GeoJournal
DOI 10.1007/s10708-008-9157-5

Comparative analyses of East Texas forest cover maps generated from Landsat and AVHRR data

Ramesh Sivanpillai · X. Ben Wu · R. Srinivasan · Charles T. Smith · Michael G. Messina

Abstract Comparing satellite data derived map products are affected by differences in data characteristics, image acquisition dates, processing techniques, and classification schemes used for assigning pixels to a thematic class. By comparing two forest maps generated from Landsat Enhanced Thematic Mapper Plus (ETM+) and Advanced Very High Resolution Radiometer (AVHRR) images acquired on the same day, and processed using identical classification scheme and methods these differences were minimized. The ETM+ derived map had higher classification accuracy values and more precise area estimates than the AVHRR derived map. In the ETM+ derived map, 87 of the 599 verification data were misclassified, whereas in the AVHRR derived map, 155 of the 469 verification data were misclassified. Detailed error analyses by land cover class revealed that a land use based definition of forest accounted for 74% (64 out of 87) and 57% (89 out of 155) of the classification errors in ETM+ and AVHRR derived maps, respectively.

Keywords USFS · Remote sensing · ETM+ · Pixel resolution · Classification

R. Sivanpillai · R. Srinivasan · C. T. Smith · M. G. Messina
Department of Forest Science, Texas A&M University, College Station, TX 77843, USA

R. Sivanpillai (✉)
Wyoming Geographic Information Science Center, University of Wyoming, 1000 East University Ave., Laramie, WY 82071, USA
e-mail: sivan@uwyo.edu

X. B. Wu
Department of Rangeland Ecology and Management, Texas A&M University, College Station, TX 77843, USA

Present Address:
C. T. Smith
Faculty of Forestry, University of Toronto, Toronto, ON, Canada M5S 3B

Introduction

Remotely sensed data, collected by different satellites and sensor characteristics, are used for mapping forest distribution at regional, continental, and global scales (Batista et al. 1997; Fernandez et al. 1997; Duchemin 1999; Gemmell et al. 2001; Pax-Lenney et al. 2001; Dymond and Johnson 2002). Information generated from these forest maps is used to estimate forest cover and assess change over time at regional, national, continental and global scales (e.g., FAO 2001). However, satellite-derived forest maps are affected by the characteristics of the input satellite data (Moore and Bauer 1990; Teillet et al. 1997; Mayaux et al. 2000; Shen et al. 2004; Wu 2004). Spatial patterns mapped from remotely sensed data are scale-dependent (Wu 2004) and inferences drawn are dependent on grain size or resolution of the input data (Shen et al. 2004). In addition to data resolution and classification methods, the classification scheme or level of thematic detail used for assigning the pixels in the satellite image to a thematic class (e.g. forest, water and others) can also influence the accuracy and spatial pattern (Buyantuyev and Wu 2007).

Several studies have attempted to assess the effect of data characteristics on forest and land cover map products (Loveland et al. 2000; Hansen and Reed 2000; Giri et al. 2005; McCallum et al. 2006). However differences in satellite data acquisition time (Salajanu and Olson 2001), definition of land cover/use classes (Hansen et al. 2000; Loveland et al. 2000; Giri et al. 2005; McCallum et al. 2006), and classification methodology have limited the ability to compare these products (Friedl et al. 2002; Raptis et al. 2003; Millington et al. 2003; Colombo et al. 2004; Neumann et al. 2007). Also the above mentioned studies did not explicitly test the effect of spatial and spectral resolutions of the input satellite data used for generating these maps. Comparison of the MODIS Land Cover (MLC) and Global Land Cover 2000 (GLC2000) map products was affected by the temporal differences between the data used (November 1999 and December 2000), and classification schemes adopted in these projects. In the MLC product, forests were defined as trees with height >5 m whereas in the GLC2000 dataset the same class was defined as trees with height >3 m resulting in differences between the forest area estimates in these datasets (Giri et al. 2005; McCallum et al. 2006). The International Geosphere Biosphere Project (IGBP) and the University of Maryland (UMD), USA generated two separate land cover products with AVHRR data acquired between April 1992 and March 1993, however, using different classification techniques (Loveland et al. 2000; Hansen and Reed 2000). Direct comparison of these datasets was not possible because the UMD dataset did not contain a crop/vegetation mosaic class that was present in the IGBP dataset. Different thematic classes and classification methods introduced differences in the thematic maps. Area estimates derived from these maps were different (McCallum et al. 2006).

