IJMGE

Int. J. Min.& Geo-Eng.
Vol.47, No.2, Dec. 2013, pp.103-113

Hydrograph Modeling Using SGSim: A Case Study of Behbahan Aquifer, Southwest of Iran

Amir Mollajan[1], Omid Asghari[2*]

1. *M.Sc., Mineral Exploration Engineering, School of Mining Engineering, University College of Engineering, University of Tehran*
2. *Assistant professor, Simulation & Data Processing Laboratory, School of Mining Engineering, University College of Engineering, University of Tehran*

Received: 18 August 2012; Received in revised form 10 December 2012; Accepted: 15 February 2013
Corresponding Author: o.asghari@ut.ac.ir

Abstract

Hydrograph modeling and prediction of groundwater levels are the main concerns of most hydrogeological calculations and water resource management process. The present study is an application of Sequential Gaussian Simulation (SGSim) method for predicting groundwater levels using recorded monthly data (180 months) related to 21 piezometers of Behbahan aquifer, southwest of Iran. To generate realization maps through SGSim method, data were transferred to Gaussian distribution and then simulated 10 times for each month. Then, E_Type maps were produced to obtain hydrograph of interest. Finally, the iterative Box and Jenkins method was used to model the obtained hydrograph. The capability of the resulted ARIMA (0, 1, 1) model was examined by calculating coefficient of determination (R^2) and estimated root mean squared error (RMSE). For the obtained model, R^2 and RMSE were equal to 0.79 and 1.93, respectively. Drawing on the obtained hydrograph, it can be concluded that there is a significant decrease in groundwater level in the plain for upcoming months.

Keywords: *Behbahan aquifer, Box & Jenkins models, E_Type map, Sequential Gaussian Simulation (SGSim).*

1. Introduction

Prediction is a key step in sustainable water resource management and of utmost importance for both present and future generations. In this regard, ground water level modeling has emerged as a powerful tool to help specialists protect the groundwater resources and optimize their performance. Aquifer depletion and dwindling groundwater levels, due to over-exploitation, threaten ground water resources and remain as a great obstacle to natural resources. Over the past several years, numerous methods have been used for simulating and analyzing groundwater hydrograph, which are, more or less, based on Thiessen polygon method.

Nowadays, the applications of geostatistics in different disciplines such as mining, geology, hydrology, remote sensing, and environmental sciences are being hugely developed. Active employment of geostatistics in hydro-sciences was carried out by Delhomme [1] for the first time to determine the most proper location for constructing a new rainfall measurement site. Recent advances in the use of geostatistical models involves comparing two Kriging methods to spatiotemporal rainfall [2], using kriging method for runoff mapping [3], a DEM-based residual kriging model for estimating groundwater levels [4], and an integral method of geostatistics and artificial neural network to estimate spatial distribution of groundwater [5].

In this paper, a novel forecasting model for simulating the unite hydrograph and predicting groundwater level fluctuations through combining Sequential Gaussian Simulation (SGSim) and Box- Jenkins method was developed. The method proposed in this paper is applied on monthly data (180 months) related to 21 piezometers of Behbahan aquifer, southwest of Iran.

2. Methodology

2.1. Geostatistical simulation

Geostatistical simulation methods preserve the variance observed in the data, instead of just the mean value as in kriging estimator, and generate several probable solutions (realizations) that can be employed to quantify and assess uncertainty. Sequential Gaussian Simulation could be assumed as a common algorithm for providing realizations of multivariate random fileds. SGSim is an efficient stochastic modeling algorithm widely used for continuous variables in the mining and petroleum industry. The actual algorithm of SGSim method is as follow [6]:

1. Calculate histogram of raw data and statistical parameters;
2. Transform data into Gaussian space;
3. Calculate and model variogram of Gaussian data;
4. Define a grid;
5. Choose a random path;
6. Krige a value at each nodes from all other values (known and simulated) and define Gaussian;
7. Draw a random value from Gaussian distribution which known as simulated value;
8. Simulate other nodes sequentially;
9. Back transform simulated value (in this step a realization is generated); and
10. To generate another realization, step 1 to 9 are repeated

2.2. Time series

Time series are a sequence of observations which are ordered in terms of the time or any other dimension. Depending on nature of observations, time series can be expressed in form of discrete or continuous series. Auto Regressive Integrated Moving Average (ARIMA) models are the most general class of the Box-Jenkins models which are commonly used in hydrogeology studies for forecasting. The model is generally expressed in form of ARIMA (p,d,q) where parameters p, d, and q are non-negative integers that refer to the order of the autoregressive, integrated, and moving average parts of the model, respectively. If d=o, then the time series plot tends to fluctuate around a horizontal line; and if d=1, then the fluctuations tend to happen around a straight line. This means, in the latter case, the series under consideration is not stable and needs to be differenced. Similarly in case of d=2, the time series under study indicates that there exist some fluctuations over second order curve, so it needs to be differenced two times [7]. The steps to build a time series model are as follows [8-9]:

a) Preliminarily model recognition: includes considering data mean/variance stability, drawing acf and pacf sample plot, and testing the existence of trend;
b) Fitting a model and estimating related parameters: includes finding tentative model using an iterative process; and
c) Considering the goodness of fit: at this step the goodness of fitted model will be tested by analyzing obtained residuals.

