Mühendislik Alanında Akademik Analiz ve Tartışmalar

Academic Analysis and Discussions in Engineering

Editörler
Prof. Dr. Mustafa BOZDEMİR • Doç. Dr. Rukiye UZUN ARSLAN



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Bölüm 10

Comparative Analysis of Seasonal Groundwater Distribution Mapping Via Empirical Bayesian Kriging and Local Polynomial Interpolation Techniques

Okan Mert KATİPOĞLU[1]

Kadir GEZİCİ[2]

Selim ŞENGÜL[3]

INTRODUCTION

Water is vital for all living organisms. Groundwater is a vital resource used in agriculture and industry. (Islam and Biswas, 2019). However, as a result of the rapidly increasing population, both urbanisation and water consumption are increasing, and considering the increase in agricultural and industrial activities and unconscious consumption due to the increasing population, a rapid decrease in groundwater resources and an increase in pollution load is inevitable (Ruybal et al., 2019). Groundwater levels should be regularly checked, especially in dry and semi-arid regions, for effective protection, improvement and sustainable policies. It is often too costly and not widely known to monitor groundwater levels in large areas. Establishing a sustainable management approach requires monitoring groundwater in time and space. For this reason, evaluations are often made as a result of interpolation methods applied by taking into account the existing well data. Spatial interpolation of the nearest neighbouring data can be estimated

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geostatistically or deterministically. Deterministic interpolation methods allow data to be combined through a specific model or function using mathematical modelling (Katipoğlu, 2022a). When interpolating, these methods take into account the relationships between the data and use these relationships to calculate the values of missing or unknown points. The statistical characteristics of the observed points serve as the foundation for geostatistical regionalization approaches, such as kriging. Geostatistical approaches consider the geographic layout of nearby sample points (Goovaerts 1997). The development of Geographic Information System (GIS) has enabled geostatistical spatial analyses to be created and evaluated more easily, quickly and in detail (Gong et al., 2014). Gundoğdu and Guney (2007) emphasised that the rational quadratic empirical semivariogram model, which has the least error, is the most successful, but other models (spherical, circular, tetraspherical, pentaspherical) produce very close results. Ahmadi and Sedghamiz (2008) emphasised the spatial variation of groundwater depth under different climatic conditions using Kriging and Cokriging methods from geostatistical methods and emphasised that although both methods are successful, the cokriging method produces more accurate results. Sun et al. (2009) conducted a GWL estimation study in Northwest China using different methods (inverse distance weighting (IDW), radial basis function (RBF), orfinary kriging (OK), simple kriging (SK), and universal kriging (UK)) which are both deterministic and geostatistical. The results were evaluated according to Cross-validation and statistical evaluation criteria and it was determined that Simple kriging was the most appropriate method.

Xiao et al. (2016) conducted groundwater level estimation studies on the Beijing plateau in China using 7 different interpolation methods. Among all methods (IDW, GPI, LPI, spline, OK, SK and UK interpolation), simple kriging model is the most appropriate model and emphasised that landuse and hydrogeology are important factors in groundwater change. It was stated that GWL decreases rapidly due to high population and industrial activities in areas close to residential areas, but the change in GWL is more reasonable in areas where agricultural activities are decreasing and technologically economical water consumption in agricultural terms. Izady et al. (2017) investigated IDW, spline, ordinary kriging and Emprical Bayesian kriging (EBK) methods for the redesign and reorganisation of groundwater monitoring networks. The results emphasised that EBK was highly successful. Rasel et al. (2019) analysed the distribution of GWL in Bangladesh, which is under water stress due to crop cultivation, using Ordinary Kriging method with 3 different variograms, Exponential,

Gaussian and Spherical, considering 23 well measurements over a 10-year period. The exponential variogram was determined as the most successful and emphasised that mapping GWL for sensitive areas is vital for sustainable groundwater management. Kazemi et al. (2021) examined the change in GWL in the Harvey River basin in Australia using the regression kriging method and found that the method was successful in regions with scarce data and also obtained high correlation between GWL change and rainfall series with short time lags.

Within the scope of this study, seasonal variation of GWL was evaluated by using 5-year values of 12 different wells of Erzurum province, which is located in the northeast of Turkey, mountainous and snow-covered most of the year, with Empirical Bayesian Kriging and Local Polynomial Interpolation Techniques. Thus, both temporal and spatial distribution of GWL for the relevant study area will be determined and will help decision makers and policy makers for an effective sustainable groundwater management approach.

2. MATERIAL AND METHODS

2.1. Study area and Dataset

Erzurum, located in northeastern Turkey, is characterised by a mountainous basin covered with snow most of the year. The study area is semi-arid according to DeMartonne and Thornthwaite climate classes (Gezici and Şengül, 2023). Erzurum is especially critical in terms of water resources management due to the fact that it is the source of transboundary waters (Çoruh, Aras, and Euphrates Basins), livestock and agricultural activities, and relatively high population in the region. For this reason, within the scope of the research field, the seasonal spatial variation of groundwater levels was evaluated for the relevant region.

