Satellite Inventory of Minnesota Forest Resources

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Abstract

The methods and results of using Landsat Thematic Mapper (TM) data to classify and estimate the acreage of forest cover types in northeastern Minnesota are described. Portions of six TM scenes covering five counties with a total area of 14,679 square miles were classified into six forest and five nonforest classes. The approach involved the integration of sampling, image processing, and estimation. Using two-stage sampling, 343 primary sampling units (PSU), each 88 acres in size, were photo interpreted and field mapped as a source of reference data for classifier training and calibration of the TM data classifications.

Classification accuracies of up to 75 percent were achieved; most misclassification was between similar or related classes. An inverse method of calibration, based on the error rates obtained from the classifications of the PSU plots, was used to adjust the TM classification proportions for classification errors. The resulting area estimate for total forestland in the five-county area was within 3 percent of the estimate made independently by the USDA Forest Service. Area estimates for conifer and hardwood forest types were within 0.8 and 6.0 percent, respectively, of the Forest Service estimates. A study of the use of multidate TM data for change detection showed that forest canopy depletion, canopy increment, and no change could be identified with greater than 90 percent accuracy. The project results have been the basis for the Minnesota Department of Natural Resources and the Forest Service to define and begin to implement an annual system of forest inventory which utilizes Landsat TM data to detect changes in forest cover.

Introduction

Forests covering 16.7 million acres, or nearly a third of the land area of Minnesota, are a significant component of the state's natural resource base and a significant contributor to its economy. In spite of growing demands for information about the state's forest resources, statewide inventories are conducted only at about 15-year intervals. Although forest stand growth models have become increasingly important for updating inventory information and projecting future forest conditions (Ek, 1983), such updates are limited because of their concentration on existing forested plots. Total forest area and area by cover type change because of cropland abandonment, harvesting, and urban development. Such changes are extremely difficult to model; that is a major reason for wanting to use satellite data to determine forest areas. Because the mean characteristics of forest strata change relatively little, the major inventory problem is to estimate the amount and location of the strata.

For many years foresters have effectively utilized aerial photography as a tool to help monitor and manage forest resources, and aerial photographs are an integral part of most forest inventory procedures. The launch of Landsat-1 in 1972 added an entirely new dimension to the capability to acquire Earth resources information, and there has been much interest in the potential of satellite data and computer-aided analysis techniques to identify and map forest resources. Although it has generally not been possible with Landsat MSS data to achieve satisfactory classification accuracy for any but the most general classifications in the Great Lakes States, a number of studies have shown that the information content of Landsat Thematic Mapper (TM) data is considerably higher than that of MSS data (Price, 1984; DeGloria, 1984), and that the additional spectral bands and finer spatial and radiometric resolution of TM data result in significant improvements in classification accuracy for more specific information classes describing forest species (Horler and Ahern, 1986; Moore and Bauer, 1990) and forest stand characteristics (Peterson *et al.*, 1986; Williams and Nelson, 1986). The results of Moore and Bauer (1990), which provided much of the impetus for this research, showed a 15 to 20 percent increase in classification accuracy of TM data over MSS data, with TM accuracies of greater than 80 percent for seven classes.

Objectives

The overall objective of the research was to develop and test procedures for using multispectral satellite data to inventory forest resources in the state of Minnesota. Specific objectives were to

- Develop a methodology to use digital satellite data and computer-aided pattern recognition to classify forest cover types which will be compatible with and complementary to the other surveys conducted by the Minnesota Department of Natural Resources and the U.S. Forest Service;

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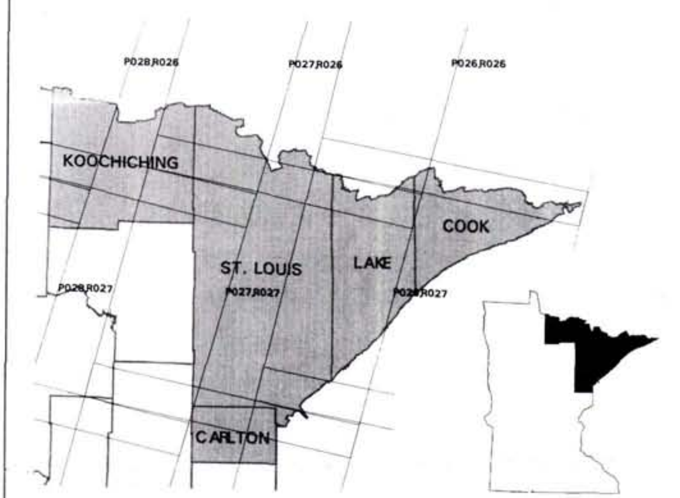

Figure 1. Location of five-county project study area in northeastern Minnesota (FIA aspen-birch unit) and Landsat TM scenes.

- Estimate forest areas and produce digital maps of the state's forest resources by species group at county, region, and state levels, and determine the accuracy and precision of the forest area estimates and maps derived from satellite data, compared to traditional forest inventory estimates;
- Investigate alternative innovative approaches to satellite data classification, sampling, and estimation and determine to what degree satellite data classifications can be used to obtain additional information such as stand density, size class, and disturbance; and
- Integrate the satellite data classification, sampling, and estimation designs and procedures into the Forest Resource Assessment and Analysis Program of the Minnesota Department of Natural Resources (DNR) and Forest Inventory and Analysis (FIA) of the U.S. Forest Service.

The goal of the project was to develop and implement a methodology to provide cover type area estimates of ± 5 percent at the 95 percent confidence level at the state level and ± 10 percent with 90 percent confidence at the county level. Other performance goals of the final inventory procedure were (1) cost $0.01 to $0.02 per forested acre, (2) one year to acquire and analyze the data, (3) procedures that can be implemented by the DNR with reasonable personnel and capital costs, and (4) enough flexibility to meet changing conditions or requirements.

Two important underlying premises of the objectives and approach tested in the investigation are (1) that the synoptic view of Landsat provides the opportunity to obtain forest inventory information over large areas (i.e., state) and (2), that by using computer data analysis methods to classify pixels distributed over counties and unique sampling designs, it is also possible to make accurate and precise estimates for local areas (i.e., counties). This approach offers a means to improve upon the sampling methods now used for making area estimates from ground-based, two-phase surveys. At the same time, the ground data (which are also used to estimate other parameters such as forest stand characteristics; therefore, its collection cannot be abandoned) will be used to remove the bias from (i.e., to correct) the satellite-based estimates. An important consideration in the proposed approach is that improved cover type estimation techniques would lead to more efficient and timely forest descriptions for a variety of purposes.

Multispectral Landsat TM data, together with ground-based forest inventory data were used to produce an inventory of Minnesota forest lands, along with a methodology for frequent updates. The following sections describe the sample design and survey model, satellite data classification methods and results, calibration and evaluation of Landsat area estimates, change detection using multidate Landsat data, and, lastly, the use of satellite remote sensing for operational forest inventories in Minnesota. The emphasis is on describing new approaches to forest inventory using satellite data.

