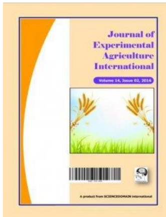

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Spatial Correlation between *Eucalyptus* Diameter at Breast High and Particle Size Fractions of an Oxisol

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Authors' contributions

This work was carried out in collaboration between all authors. Authors JSSL and DAOB did the data acquisition, data analysis, writing and editing. Authors NCF, VMQ and SAS managed the analyses of the study. All authors read and approved the final manuscript.

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ABSTRACT

Field growth of *Eucalyptus* is influenced by physical attributes of soils, which justifies comprehensive studies on these relationships within a forest system. This work was aimed at studying the spatial variability in the diameter at breast high (DBH) of Eucalyptus, trees cultivated over three years and its relationships with the particle size fractions of a Oxisol. The study was conducted on a 33.0 x 33.0 m sampling grid, totalling 94.0 georeferenced field spots. Soil samples were collected from the 0 – 0.20 m and 0.20 – 0.40 m depth layers to determine the particle size fractions and DBH was measured in 5.0 neighbour *Eucalyptus* trees, with average DBH centered at each georeferenced spot. Data were submitted to descriptive, multivariate and geostatistical analyses. Maps were built using interpolated ordinary kriging and cokriging, while principal component analysis (PCA) was performed on the clay and total sand fractions from both soil layers. The correlation coefficients between the original variables and the first principal component (PC1) were large and negative and positive in relation to the clay and total sand fractions, respectively. The primary variable DBH was successfully estimated by cokriging using the PC1 score as a secondary variable. The simple and

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cross semivariograms of the DBH adjusted to the spherical model. The cokriging technique was found to be an efficient tool in estimating variables within forest production systems with reduced sampling cost.

Keywords: Geostatistic; cokriging; multivariate analysis.

1. INTRODUCTION

The *Eucalyptus* genus includes a broad variety of plant species, whose majority is native to Australia. Currently, *Eucalyptus* trees are the most cultivated species among the planted forests in Brazil, being well adapted to edafoclimatic conditions and used for recovery of degraded areas.

The use of different genetic materials of *Eucalyptus* provided differentiated changes in soil fertility, however, there were no changes in height and diameter at breast height (DBH) at 3 years of age in different areas [1]. Paula RR, et al. [2] stated that variations in dendrometric parameters of *Eucalyptus* trees relates to slope position and soil type. These authors demonstrated that the *Eucalyptus* crop establishes a significant interaction with the environment, in which edaphic attributes influence on the crop productivity.

Silva LG, et al. [3] point out that the physical attributes (bulk density, macroporosity and total soil porosity) reflect on various aspects in the structure of soils cultivated with eucalyptus (*Eucalyptus grandis*, pine (*Pinus tecunumanii*) and carvoeiro (*sclerolobium paniculatum*) over a period greater than 20 years, with great importance in defining the quality of the soil.

New spatial analysis technologies used in agriculture has facilitated determination of the spatial and temporal variability of plant and soil attributes, including their mapping and correlations. Geostatistics is one example of these new technologies, which considers the distance the samples for representing more accurately the main factors that affect the crop productivity [4].

Ortiz JL, et al. [5] stated that classical statistical methods combined with geoprocessing allow concluding that soil physical attributes, more specifically, structure and texture, are more important in determining the *Eucalyptus* productive potential rather than chemical attributes. In this context, [6] reported that application of geostatistical techniques enables the spatial variability among attributes to be modelled and described, thus supporting the construction of thematic maps sufficiently detailed for a greater understanding of variables.

In general, the spatial variability analysis of soils requires a large number of variables, which make the analysis expensive. An alternative to this issue is to combine geostatistical studies with multivariate analysis, such as principal component analysis (PCA). Such combined approach is capable of explaining the variance structure and the covariance of a variable set through building linear combinations and reducing the dimensional number of the phenomenon under investigation. This finally aims to simplify the visualization and understanding of results.

