

Article

Evaluation of Selected Geostatistical Methods for Interpolating Hydraulic Conductivity in Shallow Alluvial Aquifers Using Cross-Validation Statistics

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Abstract

Hydraulic conductivity (K) is essential for understanding groundwater movement in shallow alluvial aquifers. Upstream of the Siret–Moldova confluence, Romania, this parameter is poorly constrained, because available K values come from only 34 wells reported in existing hydrogeological documentation. This study provides the first directional geostatistical characterization of K in this shallow alluvial aquifer and evaluates the spatial reliability of the mapped zones. K values ranged from 9.96 to 171.73 m/day. Because the raw data were positively skewed, the values were log-transformed before geostatistical modelling. Spatial continuity and anisotropy were examined using omnidirectional and directional semivariograms. Three theoretical models were tested—Spherical, Gaussian and Exponential—and their performance was compared using cross-validation statistics and prediction standard-error maps. The Gaussian and Spherical models showed comparable performance; however, the Gaussian model was retained because it produced marginally lower errors and a smoother spatial pattern (ME = 0.0055, RMSE = 0.4870, RMSSE = 0.8697, $R^2 = 0.6712$). The back-transformed K map shows three main zones: lower values in the northern and eastern sectors, intermediate values in the central sector, and the highest values toward the west. This pattern is consistent with coarser Moldova River alluvial deposits in the west and more heterogeneous lithological conditions in the central area. The prediction standard-error maps indicate the areas where the interpolated hydraulic conductivity (K) is more reliably constrained. The resulting map provides a preliminary spatial representation of the main hydraulic-conductivity zones and indicates where additional K measurements are needed before detailed groundwater-flow modelling or local groundwater-resource assessment.

Keywords: hydraulic conductivity; shallow alluvial aquifer; ordinary kriging; anisotropy; semivariogram; prediction standard-error map; groundwater-resource assessment



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1. Introduction

Hydraulic conductivity (K) is an important parameter in hydrogeology that governs the circulation of fluids through the pore spaces of the mineral matrix under the action of a hydraulic gradient, in accordance with Darcy's law [1–4]. Groundwater represents one of the most important natural resources supporting both human and ecological systems, particularly in regions where surface water is insufficient or seasonally variable [5–7]. The sustainable use of aquifers depends on the quantitative evaluation of hydraulic parameters that control groundwater flow, recharge, and storage [8,9]. The K parameter is a key indicator of aquifer permeability and productivity, indicating the ability of geological formations to transmit water [1,4,10]. Accurate estimation of this parameter is essential for the design of water-supply systems, irrigation planning, and the protection of aquifers against overexploitation and contamination [11,12]. Considering these aspects, improving the quantitative evaluation of hydraulic conductivity at local scale is essential for better understanding aquifer behaviour and supporting groundwater resource assessment [11–16].

Traditional methods for determining hydraulic conductivity, such as pumping tests, slug tests and laboratory analyses, provide accurate local estimates, but they are costly, time-consuming and spatially limited [17–19]. For this reason, geostatistical methods combined with Geographic Information Systems (GIS) are increasingly used to convert discrete hydrogeological data into continuous spatial surfaces through interpolation [20–22]. Although these geostatistical techniques are well established and widely applied in hydrogeological research, their implementation remains relatively limited in some regional contexts, particularly where local scale spatial datasets are scarce or underused. In this sense, integrating field data with geostatistical methods provides a practical approach for characterizing the spatial distribution of hydraulic conductivity [20–23]. International studies have shown the value of integrating GIS and geostatistical methods for characterizing groundwater resources. Gonçalves et al. [24] used multivariate geostatistics to map transmissivity and uncertainty in karst aquifers, showing how spatial uncertainty can be incorporated into modelling. Lora-Ariza et al. [25], for instance, estimated hydraulic conductivity using geophysical well logs in multilayered aquifers, verifying their findings with over 130 pumping tests and a calibrated regional flow model. These studies show that geostatistical and complementary hydrogeological methods can improve the spatial characterization of aquifer properties.

In Romania, research that integrates GIS with hydrogeological studies has largely concentrated on mapping groundwater potential, recharge, and vulnerability assessments [26–28]. For instance, Bogdan et al. [26] focused on the identification of groundwater potential areas in the Roman region (NE Romania), using ArcGIS 10.8.1 (Esri, Redlands, CA, USA) and the Analytical Hierarchy Process (AHP) to support decision-making in hydrogeological planning. Despite these contributions, the use of geostatistical modelling to map specific aquifer properties, such as hydraulic conductivity, remains limited, especially at the local scale.

For the Siret–Moldova confluence area, hydraulic conductivity has not been analysed so far using a directional geostatistical approach. Therefore, this study analyses the spatial distribution of K in the shallow alluvial aquifer and identifies the main hydraulic conductivity zones. The analysis is based on log-transformed values, directional semivariograms, anisotropic ordinary kriging and prediction standard-error maps. The main contribution of the study is the first directional geostatistical characterization of K for the shallow alluvial aquifer in the Siret–Moldova confluence area, based on a detailed anisotropy analysis, the comparison of three semivariogram models under the same anisotropic structure, and the joint interpretation of prediction and kriging standard-error maps. The resulting zones are

interpreted in relation to the local hydrogeological setting and may support preliminary hydrogeological conceptualization, identification of contrasting K zones, and planning of future measurements.

2. Methodology

This study examines the spatial variability of hydraulic conductivity (K) in the Ro-man-Gherăești–Mircești area using available hydrogeological data and GIS-based geostatistical techniques. The following section describes the study area, data sources, and the main stages of the applied methodology. Ordinary kriging was used as the main interpolation method because it incorporates spatial dependence and allows prediction uncertainty to be evaluated through cross-validation and prediction standard-error maps [20,21]. For comparison, the deterministic inverse distance weighting (IDW) method was also applied to the same $\ln(K)$ dataset. Cokriging was not used because no secondary variable with sufficient spatial coverage was available for the whole study area. The geological boundaries, terrace units, and river corridors were used to interpret the resulting K distribution, but they were not included as auxiliary variables because no consistent quantitative relationship with K was available for the entire study area. The main stages of the applied methodology are summarized in Figure 1.

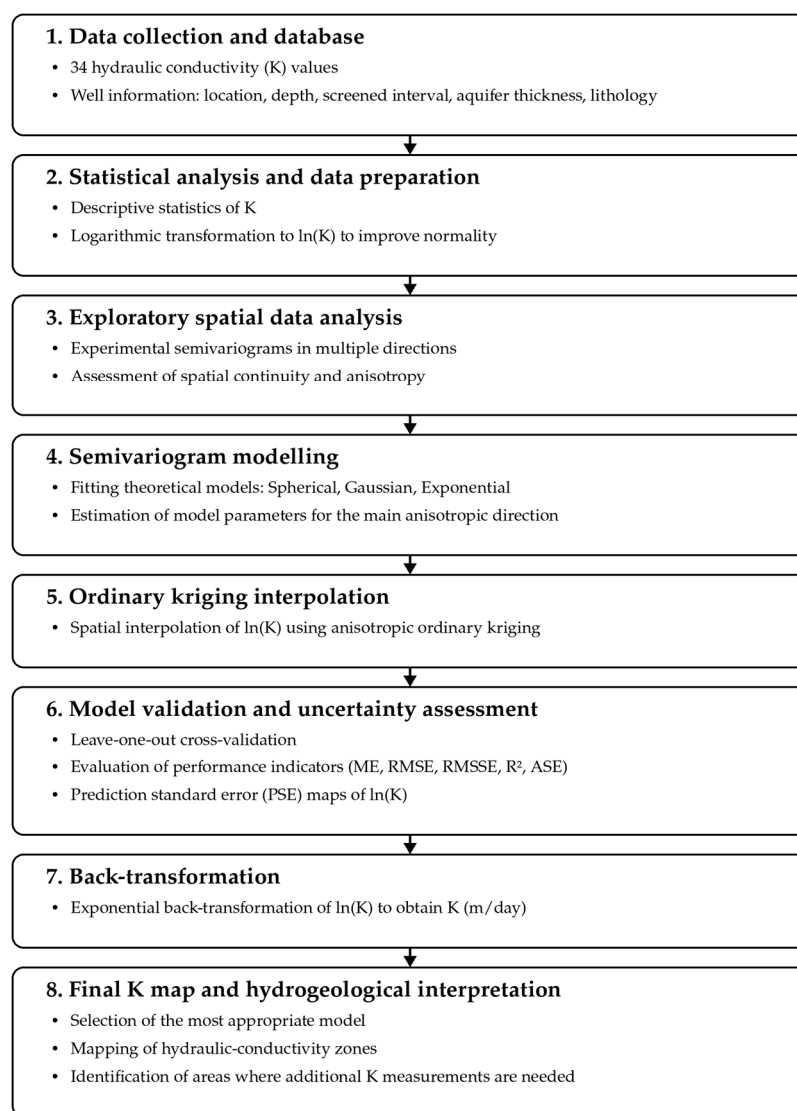


Figure 1. Flowchart of the methodology used for geostatistical mapping of hydraulic conductivity.

2.1. Study Area

This study focuses on an area located in northeastern Romania, in the eastern part of Neamţ County. The investigated area extends across the southern margin of the Fălticeni Plateau, where the Moldova River forms the western boundary and the Siret River marks the eastern limit [29]. The study region covers 180.6 km² (Figure 2). The area covers the city of Roman and the surrounding communes, extending northwards to Gherăeşti, Mirceşti, and Răchiteni. All spatial and geostatistical analyses of hydraulic conductivity (K) were performed in ArcGIS 10.8 using the Geostatistical Analyst extension, in the Romanian national projection system Stereo 70.

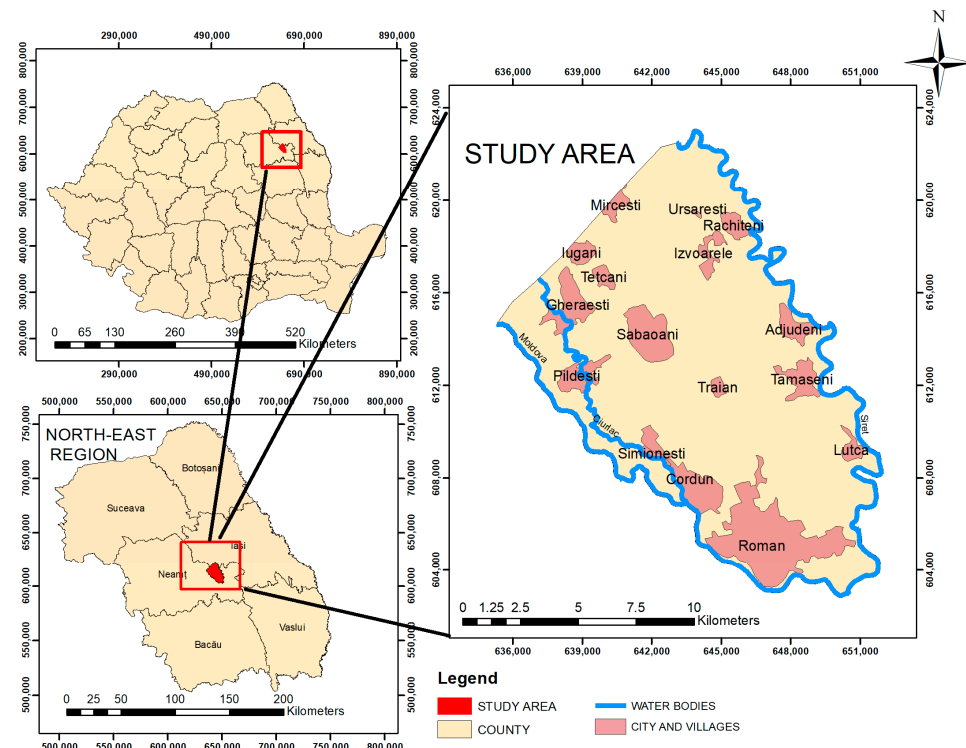


Figure 2. Study area [26].

