

Soil compaction in coffee farming under different agricultural mechanization processes

Rosalra Maria Alves de Moraes¹ , Gabriel Araújo e Silva Ferraz¹ , Aldir Carpes Marques Filho¹ , Augusto Ávila de Castro¹ ,
Alcebiades Fogaça de Souza Sobrinho² , Amara Lana de Abreu¹ , Wélson Antônio de Oliveira³ 

¹Universidade Federal de Lavras, Departamento de Engenharia Agrícola/Escola de Engenharia. Lavras, MG, Brasil

²Instituto Federal do Amapá, Departamento de Agronomia. Porto Grande, AM, Brasil

³Universidade Federal de Lavras, Instituto de Ciências Exatas e Tecnológicas/Departamento de Estatística. Lavras, MG, Brasil

*Corresponding author: rosalra.morais2@estudante.ufla.br

Editor: Samuel Pereira de Carvalho

Received in November 06, 2025 and approved in April 10, 2026

ABSTRACT

Soil compaction is a global environmental problem that affects all agricultural crops, especially those with a perennial cycle, such as coffee. Machinery traffic imposes severe loads on soils and can reduce the productivity and longevity of coffee crops in the state of Minas Gerais. Therefore, this study aimed to investigate the spatial variability of soil compaction caused by repeated passages of agricultural machinery in a coffee plantation. Georeferenced soil Penetration Resistance (PR) samples were collected after the second pass of the coffee harvester, following crop uprooting, plowing, and land leveling, in an area in southern Minas Gerais state. The data were interpolated using geostatistical spatial dependence analysis using Rstudio software, and compaction maps were created using Qgis. All treatments showed spatial dependence for soil PR data. No significant differences were found in soil moisture data. Harvesting, uprooting, and plowing operations resulted in moderate to very high soil RP levels, while leveling resulted in moderate levels of compaction. Plowing and leveling operations reduced soil compaction levels, while harvesting operations increased soil penetration resistance.

Key words: Soil preparation; harvest; soil penetration resistance; precision agriculture; agricultural mechanization.

1 INTRODUCTION

In coffee farming, the constant demand for process and product quality improvements drives the adoption of new technologies and sustainable practices. Among these, maintaining soil physical quality and reducing compaction can improve the efficiency of the coffee production process.

Compaction is one of the main causes of physical soil degradation, hindering plant growth. The process can be defined as a reduction in soil volume and increase in soil mass, typically caused by human activity, resulting in a reduction in pore space and soil water dynamics (Han & Zhen, 2020; Yang et al., 2022).

The highest degrees of compaction generally occur in the subsurface layer of the soil, restricting root development (Bento et al., 2024; Shaheb, Venkatesh and Shearer, 2021; Moura et al., 2021) and, consequently, impairing the absorption of water and nutrients by plants and reducing agricultural productivity (Colombi & Keller, 2019; Hussein et al., 2023).

Continuous agricultural machinery traffic, especially under high soil moisture conditions, can lead to excessive compaction in the soil surface and subsurface, together with the lack of plant species diversification and, often, poor soil cover provided by crop residues (Azevedo et al., 2022; Bareta Junior et al., 2022; Bresciani et al., 2024; Keller et al., 2019; Mbarki et al., 2023). Without controlled traffic, compaction can aggravate other soil degradation processes with erosion,

surface runoff, and loss of soil organic carbon, which can lead to reduced crop productivity and increase the risk of greenhouse gas emissions (Alesso et al., 2020; Machado, F. et al., 2023; Silva, P. 2021; De Sousa et al., 2024).

The development of coffee cultivation is related to the use of agricultural machinery that can cause soil compaction (Lacerda et al., 2022; Marques Filho et al., 2022; Schjønning et al., 2023), altering the environment in which the root system develops (Pulido-Moncada et al., 2020). Therefore, studies aimed at identifying, quantifying, and minimizing the effects of crop management on the soil are important to adapt management accordingly, with a view to developing sustainable coffee cultivation (Voltolini et al., 2023).

According to Eggers et al. (2025), a very common way to assess soil compaction is through soil resistance to penetration with a conical penetrometer, as it offers greater accuracy and reliability in the data. Compaction has been widely studied in the context of Precision Agriculture, and the most widely used indicator for its measurement is soil resistance to penetration using a penetrometer (Molin et al., 2015).

Understanding the spatial variability of soil physicochemical attributes is essential for sustainable crop growth planning (Abdelrahman & Arafat, 2020). Furthermore, Pathak et al. (2019) and Thompson et al. (2019) reported that only 66% of farmers perform soil sampling at appropriate densities for precision agriculture practices, and discussions about soil sampling tools have intensified, varying by soil type, management, and fertilization.

According to Santos et al. (2023), considering that coffee production is strongly influenced by several factors that can lead to a high rate of spatial variability, Precision Agriculture (PA) emerges in this context with the objective of evaluating and quantifying this spatial variability.

Classical statistical analyses that treat soils as homogeneous media are being replaced by analyses that consider correlations between various soil variables. These advances are possible thanks to the development of models and algorithms specific to agricultural engineering. The theory of local variables, or geostatistics, is a tool that enables the study of the spatial variability of soil properties.

Therefore, assessing the distribution of soil compaction within crops can enable the adoption of sustainable cultivation practices, such as localized decompaction interventions and intelligent soil management. According to (Galdos et al., 2020), management techniques used to prevent soil and nutrient losses in the Cerrado include intercropping with forage species. The use of *Brachiaria* species in intercropping systems in coffee production to generate biomass and provide soil cover has recently been adopted throughout Brazil (Franco et al., 2023).

The objective of this research was to investigate the spatial variability of soil compaction caused by different agricultural operations in a coffee plantation.

2 MATERIAL AND METHODS

The study was conducted at Fazenda Santa Helena, located in the municipality of Lavras, Minas Gerais state, Brazil, in the 2023 harvest year. The average altitude was 930 m with an average slope of 5%. According to the Köppen classification, the regional climate is characterized as subtropical with a well-defined dry season (Cwb). In Figure 1 shows the historical data for precipitation (mm) and average monthly temperature (°C) for the year 2023 up to the last month of data collection in the field.