Within the scope of the study, 12 well observation data within the borders of Erzurum province were used. The data were modelled as seasonal average values for a 5-year period between 2018-2022 (Fig. 1). The characteristics and statistical values of the wells are given in Table 1.

Table 1. Station information and statistical parameters of GWL for 2018-2022

		Statistical Parameters			
Station (ID)	Location	x_{mean}	x_{min}	x_{maks}	σ (SD)
Üniversite (9409)	39.917N-41.21E	17.27	16.86	17.9	0.267
Üniversite (1353)	39.924N-41.234E	15.32	14.05	16.94	0.948
Şıhköyü (15820)	39.938N-41.275E	22.39	21.5	23.94	0.597
Dadaşkent (21510)	39.907N-41.2E	8.32	8.02	8.58	0.123
Yarımca (60652)	39.89N-41.168E	5.96	5.35	6.37	0.276
Şekerli (63622)	40.34N-41.91E	7.72	5.77	9.4	0.762
Araköy (63623)	40.372N-41.928E	8.32	7.95	9.16	2.235
Pasinler (9714)	39.958N-41.685E	8.72	7.25	14.02	1.553
Esendere (63625)	39.988N-41.768E	2.95	1.42	4.41	0.888
Ebsemce (63626)	39.98N-41.768E	6.08	5.12	10.28	0.766
Ağcalar Yolu (63627)	39.933N-41.526E	32.85	31.63	35.48	0.875
Bulkasım yolu (63628)	39.934N-41.651E	23.53	22.62	26.3	0.869

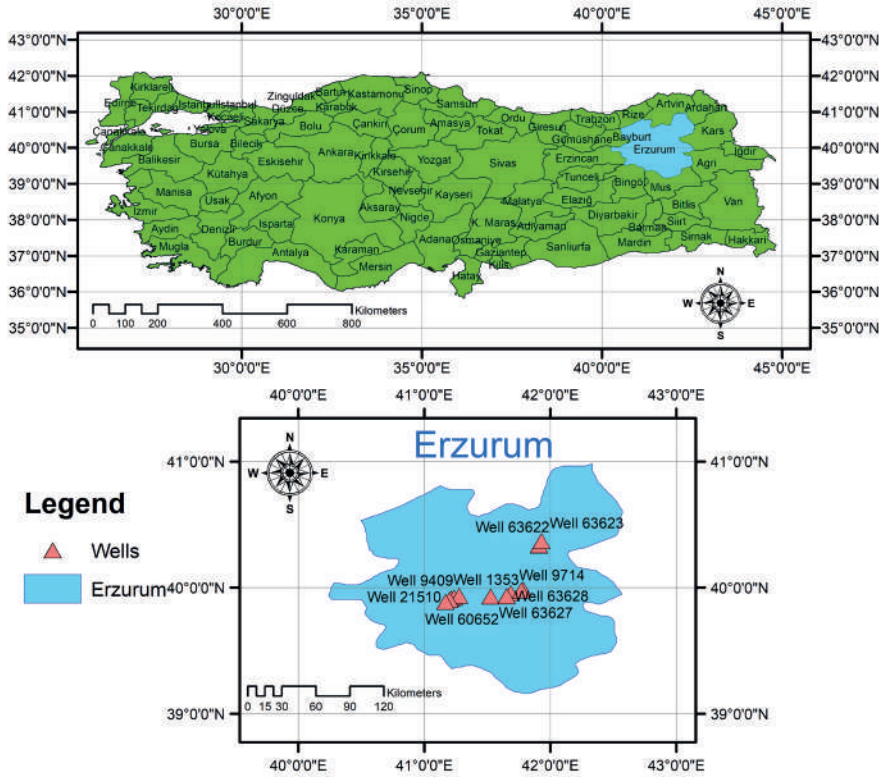


Figure 1. Location map of the study area

2.2. Empirical Bayesian Kriging

EBK is one of the geostatistical enterpolation methods and its most important advantage is that it automatically evaluates parameters that are manually set in other kriging methods using subsetting and simulation processes (Mirzaei and Sakizadeh, 2016). Unlike traditional kriging, EBK estimates several semivariograms instead of using a single semivariogram. In the first stage, the data are subdivided into subsets and a semivariogram is obtained with these data and new data are simulated. The semivariogram is created again using the new data obtained and this process continues until all subsets are evaluated (Krivoruchko, 2012).

As some important advantages of EBK (Krivoruchko and Gribov, 2019), it has the property of allowing a moderate lack of local and large stationarity in the data. This allows to obtain successful results even in cases where the spatial variability in the data set is constantly changing. It is also the ability to adapt to changing measurement errors. This feature ensures reliable results even when there are different levels of error between observation points. EBK has the ability to locally transform the data into a spatial Gaussian distribution using a Normal Score process when necessary. Thanks to this feature, it can obtain consistent results even when the data set does not fulfil the assumption of normal distribution. However, as with any model, it also has some disadvantages. Estimation of variogram parameters in EBK, which is slower than kriging methods for large datasets and imposes limitations, is performed using limited maximum likelihood (Basu, 2016; Katipoğlu, 2022b).