From a geological and hydrogeological perspective, the study area lies within the Quaternary alluvial plain between the Siret and Moldova rivers, where Holocene gravel and sand deposits dominate the lower terraces, while Pleistocene deluvial–proluvial formations occur at higher elevations [26,29]. This contrast between coarse alluvial deposits and finer terrace formations provides an important context for interpreting the spatial variability of hydraulic conductivity. The screened interval of the observation wells, illustrated in Figure 3, ranges from 0.8 to 6.45 m, with an average of about 3.5 m across the study area. The minimum value, observed at borehole no. 24, occurs in the upper terrace area formed by Pleistocene deposits, where coarser layers are less continuous, whereas the maximum value, recorded at borehole no. 29 near the northern boundary, corresponds to Holocene deposits. The aquifer thickness ranges from 1.5 to 6.9 m, with an average of approximately 4.20 m. The depth of the observation wells ranges between 5 and 30 m, with the deeper ones located mainly within the Pleistocene terrace formations. Detailed construction, lithological, and hydrogeological data for the 34 observation wells are provided in Table S1.

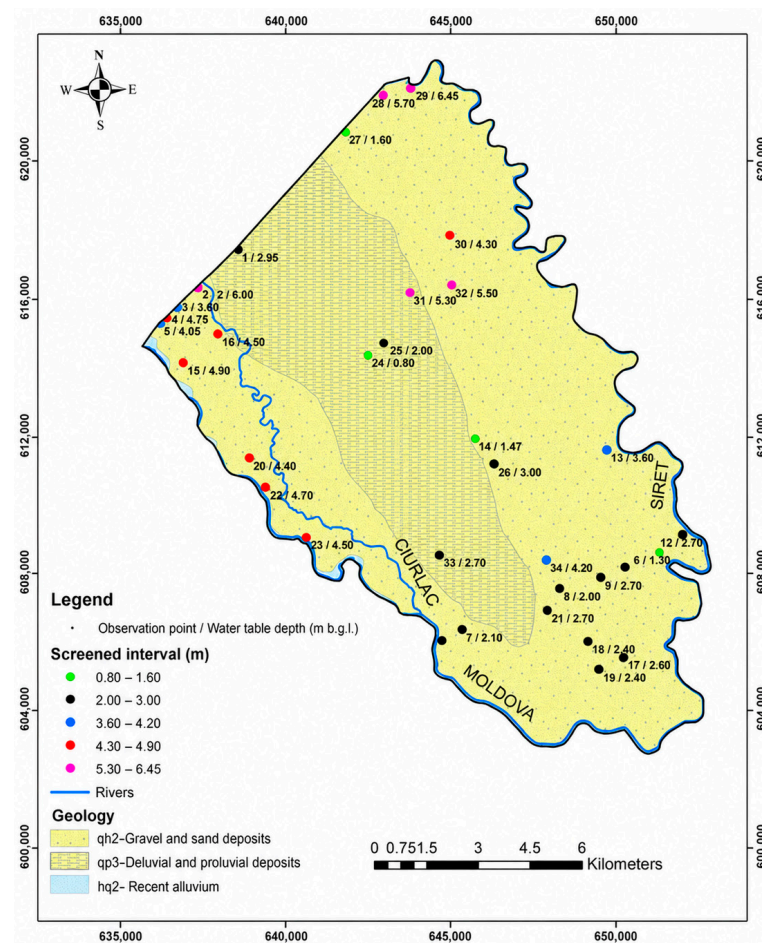


Figure 3. Geological and hydrogeological settings of the study area.

The hydraulic conductivity data were obtained from the observation points located within the study area and managed by the Siret Water Basin Administration in Bacău [30], as shown in Figure 4. The K dataset includes the final hydraulic conductivity values derived from experimental pumping tests conducted at these boreholes in one to three stages, each lasting 8 h, over an approximately five-year period, as reported in the hydrogeological documentation for these observation points. The pumping-test results were interpreted using the Dupuit equation for an unconfined aquifer, with the radius of influence estimated using the Kusakin relationship [30]. Detailed well-construction, aquifer-thickness, screened-interval, lithological, and K data are provided in Table S1. All 34 observation points were screened within the same unconfined aquifer composed of Quaternary sandy–gravel deposits. The differences in well depth and screened interval reflect local variations in aquifer geometry and lithological composition within this hydrostratigraphic unit. The values differ across the area, ranging from 9.96 to 171.73 m/day, indicating a wide range of hydraulic conductivity. In Figure 4, the observation wells are grouped according to the ranges of measured K values. The lowest K values (<20 m/day) occur mainly in the northern and central-eastern parts of the study area, where fine-grained Holocene deposits reduce permeability, while the highest values (>100 m/day) are recorded along the southern floodplain and lower terraces of the Moldova River, composed of well-sorted sandy–gravel layers that enhance groundwater flow [26,29,30].

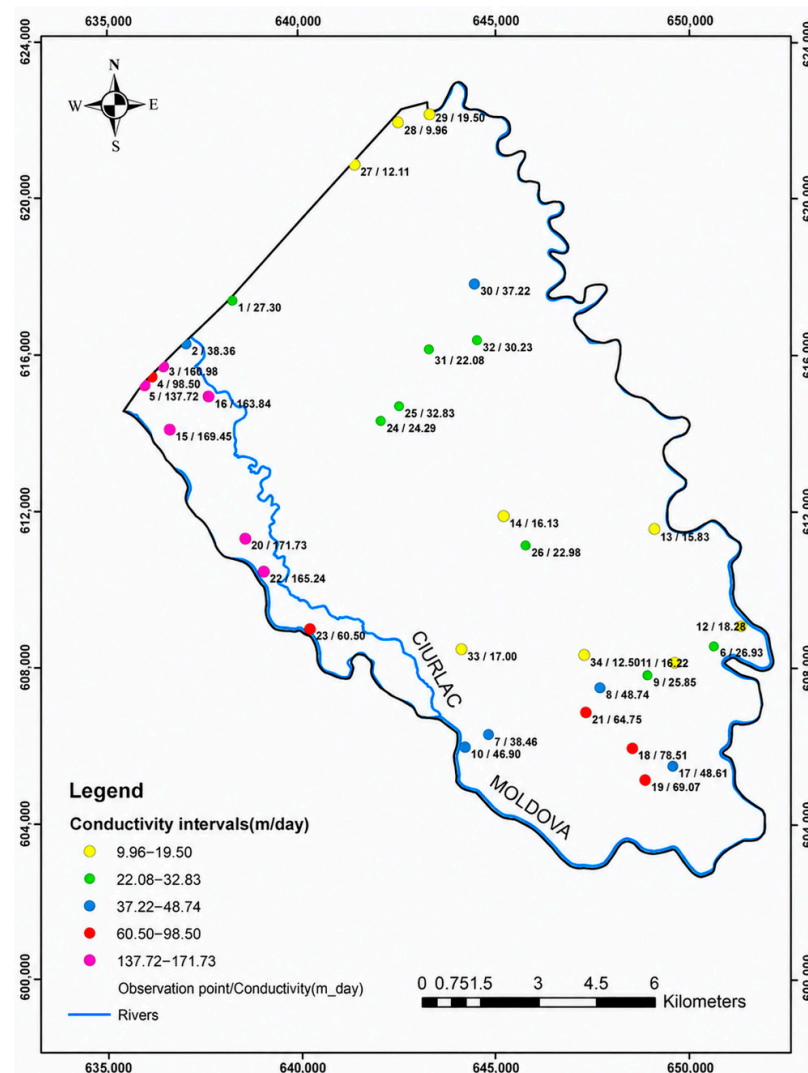


Figure 4. Hydraulic conductivity values (m/day) at observation points.

2.2. Data Analysis

The exploratory phase involved histogram inspection, trend analysis using the Trend Analysis tool, and both omnidirectional and directional semivariogram modelling. Directional semivariograms were used to identify the main anisotropy direction, which was then incorporated into the ordinary kriging models. Histograms were used to inspect skewness and guide the selection of appropriate transformation techniques [31–33]. The Trend Analysis tool was used to check for broad spatial variation in the K dataset by representing the values in three dimensions [23,32]. Their projection on the X–Z and Y–Z planes as scatter plots enabled the fitting of polynomial functions, whose shapes indicate whether significant trends are present or absent in the dataset [32,34].

Another essential step in exploratory analysis is the construction of the empirical semivariogram, which highlights the degree of spatial autocorrelation and forms the basis for geostatistical interpolation methods [21,33]. This step is important because it links spatial description with spatial prediction.

2.3. Ordinary Kriging

Ordinary kriging was used to interpolate the log-transformed K values based on the spatial structure described by the semivariogram. It assumes a constant but unknown mean across the study area and predicts each value as a weighted average of nearby observations, minimizing the estimation error [32,35,36].

In ordinary kriging, the value at an unsampled point s_0 is estimated based on a weighted average of the measured values at surrounding sampling points, as shown in Equation (1) [21,36]:

$$Z^*(s_0) = \sum_{i=1}^n \lambda_i \times Z(s_i), \quad (1)$$

where $Z(s_i)$ are the observed values at location s_i , and λ_i are the kriging weights determined from the semivariogram model.

The weights are determined from the semivariogram model and must sum to one in order to ensure unbiased predictions with minimal error [21,32].

2.4. Semivariogram Construction and Anisotropy Analysis

The semivariogram was used to quantify spatial dependence in the log-transformed K dataset by relating semivariance to lag distance and can be expressed as Equation (2) [34,36]:

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

where $\gamma(h)$ is the semivariance at distance h ; $z(x_i)$ represents the value measured at location x_i ; $N(h)$ is the number of pairs of points separated by distance h .

A semivariogram is defined by three main parameters: the range, which indicates the distance beyond which spatial correlation disappears; the sill, which corresponds to the variance where the curve levels off; and the nugget, which represents microscale variation and possible measurement errors [21,34]. The partial sill is calculated as the difference between sill and nugget. In this study, the initial semivariogram parameters were obtained using the Geostatistical Analyst tools in ArcGIS. The anisotropy direction was determined manually from the directional analysis, while the final nugget, sill, major range, minor range, and anisotropy angle were manually entered and adjusted for each theoretical model. The same $\ln(K)$ dataset and anisotropic structure were used for all models to ensure direct comparison [37–39].

An omnidirectional semivariogram was initially constructed to provide an overall assessment of spatial dependence. After anisotropy was observed, the analysis focused on directional semivariograms at 0° , 45° , 90° and 135° , followed by additional refinements using 5° and 1° angular steps. The directional semivariograms were exported from ArcGIS and plotted in Microsoft Excel for improved visualization.

