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Multitemporal Analysis Using Landsat Thematic Mapper (TM) Bands for Forest Cover Classification in East Texas

Jason Grogan
Arthur Temple College of Forestry and Agriculture, Stephen F. Austin State University, jgrogan@sfasu.edu

I-Kuai Hung
Arthur Temple College of Forestry and Agriculture, Stephen F. Austin State University, hungi@sfasu.edu

James Kroll
Arthur Temple College of Forestry and Agriculture, Stephen F. Austin State University, jkroll@sfasu.edu

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Jason C. Raines, Jason Grogan, I-Kuai Hung, and James Kroll

ABSTRACT

Land cover maps have been produced using satellite imagery to monitor forest resources since the launch of Landsat 1. Research has shown that stacking leaf-on and leaf-off imagery (combining two separate images into one image for processing) may improve classification accuracy. It is assumed that the combination of data will aid in differentiation between forest types. In this study we explored potential benefits of using multidate imagery versus single-date imagery for operational forest cover classification as part of an annual remote sensing forest inventory system. Landsat Thematic Mapper (TM) imagery was used to classify land cover into four classes. Six band combinations were tested to determine differences in classification accuracy and if any were significant enough to justify the extra cost and increased difficulty of image acquisition. The effects of inclusion/exclusion of the moisture band (TM band 5) also were examined. Results show overall accuracy ranged from 72 to 79% with no significant difference between single and multidate classifications. We feel the minimal increase (3.06%) in overall accuracy, coupled with the operational difficulties of obtaining multiple (two), useable images per year, does not support the use of multidate stacked imagery. Additional research should focus on fully utilizing data from a single scene by improving classification methodologies.

Keywords: remote sensing, unsupervised classification, pixel-based classification, land cover mapping

Satellite imagery has been used to monitor land resources and land cover/land-use change since the launch of Landsat 1 in 1972. Medium resolution imagery such as Landsat and Systeme pour l'Observation de la Terre covers a large geographic footprint, permitting (1) production of land cover maps at considerably less cost than traditional field methods and (2) producing maps in a repeatable manner on a much more regular cycle (Rack 2000, Bauer et al. 2004). Typically, land cover maps are produced using image classification procedures. The product of these classifications—the cover type map—can be used to monitor landscape change from total harvest operations, fires, or outbreaks of insects or disease, as well as to determine the distribution of various cover types (Bonn and Howarth 1983, Beaubien 1994, Jensen 2005). Additional analysis of land cover maps can aid in obtaining biometric measurements (when used alongside other data sources) and forest age class assessments and monitoring change in the landscape over time (Unger et al. 2003). Results from these analyses depend greatly on the accuracy of the initial classification and can be improved on by improving the accuracy of initial classification.

Unsupervised classification is a method used commonly by analysts when prior knowledge of the area is limited. This method allows the computer to assign each pixel of the input image into an output cluster using natural breaks in the data without interference from the analyst. The analyst then must assign each cluster into a meaningful class using reference data, generally high-resolution aerial photography, or high-resolution satellite imagery, to produce a cover type map (Campbell 2002). This study focuses specifically on producing a forest cover type map.

Several advantages and disadvantages have been identified when using unsupervised classification methods (Campbell 2002). The analyst does not need any prior knowledge of the region to perform the classification. However, the analyst must have enough knowledge of the region to classify the output clusters into meaningful classes. The analyst also limits the amount of human error introduced into the classification procedure due to the lack of input into the classification procedure besides specifying the number of output clusters. Unsupervised classification also allows for recognition of unique classes that may be missed or lumped into other classes when other classification methods are used. One limitation of unsupervised classification is that this methodology identifies spectrally homogenous classes that may not correspond to meaningful classes of interest to the analyst. The analyst has little control over the identity of each class, which can be very important when trying to match classifications for adjacent regions or similar dates. The spectral properties of an area can and will change over time, affecting the difference between spectrally similar classes as well as classes of interest to the end user.