The experimental area consisted of a coffee plantation (*Coffea Arábica* L.) of the Topázio MG 1190 cultivar, planted with a spacing of 3.5 m between rows x 0.70 m between plants, in an area of 18 hectares with a history of coffee cultivation for 40 consecutive years, 20 of which were under mechanized cultivation without the practice of controlling the traffic of agricultural machinery. The management of mechanization in the study area was conducted in order to control and characterize machine traffic during agricultural operations, considering the type of equipment used and the total mass of the mechanized units. The operational planning included defining traffic routes to minimize spatial variability associated with mechanical trampling.

In the sample area, 48 georeferenced points were determined Figure 2, whose geographic coordinates were

obtained by a GNSS receiver and later converted to UTM (Universal Transverse Mercator) coordinates with Datum (WGS 84) - UTM, zone 23 S. At each sample point, soil penetration resistance values were obtained, at a depth of 0 to 60 cm, using a Falker digital penetrometer model PLG1020. However, the present study focused on a single soil depth because the evaluated layer corresponds to the zone most directly affected by machine traffic during the analyzed operation, where the effects of compaction are expected to be more immediate and pronounced. Furthermore, this depth represents the soil layer with the highest concentration of roots in adult coffee plants, making it particularly relevant for assessing the short-term impacts of mechanized operations. Evaluating deeper soil layers would certainly provide complementary information.

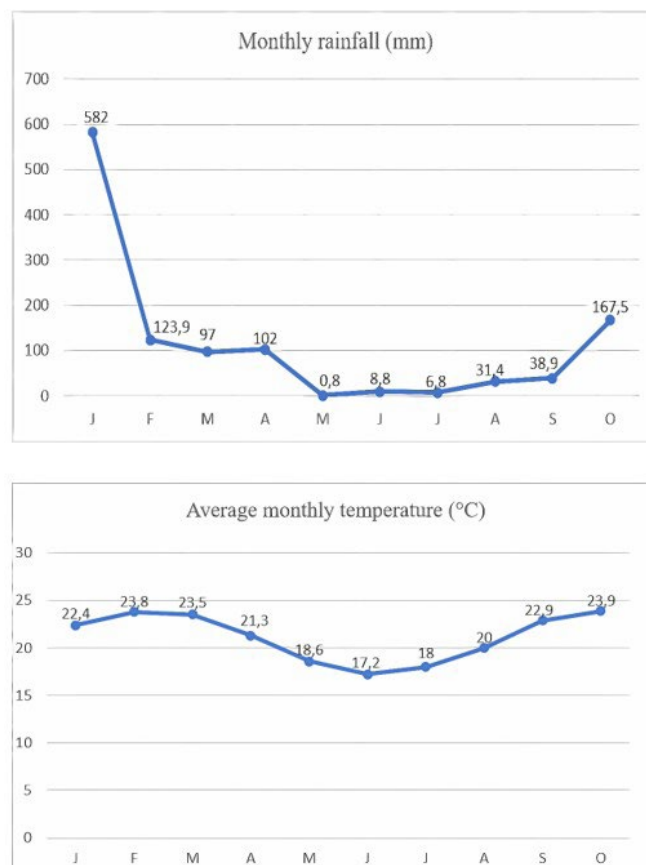


Figure 1: Historical variation of climatic conditions up to the days of sample collection in the year 2023.

Simple soil samples were collected to form composite samples that were used to determine moisture for each data collection carried out in the experiment at a depth of 60 cm in relation to the surface. Simple soil samples were systematically collected at each sampling point, at the defined depth, using a soil auger. A predefined number of subsamples were collected within a small radius around each point to capture

local variability. After collection, the soil samples were sent to the Soil Analysis Laboratory of the Federal University of Lavras. Soil moisture was selected as the main variable in this study because it plays a fundamental role in modulating soil compaction processes and directly influences the mechanical behavior of the soil during and after machine traffic. Focusing on soil moisture allowed us to isolate its effect on the evaluated operating conditions.

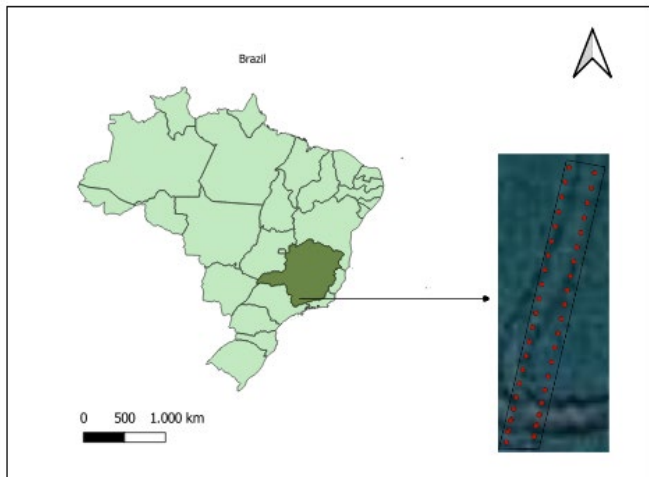


Figure 2: Sampling grid of the experimental area.

Figure 3 shows a history of the collections that were carried out during the study period.

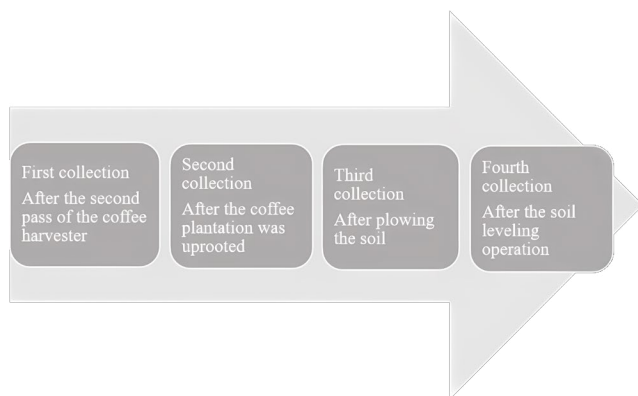


Figure 3: History of the process carried out in the study.

