Sources of Uncertainty in Annual Forest Inventory Estimates

Ronald E. McRoberts

Abstract.—Although design and estimation aspects of annual forest inventories have begun to receive considerable attention within the forestry and natural resources communities, little attention has been devoted to identifying the sources of uncertainty inherent in these systems or to assessing the impact of those uncertainties on the total uncertainties of inventory estimates. A brief overview of the annual forest inventory system under development for the North Central region is provided, sources of uncertainty within the required components are identified, and their magnitudes and impacts on Forest Inventory and Analysis (FIA) estimates are discussed.

Developers of annual forest inventory systems in the US generally agree that all such systems share requirements for several functions: (1) remote sensing; (2) an annual sample of measured plots; (3) a database of plot and tree information; and (4) a method for updating plot and tree information for plots that have not been measured in the current year. All these components are included in the annual forest inventory system that is being developed for the North Central region (fig. 1).

A brief overview of the annual forest inventory procedures under development for the North Central region describes the function of each component. Remote

Mathematical Statistician, USDA Forest Service, North Central Research Station, 1992 Folwell Avenue, St. Paul, MN, USA.

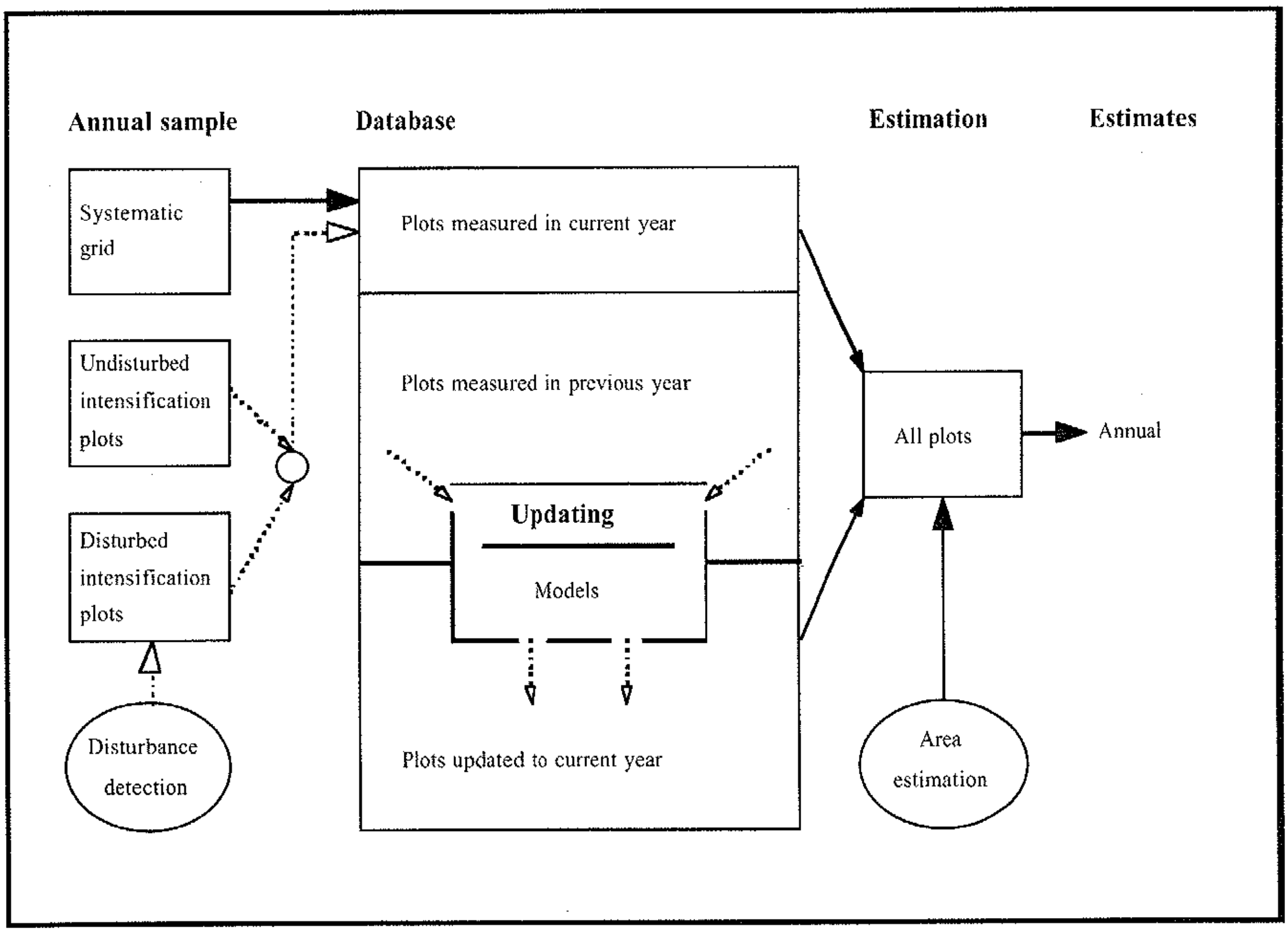

Figure 1.—*Annual forest inventories in the North Central region.*

sensing with satellite imagery is used to identify non-forested and broad strata of forested tracts, to estimate the area of these strata, to classify permanent Forest Inventory and Analysis (FIA) plots into one of these strata, and to determine the area within the strata represented by each plot. Second, an annual sample of plots is selected from two categories: first, a 20 percent sample of forested plots from a systematic grid of plots approximately uniformly distributed across each state, and second, additional non-grid plots selected for specific state-designated purposes. The set of plots selected from the grid is referred to as a single intensity inventory, and the measurement of these plots is funded by the USDA Forest Service. Some states, including Minnesota, Wisconsin, and Michigan, provide funds to measure additional plots for purposes such as increasing the precision of timberland estimates. The portion of the annual sample consisting of these supplemental plots is typically restricted to plots located on productive timberland. Plot and tree information is entered into a database where it is maintained and made accessible to users. Growth and mortality models are used to update the size and status of trees located on plots that are not measured in the current year. However, because the accuracy of the models is considered to be inadequate for trees on recently disturbed plots, first priority for the supplemental sample is given to plots that have experienced recent severe disturbance, primarily due to harvest. These disturbed plots are identified using remote sensing techniques that compare the two most recent sets of satellite imagery. Finally, FIA estimates for variables such as volume are obtained by summing across trees within plots to obtain plot-level estimates on a per acre basis, and then multiplying these plot-level per acre estimates by area expanders and summing across plots to obtain stratum, species, or regional estimates. The components of uncertainty that contribute to the uncertainty of the latter estimates are of primary interest for this study.

