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Integrated Water Quality Index and Multivariate Statistical Assessment of Surface Water Ponds Across Heterogeneous Land-Use Systems in Trivandrum District, Kerala, India.

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Abstract

Surface water ponds embedded within heterogeneous land-use systems are highly susceptible to physicochemical alteration and microbial contamination. The present investigation evaluates the integrated water quality status of eight representative ponds located in Neyyattinkara Taluk, Thiruvananthapuram District, Kerala, India, influenced by distinct anthropogenic activities including hospital discharge, temple use, aquaculture, cattle farming, agricultural runoff, laundry effluent, oil milling, and automobile service activities. Monthly sampling from February 2022 to January 2023 assessed pH, electrical conductivity (EC), total dissolved solids (TDS), turbidity, biological oxygen demand (BOD), and total coliform. Water Quality Index (WQI) was calculated using the weighted arithmetic method, and multivariate statistical analyses including Pearson correlation, Principal Component Analysis (PCA), Hierarchical Cluster Analysis (HCA), and regression modelling were applied.

Electrical conductivity and TDS showed significant spatial variability, reflecting ionic enrichment under industrial and agricultural influence. BOD and total coliform concentrations were elevated in cattle farming, laundry, and automobile service ponds, indicating strong organic and faecal contamination. WQI classification ranged from good in temple and aquaculture ponds to very poor in automobile and laundry-impacted systems. PCA identified mineralization, organic pollution, and runoff influence as dominant factors controlling water chemistry. The study demonstrates that land-use intensity governs pond water quality deterioration and highlights urgent need for decentralized management interventions.

Key words: pH, electrical conductivity (EC), total dissolved solids (TDS), turbidity, biological oxygen demand (BOD), and total coliform, Water Quality Index (WQI), multivariate statistical analyses, Pearson correlation, Principal Component Analysis (PCA), Hierarchical Cluster Analysis (HCA), and regression modelling.

1 Introduction

Freshwater ecosystems constitute one of the most vital ecological assets on Earth, sustaining biodiversity, supporting food security, regulating microclimate, and fulfilling domestic and cultural needs. However, accelerating anthropogenic land-use transformation has profoundly

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altered the structure and function of freshwater systems worldwide (Allan 2004; Foley et al. 2005). Rapid urbanization, agricultural intensification, and expansion of peri-urban infrastructure have increased the loading of nutrients, organic matter, pathogens, and synthetic contaminants into surface water bodies, thereby modifying their hydro chemical balance and ecological integrity (Meybeck 2003; Giri & Qiu 2016). In tropical regions, where hydrological regimes are strongly governed by monsoonal rainfall patterns, land-use change exerts particularly strong influence on surface runoff dynamics, sediment transport, and pollutant mobilization (Tong & Chen 2002).

Surface water ponds represent decentralized freshwater reservoirs that play a critical socio-ecological role, especially in southern India. In Kerala, ponds are traditionally associated with temple complexes, agricultural irrigation, aquaculture, and community water use. Despite their ecological and cultural significance, ponds are increasingly exposed to diffuse and point-source contamination due to their proximity to human settlements, commercial establishments, livestock units, and small-scale industries. Nutrient enrichment from agricultural runoff promotes eutrophication, while livestock and domestic wastewater discharge elevate organic loading and microbial contamination (Singh et al. 2004; Subramani et al. 2005). Such pressures result in deterioration of physicochemical quality, oxygen depletion, and increased health risks.

Among the key hydro chemical indicators, electrical conductivity (EC) and total dissolved solids (TDS) are widely recognized as measures of mineralization and ionic enrichment in aquatic systems (Meybeck 2003). Elevated EC values often reflect anthropogenic inputs such as detergents, fertilizers, industrial effluents, and urban runoff, particularly in peri-urban landscapes. Biological Oxygen Demand (BOD) serves as an important index of biodegradable organic pollution and indicates the degree of oxygen stress imposed on aquatic ecosystems (Chapman 1996). High BOD levels are typically associated with wastewater discharge, livestock waste, and decomposing organic matter. Microbiological indicators such as total coliform bacteria are essential for assessing faecal contamination and public health risks, as they signify the potential presence of pathogenic microorganisms (WHO 2017). Turbidity, another critical parameter, influences light penetration, primary productivity, and pathogen persistence in surface waters (Wetzel 2001).

