ISERME 2024 Proceedings
2nd September 2024 – Sapporo, Japan
https://doi.org/10.31705/ISERME.2024.30

Assessment of Seasonal and Spatial Water Quality Changes in Kelani River, Sri Lanka

Rathnayake[1] AGSN, Luxman[1] R., Udayanga[1] NAP, *Chaminda[1] SP, Ishankha[1] WCA, and Gunawardhana[2] L
[1]*Department of Earth Resources Engineering, Faculty of Engineering, University of Moratuwa, Sri Lanka.*
[2]*Department of Civil Engineering, Faculty of Engineering, University of Moratuwa, Sri Lanka.*
*Corresponding author – Email: chaminda@uom.lk

Abstract

The deteriorating water quality of the Kelani River over time has negatively affected environmental health and sustainability. This study aims to determine the relationship between land use types and its impact on the water quality within the Kelani River basin. The analysis utilized a dataset comprising 23 parameters related to water quality, spanning 17 sampling locations along both the primary river and its tributaries from 2003 to 2023. IBM SPSS Statistics (Version 26), was utilized for data analysis, focusing on 7 water quality parameters (pH, dissolved oxygen (DO), chemical oxygen demand (COD), biological oxygen demand (BOD), nitrate, phosphate, and turbidity) that were influenced by land use. From this analysis, 6 sampling locations were selected to represent various segments of the stream, including Aguruwella and Nakkawita for the upstream segment, Pugoda Ela and Wak Oya for the middle stream, and Rakgahawatte Ela and Maha Ela for the downstream segment. This study utilized a combination of GIS and statistical methods over 4 years with a 6-year time interval (2004, 2010, 2016, and 2022). The land use maps were generated by categorizing area into 4 land use types as agricultural area, vegetation area, built-up area, and others, using maximum likelihood supervised classification. Accuracy assessment using the kappa coefficient revealed that overall accuracy was greater than 85 %, for all six sub-catchments across all four years. From the analysis, it shows that the water quality parameters are significantly varied spatially and temporally. From upstream to downstream and over time, water quality has declined. Regression analysis shows the relationship between land use types and 7 water quality parameters. pH, DO, COD, BOD, and nitrate show a correlation with built-up lands, pH, DO, COD, nitrate and turbidity with vegetation areas, and phosphate with agricultural areas. Moreover, this study highlighted, built-up lands and agricultural lands negatively influenced the water quality, while vegetation areas positively influenced. By identifying the correlation between land use types and water quality, this study helps to preserve and enhance the water quality of the Kelani River basin by implementing proper land use management strategies.

Keywords: water quality; land use types; regression analysis; Kelani River Basin; GIS

1. Introduction

The increasing global population is significantly raising the demand for clean water across various sectors [1]. Water resources come in various forms like surface water, groundwater, and coastal waters. Clean water helps improve health and enhances the overall quality of life for households.

There is a substantial relationship between land-use types and the quality of water [2]. Agricultural lands yielded the highest concentrations of nutrients [3] and the high concentrations of BOD, COD, and DO observe in the sampling results indicate significant urban activity [4]. In most developing countries, domestic waste is generally the primary cause of river water pollution. Increased settlements (urban residential areas without proper sanitation facilities), industrial activities, and agricultural activities have a strong negative impact on water quality compared to forested areas [5,6]. Generally, watersheds with more forest cover have lower levels of sediment and nutrients in their streams. As an example, for Mitidja Basin, Algeria, urban residential land is the major factor in predicting water quality, influencing key parameters such as BOD, COD, SS (Suspended Solids), NH_3, PO_4^{3-}, DO, and pH. Vegetation primarily affects NO_3^- levels while agriculture affects PO_4^{3-} [7].

The Kelani River has been identified by the Environmental Foundation Limited (EFL) as Sri Lanka's most polluted and threatened river due to agricultural runoff, domestic sewage, municipal waste, and industrial effluents released from a rising number of factories located near its shores [8].

In the Kelani River Basin, the lower catchment is more polluted than the upper catchment. Key water quality parameters like pH, DO, turbidity, TSS, BOD, nitrite, ammonia, phosphate, and COD were worse in the lower catchment, particularly near Mattakkuliya, Kolonnawa, and Kaduwela. COD and pH were identified as the best indicators of pollution in the lower catchment. The upper catchment is less polluted, with COD and nitrate concentration being the main indicators. The upper catchment's pollution is mainly due to fertilizers used in tea cultivation, while the lower catchment's pollution is from domestic and industrial sewage [9].

Many researchers have examined the spatial and temporal water quality variations along the Kelani River [8,10-12] and identified the most suitable water quality indicators for the upper and lower catchments of the Kelani River [9]. However, there is a lack of knowledge about how specific land use types relate to the water quality parameters in the Kelani River Basin. This research aims to predict the relationship between land use types and water quality parameters and to assess the spatial and temporal variation of water quality and land use in the Kelani River Basin.