Background

Study Area

The study area for the project consisted of five forested counties in northeastern Minnesota (Figure 1), totaling some 9.4 million acres. The region stretches nearly 230 miles east/west and 170 miles north/south. The study area corresponds to the USDA Forest Service's Forest Inventory and Analysis (FIA) survey unit one, commonly referred to as the Aspen/Birch unit (Miles and Chen, 1992). The study area is comprised of a variety of forest types, with primary types being aspen-birch, spruce-fir, and pine.

The geology of this region is largely the result of glaciation (Wright, 1972). The northeastern portion of the area, Lake and Cook counties, is marked with an abundance of Canadian Shield lakes, and displays relatively large topographic variations. The western half of the region, Koochiching county, is a vast lowland with intermittent moraines. The central portion of the region is characterized by a variety of geologic formations, and is heavily forested. The central portion of St. Louis county is dominated by granite highland termed the "Iron Range," and is home to numerous mining operations. In southern St. Louis and Carlton counties, agriculture and other non-forest land uses are more prevalent. Even so, these areas are still predominately forested.

Hardware and Software Environment

Image processing was performed on SUN SparcStations and 386 microcomputers. Raster-based image processing and GIS procedures were completed using workstation ERDAS (Earth Resources Data Analysis System). Vector GIS and data development procedures were completed using PC Arc/Info 3.4D. Additional routines were developed in-house using C and other script languages.

Landsat Data

The image data for the project consisted of portions of six Landsat TM scenes (Figure 1). Data were collected between 29 May 1988 and 14 June 1988, with scenes along the same path being collected on the same day. All images were virtually cloud free, with any clouds occurring outside of the study area; however, haze was observed over water bodies within the path 26, row 26 scene covering the northeast portion of the study area.

All scenes were rectified to the UTM (zone 15) projection and coordinate system using a nearest-neighbor resampling scheme to preserve the original digital numbers. Rectification allowed for relatively easy overlay of reference data sets for training and accuracy assessment. Because of the inherent problems of working across scenes of differing acquisition dates (changes in atmosphere, sun angle, and phenology), processing was limited to within scene (or path) processing. Consequently, three separate image datasets were processed; they were merged only as classified (GIS) files.

Reference Data

Reference data sets were generated using prints (scale 1:9,400) and transparencies of 35-mm color infrared aerial photography. Seven lines of photography were gathered at equal intervals across the study area (Plate 1A). Interpretation units were defined as 88-acre (approximately 1/4- by 1/2-mile) primary sampling units (PSUs) spaced roughly one mile apart over the entire length of the flightlines (Plate 1B). A total of 343 PSUs were stereoscopically interpreted into approximately 100 cover type, size, and density classes (Table 1). Subsequent to photo interpretation, all PSUs were visited on the ground, or viewed from the air if ground access was limited. Cover type designations and boundaries were verified or, if necessary, corrected, either for errors in photo interpretation or for changes that had occurred between the Landsat and aerial photography acquisition. The PSUs were located on USGS 7.5-minute quadrangles, and the PSU and cover type boundaries were digitized using PC Arc/Info. Reference datasets were then rasterized and linked to attribute data (i.e., type, size, and density) and registered to the Landsat image data.

Survey Design

Given the emphasis on forest area estimation and satellite data, there is much potential for gains from refinements in survey design. Designs using large PSUs have been shown to be an effective means of collecting forest inventory information (Scott *et al.*, 1983). In particular, Benesslah (1985) has shown that such layouts have decided advantages for ground checking of remotely sensed data. Advantages include ease of field work, variance reduction, and the provision of area data as proportions (fractions of area) rather than binary (0-1) counts. Proportion data facilitate the use of remote sensing data because it is relatively insensitive to scale problems. The sampling design used was a single-phase design involving Landsat classifications of the entire area and ground checking of a sample of large PSUs. This exploited the synoptic coverage of satellite-acquired digital remote sensing data, with the advantage of using all of the pixels in the population for making area estimates.

The PSUs were photo interpreted, as well as observed on the ground, to assess forest type. The PSUs might be 10 to 100 or more acres in size; however, the size used here was a consistent 88 acres (equivalent to 17 by 23 TM pixels). The ground sampling (field visit) established an accurate type map for each PSU, i.e., polygons in the PSU were identified and labeled as to cover type. This meant usage of cover types and boundaries according to standards of interest to forest management (Table 1). PSUs were distributed systematically (with a random start) across the survey unit (Plate 1B). The ground sample PSUs were then used to train the classifier, and subsequently the classifications became the dependent variables for regression estimates of the population proportion of the PSUs in the various cover types.

The ground PSUs were very inexpensively mapped and field checked using large-scale color infrared aerial photography. Total costs of photography acquistion, photo interpretation and preliminary cover type of the PSUs, field verification of cover types and boundaries, and digitizing PSU and cover

Table 1. Hierarchy of Information Classes for Photo Interpretation and Classification of Landsat TM Data. The Forest Cover Types Were Further Subdivided into Three Crown Closure and Three Size Classes.

Photo Interpretation Classes	Satellite Classes	Code
Ash	Lowland Hardwoods	LH
Elm		
Aspen/Birch	Aspen/Birch	A/B
Aspen		
Paper Birch		
Northern Hardwoods	Northern Hardwoods	NH
Upland Conifers	Upland Conifers	UC
Red Pine		
White Pine		
Jack Pine		
Balsam Fir/White Spruce	Balsam Fir/White	BF/WS
Balsam Fir	Spruce	
White Spruce		
Lowland Conifers	Lowland Confiers	LC
Lowland Black Spruce		
Tamarack		
Northern White Cedar		
Cutover Area	Shrub/Cutover/Grass	S/C/G
Lowland Grass		
Upland Grass		
Brush		
Cropland, Pasture	Agriculture	Ag
Urban and Industrial	Developed	Dev
Recreational Development		
Water	Water	W
Marsh	Marsh	M/M
Muskeg		

type boundaries and attribute data were approximately $100 per PSU. The photography was essential for locating the PSUs and delineating cover type boundaries. Its use also expedited the cover type identification.

Landsat TM Classification Methodology and Results

Although more than 100 land-cover classes resulted from interpretation of the aerial photography, it was apparent that such a detailed classification was not possible with the satellite data. In many cases there were not enough pixels in the reference data for training and classification. In other cases, initial tests showed no promise in separating certain classes (e.g., aspen versus birch). The reference (ground) data classes were then condensed into 11 (six forest, five non-forest) cover types based on spectral and forest management considerations as listed in Table 1.

