Assessment of ecosystem health of a micro-level Ramsar coastal zone in the Vembanad Lake, Kerala, India

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Abstract Health of an ecosystem is very much important as we depend on its goods and services for our existence. Because of this, we need to continuously monitor its health for human benefit and for identifying areas for improvement of our natural systems. The present study tries to assess the condition of a coastal ecosystem within the Vembanad Lake, Kerala, India, using key water quality parameters at micro-level. Principal component analysis identified the minimum required water quality dataset for further analysis and was scored using linear scoring functions. The weighted additive method was used to integrate the individual scores to arrive at a final score representing the ecosystem health. Spline interpolation was applied to develop the ecosystem health map of the study area. Using this method, 35.8% area of the aquatic ecosystem studied was characterized as good, 32.2% as moderate, 26.2% as fair and 5.8% as poor. The assessment results can help the policymakers/managers to make appropriate decisions for the better management of the coastal ecosystems studied. Moreover, this methodology can be replicated for the assessment of coastal regions with similar ecosystem characteristics.

Keywords Coastal ecosystem · Principal component analysis · Minimum dataset · Linear scoring · Ecosystem health

Introduction

Humans interact with natural ecosystems in intricate ways. We depend on ecosystems to derive the resources for our living. They provide us with water, food, fibre and shelter. But we have an inclination to extract too much from them disrupting their balance, ultimately degrading them or exacerbating the pace of their degradation. Human wellbeing is primarily dependent on the health of the ecosystems they depend on for their survival (Burke et al., 2001). Hence, it is very crucial to monitor and assess the health of the ecosystem and take remedial measures if needed, for our benefit and for the long-term good of the ecosystem.
The major ecosystems identified worldwide are five, viz. agroecosystems, coastal ecosystems, forest ecosystems, freshwater ecosystems and grassland ecosystems, and together they cover 90% of the earth’s land surface excluding Greenland and Antarctica. Coastal ecosystems are having high biological productivity and play a major role in storing and cycling nutrients and filtering pollutants from inland freshwater systems and also help to protect shorelines from erosion and storms. They form the ports for carrying out commercial activities and provide resources such as fish, seaweed, fertilizer, pharmaceuticals, cosmetics, household products and construction materials (Burke et al., 2001). Moreover, they provide nursery ground for marine organisms (Remani et al., 1983; Nair et al., 1988; Sarala Devi et al., 1991; Howard et al., 2014). Multiple factors significantly and negatively impact the coastal ecosystems of the world. Some of the major stresses are loss of area, population pressure, pollution, overexploitation, injudicious fishing practices and climate change (Burke et al., 2001).

These facts imply that it is very important to scrutinize and maintain the health of the ecosystem that we are involved in. Assessing ecosystem health is an ongoing priority for governments, scientists and resource managers worldwide (O’Brien et al., 2016). The term ecosystem health is used to denote the state of a system relative to the desired reference condition or a management goal (Rapport, 1989; Schaeffer et al., 1988). We use indicators to monitor a system. Ecosystem indicators allow isolation of key aspects of a system from an array of signals (Beroya-Eitner, 2016; National Research Council, 2000), and it could be used to assess and monitor the health of the ecosystems. Ecosystem health is mainly assessed using chemical/biological/physical indicators (O’Brien et al., 2016). Nutrients, physico-chemistry and biota are in general used as indicators to reflect the condition of aquatic ecosystems (Vilmi et al., 2016).

The Vembanad Lake located in Kerala, southwest coast of India, is a Ramsar site and has a multiplicity of environmental issues arising due to the construction of regulators, spillways, overexploitation of resources and uncontrolled urbanization which is leading to its degradation (Remani et al., 2010). The lake has a spatial extent of 241 km² (Kulk et al., 2021; Menon et al., 2021), and it is under the threat of nutrient enrichment by anthropogenic interventions and terrestrial inputs via land runoff which could result in eutrophication and a decline in biodiversity (John et al., 2020). The Vembanad Lake system supports rich biological regions with a high degree of endemism, around 150 fish species and a bird population of more than 20,000 during winter. The major mangrove species of the area are Avicennia officinalis, Rhizophora apiculata and Rhizophora mucronata. The giant freshwater prawn Macrobrachium rosenbergii and clam fisheries provide a source of livelihood to the local people. Annual fish landing from the lake system is estimated to be 746 tonnes (Remani et al., 2010). Vibrio cholerae which causes cholera disease is endemic to the Vembanad Lake, and the pathogen was found to be associated with the filtered water and phyto- and zooplanktons (Anas et al., 2021). There are spatial and seasonal variations of varying degrees in the environmental parameters such as temperature, salinity, pH, dissolved oxygen, chlorophyll a, dissolved inorganic carbon, silicate, phosphate, nitrate and pCO2 content of the lake waters which are mainly driven by the freshwater discharge from the river systems and the sea water influx via the bar mouths (Kulk et al., 2021; Menon et al., 2000, 2021; Pranav et al., 2021). The lake system is also under pressure from industrial pollution, aquatic weeds, agriculture, domestic waste and sewage. Tourism activities also flourish in the Vembanad Lake area generating job opportunities and income at the same time exerting more pressure on the ecosystem. Anthropogenic activities such as reclamation and demolition of structures and dumping the debris into the lake also complicate the scenario (Kulk et al., 2021; Menon et al., 2000, 2021; Remani et al., 2010). The lake system has an inherent ability to bounce back to the normal conditions if left undisturbed for some period after a disturbing event has occurred. It was observed that the deposition of building demolition debris into the lake affected the water quality parameters such as Secchi depth, water colour, temperature, salinity, pH and dissolved oxygen. But the system bounced back to the normal levels after a period of 4–5 weeks (Menon et al., 2021). It was also observed that during the lockdown period (25 March–31 May 2020) in response to the COVID-19 global pandemic, water quality in large areas of the Vembanad Lake improved especially in the central and southern regions as indicated by a decrease in total suspended matter, turbidity and absorption by
coloured dissolved organic matter, leading to clearer waters emphasizing the role played by anthropogenic pressures in deteriorating the water quality (Kulk et al., 2021).