Studies have revealed that *Eucalyptus* trees exhibit a dissimilar growth rate in field, which justifies the need for detailed studies on their dendrometric characteristics and soil attributes determining the growth of *Eucalyptus* forest systems. Therefore, the present work was aimed at determining the spatial relationship between DBH of *Eucalyptus* at three years and particles size fractions of a Oxisol.

2. MATERIALS AND METHODS

2.1 Location and Management Area

This study was conducted on an area of São José do Calçado city, which is located at the south region of the Espírito Santo state, Brazil. This region is characterized by mild temperatures, annual rainfall superior to 1000 mm, and vegetation belonging to the Atlantic forest biome. Its landscape varies from smoothly undulated to a mountainous profile with concave-concave and concave-convex landforms, as illustrated in Fig. 1.

The soil is classified as a Oxisol, clayey texture, with moderate A horizon, low nutrient contents and high aluminium level. The clays found in this soils present low activity, which makes the soil itself poorer in nutrients.

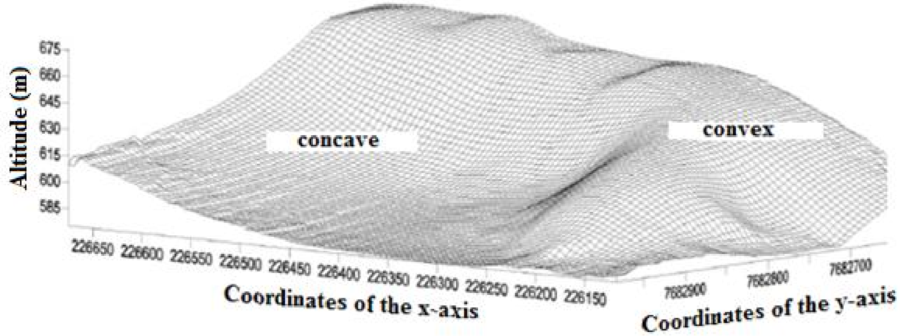

Fig. 1. Digital elevation model of the study área

The area under study has been occupied with forest trees for cellulose production purposes. Hybrid clone seedlings of *Eucalyptus urograndis* belonging to the species *Eucalyptus grandis* W. Hill ex. Maiden x *Eucalyptus urophylla* S.T. Blake have been transplanted over 10.0 hectares of this area at a spacing of 3.0 x 3.0 m.

In the area, where the topography allowed the traffic with safety was used the tractor set with subsoiler-fertilizer with single rod working at 0.50 m depth defining the lines for placement of the seedlings. Manual digging at same depth was performed on regions with steep slopes. Limestone, chemical fertilizers and herbicides were applied as recommended elsewhere.

2.2 Analyzed Parameters

At the seedling transplantation season, a regular grid with spacing of 33.0 x 33.0 m was marked with the aid of a geodetic GPS, totalling 94 sampling spots. Next, soil samples were collected from the 0 – 0.20 m and 0.20 – 0.40 m layers of each spot using a stainless probe for determining their particle size fractions (clay, total sand and silt) fractions, according to [7].

Diameters at breast height (DBH) of *Eucalyptus* trees were measured after 3.0 years of transplantation. The average DBH for each georeferenced sampling spot was determined from five trees, explicitly, four neighbouring trees distanced at 3.0 m radius from the tree positioned on the georeferenced spot.

2.3 Exploratory Data Analysis

The descriptive statistical analysis was performed on soil fractions and DBH data for determining the mean, median, standard deviation, minimum and maximum values, the coefficient of variation, skewness and kurtosis. Data normality was evaluated using the Kolmogorov-Smirnov test ($p \leq 0.05$). Correlations between DBH and clay (CLA) and total sand (TS) fractions of both soil layers were determined using the Pearson correlation analysis ($p \leq 0.05$). The t-test ($p \leq 0.05$) was realized between the average values of concentration of CLA and TS size fractions of the soil in two depths.

