Evaluation of *n*-Tree Distance Sampling for Inventory of Headwater Riparian Forests of Western Oregon

Zane Haxtema, Hailemariam Temesgen, and Theresa Marquardt

ABSTRACT

n-Tree distance sampling (NTDS), also known as *k*-tree sampling and point-to-tree sampling, has been promoted as a practical method for forest inventory. This simulation study evaluated the performance of three NTDS estimators, as compared with fixed plot sampling and horizontal point sampling, for estimating density and basal area in headwater riparian forests of western Oregon. Bias of at least one NTDS estimator was low for both density and basal area when at least six trees were captured at each sample point, but performance of NTDS for density estimation was poor on stem maps exhibiting a clustered pattern. We close with some comments regarding the statistical efficiency of NTDS for riparian area inventory in similar forest conditions.

Keywords: forest sampling, density-adapted sampling, *k*-tree sampling, Pacific Northwest

Located on the fringes of the drainage network, headwater streams are intimately connected with downstream reaches, serving as a source of sediment, woody debris, organic matter, and nutrients (MacDonald and Coe 2007). Nonetheless, forests adjoining non-fish-bearing (Type N) streams in western Oregon receive no legal protection from timber harvest (Adams 2007). Therefore, forest managers have the opportunity—and responsibility—to actively manage headwater riparian systems for a variety of wildlife habitat, watershed protection, and fiber production objectives.

Accurate and efficient estimation of stem density and basal area of trees on an area (e.g., per-acre) basis can be crucial to the success of active restoration or management programs in forests adjacent to headwater streams. Nonetheless, inventory in riparian forests can be more difficult than in their upland counterparts. Stand structure and composition can be highly variable (Pabst and Spies 1999) as a result of hydrologic disturbance and other fine-scale processes. Particularly in naturally regenerated areas, headwater streams can contain alternating patches of conifer and hardwood trees of varying sizes. The development of new inventory methods, specifically designed to mitigate these challenges, would be a welcome addition to the forest sampling toolbox.

Most forest inventories in the Pacific Northwest are conducted using fixed plot and/or horizontal point sampling designs. Circular fixed plot sampling (FPS) is one of the oldest methods of forest sampling and is still commonly used throughout much of the world. Horizontal point sampling (HPS), commonly known as variable plot sampling in the Pacific Northwest, was developed by W. Bitterlich in 1948 and introduced to North American foresters by Grosenbaugh (1952). Under FPS, density can be estimated with a simple count of "in" trees, but basal area estimation requires diameter measurements on at least some captured trees. The exact opposite is true under HPS. These practical concerns, combined with the efficiency gained when selection probability is made proportional to the attribute of interest (Grosenbaugh 1967), tend to make FPS more statistically efficient for density estimation and HPS more efficient for basal area estimation. *n*-Tree distance sampling (NTDS), also called *k*-tree sampling, density-adapted sampling, point-to-tree sampling, or simply distance sampling, was promoted as an "all-encompassing forest inventory method" by Jonsson et al. (1992). In this method, the *n* trees nearest the sample point are selected (*n* being a predetermined number that remains constant throughout the sampling effort). Because the same number of trees is captured at all sample points, empty plots and plots with too many trees can be avoided (Kleinn and Vilčko 2006a), leading to a potential increase in productivity. In addition, the distance to the center of the *n* tree, acquired as a byproduct of this system, may provide some information on the spatial distribution of trees within a forest (Lessard et al. 1994).

One important drawback of NTDS is that, unlike FPS and HPS, selection probabilities of individual trees cannot be known unless distances and azimuths to many additional trees are acquired (Kleinn and Vilčko 2006b). Therefore, design-unbiased estimation for this method is currently not operationally feasible. A plot area for all *n* trees can be computed as a circle with a radius that is equal to the horizontal distance to the center of the *n* tree. The factor used to expand per-plot estimates to a per-acre basis is then $EF = 43{,}560/A_p$, where A_p is the plot area in ft^2. Because the plot size at each sample point is computed as the smallest that could contain *n* trees, this uncorrected estimator will systematically overestimate the value of any attribute on a per-acre basis (Kleinn and Vilčko 2006a).

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Zane Haxtema (zhaxtema@scscertified.com), Oregon State University, 100 Peavy Hall, Corvallis, OR 97331; current address, Scientific Certification Systems, 2000 Powell Street, Suite 600, Emeryville, CA 94608. Hailemariam Temesgen, Oregon State University. Theresa Marquardt, Grays Harbor Conservation District. *Funding was provided through the US Geological Survey Forest and Rangeland Ecosystem Science Center. We thank Dr. Bianca Eskelson for review of an earlier draft and three anonymous reviewers for their thoughtful comments.*

Despite the lack of a practical, design-unbiased estimator for NTDS, previous authors have promoted it as an attractive sampling method on the basis of an ease in field application (Jonsson et al. 1992, Kleinn and Vilčko 2006b, Nothdurft et al. 2010). We hypothesized that the ability to control the number of trees captured at each sample point may make NTDS an attractive option for inventorying highly variable riparian stands. HPS has historically been preferred by many forest inventory professionals in the Pacific Northwest because, when a prism or Relascope is used, horizontal distance measurements are unnecessary except to check the in/out status of borderline trees—a great asset when working in steep and brushy terrain. The advent of portable rangefinders with ever more sophisticated brush-filtering capacity has increased the viability of alternative sampling systems that depend more directly on distance measurements. Now that NTDS is more technologically feasible, we hoped to explore the relative advantages and disadvantages of the method in a practical sampling application.

