

Adjusting Forest Density Estimates for Surveyor Bias in Historical Tree Surveys

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ABSTRACT.—The U.S. General Land Office surveys, conducted between the late 1700s to early 1900s, provide records of trees prior to widespread European and American colonial settlement. However, potential and documented surveyor bias raises questions about the reliability of historical tree density estimates and other metrics based on density estimated from these records. In this study, we present two complementary approaches to adjust density estimates for possible surveyor bias. We addressed the problem of surveyor bias of density estimates by simulating the effects of (1) rank of selected trees (compared to assuming the nearest trees were selected) and (2) specific surveyor bias in selection of (a) quadrant location, (b) quadrant configuration, (c) azimuth, and (d) combined species and diameter. We then developed regression equations to calculate adjustment quotients for these biases, making the adjustment quotients transferable to any similar datasets. For the rank-based approach, an unvarying rank of 2 (selection of the second nearest tree instead of always the nearest tree) decreased density estimates to about 25 to 45% of the actual density, depending on number of trees per survey point, resulting in corrected density estimates that are 2.2 to 4 times greater than uncorrected density estimates. However, constant selection of the second nearest tree did not occur; varying ranks decreased density estimates to around 55 to 65% of the density, resulting in corrected density estimates about 1.5 to 1.8 times greater than uncorrected values. For the bias-based approach, depending on the specific General Land Office dataset, bias for tree species and diameter alone may decrease density estimates by about 35%. Quadrant configuration and azimuth preference may decrease density estimates by about 15% each. The quadrant location bias has negligible effects on the density estimates. The overall density estimates may be about 35 to 55% of the actual density and correction of the density estimate will approximately double the value. These methods can provide a range of estimates, from low values of uncorrected density to high values of corrected density, about the amount that varying surveyor bias may have decreased density estimates for any areas where bias is detected (*i.e.*, non-random frequencies) in point-centered quarter surveys. Adjustments will increase reliability of historical forest density estimates and their applications for restoration.

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INTRODUCTION

Records from the United States General Land Office (GLO) provide a historical reference of the composition and structural characteristics of forests for setting ecosystem management and restoration goals; however, any bias that is present may affect quantification of reference conditions. The GLO was founded in 1812 to systematically survey and map public lands into square mile (1.6×1.6 km) sections with 36 sections per township, to make them available for settlement. Along with descriptive notes, surveyors recorded the species, diameter, bearing, and distance of two to four (bearing) trees at section corners and species and diameter of (line) trees encountered along section lines. Surveys for bearing trees most closely resembled a point-centered quarter method, where surveyors divided each location at a survey point into four equal quarters, or quadrants, delineated by cardinal directions and then recorded the distance, bearing, species, and diameter at breast height (DBH) of the nearest tree in two to four of the quadrants (White, 1983). For the most part there was strong incentive to select the nearest trees to save time and energy; however, both GLO instructions and surveyor preference may have caused surveyors to select bearing trees other than simply the nearest tree (White, 1983; Manies *et al.*, 2001; Anderson *et al.*, 2006). This can create biases that are clear departures from randomness in the data and consequently errors in reconstruction of the structure of forest vegetation. Identification and correction of bias, therefore, are important issues for making accurate estimates of the historical forest density.

There are at least five types of possible bias in bearing tree data including selection of preferred (1) size (diameter), (2) species, (3) azimuth, (4) quadrant configuration (adjacent or opposite quadrants) for points with two trees, and (5) quadrant direction from survey point to bearing trees for points with two trees. Instructions to surveyors may have caused bias due to requirements to set survey posts that were at least 7.6 to 12.7 cm (3 to 5 in) in diameter and examples of diameters in survey notes that were generally at least 15 cm (6 in); therefore, selected diameters may have exceeded those values and diameters less than 3 cm were rare (Bourdo, 1956; White, 1983). Not all, but a few of the general instructions specified bias for moderately-sized trees to blaze ("It would not be practicable to cut small trees..."), particularly those species potentially having greater longevity ("soundest and most thrifty in appearance, and of the size and kinds which experience teaches will be the most permanent and lasting," White, 1983). Surveyors additionally may have selected trees that were conspicuous, to aid in relocation, and that were easy to blaze, including species with few lower branches and smooth bark that did not require bark removal (Bourdo, 1956; White, 1983). Species and diameter are potential sources of bias, but there are other, easily documented biases, based on deviation from random frequencies, in GLO data related to the direction to bearing trees. The azimuths to bearing trees should be equally represented. Instead, surveyors tended to select bearings in the center of quadrants (*i.e.*, in the northeast, southeast, southwest, or northwest quadrant), avoiding cardinal directions (Manies *et al.*, 2001; Anderson *et al.*, 2006). For points with only two trees, surveyors should have selected bearing trees equally among the four quadrants. Nonetheless, overall quadrant frequencies were not equal because surveyors, perhaps influenced by township boundaries, often preferred northwestern quadrants (Anderson *et al.*, 2006). Also for points with two trees, there should be twice the number of trees in adjacent quadrants as in opposite quadrants for quadrant configuration, because after a quadrant is selected, there are two adjacent quadrants and one opposite quadrant remaining for tree selection (Anderson *et al.*, 2006). However, until 1834 and then again beginning in generally around 1855, instructions specifically directed selection of "two or

more adjacent trees in opposite directions, as nearly may be” (White, 1983). Additionally, surveyors had a tendency to record trees on opposite sides of sections lines encountered in the traveling direction (White, 1983).

All of these sources of bias have the potential to reduce historic forest density estimates made with GLO bearing tree data, if indeed there was bias. Forest density estimates from plotless sampling methods (such as GLO surveys) rely on plotless density estimators, which assume distances were from the survey point to the closest individual tree or, if the tree was not the closest, incorporate the distance rank (nearest, second nearest, third nearest, or a farther distance from a survey point) of the tree (*e.g.*, Morisita, 1957). With GLO information, the distance rank of bearing trees is unknown and assuming that only the nearest trees were selected during the surveys causes underestimation of the tree density estimate, if there was bias in tree selection (*i.e.*, the nearest trees were not selected in each quadrant; selection of a tree other than the nearest one in a quadrant always increased the distance rank of the selected tree in a quadrant). The survey biases had effects on the distance rank and create observed frequencies in each type of bias that are different than expected by chance; and thus for some biases, the exact amount of bias is apparent in the data and for others, bias can be estimated using reasonable assumptions. It is possible to quantify departures of the observed selection of tree position, including quadrant location, quadrant configuration, and azimuth, in a given GLO dataset from the random frequencies expected of nearest tree selection. Unfortunately, preference for species and diameter is more uncertain because the expected frequencies during the survey are unknown.

