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ORIGINAL PAPER

Identification of anthropogenic contribution to wetland degradation: Insights from the environmetric techniques

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Abstract

Wetlands provide various valuable ecosystem services and play a significant role in water supplies, livelihoods, and irrigation of farmlands. Keeping in view the growing pollution and anthropogenic stresses on aquatic ecosystems, we assessed pollution sources in three urban wetlands of Srinagar, India. Environmetric techniques, such as two-way Analysis of Variance (ANOVA), Hierarchical Cluster Analysis (HCA), and Principal Component Analysis (PCA) were applied to interpret the huge datasets for meaningful deliverables. The water quality (WQ) parameters were assessed at 22 different sites well distributed within the three wetlands. The WQ dataset comprises of 11,616 observations collected from January 2018 to February 2020 across 8 seasons. Two-way ANOVA grouping of variables (wetlands and seasons) showed significant ($p < 0.05$) interaction on WQ parameters such as water temperature, total hardness, calcium hardness, magnesium hardness, NH_4-N, NO_2^--N, and NO_3^--N. HCA generated 2 major (high and moderate) clusters based on the similarity of WQ characteristics. Wilk's λ distribution revealed that independent variables (transparency, electrical conductivity, total dissolved solids, salinity, and dissolved oxygen) contribute significantly to the separation of groups and consequently indicate their greater discriminant ability. PCA resulted in 4 principal components (PCs) with the 1st PC accounting for a cumulative variance of 56.9%, 2nd PC for 17.8%, 3rd PC for 7%, and fourth PC for 5.9%. Factor analysis resulting from PCs showed that the factors responsible for hyper-eutrophication of the wetlands are nutrient inputs resulting due to ingress of agricultural runoff, raw fecal matter from settlements, and partially treated effluents from sewage treatment plants (STPs).

Keywords Anchar · Brari Nambal · Khushalsar · Multivariate statistics · Srinagar · Water quality · Wetlands

1 Introduction

Urban wetlands offer a wide variety of key ecological services such as flood control, wildlife habitat, carbon storage, water purification, fisheries, livelihoods, and recreation (Dar et al. 2020a; Rashid and Aneaus 2020). The health and quality of urban wetlands reflect the characteristics of the catchment areas and land-use practices (Dar et al. 2021a). During the last few decades, organic and inorganic materials from urban areas have led to the accelerated deterioration of wetland ecosystems (Asgher et al. 2021). Contaminants such as nutrients, sediments, and total suspended solids occurring in agricultural and urban stormwater runoff constitute primary non-point sources of pollution (Ghane et al. 2016). Municipal wastewaters and industrial effluents which comprise of toxic substances are directly or indirectly disposed into wetlands and constitute the prompt point-sources of pollution (Carey and Migliaccio 2009; Zapana et al. 2020). During the past few decades, with the rapid increase in urbanization, industrialization, and human population, runoff from urban areas have amplified the input of nutrients (nitrogen and phosphorus) into lakes and wetlands resulting in cultural eutrophication of these important ecosystems (Romshoo and Rashid 2014; Dar et al. 2020b). Nevertheless, nutrient enrichment stimulates the growth

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and development of algae and other plants, which eventually creates impairment, degradation of WQ, and pollution of wetland ecosystems (Rashid and Aneaus 2019). This may additionally lead to adverse impacts on aquatic biodiversity, toxicity to humans, and unpleasant odors (El-Sheikh et al. 2010). Moreover, the unplanned urbanization of the world's cities has made them prone to hydro-meterological hazards such as heat waves and urban floods (Depietri et al. 2012). Under this growing threat, many urban wetlands have vanished with global environmental apprehensions (Mao et al. 2018).

Srinagar City in Kashmir Himalaya has undergone the phenomenon of rapid urban development and expansion, resulting in the degradation and pollution of wetland ecosystems (Dar et al. 2020a). Large scale land use land cover changes (LULCCs) has led to the degradation of WQ in numerous ways (Bhat et al. 2021). The increasing pressures coming from the human population growth and shortage of residential space has led to encroachments, over-exploitation, and shrinkage of wetland areas (Kuchay and Bhat 2014). The increase in built-up was largely observed due to the conversion of water bodies in Srinagar City (Chettry and Surawar 2021). This has disrupted the natural hydrobiological setup of the City making it prone to flooding (Romshoo et al. 2017). Though there are numerous lakes and wetlands in Kashmir Himalaya, most of the conservation efforts and scientific investigations in the region have centered around Dal, Manasbal, and Wular Lake (Dar et al. 2021b). Although all the water bodies are subject to rampant anthropogenic pressures, other water bodies like Anchar, Brari Nambal, and Khushalsar have received little attention for their conservation and management even though they are likewise under high stress due to human induced hyper-eutrophication (Dar et al. 2021a). Continuous monitoring of wetland ecosystems helps in developing strategies for conservation, restoration, and management of wetland ecosystems.

Surface WQ monitoring generates huge datasets that are often difficult to evaluate for meaningful explanation and understanding. Therefore the datasets need statistical treatment for simplifying and extraction of the data-structure for easy interpretation to develop management and restoration strategies. Various statistical methods have been developed and used to interpret information about the WQ parameters (Bhat et al. 2014). The application of various stochastic environmental techniques such as ANOVA, HCA, and PCA, aid in the understanding of multifaceted datasets to better understand the WQ of wetlands (Anuttarunggoon et al. 2020). Against this backdrop, the present study is aimed to evaluate the WQ characteristics and identify pollution sources of 3 urban wetlands in the Srinagar City of Kashmir Himalaya. The datasets generated is subjected to multivariate statistical treatment for interpreting huge datasets, identification of pollution sources, and categorization of the wetlands based on pollution status.

2 Materials and methods

2.1 Study area

Srinagar City, located between geographical coordinates 33°59′44″–34°12′45″ N latitudes and 74°40′50″–74°57′39″ E longitudes with the altitude extremes from 1560–1880 m asl, is a major and fast-growing urban centre in the Kashmir Valley (Fig. 1). The City is mostly plain, however there are conspicuous physiographic variations due to the presence of few isolated hills like *Shankaracharya, Hari Parbat,* and *Zabarwan* mountain range on the eastern side and alluvial tracts (Zahoor et al. 2019). The City has a mediterranean/temperate type of climate, with warm summers and cold winters (Rashid et al. 2019). The average temperature varies from 33 °C in July to about − 4 °C in January. The average annual precipitation in the Srinagar district is 730 mm, and the maximum rainfall of 220 mm is experienced in the spring season (Guhathakurta et al. 2020). Snowfall generally occurs from December to February (Rashid et al. 2020). The spring and summer seasons are characterized by peak streamflows largely associated with snow melt and lesser extent with rainfall. The main geological formations of the City comprise of Karewas and Paleozoic sedimentaries and volcanics (Bhat and Shaban 2017). These formations are overlain by Alluvial deposits (sandy clay, gravel, sand, and silt), Triassic formations (limestone, crumbling shales), Zewan series (cherts and shales), Gangamopteris beds (shales, limestone, and cherts), Panjal traps (andesite, basalt), and Agglomeratic slates (sandstone, shales, and slates). The recent Alluvium is found in the low-lying areas adjoining the rivers (Jhelum), lakes, and wetlands and it mostly consists of finely compacted detrital sediments such as clay, loam, sand, and silt. Presence of waterbodies in the City creates a depositional environment. The superficial soils in the City are thus younger sediments deposited from the streams and rivers, and sediments brought down by the gravity from hills and mountains (Chandra et al. 2018). Hence, there are mostly loose, unconsolidated fluvial sediments around the water bodies. The City has a fascinating hydrological connectivity/setup. The waterbodies (lakes, wetlands, and rivers) in the City are connected and were originally depressions formed during the formation of the Kashmir valley filled with water in the past history (Romshoo et al. 2020). River Jhelum flows through the middle of the City for about 29 kms from the south-east (Pampore) to the north-west (Panzinara) direction. Jhelum

