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Spatial relationship of the saturated hydraulic conductivity and rock fragments on the soil surface in an Andean microwatershed

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ABSTRACT

Saturated hydraulic conductivity (Ks) is an important soil variable. Multiple investigations have analysed the influence of rock fragments on saturated hydraulic conductivity, but they hardly involve the spatial component. This research spatially modelled the Ks and its relationship with the contents of rock fragments, organic carbon, and total porosity in the surface horizon of the soils of a tropical Andean micro-basin. Hydrologic response units were used to run a stratified-type sampling. Ks was determined using the constant head method and the total porosity using the tension table. Disturbed samples were used to determine rock fragments and organic carbon content. Results showed that the Ks had an exponential distribution, with high values located in areas of the middle and upper parts of the basin. The distribution was spatially related to the content of rock fragments, the total porosity and the organic carbon content using the spatial autocorrelation model with which it was obtained the best fit results between the observed values of Ks and their predicted values on the soil surface ($r = 0.883$). The inclusion of these three variables in pedotransfer functions and hydrological models would reduce the uncertainty in estimating the saturated flow of soil water in stony soils.

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Hydraulic conductivity; soil organic carbon; spatial variability; stony soil; total porosity

1. Introduction

The soil is a key factor in the functioning of the hydrological cycle since water infiltration takes place on its surface. When water enters the soil and saturates the surface horizon, base infiltration rate can be equated to saturated hydraulic conductivity (Ks) (Shukla 2013). Gabriels et al. (2006) indicate that the ease with which the pores within the soil (under saturation state) allow for movement or flow of water is called Ks.

The Ks of soils has high spatial variability (Usowicz and Lipiec 2021) and depends on the spatial variation of soil properties, the presence of cracks, biopores, or other elements that can cause preferential flows of water (Hillel 1998). Some investigations highlight the logarithmic spatial behavior of Ks in soils (Suleiman and Ritchie 2001; Zhang et al. 2020), and also, different spatial models (at different scales) have been developed to estimate or recretate Ks values both at the level of the unsaturated and saturated soil zones (Gupta et al. 2021; Patel et al. 2022; Usowicz and Lipiec 2021); however, due to the generality of the models, they usually do not involve the properties of the rock fragments, a situation that can considerably affect their accuracy (Lai et al. 2018).

The presence of rock fragments (RF) in the soil can affect the behavior of Ks in soils (Bouwer and Rice 1984; Leal et al. 2021). Rock fragments are defined as all those soil materials whose equivalent diameters are greater than or equal to 2 mm (Miller and Guthrie 1984). When there is presence of rock fragments in the soils, the Ks values can sometimes decrease (Wegehenkel et al. 2017); in other cases, the values increase (Thoma et al. 2014). In some soils, ambivalent behaviors of Ks (increases or decreases) can be observed according to fragment contents (threshold content) (Khetdan et al. 2017). This increase in saturated flow values usually occurs because rock fragments can create macroporosities, lacunar pores, and preferential flow networks due to the contacts between the fragments themselves or between them and the soil matrix (Beckers et al. 2016; Leal et al. 2021).

Although there is some research focused on the analysis of the influence of rock fragments on the Ks of soils, the spatial factor has been seldom considered; therefore, the analyses that occur between variables obey traditional statistical relationships (bivariate or multivariate correlational analyses). Only in a few cases, the variables are associated with a spatial component, usually associated with the implemented sampling design (transects, toposenquencies, plot or slope scale) (Nasri et al. 2015; Thoma et al. 2014). It is not possible to show research that executes spatial modeling techniques in order to analyze the relationship between the previously mentioned soil variables.

Spatial data analysis has received increasing attention in studies of the physical, chemical, and biological properties of soils (Haining 2003), since analyses that omit the spatial dependence of the variables are inconvenient in the analysis of modeling (Legendre 1993). Considering the effects in modeling is important as estimation and statistical inference can be unreliables (Hamel et al. 2012). For this research, area data analysis refers to the spatial pattern of an attribute in polygons previously defined by some criterion, such as, for example, the hydrological response units (HRU) of a hydrographic basin that are considered as 'distributed and heterogeneous structured model entities that comprise common land uses and pedo-topo-geological associations that generate and control their hydrological dynamics in

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a homogeneous way' (Flügel 1997). In these cases, the attribute is observed or measured for each unit or polygon one or more times. In the first case the measured data is used, while for several measurements the median of the observations can be used (Grisales Camargo and Darghan Contreras 2020). The objective in this approach is to quantify the spatial pattern through a neighborhood pattern to study the relationships between the attribute of interest or response and the explanatory variables but considering some structure of spatial dependence.