2. Methodology

2.1 Study Area

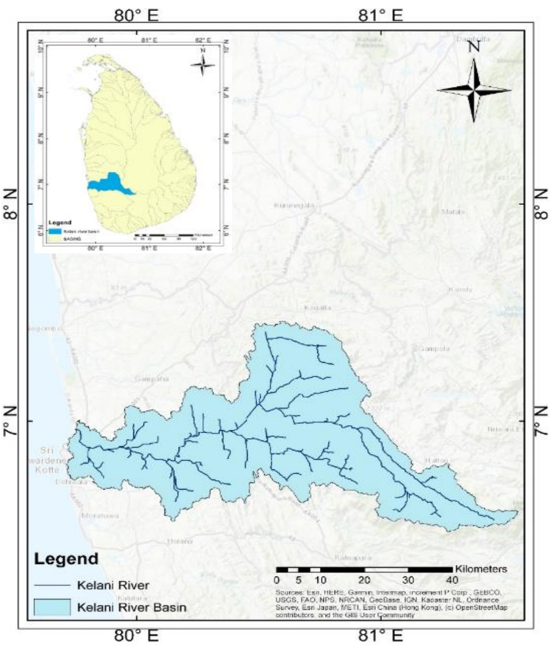

Figure 1 Study area

The Kelani River is the fourth-longest river in Sri Lanka (144 km), originates from the Sri Pada Mountain range, and coming to an end in the Mattakkuliya region. Through Colombo, Nuwara-Eliya, Gampaha, and Kegalle, the river travels 192 kilometers. Geographical location of the Kelani River basin is (Northern latitudes 6° 47' to 7° 05' and Eastern longitudes 79° 52' to 80° 13’) with the area of 2230 km^2 (Figure 1). 25% of Sri Lankans rely on the Kelani River in some capacity for their daily needs [13].

Kelani River flows through diverse landscapes, including forests, agricultural areas, industrial zones, and urban centers. Land use patterns investigation demonstrates that tea plantations and forests dominate the upper catchment, while rubber plantations and paddy fields are predominant in the middle and lower catchments [14].

2.2 Selection of Sub-Catchments

This study utilized the data set of the Central Environmental Authority (CEA), including 23 water quality parameters across the 17 sampling locations along both the main river and its tributaries from 2003 to 2023.

First, literature on water quality parameters influenced by the land use changes was reviewed [3-7], identifying seven parameters (pH, DO, COD, BOD, NO_3^-, PO_4^{3-}, and turbidity). Using IBM SPSS Statistics (Version 26), graphs were generated to show the variation of these seven parameters from 2003 to 2023 across all 17 locations. Then, mean values were compared with Sri Lankan Standard (SLS) values for drinking purposes [15]. Locations were identified where the mean values exceeded the SLS values for all parameters. Based on the locations with the highest number of exceeded parameters, six sub-catchments, representing upstream (Aguruwella, Nakkawita), middle stream (Pugoda Ela, Wak Oya) and downstream (Rakgahawatte Ela, Maha Ela) segments were selected. This study focuses only on locations within the sub-catchments.

2.3 Preparation of Watershed Areas

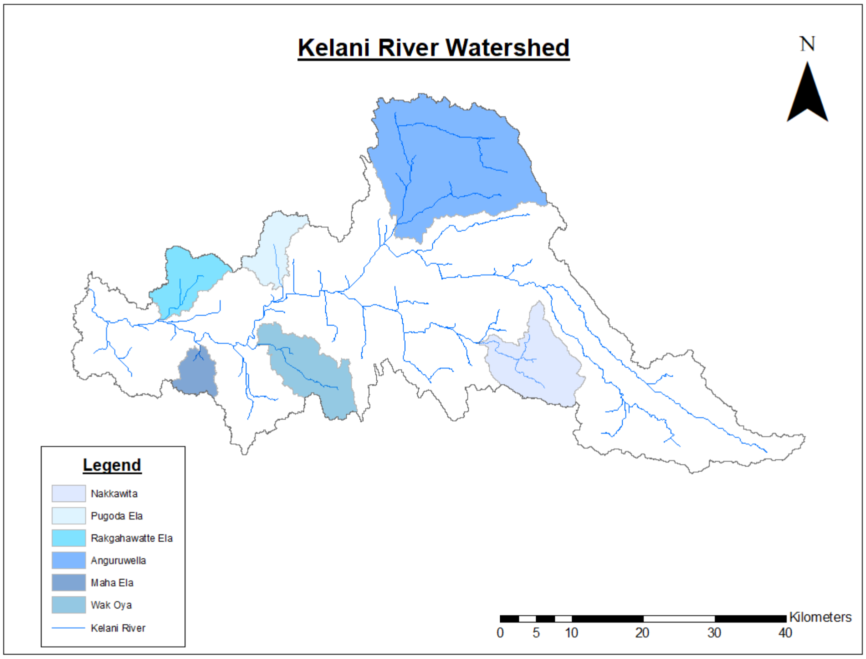

Figure 2 Selected sub-catchments.

