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Assessing soil fertility inequality at regional scale to support plot-level site-specific management

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Abstract.

Precision Agriculture (PA) practices rely on identifying the spatiotemporal variability of agronomic variables, such as soil fertility, to support site-specific management practices within-plots, including variable-rate fertilization. However, when attempting to adapt this PA approach to some contexts, e.g., smallholder systems, it may be more relevant to assume each plot as a management unit itself, and then seek methods to highlight the between-plot variability within a given farm to guide fertilization strategies according to plot-specific requirements. This variability can be described in terms of intra-farm inequality of soil physicochemical attributes, which can be quantified using statistical measures such as the Gini coefficient. Originally developed to measure economic inequality, the Gini coefficient is a dimensionless and scale-independent index ranging from 0 to 1, indicating the lowest and highest levels of disparity, respectively. If this coefficient can be adopted at the farm scale, it may also be useful for characterizing farm heterogeneity across an entire production region, particularly when large datasets comprising multiple farms and several soil attributes are available. In this sense, this study aimed to verify whether the Gini coefficient can be adopted as a standardized metric to portray the relative heterogeneity of soil fertility attributes and to identify the main drivers of this inequality across farms at a regional scale. To test this hypothesis, georeferenced soil fertility data from the 2024 growing season of 78 coffee farms comprising 742 plots located in Caconde, São Paulo State, Brazil, were analyzed. Six soil attributes measured in the 0.0-0.20 m soil layer were evaluated: pH, soil organic matter (O.M.), phosphorus (P), potassium (K), calcium (Ca), and magnesium (Mg). For each farm, Gini coefficients were calculated for all attributes. An overall inequality index was obtained as the mean Gini coefficient across attributes, and farms were subsequently classified into "low", "moderate", and "high" inequality classes using terciles. The attribute presenting the highest Gini coefficient

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within each farm was defined as the dominant driver of inequality. Summary statistics, Friedman and pairwise Wilcoxon signed-rank tests, dominant-driver frequency analyses, and Global Moran's I statistics under different k-nearest-neighbor configurations (k = 4, 6, and 8) were used to evaluate the regional behavior of the suggested metric. Our findings suggest that he proposed framework was useful to quantify the relative heterogeneity of soil fertility attributes across a study region and inequality classes, while also identifying the attributes that most strongly contributed to between-plot variability within each farm. In our case, P consistently exhibited the highest levels of inequality, followed by Ca, Mg, and K, whereas O.M. and especially pH showed lower heterogeneity. However, spatial analyses revealed no significant global spatial autocorrelation of the Gini coefficients for any soil attribute, suggesting that inequality patterns are predominantly farm-specific rather than geographically clustered. These results demonstrate that the Gini coefficient is a reasonable metric for assessing within-farm soil fertility heterogeneity, and its use represents a simple and scalable framework for extending PA concepts to smallholder production systems at both farm and regional scales.

Keywords.

Between-plot heterogeneity, small-scale agriculture, measure of statistical dispersion.

Introduction

Precision Agriculture (PA) can be defined as a management strategy that relies on temporal and spatial variability to improve the sustainability of agricultural production. The identification of such discrepancies, followed by the delineation of management zones (MZs) to support site-specific practices such as variable-rate fertilization (VRF), is commonly performed within plots of large-scale agricultural systems (Wollenhaupt et al., 1994; Fleming et al., 2000; Guerrero et al., 2021; Zhou et al., 2024, Niaz et al., 2026). However, despite the importance of improving sustainability across agricultural systems of all scales, this PA paradigm is often difficult to implement in some circumstances, such as in smallholder farming systems due to the limited plots extension and also economic and practical constraints, which prevent the delineation of MZs within individual plots. In this context, each plot already represents a cell, i.e., an operational management unit, as occur in coffee farms (Silva et al., 2025) where individual plots may differ in cultivar, plant age, biennial production cycle, fertilization requirements to attend an expected yield, and other management factors. Therefore, the most relevant source of variability in this scenario may not necessarily occur within individual plots, but rather between plots belonging to the same farm. Consequently, understanding and quantifying the extent of the heterogeneity within a farm becomes essential for supporting site-specific management strategies in small-scale agricultural systems as advocated by the PA concept.

