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[Research]

Spatial variability and estimation of tree attributes in a plantation forest in the Caspian region of Iran using geostatistical analysis

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ABSTRACT

This research was conducted to investigate spatial variability and estimate tree attributes in a plantation forest in the Caspian region of Iran using geostatistical analysis. Sampling was performed based on a 50m×125m systematic grid in a maple stand (*Acer velutinum* Boiss) 18 years of age using circular samples of 200m² area. Totally, 96 sample plots were measured in 63 hectares and 14.25 hectare was inventoried as full census area. Experimental variograms for forest stem basal area, stem density and tree height attributes were calculated and plotted using the geo-referenced inventory plots. The calculated variograms of basal area and height showed a high spatial auto-correlation, which is fitted by spherical model. However, stem density showed a large nugget effect. Estimations for basal area and height interpolated by ordinary block kriging and cross validation results showed that all the estimations were accurate. Furthermore, the estimated kriged mean of basal area showed no significant difference to the real mean in the full census area. Therefore, geostatistical analysis is able to capture and explain the spatial variability as well as estimate tree attributes (not stem density) in this kind of plantation forest, accurately.

Keywords: *Geostatistics, Spatial variability, Plantation forest, Tree attribute, Caspian region*.

INTRODUCTION

Estimation of forest resources is an inescapable premise of management, planning and research (Husch *et al*., 1982). However, conventional statistics are generally inadequate to describe spatially correlated data because some of the spatially correlated attributes have properties that cannot be analyzed through conventional statistics which take into account only non-spatial relationship. When spatial dependence is present, near neighbors are more similar than those futher apart, i.e., data are auto-correlated. Geostatistics is a useful tool to describe spatial variability and estimate forest variables. It is the branch of applied statistics that is concerned with the detection, modeling and estimation of spatial dependence of continuous distributed variables called *regionalized variables* (Isaak and Srivastava, 1989; Goovaerts, 1997). Although spatial distribution of trees in a particular stand represents a point pattern of discrete objects (Dale, 2000), tree attributes i.e., basal area, height and density can be thought to be directly influenced by different spatially continuous variables such as solar radiation, soil characteristics and water nutrient availability, thus allowing considered spatially continuous (Kint *et al*., 2003). 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 analysis is that classical design-based methods are often weak for small area estimation within global inventories, and there is also an increasing demand to use regional or national inventory data for local estimation purposes (Mandallaz, 1993). Accurate knowledge of spatial structures is needed to inform silvicultural guidelines and management decisions for long term sustainability of forests. Estimating the amount of variation due to spatial dependence at different scales provides a basis for designing effective experiments (Jeffers, 1982) and geostatistics has been used to optimize the sampling design (Bellehumeur and Legendre, 1998; Hernández and Emery, 2009) and also for estimation and mapping of forest resources based on forest scale surveys (Samra *et al*., 1989; Biondi *et al*., 1994; Gunnarsson *et al*., 1998; Tuominen *et al*., 2003; Montes *et al*., 2005; Freeman and Moisen, 2007; Pierce Jr *et al*. 2009; Akhavan *et al*., 2010), which produce geo-referenced data map on basal area, density or standing volume at scales where these variables usually show spatial auto- correlation.

The first objective of the present study is to use the variography and kriging methods of geostatistics to describe and analyze the spatial variability of tree attributes namely, basal area, height and density as well as to map them in a plantation forest in northern Iran. The second objective is to consider if kriging would improve the estimation accuracy comparison to classical approach.

MATERIALS AND METHODS

Study area

This research was accomplished in summer 2006 inside an 18 years plantation forest, located in the north of Iran, Caspian region. Elevation varied from 200m to 450m above sea level (fig 1). The plantation has a surface area of 63 ha. Dominant tree species is maple (*Acer velutinum* Boiss.) which were planted by 3m×3m spacing after partially clear cutting, inside the natural forest in 1989. Geographical coordinates for the approximate center of the area are 50˚ 48' E longitude and 36˚ 38' N latitude. Annual mean temperature and precipitation are 15.7 ˚C and 923 mm, respectively. The slope of the study domain varies from 10% to 65%. There was no silvicultural intervention in this area when the study started.