2.3. Local Polynomial Interpolation

Local Polynomial Interpolation (LPI) has important differences compared to General Polynomial Interpolation (GPI), which fits only one polynomial using many different polynomials. LPI has the ability to identify the maximum and minimum number of points, the choice of shape and configuration (Ali et al., 2012). It also provides a slider to determine the weights of nearby sampling points, a power parameter that decreases with distance, and the width of nearby locations. This allows the creation of maps that take into consideration the localised variations mentioned in the work of Johnston et al. (2001).

Unlike GPI, LPI is fit to a local polynomial using only the points within the specified neighbourhood, it does not use all the data (Antal et al., 2021).

The surface value in the neighborhood's center is then regarded as the expected value and the neighbourhoods may overlap. While LPI can

provide surfaces that capture short-range fluctuation, GPI is excellent for spotting long-term patterns in the dataset (Wang et al., 2014). The shape of the neighborhood, the maximum and lowest number of points, and the sector arrangement are all factors that might affect local polynomial interpolation, which builds a surface from several formulae, each optimized for a neighborhood. Local polynomial interpolation can create surfaces that better reflect local variation since the neighborhood can be weighted in accordance with how far away from the projected location each point is. LPI also offers estimations and estimated standard errors in the presence of impediments, among other benefits. LPI is a crucial tool for researchers who favor the local polynomial interpolation approach since it is quick and effective for data correction in a variety of geostatistical models (Gribov and Krivoruchko, 2011).

The polynomial is positioned in a local subset that is described by a window, and that window is the simplest moving window with radius R, which is a circle. The weight wi is defined as (Eq 1), where di is the distance between a grid point (x_i, y_i) and a data point (x, y) inside the circle (Ali et al., 2012).

$$w_i = (1 - \frac{d_i}{R})^p \quad (1)$$

2.4. Cross-validation

The cross-validation technique is commonly used to predict the semivariogram parameters and to compare the simulated values with the observed values (Isaaks and Srivastava 1989). In this process, the value at any position is temporarily ignored and the estimation is performed, and this step is continuously applied to all data sets.

Cross-validation means that the model is accepted in terms of the prediction of unknown values. To remove an item from the cross-validation of all points, its value is then measured against all other values, and the measured and predicted values are then compared (Katipoğlu and Acar, 2022). The primary purpose of cross-validation is to select the best model to make the more appropriate predictive informative decision.

3. RESULTS

Within the scope of this study, Geostatistics EBK and deterministic LPI techniques were used to model the spatial distribution of seasonal average GWL values in Erzurum province. Accordingly, various models'

parameters were tested and GWL estimation maps were created according to the most appropriate parameters. The parameters of the established models are presented in Table 2. Accordingly, all parameters were tested by trial and error and optimum results for EBK were generally obtained with Log-Emprical, K-Bessel Semivariogram, Standard Circular Neigborhood, while for LPI with 1st Order polynomial, Exponential Kernel function and Standard Neigborhood.

Table 2. Selected parameters of the installed interpolation models

	Spring	**Summer**	**Autumn**	**Winter**
Parameters	**EBK**			
Subset size	100	100	100	100
Overlap factor	1	1	1	1
Simulation number	100	100	100	100
Transformastion	Log-Emprical	Log-Emprical	Emprical	Log-Emprical
Semivariogram type	K-Bessel	K-Bessel	K-Bessel	K-Bessel
Neigborhood type	Standart Circular	Standart Circular	Standart Circular	Standart Circular
Max. Neigborhood	15	15	15	15
Min. Neigborhood	10	10	10	10
	LPI			
Order of polinomial	1	1	1	1
Kernel function	Exponential	Exponential	Exponential	Exponential
Neigborhood	Standart	Standart	Standart	Standart

Figure 2 shows the distribution of the semivariogram function that best fits the EBK models. Accordingly, it was determined that the K-Bessel semivariogram showed the best fit in all seasons. The EBK generates several semivariograms for each dataset. In addition, the distribution of these semivariograms indicates that the darker the blue color, the more semivariograms pass through that region. Table 3 shows the cross-validation test results of EBK and LPI interpolation techniques for GWL estimation. According to this, it is seen that the technique that gives the lowest error in all seasons is EBK. Accordingly, it has been deduced that the geostatistical EBK method can generate a reasonably accurate GWL estimation from the deterministic LPI technique.

