Arabian Journal of Geosciences (2021) 14:2800
https://doi.org/10.1007/s12517-021-09110-y

CORRECTION

Correction to: Diagnosis and removal of trend component in groundwater elevation data by using experimental semivariograms: An application to Mahdia shallow aquifer system of Tunisia

Rania Soula[1] · Ali Chebil[2] · Mahmut Cetin[3] · Rajouene Majdoub[1]

© Saudi Society for Geosciences 2021

Correction to: Arabian Journal of Geosciences (2021) 14: 2116
https://doi.org/10.1007/s12517-021-08477-2

In this article, there are errors introduced and some corrections were not carried out. Specific update comprises the article title, tables, equations and article content.

The original article has been corrected.

Please cite this article as:

Soula, R., Chebil, A., **Cetin, M.,** Majdoub, R., 2021. Diagnosis and removal of trend component in groundwater elevation data by using experimental semivariograms: An application to Mahdia shallow aquifer system of Tunisia. Arab J Geosci 14, 2116 (2021). https://doi.org/10.1007/s12517-021-08477-2

OR

Soula, R., Chebil, A., Cetin, M. *et al.* Diagnosis and removal of trend component in groundwater elevation data by using experimental semivariograms: An application to Mahdia shallow aquifer system of Tunisia. *Arab J Geosci* 14, 2116 (2021). https://doi.org/10.1007/s12517-021-08477-2

The original article can be found online at https://doi.org/10.1007/s12517-021-08477-2

✉ Rania Soula
raniaso1@hotmail.fr

[1] Department of Horticultural Systems and Natural Environment Engineering, Higher Agronomic Institute of Chott-Mariem, University of Sousse, Sousse, Tunisia

[2] National Research Institute for Rural Engineering, Water and Forestry (INRGREF), Tunis, Tunisia

[3] Department of Agricultural Structures and Irrigation, Faculty of Agriculture, Cukurova University, Adana, Turkey

Published online: 07 December 2021

Arabian Journal of Geosciences (2021) 14:2116
https://doi.org/10.1007/s12517-021-08477-2

3RD CAJG 2020

Diagnosis and removal of trend component in groundwater elevation data by using experimental semivariograms: An application to Mahdia shallow aquifer system of Tunisia

Rania Soula[1] · Ali Chebil[2] · Mahmut Cetin[3] · Rajouene Majdoub[4]

Received: 22 March 2021 / Accepted: 9 September 2021
© Saudi Society for Geosciences 2021, corrected publication 2021

Abstract

Groundwater is a precious source in arid and semi-arid regions of the world. Potentiometric level data show a non-stationary behavior due to the trend component. Consequently, it renders difficult to delineate groundwater-surface, i.e., spatial estimation. The staple objectives of this study are three-fold: (1) to diagnose trend component in potentiometric data by utilizing experimental semivariograms, (2) to model trend surface, (3) to remove trend component from groundwater elevation and demonstrate the effectiveness of the method by using experimental semivariograms of residuals. The study was conducted in the region of Mahdia, located in central-eastern Tunisia. Point-wisely scattered groundwater level data from 69 observation sites were used in the study. Data of the rainy period in 2008 and 2018 were utilized in order to elude negative anthropogenic impacts on potentiometric levels. Omnidirectional experimental semivariograms (OESs) were obtained from elevation data by using the minimum feasible lag interval. Experimental semivariograms helped us diagnose trend component, i.e., non-stationarity. Trend surface analysis was conducted through using the ANOVA technique. A very significant proportion of the variation in the observed data could be "explained" by a quadratic trend surface model. Comparing the partial cubic trend surface model with the quadratic one resulted in "statistically-not-significant" F value. Consequently, there was no real evidence that the partial cubic surface model was actually any better than the quadratic one. OESs of residuals indicated that the quadratic trend was effectively removed from the data.

Keywords Trend surface analysis · Groundwater elevation · Experimental semivariogram · Mahdia · ANOVA

Responsible Editor: Broder J. Merkel

This paper was selected from the 3rd Conference of the Arabian Journal of Geosciences (CAJG), Tunisia 2020

✉ Rania Soula
raniaso1@hotmail.fr

[1] Department of Horticultural Systems and Natural Environment Engineering, Higher Agronomic Institute of Chott-Mariem, University of Sousse, Sousse, Tunisia

[2] National Research Institute for Rural Engineering, Water and Forestry (INRGREF), Tunis, Tunisia

[3] Department of Agricultural Structures and Irrigation, Faculty of Agriculture, Cukurova University, Adana, Turkey

[4] Department of Horticultural Systems and Natural Environment Engineering, Higher Agronomic Institute of Chott-Mariem, University of Sousse, Sousse, Tunisia

Introduction

There are different kinds of water resources to put at the disposal of humankind, namely rivers, lakes, springs, and groundwater. Among these sources, groundwater is a precious as well as an essential source in arid and semi-arid regions of the world (FAO 2016). Considering the importance of this renewable resource, not only have scientists dealt with groundwater, but practitioners have also taken an interest in it for many years. As pointed out by Karamouz et al. (2003), this, in turn, has led to breakthrough developments recently. For example, groundwater hydrology has made important developments in the last decades due to the use of modelling (Tapoglou et al. 2014; Singh 2018). In this regard, mathematical equations prove useful to describe the physical groundwater system and necessitate easily measurable data time series. It has been widely accepted that the hydrological process of groundwater is more complex than surface waters. Nonetheless, the fact remains that aquifers and watershed resources are two inseparable media for

Published online: 07 October 2021

regional assessment of water and contamination movement, as well as soil–water interaction.

