



Assessment of water quality compartments in Kor River, IRAN

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Abstract A comprehensive risk assessment tool may have advantages for investigating complex water quality data and for a better understanding of the ecological status of the studied systems including aquatic ecosystems. In this paper, the impact of agricultural, industrial, and domestic sources on the quality of the Kor River in Fars Province, Iran are investigated. The study developed a procedure consists of pollution index (P_i), water quality index (WQI), and data grouping as a useful simple tool to assist water quality management. The pollution indicators used in the development of P_i and WQI are 15 physical, chemical, and biological variables in the river water. According to the world guideline standards, an appropriate weight is assigned to each indicator, scores of P_i are determined, a composite WQI is formulated, and a water quality grouping score is proposed. Pollution risk levels along the river are highlighted using the grouping score and dominant pollution sources are determined. Results revealed that pollution sources influence the water quality indicator content so that some sites are under the high influence of sewage disposal and industrial effluents and some others under the influence of agricultural runoff. Results also provide insight into the development of better pollution control strategies for the Kor River and other aquatic ecosystems affected by industrial, agricultural, and domestic pollution sources.

Keywords Risk assessment · Pollution index · Water quality · Kor River · Iran

Introduction

Water is one of the most vital natural resources for the perpetuation of life on earth. In a natural condition, earth's life forms live in equilibrium with their environment. The aquatic environment with its water quality is considered the main factor controlling the state of health and disease in living organisms including humans. The accessibility and quality of water have always displayed a main component in determining not only where people can live, but also their quality of life (Agarkar and Thombre 2006; Veni and Mohanraj 2013). In the past century, the exponential development of anthropogenic influences has resulted in a severe impact on all environmental sections, including aquatic ecosystems (Iqbal et al. 2015). The aquatic ecosystems including the rivers are one of the most productive ecosystems and freshwater resources in the world. River systems generally constitute areas with a high population density which are economically very important in fishing, agriculture, husbandry, and industry as well as ecologically significant due to the presence of many aquatic organisms, migratory and local birds, and scientific research. However, rivers offer convenient alternative drainage for the discharge of surface water runoff, and industrial and domestic wastewater which results in a high risk to the environment. Therefore, the precise determinations of pollutants in river systems are of ultimate importance for

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controlling, preventing, and eliminating the pollution (Huang et al. 2010; Shafie et al. 2014).

Due to industrialization and the discharge of municipal wastewater, the concentration of pollutants in most Iranian rivers is increasing. The Kor River is the largest source of fresh water in the Fars Province (length 280 km, watershed area 8284 km²) and is the source of water for about 600,000 inhabitants (Sheykhi and Moore 2012). The watershed is on the border area between cities of Eqlid, Sepidan, Zaqan, Marvdasht, and Kharam. The Kor River with acceptable quality water not only contributes substantially to potable, industrial, and agricultural water utilization in the basin but also has a significant role in the ecology of the basin. In the last decades, the water quality of the Kor River deteriorated by human activities to the extent that the hydrology, water quality, and ecology of much of the region have been dramatically altered (Sheykhi and Moore 2012). The high density of industries in the river basin, uncontrolled domestic and industrial wastewater discharge, and runoff from agricultural land make the Kor River one of the most significant sources of pollutants (salts, nutrients organics, and metals), which increasingly raised attention and concern.

The water quality depends on the bedrock characteristics of the watershed, as well as anthropogenic activities, including waste incineration, domestic wastewater, wastes and effluents of industrial activities, such as galvanizing works and chemical plants, leaded gasoline, and the corrosion of underground pipes, as well as urban stormwater runoff, and landfill leachate (An and Kampbell 2003; Lyons et al. 2006). In recent decades, substantial quantities of pollutants have been discharged to rivers in industrial areas of the world (Martin 2000). The discharge of industrial and municipal wastewater and manure can be considered a constant polluting source, but not so the surface runoff which is seasonal and highly affected by climate as pointed by Vega et al. (1998). Several authors have reported the effects of anthropogenic activities on high levels of variables in the aquatic systems; the runoff from agricultural land usually increases the concentration of nutrients, pesticides, and some metals (e.g., Cu, As) in the water (e.g., Sundaray et al. (2011); Hariprasad and Dayananda (2013)); Industrial activities may increase contents of metals and toxic chemicals, add suspended sediment, increase temperature, and reduce dissolved oxygen in the water (e.g., Cheung et al. (2003); Baig et al. (2009); Sentas et al. (2018)). The domestic wastewater usually

increases the concentration of nutrients, microbial pollutants (e.g., coliforms), and some metals (e.g., Mo, Zn), and lowers dissolved oxygen in the water (e.g., Tornevi et al. (2014); Sentas et al. (2016); Singh et al. (2017)). All the above researches are supportive of the effects of pollutants on physicochemical properties and microbiological quality of water, which can have a serious negative impact on the aquatic ecosystem and its surrounding food web and/or make water unsuitable for established or potential uses.

Water quality in a freshwater system is a complex subject with multiple aspects such as physical, chemical, and biological variables and their interactions. A systematic measurement of water quality variables, their characterization, and spatial variation and source apportionment can enable an improved understanding of the environmental conditions and help researchers and planners to develop prioritizing strategies for sustainable water management (Kumar and Dua 2009; Akkoyunlu and Akiner 2012). The presence of toxic metals in the environment is one of the major concerns of quality control in most parts of the world because of their toxicity, wide sources, non-biodegradable characteristics, and accumulative behaviors (Wang et al. 2016). The most important trace and toxic metals from the point of view of water quality are Fe, Ni, Cr, Mo, Pb, and Zn. Some of these metals (e.g., Cr, Ni, and Zn) are essential trace metals for living organisms but are toxic at higher concentrations. Others, such as Pb, have no known biological activity. According to the World Health Organization (WHO) guideline standards, common indicators in the microbiology field of water quality are total coliforms and fecal coliforms.

Quality state and risk-taking levels of water bodies should also be meaningful, relatively simple, understandable, and applicable for managers and decision-makers in water sector who want to know about the quality state of their local water bodies (Taner et al. 2011). Recently, various tools have been developed to assist in water quality management. However, the water quality index (WQI) for the determination of water quality in the aquatic ecosystem is advantageous since it is widely applied as a practical method for observing and representing the water quality (Akkoyunlu and Akiner 2012; Wang et al. 2015; Sun et al. 2016; Misaghi et al. 2017; Zotou et al. 2020).