Often, cover type maps are created from multidate composite images, which are needed to separate the spectral signatures of classes of interest to the user (Rack 2000, Campbell 2002). Although cover type classifications have been created using multidate and leaf-on only imagery, it may be possible to get statistically similar accuracies for a more detailed classification using leaf-off

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Jason C. Raines (rainesjason@titan.sfasu.edu) and Jason Grogan (jgrogan@sfasu.edu), Columbia Regional Geospatial Service Center, Stephen F. Austin State University, PO Box 13074, SFA Station, Nacogdoches, TX 75961. I-Kuai Hung (hungi@sfasu.edu), Arthur Temple College of Forestry, Stephen F. Austin State University, PO Box 6109 SFA Station, Nacogdoches, TX 75962. James Kroll (jkroll@sfasu.edu), Columbia Regional Geospatial Service Center, Stephen F. Austin University, PO Box 13074, SFA Station, Nacogdoches, TX 75962. *This project was funded in part by the Columbia Regional Geospatial Service Center, Arthur Temple College of Forestry and Agriculture and an appropriation from the State of Texas. We would like to thank the three anonymous reviewers for their comments, which improved the quality of this manuscript.*

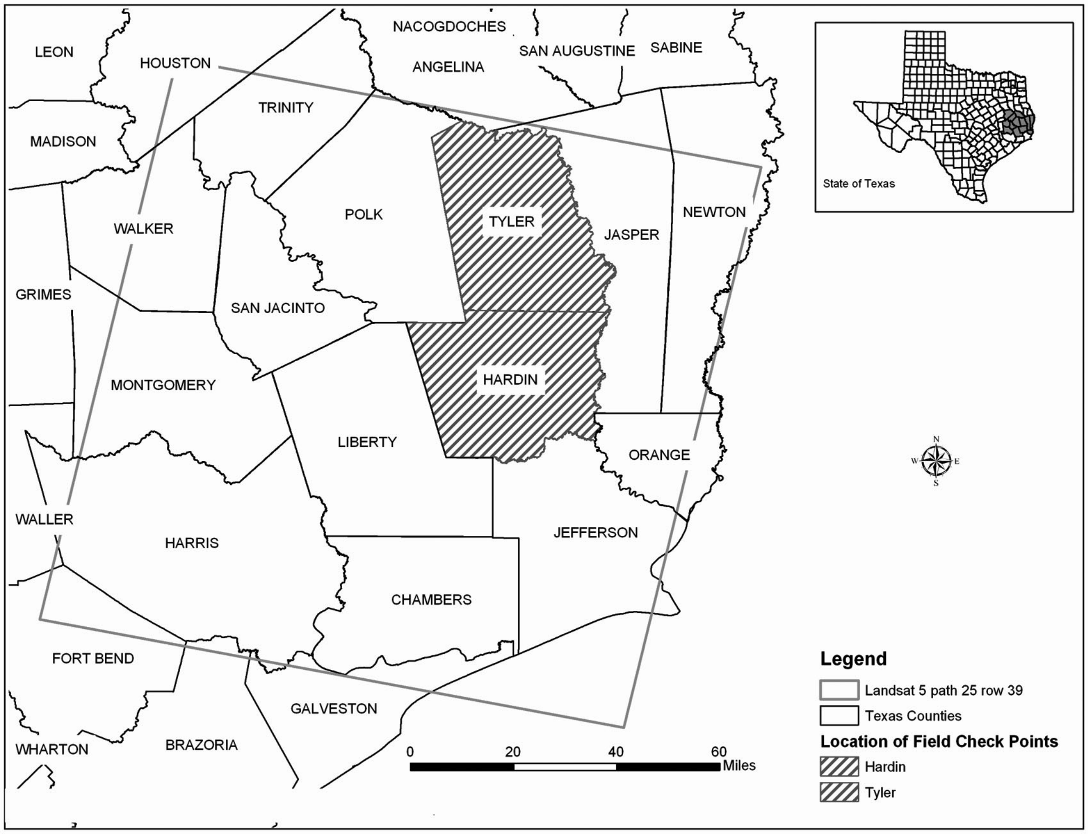


Figure 1. Study area for the ETFI—South Project.

imagery only (Dodge and Bryant 1976, Fox et al. 1983, Bauer et al. 1994, Sivanpillai et al. 2005). Six east Texas counties were successfully stratified into forest and nonforest areas in 2005 using Landsat 7 Enhanced Thematic Mapper (ETM) imagery and unsupervised classification methodologies (Sivanpillai et al. 2005). The results from this study compared favorably with Forest Inventory and Analysis phase 1 methods currently in use.