Around 1.6 million people depend on this lake system for their livelihood (George et al., 2021). Degradation of the health of the Vembanad Lake system would have wide range of ramifications and could negatively impact the services provided by this ecosystem. This makes it imperative to continuously monitor the Vembanad Lake system and make necessary interventions when required. The present study is an attempt to assess the health and grade an ecosystem at micro-level based on its water quality.

Methodology

Study area

The area for the present study is a coastal Gramma Panchayath, namely Mulavukad in Ernakulam district of Kerala State, India (Fig. 1). It has an area of 19.27 km² and a population of 22,322 of which 11,305 are women and 11,017 are men with an average population density of 1158 km⁻². The area lies between the latitudes 9°58′34″ to 10°02′21″N and longitudes 76°14′21″ to 76°16′06″ E. There are 16 administrative units or wards. The soils of the area were developed from marine alluvium and has humid tropical climate with two distinct monsoons. i.e. southwest monsoon and winter monsoon. The average annual rainfall is 3159 mm, and the mean annual temperature is 28.1 °C (Soil Survey Organization, 2011).

Data collection

Two methods, viz. expert opinion and statistical method based on principal component analysis (PCA), are mainly used to select the best-suited parameters from a set of variables to represent the system under study. The expert opinion method can introduce disciplinary bias in the selection process, while the PCA-based dataset selection procedure excludes this bias and found to be superior compared to expert opinion (Andrews & Carroll, 2001; Andrews et al., 2002; Mandal et al., 2011; Masto et al., 2008; Tesfahunegn, 2014). Out of the 25 water quality parameters collected, PCA identified the parameters that represented the ecosystem in a better way. The PCA method converts the observations of possibly correlated variables into linearly uncorrelated variables known as principal components (Andrews et al., 2002). The minimum dataset (MDS) which is to be further used for the analysis was selected using the following procedure. Principal components (PCs) receiving high eigenvalues best represent the system attributes. The PCs with eigenvalue > 1.0 were only retained for further analysis (Brejda et al., 2000). The minimum dataset (MDS) which is to be further used for the analysis was selected using the following procedure. Principal components (PCs) receiving high eigenvalues best represent the system attributes. The PCs with eigenvalue > 1.0 were only retained for further analysis (Brejda et al., 2000). For a particular PC, each variable receives a weight or factor loading that indicates its contribution to the PC. Only the highly weighted variables from each PC were selected for the MDS. The highly weighted variables are those which...
Fig. 1 Map of the study area (Mulavukad Gramma Panchayath) indicating sampling locations (Roman letters indicates the administrative ward number)
receive factor loadings within 10% of the highest factor loading for that particular PC, in terms of absolute value (Andrews et al., 2002). When more than one variable were retained within a PC, their linear correlations were calculated to determine whether any variable could be considered redundant and, therefore, eliminated from the MDS (Andrews et al., 2002). If the highly weighted variables were not well correlated (correlation coefficient < 0.60), then each one was considered important and was retained in the MDS. Among the well-correlated variables within a PC, the variable with the highest factor loading (absolute values) was chosen for the MDS (Andrews & Carroll, 2001).

After selecting datasets for further analysis, the selected system indicators were transformed into scores using linear scoring methods, which are considered more sensitive (Andrews et al., 2002; Tesfahunegn, 2014). After converting the system indicators into scores, the weighted additive (Karlen et al., 1998; Singh et al., 2013; Tesfahunegn, 2014) method was used to integrate the scores into the final ecosystem health index (EHI) value. The flow chart of the methodology adopted is given in Fig. 2. The ecosystems were categorized as poor, fair, moderate and good based on < 25th, 25th–50th, 50th–75th and > 75th percentile values of the normalized ecosystem index obtained in the study area. ArcGIS 10.0 was used for mapping, and R 4.0.3 and Microsoft Excel were used for statistical and other charting purposes.

Fig. 2 Flow chart of the methodology adopted in the study

### Results and discussion

#### MDS selection

Before running the PCA, the collected parameters were grouped into three, viz. biological productivity indicators, environmental indicators and pollution indicators. The biological indicators included GPP, NPP, chlorophyll $a$ and diatoms. The environmental indicators included air temperature, water temperature, pH, salinity, turbidity, dissolved oxygen, PO$_4$-P, SiO$_3$-Si, NO$_3$-N, dissolved CO$_2$ and TSS, while the pollution indicators included vibrio, salmonella, total coliform, faecal coliform, *E. coli*, BOD, COD, TAN, NO$_2$ and dinoflagellates. PCA was run on these subgroups separately. These sub-groupings were done to avoid the masking effect of dominant parameters on others and to easily pinpoint the factors that bring down the overall health of the ecosystem, thereby making it convenient for the managers to intervene effectively. Out of the 25 system indicators used, the minimum dataset included only 12 indicators, i.e. a reduction of 56% in the data dimensionality. Moreover, it ensures that data redundancy is avoided.