Given the multifactorial nature of water quality deterioration, comprehensive assessment requires integrative analytical frameworks. The Water Quality Index (WQI) approach has been widely applied to synthesize multiple water quality parameters into a single, interpretable value representing overall suitability for domestic or ecological use (Brown et al. 1972; Sargaonkar & Deshpande 2003). WQI simplifies complex datasets and facilitates comparison across spatial and temporal scales. However, index-based methods alone may not adequately reveal the underlying pollution sources or dominant hydro chemical processes. Therefore, multivariate statistical techniques such as Principal Component Analysis (PCA), Cluster Analysis (CA), and regression modeling have been increasingly employed to identify latent pollution factors and classify water bodies based on similarity patterns (Helena et al. 2000; Shrestha & Kazama 2007).

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In India, numerous studies have evaluated groundwater and river water quality using WQI and multivariate approaches (Singh et al. 2004; Kumar & Dua 2009; Tyagi et al. 2013). Nevertheless, pond ecosystems—particularly those influenced by heterogeneous land-use systems—remain comparatively understudied, especially in the southern state of Kerala. The hydro chemical response of ponds situated near hospitals, livestock units, aquaculture systems, laundries, oil mills, and automobile service centers may differ substantially due to variations in pollutant type and intensity. Understanding these variations is essential for designing targeted management strategies and safeguarding public health.

Therefore, the present study aims to assess the spatial and temporal variability of water quality in eight representative ponds located in Neyyattinkara Taluk, Thiruvananthapuram District, Kerala, under distinct land-use influences. By integrating Water Quality Index methodology with multivariate statistical analysis, this investigation seeks to (i) evaluate overall water quality status, (ii) identify dominant physicochemical and microbiological pollution drivers, (iii) classify ponds based on anthropogenic impact intensity, and (iv) interpret potential public health implications. The study contributes to a more comprehensive understanding of land-use–water quality interactions in tropical pond ecosystems and provides a scientific basis for decentralized water resource management.

2 Study Area Description

Neyyattinkara Taluk lies in southern Kerala under humid tropical monsoon climate. Annual rainfall exceeds 1800 mm, with distinct pre-monsoon, monsoon, and post-monsoon phases influencing surface runoff.

Eight sampling stations were selected.

S1 – Hospital area pond, S2 – Temple Pond, S3 – Fish culture pond, S4 – Cattle farming Pond, S5 – Agricultural runoff pond, S6 – Laundry discharge pond, S7 – Oil mill vicinity pond, S8 – Automobile service center pond. The stations represent increasing anthropogenic gradient from relatively protected religious water body to industrial-commercial catchment.

3 Materials and Methods

3.1 Sampling Strategy and Study Design

Surface water sampling was conducted monthly from February 2022 to January 2023 to capture seasonal variability including pre-monsoon (February–May), southwest monsoon (June–September), and post-monsoon (October–January) periods. Eight representative ponds were selected based on dominant surrounding land-use characteristics, including hospital discharge influence (S1), temple surroundings (S2), fish culture operations (S3), cattle farming activity (S4), agricultural runoff influence (S5), laundry effluent discharge (S6), oil mill vicinity (S7), and automobile service center catchment (S8).

Sampling locations within each pond were selected to represent central water mass conditions and minimize edge effects. All samples were collected in pre-cleaned high-density polyethylene bottles following standard preservation and transport protocols (APHA 2017). Samples for microbiological analysis were collected in sterilized containers and processed within 6 hours of collection.

3.2 Physicochemical Analysis

All analytical procedures followed the guidelines of the American Public Health Association (APHA 2017).

pH

pH was measured in situ using a calibrated digital pH meter. Calibration was performed daily using standard buffer solutions (pH 4.0, 7.0, and 9.2). pH provides an indication of hydrogen ion activity and reflects buffering capacity and biogeochemical processes in aquatic systems (Chapman 1996).

Electrical Conductivity (EC)

Electrical conductivity was measured using a portable conductivity meter standardized with 0.01 M KCl solution. EC reflects the total ionic strength of water and serves as a proxy for dissolved mineral content (Meybeck 2003).