3. Case study

The study area (Behbahan Aquifer) is stretched along the NW-SE direction and located 230 Km southeast of Ahvaz, Khuzestan Province, Iran (Figure1). Behbahan is an area of about 1324 Km^2. Marun River is the main drainage in this area. The most effect in recharging of the aquifer under study belongs to Illam-Sarvak and Asmari formations (east of the study area). However, due to the high level of contact of Asmari formation and alluvial sediments and fans, this formation plays an important role as an aquifer.

As the main constituent of Behbahan aquifer, the classic sediments of the Bakhtiari Formation, young alluvial deposits, river alluvium and alluvial fans that have been created as a result of mechanical erosion provide high hydraulic conductivity and are. The thickness of the alluvium is about 130 meters in the center of the area and changes

Figure 1. Location of studied area.

between 20 and 50 meters along the margin of the plain (Figure 2) [10].

Based on the data acquired from the pumping tests, the following hydrogeological parameters were obtained:

a) The amount of the transmissivity (T) range between 200 to 1100 m/day;
b) The value of hydraulic gradient ranges between 3 in thousand for the west region and 4 in thousand north and east region; and
c) The value of the storativity (S) range between 1.7 to 7 percent.

Geological analysis shows that the only source of replenishment of the aquifer is rainfall. So, the water balance can be calculated as follows [11]:

Water balance = replenishment - water abstraction

Figure3 shows the Water Resource Monitoring Well Network map of Behbahan aquifer. As it is shown, 21 drilled wells are also extended along NW-SE direction as the studied aquifer.

3.1. Implementing process simulation Data and data transformation

As SGSim similar to many statistical methods are based on the assumption of normality, to apply this technique, histograms of monthly data were plotted and Kolmogorov– Smirnov test was performed to compare distribution of data set with normal probability distribution (Figure 4b).

Also, Cox-Box transformation was used to transfer data into standard normal distribution (Figure 4d). Table 1 summarizes some statistical description of data related to the first year.

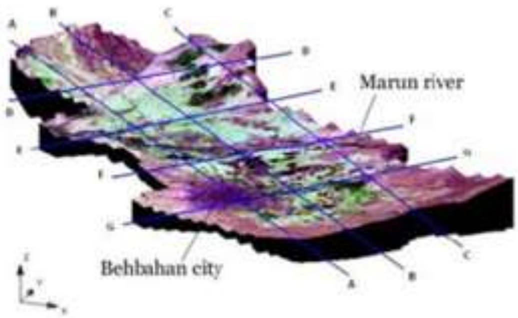


Figure 2. Conceptual model of Behbahan aquifer [10].

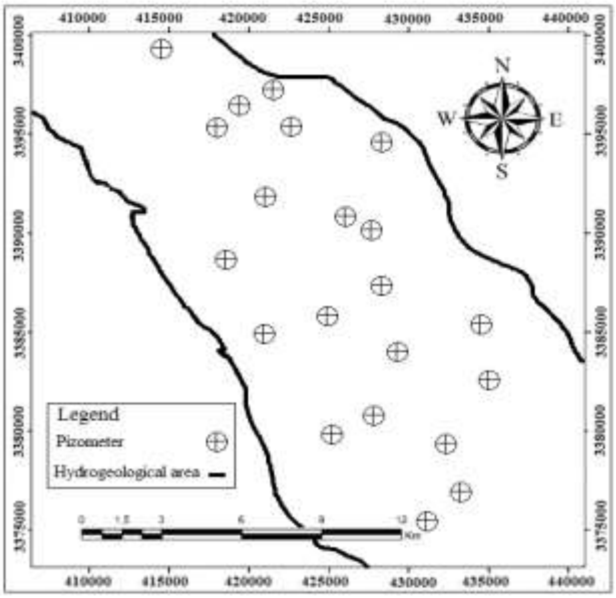


Figure 3. Piezometers position and hydrological areas in study area.

