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Considerations on the monitoring of water quality in urban streams: a case study in Portugal

Maria Simas Guerreiro · Isabel Maria Abreu · Álvaro Monteiro · Teresa Jesus · Ana Fonseca

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Abstract Monitoring water quality in urban stream is of utmost importance for water resources managers, who are pressured to optimize monitoring schemes in order to reduce costs. The present study aims to use the results of a 2-year-long water quality monitoring program of an urban stream in Portugal to identify improvement opportunities. The urban stream under study was subjected to wastewater treatment plants effluent discharges, leachates from a major sealed landfill, low-class housing effluents, and nonpoint sources of pollution. Contributing watersheds are mostly artificial surfaces and agricultural land, which irrigate directly from the river. River water quality was evaluated on 11 sampling locations for 24 months from October 2013 to September 2015. The present paper describes statistical analysis of the results obtained for 12 physicochemical parameters in order to optimize the monitoring scheme. Cluster analysis detected a seasonal variation in the water quality and a spatial pattern based on the major point sources of pollution. A factor analysis showed that the parameters that mostly contribute to water quality assessment in this urban river are alkalinity, ammonia, electrical conductivity, pH, temperature, and dissolved oxygen. Results suggest that the monitoring efforts—and associated costs—may be reduced by decreasing monitoring frequency, sampling points, and monitored parameters. The statistical analysis described in this study may be replicated in other water quality monitoring programs, providing useful and important information for the systematic and iterative assessment of the adequacy of water quality sampling programs towards a sustainable management of water quality surveillance.

Keywords Water quality · Urban stream · Monitoring scheme · Multivariate statistical analysis · Spatial variation · Temporal variation

M. S. Guerreiro (✉) · I. M. Abreu · Á. Monteiro · T. Jesus · A. Fonseca
UFP Energy, Environment and Health Research Unit (FP-ENAS), Universidade Fernando Pessoa, Portugal. Praça 9 de Abril, 349 Porto, Portugal
e-mail: mariajoao@ufp.edu.pt

I. M. Abreu
e-mail: iabreu@ufp.edu.pt

Á. Monteiro
e-mail: aamont@ufp.edu.pt

T. Jesus
e-mail: tjesus@ufp.edu.pt

A. Fonseca
e-mail: afonseca@ufp.edu.pt

Á. Monteiro
LSRE-LCM, Faculdade de Engenharia da Universidade do Porto, Porto, Portugal

Introduction

Rivers and streams have been the major sources of water for crop irrigation, energy production, drinking, transportation, and wastewater disposal. Contamination of this resource may pose a threat to the environment and

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public health. Streams provide several ecosystem services, like water provision, climate regulation, flood protection, fish production, and recreation opportunities. The recognition of the important connection existing between natural and socio-economic systems, particularly in urban environments, and the rising awareness regarding the ecosystem services provided by urban streams makes water management plans strongly supported by the general public (Everard and Moggridge 2012; Hua and Chen 2019; Sarvilinna et al. 2017).

In urban areas, land is covered by impervious and semi-impervious surfaces such as buildings, pavements, and compacted landscapes, which decrease rainfall infiltration and increase stormwater runoff in both volume and velocity. This runoff carries pollutants that may harm biodiversity, impair water use, and make recreational areas unsafe and unpleasant, contributing to spatiotemporal changes in water quality (Duan et al. 2016), pronounced in the Mediterranean region due to its seasonal precipitation patterns (Sánchez-Montoya et al. 2012).

Land use and water quality relationship has been studied for various climates and water body types (Andrade et al. 2008; Duan et al. 2016; Fataei 2011; Pejman et al. 2009; Zhang et al. 2009). Nonetheless, a definite correlation is yet to be attained due to multiple anthropogenic activities and man-made modification of watersheds characteristics (Yu et al. 2016).

In urban areas, stormwater is the major nonpoint source of pollution in water bodies because it carries pollutants like sediment from disturbed soils and construction sites; hydrocarbons from road traffic and vehicle exhausts; business, industries, and housing not connected to the sewage system; nutrients from lawn care and agricultural fields; and even pet wastes. The importance of adequately planned stormwater control measures in urban areas has been highlighted in recent studies (Bahrami et al. 2019; Sadeghi and Kharaghani 2018) due to the increasing urbanization and uncertainties associated with climate change impact. Water quality monitoring programs are essential tools to support decision-making on these issues.

Point sources of water pollution include industrial and domestic wastes and polluted tributaries and rivers that discharge into water bodies. In a study conducted by Vilmin et al. (2016) in the Seine River, it was demonstrated that wastewater treatment plants (WWTP) effluents are the major factor for water pollution and that it is highly affected by runoff.