Although the potential for bias is recognized, most analysts do not check GLO data for deviations from random frequencies (documented by Manies *et al.*, 2001; Anderson *et al.*, 2006; Liu *et al.*, 2011); and without options for adjusting density estimates, assume that any bias will not affect density estimates and subsequent comparisons to modern forest densities (Radeloff *et al.*, 1999; Zhang *et al.*, 2000; Leahy and Pregitzer, 2003), or conversely, researchers avoid determining density because of biased estimates. Corrections are not needed if there is no bias or the bias is too limited to affect density estimates (Williams and Baker, 2010; Liu *et al.*, 2011). For example, Williams and Baker (2010) determined that surveyors selected the nearest tree 95 to 98% of the time for 384 survey points in Oregon; these survey points thus should have observed frequencies (of quadrant location and configuration and azimuth) that are random. Only Kronenfeld and Wang (2007) have developed equations to correct some of the bias issues, specifically quadrant configuration, bearing angle, and species biases. The research by Kronenfeld and Wang (2007) to account for surveyor bias was innovative and timely; however, their correction for quadrant configuration decreased density estimates when increased density estimates should occur because of selection of trees that were not nearest to the survey point. Additionally, their correction for species depended on constant overall density, even though forest density is a function of (disturbance effects on) composition and site conditions and they did not examine if the number of bearing trees per survey point or bearing tree quadrant location were important sources of bias.

To provide applicable corrections for researchers who detect bias in their data, and consequent increased certainty and potentially reevaluation of historical forest densities, we examined the effects of surveyor bias on forest density estimates and determined adjustment quotients to correct surveyor bias for bearing tree species, size, and location (quadrant location, quadrant configuration, and azimuth). To do this, we simulated bearing tree biases based on either a range of (1) tree distance ranks or (2) frequencies of quadrant location, quadrant configuration, and azimuth present in GLO data from the state of Missouri, along with avoidance or preference of a general combination of species and diameter.

METHODS

DENSITY ESTIMATOR

Plotless density estimators include those equations proposed by Cottam and Curtis (1956), Morisita (1957), and Pollard (1971), among others. The Cottam and Curtis (1956) density estimator is biased mathematically (Pollard, 1971), and performs poorly in situations of nonuniform density (Bouldin, 2008). We have found that the Morisita estimator produces density estimates that were closer to actual simulated densities than those from the Pollard estimator in situations of nonuniform density and clustered distribution. There appeared to be no method to correct the Pollard estimator for nonuniform density without already knowing the true density (Hanberry *et al.*, 2011). In this study, we used Morisita's density estimator (unlike Kronenfeld and Wang, 2007), which can apply to survey data using a sampling scheme with a central survey point, where data are collected in four sections (quadrants), and the nearest tree is recorded (*see* Equation 1; using known ranks >1 or sections not equal to four will not produce accurate results; B. Hanberry, pers. obs.).

Morisita density estimator:

$$\lambda = \frac{(kq-1)}{\pi n} \sum_{i=1}^n \frac{q}{\sum_{j=1}^q r_{ij}^2} \quad (1)$$

where λ (density) is the number of trees/ha, q is the number of quadrants with recorded trees (2, 3, or 4), k is the distance rank of the tree in each quadrant, n is the number of points, and r is the survey point-to-tree distance. We found that this particular application (*i.e.*, where q is the number of quadrants with recorded trees) of Morisita's equation to the point-centered quarter method produced the most accurate results compared to the known density of simulated points. Although the Morisita estimator is robust and exactly correct for survey points with four trees (*i.e.*, the standard the point-centered quarter method), we applied a correction factor due to density overestimation from points with two or three trees, by dividing density estimates by 1.22 or 1.18, respectively (Hanberry *et al.*, 2011).

SIMULATION DESIGN FOR BIAS

We used a simulation approach that generated non-biased random tree locations, followed by biased selection of trees (Appendix 1). We have addressed the issue of corrections for regular and clustered distributions (Hanberry *et al.*, 2011) as a separate topic from surveyor bias. We simulated the location of trees using Python (<http://docs.python.org>; *see* code in Appendix 5), generating random points ranging from -50 to 50 in x and y values with a survey point at $0, 0$ coordinates. If two trees were within 0.25 units (undefined but representing meters) of each other, then one tree was eliminated. We used a minimum of four trees per point (quadrants with missing trees received a distance of 70 ; Hanberry *et al.*, 2011). We generated mean densities of 5 to 25 trees/point in steps of 5 , densities of 30 to 100 trees/point in steps of 10 , and densities of 200 to 1000 trees/point in steps of 200 . We limited density levels to 30 to 100 trees/point in steps of 10 for species and diameter combined. Although overall mean densities were specified, the number of simulated trees was drawn from a Poisson distribution, producing nonuniform density because the density for the average maximum number (of the 600 points within a trial) of trees per point was two to three times greater than the average minimum for each density level. We then non-randomly selected trees from each quadrant based on bias scenarios, specified below.

RANK-BASED APPROACH

We ran bias scenario simulations of 60 trials of 600 simulated survey points at every density for unvarying (*e.g.*, always selection of the nearest tree) and varying (*i.e.*, random tree

selection based on frequencies) selection of ranks. We ran three bias scenario simulations for unvarying ranks, one each for a rank of 1 (always selection of the nearest tree to the survey point in the quadrant from each quadrant with trees), 2 (selection of the second nearest tree to the survey point), and 3 (selection of the third nearest tree to the survey point). We also ran multiple bias scenario simulations to obtain a variety of mean distance ranks from 1 to 3, where selected trees from each quadrant had a random rank of 1, 2, 3, or 4 (following a range of overall frequencies listed in Tables 1 and 2). We then calculated density estimates for each trial (assuming that the rank was 1). Although there is no way to approximate the actual ranks and frequencies of ranks from a GLO dataset, the simulation information is useful, particularly in the absence of azimuth and line tree records, to illustrate and roughly correct the effects of rank on density estimates without the detail of the bias-based approach (below).

BIAS-BASED APPROACH

For each bias scenario simulation, which produced density estimates from each of 60 trials of 600 simulated survey points at every density, we imposed biased tree selection of randomly generated trees from each quadrant (described in detail below), covering a wide range of bias frequencies (Table 3 to 6) present in actual GLO data by ecological subsection (ECOMAP, 1993) in the state of Missouri. Although bias for species, diameter, and azimuth direction will increase the distance rank of the selected trees to ≥ 1 , biases for quadrant location and quadrant configuration, only possible for points with two trees, will not increase distance rank within a quadrant (*i.e.*, if surveyors selected the nearest tree in each of the two selected quadrants while avoiding quadrants that contained the nearest trees to the survey point; Fig. 1). We assumed that surveyors generally selected the nearest trees, producing expected frequencies equal to those from random tree locations (equal for each quadrant and azimuth grouping, 2:1 ratio for adjacent to opposite quadrant configuration, and frequencies within $\pm 10\%$ of the line tree species and diameter for combined bearing species and diameter). Any departures from the above random frequencies were considered biased selections. Any increases due to preference for the non-nearest trees caused corresponding decreases in selection of the nearest trees. Briefly (and see with greater detail in Appendices 2, 3, 4 and Fig. 2), we considered that the unbiased tree selection, or the percent nearest trees, for each frequency grouping or partition was represented by the lowest value of the bias frequencies. For combined species and diameter, we considered bearing tree selection to be the unbiased nearest trees if the frequency of bearing tree species and diameter was within 10% of the line tree species and diameter (discussed in detail below).