The present study is carried out to develop a reliable method for determining the quality state and risk-taking level of water by using a WQI in Kor River, Iran. Accordingly, the main objectives of this research are (1) to measure and evaluate the contents of quality variables in surface water; (2) to evaluate the spatial distribution of pollution variable levels in the water by the calculating pollution index (P_i); (3) to construct a composite quality index (WQI); and (4) to group river water quality into pollution levels by the introduced statistical interval sequences. The results of water quality grouping are compared with the hierarchical cluster analysis (HCA). The (P_i) values are also subjected to the principal component analysis (PCA) (Davis 2002), to identify the possible sources of pollutants and estimate the potential contribution of the pollution sources in the study area.

Materials and methods

The study area and sampling

The Kor River basin (3270000–3390000 N, 590000–710000 E) area is approximately 8284 km² in the north-east of Fars Province, Iran (Fig. 1). It is the largest river in Fars Province. The average annual temperature is 14.6 °C. The annual rainfall in the area ranges from 300 to 800 mm, with an average of 400 mm.

In this study, 18 water quality monitoring sites were designated in February 2018, to cover a wide range of determinant at key sites that reasonably represent the water quality of the Kor River (Fig. 1). The river is divided into two sections by the Drodzan dam. The locations in the Kor River from which water samples were collected are in areas known to encompass confirmed potential pollution sources (Sheykhi and Moore

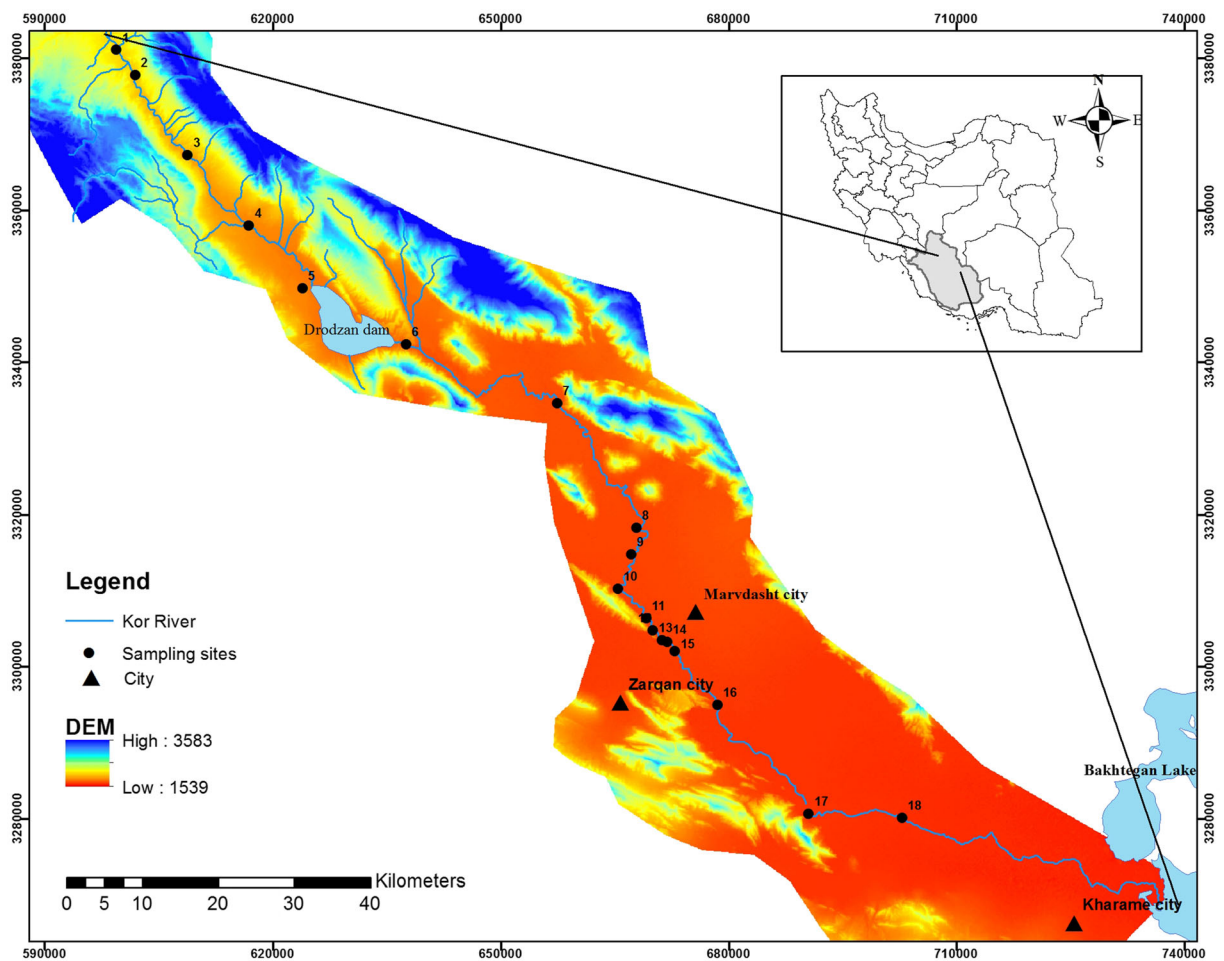


Fig. 1 Location of the study area and water quality monitoring sites

2012). Sites 1 to 5 are situated at the upstream of the Drodzan dam, where land use is mainly agricultural and residential. Site 6 is situated 1.5 km downstream of the dam which is used for drinking water supply and site 7 is used for agricultural water use. The sampling stations 8–18, however, located downstream of the Drodzan dam, receive pollution mostly from domestic wastewater (i.e., sites 13, 15, 16) and industrial effluents (i.e., 11, 12, 14). The catchment area of the river has been subject to soil erosion, agricultural intensification, industrialization, and urbanization.