When looking for an approach to quantify this heterogeneity, particularly regarding soil fertility, several statistical measures can be used for this purpose. However, most of them are scale-dependent, making comparisons between soil attributes expressed in different units and ranges difficult. In this context, the Gini coefficient (Gini, 1921) represents a useful alternative because it summarizes variability in terms of inequality through a dimensionless index ranging from 0 to 1, indicating lower and higher inequality, respectively. This feature enables direct comparisons between plots within a farm, providing a standardized framework to rank soil attributes according to their relative contribution to within-farm heterogeneity, allowing the identification of dominant drivers of variability and the classification of farms according to their overall or average inequality extent. Such an approach becomes particularly valuable in the current context of digital agriculture, where large georeferenced databases could be available, especially in production regions supported by farmers cooperatives, laboratories, extension services, and agricultural organizations. By applying the same framework to multiple farms, it becomes possible not only to characterize heterogeneity at the farm scale but, therefore, to conduct broad regional-scale analyses and evaluate if inequality patterns exhibit spatial patterns across large territories.

Thus, the objective of this study is to evaluate whether the Gini coefficient is an appropriate metric to assess between-plot soil fertility inequality within farms, identify dominant attributes driving heterogeneity, and evaluate the spatial organization of these patterns at a regional scale of production regions.

Material and methods

Study site and dataset description

The study was conducted using a regional dataset comprising georeferenced soil fertility data collected in the 2024 growing season from 742 plots distributed in 78 commercial coffee farms located in the municipality of Caconde, São Paulo State, Brazil. This dataset was provided by the Coffee Producers Cooperative in Guaxupé LTDA (i.e., Cooxupé), located in Minas Gerais State, Brazil and corresponded to soil chemical analyses from cooperative members' farms conducted by the cooperative's own laboratory. A previous data preprocessing was performed and only farms containing at least four plots were retained for the following analysis, ensuring sufficient observations for within-farm inequality determination. The soil samples regarding these soil analyses were collected in the 0.0–0.20 m soil layer.

Within-farm inequality calculation

Six soil fertility attributes measured in each plot of every farm were assumed for inequality determination, i.e., pH, soil organic matter (O.M.), phosphorus (P); potassium (K), calcium (Ca) and magnesium (Mg). For each attribute, the Gini coefficient (G) was calculated according to Equation 1 as the average pairwise difference among observations relative to the mean.

$$G= \left(\sum_{i=1}^{n} \sum_{j=1}^{n} \left|x_i-x_j\right|\right) / \left(2n^2\bar{x}\right) \quad (1)$$

Where (x_i) and (x_j) represent the values of a given soil attribute measured in the i-th and j-th plots within a farm, such that all possible pairwise differences between existing plots are considered; n is the number of plots within a farm; and $\bar{x}$ is the mean value of the attribute.

An overall inequality indicator for each farm was calculated as the arithmetic mean of the six attribute-specific Gini coefficients. After calculating G for all farms, the resulting values were ordered and classified into three inequality classes using terciles. Farms with mean Gini values below the 33.3rd percentile were classified as "Low inequality", those between the 33.3rd and 66.7th percentiles as "moderate inequality", and those above the 66.7th percentile as "high inequality".

Local and regional whitin-farm inequality analysis

After calculating the Gini coefficient and assigning farms to inequality classes, a set of local (i.e., farm) and regional-scale analyses was performed. Firstly, descriptive statistics of the Gini coefficient were calculated for each soil attribute to characterize the overall patterns of within-farm inequality across the study region. Next, to identify the main source of heterogeneity within each farm, the soil attribute presenting the highest Gini coefficient was defined as the dominant driver of inequality. The frequency of each dominant driver was then quantified for the entire dataset, providing a regional-scale assessment, and subsequently within each inequality class. Differences between soil attributes in terms of their Gini coefficients in regional scale were initially assessed using the Friedman test for repeated measures, assuming the farms as blocks, and assessing statistical significance at 5% (i.e., $\alpha = 0.05$). When significant differences were found, pairwise Wilcoxon signed-rank tests with Benjamini-Hochberg correction were used as post hoc comparisons. The same procedure was subsequently applied within each inequality class to investigate whether the relative importance of soil attributes changed according to the overall intensity of farm heterogeneity.