To create the river network, 30m resolution DEMs (Digital Elevation Model) that can cover the entire river basin, were downloaded from the USGS Earth Explorer. Using the HEC-GeoHMS toolbar, DEM data was preprocessed. The river network was extracted using a threshold value of 5000. The six sampling points of Nakkawita, Anguruwella, Pugoda Ela, Wak Oya, Maha Ela and Rakgahawatte Ela were used as the pour points for their respective sub-catchments, with an additional pour point where the river meets the sea. By snapping into pour points, watershed areas for six sub-catchments and the whole river were generated (Figure 2).

2.4 Water Quality Analysis

The data set contained water quality data from 2003 to 2023. To cover the entire data period, four years were selected for the study with a 6-year interval (2004, 2010, 2016, 2022). For the selected seven water quality parameters, the mean values for each of the 4 years were calculated. Then the variation of each parameter from 2004 to 2022 across the six sub-catchments, were plotted using Microsoft Excel 2016.

2.5 Land Use Classification

For the land use classification, Landsat series data were used from the USGS Earth Explorer. For 2016 and 2022, Landsat 8 data and for 2004 and 2010 Landsat 5 data were used with cloud cover adjusted to less than 10%. Composite images were prepared using 11 bands of Landsat 8 and 7 bands of Landsat 5.

Land uses were classified into 4 categories such as agricultural area, vegetation area, built-up area, and others using supervised classification. Polygons for each category were created using Google Earth Pro and Composite images, added to the training sample manager in ArcGIS 10.8, and signature file was created. For the classification, Maximum Likelihood Supervised Classification was used. This method assumes each statistical value is normally distributed in each band and calculates the probability of each pixel belonging to a specific category and classifies it into the category with the highest probability. Although more complex, this process is more accurate and widely used [7,16-17].

Accuracy was assessed using 100 accuracy assessment points per each sub-catchment using stratified random sampling method. The confusion matrix was generated with overall accuracy which was greater than 85% for all sub-catchments and years [7,16].

2.6 Statistical Analysis

For the statistical analysis, SPSS Version 26 was utilized. The relationship between water quality parameters and land use types was examined using the Pearson correlation coefficient, with the statistically significance levels set at 0.05 and 0.01 for two-tailed test. The percentage areas of four land use types and mean values of seven water quality parameters across 6 sub-catchments in 2016, were analyzed. Additionally, a regression model was developed using multiple stepwise linear regression method to predict, how land use types influence changes in each water quality parameter.

3. Results

3.1 Variation of Land Use Types

In upstream areas, the most dominant land use type is vegetation areas, while in the middle stream, agricultural areas are the most prevalent. Downstream, built-up areas are the dominant land use due to the high concentration of industries and housing developments (Figure 3).

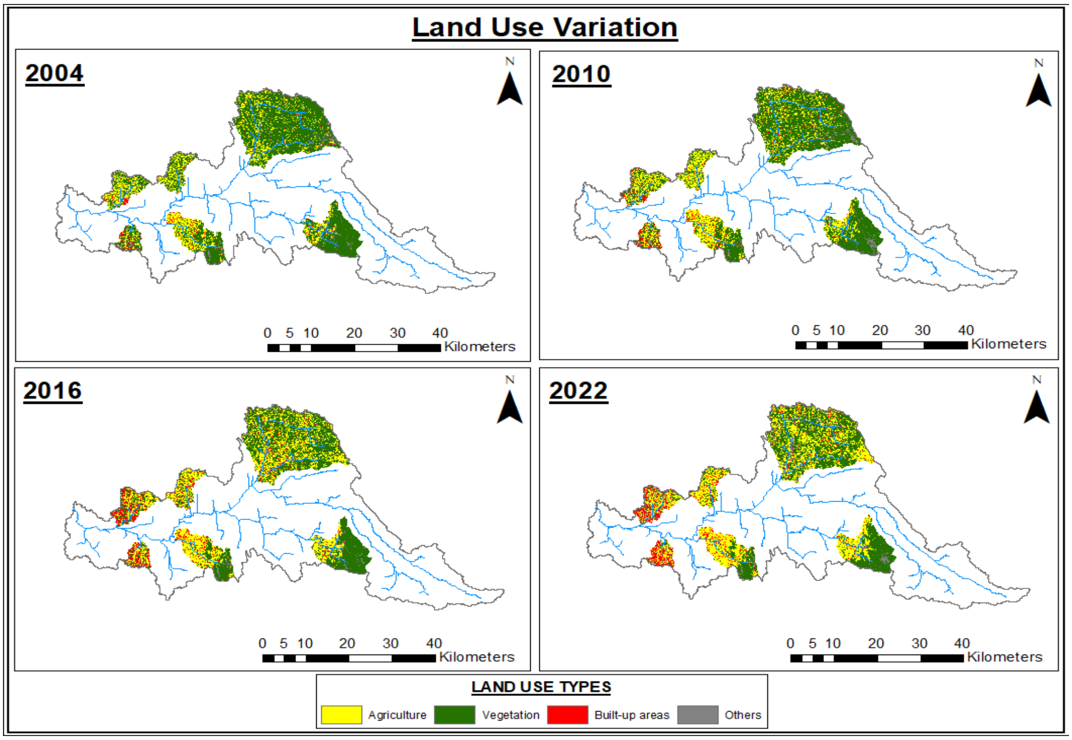

Figure 2 Land use maps for 2004, 2010, 2016 and 2022.

