PLANT SCIENCE TODAY
ISSN 2348-1900 (online)
Vol 12(sp1): 01–14
https://doi.org/10.14719/pst.5919

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RESEARCH ARTICLE

Spatio-temporal analysis of surface water quality on urban tanks in Coimbatore

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OPEN ACCESS

ARTICLE HISTORY
Received: 17 October 2024
Accepted: 03 December 2024
Available online
Version 1.0 : 28 January 2025

Check for updates

Additional information

Peer review: Publisher thanks Sectional Editor and the other anonymous reviewers for their contribution to the peer review of this work.

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CITE THIS ARTICLE
Ramachandran R, Kannan B, Sivasubramanian K, Arunadevi K, Patil SG. Spatio-temporal analysis of surface water quality on urban tanks in Coimbatore. Plant Science Today.2025; 12(sp1):01-14. https://doi.org/10.14719/pst.5919

Abstract

Effective monitoring and predicting surface water quality are vital for sustainable water resource control. Traditional in-situ techniques are regularly constrained by their time-consuming nature and restrained spatial coverage. This study seeks to develop a predictive version that combines physio-chemical water quality parameters with remote sensing indices derived from the Sentinel-2A dataset to enhance accuracy and spatial attainment. The research focuses on four urban tanks in Coimbatore namely Krishnampathy, Selvampathy, Kumaraswamy and Ukkadam Periyakulam. The physio-chemical parameters for assessing the water quality which include pH, Electrical Conductivity (EC), Total Dissolved Solids (TDS), Dissolved oxygen (DO), Calcium (Ca), Magnesium (Mg), Total hardness, Chloride (Cl^-), Carbonate ($Co3^-$) and Bicarbonate (HCo^{3-}) have been measured, additionally for the detection of surface water extent using remote sensing indices namely Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), Water Ratio Index, Normalized Difference Chlorophyll Index (NDCI) indices which were extracted from sentinel-2A datasets. The parameters such as EC, TDS, Ca^{2+}, Cl^- and Total hardness show a high coefficient of determination (R^2). Correlation and regression techniques have been employed to integrate these datasets, resulting in the development of a robust predictive model. By combining these two information sources, the model is constructed using stepwise regression analysis. The model's accuracy turned into established towards ground-truth records, showing large improvements whilst far away Remote sensing indices had been covered.

Keywords

GIS; prediction model; remote sensing; stepwise regression; water quality parameters

Introduction

Water is an inevitable source contributed through various forms of precipitation. The received precipitation in the form of water drops, a size larger than 0.5mm, contributes to both surface and groundwater. It plays a crucial role in agricultural, environmental, industrial and socio-economic aspects. Only around 1.2% of the world's freshwater is surface water. This includes tanks contributing 20.9%, Rivers contributing 0.49% Swamps and Marshes contributing 2.6% of surface freshwater. Urban tanks, often known as water storage tanks or reservoirs, are essential components of modern urban infrastructure (1). These structures are intended to collect, store and manage water resources in urban contexts, performing a variety of functions ranging from guaranteeing a consistent water supply to assisting in flood control. Urban tanks are important in modern cities in many ways. Urban tanks lessen the impact of droughts and water shortages by storing water during times of excess, such as the rainy season.

Contaminating the tank water enriches the organic content like nitrogen and it can be used by the farmers for irrigation in earlier days, later, the accumulation of heavy metals in tanks makes water unsuitable for irrigation (2). The presence of organic matter in water leads to the lowering of Dissolved oxygen (DO), due to which the aquatic organisms are unable to sustain and affects other parameters of water (3). The growth of aquatic weeds such as Water Hyacinth (*Eichhornia crassipes*), Hydrilla (Hydrilla verticillata), Eurasian Watermilfoil (*Myriophyllum spicatum*), Water Lettuce (*Pistia stratiotes*) and Giant Salvinia (*Salvinia molesta*) results from eutrophication, which adversely affects water quality (4).

GIS could be applied for surface water quality analysis, collecting satellite data to provide spatial and temporal variation in contaminated areas. Common water indices like NDWI, MNDWI, WRI and NDVI are used for evaluation of surface water detection (5).

To overcome the drawbacks of conventional in situ measurements, which are expensive and time-consuming, UAV and Sentinel-2 multispectral data were applied to analyze Ukkadam Lake's surface water quality (6). They developed predictive algorithms for optical and non-optical metrics, achieving higher correlation with Sentinel-2 data, with R2 values exceeding 0.80. Remote sensing technology could be used for continuous monitoring of water quality, providing local government with cost-effective data. Further exploration of Sentinel-2-based water quality index models is recommended.

Using biological monitoring and remote sensing to assess the water quality of Lake Timsah, an Egyptian lake facing environmental issues due to human activity. In the study water samples were collected and six models were designed, revealing poor to moderately poor water quality. The study emphasizes the need for ongoing evaluations and the effectiveness of remote sensing in monitoring water quality (7).

The variations of physicochemical water quality parameters of Lake Bunyonyi over a year, revealing significant differences between sampling stations. The findings suggest potential pollution sources and the study recommends further research to identify contamination sources and address nutrient loading for sustainable management in Lake Bunyonyi (8). The objective of the research is to analyze the temporal variation of surface water characteristics of urban tanks of Coimbatore using various remote sensing indices, to assess the surface water quality of urban tanks using different physio-chemical parameters, to observe the spatiotemporal variations of surface water quality parameters of urban tanks in Coimbatore using GIS.

Study Area

The study areas selected for the present study include urban tanks namely, Krishnampathy, Selvampathy, Kumaraswamy and Ukkadam Periyakulam which is in Coimbatore city (Table 1). These tanks were interlinked in series in which the water overflow from the upper stream tank into the downstream tank (cascade). Usually, these tanks lie in the Noyal River basin which originates from Velliangiri mountains and flows over Coimbatore city, also covers the districts of Erode, Tirupur and Karur where it drains in the river Cauvery (Fig. 1a). Due to rapid urbanization, these tanks in this city were contaminated by domestic sewage discharge and industrial effluents which led to unconsumable conditions.

Materials and Methods

In-situ water sampling

For evaluation of different physio-chemical parameters, water samples were collected from selected tanks at a depth of below 30 cm. The time of water sample collection was at 9-10 am in a repeated cycle manner of every 15th day of each month with grab sampling. The temporal variation can be assessed from the month of February to June. The autoclavable narrow-mouth bottles were used for sampling the water, to prevent errors in the outcoming results. The physio-chemical parameters in which the pH and EC values were recorded and notified on the spot of water sampling. The analysis of the Dissolved oxygen (DO) parameter was conducted on the same day as sampling. The sample was then placed in the BOD incubator, where the final DO was determined after 5 days of incubation. The parameters other than pH, EC and DO were analyzed after transferring the sampled water to the laboratory and performing the analysis according to the guidelines of the Central Pollution Control Board (9) (Table 2) and American Public Health Association (10). The samples were collected from the inlet, outlet and several interior locations of the tank, with a total of 10 sampling points, including their geographical coordinates (Fig. 1b). The data obtained from the lab were imported into GIS software, where spatial variation was analyzed with respect to each individual tank using the IDW (Inverse Distance Weighting) tool (Fig. 2a).

Analysis of Remote sensing Data

On the other hand, several remote sensing Indices can be calculated by using sentinel-2A data for evaluating spatial and temporal variation of surface water quality monitoring (Table 3). The spatial resolution, 20 meters has been selected which contains all the bands to eliminate the radiometric correction. The Indices which include Normalized difference Water Index (NDWI), Modified Normalized difference Water Index (MNDWI), Water Ratio Index (WRI), Normalized Difference Chlorophyll Index (NDCI) and Normalized Difference vegetation Index (NDVI) were analyzed for detecting the surface water extent (Table 3a).

Table 1. Details of the selected tanks for this study

S. No	Name of the Tank	Area (acres)	Capacity (m^3)	Perimeter (km)	Upstream tank	Downstream Tank
1	Krishnampathy	55.3	21,7190	2.23	Narasimpathy	Selvampathy
2	Selvampathy	56.72	28,1752	2.58	Krishnampathy	Kumaraswamy
3	Kumaraswamy	77	30,7532	2.53	Selvampathy	Ukkadam Periyakulam
4	Ukkadam Periyakulam	340	19,80,800	6.5	Kumaraswamy	Valankulam

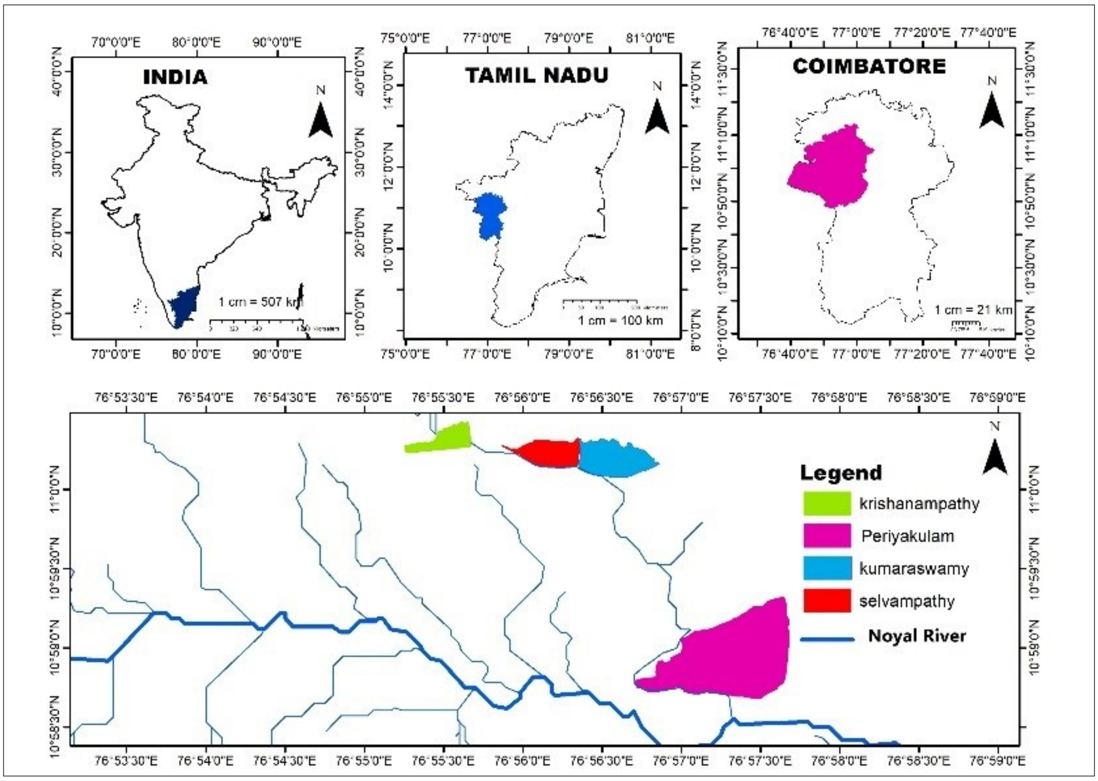

Fig. 1a. Location map of the study area.

