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Original Research

Use of Geostatistics to Determine the Spatial Variation of Groundwater Quality: A Case Study in Beijing's Reclaimed Water Irrigation Area

Niu Yong[1], Yin Shiyang[2,3]*, Liu Honglu[2,3], Wu Wenyong[2,3], Li Binghua[2]

[1]College of Soil and Water Conservation, Beijing Forestry University, Beijing 100083, China
[2]Beijing Institute of Water Science & Technology Research, Beijing 100044, China
[3]Beijing Engineering Technique Research Center for Exploration and Utilization of Non-Conventional Water Resources and Water Use Efficiency, Beijing, 100044, China

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Abstract

In order to determine the distribution variation of groundwater quality in the reclaimed water irrigation area of Beijing, the geostatistics method and ArcGIS9.3 module were used. Based on the normal distribution testing and global trends, the optimal geostatistical interpolation and optimal variogram models for each index were sampled, and the effects of artificial factors and space structure on the water quality index in the reclaimed water irrigation area were determined. The influence of human activities and structural factors on the water quality indicators of groundwater were determined using variability intensity and the nugget effect. The results showed that nitrate content was the water quality indicator in the groundwater that was most sensitive to human activities and could be used as an indicating factor to study groundwater pollution in the study area. In combination with the temporal and spatial variation of groundwater nitrate nitrogen in the study area, it was discovered that the amplification of nitrate nitrogen in the reclaimed water core irrigation area was far less than that in the non-core area. The reasons for such characteristics were vadose zone structure and human activity. The proposed results for groundwater Nitrate-nitrogen distribution can be used to quantify groundwater pollution risk and promote the utilization of wastewater.

Keywords: groundwater, water quality, geostatistics method, reclaimed water irrigation

Introduction

With the increasing population throughout the world, the water resource shortage is becoming more and more serious [1]. Moreover, actions such as living sewage disposal, industrial pollution, fertilizer application, and reclaimed water irrigation may all affect the quality of surface and groundwater [2, 3]. In particular, water crises caused by man-made pollution is becoming the most prominent in arid and semi-arid regions [1]. Compared to the monitoring method of surface water, the monitoring method of groundwater quality heavily relies on the combination of monitoring equipment and mathematical statistics [4, 5]. The development of GIS technology-the geostatistics-has played an especially important role in the evaluation of groundwater quality [6-10].

*e-mail: 150401973@qq.com
yinshiyang2001@qq.com

Geostatistics was founded in 1962 by Prof. G. Matheron of the French Paris National Superior Institute of Mining. Originally it was used to solve such problems as calculation and estimating error of reserves in ore deposits. After 60 years of development, geostatistics has been used in various fields, including edaphology, agriculture, hydrology, meteorology, ecology, oceanography, sylviculture and environmental control [11, 12]. In recent years the application of geostatistics methods in the research field of groundwater is becoming broader, mainly including the following aspects: a) A geostatistical interpolation model is applied to draw the distribution variation diagram of groundwater volume and water quality, which makes it possible to accurately predict water level [3, 13, 14] and water quality [15] in those places where there are no monitoring points; b) Combinated error analysis of a geostatistics model [16, 17] with distribution characteristics of monitoring points in the study area, the most suitable geostatistical interpolation model, is selected for corresponding index factors; c) The defects of groundwater monitoring networks are explored by the spatial variation analysis of a geostatistical model [18], then the optimal monitoring network setting plan of groundwater is determined [19]; d) The causes of groundwater pollution are analyzed and the risk of pollution is predicted by the geostatistics method, combining fertilizer with irrigation and land-use type in the study area [20-22]; and e) The source and major influence factors of typical pollution indices are discussed by geostatistics spatial variation analysis and hydrochemistry analysis methods such as isotope tracer method [23].

Beijing is a typical city that suffers from water shortage, and various measures have been taken to mitigate its water resource crisis. Reclaimed water irrigation has developed rapidly [24] since 2002. Beijing's irrigation area of reclaimed water reached 400 km^2 and the annual usage of reclaimed water reached 300 million m^3 in 2010. At the same time, the pollution risk of groundwater in the reclaimed water usage area has also attracted much attention. In this paper, the spatial variation characteristics and causes of various index factors of groundwater in the Beijing reclaimed water irrigation area are studied with the aid of the geostatistics method and the ArcGIS 9.3 module.

