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Modelling and Assessment of Irrigation Water Quality Index Using GIS in Semi-arid Region for Sustainable Agriculture

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Abstract Agriculture is the largest consumer of water, particularly in arid and semi-arid regions, so identifying and managing surface water quality in these areas is critical to preserving water resources and ensuring sustainable agriculture. Irrigation water quality (IWQ) assessment integrated with geographic information system (GIS) of West Nile Delta, Egypt, was carried out using suitability indicators such as hazards of salinity, permeability hazard, specific ion toxicity, and miscellaneous impacts on sensitive crops. In ArcGIS 10.7, inverse distance-weighted algorithms and the Model Builder function were used to categorize irrigation water quality into different classes. According to the findings, 87% and 13% of the water samples from the study area were categorized as medium and high suitability for irrigation, respectively. The heavy metal pollution index (HPI), Nemerow index (NeI), ecological risks of heavy metal index (ERI), heavy metal evaluation index (HEI), pollution load index (PLI), and modified degree of contamination (mCd) for five selected metals, namely As, Co, Cu, Ni, and Zn, were calculated to assess heavy metal contamination levels in the study area. The results showed that HPI had 3.7% medium contamination and 96.3% high contamination; NeI was 7.4% moderately contaminated and 92.6% heavily contaminated; ERI has almost 7% low risk, 30% moderate risk, 41% considerable risk, and 22% very high risk; HEI had 100% low contamination; PLI was 100% polluted; and mCd has 18.5% moderately-heavily polluted, 63% heavily polluted, and 18.5% severely polluted samples. This research can help decision-makers manage water resources more effectively for sustainable agriculture.

Keywords IWQI · GIS · Heavy metal indices · West Nile Delta-Egypt

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1 Introduction

Irrigated areas will be expanded throughout the world, particularly in arid and semi-arid regions, to meet the expected increase in food production (Asseng et al., 2018), as the world's population is expected to reach 9.0 billion people by 2030 (Godfray et al., 2010). Agriculture is the largest consumer of water in arid and semi-arid regions such as Egypt, accounting for more than two-thirds of the world's available fresh water resources (Ali et al., 2020; Ding et al., 2021). Egypt uses drainage water as its primary irrigation resource due to limited fresh water resources, an arid climate, and rapid population growth (Ding et al., 2020a; Seleiman et al., 2019), deteriorating soil quality and increasing pollution (Seleiman & Kheir, 2018b, 2018a). Consequently, the polluted soil with toxic heavy metals not only declined crop yield and quality but also increased the risk to human health (Kheir et al., 2021). Proper water quality used for irrigation management is critical to achieving long-term yield sustainability in agricultural products (Safiur Rahman et al., 2017). Thus, the quality of irrigation water must be assessed in order to avoid or, at the very least, minimize impacts on agriculture. Local and national governments work hard to protect this valuable resource for long-term development, as farming is an important part of the global economy and is regarded as the largest consumer of fresh water, as well as a significant cause of surface and groundwater quality degradation (Asadi et al., 2020; Faithful & Finlayson, 2005). Good management of various land and water resources is critical to preserving food deliveries and achieving agricultural development sustainability, but Egypt's neutral resources are under too much strain due to population growth and land degradation (Baroudy et al., 2020; El Baroudy, 2011).

Water quality is characterized as the natural, physical, and chemical state of water, as well as any human-induced changes (Ighalo & Adeniyi, 2020; Jafar Ahamed et al., 2013; Salahat et al., 2014). Water quality indices (WQIs) aid in the condensing of large datasets generated by monitoring programs into a single value that characterizes water quality (Singh et al., 2020). WQI prediction could also be accomplished using artificial intelligence techniques and evolutionary computing-based formulations (Hameed et al., 2017). GIS has also been used to predict WQI for groundwater (Oseke et al., 2021; Rawat & Singh, 2018), which necessitates further investigation in surface water and in arid regions. Numerous researchers have used hydrochemical indices such as sodium adsorption ratio (SAR), permeability index (PI), and irrigation water coefficient (Cieszynska et al., 2012; Li et al., 2013; Yıldız & Karakuş, 2020). These indices include a combination of chemical analyses, so better results are expected. Furthermore, water suitability for irrigation can be determined by evaluating electrical conductivity (EC), exchangeable sodium ratio (KR), residual sodium carbonate (RSC), magnesium adsorption ratio (MAR), and total hardness (TH) (Thapa et al., 2017). Although many studies have been conducted to assess groundwater quality based on heavy metal contamination for various uses, very few studies have been conducted with surface water quality in arid and semi-arid regions (Amiri et al., 2014; Rezaei et al., 2019; Wątor & Zdechlik, 2021). One of the important indices is the heavy metal pollution index (HPI). This method is used to characterize water quality based on the maximum desirable and maximum permissible limit of each heavy metal (Maskooni et al., 2020). Moreover, comparable indices include the heavy metal evaluation index (HEI), the Nemerow index (NeI), and the ecological risks of heavy metals (Chaturvedi et al., 2019; Mukherjee et al., 2020; Sawut et al., 2018). A geographical information system (GIS) is a powerful tool for storing, controlling, analyzing, and producing spatial distribution of information for making decisions in multiple areas at once, which aids in the resolution of relevant issues. It also serves an important purpose in demonstrating the distribution of water quality parameters (Manap et al., 2014; Nampak et al., 2014). Instead of using these parameters in isolation, this study used a GIS environment to incorporate all water quality parameters to provide a more precise predictor for surface water quality. Furthermore, GIS provides a baseline data regarding contamination by selected heavy metals to access the overall water quality in the study area and identify the areas with the highest and lowest quality, resulting in more useful outcomes for achieving sustainable development. Therefore, the following objectives were clearly defined in order to provide critical information on the suitability of the water sources.

i. Identifying the location of surface water feeding.
ii. Determine the WQI parameters in water canals.
iii. Produce interpolated maps of water properties.
iv. Modelling parameters of hazards using Model Builder in ArcGIS 10.7.
v. Comprehensive evaluation of water contamination in the study area.

To our knowledge, our research is one of the few studies that assess surface water quality in the study area, and the results provide valuable information on the water's suitability for irrigation use, which decision-makers can use as a guide for quantitative and qualitative management.