Nutrients like phosphorus and nitrogen promote weed and algae growth in streams. Nitrate sources in an urban environment include fertilizers used in small agricultural fields, lawns, and gardens, leaking septic systems, sewage treatment plants outfalls, domestic pet excreta, and combustion of fossil fuels (Halstead et al. 2014; Rauch and Morrison 2012). Phosphorus is found in rocks and soil, fertilizers, leaves and grass left on paved areas, and orthophosphate from vehicle exhaust. Because phosphorus compounds attach to soil particles, when the soil is disturbed by construction, the adsorbed phosphorus on the soil particles is free to move and to be carried by runoff.

To effectively manage river water resources, water quality assessment is imperious. The Water Framework Directive (WFD) was published with the aim to assure adequate quality in European water bodies (European Community 2000). However, considerable monitoring efforts are required, and the effective use of sampling resources is seldom practiced (Kotamäki et al. 2019). Representative sampling sites and variables must be defined to reduce monitoring costs. Multivariate statistical tools and exploratory data analysis have been used for data reduction and interpretation of large data sets in water quality assessment (Andrade et al. 2011; Arora et al. 2014; Bu et al. 2010; Pejman et al. 2009; Sánchez-Montoya et al. 2012; Vega et al. 1998).

Ongoing monitoring programs should be systematically evaluated, and for that, it is necessary to extract meaningful information from large and complicated data sets without missing useful information and optimize the monitoring network by recognizing the representative parameters, delineating monitoring sites, and identifying latent pollution sources (Kotamäki et al. 2019; Pekey et al. 2004; Shrestha and Kazama 2007). Multivariate data analysis in water quality studies has been widely used in locating monitoring sites and selecting water quality parameters (Andrade et al. 2011; Mutlu 2019).

The main objective of this study is to optimize the monitoring scheme of an urban river by reduction of sampling points and/or monitored parameters. Multivariate statistical techniques identify similarities and dissimilarities between sampling stations and corresponding pollution sources and evaluate seasonality of water quality. This analysis is expected to increase the knowledge of water quality spatiotemporal variation, enabling a more effective and sustainable management of monitoring resources.

Materials and methods

Study site

The Tinto River is located between parallels 41°08′N and 41°13′N and meridians 8°31′W and 8°36′W (Fig. 1). The river is in the Iberic-Macaronesian ecoregion based on system A classification of the WFD (European Community 2000). It is a lowland, small basin (23 km^2), granitic with clayey alluvial material. The river is a tributary (11.4 km) of the major river Douro, Portugal.

Land use within this basin is mostly artificial surface (75%), agricultural areas (20%), and forests and semi-natural areas (5%) (Fig. 1). Some low-class housings are not connected to the public sewage system and drain directly into the river. A major sealed sanitary landfill and two wastewater treatment plants effluents discharge directly into the Tinto River (Fig. 1). River water is used for irrigation of fresh produce and corn and also for the dilution of leachates from the landfill and effluents from the WWTP.

Climate is classified as Csb (dry summer) according to the Koppen-Geiger classification system (Climate - data 2020). The mean annual temperature is 14.6 °C, and the mean annual precipitation is 1223 mm, with an average of nine wet days per month (NMI & NBC 2016) distributed as shown in Fig. 2.

Data set

The Tinto River has been under a monitoring scheme to access its ecological status, according to the WFD (European Community 2000). This monitoring scheme comprises 11 sampling locations (Fig. 1) analyzed monthly for physicochemical and hydromorphological parameters and quarterly for benthic macroinvertebrate characterization. Detailed information on this monitoring scheme, including experimental methodology can be found elsewhere (Jesus et al. 2020). Monitoring point A is a spring well, where water flows from the aquifer to the surface and may be considered groundwater.

As referred above, the present study uses statistical analysis of the experimental results obtained in the Tinto River monitoring program to identify cost reduction opportunities. The parameters under analysis are listed in Table 1 and cover general physicochemical elements supporting biological elements (European Community 2000). The pooled data set comprises 3168 results (11 locations, 12 parameters, 24 months of data acquisition) obtained from October 2013 to September 2015.

Statistical methods

In this study, the statistical analysis was performed using SPSS software (version 24). Multivariate statistical methods were used for water quality assessment in time and space, classification, interpretation, and reduction of data set. Data was standardized by the *z* score method to render data dimensionless and minimize the difference of variance in variables and the influence of different units of measurement (Dillon and Goldstein 1984). The three-sigma rule was used to eliminate outliers. All data that fell outside three standard deviations from the mean were removed.