This paper is a preliminary report on a study that has three objectives: (1) to identify the sources of uncertainty associated with components of the annual forest inventory system used in the North Central region; (2) to estimate their magnitudes; and (3) to assess their impact on the overall uncertainty of annual forest inventory estimates.

REMOTE SENSING

Area Estimation

Remote sensing techniques are applied in forest inventories in the North Central region to estimate area and to classify plots into broad strata. These tasks are accomplished using remotely sensed data from two sources: satellite imagery from the Landsat Thematic Mapper (Bauer *et al.* 1994, Rack 1994, Moore and Bauer 1990, Hopkins *et al.* 1988) on an approximate 4-year cycle and recent low level aerial photography. The spectral band values from the satellite imagery are analyzed using digital methods to classify pixels into broad classes: cloud or cloud shadow, water, non-forest land, and one or more broad categories of forest land. The purpose of this level of classification is to estimate the overall forest area and to select plots for measurement that fall in forested tracts. The consequences of classification errors at this level are either to fail to include a forested plot in the sample or to include a non-forested plot in the sample. Inclusion of a non-forested plot reduces the precision of estimates, because such a plot does not contribute to estimates for the forested area. Exclusion of a forested plot from the sample generally does not reduce precision, because another forested plot will be selected in its place. However, such a failure may bias the overall volume estimate because the volume for the excluded plot was not available for inclusion in the sample that then includes non-random components.

Visual interpretation of low level photography is used to further stratify plots in forested tracts into strata that roughly correspond to categories related to land use, forest type, and size. The purpose of stratification at this level is to reduce the variances of final inventory estimates. Because of the labor intensity associated with photo interpretation, techniques for stratifying forested tracts using satellite data are also being developed, albeit for a smaller number of strata. For stratification to be beneficial, within-stratum variances must be smaller than the overall variance obtained without considering the stratification. Thus, classification errors at this level of stratification cause increases in the variances of final estimates. However, even with the finer resolution and larger number of strata obtained using photo interpretation, the relative magnitudes of the within-stratum variances for volume compared to the overall variance suggest that little benefit is being achieved with this approach (fig. 2).

The total area for each stratum, determined from remote sensing, is divided by the total number of plots in the stratum to obtain area expanders that indicate the area represented within a stratum by each plot. The sum over all plots within a stratum of the products of the per acre plot volume estimates and the corresponding area expanders produces a volume estimate for the stratum. Misclassification of plots at this level of stratification causes biased estimates of stratum area, inaccurate area expanders, and biased stratum estimates.