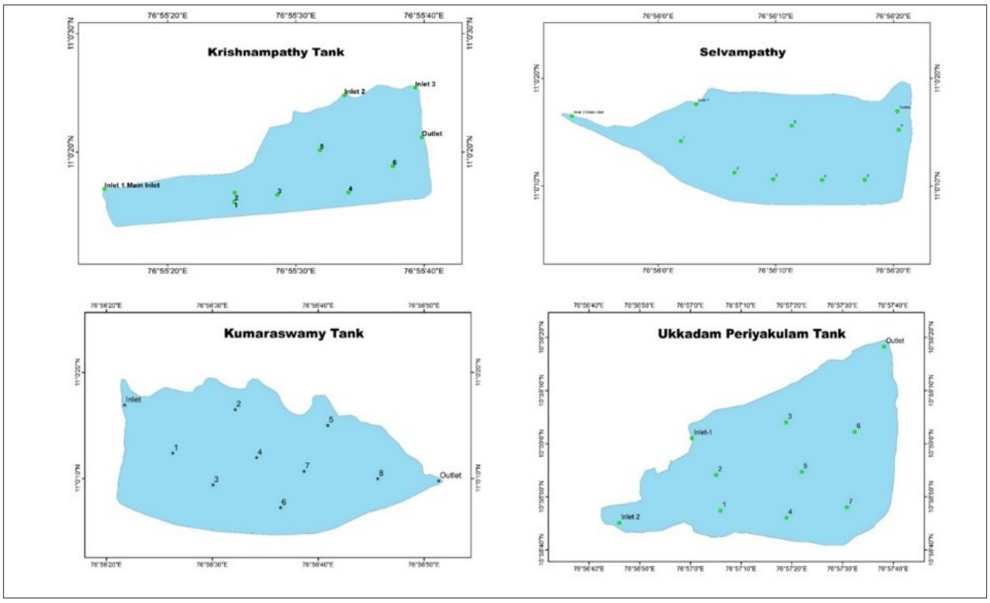

Fig. 1b Sampling location of the study area.

Table 2. Water quality standards according to CPCB

S. No	Water Quality Parameters	Methods of Analysis	Units	CPCB Standards	
				Acceptable Limits	Permissible Limits
1	pH	pH Probe	-	5.5-9	No Relaxation
2	EC	EC Probe	µS/cm	750	2250
3	TDS	Gravimetry	mg/l	500	2000
4	Calcium	EDTA Titrimetric	mg/l	75	200
5	Magnesium	EDTA Titrimetric	mg/l	30	100
6	Total Hardness	Titrimetric	mg/l	200	600
7	Carbonate	Acid Base Titration (Phenolphthalein Indicator)	mg/l	-	-
8	Bicarbonate	Acid Base Titration (Methyl Orange Indicator)	mg/l	-	-
9	Chloride	Volhard Method	mg/l	250	1000
10	Dissolved Oxygen	Winkler Azide method	mg/l	≥ 4	Not < 3.5
11	Biological Oxygen Demand	DO consumption in 3 days at 27^{0}C	mg/l	5	30
12	Chemical Oxygen Demand	Potassium Dichromate method	mg/l	20	250

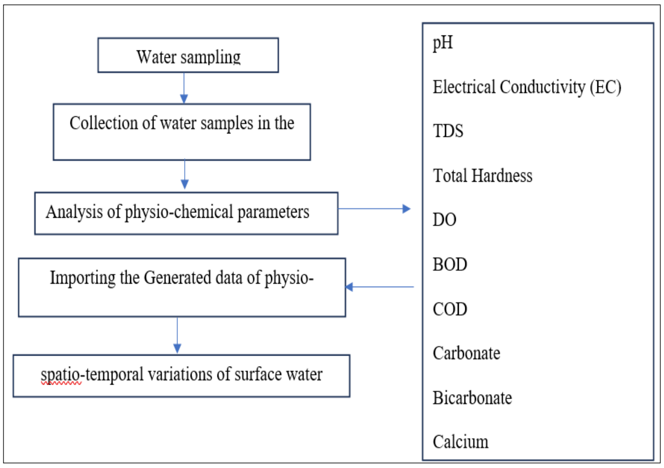

Fig. 2a. Flow chart of physio-chemical analysis of surface water quality.

Table. 3 Details of satellite imagery applied for calculating the Indices

S. No	Data Collected	Details
1	**Data**	Sentinel 2A
2	**Availability of data**	Copernicus Open Access Hub
3	**Space agency**	European Space Agency
4	**Altitude**	786 Km
5	**Orbit**	Sun synchronous
6	**Total Number of Bands**	13
7	**Spatial Resolution**	20 meters
8	**Revisit Time**	10 days (Individual satellite at equator)
9	**Swath Width**	290 km
10	**Imaging Instrument**	Multi-spectral Imager

Source: *Copernicus Data Space Ecosystem launched by European Space Agency* (30) (9)

The study is broadly carried out with both analysis of sampled surface water and Remote sensing analysis. The following flow chart delivers the spatial and temporal variation of surface water quality (Fig. 2b).

Prediction model Development

To predict water quality parameters, regression models were developed by correlating water quality parameters with remote sensing indices. However, spectral indices values also can also be used to develop the prediction modelling. But the performance was improved by incorporating the spectral indices with water

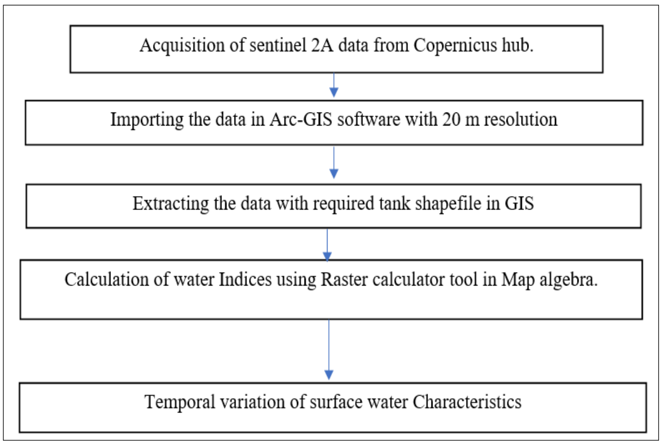

Fig. 2b. Flow chart of water indices calculation.

quality parameters than the spectral bands used (11). The development of regression model aiming to create a predictive model that accurately represents the relationship between water quality and spectral data. Stepwise regression modelling was found to be better regression technique than other models like logistic regression, ridge regression etc., (6). The coefficient of determination (R^2) a statistical measure explains the variation of data observed. The data of non-optical parameters obtained from laboratory analysis and data of optical parameters that is indices of the reflectance values extracted from Arc GIS 10.3 exported as excel data (Fig.2c).

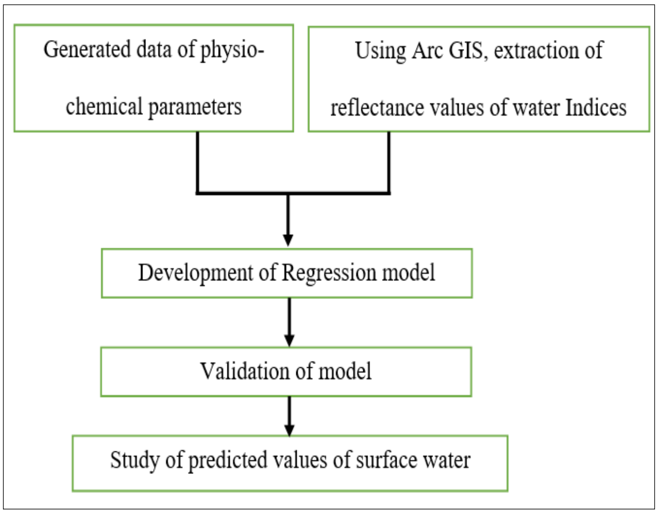

Fig. 2c. Water quality prediction model development.

Table. 3a Details of data incorporated for calculating remote sensing indices on surface water characteristics in ARCGIS

S. No	Remote sensing Indices for surface water quality	Formulae	Band Number	References
1	Normalized difference water index (NDWI)	$\mathrm{NDWI} = \frac{\mathrm{Green} - \mathrm{NIR}}{\mathrm{Green} + \mathrm{NIR}}$	Green (B3) and NIR (B8a)	(31)
2	Modified Normalized difference water index (MNDWI)	$MNDWI = \frac{\mathrm{Green} - \mathrm{MIR}}{\mathrm{Green} + \mathrm{MIR}}$	Green (B3) and MIR (B11)	(32)
3	Water ratio index (WRI)	$\mathrm{WRI} = \frac{\mathrm{Green} + \mathrm{Red}}{\mathrm{NIR} + \mathrm{MIR}}$	Green (B3), NIR (B8a), MIR (B11), Red (B4)	(33)
4	Normalized difference Vegetation index (NDVI)	$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}}$	NIR (B8a), Red (B4)	(34)
5	Normalized difference Chlorophyll index (NDCI)	$\mathrm{NDCI} = \frac{\mathrm{Rededge} - \mathrm{Red}}{\mathrm{Rededge} + \mathrm{Red}}$	Red edge (B5), Red (B4)	(35)

Results and Discussion

In this part Intra-spatial variation of tanks were represented with three different colours where green represents Low value, yellow represents middle value and red represents high value. The parameters considered for spatial variation on tank water quality assessment are pH, EC, TDS, DO, BOD and COD are discussed below.

pH

Of the most substantial indicators of ecological health and water quality in urban tanks is the pH level. As the result observed among all the four tanks the value of pH rises from February to June because of variations in water chemistry, temperature and biological activity. Higher temperatures cause carbon dioxide to be absorbed by photosynthesis, which lowers the acidity of water and raises pH. Among the tanks studied, in general Krishnampathy was noted for having a record of minimum pH value of 7.8 and a peak pH of 9.8, followed while the other three tanks maintained the pH range between (pH 8 to 9.7). This significant fluctuation highlighted the dynamic nature of the water chemistry in this tank. This pH level may be due to presence of calcium and magnesium carbonates (12, 13). The cascading nature of these tanks was also recognized as playing a critical role in the observed pH variations. This cascading effect meant that the resultant pH tended to increase as the water moved downstream, reflecting the cumulative effects of each tank's individual chemistry. The spatial variation of pH across all four tanks was found to be relatively consistent, indicating that they shared similar environmental conditions, the temporal variations changes over time showed significant differences. This discrepancy suggested that factors such as local weather patterns, seasonal changes and biological processes could impact each tank differently. Overall, an increasing trend in pH values was observed in all four tanks over the months from February to June. Selvampathy has increased the average pH value to 9.1 compared to the previously reported value of 8.6 by Dinesh Kumar et al. (14) throughout the period, followed by Krishnampathy with a pH of 8.7, Ukkadam Periyakulam also increased to 8.5 from 7.9 as previously reported by Krishnakumar et al. (15) and Kumaraswamy, with an average pH value of 8.8, was noted for its relative stability while following a similar upward trend as the other lakes (Fig.3).