Cluster analysis (CA)

Cluster analysis groups cases into classes based on the similarities and dissimilarities between classes. Cluster analysis was carried out to analyze separately the time effect and the effect of sample location on river water quality. The agglomerative hierarchical cluster analysis with a combination of the complete linkage method and the squared Euclidean distances was applied (Andrade et al. 2011; Bu et al. 2010), acknowledging that dendrogram interpretation has some degree of subjectivity on the number of clusters, which are chosen by the user (Andrade et al. 2008). The mean value of each of the analyzed parameters of the respectively formed clusters was submitted to the *t* test at a 5% significance level.

Principal component analysis/factor analysis (PCA/FA)

Principal component analysis (PCA) is a dimensionality reduction technique that changes the original variables into new uncorrelated variables, called principal components, which are linear combinations of the original ones with minimum loss of original information (Dillon and Goldstein 1984). The PCA/FA was applied to the *z*-normalized variables on the dry season and wet season clusters and also for the high pollution and low pollution clusters. The Kaiser-Meyer-Olkin (KMO) and Bartlett's Sphericity tests on the parameter correlation matrix were applied to the data set to indicate validity of the PCA (Andrade et al. 2008).

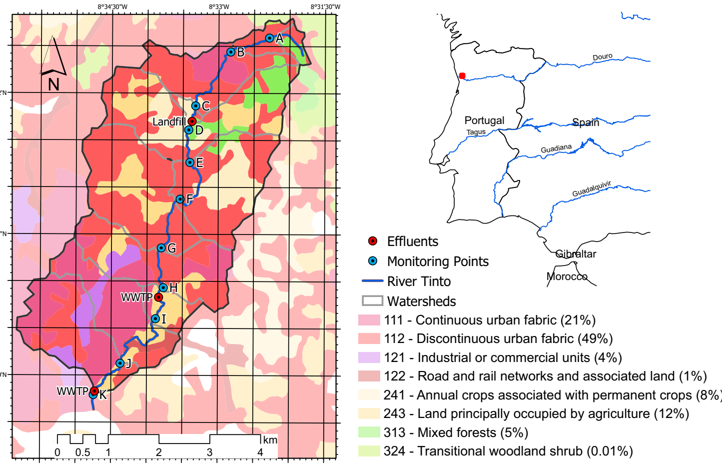

Fig. 1 Study area, monitoring points and associated watersheds, tributaries and major effluent points, and land use

The selected principal components showed an eigenvalue greater than one, a criterion that measures the significance of the factor. Factor analysis (FA) interpretation may be easier using the rotation procedure which increases the contribution of variables with higher significance and reduces the contribution of variables with less significance. Varifactors (VF) were generated based on the varimax rotation with Kaiser normalization.

Results and discussion

The mean value for each parameter and monitoring point was compared with the most restrictive Portuguese legal limiting recommended value for irrigation, fishery, and general use (DL 236/98) or indicated by the Portuguese National Water Institute (INAG 2009). Parameters ALK, EC, and COD do not have a legal limit nor an indicative one. The monitoring points in which these recommended values were not satisfied are highlighted in Table 2. TSS and TEMP are not limiting parameters for water use at any point in the river, whereas BOD5, NO_2, and NH_4 are a limiting factor for water quality at all points but point A. Point A water may be considered as groundwater, and that is evident from some parameter values (pH and alkalinity) due to the granitic nature of the bedrock, lack of aeration (DO), and less sources of pollution (NO_2, NH_4, PO_4, EC).

Parameters ALK, NH4, PO4, and DO are mostly associated with the river major sources of pollution—WWTPs (points I, and K), landfill (point D), and polluted tributary (point C). This result makes sense, because these parameters are mostly associated with sewage (EPA 2001). These parameter values show improvement in the subsequent monitoring points, indicating that the river has capacity to recover from point sources of pollution even in the presence of nonpoint sources. Nonetheless, knowing the mean annual value of a parameter does not show monthly or seasonal variation, therefore besides a spatial cluster, a temporal cluster was also developed.

