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Research Article

Simulation of the Spatial Distribution of Hydraulic Conductivity in Porous Media through Different Methods

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Seepage problems exist in water conservancy projects, groundwater research, and geological research, and hydraulic conductivity is an important factor that affects the seepage field. This study investigates the heterogeneity of hydraulic conductivity. Kriging methods are used to simulate the spatial distribution of hydraulic conductivity, and the application of resistivity and grain size is used to obtain hydraulic conductivity. The results agree with the experimental pumping test results, which prove that the distribution of hydraulic conductivity can be obtained economically and efficiently and in a complex and wide area.

1. Introduction

Access to clean water resources is a current global problem. Emerging hydrogeology research on groundwater movement and the identification and management of naturally renewable groundwater resources seek to address these critical challenges [1, 2]. Hydraulic conductivity directly influences the interactions between river water and the surrounding groundwater, aquifers, and the exploitation capacity of river water sources. Seepage deformation, hill creep, dam failure, and ground subsidence caused by groundwater exploitation are common effects of seepage flow. Therefore, the law of seepage field distribution should be mastered. The mathematical determination of the actual seepage field is restricted by the uncertainty in the seepage parameters, initial conditions, and boundary conditions [3, 4]. The uncertainty of seepage parameters is mainly due to hydraulic conductivity; thus, the exact hydraulic conductivity distribution should be obtained.

Hydraulic conductivity is a key factor that characterizes the quality of an aquifer. Currently, hydraulic conductivity is mainly determined through field tests and numerical simulations. Meyboom calculated the hydraulic conductivity of the Milk River in Canada through a pumping test. Geostatistical methods, such as Kriging interpolation, sequential indicator simulations, sequential simulations, and sequential Gauss simulations, are widely utilized in various applications. Shi et al. used these methods to generate a random seepage field [5–7]. Xi et al. obtained the spatial distribution of saturated hydraulic conductivity in the lower reaches of the Heihe River through a geostatistical method [8]. Liu et al. used different geostatistical methods to determine the hydraulic conductivity of the Massachusetts Military Reservation (MMR) in Falmouth, Cape Cod [9]. Chandra studied the relationship between resistivity and hydraulic conductivity in India's Mahabharata aquifer by adopting electrical prospecting technology. Yu and Wu used electrical resistivity tomography (ERT) data to obtain the heterogeneous distribution of hydraulic conductivity in porous media [10]. In addition, Perdomo et al. compared the results of pumping test data by combining electric well logging and vertical electrical sounding, respectively [11].

The relationship between particle size distribution and hydraulic conductivity has been widely studied, and many empirical and semiempirical formulas have been proposed. Vienken and Dietrich performed a comparative analysis to identify the application conditions of seven formulas [12]. Rogiers et al. used particle size distribution to estimate hydraulic conductivity through artificial neural networks and estimated the uncertainty [13]. The distribution of hydraulic conductivity can also be obtained by these methods.

The spatial distribution of hydraulic conductivity plays a fundamental role in the environmental assessment, evaluation of water resources, and groundwater pollutant purification. It provides real seepage characteristics of groundwater movement and solute transport [14, 15], as well as approximate aquifer models. Such models that closely resemble their real counterparts require numerical analyses. The heterogeneity of hydraulic conductivity can objectively reflect the inherent fluctuation of water potential in the material distribution field and appear to avoid aquitards and strengthen the permeable layer [3, 4]. This provides the basis for engineering design and stability analysis. Geological disasters, such as hill creep and ground subsidence, are caused by heterogeneity, which is significant for the prediction and prevention of geological disasters.

Pumping tests are expensive and complex to operate so we should obtain hydraulic conductivity from other resources. The strong relationship between hydraulic conductivity, particle size, and resistivity has been widely studied. The method of acquiring resistivity and particle size data is relatively simple, and the data involved are mass. The Kriging method is a classical algorithm for calculating the distribution of hydraulic conductivity.

In this article, we used the Kriging method to interpolate the pumping test data. The hydraulic conductivity was subsequently calculated by resistivity and particle size distributions, respectively. We then used the Kriging method to interpolate the hydraulic conductivity values again. The results of the hydraulic conductivity were then analyzed and discussed.

2. Interpolation Method

The interpolation method is mainly based on Kriging of geostatistics, which uses regionalized variables. The variogram is a basic tool in geostatistics that is used to study stochastic and structural variables. The spatial distribution pattern and its correlation are determined by analyzing a large number of sample attribute values. The sample value, location of the sample, and distance between samples are considered. The interpolation of hydraulic conductivity is used in Kriging geostatistical software to obtain an optimal, unbiased interpolation of spatial data. This method can calculate the estimated value and estimation accuracy. Geostatistical software, such as GS+, GSLIB, ArcGIS, and Stanford Geostatistical Modeling Software (SGEMS), can be used to obtain the distribution of hydraulic conductivity.