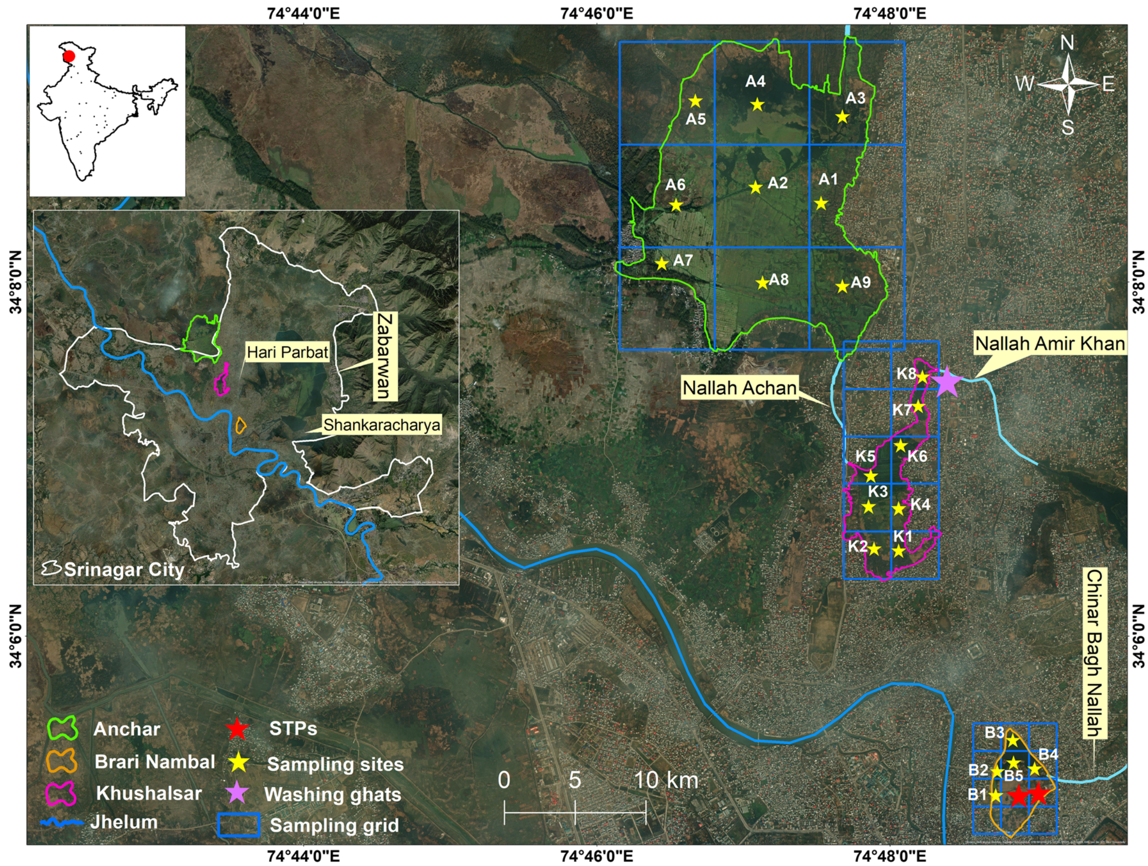

Fig. 1 Location of the study area and spatial distribution of 22 WQ sampling sites in Srinagar City

is the main river to which other lakes, streams, and wetlands are connected, discharging their water into it. The City has a population of 12.2 lakh which is projected to increase to 36 lakh by the year 2051 (Census 2011). Three prominent wetlands Anchar, Brari Nambal, and Khushalsar in the heart of Srinagar City were selected for carrying out this work (Fig. 1, Table 1). These freshwater wetlands are ecologically and socio-economically important ecosystems being source of the fisheries, irrigation, recreation, and agriculture but have been transformed greatly because of urbanization and increasing anthropogenic pressures in the catchment areas during the last few decades.

2.2 Sampling and analysis

To characterize the WQ status of the wetlands, sampling of water samples was carried out from 22 sites (Fig. 1) during eight seasons from January 2018 to February 2020. On-site measurements of WQ variables such as water temperature (WT), pH, electrical conductivity (Cond), total dissolved solids (TDS), and salinity were performed using a handheld multi-parameter probe (PCS Testr 35). The depth of the water column was measured by a graduated rod and transparency (Trans) was measured using Secchi disc. Dissolved oxygen (DO), total alkalinity (TA), total hardness (TH), calcium hardness (CH), magnesium hardness (MH), chloride (Cl^-), ammoniacal nitrogen (NH_3-N), nitrite nitrogen (NO_2^--N), nitrate nitrogen (NO_3^--N), phosphate phosphorus (OP), total phosphorus (TP), and chlorophyll-a (Chl) were assessed based on laboratory analysis following standard protocols of the American Public Health Association (Baird et al. 2017). To achieve valid conclusions about the WQ and pollution sources, quality control and quality assurance (QC/QA) guidelines were followed strictly in the field and laboratory. Proper procedures have been followed during sample collection, transportation, and experimental analysis. Before the collection of water samples, the sampling bottles were pre-cleaned and rinsed thoroughly with Millipore water. In order to achieve higher accuracy and precision, WQ parameters were analyzed in triplicates, and average values were used in final calculations. Blanks were prepared using Millipore water to ensure the QC with standard deviation $< 5\%$. The standards of known concentration were prepared using the analytical grade reagents following the standard procedures (Baird et al. 2017).

Table 1 Physical characteristics of wetlands under investigation

Parameter	Anchar	Brari Nambal	Khushalsar
Latitude	34°07′22.80″–34°09′23.5″ N	34°04′50.54″–34°05′30.30″ N	34°06′19.25″–34°07′34.00″ N
Longitude	74°46′13.87″–74°47′56.39″ E	74°48′40.31″–74°49′07.52″ E	74°47′40.50″–74°48′17.52″ E
Altitude (m)	1583	1586	1579
Area (ha)	690	43.7	109.8
Maximum length (m)	3926	1258	1381
Maximum width (m)	3261	760	624

2.3 Two-way analysis of variance (ANOVA)

Two-Way ANOVA was employed to evaluate the effect of two grouping variables (Wetlands and Seasons) on a continuous variable (WQ variables). ANOVA test was employed to compare the means of groups and to investigate the differences in means. All possible pairwise comparisons were carried out using a Bonferroni adjustment. The packages employed for two-way ANOVA included "tidyverse", "ggpubr" and "rstatix" (R Core Team 2013).

2.4 Hierarchical clustering analysis (HCA) and silhouette analysis (SA)

Cluster analysis has been adapted as an important statistical tool to identify the associations among sites and water chemistry in order to clearly explain the natural and anthropogenic activities responsible for WQ change (Osei et al. 2010; Tokatli et al. 2014). Spatial variability in WQ characteristics was determined via HCA. Ward's method which uses ANOVA, was applied as grouping function and squared Euclidean procedures as distance matrix (McKenna 2003). HCA was performed on the whole dataset from the 8 seasons.

$$SS(k) = \sum_{i=1}^{n} \sum_{i=n}^{r} \left(x_{ij} - \overline{x}_{kj}\right)^2 \quad (1)$$

where k is the cluster, x_{ij} is the value of the jth variable for the jth observation, and $\overline{x}$ is the mean of the jth variable for the kth cluster.