EC

Electrical Conductivity (EC) is among the important parameters studied to assess the quality of water in aquatic environments. It measures the water's ability to conduct electrical current, which is directly related to the concentration of dissolved salts and ions. In urban tanks, EC provides insights into total dissolved solids (TDS), essential nutrients, pollutants and other ionic compounds. The maximum EC level in the Selvampathy tank increased to 1998 µS/cm in June, up from the 1938 µS/cm reported by Dinesh Kumar et al. (14). In contrast, other tanks, namely Krishnampathy, Kumaraswamy and Ukkadam Periyakulam have maintained the EC within the range of 1904 to 1978 µS/cm, 1483 to 1507 µS/cm compared to 689 µS/cm as reported by Bala Mohan et al. (16) and 1561 to 1631 µS/cm compared to 1456 µS/cm as reported by Jeyaraj et al. (17) respectively. The observed data emphasized how interconnected processes affected the water quality,

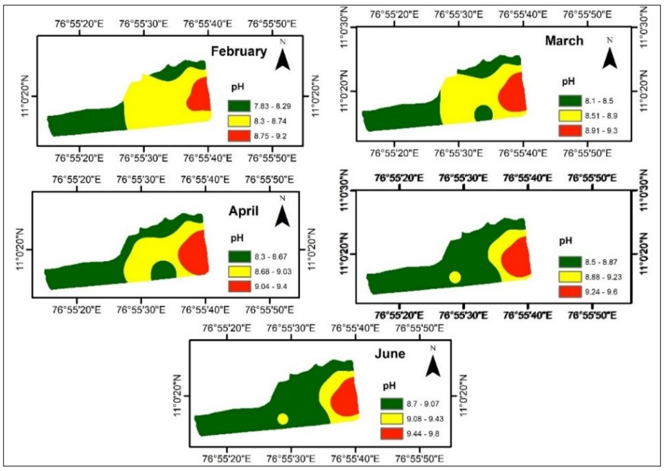

Fig. 3a. Krishnampathy Tank

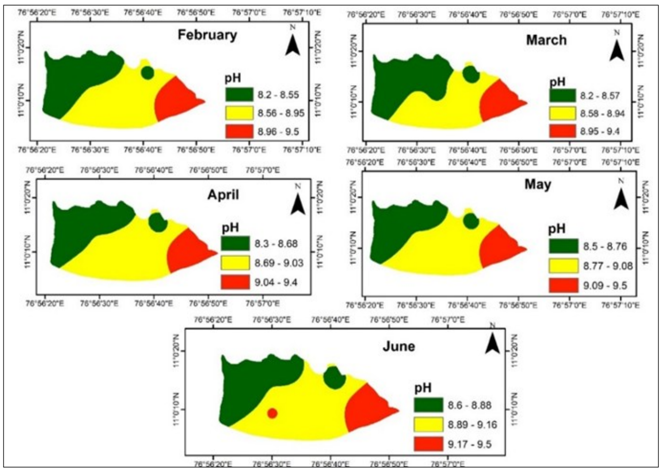

Fig. 3b. Kumaraswamy Tank

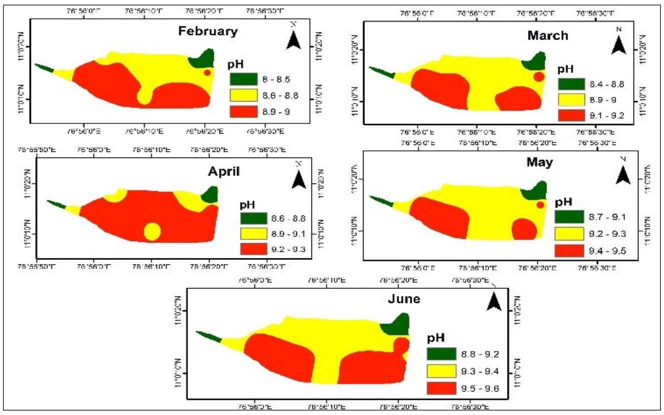

Fig. 3c. Selvampathy Tank

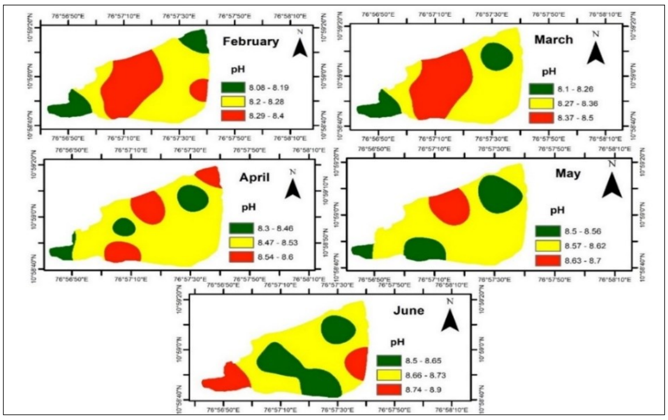

Fig. 3d. Ukkadam Tank

Fig. 3. Spatial and temporal variation on pH of selected tanks.

demonstrating the complex interactions between environmental factors and the health of urban aquatic environments. Seasonal variations in EC are influenced by factors like precipitation, temperature and anthropogenic activities (18). From February to June, urban tanks experience changes due to interconnected processes, such as rising temperatures, evaporation rates, spring rains, pollutants and increased biological activity (Fig. 4). Through systematic monitoring and analysis, it was revealed that fluctuations in EC levels could indicate broader trends in water quality and ecosystem health. The importance of understanding these trends was underscored, as they provided critical information necessary for managing and protecting urban water bodies. Ultimately, the role of EC as an indicator of water quality was solidified, reinforcing its significance in the ongoing assessment and management of aquatic environments.

TDS

Total dissolved solids (TDS) are an essential parameter to assess water quality by encompassing the organic and inorganic materials. It is impacted by both human activity and natural processes; it is an essential metric for evaluating the sustainability of urban tanks. Increasing temperatures have the potential to raise TDS levels by increasing evaporation rates, which concentrate dissolved solids (3). Since Electrical conductivity (EC) was directly proportional to TDS, the spatial variation in TDS levels across the tanks was found to be consistent with the variations observed in EC. The TDS levels in the Krishnampathy, Selvampathy, Kumaraswamy and Ukkadam Periyakulam tanks have exceeded the acceptable limit of 500 mg/L but remain within the permissible limit of 2000 mg/L. For Krishnampathy tank, the EC range was 1904-1978 µS/cm and the corresponding TDS range was 1200-1250 mg/L, indicating a proportional relationship. This similarity in trends can be attributed to the direct proportionality between EC and TDS, as EC reflects the ionic content of the water, which correlates with dissolved solids. Among the tanks studied, Kumaraswamy tank had the lowest average TDS value of 957 mg/L corresponding to EC values (1483-1507 µS/cm) across its area, where Selvampathy tank increased to 1230 mg/L, corresponding to an EC value of 1998 µS/cm, compared to the previously reported 1062 mg/L by Dinesh Kumar et al.(14) and Ukkadam Periyakulam tank has increased to 1024 mg/L, corresponding to an EC value of 1561 to 1631 µS/cm compared to the previously reported 1213 mg/L by Krishnakumar et al. This reduction indicates a consistent and progressive change in TDS values observed between the inlet and outlet points of the tank (15). This implies that the TDS levels do not change abruptly but instead increase or decrease steadily along the flow of water through the tanks. This type of variation could result from factors like sedimentation, dilution, evaporation, or the mixing of water with varying levels of dissolved solids as it moves through the tank. Pollutants from urban areas may be introduced by runoff, which can potentially contribute to increase in TDS load (19). TDS concentrations may be momentarily diluted by rainfall, but the general trend may represent the combined effects of inputs from the natural world and humans (20) (Fig.5). Therefore, the analysis of TDS levels was critical not only for assessing current water quality but also for understanding the impact of environmental and anthropogenic

