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Spatial variability of forest growing stock using geostatistics in the Caspian region of Iran

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ABSTRACT
Estimating the amount of variation due to spatial dependence at different scales provides a basis for designing effective experiments. Accurate knowledge of spatial structures is needed to inform silvicultural guidelines and management decisions for long term sustainability of forests. Furthermore, geostatistics is a useful tool to describe and draw map the spatial variability and estimation of forest variables. Therefore, this research was conducted to investigate on spatial variability and to estimate forest stock variables using geostatistical approach in a mixed hardwood forest, located in the Caspian region of Iran. Field sampling was performed based on a 150m by 200m systematic rectangular grid of 3 clustered plots (50m away). Each sample plot consisted of two concentric circles. Overall, 434 sample plots were measured in 502 hectares. Experimental variograms for forest basal area, volume and tree density were calculated and plotted using the geo- referenced inventory plots. All the variograms showed weak spatial auto- correlations between samples, even in short distances. Estimations were made using fitted variogram models and ordinary block kriging. Cross- validation results showed that all the estimations are biased, because of the large variability and weak spatial structure in the forest stock variables. Therefore, kriging could not make accurate estimations because of high spatial variability of forest growing stock related variables in this heterogeneous and uneven-aged forest.

Keywords: *Geostatistics, Growing stock, Kriging, Spatial variability, Variogram.*

INTRODUCTION
Estimation and mapping of forest resources is an inescapable premise of management, planning and research. Time and cost constraints do not usually allow exhaustive measurements; hence, sampling schemes need to be designed and implemented to estimate population values (Husch *et al*. 1982).

Conventional statistics are generally inadequate to describe spatially correlated data. Regionalized variable theory, popularly known as geostatistics, is a methodology for analysis of spatially correlated data (Clark, 1979). Geostatistics originated from mining and geology. However, it has been spread into several fields of applications, first into petroleum engineering and then into hydrogeology, meteorology, soil science, agriculture, fisheries, pollution and environmental protection (Zahedi Amiri, 1998). Nowadays, geostatistical methods have found their applications in forestry. Geostatistics provides a natural framework for estimation techniques in forest inventory sampling (Mandallaz, 1991). The motivation for using geostatistical methods is that classical design-based methods are often weak for small area estimation within global inventories (because of small number of sample plots used for the estimation), and there is also an increasing demand to use regional or national inventory data for local estimation purposes (Mandallaz, 1993).

In this context, the first contribution to forest inventory were due to Guibal (1973) who applied kriging for estimation of forest stock in a tropical uneven-aged forest in Gabon. He showed that the result of kriging, especially for small area, is more accurately than classical approach. Jost (1993) compared, under systematic sampling, the classical error estimate with their geostatistical counterparts in the forests of Germany and showed that classical error estimate is much more than geostatistical counterparts. Biondi *et al*. (1994) in their study of the spatial distribution of stem size and increment within U.S. old- growth forests found that basal area could be measured as a regionalized variable. However, that spatial dependence structure disappeared after 30m. Gunnarson *et al*. (1998) showed that hardwood volume in old stands is an example of a variable that has no or little useful spatial auto-correlation in Swedish forests and kriging interpolation is, therefore, useless to estimate hardwood volume. Mandallaz (2000) introduced geostatistical methods for double sampling schemes in forest inventory and proposed double kriging for using auxiliary information (based e.g. on aerial photographs), which is particularly useful in the context of combined forest inventories. Tuominen *et al*. (2003) found that geostatistical interpolation, which was tested on the stand level estimation in the boreal forests of Finland, did not result in any further improvement in the accuracy of the estimates. Montes *et al*. (2005) used ordinary kriging for estimation of cork oak production in Spain. They showed that all the variables involved in the cork oak production (diameter, basal area, stripped surface area and cork thickness) show spatial correlation, and ordinary kriging, estimates the total stripped surface area more accurately than design-based approach. Freeman and Moisen (2007) applied kriging to improve forest biomass maps in U.S. and found poor behavior of variograms in the scale which they studied.

