DEVELOPMENT OF A SAMPLING STRATEGY FOR YOUNG STANDS OF *Eucalyptus* sp. USING GEOSTATISTICS

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ABSTRACT: This work evaluated the potential of a geostatistical interpolator for defining strata and for comparing the stratification generated by the interpolator with stratification based on data records, on the basis of sampling error. Data were collected from a clonal stand of eucalyptus encompassing 164.08 ha of area and located in the municipality of Aracruz, Espírito Santo state. In 2003, 49 plots were allocated and in 2004 another 50 plots were distributed systematically in the area. In 2005, all plots were remeasured. The characteristic evaluated each measurement year was 'volume outside bark'. Spherical and exponential models were fitted to the experimental semivariograms using the maximum likelihood method. The selected model, following the Akaike Information Criterion, was the exponential model. Based on degree of spatial dependence (SD) it was possible to assess the spatial continuity structure of the characteristic of interest. The variable 'volume outside bark' was found to be spatially structured in all measurement years and the degree of spatial dependence varied according to forest age. This indicates that statistical analyses should consider the spatial component in the inference process at the ages considered in this study, in particular area classification based on yield. Results showed that the geostatistical interpolator can be used for establishing strata and locating permanent sample plots in young stands of *Eucalyptus* sp.

Key words: Forest inventory, stratification, spatial statistic.

DEFINIÇÃO DA ESTRATÉGIA AMOSTRAL EM PLANTIOS JOVENS DE *Eucalyptus* sp. COM O USO DA GEOESTATÍSTICA

RESUMO: *Avaliou-se o potencial do interpolador geoestatístico para definição de estratos e comparar a estratificação gerada pelo interpolador com a estratificação cadastral, com base no erro de amostragem. Os dados foram coletados em um povoamento clonal de eucalipto de 164,08 ha, localizado no município de Aracruz, ES. Em 2003 foram lançadas 49 parcelas e em 2004, 50 parcelas distribuídas de forma sistemática na área. Em 2005, todas as parcelas foram remedidas. A característica avaliada em cada ano de medição foi volume com casca. Aos semivariogramas experimentais foram ajustados os modelos exponencial e esférico pelo método da Máxima Verossimilhança. O modelo selecionado segundo o Critério de Informação de Akaike foi o exponencial. De acordo com o grau de dependência espacial (DE) foi possível avaliar a estrutura de continuidade espacial da característica de interesse. A variável volume com casca apresentou-se estruturada espacialmente em todos os anos de medição e o grau de dependência espacial variou com a idade da floresta. Isso indica que as análises estatísticas devem considerar a componente espacial no processo de inferência realizado nas idades avaliadas nesse estudo, principalmente a classificação das áreas quanto à produtividade. Os resultados mostraram que o interpolador geoestatístico pode ser utilizado no estabelecimento dos estratos e na localização das parcelas permanentes em idades jovens de Eucalyptus sp.*

Palavras-chave: Inventário florestal, estratificação, amostragem.

1 INTRODUCTION

Given the growing shortage and the difficulties in obtaining natural resources, more and more businesses require professionals to be assertive in decision-making to secure beneficial use of such resources. In order to be optimized, resources have to be understood, quantified and monitored as accurately as possible.

The use of suitable sampling techniques can be a source of reliable information at timely costs, with the monitoring of stand growth being done through permanent sample plots. Suitably locating them becomes an important task as they provide basic information for prediction of yield over time. Therefore, a sample should typify all different behaviors of a forest with respect to yield patterns, so as to ensure accurate estimations,

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present and future (PÉLLICO NETTO & BRENA, 1997).

Classic processing of forest inventory assumes sample units as independent, in other words, they are randomly distributed in space. It is not common to do data analysis to check whether the independence hypothesis assumed a priori is true. It is necessary to check whether there is a degree of correlation between sample points (VIEIRA, 2000). Simulations with eucalyptus forests showed that, even with randomized sample units, spatial dependence becomes evident, even where local control techniques such as blocking are used. Thus where spatial dependence exists, it should be taken into account if we are to improve the quality of estimations (MELLO, 2004).