Study Area and Methods

Study Area

The irrigation areas of reclaimed water in Beijing are mostly located in the southeast suburbs. As for the core irrigation area of reclaimed water, the length is 30 km long from north to south, and 37.9 km wide from east to west (as shown in the dashed line section of Fig. 1, which covers a total area of 1031km^2). The annual average temperature is 11.6ºC. The inter-annual variation of precipitation is large and the seasonal distribution is uneven. Usually it rains from June to September, and the average rainfall from 1951 to 2010 is 554.9 mm. Traditional crops are corn and wheat. The average available yield of groundwater is 184.8 million m^3 [25].

Method

Water Quality Monitoring of Groundwater

There are 196 monitoring wells for groundwater in the study area (Fig. 1) and the exploitation depth of the monitoring well ranges from 80 to 120 m (groundwater in the shallow layer of reclaimed water irrigation area). This

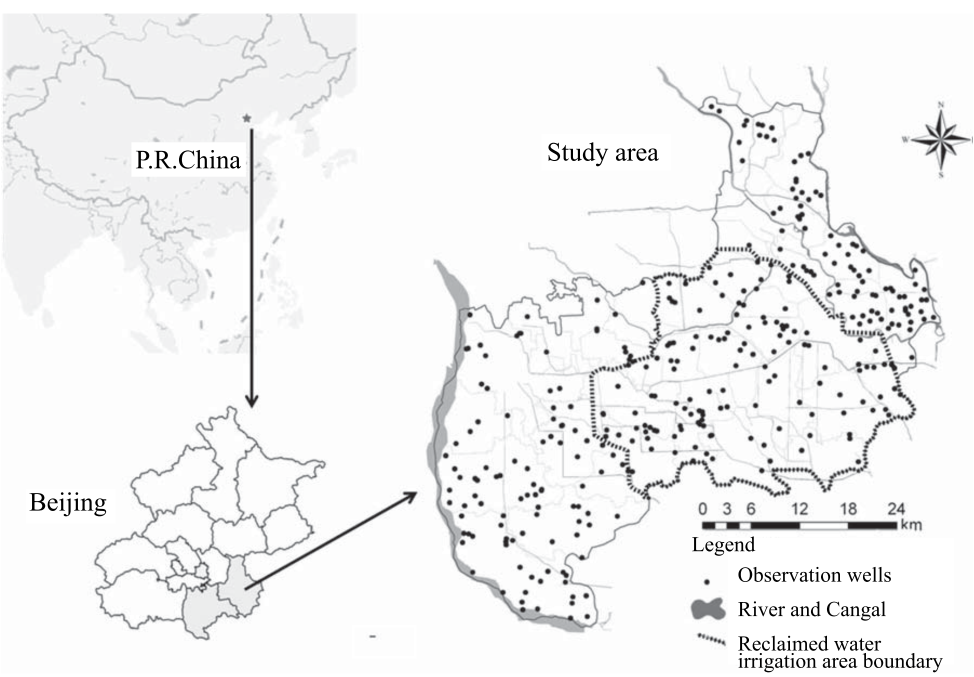

Fig. 1. Location of the study area.

Table 1. Statistical characteristic values of groundwater quality in study area.