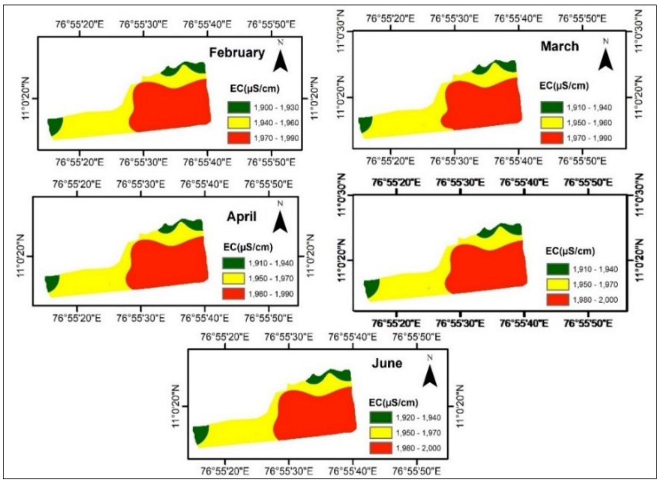

Fig. 4a. Krishnampathy Tank

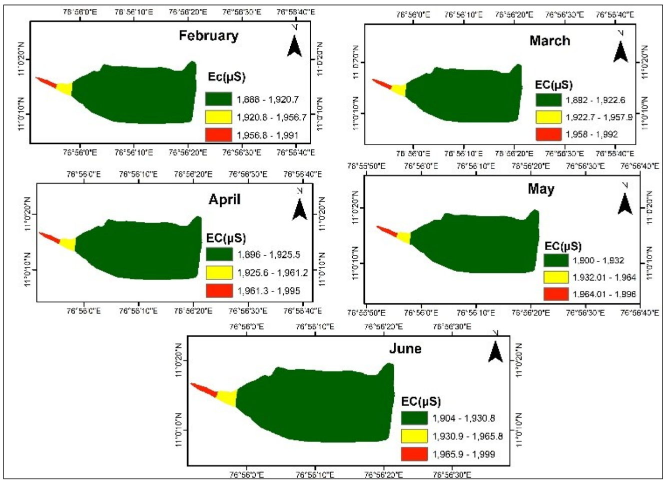

Fig. 4b. Selvampathy Tank

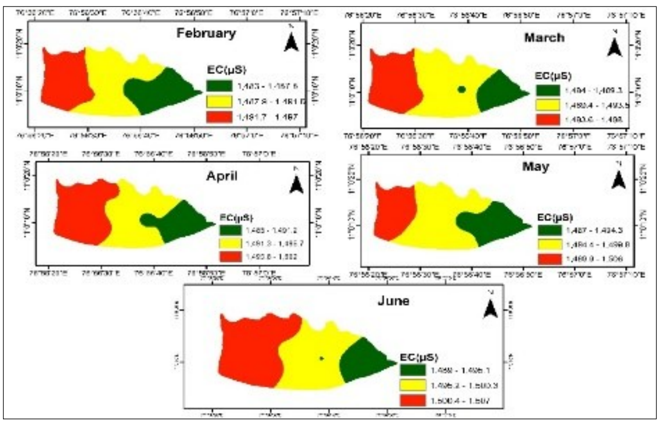

Fig. 4c. Kumaraswamy Tank

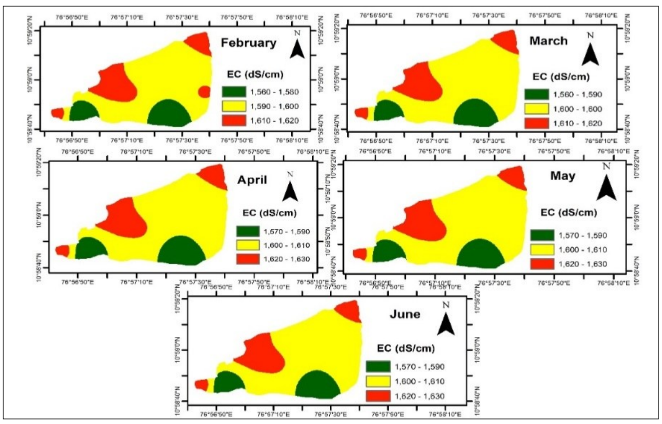

Fig. 4d. Ukkadam Tank

Fig. 4. Spatial and temporal variation on EC of selected tanks.

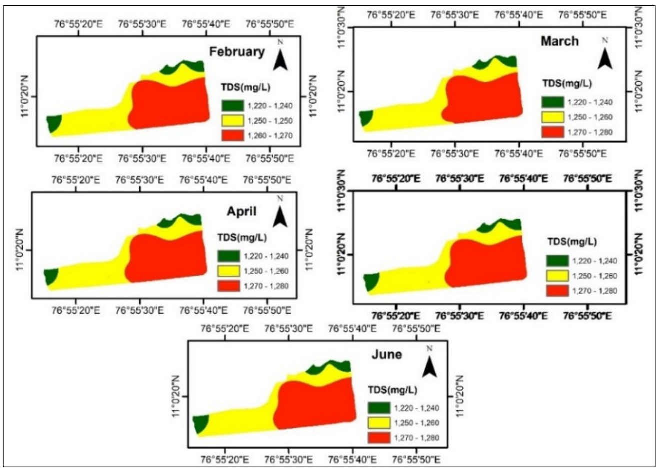

Fig. 5a. Krishnampathy Tank

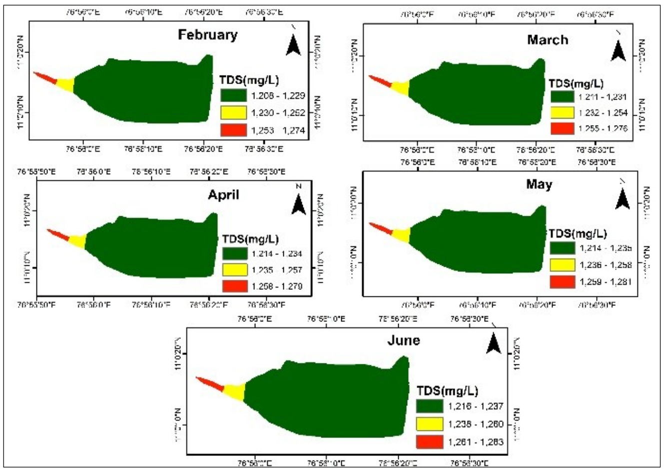

Fig. 5b. Selvampathy Tank

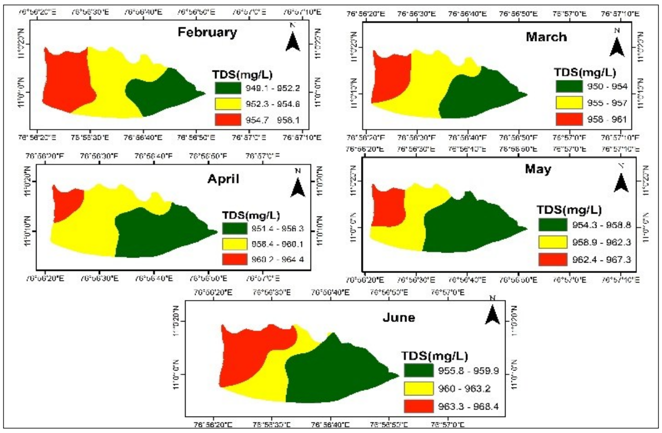

Fig. 5c. Kumaraswamy Tank

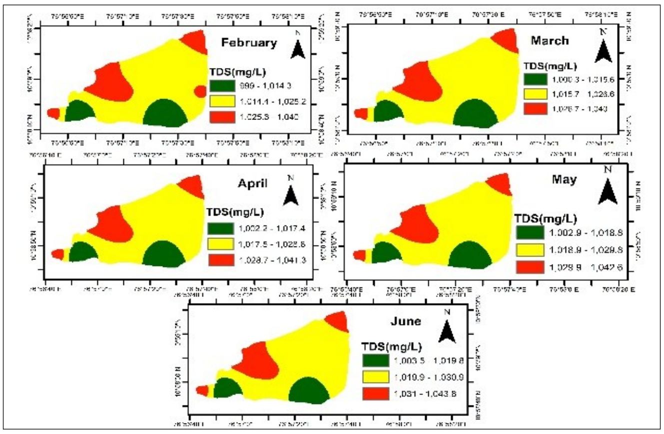

Fig. 5d. Ukkadam Tank

Fig. 5. Spatial and temporal variation on TDS of selected tanks.

factors on urban tank ecosystems (21). By monitoring TDS alongside other parameters, a more comprehensive understanding of water quality dynamics in urban settings was achieved, facilitating better management and conservation strategies.

DO

In general, Dissolved Oxygen (DO) refers to the oxygen present in water in its molecular form, available for absorption by aquatic organisms to support their respiration and metabolic processes. Temperature, salinity, air pressure and organic matter are some of the variables that affect DO levels (22). In the Kumaraswamy tank, the dissolved oxygen (DO) levels were observed to rise to 6.9 mg/L in June. This increase in DO can be attributed to favourable conditions such as improved water circulation, lower organic load and possibly higher photosynthetic activity by aquatic plants during this period. On the other hand, lower DO levels 3.3 mg/l in average, were recorded in the Krishnampathy tank. This reduction in DO can be attributed to the tank's three inlets which includes one main inlet with a DO level of 3.3 mg/L and two sewage inlets with DO levels of 2.6 mg/L and 2.7 mg/L, which carry domestic sewage from the P.N. Pudur and Vadavalli areas. The inflow of untreated or partially treated sewage introduces high amounts of organic matter and nutrients, which can lead to increased microbial activity and subsequent oxygen consumption. The presence of domestic sewage further contributes to nutrient enrichment (eutrophication), which exacerbates oxygen depletion, negatively impacting aquatic life. Photosynthetic activity in the spring can raise DO levels, but heavy organic pollutants or darkness can lower oxygen levels and cause hypoxic conditions (23) (Fig. 6). In the Selvampathy tank, lower DO levels, ranging from 3.5 to 3.7 mg/l, were recorded from February to April. A slight increase in DO levels was noted during May and June, with values ranging from 3.9 to 4.3 mg/l, which was attributed to the connection of a sewage stream with the outlet of the upstream Krishnampathy tank. The Ukkadam tank exhibited a notable range of dissolved oxygen (DO) levels, varying from 3.8 to 6.8 mg/L between February and June, with an average DO level of 4.9 mg/L, showing a moderate increase from the 4.49 mg/L reported by Rahul et al. (6). It was indicated that DO levels naturally fluctuated due to processes such as photosynthesis by aquatic plants, mixing of water caused by wind and waves and the respiration of aquatic organisms. However, in urban tanks, nutrient pollution resulting from fertilizers, sewage and runoff led to excessive algal growth, which resulted in eutrophication. While oxygen was produced by algae during the day, their respiration at night, along with the decomposition of dead algae, significantly reduced oxygen levels, causing further fluctuations in DO. This situation could lead to oxygen depletion, negatively affecting fish and other aquatic organisms.