In addition to the six reflective TM bands, a set of six vegetation indices (VIs) were added to form 12 feature sets used for classification. The VIs were chosen to be a representative sample of the possible such indices. The first set of indices consisted of the first three Tasseled Cap components – greenness, brightness, and wetness – with coefficients given by Crist and Cicone (1984). While greenness is the most indicative of vegetation cover, brightness is also related to vegetation cover. Wetness is related to moisture content and may be useful for wetland delineation and/or upland versus lowland forest types. The second group of VIs were ratios that have been found to intensify forest canopy characteristics. This group consists of TM4/TM3, TM4/TM2, and TM5/TM4 ratios. Jensen (1983), among others, states that TM4/TM3 provides information with respect to vegetation and canopy condition and that TM4/TM2 may be a promising feature for wetland identification. The TM5/TM4 ratio has been used in

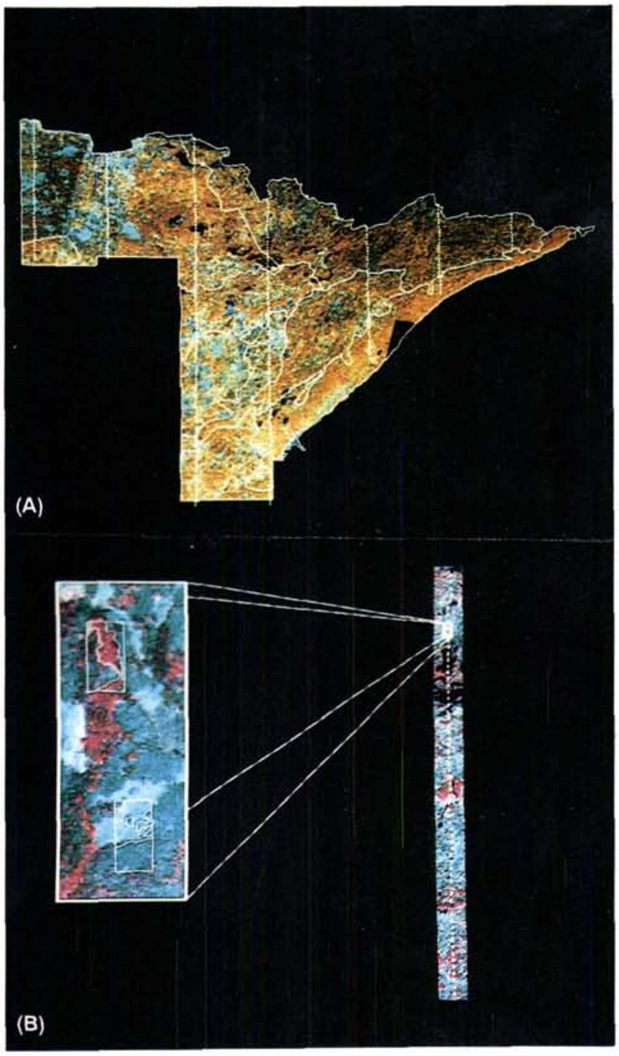

Plate 1. (A) Mosaic of Landsat TM images with overlays of aerial photography flightlines (N-S lines) and boundaries of physiographic strata. (B) Overlays of forest type polygons on Landsat TM imagery for two sample units (left). Locations of aerial photography flightlines and sample units are shown on right hand image.

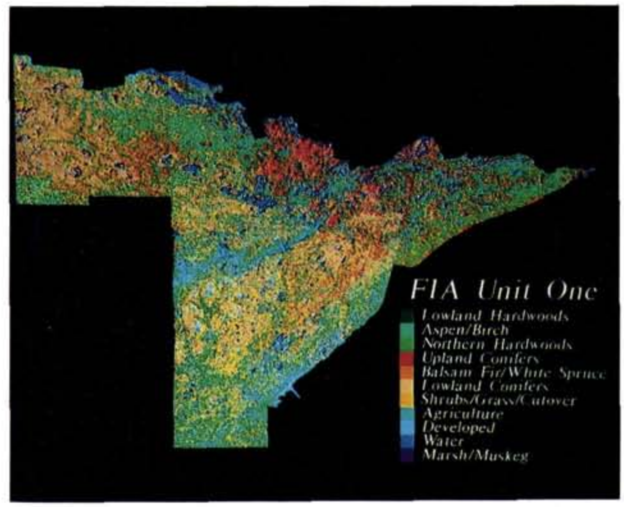

Plate 2. Final classification of Landsat TM data of five-county study area.

studies related to conifer canopy structure (Peterson *et al.*, 1986).

A number of classification processing approaches were evaluated for their utility in large area classification. Both supervised and unsupervised, and a combination of supervised and unsupervised, approaches were examined. Supervised techniques were determined to be inadequate for a number of reasons: extreme forest complexity, narrow cover type spectral separability, and limited potential for automated processing. Several types of clustering methodologies, from standard ISODATA clustering (ERDAS, 1991) to hierarchical strategies defining more than 1,000 classes, were tested. In all cases, the ability to name the resulting classes was limited by the within-class variability to a few well represented classes. In most cases, less than 50 percent of unsupervised classes could be named, and in no cases could classes be developed for all target classes.

An alternative to the supervised and unsupervised approaches is what we have called "guided" clustering. The procedure makes use of both supervised and unsupervised techniques, but avoids many of the problems associated with each individually. The method makes use of analyst defined training data, in our case, digitized cover type polygons from the interpreted photo plots (PSUs), to identify image pixels of a single class that are clustered into spectrally homogenous sub-classes. An example of two PSUs with cover type polygons delineated is shown in Plate 2. The processing stream was follows:

(1) Delineate image pixels for target class A;
(2) Using ISODATA, cluster class A pixels into sub-classes A1, A2, ..., An;
(3) Repeat Steps 1 and 2 for all 11 target classes;
(4) Perform maximum-likelihood classification using all sub-classes on the entire image;
(5) Collapse (RECODE) subclasses back to the original 11 target classes; and
(6) Perform post-processing procedures (e.g., majority filtering).

Guided clustering provided consistently superior results to any of the other methods tested. The process is highly automated, so was ideal for large area application. The approach combines the training and classification approach with statistical information from the primary sampling units.

The sheer size of the area to be classified created many obstacles that had to be overcome. It was clear from visual assessment of the Landsat imagery that land-cover gradients existed within the scenes. In addition, atmospheric and phenologic differences existed from north to south and, to a lesser extent, from east to west through the study area. To compensate for such differences, physiographic regions delineated by Wright (1972) were used to segment the study area into eight sub-regions (Plate 1A). TM images for paths 26 and 28 were not segmented into sub-regions because there was not sufficient training data for all of the physiographic

TABLE 2. DISTRIBUTION (%) OF COVER TYPES FOR EACH PHYSIOGRAPHIC REGION AS DETERMINED FROM REFERENCE DATA. SEE TABLE 1 FOR DESCRIPTION OF COVER TYPE CODES.