The objective of this study was to examine the performance of selected NTDS estimators for estimation of density and basal area of headwater riparian forests in western Oregon. We evaluated the NTDS estimators against each other, but also against FPS and HPS for both density and basal area estimation. In the last 40 years, much effort has gone toward the development of estimators for NTDS that minimize bias under a range of forest conditions (see Magnussen et al. 2008 for a good overview). However, many of these estimators are difficult to comprehend and implement without advanced statistical training, and they are therefore inaccessible to the majority of forest inventory professionals. Three estimators were chosen on the basis of their simplicity in understanding and application, as well as their track record in previous studies. These will be termed the Moore (Moore 1954), Prodan (as described in Lynch and Rusydi 1999), and Kleinn-Vilčko (Kleinn and Vilčko 2006a) estimators. Details on the computation and theoretical background of these estimators can be found in the Appendix.

Methods

Data were collected at eight different riparian sites as part of the Bureau of Land Management Density Management and Riparian Buffer Study, an interdisciplinary study on the effect of management activities on wildlife habitat and other ecosystem attributes of riparian and upland systems (Cissel et al. 2006). At each site, a 1.28-ac square plot was established so as to have an approximately equal area on both sides of the stream, within which the species, dbh, and coordinate position of every tree was recorded (see Marquardt et al. 2010 for details regarding inventory procedures). Sites were dominated by Douglas-fir (*Pseudotsuga menziesii* var. *menziesii* [Mirb.] Franco) or western hemlock (*Tsuga heterophylla* [Raf.] Sarg.), with western redcedar (*Thuja plicata* Donn ex D. Don) a minor component of some sites. Hardwood species such as red alder (*Alnus rubra* Bong.) and bigleaf maple (*Acer macrophyllum* Pursh) were present at most sites. Composition of each site, by density and basal area, is given in Table 1.

Table 1. Density and basal area of each site by tree type.

	Conifers		Hardwoods		Total	
Site	Density (trees/ac)	Basal area (ft^2/ac)	Density (trees/ac)	Basal area (ft^2/ac)	Density (trees/ac)	Basal area (ft^2/ac)
BL13	111	168	21	13	132	181
KM17	158	286	15	12	173	298
KM18	246	245	15	11	261	256
KM19	215	217	5	4	221	221
KM21	136	197	17	15	153	212
OM36	150	152	15	11	165	163
TH46	167	260	0	0	167	260
TH75	194	244	74	27	268	271

Table 2. Clark-Evans (CE) index values by species and site. The CE index takes on the following values: 0 if the spatial distribution is extremely aggregated; 1 if the spatial distribution is completely random; and 2.14 if the spatial distribution is extremely uniform.

Species	BL13	KM17	KM18	KM19	KM21	OM36	TH46	TH75
Douglas-fir	1.03	0.8	1.05	0.93	0.8	1.22	1.11	1.12
Western hemlock		1.08	0.97	0.9	0.75		0.84	
Western redcedar			0.81	0.82	0.86			0.48
Red alder		0.36	0.37		0.54			0.24
Bigleaf maple	0.21							0.58
All combined	0.99	1.22	1.09	0.96	0.99	1.25	1.14	1.08

Because the performance of NTDS estimation has been found in previous work (e.g., Lessard et al. 1994, Kleinn and Vilčko 2006a) to be highly dependent on the spatial distribution of the trees on the tract of interest, the spatial distribution of each site was quantified, by species and for the site as a whole, using the Clark-Evans (CE) index (Clark and Evans 1954). The CE index takes on values of 0 if the population is extremely aggregated (i.e., clustered), 1 if the population is distributed completely at random, and 2.14 if the population is perfectly uniform. Computation of the CE index was done using the program SIAFOR (Kint et al. 2004). Results are shown in Table 2.

The estimators were compared using a Monte Carlo sampling algorithm written in the Microsoft Visual Basic for Applications (VBA) programming language (version 6.5, Microsoft Corp., Redmond, WA). Following Kleinn and Vilčko (2006a), to provide a common basis for evaluation, the estimators were compared across a range of n (the desired number of trees per sample point) from 2 to 10. Although a certain number of trees captured does not necessarily represent an equal amount of effort across sampling methods (e.g., for a given number of trees, HPS requires less measurement time for basal area estimation than NTDS), we believe that the relative performance for different values of n will allow rough comparison of different sampling systems and more specific comparison between NTDS estimators.

The value of n was fixed for each simulation run. The FPS radius and HPS basal area factor were computed so that n trees per sample point would be captured on average. For FPS, the plot area A_{FPS}, in ac, was set as $A_{FPS} = n/\text{TPA}$, where TPA is the density (in trees/ac) of the stem map. For HPS, the basal area factor, in ft^2/ac, was set as $\text{BAF} = \text{BA}/n$, where BA is the basal area (ft^2/ac) of the stem map. Toroidal wrapping, which gives all trees the appropriate long-run probability of selection, was used to avoid underselection problems associated with edge effects.