In unconfined aquifers, referred to as water table aquifers hereafter, groundwater depth measurements are of importance in order to depict groundwater table as well as to make comprehensible assessments regarding groundwater table depletion. On the other hand, as expected, many factors govern groundwater table. Among those, topography plays an important role in shaping groundwater table (Mulyadi et al. 2020). Therefore, potentiometric level data show rather non-stationary behavior due to the trend component. Consequently, it renders difficult to delineate groundwater-surface, i.e., spatial estimation. Data obtained from groundwater wells as well as piezometers in aquifers and rain gauges in watersheds represent empirical information in statistical assessment studies. Geostatistical analysis tools, in turn, help us to make spatial estimations (Uyan and Cay 2013; Evans et al. 2020; Varouchakis et al. 2020). The spatial dependence structure of the regionalized variables (Cetin and Kirda 2003; McKillup and Dyar 2010) such as groundwater depth (Soula et al. 2019) or elevation data proves useful in the decision-making process.

In this regard, either omnidirectional or directional experimental semivariograms are commonly used to model the spatial variability of the chosen phenomenon (Olea 2006; Oktay et al. 2020). On the other hand, the one-way analysis of variance (ANOVA) technique is also widely used in conjunction with geostatistical tools in diagnosing a priori trend component in the data (Kaufman and Sain 2010; Shumway and Stoffer 2011). In this context, there exist multiple trend detection tests that allow us to compare candidate trend models. The primary objectives of this study were to: (1) diagnose trend component in potentiometric data by utilizing experimental semivariograms, (2) model trend surface, if any, and (3) remove trend component from groundwater elevation data and demonstrate the effectiveness of the method by using experimental semivariograms of residuals in conjunction with ANOVA technique.

Material and methods

Study area and source of data used

This study was conducted in a semi-agricultural catchment located in *central-eastern* Tunisia, i.e., Tunisian Sahel. The catchment covers an area of approximately 2878 km^2. The region is mainly lowland near the Mediterranean Sea while hilly and mountainous area can be found in the southwest. The local climatic conditions have characteristics of semi-arid Mediterranean climate which is a major climate type of the Köppen classification characterized by hot and dry summers; cool and wet winters are located between about 30° and 45° latitude north and south of the Equator and on the western sides of the continents. Seasonal temperature, on average, ranges between 11 °C in winter and 26 °C in the summer. The annual rainfall ranges from 140 to 300 mm. Watersheds have seasonal rivers, i.e., intermittent, that conduct water to the salt lake (Sabkhas) and then to the Mediterranean Sea. There are also hill lakes and artificial recharge structure used mainly for irrigation (Soula et al. 2020). From a geological standpoint, the multi-directional extension of the Miocene period extending from the Langhian to the Tortonian was identified in the Mahdia Sahel (Bedir 1989). Quaternary formations persist generally near salt lakes and sea (Hezzi 2014). The present study focused on an alluvial water table, i.e., unconfined, aquifer system. Data of depth to the