	Cover Type Class										
Region	LH	A/B	NH	UC	BF/WS	LC	S/G/C	Ag	D	W	M/M
Agassiz	2.0	44.0	0.0	2.3	3.0	13.3	6.0	3.6	1.0	20.3	4.5
Border Lakes	0.0	22.9	0.0	29	2.0	12.6	1.1	0.0	0.2	31.1	1.1
Laurentian	0.0	40.4	0.7	19.1	4.3	26.5	5.3	0.0	0.0	1.5	2.2
Mille Lacs	4.1	23.9	7.0	0	0.4	13.3	13.4	25.2	1.9	3.0	7.8
Iron Range	1.0	41.2	1.9	7.4	2.6	9.8	8.6	2.8	18.8	5.2	0.7
Tamarack	4.1	22.2	4.0	0.0	3.7	34.5	18.2	3.9	4.9	0.1	4.4
LS Highlands	1.1	39.9	11.8	3.0	3.6	10.2	9.4	7.1	5.1	6.4	2.4
Tamarack II	2.1	39.9	1.3	3.3	1.3	19.8	12.4	2.9	1.9	7.5	7.6

regions falling within each image. The resulting cover type distributions for the reference data are shown in Table 2. The distribution of cover types across physiographic regions is not constant, and is actually quite varied, a good indication that the segmentation scheme accomplished what we had hoped. Each physiographic region was classified using the guided clustering approach described above. The use of the physiographic stratification prior to classification increased the overall classification accuracy by 10 to 15 percent. Once classified, the subregion GIS files were re-assembled into the county and survey unit files.

After classification, the images were majority filtered to remove "salt-and-pepper" artifacts in an attempt to re-create the forest stand (polygon) structure inherent in the reference data. Tests against reference data indicated an optimal window size between 4 and 5 pixels square. A 5 by 5 window was chosen for ease of application and to minimize bias.

The final classifications for the 11 target classes for the entire study area are shown in Plate 2. Overall classification accuracies ranged from 64 to 80 percent, with average class accuracies from 63 to 76 percent (Table 3). The Kappa statistic (Congalton and Mead, 1986), which removes the contribution of correct classification due to chance, ranged from 0.56 to 0.76. Example error matrices are given in Tables 4 and 5. Overall accuracy of classification of forest, nonforest, and water for these two examples was 86 percent for Koochiching County and 85 percent for Lake Superior Highlands. The overall accuracy of classifying conifer versus hardwood forest, along with nonforest land and water, was 79 percent in Koochiching County and 77 percent for the Lake Superior Highlands. Because of the necessity to use all of the available reference data for classifier training, all of the reported classification accuracies are for training data. All pixels within the primary sampling units were included in the determination of classification accuracy.

The majority of classification errors for forest classes occurred in adjacent classes such as lowland hardwood and aspen/birch, lowland conifer and balsam fir/white spruce, and northern hardwood and aspen/birch. The classes of agriculture, developed, water, and marsh were classified relatively accurately, generally 75 percent or higher. The shrub/grassland/cutover class was the most prone to misclassification; it was confused with all classes, especially other types of forest and non-forest vegetation. In general, similar or related classes were more likely to be confused with each other than with different classes.

Part of the misclassification results from the considerable difficulty in assigning a unique label to each polygon in the reference data and pixel in the Landsat data. The traditional concept of a forest stand, which we used in developing the reference data, often does not relate to or capture the variability that is present in satellite imagery. Forest stands tend to be defined by management considerations, whereas the multispectral radiances measured by the TM data are determined by the biophysical properties of the cover type(s) within each pixel.

Two additional observations can be made about classification accuracy. First, while satellite imagery is typically referred to as having low resolution (at least in comparison to aerial photography), it actually has much higher resolution than forest cover type maps. The minimum mapping unit for our reference data was 2.5 acres, compared to the 1/4-acre pixel size of the TM data. Many inclusions of spatially small cover types were not mapped in the reference data, and, even if correctly classified in the TM data, would show up as classification errors. Second, at the pixel level the accuracy of the reference data is probably no better than 75 to 80 percent. Therefore, it is impossible to achieve measured classification accuracies of more than that. It also can be noted that large area classification is a more difficult problem, likely to result in lower classification accuracy, than found in previous studies which were typically classifications of small areas.

Calibration of Landsat Area Estimates

The satellite imagery provided estimates of type acreages for the area as a whole (Table 6). However, it is probable that those estimates have a bias associated with them. The ground survey PSUs provided observations on how the satellite data classifications compared to ground classifications

TABLE 3. NUMBER OF PRIMARY SAMPLING UNITS (N) USED FOR CLASSIFIER TRAINING AND SUMMARY EVALUATION OF CLASSIFICATION ACCURACY.

County or Physiographic Region	N	Kappa Coefficient	Overall Accuracy (%)	Average Class Accuracy (%)
Koochiching County	67	0.61	73.1	63.8
Lake and Cook Counties	68	0.60	68.2	68.8
Agassiz	43	0.62	69.2	74.6
Border Lakes	38	0.64	72.9	72.0
Laurentian	22	0.67	75.8	74.9
Mille Lacs	19	0.76	80.2	75.9
Iron Range	31	0.58	67.6	65.6
Tamarack	26	0.60	67.5	68.5
Lake Superior Highlands	42	0.64	70.3	73.3
Tamarack II	21	0.56	64.0	73.7

TABLE 4. CLASSIFICATION ERROR MATRIX FOR KOOCHICHING COUNTY.

Ground Classes	Landsat TM Classes								
	LH	A/B	BF/WS	LC	S/C/G	Ag	Dev	Water	M/M
LH	789	727	80	138	244	76	7	21	4
A/B	147	2364	111	220	332	59	18	51	0
BF/WS	86	287	801	307	78	1	3	4	0
LC	16	626	69	11471	522	10	4	18	52
S/C/G	23	309	81	344	838	43	3	8	9
Ag	28	137	59	55	169	700	26	0	0
Dev	6	64	4	0	8	3	188	5	0
Water	30	128	25	44	28	1	2	403	0
M/M	8	85	25	542	26	1	0	2	530
% Corr.	69.9	50.0	63.8	87.4	37.3	78.3	78.3	78.7	89.1

Overall accuracy = 73.1%, Average class accuracy = 63.8%, Kappa coefficient = 0.61.

TABLE 5. CLASSIFICATION ERROR MATRIX FOR LAKE SUPERIOR HIGHLAND PHYSIOGRAPHIC REGION.

Ground Classes	Landsat TM Classes										
	LH	A/B	NH	UC	BF/WS	LC	S/C/G	Ag	Dev	Water	M/M
LH	172	17	5	0	0	0	22	0	0	0	0
A/B	3	4329	174	83	70	126	331	25	43	132	54
NH	11	370	1667	20	0	23	103	39	29	0	0
UC	0	117	2	348	5	15	27	2	7	8	2
BF/WS	0	238	2	3	404	27	61	3	17	2	6
LC	0	574	86	0	79	1449	76	0	29	39	11
S/C/G	3	471	3	20	18	6	727	38	50	5	7
Ag	0	304	11	18	15	24	139	1050	119	1	0
Dev	0	122	31	4	7	24	68	34	507	6	0
Water	0	76	0	5	0	0	0	0	53	844	19
M/M	0	65	0	8	4	20	18	0	10	36	289
% Corr.	91.0	64.7	84.1	68.4	67.1	84.5	46.2	88.2	58.7	78.7	74.5

Overall accuracy = 70.3%, Average class accuracy = 73.3%, Kappa coefficient, = 0.64.

for the same types, with the ground classifications assumed to be truth. Observations from the PSUs can thus be used to adjust the satellite-data-based estimates, a procedure we hope will result in a reduction or elimination of bias. This adjustment is commonly referred to as calibration.