The percentage of vegetation area reduced over time, while built-up areas increased across all six sub-catchments (Figure 4). With time, agricultural areas gradually increased in the upstream and middle stream areas, while downstream areas did not show a clear trend.

Upstream areas consistently had the highest vegetation percentage. In 2004, 2010 and 2016, the vegetation percentages were relatively similar in both middle stream and downstream.

However, in 2022, the middle stream reported a higher vegetation percentage (65.27%, 55.54%), than the downstream areas (34.91%, 40.84%). The highest built-up areas were reported from downstream. Among all six sub-catchments, Maha Ela consistently had the highest built-up area percentages in all four years. The percentage of agricultural area was highest in the middle stream, with Pugoda Ela reporting the highest values for all four years. From 2004 to 2010, agricultural areas in upstream, were less than those in the downstream, but from 2016 onwards, both upstream and downstream showed relatively similar values.

3.2 Variation of Water Quality Parameters

According to Figure 5, most water quality parameters, except for pH, showed significant spatial variation among the six sub-catchments. The maximum DO was recorded in the upstream areas, while the minimum was observed in the downstream. Conversely, the minimum BOD was recorded from the upstream and the maximum in the downstream. The lowest COD and NO_3^- values were recorded in the upstream areas, with the highest values observed in the downstream areas. However, Pugoda Ela recorded nearly similar values to the downstream. The turbidity and PO_4^{3-} were highest in both middle stream and downstream.

Regarding temporal variation, from 2004-2016, pH, COD, BOD and PO_4^{3-} increased across all sub-catchments. From 2016-2022, these values decreased due to the pandemic influence and the economic crisis [18]. DO decreased from 2004-2016 and then increased from 2016-

2022, also due to the pandemic influence [18]. NO_3^- and turbidity didn't show a clear trend over time.

The results indicated that most water quality parameters were negatively affected from upstream to downstream. The temporal analysis revealed that most water quality parameters, instead of NO_3^- and turbidity, degraded over time. However, the trend deviated from 2016 to 2022, likely due to the pandemic and economic crisis. During this period, factors like the shutdown of industries and reduced human activities contributed to improved water quality [18].

