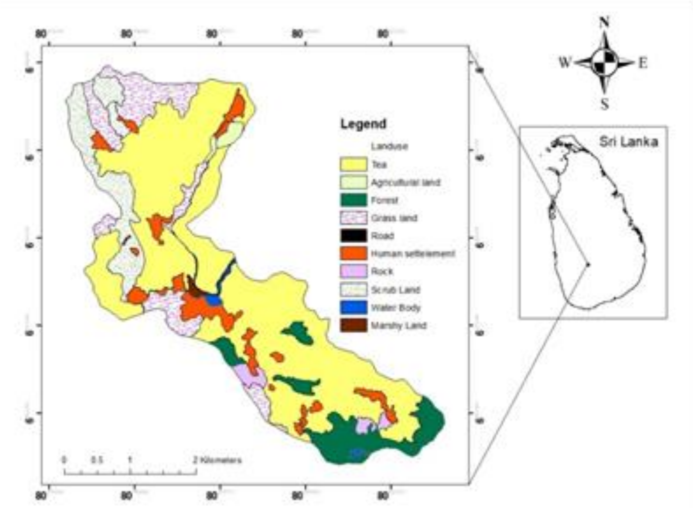

Figure 1: Land use/cover of the catchment area of Kotagala wetland

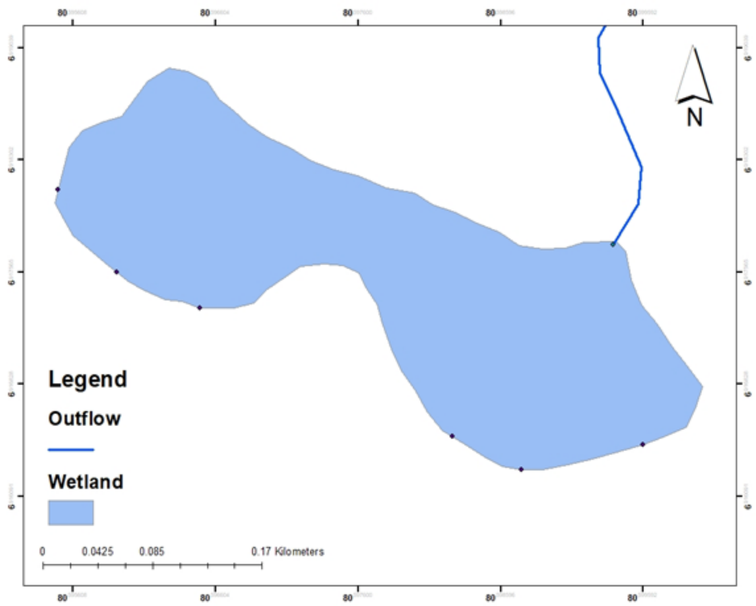

Figure 2: sampling points distribution within the wetland

Table 1: Standard methods for sampling analysis

Parameters	Abbreviation	Standard method	Unit	References
Nitrate	NO_3^-	Spectrophotometric method	mg/L	(Cataldo et al., 1987), APHA, 2017 (Method 4500-NO3-)
Phosphate	PO_4^{3-}	Spectrophotometric method	mg/L	(Murphy & Riley, 1962), APHA, 2017 (Method 4500-P)
Salinity	Salinity	Multi-parameter	psu	APHA, 2017 (Method 2520)
Electrical Conductivity	EC	Multi-parameter	µS/cm	APHA, 2017 (Method 2510)
pH	pH	Multi-parameter	pH	APHA, 2017 (Method 4500-H+)
Total Dissolved Solid	TDS	Multi-parameter	mg/L	APHA, 2017 (Method 2540 C)
Total Suspended Solid	TSS	Oven-dry method	mg/L	APHA, 2017 (Method 2540 D)

Data was analyzed initially by descriptive statistics and correlation between the measured parameters was investigated using Pearson's correlation coefficient (r). Multivariate statistical analysis includes cluster analysis, discriminant analysis and principal component analysis. Data suitability for cluster analysis, discriminant analysis and principal component analysis was evaluated using the Kaiser-Meyer-Olkin (KMO) and Bartlett's tests. The basic objective of conducting the cluster analysis (CA) was to divide the sample into discrete groups or clusters based on specific criteria, maximizing within-group similarity and minimizing between-group similarity. The most popular method, hierarchical clustering, establishes clear similarity correlations between any one sample and the entire data set (Kilic & Yucel, 2019).