One of the initial goals of the East Texas Forest Inventory (ETFI) Project was to classify current forest composition by cover types (Unger et al. 2003). The same methodology used in the initial ETFI Project was expanded into the "flatwoods" area of southeast Texas. During our attempts to produce forest cover type maps for this area, concerns over high water table/excessive soil moisture confounding the classification were noted. Because of large amounts of flooded timber and saturated soils, Landsat TM band 5 (mid-infrared (MIR)—the moisture band) may be introducing a "normalizing" effect on the data when classified, resulting in a decrease in accuracy for the resulting cover type map. Therefore, it may be possible to achieve better accuracy of a forest cover type map by excluding the moisture band(s). Furthermore, stacking multiple scenes may exacerbate the normalizing effect by "doubling" the moisture band.

Objectives

The main goal of this study was to find the most efficient methodology of producing an accurate land cover map of southeast Texas in an applied, operational setting, which consisted of three primary objectives. The first objective was to determine whether a leaf-off only or a stacked leaf-off–leaf-on Landsat TM image will result in greater accuracy when classifying forest cover types. The second was to determine if including or excluding the moisture layer (band 5) from stacked or leaf-off only TM imagery will result in greater overall accuracy. The third objective was to find any differences in classification accuracy between the six band combinations tested, to determine the most effective methodology for creating forest cover type maps of east Texas on an annual basis. The key issue here was determining a classification methodology that is highly accurate and can be consistently applied annually to the best available data. Past studies have examined the use of multidate stacks based on "ideal" circumstances, rather than the reality of difficulties of annually obtaining multiple, usable images.

Study Area

The study area was based in a single Landsat TM scene (path 25, row 39). This scene contains, partially or completely, the following Texas counties in the study area: Angelina, Hardin, Houston, Jasper, Liberty, Montgomery, Newton, Orange, Polk, San Jacinto, Trinity, Tyler, and Walker counties—referred to as southeast Texas (Figure 1). Southeast Texas is dominated by industrial and nonindustrial pine plantations (*Pinus* spp.), upland pine-hardwood communities (*Pinus* spp., *Quercus* spp., *Carya, Sassafras*, and *Ulmus*), and bottomland hardwood forests (*Quercus* spp., *Acer*, *Betula*, *Magnolia*, *Ilex*, and *Fraxinus*) along creeks, rivers, and swamps (Nixon and Cunningham 1985). Farmland and prairies also comprise a small portion of the landscape. Elevation ranges from 30 to 400 ft (9–122 m) above mean sea level with average summer temperatures around 94°F (34°C) and average winter temperatures around 40°F (4°C). Precipitation averages between 40 and 50 in. (102–127 cm) per year with a growing season lasting 241–246 days (University of Texas at Austin/Texas State Historical Association 2007).