SA was performed to validate the correctness of clusters (similar spatial areas) and an optimal number of clusters to be retained delineated by HCA (Charrad et al. 2014). The analysis displays that to what extent the planes separating the clusters can be distinguished through a predictive build model for group membership (Raykoy et al. 2016). To perform cluster analysis in R, packages "tidyverse", "cluster" and "factoextra" were used.

2.5 Distribution of Wilk's λ quotient

After the confirmation of the clusters, the effect of every WQ variable in the development of a cluster was determined using Wilk's λ distribution (Wilks 1932). Its value lies between 0 and 1. The smaller the quotient the more it determines the cluster formation (Hatvani et al. 2014).

$$\lambda = \frac{\sum_i \sum_j \left(x_{ij} - \overline{x_i}\right)^2}{\sum_i \sum_j \left(x_{ij} - \overline{x}\right)^2} \quad (2)$$

where x_{ij} is the jth element of the ith cluster, $\overline{x_i}$ the ith cluster's mean and $\overline{x}$ the total mean. The value of λ is the within-cluster sum of squares to the total sum of squares ratio.

2.6 Principal component analysis (PCA)/factor ANALYSIS (FA)

Before PCA analysis, datasets were tested using Kaiser–Meyer–Olkin (KMO) and Bartlett's sphericity test, to check the appropriateness of data for FA (Rezaee and Jafari 2015). Both the KMO (0.723) and Bartlett's sphericity result (1364) at $p < 0.05$, showed that the dataset is appropriate for FA and PCA (Lo et al. 2012). PCA is used to lessen the dimensionality of a datasets comprising of a huge number of interconnected variables, and this decrease is accomplished by converting the datasets into a new set of variables—the principal components (PCs), which are orthogonal (non-correlated) and are arranged in decreasing order of importance (Dar et al. 2021a).

The PC function is represented as

$$z_{ij} = a_{i1}x_{1j} + a_{i2}x_{2j} + \ldots + a_{im}x_{mj} \quad (3)$$

where z is the component score, a the component loading, x the measured value of parameter, i the component number, j the sample number and m the total number of parameters.

FA based on PCA was employed to interpret underlying dataset and to identify possible sources of contamination.

An eigenvalue greater than 1 considered significant was taken as the criterion for evaluation of PCs required to explain the variance in the data (Hamil et al. 2018). HCA and PCA were applied out on Z-scale transformed dataset to avoid miscalculation due to large differences in data scales and magnitudes and Wilk's lambda quotient was derived from the original data (Liu et al. 2021). PCs are represented as Dim. on graphs. Two packages "factominer" and "factoextra" were used for PCA analysis in R (Abdi and Lynne 2010; Husson et al. 2017).

3 Results and discussion

3.1 WQ and two-way ANOVA

The descriptive statistics of WQ parameters recorded from 22 test sites of the three wetlands are presented in Table 2. The two-way ANOVA identified the importance of the interactive effect of seasons and wetlands on WQ parameters. Significant ($p < 0.05$) effects of wetlands and seasons was observed on WT (F (6, 76) = 11.65, $p = < 0.0001$) (Fig. 2a). The higher water temperature in summer season and lower water temperature in the winter season are in accordance with the ambient air temperature of the Kashmir valley (Shah et al. 2017). The pH values recorded were within the recommended range of 6.5–8.5 for drinking purposes set by WHO except for the Anchar wetland where the pH value ranged upto 8.8. pH recorded being in alkaline range indicates well buffering capacity of the waters (Khanday et al. 2018). The high concentration of Cond, TDS, and salinity is an indication of high dissolved salts and nutrient inputs to wetlands (Najar and Khan 2012). Statistically no significant interaction between wetlands and seasons was observed for pH (F (6,76) = 2.18, $p = 0.054$) (Fig. 2b), Cond (F (6, 76) = 0.25, $p = 0.96$) (Fig. 2c), TDS (F (6, 76) = 0.66, $p = 0.68$) (Fig. 2d), and salinity (F (6, 76) = 1.53, $p = 0.18$) (Fig. 2e). Transparency values ranging from 12 cm in Khushalsar to 167 cm in Anchar, indicate that the wetlands belong to the hyper-eutrophic category (OECD 1982). The low depth of wetlands also indicates the higher trophic status of the wetlands (Liu et al. 2010). Overall the low DO content in the wetland waters indicates the high rates of decomposition of organic matter throughout the seasons (Dar et al. 2021c,d). The values of total alkalinity indicate that the waters of the wetlands are well buffered (Parvez and Bhat 2014). ANOVA revealed that an insignificant interaction between wetlands and seasons was observed for transparency (F (6,76) = 0.65, $p = 0.69$)

Table 2 Descriptive statistics of physico-chemical parameters of wetland water samples from January 2018 to February 2020

Parameters	Anchar				Brari Nambal				Khushalsar			
	Min	Max	Avg	Std	Min	Max	Avg	Std	Min	Max	Avg	Std
WT (°C)	5	25	14.8	6.5	7.8	25	16	5.7	7.5	23.5	16	5.7
pH	7	8.8	7.7	0.5	7.2	8.3	7.6	0.4	6.7	8.3	7.5	0.4
Cond (µS cm^{-1})	160	946	446	118	320	1600	524	242	311	1034	637	227
TDS (mg L^{-1})	178	639	317	72	228	1040	352	137	210	729	454	163
Salinity (mg L^{-1})	73	309	196	45	122	510	234	98	116	445	275	102
Trans (cm)	20	167	77.6	26	13	125	69	27	12	127	59	30
Depth (cm)	43	246	98	37	21	174	105	38	51	427	133	66
DO (mg L^{-1})	0	5.6	2.2	1.2	0	3.6	1	0.8	0	4.2	1.1	1
FC (mg L^{-1})	4.7	27.4	11	4.3	5.3	24.6	12	5	1.7	33.4	9	6
TA (mg L^{-1})	80	268	166	41	96	268	168	39	52	336	163	72
TH (mg L^{-1})	90	260	182	40	114	328	219	53	92	304	205	59
CH (mg L^{-1})	63	166	118	26	84	198	141	33	52.5	197.4	120	32
MH (mg L^{-1})	23	101	64	19	22	154	77	26	23	130	84	31
Cl^- (mg L^{-1})	2	38	19	6.5	8	64	24	12	6	72	32	19
NH_3-N (µg L^{-1})	73	985	527	235	212	1268	765	269	58	1334	545	354
NO_2-N (µg L^{-1})	10	67	31	17	13	66	31	31	14	241.4	70	49
NO_3-N (µg L^{-1})	146	837	371	165	211.5	620	352	90	210	727	459	137
TKN (mg L^{-1})	1.1	5	2.4	0.9	1.1	4.5	2.6	2.6	0.6	5	2.6	1
TN (mg L^{-1})	1.3	5.6	2.8	0.9	1.4	5	3	3	1	5.7	3	1
OP (µg L^{-1})	138	656	339	127	219	1261	428	428	221	1049	557	219
TP (µg L^{-1})	518	1945	1016	246	956	2610	1468	1468	725	2491	1351	413
Chl (mg m^{-3})	5.3	54	22	13	12.4	52	29	29	7	54	22	13