Therefore, the objectives of this study are to consider the spatial structure and variability of the forest growing stock variables, namely basal area, volume and tree density as well as investigation on the potential of kriging for estimation of them.

MATERIALS AND METHODS

Study area

Data used in this study were collected from a part (502 ha) of the educational and research forest station of Tehran University, located in the Caspian forests, northern of Iran. Geographical coordinates for the approximate center of the area are 51˚ 35' E longitude and 36˚ 34' N latitude (Fig 1). Elevation varies from 700m to 1200m above sea level and slope from 5% to 65%. The forest is typical of mixed hardwood stands of Caspian forests, currently under active management by selective cutting regime since 30 years ago.

The inventoried forest area is composed by a mix of broad-leaf deciduous tree species. The species composition and structure of the forest have been influenced by human intervention such as animal husbandry and management activities like harvesting. Dominant tree species are beech (Fagus *orientalis* Lipsky) and Hornbeam (*Carpinus betulus* L.) as well as Maple (*Acer* velutinum Boiss.), Alder (*Alnus subcordata* C.A.M.) and Oak (*Quercus castaneifolia* C.A.M.).

The average annual increment of the forest is $8m^3/ha$ with mean growing stock of $460m^3/ha$ (Zahedi Amiri, 1991). Mean annual temperature, precipitation and relative humidity are 12.23˚C, 1450 mm and 83%, respectively. Climate is cold and wet in winter and temperate in summer without any dry season. The growing season is 270 days per year. The site is naturally seeded, old-growth and uneven-aged forest. It is so heterogeneous in nature with large topographic variations.

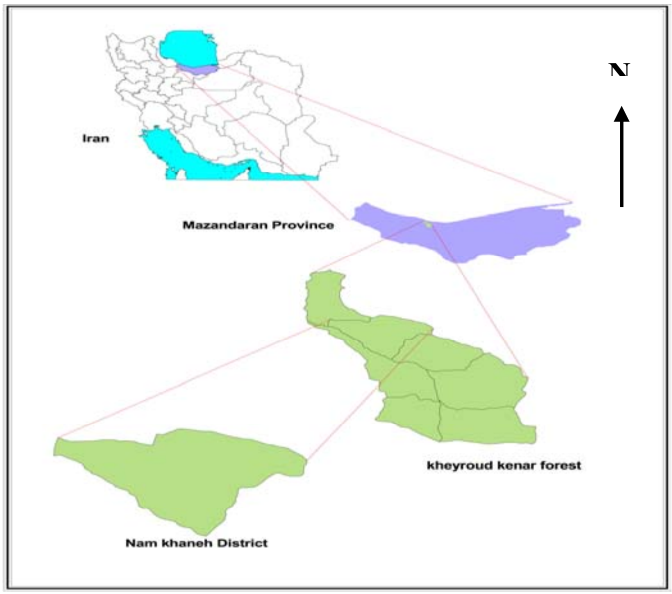


Fig. 1. Study area.

Inventory method

The conventional sampling grid in northern forests of Iran, namely 150m×200m was used for sampling. Each plot consisted of two concentric circular samples with surface areas of 300m^2 (9.77m radius) and 700m^2 (14.93m radius). Diameter at breast height (dbh in 1.3m), species, distance and azimuth from center, as well as other qualitative variables were recorded on each tree in the plot whose dbh exceeded of 7.5cm till 37.5cm at the small plot and greater than 37.5cm at the bigger one. Using concentric circles approximates a Probability Proportional to Size (PPS) inclusion rule and is therefore more efficient for forest stock estimation. The coordinates of each sample plot were established using the UTM coordinates of the starting point, which was determined by global positioning system (GPS) equipment with differential correction.

After preparatory analysis and observing large nugget effects in experimental variograms, we decided to reduce the sampling distance by measuring two extra sample plots, 50m away toward the north and the east directions from central samples, like L shaped cluster samples (Fig. 2). Finally, by the first grid, 146 and by the cluster sampling, 434 sample plots were measured in summer 2002.

