Larhyss Journal, ISSN 1112-3680, n°66, June 2026, pp. 105-126

GEOSTATISTICAL MODELLING OF HYDRODYNAMIC PARAMETERS OF ALLUVIAL AQUIFERS USING ORDINARY KRIGING

***DENDOUGA I.* [1*], *MESSAMEH A.*[2], *BENKHALED A.*[2]**

[1] PhD Student, Research Laboratory in Subterranean and Surface Hydraulics (LARHYSS), University of Biskra, PO Box 145, RP, Biskra, Algeria
[2] Professor, Research Laboratory in Subterranean and Surface Hydraulics (LARHYSS), University of Biskra, PO Box 145, RP, Biskra, Algeria

(*) imane.dendouga@univ-biskra.dz

Research Article – Available at http://larhyss.net/ojs/index.php/larhyss/index
Received August 6, 2025, Received in revised form February 25, 2026, Accepted February 27, 2026

ABSTRACT

Groundwater resources are the most conventional source usable in arid and semi-arid regions southeastern Algeria (Biskra city). This region is known for its many oases and famous dates and has been affected by drought in recent years. The extreme climate and less frequent rainfall have contributed to a decrease in the availability of groundwater. Therefore, estimating and mapping Transmissivity (T) and Hydraulic conductivity (K) are essential for understanding and evaluating the hydraulic properties of alluvial aquifers in the Biskra study area. In this context, the present research applies geostatistical techniques to estimate the spatial variability of hydrodynamic parameters using measurement data to yield a probability map. The estimation of hydrodynamic parameters T and K was mapped by ordinary kriging, where the best-fitted variogram is a Spherical model for Transmissivity and a Gaussian model for $\log_{10}$ (Hydraulic conductivity). It was validated by the cross-validation test with the root mean square error (RMSE). The results show that the geostatistical approach using ordinary Kriging is an important tool for estimating the spatial variability of hydrodynamic parameters in alluvial aquifers.

Keywords: Geo-statistics, Ordinary kriging, Variogram, Transmissivity, Hydraulic conductivity, Alluvial aquifers, Biskra, Algeria.

INTRODUCTION

Groundwater is a vital natural resource in arid and semi-arid regions worldwide (Chibane and Ali-Rahmani, 2015; Bouchemal and Achour, 2015; Bahir et al., 2015; Bemmoussat et al, 2017; Belhadj et al., 2017; Zegait et al., 2021; Rajput et al., 2023; Qureshi et al., 3024). In the Biskra study area (Algeria), it serves as the primary water source for domestic, industrial, and agricultural activities, particularly for the irrigation of palm groves (Douh et al., 2013; Rezzoug et al., 2016; Jelisavka and Goran, 2018; Remini, 2019; Derdour et al., 2022). Annually, more than 508 Hm^3 of water are extracted from aquifers to irrigate over 65,000 hectares of land, while 68 Hm^3 are allocated for drinking water supply. The region relies on more than 11,121 boreholes and wells for groundwater extraction. The volume of water stored within aquifers is estimated using robust, reliable, and practically applicable methodologies (El Moukhayar et al., 2015; Bemmoussat et al., 2017; Hountondji et al., 2020; Jaiswal et al., 2023; Deb, 2024; Later and Labadi, 2024; Remini, 2025).

In recent years, this resource has shown a decline in the water table, due to the overexploitation of underground aquifers (Baiche et al., 2015; Aroua, 2018). In addition, climate change is exerting unprecedented pressure on groundwater resources by intensifying drought frequency, reducing natural recharge rates, and accelerating aquifer depletion, thereby threatening the long-term sustainability of freshwater supplies in many regions worldwide (Khemmoudj et al., 2016; Assemian et al., 2021; Rouissat and Smail, 2022; Chadee et al., 2023). The importance of these resources leads us to an interest in knowing the main hydrodynamic parameters (Transmissivity, Hydraulic conductivity), of alluvial aquifers, which the most exploited in the city of Biskra for more than 13 boreholes, due to easiness of extraction and their geological structure.

Geo-statistics is a fundamental tool in hydraulic engineering, used to describe spatial variability by integrating mathematical and statistical approaches. it has been proposed for many years (Kitanidis, 1997); geostatistical techniques have been widely applied to solve complex engineering problems, optimize parameter estimation with minimal error, and support spatial modeling of physical processes in porous and hydraulic systems. In addition, statistical characterization has highly contributed to assess groundwater quality (Belhadj et al., 2017; Lachache et al., 2023). Shakeel and Ghislain (1987) used different comparative geostatistical techniques to determine and map the transmissivity distribution in the aquifer. Similarly, Desbarats and Dlmltrakopoulos (1990) used geostatistical modeling to represent transmissibility as a log-normal spatial variable, developing a scaling method to estimate block-averaged values for reliable of flow properties in heterogeneous aquifer systems. Pwint and Sucharit (2018) also used geostatistical method to estimate hydraulic conductivity and Transmissivity from boreholes data. The powerful of the geo-statistic technique was confirmed by Seyedmohammadi et al. (2016) which using ordinary kriging (OK) interpolation with different classical interpolation methods for estimation of groundwater electrical conductivity, where ordinary kriging was the best interpolation method compared with other interpolation methods. It is worth emphasizing that a recent study introduced a highly accurate and cost-effective instrument for measuring turbidity and electrical conductivity. Although its initial application was limited to wastewater characterization, the proposed system exhibits strong potential for extension to groundwater monitoring and assessment (Randika et al., 2022).

One of the powerful of geo-statistics over traditional methods of estimating reserves is not only the estimated value, but also the kriging variance which is a measure of the estimate's accuracy and which takes into account the spatial structure of the studied variable (Lamamra et al., 2019). Kriging is a probability stochastic method for understanding the spatial structure of the phenomenon being studied and determining the characteristics of the underground flow as precisely as possible.

The ordinary kriging technique is used to predict values from interpolation without bias and with a minimum of variance. The ordinary kriging obtained after vario-graphic analysis is based on the variogram tool for analyzing the spatial continuity of the contents that is commonly obtained by fitting the experimental variogram to theoretical models. The variogram, defined in both stationary order two and strictly intrinsic conditions, is an important tool for analyzing and modeling the regionalized variable's spatial structure. It signifies the average variability of concentrations between two points as a function of the distance h between them (Rouïl and Malherbe, 2003).

The main objective of this study was to assess the impact of aquifer heterogeneity on the spatial distribution of hydrodynamic parameters in the alluvial aquifers of Biskra study area. Specifically, the research objectives were twofold: (i) to analyze the spatial variability of Hydraulic conductivity and Transmissivity using ordinary kriging and (ii): to generate spatial estimates and probability maps of these parameters. The results are expected to support the identification of high-productivity groundwater zones and areas vulnerable to water scarcity, thereby contributing to Hydraulic characterization and effective groundwater resource management in arid and semi-arid regions.

MATERIAL AND METHODS

Description of the study area

The region of study is located 700 km South- East of Algeria (Fig. 1), between the latitudes of 32° 35' and 32° 38' and the longitudes of 5° 20' and 6° 7'. The geology and hydrogeology of this region show the existence of several heterogeneous aquifer levels, these aquifers appear in formations of Quaternary, Mio-Pliocene, Lower Eocene, Upper Senonian (Maastrichtian), and Albian ages.