At each iteration of the simulation, one sample point was randomly located using pseudorandom numbers generated by VBA. Estimates of density and basal area were computed for each estimation method simulated (FPS, HPS, and each NTDS estimator). This process was repeated 10,000 times, with a different seed set for each iteration to avoid cyclical number generation patterns. A sample size of 10,000 seemed to be adequate for characterizing the statistical performance of each estimation method, as evidenced by the low realized values of the maximum recorded relative bias of FPS for density estimation and HPS for basal area estimation (neither was greater than 3%).

The performance of each estimation method was evaluated using relative bias and relative root mean square error (RRMSE). Relative values were preferred because they allow an equal basis of comparison between attributes and sites. Relative bias was computed as follows:

$$\mathrm{RB} = \frac{(\bar{Y} - Y)*100}{Y}$$

where Y is the true value of density or basal area, $\bar{Y} = \sum_{i=1}^{10,000} \hat{Y}_i/10,000$ is the mean estimate, and $\hat{Y}_i$ is the estimate produced at iteration i.

RRMSE was computed as follows:

$$\mathrm{RRMSE} = \sqrt{\frac{\sum_{i=1}^{10,000} [(\hat{Y}_i - \bar{Y})^2]}{(10,000 - 1)*N} + (\bar{Y} - Y)^2}\left(\frac{100}{Y}\right)$$

where N is the sample size.

Results

Relative Bias

Because they are design-unbiased for estimation of density and basal area, bias results for FPS and HPS are not presented. Among NTDS estimators, the Moore estimator tended to underestimate density (Figure 1) and basal area (Figure 2) for small values of n, whereas the Prodan and Kleinn-Vilčko estimators tended to give upwardly biased estimates. For a given value of n, the Moore estimator clearly had the lowest absolute relative bias for density estimation at seven sites, particularly for $n \geq 4$. For basal area estimation, the Moore estimator clearly had the lowest absolute relative bias at six sites, with the identity of the lowest-bias estimator unclear at two sites. For density and basal area estimation, the Prodan estimator had the highest bias for small values of n, but it appeared to converge with the Kleinn-Vilčko estimator for $n > 5$.

RRMSE

RRMSE was calculated across a range of N for a moderate value of $n = 6$. For estimation of density, FPS had the lowest RRMSE across all values of N (Figure 3). HPS and the Moore estimator had roughly equal performance across most sites. A gap between the estimation methods previously mentioned and the Prodan and Kleinn-Vilčko estimators was evident across all sites, with the latter giving notably poor performance.

For estimation of basal area, HPS had the lowest RRMSE across all values of N (Figure 4), although there was not much difference in performance between HPS, FPS, and the Moore estimator. There was a gap in performance between these estimation methods and the Prodan and Kleinn-Vilčko estimators at most (though not all) sites.

Discussion

One limitation in this study is inherent in the use of toroidal wrapping as an edge-effect correction measure. As toroidal wrapping causes sample points located at the edges of the stem map to wrap around to the opposite side of the step map, the simulated RRMSE values can be different from those that would be obtained if (in the most ideal case) the study were conducted on much larger stem maps with a buffer zone surrounding a smaller 1.28-ac area wherein sample points were allowed to fall. The difference can be exacerbated by larger values of n (translating to larger inclusion areas across all estimation methods), which cause the toroidal wrapping to be used more frequently. Table 3 indicates that the plot size for $n = 6$ under FPS can be as large as 0.045 ac, whereas the largest inclusion area under HPS (corresponding to the largest-diameter tree on the stem map) for $n = 6$ can be as large as 0.244 ac. It is unlikely that the use of toroidal wrapping would result in a distorted comparison of RRMSE values among the three NTDS estimators examined, as all will have similar inclusion areas. However, the simulated RRMSE values should be taken with a slight grain of salt when the NTDS estimators are compared with FPS and (especially) HPS.

The three NTDS estimators were chosen for this study on the basis of their simplicity and ease of application. The development of new NTDS estimators is an area of current research in Canada and Europe (Magnussen et al. 2008, Nothdurft et al. 2010), and future estimators may have statistical properties different from those evaluated in this study. Therefore, the comments made about the properties of the NTDS estimators evaluated here should not be extended to other NTDS estimators that were not evaluated.

The appeal of computer-based simulation studies, such as the one reported here, is that they allow researchers to compare the performance of different forest sampling methods without the expense of fieldwork. However, they are unable to directly compare the statistical efficiency (that is, the precision gained for a given cost investment; Iles 2003, p. 28) of different sampling methods because the per-sample-point costs of the various methods being compared is not precisely known. The best way to compare the relative statistical efficiency of different sampling methods in a specific setting is through a timed field trial using experienced cruising staff, preferably in a tract in which the true density and basal area are known. As such a study has yet to be performed in this forest type, we must augment data with conjecture and experience to offer suggestions as to how the NTDS estimators examined might compare with HPS and FPS for inventory work in headwater riparian forests of western Oregon.