As part of the project, Walsh and Burk (1993) compared the classical and inverse methods of calibrating satellite classifications where the ground sampling units were pixels. They found, through extensive simulations, that the inverse method was superior. The choice of the inverse method of calibration was based on that previous result and more theoretical reasons. With the inverse method, the satellite classified proportions in the various types are used as "independent" (without error) variables in the regression-based calibrator, while the ground classified proportions act as "dependent" (with error) variables. These are reasonable roles for these variables as the satellite classified proportions are fixed once the classifier is trained (results are conditional on that training) and interest lies directly in predicting ground classified proportions (i.e., truth). Studies by the USDA Statistical Reporting Service substantiate the use of this regression method over the traditional direct expansion estimator approach (Hanuschak *et al.*, 1982). Findings by Chhikara *et al.* (1986) strongly support the use of the regression estimator over the direct expansion or stratified ratio estimators except in cases of very poor classification accuracies in the ground sample units.

The unit of observation for the calibration problem was the ground PSU. For each PSU, we have a vector of satellite data classified proportions and a vector of ground classified proportions, with the number of elements of each vector being the total number of types being classified (each vector may have several zero elements). The elements of the vectors are proportions of the total PSU area classified as belonging to a particular type. The smallest population (area) of interest in our application is the county, with each county having a number of ground PSUs on which classification results were recorded. The total population of interest, an FIA survey unit, is a set of counties (five in the present case) that are contiguous and of similar forest composition.

Eleven types (classes) were used in classification. If there are n_l ground PSUs present in county l, we can specify an $n_l \times 11$ matrix $\mathbf{X}$ for the county that contains the satellite classified proportions for the PSUs located in the county. This provides a system of 11 equations relating the true (ground) type classified proportions($\mathbf{Y}$) to $\mathbf{X}$:

$$\begin{aligned} \mathbf{Y}_1 &= \mathbf{X}\boldsymbol{\beta}_1 + \boldsymbol{\epsilon}_1 \\ \mathbf{Y}_2 &= \mathbf{X}\boldsymbol{\beta}_2 + \boldsymbol{\epsilon}_2 \\ &\vdots \\ \mathbf{Y}_{11} &= \mathbf{X}\boldsymbol{\beta}_{11} + \boldsymbol{\epsilon}_{11} \end{aligned} \qquad (1)$$

where $\mathbf{Y}_i$ = vector with n_l elements where the $\mathbf{j}^{\text{th}}$ element is the ground classified proportion of type $\mathbf{i}$ in PSU_j;

$\mathbf{X}$ = $\mathbf{n}_l \times 11$ matrix where element $\mathbf{X}_{jk}$ is the satellite classified proportion of type $\mathbf{k}$ in PSU_j;

Table 6. Uncalibrated Landsat Estimates of Area (in Thousands of Acres) of Six Forest and Five Non-Forest Classes.

Class	County					Region Total
	Carlton	Cook	Koochiching	Lake	St. Louis	
Lowland Hardwood	6.1	0.0	226.5	0.0	93.6	326.5
Aspen/Birch	212.4	439.8	412.3	401.0	1,377.9	2,843.4
Northern Hardwood	61.3	90.4	0.0	47.5	81.0	280.2
Upland Conifer	6.7	140.9	0.0	343.8	365.5	856.0
Balsam Fir/White Spruce	5.1	114.4	188.7	107.4	214.1	629.7
Lowland Conifer	77.4	75.0	811.1	274.6	888.0	2,126.1
Shrub/Grass/Cutover	65.2	18.3	128.6	25.9	399.0	637.0
Cropland/Pasture	82.0	0.0	105.6	0.0	201.1	388.6
Developed/Other	9.4	0.0	7.9	0.0	167.4	184.7
Water	13.5	123.6	83.9	201.2	433.4	855.6
Marsh/Muskeg	21.1	30.6	53.7	65.2	95.0	265.6
Total	560.4	1,033.1	2,018.5	1,466.6	4,316.0	9,394.6

Table 7. Calibrated Landsat Estimates of Area (in Thousands of Acres) of Six Forest and Five Non-Forest Classes.

Class	County					Region Total
	Carlton	Cook	Koochiching	Lake	St. Louis	
Lowland Hardwood	3.1	0.0	131.6	0.0	34.3	169.0
Aspen/Birch	209.3	474.9	548.3	547.5	1,667.4	3,447.4
Northern Hardwood	50.7	67.8	0.0	78.8	56.4	253.7
Upland Conifer	9.1	135.7	3.8	269.2	418.6	836.4
Balsam Fir/White Spruce	2.7	83.9	144.5	44.2	112.9	388.2
Lowland Conifer	74.5	104.1	789.6	306.4	771.7	2,046.3
Shrub/Grass/Cutover	83.4	17.8	223.2	42.6	415.1	718.1
Cropland/Pasture	81.3	0.0	81.1	0.0	124.7	287.1
Developed/Other	13.1	3.6	9.3	13.4	202.8	242.2
Water	16.3	115.3	65.4	149.3	453.5	799.8
Marsh/Muskeg	18.0	30.1	21.6	15.3	58.6	143.6
Total	560.4	1,033.1	2,018.5	1,466.6	4,316.0	9,394.6

$\boldsymbol{\beta}_i$ = vector whose 11 elements are the coefficients from the regression of ground classified proportions in type **i** on satellite classified proportions in all 11 types; and

$\boldsymbol{\epsilon}_i$ = vector with $\mathbf{n}_I$ elements representing the error in predicting ground classified proportions from the satellite classified proportions.

This system of equations was fit separately to each of the five counties in the survey unit. Ordinary least squares was used. The results showed that 85 percent of the variation, on average, in the ground classified proportions was explained by **X**. With few exceptions, each regression was dominated by the satellite classified proportion corresponding to the type being predicted. However, all elements of **X** were retained in each equation to insure additivity of the predicted proportions. Individual residual plots gave no indication of heterogeneous variance within any particular equation.

The system of equations (Equation 1) would appear to be a seemingly unrelated regressions problem. That is, it seems likely that errors in predicting the ground classified proportions are correlated (cross-equation correlations). While ordinary least squares provides unbiased estimates of $\boldsymbol{\beta}$ for seemingly unrelated regression problems, accounting for cross-equation correlations can result in a more efficient estimate of $\boldsymbol{\beta}$. However, Ericksson (1989, p. 45) has shown that (1) when **X** is identical for each equation in the system and (2) errors within an equation are homogeneous, seemingly unrelated regressions is equivalent to applying ordinary least squares to each equation separately. Both these requirements are met in this application; thus, ordinary least squares is an appropriate fitting criterion.

