

Using satellite imagery as ancillary data for increasing the precision of estimates for the Forest Inventory and Analysis program of the USDA Forest Service

Ronald E. McRoberts, Geoffrey R. Holden, Mark D. Nelson, Greg C. Liknes, and Dale D. Gormanson

Abstract: Forest inventory programs report estimates of forest variables for areas of interest ranging in size from municipalities, to counties, to states or provinces. Because of numerous factors, sample sizes are often insufficient to estimate attributes as precisely as is desired, unless the estimation process is enhanced using ancillary data. Classified satellite imagery has been shown to be an effective source of ancillary data that, when used with stratified estimation techniques, contributes to increased precision with little corresponding increase in cost. Stratification investigations conducted by the Forest Inventory and Analysis program of the USDA Forest Service are reviewed, and a new approach to stratification using satellite imagery is proposed. The results indicate that precision may be substantially increased for estimates of both forest area and volume per unit area.

Résumé : Les programmes d'inventaire forestier produisent des estimations des variables forestières pour des zones d'intérêt dont la dimension varie, allant des municipalités, aux comtés, aux états ou aux provinces. À cause de nombreux facteurs, l'intensité d'échantillonnage est souvent insuffisante pour estimer les attributs aussi précisément qu'on le voudrait, à moins que le processus d'estimation soit amélioré par l'utilisation de données ancillaires. Utilisée avec les techniques d'estimation stratifiée, l'imagerie satellitaire classifiée s'est avérée une source efficace de données ancillaires qui contribue à accroître la précision avec une augmentation minimale des coûts. Les enquêtes de stratification effectuées par le programme Forest Inventory and Analysis du USDA Forest Service sont revues, et une nouvelle approche de stratification qui utilise l'imagerie satellitaire est proposée. Les résultats indiquent que la précision peut être augmentée substantiellement pour l'estimation de la superficie des forêts et du volume par unité de surface.

[Traduit par la Rédaction]

Introduction

The Forest Inventory and Analysis (FIA) program of the USDA Forest Service reports estimates of forest variables for medium to large geographic areas such as counties, national forests, and states based on data collected from arrays of field plots. Because of budgetary constraints and natural variability among plots, sufficient numbers of plots frequently cannot be measured to satisfy precision guidelines for the estimates of many variables unless the estimation process is enhanced using ancillary data. Satellite imagery has been accepted as a source of ancillary data that can be used with stratified estimation techniques to increase the precision of estimates with little corresponding increase in costs (Hansen and Wendt 2000; McRoberts et al. 2002a; Hoppus and Lister 2003).

Considerable research has been conducted by the FIA program to develop better classification approaches, to determine the optimal spatial resolution of classifications from which strata are derived, and to select strata boundaries that

maximize precision. However, much of this research has been reported only in limited-distribution proceedings or theses. In addition, the strata are derived nearly exclusively from forest-nonforest classifications or proportion forest area predictions for the imagery. This feature of the stratifications likely accounts for their greater success in increasing the precision of estimates of proportion forest area (P) than for other variables such as volume per unit area (V). The objective of this study is twofold: (1) to review how the FIA program has used satellite imagery to increase the precision of forest inventory estimates and (2) to evaluate satellite image based stratifications intended to increase the precision of estimates of V without compromising the precision of estimates of P .

Background information

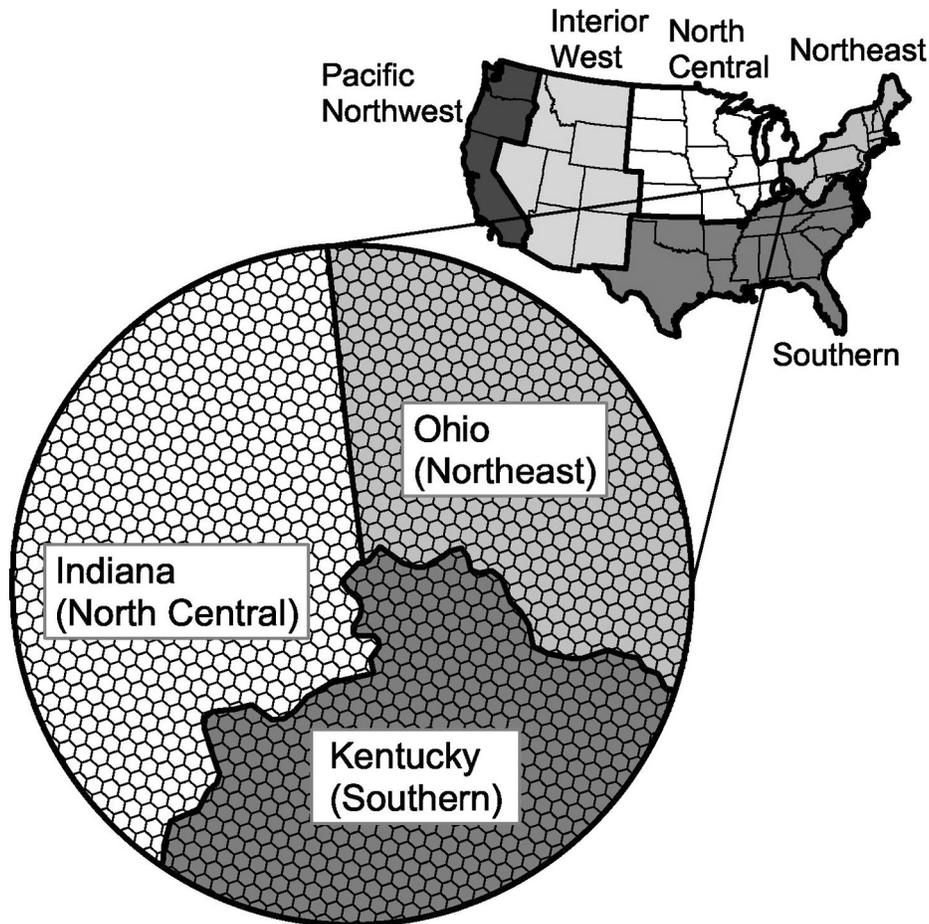
The FIA program has established field plot locations using a sampling design that is assumed to produce a random equal-probability sample (McRoberts and Hansen 1999). The

Received 4 February 2005. Accepted 20 September 2005. Published on the NRC Research Press Web site at <http://cjfr.nrc.ca> on 21 December 2005.

R.E. McRoberts,¹ G.R. Holden, M.D. Nelson, G.C. Liknes, and D.D. Gormanson. USDA Forest Service, Forest Inventory and Analysis, North Central Research Station, 1992 Folwell Avenue, St. Paul, MN 55108, USA.

¹Corresponding author (e-mail: rmcroberts@fs.fed.us).

Fig. 1. Forest Inventory and Analysis sampling hexagons.



sampling design is based on a tessellation of the United States into approximate 2400 ha hexagons derived using the Environmental Monitoring and Assessment Program methodology (White et al. 1992) (Fig. 1). The location and orientation of the hexagonal array was randomly selected, and plot locations within hexagons are assumed to be randomly distributed with respect to the hexagonal array.

In general, locations of forested or previously forested plots are determined using global positioning system (GPS) receivers, while locations of nonforested plots are determined using aerial imagery and digitization methods. Each field plot consists of four 7.31 m (24 ft) radius circular subplots (Fig. 2). The subplots are configured as a central subplot and three peripheral subplots with centers located at 36.58 m (120 ft) and azimuths of 0°, 120°, and 240° from the center of the central subplot. Among the observations field crews collect are the proportions of subplot areas that satisfy specific ground land use conditions. Subplot estimates of P are obtained by collapsing ground land use conditions into forest and nonforest classes consistent with the FIA definition of forest land. Field crews also measure the diameter at breast height (DBH) (1.37 m, 4.5 ft) and the height of each tree with DBH \geq 12.5 cm (5 in.). Statistical models are used to predict the volume of each tree from the DBH and height measurements, and volumes of all trees with DBH \geq 12.5 cm on each subplot are added to obtain subplot estimates of V . The

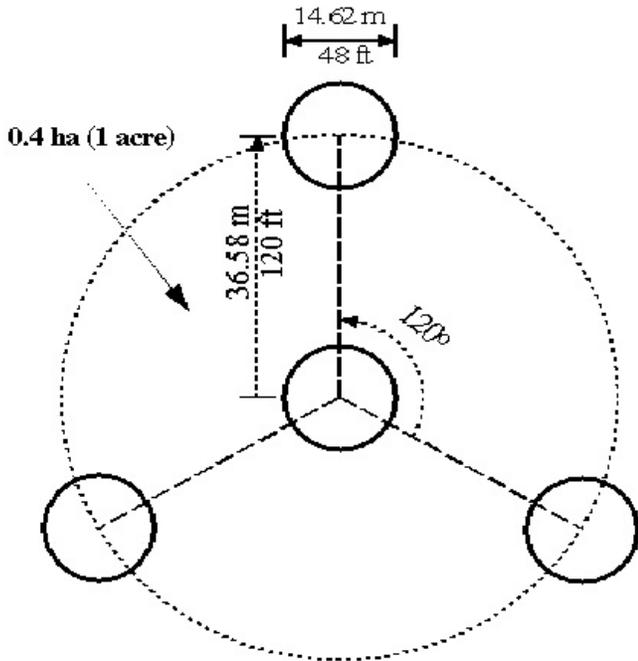
national FIA program uses an infinite sampling framework and attributes aggregations of data for the four subplots to the point corresponding to the center of the central subplot.