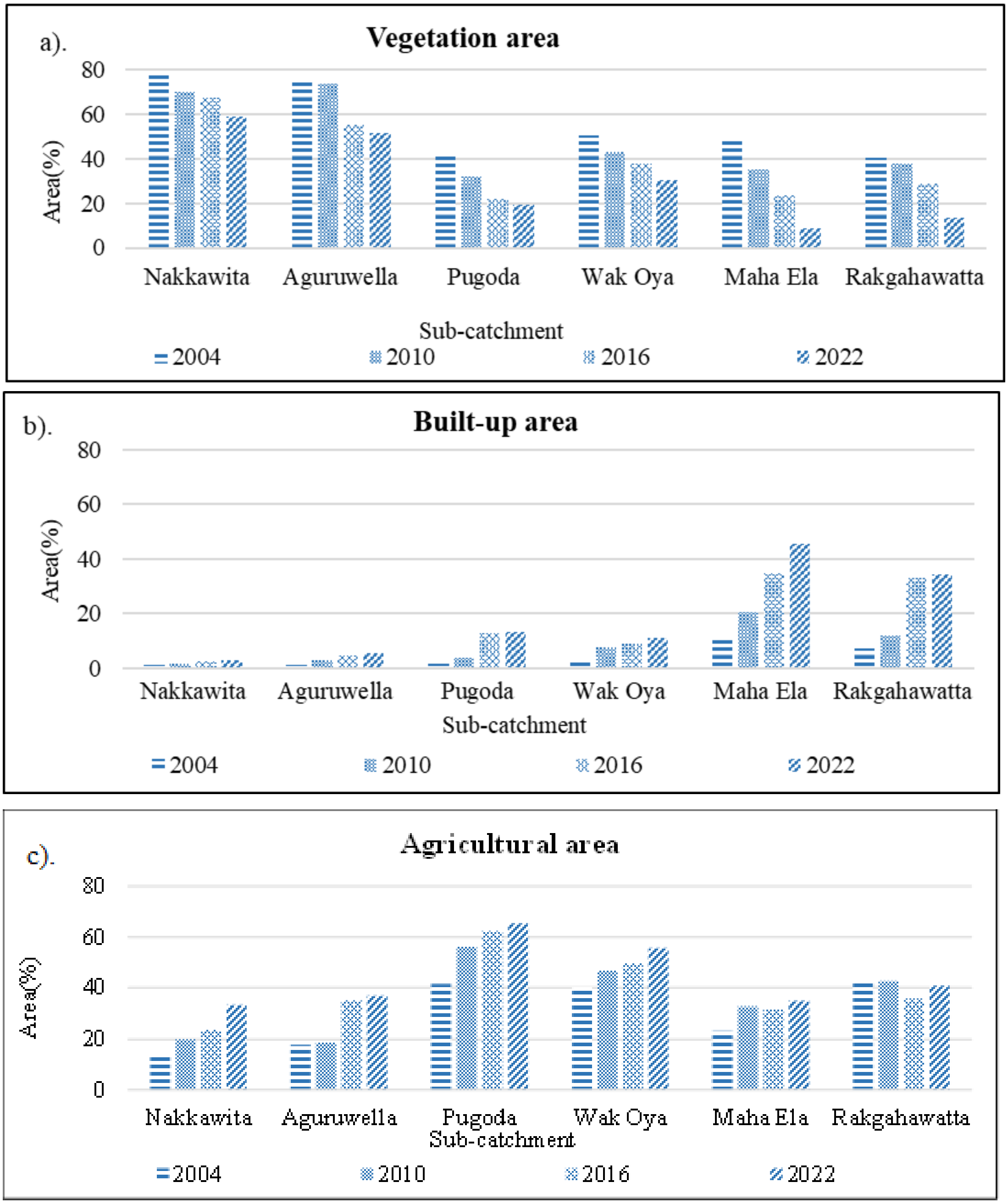

Figure 4 Land use variation from 2004-2022 across six sub-catchments (a) Vegetation area (b) Built-up area (c) Agricultural area