The CLA and TS fractions were chosen for statistical analysis because of their prevalence 93.8% on the whole particles size fractions of the 0 – 0.20 m and 0.20 – 0.40 m layers, as reported by [8]. The average CLA and TS particles size fractions determined in this work were 49.7% (0 – 0.20 m) and 57.4% (0.20 – 0.40 m) and 43.8% (0 – 0.20 m) and 36.5% (0.20 – 0.40 m), respectively.

The t-test ($p \leq 0.05$) was used to compare the mean values DBH for evaluating of the variability in terms of soil preparation method, manual digging and soil mechanical furrowing.

2.4 Multivariate Analysis

Multivariate analysis was performed by creating a matrix X, in which the variable x_{ij} corresponds the *i*th particle size fractions of CLA and TS in the 0 – 0.20 m and 0 – 0.40 m layers of the *j*th sampling spot. This matrix was used as an input for principal component analysis (PCA).

PCA was used to reduce the dimensionality of the original variables with lowest information loss possible to be attained, i.e., the information contained in the original p-variables were replaced by the information contained in the k ($k < p$) uncorrelated principal components. The interdependence structure involving these variables is represented by the correlation matrix R.

PCA takes into account the principal components associated with auto-values larger than 1, thus discounting the less important components which present variance smaller than the average variance of the original variables, as described by [9]. The variable selection was based on the importance index of variables presenting high significance (loadings) in the linear combination of first components. According to [10], correlations between principal components and particle size fractions parameters were considered to be significant for values greater than |0.70|.

2.5 Geostatistical Analysis

Geostatistical analysis was used to inspect and quantify the spatial dependence between the DBH data and the scores generated by PCA. The analysis was conducted from the adjustment of theoretical functions to the experimental semivariograms models with basis on the assumption of intrinsic hypothesis stationarity, as given by equation 1.

$$\gamma(h) = \frac{1}{2\mathrm{N}} * \sum_{i=1}^{\mathrm{N}(h)} [\mathrm{Z}(xi) - Z(xi+h)]^2 \qquad (1)$$

where *N(h)* is the number of value pairs *[*$Z(x_i)$*,* $Z(x_i+h)$*]* separated by a vector (h), *Z(xi)* is the value determined in each sampling spot and *Z(xi+h)* is the value determined at the spot plus a distance h.

Spatial analysis was applied on the data using the GS+ software. Theoretical models (spherical, Gaussian and exponential) were tested for adjusting the semivariograms. The model parameters were scaled by the data variance and the covariance in the cross semivariograms in order to standardize the semivariance and covariance scales. The following parameters were defined: nugget effect (C_0), still (C_0 + C), structural variance (C); spatial dependence range (a) and spatial dependence degree (SDD). The SDD was calculated using the equation [C_0/(C_0+C)] *x* 100 and was classified into low (SDD > 75%), medium (25% < SDD ≤ 75%) and strong (SDD ≤ 25%) according to [11].

The most appropriate semivariograms theoretical model was selected with basis on the highest determination coefficient (R^2) and the smallest sum of squared residuals (SSR). However, the definite criterion for selecting the models was the cross validation analysis with significant correlation (COR) between the observed and estimated values, as detailed by [12].

DBH distribution maps were built using ordinary kriging after proving its spatial dependence. In order to estimate the DBH by cokrigagem, was used as the secondary variable (covariable) the scores determined by the principal component one (PC1) using the original variable clay (CLA) and total sand (TS) in the layers 0 – 0.20 m and 0.20 – 0.40 m depth.