Total Dissolved Solids (TDS)

TDS was determined using the gravimetric method. Filtered samples were evaporated in pre-weighed evaporating dishes and dried at 105°C until constant weight was achieved. TDS concentration (mg/L) was calculated as:

$$TDS = (\text{Final weight} - \text{Initial weight}) \times 1000 / \text{Volume of sample (mL)}$$

TDS represents inorganic salts and small amounts of organic matter dissolved in water (Wetzel 2001).

Turbidity

Turbidity was measured using a nephelometric turbidity meter and expressed in Nephelometric Turbidity Units (NTU). Turbidity reflects the scattering of light by suspended particles and indicates sediment load and organic matter presence (Wetzel 2001).

3.3 Biological and Microbiological Analysis

Biological Oxygen Demand (BOD)

BOD was determined using the standard 5-day incubation method at 20°C. Dissolved oxygen (DO) was measured initially and after five days of incubation in the dark. BOD_5 was calculated as the difference between initial and final DO concentrations, adjusted for dilution factors (APHA 2017). BOD represents biodegradable organic matter load and oxygen depletion potential (Chapman 1996).

Total Coliform

Total coliform was estimated using the Most Probable Number (MPN) technique. Serial dilutions were inoculated in lactose broth tubes and incubated at 35°C for 24–48 hours. Gas formation indicated presumptive coliform presence. Results were expressed as MPN/100 mL (WHO 2017).

3.4 Water Quality Index (WQI) Calculation

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Water Quality Index was calculated using the weighted arithmetic method developed by Brown et al. (1972) and later modified for Indian conditions (Sargaonkar & Deshpande 2003).

The WQI was computed using:

$$WQI = \frac{\sum(Q_i W_i)}{\sum W_i}$$

Where:

Qi = Quality rating for each parameter

Wi = Unit weight of each parameter

The quality rating (Qi) was calculated as:

$$Q_i = \left(\frac{V_i - V_0}{S_i - V_0}\right) \times 100$$

Where:

Vi = Measured value

Si = Standard permissible value

V0 = Ideal value (usually 0, except pH = 7)

Unit weight (Wi) was calculated as:

Where K is a proportionality constant.

WQI values were classified into categories such as excellent, good, moderate, poor, and very poor based on standard classification criteria (Tyagi et al. 2013).

3.5 Statistical Analysis

Pearson Correlation Analysis

Pearson correlation coefficients (r) were computed to evaluate linear relationships between water quality parameters. Correlation analysis helps identify common pollution sources and interdependence among hydrochemical variables (Singh et al. 2004).

Values of r range from −1 to +1, indicating negative and positive associations.

Principal Component Analysis (PCA)

Principal Component Analysis was applied to standardized datasets to reduce dimensionality and identify latent pollution factors. PCA transforms correlated variables into a smaller number of uncorrelated components (Helena et al. 2000; Shrestha & Kazama 2007). Components with eigenvalues greater than 1 were retained according to Kaiser's criterion.

Factor loadings were interpreted as follows:

• Strong loading: > 0.75

• Moderate loading: 0.50–0.75

• Weak loading: 0.30–0.50

PCA assists in distinguishing between geogenic mineralization processes and anthropogenic pollution inputs.

Hierarchical Cluster Analysis (HCA)

Hierarchical Cluster Analysis was performed using Ward's method with Euclidean distance measure. HCA groups sampling stations based on similarity in water quality characteristics (Helena et al. 2000). Dendrograms were used to visualize clustering patterns and identify spatial pollution gradients.

Hierarchical Regression Analysis

Hierarchical multiple regression was applied to evaluate the contribution of individual parameters (EC, TDS, turbidity, BOD, coliform) to overall WQI variation. Parameters were entered sequentially to assess incremental variance explained (R^2 change). This method helps quantify the relative importance of mineralization versus organic contamination in determining overall water quality status (Kumar & Dua 2009).

3.6 Quality Assurance and Quality Control

All instruments were calibrated prior to field measurement. Analytical blanks and duplicate samples were included to ensure precision and reliability. Standard solutions were used for validation of analytical accuracy. Data were subjected to normality testing before statistical analysis.