In the case of the biological productivity indicators, PCA resulted in four principal components (Table 1) out of which only two (PC1 and PC2) had eigenvalue $> 1$. Hence, the indicators that had the highest loadings in these two principal components were considered for further analysis in the subgroup,
viz. biological productivity indicators. In PC1, diatom count was the only highly weighted indicator, and in PC2, NPP was the only highly weighted indicator. As there was only one highly weighted indicator in both of the principal components, there was no need to consider the correlation coefficients.

Primary productivity is fundamental to ecosystem functioning, and it is the result of physical, chemical and biological interactions that determine the actual fertility of an environment. Basis of the marine food web is constituted by primary producers, viz. phytoplankton, cyanobacteria and macroalgae. The productivity of any aquatic system is mainly reflected by its phytoplankton productivity, and it is depended on a number of factors such as pH, CO2 concentration, temperature, nutrients, radiation, mixing frequency and herbivore pressure (Häder et al., 2014). Primary productivity is bifurcated as gross primary productivity (GPP) and net primary productivity (NPP). GPP is the total rate of photosynthesis, while NPP is the rate of storage of organic matter in plant tissues after the respiratory utilization (Goldman & Wetzel, 1963; Verma & Srivastava, 2016), and the net primary productivity (NPP) is considered an important indicator of ecosystem health (Zhou et al., 2021).

Diatoms are one of the most diverse and ecologically important groups of phytoplankton and play critical role in nutrient-rich coastal ecosystems (Malviya et al., 2016). They contribute significantly to the productivity of aquatic ecosystems and, in most of the situations, form the base of aquatic food chains. Diatoms are sensitive to many physical, chemical and biological changes in the ecosystems and serve as the most valuable indicator for the ecological assessment of aquatic systems (Srivastava et al., 2016). Diatoms contribute around 20–25% of the Earth’s global primary production and accounts for 40% of the marine primary production making them ecologically important, supporting the aquatic food webs (Armbrust, 2009; Field et al., 1998; Sarthou et al., 2005). But the important role played by diatoms in the functioning of coastal ecosystems is impacted by ocean acidification and eutrophication (Serôdio & Lavaud, 2020). Eutrophication of coastal waters can amplify the range of pH of the coastal ecosystems (Hinga, 2002). Decrease in the pH value of water affects the enzymatic and other biochemical processes as well as calcification in phytoplankton (Häder et al., 2014). It can also lead to significant rearrangement of planktonic food web, impacting multiple trophic levels from phytoplankton to primary and secondary consumers (Spisla et al., 2021).

There were eleven parameters in the subgroup environmental indicators, and the results of the principal component analysis of this subgroup are presented in Table 2.

The first four components were having eigenvalue >1, and hence the indicators that had the highest loadings in the first four principal components were considered for further analysis in this subgroup. In PC1, there were three indicators with highly weighted factor loadings, viz. pH, AT and SST Table 3 shows that WT and AT are well correlated, and pH is not well correlated with WT or AT. So, pH was selected as one of the MDS. As WT and AT were well correlated and only one needed to be retained, we chose to retain WT as it is an indicator directly indicating the state of water rather than AT. PC 2 yielded only one parameter, DO, with highly weighted factor loading. In case of PC 3, SAL and TUR were the indicators with highly weighted factor loadings, and these two indicators were not well correlated. Hence, these two indicators were retained for further analysis. For PC 4, TSS was the only indicator with highly weighted factor loading and was considered for environmental indicators.

By way of affecting the cellular biochemical processes, water temperature plays a determining role in cellular productivity. Increase in water temperature in the tropical areas can exert more stress on cells already growing at the high limit of temperature (Häder et al., 2014; Raven, 1991), and the

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### Table 1 Summary of the principal component analysis carried out for the biological indicators

|   | PC 1 | PC 2 | PC 3 | PC 4 |
|---|------|------|------|------|
| Axis summary |      |      |      |      |
| Eigenvalue | 1.47 | 1.11 | 0.89 | 0.53 |
| % variance explained | 36.78 | 27.76 | 22.17 | 13.29 |
| Cumulative variance | 36.78 | 64.54 | 86.71 | 100.00 |
| Factor loadings |      |      |      |      |
| GPP | 0.5247 | 0.4648 | 0.4882 | -0.5199 |
| NPP | -0.1370 | **0.8655** | -0.2202 | 0.4286 |
| Chl_a | -0.4902 | -0.0046 | 0.8264 | 0.2771 |
| Dia | **0.6823** | -0.1869 | 0.1740 | 0.6850 |

The bold entries indicate PCs with eigenvalue >1 and factor loadings of highly weighted variables.
temperature-driven mixing processes also play a pivotal role in the phytoplankton ecology (Silva, 2006).

Dissolved oxygen is fundamental to the aquatic life and is considered a key indicator of water quality. Nutrient enrichment in coastal and estuarine systems is identified as one of the reasons for the development of oxygen-deficient zones (O’Boyle et al., 2009). Climate change also contributes to deoxygenation by way of increased temperature leading to enhanced stratification and decreasing the solubility of oxygen in water. One of the main impacts of deoxygenation is drastic reduction in biodiversity as the organisms that depend on aerobic respiration fail to recruit, remain or survive (Global Ocean Oxygen Network et al., 2018; Laffoley & Baxter, 2019).