In the study area, 13 wells have been drilled to exploit the water of the alluvial aquifer of Oued Biskra is of quaternary age and located just upstream from Biskra, this aquifer has an elongated shape and a general south -north direction. This shape was formed by the flow of the Biskra valley, which dug into the impermeable Miocene marls and filled them with alluvial deposits. It has a 5 km^2 surface area. The upstream sill of the aquifer is defined by the Turonian limestone bar of the periclinal closure of the Djebel Boughezal to the west and the closure of the Oued Besbes to the east. The downstream sill is located on the Pliocene puddingstone cluster.

The lithological nature of the aquifer is homogeneous throughout, it is composed of pebbles, gravel, and alternating layers of clay, due to its high permeability and porosity, the alluvial material effectively stores water, resulting in the formation of a significant groundwater reservoir known as the alluvial water table of Wadi Biskra. The depth of this aquifer ranges from 40 to 60 meters and is fed by the infero-flow of a valley. With an average thickness of 20 meters, the volume of alluvium is 100 hm^3, and it has a flow rate ranging between 5 and 20 l/s.

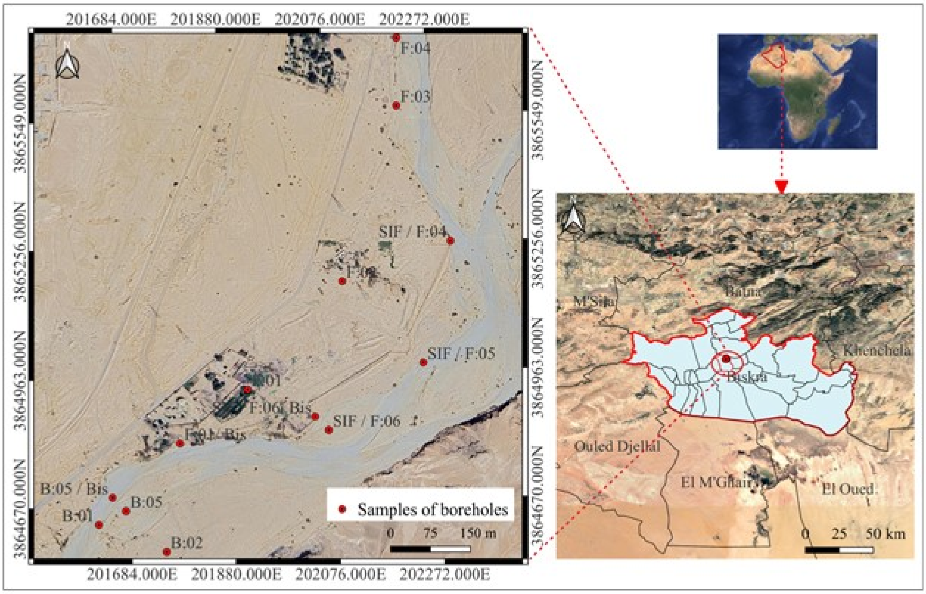


Figure 1: Location map of the study area and sampled boreholes of the alluvial aquifer

The geostatistical method

The geostatistical interpolation technique is a powerful approach that can estimate and interpolate the spatial continuity of regional variables at unsampled locations using known points (Belkhiri and Narany, 2015). Geostatistical methods have been applied in various scientific disciplines, especially in the earth sciences. This study used geostatistical methods for spatial prediction of hydrodynamic parameters of alluvial aquifers, which consist of four main steps:

The first step is exploratory statistics, which is used to check for normal distribution and stationarity; if the analysis is not checked, the data must be transformed by logarithmic transformation, which often improves the fit of the data to a normal distribution.

The second step in geostatistical analysis involves variogram modeling, specifically the construction of the experimental semi-variogram, which examines the spatial correlation of the studied variables. It represents the relationship between pairs of observed values as a function of the distance and direction of their separation (Fig. 2a). The experimental semi-variogram is calculated as half the squared difference between paired values, divided by the distance separating them, as expressed in the following equation:

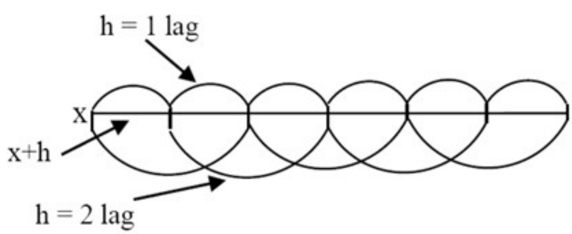
$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[Z(x_i) - Z(x_i + h) \right]^2 \quad (1)$$

Where γ (h) is the experimental variogram for a distance (lag) h between observations $z(x)$ and z ($x + h$), representing the values of the regionalized variable under study at location (x) and ($x + h$), respectively, N (h) is the number of pairs of observations at distance lag (h).

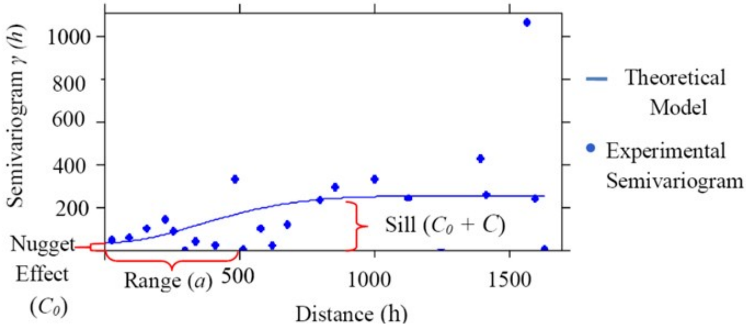
In the third step, known as structural analysis, a theoretical model is fitted to the experimental semi-variogram using three popular semi-variogram models: Gaussian, spherical, and exponential. Fig. 2b represents the Gaussian theoretical model as an example. This model defines the spatial structure through three main parameters:

The nugget effect (C_0) is the value of γ (h) at $h = 0$. The nugget effect reflects measurement error or microscale variation.

The Sill ($C_0 + C$) represents the maximum value of the semi-variogram, which corresponds to the total variance of the studied variable. It indicates the point at which the spatial correlation between sampled points ceases. In practice, the semi-variogram increases with distance until it reaches a nearly constant value (about 95% of the total variance), beyond which it stabilizes due to boundary effects. For a strictly stationary variable, this level is approximately equal to the variance of the variable (Chauvet, 1992). The range (a) represents the distance (lag) at which the semi-variogram reaches the sill, indicating the limit of spatial correlation between sampled points. Beyond this distance, the data become spatially uncorrelated. The range is often related to the characteristic dimensions of the hydro-facies or the spatial extent of geological structures.