Factor	Maximum	Minimum	Mean	Standard deviation	Coefficient of variation	Without transformation		Logarithm transformaiton		Power transformation		Distribution pattern
						Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	
pH	8.61	7	7.90	0.32	0.04	0.076	2.36	–	–	–	–	Normal distribution
Nitrate nitrogen	11.7	0.08	0.96	1.64	1.70	3.2	17.3	0.52	1.79	–	–	Lognormal distribution
Total hardness	751	62	269	129.5	0.48	0.69	3.59	–	–	–	–	Normal distribution
Sulfate	175	6.38	48.19	29.55	0.61	3.56	23.8	–0.87	8.88	3.47	22.4	No obedience of simple distribution
Chloride	319	0.88	38.2	34.2	0.90	3.88	26.4	–0.27	5.72	–	–	Approximate lognormal distribution
Total solids	1480	223	458.5	162.1	0.35	1.76	9.39	–	–	–	–	Approximate normal distribution
Oxygen consumption	2.9	0.41	1.31	0.44	0.34	0.2	2.59	–	–	–	–	Normal distribution
Ammonia nitrogen	1.05	0.005	0.18	0.20	1.12	1.71	5.99	0.4	1.54	–	–	Approximate lognormal distribution
Nitrite nitrogen	0.045	0.001	0.005	0.01	1.13	0.48	2.1	–	–	–	–	Normal distribution
Fluoride	1.8	0.13	0.58	0.28	0.48	1.43	5.13	0.14	2.87	–	–	Approximate lognormal distribution
Cyanide	0.004	0.002	0.003	0.001	0.35	0.4	1.17	–	–	–	–	Approximate normal distribution
Iron	9.58	0.009	0.37	0.88	2.35	7.94	78.5	0.03	2.88	–	–	Lognormal distribution
Manganese	0.674	0.002	0.09	0.10	1.13	2.84	14.3	–0.45	2.9	–	–	Lognormal distribution

Table 2. Statistical characteristic values of pH value distribution of groundwater in the study area.

Transformation form	Order	Calculation model	ME	RMSE	ASE	MSE	RMSSE	Total error
log	none	Spherical	0.01093	1.41	10.82	0.03238	0.3216	0.806
		Exponential	0.02523	1.408	9.481	0.04492	0.4063	0.880
		Gaussian type	0.008520	1.441	3.236	0.02704	0.2943	0.516
	1st-order	Spherical	0.02781	1.425	3.229	0.1549	1.53	1.060
		Exponential	0.04764	1.421	3.523	0.1507	1.492	1.179
		Gaussian	0.02414	1.428	3.248	0.1382	1.471	0.998
	2nd-order	Spherical	0.04779	1.463	3.762	0.1508	1.523	1.200
		Exponential	0.06486	1.468	4.084	0.1389	1.314	1.260
		Gaussian	0.03386	1.47	3.652	0.1481	1.492	1.101

ME (mean) refers to the mean of error; the closer its absolute value is to 0, the better the predicted model is. RMSE (root-mean-square) refers to root mean square error; the smaller, the better. ASE (average standard error) refers to standard error of mean; it approximates the RMSE; if it is larger than the RMSE, then the predicted value will be overestimated; otherwise, the predicted value is underestimated. MSE refers to standard mean error; the closer it is to 0, the better. RMSSE (root-mean-square standardized) refers to standard root mean square error. The closer it is to 1, the better; if it is larger than 1, then the predicted value will be overestimated; otherwise the predicted value is underestimated.

depth has been the main exploitation layer of groundwater since the 1980s. The monitoring indexes of groundwater quality include pH value, chloride, ammonium nitrogen, nitrite nitrogen, nitrate nitrogen, total hardness, cyanide, fluoride, sulfate, dissolved solids, iron, manganese, and oxygen consumption.

Analysis Method

The spatial variation characteristics and causes of groundwater quality index are analyzed in the following steps. The first step is to obtain the location data and attribute data of monitoring wells, and store them in the basic information database as the basic data for the geostatistical model calculations. The second step is to conduct a normal distribution test for the data using ArcGIS, and determine whether the data obey normal distribution after logarithm or power transformation. The third step is to compare the calculation errors using different interpolation calculation models, and select the most suitable geostatistical interpolation calculation model. The final step is to calculate the spatial variation parameters for the most suitable geostatistical model of groundwater quality factors, and analyze its range, nugget, sill, and nugget effects, and then find their spatial correlations, thereby exploring the pollution influence factors and factors vulnerable to pollution.

Table 3. Optimal variograms of groundwater quality factor calculation.

