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Estimating regional forest cover in East Texas using Enhanced Thematic Mapper (ETM+) data

Ramesh Sivanpillai [a,*], Charles T. Smith [a], R. Srinivasan [a], Michael G. Messina [a], X. Ben Wu [b]

[a] *Department of Forest Science, Texas A&M University, College Station, TX 77843, USA*
[b] *Department of Rangeland Ecology and Management, Texas A&M University, College Station, TX 77843, USA*

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Abstract

The USDA Forest Service, through its Forest Inventory and Analysis (FIA) program, periodically estimates forest/non-forest area at the county level using aerial photographs. Satellite-based remotely sensed data and digital image processing techniques could substantially reduce the time required to generate this information. Satellites collect data on a repeat basis and with higher frequency than the aerial photos that are currently used for this purpose. In addition to the forest cover estimates, the USDA could use satellite data to generate maps depicting the spatial distribution of forest cover. However, few studies have tested the utility of medium-resolution satellite data for FIA purposes. We tested the potential for using LANDSAT satellite data to obtain forest cover estimates for a six-county region in East Texas. Satellite data were processed using a combination of image classification techniques that could be repeated in other regions of the USA. Results were compared with the results of traditional photo-based estimation techniques and were comparable within a 95% confidence interval. Based on this study we recommend that medium-resolution satellite data can be used for obtaining county-level forest cover estimates.

Keywords: USDA Forest Service; Forest inventory; FIA; LANDSAT; East Texas

1. Introduction

The US Department of Agriculture-Forest Service (USFS) has periodically estimated and published the extent of forest cover and timber resources in the United States as part of its Forest Inventory and Analysis (FIA) program (USFS, 1992; Frayer and Furnival, 1999; Reams and van Deusen, 1999). This information, published since the 1930s, is used by state forest agencies, private timber companies and individual foresters for planning and decision making. In addition to this, FIA results are used for assessing sustainability of forest management practices and predicting the effects of global change (USFS, 2004). The FIA program uses a variation of the double

* Corresponding author at: Wyoming GISc Center, Department 4008, 1000 E University Avenue, University of Wyoming, Laramie, WY 82071, USA. Tel.: +1 307 766 2721; fax: +1 307 766 2744.
E-mail address: sivan@uwyo.edu (R. Sivanpillai).

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sampling method for collecting data about forest resources. In the first phase, points are placed on aerial photographs and are classified as either forest or non-forest. In the second phase, detailed information about forests is collected by visiting a predefined number of photo-points on the ground. The estimates obtained in the first phase are refined based on the ground information and standard errors are computed (McWilliams and Bertelson, 1986; Kelly et al., 1992; Hansen and Wendt, 1999; Reams and van Deusen, 1999). This information is used for periodically publishing statistical estimates of forest cover at the county level (Wynne et al., 2000; McRoberts et al., 2002).

Wayman et al. (2001) and McRoberts et al. (2002) summarize the limitations of aerial photographs for FIA purposes. Interpretation of the photos is a labor-intensive and time-consuming process. Photographs are expensive and cumbersome to handle, store and transfer. Also, obtaining current aerial photographs for FIA purposes is often difficult. Reams and van Deusen (1999) identified the inability to produce maps using county-level estimates. County-level estimates cannot be used to capture the spatial variability of forest cover within each county. In addition, it takes approximately 8 years for the FIA program to update estimates for the southern region (13 states, Puerto Rico and the Virgin Islands) of the US.

Satellite-based remotely sensed data in combination with semi-automated digital processing could reduce the time required to generate forest and non-forest estimates (Lannom et al., 1995; Cooke, 1999; Czaplewski, 1999; Wayman et al., 2001). Orbiting satellites collect data more frequently and regularly on a global basis than do aerial photography programs. Currently, satellites from the US (LANDSAT-http://landsat.usgs.gov), France (SPOT-http://www.spotimage.fr) and India (IRS-http://www.nrsa.gov.in, http://www.antrix.org) provide medium-resolution multi-spectral data. These satellites collect information in the green, red and infrared regions of the electromagnetic spectrum that is useful for discriminating vegetation. The current LANDSAT satellite (ETM+) developed an anomaly (Scan Line Corrector malfunction) in May 2003 that reduces its utility, but data from an earlier LANDSAT satellite (LANDSAT 5) are nearly identical in character and are still available for use. Plans are underway to include the next LANDSAT sensor in a NOAA satellite scheduled for launch in 2009. Should LANDSAT TM5 fail before 2009, data collected by the IRS and SPOT satellites could be used for forest estimation using methods similar to those described here.