2.1. Ordinary Kriging Algorithm. The observation point is $x_1, x_2, \ldots, x_n$; the computed point is x; observed data are $z(x_1), z(x_2), \ldots, z(x_n)$; and computed data are $z^*(x)$. Computed data are represented by linear combinations of observed data (see (1)).

$$z^*(x) = \sum_{i=1}^{n} \lambda_i z(x_i), \tag{1}$$

where weight is used to express the estimated points according to the measured data. Weights are calculated with two conditions. Kriging is an unbiased optimal estimation method. The mathematical expectation of the deviation between the observation point and the calculated point is 0 (see (2)). Optimality is the sum of squares of the difference between the two (see (4)).

One condition is unbiased as follows:

$$E\left[z^*(x) - z(x)\right] = 0. \tag{2}$$

Substituting (1) into (2) yields

$$E\left[\sum_{i=1}^{n} \lambda_i z(x_i) - z(x)\right] = 0. \tag{3}$$

We obtain $\sum_{i=1}^{n} \lambda_i = 1$.

The second condition is the optimal estimated variance as follows:

$$\delta^2 = E\left[z^*(x) - z(x)\right]^2 \longrightarrow \min. \tag{4}$$

Equation (5) can be obtained from making a complex deduction of (4), where $c(x_i, x_j)$ is the covariance of the study area.

$$\delta^2 = \sigma^2 + \sum_{i=1}^{n}\sum_{j=1}^{n} \lambda_i \lambda_j c(x_i, x_j) - 2\sum_{i=1}^{n} \lambda_i c(x_i, x). \tag{5}$$

δ^2 is the minimum variance and is combined with $\sum_{i=1}^{n} \lambda_i = 1$ using Lagrangian principles to obtain

$$F = \delta^2 - 2\mu\left(\sum_{i=1}^{n} \lambda_i - 1\right). \tag{6}$$

Equation (6) can be used to solve the $\lambda\mu$ partial derivative to arrive at $n+1$ linear equations. These equations are solved by obtaining the weights. By substituting the weights into (1), we can calculate the estimated value of hydraulic conductivity.

2.2. Engineering Case. The selected area is a fine plain stream segment of the lower reaches of the Golmud River where the difference in grain size is very small. The location is a continuous and slightly heterogeneous formation that covers a $14 \times 30\,\mathrm{m}^2$ area. The purpose of this case is to study the variation of the hydraulic conductivity of the riverbed. Three rows of boreholes with a row spacing of 7 m and borehole spacing of 2 m in a row were set up. The distribution of the drill holes is shown in Figure 1. From top to bottom, the first row is the center of the riverbed, the second row is the riverbed, and the third row is the riverbank.

A total of 48 observational data sets were obtained. Based on statistical analysis, the frequency distribution histogram of hydraulic conductivity is shown in Figure 2.

As shown in Figure 2, the 48 data sets roughly conform to the normal distribution.

The variogram model includes exponential, spherical, and Gaussian models. A comparative analysis of these models reveals that the most appropriate model, GS+, can automatically fit the variogram. An accurate variogram is determined to form an exact interpolation; however, the interpolation effect of GS+ is not ideal. Nevertheless, GS+ fits the

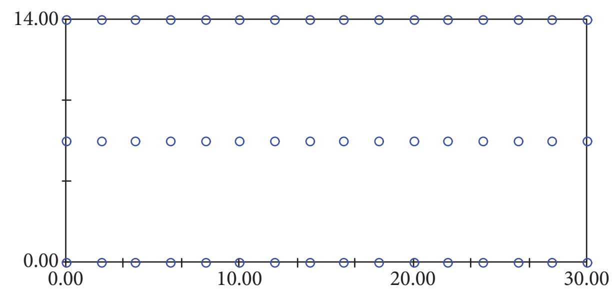

Figure 1: Distribution of drill holes.

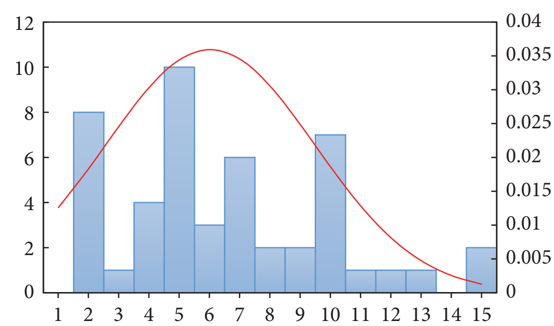

Figure 2: Frequency distribution histogram of hydraulic conductivity.

variogram, and SGEMS interpolates hydraulic conductivity. As the extension of GSLIB, SGEMS can be used to effectively describe the heterogeneity [16, 17]. Figures 3–5 show three types of function models. Table 1 presents the basic information of these models.

According to the distribution of hydraulic conductivity, the resolution from the Gaussian model is the highest, and the estimated value is close to the actual value. A comprehensive comparison shows that the Gaussian model is the most suitable for interpolation in this region. The distribution of the hydraulic conductivity of the Gaussian model is shown in Figure 6.

As range (A) increases, the estimation value becomes stable. As the range decreases, the interpolation is reflected in the small domain with a relatively large fluctuation. As shown in Figure 6, the heterogeneity of the hydraulic conductivity is relatively low. This result is due to the difference in particle size since the particle size of the fine-grain plain riverbed sediment is low and thus not highly heterogeneous. The hydraulic conductivity increases gradually from the bank to the center of the riverbed. The range of hydraulic conductivity is 0.46–17.23 m/d in the riverbank, 7.46–38.29 m/d in the riverbed, and 10.33–43.28 m/d in the center of the riverbed. Given the high velocity of the riverbed center, small particles are deposited by the water leaving with large particles, and the flow rate of the riverbank is low with the easy deposition of silt.