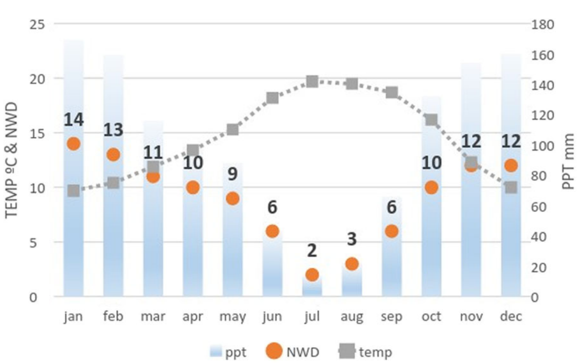

Fig. 2 Weather characterization of Tinto River basin

Clusters analysis

Temporal cluster (TC)

The dendrogram (Fig. 3) indicates two clusters, consistent with the climate and hydrological conditions: dry season, July, August, September, and October, and wet season, November, December, January, February, March, April, May, and June (Fig. 2). It is evident that there is a difference between the summer/early autumn seasons (July–October) and the rest of the year. The dry season begins with the month in which the temperature

Table 1 Physicochemical parameters under analysis and its correspondence with the WFD ((European Community 2000)

WFD	Parameters	Method
Thermal conditions	Water temperature (TEMP)	In loco using a portable apparatus (HANNA Instruments-HI 99300)
	pH	In loco using a portable apparatus (WTW - PH 315i)
Acidification status	Alkalinity (ALK)	In lab standard method 2320B (APHA - American Public Health Association 1999)
	Dissolved oxygen (DO)	In loco using a portable apparatus (YSI-ProODO)
	Biochemical oxygen demand, 5 days (BOD5)	In lab standard method 5210B (APHA - American Public Health Association 1999)
Oxygenation	Chemical oxygen demand (COD)	In lab standard method 5220B (APHA - American Public Health Association 1999)
Nutrients	Nitrates (NO_3)	In lab standard method 4500-NO_3^-B (APHA - American Public Health Association 1999)
	Nitrites (NO_2)	In lab standard method 4500-NO_2^-B (APHA - American Public Health Association 1999)
	Ammonia (NH_4)	In lab standard method 4500-NH_3^-G (APHA - American Public Health Association 1999)
	Phosphates (PO_4)	In lab standard method 4500-P E (APHA - American Public Health Association 1999)
Salinity	Electrical conductivity (EC)	In loco using a portable apparatus (HANNA Instruments-HI 99300)
	Total suspended solids (TSS)	In lab standard method 2540 D (APHA - American Public Health Association 1999)

is the highest and rainfall is the lowest of the year (Fig. 2), reflecting the watersheds hydrologic response to the lowest runoff and dryer soil conditions.

Spatial cluster (SC)

The dendrogram (Fig. 4) indicates three clusters from the 11 monitoring points: Point A; points, B, E, F, G, and H; and points C, D, I, J, and K. Point A is a spring protected by a hut, for which the cluster was called spring (Fig. 1). Points C, D, I, J, and K are downstream from point sources of pollution—a polluted tributary, a sanitary landfill, and two wastewater treatment plants—for which the cluster was called high pollution. The other monitoring points were clustered in what was called the low pollution cluster. Results suggest that water quality does not depend on the geographic position because clusters were not formed by neighboring sites.

Mean pH and TSS showed no statistical difference (*t* test with $\alpha = 0.05$) between the dry season and wet season (Fig. 5). DO was statistically lower for the dry season, probably due to the increase in oxygen consumption by the processes of biological degradation of organic matter, lower runoff and turbulence resulting in less aeration, and also warmer water that holds less dissolved oxygen (Pejman et al. 2009). All other parameters were statistically higher for the dry season than for the wet season, possibly due to a higher precipitation in the wet season and resulting runoff that dilutes pollutants and due to increased agricultural activities in the dry season.

It is evident from Table 2 and Fig. 4 that point A (spring cluster) is different from the other monitoring points, and therefore, a t-test was performed only on the high pollution and low pollution cluster. The mean pH and NO_3 showed no statistical difference between the high pollution and low pollution clusters. DO was statistically lower for the high pollution cluster, implying an organic pollution source. All other parameters are statistically higher for the high pollution cluster. This result suggests that the point sources of pollution overcome the nonpoint sources of pollution in the Tinto River water quality.

Principal component analysis/factor analysis (PCA/FA)

Temporal cluster (TC)

The PCA/FA applied to the *z*-normalized variables on the dry season and wet season clusters showed a KMO of 0.56 and 0.71 for the dry season and wet season, respectively, and the Bartlett's test of sphericity was significant in both cases indicating adequacy of PCA/FA to provide significant reductions in dimension (Andrade et al. 2008; Zhang et al. 2009).