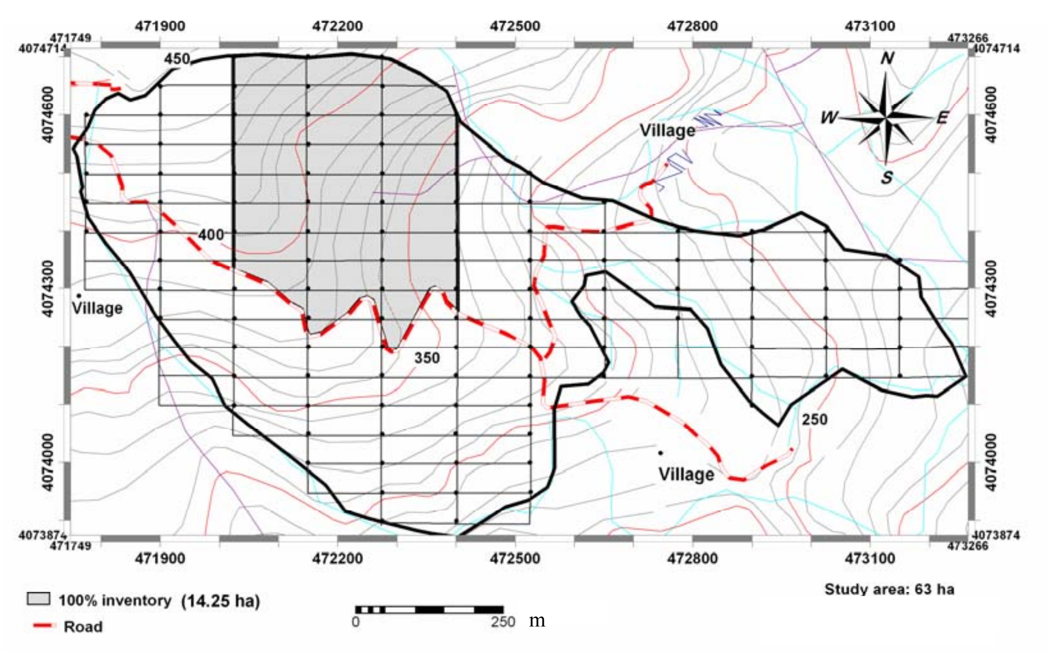

Fig 1. Study area and sampling grid

Field measurements

We used a systematic grid for sampling strategy. Based on surface area (63 ha) and optimal number of sample plots for variography in geostatistical approach (at least 100 samples), a network with 50m (N-S) ×125m (W-E) grid was designed for sampling (figure 1). The sample plots were in circular shape with surface area of 200m². Diameter at breast height (d.b.h. in 1.3m) was recorded on each tree in the plot whose d.b.h. exceeded 7.5cm. Also the height of the nearest tree to each plot center point was measured. The UTM coordinates were recorded for each sample plot center, as well. The interested attributes were forest stem basal area (BA), stem density (N) and tree height (H).

Furthermore, in order to obtain the real mean of BA, a part of the study area was selected randomly for full census inventory. The surface area was 14.25 ha which contained 32 sample plots of the so called grid (figure 1).

Spatial auto-correlation analysis

A basic principle of geostatistics is that samples located closer in space are more related and therefore, more similar than distant ones and their attributes are more continuous (Isaak and Srivastava, 1989; Cressie, 1993; Goovaerts, 1997). In general, geostatistics consists of two steps: variography and kriging (Cressie, 1993).

Variography

The semi-variogram (also referred to as variogram for simplicity), a statistical model of structural spatial dependence, is the most common tool in geostatistics for characterizing spatial continuity (Isaaks and Srivastava, 1989). The variogram indicates the degree of similarity among the values of a variable when the samples are at sequential distance increments called lag distances, away from each other and in a specified direction. The semi-variance function is thus estimated from each lag distance and direction by following formula (Webster and 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 x at locations of i and $i+h$.

