Study of the spatial distribution of groundwater quality index using geostatistical models

Article *in* Groundwater for Sustainable Development · August 2020

DOI: 10.1016/j.gsd.2020.100473

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Groundwater for Sustainable Development 11 (2020) 100473

Contents lists available at ScienceDirect

Groundwater for Sustainable Development

journal homepage: http://www.elsevier.com/locate/gsd

Research paper

Spatial distribution of the groundwater quality using kriging and Co-kriging interpolations

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ARTICLE INFO

Keywords:
Groundwater quality
Hydrochemical parameters
GWQI
Kriging
Co-kriging methods

ABSTRACT

The present work is aimed for investigation the groundwater quality for drinking purposes in El Mila plain, Algeria. This is carried out through an integrated approach of groundwater quality index (GWQI) and geostatistical method for mapping this index based on 35 wells and then hydrochemical parameters. Kriging has become a widely used interpolation method to estimate the spatial distribution of the groundwater quality index. The main objective of this study is to evaluate two geostatistical interpolation methods such as Ordinary kriging (OK) and Co-kriging (CK) for enhanced spatial interpolation of the groundwater quality index. The results of GWQI show that about 11.43% of the total samples fall in the excellent water class, and 85.71% samples reported good water quality type, whereas 2.86% groundwater samples exhibited poor water quality type. GWQI had a very strong significant correlation with EC, Ca, Mg, SO_4 and HCO_3. Therefore, these parameters were used as covariables for Co-kriging method. The prediction performance of the adopted interpolation methods is assessed through cross-validation test. The results show that Co-kriging model with electrical conductivity (EC) as covariable is superior to the other models to predict the groundwater quality index.

1. Introduction

Groundwater is the most important natural resource used for drinking by many people around the world. The variation of the groundwater quality is a function of physical and chemical patterns in an area determined by geological and anthropogenic activities. Since the quality of groundwater resources is as important as its quantity; thus, it is also necessary that the quality of the groundwater resources should be essentially taken into the full consideration (Neisi et al., 2018; Abbasnia et al., 2018). In recent years, with increasing number of physical and chemical parameters of groundwater, a broad scope of geostatistical methods is now utilized for proper analysis and interpretation of information. More and more researchers are concentrating on the evaluation of the spatial distribution of groundwater quality using many geostatistical methods in recent decades (Guettaf et al., 2014; Kumar et al., 2014; Singh et al., 2013; Belkhiri and Lotfi, 2014).

Geostatistical method is a useful tool for analyzing the structure of spatial variability, interpolating between point observations and creating the map of interpolated values with an associated error map (Zhou et al., 2011; Arslan, 2012). Several studies have reported that groundwater quality is generally characterized by a significant spatial variation (Taghizadeh-Mehrjardi, 2014; Alexander et al., 2017; Maroufpoor et al., 2017). This suggests that geostatistical methods, which are explicitly able to incorporate the spatial variability of groundwater quality into the estimation process should be employed. Nowadays, different geostatistical techniques methods being widely used for prediction of spatial variations of groundwater quality (Nazari Zade et al., 2006; Jasmin and Mallikarjuna, 2014; Belkhiri and Narany, 2015, 2017). Kriging is one of the geostatistical interpolation approaches consist of several methods, including Indicator kriging, Simple kriging, Ordinary kriging and Co-kriging, which commonly applied in estimating spatial distribution of variables (Lee et al., 2007; Babiker et al., 2007; Dindaroglu, 2014; Gyamfi et al., 2016). Ahmadi and Sedghamiz (2007) analyzed the spatial and temporal variations of groundwater level using Ordinary kriging and Co-kriging methods. Delbari (2010) estimated the salinity and the depth of groundwater using Ordinary kriging, Co-kriging, and the inverse fourth power of distance methods. Also, Hooshmand et al. (2011) applied kriging and Co-kriging methods to evaluate the chloride content and sodium adsorption ratio in the groundwater.

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https://doi.org/10.1016/j.gsd.2020.100473
Received 6 February 2020; Received in revised form 24 June 2020; Accepted 17 August 2020
Available online 22 August 2020

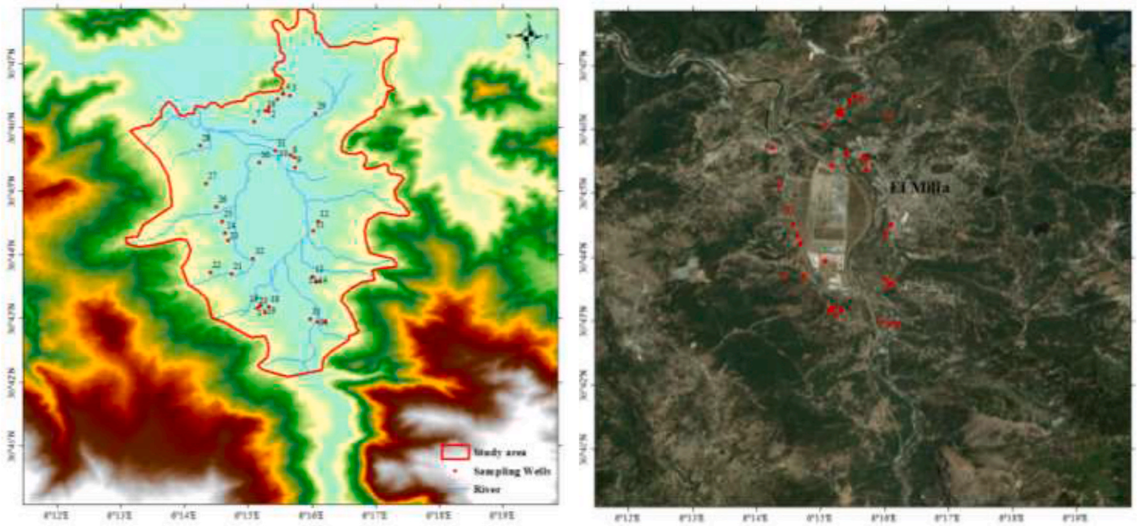

Fig. 1. Location of the study are and groundwater samples.