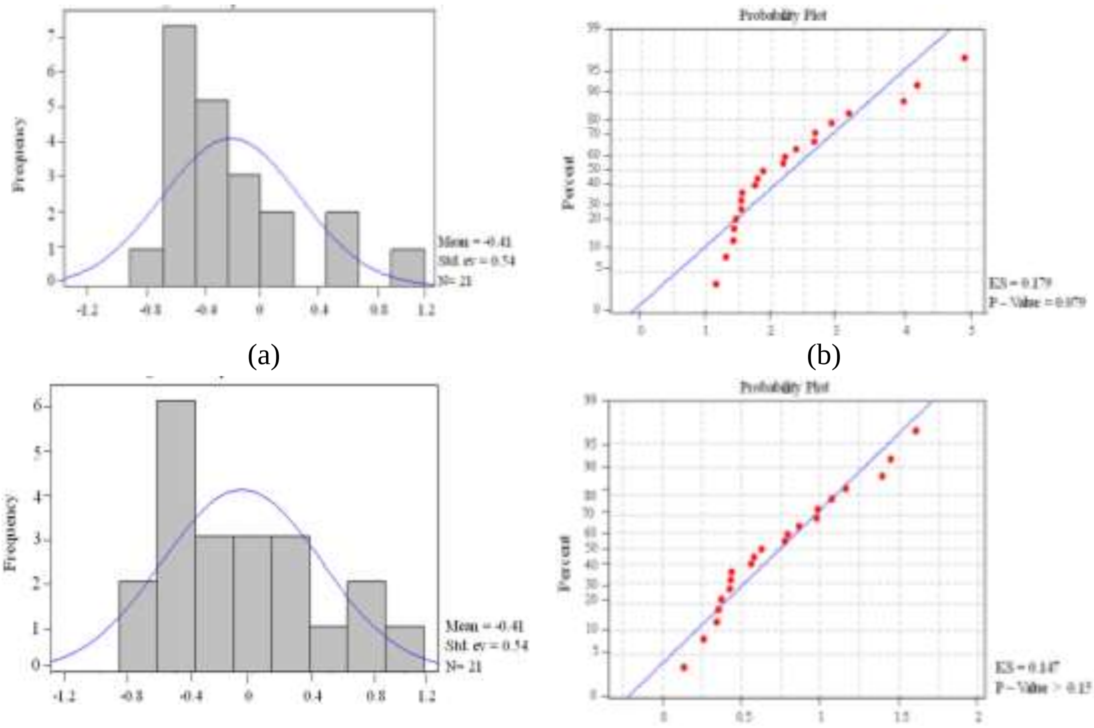


Figure 4. Behbahan aquifer data distribution for the first month along with Kolmogorov-Smirnov test results. a and b represent histogram and test result associated with raw data. Also, c and d show histogram and test result after applying Cox-Box transformation respectively.

3.2. Variogram plotting

Anisotropy was also investigated and modeled based on calculating the experimental variograms for drawdown in piezometers in four different azimuths: 0, 45, 90, and 135, for each month (Figure 5). As the monitoring wells are mainly drilled in N30W direction, we adjusted the four considered azimuths to this direction. Table 2 summarizes properties of all variograms related to the first month.

3.3. Sensitivity analysis

Before performing the operation, the sensitivity analysis for essential parameters (e.g. dimension of decided pixels, search radius and number of points) was implemented through cross validation method. To this end, decided pixels were changed in multiple stages and then the statistical parameters were calculated to simulate data in new dimensions. Table 3 displays the results of this investigation. As shown in the figure, there is no meaningful difference among statistics and the variance reaches its lowest value where dimension is 50 m^2. Figures 4a and 4b represent histogram and test result associated with raw data. Also, Figures 4c and 4d show histogram and test result after applying Cox-Box transformation, respectively.

This process was repeated to search for radius and number of point used in the simulation process, the results of which are given in Tables 4 and 5, respectively.

3.4. Simulation

Based on SGSim modeling, 10 realizations of groundwater levels spatial distributions were generated for each month on a 50×50 (m^2) cell within a network with an area of 20*22.5 (Km^2) (Figure 6). Simulation was performed using the ordinary kriging estimator and the fitted variogram models. It should be noted that in order to obtain the hydrograph of interest, the varigraphy and simulation process were performed 180 times.

To investigate the capability of the simulation results in reproducing of original data, variogram properties and statistical parameters of three randomly selected realizations were checked to examine the sample statistics reproduction. As Figure 7 displays, the model of variogram fitted to simulated data is spherical with ceil: 0.2 $(\%)^2$, nugget effect: 0 $(\%)^2$ and range: 5000 m.

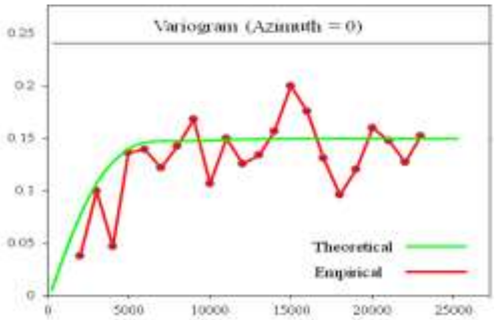
Table 6 provides the stratistical properties related to 4 randomly selected realizations of the first month. High variance value pixels belong to the points with low available data for estimation. Figure 8 shows histograms of realization 2 (with high variance value) and realization 3 (with low variance value).