The above example shows that the interpolation results coincide with the measured results; however, direct data (e.g., pumping tests or slug tests) found that the cost is relatively large and not suitable for wide regions. Thus, we can obtain hydraulic conductivity from other resources. The following is the application of resistivity and grain size to get hydraulic conductivity, respectively.

3. Using the Geoelectrical Method to Obtain Hydraulic Conductivity

Resistivity was measured through vertical electrical sounding, electrical profiling, or electrical resistivity tomography to determine its relationship with hydraulic conductivity, as described by Archie and Kozeny-Carman laws. The geoelectrical method is to use resistivity to calculate hydraulic conductivity by combining Archie and Kozeny-Carman laws. The method of determining a and m values is different in the Archie law. The determination of a and m depends on laboratory tests or appropriate values from the literature. Some people propose that a is close to 1 and the value of m is shown in Table 2 [18]. The distribution of the hydraulic conductivity of the porous aquifer in the Anthemountas basin with known partial hydraulic conductivity data was studied. With known data on the Anthemountas basin, we selected the optimal a and m values through regression analysis [19].

3.1. Geoelectrical Algorithm. According to Archie law, the relationship between resistivity and porosity is expressed as

$$\rho_0 = a\rho_w\varphi^{-m}, \tag{7}$$

where ρ_0 and ρ_w are the bulk electrical resistivity and fluid electrical resistivity, respectively (ohm-m), φ is the porosity of the medium, and a and m are the values associated with the medium.

The Archie law was proposed to solve the problems of sandstone with clean, clay-free consolidated sediments. It

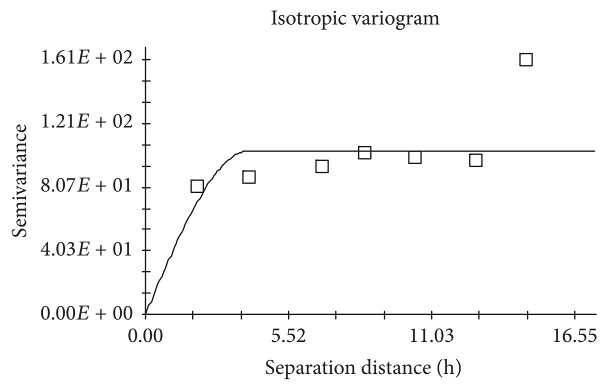

Figure 3: Variogram of the spherical model. Spherical model ($C0 = 0.00000$; $C0 + C = 104.00000$; $A0 = 4.00$; $r2 = 0.133$; RSS = 3832).

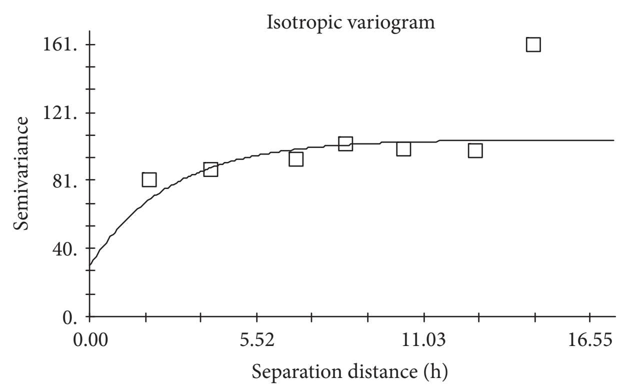

Figure 4: Variogram of the exponential model. Exponential model ($C0 = 30.00000$; $C0 + C = 105.00000$; $A0 = 2.67$; $r2 = 0.283$; RSS = 3442).

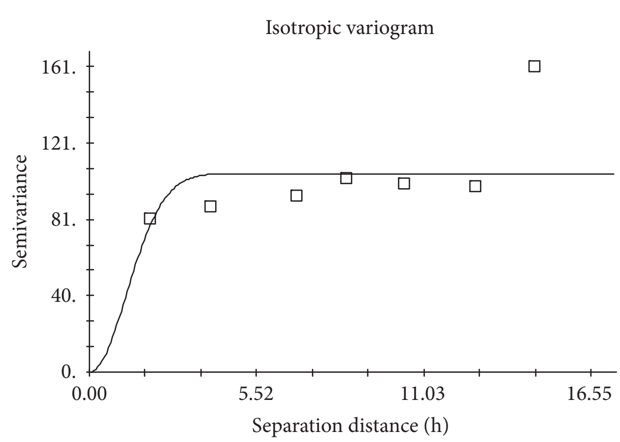

Figure 5: Variogram of the Gaussian model. Gaussian model ($C0 = 0.00000$; $C0 + C = 105.00000$; $A0 = 1.73$; $r2 = 0.137$; RSS = 3702).