2 Methods

2.1 Location of the Study Area

The study area is located in the Northwest of Nile Delta, Egypt. It lies between longitudes 30° 15′ 0″ and 30° 40′ 0″ E, and latitudes 31° 7′ 15″ and 31° 30′ 45″ N, with total area of 767 km^2 (Fig. 1). The area is characterized by a Mediterranean Sea climate. The average maximum temperature is relatively high in the dry season as it recorded 30.0 °C in August. The average minimum temperature was 13.0 °C in January. Winter rainfall is typically light and showery from November to February with a total amount of about 190 mm annually. The lowest value of evaporation was observed in January and December due to low temperatures, while the highest value was observed in June and September due to relatively high temperatures. The annual average of evaporation ranges from 3.3 to 4.8 mm/day. The lowest proportion of relative humidity was observed in April (51%) and the highest was observed in December (58.4%). The soil temperature regime is "Thermic" and the soil moisture regime could be defined as "Torric" and the studied area is formed by Holocene deposits (Dawoud et al., 2005). The irrigation system is mostly surface irrigation, with water pumped from irrigation canals and drains into furrows and basins. The source of irrigation water in the study area is the Rosetta branch (239 km long), which emerges from the Nile 20 km north of Cairo and runs west, ending in the sea at the City of Rosetta. Open drains, which are widely used to drain excess irrigation water as well as irrigation, are widely distributed.

2.2 Collecting Samples and Laboratory Analyses

The performed working methodology of this study is shown in Fig. 2.

During the 2019 field inventory, 27 surface water samples were collected from irrigation canals and drains (Fig. S1). Samples were collected in freshly washed plastic bottles and placed in an ice box for laboratory analysis. Chemical analysis of water samples was performed by the accredited soil, water, and plant laboratory at Tanta University's Faculty of Agriculture in accordance with ISO/IEC 17,025:2017 requirements. The chemical analysis included the determination of the major ions (i.e., Na^+, K^+, Ca^{++}, Mg^{++}, Cl^-, CO_3^{--}, HCO_3^-, and SO_4^{--}, pH, and the EC) as well as trace elements (As, Co, Cu, Ni, and Zn). Laboratory analyses were carried out according to the American Public Health Association (APHA, 2012). Electrical conductivity (EC) was measured by a EUTECH conductivity meter and the pH was

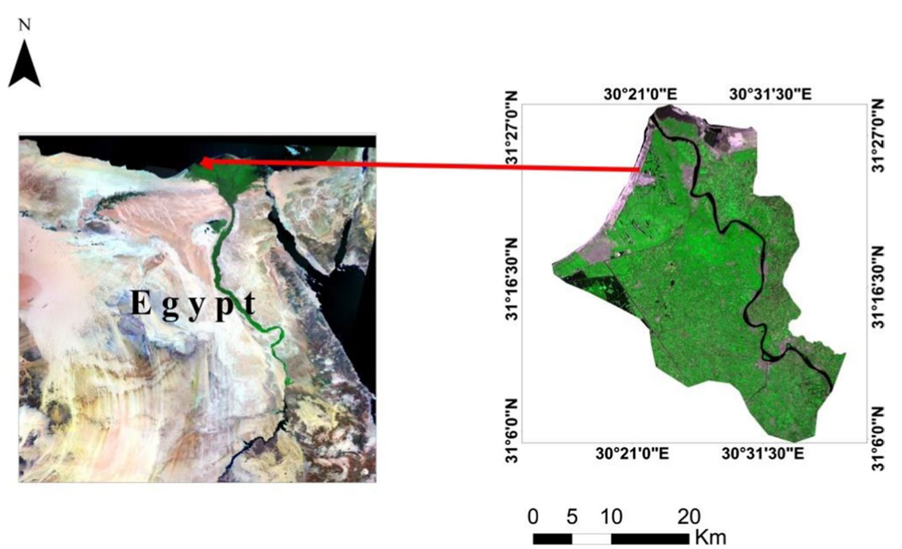


Fig. 1 Location of the study area relative to Egypt map

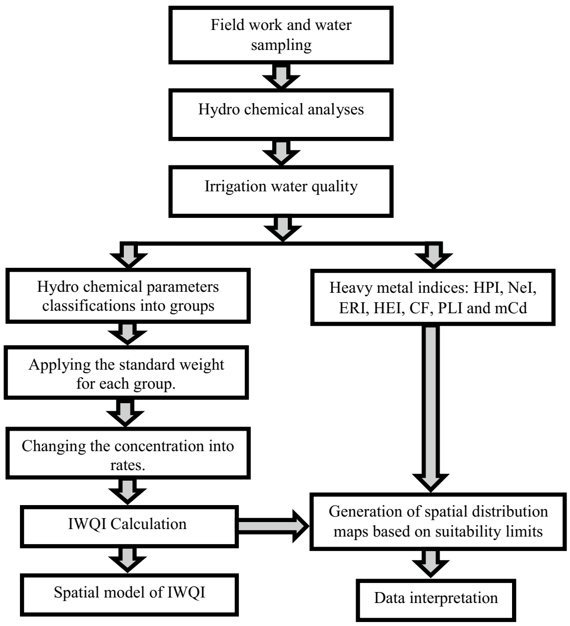


Fig. 2 Flow chart showing the working methodology

measured using a HANNA pH meter. Direct titration with EDTA solution was used to determine calcium and magnesium levels. A flame photometer was used to measure the Na^+ and K^+ directly. Titration with a regular sulfuric acid solution was used to measure carbonate and bicarbonate. Chloride was measured using potassium chromate as an indicator and a titration against a regular solution of silver nitrate. Sulfate was calculated by the difference between the content of soluble cations and soluble anions (Cl^-, HCO_3^-, and CO_3^{--}). Heavy metal concentrations were measured by inductively coupled plasma (ICP) optical emission spectroscopy.

2.3 Irrigation Water Quality Index (IWQI) Calculation

It is widely accepted that the types and severity of problems caused by irrigation water quality differ depending on a variety of factors, including soil type and crops, the environment of the region, and the farmers who use the water. In general, irrigation water quality is assessed based on five measures (salinity danger, penetration and permeability issues, toxicity hazard, and other issues) (De La Mora-Orozco et al., 2017; Simsek & Gunduz, 2007). Toxicity risks are further subdivided into those associated with specific ions as well as those associated with the presence of trace elements and heavy metals. Weights of 1–5 were assigned to various hazards based on their importance for irrigation water (Table 1), and the rating scale for each parameter was changed from 1 to 3, with 1 indicating low water suitability and 3 indicating high irrigation suitability (Asadi et al., 2020). The proposed IWQI, which evaluates the mutual effect of quality parameters, was calculated using Eqs. 1 and 2.

$$\boldsymbol{G} = \frac{\boldsymbol{w}}{\boldsymbol{N}} \sum_{\boldsymbol{k}=1}^{\boldsymbol{N}} \boldsymbol{r_k} \tag{1}$$

where k is an incremental index, w is the weight of each hazard, N is the total number of parameters, and r is the rating value of each parameter as given in Table 1.

$$\mathrm{IWQ_{index}} = \sum_{i=1}^{5} G_i \tag{2}$$

where i is an incremental index and G is participating of each water quality parameter, which mentioned before including salinity, infiltration, specific ion toxicity, trace element toxicity, and miscellaneous effects.

