International Journal of Applied Earth Observation and Geoinformation 9 (2007) 41–49

INTERNATIONAL JOURNAL OF APPLIED EARTH OBSERVATION AND GEOINFORMATION

www.elsevier.com/locate/jag

Estimating regional forest cover in East Texas using Advanced Very High Resolution Radiometer (AVHRR) data

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Received 15 December 2005; accepted 12 May 2006

Abstract

This study tested the degree to which single date, near-nadir AVHRR image could provide forest cover estimates comparable to the phase I estimates obtained from the traditional photo-based techniques of the Forest Inventory and Analysis (FIA) program. FIA program is part of the United States Department of Agriculture-Forest Service (USFS). A six-county region in east Texas was selected for this study. Manual identification of ground control points (GCPs) was necessary for geo-referencing this image with higher precision. Through digital image classification techniques forest classes were separated from other non-forest classes in the study area. Classified AVHRR imagery was compared to two verification datasets: photo-center points and the USFS FIA plots. The overall accuracy values obtained were 67 and 71%, respectively. Analyses of the error matrices indicated that the AVHRR image correctly classified more forested areas than non-forested areas; however, most of the errors could be attributed to certain land cover and land use classes. Several pastures with tree cover, which were field-identified as non-forest, were misclassified as forest in the AVHRR image using the image classification system developed in this study. Recently harvested and young pine forests were misclassified as non-forest in the imagery. County-level forest cover estimates obtained from the AVHRR imagery were within the 95% confidence interval of the corresponding estimates from traditional photo-based methods. These results indicate that AVHRR imagery could be used to estimate county-level forest cover; however, the precision associated with these estimates was lower than that obtained through traditional photo-based techniques.

Keywords: AVHRR; Forest cover; USDA-Forest Service; FIA; Remote sensing; Texas

1. Introduction

Forests are an important global resource and information about their characteristics and spatial distribution is useful for assessing timber resources, wildfire risks, wildlife habitats, and modeling environmental processes such as carbon sequestration (Foody et al., 1996; Wulder et al., 2004; Ney et al., 2002; MaCGraken, 2005). Periodically updated spatial information about forest resources is also important to monitor change and assess the impact of change on atmospheric and hydrologic processes. Several international and national organizations have implemented programs to inventory forest resources at various spatial scales.

The Forest Inventory and Analysis (FIA) program of the United States Department of Agriculture-Forest

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0303-2434/$ – see front matter
doi:10.1016/j.jag.2006.05.002

Service (USFS) has been estimating the forest resources in the US and its territories since the 1930s. FIA data are used for estimating US forest carbon stocks for identifying carbon sources and sinks (Reams et al., 1999). The FIA program relies on a combination of aerial photographs and field surveys to sample and estimate forest resources. In the first phase of the FIA program, aerial photos are used to obtain forest and non-forest estimates; these estimates are subsequently adjusted in the second phase based on plot-level field surveys (Hansen and Wendt, 1999; McRoberts et al., 2002; Sivanpillai et al., 2005). One of the limitations of the FIA program is the time required to generate forest cover estimates from aerial photos. Satellite-based remotely sensed data could enable us to obtain forest cover estimates and generate maps that are unavailable through current methods. The FIA program has tested the utility of different types of satellite data for obtaining forest cover estimates. If satellite data could be used for forest area estimation, it would reduce the time required to update forest resource information as well as improve the usefulness of published data (Czaplewski, 1999). This paper reports a study that tested the utility of Advanced Very High Resolution Radiometer (AVHRR) data to map and estimate the regional forest resources in east Texas at the FIA phase I (forest and non-forest) level. Area of the forest cover as a proportion of the total area for each county was derived from AVHRR imagery.

AVHRR data, collected by National Oceanic and Atmospheric Administration (NOAA) Polar Orbiting Environmental Satellites (POES), are widely used for obtaining information about earth surface features such as vegetative cover (Loveland et al., 1991; Tucker, 1996), agricultural production (Hayes and Decker, 1996; Mkhabela et al., 2005), and processes such as wild fires (D'Souza et al., 1996; Cracknell, 1997; Randriambelo et al., 1998) and droughts (Seiler et al., 1998). High temporal resolution of the AVHRR data will be useful for assessing areas that are undergoing rapid changes due to natural (wildfires, pest outbreak) or human-caused (forest clearing) agents (Justice et al., 1985; Loveland et al., 1991; Zhu and Evans, 1992). AVHRR data acquisition and processing time are also lower in comparison to medium resolution data such as Landsat. One limitation of AVHRR data is its lower resolution (spatial and spectral) as compared to Landsat. To overcome this limitation, researchers often use multi-temporal data and rely on the phenological changes in vegetation for identification and mapping. Multiple images collected throughout a growing season, or over several years, are often used to capture phenological changes within different crops or vegetation types (Mkhabela et al., 2005). Other studies have also incorporated ancillary data such as climatological and meteorological information for generating vegetation information (Norwine and Greegor, 1983).

