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Evaluation of *K*-tree Distance and Fixed-Sized Plot Sampling in Zagros Forests of Western Iran

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ABSTRACT

Three *k*-tree distance and fixed-sized plot designs were used for estimating tree density in sparse Oak forests. These forests cover the main part of the Zagros mountain area in western Iran. They are non-timber-oriented forest but important for protection purposes. The main objective was to investigate the statistical performance of *k*-tree distance and fixed-sized plot designs in the estimation of tree density. In addition, the cost (time required) of data collection using both *k*-tree distance and fixed-sized plot designs was estimated. Monte-Carlo sampling simulation was used in order to compare the different strategies. The bias of the *k*-tree distance designs estimators decreased with increasing the value of *k*. The Moore's estimator produced the smallest bias, followed by Kleinn and Vilcko and then Prodan. In terms of cost-efficiency, Moore's estimator was the best and Prodan's estimator was superior to Kleinn and Vilcko's estimator. Cost-efficiency of *k*-tree distance design is related to three factors: sample size, the value of *k*, and spatial distribution of trees in a forest stand. Moore's estimator had the best statistical performance in terms of bias, in all four-study sites. Thus, it can be concluded that Moore's estimator can have a better performance in forests with different tree distribution.

Keyword: Boundary correction, Monte-Carlo simulation, Oak forest, Plot less sampling, Variable plot sampling.

INTRODUCTION

Accurate and efficient estimation of tree density on an area can be vital to the success of activities in forest management or conservation (Haxtema *et al.*, 2012; Kleinn and Vilcko, 2006b). A set of plot designs, for example, line-shaped plots, circular plots, and Bitterlich plots (plotless) has been developed for the purpose of tree density estimation (e.g., Kleinn and Vilcko, 2006a; Magnussen, 2012; Magnussen *et al.*, 2008; Prodan, 1968). These designs can be classified into general categories (Payandeh and Ek, 1986): (i) fixed-sized plot design and (ii) *k*-tree distance design.

Fixed-sized plot design is a commonly used approach in forest inventories across the world. The design is often applied in timber production forests, but it is also used for inventorying non-timber attributes such as biodiversity (Tomppo *et al.*, 2009). Depending on the survey objective, the shape of the sample plot may vary. A circular shape is usually used in field surveys, although other plot shapes, for instance squares and rectangular shapes, may be used (Köhl, 2003). Keeley and Fotheringham (2005) demonstrated that in

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plant species diversity assessment, squares or rectangular shapes are to be preferred. Paulo *et al*. (2005) showed that fixed-sized plot design was preferable for estimating cork volume and Schreuder *et al*. (1987) found that it was statistically efficient for tree density estimation. Fixed-sized plot design has its own advantage, for instance, the selection probability of individual trees is known. In addition, the design produces an unbiased estimate of tree density.

An alternative to fixed-sized plot design is *k*-tree distance design. This design is also called density-adapted sampling or point-to-tree sampling (Haxtema *et al*., 2012; Kleinn and Vilcko, 2006b). Various estimators for this design have been introduced and the estimators are often applied in plant ecology (Pielou, 1977). However, Jonsson *et al*. (1992) describe a forest inventory method through density-adapted circular plot sizes. The *k*-tree distance design not only is a simple approach but also has suitable statistical properties in order to estimate some forest population parameters. The design also has potential for estimation of forest structural variables such as tree species mingling indices (Nothdurft *et al*., 2010). With this design, the distance of the center of the *k*-nearest tree from the sampling location is measured, and it is used as the radius of a circular plot.

In *k*-tree distance design, the number of sample trees is fixed for each sampling location and determined in advance whereas plot size varies based on the distance to the k^{th} nearest tree and in general produces a biased estimator (Jonsson *et al*., 1992). In contrast to the fixed-sized plot design, in a *k*-tree distance design, the selection probabilities of individual trees are unknown in practice (Kleinn and Vilcko, 2006a). In addition, the design yield an unbiased estimation of stand density under a homogeneous spatial Poisson point process for tree locations, i.e. the bias will be small in forests that have a completely random spatial pattern (Moore, 1954; Eberhardt, 1967). However, many natural and plantation forests might exhibit clustered or uniform spatial pattern (Lynch, 2012).

The Zagros forests that are open sparse forests of Oak cover the main parts of the Zagros mountain area in western Iran. These forests cover approximately an area of five million hectares. The Zagros forests are non-timber oriented forests as they are important for protection purposes. The forests provide various non-timber products and services and have multiple socio-economic and ecological functions (Riyahi, 2010; Salehi, 2009). These forests have been the most important source of energy (firewood and charcoal) for rural people for thousands of years.

The performance of *k*-tree distance designs is highly dependent on the spatial distribution of the trees (Kleinn and Vilcko, 2006a), hence, it is difficult to extrapolate the findings to other forest types. However, it is important to understand how *k*-tree estimators perform in different forest types. In the previous efforts in Zagros forests (e.g., Haidari, 2013; Askari and Tahmasebi, 2013) other sampling methods and estimators, for instance, second nearest neighbor method of Cottam and Courtis (1956) and distance method of Byth and Riple (1980) were used for estimation of tree density. Furthermore, the effort of comparing different sampling strategies was based on single samples. However, from a statistical point of view, the obtained results are more reliable when a sampling simulation with a large number of replications is applied. The appeal of a simulation study is that it allows researchers to compare the performance of different forest sampling methods and different estimators without the expense of fieldwork. Furthermore, economic constraint is also an underlying concern in forest inventory, particularly in the Zagros forests, which are non-commercial. The above-mentioned issues motivate further exploration of the properties of tree density estimators, including cost and bias, compared to the traditional fixed-sized plot design.

