EFFICIENCY AND PRECISION FOR ESTIMATING TIMBER AND NON-TIMBER ATTRIBUTES USING LANDSAT-BASED STRATIFICATION METHODS IN TWO-PHASE SAMPLING IN NORTHWEST CALIFORNIA

Antti T. Kaartinen, Jeremy S. Fried, and Paul A. Dunham [1]

ABSTRACT.—Three Landsat TM-based GIS layers were evaluated as alternatives to conventional, photointerpretation-based stratification of FIA field plots. Estimates for timberland area, timber volume, and volume of down wood were calculated for California's North Coast Survey Unit of 2.5 million hectares. The estimates were compared on the basis of standard errors, conformance to FIA accuracy standards, and gain in precision achieved by stratification relative to simple random sampling and to conventional photointerpretation. Some satellite imagery-based approaches were found to be far less costly than the conventional method, with very little sacrifice in precision.

National forest inventories in the United States, conducted by the USDA Forest Service's Forest Inventory and Analysis (FIA) program, have traditionally relied on two-phase (or double) sampling for stratification. This technique leverages expensive-to-measure data collected from field plots with cheap-to-measure attributes derived from remote sensing imagery to achieve reductions in the variance of the inventory estimates. Cochran (1977) described the underlying theory and Poso and others (1990) applied this theory in a forest inventory using remote sensing as the Phase 1 data source. Chojnacky (1998) described the application of double sampling to FIA inventories.

At the Pacific Northwest Research Station, the FIA unit with responsibility for forest inventory in California, Oregon, Washington, Hawaii, and the Pacific Islands, Phase 1 has long consisted of a primary (0.85 mile) grid of points stratified according to forest characteristics via ocular interpretation of aerial photography. In Phase 2, crews visit a systematic 6-percent sample of the Phase 1 points to install field plots and collect a rich suite of plot and vegetation attributes. Photointerpretation (PI), while less costly than field installation of plots, is still very labor intensive and prone to producing interpreter-dependent results. Other problems with PI include inconsistent photo quality, cost of photography, logistical challenges of handling and storing large numbers of photographs, and difficulty in ensuring independence between PI and field plot measurement (because interpreters often know which PI points are also field plots) (Hansen 2000). These issues led the FIA program to seek an alternative approach to stratification. Recently, remote sensing techniques and digital data processing hardware and software have developed rapidly. Semi-automated digital remote sensing approaches offer many benefits compared to photointerpretation, such as generating useful maps as byproducts, allowing better understanding of spatial relationships, and permitting capture of data not obtainable via ocular PI; e.g., infrared portions of the spectrum (Congalton and Green 1999).

As with national-scale forest inventories elsewhere, FIA is completing a transition from a primarily timber-focused resource inventory to a multipurpose ecological inventory designed to assess attributes considered essential to more complete characterization of forest habitats and biodiversity. For example, down wood (DW) volume can serve as a useful indicator of biodiversity because it is a measurement with high repeatability and it affects many resource qualities, including species richness, species interactions, and temporal processes (Carroll 1993). An important question then is: Whether, and how much, any kind of stratification improves precision of non-timber attributes? Given that both manual and semi-automated types of approaches rely on classification of

[1] Volunteer Forester, Research Forester and Team Leader, and Forester, respecively. UDSA Forest Service, Pacific Northwest Research Station, P.O. Box 3890, Portland, OR 97208. Phone: 503-808-2058 (Fried); fax: 503-808-2020 (Fried); e-mail: antti.t.kaartinen@helsinki.fi (Kaartinen); e-mail: jsfried@fs.fed.us (Fried); e-mail: pdunham@fs.fed.us (Dunham).

overstory, we had no basis for assuming that stratification would improve precision for such estimates.

In this study, four stratification approaches were evaluated: three semi-automated approaches based on vegetation estimates derived primarily from Landsat Thematic Mapper (TM) satellite imagery and aerial photointerpretation. The principal hypothesis we sought to evaluate is that one or more semi-automated remote sensing approaches to stratification would yield accuracies comparable to that achieved with a traditional PI, at a reduced cost. We compared precision achieved for selected FIA estimators, time requirements, and the economic considerations implied by the cost of data acquisition, preparation, and analysis. Attributes included timberland area[2], timber volume on timberland, and volume of down wood (diameter ≥ 5 inches). Indications of precision were obtained by comparing approaches for each attribute the population estimates, standard errors, and the gain in statistical efficiency resulting from stratification (as compared to random sampling). We also compared the degree of conformance with FIA program goals for sampling error for selected variables, where:

$$E_O = \frac{(\text{Standard Error})}{\text{Estimate}} \qquad (1)$$

and

$$E_A = \frac{(E_{SP})\sqrt{\textit{Specified volume or area}}}{\sqrt{(\textit{Estimated total volume or area})}} \qquad (2)$$

where

E_O = observed sampling error

E_A = allowable sampling error

E_{SP} = specified sampling error in percentage at the specified volume or area, which is:

10 percent per 1 billion cubic feet of growing stock on timberland, or

3 percent per 1 million acres of timberland

(USDA Forest Service 1967). Observed sampling errors can be converted to a specified area or volume (i.e., 1 million acres or billion cubic feet) basis by using formula 3 (Hansen 2000):

$$E_S = \frac{(E_O)\sqrt{\textit{Estimated total volume or area}}}{\sqrt{(\textit{Specified volume or area})}} \qquad (3)$$

where

E_S = sampling error for the specified area or volume

The most important accuracy requirement in FIA inventory is 3 percent sampling error per 1 million acres of timberland (USDA Forest Service 1967). For total volume on timberland, the goal is 10 percent per 1 billion cubic feet, but this is “error to be achieved as closely as practicable.”

STUDY AREA

We selected the field-sampled area of 2.5 million hectares within California’s North Coast Survey Unit[3] (fig. 1) because there was a recent (1994) FIA inventory data set available for this area and because the vegetation ranges from dense forest to oak woodland and shrub savannah, which makes for a challenging test of the alternative approaches. Three satellite imagery-based vegetation map products were available for this area, which allowed a comprehensive comparison of different approaches.

Dominant forest cover in the timberland portions of the study area consists of redwood (*Sequoia sempervirens*), Douglas-fir (*Pseudotsuga menziesii*), and tanoak (*Lithocarpus densiflorus)* with white fir (*Abies concolor*), grand fir (*Abies grandis*), ponderosa pine (*Pinus ponderosa*), sugar pine (*Pinus lambertiana*), Pacific madrone (*Arbutus menziesii*) and California black oak (*Quercus kelloggii*) accounting for most of the rest of the trees (Waddell and Bassett 1996). Elevation ranges from sea level to > 2,000 m, and precipitation ranges from 0.6 to 3.2 m per year.

METHODS

Data Sources

Four different vegetation coverage datasets were used in the study. In the first one, ocular PI was applied. Classifications of Landsat TM satellite imagery into vegetation cover types

[2] Timberland is forest land capable of growing continuous crops of trees to industrial roundwood size, quality, and quantity, with a mean annual increment of 1.4 m^3/ha/year at culmination; forest land is, or has been and is likely to be again, at least 10 percent stocked by trees and is not converted to nonforest use (Phillips 1991).

[3] Consists of 6.2 million acres of private and non-reserved public lands outside of national forests and national parks in the counties of Del Norte, Humboldt, Mendocino, and Sonoma (Waddell and Bassett 1996) (fig. 1).