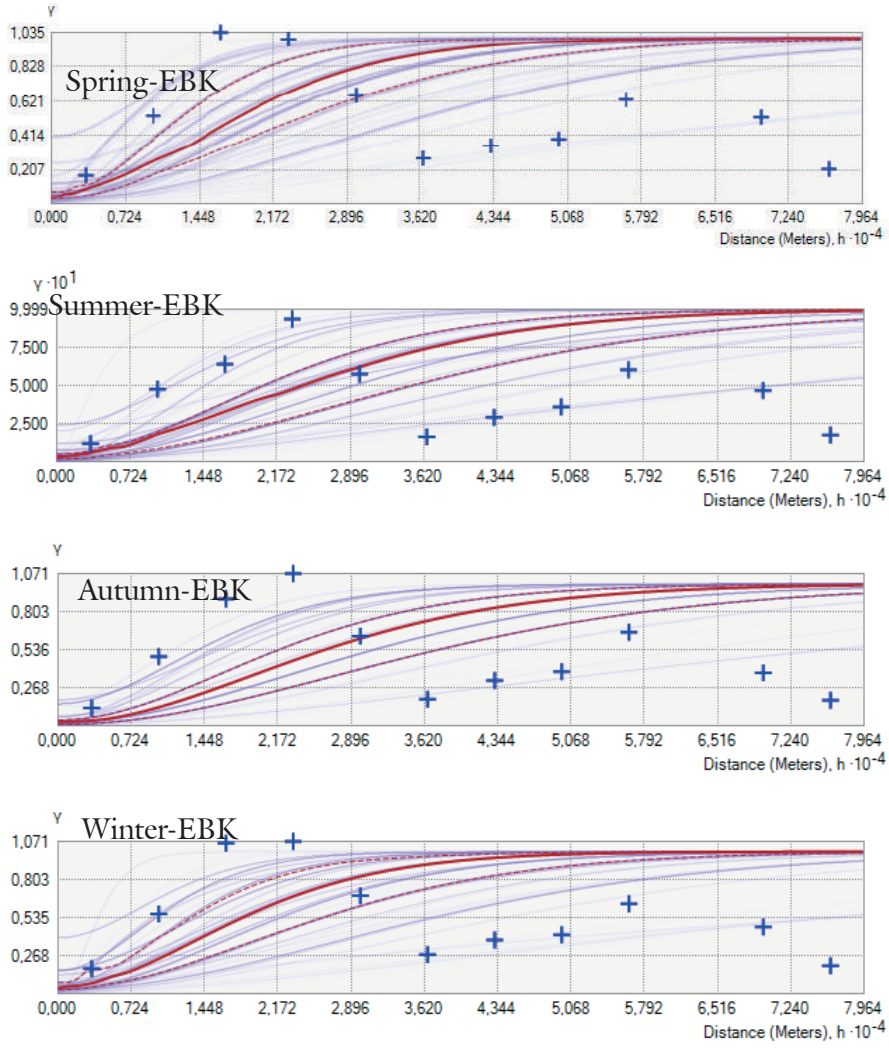


Figure 2. Semi-variogram functions of EBK models

Table 3 Performance evaluation of techniques used in GWL estimation

RMSE (M)				
	Spring	Summer	Autumn	Winter
EBK	4.41	3.74	3.96	4.37
LPI	5.93	5.57	5.83	5.93

Figure 3 shows bar plots of errors in seasonal GWL estimation of EBK and LPI techniques. Accordingly, the obtained errors were evaluated by taking the differences between the actual data and the estimated data. Accordingly, it has been deduced that the EBK technique produces more accurate GWL estimations since it has very low errors compared to LPI.

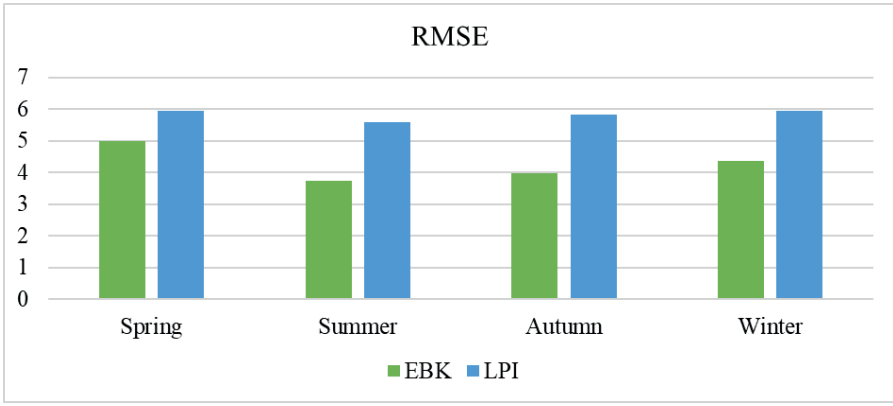


Figure 3. Bar plots of interpolation errors

In Figure 4, scatter plots are presented to evaluate the estimation accuracy of GWL values in the spring and summer seasons. These charts effectively assess the relationship between actual and predicted values. Aggregation of the data around the 1:1 regression line indicates the success of the estimation. Accordingly, when the actual and interpolation and estimated GWL values were compared, it was concluded that the EBK technique produced significantly accurate predictions in spring and summer compared to LPI.