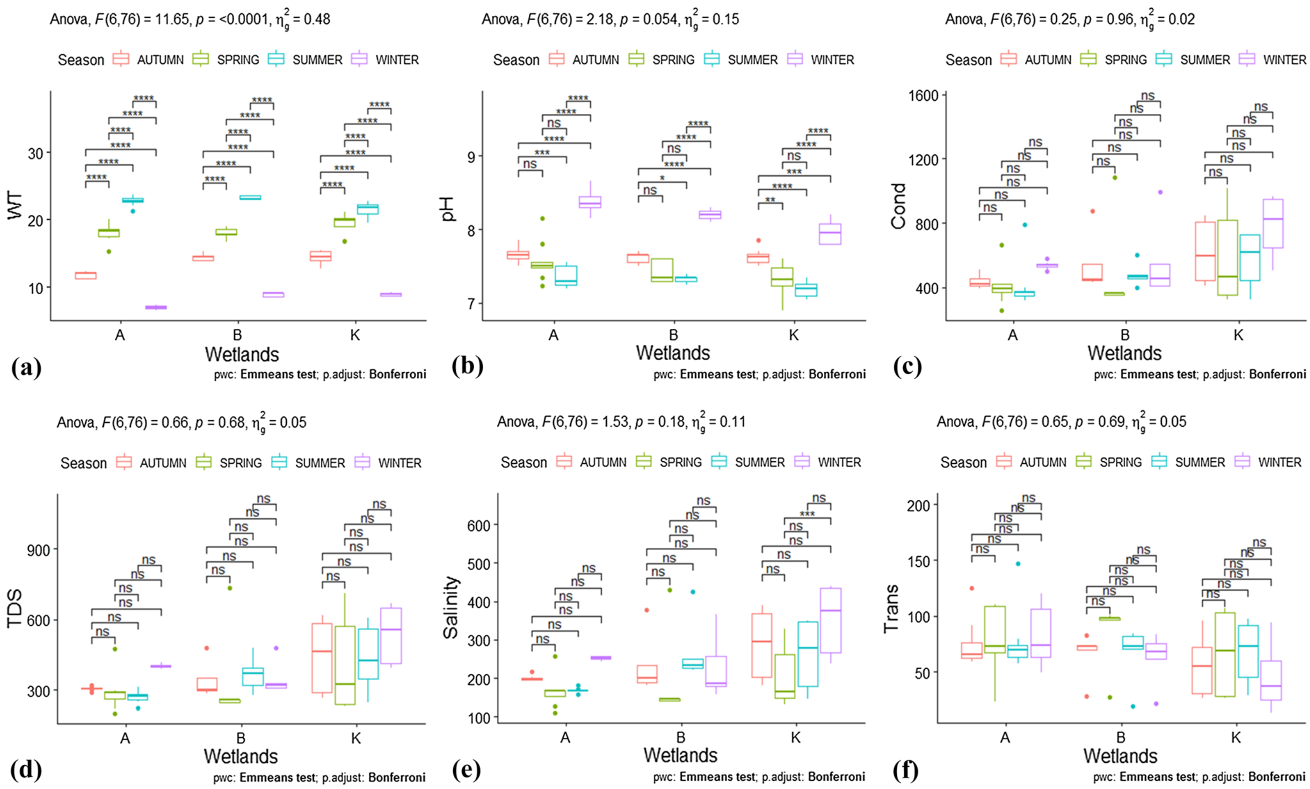

Fig. 2 ANOVA **a** water temperature, **b** pH, **c** electrical conductivity, **d** total dissolved solids, **e** salinity, and **f** transparency

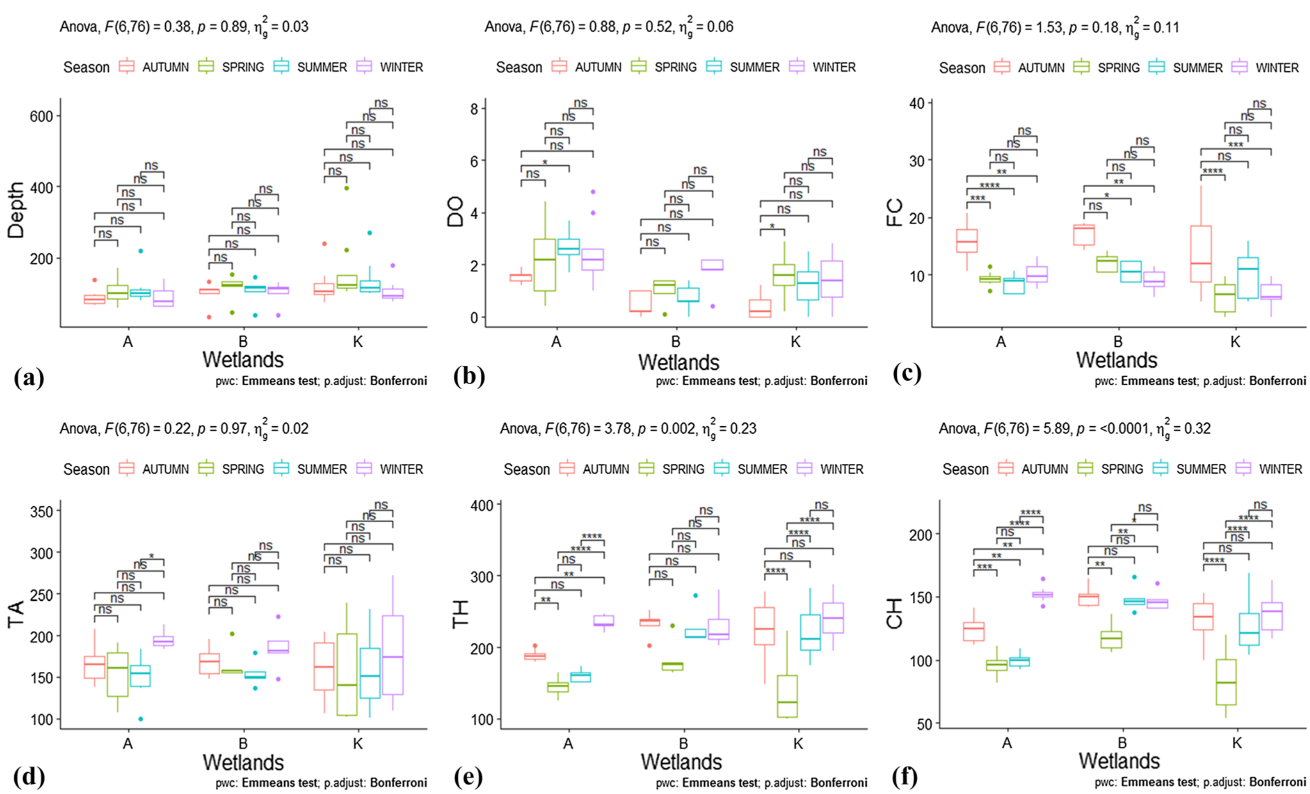

Fig. 3 ANOVA **a** depth, **b** dissolved oxygen, **c** free carbon dioxide, **d** total alkalinity, **e** total hardness, and **f** calcium hardness

(Fig. 2f), depth (F (6,76) = 0.38, $p = 0.89$) (Fig. 3a), DO (F (6, 76) = 0.88, $p = 0.52$) (Fig. 3b), FC (F (6, 76) = 1.53 $p = 0.18$) (Fig. 3c), and TA (F (6, 76) = 0.22, $p = 0.97$) (Fig. 3d). The wetlands were having moderately to very hard waters (Sawyer and McCarthy 1967). Statistically significant interaction between wetlands and seasons was observed for TH (F (6, 76) = 3.78, $p = 0.002$) (Fig. 3e), CH (F (6, 76) = 5.89, $p = < 0.0001$) (Fig. 3f), and MH (F (6, 76) = 8.38, $p = 0.0001$) (Fig. 4a), however no significant interaction between wetlands and seasons was observed for Cl^- (F (6, 76) = 0.16, $p = 0.99$) (Fig. 4b). There was a statistically significant variation in mean NH_3-N (F (6, 76) = 2.25, $p = 0.026$) (Fig. 4c), NO_2^--N (F (6, 76) = 2.4, $p = 0.035$) (Fig. 4d), and NO_3^--N (F (6, 76) = 4.1, $p = 0.001$) (Fig. 4e). However, no significant interaction between wetlands and seasons was observed on TKN (F (6, 76) = 1.11, $p = 0.37$) (Fig. 4f), TN (F (6, 76) = 1.49, $p = 0.19$) (Fig. 5a), OP (F (6, 76) = 1.52, $p = 0.18$) (Fig. 5b), TP (F (6, 76) = 1.93, $p = 0.086$) (Fig. 5c), and Chl (F (6, 76) = 1.57, $p = 0.17$) (Fig. 5d). The main sources of nitrogen and phosphorus loadings in the wetlands are the domestic wastewaters and sewage effluents. The increased concentrations of nitrogen and phosphorus results in enhanced productivity and accelerated eutrophication of these systems (Pandit and Yousuf 2002; Parvez and Bhat 2012). Besides, the high chlorophyll content is also related to the increased nutrient inputs, resulting in phytoplankton blooms (Nissa and Bhat 2016).

