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REGULAR ARTICLE

# Distribution and spatial autocorrelation of physical-water attributes of an Oxisol

**Job Teixeira de Oliveira[1*], Rubens Alves de Oliveira[2], Gloria Milena Rojas Plazas[3], Sinomar Moreira Andrade[4], Fernando França da Cunha[2]**

[1]Professor UFMS, Department Agronomy, Universidade Federal de Mato Grosso do Sul (UFMS), CPCS, Chapadão do Sul-MS, Brazil.
[2]Professor UFV, Departament Agricultural Engineering UFV, Universidade Federal de Viçosa (UFV), Viçosa-MG, Brazil.
[3]Pos graduate UFV, Departament Agricultural Engineering UFV, Universidade Federal de Viçosa (UFV), Viçosa-MG, Brazil.
[4]Ms, Department Agronomy, Universidade Federal de Mato Grosso do Sul (UFMS), CPCS, Chapadão do Sul-MS, Brazil.

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All data will be shared if requested.

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The authors declare no conflict of interest.

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***Autor contribution***
J.T.deO.: conceptualization, supervision, experimental data collection, data custody, data analysis, literature review, writing the manuscript, manuscript review; R. A.deO.: conceptualization, manuscript review, responsible for funding; G.M.R.P.: literature review, writing the manuscript, manuscript review. S.M.A.: literature review, writing the manuscript, manuscript review. F.F.daC.: literature review, writing the manuscript, manuscript review. DFP: Conceptualization, Data analysis, Writing the manuscript, Manuscript Review, Supervision.

## Abstract

Spatial autocorrelation, which in this work was calculated using Moran's bivariate analysis, can be defined as the coincidence of similar values in nearby locations, or the absence of randomness of a variable due to its spatial distribution. Therefore, the objective of this study is to analyze the distribution and spatial autocorrelation of physical attributes of an Oxisol. The experiment was carried out in the irrigation and drainage area of the Universidade Federal de Viçosa, in Viçosa, Minas Gerais, Brazil. The soil in which the experimental meshes were installed was classified as a sandy clayey Oxisol. The attributes were determined: soil moisture on a dry basis, % (DB), soil moisture on a wet basis, % (WB), volumetric soil moisture, % (VS), particle density, g cm-1 (PD), sampled at different depths and within a grid of 90 georeferenced points. For spatial autocorrelation, the global Moran and local Moran indexes (LISA) were used as statistical tools. Bivariate analysis revealed that soil volumetric moisture is closely related to wet and dry basis moisture. It was also found that the surface particle density is related to the deeper layers of the soil, thus reinforcing that the solid fraction of a soil sample, without considering porosity, tends to remain constant. This happens because the predominant mineral constituents in soils are quartz, feldspars, and colloidal aluminum silicates, whose particle densities are around 2.65 g $cm^{-3}$.

## Keywords

Geostatistics; Moran bivariate; Precision agriculture.



## Introduction

Variability in soil properties can result from pedogenic processes and factors. This soil variability occurs horizontally (space) and vertically (in-depth). It can play an important role in crop productivity (Mitchell-Fostyk & Haruna, 2021).

The evaluation of the spatial correlation of soil attributes is important in the optimization of agricultural inputs. This assessment can be done using various tools, such as georeferencing, spatial distribution, and the interpretation of thematic maps in productive fields (Oliveira et al., 2020). Spatial autocorrelation can be defined as the coincidence of similar values in nearby locations, or the absence of randomness of a variable due to its spatial distribution.

Any change in the topsoil layer is caused by natural factors such as rain, plant root growth, and deterioration, shrinkage and swelling, or human interventions such as tillage treatments, wheel traffic compaction, etc. soil porosity. These changes can seriously affect hydraulic conductivity and, consequently, soil water storage (Kargas et al., 2021).

The high spatial and temporal variability of soil moisture content is a fundamental aspect of describing and predicting land surface processes such as soil erosion, flooding, environmental quality, and agricultural economics, including greenhouse gas assessment, solution and transport of nutrients, crop yields, site-specific agricultural management, natural ecosystems and biodiversity (Tunçay, 2021).