Cokriging is a multivariate extension of the kriging technique and is based on the parameters expressed by a semivariograms crossed between two variables (equation 2). It involves an unbiased linear estimator with minimum variance and takes into account the spatial variability structure found for each variable. Points near the position to be interpolated have larger weights [12,13].

$$\gamma_{1,2(h)} = \frac{1}{2\mathrm{N}} \left\{ \sum_{i=1}^{\mathrm{N}(h)} \begin{matrix} [\mathrm{Z}_1(xi) - \mathrm{Z}_1(xi+h)] \\ * [\mathrm{Z}_2(xi) - \mathrm{Z}_2(xi+h)] \end{matrix} \right\} \qquad (2)$$

where $\gamma_{1,2}$(h) is the cross semivariograms between the primary and the secondary variables, $Z_1(x_i)$ is the primary variable value at the point x_i, $Z_1(x_i+h)$ is the primary variable value at the point x_i plus a distance h, $Z_2(x_i)$ is the secondary variable value at the point x_i, $Z_2(x_i+h)$ is the secondary variable value at the point x_i plus a distance h, and N is the number of point pairs formed for a given distance h.

In cokriging, the estimation of the variable $Z_2^*(x_0)$ for any point x_0 must be a linear combination between Z_1 and Z_2, as expressed by equation 3.

$$Z_2^*(x_0) = \sum_{i=1}^{\mathrm{N1}} \lambda_{1i} Z_1(x_{1i}) + \sum_{j=j}^{\mathrm{N2}} \lambda_{2j} Z_2(x_{2j}) \qquad (3)$$

where N_1 and N_2 are the neighbor numbers measured for Z_1 and Z_2, λ_1 and λ_2 are the weights associated with Z_1 and Z_2, respectively, which are distributed according to the spatial dependence of each variable to one another and the cross correlation between them.

The performance of the DBH interpolation methods (kriging and cokriging) was based on the root mean square error (RMSE) and the mean bias error (MBE), with experimental and theoretical values generated by cross-validation, as given by equations 4 and 5 [14].

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\mathrm{VOBS}-\mathrm{VEST})^2}{n}} \tag{4}$$

$$MBE = \frac{\sum_{i=1}^{n}(VOBS-VEST)}{n} \tag{5}$$

where: VOBS and VEST are the observed and estimated values, respectively, and n is the number of observations.

RMSE corresponds to the average magnitude of the estimated errors and is always positive. The closer RMSE is to zero the higher the quality of the experimental and theoretical data. In turn, MBE indicates the underestimation (negative value) or overestimation (positive value) degree of the model.

3. RESULTS AND DISCUSSION

3.1 Statistical Analysis

The DBH values collected for the sampling spots located both in the manually and mechanical furrowed areas were submitted to t-test ($p \leq 0.05$) for assessing the influence of the soil preparation method on the *Eucalyptus* trees growth. As shown in Table 1, there was no statistical variation in *Eucalyptu*s DBH with respect to the type of soil furrowing method. This descriptive analysis involved all 94.0 sampling spots including their particle size fractions.

The average DBH of the eucalyptus trees grown over three years after transplantation was 14.8 cm (0.148 m), which is considered to be satisfactory for cellulose production. The DBH, CLA12 and TS12 (CLA and TS from the layers 1 and 2) were normal distribution by the Kolmogorov-Smirnov ($p \leq 0.05$), which confirms the values of Ks and Kc around zero.

The DBH and TS2 present positive asymmetry, with a mean value higher than the median, and this indicates concentration of values below the mean. The CLA2 presented leptokurtic distribution, with positive Kc, indicating concentration of data around the mean.

According to [15], the parameter variability may be classified by the coefficient of variation (CV) into: low (CV ≤10%) for the DBH, middle (CV < 10% ≤ 20%) for CLA12 and TS12. The CV of the Eucalyptus DBH determined here was low (5.6%), which may be explained by the use of clonal seedlings in the forestation, likeness of seedlings transplantation period and little influence of the soil furrowing type on DBH. Rosa Filho G, et al. [6] found a average CV of 15.4% for DBH of *Eucalyptus urophylla*, whereas [4] observed a average CV of 11.8% for *Eucalyptus camaldulensis* trees propagated by seeds. The particle size fractions presented average variability, with CV between 10 and 20%, therefore, in general, these values are similiar to those found by [16] in areas cultivated with pasture and natural vegetation in Ultisol and by [17] in planted area of conilon coffee in Oxisol.

