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Multiple linear and spatial regressions to estimate the influence of Latosol properties on black pepper productivity

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Abstract

There is little knowledge available on the best techniques for transferring spatial information such as stochastic interpolation and multivariate analyses for black pepper. This study applies multiple linear and spatial regression to estimate black pepper productivity based on physical and chemical properties of the soil. A multiple linear regression including all properties of a Latosol was performed and followed by variance analysis to verify the validity of the model. The adjusted variograms and data interpolation by kriging allowed the use of spatial multiple regression with the properties that were significant in the multiple linear regression. The forward stepwise method was used and the model was validated by the F-test. The influence of the Latosol properties was greater than the residual on the prediction of productivity. The model was composed by the physical properties fine sand (FS), penetration resistance (PR), and Bulk density (BD), and by the chemical properties K, Ca, and Mg (except for Mg in the spatial regression). The physical properties were of greater relevance in determining productivity, and the maps estimated by ordinary kriging and predicted by the spatial multiple regression were very similar in shape.

Keywords: mapping, multivariate analysis, geostatistics.
Abbreviations: BD_Bulk density; CEC_Cation exchange capacity: CS_Coarse sand; ESP_Spherical model; EXP_Exponential model; Fcal_Test statistics; FS_Fine sand; LIN_Linear model; PNE_Pure nugget effect; PR_Penetration resistance; PRODUT_Producivity; R^2_Regression coefficient; SB_Sum of basis; SDI_Space dependence index; V%_Base saturation; Vp_Total volume of pores.

Introduction

According to Boari (2008), black pepper is an important spice for the international agricultural trade, and Brazil is one of the greatest producers of this commodity. In Brazil, plantations are concentrated in the states of Pará and Espírito Santo. In Espírito Santo, black pepper is usually cultivated in soil with low natural fertility. Because of the high nutritional requirements of the crop, the use of fertilizers is considered essential for rapid development and good productivity (Quartezani et al., 2013b). Quartezani et al. (2013a) studied the physical properties of soils of these areas and mapped soil particle-size fractions. This allowed for a visual diagnosis aiming at better managing black pepper plantations. Quartezani et al. (2013b), working with chemical properties, mapped the intensity of liming in black pepper plantations and confirmed the low fertility of the soils and the need to correct acidity to increase nutrient levels. This same study also enabled to identify priority areas for liming. The lack of knowledge on the preferential use and interaction of elements essential to achieve a more productive and profitable crop production demands the application of techniques of spatial information transfer. The main techniques for transfer are associated with deterministic or stochastic interpolation or with multiple regression analyses that consider spatially intervening parameters (Boni et al., 2008). The multiple regression analysis is a statistical method used to predict the values of one or more response variables (dependent) through a set of explanatory variables (independent) (Naghettini and Pinto, 2007). The more significant the weight of an isolated variable or a set of explanatory variables, the more we can be sure that certain factors affect the behavior of a specific response variable as opposed to others (Kasznar and Gonçalves, 2007). Lado et al. (2007) used multiple linear regression and ordinary kriging for modeling maximum, minimum, and average temperatures in the state of São Paulo. Gonçalves et al. (1990) found correlation between the solid volume of wood and the physical and chemical properties of the soil. The authors adjusted multiple regression models for sandy and medium texture soils of São Paulo. Gonçalves et al. (2008) sorted the environmental limitations to productivity in a descending order of importance: water deficit, nutrient deficiency, soil depth, and soil strength. Multiple and spatial regression techniques can be used to correlate predictive variables, such as soil properties with average crop productivity in large areas, thus providing equations or mathematical models to estimate the dependent variable at any point in those areas. Such analyses also provide the margin of error in the variable estimate as a quantitative unit. Therefore, the objective of this study was to apply multiple linear and spatial regression models to estimate black pepper productivity using chemical and physical properties of the soil as predictors.