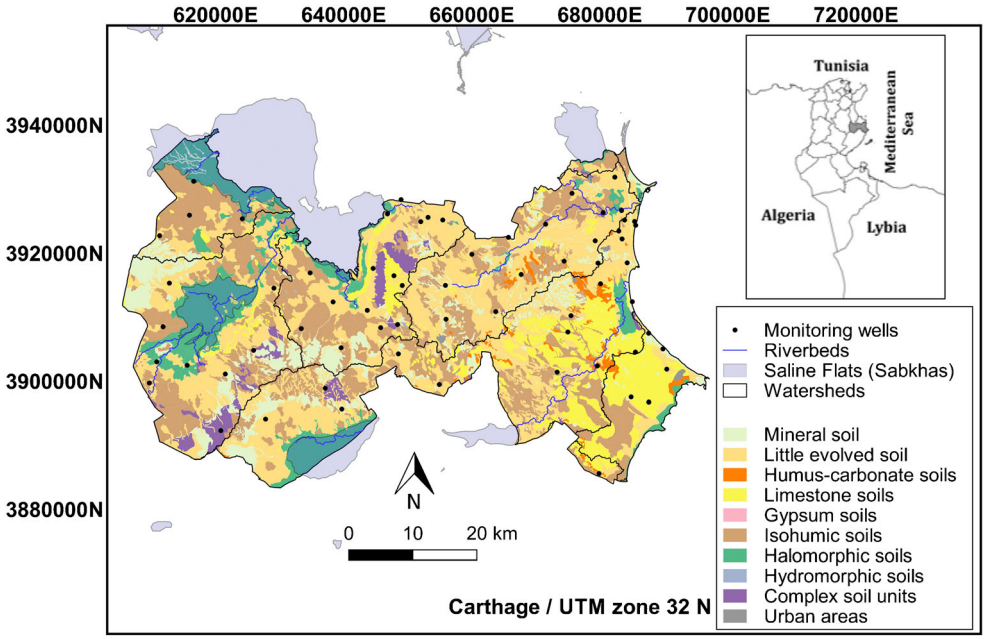


Fig. 1 Location of the study site Mahdia (Tunisia) and spatial distribution of the 69 groundwater wells constructed in a shallow water table aquifer system (CRDA 2018)

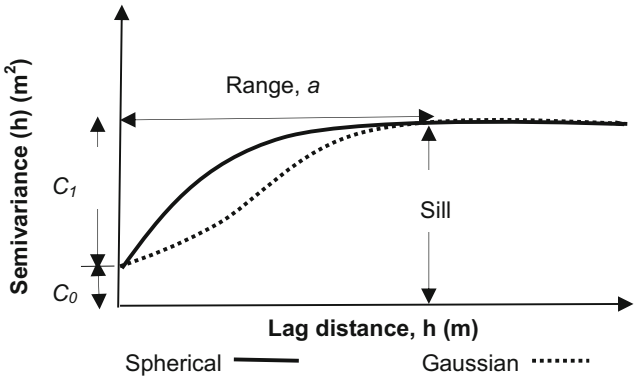


Fig. 2 Typical parameters for theoretical semivariograms (Gaussian and spherical)

groundwater level -where the gage pressure is zero- were utilized in the study. The data, consisting of 69 hydraulic head measurements, were provided by the Regional Commissariat for Agricultural Development (CRDA). The range of hydraulic heads varies from a low value of minus 6 m above mean sea level (masl) to a high value of +111 m (Fig. 1).

A review of experimental semivariograms and modelling

Before applying any kriging interpolation technique (e.g., ordinary kriging, OK), it is necessary to determine the semivariogram function or model (Cetin and Kirda 2003) that describes the spatial dependence structure of the data used in the interpolation (Ohmer et al. 2017). Experimental semivariance values to model semivariograms are computed by means of squared differences between pairs of observations (Olea 2018) as the following:

$$\gamma^{*}(h)=\frac{1}{2N(h)}\sum_{i\neq j}^{N(h)}\left(z_i-z_j\right)^2 \quad (1)$$

where $N(h)$ denotes the number of pairs separated by a vector of h (i.e., distance between sample pairs); (z_i), (z_j) are the data values observed at the points i and j, respectively.

The magnitude of interpolated value of a physically continuous surface such as water table depends on the selected semivariogram model, and its parameters are defined, as well as kriging search parameters (Cetin and Kirda 2003). Soula et al. (2019), among the others, point out that several candidate spatial functions are available for semivariogram modelling. These are, to mention but e few, linear, Gaussian, spherical, exponential, and circular (Grynyshyna-Poliuga 2019). Gaussian and spherical theoretical semivariograms (Cetin and Kirda 2003) in Eqs. 2 and 3, respectively, were used in this study as shown in Fig. 2.

- Gaussian model:

$$\gamma(|h|)=\begin{cases} C_0+C_1\left(1-\exp\left(\dfrac{-3|h|^2}{a^2}\right)\right), & |h|\leq a \\ C, & |h|>a \end{cases} \quad (2)$$

where

- *a:* practical range of influence (in the unit of distance),
- *h:* separation distance between sample pairs (in the unit of distance), and
- *C:* the sill value of semivariogram, consisting of nugget (C_o) and stochastic (C_1) variance, i.e., $C=C_o+C_1$.

- Spherical model:

$$\gamma(|h|)=\begin{cases} C_0+C_1\left[1.5\,\dfrac{|h|}{a}-0.5\left(\dfrac{|h|}{a}\right)^3\right], & |h|\leq a \\ C, & |h|>a \end{cases} \quad (3)$$

where a stands for the range of influence (in the unit of distance).