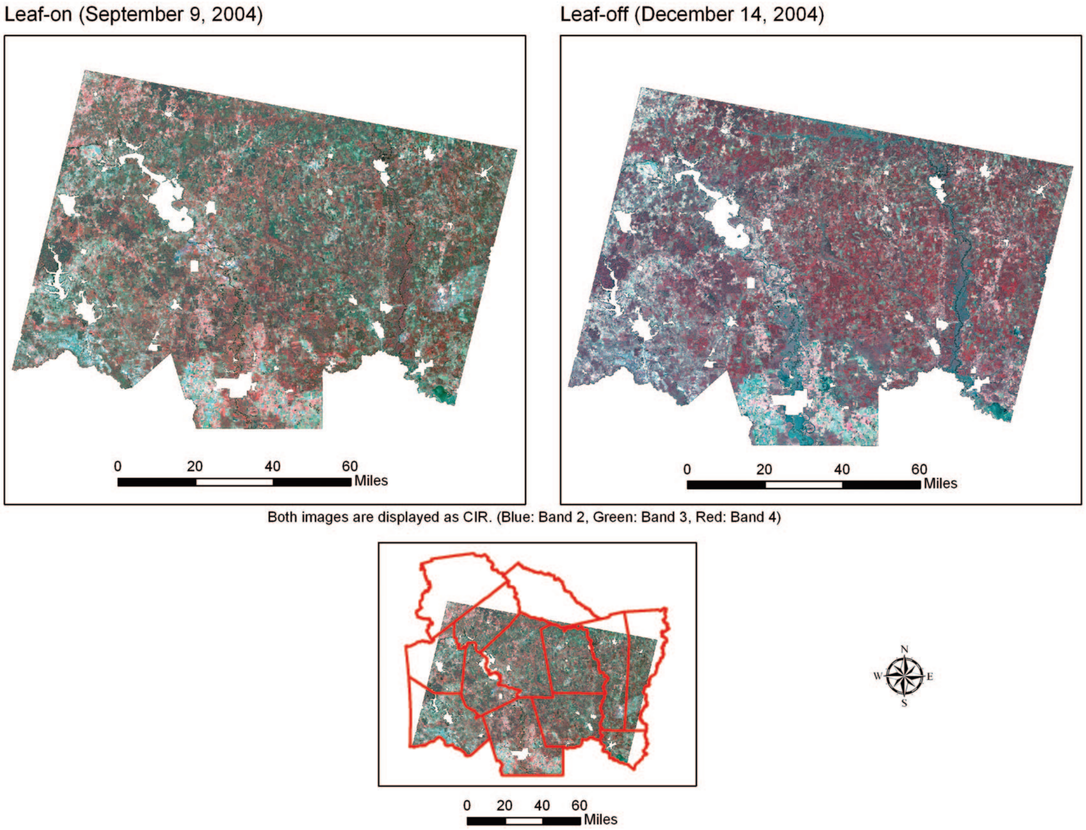


Figure 2. Landsat imagery used to perform forest cover classification analysis after preprocessing.

Methods

Landsat TM imagery from two acquisition dates was used in this study (Sept. 9, 2004 as leaf-on and Dec. 14, 2004 as leaf-off), which were acquired from the USGS Earth Resources Observation and Science Data Center. ERDAS Imagine 8.7 (Leica Geosystems AG, St. Gallen, Switzerland) and ArcGIS 9.1 (Environmental Systems Research Institute, Inc., [ESRI] Redlands, CA) software were used for image processing purposes. Radiometric correction was performed via dark object subtraction to remove atmospheric haze and environmental noise from both scenes (Campbell 2002, Jensen 2005). Some clouds present in the leaf-on image were removed by manual digitization. These areas were replaced using another leaf-on Landsat TM image acquired on Nov. 11, 2003. The Gulf Coastal Prairie and Houston metropolitan areas were removed from both scenes because these areas are not of interest in this study and could introduce bias and confusion into the classification. Other urban areas inside the study area were removed as well using a vector layer from the Texas Natural Resources Information System created by the Strategic Mapping Program (StratMap). Water bodies were removed using a vector layer from the National Hydrography Dataset. Figure 2 shows both Landsat TM scenes after preprocessing.

Once preprocessing was completed, six band combinations were created (Table 1), tested, and analyzed using ERDAS Imagine 8.7 software. Band combinations were selected based on combinations of leaf-on and leaf-off imagery that included and excluded the moisture layer—TM band 5 (Campbell 2002). Previous studies have delineated forest cover types with TM band 7 (second MIR band) excluded, and also with leaf-off only Landsat imagery; therefore, TM band 7 was not included in any combination, and no leaf-on only combinations were tested (Londo et al. 2000, Collins et al. 2005). Each band combination went through an unsupervised classification using the Iterative Self-Organizing Data Analysis algorithm to obtain 100 unknown clusters of pixels (ERDAS 2006). Then, each cluster was recoded into one of four cover type classes (pine forest, hardwood forest, mixed pine-hardwood forest, and nonforest) using nine 2004, leaf-off, high-resolution aerial photographs purchased from the Texas Forest Service as a visual reference. All band combinations were classified and recoded by the same analyst to eliminate skill level differences between multiple analysts. Class description was determined using an 80% majority coverage rule. That is, if hardwood or pine canopy covered 80% or greater of a pixel area, the pixel was coded as pure hardwood or pure pine, respectively. A forested pixel was classified as mixed pine-hardwood if neither pine nor hardwood canopy occupied more than 80% of the pixel area (Collins et al. 2005).