Spatial regression is one of the methods used in this type of spatial technique, and in its modeling several proposals are usually considered, such as those described in the taxonomy presented by Elhorst (2014) that considers the most complete case (general nested) to the pure autoregressive. Although several of these models can be explored, the final selection will depend on the fulfillment of the assumptions inherent in each model (Arbia 2014). In this technique it is important to recognize the neighborhood pattern used, since in the case of polygons and their centroids, there are different criteria to create the matrix of spatial weights that generate the spatial lag of both the response, the explanatory variables, or the residuals of the model.

The objective of this research was to establish the spatial relationships between the saturated hydraulic conductivity of the surface horizon of soils with rock fragments and other soil variables, using spatial modeling tools. This allowed the select of the best fit model for examining its adjusted attributes, assumptions, and predictions for mapping the response variables in the different HRUs in the micro-basin. The results were meant to contribute to the reduction of uncertainty in hydrological models in basins with stony soils and that use the Ks parameter of the soil in their approach.

2. Materials and methods

2.1. Study area

The Zanja Honda micro-watershed is located in the Combeima River basin (Ibagué, Colombia). The study area had an approximate extension of 231.63 ha between the geographic coordinates 4°24.55‘N and 75°13.18‘W (Corporación Autónoma Regional del Tolima 2016). In the area there are elevations above sea level between 941 m and 1631 m with slopes between 0% and 107% (JAXA/METI 2010). Climatologically the basin has an average temperature of 22°C and an average annual rainfall of 1,850 mm (Instituto de Hidrológia Meteorológia y Estudios Ambientales 2022). In the basin there is a predominance of biotite granite rocks and hornblend. Also, sandstone, conglomerate and compact claystone rocks, aphanitic, and porphyritic rocks of dacitic-andesitic composition, unconsolidated sediments and some deposits of extrusive igneous material (ash, lapilli and bombs) are reported (Corporación Autónoma Regional del Tolima 2018; Nuñez et al. 2001). A wide extension in the basin is occupied by Typic Eutrudepts -Typic Udorthents – Entic Hapludolls, and Typic Udorthents – Typic Dystrudept associations. Such soils have rapid drainage, loam to sandy loam textures, and the presence of moderate to highly weathered rock fragments (Fajardo 2005; Instituto Geográfico Agustín Codazzi 2004). The presence of the Typic Haplustalfs consociation and the association Rocky Outcrops are presented, both soils report the presence of rock fragments on the surface and in the soil profile (Instituto Geográfico Agustín Codazzi 2004).

2.2. Soil sampling

A stratified random sampling was carried out, so the strata were defined through hydrological response units (HRUs) that were selected because it allowed obtaining polygons with greater edaphic homogeneity. The HRUs were delineated according to the secondary data available for the area on topics such as use and land cover, slope ranges, and soil units. A total of 46 representative sampling sites were distributed among the 86 hydrological response units initially delineated for the hydrographic area, according to the criteria set forth by the United States Office of Environmental Protection Agency (2002). This allowed establishing the sampling sites in 23 HRUs that represented at least 80% of the basin´s area, as shown in Figure 1.

2.3. Measurement of variables

At each sampling site, three undisturbed samples of the soil surface horizon were collected in metallic cylinders (approximate volume of 98.1 cm^3) in order to determine the total porosity using the tension table method proposed by Romano et al. (2002). The saturated hydraulic conductivity (Ks) was determined using the constant head permeameter (Reynolds et al. 2002).

To determine the rock fragments content in the soil surface horizon at each sampling site, disturbed samples of approximately 7 kg were taken which were initially sieved by 2 mm to separate the coarse fraction of the soil matrix. The coarse fraction was sieved again wet using sieves with openings of 5 mm and 20 mm. The collected rock fragments were dried and weighed to determine the gravimetric content with respect to the soil sample. From the soil matrix of the sieved samples, a small sub-sample was used to determine the soil organic carbon content using the wet digestion method (Walkley and Black 1934).