Given the importance of knowing the reality of each point of the crop, exploratory studies that use data on soil attributes should be carried out. Therefore, the objective of this study is to analyze the distribution and spatial autocorrelation of soil moisture and particle density in a Red Yellow Latosol.

*Corresponding author
E-mail address: job.oliveira@hotmail.com (J. T. de Oliveira)

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## Materials and methods

The work was carried out in the irrigation and drainage area of the Universidade Federal de Viçosa, in Viçosa, Minas Gerais, Brazil, close to the geographic coordinates: 23 K, 722569.09 m E; 7701897.59 m S (UTM) (Figure 1). According to Köppen and Geiger, the climate is classified as Cwa. The average temperature in Viçosa is 20.6 °C. The average annual rainfall is 1229 mm, with the summer having higher rainfall compared to the winter season.

The soil in which the experimental meshes were installed was classified according to (Santos et al., 2018) as a sandy clayey Oxisol. The value of the granulometric analysis (from 0.0 to 0.2 m depth) was 460, 150, and 390 g kg$^{-1}$ of sand, silt, and clay, respectively. The pH value (in H2O) is 6.0 and the organic matter content is 2.18 dag kg$^{-1}$. The P and K values were 21.2 and 135.0 mg dm$^{-3}$, respectively. The sum of bases 3.7 cmolc dm$^{-3}$ and the cation exchange capacity soil was 6.1 cmolc dm$^{-3}$.

The physical components of the soil were determined individually and collected in the useful area of the sampling point, in a mesh composed of 90 points. The laboratory stages of the analysis were carried out between October and November 2018.

The methodology for determining the physical attributes of the soil followed the recommendations proposed by Teixeira et al. (2017). The attributes were determined: soil moisture on a dry basis from 0 to 0.10 m depth, % (DB1), soil moisture on a wet basis from 0 to 0.10 m depth, % (WB1), volumetric moisture of soil at depths 0 to 0.10 m and 0.10 to 0.20 m depth, % (VS1 and VS2) and density of soil particles at depths 0 to 0.10 m and 0.10 to 0.20 m, g cm-1 (PD1 and PD2).

To graphically express the functional relationship between the correlation estimates between the traits, a correlation network was used, in which the proximity between nodes (traces) was proportional to the absolute value between their correlation. The thickness of the edges was controlled by applying a cutoff value of 0.50, which meant that only |rij| ≥ 0.50 had the margins highlighted. The thicker the line, the greater the correlation. Finally, positive correlations were represented in green, while negative correlations were represented in red.

To test the existence of spatial correlation, the bivariate Moran's I was used (Equation 1), according to Almeida (2012):

$$I^{Z_1Z_2} = \frac{n}{S_o}\,\frac{Z_1'\,W\,Z_2}{Z_1'\,Z_1} \tag{1}$$

If the matrix W is normalized on the line, the equation is expressed as (Equation 2):

$$I = \frac{Z'\,W\,Z_2}{Z_1'\,Z_1} \tag{2}$$

where Z1 is a variable of interest (moisture), Z2 is the values of the other variable of interest in the neighboring region, W is the spatial weighting matrix. Almeida (2012) points out that this coefficient has two distinct variables, so “the numerator refers to a cross-point measure of covariance, while the denominator refers to a rescaling, using the variance of the data”.

In the bivariate Moran I scatter diagram, on the abscissa axis are plotted the volumetric humidity values from 0 to 0.10 m (Z2), observed in the 90 sampling points of the grid. On the ordinate axis are plotted the values of humid base and dry base from 0 to 0.10 m, in addition to the humid base humidity from 0.10 to 0.20 m (Z1), observed between neighboring points (Figure 1).