The Euclidean distance is a widely used distance coefficient that typically indicates how comparable two samples are as well as the "distance" that can be modeled by the "difference" between analytical values from both samples. A dendrogram is frequently used to show the outcome of hierarchical grouping. In this study, Ward's approach was used to perform hierarchical CA on the normalized data set, utilizing Euclidean distances as a metric of similarity (Johnson & Wichern, 2007). Principal component analysis (PCA) is the approach of getting factors that is most frequently employed. The covariance matrix of the original data is used by the PCA technique to extract the eigenvalues and eigen vectors. (Singh et al., 2004). To minimize the impact of less significant parameters on the data structure obtained from PCA (Helena et al., 2000), Varimax rotation was performed by rotating the axes defined by PCA, following well-established guidelines. This rotation enhances the clarity of the component structure by redistributing the variance among the factors, making the interpretation of the data more meaningful and focused on the most influential parameters. The tests for PCA, CA, KMO, and Bartlett were performed using the SPSS statistical package. The inter-relationship between physio-chemical characteristics was investigated using Microsoft Excel 2013 program by computing Pearson's correlation coefficient (r).

RESULTS AND DISCUSSION

Physio-chemical Analysis

Table 2 provides the overall status of the water quality of the Kotagala wetland during the study period. Data represent the mean values of all locations within the study period. The pH of water samples ranged between 6.11 and 6.67 which implies a reasonably narrow range. The maximum permissible level for inland waters for bathing, contact recreational water, irrigation, and agricultural activities ranges from 6-8.5 (CEA, 2019). The measured range and low standard deviation (0.19) indicate that the pH values are relatively stable. The ability of a sample to conduct electricity, as measured by Electrical Conductivity (EC), is proportional to the concentration of dissolved ions. The average EC value of 102.12 µS/cm indicates moderate conductivity. The range of 75.90 - 138.56 µS/cm indicates that the ion concentration in the samples varied widely.

TDS values ranged from 40.41 – 75.90 mg/L and with a mean of 53.34 mg/L. TSS, values ranged between 773.60 and 844.12 mg/L, and the maximum permissible level for the TSS is 2100 mg/L (CEA, 2019). Thus, the measured TSS values fall within the maximum permissible level. The mean nitrate content of 1.44 mg/L indicates a moderate nitrate level. The observed nitrate level of the samples ranged from 0.79 - 2.94 mg/L. The maximum permissible level for nitrate is 10 mg/L (CEA, 2019). Therefore, nitrate level in the samples were within the maximum permissible level. The measured phosphate level of the samples throughout the study period ranged between 0.07 - 0.9 mg/L, and the maximum permissible level of phosphate is about 0.7 mg/L. It was noted that the observed level exceeded the permissible level in some samples (22% of samples).

Correlation among water quality parameters

Table 3 shows the correlation matrix for analyzed water quality parameters. Each row and column in the matrix represent a different water quality parameter with the correlation coefficient. EC showed a negative correlation (r = -0.395) with pH, which implies that when pH rises, electrical conductivity falls, and vice versa. This makes sense because variations in pH can change the concentration of ions in water, hence affecting its conductivity. Similar to EC, salinity had a negative association (r = -0.446) with pH.