Disturbance Detection

A class of plots for which models are generally regarded as inadequate for predicting growth consists of plots that have experienced recent, severe disturbance. This class includes the approximately 1.5 percent of plots that are

Figure 2.–*Results of stratification using photo interpretation.*

harvested in Minnesota annually. Digital disturbance detection is used to identify these plots so they can be selected for measurement as soon as regeneration has been established; for current applications this is approximately 5 years after disturbance. Digital disturbance detection consists of comparing the digital values for the Landsat Thematic Mapper spectral bands using computer-based algorithms. For each pixel, differences between the digital value for the two most recent sets of imagery are calculated and used to calculate values of an index that has been selected to be highly correlated with actual vegetation change on the ground. Based on their index values, pixels are classified into broad strata corresponding to vegetation gain, vegetation loss, and little vegetation change. Pixel-based maps representing disturbance classes are overlaid on the array of permanent FIA plots, and each plot receives a disturbance value.

The accuracy of disturbance detection has been partially assessed for plots whose loss of vegetation has been predicted to fall beyond one standard deviation of a mean index value (table 1). For predicted disturbance based on digital analysis of Landsat Thematic Mapper data at 4-year intervals and true disturbance based on examination of plot sheet comments recorded by field crews, 95 percent of plots predicted to be undisturbed were found to be actually undisturbed, while 69 percent of the plots predicted to be disturbed were found to have actually experienced disturbance. Because the purpose of disturbance detection is to identify plots for which growth

Table 1.—*Accuracy of digital disturbance detection*

Landsat TM status	Field observation		Total	Prediction success
	No change	Change		
	- - - -	*no. plots*	- - - -	
No change	332	19	351	0.95
Change	53	116	169	0.69
Total	385	135	520	

models may be biased, there is little loss associated with failure to discover disturbance on plots where it was predicted to have occurred. Measurements for these plots are simply included with measurements for other undisturbed plots. However, failure to identify and measure a disturbed plot is much more serious, and although the cumulative error rate over the 4-year imagery cycle is only about 5 percent, it applies to approximately 96 percent of the plots. In such cases, pre-harvest volume, updated using the growth models, will erroneously be used for these plots rather than the minimal volume that will have regenerated in the approximately 5 years since harvest.

ANNUAL SAMPLE

The characterization of forest inventories as annual is based on the measurement of an annual sample of plots and the capability of producing annual FIA estimates, not on a complete annual inventory of all plots. FIA precision standards for the North Central region require a sampling intensity of one plot for approximately every 6,000 acres. To satisfy this requirement, a grid of hexagons, each approximately 5,900 acres in area, has been established by subdividing the hexagons established for the Forest Health Monitoring (FHM) program (Eagar *et al.* 1991, White *et al.* 1992). A permanent FIA field plot was either established or selected from existing plots to represent each smaller hexagon. The single intensity inventory, funded by the USDA Forest Service, consists of a 20 percent systematic sample from this grid each year. The State of Minnesota traditionally provides additional funding to increase the precision of inventory estimates for areas considered to be productive timberland. These supplemental plots are non-grid, permanent FIA plots on productive timberland selected according to two criteria: (1) plots that are predicted to have experienced substantial vegetation loss approximately 5 years ago are selected to determine how these plots have regenerated; and (2) a sample from the remaining non-grid plots that have not been predicted to have experienced harvest or other disturbance are either randomly selected or are selected to address specific issues such as the effects of drought, blow-downs, ice storms, or growth and mortality for particular species.

Three primary sources of uncertainty are of concern in the sampling component: among-plot sampling variability, within-plot sampling variability, and measurement error. Variability among plots cannot be controlled although its effects can be partially mitigated by stratification of plots to reduce its overall effects as previously discussed under remote sensing for area estimation. The term within-plot sampling variability is used to describe the variation in plot-level variables such as site index that are obtained via a sample. McRoberts (1996a) reported that site index estimates, obtained using age and height measurements from two or more dominant or codominant trees and site index curves, had coefficients of variation that ranged from 0.07 for 70-year-old trees on high site index plots to 0.13 for 50-year-old trees on low site index plots. The magnitudes of measurement errors for plot- and tree-level variables vary considerably depending on the variable measured. In a North Central Station study of field crew measurement error, each of nine field crews made standard FIA measurements on the same plot (McRoberts *et al.* 1994). For diameter, measured to the nearest 0.1 inch with a diameter tape, coefficients of variation ranged from 0.015 for small trees to 0.025 for large trees. Uncertainty in diameter measurements not only affects estimates of diameter and variables based on them such as basal area and volume, but for variable-radius plots it also affects tree expanders that indicate the number of trees per acre represented by each tree. Measurements of crown ratio, visually estimated as the ratio of living crown to height, ranged ±0.3 from the median. Frequently, these variables are selected as predictors in diameter growth models. A primary consequence of their uncertainties is to increase the uncertainty of growth predictions for trees on plots not measured in the current year (McRoberts 1996b). Finally, plot location errors may be relevant in this discussion, but they are expected to be minimized through application of global positioning systems.