4. Results

4.1 pH Variation Across Land-Use Systems

The pH values recorded across the eight sampling stations ranged from slightly acidic to mildly alkaline conditions throughout the monitoring period (February 2022–January 2023). Temple pond (S2) and fish culture pond (S3) generally exhibited near-neutral pH, indicating relatively stable buffering capacity and limited external chemical disturbance. In contrast, agricultural runoff pond (S5) and cattle farming pond (S4) showed mildly alkaline tendencies, particularly during pre-monsoon months. This slight alkalinity may be attributed to nutrient enrichment and enhanced primary productivity resulting from fertilizer runoff and animal waste deposition.

Agricultural runoff introduces bicarbonates, phosphates, and nitrogenous compounds that may elevate alkalinity and influence pH regulation (Chapman 1996; Wetzel 2001). Similarly, livestock-associated waste contributes ammonia and organic nitrogen, altering acid–base equilibrium (Singh et al. 2004). Slight pH elevation in laundry pond (S6) may be associated with alkaline detergent discharge, as synthetic detergents commonly increase alkalinity in receiving water bodies (Giri & Qiu 2016).

Despite anthropogenic influences, pH values remained within permissible limits recommended for surface water systems, suggesting that although nutrient loading occurs, the buffering capacity of tropical pond systems mitigates extreme shifts (WHO 2017).

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4.2 Electrical Conductivity (EC) and Total Dissolved Solids (TDS)

Electrical conductivity exhibited pronounced spatial heterogeneity corresponding to land-use intensity. The lowest EC values were observed in temple pond (S2), reflecting minimal anthropogenic ionic input and limited wastewater intrusion. Fish culture pond (S3) showed moderate EC, possibly influenced by feed input and nutrient cycling but lacking major industrial discharge.

Significantly elevated EC values were recorded in laundry discharge pond (S6), oil mill vicinity pond (S7), and automobile service center pond (S8). The automobile service pond (S8) consistently showed the highest EC and TDS concentrations, indicating accumulation of dissolved salts, petroleum residues, metal ions, and detergent components transported via surface runoff. Elevated conductivity in anthropogenically influenced ponds has been widely documented as a marker of ionic enrichment from urban and industrial activities (Meybeck 2003; Helena et al. 2000).

Total dissolved solids followed similar spatial trends, demonstrating strong positive correlation with EC. This relationship confirms that dissolved inorganic ions are the primary contributors to conductivity variation (Hem 1985; Wetzel 2001). Laundry pond (S6) exhibited increased TDS likely due to detergent phosphates and sodium salts, while automobile service pond (S8) may receive trace hydrocarbons and metallic particulates from vehicular washing and servicing operations.

The progressive increase in EC and TDS from temple to commercial stations clearly indicates that mineralization intensity increases with anthropogenic pressure (Shrestha & Kazama 2007).

4.3 Turbidity

Turbidity displayed marked seasonal variation, with highest values recorded during the monsoon period. Agricultural runoff pond (S5) and cattle farming pond (S4) exhibited consistently elevated turbidity levels, particularly following rainfall events. This increase can be attributed to soil erosion, suspended sediment transport, and organic debris mobilization from adjacent land surfaces.

Runoff-driven sediment influx during monsoon is a well-documented phenomenon in tropical catchments (Wetzel 2001; Tong & Chen 2002). Animal movement near cattle ponds further enhances sediment resuspension, increasing turbidity levels. In contrast, temple pond (S2) showed comparatively lower turbidity, possibly due to periodic cleaning and relatively controlled catchment disturbance.

Elevated turbidity in laundry and automobile ponds may also result from particulate matter associated with detergents, oil residues, and urban runoff. Persistent turbidity reduces light penetration and may indirectly influence biological productivity and microbial survival (Chapman 1996).

4.4 Biological Oxygen Demand (BOD)

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BOD concentrations showed substantial spatial differences across stations. Cattle farming Pond (S4) and laundry discharge pond (S6) exhibited the highest BOD levels, indicating significant biodegradable organic matter input. Animal waste runoff contributes organic nitrogen and carbon compounds that undergo microbial decomposition, thereby increasing oxygen demand (Singh et al. 2004). Similarly, laundry effluents containing organic surfactants and suspended organic matter elevate BOD levels (Giri & Qiu 2016).