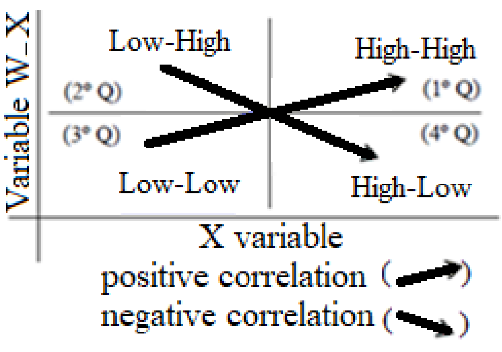


**Figure 1**. Moran scatter diagram adapted from Almeida (2012).

The point cloud scatters plot shows the values of the two variables analyzed, this indicates the slope of the regression line. To achieve this slope, a simple linear regression by the Ordinary Least Squares (OLS) is necessary, expressed according to Almeida (2012) (Equation 3):

$$W_{Z_2} = \propto + \beta_{Z_1} + \varepsilon \tag{3}$$

where $\propto$ is the constant, $\beta$ is the slope and $\varepsilon$ the random error.

The bivariate Moran's I coefficient can be estimated by the OLS (Equation 4):

$$\hat{\beta} = I^{Z_1Z_2} = \frac{Z_1\,W\,Z_2}{Z_1'\,Z_1} \tag{4}$$

where *W Z2* is the slope of the spatial lag regression line against the variable of interest *Z1*.

To understand the bivariate Moran diagram (Figure 2), four quadrants are presented. The first quadrant displays the grouping of High-High (HH) values, in this quadrant, the points with high VS1 values are presented, surrounded by points with also high values of the other analyzed variables. In the second quadrant, it shows the grouping of Low-High (LH) values, that is, it is the grouping of points with low values of VS1, surrounded by points with high values of WB1, DB1, VS2. The third quadrant is the grouping of Low-Low (LL) values, which present the points with low VS1 values that are neighbors of points with low values of the other analyzed humidity. Finally, the fourth quadrant is the grouping of High-Low values (HL), that is, the grouping of points that exhibit high values of VS1, surrounded by points with low values of WB1, DB1, VS2.

It is worth mentioning that analysis was carried out between the particle density from 0 to 0.10 m and the particle density from 0.10 to 0.20 m, in order to understand the relationship between these attribute at different depths.

## Results and discussion

It can be seen in Figure 2 that the density of particles (PD1 and PD2) in the soil has a positive relationship at different depths. Results indicate that volumetric moisture, dry basis moisture, and wet basis moisture are closely related. Tunçay (2021) highlights that the surface layer of the soil is the layer most affected by variations in the rate of evaporation and precipitation, and the amounts and moisture content of the soil at the surface can vary greatly, depending on soil characteristics, including texture, depth, and type of land use.

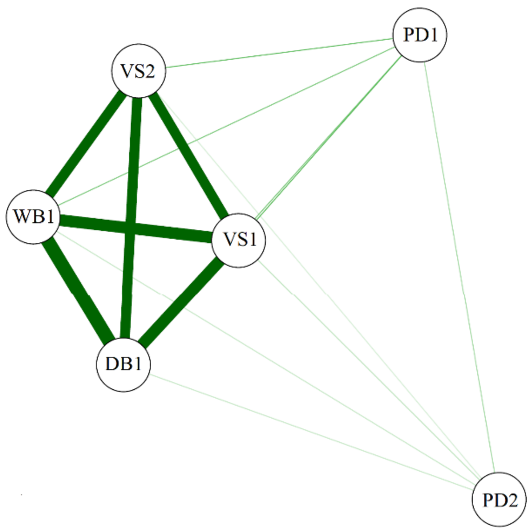


**Figure 2.** Network of correlations between the attributes studied: soil moisture on a dry basis, % (DB1), soil moisture on a wet basis, % (WB1), volumetric soil moisture from 0 to 0.10 m and 0.10 to 0 .20 m depth, % (VS1 and VS2) and particle density from 0 to 0.10 m and 0.10 to 0.20 m depth, g cm$^{-1}$ (PD1 and PD2).