Table 1
Relative weight of hydrochemical parameters in study area.

Parameters	S_i=WHO Standard (2004)	Weight (w_i)	Relative weight (W_i)
pH	8.5	3	0.081
EC	500	5	0.135
Ca	75	5	0.135
Mg	50	4	0.108
Na	200	3	0.081
K	12	2	0.054
Cl	250	5	0.135
SO_4	250	3	0.081
HCO_3	500	5	0.135
NO_3	45	2	0.054
Sum		37	1.000

Table 2
Classification of groundwater based on GWQI (Sahu and Sikdar, 2008).

Range	Type of water	Numbers of wells
<50	Excellent water	4
50–100.1	Good water	30
100–200.1	Poor water	1
200–300.1	Very poor water	0
>300	Water unsuitable for drinking purposes	0

Table 3
Statistical descriptive of the hydrochemical parameters and GWQI.

Parameters	Min	Max	Mean	Std. dev	Coef. var	Numbers of wells exceeding the standard
pH	6	7.5	6.77	0.26	4	0
EC	228	1411	821	279	34	30
Ca	16	198	96	32	34	28
Mg	11.02	61.32	37.39	12.01	32.12	5
Na	12.47	38.14	24.57	4.99	20.29	0
K	1.78	5.45	3.51	0.71	20.29	0
Cl	63.90	255.60	150.08	53.12	35.40	1
SO_4	61.39	270.00	125.97	49.93	39.64	2
HCO_3	97.60	524.60	232.02	90.22	38.88	1
NO_3	0.02	47.54	23.47	14.77	62.90	2
GQWI	44.55	102.49	70.11	15.05	21	

Min: Minimum; Max: Maximum; Std.dev: Standard deviation; Coef.var: Coefficient of variation.

The objectives of this study are: (1) to compute the groundwater quality index (GWQI), (2) to determine the relationships between GWQI and hydrochemical parameters in groundwater, and (3) to evaluate and compare the Kriging and the Co-kriging procedures to estimate the groundwater quality index on unobserved points.

2. Study area and data description

Fig. 1 shows the geographical locations of the study area and groundwater sampling wells. The study area is situated in El Mila plain at a few kilometers from the Mediterranean Sea and between eastern longitude of $6^0 10^{'}$-$6^0 20^{'}$E and northern latitude of $36^0 40^{'}$-$36^0 47^{'}$N. The El Milia region has a Mediterranean climate characterized by warm summers and mild winters but is very humid. The average annual of temperature and precipitation is 17 °C and 930 mm, respectively (Belkhiri et al., 2018).

Groundwater samples were collected from 35 wells during April 2015, located in the alluvial aquifer (Mio-Plio-Quaternary). Hydrogeologically, this aquifer is considered as an important reservoir and source of water in this region.

3. Methodology

3.1. Hydrochemical parameter analyzed

The hydrochemical parameters used in this study consist of pH, electrical conductivity (EC) and major dissolved ions such as calcium (Ca), magnesium (Mg), sodium (Na), potassium (K), chloride (Cl), sulfate (SO_4), bicarbonate (HCO_3), and nitrate (NO_3). The samples were collected in April 2015 using standard methods (APHA, 2005; ISO, 1993). pH and EC were measured with a multi-parameter WTW (P3 MultiLine pH/LF-SET). Ca and Mg were estimated titrimetrically using 0.05N–0.01 N EDTA. Na and K were analyzed by flame photometer. HCO_3 and Cl by H_2SO_4 and $AgNO_3$ titration, respectively, and SO_4 by turbidimetric method (Clesceri et al., 1998). NO_3 was analyzed with UV–visible spectrophotometer. The accuracy of the chemical analysis was verified by calculating ion-balance errors where the errors were generally around 5%. The accuracy of the chemical ion data was calculated using charge balance equation given below, and the charge balance error (CBE) of the groundwater samples was within the accepted limits of ±5%.

$$CBE(\%) = \frac{\sum cations - \sum anions}{\sum cations + \sum anions} * 100 \quad (1)$$

Table 4
Correlation coefficient matrix of hydrochemical parameters.

	pH	EC	Ca	Mg	Na	K	Cl	SO_4	HCO_3	NO_3	GWQI
pH	1										
EC	0.02	1									
Ca	0.06	0.28	1								
Mg	0.19	0.41	0.16	1							
Na	0.11	0.54	0.07	0.22	1						
K	0.11	0.54	0.07	0.22	1.00	1					
Cl	0.13	0.08	−0.25	−0.10	−0.02	−0.02	1				
SO_4	0.38	0.61	0.42	0.22	0.23	0.23	0.14	1			
HCO_3	0.16	0.44	0.23	0.15	0.22	0.22	0.28	0.38	1		
NO_3	0.05	0.00	−0.07	0.12	0.26	0.26	−0.19	−0.31	0.13	1	
GWQI	0.26	0.85	0.59	0.51	0.47	0.47	0.16	0.71	0.63	0.08	1
Significant coefficients at the 0.05 and 0.01 levels											
pH	0										
EC	0.928	0									
Ca	0.741	0.105	0								
Mg	0.282	0.014	0.372	0							
Na	0.520	0.001	0.698	0.194	0						
K	0.520	0.001	0.699	0.194	0.000	0					
Cl	0.468	0.668	0.144	0.581	0.895	0.896	0				
SO_4	0.023	0.000	0.013	0.204	0.190	0.190	0.434	0			
HCO_3	0.361	0.008	0.177	0.403	0.201	0.201	0.102	0.023	0		
NO_3	0.788	0.991	0.671	0.488	0.131	0.130	0.284	0.071	0.458	0	
GWQI	0.137	0.000	0.000	0.002	0.005	0.005	0.350	0.000	0.000	0.662	0