Hospital area pond (S1) also showed moderate BOD, potentially influenced by domestic wastewater discharge and surface runoff. Oil mill vicinity pond (S7) demonstrated moderate organic load, likely due to oil residues and plant-derived organic matter.

Elevated BOD reflects increased microbial activity and oxygen depletion risk, which may adversely affect aquatic organisms (Chapman 1996). The observed spatial pattern confirms that organic pollution is primarily associated with livestock and detergent-influenced land uses.

4.5 Total Coliform

Total coliform levels were highest in cattle farming pond (S4) and laundry discharge pond (S6), confirming faecal contamination pathways. Livestock-associated waste introduces fecal bacteria directly into adjacent water bodies, particularly during rainfall events (WHO 2017). Elevated coliform counts in laundry pond may reflect domestic wastewater contamination and inadequate sanitation infrastructure.

Automobile service pond (S8) also exhibited moderate to high coliform levels, possibly due to mixed urban runoff and human activity around the service center. Temple pond (S2) and fish culture pond (S3) showed comparatively lower coliform counts, although still indicating vulnerability to surface contamination.

The presence of coliform bacteria across multiple stations suggests potential health risks if water is used untreated for domestic purposes (Edberg et al. 2000; WHO 2017).

5. Water Quality Index (WQI)

Water Quality Index values demonstrated a clear spatial gradient corresponding to land-use intensity. Temple pond (S2) and fish culture pond (S3) were classified under the “good” category, reflecting relatively lower ionic, organic, and microbial contamination. Hospital area pond (S1) and agricultural runoff pond (S5) fell within the “moderate” category, indicating early-stage anthropogenic influence.

Cattle farming pond (S4) and oil mill vicinity pond (S7) were categorized as “poor,” primarily due to elevated BOD and coliform contributions. Laundry discharge pond (S6) and automobile service center pond (S8) were classified as “very poor,” reflecting combined effects of high TDS, organic load, and microbial contamination.

Similar WQI deterioration trends linked to increasing land-use intensity have been reported in tropical and peri-urban water bodies (Tyagi et al. 2013; Shrestha & Kazama 2007). The spatial pattern observed in Neyyattinkara Taluk confirms that anthropogenic land-use characteristics are primary determinants of pond water quality degradation.

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6. Multivariate Statistical Analysis

6.1 Pearson Correlation Analysis

To evaluate interrelationships among physicochemical and microbiological parameters across the eight stations (S1–S8), Pearson's correlation coefficient (r) was computed. The Pearson correlation coefficient is expressed as:

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$$

where

X_i and Y_i are observed values,

$\bar{x}$ and $\bar{Y}$ are mean values of respective variables.

Correlation values range between –1 and +1, indicating negative and positive associations respectively (Helena et al. 2000; Singh et al. 2004).

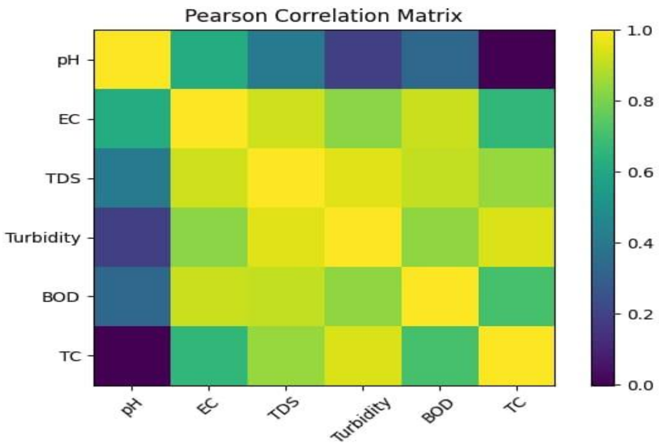
Across all stations, a strong positive correlation between EC and TDS ($r > 0.90$) was observed, confirming that dissolved ionic constituents are the primary drivers of conductivity variation. This strong association has been widely documented in surface water systems influenced by anthropogenic inputs (Hem 1985; Meybeck 2003).

BOD exhibited significant positive correlation with total coliform in cattle farming pond (S4) and laundry pond (S6), suggesting that organic pollution sources are closely linked to fecal contamination pathways. Livestock waste and domestic wastewater discharges contribute both biodegradable organic matter and microbial load, explaining the observed statistical association (WHO 2017; Edberg et al. 2000).