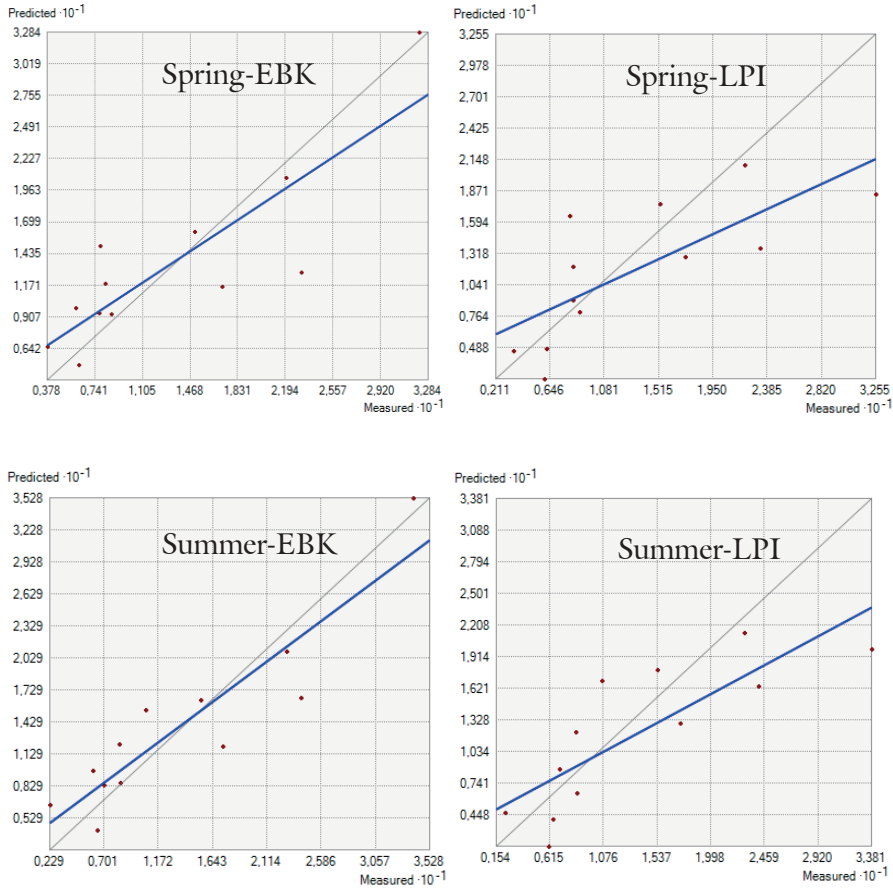


Figure 4. Scatter plots of GWL values in spring and summer

In Figure 5, scatter plots are given to evaluate the estimation accuracy of GWL values in autumn and winter. Accordingly, when the actual and interpolation and estimated GWL values were compared, the EBK technique showed a closer distribution to the regression line than LPI in the spring and summer seasons. Accordingly, it is deduced that the EBK technique makes significantly correct predictions from the LPI.