There exists a functional relationship between salinity and species diversity. The changes in salinity in the brackish water systems due to climate change-induced variations in precipitation pattern and sea level rise may impact species diversity and ecosystem productivity and functioning (Harding et al., 2015, 2016). It is also observed that the salinity plays a major role in the phytoplankton composition and dynamics in the coastal ecosystems (Olli et al., 2019). The spatial patterns of physical properties, biota and biogeochemical processes in estuaries are mainly determined by the salinity gradients (Cloern et al., 2017).

In a coastal ecosystem, phytoplankton productivity is found to be more in areas where turbidity is less, and it is attained by influencing the depth of photic zone affecting the phytoplankton production and turnover rate (Cloern, 1987). In nutrient-rich waters, phytoplankton growth rate is mainly determined by light availability which is controlled by solar irradiance, turbidity and mixed layer depth. Turbidity restricts the photic zone to a narrow layer, limiting photosynthesis over the water column leading to slow incorporation of nutrients into phytoplankton biomass (Alpine & Cloern, 1988; Cloern et al., 2014; Wofsy, 1983). Poor water quality and increase in the temperature of upper layer of water column are the resultant effects of high sediment loads (Balasubramanian et al., 2020). Higher concentrations of suspended solids can cause poor nutrient and light conditions such as suboptimal nutrient ratios, low irradiance due to shading effect leading to reduction in phytoplankton abundance, diversity and biomass (Kumar et al., 2021; Sew & Todd, 2020).

In the case of pollution indicators, PCA yielded ten principal components (Table 4) out of which the first four components were with eigenvalue > 1. The indicators that had the highest loadings in the first four principal components were considered for further analysis in this subgroup. In PC1, the indicators with highly weighted loadings were TC, FC and EC.

| Table 2 Summary of the principal component analysis on the environmental indicators |
|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
|                     | PC 1    | PC 2    | PC 3    | PC 4    | PC 5    | PC 6    | PC 7    | PC 8    | PC 9    | PC 10   | PC 11   |
| Axis summary        | 2.71    | 2.06    | 1.52    | 1.16    | 0.92    | 0.76    | 0.70    | 0.55    | 0.35    | 0.14    | 0.12    |
| Eigenvalue          | 24.61   | 18.77   | 13.84   | 10.57   | 8.36    | 6.94    | 6.40    | 4.99    | 3.15    | 1.29    | 1.08    |
| % variance explained | 24.61   | 43.37   | 57.21   | 67.78   | 76.14   | 83.08   | 89.48   | 94.48   | 97.63   | 98.92   | 100.00  |
| Cumulative variance | 24.61   | 43.37   | 57.21   | 67.78   | 76.14   | 83.08   | 89.48   | 94.48   | 97.63   | 98.92   | 100.00  |
| Factor loadings     | AT      | WT      | pH      | SAL     | TUR     | DO      | PO4     | SiO3    | NO3     | TSS     | CO2     |
|                     | −0.451  | −0.440  | 0.460   | 0.003   | 0.022   | 0.255   | 0.335   | −0.365  | −0.272  | −0.137  | 0.218   |
|                     | 0.241   | 0.262   | −0.006  | 0.099   | 0.092   | 0.139   | −0.328  | −0.272  | −0.225  | 0.129   | 0.032   |
|                     | 0.058   | 0.275   | −0.071  | 0.092   | 0.662   | −0.184  | −0.089  | −0.330  | −0.255  | 0.155   | 0.487   |
|                     | −0.078  | 0.064   | −0.095  | −0.042  | −0.042  | −0.112  | −0.232  | −0.300  | −0.275  | −0.032  | −0.495   |
|                     | 0.354   | 0.422   | −0.066  | −0.452  | 0.032   | 0.029   | −0.182  | −0.278  | 0.305   | 0.110   | 0.544   |
|                     | 0.249   | 0.062   | 0.298   | 0.110   | 0.282   | 0.286   | 0.581   | 0.303   | 0.163   | 0.123   | 0.155   |
|                     | 0.256   | 0.047   | 0.232   | 0.123   | 0.281   | 0.654   | 0.201   | 0.026   | 0.169   | 0.155   | 0.123   |
|                     | −0.306  | 0.326   | 0.127   | 0.250   | 0.165   | 0.629   | −0.018  | −0.026  | 0.275   | 0.155   | 0.123   |
|                     | 0.584   | −0.564  | 0.078   | 0.250   | 0.165   | 0.078   | 0.431   | 0.064   | 0.275   | 0.165   | 0.123   |
|                     | 0.006   | 0.196   | 0.346   | 0.052   | 0.054   | 0.028   | 0.413   | 0.155   | 0.075   | 0.054   | 0.127   |

The bold entries indicate PCs with eigenvalue > 1 and factor loadings of highly weighted variables.
But, these three indicators were highly correlated (Table 5), and we chose to retain TC as it contains the information of both the other two indicators, i.e. FC and EC, in the MDS from PC1. In PC2, BOD was the only indicator with highly weighted loadings. Similarly, in PC3 and PC4, Vibrio and NO₂ were the indicators with highly weighted loadings (Table 4) in the respective principal components. These highly weighted indicators were considered for further analysis in the negative indicators group (TC, BOD, Vib and NO₂).