The main objective of this study was to investigate the statistical performance of three *k*-tree distances and fixed-sized plot designs in estimation of tree density in sparse Oak forests. In addition, we aimed to estimate the cost (time required) of data collection using both *k*-tree distance design and fixed-sized plot design, allowing assessment of cost efficiency for the different strategies. Furthermore, a mirage boundary correction method (described in § 2.5) recently developed by Lynch (2012), was evaluated in four study sites with different spatial patterns.

METHODS AND MATERIALS

Study Area

The Zagros Oak forests cover a vast area of the Zagros mountain ranges, approximately 1300 km north to south and 200 km east to west. These forests are classified as semi-arid and constitute 40% of Iran's forests (SaghebTalebi *et al*., 2003). The study area was between 48° 27' 32"– 48° 34' 07" E and 33° 14' 39"– 33° 18' 07" N in Loristan province, with the elevation ranging from 1860 m to approximately 2070 m above sea level and the mean annual precipitation and temperature of 530.15 mm and 18.3° C, respectively. The Persian Oak (*Quercus brantii var.persica*) is the most abundant tree species in the study area (99 %) and other species are Azarole (*Crataegus aronia*), Maple tree (*Acer monspessulanum*) and *Pistacia atlantica* (Sabeti 2002).

Data were collected at four sites (rectangular plots of size 250 m × 200 m, over a 5 ha area) in open sparse forests of Oak. At each site, the coordinate position of each tree was recorded using global positioning system (GPS). Maps of the distribution of trees in the four study sites are presented in Figure 2.

Spatial Distribution Quantification

It is recognized that the performance of *k*-tree estimation is highly dependent on the spatial pattern of the trees on the tract of interest (Lessard *et al*., 1994; Kleinn and Vilcko, 2006a). In the present study, in order to explore the relationship between spatial pattern of trees and the performance of tree density estimators, the spatial pattern was first quantified using the Clark-Evans (CE) index (Clark and Evans, 1954). Computation

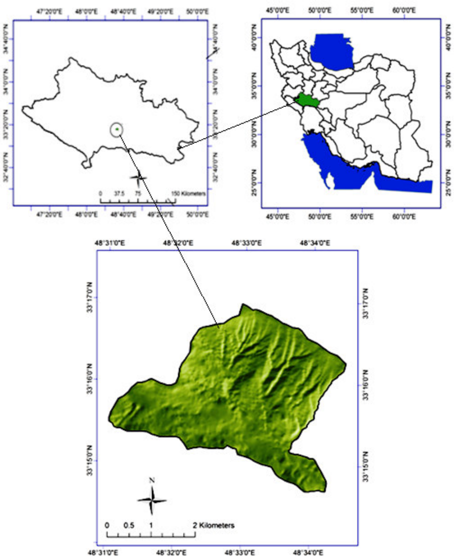

Figure 1. Geographical position of the study area in western Iran, Loristan province.

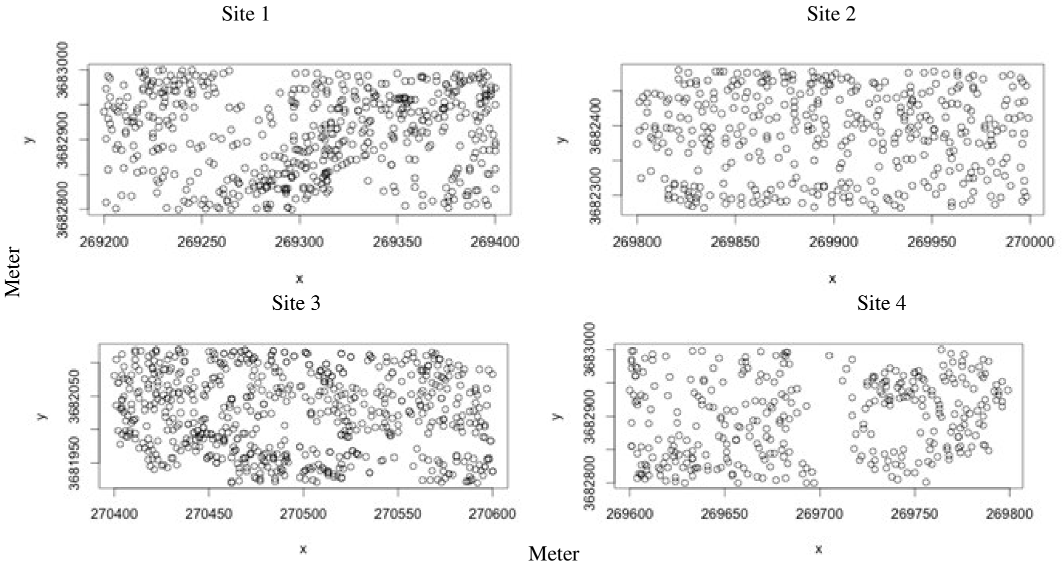

Figure 2. Map of tree distribution at four study sites.

of the CE index was done using the R-package "Spatstat". The CE index takes values between 0 and 2.1419, and the values can be interpreted as follows: CE > 1 for a pattern that is less clustered (i.e. more uniform) than completely random, while CE < 1 indicates more clustering than a completely random distribution. A population with completely random distribution is likely to be the result of an underlying homogeneous spatial Poisson point process, i.e. where points are independently distributed with uniform intensity over the area. In a uniform point pattern, the average distance between a point and its nearest neighbor is larger than it is in a completely random distribution. A pattern is called clustered if many points are concentrated close together, and there are areas which contain very few, if any, points. A test of the complete spatial randomness (CSR) hypothesis was also conducted to explore whether or not the spatial pattern of the study sites significantly departed from the CSR, where the homogeneous spatial Poisson point process serves as a reference model.

Sampling Simulation

To investigate the statistical performance of tree density estimators, a sampling simulation (Monte-Carlo simulation) with a large number of replications (15,000) was conducted for each of the four study sites with different sample sizes (50, 100, 150, and 200 points), and four tree density estimators. We used independent random sampling design, i.e. the points were generated independently with uniform distribution over the sites. At each sampling location, fixed-sized plots of 5 m and 10 m radius and three *k*-tree distance designs (with *k* ranging from 3 to 10) were conducted. The estimators applied in this study are described below.