To illustrate the inequality patterns at the farm scale, Lorenz curves were generated for representative farms belonging to the low, moderate, and high inequality classes. Representative farms were selected based on their overall mean Gini coefficient and dominant driver of inequality.

Finally, to formally evaluate whether within-farm inequality patterns exhibited regional spatial organization, Global Moran's I statistics were calculated for the Gini coefficients of each soil attribute. Spatial relationships among farms were defined using different k-nearest-neighbor networks (i.e., k = 4, 6, and 8), and also evaluating statistical significance at 5% level ($\alpha = 0.05$).

Results and discussion

Descriptive statistics and main drivers of within-farm inequality

Table 1 presents the descriptive statistics concerning Gini coefficient of soil attributes at regional scale and for each Gini classes. In the set of all coffee farms evaluated, the Gini values were not extremely high (i.e., close to one), once all attribute presented lower median values, which indicates that most farms did not exhibit extreme heterogeneity concerning soil fertility. The highest median Gini values were observed for P, followed by Ca, Mg, and K. In contrast, O.M. and especially pH showed the lowest levels of inequality within the coffee farms.

Table 1. Descriptive statistics of the Gini coefficient calculated for six soil fertility attributes measured in 78 coffee farms throughout the coffee production region of Caconde, São Paulo State, Brazil.

Attribute	n	Mean	Median	SD	Variance	Min.	Q1	Q3	Max	IQR	CV(%)	Skewness	Kurtosis
P	78	0.26	0.26	0.10	0.01	0.06	0.18	0.33	0.51	0.15	39.83	0.36	2.38
Ca	78	0.23	0.24	0.08	0.01	0.05	0.16	0.28	0.44	0.12	35.31	0.06	2.60
Mg	78	0.22	0.22	0.09	0.01	0.05	0.15	0.28	0.48	0.13	41.46	0.41	2.89
K	78	0.19	0.19	0.07	0.01	0.04	0.14	0.24	0.36	0.11	39.05	0.06	2.50
O.M.	78	0.09	0.08	0.04	0.00	0.01	0.06	0.11	0.22	0.04	41.97	1.09	4.87
pH	78	0.05	0.05	0.02	0.00	0.01	0.03	0.06	0.09	0.03	38.79	0.26	2.65

SD: standard deviation; Min. and Max.: minimum and maximum values; Q1 and Q3: first and third quantile; IQR: interquartile range; CV(%) coefficient of variation (in %).

Figure 1 shows the frequency of each soil attribute identified as the main driver of within farms variability at regional and mean Gini classes scale. As the descriptive statistics of the Gini results had already suggested, P was the dominant driver of internal heterogeneity in almost half of the evaluated farms (46.2%). Ca appeared in second place (23.1%), followed by Mg (15.4%) and K (14.1%) that showed intermediate frequencies. For our dataset M.O. was dominant in only one property.

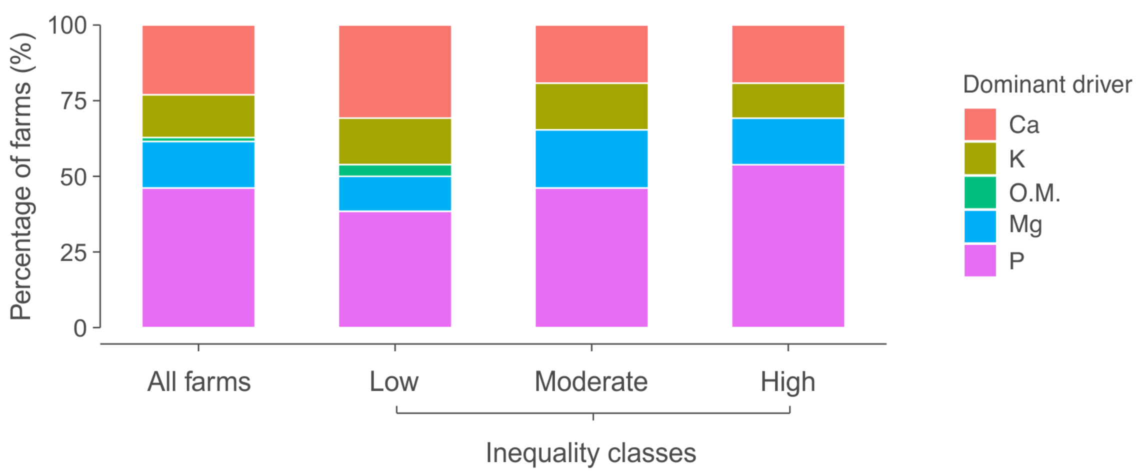

Fig 1. Dominant driver of within-farm inequality regarding soil fertility attributes across the coffee production region of Caconde, São Paulo State, Brazil, and by within-farm inequality class.