Table 2 Mean values vs. legal limiting values and indicative values (INAG 2009)

Parameter	Units	Limit values	A	B	C	D	E	F	G	H	I	J	K
TEMP	°C	< 28	16	16	16.5	16.2	16.3	16.4	16.9	17.7	18.5	18.1	19.4
pH	Sor.	6.5 – 8.4	5.1	6.3	6.9	7	7	7	7.3	7.2	7.1	7.3	7
ALK	mg $CaCO_3$/L		11.6	20.9	80.7	100	72.2	60.6	56	56.2	84.4	85.3	89.3
DO	mg O_2/L	> 5	2.7	7.7	4.7	5.4	6.6	6.2	7.2	7.1	4.7	6.7	6
BOD5	mg O_2/L	< 5	4.7	5.1	14.7	13.1	9	9.7	9.3	9.2	19.8	20.1	16.1
COD	mg O_2/L		13.8	26.6	45.4	38.5	29.6	31	29.9	24.5	52.6	49.5	45
NO_2	mg NO_2/L	<0.03	0	0.1	0.9	1.2	1.2	1.4	1.5	1.3	2.4	2.4	1.6
NO_3	mg NO_3/L	< 25	26.9	24.5	20.2	30	37.2	33.3	39.5	43.8	58.2	49.6	45.7
NH_4	mg NH_4/L	< 0.2	0	0.4	6.3	9.7	6	3.8	2.5	1.9	10.9	9.7	6.9
PO_4	mg PO_4/L	< 0.1	0.1	0.1	0.8	0.4	0.2	0.2	0.2	0.2	1.4	1.2	2.1
EC	μS/cm		158	181	373	410	350	344	348	350	513	473	541
TSS	mg/L	< 25	4.2	10.9	14.6	8.9	6.8	8.6	6.4	9.2	14.5	16.3	17.7

Highlighted cell values indicate that the parameter is not within the legal limits

Four VFs were selected, which explain 74.9% and 75.0% of the variance for dry season and wet season, respectively. The variables that most significantly contribute to temporal variations of water quality are indicated in Fig. 6 considering the loadings of varimax rotation factors (VF). A factor loading above 0.5 is considered moderate up to 0.75, after which is considered strong, while values under 0.5 are weak and are not to be considered (Bu et al. 2010; Liu et al. 2003; Pejman et al. 2009).

In the dry season cluster, VF1 explained that 37.5% of total variance had strong positive loadings from EC, pH, and TEMP and moderate positive loadings of NO_2, PO_4, and ALK. VF2 explained 15.3% of total variance, with strong positive loadings from NH_4, moderate loadings from ALK, and strong negative loadings from DO (as described above, DO is inversely proportional). VF3 explained 13.4% of total variance and had strong positive loadings from BOD5 and moderate positive loadings from TSS and NO_3. VF4 explained 8.7% of total variance and showed a strong positive loading from COD. The EC, pH, TEMP, and NH_4 are the most significant parameters contributing to water quality variations for the dry season, associated with soil genesis, agricultural fertilization, and sewage

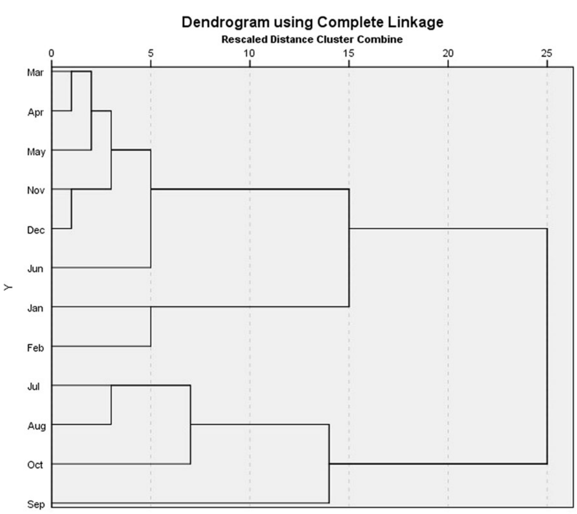

Fig 3 Dendrogram based on seasonality (month of the year)

