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SAMPLING SIMULATION WITH A MICROCOMPUTER

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Abstract. A Forest Sampling Simulator (FOSS) interactive computer program has been developed to investigate the merits of various sampling designs for instruction and research. FOSS allows the user to study aspects of sampling efficiency as affected by spatial patterns of trees in a forest, number of observations, size and shape of individual sampling units, and method of selecting samples. A large variety of field conditions can be simulated, and relevant statistics allow comparisons among sampling schemes. The program is written in BASICA and runs on an IBM personal computer or other fully compatible units. This software package was developed as a teaching tool and does not process field data.

Introduction

Many decisions and inferences about forest and other plant community characteristics are based on samples. In each case, the reliability of the final outcome is affected by the sampling method. Since there is more than one possible solution to a given sampling problem, the concept of efficiency or relative precision is used to evaluate the merits of various sample estimators. In comparing two unbiased estimators of the same population characteristics, the one with the smallest variance is said to be more efficient, thus more precise, than the other. For biased estimators, the mean square error is used instead of the variance (Cochran 1977). When cost is also taken into consideration, then the cost-effectiveness of a sample estimator is determined by the product of its variance and the respective cost of the survey (Arvanitis and O'Regan 1967, Sukhatme and Sukhatme 1977, Vries 1986).

An efficient sampling scheme must yield the highest possible precision for a fixed cost or the desired level of precision at the lowest possible cost. In the vast majority of real-world cases, precision and cost must both be considered as constraints of an intelligent sampling design. For example, if measurement costs exceed the budget, one may sacrifice precision by reducing the sample size. Alternatively, the sampler could explore other designs, which may provide the specified level of precision within the available budget.

To assist foresters, ecologists, range specialists and other plant scientists in becoming better acquainted with sampling efficienty, a microcomputer program has been developed, which allows users to evaluate the merits of various sampling methods using a computer simulation approach. The use of computers as teaching and learning tools is well documented by Heermann (1988). To the best of our knowledge, computer simulation of forest sampling methods was first introduced by Palley and O'Regan (1961). The senior author of this paper has benefited greatly from Palley and O'Regan's work as graduate student on the same subject at the University of California, Berkeley. Podani (1987), in his well documented paper, has summarized a good number of simulation cases in forest and other vegetation studies that have been conducted during the last twenty five years. Simulation encourages intensive exploration of a model and development of problem-solving skills, the result of creative thinking.

Main features of Forest Sampling Simulator (FOSS)

The software package, Forest Sampling Simulation (FOSS), was developed to complement an introductory course in forest sampling. It may also serve professionals who need to expand their understanding of factors involved in conducting forest or other plant inventories. FOSS offers opportunities for research on sampling as well.

FOSS is divided into three main modules or programs: POPULATION, PLOT CONFIGURATION, and SAMPLING DESIGN. Each module allows users to experiment with and compare various sampling strategies. For example, POPULATION generates stands of trees with different spatial patterns (such as random, aggregated, or plantation-type), diameter distributions, and density gradients. PLOT CONFIGURATION provides an opportunity to choose sampling units with specific size and shape characteristics: circular, square, or rectangular fixed area plots; points, lines and strips. SAMPLING DESIGN allows users to study the relative efficiency of different sampling designs: simple random, systematic, list, 3-P, stratified, vertical point, vertical line, quadrat, distance, multiphase and multistage.

To run FOSS, which handles both, English and metric units, the user needs to:

a. Choose a spatial pattern of trees (POPULATION).
b. Specify a diameter distribution for the trees (Normal or Weibull).

c. Select a density gradient for the forest (optional).
d. Select the size and shape of the elementary sampling unit (PLOT CONFIGURATION).
e. Specify cost and precision requirements.
f. Enter the sample size or allow FOSS to compute this value.
g. Select a specific sampling method (SAMPLING DESIGN).

Module POPULATION

In POPULATION, the user creates a forest stand, which is superimposed onto a 162×621 rectangular matrix and displayed on the screen through high resolution graphics. The population (forest) may consist of a maximum of 2000 tree centers represented by points on the screen. For each tree, the program generates a diameter at breast height (DBH), a total tree height (THT), and a corresponding cubic volume (VOL).

Spatial Patterns

Upon selecting the desired POPULATION, the user is expected to read the discussion section, which appears on the screen and subsequently choose one of three spatial patterns: random, aggregated, or uniform (plantation-type).