Three parameters are commonly used to describe and model the behavior of variograms: *range*, *sill* and *nugget effect*. The range is the distance where the spatial correlation disappears and the variogram levels off. The height of the variogram after leveling off is known as the sill. The intercept of the variogram on the ordinate axis is the nugget eff\ect which represents the random component of the spatial structure. A variogram can be isotropic (omni-directional) when the spatial dependence is a function of the distance between the samples only and anisotropic (directional) when the spatial dependence is also a function of the direction.

The first step in kriging is to fit a model to the experimental variogram. In the current study, all the experimental variograms obtained were modeled using spherical model to which a nugget effect was added. The selection criterion used was the minimal residual sum of squares. The spherical model is given by:

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

$$\gamma(h) = c_0 + c \quad for \ h > a \qquad (2)$$

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

Kriging

Kriging computes surfaces of the best linear unbiased estimation of regionalized variables at un-sampled points based on the spatial structure defined by the experimental semi-variogram. Ordinary kriging $\hat{z}(x)$ (the most common type of kriging in practice, particularly in environmental sciences) of the regionalized variable x at point i is given by (Webster and Oliver, 2000):

$$\hat{z}(x) = \sum_{i=1}^{n} \lambda_i z(x_i) \qquad (3)$$

Where, λ_i is the weight associated with value of $z(x_i)$ at the sampled point i with the nonbiased condition:

$$\sum_{i=1}^{n} \lambda_i = 1 \quad (4)$$

Kriging may be used for estimation at a single point (point kriging) or over an area (block kriging). In this study, since the mean is assumed stationary and unknown as well as no large-scale trend was observed, ordinary block kriging without trend was used. A 15m×15m mesh (approximately the same area as a sample plot to emphasize the local variation around the sampling plots) was used to discretize the study area for estimation. The estimations were done on the nearest 16 data plots, within the maximum effective range of variograms which corresponds to the scale of auto-correlation.

Validation

We used cross validation approach. All the samples were excluded one by one from the data set and estimated again by kriging using the remaining samples. Then measured data and estimated values were compared to evaluate the kriging results (Webster and Oliver, 2000).

Cross validation was evaluated by calculation of Mean bias Error (ME) which should ideally be equal to zero, because kriging is unbiased (Webster and Oliver, 2000):

$$ME = \frac{1}{N}\sum_{i=1}^{N}\left[z(x_i) - \hat{z}(x_i)\right] \quad (5)$$

The accuracy of kriging was measured using Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[z(x_i) - \hat{z}(x_i)\right]^2} \quad (6)$$

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

RESULTS

Sampling

In total, 96 sample plots were measured in the study area. Normalization test showed that the distributions of the data are approximately normal and there is no need for transformation. Table 1 shows the summary statistics of the sample plots.

Geostatistical Analysis

Variography

We calculated experimental variograms for forest stem basal area (BA), stem density (N) and tree height (H). Variogram anisotropies were not found; consequently, only omni-directional variograms fitted using spherical model, to which nugget effects were added. Results are shown in table 2 and figure 2.

Table 1. Summary statistics of sample plots

Attribute	No. of samples	Mean	Min	Max	SD	CV %	Skewness
BA (m^2/ha)	96	12.13	0.66	30.86	5.73	47.24	0.09
N (n/ha)	96	779.16	50	1550	372.16	47.76	0.04
H (m)	96	13.76	8.00	23.75	2.89	21.00	0.48

SD: Standard Deviation; CV: Coefficient of Variation

Table 2. Characteristics of fitted variograms for tree attributes

Attribute	Lag (m)	Variogra m	Fitted model	Nugget effect	Sill	Range (m)	R^2 %	SP %
BA (m^2/ha)	50	Isotropic	Spherical	5.9	23.6	246	77.0	75
N (n/ha)	58	Isotropic	Spherical	80000.0	140200.0	200	66.3	43
H (m)	60	Isotropic	Spherical	5.3	10.6	527	87.0	50

SP% (Structured Part) = (Sill - Nugget/Sill)×100

Comparison the ranges of auto-correlation reveal that among three mentioned attributes, height has the largest auto-correlation range while density has the shortest one. At the same time, the structured part (SP%) of density is below 50% which is an indication of existence a fairly high nugget effect in the experimental variogarm (fig 2b).