Table 1. Statistical descriptions of data in the first year.

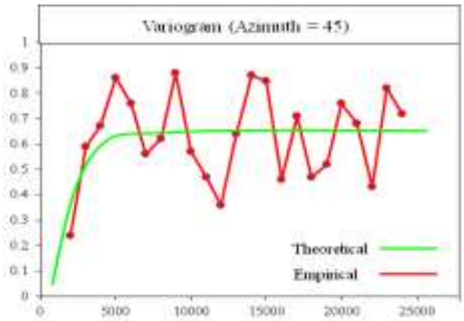
Month	Data No.	Mean	Median	Variance	Standard Deviation
Oct	21	0.03	-0.01	0.52	0.27
Nov	21	-1.22	-1.37	0.28	0.08
Dec	21	-2.41	-2.25	0.52	0.27
Jan	21	-0.23	-0.19	0.40	0.16
Feb	21	-2.41	-2.67	0.56	0.31
Mar	21	-1.26	-1.30	0.26	0.07
Apr	21	-1.50	-1.52	0.34	0.12
May	21	-0.42	-0.18	0.50	0.25
Jun	21	-0.82	-0.78	0.20	0.04
Jul	21	-4.33	-4.51	0.48	0.23
Aug	21	-2.30	-2.33	0.47	0.22
Sep	21	-0.41	0.00	0.74	0.54

Table 2. The models fitted to the experimental variogram of the first month data.

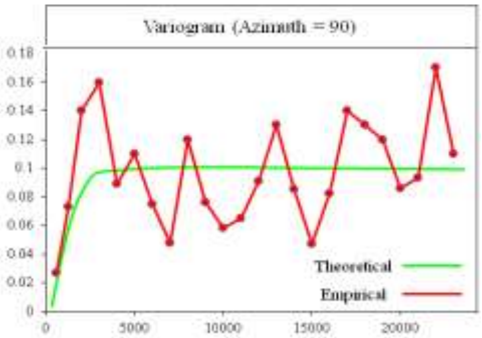
Fitted Model	Azimuth	Nugget Effect	sill	Range(m)
Spherical	0	0	0.15	5000
Spherical	45	0	0.6	4900
Spherical	90	0	0.1	3800
Spherical	135	0	0.1	98000



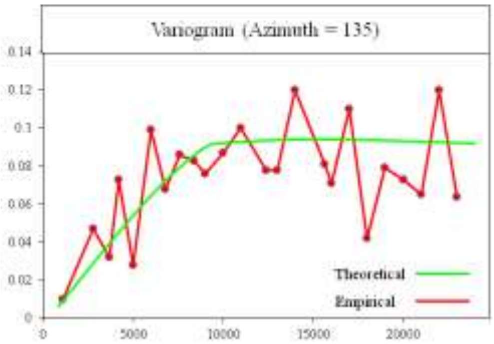
(a)



(b)



(c)



(d)

Figure 5. The plotted variograms of Behbahan aquifer. Figures 5a, 5b, 5c and 5d are related to azimuths 0, 45, 90 and 135 respectively.

Table 3. The result of sensitivity analysis of pixel size.

300	250	200	150	100	50	(m^2)
10.21	10.37	11.05	10.48	10.36	10.45	**Mean**
5.91	5.83	5.76	6.03	5.83	5.73	**Median**
1.81	2.01	1.62	1.38	1.52	1.43	**Kurtosis**
10.72	10.47	10.86	11.03	10.57	10.39	**Variance**
1.85	1.63	1.8	1.82	1.75	1.73	**Skewness**
3.17	3.35	3.41	3.19	3.25	3.21	**St. Deviation**

Table 4. Number of points used in simulation.

30	25	20	15	10	5	No.
10.74	10.52	10.83	10.35	10.41	10.38	**Mean**
5.81	5.48	5.92	5.57	5.73	5.62	**Median**
1.73	1.46	1.76	1.51	1.47	1.53	**Kurtosis**
11.12	10.58	10.63	11.02	10.72	10.38	**Variance**
1.82	1.72	1.61	1.74	1.59	1.65	**Skewness**
3.37	3.68	3.47	3.25	3.53	3.41	**St. Deviation**

Table 5. Sensitivity analysis for search radius.