Random - The sub-module *Random* generates a stand of trees with a random spatial pattern (Fig. 1). The location of any other tree within the same forest. Individal tree centers are specified by rectangular coordinates obtained from a pseudo-random number generator. The seed (or starting point) is randomly determined by an internal clock, which prevents identical populations from being generated in repeated simulations. Although random patterns are not common in biological populations, they allow for comparison of sample statistics among different spatial patterns. Sub-module *Random* requires only one input, the population size (N).

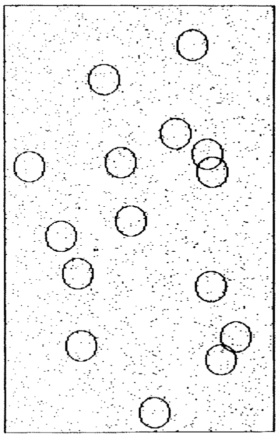

Fig. 1. Random spatial pattern of 2000 tree centers within an area of 3,48 ha. An example of simple random sampling with replacement. Fifteen circular samples about 202 m^2 each in size.

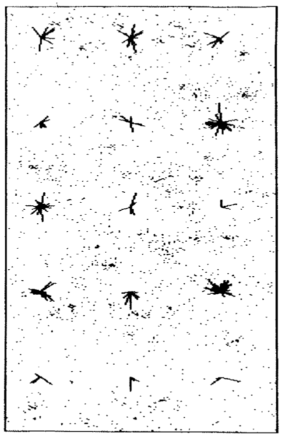

Fig. 2. Aggregated spatial pattern of 2000 tree centers within an area of 3,48 ha. Number of clusters 50; scaling factor 0.01; probability of aggregation 0.80. Fifteen sample points of 2,3 m^2 basal area factor systematically arranged.

Aggregated - This sub-module generates a stand in which the trees occur in clusters or groups (Fig. 2). The average number of trees per cluster and the size of individual clusters are functions of a probability parameter (P) and a scaling factor (S). The parameter (P) specifies the probability that a given tree will be located within a randomly selected cluster. For each tree in the forest, a pseudo-random number is generated between 0 and 1. If this number is greater than P, the tree is randomly located within the boundaries of the forest. If the number is less than P, the tree is randomly assigned to a cluster. Its distance from the cluster center is determined as follows (Reich 1980):

$$D = ABS\,(LN\,(RND))/S \tag{1}$$

where

D distance from cluster center,
ABS absolute value,
LN natural logarithm,
RND random number, $0 < RND < 1$,
S scaling factor, $.01 < S < .2$.

The azimuth of an individual tree from the vertex of the cluster center is determined by generating a random angle between 0 and 360 degrees. Tree distances extending beyond the population boundaries are continued along the same azimuth on the opposite side of the forest.

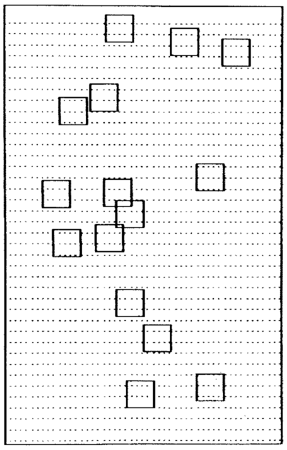

Fig. 3. Plantation-type spatial pattern of 2000 tree centers in a forest of 3,48 ha. Distance between rows 12 units; distance between trees in a row 6 units. Simple random sampling with square plots about 202 m^2 each in size.

Aggregated requires four inputs:

a. Population size (N)
b. Probability of aggregation (P), $0<P<1$
c. Number of cluster centers (C), $1<C<100$
d. Cluster scaling factor (S), $.01<S<.2$.

In the field, tree aggregation results from factors such as site quality differences, regeneration methods, cutting practices, species competition, and diseases, to mention but a few. As a result, the degree of aggregation or clustering will vary considerably depending on the above input values. A very large number of real-world cases may be simulated ranging from diffused to very condensed clusters of trees or other plants.

Uniform - The sub-module *Uniform* generates a plantation-type spatial pattern in which trees are regularly spaced over a given area on vertices of a square or rectangular lattice (Fig. 3). Uniform requires three inputs:

a. Population size
b. Spacing between rows
c. Spacing within rows.