In addition to forest and non-forest estimates, information about forests could also be produced from satellite data in a variety of formats including maps (Dymond et al., 2002). Among other applications, these maps could be produced at regular time intervals and would improve the spatial accuracy and precision of forest cover estimates, provide spatially explicit estimates of changes in forest cover and condition, fuel availability and wildlife habitat among others (Beaubien, 1994; Wayman et al., 2001).

The 1998 Farm bill recommended that the USFS and NASA work together to integrate satellite-based remotely sensed data for the forest inventory program. This bill also mandated that the USFS sample 20% of the plots in a state every year, a substantial increase in sampling density (Wayman et al., 2001). In addition, the FIA was one of several federal government programs reviewed by a study commissioned by the Office of Science and Technology Program (OSTP). One of the recommendations made by this study was to incorporate satellite data in general and LANDSAT Thematic Mapper data in particular into this process to reduce the dependency on aerial photographs for FIA purposes (Peterson et al., 1999).

In order for the USFS to incorporate satellite-based estimates into its FIA program, additional research is required to address the following issues: transferability of image processing and classification methods for other regions, sources of misclassification related to landscape pattern, and precision of the estimated area for each thematic class that incorporates uncertainty. Only comprehensive studies will enable the USFS to evaluate the usefulness of satellite-based estimates in comparison to traditional photo-based estimates. This paper describes such a study where the utility of LANDSAT data to map and estimate forest resources was tested in East Texas.

Satellite image processing and classification of forest resources involves assigning the pixels in the image to predefined forest types. Methods such as unsupervised or supervised classification or a combination of these two are available for grouping pixels into forest or non-forest classes (Lillesand and Kiefer,

2000; Jensen, 2000). Numerous advances have recently been made in image classification algorithms such as fuzzy logic (Liu and Samal, 2002) and neural networks to derive information from satellite images. These advances coupled with developments in computing, have significantly increased the amount of data that can be processed in a given time and the quality of the results.

After classifying a satellite image, an analyst assesses how accurately the image was classified by using verification data, which is usually collected in the field or from high resolution aerial photographs. Classification accuracy is typically reported in an error matrix (Congalton, 1991) consisting of an equal number of rows and columns representing the number of classes, with mapped types on one axis of the table and reference classes on the other. If most of the elements of this matrix fall along the diagonal, there is relatively high agreement between mapped types and ground reference data. Deviations from the diagonal indicate mismatches between the two. The kappa agreement index can also be computed for the error matrix and indicates the level of agreement between the classified image and verification data (Congalton, 1991).

A review of several published studies by Holmgren and Thuresson (1998) found that most studies used randomly distributed verification sites to assess the accuracy of classified images. The number of verification sites used depends on the variance in accuracy among the mapped sites and the statistical precision required. This review also found that in several studies the overall accuracy of the classified image was inflated because the analyst included relatively more verification data corresponding to easily identifiable features in a satellite image. One of the recommendations of this review is that future studies should use some form of systematic sampling to select verification data, and that the total number of verification sites must be based on statistical principles of sampling. Systematic sampling procedures will minimize the bias in the number of data points assigned to different classes.

Inadequate information about the precision of area estimates derived from maps limits the user's ability to understand the uncertainty associated with these estimates. Classified images have errors that can be expressed as overall or individual class accuracy. However, area estimates obtained from any classified image are often reported as a single number, such as 3600 ha of coniferous forests (Wynne et al., 2000). Card (1982) developed a method for incorporating classification errors into area estimates obtained from satellite images. However, this method has been incorporated in few studies (Wynne et al., 2000; Wayman et al., 2001).