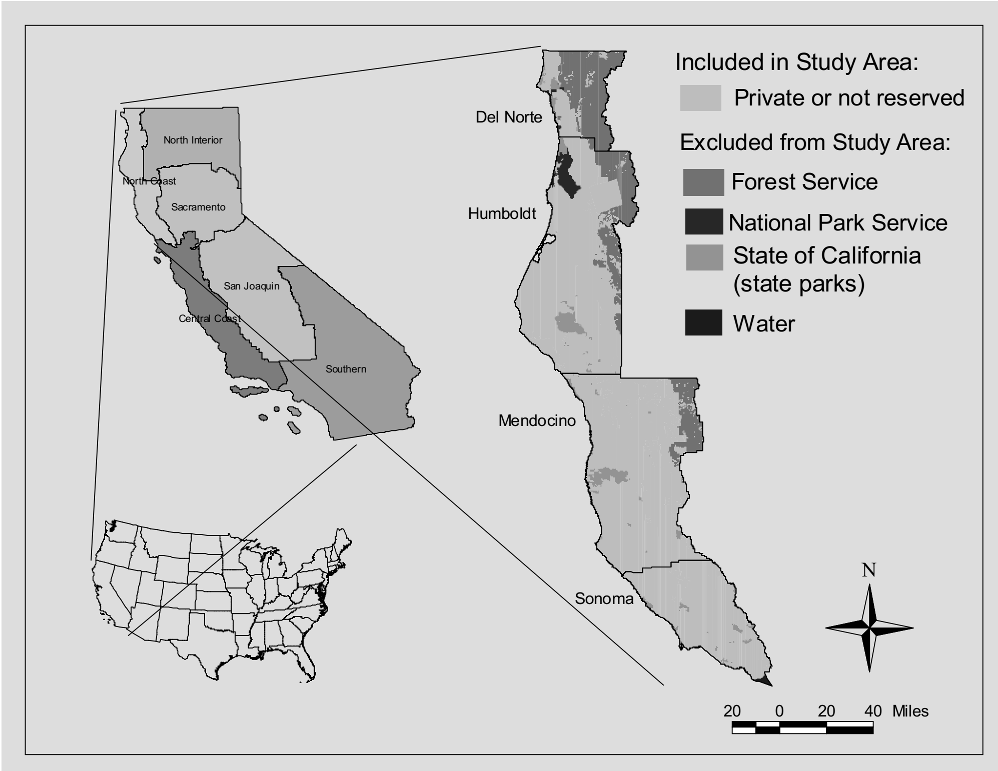

Figure 1.—*Land ownership in the North Coast Survey Unit of California.*

were at the core of all three semi-automated stratification approaches. In all three cases, 30-m Landsat TM images from the early 1990s were used.

FIA Data

Ocular PI of 10,691 points on 1:32,000 scale, 1988 vintage black and white photography was performed by four interpreters for the study area in 1991. The information interpreted for a 5-acre circle around each PI point included forest land stratum (FLS) (with 16 possible classes based on productivity and crown closure), crown cover (percent), stage of stand development, and plant community (Phillips 1991).

Field plots, which were installed on a 3.4-mile square grid, consisted of clusters of five variable-radius subplots, inscribed within a 2.5 ha circle, on which trees > 5 inches d.b.h. were assessed for a rich suite of attributes, including size (d.b.h., h), species, and timber quality (crown ration etc.). Understory vegetation, seedlings, and saplings were assessed on smaller areas within subplots, and down wood was sampled on three transects per subplot.

Classification and Assessment with Landsat of Visible Ecological Groupings

The CALVEG (Classification and Assessment with Landsat of Visible Ecological Groupings) GIS coverage[4] (figs. 2 and 3) is essentially a modeled vegetation typing (5-ac minimum mapping unit (MMU)) generated from Landsat imagery, unsystematic, non-random field observations of vegetation, DEM-estimated elevation, slope and aspect, and the expert opinion of local forest managers. The modeling is highly localized, with over 100 variants needed to cover the whole state. Validation is based on FIA plot data and both error matrix and fuzzy set approaches (FIA User's Guide 2001).

National Land Cover Dataset

The NLCD (National Land Cover Dataset) GIS layer [5] (figs. 2 and 3) was modeled via unsupervised classification of terrain-corrected, 1992 vintage Landsat 5 TM imagery from

[4] Provided *gratis* by the Remote Sensing Lab at the USDA Forest Service, Pacific Southwest Region, in Sacramento, CA; available for most of California.

[5] Available for the lower 48 states from the Multi-Resolution Land Characteristics Consortium (MRLC) at the USGS EROS Data Center, Sioux Falls, SD.