The Moore estimator emerged as the best candidate among the NTDS estimators examined. The Moore estimator had the lowest bias for estimation of density and basal area on most stem maps. Similarly, the Moore estimator had the lowest RRMSE values on most stem maps when larger sample sizes were considered, particularly for estimation of density. The Prodan estimator performed poorly on the stem maps examined. In evaluating the same NTDS estimators, Kleinn and Vilčko (2006a) found that the Prodan estimator had the highest bias on all stem maps except those with a uniform spatial distribution. Lynch and Rusydi (1999) found that the Prodan estimator had negligible bias in uniformly spaced teak plantations, where the Moore estimator tended to underestimate volume and density. The poor performance of the Prodan estimator in this study may be due to the nonuniform spatial distribution of trees in the sites examined. The performance of the Kleinn-Vilčko estimator was intermediate between that of the Moore and Prodan estimators. Kleinn and Vilčko (2006a) found that the Kleinn-Vilčko estimator had higher bias than the Moore estimator, which they refer to as the Eberhardt estimator, for estimation of density and basal area on most stem maps. However, in contrast to this study, they did not find substantial differences in root squared error (similar to the RRMSE statistic) between the two estimators.

As a measure of statistical performance, RRMSE incorporates both the standard error of the sample mean (which decreases as sample size increases) and the bias of the sample mean (which is not

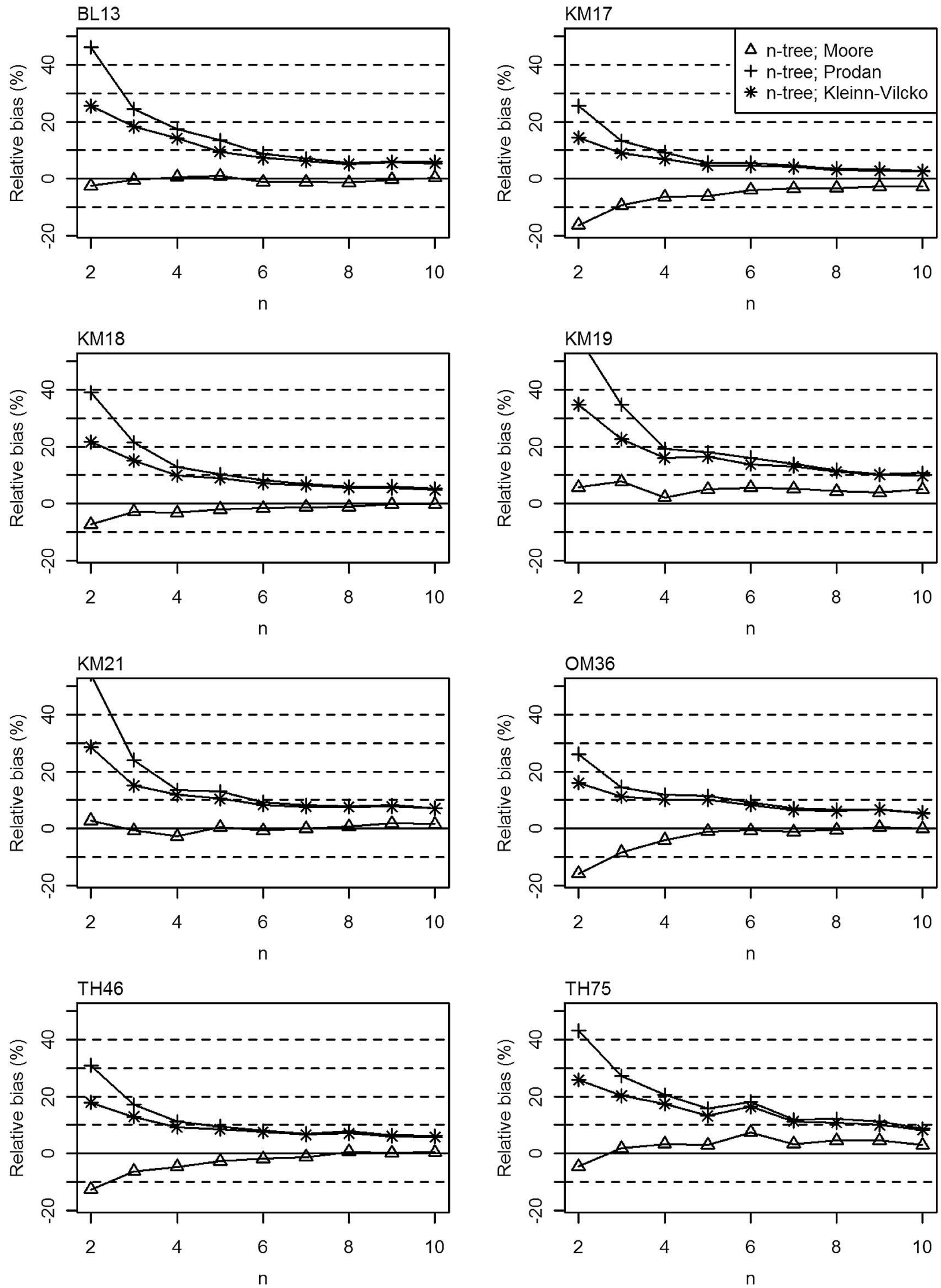

Figure 1. Relative bias of the *n*-tree distance sampling estimators for estimation of density.

affected by sample size). As predicted by theory, FPS and HPS had the lowest RRMSE values for estimation of density and basal area, respectively. For estimation of basal area, RRMSE values for the Moore estimator and FPS appeared to converge with those of HPS with increasing sample size. For estimation of density, RRMSE values for the Moore estimator and HPS appeared to likewise converge with those of FPS on most stem maps. The increasing competitiveness of FPS and HPS for basal area and density estimation, respectively, with larger sample size is reflective of the design-unbiasedness of these sampling methods. Similarly, the competitiveness exhibited by the Moore estimator was due in part to low absolute bias on most stem maps for reasonable values of n (≥ 4).