The experimental design was structured to evaluate the cumulative effect of mechanized traffic during coffee harvesting under commercial field conditions. For this reason, soil sampling was carried out after the second pass of the self-propelled coffee harvester and the associated tractor-trailer operation, without prior baseline characterization of the area. This approach aimed to represent the operational reality of coffee harvesting, in which successive machine passes occur within a short time interval. Therefore, the effects observed in

soil moisture reflect the combined influence of the mechanized operations rather than the isolated impact of each machine.

The first data collection was carried out in June 2023, after the second pass of a TDI Top Harvester self-propelled coffee harvester, with a total mass of 7800 kg, equipped with four F-3 diagonal tires and dimensions 7.50-16, with a total width of 3.2 meters, in addition to a 4x2 coffee tractor model MF 4275, with a total mass of 3100 kg, equipped with F-1 and F-2 directional tires and dimensions 6.00-16, 6.50-16, respectively. A trailer equipped with I-1 tires used to transport the harvested coffee beans was attached to this tractor.

The second data collection took place in August 2023, after the existing coffee trees in the area were uprooted at the beginning of the land renovation process. This process was performed using a Caterpillar D5 metal track-type tractor weighing 17,627 kg and equipped with a blade-type implement used to cut the coffee plants.

The third data collection was conducted in September 2023, after plowing the soil. A 4x2 tractor, model MF 4275, weighing 3,100 kg and equipped with F-2 directional tires, and a 1,450 kg disc harrow with 14 26-inch discs were used. The fourth data collection was conducted in October 2023, after the leveling harrow, used to break up the soil clods formed during the plowing process and level the land for subsequent renovation of the coffee plantation. For the soil harrowing stage, a 4x2 tractor, model MF 4275, weighing 3,100 kg and equipped with F-2 directional tires, was used. A lightweight disc harrow with 18 20-inch discs weighing a total of 847 kg was attached to the tractor.

During each data collection, soil samples were obtained throughout the experimental period. These samples were analyzed and sent to the Soil Analysis Laboratory of the Federal University of Lavras to determine the gravimetric soil moisture index. According to Jury and Horton (2004), gravimetric soil moisture is the amount of water present in the soil relative to the dry soil mass, expressed by (Equation 1).

$$U_g = \frac{m_{\text{água}}}{m_{\text{solo seco}}} * 100\% \quad (1)$$

Where: U_g is the gravimetric soil moisture, m_{water} is the mass of water in the soil (g or Kg) and $m_{\text{dry soil}}$ is the mass of dry soil (g or Kg), measured after drying in an oven at 105°C for 24h.

After this process, geostatistical models were applied to the soil compaction data obtained by the penetrometer, and semivariograms adjusted by the Matheron (1962) estimator (Equation 2) were produced to evaluate the spatial dependence of the variables collected in the field.

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(X_i) - Z(X_i + h)]^2 \quad (2)$$

Where: $\hat{\gamma}(h)$ is the semivariance, $N(h)$ is the number of experimental pairs of observations $Z(X_i)$ and $Z(X_i + h)$ at locations X_i and $X_i + h$, separated by distance h . The first model worked on was the spherical model (Equation 3), due to its recommendation for use in cases where phenomena present transition in the study region, that is, some areas (patches) present large values and others small. The average diameter of the patches is represented by the range of the Matheron model (1962).

$$\gamma(h) = \begin{cases} C_o + C \left[\frac{3}{2} \left(\frac{h}{a} \right) - \frac{1}{2} \left(\frac{h}{a} \right)^2 \right] & (0 \leq h \leq a) \\ C_o + C & (h > a) \end{cases} \quad (3)$$

$$(0 \leq h \leq a)$$

$$\gamma(h) = C_o + C$$

$$(h > a)$$

The second model worked was the Gaussian model (Equation 4), and the function with reverse curvature near the origin is continually repeated in geostatistical texts and software packages. c is the limit and r is a distance parameter. The function approaches its limit asymptotically and can be considered to have an effective range of approximately $\sqrt{3} r$. Where it reaches 95% of its level variation (Matheron, 1962).

$$\gamma(h) = C_o + C \left[1 - e^{-3 \left(\frac{h}{a} \right)^2} \right] \quad (4)$$

$$(0 \leq h \leq a)$$

The third model tested was the exponential model (Equation 5), but for practical purposes it is convenient to assign it a practical range, and this is generally considered as a distance at which γ is equal to approximately 95% of the variation of the Matheron (1962) plateau variation.

$$\gamma(h) = C_o + C \left[1 - e^{-3 \left(\frac{h}{a} \right)} \right] \quad (5)$$

$$(0 < h < a)$$

One of the objectives of geostatistical analysis is not only to obtain a spatial dependence model, but also to predict values at unsampled points (Hussain et al., 2022). The

interest may lie in one or more specific points in the area or in obtaining a grid of interpolated points that allows visualizing the behavior of the variable through a map.

To analyze the degree of spatial dependence of the variable, a quantitative assessment of spatial variability called the degree of spatial dependence (DSD) was used, which is the percentage relationship between the nugget effect (C_o) and the variance of the sill ($C = C_1 + C_o$), that is, the higher this coefficient, the lower the spatial variability.

According to Leandro Junior et al. (2020) and Nassar et al. (2023), the nugget effect coefficient with a value up to 25% is classified as having strong spatial dependence, values between 25% and 75% as moderate and above 75% as having weak spatial dependence.

The restricted maximum likelihood (REML) method was used to fit a mathematical model. Spherical, exponential, and Gaussian models were tested for each field sample. As described by Diggle and Giorgi (2019), the principle of REML is to estimate semivariogram parameters by maximum likelihood applied to the data using linear transformation to maximize the likelihood of the semivariogram parameter profile based on the variable transformation.

To choose the best fitting model for the semivariogram, cross-validation of the data was considered (Dalpasso et al., 2019). According to Hengl and Heuvelink (2020), cross-validation is the technique for evaluating estimation errors that allows comparing predicted values with sampled values. This made it possible to analyze the choice of the best fitting method based on the Mean Error (ME) (Equation 6), which should be closest to zero.

$$EM = \frac{1}{n} \sum_{i=1}^n \left(Z(s_i) - \hat{Z}(s_i) \right) \quad (6)$$

Where: n is the number of data; $Z(s_{(i)})$ is the observed value at point $s_{(i)}$, $\hat{Z}(s_{(i)})$ refers to the value predicted by ordinary kriging at point $(s_{(i)})$, without considering the observation $Z(s_{(i)})$ (Dalposso et al., 2020).

