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Original Article

# Spatial Variability and Sampling Structures for Forest Fuel Material Estimation

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## ABSTRACT

The aim of this work was to model the spatial dependence of fuel material deposition on the ground in a pine stand, and to simulate and evaluate sampling procedures for estimating it. Branches with diameters up to 0.7 cm (A) and from 0.71 to 2.5 cm (B) were collected. Subsequently, the structures of systematic sampling and linear clusters were simulated for 50%, 33% and 23% of the total sample size, and the spatial dependence was evaluated through geostatistical modeling. The systematic sampling was suitable, with representative spatial coverage and accurate estimators, whereas linear clusters were inadequate. The reduction of the number of sample units affected the estimators, but their sampling errors did not exceed 10% for the sample sizes of 23% for class A of fuel material and 50% for class B in the systematic structure, resulting in consistent estimates.

**Keywords:** intensity of sample size, sampling errors, consistency of the estimators.

## 1. INTRODUCTION

Forest fuel material consists in every living or dead biomass susceptible to ignition and burn in forest fires (Fuller, 1991; Agee & Skinner, 2005) and is the main driver of nutrient cycling in forest formations. However, despite the ecological importance of biomass deposited on the soil, sampling of fuel material has rarely been addressed in forest inventories (Ribeiro et al., 2012). Yet, surveying the amount of fuels in forest stands is important for adoption of preventive silvicultural practices (Soares, 2002).

Normally, thinner materials with diameters up to 2.5 cm are the first to burn in a forest fire, and for that reason, they are considered dangerous or semi-dangerous (Beutling, 2009). Thus, according to Bartlett et al. (2001), the main objective of studies employing statistical inference is to collect data that may be representative of the whole population, considering a maximum acceptable error. However, the optimization problem in forest inventories is important to choose an optimal sample structure that maximizes the value of the necessary data, taking into account a limited available budget (Brassel & Lischke, 2001).

Appropriate methodologies applied in forest fuel material inventories should aim to optimize the sampling procedure, to provide accurate assessments (Péllico & Brena, 1997). Overestimation can result in economic adversities for forestry companies due to the high costs of inventories (Fink, 2003). On the other hand, underestimation can negatively affect the planning of silvicultural activities and the allocation of resources for preventing and fighting fires. Other factors are related to greenhouse gas release from biomass combusted in forest fires (Smith et al., 2004) and the production of clean energy (Nogueira et al., 2000; Souza, 2010).

Thus, considering the hypothesis that production of forest residues has spatial variability and that systematization of sampling units allows obtaining statistically appropriate estimates in forest inventories, the objective of this study was to simulate and evaluate sampling procedures for estimation of forest fuel material with different sample sizes, and to model the spatially dependent variation of this material on the ground of a pine stand.

## 2. MATERIAL AND METHODS

### 2.1. Study area

The study was developed in the experimental station of the Federal University of Paraná located in the municipality of Rio Negro, Paraná State, Brazil (26° 06' S and 49° 47' W), with average altitude of 780 m. According to Batista (1995) and Maack (2002), the climate of the area is temperate humid (Cfb), based on Koppen classification, with average temperatures of 22 °C in the hottest month and more than five frosts per year.

The experimental station covers an area of approximately 120 ha, with a significant part consisting of forest plantations. A *Pinus elliottii* Engelm stand established on flat terrain in 1984, with initial spacing of 2 × 2.5 m and without silvicultural treatment since its deployment, was selected for the present study. The last inventory in the area was conducted in 2005 and estimated a volume of 560 $m^3$ $ha^{-1}$ and basal area of 47.16 $m^2$ $ha^{-1}$ (Pereira, 2009).