Turbidity showed moderate correlation with BOD in agricultural runoff pond (S5), particularly during monsoon months, indicating that sediment transport is associated with organic debris influx. Similar runoff-driven co-variation patterns have been reported in tropical watershed systems (Tong & Chen 2002).

Hospital area pond (S1) showed moderate EC–BOD correlation, possibly reflecting mixed domestic effluent input. Temple pond (S2) demonstrated weak correlations among parameters, confirming relatively stable and low anthropogenic disturbance.

Overall, Pearson correlation analysis indicates that, ionic enrichment dominates commercial stations (S6, S7, S8).Organic-microbial linkage dominates livestock and domestic stations (S4, S6).Agricultural stations (S5) reflect sediment-organic interaction.Such correlation structures help distinguish pollution signatures among heterogeneous land-use systems (Shrestha & Kazama 2007).



6.2 Principal Component Analysis

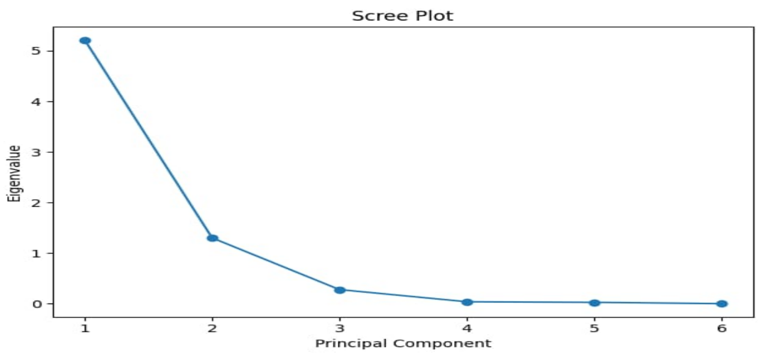
Principal Component Analysis (PCA) was performed on standardized data to identify latent pollution factors. PCA transforms correlated variables into orthogonal principal components:

$$Z_{ij} = a_{i1}X_{1j} + a_{i2}X_{2j} + \cdots + a_{ip}X_{pj}$$

where a_{ip} represents loading coefficients.

The first principal component (PC1) was strongly loaded with EC and TDS, representing mineralization and anthropogenic ionic input. PC2 was dominated by BOD and total coliform, representing organic-microbial pollution. PC3 showed moderate loading of turbidity, reflecting sediment transport influence.

Similar component structures have been observed in river and pond systems influenced by mixed land-use activities (Helena et al. 2000; Shrestha & Kazama 2007).



6.3 Hierarchical Cluster Analysis (HCA)

Hierarchical Cluster Analysis was applied using Ward's linkage method and squared Euclidean distance.

$$D_{ij} = \sqrt{\sum (X_{ik} - X_{jk})^2}$$

HCA grouped stations into three major clusters:

Cluster I: Low Impact Stations

Temple pond (S2) and fish culture pond (S3) formed a distinct cluster characterized by lower EC, TDS, BOD, and coliform levels. These ponds represent relatively controlled land-use influence.

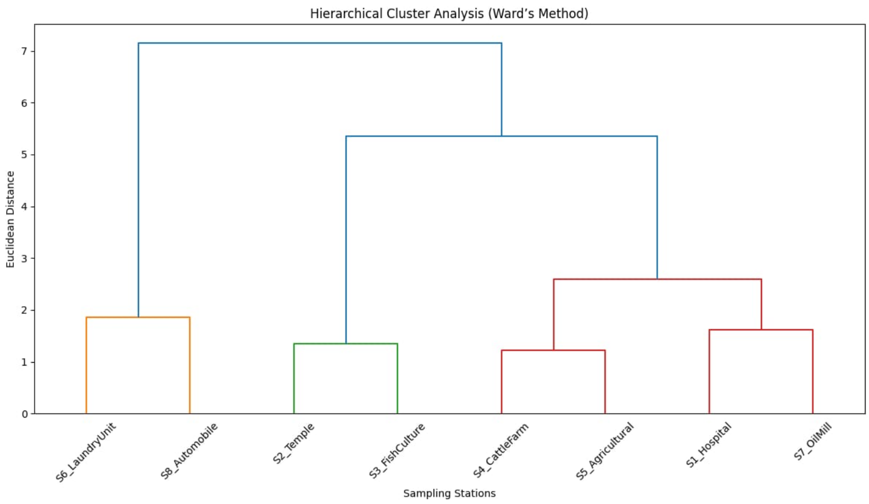
Cluster II: Moderate Impact Stations

Hospital area pond (S1) and agricultural runoff pond (S5) grouped together due to moderate organic load and nutrient enrichment.