According to Cressie and Wikle (2015), the reduced mean error (ER), the standard deviation of the mean errors (SDME), and the standard deviation of the reduced mean errors (SER) can be used to evaluate the models. The reduced mean error (ER) is defined by (Equation 7).

$$ER = \frac{1}{n} \sum_{i=1}^n \frac{Z(s_i) - \left(\hat{Z}(s_i) \right)}{\sigma \left(\hat{Z}(s_i) \right)} \quad (7)$$

Where: $\sigma(Z(s_i))$ is the standard deviation of kriging at point s_i , without considering observation $Z(s_i)$, is defined by (Equation 8).

$$S_{ER} = \sqrt{\frac{1}{n} \sum_{i=1}^n \left\{ \frac{Z(s_i) - (\hat{Z}(s_i)))^2}{\sigma(\hat{Z}(s_i)))} \right\}} \quad (8)$$

The normality of the data was assessed using the Shapiro-Wilk test, and a normal distribution was obtained after logarithmic transformation ($p > 0.05$) and correlation. However, despite meeting the normality assumption, ANOVA could not be applied due to the experimental design, which did not allow for the estimation of treatment effects due to a lack of replication. Therefore, the results were analyzed using descriptive statistics.

Using data acquired by the digital penetrometer, descriptive statistics were generated to demonstrate the variation in Maximum Pressure (MPa) values. Mean, standard deviation, median, variance, and coefficient of variation were determined using the (R Core Team, 2023) statistical software, using the geoR library (Dumelle et al., 2023). After adjusting the best semivariograms, data interpolation was performed using ordinary kriging in Qgis version 3.34 to create isocolor maps for visualizing the spatial distribution patterns of compaction levels in the field.

3 RESULTS

Initially, the data were evaluated for compliance with the assumptions necessary for inferential statistical analyses. Normality was assessed using the Shapiro-Wilk test. Although the original data did not present a normal distribution, the logarithmic transformation resulted in data with a normal distribution ($p > 0.05$), as shown in Table 1.

Table 1: Normality test of the data collected for the study.

Treatment	Normality test	($p > 0.05$)
Harvest	0.967	0.193
Dragging	0.970	0.254
Plowing	0.964	0.147
Leveling	0.890	0.309

However, despite meeting the normality assumption, the experimental design did not allow the application of analysis of variance (ANOVA). Correlation analysis was also performed, the data from the second pass of the coffee harvester and the other collected data showed a variation from -0.017 to 0.33, which revealed weak associations between the variables evaluated.

Although the data met the assumption of normality, the absence of a statistically significant correlation among

treatments and the lack of experimental replication prevented the application of inferential statistical tests such as ANOVA. Similar behavior has been reported in soil compaction studies, where spatial variability and intrinsic soil heterogeneity often mask treatment effects.

Even though data normality was achieved after transformation, the experimental design did not allow the application of ANOVA due to insufficient replication to estimate treatment effects. Additionally, correlation analysis indicated weak relationships among variables, suggesting that the observed variation is primarily related to inherent soil variability rather than treatment effects. For this reason, the results were interpreted using descriptive statistics, which is a common approach in soil compaction studies under field conditions.

Regarding soil moisture, all samples collected and sent to the Soil Analysis Laboratory of the Federal University of Lavras showed variations between the composite soil samples. For the collection taken after the second pass of the coffee harvester, the moisture content was 36.85%, while for the uprooted soil, it was 36.11%. Both collections were conducted two months apart during the region's dry winter, showing a slight drop in soil moisture between collections. For the plowed soil, the moisture content was 38.26%, and for the leveling soil, 39.65%, an increase compared to previous moisture levels due to the onset of spring and the consequent rainy season in the region, naturally reducing soil penetration resistance.

This moisture content present in the collected soil samples contributed to increased soil resistance in areas with higher agricultural machinery traffic. According to Campos et al. (2013), soil moisture can influence the collection of penetration resistance data and affect the results.

The arithmetic mean of the treatments evaluated in this study represents the center of the data distribution. The uprooting treatment had the highest mean among the others, a result attributed to the soil condition, which had not undergone prior decompaction, and to the moisture content, which decreased compared to the pre-uprooting treatment. Compaction was intensified by the second pass of the harvester and the mechanized uprooting of the coffee trees by the tracked tractor, contributing to the increase in the mean. With plowing, there was a reduction in maximum soil pressure levels. However, subsequent leveling activities promoted a further increase in compaction, although at lower levels than those observed after harvest and uprooting.

As presented, the data referring to the arithmetic mean allowed us to observe the variation in the values expressed by the studied variables. However, knowledge of these measures alone is not sufficient to accurately characterize the spatial expression of a variable in a given area (Carvalho et al., 2013).

In this case, the median is represented by the point at which half of the observations are above the value and half of the observations are below it. The standard deviation and variance presented demonstrate how dispersed the data are in relation to the arithmetic mean; that is, the further away the data are from the mean, the greater the dispersion. The coefficient of variation ranged from 19.35% to 35.92%, demonstrating that the data collected after uprooting had greater variation in relation to the mean, compared to the other treatments.

None of the samples studied presented a coefficient of variation lower than 10%, indicating that they all had variability, since according to (Machado, T. et al., 2023), a coefficient of variation lower than 10% would indicate homogeneity. According to (Liu et al., 2021), high values of the coefficient of variation can be considered as the first indicators of the existence of heterogeneity in the data.

Table 2 presents the results of the descriptive statistics of the harvesting, uprooting, plowing and harrowing samples collected from 0 to 60 cm deep in the soil.

Descriptive statistics revealed variation in the data, but this data alone was insufficient to identify the locations of high and low soil compaction rates in the study area. In this case, geostatistical techniques were required to identify the spatial variability of the penetrometer data, enabling detailed analyses of compaction variations using geostatistics.