To assess the effect of data characteristics on land cover mapping, it is important to minimize the influence of differences caused by data acquisition, class definition and image processing. These results will provide useful insights to data users about the utility of different map products. In this study, we compared two East Texas forest maps generated from Landsat ETM+ and AVHRR images. Landsat Enhanced Thematic Mapper Plus (ETM+) images (or data) are collected every 14 days, in six spectral regions (three visible and three infrared bands) with a spatial resolution of 30 m. Advanced Very High Resolution Radiometer (AVHRR) data are collected daily with a spatial resolution of 1,000 m, for a large area (2,400 × 6,400 km). AVHRR data are collected in either four (NOAA satellites 6, 8, 10, and 12) or six (NOAA satellites 7, 9, and 11) regions (or channels) of the electromagnetic spectrum. Spatial and spectral resolutions determine detection of features in the landscape and how they are represented in the remotely sensed image. Both satellite images were acquired on the same day, processed using identical image processing methodology (iterative unsupervised ISODATA classification), reference data, and classification scheme to minimize the temporal differences in input data, effects of data processing, and classification scheme (Sivanpillai 2002). Six Landsat ETM+ multispectral bands and two AVHRR bands that were radiometrically corrected were used to generate the forest cover maps. Objectives of this study were to: (1) assess the similarities and differences in the forest cover maps generated from Landsat and AVHRR images acquired on the same day, (2) compare the sources of classification errors that could be attributed to different land cover/use classes, and (3) compare the area estimates derived from these images. Information on uncertainties associated with the area estimates and sources of error would enable users to make informed decisions about the suitability of forest cover maps from different satellite data sources. These results will provide insights while assessing changes in forest cover using maps derived from different satellites.

Study area

Six counties in East Texas were mapped using the same-day ETM+ and AVHRR satellite data: Angelina, Nacogdoches, Panola, Rusk, San Augustine, and Shelby (Fig. 1). The geographic center of the study site was located at: 31°43′ N, 94°24′ W. Timber production is the predominant land use and loblolly

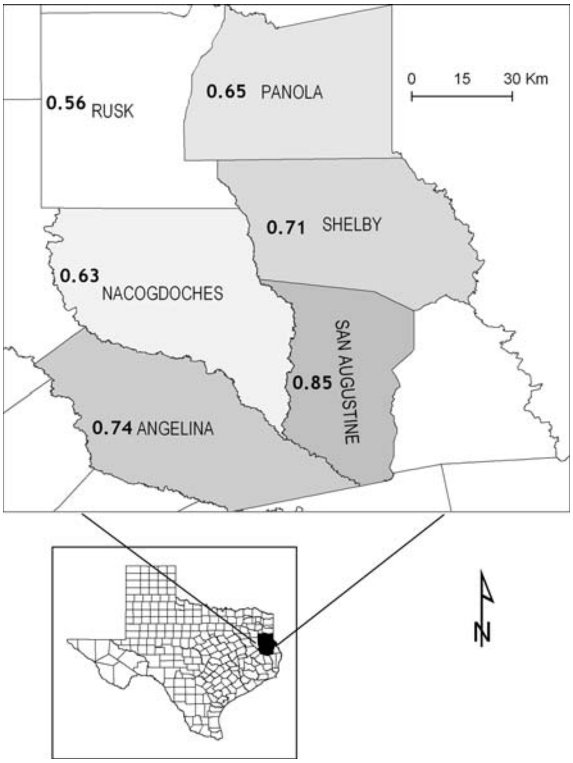

Fig. 1 Location of the study area in East Texas and the US Department of Agriculture—Forest Service (c.1992) estimates of forest cover as proportion of total area in each county

(*Pinus taeda* L.), shortleaf (*P. echinata* Mill.), and longleaf (*P. palustris* Mill.) pine are the major tree species found in this region's forests. Some Slash pine (*P. elliottii* L.) plantations are also present. Gould et al. (1960), Murphy (1976) and McWilliams and Bertelson (1986) provide detailed descriptions of the region's vegetation and timber production activities. Based on the 1992 US Forest Service estimates, Angelina, Nacogdoches and San Augustine counties had higher proportion of forested areas than the rest of the counties selected for this study.

Materials and methods

Forest cover map derived from ETM+ data

The first forest cover map was generated from a Landsat ETM+ scene (path 25; row 38) obtained on 6 October 1999 through iterative, unsupervised classification method (Wayman et al. 2001; Sivanpillai et al. 2005). Overall accuracy of this map was 85%, when compared to the photo-based verification data obtained from the Texas Forest Service (TFS). The accuracy values at the county-level ranged between 78 and 96%. Producer accuracy for the forest class was 94% (study area), whereas at the county-level it ranged between 88 and 100%. User accuracy for the forest class was 85% (study area), and at the county-level it ranged between 73 and 95%.

