Multivariate geostatistical analysis of soil permeability and spatial variability using deterministic and stochastic approaches

Yimmy López Solórzano[1], Keyla Yamira Mendoza Intriago[1], Carlos Ricardo Delgado Villafuerte[1], Jofree Alberto Andrade Candell[1] Fabian Fabricio Peñarrieta Macias[1]

[1]*Escuela Superior Politécnica Agropecuaria de Manabí Manuel Félix López, Carrera de Ingeniería Ambiental, Calceta, Manabí, Ecuador,130250*

Abstract

The present research modeled the spatial variability of the apparent permeability of the Chone canton soil, Ecuador, through a combined physical-statistical and geostatistical approach. The study was developed under a quantitative, applied, non-experimental and cross-sectional design, integrating direct measurements of permeability in the field, complementary soil physical variables and spatial interpolation tools in S-GeMS. A total of 64 permeability observations and a spatial mesh of 1600 porosity values were analyzed, obtaining a mean of 17.74, a median of 17.79 and a range between 9.27 and 23.65, while porosity presented a mean of 5.82 and lower relative dispersion. The bivariate analysis showed a moderate positive correlation between permeability and porosity (r = 0.580685), which confirmed the usefulness of the latter as an auxiliary covariate, although insufficient to explain the hydraulic response of the soil on its own. The variographic analysis showed spatial dependence of permeability and moderate anisotropy, indicating that the continuity of flow in the soil changes according to direction and responds to local structural controls. Modelling by kriging and cokriging allowed the generation of continuous surfaces of spatial distribution, identifying sectors with lower hydraulic response and, therefore, greater potential susceptibility to waterlogging or poor drainage. Overall, the findings show that soil permeability in the study area is not a homogeneous or static property, but a spatially structured variable whose geostatistical representation provides key information for local hydrological interpretation and for territorial management of vulnerable areas

Keywords: soil permeability, porosity, spatial variability, geostatistics, kriging, cokriging.

1. Introduction

Soil permeability is a fundamental hydrodynamic property to interpret the circulation of water in the unsaturated zone, the infiltration capacity and the response of the land to rainfall events of different intensity. From an environmental perspective, its behavior conditions processes such as the partition of precipitation between infiltration and runoff, the recharge of moisture in the profile, the mobilization of solutes and the susceptibility of the soil to surface waterlogging. Consequently, the study of this property is not only relevant for soil physics, but also for environmental engineering, drainage management, and the assessment of risks associated with the functional deterioration of the terrain (Blanchy et al., 2023; Bargués-Tobella et al., 2024).

This problem acquires greater importance in areas where anthropic pressure, alterations of natural drainage and sanitary infrastructure converge. In these scenarios, the decrease in the capacity of water to conduct water through the soil can favor the permanence of surface sheets, intensify runoff and limit the hydraulic dissipation of excess moisture. In addition, compaction, modification of the structure and reduction of functional porosity can alter the balance between infiltration, temporary storage and lateral flow, with direct implications on the physical stability of the soil and on the dynamics of pollutants in vulnerable environments. Therefore, permeability should be understood as an integrating variable of local hydrological functioning and not only as an isolated laboratory parameter (Blanchy et al., 2023; Weber et al., 2024).

Despite its importance, the direct determination of permeability or saturated hydraulic conductivity in the field and laboratory has known operational limitations. In situ tests and instrumental measurements, although indispensable, are often costly, time-consuming and difficult to extrapolate when there is marked spatial heterogeneity. This condition is especially critical in soils subjected to changes in use, microtopographic variations and anthropic disturbances, where the hydraulic response can change over relatively short distances. In this context, recent literature has reinforced the value of predictive approaches that allow estimating soil hydraulic properties based on physical variables that are easier to determine, in order to expand the spatial interpretation of the phenomenon without relying exclusively on point measurements (Borek et al., 2021; Weber et al., 2024; Qin et al., 2024).

Among these approaches, pedotransfer functions and physical-statistical models have shown special utility to infer hydraulic conductivity or apparent permeability from attributes such as texture, bulk density, effective porosity, moisture content and variables associated with infiltration. Its basis lies in the fact that the movement of water in the soil depends to a large extent on the geometry, connectivity and continuity of the porous system; Therefore, changes in bulk density or porosity have a direct impact on the flow transmission capacity. Recent studies have confirmed that, in many contexts, effective porosity and bulk density have an even greater predictive weight than some traditional textural variables, which reinforces the relevance of integrating these properties into estimation schemes applied at local and detail scales (Qin et al., 2024; Bargués-Tobella et al., 2024).

However, in applied studies, it is not enough to estimate an average value of permeability; it is also necessary to represent their spatial variability. At this point, geostatistics offers robust tools to model spatial patterns and reduce the uncertainty associated with terrain heterogeneity. Kriging allows interpolating the variable of interest from its spatial dependence structure, while cokriging improves estimation when correlated and spatially continuous covariates are available, such as porosity, bulk density, humidity or infiltration rate. This combination is methodologically relevant when the objective is not only to describe the soil, but also to generate useful predictive surfaces to interpret the hydrological behavior of an area under real conditions of management and vulnerability (Motaghian & Mohammadi, 2011; Espinosa Marín et al., 2023).

In Ecuador, the available literature shows valuable, although still punctual, advances in the spatial modeling of soil hydraulic properties. A relevant precedent is the work carried out in the province of Loja by Espinosa Marín et al. (2023), who integrated infiltration trials, edaphic variables, and a pedotransfer approach to generate permeability maps. This type of contribution confirms the feasibility of transferring field measurements to spatial models with applied utility; however, its extension to environments adjacent to health infrastructure, where surface saturation, compaction and exposure to recurrent flooding converge, continues to require greater methodological and contextual development.

This need is particularly pertinent in the Chone canton, province of Manabí, where territorial and hydrological conditions have historically configured a scenario of high sensitivity to flooding. The canton's Development and Territorial Planning Plan recognizes a high occurrence of flooding in low-lying areas and reports a large area vulnerable to this type of event. Within this framework, the study of the soils adjacent to a wastewater treatment plant acquires relevance not only for its edaphic interest, but also for its potential contribution to the understanding of the factors that favor waterlogging, deficient drainage and the persistence of surface moisture in an intervened environment (GAD Municipal of the Canton Chone, 2014).

Based on the above, it was proposed to spatially model the apparent permeability of the soil in an area adjacent to the wastewater treatment plant of the Chone canton through a combined physical-statistical and geostatistical approach. To this end, porosity was integrated as an auxiliary covariate within kriging and cokriging schemes, with the purpose of representing the spatial variability of water transmission capacity in the soil and providing technical evidence for local hydrological interpretation and the identification of sectors with potential susceptibility to waterlogging.

Materials and methods

The research was carried out in a peri-urban area adjacent to the wastewater treatment plant (WWTP) of the city of Chone, located in the canton of Chone, province of Manabí, Ecuador. The geographical location of the area corresponds approximately to the coordinates 0°43′04.85" S and 80°06′09.10" W, with an average altitude of 16.8 m a.s.l.