For notational convenience, we stack the system of 11 equations (Equation 1) for a particular county and write them as

$$\mathbf{Y}_I = \mathbf{X}_I\boldsymbol{\beta}_I + \boldsymbol{\epsilon}_I \tag{2}$$

where the subscript **I** denotes the county. Here $\mathbf{Y}_I$ and $\boldsymbol{\epsilon}_I$ are vectors with $11\mathbf{n}_I$ elements, $\mathbf{X}_I$ is a matrix with blocks of **X** along the diagonal, and $\boldsymbol{\beta}_I$ is a vector of length 121 (the coefficients are allowed to vary by county).

While, overall, the results of fitting Equation 2 were satisfactory, individual equations, where there were few non-zero observations of ground type in a county, had high standard errors of prediction, often exceeding 100 percent of the estimated proportion. As an alternative to calibrating counties separately, data across counties (within the survey unit) can be combined to estimate a pooled regression equation. The assumption needed to justify such an approach is that the *coefficients* relating ground classified proportions to satellite classified proportions are similar across counties within a survey unit (*not* that the classified proportions of the various types are themselves similar across counties). Under this assumption, the calibration equation becomes

$$\mathbf{Y}_I = \mathbf{X}_I\boldsymbol{\theta} + \mathbf{v}_I \tag{3}$$

where the θ are pooled or survey unit wide coefficients. Each type has a separate set of calibration coefficients, but the

Table 8. Comparison of FIA and Calibrated Landsat TM Estimates (in Thousands of Acres) of Conifers, Hardwoods, and Total Forest Land.

Class	Estimate	County					Region Total
		Cook	Carlton	Koochiching	Lake	St. Louis	
Conifer	FIA	79.6	376.9	975.1	559.5	1,253.1	3,244.2
	TM	86.3	323.7	937.9	619.8	1,303.2	3,270.9
Hardwood	FIA	273.1	478.0	757.7	639.5	1,970.6	4,118.9
	TM	263.1	542.7	679.9	626.3	1,758.1	3,870.1
Total Forest	FIA	352.7	854.9	1,732.8	1,199.0	3,223.7	7,363.1
	TM	349.4	866.4	1,617.8	1,246.1	3,061.3	7,141.1

coefficients for a type are constant across counties. Equation 3 was also fit to the PSU data.

If $\mathbf{x}_I$ is the vector of satellite classified proportions for county I (classifying the entire land area in the county), we have two calibrated estimates of percent land area by type:

$$y_I = \mathbf{x}_I\hat{\beta}_I \text{ and } y_I^* = \mathbf{x}_I\hat{\theta}$$

The two calibrated estimates y_I and y_I^* can be combined to produce an estimate that should have lower error than either of the two individually (Burk and Ek, 1982):

$$\bar{y} = wy_I + (1 - w)y_I^* \quad (4)$$

Both y_I and y_I^* are additive; the predicted type proportions add to 1. For the combined estimate to be additive requires that w be a constant across types. The optimal w for a type is a function of the ratio of the prediction variances of y_I and y_I^* (Burk and Ek, 1982). Computation of estimates of those variances indicated that their ratios were relatively constant across type. An average value (0.65) was used to obtain final estimates: this gives weights 0.606 and 0.394 for y_I and y_I^*, respectively. The final calibrated acreages of each cover type are given in Table 7.

Evaluation of Landsat Area Estimates

By aggregating the FIA statistics of cover type acreages from Miles and Chen (1992), we are able to make a rough comparison of estimates from the calibrated Landsat classifications and the FIA statistics for conifer, hardwood, and total forestland at the county and region (survey unit) levels (Table 8). Because of differences in definition of classes in the two inventories, it is difficult to make comparisons of more specific cover types. The problem is that, on the one hand, the FIA cover type area statistics are typically reported only for commercial forests or "timberland" (defined as forest land capable of producing 20 cubic feet per acre of industrial wood crops ...) and, therefore, do not include detailed breakdowns of the cover types for non-commercial, as well as reserved, forest land (reserved land includes state parks and the Boundary Water Canoe Area Wilderness). On the other hand, the Landsat classifications are for all forest lands.

In comparing the results of the two surveys, we have assumed the same proportions of cover types for unproductive and reserved lands as for the timberland. However, it is well understood that much of the unproductive land is in lowland conifer types such as black spruce. We have, therefore, restricted the comparison to conifer, hardwood, and total forest. At the region level, the differences in the two estimates (with FIA as the standard or base) are +0.8, −6.0, and −3.0 percent for conifer, hardwood, and total forest, respectively. Differences in total forest area estimates at the county level range from −5.0 percent to +3.9 percent. The sampling errors for FIA estimates of timberland (not total forestland) for the Forest Service FIA estimates range from 0.85 to 2.39 percent at the county level and 0.57 percent at the region level.

There are several sources or causes for differences in the two estimates. The first is that, in three cases, the available reference data did not include samples of all FIA classes; in other words n, as reported in Table 3, was too small. A larger, more fundamental problem is that the forest lands in northern Minnesota are very complex ecosystems with a wide range of variability in composition and uniformity. This heterogeneity limits the accuracy of the photo interpretation and field checking and, in turn, the reference data. This, in turn, affects the accuracy of class labeling. In many respects we are attempting to classify continuous data into discrete classes; doing so results in errors in the areas of transition from one type to another. The Forest Service recognizes the complexity of the forests and the presence of mixtures in its definitions of classes. For example, the description of red pine is, "forests in which red pine comprises a *plurality* of the stocking; common associates include eastern white pine, jack pine, aspen, birch, and maple."

PSU-Based Estimation of FIA Cover Type Areas

While the satellite data classifications were limited to six forest types, forest management needs are often more specific. However, the $\mathbf{Y}_I$ need not be constrained to the same classes used for the image classification; instead, they can be defined as *any* ground truth variable. For example, the PSUs used in this study were originally typed as 14 forest types. To estimate FIA cover type acreage directly, we define $\mathbf{Y}_i$, $i = 1, ..., 14$, as the proportion of a PSU in FIA, type i. The estimation model is then the same as Equation 1. Again, this system of equations is additive.

A preliminary trial of the PSU-based approach on the five-county Aspen/Birch FIA survey unit led to comparisons of total forest area and area by cover type with FIA statistics. Study estimates for conifer, hardwood, and total forest cover type aggregations were −8.4, −0.5, and −3.0 percent different from FIA values. However, further cover type breakdowns often showed much larger differences. Inspection of results further suggests differences in definition and procedure for identifying cover types as a major factor in the lack of agreement. The cover types on PSUs in this study were identified by photointerpretation followed by field checking. However, FIA cover types are determined by an algorithm applied to ground plot tree data (Hansen and Hahn, 1982). Studies by Jaakko Pöyry Consulting, Inc. (1992) have noted that changes in the algorithm applied to this plot tree data can lead to major changes in estimated acreage. Consequently, the ability to compare results to the FIA acreage for the 14 cover types is limited in this case by definitional and procedural factors. Analyses to sharpen these comparisons are part of a continuing study.