However, relatively few studies have tested AVHRR data utility for FIA forest estimation purposes. Iverson et al. (1989) found that forest estimates obtained from multi-temporal AVHRR data were highly correlated ($r = 0.89$) with traditional USFS–FIA estimates. Teuber (1990) used single-date AVHRR data to obtain state-level forest cover estimates for Arkansas, Louisiana, and Mississippi and found that the estimates were within the 95% confidence interval of the FIA. Zhu and Evans (1992) adapted the methodology developed by Iverson et al. (1989) to generate a forest cover map for the Southeastern U.S. using multi-temporal AVHRR data. Zhu and Evans (1994) and Zhu (1994) extended this methodology to generate a forest cover map for the U.S. However, the above mentioned studies did not conduct accuracy assessment for the classified images. Lannom et al. (1995) found that the estimates obtained from the AVHRR image were within the 95% confidence interval of estimates obtained from aerial photo interpretation and the dot count method used by USFS. In this study, an accuracy assessment of the classified AVHRR image was also conducted.

In the studies discussed above, forest cover (area) estimates obtained from AVHRR data were compared to the FIA estimates and conclusions were drawn about its suitability. In most cases, an accuracy assessment of the classified image was not conducted and sources of classification errors were not quantified. Given the large pixel size (1 km) of the AVHRR data, it was hypothesized that small geographic features could not be identified and mapped (Teuber, 1990). Additional studies are required to assess AVHRR data suitability for FIA since the utility of satellite data could vary between different geographic regions (Lu et al., 2004). In addition to reporting traditional classification accuracy estimates these studies must provide additional insights about the sources of error and the uncertainty associated with forest area estimates.

Thematic maps generated from satellite data contain classification errors and are reported in the form of overall classification, producer and user accuracies (Jensen, 2004). However, these metrics do not capture the sources of misclassification. Incorporating information about the sources of errors would enable the users to gain insights about suitability of satellite data for estimating forest cover. For example, if most of the classification errors are associated with certain land cover classes suitable post-classification methods could be developed to minimize the errors. However, if the errors are random and attributed to several land cover classes it would require several additional data processing. Since these errors could vary based on a landscape it is important that insights are provided about the error distribution.

Area estimates derived from classified images for thematic classes are often reported as either a single number (e.g. 5000 ha) or a percentage of the study area (Wynne et al., 2000). However, area estimates derived from a classified image with lower classification accuracy would have more uncertainty than similar estimates derived from a classified images with higher classification accuracy. Card (1982) developed a technique to incorporate this uncertainty and compute the precision of area estimates derived from classified imagery. Precision of area estimates associated with satellite data could provide insights about the suitability of different satellite data and processing methods for FIA or other forest inventory programs (Wynne et al., 2000). The objectives of this study were to (1) obtain the area of forest and non-forest (phase I) estimates from a single-date AVHRR image that are comparable to the traditional photo estimates, and (2) identify the sources of thematic error in the classified AVHRR image. Using this information, insights could be gained about the suitability of AVHRR image for estimating forest cover in East Texas.