### 2.2. Fuel material collection

The experiment was carried out in the total area of four tracks positioned between planting rows on the North-South direction. Each track was segmented in 15 rectangular sampling units of 1.2 m × 0.6 m (Figure 1), in which fuel material was collected and separated according to diametric classes following the methodology proposed by Brown et al. (1982). For this, two classes of material were adopted: A) branches with diameters of up to 0.7 cm; and B) branches with diameters between 0.71 cm and 2.5 cm. Material with

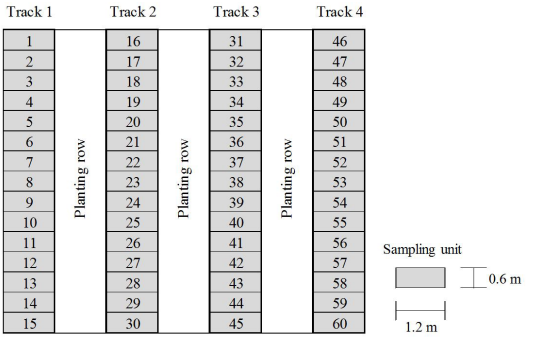


**Figure 1.** Design of the sampling structure used for quantification of fuel material in a pine stand.

diameter greater than 2.5 cm was not sampled, since they represent a small fraction of fuel material, high moisture content variation, as well as slow deterioration speed and, thus, do not present high risk for fire occurrence (Beutling, 2009).

## 2.3. Geostatistical modeling

Average production of fuel material and the coefficient of variation (*cv*) were calculated for classes A and B. Posteriorly, geostatistical analysis was employed to model spatial patterns of fuel material in the pine stand for the following sampling intensities: 100% (Figure 1), 50% (Figure 2a), 33% (Figure 2b) and 23% (Figure 2c) of the potential sample size, through calculation of experimental semivariance (1), taking into account the central geographical positioning of sampling units in the field, the subsequent calculation of distances ($h$) and numerical differences of the variable in the grid.

In order to estimate semivariances, Spherical (2), Exponential (3) and Gaussian (4) models were adjusted. The structure of the semivariogram included the nugget effect ($C_0$), corresponding to the semivariance for a distance value equal to zero; the sill ($C_0 + C$), representing the stabilization of semivariogram values near to the variance of the data; the variance a priori (C), given by the difference between the sill ($C_0 + C$) and the nugget effect ($C_0$); and the range ($a$), defined as the distance at which the semivariogram reaches a sill, indicating the boundary where sampling units correlate among themselves (Vieira 2000).

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

$$\gamma(h)=\begin{cases} C_0+C\left[\left(\frac{3}{2}\right)\left(\frac{h}{a}\right)-\left(\frac{1}{2}\right)\left(\frac{h}{a}\right)^3\right] & se\ h\le a \\ C_0+C & se\ h>a \end{cases} \quad (2)$$

$$\gamma(h)=C_0+C\left(1-e^{-h/a}\right) \quad (3)$$

$$\gamma(h)=C_0+C\left(1-e^{-h^2/a^2}\right) \quad (4)$$

Where: $\gamma(h)$ = semivariance of the variable $Z(x_i)$; $h$ = distance (m); $N(h)$ = number of pairs of measured points $Z(x_i)$ and $Z(x_i + h)$, separated by $h$; $C_0$ = nugget effect; $C$ = variance a priori; and $a$ = range.

The GS+ version demonstration program 5.1 (Robertson, 2008) was used to adjust the semivariogram. Evaluation and selection of the best adjustments were based on the least sum of squared deviations (*SQD*) and the largest determination coefficient ($R^2$). Finally, with the parameters of adjusted semivariogram and with the observed values of neighboring sampling units, production of fuel material was spatialized along the forested area by punctual ordinary kriging (Andriotti, 2003; Yamamoto & Landim, 2013).