It is worth to highlight that the distribution of the overall inequality indicator (i.e., the average Gini value) for each farm was perfectly balanced according to tercile rule, resulting in 26 farms categorized in each “low”, “moderate” and “high” average inequality class. Thus, when looking for the dominant drivers in each class, we again notice the predominance of P. Additionally, as described in Figure 2, as global inequality increases, so does the likelihood that P is the main driver of this heterogeneity. From the perspective of PA, these findings suggested that if the goal is to prioritize a variable for a possible site-specific management in the evaluated context, strategies focused on VRF of P may produce the greatest benefits, particularly on coffee farms classified as having “high” inequality.

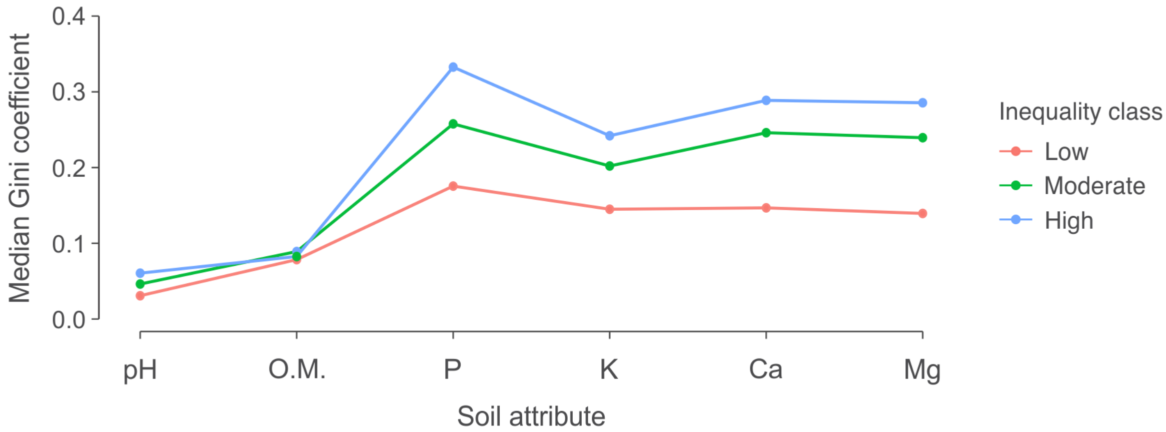

Fig 2. Changes in the median Gini coefficient of soil fertility attributes across within-farm inequality classes.

Formal statistical comparison between soil attributes inequality

Figure 3 presents the boxplot of the Gini coefficients corresponding to each soil attributes at regional scale and by inequality class for formal comparison purpose, to complement the previous results. According to the Friedman test, there was a general statistically significant effect of soil attribute on within-farm inequality across the study site, with $\chi^2(5) = 256.0$, $p < 0.001$, and $W = 0.657$, indicating a large effect size. Post hoc pairwise showed that P presented significantly higher Gini coefficients than K (adjusted $p < 0.001$), Ca (adjusted $p = .015$), and Mg (adjusted $p < 0.001$). K exhibited significantly lower Gini coefficients than Ca (adjusted $p = 0.001$) and Mg (adjusted $p = 0.029$), whereas no significant difference was observed between Ca and Mg (adjusted $p = 0.110$). On the other hand, pH exhibited significantly lower Gini coefficients than all other soil attributes, and O.M. presented significantly lower Gini coefficients than P, K, Ca, and Mg (adjusted $p < 0.001$ for all comparisons).