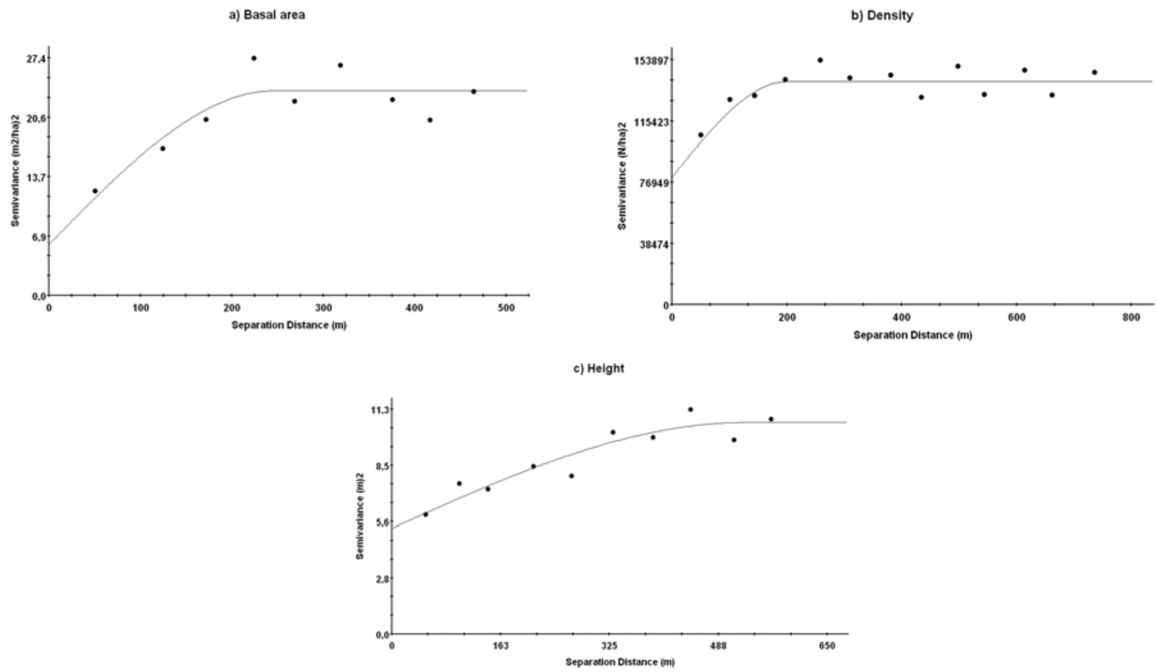

Fig 2. Isotropic experimental variograms and the fitted spherical models for the three attributes

Kriging

Ordinary block kriging was applied to produce continuous map of different attributes over the study area. A mesh of 15m×15m was used for discretization. Kriging results are shown in table 3.

Kriging results and maps for stem density have not been shown here and the reason is declared in the next section.

Comparison of tables 1 and 3 reveals that the means of BA and H are almost identical. However, the ranges between minimum and maximum of kriged data compare to measured data have been reduced. In fact, about 70% variance reduction has been occurred which is due to smoothing effect of kriging method.

Figure 3 shows the spatial distribution (kriging map) for basal area and height over the study area.

Figure 4 shows standard deviation (kriging error) map of estimation for basal area and height over the study area.