Trend model selection by one-way analysis of variance technique

Trends in the data may be modelled by using linear, quadratic, cubic, or higher-order trend surface models. One-way analysis of variance (ANOVA) may be used in deciding whether to add additional parameters to the existing trend model or not. In this regard, sums of squares allow computing the mean square (variance) in the ANOVA table. The one-way ANOVA technique is a useful tool to test hypotheses on trend models (Clark and Harper 2002). The calculation procedure of

Table 1 Analysis of variance (ANOVA) table

Source of variation	Sum of squares	Degree of freedom	Mean square	*F* value
Regression	SSR=$\sum_{i=1}^{n}(\hat{y}_i-\bar{y})^2$	*m*-1	MSR=$\frac{SSR}{m-1}$	$F^*=\frac{MSR}{MSE}$
Residual error	SSE=$\sum_{i=1}^{n}(y_i-\hat{y}_i)^2$	*n*-*m*	MSE=$\frac{SSE}{n-m}$	
Total	SST=$\sum_{i=1}^{n}(y_i-\bar{y})^2$	*n*-1		

Source : Shumway and Stoffer (2011), Clark and Harper (2002)

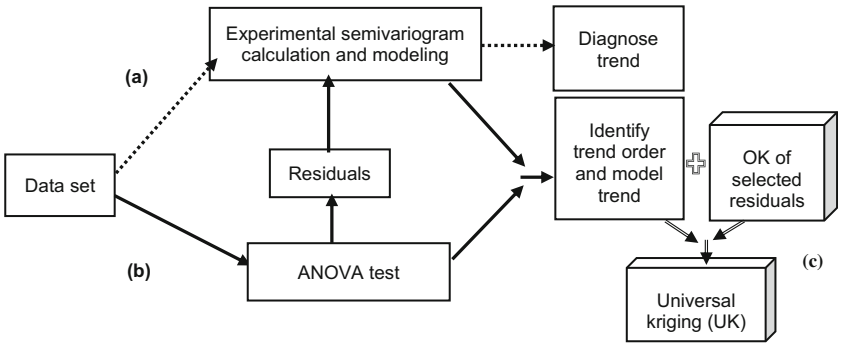


Fig. 3 Detrending procedure by using experimental semivariograms and ANOVA analysis

the ANOVA table is given in a tabular form (Table 1) as follows:

Removing trend component from the observed data

The proposed detrending procedure in this study consists of three distinct steps as shown in Fig. 3: (a) Starting with a diagnosis of trend existence in a given data set by visually examining experimental semivariogram graphs; (b) if experimental semivariogram indicates any trend sign, in turn, non-stationarity in the data, then trend surface is modelled by utilizing ANOVA technique, and (c) removal of trend component, i.e., detrending, from data is done by employing the trend surface models of linear, quadratic, and cubic type. At the detrending stage, the trend component is subtracted from the observed data in order to obtain a trend-free part of the data, i.e., residuals.

Clark and Harper (2002), Vieira et al. (2010), Cetin and Kirda (2003), Soula et al. (2019), among the others, give details of geostatistical analysis techniques and detrending procedure, too. During the kriging estimation procedure, detrending may be done either separately or jointly as in ordinary kriging (OK) and universal kriging (UK), respectively. Details may be followed from Fig. 3.

Results and discussions

Experimental and theoretical semivariograms via ANOVA analysis

Experimental semivariograms and theoretical semivariogram models fitted to the experimental ones for the data sets of the years 2008 and 2018 were prepared and presented in Fig. 4. As seen from Fig. 4, experimental semivariograms show a gradual increase by the increasing distances. However, after the distance of 75 km, there appears a sharp increase in semivariance values in Fig. 4a and b. The graphs indicated the existence of a trend in the values on the larger scale. Although not given here, the remaining parts of the graph after the distance of 82 km imitated a parabola. As emphasized clearly by Clark and Harper (2002), a parabolic behavior in a semivariogram is known as an instant diagnosis of trend or drift in the values. Based on this interpretation, it can be deduced from Fig. 4a and b that the drift in the data proves to be evident if the distance between sample pairs are greater than 50 km in the study area.

Although experimental semivariograms prove useful in the diagnostic check of trend in the data, they do not provide any information on the degree of trend surface. Therefore, trend surface was separately modelled starting from the lowest trend surface model which is linear type, then to the higher-degree models. In this regard, the final decision is made by interpreting ANOVA results. ANOVA results of this study were summarized in Tables 2 and 3 for data sets of 2008 and 2018, respectively. Firstly, the trend component in the data was modelled as linear. Then, the linear trend was removed from the data, and omnidirectional experimental semivariograms (OESs) were regenerated as seen in Fig. 4c and d. ANOVA results showed that the linear trend is pretty capable of explaining the variation in the data by a factor of $F>44.0$. The effects of detrending are noticeable in Fig. 4c and d, indicating the removal of drift in the larger scale. On the other hand, ANOVA results given in Tables 2 and Table 3 manifest that the F ratio ($F>15.0$) of the difference between quadratic and linear trend models is statistically significant ($\alpha=5\%$). This suggests that although a linear trend model is necessary for trend surface modelling, it is not sufficient enough to get trend-free data, suggesting the use of quadratic model. Detrending has been done by utilizing the quadratic model. The resulting experimental semivariograms were given in Fig. 4e and f. Furthermore, ANOVA tables (Tables 2 and 3) indicate that there is no need taking higher order trend surface models due to the fact that F ratio of the difference between quadratic and cubic model is statistically insignificant ($F=0.22–0.23$). It is worth emphasizing that fully or partially cubic trend model is far from improving trend removal from the data. Negative sum of squares -which is unexplainable- for the difference between cubic and quadratic models in Tables 2 and 3 manifests that cubic model is not a suitable one for trend removal. Notwithstanding ANOVA results, the cubic model was intentionally adapted to the data and the trend was removed from the data. Then, OESs were prepared for the residuals. As seen from Fig. 4g and h, there are no further improvements in the spatial dependence structure of groundwater elevation data if we assimilate a cubic model