3.2 Cluster analysis

Hopkin's statistics with a value 0.74 indicated that the data is highly clusterable. Cluster analysis generated two assemblages of sites based on WQ characteristics of physio-chemical parameters (Fig. 6a, b). Cluster 1 comprises sites A1, B3, B5, B2, B4, A3, A4, A9, A5, A6, A2, A7, A8, K5, K6, K7, and K8 categorized as moderately polluted sites. These sites are characterized by comparatively high pH, DO, and Transparency. The Cluster 1 sites receive pollutants mostly from agriculture diffuse source and catchment runoff. Cluster 2 comprises sites K1, K2, K3, K4, and B1 categorized as highly polluted sites and receive pollutants from direct drains, urban wastewater, municipal sewage discharge, and slaughterhouses. The unique grouping of the environmental settings such as the direct disposal of sewage through point sources for Cluster 2 sites is accountable for high ionic and nutrient levels, lower DO, and transparency as detected in the study. The untreated raw wastewater and sewage are recognized to hold high levels of total phosphorus, total Kjeldahl nitrogen, total nitrogen, ammoniacal-nitrogen, total dissolved solids, and low dissolved oxygen (Van Puijenbroek 2019).

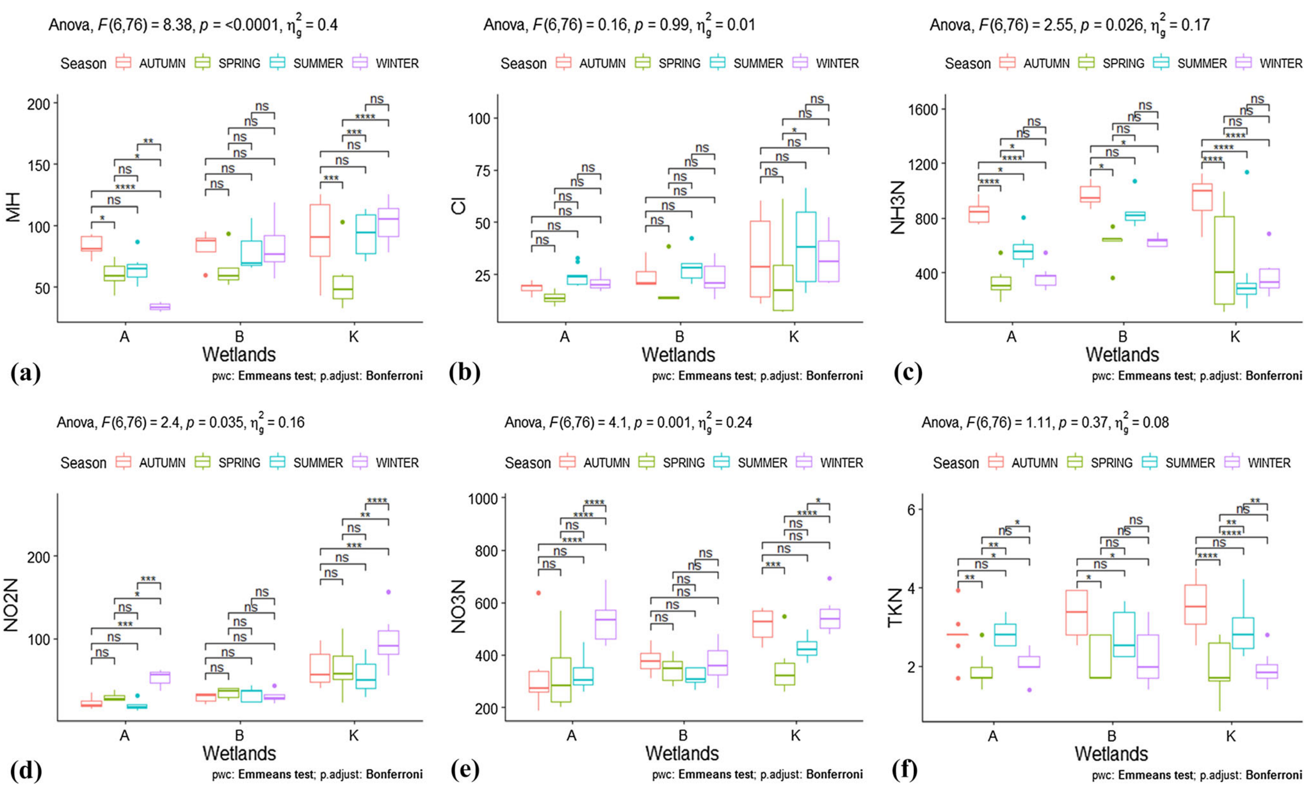

Fig. 4 ANOVA **a** magnesium hardness, **b** chloride, **c** ammoniacal nitrogen, **d** nitrite nitrogen, **e** nitrate, and **f** total Kjeldahl nitrogen

