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An ontology-based approach for modeling the heavy metals' temporal and spatial variations in groundwater resources by using fuzzy multi-criteria group decision-making models and geographical information system

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ABSTRACT

In water quality monitoring, one of the main concerns is the increasing level of heavy metals in water resources due to human activities. This study aimed to present a framework in which, first, a new ontology-based water quality index (WQI) was developed by multi-criteria decision-making models in fuzzy environment and then, it was coupled with geographic information system (GIS) in order to model the temporal and spatial water quality changes in groundwater resources that are being supplied for drinking. The study screened for heavy metals in 45 wells in the west and northwest side of Shiraz, Iran from for a 5-year period. Six heavy metals including Pb, Zn, Hg, Cd, As, and Cr were embedded in the WQI among which the annual mean concentrations of Pb, Zn, Cd, Cr, and As increased during the research period but remained below World Health Organization (WHO) standard values in all years but, only the mean concentration of mercury exceeded the recommended WHO standard values. The methodology clearly discovered that over the time, water quality degradation has been moved from the northern part to the middle and then the southern part of Shiraz because of significant increase in heavy metals concentration which was due to the industrial development in the eastern part of the city. Groundwater quality declined over the time leading to a gradual increase in number of wells with poor water quality; however, most of them demonstrated excellent or good quality for drinking purpose. The presented framework could provide a practical pathway to portray and predict how urban development will affect the groundwater quality in future and find out its pattern.

Keywords: Ontology; Heavy metals; Groundwater; WQI; GIS; Shiraz

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1. Introduction

Groundwater is one of the principal sources for water supply in areas where surface water is not sufficiently available, especially in arid and semi-arid regions [1]. Uncontrolled exploitation of groundwater due to population growth and industrial development is undermining this vital resource. In addition, various organic pollutants, nitrates, heavy metals, etc., which stem from direct and indirect discharge of wastewater from urban, industrial, agricultural and landfill sites along with runoffs and floods are contaminating groundwater resources [2,3]. According to World Health Organization (WHO), about 80% of human diseases are water-related; in addition to the fact that the quality of an infected groundwater source is not easily recovered even after the pollutant emissions have ceased [3]. Therefore, providing healthy and sanitary drinking water is a key issue for improving human health, civilization and culture, and is, in fact, one of the criteria for sustainable development [4]. Water quality monitoring is necessary to preserve these resources from contamination [5].

Various studies have been conducted to determine the water quality in various resources [4,6,7]. In a study conducted by Singh et al. [8], the Uttar Pradesh groundwater quality which is located in northern India was evaluated by measuring the major cations and anions, and its suitability for drinking and agricultural purposes was assessed. In another study [9,10], the groundwater quality in Nigeria was evaluated by measuring four general parameters including coliform bacteria, lead, cadmium, and nitrate. In a study by Annapoorna et al. [10], the quality of the groundwater was evaluated by measuring five parameters in the Karnataka state in southwestern India. These types of studies may not be able to appropriately apply the cumulative effect of various parameters in water quality zoning. Therefore, to fill in this blank it is necessary to use appropriate tools that accurately and comprehensively demonstrate the water quality. Hence, numerous water quality indices (WQIs) that combine multiple parameters and compare them with a single global criteria number are used to study the water quality changes. These indicators can reflect the water quality and can be used as a comprehensive management tool for decision-making and pollution analysis [6,11]. Aboyeji and Eigbokhan [36] evaluated the quality of groundwater around Olusosun open solid waste dump site in Lagos metropolis, using WQI and IDW as a geospatial technique. The results demonstrated acidic water with high dissolved oxygen while, 40% of the samples contained concentration of K^+ above the recommended limit. The heavy metals' concentrations were generally low. Acharya et al. [12] studied groundwater quality for irrigation and drinking purposes in South West Delhi using WQI. The index values indicated that 34% of the samples were in the range of good quality and in contrast, 66% of the samples were pronounced as poor or unsuitable for drinking [12].

Ontology refers to processing a natural language and automatic conversion of semantic concepts to the most similar numerical score based on the observed evidence. As Sánchez et al. [13], and Wimalasuriya and Dou [14] implied, different MCDM (multi-criteria decision-making) models are identified as ontology-based approaches according to the knowledge source and the way they are used.