In forest inventories, stratification helps improve the accuracy of population estimators, also helping reduce sample size and costs due to its capability to control variation influencing the characteristic of interest. Typically, stand stratification is based on data records such as age, genetic material, spacing or management regime. However, a stratification based on the variable of interest itself should be ideal (SCOLFORO & MELLO, 2006).

According to ESRI (2001), kriging is a geostatistical interpolator that uses statistical attributes and spatial configuration estimations of a known location to estimate an unknown location. Kriging techniques are based on the study of spatial variability of a characteristic of interest, proving better than other interpolation techniques in that it allows calculating the error associated with each estimation - kriging variance (JOURNEL & HUIJBREGTS, 1978). Kriging techniques can be applied to stand stratification, since by controlling the variability of a characteristic of interest it is possible to establish defined strata among young forest stands (KANEGAE JÚNIOR et al. 2007).

This study aimed to assess potential use of the geostatistical interpolator for defining strata and then comparing the generated stratification to stratification based on data records, on the basis of sampling error.

2 MATERIAL AND METHODS

2.1 Study site

The study was performed in an area of 164.08 ha housing a clonal eucalyptus stand with spacing of 3 m X 3 m, in the municipality of Aracruz, Espírito Santo, located at geographical coordinates 19º35' and 20º15' south latitude, and 40º00' and 40º20' west longitude. The local climate, according to Köppen classification, is midway between Aw and Am, which reads as humid tropical climate (EMBRAPA, 2000). The altitude ranges between 30 and 100 meters, with predominance of red-yellow dystrophic latosol and red-yellow podzolic soil (BRASIL 1998, cited by EMBRAPA 2000).

2.2 Database

Data were obtained from continuous inventories in 2003, 2004, and 2005. In 2003, when the stand had reached 12 months, 49 circular permanent plots were installed with an area of 360 m², all systematically distributed across the entire study area. The following year, when the stand had reached 2 years, another 50 permanent circular plots of 360 m² were installed, to a total of 99 plots. In 2005, all plots installed in 2003 and 2004 were remeasured.

On each occasion, measurements were taken for the circumference 1.3m above the ground (CBH) of all trees within the plot, for the total height of 50% of these individuals, and for the height of dominant trees, according to a description by Assmann (PRODAN et al. 1997). The variable assessed in each plot over these three measurement years was 'volume outside bark' up to 4 cm of diameter. Table 1 provides the area covered by each stand and respective number of plots, each measurement year.

Table 1 – Area of each stand and respective number of plots in 2003 and 2004.

***Tabela 1** – Área dos talhões e seus respectivos números de parcelas em 2003 e 2004.*

Stand	Area	Measurement Year	
		2003	2004
01	20.09	4	5
02	24.25	5	5
03	4.34	3	3
04	6.21	3	3
05	6.18	3	3
06	5.51	3	3
07	10.92	3	3
08	12.29	3	3
09	9.07	3	3
10A	19.68	4	4
10B	0.56	3	3
11	13.50	3	3
12	28.32	6	6
13	3.16	3	3
Total	164.08	49	50

2.3 Exploratory data analysis

The first stage of data analysis was intended to understand their general behavior as to shape of distribution and central tendency. Although this type of analysis ignores the spatial dependence structure, it allows identification of inconsistent data – or outliers – which in turn affect the quality of geostatistical analyses, allowing also comparison with results from other works. The exploratory data analysis consisted of determining measures of position and dispersion for the characteristic of interest each measurement year. The hypothesis of data normality for the characteristic of interest was assessed using frequency histograms and box plot graphs. According to Sargent (1996), graphic assessments are important even if subjective as they can be applied to correlated data, with any statistical distribution, or to a limited number of observations, which are the main limiting factors to using objective statistical tests.