2.4. Statistical analysis

Initially, an exploratory analysis of the data was carried out to detect spatial dependency structures of the variables involved in the spatial regression model by mapping the medians for each polygon associated with the HRUs. This exploration allowed us to establish the LnKs as a response variable due to its distributional behavior and thus we generated the model with the explanatory variables of total porosity, organic carbon content, and gravimetric content of rock fragments with sizes from 5 mm to 20 mm. Next, the spatial autocorrelation model (SAC) was adjusted, given by the matrix expression of Equation 1.

$$\boldsymbol{Y} = \lambda \boldsymbol{WY} + \alpha \boldsymbol{1_n} + \boldsymbol{X}\beta + \boldsymbol{u} |\lambda| < \boldsymbol{1} \tag{1}$$

$$\boldsymbol{u} = \rho \boldsymbol{Wu} + \varepsilon$$

Where **Y** was associated with the response (LnK_s), $\boldsymbol{\lambda}$ represented the autoregressive coefficient for the response, **W** was associated with the matrix of spatial weights based on the inverses of the Euclidean distances (standardized by

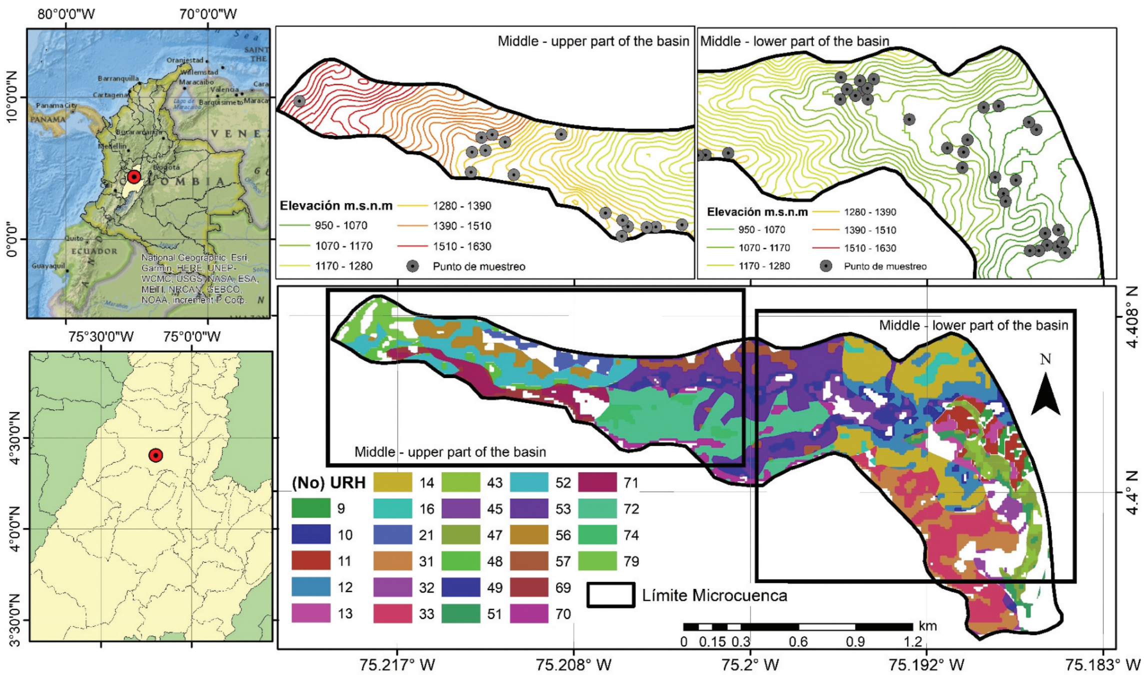

Figure 1. Spatial distribution of sampling sites in the study area.

rows), $\boldsymbol{\alpha}$ is the coefficient of the intercept, $\mathbf{1_n}$ is a vector of ones of length equal to the number of rows of $\mathbf{Y}$, $\mathbf{X}$ was associated with the matrix of explanatory variables of dimension $n \times 3$, $\boldsymbol{\beta}$ represented the vector of parameters associated with the explanatory variables, $\mathbf{u}$ represented the vector of residuals with spatial dependence and $\boldsymbol{\varepsilon}$ are the residuals with normal distribution, independent and identically distributed with parameters $(0,\sigma_\varepsilon^2\mathbf{I})$, where $\mathbf{I}$ is an identity matrix of dimension n×n. This assumption is checked after extraction of the residuals from the model to see if the variables specified in the model are sufficient to explain the spatial autocorrelation that might still be present after modeling. The assumptions of normality of the residuals (Shapiro-Wilk) and their independence (Moran's index) were verified.