Diameter Distribution

For a given spatial pattern (*i.e.*, random, aggregated, or uniform), FOSS will prompt the user to select a tree diameter distribution: normal or Weibull. If the normal distribution is selected, the user must enter a mean and a standard deviation. Tree diameters are then generated using the following algorithm:

$$DBH = Mean + Z^* (standard\ deviation)$$

where Z is a standard normal random variate. If the user selects the Weibull distribution, the program will ask for three values:

a. The smallest tree diameter in the stand "a", $(a>0)$,
b. The scaling parameter "b", such that 63% of the tree diameters are between "a" and "b",
c. The shape parameter "c", $(0.2<c<6)$.

If "c" is less than or equal to 1, tree diameters will have an exponential distribution. If "c" is greater than 1, diameters will have a modal or mound-shape distribution. For $c=3.4$, the Weibull and normal distributions are identical. Distributions with $c>3.4$ are shewed to the left while distributions with $c<3.4$ are skewed to the right. After the user enters the appropriate Weibull values, tree diameters are generated using the following relationship:

$$DBH = a + b\ [-LN\ (RN)]^{1/c} \qquad (2)$$

Table 1. Results from simple random sampling with 202 m^2 circular plots in a random spatial pattern of trees.

STATISTICS	INDIVIDUAL TREE DBH (CM.)	INDIVIDUAL TREE THT (M.)	INDIVIDUAL TREE VOL (CU. M.)	MEAN BA (SQ. M./HA)	MEAN VOL (CU. M./HA)
POINT ESTIMATOR	23.126	17.911	0.130	24.924	73.607
ST. ERROR	0.504	0.103	0.006	2.330	7.013
% ERROR	2.178	0.574	4.402	9.349	9.528
95% CONFIDENCE INTERVAL					
LOWER BOUND	22.046	17.690	0.117	19.924	58.558
UPPER BOUND	24.207	18.132	0.142	29.924	88.655
POPULATION					
MEAN	22.942	17.960	0.128	24.886	73.721

RANDOM. (NO. HECTARES = 3.48, NO. TREES = 2000, SAMPLE SIZE = 15); PLOT SHAPE - CIRCLE.

Table 2. Results from horizontal point sampling with Basal Area Factor 2,3 m^2/ha in an aggregated spatial pattern (50 clusters of trees).

STATISTICS	INDIVIDUAL TREE DBH (CM.)	INDIVIDUAL TREE THT (M.)	INDIVIDUAL TREE VOL (CU. M.)	MEAN BA (SQ. M./HA)	MEAN VOL (CU. M./HA)
POINT ESTIMATOR	21.440	16.865	0.104	30.150	71.307
ST. ERROR	1.628	1.216	0.005	4.903	11.555
% ERROR	7.594	7.209	4.458	16.261	16.205
95% CONFIDENCE INTERVAL					
LOWER BOUND	17.946	14.256	0.094	19.630	46.512
UPPER BOUND	24.934	19.474	0.114	40.670	96.102
POPULATION					
MEAN	22.872	17.976	0.101	30.480	71.953

AGGREGATED. (NO. HECTARES = 3.48, NO. TREES = 2000, SAMPLE SIZE = 15). PLOT SHAPE: HORIZONTAL POINT SAMPLE.

where RN is a uniformly distributed random variate in the interval 0 to 1, and LN is the natural logarithm.

Once the tree diameters have been generated, the program calculates the total height (THT) of each tree and its cubic volume (VOL) using the following two equations:

$$THT = \exp\,[4.29989 - 1.92889/DBH],$$

and

$$VOL = \exp\,[-5.50594 + 1.69040\ LN\,(DBH) +$$

$$+\ 1.14862\ LN\,(THT)]$$

The coefficients of these two equations were computed from diameters, heights and volumes measured in English units. The results are subsequently converted into metric units, which are included in Tables 1, 2, 3 and 4.

Gradient

This is an important feature of FOSS. After the population (forest) has been generated, the user has the option of creating a density gradient (Fig. 4). This is accomplished by transforming the rectangular X and/or Y tree coordinates as follows:

$$Z' = a^* \exp\,(b^*Z) \qquad (3)$$

where

Table 3. Results from simple random sampling with 202 m^2 square plots in a plantation-type forest pattern.