Forest cover map derived from AVHRR data

The second forest cover map was generated from an AVHRR image also obtained on 6 October 1999 using identical classification methods used to classify the ETM+ data (Sivanpillai et al. 2007). For the study area, overall accuracy was 67% and for the counties it ranged between 52 and 85% when compared to TFS photo- based verification data. Producer accuracy for the forest class in the study area was 82% and at the county-level it ranged between 68 and 92%. For the forest class the user accuracy for the entire study area was 71%, whereas at the county-level values ranged between 46 and 90%.

Verification data

TFS personnel interpreted 1:12000 nominal scale aerial photographs and assigned them to either one of the five forest (Pine, Pine—Hardwood, Hardwood—Pine, Upland Hardwood, and Bottomland Hardwood) or to one of the five non forest (Urban—Commercial—Mines, Agriculture, Pasture with no trees, Pasture with trees, and Water) classes. Consistent with the United States Forest Service (USFS)—Forest Inventory and Analysis (FIA) definitions, class membership in forest or non-forest classes was based on land use rather than land cover (Sivanpillai et al. 2005). For example, pastures with trees were identified as non-forest based on land use. However, a classification based on land cover would have resulted in these locations being identified as forest. Similarly, recently harvested areas or areas with young plantation were identified as forest based on land use. A land cover (mostly bare soil) based classification would have resulted in these locations being identified as non-forest.

Classification accuracy and sources of error

Overall, producer and user accuracies of the forest cover maps obtained for each county and the study area were compared to assess the utility of ETM+ and AVHRR imagery (Story and Congalton 1986; Congalton and Green 1999). Overall accuracy reports the number of locations where the classes in the classified image and the verification data matches correctly. Producer accuracy is similar to overall accuracy however it is reported separately for each class. This enables us to compare accuracies at the class level. User accuracy is a measure of how useful the classified image is from a user's perspective. Higher user accuracy values mean that a user could find the same class on the ground as depicted in the classified image. Kappa agreement indices for each county and the entire study area for the ETM+ and AVHRR derived maps were compared to determine the statistical differences in the error matrices (Congalton and Meed 1983). Sources of classification error were also compared to identify the sources of misclassification and determine whether the sources of classification error were random or due to misclassification of certain thematic classes. If the sources of error could be attributed to fewer classes, then suitable post-processing methodologies can be used to minimize these errors. Also, if the sources of error were random in AVHRR data but attributed to fewer classes in Landsat data, inferences could be drawn about the effect of spatial resolution.

Comparison of area estimates

Precision of the area estimates obtained from classified satellite images depends on the classification (i.e., omission and commission) errors. For example, estimates obtained from a satellite image with lower classification accuracy are less reliable than the estimates obtained from another image with higher classification accuracy. Card (1982) developed a methodology to adjust the area estimates based on the classification errors and provide a measure of precision. Wynne et al. (2000) provide a methodology to adjust the area estimate and derive a 95% confidence interval. Margin totals from the error matrix (or contingency table) are used to adjust the area estimates derived from satellite data. Within the 95% confidence interval lies the true value for the area of forest cover. The width of the confidence interval is a measure of precision of the area estimates and it incorporates the omission and commission errors for the thematic class (Wayman et al. 2001). Area estimates derived from the ETM+ and AVHRR derived images were adjusted using the corresponding omission and commission error values. Adjusted area estimates and the confidence interval would enable users to gain insights about the utility of ETM+ and AVHRR data for mapping forests.

Results and discussion

Classification and accuracy analysis

When ETM+ and AVHRR derived forest maps were compared to the verification data, fewer forest verification data were misclassified as non-forest than the number of non-forest verification data that were misclassified as forest (Table 1). In the ETM+ derived map, 23 forest photo verification data were misclassified as non-forest and 64 non-forested photo verification data were misclassified as forest. In the AVHRR derived map, 53 forest photo verification data were misclassified as non-forest, and 102 non-forest photo verification data were misclassified as forest. In the AVHRR derived map, more non-forest verification data were misclassified as forest than the number of data that were correctly classified (Table 1). These results suggest that both ETM+ and AVHRR derived maps could over-estimate the

Table 1 Error matrices generated by comparing the classified ETM+ and AVHRR images to the photo verification points

	ETM+		PA	AVHRR		PA
	Forest	Non-forest		Forest	Non-forest	
Forest	366	23	94%	249	53	82%
Non-forest	64	146	70%	102	65	61%
UA	85%	86%		71%	55%	

Notes: (1) Overall accuracy of the ETM+ derived map was estimated from 599 verification data points and the overall accuracy of the AVHRR derived map was estimated from 469 verification data points

(2) PA and UA are producer and user accuracy values, respectively

area of forest cover, with higher error in the AVHRR derived map than in the ETM+ derived map.