UPDATING

Tree Variables

The Forest Inventory and Analysis program at the North Central Research Station currently uses the STEMS (Belcher *et al.* 1982) growth models to update plots and trees not measured in the current year. These regional models were developed from data collected primarily from research plots and have generally been accepted for application in the North Central region. If the updating procedure is sufficiently precise, the precision of the inventory estimates can be improved by inclusion of this large class of plots measured in previous years but without the adverse effects of using out-of-date information.

Although the STEMS models are generally accepted as adequately unbiased on a regional basis, there has been little analysis of their associated prediction uncertainty. The conclusions of a detailed report of recent simulation work in this area, reported in another session of this meeting (McRoberts *et al.* 2000), as they affect this discussion, are threefold: (1) although the uncertainty in diameter predictions may be large for individual trees, the effects are greatly attenuated for estimates at plot- and region-levels (fig. 3); (2) the effects of uncertainty in the model predictions, although relatively small on a regional basis, should not be ignored; and (3) the overall prediction uncertainty may possibly be reduced by excluding from the models some predictor variables, even though they

Figure 3.—*Uncertainty of predictions using STEMS diameter growth models based on 1,000 simulations that included uncertainty due to residual variability, dbh and crown ratio measurement errors, and site index sampling variability.*

significantly increase the quality of fit of the model to the calibration data.

Plot Regeneration

Although disturbances due to clearcuts can be detected with reasonable accuracy, the nature of the regeneration on these clearcut plots is usually uncertain for approximately 5 years after harvest. Thus, in Minnesota, field crews will not visit clearcut plots until approximately 5 years after harvest. However, because it is inappropriate to classify harvested plots as unstocked for 5 years, a procedure for estimating initial regeneration is being developed. While this procedure is being developed, regeneration of harvested plots is predicted to be in the same ground cover class as before harvest. This technique is regarded as a reasonable interim solution, but it generates uncertainty about the cover on harvested plots as will any technique that does not involve actual measurement of the plots.

DATABASE

The heart of annual forest inventories is the database of plot- and tree-level information. For all permanent FIA plots and for all trees on them, these data are entered into the database repository, updated when appropriate in subsequent years, and used to calculate FIA estimates. Although data entry and transcription errors contribute to the overall uncertainty in forest inventory estimates, no investigation of the magnitude or consequences of this source of uncertainty has been initiated at this time. The database is made accessible using increasingly user-friendly interfaces that allow users to conduct their own analyses.

CONCLUSIONS

The previous discussion on sources of uncertainty for annual forest inventories is summarized in table 2. Three conclusions can be drawn from the discussion: (1) additional analyses are required to quantify the uncertainty associated with the components of inventory systems and to quantify their impacts on the uncertainty of FIA estimates; (2) analyses should be undertaken to determine if the traditional variance reduction techniques such as stratification are producing the desired and expected benefits; and (3) careful analyses are required to properly determine the sources of uncertainty that are contributing most to the uncertainty of FIA estimates and

Table 2.—*Sources of uncertainty in annual forest inventories*

Component	Source of uncertainty	Magnitude	Impact	Comments
Remote sensing	Area estimation	Small	Small	
	Stratification	Small	Small	Perhaps little benefit
	Disturbance detection	Large	__?__	5% error on 96% of plots
Annual sample	Plot location	Small	Small	
	Sampling variability			
	Among plots	Large	Large	Unavoidable
	Within plots	Large	__?__	Contributes to model error
	Measurement error	Varies	__?__	Contributes to model error
Updating	Prediction uncertainty			
	Residual variability	Large	__?__	Less impact at regional level
	Parameter uncertainty	__?__	__?__	Less impact at regional level
	Propagation of uncertainty	Large	__?__	Less impact at regional level
	Regeneration	__?__	Small	Little volume involved
Data base	Recording	Small	Small	
	Data entry	Small	Small	
	User errors	__?__	__?__	

to develop techniques for eliminating or mitigating their adverse effects. Very simply, the time is upon us for detailed and thorough analyses of uncertainties in all inventories, whether annual or periodic, if we are to provide the public with defensible estimates of forest resources.

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