For the comparisons between soil attributes inequality in each Gini class, significant differences were also detected. For the “low” inequality class, the test revealed a significant effect of soil attribute on within-farm Gini coefficients, with $\chi^2(5) = 80.6$, $p < 0.001$, $W = 0.620$. Similarly, significant effects were observed for the “moderate” class, with $\chi^2(5) = 83.4$, $p < 0.001$, $W = 0.641$, and for the “high” class, with $\chi^2(5) = 95.8$, $p < 0.001$, $W = 0.737$. All Kendall’s W values indicated large effect sizes. Post hoc Wilcoxon signed-rank tests showed a consistent pattern across the three inequality classes similar to the one found for the regional scale analysis. In all classes, P consistently displayed the highest inequality levels and differed significantly from K in all classes. Differences between P and Ca or Mg were weaker and depended on the inequality class, becoming statistically significant in the “high” inequality group. Ca and Mg did not differ significantly in any inequality class. Finally, pH and O.M. exhibited significantly lower Gini coefficients than the macronutrients abovementioned (adjusted $p < 0.01$).

Overall, the results indicated a clear hierarchy of intra-farm inequality, with P exhibiting the highest levels of heterogeneity, followed by Ca and Mg, whereas pH and O.M. showed the lowest levels of inequality between plots within the coffee farms.

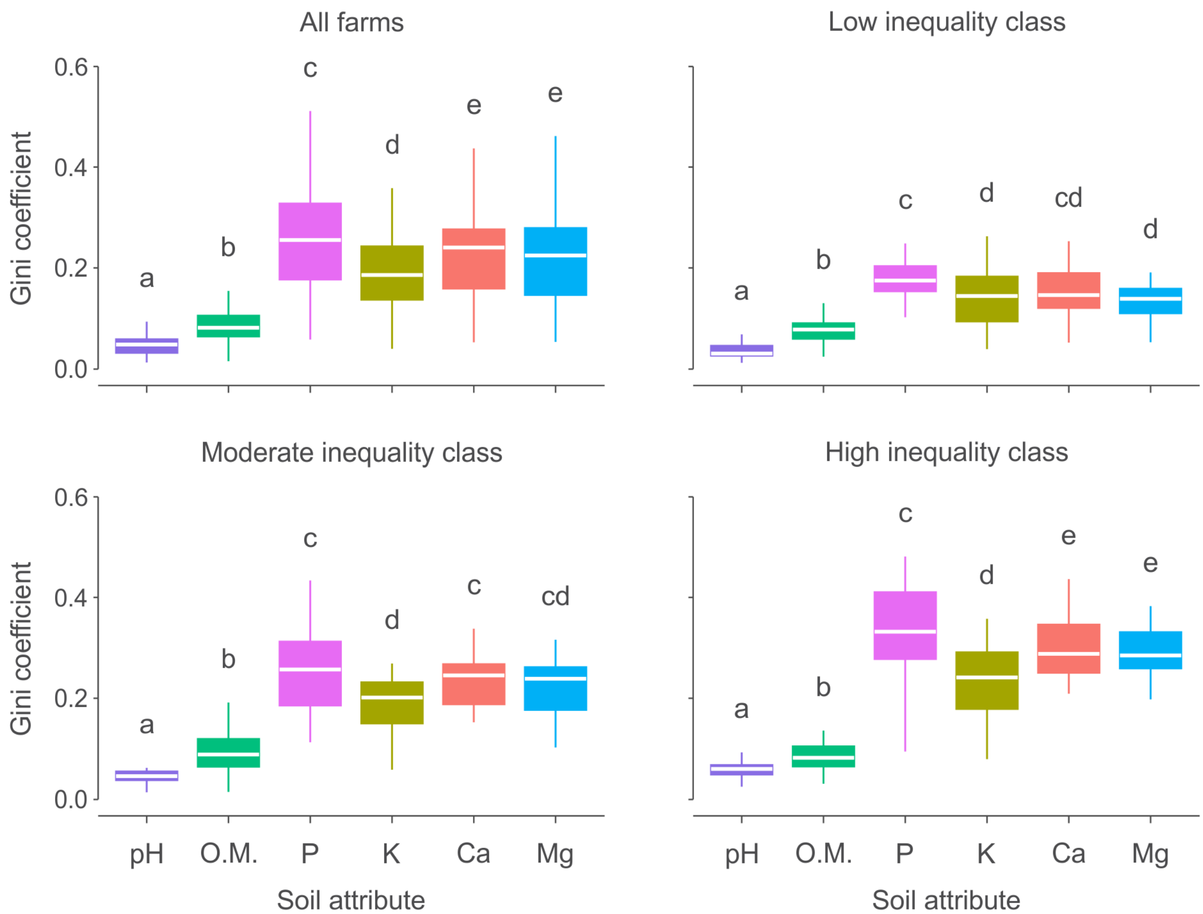

Fig 3. Multiple comparisons between soil fertility attributes concerning Gini coefficient results across the coffee production region of Caconde, São Paulo State, Brazil, and by within-farm inequality class.