Table 3. Summary statistics of kriging results for basal area and height

Attribute	Mean	Min	Max	SD	CV%
BA (m^2/ha)	12.21	5.58	20.32	2.96	24.25
H (m)	13.87	11.13	18.43	1.33	9.60

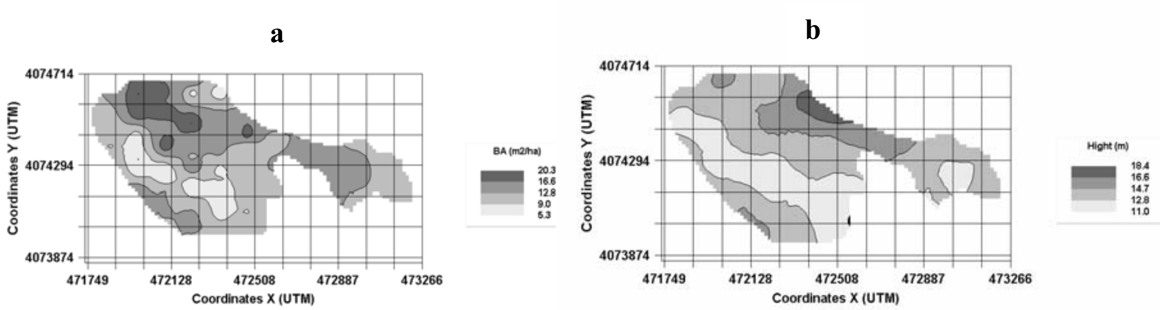

Fig 3. Kriging maps for a) basal area and b) height

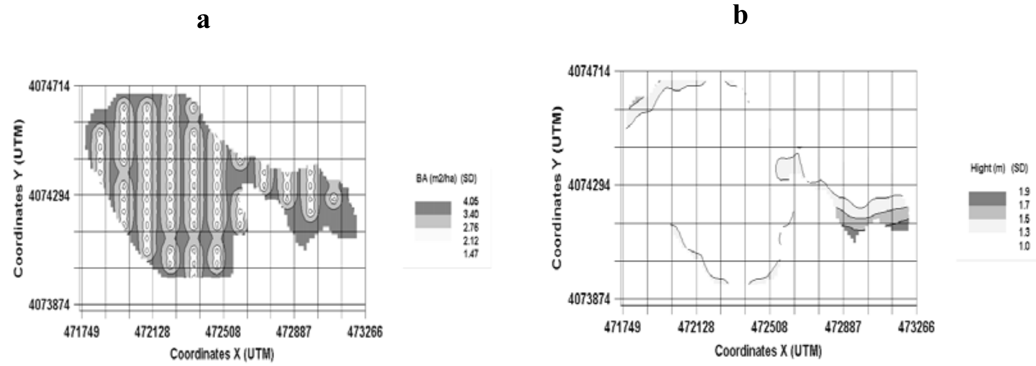

Fig 4. Kriging standard deviation maps for a) basal area and b) height

Validation

Table 4 shows validation results. Cross validation graphs are in figure 5.

According to table 4, the amount of estimation error (RMSE) and bias (ME) is so high for the stem density. It means that, also based on figures 2b and 5b, this attribute does not behave like a regionalized variable. Therefore, it is ignored for calculating kriging map.