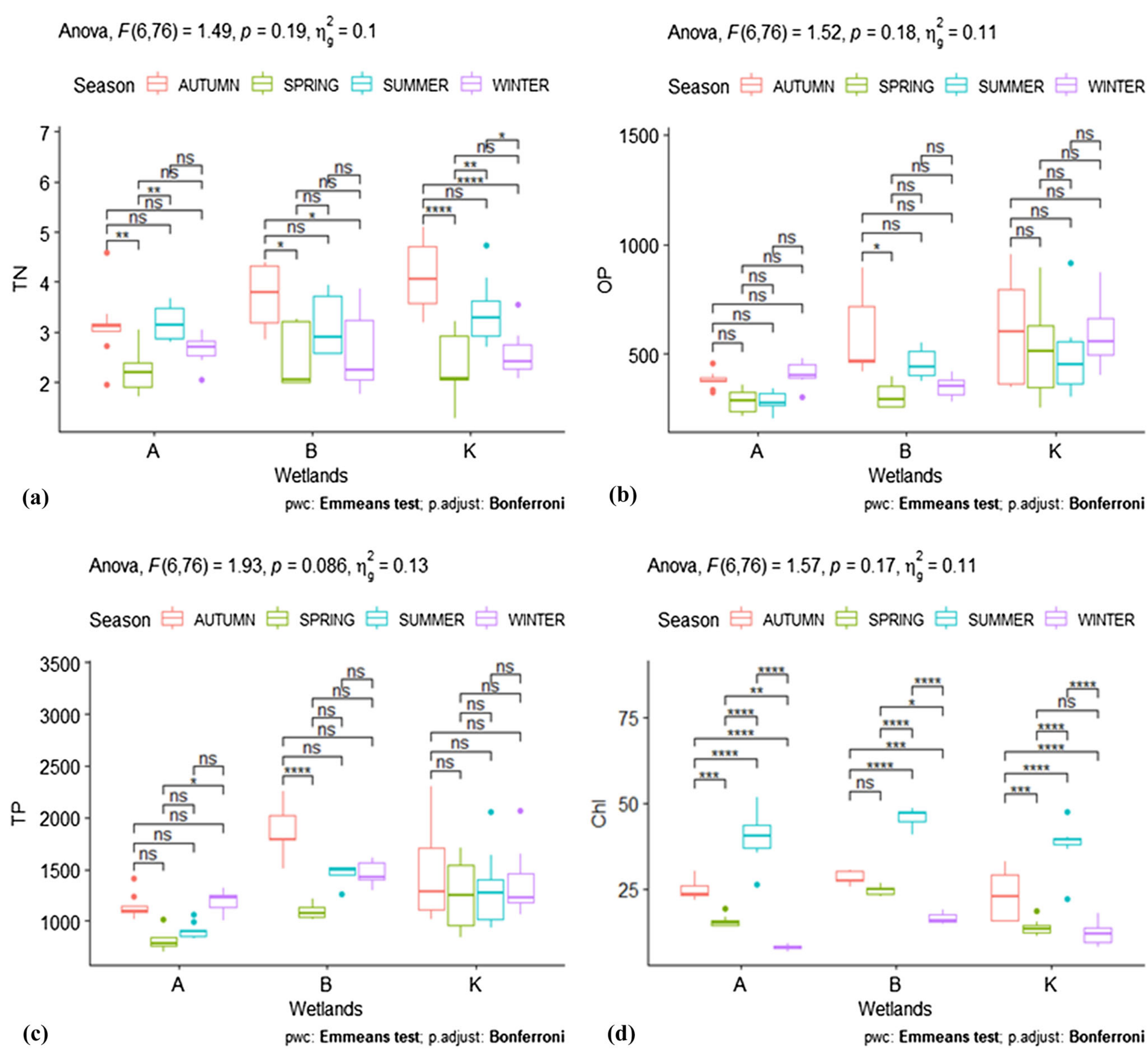

Fig. 5 ANOVA **a** total nitrogen, **b** orthophosphate phosphorus, **c** total phosphorus, and **d** chlorophyll-a

Anthropogenic activities (agricultural runoff, land use changes, and sewage disposal,) and natural processes (erosion and weathering of rocks and minerals) deteriorate surface WQ and render it unfit for drinking, irrigation, and industrial uses (Li et al. 2009). In the present study, the clustered groups correspond well with the background features and the WQ characteristics that are affected by different contaminants and pollutants the various sites are exposed to, as also opined by Najar and Khan (2012). Our analysis highlighted the usefulness of cluster analysis in the water quality evaluation besides helping draw key insights into the spatiotemporal variations and pollution sources (Bonansea et al. 2015; Hong et al. 2020).

3.3 Silhouette analysis and cluster validation

The average silhouette method measures the quality and specifies the number of clusters to use (Islam et al. 2021). The validation of the clusters was done using the cluster plot (Fig. 6c, d) which indicated that the cluster groups are well clustered. The results show that 2 clusters maximize the value of the average silhouette method. The cluster plot PC1 explained 56.9% variation and PC2 explained 17.8% variation in the dataset.

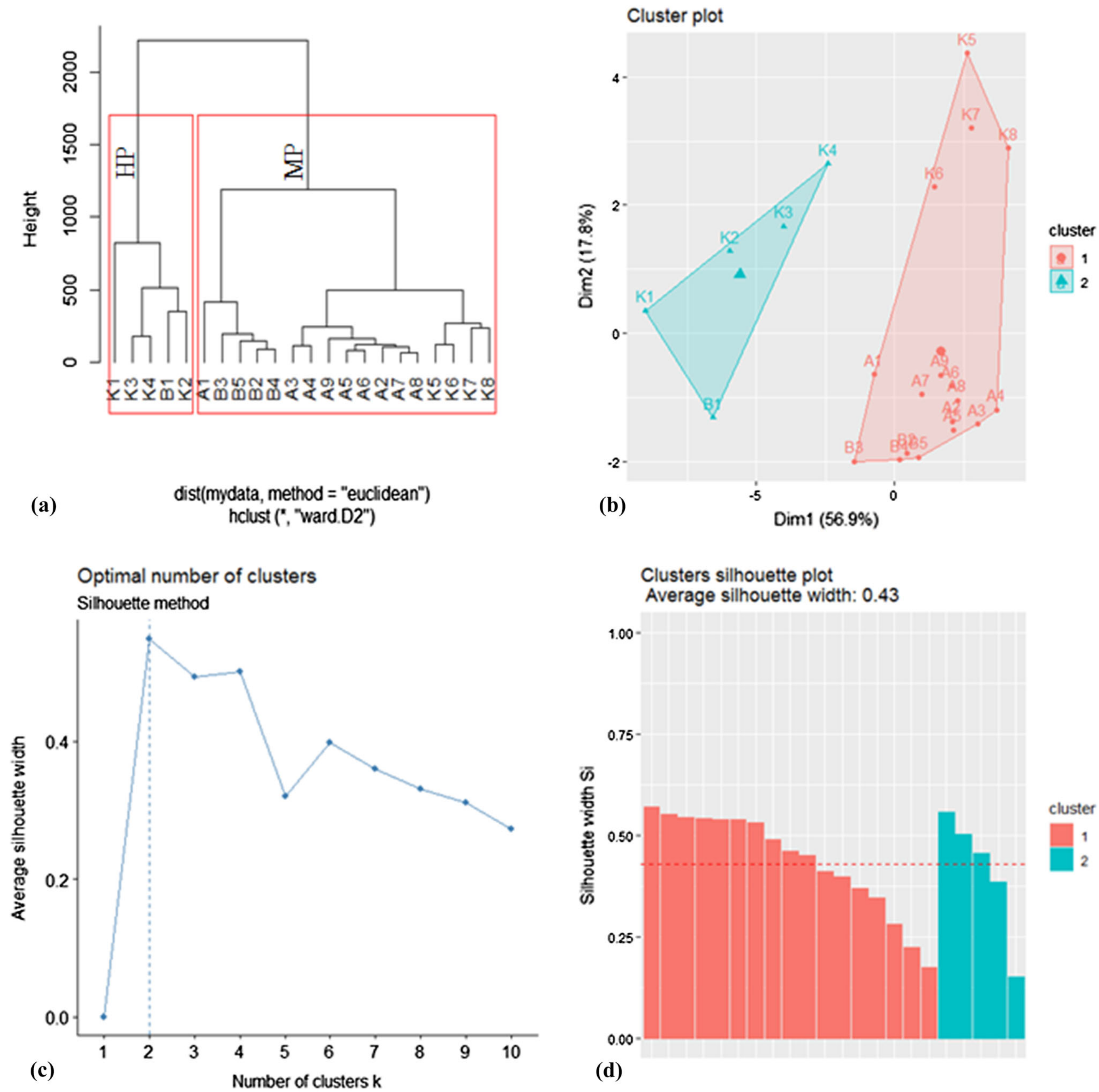

Fig. 6 Dendrogram of cluster analysis showing the grouping of sites based on surface WQ characteristics

3.4 Wilk's Lambda distribution

The lower Wilk's λ quotient values were shown by transparency (0.286), Cond (0.111), TDS (0.084), Salinity (0.112), DO (0.54), TA (0.576), TH (0.361), CH (0.655), MH (0.255), Cl (0.151), OP (0.232), and TP (0.461) (Table 3). Wilk's λ distribution displayed the dominant role of ionic variables: Cond, TDS, Salinity, TA, TH, and nutrients (OP and TP) in cluster formation. This indicates that the waters of the wetlands under investigation in addition to being hard and well buffered face substantial human pressures in the form of sewage, raw fecal matter, and slaughterhouse wastes.