Comprehensive interpretation of within-farm inequality from Lorenz curves

Figure 4 presents the Lorenz curves for P, the predominant driver of within-farm inequality identified in this study, fitted for representative farms from each inequality class to facilitate the interpretation of the Gini coefficient. The progressive distancing of the Lorenz curves from the line of perfect equality illustrates the increasing levels of within-farm inequality captured by the Gini coefficient. In this sense, for the lowest Gini coefficient class (i.e., “low” inequality), the curve remains close to the diagonal line of perfect equality, indicating a relatively uniform distribution of P across the plots of this first farm. In contrast, for the “moderate” inequality class, the curve deviates moderately from the diagonal, suggesting that some plots begin to concentrate a larger share of the available P within the farm. Finally, for the highest Gini coefficient class (i.e., “high inequality), the curve exhibits a noticeable curvature, indicating that a small proportion of plots concentrates a substantial share of the available local P content.

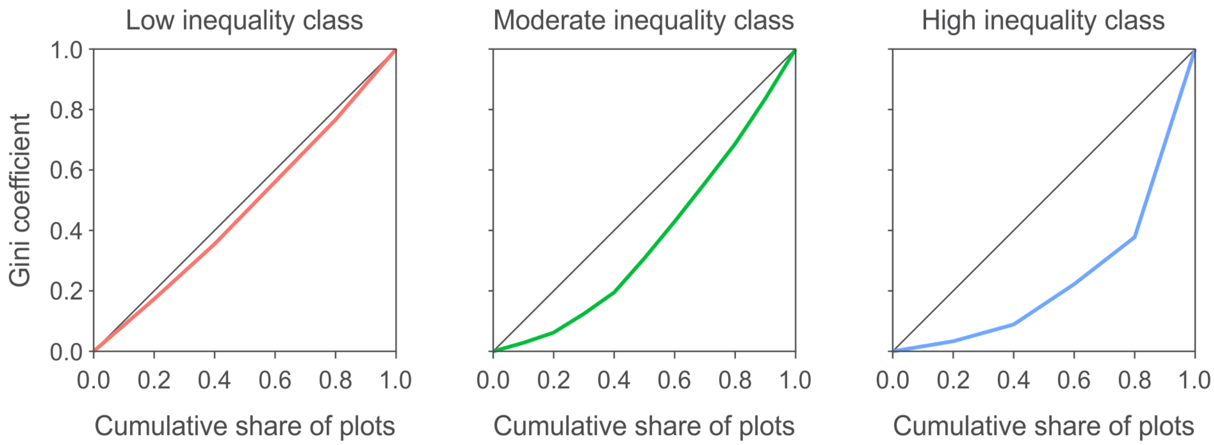

Fig 4. Lorenz curves for P in three representative farms selected by lowest, median and highest Gini coefficient classes.

Spatial patterns of within-farm inequality

Figure 5 and 6 shows the distribution of the inequality classification and main drivers of within-farms heterogeneity across the municipality of Caconde. We visually do not observe evident clusters of farms, as inequality classes and dominant drivers are randomly distributed and mixed throughout the study area.

Figure 7 presents the Moran's I results which confirmed the visual inspection, once there was not consistent evidence of spatial autocorrelation in within-farm inequality patterns across the municipality ($p > 0.05$). Moran's I values were generally close to zero for all soil attributes and neighborhood configurations ($k = 4$, 6 and 8), indicating weak spatial dependence. Although Ca exhibited a marginally significant positive autocorrelation for $k = 8$ ($I = 0.070$, $p = 0.049$), this pattern was not replicated under alternative neighborhood definitions and, therefore, we did not assume it as relevant evidence of a regional spatial structure concerning inequality. This absence of clear spatial patterns suggested that the processes responsible for the internal heterogeneity of the coffee farms are predominantly local (i.e., farm specific), possibly influenced by crop management history rather than geographic factors.