Results and Discussion

Descriptive statistics and geostatistics

Table 1 presents the models and parameters of the variograms adjusted for soil properties and black pepper productivity. The Pearson's linear correlation analysis between chemical properties and productivity showed a low significant correlation of K with V% (0.28) but not with the other parameters. A high correlation between K and the properties related to soil fertility were expected, especially with SB, but this was not observed in the results. One explanation might be that the medium texture of the soil in the study area favors mobility, which is an intrinsic feature of this element. In fact, according to Werle et al. (2008), K tends to be scarcer in sandy soils due to its high mobility. Another explanation might be this crop high demand for K since sampling was conducted after harvest. The results suggest this kind of soil has no potassium supply capacity and that the exchangeable potassium is not enough to sustain crops for long periods. Therefore, the soil demands more frequent inputs of this nutrient. When the soil pH is high, a high and positive correlation of CEC with SB is expected, which did not occur in the analysis. Under high pH, the negative exchange sites on the soil colloids are freed up and basic cations are made available with the accompanying basic anion. At the same time, there is a moderate negative correlation between the pH value and the potential acidity (H + Al) as well as a high correlation with the amount of free Al. This is the case because when active acidity is reduced, more Al is precipitated and less hydrogen becomes available while the basic cations remain in the exchanging sites previously occupied by H and Al. However, in this study, the pH values were low, revealing an acidic soil with low Al precipitation and high hydrogen availability. The Pearson linear correlation between the physical properties and productivity showed a low negative correlation of BD with CS and a high correlation with Vp (-1.0). This was expected since Vp is calculated from the values of BD. PROD showed low positive and significant correlation with PR (0.43) and negative correlation with FS (-0.46).

The non-violation of the intrinsic hypothesis, a condition required for the use of geostatistics, was confirmed by the study of the stationarity of data using the trend analysis. The trend analysis showed that the soil properties in this study had little variation in all directions. It also allowed for spatial variability analysis by means of variograms standardized by variance. Due to the lack of stationarity of CS in the area as shown in Figure 1 (A), it was estimated using the parabolic trend surface as a function of the coordinates (x and y) and by working with the residuals from the model CSest = a + bx. As shown in Figure 1 (B), the variogram did not reach the sill expected in this analysis by failing to remove the linear trend between the semivariance and the sampling distance. In this circumstance, the original data was employed. Myers (1989) quoted by Lima et al. (2007) stated that working with residuals by fitting polynomials with the least squares method is reasonable, but not infallible.

It is worth noting that of the 20 properties studied, 16 fit the EXP model. The properties P and Mg showed no spatial dependence for distances larger than the shortest distance adopted in the sample and fit the PNE model. This implies the construction of a denser sampling grid with closer spacing to possibly define the spatial dependence distance. In this case, the mean value of the data is a good statistical measure to represent those properties. It is apparent from Table 1 that the chemical attributes Al, H+Al, and m% (aluminum saturation) display the same spatial distribution pattern. They reach sills close to 35.1, 38.7, and 33.9 m respectively and fit the same EXP model for the theoretical variogram, due to existing correlations in their determinations.

Multiple linear regression

In the multiple linear regression model, three physical properties (FS, PR, and BD) and three chemical properties (K, C, and Mg) were used to predict PRODUT and explained 55.1% of the total variance in productivity. This model can be accepted because the statistics (F_{cal}) indicates that these explanatory variables significantly reduce the variance of the dependent variable. In other words, the soil properties that entered the model have greater influence on the variation in productivity than the residuals at 5% probability level (Table 2). The results of the spatial multiple regression analysis in Table 3 shows, based on R^2, that the five dependent properties that entered the model explain 42.39% of the variability in productivity. However, as with the multiple linear regression, the analysis of variance of the spatial multiple regression statistically confirms, at 1% significance, the effect of soil properties on the productivity of black pepper.