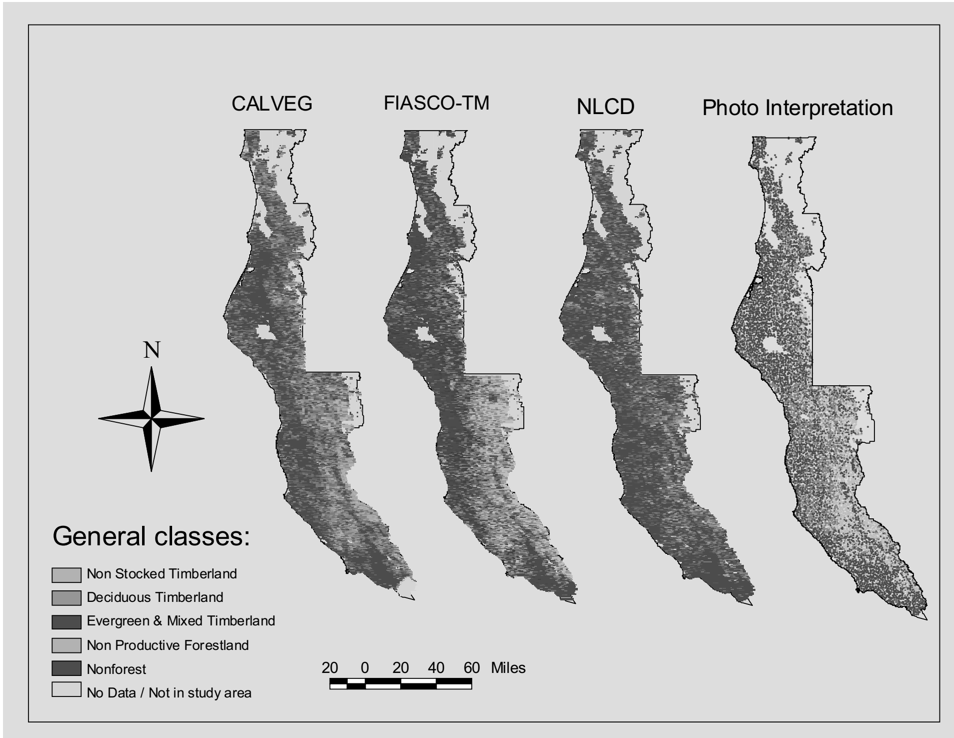

Figure 2.—*Forest classification of the four stratification sources tested for the North Coast Survey Unit.*

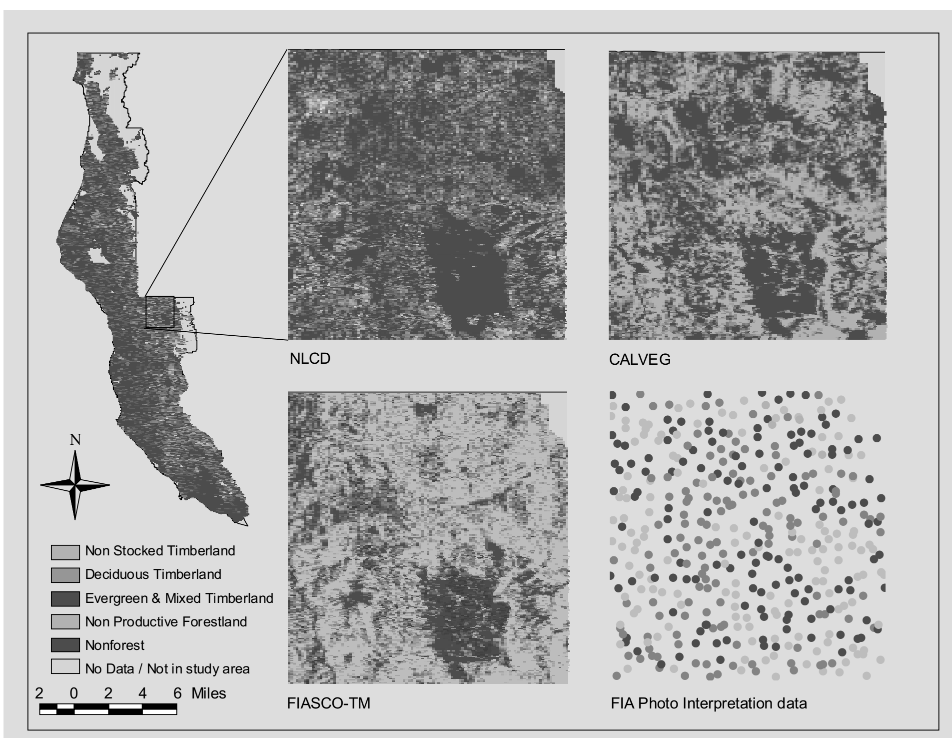

Figure 3.—*Fine-scale inspection of the four stratification sources tested reveals effects of differences in class definitions among stratification sources.*

at least two different seasons (e.g., leaf-on and leaf-off), census tracts, existing mid-scale cover layers, wetland inventory, and maps of soil attributes (water capacity and organic carbon) (Vogelmann and others 2001). Accuracy assessment was based on interpretations of 1990 National Aerial Photography Program photographs and probability sampling (Vogelmann and others 2001).

Forest Inventory and Analysis Stratification with Classification of Thematic Mapper

The FIASCO-TM (Forest Inventory and Analysis Stratification with Classification of Thematic Mapper) vegetation coverage was constructed via a combination of supervised classification of Landsat TM imagery and a reduced intensity sample of photointerpreted Phase 1 points. The classification program[6] applied a supervised maximum likelihood classification algorithm, described by Richards (1994) and Campbell (1987), that used a subset of FIA PI points as a training sample. Regions of interest were created around each PI point, and the spectral signatures of these regions were used as seeds for the classes created. Error statistics for the classification were calculated with FIA plot data. The result of the FIASCO-TM classification was a classified raster image (figs. 2 and 3) with error statistics describing the accuracy of the classification. In this study, the Landsat imagery was classified to FIA FLS classes; however, the FIASCO-TM approach could just as easily use any other classification system.