Fixed-sized Plot Design

Fixed-sized plot design is a very common sampling approach in forest surveys. With this design, stand density is estimated by dividing the number of trees on each plot by the plot area, and then averaging over the *n* plots. For the fixed-sized plot design the tree density estimator (Husch,1963), Y_F per hectare, for a single plot *j* is defined as

$$\hat{Y}_{F,j} = \frac{k_j}{a} \times 10000 \qquad (1)$$

And for *n* replicated sampling points, the estimator is

$$\hat{Y}_{F,rep} = \frac{1}{n}\sum_{j=1}^{n}\hat{Y}_{F,j} \qquad (2)$$

Where, k_j is the number of trees sampled on the *j*th plot and a is the plot size (ha). Note that the mirage method was used to overcome the boundary overlap problem for trees close to forest border.

The *k*-tree Distance Designs

The *k*-tree distance designs applied in the present study are basic and easy to apply in practical application.

Moore's estimator

According to Moore (1954), the estimator of tree density, Y_M for a single sampling point *j* is defined as:

$$\hat{Y}_{M,j} = \frac{10000}{\pi} \times \frac{(k-1)}{d_{k,j}^2} \qquad (3)$$

And for *n* replicated sampling points the estimator is

$$\hat{Y}_{M,rep} = \frac{1}{n}\sum_{j=1}^{n}\hat{Y}_{M,j} \qquad (4)$$

Where, $d_{k,j}$ is the distance from sampling point to the k^{th} closest tree on plot *j* in meter and *n* is the number of sampling points in the study area. Note that, in Eq. 3, *k* is fixed and thus the density estimate depends on the mean inverse plot radius squared.

Prodan's estimator

According to Prodan (Prodan, 1968), the estimator of tree density, Y_P, for a single sampling point *j* is defined as:

$$\hat{Y}_{P,j} = \frac{10000}{\pi} \times \frac{(n-0.5)}{d_{k,j}^2} \qquad (5)$$

And for *n* replicated sampling points, the estimator is

$$\hat{Y}_{P,rep} = \frac{1}{n}\sum_{j=1}^{n}\hat{Y}_{P,j} \qquad (6)$$

Kleinn and Vilckos' estimator

According to Kleinn and Vilcko (2006), the tree density estimator, Y_{KV}, for a single sampling point *j* is defined as:

$$\hat{Y}_{KV,j} = \frac{10000}{\pi} \times \frac{k}{\left[(d_{k,j} + d_{k+1,j})/2\right]^2} \qquad (7)$$

And for *n* replicated sampling points, the estimator is

$$\hat{Y}_{KV,rep} = \frac{1}{n}\sum_{j=1}^{n}\hat{Y}_{KV,j} \qquad (8)$$

Where, $d_{k,j}$ and $d_{k+1,j}$ are the distances to the k^{th} and the $(k+1)^{th}$ tree in meters, respectively. In this case, the denominator of Eq. 7 is the squared average distance between the k^{th} and $(k + 1)^{th}$ closest trees to the sample point.

Variance Estimation

In the present study, we compared the tree density estimators by performing a Monte-Carlo simulation with a large number of replications. In this case, the estimator of variance can be expressed as sample means (Thompson 2002), which means that the variance can be estimated by the following:

$$\hat{V}(\hat{Y}_{sim}) = \frac{1}{n(n-1)}\sum_{j=1}^{n}(\hat{Y}_j - \bar{\hat{Y}}_{sim})^2 \qquad (9)$$

Where, $\bar{\hat{Y}}_{sim}$ is the average of all the simulations and $\hat{Y}_j$ is the estimate of simulation *j*.

Boundary Correction

Trees close to the border of a forest stand have a smaller inclusion probability, hence, in forest inventory, a boundary correction

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method is frequently used to overcome this problem. In traditional plot sampling and relascope sampling, a set of correction methods have been developed (Gregoire and Valentine, 2008). More recently, however, a mirage boundary correction method has been proposed by Lynch (2012) for the *k*-tree distance sampling method. By this method, if the distance between a sample point and the k^{th} nearest tree is greater than the distance between the sample point and a tract boundary, a correction is required. In other words, it is necessary to check the distance between the k^{th} tree from mirage point, which is established outside the boundary, and this distance is used as the plot radius in *k*-tree distance estimators (Eqs 3, 5, and 7). Boundary correction is accomplished by establishing a mirage sample point outside the forest border at a distance equal to that between the original interior point and the boundary on a line perpendicular to the boundary. Then, the *k* sample trees closest to either the original sample point or the mirage point are selected for use in one of the *k*-tree sampling estimation methods. A schematic of the correction method is illustrated in Figure 3, where tree selection is with 4-tree sampling. As illustrated, the distance between the original sample point to the k^{th} nearest tree (no.4) is larger than between the sample point and the forest border.

Time Study

The time needed for data acquisition was recorded for both fixed-sized plot and *k*-tree distance designs. The study was conducted on 50 sampling locations in the field. To measure the distance between sampling location and sampled tree, a standard tape was used. The average time needed for different designs is provided in Table 1.