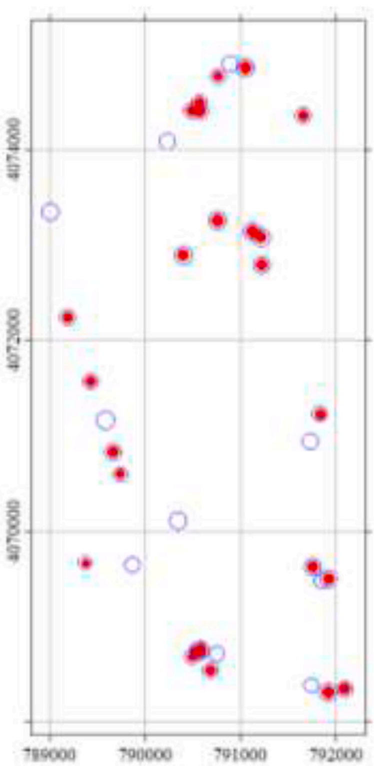

Fig. 2. Plot of training (blue color) and testing (red color) data. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

where $\sum cations$ and $\sum anions$ are the sum of cations and anions, respectively, expressed in equivalents par liter.

3.2. Groundwater quality index (GWQI)

Groundwater quality index (GWQI) method reflects the influence of the hydrochemical parameters of groundwater on the suitability for drinking purposes (Sahu and Sikdar, 2008; Belkhiri et al., 2018). The estimation of the GWQI index was based on parameter weighting. In the current study, three steps were followed in to order to calculate GWQI based on 10 parameters at each well.

In the first step, the relative weight (W_i) of each parameter was estimated as follows:

$$W_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \tag{2}$$

where w_i is the weight of each parameter, and n is the number of parameters. Assigning of weight (w_i) to the different groundwater parameters according to their relative importance in the overall quality of groundwater for drinking purposes (weight ranged from 1 to 5). The weights according to the World Health Organization standards (WHO, 2004) are presented in Table 1.

In the second step, the quality rating scale (q_i), which related the value of the parameter to the WHO standards, was calculated as follows:

$$q_i = \left(\frac{C_i - C_{i0}}{S_i - C_{i0}}\right)*100 \tag{3}$$

where C_i is the concentrations of each parameter (mg/l), S_i is the standard permissible value of each parameter (mg/l). For all parameters, and C_{i0} is the ideal value of each parameter in pure water (consider

Table 5
Best fitted semivariogram models and model parameters for GWQI.

Models	Range	Nugget (C_0)	p-sill (C)	Nugget-sill ratio ((C_0/C_0+C)*100)	SSErr	R^2
Exponential	434.6967	0.001951	0.009784	16.63	3.25E-11	0.977175
Spherical	1344.937	0.004263	0.007399	36.55	1.57E-11	0.990538
Gaussian	421.247	0.000802	0.010959	6.82	3.28E-11	0.982465
Linear	1373.8412	0.005699	0.00609	48.34	1.72E-11	0.990209
Matern	434.6967	0.001951	0.009784	16.63	3.25E-11	0.977175

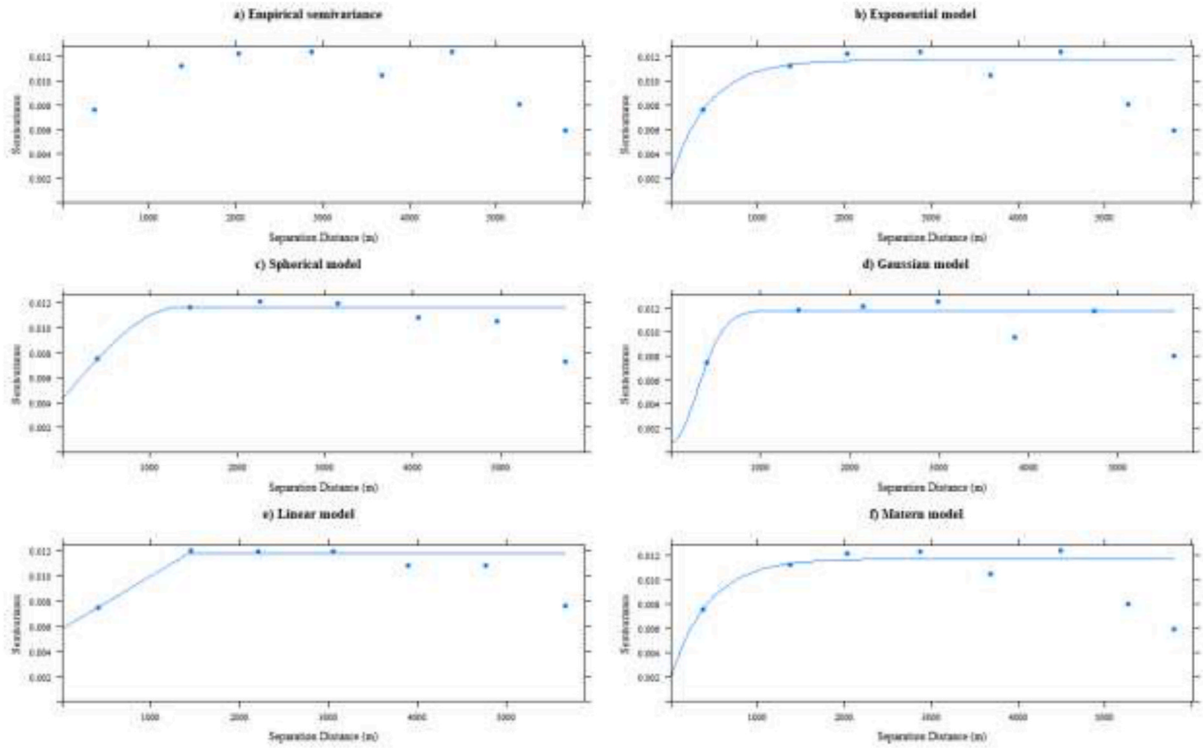

Fig. 3. a) Empirical semivariance of GWQI and its fitted model: **b)** Exponential model, **c)** Spherical model, **d)** Gaussian model, **e)** Linear model and **f)** Matren model.