Based on geostatistical analyses, the nugget effect is an important semivariogram parameter, indicating the unexplained variability of sample data (Jin et al., 2019; Zhao et al., 2020). The nugget effect can be expressed as a percentage of the threshold to compare the degree of spatial dependence of the variables under study (Silva, P. et al., 2021) (Table 2).

The variables submitted to geostatistical analyses showed spatial dependence (Table 2), thus, there was stability in the semivariogram, defining the maximum distance at which the variables showed spatial dependence. (Secondi, 2021).

According to Cressie and Wikle (2015), the range determines the space over which the variable is correlated. The largest range was 7.74 m for the spherical model of the harvest sample, and the smallest range was 1.16 m in the Gaussian model for the uprooting operation. For the practical range, which is defined as the distance at which the model value is 95% of the threshold (Hengl & Heuvelink, 2020), the largest practical range value of 10.29 m was for the exponential

model of plowing, and the smallest value of 1.53 m was for the spherical model of leveling.

The estimated variables presented in this study using the residual maximum likelihood (REML) method were adjusted by the spherical, exponential, and Gaussian models. According to (Nassar et al., 2023), the studied samples showed a moderate degree of spatial dependence for the spherical and Gaussian models for harvesting, and for plowing in the spherical exponential and Gaussian models. For uprooting, the spherical and Gaussian models showed a strong degree of spatial dependence; however, for the exponential model for harvesting and the spherical, exponential, and Gaussian models for leveling, they showed a weak degree of spatial dependence.

In this study, the model that best fitted the data, according to the smallest mean and reduced errors presented; the closer to zero, the better the fit. For the harvest and leveling samples, it was the spherical model with a mean error of $-9,58 \times 10^{-4}$ e $-2,25 \times 10^{-4}$, respectively, and the reduced errors of $-1,3 \times 10^{-3}$ e $-5,33 \times 10^{-4}$, in that order. In the beginning, the model that best fitted the collected data was the Gaussian, with an average error of $-6,5 \times 10^{-3}$ and reduced error $-6,4 \times 10^{-3}$. For plowing, the best fitted model was the exponential one with an average error value of $3,29 \times 10^{-3}$ and reduced error $6,54 \times 10^{-3}$.

Based on the geostatistical analysis methodology, it was possible to quantify the magnitude and spatial dependence of the study samples, as shown in Table 3.

According to Figure 4, penetration resistance values ranged from moderate to very high in the samples collected after the second pass of the coffee harvester. This means that the study area experienced a greater impact, with points with a high compaction index due to the lack of decompression in the area during the 20 years the crop was present. If the coffee plant had remained in the area without intervention to renew the crop, it would have been necessary to decompress the soil through the cultivation of forage plants, improving soil structure, fertility, and water retention capacity (Franco et al., 2023).

Furthermore, the Soil Survey Staff (2017) and (Bento et al., 2024) Classified penetration resistance below 0.01 MPa as extremely low, from 0.01 to 0.1 MPa as very low, from 0.1 to 1.0 MPa as low, from 1.0 to 2.0 MPa as moderate, from 2.0 to 4.0 MPa as high, from 4.0 to 8.0 MPa as very high and above 8.0 MPa as extremely high.

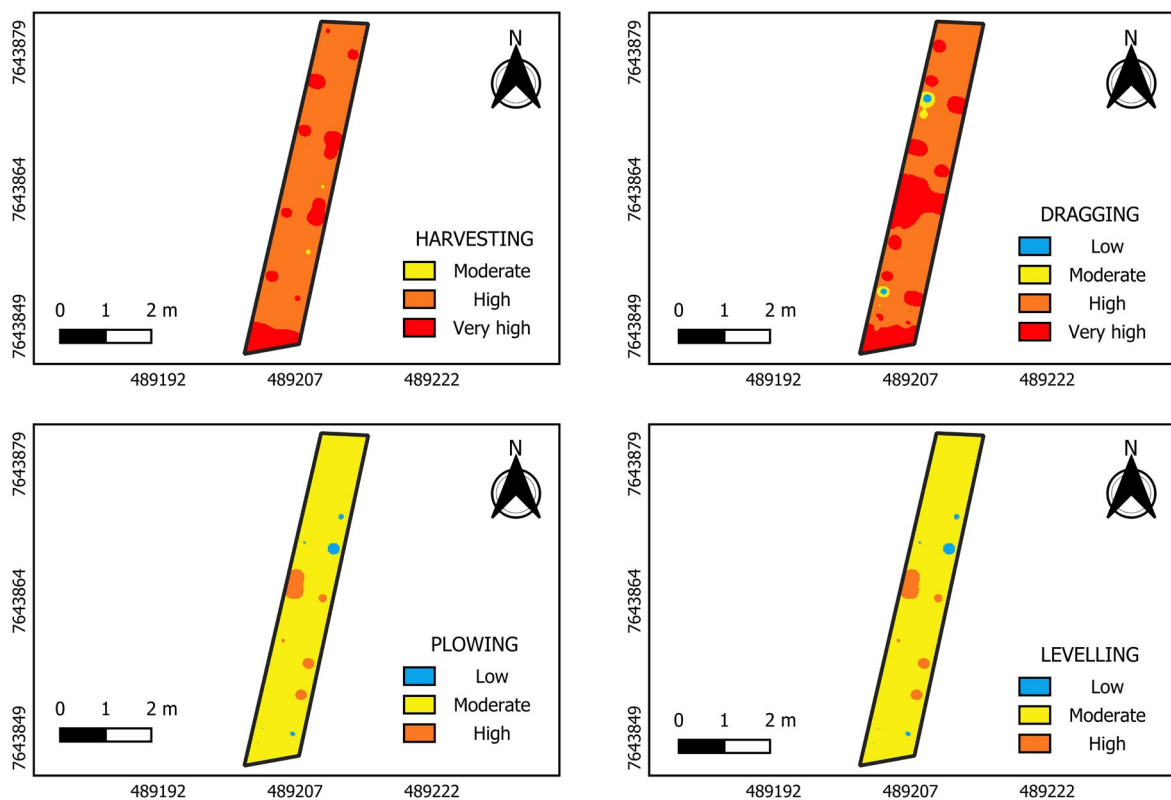
Table 2: Descriptive statistics data.