Following the calculation of the index value, an appropriate investigation was conducted in light of three guide classes. The IWQI was classified as low if it was less than 22, medium if it was between 22 and 37, and high if it was greater than 37. The qualities were developed using a large number of rating factors such as 1, 2, and 3 for each parameter while measuring coefficients remained constant, resulting in three different values for indices (i.e., 15, 30, 45) to set the upper and lower limits. The medians of these values were calculated and used as part of each specific classification (Asadi et al., 2020).

2.4 Producing Interpolation Maps

The ArcGIS 10.7 software's inverse distance-weighed (IDW) algorithm was used to generate interpolated maps of chemical parameters. This method is based on calculating of grid note by taking into account nearby points that are within a user-defined search radius. As shown in the following equation, the local influence of the measuring point decreases with distance.

Table 1 Classification for IWQ index parameters

Hazard	Weight	Parameter			Range	Rating	Suitability
Salinity hazard	5	EC (µS/cm)			EC < 700	3	High
					700 ≤ EC ≤ 3000	2	Medium
					EC > 3000	1	Low
Infiltration and permeability hazard	4	SAR	0–3	and EC	> 700	3	High
					700–200	2	Medium
					< 200	1	Low
			3–6		> 1200	3	High
					1200–300	2	Medium
					< 300	1	Low
			6–12		> 1900	3	High
					1900–500	2	Medium
					< 500	1	Low
			12–20		> 2900	3	High
					2900–1300	2	Medium
					< 1300	1	Low
			20–40		> 5000	3	High
					5000–2900	2	Medium
					< 2900	1	Low
Specific ion toxicity	3	SAR			SAR < 3	3	High
					3 ≤ SAR ≤ 9	2	Medium
					SAR > 9	1	Low
		Chloride (mg/l)			Cl < 140	3	High
					140 ≤ Cl ≤ 350	2	Medium
					Cl > 350	1	Low
Trace element toxicity	2	Arsenic (mg/l)			As < 0.1	3	High
					0.1 ≤ As ≤ 2.0	2	Medium
					As > 2.0	1	Low
		Cobalt (mg/l)			Co < 0.05	3	High
					0.05 ≤ Co ≤ 5.0	2	Medium
					Co > 5.0	1	Low
		Copper (mg/l)			Cu < 0.2	3	High
					0.2 ≤ Cu ≤ 5.0	2	Medium
					Cu > 5.0	1	Low
		Nickel (mg/l)			Ni < 0.2	3	High
					0.2 ≤ Ni ≤ 2.0	2	Medium
					Ni > 2.0	1	Low
		Zinc (mg/l)			Zn < 2	3	High
					2 ≤ Zn ≤ 10	2	Medium
					Zn > 10.0	1	Low

Table 1 (continued)

Hazard	Weight	Parameter	Range	Rating	Suitability
Miscellaneous effects to sensitive crops	1	Bicarbonate (mg/l)	$HCO_3 < 90$	3	High
			$90 \leq HCO_3 \leq 500$	2	Medium
			$HCO_3 > 500$	1	Low
		pH	$7.0 \leq pH \leq 8.0$	3	High
			$6.5 \leq pH < 7.0$ and $8.0 < pH \leq 8.5$	2	Medium
			$pH < 6.5$ or $pH > 8.5$	1	Low

$$z_p = \frac{\sum_{I=1}^{n}\left(\frac{z_i}{d_i}\right)}{\sum_{i=1}^{n}\left(\frac{1}{d_i}\right)} \tag{3}$$

where z_p denotes the value predicted at point P, z_i represents the z value at the measured point i, and d_i is the distance between point 0 and the point "i".

2.5 Modelling of IWQI Parameters

The Model Builder tool in ArcGIS 10.7 was used to create a spatial model. This tool was used to automate selected spatial analysis documentation and data management processes, which were then displayed in a diagram chain (Shokr et al., 2021) (Fig. 3). Each process's output is used as the input to another process. The following steps were applied in this research to obtain the final IWQI map of the study area: (a) interpolation of different water properties from point based to raster layer; (b) the output from (a) reclassified into three classes (i.e., low, medium, high); (c) the reclassified values assigned to a rating scale from 1 (low quality) to 3 (high quality); (d) Assigning weight for each IWQI parameter according to Table 1; (f) feeding Eq. (3) using the raster calculator tool; (g) the output from (f) used as input in weight sum function to produce and display the IWQI final map.

2.6 Assessment of Water Contamination

2.6.1 Heavy Metal Pollution Index (HPI)

The HPI method was created by assigning a ranking or weightage (W_i) to each parameter and choosing the pollution parameter on which the index would be based. The rating is a random number between 0 and 1 that represents the relative significance of individual quality factors. In the absence of any other water source, the uppermost permissive value for irrigation water (S_i) refers to the maximum permissible concentration of irrigation water. The concentration limit (i.e., the maximum permissible value for irrigation water (S_i)) is taken from this analysis. The HPI was according to Bhuiyan et al. (2010). The following expression is used to assign a ranking or weightage (W_i) to each selected parameter.

$$HPI = \frac{\sum_{i=1}^{n} W_i Q_i}{\sum_{i=1}^{n} W_i} \tag{4}$$

where Q_i is the ith parameter sub-index of the, W_i is the weight of the ith parameter unit, and n is the number of parameters. Q_i was determined according to the following equation:

$$Q_i = \sum_{i=1}^{n} \frac{\left[M_i(-)I_i\right]}{S_i - I_i} * 100 \tag{5}$$

where M_i is the measured heavy metal, I_i is the ideal values of the ith parameter, and S_i is the standard values of the ith parameter. The sign $(-)$ indicates numerical difference of the two values, ignoring the algebraic sign.

2.6.2 Nemerow Index (NeI)

This index is based on a multifactorial and integrated assessment method, where it is calculated using the following equation according to Vu et al. (2017):

Fig. 3 Spatial model structure for assessing the irrigation water quality index

$$\mathrm{NeI} = \left[\frac{\left\{ \left(M_i|I_i\right)^2_{\mathrm{mean}} + \left(M_i|I_i\right)^2_{\mathrm{max}} \right\}}{n} \right]^{\frac{1}{2}} \quad (6)$$

where $(M_i/I_i)_{\text{mean}}$ is the average value of (M_i/I_i) for all measured heavy metals in water samples and $(M_i/Ii)_{\max}$ is the maximum values.