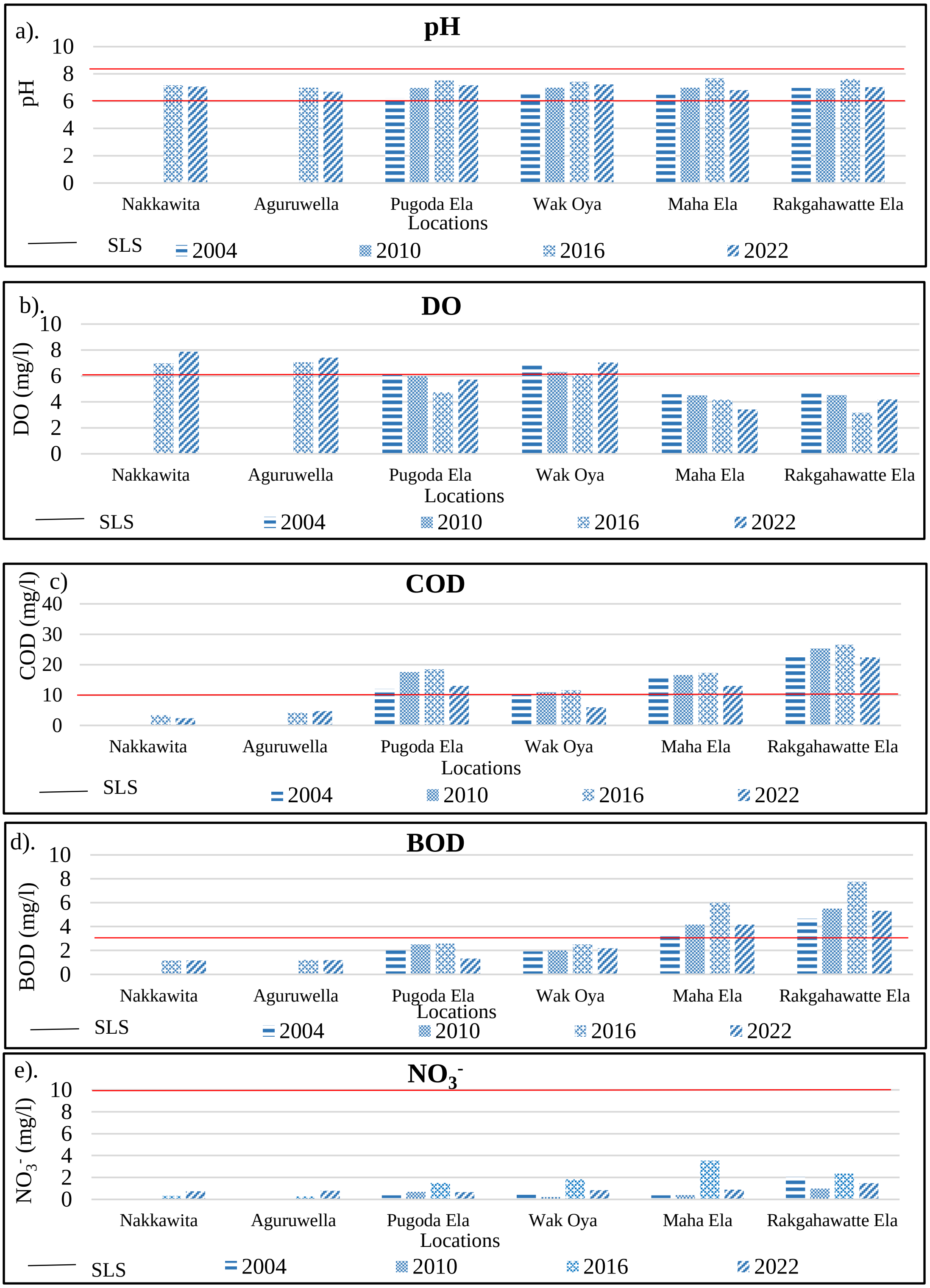

Figure 5 Variation of (a)pH (b)DO (c)COD (d)BOD (e)NO_3 (f)PO_4^{3-} and (g)Turbidity from 2004-2022 across six sub-catchments

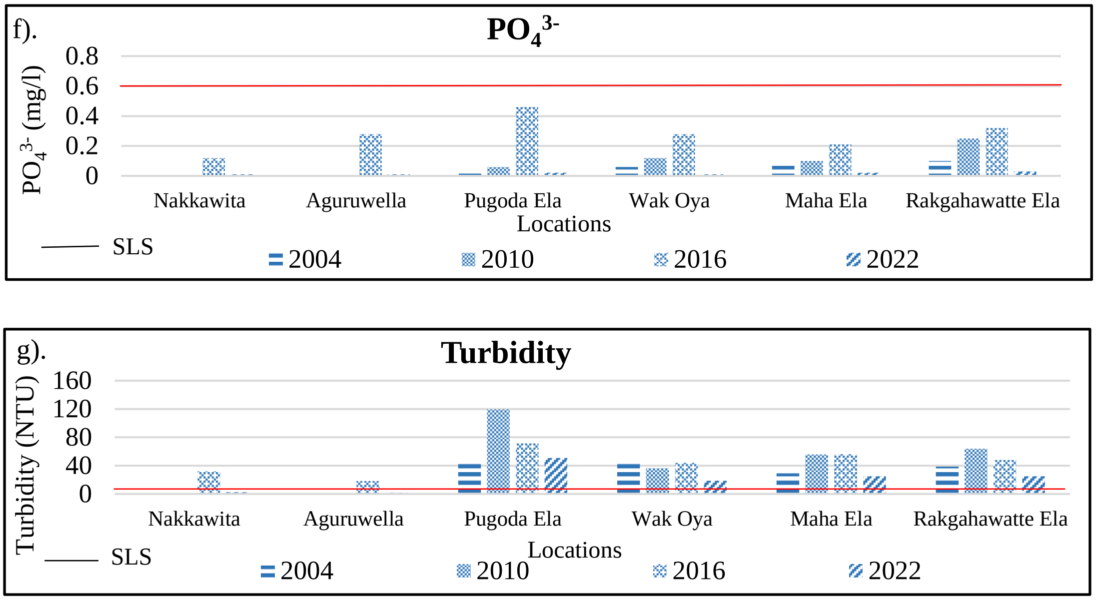

Figure 5 Variation of (f)PO_4^{3-} and (g)Turbidity from 2004-2022 across six sub-catchments

3.3 Single Factor Correlation Analysis

The land use types and water quality parameters showed a significant relationship according to the Pearson correlation coefficient (Table 1). Based on the significance level, built-up areas were strongly positively correlated with BOD and strongly negatively correlated with DO at the 0.01 significance level, while being positively correlated with pH, COD, and NO3- at the 0.05 significance level. Vegetation was positively correlated with DO and negatively correlated with pH, COD, NO3-, and turbidity at the 0.05 significance level. Agriculture was positively correlated only with PO43- at the 0.05 significance level.

Table 1 Pearson Correlation Coefficient between land use types and water quality parameters in 2016

Water Quality Parameter	Agriculture (%)	Vegetation (%)	Built-up areas (%)
pH	0.282	-0.878*	0.851*
DO	-0.188	0.839*	-0.918**
COD	0.341	-0.862*	0.836*
BOD	-0.109	-0.672	0.964**
NO_3^-	0.095	-0.819*	0.905*
PO_4^{3-}	0.889*	-0.662	0.120
Turbidity	0.635	-0.858*	0.513

*Significance at 0.05 probability level (2-tailed). **Significance at 0.01 probability level (2-tailed).

3.4 Multiple linear regression analysis

Multiple Linear Regression (MLR) model was developed to predict the relationship between three land use types (Agriculture, Vegetation and Built-up) and water quality parameters. From the significance probability level, tolerance, and variance inflation factor (VIF), which are characteristic parameters of the collinearity diagnostics, indicated no collinearity among the independent variables. However, for developing the MLR model, Built-up area was excluded for pH and COD, and Vegetation was excluded for DO and NO_3^-. This exclusion is likely due to the effect of excluded factors masked by the included factors.