Several studies in the US assessed the utility of satellite imagery such as from the LANDSAT multispectral scanner (MSS) (Dodge and Bryant, 1976; Fox et al., 1983; Moore and Bauer, 1990), Thematic Mapper (Moore and Bauer, 1990; Bauer et al., 1994; Wayman et al., 2001), and the AVHRR (Iverson et al., 1989; Nelson, 1989; Teuber, 1990; Zhu and Evans, 1992, 1994) for mapping forest cover, and in certain instances for obtaining FIA estimates (Teuber, 1990; Zhu and Evans, 1992, 1994; Hansen and Wendt, 1999; Franco-Lopez et al., 2001). Attempts have been made to use products developed from other projects such as the Gap Analysis Program (Hansen and Wendt, 1999) or the National Land Cover Dataset (McRoberts et al., 2002), to estimate forest cover. However, most of these studies have not addressed all of the issues related to systematic sampling and precision.

The primary objective of this study was to develop a methodology using LAND SAT ETM+ imagery to obtain forest and non-forest estimates comparable to those obtained from aerial photos for East Texas. A secondary objective of this study was to generate maps of forest and non-forest classes with sufficient thematic accuracy to be useful for further stratification and analyses. It is hypothesized that "error-corrected" area estimates obtained from satellite imagery would not be different from the estimates obtained from aerial photographs at the 95% confidence level and that the sources of error in the classified images can be attributed to a limited number of land cover or land use classes. If this hypothesis is supported, LANDSAT imagery may be a cost effective and robust alternative to air photo-interpretation for making FIA estimates.

2. Methods

2.1. Study area

Angelina, Nacogdoches, Panola, Rusk, San Augustine, and Shelby Counties in East Texas (31°43′N,

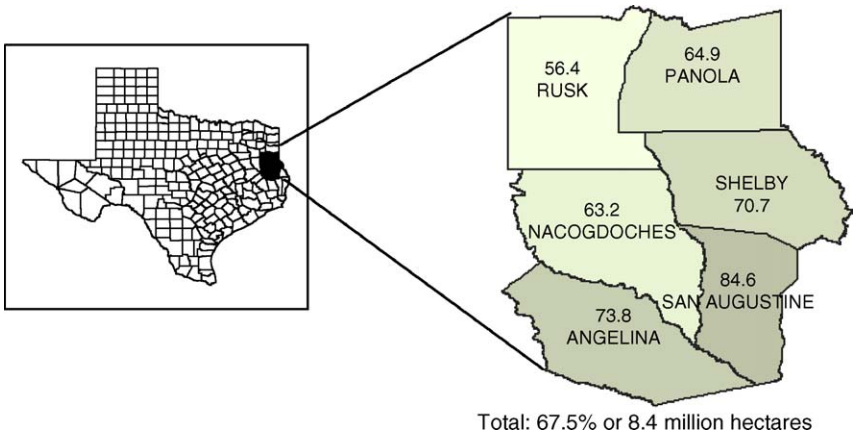

Fig. 1. Location of the study area in East Texas and 1992—USDA Forest Service estimates of forest cover within each county expressed as proportion of the total area. *Notes*: Sources for administrative boundary, Texas Natural Resources Information System (TNRIS) and 1992 forest estimates, Southern Research Station, FIA, Knoxville, TN, http://ncrs2.fs.fed.us/4801/FIADB/fim_tab/we_fim_tab.asp.

94°24′W) were chosen for this study (Fig. 1). This region receives an average of 119.2 cm of rainfall every year but precipitation varies on an average monthly basis from 5.5 cm in July and 11.64 cm in May. Average annual minimum and maximum temperature vary between 12.8 °C and 25.5 °C. Average summer maximum can reach 35 °C.

The USFS estimated that about 8.4 million hectares (67.5%) of the total area (12.44 million hectares) of these six counties (Fig. 1), which include Angelina and Davy Crockett National Forests, is forested. Two major pine forest types found in this region are loblolly pine (*Pinus taeda* L.)–shortleaf pine (*P. echinata* Mill.) and longleaf pine (*P. palustris* Mill.)–slash pine (*P. elliottii* L.). The rest of the timberland consists of oak (*Quercus* spp.)–hickory (*Carya* spp.), oak–gum (*Nyssa* spp.)–cypress (*Taxodium* spp.), and oak–pine mix (Murphy, 1976; McWilliams and Bertelson, 1986).