2.6.3 *Ecological Risks of Heavy Metal Index (ERI)*

This index was used in this research to assess the potential ecological hazards which occurred by heavy metals (Sharifi et al., 2016; Wen et al., 2019). The ecological risk index was determined as follows:

$$\mathrm{ERI} = \sum_{i=1}^{n} \left[T_i * \left(\frac{M_i}{I_i} \right) \right] \quad (7)$$

where T_i is the ith target heavy metal biological toxicity factor metal. The toxic-response factor of heavy metals is given as As = 10; Co, Cu, and Ni = 5; and Zn = 1 (Hakanson, 1980).

2.6.4 *Heavy Metal Evaluation Index (HEI)*

The heavy metal evaluation index provides a snapshot of water quality in terms of heavy metals. It is calculated based on the MAC for each specific heavy metal using the following equation:

$$\mathrm{HEI} = \sum_{i=1}^{n} \mathrm{HEI}_i$$

where $\mathrm{HEI_i}$ is the pollution index of the ith heavy metal calculated as:

$$\mathrm{HEI}_i = \frac{M_i}{H_{\mathrm{imac}}} \quad (8)$$

where H_{imac} is the ith heavy metal maximum permissible concentration.

2.6.5 Contamination Factor (CF)

The CF index is used to assess contamination levels by dividing the target mean heavy metal concentration (C_{metal}) by the background concentration of water or sediment ($C_{background}$). The following equation was used to calculate this index.

$$CF = \frac{C_{metal}}{C_{background}} \tag{9}$$

2.6.6 Pollution Load Index (PLI)

PLI reveals the quantity of a pollutant in the environment. The index was determined using the following equation:

$$PLI = \left(CF_1 * CF_2 * CF_3 * \ldots\ldots\ldots CF_n\right)^{\frac{1}{n}} \tag{10}$$

where n is the number of target heavy metals and CF is the contamination factor. The contamination factor index was calculated, as shown in Eq. (9).

2.6.7 Modified Degree of Contamination (mCd)

The modified degree of contamination (mCd) index is superior to single-element indices because it considers the synergistic effects of contaminants at a study site (Brady et al., 2015). Modified degree of contamination (mCd) is calculated as follows:

$$mC_d = \frac{1}{n}\sum_{i=1}^{n} CF \tag{11}$$

3 Results and Discussion

3.1 Physiochemical Characteristics of Irrigation Water in the Study Area

3.1.1 Electrical Conductivity (EC)

Crop productivity generally decreases when the EC in irrigation water exceeds 3000 dS/m. The accumulation of salts in the crop root causes salinity hazards by reducing water availability to levels that have a severe impact on crop yield (Ding et al., 2020a, 2020b; Liu et al., 2021). Salts are frequently derived from dissolved minerals in irrigation water or a high saline water table. Crop yield decreases are caused by high osmotic pressure, and as a result, the crop is no longer able to extract enough water from the soil (Zouahri et al., 2014). On the contrary, low salt concentrations are beneficial for irrigation; however, irrigation water should not be free of salts, as this reduces soil permeability and fertility. EC values in the study area ranged from 492 to 10,210 µs/cm with an average of 2208.3 µs/cm. The data show that EC values vary greatly within the study area as standard division (STD = 2090.9) (Table S1). The spatial distribution of salinity in the study area reveals that the northeast of the study area has the highest value, which could be due to the discharge of drain water in irrigation canals (Fig. 4a).

3.1.2 Infiltration and Permeability Hazard

The combined EC-SAR parameter is used to assess the potential infiltration hazard that may develop in a soil, as low salinity with high SAR values causes a critical infiltration hazard, whereas high salinity with low SAR values does not cause any infiltration problem. These hazards typically occur in the soil's surface layer because they are strongly related to the stability of the soil structure. According to this parameter, approximately half of the study area is classified as high, while the remainder is classified as medium (Fig. 4a, b).

3.1.3 Specific Toxicity

Because of its specific negative effects on soil physical properties and plant survival, sodium hazard is commonly abbreviated as SAR. When evaluating irrigation water, this parameter should be identified (Kavurmaci & Apaydin, 2019). In general, irrigation water with SAR values less than 3 is considered to be of high quality. It is clear from Fig. 4b that the majority of the samples are excellent for irrigation, while the remaining samples are good. The data show that SAR values vary greatly within the study water samples as standard division (STD = 3.77) (Table S1). Chloride is commonly found in irrigation water and is very important for crops, but only in low concentrations because high concentrations can cause

Fig. 4 Spatial distribution of irrigation water quality parameters: (**a**) electrical conductivity (EC: µS/cm), (**b**) sodium adsorption ratio (SAR), (**c**) chloride (Cl: mg/l), (**d**) arsenic (As: mg/l), (**e**) cobalt (Co: mg/l), (**f**) copper (Cu: mg/l), (**g**) nickel (Ni: mg/l), (**h**) zinc (Zn: mg/l), (**i**) bicarbonate (HCO_3: mg/l), and (**j**) soil reaction (pH)