The results revealed that all seven water quality parameters across the six sub-catchments could be predicted using these three land use types. Most of the water quality parameters correlated with built-up areas and vegetation, while only PO_4^{3-} correlated with agriculture (Table 2). Therefore, vegetation and built-up areas were the most suitable predictors for water quality in the Kelani River Basin.

Table 2 MLR model between land use types and water quality parameters in 2016

Dependent Variable	**Independent variables**	**Regression**	**R^2**	**Adjusted R^2**	**P**
pH	Ve	7.908-0.013Ve	0.77	0.713	0.022
DO	Bu	7.055-0.103Bu	0.843	0.804	0.01
COD	Ve	30.056-0.419Ve	0.743	0.678	0.027
BOD	Bu	0.578+0.184Bu	0.929	0.912	0.002
NO_3^-	Bu	0.362+0.079Bu	0.819	0.774	0.013
PO_4^{3-}	Ag	-0.010+0.007Ag	0.79	0.737	0.018
Turbidity	Ve	78.973-0.864Ve	0.736	0.67	0.029

4. Discussion

In the upstream areas of the Kelani River basin, high vegetation cover and less urban areas result in less addition of pollutants to the water sources, effective erosion control, and fast purification processes. Therefore, the overall water quality in upstream areas is high. In contrast, the downstream areas suffer from high urban areas, reduced vegetation cover and intensive human activities. These factors contribute to increased residential and industrial discharges into the water, high erosion, and street runoffs, leading to degraded water quality downstream. Middle stream areas of the Kelani River basin contain extensive agricultural areas. Agricultural activities increase soil erosion and cause fertilizers and pesticides to enter the river through rainfall runoff, which degrades water quality. All water quality parameters recorded their best values in upstream areas. Turbidity and PO_4^{3-} levels were at their worst in both middle stream and downstream, while other parameters recorded their worst in downstream areas. Overall, water quality shows a declining trend from upstream to downstream.

With time, the reduction in vegetation areas coupled with an increase in built-up and agricultural areas result in the deterioration of most water quality parameters. This shows that overall water quality in the Kelani River Basin degraded over time.

Regression analysis showed that built-up areas negatively correlate with DO and positively correlate with pH, COD, BOD, and NO_3^-. Increased organic pollutant loads from residential and industrial discharges lead to decreasing DO levels, while other parameters increase. Vegetation areas, on the other hand, show a positive correlation with DO and negative correlation with pH, COD, NO_3^- and turbidity. High vegetation cover helps to control erosion and reduce runoffs, which lowers turbidity. Also, due to the less human activities and urban waste discharges in vegetated areas lead to increased DO levels and decreased COD and BOD levels. Agricultural areas increase soil erosion and introduce fertilizers and pesticides into river from the rainfall runoff, particularly affecting PO_4^{3-}, NO_3^-, and turbidity levels [5-7]. However, regression analysis indicates that agriculture only positively correlates with PO_4^{3-}. Therefore, regression results may not fully capture the relationship between agriculture and water quality parameters.

Throughout the study period, certain water quality parameters consistently exceeded SLS limits for drinking purposes. Parameters such as pH, NO_3^- and PO_4^{3-} remained within acceptable range across all six sub-catchments for all years. COD exceeded acceptable limits in both middle stream and downstream, while BOD exceeded limits only in downstream. DO exceeded in downstream and in Pugoda Ela from 2016 onwards. Turbidity levels were consistently above acceptable limits across all sub-catchments for all years.

5. Conclusion

The purpose of this research was to assess the special and temporal water quality variations and examine the relationship between water quality parameters and land use types in the Kelani River Basin. Upstream areas maintained higher water quality due to extensive vegetation and minimal human impact, whereas downstream areas experienced poor water quality due to urbanization and industrialization. Overall, water quality showed a degradation from upstream to downstream in the Kelani River Basin.

Over time, overall water quality degraded as agricultural and built-up areas increased, while vegetation areas decreased. However, in 2022, water quality improved due to the pandemic influence and economic crisis, which reduced human activity and industrial discharge.

Built-up areas negatively correlated with DO and positively correlated with pH, COD, BOD, and NO_3^-. In contrast, vegetation areas positively correlated with DO and negatively correlated with pH, COD, NO_3^- and turbidity. Agriculture only positively correlated with PO_4^{3-}. Therefore, Built-up areas and vegetation areas were the most relevant predictors of the water quality in the Kelani River Basin.

This study considered three main land use types (vegetation, agriculture, and built-up areas). Among them, vegetation positively impacts the water quality, while built-up areas negatively impact. The protection of vegetation cover is crucial to preserve the water quality. Therefore, implementing proper land use management strategies is essential to mitigate the effects of urbanization and development on water quality in the Kelani River Basin.