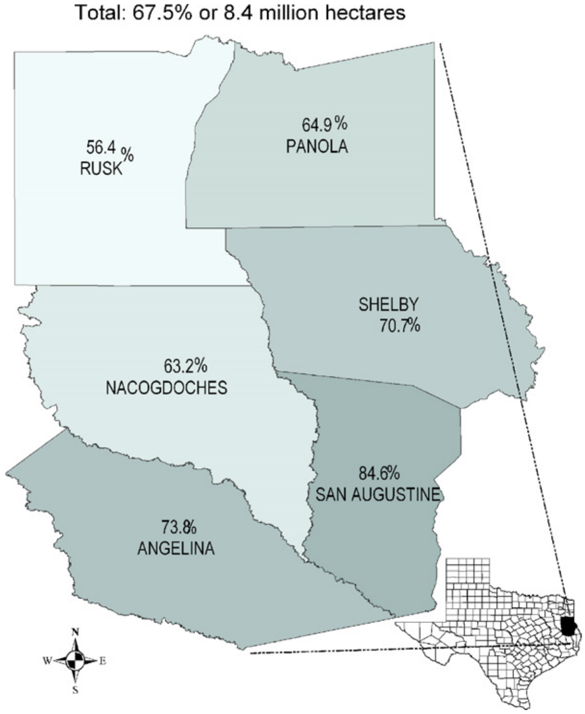

Fig. 1. Location of the six counties used in this study along with the 1992 USDA-Forest Service estimates of forest cover within each county expressed as proportion of the total area. *Notes*: 1992 forest estimates were obtained from the Southern Research Station, FIA, Knoxville, TN, http://www.ncrs2.fs.fed.us/4801/FIADB/fim_tab/wc_fim_tab.asp and Texas administrative boundary was obtained from the Texas Natural Resources Information System (TNRIS).

2. Methods

2.1. Study area

A six-county area within the Pineywoods ecoregion (Gould et al., 1960) in East Texas (31°43′N, 94°24′W) was chosen for this study (Fig. 1). Loblolly (*Pinus taeda* L.), shortleaf (*P. echinata* Mill.), and longleaf (*P. palustris* Mill.) are the native pines found in this region. Slash pine (*P. elliottii* L.) is also planted in this area. Oak (*Quercus* spp.), hickory (*Carya* spp.), gum (*Nyssa* spp.), cypress (*Taxodium* spp.), and hardwood–pine mixtures constitute the rest of the timberland (Murphy, 1976; McWilliams and Bertelson, 1986). According to the recent USFS–FIA estimates, about 0.84 million ha (or 68%) of the study area are forested (Fig. 1) and receive an average annual precipitation of 119 cm. Precipitation varies on an average monthly basis from 6 cm in July and 12 cm in May. Average annual minimum and maximum temperatures vary between 13 °C in January and 22 °C in July. Topography varies from nearly level to gently undulating, and Ultisols and Alfisols are the two major soil orders found in this ecoregion (Godfrey et al., 1973). Timber production is the primary land use and pine plantation forests are found in previously forested or cultivated areas. Further information about these forest types can be found at the Texas Parks and Wildlife Department's website at http://www.tpwd.state.tx.us/publications/pwdpubs/pwd_bn_w7000_0120/forest/ (accessed on 15 March 2006).

2.2. Satellite data

AVHRR data down-linked from NOAA-14 satellite and archived at the Blackland Research and Extension Center (BRC), Temple, TX were obtained for this study. Earlier studies conducted at Texas A&M University have shown that satellite imagery acquired in autumn were suitable for mapping forests in this region. Data received in October 1999 were screened for potential transmission and omission errors. An AVHRR image received on 6 October 1999 was selected for this study because it was free from clouds, shadows and other transmission errors such as missing rows. Single-date imagery, with near-nadir view of the study area, was selected in order to compare the results of this study with the corresponding results obtained from a Landsat Enhanced Thematic Mapper Plus image acquired on the same day (Sivanpillai, 2002).

2.3. Reference data

Reference data required to classify the satellite image were collected through field visits using a Trimble (Sunnyvale, CA, USA) Global Positioning System (GPS). Pertinent information about forest stands were recorded along with their geographic coordinates. Additional reference data were digitized directly on a Landsat image and digital aerial photographs as points and polygons in ESRI (Redlands, CA, USA) Arc View (Version 3.2) using the information provided by Texas Forest Service (TFS) personnel who were familiar with the local forest resources. High resolution aerial photographs and hardcopy maps were used as additional reference data.