Stratified estimation

Stratified estimation is a statistical technique that can be used to increase the precision of estimates without increasing sample sizes. Cochran (1977) indicates that there is little additional benefit when more than six to eight strata are used. Past FIA experience indicates that effective stratifications may be obtained by aggregating classes or predictions into four or five strata. For example, the multiple classes of general land cover classifications such as the National Land Cover Dataset (NLCD) (Vogelmann et al. 2001a) or the Gap Analysis Program classification (Scott et al. 1993) may be aggregated into classes related to forest and nonforest or continuous predictions of proportion forest cover may be aggregated into classes such as 0.00–0.10, 0.11–0.50, 0.51–0.90, and 0.91–1.00.

The effectiveness of the stratifications for decreasing variances and increasing precision is enhanced when the classification or prediction variables are closely related to the estimation variables, when the sampling units can be accurately registered to the classified imagery, when the dates of the satellite imagery are close to the dates of the plot measurements, and when the classifications are unbiased, with small misclassifi-

Fig. 2. Forest Inventory and Analysis national plot configuration.



cation rates. Numerous factors contribute to misclassification, including errors in the training data, errors in the registration of plot locations to imagery, the effects of pixels with mixed land covers, the diffusion of spectral information among adjacent pixels, and the averaging of spectral information for multiple pixels to accommodate plots that are larger than a single pixel. Although stratifications are more effective when the misclassification rates are low, the only effect of misclassification is to decrease the efficiency of the stratifications with respect to increasing precision; misclassification, as long as it is consistent, does not induce bias into estimates. Thus, the effects of misclassification due to these causes are characterized by increased variances, not biased estimates.

Stratified estimation requires that two tasks be accomplished: (1) calculation of the relative proportion of the land area corresponding to each stratum and (2) assignment of each plot to a single stratum. Once the classifications or predictions for the satellite imagery have been obtained and aggregated into strata, the two required tasks are relatively easy to accomplish. The first task is accomplished by counting the number of pixels in each stratum and then calculating the relative proportions of pixels per strata. The second task is accomplished by assigning plots to strata on the basis of the stratum assignments of their associated pixels.

The second task, assignment of plots to strata, merits additional discussion. Stratified estimation assumes that a plot is assigned to only one stratum; typically, this is accomplished by assigning the plot to the stratum to which the pixel containing the plot center is assigned. However, depending on the plot dimensions and the resolution of the classified satellite imagery, different plot components may be associated with different pixels. Such is the case when FIA plots with dimensions in excess of 60 m × 70 m are assigned to strata derived from classified 30 m Landsat Thematic Mapper (TM) imagery. If all the pixels associated with

plot components are not assigned to the same stratum, the plot may sample multiple strata. Accommodation of this phenomenon frequently requires that classifications or predictions for individual pixels be based on a multiple pixel context.

Stratified estimates for FIA variables are calculated using standard methods (Cochran 1977):

$$[1] \quad \bar{Y}_{Str} = \sum_{h=1}^H w_h \bar{Y}_h$$

and

$$[2] \quad \text{Var}(\bar{Y}_{Str}) = \sum_{h=1}^H w_h^2 \frac{\hat{\sigma}_h^2}{n_h}$$

where

$$[3] \quad \bar{Y}_h = \frac{1}{n_h} \sum_{i=1}^{n_h} Y_{hi}$$

$$[4] \quad \hat{\sigma}_h^2 = \frac{1}{n_h - 1} \sum_{i=1}^{n_h} (Y_{hi} - \bar{Y}_h)^2$$

Y_{hi} is the i th observation in the h th stratum of the variable of interest; $h = 1, 2, \dots, H$ denotes strata; w_h is the weight for the h th stratum, calculated as the proportion of pixels in the area of interest (AOI) assigned to the stratum; n_h is the number of plots assigned to the h th stratum; \bar{Y}_h is the sample mean for the h th stratum, and $\hat{\sigma}_h^2$ is the sample estimate for the stratum variance.

The FIA program uses stratified estimation but not stratified sampling. For estimation purposes, at least five plots per stratum are considered necessary to obtain reliable stratified estimates. If fewer than five plots are assigned to a stratum, then similar strata are combined, the AOI is increased so that it includes sufficient numbers of plots per stratum, or stratified estimation is not used.

With the infinite population sampling framework used by the FIA program, no finite population correction factor adjustments are necessary. However, depending on how the classification or prediction for the satellite imagery for an AOI is considered, adjustment for estimated rather than known stratum weights may be necessary. If the classifications or predictions for a satellite image are considered as complete coverage, then the stratum weights are considered known. However, if the classification or prediction for an image pixel is considered applicable only to a single point in the pixel (e.g., the pixel center), then the construction of strata using classified satellite imagery should be considered as the first phase of double sampling for stratification. In this case, stratum weights obtained as relative proportions of points assigned to strata are estimates rather than known quantities. Cochran (1977) provides the following formula for the stratified variance when using estimated stratum weights:

$$[5] \quad \text{Var}(\bar{Y}_{Str}) = \sum_{h=1}^H w_h^2 \hat{\sigma}_h^2 \left(\frac{1}{n_h} - \frac{1}{w_h N} \right) + \frac{1}{n'} \left(\frac{N - n'}{N - 1} \right) \sum_{h=1}^H w_h (\bar{Y}_h - \bar{Y}_{Str})^2$$

where N is the population size and n' is the size of the first sample. For an infinite population, $\frac{1}{N} = 0$, and when using classified satellite imagery as the basis for stratifications, n' is the number of pixels with centers in the AOI. For sizes of AOIs relevant for FIA applications and for the spatial resolution of satellite imagery on which stratifications are generally based, n' is so large that $\frac{1}{n'} \approx 0$. For $\frac{1}{N} = 0$ and $\frac{1}{n'} \approx 0$, [5] reduces to [2]. The result is that for both known stratum weights and estimated stratum weights from pixel classifications or predictions, [2] may be used with confidence.

Stratified estimation is effective when the elements of a heterogeneous population are grouped into strata so that variances of stratum means are substantially smaller than the variance of the overall mean obtained under the assumption of simple random sampling (SRS) or when strata with large variances for stratum means are small in size. Stratified estimation may be ineffective if the AOI is partitioned into strata for which several have similar means and variances. Consider a stratification that includes three strata with weights w_1 , w_2 , and w_3 ; sample sizes n_1 , n_2 , and n_3 ; similar means $\bar{x}_1 = \bar{x}_2 = \bar{x}_3 = \bar{x}_0$; and similar variances $\hat{\sigma}_1^2 = \hat{\sigma}_2^2 = \hat{\sigma}_3^2 = \hat{\sigma}_0^2$. Because

$$\begin{aligned} w_1^2 \frac{\hat{\sigma}_1^2}{n_1} + w_2^2 \frac{\hat{\sigma}_2^2}{n_2} + w_3^2 \frac{\hat{\sigma}_3^2}{n_3} &= \sigma_0^2 \left(\frac{w_1^2}{n_1} + \frac{w_2^2}{n_2} + \frac{w_3^2}{n_3} \right) \\ &\geq \hat{\sigma}_0^2 \frac{(w_1 + w_2 + w_3)^2}{n_1 + n_2 + n_3} \end{aligned}$$

multiple similar strata may have a detrimental effect on stratified estimates of variances.

The effectiveness of a stratification is often evaluated using relative efficiency (RE), calculated as

$$[6] \quad RE = \frac{\text{V}\hat{\text{a}}\text{r}(\bar{Y}_{\text{SRS}})}{\text{V}\hat{\text{a}}\text{r}(\bar{Y}_{\text{Str}})}$$

where $\text{V}\hat{\text{a}}\text{r}(\cdot)$ is estimated variance, \bar{Y}_{SRS} is the estimate of the mean obtained under the SRS assumption, and \bar{Y}_{Str} is the estimate of the mean obtained using stratified estimation. $RE > 1.0$ indicates that the strata and stratified estimation have the desired effect of reducing variance and increasing precision, while $RE \approx 0$ indicates the strata are having little beneficial effect. $RE - 1.0$ may be interpreted as the factor by which the sample size would have to be increased to achieve the same precision under the SRS assumption as is achieved with stratified estimation.