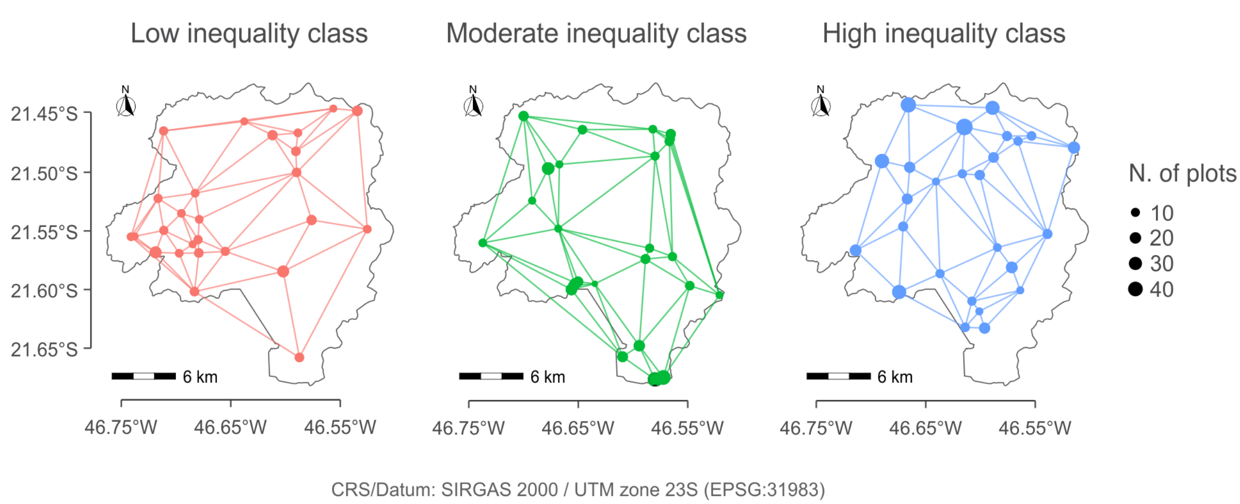

Fig 5. Spatial distribution and local triangulation between farms within one mean Gini class across the coffee production region of Caconde, São Paulo State, Brazil.