The overall accuracy was lower for all counties in the AVHRR derived map than the corresponding accuracies in the ETM+ derived map (Table 2). The overall accuracy of the AVHRR derived map was 18% lower than the overall accuracy of the ETM+ derived map. At the county-level, difference in overall accuracy was smallest for San Augustine County (11%) and highest for Shelby County (28%). In the ETM+ derived map, all the counties except Rusk had overall accuracy values above 80%. Overall accuracy values for San Augustine and Angelina counties, with higher proportion of forest cover, were greater than 90%. However, in the AVHRR derived map the overall accuracies for five counties were lower than 75% and higher for San Augustine County (85%).

Omission and commission errors associated with the forest class in the ETM+ derived map were lower than the AVHRR derived map when compared to the photo verification data (Table 2). San Augustine County had the lowest omission and commission errors for the forest class in both maps, whereas Rusk County had the highest omission and commission errors for the forest class in both maps. These results indicate that the ETM+ derived map had fewer misclassification errors associated with forest class than the AVHRR derived map at both the regional and county levels.

When the kappa agreement values (Congalton and Meed 1983) for the forest maps were compared, the *Z*-values exceeded the threshold value of 1.96 (Table 2), indicating that the error matrices associated with the ETM+ and AVHRR derived maps are statistically different. In other words, classification error in AVHRR map was higher than the corresponding classification error in ETM+ derived map.

Sources of classification error

Among the five types of non-forest verification data, "pastures with trees" class was misclassified as forest more often than other type in both the ETM+ and AVHRR derived maps (Table 3). "Pastures with trees" were somewhat similar to the forests in terms of canopy cover but were identified as non-forest based on land use. In the satellite images, their reflectance values were similar to the values from forest stands, hence they were misclassified as forests. This source of misclassification was present in AVHRR (61% of 102 points) and ETM+ (72% of 64 points) derived maps. Among the counties, Rusk County had the highest number of misclassification errors in this type, whereas San Augustine County had the lowest. It is also important to note that, relatively few "pastures without trees" data were misclassified as forest in the AVHRR (7%) and ETM+ (3%). Spectral reflectance values from "pastures without trees" were similar to bare ground or grassland and therefore misclassification of this non-forest type as forest.

Several water bodies were not identifiable in the AVHRR derived map (25%) whereas this was a lesser problem in the ETM+ derived map (9%). There were several small water bodies within the pastures used as storage tanks and AVHRR data had

Table 2 Overall accuracy (%), omission (%) and commission (%) errors, and kappa agreement values obtained for the forest cover maps derived from ETM+ and AVHRR data when compared to the photo verification points

County	Overall accuracy		Omission error		Commission error		Kappa value		*Z*-value
	ETM+	AVHRR	ETM+	AVHRR	ETM+	AVHRR	ETM+	AVHRR	
Angelina	91	69	3	19	9	23	0.77	0.21	4.088*
Nacogdoches	85	71	6	22	14	19	0.60	0.31	2.127*
Panola	85	67	8	12	15	30	0.65	0.17	2.791*
Rusk	78	52	12	32	29	54	0.57	0.07	3.373*
San Augustine	96	85	0	8	5	10	0.84	0.52	2.011*
Shelby	82	54	8	13	19	35	0.61	0.15	2.956*
Study area	85	67	6	18	15	29	0.67	0.23	7.997*

Note: * *Z*-value greater than 1.96 indicates that error matrices were statistically different at 95% confidence interval

Table 3 Sources of commission error in the forest class in the ETM+ and AVHRR derived forest cover maps