## 2.4. Sampling procedures

Deposition of fuel material, expressed in megagrams per hectare (Mg ha$^{-1}$), was quantified in all sampling units, representing the maximum value of deposition of the two classes of sampled materials. Subsequently, estimates were calculated for 50% (Figure 2a), 33% (Figure 2b) and 23% (Figure 2c) of the potential sample size, in respectively 30, 20 and 14 sampling units, whereas tracks were the primary units ($k_1$) and

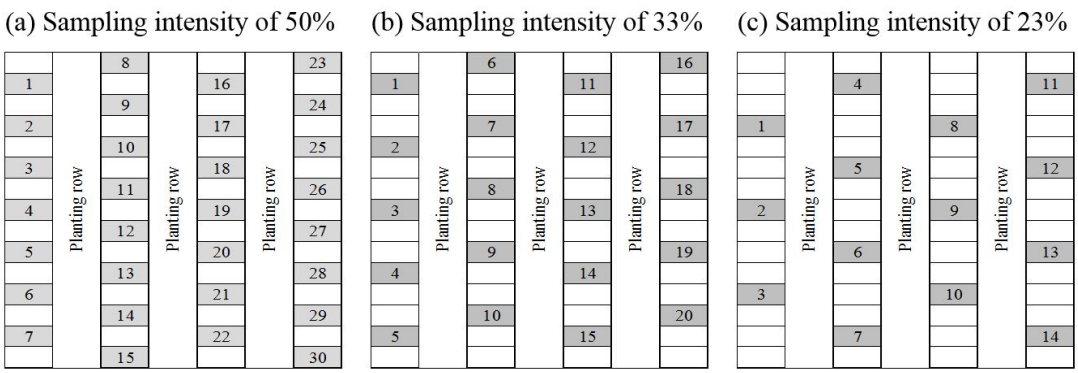


**Figure 2.** Structure allocation of units in different intensities of systematic sampling for evaluation of fuel material in a pine stand.

plots within these tracks were the secondary units ($k_2$) systematically sampled.

Additionally, the statistical formulation presented by Péllico & Brena (1997) for systematic sampling was used to estimate the mean (5), variance of the mean (6), standard error (7), absolute sampling error (8) and sampling error in percentage (9), and confidence interval for the mean (10), which were calculated for the different simulated sample sizes as follows:

Sample mean $(\bar{x})$ $$\bar{x} = \frac{\sum_{j=1}^{m}\sum_{i=1}^{n_j} X_{ij}}{m n_j} \quad (5)$$

Variance of the mean $\left(s_{\bar{x}}^2\right)$ $$s_{\bar{x}}^2 \cong \frac{\sum_{j=1}^{m}\sum_{i=1}^{n_j}\left[X_{ij} - X_{(i+1)j}\right]^2}{2n\sum_{j=1}^{m}(n_j - 1)}(1-f) \quad (6)$$

Standard Error $\left(s_{\bar{x}}\right)$ $$s_{\bar{x}} = \sqrt{s_{\bar{x}}^2} \quad (7)$$

Absolute sampling error ($Ea$) $$E_a = \pm t s_{\bar{x}} \quad (8)$$

Sampling error in percentage ($E\%$) $$E\% = \pm\frac{t\, s_{\bar{x}}}{\bar{x}}100 \quad (9)$$

Confidence interval for the mean ($CI$)

$$CI\left[\bar{x} - ts_{\bar{x}} \le \bar{X} \le \bar{x} + ts_{\bar{x}}\right] = P \quad (10)$$

Where: $m$ = number of tracks sampled; $n_j$ = number of units sampled within tracks; $Xij$ = value of unit $i$ observed in the range $j$; $n = \sum_{j=1}^{m} n_j$ number of units sampled; $\sum_{j=1}^{m}(n_j - 1) = n - m$; $f = \frac{n}{N}$; $N$ = number of potential sample units; $t$ = value of Student's $t$ distribution; and $P$ = associated probability.

Moreover, each track was considered as a linear cluster (Figure 3a) and, for the application of this sampling procedure, the following estimators were calculated for the simulated sample intensities (Péllico & Brena, 1997): sample mean (11), intra-cluster correlation coefficient (12), variance of the mean (13), standard error (14), absolute sampling error (15) and sampling error in percentage (16) and confidence interval for the mean (17).