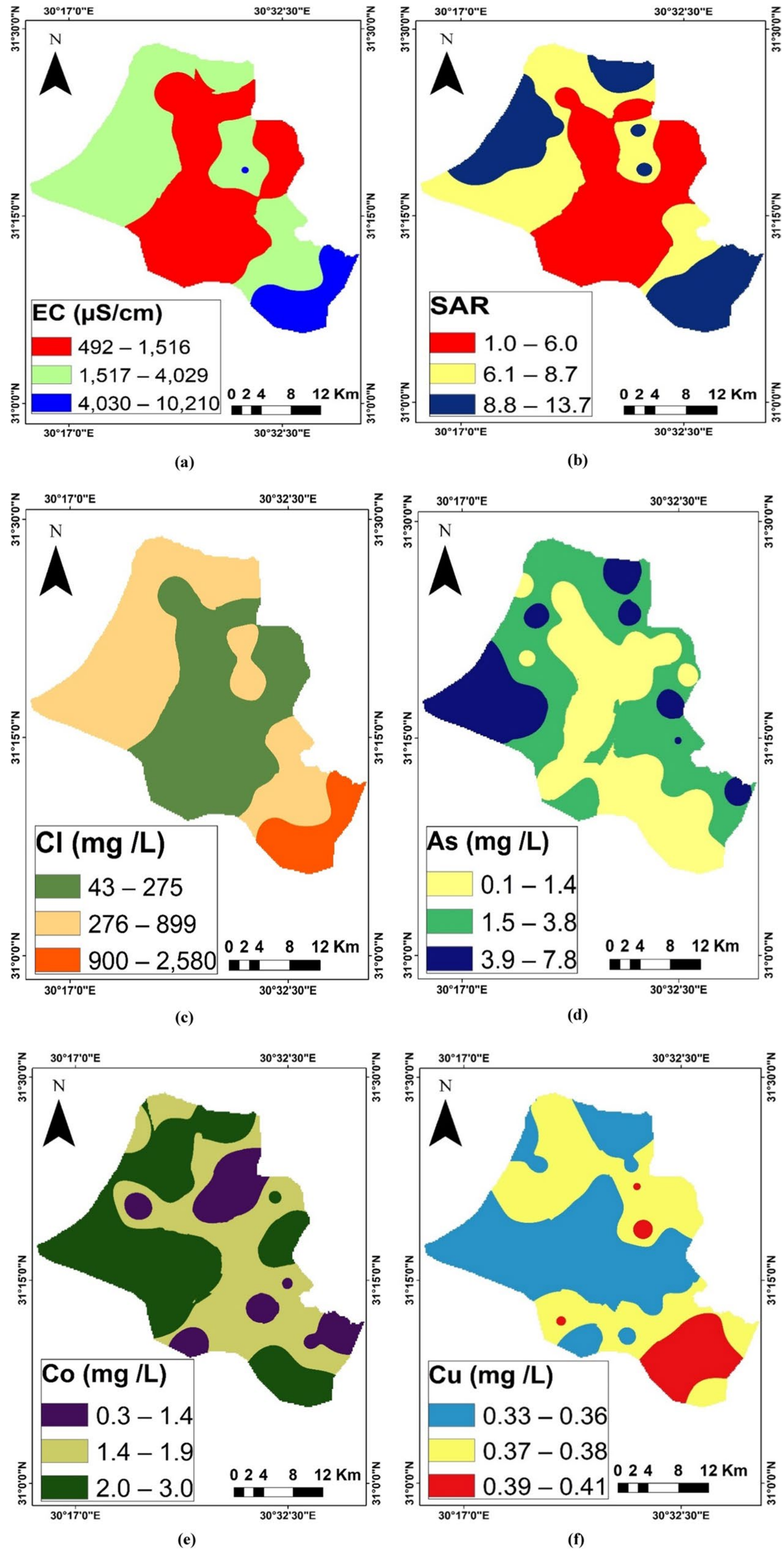
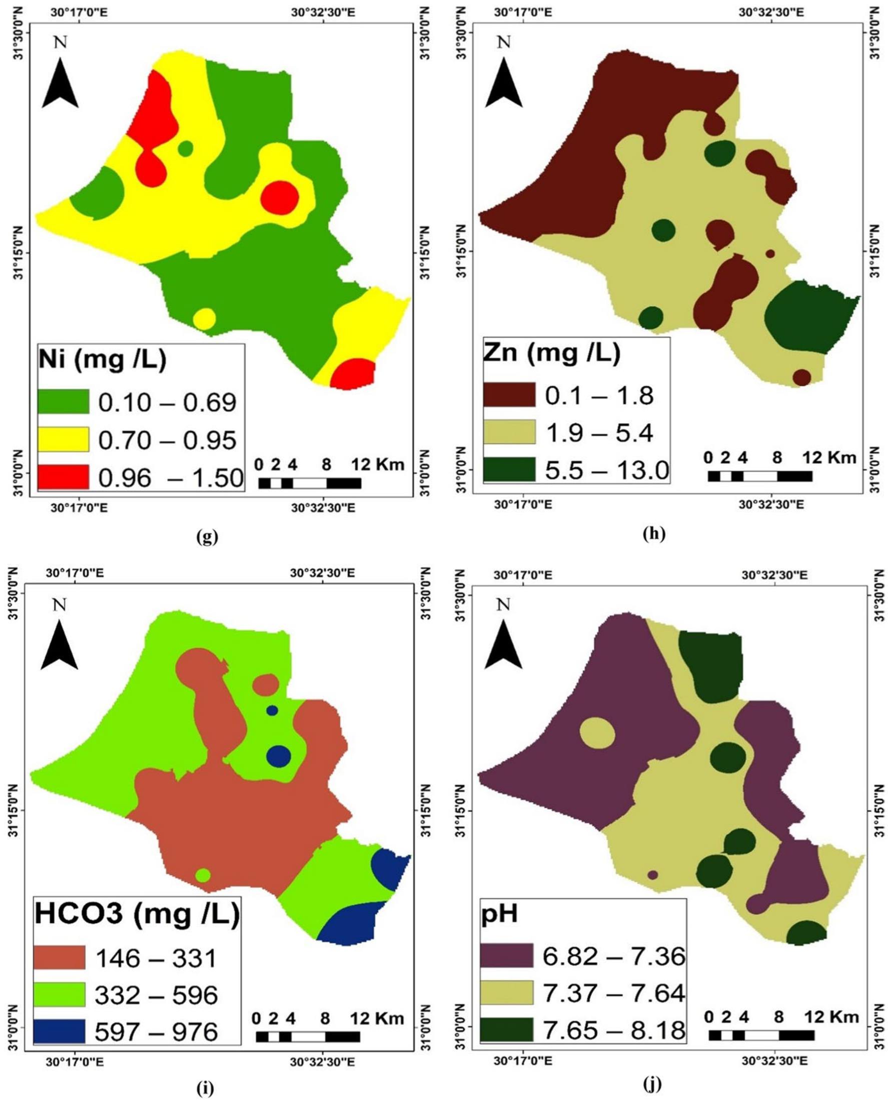


Fig. 4 (continued)



toxicity in sensitive crops, resulting in leaf burns or leaf tissue death (Bouaroudj et al., 2019). Chloride levels range from 42.6 to 2577.3 mg/l, with an average of 434.94 mg/l (Table S1). In general, water is considered good quality for irrigation when the chloride concentration is less than 140 mg/l. Chloride concentration in the study area was classified into three categories: high (43–275 mg/l), medium (276–899 mg/l), and low (900–2580 mg/l) (Fig. 4c). The chloride interpolation map revealed that the highest value was found on the western east side, as shown in Fig. 4c .