$C_{i0} = 0$ for all parameters) except the pH value where $C_{i0} = 7$).

In the final step, GWQI of each well was given as follows:

$$GWQI = \sum_{i=1}^{n} W_i{}^{*}q_i \tag{4}$$

The groundwater quality based on GWQI can be classified into five classes, as listed in Table 2.

3.3. Geostatistical methods

Kriging and Co-kriging analysis were performed to produce prediction maps of the groundwater quality index (GWQI). Kriging is a geostatistical technique that is used to interpolate a surface from a scattered set of known points in which a continuous surface of values can be predicted between the known locations. Variogram model controls Kriging weights. Variogram is mathematically defined as a measure of semi-variance as a function of distance.

$$\gamma(h) = \frac{1}{2N(h)}\sum_{i=1}^{N(h)}[z(x_i) - z(x_i + h)]^2 \tag{5}$$

where $\gamma(h)$ is the semi-variance; $N(h)$ the number of pairs separated by distance or lag h; $Z(x_i)$ the measured sample at point x_i; and $Z(x_i + h)$ the measured sample at point $(x_i + h)$. The spatial structure of the data is determined by fitting a mathematical model to the experimental. The mathematical models provide information about the structure of the spatial variation, as well as the input parameters for kriging. The model was fitted to the environmental variables, which showed that these variables had a spatial autocorrelation in their effective ranges. Exponential, spherical, Gaussian and Linear models were used to fit the experimental variogram of data pairs.

3.3.1. Ordinary kriging (OK)

OK is a geostatistical interpolation method based on spatially dependent variance, which used to find the best linear unbiased estimate (Goovaerts, 1997). The general form of Ordinary kriging equation can be written as:

$$\widehat{Z}(x_p) = \sum_{i=1}^{n} \lambda_i Z(x_i) \tag{6}$$

In order to achieve unbiased estimations in kriging the following set of equations should be solved simultaneously:

$$\begin{aligned} &\sum_{i=1}^{n} \lambda_i \gamma(x_i, x_j) - \mu = \gamma(x_i, x_p) \ where\ j = 1, \dots, n \\ &with \quad \sum_{i=1}^{n} \lambda_i = 1 \end{aligned} \tag{7}$$

where $\widehat{Z}(x_p)$ is the estimated value of variable Z (*i.e.*, GWQI) at location x_p; $Z(x_i)$ is the known value at location x_i; λ_i is the weight associated with the data; μ is the Lagrange coefficient; $\gamma(x_i, x_j)$ is the value of variogram corresponding to a vector with origin in x_i and extremity in x_j; and n is the number of sampling points used in estimation.

3.3.2. Co-kriging method (CK)

CK estimator is the multivariate equivalent to kriging, which has secondary variables. By using multiple datasets, it is a very flexible interpolation method, allowing the user to investigate graphs of cross-correlation and autocorrelation. Co-Kriging estimation is introduced by the following equation:

$$\begin{aligned} &\sum_{l=1}^{v}\sum_{i=1}^{n} \lambda_{il}\lambda_{lv}\gamma(x_i, x_j) - \mu_v = \gamma_{uv}(x_i, x_p) \ where\ j = 1, \dots, n \ and\ u = 1, \dots, v \\ &with \ \sum_{i=1}^{nl} \lambda_{il} = \begin{cases} 1, & 1 = u \\ 0, & 1 \neq 1u \end{cases} \end{aligned} \tag{8}$$

where u and v are the primary and covariate (secondary) variables, respectively. The two variates u and v are cross-correlated and the covariate contributes to the estimation of the primary variate.