Efficiency Evaluation

The performance of tree density estimators was evaluated through relative bias (bias%). Our comparison was based on the simulation independent samples of a large number of times and to estimate the properties of the estimators. The MSE was calculated as

$$MSE = \frac{\sum_{sim=1}^{15000} (\hat{Y}_{sim} - Y)^2}{15000} \tag{10}$$

Where, *sim* is the number of simulations, $\hat{Y}_{sim.}$ is the estimated attribute (here tree density) for the sim^{th} simulation

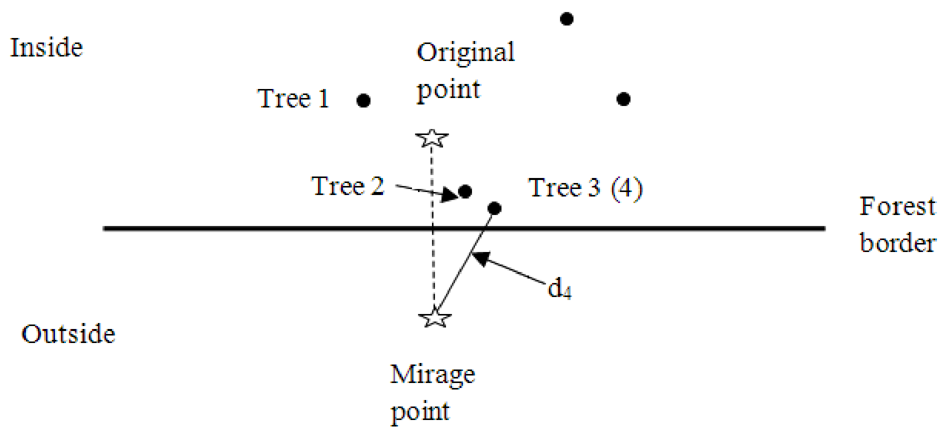

Figure 3. Boundary correction method where tree selection is with 4-tree sampling. Stars show sampling locations and dots show trees. Tree selection with 4-tree sampling and mirage boundary correction, with tree 3, (4) selected from the sample point and the mirage point, showing distance d4 to the fourth closest tree.

Table 1. Averaged time for measuring distance from *k*th tree to sampling point and establishing fixed-sized plot sampling method.

k-tree distance methods	Time (s point^{-1}) (*n*th tree)								Fixed-sized plot sampling	
	3	4	5	6	7	8	9	10	Radius 5 m	Radius 10 m
M [a] and P [b]	20	25	33	37	49	55	67	92	46	98
K & V [c]	37	49	56	69	75	83	98	120		

[a] Moore's estimator (Eq.3), [b] Prodan's estimator (Eq. 5) [c] Kleinn –Vilckos' estimator (Eq.7)

and Y is the attribute's true value (reference value). The relative bias was estimated as:

$$Bias(\%) = \frac{\bar{\hat{Y}} - Y}{Y} \times 100 \qquad (11)$$

Where, $\bar{\hat{Y}}$ is the average of all of the simulations.

The relative efficiency method is a commonly used approach to determine the best design in forest inventory, where both costs and population variability are taken into account (Husch, 1963). By this method, a standard design, here a fixed-sized plot design, serves as the reference. The efficiency ratio can be computed by:

$$RE_m = \frac{MSE_m \times T_m}{MSE_S \times T_S} \times 100 \qquad (12)$$

Where, RE_m is the relative efficiency of the sampling method being compared; MSE_m is the mean square error of method m; MSE_S is the mean square error of the standard method i.e., fixed-sized plot sampling; T_m is the average time needed for each sampling point with method m and T_S is the average time needed for each sample unit with the standard method. An *RE* greater than 100 indicates that the corresponding sampling method is less efficient than fixed radius plot sampling, whereas an *RE* smaller than 100 indicates that the corresponding sampling method is more efficient than the fixed-radius plot design.

RESULTS

In this study, the statistical properties of tree density estimators, *k*-tree distance and fixed-sized plot sampling methods, were investigated. In addition, the efficiency of the estimators was investigated in terms of time required for different values of *k* and plot sizes.

The spatial distributions of trees in the study sites were quantified by the Clark-Evans (CE) index. Based on the CE index values, the sites were classified into two categories: 1) in sites no. 1, 3, and 4, trees tended to be more clustered than a completely random

Table 2. Clark-Evans (CE) index and test of the complete spatial randomness (CSR) of CE for four study sites. The interpretation of the CE values is as follows: CE > 1 for a pattern that is less clustered (i.e. more uniform) than completely random, while CE < 1 indicates more clustering than a completely random distribution. CE index was conducted for none edge correction and two edge correction methods.

Study sites	N [a]	D [b]	C [c]	P-value
1	0.92	0.91	0.91	P=0.002
2	1.10	1.00	1.10	P=0.0006
3	0.81	0.79	0.80	P=0.0002
4	0.97	0.95	0.97	P= 0.3949

[a] No edge correction, [b] Edge correction of Donnelly, [C] Cumulative Distribution Function method

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distribution (CE < 1), and 2) in site no. 2, trees had a pattern that was less clustered i.e. more uniform than completely random (CE > 1). The statistical test of the complete spatial randomness was rejected (P<0.05) for sites no. 1, 2, and 3, whereas it was not rejected for site no. 4 (P>0.05). Results are shown in Table 2.

Because the fixed-sized plot sampling is design-unbiased for estimation of tree density, result of bias was not presented for fixed-sized design. However, the above-mentioned three *k*-tree distance estimators were biased and the relative bias tended to decrease with increasing *k*. Figure 4 shows the relationship between relative bias versus the value of *k* for four study sites using a boundary correction method. The Moore's estimator produced the smallest relative bias for all of the considered values of *k,* whereas the Prodan's estimator resulted in largest relative bias. This was true for all four sites. With value of *k,* there was no difference between Prodan's and Kleinn and Vilckos' estimators.

Three *k*-tree distance designs were compared in terms of boundary correction methods applied in this study in the four study sites and this comparison is shown in Figures 5 and 6. The best performance of boundary correction was found for Moore's estimator in general and site no. 2 in particular.

Results of the relative efficiency of the three *k*-tree distance estimators for different values of *k*, different sample sizes, and for the four study sites are given in Tables 3, 4, 5, and 6. The digits printed in bold in the tables show that *k*-tree distance design is more efficient than fixed-sized plot design for the estimation of tree density.