3.1.4 Toxicity of Heavy Metals

Some trace elements and heavy metals in irrigation water are responsible for soil contamination and are important for irrigation water quality due to properties such as resistance to biodegradation and thermo-degradation (Antoniadis et al., 2019). These elements are dangerous because they can accumulate to extremely high toxic concentrations before affecting plant, animal, and human health (Kheir et al., 2021). The data shown in the interpolation map indicated that arsenic (As) levels were high in the north-western side of the study area, as well as in some small areas in the north-eastern and west sides (Fig. 4d). The highest concentration was found in canal 5, and all samples, with the exception of canal 7 (0.05 mg/l), significantly exceeded the FAO 1985 values (Table 2). These concentrations might cause stem chlorosis and root growth suppression (Singh et al., 2016). About 33.33% of samples got rate 1 (low suitability), 59.26% rate 2 (medium suitability), and 7.41% rate 3 (high suitability) as shown in Fig. 4d . The concentrations of cobalt (Co) ranged from 0.25 to 3.04 mg/l, with an average of 1.79 mg/l (Table 2). The highest measured concentrations of Co tended to be in the study area's north and northeast (Fig. 4e), and their concentrations were higher than the limit (0.05 mg/l). However, all samples are categorized into medium suitability (Table 3). Cupper (Cu) concentration ranged from 0.33 to 0.41 mg/l with an average of 0.37 mg/l. The highest concentration (0.41 mg/l) was in canals 1 and 2 which may be contaminated from sewage water of this area. The spatial interpolation shows a trend of increasing concentrations from northwest to southeast (Fig. 4f). The data indicate high similarity of Cu concentration within the study area as STD = 0.02. All samples are present medium class (2) in the study area (Table 2). Nickel (Ni) concentration values are flocculated around 0.1 and 1.53 mg/l and the values were above permissible limits (0.2 mg/l) except for canals 6, 9, 12, and 14 (Table 2). Domestic wastewater effluents are the primary source of nickel (Ni), which can be absorbed by biota via sorption on clay particles (Lee et al., 2017). From the interpolation map, the highest range of Ni (0.96–1.5 mg/l) covers scattered areas (Fig. 4g). Ni concentration was high in canal 20 and exceeded the permissible limit (0.2 mg/l), as shown in Table 2. The water samples of the study area were classified as high and medium suitability for irrigation (Fig. 4g). Zinc (Zn) could be found in virtually all food and potable water as salts or organic complexes. Zn concentrations in the study area gradually increased from north to southeast, as shown in Fig. 4h. Levels of Zn in surface water of the study area exceed the maximum concentration limit (2 ppm) except for canal 18, which has the least concentration (Table 2). As a result, the majority of samples are classified as medium or high suitability (Fig. 4h). High variation of Zn values was observed in the study water samples as STD > 3 (Table 2).

Table 2 Trace element concentrations in the study water samples and recommended limits for use in irrigation water

Sample no	Trace element concentrations (ppm)				
	As	Co	Cu	Ni	Zn
1	0.71	1.37	0.41	0.78	12.73
2	0.66	2.59	0.41	0.42	3.54
3	6.45	2.57	0.36	1.19	0.24
4	6.29	2.51	0.34	0.80	1.32
5	7.83	2.68	0.36	0.49	0.84
6	0.32	0.69	0.33	0.19	4.28
7	0.05	2.04	0.37	0.70	0.65
8	0.82	1.96	0.37	0.58	0.80
9	0.95	1.16	0.36	0.19	0.17
10	0.92	2.64	0.36	0.75	6.21
11	0.63	2.51	0.38	0.60	4.13
12	3.85	1.37	0.36	0.10	1.76
13	5.26	0.99	0.36	0.22	0.57
14	4.88	2.38	0.35	0.18	0.65
15	4.49	1.01	0.37	0.84	10.80
16	0.91	2.55	0.37	1.23	1.46
17	0.66	2.36	0.37	0.60	3.24
18	1.01	0.78	0.37	1.09	0.09
19	0.78	1.66	0.36	1.21	0.31
20	0.39	1.43	0.39	1.53	3.69
21	0.09	2.02	0.37	0.87	0.84
22	0.92	1.96	0.37	0.58	0.80
23	0.69	1.47	0.36	0.23	0.32
24	1.53	1.68	0.34	0.62	0.91
25	2.30	0.76	0.35	0.73	6.06
26	6.16	3.04	0.34	0.68	3.84
27	0.64	0.25	0.38	0.90	9.76
Maximum	7.83	3.04	0.41	1.53	12.73
Minimum	0.05	0.25	0.33	0.10	0.09
Average	2.23	1.79	0.37	0.68	2.96
Std. dev	2.35	0.74	0.02	0.36	3.39
Limit for long-term use (mg/l)	0.1	0.05	0.2	0.2	2.0
Limit for short-term use (mg/l)	2.0	5.0	5.0	2.0	10.0

3.1.5 Miscellaneous Effects

The pH value and bicarbonate ion concentrations are two examples of unintended consequences for sensitive crops. The pH values influence the equilibrium of carbonate, heavy metal mobility and availability, as well as the relative ratio of nitrogen

Table 3 Classification of irrigation water quality (IWQ) index in the study water samples and evaluation limits of the IWQ index

IWQ index	Suitability of water for irrigation	No. of samples	%	Samples	IWQ index value
˂ 22	Low suitability	--	--	--	--
22–37	Medium suitability	21	77.78	1	30.6
				2	26.5
				3 and 27	31
				4 and 19	33
				5 and 18	31.5
				8	36.9
				10 and 11	37
				12	33.4
				13	29.6
				14	27.4
				15 and 16	25.6
				17	23
				20	25.5
				24	36
				25	34.1
				26	36.6
˃ 37	High suitability	6	22.22	6	37.4
				7 and 9	37.8
				21	38.9
				22	38
				23	38.5

components, and thus influence soil quality and plant cultivation (Houben et al., 2013). The pH values of the water samples studied ranged from 6.82 to 8.18, with an average of 7.36 (Table S1). The interpolation map (Fig. 4j) showed that the central northeast parts of the study area have high pH values (7.65–8.18) and the western parts have low pH values (6.82–7.36), and more than 74% of samples are highly suitable for irrigation. Bicarbonate ions are appropriate for high alkalinity, greater than 8.5, as high bicarbonate levels cause dominating sodium in solution, which is responsible for the hazards of high sodium concentrations on plants and soil, and it is possible to conclude that long-term application of highly alkaline irrigation water could lead to sodic soils and loss of fertility (Ding et al., 2020a). The variation of HCO_3 is shown in Fig. 4i . The highest values can be found on the southeast side of the study area. HCO_3 concentrations, in the study water samples, ranged from 146.4 to 976 mg/l with a mean of 375.49 mg/l (Table S1).

3.2 Irrigation Water Quality Index (IWQI)

Surface water quality parameters such as EC, SAR, Cl, As, Co, Cu, Ni, Zn, HCO_3, and pH interpolation maps were used for overlay integration analysis to prepare the surface water quality map of the West Nile Delta, Egypt, as shown in Fig. 5. This method is based on converting multiple water parameters into a single indicator. The IWQ index had a minimum value of 23 and a maximum value of 38.9, with an average value of 32.78 (Table 3). Out of the 27 composite samples obtained from the main canal, 87% of the study area water was classified as medium suitability for irrigation, while 13% of the study area water samples were classified as high suitability. The IWQI map of the study area (Fig. 5) was created using the three categories listed in Table 3. When the computed index value is greater than 37, the corresponding area is considered to have minimal irrigation quality issues. When the IWQI value is between 22 and 37, the corresponding values show moderate suitability for irrigation. Water can be easily used on resistant crops within this range, but it should be used with caution and avoided on sensitive crops. IWQI values less than 22 are considered poor-quality irrigation water and should not be used to irrigate agricultural fields. Such waters have the potential to degrade soil quality and reduce yield. The study area has no such low-quality water, and the IWQI map is thought to be a useful tool in future agricultural management plans.