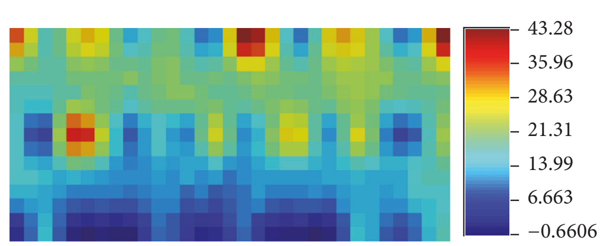

Figure 6: Distribution of hydraulic conductivity of the Gaussian model.

Table 1: Variogram model information.

	$C0$	$C + C0$	A	Cross-validation		
				Regression coefficient	SE	SE predicted value
Spherical model	0	104	4	0.740	0.232	10.04
Exponential model	30	105	8	0.714	0.242	10.16
Gaussian model	0	105	3	0.806	0.252	10.04

Notes. SE is the standard error of the regression coefficient, and SE predicted value is the standard error prediction.

Table 2: Values of m.

Formation type	m value
Unconsolidated sand	1.3
Very slightly cemented sandstone	1.4–1.5
Slightly cemented sandstone	1.5–1.7
Moderately cemented sandstone	1.8–1.9
Highly cemented sandstone	2.0–2.2

only applies to sandstone and clay contents that are less than 5% of the geosphere. Formula (8) is used to obtain the clay content and prove that the formula is applicable for the soil in the study area:

$$V \leq V_C = \frac{(\mathrm{GR} - \mathrm{GR}_{\min})}{(\mathrm{GR}_{\max} - \mathrm{GR}_{\min})}, \tag{8}$$

where V_C is the upper limit of clay content. GR can be used to measure clay content.

If the clay content exceeds the standard, this condition can lead to inaccurate solutions. Improving the accuracy of solutions requires a slight modification of the Archie law. The modified Archie law is $F_c = a\varphi^{-m}$. F_c is the apparent formation factor. The relationship between F_a and F_c is

$$\frac{\rho_0}{\rho_w} = F_c \left(1 + BQ_V \rho_W\right)^{-1}, \tag{9}$$

where BQ_V is related to the effects of surface conduction, mainly due to clay particles. However, obtaining BQ_V is still difficult.

Resistivity is used to deduce porosity from (7). The obtained porosity is then substituted into the Kozeny-Carman law to solve the hydraulic conductivity.

Kozeny-Carman is a common formula to express the relationship between hydraulic conductivity and porosity. Kozeny-Carman law is expressed in (10) as

$$k = \frac{\delta_w g d^2 \varphi^3}{180\mu (1 - \varphi^2)}, \tag{10}$$

where k is the hydraulic conductivity, δ_w is the water density (1,000 kg/m^3), g is the acceleration due to gravity (9.81 m/s^2), μ is the dynamic viscosity of water, and d is the grain size.

3.2. Method Application. $a = 1.0$, and $m = 1.65$. ρ and ρ_w are measured. The hydraulic conductivity was obtained using (1) and (2). Figure 7 is a comparison of experimental and calculated hydraulic conductivity values from pumping tests and resistivity. Kriging is used to interpolate the hydraulic conductivity. The results are shown in Figure 8.

Figure 8 shows that resistivity can be used to obtain the distribution of hydraulic conductivity. Compared with other field measurements, resistivity measurements save time and cost and are applicable to a larger area. They are also suitable for complex and contaminated geospheres. However, there will also be errors due to the determination of a and m.

4. Using Grain Size Distribution to Obtain Hydraulic Conductivity

The relationship between grain gradation and hydraulic conductivity is established through an artificial neural network (ANN) to deal with highly heterogeneous problems when samples are typical and numerous. Research on ANNs has made significant progress. In pattern recognition, intelligent robotics, automatic control, predictive estimation, biology, medicine, economics, and other fields, ANNs have successfully solved practical problems that many modern computers cannot easily solve. These characteristics indicate the intelligence of this method. The BP algorithm is one of the most widely used neural network algorithms. We regard the complete granularity component data and the number of hidden layer nodes as input parameters of the network and output data for the sample hydraulic conductivity. The BP toolbox of neural networks in MATLAB is generally used to calculate the relevant functions. The relationship between grain size and hydraulic conductivity is established with an ANN. Through the transmission between neurons, the method is run according to the error. Then, the weights and thresholds are modified for training until the required accuracy is met.

4.1. ANN Algorithm. The calculation principle of the BP neural network algorithm is from (11) to (14).

The transmit function is

$$a = f(wp + b). \tag{11}$$

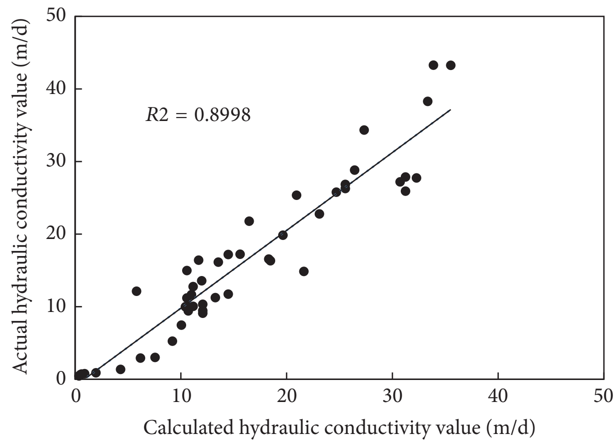

FIGURE 7: Comparison of hydraulic conductivity experimental values and calculated values.