2.4 Variographic analysis

According to Duarte (2000), a variographic analysis is designed to verify the spatial dependence structure between sample units and the spatiotemporal structure for characteristics being assessed. A variogram function 2g(h) is defined as the expected squared difference between paired data values separated by a lag distance (h). A semivariogram function is one half the variogram function. A semivariance estimator is given by the arithmetic mean of the squared differences between pairs of experimental values, at all points separated by distance h:

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

where $\hat{y}(h)$ is the estimated semivariance between pairs of points for lag distance h; $N(h)$ is the number of pairs of points separated by vector h; $Z(x_i)$ is the value of the regionalized variable at point x; $Z(x_i+h)$ is the data value for point $x+h$ (JOURNEL & HUIJBREGTS, 1978).

With this function it was possible to generate the experimental semivariogram, and through the data set semivariogram models were fitted. The following model parameters were obtained: nugget effect (t^2), which indicates the unexplained variation; sill (s^2), which indicates the explained variation, and range (f), the point at which data items become independent. With the spatial model parameters the degree of spatial dependence (SD) was determined, which is the percentage ratio of structured variation s^2 to sill (t^2+s^2), as presented by Biondi et al. (1994).

2.5 Semivariogram models, model fit and selection methods

Spherical and exponential models were used in this study, as cited by Isaacks & Srivastava (1989). In order to fit the semivariogram models the maximum likelihood method was used which, according to Cressie (1993), is widely used for its interesting asymptotic properties of efficiency and consistency.

To evaluate performance of each semivariogram model in estimating volume, the Akaike Information Criterion (AIC) was used, as proposed by Burnhan & Anderson (2002). AIC was obtained using the maximum likelihood function, based on fitted parameters for exponential and spherical models.

2.6 Kriging and stratification

Kriging is a geostatistical interpolator that uses spatial inference to predict values at unobserved points on the basis of observations at nearby locations, considering the spatial dependence structure of the characteristic being studied (RIBEIRO JÚNIOR, 1995). The estimations of unobserved points were done based on punctual kriging, as described by Vieira (2000).

In this particular study, the kriging process considered three productivity classes for variable 'volume outside bark'. The variographic study and kriging process were performed using the geoR package of statistical program R (RIBEIRO JÚNIOR & DIGGLE, 2001).

After kriging the study area using measurement data from 2003, 2004 and 2005, comparisons were made between stratifications obtained on each of these occasions. These comparisons were intended to evaluate the stability of strata established in the first year so that plots could be selected for annual remeasurement, starting with this measurement.

One of the greatest advantages of suitable stratification is the possibility of precision gains for a given sampling intensity, in comparison to other sampling strategies with a similar intensity. Another possibility is a reduction in sampling intensity, falling within an acceptable error value (SCOLFORO & MELLO, 2006). To evaluate data behavior in relation to inventory errors, three different situations were examined:

Situation 1: Considering the entire area as a single stratum. Mean, coefficient of variation and standard error of mean were calculated for the entire area, using Simple Random Sampling, at each age being assessed. This situation was considered super sampling of the area (1 plot for every 3.3 ha), thus serving as a benchmark for comparison with the other described situations.

Situation 2: Considering the stratification obtained through kriging at each age being assessed. Here, spatial mean and spatial mean variance were calculated as described by Cressie (1993).

Situation 3: Considering the strata generated by kriging, according to the number of plots per stand recommended by the company (1 plot for every 10 ha). The selected plots were analyzed using Stratified Random Sampling, at each age being assessed.

3 RESULTS AND DISCUSSION

Judging by the tendency, box plot and normality graphs, good performance was verified for variable 'volume outside bark' (VOB) in the exploratory data analysis. The analysis covered 2003 and 2004 measurements and their respective 2005 remeasurements. It was observed from all measurements that variable VOB did not present any tendency in regard to latitude and longitude. This is an important factor in geostatistical studies, since in the presence of a tendency no stationarity exists, which means that in such situation geostatistical techniques should not be applied.