3.3 Assessment of Heavy Metal Indices

To assess heavy metal contamination in surface water samples for the study area, all HPI, NeI, ERI, HEI, PLI, and mCd for five selected metals, namely As Co, Cu, Ni, and Zn, were used. The values, classification, and spatial distribution of indices are depicted in Tables 4 and 5 and Fig. 6. The HPI values ranged from 456.96 to 6339.42, indicating that all samples are highly contaminated except for canal 27 in the study area's south. High HPI values could be caused by the discharge of drainage water and domestic sewage. The NeI values ranged from 3.49 to 37.11, with an average of 19.14 (Table 4). According to the NeI water quality scale, nearly 7% of the samples were found to be moderately contaminated in the south-eastern part of the study area, while 93% were found to be below the heavily contaminated class (Table 5). It expresses the potential risks of surface water in the study area, according to ERI, as can be seen in Fig. 6 c. The ERI values of the study area varied from 116.44 to 1072.79 with an average of 429.71 (Table 4), whereas 7.4% of samples were classified in the category of low risk, 29.65% of samples were found to expose moderate risk class, 40.7% were categorize as considerable risk, and finally the remaining samples are classified as very high risk (Table 5). As and Co were the main contributors to the risk in the study area due to their higher concentrations and biological toxicity. The lowest HEI value (21.80) was recorded in canal 6 and the highest value (136.54) was observed in canal 5. All values are below the recommended limit of 150, so all samples were classified as lowly contaminated (Table 4 and Table 5). In other words, PLI values for all canals were found to be far greater than the permissible value of 1, ranging from 1.99 to 8.39. Based on this indicator, the canals of the West Nile Delta are severely polluted (Table 5 and Fig. 6e). Based on the mCd index, 63% of samples are considered to have heavily polluted surface