In this research, the original variable Ks were initially modeled, but in the series of models obtained, the residuals

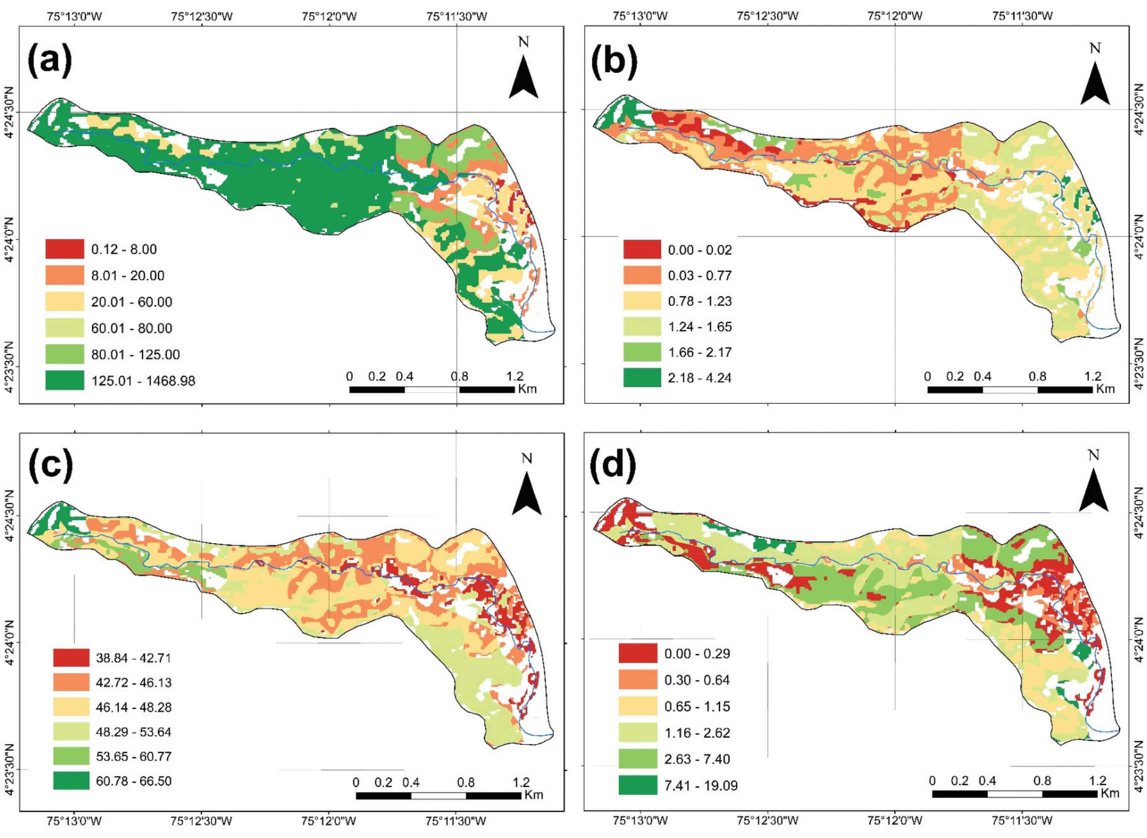

Figure 2. Spatial distribution of medians of (a) observed Ks (mm.h^{-1}), (b) soil organic carbon content (%), (c) soil total porosity (%), and (d) gravimetric content of rock fragments with sizes between 5 mm and 20 mm (%).

showed an approximately exponential behavior, so the natural logarithm operator was applied to the natural response to finally use the Ln(Ks). Once the model was adjusted, the predicted values were extracted and simultaneously mapped in the regions that generated the polygons, the observed and predicted values of Ks, and the respective magnitudes of the explanatory variables. All the results were obtained by using the 'errorsarlm' function of the R spatialreg library (Bivand et al. 2021) and they were mapped using the WGS84 projection system (EPSG 4326) in the program ArcGIS 10.8 (ESRI (Environmental Systems Research Institute) 2019).

3. Results

3.1. Spatial visualization

The spatial distributions of the medians of the explanatory and response variables used in this study are shown in Figure 2.