Analytical procedures

Twenty-four variables were measured/determined in 18 sampling sites across the Kor River. Sampling, preservation, and transportation of the water samples to the laboratory followed standard and recommended methods of analysis (APHA-AWWA-WEF 2005). The variables included phosphate, pH, Eh, electrical

conductivity (EC), total dissolved solids (TDS), dissolved oxygen (DO), chemical oxygen demand (COD), chloride (Cl), sulfate (SO₄), potassium (K), sodium (Na), calcium (Ca), magnesium (Mg), SAR, total coliform (T.C), fecal coliform (F.C), iron (Fe), zinc (Zn), chromium (Cr), molybdenum (Mo), nickel (Ni), lead (Pb), bicarbonate (HCO₃), phosphate (PO₄), and nitrate (NO₃). The pH, Eh, conductivity, and dissolved oxygen measurements were performed in situ. The water quality variables, their units, and methods of analysis are summarized in Table 1. The precision of the metal analysis was controlled by including triplicate samples in analytical batches and blanks.

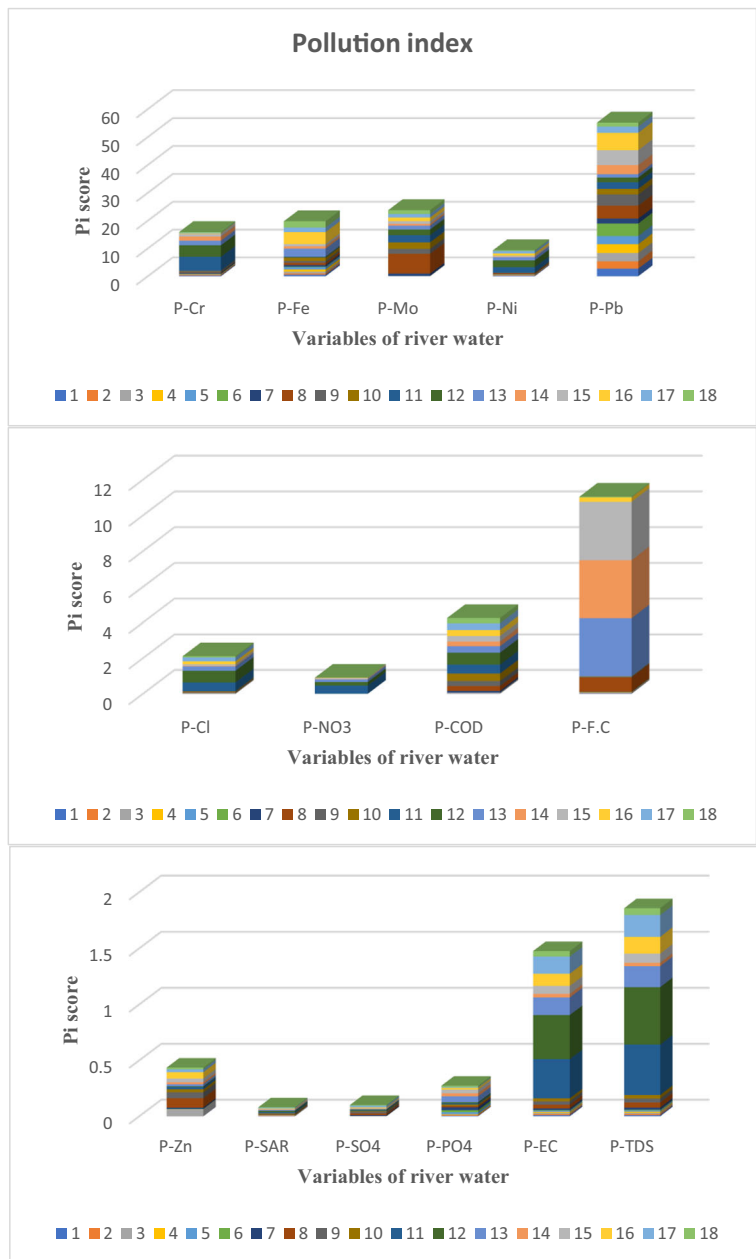
Water quality index calculation

Basically, a WQI is an alternative to summarize large numbers of water quality variables (Fig. 2) into simple terms (e.g., clean) for reporting to authorities in the water sector (Wang et al. 2015; Sun et al. 2016; Misaghi

Table 1 Physicochemical variables measured, and analytical techniques used

Variable	Abbreviation	Analytical technique	Units
pH	pH	pH meter	pH unit
Eh	Eh	Eh meter	mv
Electrical conductivity	EC	EC meter	μS/cm
Dissolved oxygen	DO	DO meter	mg/l
Chemical oxygen demand	COD	Dichromate reflex method	mg/l
Na	Na	Flame AAS	mg/l
K	K	Flame AAS	mg/l
Magnesium	Mg	Flame AAS	mg/l
Calcium	Ca	Flame AAS	mg/l
Chloride	Cl	Titrimetric	mg/l
Sulfate	SO ₄	Spectrophotometric	mg/l
Bicarbonate	HCO ₃	Titrimetric	mg/l
Phosphate	PO ₄	Spectrophotometric	mg/l
Nitrate	NO ₃	Spectrophotometric	mg/l
Total dissolved solids	TDS	Gravimetric	mg/l
Total coliform	T.C	Multiple tube	MPN/100
Fecal coliform	F.C	Multiple tube	MPN/100
Chromium	Cr	ICP-MS	μg/l
Molybdenum	Mo	ICP-MS	μg/l
Nickel	Ni	ICP-MS	μg/l
Zinc	Zn	ICP-MS	μg/l
Iron	Fe	ICP-MS	μg/l
Lead	Pb	ICP-MS	μg/l

Fig. 2 Pollution index values of water quality variables in the Kor River



et al. 2017). WQI procedure is selected for this study since simply by looking at a single number and corresponding scale, quality of the water can be understood effectively. In summary, the construction of WQIs is based on variable selection, weighting variable, applying an aggregation model, and applying a grouping procedure.

Determination of risk-taking level corresponding to a WQI is defined by the following equations:

$$WQI = \sum_{i=1}^n P_i \tag{1}$$

$$P_i = C_i \times W_i \tag{2}$$

$$W_i = \frac{1}{S_i \left(\sum_{i=1}^n \frac{1}{S_i} \right)} \tag{3}$$

where n is the number of chemical variables, W_i is the weight assigned to each parameter corresponding to water quality guidelines (e.g., WHO), between 0 and 1, (Table 2), S_i is the WHO standard for each chemical parameter, P_i is the pollution index or score quantifying the level of risk for each influencing variable in the region, and C_i is the concentration of each chemical parameter in each water sample. The P_i values are represented by a non-dimensional number; the lower the value is the better water quality. This enabled us to better compare the quality of water along the river with respect to the selected variables.