2.2. Image data

A cloud free, LANDSAT Enhanced Thematic Mapper 7 (ETM+) scene (row 25, path 37 from the Worldwide Reference System-2) acquired on 6 October 1999 was obtained from the Texas Natural Resources Information System (TNRIS), Austin, TX. The image was corrected by the USGS EROS Data Center, Sioux Falls, SD for geometric and terrain distortions. This image was used as a basis for classification and methods development for this study.

2.3. Ground reference data

Ground reference data are examples of vegetation types that are used to associate pixels in the satellite image with features on the ground. For this study these data were collected using field visits and heads-up digitizing of the satellite image. Examples of forest and non-forest classes were mapped using a Trimble (Sunnyvale, CA, USA) Global Positioning System (GPS) in winter and spring of 2001. For forest stands, attributes pertaining to stand conditions including type and density were recorded. Care was taken to avoid narrow stands along roads to minimize confusion during the image classification process caused by the presence of multiple features in a pixel. Reference data were also digitized directly on the satellite image as points and polygons using the information provided by Texas Forest Service (TFS) personnel, who visit these stands regularly and are familiar with local stand conditions. Hardcopy maps and high resolution imagery such as aerial photographs were used as additional references. In total, 173 points and polygons were digitized for use as reference data (Sivanpillai, 2002).

2.4. Verification data

USFS plot-level FIA data and TFS black and white aerial photographs were used for assessing the accuracy of the classified imagery. The USFS had

surveyed 204 FIA permanent plots within the six-county region since 2001. The classified thematic satellite image was sent to the USFS field office for verification because FIA plot locations were not disclosed to us due to issues related to security and privacy. Because we did not have access to the location of the USFS plot data, it was desirable for us to collect another set of verification data using systematic sampling as described by Fitzpatrick-Lins (1981) so that we could characterize the spatial distribution of map errors generated in our study.

Aerial photo-negatives (nominal scale 1:15,840) archived at the forest pest management unit of the TFS office at Lufkin, TX, were used to collect the second set of verification information about land cover/use. These photos are obtained periodically on a county basis along predefined flight lines. Every sixth photo from each flight line flown between 2000 and 2001 was chosen and approximately 600 verification data points were obtained at photo-centers and assigned to one of the 10 land cover/use classes by Texas Forest Service personnel (Table 1). These alternative verification data were digitized as a point data layer in ESRI (Redlands, CA, USA) Arc view 3.2. Digital Ortho Quarter Quads (DOQQs) were used as image backdrop to locate the photo-center to the real world coordinates (Sivanpillai, 2002). These verification points were used to obtain an estimate of percent forest cover and error measurements similar to the FIA estimates (Lund and Thomas, 1989).

Table 1
Land cover/use of the study area identified from the Texas Forest Service black and white aerial photographs

Code	Land cover/use class
1	Pine
2	Pine–hardwood
3	Hardwood–pine
4	Hardwood-predominantly upland
5	Hardwood bottomland
6	Urban–commercial–mines
7	Agriculture
8	Pasture with no trees
9	Pasture with trees
10	Water

Note: Classes 1 through 5 are forest classes, whereas 6 through 10 are non-forest classes.

2.5. Image data processing

Six bands (three visible and three infrared) of the ETM+ image were imported and a sub-scene of the study area was extracted using a vector data layer obtained from TNRIS. Image processing was performed using ERDAS (Atlanta, GA, USA) IMAGINE software (PC version 8.4). The sub-scene was classified using an unsupervised classification approach—the Iterative Self-Organizing Data Analysis (ISODATA) algorithm (ERDAS, 1996) and pixels were grouped into spectrally homogeneous clusters. Labeling of the clusters was accomplished using a combination of techniques described by Stenback and Congalton (1990) and Thenkabail et al. (2000). Spectral patterns, reference data, and the spatial pattern of the clusters were used to assign the clusters to land cover/use classes (Thenkabail et al., 2000). First, clusters representing water were identified and labeled by comparing them to existing hydrology data obtained from the TNRIS website. Clusters representing urban areas were identified and labeled using a city, county, and transportation network data layer also obtained from TNRIS website. Clusters representing forest classes had relatively higher reflectance values in green and infrared bands than other cover types and this allowed them to be distinguished from other types. DOQQs, field data and polygons digitized on the imagery and DOQQs, were used in conjunction with the characteristics described above to assign the clusters either to a forest or non-forest class (Zhu and Evans, 1992). This process was repeated until all clusters were labeled. To generate the final forest and non-forest map, clusters representing water, urban, and other non-forest classes were combined to a single non-forest class and remaining clusters were combined into a single forest class.