Evaluation index	Mean (mg/L)	Optimal variogram
pH value	7.9	2-order exponential model
Ammonia nitrogen	0.18	2-order exponential model
Iron	0.37	0-order Gaussian model
Nitrate nitrogen	0.96	0-order Gaussian model
Manganese	0.079	1-order Gaussian model
Oxygen consumption	0.13	1-order Gaussian model
Chloride	38.22	1-order Gaussian model
Sulfate	48.19	0-order spherical model (disjunctive KrigingKriging)
Total solids	458.5	1-order Gaussian model
Fluoride	0.13mg/L	2-order spherical model
Total hardness	284mg/L	1-order Gaussian model
Ntrite nitrogen	0.005mg/L	1-order exponential model

Results and Discussion

Spatial distribution of water quality is conducted with various water quality data acquired from groundwater monitoring wells. The coefficients of variation, skewness, and kurtosis of spatial data are calculated for further study of groundwater spatial distribution. The coefficients of skewness and kurtosis of the evaluation factors are counted to determine whether they obey normal distribution. The data approaches normal distribution characteristics if the coefficient of skewness approaches 0 and the coefficient of kurtosis approaches 3 [3]. Table 1 showed that the pH value, total hardness, oxygen consumption, nitrite nitrogen, total solids, and cyanide of groundwater are in normal distribution, and nitrate nitrogen, iron, manganese, chloride, and ammonia nitrogen obey lognormal distribution, while the spatial variation of sulfate in the groundwater is large and does not obey normal distribution.

Table 4. Semi-variogram models and parameters of different factors.

Evaluation factor	Trend effect	Model type	Anisotropy ratio	Nugget	Sill	Nugget effect
pH value	2-order	Exponential	2.01	0.026571	0.04187	0.63
Nitrate nitrogen	1-order	Gaussian	1.96	1.3624	1.70214	**0.80**
Nitrite nitrogen	1-order	Exponential	1.28	1.337	2.4906	0.53
Ammonia nitrogen	2-order	Spherical	2.62	0.85921	1.09938	**0.78**
Fluoride	2-order	Spherical	2.36	0.13213	0.293	0.45
Oxygen consumption	1-order	Gaussian	2.63	0.073522	0.106557	0.69
Sulfate	0-order	Gaussian	1.17	787.3	1637.7	0.48
Chloride	1-order	Gaussian	1.16	0.33213	0.5659	0.59
Manganese content	1-order	Gaussian	1.45	0.80608	1.86828	0.43
Total solids	1-order	Gaussian	1.66	16869	24972.7	0.67
Iron content	0-order	Gaussian	1.37	1.008	2.8242	0.36
Total hardness	1-order	Gaussian	1.03	8407	11300	0.74

During the process of applying geostatistics, the selection of interpolation models is directly associated with calculation errors and the model's predictive accuracy [26]. Until now, many studies have not considered the applicability of statistical models and have instead used ordinary Kriging, which has led to poor prediction accuracy [26]. It is particularly important to select the appropriate interpolation models based on the distribution characteristics of data and on the applicable conditions of the models. A previous study indicated that the disjunctive Kriging interpolation method was more suitable for analyzing the risk assessment of groundwater pollution [15]. In addition, for non-simple normal distribution data, universal Kriging should be used for interpolation instead of ordinary Kriging [27].

Based on the interpolation model selected for each index, calculus of interpolation is respectively conducted for groundwater quality with 0-order, 1st-order, and 2nd-order of spherical variogram, as well as exponential spherical variogram and Gaussian variogram. Adhikary et al. proposed that variogram models are suitable for different groundwater quality indicators according to examining the errors between the predicted fitted values generated by various theoretical models and the measured data [26]. A platform is built for comparison and analysis of the forecast error of each model. Therefore an optimal variogram for groundwater quality index can be selected by forecast error calculation [28]. Taking the spatial interpolation model of the pH value of groundwater as an example, the non-converted 2nd-order exponential variogram is the most suitable for the pH value distribution of groundwater in the reclaimed water irrigation area (as shown in Table 2). Using same analytical method, optimal variograms of other groundwater quality indexes are given as shown in Table 3.