TDS showed strong positive relationship with EC (r = 0.944) and salinity (r = 0.950). This is since calcium, magnesium, potassium, bicarbonates, chlorides and sulphates are the major inorganic salts that makeup TDS by dissolving in water (NWSDB, 2020) and EC is also totally depending on the irons that are dissolved in the water. Nitrate showed a moderate relationship with EC (r = 0.628), salinity (r = 0.602) and TDS (r = 0.551) and it had a weak positive relationship with pH (r = 0.191). But these relationships were not significant (P>0.05). Generally higher pH values may enhance the conversion of ammonium to nitrate via nitrification processes marginally. Phosphate showed a moderate negative relationship with the nitrate (r = -0.626), salinity (r = -0.65) and slight negative connection with pH (-0.307), but these were not significant (P>0.05).

Table 2: Descriptive statistics of analyzed water quality parameters.

Parameter	Mean	Max	Min	SD
pH	6.29	6.67	6.11	0.19
EC (µS/cm)	102.12	138.56	75.90	19.45
Salinity (PSU)	0.11	0.13	0.09	0.01
TDS (mg/L)	53.34	75.28	40.41	11.62
TSS (mg/L)	810.9	844.12	773.60	18.44
Nitrate mg/L	1.44	2.94	0.79	0.68
Phosphate mg/L	0.37	0.9	0.07	0.26

Table 3: Calculated Pearson's values for samples

	pH	EC	Salinity	TDS	TSS	Nitrate	Phosphate
pH							
EC	-0.395						
Salinity	-0.446	***0.847****					
TDS	-0.487	***0.944*****	***0.950*****				
TSS	0.374	-0.349	0.058	-0.198			
Nitrate	-0.191	**0.628**	**0.602**	**0.551**	-0.240		
Phosphate	0.307	-0.272	**-0.650**	-0.425	-0.317	**-0.626**	

Note: Bold italic values show strong (>0.75) correlation among parameters while bold values show a moderate (0.5-0.75) correlation among parameters. *, ** and *** indicates values that are significant at P<0.05, P<0.01 , P<0.001 respectively.

Spatial variation of water quality

Spatial cluster analysis was generated to identify the groups of similar monitoring sites and explore spatial heterogeneity of water quality with the help of all monitored parameters. It has generated a dendrogram, grouping the monitored 7 sites into 2 distinct clusters. Cluster 1 comprises station 1, 3, 4, 6 and 7 whereas, cluster 2 comprises station 2. Stations 2 is located just below the urbanized area and intensive agricultural activities were also present in the area. Therefore, study has indicated that the quality of water tends to decline in proximity to urban areas and places with high agricultural activity. This should be because of the increasing runoff of pollutants from these land uses. Boyacioglu (2008) mentioned that uncontrolled residential discharges from growing urbanization caused additional hazard to surface water quality. Liu et al. (2021) also found that sites closer to urban and industrial areas exhibited poorer water quality due to higher concentrations of pollutants.

Spatial clustering in water quality emphasizes that to increase resource use efficiency in water quality monitoring without compromising the thoroughness of water quality analyses, future research should focus on improving the monitoring site selection strategies. The discrete separation of two clusters raises the potential of fewer monitoring sites while retaining the necessary diversity of water quality conditions. To do this, it is advised to concentrate on keeping the most significant sites in each cluster because they frequently show traits of the surrounding sites. Kumar et al. (2022) emphasized in their study, the need for site-specific guidelines and the use of models to understand water quality, which aligns with the idea of optimizing monitoring site selection to maintain resource efficiency during monitoring.

In the spatial discriminant analysis, the high value of wilks's lambda (Value is distributed between 0-1) shows low significance, means less discriminating power of the model. In this model wilk's lambda is indicating as 0.00 which reflects better discriminating power of the model. The probability value of F test shows discrimination between the groups is highly significant ($P< 0.05$). EC, pH and nitrate concentrations have more explanatory power with coefficients of 11.966, 5.593 and 0.448 among the tested parameters (Table 4). These coefficients represent the amount and direction of the relationship between the predictors and the discriminant function, and they aid in understanding the significance of each variable in discriminating across groups or categories.