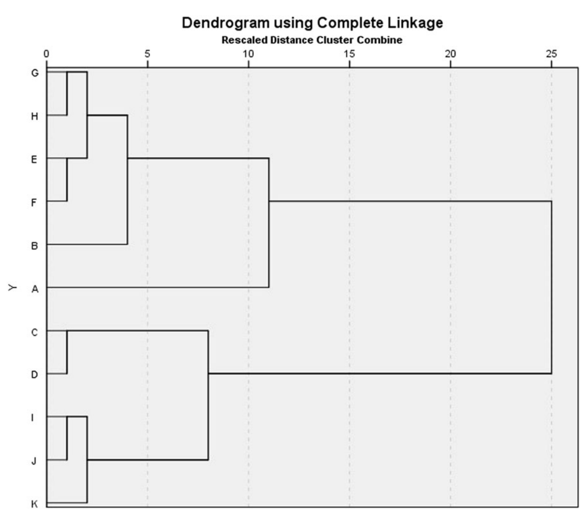

Fig. 4 Dendrogram based on monitoring point location

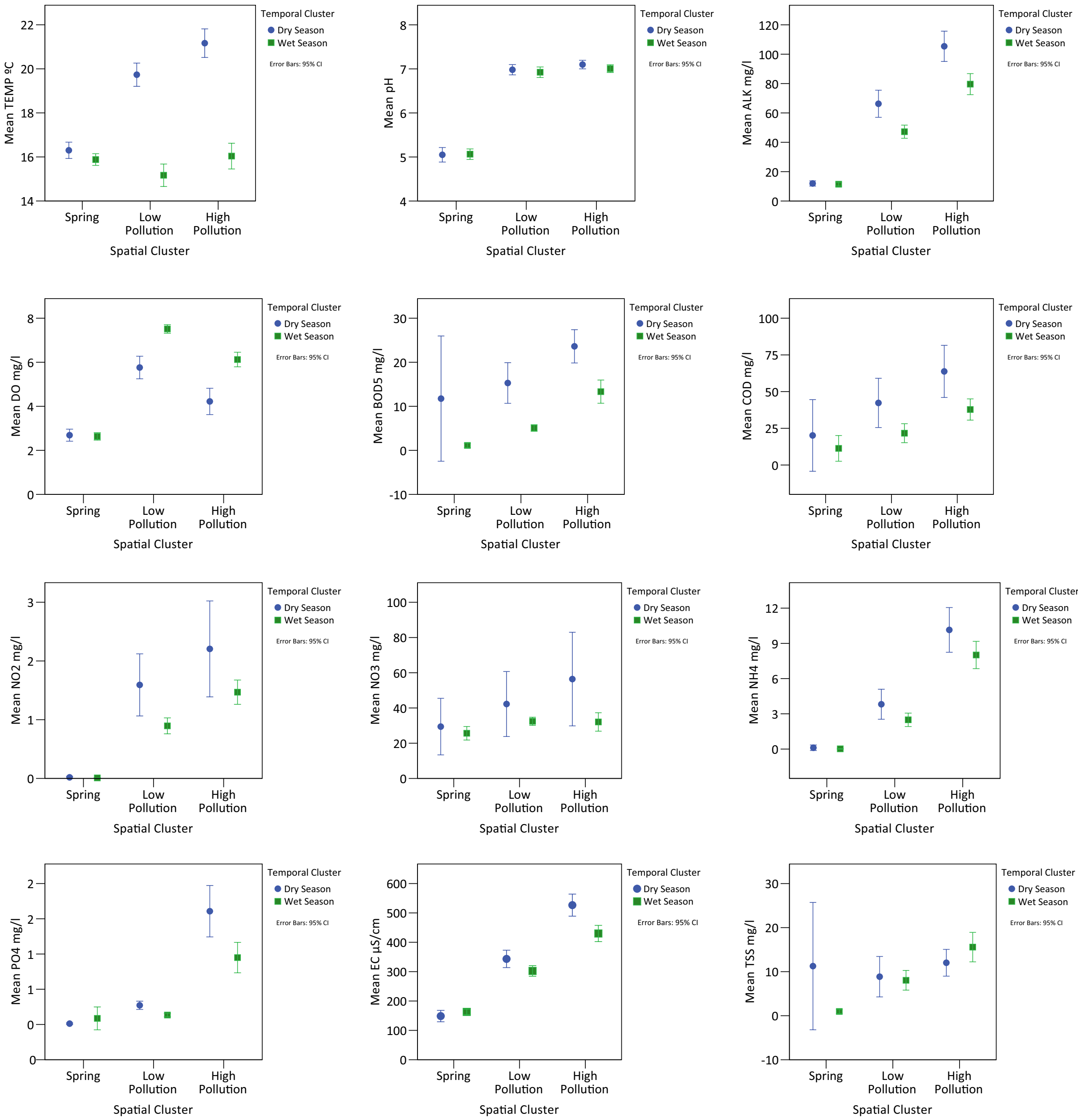

Fig. 5 Spatial and temporal variability of Tinto River water quality parameters (O dry season; □ wet season)

effluents, explaining the impact of irrigated agricultural practices in the dry summer season.