Spatial interpolation is conducted for groundwater quality indexes with the selected optimal variograms and four important parameters including nugget, range, sill, and partial sill, which are calculated (as shown in Table 4). The nugget effect for each indicator was obtained through an analysis of the optimal variogram; when this information was combined with spatial variability, the degree of influence of human and structural factors on each water quality parameter was obtained and, therefore, the pollution vulnerability factors of groundwater in the study area were determined. The value of the nugget effect of the variogram was between 0 and 1; a value below 0.25 indicated that it was mainly influenced by external factors of human activities, a value above 0.75 indicated that it was mainly affected by intrinsic structural factors, and a value between 0.25 and 0.75 indicated that it was affected both by structural factors and human activities [29]. It can be seen from Table 4 that the nugget effects of nitrate nitrogen and ammonia nitrogen are 0.80 and 0.78 respectively, and the spatial correlation is weak and is greatly affected by random factors. The nugget effects of total harness, nitrite nitrogen, chloride, total solids, and pH are 0.53, 0.59, 0.67, and 0.63 respectively, which indicates that the spatial correlation is moderate and is prone to the effects of artificial factors and spatial structure. The nugget effects of fluoride, sulfate manganese, and iron are 0.45, 0.48, 0.43, and 0.36, respectively, which reveals that the spatial correlation is strong and those indices may be affected by spatial structural factors.

As shown in Table 4, the spatial variation of nitrate nitrogen and ammonia nitrogen in the aquifer of the study area is strong, and is greatly affected by random factors. In addition, the content of nitrate nitrogen in the groundwater is far greater than the other existent forms of nitrogen and ammonia nitrogen under the effects of the oxidation environment of the vadose zone [30]; therefore, nitrate nitrogen can be regarded as an indicating factor and it can be used for the pollution analysis of groundwater in the study area.

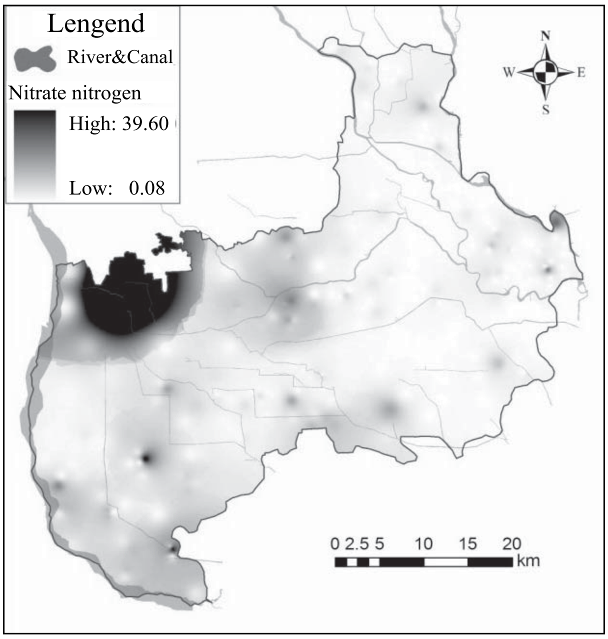

Fig. 2. The spatial distribution of nitrate nitrogen content of groundwater in 2004.

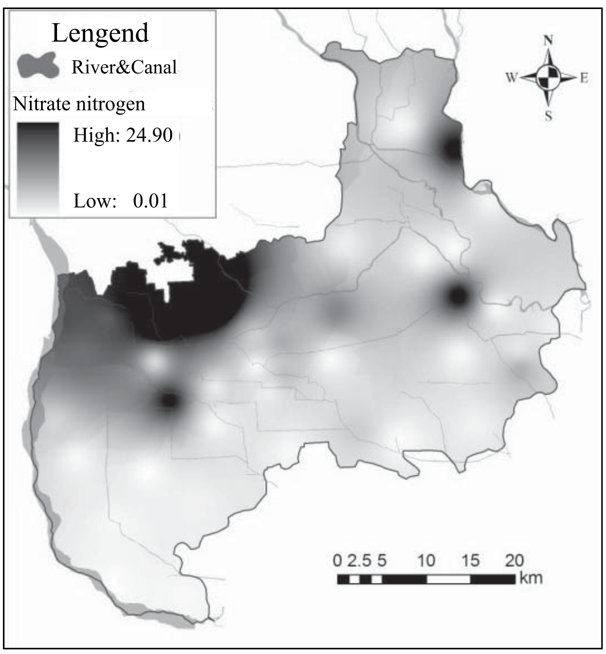

Fig. 3. The spatial distribution of nitrate nitrogen content of groundwater in 2010.