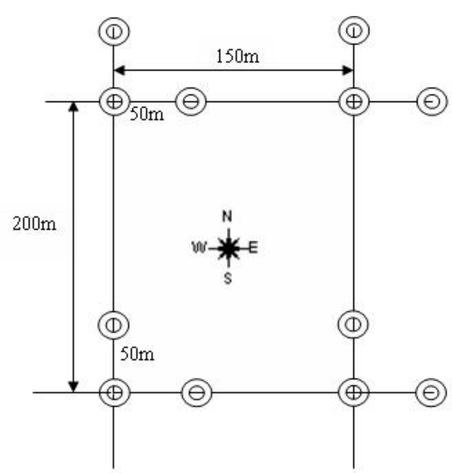


Fig. 2. Arrangement of sample plots in the study area

Geostatistical analysis

Geostatistics was developed to study variables that are distributed continuously in space, called "regionalized variables"(Isaak & Srivastava, 1989; Goovaerts, 1997). The basic principal of geostatistics is that correlation between values of a regionalized variable will decrease as distance between the sample points increases. The semi-variogram or simply variogram indicates the degree of similarity among the values of a regionalized variable when they are located in given separation distance (lag) as well as direction away from each other. The spatial structure is analyzed by means of experimental variogram and is calculated by following formula (Webster & Oliver, 2000):

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

Where $\hat{\gamma}(h)$ is the semi-variance estimator for N data pairs, separated by a particular lag vector of h. $z(x_i)$ and $z(x_i + h)$ are the values of regionalized variable z at locations of i and $i + h$.

The variogram is the corner stone of geostatistics, and it is therefore vital to estimate and model it correctly (Webster & Oliver, 2000). The parameters of the theoretical variogram can be estimated by fitting a model to the experimental variogram. When spatial dependence is present, the modeled variogram will generally increase with distance up to a constant value called the sill. The distance at which the sill reached is referred to as the range. Theoretically, the variogram should pass through the zero variance. However, in practice, there is often a nonzero variance known as the nugget effect, which represents the random component of the spatial structure. The nugget effect can also be caused by spatial variability at distances below the minimum sampling interval and measurement errors, as well. The variogram is function of both distance and direction. When the spatial dependence is only a function of distance between the samples, then the variogram is isotropic (omni directional). When the opposite On the contrary, it is said to be anisotropic (directional).

In the current study, the models considered in fitting the variograms were spherical (2), exponential (3) and pure nugget effect (4) (Cressie, 1993), which fitted to the experimental variograms using the weighted least squares (WLS) method. These models are defined as:

$$\gamma(h) = c_0 + c\left\{\frac{3h}{2a} - \frac{1}{2}\left(\frac{h}{a}\right)^3\right\} \quad \text{for } 0 < h \le a \qquad (2)$$

$$\gamma(h) = c_0 + c \qquad \text{for } h > a$$

$$\gamma(h) = c_0 + c\left\{1 - \exp(-\frac{h}{a})\right\} \Rightarrow h \ge 0 \qquad (3)$$

$$\gamma(h) = c_0 \qquad \text{for } h \neq 0 \qquad (4)$$

$$\gamma(h) = 0 \qquad \text{for } h = 0$$

where c_0, c, h and a represent nugget variance, structural variance, lag distance and range, respectively.

Prediction or estimation is the task for which, geostatistics was initially developed and it is generally called Kriging after D.G. Krige (1951). Kriging is a procedure for estimating regionalized variables at un-sampled points, based on initial data value. However, ordinary kriging, the workhorse of geostatistics, is the most common type of kriging in practice, particularly in environmental sciences (Webster & Oliver, 2000). It is given by:

$$\hat{z}(x) = \sum_{i=1}^{n} \lambda_i z(x_i) \qquad (5)$$

Where, λ_i is the weight associated with each sample location value.