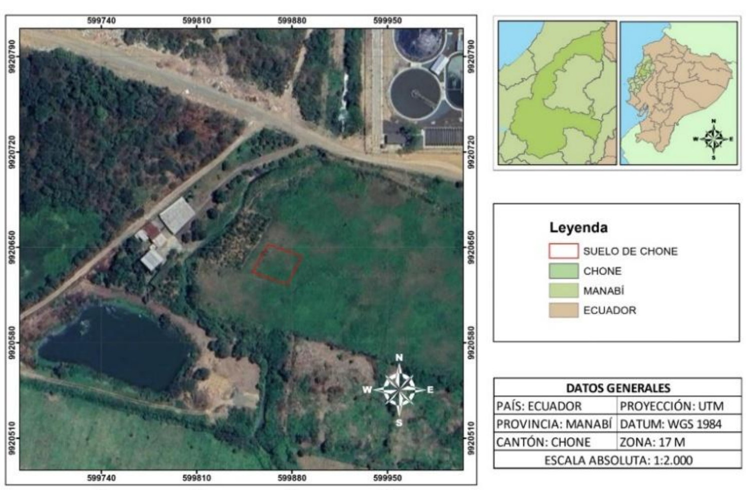

Figure 1. Location of study place

Type of research

The research is quantitative, applied, non-experimental and cross-sectional, with a descriptive and predictive scope, because it measures soil variables in natural conditions and spatially models permeability using geostatistical techniques.

Spatial design of sampling

The study was carried out in an area adjacent to the wastewater treatment plant in the canton of Chone, Ecuador. The distribution of the sampling points was defined using a geographic information system (GIS), based on coordinates obtained with a handheld GPS receiver. A regular mesh of 40 × 40 sampling units was established on the study polygon, equivalent to an approximate spacing of 0.62 m between points within an area of 625 m². This resolution was defined with the purpose of capturing the short-range spatial variability of soil permeability and generating a sufficiently dense base for subsequent geostatistical analysis (Vargas et al., 2023; Karami et al., 2024).

Measuring Soil Hydraulic Response

The hydraulic response of the soil was evaluated by constant load infiltration tests. At each point, a rigid PVC cylinder with an internal diameter of 10 cm and a height of 15 cm was used, carefully inserted into the ground to a depth of 10 to 15 cm, trying to minimize the alteration of the natural structure. Once the device was installed, a constant sheet of water was applied and the time required for infiltration was recorded, from which the apparent saturated hydraulic conductivity (Ks) was estimated as an indicator of the soil's ability to transmit water under conditions close to saturation. This procedure made it possible to obtain an operational measure of soil permeability under field conditions (Adaikwu et al., 2022; Borek et al., 2021; Singh et al., 2022; Pinheiro et al., 2021).

Complementary physical characterization of the soil (Porosity)

In order to support the interpretation of permeability and strengthen the multivariate analysis, samples were collected using 100 cm³ stainless steel cylinders. The samples were extracted with uniform pressure, avoiding deformations and losses of material, and then transferred to the laboratory in sealed containers to preserve their physical and water condition. From these samples, bulk density, moisture content, and total porosity were determined, variables considered relevant to explain the dynamics of water transmission in the soil and its functional variability in the study area (Chukwu et al., 2023; De Souza et al., 2024).

The determination of permeability and porosity was carried out using the following equations:

Table 1. Variables together with their methods.

Variable	**Method**	**Formula**	**Unity Measuring**
Permeability (K)	Constant load permeameter	$K = QL/A\Delta Ht$	cm/s
Porosity (n)	Empty Volume	$n = Vv/Vt \times 100$	%

Source: (Adaikwu et al., 2022; Pramoedyo et al., 2022).

Where:

Q is the flow of water flowing through the soil (cm³/s).

L is the length of the soil sample (cm).

A is the cross-sectional area of the sample (cm²).

ΔH is the difference in hydraulic load (cm).

t is the measurement time of the flow(s).

Vv is the volume of voids.

Vt is the total volume of the sample.

Organization, quality control and exploratory analysis

The data obtained in the field and laboratory were integrated into a structured base with unique identification of each point, spatial coordinates, and edaphic and hydrodynamic variables. Subsequently, the consistency of the coordinates, the homogeneity of the units of measurement and the absence of duplications or incompatible records were verified. As part of the quality control, histograms, box plots and quantile–quantile plots were made to examine the way the variables are distributed and detect outliers. Extreme records were reviewed individually and were only excluded when there was technical justification associated with measurement, georeferencing or typing error. In addition, descriptive measures of central tendency and dispersion, including mean, median, standard deviation, and coefficient of variation, were calculated in order to establish an initial diagnosis of the statistical behavior of the data (Dong, 2023; Valadares et al., 2022; Espinosa Marín et al., 2023).

Table 2. Data registration form.

Sample ID	Coordinates (Lat, Long)	Depth (cm)	Permeability (cm/h)	Porosity (%)	Observations
P001	-	-	-	-	-
P002	-	-	-	-	-

Bivariate and structural analysis

Spatial database integration and preparation

As an initial stage of the geostatistical modeling, the database was prepared and imported into S-GeMS in GSLIB format (.dat), ensuring the correct incorporation of the spatial coordinates (X, Y, Z) and the variables of interest, particularly permeability and porosity. This stage allowed the input information to be structured consistently for subsequent statistical and spatial analysis, ensuring that each observation was correctly linked to its location within the study area (Deutsch & Journel, 1998; Remy et al., 2009).

Bivariate exploration of the permeability-porosity relationship

From the loaded database, a bivariate analysis was performed to explore the relationship between permeability and porosity using scatter plots and descriptive statistics, including Pearson's correlation coefficient. This procedure allowed to identify the strength and direction of the linear association between the main variable and the potential covariate, constituting a preliminary criterion to evaluate the relevance of incorporating auxiliary information in the spatial modeling. In addition, the possible spatial variability of this relationship was examined by analyzing subregions or local domains, in order to detect spatial changes in the degree of association within the evaluated area (Webster & Oliver, 2007; Goovaerts, 1997).

Defining the Interpolation Mesh and Spatial Support for Analysis

Subsequently, an interpolation mesh was defined according to the spatial resolution of the sampling and the scale of the phenomenon analyzed. To do this, the number of cells in the X, Y and Z directions, the cell size and the point of origin were established, so that the spatial prediction support was consistent for both interpolation and geostatistical simulation. This configuration is a key step in workflows implemented in S-GeMS and in libraries such as GSLIB, since it conditions the final spatial representation of the estimates (Deutsch & Journel, 1998; Remy et al., 2009).

Characterization of the spatial structure of permeability

Based on the defined mesh, experimental variograms were calculated in an omnidirectional and directional manner in order to characterize the spatial continuity of permeability, identify anisotropies and determine the scale of spatial dependence of the phenomenon. The analysis configuration considered parameters such as lag spacing and the total number of lags, evaluating at least two main directions to recognize possible anisotropic patterns. This stage made it possible to establish the way in which the similarity between observations decreases with distance and direction, constituting the basis of subsequent geostatistical modeling (Journel & Huijbregts, 1978; Goovaerts, 1997; Webster & Oliver, 2007).

Variographic model tuning and cross-structuring between variables

From the experimental variograms, theoretical models of spherical, exponential or Gaussian type were adjusted, selecting the one that best represented the spatial behavior of the data. For this adjustment, the parameters of nugget effect, threshold and range were estimated, as well as the anisotropy range when necessary. In the case of cokriging, in addition to direct variograms, the joint spatial structure between permeability and porosity was considered through the use of the cross-variogram, since this constitutes the basis for modeling the spatial dependence between the main and secondary variables in multivariate schemes (Goovaerts, 1997; Hooshmand et al., 2011; Adhikary et al., 2017).

Geostatistical modeling and simulation

Spatial estimation using ordinary kriging and cokriging

Based on the previously defined spatial structure, geostatistical estimation of permeability was carried out using two interpolation approaches: ordinary kriging and cokriging. Ordinary kriging was applied using permeability as the main variable, incorporating the adjusted variographic model and its structural parameters. At the same time, cokriging was implemented incorporating porosity as a secondary variable, considering both the statistical association identified in the bivariate analysis and the joint spatial structure represented by the cross-variogram. Both methods were executed on the same prediction mesh in order to generate comparable continuous surfaces of spatial distribution of permeability (Goovaerts, 1997; Hooshmand et al., 2011; Remy et al., 2009).