2.4. Verification data

Two verification datasets were used to assess the classification accuracy of the processed AVHRR imagery. The first set consisted of 204 permanent plots within the six-county region surveyed by the USFS. Each FIA sample plot consists of four center points with fixed-radius (7.3 m) that are separated by 36.6 m (McRoberts et al., 2002). However, the geographic locations of these plots were not disclosed due to security and privacy issues. The classified AVHRR image was sent to the USFS field office in Mississippi, USA for verification and error analyses. A second set of verification data was obtained from black and white photos (nominal scale 1:15,840) acquired by the Forest Pest Management Unit of the TFS in Lufkin, TX. Using the systematic sampling procedure described by Fitzpatrick-Lins (1981), 599 photos were selected. TFS personnel interpreted the effective area of these photos based on the classification scheme described in Table 1. These classes were defined based on a combination of land cover and land use parameters and were digitized as a point data (photo-center point) layer in Arc View (ESRI, 2000). For example, ‘‘pasture with trees’’ was identified as non-forest based on land use (pasture) rather than land cover (mostly trees). Digital Ortho Quarter Quads (DOQQs) were used as image backdrop to assign points to real world coordinates (Sivanpillai, 2002). Distance between 130 pairs of verification points was less than 1 km (pixel size of an AVHRR pixel); therefore, only one point per pair was selected, resulting in 469 photo-center verification points.

Table 1
Land cover/use of the study area identified from the black and white (nominal scale—1:15,840) aerial photographs

Forest classes	Non-forest classes
Pine	Urban–commercial–mines
Pine–hardwood	Agriculture
Hardwood–pine	Pasture with no trees
Hardwood–predominantly upland	Pasture with trees
Hardwood–bottomland	Water

2.5. Image processing and forest cover estimation

AVHRR data were converted to level 1b format using the NOAA-1b software (NOAA, 1996), along with the appropriate two-line element file containing satellite orbital information (http://www.celestrak.com/NORAD/elements). Level 1b format conversion involves error checks, calibration, and appending earth locations and instrument calibration information to AVHRR data. Resulting level 1b data were imported into ERDAS Imagine using the Import module to create an image file (ERDAS, 1996). A subset corresponding to east Texas, but larger than the study area extent, was extracted using the subset tool. This image, consisting of all five channels, was geo-rectified using a second-order polynomial. Reservoirs and coastal boundaries from the Texas hydrography data were used to collect 14 ground control points (GCPs). Root mean square (RMS) error was 0.62, and the pixel size of the geo-referenced image was resampled to 1000 m.

Iterative self-organizing data analysis (ISODATA) algorithm, with a 95% convergence threshold and nine iterations, was used to separately generate 25, 50, 100 and 150 spectrally homogeneous clusters (Jensen, 2004). Mean spectral values for each cluster were analyzed to determine the adequacy of these clusters. The classified image with 50 spectral classes adequately captured the variability of the landscape and used for subsequent analyses. First, with the aid of hydrography data and spectral reflectance values clusters representing water bodies were identified and labeled. Similarly with the aid of municipal administration and transportation data layers, clusters representing urban areas were labeled. Remaining clusters were either assigned to either forests or other non-forest classes such as pastures and bare ground, using a combination of spectral statistics and image interpretation methods outlined by Thenkabail et al. (2000) and Sivanpillai (2002). Clusters representing these classes had different reflectance values in the visible and infrared channels of AVHRR. Clusters that were labeled as forest were merged to generate a single forest class in the final map. This process was repeated for all non-forest and water clusters, and the final map consisted of three thematic classes. For error analyses non-forest and water were combined into a single non-forest class.

An error matrix was constructed for the classified image using 469 photo-center points (Jensen, 2004). Similarly, pixels in the classified image were compared with corresponding plot-level data at the USFS Laboratory and another error matrix was generated. The overall accuracy, omission, and commission errors for the six-county region were computed for each matrix. Using the county boundary data, a subset image for each county was clipped from the classified image and forest cover estimates (ratio of the number of pixels classified as forest and the total number of pixels in that county) for each county were obtained. A county-level error matrix was computed along with the overall accuracy, omission, and commission errors using the photo-center points. Error associated with the estimate for each county was computed based on the corresponding error matrix (Card, 1982) and the raw estimate of the proportion of forest area was adjusted. Based on this error, the 95% interval estimate for forest cover was calculated (Wynne et al., 2000).

Photo-center points that were originally assigned to the 10 land cover and land use classes were reclassified as forest or non-forest. An estimate of the forest area for each county was obtained using the methodology described by Lund and Thomas (1989). This methodology is based on sampling without replacement design, and estimates for area of forest cover for each county was based on the number of photo-center points that were classified as forest.