1	0.7	0.3	Radius
10.42	10.48	10.31	**Mean**
5.72	5.61	5.58	**Median**
1.52	1.61	1.56	**Kurtosis**
10.62	10.57	10.46	**Variance**
1.81	1.76	1.73	**Skewness**
3.61	3.43	3.52	**St. Deviation**

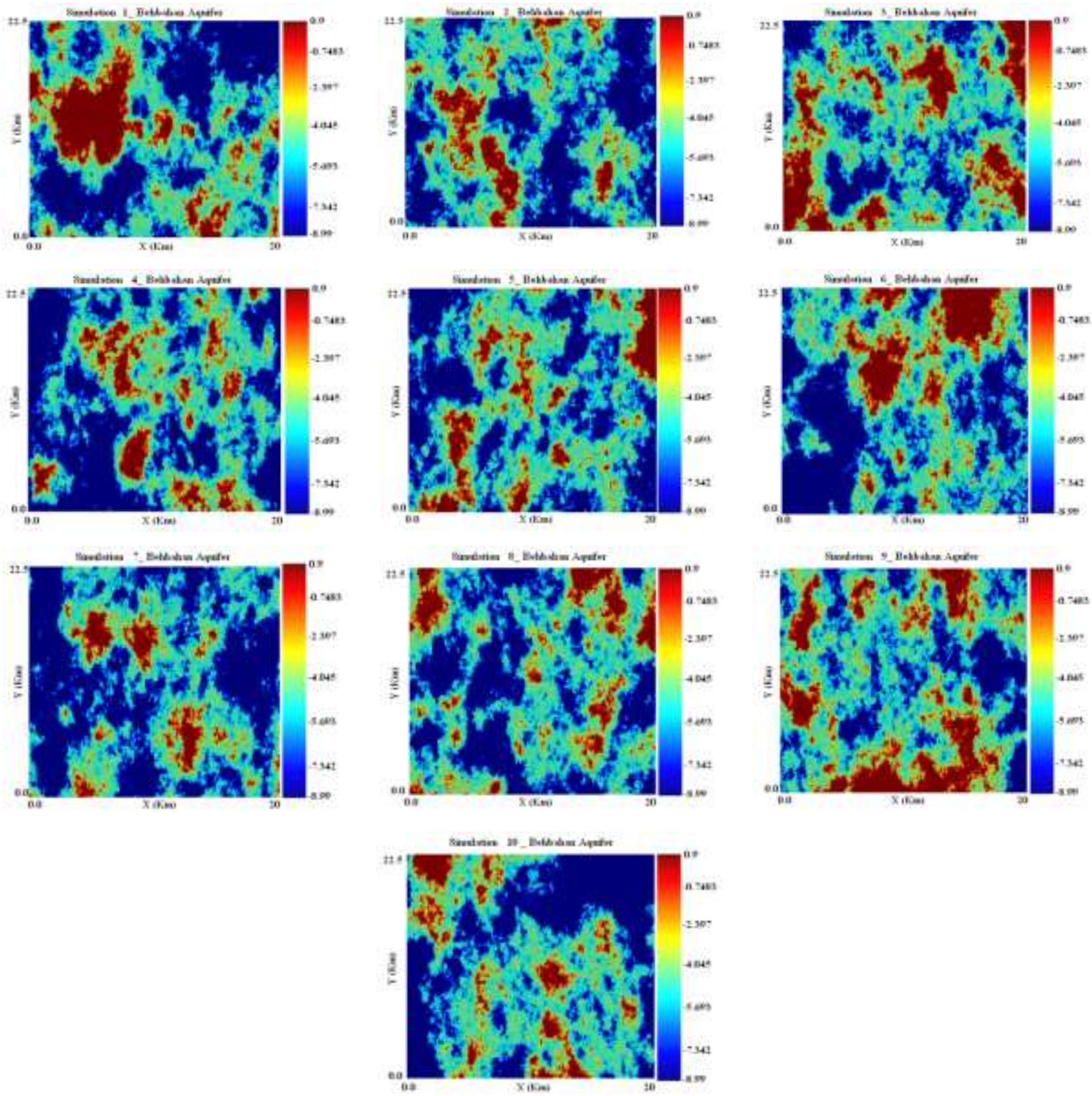


Figure 6. Ten realization Maps for the first month.