Recent studies stated that a combination of MCDM with GIS presented fair analysis on spatial and managerial data, simultaneously [15]. As an example, Niaraki and Kim [16] successfully merged analytic hierarchy process (AHP) as ontology-based MCDM with GIS to present a framework for user-centric selection of the most suitable pathway for traveling. Moreover, studies such as the ones conducted by Jeong et al. [17] planning the most suitable place for rural houses that are encountered with tourism, Gigović et al. [15] working on selecting the ecoutorism sites, and Pourahmad et al. [18] in which the best places for leisure time in urban aerias were determined are other examples of coupling DEMATEL (Decision Making Trial and Evaluation Laboratory) or Fuzzy DEMATEL as MCDM models with GIS. Also, Stević et al. [19] applied a fuzzy BWM (Best-Worst Method) as an other MCDM model in internal transport systems.

FOWA (fuzzy ordered weighting average) is one of fuzzy MCDM models that having some outstanding features made it quintessential comparing with other MCDM models such as DEMATEL and BWM. In a real decision-making condition some obscure points come up that should be detected and made clear. These are the level of influence each stakeholder has in the final decision-making result and also the how of their attitude toward the decision problem which, somehow, boils down to the sensitivity of the issue. All of these factors would make the process face with uncertainties that have stem from human thoughts and should be modeled appropriately in group decision-making. FOWA has exerted more aspects of human behaviors and thoughts in aggregating the group's opinion and weighting the criteria by considering two measures and could model the risks that are so present in group decision-making conditions by taking advantage of fuzzy modeling. It seems that incorporating this ontology-based decision-making model with GIS has also potential in water quality research and this is while, to our knowledge, no previous studies has accomplished on incorporating AHP-FOWA and GIS in which modeling the heavy metals' changes in groundwater resources be pursued Therefore, this study aimed to present a framework in which a new ontology-based WQI developed by MCDM models in fuzzy environment is coupled with GIS in order to model the temporal and spatial changes of heavy metals in water bodies. This methodology was examined on groundwater resources in Shiraz plain, Iran between 2011 and 2015.

2. Methodology

2.1. Site specification

Shiraz is the sixth largest metropolis in Iran, and is one of its most populous cities. It is located in the southeastern part of the country, at an altitude of 1,486 m (29°36′37″ N and 52°31′52″ E). It covers an area of about 240 km^2 and has a population of more than 1.4 million people [20,21]. The study area is located in the western and northwestern parts of the Shiraz plain with an area of about 1,268 m^2. The study area and the location of sampling points are shown in Fig. 1.

2.2. Data collection

This study was conducted on drinking water wells in the western and northwestern parts of Shiraz plain, Iran from 2011 to 2015.

