PHASE I FOREST AREA ESTIMATION USING LANDSAT TM AND ITERATIVE GUIDED SPECTRAL CLASS REJECTION: ASSESSMENT OF POSSIBLE TRAINING DATA PROTOCOLS[1]

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Abstract—Two methods of training data collection for automated image classification were tested in Virginia as part of a larger effort to develop an objective, repeatable, and low-cost method to provide forest area classification from satellite imagery. The derived forest area estimates were compared to estimates derived from a traditional photo-interpreted, double sample. One method used maplets digitized from ancillary imagery. Seed pixels, the other approach, used only available ground plot data and the image to be classified. Both methods of training data collection resulted in classification accuracy approaching 89 percent, and area estimation precision surpassing the FIA standard of 3 percent per million acres of timberland. However, the precision estimate was met in large part from the additional ground truth data collected supplemental to the national standard sample frame of one plot per 6,000 ac. The seed pixel approach is recommended over maplets, because it does not require ancillary imagery and is less costly in analyst time.

INTRODUCTION

The Agricultural Research, Extension and Education Reform Act of 1998 called upon the Forest Service to develop and implement a strategy to improve the performance of the Forest Inventory Analysis program. A study by the RAND Corporation recommended that FIA explore utilization of Landsat Thematic Mapper (TM) data for area measurements on a national scale (Peterson and others 1999). Rich Guldin, Director of Science Policy, Planning, Inventory, and Information, USDA Forest Service, recently set the goal of completing " . . . the transition from reliance on aerial photography to use of remotely sensed satellite imagery by the end of FY 2003" (Guldin 2000).

The first phase of this transition to operational satellite image utilization will be its use to produce forest area estimates and provide Phase I stratification for the ground sample.

If classification of raw TM data is to be used on an operational basis for FIA area estimation, two things are required:

1. Image analysis techniques that are low-cost, fast, objective, and repeatable.
2. Standard protocols for the collection of training and validation reference data.

If reference data protocols can be based upon existing field protocols, with little or no modification, this transition can be smooth and cost-effective.

This paper reports on work done in Virginia using an automated classification procedure, Landsat TM imagery, and training data collected from the FIA data sampling frame. The objectives of this work were

1. To further develop an objective, repeatable, and low cost process to obtain forest/nonforest stratification (classification) with TM imagery.
2. To use this stratification in conjunction with Phase II and III ground truth to provide adjusted forest land estimates.
3. To develop more objective, low-cost and effective methods of obtaining training data for use in the classification process.
4. To compare the precision of forest area estimates obtained using classified imagery with those obtained through traditional photo-interpretation methods and double sampling.

DATA

A Landsat 7 Enhanced Thematic Mapper Plus (ETM+) scene covering eastern Virginia, WRS Path 15, Row 34, acquired on March 3, 2000, was used for this analysis. The scene was geo-rectified using 30 ground control points and a first-order polynomial model. The root mean square error (RMSE) for the geo-rectification model was 11.8 m. For a sample of 10 independent ground control checkpoints, the RMSE was 11.9 m. Spectral bands 1–5 and 7 were used for the analysis.

Ground reference data came from annual forest inventory field measurements made in the years 1997-2000 in Virginia. At the time of analysis, 978 Phase II and 24 Phase III ground plots were available, representing slightly > than three of the five panels of the 5-year annual sampling frame. Also available were land use classifications from 285 deleted plots (ground plots for the last survey that had been dropped from the five-panel system but remeasured by Virginia crews). Precise coordinates from differentially corrected GPS observations were collected for all of these points, with an estimated accuracy of better than 10 m. Also available were 753 intensification plots, where aerial photo-interpreted land use points were verified on the ground by field crews. Coordinates for the intensification plots were digitized using 10 m SPOT panchromatic imagery, dated 1993 to 1994. In total, 2,040 land use ground truth points were available. For collections of training data, 430 Phase II

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plots and 24 Phase III plots were used. Of the remaining plots, 131 could not be used for validation due to clouds or bad ETM+ data, leaving 1,455 plots for validation. The resulting validation sampling intensity was one point per 4,600 ac. Table 1 summarizes the training and validation ground truth data.

The entire scene was used in the classification process; however, a 30 county subset of the image was used for stratification and land use estimation, because the county is the smallest unit for each that estimates are traditionally derived. The 30 county subset contains 5.2 million ac of land, and was 67.1 percent forested, with 3.38 million ac of forest land in 1992, the date of last survey. The entire scene covers approximately 7.6 million ac, with a similar proportion of forest land.

Available for comparison are preliminary, county-level, forest area estimates obtained using the traditional double-sampling technique with a large sample of photo-interpreted points, corrected with ground truth from both Phase II and intensification points. For the 30 county subset, the large sample of photo-interpreted points was 41,275 in size. The standard errors of these estimates were estimated using the formulae of Li and others (1992).