(a)



(b)

Figure 2: (a) Estimation of the experimental variogram (b) Example of an experimental and fitted theoretical model

The best fitting theoretical semi-variogram models were determined by calculating the estimation error according to mean error (ME), mean standard error (MSE), root mean square error (RMSE), mean square standard error (MSSE), and root mean square standardized error (RMSSE), using the following expression:

$$\mathrm{ME} = \frac{1}{N}\sum_{i=1}^{N}\left[Z(x_i) - Z'(x_i)\right] \tag{2}$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left[Z(x_i) - Z'(x_i)\right]^2 \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[Z(x_i) - Z'(x_i)\right]^2} \tag{4}$$

$$\mathrm{MSSE} = \frac{1}{N}\sum_{i=1}^{N}\frac{\left[Z(x_i) - Z'(x_i)\right]^2}{\sigma_{ki}^2} \tag{5}$$

$$\mathrm{RMSSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{\left[Z(x_i) - Z'(x_i)\right]^2}{\sigma_{ki}^2}} \tag{6}$$

With the observed value Z (xi) and the predicted value Z' (xi) and σ_k^2 the estimation variance at points xi, N represents the sample size used; the ME and MSE must be as small as possible and should be close to zero with a smaller RMSE.

The fourth step includes the use of a kriging technique to interpolate the studied variables at unsampled locations, based on the spatial correlation identified in the variogram model. There are three classical types of kriging: simple kriging, universal kriging, and ordinary kriging, which is the most frequently utilized approach in many environmental applications. The kriging estimate is given by the following formula:

$$Z^*(x_0) = \sum_{i=1}^{N} \lambda_i Z(x_i) \quad i = 1 \tag{7}$$

Where $z^*(x_0)$ is the estimated value at x_0, $Z(x_i)$ is the observed values at points x_i, N is the sample size, and λ_i are the weights chosen for xi, is a non-biased linear estimation method that minimizes estimation variance calculated according to the following statistical conditions:

Unbiasedness:

$$\mathbb{E}\left[Z^*(x_0) - Z(x_0)\right] = 0 \tag{8}$$

Minimum variance:

$$\mathrm{Var} = \left[z^*(x_0) - z(x_0)\right] = \text{minimum} \tag{9}$$

To find the weights that minimize the kriging variance conditional on the unbiasedness condition, the sum of the weights should be one $\sum_{i=1}^{N} \lambda_i = 1$ (Budiman et al., 2022). The Kriging system of equations to be solved is as follows:

$$\sum_{i=1}^{N} \lambda_i \gamma(x_i - x_0) + \mu = \gamma(x_j - x_0) \tag{10}$$

Where μ is a Lagrange multiplier, and $\gamma(x_i - x_0)$ is the semivariogram between two points x_i and x_0.

RESULTS AND DISCUSSION

Spatial structure of hydrodynamic parameters

Alluvial aquifer environments are characterized by strong vertical heterogeneity and significant spatial variability. In this study, geostatistical methods were employed to analyze the spatial patterns and structural variability of key hydrodynamic parameters specifically Transmissivity (T) and Hydraulic conductivity (K), based on data collected from 13 boreholes. Fig. 3 illustrates the spatial distribution of these parameters based on UTM coordinates, where (a) represents Transmissivity (T) and (b) represents Hydraulic conductivity (K), reflecting the geographical position of each sampling point within the study area. The figure has been enhanced to improve the legibility of the numbers and provide a clearer visualization of the spatial data distribution.

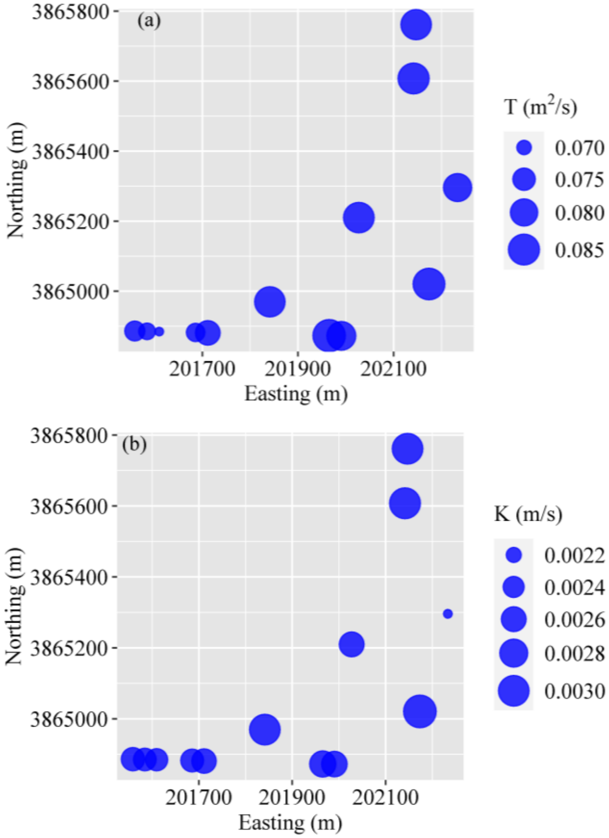


Figure 3: Geospatial distribution of (a) transmissivity, and (b) hydraulic conductivity

Statistical analysis of the data

The first requirement of geostatistical analysis is to check the normal distribution of the datasets. This probability was evaluated using several statistical indicators. Table 1 presents the descriptive statistics of the measured parameters (Transmissivity and Hydraulic conductivity) before and after logarithmic transformation ($\log_{10}$). The logarithmic transformation was applied to make the datasets more suitable for geostatistical analysis by improving their approximation to a normal distribution.

Table 1: Descriptive statistics of the datasets before and after Log_{10} transformation

Statistics	Transmissivity T (m^2/s)	Log_{10} Transmissivity T (m^2/s)	Hydraulic conductivity K(m/s)	Log_{10} Hydraulic conductivity K(m/s)
Min	0.069	-1.16	0.002	-2.67
Max	0.087	-1.06	0.003	-2.49
Mean	0.079	-1.10	0.003	-2.57
Skewness	-0.4487	-0.4907	0.147	-0.056
Kurtosis	-1.5872	-1.5459	-1.024	-0.83
Shapiro-Wilk	0.0555	0.0455	0.3032	0.3339
Standard-deviation	0.00638	0.03564	0.0003	0.048
Kolmogorov-Smirnov	0.1083	0.1036	0.2512	0.3978

The descriptive statistical analysis of Hydraulic conductivity (K) and Transmissivity (T) illustrated that the Kolmogorov–Smirnov test gets values of 0.2512 m/s for K and 0.1083 m^2/s for T, whereas the Shapiro–Wilk test has p-values of 0.3032 m/s and 0.0555 m^2/s, respectively. As both tests yielded values higher than the 0.05 significance level, the results test indicate that the data for both variables can be considered normally distributed.

After a logarithmic transformation of the data, the $\log_{10}$ (Hydraulic conductivity) showed better normality after a logarithmic adjustment. It was confirmed by the Shapiro-Wilk and Kolmogorov-Smirnov tests, which yielded p-values of 0.3339 and 0.3978, respectively. Whereas, the $\log_{10}$ (Transmissivity) data produced slightly lower p-values of 0.046 for Shapiro-Wilk and 0.104 for Kolmogorov-Smirnov, indicating that the transformation had only a limited effect in improving the normality of T compared to its original data.