Pixels in the classified image were aggregated to the minimum mapping unit of four pixels, which is approximately equal to 1 acre. For inventory purposes, the USFS defines forestland as patches that are at least one acre in size (Hansen and Wendt, 1999). This step removed isolated groups of pixels that were less than an acre in size.

2.6. Accuracy assessment

The classified image was compared with the two sets of verification data (described above) obtained

from TFS photo-data and the USFS plot-level FIA data. The latter comparison was conducted by USFS personnel at the Forest Research Laboratory at Mississippi State University, USA to maintain confidentiality of site locations. Five hundred and ninety-nine data points obtained from photos (our second verification data set) and 204 points obtained from FIA plots were used to construct two error matrices (Congalton, 1991; Jensen, 2000). Overall accuracy and omission and commission errors were computed for both matrices. The kappa value and its variance were computed using methods described by Story and Congalton (1986) and Hudson and Ramm (1987).

Accuracy statistics for the two assessment matrices were compared to determine if the two sets of verification data yielded similar results. Similar accuracy results from the two data sets would suggest that our spatial error estimates reflect those that could be determined using FIA data alone if those site locations were available. Using the kappa values from the two error matrices, a Z value was computed for an overall comparison (Congalton and Mead, 1983). A Z value greater than 1.96 indicates that at the 95% confidence level the two matrices were significantly different (Congalton et al., 1983; Rosenfield and Fitzpatrick-Lins, 1986).

2.7. Forest area estimates

Estimates of forest cover were obtained using the photo-center points and the USFS plot-level data using the method described by Lund and Thomas (1989, p. 33). Estimates included forest area, standard error of the mean, and sampling error of the mean for each county. Forest and non-forest area estimates from the satellite imagery were obtained within the image processing software for each county. Using the method developed by Card (1982) and described by Wynne et al. (2000), a 95% confidence interval for the area estimates from the satellite classification was estimated.

3. Results

3.1. Overall accuracy and class agreement assessment

The overall accuracy for all the counties, when the image was compared to photo-point data, was 85% for the study area and varied from 78% for Rusk County to 96% for San Augustine County (Table 2). Kappa values (Table 2) for the study area (0.67 or 67%) were lower than the overall accuracy, because they incorporated off-diagonal elements of the error matrix, thus providing a more comprehensive view of agreement than the overall accuracy measure. San Augustine County had the highest kappa agreement value (0.84), whereas Rusk County had the lowest (0.54). The overall accuracy for the total area, when the image was compared to the FIA plot-level data, was 78%, and the kappa value was also lower. However, the Z value computed from the kappa values of the two error matrices was 1.7364 indicating that the errors in these two matrices were not significantly different at the 95% confidence level.

Omission error in the satellite-based classification for the forest class captures the number of forest verification points misclassified as non-forest, leading to under-prediction of forest area. Only 6% of the forest verification data were not classified as forest, whereas 31% of the non-forest verification data were not classified as non-forest (Table 3). At the county level, San Augustine County had the lowest (0%) and Rusk County had the highest (12%) omission error for the forest class (Fig. 2). Commission error for the forest class is a measure of the number of non-forest verification points misclassified as forest, leading to over-prediction of forest area. Fourteen percent of the forest verification data were misclassified as non-forest whereas 15% of the non-forest verification data were misclassified as forest (Table 3). At the county level, San Augustine County had the lowest (5%) and Rusk County had the highest (29%) commission error

Table 2
Overall accuracy, kappa agreement values (K-hat) and its variance obtained for the classified image (by county) when compared with photo-data