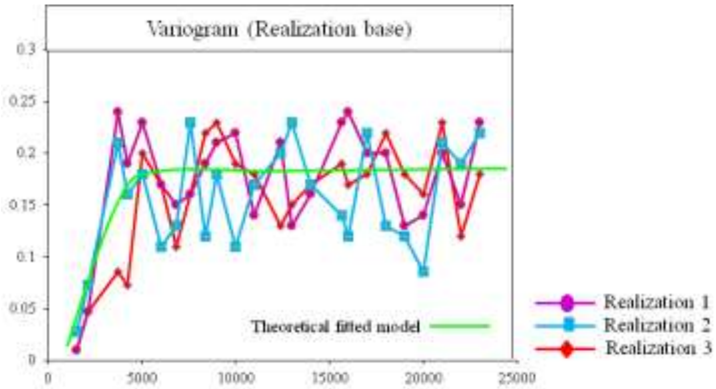
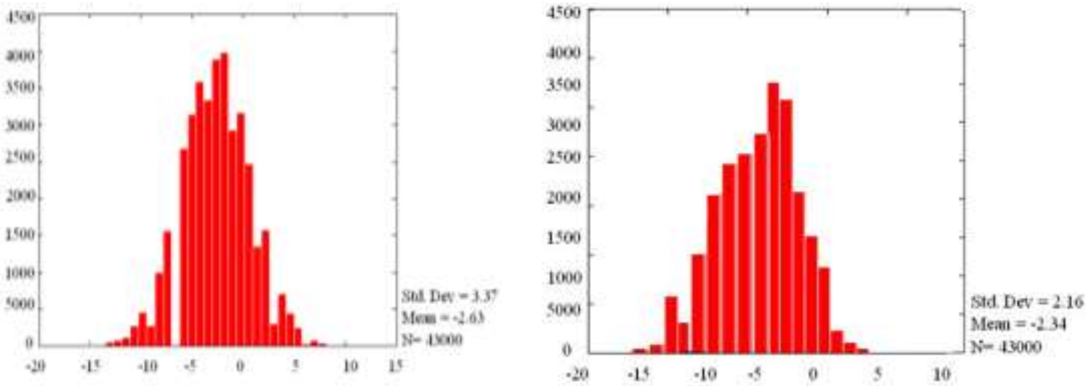


Figure 7. Example of experimentalvariograms for three realizations.

Table 6. Statistical descriptions of simulation, based on realizations for the first month.

Statistic	Realization 1	Realization 2	Realization 3	Realization 4	Original Data
Data No.	43000	43000	43000	43000	21
Mean	-1.54	-2.63	-2.34	-2.74	-2.14
Median	-1.49	-1.82	-1.65	-2.17	-1.5
Standard Deviation	2.14	3.37	2.16	2.69	2.58
Variance	4.58	11.36	4.67	7.24	6.66
Kurtosis	1.41	1.02	1.63	1.49	1.57
Skewness	-1.42	-1.58	-1.32	-1.47	-1.44



(a) (b)

Figure 8. Histograms of two selected realization: realization with high variance value (a), and realization with low variance value (b).

By omitting the cells out of the studied area, E_Type maps were obtained (Figure 9). These maps represent the approximated value for each cell by averaging deferent realization results.

Therefore, a mean map will be obtained for the entire aquifer. By increasing the number of realizations, the more similarity is attained between this map and map obtained from the kriging.

Figure 10 shows the concluded hydrograph using E_Type maps. As observed, the series is not stable in average. Figure 11 demonstrates the same series, after implementing difference transformation.

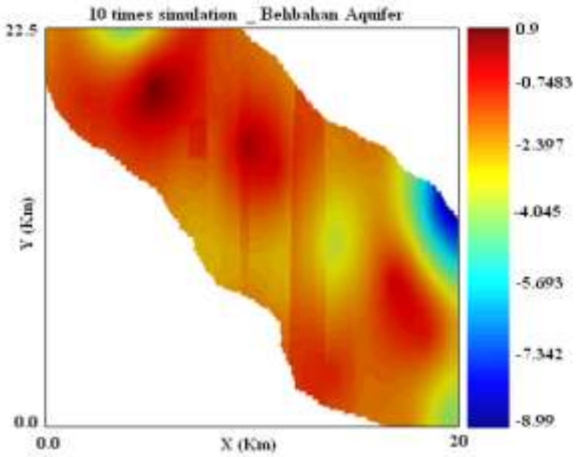


Figure 9. Example of E_Type map for first month.

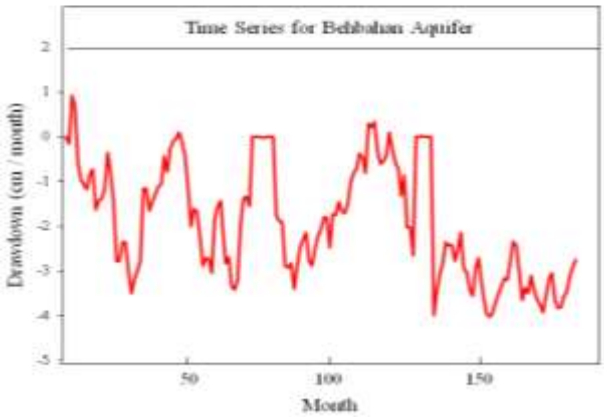


Figure 10. Simulated unit hydrograph.