2.5. Theoretical Models

The empirical semivariogram was modelled using three theoretical functions: Spherical, Gaussian, and Exponential, which are frequently applied in geostatistical analysis, because they capture different types of spatial correlations [22,34,40]. Every semivariogram model is defined by three parameters: the nugget effect γ^0 sill ($\gamma^0 + c$), and range (a), which govern fine-scale variability, total variance, and the distance of spatial dependence [20,21,41]. The equations of the three models are presented in Equations (3)–(5) [20,21]:

- Spherical model:

$$\gamma(h) = \begin{cases} \gamma^0 + c \left[\frac{3h}{2a} - \frac{1}{2} \left(\frac{h}{a} \right)^3 \right], & \text{if } h < a \\ \gamma^0 + c, & \text{if } h \geq a \end{cases}, \quad (3)$$

- Gaussian model:

$$\gamma(h) = \gamma^0 + c \left[1 - e^{-\left(\frac{h}{a}\right)^2} \right], \quad (4)$$

- Exponential model:

$$\gamma(h) = \gamma^0 + c \left[1 - e^{-\frac{h}{a}} \right], \quad (5)$$

where h is the lag distance; γ^0 is nugget effect; c is partial sill; a is range parameter.

2.6. Cross-Validation and Model Performance

To evaluate the performance of the interpolation models, several cross-validation statistics were computed: mean error (ME), root mean square error (RMSE), average standard error (ASE), mean standardized error (MStE), and root-mean-square standardized error (RMSSE), as defined in Equations (6)–(10) [32,41,42]:

$$ME = \frac{1}{n} \sum_{i=1}^n (z_i^{pred} - z_i^{obs}), \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (z_i^{pred} - z_i^{obs})^2}, \quad (7)$$

$$ASE = \frac{1}{n} \sum_{i=1}^n \sigma_i, \quad (8)$$

$$MStE = \frac{1}{n} \sum_{i=1}^n \frac{z_i^{pred} - z_i^{obs}}{\sigma_i}, \quad (9)$$

$$RMSSE = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{z_i^{pred} - z_i^{obs}}{\sigma_i} \right)^2}, \quad (10)$$

where n is the number of observation points; z_i^{pred} is the predicted value at location i ; z_i^{obs} is the observed value at location i ; σ_i is the standard error of prediction at location i .

For the theoretical models (Spherical, Gaussian, Exponential), the fitted semivariograms and their graphs were generated directly using the Geostatistical Analyst tool.

In addition, the coefficient of determination (R^2) was calculated to quantify the proportion of variance in the observed data that is explained by the interpolation results. This parameter was obtained using Microsoft Excel, providing an additional measure of model performance [21]. For comparison with ordinary kriging, the inverse distance weighting (IDW) method was also applied to the same $\ln(K)$ dataset. Power values of 1, 1.5, 2, 2.5, and 3 were tested. The same search-neighborhood configuration used for kriging was retained, with a minimum of 8 and a maximum of 15 neighbours, four sectors, a major semiaxis of 16,744 m, a minor semiaxis of 6103 m, and an angle of 166° . The final IDW model was selected based on the lowest RMSE.

The best interpolation model is expected to have: (i) ME close to zero; (ii) the smallest RMSE; (iii) higher R^2 values. For kriging models, ASE should also be close to RMSE and RMSSE close to one [32,42].

In this study, uncertainty refers specifically to spatial interpolation uncertainty and was evaluated using cross-validation statistics and prediction standard-error maps. These maps do not account for uncertainty in the original pumping-test-derived K values, which could not be quantified because homogeneous information on pumping rates, drawdown stabilization, transient or steady-state conditions, and partial penetration was not available.

After selecting the final kriging model, the predicted $\ln(K)$ values were back-transformed to the original scale using the exponential function. Under the lognormal assumption, the resulting surface represents the conditional median of hydraulic conductivity rather than its conditional arithmetic mean. Because the aim of this study was to characterize the spatial pattern of hydraulic conductivity, no bias correction based on

kriging variance was applied. The prediction standard error maps were retained on the $\ln(K)$ scale and were not back-transformed to m/day.

3. Results

3.1. Geostatistical Analysis of Hydraulic Conductivity

All 34 hydraulic conductivity (K) values were statistically analysed to assess their distribution and to determine whether data transformation was required before semivariogram modelling [20,21]. The dataset ranged from 9.96 to 171.73 m/day, with a mean of 57.55 m/day and a median of 35.03 m/day, as shown in Table 1.

Table 1. Hydraulic conductivity (K): raw and log-transformed values.

Statistical Indicator	Raw Values	Unit	Log-Transformed Values ($\ln K$) (Dimensionless)
Mean	57.55	m/day	3.68
Standard Error	9.20	m/day	0.15
Median	35.03	m/day	3.55
Standard Deviation	53.64	m/day	0.86
Sample Variance	2877.43	(m/day) ²	0.74
Kurtosis	0.33	Dimensionless	−0.91
Skewness	1.33	Dimensionless	0.42
Range	161.77	m/day	2.85
Minimum	9.96	m/day	2.30
Maximum	171.73	m/day	5.15
Count (n)	34	Observation number	34

The histogram of raw values presented in Figure 5a indicates a right-skewed distribution, with a skewness coefficient of 1.33, reflecting the effect of high K values and the heterogeneity of the dataset. Similar patterns have been reported in hydrogeological studies where high values distort the overall distribution [41,43,44]. To reduce skewness and approximate normality, a logarithmic transformation was applied. After transformation, the mean and median were 3.68 and 3.55, respectively, while the skewness coefficient decreased to 0.42, as illustrated in Figure 5b. These results indicate a more symmetrical distribution, closer to normal, which provides a stronger basis for geostatistical modelling. Logarithmic transformation is widely applied in soil and hydrogeological studies to improve data normality and reduce the influence of extreme values [44,45]. The descriptive statistics for both raw and log-transformed values are summarized in Table 1, while the comparison of distributions is illustrated in Figure 5. The histograms of K values were created directly in Microsoft Excel to improve visualization clarity.

Given the improved statistical properties, the log-transformed K values were used for constructing and calibrating the experimental semivariograms, as well as for ordinary kriging interpolation.

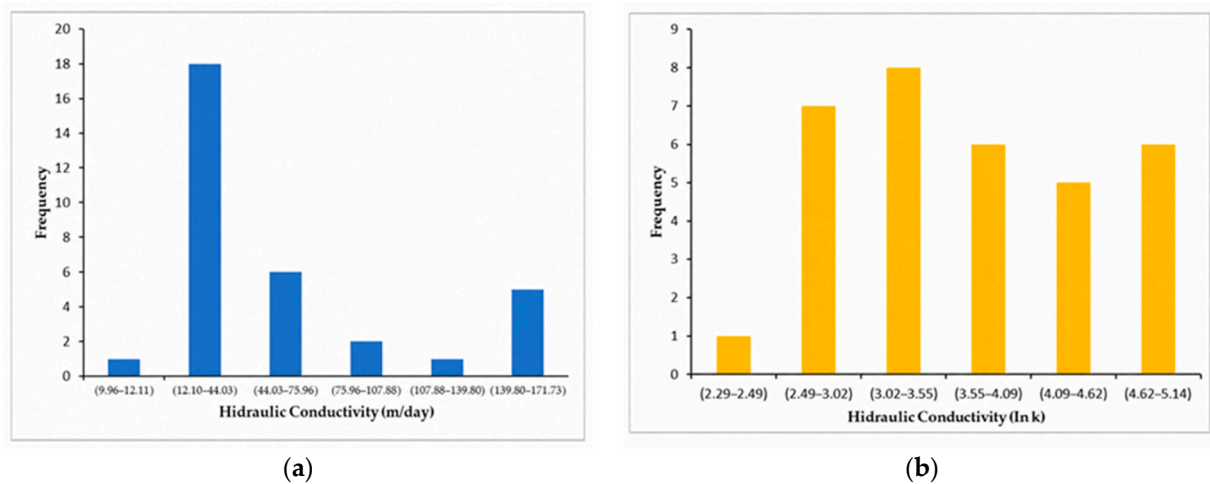


Figure 5. Frequency distribution of conductivity (K): (a) raw values (m/day); (b) log-transformed values (ln K).

3.2. Trend Analysis

Trend analysis was performed using the log-transformed $\ln(K)$ values to verify the presence of large-scale spatial variations that could influence semivariogram modelling [21,42]. This step was used as an exploratory check to identify any broad spatial gradient that could have required detrending before kriging interpolation. As shown in Figure 6, the polynomial curve in the X–Z plane (blue line) suggests a weak inverted U-shape trend, with slightly higher values in the central part and lower values at the boundaries. In the Y–Z plane (green line), the curve was almost flat, indicating no clear trend.

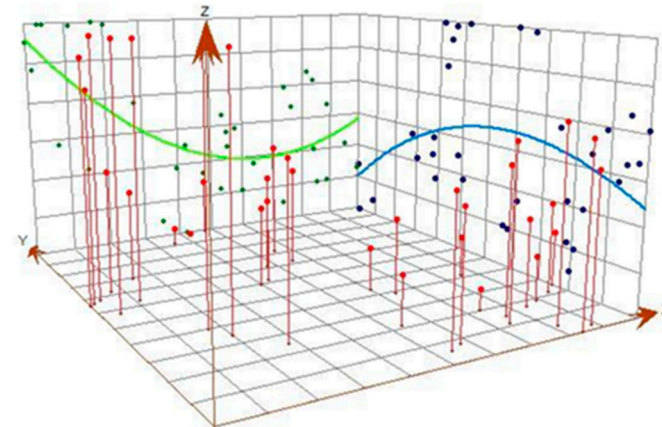


Figure 6. Trend analysis of log-transformed hydraulic conductivity, $\ln(K)$. Red points and vertical lines represent the observed values and their spatial positions; the blue and green curves represent the polynomial trends in the X–Z and Y–Z planes, respectively.

Because the dataset did not display a strong overall trend, no detrending was applied. The log-transformed values were used directly in semivariogram modelling and kriging interpolation [21,42].

3.3. Experimental Semivariograms and Anisotropy

The spatial variability analysis of the log-transformed hydraulic conductivity is an important step in characterizing this parameter within the study area. The geostatistical approach used was based on experimental semivariograms [21,43].

3.3.1. Omnidirectional Semivariogram

The omnidirectional experimental semivariogram generated in ArcGIS 10.8 (Figure 7) reveals spatial dependence through a progressive increase in semivariance with distance. This behavior indicates positive spatial autocorrelation in the log-transformed K dataset and justifies further modelling using directional semivariograms. The ‘Distance’ on the X-axis of Figure 7 refers to the Euclidean distance between sampling points in meters, scaled by 10^4 , while the Y-axis represents the semivariance of log-transformed hydraulic conductivity ($\ln(K)$) values, illustrating how variability grows with separation distance [21,34].