Observing the frequency histograms for the three measurement years, data distribution was found to be approximately normal. Although geostatistics does not require normal distribution of data in order for it to be used, normality provides desirable statistical properties to inferences, such as maximum likelihood. The variables considered in this study allowed for application of the maximum likelihood fit method.

The box plot graphs allowed verification of the presence of possible inconsistent data, or outliers, which can significantly affect the semivariogram behavior, particularly in its initial portion (DIGGLE & RIBEIRO JÚNIOR, 2000). The database did not present any inconsistent data for the variable in question, at all three measurement ages.

3.1 Selection of a kriging model

The assessed semivariogram models were compared using the Akaike Information Criterion (AIC), according to the work of Burnhan & Anderson (2002). Where the difference between AIC values is higher than 2, model curves will differ statistically. In this study, based on this information, the curves of exponential and spherical models did not differ from each other, within the same measurement, as can be observed in Table 2. The model chosen in this particular study was the exponential model, as in all measurements it presented a degree of spatial dependence higher than 70%. According to Biondi et al. (1994), a degree of spatial dependence (SD)> 75% is considered high, while between 35% and 75% is considered average. Mello (2004) also selected the exponential model for modeling the spatial structure of 'volume outside bark' in *Eucalyptus grandis* at age seven years.

In Table 2, in assessing the degree of spatial dependence (SD) according to Biondi et al. (1994), the characteristic of interest proved spatially structured in all measurement years, in other words, semivariances can be modeled by an authorized model (ISAAKS & SRIVASTAVA, 1989). The spatial dependence behavior for variable 'volume outside bark' was similar to that found by Mello (2004) and Samra et al. (1989). The degree of spatial dependence proved average at 12 months old, and high from 24 months old.

Table 2 – Estimated parameters for the two tested models and respective Akaike Information Criterion (AIC) and Spatial Dependence (SD) values, for 2003 and 2004 measurements and 2005 remeasurements.

***Tabela 2** – Parâmetros estimados para os modelos testados e os respectivos valores de Critério de Informação de Akaike (AIC) e Dependência Espacial (DE) para as medições realizadas em 2003, 2004 e para as remedições dessas duas situações em 2005.*

	Exponential					Spherical				
Measurement Year	τ^2 (m^6)	σ^2 (m^6)	ϕ (m)	SD (%)	AIC	τ^2 (m^6)	σ^2 (m^6)	ϕ (m)	SD (%)	AIC
2003	1.450	3.710	350.00	71.9	208.06	1.510	3.343	641.7	68.9	206.9
2004	24.22	108.54	108.99	81.7	390.26	19.71	110.4	212.4	84.8	390.3
2005/2003	50.00	247.10	109.00	83.2	388.00	50.00	272.2	427.0	84.4	388.0
2005/2004	0.000	436.90	95.50	100.0	448.80	50.00	375.7	199.0	88.3	447.0

Random variable VOB was found to be spatially structured in the remeasurements of the stand. This is an important fact in that it allows use of geostatistical techniques at different forest ages, being also indicative that the spatial structure of that variable was not affected by age.

Model parameters varied between measurements. This variation suggests that the structure of spatial continuity detects the changes undergone by the forest with growth. This indicates that statistical analyses should consider the spatial component in the inference process for the ages assessed in this study, particularly land productivity classification.

3.2 Stratification based on kriging

Table 3 presents 'volume outside bark' intervals for each of the three classes defined by kriging, each measurement year being considered. Based on these classes it was possible to evaluate the representativeness of super sampling on forest variability. These classes also helped select plots to be turned into permanent sample plots in successive inventories.