Factor analysis by principal component analysis (PCA) with varimax rotation was used to compare the compositional patterns of the analyzed water samples and to discover the factors that influence each one. PCA of the complete spatial data set produced the 2 principal components with Eigen value of 4.731 and 1.485, which are Eigen values greater than 1. The first component explained 67.595 % of the total variation in the water quality data set while the second component explained 21.217% of the total variance. Therefore, 88.81% of the total variance was explained by the first two components. After applying varimax rotation, the variance explained by Component 1 slightly decreased to 66.12%, while Component 2 increased to 22.69%. Despite this redistribution of variance, the total explained variance remains 88.81%. (Table 5).

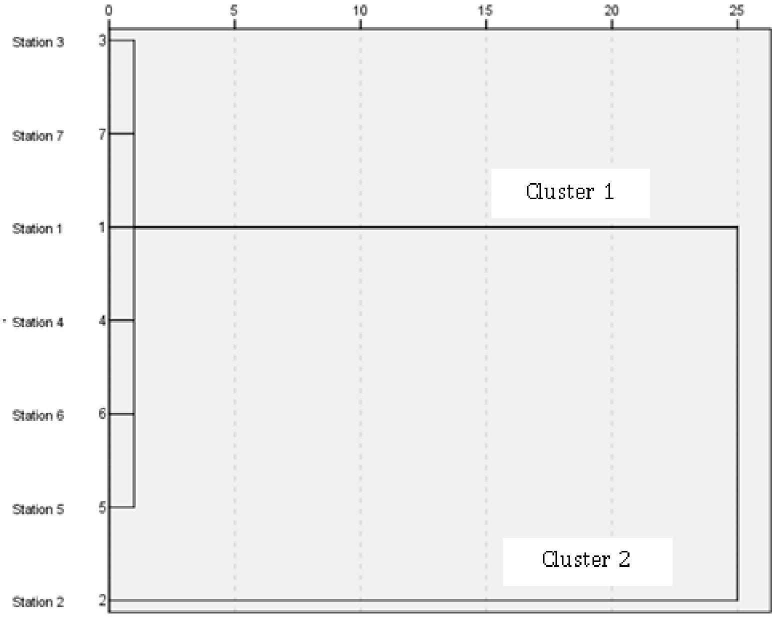

Figure 3: Dendrogram related as a results of spatial CA

Table 4: Calculated coefficients by discriminant function

Parameter	Discriminant Coefficient
pH	5.593
EC	11.966
Salinity	-6.601
TSS	-0.386
Nitrate	0.448

Table 5: Total Variance Explained

Component	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Eigen Value	% of Variance	Cumulative %	Eigen Value	% of Variance	Cumulative %
1	4.732	67.594	67.594	4.628	66.118	66.118
2	1.485	21.217	88.811	1.589	22.693	88.811

Note: Extraction Method: Principal Component Analysis.

According to the rotated component matrix (Table 6), a PCA was performed on a dataset containing seven variables: pH, EC, Salinity, TDS, TSS, nitrate, and phosphate. The analysis yielded two major components. Component 1 has a low positive loading from pH (0.032). Positive loadings of EC (0.986), Salinity (0.985), TDS (0.986), and TSS (0.885) on Component 1 indicate a strong positive connection. Component 1 tends to increase as these variables rise. Nitrate also has a significant positive loading on Component 1 (0.942), showing a strong positive association. However, Component 1 has a negative loading from phosphate (-0.209), indicating an inverse relationship, meaning Component 1 decreases when phosphate increases.

Component 2 has a significant positive loading for pH (0.804), indicating a strong positive connection. Component 2 increases as pH rises. Additionally, phosphate also shows a strong positive loading (0.867) on Component 2, reflecting a positive relationship. Low negative loadings of EC, Salinity, TDS, and nitrate on Component 2 indicate comparatively inverse connections.

Temporal variation of water quality

Temporal cluster analysis generated a dendrogram grouping 10 months into 2 clusters (Figure 4). While cluster 2 comprises month of January, March and April and rest of the months were fallen under the cluster 1, and those are comparatively high rainfall months than cluster 2 (Figure 5).