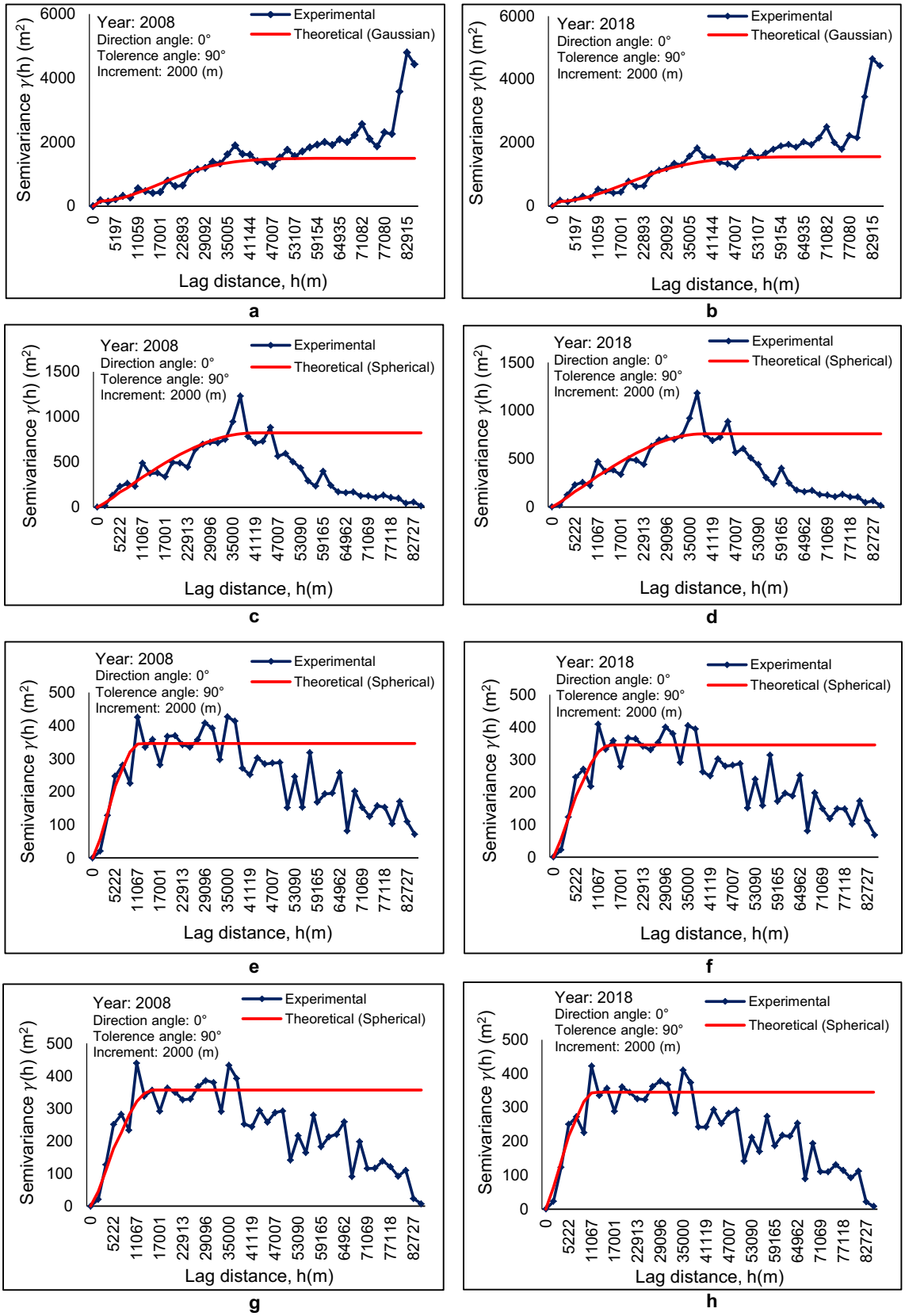


Fig. 4 Omnidirectional experimental semivariograms and trend removal from the data sets in 2008 and 2018. a Data set in 2008. b Data set in 2018. c, d Linear residuals. e, f Quadratic residuals. g, h Cubic residuals

Table 2 Analysis of variance (year 2008)

Trend model	Sum of squares	Degrees of freedom	Mean square	F ratio
Linear	48894.64	2	24447.32	45.8
Linear residuals	35222.98	66	533.68	
Quadratic	63946.67	5	12789.33	39.94
Diff (linear and quadratic)	15052.03	3	5017.34	15.67
Quadratic residuals	20170.95	63	320.17	
Partial cubic	64023.07	6	10670.51	32.92
Diff (quadratic and partial cubic)	76.40	1	76.40	0.23
Partial cubic residuals	20094.55	62	324.10	
Cubic	45682.74	9	5075.86	7.79
Diff (quadratic and cubic)	-18263.92	4	4565.98	-7
Cubic residuals	38434.88	59	651.43	
Total variation	84117.62	68	1237.02	

instead of a quadratic one. ANOVA and experimental semivariogram analysis results led us to conclude that a quadratic trend model is well enough to remove the drift component in the elevation data.