County	Sensor	Total	Pasture with trees	Pasture no trees	Urban	Agriculture	Water
Angelina	ETM+	7	2	0	3	1	1
	AVHRR	14	9	1	2	0	2
Nacogdoches	ETM+	13	11	0	1	1	0
	AVHRR	12	11	0	0	0	1
Panola	ETM+	10	6	1	1	0	2
	AVHRR	16	9	2	1	0	4
Rusk	ETM+	18	14	0	3	0	1
	AVHRR	31	18	1	2	1	9
San Augustine	ETM+	3	2	1	0	0	0
	AVHRR	5	2	2	0	0	1
Shelby	ETM+	13	11	0	0	0	2
	AVHRR	24	13	1	1	0	9
Study area	ETM+	64	46	2	8	2	6
	AVHRR	102	62	7	6	1	26

difficulties in detecting them due to the larger pixel size (1,000 m). For mapping small water bodies within the pastures the relatively higher spatial resolution of ETM+ data was an advantage. However, in the ETM+ derived map, several green lots within urban areas were misclassified as forest (13%), whereas in the AVHRR derived map only 8% of the misclassified data belonged to the urban class. Under these circumstances the relatively higher resolution of ETM+ data lead to more commission error in the forest class.

More verification data corresponding to pine forest were misclassified as non-forest, in both ETM+ and AVHRR derived maps than any other forest class (Table 4). Based on USFS definition recently harvested pine stands and young pine plantations were grouped with other pine stands. However, reflectance from recently harvested pine stands and young pine plantations were similar to bare ground reflectance due to lack of or sparse vegetative cover. Such areas were identified as non-forest in both AVHRR and ETM+ derived maps. This source of error was

Table 4 Sources of omission error in the forest class in the ETM+ and AVHRR derived forest cover maps

County	Sensor	Total	Pine	Pine Hardwood	Hardwood Pine	Upland Hardwood	Bottomland Hardwood
Angelina	ETM+	2	2	0	0	0	0
	AVHRR	11	6	2	0	3	0
Nacogdoches	ETM+	5	2	1	2	0	0
	AVHRR	14	4	2	7	0	1
Panola	ETM+	5	4	0	1	0	0
	AVHRR	5	2	0	1	0	2
Rusk	ETM+	6	6	0	0	0	0
	AVHRR	12	8	1	2	1	0
San Augustine	ETM+	0	0	0	0	0	0
	AVHRR	4	3	0	1	0	0
Shelby	ETM+	9	4	1	3	1	0
	AVHRR	7	4	0	1	1	1
Study area	ETM+	23	18	1	3	1	0
	AVHRR	53	27	5	12	5	4

present in the AVHRR (51% of 53 points) and ETM+ (78% of 23 points) derived maps for the study area. Among the counties, Rusk had the highest number of instances where pine forests were misclassified as non-forest in the AVHRR and ETM+ derived maps. The second largest contributor to omission errors in the forest class was the hardwood/pine mixed forest type. In the AVHRR derived map, 23% of this class was misclassified as non-forest and in the ETM+ derived map only 13% of verification data were misclassified. San Augustine County had the fewest number of omission errors in the forest class.

Analysis of the commission and omission errors in both maps found that defining the forest class based on land use was a major contributor to classification error. The USFS definition of forest includes recently harvested forest stands and land that is prepared for forest plantation, but excludes pastures that contain trees because the land is not used for forestry operations. Since satellite sensors record reflectance values based on land cover and this fundamental difference could contribute to differences in estimates derived from traditional photo interpretation (land use) and satellite estimates (land cover). One approach to minimize these errors would be to use ancillary data such as property ownership records, tax receipts and administrative boundaries to reassign the misclassified pixels. For example, property ownership records would include information on land use (e.g. pasture), which could then be used to reassign the pixels to the correct thematic class.

The finer resolution of ETM+ data captured adequate detail in terms of land cover (e.g. green lots within urban areas), whereas the coarser resolution AVHRR data were unable to capture small features (e.g. small water bodies). Tueber (1990) concluded that several small features were not adequately captured by the AVHRR image while generating forest cover map for Arkansas, Mississippi and Alabama. Xiao et al. (2003) arrived at a similar conclusion regarding AVHRR's ability to map small agricultural fields in comparison to Landsat data. Raptis et al. (2003) observed that AVHRR data classified residential areas more accurately than the Landsat TM data. Roads, buildings and parks in a city produced a more complicated mix of signatures at 30 m resolution, whereas at 1,000 m a mixture of these signatures produced an 'urban' signature resulting in better classification of urban features in the AVHRR data. The magnitude of these errors was smaller in comparison to the misclassifications based on the definition of forest. Incorporating ancillary data such as city administrative boundaries in post-classification sorting will minimize the possibility of identifying wooded areas within a city as forest. The large pixel size of AVHRR data did not capture this detailed information because other urban features (buildings and parking lots) dominated the pixel. Omission of other small land cover features in the study area by the AVHRR sensor is of concern, especially in highly fragmented landscapes. One approach would be to use sub-pixel techniques to disaggregate the mixed response from multiple features and estimate the proportion of features within each pixel. However, coarser spatial resolution data might not adequately detect features in highly fragmented landscapes due to the scaling effect.