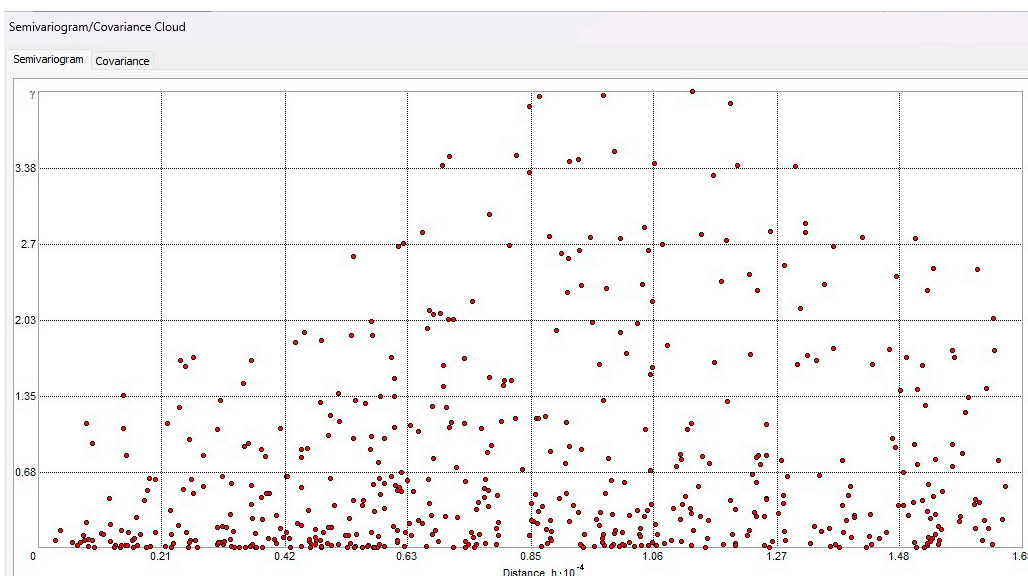


Figure 7. Omnidirectional experimental semivariogram of $\ln(K)$ automatically generated in ArcGIS 10.8.

3.3.2. Directional Semivariograms and Anisotropy Analysis

Omnidirectional semivariograms may mask directional variations—commonly encountered in aquifer systems, where sedimentary layering and groundwater flow directions introduce spatial anisotropy [21,34,46].

To investigate this, directional semivariograms were generated for key orientations: 0° , 45° , 90° , and 135° , using a lag size of 920 m, 19 lags, and an angular tolerance of $\pm 45^\circ$. The initial lag size was generated in ArcGIS Geostatistical Analyst and then adjusted to the spatial distribution of the observation points and the empirical semivariogram. The selected lag size and number of lags were kept constant for all directional comparisons. These initial orientations were used to examine directional differences in spatial continuity. The resulting anisotropy pattern was subsequently interpreted in relation to the sedimentological structure and lithological information from the boreholes.

The results of these directional semivariograms are illustrated in Figure 8a–d, which show differences in the spatial range of influence along each direction. The directional analysis was subsequently evaluated using 5° and 1° angular increments. The spatial continuity range varied from approximately 6100 m to more than 16,700 m. As shown in Table 2, the maximum range was obtained at 166° (16,744.62 m), but very similar values were obtained throughout the 165 – 170° interval. Because the $\pm 45^\circ$ angular tolerance causes substantial overlap between neighbouring directional semivariograms, these results support a broad preferred continuity sector around 165 – 170° , rather than a precisely determined anisotropy angle. The value of 166° was retained as the representative angle used in the kriging model. Figure 9 illustrates the variation of the range with directional angle.

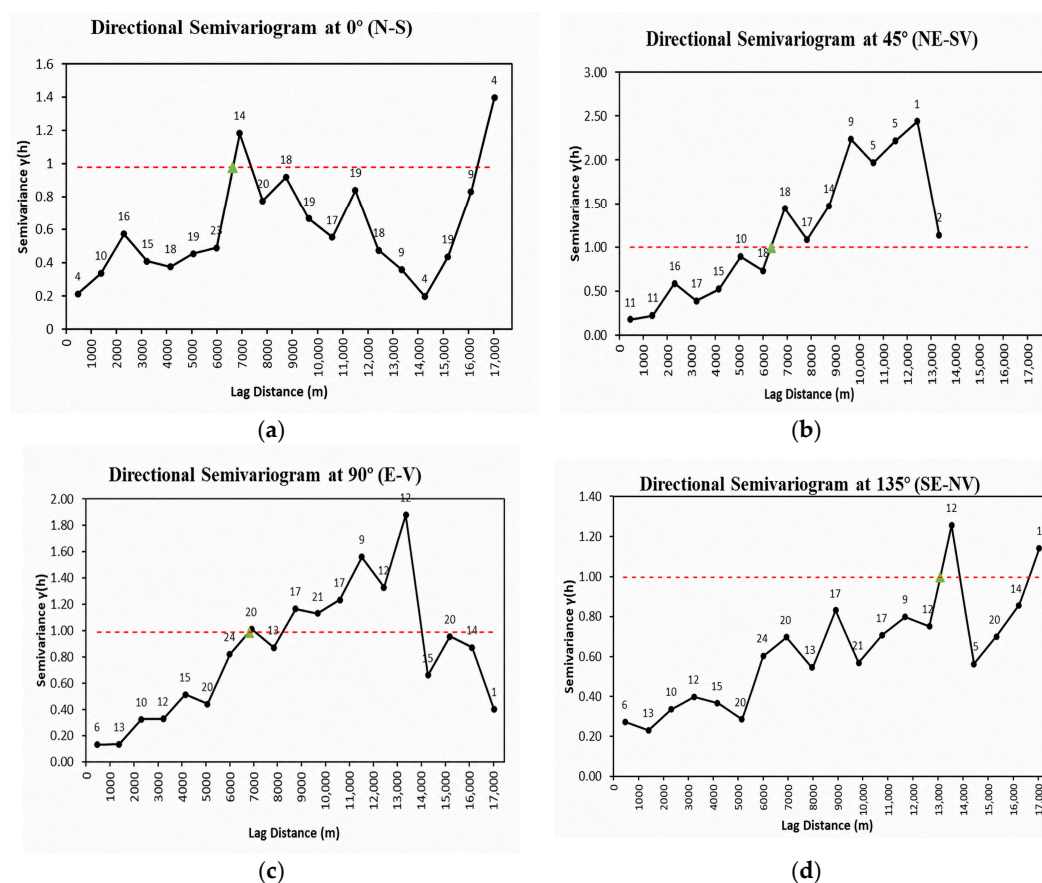


Figure 8. Directional semivariograms of log-transformed hydraulic conductivity for four orientations: (a) 0°; (b) 45°; (c) 90°; (d) 135°. The green triangle marks the range; the red dashed line represents the sill.

Table 2. Geostatistical parameters (nugget, sill, range) derived from directional semivariograms.

No.	Direction	Sill (γ)	Nugget (γ_0)	Partial Sill	Range (m)
1	0	0.978	0.247	0.731	6629
2	45	1.000	0.176	0.824	6326
3	90	0.988	0.265	0.723	6789
4	135	1.000	0.176	0.824	12,867
5	150	0.779	0.000	0.779	12,755
6	160	0.986	0.230	0.755	13,175
7	165	0.979	0.239	0.740	16,743
8	166	0.980	0.241	0.739	16,745
9	167	0.979	0.243	0.736	16,742
10	168	0.980	0.244	0.736	16,744
11	170	0.980	0.247	0.733	16,744
12	171	0.980	0.249	0.731	16,663
13	172	0.981	0.251	0.731	16,562
14	173	0.983	0.252	0.731	16,541
15	175	0.984	0.255	0.729	16,497
16	180	0.996	0.265	0.731	16,369

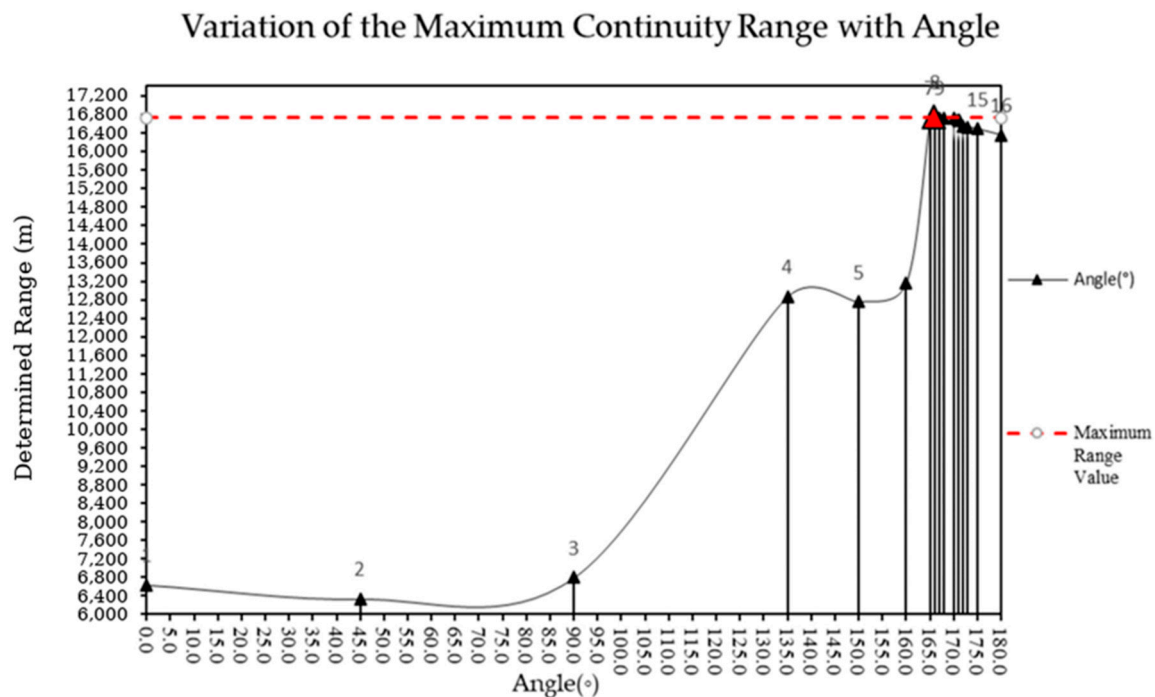
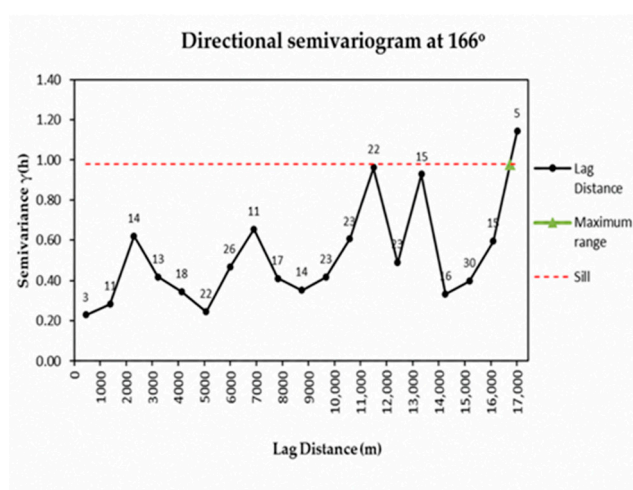
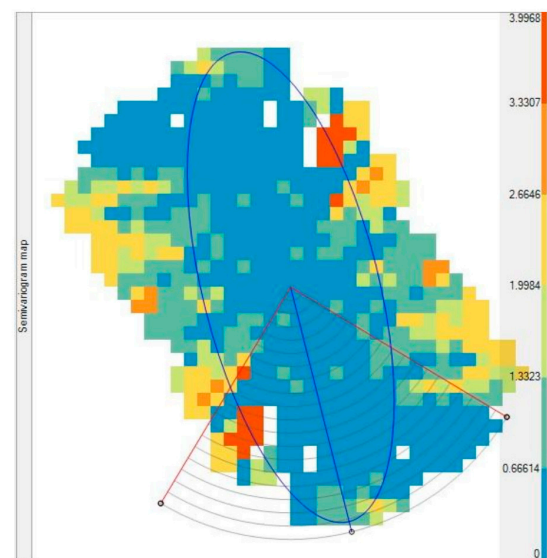


Figure 9. Variation of the maximum spatial continuity range as a function of angle. The red triangle indicates continuity range at 166°.