The estimator may be used for estimation at a single point (point kriging) or over an area (block kriging).

Within a probabilistic framework, kriging attempts to minimize the expected mean square error under the constraint of unbiasedness. Hence, kriging is the Best Linear Unbiased Estimator (BLUE) as:

$$\sum_{i=1}^{n} \lambda_i = 1 \quad (6)$$

Meanwhile, Kriging supplements estimation with an error variance map besides the estimation map.

In this study for estimation, ordinary block kriging without trend was used, since the mean is assumed stationary and unknown as well as no large-scale trend was observed. A 25m×25m grid was used to discretize the area for estimation. The size of the grid was chosen to be approximately the same as that of the sample plots to emphasize the local variation around the sampling plots.

The estimations were done on the nearest 16 data plots, within the maximum search radius, which corresponded to the scale of auto-correlation.

To evaluate the results of kriging usually, a Jack-knife cross-validation approach is used. All the samples are excluded one by one from the data set and estimated again by kriging using the remaining samples. Then measured data and estimated values are compared to evaluate the kriging results (Webster & Oliver, 2000).

In this study, the accuracy of kriging is measured using Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[z(x_i) - \hat{z}(x_i)\right]^2} \quad (7)$$

where $\hat{z}(x_i)$ is the estimated value of regionalized variable z at location of i and cross-validation is evaluated by calculation of Mean Error (ME) which should ideally be equal to zero, because kriging is unbiased (Webster and Oliver, 2000):

$$ME = \frac{1}{N}\sum_{i=1}^{N}\left[z(x_i) - \hat{z}(x_i)\right] \quad (8)$$

The software package used for geostatistical analysis was Gs+ version 9 (Gamma Design Software, LLC, Plain well, MI).

RESULTS

Firstly, we used the 146 sample plots of the 150m×200m grid for variography. Normalization trials using Kolmogorov-Smirnov test showed that all the variables have approximately normal distribution (P>0.05) and do not need to transform them (results not shown). Descriptive statistics of the three variables (table 1) shows that the coefficient of variation of data and therefore, variability is rather high with low intra-cluster correlation coefficient, ρ among the sample plots.

In this study, variograms were used as a measure of spatial dependence between two points. Variogram anisotropy, as invest-tigated through the experimental variogram surfaces, were not found; consequently, only omni- directional variograms were modeled. Parameters of the models fitted to experimental variograms are indicated in table 2. Experimental variogram plots and fitted models are shown in figure 3. As it is clear in table 2, the structured part of basal area and volume are 58% and 41%, respectively, while there is no spatial structure (pure nugget effect) for tree density.

Table 1. Summary statistics of the 3 variables using 150m×200m sampling grid.

Variable	No. of Sample	Mean	Min	Max	SD	CV (%)	ρ
Basal area (m^2/ha)	146	30.2	0.8	58.2	11.4	37.7	0.10
Volume (m^3/ha)	146	442.7	6.5	859.0	182.6	41.2	0.12
Density (n/ha)	146	245.9	14.3	666.7	139.7	56.8	0.09

SD, Standard deviation   CV, Coefficient of variation
ρ, Intra-cluster correlation coefficient (optimal value: ±1)

Table 2. Parameters of the models fitted to experimental isotropic variograms using 146 sample plots.

Variable	Model	Nugget effect	Sill	Range (m)	SP (%)
Basal area	Spherical	56 (m^2/ha)^2	133 (m^2/ha)^2	360	58
Volume	Exponential	20000 (m^3/ha)^2	33930 (m^3/ha)^2	360	41
Density	Pure nugget effect	19170 (n/ha)^2	19170 (n/ha)^2	-	0