Relevant previous studies

Nordic experiences

Although the use of remotely sensed data for increasing the precision of inventory estimates has been investigated in several regions (Bowden 1979; Holt and Smith 1979; Johnston 1982; Köhl 1990), many of the early and important contributions came from scientists in the Nordic countries. Poso (1972) used information from aerial photographs in a double sampling for stratification approach, and Poso et al.

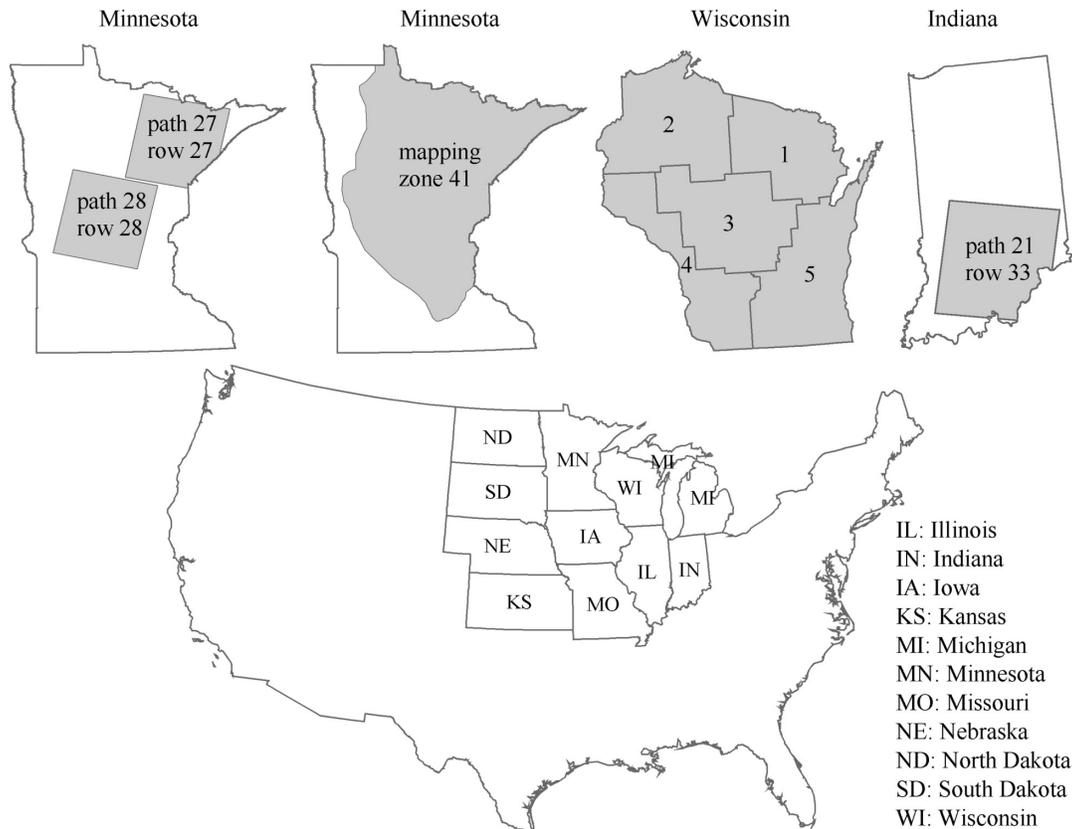
(1984, 1987) derived stratifications from unsupervised classifications of satellite imagery to increase the precision of inventory estimates of volume and age in Finland. Muinonen and Tokola (1990) used a nearest-neighbor technique with field data to predict forest attributes for Landsat TM pixels. Strata were then derived from the pixel predictions, and stratified estimation was used to obtain estimates of forest attributes. More recently, Nilsson et al. (2003, 2005) used the k -nearest neighbour (k -NN) technique and poststratification to reduce standard errors (SE) for the Swedish National Forest Inventory.

The North Central (NC) Research Station approach to stratification

The first objective of the overall study is to review how the FIA program has used classified satellite imagery to increase the precision of forest inventory estimates. Hansen and Wendt (2000) proposed constructing strata by collapsing the classes of the GAP (Scott et al. 1993) classification into forest and nonforest strata and then constructing forest edge and nonforest edge strata along forest–nonforest boundaries. They compared sampling errors for two sets of estimates: (1) 1986 estimates of P and V for the states of Illinois and Indiana, USA (Fig. 3), obtained using a double sampling for stratification approach based on first-phase interpretation of aerial photographs and (2) 1998 estimates of P and V for the same states using the GAP classification as the source of stratification data. They found that the variances of estimates were slightly larger for the approach based on satellite imagery. However, the consistency of the stratification, the ease of constructing strata, and the generally greater utility of the approach based on satellite imagery made it preferable.

McRoberts et al. (2002a) derived the same four strata from the NLCD and investigated optimal widths for the forest edge and nonforest edge strata. The first NLCD classification, designated NLCD-92, is based on nominal 1992 Landsat TM satellite imagery and a variety of ancillary data (Vogelmann et al. 2001a), and the second, designated NLCD-01, is based on nominal 2001 Landsat TM satellite imagery and is currently available for only a few mapping zones. The FIA program of the North Central Research Station, USDA Forest Service, derives strata from the NLCD-92 using a three-step process. First, selected NLCD-92 classes are aggregated into a forest stratum, and the remaining classes are aggregated into a nonforest stratum. Second, a clump and eliminate algorithm (ERDAS 1997) is used to reassign isolated groups of small numbers of contiguous forest and nonforest pixels to the nonforest and forest strata, respectively. Groups of fewer than four pixels are reassigned because of the approximate correspondence of the four-pixel aggregated area of 0.36–0.39 ha (1.0 acre) to the minimum area necessary to be designated FIA forest land. Third, two additional strata are created by subdividing the forest stratum into forest and forest-edge strata and by subdividing the nonforest stratum into nonforest and nonforest-edge strata. The edge strata are created by assigning pixels in the original forest stratum within two pixels of the forest–nonforest boundary to the forest-edge stratum and pixels in the original nonforest stratum within two pixels of the forest–nonforest boundary to the nonforest-edge stratum. This approach to stratification is

Fig. 3. US states in which studies were conducted.



designated the NC approach, and the four strata are denoted F (forest), FE (forest edge), NFE (nonforest edge), and NF (nonforest). Plots are assigned to the stratum of the pixel containing the plot center. Using this approach, McRoberts et al. (2002a) obtained RE estimates for P for the states of Indiana, Iowa, Minnesota, and Missouri (Fig. 3) that ranged from 1.72 to 3.22.

Comparing classification and prediction approaches

For Mapping Zone 41 (Fig. 3), Nelson et al. (2002) compared REs for stratifications derived from NLCD-01 and stratifications derived from the same underlying 30 m Landsat TM imagery using maximum likelihood (ML), fuzzy convolution (FC), logistic regression (LOG), and the k -NN techniques. The ML and FC techniques produced binary forest–nonforest classifications from which the four NC strata were derived. The LOG and k -NN approaches yielded continuous predictions of P from which four strata consisting of intervals of predicted P were derived. The four approaches produced similar estimates of both P and RE_p , with values of the latter ranging from $RE_p = 1.53$ for the ML approach and $RE_p = 1.61$ for the other approaches.

MODIS-based stratifications

Liknes et al. (2004) investigated stratifications derived from 500 m and 1 km MODIS-based products for estimating P using data for 6635 FIA plots measured between 1999 and 2002. Although MODIS imagery and associated products are available more frequently than 30 m NLCD-based products, the question is whether coarser resolution classifications or

predictions have an adverse effect on RE. For Mapping Zone 41 (Fig. 3), forest–nonforest stratifications derived from the 500 m MODIS Vegetation Continuous Fields (VCF) data set (Hansen et al. 2003) and the 1 km MOD12Q1 land cover data set (Friedl et al. 2002) were compared with forest–nonforest stratifications derived from NLCD-92 and NLCD-01. Estimates of P obtained for the four stratification approaches and under the SRS assumption were comparable. However, $RE_p = 2.37$ for NLCD-92 and $RE_p = 2.25$ for NLCD-01 were greater than $RE_p = 1.50$ for the VCF-derived stratification and $RE_p = 1.41$ for MOD12Q1. Although these results could be attributed to the coarser resolution of the MODIS imagery, they could also be attributed to other factors. First, the 0.0672 ha FIA plot area is likely not an adequate sample of the 25 ha area of the VCF MODIS pixel or the 100 ha area of the MOD12Q1 pixel area. Second, the small differences in the results could also be attributed to random effects, particularly if there had been little change in forest area in the AOI between the 1992 date of the TM imagery for the NLCD-92 and the 2000–2001 dates of the MODIS imagery used to create VCF and MOD12Q1. Third, the 30 m NLCD classifications, which use a variety of other ancillary data in addition to satellite imagery, may better represent Mapping Zone 41 forests.