In timed field trials, Lessard et al. (1994) and Lynch and Rusydi (1999) found NTDS to be cost-competitive with FPS for density estimation in two very different landscapes (northern hardwoods and red pine forests of northern Michigan and Indonesian teak plantations, respectively). Because density estimation for the NTDS estimators examined requires only measurement of the distance to

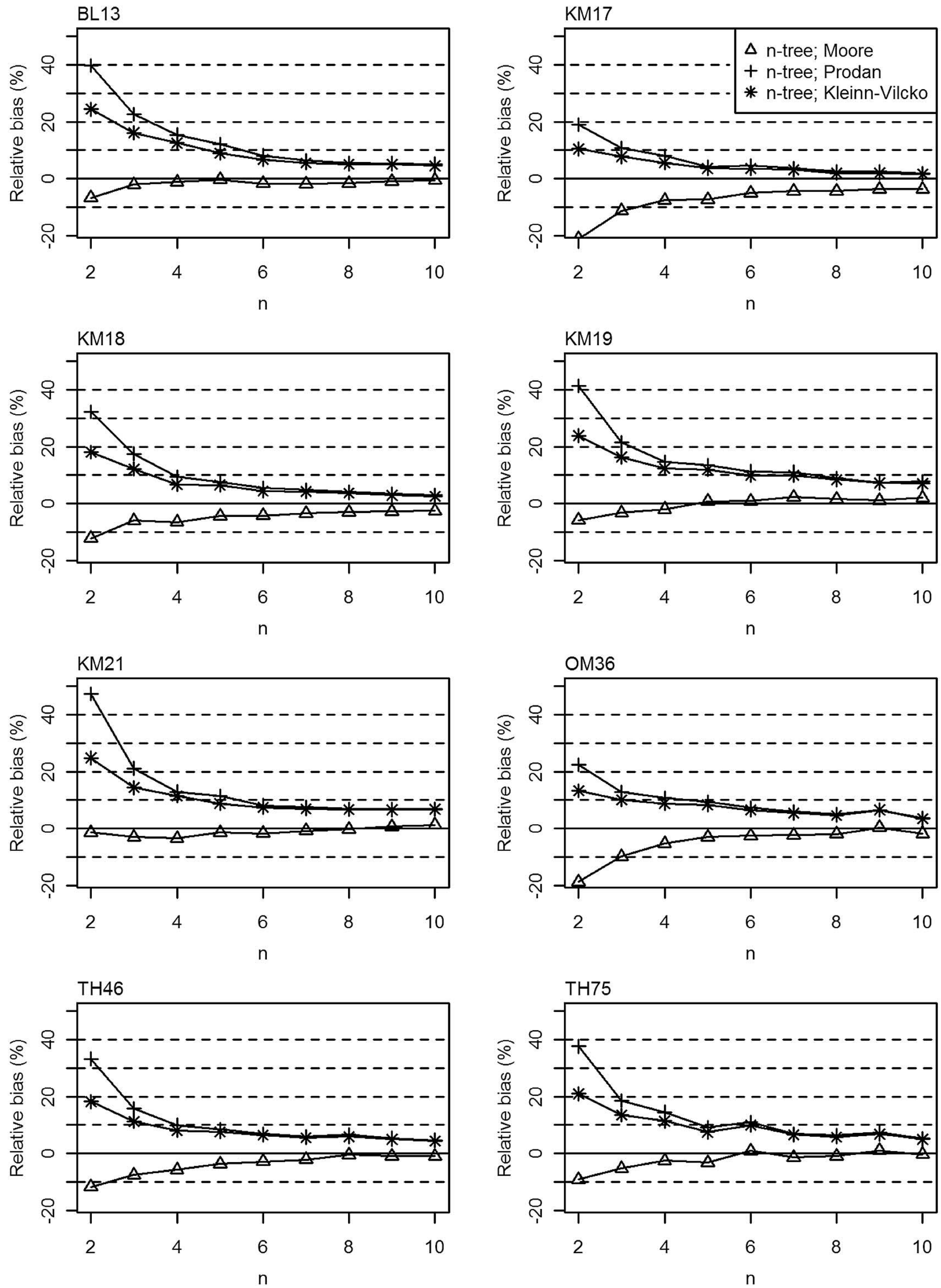

Figure 2. Relative bias of the *n*-tree distance sampling estimators for estimation of basal area.

the *n* tree (and, if implementing the Kleinn-Vilčko estimator, the distance to the $n + 1$ tree as well), NTDS may be most promising as a sampling method for density estimation.

However, HPS and the Moore estimator gave notably poor performance for density estimation at TH75, the only site with a large hardwood component. At this site, bigleaf maple made up 25% of total stems but only 8% of total basal area. Red alder was also present, making up 2% of all stems and 2% of total basal area.