The risk-taking assessment model is the aggregation model of the weighted scores for all variables of water sample in a site or area as presented in Eq. (1).

The most important advantages of the abovementioned pollution index are the use of weighting factor instead of direct use of different recommended guide levels, which at the same time provide a better view of the region's pollution condition and could reduce the confusion of choosing the type of guideline for a particular variable.

To facilitate practical use, scores of P_i and WQI were grouped into three: low, moderate, and high groups based on the following statistical interval sequences:

Table 2 Water quality variables: their standards ($\sim \mu\text{g/l}$) and assigned weights

Variable	Variable standard (S_i)	Weight (W_i)
Cr	50	0.123
Mo	70	0.088
Ni	70	0.088
Zn	5000	0.0012
SO ₄	250,000	0.000025
PO ₄	100	0.062
NO ₃	50,000	0.00012
Fe	300	0.02052
EC	750,000	0.0000082
TDS	500,000	0.0000123
Cl	200,000	0.0000308
SAR	15,000	0.00041
F.C	10,000	0.000616
Pb	10	0.62
COD	10,000	0.00062

If $(d_{\text{median}}) < (d_{\text{mean}})$, and $(d_{\text{median}} - d_{\text{min}}) > d_{\text{min}}$.
 (d_{min}) to $(d_{\text{median}} - d_{\text{min}})$ Low
 $(d_{\text{median}} - d_{\text{min}})$ to $(d_{\text{min}} + d_{\text{mean}})$ Moderate
 $(d_{\text{min}} + d_{\text{mean}})$ to (d_{max}) High
 Otherwise
 (d_{min}) to $(d_{\text{mean}} - d_{\text{min}})$ Low
 $(d_{\text{mean}} - d_{\text{min}})$ to $(d_{\text{min}} + d_{\text{median}})$ Moderate
 $(d_{\text{min}} + d_{\text{median}})$ to (d_{max}) High where d is the score of P_i and WQI.

Multivariate statistical analysis

To obtain information about characteristics, relationships, and the water quality variable's associations in the Kor River, basic statistical methods including PCA and HCA are carried out on the P_i data using SPSS 17.0 version (SPSS Inc., Chicago, IL, USA).

The hierarchical cluster analysis (HCA) is a connectivity-based clustering algorithm, and is often used for water quality assessment (Du et al. 2017). The significant reasons for influencing the consequences of HCA are the option of similarity (or distance) measures and the choice of linkage algorithms (Everitt et al. 2011; Primpas et al. 2008). In this study, we apply HCA based on squared-Euclidean distance to cluster the Kor River water P_i data. All the P_i data of the Kor River are considered for HCA. The squared-Euclidean distance is calculated between beach a and beach b from the standardized values by the following equation (Priddy and Keller 2005; Kamble and Vijay 2011):

$$D^2 = \sum_{i=1}^n (a_i - b_i)^2 \quad (4)$$

where D^2 is the squared-Euclidean distance, a_i is the standardized values of i variables for the beach a , b_i is the standardized values of i variables for beach b , n is a number of variables, and i is the P_i data.

Results

Water quality assessment by raw data

Table 3 summarizes the descriptive statistical results of 24 measured variables in the water samples from the 18 stations of the Kor River, and the results are compared with the values of the World Health Organization

Table 3 Summary statistics of measured variables in the Kor River

Variable	Min	Max	Mean	SD	Variance	Skewness	Kurtosis	WHO 2006	<i>a</i>
pH	7.42	9.54	8.1	0.5	0.28	0.80	1.51	6.5–8.5	–
Eh	100.2	208.4	152.5	36.6	1340.06	0.13	– 1.50	–	–
DO	4.1	11.9	8.99	1.9	3.5	– 0.75	1.75	–	–
EC	622	48,000	9987.8	14,141.9	199,994,261.48	2.00	3.29	750	–
Na	58.88	7169.10	1512.1	2112.3	4,461,883.34	2.02	3.35	200	–
K	1.17	1638.00	102.0	383.8	147,268.11	4.23	17.91	12	–
HCO ₃	170	536	317.8	103.8	10,782.71	0.69	– 0.49	–	–
Cl	142	21,442	3807.0	6002.6	36,031,103.70	2.14	4.16	200	–
Mg	12.0	522.0	167.6	156.8	24,574.02	1.01	0.08	50	–
Ca	20	4620	772.0	1332.4	1,775,420.24	2.26	4.45	100	–
SO ₄	16.8	600.0	228.5	198.1	39,233.22	0.68	– 0.40	250	–
NO ₃	.1	3720.0	408.1	942.5	888,354.62	2.98	9.46	50	–
PO ₄	.01	.86	0.2	0.2	0.04	1.61	3.16	–	–
TDS	502	41,633	8378.7	12,245.8	149,960,820.68	2.04	3.45	500	–
COD	.5	1094.0	382.9	324.5	105,328.43	0.35	– 0.45	–	–
F.C	2	5300	996.9	2003.7	4,014,797.30	1.87	1.80	–	–
T.C	2	5300	1864.8	1996.3	3,985,338.36	1.09	– 0.41	–	–
SAR	1.6	27.2	11.0	7.4	54.70	1.00	0.53	18	–
Cr	.75	40.67	7.1817	11.63336	135.335	2.284	4.509	50	0.3–2.1
Mo	.075	80.980	15.02167	19.094511	364.600	2.587	8.545	70	0.04–1.3
Ni	.75	27.91	5.9072	8.03972	64.637	1.910	3.038	20	0.15–10.39
Zn	.75	69.04	19.6639	20.00317	400.127	1.147	.682	10	3.3–10.3
Fe	8	210	53.56	52.186	2723.408	1.999	4.080	300	10–50
Pb	1.91	10.11	4.9789	2.25706	5.094	.812	.090	10	0.04–3.8