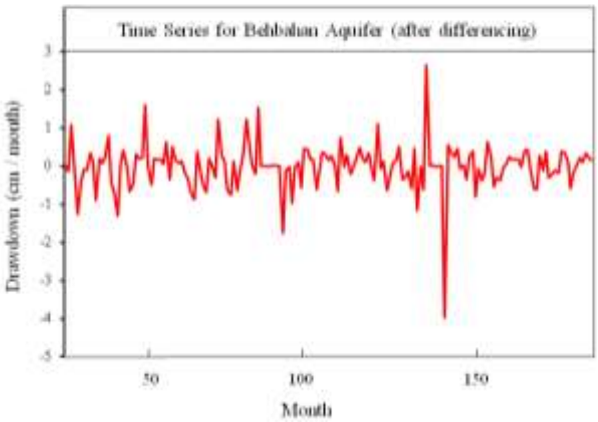


Figure 11. Resulted hydrograph after implementing difference transformation.

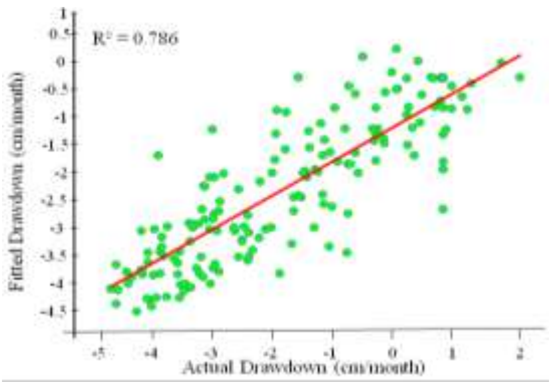


Figure 12. Comparison between the real and predicted drawdown for ARIMA model.

Table 7. The results of fitted models.

Model	P	d	q	MSE	Box – Pierce test's sig (Lag No.24)	AIC
M1	1	1	1	0.0086	0.713	-175.35
M2	1	1	2	0.0090	0.920	-176.52
M3	0	1	1	0.0083	0.547	-178.94

3.5. Hydrograph modeling

In order to model the resulted hydrograph, the Box and Jenkins method was used. Table 7 summarizes the results of model fitting process. According to this table, the ARIMA (0,1,1) model can be selected as the final one to predict the fluctuations of groundwater level of Behbahan aquifer. Based on the resulting coefficients, this model can be expressed as follows:

$$\tilde{Z}_t = -0.0588\,\tilde{Z}_t + a_t - 1.2214a_{t-1} + 0.8258a_{t-2} + 2.8103 \quad , \quad (5)$$

$$\tilde{Z}_t = Z_t - 2.6542 \quad (6)$$

where, $\tilde{Z}_t$ is the value of drawdown in monitoring wells of aquifer under study in month t, and a_{t-i} shows the shock (white noise) that imposes to the system at the moment t-i.

3.6. Performance evaluation

To validate and compare the results obtained from the ARIMA model and real data, correlation coefficient (R^2) (Eq.7) and Root

Mean Square Error (RMSE) (Eq.8) can be used.

Here R^2 is used to validate the predictive models based on the comparing predicted (fitted) and measured (actual) values; also, RMSE is used to compare the result of the concluded model and the real data.

$$R^2 = 100\left[\frac{\sum_{i=1}^{n}\left(x_{ipred} - \bar{x}_{pred}\right)\left(x_{imeas} - \bar{x}_{meas}\right)}{\sqrt{\sum_{i=1}^{n}(x_{ipred} - \bar{x}_{pred})^2 \sum_{i=1}^{n}(x_{imeas} - \bar{x}_{meas})^2}}\right]^2 \tag{7}$$

$$RMSE(x) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{imeas} - x_{ipred})^2} \tag{8}$$

where A_{imeas} is the ith measured element, A_{ipred} is the ith predicted element and n is the number of dataset.

Figure 12 draws a comparison between the real and predicted groundwater levels for ARIMA model. As shown in the figure, the square determination coefficient (R^2) and RMSE are 0.786 and 1.926, respectively.

The measured (actual) and predicted (fitted) drawdown from concluded ARIMA model is shown in Figure 13. The obtained hydrograph could be considered as a precise representative of the studied aquifer, which predicts a significant decrease in groundwater level in the plain for upcoming months.