To determine accuracy of the classified images, field check points were selected based on a stratified random sample with a minimum

Table 1. Landsat TM band combinations tested on southeast Texas for forest cover type classification.

Band combination	Bands		Total number of bands
	Leaf-off	Leaf-on	
A	1–4		4
B	1–5		5
C	1–4	1–4	8
D	1–4	1–5	9
E	1–5	1–4	9
F	1–5	1–5	10

Band 1: blue-green, 0.45–0.52 μm; band 2: green, 0.52–0.60 μm; band 3: red, 0.63–0.69 μm; band 4: near infrared, 0.76–0.90 μm; band 5: midinfrared, 1.55–1.75 μm (Campbell 2002)

Table 2. Accuracy assessment for band combination A (bands 1–4 leaf-off).

Classified Data Class	Reference data				Total	User's (%)	Kappa (%)
	Nonforest	Pine	Hardwood	Mixed			
Nonforest	39	3	1	0	43	90.70	89.07
Pine	0	114	6	13	133	85.71	70.99
Hardwood	0	5	33	7	45	73.33	65.92
Mixed	0	11	17	13	41	31.71	21.87
Total	39	133	57	33	262	Overall	
Producer's (%)	100.00	85.71	57.89	39.39		75.95	63.61

Table 3. Accuracy assessment for band combination B (bands 1–5 leaf-off).

Classified Data Class	Reference data				Total	User's (%)	Kappa (%)
	Nonforest	Pine	Hardwood	Mixed			
Non-forest	39	4	1	2	46	84.78	82.12
Pine	0	118	10	14	142	83.10	65.67
Hardwood	0	2	25	4	31	80.65	75.26
Mixed	0	9	21	13	43	30.23	20.18
Total	39	133	57	33	262	Overall	
Producer's (%)	100.00	88.72	43.86	39.39		74.43	60.80

Table 4. Accuracy assessment for band combination C (bands 1–4 leaf-off and bands 1–4 leaf-on).

Classified Data Class	Reference data				Total	User's (%)	Kappa (%)
	Nonforest	Pine	Hardwood	Mixed			
Nonforest	39	6	1	1	47	82.98	80.00
Pine	0	116	2	10	128	90.63	80.96
Hardwood	0	2	46	16	64	71.88	64.05
Mixed	0	9	8	6	23	26.09	15.44
Total	39	133	57	33	262	Overall	
Producer's (%)	100.00	87.22	80.70	18.18		79.01	68.25

Table 5. Accuracy assessment for band combination D (bands 1–4 leaf-off and bands 1–5 leaf-on).

Classified Data Class	Reference data				Total	User's (%)	Kappa (%)
	Nonforest	Pine	Hardwood	Mixed			
Nonforest	39	14	1	0	54	72.22	67.36
Pine	0	107	3	9	119	89.92	79.52
Hardwood	0	1	38	11	50	76.00	69.33
Mixed	0	11	15	13	39	33.33	23.73
Total	39	133	57	33	262	Overall	
Producer's (%)	100.00	80.45	66.67	39.39		75.19	63.43

of 30 points in each class (Congalton and Green 1999). A total of 262 points were created in Tyler and Hardin counties. Field check plots were located using an Archer field computer by Juniper Systems (Juniper Systems, Inc., Logan, UT) with ArcPad software (ESRI) and a Geneq SXBlue global positioning systems receiver (Geneq, Inc., Montreal, QB, Canada). Cover type of each plot was determined in the field during the summer of 2006. Normally, very little change in cover type occurs over a short time period (1–2 years); however, in areas where obvious change had occurred, attempts were made to reconstruct 2004 conditions. Accuracy assessment was performed using the accuracy assessment tool present in ERDAS Imagine 8.7.

Kappa-analysis was performed to determine statistically if error matrices were different from one another (Congalton and Green 1999). Additional statistical testing, focusing on the binary distinction between correct and incorrect reference point classification was performed using the McNemar test (Foody 2004, Leeuw et al. 2006). This test has been used in remote sensing to determine significant differences between two thematic maps when the same set of reference points was used to determine accuracy. All statistical calculations were performed at the 90% confidence level ($\alpha = 0.1$).