Many authors, such as Delhomme (1978), Kitanidis (1997), and Rotzoll et al. (2007), highlighted the lognormal character of the distribution of Hydraulic conductivities. To achieve this, a logarithmic transformation was applied to the original data. Fig. 4 illustrates the changes in the histogram and probability density distribution of Hydraulic conductivity (K), where (a) represents the data before transformation and (b) represents the data after logarithmic transformation. According to the Hydraulic conductivity histogram, we notice that the distribution law is not Gaussian, where the logarithm of the Hydraulic conductivity is more acceptable than before the transformation but is not a perfectly normal distribution. In general, this is an acceptable approximate value, and it is possible to improve it with more data.

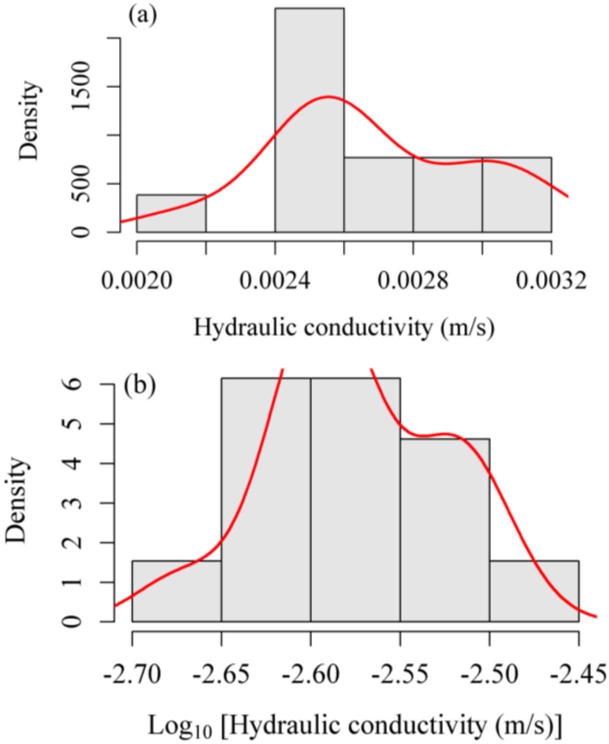


Figure 4: Histogram of Hydraulic conductivity before transformation (a), and after logarithmic transformation (b)

Vario-graphic analysis

The best-fitting theoretical semi-variogram models were determined by calculating the estimation error based on the root mean square error (RMSE), as depicted in the variogram results Table 2 and Fig. 5. The results indicate that the Spherical model provides the best fit to the Transmissivity variogram based on the original data, with the lowest prediction error (Fig. 5a). This model exhibits a nugget effect (C_0) equal to zero, a range (a) of 190 m, and a sill ($C_0 + C$) = 0.57 x 10^{-4}. Conversely, the Gaussian model proved to be the most appropriate for $\log_{10}$ (Hydraulic conductivity) (Fig. 5b), also showing a nugget effect equal to zero, with a range of 200 m and sill ($C_0 + C$) = 0.0035.

Table 2: Results of the best-fit variogram models based on RMSE for Transmissivity and log₁₀ (Hydraulic conductivity) parameters

Parameter	Fit models	Sill (C_0 +C)	Range (a)	Nugget effect (C_0)	RMSE
Transmissivity	Spherical	0.43 x 10^{-5}	200	0	0.0033
Log_{10} (Hydraulic conductivity)	Gaussian	1.63 x 10^{-7}	200	0.1 x 10^{-8}	0.00034

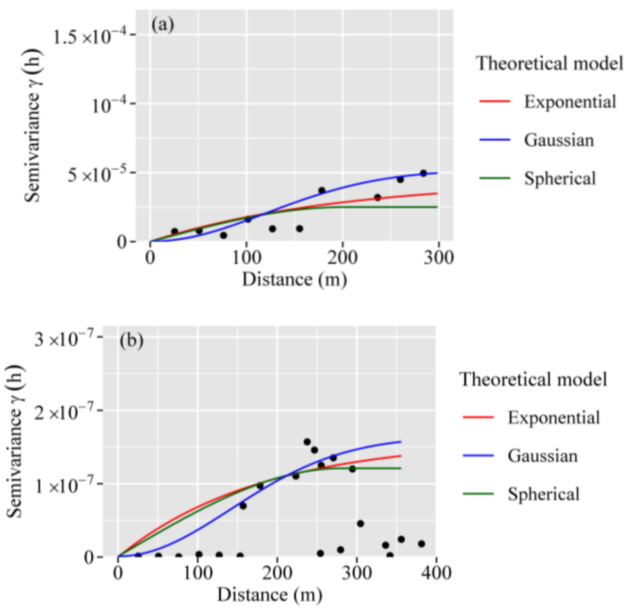


Figure 5: Experimental semi-variograms and fitted theoretical models of (a) Transmissivity T (m^2/s), and (b) log_{10} [Hydraulic conductivity K (m/s)]

The cross-validation test is a procedure that evaluates the goodness of fit of the variogram model, as well as the appropriateness of the neighborhood and the type of kriging estimation used (Seyedmohammadi et al., 2016). The cross-validation scatter plot, presented in Fig. 6, illustrates the comparison between measured and predicted values, which should be at a line with a slope of 1:1, where it is most around and close to the line. Generally, the closer the dots are to the line, the higher degree of compatibility of the data and, consequently, the more valid the modeling generated (Hosseini et al., 2019). The measured and predicted values appear fairly reasonable and acceptable, indicating that the ordinary kriging method effectively captures the spatial variation of Transmissivity (Fig. 6a) and Hydraulic conductivity (Fig. 6b). This validation suggests that the model is reliable for predicting these parameters at unsampled sites.

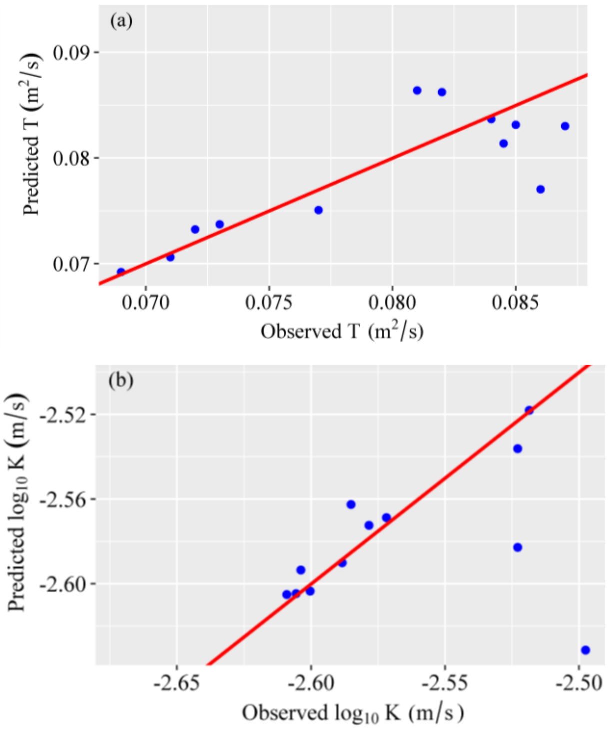


Figure 6: Cross-validation between observed and predicted values of (a) Transmissivity T (m²/s), and (b) $\log_{10}$ [Hydraulic conductivity K (m/s)]

Spatial distribution using ordinary kriging

The spatial distribution maps of Hydraulic conductivity and Transmissivity Figs. 7 and 8 were generated using the ordinary Kriging (OK) method, which proved to be the most appropriate among several interpolation techniques and is widely recognized as a reliable estimator for spatial data. Several authors, including Jennings et al. (2000), and Rotzoll et al. (2007) have used OK to produce probability maps for Hydraulic conductivity, Similarly, Sattar et al. (2016) demonstrated the effectiveness of OK in mapping the spatial distribution of Transmissivity. In the present study, Ordinary Kriging was applied using a Spherical semi-variogram model to estimate Transmissivity, and a Gaussian model to estimate Hydraulic conductivity in the alluvial aquifer of the Biskra study area southeastern Algeria.