Comparing resolutions of classifications

Nelson et al. (2005) challenged the assumption that finer resolution classifications produce more efficient stratifications and compared the effectiveness of strata derived from predictions of P for 30 m Landsat TM data sets and strata

that were derived from aggregations of the 30 m predictions into data sets with blocks ranging in size from 3×3 pixel groupings to 33×33 pixel groupings. A logistic regression model was used to predict P for each pixel, and two stratified estimation approaches based on aggregating pixel predictions into coarser resolution data sets were investigated. The average approach designated a block as a forest if the average of predictions of P for pixels in the block exceeded a threshold; if the average failed to exceed the threshold, the block was designated nonforest. The majority approach designated a block as forest if the majority of predictions of P for pixels in the block exceeded a threshold; if not, the block was designated nonforest. Stratifications were derived from the forest–nonforest classifications of the blocks obtained with each approach for a heavily forested Landsat TM scene (path 28, row 28) and a sparsely forested scene (path 27, row 27) in north-central Minnesota, USA (Fig. 3).

For both approaches, differences in estimates of forest area obtained by counting 30 m pixels and by counting blocks classified as forest generally increased as block size increased, suggesting the possibility of increasing bias as block size increased. The largest REs were obtained for classifications with 90–150 m spatial resolutions. The conclusion of the study was that stratifications derived from finer resolution classifications should not necessarily be assumed to produce larger REs when using stratified estimation for P .

Stratification based on continuous volume predictions

All the stratification approaches discussed to this point are based on underlying or derived forest–nonforest classifications that, as previously noted, are more effective in reducing the variances of estimates of P than estimates of V , because the aggregated forest class is more closely related to P than it is to V . Thus, there is reason to expect that if the classifications or predictions for the pixels of the underlying satellite imagery were based on variables more closely related to V , then the resulting stratifications might be more effective at increasing the precision of V .

Holden et al. (2005) investigated the effectiveness of a 250 m resolution biomass map for deriving strata for the stratified estimation of biomass for 11 North Central states of the United States (Fig. 3). The map was based on MODIS imagery and training data obtained from FIA plot measurements of V . As a source of stratification data, the map was only marginally effective at increasing the precision of biomass estimates. Although statewide estimates of mean biomass per unit area obtained from pixel predictions for states were within 10% of the mean for plot observations, the correlation between biomass observations for an independent subset of FIA plots and biomass predictions for pixels containing the centers of the plots was $r = 0.44$. Thus, even though the map produced approximately correct estimates at the spatial scale of states, the accuracy at the pixel level was relatively low. For stratification purposes, accuracy at the pixel level is important because plots are assigned to strata on the basis of the stratum assignments of the pixels containing their centers. Therefore, because of the low pixel-level accuracy of the biomass map, the results of this study are inconclusive as to the utility of V or V -related maps for increasing the precision of estimates of V .

Change stratifications

Despite the effectiveness of stratifications derived from forest–nonforest classifications for increasing the precision of estimates of both P and V , these same stratifications are much less effective for increasing the precision of estimates of change between inventories such as change in P , change in V , mortality, and change in number of trees. McRoberts et al. (2005) reasoned that if a current forest–nonforest classification produces effective stratifications for estimating current P and current V , then perhaps, by analogy, a forest–nonforest change classification would produce effective stratifications for the change estimates. For Mapping Zone 41 (Fig. 3), they derived the F, FE, NFE, and NF strata from both the NLCD-92 and NLCD-01 classifications and then constructed change stratifications by combining the two stratifications. For example, a pixel assigned to the F stratum derived from NLCD-92 and the FE stratum derived from NLCD-01 would be assigned to the F–FE change stratum. In this manner, 16 change strata were derived from NLCD-92 and NLCD-01. Accuracies of both underlying forest–nonforest classifications were estimated as approximately 85%.

The change strata were relatively ineffective in increasing the precision of estimates of annual change in P , V , and number of trees. These results are attributed to several factors: (1) approximately 80% of the AOI was assigned to the no-change strata; (2) several of the change strata were very small, less than 0.5% of the AOI; (3) the estimate of mean change in P was not statistically significantly greater than zero ($\alpha = 0.05$) for most strata, suggesting very little heterogeneity in the population; (4) the proportion of the AOI assigned to change strata, approximately 0.20, was of the same order of magnitude as the proportion of the AOI that was misclassified, suggesting that the total area of the AOI that was classified as changed could conceivably be attributed to classification errors; and (5) the estimate of annual proportion change in forest area for the entire AOI over the 11-year interval, approximately 0.0165, is an order of magnitude smaller than the approximate 0.15 misclassification rate, suggesting that a high proportion of plots that experienced change could have been assigned to incorrect strata.

Summary

From these studies, four conclusions may be drawn. First, stratifications based on satellite imagery may contribute substantially to increasing the precision of forest inventory estimates. For P , RE values were typically in the range of $1.7 \leq RE_p \leq 3.2$ for 30 m Landsat TM imagery. These results are similar to the $RE_p = 3.00$ reported by Nilsson et al. (2003). Second, stratifications are apparently more effective when they are based on classifications closely related to the attribute of interest. Third, multiple approaches to classification and prediction and multiple approaches to deriving strata from classes and predictions are effective. Fourth, the optimal resolution of underlying classifications from which stratifications are derived is uncertain, although very coarse resolution is considerably less than optimal. Stratifications based on 500 m and 1 km MODIS imagery were inferior to 30 m stratifications, as were aggregations of 30 m pixels to blocks of 250 m resolution and larger. These results are consistent with those of Poso et al. (1987), who found that stratifica-

tions of 30 m resolution were superior to those of 79 m resolution, and those of Nilsson et al. (2003, 2005), who found 30 m stratifications superior to 250 and 500 m stratifications. Nelson et al. (2005) indicate that the optimal larger resolution may be in the 90–150 m range.

Materials and methods

The second objective of this study is to evaluate new approaches to stratifications based on satellite imagery with respect to their effectiveness in increasing the precision of estimates of P and V . This second objective is addressed in two separate but related studies. The first used FIA plot data and compared approaches to deriving stratifications from the NLCD-92 for the state of Wisconsin, and the second used FIA plot data and compared two approaches to prediction for Landsat TM scenes in the states of Indiana and Minnesota.

Wisconsin study

Three approaches to deriving stratifications from the NLCD-02 were compared. The first was the NC approach, as previously described (McRoberts et al. 2002a), which captures information on plot context through the use of edge classes. The second and third approaches capture plot context information in different ways. The second approach, described by Hoppus and Lister (2002) and used in the northeastern portion of the United States, begins with a forest–nonforest classification, and then assigns the center pixels of 5×5 blocks of pixels to strata on the basis of a summary of the forest–nonforest classifications of pixels in the blocks. The center pixel of each 5×5 block is assigned to one of 26 strata depending on the number of forested pixels in the block, and the 26 strata are then collapsed into a smaller number by combining adjacent strata. For this study, the 26 classes were collapsed to form four strata, and the approach was designated the Northeast (NE) approach. The third approach is based on the reclassification of NLCD-92 pixels by Riitters et al. (2002) into 14 fragmentation classes based on the number and configuration of forest–nonforest pixels in 5×5 pixel blocks. Five strata were derived by aggregating the 14 fragmentation classes into five broader classes: interior, edge, transitional, patch, and nonforest. This approach was designated the FRAG approach. For the five inventory units in the state of Wisconsin (Fig. 3), the SRS, NC, NE, and FRAG stratification approaches were compared with respect to RE_P and RE_V calculated using [6].

Indiana–Minnesota study

The emphasis of this study is a comparison of four approaches to stratification with respect to the effectiveness of increasing the precision of estimates of P and V for a Landsat TM scene in southern Indiana and a scene in northern Minnesota (Fig. 3). The four included the NC and NE approaches, a k -NN approach, and a logistic model approach. The latter two approaches are based on predicting both P and V for 30 m Landsat TM pixels, using FIA plot observations as training or reference data.

Plot data

Observations were available for 1211 plots in the Indiana study area and 2114 plots in the Minnesota study area. All plots were observed between 1999 and 2003. Three variables were used as the basis for classifications or predictions for the satellite imagery: (1) P , (2) relative volume (RV), calculated as the ratio of observed V and the maximum observed V for the AOI, and (3) $P + RV$, calculated as the average of P and RV. The range of each variable is the closed interval [0,1]. The rationale for using RV rather than V was so that the combination of P and V would not be dominated by the larger values of V .