Table 6: Loading values for rotated component matrix

	Component	
	1	**2**
pH	0.032	0.804
EC	0.986	-0.130
Salinity	0.985	-0.151
TDS	0.986	-0.142
TSS	0.885	0.263
Nitrate	0.942	-0.246
Phosphate	-0.209	0.867

Note: Extraction Method: Principal Component Analysis. Varimax Rotation Method

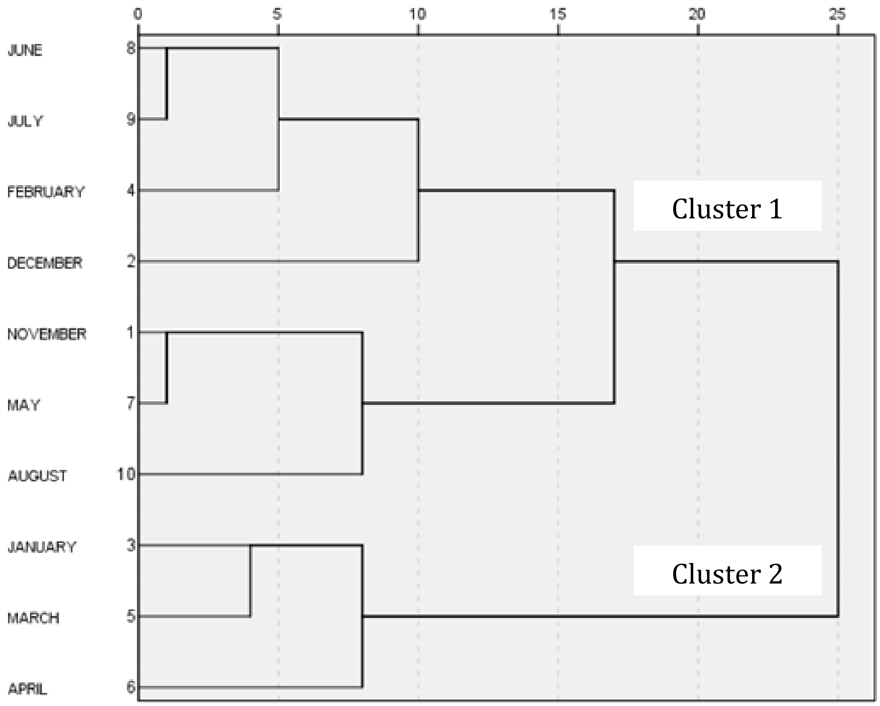

Figure 4: Dendrogram generated in temporal CA

The analysis of the rainfall distribution (Figure 5) reveals distinct patterns across different months of data collection period, with December, January, February, and March emerging as relatively dry months. Figure 6 shows average monthly rainfall distribution for average 30 years of period from1992 - 2022. It seems both graphs are following the same distribution pattern. However, when subjecting the data to cluster analysis, a contrasting outcome arises. Here, the dry cluster is composed of January, March, and April months, despite April recording a notably higher amount of rainfall. In a similar manner, December exhibits lower precipitation compared to other months categorized within the wet cluster. But December is placed in the wet cluster, similar to the dry season's positioning after a month with an abundance of rainfall. These differences suggest a decoupling between rainfall fluctuations and immediate temporal shifts in clusters. This phenomenon appears similar to the observed insensitivity of rainfall variations to rapid temporal changes. Evidently, the interaction of multifaceted factors beyond absolute precipitation influences the cluster analysis outcomes, demonstrating the nuanced nature of seasonal characterization that extends beyond mere quantitative rainfall metrics. Marzban and Sandgathe (2006) have also highlighted, how cluster analysis can reveal patterns that are not immediately apparent from raw data, supporting the idea that multifaceted factors influence cluster outcomes.