Particle density is higher in sandy soils, as they have more iron oxides. These soils, due to their low microporosity, are also known to retain less water. Therefore, soil with higher particle density tends to have less moisture, whether volumetric, on a dry basis, or on a wet basis, over the days after irrigation or precipitation. The solid mineral particles of soils have different sizes and arrangements, giving them different configurations and behaviors. The granulometric analysis determines the texture of the soil and makes it possible to propose different management actions (Lima et al., 2021). The particle density is dependent on the mineralogical nature of the soil particles, which is around 2.60 to 2.75 g cm$^{-3}$.

Surface soils, ie, at a depth of 0 to 0.10 m, are expected to have lower particle density due to the higher content of organic matter. Soil organic matter (SOM) has a lower density than soil density. According to Oliveira et al. (2016), soil physical properties can be influenced by SOM, in relation to its apparent density, structure, soil aeration, drainage, water retention, and consistency. SOM is also capable of reducing the apparent density of soils, due to its union with soil granules that have a density between 1.2 and 1.4 g cm$^{-3}$. SOM has a variable density from 0.2 to 0.4 g cm$^{-3}$ and indirectly has an effect on soil structuring, increasing pore space and making the soil less dense (Arruda et al., 2021).

The use of the Moran bivariate index becomes an appropriate tool to determine the spatial correlation. Figure 3 shows a Moran scatter diagram between soil attributes that present global bivariate Moran indices.