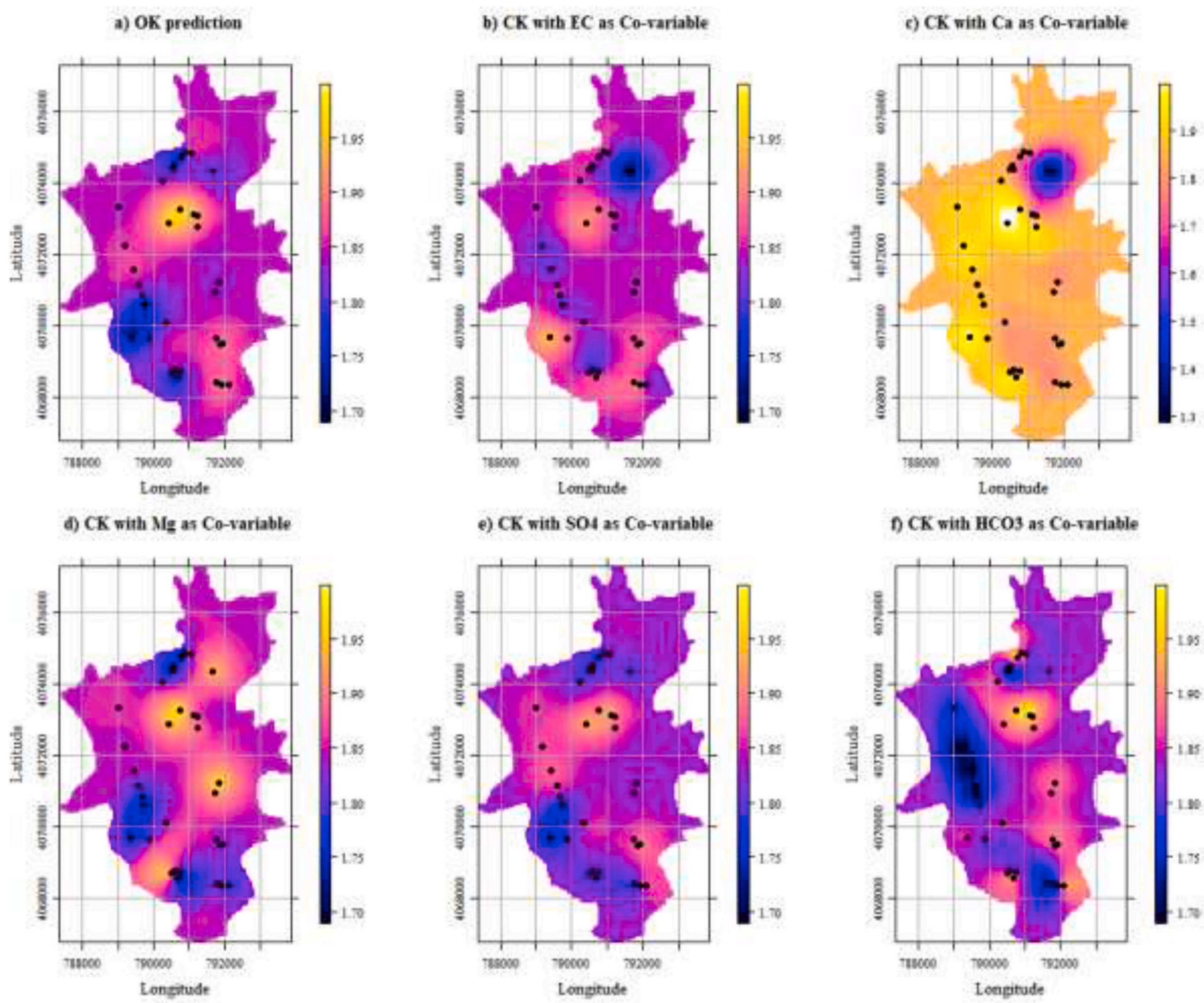

Fig. 4. Spatial prediction map of GWQI (log_{10}) obtained by a) Ordinary Kriging (OK), b) Co-Kriging (CK) with EC, c) CK with Ca, d) CK with Mg, e) CK with SO_4 and f) CK with HCO_3. Black dots are groundwater samples.

For CK analysis, the cross-variogram should be determined in prior. The cross-variogram models between the primary and secondary variables are obtained by fitting with an experimental cross-variogram that is given by

$$\gamma_{uv}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z_u(x_i) - z_u(x_i + h)][z_v(x_i) - z_v(x_i + h)] \tag{9}$$

Ordinary kriging (OK) and Co-kriging (OK) analysis were performed to produce prediction maps of the groundwater quality index (GWQI) values. The different covariates used in this study are determined based on the significant correlation between groundwater quality index and the different hydrochemical parameters.

3.3.3. Cross-validation method

To evaluate the performance of interpolation methods is used the cross-validation method. In this study, estimated and observed values were compared using mean errors (bias: ME), root mean square errors (precision: RMSE) and squared deviation ratio (MSDR). The smallest ME, RMSE and MSDR indicate the most accurate predictions.

Some R packages are designed delicately for kriging, in this study, we use “gstat”, “rgdal”, “maptools”, “sp”, “lattice” packages to implement a common type of spatial interpolation.

4. Results and discussions

4.1. Statistical descriptive of the hydrochemical parameters

A statistical summary of hydrochemical data of groundwater samples is given in Table 3. All the groundwater samples showed the pH values ranged from 6 to 7.5 with a mean value of 6.77, indicating acidic to slight alkaline in nature. The electrical conductivity values of the samples ranged from 228 to 1411 μS/cm with a mean of 821 μS/cm which presents the high amount of salts in the groundwater. Most of the groundwater samples (86%) showed high value of EC and may not be suitable for drinking purposes (WHO, 2004). The calcium and magnesium values of the samples ranged from 16 to 198 and 11.02–61.32 mg/l mg/l with a mean of 96 and 37.39 mg/l respectively. The results revealed that, 80% and 14% of total samples for Ca and Mg, respectively, were above the limits fixed by WHO (2004). High concentration of Ca and Mg in groundwater could cause some negative effects like health effect such as abdominal ailments as well as economic and hydraulic effect such as scaling. The values of sodium and potassium varied from 12.47 to 38.14 mg/l and 1.78–5.45 mg/l, respectively, indicating that all values for both cations were lower than the WHO standard level (WHO, 2004). Cl concentration in the area varied from 63.9 to 255.6 mg/l with a mean of 150.08 mg/l. SO_4 values in the area ranged from 61.39 to 270 mg/l with mean value 125.97 mg/l. Bicarbonate concentration in groundwater ranged from 97.60 to 524.6 with a