Evaluating the predictive performance of models

The comparison between the kriging and cokriging results was made based on their predictive capacity and the spatial coherence of the estimated patterns. To this end, a cross-validation process was developed, in which the values observed at the sampling points were compared with the values estimated by each model. The mean error (ME), root mean square error (RMSE), and coefficient of determination (R^2) were considered as performance indicators, since these statistics are widely used to evaluate accuracy, bias, and predictive capacity in spatial interpolation studies (Webster & Oliver, 2007; Ouabo et al., 2020; Farooq et al., 2022).

Gaussian data transformation and simulation readiness

In order to represent the uncertainty associated with the estimation process, a sequential Gaussian simulation (SGS) on permeability was applied. Previously, the original data were transformed to a standard normal distribution by means of a normal score transformation, verifying the coherence of this procedure through the comparison between the histograms of the original data and the transformed data. This transformation is a classic step in the implementation of SGS on continuous variables, as it favors compliance with the assumptions required by the multi-Gaussian simulation (Deutsch & Journel, 1998; Remy et al., 2009; Gómez-Hernández, 2021).

Sequential Gaussian simulation of spatial uncertainty

The SGS was executed from the previously adjusted variographic model, defining its nugget, threshold and range effect parameters, and generating 100 equiprobable realizations of the permeability spatial field, with the purpose of capturing the uncertainty associated with the phenomenon studied. To do this, the same simulation mesh defined in the interpolation stages was used, guaranteeing spatial consistency between the different products obtained. This approach is widely used to complement deterministic interpolation with probabilistic representations of the spatial behavior of hydraulic and edaphic variables (Deutsch & Journel, 1998; Remy et al., 2009; Siqueira et al., 2019).

Convergence verification and validation of simulated realizations

The convergence and stability of the simulation were evaluated by the comparative analysis of descriptive statistics between the generated realizations and the original distribution of the data, as well as by quantile and variability plots. In addition, the validation of the simulation model was complemented with cross-validation schemes, comparing predicted and observed values in subsets of data. This procedure made it possible to verify that the simulations reasonably reproduced both the spatial structure and the global variability of the original phenomenon (Deutsch & Journel, 1998; Gómez-Hernández, 2021; dos Santos et al., 2024).

Probabilistic mapping and spatial analysis of uncertainty

From the realizations obtained, P10, P50 and P90 quantile maps, exceedance probability maps and standard deviation surfaces were constructed, with the purpose of spatially representing the uncertainty associated with soil permeability. These products made it possible to identify areas of greater and lesser variability, complementing the interpretation derived from kriging and cokriging with a probabilistic perspective of soil hydraulic behavior (Remy et al., 2009; Gómez-Hernández, 2021; dos Santos et al., 2024).

Export of results and generation of final cartographic products

Finally, the results of the geostatistical modeling were exported in formats compatible with geographic information systems for the elaboration of thematic maps of permeability and uncertainty. These cartographic outputs constituted the basis for interpreting the spatial distribution of the hydraulic response of the soil and its possible relationship with areas of low infiltration, surface water accumulation and susceptibility to waterlogging in the vicinity of the wastewater treatment plant, thus integrating the geostatistical analysis with the territorial interpretation of the study area (Remy et al., 2009; Goovaerts, 1997)

Results

Exploratory analysis of the variables

From the data files and the graphic outputs, 64 permeability observations and 1600 porosity values of the spatial mesh were analyzed. The observed permeability presented an average of 17.74, median of 17.79 and a range between 9.27 and 23.65. The mesh porosity presented an average of 5.82, a median of 5.83 and a range between 3.91 and 8.18, showing a comparatively lower dispersion.

Variable	n	Media	Medium	Minimum	Maximum
Permeability (64 points)	64	17.74	17.79	9.27	23.65

Porosity (1600 node mesh)	1600	5.82	5.83	3.91	8.18

Table 1. Basic descriptive statistics of the variables used in the analysis.

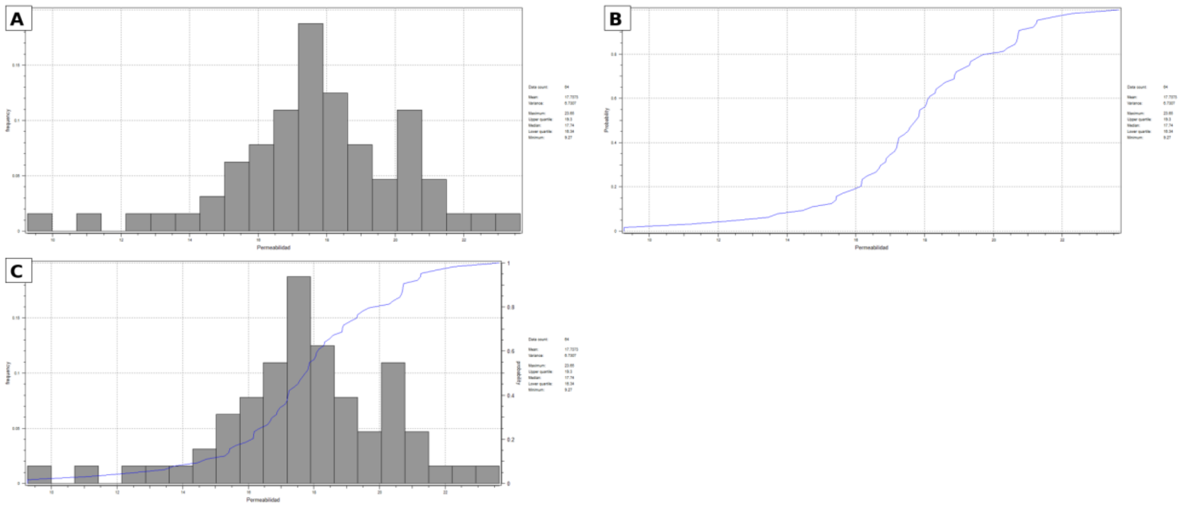

Figure 1. Permeability distribution: (A) histogram/PDF, (B) cumulative distribution function, and (C) joint representation PDF+CDF.

Permeability concentrates most of its values around 17–19 units, but retains a lower and an upper tail that show hydraulic heterogeneity. The CDF shows a continuous transition, without abrupt jumps, so the variable retains sufficient statistical continuity for spatial analysis.

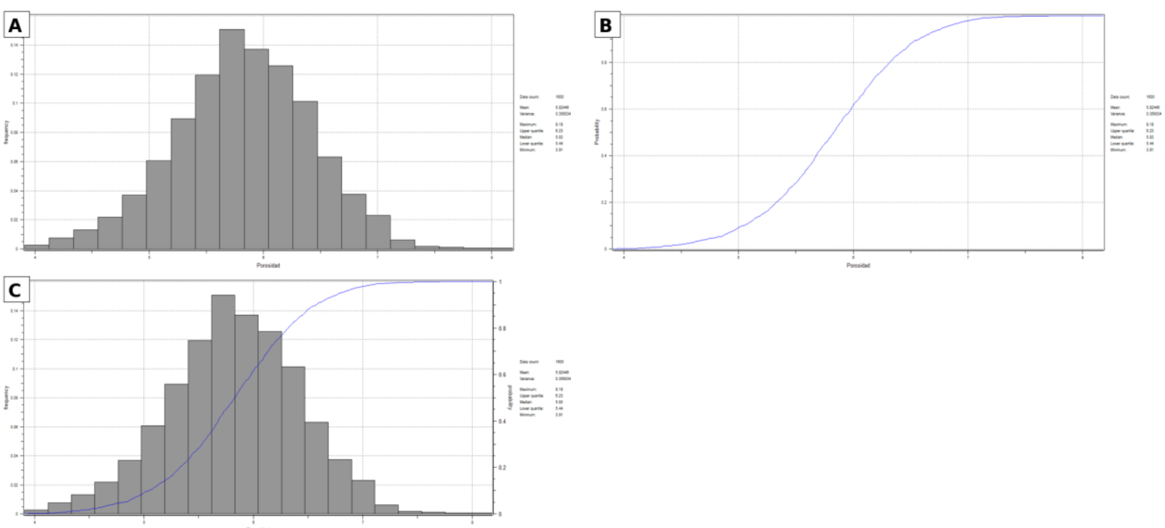

Figure 2. Porosity distribution: (A) histogram/PDF, (B) cumulative distribution function, and (C) joint representation PDF+CDF.