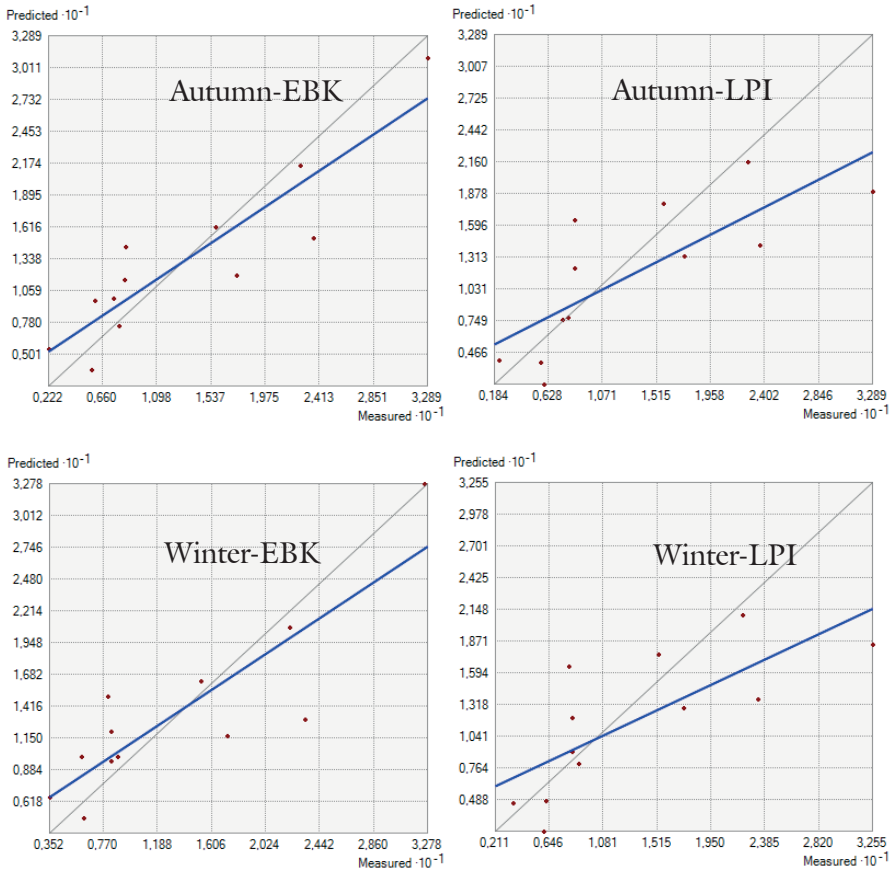


Figure 5. Scatter plots of GWL values in Autumn and Winter

Figure 6-9 shows the maps of GWL values obtained by EBK in the spring, summer, autumn and winter seasons. GWL values are expressed in different colors on the maps. Accordingly, while GWL is low in the Erzurum center in all seasons, it is high in the eastern and western parts of the province. In addition, while the GWL values are around 23 m in the north of the province in spring, it is in the range of 23-25 m in the south. In summer, the value is around 8 m in the north and south of the province. In autumn, the GWL values in the north and south of the province are between 14.69 and 18.30 m. In winter, it takes a value between 22.75 and 25.14 m.