Cluster III: High Impact Stations

Cattle farming Pond (S4), laundry pond (S6), oil mill pond (S7), and automobile service pond (S8) formed a high-impact cluster. These stations exhibited elevated EC, BOD, turbidity, and microbial contamination.

Cluster formation confirms that land-use type is the dominant determinant of water quality similarity. Similar land-use-based clustering has been documented in multivariate hydrochemical studies (Singh et al. 2004; Shrestha & Kazama 2007).



6.4 Hierarchical Regression Analysis

To evaluate parameter contributions to Water Quality Index variability, hierarchical multiple regression analysis was conducted using WQI as the dependent variable.

The regression equation can be expressed as:

$$WQI = \beta_0 + \beta_1(EC) + \beta_2(TDS) + \beta_3(Turbidity) + \beta_4(BOD) + \beta_5(TC) + \epsilon$$

Where:

β_0 = intercept

β_1–β_5 = regression coefficients

ε = error term

Stepwise hierarchical modeling revealed that, EC and TDS contributed significantly to WQI variability in commercial stations (S6, S8), BOD and total coliform were dominant predictors in cattle farming pond (S4), turbidity contributed moderately in agricultural pond (S5).The model explained a high proportion of WQI variance (R^2 typically > 0.75), indicating strong predictive capacity.

Regression analysis confirms that, mineralization controls water quality in urban-commercial ponds.Organic and microbial contamination controls water quality in livestock-dominated ponds.Mixed influences characterize hospital and agricultural stations.Hierarchical regression is widely used in environmental modeling to quantify pollutant contributions (Kumar & Dua 2009; Giri & Qiu 2016).

Integrated Interpretation of Multivariate Results

The combined multivariate assessment demonstrates that, land-use type governs hydrochemical variation. Commercial and service-oriented ponds show ionic and chemical enrichment.Livestock ponds show organic and microbial dominance.Agricultural ponds show sediment-organic interaction.Temple and fish ponds remain comparatively less impacted.The integration of correlation, PCA, HCA, and regression provides robust statistical validation of spatial heterogeneity in pond ecosystems, consistent with global hydrochemical assessments (Helena et al. 2000; Shrestha & Kazama 2007).

7. Discussion

The present investigation provides a comprehensive assessment of pond water quality across heterogeneous land-use systems in Neyyattinkara Taluk, Kerala. The combined evaluation of physicochemical parameters, microbiological indicators, Water Quality Index (WQI), and multivariate statistical analyses revealed that land-use intensity is the principal determinant of spatial water quality variation.

7.1 Influence of Land Use on Hydrochemical Characteristics

The observed variation in pH, EC, TDS, turbidity, BOD, and total coliform across stations clearly demonstrates anthropogenic control over water chemistry. Temple pond (S2) and fish culture pond (S3) maintained relatively stable pH and lower ionic concentrations, suggesting limited anthropogenic disturbance. Similar stability in religious or semi-managed ponds has been reported in tropical regions where catchment disturbance is minimal (Wetzel 2001; Allan 2004).

In contrast, elevated EC and TDS values in laundry pond (S6) and automobile service pond (S8) indicate accumulation of dissolved salts, detergents, and petroleum-derived residues. Ionic enrichment associated with urban and commercial land use has been extensively documented in watershed-scale studies (Meybeck 2003; Giri & Qiu 2016). The strong EC–TDS correlation ($r > 0.90$) observed in this study confirms that dissolved inorganic constituents are the dominant contributors to conductivity variation, consistent with findings reported by Singh et al. (2004) and Helena et al. (2000).