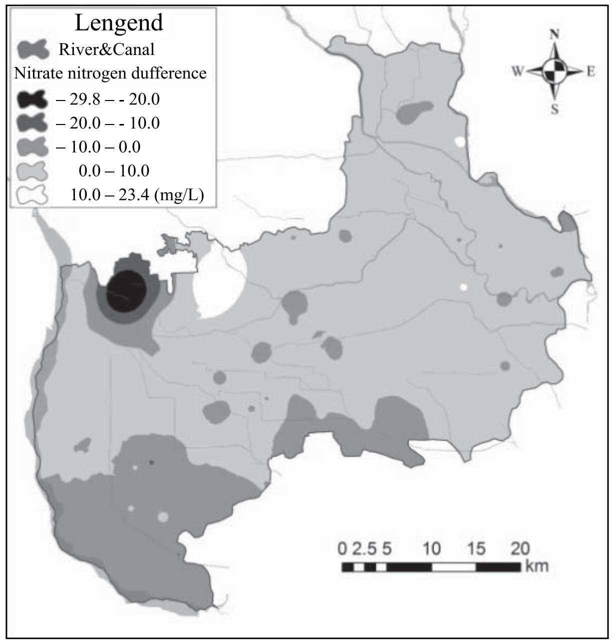

Fig. 4. Concentration differences of nitrate nitrogen in groundwater between 2004 and 2010.

Here Kriging is applied for those factors based on 1st-order Gaussian models to acquire the spatial distribution diagram of nitrate nitrogen concentration in 2004 and 2010 in the study area. As shown in Figs 3 and 4, in 2004 the nitrate nitrogen content of groundwater in the study area was between 0.08 and 39.6 mg/L – with an average of 2.0 mg/L. In 2010 the nitrate nitrogen content of groundwater was between 0.009 and 24.9 mg/L – with an average of 3.2 mg/L. These levels do not meet the main standard limits all over the world; for WHO [31] and EC [8], the limit of nitrate is given to be 50 mg/L, with 44.27 mg/L from the EPA [32] for drinking water. But in the northwest section of the study area the nitrate nitrogen content of groundwater in 2004 was 25 mg/L over the standards limit for groundwater in China [33]. As seen from the spatial variation diagram, nitrate nitrogen concentration of groundwater tends to decrease from west to east, as well as from north to south. This is due to the fact that the northwest section of the study area is located on the alluvial-proluvial fan of the Yongding River, and the vadose zone has strong permeability. In addition, the population in the northwest section of the area is dense, and pollution also led to the dramatic increase of the nitrate nitrogen concentration, making it higher than that in other areas.

The concentration difference of nitrate nitrogen in groundwater between 2004 and 2010 was shown in Fig. 4, which shows that the nitrate nitrogen level in groundwater in 2010 showed variations between -29.8 and 23.4 mg/L compared with 2004, which represents an average increase of 1.2 mg/L. Over the years this has indicated the concentration variation of nitrate nitrogen in the reclaimed water core irrigation area (the dashed line section in Fig. 4) is small and far less than that in the reclaimed water non-core irrigation area. Therefore, it can be inferred that the reclaimed water irrigation is not the major factor influencing the spatial variation of nitrate nitrogen. Compared with a similar study in this area, there are some important results. For example, Chen Liang-qing and Feng Shaoyuan et al. applied the method of fuzzy clustering to analyze dynamic changes of nitrate nitrogen content in Beijing, and considered that the increasing of nitrate nitrogen content was caused by perennial fertilization and emission of high-concentrated effluent generated by industrial pollution and living [34]. Xu found that the recycled water spreading on both sides of the river or channel is limited [35]. Those discoveries in Beijing confirm our result from different perspectives.

Conclusions

This study of an alluvial fan area utilized a geostatistical method and the geostatistical analysis module in the ArcGIS 9.3 to perform a normal distribution test that was combined with an overall trend analysis and used to select the optimal geostatistical interpolation model for various groundwater indicators. The optimal variogram model of each indicator was determined through a prediction error analysis; combined with variability strength and nugget effects, the water quality indicators of groundwater in the study area were classified based on human factors and spatial structural factors. The results show that nitrate nitrogen in the study area is one of the groundwater quality indicators that was most sensitive to human activities and that this parameter might be used as an indicating factor to study groundwater pollution in the study area.