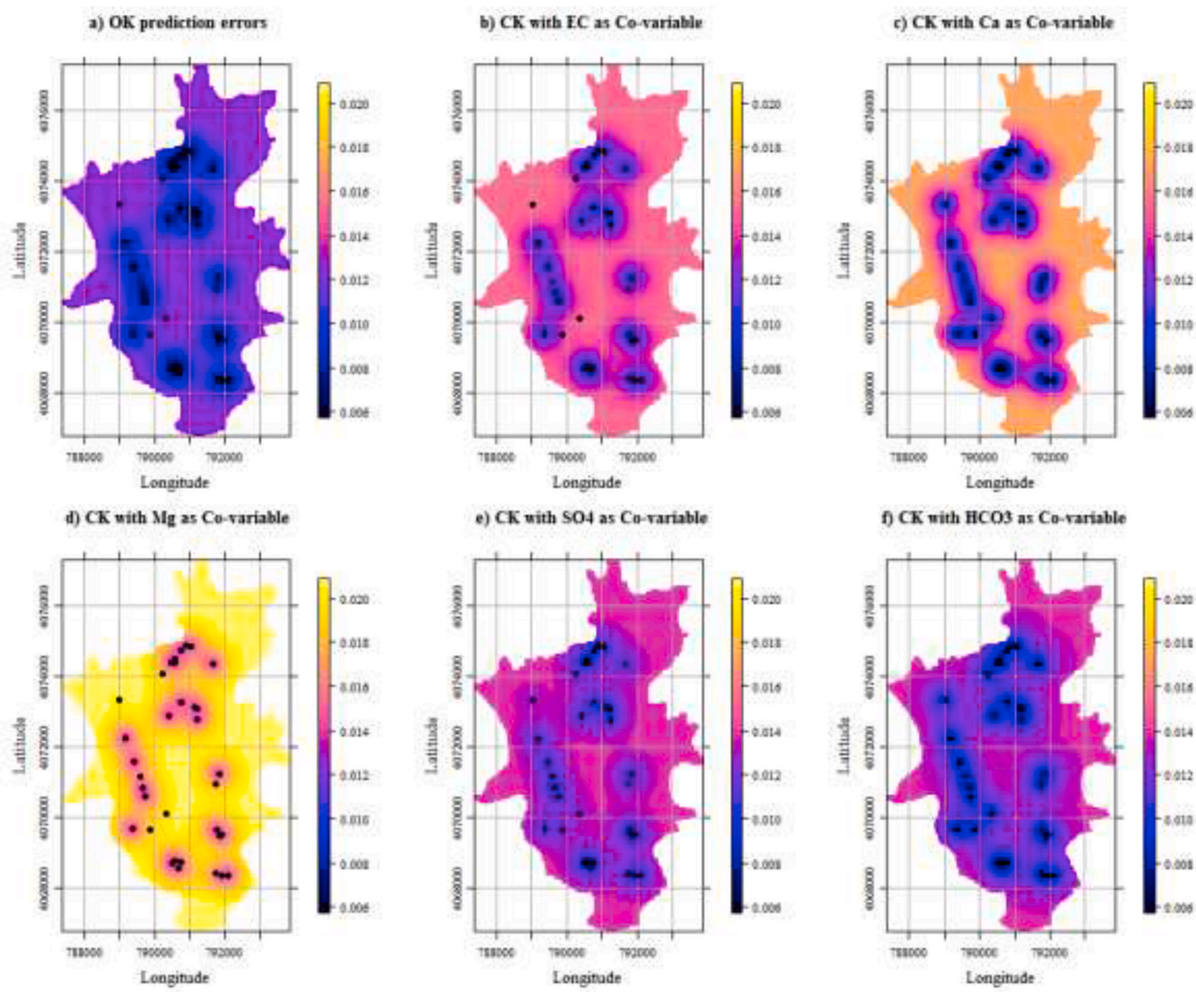

Fig. 5. Spatial prediction errors map of GWQI ($\log_{10}$) obtained by a) Ordinary Kriging (OK), b) Co-Kriging (CK) with EC, c) CK with Ca, d) CK with Mg, e) CK with SO_4 and f) CK with HCO_3. Black dots are groundwater samples.

Table 6
Compare the cross-evaluation errors for different models.

Models	Min	Mean	Max	ME	RMSE	MSDR
OK	−0.1816	−0.00235	0.171359	−0.00235	0.100787	1.163582
CK with EC	−0.15326	0.001778	0.115835	0.001778	0.051449	0.747344
CK with Ca	−0.2334	−0.00469	0.390785	−0.00469	0.116067	8.181616
CK with Mg	−0.24811	0.00435	0.217444	0.00435	0.098116	2.615486
CK with SO_4	−0.17292	−0.00028	0.153277	−0.00028	0.080772	4.094798
CK with HCO_3	−0.24523	−0.00325	0.13982	−0.00325	0.094937	4.930154

mean of 232.02 mg/l. Only one sample for chloride and bicarbonate and two samples for sulfate were lower than the WHO standard level (WHO, 2004), while the other samples were within the WHO standard for drinking water. Nitrate and nitrite concentration were found in samples ranged from 0.02 to 47.54 mg/l and 0.01–47.54 mg/l, respectively. Two samples were found to be exceeding the WHO for NO_3.

Understanding the relationship and variations between the different hydrochemical parameters and explaining the interaction between them could be carried out based on the statistical analysis (Meireles et al., 2010; Ahamad et al., 2018). The contamination of groundwater is primarily accountable for the variations in electrical conductivity. The relationship between different parameters is shown in Table 4. According to the results, pH-SO_4 (0.38), Ca–SO_4 (0.42), Na–K (1.00), and SO_4–HCO_3 (0.38) indicate significant correlations. Significant positive correlation between EC and Mg (0.41), Na–K (0.54), SO_4 (0.61), and HCO_3 (0.44) is suggestive of significant natural and anthropogenic activities leading to the addition of these ions into the groundwater of the region.

4.2. Evaluation of drinking water quality

Suitability of groundwater quality for drinking water purposes could be distinguished based on the hydrochemical parameters. Rating of groundwater in the aspect of quality and consumption using the influence of individual water quality parameters can be helpful in making decision by managers and administrative organizations.