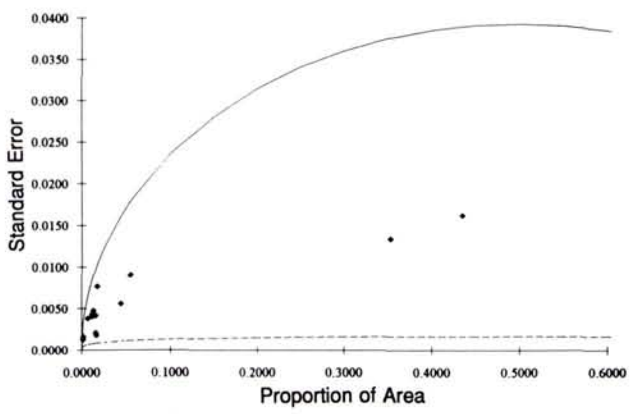

Figure 2. Standard error comparisons for estimates of proportions of 14 FIA cover types, plus non-forest category for 163 PSUs in St. Louis County. —— = *n* (163) plots, ----- = *n* × acres of PSU, ♦ = actual PSUs.

The approach is described further for St. Louis County. Figure 2 shows the standard errors of the mean proportions for 14 standard FIA cover types, plus an other/non-forest category, as estimated from the 88-acre PSUs, in comparison with theoretical standard errors. The theoretical standard errors were developed in two ways: (1) assuming each PSU location was instead the location of a standard FIA plot (covering approximately one-acre) and (2) a lower bound assuming the PSUs were broken up and distributed as *n* × 88 one-acre FIA plots. The fact that the standard errors for the PSU sample lie approximately midway between the two theoretical curves suggests that the PSUs are far more effective at error reduction than a sample of n FIA plots and substantially less effective than the much larger number of plots that might have been distributed at random had the PSUs been broken up and checked as one-acre components.

Ultimately, the choice of survey design must be considered on a cost basis. While the PSUs are clearly less efficient than an equivalent acreage of random plots, the travel costs are dramatically reduced (fewer PSUs than plots), and the cost of a PSU need not be much if any more expensive than the current FIA plots. The latter typically cost $150 to $300 each and involve one to two people and approximately one day of time, including travel. Of that day, much of the effort goes into establishing and measuring a ten-point PSU of small plots on an acre. We propose instead that those small plots be spread across the PSU and be used to verify the cover type of the polygons on the PSU. Use of large PSUs is not unlike what has been done in Scandinavia (Kuusela, 1978; Svenson, 1980) and what was found as an optimal "super PSU" or cluster plot by Scott *et al.* (1984).

A spreadsheet analysis of alternative forest inventory designs is currently being developed, including this PSU design, the current multiphase FIA procedures, and other designs. That effort will also consider optimal PSU size. However, the optimal PSU size will also depend on practical concerns for being able to locate it and potential data analysis as described below. For analysis, precision of this approach will be developed empirically from these results and additional PSU sizes to be tested. It is probable that a planning model useful to inventory design and analysis will express sampling error (or variance) as a function of the cover type proportion and the area or size of a PSU for any given classifier and costs.

Additional important aspects of the PSU-based design are its statistical simplicity and its potential utility for monitoring landscape patterns. The simplicity comes from observation of operational sized land units and the fact that it requires only single phase estimation and ordinary least-squares procedures for area estimates. The power of the approach is that it uses as covariates *all* of the pixels in the county or area of interest, yet it doesn't necessarily require high accuracy in the satellite classification. Additionally, one could improve estimates by the methods described in the earlier calibration section. Statistically, one may view the PSU as simply a large number of large image classification plots. The precision of PSUs overall will be less than the same acreage of small plots distributed randomly over the survey unit. However, the cost of assessing the PSUs on the ground is modest, and the realism that step adds to classifier training can provide significant gains for the survey design.

Change Detection Using Multidate Landsat Data

Renewable natural resources such as forests are continually changing. Some forest cover modifications are human-induced, such as harvest, while others have natural causes, such as insect or disease damage. The rate of change may be abrupt (e.g., logging) or subtle/gradual (e.g., growth). The potential of using satellite data to detect and characterize changes in forest cover depends on the ability to quantify temporal effects using multitemporal data sets. As a part of the project research, we investigated the potential of multitemporal Landsat TM for forest cover change detection (Coppin, 1991).

TM data, along with detailed ground reference data, for three different years (1984, 1986, and 1990) covering a 400 km^2 (five townships) test site in Beltrami County were acquired. To minimize sensor calibration effects and standardize data acquisition effects, the TM data were calibrated to exoatmospheric reflectance following the algorithms of Markham and Barker (1986). After geometric rectification and registration, an atmospheric correction routine was applied, combining two major components: atmospheric normalization and transformation to ground reflectance. The normalization consisted of a statistical regression over time, based on five spatially well defined landscape features with unchanging spectral-radiometric characteristics. Subsequently, a dark object subtraction technique for atmospheric scattering was applied. The general procedures were similar to those described by Caselles and Garcia (1989). Linear correlation coefficients for all bitemporal band pairs ranged from 0.9884 to 0.9998; an example for TM4 for 1986-90 is shown in Figure 3.

For each time interval (two, four, and six) years, 14 change features were determined. The change features involved seven vegetation indices and two change detection algorithms (standardized differencing and pairwise principal components). The best four features for classification were selected based on J-M distance calculations of the best minimum separability between change signatures. A maximum-likelihood classifier was used for the final classification. Classification accuracy and areal correspondence were evaluated from contingency matrices and Kappa coefficients of agreement.

The results (Figure 4) demonstrated that disturbances

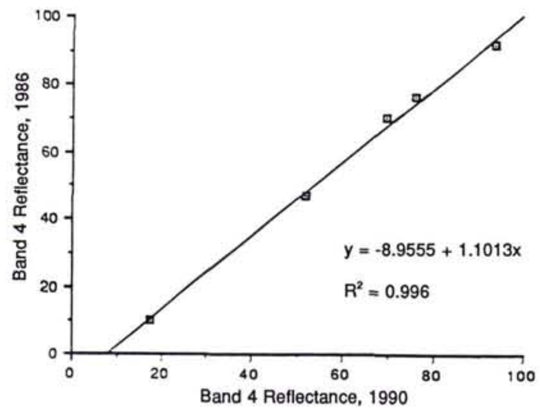

Figure 3. Example of the relationship between band-specific scaled reflectances of calibration sites over time.

and other changes can be detected very accurately if categorized in classes that relate to their effect on the forest canopy, and if their size exceeds one hectare. Pixel-based classification accuracies are shown in Table 9 for thematic classification of pure pixels and for classification of all pixels including mixed or boundary pixels. Forest stands as the classical management units were ascertained to be too spectrally heterogeneous to have the change phenomena differentiated at that level. However, for the three classes, canopy decrease, canopy increase, and no change, the methodology correctly identified 714 out of 759 stands (94 percent) reported as disturbed over the six-year interval, indicating that the change event was portrayed in a majority of the stand's pixels. A detailed analysis of the classifications error structure at the pixel level, together with a post-classification assessment of a large sample of commission errors and omission errors, indicated that a large majority of the classification errors might not have been errors at all, but instead emanated from the generalization of pixels to the stand level in the reference data generation. The results show that the preprocessing sequence summarized above is critical to the forest cover monitoring; similar preprocessing and calibration procedures are being used in the large scale application of this technology by the Minnesota DNR described below.