Forest area estimates

Proportional estimates were adjusted based on the county-level omission and commission errors in the satellite derived maps (Fig. 2). Overlapping confidence intervals indicate that the estimates were not statistically different and the true value could be anywhere within this range. However, the confidence intervals associated with the ETM+ estimates were narrower than corresponding AVHRR estimates, indicating higher precision. Precision of the ETM+ estimates for all counties was higher than that of the AVHRR estimates. In the ETM+ derived map, the confidence intervals ranged between ±4.5% (San Augustine County) and ±7.9% (Rusk County). Corresponding values for the AVHRR derived map ranged between ±8.8% (San Augustine County) and ±11.5% (Panola County). San Augustine County had the lowest omission and commission errors, thus the 95% confidence interval estimates were narrow in both ETM+ and AVHRR derived maps, indicating higher precision. However, the estimates for Rusk and Panola counties had the lowest precision due to higher omission and commission errors in both maps. These results indicate that the estimates derived from single-date AVHRR are less precise than similar estimates derived from ETM+ data.

Incorporation of commission and omission errors and associating confidence intervals with the area

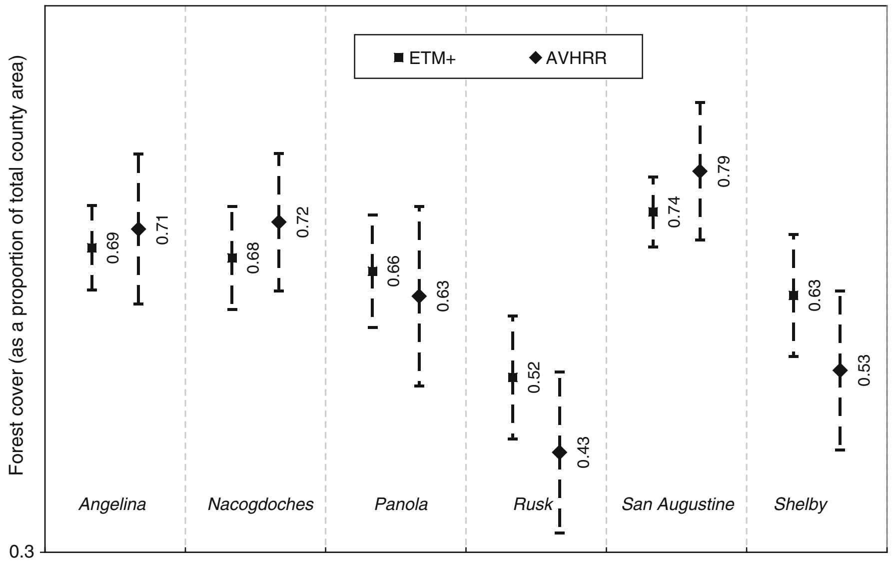

Fig. 2 Proportion of forest cover estimates for the counties along with the 95% confidence interval

estimates enable their meaningful comparison. Most studies often report a single number for the area estimate ignoring the commission and omission errors in the classified image, and comparisons drawn from such estimates could be misleading.

Results from these comparative analyses indicate that both ETM+ and AVHRR derived maps had similar problems relating to classification of forests. More errors were found in the classified images due to a land use based definition of forest rather than one based on land cover. Users of these and other satellite derived map products must take into account the differences in class definition and how it affects the overall accuracy of the maps prior to using them for estimating forest area or changes over time. On the other hand, agencies, similar to the USFS might find that information generated from satellite data does not match their existing definition of certain thematic classes. Differences similar to these would be of further importance when map products generated using different classification schemes are combined to compile continental or global scale maps.

Conclusions

Results obtained in this study demonstrate the difficulties in using a land use-based definition of landscape features for classifying digital remote sensing reflectance data that are based on land cover. Defining forests based on land use was the major source of error in both ETM+ and AVHRR derived maps.

Large spatial resolution of AVHRR data limited its ability to distinguish some small land cover features resulting in classification errors. These errors were smaller in comparison to the errors associated with defining forests; however in fragmented landscapes these errors could be large thus diminishing the utility of coarser spatial resolution remotely sensed data for mapping land cover. Forest area estimates obtained from the AVHRR derived map were less precise than the corresponding estimates obtained from the ETM+ derived map.