Porosity has a lower dispersion than permeability and a clearer concentration of intermediate values. This indicates that the pore volume is more homogeneous than the hydraulic response, so permeability depends not only on the number of pores, but also on their connectivity.

Relationship between permeability and porosity

The bivariate relationship was evaluated with the scatter and quantile plots corresponding to the 64 points with permeability measurement. In the output of the software, a correlation of 0.580685 is reported, a slope of 0.134175 and an intercept of 3.5251 is reported.

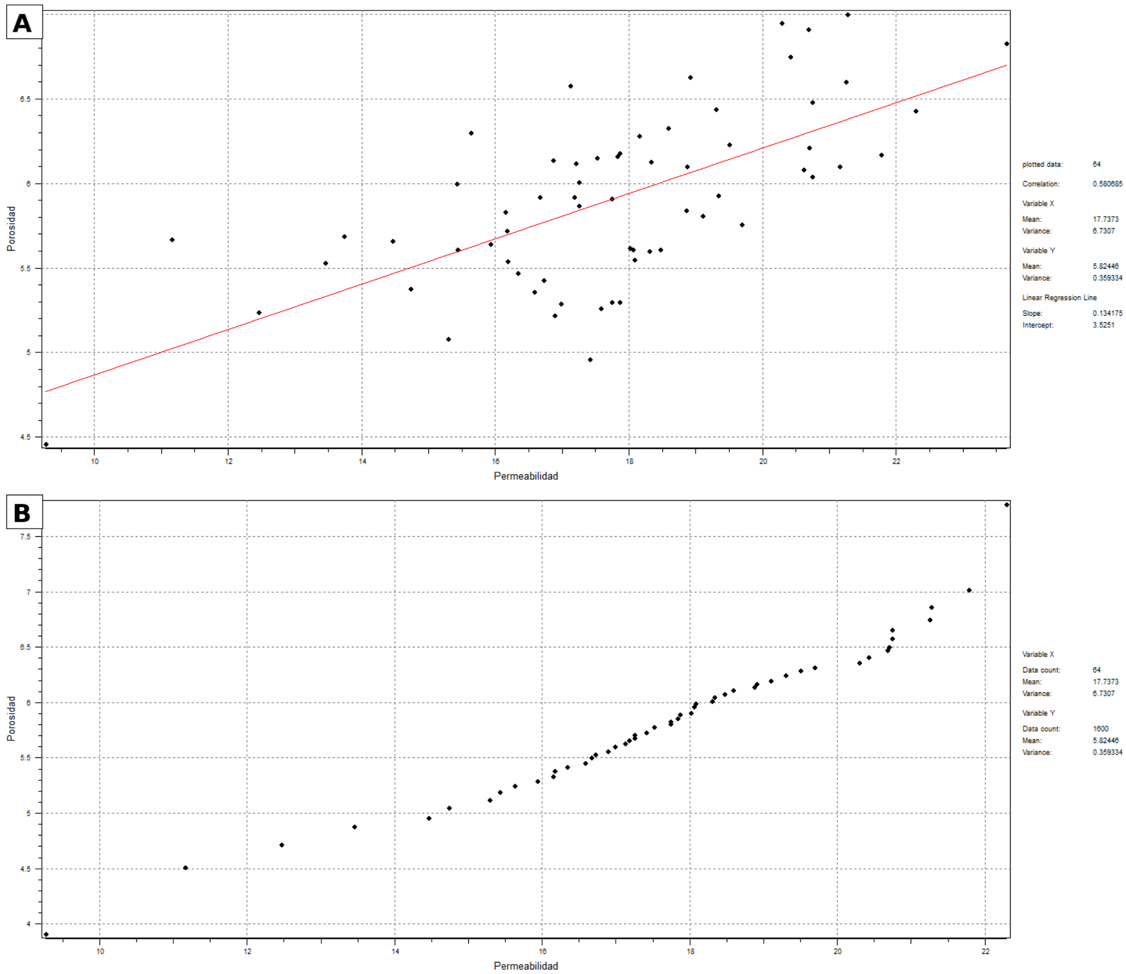

Figure 3. Relationship between permeability and porosity: (A) scatter plot with regression line and fit parameters, and (B) quantile plot.

The relationship is positive and moderate. Porosity provides useful information, but the scattering of the point cloud shows that it alone does not explain the permeability. This supports the use of porosity as a covariate in cokriging, not as a direct replacement for the primary variable.

Spatial structure of permeability

Omnidirectional variogram

The omnidirectional variogram shows the general pattern of spatial continuity of permeability and forms the basis of geostatistical adjustment.

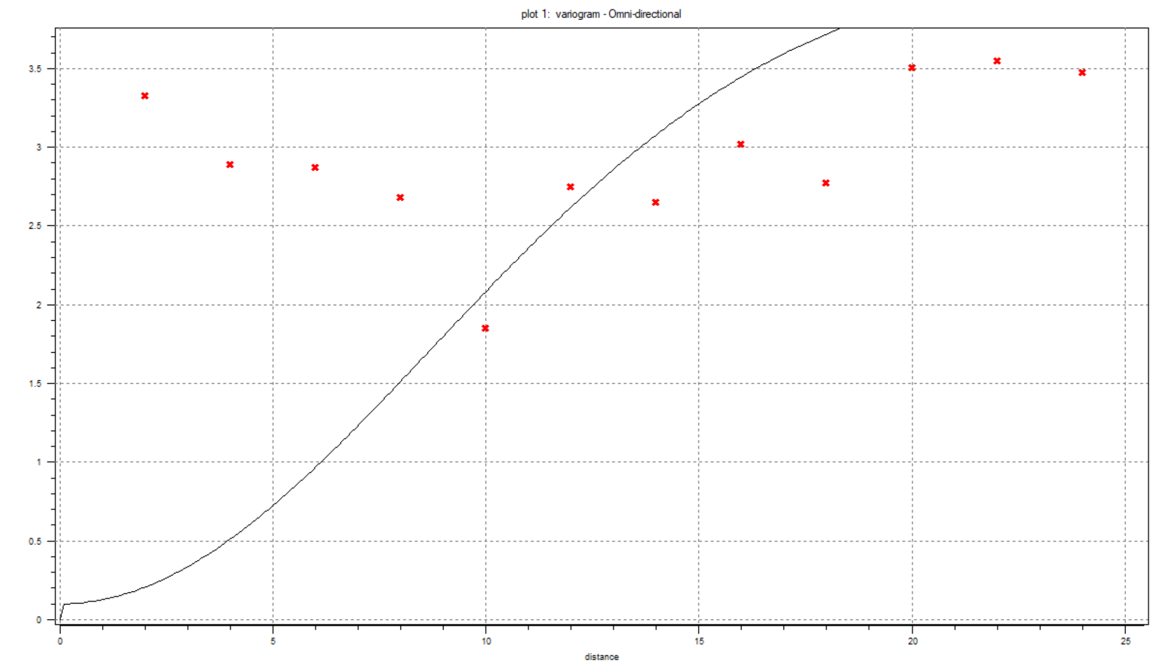

Figure 4. Omnidirectional variogram of permeability with experimental points and adjusted curve.