ITERATIVE GUIDED SPECTRAL CLASS REJECTION

Iterative Guided Spectral Class Rejection (IGSCR) is a hybrid classification method that builds and labels spectral classes for use in supervised approaches such as the maximum likelihood classifier (Wayman and others 2000). The IGSCR algorithm is, in essence, an objective and guided "cluster busting" (Jensen and others 1987, Rutchey and Vilchek 1994) approach that uses specific rejection criteria and large numbers of training pixels.

The IGSCR method accepts and labels a spectral class when it meets the desired inclusion threshold and rejects it if it does not. In this case, the inclusion threshold required at least 90 percent homogeneity within spectral classes and a minimum of at least 20 training data pixels per class. All pixels in spectral classes meeting the 90 percent homogeneity/minimum pixel test are labeled and removed from the original raw image. The unlabeled pixels from the raw image are then clustered into new spectral classes and the next iteration begins. Each of the iterations increases the number of pixels (and spectral classes) with known identity and decreases the number of unclassified training pixels. Once the iterations are complete (based on user-defined parameters such as the percentage of pixels classified or the classification of all training pixels), the known spectral classes are combined into a single signature file. The pure spectral classes are then used with the maximum likelihood decision rule to classify the image.

TRAINING DATA

Maplets

Classifications of forest and nonforest land use, termed maplets, were created via heads-up digitizing for relatively small landscape areas within the scene. The image backdrops used were digital orthophoto quarter quadrangles (DOQQ), obtained from the U.S. Geological Survey. DOQQs with image acquisition dates of 1994-1996 were available for 24 of the existing 26 Phase III plots in the pilot study area. Twenty-four 1 km x 5 km maplets were created, approximately centered on each of the 24 Phase III plots. Three categories (forest, nonforest, and uncertain) were used. Any natural or cultural feature as large as a TM pixel (or that dominates the spectral response of a TM pixel) was digitized. Visual inspection of the Landsat 7 ETM+ imagery (panchromatic, multi-spectral, and pan-sharpened) was conducted to determine whether the area mapped had changed since the date of the DOQQ. Areas that changed were edited.

Table 2 summarizes the amount of training data generated, expressed as percent of the image. Water was not sufficiently represented in the maplet sample so additional training data for water were collected visually from the TM image.

Advantages to the maplet process include (1) their potential utility for the FIA program for other uses and (2) the ability to accurately map areas that are traditionally problematic in TM forest/nonforest classifications such as low-density residential areas and recent harvests. The primary disadvantages are (1) the subjective, analyst intensive nature of the process and (2) the lack of national availability of DOQQs or equivalent imagery. These disadvantages led us to examine a process that has high potential to be objective, repeatable, and highly automated. This process uses a subset of FIA plot centers as "seed pixels" to segment areas of the image into training data.

Seed Pixels

The seed pixel approach started with a random selection of 500 Phase II plots to be used in obtaining training data.

Table 1—Ground plot location numbers for validation and training data from Phase II, Phase III, and intensification plots

Source	Total	Training	Unusable	Validation
Phase II plots	978	255	69	654
Phase III plots	24	23	1	—
Deleted Phase II	285	152	18	115
Intensification	753	—	67	686
Total	2,040	430	155	1,455

Table 2—Training data amounts for IGSCR forest/nonforest classification of Landsat 7 Scene 15/34, March 3, 2000

	Maplet	Seed pixels
Total (percent of image)	0.52	0.88
Composition (percent of total)		
Forest	50.1	69.6
Nonforest	15.3	10.1
Water	34.6	20.3

Seventy of these had to be dropped due to plot location in apparent mixed-land-use pixels, locations under clouds in the imagery, or location on some bad data lines in the image, leaving 430 plots. The sampling intensity for seed pixel initiation was one point per 13,200 ac.

At each of the FIA plots, the analyst located the plot center on the image, visually confirmed the land use call, and initiated a seed pixel. ERDAS Imagine software's seed pixel function works by appending adjacent pixels that are within a specified spectral distance of the mean of the pixels already within the cluster. The only analyst input required is the decision as to what maximum spectral distance should be used. The analyst varied the spectral distance parameter in order to create as large a cluster of pixels that appeared to be clearly within the same land use condition as possible. Development of a more objective and automated approach to seed pixel reference data generation, would help speed this process.

Table 2 summarizes the amount of training data generated by the seed pixel methods as well. Again, water was not adequately represented and the same ancillary water reference data were used as in the maplet training approach.

AREA ESTIMATION

For the photo-interpreted double sample, forest land percentage estimates and standard errors were computed with the formulae of Li and others (1992). Since the estimates obtained from image classification are "wall-to-wall", or a complete enumeration of the landscape, the double sampling estimates are not appropriate for estimating forest area. Instead, we used the approach for adjusted map marginals formulated by Card (1982).