The input to FIASCO-TM consists of georeferenced Landsat imagery, data for the training areas, and plot data for accuracy assessment. Four Landsat scenes for July 1990 covering the North Coast study area were georeferenced, normalized, and mosaicked[7]. Total root mean square error of the georeferencing was close to one-half of the pixel size, which is appropriate for this purpose (ERDAS 1997, Vogelman and others 2001).

Sampling Techniques

Alternative stratifications were applied using a SAS-based 'Tabling' application[8] to generate population estimates and associated variances under three sampling scenarios: double sampling for stratification, stratified random sampling, and simple random sampling (Cochran 1977).

The theory of two-phase sampling is described by Cochran (1977). The technique uses a relatively large sample of more general and cheaper-to-obtain Phase 1 data to divide the population of interest into subpopulations from which the Phase 2 sample is drawn in order to reduce the variance of the population estimates. Based on the values of some variable, the population is stratified into a number of classes. The first sample is a simple random sample; this sample corresponds with PI points in FIA inventory parlance. The second sample can be a subsample from the first sample (e.g., in FIA inventories, field plots are a subsample of PI points), or it can be drawn independently. The cost per sample unit is usually low in Sample 1 compared to Sample 2, and the Sample 2 data are more detailed. When a double-sampling approach is used, the key problem is to choose the size of the samples and the number of sample units in each stratum so that the variance of the estimate is minimized for any given cost.

In stratified sampling a population is divided into subpopulations called strata. When the strata have been determined, a sample is drawn from each. If the sample taken from each stratum is a random sample, the whole procedure is called stratified random sampling. The use of stratification can improve the accuracy of estimates for the whole population. A heterogeneous population can be divided into homogeneous strata based on an attribute thought likely to be related to the attributes for which population estimates are sought, and precise estimates of stratum means can be achieved by drawing a sample from within a stratum. These estimates can then be combined to obtain estimates for the entire population.

Simple random sampling, where no Phase 1 exists and each field plot represents the same proportion of the total population, is considered in this study as the cheapest and most straightforward way to implement a forest inventory.

Sarndal and others (1992) define a stratification design effect—a measure of the gain in statistical efficiency achieved through stratification—as the ratio of the variance with stratification and the variance with simple random sampling. Here, five different levels of design effect were considered, as shown in table 1.

[6] Written in IDL macro language of the ENVI GIS software environment by Dr. Michael Lefsky.

[7] Using ERDAS Imagine and IDL macro language programs.

[8] Documentation by Larry Bednar (2001) on file at the USDA Forest Service, Pacific Northwest Research Station, Portland OR.

Table 1.—*Levels of statistical efficiency used to evaluate the gain of precision via stratification*

Design effect (*percent*)	Level of statistical efficiency
80-100	No effect
67-80	Minimal
50-67	Moderate
25-50	Substantial
0-25	Excellent

The NLCD and FIASCO GIS layers were segmented and sieved (ERDAS 1997) to achieve minimum mapping units consistent with FIA field plot condition mapping rules. In essence, this procedure replaces homogeneous areas smaller than 4 pixels (about 1 acre) with the majority value from surrounding cells.

Areas of forest transition (e.g., from forest to nonforest or from well-stocked to non-productive) typically exhibit greater heterogeneity than pure stands, and such transitions are often so gradual as to make delineation of an exact border challenging. Not surprisingly, such transition zones are loci with a high probability of classification errors resulting from class definitions and layer registration issues. To address these issues, we created edge strata along the edges of productive forest, other forest, and nonforest following an approach pioneered by Hansen (2000). For each Landsat-derived stratification layer, 2-pixel-wide edge classes were created for each of three land classes. Standard errors for timberland area estimates were always lower when edge strata were used, and they were usually lower for timber volume.

Differences in attribute detail and classification systems among the GIS layers meant that each had to be simplified and cross-walked separately, and iteratively, to produce stratification systems capable of near optimal precision gain. Stratification performance was evaluated iteratively, as strata count, edge class configurations, and assorted crosswalk criteria were adjusted by comparing calculated standard errors, conformance to FIA accuracy standards, and design effect for timberland area, timber volume, and DW volume estimates among candidate stratification systems.