QUADRANT LOCATION BIAS

For unbiased bearing tree selection, quadrants should have been selected equally, so that each quadrant represents about 25% of the sample (Appendix 2). Any value $> 25\%$ was biased, and any increases in selection of one quadrant causes decreases in another quadrant. We considered the decreased value to represent unbiased selection of the nearest trees in each quadrant. We used a range of quadrant location frequencies in our simulations (Table 3). Further options that we included in the simulations for quadrant frequency included allocating the biased quadrant selection into one, two, or three quadrants.

QUADRANT CONFIGURATION BIAS

For unbiased bearing tree selection, quadrant configuration will have a random ratio of trees in adjacent quadrants to trees in opposite quadrants of 2:1; we assumed that the

TABLE 1.—Estimator summary statistics for density estimates based on Morisita estimator for two to four trees per survey point, when tree distance rank is 2 to 3 but assuming rank equal to 1, for 60 trials and 600 plots. An unvarying mean rank (100% selection of that rank) will reduce the adjustment quotient compared to a varying mean rank

Tree		Adj. quotient ¹	Bias ²	sd ³	% rank 1	% rank 2	% rank 3	% rank 4
Number	Rank							
Two trees	1.00	0.99	-1.63	27.80	100	0	0	0
	2.00	0.56	-93.21	131.99	50	0	50	0
	2.00	0.40	-126.98	177.85	25	50	25	0
	2.00	0.24	-160.61	224.28	0	100	0	0
	2.80	0.23	-162.22	226.83	10	25	40	25
	3.00	0.19	-171.81	240.30	5	25	35	35
	3.00	0.13	-183.59	256.28	0	0	100	0
Three trees	1.00	1.00	1.08	15.42	100	0	0	0
	2.00	0.61	-83.38	116.94	50	0	50	0
	2.00	0.48	-111.12	155.38	25	50	25	0
	2.00	0.35	-138.72	193.71	0	100	0	0
	2.60	0.39	-129.90	181.24	20	25	30	25
	2.80	0.31	-146.95	205.17	10	25	40	25
	3.00	0.26	-156.66	218.91	5	25	35	35
Four trees	3.00	0.21	-168.03	234.65	0	0	100	0
	1.00	1.00	1.34	11.39	100	0	0	0
	2.00	0.65	-75.50	105.60	50	0	50	0
	2.00	0.54	-97.57	136.42	25	50	25	0
	2.00	0.44	-119.63	167.13	0	100	0	0
	2.60	0.45	-117.32	163.79	20	25	30	25
	2.80	0.38	-132.61	185.26	10	25	40	25
	3.00	0.34	-141.92	198.34	5	25	35	35
3.00	0.29	-152.37	212.92	0	0	100	0	

¹ Adjustment quotient = mean density estimate/mean simulation density

² Mean of (density estimate - simulation density)

³ Standard deviation of bias

nearest trees were selected a certain percentage of the time (Appendix 4). We used a range of quadrant configuration frequencies in the simulations (Table 4). We also created scenarios that included alternatives for quadrant configuration, including picking the first nearest tree and then the opposite or adjacent tree, or else the two nearest opposite or adjacent trees.

AZIMUTH BIAS

For unbiased bearing tree selection, azimuth groups should have been selected equally. We partitioned the bearing tree azimuths into three groups of 30 degrees each in each quadrant but divided based on cardinality, producing a most cardinal group of 0 to 15 and 75 to 90 degrees, a group of 15 to 30 and 60 to 75 degrees, and a central group of 30 to 60 degrees (Fig. 2); again, we assumed that the nearest trees were selected a certain percentage of the time (Appendix 3). We simulated a range of frequencies, with increasing representation of the angular groups toward the center of the quadrant (Table 5). We set a limit of four trees per quadrant to skip before tree selection had to occur; if the first four trees were skipped, then the first tree was selected.

TABLE 2.—Rank-based adjustments for density estimates based on Morisita estimator for two to four trees per survey point, when tree distance mean rank ranges from 1.35 to 1.95 but assuming rank equal to 1, for 60 trials and 600 plots

Tree		Adj. quotient ¹	Bias ²	sd ³	% rank 1	% rank 2	% rank 3	% rank 4
Number	Rank							
Two trees	1.35	0.83	-36.48	56.78	80	10	5	5
	1.39	0.79	-43.10	64.53	75	15	6	4
	1.50	0.75	-52.84	77.02	70	15	10	5
	1.60	0.67	-69.11	98.43	60	25	10	5
	1.69	0.62	-80.96	114.23	53	30	12	5
	1.70	0.60	-86.26	122.15	50	35	10	5
	1.75	0.56	-92.76	130.19	45	40	10	5
	1.75	0.59	-86.95	122.80	50	30	15	5
	1.80	0.53	-100.21	140.75	40	45	10	5
	1.80	0.55	-94.07	132.77	45	35	15	5
	1.80	0.59	-86.70	122.67	50	25	20	5
	1.85	0.52	-101.29	141.74	40	40	15	5
	1.85	0.59	-87.66	123.89	50	25	15	10
	1.90	0.54	-96.44	136.24	45	30	15	10
	1.95	0.51	-103.83	145.53	40	35	15	10
Three trees	1.35	0.85	-30.56	44.63	80	10	5	5
	1.39	0.82	-36.95	52.25	75	15	6	4
	1.50	0.78	-45.54	63.71	70	15	10	5
	1.60	0.71	-60.10	84.10	60	25	10	5
	1.69	0.67	-70.40	97.99	53	30	12	5
	1.70	0.65	-74.33	104.21	50	35	10	5
	1.75	0.62	-80.60	112.28	45	40	10	5
	1.75	0.64	-75.71	105.79	50	30	15	5
	1.80	0.59	-87.51	122.11	40	45	10	5
	1.80	0.61	-82.30	115.32	45	35	15	5
	1.80	0.64	-76.58	107.30	50	25	20	5
	1.85	0.58	-88.58	123.49	40	40	15	5
	1.85	0.63	-77.59	108.41	50	25	15	10
	1.90	0.60	-84.51	118.52	45	30	15	10
	1.95	0.57	-90.88	126.37	40	35	15	10
Four trees	1.35	0.87	-26.93	38.28	80	10	5	5
	1.39	0.84	-32.65	45.60	75	15	6	4
	1.50	0.81	-40.40	56.13	70	15	10	5
	1.60	0.75	-52.79	73.30	60	25	10	5
	1.69	0.71	-62.04	86.44	53	30	12	5
	1.70	0.69	-65.02	90.82	50	35	10	5
	1.75	0.67	-70.67	98.39	45	40	10	5
	1.75	0.68	-66.76	92.95	50	30	15	5
	1.80	0.64	-76.86	107.34	40	45	10	5
	1.80	0.66	-72.38	101.02	45	35	15	5
	1.80	0.68	-67.88	94.54	50	25	20	5
	1.85	0.63	-78.05	108.95	40	40	15	5
	1.85	0.67	-69.12	96.33	50	25	15	10
	1.90	0.65	-75.01	104.91	45	30	15	10
	1.95	0.62	-80.59	111.88	40	35	15	10