Treatment	Arithmetic Mean (Mpa)	Standard Deviation (Mpa)	Median (Mpa)	Variance (Mpa)	Coefficient of Variation	Humidity
Harvest	3.472	1.123	3.420	1260.857	32.33%	36.85%
Dragging	3.739	1.343	3.782	1803.695	35.92%	36.11%
Plowing	1.383	0.477	1.260	227.275	34.49%	38.26%
Leveling	2.800	0.542	2.737	294.170	19.35%	39.65%

Table 3: Geostatistical analysis of samples collected in the experiment.

Harvest													
	Model	Nugget Effect	Contribution	Level	Range	Practical Range	Sum of Squares	GD		ME	SDME	RE	SDRE
REML	Esph	0.0466	0.0565	0.1031	2.6641	2.2935	WLS	45.19	Moderate	-9.58e-04	0.3008	-1.3e-03	0.9919
	Gaus	0.0485	0.0548	0.1033	1.3251	2.2935	WLS	46.95	Moderate	1.54e-03	2.42e-03	0.2983	0.9895
Start-up													
	Model	Nugget Effect	Contribution	Level	Range	Practical Range	Sum of Squares	GD		ME	SDME	RE	SDRE
REML	Esph	0.0698	0.2764	0.3462	2.3405	2.3405	WLS	20.16	Strong	-5.8e-03	0.5858	-5.4e-03	1.0522
	Gaus	0.1001	0.2444	0.3445	1.1646	2.0157	WLS	29.05	Strong	-6.5e-03	0.5856	-6.4e-03	1.0501
Plowing													
	Model	Nugget Effect	Contribution	Level	Range	Practical Range	Sum of Squares	GD		ME	SDME	RE	SDRE
	Esph	0.0422	0.0381	0.0803	7.7492	7.7492	WLS	52.55	Moderate	2.71e-03	0.2531	5.51e-03	1.0126
REML	Exp	0.0421	0.0398	0.0819	3.4381	10.2995	WLS	51.40	Moderate	3.29e-03	0.2587	6.54e-03	1.0125
	Gaus	0.0461	0.0360	0.0821	3.9631	6.8594	WLS	56.15	Moderate	2.39e-03	0.2498	4.88e-03	1.0131
Leveling													
	Model	Nugget Effect	Contribution	Level	Range	Practical Range	Sum of Squares	GD		ME	SDME	RE	SDRE
REML	Esph	0.0372	0.0078	0.045	1.5319	1,5318	WLS	82.66	Low	-2.25e-04	0.2179	-5.33e-04	1.0205

REML = Residual Maximum Likelihood; Esph. = Spherical; Exp. = Exponential; Gaus. = Gaussian; WLS = Weighted Least Squares Classical estimator; GD = Degree of Dependence; ME = Mean Error; SDME = Standard Deviation of the Mean Error; RE = Reduced Mean Error; SDRE = Standard Deviation of the Reduced Error.

**Figure 4:** Thematic maps of soil compaction in the study area.

4 DISCUSSION

After crop removal, soil penetration resistance showed marked spatial variability, ranging from low values in small, localized areas indicating the beginning of soil decompaction to very high values in a large part of the cultivated area. This increase in compaction, compared to the previous sampling, is mainly attributed to the traffic of tracked tractors, particularly in areas adjacent to the old coffee planting rows. After plowing, penetration resistance values ranged from low to high, indicating a general reduction in surface compaction; however, isolated zones of high compaction persisted and showed a wider spatial distribution than those observed after coffee crop removal.

Following the soil leveling operation, the penetration resistance patterns were similar to those observed in the previous sampling. Although partial decompaction was evident, a large part of the area remained moderately compacted. The zones that showed high compaction coincided with areas subjected to repeated heavy machinery traffic over successive years, including soil preparation operations such as plowing and leveling. These results highlight the cumulative effect of mechanized traffic on the physical degradation of the soil.

According to Palma et al. (2013), coffee cultivation systems tend to exhibit greater resistance to deep soil penetration compared to annual crops, mainly due to repeated machine traffic along fixed strips parallel to the planting lines. Furthermore, the inadequate weight of the machines was identified as one of the main factors in agricultural soil compaction (Mileusnić et al., 2022). Repeated machine passages or increased load intensity over time promote physical and mechanical changes in the soil, with direct consequences for both soil structure and plant development (Silva, P.L.F., 2021).

The persistence of moderate levels of compaction after leveling suggests that an additional leveling operation may be necessary to achieve more effective soil decompaction and adequately prepare the area for replanting. In this context, understanding the soil's load-bearing capacity and moisture conditions during mechanized operations is essential to avoid further compaction induced by machine traffic (Sandoval et al., 2020).

The spatial distribution maps generated in this study demonstrated that the sampling carried out after the second pass of the coffee harvester and after the uprooting of the crop showed the highest values of soil penetration resistance, reflecting the increased weight and intensity of the machine's traffic. These results reinforce the relationship between the intensity of machine traffic and the progressive increase in soil compaction.

The decision to evaluate a single soil depth was based on the fact that this layer is the most directly affected by machine traffic, where the effects of compaction tend to be

more immediate and pronounced. Furthermore, this depth corresponds to the zone of greatest root density in adult coffee plants, making it particularly relevant for interpreting the short-term impacts of mechanized operations on crop development. Although deeper soil layers were not evaluated in this study, their inclusion could provide complementary information on the vertical propagation of compaction effects. Andrade et al. (2018) reported that compaction variability is typically greater in surface layers, where the effects of machine traffic are more strongly expressed.

The evidence of soil compaction observed in the analyzed layer, expressed by the increased resistance to penetration, indicates a structural condition that may restrict water movement and root growth in the short term. In this context, the adoption of *Brachiaria* species emerges as a promising management strategy to mitigate the effects of compaction. The aggressive and extensive root system of *Brachiaria* promotes the formation of biopores, improves soil aggregation, and increases hydraulic conductivity, thus contributing to the improvement of soil physical quality and microbial activity. Although the establishment of the cover crop was not directly evaluated in this study, the identified compaction patterns corroborate the relevance of these practices as complementary strategies for soil recovery and the long-term sustainability of the system.