The particle size fractions CLA2 (layer 0.20 – 0.40 m) and TS1 (layer 0 – 0.20 m) with the higher concentrations (t-test). The Pearson correlation coefficients between DBH and the CLA and TS fractions of the 0 – 0.20 m layer were -0.24 and 0.23, respectively. Concerning the 0.20 – 0.40 m layer, the correlation coefficients between DBH and the CLA and

Table 1. Descriptive Analysis to *Eucalyptus* DBH (cm) to three years of cultivation and size fractions of soil and Tukey test ($p \leq 0.05$) between the mean layers of 0-0.20 m and 0.20-0.40 m (%)

Variable	M	Md	Min	Max	Q1	Q3	S	Ks	Kc	CV	DN
DBH	14.8	14.8	12.6	17.2	14.3	15.4	0.83	0.04	0.21	5.6	N
CLA1	49.7b	49.3	31.3	64.1	44.7	55.9	7.21	-0.32	-0.49	14.5	N
CLA2	57.4a	58.0	41.9	70.3	53.7	61.2	5.80	-0.39	0,21	10.0	N
TS1	43.8a	46.3	30.4	60.4	38.4	49.0	6.97	-0.17	-0.64	15.9	N
TS2	36.5b	36.0	23.5	53.9	31.7	41.6	6.59	0.29	-0.28	18.1	N

DBH: diameter at breast high CLA1: clay layer of 0-0.20 m; CLA2: clay layer of 0.20-0.40 m; TS1: total sand layer 0-0.20 m; TS2: total sand layer of 0.20-0.40 m; M: média; Md: mediana; Mim: valor mínimo; Max: valor máximo; Q1: primeiro quartil; Q3: terceiro quartil; s: desvio padrão;Ks: coeficiente de assimetria; Kc: coeficiente de curtose; CV: coeficiente de variação; N: distribuição normal.

TS fractions were -0.25 and 0.21, respectively. Thus, all Pearson correlations between DBH and particles size fractions were statistically significantly ($p \leq 0.05$).

According to [13], a low correlation coefficient does not nullify the hypothesis of cross semivariograms between two variables. The correlation between the *Eucalyptus* DBH and the CLA and TS soil fractions were negative and positive, respectively. The positive correlation implies that two variables are directly proportional, while the opposite trend is indicated by negative correlations. In this case, the largest DBH values were observed for the areas comprising the highest TS contents (positive correlation). Considering that the rainfall regime is well distributed in the area under investigation, the positive correlation between DBH and TS is most likely due to the good development of the *Eucalyptus* trees' root system, once soils characterized by high TS contents tend to be more porous, which favors root development and, consequently, greater exploitation of their deeper layers.

3.2 Multivariate Analysis

Four principal components (PCs) were found when including the CLA and TS fractions from both soil layers (0 – 0.20 m and 0.20 – 0.40 m) in the PCA. Only the first principal component (PC1) presented auto-value larger than 1 (3.09) and explained 77.2% of the total variance. Silva SA, et al. [13] have stated that one or two PCs are usually sufficient for explaining all variation of soil properties.

The correlation coefficients between the four original variables (CLA and TS) and the PC1 was -89.0% for CLA1 (0 – 0.20 m), 91.0% for TS1 (0 – 0.20 m), -85.0% for CLA2 (0.20 – 0.40 m) and 87.0 % for TS2 (0.20 – 0.40 m). The PC1 is described by the following equation: PC1 = -0.505xCLA1 + 0.517xTS1 - 0.487xCLA2 – 0.493xTS2. The negative signal of the PC1 coefficient indicates that high clay concentrations lead to small DBH.