3. Results

3.1. Overall accuracy and error assessment

The error matrix generated using the 469 photo-center points yielded an overall accuracy of 67% (Table 2). Only 53 (18%) verification points corresponding to the forest class were misclassified as non-forest in the image. However, 102 (61%) non-forest verification points were misclassified as forest. The overall accuracy was 71% when the classified AVHRR image was compared with the FIA plot measured data (Table 2). Only 7 (6%) of the FIA forest plots were misclassified as non-forest. However, 52 (59%) of the FIA non-forest plots were incorrectly identified as forests. The pattern of misclassification errors was similar for both sets of verification data. Fewer forest verification data were misclassified as non-forest, while non-forest verification data were more often misclassified as forest in the AVHRR image.

Table 2
Error matrices, omission and commission errors for the classified AVHRR image (columns) was compared to aerial photo and FIA plot-level data (rows)

	Forest	Non-forest	OE (%)	CE (%)
Photo-center points				
Forest	249	53	17.6	29.1
Non-forest	102	65	61.0	44.9
FIA plot data				
Forest	109	07	6.0	32.0
Non-forest	52	36	59.0	16.0

OE and CE: omission and commission error in percent. Overall accuracy with photo-center points = 67% (n = 469); overall accuracy with FIA plot data = 71% (n = 204).

3.2. County-level accuracy and error assessment

At the county level, the overall accuracy values obtained were between 52 and 71% for all counties except San Augustine County, which was 85% (Table 3). Rusk County had the lowest overall accuracy (52%), whereas San Augustine County was highest. The omission error associated with the forest class ranged between 8% (San Augustine) and 32% (Rusk). The commission error associated with the forest class ranged between 10% (San Augustine) and 54% (Rusk). San Augustine County had the lowest omission and commission errors for the forest class. These results show that, except for Nacogdoches County, more non-forest verification points were misclassified as forest than forest verification

Table 3
County-level overall accuracy, omission and commission errors for forest class when satellite image was compared with photo verification data

County	Overall	OE (%)	CE (%)
Angelina	69.1	18.9	22.9
Nacogdoches	71.1	21.9	19.4
Panola	67.1	11.9	30.2
Rusk	51.7	31.6	54.4
San Augustine	85.0	8.3	10.2
Shelby	54.0	13.5	34.8

OE and CE: omission and commission error in percent.

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

County	UR	AG	PNT	PWT	WA	Total
Angelina	2	0	1	9	2	14
Nacogdoches	0	0	0	11	1	12
Panola	1	0	2	9	4	16
Rusk	2	1	1	18	9	31
San Augustine	0	0	2	2	1	5
Shelby	1	0	1	13	9	24
Study area	6	1	7	62	26	102

Notes: UR, urban; AG, agriculture; PNT, pasture (no trees); PWT, pasture with trees; WA, water.

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

County	PI	PH	HP	HUP	HBL	Total
Angelina	6	2	0	3	0	11
Nacogdoches	4	2	7	0	1	14
Panola	2	0	1	0	2	5
Rusk	8	1	2	1	0	12
San Augustine	3	0	1	0	0	4
Shelby	4	0	1	1	1	7
Study area	27	5	12	5	4	53

Notes: PI, pine; PH, pine/hardwood; HP, hardwood/pine; HUP, upland hardwood; HUL, bottomland hardwood.

points that were misclassified as non-forest. Higher commission error in the forest class will result in the over-prediction of forest area.

3.3. Sources of classification error

Non-forest verification points misclassified as forest ($n = 102$) in the classified image were tabulated by county (Table 4). Most of the commission error (87%) in the forest class could be attributed to the following two classes: (1) pasture with trees and (2) water. Contributions by these two classes were 61% (62 points) and 25% (26 points), respectively (Table 4). The urban class contributed only 6% toward the total commission error.

Forest verification points misclassified as non-forest ($n = 53$) in the classified image were tabulated by county (Table 5). Most of the omission errors were due to pine forests misclassification as non-forest. Of the 53 points that were misclassified, 27 (51%) points corresponded to pine class. Mixed hardwood–pine class contributed 12 points (23%) toward the total omission error.

3.4. Forest cover estimates

The proportion of forest cover for each county was adjusted to incorporate omission and commission errors and the 95% confidence interval was computed (Fig. 2). Confidence intervals ranged between ±8.8% (San Augustine and Nacogdoches counties) and ±11.5% (Panola County). Forest cover estimates obtained from the satellite image were within the 95% confidence interval of the photo estimates.