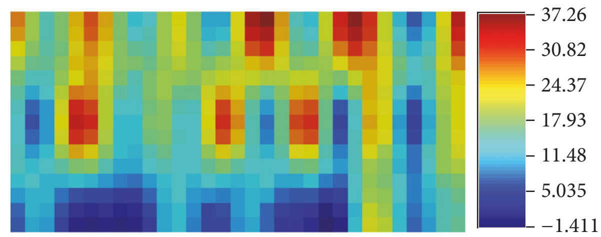

FIGURE 8: The distribution of hydraulic conductivity from resistivity.

The hidden layer output node is

$$y_j = f\left(\sum_i w_{ij} - b_j\right). \quad (12)$$

The output node is

$$z_1 = f\left(\sum_j v_{lj} y_j - b_j\right). \quad (13)$$

The error is

$$E = \frac{1}{2}\sum_l \left(t_l - z_l\right)^2. \quad (14)$$

In the equations, p is the input data, w and v are the weights, b is the threshold, and t is the target data. The error function differentiates the nodes and thresholds of the hidden and output layers. The purpose of the derivation is to correct the variation Δv_{lj}, Δw_{ji}. According to (12), w and b are modified along the negative gradient direction. The training is continued until the required accuracy is reached. The structure of the neural network is shown in Figure 9. The training progress is depicted in Figure 10.

4.2. Method Application. Training program: net= newff(minmax(p), t, 6,{'logsig','purelin'}, 'trainlm').

Hydraulic conductivity is obtained from the ANN compared with the experimental values as shown in Figure 11. The distribution of hydraulic conductivity was obtained using Kriging interpolation. The result is shown in Figure 12.

A significant relationship exists between particle size distribution and hydraulic conductivity. The relationship was established with ANN. The fitting results are relatively ideal in cases involving voluminous data. At the same time, the training of the neural network is affected by initialization, the predicted value is unstable, and repeated training is required to achieve improved prediction. This outcome shows that the relationship of particle size and hydraulic conductivity can achieve desirable results through iteration. It also proves the feasibility of the method. The validity of the method is proven by the comparison of actual and predicted values. This method is applicable to a large area with a large particle size distribution.

5. Discussion

In summary, the resistivity and grain size can also be used to obtain the value of hydraulic conductivity. Operation is simple and the data involved are voluminous. The advantages and disadvantages of the two methods and their applicable conditions are listed in Table 3.

The selected area is a fine plain stream segment, there is not much clay content, and the hydraulic conductivity is small because of the relatively large amount of sand. This requires the use of the Archie formula to achieve a significant amount of data, and constants a and m can be further determined on the basis of known hydraulic conductivity data. The accuracy of geoelectrical data can also be improved. The study area has

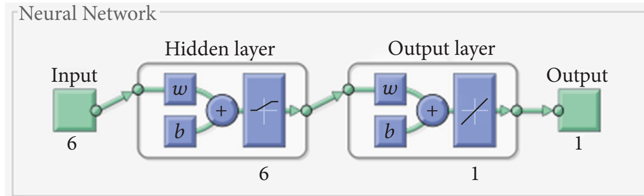

Figure 9: Structure of the neural network.

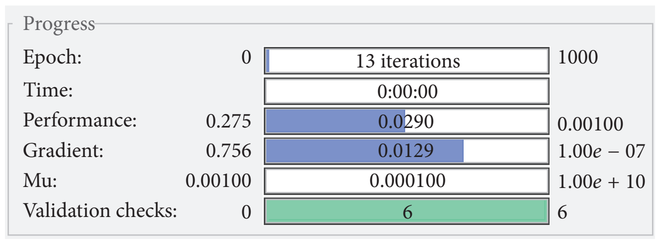

Figure 10: Training progress.

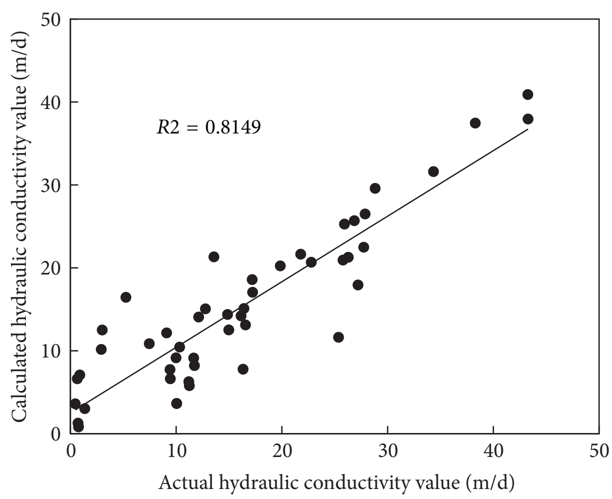

Figure 11: Comparison of actual and calculated values.