Of the 46 established sampling sites, only in one of the sites was it impossible to extract undisturbed samples (URH31P03h1) because the surface horizon consisted of an organic layer. Therefore, this horizon was excluded in the statistical analyses performed. The results showed that in the surface horizons of the evaluated sites there was an average total porosity of 48.54% with minimum values of 38.33% (URH 11) and maximum values of 66.50% (URH 79). The highest values of total soil porosity were in the upper part of the basin, while the lowest total porosity values were found in the lower part.

Regarding organic carbon content, the soils studied had a low concentration of this element, with an average value of 1.23% (CV 75.75%). The highest values were detected in URH 9 (4.24%), while in URH 70 no levels of organic carbon were detected with the implemented method. The soils with lower carbon contents were in the middle and upper part of the basin, associated with areas of high slope and granitic parent material. The highest part of the basin and the lowest parts had the highest content of organic carbon; in both cases these soils showed lower content of rock fragments.

The gravimetric content of rock fragments (whose sizes are between 5 mm and 20 mm) averaged 3.04% (CV 152.45%). In the superficial horizon of URH 11 no rock fragments were detected in this size category, while in URH 32 the highest contents of these fragments (19.08%) were detected. The soils with the greatest stoniness were spatially located in a large part of the basin´s area that had steep slopes, which usually came from granitic rocks.

The average Ks in the evaluated sampling points corresponded to 315.43 $mm.h^{-1}$ (CV 115.11%). This indicated the presence of sites with high saturated flow velocities in the area. The median of the data was 155.85 $mm.h^{-1}$, while the first quartile corresponded to 39.95 $mm.h^{-1}$. The behavior of the variable did not follow the characteristics of normality and was more like a logarithmic-exponential type distribution. The HRUs with the lowest Ks corresponded in their order to number 9 and 47 that were spatially located on both banks of the channel in the middle-low part of the hydrographic basin. These areas were usually used for livestock and had different slope ranges.

In contrast, HRUs 69 and 32 had the highest values of Ks. Spatially, the soils with higher saturated soil flow velocities were in the middle-upper part of the basin on both margins of the stream. However, a greater extension of this class of soils towards the upstream left margin was found. These areas of the middle-high part were characterized by being areas of agricultural exploitation with the presence of some relicts of secondary vegetation, especially in areas close to the main channel. The slopes in these areas were usually steep, and 73% of the HRUs evaluated had average values of hydraulic conductivity in fast to very fast categories (>60 $mm.h^{-1}$).

3.2. Spatial modelling

Regarding the weight matrix, the inverse of the quadratic distances was used. Once built, modeling was carried out with the spatial regression method using the model of Equation 1, the fitted model is presented in Equation 2.

$$\begin{aligned} \mathrm{Ln(Ks)} = -2.072 - 0.795\mathrm{WLn(Ks)} - 0.827\mathrm{C} \\ +0.108\mathrm{P} + 0.164\mathrm{R} + u \end{aligned} \quad (2)$$

$$\mathrm{u} = 0.470\mathrm{Wu} + \varepsilon$$

Where C represented the soil organic carbon content (%), P was the soil total porosity (%) and R was the gravimetric content of rock fragments (2 mm to 20 mm) (%); W was the matrix of spatial weights, u represented the vector of residuals with spatial dependence and **ε** are the residuals with normal distribution. The adjustment of the model in Table 1 showed how the data provided evidence against the null effect for the coefficients of the variables listed in the table.

With the same function of R (sacsarlm) it was possible to extract complementary information (Table 2) both to validate the model and to produce other useful metrics for other researchers who have related information.

The first two columns in Table 2 show the autoregressive nature with respect to the residuals and the response variable, respectively. The column with the Moran index shows the spatial independence achieved in the residuals once the model has been adjusted and the last column

Table 1. Statistical summary of modelling using spatial regression (SAC model).

Coefficients	Estimated	Standard Deviation	Z value	Pr(>|z|)
Intercept	-2.072	1.488	-1.392	0.164
Organic carbon	-0.827	0.305	-2.713	0.007
Total porosity	0.108	0.049	2.213	0.027
Gravimetric content of rock fragments (5 mm to 20 mm)	0.164	0.051	3.239	0.001

Table 2. Supplementary information on the fit of the SAC model.