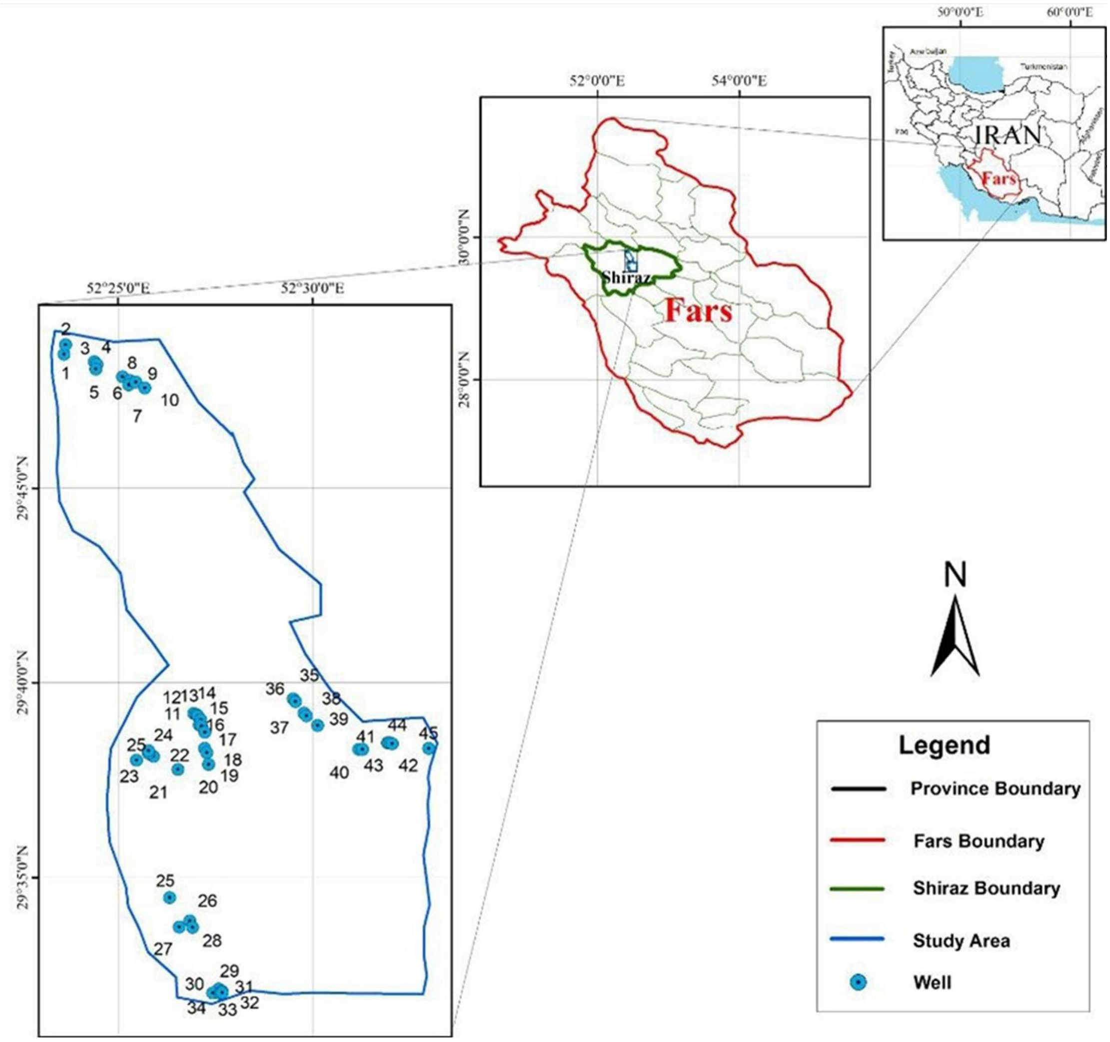

Fig. 1. Study area and location of the evaluated wells.

The number of sampling wells was estimated to be equal to 42 using Eq. (1).

$$n = \frac{z^2 SD^2}{D^2} \quad (1)$$

where n = the sample size; Z-score = 1.96 for a confidence level of 95% and standard deviation (SD) equal to 0.309; D = the maximum acceptable difference, which is considered to be 0.06.

Finally, the water quality data of 45 wells was collected for 5 years (from 2011 to 2015). All of the parameters were measured in the laboratory of Shiraz Water and Wastewater Co. based on the techniques proposed by the Standard Methods for Examination of Water and Wastewater [22].

2.3. Developed WQI

In this study first, a specific WQI was developed serving as the ontology-based decision-making module of the framework. Then, the results were used for further processing of heavy metals' changes in GIS environment. Six heavy metals including Pb, Zn, Hg, Cd, As, and Cr were considered for WQI calculation.

This index is based on weighting the heavy metals using a combination of AHP and FOWA models followed by expanding the qualitative rank of each heavy metal and computing the final index values.

In the weighting process, primarily, the decision makers' perceptions about the importance of each metal were measured through the paired comparison matrix of AHP method, and then the AHP outputs (individual weights) were integrated by applying three measures including the optimistic degree, decision-makers' power, and DMs'/criteria consensus degree in order to calculate the group weight of each heavy metal as their final weights by using FOWA operator.

OWA was founded in 1988 by Yager [23], the entrance of fuzzy modeling in the model provided the risks to be taken into account in aggregating the decision-makers' perspective and weighting the criteria. This operator is defined in Eq. (2) as follows:

$$F_i(r_{i1}, r_{i2}, \ldots, r_{in}) = \sum_{j=1}^{n} w_j b_j = w_1 b_1 + w_2 b_2 + \cdots w_n b_n \quad (2)$$

where b_j: the jth large value in the input data set $\{a_j\}$ and the vector b includes the descending ordered values of vector a; n: the number of decision-makers; a: the weight of a criteria from the viewpoint of each decision-maker considering his decision-making power; w_j: the orders weight that has the following conditions:

$$\sum_{j=1}^{n} w_j = 1, \quad w_j \geq 0 \quad (3)$$

Three measures have been applied in this model. First, DMs' optimistic degree that shows to what extent they are risk prone or risk aversion about the heavy metals in water resources. In other words, this degree reflexes the issue that in what level of sensitivity the decision-maker group, according to the group's expertise, may think about the presence of heavy metals in drinking water.