¹ Adjustment quotient = mean density estimate/mean simulation density

² Mean of (density estimate - simulation density)

³ Standard deviation of bias

TABLE 3.—Estimator summary statistics for quadrant location, for 60 trials and 600 plots

% quadrants with nearest tree (unbiased)	% three quadrants (unbiased)	% one quadrant (biased)	Adj. quotient ¹	Bias ²	sd ³
95	23.75	28.75	0.98	-4.77	35.51
90	22.5	32.5	0.96	-7.69	37.41
85	21.25	36.25	0.95	-11.40	38.70
80	20	40	0.93	-14.25	39.72
75	18.75	43.75	0.91	-17.74	42.38
70	17.5	47.5	0.90	-21.01	39.91
60	15	55	0.86	-27.91	47.76
50	12.5	62.5	0.83	-33.60	54.43

¹ Adjustment quotient = mean density estimate/mean simulation density

² Mean of (density estimate - simulation density)

³ Standard deviation of bias

SPECIES AND DIAMETER BIASES

To calculate actual species and diameter frequencies as closely as possible, we used the line trees (from the Missouri GLO dataset), or trees encountered along the survey lines and that did not have the same constraints from the GLO instructions. Although we realize that there are also potential biases in line tree selection (and documented in northern Wisconsin by Liu *et al.*, 2011), the comparison between line trees and bearing trees is the best and only comparison available in most cases. Line trees provide another sample from historical forests; and as such, the differences between the bearing and line trees may represent the magnitude of surveyor preference and avoidance of certain tree species or diameters. If line trees are not recorded or if researchers consider the line trees to be

TABLE 4.—Estimator summary statistics for quadrant configuration, for 60 trials and 600 plots

% quadrants with nearest tree (unbiased)	% adjacent quadrants (biased above 67%)	% opposite quadrants (biased above 33%)	Adj. quotient ¹	Bias ²	sd ³
30	90	10	0.86	-26.49	47.04
60	80	20	0.92	-16.33	35.50
75	75	25	0.94	-11.16	31.38
90	70	30	0.97	-5.54	27.95
92.5	61.67	38.33	0.96	-8.64	30.49
90	60	40	0.95	-10.86	33.75
82.5	55	45	0.92	-17.66	39.64
75	50	50	0.89	-23.28	45.25
67.5	45	55	0.86	-29.75	52.02
60	40	60	0.82	-36.18	60.69
52.5	35	65	0.79	-42.48	68.61
45	30	70	0.75	-49.13	77.36
37.5	25	75	0.73	-54.55	84.70
30	20	80	0.69	-61.73	91.89
15	10	90	0.63	-74.04	109.41
7.5	5	95	0.60	-80.35	117.93

¹ Adjustment quotient = mean density estimate/mean simulation density

² Mean of (density estimate - simulation density)

³ Standard deviation of bias

TABLE 5.—Estimator summary statistics for azimuth selection, for 60 trials and 600 plots

% quadrants with nearest tree (unbiased)	% quadrants selected				Adj. quotient ¹	Bias ²	SD ³	Mean rank	% rank 1	% rank 2	% rank 3	% rank 4
	0–15° 75–90° (unbiased)	15–30° 60–75° (biased)	30–60° (biased)	60–90° (biased)								
92	31	33	36	0.94	-12.31	32.32	1.08	95	2	2	1	
87	29	30	41	0.91	-16.77	34.24	1.13	93	4	2	1	
82	27	35	38	0.88	-22.58	40.00	1.18	90	5	3	2	
79	26	31	43	0.87	-26.12	46.84	1.20	88	6	4	2	
76	25	39	35	0.85	-28.68	47.52	1.23	86	7	4	3	
73	24	36	40	0.83	-32.91	52.98	1.27	84	8	5	3	
67	22	29	49	0.79	-39.74	63.06	1.33	81	9	6	4	
63	21	37	43	0.77	-44.19	67.59	1.37	79	10	7	4	
55	18	28	54	0.72	-53.77	82.10	1.45	74	13	8	5	
42	14	30	56	0.65	-67.46	100.96	1.57	67	16	10	7	

¹ Adjustment quotient = mean density estimate/mean simulation density

² Mean of (density estimate - simulation density)

³ Standard deviation of bias

TABLE 6.—Estimator summary statistics for species and diameter, for 60 trials and 600 plots

Similar bearing tree) species and diameter group (unbiased)	% bearing tree "preferred" group (biased)	% line tree "preferred" group (biased)	Adj. quotient ¹	Bias ²	sn ³	Mean rank	% rank 1	% rank 2	% rank 3	% rank 4	% rank 5
60	26	35	0.80	-12.71	8.49	1.37	81	9	5	3	2
50	27	35	0.76	-15.62	7.16	1.42	77	11	6	4	2
40	40	35	0.70	-19.53	8.79	1.55	70	14	8	5	3
35	50	35	0.66	-21.82	8.78	1.63	67	15	9	6	3
35	40	35	0.68	-20.50	8.51	1.58	69	15	8	5	3
30	50	30	0.65	-22.96	9.30	1.70	65	15	10	6	4
30	46	40	0.65	-22.50	9.66	1.62	66	17	9	5	3
30	38	25	0.69	-20.13	8.34	1.61	70	13	8	5	4
25	55	40	0.62	-24.63	9.52	1.68	63	18	10	6	3
25	42	30	0.65	-22.72	9.46	1.65	66	16	9	5	4
20	54	30	0.60	-26.06	10.24	1.77	61	17	10	7	5
20	50	40	0.61	-25.53	9.65	1.69	62	19	10	6	3
15	62	30	0.56	-28.41	10.79	1.86	57	18	12	8	5
15	53	35	0.59	-26.95	10.25	1.76	60	19	11	6	4
10	62	30	0.55	-29.40	10.90	1.88	56	19	12	8	5
10	57	20	0.57	-27.89	10.56	1.90	59	14	11	9	7
10	56	33	0.57	-28.16	10.68	1.82	57	20	12	7	4
5	70	26	0.51	-32.15	11.87	2.00	53	18	13	9	7
5	65	40	0.53	-30.50	11.41	1.84	54	23	12	7	4
5	62	26	0.53	-30.33	11.19	1.93	55	18	12	9	6
5	59	37	0.54	-29.58	10.88	1.83	55	22	12	7	4

¹ Adjustment quotient = mean density estimate/mean simulation density

² Mean of (density estimate - simulation density)