3.5 PCA/FA

The PCA of the entire dataset yielded four PCs which explained 87.6% of the total variance (Fig. 7a, b, c, d). The PC1, explaining 56.9% of the total variance, with strong positive loading on Salinity, Cond, TDS, FC, TA, TH, CH, MH, Cl^-, NH_3^--N, TKN, TN, OP, and TP and strong negative loadings from DO and transparency, suggesting

Table 3 Wilk's λ statistics for water quality parameters

Parameters	Wilks' Lambda	F	Sig.
WT	0.99	0.207	0.654
pH	0.644	11.069	0.003
Cond	0.111	160.919	0.000
TDS	0.084	217.416	0.000
Salinity	0.112	159.233	0.000
Trans	0.286	49.959	0.000
Depth	0.921	1.714	0.205
DO	0.54	17.014	0.001
FC	0.794	5.174	0.034
TA	0.576	14.706	0.001
TH	0.361	35.376	0.000
CH	0.655	10.551	0.004
MH	0.255	58.504	0.000
Cl	0.151	112.171	0.000
NH_3-N	0.748	6.747	0.017
NO_2-N	0.914	1.875	0.186
NO_3-N	0.883	2.658	0.119
TKN	0.692	8.889	0.007
TN	0.655	10.557	0.004
OP	0.232	66.245	0.000
TP	0.461	23.367	0.000
Chl	0.958	0.874	0.361

the main variables driving the separation of sites. The factor loadings on PC1 indicate that water mainly includes substances that decrease the oxygen-level and transparency, which may be related to erosion from the catchment and high plankton load (Gerasimova and Pogozhev 2010), urban wastewater, agricultural diffuse sources, and municipal sewage discharges (Liu et al. 2021). The PC2 explaining 17.8% of the total variance, with strong positive loadings from NO_2^--N and NO_3^--N and negative loading from pH, Chl, and FC. The factor loadings on PC2 indicate nitrate and nitrite pollution mainly arouse from domestic sewage and agriculture runoff from the catchment (Duan et al. 2016), and natural interactive effect between pH, Chl, and FC (Abinandan and Shanthakumar 2016). The PC3 accounted for 7% of the total variance with strong positive loadings from WT and moderate negative loading from TKN and TN. The WT of a water body is mainly determined by the seasonal factor and negative loading of TKN and TN indicates the effect of wastewater from slaughterhouses (Alayu and Yirgu 2018). The PC4 explained 5.9% of the total variance with moderate positive loadings from Depth and Chl. The factor loadings on PC4, displays the seasonal variation in water depth (Dai et al. 2019) and chlorophyll production (Perry et al. 2008). PCA biplot indicated clear separation of sites into moderately and highly polluted sites. The cluster wise PCA with variable loadings and % variance for the first four components derived for the three wetlands are given in Table 4. The results obtained from cluster wise PCA were in consonance with the PCA of the entire dataset of three wetlands. The first PCs explained 31.8% and 66.3% of the total variance, with strong positive loading from pH, EC, TDS, Salinity, FC, TA, TH, CH, MH, Cl^-, NH_3-N, TKN, TN, TP, Chl, and strong negative loadings from transparency, DO, NO_2^--N, and NO_3^--N. The second PCs accounts for 23.4 and 19.89% of the total variance with positive loadings from WT, Depth, EC, TDS, Salinity, MH, Cl^-, NO_3^--N, and OP. The third PCs accounts 14.6% and 7.7% of variance with strong negative loadings from TKN, and TN. The fourth PCs accounting for 13.6% and 5.9% of variance with strong positive loadings from WT and strong negative loadings from transparency and Depth. Multivariate statistical methods, such as PCA/FA, allowed better understanding of WQ status of wetlands under study, without losing the useful information (Alberto et al. 2001). PCA/FA analysis provides information about the seasonal variation in WQ and identification of potential sources (Shrestha et al. 2008). The surface WQ of wetlands is influenced by the seasonal variation of climatic factors (insolation, temperature, precipitation inputs, erosion, and weathering of rocks, and minerals) and anthropogenic activities (urban, and industrial activities) (Papatheodorou et al. 2006). Spatial variation in the WQ is also induced by the landscape characteristics including land system dynamics (Drewry et al. 2006). The results obtained from the PCA/FA indicated that most of the variation in WQ of the studied wetlands are mainly due to nutrients and organic contaminants. A significant contribution came from the group of ions (erosion and weathering), depth, and transparency. The fluctuations in the concentration of ions and nutrients are mainly due to seasonal variation in climatic factors controlling depth and other hydrological properties of the wetlands under investigation. Thus, the study exemplifies the beneficial application of environmetric techniques for the analysis and understanding of wetland WQ data, identification of pollution sources, and their classification on the basis of pollution status as part of the efforts towards sustainable management of these ecosystems.

4 Strategies for prevention and control of wetland pollution

This analysis reveals that the domestic and municipal sewage, agricultural runoff, and the changes in land cover of the wetland catchments are the main causal factors