DISCUSSION

In this study, we investigated the statistical properties in terms of bias and cost-efficiency of different *k*-tree distance estimators in Zagros forests in west of Iran. In spite of the drawback of *k*-tree distance estimators i.e., biasedness, it was still an attractive method and there have been many

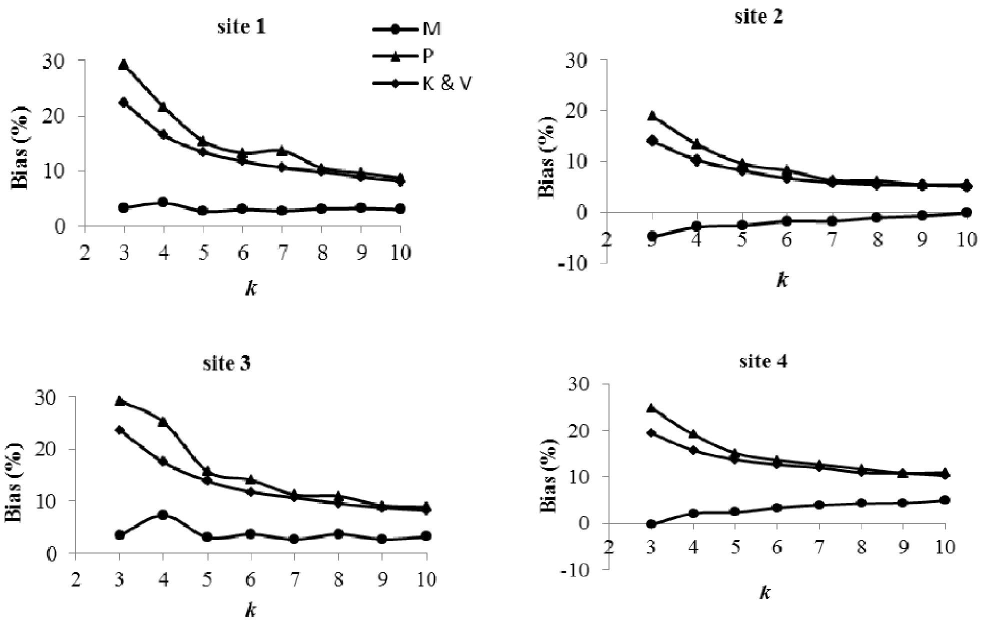


Figure 4. Relationship between bias and the value of *k* for three *k*-tree distance sampling methods and in different study sites using the boundary correction method. M is Moore's estimator (Eq. 3), p is Prodan's estimator (Eq. 5), and K and V is Kleinn and Vilckos' estimator (Eq. 7).

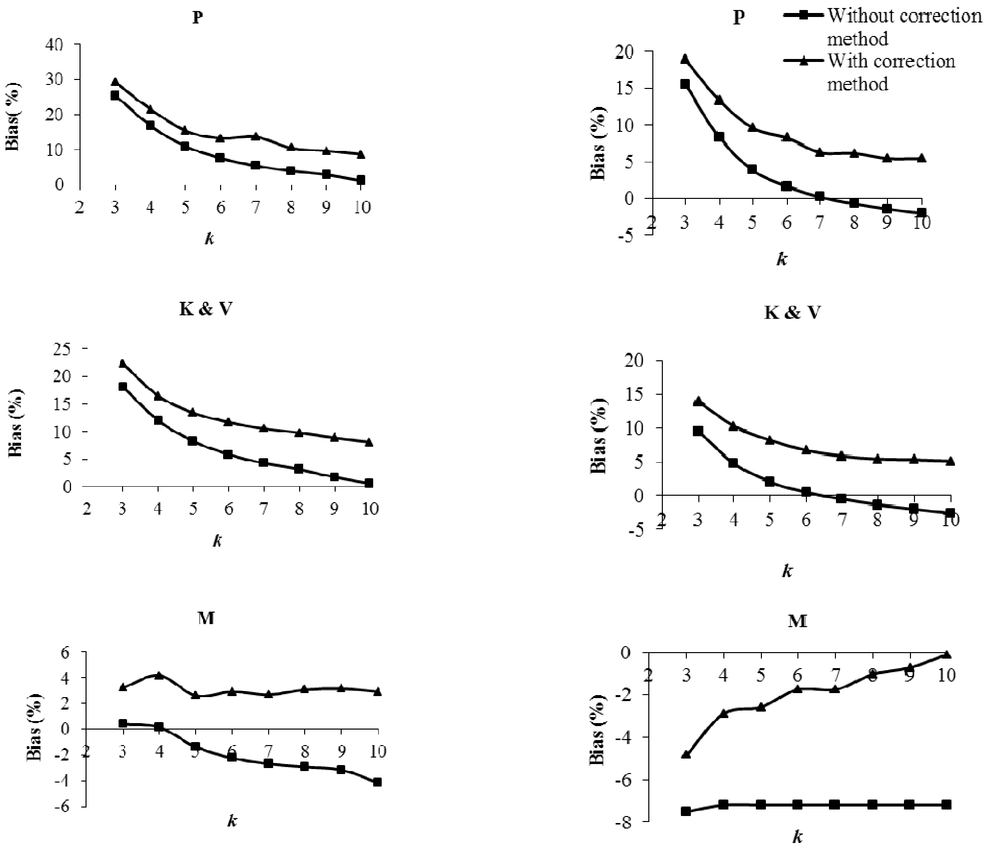


Figure 5. Comparison of the bias of *k*-tree distance estimators with and without boundary correction methods in study site no. 1 and 2. M is Moore's estimator (Eq. 3), P is Prodan's estimator (Eq. 5) and K and V is Kleinn and Vilckos' estimator (Eq. 7).