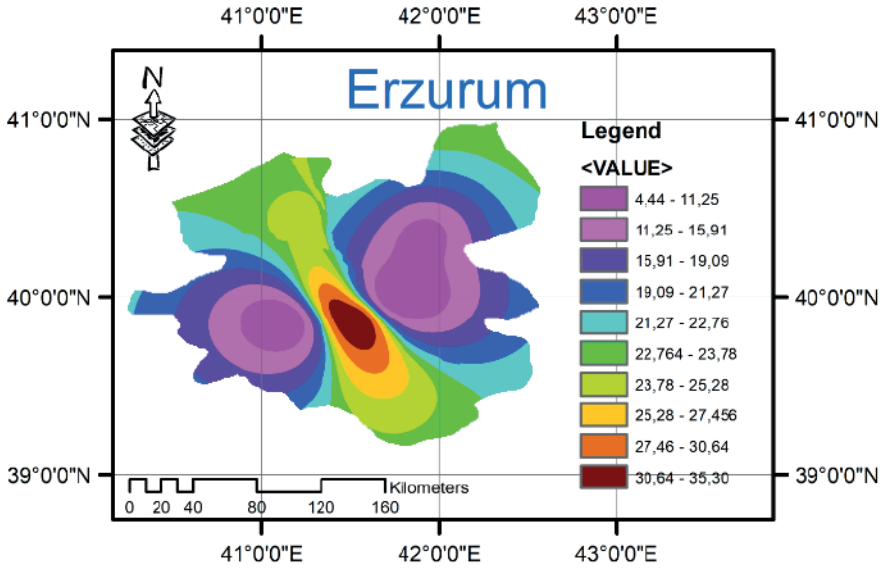


Figure 6. Spatial analysis of GWL values in Spring

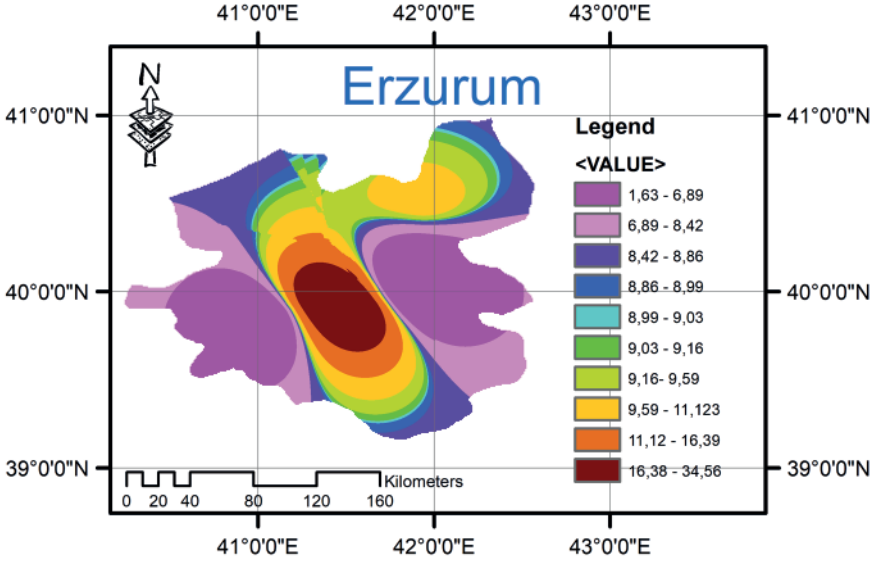


Figure 7. Spatial analysis of Summer GWL values

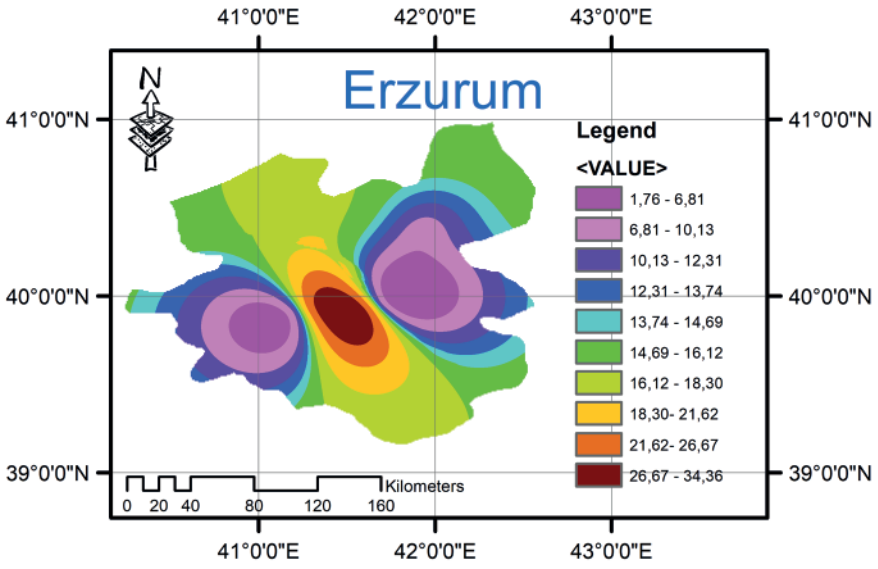


Figure 8. Spatial analysis of GWL values in Autumn

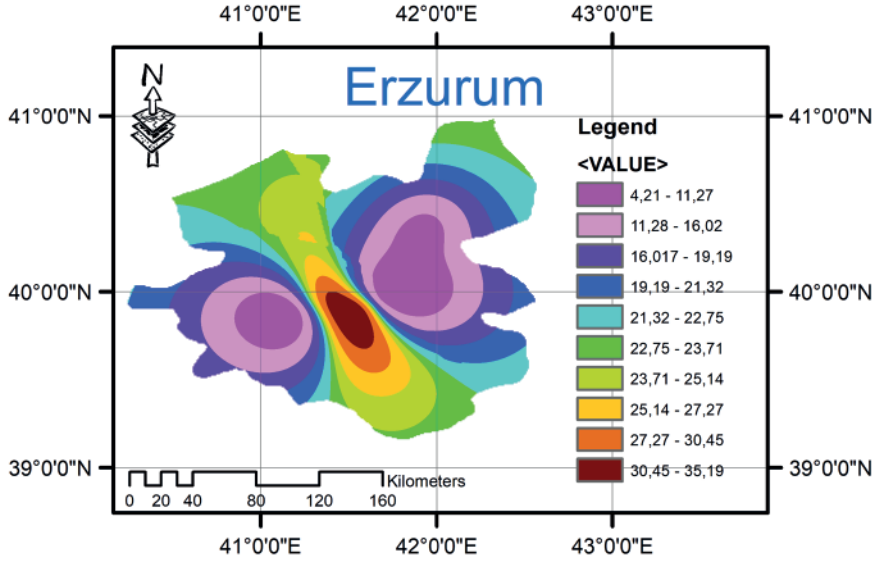


Figure 9. Spatial analysis of GWL values in Winter

4. DISCUSSION

Accurate estimation of GWL maps is a significant challenge and vital to effectively managing and planning groundwater. This study compares various interpolation techniques for the estimation of seasonal GWL values. Model prediction successes were tested according to the cross-validation technique. Accordingly, it has been deduced that the geostatistical EBK method can generate a reasonably accurate GWL estimation from the deterministic LPI technique. Izady et al. (2017); Katipoglu (2022); Bouhout et al. (2022) studies support the study. Izady et al. (2017) compared spline, IDW, normal kriging and EBK methods for the regionalization of monthly GWL values and it was concluded that EBK was the most successful. Katipoğlu (2022a) found that the K-Bessel-based EBK interpolation technique showed successful predictions in the spatial analysis of temperature trends. Bouhout et al. (2022) compared Ordinal kriging and EBK models for the mapping of GWL values, and the superior performance of EBK was revealed.

5. CONCLUSION

This study evaluated the seasonal variation of the GWL by using 5-year values of 12 different wells of Erzurum province, which is located in northeastern Turkey, mountainous and snow-covered most of the year, using EBK and LPI techniques. The most appropriate semivariogram for the EBK models was found to be K-Bessel for all seasons. Within 4 seasons, it was observed that the geostatistical approach EBK produced more successful results compared to the deterministic method LPI. GWL is low in Erzurum centre in all seasons, it is high in the eastern and western parts of the province. The outputs of the study are of crucial importance for water resources managers, decision makers and planners in terms of effective water management.

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REFERENCES

Ahmadi, S. H., Sedghamiz, A. (2008). Application and evaluation of kriging and cokriging methods on groundwater depth mapping. *Environmental monitoring and assessment*, 138, 357-368.

Ali, S. M., Mahdi, A. S., Shaban, A. H. (2012). Wind speed estimation for Iraq using several spatial interpolation methods. *Environ. Prot*, 1(2).

Antal, A., Guerreiro, P. M., Cheval, S. (2021). Comparison of spatial interpolation methods for estimating the precipitation distribution in Portugal. *Theoretical and Applied Climatology*, 145(3-4), 1193-1206.