³ Standard deviation of bias

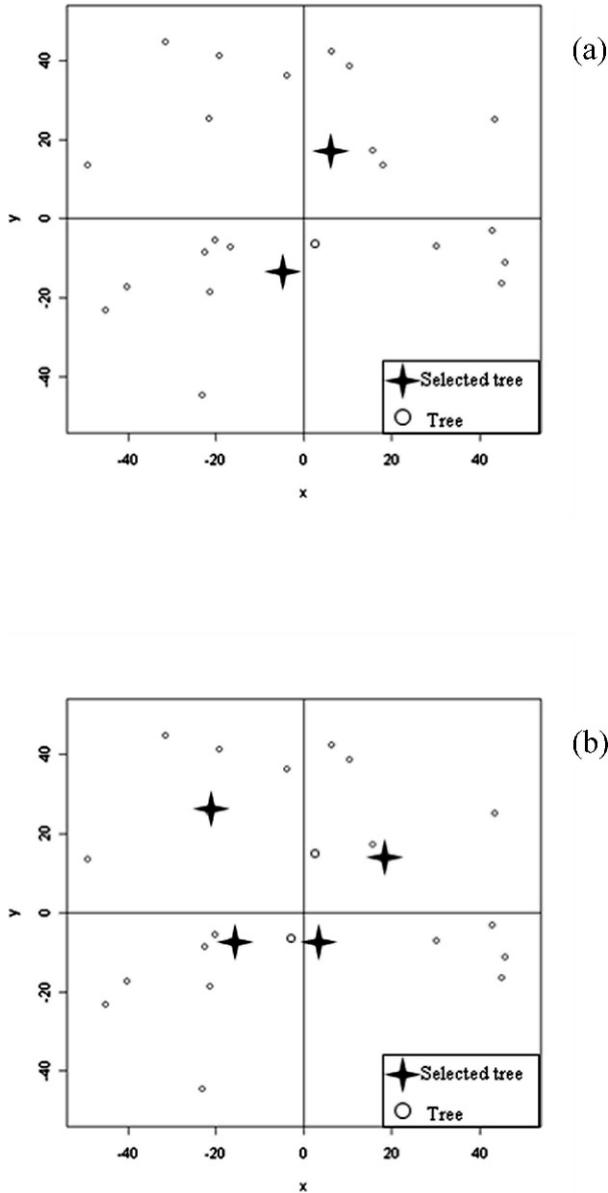


FIG. 1.—Example of (a) point with two trees, where bias caused the southeastern quadrant with the nearest tree to not be selected but did not increase the distance rank within the quadrants with selected trees and (b) a point with four trees selected, where bias increased the distance rank of selected trees

problematic for correction of biases in density estimation, then using this adjustment is not necessary. After azimuth bias correction it is possible to determine the mean tree distance rank, and then adjustment can be made based on meeting a reasonable overall tree distance rank, or range of ranks, instead of based on species and diameter deviations.

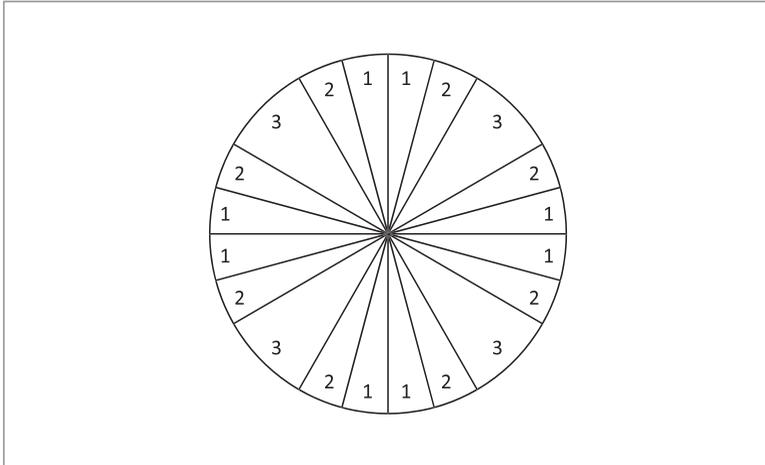


FIG. 2.—Azimuth degree groupings. For the northeast quadrant, group 1 is the most cardinal and contains 0–15 and 75–90, group 2 is moderate and includes 15–30 and 60–75, and group 3 is the most central and contains 30–60. The groupings are repeated for the other three quadrants after adding 90, 180, and 270 degrees

We compared ratios of line trees and bearing trees by species and diameter classes to determine bias ratios, but because we used general categories of similar, preferred, or avoided, these groupings can be determined by the user. We grouped the bearing and line trees into three categories: “similar” representation if the ratio of bearing tree to line tree was 90% to 110%; “preferred” if $>110\%$; and “avoided” if $<90\%$. We placed line trees into the preferred bearing tree group; there was no preferred line tree group. We determined the frequencies of similar, preferred, and avoided for bearing and line trees by ecological subsection.

For each point, we then used a range of bearing tree frequencies (Table 6) to generate a random surveyor ‘choice’ of one of the three groups and we used line tree frequencies to generate a group to represent each tree in a quadrant. If the generated ‘choice’ group was ‘similar’, then the first tree was selected, which was equivalent to unbiased selection of the nearest tree. Otherwise, if the “choice” group and the generated tree group in a quadrant were of the same group, that tree was selected, else, another tree group was generated, with the second distance from the point, then a third and fourth group, and finally a fifth tree group in each quadrant. If the fifth generated tree group in a quadrant never matched the ‘choice’ group, the first tree group was selected.

TARGET RANKS

Both for the rank-based method and bias-based method when azimuth or line trees are not recorded in GLO surveys, researchers need to select a reasonable mean tree distance rank (*i.e.*, a target rank), and a range of ranks, to determine the appropriate amount of adjustment. It seems rational that the surveyor would try to select the nearest tree to the survey point; therefore, the mean distance rank should be no greater than 2. To help select a realistic mean range of target ranks, we used a modern dataset that had points with witness trees, which provided information about the distance order of selected trees, assuming that tree selection is a repeatable process. However, one modern dataset may not provide a

realistic or constant target rank; therefore, another target rank can be selected. The dataset consisted of tree inventory information from about 180 nested fixed-area plots in the Missouri Ozarks. Trees from 12.7 to 30 cm (5 to 11 in) DBH were tallied in 0.02 ha (1/20th ac) plots nested within 0.04 ha (1/10th ac) plots where trees >30 cm (11 in) DBH were tallied (D. Larson, University of Missouri, raw data). At each plot, two witness trees had been selected and diagrammed with the other trees. We digitized plot diagrams and assigned rank based on distance for bearing trees in different quadrants. The first witness tree on average was 1.8 in rank of distance order, which is close to being the second tree; and the second witness tree on average was 3.7 in distance rank, which is close to being the fourth tree. For four trees (but not necessarily in quadrants), the first tree was skipped, the second was selected, the third tree was skipped, and the fourth was selected. Depending on whether the skipped trees were in the same quadrant as the selected trees, it appears that the witness trees were at most second in rank, and possibly close to first, again given that small trees were not included in the density estimation. Therefore, we concluded that the mean rank for selected trees probably was at most 2, and specifically 1.8. Although this rank will not be correct for all GLO surveys, it falls within the range of mean rank between 1 and 2 that we expect for most GLO surveys.