^aWorld river water range (Kabata-Pendias and Mukherjee 2007)

recommended limits (WHO 2006). From the measured data, it is evident that the hydroxyl ion concentration of the samples is alkaline condition and within the permissible limit of WHO except at site 10 (pH = 9.5). DO and COD values in the Kor River fluctuated from 4.1 to 11.9 mg/l and 0.5 to 1094 mg/l, respectively. The water samples of the Kor River have phosphate concentrations ranging from 0.1 to 0.86 mg/l, and the nitrate values of 0.1 mg/l to 3720 mg/l. The range of T.C and F.C values in the Kor River are recorded from 4 to 5300 MPN/100 ml and 1.5 to 5300 MPN/100 ml, respectively. The descriptive statistical values of selected heavy metals (Cr, Mo, Ni, Pb, Fe, and Zn) in Kor River water are also tabulated in Table 3. Contents of heavy metals (µg/l) in river water varied spatially from 0.75 to 40.67 for Cr, 0.075 to 80.98 for Mo, 0.75 to 27.91 for Ni, 0.75 to 69.04 for Zn, 8 to 210 for Fe, and 1.91 to 10.11 for Pb.

By reviewing the 24 measured variables, 15 physical, chemical, and biological variables in the river water were selected and subjected to indexing and multivariate statistical procedures (Table 2). Boyacıoğlu and Boyacıoğlu (2020) used factor analysis to optimize number of index components in proposing a surface water quality index based on German legislation. In this study however, water quality variables were selected based on analysis availability, importance in water quality tracing and pollution source identification, land use in the study area, and financial constraints.

Weighting factor

The weights of variables are given by the inverse relationship with their permissible limits (Kumar and Dua 2009) as expressed by Eq. (3). As expected, variables that have higher permissible limits are less harmful since

Table 4 Grouping matrix of P_i for calculating WQI in the Kor River

S.N	Pi-Cr	Pi-Fe	Pi-Mo	Pi-Ni	Pi-Pb	Pi-Zn	Pi-EC	Pi-Cl	Pi-SAR	Pi-SO4	Pi-NO3	Pi-PO4	Pi-TDS	Pi-COD	Pi-F.C	WQI
1	0.26	0.55	0.007	0.21	2.74	0.0009	0.0105	0.013	0.0023	0.0006	0.00001	0.00431	0.0105	0.00031	0.0179	3.84
2	0.25	0.45	0.007	0.17	2.64	0.0009	0.0102	0.012	0.0020	0.0006	0.00001	0.00739	0.0104	0.00185	0.0148	3.58
3	0.09	0.62	0.114	0.07	2.96	0.0612	0.0085	0.009	0.0026	0.0005	0.00027	0.00246	0.0097	0.06896	0.0400	4.05
4	0.09	0.82	0.007	0.07	3.19	0.0009	0.0102	0.012	0.0016	0.0005	0.00027	0.00431	0.0108	0.00123	0.0092	4.23
5	0.09	0.82	0.007	0.07	2.96	0.0009	0.0107	0.012	0.0018	0.0006	0.00038	0.01786	0.0113	0.00031	0.0068	4.01
6	0.09	0.15	0.013	0.07	4.49	0.0009	0.0051	0.004	0.0007	0.0004	0.00058	0.01786	0.0062	0.00062	0.0105	4.86
7	0.25	0.62	0.806	0.07	1.79	0.0116	0.0148	0.009	0.0013	0.0073	0.00038	0.02648	0.0188	0.08928	0.0148	3.72
8	0.15	0.82	7.123	0.38	4.61	0.0850	0.0334	0.026	0.0052	0.0148	0.00037	0.01108	0.0454	0.27155	0.8005	14.38
9	0.62	0.62	1.776	0.07	4.03	0.0518	0.0301	0.021	0.0047	0.0142	0.00042	0.00062	0.0353	0.27955	0.0277	7.57
10	0.09	1.23	2.344	0.07	2.01	0.0267	0.0271	0.024	0.0049	0.0068	0.00010	0.01293	0.0316	0.42302	0.0234	6.33
11	5.01	0.21	2.566	2.04	2.36	0.0208	0.3506	0.492	0.0109	0.0065	0.45812	0.01047	0.4516	0.50060	0.0009	14.49
12	4.16	0.15	2.065	2.46	1.72	0.0058	0.3941	0.660	0.0111	0.0074	0.19950	0.00985	0.5127	0.67363	0.0009	13.03
13	1.63	2.87	1.378	1.10	1.18	0.0191	0.1575	0.238	0.0071	0.0047	0.14039	0.05295	0.1870	0.36514	3.2635	12.59
14	1.52	0.82	0.655	0.12	3.28	0.0182	0.0313	0.028	0.0033	0.0027	0.01016	0.02648	0.0307	0.26231	3.2635	10.07
15	0.89	0.82	0.950	0.47	5.34	0.0328	0.0716	0.097	0.0046	0.0065	0.06773	0.03325	0.0809	0.31034	3.2635	12.44
16	0.22	4.31	1.330	0.82	6.23	0.0567	0.1084	0.167	0.0054	0.0068	0.01860	0.01663	0.1493	0.33558	0.2525	14.02
17	0.18	1.64	1.250	0.87	2.24	0.0254	0.1531	0.221	0.0072	0.0142	0.00690	0.00616	0.1943	0.36822	0.0068	7.18
18	0.31	2.26	1.388	0.26	1.43	0.0163	0.0488	0.066	0.0043	0.0064	0.00039	0.01293	0.0607	0.29125	0.0283	6.19

	Low index level
	Moderate index level
	High index level

they can damage the quality of river water when they are available in a very high quantity (Akkaraboyina and Raju 2012; Zotou et al. 2020). The weighting factor for each of these physiochemical variables is determined using Eq. (3). Accordingly, Pb, Cr, Mo, and Ni are the most important, followed by PO₄, Fe, Zn, COD, F.C, SAR, NO₃, and Cl, while SO₄, TDS, and EC are on the last rating (Table 2).

Assessment of pollution degree based on P_i

The P_i values calculated by Eq. (2) are tabulated in Table 4 and plotted in Fig. 4. The P_i values provide a meaningful yet quantitative visualization of the quality status of water variables. The P_i values of Mo, Pb, Cr, Fe, F.C, and Ni in the river water fluctuated greatly, varying from 0.007 to 7.123, 1.18 to 6.23, 0.09 to 5.01, 0.15 to 4.31, 0.0009 to 3.26, and 0.07 to 2.46, respectively. Moreover, high P_i values (higher than 1) were detected in 100% of the samples for Pb, 50% for Mo, 28% for Fe, and 17% for Ni and F.C.