Intensive mechanization in coffee production has been associated with physical soil degradation due to increased traffic of machinery and implements (Franco et al., 2022). With the increase in soil bulk density, there is a reduction in water content and aeration, resulting in greater resistance to penetration (Keller et al., 2019). Although agricultural mechanization can increase the load-bearing capacity of the soil (Vogelmann et al., 2012), repeated traffic generally results in soil compaction, increasing bulk density and mechanical resistance to penetration (Ribeiro et al., 2024), which can negatively affect root development and water dynamics.

Despite these challenges, mechanization in coffee cultivation represents a significant advance, increasing operational efficiency, reducing production costs and, when properly managed and supported by precision agriculture tools, contributing to more sustainable production systems.

5 CONCLUSIONS

Geostatistical analysis confirmed the spatial dependence of soil penetration resistance across the coffee plantation, highlighting the influence of mechanized operations on soil compaction. While soil moisture remained relatively uniform, penetration resistance varied substantially among operations. The second pass of the coffee harvester produced the greatest compaction effect, whereas soil leveling had the lowest impact. These findings demonstrate the value of geostatistical tools for

identifying compaction patterns and supporting site-specific soil management in mechanized coffee production.

6 AUTHOR CONTRIBUTIONS

Conceptual idea: Morais, R.M.A.; Abreu, A.L.; Morais, R.M.A.; Abreu, A.L.; Methodology design: Morais, R.M.A.; Abreu, A.L.; Sobrinho, A.F.S.; Filho, A.C.M.; Data collection: Morais, R.M.A.; Abreu, A.L.; Data analysis and interpretation: Oliveira, W.A. Castro, A.A.; Morais, R.M.A.; and Writing and editing: Morais, R.M.A.; Ferraz, G.A.S.; Filho, A.F.S.; Sobrinho, A.F.S.

7 DATA AVAILABILITY STATEMENT

Data available upon request to authors.

8 REFERENCES

- Abdelrahman, M. A. E., & Arafat, S. M. (2020). An approach of agricultural courses for soil conservation based on crop soil suitability using geomatics. *Earth Systems and Environment*, 4:273-285.
- Alesso, C. A. et al. (2020). Spatial distribution of soil mechanical strength in a controlled traffic farming system as determined by cone index and geostatistical techniques. *Agronomy Research*, 18(S2):1115-1126.
- Andrade, A. D. et al. (2018). Spatial variability of soil penetration resistance in coffee growing. *Coffee Science*, 13(3):341-348.
- Azevedo, R. P. et al. (2022). Deep tillage strategies in perennial crop installation: Structural changes in contrasting soil classes. *Plants*, 11(17), 2255.
- Bareta Junior, E. et al. (2022). Critical limits of soil physical attributes for corn and black oat in a Xanthic Hapludox. *Revista Ciência Agronômica*, 3:e20207533.
- Bento, N. L. et al. (2024). Soil compaction mapping by plant height and spectral responses of coffee in multispectral images obtained by remotely piloted aircraft system. *Precision Agriculture*, 25(2):729-750.
- Bresciani, L. et al. (2024). Partitioning the effects of coffee-Urochloa intercropping on soil microbial properties at a centimeter-scale. *Applied Soil Ecology*, 195:105264.
- Campos, M. C. C. et al. (2013). Variabilidade Espacial da resistência mecânica do solo à penetração e umidade do solo em área cultivada com cana-de-açúcar na região de Humaitá, Amazonas, Brasil. *Revista Brasileira de Ciências Agrárias*, 8(2):305-310.
- Carvalho, L. C. C. et al. (2013). Variabilidade espacial de atributos físicos do solo e características agronômicas da cultura do café. *Coffee Science*, 8(3):265-275.
- Colombi, T., & Keller, T. (2019). Developing strategies to recover crop productivity after soil compaction-A plant eco-physiological perspective. *Soil and Tillage Research*, 191:156-161.
- Cressie, N., & Wikle, C. K. (2015). *Statistics for spatio-temporal data*. Nova York: J. Wiley. 900p.
- Dalposso, G. H. et al. (2019). Geostatistical modeling of soybean yield and soil chemical attributes using spatial bootstrap. *Engenharia Agrícola*, 39(3):350-357.
- De Souza, T. R. (2024). Dynamics of carbon and soil enzyme activities under arabica coffee intercropped with brachiaria decumbens in the Brazilian Cerrado. *Plants*, 13(6):835.
- Diggle, P. J., & Giorgi, E. (2019). *Model based geostatistics for global public health: Methods and applications*. Chapman & Hall/CRC, Boca Raton, FL.
- Dumelle, M. et al. (2023). Spmodel: Spatial statistical modeling and prediction in R. *PLoS ONE*, 18(3):e0282524.
- Eggers, H. S. et al. (2025). Impactos do manejo agrícola na resistência a penetração do solo: Comparação entre cultivos de cana-de-açúcar e floresta nativa. *REVISTA DELOS*, 18(63):e3467.
- Franco, T. C. R. et al. (2022). Variabilidade espacial das propriedades físicas do solo em perfis longitudinais. *Anais da Academia Brasileira de Ciências*, 94(2):e20200411.
- Franco J. K. S. et al. (2023). Distance of brachiaria management in between the rows of Coffee trees. *Revista Brasileira de Engenharia de Biosistemas*, 17:1184.
- Galdos, M. V. et al. (2020). Brachiaria species influence nitrate transport in soil by modifying soil structure with their root system. *Scientific Reports*, 10:5072.
- Han-Lin, W., & Zhen-Yu, Y. (2020). High performance prediction of soil compaction parameters using multi expression programming. *Engineering Geology*, 276:105758.
- Hengl, T., & Heuvelink, G. B. M. (2020). *Spatial data science: With Applications in R*. Boca Raton: CRC Press.
- Hussain, Z. et al. (2022). Spatiotemporal distribution patterns of pest species (Lepidoptera: Noctuidae) affected by meteorological factors in an agroecosystem. *Agriculture*, 12(12):2003.