EVALUATION

To evaluate density estimates, we used the mean value of the ratios of the density estimates to the simulated mean densities for each trial, which we termed the adjustment quotient. The adjustment quotient is the amount that surveyor bias has decreased the value of the density estimate and therefore the density estimate must be increased through division by that value. We also measured bias and precision of the density estimators compared to simulated density. We assigned the mean difference between the estimated and simulated values as bias and standard deviation as precision. The exact bias frequencies may not be present in a given GLO dataset for a specific ecological area, so we then created simple regression equations to predict the adjustment quotient (SAS software, Version 9.1, Cary, North Carolina, USA) to calculate density adjustments.

RESULTS

DENSITY LEVELS AND NUMBER OF TREES PER POINT

For the rank-based approach, at a density of five there was a relatively elevated adjustment quotient, so we excluded that density. Also for the rank-based approach, there were differences in adjustment quotients by number of trees per point, due to the additional bias from quadrant location and configuration that was not incorporated into rank but into selection of quadrants. For the bias-based approach, there were no trends in bias by density level in the simulations; therefore, all density levels were combined and as there was little difference in the density estimates by number of trees per quadrant, only the scenario of points with two trees is presented.

RANK

If density estimates are made assuming the nearest trees were selected, the unvarying distance rank of 2 decreased the adjustment quotient of the biased density estimate to the actual simulation mean to 24% for points with two trees and to 35 to 44% for points with three or four trees, respectively (Table 1). An unvarying rank of 3 decreased the density estimates to 13 to 29% of the simulation mean, depending on the number of trees per survey point.

The density estimates changed when the distance rank was not constant (*e.g.*, instead of always selection of the second nearest tree). Density estimates varied based on frequency of trees with distance ranks of 1 to 4 because the distance at a rank of 1 influenced the density estimate relatively more than the distance of a greater rank. Therefore, the adjustment quotient for an unvarying rank of 2 actually corresponded to a greater mean rank of about 2.6 to 2.8 (Table 1).

Surveyors were more likely to select a ranging frequency of distance ranks, rather than only selecting the nearest trees (Table 2). Adjustment quotients ranged from 0.84 to 0.52 for mean ranks of 1.4 to 1.9 respectively and varied by the number of trees per point and the percentage of each rank. For a target rank of 1.8, adjustment quotients ranged from about 0.56 for points with two trees to about 0.65 for points with four trees. A regression of the adjustment quotient (biased estimate to actual density) as the dependent variable and percent rank 1 and percent rank 2 as the predictor variables, yielded R^2 values of 0.99 (Table 7).

QUADRANT LOCATION BIAS

Density estimates remained similar regardless of how the bias was distributed and thus for simplicity, we present results when the bias was loaded in one quadrant (Table 3). Quadrant location effects were trivial and did not affect density estimates by more than 5% (*i.e.*, mean adjustment quotients will be 0.95, based on bias in ecological subsections from Missouri data). A regression of the adjustment quotient (biased estimate to actual density) as the dependent variable and percent quadrants with nearest trees (*i.e.*, the maximum level where all the quadrants share the same base frequency) as the predictor variable, yielded an R^2 of 0.99 (Table 7).

QUADRANT CONFIGURATION BIAS

There were similar density estimates regardless of quadrant configuration resulting from selecting (1) the nearest tree and the nearest adjacent or opposite tree or (2) the two

TABLE 7.—Regression equation coefficients for variables to adjust density estimates

Type of bias	β_0	β_1	β_2	β_3
Rank, based on number of trees per survey point	Intercept	% rank 1	% rank 2	
2	0.1234	0.0087	0.0011	
3	0.1979	0.0080	0.0014	
4	0.2745	0.0073	0.0016	
Quadrant location	Intercept	% quadrants with nearest trees		
	0.6691	0.0033		
Quadrant configuration	Intercept	% quadrants with nearest trees	% trees in adjacent quadrants	
	0.5650	0.0027	0.0024	
Azimuth	Intercept	% quadrants with nearest trees		
	0.4051	0.0058		
Species and diameter	Intercept	% similar bearing and line tree group	% bearing trees in preferred group	% line trees in preferred group
	0.7374	0.0028	-0.0031	-0.0006

nearest adjacent or opposite trees. Therefore, only the nearest point and the nearest adjacent or opposite tree is presented (Table 4). Quadrant configuration adjustments ranged between 0.8 to 0.9 (based on Missouri data). A regression of adjustment quotient (ratio of biased estimate to actual density) as the dependent variable and percent quadrants with nearest trees and percent adjacent quadrants selected as the predictor variables, yielded an R^2 of 0.99 (Table 7).

AZIMUTH BIAS

Varying the distribution of bias into different azimuth groupings had little effect on density estimates (Table 5). Azimuth adjustments ranged between 0.8 to 0.9 (based on Missouri data). A regression, of adjustment quotient (ratio of biased estimate to actual density) as the dependent variable and percent quadrants with nearest trees as the predictor variable, yielded an R^2 of 0.99 (Table 7).

SPECIES AND SIZE BIAS

For species and diameter, the mean adjustment ranged between 0.55 and 0.70 (Table 6; based on Missouri data). A regression, of adjustment quotient (ratio of biased estimate to actual density) as the dependent variable and predictor variables of the percent similar bearing and line tree group, percent of all bearing tree species and diameter in the preferred group, and percent of all line tree species and diameter in the preferred group, yielded an R^2 of 0.99 (Table 7).

APPLICATION OF BIAS-BASED APPROACH TO SURVEY DATA

After simulations, we produced adjustment quotients as ratios of biased density estimates to actual densities. To account for underestimates due to bias, the density estimate was divided by this quotient. This process is repeated for every bias present in quadrant frequency, configuration, azimuth, and combined species and diameter.

Example 1: The density estimate was 100 trees/ha before adjusting for surveyor bias for one ecological unit of at least 50 to 2000 points to fall within certain ranges of accuracy, the points had four trees, and the azimuth bias percent frequency was 31 (most cardinal grouping):33:36 (central grouping), and the species and size bias was unknown. For points with four trees, there was no quadrant selection (*i.e.*, all quadrants were selected), and thus adjustment was not necessary (or possible) for quadrant location and configuration. For the azimuth adjustment, we divided 100 trees/ha by the adjustment quotient of 0.94 (Table 5), increasing the density estimate to 106 trees/ha. We then determined the approximate rank, which was 1.08, of nearest trees due to bias in azimuth selection. We selected a rank from the species and diameter table (Table 6) that placed the overall rank at around 1.8 (suggested by the witness tree dataset). We used a rank of 1.7 (reaching a total rank of 1.78), which had an adjustment quotient of 0.65, increasing the density estimate to a mean of 163 trees/ha. However, we incorporated variability in the density estimate by dividing the density estimate of 106 trees/ha after azimuth adjustment by the mild species and diameter adjustment of 0.8 (rank of 1.37) and the extreme species adjustment of 0.5 (rank of 2), producing a final density estimate range of 133 to 213 trees/ha. The extreme density estimate of 213 trees/ha did not exceed the value of 233 trees/ha ($100/0.43$, where 0.43 is the adjustment quotient for a rank of 2 and points with four trees from Table 1), if the correction was made based on an unvarying rank of 2.