Rho coefficient (*p*-value)	Lambda coefficient (*p*-value)	LR test (*p*-value)	Residual variance	AIC	Moran index (p-value)	Shapiro-Wilk
0.470 (0.025)	-0.795 (8.08e-5)	0.078	0.869	84.806	0.392	0.700

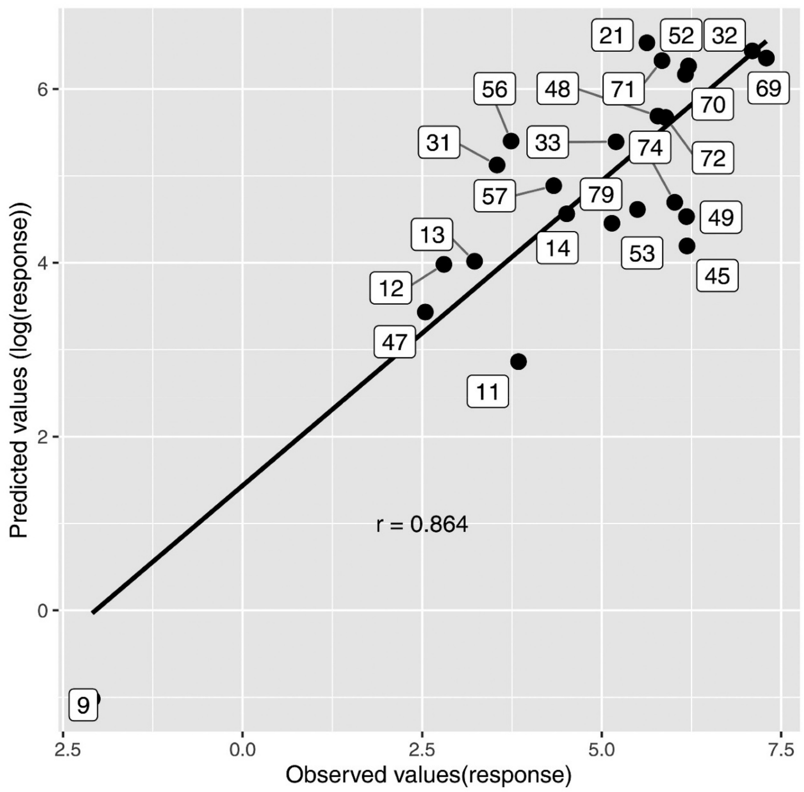

Figure 3. Dispersion of observed and adjusted values of the response in the SAC model and Pearson's correlation coefficient.

corroborates the hypothesis of normality in the residuals of the adjusted model. The remaining columns could be informative for readers from a comparative point of view, for example, in the Akaike Information criterion and the residual variance.

Figure 3 shows a high correlation (r = 0.864) between the observed values of Ln(Ks) against the values predicted by the model for the same response.

Figure 4 shows the spatial distribution of the observed Ks values and the values predicted by the SAC model (the Ks