County	Overall accuracy (%)	K-hat	Variance
Angelina	91.43	0.774	0.005119
Nacogdoches	84.62	0.599	0.007225
Panola	84.54	0.648	0.006830
Rusk	78.38	0.572	0.006015
San Augustine	95.71	0.844	0.007567
Shelby	81.82	0.610	0.006824
Photo-total	85.48	0.666	0.001073
FIA-total	78.40	0.547	0.003647

Table 3
Error matrices, omission and commission errors for the classified images when compared to photo and FIA plot-level data (reference data are in rows)

	Forest	Non-forest	Omission error (%)	Commission error (%)
Photo ($n = 599$)				
Forest	366	23	5.9	14.9
Non-forest	64	146	30.5	13.6
FIA plot data ($n = 204$)				
Forest	105	11	9.5	24.0
Non-forest	33	55	38.0	17.0

for the forest class (Fig. 3). Results obtained from this study indicate that the commission error for the forest class (15%) was higher than the corresponding omission error (6%) for all six counties. In summary, more non-forest verification points were misclassified as forest than forest misclassified as non-forest, resulting in a net over-estimation of forest area.

3.2. Sources of classification error

To explore the nature of classification error in the map derived from satellite imagery, sixty-four non-forest photo-verification points that were misclassified as forest (Table 3) were assigned to their original more detailed land cover/use listed in Table 1. Most (60 out of 64 points or 94%) of the commission errors in the forest class involved three non-forest classes: pasture with trees, urban, and water (Table 4). The individual

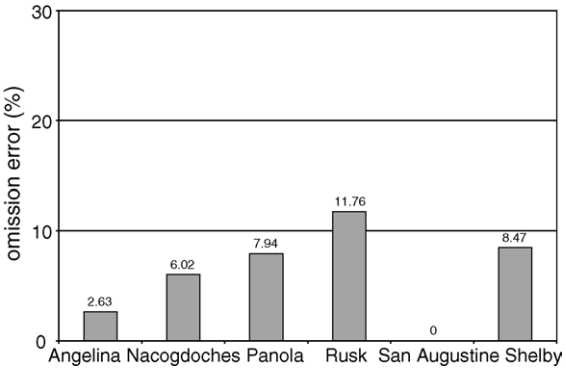

Fig. 2. Percentage of forest verification points that were misclassified as non-forest (omission error) in the classified image listed by county.

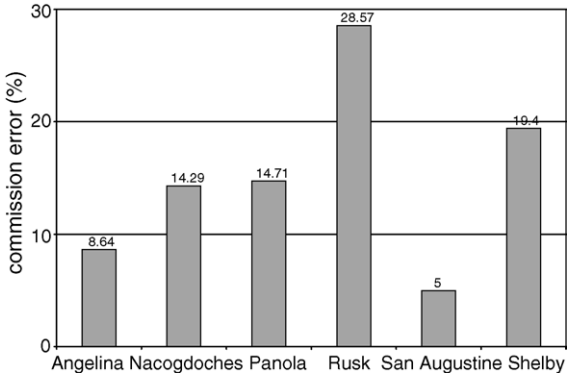

Fig. 3. Percentage of non-forest verification points that were misclassified as forest (commission error) in the classified image listed by county.

contribution by these three classes was 72% (46 points), 13% (8 points), and 9% (6 points), respectively. Similarly, 23 forest sites that were misclassified as non-forest in the satellite image (Table 3) were assigned to their detailed land cover/use listed in Table 1. Most of the omission errors (Table 5) in the forest class (18 out of 23 or 79%) were due to pine (class 1). The rest of the photo-verification points corresponding to other forested classes had fewer omission errors.

3.3. Forest cover estimates

The 95% confidence interval associated with the forest cover estimates obtained from ETM+ data overlapped with the corresponding 95% confidence

Table 4
Non-forest photo-points misclassified as forest in the classified image, categorized by five subclasses

County	Non-forest classes					
	U	A	PNT	PWT	W	Total
Angelina	3	1	0	2	1	7
Nacogdoches	1	1	0	11	0	13
Panola	1	0	1	6	2	10
Rusk	3	0	0	14	1	18
San Augustine	0	0	1	2	0	3
Shelby	0	0	0	11	2	13
Total	8	2	2	46	6	64

Notes: U: urban, A: agriculture, PNT: pasture with no trees, PWT: pasture with trees and W: water.