Table 4. Validation results for tree attributes

Attribute	ME	RMSE
BA (m^2/ha)	0.05	3.92
N (n/ha)	-14.8	362
H (m)	0.02	2.67

ME: Mean Error

RMSE: Root Mean Square Error

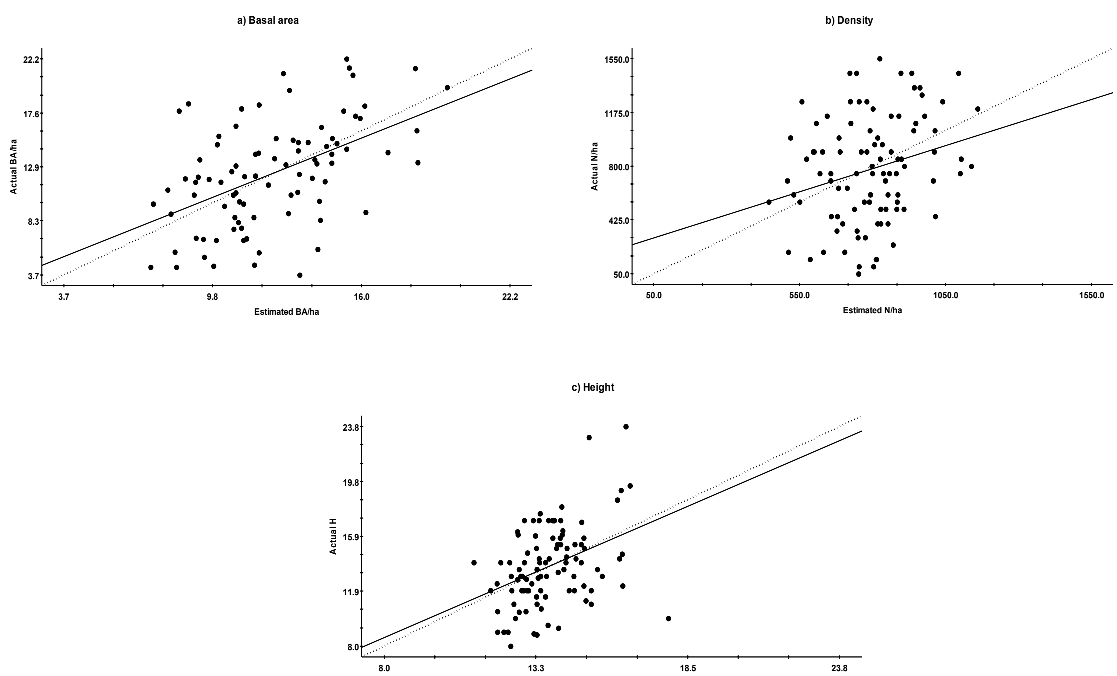

Fig 5. Cross validation graphs for the three attributes

Full census inventory

Using full callipering inventory, we tallied 13036 trees with d.b.h. over 7.5 cm in 14.25 ha. Thus, mean stem density would be 914.80 trees per hectare in this area. We calculated mean basal area equal to 15.82 m^2/ha and considered it as real mean. As mentioned before, this area consisted of 32 sample plots. To have an idea of spatial variability of basal area and compare it to other approaches, we also applied geostatistical approach in this area. Figure 6 shows the spatial structure of basal area in the full census area.

As it is clear from the figure 6, basal area shows strong spatial structure with low nugget effect in the full census area which fitted by spherical model. Cross validation graph is shown in figure 7.

Therefore, three approaches were used here:

1- Full callipering inventory (100%)
2- Sampling (Classical approach)
3- Kriging (Geostatistical approach)

and results have been compared in table 5:

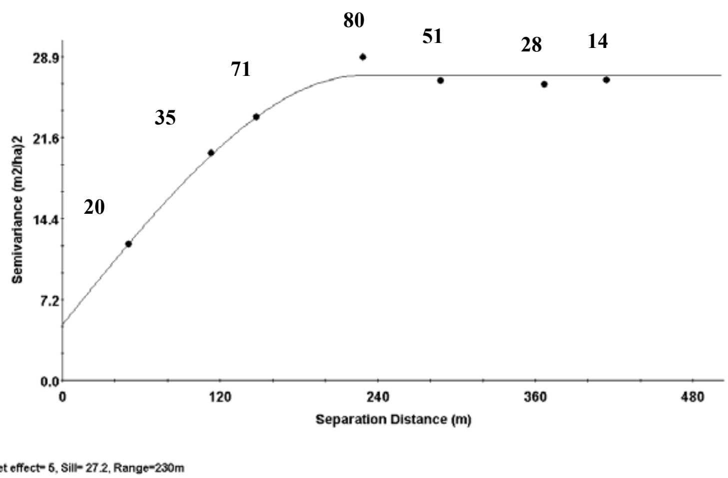

Fig 6. Isotropic experimental variogram and the fitted spherical model for basal area in the full census area with number of pairs per each lag distance