Our investigation showed that in the reclaimed water core irrigation area (the dashed line section) the nitrate nitration level is small and far less than that in the reclaimed water non-core irrigation area, it can be inferred that the reclaimed water irrigation is not the major factor influencing the spatial variation of nitrate nitrogen. In addition, the nitrate nitrogen level groundwater in 2010 represents an average increase of 1.2 mg/L. Therefore, on one hand the over-extraction of groundwater in urban and industrial areas in the study area should be strictly controlled on the other hand, wastewater treatment should be strengthened to reduce the input of pollutants into the groundwater and to promote the improvement of groundwater quality in the area.

Acknowledgements

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References

1. GHAMARNIA H., SEPEHRI S., Different irrigation regimes affect water use, yield and other yield components of safflower (Carthamus tinctorius L.) crop in a semi-arid region of Iran. Journal of food agriculture & environment. **8**, (2), 590, **2010**.
2. NOSHADI M., SEPASKHAH A. R., Application of geostatistics for potential evapotranspiration estimation. Iranian Journal of Science and Technology. Transaction B,Technology. **29**, (3), 343, **2005**.
3. ASSAF H., SAADEH M., Geostatistical assessment of groundwater nitrate contamination with reflection on DRASTIC vulnerability assessment: the case of the upper Litani basin Lebanon. Water Resour. Manag., **23**, (4), 775, **2009**.
4. VAFAKHAH M., Application of artificial neural networks and adaptive neuro-fuzzy inference system models to short-term streamflow forecasting. Can. J. Civ. Eng. **39**, (4), 402, **2012**.
5. IZADY K., DAVARY A., ALIZADEH A., MOGHADDAM N. N., ZIAEI S., HASHEMINIA M., Application of NN-ARX Model to Predict Groundwater Levels in the Neishaboor Plain, Iran, Water Resour. Manag., **27**, 4773, **2013**.
6. TA′ ANY R. A., TAHBOUB A. B., SAFFARINI G. A., Geostatistical analysis of spatiotemporal variability of groundwater level fluctuations in Amman-Zarqa basin, Jordan: a case study. Environ. Geol., **57**, (3), 525, **2009**.
7. TRIKI I., TRABELSI N., HENTATI I., ZAIRI M., Groundwater levels time series sensitivity to pluviometry and air temperature: A geostatistical approach to Sfax region, Tunisia. Environ. Monit. Assess., **186**, 1593, **2014**.
8. NAS B., Geostatistical Approach to Assessment of Spatial Distribution of Groundwater Quality. Pol. J. Environ. Stud., **18**, 1073, **2009**.
9. ANNA P., Spatial Variability of Total and Mineral Nitrogen Content and Activities of the N-Cycle Enzymes in a Luvisol Topsoil. Pol. J. Environ. Stud., **20**, (6), 1565, **2011**.
10. LOKMAN H. T., SERMIN T. Spatial-Temporal Variation of Sulphur Dioxide Concentration, Source, and Probability Assessment Using a GIS-Based Geostatistical Approach. Pol. J. Environ. Stud., **22**, 1491, **2013**.
11. ELSHALL A. S., TSAI F. T. C., HANOR J. S., Indicator geostatistics for reconstructing Baton Rouge aquifer-fault hydrostratigraphy, Louisiana, USA. Hydrogeol. J., **21**, (8), 1731, **2013**.
12. ZAWADZKI J., FABIJANCZYK P., BADURA H., Estimation of methane content in coal mines using supplementary physical measurements and multivariable geostatistics. Int. J. Coal Geol., **118**, 33, **2013**.
13. CHRISTAKOS G., Modern spatiotemporal geostatistics, New York, USA: Oxford universAHMADI S. A., SEDGHAMIZ. Geostatistical analysis of spatial and temporal variations of groundwater level. Environ. Monit. Assess., **129**, 277, **2007**.
14. BARCA E., PASSARELLA G., Spatial evaluation of the risk of groundwater quality degradation. A comparison between disjunctive Kriging and geostatistical simulation. Environ. Monit. Assess., **137**, 261, **2008**.
15. ADHIKARY P., CHANDRASEKHARAN H., CHAKRABORTY D., KAMBLE K., Assessment of groundwater pollution in West Delhi, India using geostatistical approach. Environ. Monit. Assess., **167**, 599, **2010**.
16. ADHIKARY P., CH. JYOTIPRAVA D., RENUKABALA B., CHANDRASEKHARAN H., Indicator and probability Kriging methods for delineating Cu, Fe, and Mn contamination in groundwater of Najafgarh Block, Delhi, India. Environ. Monit. Assess., **176**, 663, **2011**.
17. THEODOSSIOU N., LATINOPOULOS P., Evaluation and optimization of groundwater observation networks using the Kriging methodology. Environ. Modell. Softw., **21**, 991, **2006**.