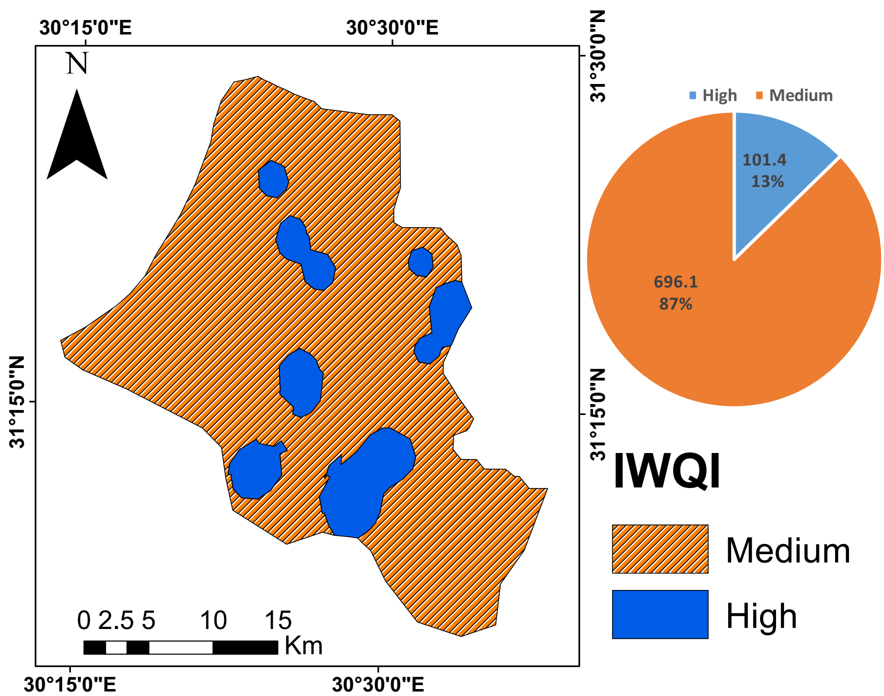


Fig. 5 The IWQ index map of the study area

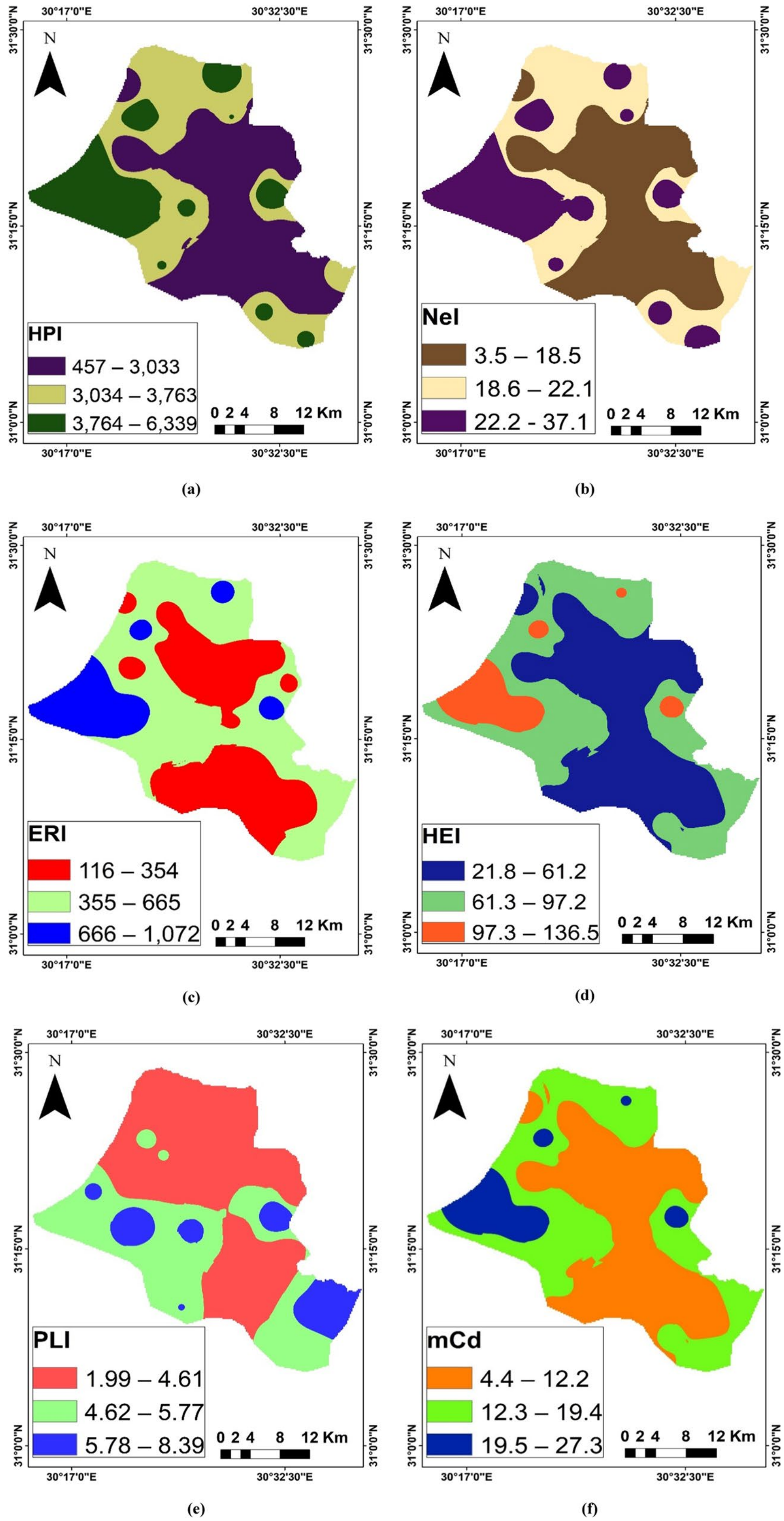


Fig. 6 Spatial distribution of water contamination indices: (**a**) heavy metal pollution index (HPI), (**b**) Nemerow index (NeI), (**c**) ecological risk index (ERI), (**d**) heavy metal evaluation index (HEI), (**e**) pollution load index (PLI), and (**f**) modified degree of contamination (mCd)

Table 4 Water contamination index values in the study area

Sample no	HPI	NeI	ERI	HEI	PLI	mCd
1	1676.86	12.93	243.53	46.73	6.29	9.35
2	3994.93	23.89	347.71	64.37	4.83	12.87
3	5413.04	30.89	940.97	123.80	5.32	24.76
4	5262.38	30.09	909.26	119.47	6.79	23.89
5	6339.42	37.11	1072.79	136.54	5.98	27.31
6	783.74	6.49	116.44	21.80	2.73	4.36
7	3271.26	18.76	236.62	47.06	2.14	9.41
8	2810.57	18.14	301.54	52.47	3.68	10.49
9	1481.31	10.82	224.05	35.43	1.99	7.09
10	3994.55	24.40	385.85	70.49	6.32	14.10
11	3856.31	23.14	340.42	63.45	5.19	12.69
12	2934.17	18.27	533.73	68.99	3.84	13.80
13	3829.03	24.48	639.80	75.58	3.60	15.12
14	4358.86	23.54	739.29	99.37	4.12	19.87
15	3248.96	21.21	585.42	76.51	8.25	15.30
16	3861.12	23.63	386.28	68.79	5.21	13.76
17	3572.98	21.79	327.78	60.27	4.89	12.05
18	1052.26	7.55	215.74	33.04	2.36	6.61
19	2340.75	15.51	283.24	49.01	3.38	9.80
20	2053.40	13.39	232.06	43.99	4.99	8.80
21	3215.87	18.59	242.92	47.99	2.63	9.60
22	2792.23	18.16	311.54	53.47	3.77	10.69
23	1986.29	13.64	231.11	39.47	2.32	7.89
24	2342.04	15.83	345.83	54.24	4.15	10.85
25	1616.88	11.10	335.51	46.51	5.81	9.30
26	5654.08	29.89	947.27	129.37	8.39	25.87
27	456.96	3.49	125.51	22.64	4.21	4.53
Maximum	6339.42	37.11	1072.79	136.54	8.39	27.31
Minimum	456.96	3.49	116.44	21.80	1.99	4.36
Average	3118.53	19.14	429.71	64.85	4.56	12.97
Std. dev	1481.65	7.80	265.87	30.91	1.71	6.18

water for irrigation, while the remaining samples range between moderately and severely polluted, with canal 6 having the lowest value (4.36) and canal 5 having the highest value of 27.31 (Tables 4 and 5 and Fig. 6f).

4 Conclusion

GIS is a critical tool for storing, retrieving, and manipulating massive amounts of data required to calculate and map various water quality parameters. The creation of spatial distribution maps for physical and chemical properties is the most important step in the assessment of IWQI. In this study, a spatial model based on the Model Builder tool in ArcGIS 10.7 was used to create an accurate model for assessing water quality index based on weighting physical and chemical water parameters. According to the findings, 87% (696.1 km^2) and 13% (101.4 km^2) of the study area water samples were categorized as medium and high suitability for irrigation, respectively. Furthermore, heavy metal indices from the study water samples, such as HPI, NeI, HEI, PLI, ERI, and mCd, were calculated in order to provide an integrated study about the water quality status in the study area. The results showed that HPI had 3.7% medium contamination and 96.3% high contamination, while NeI was 7.4%

Table 5 Contamination evaluation indices of surface water samples in the study area

Indices	Ranges	Characteristics	No. of sample
Heavy metal pollution index (HPI)	˂ 300	Low contamination	–
	300–600	Medium contamination	27
	˃ 600	High contamination	All samples except no. 27
Nemerow index (NeI)	˂ 1	Insignificant	–
	1–2.5	Slightly contaminated	–
	2.5–7	Moderately contaminated	(6 and 27)
	≥ 7	Heavily contaminated	Remain samples
Ecological risk index (ERI)	˂ 150	Low risk	(6 and 27)
	150–300	Moderate risk	(1, 7, 9, 18, 19, 20, 21, and 23)
	300–600	Considerable risk	(2, 8, 10, 11, 12, 15, 16, 17, 22, 24, and 25)
	≥ 600	Very high risk	(3, 4, 5, 13, 14, and 26)
Heavy metal evaluation index (HEI)	˂ 150	Low contamination	All samples
	150–300	Medium contamination	–
	≥ 300	High contamination	–
Pollution load index (PLI)	˂ 1	Not polluted	–
	≥ 1	Polluted	All samples
Modified degree of contamination (mCd)	< 1.5	Unpolluted	–
	1.5–2	Slightly polluted	–
	2–4	Moderately polluted	–
	4–8	Moderately-heavily polluted	(6, 9, 18, 23, and 27)
	8–16	Heavily polluted	(1, 2, 7, 8, 10, 11, 12, 13, 14, 15, 16, 17, 19, 20, 21, 22, 24, and 25)
	16–32	Severely polluted	(3, 4, 5, 14, and 26)
	≥ 32	Extremely polluted	–

moderately contaminated and 92.6% heavily contaminated. ERI has nearly 7% low risk, 30% moderate risk, 41% significant risk, and 22% very high risk. PLI and HEI were completely polluted and contaminated, respectively. The results provide valuable information on the suitability of water for irrigation use, allowing decision-makers to effectively manage water resources for sustainable agriculture.

Data Availability The authors declare that all data supporting the findings of this study are available within the article and its supplementary information files.

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