As shown in Figure 10, the directional semivariogram at 166°, which had the longest range within the 165–170° sector, served as the basis for theoretical modelling and kriging interpolation. The number of point pairs per lag class ranged from 3 to 30, with most classes containing more than 10 pairs, indicating that most lag classes were supported by a reasonable number of data pairs. Panel (a) shows the range obtained at 166° (~16,744 m), while panel (b) shows this anisotropic trend via the surface semivariogram map. These findings justify the use of an anisotropic kriging model, with 166° used as the representative angle.



(a)



(b)

Figure 10. Directional semivariogram and anisotropy map (166°): (a) Experimental semivariogram based on averaged lag values; (b) surface semivariogram map with anisotropy ellipse indicating maximum continuity direction.

3.4. Theoretical Semivariogram Models and Model Selection

In addition to the directional semivariograms manually derived and plotted from the experimental data, initial theoretical semivariogram models were generated in ArcGIS 10.8. Their parameters were then manually adjusted based on the experimental semivariogram and the identified anisotropic structure. The final nugget and sill values were adjusted separately for each theoretical model, whereas the major range (16,744 m), minor range (6103 m), and anisotropy angle (166°) were kept constant across the three models to allow direct comparison. The resulting models were evaluated for structural consistency and spatial fit, as shown in Figure 11a–c. The Gaussian model shows a smoother fitted structure and follows the averaged semivariogram values more closely, especially at higher lag distances, while the Spherical model offers a moderate fit and the Exponential model provides a simpler representation of the spatial structure [20,21,36].

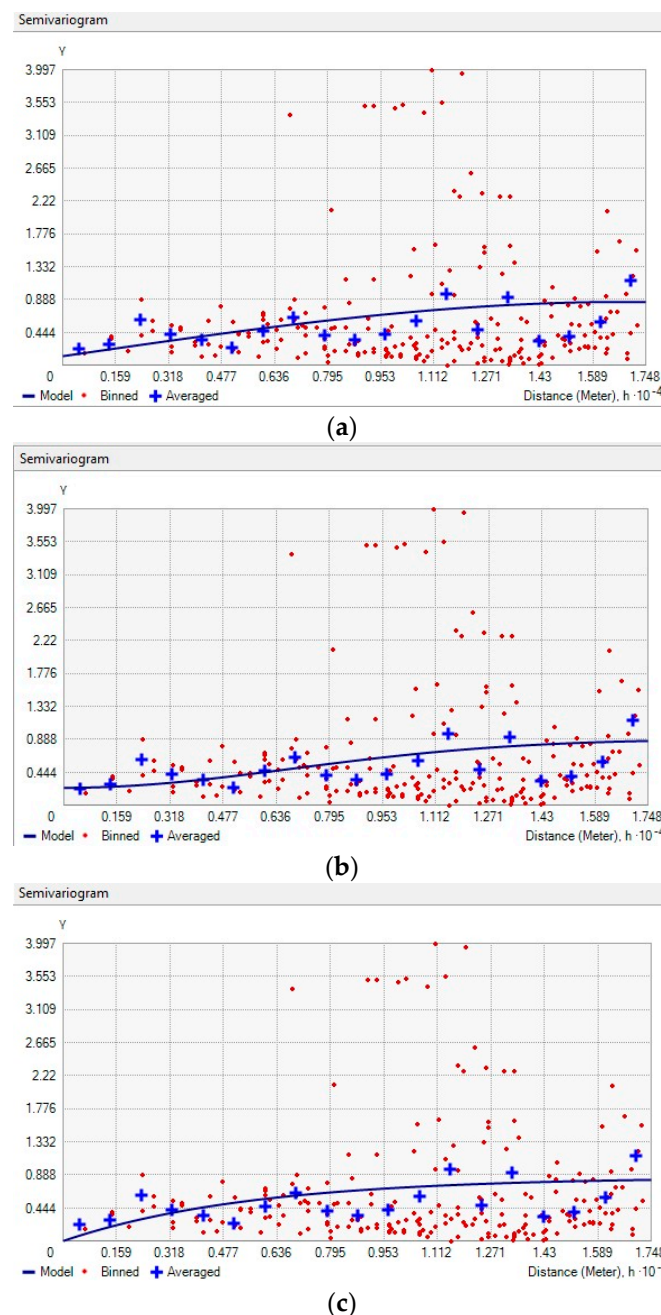


Figure 11. Modelled semivariograms: (a) Spherical; (b) Gaussian; (c) Exponential.

The fitted parameters for each theoretical model are listed in Table 3. The Gaussian model recorded the highest sill (0.907) and a nugget of 0.234, indicating a smooth spatial structure. The Spherical model had a sill of 0.860 and a lower nugget (0.122), while the Exponential model, with a sill of 0.859 and a nugget equal to 0, indicates a simplified structure that may underestimate variance at longer distances [20,21,47].

Table 3. Final parameters of the theoretical semivariogram models under the same anisotropic structure.

Model	Nugget	Partial Sill	Sill	Major Range (m)	Minor Range (m)	Anisotropy Angle (°)
Spherical	0.122	0.738	0.860	16,744	6103	166°
Gaussian	0.234	0.673	0.907	16,744	6103	166°
Exponential	0.000	0.859	0.859	16,744	6103	166°

3.5. Cross-Validation and Model Selection

To assess the predictive performance of each theoretical model, a cross-validation procedure was applied using observed versus estimated values of log-transformed hydraulic conductivity. Several statistical indicators were computed: mean error (ME), root mean square error (RMSE), average standard error (ASE), mean standardized error (MStE), root mean square standardized error (RMSSE), and the coefficient of determination (R^2), as presented in Table 4.

Table 4. Cross-validation statistics for the ordinary kriging and IDW models.

No.	Model	ME	RMSE	MStE	RMSSE	ASE	R^2
1	Spherical	0.0199	0.4886	0.0097	0.8858	0.5741	0.6689
2	Gaussian	0.0055	0.4870	−0.0024	0.8697	0.5735	0.6712
3	Exponential	0.0266	0.5011	0.0127	0.9553	0.5772	0.6522
4	IDW (Power = 2)	0.0858	0.5511	-	-	-	0.5882

MStE, RMSSE, and ASE are not applicable to IDW because this deterministic method does not provide prediction standard errors.

Table 4 summarizes the performance of the three ordinary kriging models and the IDW method. The kriging models produced relatively similar R^2 values: 0.6689, 0.6712 and 0.6522 for the Spherical, Gaussian and Exponential models, respectively. The IDW model produced a lower R^2 value of 0.5882 and a higher RMSE of 0.5511. The Gaussian model showed a slightly better combination of validation indicators, with the lowest RMSE (0.4870), ASE (0.5735), and MStE (−0.0024). The differences from the Spherical model were small, but the Gaussian model also produced a smoother spatial pattern, consistent with the gradual variation expected in the alluvial deposits. The RMSSE value of 0.8697, although slightly below 1, indicates an acceptable estimation of prediction uncertainty [32,36,47]. As shown in Figure 12, the R^2 plots support the selection of the Gaussian model, although the differences from the Spherical model remain minor. Overall, all three ordinary kriging models performed better than IDW for the analysed dataset.

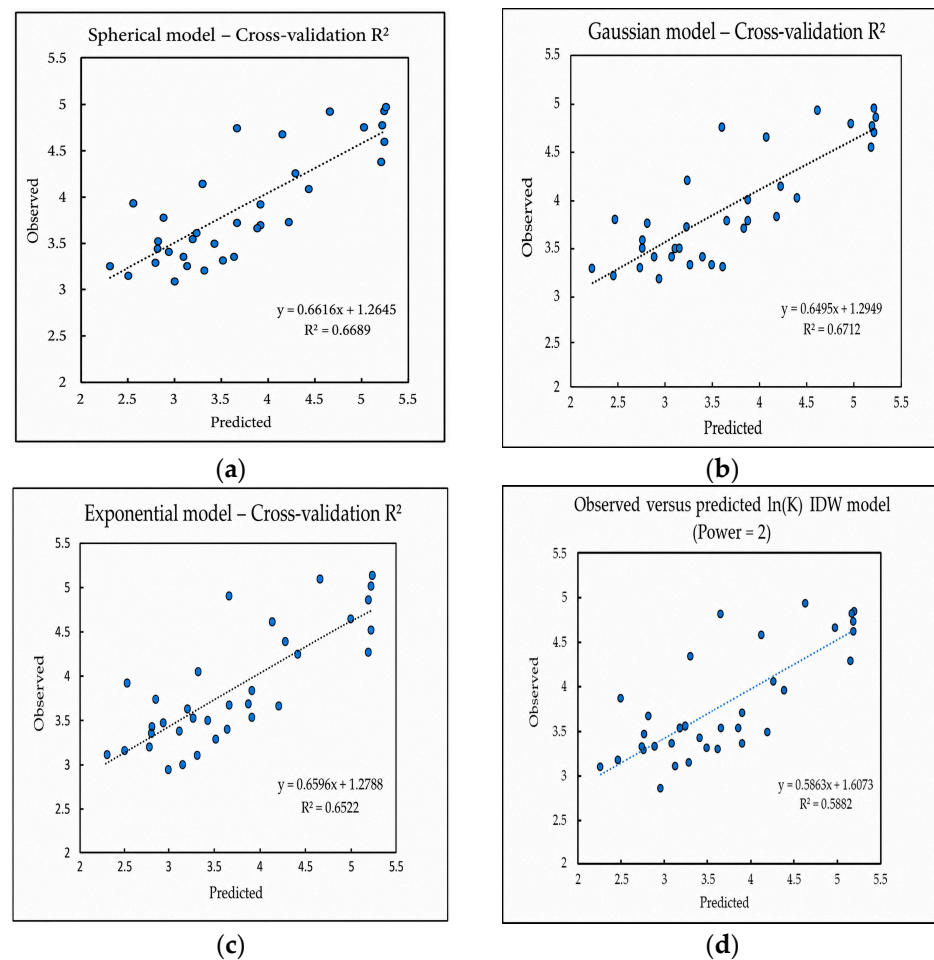


Figure 12. Observed versus predicted $\ln(K)$ values obtained by cross-validation models: (a) Spherical; (b) Gaussian; (c) Exponential; (d) IDW.

3.6. Comparison with the IDW Method

The IDW model with Power = 2 was selected because it produced the lowest RMSE among the tested power values. The resulting $\ln(K)$ map, presented in Figure 13, shows the general spatial contrast between the western and eastern sectors, but it presents stronger local effects around observation points and a less continuous spatial pattern than ordinary kriging.

3.7. Predicted Hydraulic-Conductivity Zones and Prediction Standard-Error Maps

The spatial distribution maps of predicted $\ln(K)$ and the corresponding prediction standard error maps, both expressed on the dimensionless $\ln(K)$ scale, were generated for each theoretical semivariogram model—Spherical, Gaussian, and Exponential (Figures 14–16). The maps were used to compare how each model represents the spatial variability of hydraulic conductivity and make it easier to identify the areas where predictions are less certain [21,36,48]. In this way, the predicted maps were not interpreted alone, but together with the prediction standard-error maps, in order to separate better constrained sectors from areas that require more caution.