- Hussein, S. A. et al. (2023) Mechanization assessment of soil compaction induced by traffic of farm machinery. *IOP Conference Series: Earth and Environmental Science*, 1214:012051.
- Jin, Y. et al. (2019). Assessment of sources of heavy metals in soil and dust at children's playgrounds in Beijing using GIS and multivariate statistical analysis. *Environment International*, 124:320-328.
- Jury, W. A., & Horton, R. (2004). *Soil physics*. (6th edition). Nova York: John Wiley & Sons.
- Keller, T. et al. (2019). Historical increase in agricultural machinery weights enhanced soil stress levels and adversely affected soil functioning. *Soil and Tillage Research*, 194:104293.
- Lacerda, K. S. et al. (2022). Load-bearing capacity and critical water content of the coffee plantation soil with management in full sun and shaded. *Revista Brasileira de Ciência do Solo*, 46:e0220051.
- Leandro Junior, E. F. et al. (2020). Variabilidade espacial de atributos químicos do solo a partir de diferentes malhas amostrais em duas safras agrícolas. *Caderno de Ciências Agrárias*, 12:1-9.
- Liu, Y. et al. (2021). Spatial multi-scale variability of soil nutrients in relation to environmental factors in a typical agricultural region, Eastern China. *Science of The Total Environment*, 450-451:108-119.
- Machado, F. J. B. et al. (2023). Avaliação de métodos estatísticos para comparação de médias em experimentos com café arábica. *Coffee Science*, 18:e187073.
- Machado, T. M. et al. (2023). Níveis de compactação e sistemas de preparo sobre atributos físicos do solo e componentes de produção da soja. *Agrarian*, 16(56):e17037.
- Mbarki, Y. et al. (2023). Study of the effect of the compaction level on the hydrodynamic properties of loamy sand soil in an agricultural context. *Frontiers in Water*, 5:1255495.
- Marques Filho, A. C. et al. (2022). Can the straw remaining on the ground reduce the wheelsets impact on sugarcane crop? *Sugar Tech*, 24(6):1814-1820.
- Matheron, G. (1962). *Traité de géostatistique appliquée*. Tome I Editions Technip, vol. 14., 333p.
- Mileusnić, Z. I. et al. (2022). Soil compaction due to agricultural machinery impact. *Journal of Terramechanics*, 100:51-60.
- Molin, J. P. et al. (2015). *Agricultura de Precisão*. São Paulo: Oficina de Textos, 224p.
- Moura, M. S de. et al. (2021). Soil management and diverse crop rotation can mitigate early-stage no-till compaction and improve least limiting water range in a Ferralsol. *Agricultural Water Management*, 243:106523.
- Nassar, I. N. et al. (2023). Variability of soil thermal diffusivity in three Iowa fields. *SSSA Journal*, 88(1):180-184.
- Palma, M. A. S. et al. (2013). Resistência do solo à penetração em cafezais cultivados com sistemas mecanizado e manual. *Coffee Science*, 8(3):364-370.
- Pathak, H. S. et al. (2019). A systematic literature review on factors affecting the adoption process of precision agriculture. *Precision Agriculture*, 20:1292-1316.
- Pulido-Moncada, M. et al. (2020). Impact of bio-subsoilers on pore network of a severely compacted subsoil. *Geoderma*, 363:114154.
- Ribeiro, D. et al. (2024). Effectiveness of proximal and remote sensing to trace soils spatial variability: A study case in a Brazilian Cerrado coffee farm. *Ciência e Agrotecnologia*, 48:e013824.
- R Core Team. (2023) R: *A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna.
Available in: <https://www.R-project.org/>.
- Sandoval, F. H. B. et al. (2020). Structural quality and load-bearing capacity of an Ultisol (Argissolo Vermelho amarelo) in mechanized coffee areas with different deployment times. *Revista Brasileira de Ciência do Solo*, 44:e0190009.
- Santos, S. A. et al. (2023) Spatial and temporal variability of productivity of coffee plants grown in an experimental field located in Três Pontas, Brazil. *Agronomy Research*, 21:1567-1580.
- Schjønning, P. et al. (2023) The challenge in estimating soil compressive strength for use in risk assessment of soil compaction in field traffic. *Advances in Agronomy*, 178:61-105.
- Secondi, L. (2021). Estimating household consumption expenditure at local level in Italy: The potential of the cokriging spatial predictor. *Social Indicators Research*, 153(2):651-674.
- Shaheb, M. R., Venkatesh, R., & Shearer, S. A. (2021). A Review on the effect of soil compaction and its management for sustainable crop production. *Journal of Biosystems Engineering*, 46:417-439.

- Silva, M. V. et al. (2021). Spatial modeling of rainfall patterns and groundwater on the coast of northeastern Brazil. *Urban Climate*, 38:100911.(1)
- Silva, P. L. F. (2021). Compactação e seus efeitos sobre o funcionamento do solo e a absorção de nutrientes pelas plantas: Uma revisão bibliográfica. *Meio Ambiente*, 3(2):24-33 (2).
- Silva, R. F. (2021). Changes in soil profile hydraulic properties and porosity as affected by deep tillage soil preparation and Brachiaria grass intercropping in a recent coffee plantation on a naturally dense Inceptisol. *Soil and Tillage Research*, 213:105127 (3).
- Soil Survey Staff (2017). *Soil Survey Manual*. USDA Handbook 18. Washington, DC: U.S. Government Printing Office. Available in: <https://www.nrcs.usda.gov/>.
- Thompson, N. M. et al. (2019). Percepções dos agricultores sobre os benefícios da tecnologia da agricultura de precisão. *Revista de Economia Agrícola e Aplicada*, 51:142-163.
- Vogelmann, E. S. et al. (2012). Compressibilidade de um Argissolo Vermelho-Amarelo trafegado e escarificado. *Ciência Rural*, 42(2):291-7.
- Voltolini, G. B. (2023). Techniques for sustainable coffee crop management: Impacts on growth and yield. *Archives of Agronomy and Soil Science*, 69(12):2413-2429.
- Yang, P et al. (2022). Soil compaction prevention, amelioration and alleviation measures are effective in mechanized and smallholder agriculture: A meta-analysis. *Land*, 11(5):645.
- Zhao, K. et al (2020). Risk assessment, spatial patterns and source apportionment of soil heavy metals in a typical Chinese hickory plantation region of southeastern China. *Geoderma*, 360:114011.