The results of GWQI of the groundwater samples are presented in Tables 2 and 3 The GWQI values ranged from 44.55 to 102.49 with a mean value of 70.11, which can be placed in three classes, namely poor water, good water, and excellent water quality. The results revealed that

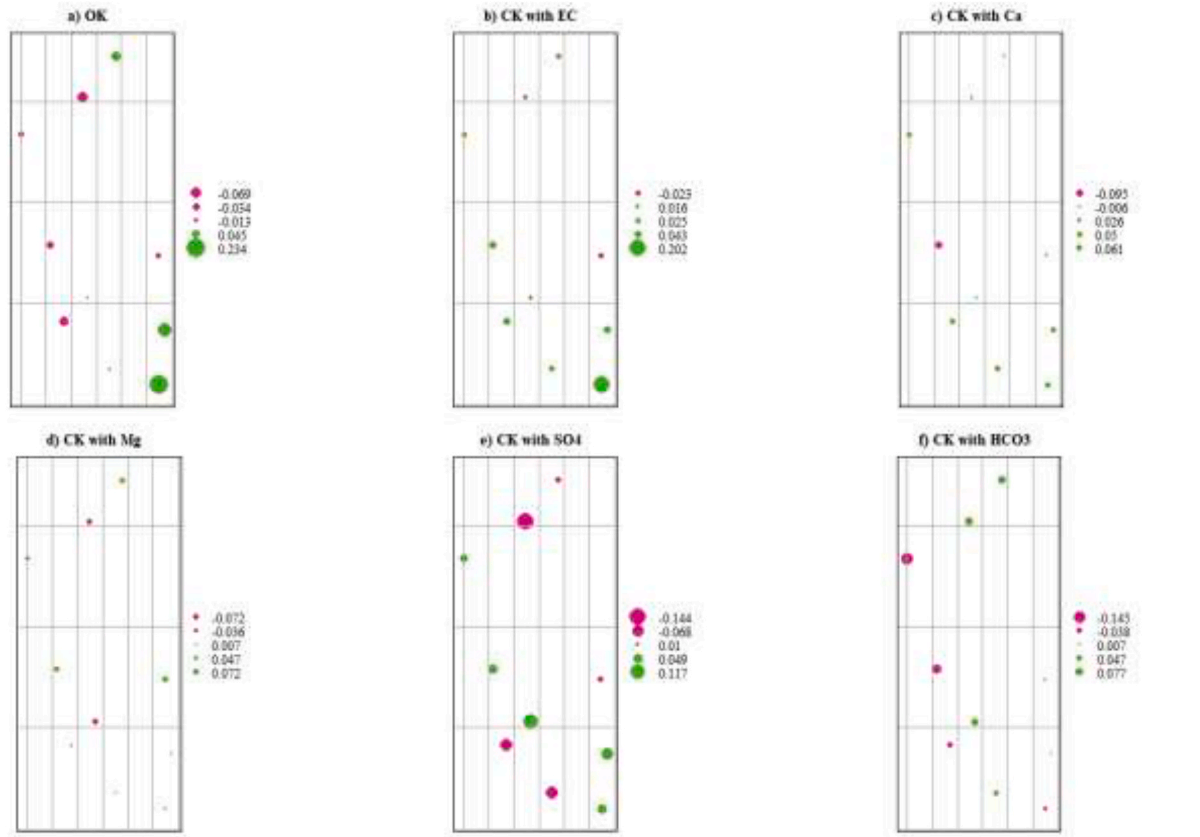

Fig. 6. Spatial distribution of the evaluation errors for: a) Ordinary Kriging (OK), b) Co-Kriging (CK) with EC, c) CK with Ca, d) CK with Mg, e) CK with SO_4 and f) CK with HCO_3.

about 11.43% of the groundwater samples fall in the excellent water class, and 85.71% samples reported good water quality type, whereas 2.86% groundwater samples exhibited poor water quality type. Form Table 4, we can see that GWQI had a significant positive correlation with EC (0.85), SO_4 (0.71), HCO_3 (0.63), Ca (0.59), Mg (0.51), and Na–K (0.47). The strong significant correlation of the parameters such as EC, Ca, Mg, SO_4 and HCO_3 with GWQI is selected as co-variables to predicted spatially the groundwater quality index. In this study, we compared five possible co-variables based on their strong significant correlation with GWQI.

4.3. Spatial interpolation method

The groundwater quality index (GWQI was interpolated by Kriging and Co-kriging (CK) methods. The data frame of water sample points contains 35 wells (observations) and the prediction grid has 15088 locations, spaced every 50 m in both the East and North grid directions, covering the irregularly-shaped study area. Because of the wide numerical range of the GWQI values we worked with the log-transformed target variable; to allow easy interpretation of the results we used base-10 logarithms ($\log_{10}$) for each parameter. In order to experiment an independent validation, we first need to separate the data into a training data and test data. Then we use the training dataset to predict the value in the test dataset. In this study, 30% of the data has been excluded for testing (Fig. 2).

4.3.1. Selecting the best fitted variogram models

The spatial dependence of the groundwater quality index was determined by semivariance analysis, which indicated that the calculated index was modeled with different semivariogram models with a nugget effect. Sum of squares errors (SSErr) and regression coefficient (R^2) provided an exact measure of how well the model fit the variogram data, with lower SSErr and higher R^2 indicating better model fits. The parameter values of the different fitted models are presented in Table 5. Theory and empirical semivariogram were prepared for the GWQI as shown in Fig. 3. The results of the selecting of the best fitted variogram model show that spherical model was found as the most accurate model for GWQI.

Spatial dependency is commonly accessed in terms of the ratio of nugget (C_0) to sill (C_0+C) expressed in percentage. In this respect, the GWQI index is considered as a strong spatial dependence when the value of ratio is less than 25%, a moderate spatial dependence when this value is between 25% and 75%, and a weak spatial dependence when the value is greater than 75%. Form Table 5, we see clearly that the spatial dependence of GWIQ for the best fitted semivariogram model is moderate with a ratio of 36.55%.

4.3.2. Ordinary Kriging and Co-Kriging interpolations of the GWQI

The best fitted model (spherical model) of regionalization is used to interpolate the groundwater quality index ($\log_{10}$ GWQI) with both Ordinary kriging (OK) and Co-kriging (CK) methods on the prediction grid. First, we predict the GWQI without the co-variables. Then, CK method is applied with EC, Ca, Mg, SO_4, and HCO_3 as co-variables to predicted the groundwater quality index.