Acknowledgements This work was conducted as part of the first author's dissertation work at Texas A&M University. Financial support was provided to the first author by the Heep Foundation and the Texas Agricultural Experiment Station. Technical assistance provided by Mr. Thomas Spencer and Mr. Curt Stripling, Texas Forest Service is gratefully acknowledged. We thank Dr. William Cooke III (USFS/MSU) for assessing the accuracy of classified satellite data at the USFS lab. Dr. Balaji Narashiman and Dr. Rajaraman Jayakrishnan (Parsons Engineering, FL) assisted in obtaining and preprocessing the AVHRR data. We thank Mr. Phil Polzer, Ms. Teal Wyckoff, WYGISC, UW, for reviewing an earlier version of this manuscript.

References

Batista, G. T., Shimabukuro, Y. E., & Lawrence, W. T. (1997). Long-term monitoring of vegetation cover in the Amazonian region of northern Brazil using NOAA-AVHRR

data. *International Journal of Remote Sensing, 18*, 3195–3210.
Buyantuyev, A., & Wu, J. (2007). Effects of thematic resolution on landscape pattern analysis. *Landscape Ecology, 22*, 7–13.
Card, D. H. (1982). Using known map category marginal frequencies to improve estimates of thematic map accuracy. *Photogrammetric Engineering & Remote Sensing, 48*, 431–439.
Colombo, S., Chica-Olmo, M., Abarca, F., & Eva, H. (2004). Variographic analysis of tropical forest cover from multiscale remotely sensed imagery. *ISPRS Journal of Photogrammetry & Remote Sensing, 58*, 330–341.
Congalton, R. G., & Green, K. (1999). *Assessing the accuracy of remotely sensed data: Principles and practices*. Florida: Lewis Publishers.
Congalton, R. G., & Meed, R. A. (1983). A quantitative method to test for consistency and correctness in photointerpretation. *Photogrammetric Engineering & Remote Sensing, 49*, 69–74.
Duchemin, B. (1999). NOAA/AVHRR bidirectional reflectance: Modeling and application for the monitoring of a temperate forest. *Remote Sensing of Environment, 67*, 51–67.
Dymond, C. C., & Johnson, E. A. (2002). Mapping vegetation spatial patterns from modeled water, temperature and solar radiation gradients. *ISPRS Journal of Photogrammetry & Remote Sensing, 57*, 69–85.
FAO. (2001). *Global Forest Resources Assessment 2000—Main report*. FAO forestry paper 140. Food and Agriculture Organization of the United Nations: Rome, Italy.
Fernandez, A., Illera, P., & Casanova, J. L. (1997). Automatic mapping of surfaces affected by forest fires in Spain using AVHRR NDVI composite image data. *Remote Sensing of Environment, 60*, 153–162.
Friedl, M. A., McIver, D. K., Hodges, J. C. F., Zhang, X. Y., Muchoney, D., Strahler, A. H., et al. (2002). Global land cover mapping from MODIS: Algorithms and early results. *Remote Sensing of Environment, 83*, 287–302.
Gemmell, F., Varjo, J., & Strandstrom, M. (2001). Estimating forest cover in a boreal forest test site using thematic mapper data from two dates. *Remote Sensing of Environment, 77*, 197–211.
Giri, C., Zhu, Z., & Reed, B. (2005). A comparative analysis of the global land cover 2000 and MODIS land cover data sets. *Remote Sensing of Environment, 94*, 123–132.
Gould, F. W., Hoffman, G. O., & Rechenthin, C. A. (1960). *Vegetational areas of Texas. L-492*. College Station, USA: Texas Agricultural Extension Service.
Hansen, M. C., Defries, R. S., Townshend, J. R. G., & Sohlberg, R. (2000). Global land cover classification at 1 km spatial resolution using a classification tree approach. *International Journal of Remote Sensing, 21*, 1331–1364.
Hansen, M. C., & Reed, B. (2000). A comparison of the IGBP DISCover and University of Maryland 1 km global land cover products. *International Journal of Remote Sensing, 21*, 1365–1373.
Loveland, T. R., Reed, B. C., Brown, J. F., Ohlen, D. O., Zhu, Z., Yang, L., et al. (2000). Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. *International Journal of Remote Sensing, 21*, 1303–1330.
Mayaux, P., Grandi, G. D., & Malingreau, J. P. (2000). Central African forest cover revisited: A multisatellite analysis. *Remote Sensing of Environment, 71*, 183–196.