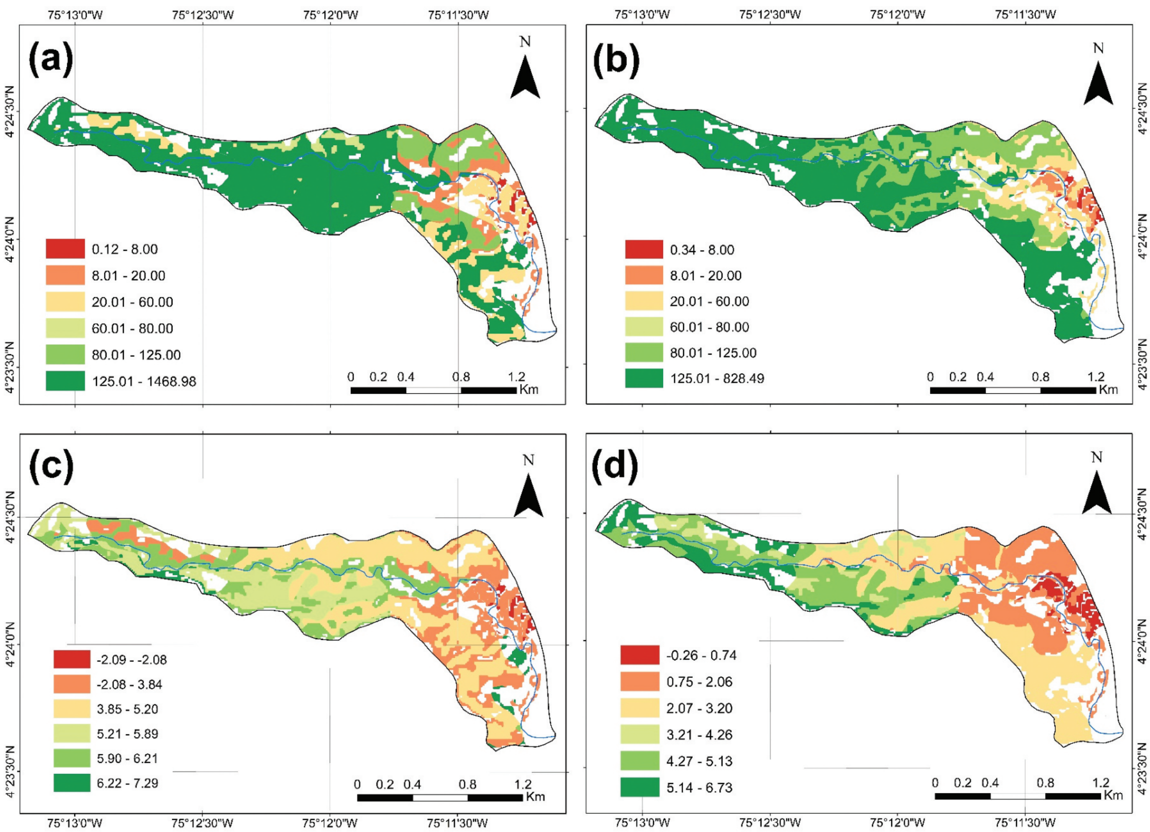

Figure 4. Patterns of Ks (a) observed (mm.h^{-1}), (b) estimated by the model (mm.h^{-1}), (c) Ln(Observed Ks), and (d) Ln(Ks estimated by the model).

estimated values in mm.h^{-1} were calculated by applying the natural antilogarithm to the variable used in the model). A general concordance between the spatial location of the areas with high and low values of the variables was evident. However, the model tended to reduce the magnitude of the variable to some extent.

4. Discussion

The textural porosity of the soil usually determines the saturated flow conditions of the soil column (Hillel 1998); however, the presence of elements such as rock fragments, cracks, biopores and the like affect the homogeneity of the flow and may even become paths for the preferential flow of water (Beckers et al. 2016). In addition, Weil and Brady (2017) comment that the organic carbon content of the soil is related to the process of soil aggregation, the increase in porosity, the flow rate and water retention capacity.

Mapping the spatial distribution of Ks on the soil surface horizon of each HRU of the basin made it possible to show that the highest values of saturated flow in the soil usually occurred in the middle – upper part. These areas were characterized by soils with steep slopes, coming from granitic rocks, and with generalized agricultural activity. In contrast, the areas with lower Ks were generally located in the lower part of the basin, where a large part of these areas had direct influence of the volcanic activity of the Guacharacos volcanic complex. These areas had moderate slopes and their predominant cover was pastures with livestock activity. When making a general comparison of the cartographic results obtained by the model and the observed data, the model values, to a certain extent, tended to smooth the Ks data, reducing the CV% between HRUs up to 23.3 %.

The results obtained showed a relationship between the rock fragments (with sizes between 5 mm and 20 mm) and the saturated hydraulic conductivity values of the soils. Although the spatial analyses initially included the gravimetric contents of various sizes of rock fragments (2 to 5 mm, 5 to 20 mm, 20 to 76 mm and greater than 76 mm), the response variable was only related to a single size range. This is probably because the contents of this size category were the second most common in the soils of the basin, and that due to their larger size (compared to those of 2 mm to 5 mm) it was possible that they generate macropores and cavities that allowed the flow of water more quickly in the soil.

In the hydrological modeling of basins, the Ks values of the soils are usually parameterized by means of pedotransfer functions since detailed sampling of this variable in the field can be expensive due Ks values are highly variable in space (which would require a greater number of samples) and it is easier to obtain it from other variables that are more easily measurable (such as bulk density, soil carbon content, texture, etc.). The results obtained in this research allowed us to establish that the pedotransfer functions that were to be implemented to hydrologically model the basin must consider in their approach the variables soil organic carbon content, total porosity, and gravimetric content of rock fragments in the soil (especially with sizes between 5 mm and 20 mm). The use of functions with these variables will allow the generation of more representative Ks values, and the models used will have less uncertainty because of the three mentioned variables on the saturated behavior of the water flow in the soils.