Groundwater contour maps

Firstly, omnidirectional experimental semivariograms (OESs) of the data were obtained. Visual examination of OESs indicated that data consisted of a strong trend (Objective 1) after the distance of 75 km. Then, after having been modelled the trend component (Objective 2) of the elevation data through using the ANOVA technique (Shumway and Stoffer 2011), the trend component has been removed (Objective 3) from the data in order to get residuals. Finally, omnidirectional experimental semivariograms (OESs) of residuals, i.e., a priori trend free data, have been modelled, and their parameters were estimated, diagnostically checked as suggested by McKillup and Dyar (2010). OESs of residuals showed no evidence of non-stationarity in residuals. Therefore, the spherical theoretical model is better fitted for the OESs of residuals. Ordinary Kriging process (Setiyoko et al. 2020) was applied to residuals. Spatial distribution

Table 3 Analysis of variance (year 2018)

Trend model	Sum of squares	Degrees of freedom	Mean square	F ratio
Linear	47247.50	2	23623.75	44.89
Linear residuals	34728.59	66	526.19	
Quadratic	62215.44	5	12443.08	39.67
Diff (linear and quadratic)	14967.94	3	4989.31	15.90
Quadratic residuals	19760.65	63	313.66	
Partial cubic	62286.95	6	10381.15	32.68
Diff (quadratic and partial cubic)	71.50	1	71.50	0.22
Partial cubic residuals	19689.15	62	317.56	
Cubic	-2644.24	9	-293.80	-0.2
Diff (quadratic and cubic)	-64859.69	4	-16214.92	-11.3
Cubic residuals	84620.34	59	1434.24	
Total variation	81976.10	68	1205.53	

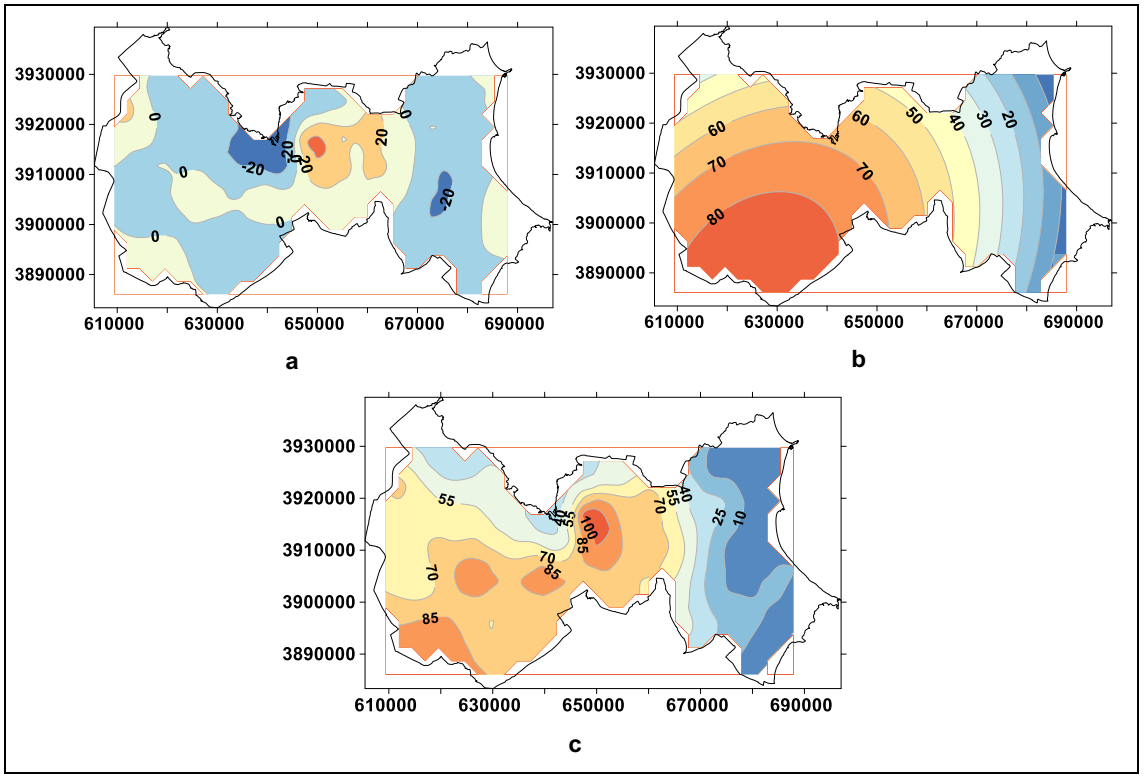


Fig. 5 Maps of the year 2008. a OK of quadratic residuals. b Quadratic trend. c Groundwater elevation

map of residuals, in turn, was obtained from the data of 2008 (Fig. 5a) and 2018 (Fig. 6a). All the mapping procedure was done in geographic information systems (GIS) platform as done by Soula et al. (2019).