Multiple linear regression and spatial multiple regression

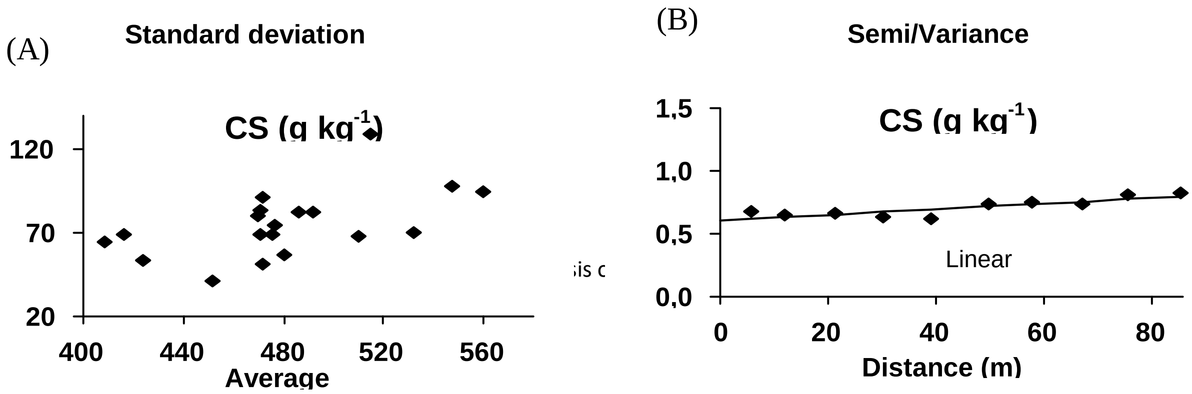
The low R^2 of the spatial multiple regression (42.39%) compared with that obtained for the multiple linear regression (55.1%) is due to the fact that in the spatial multiple regression, we compare continuous surfaces created by interpolation using ordinary kriging and therefore, formed by a grid of interpolated values and not solely by "xyz" values . Moreover, the number of properties that entered the regression model to predict productivity is lower than that used in the multiple linear regression, and the adjustments to the variograms influence the accuracy of the kriging interpolation.

The results in this study confirmed the greater importance of the soil physical properties in comparison to the chemical properties for determining black pepper productivity. This

Table 1. Adjusted models and variogram parameters scaled to the soil properties and black pepper crop.

Property	Model	a (m)	C_0	C_0+C	SDI (%)	R^2 (%)	Cross-validation	
							R	p-value
pH	EXP	45.6	0.04	1.07	96.3	85.2	0.35	0.001
P	PNE	-	-	-	-	-	-	-
K	EXP	83.4	0.25	1.15	78.3	92.3	0.38	0.000
Ca	EXP	50.7	0.31	1.05	70.1	90.7	0.24	0.036
Mg	PNE	-	-	-	-	-	-	-
Al	EXP	35.1	0.13	1.07	88.4	87.0	0.35	0.006
H+Al	EXP	38.7	0.22	0.97	77.5	88.5	0.40	0.000
SB	ESP	24.4	0.16	1.03	84.2	97.4	0.30	0.007
CEC	EXP	97.8	0.47	1.12	57.8	72.5	0.25	0.021
V%	EXP	51.6	0.27	1.07	93.7	93.7	0.35	0.001
m%	EXP	33.9	0.23	1.09	79.3	75.9	0.30	0.005
U%	EXP	66.0	0.37	0.98	61.7	86.2	0.52	0.000
PR	EXP	51.0	0.00	1.11	99.9	81.3	0.46	0.000
CS	LIN	-	0.61	0.79	23.9	69.0	-	-
FS	EXP	25.8	0.27	1.03	73.9	78.0	0.24	0.025
Sil	EXP	25.8	0.25	0.89	72.0	87.6	0.32	0.030
CL	EXP	28.2	0.18	0.73	75.2	72.3	0.58	0.000
BD	EXP	27.6	0.26	0.84	69.4	88.7	0.42	0.000
Vp	EXP	25.8	0.26	0.85	69.5	87.6	0.41	0.000
PROD.	EXP	43.3	0.16	1.15	85.9	83.1	0.21	0.040

ESP: spherical model; EXP: exponential model; PNE: pure nugget effect; LIN: linear model; s: sill; C_0: nugget effect; C_0+C: range; SDI: space dependence index (C/C_0+C); R^2: adjusted coefficient of determination; r: cross validation correlation coefficient; e p-value: level of significance of the observed value estimated by the cross validation.



(B)

Fig 1. (A) Plot of standard deviation versus mean in the analysis of the proportional effect of the physical property Coarse Sand; (B) Scaled variogram of the physical property Coarse Sand.

Table 2. Stepwise multiple linear regression model of black pepper productivity and chemical and physical properties of the soil.