As regards the area occupied by each stratum, Table 4 illustrates that, overall, the tendencies observed in the measurement at 12 months (2003) were confirmed in the measurement at 24 months (2004), with the intermediate class showing an increase in area. At first, one can consider establishing a sampling procedure that accommodates a larger number of plots in that class. That way, in average terms, the sampling of the forest would represent existing variability sufficiently well. It was interesting to note that the geostatistical techniques followed a normal curve pattern, both in number of plots and in area, with higher values in intermediate classes.

According to Table 4, the sampling proportion in each stratum remained stable, suggesting that population representativeness remained stable. This result indicated that the sampling adopted based on the kriging map, assuming a structure of spatial continuity, produced a much desired situation in inventories, which is productivity class representativeness. It proves an interesting alternative for allocating permanent sample plots.

Figure 1 presents kriging maps for 2003 and 2004 measurements and their respective 2005 remeasurements. Higher values are shown in yellow (Class 1), intermediate values are shown in orange (Class 2), and lower values are in red (Class 3). As was observed in Table 4, the intermediate class showed an increase in area. From visual analysis of the kriging maps, it can be inferred that permanent sample plots could be established at 24 months, that is, based on 2nd measurement results.

It was verified from the first to the second measurement that several plots shifted productivity class. Thus, the establishment of site classes based on the characteristic of interest should not be done at young ages, though such classification can help establish the sampling design.

3.3 Analysis of estimation accuracy

Table 5 presents results for the entire database, using Simple Random Sampling in a single stratum; using Stratified Random Sampling with stratification by kriging; and results of spatial means and variances considering all sampled plots. Treating data based on the stratification concept allows better control of variability, consequently leading to lower standard error of mean values. However, if plot stands is maintained, kriging can be used as a basis for post-stratification of the area, generating precision gains for volume estimations.

Table 3 – Volume outside bark intervals (VOB) according to kriging of data from different measurement years.

Tabela 3 – *Intervalos de volume com casca por (VCC), conforme a krigagem para as diferentes medições realizadas.*

VOB (m^3/plot)	Measurement Year							
	2003		2005/2003		2004		2005/ 2004	
	LL	UL	LL	UL	LL	UL	LL	UL
Class 3	1.53	3.60	84.62	106.00	39.60	51.95	82.63	106.85
Class 2	3.61	5.60	106.01	127.39	51.96	64.31	106.86	131.08
Class 1	5.61	7.60	127.40	148.78	64.32	76.67	131.09	155.31

Table 4 – Area stratification and number of plots in different strata (classes) using kriging, based on variable ‘volume’, for 2003/05 and 2004/05 measurements.

Tabela 4 *– Estratificação da área e número de parcelas nos diferentes estratos (classes), a partir da krigagem com base na variável volume, para as medições 2003/05 e 2004/05.*

Measurement Yr.	Class	Area (ha)	Plot	ha/Plot
2003	Class 3	49.99	17	2.94
	Class 2	92.27	19	4.86
	Class 1	37.73	12	3.14
2005/2003	Class 3	25.67	16	1.60
	Class 2	146.87	25	5.87
	Class 1	7.46	7	1.07
2004	Class 3	41.46	19	2.18
	Class 2	128.12	20	6.41
	Class 1	10.42	11	0.95
2005/2004	Class 3	17.94	10	1.79
	Class 2	135.34	25	5.41
	Class 1	26.71	15	1.78