Variance kriging maps

Kriging is best linear unbiased estimate with minimum estimation variance, known as kriging variance (Hosseini et al., 2019). Fig. 7a shows the estimated variance map of Transmissivity, where the maximum estimated variance exceeds $3.5\times10^{-5}$are observed in the northwestern directions (represented by dark colors). This can be attributed to a lack of data in these zones. The estimation variance decreases progressively rapidly toward the central and southeastern boundaries of the map (light colors), with values ranging from 5×10^{-6} to 2×10^{-5}. This suggests that the estimated Transmissivity parameter is more reliable in the central and southeastern parts of the study area. As shown in Fig. 7b, the estimation variance of the Hydraulic conductivity is higher in the northwest at the corners of the study area (dark colors), with a value of 1.8×10^{-7}, where there are no boreholes to monitor. Furthermore, the values gradually decrease as we move towards the opposite side of the map. Overall, the variance is low only in areas where boreholes are distributed, indicating a highly reliable estimate (Zhao et al., 2014).

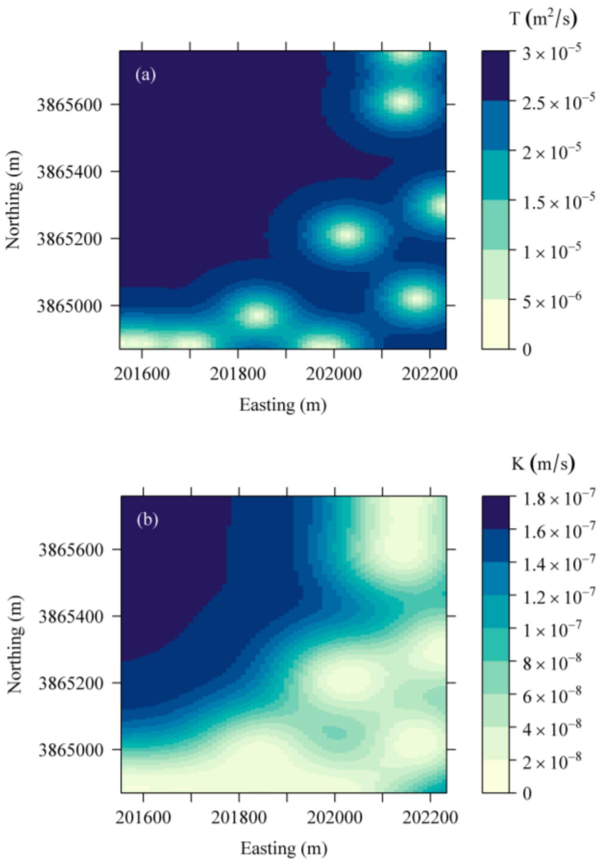


Figure 7: Kriging variance maps of (a) Transmissivity, and (b) Hydraulic conductivity

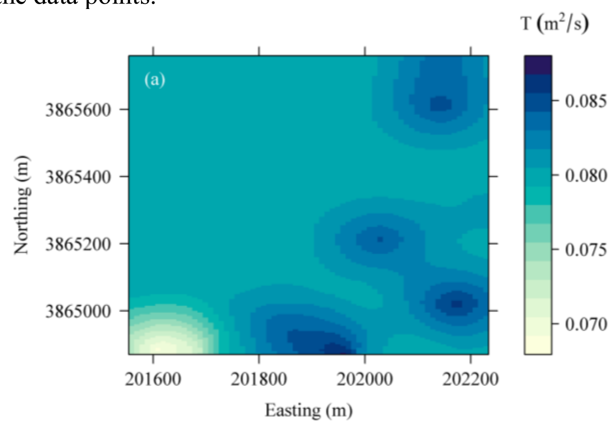
Estimation kriging maps

Estimation Kriging maps are used to visualize the spatial distribution of a variable and to predict values at unsampled locations. These maps are typically presented as continuous surfaces that illustrate the estimated values throughout the study area. In a Kriging variance map, higher values indicate greater uncertainty in the estimation, whereas lower variance values reflect increased confidence in the predicted results (Shazia and Mushtaq, 2018).

The Transmissivity estimation map Fig. 8a shows that the higher value patches (≥0.085 m^2/s) are mainly concentrated in the eastern and southeast regions of the study area corresponding to the center of the waveform. Furthermore, Transmissivity values exhibit a gradual decrease toward the northern and western regions of the map, where the lowest values are located.

The spatial distribution of Hydraulic conductivity Fig. 8b indicates that the highest values (≥0.0032 m/s) are concentrated in the southwestern and southeastern corners of the map. In contrast, the lowest values are observed in the northeastern corner and the central-southern part of the study area, corresponding to the lighter-colored patches.

This indicates a heterogeneous distribution of Hydraulic conductivity across the site, with higher concentrations particularly observed in the southeastern dark blue patches, along with the locations of the boreholes. Since a large number of boreholes cover the downstream part of the aquifer, the krige map demonstrates high accuracy in this region. In contrast, in areas with fewer boreholes, the precision rapidly decreases with increasing distance from the data points.



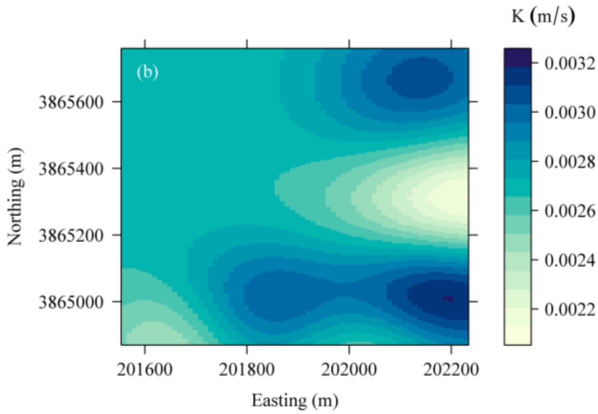


Figure 8: Kriging predictive maps of (a) Transmissivity, and (b) and Hydraulic conductivity

Spatial estimation and probability distribution of hydrodynamic parameters

Groundwater flow and transport models depend on a detailed characterization of subsurface hydraulic properties (Renard et al., 2020). In the study area, the estimated Transmissivity and Hydraulic conductivity values exhibit significant variation due to the high heterogeneity of porous geological formations. Several researchers, including Dassargue (1997), and Sattar et al. (2016), have examined the relationship between aquifers and geophysical parameters, considering the geological and hydrodynamic characteristics of the aquifers and the subsurface.