The half-variance increases with distance and the adjusted curve reproduces that general trend, indicating spatial dependence and ruling out a completely random distribution. Although the experimental cloud is irregular, the overall pattern is sufficient for geostatistical interpolation.

Directional variograms and anisotropy

Anisotropy was assessed by overlapping all directions and examination for positive and negative azimuths.

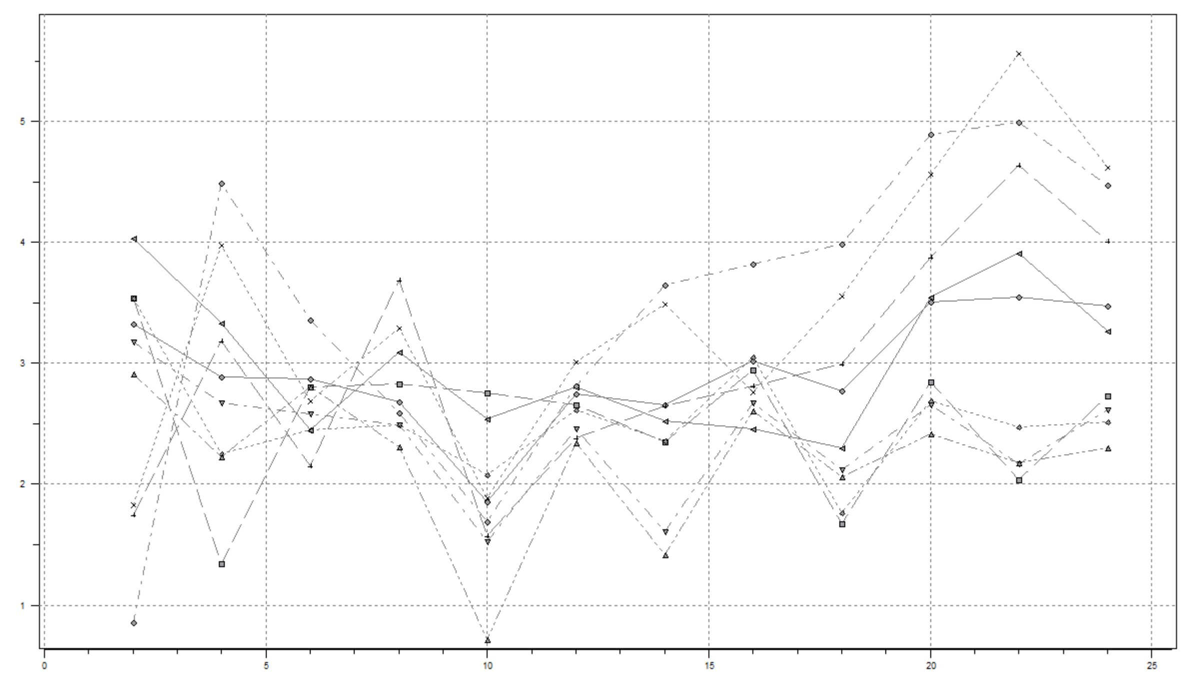

Figure 5. Superposition of directional variograms to evaluate anisotropy in permeability.

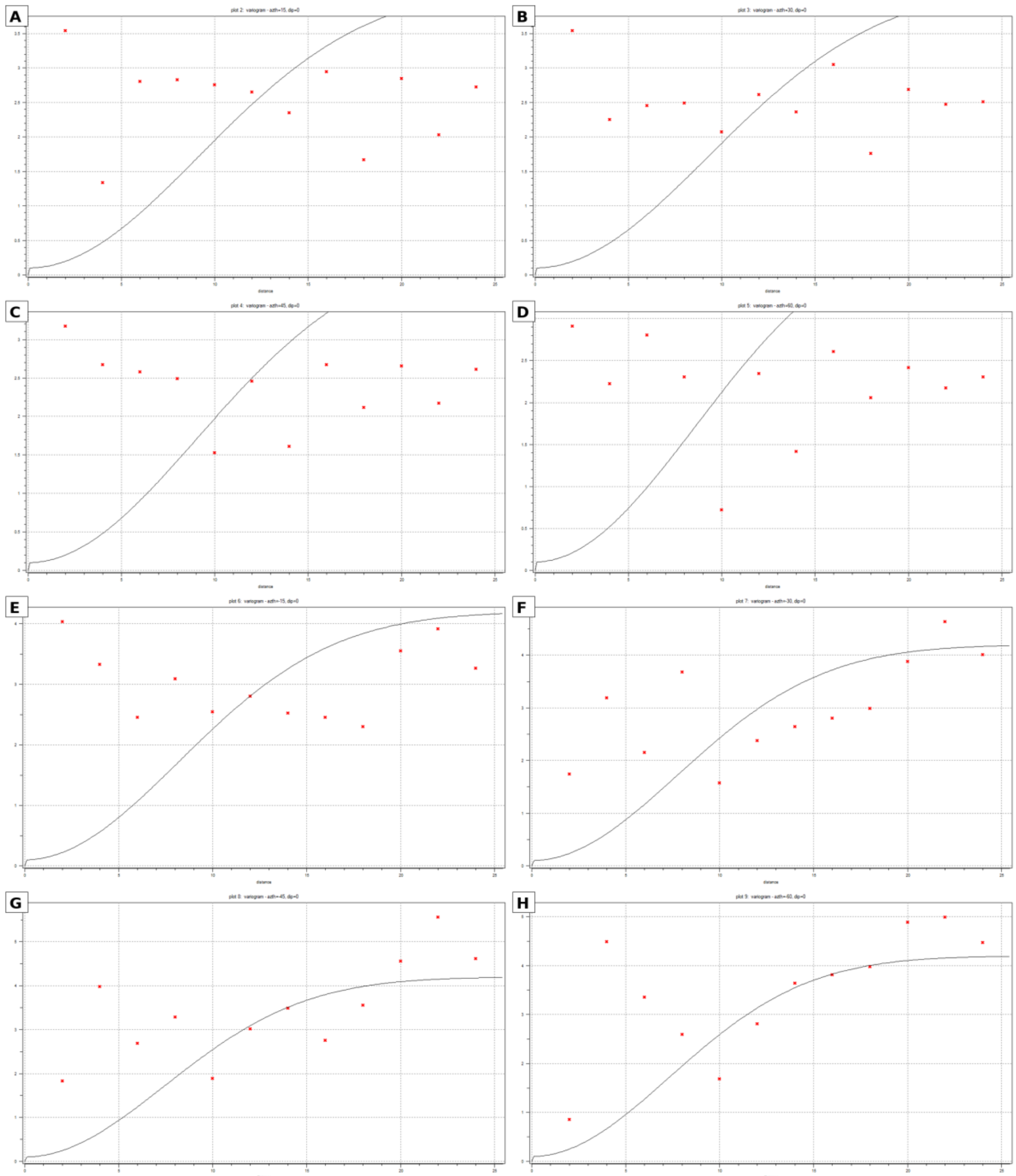

Figure 6. Individual directional variograms: (A) 15°, (B) 30°, (C) 45°, (D) 60°, (E) -15°, (F) -30°, (G) -45° and (H) -60°.

Differences between directions show moderate anisotropy: some orientations achieve greater semivariances or respond more abruptly to medium and long distances. Consequently, the spatial continuity of permeability depends on direction, which can be associated with differential compaction, microtopography or preferential flow routes.

Spatial distribution and geostatistical modelling

The cartographic products allow the location of the observed data to be contrasted with the estimated spatial continuity for permeability and with the distribution of porosity in the mesh.