SP, Structured Part, given by the ratio: (Sill- Nugget effect / Sill) ×100

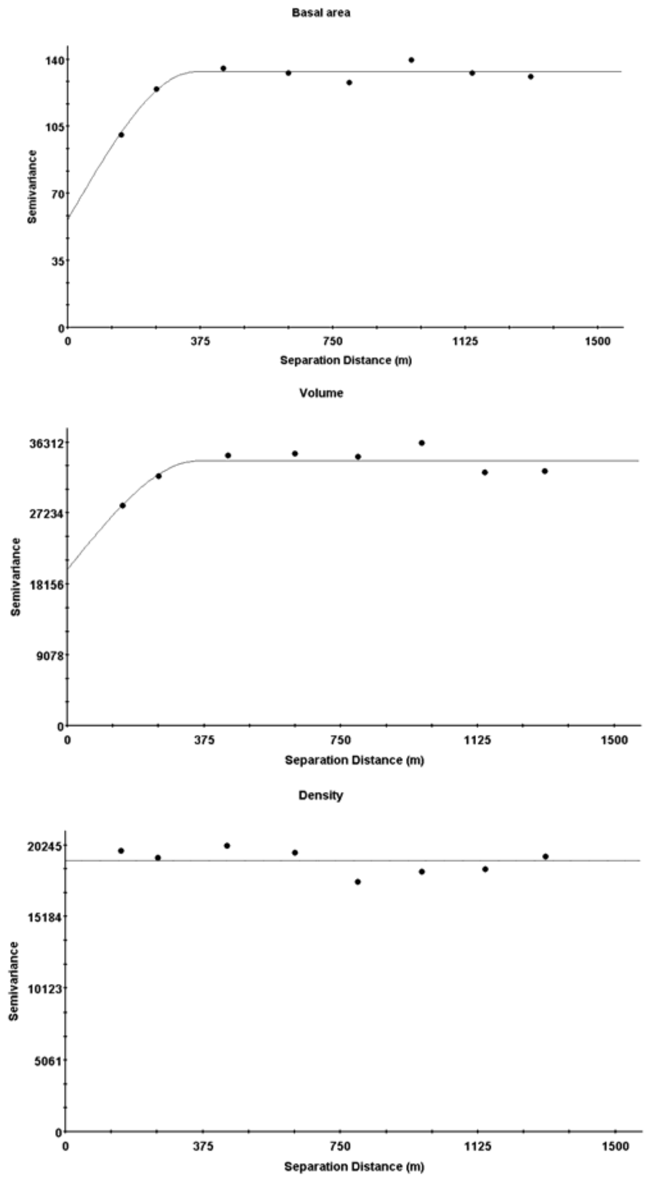


Fig. 3. Isotropic variograms (omnidirectional) with the fitted models using the WLS method for the 3 variables by the 146 sample plots. Filled circles represent experimental variograms and solid lines represent fitted models.

Then ordinary block (25m ×25m) kriging was applied for estimation of three variables over the study area. Results of kriging showed that the estimated values have a much smaller variance than the measured data because of the smoothing effect of kriging. However, the estimated mean is close to the measured data mean (Tables 1 and 3).

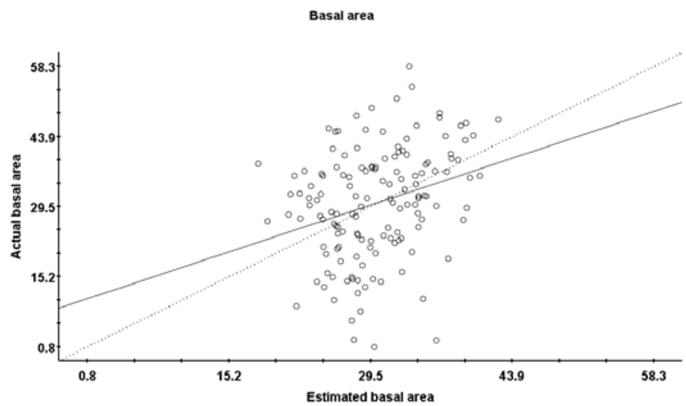
Table 3. Results of kriging and cross-validation for the 3 variables using 146 sample plots.