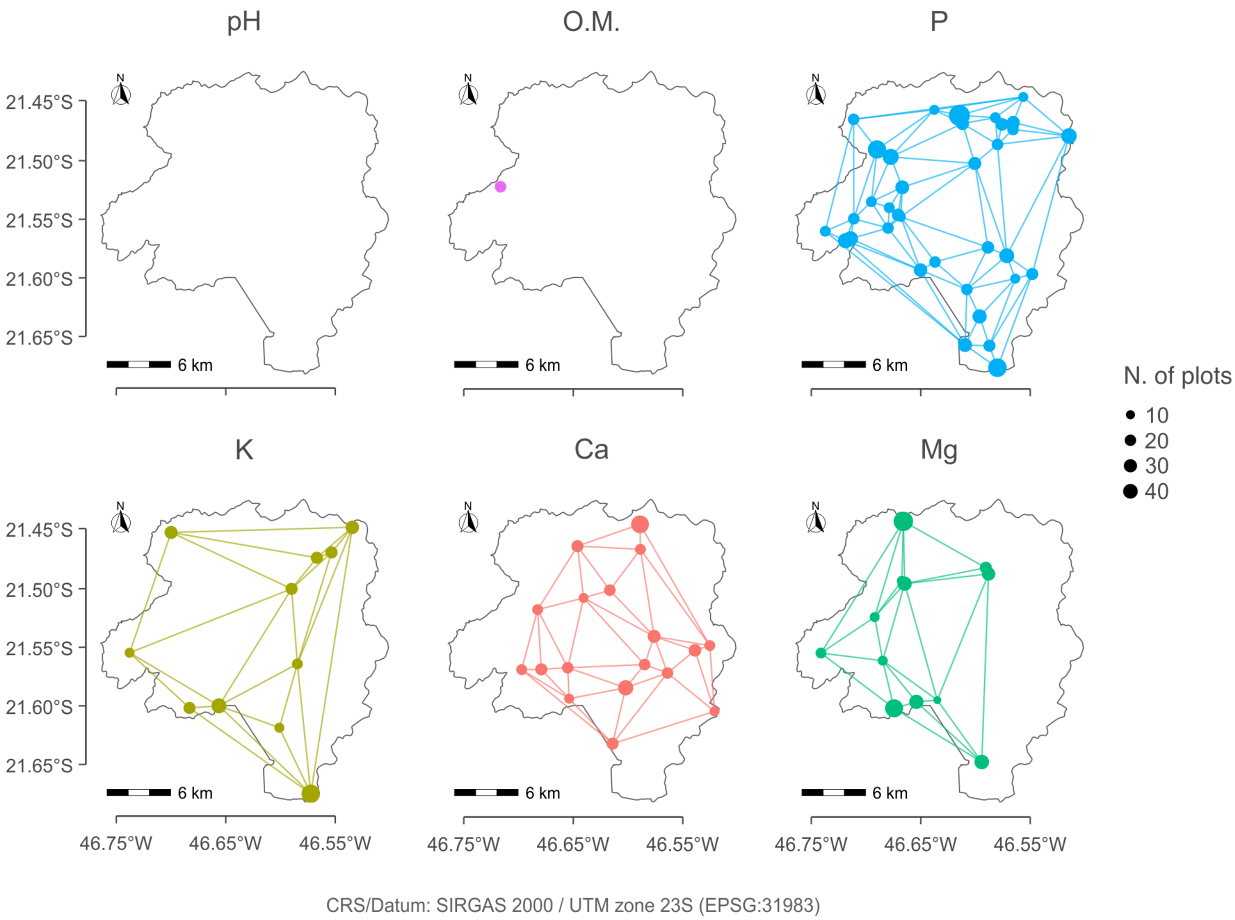

Fig 6. Spatial distribution and local triangulation between farms with one dominant driver soil attribute across the coffee production region of Caconde, São Paulo State, Brazil.

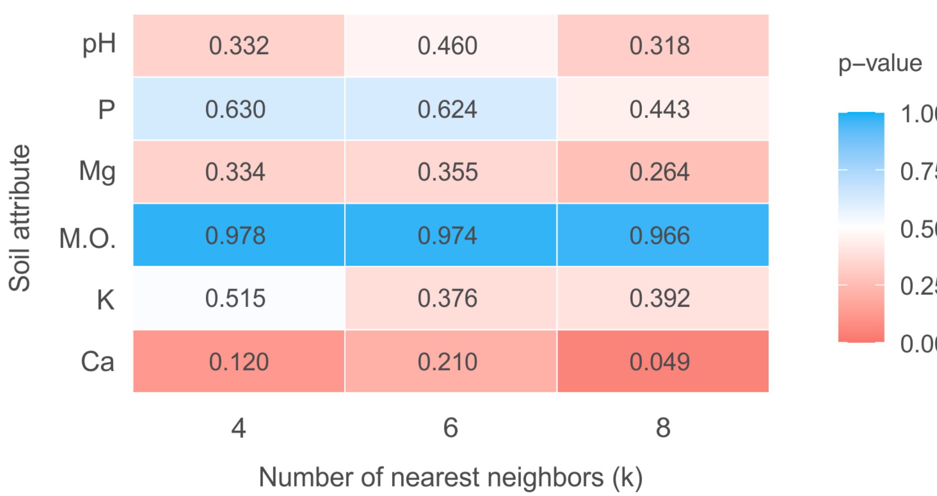

Fig 7. Global Moran's I p-values for Gini coefficients regarding soil fertility attributes across the coffee production region of Caconde, São Paulo State, Brazil.

Conclusion

The Gini coefficient can be a reasonable metric to highlight between-plot differences within farms concerning soil fertility attributes The identification of dominant drivers of inequality provided by this metric allows the identification of soil attributes that potentially could be prioritized for site-specific management, particularly to guide VRF practices at plot-level. The proposed framework applied to soil fertility data is scalable, allowing the assessment of within-farm inequality concerning multiple soil attributes and farms while preserving interpretability. Thus, it proving useful for regional analysis and to identify opportunities for PA applications, especially in smallholder systems.

Acknowledgments

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