Sample mean $(\bar{x})$ $$\bar{x} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{M} X_{ij}}{nM} \quad (11)$$

Intra-cluster correlation coefficient ($r$) $$r = \frac{s_e^2}{s_e^2 + s_d^2} \quad (12)$$

Variance of the mean $\left(s_{\bar{x}}^2\right)$ $$s_{\bar{x}}^2 = \frac{s_x^2}{nM}\left[1 + r\left(M - 1\right)\right] \quad (13)$$

Standard Error $\left(s_{\bar{x}}\right)$ $$s_{\bar{x}} = \sqrt{s_{\bar{x}}^2} \quad (14)$$

Absolute sampling error ($Ea$) $$E_a = \pm t s_{\bar{x}} \quad (15)$$

Sampling error in percentage ($E\%$) $$E\% = \pm\frac{t\, s_{\bar{x}}}{\bar{x}}100 \quad (16)$$

Confidence interval for the mean ($CI$)

$$CI\left[\bar{x} - ts_{\bar{x}} \le \bar{X} \le \bar{x} + ts_{\bar{x}}\right] = P \quad (17)$$

Where: $M$ = number of subunits of the cluster; $n$ = number of cluster sampled; $Xij$ = value of unit $i$ observed in the

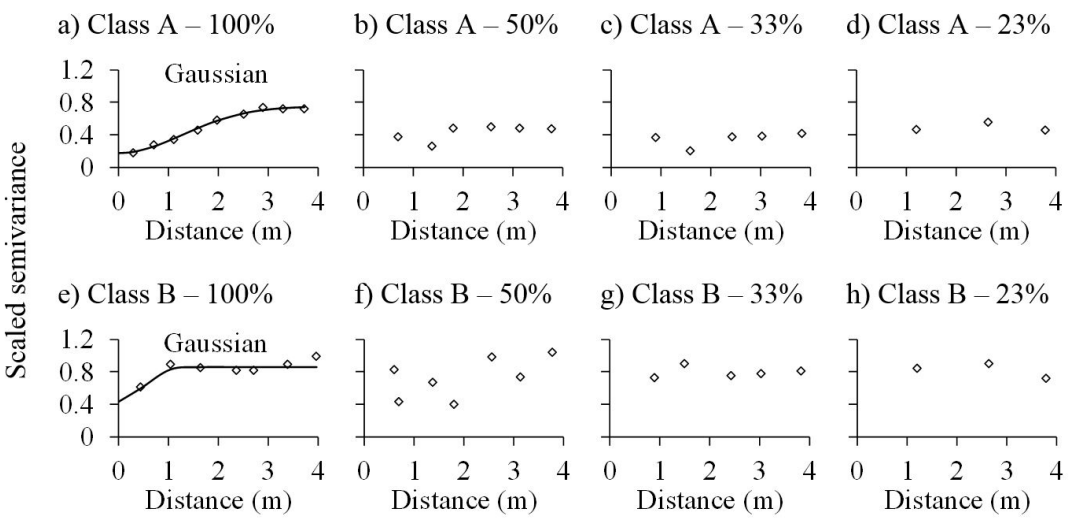


**Figure 3.** Semivariograms, in different sampling intensities, for classes A and B of fuel material deposition in a pine stand.

cluster *j*; $s_e^2$ = variance between clusters; $s_d^2$ = variance within clusters; $s_x^2 = s_e^2 + s_d^2$ = total variance; $t$ = Value of Student's $t$ distribution; and $P$ = associated probability.

## 4. RESULTS AND DISCUSSION

The average production of fuel material was equal to 5.66 Mg ha$^{-1}$ ($cv$ = 16%) and 0.61 Mg ha$^{-1}$ ($cv$ = 28%) for classes A and B, respectively, where the spatial dependence of fuel material deposited in pine stand was confirmed by the possibility of adjustment of semivariogram models (Table 1). Lower values were obtained to a unit of nugget effect ($C_0$), varying from 0.060 to 0.143 for class A and from 0.010 to 0.013 for class B of fuel material. This showed that the variance caused by non-sampling errors or unidentified variations was low (Vieira, 2000).