STATISTICS	INDIVIDUAL TREE DBH (CM.)	INDIVIDUAL TREE THT (M.)	INDIVIDUAL TREE VOL (CU. M.)	MEAN BA (SQ. M./HA)	MEAN VOL (CU. M./HA)
POINT ESTIMATOR	22.739	17.160	0.122	24.723	70.741
ST. ERROR	0.319	0.059	0.003	1.481	4.271
% ERROR	1.404	0.344	2.715	5.990	6.038
95% CONFIDENCE INTERVAL					
LOWER BOUND	22.054	17.034	0.115	21.545	61.576
UPPER BOUND	23.424	17.287	0.130	27.232	79.906
POPULATION					
MEAN	22.907	17.188	0.124	24.232	69.3791

UNIFORM. (NO. HECTARES = 3.48, NO. TREES = 2000, SAMPLE SIZE = 15). PLOT SHAPE: SQUARE.

Table 4. Results from random line-point sampling in a spatial pattern with East-West gradient.

STATISTICS	INDIVIDUAL TREE			MEAN	
	DBH (IN.)	THT (FT.)	VOL (CU. FT.)	BA (SQ. FT./A)	VOL (CU. FT./A)
POINT ESTIMATOR	21.967	17.705	0.118	25.739	75.921
ST. ERROR	8.271	3.316	0.087	6.181	18.243
% ERROR	37.650	18.731	73.467	24.016	24.029
95% CONFIDENCE INTERVAL					
LOWER BOUND	4.220	10.589	−0.068	12.475	36.777
UPPER BOUND	39.714	24.821	0.070	169.895	115.066
POPULATION					
MEAN	22.915	17.974	0.128	24.797	73.478

GRADIENT. (NO. HECTARES = 3.48, NO. TREES = 2000, SAMPLE SIZE = 15). PLOT SHAPE: H. LINE.

Z original X or Y data coordinate,
Z' transformed data coordinate,
a, b model coefficients
exp exponential.

The user selects an appropriate gradient (North-South, East-West or both N-S and E-W) by entering 0, 1, 2, or 3 when prompted by the program. A N-S gradient changes the Y coordinate and an E-W gradient changes the X coordinate. As the gradient value increases from 0 to 3, the rate of change also increases. For example, suppose the original (X, Y) coordinates for a tree center are (408.22, 43.67). If an E-W gradient value of 0 were selected, the coordinates would remain unchanged. A value of 1 would transform the X coordinate to 281.40, while a value of 3 would transform it to 106.54. This feature of FOSS allows simulation of field conditions where, for various reasons, *e.g.*, exposure, regeneration pattern and other prevailing ecological factors, more plants may be found close to one side of the population under study. In such cases, the plant density diminishes proportionally to the distance from the edge.

Module PLOT CONFIGURATION

In the module PLOT CONFIGURATION, the user selects the elementary sampling units, which are classified as fixed area plots, variable plots or points, lines and strips. In choosing the most efficient configuration, the user must consider the cost and workload associated with carrying out the various alternative sampling designs.

Fixed Area Plots

FOSS offers a choice of four plot shapes: square, rectangular, circular, and strip. A plot center is generated at random, and plot boundaries are laid out. Strips run at random or systematically from a starting point within the inventory tract.

After a plot shape is selected, the program allows selection from two sizes of strip widths (20×1 and 20×2 units) and four sizes of other plot shapes: 51, 202, 506, and 809 m^2 each. At this stage of the program, the user needs to consider cost and precision, weighing plot size against number of plots. Which would be more efficient, sampling with many small plots or with fewer large plots? Often small plots are preferable because they are spread more than large ones over the area of interest. However, travel cost increases proportional to the number of plots and so does the likelihood of more

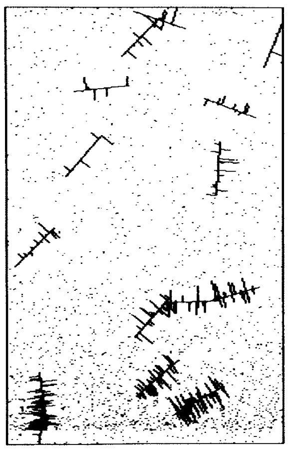

Fig. 4. Spatial pattern of 2000 tree centers within an area of 3,48 ha. An East-West gradient of value 2 is present. Fifteen random transects with point sampling (basal area factor 2,3 m^2) are the elementary sampling units. Lines perpendicular to the transects indicate distances to trees included in the sample.

plots being located near the population perimeter. The latter introduces a bias known as statistical edge effect; special provisions are needed to correct for such a bias (Fowler and Arvanitis 1979, 1981; Arvanitis and Fowler 1987). Sampling with fewer but larger plots can be advantageous when rough terrain, lack of accessibility or dense stands and undergrowth increase the travel time between plots, as is the case in the tropics. Thus, the user needs to be aware of trade-offs and compromises involved in making a good choice between number of plots and size of individual plots (Arvanitis and O'Regan 1967, Zeide 1980).