Input property	Model (Y = Productivity)	R^2 (%)	F_{cal}
FS	Y = 38.35 -0.21 * FS	24.0	11
K	Y = -0.17 * 38.07 FS-0.04 * K	34.2	8.8
PR	Y = -0.14 * AF-26.79 0.04 * K + 2.38 * PR	44.0	8.6
Ca	Y = 30.13 * FS-0.04 * K + 2.32 * PR-2.55 * Ca	49.7	7.9
BD	Y = -0.14 * 4.98 FS-0.04 * K + 2.55 * PR-2.48 * Ca + 14.9 * BD	52.9	7.0
Mg	Y = -5.13 -0.12 * FS-0.04 * K + 2.55 * PR-3.66 * Ca + 25.56 * BD + 2.99 * Mg	55.1	6.1

FS: Fine sand; K: Potassium; PR: Penetration Resistance; Ca: Calcium; BD: Bulk Density; Mg: Magnesium; R^2: Regression coefficient; F_{cal}: test statistics.

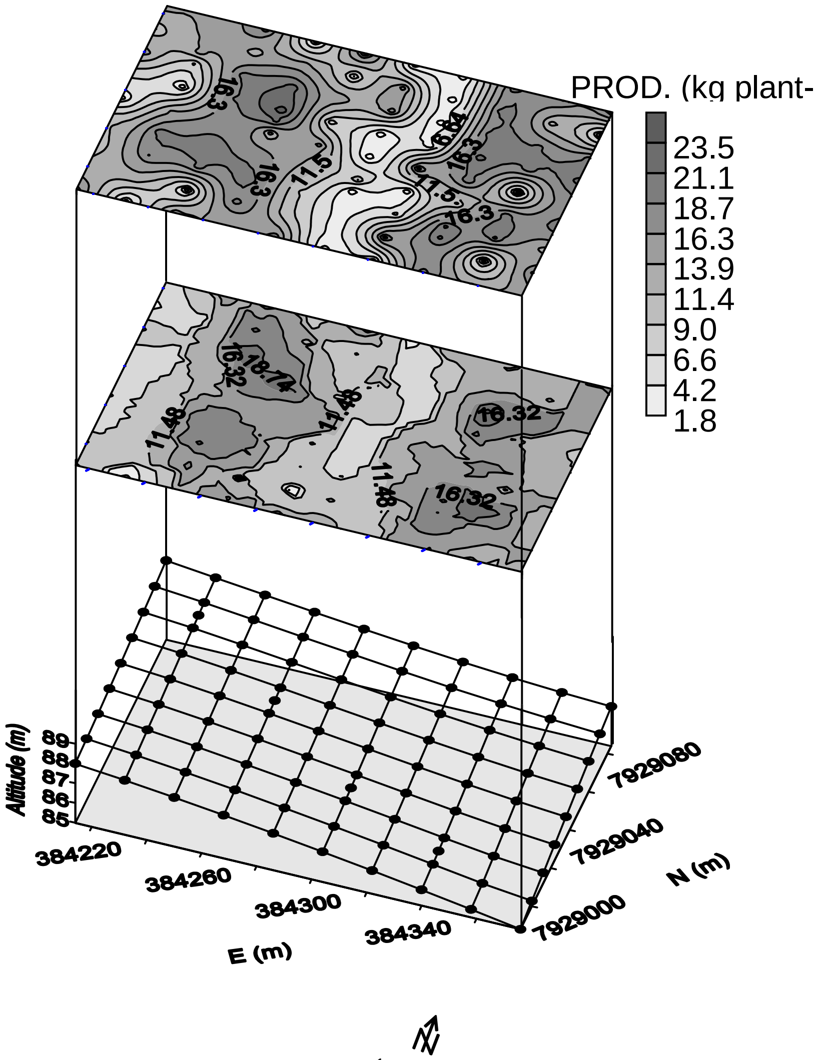


Fig 2. Maps of black pepper productivity (kg plant^{-1}) predicted by spatial multiple regression analysis (bottom layer) and estimated by ordinary kriging interpolation (top layer) over a 3D plane of the area.

Table 3. Spatial multiple regression model of black pepper productivity and chemical and physical properties of the soil.