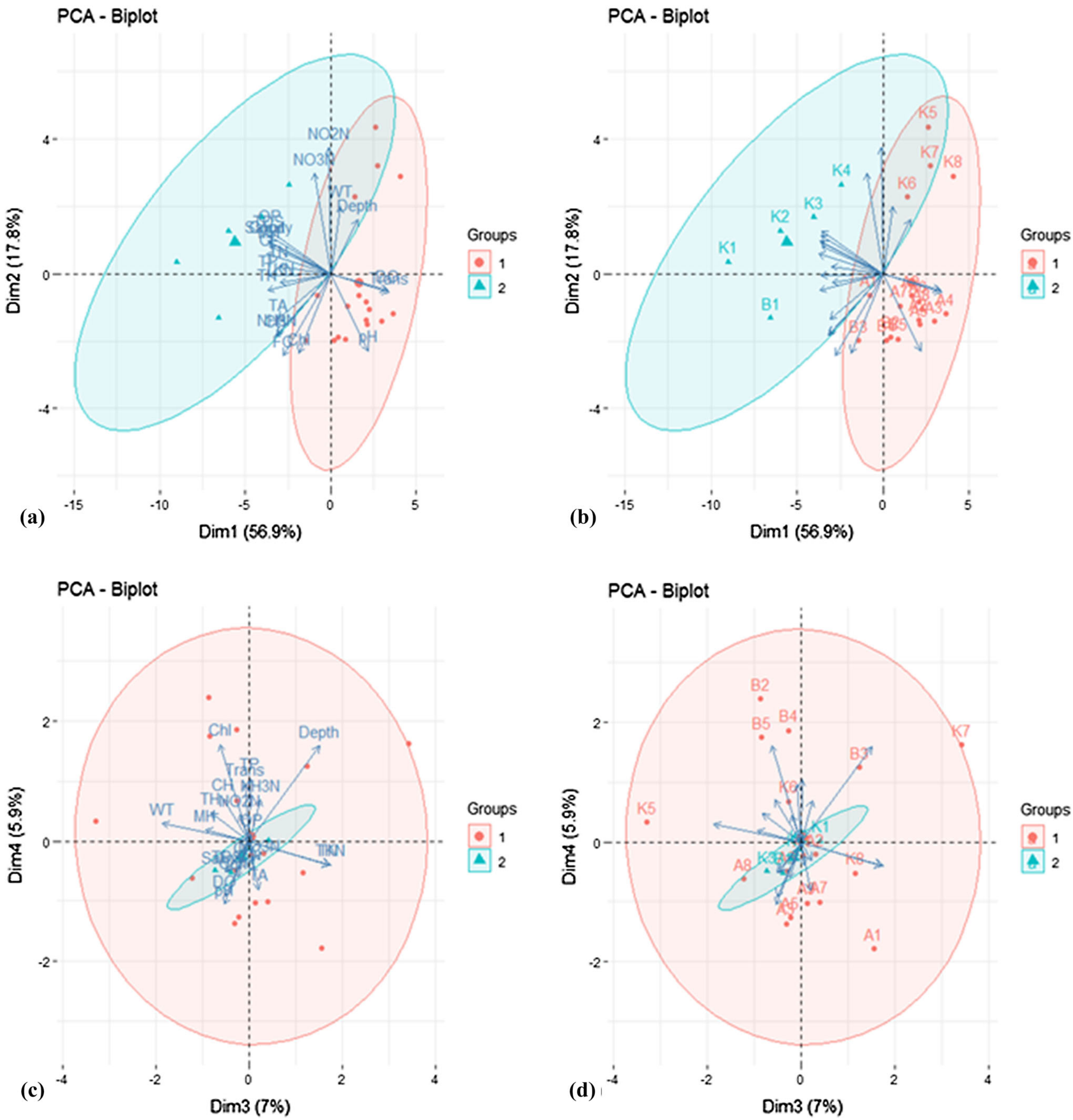

Fig. 7 Biplots for principal component analysis (**a**, **b**) PC1 and PC2 with variables and sites, and (**c**, **d**) PC3 and PC4 with variables and sites

responsible for the degradation of WQ of wetlands in Srinagar City. In order to ensure sustained ecosystem goods and services from these wetlands, it is imperative to adapt relevant management strategies like installation of more robust and efficient STPs to prevent ingress of untreated sewage in the wetlands. In this direction, an efficient sewerage system integrated with robust STPs for the management of stormwater runoff is also essential for pollution control. Setting up of sediment settling basins at inlet points of wetlands is paramount to reduce the silt load, sediments, and other eroded materials. Given the fact that the natural channels have been landfilled or got choked (Rashid and Aneaus 2020), it is suggested that extensive dredging of the choked channels should be carried out. Buffer zones need to be created for maintaining the WQ and wetland habitat, this will help in moderating the impacts of altered hydrological regimes. Reinforced cement boundaries or iron fencing need to be raised around

Table 4 Factor loadings values and explained variance of water quality parameters of three wetlands

Parameters	Cluster 1				Cluster 2			
	PC 1	PC 2	PC 3	PC 4	PC 1	PC 2	PC 3	PC 4
WT	− 0.33523	0.64654	0.50233	0.031696	− 0.25818	− 0.49023	0.11328	0.82473
pH	0.10571	− 0.60258	0.39304	0.47283	0.7094	− 0.52231	− 0.41765	− 0.22253
Cond	0.24125	0.72269	− 0.020254	0.51544	0.93476	-0.13838	0.32247	− 0.055592
TDS	0.03196	0.7379	0.39418	0.45012	0.66981	0.59502	0.41054	0.16959
Salinity	0.070995	0.79624	0.29225	0.38907	0.84298	− 0.35627	0.402	− 0.029368
Trans	− 0.35681	− 0.29	0.2542	− 0.41593	− 0.77775	0.47515	0.02463	− 0.41076
Depth	− 0.49961	− 0.02941	− 0.48538	− 0.51635	− 0.54964	0.80995	0.0050335	0.20458
DO	− 0.48428	− 0.55884	0.40069	0.35358	− 0.94051	0.10332	0.32124	− 0.039733
FC	0.87747	− 0.21496	0.018684	0.27413	0.95736	0.050074	− 0.12396	0.25611
TA	0.73389	− 0.37839	− 0.11166	0.41672	0.61782	0.38422	0.64163	− 0.24286
TH	0.78758	0.21409	0.41258	− 0.36802	0.99969	− 0.019458	0.012759	0.0085944
CH	0.8934	− 0.10314	0.20385	− 0.28547	0.93575	− 0.31338	− 0.16115	− 0.014211
MH	0.25532	0.6079	0.54488	− 0.32474	0.91154	0.34342	0.22342	0.035068
Cl	0.74364	0.37685	0.067772	0.356	0.62506	0.77802	− 0.047908	− 0.041046
NH_3-N	0.89375	− 0.018544	− 0.1375	− 0.17482	0.94998	− 0.016129	− 0.08815	− 0.29918
NO_2-N	− 0.70235	0.62059	− 0.066592	− 0.24701	− 0.94234	0.33369	− 0.010275	0.023152
NO_3-N	− 0.59905	0.52988	− 0.11435	0.13298	0.16481	0.83639	− 0.52101	0.043004
TKN	0.36808	0.16754	− 0.82882	0.28313	0.97848	− 0.069676	− 0.19386	0.012028
TN	0.247	0.27038	− 0.83997	0.28742	0.96742	0.035088	− 0.24998	0.019524
OP	0.083842	0.78255	− 0.30732	− 0.30909	0.5859	0.73121	− 0.09261	0.33685
TP	0.66036	0.36294	− 0.14036	− 0.56733	0.91311	0.36229	− 0.18531	0.025385
Chl	0.75024	− 0.096364	0.19758	− 0.44838	0.96067	− 0.12289	0.24544	0.042186
Eigen value	6.99784	5.15739	3.21695	2.99727	14.6002	4.37596	1.71318	1.31065
% Variance	31.808	23.443	14.623	13.624	66.365	19.891	7.7872	5.9575
Cumulative %Variance	31.808	55.25	69.876	83.5	66.365	86.56	94.03	99.98

the wetland boundaries for preventing the encroachments and restraining the harmful anthropogenic activities in the vicinity of wetlands. Enactment of a complete prohibition on all construction activities upto 50 m from the boundary of wetlands as recommended by the National Disaster Management Authority (Urban Wetlands/Water bodies Management Guidelines 2021; National Disaster Management Guidelines: Management of Urban Flooding 2010) from the wetlands along with a comprehensive plan of land management would be beneficial for controlling the wetland degradation.

5 Conclusion

The present study provided a detailed insight into the identification and apportioning of various anthropogenic pollution sources contributing to the deterioration of urban wetlands in Srinagar City using environmentric tools. Obtained datasets were subjected to clustering tendency using 'Hopkin's test' followed by HCA categorizing the sampling locations from the study area into two statistically distinct clusters. The clustering analysis was further validated using 'Silhouette's analysis'. It was found that the sites representing cluster I are moderately polluted and cluster II sites are considered highly polluted. After proper validation of the clusters, obtained Wilk's λ values further validated that the clusters formed are distinct with minimum overlapping. Cond, TDS, Salinity, TA, TH, and nutrients (OP and TP) were responsible for cluster formation, and spatial variation among clusters. PCA/FA applied to the entire and cluster wise datasets yielded four significant PCs, which helped in the identification of the pollution sources. FA/PCA revealed that the domestic sewage, effluents from inefficient STPs, stormwater, and surface runoff from urban and agricultural fields are the main sources of pollution impurities to the wetlands. Spatio-temporal variability observed in principal WQ parameters, and the seasonal variations are attributed to the changes in precipitation, hydrology, and agricultural activities. The results also provide a database about the spatiotemporal patterns of physical and chemical changes in surface WQ and offer a scientific understanding to wetland management authorities, policymakers, conservationists, and scientists working for sustainable management of wetland ecosystems. The study highlights the need for pollution control of wetlands so as to maintain their ecological character and integrity.

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Data availability The datasets generated during and/or analyzed during the current study are available in this manuscript.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval Research ethics stand adhered while submitting the manuscript.

Consent to participate and publish All the authors approved the manuscript to be published.

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