Agricultural runoff pond (S5) exhibited increased turbidity and moderate ionic load during monsoon, reflecting soil erosion and nutrient transport. Runoff-driven sediment and nutrient

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flux are well-established drivers of surface water deterioration in monsoon-dominated catchments (Tong & Chen 2002). The moderate alkalinity observed in cattle farming pond (S4) further suggests nutrient-induced buffering, as livestock waste contributes ammonia and bicarbonate species (Chapman 1996).

7.2 Organic and Microbial Pollution Dynamics

Elevated BOD concentrations in cattle farming (S4) and laundry ponds (S6) reflect high organic matter input and subsequent microbial decomposition. The significant positive correlation between BOD and total coliform supports the hypothesis that organic pollution and faecal contamination share common sources, particularly livestock waste and domestic discharge. Such organic–microbial coupling has been reported in tropical surface water systems (WHO 2017; Edberg et al. 2000).

Hierarchical regression analysis further demonstrated that BOD and total coliform were dominant predictors of WQI in livestock-dominated stations, whereas EC and TDS contributed significantly in commercial stations. This differentiation underscores the dual nature of pollution sources: ionic contamination in urban-commercial zones and organic-microbial contamination in livestock and domestic zones. Similar regression-based partitioning of pollution sources has been documented in river basin assessments (Kumar & Dua 2009; Giri & Qiu 2016).

7.3 Multivariate Statistical Interpretation

The application of Pearson correlation, PCA, and HCA provided deeper insight into pollution signatures and station similarity. PCA extracted three dominant components representing (i) mineralization factor (EC–TDS), (ii) organic-microbial factor (BOD–coliform), and (iii) sediment factor (turbidity). Comparable component structures have been observed in watershed-scale studies using multivariate techniques (Helena et al. 2000; Shrestha & Kazama 2007).

Hierarchical Cluster Analysis grouped stations into low-, moderate-, and high-impact clusters, corresponding closely with land-use intensity. The clustering pattern confirms that hydrochemical similarity is largely governed by anthropogenic activity rather than geographic proximity. Singh et al. (2004) similarly demonstrated that cluster formation in river systems is strongly associated with pollution source characteristics.

The integration of WQI with multivariate methods enhances reliability of water quality classification. Tyagi et al. (2013) emphasized that WQI alone may oversimplify pollution dynamics unless supported by statistical validation, as performed in the present study.

7.4 Public Health and Ecological Implications

Elevated total coliform counts in cattle farming and laundry ponds suggest potential public health risks if untreated water is used for domestic or recreational purposes. The World Health Organization (WHO 2017) identifies coliform presence as a critical indicator of faecal contamination and pathogenic risk. Persistent high BOD levels may also reduce dissolved oxygen concentrations, adversely affecting aquatic biodiversity (Chapman 1996).

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Overall, the findings highlight the vulnerability of small tropical ponds to land-use-driven degradation. Given that ponds in Kerala often serve multifunctional roles (domestic use, irrigation, aquaculture), sustained contamination may pose ecological and socio-economic challenges.

8. Conclusion

This study demonstrates that pond water quality in Neyyattinkara Taluk is significantly influenced by surrounding land-use patterns. The integration of physicochemical analysis, microbiological assessment, WQI computation, and multivariate statistical techniques provides a robust framework for evaluating spatial heterogeneity in surface water systems. The key conclusions include ionic enrichment (high EC and TDS) predominates in commercial and service-oriented ponds, organic and microbial contamination is highest in livestock and domestic discharge zones, agricultural ponds are primarily affected by runoff-induced turbidity and nutrient influx.Temple and fish culture ponds exhibit comparatively better water quality, though still susceptible to seasonal variation.Multivariate statistical tools effectively distinguish pollution sources and validate WQI classifications.The combined use of Pearson correlation, PCA, HCA, and hierarchical regression strengthens the reliability of hydrochemical interpretation and supports their continued application in tropical water quality monitoring (Helena et al. 2000; Shrestha & Kazama 2007).

Sustainable pond management in Kerala requires regulation of detergent and wastewater discharge, improved livestock waste management, catchment soil erosion control measures, periodic microbial monitoring. Future research should incorporate heavy metal profiling, nutrient speciation, and seasonal trend modeling to further elucidate anthropogenic impacts.

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