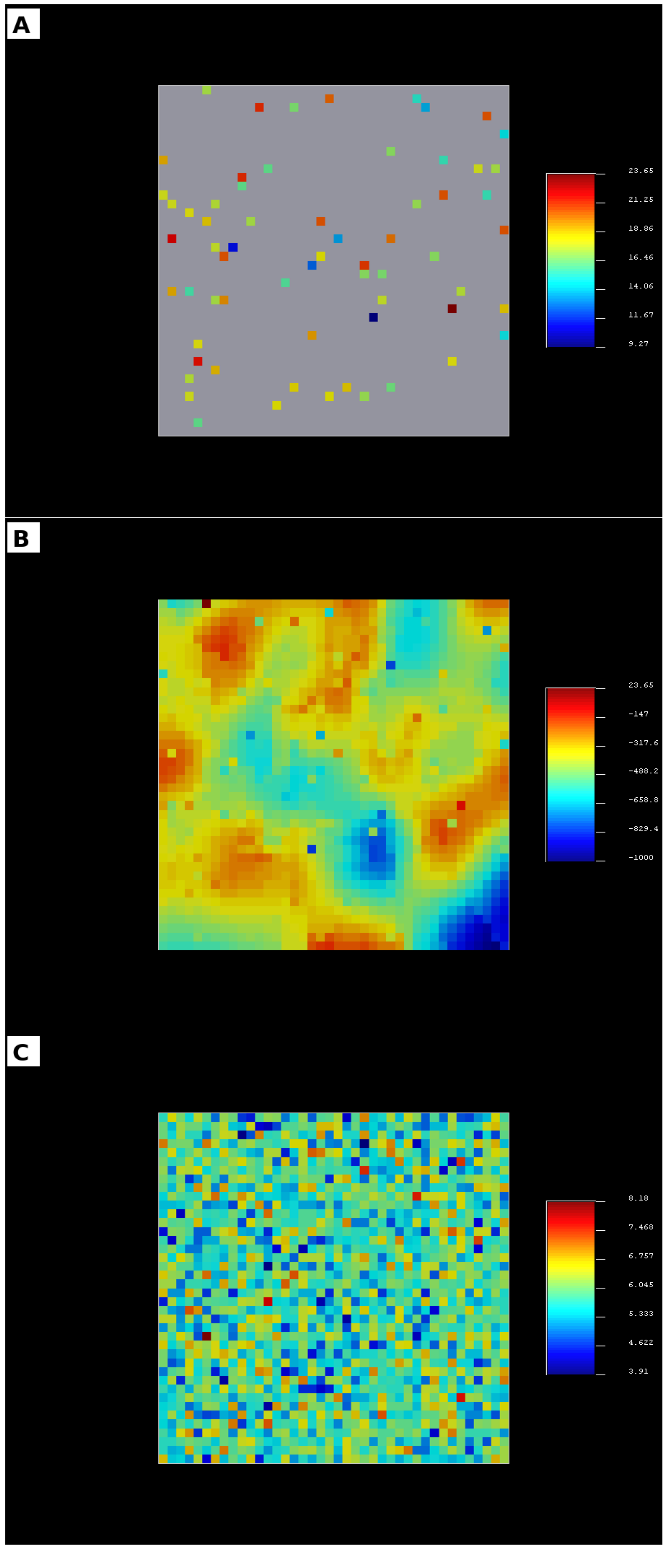

Figure 7. Mapping products of the analysis: (A) observed permeability points, (B) simulated/interpolated permeability surface, and (C) mesh porosity map.

The point distribution of the direct measurements shows high and low values scattered within the grid. The simulated/interpolated surface transforms this information into a continuous structure where sectors with less hydraulic response and relatively higher areas are distinguished. The porosity map shows lower spatial contrast, in agreement with the histograms and with the moderate correlation of the bivariate analysis.

Discussion

The descriptive statistics reported for permeability show an appreciable dispersion and a wide range between minimum and maximum values, which confirms that the evaluated soil environment cannot be interpreted as homogeneous either from the hydraulic or from the functional point of view. In hydro-edaphological terms, this heterogeneity is to be expected because saturated hydraulic conductivity is an emergent property highly sensitive to pore architecture, particle arrangement, degree of compaction and the presence of preferential flow paths. Therefore, even when textural variation is not extreme, small differences in structure can result in marked permeability contrasts. In recent studies at the regional, basin and plantation scales, hydraulic conductivity has been one of the physical variables with the highest coefficient of variation within the set of soil properties, precisely because it simultaneously integrates textural and structural controls. In this logic, the behavior observed in your results does not constitute a methodological anomaly; on the contrary, it is consistent with the intrinsically variable nature of permeability in soils subjected to processes of use, transit, rearrangement of aggregates, and changes in macropore connectivity (Usowicz & Lipiec, 2021; Bargués-Tobella et al., 2024; Álvarez-Herrera et al., 2025).

The frequency distribution of permeability, with data concentration around intermediate values but maintaining tails towards low and high values, suggests that the system presents contrasting hydraulic domains within the same analyzed mesh. From a physical perspective, this means that there are sectors where the potential flow would be more restricted and others where water transport could occur with less resistance. This interpretation is especially relevant because permeability does not depend only on the volume of voids, but also on the existence of continuous, well-connected pores of hydraulically effective size. Recent literature has reinforced this idea by showing that macropore connectivity and hierarchy explain a large part of the hydraulic response of the soil, and that metrics derived from tomography or morphological pore analysis tend to correlate better with conductivity than total porosity alone. Consequently, the presence of extremes in the permeability distribution of your study can be interpreted as the quantitative expression of an uneven internal organization of the porous system, rather than as simple statistical noise or measurement error (Wang & Zhang, 2024; Talat et al., 2025; Cao et al., 2024).

In contrast to permeability, porosity showed a relatively lower dispersion and a more marked concentration of intermediate values, which indicates a more stable spatial behavior. This result is conceptually important because it confirms that the total pore volume can be kept within a comparatively narrow range while the hydraulic response changes much more abruptly. In other words, two sectors with similar porosity can differ significantly in permeability if the shape, continuity, tortuosity and size distribution of their pores is not equivalent. Contemporary studies on porous structure insist that total porosity is a necessary but insufficient metric to explain the movement of water, since hydraulic functionality depends especially on the subset of pores effectively connected and active during flow. Therefore, the lower porosity variability observed in your results strengthens the interpretation that the dominant control over permeability would be given by the structural configuration of the soil and not only by the overall amount of pore space available (Wang & Zhang, 2024; Bargués-Tobella et al., 2024; Talat et al., 2025).

The moderate positive correlation between permeability and porosity is one of the most consistent findings of the set of results, because it reveals a physically logical, although not deterministic, association between both variables. The fact that the correlation is moderate and not high implies that porosity does provide explanatory information, but does not exhaust the hydraulic phenomenon. This pattern coincides with recent studies that have shown that the porosity-permeability relationship improves when complementary attributes such as bulk density, organic carbon, vegetation cover, particle size distribution or structure indicators are incorporated; otherwise, the predictive power of isolated porosity tends to be limited. In terms of scientific writing for a high-impact paper, this allows you to argue that porosity functions as a useful and physically grounded covariate, but not as a surrogate for the primary variable. The scattering cloud, therefore, does not weaken the analysis; on the contrary, it methodologically justifies the use of multivariate or co-estimation approaches, where partial relationships between soil attributes are exploited to improve spatial representation without forcing a simplistic equivalence between pore content and hydraulic conductivity (Soares et al., 2023; Cheng, 2025; Ahmad et al., 2022).