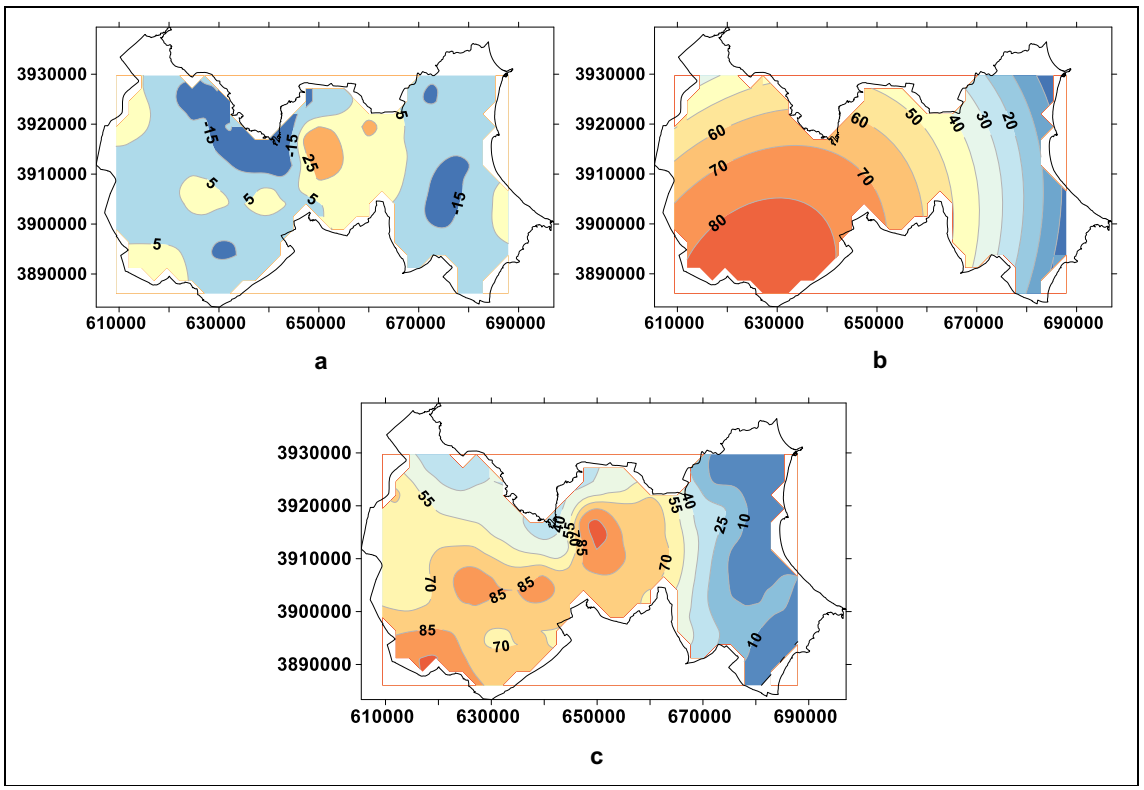


Fig. 6 Maps of the year 2018. a OK of quadratic residuals. b Quadratic trend. c Groundwater elevation

Besides the residual maps, the trend component of the data sets was mapped by using the quadratic trend model. Generated trend maps were given in Figs. 5b and 6b of 2008 and 2018, respectively. Residual maps and trend maps were summed up in the GIS media to get groundwater elevation maps for the respective years of 2008 and 2018. Figs. 5 c and 6 c are the final maps of the study.

As seen from the quadratic trend maps (Figs. 5b and 6b), high values are located in the southwest of the catchment. It was concluded that trend components of the groundwater elevations coincided well with topographic relief distribution in the area of study. On the other hand, groundwater elevation maps, which in turn were given in Figs. 5c and 6c, show that the study area does not consist of a unique groundwater divide, i.e., catchment, but many different sub-catchments with miscellaneous dimensions. Notwithstanding the dimension of the sub-catchments, it is clear from Figs. 5c and 6c that all the groundwater sub-catchments are connected directly to the Mediterranean Sea or salt lakes.