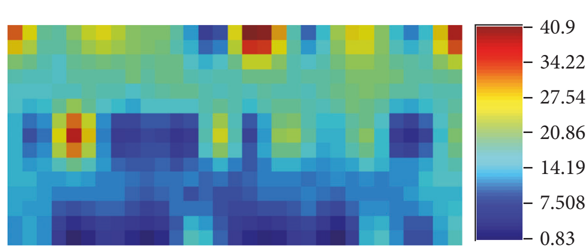

Figure 12: Distribution of hydraulic conductivity from ANN.

saturated flow, and thus the Archie formula can be simplified. The geoelectrical method is easy to operate, economic, nondestructive, and efficient. By calculating a significant amount of hydraulic conductivity data, the accuracy of the hydraulic conductivity distribution obtained by interpolation calculations will be greatly improved. Besides the porosity, there are other factors affecting the hydraulic conductivity. The geoelectrical method only considers the relationship between hydraulic conductivity and porosity, thereby reducing the accuracy. However, in this case, because the study area is simple and smaller, there is no complicated geological condition. Even if there are other influential factors, the range of influence is very small, so it is possible to calculate porosity only.

Table 3: Comparison of the methods.

Geoelectrical	Advantages	The method is easy to operate, economic, nondestructive, efficient, and effective at rapidly accessing large amounts of data.
	Disadvantages	The method does not adequately consider relevant factors, thus affecting porosity and hydraulic conductivity as well as the medium composition, saturation degree structure, and so forth. In addition, the determination of a and m values leads to a large error. When measuring resistivity, the method also causes errors, such as contact resistance.
	Applicable conditions	It is more suitable for a wide area, contaminated strata, semiarid regions, and complex geological conditions. It is especially suitable for the delineation of aquifers and the investigation of water pollution in water-rich media. It is unsuitable for strata with high clay content.
Grain size distribution method	Advantages	The method is economical and can obtain a large amount of particle size data. Through its automatic training with ANN, it is a fast and convenient method. ANNs can perform a large amount of calculations and feature a strong nonlinear fitting ability.
	Disadvantages	This method controls training settings and prevents overtraining, thereby relying heavily on computers. Given that the initial value is not set, the predicted value is unstable. The evaluation of its estimated hydraulic conductivity needs further examination.
	Applicable conditions	Its application is broad. It can be applied to highly heterogeneous and complex regions.

ANNs require known hydraulic conductivity values. When the known data is limited, the relationship between the grain size distribution and the hydraulic conductivity can be calculated, but the uncertainty is relatively large. Since this case has a lot of known data, the target data is large enough to guarantee the accuracy of the results from the grain size distribution method. The grain size distribution of soil is closely related to the hydraulic conductivity, but the data of the grain size distribution is too large. The simple empirical and semiempirical formula is not sufficient to fully and adequately express the relationship between the grain size and the hydraulic conductivity.

The main purpose of this paper is to economically and efficiently determine the distribution of the hydraulic conductivity in the study area. There is no clay layer in this paper; a sufficient number of hydraulic conductivity data can be used for target data of artificial neural network. Thus, the two methods are feasible. Since the geoelectrical method has known data, the constants a and m are derived using this method, which makes the geoelectrical method more accurate. Although the geoelectrical method uses more known data, and thus more accurate a and m, no known hydraulic conductivity data can be used to obtain the hydraulic conductivity. However, the ANN is not possible, and there is not enough known data to accurately calculate the hydraulic conductivity.

This study involves a small area, and the correlation between the calculated and the known hydraulic conductivity is very strong, thus proving the feasibility of this method. Resistivity and grain size distributions are readily available to extend this method to a wide range of areas. There are many factors that influence the resistivity measurements; however, the grain size distribution is more closely related to the hydraulic conductivity, and there are few factors affecting the measurement of the grain size distribution. Grain size distribution is recommended when additional data is known.

The geoelectrical method is not applicable to clay layers, so grain size distribution can be chosen. Grain size distribution is not applicable in the absence of known hydraulic conductivity data. If the grain size distribution is combined with pumping tests, drilling many holes is not economical and is inefficient. Therefore, the vertical electric sounding method (VES) combined with the pumping test should be selected since less known data is required. The inevitable problem is that no known hydraulic conductivity data exists for clay layers. Thus, the two methods described in this article are not applicable. A small area can use pumping tests and direct interpolation. VES combined with the pumping test can be used in a wide range of clay layers. Archie formula is not applicable as the accuracy cannot be guaranteed. ANN can be used to establish a relationship between the resistivity and hydraulic conductivity. The grain size distribution method is the training of the relationship between the grain size and the hydraulic conductivity and requires several input parameters. However, the relationship between the resistivity and the hydraulic conductivity only needs an input parameter. The required hydraulic conductivity is also less than that required by grain size distribution. Therefore, the combination of VES and the pumping test is selected by means of ANNs.

6. Conclusion

This study calculated the distribution of hydraulic conductivity using Kriging interpolation. The Kriging method carries out the interpolation of optimal and unbiased values. Since resistivity and particle size distribution are related to hydraulic conductivity, their relationships are used to determine hydraulic conductivity. The results are satisfactory compared to the results of the pumping test data. The two methods possess their own advantages and disadvantages as well as application conditions.