Results

Accuracy assessment showed each band combination had an overall accuracy of between 72 and 80% and overall kappa-values between 59 and 69%, indicating moderate agreement between the classified data and the reference data (Congalton and Green 1999). Tables 2–7 show the error matrices for each band combination. These tables also show where many of the misclassification errors occurred. The most common source of misclassification was in the mixed class, which had by far the lowest average accuracy. Pine accuracy generally was over 80%, indicating good separation of pine pixels from others by the unsupervised classification. *Z*-scores were calculated for each individual band combination to determine whether or not results of the classification were better than random chance. *Z*-scores ranged from 15.4 to 18.97, and when compared

Table 6. Accuracy assessment for band combination E (bands 1–5 leaf-off and bands 1–4 leaf-on).

Classified Data Class	Reference data						
	Nonforest	Pine	Hardwood	Mixed	Total	User's (%)	Kappa (%)
Nonforest	39	4	1	1	45	86.67	84.33
Pine	0	108	4	11	123	87.80	75.23
Hardwood	0	2	45	10	57	78.95	73.09
Mixed	0	19	7	11	37	29.73	19.60
Total	39	133	57	33	262	Overall	
Producer's (%)	100.00	81.20	78.95	33.33		77.48	66.44

Table 7. Accuracy assessment for band combination F (bands 1–5 leaf-off and bands 1–5 leaf-on).

Classified Data Class	Reference data						
	Nonforest	Pine	Hardwood	Mixed	Total	User's (%)	Kappa (%)
Nonforest	39	6	1	1	47	82.98	80.00
Pine	0	102	3	8	113	90.27	80.23
Hardwood	0	1	35	11	47	74.47	67.37
Mixed	0	24	18	13	55	23.64	12.63
Total	39	133	57	33	262	Overall	
Producer's (%)	100.00	76.69	61.40	39.39		72.14	59.55

Table 8. Results of kappa-analysis for the comparison of six band combinations using the delta-method (tested at $\alpha = 0.10$).

	Band combinations				
	B	C	D	E	F
A	0.5147 (0.6068)	0.8835 (0.3770)	0.0347 (0.9723)	0.5284 (0.5972)	0.7493 (0.4537)
B		1.4066 (0.1595)	0.4849 (0.6277)	1.0455 (0.2958)	0.2304 (0.8177)
C			0.9279 (0.3534)	0.3504 (0.7261)	1.6531 (0.0983)
D				0.5686 (0.5696)	0.7216 (0.4706)
E					1.2857 (0.1985)

Z-value (*P*-value).

Table 9. Results of McNemar test for the comparison of six band combinations (tested at $\alpha = 0.10$).

	Band combinations				
	B	C	D	E	F
A	0.5000 (0.4795)	1.5238 (0.2170)	0.1667 (0.6830)	0.5000 (0.4795)	2.7778 (0.0956)
B		2.7692 (0.0961)	0.0909 (0.7630)	1.6000 (0.2059)	0.9000 (0.3428)
C			2.9412 (0.0863)	0.4000 (0.5271)	8.1000 (0.0044)
D				1.3846 (0.2393)	2.1333 (0.1441)
E					6.5333 (0.0106)