Coastal ecosystems are prone to wastewater discharges which can bring allochthonous organic matter and microbes into the system (Orel et al., 2022). Coliform bacteria presence in the coastal waters can serve as an indicator of water quality and can also form a basis for the environmental governance strategies (Cui et al., 2021; Guerrya et al., 2012; Orel et al., 2022). Coliform and Vibrio bacteria are reported from Vembanad Lake ecosystem (Anas et al., 2021; Chandran et al., 2008; Shankar et al., 2020). Precipitation and organic matter were found to be the most predominant factors positively affecting the abundance of total coliforms. Suspended solids and phosphate phosphorus content in waters also had a positive effect. It was also observed that the coliform

Table 3  Correlation matrix ($R$-values and significance) for the environmental indicators

|      | AT  | WT  | pH  | SAL | TUR | DO  | PO₄ | SiO₃ | NO₃ | TSS |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| WT   | 0.70*** |     |     |     |     |     |     |     |     |     |
| pH   | -0.33* | -0.36* |     |     |     |     |     |     |     |     |
| SAL  | -0.15 | 0.18 | 0.04 |     |     |     |     |     |     |     |
| TUR  | 0.06 | -0.01 | -0.03 | -0.15 |     |     |     |     |     |     |
| DO   | 0.02 | -0.05 |     |     |     |     |     |     |     | 0.74*** |
| PO₄  | -0.47** | -0.3 | 0.12 | -0.03 | -0.13 | -0.14 |     |     |     |     |
| SiO₃ | 0.28 | 0.13 | -0.51*** | -0.23 | -0.03 | -0.38* | -0.31* |     |     |     |
| NO₃  | -0.16 | -0.36* | -0.1 | -0.08 | 0.09 | -0.34* | 0.38* | 0.19 |     |     |
| TSS  | 0.19 | 0.21 | -0.1 | 0 | 0.01 | 0.02 | -0.12 | -0.02 | -0.03 |     |
| CO₂  | -0.06 | -0.17 | 0.28 | -0.11 | 0.27 | 0.13 | 0.15 | -0.13 | 0.21 | 0.12 |

The bold entries indicate correlation coefficients of highly correlated variables

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; negative sign denotes negative correlation
abundance was negatively affected by pH, dissolved oxygen, biochemical oxygen demand and electric conductivity (Seo et al., 2019). While the water quality variables such as temperature and salinity were found to strongly influence the Vibrio abundance in the coastal systems (Takemura et al., 2014).

Biological oxygen demand (BOD) is considered to be a better indicator for the water quality, and it could be used as a bio-indicator of the phytoplankton diversity (Lv et al., 2022; Mizwar & Surapati, 2020). High organic pollution levels or nitrate levels that in turn result in higher phytoplankton levels can lead to high BOD values (UNEP, 2005).

Nitrite nitrogen (NO$_2$-N) in the aquatic system plays a major role in the global nitrogen and carbon cycles, providing a key resource for significant microbial metabolisms (Zakem et al., 2018). Nitrogen as ammonium (NH$_4^+$), nitrite (NO$_2^-$) and nitrate (NO$_3^-$) has been considered the main limiting nutrient for phytoplankton growth and biomass in coastal waters (Moschonas et al., 2017). The ammonium (NH$_4^+$) oxidation is a two-step process that has important implications for water column productivity. The first step, converts NH$_4^+$ to nitrite (NO$_2^-$) and then the nitrite on oxidation, converts NO$_2^-$ to nitrate (NO$_3^-$). The nitrate thus formed may become the substrate for denitrification process that removes around 30–50% of the N load from deoxygenated coastal systems. Denitrification is also an important part of nitrogen cycle as excess N can lead to a variety of negative consequences in coastal waters such as eutrophication and reduction in biodiversity. The ammonium oxidizers compete with phytoplankton and heterotrophic bacteria for the substrate. Temperature, salinity, dissolved oxygen and substrate availability are the variables that affect the ammonium oxidation rates in a coastal ecosystem (Heiss & Fulweiler, 2016; Voss et al., 2013).

Our understanding of the outcomes of the interactions between different players of an ecosystem and its cumulative effect on the ecosystem health is not complete. The effects can vary between ecosystems and regions. Hence, care should be taken while making comparisons or interpretations, and it should be done on a case-by-case basis (Boyd & Brown, 2015).

Linear scoring functions of MDS

The PCA identified parameters under each group, viz. diatoms and NPP in the biological group; SST, pH, DO, SAL, TUR and TSS in the environmental parameters and TC, BOD, Vib and NO$_2$ in the pollution parameters were converted into scores using the linear scoring functions. The optimal ranges of these parameters were selected based on international guidelines for water quality criteria/expert

Table 4 Summary of the principal component analysis on the pollution indicators

|         | PC 1 | PC 2 | PC 3 | PC 4 | PC 5 | PC 6 | PC 7 | PC 8 | PC 9 | PC 10 |
|---------|------|------|------|------|------|------|------|------|------|-------|
| Axis summary | 2.83 | 1.53 | 1.23 | 1.18 | 0.95 | 0.79 | 0.63 | 0.55 | 0.25 | 0.06  |
| % variance explained | 28.30 | 15.28 | 12.34 | 11.80 | 9.49 | 7.92 | 6.29 | 5.47 | 2.50 | 0.61  |
| Cumulative variance | 28.30 | 43.58 | 55.93 | 67.73 | 77.22 | 85.14 | 91.42 | 96.89 | 99.39 | 100.00 |