Point and Line Sampling

FOSS includes point and transect sampling (Fig. 2 and 4). In this type of sampling there is no fixed area associated with plot centers. For instance, in horizontal point sampling, each tree in the population can be thought of as the center of its own circular plot. The size of the plot is a function of the tree DBH and a critical angle or basal area factor (Bitterlich 1948; Grosenbaugh 1958). If a sample point falls within this imaginary plot, the tree is counted as a sample tree. For vertical point sampling, the tree height is used as a criterion in place of DBH. In line sampling, trees are sighted for inclusion from transects in random or systematic intervals (Figure 4). The criteria for counting sample trees in line sampling are the same as in point sampling. FOSS provides a choice of four lengths of lines: One, two, three and four units each.

Unlike the equal probability fixed area sampling, variable plot or point sampling is based on selection probabilities proportional to some measure of tree size such as diameter or height. When properly applied, this type of sampling yields more efficient estimates of certain forest characteristics, such as basal area and volume, for the same amount of effort or cost than fixed area sampling.

Edge Effect

As stated earlier, in determining the most desirable combination of number of plots and the size of each individual plot or basal area factor, one must consider correcting for bias due to the statistical edge effect. This type of bias is more serious in small elongated tracts than in larger ones. One source of bias results when an adjustment is not made for those sampling units, which extend beyond the tract boundaries. For example, suppose a tract of land were to be sampled using fixed area circular plots. Each tree may be thought of as the center of an imaginary circle with an area equal to that of the plot being used. The probability of a tree being selected in a random drawing is equal to the area of this imaginary circle divided by the total area of the tract. Trees that lie near the tract border may have circles that extend past the boundary. As a result, the probabilities of including such trees in the sample are reduced. This reduction introduces bias in the sample estimates (Grosenbaugh 1958, Arvanitis and O'Regan 1967, Schmid 1969; Beers 1977).

A second source of bias occurs when the sampling units are restricted from crossing the tract boundaries. This type of restriction, which is applied too often in practice, can result in an undersampling of those trees close to the tract border.

In its present version, FOSS corrects for edge effect bias in point and line sampling but not in fixed area plot sampling. This does not diminish the value of the program, which is intended to help users understand the basics of sampling efficiency. However, one needs to be aware that statistical bias due to edge effect is present in most forest inventories and it must be dealt with appropriately (Arvanitis and Fowler 1987). Its magnitude depends upon the size and the shape of the forest as well as the sampling intensity.

Module SAMPLING DESIGN

In the module SAMPLING DESIGN, the user sets cost and/or precision requirements, chooses the method of allocating the sample units, and determines the sample size. FOSS includes eight sampling methods: simple random, systematic, stratified random, list, 3-P, distance, multiphase and multistage sampling.

For square, rectangular or strip plots, the population (forest) can be divided into a finite number of sampling units. In the case of circular plots or points, the number of possible sampling units is infinite. For finite populations, samples are drawn from the sampling frame, which is the list of all elementary sampling units (trees, plots, strips) in the population.

Simple random sampling: Sample units are selected with equal or unequal probabilities. The latter applies to point sampling, list sampling, and 3P sampling.

Systematic sampling: Selects sampling units at fixed intervals throughout the population.

Stratified random sampling: The population (forest) is divided into strata that share a common attribute. These non-overlapping strata can be identified by age, topography, forest-cover type, tree density, size, and many other stand characteristics. FOSS, which stratifies by DBH, offers three methods for allocating the sampling units among strata: a) proportional allocation, in which the sample size for each stratum is directly related to stratum size (*e.g.*, area, volume, value); b) Neyman's allocation, which distributes sample observations among strata according to stratum size and variability (*e.g.*, variance, standard deviation, coefficient of variation); c) optimal allocation, in which the size, variability, and sampling cost per stratum are considered in determining a sample size needed to meet specified precision requirements and/or budgetary constraints.

List sampling: The user is working with individual trees of the forest. The probabilities of selection are proportional to tree size denoted by the product: $[(DBH)^2$ (Total Tree Height)$]$. The statistics from each list sample are compared against those of an equal probability simple random sample to determine its relative efficiency. This type of sampling is not very practical for large forests because complete lists of individual trees are not readily available. However, the procedure can easily be applied when group of trees, stands or small compartments are the elementary sampling units.