RESULTS

Several classifications with different starting parameters, specifically the number of ISODATA classes allowed at the first iteration, were tried and all achieved very similar results. Hence, we will report here only the results of 4 classifications, those starting with up to 300 ISODATA classes. Two such classifications were made of the entire scene, and 2 were made for just the 30 county subset. Within each image extent, one used maplets for training data and the other used seed pixel training data. Whole and subset results were very similar. For simplicity and ease of comparison with double-sample methods, we report only the subset results starting with 300 ISODATA classes.

Table 3 presents the Kappa statistics, overall map accuracy, and producers and user's accuracy for the forest and nonforest classes. Overall map accuracy ranged from 88.5 to 88.8 percent.

Table 4 presents the unadjusted and adjusted map marginal estimates of percent forest land, with standard errors. Also presented are results from the traditional photo-interpreted double-sampling estimation (PI). The PI estimate for the 30 county subset was 64.51 percent forest, with a standard error of 0.82 percent. On a per million acres of forest land basis, the standard error is 1.51 percent, well under the national FIA standard of 3 percent per million acres.

Table 3—Classification accuracy for forest/nonforest by photo-interpretation, and various IGSCR classifications of Landsat 7 Scene 15/34, March 3, 2000

		Image Subset	
Accuracy	Photo-interpretation	IGSCR maplet	IGSCR seed pixel
	- - - - - - - - - - - *Percent* - - - - - - - - - - -		
Overall	93.8	88.8	88.9
User's			
Forest	94.5	87.9	87.3
Nonforest	—	90.8	92.6
Producer's			
Forest	—	95.3	96.4
Nonforest	—	77.8	76.3
Kappa statistic	—	0.7534	0.7541

Table 4—Estimates and standard errors of forest land for 30-county subset of Scene 15/34, from photo-interpreted double sampling and IGSCR image classifications

	Photo-interpreted double sample	IGSCR maplet	IGSCR seed pixel
	- - - - - - - - - - *Percent* - - - - - - - - - -		
Unadjusted Map marginals	65.26	71.57	70.36
Adjusted Map marginals	64.51	65.43	64.51
Standard error	0.82	1.06	1.05
Standard error (per million acres)	1.51	1.95	1.93

For the IGSCR classifications, the adjusted map marginal estimates are very close to the PI estimates: 65.43 percent (maplet) and 64.51 (seed pixel). As expected, the standard errors are higher: 1.06 percent (maplet) and 1.05 percent (seed pixel). On a per million acres of forest land basis, at 1.95 percent (maplet) and 1.93 percent (seed pixel), the estimates still surpass the FIA precision goal of 3 percent.

Note the 5 to 6 percent overestimate of forest land by the unadjusted map marginals (table 4). This suggests that the IGSCR method is overclassifying forest. Knowledge of the area and visual inspection of the image suggest that the major problems are urban and suburban areas with tree cover similar to areas of forest land use. This suggests that masking of known urban/suburban areas could improve the accuracy of the IGSCR classifications.

DISCUSSION

The IGSCR classification method performed well in estimating forest land area using adjusted map marginals. The precision of the estimates exceeded the FIA national standard of 3 percent per million acres of forest land. The method compared favorably to photo-interpreted double sampling, although with some loss of precision.

Within the limits of this case study, the IGSCR method proved to be objective and repeatable. Since this work was still developmental, operational costs were not estimated. However, we feel that its cost should be comparable to, if not considerably less than, photo-interpretation and supervised image classification approaches.

Two different protocols for collection of training data were examined and both performed equally well. Further work on the IGSCR method could possibly improve the current classification accuracy (89-90 percent) to approach that of the photo-interpretation methods (93-94 percent).

The amount of training data collected by either method was less than one percent of the image. Previous IGSCR development work (Wayman and others 2000) used 3 to 6 times the amount of training data, however, the classifier's performance was not any better. This result implies that possibly even less training data could be used. Furthermore, the maplet and seed pixel approaches had significantly different proportions of forest and nonforest training data (see table 2), but that seemed to make no difference in accuracy of classification, either overall or by class.

This work has shown that either maplets or seed pixels can work well as training data. Given the extra work involved in creating maplets, we do not recommend this approach unless the maplets are desired for other reasons, such as examination of landscape patterns. The seed pixel approach requires no additional imagery or ground truth other than a portion of the Phase II plots. Higher precision can be gained by either better classification accuracy or more ground validation points. Focusing on problem classes, e.g. suburban areas and recent harvests, could narrow the accuracy gap.

The IGSCR classifications, and resulting forest land estimates, meet the FIA precision standard of 3 percent per million acres. Much of the credit for reaching this goal, however, should be placed on the additional ground truth provided beyond Phase II and Phase III ground plots. In this study, deleted plots and intensification plots were also used. If this same project had been limited to one ground truth plot per 6,000 ac, the estimated standard errors per million acres of forest land would have been approximately 2.7 percent for the PI double sample and 3.5 percent for the IGSCR classifications. FIA programs should consider continuing, or initiating, land use intensification samples to achieve land use precision goals.

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