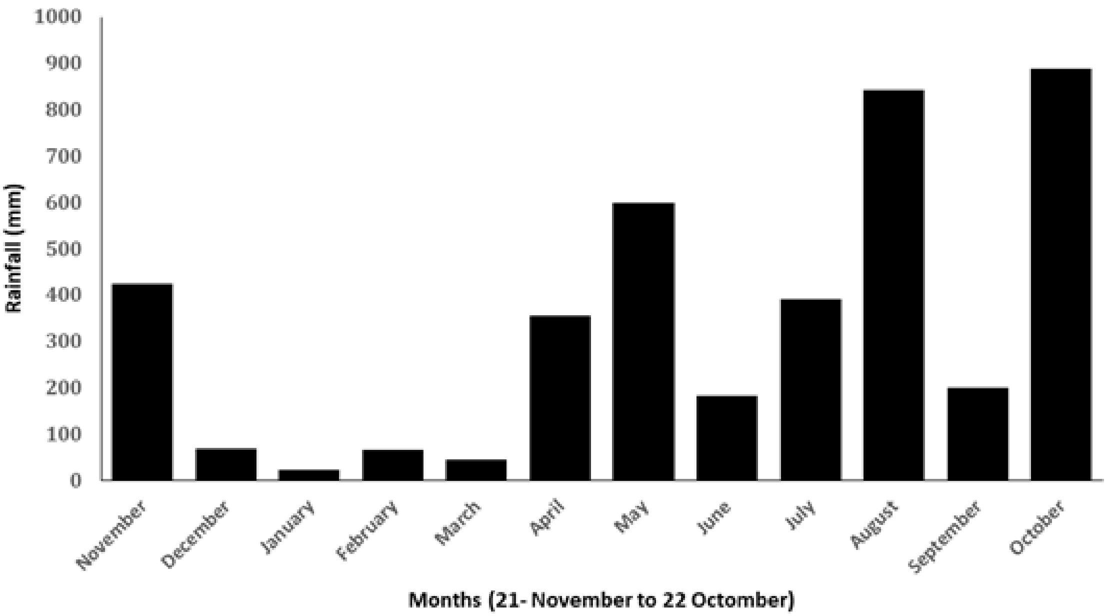

Figure 5: Rainfall distribution of 2021 November -2022 October

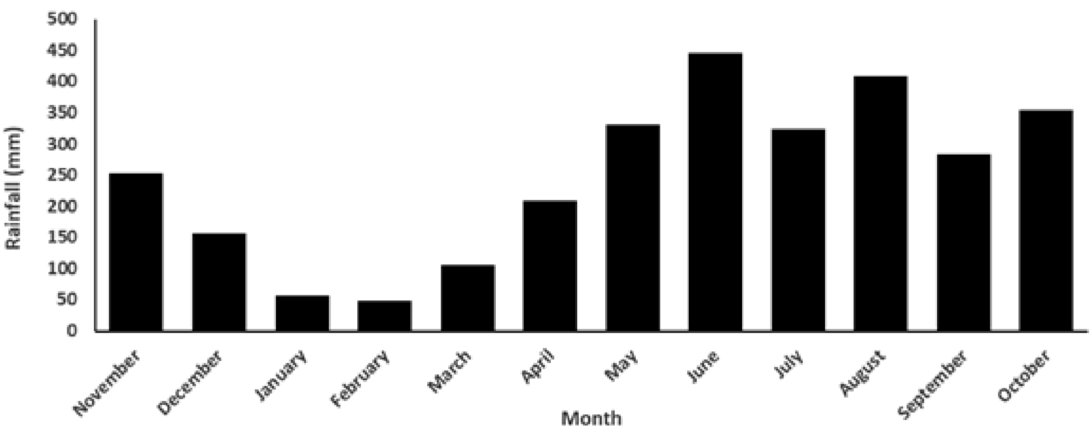

Figure 6: Average monthly rainfall distribution for1992-2022

Temporal discriminant analysis was applied, after dividing 10 months into 2 clusters by cluster analysis as dry and wet. The wilks's lambda value (0.018) shows a better discriminating power of the model since it is near to zero. Temporal discriminant analysis resulted that EC, TDS, TSS and nitrate are the most significant parameters to discriminate into clusters as wet and dry. The probability value of F test shows discrimination between the groups in highly significant $P< 0.05$. EC, TDS, TSS and nitrate concentrations have more explanatory power with coefficients of 1.427, 7.220, 6.56 and 0.447 compared to other parameters.