The purpose of the pumping test is to obtain the hydraulic conductivity directly; thus, its accuracy is greater than the geoelectrical method and the grain size distribution method, but the operation is complicated and the cost is high. The geoelectrical method and the grain size distribution method easily access large amounts of data; however, the geoelectrical method cannot be applied in clay content areas, and the determination of a and m will also affect the accuracy of the output. Artificial neural networks make full use of the relationship between the grain size distribution and the hydraulic conductivity, but they rely too much on computers. The results of these two methods show a little difference.

We obtain hydraulic conductivity from resistivity by comparing the pumping test data, $R^2 = 0.8998$, from grain size, $R^2 = 0.8149$. In other words, it is reasonable to obtain hydraulic conductivity from resistivity and grain size. By comparing Figure 6 to Figures 2 and 3, we can see that the trend is roughly the same from the bank to the center of the riverbed. This proves that it is feasible to get the distribution of the hydraulic conductivity from two methods. The estimated values are different from the experimental values due to the error of the measurement process. Kriging interpolation exhibits a high-value underestimation and a low-value overestimation phenomenon.

The selected area is a fine plain stream segment of the lower reaches of the Golmud River, with a relatively uniform grain size distribution. The hydraulic conductivity increases gradually from the bank to the center of the riverbed. This is because, given the high velocity of the riverbed center, small particles are deposited by the water leaving with large particles, and the flow rate of the river bank is low with the easy deposition of silt.

The method of acquiring resistivity and particle size data is relatively simple, and the data involved are voluminous; they are suitable for a wide area. We can solve the distribution of hydraulic conductivity in wide areas. It is economical and efficient. This study of the distribution of hydraulic conductivity provides the basis for the study of groundwater and contributes to the management and control of water resources and advocates for the formation of an accurate seepage field.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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References

[1] J. Batlle-Aguilar, Y. Xie, and P. G. Cook, "Importance of stream infiltration data for modelling surface water-groundwater interactions," *Journal of Hydrology*, vol. 528, pp. 683–693, 2015.

[2] R. Ma, J. Shi, and J. Liu, "Dealing with the spatial synthetic heterogeneity of aquifers in the North China Plain: A case study of Luancheng County in Hebei Province," *Acta Geologica Sinica*, vol. 86, no. 1, pp. 226–245, 2012.

[3] L. Wang and Q. Xu, "Analysis of three dimensional random seepage field based on Monte Carlo stochastic finite element method," *Rock and Soil Mechanics*, vol. 35, no. 1, pp. 287–292, 2014.

[4] Y. J. Wang, W. H. Zhang, and H. L. Chen, "Threedimensional random seepage field analysis for main embankment of yangtze river," *Chinese Journal of Rock Mechanics and Engineering*, vol. 26, no. 9, pp. 1824–1831, 2007.

[5] X. Q. Shi, B. L. Jiang, and J. Y. Bian, "Geostatistical analysis for estimating the spatial variability of hydraulic conductivity in the third confined aquifer of Shanghai City," *Geotechnical Investigation Surveying*, vol. 37, no. 1, pp. 36–41, 2009.

[6] X. Q. Shi, J. C. Wu, and Y. S. Yuan, "Effect of the anisotropy in porous media on the spatial variability of the hydraulic conductivity," *Advances in Water Science*, vol. 16, no. 5, pp. 679–684, 2005.

[7] X. Q. Shi, J. C. Wu, and Y. S. Yuan, "Study on the spatial variability of hydraulic conductivity," *Advances in Water Science*, vol. 16, no. 2, pp. 210–215, 2005.

[8] H. Xi, L. Zhang, Q. Feng et al., "The spatial heterogeneity of riverbed saturated permeability coefficient in the lower reaches of the Heihe River Basin, Northwest China," *Hydrological Processes*, vol. 29, no. 23, pp. 4891–4907, 2015.

[9] L. L. Liu, J. F. Wu, and J. C. Wu, "A comparative study of four geostatistical methods for identifying the hydraulicconductivity fields based on test data," *Hydrogeology and Engineering Geology Journal*, vol. 36, no. 5, pp. 66–71, 2009.

[10] Y. X. Yu and J. C. Wu, "Application of electrical resistivity tomography data to estimate hydraulic conductivity in porous medium," *Hydrogeology and Engineering Geology*, vol. 33, no. 2, pp. 41–44, 2006.

[11] S. Perdomo, J. E. Ainchil, and E. Kruse, "Hydraulic parameters estimation from well logging resistivity and geoelectrical measurements," *Journal of Applied Geophysics*, vol. 105, pp. 50–58, 2014.

[12] T. Vienken and P. Dietrich, "Field evaluation of methods for determining hydraulic conductivity from grain size data," *Journal of Hydrology*, vol. 400, no. 1-2, pp. 58–71, 2011.

[13] B. Rogiers, D. Mallants, O. Batelaan, M. Gedeon, M. Huysmans, and A. Dassargues, "Estimation of Hydraulic Conductivity and Its Uncertainty from Grain-Size Data Using GLUE and Artificial Neural Networks," *Mathematical Geosciences*, vol. 44, no. 6, pp. 739–763, 2012.