Range ($a$) expresses the maximum distance at which two sampling points were spatially correlated, corresponding to the radius of the areas within which spatial variability of neighboring samples was more similar. Thus, the ranges between 1.797 m and 4.575 m for class A, and 1.100 m and 1.500 m for class B (Table 1) represented the distances within which the analyses led to the estimates with greater precision (Vieira, 2000; Chig et al., 2008), while evaluations in intervals beyond the range were independent from each other.

In addition, coefficients of determination ($R^2$) were above 0.6 for class A (Table 1), what shows that the sampling grid was efficient to detect spatial characteristics of fuel material deposition, particularly with the Gaussian model for classes A and B, with which the lowest values of the sum of squared deviations ($SQD$) were obtained.

Thus, the semivariograms selected for estimating the spatial distribution of fuel material deposition in the pine stand (Figures 3a, e) demonstrated the effect of increasing semivariances related to increasing distances until reaching a regular value (Pereira et al., 2011). However, this was not identified for 50%, 33% and 23% sampling intensities, where semivariances showed irregular distribution in scaled semivariograms. This indicates that the spatial component for smaller distances was not detected.

Table 2 shows the parametric mean ($\bar{X}$) and estimates of fuel material deposition for the two classes, the three systematic sampling intensities and the linear clusters. The mean quantity of material of class A, 5.66 Mg ha$^{-1}$, was nine-fold superior than the quantity in class B, 0.61 Mg ha$^{-1}$. This is probably due to the time of permanence of fuel material after falling on the ground, as the methodology used in the present study aimed to include newly fallen but also the oldest material.

Considering the selected semivariograms, thematic maps of fuel material deposition were built through punctual ordinary kriging (Figure 4). The apparent homogeneity of fuel material on the ground was contrasted with the real spatial heterogeneity (Figure 4a, b) in the pine stand detected through geostatistical evaluation of the fuel material deposition. This heterogeneity is mainly a result of the variability of growth and size of individuals measured in adjacent areas where the fuel material was collected. Therefore, sampling procedures that capture such spatial variability is essential for quantitative accurate statistical estimates of fuel material deposition.

Estimated fuel material deposition means ($\bar{x}$) ranged from 5.64 Mg ha$^{-1}$ to 5.69 Mg ha$^{-1}$ in class A, while varied from 0.62 Mg ha$^{-1}$ to 0.63 Mg ha$^{-1}$ in class B (Table 1). In both cases, the means were close to the parametric values, which indicated the effectiveness of the sampling structures used in the population.

**Table 1.** Parameters of the semivariogram adjusted for fuel material deposition in classes A and B in a pine stand.

| Fuel material | Geostatistical model | $C_0$ | $C$ | $a$ (m) | $R^2$ | $SQD$ |
|---|---|---|---|---|---|---|
| Class A | Spherical | 0.060 | 0.593 | 3.542 | 0.991 | $2.2 \times 10^{-3}$ |
| | Exponential | 0.086 | 1.083 | 4.575 | 0.968 | $7.5 \times 10^{-3}$ |
| | Gaussian | 0.143 | 0.608 | 1.797 | 0.993 | $1.8 \times 10^{-3}$ |
| Class B | Spherical | 0.010 | 0.025 | 1.120 | 0.622 | $2.6 \times 10^{-5}$ |
| | Exponential | 0.010 | 0.025 | 1.500 | 0.614 | $2.6 \times 10^{-5}$ |
| | Gaussian | 0.013 | 0.025 | 1.100 | 0.660 | $2.3 \times 10^{-5}$ |

Where: $C_0$ = nugget effect; $C$ = variance a priori; $a$ = range; $R^2$ = coefficient of determination; and $SQD$ = sum of squared deviations.