Second, decision-makers' power which shows the degree of influence of each stakeholder according to his/her knowledge, departmental capacity, or experience. This factor is separately determined by the manager of the team for each decision-maker.

The third feature of FOWA operator is consensus degree. It falls into two types including DM's (Decision-Maker) consensus degree and criteria's consensus degree. The consensus degree measures the level of DMs' compromise on the selected criteria as well as their opinions' closeness to each other. It is noteworthy that the consensus degree is totally different from criteria's group weight and is used to determine the eligibility of each criterion or DM for contributing in the decision-making process. Turn to [24] for more details and mathematics of FOWA operator and its measures.

After the heavy metals' group weights were determined, the following steps were taken to calculate WQI value for each sampling point:

The relative weight of each criterion (w_{rj}) was calculated using Eq. (4) as follows:

$$w_{rj} = \frac{w_j}{\sum_{j=1}^{n} w_j} \quad (4)$$

The qualitative rank of each parameter (q_j) was calculated according to Eq. (5) as follows:

$$q_j = \frac{c_{mj}}{c_{sj}} \times 100 \quad (5)$$

where c_{mj}: measured concentration of each parameter; c_{sj}: standard concentration.

The index value for each sampling point was computed according to Eq. (6) as follows:

$$\text{GWQI} = \sum_{j=1}^{n} (w_{rj} \times q_j) \quad (6)$$

This WQI uses drinking water quality standards, provided by ISIRI (Standard No. 1053, Table 1) for c_{sj}. Therefore, c_{sj} values can be adapted from local standards on water quality in other studies depend on the country or state. The linguistic classification of water quality is presented according to Table 2.

2.4. Pollution zoning

Interpolation method was used for mapping and characterizing WQI variations by using ArcGIS ver. 10.1.1. This method can estimate unknown values based on various mathematical and statistical models as well as known values in sampling points [4]. In this context, semi-variance of the variables and semi-variogram curves were prepared in order to select the best interpolation method. With regard to distribution of wells (cluster distribution), it was found that inverse distance weight (IDW) is a more appropriate method. IDW method is used when enough sample points (at least 14 points) are projected to be examined and there is a suitable dispersion in local scale levels. This method assumes that the rate of correlations and similarities between neighbors is proportional to the distance between them and the definition of neighboring radius and the related power to the distance reverse function are considered as important problems [26]. In this way, for each well first, WQI was calculated using the heavy metals' concentrations for every individual study years. A handheld GPS device (GPSMAP 64s, Garmin, USA) was used to determine the latitude and longitude of sampling wells, and their coordinates were obtained as the UTM format. In the next step, index values as well as the coordinates of wells were imported into GIS. Then, the exact location of each well was determined on the map and the point layer was digitized. Finally, the interpolation was conducted using quantitative data and WQI variations between different wells. The output of GIS includes five interpolated

Table 1
Water quality parameters used in WQI and their national standards [25]

Parameter	Maximum standard level
Pb, μg/L	10.0
Zn, mg/L	03.0
Hg, μg/L	06.0
Cd, μg/L	03.0
As, μg/L	10.0
Cr, μg/L	50.0

Table 2
Water quality classification based on WQI [7]

WQI	Quality classification
<50	Excellent
50–100	Good
100–200	Bad
200–300	Very bad
>300	Unsuitable for drinking

maps from 2011 to 2015. The intervals of maps in GIS were defined in five colors complying with the linguistic classification shown in Table 2.

3. Results and discussion

3.1. Heavy metals concentration

WQI is used as an important and powerful tool to determine water quality for drinking purposes and to indicate potential environmental problems [27,28]. The box plot of the mean concentrations of studied heavy metals in the 45 wells is shown in Fig. 2. Cr and As had the highest mean concentrations (Cr = 2.900 ± 2.475 µg/L, As = 2.625 ± 1.702 µg/L), while Zn had the lowest mean concentration (Zn = 0.023 ± 0.014 µg/L) during the study period. Similar studies of Reza et al. [29], and Bodrud-Doza et al. [30] have measured high levels of As in groundwater in Bangladesh.