The gap in performance appears to stem from the clustered nature of the hardwood species. Bigleaf maple had a CE index of 0.58, and red alder had a CE index of 0.24, indicating a strong tendency toward a clustered spatial distribution for both species. When the distance to the *n* tree is extremely small (as might happen when a sample point is located inside a hardwood clump), a large overestimate of stem density can be produced. Similarly, the clustered distribution of the hardwood trees, in combination with their small size

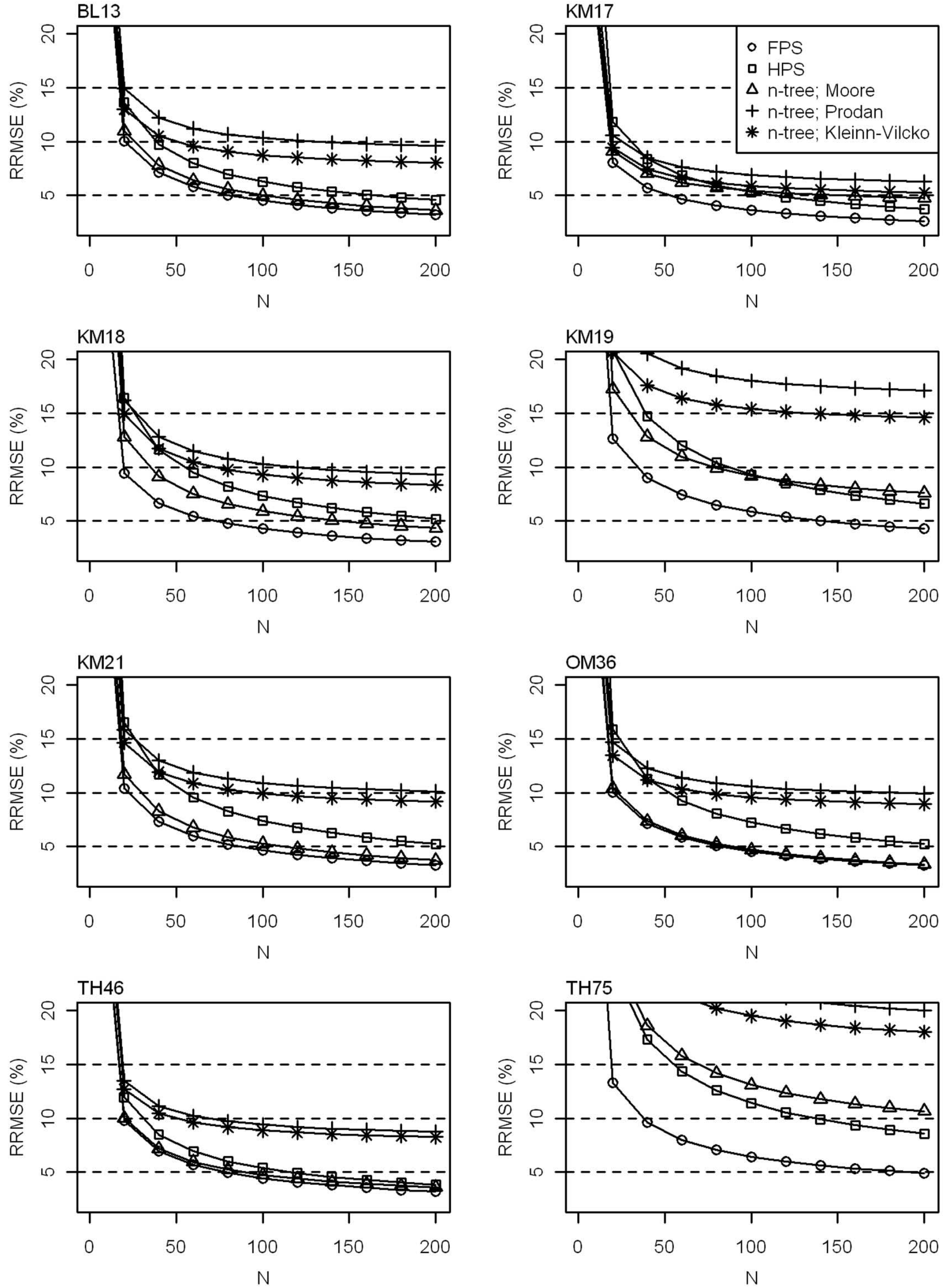

Figure 3. Relative root mean square error of the *n*-tree distance sampling estimators, fixed plot sampling (FPS), and horizontal point sampling (HPS) for estimation of density across a range of *N* for $n = 6$.

relative to the population as a whole (the quadratic mean diameter of hardwood trees was 8 in., whereas the overall quadratic mean diameter was 14 in.) may have contributed to the poor performance of HPS at this site.

In timed trials in mixed pine-hardwood forests of southern Maine and New Hampshire, Kenning et al. (2005) found that the Moore estimator (although not referred to by that name) consistently underestimated snag density for very low values of *n* (one-, two-, and three-tree sampling), a result that is consistent with our findings regarding the underestimation bias of the Moore estimator for very low values of *n*. They found that the Moore estimator did not offer productivity gains sufficient to compensate for the loss of design-unbiasedness, although a distance-limited modification of the Moore estimator showed some promise. They mentioned that snags in the compartments they sampled exhibited a clustered spatial distribution and indicated that this was at least partly due to "the