Factor loadings

|         | Vibr | Salm | TC | FC | EC | BOD | TAN | NO2 | COD | Dino |
|---------|------|------|----|----|----|-----|-----|-----|-----|------|
| 0.057  | 0.279 | 0.670 | -0.103 | -0.187 | -0.421 | 0.413 | 0.131 | 0.241 | 0.026 |
| -0.099 | 0.435 | 0.423 | 0.206 | 0.196 | 0.622 | 0.009 | -0.327 | -0.218 | 0.031 |
| 0.518  | 0.130 | -0.099 | -0.153 | 0.317 | -0.046 | 0.070 | -0.227 | 0.277 | 0.668 |
| 0.537  | 0.188 | -0.010 | -0.154 | 0.210 | -0.037 | -0.036 | -0.175 | 0.203 | -0.731 |
| 0.508  | 0.114 | 0.085 | 0.106 | -0.137 | -0.188 | -0.010 | 0.253 | -0.766 | 0.076 |
| -0.195 | 0.536 | -0.056 | 0.076 | 0.327 | -0.237 | -0.566 | 0.414 | 0.103 | 0.042 |
| 0.270  | 0.271 | -0.149 | 0.178 | -0.676 | 0.372 | -0.080 | 0.268 | 0.352 | 0.056 |
| 0.018  | 0.054 | -0.251 | 0.752 | 0.281 | -0.091 | 0.493 | 0.148 | 0.103 | -0.073 |
| 0.194  | -0.453 | 0.375 | -0.033 | 0.323 | 0.366 | -0.042 | 0.595 | 0.148 | 0.003 |
| -0.154 | 0.316 | -0.354 | -0.533 | 0.130 | 0.248 | 0.502 | 0.335 | -0.152 | -0.037 |

The bold entries indicate PCs with eigenvalue >1 and factor loadings of highly weighted variables.
opinion/other published research (Boyd & Pillai, 1985; USEPA, 2006; CPCB, 2008; Rao et al., 2013; FAO/WHO, 2016; Aswathy et al., 2020). The linear scoring functions developed and the criteria used for the study are given in Fig. 3 and Table 6.

The selected indicators were ranked in ascending order for “more is better” or descending order for “less is better” in terms of indicator values. In the case of “more is better” indicators, the indicator values were divided by the highest value in the group, so that the highest value gets a score of 1 and the remaining ones get scores based on their percentage of the highest group value, i.e. a score of $< 1$. For the indicators with “less is better” criteria, the indicator values were divided by the lowest value in the group, so that the lowest value gets a score of 1 and the remaining ones get scores based on their percentage of the lowest group value, i.e. a score of $< 1$. For “optimum is better” indicators, observations were scored as “more is better” up to the threshold value and then scored

### Table 5 Pearson correlation matrix ($R$-values and significance) for the negative indicators

|          | Vibrio | Salmonella | TC  | FC  | EC  | BOD  | TAN  | NO$_2$ | COD  |
|----------|--------|------------|-----|-----|-----|-------|-------|--------|-------|
| Vibrio   |        |            |     |     |     |       |       |        |       |
| Salmonella | 0.25   |            |     |     |     |       |       |        |       |
| TC       | -0.11  | -0.08      |     |     |     |       |       |        |       |
| FC       | -0.03  | -0.03      |     |     | 0.92*** |       |       |        |       |
| EC       | 0.08   | -0.12      |     |     | 0.62*** | 0.70*** |       |        |       |
| BOD      | 0.11   | 0.26       | -0.15 | -0.11 | -0.15 |       |       |        |       |
| TAN      | -0.06  | 0.06       | 0.21  | 0.3  | 0.44** | -0.08 |       |        |       |
| NO$_2$   | -0.15  | 0.06       | 0.03  | -0.05 | 0.08  | 0.08  | 0.04  |        |       |
| COD      | -0.05  | -0.04      | 0.18  | 0.18 | 0.2  | -0.32* | -0.11 | -0.07  |       |
| Dino     | -0.03  | 0.04       | -0.03 | -0.07 | -0.26 | 0.21  | -0.04 | -0.16 | -0.25 |

The bold entries indicate correlation coefficients of highly correlated variables

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$; negative sign denotes negative correlation
as “less is better” above that threshold. The optimum range of the indicator values is given a score of 1 (Gui et al., 2010; Liebig, et al., 2001; Singh et al., 2013; Tesfahunegn, 2014).

Development of normalized equation for estimating EHI

In the case of biological indicators, the first two principal components were considered, and the variances explained by these two principal components were 36.78 and 27.76%, respectively (Table 1). So, the weightage for the first component is 0.37, and the second component is 0.28, and the equation for the biological group becomes;

\[ \text{BIO\_Score} = 0.37 \times \text{Diatom\_Score} + 0.28 \times \text{NPP\_Score} \]

To normalize the equation, it was divided by 0.65 (0.37 + 0.28 = 0.65), and the equation becomes;

\[ \text{BIO\_Score\_N} = 0.57 \times \text{Diatom\_Score} + 0.43 \times \text{NPP\_Score} \]

For the environmental indicators, the first four principal components were considered, and they explained 24.61, 18.77, 13.84 and 10.57% of the variances, respectively (Tables 2 and 3). So, the equation for environmental indicator becomes;

\[ \text{ENV\_Score} = 0.246 \times \text{pH\_Score} + 0.246 \times \text{WT\_Score} + 0.188 \times \text{DO\_Score} + 0.138 \times \text{SAL\_Score} + 0.138 \times \text{TURB\_Score} + 0.106 \times \text{TSS\_Score} \]

To normalize the equation, it was divided by 1.062 (0.246 + 0.246 + 0.188 + 0.138 + 0.138 + 0.106 = 1.062), and the equation becomes;

\[ \text{ENV\_Score\_N} = 0.232 \times \text{pH\_Score} + 0.232 \times \text{WT\_Score} + 0.177 \times \text{DO\_Score} + 0.13 \times \text{SAL\_Score} + 0.13 \times \text{TURB\_Score} + 0.1 \times \text{TSS\_Score} \]