Properties	Models (Y = Productivity)	R^2 (%)	F_{cal}
FS, K, PR, Ca and BD	Y = -0.25 * FS-0.10 0.04 * K + 0.68 * PR-0.05 * Ca + 0.11 * BD	42.39	395.86

FS: Fine sand; K: Potassium; PR: Penetration Resistance; Ca: Calcium; BD: Bulk density; R^2: Regression coefficient; F_{cal}: test statistics.

Table 4. Chemical and physical parameters of the studied soil.

pH	$P^{1/}$	$K^{1/}$	$Ca^{2/}$	$Mg^{2/}$	$Al^{2/}$	$H+Al^{2/}$	$V^{3/}$	$CS^{4/}$	$FS^{4/}$	$Sil^{4/}$	$AR^{4/}$
4.8	83.2	75.7	1.5	1.1	0.4	4.5	39.5	476.1	108.6	131.1	286.1

$^{1/}$ mg dm^{-3}; $^{2/}$ cmol$_c$ dm^{-3}; $^{3/}$ %; $^{4/}$ g kg^{-1}; CS: Coarse sand; FS: Fine sand

finding is in accordance with those of other studies (Ortiz et al., 2006). According to Veloso and Carvalho (1999) quoted by Santos et al. (2012), studies undertaken in the top black pepper producing countries consistently show that the macronutrient requirement of the crop, in descending order, is as follows: N and K > Ca > Mg > P. The crop removes large amounts of nutrients, primarily N and K, from the soil. Interestingly,K is the first chemical property to enter the model and Ca is the second. Both variables have negative values, which indicates greater productivity in areas with low post-harvest levels of these elements due to crop intake. The low nutrient level and the minimal influence of chemical properties on productivity may be related to sampling during the harvest and to the great mobility of nutrients like K. On the other hand, it is clear that crop productivity is mainly influenced by physical properties such as PR, BD, and fine sand particle (FS). PR entered the model with a significant and positive value, thus revealing a direct contribution to productivity. In general, an inverse relationship between penetration resistance and crop productivity is found in publications since soil compaction tends to limit the crop root system (Lima et al., 2010). However, according to Embrapa (2006), this might not be the case for some tropical soils of the Latosol class, as those in the area of study, with high macroporosity and permeability.

Figure 2 presents and compares, in the same plane, the map of black pepper productivity (kg $plan^{-1}$) estimated by the ordinary kriging of values measured in the field with the map of productivity predicted by the spatial multiple regression analysis. The maps display similar behaviors with productivity varying in the same direction over the area and overlaying areas of low and high productivity. The map of the productivity predicted by spatial multiple regression was reclassified to match the scale of the map generated by kriging. With this, a difference can be seen between the maps regarding the range of each data series.

The data on productivity predicted by the regression had a lower range, or variability, than the data estimated by kriging. This was an expected result since productivity was determined by a multiple linear regression equation. As with Miranda et al. (2013), who estimated forest productivity using soil properties as predictors, we found a high degree of similarity between the two maps. Therefore, our findings confirm the feasibility of the model to predict black pepper productivity in areas with similar environments.

Materials and Methods

Plant material, location and designs

The study was conducted in a commercial black pepper plantation located in the municipality of São Mateus in the state of Espírito Santo, Brazil (18° 43' 37" south and 40° 05' 51" west and 87 m average altitude). The soils were classified, according to the Brazilian System of Soil Classification, as typical RED-YELLOW DYSTROPHIC LATOSOLS of sandy clay loam texture (Table 4). The soils have good physical characteristics, are well-drained with good infiltration rate and depth, but with low natural fertility. Four-year-old black pepper plants derived from the vegetative propagation of herbaceous cuttings of the high-yield variety Bragantina were used in the study. The plants were grown in the usual spacing of 3.0 x 2.0 m, in a single row system on ridges to avoid waterlogging. Data were collected in a selected plotof 15,500 m^2 (162 m long and 96 m wide), with 94 sample points spaced 18 m x 12 m apart forming a regular grid. Each sample point represented an area of 216 m^2.