BOD

The term "BOD" (Biological Oxygen Demand) was defined as the amount of dissolved oxygen consumed by microbes in water during the breakdown of organic matter. The BOD level in water bodies was influenced by the introduction of organic content through various sources, such as untreated waste discharges,

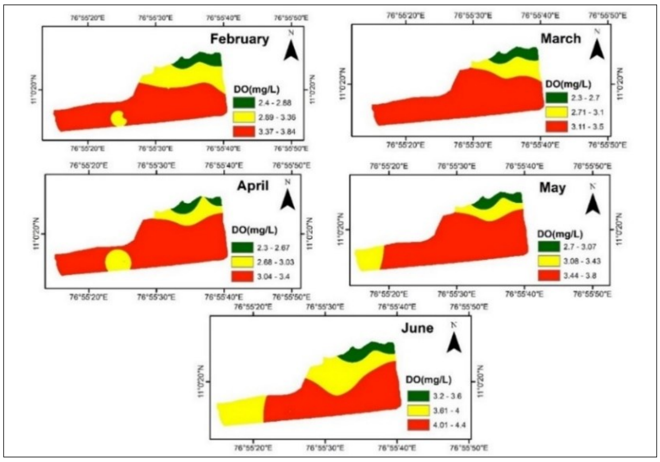

Fig. 5a. Krishnampathy Tank

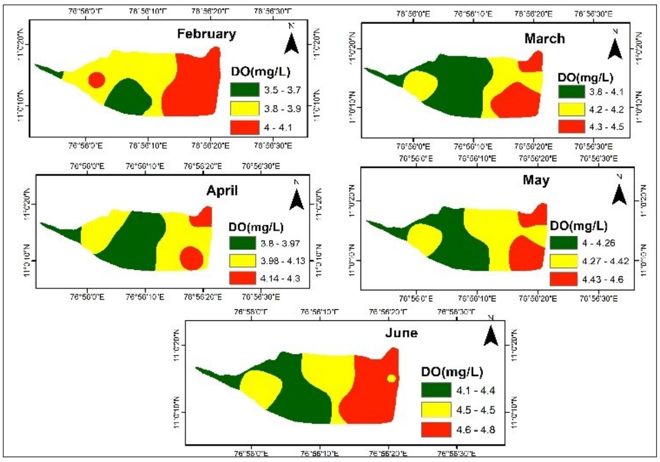

Fig. 5b. Selvampathy Tank

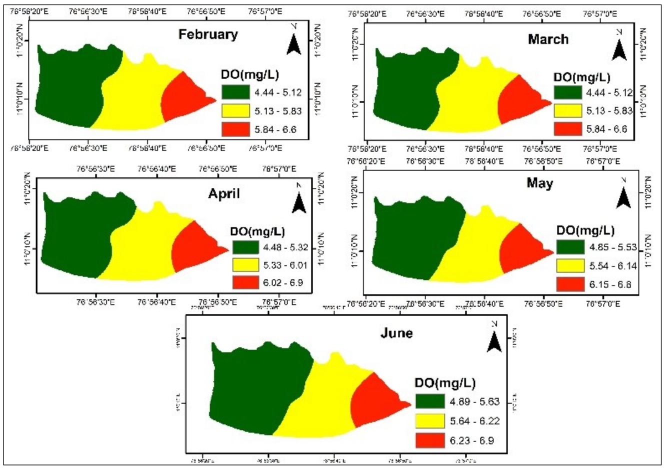

Fig. 6c. Kumaraswamy Tank

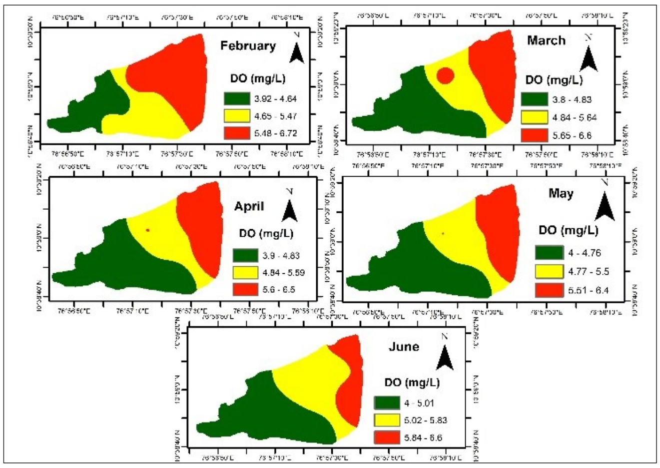

Fig. 6d. Ukkadam Tank

Fig. 6. Spatial and temporal variation on DO of selected tanks.

which resulted in increased BOD levels. As the amount of organic matter rose, more oxygen was required by bacteria to decompose the material, leading to a reduction in the oxygen levels present in the water (24). Significant variations in BOD levels were observed across different tanks. Elevated BOD levels were recorded in the Selvampathy tank, reaching 43.1 mg/L, a reduction from the 60 mg/L reported by Dinesh Kumar et al. (14), indicating a substantial organic load and the potential presence of increased pollutant concentrations. Following Selvampathy, progressively lower BOD levels were noted in Krishnampathy, Ukkadam Periyakulam and Kumaraswamy tanks (18.6 mg/l). The Krishnampathy tank, located just outside the city limits, BOD levels are relatively low (19.7 mg/L), possibly due to lower urban pollution compared to tanks situated within the city. Seasons can cause variations in BOD levels because of temperature, precipitation patterns and human activity (25). Increased BOD can cause ecological instability, fish deaths, hypoxia and biodiversity loss. Finding the origins of pollution and creating efficient control plans depend on BOD monitoring (Fig.7). Although the Ukkadam tank was located within the city of Coimbatore, its BOD levels were lower (20-28 mg/l, with an average of 28 mg/l) compared to the other tanks. This lower BOD level was attributed to the influence of the Noyyal River, which flowed into the tank during the monsoon season, diluting the concentration of pollutants and helping to reduce the overall organic load. Thus, seasonal water flow was seen to play a mitigating role in the pollution levels of urban tanks, as evidenced by Ukkadam's comparatively lower BOD values.

COD

When evaluating the amount of organic and inorganic contaminants in aquatic ecosystems, particularly in urban tanks, Chemical Oxygen Demand (COD) is a critical water quality metric. It quantifies the total quantity of oxygen needed in water to chemically oxidize organic substances that are biodegradable and those that are not. For instance, the highest COD level (147.8 mg/l) was recorded in SelvampathyTank tank at the inlet point during June, indicating a substantial load of contaminants entering the water. In contrast, a lower COD value (83.16 mg/l) was exhibited by Krishnampathy tank at the outlet point in April, suggesting comparatively better water quality or a lesser pollutant load. The COD level in Ukkadam Periyakulam tank increased to 99.6 mg/L, up from 94.5 mg/L as reported in previous studies by Rahul et al. (6). The COD levels in Kumaraswamy (96.3 mg/l) were also found to be elevated, though they remained below those observed in SelvampathyTank (104.5 mg/l), reflecting moderate levels of pollution across these urban water bodies. The fluctuations in COD levels across the tanks were largely influenced by various factors, including stormwater runoff, industrial discharges and household wastewater inputs, which contributed to the overall contaminant load in the water (26). Temperature, precipitation and human activity can all affect COD levels during seasonal variations, especially from February to June. Increased concentrations of contaminants that can cause oxygen depletion and negatively impact aquatic life are indicated by high COD levels, which are frequently linked to worse water quality (27, 28) (Fig.8). Seasonal changes were found to play a significant role in altering COD levels,

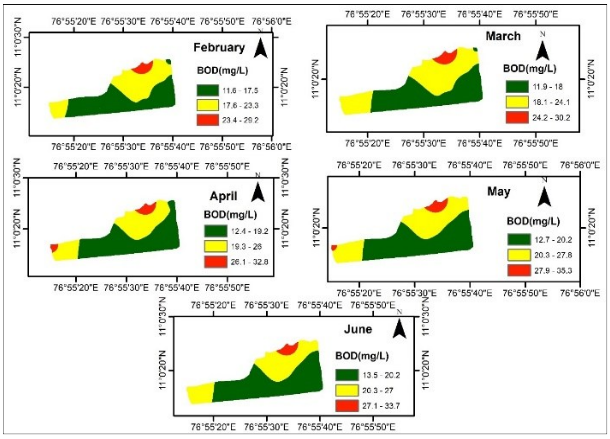

Fig.7a. Krishnampathy Tank

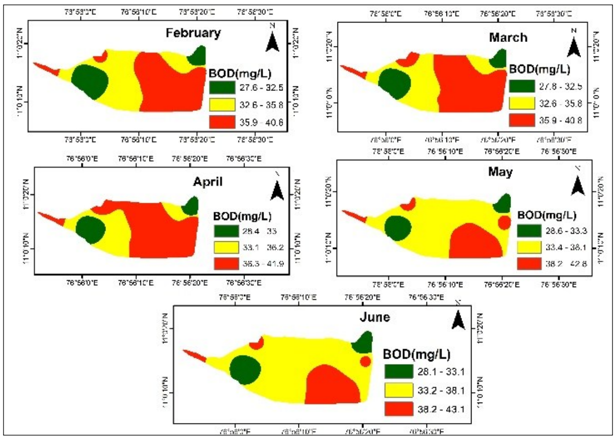

Fig. 7b. Selvampathy Tank

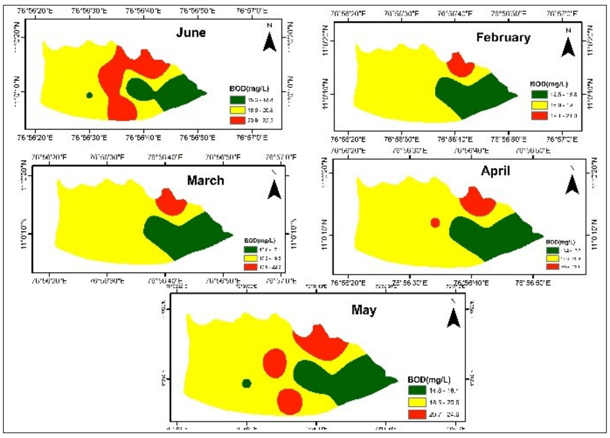

Fig. 7c. Kumaraswamy Tank

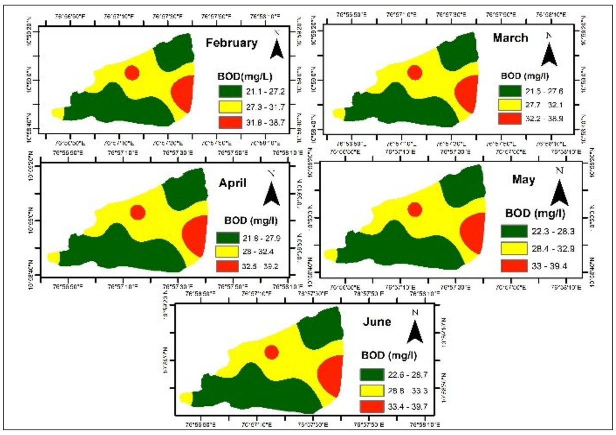

Fig. 7d. Ukkadam Tank

Fig. 7. Spatial and temporal variation on BOD of selected tanks.