In the case of pollution indicators, the first four principal components were considered, and they explained 28.30, 15.28, 12.34 and 11.80% variances, respectively (Tables 4 and 5). The equation for negative indicators can be written as,

\[ \text{POL\_Score} = 0.283 \times \text{TC\_Score} + 0.153 \times \text{BOD\_Score} + 0.123 \times \text{Vib\_Score} + 0.118 \times \text{NO2\_Score} \]
To normalize the equation, it was divided by 0.677
\((0.283 + 0.153 + 0.123 + 0.118 = 0.677)\), and the equation becomes;

\[
POL_{\text{Score}_N} = 0.418 \times TC_{\text{Score}} + 0.226 \times BOD_{\text{Score}} + 0.182 \times Vib_{\text{Score}} + 0.174 \times NO_{2}\_\text{Score}
\]

The scores for biological, environmental and pollution scores were again combined to derive the ecosystem health index (EHI) in the same manner, and the weightage for the three indicator groups was considered as equal, and the equation for EHI becomes,

\[
EHI = 0.333 \times BIO_{\text{Score}_N} + 0.333 \times ENV_{\text{Score}_N} + 0.333 \times POL_{\text{Score}_N}
\]

Ecosystem health indices (EHI) are widely used for ecosystem health reporting. EHIs provide the means to summarize, assess and communicate the health of a system, including the effects on the environment from natural and anthropogenic activities (Flint et al., 2017). As it is a comprehensive rating of the ecosystem under consideration, it could be used by the policymakers and managers to take appropriate actions.

The range of BIO_Scores_N, ENV_Scores_N and POL_Score_N were 0 to 0.745, 0.362 to 0.871 and 0.174 to 1.000, respectively (Table 7). The grouping of the parameters to biological, environmental and pollution indicators could help to focus the attention to a particular group of indicators that affect the system health. This makes the task of environmental managers easy and assists them to focus their attention on the particular set of indicators, whichever can be corrected by taking appropriate interventions.

The range of EHI values derived were 0.34 to 0.81. Applying spline interpolation on the EHI values developed for the sampling sites, an EHI map of the study area was generated (Fig. 4) and classified into different EHI grades, viz. poor, fair, moderate and good. The extracted spatial extent of EHI categories (i.e. poor, fair, moderate and good) from the mapped area is given in Table 8. The total area of the aquatic ecosystem of the studied coastal Gramma Panchayath is 1152.7 ha. Out of this, 35.8% area was categorized as good, 32.2% as moderate, 26.2% fair and 5.8% area as poor based on the EHI values. The land-use types falling under each category were identified (Fig. 5). In the case of mangroves, 75% was under the fair category and 25% under the poor category. In the case of abandoned farms, there was no poor category, and all the other three categories were equally distributed. For active farms, 50% was good and poor and moderate categories covered 25% each. Estuary performed well with 35.29% in the good category and 23.53% in the moderate category. The inland waters showed poor condition with 50% under the poor category and only 16.67% under the good category. The unused water bodies also showed a similar trend with 37.5% under the poor category, 12.5% under the fair and 12.5% under the good category.

The ecosystem assessment of the present study showed that stagnant waters with impaired water flow were found to be more polluted and rated as poor category. Plastic litter was found to be a major problem affecting the ecosystem, causing clogging and creating biologically dead zones.

Such ecosystems need consistent monitoring for assessing their ecosystem health, for any time intervention as and when needed. There were successful efforts at regional scale to monitor the water quality of Vembanad Lake involving citizen scientists by observing water quality parameters such as Secchi depth, colour, temperature, pH, salinity, dissolved oxygen and total suspended matter and to provide support to selected Sustainable Development Goals in urgent situations. Making use of citizen scientists can also ensure that the regular monitoring of a system becomes less cumbersome and less expensive task (George et al., 2021; Kulk et al., 2021; Menon et al., 2021). The present investigation aimed at development of a stable and integrated tool to measure the detailed status of the natural health including seasonal influence of a coastal ecosystem for a reasonably long time, at micro-level (the extent of the water body under the present investigation is only 11.53 km²), giving due consideration to the feeder systems using multivariate approach rather than a real-time monitoring of the water quality of a comparatively more dynamic macro-level system. Involving the citizen scientists in the present kind of assessment of the environment, making use of the suggested ecosystem health index, would require imparting specific training to the citizen scientists, and they could be
utilized for regular collection of samples which could be handed over to the scientists for further laboratory analysis and interpretation. Here, the network

![Fig. 4 EHI map of the study area (Roman letters indicates the administrative ward number)](image)