Example 2: The density estimate was 100 trees/ha for points with two trees, the quadrant location bias frequency was 22.5 NE:22.5 SE:22.5 SW:32.5 NW, the quadrant configuration

bias frequency was 40 adjacent:60 opposite, the azimuth bias frequency was 29:30:41, and for species and diameter the unbiased ratio was 50% (total bearing and line tree frequencies within 10% of each other) with 27% bearing trees in the preferred bearing tree group (total of the bearing tree frequencies >110% of the line tree frequencies) and 35% of the line trees in the preferred bearing tree group. We divided 100 trees/ha by 0.96 from Table 3 (now 104 trees/ha), by 0.82 from Table 4 (127 trees/ha), by 0.91 from Table 5 (now 140 trees/ha), and 0.76 from Table 6, resulting in an adjusted density estimate of 184 trees/ha. The mean rank was about 1.55 (from rank 1.13 plus 0.42 from rank 1.42). Note that the adjusted density estimate of 184 trees/ha was about half (0.55) of the 345 trees/ha value of 100 trees/ha corrected for an unvarying rank of 2. This shows that correction for an unvarying rank of 2 is extreme because an unvarying rank of 2 represents a mean rank of about 2.6 to 2.8.

DISCUSSION

Our simulations showed that, in cases where surveyor bias is documented, assuming that the GLO bearing trees were the nearest trees caused forest density to be underestimated using the Morisita estimator and created important consequences for suppositions about density and structure of historical forests. If there is bias present in the historical tree surveys, as there was in Missouri GLO surveys, then after density estimate correction, historical forests may not be as open as previous calculations had suggested. Depending on the specific GLO dataset, bias for combined species and diameter alone may reduce the density estimates by at least 30% and to an extreme of 40% to 50%. Preference for azimuth and quadrant configuration may reduce density estimates in most cases by 10% to 20%. The quadrant location bias had a small effect on the density estimates. In total, surveyor bias may produce density estimates that are 35% to 55% of the actual density and corrected density estimates then will range from about 1.75 to 2.8 of the uncorrected value. A range of values incorporates both uncertainty and variation in the landscape, and uncorrected density estimates perhaps supply the most appropriate low value.

Using a rank-based approach produced similar, but stronger, adjustment quotients. If the distance rank was assumed to be 1 but it actually was unvaryingly 2, the density estimates will be about 25% to 45% of the actual density and the corrected density estimates will increase by 2 to 4 times. Bouldin (2008) also examined tree distance rank effects on Morisita density estimates for four trees and although the methods were different, the adjustment quotients were similar to ours, at 42.9% for rank 2 and 27.3% for rank 3, for points with four trees and unvarying ranks of 2 and 3. Due to additional bias from quadrant selection, points with two and three trees resulted in lower density estimates compared to actual density.

Mean distance ranks, based on varying frequencies of distance ranks, produced more moderate adjustment quotients ranging around 0.55 to 0.65 at a target mean rank of 1.8, increasing density estimates by a factor of 1.5 to 1.8. Using a range of mean ranks from 1.4 to 1.95 will increase density estimates by 1.2 to 2 times. A rank-based approach will provide a rough range of corrected density estimates, but if possible, we do not advise using the rank-based approach alone to correct density estimates. This is because (1) rank will vary by tree rather than remain constantly a single value of 1, 2, 3, or more resulting in different adjustment quotients depending on frequencies of each rank (*e.g.*, 80% of rank 1 and 15% of rank 2 will have a different adjustment quotient than other frequencies), (2) it is unclear what frequencies and number of ranks to use, (3) most importantly, the GLO data impart information about bias that can be specifically adjusted. Simply increasing density estimates by 1.2 to 2 times (the general range of correction based on varying mean ranks of 1.4 to 1.95) will provide an adequate range of density estimates but will not reflect the unique bias present in each

ecological area. Indeed, it would not be appropriate to correct for biased frequencies without first identifying that bias was present, so as not to overestimate densities if there was no bias.

For a bias-based approach, adjusting for bias mostly is a matter of simple division of the (original) density estimate by the adjustment quotient for each bias. If the bias ratios are different than those shown in the tables (3 to 6), or to automate corrections, it will be necessary to use the regression equations (Table 7) to calculate the adjustment quotient for the bias. Some decisions are necessary to correct for species and diameter when the line tree records are unknown or for unrecorded azimuth values. In addition to targeting a rank, we suggest that in general the correction for species and diameter should be greater than correction for either quadrant or azimuth but less than the correction for an unvarying rank of 2, and perhaps less than the varying mean rank of 2. We believe that the estimated adjustment quotient is a maximum value, that is, the actual density will not exceed the estimated density, because we used a minimum value for the percent nearest trees selected. Although this method still is approximate, our adjustment factor for species bias does not assume trees were at equal density, unlike Kronenfeld and Wang (2007). However, our correction for azimuth bias is similar to Kronenfeld and Wang (2007) but with a more conservative adjustment (our adjustment quotient values are about 0.1 greater).

Our adjustments for both the rank-based approach and the bias-based approach for species and diameter with unknown (or uncertain) line tree records or unrecorded azimuths depend on a goal for rank distance between 1 and 2 to be most accurate. Historical records of the species and diameter frequencies generally do not exist, making identification of bias more difficult. The witness tree dataset suggested that a rank somewhere between 1 and 2 is appropriate, with the limitation that any density description only can be for trees with diameters equal to or greater than the 12.7 cm diameter cut-off in tree selection, generally corresponding to the 7.6 to 12.7 cm cut-off for GLO notes. However, other datasets may be available that point towards a more specific mean distance rank or users may feel a more conservative rank is necessary, and then the target rank should be different than 1.8.

CONCLUSION

Potential bias has long been recognized by researchers (Bourdo, 1956; Almendinger, 1996), and from our use of simulations, we produced adjustment quotients to increase the underestimation of density estimates that results from surveyor bias. We have provided an appropriate option for density estimate corrections where deviation from random frequencies is documented in large ecological extents (*e.g.*, 50 to 2000 points). Correction factors are not mutually exclusive with uncorrected density estimates, which can represent the low end of density estimates, whereas a mild adjustment can represent density adjusted for bias. Correction of density estimates may be necessary to provide a reliable range of density estimates, rather than presumption, about historical forest conditions.

We provided two complementary approaches that use the Morisita estimator to correct for surveyor bias, if present in quadrant location, configuration, azimuth, species, and diameter frequencies for larger ecological areas. We assumed that surveyors tended to pick the nearest trees and that, for most GLO datasets, the mean distance rank of selected trees will be between 1 and 2. With the bias-based method, if all information is available, corrections can occur without a need to apply an unknown rank. If azimuth values and line trees are missing, although corrections for azimuth and species and diameter may not be exact because of unknown rank, they will produce less biased estimates than estimates that are unadjusted. If the adjustments using the bias-based approach appear too great, combination with the varying rank-based approach may be useful. That is, the bias-based approach may

produce a greater value than the varying rank-based approach, with an approximate density increase by a factor of 2. Density estimates should include a range of low and high values, to take into account uncertainty and variation in the landscape.