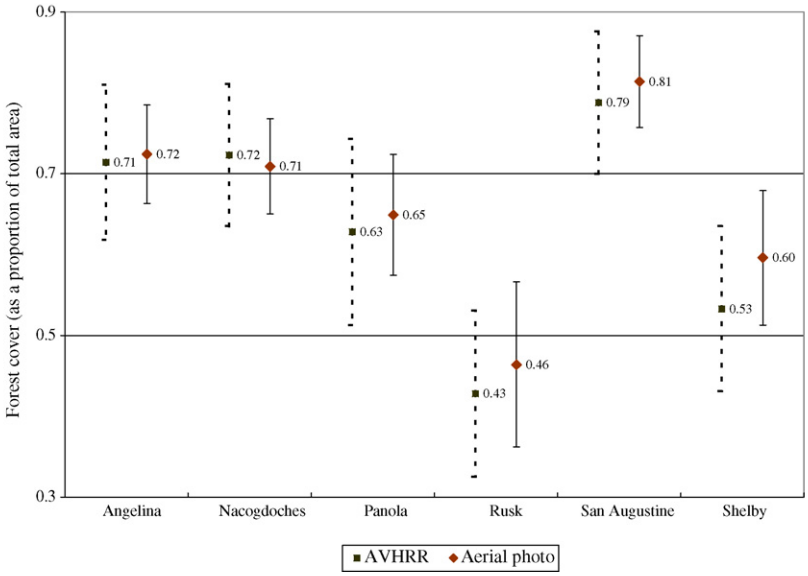

Fig. 2. Proportion of forest cover estimates along with the 95% confidence interval obtained from AVHRR data and aerial photos listed by county.

4. Discussion

Spectral information available in the near-nadir AVHRR imagery enabled us to distinguish forest from non-forest classes and obtain forest cover estimates. Contrast provided by the land-water interface was distinct in the image and enabled us to locate several GCPs for geo-referencing the image. Manual GCP identification was required to reduce the overall RMS error associated with image registration. Estimated GCPs derived from the orbital model had higher RMS errors. This could pose problems for those geographic regions without easily distinguishable features in the image. Under those circumstances complex automatic registration methods described by Marcal (1999) and Brunel and Marsouin (2000) could be used for geo-referencing the AVHRR data.

4.1. Sources of classification error

Overall accuracy was higher when the classified image was compared to the FIA field data (71%) than to the photo-center verification points (67%). AVHRR image and the classification algorithm were able to correctly identify more forest verification points than non-forest verification points. However, there was more misclassification in the non-forested areas (Table 2). This could result in over-prediction of forested areas. At the county level, fewer forest reference points were misclassified as non-forests than non-forest reference points that were misclassified as forests, for all counties expect Nacogdoches (Table 3). Counties with contiguous patches of forest cover (San Augustine, Nacogdoches and Angelina) had higher overall accuracy and the values ranged between 70 and 85%. For counties with a mix of forests and other land cover types the overall accuracy was lower and the values varied between 52 and 67%. Based on the error matrix analyses, one could conclude that AVHRR data are suitable for regions with large forested areas. Smaller patches of land cover classes might be dissolved with the adjacent dominant land cover classes (Teuber, 1990). However, when the sources of classification errors were analyzed further, it was found that a majority of errors could be attributed to a few land cover and land use types.

Analyses of 102 non-forest photo verification points that were misclassified as forest indicated that pasture with trees (62 points) and water (26 points) contributed most of the error (Table 4). This corresponds to the commission error in the forest class, where pixels representing other non-forest classes are misclassified as forest. Definition of the ''pasture with trees'' class was based on land use, whereas the reflectance from these areas could be similar to other forested areas. In the AVHRR imagery, several pastures were classified as forest and this could have resulted in over-prediction of forest cover. One method to minimize this error could be to incorporate property ownership records and sort the pixels in the classified AVHRR image. Property ownership and tax records often contain information about the land use, such as ranch or forest. In case of pasture with trees, property ownership information could be used to minimize errors. This technique could be useful for large land holdings. However, such data might not be available for other regions and image analysts would have to use other types of satellite data to overcome this problem.

There were several small water bodies in the study area that were easily identified on the photos. Several pastures also had small water retention tanks and ponds. Amount of water stored in these tanks and ponds varied based on rainfall received and time of the year. Large pixel size of the AVHRR data could have resulted in the misclassification of smaller water bodies as forest due to mixed response of several features in a single pixel. Misclassification of urban areas as forests, however, was lower in the AVHRR imagery. When medium resolution satellite data such as Landsat were used for mapping forest cover, pixels corresponding to the vegetated areas within an urban environment (parks, wooded areas) were often misclassified as forest (Sivanpillai et al., 2005).