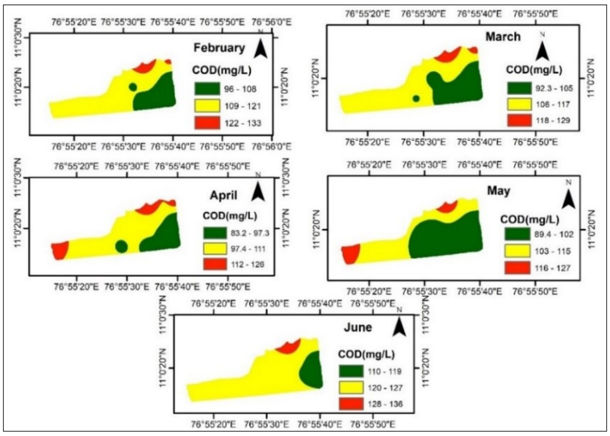

Fig. 8a. Krishnampathy Tank

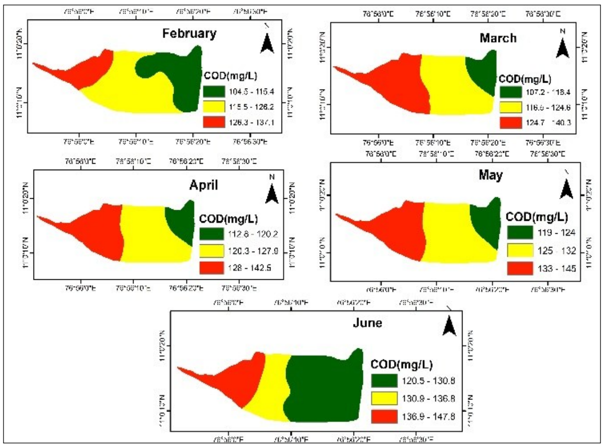

Fig. 8b. Selvampathy Tank

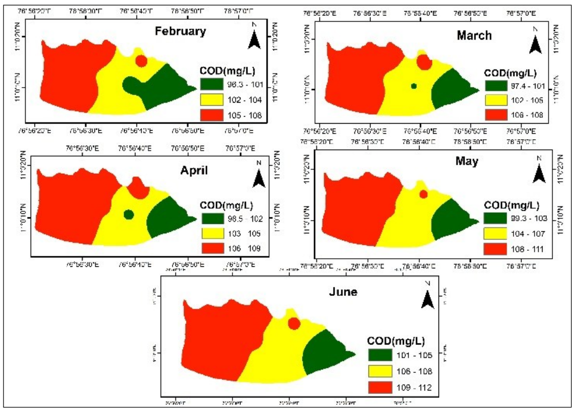

Fig. 8c. Kumaraswamy Tank

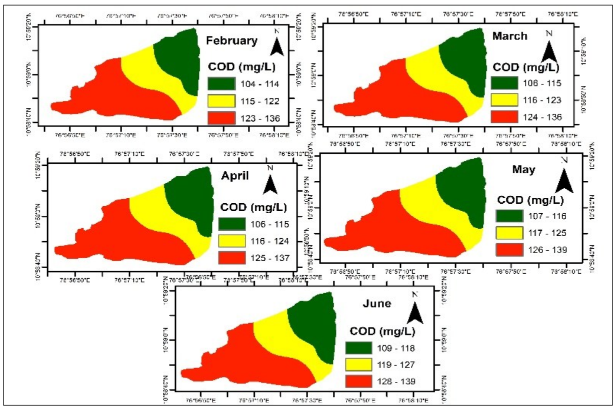

Fig. 8d. Ukkadam Tank

Fig. 8. Spatial and temporal variation on COD of selected tanks.

especially during the period from February to June. High COD levels were often associated with increased concentrations of pollutants, leading to oxygen depletion and negatively impacting aquatic life. These elevated COD levels, commonly linked with poorer water quality, underscored the need for continuous monitoring and effective management of urban tanks to mitigate the effects of pollution

Statistical Analysis

Relationship between optical and non-optical parameters is studied using Pearson correlation and scatter plot. To understand the contribution of variables PCA perform and used for variables selection. Selected variables were further used in regression modelling to predict non-optical parameters.

Box Plot

In Order to improve the surface water quality of urban areas the important variables such as TDS, BOD, Hardness, Dissolved oxygen and chlorides are selected for investigating the urban tank water through Box plots (also known as whisker plots). The box plot contains three quartiles first quartile (Q1), second quartile (Q2), third Quartile (Q3). The horizontal line where the data is skewed denotes as median (Q2). If the data shows symmetric the quartiles Q1 and Q3 are equally divided. If Q3- Q2 > Q2-Q1 it shows positive skewness and Q3- Q2 < Q2-Q1 it shows the negative skewness of the dataset (29). The spatio-temporal box plots were used to showcase the selected parameters. The box plot indicates that the parameters of EC, TDS, Ca, Mg and total hardness (TH) levels exhibited higher values in Krishnampathy across all clusters. This increase was observed with the rise in temperature and the discharge of domestic sewage, in comparison to other tanks. (Fig.9). The total dissolved solids (TDS) levels are relatively higher in Selvampathy and Krishnampathy, with some variation observed in the Krishnampathy tank. Kumaraswamy has the lowest and most consistent TDS values, indicating better water quality with fewer dissolved salts or pollutants. The Krishnampathy tank shows the lowest DO values, which is expected given the influence of sewage and other organic waste inflows. Kumaraswamy tank, in contrast, exhibits the highest and more consistent DO values, suggesting better water quality and oxygen availability for aquatic life. pH values show a stable trend across the tanks, with only minor fluctuations. Selvampathy tank maintains the highest pH values, indicating more alkaline water compared to the others. The BOD values are relatively consistent within each tank, with higher values in Krishnampathy and Ukkadam Periyakulam, suggesting higher organic pollution. Kumaraswamy shows lower BOD levels, which is indicative of better water quality with less organic material requiring oxygen for decomposition.

Correlation

The positive correlation observed between non-optical physico-chemical parameters (such as TDS, BOD, total hardness and chlorides) and optical parameters (such as NDVI, DO, NDWI, MNDWI and WRI) suggests an indirect relationship, as there is no direct correlation between optical and non-optical parameters. As there is no direct relationship between optical and non-optical parameters, the indirect relationship is estimated by developing regression models. The non-optical parameters pH, bicarbonate, BOD and the optical parameters shows correlation. Hence, not consider in further analysis. The correlation reveals that the pairwise relationship with optical parameters are statistically significant. The krishnampathy tank shows negative correlation with EC and TDS. The correlation matrix shown as heat map shows the relationships between various variables, where each cell in the matrix represents the correlation coefficient between two variables. The pH Shows weak to no correlation with most of the other parameters namely EC, TDS and CA with the maximum correlation (0.2). Variables such as EC, TDS, CA and MG are highly correlated, indicating that they are likely influence or depend on each other in the water body being studied. The indices like NDWI, NDCI and NDVI have strong negative correlations with each other, suggesting different environmental conditions or processes they might be capturing. Variables like pH have weak correlations with other parameters, suggesting that pH might be relatively independent or influenced by other factors not included in this matrix (Fig.10).

Heat map of the correlation between the optical and non-optical parameters

Comprehensive scatterplot matrix that displays pairwise relationships between various variables. Along with the scatterplots, the matrix includes correlation coefficients, significance values and density plots for each variable. The scatterplot matrix contains comparisons between various water quality parameters and environmental indices, with data points color-coded, likely representing different tanks. The points in the scatterplots are likely color-coded based on the specific tanks from which the data was collected (e.g., Ukkadam, Krishnampathy, Kumarasamy). This differentiation allows to

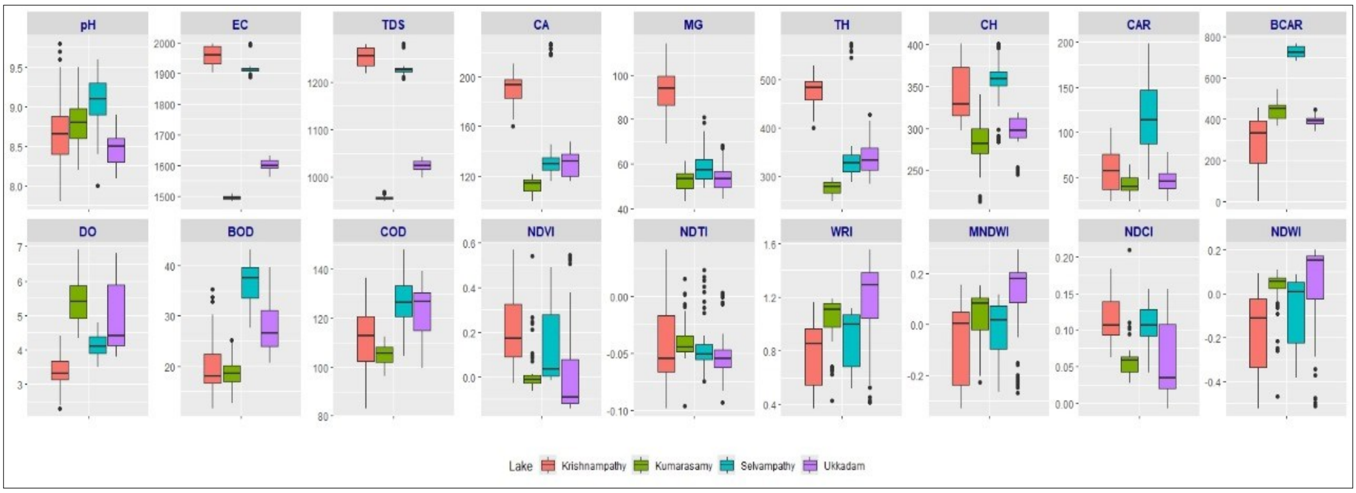

Fig. 9. Box plot represents tank wise variation of the optical and non-optical parameters.