Optimizing Precision for Each Stratification System

Two PI-based stratification systems were tested. The "production PI" mimicked the 1994 FIA inventory of the North Coast Survey Unit, for which PI points were divided into groups by FLS code and owner only, and this layer was used to stratify the field plots. Because the available PI data include considerably more detailed information than FLS code alone, and some of this information could considerably improve stratification, a second "optimal PI" stratification system was developed, making use of stage of stand development, plant community, and density information in addition to FLS class. From PI data, we separated all groups that had different combinations of these attributes, and we combined strata that had only a few field plots with the closest remaining stratum. Optimal PI did not improve precision as compared to production PI for timberland area estimates but did for timber volume.

Four stratification systems were tested using the CALVEG GIS layer. One used only the size class information and the second used only density class. Both of these resulted in remarkably high standard errors for timberland area and timber volume because the attributes that were used to define the strata did not form homogeneous classes in terms of these attributes. The third involved a cross-walk from CALVEG to FIA FLS classes that combined vegetation cover type, size, density, and species information in the GIS layer. These strata were much more homogeneous within strata with respect to, for example, plot volume. The fourth added the edge classes (fig. 4) to CALVEG–FLS classification, further reducing the standard error of timberland area but increasing standard error on timber volume estimates.

Following Hansen (2000), segmentation and sieving were applied to transform the NLCD to achieve a MMU of 1 acre, cross-walked to forest and nonforest classes and added forest and nonforest edge classes (designated "fnf") (fig. 4). This reduced standard errors for timberland area estimates compared to stratifications based on the stock NLCD GIS layer. Recoding the NLCD GIS layer to three classes: forest, other forest,[9] and nonforest, and building edge classes for each ("fofnf"), improved precision for timber volume estimates.

[9] Below a productivity threshold implied by the cover type designation.

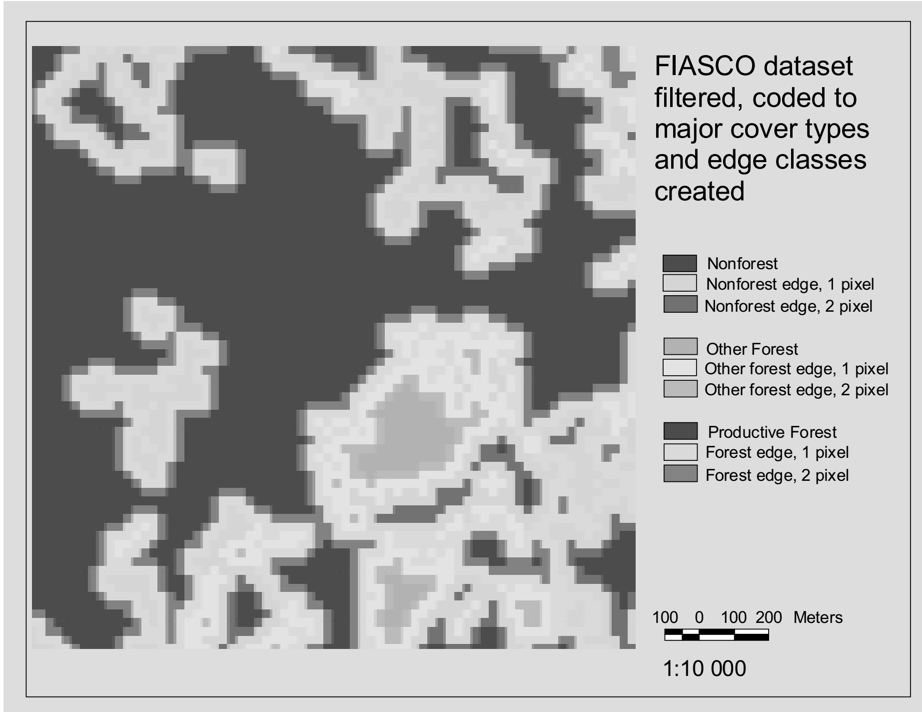

Figure 4.—*Sample from FIASCO-TM GIS layer after 2-pixel-wide edge classes around forest, other forest, and nonforest classes are generated.*

We tested a FIASCO-TM classification using a 20-percent sample of the PI points clustered by photo so that all points on a photo are used but only 20 percent of photos. This clustered approach is essential to reducing the photo and labor costs associated with the PI component of the FIASCO-TM approach. A post-processed version that was filtered and augmented with edge strata for forest, other forest, and nonforest (fiasco_fofnf) improved precision for estimates of timberland area and down wood.