The probability maps Figs. 9 and 10 illustrate the spatial distribution and estimation of hydrodynamic parameters in the alluvial aquifer, including areas lacking borehole data. These maps primarily highlight zones of low and high concentration values. The northeastern part of the study area shows a high probability of elevated concentrations, with Transmissivity ($T \geq 0.085$ m^2/s) and Hydraulic conductivity ($K \geq 0.0028$ m/s) represented by the red color where it covers a limited area.

The elevated values of Transmissivity and Hydraulic conductivity observed in this region are primarily governed by the geological structure of the alluvial aquifers. These aquifers are composed of highly permeable sediments, including pebbles, gravel, and sand, which facilitate efficient groundwater flow. Their direct connectivity with the land surface further facilitates groundwater recharge through infiltration. Moreover, the aquifer system may also receive recharge from distant mountainous regions, such as the Aurès Mountains, where precipitation and surface runoff infiltrate the subsurface and contribute to the groundwater recharge.

The influence of recharge gradually decreases from the northwestern part of the study area, particularly around Djebel Bou Rhezel, and continues to decline toward the southern and southeastern regions. This trend is reflected in the lower probability values of Transmissivity ($T \leq 0.073$ m^2/s) and Hydraulic conductivity ($K \leq 0.0025$ m/s), represented by the blue color, which cover a significant portion of the study area. Geologically, this region is characterized by a complex formation consisting of Mio-Pliocene and Quaternary alluvial aquifers, composed of sandy alluvium derived from the Great Plains, as well as sandstone, clay, and marl. The presence of perched and partially saturated sandy-clayey units contributes to a lower Transmissivity and reduced hydraulic capacity in these areas.

Discussion

The characteristics and performance of aquifers in the study area are directly reflected by hydrodynamic parameters, including Transmissivity (T) and Hydraulic conductivity (K). These parameters are essential for evaluating the ability of porous formations to transmit water and for characterizing the spatial variability of subsurface flow conditions. In this study, a geostatistical approach was applied to estimate and map the probability distributions of T and K, thereby enhancing the understanding of hydraulic heterogeneity across the Biskra region.

The spatial variability of hydrodynamic parameters indicates that zones with higher values of Transmissivity ($T \geq 0.085 m^2/s$) and Hydraulic conductivity ($K \geq 0.0028$ m/s) are primarily located in the northeastern part of the study area. The permeability of the alluvial aquifer is primarily controlled by their lithological composition, which consists mainly of coarse-grained materials such as gravel and sand. These characteristics enhance Hydraulic conductivity and promote greater subsurface flow potential. On the other hand, lower K and T values are observed in the southern and southwestern zones, which are mainly composed of fine-grained formations such as clay and marl. These fine-grained materials reduce permeability and restrict subsurface flow, thereby limiting the hydraulic performance of the aquifer.

These findings are consistent with the results of several studies that have investigated the spatial variability of Transmissivity and Hydraulic conductivity in porous formations. As reported by Belcher et al. (2002), Bruen and Osman (2004), Kalbus et al. (2009), and Chen et al. (2018), these parameters commonly demonstrate spatial variation due to aquifer heterogeneity, which is influenced by a combination of geological structures and anthropogenic or technical factors. While the application of the geostatistical kriging method yielded generally reliable estimations, the limited number of boreholes may have introduced uncertainty in certain interpolated zones. Therefore, future studies should use more boreholes and pumping test data to improve the models and reduce this uncertainty.

Overall, the spatial distribution maps of Transmissivity and Hydraulic conductivity demonstrate their significance in characterizing the hydraulic behavior of alluvial aquifer. Understanding the spatial variability of these hydrodynamic parameters is essential for assessing subsurface hydraulic potential and for supporting regional-scale hydraulic modeling and aquifer system analysis, particularly in arid and semi-arid regions such as the Biskra study area.

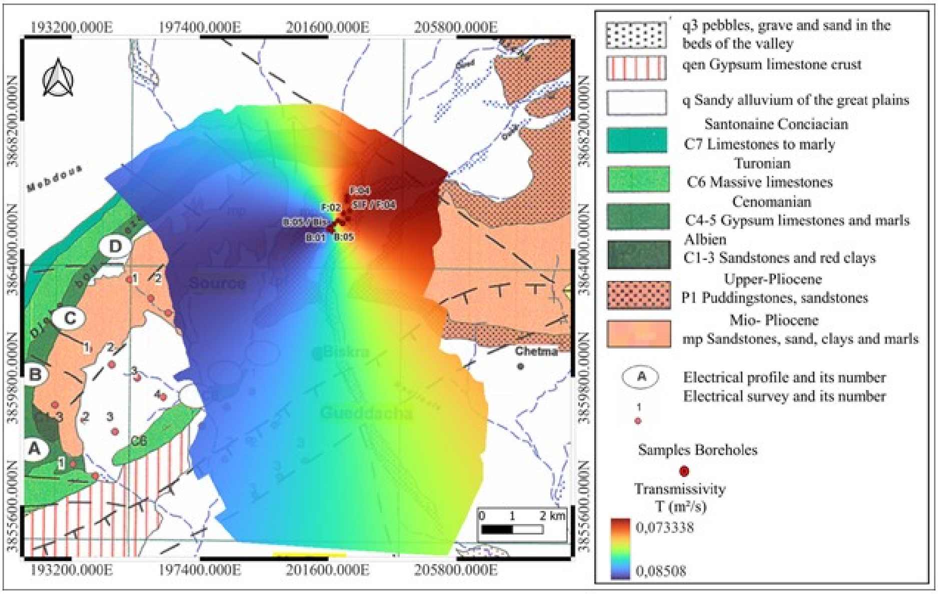


Figure 9: Spatial probability map of Transmissivity in the alluvial aquifer of Biskra City

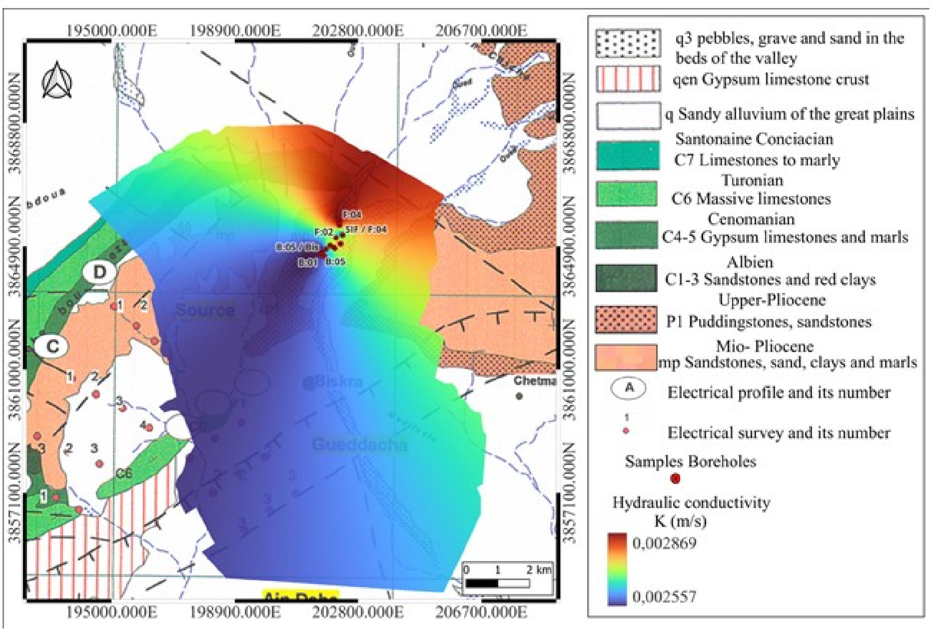


Figure 10: Spatial probability map of Hydraulic conductivity in the alluvial aquifer of Biskra City