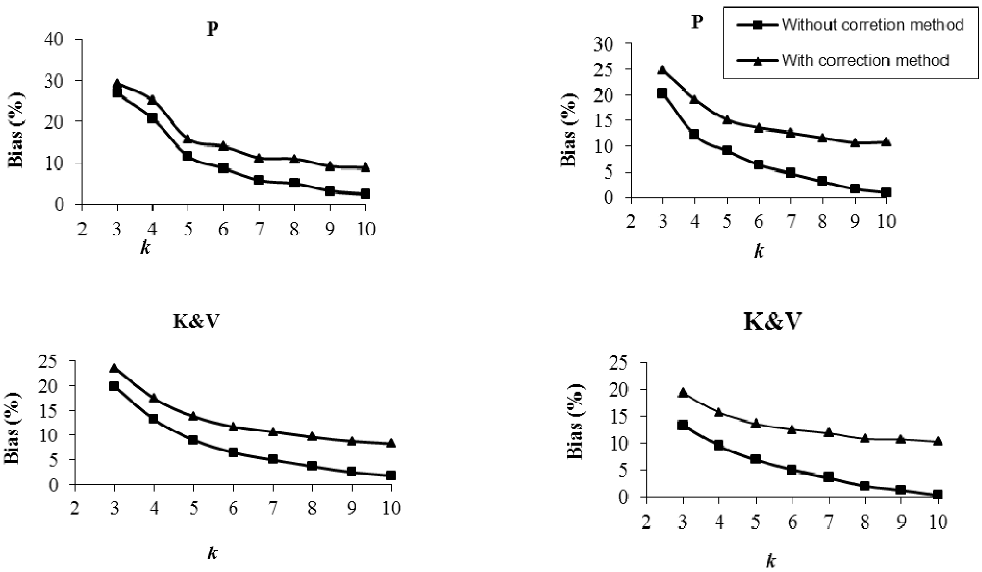
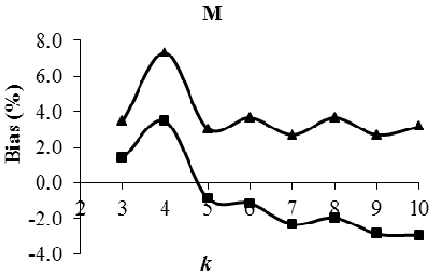
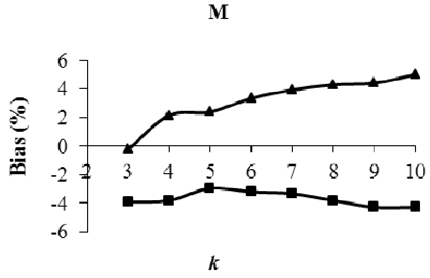


Figure 6. Comparison of the bias of *k*-tree distance estimators with and without boundary correction methods in study site no. 3 and 4. M is Moore's estimator (Eq. 3), P is Prodan's estimator (Eq. 5) and K and V is Kleinn and Vilckos' estimator (Eq. 7).

Figure 6 continued ….





Continue of Figure 6.

Table 3. Relative efficiency of three *k*-tree distance estimators for four sample sizes, two fixed plot sizes, without correction method in study site 1.

k	No. of points	Relative efficiency [a] (%)			Relative efficiency [b] (%)		
		M [c]	P [d]	K &V [e]	M [c]	P [d]	K &V [e]
3	50	80	228	341	82	234	351
3	100	77	323	483	72	301	450
3	150	76	424	646	63	349	532
3	200	73	495	746	56	381	574
4	50	54	126	193	56	130	198
4	100	53	172	267	49	160	249
4	150	53	221	347	43	182	286
4	200	52	260	406	40	200	312
5	50	44	84	112	46	87	115
5	100	45	112	152	42	105	141
5	150	44	137	189	36	113	155
5	200	43	159	219	33	123	169
6	50	42	64	86	43	66	88
6	100	43	80	109	40	74	101
6	150	43	92	127	36	76	105
6	200	43	103	144	33	79	111
7	50	47	62	80	48	63	82
7	100	48	70	93	44	66	87
7	150	50	78	104	41	64	86
7	200	50	83	112	38	64	86
8	50	53	63	81	54	65	83
8	100	55	70	89	51	65	83
8	150	58	74	95	47	61	78
8	200	59	77	100	45	59	77
9	50	64	71	89	66	73	92
9	100	67	75	96	63	70	89
9	150	73	78	95	60	64	83
9	200	74	78	100	57	60	77
10	50	80	77	91	82	79	93
10	100	89	78	93	83	73	87
10	150	96	76	93	79	62	77
10	200	96	75	91	74	57	70

[a] Reference method, Fixed-sized plot sampling with radius 5 meters. [b] Reference method, Fixed-sized plot sampling with radius 10 meters. [c] Moore's estimator (Eq. 3). [d] Prodan's estimator (Eq. 5). [e] Kleinn -Vilckos' estimator (Eq. 7). In bold print, RE (%) values, which indicate, *k*-tree distance Sampling method is more efficient than fixed-size plot sampling.

Table 4. Relative efficiency of three *k*-tree distance estimators for four sample sizes, two fixed plot sizes, without correction method in study site 2.

k	No. of points	Relative efficiency[a] (%)			Relative efficiency[b] (%)		
		M[c]	P[d]	K &V[e]	M[c]	P[d]	K &V[e]
3	50	34	82	127	45	109	167
3	100	44	126	930	50	142	970
3	150	52	164	209	53	165	211
3	200	65	204	325	55	182	289
4	50	26	35	56	34	45	74
4	100	36	50	84	41	57	95
4	150	48	62	86	48	63	87
4	200	72	76	131	61	68	116
5	50	32	23	31	43	31	41
5	100	49	28	39	55	31	45
5	150	63	30	35	63	30	36
5	200	82	34	51	69	30	45
6	50	33	19	24	43	25	32
6	100	51	20	26	58	22	30
6	150	65	20	25	66	20	25
6	200	86	20	28	73	18	25
7	50	38	19	24	50	25	31
7	100	60	19	24	67	21	27
7	150	78	19	23	78	19	23
7	200	103	19	23	87	17	20
8	50	47	23	27	61	30	36
8	100	73	23	27	82	26	31
8	150	94	22	27	95	22	27
8	200	125	22	26	106	19	23
9	50	57	28	34	75	37	45
9	100	88	29	35	99	33	40
9	150	117	28	35	118	28	35
9	200	155	30	37	131	27	33
10	50	73	37	41	97	48	54
10	100	114	40	43	129	45	49
10	150	152	42	45	153	43	45
10	200	205	46	48	173	41	43