From the geostatistical point of view, the omnidirectional variogram showed a progressive increase in semivariance with distance, which shows that permeability is spatially dependent and that nearby values are more similar to each other than distant values. This result is fundamental because it validates the application of spatial interpolation techniques based on autocorrelation, such as kriging or cokriging, and rules out the assumption of complete randomness. In practice, the ascending shape of the variogram indicates that the soil retains spatial memory at certain scales, probably associated with patterns of deposition, compaction, management or structural reorganization of the environment. Recent literature on spatial characterization of hydraulic properties insists that this step is not just a statistical formality: the variogram defines the effective scale of continuity and, therefore, directly conditions the quality of the interpolated surfaces and the validity of the spatial inferences. Therefore, the fact that your data has allowed you to adjust an interpretable variographic structure constitutes an important methodological strength of the study (Usowicz & Lipiec, 2021; Heße et al., 2024; Mouaddine et al., 2025).

The relative irregularity of the experimental variogram cloud does not invalidate the analysis; rather it reflects the inherently complex and multi-scalar nature of permeability. In real soil media, the spatial structure rarely manifests as a perfectly smooth curve, as the parameter integrates microheterogeneity, scale effects, local disturbances, and sampling-induced variability. The scientific discussion must emphasize that what is relevant is not the geometric perfection of the experimental variogram, but the possibility of capturing its general trend through a reasonable theoretical model that is coherent with the behavior of the variable. In this sense, recent work aimed at the parameterization of subsurface heterogeneity shows that the estimation of variographic parameters is always traversed by uncertainty, but even so it is still indispensable to formulate priors, compare spatial structures and improve the realism of modeling. Thus, the variography of your study should be presented as a parsimonious representation of a complex phenomenon, not as a flawed simplification (Heße et al., 2024; Cheng, 2025; Usowicz & Lipiec, 2021).

One of the most relevant aspects of the analysis was the identification of moderate anisotropy in the directional variograms. This finding implies that the spatial continuity of permeability changes with direction, i.e., that the process is not organized isotropically within the study area. Hydrologically, anisotropy can be associated with differential compaction, preferential orientation of voids, deposition gradients, stratification, mechanical transit or directional development of macropores. Recent studies have shown that repeated machinery traffic, moisture content at the time of compaction, and subsequent structural reorganization alter the connectivity of the porous system in a directional manner, increasing or reducing hydraulic transmission depending on the axis considered. Therefore, recognizing anisotropy in your results not only adds sophistication to the analysis, but also suggests that the structure of the medium contains an interpretable physical signal. In a high-level manuscript, this point should be used to argue that hydraulic continuity responds to oriented spatial processes and that, therefore, isotropic modeling would be a potentially biased simplification (Salazar et al., 2024; Talat et al., 2025; Wang & Zhang, 2024).

The cartography resulting from the interpolation reinforces the previous interpretation by showing sectors with less hydraulic response and others relatively more favorable to flow. These types of surfaces should not be described only as a visual product; It should be discussed as a spatial synthesis tool that integrates observed information, autocorrelation structure, and analytical support for decision-making. In recent studies, maps derived from kriging and cokriging have been used to delimit critical areas of infiltration, optimize complementary sampling, identify physical-water constraints and guide soil management strategies. In your case, the contrast between the greater heterogeneity mapped for permeability and the greater spatial uniformity of porosity is a very solid result, because it confirms in the spatial plane what the histograms and the bivariate analysis already suggested. In other words, cartography not only illustrates the results, but validates them by interpretative convergence between descriptive statistics, correlation, and spatial structure (Soares et al., 2023; Álvarez-Herrera et al., 2025; Mouaddine et al., 2025).

Methodologically, the sequence applied in the study—exploratory analysis, bivariate evaluation, variography, directional analysis, and geostatistical interpolation—is consistent with recent best practices for the characterization of soil hydraulic properties. The current literature emphasizes that reliable estimation of saturated conductivity requires integrated approaches, because direct measurements are expensive, sensitive to the field or laboratory method, and difficult to extrapolate without spatial support or auxiliary covariates. For this reason, the most recent studies have explicitly compared univariate and multivariate methods, showing that the incorporation of physically related secondary variables improves predictive capacity and reduces uncertainty. From that perspective, your results are not only technically valid, but also align with a contemporary methodological trend: moving from a punctual description of conductivity to a spatially explicit, multivariate, and quantifiable understanding of its heterogeneity. This is a clear strength of the manuscript and should be explicitly highlighted in the discussion (Cheng, 2025; Soares et al., 2023; Heße et al., 2024).

Finally, the scientific value of the set of results lies in the fact that it demonstrates that soil permeability cannot be discussed in isolation or as a static property, but as the integrated result of textural, structural and spatial controls. The coexistence of statistical variability, partial correlation with porosity, spatial dependence and anisotropy indicates that the system analyzed is organized by multiple and hierarchical processes. This reading is especially pertinent when the objective of the study is to produce useful information for environmental interpretation, evaluation of soil water functioning or support for territorial management decisions. In that context, your results chapter provides a strong basis for arguing that the geostatistical representation of permeability not only describes patterns, but translates the physical complexity of the medium into a usable analytical form. A high-level discussion must close with precisely this idea: the observed heterogeneity is not an obstacle to the study, but the main finding that justifies the methodological approach used and the scientific relevance of the work (Bargués-Tobella et al., 2024; Cheng, 2025; Usowicz & Lipiec, 2021).

Conclusions

The permeability of the soil in the vicinity of the Chone wastewater treatment plant presented a marked spatial heterogeneity, evidenced by its wide range of variation, its non-uniform distribution and the existence of spatial dependence, which confirms that the hydraulic behavior of the area cannot be interpreted as homogeneous.

Porosity showed a moderate positive relationship with permeability, making it a useful covariate to strengthen spatial modeling; however, its lower variability and partial explanatory capacity indicate that the hydraulic response of the soil also depends on structural factors such as porous connectivity, differential compaction and the internal organization of the soil environment.

The integrated use of kriging, cokriging and variographic analysis made it possible to consistently represent the spatial distribution of permeability and identify areas with lower water transmission capacity, providing a relevant technical basis for the evaluation of susceptibility to waterlogging, drainage management and territorial decision-making in intervened and environmentally sensitive areas.

As a methodological contribution, the study demonstrates that the integration of direct permeability measurements with a physically related edaphic covariate allows to convert point observations into a spatially explicit representation of the hydraulic functioning of the soil, strengthening its hydroedaphological interpretation and its usefulness for applied environmental analysis.