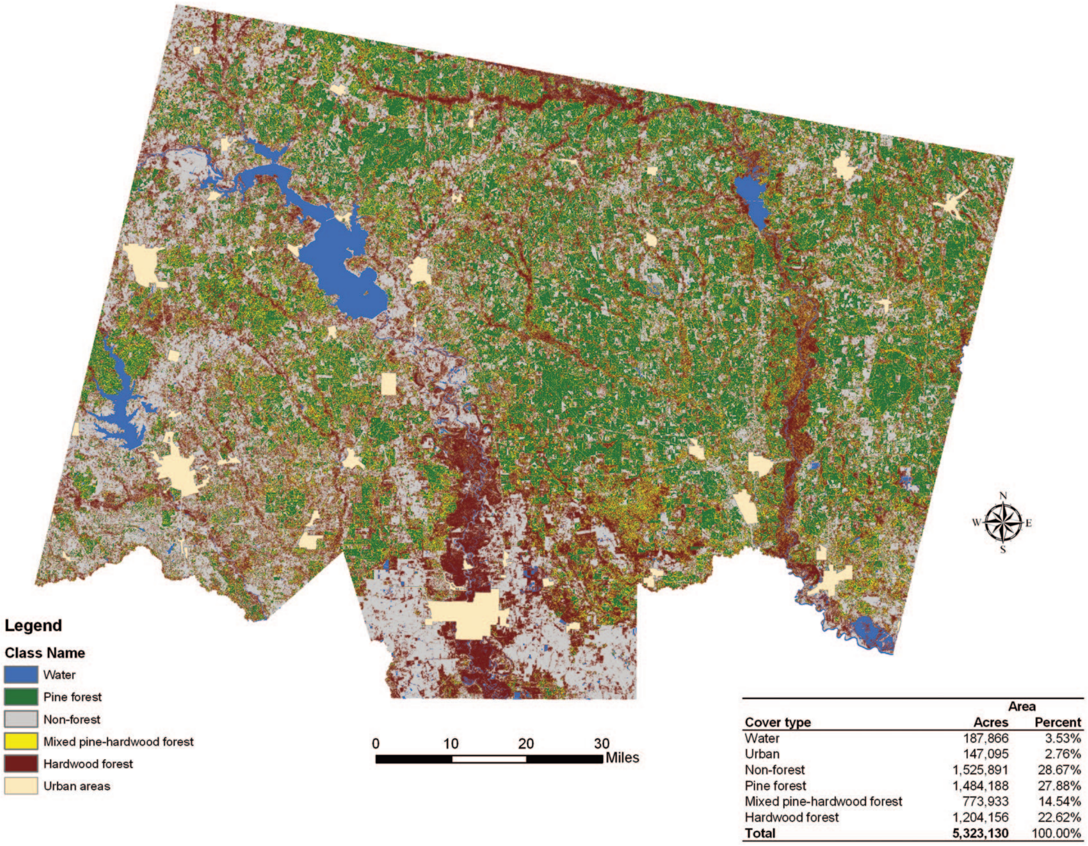
Chi-square value (*P*-value).

with a critical *Z*-value of 1.6449, indicate all the classified images were classified better than random.

Statistical analysis performed using pairwise comparison methodologies is shown in Tables 8 and 9. Band combinations were compared two at a time for a total of 15 statistical comparisons. A statistically significant difference is present if the *Z*-value is greater than 1.6449 ($P < 0.1$) for the kappa-analysis or a chi-square value of 2.706 ($P < 0.1$) for the McNemar test. The only band combinations that showed any statistically significant difference using kappa-analysis was between combination F (bands 1–5 leaf-off with bands 1–5 leaf-on) and combination C (bands 1–4 leaf-off with bands 1–4 leaf-on). In this case, combination C produced a significantly better forest cover type classification than combination F. Figure 3 shows the forest cover type classification produced by band combination C, which had an overall classification accuracy of 79.01%. Using the McNemar test, a total of six band combination comparisons were found to have significant differences (Table 9). Based on this test, combinations A, E, and F produced statistically superior results (overall accuracies of 75.95, 77.48, and 79.01%, respectively) to other combinations. Combinations B, C, and D all produced statistically inferior results to at least one of the aforementioned band combinations.

Discussion

The large majority of misclassification occurred within the mixed pine-hardwood cover type class. This could be for several reasons. One reason could be not enough initial clusters were created to discriminate between over 80% majority coverage and under 80% majority coverage. Misclassification in the mixed forest category could be caused by a lack of enough aerial photographs acquired for reference data to provide an accurate representation of the entire study area for recoding the original clusters. All mixed forest classification errors were split almost evenly between pine and hardwood classes, which indicate neither pure cover type was biased over the other.



	Area	
Cover type	Acres	Percent
Water	187,866	3.53%
Urban	147,095	2.76%
Non-forest	1,525,891	28.67%
Pine forest	1,484,188	27.88%
Mixed pine-hardwood forest	773,933	14.54%
Hardwood forest	1,204,156	22.62%
Total	**5,323,130**	100.00%

Figure 3. Forest cover type map resulting from band combination C (79.01% overall accuracy).