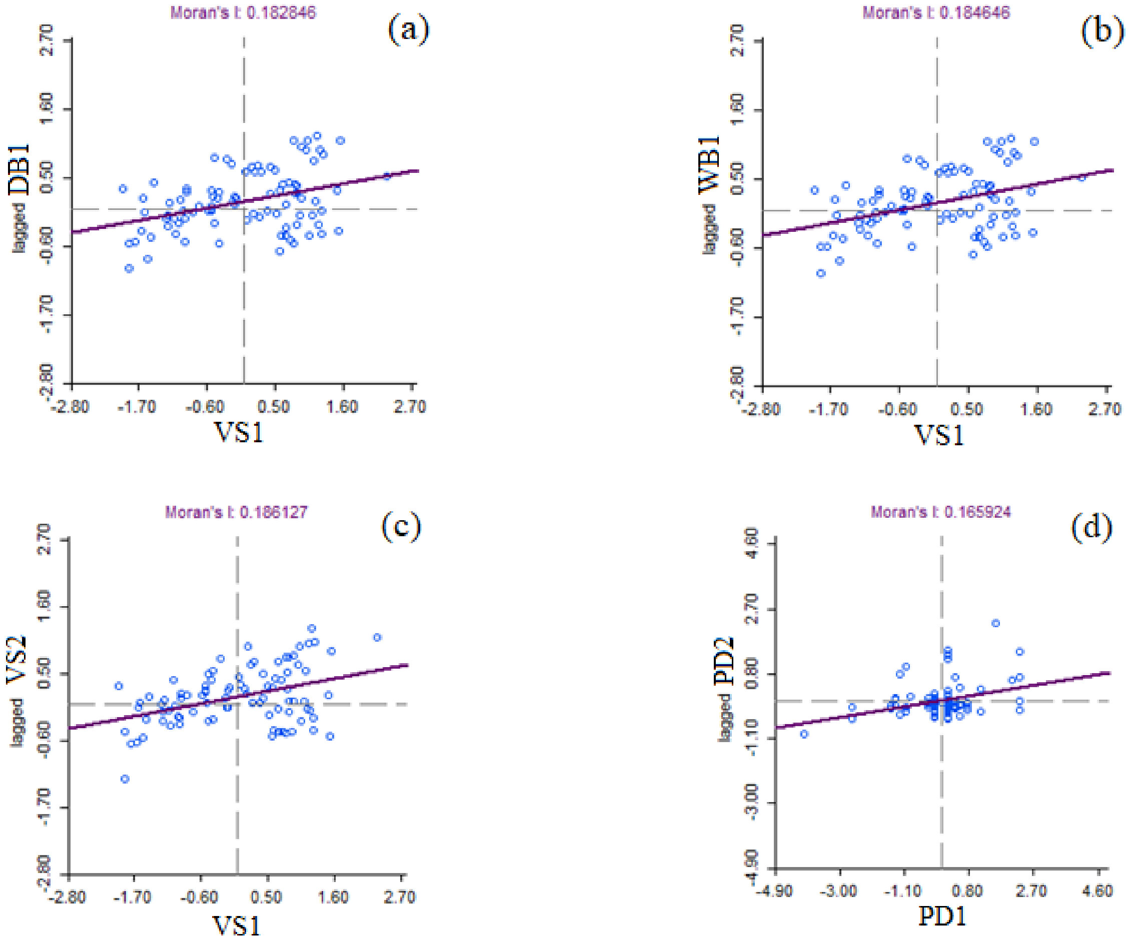


**Figure 3**. Moran scatter diagram between (a) VS1=f(DB1), (b) VS1=f(WB1), (c) VS1=f(VS2) and (d) PD1=f(PD2).

After adjusting the scatter diagrams (Figures 3a, 3b, 3c, 3d) in relation to soil attributes, values were estimated using cluster maps. In this way, it was possible to build maps with the concentration patterns for the variables of this study (Figures 4a, 4b, 4c, 4d), which allowed visualizing and showing where the significant spatial clusters were formed.

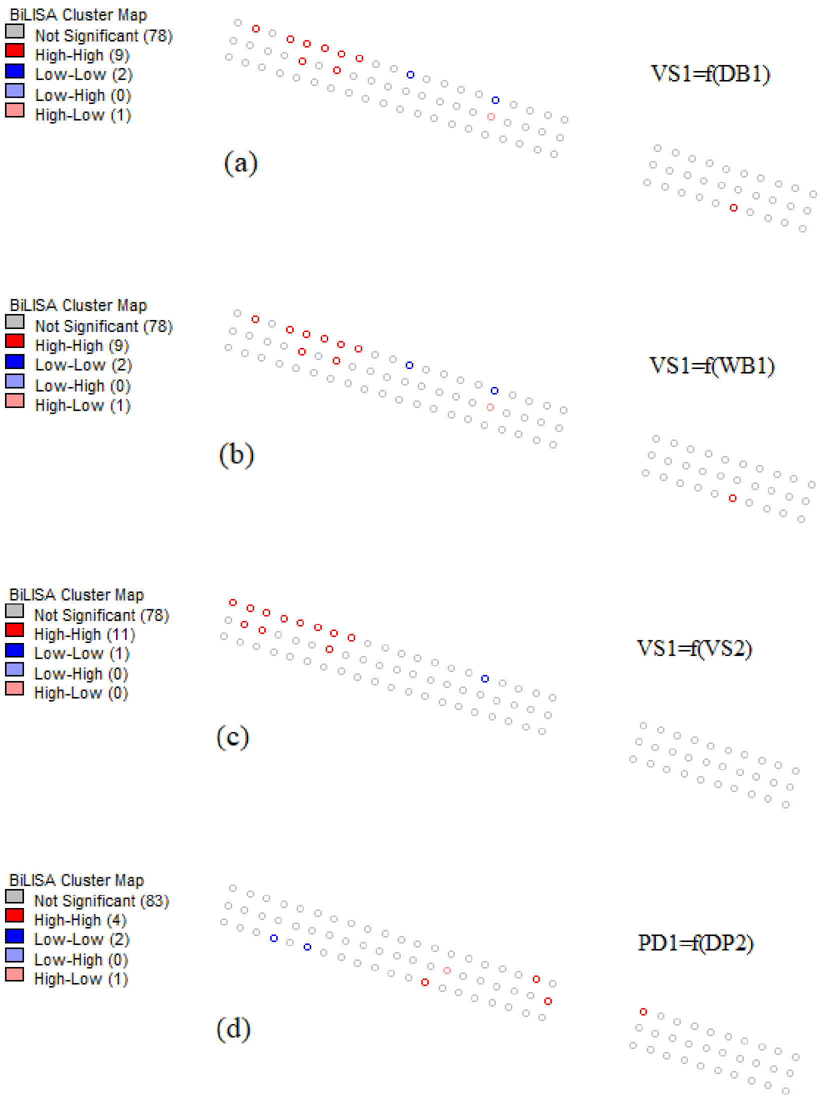


**Figure 4**. Cluster maps of the Moran bivariate indices between (a) VS1=f(DB1), (b) VS1=f(WB1), (c) VS1=f(VS2) and (d) PD1=f(PD2).