CONCLUSION

This study focuses on a geostatistical probabilistic approach to predicting the spatial distribution and variability of hydrodynamic parameters, specifically Transmissivity (T) and Hydraulic conductivity (K), in an alluvial aquifer in the Oued Biskra area, East-South Algeria. Ordinary kriging (OK) was employed to analyze the spatial distribution and variability of these parameters using semi-variogram models. The best-fit model for each semi-variogram was validated and refined through cross-validation test, assessed using the root mean square error (RMSE). The spherical model was fitted to the experimental semi-variogram of Transmissivity, while the Gaussian model was applied to Hydraulic conductivity, and these models were then integrated with kriging to predict the hydrodynamic parameters (T, K).

The Kriging variance maps exhibited a reasonable pattern, with the lowest variances occurring in areas of high sample density and higher variances in regions with fewer samples. Consequently, higher variance values in the Kriging map indicate greater uncertainty in the predictions, whereas lower values correspond to estimates that are more reliable.

The spatial distribution probability maps of the hydrodynamic parameters indicate that the northeastern part of the study area has a high probability of elevated parameter concentrations, which gradually decrease toward the northwest and southeast. The estimated parameter distribution reveals a distinct directional trend in groundwater flow within the aquifer. Understanding these patterns is crucial for improving groundwater resource management in the region. This contributes to informed decision-making for the sustainable groundwater resource management, protection strategies, and characterization of hydrodynamic parameters in aquifer systems.

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.

REFERENCES

AROUA N. (2018). Water resources in SNAT 2030. between economic needs and ecological requirements, Larhyss Journal, No 35, pp. 153-168. (In French)

ASSEMIAN A.E., DJE BI DOUTIN S., SAMAKÉ Y. (2021). Consequences of the effects of climate change on water resources in a humic tropical zone of central eastern Côte d'Ivoire, Larhyss Journal, No 45, pp. 95-105.

BAHIR M., EL MOUKHAYAR R., CARREIRA P. SOUHEL A. (2015). Isotopic tools for groundwater management in semi-arid area: case of the wadi Ouazzi basin (Morocco), Larhyss Journal, No 23, pp. 23-39.

BAICHE A., SIDI MOHAMED H., ABLAOUI H. (2015). Overexploitation of water resources of the Mostaganem plateau aquifer, Larhyss Journal, No 22, pp. 153-165. (In French)

BELCHER W.R., SWEETKIND D.S., ELLIOTT P.E. (2002). Probability distributions of hydraulic conductivity for the hydrogeologic units of the Death Valley regional ground-water flow system, Nevada and California, U.S. Geological Survey Water Resources Investigations Report 2002-4212, U.S. Geological Survey, Carson City, Nevada, USA, 18 p.

BELHADJ M.Z., BOUDOUKHA A., AMROUNE A., GAAGAI A., ZIANI D. (2017). Statistical characterization of groundwater quality of the northern area of the basin of Hodna, M'sila, southeastern Algeria, Larhyss Journal, No 31, pp. 177-194. (In French)

BELKHIRI L., NARANY T.S. (2015). Using multivariate statistical analysis geostatistical techniques and structural equation modeling to identify spatial variability of groundwater quality, Jornal of Water Resources Management, Vol. 29, Issue 6, pp. 2073-2089.

BEMMOUSSAT A., ADJIM M., BENSAOULA F (2017). Use of the ZYGOS model for the estimation of groundwater recharge in Sikkak watershed (Northen west of Algeria), Larhyss Journal, No 30, pp. 105-119. (In French)

BRUEN M.P., OSMAN Y.Z. (2004). sensitivity of stream-aquifer seepage to spatial variability of the saturated hydraulic conductivity of the aquifer, Journal of Hydrology,Vol. 293, Issues 1-4, pp. 289-302.

BOUCHEMAL F., ACHOUR S. (2015). Physico-chemical quality and pollution parameters of groundwater in the Biskra region, Larhyss Journal, No 22, pp. 197-212. (In French)

BUDIMAN J.S., Al-AMRI N.S., CHAABANI A., ELFEKI A.M.M. (2022). Geostatistical based framework for spatial modeling of groundwater level during dry and wet seasons in an arid region: A case study at Hadat Ash-Sham experimental station, Saudi Arabia, Journal of Stochastic Environmental Research and Risk Assessment, Vol. 36, Issue 8, pp. 2085-2099.

CHADEE A., NARRA M., MEHTA D., ANDREW J., AZAMATHULLA H. (2023). Impact of climate change on water resource engineering in Trinidad and Tobago, Larhyss Journal, No 55, pp. 215-229.

CHAUVET P. (1992). Report on the processing of spatial data: geo-statistics and its applications, Center for Geo-statistics, National School of Mines of Paris (In French).

CHEN Y.F., LING X.M., LIU M.M., HU R., YANG Z. (2018). Statistical distribution of hydraulic conductivity of rocks in deep-incised valleys, southwest China, Journal of Hydrology, Vol. 566, pp. 216-26.

CHIBANE B., ALI-RAHMANI S.E. (2015). Hydrological based model to estimate groundwater recharge, real- evapotranspiration and runoff in semi-arid area, Larhyss Journal, No 23, pp. 231-242.

DASARGUES A. (1997). Modeling base flow from an alluvial aquifer using hydraulic-conductivity data obtained from a derived relation with apparent electrical resistivity, Journal of Hydrogeology, Vol. 5, Issue 3, pp. 97-108.

DEB S. (2024). Optimizing hydrological exploration through GIS-based groundwater potential zoning in Gomati district, Tripura, India, Larhyss Journal, No 60, pp. 231-256.

DELHOMME J.P. (1978). Kriging in the hydrosciences, Journal of Advances in Water Resources,Vol. 1, Issue 5, pp. 251-266.

DERDOUR A., BELAM N., CHEBAB W. (2022). Traditional irrigation system and methods of water harvesting in the oasis of Sfissifa Ksour mountains – Algeria, Larhyss Journal, No 49, pp. 17-35.

DESBARATS A.J., DLMLTRAKOPOULOS R. (1990). Geostatistical modeling of heterogeneity, Society of Petroleum Engineers (SPE) Formation Evaluation, Vol. 5, Issue 4, pp. 437-443.

DOUH B., BOUJELBEN A., KHILA S., BEL HAJ MGUIDICHE A. (2013). Effect of subsurface drip irrigation system depth on soil water content distribution at different depths and different times after irrigation, Larhyss Journal, No 13, pp. 7-16.