Variable	Mean	Min	Max	SD	CV (%)	RMSE	ME
Basal area (m^2/ha)	29.95	14.17	48.03	5.95	19.86	11.01	0.13
Volume (m^3/ha)	438.30	244.33	575.77	78.24	17.85	180.50	1.76
Density (n/ha)	248.49	141.07	331.25	36.30	14.60	142.04	-4.75

RMSE, Root Mean Square Error ME, Mean Error

The measured data are plotted versus the estimated values in figure 4. A bias can be observed, which agrees with the high nugget effect in the models (table 2) and low intra-cluster correlation coefficient, ρ (table 1) as well. The RMSE amounts appear to be large and the ME values are far from zero, indicating that kriging did not produce an accurate estimation for each point (table 3).

(a)



(b)

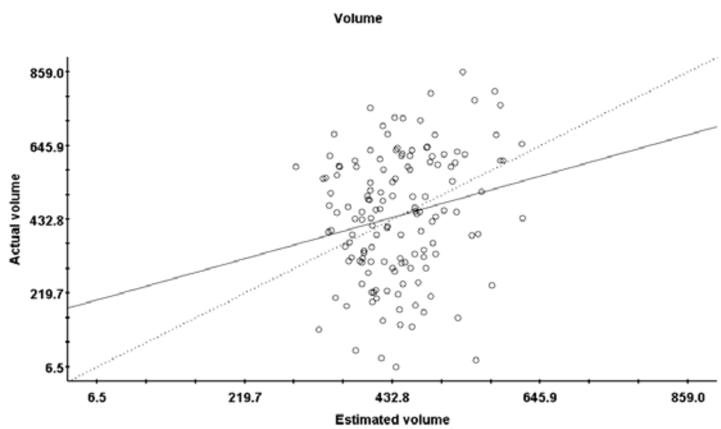


Fig. 4 . (a, b). Comparison between measured and estimated values for the basal area and volume using 146 sample plots.

Secondly, after gaining the poor results from variography and kriging, we used the extra L shaped cluster samples (the 434 sample plots) for variography (Fig 5). Table 4 shows descriptive statistics of the three variables and table 5 is the results of variogram modeling. Surprisingly, by decreasing the sampling interval from 150m to 50m, the nugget effect went higher and no improvement happened in cross-validation results.

Table 4. Summary statistics of the 3 variables using L shaped cluster samples

Variable	No. of Sample	Mean	Min	Max	SD	CV (%)	ρ
Basal area (m^2/ha)	434	31.3	0.7	72.2	11.8	37.7	0.08
Volume (m^3/ha)	434	462.9	6.5	1153.3	198.0	42.7	0.11
Density (n/ha)	434	239.6	14.3	1066.7	144.0	60.1	0.08

SD, Standard deviation CV, Coefficient of variation
ρ, Intra-cluster correlation coefficient (optimal value: ±1)