3.3 Geostatistical Analysis

The *Eucalyptus* DBH and the PC1 score were found to be spatially dependent. The parameters and models of spatial dependence analysis for DBH and PC1 of simple and cross semivariograms (DBHxPC1) are reported in Table 2.

After proving the spatial dependence of the variables under investigation, ordinary kriging interpolations were performed for estimating the DBH values of non-sampled regions at pixel of 3.0x3.0 m (Fig. 2). DBH spatial distribution maps were then determined by adjusting the cross semivariograms, in which the DBH and the PC1 scores were the primary (Z1) and secondary (Z2) variables, respectively.

The linear correlations between the observed DBH values and those estimated by the cross validation technique were found to be significant ($p \leq 0.05$) for each variable. This was the definitive criterion for selecting the adjustments of the semivariograms.

The spherical model presented the best fit for all variables, with spatial dependence range of 66.0 m for the DBH spatial distribution, 160.0 m for PC1 and 168.0 m for the cross semivariograms having PC1 as a covariable. The spherical cross semivariograms displayed a positive spatial correlation between PC1 (soil fractions from both layers) and DBH. Rosa Filho G, et al.[6] studied the spatial variability of *Eucalyptus* dendrometric parameters and found that the spherical model had the best fit for DBH with a range of 24.0 m.

According to [13], the sampling spots located at an area whose radius is smaller or equal to its range are near and spatially dependent to one another. In this sense, these sampling spots can be used to estimate parameters of non-sampled locations. Estimations obtained by ordinary kriging interpolation involving large ranges tend to be more reliable, thus leading to more representative maps.

Table 2. Models and parameter standardized semivariograms to the DBH, the PC1 and cross semivariograms DBH x PC1

Variable	Model	C_0	C_0+C	a(m)	R^2(%)	SDD(%)	CR
			1 and 2 layers				
DBH	Spherical	0.38	1.03	66.0	83.0	36.0	0.30
PC1	Spherical	0.14	1.05	160.0	99.0	13.0	0.75
DBHxPC1	Spherical	0.04	0.94	168.0	91.0	24.0	0.35

C_0: nugget effect; C_0+C: still; a (m): range; R^2: determination coefficient; SDD (%): spatial dependence degree and CR: Correlation between observed value and estimated by cross validation

The use of cross semivariograms was positive (DBHxPC1), enabling higher spatial continuity with larger range (168 m) for the parameters of interest (DBH). Due to this, the information related to the particle size fractions (clay and total sand) contributed to the higher continuity of the spatial variation. The cross semivariograms provides further information on the covariable, with estimated results tending to be represent more consistently the spatial DBH behavior throughout the area.

[18] used geostatistical techniques (kriging and cokriging) to build predictive maps for volume gains of *Pinus taeda* L. as influenced by the soil CLA content. The average volume estimations were adequate and according to these authors, the dendrometric feature evaluated in the forest inventory presented spatially dependent structures.

[19] found moderate spatial dependence for volume and basal area per hectare for *Tectona grandis*. Therefore, the usual pratic of mean values of samples does not allow to characterize the variability of the dendrometric structure of forested areas. Thus, the combination of the geostatistical analysis with the data of the forest inventories allows to provide images of the spatial structure of the plantations. Lima CGR, et al. [4] reported a spatial relationship between soil attributes and *Eucalyptus* tree features. On the other hand, [6] did not observe spatial relationships between *Eucalyptus* growth indicators and soil physical attributes.

The results disclosed in this work suggest that the sampling areas must be distanced from one another until a distance two-fold larger than the range in order not to be assumed as spatially dependent areas. This is particularly important in the forest inventory processing in presence of spatial continuity structure.