Operational Considerations

Cost and operational issues also figure prominently in choosing a stratification system. Depending on the system, several expenses must be accounted for such as photo acquisition, photo setup and interpretation, Landsat image or GIS product acquisition and processing, and geoprocessing. Time requirements and costs were estimated based on recent PI projects and expenses incurred for this analysis, converted to a per million acres basis, and expanded to generate estimates for states in the PNW region for which a decision on Phase 1 is imminent.

RESULTS

Timberland Area

Only the PI-based stratifications were successful in achieving an error per million acres rate below the 3-percent goal specified in the Forest Service Handbook (USDA Forest Service 1967) as the most important benchmark (table 2). The best precision obtained from a semi-automated stratification system for timberland area was CALVEG with edge classes. Two of the three semi-automated stratification systems achieved substantial to excellent design effects, and one was just below substantial.

Total Volume on Timberland

The remarkable reduction in sampling error achieved for volume by substituting “optimal PI” for “production PI” suggests that considerable volume variation cannot be explained by broad forest type alone. There is very little difference in precision between the production PI and the semi-automated stratification systems, and the statistical efficiency of stratification for volume estimation is moderate at best (table 3).

Table 2.—*Timberland area in the North Coast Survey Unit based on the best stratification from each data set*

Method	Standard error	Timberland area	Sampling error per million acres	Design effect
	Acres	*Acres*	*Percent*	*Percent*
Production PI	49,852	2,924,100	2.92	30
Optimal PI	50,573	2,911,300	2.96	31
CALVEG Edge	58,599	2,854,800	3.47	41
NLCD fnf	63,002	2,911,700	3.69	48
FIASCO fofnf	69,696	2,809,200	4.16	58
Random Sample	69,696	2,847,300	5.42	100

Table 3.—*Total volume on timberland in the North Coast Survey Unit based on the best stratification from each data set*

Method	Standard error	Timber volume	Sampling error per billion cu ft	Design effect
	Thousand cu ft	*Thousand cu ft*	*Percent*	*Percent*
Optimal PI	417,300	10,490,000	12.88	58
Production PI	464,730	10,618,000	14.26	72
CALVEG FLS	470,970	10,297,000	14.68	73
NLCD fofnf	474,250	10,410,000	14.70	74
FIASCO fofnf	465,940	10,050,000	14.70	72
Random Sample	550,100	10,245,000	17.19	100

Total Volume of Down Wood

Down wood, down logs, and branches with diameter ≥ 5 inches are important habitat components for a number of wildlife species and may be good indicators of biodiversity, but there is no precision standard for this attribute in the FS inventory system. None of the stratification systems improve the estimates of DW very much; the design effect is minimal at best (table 4). However, sampling error per billion cubic feet of DW is not much higher than it is for standing volume, so even without stratification, precision would likely be acceptable for most applications.

Operational Considerations

Costs per million acres range from $854 for NLCD to $82,218 for CALVEG in areas (i.e., outside of California) where that classification layer does not yet exist (table 5). Except for CALVEG outside California, all of the methods tested would be far less expensive than PI. For methods implemented across all of California, Oregon, and Washington, the cost of stratification ranges from $113,000 (for NLCD) to nearly $6 million for CALVEG (table 6).

DISCUSSION

No semi-automated approach tested resulted in more precise estimates of timberland area or timber volume than can be achieved by using PI. The tradeoff curve between precision and cost (fig. 5) suggests that substantial cost savings can be achieved by transitioning to a semi-automated approach, with only modest reductions in precision. It was also shown that volume precision targets cannot be achieved using any stratification approach tested. One potential ancillary benefit not included in this analysis is the value of the forest land strata maps derived from a stratification approach like FIASCO-TM. Such GIS layers could prove useful as a spatial component in other forest research projects, particularly those involving interpolation of FIA plot attributes to the larger landscape.

Table 4.—*Total volume of down wood in the North Coast Survey Unit based on the best stratification from each data set*

Method	Standard error	Timber volume	Sampling error per billion cu ft	Design effect
	Thousand cu ft	*Thousand cu ft*	*Percent*	*Percent*
Production PI	347,630	5,692,500	14.57	78
FIASCO fofnf	367,330	5,386,000	15.83	87
CALVEG density	369,410	5,392,200	15.91	88
NLCD fnf	376,670	5,525,300	16.02	92
Random Sample	393,510	5,393,400	16.94	100

Table 5.—*Estimated costs for each stratification approach on a per million acre basis*