Assessment of potential pollution sources

In this study, principal component analysis is applied to the P_i values of each variable of sampling stations to achieve a significant reduction of the dimensionality of the original dataset. Three PCs were obtained, which have eigenvalues greater than unity and explain 80.8% of the variance or information contained in the original dataset (Table 6).

The PC1 which accounts for 48.9% of the total variance is correlated with EC, TDS, Cl, Ni, Cr, SAR, NO₃, and COD. The PC2 explains 18.5% of the total variance and includes Zn, SO₄, Mo, and Pb, and with a less extent COD and Fe. The PC3 (13.3% of the total variance) is positively contributed by PO₄, F.C, and Fe, and, with a less extent, by COD and NO₃.

Assessment of potential risk-taking degree based on the aggregated model (WQI)

The WQI expressed by Eq. (1) is calculated for each measuring site along the Kor River and presented in

Table 5 (the last row) to assess the water quality of the Kor River and to define the potential risk-taking level of the water samples. Based on the values of WQI, and the above statistical intervals, the Kor River water is classified into three groups: low-risk group ($WQI < 5$), moderate-risk group ($5 < WQI < 10$), and the high-risk group ($WQI > 10$). The geographical distribution of WQI in accordance with these three groups is illustrated in Fig. 3.

The grouping of potential risk-taking degree based on the HCA

Furthermore, in this study, P_i data from 18 water samples with 15 variables were analyzed and classified with the hierarchical cluster analysis (HCA) to group sampling stations and compared with the WQI grouping results (Fig. 4). All the sampling stations on the study area were grouped into two clusters of similar water quality characteristics: cluster 1 (sampling stations 1 to 7 and 9, 10, 17, 18), and cluster 2 (sampling stations 8, 11 to 16).

Discussion

The objective of this research was to determine the quality status of the Kor River water based on physical, chemical, and biological variables and to develop a water quality index (WQI) that enables to identify pollution sources and their impact on different sections of the river. From Table 3, the high dispersion of most variables (high standard deviations) can be seen, which indicates variability in chemical composition between samples, thus pointing to the presence of temporal variations caused likely by polluting sources and/or climatic factors. The variation can also be because of the processes such as adsorption and desorption of variables and buffering action of sediment under varying environmental conditions (Sankar et al. 2010). The minimum value of DO and the maximum value of COD are recorded in sites 15 and 12, respectively. The decomposition of high levels of organic matter and soluble organics of raw materials and chemicals existing in the industrial wastewater and municipal sewage contribute to changes of DO and COD in the surface water. In the

Table 5 Scale values of P_i and WQI for water quality grouping

Variable	Mean	Min	Max	Median	Low		Moderate		High	
Cr	0.884	0.09236	5.008505	0.251841	0.092	0.159	0.159	0.977	0.977	5.009
Fe	1.099	0.15394	4.310245	0.820999	0.154	0.667	0.667	1.253	1.253	4.310
Mo	1.321	0.00660	7.12334	1.099992	0.007	1.093	1.093	1.328	1.328	7.123
Ni	0.520	0.06597	2.45508	0.192202	0.066	0.126	0.126	0.586	0.586	2.455
Pb	3.066	1.17608	6.225225	2.850919	1.176	1.675	1.675	4.242	4.242	6.225
Cl	0.117	0.00437	0.660145	0.025411	0.004	0.021	0.021	0.122	0.122	0.660
NO ₃	0.050	0.000012	0.458117	0.000406	0.000	0.000	0.000	0.050	0.050	0.458
COD	0.236	0.00031	0.67363	0.275548	0.000	0.235	0.235	0.276	0.276	0.674
F.C	0.614	0.00092	3.263471	0.020628	0.001	0.020	0.020	0.615	0.615	3.263
Zn	0.024	0.00092	0.085023	0.018614	0.001	0.018	0.018	0.025	0.025	0.085
SAR	0.005	0.00066	0.011147	0.004441	0.001	0.004	0.004	0.005	0.005	0.011
SO ₄	0.006	0.00041	0.014778	0.006461	0.000	0.005	0.005	0.007	0.007	0.015
PO ₄	0.015	0.00062	0.052954	0.012007	0.001	0.011	0.011	0.016	0.016	0.053
EC	0.082	0.00511	0.39408	0.030705	0.005	0.026	0.026	0.087	0.087	0.394
TDS	0.103	0.00618	0.51271	0.033497	0.006	0.027	0.027	0.109	0.109	0.513
WQI	8.142	3.57953	14.48547	6.753585	3.580	5	5	10	10	15