With the maps of bivariate clusters, shown in Figure 4, it is possible to observe in which regions statistically significant spatial clusters were formed at least 5% of the relationship between the indicators of soil attributes. These mappings of bivariate regimes allow a more adequate geographic visualization of the degree of concentration of the studied variables, referring to the local bivariate Moran indices or local spatial autocorrelation analysis (Moran LISA).

Four statistically significant categories are presented. The regions denoted in red represent the agglomerations that exhibit a high concentration of the attribute under analysis. The locations denoted in dark blue show the spatial associations that show a low concentration of the attribute under analysis. The units highlighted in lighter blue and red represent the atypical associations, low-high, and high-low, respectively (Oliveira et al., 2021).

When analyzing the Cluster map of volumetric humidity from 0 to 0.10 m in relation to dry basis humidity from 0 to 0.10 m (Figure 4a), it can be seen that 10% of the area (dots in red), concentrated in the left region, showed similar results, that is, “high-high” autocorrelation. A high-high cluster means that the spatial units that are there exhibit high values of the variable of interest surrounded by spatial units that also have high values. The same observations are clearly verified in Figures 4b and 4c. This observation emphasizes the close relationship between volumetric, dry, and wet base moistures. In addition, a relationship between humidities at different depths was studied (Figure 4c).

Considering that the samplings and analyzes were carried out on the same day, it is clear that the regions on the left of the sampling grid are those with the highest humidity. This is very important information for the producer who has, for example, an irrigated area. Possibly this is a region that has a higher concentration of clay and consequently has a greater potential for water retention. In this way, the producer performs differentiated irrigation management, increasing the irrigation shift in this region. With this, he will be able to save water and energy without a decrease in the productive potential of crops in this region.

The maintenance of plant residues and the absence of soil disturbance are the main factors for the improvement of the soil quality state of an agricultural system, for causing an increase in the organic matter contents in the soil, which improves its structuring, stimulating the activity of biological, increasing the water retention and infiltration capacity, increasing the reach of the roots in the soil profile and reducing soil losses by erosion (Vieira et al., 2021). This report may be an explanation for the results found in this work, where the points of higher soil moisture may also be those that had higher organic matter content or higher soil cover residues. These results further reinforce the advantage of having a good straw formation, thus reducing moisture losses and contributing to better soil quality.

Figure 4d shows predominant results from areas with high ratios between different particle density depths. The same is reinforced by the scatter diagram of Figure 3d in which the correlation value found was 0.1659, emphasizing that the surface particle density is related to the deeper layers of the soil. Ribeiro et al. (2021) report that at depth, the density of particles did not differ statistically between different systems of use and management ($p>0.05$), with the surface layer (0.00-0.10 m) and subsurface layer (0.40 - 0.50 m) values statistically equal to each other, in the order of 2.55 and 2.60 g $cm^{-3}$, respectively. Giacomo et al. (2015) observed particle density ranging from 2.55 to 2.73 g $cm^{-3}$ to a depth of 0.40 m in different phytophysiognomies of the Cerrado biome (mesophytic forest, cerradão, and cerrado sensu stricto) under Latosol.

This work can serve as a basis for irrigation management or soil management (fertility) at different rates, also thinking about genetic improvement or the use of drones in agriculture, aiming at greater productivity and income increase for the producer (Oliveira et al., 2021).

## Conclusions

Moran's bivariate analysis emphasizes that soil volumetric moisture is closely related to wet-base and dry-base moisture.

It was also found that the surface particle density is related to the deeper layers of the soil, thus reinforcing that the solid fraction of a sample, without considering porosity, tends to remain constant. This is because the predominant mineral constituents in soils are quartz, feldspars, and colloidal aluminum silicates, whose particle densities are around 2.65 g $cm^{-3}$.

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