Landsat TM satellite imagery

Landsat TM imagery for one Indiana scene (path 21, row 33) and one Minnesota scene (path 27, row 27) was obtained from the Multi-Resolution Land Characteristics 2001 land cover mapping project (Homer et al. 2004) of the US Geological Survey. The imagery was characterized by several salient features: (1) a combination of Landsat 5 TM and Landsat 7 ETM+ data after radiometric conversion of Landsat 5 TM data to Landsat 7 data (Vogelmann et al. 2001b), (2) geometrically and radiometrically corrected including terrain correction using methods described by Irish (2000), (3) cubic convolution resampling to $30 \text{ m} \times 30 \text{ m}$ spatial resolution, (4) visible and infrared bands (1–5, 7), and (5) conversion to at-satellite reflectance in accordance with Markham and Barker (1986) and the *Landsat 7 Science Data User's Handbook* (Irish 2000). Imagery for three dates corresponding to early, peak, and late vegetation green-up (Yang et al. 2001) was obtained for each scene: April 2001, July 2000, and October 2001 for the Indiana scene and April 2000, July 2001, and November 1999 for the Minnesota scene. Preliminary analyses indicated that the normalized difference vegetation index (Rouse et al. 1973) and the tasseled cap transformations (brightness, greenness, and wetness) (Kauth and Thomas 1976; Crist and Cicone 1984) were superior to both the spectral band data and principal component transformations with respect to predicting the probability of forest cover. Thus, 12 satellite image based predictor variables, normalized difference vegetation index, and three tasseled cap transformations for each of the three image dates were used. Because plots would eventually be assigned to strata derived from pixel classifications or predictions, and because it was necessary to accommodate the possibility that a plot could sample multiple strata, the mean of each transformation of the spectral values was calculated for each 3×3 block of pixels and attributed to the center pixel of each block.

Prediction approaches

Predictions of RV for individual pixels in each study area were obtained using two techniques, k -NN and LOG. For the k -NN approach (Franco-Lopez et al. 2001; Katila and Tomppo 2001; McRoberts et al. 2002b), the set of pixels with associated plots was denoted the reference set, and the set of pixels requiring predictions was denoted the target set. For each pixel in the target set, the k closest pixels in the reference set were determined using Euclidean distance

$$[7] \quad d = \sqrt{\sum_{i=1}^{12} (x_{il} - x_{jl})^2}$$

where i indexes the target set, j indexes the reference set, l indexes the 12 spectral transformations, x_{il} is the value of the l th transformation for the i th pixel in the target set, and x_{jl} is the value of the l th transformation for the j th pixel in the reference set. The prediction, \hat{y}_i , for the i th pixel is

$$[8] \quad \hat{y}_i = \frac{1}{k} \sum_{j=1}^k y_j$$

where j indexes the k neighbors in the reference set nearest to the i th pixel with respect to [7], and y_j is the observed value of the variable for the plot associated with the j th pixel in the reference set. As recommended by Trotter et al. (1997), Tokola et al. (1996), Tokola (2000), Franco-Lopez et al. (2001), and Katila and Tomppo (2001), a small k value was selected; that is, $k = 5$ for this study. Thus, the prediction for each pixel was closely associated with the five observations for the five nearest neighbors in the reference set.

An assumption underlying stratified estimation is that the plot observations assigned to a stratum are a random sample of the stratum. Therefore, caution must be exercised when using the k -NN method with a small k value to obtain predictions from which strata will be derived. The concern is that for small k values, the set of plots assigned to each stratum will be very similar to the mathematical union of the sets of k -nearest neighbors used to obtain predictions for the pixels assigned to the stratum. The result is that the plots assigned to a stratum may not be a random sample of the stratum. To circumvent this problem, each study area was divided into two subareas of approximately equal size, and the plots geographically located in one subarea formed the reference set for obtaining predictions for pixels in the other subarea. In this manner, the predictions from which strata are derived for a subarea are independent of the observations for the plots assigned to the strata.

The LOG approach to prediction used the logistic regression model

$$[9] \quad E(y) = \frac{1}{1 + \exp(\beta_0 + \beta_1 X_1 + \dots + \beta_{12} X_{12})}$$

where $E(\cdot)$ is statistical expectation, $\exp(\cdot)$ is the exponential function, the β s are parameters to be estimated, and the X s are the 12 transformations of the spectral values. Separate sets of parameter estimates were obtained for each variable in each study area. An operational advantage accrues when the model predictions are grouped into the same strata across states. Because RV for each study area is based on the maximum V for the study area, classes of RV predictions will not be equivalent for the two study areas. To obtain classes for the two study areas that are equivalent, the classified or predicted variable must be the same. Therefore, a second relative volume variable, RV' , was calculated as the ratio of observed V and the maximum V observed over both study areas considered together. Separate sets of parameter estimates were obtained for each study area using RV' . Classes of RV' predictions and groupings of the classes into strata were equivalent for both study areas.

Because the estimate of each parameter of [9] is based on all observations in the study area, the prediction for each image pixel will similarly be based on the observations for all

plots in the study area. This is unlike the situation with the k -NN approach for which the prediction for each image pixel is based on only five plots in the study areas. The result is that when using a regression model with parameters estimated from the entire data set to predict values of pixels, there is little concern that the plots assigned to a stratum are not a random sample of the stratum (Breidt and Opsomer 2002).

Analyses

For each study area, the pixel predictions of P , RV , and RV' were grouped into 0.01-wide classes beginning with 0.00 and ending with 1.00. Plots were assigned to the resulting 101 classes on the basis of the class assignments of the pixels containing the plot centers. The 101 classes were grouped into four strata, subject to the constraint that no stratum with fewer than five plots was permitted. Strata boundaries were separately selected to maximize indices: (1) RE_p , within each study area, (2) RE_v , within each study area, (3) the sum, $RE_p + RE_v$, within each study area, and (4) the sum, $RE_p + RE_v$, for the two study areas together. For (1) and (2), the 101 classes for a study area were based on predictions of P and V , respectively, within the study area; for (3), the classes were based on predictions of RV within the study area; and for (4), the classes were based on predictions of RV' across the two study areas. Groupings were based on four criteria: (1) RE_p within study areas, (2) RE_v within study areas, and (3) $RE_p + RE_v$, within study areas. As a basis for comparison, RE_p and RE_v were also obtained for the NC and NE approaches. For the Indiana study area, the NC and NE approaches were based on NLCD-92, while for the Minnesota study area, the approaches were based on NLCD-01. Estimates were also obtained under the SRS assumption.

Results

Wisconsin study

The four approaches produced estimates of P and V that were nearly indistinguishable, and there were few substantial differences in RE (Table 1). The FRAG approach produced the smallest RE values for both P and V and as a result is not considered further. The NE approach was generally slightly better than the NC approach.

Indiana–Minnesota study

The estimates of P and V were nearly indistinguishable for the different approaches to stratification (Table 2). $RE_p > RE_v$, which is consistent with previous findings. In addition, SE estimates for the Indiana study area were slightly smaller than those for the Minnesota study area, although they were comparable. The larger REs for the Indiana study area are attributable to the larger SE of the SRS mean for both P and V , the denominator in the RE calculation.

The NE and NC approaches produced RE values that were similar, although RE for the NE approach for each variable and study area was marginally greater than RE for the NC approach. The groupings of the 26 NE classes into strata were quite stable as indicated by the only slight reduction in RE_p and RE_v for the three optimality criteria: RE_p and RE_v separately within study areas, $RE_p + RE_v$ within study areas, and $RE_p + RE_v$ across study areas.

Table 1. Comparison of approaches to stratification based on forest–nonforest classifications for the state of Wisconsin, USA.

Approach*	Inventory unit [†]									
	1		2		3		4		5	
	Mean	RE	Mean	RE	Mean	RE	Mean	RE	Mean	RE
Proportion forest area										
SRS	0.7104	1.00	0.6614	1.00	0.4268	1.00	0.3124	1.00	0.1343	1.00
NC	0.7130	2.36	0.6735	2.23	0.4380	2.22	0.3150	2.40	0.1341	1.67
NE	0.7170	3.05	0.6714	2.40	0.4318	2.50	0.3170	2.66	0.1340	1.94
FRAG	0.7108	1.43	0.6627	1.33	0.4391	1.29	0.3144	1.30	0.1369	1.21
Volume (m³/ha)										
SRS	77.36	1.00	65.12	1.00	40.31	1.00	36.05	1.00	16.33	1.00
NC	77.64	1.34	66.33	1.27	41.38	1.39	36.38	1.63	16.32	1.55
NE	76.63	1.37	65.88	1.31	40.71	1.47	36.44	1.71	15.79	1.70
FRAG	77.33	1.14	65.23	1.14	41.40	1.11	36.28	1.17	16.54	1.14

Note: RE, relative efficiency.

*SRS, simple random sampling; NC, North Central; NE, Northeast; FRAG, fragmentation classes.