Basu, K. (2016). Spatio temporal mapping of tuberculosis using log-empirical Bayesian kriging methods. *Technical Report Indian Statistical Institute/ Applied Statistics Unit*.

Bouhout, S., Haboubi, K., Zian, A., Elyoubi, M. S., Elabdouni, A. (2022). Evaluation of two linear kriging methods for piezometric levels interpolation and a framework for upgrading groundwater level monitoring network in Ghiss-Nekor plain, north-eastern Morocco. *Arabian Journal of Geosciences*, *15*(10), 1016.

Gezici, K., Şengül, S. (2023). Estimation and analysis of missing temperature data in high altitude and snow-dominated regions using various machine learning methods. Environmental Monitoring and Assessment, 195(4), 1-19.

Gong, G., Mattevada, S., O'Bryant, S. E. (2014). Comparison of the accuracy of kriging and IDW interpolations in estimating groundwater arsenic concentrations in Texas. *Environmental research*, 130, 59-69.

Goovaerts P. (1997) Geostatistics for natural resources evaluation. Oxford University Press, New York

Gribov, A., & Krivoruchko, K. (2011). Local polynomials for data detrending and interpolation in the presence of barriers. *Stochastic environmental research and risk assessment*, 25, 1057-1063.

Gundogdu, K. S., Guney, I. (2007). Spatial analyses of groundwater levels using universal kriging. *Journal of earth system science*, 116, 49-55.

Isaaks, E., & Srivastava, R. M. (1989). An introduction to applied geostatistics. New York: Oxford University Press.

Islam, A., Biswas, H.A., Optimal Planning and Management of Groundwater Level Declination: A Mathematical Model. In Proceedings of the 2nd International Conference on Industrial and Mechanical Engineering and Operations Management, Dhaka, Bangladesh, 12–13 December 2019.

Izady, A., Abdalla, O., Ahmadi, T., Chen, M. (2017). An efficient methodology to design optimal groundwater level monitoring network in Al-Buraimi region, Oman. *Arabian Journal of Geosciences*, 10, 1-14.

Katipoğlu, O. M. (2022a). Analysis of spatial variation of temperature trends in the semiarid Euphrates basin using statistical approaches. *Acta Geophysica*, *70*(4), 1899-1921.

Katipoğlu, O. M. (2022b). Spatial analysis of seasonal precipitation using various interpolation methods in the Euphrates basin, Turkey. *Acta Geophysica,* 70(2), 859-878.

Katipoğlu, O. M., Acar, R. (2022). Space-time variations of hydrological drought severities and trends in the semi-arid Euphrates Basin, Turkey. *Stochastic Environmental Research and Risk Assessment*, 1-24.

Kazemi, H., Sarukkalige, R., Shao, Q. (2021). Evaluation of non-uniform groundwater level data using spatiotemporal modeling. *Groundwater for Sustainable Development*, 15, 100659.

Krivoruchko, K., Gribov, A. (2019). Evaluation of empirical Bayesian kriging. *Spatial Statistics,* 32, 100368.

Krivoruchko, K., 2012, Empirical bayesian kriging: ArcUser Fall, v. 2012, p. 6-10.

Mirzaei, R., Sakizadeh, M. (2016). Comparison of interpolation methods for the estimation of groundwater contamination in Andimeshk-Shush Plain, Southwest of Iran. *Environmental Science and Pollution Research*, 23, 2758-2769.

Rasel, H. M., Alam, S., Hasnat, A., Hossain, I., Hasan, M., Ahsan, A. (2019). Geospatial analysis of groundwater level variations using Kriging Method. *J Eng Appl Sci*, 3(2), 21-34.

Ruybal, C. J., Hogue, T. S., McCray, J. E. (2019). Evaluation of groundwater levels in the Arapahoe aquifer using spatiotemporal regression kriging. *Water Resour. Res*. 55, 2820–2837. https://doi.org/10.1029/2018WR023437.

Sun Y, Kang S, Li F, Zhang L (2009) Comparison of interpolation methods for depth to groundwater and its temporal and spatial variations in the Minqin oasis of northwest China. *Environ Model Softw*., 24(10):1163–1170

Varouchakis, E. A., Hristopulos, D. T. (2013). Comparison of stochastic and deterministic methods for mapping groundwater level spatial variability in sparsely monitored basins. *Environmental monitoring and assessment*, 185, 1-19.

Wang, S., Huang, G. H., Lin, Q. G., Li, Z., Zhang, H., Fan, Y. R. (2014). Comparison of interpolation methods for estimating spatial distribution of precipitation in Ontario, Canada. *International Journal of Climatology*, 34(14), 3745-3751.

Xiao, Y., Gu, X., Yin, S., Shao, J., Cui, Y., Zhang, Q., Niu, Y. (2016). Geostatistical interpolation model selection based on ArcGIS and spatio-temporal variability analysis of groundwater level in piedmont plains, northwest China. *SpringerPlus*, 5(1), 1-15.