	Low index level
	Moderate index level
	High index level

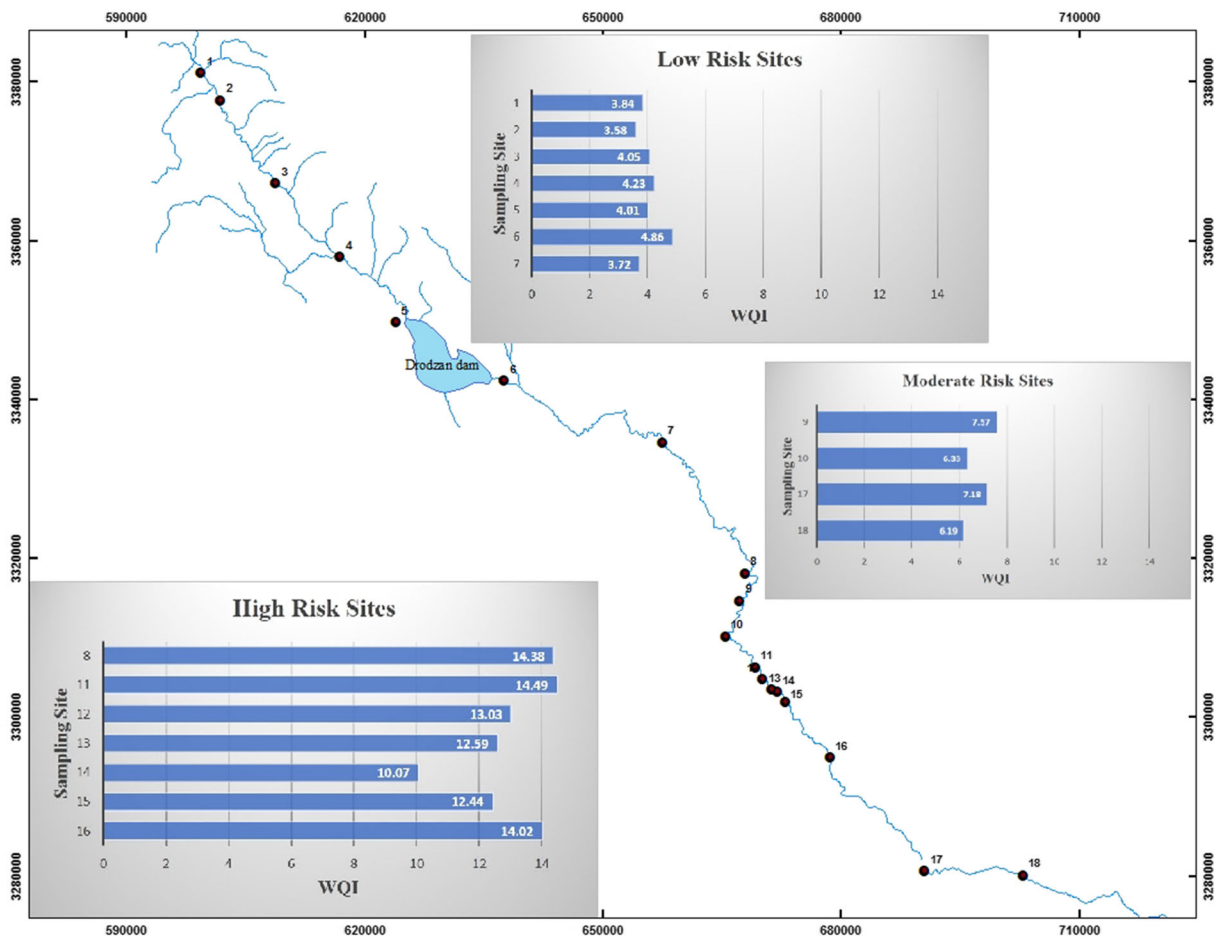
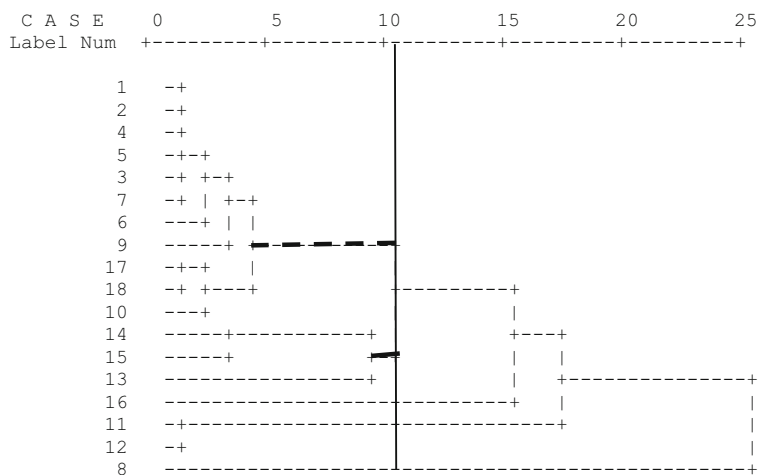


Fig. 3 Grouping WQI along the Kor River

present investigation, the EC and TDS values are found to be higher than the WHO permissible level, except at site 6. High EC represents water with high electrolyte

concentration, which can be due to the high evaporation rate. Moreover, higher TDS values of study area might be attributed to a large number of ionic substances such

Fig. 4 Dendrogram showing relationship among sampling sites through water quality variables along the Kor River



as Na⁺, Cl⁻, and SO₄²⁻ released due to the mixing of municipal wastewater, industrial wastewater, and agricultural runoff. A small quantity of phosphorus in the surface water is necessary for biological life but excess amount promotes the abundant growth of the nuisance algae. In this study, the higher PO₄³⁻ ion is found in sites 13 and 15 due to the agriculture runoff of PO₄³⁻ containing fertilizer, domestic detergents, and sewage water discharged into water bodies (Nyarumbu and Magadza 2016; Sunantha and Namasivayam 2016). The higher values of nitrate are observed in the sites 11 to 16. The presence of high nitrate in the river section sampled is suspected to originate from industry wastewater discharges (sites 11 and 12), as well as due to overland runoff from riverine agricultural fields where irrigated different crops are grown and the use of inorganic fertilizers (usually as ammonium nitrate) is rather frequent. Another possible way of nitrate input may be through the decomposition of nitrogen-containing organic compounds such as proteins and urea occurring in municipal wastewater discharges (site 15). Microbial studies related to water quality are reported by many researchers. In many cases, the occurrence of coliform groups, total coliform (T.C), and fecal coliform (F.C) in the aquatic medium have been used as principal microbial indicators of water pollution. Pollution indicator bacteria are enumerated using a multiple-tube fermentation method. So, this study determined the microbial quality of the Kor River water with the most probable number (MPN) test. In developing and underdeveloped countries with inadequate sanitation, microbial contamination of freshwater plays a vital role in causing pathogenic diseases in humans and animals. According to DWAF (1996), the range of coliform >2000 MPN/100 ml raises the risk of contracting gastrointestinal illness among water users (Singh et al. 2017). The water samples at some Kor River sections, such as sites 8, 13, 14, and 15, have an extremely high density of coliforms because of the open defecation and the discharge and infiltration of effluent from sewage treatments to the water, which may be significant health risks to the public (Sunantha and Namasivayam 2016).