Examination of forest photo verification points that were misclassified as non-forest indicates that pine forests contributed to most (51%) of the error (Table 5). This error corresponds to the omission error for the forest class and could result in the under estimation of the total area of forest cover. Recently harvested areas, sites prepared for planting and young pine plantations are identified as forests based on land use. Reflectance values from these pixels would be similar to those from non-forested features such as bare ground and grasslands. Hence, there is a higher chance for misclassification of such areas as non-forest. Land ownership records and tax receipts could be used to identify these forested areas using post-classification sorting procedure. Misclassification of mixed hardwoods–pine stands as non-forest was the second major source (23%) of omission error and most of these misclassification errors (7 out of 12 or 58%) occurred in Nacogdoches County. Hardwood–pine mixed stands are also harvested similar to pine stands and, in cases of recently harvested mixed stands, they would be classified as non-forest in the satellite image. Defining forests based on land use rather than land cover contributed to most of the omission errors. Satellite data acquired in autumn minimized atmospheric interferences such as clouds and haze and reduced misclassification. Addition of multi-temporal imagery could improve the classification accuracy, if errors associated with geo-referencing of individual images are minimized.

4.2. Forest cover estimates

Forest area estimates obtained from classified AVHRR imagery were within the 95% confidence interval of the corresponding estimates obtained from the photo-based estimates (Fig. 2). San Augustine County had more forest cover and the precision associated with its estimate was also higher. Confidence intervals associated with the AVHRR estimates were wider for each county, indicating lower precision. By associating a measure of precision along with the area estimates we gained insights about the utility of the satellite data for estimating forest resources. Incorporating land ownership records, classification errors could be reduced and the precision of the estimates could be increased. Teuber (1990) found that forest estimates obtained for Arkansas and Mississippi were higher than traditional FIA estimates, due to presence of clouds and haze in the AVHRR image. Imagery used in this study did not have clouds and therefore estimates obtained from it should not be influenced by clouds or shadows. Obtaining a single, cloud-free AVHRR imagery could be problematic for certain parts of the world and multi-temporal composites have to be used under those circumstances.

Based on the results obtained in this study, near-nadir AVHRR data could be used to obtain county-level estimates of forest cover, though the precision associated with those estimates was lower than the traditional photo-based estimation techniques. However, further investigation is required to minimize the classification errors associated with the AVHRR image. These techniques could be adapted for other regions to monitor forest cover and provide periodic updates.

5. Conclusion

AVHRR image could be used to estimate county-level forest cover, however the precision associated with the area estimates were lower than photo-based estimates. More non-forest verification points were misclassified as forests than the number of forest verification points misclassified as non-forests. This pattern of misclassification was similar when classified AVHRR image was compared with photo verification points and FIA plot-level data. The majority of the misclassification in the forest class could be attributed to pastures with trees (misclassified as forest) and certain types of pine forests (misclassified as non-forest). Misclassification of pastures with trees as forest resulted in the overestimation (commission error) of forest cover. Misclassification of pine forests as non-forest resulted in underestimation (omission error) of forest cover. Forest cover estimates obtained from the AVHRR image were within the 95% confidence interval of the estimates obtained from aerial photos. However, high commission error obtained in the study for the forest class might require the use of ancillary data to improve the classification accuracy.

Acknowledgements

This study was conducted as part of the first author's doctoral dissertation research at Texas A&M University. Technical support provided by Mr. Thomas Spencer and Mr. Curt Stripling of Texas Forest Service, are gratefully acknowledged. We would like to extend our thanks to Dr. R. Jayakrishnan (Boyle Engineering Corporation, FL), Dr. P. Chen (BREC, TAMUS, Temple, TX) and Dr. B. Narasimhan (SSL, TAMU) for their valuable support to download and preprocess AVHRR data. We thank Mr. Damon Holzer (NOAA, WA) for his assistance with GIS data processing. Contributions of Dr. William Cooke III, USDA-Forest Service were valuable for successful completion of this research. Partial financial support was provided to the first author by the Texas Agricultural Experiment Station (TAES) and the Heep Foundation for conducting this study. We would like to thank the two anonymous reviewers for their valuable comments and suggestions.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.jag.2006.05.002.

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