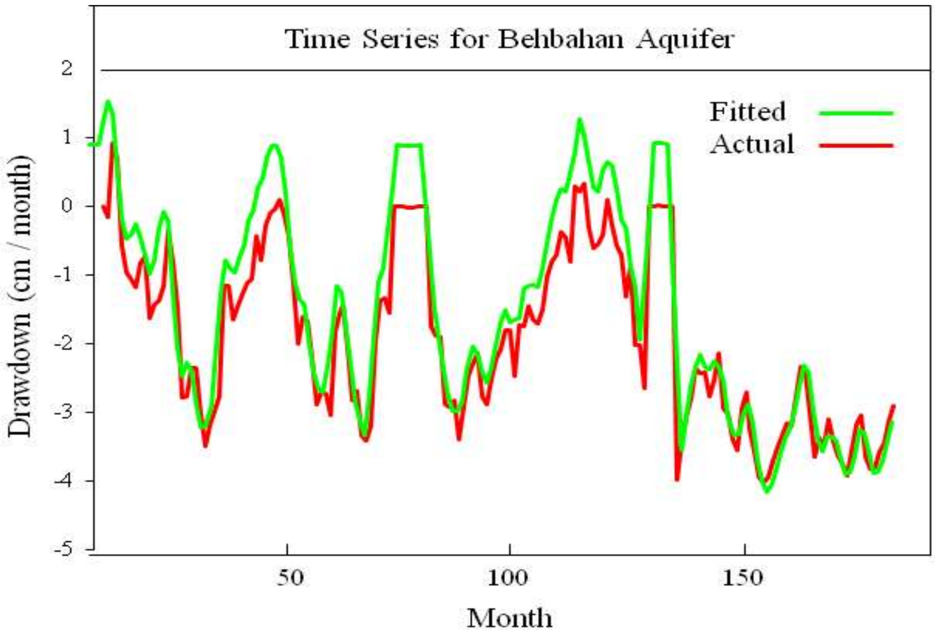


Figure 13. The measured and predicted drawdown from concluded ARIMA model.

4. Conclusion

We employed SGSim algorithm along with Box & Jenkins method to predict groundwater levels using recorded monthly data of available 21 monitoring wells drilled in Behbahan aquifer in the southwest of Iran.

To obtain the hydrograph of interest, data associated with drawdown of water level in monitoring wells were transferred to Gaussian distribution and then simulated 10 times for 180 months (1800 simulation results). All realizations could reproduce the histogram and variogram of raw data, which indicates the simulation process honors and the first and the second order stationary of the data. Then, E_Type maps for each month were formed and representative hydrograph of Behbahan aquifer was achieved. R^2 and RMSE of the fitted ARIMA (0, 1, 1) model obtained from Box & Jenkins method were equal to 0.79 and 1.93, respectively, which predict a significant decrease in groundwater level in the plain for the forthcoming months.

References

[1]. Delhomme, J.P., (1978). “Kriging in hydrogeoscience”. Adv. Water resource. 1(5). p.251-266.

[2]. Bargaoui, Z.K., Chebbi, A., (2009). “Comparison of two kriging interpolation methods applied to spatiotemporal rainfall” journal of Hydrology. p.365 56–73.

[3]. Di Piazza, A., Caraccilo, D., Noto, L.V., Viola, F., La Loggia, G., (2011). “Geostatistical techniques for fun off mapping: An application to Sicily, Italy”. European water 35, p.31-34.

[4]. Zhu, K., Cui, Z., Jiang, B., Yang, G., Chen, Zh., Meng, Q., Yao, Y., (2013). “A DEM-based residual kriging for estimating groundwater levels within a large-scale domain: a case study for Fuyang River Basin”. Clean Tech Environ Policy. 15, p.687 – 698.

[5]. Mosheri, S.A., Rezapour, O.M., Beyranvand, Z., Poornoori, Z., (2013). “Estimating the spatial distribution of groundwater quality parameters of Kashan plain with integration method of Geostatistics - Artificial Neural Network Optimized by Genetic-Algorithm”. International Journal of Agriculture and Crop Sciences. Vol., 5 (20), p. 434-2442.

[6]. Asghari, A. Soltni F, Bakhshandeh Amnieh H., (2009). “The Comparison Between Sequential Gaussian Simulation (SGS) of Choghart Ore Deposit and Geostatistical Estimation Through Ordinary Kriging”. Australian Journal of Basic and Applied Sciences.3(1) p.330-341.

[7]. Brockwell, Peter, J., and Davis, Richard, A., (1998). ”Introduction to Time Series and Forecasting”. Springer-Verlag, New York.

[9]. Wei, W.W.S., (1990). Time Series Analysis: Univariate and Multivariate Methods. Addison-Wesley, Reading, MA.

[8]. Box, G.E.P. and Jenkins ,G.M., (1960). “Time Series Analysis, Forecasting and Control” Holden Day, San Francisco.

[10]. Shahid Beheshti institute of applies science, 2002, “Hydroclimatological balance studies for Behbahan aquifer”.Report.

[11]. Theodossiou, N., Latinopoulos, P., (2006). “Evaluation and optimisation of groundwater observation networks using the Kriging methodology”. Environmental Modeling & Software 21, p. 991-1000.