Statistical analysis

Before running the spatial multiple regression, there are assumptions that have to be confirmed: that the dependent variable is normally distributed; that the number of observations is greater than the number of independent variables; and that there is no exact or close linear relationship between independent variables (no multicollinearity). When two independent variables showed a correlation coefficient greater than 0.80, one of them was excluded from the multiple linear regression model to avoid multicollinearity. Initially, a multiple linear regression analysis was performed with the chemical and physical data, which were considered mutually independent. Then, an analysis of variance was also performed to validate the model for prediction of productivity. The stepwise regression, which is often chosen for exploratory studies, was used. In this regression, the input sequence of parameters into the equation follows no theoretical model and is set statistically (Abbad and Torres, 2002). Productivity, the dependent variable (Y), was estimated based on the procedures described by Ortiz et al. (2006) and Diggle and Ribeiro Jr. (2007) by including the independent variables (X) into the model at each step (forward stepwise) to explain the Y behavior. In this case, the model required a multiple linear regression to verify the relationship between "xyz" data. It is possible, however, to perform this analysis with a spatial approach by examining the relationship between the resulting maps. To do this, the spatial multiple regression tests cumulative dependencies of a single dependent variable in relation to a number of independent variables based on their known geographical coordinates. Thus, for example, when three independent variables are used to explain one dependent variable, the equation of the spatial multiple regression becomes:

$$Y = a + b_1x_1 + b_2x_2 + b_3x_3$$

Where, Y is the dependent variable; x1, x2, and x3 are the independent variables; a is the intercept; and b1, b2, and b3 are the coefficients of the independent variables which define the increase (or decrease) of variable Y for a one-unit change in variable Xi.

Stationarity conditions must be fulfilled to build and interpret the variogram, which was tested by plotting means against standard deviations calculated for each row and column of the soil parameters. For stationarity to occur requires that the mean and variance are not correlated, given that the proportionality of the variance to the mean is determined by the significance of the linear regression analysis at 5 % probability. Since the data did not comply with stationarity, a second-degree parabolic trend surface was applied by working with the residuals towards an intrinsically stationary process. Once stationarity was assumed, the geostatistics analysis attested the spatial dependence of the soil properties with the equation:

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

where N(h) is the number of pairs of the measured values Z (xi) and Z (xi + h) separated by a vector h; and Z (xi) is the random variable in the i-th position.

Gaussian, exponential, and spherical models were tested for adjusting the variograms with determination of the parameters nugget effect (C_0), sill (C_0 + C), and range (a) of spatial dependency.

Ordinary kriging was used to estimate soil properties in unsampled locations. This method of interpolation applies a linear unbiased estimator with minimal variance and takes into account the structure of the spatial variability found for each property. It is defined by the following equation:

$$Z(x_0) = \sum_{i=1}^{N} \lambda_i Z(x_i)$$

where $Z(x_0)$ is the value estimated for the x_0 unsampled location; $Z(x_i)$ is the value obtained by sampling in the field; and e λ_i is the weight associated with the measured value at x_i position.

The data interpolated by ordinary kriging allowed the creation of thematic maps for each of the soil properties and crop productivity, thus it was possible to run the spatial multiple regression using the properties that were significant for productivity in the multiple linear regression. A map of crop productivity was modeled by multiple regression aiming to decrease the number of properties in the analysis to simplify the process and reduce the effect of errors accumulated.

In order to determine the number of explanatory properties (predictors) in the adjustment of the spatial multiple linear regression model, a stepwise forward regression was performed with STATÍSTICA 8.0. The method begins with an empty equation in which the predictors are entered individually until the best predictors are identified. The validation of the results was tested by the F statistics and R^2 values. R^2 shows how much of the total variability of the dependent variable can be explained by the model. In other words, it shows how much of the variance of the dependent variable can be explained by this specific group of independent variables. For visual analysis, an isoline map was created and compared with both the productivity values predicted by the multiple regression model and with the values estimated by kriging.

Conclusions

1. Both the multiple linear regression and the multiple spatial regression resulted in models that are suitable to predict the productivity of black pepper.
2. The physical properties of the soil are more relevant to the productivity of black pepper than the chemical properties, with the multiple spatial regression having a lower coefficient of determination (R^2) than the multiple linear regression.
3. The maps estimated by kriging and predicted by spatial multiple regression were highly similar thus confirming the feasibility of regression models to predict black pepper productivity in areas with similar environments.

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