The annual mean concentrations of Pb, Zn, Cd, Cr, and As increased during the research period but remained below WHO standard values in all years. However, in 2014 and 2015, the mean concentration of Hg reached to 1.262 ± 0.441 µg/L which exceeded the WHO standard value (1 µg/L). This can be attributed to urban development and expansion of the industrial area in eastern side of Shiraz. Therefore, the leakage of industrial wastewater and heavy metals into the soil led to increasing heavy metal concentrations in groundwater. The conclusion seems much supported by other research [31,32]. Asubiojo et al. [33] measured high concentrations of Pb and Cd in groundwater resources in southern Nigeria due to industrial activities such as wood mills, wood workshops and production of wooden artifacts, mining, gas stations and car service centers [33].

3.2. Estimation and spatial analysis of GWQI

As pointed out in the methodology, the first step in WQI extension was the weighting process that was done through an incorporation of AHP and FOWA. The AHP outputs which is the initial weight of heavy metals that have determined by

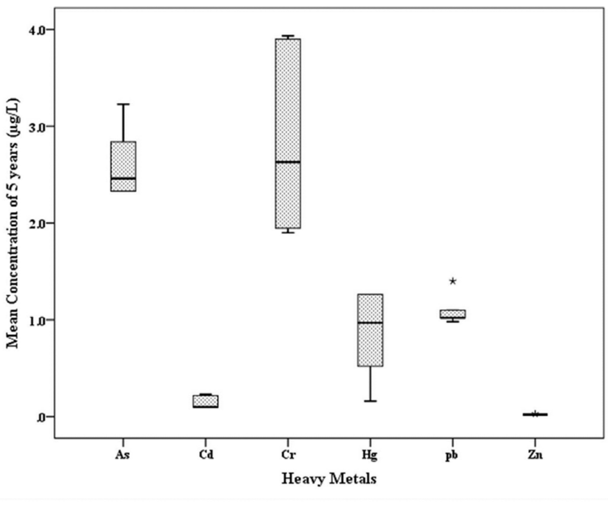

Fig. 2. Box plot of the mean concentrations of heavy metals during the study years.

each DM along with FOWA results that are the integrated group weight of heavy metals are reported in Table 3. In this study, the decision-making team had pessimistic attitude toward the presence of heavy metals in drinking water (optimistic degree was equal to 0.091) and DMs' powers were determined as fairly high, medium, high, and very high for DM_1, DM_2, DM_3, and DM_4, respectively.

From the viewpoint of MCDM models being integrated with GIS, studies of Gigović et al. [15], Jeong et al. [17], Pourahmad et al. [18], and Stević et al. [19] could be pointed out so that, the combination of FAHP and DEMATEL or BWM are beholden in these studies. Comparing AHP-FOWA set used in the present study with FAHP-DEMATEL and BWM states substantial differences in their structure and approach. In the mentioned studies, fuzzy theory was basically used as the values of criteria that encounter uncertainty that was mentioned as rough numbers in the case of BWM. This is while fuzzy modeling in FOWA exerts the uncertainties stem from the groups' decision-making risks in cumulative result of DMs' thoughts and attitudes in weighting the criteria. This fuzzy modeling is infused in optimistic degree and DMs' power calculation. Therefore, incorporation of these measures in FOWA with AHP and embedding these two models in GIS is the difference and outstanding features of the presented methodology comparing with Gigović et al. [15], Jeong et al. [17], and Pourahmad et al. [18].

The calculated WQI in sampling wells is shown in Table 4.

WQI values varied over the study period ranging from 38.691 to 71.925 in 2011, 9.610 to 103.606 in 2012, 9.626 to 107.174 in 2013, 22.719 to 146.504 in 2014, and 21.564 to 149.486 in 2015. According to Table 4 and referring to Table 2, the results showed that the water quality varied among excellent, good, and poor quality, depending on the years and sampling wells. Well no. 8 in the northern part of the study area was categorized as having excellent water quality in 2012, with the study's lowest WQI of 9.610. Conversely, poor water quality was observed in well no. 29 in 2015, with the study's highest WQI of 149.486.