**Table 2.** Estimates of the fuel material in classes A and B, in different sampling intensities using systematic sampling and linear clusters, in pine stand.

| Fuel material | $\overline{X}$ | $n$ | $\overline{x}$ | $r$ | $s_{\overline{x}}$ | $Ea$ | $E\%$ | $CI\left[\overline{x} - ts_{\overline{x}} \leq \overline{X} \leq \overline{x} + ts_{\overline{x}}\right] = P$ |
|---|---|---|---|---|---|---|---|---|
| | Mg ha$^{-1}$ | | Mg ha$^{-1}$ | | Mg ha$^{-1}$ | | | |
| Systematic sampling procedure | | | | | | | | |
| Class A | 5.66 | 50% | 5.69 | - | 0.08 | 0.16 | 2.7% | 5.53 Mg ha$^{-1}$ ≤ $\overline{X}$ ≤ 5.85 Mg ha$^{-1}$ |
| | | 33% | 5.64 | - | 0.11 | 0.23 | 4.1% | 5.41 Mg ha$^{-1}$ ≤ $\overline{X}$ ≤ 5.87 Mg ha$^{-1}$ |
| | | 23% | 5.68 | - | 0.18 | 0.39 | 6.9% | 5.28 Mg ha$^{-1}$ ≤ $\overline{X}$ ≤ 6.07 Mg ha$^{-1}$ |
| Class B | 0.61 | 50% | 0.62 | - | 0.02 | 0.05 | 7.7% | 0.57 Mg ha$^{-1}$ ≤ $\overline{X}$ ≤ 0.66 Mg ha$^{-1}$ |
| | | 33% | 0.62 | - | 0.04 | 0.08 | 12.8% | 0.54 Mg ha$^{-1}$ ≤ $\overline{X}$ ≤ 0.70 Mg ha$^{-1}$ |
| | | 23% | 0.63 | - | 0.04 | 0.10 | 15.2% | 0.53 Mg ha$^{-1}$ ≤ $\overline{X}$ ≤ 0.72 Mg ha$^{-1}$ |
| Sampling procedure in linear clusters | | | | | | | | |
| Class A | 5.66 | 50% | 5.69 | 0.65 | 0.28 | 0.90 | 15.9% | 4.79 Mg ha$^{-1}$ ≤ $\overline{X}$ ≤ 6.59 Mg ha$^{-1}$ |
| | | 33% | 5.64 | 0.48 | 0.31 | 1.00 | 17.6% | 4.64 Mg ha$^{-1}$ ≤ $\overline{X}$ ≤ 6.63 Mg ha$^{-1}$ |
| | | 23% | 5.68 | 0.60 | 0.39 | 1.24 | 21.8% | 4.44 Mg ha$^{-1}$ ≤ $\overline{X}$ ≤ 6.92 Mg ha$^{-1}$ |
| Class B | 0.61 | 50% | 0.62 | 0.58 | 0.08 | 0.17 | 27.7% | 0.45 Mg ha$^{-1}$ ≤ $\overline{X}$ ≤ 0.79 Mg ha$^{-1}$ |
| | | 33% | 0.62 | 0.43 | 0.07 | 0.23 | 37.2% | 0.39 Mg ha$^{-1}$ ≤ $\overline{X}$ ≤ 0.85 Mg ha$^{-1}$ |
| | | 23% | 0.63 | 0.57 | 0.08 | 0.25 | 40.2% | 0.37 Mg ha$^{-1}$ ≤ $\overline{X}$ ≤ 0.88 Mg ha$^{-1}$ |

Where: $\overline{X}$ = reference mean; $n$ = number of sample units; $\overline{x}$ = sample mean; $r$ = intra-cluster coefficient of correlation; $s_{\overline{x}}$ = standard error; $E_a$ = absolute sampling error; $E\%$ = sampling error in percentage; $CI$ = confidence interval for the mean; and $P$ = probability level of 95%.