Table 5
Forest photo-points misclassified as non-forest in the classified image, categorized by five subclasses

County	Forest classes					
	P	PH	HP	HU	HB	Total
Angelina	2	0	0	0	0	2
Nacogdoches	2	1	2	0	0	5
Panola	4	0	1	0	0	5
Rusk	6	0	0	0	0	6
San Augustine	0	0	0	0	0	0
Shelby	4	1	3	1	0	5
Total	18	1	3	1	0	23

Notes: P: pine, PH: pine–hardwood, HP: hardwood–pine, HU: hardwood upland, HB: hardwood bottomland.

interval associated with the traditional photo-based estimates (Fig. 4). Overlap of the confidence intervals associated with each technique is further evidence of the similarity between them. San Augustine County had the lowest omission (0%) and commission (5%) errors, thus the 95% confidence interval estimate for this county was very narrow, indicating higher precision. The true value (95% confidence) of the forest cover for this county ranged between 69 and 78%. Rusk County had the lowest precision since it had higher omission (12%) and commission (29%) errors. Thus, the true value (95% confidence) for the percent forest cover in Rusk County ranged between 45 and 60%. The 95% confidence interval estimate obtained for Nacogdoches and Panola Counties were closer to their corresponding standard errors obtained from the photo-estimates.

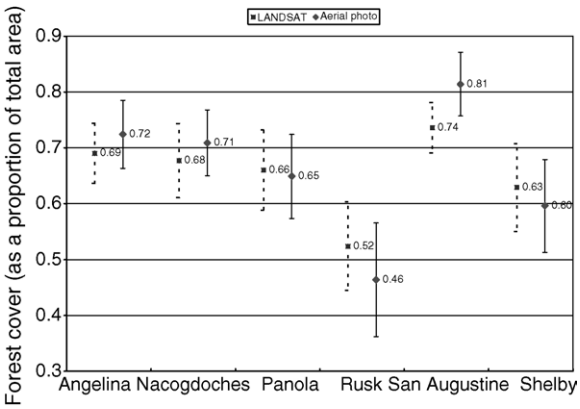

Fig. 4. Proportion of forest cover estimates along with the 95% confidence interval obtained from satellite image and aerial photos listed by county.

4. Discussion

4.1. Image classification

This study used satellite-based unsupervised classification techniques and successfully matched forest area estimates obtained from more labor intensive traditional photo-interpretation. This suggests that satellite data may be an economical alternative for the USFS FIA process. Other researchers have obtained comparable results, but with more complex iterative classification methodologies (Holmgren and Thuresson, 1998; Wayman et al., 2001). The method described in this paper is simple, robust and potentially extendable to other regions of the US.

4.2. Sources of classification errors

One of the major sources of classification error in this study was the confusion between tree and non-tree classes resulting from land use definitions. For example, for Forest Service purposes, pastures should not be classified as forest even when trees dominate a pasture area. Photo-interpreters often use non-spectral keys, such as presence of roads and feeding areas, to classify air photos as non-forest, where the satellite image classification relies primarily on the spectral response of the dominant feature, causing wooded pasture to be classified as forest. When the misclassified reference points were analyzed it was evident that this type of confusion contributed to most of the errors in our study.

Classified satellite imagery had more non-forest misclassified as forest (forest commission) than forest misclassified as non-forest (forest omission). This pattern was the same for all six counties. Errors were lower in San Augustine County and the southeast portion of Angelina County where state and national forests are present and where forest fragmentation and pasture with trees are relatively low. However, errors were higher in Rusk County where several ‘pastures with trees’ were misclassified as forest. Pastures in San Augustine and Angelina had fewer trees than pastures in Rusk and Panola, suggesting that the distinction between ‘pasture with trees’ and ‘forest’

classes was not as clear in Rusk and Panola Counties, leading to higher error there.