The spatial dependence degree (SDD) was high for all variables (SDD≤25%), according to [11]. This may be explained by the reduced C_0 values that describe the behaviour of the implicit correlation function in the model when the distance between samples tends to zero. This shows that a high still proportion is occupied by the structural variance (C), which supports estimations in non-investigated areas, indicating good accuracy of the sampling methods for determining both soil and *Eucalyptus* attributes.

The linear correlations (CR) between the observed values and those estimated by the cross validation technique were significant ($p \leq 0.05$) for each variable, being this the definitive criterion used to choose the adjustments of the semivariograms models.

The DBH estimates for non-sampled sites made by ordinary kriging presented a RMSE of 0.786, while for cokriging using PC1 as a covariable, a mean error of 1.431 was obtained. The MBE found for kriging was 0.028 (overestimating) and for cokriging it was -0.239 (underestimating). The values of the errors reflect the low linear correlation, although significant, between the particles size fractions and the DBH of the *Eucalyptus* at three years, thus producing greater errors than in the kriging method. This fact implies in the existence of other variables, that together with the particle size fractions, influence in the development of *Eucalyptus*, but that were not considered in this study.

The DBH spatial distribution map (Fig.2) obtained by kriging presented values from 14.5 to 15.0 cm (0.145 to 0.150 m) in most of its area. Lima JSS, etr al. [8] have determined the spatial distribution of the CLA and TS fractions over the area investigated in this work. They showed that the TS concentrates more at the concave landforms, including the central and lower area regions, and both in the 0 – 0.20 m and 0.20 – 0.40 m layers. This fact contributed to the positive and significant correlation between DBH and TS fraction.

The DBH map estimated by the PC1 scores of the CLA and TS collected from both layers (Fig. 3), i.e., by cokriging, provided satisfactory results in estimating the *Eucalyptus* DBH, suggesting that the *Eucalyptu*s development over three years is correlated spatially with the CLA and TS fraction from both soil layers. The right and left parts of the map correspond to regions characterized by the lowest DBH and largest CLA concentrations. The regions comprising the highest DBH (>15.0 cm) (>0.15 m) are in agreement with those displayed in Fig. 2, which are regions characterized by the highest TS concentrations, as estimated by kriging. In the left and lower region of the area shows the underestimation shown by MBE in cokriging with increase in area in the class of 11.0 to 14.0 cm (0.11 to 0.14 m) of DBH. The increase in RMSE occurred as shown in Fig. 3 as a function of the increase of the DBH area in the class of 11.0 to 14.0 cm (0.11 to 0.14 m), low DBH, as well as in the class with DBH greater than 15.0cm (0.15m).

The results obtained in this work differ from those reported by [20]. These authors evaluated the influence of soil physical attributes on productivity and quality of the *Eucalyptus grandis* wood for cellulose production and concluded that the clay content related to the available water was the most positive influence on productivity.

[16] examined the spatial distribution of particle size fractions in a pasture comprising an Ultisol and found the highest TS concentrations at the lower parts of the area, while the highest CLA fractions were found at the top parts, in declivous area. Ortiz JL, et al. [5] also found highest TS concentrations at lower regions. According to the author, this TS spatial distribution pattern increases the porosity and permeability of the soil, which facilitate aeration, penetration and root growth. Absorption of nutrients and water by the roots is consequently favored, once larger soil volumes become accessible to trees.