The moisture band (TM band 5—MIR) did tend to have a normalizing effect on pixels representing forested areas when unsupervised classification was conducted. Initially, a total of 100 clusters were generated. When moisture bands were included, the first 20–25 clusters represented pine pixels, the middle 40–50 clusters represented hardwood and mixed forest pixels, and the last 25–30 clusters represented nonforest pixels. In comparison, when the moisture bands were removed, as in combinations C and A, the first 65–75 clusters represented all three types of forest cover pixels and the last 20–30 clusters represented nonforest pixels. This indicates a normalizing effect on the unsupervised classification occurred when the moisture bands were included in the analysis. However, excluding the moisture bands only significantly increased accuracy when using a multidate composite image, where both moisture bands were excluded, but not when using a single-date image.

Table 10. Budget comparison of 2004 forest cover type classifications in southeast Texas using Landsat TM imagery.

Costs	Date	Price
Leaf-off only		
5025039000434910	Dec. 14, 2004	$500.00
Analyst costs (55 hr)[a]		$1,084.05
Total		$1,584.05
Stacked		
5025039000434910	Dec. 14, 2004	$500.00
5025039000425310	Sept. 9, 2004	$500.00
5025039000331410[b]	Nov. 11, 2003	$500.00
Analyst costs (70 hr)[a]		$1,379.70
Total		$2,879.70
Total saved using leaf-off only versus stacked		$1,295.65
Percent savings using leaf-off versus stacked		55.01%

[a] Rate based on $41,000/yr salary (salary.com, Inc. 2007).
[b] Used to replace cloud areas in 5025039000425310.

The multidate composite combinations failed to increase accuracy significantly when compared with the leaf-off only combination with the moisture band (band 5) removed. Therefore, increased cost in terms of imagery needed and processing time by the analyst may not be justified (Table 10). Using only a single leaf-off image to produce a forest cover type map of southeast Texas eliminates the need to find multiple cloud-free images for the same year, which in some years can be very difficult, if not impossible. Also, it eliminates the need for the preprocessing of an extra image, or in the case of this study, two extra images. The use of a single-date image of four bands (combination A) also decreases time required by the analyst for preprocessing procedures, storage space, and processing requirements of the computer used to complete the task. Besides reduced cost and preprocessing requirements, another main advantage of using only a single image is the ability to capture the conditions of an area at a single point in time. This can be a major advantage for change detection studies in areas that are rapidly changing, where a multidate image could potentially introduce significant error.

Conclusions

Landsat TM data using various band combinations can be used successfully to discriminate between forest cover types in southeast Texas. However, a single leaf-off Landsat TM scene can produce statistically similar results as multidate composite Landsat TM images when classifying forest cover type. This translates into tremendous savings in image acquisition, analysis, and analyst time and effort required for processing. These savings, when considered as a single instance, may seem insignificant. However, in an operational, annual inventory system, savings could be tremendous over just a few years. Also, often times, it is difficult to obtain a single useable Landsat scene annually, and in many years multiple cloud-free scenes simply are not available. The success of an operational truly annual system only can be achieved when necessary imagery is available annually. With statistically similar accuracies between single and multidate classifications, truly annual updates seem more likely to be a reality with single-date imagery. The methodology used here could allow analysts to produce a forest cover type map on an annual or biannual basis, which could help natural resource managers and policymakers make decisions based on current information. In fact, data from the ETFI project already have been used to monitor annual change (harvesting and reforestation) from 2002 to 2006 for a different study area. In addition, results show that the moisture band (Landsat TM band 5) can be excluded in areas with saturated and/or flooded soils without significant change in accuracy.

Additional studies should focus on several areas that are currently and continue to be researched. An objective methodology of determining cover type in the field should be standardized so it does not depend solely on the experience of the analyst. Other areas of research should and currently do focus on using elevation data (digital elevation model) and/or indices such as Normalized Difference Vegetation Index, Tasseled Cap transformation or other vegetation indices in combination with the Landsat TM data to enhance information already present in the satellite imagery. New object-oriented classifiers and supervised classification also should be researched to determine if there is any increase in accuracy when classifying forest cover type from Landsat data. Finally, we propose methods using data from a single TM image should be researched before adding additional bands (images), which potentially could confound the classification.

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