3-P sampling: The selection probabilities are proportional to an ocular prediction of some characteristic of interest, such as volume or value (Grosenbaugh 1964). It requires relatively few field measurements, and the method may yield more efficient estimates than sampling with equal probability when good and consistent ocular estimates are secured. 3-P sampling may be used alone or in combination with other designs such as multistage sampling. To apply 3-P sampling, which does not require a list, the user needs to specify the sample size and the method used in obtaining ocular estimates, such as tree volume. For a given forest, FOSS keeps track of the volume of the largest individual tree, the total forest volume and the total number of trees in the forest. Tree volume estimates may be based on DBH, DBH^2 or (DBH^2*THT). The user may also specify the percent error and bias associated with the ocular estimates of DBH and/or height of the trees. This option allows the user to evaluate the impact of systematic and random errors on the precision and accuracy of 3-P sampling. FOSS does not take into consideration the presence of any strata when estimating cubic volume, basal area or any other stand characteristics.

Distance sampling: Employed to estimate tree density using Hopkins' modified coefficient of aggregation A*, defined as follows:

$$A^* = \frac{A}{1+A}$$

where

$$A = \Sigma\, w_1^2/w_2^2$$

$\Sigma\, w_1^2$ sum of square distances from randomly selected points to the nearest tree, and

$\Sigma\, w_2^2$ sum of square distances from randomly selected trees to their nearest neighbor.

A* is particularly suitable for identifying spatial patterns of trees and other plants. Among five distance estimators tested by Reich (1980), A* was the best in consistency and relative efficiency. It is a very useful index for determining spatial pat terns of diseased trees in a forest. FOSS simulates distance sampling and computes A* in each trial, which may then be used to identify one of the three spatial patterns: Random, aggregated and uniform (plantation type). For example, using a 95% confidence level and sample size of 150, a hypothesis of a random spatial pattern ($A^* = 0.50$) would be acceptable only if $0.444 \leq A^* \leq 0.556$ with .95 power of the test. For plantation-type patterns $A^* < 0.4$, and for aggregated $A^* > 0.6$.

Multiphase sampling: As the term implies, sampling is performed in more than one phase. The familiar double sampling is a two-phase sampling design. In the first phase, FOSS selects a large random sample of an easily measured tree characteristics, *e.g.* $(DBH)^2$, which is highly correlated with the variable of interest, such as volume. In phase two, a sub-sample of trees selected in the first phase is identified and both measured characteristics (DBH and volume) are recorded. The two phases are combined using regression to estimate the volume of the forest under consideration. The procedure may be extended to more than two phases. Statistics are provided to make comparisons for relative efficiency with other designs, such as simple random or systematic sampling.

Multistage sampling: FOSS divides the forest into a number of primary units (first stage). Each of these units is further subdivided into second stage units, etc. Sampling is performed independently for each stage and their variances are combined to make inferences about the forestry total. The main objective of both, multiphase and multistage sampling designs is to minimize the field work, the most expensive component of forest and other plant surveys and provide cost-effective estimates.

Concluding remarks

For each sampling method, statistics appear on the screen (such as in Tables 1, 2, 3 and 4, corresponding to respective figures) and may be printed for subsequent study. Users can also view the location and distribution of trees and sampling units on the screen and observe change of numerical values of estimators in repeated sampling. An understanding of sampling variability and confidence intervals emerges as the user observes the effects of varying the location and number of observations, the size and shape of individual sampling units and confidence coefficient on the precision (standard error) of sample estimates.

Forest sampling simulation with a microcomputer enhances the ability of users to comprehend basic concepts of inventory methodology. Our tests and experience suggest that students and professionals respond very favorably to this instructional aid, which is intended to supplement traditional classroom teaching and field work. Researchers also find FOSS intriguing. To perform similar experiments in real forests is seldom feasible because of budget, time and personnel constraints. In addition, computer simulation provides an opportunity to explore a wide range of sampling designs and gain a good appreciation of the factors that affect sampling efficiency. It fosters critical thinking and encourages exploration of unknown relationships difficult to comprehend otherwise.

Finally, a word of caution. Simulation models are, at best, abstracts of the real world. As such, they cannot depict fully the complexities of natural systems. Oversimplification is one of the main disadvantages. However, careful design and proper communication with the user as to the limitations of simulated cases will minimize misuse of this challenging tool. The authors are of the opinion that FOSS falls in this category. Like every other computer simulation model, its effectiveness will improve with the availability of more powerful microcomputers, supporting software, and innovative users.

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