In this step, we compare graphically the predictions and their errors of the GWQI variable form OK and CK. Figs. 4 and 5 show the predictions and their errors of the GWQI ($\log_{10}$) distribution across the study area from different models. The maps of CK with co-variables provide some new regions where the GWQI values are high. The high values of GWQI could be observed in the center of the plain near to the El Milia city and southern region, which might be principally caused by both anthropogenic activities and erosion of natural deposits.

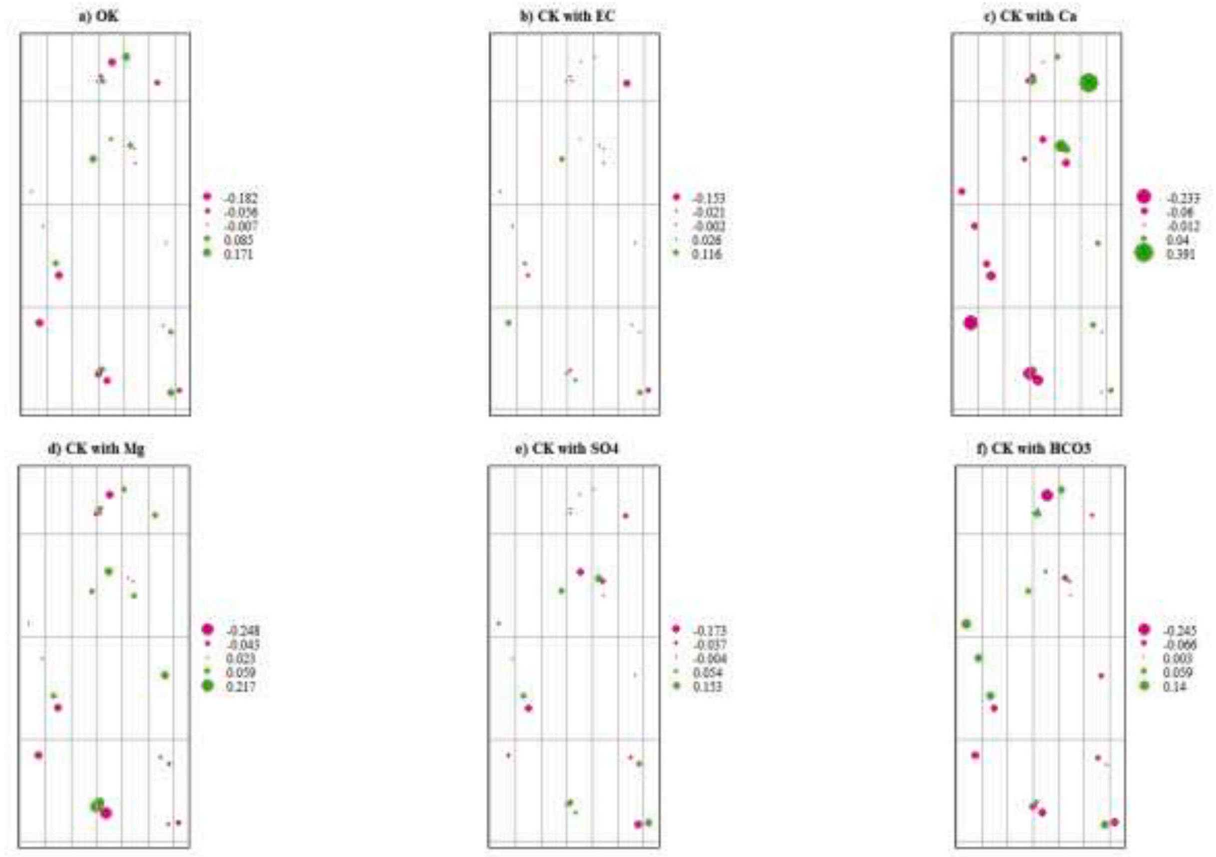

Fig. 7. Spatial distribution of the cross-evaluation errors for: a) Ordinary Kriging (OK), b) Co-Kriging (CK) with EC, c) CK with Ca, d) CK with Mg, e) CK with SO_4 and f) CK with HCO_3.

From Fig. 5, we can see that the OK prediction errors map shows the expected low errors near the water sample points, whereas CK with different co-variables gives the lowest errors averaged across the map. This is because the co-kriging predictions are based not only on the target variable (GWQI) but also the co-variable at these points as well as their covariance (Rossiter, 2018).

4.3.3. *Evaluation of geostatistical methods*

For the evaluation, we used the cross-validation performance to evaluate the performance of the different interpolations based on the testing dataset (30%). To compare the evaluations for the different models, diagnostic measures such as ME (mean errors), RMSE (root mean square errors) and MSDR (squared deviation ratio) of the residuals to the prediction errors are calculated (Table 6). Fig. 6 shows bubble plots of the cross-evaluation errors for all models where positive values are plotted in green blue and negative in red, with the size of the bubble proportional to the distance from zero. From Table 6 and Fig. 7, we see clearly that the Co-kriging model with EC as co-variable is superior to the other models in all measures.

5. Conclusion

In this study, geostatistical interpolation methods were used in order to understand the spatial distribution of the groundwater quality index (GWQI). Descriptive and correlation analysis were conducted to determine the significant correlations between GWQI and all parameters. Strong significant correlation was observed between GWQI and EC, Ca, Mg, SO_4 and HCO_3, indicating the significant natural and anthropogenic activities leading to the addition of these ions into the groundwater. Ordinary Kriging and Co-kriging procedures were applied to estimate the spatial distribution of GWQI values at the unobserved locations of the study area. For CK method, EC, Ca, Mg, SO_4 and HCO_3 were considered as co-variables. Cross-validation was estimated to evaluate and compare the performance of the different proposed models. The results show that Co-kriging with electrical conductivity as co-variable is higher than the other models which means its higher accuracy than Kriging method to predict the groundwater quality index.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors thank the editor Prof. Prosun Bhattacharya and anonymous reviewers for their comments which greatly improved this manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gsd.2020.100473.

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