Confusion between the forest class and vegetated urban areas was another common source of error in the satellite classification (Table 4). Together, forested pastures and urban areas contributed about 85% of the total commission error. In general, ambiguity between wooded non-forest land use types and true forest contributed disproportionately to classification error. A solution might be to use percent tree cover more directly to estimate forest cover, rather than relying on land use classes. Quantitative measurements of the percent forest could be obtained and these values could be compared to the classified ETM+ imagery.

Recently harvested forest stands and young pine plantations were omitted from the forested class in the satellite classification more than any other ground types (Table 5). One of the reasons for this may be that the satellite image used in this study was obtained in 1999 whereas TFS black and white aerial photos were obtained in 2001. Recently harvested stands identified in 2001 could have been identified as forests in 1999. In total, 79% of the omission errors in the satellite classification corresponded to points identified on the ground as either young pine plantations or recently harvested stands. The reflectance of recently harvested stands in the satellite image was similar to that of barren soils and, in several instances, caused these areas to be grouped with barren soils. Under these circumstances, multi-temporal data sets may be required to detect clear-cut areas (Wilson and Sader, 2002). Another method for minimizing this error would be to obtain timber harvest records and reclassify clear-cut and regeneration areas as forests.

4.3. Comparison with FIA plot data

The classification error observed when the satellite map was compared with the FIA plot data was similar to that from comparison with the photo-center points allowing us to compare the validity of our satellite-derived map to maps produced using traditional photo-interpretation and assessed using FIA plots. However, since the FIA plot locations were confidential, further interpretation was hampered in several ways: (1) distribution of the plots within the study area could not be assessed; (2) knowledge of classes contributing to the omission and commission errors could not be used; and (3) the spatial pattern of the omission and commission errors could not be determined. Knowledge of these errors determined by our independent photo-based validation provided further insights about the utility of ETM+ for estimating forest cover in East Texas and elsewhere.

4.4. Forest cover estimates

Overlap in the 95% confidence intervals for both techniques indicates the similarities of the estimates derived from ETM+ imagery and traditional photo-estimates (Fig. 4). Estimates for San Augustine County had the highest precision suggesting that the utility of LANDSAT data for mapping forest cover is high for areas with distinct forest and non-forest landscapes. In other areas where the distinction between forest and non-forest is more ambiguous (e.g., Rusk County) there were higher differences in estimates (lower precision from satellite data). Such error estimates with confidence intervals allow the analyst to better convey the precision of the classification, rather than reporting estimates as a single number, which is was done in several published studies (Holmgren and Thuresson, 1998; Wynne et al., 2000). Counties with higher classification accuracy have more precise estimates and this information would enable the map user to obtain insights about the usefulness of these data at the county level.

Results obtained from this study were encouraging since the overall accuracy of the classified ETM+ images was high and most of the commission and omission errors were due to classification confusion among a few land cover/use classes. Obtaining GIS data about urban areas and vegetated lots within suburban areas would minimize the areas misclassified as forest. The results from the current study demonstrate the utility of ETM+ data for obtaining forest and non-forest estimates.

5. Conclusions

Satellite data can provide FIA phase I estimates of forest area which are comparable in precision to those obtained using the traditional photo-estimation method. The method described in this paper allows routine classification of satellite images with minimal training required for USFS personnel. As a result, the USFS can

obtain and publish area estimates faster than is possible using traditional photo-interpretation because the time required for classifying a LANDSAT or similar satellite image is much less. The time needed for generating forest cover estimates is also reduced since the photos currently used by the USFS are obtained approximately once in 10 years, whereas LANDSAT images are acquired approximately twice a month for the entire US. In addition to LANDSAT, several satellites such as SPOT and Indian Remote Sensing (IRS) satellites, collect data with similar characteristics.

This study demonstrated that most of the errors in East Texas satellite image classification were caused by confusion among only a few land cover and land use classes. Defining an area as non-forest based on land use (e.g., pasture with trees) versus land cover (e.g., sparse trees) also introduced some errors in the classified image that might be solved using a land cover based classification. In addition to cover estimates described here, maps depicting forest cover map created from ETM+ data could provide a better spatial context for forest management.

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