McCallum, I., Obersteiner, M., Nilsson, S., & Shvidenko, A. (2006). A spatial comparison of four satellite derived 1 km global land cover datasets. *International Journal of Applied Earth Observation and Geoinformation, 8*, 246–255.
McWilliams, W. H., & Bertelson, D. F. (1986). *Forest statistics for southeast Texas counties—1986*. Resourc. Bull. SO-114. New Orleans, USA: US Department of Agriculture, Forest Service, Southern Forest Research Station.
Millington, A. C., Velez-Liendo, X. M., & Bradley, A. V. (2003). Scale dependence in multitemporal mapping of forest fragmentation in Bolivia: Implications for explaining temporal trends in landscape ecology and applications to biodiversity conservation. *ISPRS Journal of Photogrammetry & Remote Sensing, 57*, 283–299.
Moore, M. M., & Bauer, M. E. (1990). Classification of forest vegetation in north-central Minnesota using Landsat multispectral scanner and thematic mapper data. *Forest Science, 36*, 330–342.
Murphy, P. A. (1976). *East Texas forests: Status and trends*. Resourc. Bull. SO-61. New Orleans, USA: US Department of Agriculture, Forest Service, Southern Forest Research Station.
Neumann, K., Herold, M., Hartley, A., & Schmullius, C. (2007). Comparative assessment of CORINE2000 and GLC2000: Spatial analysis of land cover data for Europe. *International Journal of Applied Earth Observation and Geoinformation, 9*, 425–437.
Pax-Lenney, M., Woodcock, C. E., Macomber, S. A., Gopal, S., & Song, C. (2001). Forest mapping with a generalized classifier and Landsat TM data. *Remote Sensing of Environment, 77*, 241–250.
Raptis, V. S., Vaughan, R. A., & Wright, G. G. (2003). The effect of scaling on land cover classification from satellite data. *Computers and Geosciences, 29*, 705–714.
Salajanu, D., & Olson, C. E. (2001). The significance of spatial resolution. *Journal of Forestry, 99*, 32–38.
Shen, W., Jenerette, D., Wu, J., & Gardner, R. H. (2004). Evaluating empirical scaling relations of pattern metrics with simulated landscapes. *Ecography, 27*, 459–469.
Sivanpillai, R. (2002). *Mapping and monitoring forest cover in east Texas using multi-resolution satellite imagery*. College Station, TX, USA: Doctoral Dissertation, Texas A&M University.
Sivanpillai, R., Smith, C.T., Srinivasan, R., Messina, M., & Wu, X.B. (2005). Estimating regional forest cover in east Texas using Enhanced Thematic Mapper (ETM+) data. *Forest Ecology and Management, 218*, 342–352.
Sivanpillai, R., Srinivasan, R., Smith, C.T., Messina, M., & Wu, X.B. (2007). Estimating regional forest cover in East Texas using Advanced Very High Resolution Radiometer (AVHRR) data. *International Journal of Applied Earth Observation and Geoinformation, 9*, 41–49.
Story, M., & Congalton, R. G. (1986). Accuracy assessment: A user's perspective. *Photogrammetric Engineering and Remote Sensing, 52*, 397–399.

Teillet, P. M., Staenz, K., & Williams, D. J. (1997). Effects of spectral, spatial and radiometric characteristics on remote sensing vegetation indices of forest regions. *Remote Sensing of Environment, 61*, 139–149.

Teuber, K. B. (1990). Use of AVHRR imagery for large-scale forest inventories. *Forest Ecology and Management, 33*(34), 621–631.

Wayman, J. P., Wynne, R. H., Scrivani, J. A., & Reams, G. R. (2001). Landsat TM-based forest area estimation using iterative guided spectral class rejection. *Photogrammetric Engineering and Remote Sensing, 67*, 1155–1165.

Wu, J. (2004). Effects of changing scale on landscape pattern analysis: Scaling relations. *Landscape Ecology, 19*, 125–138.

Wynne, R. H., Oderwald, R. G., Reams, G. R., & Scrivani, J. A. (2000). Optical remote sensing for forest area estimation. *Journal of Forestry, 98*, 31–36.

Xiao, X., Liu, J., Zhuang, D., Frolking, S., Boles, S., Xu, B., et al. (2003). Uncertainties in estimates of cropland area in China: A comparison between an AVHRR-derived dataset and a Landsat TM-derived dataset. *Global and Planetary Change, 37*, 297–306.