Metals in the aquatic environment are reported to be well concentrated in the water, sediments, and aquatic organisms. These metals in trace content can play an important role in the biochemical life process of the aquatic organisms. However, their sublethal concentrations become lethal to aquatic organisms when the period of exposure to these metals is lengthened (Lawson

2011). According to high standard deviations, the distribution of heavy metals is not uniform along the river (Table 3). Variability in the distribution of metals may be due to the differences in the sources of the metals and prevailing physicochemical conditions and complex reactions such as adsorption, flocculation, and redox condition taking place in the sediment (Sekhar et al. 2004). Compare with the maximum value of world rivers (Kabata-Pendias and Mukherjee 2007), the mean metal values in the Kor River (except Fe and Ni) have higher values (Table 3). The mean metal values measured in this study are somewhat lower to those previously reported by Sheykhi and Moore (2012), although, a similar order of magnitude and trends has been observed earlier. In addition, comparing the metal values from different sampling sites, it can be concluded that Cr (at sites 12, 15, 17), Mo (at sites 10 to 18), Ni (at sites 12, 15, 17), Zn (at sites 11, 14, 18), and Pb (at sites 9, 11, 14, 18) from downstream Drodzan dam show higher levels, which is closely related with the low flow conditions and anthropogenic intrusions in the study area.

The *P_i* values indicated that the variables Pb, Mo, Fe, Cr, F.C, and Ni had the highest score, and the COD, Cl, TDS, EC, NO₃, and Zn are included in the next level of the highest score of pollution, while the lowest score of *P_i* is found in PO₄, SO₄, and SAR. Based on the *P_i*

Table 6 Rotated component matrix of 15 quality variables according to the varimax normalized along the Kor River

	Component		
	1	2	3
Pi-EC	.990	.038	-.012
Pi-TDS	.987	.049	-.035
Pi-Cl	.979	.008	-.017
Pi-Ni	.974	.051	.022
Pi-Cr	.939	-.119	.008
Pi-SAR	.930	.316	.056
Pi-NO ₃	.887	-.096	.019
Pi-COD	.814	.412	.181
Pi-Zn	-.106	.900	.065
Pi-SO ₄	.255	.828	-.051
Pi-Mo	.267	.806	-.027
Pi-Pb	-.344	.452	.121
Pi-PO ₄	.092	-.160	.924
Pi-F.C	.035	.004	.893
Pi-Fe	-.054	.321	.540

values, the Kor River water is classified into three levels: low-pollution level, moderate-pollution level, and high-pollution level. The grouping scale for the values of P_i is presented in Table 5. These three numerical levels of P_i were directly applied to assess possible risk arises from the variable contamination in the water of the study area, which is tabulated in Table 4. The grouping reveals that for example, scores of Cr, Ni, COD, EC, TDS, and SAR primarily existed in high pollution levels at sites 11 and 12. The scores of Pb increased at sites 15 and 16, while F.C and PO_4 most strongly enriched at site 13 (Table 4). Therefore, the risk assessment performed in this study can identify the levels of the variables in the river that are clearly high and likely posed an ecological risk for the water at some sites.

As can be seen in Table 6, PC1 is highly participated by most variables, and high and positive scores on this component indicated high mineral content, and can be interpreted as a soil leaching and erosion origin and dissolution of river basin minerals, such as limestone, marl, and gypsum. In the same way, variables related to anthropogenic pollution like Mo, Pb, and Zn have high participation in PC2. The municipal wastewater and industrial effluents and agricultural runoff in the river catchments are major sources of PC2 variables in the water. The PC3 can be explained taking into account the nutrient and bacteria influence from non-point sources such as atmospheric deposition and agricultural runoff.

According to the results of WQI grouping, there are clear differences in the pollution level of variables between the groups (Fig. 3 and Table 4): The moderate and high-risk groups are consisted of the sites located in the lower area of the map, while the sites in the low-risk group are distributed in a mountainous area (Fig. 3). The low-risk group includes sites 1 to 7, all of them located at the upstream portion of the Kor River. From the value of pollution indices (Table 4), it is seen that these sampling stations are characterized by a low pollution level of physicochemical and microbial variables. However, nutrients and metals are high in some stations (e.g., Zn at site 3, and PO_4 at sites 5, 6, 7). These results are not surprising knowing that agriculture dominates the upper catchment of the Kor River. Tian et al. (2019) and Edoreh et al. (2019) also found that high PO_4 content is affected by agricultural activities and aquaculture. The moderate-risk group is defined by sites 9, 10, 17, and 18. They are characterized by variable concentrations of moderate-high pollution index (P_i) (Table 4). These sampling stations are in areas influenced by diffuse

pollution sources. Seven sites are included in the high-risk group, namely 8 and 11 to 16. The water quality index for these sites ranges from 10.07 to 14.49. The risk caused by toxic variable assemblage in these sites is important and highly localized, which can be the result of the industrial wastewater discharges (e.g., petrochemical industry) and overland runoff from riverine agricultural fields in surrounding regions.

The grouping results of potential risk-taking degree based on the HCA indicated that the low-risk to moderate-risk stations fall in cluster 1 and high-risk stations fall in cluster 2.

Astel et al. (2007), Voyslavov et al. (2012), and Tian et al. (2019) stated the experience of research on different approaches for data clustering, specifically with the multiple of the median or mean data (e.g., Edet and Offiong (2002); Sheykhi and Moore (2012); Tian et al. (2019)), self-organizing map, SOM (e.g., Astel et al. (2007)), weighted arithmetic water quality index (Anyanwu and Emeka 2019), and HCA (Shrestha and Kazama 2007; Charizopoulos et al. 2018). However, our results indicate that setting up P_i and WQI data of physical, chemical, and biological indicators in combination with the proposed statistical interval sequence approach allows one to better assess the quality and potential risk-taking level of the river water.

Conclusions

In this study, characteristics of water quality conditions obtained in the case study may provide baseline information for the local authorities for the pollution control and management of the Kor River.

The results of the environmental analytical chemistry obtained in this study have demonstrated that river water is polluted, especially due to industrial wastewater, agricultural land runoff, and domestic wastes. The higher level of NO_3 , F.C, COD, Mo, and Cl was presented in water samples, and other variables were also observed in considerable contents. The results indicate that compared with HCA, the application of the WQI model with the statistical sequence grouping has achieved the meaningful classification of river water samples. The sampling sites on the river were grouped into three groups of similar water quality characteristics: group 1 (sampling sites 1 to 7), group 2 (sampling sites 9, 10, 17, 18), and group 3 (sampling sites 8, 11 to 16) and therefore

represented as low, moderate, and high-risk regions, respectively.

The quality of industrial and domestic effluents of the study area (e.g., sites of group 3) can be improved before their discharge to the watercourses via effective techniques.

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