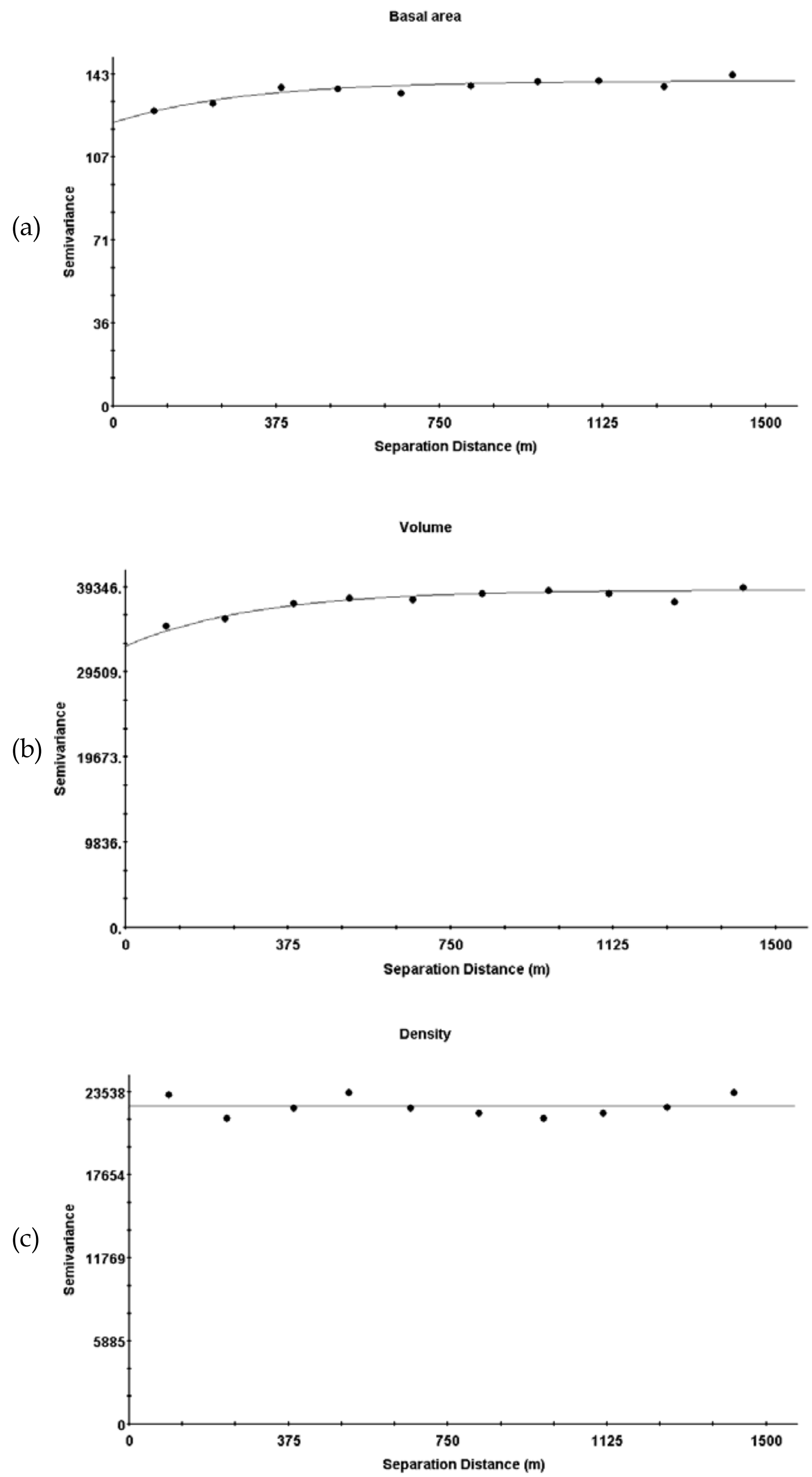


Fig. 5. (a, b, c). Isotropic variograms (omnidirectional) with the fitted models using the WLS method for the 3 variables by the 434 sample plots. Filled circles represent experimental variograms and solid lines represent fitted models.

Table 5. Parameters of the models fitted to experimental isotropic variograms using 434 sample plots.

Variable	Model	Nugget effect	Sill	Range (m)	SP (%)
Basal area	Exponential	122 $(m^2/ha)^2$	140 $(m^2/ha)^2$	300	13
Volume	Exponential	32500 $(m^3/ha)^2$	39000 $(m^3/ha)^2$	300	16
Density	Pure nugget effect	22500 $(n/ha)^2$	22500 $(n/ha)^2$	-	0

SP, Structured Part, given by the ratio: (Sill- Nugget effect / Sill) ×100

Discussion

Three forest variables; basal area, volume and tree density, were investigated in this study in view point of spatial structure in a natural hardwood forest. Both basal area and volume showed medium spatial dependence and well behaved but weak auto-correlation in the first studied scale (by 150m×200m grid), while no auto-correlation found in the second scale (L shaped 50m away sample plots). However, tree density revealed as the pure nugget effect, which was not auto-correlated neither in first scale nor in the second one, indicated that no spatial organization of the values were recognized. Overall, the nugget component was rather large, which agrees to low intra-cluster correlation coefficient, ρ (tables 1 and 4). Large nugget effect is typical for forest inventory data (Jost, 1993). The large nugget effect in the variograms of the studied variables can be explained, according to Chiles and Delfiner (1999), by three causes:

1- Structures with a range shorter than the smallest inter-point distance (short-range variability)
2- Estimation errors of random effects or stand density
3- Micro- structures that is a component of a range shorter than the sampling support (inventory plot)

Therefore, we reduced the sampling distance from 150m to 50m. Normally, nugget effect should go down by decreasing the sampling distance. However, in this research surprisingly by decreasing the distance, the nugget effect went higher and the spatial structure became weaker. This is implying an inherent variation in forest stock variables in this forest, even in 50m, which confirmed the poor results of cross-validation (figure 4). The results emphasis that tree variables are not exactly regionalized variables, because according to Kint et al. (2003), trees are basically discrete objects. In fact, forest growing stock has scattered randomly over the study area without any significant continuity, due to the selective cutting regime employed. The dominating causes of this abrupt spatial variations, besides the randomly distribution of trees are first, human intervention, such as road construction and animal husbandry, and second, natural causes such as wind throw and outbreaks of insects and diseases. Furthermore, physiographic and topographic agents are major factors in short distance variability. In fact, the site is quite heterogeneous in nature. This high heterogeneity and weak spatial structure caused anisotropy which is expected in such naturally heterogeneous area, vanished and can't be seen in experimental variograms.

Results of kriging showed that due to smoothing effect of kriging, the variance of estimated values is much lower than the measured data (Tables 1, 3 and 6), while the estimated mean is close to the data mean. However, the cross-validation results indicated a bias between kriged and measured data. In fact, all the estimated values are scattered vertically around the over all data mean (Fig. 4). We examined kriging by different block sizes (25m×25m, 50m×50m and 100m×100m) and plot sizes ($300m^2$ and $700m^2$). However, the results were the same, approximately. Therefore, the three variables are not good candidates for kriging.

Table 6. Results of kriging and cross-validation for the 3 variables using 434 sample plots

Variable	Mean	Min	Max	SD	CV (%)	RMSE	ME
Basal area (m^2/ha)	31.02	21.13	44.18	3.89	12.55	11.58	0.23
Volume (m^3/ha)	457.56	280.01	698.10	70.87	15.49	191.58	3.42
Density (n/ha)	240.54	129.7	391.8	47.06	19.56	143.67	-2.85

RMSE, Root Mean Square Error ME, Mean Error

Overall, basal area, volume and tree density did not behave as a regionalized variable in the forest. Consequently, spatial distribution of them are not auto-correlated over distance. As a result of these discontinuities, kriging might not be a suitable alternative for estimating hardwood stock in this forest and therefore, the best estimator would be the simple mean. This is in contradiction to the results of Biondi et al. (1994) who used basal area as a continuous variable within U.S. old- growth forests as well as to those of Montes et al. (2005) who used ordinary kriging for estimation of cork oak production in Spain. On the other hand it confirms the results of Gunnarson et al. (1998) and Tuominen et al. (2003):

Weighting procedures based on spatial auto-correlation do not generally perform very well when (growing stock related) variables are estimated in managed forests (Gunnarson et al. 1998). The main reason for this is that human interventions produce abrupt changes in the forest, whereas geostatistical methods are best suited for data, in which the value of the measured attribute changes slowly in stages. (Tuominen et al. 2003).

Therefore, it is proposed to apply geostatistical approach in unmanaged natural forests, such as forest reserves (lack of abrupt changes), to obtain insight of natural processes which is necessary for close to nature forestry or in the plantation forests.

Finally, since the forest is a varied study area with multiple populations, stratification of the forest is a straightforward way to increase the structured part of variograms for future researches in this context.

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