EL MOUKHAYAR R., BAHIR M., CARREIRA P. (2015). Estimation of groundwater recharge in arid region through hydrochemistry and isotope: a case study Kourimat basin Morocco, Larhyss Journal, No 23, pp. 87-104.

HOSSEINI E., GHOLAMI R., HAJIVAND F. (2019). Geostatistical modeling an spatial distribution analysis of porosity and permeability in the Shurijeh-B reservoir of Khangiran gas field in Iran, Journal of Petroleum Exploration and Production Technology, Vol. 9, Issue 2, pp. 1051-1073.

HOUNTONDJI B., CODO F.P., AINA M.P. (2020). Characterization of hydrogeological conditions from the Monzoungoudo groundwater reservoir in Benin, Larhyss Journal, No 41, pp. 223-232. (In French)

JAISWAL T., JHARIYA D., SINGH S. (2023). Identification and mapping of groundwater potential zone using analytical hierarchy process and GIS in lower Kharun basin, Chhattisgarh, India, Larhyss Journal, No 53, pp. 117-143.

JELISAVKA B., GORAN R. (2018). Irrigation of agricultural land in Montenegro: overview, Larhyss Journal, No 33, pp. 7-24.

JENNINGS J.R., RUPPEL S.C., WARD W.B. (2000). Geostatistical analysis of permeability data and modeling of fluid-flow effects in carbonate outcrops, Journal of SPEReservoir Evaluation and Engineering, Vol. 3, Issue 4, pp. 292- 303.

KALBUS E., SCHMIDT C., MOLSON J.W., REINSTORF F., SCHIRMER M. (2009). Influence of aquifer and streambed heterogeneity on the distribution of groundwater discharge, Journal of Hydrology and Earth System Sciences, Vol. 13, Issue 1, pp. 69–77.

KHEMMOUDJ K., BENDADOUCHE H., MERABET S. (2016). Water resources in semi-arid and sustainable development, case Djemila northeast Algerian region, Larhyss Journal, No 26, pp. 249-258. (In French)

KITANIDIS P.K. (1997). Introduction to geo-statistics applications to hydrogeology, Book, Cambridge University Press, published by the Press Syndicate of the University of Cambridge, United Kingdom, 249p.
ISBN 0-521-58312-8 (Hardback); 0-521-58747-6 (Paperback)

LACHACHE S., DERDOUR A., MAAZOUZI I., AMROUNE A., GUASTALDI E. (2023). Statistical approach of groundwater quality assessment at Naama region, South-West Algeria, Larhyss Journal, No 55, pp. 125-144.

LAMAMRA A., NEGURITSA D., MAZARI M. (2019). Geostatistical modeling by the ordinary kriging in the estimation of mineral resources on the kieselguhr mine, Journal of Earth and Environmental Science, Vol. 362.
doi:10.1088/1755-1315/362/1/012051

LATER F., LABADI A.S. (2024). Origin of the alluvial aquifer's groundwater in wadi Biskra (Algeria), Larhyss Journal, No 57, pp. 145-158.

PWINT P.A., SUCHARIT K. (2018). Hydrogeological parameter distribution estimation by geostatistical methods in regional groundwater modeling in the upper central plain, Thailand, Journal of Civil Engineering and Technology, Vol. 9, Issue 3, pp. 313-32.

QURESHI H.U., ABBAS I., SHAH S.M.H., TEO F.Y. (2024). Hydrologic evaluation of monthly and annual groundwater recharge dynamics for a sustainable groundwater resources management in Quetta city, Pakistan, Larhyss Journal, No 60, pp. 27-53.

RAJPUT D.C., MISTRY K.P., BHORANIYA J.K., UMRIGAR J.N., WAIKHOM S.I. (2023). Assessing the decadal groundwater level fluctuation-a case study of Gujarat, India, Larhyss Journal, No 54, pp. 175-191.

RANDIKA M.A., AMARASOORIYA A.A.G.D., WERAGODA S.K. (2022). Development of an Arduino-based low-cost turbidity and electric conductivity meter for wastewater characterization, Larhyss Journal, No 51, pp. 115-127.

REMINI B. (2019). The Oasis of El Guerrara (Algeria): irrigation and recharge of the aquifers ensured by the floods, Larhyss Journal, No 40, pp. 135-163. (In French)

REMINI B. (2025). Algeria's groundwater: an untapped strategic resource for water security, Larhyss Journal, No 61, pp. 401-431.

RENARD P., DEMOUGEOT-RENARD, H., FROIDEVAUX R. Editions. (2005). Geo-statistics for Environmental Applications: Proceedings of the Fifth European Conference on Geo-statistics for Environmental Applications (geo ENV V, 13-15 October 2004), Berlin, Heidelberg: Springer-Verlag. ISBN 978-3-540-26533-7.

REZZOUG C., REMINI B., HAMOUDI S. (2016). Modern irrigation in oasis of Lahmar (Bechar, Algeria): problems and consequences, Larhyss Journal, No 25, pp. 259-267. (In French)

ROTZOLL K., EL-KADI A.I., GINGERICH S.B. (2007). Estimating hydraulic properties of volcanic aquifers using constant-rate and variable-rate aquifer tests, Journal of the American Water Resources Association , Vol. 43, Issue 2, pp. 334-345.

ROUÏL L., MALHERBE L. (2003). Report on methods for representing air quality: guide to the use linear geostatistical methods, National Institute for Industrial Environment and Risks (INERIS) of France, Vol. 1. (In French)

ROUISSAT B., SMAIL N. (2022). Contribution of water resource systems analysis for the dynamics of territorial rebalancing, case of Tafna system, Algeria, Larhyss Journal, No 50, pp. 69-94

SATTAR G., KERAMAT M., SHAHID S. (2016). Deciphering transmissivity and hydraulic conductivity of the aquifer by vertical electrical sounding (ves) experiments in northwest Bangladesh, Journal of Applied Water Science, Vol. 6, Issue 1, pp. 35–45.

SEYEDMOHAMMADI J., ESMAEELNEJAD L., SHABANPOUR M. (2016). Spatial variation modeling of groundwater electrical conductivity using geostatistics and GIS, Journal of Modeling Earth Systems and Environment, Vol. 2, pp. 1-10.

SHAKEEL A., GHISLAIN D. M. (1987). Comparison of geostatistical methods for estimating transmissivity using data on transmissivity and specific capacity, Water Resources Research, Vol. 23, Issue 9, pp. 1717-1737.

SHAZIA R., MUSHTAQ A.W. (2018). Communications in soil science and plant analysis geographic information system and geostatistical techniques to characterize spatial variability of soil micronutrients including toxic metals in an agricultural farm geographic information system and geost, Journal of Communications in Soil Science and Plant Analysis, Vol. 49, Issue 4, pp. 463- 477.

ZEGAIT R., REMINI B., BENSAHA H. (2021). Groundwater vulnerability assessment in the M'Zab valley - southern Algeria, Larhyss Journal, No 48, pp. 211-234.

ZHAO S., ZHOU Y., WANG M., XIN X., CHEN F. (2014). Thickness, porosity, and permeability prediction: comparative studies and application of the geostatistical modeling in an oil field, Journal of Environmental Systems Research, Vol. 3, Issues 1, Article number 7.