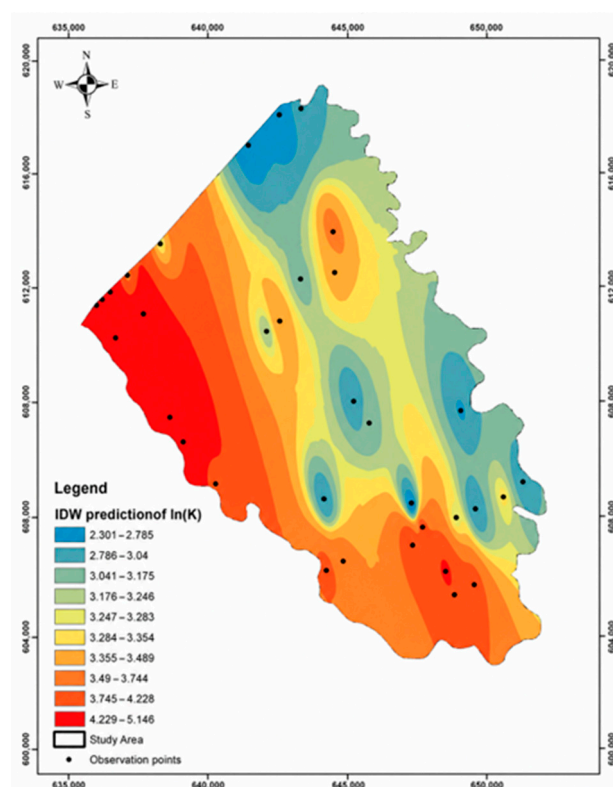


Figure 13. Spatial distribution of $\ln(K)$ obtained using the IDW method with Power = 2.

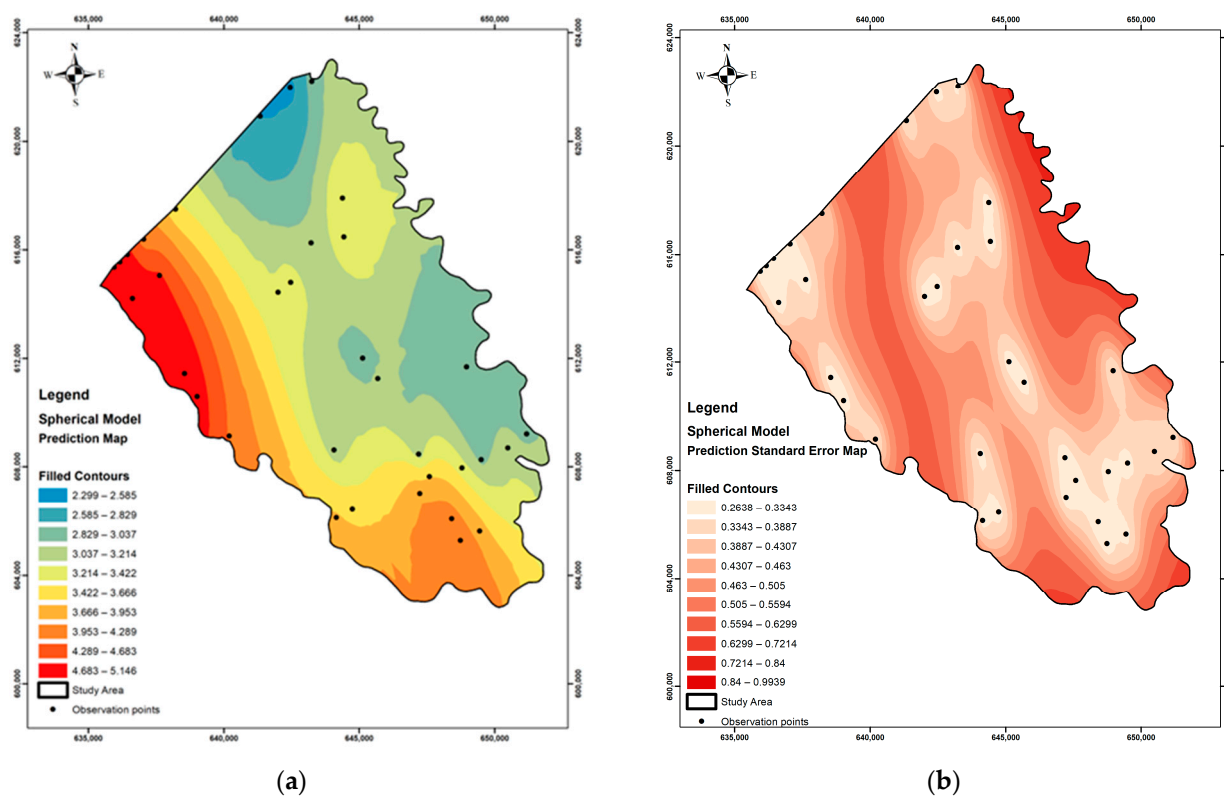


Figure 14. Spherical model output: (a) Prediction map of $\ln(K)$; (b) prediction standard-error map of $\ln(K)$.

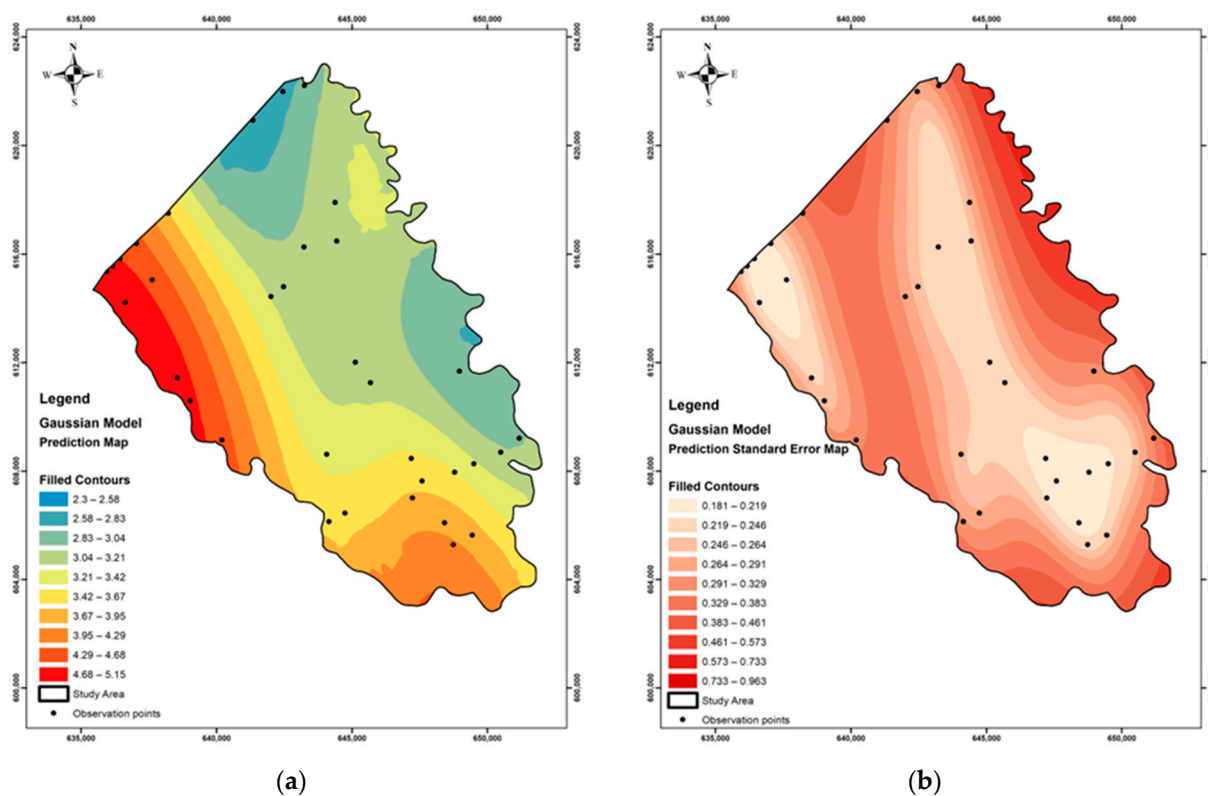


Figure 15. Gaussian model output: (a) Prediction map of $\ln(K)$; (b) prediction standard-error map of $\ln(K)$.

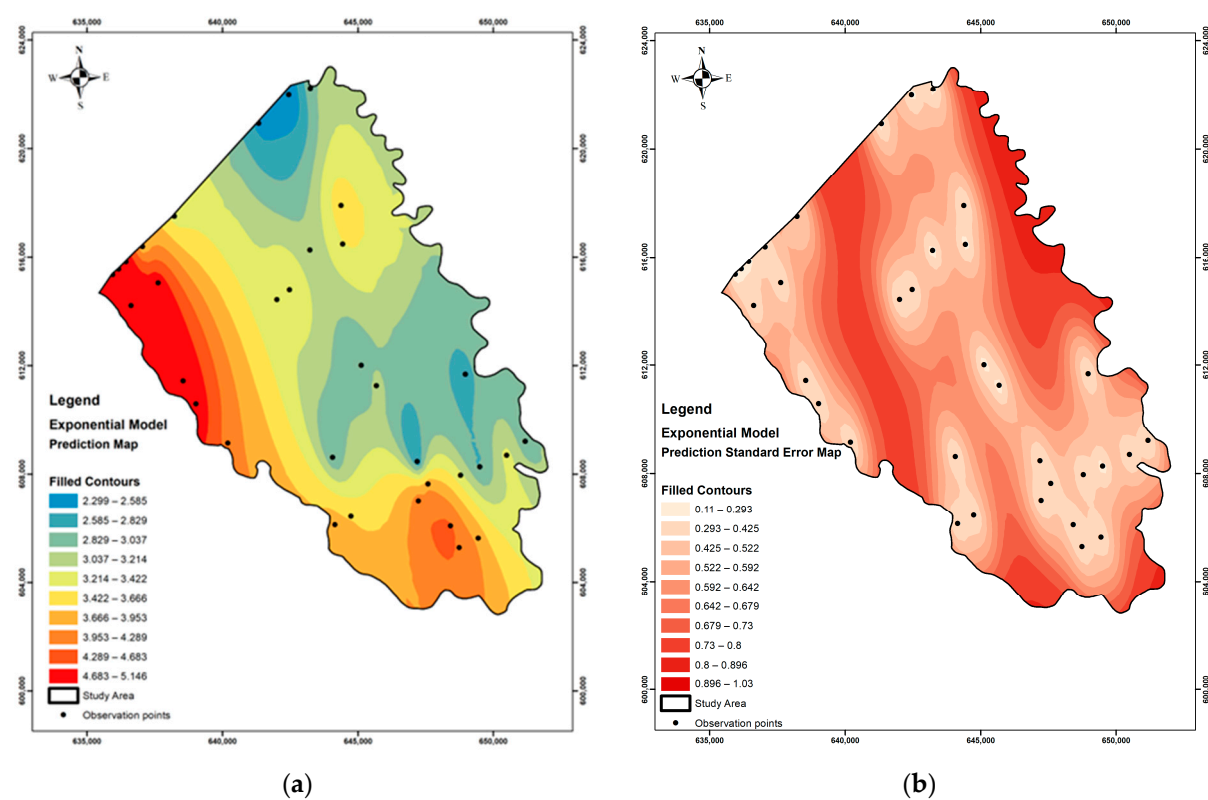


Figure 16. Exponential model output: (a) Prediction map of $\ln(K)$; (b) prediction standard-error map of $\ln(K)$.