The percentage of studied wells in each water quality category is shown in Fig. 3. Groundwater quality declined over the time, led to a gradual increase in number of wells with poor water quality; however, most of them demonstrated excellent or good quality for drinking purpose. In 2011, 31% and none of the wells had good and bad water quality for

Table 3
Results of weighting the heavy metals by AHP and FOWA

Heavy metal	Individual weights (AHP)				Group weight (FOWA)
	DM_1	DM_2	DM_3	DM_4	
Pb	0.099	0.273	0.474	0.266	0.177
Zn	0.030	0.022	0.049	0.026	0.020
Hg	0.435	0.163	0.187	0.091	0.130
Cd	0.230	0.167	0.072	0.309	0.123
Cr	0.146	0.102	0.058	0.091	0.064
As	0.060	0.273	0.160	0.218	0.112
Inconsistency coefficient	0.19	0.04	0.15	0.13	

Table 4
WQI for each sampling well, Shiraz, Iran (2011–2015)

Wells number	Index value				
	2011	2012	2013	2014	2015
1	47.607	35.373	37.404	38.769	37.962
2	48.955	54.019	57.633	64.013	61.353
3	58.795	40.533	44.541	38.559	33.850
4	40.697	26.715	27.504	23.527	23.492
5	54.038	32.117	27.582	40.449	38.341
6	47.376	24.344	20.651	33.391	34.335
7	48.394	94.819	120.542	28.552	28.118
8	44.788	9.610	9.626	22.719	21.564
9	42.037	18.328	20.814	30.678	28.146
10	39.797	20.247	22.396	30.999	30.466
11	50.377	43.001	43.144	47.204	45.292
12	61.329	77.151	87.081	89.111	86.758
13	56.917	39.160	39.402	38.729	37.631
14	71.925	27.120	27.554	28.971	28.521
15	61.124	28.522	28.696	48.867	29.210
16	42.189	30.686	31.059	31.249	31.077
17	49.796	24.117	33.829	36.798	32.267
18	41.912	29.416	30.454	28.819	28.139
19	39.085	75.676	77.056	79.692	77.105
20	47.235	23.242	24.396	26.165	24.461
21	38.691	23.937	24.796	35.077	29.196
22	44.622	35.460	32.967	32.146	32.919
23	40.645	38.196	39.289	45.954	44.234
24	44.810	32.815	34.907	29.037	21.602
25	46.496	29.829	30.543	29.830	31.366
26	44.072	30.842	26.191	45.068	49.171
27	54.584	30.575	30.773	28.028	31.013
28	50.037	27.457	27.435	44.910	48.416
29	52.070	63.828	68.370	146.504	149.486
30	47.922	31.778	31.135	29.376	30.662
31	47.229	26.638	30.534	43.276	41.963
32	46.271	35.248	35.833	37.218	36.514
33	52.048	39.344	39.656	38.802	37.052
34	52.385	23.034	23.832	37.755	38.359
35	41.833	27.415	27.829	27.366	24.409
36	44.915	25.200	25.777	37.032	24.943
37	50.722	60.973	61.949	36.313	36.574
38	48.903	31.163	30.833	37.251	36.229
39	48.984	103.606	107.174	48.336	61.495
40	42.711	20.378	21.461	36.103	35.495
41	43.672	27.310	22.699	45.935	47.814
42	45.687	43.133	32.044	83.593	82.490
43	43.206	36.035	31.386	48.817	47.956
44	39.227	26.302	26.658	33.301	29.112
45	39.76	35.011	39.553	34.244	32.587

drinking, respectively. However, by the final study year, only 11% of wells had good water quality, while wells with poor water quality had reached to 2%.

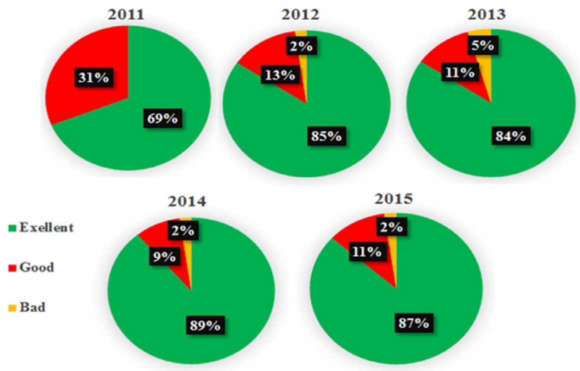

Fig. 3. Water quality changes by different linguistic groups in studied wells, Shiraz, Iran (2011–2015).