**Table 7** BIO_Score_N, ENV_Score_N, POL_Score_N EHI and EHI grades of the sampled locations

| Sl. No | BIO_Score_N | ENV_Score_N | POL_Score_N | EHI   | EHI grade |
|--------|-------------|-------------|-------------|-------|-----------|
| 1      | 0.503       | 0.805       | 0.671       | 0.659 | Fair      |
| 2      | 0.677       | 0.792       | 0.963       | 0.810 | Good      |
| 3      | 0.262       | 0.848       | 0.776       | 0.628 | Fair      |
| 4      | 0.579       | 0.813       | 0.666       | 0.685 | Fair      |
| 5      | 0.611       | 0.779       | 0.461       | 0.616 | Poor      |
| 6      | 0.553       | 0.730       | 0.854       | 0.712 | Moderate  |
| 7      | 0.592       | 0.824       | 0.582       | 0.665 | Fair      |
| 8      | 0.647       | 0.702       | 0.981       | 0.776 | Good      |
| 9      | 0.460       | 0.871       | 0.820       | 0.716 | Moderate  |
| 10     | 0.549       | 0.771       | 0.420       | 0.579 | Poor      |
| 11     | 0.654       | 0.771       | 0.820       | 0.748 | Good      |
| 12     | 0.570       | 0.771       | 1.000       | 0.780 | Good      |
| 13     | 0.742       | 0.871       | 0.732       | 0.781 | Good      |
| 14     | 0.484       | 0.750       | 0.779       | 0.670 | Fair      |
| 15     | 0.564       | 0.757       | 0.818       | 0.712 | Moderate  |
| 16     | 0.570       | 0.818       | 0.752       | 0.713 | Moderate  |
| 17     | 0.574       | 0.848       | 0.774       | 0.731 | Good      |
| 18     | 0.000       | 0.791       | 0.854       | 0.548 | Poor      |
| 19     | 0.589       | 0.817       | 0.857       | 0.753 | Good      |
| 20     | 0.614       | 0.530       | 0.958       | 0.700 | Moderate  |
| 21     | 0.570       | 0.718       | 1.000       | 0.762 | Good      |
| 22     | 0.033       | 0.771       | 0.592       | 0.465 | Poor      |
| 23     | 0.570       | 0.712       | 1.000       | 0.760 | Good      |
| 24     | 0.546       | 0.716       | 0.686       | 0.649 | Fair      |
| 25     | 0.570       | 0.718       | 0.818       | 0.701 | Moderate  |
| 26     | 0.000       | 0.711       | 0.517       | 0.409 | Poor      |
| 27     | 0.508       | 0.746       | 1.000       | 0.751 | Good      |
| 28     | 0.570       | 0.554       | 0.459       | 0.527 | Poor      |
| 29     | 0.570       | 0.678       | 0.931       | 0.726 | Moderate  |
| 30     | 0.083       | 0.362       | 0.600       | 0.348 | Poor      |
| 31     | 0.026       | 0.733       | 0.511       | 0.423 | Poor      |
| 32     | 0.622       | 0.752       | 0.818       | 0.730 | Moderate  |
| 33     | 0.570       | 0.684       | 0.854       | 0.702 | Moderate  |
| 34     | 0.621       | 0.616       | 0.854       | 0.696 | Moderate  |
| 35     | 0.570       | 0.771       | 0.854       | 0.731 | Good      |
| 36     | 0.083       | 0.594       | 0.680       | 0.452 | Poor      |
| 37     | 0.579       | 0.767       | 0.659       | 0.668 | Fair      |
| 38     | 0.484       | 0.631       | 0.174       | 0.429 | Poor      |
| 39     | 0.546       | 0.791       | 0.574       | 0.636 | Fair      |
| 40     | 0.497       | 0.722       | 0.814       | 0.677 | Fair      |
| 41     | 0.554       | 0.846       | 0.356       | 0.585 | Poor      |
| 42     | 0.591       | 0.810       | 0.532       | 0.644 | Fair      |

Percentile values of EHI
25th percentile, 0.619; 50th percentile, 0.691; 75th percentile, 0.731

EHI grading
Poor: EHI < 0.619; fair: EHI 0.619–0.691; moderate: EHI 0.691–0.731
good: EHI > 0.731
would be localized so as to ensure continuous monitoring of such micro-level ecosystem for timely intervention with micro-level environment management plans implemented via participatory approach. There was such a mediation on reduction of plastic litter at source at micro-level, for restoration of degraded habitats, which were assessed using the ecosystem health index (CMFRI, 2019).

| EHI category | Area (ha) | % of the geographical area |
|--------------|----------|---------------------------|
| Poor         | 67.3     | 5.8                       |
| Fair         | 302.2    | 26.2                      |
| Moderate     | 370.7    | 32.2                      |
| Good         | 412.5    | 35.8                      |
| Total        | 1152.7   | 100.0                     |

**Fig. 5** Distribution of different categories of ecosystems. (a) Estuary, (b) active farms, (c) mangroves, (d) abandoned farms (e) inland waters and (f) unused water bodies

**Table 8** Spatial extent of different EHI categories in the study area
Conclusion

The paper presents a methodology to evaluate coastal ecosystems using water quality based on physical, chemical, biological and microbiological indicators employing standard methods. The selection of indicator parameters was based on PCA and was devoid of personal/disciplinary biases and ensures that they represent the health condition of the specific ecosystem under consideration. The use of different indicator groups, viz. BIO, ENV and POL, to derive the EHI value and the overall health grade of the location help us to easily pinpoint the indicators/indicator groups that bring down the grade of the location. This makes the task of environmental managers easy. The methodology adopted here being multivariate in nature, less biased and very flexible can be effectively replicated/adopted in other locations. The PCA-based MDS selection ensures that the indicators truly represent the system conditions and evaluate its health or the state of affairs. Involving citizen scientists with proper training for regular monitoring of ecosystem system seems to be a practical approach that could be attempted in the future efforts.

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Availability of data and material Data used in the analysis is provided along with the manuscript.

Code availability ArcGIS 10.0 licenced to the Central Marine Fisheries Research Institute for concurrent use.

Declarations

Competing interests The authors declare no competing interests.

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