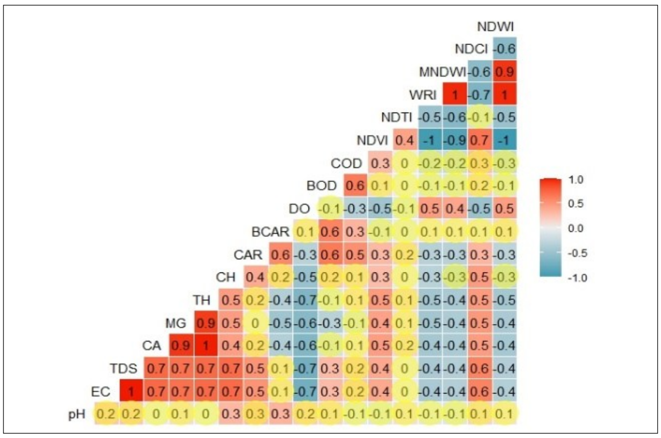

Fig. 10. Heat map of the correlation between the optical and non-optical parameter.

compare how the relationships between variables vary across different tanks. Most of the scatterplot cells for Krishnampathy Lake show high correlation coefficients, which suggests that this lake has the strongest relationships between the parameters. The correlation values follow the order: Krishnampathy > Kumaraswamy > Selvampathy > Ukkadam. The differences in correlation patterns across tanks suggest that each lake might require different management strategies. For instance, if one tank shows a strong correlation between DO and COD, efforts to improve water quality could focus on reducing organic pollutants. For lakes with weaker correlations or distinct patterns, it may be necessary to investigate specific local factors (e.g., pollution sources, inflows, vegetation) that could be influencing the water quality dynamics. The data allows for a comparative analysis of water quality parameters across lakes, helping to identify which lakes are more vulnerable which is krishnampathy tank leads to certain types of pollution or environmental changes (Fig.11).

PCA

PCA is considered as a multivariate statistical method, which provides the interrelationship between the optical and non-optical parameters. PC1 performs 54.5% of the total variance with eigen value 7.632, which comprises the EC (0.836), TDS (0.836), Ca (0.810), Mg (0.770), Total Hardness (0.817) and NDVI (0.792) as shown in (Table 4.1) are majorly influenced by anthropogenic activities, NDVI is influenced by growth of aquatic weeds through the input of organic loads and seasonal influences like erosion where the surface material contacted in the streams of the tank catchments. PC2 performs 17.06% gives the total variance with eigen value 2.389 which involves the DO (-0.228), NDWI (0.594), MNDWI (0.589) and WRI (0.563) shows that dissolved oxygen is more where the depth of water availability is more and vice versa. The cumulative variance of PC1, PC2 and PC3 accounts for 83.19%, as represented in the scree plot. Principal Component Analysis (PCA) was performed on 14 parameters, revealing the divergence and dissimilarities among the lakes (Fig.12 and 13). The cluster analysis reveals that the Krishnampathy tank forms a cluster influenced by parameters such as chloride, magnesium (Mg), total hardness (TH), electrical conductivity (EC) and total dissolved solids (TDS). The Ukkadam lake is predominantly characterized by optical parameters, including the Water Reflectance Index (WRI) and the Normalized Difference Water Index (NDWI). The Kumaraswamy tank is distinguished by its association with dissolved oxygen (DO), while another cluster, influenced by parameters such as carbonate, chemical oxygen demand (COD), the Normalized Difference Chlorophyll Index (NDCI) and the Normalized Difference Vegetation Index (NDVI), includes data points from both the Ukkadam and Krishnampathy tanks (Fig.14).

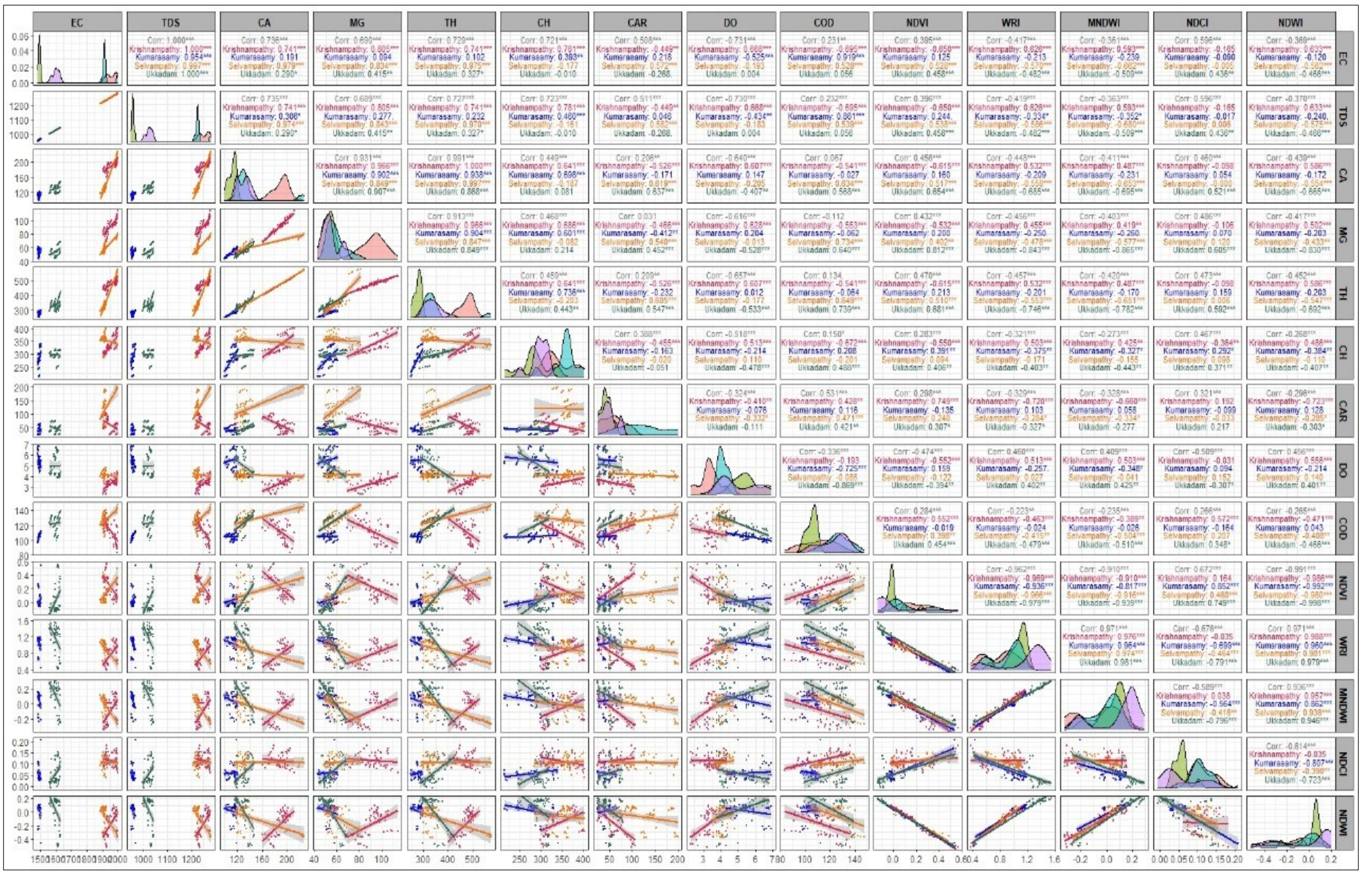

Fig. 11. Scatter plot matrix shows the pairwise relationship among optical and non-optical parameters with respect to selected tanks.

Table. 4.1 PCA values obtained for different water quality parameters and indices

Parameters	PC1	PC2	PC3	PC4	PC5	PC6	PC7
EC	**0.836**	0.428	0.207	0.132	-0.028	-0.036	0.12
TDS	**0.836**	0.426	0.21	0.134	-0.03	-0.035	0.118
CA	**0.81**	0.389	-0.296	-0.255	-0.142	-0.067	-0.087
MG	0.77	0.391	-0.452	-0.083	-0.025	-0.041	-0.055
TH	**0.817**	0.368	-0.262	-0.292	-0.096	-0.055	-0.13
CH	0.63	0.339	0.261	0.481	0.071	0.249	-0.337
CAR	0.466	-0.058	**0.726**	0.002	-0.445	-0.1	0.105
DO	-0.**773**	-0.228	-0.114	0.171	-0.302	-0.309	-0.313
COD	0.31	-0.216	**0.706**	-0.498	0.223	-0.008	-0.227
NDVI	**0.792**	-0.57	-0.124	-0.004	0.019	0.03	-0.007
WRI	**-0.802**	0.563	0.132	-0.086	0.052	-0.037	-0.014
MNDWI	-0.75	0.589	0.123	-0.044	0.119	-0.083	0.008
NDCI	0.76	-0.161	0.063	0.23	0.348	-0.452	0.022
NDWI	-0.774	0.594	0.139	0.006	0.036	-0.093	0.006
Eigenvalue	7.632	2.389	1.626	0.763	0.516	0.401	0.33
Variance percentage	54.515	17.061	11.614	5.453	3.686	2.865	2.361
cumulative variance	54.515	71.576	83.189	88.643	92.329	95.194	97.554

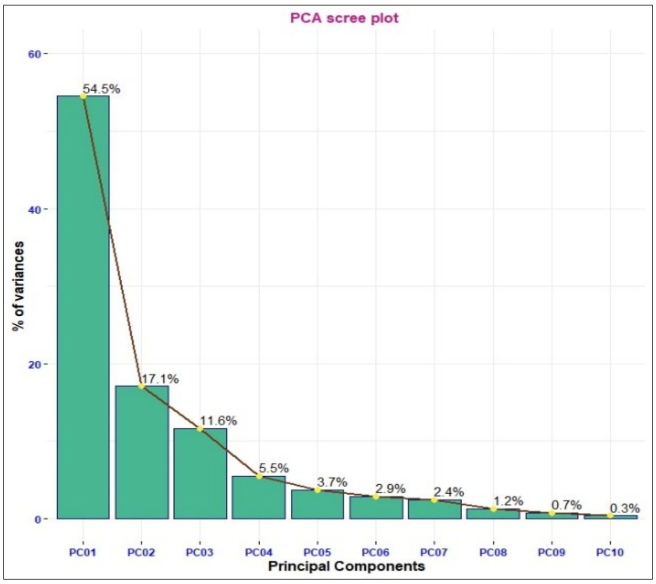

Fig. 12. Scree plot of the optical and non-optical parameters of all the four tanks studied.