References

1. Alves, M. A. B., Borella, D. R., Paulista, R. S. D., Almeida, F. T. de, de Souza, A. P., & de Carvalho, D. F. (2024). Water infiltration in different soil covers and management in the Cerrado–Amazon ecotone, Brazil. Soil Systems, 8(1), 31. doi:10.3390/soilsystems8010031
2. Bargués-Tobella, A., Winowiecki, L. A., Sheil, D., & Vågen, T.-G. (2024). Determinants of field-saturated soil hydraulic conductivity across Sub-Saharan Africa: Texture and beyond. Water Resources Research, 60(1), e2023WR035510. doi:10.1029/2023WR035510
3. Blanchy, G., Albrecht, L., Bragato, G., Garré, S., Jarvis, N., & Koestel, J. (2023). Impacts of soil management and climate on saturated and near-saturated hydraulic conductivity: Analyses of the Open Tension-disk Infiltrometer Meta-database (OTIM). Hydrology and Earth System Sciences, 27(14), 2703–2724. DOI:10.5194/HESS-27-2703-2023
4. Borek, Ł., Bogdał, A., & Kowalik, T. (2021). Use of pedotransfer functions in the Rosetta model to determine saturated hydraulic conductivity (Ks) of arable soils: A case study. Land, 10(9), 959. DOI:10.3390/Land10090959
5. Espinosa Marín, J. A., Rivera, D., & Haro Prado, R. (2023). Generation of soil permeability maps. Case study in two cantons of Loja province, Ecuador. Sowing, 10(1), e4321. doi:10.29166/siembra.v10i1.4321
6. Municipal Decentralized Autonomous Government of the Chone Canton. (2014). Development and Territorial Planning Plan of the Chone canton.
7. Motaghian, H. R., & Mohammadi, J. (2011). Spatial estimation of saturated hydraulic conductivity from terrain attributes using regression, kriging, and artificial neural networks. Pedosphere, 21(2), 170–177. doi:10.1016/S1002-0160(11)60115-X
8. Qin, L., Tian, Z., Lin, L., Yi, C., & Chen, J. (2024). Evaluation and development of pedotransfer functions of saturated hydraulic conductivity for subtropical soils. Geoderma, 448, 116976. doi:10.1016/j.geoderma.2024.116976
9. Weber, T. K. D., Weihermüller, L., Nemes, A., Bechtold, M., Degré, A., Diamantopoulos, E., Fatichi, S., Filipović, V., Gupta, S., Hohenbrink, T. L., Hirmas, D. R., Jackisch, C., de Jong van Lier, Q., Koestel, J., Lehmann, P., Marthews, T. R., Minasny, B., Pagel, H., van der Ploeg, M., Shojaeezadeh, S. A., Svane, S. F., Szabó, B., Vereecken, H., Verhoef, A., Young, M., Zeng, Y., Zhang, Y., & Bonetti, S. (2024). Hydro-pedotransfer functions: A roadmap for future development. Hydrology and Earth System Sciences, 28(14), 3391–3433. DOI:10.5194/HESS-28-3391-2024
10. Adhikary, S. K., Muttil, N., Yilmaz, A. G., & Cresswell, H. P. (2017). Cokriging for enhanced spatial interpolation of rainfall in two Australian catchments. Hydrological Processes, 31(12), 2143–2161.
11. Deutsch, C. V., & Journel, A. G. (1998). GSLIB: Geostatistical software library and user's guide (2nd ed.). Oxford University Press.
12. dos Santos, R. C. V., Siqueira, T. M., & Soares, M. F. (2024). Sequential Gaussian simulation for mapping the spatial variability of saturated soil hydraulic conductivity at watershed scale. Applied Geomatics, 16(6). https://doi.org/10.1007/s12518-024-00580-9.
13. Gómez-Hernández, J. J. (2021). Sequential Gaussian Simulation. Universitat Politècnica de València.
14. Goovaerts, P. (1997). Geostatistics for natural resources evaluation. Oxford University Press.
15. Hooshmand, A., Delghandi, M., Izady, A., & Ahmad Aali, K. (2011). Application of kriging and cokriging in spatial estimation of groundwater quality parameters. African Journal of Agricultural Research, 6(14), 3402–3408.
16. Journel, A. G., & Huijbregts, C. J. (1978). Mining geostatistics. Academic Press.
17. Ouabo, R. E., Ndzié, J. P., & Ndzié, N. R. (2020). Assessment of ordinary kriging and inverse distance weighting methods for modeling chromium and cadmium soil pollution in e-waste sites in Douala, Cameroon. Environmental Health Insights, 14, 1–13.
18. Remy, N., Boucher, A., & Wu, J. (2009). Applied geostatistics with SGeMS: A user's guide. Cambridge University Press.
19. Siqueira, T. M., Fiorin, J. E., & Tiecher, T. (2019). Soil physical and hydraulic properties in the Donato stream watershed using a geostatistical approach. Brazilian Journal of Agricultural and Environmental Engineering.
20. Webster, R., & Oliver, M. A. (2007). Geostatistics for environmental scientists (2nd ed.). John Wiley & Sons.
21. Ahmad, M., Tang, X.-W., Qiu, J.-N., Ahmad, F., Iqbal, R., Jabeen, M., Alghamdi, A. A., Elshikh, M. S., & Siyal, A. A. (2022). Novel approach to predicting soil permeability coefficient using Gaussian process regression. Sustainability, 14(14), 8781. https://doi.org/10.3390/su14148781
22. Álvarez-Herrera, J. G., Jaime-Guerrero, M., & Fernández-Pérez, C. J. (2025). Spatial variability and geostatistical modeling of soil physical properties under Eucalyptus globulus plantations. Geomatics, 5(3), 41. https://doi.org/10.3390/geomatics5030041

23. Bargués-Tobella, A., Winowiecki, L. A., Sheil, D., & Vågen, T.-G. (2024). Determinants of field-saturated soil hydraulic conductivity across sub-Saharan Africa: Texture and beyond. Water Resources Research, 60(1), e2023WR035510. https://doi.org/10.1029/2023WR035510
24. Cao, Y., Zhang, K., Liu, S., & Wang, Y. (2024). A review of advancements in the theory and characterization of soil macropore structure. PeerJ, 12, e18442. https://doi.org/10.7717/peerj.18442
25. Cheng, L. (2025). Comparison of geostatistical and response surface methodology for estimating soil saturated hydraulic conductivity. Scientific Reports, 15, 34103. https://doi.org/10.1038/s41598-025-19820-y
26. Gupta, S. K., Kumar, M., & Srivastava, A. K. (2024). Hydraulic conductivity of soils: A comprehensive review of the impacts of chemicals, soil salinity, organic matter, and land use. IOP Conference Series: Earth and Environmental Science, 1327(1), 012032. https://doi.org/10.1088/1755-1315/1327/1/012032
27. Heße, F., Müller, S., & Attinger, S. (2024). Data-driven estimates for the geostatistical characterization of subsurface hydraulic properties. Hydrology and Earth System Sciences, 28, 357–374. https://doi.org/10.5194/hess-28-357-2024
28. Mouaddine, A., Bouzekraoui, H., Barakat, A., El Hassania, E. H., Hajaj, S., Bni, Z., & El-Harram, M. (2025). Spatial variability of saturated hydraulic conductivity in irrigated agricultural soils of Beni Moussa sub-perimeter, Tadla, Morocco. Quaestiones Geographicae, 45(1), 5–18. https://doi.org/10.14746/quageo-2026-0001
29. Salazar, M. P., Lozano, L. A., Polich, N. G., Bellora, G. L., Miguel, C., Villarreal, R., Palancar, T. C., & Soracco, C. G. (2024). Anisotropy of soil hydraulic properties induced by repeated machinery traffic in a Typic Argiudoll of the Argentinean Pampas Region. Soil and Tillage Research, 237, 105975. https://doi.org/10.1016/j.still.2023.105975
30. Soares, M. F., Timm, L. C., Siqueira, T. M., dos Santos, R. C. V., & Reichardt, K. (2023). Assessing the spatial variability of saturated soil hydraulic conductivity at the watershed scale using the sequential Gaussian co-simulation method. Catena, 220, 106756. https://doi.org/10.1016/j.catena.2022.106756
31. Talat, A. E., Wang, J., & El-Sorogy, A. S. (2025). Impact of soil compaction on pore characteristics and hydraulic properties by using X-ray CT and soil water retention curve in China's Loess Plateau. Water, 17(8), 1144. https://doi.org/10.3390/w17081144
32. Usowicz, B., & Lipiec, J. (2021). Spatial variability of saturated hydraulic conductivity and its links with other soil properties at the regional scale. Scientific Reports, 11, 8293. https://doi.org/10.1038/s41598-021-86862-3
33. Wang, N., & Zhang, T. (2024). Soil pore structure and its research methods: A review. Soil and Water Research, 19(1), 1–24. https://doi.org/10.17221/64/2023-SWR