Conclusions

The use of geostatistical techniques in the analysis of groundwater level data may provide additional information to the practitioners and decision-makers. Such information may help the decision-makers as well as decision takers in order to make reasonable assessments and to take precautions in advance. In this regard, either directional or omnidirectional experimental semivariograms of the given data set could help us to identify visually the trend component, if any, in the data. Furthermore, the joint use of experimental semivariograms with the ANOVA technique led us to define the degree of the trend surface model. Semivariograms of residuals might be used as a justification tool for deciding if the trend removal process is sufficient enough or not. Results obtained from theoretical semivariograms may be used by groundwater network optimizers. Groundwater elevation contours obtained by adding residual and trend component maps indicated the existence of groundwater watersheds that looked similar to superficial water watersheds located in the region.

Acknowledgements This study was made possible with the occasion of the opportunity given by the Rectorate of Sousse University (Tunisia) to go to Cukurova University (Turkey), located in Adana, for the duration of 4 months.

Funding The financial support for this study was provided by the Erasmus+ mobility program.

Declarations

Conflict of interest The authors declare that they have no competing interests.

References

Bedir M (1989) Tectonic control and seismic image of miocene syn-sedimentary mega-structures in the Mahdia Sahel Eastern Tunisia. J Afr Earth Sci Middle East 9:657–663

Cetin M, Kirda C (2003) Spatial and temporal changes of soil salinity in a cotton field irrigated with low-quality water. J Hydrol 272:238–249

Clark I, Harper WV (2002) Practical geostatistics 2000. Columbus, Ohio

CRDA (2018) Water resources in Mahdia. Mahdia, Tunisia

Evans SW, Jones NL, Williams GP, Ames DP, Nelson EJ (2020) Groundwater level mapping tool: an open source web application for assessing groundwater sustainability. Environ Model Softw 131:104–782

FAO (2016) Global Diagnostic on Groundwater Governance. http://www.fao.org/3/a-i5706e.pdf. Accessed 06 January 2021

Grynyshyna-Poliuga O (2019) Characteristic of modelling spatial processes using geostatistical analysis. Adv Space Res 64:415–426

Hezzi I (2014) Geophysical characterization of the Sahel platform, northeastern Tunisia and its geodynamic consequences. Dissertation, University of Rennes 1

Karamouz M, Szidarovszky F, Zahraie B (2003) Water resources systems analysis. Washington, USA

Kaufman CG, Sain SR (2010) Bayesian functional ANOVA modeling using Gaussian process prior distributions. Baysn Anal 5:123–150

McKillup DS, Dyar MD (2010) Geostatistics explained: an introductory guide for earth scientists. Cambridge University, Cambridge

Mulyadi A, Dede M, Widiawaty MA (2020) Spatial interaction of groundwater and surface topographic using geographically weighted regression in built-up area. IOP Conf Ser Earth Environ Sci 477:012–023

Ohmer M, Liesch T, Goeppert N, Goldscheider N (2017) On the optimal selection of interpolation methods for groundwater contouring: an example of propagation of uncertainty regarding inter-aquifer exchange. Adv Water Resour 109:121–132

Oktay E, Pardo-Igúzquiza E, Olea RA (2020) Assessment of experimental semivariogram uncertainty in the presence of a polynomial drift. Nat Resour Res 29:1087–1099

Olea RA (2006) A six-step practical approach to semivariogram modeling. Stoch Environ Res Risk Assess 20(5):307–318

Olea RA (2018) A practical primer on geostatistics. U S Geological Survey. https://doi.org/10.3133/ofr20091103

Setiyoko A, Basaruddin T, Arymurthy AM (2020) Minimax approach for semivariogram fitting in ordinary kriging. IEEE Access 8:82054–82065

Shumway RH, Stoffer DS (2011) Time series analysis and its applications: with R examples, New York

Singh VP (2018) Hydrologic modeling: progress and future directions. Geosci Lett 5(1):15 https://geoscienceletters.springeropen.com/articles/10.1186/s40562-018-0113-z

Soula R, Chebil A, Cetin M, Majdoub R (2019) The use of universal kriging interpolation technique to determine groundwater levels in dry and wet years: a case study in a semi-arid region of Mahdia in Tunisia. MKU J Agric Sci 24:155–162

Soula R, Chebil A, McCann L, Majdoub R (2020) Water scarcity in the Mahdia region of Tunisia: are improved water policies needed? Groundw Sustain Dev 12:100–510

Tapoglou E, Karatzas GP, Trichakis IC, Varouchakis EA (2014) A spatio-temporal hybrid neural network-kriging model for groundwater level simulation. J Hydrol 519:3193–3203

Uyan M, Cay T (2013) Spatial analyses of groundwater level differences using geostatistical modeling. Environ Ecol Stat 20:633–646

Varouchakis EA, Theodoridou PG, Karatzas GP (2020) Decision-making tool for groundwater level spatial distribution and risk assessment using geostatistics. J Hazard Toxic Radioact Waste 24(1):0401–9031

Vieira SR, Carvalho JRP, Ceddia MB, Gonzalez AP (2010) Detrending non stationary data for geostatistical application. Bragantia 69:1–8