Spatial distribution of WQI based on the heavy metals' concentration in different years is shown in Fig. 4 which reflects the water quality changes. In 2011, all calculated indices were under 100, and all sampled water wells were classified as having excellent or good quality. However, in 2012 and 2013, the groundwater in well no. 39 in the middle part of the study area had poor quality for drinking and in 2014 and 2015 well no. 29 in the southern region of the study area showed poor quality.

The interpolation maps and spatial variations demonstrate that from 2011 to 2015 the water quality has dipped by increasing index values from the north to the southern part of the study area. During the study, water quality degradation was observed from the northern to the middle and then southern parts of the research area, with a wider range of the study area experiencing water quality deterioration over time.

It is clear that for the majority of sampled wells, the WQI and heavy metals' concentrations have increased from 2011 to 2015. Somehow, this can be attributed to the fact that the hydraulic slope of Shiraz aquifer descends from the north to the south and to some extent it is related to increased concentrations of various environmental pollutants due to industrialization and urbanization in the study area. that has included construction of new fuel stations and expansion of the industrial area on the east side of Shiraz and development of new industries including Iranian Electronics Industry namely SAIRAN, metal, cellulose, paper, cardboard, and wood products. With industrial processes such as melting furnaces in the southern part, heavy metals' presence in groundwater could be related to the leakage of industrial wastewater into the soil and the subsequent leaching of metals from the contaminated soil into the groundwater. Similar results were observed in a study by Ponsadailakshmi et al. [34] in Tamil Nadu, South India, in which WQI was used to assess groundwater quality for drinking. They reported that deteriorated water quality and increase in Cr and Pb concentration were attributed to human activities such as leaching of domestic wastewater and sewage from silk industry. In another study, Bodrud-Doza et al. [30] measured groundwater quality using GWQI and interpolation maps. It was found that the quality of groundwater was good in the northern parts of their study area while declined in the southern parts. The reasons were reported to be ion leaching, over-exploitation of groundwater, direct discharge of wastewater, and agricultural effects [30].