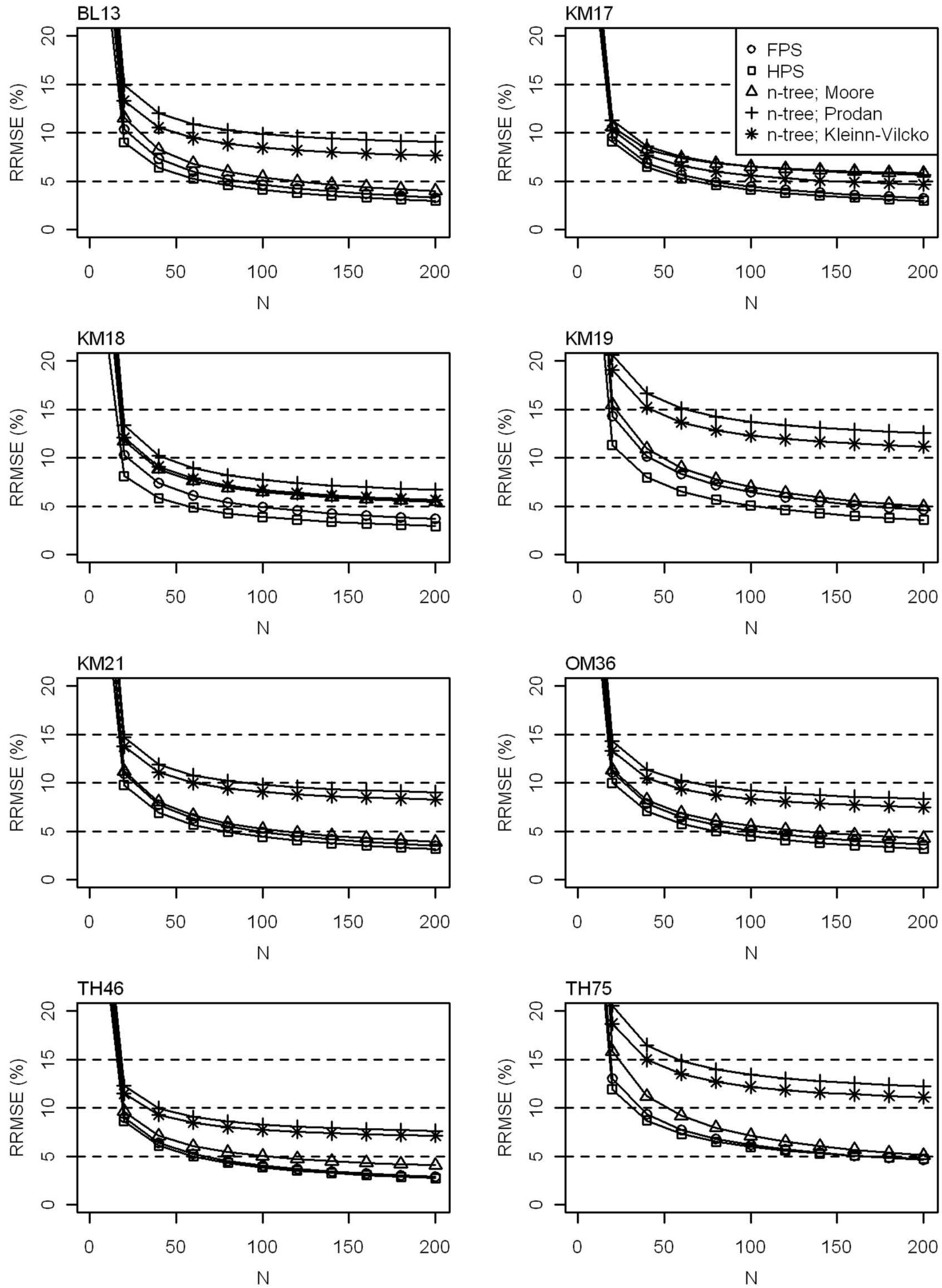

Figure 4. Relative root mean square error (RRMSE) of the *n*-tree distance sampling estimators, fixed plot sampling (FPS), and horizontal point sampling (HPS) for estimation of basal area across a range of *N* for *n* = 6.

abundance of dead sprouts of *Acer rubrum*." Similarly, Lessard et al. (1994) found that the Moore estimator performed poorly in the "clumped, mixed hardwood stands" of northern Michigan.

For basal area estimation, RRMSE of the Moore estimator converged with that of FPS and HPS with larger values of *N* at most sites. However, it seems difficult to imagine that any NTDS estimator could be more statistically efficient than HPS for basal area estimation, because trees must be measured for diameter under NTDS but only counted in HPS. Nonetheless, Lessard et al. (1994) found that for a fixed sampling time, NTDS using the Moore estimator sometimes gave a lower sampling error than HPS. In another trial, Lynch and Rusydi (1999) found that NTDS was far more efficient for basal area estimation than HPS.

Although HPS can be a highly efficient system for basal area estimation, the initial investment in training required for proper application of the method is probably greater than for FPS or

Table 3. Fixed plot sampling (FPS) plot sizes, horizontal point sampling (HPS) basal area factors, and maximum inclusion areas under HPS, by site, for $n = 6$.

Site	FPS plot size (ac)	HPS basal area factor (ft^2/ac)	HPS maximum inclusion area (ac)
BL13	0.045	30	0.244
KM17	0.035	50	0.100
KM18	0.023	43	0.111
KM19	0.027	37	0.133
KM21	0.039	35	0.114
OM36	0.036	27	0.209
TH46	0.036	43	0.088
TH75	0.022	45	0.080

NTDS. Neither study discloses the prior training level of the technicians who performed the sampling. However, the results may be more easily understood if the technicians had little or no prior experience with HPS. In the Pacific Northwest, where HPS has been widely used for more than 50 years, qualified inventory personnel are readily available, and a study using professional cruisers with multiple years of experience in HPS would perhaps yield very different results.