In the wet season, VF1 explained 40.2% of total variance, with strong positive loadings from ALK, NH_4, and EC and moderate positive loadings from NO_2 and pH. VF2 explained 14.7% of total variance, with strong positive loadings from TSS and moderate positive loadings from BOD5. VF3 explained 11.0% of total variance, with strong positive loadings from DO, moderate positive loadings from pH, and moderate negative loadings from TEMP. VF4 explained 9.2% of total variance, with strong positive loadings from NO_3 and moderate positive loadings from PO_4. ALK, NH_4, EC, and TSS are the

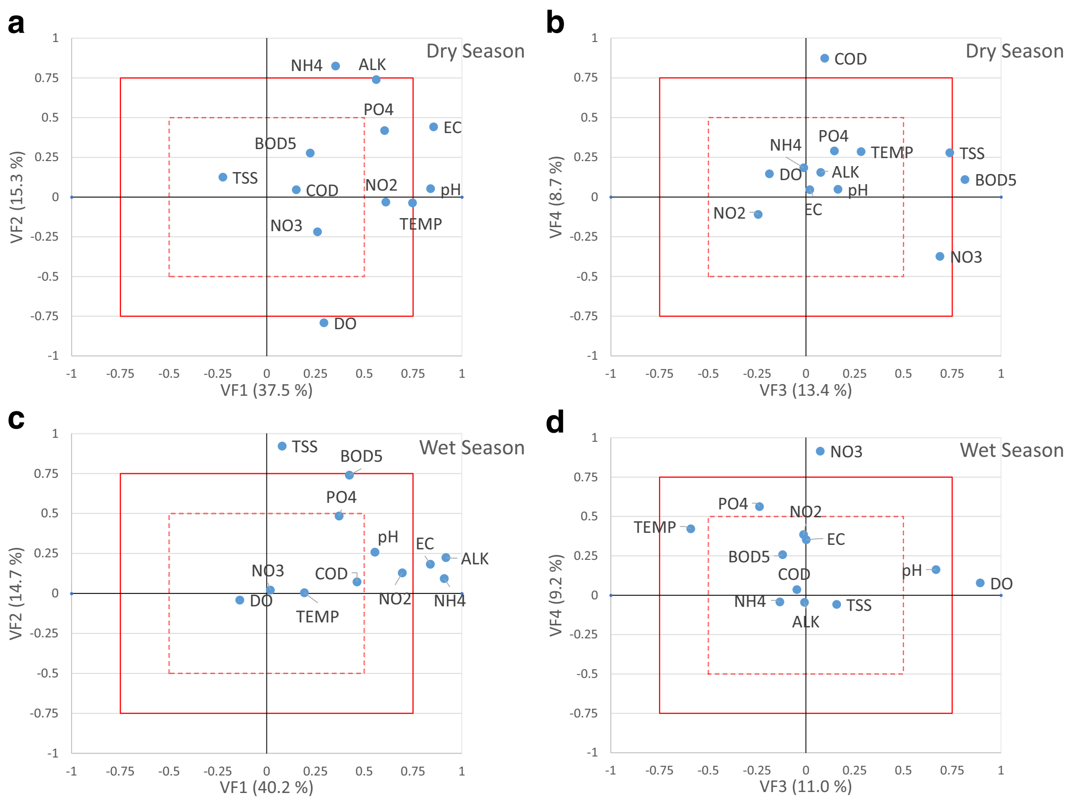

Fig. 6 Loading scatter plot for temporal clusters

most significant parameters contributing to water quality variations for the wet season, mostly associated with sewage discharges and sediment erosion and transport from natural surface runoff, highlighting the contribution of NH_4, NO_2, and NO_3 produced by combustion processes (Nabelkova et al. 2012).

Spatial cluster (SC)

The PCA/FA applied to the *z*-normalized variables on the high pollution and low pollution clusters showed a KMO of 0.71 and 0.41 for the high pollution and low pollution, respectively, and the Bartlett's test of sphericity was significant in both cases indicating adequacy of PCA/FA to provide significant reductions in dimension (Andrade et al. 2008; Zhang et al. 2009).

Three and four VFs were selected for the high pollution and low pollution, respectively. VFs explain 65.5% and 71.8% of the variance for the high pollution and low pollution, respectively. The variables that most significantly contribute to temporal variations of water quality are indicated in Fig. 7 considering the loadings of varimax rotation factors (VF).

In the high pollution cluster, VF1 explained 38.2% of total variance and had strong positive loadings from ALK and NH_4 and strong negative loadings from DO and moderate positive loadings of EC. VF2 explained 14.8% of total variance, with moderate positive loadings from PO_4, NO_3, TEMP, NO_2, and EC. VF3 explained 12.6% of total variance and had strong positive loadings from TSS and moderate positive loadings from PH and BOD.