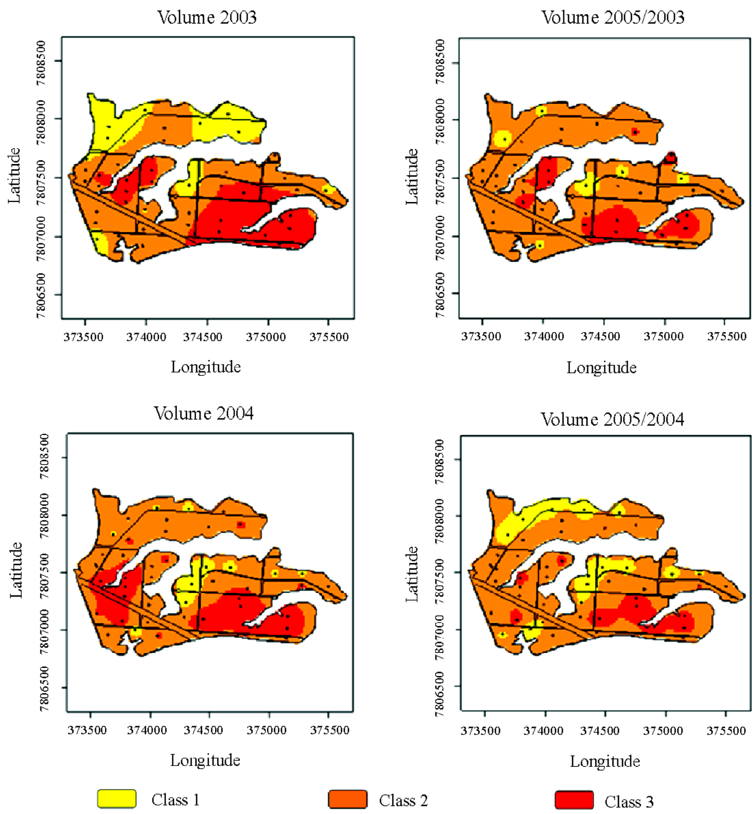

Figure 1 – Kriging maps of all measurements.

Figura 1 *– Mapas de krigagem para as medições efetuadas.*

Table 5 – Mean, coefficient of variation and standard error of mean for all plots, using Simple Random Sampling in a single stratum (SRS), results of spatial means and variances (GEO), and using Stratified Random Sampling (StRS) based on volume.

Tabela 5 *– Médias, coeficientes de variação e erro padrão da média para o total de parcelas, tratadas como Amostragem Casual Simples em um único estrato (ACS), das médias e variâncias espaciais (GEO) e o tratamento dos dados como Amostragem Casual Estratificada, com base no volume.*

Measurement Year	Sampling	Mean	Coefficient of Variation	Standard Error of Mean
2003	SRS	4.26	51.42	1.06
	GEO*	4.84	-	0.80
	StRS	4.26	15.95	0.33
2005_03	SRS	116.02	18.10	1.94
	GEO*	114.00	-	2.23
	StRS	117.75	11.26	1.22
2004	SRS	55.79	20.91	1.55
	GEO*	56.36	-	3.44
	StRS	54.74	6.85	0.50
2005_04	SRS	118.62	17.70	1.92
	GEO*	120.03	-	3.97
	StRS	115.69	4.81	0.51

* Results of spatial means and variances

An expressive reduction was noted in the standard error of mean from SRS to StRS, based on kriging (post-stratification in volume). A reduction in the standard error of mean denotes improved accuracy and reduced inventory error. Stratification by kriging therefore promoted considerable precision gains in comparison to SRS (Table 5). The inventory processing, considering spatial correlation (GEO), presented a higher standard error of mean. This will always occur in the presence of correlation, that way the weights of sample units (SU) are defined according to the correlation. Where two SU are close, only one will be ascribed more weight, since in a correlation context information from the other is redundant and therefore will be ascribed less weight. In the case of SRS, the SU have the same weight, and the larger the sample the lower the standard error of mean. This topic was investigated by Mello (2004) and produced similar results.

4 CONCLUSIONS

The dendrometric characteristic being assessed in this study proved spatially structured in all measurements, whereas the degree of spatial continuity varied with the age of the forest. Spatial structure should thus be considered in estimations.

The selection of permanent sample plots from age 12 months is possible, although variable 'volume' proved unstable to serve as a basis for kriging, at 12 months.

The geostatistical interpolator known as kriging proved to be efficient to define strata based on the characteristic of interest, generating precision gains for 'volume outside bark' estimations. In conclusion, it has potential for use in defining strata and locating permanent sample plots in young *Eucalyptus* sp. stands.

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