[a] Reference method, Fixed-sized plot sampling with radius 5 meters; [b] Reference method, Fixed-sized plot sampling with radius 10 meters; [c] Moore's estimator (Eq. 3); [d] Prodan's estimator (Eq. 5); [e] Kleinn-Vilckos' estimator (Eq. 7); In bold print, RE (%) values, which indicate, *k*-tree distance Sampling method is more efficient than fixed-size plot sampling.

attempts to improve statistical properties (reduce bias) of the method. It was recognized that some *k*-tree distance estimators are easy to use in practical applications and are inexpensive in comparison to fixed-sized plot sampling, in some cases (Kleinn and Vilcko, 2006). Our results also showed that, in most cases, *k*-tree distance estimators were superior to fixed-sized plot sampling in terms of cost-efficiency.

Various surveys have been conducted in Zagros forests to quantify the spatial pattern of trees, but the obtained results are inconsistent. For instance, Heidari (2006) and Shabanian *et al*. (2013) found that trees had a uniform distribution whereas Askari and Tahmasebi (2013) found that trees had a clustered distribution. Our findings were similar to the previous studies, that is, the sites showed both more clustering than a completely random distribution (CE < 1) and less clustering (i.e. more uniform) than completely random (CE > 1). However, the CE indexes were all rather close to 1, which indicate that the patterns were not far from completely random even though it was sometimes a statistically significant

Table 5. Relative efficiency of three *k*-tree distance estimators for four sample sizes, two fixed plot sizes, without correction method in study site 3.

k	No. of points	Relative efficiency [a] (%)			Relative efficiency [b] (%)		
		M [c]	P [d]	K &V [e]	M [c]	P [d]	K &V [e]
3	50	70	255	445	74	271	474
3	100	72	396	695	65	354	622
3	150	67	525	933	54	424	753
3	200	68	666	1193	47	463	830
4	50	51	165	212	55	176	225
4	100	55	261	332	49	233	297
4	150	57	356	453	46	287	366
4	200	57	445	567	40	309	394
5	50	34	85	120	36	90	128
5	100	34	120	177	30	108	158
5	150	34	160	238	27	129	192
5	200	33	197	297	23	137	206
6	50	34	67	85	36	71	91
6	100	33	89	114	30	79	102
6	150	33	114	148	27	92	119
6	200	33	137	178	23	95	124
7	50	35	54	72	37	57	77
7	100	37	64	89	33	57	79
7	150	38	78	110	31	63	89
7	200	40	90	128	28	62	89
8	50	40	58	71	43	62	75
8	100	42	69	82	38	61	73
8	150	45	81	97	36	65	78
8	200	50	93	111	35	65	77
9	50	48	55	73	51	59	78
9	100	54	60	81	48	54	72
9	150	57	66	81	46	54	74
9	200	63	71	100	44	50	69
10	50	60	65	74	64	69	79
10	100	69	69	79	62	62	71
10	150	74	73	84	60	59	68
10	200	83	77	88	58	53	61

[a] Reference method, Fixed-sized plot sampling with radius 5 meters; [b] Reference Method, Fixed-sized plot sampling with radius 10 meters; [c] Moore's estimator (Eq. 3); [d] Prodan's estimator (Eq. 5); [e] Kleinn-Vilckos' estimator (Eq. 7); In bold print, RE (%) values, Which indicate, *k*-tree distance sampling method is more efficient than fixed-size plot sampling.

difference. In the previous studies, different indices were used for the quantification and the studies were conducted on different geographical areas of the Zagros forests. Thus, direct comparisons of results are difficult.

The *k*-tree distance estimators considered in this study are design-biased estimators, although many model-based unbiased estimators have been developed to overcome the bias problem (Magnussen *et al.*, 2008). However, practical application of the model-based estimators appears to be complicated. Kleinn and Vilcko (2006a) developed a design-unbiased estimator, but additional measurements are needed and its practical application is limited due to the calculation of the inclusion probability of trees.

As our results showed, the Moore's estimator had the smallest bias, followed by Kleinn and Vilckos' and Prodan's estimators. This is consistent with Lessard *et*

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Table 6. Relative efficiency of three *k*-tree distance estimators for four sample sizes, two fixed plot sizes, without correction method in study site 4.

k	No. of points	Relative efficiency [a] (%)			Relative efficiency [b] (%)		
		M[c]	P[d]	K &V[e]	M[c]	P[d]	K &V[e]
3	50	29	93	139	32	102	154
3	100	32	144	219	31	140	214
3	150	33	196	302	29	174	268
3	200	34	236	364	27	191	293
4	50	21	46	72	23	51	80
4	100	23	67	107	22	65	105
4	150	25	90	154	22	80	129
4	200	27	106	172	21	86	139
5	50	22	42	52	25	46	58
5	100	24	56	72	23	55	70
5	150	26	74	94	23	65	84
5	200	29	85	110	23	68	88
6	50	22	33	44	25	36	48
6	100	24	40	55	24	39	54
6	150	29	51	70	25	45	63
6	200	31	57	79	25	46	64
7	50	25	31	40	28	34	44
7	100	28	36	47	27	35	46
7	150	34	42	57	30	37	51
7	200	37	46	62	30	37	50
8	50	30	31	40	33	34	44
8	100	34	33	44	33	32	43
8	150	42	38	51	37	33	45
8	200	47	38	52	38	30	42
9	50	37	34	43	40	37	47
9	100	44	34	45	43	33	44
9	150	51	35	48	46	32	43
9	200	57	34	48	46	28	39
10	50	47	40	46	52	45	51
10	100	56	41	48	55	40	46
10	150	68	42	48	61	38	42
10	200	73	39	48	59	32	38