According to the above, it was theoretically possible that the rock fragments influenced a more rapid flow of water than that presented by a soil matrix without these elements, since they could create macroporosities and lacunar pores (Beckers et al. 2016). Rock fragments could create preferential flows into the soil (depending on their properties such as content, size, shape, position, etc.) (Fies et al. 2002). If the rock fragments were small and their content was low, the tortuosity of the flow could be increased and the Ks decreased accordingly; but, if its size range was larger or if there were higher contents of these fragments, it was possible that the preferential flow effect appeared and considerably exceeded the increase in flow tortuosity (increasing the Ks compared to a soil matrix without fragments) as shown in Figure 5.

It is important to mention that one of the main limitations of the established model is that it works with the transformed values of the variable (natural logarithm), implying that obtaining values in units of mm.h^{-1} requires application of the respective antilogarithm. This situation arises due to the non-normal behavior of the Ks. It should be remembered that the model, being an abstract representation of reality, contains some related predictor and predicted variables, but this does not directly imply

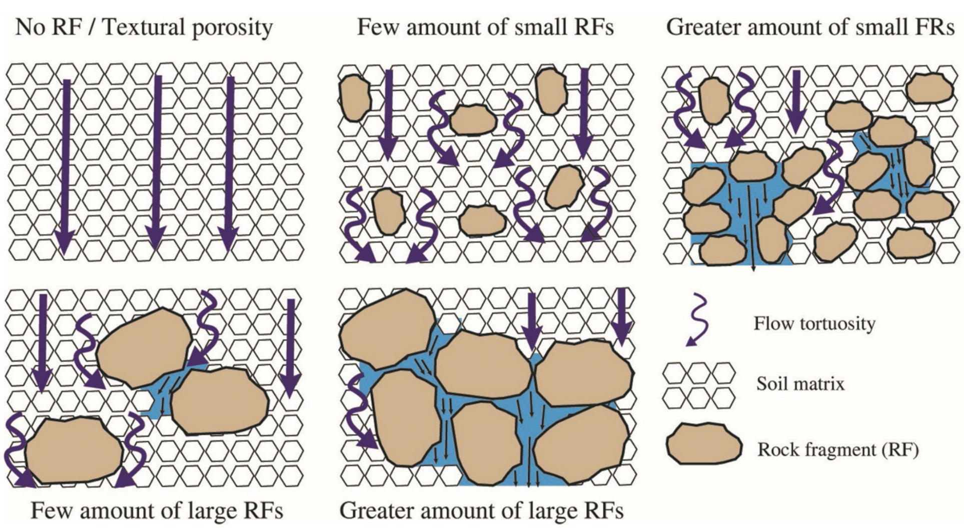

Figure 5. Diagram of the formation of macropores and lacunar pores because of increases in RF content and size in the soil.

a direct cause-effect situation between them. The foregoing implies greater analyzes from the spatial ones in order to establish more precisely cause-effect relationships between the aforementioned variables. Similarly, the proposed model was created for a specific area with its particular climatic conditions, indicating that in order to be applied to other areas, a prior validation of it must be carried out.

5. Conclusions

The objective of developing a spatial model that explained the behavior of the Ks of the soil surface horizon in an Andean micro-basin was fulfilled, considering as predictor variables the total porosity, the gravimetric content of rock fragments with sizes between 5 mm and 20 mm, and the organic carbon content. The observed saturated hydraulic conductivity values had a logarithmic-exponential behavior that inferred a possible spatial dependence of this variable.

The Ks of the soils in the study area were related to the organic carbon content, the total porosity, and the gravimetric content of rock fragments (with sizes between 5 mm and 20 mm) in the soil. This implied that the three previous variables had to be considered when proposing or implementing pedotransfer functions to estimate Ks in hydrological models, thereby reducing the uncertainty of the models due to the spatial variability of Ks and allowing more representative values to be obtained of the variables.

Of the various spatial models used in the study, the spatial autocorrelation model (SAC) obtained the best fit results between the observed values of Ks and their predicted values on the soil surface horizon of the micro-watershed ($r = 0.883$).

The Zanja Honda micro-basin showed high variability in the values of saturated hydraulic conductivity seen in the superficial horizons of the soils. The highest values were in the middle-high part of the basin and the lowest values in the lower part. The foregoing may infer that Ks had some relationship with other factors such as parent material, slope range, and land cover and use.

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Disclosure statement

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