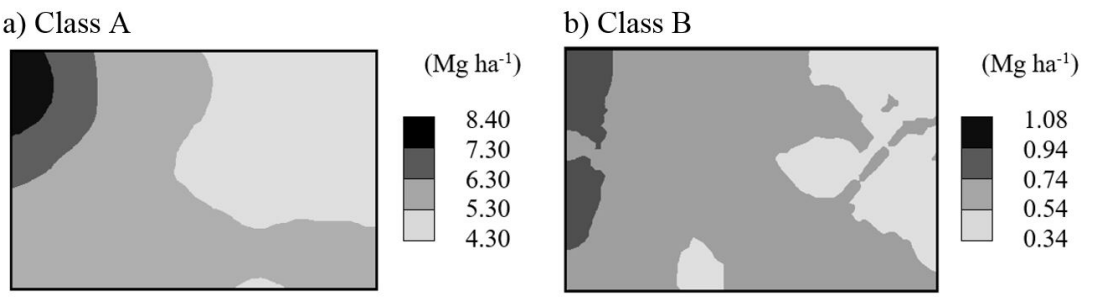


**Figure 4.** Spatial distribution of fuel material deposition in classes A and B in a pine stand.

However, the values of the standard error ($s_{\overline{x}}$) tended to increase with the reduction of the sample size ($n$). In general, the larger the numbers of observations are, the more precise are the estimates, although this does not prevent an experiment with lower sampling intensity to provide estimates closer to parametric values (Pimentel-Gomes, 2009).

The intra-cluster correlation coefficient ($r$) showed greater heterogeneity of fuel material deposition between clusters than between sampling units within linear clusters. This indicates that this sampling procedure is not suitable for this type of evaluation, as it is recommended that, for the effective application of this sampling process, $r$ values should not exceed the interval between 0 and 0.4 for intra-cluster correlation (Péllico & Brena, 1997). Thus, $r$ values between 0.43 and 0.65 observed in classes A and B of fuel material are related to greater spatial variability of deposition in the forest stand, indicating that the variance between clusters is superior to the variance within clusters and corroborating with the spatial variability observed in the geostatistical modeling (Figure 4).

Furthermore, the absolute sampling error ($E_a$) and the sampling error in percentage ($E$%) increased with the reduction of the sample size ($n$). According to Pimentel-Gomes (2009), for the same standard error, sampling errors tend to decrease with the increase of sample size, enhancing the accuracy of the estimate of the mean due to more degrees of freedom in the $t$ distribution. It was also observed that in both classes of fuel material, the reduction of the sampling grid caused expansion of the confidence interval for the mean ($CI$).

The confidence interval for the mean ($CI$) tended to increase with decreasing sample size ($n$), so that the parametric mean $(\bar{X})$ remained within a larger interval for the samples of 23% of the population, due to its weak representativeness of population variability. However, the parametric mean was expected to occur within a limited interval range, so as to ensure the validity of the less intense sampling. Moreover, simulations showed that, in many cases, sample sizes around 30 sampling units provide appropriate approximations for practical applications.

Authors such as Brown (1974) and Ribeiro et al. (2012) have considered that sampling errors of up to 20% are acceptable for estimating forest fuel material, because of the high variability of dimensions of the objects measured. On the other hand, when there is an interest in the potential use of this product, errors of up to 10% are most appropriate. Consequently, the values found in the present study are within acceptable limits for the sample sizes of 23% for the class A and 50% for the class B when evaluating fuel material using the systematic sampling process.

## 5. CONCLUSION

Fuel material deposition of branches with diameters up to 0.7 cm, and branches with diameters from 0.71 cm to 2.5 cm is spatially dependent and presents a pattern that can be assessed through geostatistical analysis. Variability comes from the growth and size of individuals measured in adjacent areas where the fuel material was collected. Spatial behavior of fuel material confirms the need of using appropriate sampling methods to accurately detect this variable in forest inventories.

Systematic sampling is appropriate and recommended for estimating fuel material deposition in pine stands when representative spatial coverage of the population and accurate statistical estimators are employed. On the other hand, the sampling structure in linear clusters was considered inadequate for estimating this variable in the study area due to the heterogeneity among the clusters.

The reduction in the number of sampled units affect the estimators of fuel material deposition in the pine stand, but the respective sampling errors do not exceed the maximum limit of 10% for sample sizes of 23% in class A and of 50% in class B using the systematic sampling process, consequently resulting in consistent estimates.

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