18. BAALOUSHA H., Assessment of a groundwater quality monitoring network using vulnerability mapping and geostatistics: A case study from Heretaunga Plains. New Zealand, Agr. Water Manage., **97**, 240, **2010**.
19. WA'IL Y, RIHANI J., Application of the high performance computing techniques of parflow simulator to model groundwater flow at Azraq basin. Water Resour. Manag., **21**, 409, **2007**.
20. ANDRADE A. I. A. S., STIGTER T. Y., Multi-method assessment of nitrate and pesticide contamination in shallow alluvial groundwater as a function of hydrogeological setting and land use. Agr. Water Manage., **96**, 1751, **2009**.
21. BONTONA A., ROULEAUB A., BOUCHARDA C., RODRIGUEZC M., Assessment of groundwater quality and its variations in the capture zone of a pumping well in an agricultural area. Agr. Water Manage., **97**, 824, **2010**.
22. CARREIRA P., MARQUES J., PINA A., GOMES A., FERNANDES P., SANTOS F., Groundwater assessment at Santiago Island (Cabo Verde): A multidisciplinary approach to a recurring source of water supply. Water Resour. Manag., **24**, 1139, **2010**.
23. Beijing Water Resources Bureau. Report of Beijing Water Resources Bureau. Beijing Water Resources Bulletin. **2011**.
24. YIN S., WU W., LIU H., ZHANG X., Spatial variability and pollution cause analysis of nitrate content for area irrigated with reclaimed water. Transactions of the Chinese Society of Agricultural Engineering. **28**, (18), 200, **2012**.
25. ADHIKARY P., DASH C., BEJ R., CHANDRASEKHARAN H., Indicator and probability Kriging methods for delineating Cu, Fe, and Mn contamination in groundwater of Najafgarh Block, Delhi, India. Environ. Monit. Assess., **176**, (1), 663, **2011**.
26. GUNDOGDU K., GUNEY I. Spatial analysis of groundwater levels using universal Kriging. J Earth Syst Sci. **116**, (1), 49, **2007**.
27. CARUSO C, QUARTA F. Interpolation methods comparison[J]. Comput. Math. Appl., **35**,(12): 109, **1998**.
28. LI W. Q., ZHANG M., LI H. F., The study of soil nitrate status in fields under plastic house gardening. Acta Pedologica Sinica. **39**, (2), 283, **2002**.
29. NOSHADI M., SEPASKHAH A.R., Application of geostatistics for potential evapotranspiration estimation. Iran. J. Sci. Technol., **29**, (3), 343, **2005**.
30. WHO (World Health Organization). Guidelines for drinking water quality, third edition. Geneva: WHO. **2004**.
31. EPA (U.S. Environmental Protection Agency). Primary Drinking Water Regulations. **2001**.
32. Quality standard for ground water (GB/T14848-93, CHN). **1993**.
33. CHEN L., FENG S., HAN Z., MENG G., CHEN S., Evaluation of the Shallow Groundwater Quality in Daxing District of Beijing City. China Rural Water and Hydropower. (5), 2, **2004**.
34. XU K., Analysis on the Influence of Infiltration of Recycled Water to the Groundwater Quality. Yellow River. **34**, (4), 55, **2012**.