Table 2. Comparison of approaches to stratification based on forest–nonforest classifications and on continuous predictions of proportion forest area and volume for the states of Indiana and Minnesota, USA.

Approach*	Classification or predictor variable	Optimization		Indiana			Minnesota		
		Criterion	Area	Mean	SE	RE	Mean	SE	RE
Proportion forest area (P)									
SRS				0.3383	0.0127	1.00	0.7279	0.0091	1.00
NC	Forest			0.3545	0.0067	3.60	0.7267	0.0073	1.53
NE	Forest	RE _p	Within	0.3390	0.0065	3.79	0.7296	0.0071	1.64
NE	Forest	RE _p	Across	0.3390	0.0065	3.79	0.7290	0.0072	1.60
NE	Forest	RE _p + RE _v	Within	0.3390	0.0065	3.79	0.7296	0.0071	1.64
NE	Forest	RE _p + RE _v	Across	0.3433	0.0062	3.79	0.7290	0.0072	1.60
k-NN	RV	RE _p + RE _v	Within	0.3433	0.0062	4.13	0.7330	0.0066	1.91
LOG	P, RV	RE _p	Within	0.3373	0.0052	5.87	0.7298	0.0060	2.33
LOG	P	RE _p	Across	0.3373	0.0052	5.87	0.7298	0.0060	2.33
LOG	P + RV	RE _p + RE _v	Within	0.3393	0.0053	5.72	0.7298	0.0060	2.33
LOG	P + RV'	RE _p + RE _v	Across	0.3385	0.0053	5.70	0.7281	0.0060	2.26
Volume (V; m³/ha)									
SRS				47.44	2.15	1.00	48.91	1.25	1.00
NC	Forest			49.75	1.53	1.99	48.78	1.17	1.13
NE	Forest	RE _v	Within	47.72	1.46	2.19	48.74	1.16	1.15
NE	Forest	RE _p	Within	47.55	1.46	2.17	49.03	1.17	1.13
NE	Forest	RE _p	Across	47.55	1.46	2.17	49.00	1.17	1.13
NE	Forest	RE _p + RE _v	Within	47.55	1.46	2.17	49.03	1.17	1.13
NE	Forest	RE _p + RE _v	Across	47.55	1.46	2.17	49.00	1.17	1.13
k-NN	RV	RE _p + RE _v	Within	48.21	1.43	2.28	49.37	1.14	1.19
LOG	P, RV	RE _v	Within	46.97	1.31	2.71	48.62	1.06	1.37
LOG	P	RE _p	Within	47.32	1.37	2.47	49.12	1.09	1.32
LOG	P	RE _p	Across	47.32	1.37	2.47	48.71	1.11	1.26
LOG	P + RV	RE _p + RE _v	Within	47.57	1.35	2.54	49.12	1.09	1.32
LOG	P + RV'	RE _p + RE _v	Across	47.46	1.35	2.54	49.05	1.10	1.29

Note: RV, relative volume; RE, relative efficiency; SE, standard error.

*SRS, simple random sampling; NC, North Central; NE, Northeast; k-NN, k-nearest neighbour; LOG, logistic regression.

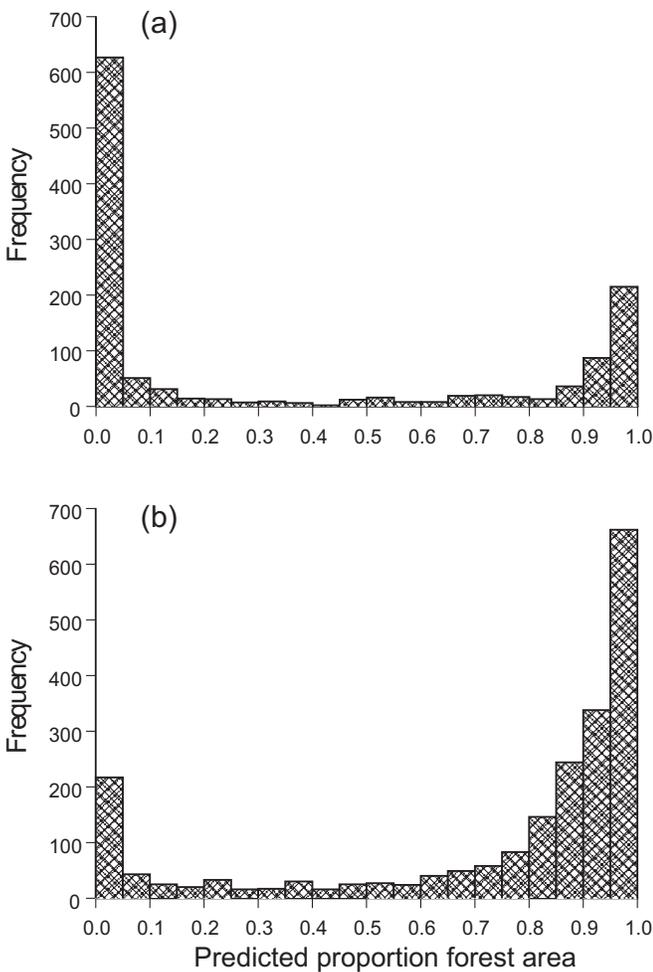
The LOG approaches were superior to the NC, NE, and k-NN approaches for P and V for both study areas. Because the k-NN approach is more difficult and time consuming to

implement, is subject to several precautions (McRoberts et al. 2002b), and produces inferior results relative to the LOG approaches, it is not further considered. As evidenced by the

Table 3. Stratum statistics for logistic regression (LOG) predictions of proportion forest area (P) and volume (V), optimizing across the states of Indiana and Minnesota, USA.

Stratum	Stratum boundary		Weight	Sample size	P		V (m ³ /ha)	
	Lower	Upper			Mean	SE	Mean	SE
Indiana								
1	0.00	0.45	0.631	761	0.0405	0.1435	4.88	0.79
2	0.46	0.64	0.034	43	0.4095	0.3637	58.10	11.80
3	0.65	0.91	0.107	132	0.7364	0.3280	98.17	6.08
4	0.92	1.00	0.228	275	0.9601	0.1413	139.20	4.47
Overall				1211	0.3373	0.0052	47.32	1.37
Minnesota								
1	0.00	0.45	0.200	423	0.1213	0.2881	5.49	1.08
2	0.46	0.64	0.056	110	0.5905	0.4256	21.35	3.32
3	0.65	0.91	0.329	697	0.8334	0.3274	48.69	2.10
4	0.92	1.00	0.415	883	0.9524	0.1825	73.33	1.98
Overall				2113	0.7263	0.0060	48.71	1.11

Fig. 4. (a) Frequency distribution of Indiana study area plots by predictions of proportion forest area. (b) Frequency distribution of Minnesota study area plots by predictions of proportion forest area.



only slight reduction in RE_P and RE_V , as the optimality criterion changed from RE_P and RE_V within study areas to $RE_P +$

RE_V across study areas, the optimal combination of the 101 LOG prediction classes into four strata appears quite stable.

The superiority of the LOG approach is attributed more to the nature of the 101 prediction classes than to incorporation of a V component into the prediction variable that defined the classes. First, when estimating V , RE values for strata derived from classes based only on predictions of P were only slightly less than RE values for strata derived from classes based only on predictions of RV ; for the Indiana study area the reduction was from $RE = 2.71$ to 2.47 , and for the Minnesota study area the reduction was from $RE = 1.37$ to 1.32 . Second, RE values for strata derived from classes based on predictions of P were only slightly less than RE values for strata derived from classes based on predictions of $P + RV$; for the Indiana study area the decrease was from $RE = 2.54$ to 2.47 , and for the Minnesota study area the decrease was from $RE = 1.32$ to 1.26 . Thus, strata derived from the 101 classes of predictions of P are nearly as effective as strata derived from predictions of a combination of P and RV or from predictions of RV alone and are better than strata derived using the NC and NE approaches.

The LOG approach with classes derived from predictions of P and grouped into four strata selected to minimize RE_P across study areas produced strata that were equivalent with respect to the classes of predictions of P that they combined. However, the strata were somewhat different by study area with respect to within-stratum means and variances (Table 3). The strata were similar in that in each study area there was a positive correlation between means for P and means for V , one stratum had small P and small V and one had large P and large V , and the rankings of the strata with respect to variances were the same. However, the within-stratum means and variances were not very similar for the two study areas. These differences are attributed to different relationships between canopy and below-canopy attributes, different distributions of plots with respect to canopy attributes (Figs. 4a and 4b), and perhaps different prediction accuracies.

Greater RE values could possibly have been achieved with a few more strata for these data sets. However, the bimodal distributions of the plot observations (Figs. 4a and 4b) with respect to predicted P , with most plots either completely for-

Table 4. Potential cost savings achievable with the logistic regression (LOG) approach.