- Spherical Model

The Spherical model provided a moderate structural fit, with clear spatial boundaries and moderate predictive performance. The interpolated map of log-transformed hydraulic conductivity (Figure 14a) shows distinct zones, with lower predicted values (2.29–2.58) located in the northern area, corresponding to lower-permeability lithologies, and higher values (4.68–5.14) found in the western sector, near the Moldova River, where coarse alluvial deposits such as gravels occur.

The associated prediction error map (Figure 14b) indicates relatively low errors (0.26–0.38) around observation points, and higher values (0.84–0.99) concentrated in the eastern part of the study area. This pattern reflects both the scarcity of data points and increased lithological variability, which likely contribute to greater model uncertainty in that region.

- Gaussian Model

Of the three kriging models tested, the Gaussian model achieved a marginally more favourable combination of validation metrics, with a reported coefficient of determination of $R^2 = 0.6712$ and the lowest RMSE (0.4870), as summarized in Table 4, although its predictive performance was comparable to that of the Spherical model. This model produced smoother and more spatially continuous predictions (Figure 15a), particularly in areas with gradual lithological variation. The associated error map (Figure 15b) revealed low error values near the observation points (0.18–0.21), while higher values (0.73–0.96) were concentrated in the eastern zone, where the lower density of control points may have increased model uncertainty. Compared to the Spherical model, the Gaussian approach showed a slight reduction in error amplitude and a more uniform spatial distribution, although the highest errors remained concentrated in the eastern sector. These findings support the use of the Gaussian model for representing gradual spatial variation in the alluvial aquifer [21,43,48].

- Exponential Model

In the Exponential model presented in Figure 16a, the log-transformed hydraulic conductivity values range between 2.29 and 2.58 in the northern area and between 4.68 and 5.14 in the west; however, compared to the other two models, the spatial distribution appears more fragmented, with values clustered around control points.

The prediction-error map, illustrated in Figure 16b, shows minimum values between 0.11 and 0.29, generally concentrated near the control points, while the maximum errors—which are higher than those in the other two models (0.89–1.03)—are observed mainly in the eastern part, but also in the central and southern areas of the study region.

Overall, the Gaussian model provided the most uniform spatial distribution and the lowest error amplitude. The Spherical model showed clearer transitions but with more abrupt variations, while the Exponential model highlighted pronounced local accumulations and produced higher maximum errors spread over a wider area. This comparison supports the selection of the Gaussian model for further analysis.

3.8. Spatial Interpolation of Hydraulic Conductivity

Based on the cross-validation metrics, prediction standard-error maps and spatial continuity analysis, the Gaussian model was selected for the final ordinary kriging interpolation of hydraulic conductivity. The predicted $\ln(K)$ values were then back-transformed to the original K scale using the exponential function, and the resulting map represents median-type hydraulic-conductivity estimates in m/day (Figure 17).

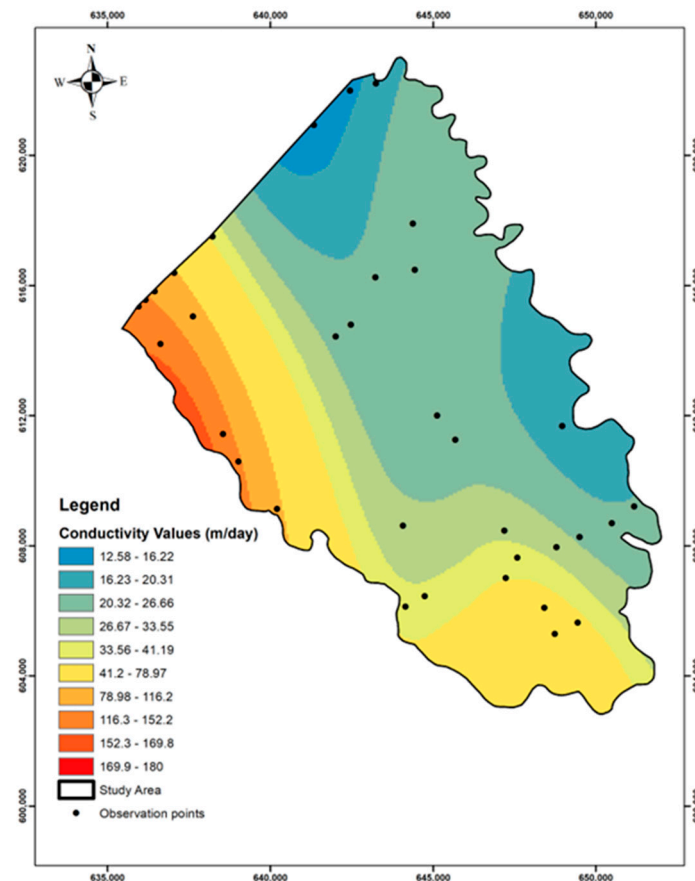


Figure 17. Spatial distribution map of hydraulic conductivity (m/day) obtained using the Gaussian model.

4. Discussion

The log-transformation reduced the influence of the highest K values on the interpolation. Directional variogram analysis showed that K is not randomly distributed but follows a preferred continuity direction within the alluvial deposits. This anisotropy agrees with the geological setting of the area, especially with the alignment of the alluvial deposits along the Moldova and Siret River corridors. The maximum fitted range was obtained at 166° , within a broad preferred continuity sector around $165\text{--}170^\circ$, with a range of 16,744 m. Directional semivariograms were therefore used in the kriging procedure, with 166° retained as the representative angle. This sector may reflect the organization of the alluvial deposits along the Moldova and Siret river corridors. With this anisotropic structure defined, the Gaussian and Spherical models showed comparable predictive performance. The Gaussian model was retained because it had a marginally lower RMSE and produced a smoother K distribution. The comparison with IDW also supports the use of ordinary kriging, which produced lower RMSE and higher R^2 values. Although the statistical difference from the Spherical model was minor, the Gaussian model represented the gradual transition between low-, medium-, and high-permeability areas more clearly. After back-transformation, the K map shows the spatial distribution of hydraulic conductivity and the main zones of contrasting permeability. The highest values, above 150 m/day, occur in the western sector, where coarse alluvial deposits associated with the Moldova River favour groundwater flow.

In the central part of the study area, away from the western high-K sector, intermediate values of 20–35 m/day are dominant. These values are associated with mixed alluvial deposits, where variations in grain size result in moderate permeability. The lowest values,

between 12 and 20 m/day, occur mainly in the northern part of the study area and are related to fine-grained, clayey sediments. Similar low-permeability conditions are also observed in the eastern meandering sector of the Siret River. These areas can therefore be interpreted as hydraulic-conductivity zones reflecting different permeability conditions. The spatial pattern obtained in this study is consistent with the lithological descriptions from the 34 boreholes summarized in Table S1 and points to a lithological control on hydraulic conductivity in the shallow alluvial aquifer. At the pore scale, gravel- and cobble-rich deposits contain larger and better-connected pore spaces, which form more continuous groundwater-flow paths and help explain the higher K values. In finer-grained deposits, smaller pores, reduced pore connectivity, and greater flow-path tortuosity restrict groundwater movement and result in lower K values. Similar effects of pore structure and porosity on permeability and hydraulic behaviour have been reported in recent studies [49,50]. The preferred continuity direction of 166° may also reflect the lateral continuity of the coarser alluvial deposits. This interpretation agrees with Gupta et al. [51], who showed that variogram analysis and kriging can be used to describe the spatial variability of hydraulic conductivity. It is also consistent with the results of Köhn et al. [52] from the Mojotoro River basin, where coarse-grained sediments and local heterogeneity influenced the kriged hydraulic-conductivity field. The K range obtained in the present study (9.96–171.73 m/day) is comparable to the values reported for this similar shallow alluvial aquifer, while its wider variability may reflect the local transition from fine-grained sediments to coarse sandy-gravel deposits. The K values were assigned to individual boreholes, while differences in screened interval and local lithological composition may also contribute to the observed variability. In the Roman-Gherăești-Mircești sector, the K map separates areas with different permeability conditions and is therefore useful for local groundwater-resource assessment. The high K values identified in the western sector, near the Moldova River, indicate zones with better groundwater-flow conditions. The associated prediction standard error maps show that the western and central sectors, where kriging standard errors are lower, are better constrained and can support a preliminary interpretation of the K distribution. The eastern sector, particularly along the Siret River, shows higher uncertainty and requires additional K measurements before detailed groundwater-flow modelling. The main limitations are related to the 34 available K values, their uneven spatial distribution, and possible methodological differences among pumping tests conducted over an approximately five-year period. The available documentation did not allow separate quantification of uncertainty in the original K estimates or of possible effects related to pumping rates, drawdown stabilization, transient or steady-state conditions, screened intervals, and partial penetration. Model performance was assessed by leave-one-out cross-validation rather than by a fully independent dataset, and no formal sensitivity analysis was performed for alternative lag sizes or angular tolerances. Accordingly, the back-transformed map represents conditional median-type estimates of the main spatial K pattern. These findings provide the first directional characterization of hydraulic conductivity for the investigated aquifer. By integrating detailed anisotropy analysis, model comparison, and prediction-error mapping, this study maps local K distributions and isolates specific sectors requiring high-priority future measurements.

5. Conclusions

Hydraulic conductivity (K) in the shallow alluvial aquifer upstream of the Siret-Moldova confluence was analysed using directional semivariograms and ordinary kriging. The K values showed an anisotropic structure, with the longest range obtained at 166° (16,744 m), suggesting a preferred continuity sector between 165° and 170° . This representative angle was included in the final kriging interpolation, indicating that K is not randomly

distributed across the aquifer, but follows, at least partly, the organisation of the alluvial deposits. The original dataset was positively skewed, mainly because of several high K values recorded in the more permeable sectors. For this reason, the data were log-transformed before variogram modelling. After transformation, skewness decreased from 1.33 to 0.42, reducing the influence of extreme values on the semivariogram and on the interpolated surface. The Gaussian and Spherical models showed comparable predictive performance, while all three ordinary kriging models performed better than IDW. The Gaussian model was retained for the final interpolation because it combined marginally lower error statistics with a smoother spatial representation, with ME = 0.0055, RMSE = 0.4870, RMSSE = 0.8697 and $R^2 = 0.6712$. The final K map shows a contrast between the western and north-eastern sectors of the study area. Values higher than 150 m/day occur near the Moldova River, where coarse alluvial deposits are present. In the northern and eastern sectors, K decreases below 20 m/day, in areas dominated by finer sediments. This spatial pattern indicates that lithology appears to exert an important control on hydraulic conductivity, while directional anisotropy reflects the continuity of the alluvial bodies.

For the Roman–Gherăești–Mircești sector, this study provides the first detailed directional map of hydraulic conductivity based on geostatistical modelling. Because the map is based on 34 K values distributed over an area of 180.6 km², the mapped zones should be regarded as a preliminary spatial characterization rather than as definitively established boundaries and can be refined as additional K data become available. By incorporating the 166° direction into the interpolation, the map represents the anisotropic structure of the alluvial aquifer more realistically. The map provides a preliminary spatial framework for hydrogeological conceptualization, identification of contrasting K zones, and planning of additional measurements, while offering an initial basis for future groundwater-flow modelling and groundwater-resource assessment. The prediction standard-error maps reflect the limited distribution of available K values, highlighting high-uncertainty sectors that require additional K data, as well as areas where the interpolation results are more reliable. The workflow can also be applied to other shallow alluvial aquifers where K data are limited and anisotropy is expected.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/w18151876/s1>. Table S1: Construction, lithological, and hydrogeological data for the 34 observation wells used in the hydraulic-conductivity analysis.