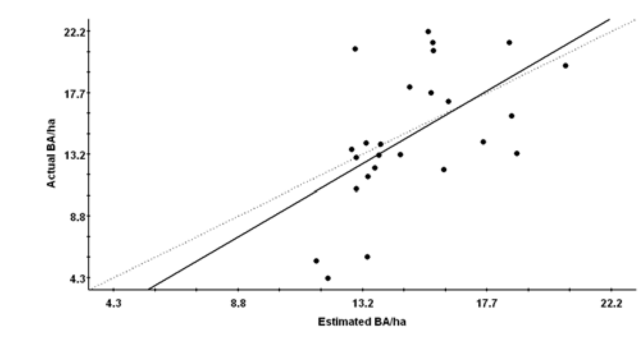

Fig 7. Cross validation graph for stem basal area in the full census area

Table 5. Summary statistics of 3 approaches for estimation of basal area

Method	Mean (m^2/ha)	SD (m^2/ha)	CV %	Confidence limits (95%) Low	Confidence limits (95%) Up
Full callipering	15.82	2.01	12.70	-	-
Sampling	14.67	6.13	41.78	12.50	16.84
Kriging	14.80	3.10	20.94	13.71	15.90

DISCUSSION

Three forest tree attributes; basal area, density and height, were investigated in this research in spatial structure point of view in an 18 years maple plantation. Both basal area and height showed spatial auto-correlation and were well behaved as a regionalized variable without any clue of variogram anisotropy. However, variogarm of tree density had a large nugget effect and was not spatially

auto- correlated despite measurement errors. This is because the trees were planted in regular spacing (3m×3m) and are in the initial stages, as well (typical rotation period is 80 years). Therefore, the essential competition has not started yet to produce any spatial structure for stem density attribute. At the same time, basal area showed 246m range of spatial auto-correlation while for height it was 527m (table 2). The longer the auto-correlation range, the more homogenous the variable. Therefore, height is more homogenous than basal area here. It means that again, light competition has not started yet, indicating that trees in general have similar heights. Furthermore, it is well known that any stress or differences in soil, growing conditions and site variables affect firstly, on diameter increment and then on height.

Since basal area and height showed spatial continuity, we applied kriging interpolation to produce continuous maps of their spatial distributions. According to these maps, the highest values of basal area are seen in the north-western part of the studied area (figure 3) which partially overlaps the full census area. Since there was no silvicultural activity in the area when this research started, the higher values in this part return to soil fertility and rate of trees mortality.

The means of basal area and height attributes, obtained from classical and geostatistical approaches were almost identical with no significant differences (tables 1 and 3). However, the variance reductions in geostatistical approach obtained from kriging were around 70%. It means that kriging estimates basal area and height more accurately than classical approach in terms of the coefficient of variation. This is because of the smoothing effect of kriging which decreases the range between minimum and maximum kriged data compare to measured data. Due to this feature, kriging cannot be used on unregionalized stand attributes; otherwise cross validation shows a big bias (figure 5b).

As with all statistical methods, each estimation has its own error where in geostatistics can be quantified precisely by kriging error map (figure 4). Using this kind of error map we can cover the high error area with sufficient extra sample plots to reduce the estimation error.

Validation results indicated that kriging estimates basal area and height, accurately. However, because of the large nugget effect and weak spatial structure in the experimental variogram of stem density, this estimation was biased (table 4 and figure 5b).

We compared the results of basal area estimation using three approaches in the full census area. As it is clear from table 5, both classical and geostatistical approaches underestimated the real mean while, the differences were not significant, statistically. However, again in terms of the coefficient of variation, kriging estimated more accurately than classical approach.