In the temporal set of data, PCA of the complete data set produced 2 principal components with Eigen values of 3.992 and 1.485 which are greater than 1. The first component explains 56.03% of the total variation in the water quality data set. The second component explains 20.82% of the total variance. When combined, components 1 and 2 explained 76.86% of the total variance. After applying varimax rotation, the variance explained by Component 1 slightly decreased to 54.66%, and Component 2 increased to 22.20%. However, the total variance explained by the two components remains the same at 76.86%, although the rotation redistributed the variance.

According to the rotated component matrix (Table 9), Component 1 shows a strong positive correlation with EC (0.837), salinity (0.968), TDS (0.906), and nitrate (0.762), indicating that higher values of these variables are associated with higher Component 1 values. Phosphate has a negative correlation with Component 1 (-0.741), suggesting that increased phosphate levels lead to lower Component 1 values. pH shows a weak negative correlation with Component 1 (-0.486). For Component 2, TSS has a strong positive correlation (0.930), while pH also positively correlates (0.454). EC (-0.407) and TDS (-0.265) show negative correlations with Component 2. Phosphate has a moderate negative correlation with Component 2 (-0.495), indicating lower Component 2 values with higher phosphate levels.

Table 7: Calculated coefficients by discriminant function

Parameter	Coefficients
pH	-1.893
EC	1.427
Salinity	-6.216
TDS	7.220
TSS	6.560
Nitrate	0.447
Phosphate	-0.013

Table 8: Total Variance Explained

Component	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Eigen Value	% of Variance	Cumulative %	Eigen Value	% of Variance	Cumulative %
1	3.922	56.032	56.032	3.826	54.656	54.656
2	1.458	20.828	76.860	1.554	22.204	76.860

Table 9: Loading values for rotated component matrix

	Component	
	1	2
pH	-0.486	0.454
Salinity	0.968	0.024
TDS	0.906	-0.265
TSS	-0.036	0.930
EC	0.837	-0.407
Nitrate	0.762	-0.043
Phosphate	-0.741	-0.495

Note: Extraction Method: Principal Component Analysis. Varimax Rotation Method

CONCLUSION

A thorough understanding of the status of the water quality is essential for effective wetland management, and pertinent contributing elements may offer scientific justification for the reduction of water pollution in wetlands. Water-quality monitoring methods create complicated multidimensional data that require multivariate statistical treatment for the analysis and interpretation. Spatial hierarchical cluster analysis (CA) facilitated the categorization of the seven sampling locations into two distinct clusters in Kotagala wetland, distinguishing between polluted and less polluted areas. Due to uncontrolled discharge from the expanses of agricultural area, station 2 can be introduced as a highly polluted station among other sampling points. Notably, the significant parameters contributing to this clustering were found to be electrical conductivity (EC), pH, and nitrate concentrations by the discriminant analysis. Simultaneously, the temporal hierarchical cluster analysis proficiently categorized the data collection months into distinct groups representing either dry or wet seasons, predicated on their harmonious water quality characteristics. In this classification, a discriminant analysis revealed that electrical conductivity (EC), total dissolved solids (TDS), total suspended solids (TSS), and nitrate concentrations emerged as the most influential parameters. PCA analysis indicated that the variance was explained by the first two components for spatial and temporal variations of water quality were 88.81% and 76.86%, respectively. The findings of the present study highlighted the dynamic changes in water quality that occur within the Kotagala wetland by elucidating both spatial and temporal fluctuations. The study also emphasizes the value of using modern multivariate statistical methods for the in-depth analysis and interpretation of complicated water quality datasets.

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