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References

1. Bear, J. *Hydraulics of Groundwater*; Courier Corporation: North Chelmsford, MA, USA, 2012.
2. Dassargues, A. *Hydrogeology: Groundwater Science and Engineering*, 1st ed.; CRC Press: Boca Raton, FL, USA, 2018. [[CrossRef](#)]
3. Domenico, P.A.; Schwartz, F.W. *Physical and Chemical Hydrogeology*, 2nd ed.; John Wiley & Sons: New York, NY, USA, 1997.
4. Fitts, C.R. *Groundwater Science*, 1st ed.; Academic Press: Cambridge, MA, USA, 2002.
5. Alley, W.M.; Reilly, T.E.; Franke, O.L. *Sustainability of Ground-Water Resources*; U.S. Geological Survey Circular 1186; U.S. Geological Survey: Reston, VA, USA, 1999. Available online: <https://pubs.usgs.gov/circ/circ1186/> (accessed on 5 October 2025).

6. Llamas, M.R.; Custodio, E. (Eds.) *Intensive Use of Groundwater: Challenges and Opportunities*; A.A. Balkema: Lisse, The Netherlands, 2001.
7. Todd, D.K.; Mays, L.W. *Groundwater Hydrology*, 3rd ed.; John Wiley & Sons: Hoboken, NJ, USA, 2005.
8. de Marsily, G. *Quantitative Hydrogeology: Groundwater Hydrology for Engineers*; Academic Press: Orlando, FL, USA, 1986.
9. Alley, W.M.; Konikow, L.F. Bringing GRACE down to Earth. *Groundwater* **2015**, *53*, 826–829. [[CrossRef](#)] [[PubMed](#)]
10. Freeze, R.A.; Cherry, J.A. *Groundwater*; Prentice-Hall: Englewood Cliffs, NJ, USA, 1979.
11. Albarrán-Ordás, A.; Zosseder, K. Estimation of 3D hydraulic conductivity fields from fictive grain-size distributions derived from 3D geological modeling. *Hydrogeol. J.* **2024**, *32*, 2121–2145. [[CrossRef](#)]
12. Sun, D.; Luo, N.; Vandenhoff, A.; McCall, W.; Zhao, Z.; Wang, C.; Rudolph, D.L.; Illman, W.A. Evaluation of hydraulic conductivity estimates from various approaches with groundwater flow models. *Groundwater* **2024**, *62*, 384–404. [[CrossRef](#)] [[PubMed](#)]
13. Cuthbert, M.O.; Gleeson, T.; Bierkens, M.F.P.; Ferguson, G.; Taylor, R.G. Defining renewable groundwater use and its relevance to sustainable groundwater management. *Water Resour. Res.* **2023**, *59*, e2022WR032831. [[CrossRef](#)]
14. Liu, S.; Zhou, Y.; Eiman, F.; McClain, M.E.; Wang, X.S. Towards sustainable groundwater development with effective measures under future climate change in Beijing Plain, China. *J. Hydrol.* **2024**, *633*, 130951. [[CrossRef](#)]
15. Quandt, A.; Larsen, A.E.; Bartel, G.; Okamura, K.; Sousa, D. Sustainable groundwater management and its implications for agricultural land repurposing. *Reg. Environ. Change* **2023**, *23*, 120. [[CrossRef](#)]
16. Elshall, A.; Arik, A.; El-Kadi, A.; Pierce, S.; Ye, M.; Burnett, K.; Wada, C.; Bremer, L.; Chun, G. Groundwater sustainability: A review of the interactions between science and policy. *Environ. Res. Lett.* **2020**, *15*, 093004. [[CrossRef](#)]
17. Bouwer, H.; Rice, R.C. A slug test for determining hydraulic conductivity of unconfined aquifers with completely or partially penetrating wells. *Water Resour. Res.* **1976**, *12*, 423–428. [[CrossRef](#)]
18. De Smedt, F. Shape factor for analysis of a slug test. *Water* **2023**, *15*, 2551. [[CrossRef](#)]
19. Hvorslev, M.J. *Time Lag and Soil Permeability in Groundwater Observations*; U.S. Army Corps of Engineers Bulletin No. 36; U.S. Army Corps of Engineers: Vicksburg, MS, USA, 1951.
20. Goovaerts, P. *Geostatistics for Natural Resources Evaluation*; Oxford University Press: New York, NY, USA, 1997.
21. Isaaks, E.H.; Srivastava, R.M. *An Introduction to Applied Geostatistics*; Oxford University Press: New York, NY, USA, 1989.
22. Rock, N.M.S. *Numerical Geology: A Source Guide, Glossary and Selective Bibliography to Geological Uses of Computers and Statistics*; Springer: Berlin/Heidelberg, Germany, 1988.
23. Esri. *ArcGIS Desktop Release 10.8.1*; Environmental Systems Research Institute: Redlands, CA, USA, 2020.
24. Gonçalves, T.d.S.; Klammler, H.; Leal, L.R.B.; de Queiroz Salles, L. Multivariate geostatistics for mapping of transmissivity and uncertainty in karst aquifers. *Water* **2024**, *16*, 2430. [[CrossRef](#)]
25. Lora-Ariza, B.; Silva Vargas, L.; Donado, L.D. Estimation of hydraulic conductivity from well logs for the parameterization of heterogeneous multilayer aquifer systems. *Water* **2025**, *17*, 2439. [[CrossRef](#)]
26. Bogdan, P.L.; Nedeff, V.; Panainte-Lehadus, M.; Chitimuș, D.; Bârsan, N.; Nedeff, F.M. Delineation of groundwater potential zones using geospatial techniques: Case study—Roman City and surrounding area, Northeastern Romania. *Water* **2024**, *16*, 3013. [[CrossRef](#)]
27. Minea, I.; Iosub, M.; Boicu, D. Groundwater resources from Eastern Romania under human and climatic pressure. *Sustainability* **2020**, *12*, 10341. [[CrossRef](#)]
28. Vasile, T.A. Analysis of the relationships between the phreatic aquifer and Natura 2000 habitats from ROSCI0224 Scroviștea. *Forum Geogr.* **2021**, *20*, 43–54. [[CrossRef](#)]
29. Posea, G. *Geomorfologia României: Relief—Tipuri, Geneză, Evoluție, Regionale*; Editura Fundației România de Măine: București, Romania, 2002.
30. Romanian Waters National Administration—Siret Water Basin Administration. *Basin Forecast Service, Hydrology, Hydrogeology—Internal Data Archive*; Romanian Waters National Administration: Bucharest, Romania, 2025.
31. Burrough, P.A.; McDonnell, R.A.; Lloyd, C.D. *Principles of Geographical Information Systems*, 3rd ed.; Oxford University Press: Oxford, UK, 2015.
32. Johnston, K.; Ver Hoef, J.M.; Krivoruchko, K.; Lucas, N. *Using ArcGIS Geostatistical Analyst*; Esri Press: Redlands, CA, USA, 2001.
33. Webster, R.; Oliver, M.A. *Geostatistics for Environmental Scientists*, 2nd ed.; John Wiley & Sons: Chichester, UK, 2007.
34. Wackernagel, H. *Multivariate Geostatistics: An Introduction with Applications*, 3rd ed.; Springer: Berlin/Heidelberg, Germany, 2003.
35. Li, J.; Heap, A.D. Spatial interpolation methods applied in the environmental sciences: A review. *Environ. Model. Softw.* **2014**, *53*, 173–189. [[CrossRef](#)]
36. Chilès, J.-P.; Delfiner, P. *Geostatistics: Modeling Spatial Uncertainty*, 2nd ed.; John Wiley & Sons: Hoboken, NJ, USA, 2012.
37. Biernacik, P.; Kazimierski, W.; Włodarczyk-Sielicka, M. Comparative analysis of selected geostatistical methods for bottom surface modeling. *Sensors* **2023**, *23*, 3941. [[CrossRef](#)] [[PubMed](#)]
38. Kumar, V.; Remadevi, V. Kriging of groundwater levels—A case study. *J. Spat. Hydrol.* **2006**, *6*, 81–100.

39. Delbari, M.; Afrasiab, P.; Gharabaghi, B.; Amiri, M.; Salehian, A. Spatial variability analysis and mapping of soil physical and chemical attributes in a salt-affected soil. *Arab. J. Geosci.* **2019**, *12*, 68. [CrossRef]
40. Ramachandran, J.; Lalitha, R.; Kannan, S.V.; Sivasubramanian, K. Geo-statistical assessment of spatial variability of soil water-holding capacity for optimal irrigation under semi-arid vertisols in South India. *J. Agric. Ecol.* **2024**, *19*, 103–119. [CrossRef]
41. Ahmed, S.; de Marsily, G. Comparison of geostatistical methods for estimating transmissivity using data on transmissivity and specific capacity. *Water Resour. Res.* **1987**, *23*, 1717–1737. [CrossRef]
42. Journel, A.G.; Huijbregts, C.J. *Mining Geostatistics*; Academic Press: London, UK, 1978.
43. Bissell, E.; Aichele, S.S. *Geostatistical Analysis of Effective Vertical Hydraulic Conductivity and Presence of Confining Layers in the Shallow Glacial Drift Aquifer, Oakland County, Michigan*; U.S. Geological Survey Scientific Investigations Report 2004-5167; U.S. Geological Survey: Reston, VA, USA, 2004. Available online: <https://pubs.usgs.gov/sir/2004/5167/> (accessed on 6 October 2025).
44. Patriarche, D.; Castro, M.C.; Goovaerts, P. Estimating regional hydraulic conductivity fields—A comparative study of geostatistical methods. *Math. Geol.* **2005**, *37*, 587–613. [CrossRef]
45. Vasile, T. Statistical processing of geological data for the ROIL16 groundwater body. In *Proceedings of the 19th International Multidisciplinary Scientific GeoConference SGEM 2019, Albena, Bulgaria, 30 June–6 July 2019*; STEF92 Technology: Sofia, Bulgaria, 2019; Volume 19, pp. 493–500. [CrossRef]
46. Kitanidis, P.K. *Introduction to Geostatistics: Applications in Hydrogeology*; Cambridge University Press: Cambridge, UK, 1997.
47. Yamamoto, J.K.; Landim, P.M.B. *Geostatística: Conceitos e Aplicações*; Oficina de Textos: São Paulo, Brazil, 2013.
48. Rubin, Y. *Applied Stochastic Hydrogeology*; Oxford University Press: New York, NY, USA, 2003.
49. Luo, Y.; Wen, T.; Lin, X.; Chen, X.; Shao, L. Quantitative analysis of pore-size influence on granite residual soil permeability using CT scanning. *J. Hydrol.* **2024**, *645*, 132133. [CrossRef]
50. Wen, T.; Song, Z.; Chen, Z. Hydro-thermal behavior of biochar-amended and saline granite residual soils under high compaction. *Acta Geotech.* **2026**. [CrossRef]
51. Gupta, N.; Rudra, R.P.; Parkin, G. Analysis of spatial variability of hydraulic conductivity at field scale. *Can. Biosyst. Eng.* **2006**, *48*, 1.55–1.62.
52. Köhn, J.; Kruse, E.E.; Santos, J.E. Hydrogeologic behavior of an alluvial aquifer, Salta Province, Argentina: Simulations of hydraulic conductivity field, groundwater flow, and chloride migration. *Nat. Resour. Res.* **2002**, *11*, 157–166. [CrossRef]

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