[14] J. Liang, G. M. Zeng, and S. L. Guo, "Effect of hydraulic conductivity heterogeneity on solute transport in groundwater," *Journal of Hydraulic Engineering*, vol. 39, no. 8, pp. 900–906, 2008.

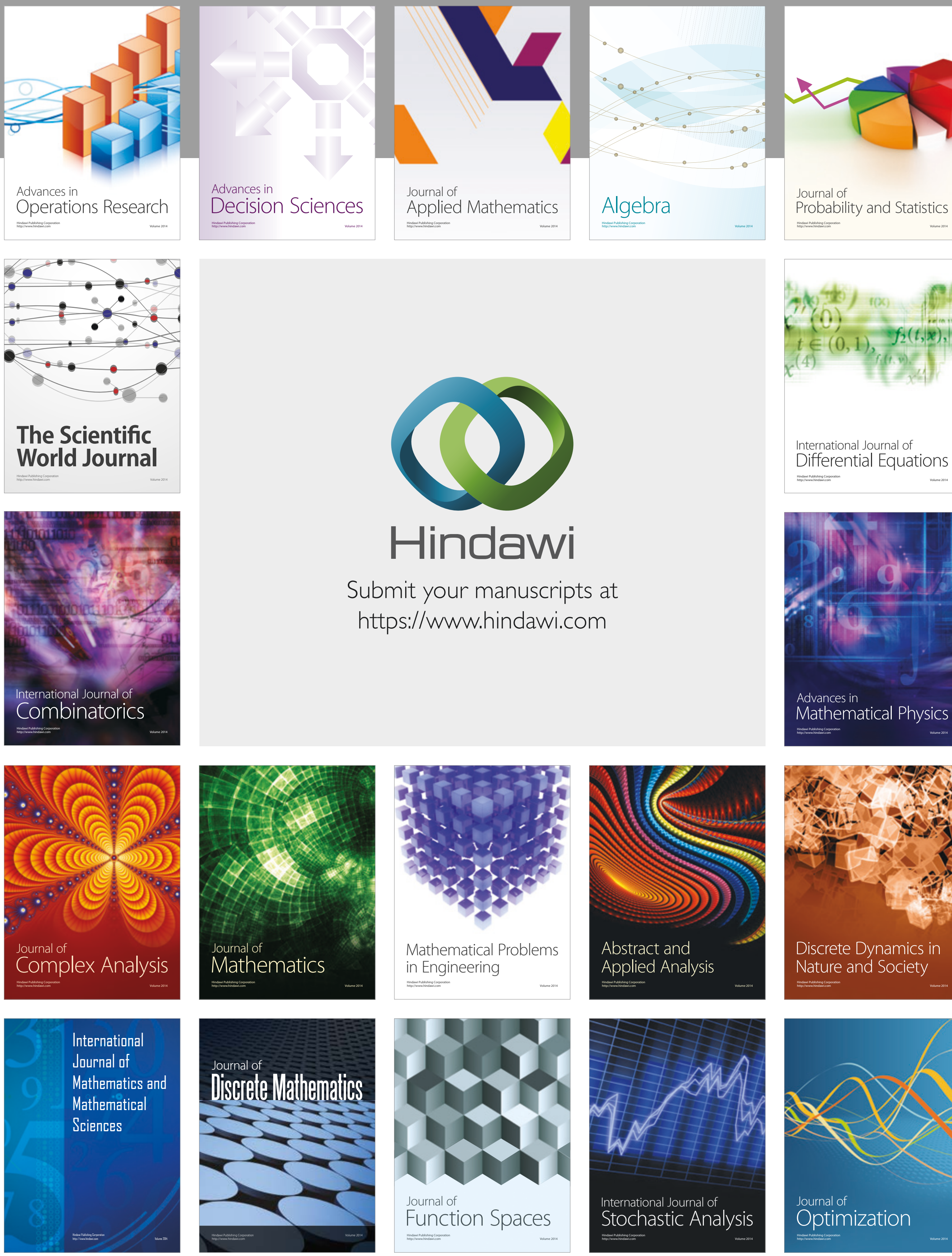
[15] R. G. Qin, G. Z. Cao, and Y. Q. Wu, "Review of the study of groundwater flow and solute transport in heterogeneous aquifer," *Advances in Earth Science*, vol. 29, no. 1, pp. 30–41, 2014.

[16] M. Bianchi, "SGeMS: A free and versatile tool for three-dimensional geostatistical applications," *Groundwater*, vol. 47, no. 1, pp. 8–12, 2009.

[17] R. Nicolas, *Applied Geostatistics with SGeMS: A User's Guide*, Cambridge University Press, Cambridge, UK, 2009.

[18] J. H. Doveton, *Log Analysis of Subsurface Geology*, Wiley, New York, NY, USA, 1986.

[19] N. Kazakis, G. Vargemezis, and K. S. Voudouris, "Estimation of hydraulic parameters in a complex porous aquifer system using geoelectrical methods," *Science of the Total Environment*, vol. 550, pp. 742–750, 2016.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