All of the NTDS estimators examined, and the Moore estimator in particular, generally exhibited lower absolute bias with increasing values of n, and therefore the NTDS estimators examined may be more attractive with larger values of n. However, the limited field experience of the primary author in attempting to identify the nearest n trees to a given point suggests that the amount of time required to perform NTDS may increase disproportionately with the value of n desired, particularly when steep terrain or brushy conditions are encountered. Unlike FPS and HPS, where inclusion areas are never mutually exclusive, under NTDS the n tree will always be selected at the expense of the $n + 1$ tree. Therefore, a sophisticated recording system or a good memory will be required to efficiently track the distances to all potentially included trees, and this could be challenging with larger values of n.

Conclusion

Of the NTDS estimators examined, only the Moore estimator remained competitive with FPS and HPS at larger sample sizes. The relatively low bias exhibited by the Moore estimator at most sites indicates that it may have potential for estimation of both density and basal area in some forest types. However, hardwood trees exhibiting a clustered spatial distribution (e.g., red alder and bigleaf maple) are common in riparian areas, and our results and those of others (Payandeh and Ek 1986, Lessard et al. 1994) show the Moore estimator to perform poorly for estimating density of clustered populations.

Edge-related bias, which can be a particularly problematic issue when sampling long, narrow riparian areas (Lynch 2006), is also of concern. Although unbiased correction techniques exist for FPS and HPS (e.g., Ducey et al. 2004), such techniques have only recently been developed for use with NTDS (Lynch 2012). In riparian forests, which inherently have a high edge-to-area ratio, severe underestimation bias could result from application of NTDS when estimates are not edge-corrected, and therefore the implementation of appropriate correction measures is highly recommended.

As sample size increases, the attractiveness of estimation methods that have little or no bias increases relative to estimation methods that have higher bias. This suggests that inventory personnel seeking long-run performance over a large number of sample points will continue to be best served through the use of methods that minimize bias. Although this study has demonstrated that the Moore estimator may have minimal bias in some forest types, it is the opinion of the primary author that none of the NTDS estimators examined (including the Moore estimator) is likely to result in a reduction in measurement costs, relative to FPS and HPS, sufficient to offset uncertainty regarding any insidious bias that may result. The forest inventory community has historically favored design-unbiased estimation methods, and it is recommended that such a preference be retained in this context.

Sampling in a highly variable forest type is difficult. Finding too many trees at a sample point, or a string of sample points with no trees, can be psychologically painful, and it is only natural to search for alternatives to this headache. A similar search led some inventory groups to adopt a policy of changing the basal area factor used in HPS so as to get a constant tree count at each sample point (Bell 1994), a policy that has been demonstrated to lead to biased (Wensel et al. 1980, Iles and Wilson 1988) and more variable (Iles and Wilson 1988) results. As an unbiased solution for sample points with too many trees, Iles and Wilson (1988) recommend the plot be split in half, with one side randomly chosen for sampling. This protocol would be useful in FPS as well. There does not appear to be an easy answer for plots with too few trees, but it may be better to accept the added variability and keep the process unbiased.

In conclusion, although the ability to control the number of trees sampled for density estimation under NTDS is theoretically attractive, we suggest that none of the NTDS estimators examined will offer operational gains sufficient to offset the relatively poor statistical performance that may result under conditions that surface often in riparian forest sampling. However, the development of new NTDS estimators is currently an area of active research, and future developments may result in estimators that offer sound statistical performance while also being cost-competitive with traditional methods. An estimator developed by Nothdurft et al. (2010), which requires stem mapping of all n sampled trees, holds particular promise for sampling the clustered spatial patterns characteristic of riparian areas.

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Appendix

The Moore (1954) estimator applies an $(n - 1)/n$ multiplier to mitigate the overestimation bias of the uncorrected NTDS estimator. The sample-point-based estimators for density (trees/ac) and basal area (ft^2/ac) are, respectively:

$$N_M = \frac{n-1}{A_p};\ G_M = \frac{n-1}{n} \sum_{t=1}^{n} \left[\frac{g_t}{A_p}\right]$$

where n is the number of trees to be captured at the sample point; $A_p = \pi(d_n^{\,2})/43{,}560$ is the area, in ac, of a circle with radius d_n; d_n is the distance to the n tree; and g_t is the basal area of tree t.

Under the Prodan estimator, the n tree is considered borderline and counted as a half-tree. The sample-point-based estimators for density and basal area are as follows:

$$N_P = \frac{n-0.5}{A_p};\ G_p = \frac{\sum_{t=1}^{n} [g_t] - 0.5g_n}{A_p}$$

Kleinn and Vilčko (2006a) developed an approach based on the arithmetic average of the distances to the n and $n + 1$ trees. Because the distance to the n tree would result in systematic overestimation and the distance to the $n + 1$ tree would result in systematic underestimation, they reasoned that using the average distance would result in more reasonable estimates. The sample-point-based estimators for density and basal area are as follows:

$$N_K = \frac{n}{A_m};\ G_K = \frac{\sum_{t=1}^{n} g_t}{A_m}$$

where

$$A_m = \frac{\pi[(d_n + d_{n+1})^{*}0.5]^2}{43{,}560}$$

where d_n is the distance to the n tree; and d_{n+1} is the distance to the $n + 1$ tree.