Nevertheless, this study revealed that geostatistics has the potential to capture and explain the spatial variability of basal area and height attributes in the plantation. This result is in contradiction to the results of Gunnarson *et al*. (1998) who showed that hardwood volume (in 314m^2 plot size) is an example of a variable that has no or little useful spatial auto-correlation in Sweden, and Tuominen *et al*. (2003) who found that geostatistical interpolation on the stand level estimation did not result in any further improvement in the accuracy of estimates in the boreal forests of Finland and Akhavan *et al*. (2010) who indicated that kriging has no potential for estimation of natural forest stock in the Caspian region of Iran, as well. On the other hand, it confirms the results of Biondi *et al*. (1994) who used basal area as a continuous variable within U.S. old- growth forests as well as Montes *et al*. (2005) who used ordinary kriging for estimation of cork oak production in Spain. Also Kint *et al*.

(2003) in a research at the Campine region of Belgium indicated that, height attribute is spatially auto-correlated for all tree species in planted *Pinus sylvestris* stands.

CONCLUSIONS

Spatial interpolation of forest tree attributes using geostatistical approach provides us with valuable outputs on a regional scale. Kriging geo-referenced maps can be very useful for forest owners and managers as a suitable tool to have an insight of forest stock distribution. This kind of information is applicable as a guide map in forest management plans; for instance, to identify harvesting area based on growing stock density, road network planning based on stock distribution, inter-planting in plantation forest, and silvicultural interventions such as thinning and light thinning based on forest density.

Furthermore, as we observed in this study, kriging would improve the estimation accuracy compared to classical approach. Therefore, it is better to use kriging interpolation to calculate forest growing stock accurately, for forest management planning.

Finally, kriging geo-referenced map in regional scale allows us to make rapid spatial analyses, which in connection with GIS methods enables the user to test the influence of different factors on forest stock attributes. Today, using this kind of spatial information in forest sampling inventory and management is not conventional in Iran. Therefore, we propose to apply geostatistical approach in this kind of plantation forest.

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تغییرات مکانی و برآورد مشخصه‌های درختان به‌روش زمین‌آمار در یک جنگلکاری در ناحیه خزری ایران

ر. اخوان و ح. کیادلیری

چکیده

این تحقیق به‌منظور بررسی تغییرات مکانی و برآورد مشخصه‌های درختان در یک جنگلکاری در ناحیه خزری ایران انجام شد. بدین منظور نمونه‌برداری به‌روش منظم- تصادفی با شبکه‌ای به ابعاد ۱۲۵×۵۰ متر در یک توده پلت (*Acer velutinum* Boiss.) ۱۸ ساله به مساحت ۶۳ هکتار و با قطعات نمونه دایره‌ای شکل ۲ آری انجام شد. در مجموع ۹۶ قطعه نمونه در این عرصه نمونه‌برداری و همچنین محدوده‌ای به مساحت ۱۴/۲۵ هکتار به‌منظور مقایسه روشها، آماربرداری صددرصد شد. سپس واریوگرام تجربی برای مشخصه‌های رویه‌زمینی، تراکم و ارتفاع کل درختان با استفاده ار داده‌های قطعات نمونه زمین‌مرجع، محاسبه و ترسیم شد. مشخصه‌های رویه‌زمینی و ارتفاع کل درختان، ساختار مکانی خوبی از خود نشان داده که با استفاده از مدل کروی برازش داده شدند، در حالی‌که مشخصه تراکم درختان، از اثر قطعه‌ای زیادی در واریوگرام تجربی برخوردار بود. بنابراین فقط برای مشخصه‌های رویه‌زمینی و ارتفاع کل، برآورد به‌روش کریجینگ معمولی- بلوکی انجام شد که نتایج ارزیابی صحت آن نشان داد که هر دو برآورد نااریب و قابل قبول هستند. همچنین در منطقه آماربرداری صددرصد، میانگین برآورد مشخصه رویه‌زمینی به‌روش کریجینگ، تفاوت معنی‌داری را با میانگین واقعی آن نشان نداد. بنابراین روش زمین‌آمار قادر به نمایش و توصیف تغییرات مکانی مشخصه‌های رویه‌زمینی و ارتفاع کل درختان و نیزبرآورد نااریب آنها در چنین جنگلکاریهایی می‌باشد، اما برای مشخصه تراکم جنگلکاری حداقل تا سنین کم، قابل استفاده نیست.