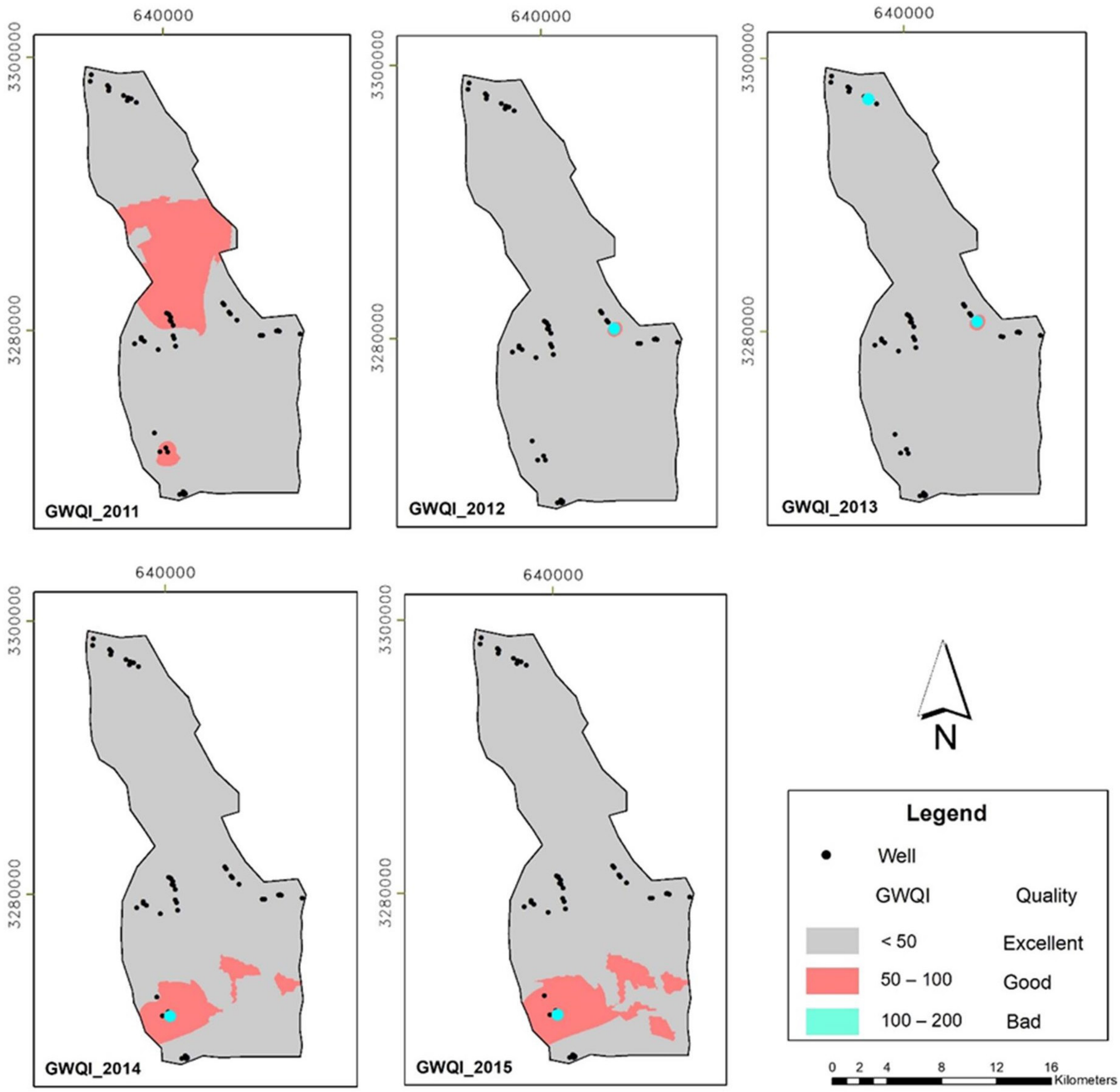

Fig. 4. Spatial distribution of WQI from 2011 to 2015, western and northwestern parts of Shiraz, Iran.

According to other studies, it was found that this method is better than other interpolation method. Gong et al. [35] compared the accuracy of kriging and IDW interpolations in estimating groundwater arsenic concentrations in Texas. They concluded that IDW method is more suitable and correlate than other method for arsenic levels in groundwater as a heavy metal [35]. In a study by Aboyeji and Eigbokhan [36], the quality of groundwater was evaluated around an open solid waste dumpsite in Lagos metropolis. The results of WQI calculating and IDW interpolation were shown that 35% of the water samples were unsuitable for consumption. The concentration of Zn, Mn, Ni, Cd, Ag, and Pb was below the detection level of atomic absorption spectrophotometry in many samples. However, a high level of Pb (higher than the WHO guideline value) was detected in one well. The groundwater near the dumpsite was generally not of good quality compared with locations where there were no solid waste dumps. This is somehow due to contamination by leachates from the waste dumps that moved downslope to the well [36].

4. Conclusion

This study by merging AHP-FOWA with GIS presented a new approach in studies intending to assess and predict the toxic materials' trends in water resources. The presented methodology looked into some planks of group decision-making conditions such as fuzzy modeling of decision-making risks that have not been considered in previous GIS-based studies. The presented framework portrayed how toxic materials such as heavy metals could affect the water quality by constructing various digital thematic layers and maps and figure out the spatial and temporal distribution of water quality changes in an area. As it is important to make for closer-to-real modeling approach to reach out more precise results, the presented methodology could be applied for any toxic material (not only heavy metals) in order to level up the interpretation and prediction accuracy in predicting the toxic materials' trends in drinking water resources. The applied example on one of Iranian metropolitans clearly showed that drinking water quality was slowly declining over a 5-year period of the study (from 2011 to 2015). This decline pronounced because of increased concentration of heavy metals which was influenced by continuous release of industrial effluents from different industries. Since heavy metals have many adverse human health effects, including carcinogenic impacts, such ontology-based MCDM methodologies are required to couple with GIS to determine the exact pollutant sources and to develop methods for decreasing emissions of them to the environment and ground water resources. Finally, it is recommended that prospective researchers would couple FOWA with other MCDMs such as ANP and DEMATEL and examine their application in environmental GIS-based studies.

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Conflict of interest

None declared.

Symbols

N	—	Sample size
Z-score	—	1.96 for a confidence level of 95% and standard deviation (SD) equal to 0.309
D	—	Maximum acceptable difference, which is considered to be 0.06
b_j	—	jth large value in the input data set $\{a_j\}$ and the vector b includes the descending ordered values of vector a
n	—	Number of decision-makers
a	—	Weight of a criteria from the viewpoint of each decision maker considering his decision-making power
w_j	—	Orders weight that has the following conditions
c_{mj}	—	Measured concentration of each parameter
c_{sj}	—	Standard concentration

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