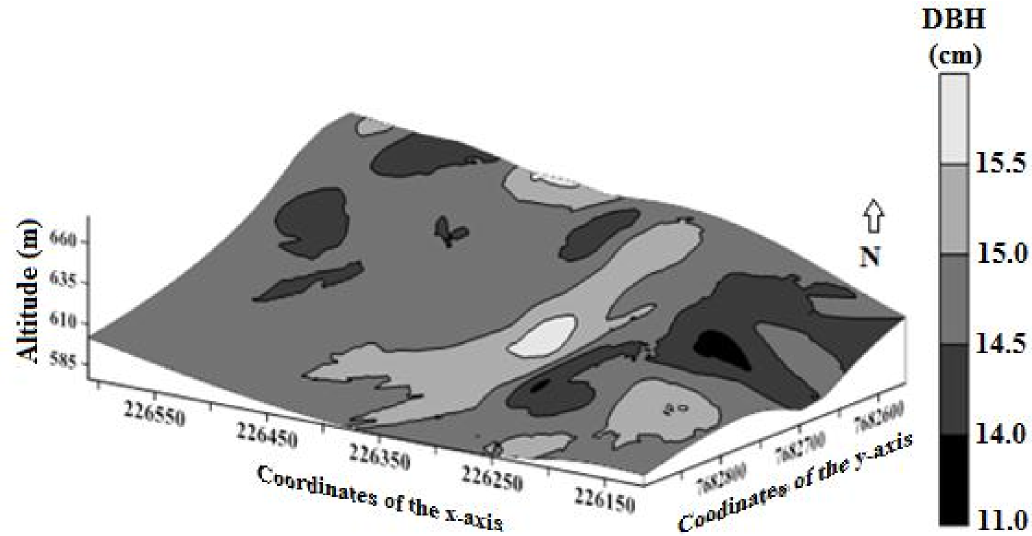

Fig. 2. Map of the spatial distribution of *Eucalyptus* DBH by kriging

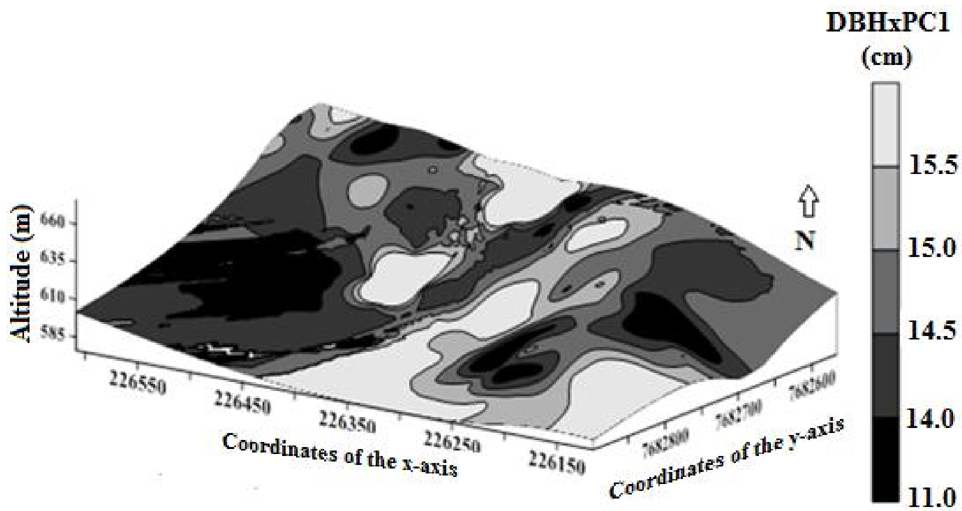

Fig. 3. Map of the spatial distribution *Eucalyptus* DBH cokriging determined by taking as a covariate scores of one principal component (PC1) using the CLA1 (0 – 0.20 m), CLA2 0.20 – 0.40 m), TS1 (0 – 0.20 m) e TS2 (0.20 – 0.40 m)

4. CONCLUSIONS

- Diameter at breast height (DBH) of *Eucalyptus* trees were found to be spatially dependent. The largest DBH values were observer for areas characterized by the highest total sand contents.
- The spatial correlation between *Eucalyptus* DBH and clay and total sand fractions reveals the importance of considering these soil parameters for demarcating sampling areas.
- The kriging and cokriging interpolation methods were efficient in estimating the DBH of *Eucalyptus* trees located at non-sampled areas.
- The cokriging technique was proven to be an efficient tool for assessing variables of forest production systems, despite its higher estimated errors in comparison with those obtained by kriging.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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