[a] Reference method, fixed-sized plot sampling with radius 5 meters; [b] Reference method, Fixed-sized plot sampling with radius 10 meters; [c] Moore's estimator (Eq. 3); [d] Prodan's estimator (Eq. 5); [e] Kleinn -Vilckos' Estimator (Eq. 7); In bold print, RE (%) values, Which indicate, *k*-tree distance sampling method is more efficient than fixed-size plot sampling.

al. (1994), Kleinn and Vilcko (2006b) and Haxtema *et al*. (2012), yet inconsistent with Lynch and Rusydi (1999) where Prodan's estimator had the best statistical performance, in terms of bias. The reason is probably the spatial pattern of the forest to be inventoried. Lynch and Rusydi (1999) conducted their study on teak plantation forests where trees were uniformly distributed. In the teak plantation, the Moore's estimator tended to underestimate tree density. In the present study, the poor statistical performance of Prodan's estimator may be due to the non-uniform spatial pattern of trees in the sites surveyed. Askari *et al*. (2013) conducted a sample survey in Zagros forests to estimate tree density, but direct comparison of results is impossible because the authors used different distance sampling methods.

Similar to bias, cost-efficiency is also dependent on the spatial distribution of trees

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in the forest. Based on the result, Kleinn and Vilckos' estimator is superior to Prodan in terms of bias, but in terms of cost-efficiency Prodan's estimator is better. The reason is that with Kleinn and Vilckos' estimator, the distance of the two nearest trees to the sampling location should be measured and this requires more time. This drawback might be improved where a laser device is used for measuring distance instead of a standard tape. Thus, the efficiency of the *k*-tree distance sampling methods depends on how the trees to be inventoried are spatially distributed in the forest. In addition to spatial pattern of trees, understory may affect the efficiency of *k*-tree distance sampling in terms of time needed.

A given *k*-tree estimator shows different behavior in different sites. For instance, Moore's estimator showed negative bias in site no. 2 whereas in the other three sites it had positive bias. This is consistent with Haxtema *et al*. (2012), where the comparison was conducted on riparian forest in USA (western Oregon). The cost-efficiency of *k*-tree distance estimators depends on three factors: sample size, the value of *k*, and the spatial distribution of trees in a forest stand. In the case presented in this paper, the best result was obtained in site study no. 2 with a sample size of 150 and 7-tree sampling, where relative efficiency was 19%.

Our empirical results showed that, in some cases, the boundary correction method applied in this study could reduce bias of the tree density estimator. In the other words, the boundary correction has had a better performance for Moore's estimator (Eq. 3), as demonstrated in Lynch (2012). Thus, the correction method may not be recommended for all *k*-tree estimators. For instance, in study site no. 3, where trees had clustered pattern i.e., CE< 1, all three *k*-tree estimators had better performance without boundary correction (see Figure 6). It is thus of interest for further studies to develop an improved correction method.

CONCLUSION

Fixed-sized plot sampling is more accurate than *k*-tree distance estimators in the estimation of tree density. The distance sampling methods, however, appears to be compatible to the traditional plot sampling in all forest types, in particular with moderate and large value of *k,* and if electronic device (e.g., laser meter) were to be used for the measurement of distance. Thus, it would be of interest to evaluate distance-sampling methods using an electronic device for measuring distance rather than a standard tape measurement. In our case, Moore's estimator had the best statistical performance, in terms of bias, in all four-study sites. Thus, it can be concluded that Moore's estimator can have a better performance in forests with different tree distribution.

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بررسی روش های آماربرداری پلات دایره ای با مساحت ثابت وk – درخت در جنگل های زاگرس در غرب ایران

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چکیده

در این تحقیق از روشهای آمار برداری پلات دایره ای با مساحت ثابت و K- درخت برای برآورد تراکم درخت در واحد سطح در جنگلهای زاگرس استفاده گردید. این جنگلها بخش عمده منطقه زاگرس در غرب ایران را در بر میگیرد. جنگلهای زاگرس بیشتر نقش حمایتی و حفاظتی دارد. هدف اصلی این تحقیق بررسی عملکرد آماری پلات با مساحت ثابت و K- درخت در براورد تراکم درخت بود. علاوه بر این، هزینه (زمان مورد نیاز) برای جمع آوری داده ها برای هر دو روش نیز ثبت گردید. به منظور مقایسه عملکرد آماری روشهای آمار برداری از شبیه ساز نمونه برداری مونت کارلو استفاده گردید. میزان اریبی در روشK – درخت با افزایش مقدار K کاهش یافته است. براورد کننده Moore کمترین اریبی را تولید میکند و به دنبال ان براورد کنندهای Kleinn& VilckoوProdan تولید کمترین اریبی میکنند. از نقطه نظر شاخص هزینه- بهره وری، براورد کننده Moore بهترین بود و براورد کننده Prodan نسبت به براورد کننده Kleinn& Vilckoبهتر بوده است. میزان شاخص هزینه- بهره وری بستگی به سه عامل دارد ;۱) تعداد واحد های نمونه برداری ۲) مقدار K و ۳) نحوه پراکنش مکانی درختان در جنگل. در تمام چهار منطقه مورد مطاله براورد کننده Moore بهترین عملکرد آماری را نشان داد. بنابراین میتوان نتیجه گرفت که براورد کننده Moore عملکرد بهتری نسبت به دو براورد کننده دیگر در جنگل هایی با ساختار متفاوت دارد.

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