In the low pollution cluster, VF1 explained 35.5% of total variance, with strong positive loadings from ALK and NH_4 and moderate positive loadings from EC, PO_4, and pH. VF2 explained 14.6% of the total variance, with strong positive loadings from TEMP, moderate positive loadings from NO_2, and moderate negative loadings from DO. VF3 explained 12.0% of total variance, with moderate positive loadings from BOD, TSS, and NO_3. VF4 explained 9.7% of total variance, with moderate positive loadings from pH and moderate negative loadings from COD. Interestingly, the parameters that

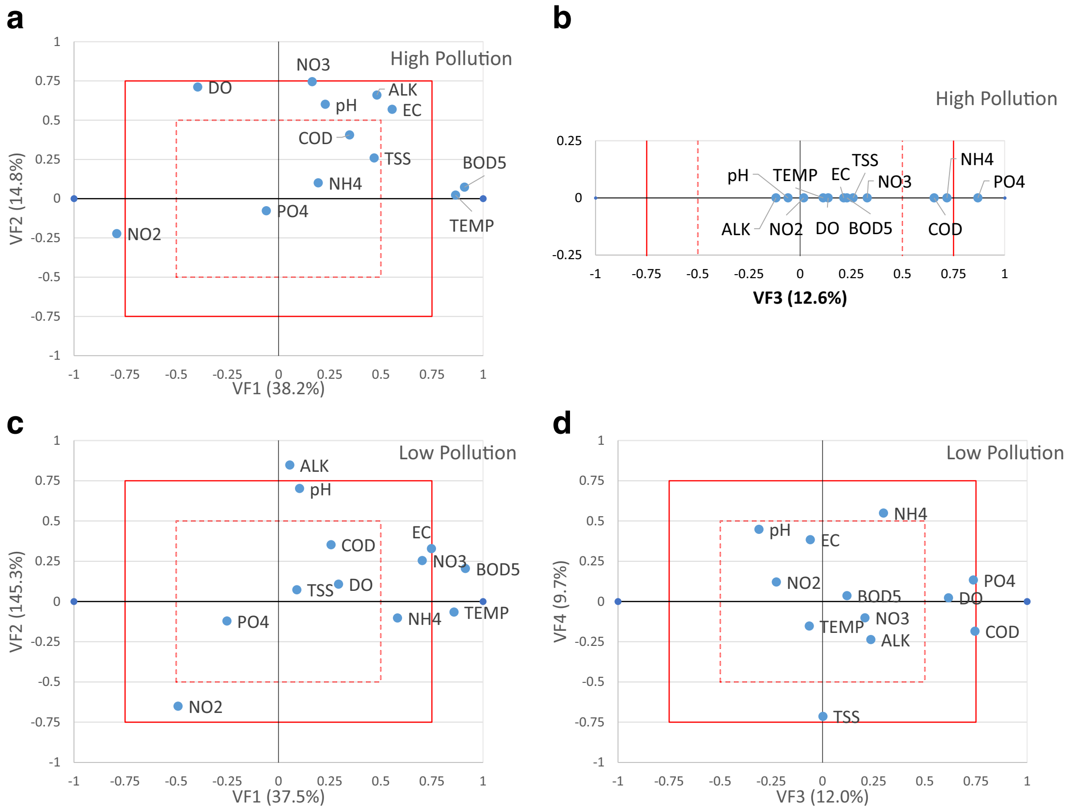

Fig. 7 Loading scatter plot for spatial clusters

mostly contribute to water quality evaluation are ALK and NH_4, in both high and low pollution clusters and also DO for the high pollution cluster.

Conclusions

The health and well-being of urban populations are greatly influenced by urban streams and their ecosystem services, justifying the need for adequate water quality monitoring programs. However, effective use of monitoring resources is required to assure the sustainable management of water quality surveillance.

Statistical analysis performed on the results of a 2-year-long monitoring program in urban Tinto River suggested improvement opportunities. It was found that six of the 12 analyzed physicochemical parameters had a major contribution on the assessment of water quality: alkalinity, ammonia concentration, electrical conductivity, pH, water temperature, and dissolved oxygen concentration. It was also found that monitoring points were spatially clustered based not on geographic proximity but on proximity to a major point source of pollution (WWTP, landfill, polluted tributary) and that monitoring points were temporally clustered based on the climatic conditions of dry hot summers and cold wet winters.

As a main conclusion of the present study, the results obtained with cluster analysis and principal component analysis/factorial analysis suggest that the monitoring program of urban Tinto River could comprise fewer monitoring sites and monitored parameters and that the sampling frequency could be reduced. These measures would have considerable impact on monitoring costs without compromising the quality of the results obtained in the monitoring program. Simple statistical analysis as those described in this paper could be used by water resources managers to systematically and iteratively evaluate the adequacy of urban water quality sampling programs, in order to optimize the use of resources.

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