Component	Traditional PI	FIASCO-TM	NLCD	CALVEG CA	CALVEG outside CA
	- - - - - - - - - - *Cost ($) per million acres* - - - - - - - - - -				
Photo acquisition	1,945	778			
Photo setup	14,140	5,998			
Photo interpretation	2,203	441			
Landsat scenes		36	0	0	0
GIS layer preparation		251	251	251	251
Filter and edge		503	503	1,715	1,715
Administration etc.		251	101	251	251
CALVEG creation					80,000
Total	18,288	8,259	854	2,218	82,218

Table 6.—*Estimated costs for each stratification approach, by State*

State	Traditional PI	FIASCO-TM	NLCD	CALVEG
	- - - *Cost (thousands of $) for entire states* - - -			
California	1,116	504	52	135
Oregon	720	325	34	3,236
Washington	582	263	27	2,618
Total	2,418	1,092	113	5,989

If money is the principal concern, NLCD is very attractive for the precision achievable relative to acquisition and processing cost. However, NLCD is a pre-classified product, so FIA staff cannot fine-tune the class definitions or the number of classes that are used to describe forested areas, for example. In this regard, FIASCO-TM offers more flexibility and opportunities to tune the training information and class definitions to match any particular or current needs. By selecting the FIASCO-TM method, the FIA program would escape dependence on update cycles and priorities of the other agencies and would be able to directly design the information included in the resulting vegetation map.

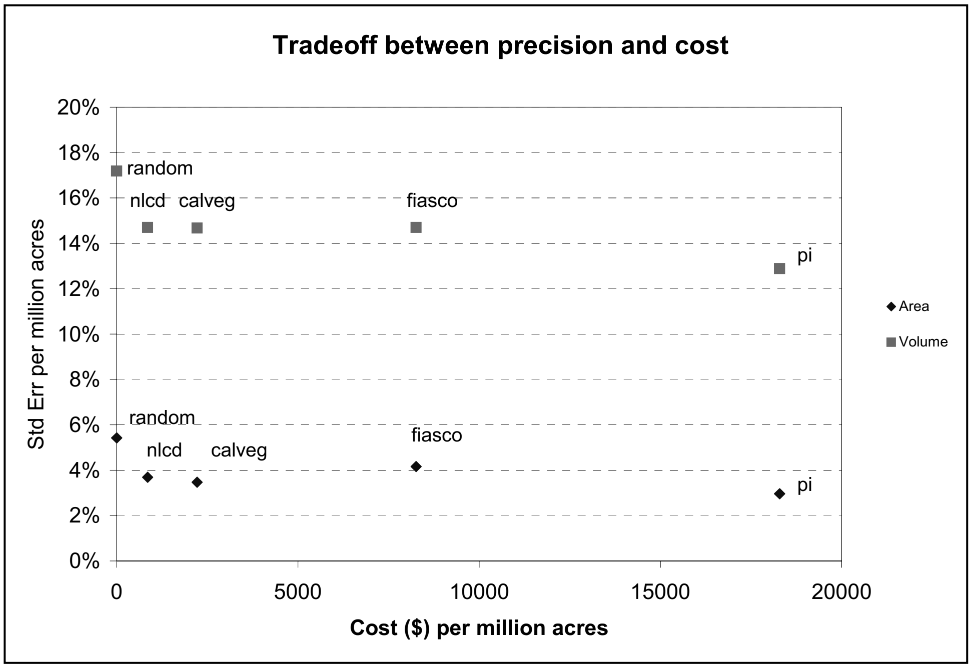

Figure 5.—*Precision and estimated cost for random sample, convetional PI, and three semi-automated approaches to stratification.*

Forest types vary widely in California's North Coast Survey Unit, ranging from low elevation redwood forests to alpine forest types and chaparral. However, the survey unit contains almost no sparse or transitional forest such as can be found in abundance on the east side of the Cascade Mountains. Such areas have extensive intermixing of types, potentially generating considerable confusion in stratification. Further research is needed to assess the performance of these alternatives on sparse forests. It is conceivable that different stratification systems may be needed in different parts of the PNW region. One possibility, not directly tested in this study, is to use digital elevation data to separate vegetation zones on the mountain slopes and combine this information with NLCD data. While CALVEG inherently contained some elements of this approach, there may well be opportunities to optimize for this application.

The general conclusion of this work is that Phase 1 stratifications based on digital remote sensing data can lead to precision nearly comparable to that achieved via conventional PI, and at a cost, in most cases, that is significantly lower. For non-timber attributes, stratification may provide additional precision in some cases, and the precision obtained from remote sensing stratifications for down wood abundance was essentially the same as from PI. Ultimately, the ways in which this kind of large-scale forest inventory data are used will determine the importance of attaining accuracy standards that were set for timber attributes 35 years ago.

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