Variable*	Sample size	Mean P	Relative efficiency (RE)			Cost savings (US\$)
			LOG [†]	Max. for NC and NE approaches [‡]	Difference	
Indiana						
P	1211	0.34	5.87	3.79	2.08	642 000
V	1211	0.34	2.47	2.19	0.28	86 000
Minnesota						
P	2113	0.73	2.33	1.64	0.69	798 000
V	2113	0.73	1.26	1.15	0.11	127 000

* P , proportion forest area; V , volume per unit area.

[†]LOG approach using predictions of P and optimizing across study areas.

[‡]NC, North Central; NE, Northeast.

ested or completely nonforested, suggests that the minimum of five plots per stratum would be difficult to achieve with larger numbers of strata, particularly for the smaller geographic areas for which the FIA program reports estimates.

Conclusions

The primary conclusions from the Wisconsin study are that the NC and NE approaches produce similar and substantial increases in precision and that both are superior to the FRAG approach. The ranges of relative efficiencies obtained for this study, $1.2 \leq RE_P \leq 3.1$ and $1.1 \leq RE_V \leq 1.7$, are consistent with those obtained in previous FIA studies. For P , the results are generally in the same range of results obtained by Poso et al. (1987) and Nilsson et al. (2003, 2005). However, for V the RE values are marginally less than those obtained by Poso et al. (1987) and Nilsson et al. (2003, 2005). The latter result is attributed to greater homogeneity in Finnish and Swedish forests than in the naturally regenerated, mixed species, uneven-aged forests characteristic of the state of Wisconsin.

Three conclusions may be drawn from the Indiana–Minnesota study. The first conclusion is that the LOG approach produced RE values for both P and V that were substantially greater than RE values produced by either the NC or NE approaches. The k -NN approach also produced greater RE values than did the NC and NE approaches, but because the LOG approach is easier and less time consuming to implement and produced greater RE values than the k -NN approach, the LOG approach is preferable. For the LOG approach, strata based on predictions of P for the underlying satellite imagery were nearly as effective in increasing RE_V as were predictions for a combination of P and RV or RV alone. In addition, derivation of strata from predictions of P is fairly easy because observations of P by definition are in the interval $[0,1]$ and require no scaling for individual AOIs or for optimization of classes into strata across AOIs. However, derivation of strata from predictions of V or a combination of P and V is more difficult because observations of V must be scaled to make them commensurate with observations of P and to group them into a smaller number of strata across AOIs. Thus, derivation of strata from predictions of P obtained with the LOG approach is preferable because of ease of implementation.

The RE values obtained with the LOG approach for Indiana are comparable to those obtained by Poso et al. (1987) and Nilsson (2003, 2005) for both P and V , although they are less so for Minnesota. The reasons for smaller RE values for Minnesota are not apparent, although Minnesota forests in the study area are characterized by a greater mixture of deciduous and coniferous species than are the Indiana, Finnish, or Swedish forests. In addition, RE_P values for both Indiana and Minnesota were similar to or greater than the $RE_P = 2.7$ reported by Deppe (1998) using a regression estimator, an approach related to stratified estimation.

The second conclusion is that strata derived from V -based predictions were only slightly more effective in increasing the precision of V estimates than strata derived from predictions of P . This result is attributed to two factors. First, predicting V or constructing classes of V is a difficult task using passive sensors such as Landsat TM. Passive sensors respond to reflected sunlight, most of which comes from the forest canopy, while V is a below-canopy attribute. Second, P is much more highly correlated with V than is a binary forest–nonforest variable. Thus, the aggregated classes of the predictions of P apparently capture most of the information pertaining to V in the satellite imagery, certainly more than is captured by forest–nonforest classifications or the NC and NE variations of them.

The third conclusion is that overall the NC and NE approaches produced similar results, but with each having advantages and disadvantages. Overall, the advantage of the NE approach is that it was slightly better than the NC approach with respect to RE. However, the NC approach is more intuitive in the sense that the F, FE, NFE, and NF strata correspond to easily interpreted landscape features. Although the 26 classes of the NE approach could be used directly as strata, they would usually have to be combined to comply with the five plots per stratum constraint for reporting areas such as counties. Thus, for each implementation, a decision must be made as to which classes to combine. If the same decision is not made at each implementation, the strata will not be equivalent. The four strata for the NC approach, however, are equivalent wherever they are constructed.

Finally, it is useful to express differences in RE in terms of a tangible quantity. Differences in RE may be interpreted as the factor by which a sample size would have to be increased to achieve the same precision with the approach pro-

ducing the smaller RE as was achieved with the approach producing the larger RE. Cost savings associated with the approach to stratification yielding the greater RE may be estimated as the product of four factors: (1) the difference in RE, (2) the sample size, (3) mean proportion forest area (P); that is, an estimate of the proportion of plots that require field measurement; and (4) the per-plot field measurement cost of approximately US\$750 in 2005. The potential cost savings achievable using the LOG approach with predictions of P and optimizing over study areas relative to the better of the NC and NE approaches are \$625 000 for estimating P in Indiana, \$86 000 for estimating V in Indiana, \$798 000 for estimating P in Minnesota, and \$127 000 for estimating V in Minnesota (Table 4). These cost savings are substantial even though, in several cases, the differences in RE are relatively small.

References

- Bowden, D.C. 1979. Multi-level sampling designs for resource inventories. USDA Forest Service, Fort Collins, Colo.
- Breidt, F.J., and Opsomer, J.D. 2002. Endogenous post-stratification in surveys: classifying with a sample fitted model. Preprint Series No. 02-23, Department of Statistics, Iowa State University, Ames, Iowa.
- Cochran, W.G. 1977. Sampling techniques. 3rd ed. Wiley, New York.
- Crist, E.P., and Cicone, R.C. 1984. Application of the tasseled cap concept to simulated Thematic Mapper data. *Photogramm. Eng. Remote Sens.* **50**: 343–352.
- Deppe, F. 1998. Forest area estimation using sample surveys and Landsat MSS and TM data. *Photogramm. Eng. Remote Sens.* **64**: 285–292.
- ERDAS. 1997. ERDAS field guide. 4th ed. ERDAS, Atlanta, Ga.
- Franco-Lopez, H., Ek, A.R., and Bauer, M.E. 2001. Estimation and mapping of forest stand density, volume, and cover type using the k -nearest neighbour method. *Remote Sens. Environ.* **77**: 251–274.
- Friedl, M.A., McIver, D.K., Hodges, J.C.F., Zhang, X.Y., Muchoney, D., Strahler, A.H. et al. 2002. Global land cover mapping from MODIS: algorithms and early results. *Remote Sens. Environ.* **83**: 287–302.
- Hansen, M.H., and Wendt, D.G. 2000. Using classified Landsat Thematic Mapper data for stratification in a statewide forest inventory. *In Proceedings of the First Annual Forest Inventory and Analysis Symposium, San Antonio, Tex., 2–3 November 1999. Edited by R.E. McRoberts, G.A. Reams, and P.C. Van Deusen. USDA For. Serv. Gen. Tech. Rep. NC-213. pp. 20–27.*
- Hansen, M.C., DeFries, R.S., Townshend, J.R.G., Carroll, M., DiMiceli, C., and Sohlberg, R. 2003. Global percent tree cover at a spatial resolution of 500 meters: first results of the MODIS Vegetation Continuous Fields algorithm. *Earth Interactions*, **7**: 1–15.
- Holden, G.R., Nelson, M.D., and McRoberts, R.E. 2005. Accuracy assessment of FIA's nationwide biomass mapping products: results from the NC-FIA region. *In Proceedings of the Fifth Annual Forest Inventory and Analysis Symposium, New Orleans, La., 18–20 November 2003. Edited by R.E. McRoberts, G.A. Reams, P.C. Van Deusen, W.H. McWilliams, and C.J. Cieszewski. USDA For. Serv. Gen. Tech. Rep. WO-69. pp. 139–147.*
- Holt, D., and Smith, T.M.F. 1979. Post-stratification. *J. R. Stat. Soc. Ser. A*, **142**: 33–46.
- Homer, C., Huang, C., Yang, L., Wylie, B., and Coan, M. 2004. Development of a 2001 national landcover database for the United States. *Photogramm. Eng. Remote Sens.* **70**(7): 829–840.
- Hoppus, M.L., and Lister, A.J. 2003. A statistically valid method for using FIA plots to guide spectral class rejection in producing stratification maps. *In Proceedings of the Third Annual Forest Inventory and Analysis Symposium, Traverse City, Mich., 17–19 October 2001. Edited by R.E. McRoberts, G.A. Reams, P.C. Van Deusen, and J.W. Moser. USDA For. Serv. Gen. Tech. Rep. NC-230. pp. 44–49.*
- Irish, R.R. 2000. Landsat 7 science data user's handbook. Report 430-15-01-003-0. Landsat Project Science Office, NASA, Greenbelt, Md. Available from http://ftpwww.gsfc.nasa.gov/IAS/handbook/handbook_toc.html.
- Johnston, D.C. 1982. Theory and application of selected multilevel sampling designs. Ph.D. thesis, Colorado State University, Fort Collins, Colo.
- Katila, M., and Tomppo, E. 2001. Selecting estimation parameters for the Finnish multisource National Forest Inventory. *Remote Sens. Environ.* **76**: 16–32.
- Kauth, R.J., and Thomas, G.S. 1976. The Tasseled Cap – a graphic description of the spectral-temporal development of agricultural crops as seen by Landsat. *In Proceedings of the Symposium on Machine Processing of Remotely Sensed Data, West Lafayette, Ind., 29 June – 1 July 1976. Edited by Phillip H. Swain and D.B. Morrison. Purdue University, West Lafayette, Ind. pp. 41–51.*
- Köhl, M. 1990. Double sampling in the Swiss National Forest Inventory: results of a pilot study. *In The Usability of Remote Sensing for Forest Inventory and Planning: Proceedings from SNS/IUFRO Workshop, Umeå, Sweden, 26–28 February 1990. Report 4. Edited by R. Sylkvander and S. Poso. Remote Sensing Laboratory, Swedish University of Agricultural Sciences, Umeå, Sweden. pp. 76–83.*
- Liknes, G.C., Nelson, M.D., and McRoberts, R.E. 2004. Evaluating classified MODIS satellite imagery as a stratification tool. *In Proceedings of the Joint Meeting of the 15th Annual Conference of The International Environmetrics Society and the 6th International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences, Portland, Maine, 28 June – 1 July 2004 [online]. Edited by H.T. Mower, R.E. McRoberts, and P.C. Van Deusen. Available from <http://www.spatial-accuracy.org/> [accessed 8 December 2005].*
- McRoberts, R.E., and Hansen, M.H. 1999. Annual forest inventories for the North Central region of the United States. *J. Agric. Biol. Environ. Stat.* **4**: 361–371.
- McRoberts, R.E., Wendt, D.G., Nelson, M.D., and Hansen, M.H. 2002a. Using a land cover classification based on satellite imagery to improve the precision of forest inventory area estimates. *Remote Sens. Environ.* **81**: 36–44.
- McRoberts, R.E., Nelson, M.D., and Wendt, D.G. 2002b. Stratified estimation of forest area using satellite imagery, inventory data, and the k -nearest neighbors technique. *Remote Sens. Environ.* **812**: 457–468.
- McRoberts, R.E., Gormanson, D.D., and Hansen, M.H. 2005. Can a land cover change map be used to increase the precision of forest inventory estimates of change in forest area, volume growth, and mortality. *In Proceedings of the 1st GIS and Remote Sensing Days — Environmental Studies, Göttingen, Germany, 7–8 October 2004. Edited by C. Kleinn, J. Nieschulze, and B. Sloboda. Sauerländer's Verlag, Frankfurt am Main, Germany. pp. 63–73.*
- Markham, B.L., and Barker, J.L. 1986. Landsat MSS and TM post-calibration dynamic ranges, exoatmospheric reflectances and satellite temperatures. *EOSAT Landsat Tech. Notes*, **1**: 3–8.