Our corrections should be applicable to non-random frequencies of tree selection for any surveys using the point-centered quarter method. Researchers should determine if their data contain bias, and if so, they can simply place their specific frequencies into regression equations or use a table to adjust density estimates to account for surveyor bias (tree species, size, quadrant location, quadrant configuration, and azimuth). Although there is no reason to believe that biases were limited to GLO surveys in Missouri, surveyors selected trees that were at least 7.6 to 12.7 cm in diameter and thus GLO density estimates are only applicable to trees of at least that diameter. Density estimates of historical forests that include a corrected value are relevant to land managers and others to provide an ecological concept of structure and specific restoration targets.

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APPENDIX 1.—Simulation steps

1. Generate random points for each survey point
2. Select points from each quadrant based on bias scenarios
 - a. Bias scenarios of rank-based approach
 - i. Unvarying selection of tree distance ranks (*e.g.*, always the nearest tree)
 - ii. Varying selection of ranks to reach a mean distance rank (*e.g.*, mean rank of 1.8)
 - b. Bias scenarios of bias-based approach
 - i. Biased selection of quadrant location
 - ii. Biased selection of quadrant configuration
 - iii. Biased selection of azimuth direction
 - iv. Biased selection of species and diameter
3. Calculate one density estimate using Morisita density estimator after generating 600 simulated survey points.
4. Run 60 trials and repeat for a range of densities
5. Calculate the adjustment quotient (ratio of density estimate to simulated mean density) for each trial and density
6. Calculate mean adjustment quotients for each bias scenario

APPENDIX 2.—Steps to determine unbiased (quadrants with nearest tree) for quadrant location, based on departures from the expected frequency of 25 NE : 25 SE : 25 SW : 25 NW

1. Calculate frequencies → 25 NE : 20 SE : 25 SW : 30 NW
2. Identify smallest partitioned value → 35 NE : **20 SE** : 25 SW : 30 NW
3. Multiply smallest value by number of groupings to determine total unbiased percent → $20 * 4 = 80$

APPENDIX 3.—Steps to determine unbiased (quadrants with nearest tree) for azimuth, based on an expected frequency of 33 group 1 : 33 group 2 : 33 group 3

1. Calculate frequencies → 29 group 1 : 30 group 2 : 41 group 3
2. Identify smallest partitioned value → **29 group 1** : 30 group 2 : 41 group 3
3. Multiply smallest value by number of groupings to determine total unbiased percent → $29 * 3 = 87$

APPENDIX 4.—Steps to determine unbiased (quadrants with nearest tree) for quadrant configuration, based on the expected frequency of 67 adjacent quadrant: 33 opposite quadrant

If the percent adjacent quadrants >67:

1. Calculate frequencies → 75 adjacent : 25 opposite
2. The percent opposite quadrants is unbiased → 75 adjacent : **25 opposite**
3. Multiply opposite value by 2 to determine unbiased adjacent percent → $25 * 2 = 50$
4. Add opposite value and unbiased adjacent percent to determine total unbiased percent → 50 adjacent + 25 opposite = 75

If the percent opposite quadrants >33:

1. Calculate frequencies → 50 adjacent : 50 opposite
2. The percent adjacent quadrants is unbiased → **50 adjacent** : 50 opposite
3. Multiply adjacent value by 0.5 to determine unbiased opposite percent → $50 * 0.5 = 25$
4. Add adjacent value and unbiased opposite percent to determine total unbiased percent → 50 adjacent + 25 opposite = 75

APPENDIX 5.—Example Python module

```
def sim_2tree(Ntree, Npoint, Nrank):
    from random import randint, uniform, seed
    from math import sqrt, pi
    from numpy.random import poisson
    import sys
    dist_points = []
    simtrees = []
    xlist = []
    ylist = []
    for k in range(Npoint):
        xydata3 = []
        dist_temp = []
        trees = poisson(lam = Ntree, size = None)
        if trees < 4:
            trees = 4
        point_x = []
        point_y = []
        xdata2 = []
        ydata2 = []
        xdata3 = []
        ydata3 = []
        dist_NE = []
        dist_SE = []
        dist_NW = []
```

```

dist_SW = []
for i in range(trees):
    x = uniform(-50,50)
    y = uniform(-50,50)
    point_x.append(x)
    point_y.append(y)
for k in range(len(point_x)):
    ID = 0
    for l in range(len(point_x)):
        dista = abs ((point_x[k]-point_x[l])**2) + ((point_y[k]-point_y[l])**2)
        dist2 = sqrt (dista)
        ID = 0
        if dist2 <= .25 and dist2 > 0:
            ID = 1
        if ID == 1:
            xdata3.append (point_x[k])
            ydata3.append (point_y[k])
            break
    if ID == 0:
        xdata2.append (point_x[k])
        ydata2.append (point_y[k])
xseq = xdata3[:,2]
yseq = ydata3[:,2]
xdata2.extend (xseq)
ydata2.extend (yseq)
xydata2 = zip (xdata2, ydata2)
[xydata3.append(i) for i in xydata2 if not xydata3.count(i)]
xlist, ylist = zip(*xydata3)
simtr = float(len(xlist))
simtrees.append (simtr)
for m, (x, y) in enumerate (xydata3):
    dist = sqrt (x**2 + y**2)
    if x >= 0 and y > 0:
        dist_NE.append(dist)
    if x > 0 and y <= 0:
        dist_SE.append(dist)
    if x < 0 and y >= 0:
        dist_NW.append(dist)
    if x <= 0 and y < 0:
        dist_SW.append(dist)
dist_NE.sort()
dist_SE.sort()
dist_NW.sort()
dist_SW.sort()
if dist_NE == []:
    dist_NE = [70.00, 70.00]
if dist_SE == []:
    dist_SE = [70.00, 70.00]

```

```

if dist_NW == []:
    dist_NW = [70.00, 70.00]
if dist_SW == []:
    dist_SW = [70.00, 70.00]
sample = dist_NE[Nrank-1]
dist_temp.append(sample)
sample = dist_SE[Nrank-1]
dist_temp.append(sample)
sample = dist_NW[Nrank-1]
dist_temp.append(sample)
sample = dist_SW[Nrank-1]
dist_temp.append(sample)
dist_points.append (dist_temp)
sim = (sum (simtrees)/Npoint)
return dist_pointssim
def method(dist_points, method):
    from random import randint, uniform, seed
    dist_extracted = []
    for ij in enumerate (dist_points):
        if (method == "near"):
            dist_points[i].sort()
            dist_extracted.append(dist_points [i][0])
            dist_extracted.append(dist_points [i][1])
    return dist_extracted
def Morisita(new_L, Npoint, Nquad, Npoint, Nrank):
    from math import sqrt, pi
    Mor3 = (Nrank*Nquad-1)/(pi*Npoint)
    Mor2 = 0
    if (Nquad == 2):
        for ind in range(0,len(new_L)-1, 2):
            Mor2 += Nquad/((new_L[ind]**2) + (new_L[ind + 1] **2))
    morisita = Mor2*Mor3
    return morisita

```