References

[1] Tortajada, C., & Biswas, A. K. (2018). Achieving universal access to clean water and sanitation in an era of water scarcity: strengthening contributions from academia. Current Opinion in Environmental Sustainability, 34(34), 21–25. https://doi.org/10.1016/j.cosust.2018.08.001

[2] Tong, S. T. Y., & Chen, W. (2002). Modeling the relationship between land use and surface water quality. Journal of Environmental Management, 66(4), 377–393. https://doi.org/10.1006/jema.2002.0593

[3] Lenat', D., & Crawford2, J. (1994). Effects of land use on water quality and aquatic biota of three north carolina piedmont streams.Hydrobiologia, 294(0018-8158, 1573-5117), 185–199.

[4] Effendi, H., Muslimah, S., & Permatasari, P. A. (2018). Relationship between land use and water quality in pesanggrahan river. IOP Conference Series: Earth and Environmental

Science, 149(1755-1307, 1755-1315), 012022. https://doi.org/10.1088/1755-1315/149/1/012022

[5] Kibena, J.,Nhapi, I., & Gumindoga, W. (2014). Assessing the relationship between water quality parameters and changes in landuse patterns in the upper manyame river, zimbabwe. Physics and Chemistry of the Earth, Parts A/B/C, 67-69(14747065), 153–163. https://doi.org/10.1016/j.pce.2013.09.017

[6] Little, J. L., Saffran, K. A., & Fent, L. (2003). Land Use and Water Quality Relationships in the Lower Little Bow River Watershed, Alberta, Canada. Water Quality Research Journal, 38(4), 563–584. https://doi.org/10.2166/wqrj.2003.037

[7] Chen, D., Elhadj, A., Xu, H., Xu, X., & Qiao, Z. (2020). A Study on the Relationship between Land Use Change and Water Quality of the Mitidja Watershed in Algeria Based on GIS and RS. Sustainability, 12(9), 3510. https://doi.org/10.3390/su12093510

[8] Abeysinghe, N. M. D. A., & Samarakoon, M. B. (2017). Analysis of Variation of Water Quality in Kelani River, Sri Lanka. International Journal of Environment, Agriculture and Biotechnology, 2(6). http://ijeab.com/detail/analysis-of-variation-of-water-quality-in-kelani-river-sri-lanka/

[9] Narangoda, C., Amarathunga, D., & Dangalle, C. D. (2023). Evaluation of water quality in the upper and lower catchments of the Kelani River Basin, Sri Lanka. Water Practice and Technology, 18(3), 716–737. https://doi.org/10.2166/wpt.2023.034

[10] Mahagamage, M. G. Y. L., Chinthaka, S. D. M., & Manage, P. M. (2014). Multivariate analysis of physico-chemical and microbial parameters of surface water in Kelani River basin. International Journal of Multidisciplinary Studies, 1(1), 55. https://doi.org/10.4038/ijms.v1i1.37

[11] Makubura, R., Meddage, D. P. P., Azamathulla, H. Md., Pandey, M., & Rathnayake, U. (2022). A Simplified Mathematical Formulation for Water Quality Index (WQI): A Case Study in the Kelani River Basin, Sri Lanka. Fluids, 7(5), 147. https://doi.org/10.3390/fluids7050147

[12] Sawmika, H., Ga Thusitha, Samarakoon, M., Watta, A., Kadawatha, M., & Lanka, S. (1994). Impact of land use on water quality of kelani river.

[13] Jean-Francois Vuillaume, Singay Dorji, Akinola Adesuji Komolafe, & Herath, S. (2018). Sub-seasonal extreme rainfall prediction in the Kelani River basin of Sri Lanka by using self-organizing map classification. Natural Hazards, 94(1), 385–404. https://doi.org/10.1007/s11069-018-3394-9

[14] Surasinghe, T., Kariyawasam, R., Sudasinghe, H., & Karunarathna, S. (2019). Challenges in Biodiversity Conservation in a Highly Modified Tropical River Basin in Sri Lanka. Water, 12(1), 26. https://doi.org/10.3390/w12010026

[15] Central Environmental Authority. (2019). part I: sec. (I) -gazette extraordinary of the democratic socialist republic of sri lanka. https://www.cea.lk/web/images/pdf/epc/2148-20_e-1.pdf

[16] Ganesh, B., Vincent, S., Pathan, S., & Raquel, S. (2023). Utilizing LANDSAT data and the Maximum Likelihood Classifier for Analysing Land Use Patterns in Shimoga, Karnataka. Journal of Physics: Conference Series, 2571(1), 012001–012001. https://doi.org/10.1088/1742-6596/2571/1/012001

[17] Zhang, H., He, J., Chen, S., Zhan, Y., Bai, Y., & Qin, Y. (2023). Comparing Three Methods of Selecting Training Samples in Supervised Classification of Multispectral Remote Sensing Images. Sensors, 23(20), 8530–8530. https://doi.org/10.3390/s23208530

[18] Yapabandara, I., Wei, Y., Ranathunga, B., Indika, S., Jinadasa, K. B. S. N., Weragoda, S. K., Weerasooriya, R., & Makehelwala, M. (2023). Impact of Lockdown on the Surface Water Quality in Kelani River, Sri Lanka. Water, 15(21), 3785. https://doi.org/10.3390/w15213785