- Muironen, E., and Tokola, T. 1990. An application of remote sensing for communal forest inventory. *In* The Usability of Remote Sensing for Forest Inventory and Planning: Proceedings from SNS/IUFRO Workshop, Umeå, Sweden, 26–28 February 1990. Report 4. *Edited by* R. Sylkvander and S. Poso. Remote Sensing Laboratory, Swedish University of Agricultural Sciences, Umeå, Sweden. pp. 35–42.
- Nelson, M.D., McRoberts, R.E., Liknes, G.C., and Holden, G.R. 2002. Comparing forest/nonforest classifications of Landsat TM imagery for stratifying FIA estimates of forest land area. *In* Proceedings of the Fourth Annual Forest Inventory and Analysis Symposium, New Orleans, La., 19–21 November. *Edited by* R.E. McRoberts, G.A. Reams, P.C. Van Deusen, and W.H. McWilliams. USDA For. Serv. Gen. Tech. Rep. NC-252. pp. 121–128.
- Nelson, M.D., McRoberts, R.E., Holden, G.R., and Bauer, M.E. 2005. Satellite image spatial aggregation and resolution effects on forest land area estimates. *In* Satellite remote sensing for enhancing national forest inventory. M.D. Nelson. Ph.D. thesis, University of Minnesota, St. Paul, Minn. pp. 111–157.
- Nilsson, M., Folving, S., Kennedy, P., Puumalainen, J., Chirici, G., Corona, P. et al. 2003. Combining remote sensing and field data for deriving unbiased estimates of forest parameters over large regions. *In* Advances in forest inventory for sustainable forest management and biodiversity monitoring. *Edited by* P. Corona, M. Köhl, and M. Marchetti. Kluwer Academic Publishers, Dordrecht, Netherlands. pp. 19–32.
- Nilsson, M., Holm, S., Reese, H., Wallerman, J., and Engberg, J. 2005. Improved forest statistics from the Swedish National Forest Inventory by combining field data and optical satellite data using post-stratification. *In* Proceedings of ForestSat 2005, Borås, Sweden, 31 May – 3 June 2005. *Edited by* H. Olsson. National Board of Forestry, Jönköping, Sweden. pp. 22–26.
- Poso, S. 1972. A method of combining photo and field samples in forest inventory. *Commun. Inst. For. Fenn.* 76.
- Poso, S., Hame, T., and Paananen, R. 1984. A method of estimating the stand characteristics of a forest component using satellite imagery. *Silva Fenn.* 18: 261–292.
- Poso, S., Paananen, R., and Simila, M. 1987. Forest inventory by compartments using satellite imagery. *Silva Fenn.* 21: 69–64.
- Riitters, K.H., Wickham, J.D., O'Neill, R.V., Jones, K.B., Smith, E.R., Coulston, J.W., Wade, T.G., and Smith, J.H. 2002. Fragmentation of continental United States forests. *Ecosystems*, 5: 815–822.
- Rouse, J.W., Jr., Haas, R.H., Schell, J.A., and Deering, D.W. 1973. Monitoring the vernal advancement and retrogradation (green wave effect) of natural resources. Progress Report RSC 1978-1. Remote Sensing Center, Texas A&M University, College Station, Tex.
- Scott, J.M., Davis, F., Csuti, B., Noss, R., Butterfield, B., Groves, C. et al. 1993. Gap analysis: a geographical approach to protection of biological diversity. *Wildl. Monogr.* 123: 1–41.
- Tokola, T. 2000. The influence of field sample data location on growing stock volume in Landsat TM-based forest inventory in eastern Finland. *Remote Sens. Environ.* 74: 422–431.
- Tokola, T., Pitkanen, J., Partinen, S., and Muironen, E. 1996. Point accuracy of a non-parametric method in estimation of forest characteristics with different satellite materials. *Int. J. Remote Sens.* 17: 2333–2351.
- Trotter, C.M., Dymond, J.R., and Goulding, C.J. 1997. Estimation of timber volume in a coniferous plantation forest using Landsat TM. *Int. J. Remote Sens.* 18: 2209–2223.
- Vogelmann, J.E., Howard, S.M., Yang, L., Larson, C.R., Wylie, B.K., and Van Driel, N. 2001a. Completion of the 1990s National Land Cover Data Set for the conterminous United States from Landsat Thematic Mapper data and ancillary data sources. *Photogramm. Eng. Remote Sens.* 67: 650–662.
- Vogelmann, J.E., Helder, D., Morfitt, R., Choate, M.J., Merchant, J.W., and Bulley, H. 2001b. Effects of Landsat 5 Thematic Mapper and Landsat 7 Enhance Thematic Mapper Plus radiometric and geometric calibrations and corrections on landscape characterization. *Remote Sens. Environ.* 78: 55–70.
- White, D., Kimerling, J., and Overton, S.W. 1992. Cartographic and geometric components of a global sampling design for environmental monitoring. *Cartogr. Geogr. Info. Sci.* 19: 5–2.
- Yang, L., Homer, C.G., Hegge, K., Huang, C., Wylie, B., and Reed, B. 2001. A Landsat 7 scene selection strategy for a National Land Cover Database. *In* International Geoscience and Remote Sensing Symposium, Sydney, Australia, 9–13 July 2001 [online]. IGARSS '01. IEEE 2001. Vol. 3. IEEE, Piscataway, N.J. pp. 1123–1125. Available from <http://ieeexplore.ieee.org/xpl/RecentCon.jsp?punumber=7695>.