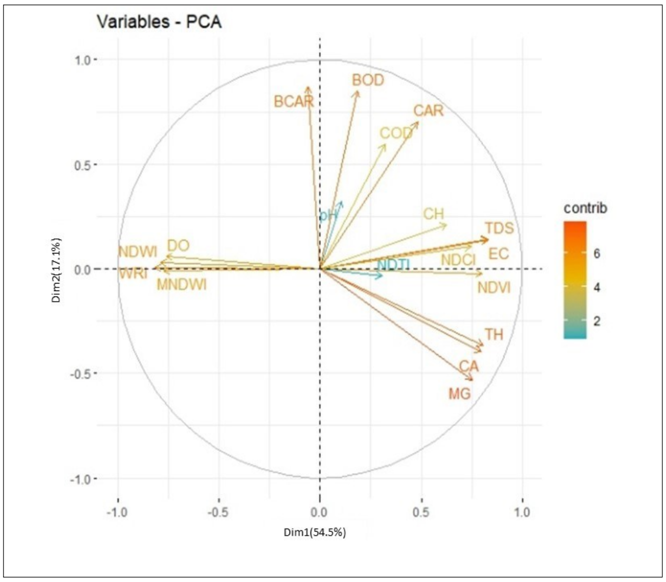

Fig. 13. PCA variables of the optical and non-optical parameters of all the four tanks studied.

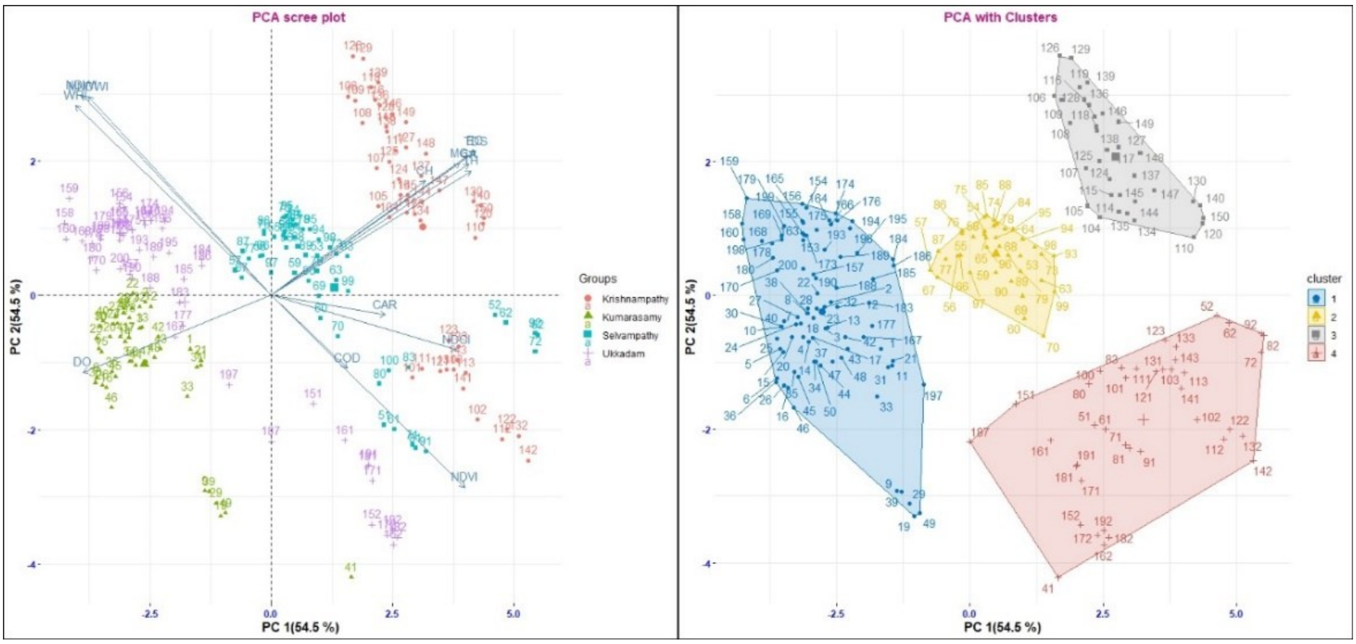

Fig. 14. PCA with cluster for the optical and non-optical parameters of all the four tank studied.

Regression

The coefficient of determination (R^2) a statistical measure explains the variation of data observed. The data of non-optical parameters obtained from laboratory analysis and data of optical parameters that is Indices of the reflectance values extracted from Arc GIS 10.3 exported as excel data. Among the regression models like linear regression, Lasso regression, logistic regression the stepwise regression is to be preferred. Prediction models were developed by incorporating the water indices and water quality parameters. However, there is no direct relationship between optical and non-optical parameters where the $R^2 > 0.3$ and significance value (p) around 2.2×10^{-16}. The illustration on effect of water indices on the prediction model as shown in (Table 4.2). Based on the R^2 values, the models most affected are carbonate (0.1378) and COD (0.1963). The water quality parameters (EC, TDS, Ca^{2+}, TH, Cl^-, CO^{3-}, DO and COD) appeared with all the water indices with respect to water quality parameters. Considering the data of in-situ field measurement and laboratorial analysis to very time-consuming process. Regression models developed using water quality parameters and water indices which play a crucial role in monitoring the tanks and facilitating effective planning. To reduce the time and cost of estimating the levels of parameter, the regression model helps to retrieve the physio chemical parameters of the surface water.

Conclusion

Urban tanks in Coimbatore are experiencing daily water quality issues due to the mixing of domestic sewage discharges and industrial effluents. The most affected tank, Krishnampathy, has higher organic pollutant load, leading to increased BOD and COD. The other tanks, SelvampathyTank, Kumaraswamy and Ukkadam Periyakulam, shows reduced pollution load. A predictive model was developed to integrate surface water quality parameters with remote sensing indices, demonstrating the potential of combining in-situ measurements with satellite data for enhanced water quality monitoring. The model improved accuracy and spatial coverage of water quality predictions, providing comprehensive insights into water quality variations. Future research could refine the model to include additional parameters like nutrient levels or contaminants, expanding its applicability and exploring real-time monitoring possibilities.

Acknowledgements

The authors sincerely thank the Department of Soil and Water Conservation Engineering for awarding the scholarship that was vital for the successful completion of their research. They are deeply grateful to Tamil Nadu Agricultural University for providing access to laboratory facilities for water quality analysis. Special appreciation is extended to Dr. Balaji Kannan, Chairperson and the advisory committee for their unwavering guidance and valuable support throughout the research process and in the preparation of this article. The authors also express their heartfelt gratitude to Tamil Nadu Agricultural University for funding this study under the Venture Capital Scheme.

Authors' contributions

BK provided comprehensive guidance throughout the research, with a particular focus on data visualization and overall strategic direction. KS contributed significantly by guiding the processes of sample collection and analysis, ensuring accuracy and reliability in the experimental methodology. KA provided the valuable suggestions which were crucial to the progression and completion of the research. SP conceived in performing statistical analyses, aiding in the interpretation of data and enhancing the rigor of the research findings. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None

Table. 4.2 Prediction models of water quality parameters for the selected tanks

S. No	Parameters	Model	R^2	F-value	P-value
1.	EC	1897.7 - 870.4(NDVI) - 360.1(WRI) + 405 (MNDWI) + 2822.2(NDCI) -580.8 (NDWI)	0.3643	22.24	2.2×10^{-16}
		1509.55 + 2742.90(NDCI)	0.3547	108.8	2.2×10^{-16}
2.	TDS	1218.7 -556.5(NDVI)-233.8(WRI)+257.2(MNDWI)+1803.9(NDCI)-366(NDWI)	0.3653	22.33	2.2×10^{-16}
		966.37+1758.34 (NDCI)	0.3554	109.2	2.2×10^{-16}
3.	Ca^{2+}	117.342+17.942(NDVI)+2.292(WRI)+1.438(MNDWI)+228.131(NDCI)-32.386 (NDWI)	0.251	13	6.468×10^{-11}
		120.210+233.618(NDCI)-43.867(NDWI)	0.2508	32.97	4.47×10^{-13}
4.	TH	238.36+58.62(NDVI)+58.16(WRI)-32.01(MNDWI)+629.25(NDCI)-116.89 (NDWI)	0.267	14.43	8.66×10^{-12}
		301.56+607.07(NDCI)-113.73(NDWI)	0.2658	35.66	6.055×10^{-14}
5.	Cl^-	422.73-320.96(NDVI)-132.95(WRI)+146.62(MNDWI)+492.99(NDCI)-203.63 (NDWI)	0.249	12.9	7.696×10^{-11}
		354.22-111.35(NDVI)-66.45(WRI)+453.43(NDCI)	0.2351	20.08	2.17×10^{-11}
6.	CO_3	64.653-57.783(NDVI)-10.581(WRI)-83.196(MNDWI)+220.311-8.427(NDWI)	0.1378	6.203	2.33×10^{-11}
		52.116-56.715(MNDWI)+185.458(NDCI)	0.1326	15.06	8.22×10^{-07}
7.	DO	5.2818+3.1281(NDVI)+0.1043(WRI)-1.9706(MNDWI)-10.4106(NDCI) +5.3383(NDWI)	0.299	16.55	1.338×10^{-13}
		5.3327-9.0173(NDCI)+1.2948(NDWI)	0.292	40.63	1.686×10^{-15}
8.	COD	-3.856+99.564(NDVI)+108.373(WRI)-106.067(MNDWI)+91.984(NDCI) +8.860(NDWI)	0.1963	9.478	4.20×10^{-08}
		-4.285+91.703(NDVI)+109.058(WRI)-104.724(MNDWI)+95.712(NDCI)	0.1962	11.9	1.136×10^{-08}

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