Operational Use of Landsat Data for Forest Inventory in Minnesota

As a result of the research described above, the Minnesota DNR and the U.S. Forest Service have jointly undertaken to develop an Annual Forest Inventory System (AFIS) based on annual sampling of existing Forest Inventory and Analysis (FIA) ground plots in Minnesota (Befort and Heinzen, 1992; Hahn *et al.*, 1992). Satellite remote sensing plays an important role in the AFIS plan, and initial Landsat data analysis is well under way. Because of its annual schedule, the AFIS plan requires current, inexpensive, large-area imagery together with low-cost, but robust, interpretation methods for both stratification and disturbance detection. The research by Coppin (1991) has indicated that computer analysis of multidate Landsat data (summarized above) offers a cost-effective alternative to reliance on aerial photography.

The objective of AFIS is to create and maintain a current and continuously updated FIA database. Under the proposed system, a relatively small proportion of FIA plots will be chosen each year for field remeasurement; information on other plots will be updated by use of forest growth models. Selection of plots for measurement is to be based on (1) likelihood of plot disturbance since the last field measurement, and (2) requirements of a 20-year sampling rotation in which all plots are ultimately field-visited. Satellite remote sensing has two roles: first, to stratify a statewide array of some 45,000 established FIA plot locations as a means to reduce the variance of area and volume estimates, and second, to estimate the likelihood of change or disturbance on each plot in order to prioritize plots for field measurements. Aerial photography has been customarily used for both these purposes, but obtaining and interpreting statewide airphoto coverage on the schedule required by AFIS is impracticable. The use of satellite imagery is expected to reduce costs and allow an increase in the frequency of inventory updates.

The general remote sensing approach is to move through the state on a four-year rotation, covering one of the four ma-

Figure 4. Comparison of Landsat classification of change events between 1984 and 1990 to the reference map of Jones Township.

TABLE 9. SUMMARY OF STATISTICS EVALUATING CHANGE DETECTION CLASSIFICATION ACCURACY.

Time Interval (Years)	Thematic Accuracy*		Cartographic Accuracy**	
	Overall Correct (%)	Kappa Statistic	Overall Correct (%)	Kappa Statistic
2	97	.76	93	.64
4	96	.83	89	.68
6	94	.82	87	.69

*Classification of pure pixels; **areal correspondence of all pixels.

jor forest inventory regions each year. For each region, georeferenced Landsat data of the most recent late summer date is obtained. (Work on the Aspen-Birch (unit 1) region is currently underway using Landsat data acquired in 1988 and 1992.) After preprocessing, including rectification, radiometric calibration, and atmospheric normalization, a general land-cover classification (stratification) is performed across multi-county survey units. Because of the difficulties in achieving accurate Landsat classifications of forest cover types, only broad categories (strata) of water, agriculture, other nonforest (e.g., developed/urban, clouds, etc.), conifer forest, and hardwood forest will be mapped. The new imagery is then registered to that of the previous iteration and analyzed for change. Based on changes in the vegetation index (e.g., greenness), a change ranking or probability is generated for the pixels in the two forest classes. Digitized locations of the FIA plots are then queried for stratum identity and change ranking. These two data elements, together with area expansion factors for all cover classes, are entered into the plot database for use in an algorithm that selects plots for field measurements in the following season or for projection forward by a forest growth model. Annual field measurements will serve as a check on image processing accuracy.

Summary and Conclusions

The objective of this research was to develop and test the use of multispectral satellite data together with improved classification and sampling designs to inventory the forest resources of northeastern Minnesota. Two design alternatives were considered: one based on PSU sampling concepts and a second that considered disturbance classification as the basis for stratified, two-phase sampling. Classification accuracies of up to 75 percent for six forest classes and five nonforest classes were achieved. Misclassification tended to be between similar-related classes. A major contributing factor to the difficulty in classification is the fact that the majority of forest stands are complex mixtures of two or more species which may also differ in size, density, crown closure, and age.

An inverse method of calibration was used to adjust the classifications for classification bias. At the survey unit level, the resulting estimates of forest land area were 3 percent less than comparable Forest Service estimates. Agreement between the two surveys at the county level ranged from −5.0 to +3.9 percent. The difference in estimates is attributed to differences in definitions and approaches used in the two surveys, as well as to the complexity and variability of the forest landscape. Although the forest cover type estimates were somewhat less accurate than hoped for, the Landsat TM classifications have the advantage of providing information on the geographical distribution of the cover types that is not available from the conventional FIA survey. On the other hand, the FIA survey provides information on timber volume which was not obtained at least with this classification of Landsat data. Thus, the two approaches to inventory are complimentary, with each providing information not available from the other.

A trial of estimating the areas of 14 traditional forest cover types as determined from sample 88-acre PSUs as a function of the six Landsat forest classes using a system of additive linear equations was also conducted. The results indicated that the PSU-based approach can provide gains in precision, but comparisons with FIA statistics were hindered by differences in definition of cover types by the FIA and this study. This type of PSU-based estimation is potentially very cost-effective and provides data of increasing interest to the assessment of cover type and land use patterns over landscapes.

Change detection or disturbance classification involving multidate imagery resulted in overall classification accuracies of greater than 90 percent for the time intervals of two, four, and six years for the classes canopy decrease, canopy increase, and no change. The success rate for the detection of stand-based canopy change events over the six year interval was 94 percent. The key to obtaining these results was a rigorous approach to reflectance calibration and normalization for atmospheric effects.

The project results have provided the basis for the Minnesota Department of Natural Resources and the USDA Forest Service to define and begin to implement an annually updated statewide inventory system which utilizes multidate Landsat TM data to detect changes in forest cover. Landsat TM imagery acquired at four-year intervals will be used to detect major changes in forest inventory plot characteristics. The likelihood of change as determined from the satellite data will be used to determine which plots should be revisited for field measurement. The general approach will be to classify one of the four major forest inventory regions of the state each year. Forest growth models will be used to project the growth of plots which are not measured in a given year. Satellite-acquired data are an integral part of the system, along with model predictions, sampling, and datebase techniques. We believe that Minnesota is the first state to incorporate satellite remote sensing into its forest inventory system; if successful, the techniques could easily be modified for implementation in other states.

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